NumPyro Documentation

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Contents

CHAPTER 1

Getting Started with NumPyro

Probabilistic programming with NumPy powered by JAX for autograd and JIT compilation to GPU/TPU/CPU.

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1.1 What is NumPyro?

NumPyro is a small probabilistic programming library that provides a NumPy backend for Pyro. We rely on JAX for automatic differentiation and JIT compilation to GPU / CPU. This is an alpha release under active development, so beware of brittleness, bugs, and changes to the API as the design evolves.

NumPyro is designed to be *lightweight* and focuses on providing a flexible substrate that users can build on:

- **Pyro Primitives:** NumPyro programs can contain regular Python and NumPy code, in addition to Pyro primitives like `sample` and `param`. The model code should look very similar to Pyro except for some minor differences between PyTorch and Numpy's API. See the example below.
- **Inference algorithms:** NumPyro currently supports Hamiltonian Monte Carlo, including an implementation of the No U-Turn Sampler. One of the motivations for NumPyro was to speed up Hamiltonian Monte Carlo by JIT compiling the verlet integrator that includes multiple gradient computations. With JAX, we can compose `jit` and `grad` to compile the entire integration step into an XLA optimized kernel. We also eliminate Python overhead by JIT compiling the entire tree building stage in NUTS (this is possible using Iterative NUTS). There is also a basic Variational Inference implementation for reparameterized distributions together with many flexible (auto)guides for Automatic Differentiation Variational Inference (ADVI).
- **Distributions:** The numpyro.distributions module provides distribution classes, constraints and bijective transforms. The distribution classes wrap over samplers implemented to work with JAX's functional pseudo-random number generator. The design of the distributions module largely follows from PyTorch. A major subset of the API is implemented, and it contains most of the common distributions that exist in PyTorch. As a result, Pyro and PyTorch users can rely on the same API and batching semantics as in `torch.distributions`. In addition to distributions, `constraints` and `transforms` are very useful when operating on distribution classes with bounded support.

- **Effect handlers:** Like Pyro, primitives like `sample` and `param` can be provided nonstandard interpretations using effect-handlers from the numpyro.handlers module, and these can be easily extended to implement custom inference algorithms and inference utilities.

1.2 A Simple Example - 8 Schools

Let us explore NumPyro using a simple example. We will use the eight schools example from Gelman et al., Bayesian Data Analysis: Sec. 5.5, 2003, which studies the effect of coaching on SAT performance in eight schools.

The data is given by:

```
>>> import numpy as np


>>> J = 8

>>> y = np.array([28.0, 8.0, -3.0, 7.0, -1.0, 1.0, 18.0, 12.0])

>>> sigma = np.array([15.0, 10.0, 16.0, 11.0, 9.0, 11.0, 10.0, 18.0])
```

, where `y` are the treatment effects and `sigma` the standard error. We build a hierarchical model for the study where we assume that the group-level parameters `theta` for each school are sampled from a Normal distribution with unknown mean `mu` and standard deviation `tau`, while the observed data are in turn generated from a Normal distribution with mean and standard deviation given by `theta` (true effect) and `sigma`, respectively. This allows us to estimate the population-level parameters `mu` and `tau` by pooling from all the observations, while still allowing for individual variation amongst the schools using the group-level `theta` parameters.

```
>>> import numpyro

>>> import numpyro.distributions as dist


>>> # Eight Schools example

... def eight_schools(J, sigma, y=None):

...     mu = numpyro.sample('mu', dist.Normal(0, 5))

...     tau = numpyro.sample('tau', dist.HalfCauchy(5))

...     with numpyro.plate('J', J):

...         theta = numpyro.sample('theta', dist.Normal(mu, tau))

...         numpyro.sample('obs', dist.Normal(theta, sigma), obs=y)
```

Let us infer the values of the unknown parameters in our model by running MCMC using the No-U-Turn Sampler (NUTS). Note the usage of the `extra_fields` argument in MCMC.run. By default, we only collect samples from the target (posterior) distribution when we run inference using `MCMC`. However, collecting additional fields like potential energy or the acceptance probability of a sample can be easily achieved by using the `extra_fields` argument. For a list of possible fields that can be collected, see the HMCState object. In this example, we will additionally collect the `potential_energy` for each sample.

```
>>> from jax import random

>>> from numpyro.infer import MCMC, NUTS


>>> nuts_kernel = NUTS(eight_schools)

>>> mcmc = MCMC(nuts_kernel, num_warmup=500, num_samples=1000)

>>> rng_key = random.PRNGKey(0)

>>> mcmc.run(rng_key, J, sigma, y=y, extra_fields=('potential_energy',))
```

We can print the summary of the MCMC run, and examine if we observed any divergences during inference. Additionally, since we collected the potential energy for each of the samples, we can easily compute the expected log joint density.

```
>>> mcmc.print_summary()


                mean       std    median      5.0%     95.0%     n_eff     r_hat
        mu      4.14      3.18      3.87     -0.76      9.50    115.42      1.01
       tau      4.12      3.58      3.12      0.51      8.56     90.64      1.02
  theta[0]      6.40      6.22      5.36     -2.54     15.27    176.75      1.00
  theta[1]      4.96      5.04      4.49     -1.98     14.22    217.12      1.00
  theta[2]      3.65      5.41      3.31     -3.47     13.77    247.64      1.00
  theta[3]      4.47      5.29      4.00     -3.22     12.92    213.36      1.01
  theta[4]      3.22      4.61      3.28     -3.72     10.93    242.14      1.01
  theta[5]      3.89      4.99      3.71     -3.39     12.54    206.27      1.00
  theta[6]      6.55      5.72      5.66     -1.43     15.78    124.57      1.00
  theta[7]      4.81      5.95      4.19     -3.90     13.40    299.66      1.00


Number of divergences: 19


>>> pe = mcmc.get_extra_fields()['potential_energy']

>>> print('Expected log joint density: {:.2f}'.format(np.mean(-pe)))

Expected log joint density: -54.55
```

The values above 1 for the split Gelman Rubin diagnostic (`r_hat`) indicates that the chain has not fully converged. The low value for the effective sample size (`n_eff`), particularly for `tau`, and the number of divergent transitions

looks problematic. Fortunately, this is a common pathology that can be rectified by using a non-centered paramaterization for `tau` in our model. This is straightforward to do in NumPyro by using a TransformedDistribution instance together with a reparameterization effect handler. Let us rewrite the same model but instead of sampling `theta` from a `Normal(mu, tau)`, we will instead sample it from a base `Normal(0, 1)` distribution that is transformed using an AffineTransform. Note that by doing so, NumPyro runs HMC by generating samples `theta_base` for the base `Normal(0, 1)` distribution instead. We see that the resulting chain does not suffer from the same pathology — the Gelman Rubin diagnostic is 1 for all the parameters and the effective sample size looks quite good!

```
>>> from numpyro.infer.reparam import TransformReparam


>>> # Eight Schools example - Non-centered Reparametrization
... def eight_schools_noncentered(J, sigma, y=None):
...     mu = numpyro.sample('mu', dist.Normal(0, 5))
...     tau = numpyro.sample('tau', dist.HalfCauchy(5))
...     with numpyro.plate('J', J):
...         with numpyro.handlers.reparam(config={'theta': TransformReparam()}):
...             theta = numpyro.sample(
...                 'theta',
...                 dist.TransformedDistribution(dist.Normal(0., 1.),
...                                              dist.transforms.AffineTransform(mu,␣
↪tau)))
...         numpyro.sample('obs', dist.Normal(theta, sigma), obs=y)


>>> nuts_kernel = NUTS(eight_schools_noncentered)
>>> mcmc = MCMC(nuts_kernel, num_warmup=500, num_samples=1000)
>>> rng_key = random.PRNGKey(0)
>>> mcmc.run(rng_key, J, sigma, y=y, extra_fields=('potential_energy',))
>>> mcmc.print_summary(exclude_deterministic=False)


                mean       std    median      5.0%     95.0%     n_eff     r_hat
          mu      4.08      3.51      4.14     -1.69      9.71    720.43      1.00
         tau      3.96      3.31      3.09      0.01      8.34    488.63      1.00
    theta[0]      6.48      5.72      6.08     -2.53     14.96    801.59      1.00
```

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```
     theta[1]      4.95      5.10      4.91     -3.70     12.82   1183.06      1.00
     theta[2]      3.65      5.58      3.72     -5.71     12.13    581.31      1.00
     theta[3]      4.56      5.04      4.32     -3.14     12.92   1282.60      1.00
     theta[4]      3.41      4.79      3.47     -4.16     10.79    801.25      1.00
     theta[5]      3.58      4.80      3.78     -3.95     11.55   1101.33      1.00
     theta[6]      6.31      5.17      5.75     -2.93     13.87   1081.11      1.00
     theta[7]      4.81      5.38      4.61     -3.29     14.05    954.14      1.00
theta_base[0]      0.41      0.95      0.40     -1.09      1.95    851.45      1.00
theta_base[1]      0.15      0.95      0.20     -1.42      1.66   1568.11      1.00
theta_base[2]     -0.08      0.98     -0.10     -1.68      1.54   1037.16      1.00
theta_base[3]      0.06      0.89      0.05     -1.42      1.47   1745.02      1.00
theta_base[4]     -0.14      0.94     -0.16     -1.65      1.45    719.85      1.00
theta_base[5]     -0.10      0.96     -0.14     -1.57      1.51   1128.45      1.00
theta_base[6]      0.38      0.95      0.42     -1.32      1.82   1026.50      1.00
theta_base[7]      0.10      0.97      0.10     -1.51      1.65   1190.98      1.00

Number of divergences: 0

>>> pe = mcmc.get_extra_fields()['potential_energy']
>>> # Compare with the earlier value
>>> print('Expected log joint density: {:.2f}'.format(np.mean(-pe)))
Expected log joint density: -46.09
```

Note that for the class of distributions with `loc, scale` paramaters such as `Normal`, `Cauchy`, `StudentT`, we also provide a LocScaleReparam reparameterizer to achieve the same purpose. The corresponding code will be

```
with numpyro.handlers.reparam(config={'theta': LocScaleReparam(centered=0)}):
    theta = numpyro.sample('theta', dist.Normal(mu, tau))
```

Now, let us assume that we have a new school for which we have not observed any test scores, but we would like to generate predictions. NumPyro provides a Predictive class for such a purpose. Note that in the absence of any observed data, we simply use the population-level parameters to generate predictions. The `Predictive` utility conditions the unobserved `mu` and `tau` sites to values drawn from the posterior distribution from our last MCMC run, and runs the model forward to generate predictions.

```
>>> from numpyro.infer import Predictive


>>> # New School
... def new_school():
...     mu = numpyro.sample('mu', dist.Normal(0, 5))
...     tau = numpyro.sample('tau', dist.HalfCauchy(5))
...     return numpyro.sample('obs', dist.Normal(mu, tau))


>>> predictive = Predictive(new_school, mcmc.get_samples())
>>> samples_predictive = predictive(random.PRNGKey(1))
>>> print(np.mean(samples_predictive['obs']))
3.9886456
```

1.3 More Examples

For some more examples on specifying models and doing inference in NumPyro:

- Bayesian Regression in NumPyro - Start here to get acquainted with writing a simple model in NumPyro, MCMC inference API, effect handlers and writing custom inference utilities.
- Time Series Forecasting - Illustrates how to convert for loops in the model to JAX's `lax.scan` primitive for fast inference.
- Baseball example - Using NUTS for a simple hierarchical model. Compare this with the baseball example in Pyro.
- Hidden Markov Model in NumPyro as compared to Stan.
- Variational Autoencoder - As a simple example that uses Variational Inference with neural networks. Pyro implementation for comparison.
- Gaussian Process - Provides a simple example to use NUTS to sample from the posterior over the hyper-parameters of a Gaussian Process.
- Statistical Rethinking with NumPyro - Notebooks containing translation of the code in Richard McElreath's Statistical Rethinking book second version, to NumPyro.
- Other model examples can be found in the examples folder.

Pyro users will note that the API for model specification and inference is largely the same as Pyro, including the distributions API, by design. However, there are some important core differences (reflected in the internals) that users should be aware of. e.g. in NumPyro, there is no global parameter store or random state, to make it possible for us to leverage JAX's JIT compilation. Also, users may need to write their models in a more *functional* style that works better with JAX. Refer to *FAQs* for a list of differences.

1.4 Installation

> **Limited Windows Support:** Note that NumPyro is untested on Windows, and might require building jaxlib from source. See this JAX issue for more details. Alternatively, you can install Windows Subsystem for Linux and use NumPyro on it as on a Linux system. See also CUDA on Windows Subsystem for Linux and this forum post if you want to use GPUs on Windows.

To install NumPyro with a CPU version of JAX, you can use pip:

```
pip install numpyro
```

To use NumPyro on the GPU, you will need to first install `jax` and `jaxlib` with CUDA support.

To run NumPyro on Cloud TPUs, you can use pip to install NumPyro as above and setup the TPU backend as detailed here.

> **Default Platform:** In contrast to JAX, which uses GPU as the default platform, we use CPU as the default platform. You can use set_platform utility to switch to other platforms such as GPU or TPU at the beginning of your program.

You can also install NumPyro from source:

```
git clone https://github.com/pyro-ppl/numpyro.git

# install jax/jaxlib first for CUDA support

pip install -e .[dev]  # contains additional dependencies for NumPyro development
```

1.5 Frequently Asked Questions

1. Unlike in Pyro, `numpyro.sample('x', dist.Normal(0, 1))` does not work. Why?

You are most likely using a `numpyro.sample` statement outside an inference context. JAX does not have a global random state, and as such, distribution samplers need an explicit random number generator key (PRNGKey) to generate samples from. NumPyro's inference algorithms use the seed handler to thread in a random number generator key, behind the scenes.

Your options are:

- Call the distribution directly and provide a `PRNGKey`, e.g. `dist.Normal(0, 1).sample(PRNGKey(0))`
- Provide the `rng_key` argument to `numpyro.sample`. e.g. `numpyro.sample('x', dist.Normal(0, 1), rng_key=PRNGKey(0))`.
- Wrap the code in a `seed` handler, used either as a context manager or as a function that wraps over the original callable. e.g.

  ‘‘‘python

  with handlers.seed(rng_seed=0): # random.PRNGKey(0) is used

  ```
  x = numpyro.sample('x', dist.Beta(1, 1))     # uses a PRNGKey split from random.
  ↪PRNGKey(0)

  y = numpyro.sample('y', dist.Bernoulli(x))  # uses different PRNGKey split from␣
  ↪the last one
  ```

‘‘‘

, or as a higher order function:

‘‘‘python

def fn():

```
x = numpyro.sample('x', dist.Beta(1, 1))

y = numpyro.sample('y', dist.Bernoulli(x))

return y
```

print(handlers.seed(fn, rng_seed=0)())

‘‘‘

2. Can I use the same Pyro model for doing inference in NumPyro?

As you may have noticed from the examples, NumPyro supports all Pyro primitives like `sample`, `param`, `plate` and `module`, and effect handlers. Additionally, we have ensured that the distributions API is based on `torch.distributions`, and the inference classes like `SVI` and `MCMC` have the same interface. This along with the similarity in the API for NumPy and PyTorch operations ensures that models containing Pyro primitive statements can be used with either backend with some minor changes. Example of some differences along with the changes needed, are noted below:

- Any `torch` operation in your model will need to be written in terms of the corresponding `jax.numpy` operation. Additionally, not all `torch` operations have a `numpy` counterpart (and vice-versa), and sometimes there are minor differences in the API.
- `pyro.sample` statements outside an inference context will need to be wrapped in a `seed` handler, as mentioned above.
- There is no global parameter store, and as such using `numpyro.param` outside an inference context will have no effect. To retrieve the optimized parameter values from SVI, use the SVI.get_params method. Note that you can still use `param` statements inside a model and NumPyro will use the substitute effect handler internally to substitute values from the optimizer when running the model in SVI.
- PyTorch neural network modules will need to rewritten as stax neural networks. See the *VAE* example for differences in syntax between the two backends.
- JAX works best with functional code, particularly if we would like to leverage JIT compilation, which NumPyro does internally for many inference subroutines. As such, if your model has side-effects that are not visible to the JAX tracer, it may need to rewritten in a more functional style.

For most small models, changes required to run inference in NumPyro should be minor. Additionally, we are working on pyro-api which allows you to write the same code and dispatch it to multiple backends, including NumPyro. This will necessarily be more restrictive, but has the advantage of being backend agnostic. See the documentation for an example, and let us know your feedback.

3. How can I contribute to the project?

Thanks for your interest in the project! You can take a look at beginner friendly issues that are marked with the good first issue tag on Github. Also, please feel to reach out to us on the forum.

1.6 Future / Ongoing Work

In the near term, we plan to work on the following. Please open new issues for feature requests and enhancements:

- Improving robustness of inference on different models, profiling and performance tuning.
- Supporting more functionality as part of the pyro-api generic modeling interface.
- More inference algorithms, particularly those that require second order derivaties or use HMC.
- Integration with Funsor to support inference algorithms with delayed sampling.
- Other areas motivated by Pyro's research goals and application focus, and interest from the community.

1.7 Citing NumPyro

The motivating ideas behind NumPyro and a description of Iterative NUTS can be found in this paper that appeared in NeurIPS 2019 Program Transformations for Machine Learning Workshop.

If you use NumPyro, please consider citing:

```
@article{phan2019composable,

  title={Composable Effects for Flexible and Accelerated Probabilistic Programming in␣
↪NumPyro},

  author={Phan, Du and Pradhan, Neeraj and Jankowiak, Martin},

  journal={arXiv preprint arXiv:1912.11554},

  year={2019}

}
```

as well as

```
@article{bingham2018pyro,

  author = {Bingham, Eli and Chen, Jonathan P. and Jankowiak, Martin and Obermeyer,␣
↪Fritz and

            Pradhan, Neeraj and Karaletsos, Theofanis and Singh, Rohit and Szerlip,␣
↪Paul and

            Horsfall, Paul and Goodman, Noah D.},

  title = {{Pyro: Deep Universal Probabilistic Programming}},

  journal = {arXiv preprint arXiv:1810.09538},

  year = {2018}

}
```

CHAPTER 2

API Reference

2.1 Modeling

2.1.1 Pyro Primitives

param

param(*name*, *init_value=None*, ***kwargs*)

Annotate the given site as an optimizable parameter for use with `jax.experimental.optimizers`. For an example of how *param* statements can be used in inference algorithms, refer to `SVI`.

Parameters

- **name** (*str*) – name of site.
- **init_value** (*numpy.ndarray or callable*) – initial value specified by the user or a lazy callable that accepts a JAX random PRNGKey and returns an array. Note that the onus of using this to initialize the optimizer is on the user inference algorithm, since there is no global parameter store in NumPyro.
- **constraint** (`numpyro.distributions.constraints.Constraint`) – NumPyro constraint, defaults to `constraints.real`.
- **event_dim** (*int*) – (optional) number of rightmost dimensions unrelated to batching. Dimension to the left of this will be considered batch dimensions; if the param statement is inside a subsampled plate, then corresponding batch dimensions of the parameter will be correspondingly subsampled. If unspecified, all dimensions will be considered event dims and no subsampling will be performed.

Returns value for the parameter. Unless wrapped inside a handler like *substitute*, this will simply return the initial value.

sample

sample(*name*, *fn*, *obs=None*, *rng_key=None*, *sample_shape=()*, *infer=None*, *obs_mask=None*)

Returns a random sample from the stochastic function *fn*. This can have additional side effects when wrapped inside effect handlers like *substitute*.

Note: By design, *sample* primitive is meant to be used inside a NumPyro model. Then *seed* handler is used to inject a random state to *fn*. In those situations, *rng_key* keyword will take no effect.

Parameters

- **name** (*str*) – name of the sample site.
- **fn** – a stochastic function that returns a sample.
- **obs** (*numpy.ndarray*) – observed value
- **rng_key** (*jax.random.PRNGKey*) – an optional random key for *fn*.
- **sample_shape** – Shape of samples to be drawn.
- **infer** (*dict*) – an optional dictionary containing additional information for inference algorithms. For example, if *fn* is a discrete distribution, setting *infer={'enumerate': 'parallel'}* to tell MCMC marginalize this discrete latent site.
- **obs_mask** (*numpy.ndarray*) – Optional boolean array mask of shape broadcastable with `fn.batch_shape`. If provided, events with mask=True will be conditioned on `obs` and remaining events will be imputed by sampling. This introduces a latent sample site named `name + "_unobserved"` which should be used by guides.

Returns sample from the stochastic *fn*.

plate

class plate(*name*, *size*, *subsample_size=None*, *dim=None*)

Construct for annotating conditionally independent variables. Within a *plate* context manager, *sample* sites will be automatically broadcasted to the size of the plate. Additionally, a scale factor might be applied by certain inference algorithms if *subsample_size* is specified.

Note: This can be used to subsample minibatches of data:

```
with plate("data", len(data), subsample_size=100) as ind:
    batch = data[ind]
    assert len(batch) == 100
```

Parameters

- **name** (*str*) – Name of the plate.
- **size** (*int*) – Size of the plate.
- **subsample_size** (*int*) – Optional argument denoting the size of the mini-batch. This can be used to apply a scaling factor by inference algorithms. e.g. when computing ELBO using a mini-batch.

- **dim** (*int*) – Optional argument to specify which dimension in the tensor is used as the plate dim. If *None* (default), the leftmost available dim is allocated.

plate_stack

plate_stack (*prefix*, *sizes*, *rightmost_dim=-1*)

Create a contiguous stack of *plate* s with dimensions:

```
rightmost_dim - len(sizes), ..., rightmost_dim
```

Parameters

- **prefix** (*str*) – Name prefix for plates.
- **sizes** (*iterable*) – An iterable of plate sizes.
- **rightmost_dim** (*int*) – The rightmost dim, counting from the right.

subsample

subsample (*data*, *event_dim*)

EXPERIMENTAL Subsampling statement to subsample data based on enclosing *plate* s.

This is typically called on arguments to `model()` when subsampling is performed automatically by *plate* s by passing `subsample_size` kwarg. For example the following are equivalent:

```
# Version 1. using indexing
def model(data):
    with numpyro.plate("data", len(data), subsample_size=10, dim=-data.dim()) as␣
↪ind:
        data = data[ind]
        # ...

# Version 2. using numpyro.subsample()
def model(data):
    with numpyro.plate("data", len(data), subsample_size=10, dim=-data.dim()):
        data = numpyro.subsample(data, event_dim=0)
        # ...
```

Parameters

- **data** (*numpy.ndarray*) – A tensor of batched data.
- **event_dim** (*int*) – The event dimension of the data tensor. Dimensions to the left are considered batch dimensions.

Returns A subsampled version of `data`

Return type ndarray

deterministic

deterministic (*name*, *value*)

Used to designate deterministic sites in the model. Note that most effect handlers will not operate on deterministic sites (except *trace()*), so deterministic sites should be side-effect free. The use case for deterministic nodes is to record any values in the model execution trace.

Parameters

- **name** (*str*) – name of the deterministic site.
- **value** (*numpy.ndarray*) – deterministic value to record in the trace.

prng_key

prng_key()
A statement to draw a pseudo-random number generator key `PRNGKey()` under *seed* handler.

Returns a PRNG key of shape (2,) and dtype unit32.

factor

factor(*name*, *log_factor*)
Factor statement to add arbitrary log probability factor to a probabilistic model.

Parameters

- **name** (*str*) – Name of the trivial sample.
- **log_factor** (*numpy.ndarray*) – A possibly batched log probability factor.

get_mask

get_mask()
Records the effects of enclosing `handlers.mask` handlers. This is useful for avoiding expensive `numpyro.factor()` computations during prediction, when the log density need not be computed, e.g.:

```
def model():
    # ...
    if numpyro.get_mask() is not False:
        log_density = my_expensive_computation()
        numpyro.factor("foo", log_density)
    # ...
```

Returns The mask.

Return type None, bool, or numpy.ndarray

module

module(*name*, *nn*, *input_shape=None*)
Declare a `stax` style neural network inside a model so that its parameters are registered for optimization via *param()* statements.

Parameters

- **name** (*str*) – name of the module to be registered.
- **nn** (*tuple*) – a tuple of *(init_fn, apply_fn)* obtained by a `stax` constructor function.
- **input_shape** (*tuple*) – shape of the input taken by the neural network.

Returns a *apply_fn* with bound parameters that takes an array as an input and returns the neural network transformed output array.

flax_module

flax_module(*name*, *nn_module*, *, *input_shape=None*, ***kwargs*)

Declare a `flax` style neural network inside a model so that its parameters are registered for optimization via *param()* statements.

Parameters

- **name** (*str*) – name of the module to be registered.
- **nn_module** (*flax.nn.Module*) – a *flax* Module which has .init and .apply methods
- **input_shape** (*tuple*) – shape of the input taken by the neural network.
- **kwargs** – optional keyword arguments to initialize flax neural network as an alternative to *input_shape*

Returns a callable with bound parameters that takes an array as an input and returns the neural network transformed output array.

haiku_module

haiku_module(*name*, *nn_module*, *, *input_shape=None*, ***kwargs*)

Declare a `haiku` style neural network inside a model so that its parameters are registered for optimization via *param()* statements.

Parameters

- **name** (*str*) – name of the module to be registered.
- **nn_module** (*haiku.Module*) – a *haiku* Module which has .init and .apply methods
- **input_shape** (*tuple*) – shape of the input taken by the neural network.
- **kwargs** – optional keyword arguments to initialize flax neural network as an alternative to *input_shape*

Returns a callable with bound parameters that takes an array as an input and returns the neural network transformed output array.

random_flax_module

random_flax_module(*name*, *nn_module*, *prior*, *, *input_shape=None*, ***kwargs*)

A primitive to place a prior over the parameters of the Flax module *nn_module*.

Note: Parameters of a Flax module are stored in a nested dict. For example, the module *B* defined as follows:

```
class A(nn.Module):
    def apply(self, x):
        return nn.Dense(x, 1, bias=False, name='dense')

class B(nn.Module):
    def apply(self, x):
        return A(x, name='inner')
```

has parameters *{'inner': {'dense': {'kernel': param_value}}}*. In the argument *prior*, to specify *kernel* parameter, we join the path to it using dots: *prior={"inner.dense.kernel": param_prior}*.

Parameters

- **name** (*str*) – name of NumPyro module
- **flax.nn.Module** – the module to be registered with NumPyro
- **prior** – a NumPyro distribution or a Python dict with parameter names as keys and respective distributions as values. For example:

```
net = random_flax_module("net",
                         flax.nn.Dense.partial(features=1),
                         prior={"bias": dist.Cauchy(), "kernel":␣
↪dist.Normal()},
                         input_shape=(4,))
```

- **input_shape** (*tuple*) – shape of the input taken by the neural network.
- **kwargs** – optional keyword arguments to initialize flax neural network as an alternative to *input_shape*

Returns a sampled module

Example

```
# NB: this example is ported from https://github.com/ctallec/pyvarinf/blob/master/
↪main_regression.ipynb
>>> import numpy as np; np.random.seed(0)
>>> import tqdm
>>> from flax import nn
>>> from jax import jit, random
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.contrib.module import random_flax_module
>>> from numpyro.infer import Predictive, SVI, TraceMeanField_ELBO, autoguide,␣
↪init_to_feasible
>>>
>>> class Net(nn.Module):
...     def apply(self, x, n_units):
...         x = nn.Dense(x[..., None], features=n_units)
...         x = nn.relu(x)
...         x = nn.Dense(x, features=n_units)
...         x = nn.relu(x)
...         mean = nn.Dense(x, features=1)
...         rho = nn.Dense(x, features=1)
...         return mean.squeeze(), rho.squeeze()
>>>
>>> def generate_data(n_samples):
...     x = np.random.normal(size=n_samples)
...     y = np.cos(x * 3) + np.random.normal(size=n_samples) * np.abs(x) / 2
...     return x, y
>>>
>>> def model(x, y=None, batch_size=None):
...     module = Net.partial(n_units=32)
...     net = random_flax_module("nn", module, dist.Normal(0, 0.1), input_
↪shape=())
...     with numpyro.plate("batch", x.shape[0], subsample_size=batch_size):
...         batch_x = numpyro.subsample(x, event_dim=0)
...         batch_y = numpyro.subsample(y, event_dim=0) if y is not None else None
...         mean, rho = net(batch_x)
```

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```
...         sigma = nn.softplus(rho)
...         numpyro.sample("obs", dist.Normal(mean, sigma), obs=batch_y)
>>>
>>> n_train_data = 5000
>>> x_train, y_train = generate_data(n_train_data)
>>> guide = autoguide.AutoNormal(model, init_loc_fn=init_to_feasible)
>>> svi = SVI(model, guide, numpyro.optim.Adam(5e-3), TraceMeanField_ELBO())
>>>
>>> n_iterations = 3000
>>> params, losses = svi.run(random.PRNGKey(0), n_iterations, x_train, y_train,␣
↪batch_size=256)
>>> n_test_data = 100
>>> x_test, y_test = generate_data(n_test_data)
>>> predictive = Predictive(model, guide=guide, params=params, num_samples=1000)
>>> y_pred = predictive(random.PRNGKey(1), x_test[:100])["obs"].copy()
>>> assert losses[-1] < 3000
>>> assert np.sqrt(np.mean(np.square(y_test - y_pred))) < 1
```

random_haiku_module

random_haiku_module (*name*, *nn_module*, *prior*, *, *input_shape=None*, ***kwargs*)

A primitive to place a prior over the parameters of the Haiku module *nn_module*.

Parameters

- **name** (*str*) – name of NumPyro module
- **haiku.Module** – the module to be registered with NumPyro
- **prior** – a NumPyro distribution or a Python dict with parameter names as keys and respective distributions as values. For example:

```
net = random_haiku_module("net",
                          haiku.transform(lambda x: hk.
↪Linear(1)(x)),
                          prior={"linear.b": dist.Cauchy(),
↪"linear.w": dist.Normal()},
                          input_shape=(4,))
```

- **input_shape** (*tuple*) – shape of the input taken by the neural network.

Returns a sampled module

scan

scan (*f*, *init*, *xs*, *length=None*, *reverse=False*, *history=1*)

This primitive scans a function over the leading array axes of *xs* while carrying along state. See `jax.lax.scan()` for more information.

Usage:

```
>>> import numpy as np
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.contrib.control_flow import scan
>>>
```

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```
>>> def gaussian_hmm(y=None, T=10):
...     def transition(x_prev, y_curr):
...         x_curr = numpyro.sample('x', dist.Normal(x_prev, 1))
...         y_curr = numpyro.sample('y', dist.Normal(x_curr, 1), obs=y_curr)
...         return x_curr, (x_curr, y_curr)
...
...     x0 = numpyro.sample('x_0', dist.Normal(0, 1))
...     _, (x, y) = scan(transition, x0, y, length=T)
...     return (x, y)
>>>
>>> # here we do some quick tests
>>> with numpyro.handlers.seed(rng_seed=0):
...     x, y = gaussian_hmm(np.arange(10.))
>>> assert x.shape == (10,) and y.shape == (10,)
>>> assert np.all(y == np.arange(10))
>>>
>>> with numpyro.handlers.seed(rng_seed=0):  # generative
...     x, y = gaussian_hmm()
>>> assert x.shape == (10,) and y.shape == (10,)
```

Warning: This is an experimental utility function that allows users to use JAX control flow with NumPyro's effect handlers. Currently, *sample* and *deterministic* sites within the scan body *f* are supported. If you notice that any effect handlers or distributions are unsupported, please file an issue.

Note: It is ambiguous to align *scan* dimension inside a *plate* context. So the following pattern won't be supported

```
with numpyro.plate('N', 10):
    last, ys = scan(f, init, xs)
```

All *plate* statements should be put inside *f*. For example, the corresponding working code is

```
def g(*args, **kwargs):
    with numpyro.plate('N', 10):
        return f(*arg, **kwargs)

last, ys = scan(g, init, xs)
```

Note: Nested scan is currently not supported.

Note: We can scan over discrete latent variables in *f*. The joint density is evaluated using parallel-scan (reference [1]) over time dimension, which reduces parallel complexity to *O(log(length))*.

A `trace` of *scan* with discrete latent variables will contain the following sites:

- **init sites: those sites belong to the first *history* traces of *f*.** Sites at the *i*-th trace will have name prefixed with *'_PREV_' * (2 * history - 1 - i)*.
- **scanned sites: those sites collect the values of the remaining scan** loop over *f*. An addition time dimension *_time_foo* will be added to those sites, where *foo* is the name of the first site appeared in *f*.

Not all transition functions f are supported. All of the restrictions from Pyro's enumeration tutorial [2] still apply here. In addition, there should not have any site outside of *scan* depend on the first output of *scan* (the last carry value).

** References **

1. *Temporal Parallelization of Bayesian Smoothers*, Simo Sarkka, Angel F. Garcia-Fernandez (https://arxiv.org/abs/1905.13002)
2. *Inference with Discrete Latent Variables* (http://pyro.ai/examples/enumeration.html#Dependencies-among-plates)

Parameters

- **f** (*callable*) – a function to be scanned.
- **init** – the initial carrying state
- **xs** – the values over which we scan along the leading axis. This can be any JAX pytree (e.g. list/dict of arrays).
- **length** – optional value specifying the length of *xs* but can be used when *xs* is an empty pytree (e.g. None)
- **reverse** (*bool*) – optional boolean specifying whether to run the scan iteration forward (the default) or in reverse
- **history** (*int*) – The number of previous contexts visible from the current context. Defaults to 1. If zero, this is similar to `numpyro.plate`.

Returns output of scan, quoted from `jax.lax.scan()` docs: "pair of type (c, [b]) where the first element represents the final loop carry value and the second element represents the stacked outputs of the second output of f when scanned over the leading axis of the inputs".

2.1.2 Effect Handlers

This provides a small set of effect handlers in NumPyro that are modeled after Pyro's poutine module. For a tutorial on effect handlers more generally, readers are encouraged to read Poutine: A Guide to Programming with Effect Handlers in Pyro. These simple effect handlers can be composed together or new ones added to enable implementation of custom inference utilities and algorithms.

Example

As an example, we are using *seed*, *trace* and *substitute* handlers to define the *log_likelihood* function below. We first create a logistic regression model and sample from the posterior distribution over the regression parameters using `MCMC()`. The *log_likelihood* function uses effect handlers to run the model by substituting sample sites with values from the posterior distribution and computes the log density for a single data point. The *log_predictive_density* function computes the log likelihood for each draw from the joint posterior and aggregates the results for all the data points, but does so by using JAX's auto-vectorize transform called *vmap* so that we do not need to loop over all the data points.

```
>>> import jax.numpy as jnp
>>> from jax import random, vmap
>>> from jax.scipy.special import logsumexp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro import handlers
>>> from numpyro.infer import MCMC, NUTS
```

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```
>>> N, D = 3000, 3
>>> def logistic_regression(data, labels):
...     coefs = numpyro.sample('coefs', dist.Normal(jnp.zeros(D), jnp.ones(D)))
...     intercept = numpyro.sample('intercept', dist.Normal(0., 10.))
...     logits = jnp.sum(coefs * data + intercept, axis=-1)
...     return numpyro.sample('obs', dist.Bernoulli(logits=logits), obs=labels)

>>> data = random.normal(random.PRNGKey(0), (N, D))
>>> true_coefs = jnp.arange(1., D + 1.)
>>> logits = jnp.sum(true_coefs * data, axis=-1)
>>> labels = dist.Bernoulli(logits=logits).sample(random.PRNGKey(1))

>>> num_warmup, num_samples = 1000, 1000
>>> mcmc = MCMC(NUTS(model=logistic_regression), num_warmup, num_samples)
>>> mcmc.run(random.PRNGKey(2), data, labels)
sample: 100%|| 1000/1000 [00:00<00:00, 1252.39it/s, 1 steps of␣
↪size 5.83e-01. acc. prob=0.85]
>>> mcmc.print_summary()


                mean       sd       5.5%      94.5%      n_eff       Rhat
    coefs[0]       0.96       0.07       0.85       1.07     455.35       1.01
    coefs[1]       2.05       0.09       1.91       2.20     332.00       1.01
    coefs[2]       3.18       0.13       2.96       3.37     320.27       1.00
   intercept      -0.03       0.02      -0.06       0.00     402.53       1.00

>>> def log_likelihood(rng_key, params, model, *args, **kwargs):
...     model = handlers.substitute(handlers.seed(model, rng_key), params)
...     model_trace = handlers.trace(model).get_trace(*args, **kwargs)
...     obs_node = model_trace['obs']
...     return obs_node['fn'].log_prob(obs_node['value'])

>>> def log_predictive_density(rng_key, params, model, *args, **kwargs):
...     n = list(params.values())[0].shape[0]
...     log_lk_fn = vmap(lambda rng_key, params: log_likelihood(rng_key, params,␣
↪model, *args, **kwargs))
...     log_lk_vals = log_lk_fn(random.split(rng_key, n), params)
...     return jnp.sum(logsumexp(log_lk_vals, 0) - jnp.log(n))

>>> print(log_predictive_density(random.PRNGKey(2), mcmc.get_samples(),
...       logistic_regression, data, labels))
-874.89813
```

block

class block (*fn=None*, *hide_fn=None*, *hide=None*)

Bases: `numpyro.primitives.Messenger`

Given a callable *fn*, return another callable that selectively hides primitive sites where *hide_fn* returns True from other effect handlers on the stack.

Parameters

- **fn** (*callable*) – Python callable with NumPyro primitives.
- **hide_fn** (*callable*) – function which when given a dictionary containing site-level

metadata returns whether it should be blocked.

- **hide** (*list*) – list of site names to hide.

Example:

```
>>> from jax import random
>>> import numpyro
>>> from numpyro.handlers import block, seed, trace
>>> import numpyro.distributions as dist

>>> def model():
...     a = numpyro.sample('a', dist.Normal(0., 1.))
...     return numpyro.sample('b', dist.Normal(a, 1.))

>>> model = seed(model, random.PRNGKey(0))
>>> block_all = block(model)
>>> block_a = block(model, lambda site: site['name'] == 'a')
>>> trace_block_all = trace(block_all).get_trace()
>>> assert not {'a', 'b'}.intersection(trace_block_all.keys())
>>> trace_block_a =  trace(block_a).get_trace()
>>> assert 'a' not in trace_block_a
>>> assert 'b' in trace_block_a
```

process_message(*msg*)

collapse

class collapse(**args*, ***kwargs*)

Bases: *numpyro.handlers.trace*

EXPERIMENTAL Collapses all sites in the context by lazily sampling and attempting to use conjugacy relations. If no conjugacy is known this will fail. Code using the results of sample sites must be written to accept Funsors rather than Tensors. This requires `funsor` to be installed.

process_message(*msg*)

condition

class condition(*fn=None*, *data=None*, *condition_fn=None*)

Bases: `numpyro.primitives.Messenger`

Conditions unobserved sample sites to values from *data* or *condition_fn*. Similar to *substitute* except that it only affects *sample* sites and changes the *is_observed* property to *True*.

Parameters

- **fn** – Python callable with NumPyro primitives.
- **data** (*dict*) – dictionary of *numpy.ndarray* values keyed by site names.
- **condition_fn** – callable that takes in a site dict and returns a numpy array or *None* (in which case the handler has no side effect).

Example:

```
>>> from jax import random
>>> import numpyro
>>> from numpyro.handlers import condition, seed, substitute, trace
```

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```
>>> import numpyro.distributions as dist

>>> def model():
...     numpyro.sample('a', dist.Normal(0., 1.))

>>> model = seed(model, random.PRNGKey(0))
>>> exec_trace = trace(condition(model, {'a': -1})).get_trace()
>>> assert exec_trace['a']['value'] == -1
>>> assert exec_trace['a']['is_observed']
```

process_message(*msg*)

do

class do(*fn=None*, *data=None*)

Bases: numpyro.primitives.Messenger

Given a stochastic function with some sample statements and a dictionary of values at names, set the return values of those sites equal to the values as if they were hard-coded to those values and introduce fresh sample sites with the same names whose values do not propagate.

Composes freely with *condition()* to represent counterfactual distributions over potential outcomes. See Single World Intervention Graphs [1] for additional details and theory.

This is equivalent to replacing *z = numpyro.sample("z", ...)* with *z = 1.* and introducing a fresh sample site *numpyro.sample("z", ...)* whose value is not used elsewhere.

References:

1. *Single World Intervention Graphs: A Primer*, Thomas Richardson, James Robins

Parameters

- **fn** – a stochastic function (callable containing Pyro primitive calls)
- **data** – a dict mapping sample site names to interventions

Example:

```
>>> import jax.numpy as jnp
>>> import numpyro
>>> from numpyro.handlers import do, trace, seed
>>> import numpyro.distributions as dist
>>> def model(x):
...     s = numpyro.sample("s", dist.LogNormal())
...     z = numpyro.sample("z", dist.Normal(x, s))
...     return z ** 2
>>> intervened_model = handlers.do(model, data={"z": 1.})
>>> with trace() as exec_trace:
...     z_square = seed(intervened_model, 0)(1)
>>> assert exec_trace['z']['value'] != 1.
>>> assert not exec_trace['z']['is_observed']
>>> assert not exec_trace['z'].get('stop', None)
>>> assert z_square == 1
```

process_message(*msg*)

infer_config

class infer_config (*fn=None*, *config_fn=None*)
Bases: numpyro.primitives.Messenger

Given a callable *fn* that contains NumPyro primitive calls and a callable *config_fn* taking a trace site and returning a dictionary, updates the value of the infer kwarg at a sample site to config_fn(site).

Parameters

- **fn** – a stochastic function (callable containing NumPyro primitive calls)
- **config_fn** – a callable taking a site and returning an infer dict

process_message (*msg*)

lift

class lift (*fn=None*, *prior=None*)
Bases: numpyro.primitives.Messenger

Given a stochastic function with `param` calls and a prior distribution, create a stochastic function where all param calls are replaced by sampling from prior. Prior should be a distribution or a dict of names to distributions.

Consider the following NumPyro program:

```
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.handlers import lift
>>>
>>> def model(x):
...     s = numpyro.param("s", 0.5)
...     z = numpyro.sample("z", dist.Normal(x, s))
...     return z ** 2
>>> lifted_model = lift(model, prior={"s": dist.Exponential(0.3)})
```

`lift` makes `param` statements behave like `sample` statements using the distributions in `prior`. In this example, site *s* will now behave as if it was replaced with `s = numpyro.sample("s", dist.Exponential(0.3))`.

Parameters

- **fn** – function whose parameters will be lifted to random values
- **prior** – prior function in the form of a Distribution or a dict of Distributions

process_message (*msg*)

mask

class mask (*fn=None*, *mask=True*)
Bases: numpyro.primitives.Messenger

This messenger masks out some of the sample statements elementwise.

Parameters **mask** – a boolean or a boolean-valued array for masking elementwise log probability of sample sites (*True* includes a site, *False* excludes a site).

process_message (*msg*)

reparam

class reparam(*fn=None*, *config=None*)
Bases: numpyro.primitives.Messenger

Reparametrizes each affected sample site into one or more auxiliary sample sites followed by a deterministic transformation [1].

To specify reparameterizers, pass a `config` dict or callable to the constructor. See the *numpyro.infer.reparam* module for available reparameterizers.

Note some reparameterizers can examine the `*args,**kwargs` inputs of functions they affect; these reparameterizers require using `handlers.reparam` as a decorator rather than as a context manager.

[1] Maria I. Gorinova, Dave Moore, Matthew D. Hoffman (2019) "Automatic Reparameterisation of Probabilistic Programs" https://arxiv.org/pdf/1906.03028.pdf

Parameters **config** (*dict or callable*) – Configuration, either a dict mapping site name to *Reparam*, or a function mapping site to *Reparam* or None.

process_message(*msg*)

replay

class replay(*fn=None*, *guide_trace=None*)
Bases: numpyro.primitives.Messenger

Given a callable *fn* and an execution trace *guide_trace*, return a callable which substitutes *sample* calls in *fn* with values from the corresponding site names in *guide_trace*.

Parameters

- **fn** – Python callable with NumPyro primitives.
- **guide_trace** – an OrderedDict containing execution metadata.

Example

```
>>> from jax import random
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.handlers import replay, seed, trace

>>> def model():
...     numpyro.sample('a', dist.Normal(0., 1.))

>>> exec_trace = trace(seed(model, random.PRNGKey(0))).get_trace()
>>> print(exec_trace['a']['value'])
-0.20584235
>>> replayed_trace = trace(replay(model, exec_trace)).get_trace()
>>> print(exec_trace['a']['value'])
-0.20584235
>>> assert replayed_trace['a']['value'] == exec_trace['a']['value']
```

process_message(*msg*)

scale

class scale (*fn=None*, *scale=1.0*)
Bases: numpyro.primitives.Messenger

This messenger rescales the log probability score.

This is typically used for data subsampling or for stratified sampling of data (e.g. in fraud detection where negatives vastly outnumber positives).

Parameters **scale** (*float or numpy.ndarray*) – a positive scaling factor that is broadcastable to the shape of log probability.

process_message (*msg*)

scope

class scope (*fn=None*, *prefix=''*, *divider='/'*)
Bases: numpyro.primitives.Messenger

This handler prepend a prefix followed by a divider to the name of sample sites.

Example:

```
.. doctest::
```

```
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.handlers import scope, seed, trace
>>>
>>> def model():
...     with scope(prefix="a"):
...         with scope(prefix="b", divider="."):
...             return numpyro.sample("x", dist.Bernoulli(0.5))
...
>>> assert "a/b.x" in trace(seed(model, 0)).get_trace()
```

Parameters

- **fn** – Python callable with NumPyro primitives.
- **prefix** (*str*) – a string to prepend to sample names
- **divider** (*str*) – a string to join the prefix and sample name; default to *'/'*

process_message (*msg*)

seed

class seed (*fn=None*, *rng_seed=None*)
Bases: numpyro.primitives.Messenger

JAX uses a functional pseudo random number generator that requires passing in a seed PRNGKey() to every stochastic function. The *seed* handler allows us to initially seed a stochastic function with a PRNGKey(). Every call to the sample() primitive inside the function results in a splitting of this initial seed so that we use a fresh seed for each subsequent call without having to explicitly pass in a *PRNGKey* to each *sample* call.

Parameters

- **fn** – Python callable with NumPyro primitives.
- **rng_seed** (*int, jnp.ndarray scalar, or jax.random.PRNGKey*) – a random number generator seed.

Note: Unlike in Pyro, *numpyro.sample* primitive cannot be used without wrapping it in seed handler since there is no global random state. As such, users need to use *seed* as a contextmanager to generate samples from distributions or as a decorator for their model callable (See below).

Example:

```
>>> from jax import random
>>> import numpyro
>>> import numpyro.handlers
>>> import numpyro.distributions as dist

>>> # as context manager
>>> with handlers.seed(rng_seed=1):
...     x = numpyro.sample('x', dist.Normal(0., 1.))

>>> def model():
...     return numpyro.sample('y', dist.Normal(0., 1.))

>>> # as function decorator (/modifier)
>>> y = handlers.seed(model, rng_seed=1)()
>>> assert x == y
```

process_message(*msg*)

substitute

class substitute(*fn=None*, *data=None*, *substitute_fn=None*)

Bases: numpyro.primitives.Messenger

Given a callable *fn* and a dict *data* keyed by site names (alternatively, a callable *substitute_fn*), return a callable which substitutes all primitive calls in *fn* with values from *data* whose key matches the site name. If the site name is not present in *data*, there is no side effect.

If a *substitute_fn* is provided, then the value at the site is replaced by the value returned from the call to *substitute_fn* for the given site.

Parameters

- **fn** – Python callable with NumPyro primitives.
- **data** (*dict*) – dictionary of *numpy.ndarray* values keyed by site names.
- **substitute_fn** – callable that takes in a site dict and returns a numpy array or *None* (in which case the handler has no side effect).

Example:

```
>>> from jax import random
>>> import numpyro
>>> from numpyro.handlers import seed, substitute, trace
>>> import numpyro.distributions as dist

>>> def model():
```

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```
...     numpyro.sample('a', dist.Normal(0., 1.))

>>> model = seed(model, random.PRNGKey(0))
>>> exec_trace = trace(substitute(model, {'a': -1})).get_trace()
>>> assert exec_trace['a']['value'] == -1
```

process_message(*msg*)

trace

class trace(*fn=None*)

Bases: numpyro.primitives.Messenger

Returns a handler that records the inputs and outputs at primitive calls inside *fn*.

Example

```
>>> from jax import random
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.handlers import seed, trace
>>> import pprint as pp

>>> def model():
...     numpyro.sample('a', dist.Normal(0., 1.))

>>> exec_trace = trace(seed(model, random.PRNGKey(0))).get_trace()
>>> pp.pprint(exec_trace)
OrderedDict([('a',
              {'args': (),
               'fn': <numpyro.distributions.continuous.Normal object at␣
↪0x7f9e689b1eb8>,
               'is_observed': False,
               'kwargs': {'rng_key': DeviceArray([0, 0], dtype=uint32)},
               'name': 'a',
               'type': 'sample',
               'value': DeviceArray(-0.20584235, dtype=float32)})])
```

postprocess_message(*msg*)

get_trace(**args*, ***kwargs*)

Run the wrapped callable and return the recorded trace.

Parameters

- ***args** – arguments to the callable.
- ****kwargs** – keyword arguments to the callable.

Returns *OrderedDict* containing the execution trace.

2.2 Distributions

2.2.1 Base Distribution

Distribution

class Distribution(*batch_shape=()*, *event_shape=()*, *validate_args=None*)

Bases: object

Base class for probability distributions in NumPyro. The design largely follows from `torch.distributions`.

Parameters

- **batch_shape** – The batch shape for the distribution. This designates independent (possibly non-identical) dimensions of a sample from the distribution. This is fixed for a distribution instance and is inferred from the shape of the distribution parameters.
- **event_shape** – The event shape for the distribution. This designates the dependent dimensions of a sample from the distribution. These are collapsed when we evaluate the log probability density of a batch of samples using *.log_prob*.
- **validate_args** – Whether to enable validation of distribution parameters and arguments to *.log_prob* method.

As an example:

```
>>> import jax.numpy as jnp
>>> import numpyro.distributions as dist
>>> d = dist.Dirichlet(jnp.ones((2, 3, 4)))
>>> d.batch_shape
(2, 3)
>>> d.event_shape
(4,)
```

arg_constraints = {}

support = None

has_enumerate_support = False

is_discrete = False

reparametrized_params = []

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

static set_default_validate_args(*value*)

batch_shape

Returns the shape over which the distribution parameters are batched.

Returns batch shape of the distribution.

Return type tuple

event_shape

Returns the shape of a single sample from the distribution without batching.

Returns event shape of the distribution.

Return type tuple

event_dim

Returns Number of dimensions of individual events.

Return type int

has_rsample

rsample(*key*, *sample_shape=()*)

shape(*sample_shape=()*)
The tensor shape of samples from this distribution.

Samples are of shape:

```
d.shape(sample_shape) == sample_shape + d.batch_shape + d.event_shape
```

Parameters **sample_shape** (*tuple*) – the size of the iid batch to be drawn from the distribution.

Returns shape of samples.

Return type tuple

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

sample_with_intermediates(*key*, *sample_shape=()*)
Same as `sample` except that any intermediate computations are returned (useful for *TransformedDistribution*).

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(*value*)
Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

mean
Mean of the distribution.

variance
Variance of the distribution.

to_event(*reinterpreted_batch_ndims=None*)
Interpret the rightmost *reinterpreted_batch_ndims* batch dimensions as dependent event dimensions.

Parameters **reinterpreted_batch_ndims** – Number of rightmost batch dims to interpret as event dims.

Returns An instance of *Independent* distribution.

Return type *numpyro.distributions.distribution.Independent*

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

expand(*batch_shape*)
Returns a new *ExpandedDistribution* instance with batch dimensions expanded to *batch_shape*.

Parameters **batch_shape** (*tuple*) – batch shape to expand to.

Returns an instance of *ExpandedDistribution*.

Return type *ExpandedDistribution*

expand_by(*sample_shape*)
Expands a distribution by adding `sample_shape` to the left side of its *batch_shape*. To expand internal dims of `self.batch_shape` from 1 to something larger, use *expand()* instead.

Parameters **sample_shape** (*tuple*) – The size of the iid batch to be drawn from the distribution.

Returns An expanded version of this distribution.

Return type *ExpandedDistribution*

mask(*mask*)
Masks a distribution by a boolean or boolean-valued array that is broadcastable to the distributions *Distribution.batch_shape*.

Parameters **mask** (*bool or jnp.ndarray*) – A boolean or boolean valued array (*True* includes a site, *False* excludes a site).

Returns A masked copy of this distribution.

Return type *MaskedDistribution*

Example:

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.distributions import constraints
>>> from numpyro.infer import SVI, Trace_ELBO

>>> def model(data, m):
...     f = numpyro.sample("latent_fairness", dist.Beta(1, 1))
...     with numpyro.plate("N", data.shape[0]):
...         # only take into account the values selected by the mask
...         masked_dist = dist.Bernoulli(f).mask(m)
...         numpyro.sample("obs", masked_dist, obs=data)


>>> def guide(data, m):
...     alpha_q = numpyro.param("alpha_q", 5., constraint=constraints.
↪positive)
...     beta_q = numpyro.param("beta_q", 5., constraint=constraints.positive)
...     numpyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))
```

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```
>>> data = jnp.concatenate([jnp.ones(5), jnp.zeros(5)])
>>> # select values equal to one
>>> masked_array = jnp.where(data == 1, True, False)
>>> optimizer = numpyro.optim.Adam(step_size=0.05)
>>> svi = SVI(model, guide, optimizer, loss=Trace_ELBO())
>>> svi_result = svi.run(random.PRNGKey(0), 300, data, masked_array)
>>> params = svi_result.params
>>> # inferred_mean is closer to 1
>>> inferred_mean = params["alpha_q"] / (params["alpha_q"] + params["beta_q"])
```

classmethod infer_shapes(**args*, ***kwargs*)

Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

cdf(*value*)

The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)

The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

ExpandedDistribution

class ExpandedDistribution(*base_dist*, *batch_shape=()*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {}

has_enumerate_support

bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

is_discrete
bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

has_rsample

rsample(*key*, *sample_shape=()*)

support

sample_with_intermediates(*key*, *sample_shape=()*)
Same as `sample` except that any intermediate computations are returned (useful for *TransformedDistribution*).

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape + batch_shape + event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(*value*)
Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

ImproperUniform

class ImproperUniform(*support*, *batch_shape*, *event_shape*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

A helper distribution with zero *log_prob()* over the *support* domain.

Note: *sample* method is not implemented for this distribution. In autoguide and mcmc, initial parameters for improper sites are derived from *init_to_uniform* or *init_to_value* strategies.

Usage:

```
>>> from numpyro import sample
>>> from numpyro.distributions import ImproperUniform, Normal, constraints
>>>
>>> def model():
...     # ordered vector with length 10
...     x = sample('x', ImproperUniform(constraints.ordered_vector, (), event_
↪shape=(10,)))
...
...     # real matrix with shape (3, 4)
...     y = sample('y', ImproperUniform(constraints.real, (), event_shape=(3, 4)))
...
...     # a shape-(6, 8) batch of length-5 vectors greater than 3
...     z = sample('z', ImproperUniform(constraints.greater_than(3), (6, 8),␣
↪event_shape=(5,)))
```

If you want to set improper prior over all values greater than a, where a is another random variable, you might use

```
>>> def model():
...     a = sample('a', Normal(0, 1))
...     x = sample('x', ImproperUniform(constraints.greater_than(a), (), event_
↪shape=()))
```

or if you want to reparameterize it

```
>>> from numpyro.distributions import TransformedDistribution, transforms
>>> from numpyro.handlers import reparam
>>> from numpyro.infer.reparam import TransformReparam
>>>
>>> def model():
...     a = sample('a', Normal(0, 1))
...     with reparam(config={'x': TransformReparam()}):
...         x = sample('x',
...                    TransformedDistribution(ImproperUniform(constraints.
↪positive, (), ()),
...                                            transforms.AffineTransform(a, 1)))
```

Parameters

- **support** (*Constraint*) – the support of this distribution.
- **batch_shape** (*tuple*) – batch shape of this distribution. It is usually safe to set *batch_shape=()*.
- **event_shape** (*tuple*) – event shape of this distribution.

arg_constraints = {}

support = <numpyro.distributions.constraints._Dependent object>

log_prob(**args*, ***kwargs*)

tree_flatten()

Independent

class Independent(*base_dist*, *reinterpreted_batch_ndims*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

Reinterprets batch dimensions of a distribution as event dims by shifting the batch-event dim boundary further to the left.

From a practical standpoint, this is useful when changing the result of *log_prob()*. For example, a univariate Normal distribution can be interpreted as a multivariate Normal with diagonal covariance:

```
>>> import numpyro.distributions as dist
>>> normal = dist.Normal(jnp.zeros(3), jnp.ones(3))
>>> [normal.batch_shape, normal.event_shape]
[(3,), ()]
>>> diag_normal = dist.Independent(normal, 1)
>>> [diag_normal.batch_shape, diag_normal.event_shape]
[(), (3,)]
```

Parameters

- **base_distribution** (*numpyro.distribution.Distribution*) – a distribution instance.
- **reinterpreted_batch_ndims** (*int*) – the number of batch dims to reinterpret as event dims.

arg_constraints = {}

support

has_enumerate_support

bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

is_discrete

bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

reparameterized_params

mean

Mean of the distribution.

variance

Variance of the distribution.

has_rsample

rsample(*key*, *sample_shape=()*)

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(*value*)
Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

expand(*batch_shape*)
Returns a new *ExpandedDistribution* instance with batch dimensions expanded to *batch_shape*.

Parameters **batch_shape** (*tuple*) – batch shape to expand to.

Returns an instance of *ExpandedDistribution*.

Return type *ExpandedDistribution*

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

MaskedDistribution

class MaskedDistribution(*base_dist*, *mask*)
Bases: *numpyro.distributions.distribution.Distribution*

Masks a distribution by a boolean array that is broadcastable to the distribution's *Distribution.batch_shape*. In the special case `mask is False`, computation of *log_prob()* , is skipped, and constant zero values are returned instead.

Parameters **mask** (*jnp.ndarray or bool*) – A boolean or boolean-valued array.

arg_constraints = {}

has_enumerate_support
bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

is_discrete
bool(x) -> bool

Returns True when the argument x is true, False otherwise. The builtins True and False are the only two instances of the class bool. The class bool is a subclass of the class int, and cannot be subclassed.

has_rsample

rsample(*key*, *sample_shape=()*)

support

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape + batch_shape + event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(*value*)
Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

TransformedDistribution

class TransformedDistribution(*base_distribution*, *transforms*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

Returns a distribution instance obtained as a result of applying a sequence of transforms to a base distribution. For an example, see `LogNormal` and `HalfNormal`.

Parameters

- **base_distribution** – the base distribution over which to apply transforms.
- **transforms** – a single transform or a list of transforms.
- **validate_args** – Whether to enable validation of distribution parameters and arguments to *.log_prob* method.

arg_constraints = {}

has_rsample

rsample(*key*, *sample_shape=()*)

support

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

sample_with_intermediates(*key*, *sample_shape=()*)
Same as `sample` except that any intermediate computations are returned (useful for *TransformedDistribution*).

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

Delta

class Delta(*v=0.0*, *log_density=0.0*, *event_dim=0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'log_density': <numpyro.distributions.constraints._Real object>, 'v

reparameterized_params = ['v', 'log_density']

is_discrete = True

support

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

Unit

class Unit(*log_factor*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

Trivial nonnormalized distribution representing the unit type.

The unit type has a single value with no data, i.e. `value.size == 0`.

This is used for `numpyro.factor()` statements.

arg_constraints = {'log_factor': <numpyro.distributions.constraints._Real object>}

support = <numpyro.distributions.constraints._Real object>

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(*value*)
Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

2.2.2 Continuous Distributions

Beta

class Beta(*concentration1*, *concentration0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'concentration0': <numpyro.distributions.constraints._GreaterThan ob

reparametrized_params = ['concentration1', 'concentration0']

support = <numpyro.distributions.constraints._Interval object>

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

cdf(*value*)
The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

Cauchy

class Cauchy(*loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['loc', 'scale']

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

cdf(*value*)
The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)
The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

Chi2

class Chi2(*df*, *validate_args=None*)
Bases: *numpyro.distributions.continuous.Gamma*

arg_constraints = {'df': <numpyro.distributions.constraints._GreaterThan object>}

reparametrized_params = ['df']

Dirichlet

class Dirichlet(*concentration*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'concentration': <numpyro.distributions.constraints._IndependentCon

reparametrized_params = ['concentration']

support = <numpyro.distributions.constraints._Simplex object>

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

static infer_shapes(*concentration*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

Exponential

class Exponential(*rate=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

reparametrized_params = ['rate']

arg_constraints = {'rate': <numpyro.distributions.constraints._GreaterThan object>}

support = <numpyro.distributions.constraints._GreaterThan object>

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

Mean of the distribution.

variance

Variance of the distribution.

Gamma

class Gamma(*concentration*, *rate=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

support = <numpyro.distributions.constraints._GreaterThan object>

reparametrized_params = ['concentration', 'rate']

sample (*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

Gumbel

class Gumbel (*loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['loc', 'scale']

sample (*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

GaussianRandomWalk

class GaussianRandomWalk (*scale=1.0*, *num_steps=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'scale': <numpyro.distributions.constraints._GreaterThan object>}

support = <numpyro.distributions.constraints._IndependentConstraint object>

reparametrized_params = ['scale']

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

HalfCauchy

class HalfCauchy(*scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

reparametrized_params = ['scale']

support = <numpyro.distributions.constraints._GreaterThan object>

arg_constraints = {'scale': <numpyro.distributions.constraints._GreaterThan object>}

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

HalfNormal

class HalfNormal(*scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

reparametrized_params = ['scale']

support = <numpyro.distributions.constraints._GreaterThan object>

arg_constraints = {'scale': <numpyro.distributions.constraints._GreaterThan object>}

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

InverseGamma

class InverseGamma(*concentration*, *rate=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.TransformedDistribution*

Note: We keep the same notation *rate* as in Pyro but it plays the role of scale parameter of InverseGamma in literatures (e.g. wikipedia: https://en.wikipedia.org/wiki/Inverse-gamma_distribution)

---

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

reparametrized_params = ['concentration', 'rate']

support = <numpyro.distributions.constraints._GreaterThan object>

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

Laplace

class Laplace(*loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['loc', 'scale']

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

Mean of the distribution.

variance

Variance of the distribution.

cdf(*value*)

The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)

The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

LKJ

class LKJ(*dimension*, *concentration=1.0*, *sample_method='onion'*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.TransformedDistribution*

LKJ distribution for correlation matrices. The distribution is controlled by `concentration` parameter η to make the probability of the correlation matrix M propotional to $\det(M)^{\eta-1}$. Because of that, when `concentration == 1`, we have a uniform distribution over correlation matrices.

When `concentration > 1`, the distribution favors samples with large large determinent. This is useful when we know a priori that the underlying variables are not correlated.

When `concentration < 1`, the distribution favors samples with small determinent. This is useful when we know a priori that some underlying variables are correlated.

Parameters

- **dimension** (*int*) – dimension of the matrices
- **concentration** (*ndarray*) – concentration/shape parameter of the distribution (often referred to as eta)

- **sample_method** (*str*) – Either "cvine" or "onion". Both methods are proposed in [1] and offer the same distribution over correlation matrices. But they are different in how to generate samples. Defaults to "onion".

References

[1] *Generating random correlation matrices based on vines and extended onion method*, Daniel Lewandowski, Dorota Kurowicka, Harry Joe

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

reparametrized_params = ['concentration']

support = <numpyro.distributions.constraints._CorrMatrix object>

mean
Mean of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

LKJCholesky

class LKJCholesky(*dimension*, *concentration=1.0*, *sample_method='onion'*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

LKJ distribution for lower Cholesky factors of correlation matrices. The distribution is controlled by `concentration` parameter η to make the probability of the correlation matrix M generated from a Cholesky factor propotional to $\det(M)^{\eta-1}$. Because of that, when `concentration == 1`, we have a uniform distribution over Cholesky factors of correlation matrices.

When `concentration > 1`, the distribution favors samples with large diagonal entries (hence large determinent). This is useful when we know a priori that the underlying variables are not correlated.

When `concentration < 1`, the distribution favors samples with small diagonal entries (hence small determinent). This is useful when we know a priori that some underlying variables are correlated.

Parameters

- **dimension** (*int*) – dimension of the matrices
- **concentration** (*ndarray*) – concentration/shape parameter of the distribution (often referred to as eta)
- **sample_method** (*str*) – Either "cvine" or "onion". Both methods are proposed in [1] and offer the same distribution over correlation matrices. But they are different in how to generate samples. Defaults to "onion".

References

[1] *Generating random correlation matrices based on vines and extended onion method*, Daniel Lewandowski, Dorota Kurowicka, Harry Joe

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

reparametrized_params = ['concentration']

support = <numpyro.distributions.constraints._CorrCholesky object>

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

LogNormal

class LogNormal(*loc=0.0*, *scale=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.TransformedDistribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._GreaterThan object>

reparametrized_params = ['loc', 'scale']

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

Logistic

class Logistic(*loc=0.0*, *scale=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['loc', 'scale']

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape + batch_shape + event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

cdf(*value*)
The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)
The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

MultivariateNormal

class MultivariateNormal(*loc=0.0*, *covariance_matrix=None*, *precision_matrix=None*, *scale_tril=None*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'covariance_matrix': <numpyro.distributions.constraints._PositiveDe

support = <numpyro.distributions.constraints._IndependentConstraint object>

reparametrized_params = ['loc', 'covariance_matrix', 'precision_matrix', 'scale_tril']

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

covariance_matrix

precision_matrix

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

static infer_shapes(*loc=()*, *covariance_matrix=None*, *precision_matrix=None*, *scale_tril=None*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

LeftTruncatedDistribution

class LeftTruncatedDistribution(*base_dist*, *low=0.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'low': <numpyro.distributions.constraints._Real object>}

reparametrized_params = ['low']

supported_types = (<class 'numpyro.distributions.continuous.Cauchy'>, <class 'numpyro.

support

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

LowRankMultivariateNormal

class LowRankMultivariateNormal(*loc*, *cov_factor*, *cov_diag*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'cov_diag': <numpyro.distributions.constraints._IndependentConstrai

support = <numpyro.distributions.constraints._IndependentConstraint object>

reparametrized_params = ['loc', 'cov_factor', 'cov_diag']

mean
Mean of the distribution.

variance

scale_tril

covariance_matrix

precision_matrix

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

entropy()

static infer_shapes(*loc*, *cov_factor*, *cov_diag*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

Normal

class Normal(*loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'scale': <

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['loc', 'scale']

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

cdf(*value*)
The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)
The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

mean
Mean of the distribution.

variance
Variance of the distribution.

Pareto

class Pareto(*scale*, *alpha*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.TransformedDistribution*

arg_constraints = {'alpha': <numpyro.distributions.constraints._GreaterThan object>, '

reparametrized_params = ['scale', 'alpha']

mean
Mean of the distribution.

variance
Variance of the distribution.

support

tree_flatten()

RightTruncatedDistribution

class RightTruncatedDistribution(*base_dist*, *high=0.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'high': <numpyro.distributions.constraints._Real object>}

reparametrized_params = ['high']

supported_types = (<class 'numpyro.distributions.continuous.Cauchy'>, <class 'numpyro.

support

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

StudentT

class StudentT(*df*, *loc=0.0*, *scale=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'df': <numpyro.distributions.constraints._GreaterThan object>, 'loc

support = <numpyro.distributions.constraints._Real object>

reparametrized_params = ['df', 'loc', 'scale']

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

Mean of the distribution.

variance

Variance of the distribution.

cdf(*value*)

The cummulative distribution function of this distribution.

Parameters **value** – samples from this distribution.

Returns output of the cummulative distribution function evaluated at *value*.

icdf(*q*)
The inverse cumulative distribution function of this distribution.

Parameters **q** – quantile values, should belong to [0, 1].

Returns the samples whose cdf values equals to *q*.

TruncatedCauchy

class TruncatedCauchy(*low=0.0*, *loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.continuous.LeftTruncatedDistribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'low': <nu

reparametrized_params = ['low', 'loc', 'scale']

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

TruncatedDistribution

TruncatedDistribution(*base_dist*, *low=None*, *high=None*, *validate_args=None*)
A function to generate a truncated distribution.

Parameters

- **base_dist** – The base distribution to be truncated. This should be a univariate distribution. Currently, only the following distributions are supported: Cauchy, Laplace, Logistic, Normal, and StudentT.
- **low** – the value which is used to truncate the base distribution from below. Setting this parameter to None to not truncate from below.
- **high** – the value which is used to truncate the base distribution from above. Setting this parameter to None to not truncate from above.

TruncatedNormal

class TruncatedNormal(*low=0.0*, *loc=0.0*, *scale=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.continuous.LeftTruncatedDistribution*

arg_constraints = {'loc': <numpyro.distributions.constraints._Real object>, 'low': <nu

reparametrized_params = ['low', 'loc', 'scale']

mean
Mean of the distribution.

variance
Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

TruncatedPolyaGamma

class TruncatedPolyaGamma(*batch_shape=()*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

truncation_point = 2.5

num_log_prob_terms = 7

num_gamma_variates = 8

arg_constraints = {}

support = <numpyro.distributions.constraints._Interval object>

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

TwoSidedTruncatedDistribution

class TwoSidedTruncatedDistribution(*base_dist*, *low=0.0*, *high=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'high': <numpyro.distributions.constraints._Dependent object>, 'low

reparametrized_params = ['low', 'high']

supported_types = (<class 'numpyro.distributions.continuous.Cauchy'>, <class 'numpyro.

support

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

Uniform

class Uniform(*low=0.0*, *high=1.0*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'high': <numpyro.distributions.constraints._Dependent object>, 'low

reparametrized_params = ['low', 'high']

support

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

Mean of the distribution.

variance

Variance of the distribution.

tree_flatten()

classmethod tree_unflatten(*aux_data*, *params*)

static infer_shapes(*low=()*, *high=()*)

Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

2.2.3 Discrete Distributions

Bernoulli

Bernoulli(*probs=None*, *logits=None*, *validate_args=None*)

BernoulliLogits

class BernoulliLogits(*logits=None*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'logits': <numpyro.distributions.constraints._Real object>}

support = <numpyro.distributions.constraints._Boolean object>

has_enumerate_support = True

is_discrete = True

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

probs

mean

Mean of the distribution.

variance

Variance of the distribution.

enumerate_support(*expand=True*)

Returns an array with shape *len(support) x batch_shape* containing all values in the support.

BernoulliProbs

class BernoulliProbs(*probs*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'probs': <numpyro.distributions.constraints._Interval object>}

support = <numpyro.distributions.constraints._Boolean object>

has_enumerate_support = True

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

logits

mean
Mean of the distribution.

variance
Variance of the distribution.

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

BetaBinomial

class BetaBinomial(*concentration1*, *concentration0*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

Compound distribution comprising of a beta-binomial pair. The probability of success (`probs` for the `Binomial` distribution) is unknown and randomly drawn from a `Beta` distribution prior to a certain number of Bernoulli trials given by `total_count`.

Parameters

- **concentration1** (*numpy.ndarray*) – 1st concentration parameter (alpha) for the Beta distribution.
- **concentration0** (*numpy.ndarray*) – 2nd concentration parameter (beta) for the Beta distribution.
- **total_count** (*numpy.ndarray*) – number of Bernoulli trials.

arg_constraints = {'concentration0': <numpyro.distributions.constraints._GreaterThan ob

has_enumerate_support = True

is_discrete = True

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.

- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

support

Binomial

Binomial(*total_count=1*, *probs=None*, *logits=None*, *validate_args=None*)

BinomialLogits

class BinomialLogits(*logits*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'logits': <numpyro.distributions.constraints._Real object>, 'total_

has_enumerate_support = True

is_discrete = True

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape + batch_shape + event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

probs

mean
Mean of the distribution.

variance
Variance of the distribution.

support

BinomialProbs

class BinomialProbs(*probs*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'probs': <numpyro.distributions.constraints._Interval object>, 'tota

has_enumerate_support = True

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

logits

mean
Mean of the distribution.

variance
Variance of the distribution.

support

enumerate_support(*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

Categorical

Categorical(*probs=None*, *logits=None*, *validate_args=None*)

CategoricalLogits

class CategoricalLogits(*logits*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'logits': <numpyro.distributions.constraints._IndependentConstraint

has_enumerate_support = True

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

probs

mean
Mean of the distribution.

variance
Variance of the distribution.

support

enumerate_support (*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

CategoricalProbs

class CategoricalProbs (*probs*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'probs': <numpyro.distributions.constraints._Simplex object>}

has_enumerate_support = True

is_discrete = True

sample (*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape + batch_shape + event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape + batch_shape + event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

logits

mean
Mean of the distribution.

variance
Variance of the distribution.

support

enumerate_support (*expand=True*)
Returns an array with shape *len(support) x batch_shape* containing all values in the support.

DirichletMultinomial

class DirichletMultinomial(*concentration*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

Compound distribution comprising of a dirichlet-multinomial pair. The probability of classes (`probs` for the `Multinomial` distribution) is unknown and randomly drawn from a `Dirichlet` distribution prior to a certain number of Categorical trials given by `total_count`.

Parameters

- **concentration** (*numpy.ndarray*) – concentration parameter (alpha) for the Dirichlet distribution.
- **total_count** (*numpy.ndarray*) – number of Categorical trials.

arg_constraints = {'concentration': <numpyro.distributions.constraints._IndependentCon

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

support

static infer_shapes(*concentration*, *total_count=()*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

GammaPoisson

class GammaPoisson(*concentration*, *rate=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

Compound distribution comprising of a gamma-poisson pair, also referred to as a gamma-poisson mixture. The `rate` parameter for the `Poisson` distribution is unknown and randomly drawn from a `Gamma` distribution.

Parameters

- **concentration** (*numpy.ndarray*) – shape parameter (alpha) of the Gamma distribution.
- **rate** (*numpy.ndarray*) – rate parameter (beta) for the Gamma distribution.

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

support = <numpyro.distributions.constraints._IntegerGreaterThan object>

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

Geometric

Geometric(*probs=None*, *logits=None*, *validate_args=None*)

GeometricLogits

class GeometricLogits(*logits*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'logits': <numpyro.distributions.constraints._Real object>}

support = <numpyro.distributions.constraints._IntegerGreaterThan object>

is_discrete = True

probs

sample (*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

mean
Mean of the distribution.

variance
Variance of the distribution.

GeometricProbs

class GeometricProbs (*probs*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'probs': <numpyro.distributions.constraints._Interval object>}

support = <numpyro.distributions.constraints._IntegerGreaterThan object>

is_discrete = True

sample (*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob (**args*, ***kwargs*)

logits

mean
Mean of the distribution.

variance
Variance of the distribution.

Multinomial

Multinomial (*total_count=1*, *probs=None*, *logits=None*, *validate_args=None*)

MultinomialLogits

class MultinomialLogits(*logits*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'logits': <numpyro.distributions.constraints._IndependentConstraint

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

probs

mean
Mean of the distribution.

variance
Variance of the distribution.

support

static infer_shapes(*logits*, *total_count*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

MultinomialProbs

class MultinomialProbs(*probs*, *total_count=1*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'probs': <numpyro.distributions.constraints._Simplex object>, 'tota

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

logits

mean
Mean of the distribution.

variance
Variance of the distribution.

support

static infer_shapes(*probs*, *total_count*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

OrderedLogistic

class OrderedLogistic(*predictor*, *cutpoints*, *validate_args=None*)
Bases: *numpyro.distributions.discrete.CategoricalProbs*

A categorical distribution with ordered outcomes.

References:

1. *Stan Functions Reference, v2.20 section 12.6*, Stan Development Team

Parameters

- **predictor** (*numpy.ndarray*) – prediction in real domain; typically this is output of a linear model.
- **cutpoints** (*numpy.ndarray*) – positions in real domain to separate categories.

arg_constraints = {'cutpoints': <numpyro.distributions.constraints._OrderedVector obje

static infer_shapes(*predictor*, *cutpoints*)

Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

Poisson

class Poisson(*rate*, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'rate': <numpyro.distributions.constraints._GreaterThan object>}

support = <numpyro.distributions.constraints._IntegerGreaterThan object>

is_discrete = True

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

Mean of the distribution.

variance

Variance of the distribution.

PRNGIdentity

class PRNGIdentity
Bases: *numpyro.distributions.distribution.Distribution*

Distribution over `PRNGKey()`. This can be used to draw a batch of `PRNGKey()` using the *seed* handler. Only *sample* method is supported.

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

ZeroInflatedPoisson

class ZeroInflatedPoisson(*gate*, *rate=1.0*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

A Zero Inflated Poisson distribution.

Parameters

- **gate** (*numpy.ndarray*) – probability of extra zeros.
- **rate** (*numpy.ndarray*) – rate of Poisson distribution.

arg_constraints = {'gate': <numpyro.distributions.constraints._Interval object>, 'rate

support = <numpyro.distributions.constraints._IntegerGreaterThan object>

is_discrete = True

sample(*key*, *sample_shape=()*)
Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(**args*, ***kwargs*)

mean

variance

2.2.4 Directional Distributions

ProjectedNormal

class ProjectedNormal(*concentration*, *, *validate_args=None*)

Bases: *numpyro.distributions.distribution.Distribution*

Projected isotropic normal distribution of arbitrary dimension.

This distribution over directional data is qualitatively similar to the von Mises and von Mises-Fisher distributions, but permits tractable variational inference via reparametrized gradients.

To use this distribution with autoguides and HMC, use `handlers.reparam` with a *ProjectedNormalReparam* reparametrizer in the model, e.g.:

```
@handlers.reparam(config={"direction": ProjectedNormalReparam()})
def model():
    direction = numpyro.sample("direction",
                               ProjectedNormal(zeros(3)))
    ...
```

Note: This implements *log_prob()* only for dimensions {2,3}.

[1] D. Hernandez-Stumpfhauser, F.J. Breidt, M.J. van der Woerd (2017) "The General Projected Normal Distribution of Arbitrary Dimension: Modeling and Bayesian Inference" https://projecteuclid.org/euclid.ba/1453211962

arg_constraints = {'concentration': <numpyro.distributions.constraints._IndependentCon

reparametrized_params = ['concentration']

support = <numpyro.distributions.constraints._Sphere object>

mean

Note this is the mean in the sense of a centroid in the submanifold that minimizes expected squared geodesic distance.

mode

sample(*key*, *sample_shape=()*)

Returns a sample from the distribution having shape given by *sample_shape* + *batch_shape* + *event_shape*. Note that when *sample_shape* is non-empty, leading dimensions (of size *sample_shape*) of the returned sample will be filled with iid draws from the distribution instance.

Parameters

- **key** (*jax.random.PRNGKey*) – the rng_key key to be used for the distribution.
- **sample_shape** (*tuple*) – the sample shape for the distribution.

Returns an array of shape *sample_shape* + *batch_shape* + *event_shape*

Return type numpy.ndarray

log_prob(*value*)

Evaluates the log probability density for a batch of samples given by *value*.

Parameters **value** – A batch of samples from the distribution.

Returns an array with shape *value.shape[:-self.event_shape]*

Return type numpy.ndarray

static infer_shapes(*concentration*)
Infers `batch_shape` and `event_shape` given shapes of args to `__init__()`.

Note: This assumes distribution shape depends only on the shapes of tensor inputs, not in the data contained in those inputs.

Parameters

- ***args** – Positional args replacing each input arg with a tuple representing the sizes of each tensor input.
- ****kwargs** – Keywords mapping name of input arg to tuple representing the sizes of each tensor input.

Returns A pair `(batch_shape, event_shape)` of the shapes of a distribution that would be created with input args of the given shapes.

Return type tuple

VonMises

class VonMises(*loc*, *concentration*, *validate_args=None*)
Bases: *numpyro.distributions.distribution.Distribution*

arg_constraints = {'concentration': <numpyro.distributions.constraints._GreaterThan ob

reparametrized_params = ['loc']

support = <numpyro.distributions.constraints._Interval object>

sample(*key*, *sample_shape=()*)
Generate sample from von Mises distribution

Parameters

- **key** – random number generator key
- **sample_shape** – shape of samples

Returns samples from von Mises

log_prob(**args*, ***kwargs*)

mean
Computes circular mean of distribution. NOTE: same as location when mapped to support [-pi, pi]

variance
Computes circular variance of distribution

2.2.5 TensorFlow Distributions

Thin wrappers around TensorFlow Probability (TFP) distributions. For details on the TFP distribution interface, see its Distribution docs.

BijectorConstraint

class BijectorConstraint(*bijector*)
A constraint which is codomain of a TensorFlow bijector.

Parameters **bijector** (*Bijector*) – a TensorFlow bijector

BijectorTransform

class BijectorTransform(*bijector*)
A wrapper for TensorFlow bijectors to make them compatible with NumPyro's transforms.

Parameters **bijector** (*Bijector*) – a TensorFlow bijector

TFPDistributionMixin

class TFPDistributionMixin(*batch_shape=()*, *event_shape=()*, *validate_args=None*)
A mixin layer to make TensorFlow Probability (TFP) distribution compatible with NumPyro internal.

Autoregressive

class Autoregressive(*distribution_fn*, *sample0=None*, *num_steps=None*, *validate_args=False*, *allow_nan_stats=True*, *name='Autoregressive'*)
Wraps tensorflow_probability.substrates.jax.distributions.autoregressive.Autoregressive with *TFPDistributionMixin*.

BatchBroadcast

class BatchBroadcast(*distribution*, *with_shape=None*, ***, *to_shape=None*, *validate_args=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.batch_broadcast.BatchBroadcast with *TFPDistributionMixin*.

BatchConcat

class BatchConcat(*distributions*, *axis*, *validate_args=False*, *allow_nan_stats=True*, *name='BatchConcat'*)
Wraps tensorflow_probability.substrates.jax.distributions.batch_concat.BatchConcat with *TFPDistributionMixin*.

BatchReshape

class BatchReshape(*distribution*, *batch_shape*, *validate_args=False*, *allow_nan_stats=True*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.batch_reshape.BatchReshape with *TFPDistributionMixin*.

Bates

class Bates(*total_count*, *low=0.0*, *high=1.0*, *validate_args=False*, *allow_nan_stats=True*, *name='Bates'*)
Wraps tensorflow_probability.substrates.jax.distributions.bates.Bates with *TFPDistributionMixin*.

Bernoulli

class Bernoulli(*logits=None*, *probs=None*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='Bernoulli'*)
Wraps tensorflow_probability.substrates.jax.distributions.bernoulli.Bernoulli with *TFPDistributionMixin*.

Beta

class Beta(*concentration1*, *concentration0*, *validate_args=False*, *allow_nan_stats=True*, *name='Beta'*)
Wraps tensorflow_probability.substrates.jax.distributions.beta.Beta with *TFPDistributionMixin*.

BetaBinomial

class BetaBinomial(*total_count*, *concentration1*, *concentration0*, *validate_args=False*, *allow_nan_stats=True*, *name='BetaBinomial'*)
Wraps tensorflow_probability.substrates.jax.distributions.beta_binomial.BetaBinomial with *TFPDistributionMixin*.

BetaQuotient

class BetaQuotient(*concentration1_numerator*, *concentration0_numerator*, *concentration1_denominator*, *concentration0_denominator*, *validate_args=False*, *allow_nan_stats=True*, *name='BetaQuotient'*)
Wraps tensorflow_probability.substrates.jax.distributions.beta_quotient.BetaQuotient with *TFPDistributionMixin*.

Binomial

class Binomial(*total_count*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.binomial.Binomial with *TFPDistributionMixin*.

Blockwise

class Blockwise(*distributions*, *dtype_override=None*, *validate_args=False*, *allow_nan_stats=False*, *name='Blockwise'*)
Wraps tensorflow_probability.substrates.jax.distributions.blockwise.Blockwise with *TFPDistributionMixin*.

Categorical

class Categorical(*logits=None*, *probs=None*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='Categorical'*)
Wraps tensorflow_probability.substrates.jax.distributions.categorical.Categorical with *TFPDistributionMixin*.

Cauchy

class Cauchy(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Cauchy'*)
Wraps tensorflow_probability.substrates.jax.distributions.cauchy.Cauchy with *TFPDistributionMixin*.

Chi

class Chi(*df*, *validate_args=False*, *allow_nan_stats=True*, *name='Chi'*)
Wraps tensorflow_probability.substrates.jax.distributions.chi.Chi with *TFPDistributionMixin*.

Chi2

class Chi2(*df*, *validate_args=False*, *allow_nan_stats=True*, *name='Chi2'*)
Wraps tensorflow_probability.substrates.jax.distributions.chi2.Chi2 with *TFPDistributionMixin*.

CholeskyLKJ

class CholeskyLKJ(*dimension*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='CholeskyLKJ'*)
Wraps tensorflow_probability.substrates.jax.distributions.cholesky_lkj.CholeskyLKJ with *TFPDistributionMixin*.

ContinuousBernoulli

class ContinuousBernoulli(*logits=None*, *probs=None*, *lims=(0.499, 0.501)*, *dtype=<class 'jax._src.numpy.lax_numpy.float32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='ContinuousBernoulli'*)
Wraps tensorflow_probability.substrates.jax.distributions.continuous_bernoulli.ContinuousBernoulli with *TFPDistributionMixin*.

DeterminantalPointProcess

class DeterminantalPointProcess(*eigenvalues*, *eigenvectors*, *validate_args=False*, *allow_nan_stats=False*, *name='DeterminantalPointProcess'*)
Wraps tensorflow_probability.substrates.jax.distributions.dpp.DeterminantalPointProcess with *TFPDistributionMixin*.

Deterministic

class Deterministic(*loc*, *atol=None*, *rtol=None*, *validate_args=False*, *allow_nan_stats=True*, *name='Deterministic'*)
Wraps tensorflow_probability.substrates.jax.distributions.deterministic.Deterministic with *TFPDistributionMixin*.

Dirichlet

class Dirichlet(*concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='Dirichlet'*)
Wraps tensorflow_probability.substrates.jax.distributions.dirichlet.Dirichlet with *TFPDistributionMixin*.

DirichletMultinomial

class DirichletMultinomial(*total_count*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='DirichletMultinomial'*)
Wraps tensorflow_probability.substrates.jax.distributions.dirichlet_multinomial.DirichletMultinomial with *TFPDistributionMixin*.

DoublesidedMaxwell

class DoublesidedMaxwell(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='doublesided_maxwell'*)
Wraps tensorflow_probability.substrates.jax.distributions.doublesided_maxwell.DoublesidedMaxwell with *TFPDistributionMixin*.

Empirical

class Empirical(*samples*, *event_ndims=0*, *validate_args=False*, *allow_nan_stats=True*, *name='Empirical'*)
Wraps tensorflow_probability.substrates.jax.distributions.empirical.Empirical with *TFPDistributionMixin*.

ExpGamma

class ExpGamma(*concentration*, *rate=None*, *log_rate=None*, *validate_args=False*, *allow_nan_stats=True*, *name='ExpGamma'*)
Wraps tensorflow_probability.substrates.jax.distributions.exp_gamma.ExpGamma with *TFPDistributionMixin*.

ExpInverseGamma

class ExpInverseGamma(*concentration*, *scale=None*, *log_scale=None*, *validate_args=False*, *allow_nan_stats=True*, *name='ExpInverseGamma'*)
Wraps tensorflow_probability.substrates.jax.distributions.exp_gamma.ExpInverseGamma with *TFPDistributionMixin*.

ExpRelaxedOneHotCategorical

class ExpRelaxedOneHotCategorical(*temperature*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name='ExpRelaxedOneHotCategorical'*)
Wraps tensorflow_probability.substrates.jax.distributions.relaxed_onehot_categorical.ExpRelaxedOneHotCategorical with *TFPDistributionMixin*.

Exponential

class Exponential(*rate*, *force_probs_to_zero_outside_support=False*, *validate_args=False*, *allow_nan_stats=True*, *name='Exponential'*)
Wraps tensorflow_probability.substrates.jax.distributions.exponential.Exponential with *TFPDistributionMixin*.

ExponentiallyModifiedGaussian

class ExponentiallyModifiedGaussian(*loc*, *scale*, *rate*, *validate_args=False*, *allow_nan_stats=True*, *name='ExponentiallyModifiedGaussian'*)
Wraps tensorflow_probability.substrates.jax.distributions.exponentially_modified_gaussian.ExponentiallyModifiedGaussian with *TFPDistributionMixin*.

FiniteDiscrete

class FiniteDiscrete(*outcomes*, *logits=None*, *probs=None*, *rtol=None*, *atol=None*, *validate_args=False*, *allow_nan_stats=True*, *name='FiniteDiscrete'*)
Wraps tensorflow_probability.substrates.jax.distributions.finite_discrete.FiniteDiscrete with *TFPDistributionMixin*.

Gamma

class Gamma(*concentration*, *rate=None*, *log_rate=None*, *validate_args=False*, *allow_nan_stats=True*, *name='Gamma'*)
Wraps tensorflow_probability.substrates.jax.distributions.gamma.Gamma with *TFPDistributionMixin*.

GammaGamma

class GammaGamma(*concentration*, *mixing_concentration*, *mixing_rate*, *validate_args=False*, *allow_nan_stats=True*, *name='GammaGamma'*)
Wraps tensorflow_probability.substrates.jax.distributions.gamma_gamma.GammaGamma with *TFPDistributionMixin*.

GaussianProcess

class GaussianProcess(*kernel*, *index_points=None*, *mean_fn=None*, *observation_noise_variance=0.0*, *marginal_fn=None*, *jitter=1e-06*, *validate_args=False*, *allow_nan_stats=False*, *name='GaussianProcess'*)
Wraps tensorflow_probability.substrates.jax.distributions.gaussian_process.GaussianProcess with *TFPDistributionMixin*.

GaussianProcessRegressionModel

class GaussianProcessRegressionModel(*kernel*, *index_points=None*, *observation_index_points=None*, *observations=None*, *observation_noise_variance=0.0*, *predictive_noise_variance=None*, *mean_fn=None*, *jitter=1e-06*, *validate_args=False*, *allow_nan_stats=False*, *name='GaussianProcessRegressionModel'*)

Wraps tensorflow_probability.substrates.jax.distributions.gaussian_process_regression_model.GaussianProcessRegressionModel with *TFPDistributionMixin*.

GeneralizedExtremeValue

class GeneralizedExtremeValue(*loc*, *scale*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='GeneralizedExtremeValue'*)

Wraps tensorflow_probability.substrates.jax.distributions.gev.GeneralizedExtremeValue with *TFPDistributionMixin*.

GeneralizedNormal

class GeneralizedNormal(*loc*, *scale*, *power*, *validate_args=False*, *allow_nan_stats=True*, *name='GeneralizedNormal'*)

Wraps tensorflow_probability.substrates.jax.distributions.generalized_normal.GeneralizedNormal with *TFPDistributionMixin*.

GeneralizedPareto

class GeneralizedPareto(*loc*, *scale*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name=None*)

Wraps tensorflow_probability.substrates.jax.distributions.generalized_pareto.GeneralizedPareto with *TFPDistributionMixin*.

Geometric

class Geometric(*logits=None*, *probs=None*, *force_probs_to_zero_outside_support=False*, *validate_args=False*, *allow_nan_stats=True*, *name='Geometric'*)

Wraps tensorflow_probability.substrates.jax.distributions.geometric.Geometric with *TFPDistributionMixin*.

Gumbel

class Gumbel(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Gumbel'*)

Wraps tensorflow_probability.substrates.jax.distributions.gumbel.Gumbel with *TFPDistributionMixin*.

HalfCauchy

class HalfCauchy(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='HalfCauchy'*)

Wraps tensorflow_probability.substrates.jax.distributions.half_cauchy.HalfCauchy with *TFPDistributionMixin*.

HalfNormal

class HalfNormal(*scale*, *validate_args=False*, *allow_nan_stats=True*, *name='HalfNormal'*)
Wraps tensorflow_probability.substrates.jax.distributions.half_normal.HalfNormal with *TFPDistributionMixin*.

HalfStudentT

class HalfStudentT(*df*, *loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='HalfStudentT'*)
Wraps tensorflow_probability.substrates.jax.distributions.half_student_t.HalfStudentT with *TFPDistributionMixin*.

HiddenMarkovModel

class HiddenMarkovModel(*initial_distribution*, *transition_distribution*, *observation_distribution*, *num_steps*, *validate_args=False*, *allow_nan_stats=True*, *time_varying_transition_distribution=False*, *time_varying_observation_distribution=False*, *name='HiddenMarkovModel'*)
Wraps tensorflow_probability.substrates.jax.distributions.hidden_markov_model.HiddenMarkovModel with *TFPDistributionMixin*.

Horseshoe

class Horseshoe(*scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Horseshoe'*)
Wraps tensorflow_probability.substrates.jax.distributions.horseshoe.Horseshoe with *TFPDistributionMixin*.

Independent

class Independent(*distribution*, *reinterpreted_batch_ndims=None*, *validate_args=False*, *experimental_use_kahan_sum=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.independent.Independent with *TFPDistributionMixin*.

InverseGamma

class InverseGamma(*concentration*, *scale=None*, *validate_args=False*, *allow_nan_stats=True*, *name='InverseGamma'*)
Wraps tensorflow_probability.substrates.jax.distributions.inverse_gamma.InverseGamma with *TFPDistributionMixin*.

InverseGaussian

class InverseGaussian(*loc*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='InverseGaussian'*)
Wraps tensorflow_probability.substrates.jax.distributions.inverse_gaussian.InverseGaussian with *TFPDistributionMixin*.

JohnsonSU

class JohnsonSU(*skewness*, *tailweight*, *loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.johnson_su.JohnsonSU with *TFPDistributionMixin*.

JointDistribution

class JointDistribution(*dtype*, *reparameterization_type*, *validate_args*, *allow_nan_stats*, *parameters=None*, *graph_parents=None*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution.JointDistribution with *TFPDistributionMixin*.

JointDistributionCoroutine

class JointDistributionCoroutine(*model*, *sample_dtype=None*, *validate_args=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_coroutine.JointDistributionCoroutine with *TFPDistributionMixin*.

JointDistributionCoroutineAutoBatched

class JointDistributionCoroutineAutoBatched(*model*, *sample_dtype=None*, *batch_ndims=0*, *use_vectorized_map=True*, *validate_args=False*, *experimental_use_kahan_sum=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_auto_batched.JointDistributionCoroutineAutoBatched with *TFPDistributionMixin*.

JointDistributionNamed

class JointDistributionNamed(*model*, *validate_args=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_named.JointDistributionNamed with *TFPDistributionMixin*.

JointDistributionNamedAutoBatched

class JointDistributionNamedAutoBatched(*model*, *batch_ndims=0*, *use_vectorized_map=True*, *validate_args=False*, *experimental_use_kahan_sum=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_auto_batched.JointDistributionNamedAutoBatched with *TFPDistributionMixin*.

JointDistributionSequential

class JointDistributionSequential(*model*, *validate_args=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_sequential.JointDistributionSequential with *TFPDistributionMixin*.

JointDistributionSequentialAutoBatched

class JointDistributionSequentialAutoBatched(*model*, *batch_ndims=0*, *use_vectorized_map=True*, *validate_args=False*, *experimental_use_kahan_sum=False*, *name=None*)

Wraps tensorflow_probability.substrates.jax.distributions.joint_distribution_auto_batched.JointDistributionSequentialAutoBatche with *TFPDistributionMixin*.

Kumaraswamy

class Kumaraswamy(*concentration1=1.0*, *concentration0=1.0*, *validate_args=False*, *allow_nan_stats=True*, *name='Kumaraswamy'*)

Wraps tensorflow_probability.substrates.jax.distributions.kumaraswamy.Kumaraswamy with *TFPDistributionMixin*.

LKJ

class LKJ(*dimension*, *concentration*, *input_output_cholesky=False*, *validate_args=False*, *allow_nan_stats=True*, *name='LKJ'*)

Wraps tensorflow_probability.substrates.jax.distributions.lkj.LKJ with *TFPDistributionMixin*.

Laplace

class Laplace(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Laplace'*)

Wraps tensorflow_probability.substrates.jax.distributions.laplace.Laplace with *TFPDistributionMixin*.

LinearGaussianStateSpaceModel

class LinearGaussianStateSpaceModel(*num_timesteps*, *transition_matrix*, *transition_noise*, *observation_matrix*, *observation_noise*, *initial_state_prior*, *initial_step=0*, *mask=None*, *experimental_parallelize=False*, *validate_args=False*, *allow_nan_stats=True*, *name='LinearGaussianStateSpaceModel'*)

Wraps tensorflow_probability.substrates.jax.distributions.linear_gaussian_ssm.LinearGaussianStateSpaceModel with *TFPDistributionMixin*.

LogLogistic

class LogLogistic(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='LogLogistic'*)

Wraps tensorflow_probability.substrates.jax.distributions.loglogistic.LogLogistic with *TFPDistributionMixin*.

LogNormal

class LogNormal(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='LogNormal'*)

Wraps tensorflow_probability.substrates.jax.distributions.lognormal.LogNormal with *TFPDistributionMixin*.

Logistic

class Logistic(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Logistic'*)
Wraps tensorflow_probability.substrates.jax.distributions.logistic.Logistic with *TFPDistributionMixin*.

LogitNormal

class LogitNormal(*loc*, *scale*, *num_probit_terms_approx=2*, *validate_args=False*, *allow_nan_stats=True*, *name='LogitNormal'*)
Wraps tensorflow_probability.substrates.jax.distributions.logitnormal.LogitNormal with *TFPDistributionMixin*.

Masked

class Masked(*distribution*, *validity_mask*, *safe_sample_fn=<function _fixed_sample>*, *validate_args=False*, *allow_nan_stats=True*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.masked.Masked with *TFPDistributionMixin*.

MatrixNormalLinearOperator

class MatrixNormalLinearOperator(*loc*, *scale_row*, *scale_column*, *validate_args=False*, *allow_nan_stats=True*, *name='MatrixNormalLinearOperator'*)
Wraps tensorflow_probability.substrates.jax.distributions.matrix_normal_linear_operator.MatrixNormalLinearOperator with *TFPDistributionMixin*.

MatrixTLinearOperator

class MatrixTLinearOperator(*df*, *loc*, *scale_row*, *scale_column*, *validate_args=False*, *allow_nan_stats=True*, *name='MatrixTLinearOperator'*)
Wraps tensorflow_probability.substrates.jax.distributions.matrix_t_linear_operator.MatrixTLinearOperator with *TFPDistributionMixin*.

MixtureSameFamily

class MixtureSameFamily(*mixture_distribution*, *components_distribution*, *reparameterize=False*, *validate_args=False*, *allow_nan_stats=True*, *name='MixtureSameFamily'*)
Wraps tensorflow_probability.substrates.jax.distributions.mixture_same_family.MixtureSameFamily with *TFPDistributionMixin*.

Moyal

class Moyal(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Moyal'*)
Wraps tensorflow_probability.substrates.jax.distributions.moyal.Moyal with *TFPDistributionMixin*.

Multinomial

class Multinomial(*total_count*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name='Multinomial'*)
Wraps tensorflow_probability.substrates.jax.distributions.multinomial.Multinomial with *TFPDistributionMixin*.

MultivariateNormalDiag

class MultivariateNormalDiag(*loc=None*, *scale_diag=None*, *scale_identity_multiplier=None*, *validate_args=False*, *allow_nan_stats=True*, *experimental_use_kahan_sum=False*, *name='MultivariateNormalDiag'*)

Wraps tensorflow_probability.substrates.jax.distributions.mvn_diag.MultivariateNormalDiag with *TFPDistributionMixin*.

MultivariateNormalDiagPlusLowRank

class MultivariateNormalDiagPlusLowRank(*loc=None*, *scale_diag=None*, *scale_perturb_factor=None*, *scale_perturb_diag=None*, *validate_args=False*, *allow_nan_stats=True*, *name='MultivariateNormalDiagPlusLowRank'*)

Wraps tensorflow_probability.substrates.jax.distributions.mvn_diag_plus_low_rank.MultivariateNormalDiagPlusLowRank with *TFPDistributionMixin*.

MultivariateNormalFullCovariance

class MultivariateNormalFullCovariance(*loc=None*, *covariance_matrix=None*, *validate_args=False*, *allow_nan_stats=True*, *name='MultivariateNormalFullCovariance'*)

Wraps tensorflow_probability.substrates.jax.distributions.mvn_full_covariance.MultivariateNormalFullCovariance with *TFPDistributionMixin*.

MultivariateNormalLinearOperator

class MultivariateNormalLinearOperator(*loc=None*, *scale=None*, *validate_args=False*, *allow_nan_stats=True*, *experimental_use_kahan_sum=False*, *name='MultivariateNormalLinearOperator'*)

Wraps tensorflow_probability.substrates.jax.distributions.mvn_linear_operator.MultivariateNormalLinearOperator with *TFPDistributionMixin*.

MultivariateNormalTriL

class MultivariateNormalTriL(*loc=None*, *scale_tril=None*, *validate_args=False*, *allow_nan_stats=True*, *experimental_use_kahan_sum=False*, *name='MultivariateNormalTriL'*)

Wraps tensorflow_probability.substrates.jax.distributions.mvn_tril.MultivariateNormalTriL with *TFPDistributionMixin*.

MultivariateStudentTLinearOperator

class MultivariateStudentTLinearOperator(*df*, *loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='MultivariateStudentTLinearOperator'*)

Wraps tensorflow_probability.substrates.jax.distributions.multivariate_student_t.MultivariateStudentTLinearOperator with *TFPDistributionMixin*.

NegativeBinomial

class NegativeBinomial(*total_count*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name='NegativeBinomial'*)
Wraps tensorflow_probability.substrates.jax.distributions.negative_binomial.NegativeBinomial with *TFPDistributionMixin*.

Normal

class Normal(*loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Normal'*)
Wraps tensorflow_probability.substrates.jax.distributions.normal.Normal with *TFPDistributionMixin*.

NormalInverseGaussian

class NormalInverseGaussian(*loc*, *scale*, *tailweight*, *skewness*, *validate_args=False*, *allow_nan_stats=True*, *name='NormalInverseGaussian'*)
Wraps tensorflow_probability.substrates.jax.distributions.normal_inverse_gaussian.NormalInverseGaussian with *TFPDistributionMixin*.

OneHotCategorical

class OneHotCategorical(*logits=None*, *probs=None*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='OneHotCategorical'*)
Wraps tensorflow_probability.substrates.jax.distributions.onehot_categorical.OneHotCategorical with *TFPDistributionMixin*.

OrderedLogistic

class OrderedLogistic(*cutpoints*, *loc*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='OrderedLogistic'*)
Wraps tensorflow_probability.substrates.jax.distributions.ordered_logistic.OrderedLogistic with *TFPDistributionMixin*.

PERT

class PERT(*low*, *peak*, *high*, *temperature=4.0*, *validate_args=False*, *allow_nan_stats=False*, *name='PERT'*)
Wraps tensorflow_probability.substrates.jax.distributions.pert.PERT with *TFPDistributionMixin*.

Pareto

class Pareto(*concentration*, *scale=1.0*, *validate_args=False*, *allow_nan_stats=True*, *name='Pareto'*)
Wraps tensorflow_probability.substrates.jax.distributions.pareto.Pareto with *TFPDistributionMixin*.

PlackettLuce

class PlackettLuce(*scores*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='PlackettLuce'*)
Wraps tensorflow_probability.substrates.jax.distributions.plackett_luce.PlackettLuce with *TFPDistributionMixin*.

Poisson

class Poisson(*rate=None*, *log_rate=None*, *force_probs_to_zero_outside_support=None*, *interpolate_nondiscrete=True*, *validate_args=False*, *allow_nan_stats=True*, *name='Poisson'*)
Wraps tensorflow_probability.substrates.jax.distributions.poisson.Poisson with *TFPDistributionMixin*.

PoissonLogNormalQuadratureCompound

class PoissonLogNormalQuadratureCompound(*loc*, *scale*, *quadrature_size=8*, *quadrature_fn=<function quadrature_scheme_lognormal_quantiles>*, *validate_args=False*, *allow_nan_stats=True*, *name='PoissonLogNormalQuadratureCompound'*)
Wraps tensorflow_probability.substrates.jax.distributions.poisson_lognormal.PoissonLogNormalQuadratureCompound with *TFPDistributionMixin*.

PowerSpherical

class PowerSpherical(*mean_direction*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='PowerSpherical'*)
Wraps tensorflow_probability.substrates.jax.distributions.power_spherical.PowerSpherical with *TFPDistributionMixin*.

ProbitBernoulli

class ProbitBernoulli(*probits=None*, *probs=None*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='ProbitBernoulli'*)
Wraps tensorflow_probability.substrates.jax.distributions.probit_bernoulli.ProbitBernoulli with *TFPDistributionMixin*.

QuantizedDistribution

class QuantizedDistribution(*distribution*, *low=None*, *high=None*, *validate_args=False*, *name='QuantizedDistribution'*)
Wraps tensorflow_probability.substrates.jax.distributions.quantized_distribution.QuantizedDistribution with *TFPDistributionMixin*.

RelaxedBernoulli

class RelaxedBernoulli(*temperature*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name='RelaxedBernoulli'*)
Wraps tensorflow_probability.substrates.jax.distributions.relaxed_bernoulli.RelaxedBernoulli with *TFPDistributionMixin*.

RelaxedOneHotCategorical

class RelaxedOneHotCategorical(*temperature*, *logits=None*, *probs=None*, *validate_args=False*, *allow_nan_stats=True*, *name='RelaxedOneHotCategorical'*)
Wraps tensorflow_probability.substrates.jax.distributions.relaxed_onehot_categorical.RelaxedOneHotCategorical with *TFPDistributionMixin*.

Sample

class Sample(*distribution*, *sample_shape=()*, *validate_args=False*, *experimental_use_kahan_sum=False*, *name=None*)
Wraps tensorflow_probability.substrates.jax.distributions.sample.Sample with *TFPDistributionMixin*.

SigmoidBeta

class SigmoidBeta(*concentration1*, *concentration0*, *validate_args=False*, *allow_nan_stats=True*, *name='SigmoidBeta'*)
Wraps tensorflow_probability.substrates.jax.distributions.sigmoid_beta.SigmoidBeta with *TFPDistributionMixin*.

SinhArcsinh

class SinhArcsinh(*loc*, *scale*, *skewness=None*, *tailweight=None*, *distribution=None*, *validate_args=False*, *allow_nan_stats=True*, *name='SinhArcsinh'*)
Wraps tensorflow_probability.substrates.jax.distributions.sinh_arcsinh.SinhArcsinh with *TFPDistributionMixin*.

Skellam

class Skellam(*rate1=None*, *rate2=None*, *log_rate1=None*, *log_rate2=None*, *force_probs_to_zero_outside_support=False*, *validate_args=False*, *allow_nan_stats=True*, *name='Skellam'*)
Wraps tensorflow_probability.substrates.jax.distributions.skellam.Skellam with *TFPDistributionMixin*.

SphericalUniform

class SphericalUniform(*dimension*, *batch_shape=()*, *dtype=<class 'jax._src.numpy.lax_numpy.float32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='SphericalUniform'*)
Wraps tensorflow_probability.substrates.jax.distributions.spherical_uniform.SphericalUniform with *TFPDistributionMixin*.

StoppingRatioLogistic

class StoppingRatioLogistic(*cutpoints*, *loc*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *validate_args=False*, *allow_nan_stats=True*, *name='StoppingRatioLogistic'*)
Wraps tensorflow_probability.substrates.jax.distributions.stopping_ratio_logistic.StoppingRatioLogistic with *TFPDistributionMixin*.

StudentT

class StudentT(*df*, *loc*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='StudentT'*)
Wraps tensorflow_probability.substrates.jax.distributions.student_t.StudentT with *TFPDistributionMixin*.

StudentTProcess

class StudentTProcess(*df*, *kernel*, *index_points=None*, *mean_fn=None*, *jitter=1e-06*, *validate_args=False*, *allow_nan_stats=False*, *name='StudentTProcess'*)

Wraps tensorflow_probability.substrates.jax.distributions.student_t_process.StudentTProcess with *TFPDistributionMixin*.

TransformedDistribution

class TransformedDistribution(*distribution*, *bijector*, *kwargs_split_fn=<function _default_kwargs_split_fn>*, *validate_args=False*, *parameters=None*, *name=None*)

Wraps tensorflow_probability.substrates.jax.distributions.transformed_distribution.TransformedDistribution with *TFPDistributionMixin*.

Triangular

class Triangular(*low=0.0*, *high=1.0*, *peak=0.5*, *validate_args=False*, *allow_nan_stats=True*, *name='Triangular'*)

Wraps tensorflow_probability.substrates.jax.distributions.triangular.Triangular with *TFPDistributionMixin*.

TruncatedCauchy

class TruncatedCauchy(*loc*, *scale*, *low*, *high*, *validate_args=False*, *allow_nan_stats=True*, *name='TruncatedCauchy'*)

Wraps tensorflow_probability.substrates.jax.distributions.truncated_cauchy.TruncatedCauchy with *TFPDistributionMixin*.

TruncatedNormal

class TruncatedNormal(*loc*, *scale*, *low*, *high*, *validate_args=False*, *allow_nan_stats=True*, *name='TruncatedNormal'*)

Wraps tensorflow_probability.substrates.jax.distributions.truncated_normal.TruncatedNormal with *TFPDistributionMixin*.

Uniform

class Uniform(*low=0.0*, *high=1.0*, *validate_args=False*, *allow_nan_stats=True*, *name='Uniform'*)

Wraps tensorflow_probability.substrates.jax.distributions.uniform.Uniform with *TFPDistributionMixin*.

VariationalGaussianProcess

class VariationalGaussianProcess(*kernel*, *index_points*, *inducing_index_points*, *variational_inducing_observations_loc*, *variational_inducing_observations_scale*, *mean_fn=None*, *observation_noise_variance=None*, *predictive_noise_variance=None*, *jitter=1e-06*, *validate_args=False*, *allow_nan_stats=False*, *name='VariationalGaussianProcess'*)

Wraps tensorflow_probability.substrates.jax.distributions.variational_gaussian_process.VariationalGaussianProcess

with *TFPDistributionMixin*.

VectorDeterministic

class VectorDeterministic(*loc*, *atol=None*, *rtol=None*, *validate_args=False*, *allow_nan_stats=True*, *name='VectorDeterministic'*)
Wraps tensorflow_probability.substrates.jax.distributions.deterministic.VectorDeterministic with *TFPDistributionMixin*.

VectorExponentialDiag

class VectorExponentialDiag(*loc=None*, *scale_diag=None*, *scale_identity_multiplier=None*, *validate_args=False*, *allow_nan_stats=True*, *name='VectorExponentialDiag'*)
Wraps tensorflow_probability.substrates.jax.distributions.vector_exponential_diag.VectorExponentialDiag with *TFPDistributionMixin*.

VonMises

class VonMises(*loc*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='VonMises'*)
Wraps tensorflow_probability.substrates.jax.distributions.von_mises.VonMises with *TFPDistributionMixin*.

VonMisesFisher

class VonMisesFisher(*mean_direction*, *concentration*, *validate_args=False*, *allow_nan_stats=True*, *name='VonMisesFisher'*)
Wraps tensorflow_probability.substrates.jax.distributions.von_mises_fisher.VonMisesFisher with *TFPDistributionMixin*.

Weibull

class Weibull(*concentration*, *scale*, *validate_args=False*, *allow_nan_stats=True*, *name='Weibull'*)
Wraps tensorflow_probability.substrates.jax.distributions.weibull.Weibull with *TFPDistributionMixin*.

WishartLinearOperator

class WishartLinearOperator(*df*, *scale*, *input_output_cholesky=False*, *validate_args=False*, *allow_nan_stats=True*, *name='WishartLinearOperator'*)
Wraps tensorflow_probability.substrates.jax.distributions.wishart.WishartLinearOperator with *TFPDistributionMixin*.

WishartTriL

class WishartTriL(*df*, *scale_tril=None*, *input_output_cholesky=False*, *validate_args=False*, *allow_nan_stats=True*, *name='WishartTriL'*)
Wraps tensorflow_probability.substrates.jax.distributions.wishart.WishartTriL with *TFPDistributionMixin*.

Zipf

class Zipf(*power*, *dtype=<class 'jax._src.numpy.lax_numpy.int32'>*, *force_probs_to_zero_outside_support=None*, *interpolate_nondiscrete=True*, *sample_maximum_iterations=100*, *validate_args=False*, *allow_nan_stats=False*, *name='Zipf'*)

Wraps tensorflow_probability.substrates.jax.distributions.zipf.Zipf with *TFPDistributionMixin*.

2.2.6 Constraints

Constraint

class Constraint

Bases: object

Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

event_dim = 0

check(*value*)

Returns a byte tensor of *sample_shape + batch_shape* indicating whether each event in value satisfies this constraint.

feasible_like(*prototype*)

Get a feasible value which has the same shape as dtype as *prototype*.

boolean

boolean = <numpyro.distributions.constraints._Boolean object>

corr_cholesky

corr_cholesky = <numpyro.distributions.constraints._CorrCholesky object>

corr_matrix

corr_matrix = <numpyro.distributions.constraints._CorrMatrix object>

dependent

dependent = <numpyro.distributions.constraints._Dependent object>

Placeholder for variables whose support depends on other variables. These variables obey no simple coordinate-wise constraints.

Parameters

- **is_discrete** (*bool*) – Optional value of `.is_discrete` in case this can be computed statically. If not provided, access to the `.is_discrete` attribute will raise a NotImplementedError.
- **event_dim** (*int*) – Optional value of `.event_dim` in case this can be computed statically. If not provided, access to the `.event_dim` attribute will raise a NotImplementedError.

greater_than

greater_than(*lower_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

integer_interval

integer_interval(*lower_bound*, *upper_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

integer_greater_than

integer_greater_than(*lower_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

interval

interval(*lower_bound*, *upper_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

less_than

less_than(*upper_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

lower_cholesky

lower_cholesky = <numpyro.distributions.constraints._LowerCholesky object>

multinomial

multinomial(*upper_bound*)
Abstract base class for constraints.

A constraint object represents a region over which a variable is valid, e.g. within which a variable can be optimized.

nonnegative_integer

nonnegative_integer = <numpyro.distributions.constraints._IntegerGreaterThan object>

ordered_vector

ordered_vector = <numpyro.distributions.constraints._OrderedVector object>

positive

positive = <numpyro.distributions.constraints._GreaterThan object>

positive_definite

positive_definite = <numpyro.distributions.constraints._PositiveDefinite object>

positive_integer

positive_integer = <numpyro.distributions.constraints._IntegerGreaterThan object>

positive_ordered_vector

positive_ordered_vector = <numpyro.distributions.constraints._PositiveOrderedVector object>

Constrains to a positive real-valued tensor where the elements are monotonically increasing along the *event_shape* dimension.

real

real = <numpyro.distributions.constraints._Real object>

real_vector

real_vector = <numpyro.distributions.constraints._IndependentConstraint object>

Wraps a constraint by aggregating over `reinterpreted_batch_ndims`-many dims in `check()`, so that an event is valid only if all its independent entries are valid.

softplus_positive

softplus_positive = <numpyro.distributions.constraints._SoftplusPositive object>

softplus_lower_cholesky

softplus_lower_cholesky = <numpyro.distributions.constraints._SoftplusLowerCholesky object>

simplex

simplex = <numpyro.distributions.constraints._Simplex object>

sphere

sphere = <numpyro.distributions.constraints._Sphere object>
Constrain to the Euclidean sphere of any dimension.

unit_interval

unit_interval = <numpyro.distributions.constraints._Interval object>

2.2.7 Transforms

biject_to

biject_to(*constraint*)

Transform

class Transform
Bases: object

domain = <numpyro.distributions.constraints._Real object>

codomain = <numpyro.distributions.constraints._Real object>

event_dim

inv

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

call_with_intermediates(*x*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

AbsTransform

class AbsTransform
Bases: *numpyro.distributions.transforms.Transform*

domain = <numpyro.distributions.constraints._Real object>

codomain = <numpyro.distributions.constraints._GreaterThan object>

AffineTransform

class AffineTransform(*loc*, *scale*, *domain=<numpyro.distributions.constraints._Real object>*)
Bases: *numpyro.distributions.transforms.Transform*

Note: When *scale* is a JAX tracer, we always assume that *scale > 0* when calculating *codomain*.

---

codomain

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

CholeskyTransform

class CholeskyTransform
Bases: *numpyro.distributions.transforms.Transform*

Transform via the mapping $y = cholesky(x)$, where *x* is a positive definite matrix.

domain = <numpyro.distributions.constraints._PositiveDefinite object>

codomain = <numpyro.distributions.constraints._LowerCholesky object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

ComposeTransform

class ComposeTransform(*parts*)
Bases: *numpyro.distributions.transforms.Transform*

domain

codomain

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

call_with_intermediates(*x*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

CorrCholeskyTransform

class CorrCholeskyTransform
Bases: *numpyro.distributions.transforms.Transform*

Transforms a uncontrained real vector x with length $D * (D-1)/2$ into the Cholesky factor of a D-dimension correlation matrix. This Cholesky factor is a lower triangular matrix with positive diagonals and unit Euclidean norm for each row. The transform is processed as follows:

1. First we convert x into a lower triangular matrix with the following order:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ x_0 & 1 & 0 & 0 \\ x_1 & x_2 & 1 & 0 \\ x_3 & x_4 & x_5 & 1 \end{bmatrix}$$

2. For each row X_i of the lower triangular part, we apply a *signed* version of class *StickBreakingTransform* to transform X_i into a unit Euclidean length vector using the following steps:

   a. Scales into the interval $(-1, 1)$ domain: $r_i = \tanh(X_i)$.

   b. Transforms into an unsigned domain: $z_i = r_i^2$.

   c. Applies $s_i = StickBreakingTransform(z_i)$.

   d. Transforms back into signed domain: $y_i = (sign(r_i), 1) * \sqrt{s_i}$.

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._CorrCholesky object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

CorrMatrixCholeskyTransform

class CorrMatrixCholeskyTransform
Bases: *numpyro.distributions.transforms.CholeskyTransform*

Transform via the mapping $y = cholesky(x)$, where *x* is a correlation matrix.

domain = <numpyro.distributions.constraints._CorrMatrix object>

codomain = <numpyro.distributions.constraints._CorrCholesky object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

ExpTransform

class ExpTransform(*domain=<numpyro.distributions.constraints._Real object>*)
Bases: *numpyro.distributions.transforms.Transform*

codomain

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

IdentityTransform

class IdentityTransform
Bases: *numpyro.distributions.transforms.Transform*

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

InvCholeskyTransform

class InvCholeskyTransform(*domain=<numpyro.distributions.constraints._LowerCholesky object>*)
Bases: *numpyro.distributions.transforms.Transform*

Transform via the mapping $y = x@x.T$, where *x* is a lower triangular matrix with positive diagonal.

codomain

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

LowerCholeskyAffine

class LowerCholeskyAffine(*loc*, *scale_tril*)

Bases: *numpyro.distributions.transforms.Transform*

Transform via the mapping $y = loc + scale\_tril \mathbin{@} x$.

Parameters

- **loc** – a real vector.
- **scale_tril** – a lower triangular matrix with positive diagonal.

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._IndependentConstraint object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)

Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)

Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

LowerCholeskyTransform

class LowerCholeskyTransform

Bases: *numpyro.distributions.transforms.Transform*

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._LowerCholesky object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)

Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)

Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

OrderedTransform

class OrderedTransform

Bases: *numpyro.distributions.transforms.Transform*

Transform a real vector to an ordered vector.

References:

1. *Stan Reference Manual v2.20, section 10.6*, Stan Development Team

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._OrderedVector object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

PermuteTransform

class PermuteTransform(*permutation*)
Bases: *numpyro.distributions.transforms.Transform*

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._IndependentConstraint object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

PowerTransform

class PowerTransform(*exponent*)
Bases: *numpyro.distributions.transforms.Transform*

domain = <numpyro.distributions.constraints._GreaterThan object>

codomain = <numpyro.distributions.constraints._GreaterThan object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

SigmoidTransform

class SigmoidTransform
Bases: *numpyro.distributions.transforms.Transform*

codomain = <numpyro.distributions.constraints._Interval object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

SoftplusLowerCholeskyTransform

class SoftplusLowerCholeskyTransform
Bases: *numpyro.distributions.transforms.Transform*

Transform from unconstrained vector to lower-triangular matrices with nonnegative diagonal entries. This is useful for parameterizing positive definite matrices in terms of their Cholesky factorization.

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._SoftplusLowerCholesky object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

SoftplusTransform

class SoftplusTransform
Bases: *numpyro.distributions.transforms.Transform*

Transform from unconstrained space to positive domain via softplus $y = \log(1 + \exp(x))$. The inverse is computed as $x = \log(\exp(y) - 1)$.

domain = <numpyro.distributions.constraints._Real object>

codomain = <numpyro.distributions.constraints._SoftplusPositive object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

StickBreakingTransform

class StickBreakingTransform
Bases: *numpyro.distributions.transforms.Transform*

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._Simplex object>

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)

forward_shape(*shape*)
Infers the shape of the forward computation, given the input shape. Defaults to preserving shape.

inverse_shape(*shape*)
Infers the shapes of the inverse computation, given the output shape. Defaults to preserving shape.

2.2.8 Flows

InverseAutoregressiveTransform

class InverseAutoregressiveTransform(*autoregressive_nn*, *log_scale_min_clip=-5.0*, *log_scale_max_clip=3.0*)
Bases: *numpyro.distributions.transforms.Transform*

An implementation of Inverse Autoregressive Flow, using Eq (10) from Kingma et al., 2016,

$$\mathbf{y} = \mu_t + \sigma_t \odot \mathbf{x}$$

where $\mathbf{x}$ are the inputs, $\mathbf{y}$ are the outputs, μ_t, σ_t are calculated from an autoregressive network on $\mathbf{x}$, and $\sigma_t > 0$.

References

1. *Improving Variational Inference with Inverse Autoregressive Flow* [arXiv:1606.04934], Diederik P. Kingma, Tim Salimans, Rafal Jozefowicz, Xi Chen, Ilya Sutskever, Max Welling

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._IndependentConstraint object>

call_with_intermediates(*x*)

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)
Calculates the elementwise determinant of the log jacobian.

Parameters

- **x** (*numpy.ndarray*) – the input to the transform

- **y** (*numpy.ndarray*) – the output of the transform

BlockNeuralAutoregressiveTransform

class BlockNeuralAutoregressiveTransform(*bn_arn*)
Bases: *numpyro.distributions.transforms.Transform*

An implementation of Block Neural Autoregressive flow.

References

1. *Block Neural Autoregressive Flow*, Nicola De Cao, Ivan Titov, Wilker Aziz

domain = <numpyro.distributions.constraints._IndependentConstraint object>

codomain = <numpyro.distributions.constraints._IndependentConstraint object>

call_with_intermediates(*x*)

log_abs_det_jacobian(*x*, *y*, *intermediates=None*)
Calculates the elementwise determinant of the log jacobian.

Parameters

- **x** (*numpy.ndarray*) – the input to the transform
- **y** (*numpy.ndarray*) – the output of the transform

2.3 Inference

2.3.1 Markov Chain Monte Carlo (MCMC)

class MCMC(*sampler*, *num_warmup*, *num_samples*, *num_chains=1*, *thinning=1*, *postprocess_fn=None*, *chain_method='parallel'*, *progress_bar=True*, *jit_model_args=False*)
Bases: object

Provides access to Markov Chain Monte Carlo inference algorithms in NumPyro.

Note: *chain_method* is an experimental arg, which might be removed in a future version.

Note: Setting *progress_bar=False* will improve the speed for many cases. But it might require more memory than the other option.

Parameters

- **sampler** (MCMCKernel) – an instance of *MCMCKernel* that determines the sampler for running MCMC. Currently, only *HMC* and *NUTS* are available.
- **num_warmup** (*int*) – Number of warmup steps.
- **num_samples** (*int*) – Number of samples to generate from the Markov chain.
- **thinning** (*int*) – Positive integer that controls the fraction of post-warmup samples that are retained. For example if thinning is 2 then every other sample is retained. Defaults to 1, i.e. no thinning.

- **num_chains** (*int*) – Number of MCMC chains to run. By default, chains will be run in parallel using `jax.pmap()`. If there are not enough devices available, chains will be run in sequence.
- **postprocess_fn** – Post-processing callable - used to convert a collection of unconstrained sample values returned from the sampler to constrained values that lie within the support of the sample sites. Additionally, this is used to return values at deterministic sites in the model.
- **chain_method** (*str*) – One of 'parallel' (default), 'sequential', 'vectorized'. The method 'parallel' is used to execute the drawing process in parallel on XLA devices (CPUs/GPUs/TPUs), If there are not enough devices for 'parallel', we fall back to 'sequential' method to draw chains sequentially. 'vectorized' method is an experimental feature which vectorizes the drawing method, hence allowing us to collect samples in parallel on a single device.
- **progress_bar** (*bool*) – Whether to enable progress bar updates. Defaults to `True`.
- **jit_model_args** (*bool*) – If set to *True*, this will compile the potential energy computation as a function of model arguments. As such, calling *MCMC.run* again on a same sized but different dataset will not result in additional compilation cost.

post_warmup_state
The state before the sampling phase. If this attribute is not None, *run()* will skip the warmup phase and start with the state specified in this attribute.

Note: This attribute can be used to sequentially draw MCMC samples. For example,

```
mcmc = MCMC(NUTS(model), 100, 100)
mcmc.run(random.PRNGKey(0))
first_100_samples = mcmc.get_samples()
mcmc.post_warmup_state = mcmc.last_state
mcmc.run(mcmc.post_warmup_state.rng_key)  # or mcmc.run(random.PRNGKey(1))
second_100_samples = mcmc.get_samples()
```

---

last_state
The final MCMC state at the end of the sampling phase.

warmup(*rng_key*, **args*, *extra_fields=()*, *collect_warmup=False*, *init_params=None*, ***kwargs*)
Run the MCMC warmup adaptation phase. After this call, *self.warmup_state* will be set and the *run()* method will skip the warmup adaptation phase. To run *warmup* again for the new data, it is required to run *warmup()* again.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to be used for the sampling.
- **args** – Arguments to be provided to the *numpyro.infer.mcmc.MCMCKernel.init()* method. These are typically the arguments needed by the *model*.
- **extra_fields** (*tuple or list*) – Extra fields (aside from *default_fields()*) from the state object (e.g. *numpyro.infer.hmc.HMCState* for HMC) to collect during the MCMC run.
- **collect_warmup** (*bool*) – Whether to collect samples from the warmup phase. Defaults to *False*.

- **init_params** – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **kwargs** – Keyword arguments to be provided to the *numpyro.infer.mcmc.MCMCKernel.init()* method. These are typically the keyword arguments needed by the *model*.

run(*rng_key*, **args*, *extra_fields=()*, *init_params=None*, ***kwargs*)
Run the MCMC samplers and collect samples.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to be used for the sampling. For multi-chains, a batch of *num_chains* keys can be supplied. If *rng_key* does not have batch_size, it will be split in to a batch of *num_chains* keys.
- **args** – Arguments to be provided to the *numpyro.infer.mcmc.MCMCKernel.init()* method. These are typically the arguments needed by the *model*.
- **extra_fields** (*tuple or list*) – Extra fields (aside from *z*, *diverging*) from `numpyro.infer.mcmc.HMCState` to collect during the MCMC run.
- **init_params** – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **kwargs** – Keyword arguments to be provided to the *numpyro.infer.mcmc.MCMCKernel.init()* method. These are typically the keyword arguments needed by the *model*.

Note: jax allows python code to continue even when the compiled code has not finished yet. This can cause troubles when trying to profile the code for speed. See https://jax.readthedocs.io/en/latest/async_dispatch.html and https://jax.readthedocs.io/en/latest/profiling.html for pointers on profiling jax programs.

---

get_samples(*group_by_chain=False*)
Get samples from the MCMC run.

Parameters **group_by_chain** (*bool*) – Whether to preserve the chain dimension. If True, all samples will have num_chains as the size of their leading dimension.

Returns Samples having the same data type as *init_params*. The data type is a *dict* keyed on site names if a model containing Pyro primitives is used, but can be any `jaxlib.pytree()`, more generally (e.g. when defining a *potential_fn* for HMC that takes *list* args).

get_extra_fields(*group_by_chain=False*)
Get extra fields from the MCMC run.

Parameters **group_by_chain** (*bool*) – Whether to preserve the chain dimension. If True, all samples will have num_chains as the size of their leading dimension.

Returns Extra fields keyed by field names which are specified in the *extra_fields* keyword of *run()*.

print_summary(*prob=0.9*, *exclude_deterministic=True*)
Print the statistics of posterior samples collected during running this MCMC instance.

Parameters

- **prob** (*float*) – the probability mass of samples within the credible interval.
- **exclude_deterministic** (*bool*) – whether or not print out the statistics at deterministic sites.

MCMC Kernels

class MCMCKernel
Bases: abc.ABC

Defines the interface for the Markov transition kernel that is used for *MCMC* inference.

Example:

```
>>> from collections import namedtuple
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import MCMC

>>> MHState = namedtuple("MHState", ["u", "rng_key"])

>>> class MetropolisHastings(numpyro.infer.mcmc.MCMCKernel):
...     sample_field = "u"
...
...     def __init__(self, potential_fn, step_size=0.1):
...         self.potential_fn = potential_fn
...         self.step_size = step_size
...
...     def init(self, rng_key, num_warmup, init_params, model_args, model_
↪kwargs):
...         return MHState(init_params, rng_key)
...
...     def sample(self, state, model_args, model_kwargs):
...         u, rng_key = state
...         rng_key, key_proposal, key_accept = random.split(rng_key, 3)
...         u_proposal = dist.Normal(u, self.step_size).sample(key_proposal)
...         accept_prob = jnp.exp(self.potential_fn(u) - self.potential_fn(u_
↪proposal))
...         u_new = jnp.where(dist.Uniform().sample(key_accept) < accept_prob, u_
↪proposal, u)
...         return MHState(u_new, rng_key)

>>> def f(x):
...     return ((x - 2) ** 2).sum()

>>> kernel = MetropolisHastings(f)
>>> mcmc = MCMC(kernel, num_warmup=1000, num_samples=1000)
>>> mcmc.run(random.PRNGKey(0), init_params=jnp.array([1., 2.]))
>>> samples = mcmc.get_samples()
>>> mcmc.print_summary()
```

postprocess_fn(*model_args*, *model_kwargs*)
Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

init(*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample(*state*, *model_args*, *model_kwargs*)
Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

sample_field
The attribute of the *state* object passed to *sample()* that denotes the MCMC sample. This is used by *postprocess_fn()* and for reporting results in *MCMC.print_summary()*.

default_fields
The attributes of the *state* object to be collected by default during the MCMC run (when `MCMC.run()` is called).

get_diagnostics_str(*state*)
Given the current *state*, returns the diagnostics string to be added to progress bar for diagnostics purpose.

class BarkerMH(*model=None*, *potential_fn=None*, *step_size=1.0*, *adapt_step_size=True*, *adapt_mass_matrix=True*, *dense_mass=False*, *target_accept_prob=0.4*, *init_strategy=<function init_to_uniform>*)
Bases: *numpyro.infer.mcmc.MCMCKernel*

This is a gradient-based MCMC algorithm of Metropolis-Hastings type that uses a skew-symmetric proposal distribution that depends on the gradient of the potential (the Barker proposal; see reference [1]). In particular the proposal distribution is skewed in the direction of the gradient at the current sample.

We expect this algorithm to be particularly effective for low to moderate dimensional models, where it may be competitive with HMC and NUTS.

Note: We recommend to use this kernel with *progress_bar=False* in `MCMC` to reduce JAX's dispatch overhead.

References:

1. The Barker proposal: combining robustness and efficiency in gradient-based MCMC. Samuel Livingstone, Giacomo Zanella.

Parameters

- **model** – Python callable containing Pyro *primitives*. If model is provided, *potential_fn* will be inferred using the model.
- **potential_fn** – Python callable that computes the potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to *init()* has the same type.
- **step_size** (*float*) – (Initial) step size to use in the Barker proposal.
- **adapt_step_size** (*bool*) – Whether to adapt the step size during warm-up. Defaults to `adapt_step_size=True`.
- **adapt_mass_matrix** (*bool*) – Whether to adapt the mass matrix during warm-up. Defaults to `adapt_mass_matrix=True`.
- **dense_mass** (*bool*) – Whether to use a dense (i.e. full-rank) or diagonal mass matrix. (defaults to `dense_mass=False`).
- **target_accept_prob** (*float*) – The target acceptance probability that is used to guide step size adapation. Defaults to `target_accept_prob=0.4`.
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.

Example

```
>>> import jax
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import MCMC, BarkerMH

>>> def model():
...     x = numpyro.sample("x", dist.Normal().expand([10]))
...     numpyro.sample("obs", dist.Normal(x, 1.0), obs=jnp.ones(10))
>>>
>>> kernel = BarkerMH(model)
>>> mcmc = MCMC(kernel, num_warmup=1000, num_samples=1000, progress_bar=True)
>>> mcmc.run(jax.random.PRNGKey(0))
>>> mcmc.print_summary()
```

model

sample_field
The attribute of the *state* object passed to *sample()* that denotes the MCMC sample. This is used by *postprocess_fn()* and for reporting results in *MCMC.print_summary()*.

get_diagnostics_str(*state*)
Given the current *state*, returns the diagnostics string to be added to progress bar for diagnostics purpose.

init(*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.

- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

postprocess_fn(*args*, *kwargs*)

Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

sample(*state*, *model_args*, *model_kwargs*)

Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

class HMC(*model=None*, *potential_fn=None*, *kinetic_fn=None*, *step_size=1.0*, *adapt_step_size=True*, *adapt_mass_matrix=True*, *dense_mass=False*, *target_accept_prob=0.8*, *trajectory_length=6.283185307179586*, *init_strategy=<function init_to_uniform>*, *find_heuristic_step_size=False*, *forward_mode_differentiation=False*)

Bases: *numpyro.infer.mcmc.MCMCKernel*

Hamiltonian Monte Carlo inference, using fixed trajectory length, with provision for step size and mass matrix adaptation.

References:

1. *MCMC Using Hamiltonian Dynamics*, Radford M. Neal

Parameters

- **model** – Python callable containing Pyro *primitives*. If model is provided, *potential_fn* will be inferred using the model.
- **potential_fn** – Python callable that computes the potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to *init()* has the same type.
- **kinetic_fn** – Python callable that returns the kinetic energy given inverse mass matrix and momentum. If not provided, the default is euclidean kinetic energy.
- **step_size** (*float*) – Determines the size of a single step taken by the verlet integrator while computing the trajectory using Hamiltonian dynamics. If not specified, it will be set to 1.
- **adapt_step_size** (*bool*) – A flag to decide if we want to adapt step_size during warm-up phase using Dual Averaging scheme.

- **adapt_mass_matrix** (*bool*) – A flag to decide if we want to adapt mass matrix during warm-up phase using Welford scheme.
- **dense_mass** (*bool*) – A flag to decide if mass matrix is dense or diagonal (default when `dense_mass=False`)
- **target_accept_prob** (*float*) – Target acceptance probability for step size adaptation using Dual Averaging. Increasing this value will lead to a smaller step size, hence the sampling will be slower but more robust. Default to 0.8.
- **trajectory_length** (*float*) – Length of a MCMC trajectory for HMC. Default value is 2π.
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.
- **find_heuristic_step_size** (*bool*) – whether to a heuristic function to adjust the step size at the beginning of each adaptation window. Defaults to False.
- **forward_mode_differentiation** (*bool*) – whether to use forward-mode differentiation or reverse-mode differentiation. By default, we use reverse mode but the forward mode can be useful in some cases to improve the performance. In addition, some control flow utility on JAX such as *jax.lax.while_loop* or *jax.lax.fori_loop* only supports forward-mode differentiation. See JAX's The Autodiff Cookbook for more information.

model

sample_field
The attribute of the *state* object passed to *sample()* that denotes the MCMC sample. This is used by *postprocess_fn()* and for reporting results in *MCMC.print_summary()*.

default_fields
The attributes of the *state* object to be collected by default during the MCMC run (when `MCMC.run()` is called).

get_diagnostics_str(*state*)
Given the current *state*, returns the diagnostics string to be added to progress bar for diagnostics purpose.

init(*rng_key*, *num_warmup*, *init_params=None*, *model_args=()*, *model_kwargs={}*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

postprocess_fn(*args*, *kwargs*)
Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

sample(*state*, *model_args*, *model_kwargs*)
Run HMC from the given *HMCState* and return the resulting *HMCState*.

Parameters

- **state** (*HMCState*) – Represents the current state.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state* after running HMC.

class NUTS(*model=None*, *potential_fn=None*, *kinetic_fn=None*, *step_size=1.0*, *adapt_step_size=True*, *adapt_mass_matrix=True*, *dense_mass=False*, *target_accept_prob=0.8*, *trajectory_length=None*, *max_tree_depth=10*, *init_strategy=<function init_to_uniform>*, *find_heuristic_step_size=False*, *forward_mode_differentiation=False*)
Bases: *numpyro.infer.hmc.HMC*

Hamiltonian Monte Carlo inference, using the No U-Turn Sampler (NUTS) with adaptive path length and mass matrix adaptation.

References:

1. *MCMC Using Hamiltonian Dynamics*, Radford M. Neal
2. *The No-U-turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo*, Matthew D. Hoffman, and Andrew Gelman.
3. *A Conceptual Introduction to Hamiltonian Monte Carlo'*, Michael Betancourt

Parameters

- **model** – Python callable containing Pyro *primitives*. If model is provided, *potential_fn* will be inferred using the model.
- **potential_fn** – Python callable that computes the potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to *init_kernel* has the same type.
- **kinetic_fn** – Python callable that returns the kinetic energy given inverse mass matrix and momentum. If not provided, the default is euclidean kinetic energy.
- **step_size** (*float*) – Determines the size of a single step taken by the verlet integrator while computing the trajectory using Hamiltonian dynamics. If not specified, it will be set to 1.
- **adapt_step_size** (*bool*) – A flag to decide if we want to adapt step_size during warm-up phase using Dual Averaging scheme.
- **adapt_mass_matrix** (*bool*) – A flag to decide if we want to adapt mass matrix during warm-up phase using Welford scheme.
- **dense_mass** (*bool*) – A flag to decide if mass matrix is dense or diagonal (default when `dense_mass=False`)
- **target_accept_prob** (*float*) – Target acceptance probability for step size adaptation using Dual Averaging. Increasing this value will lead to a smaller step size, hence the sampling will be slower but more robust. Default to 0.8.

- **trajectory_length** (*float*) – Length of a MCMC trajectory for HMC. This arg has no effect in NUTS sampler.
- **max_tree_depth** (*int*) – Max depth of the binary tree created during the doubling scheme of NUTS sampler. Defaults to 10.
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.
- **find_heuristic_step_size** (*bool*) – whether to a heuristic function to adjust the step size at the beginning of each adaptation window. Defaults to False.
- **forward_mode_differentiation** (*bool*) – whether to use forward-mode differentiation or reverse-mode differentiation. By default, we use reverse mode but the forward mode can be useful in some cases to improve the performance. In addition, some control flow utility on JAX such as *jax.lax.while_loop* or *jax.lax.fori_loop* only supports forward-mode differentiation. See JAX's The Autodiff Cookbook for more information.

class HMCGibbs(*inner_kernel*, *gibbs_fn*, *gibbs_sites*)

Bases: *numpyro.infer.mcmc.MCMCKernel*

[EXPERIMENTAL INTERFACE]

HMC-within-Gibbs. This inference algorithm allows the user to combine general purpose gradient-based inference (HMC or NUTS) with custom Gibbs samplers.

Note that it is the user's responsibility to provide a correct implementation of *gibbs_fn* that samples from the corresponding posterior conditional.

Parameters

- **inner_kernel** – One of *HMC* or *NUTS*.
- **gibbs_fn** – A Python callable that returns a dictionary of Gibbs samples conditioned on the HMC sites. Must include an argument *rng_key* that should be used for all sampling. Must also include arguments *hmc_sites* and *gibbs_sites*, each of which is a dictionary with keys that are site names and values that are sample values. Note that a given *gibbs_fn* may not need make use of all these sample values.
- **gibbs_sites** (*list*) – a list of site names for the latent variables that are covered by the Gibbs sampler.

Example

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import MCMC, NUTS, HMCGibbs
...
>>> def model():
...     x = numpyro.sample("x", dist.Normal(0.0, 2.0))
...     y = numpyro.sample("y", dist.Normal(0.0, 2.0))
...     numpyro.sample("obs", dist.Normal(x + y, 1.0), obs=jnp.array([1.0]))
...
>>> def gibbs_fn(rng_key, gibbs_sites, hmc_sites):
...    y = hmc_sites['y']
...    new_x = dist.Normal(0.8 * (1-y), jnp.sqrt(0.8)).sample(rng_key)
...    return {'x': new_x}
...
>>> hmc_kernel = NUTS(model)
```

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```
>>> kernel = HMCGibbs(hmc_kernel, gibbs_fn=gibbs_fn, gibbs_sites=['x'])
>>> mcmc = MCMC(kernel, 100, 100, progress_bar=False)
>>> mcmc.run(random.PRNGKey(0))
>>> mcmc.print_summary()
```

sample_field = 'z'

model

get_diagnostics_str(*state*)
Given the current *state*, returns the diagnostics string to be added to progress bar for diagnostics purpose.

postprocess_fn(*args*, *kwargs*)
Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

init(*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample(*state*, *model_args*, *model_kwargs*)
Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

class DiscreteHMCGibbs(*inner_kernel*, *, *random_walk=False*, *modified=False*)
Bases: *numpyro.infer.hmc_gibbs.HMCGibbs*

[EXPERIMENTAL INTERFACE]

A subclass of *HMCGibbs* which performs Metropolis updates for discrete latent sites.

Note: The site update order is randomly permuted at each step.

Note: This class supports enumeration of discrete latent variables. To marginalize out a discrete latent site, we can specify *infer={'enumerate': 'parallel'}* keyword in its corresponding *sample()* statement.

Parameters

- **inner_kernel** – One of *HMC* or *NUTS*.
- **random_walk** (*bool*) – If False, Gibbs sampling will be used to draw a sample from the conditional *p(gibbs_site | remaining sites)*. Otherwise, a sample will be drawn uniformly from the domain of *gibbs_site*. Defaults to False.
- **modified** (*bool*) – whether to use a modified proposal, as suggested in reference [1], which always proposes a new state for the current Gibbs site. Defaults to False. The modified scheme appears in the literature under the name "modified Gibbs sampler" or "Metropolised Gibbs sampler".

References:

1. *Peskun's theorem and a modified discrete-state Gibbs sampler*, Liu, J. S. (1996)

Example

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import DiscreteHMCGibbs, MCMC, NUTS
...
>>> def model(probs, locs):
...     c = numpyro.sample("c", dist.Categorical(probs))
...     numpyro.sample("x", dist.Normal(locs[c], 0.5))
...
>>> probs = jnp.array([0.15, 0.3, 0.3, 0.25])
>>> locs = jnp.array([-2, 0, 2, 4])
>>> kernel = DiscreteHMCGibbs(NUTS(model), modified=True)
>>> mcmc = MCMC(kernel, 1000, 100000, progress_bar=False)
>>> mcmc.run(random.PRNGKey(0), probs, locs)
>>> mcmc.print_summary()
>>> samples = mcmc.get_samples()["x"]
>>> assert abs(jnp.mean(samples) - 1.3) < 0.1
>>> assert abs(jnp.var(samples) - 4.36) < 0.5
```

init (*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.

- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample(*state*, *model_args*, *model_kwargs*)

Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

class MixedHMC(*inner_kernel*, *, *num_discrete_updates=None*, *random_walk=False*, *modified=False*)

Bases: *numpyro.infer.hmc_gibbs.DiscreteHMCGibbs*

Implementation of Mixed Hamiltonian Monte Carlo (reference [1]).

Note: The number of discrete sites to update at each MCMC iteration (*n_D* in reference [1]) is fixed at value 1.

References

1. *Mixed Hamiltonian Monte Carlo for Mixed Discrete and Continuous Variables*, Guangyao Zhou (2020)
2. *Peskun's theorem and a modified discrete-state Gibbs sampler*, Liu, J. S. (1996)

Parameters

- **inner_kernel** – A *HMC* kernel.
- **num_discrete_updates** (*int*) – Number of times to update discrete variables. Defaults to the number of discrete latent variables.
- **random_walk** (*bool*) – If False, Gibbs sampling will be used to draw a sample from the conditional *p(gibbs_site | remaining sites)*, where *gibbs_site* is one of the discrete sample sites in the model. Otherwise, a sample will be drawn uniformly from the domain of *gibbs_site*. Defaults to False.
- **modified** (*bool*) – whether to use a modified proposal, as suggested in reference [2], which always proposes a new state for the current Gibbs site (i.e. discrete site). Defaults to False. The modified scheme appears in the literature under the name "modified Gibbs sampler" or "Metropolised Gibbs sampler".

Example

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import HMC, MCMC, MixedHMC
...
```

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```
>>> def model(probs, locs):
...     c = numpyro.sample("c", dist.Categorical(probs))
...     numpyro.sample("x", dist.Normal(locs[c], 0.5))
...
>>> probs = jnp.array([0.15, 0.3, 0.3, 0.25])
>>> locs = jnp.array([-2, 0, 2, 4])
>>> kernel = MixedHMC(HMC(model, trajectory_length=1.2), num_discrete_updates=20)
>>> mcmc = MCMC(kernel, 1000, 100000, progress_bar=False)
>>> mcmc.run(random.PRNGKey(0), probs, locs)
>>> mcmc.print_summary()
>>> samples = mcmc.get_samples()
>>> assert "x" in samples and "c" in samples
>>> assert abs(jnp.mean(samples["x"]) - 1.3) < 0.1
>>> assert abs(jnp.var(samples["x"]) - 4.36) < 0.5
```

init(*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)

Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample(*state*, *model_args*, *model_kwargs*)

Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

class HMCECS(*inner_kernel*, *, *num_blocks=1*, *proxy=None*)

Bases: *numpyro.infer.hmc_gibbs.HMCGibbs*

[EXPERIMENTAL INTERFACE]

HMC with Energy Conserving Subsampling.

A subclass of *HMCGibbs* for performing HMC-within-Gibbs for models with subsample statements using the `plate` primitive. This implements Algorithm 1 of reference [1] but uses a naive estimation (without control variates) of log likelihood, hence might incur a high variance.

The function can divide subsample indices into blocks and update only one block at each MCMC step to improve the acceptance rate of proposed subsamples as detailed in [3].

Note: New subsample indices are proposed randomly with replacement at each MCMC step.

References:

1. *Hamiltonian Monte Carlo with energy conserving subsampling*, Dang, K. D., Quiroz, M., Kohn, R., Minh-Ngoc, T., & Villani, M. (2019)
2. *Speeding Up MCMC by Efficient Data Subsampling*, Quiroz, M., Kohn, R., Villani, M., & Tran, M. N. (2018)
3. *The Block Pseudo-Margional Sampler*, Tran, M.-N., Kohn, R., Quiroz, M. Villani, M. (2017)
4. *The Fundamental Incompatibility of Scalable Hamiltonian Monte Carlo and Naive Data Subsampling* Betancourt, M. (2015)

Parameters

- **inner_kernel** – One of *HMC* or *NUTS*.
- **num_blocks** (*int*) – Number of blocks to partition subsample into.
- **proxy** – Either *taylor_proxy()* for likelihood estimation, or, None for naive (in-between trajectory) subsampling as outlined in [4].

Example

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import HMCECS, MCMC, NUTS
...
>>> def model(data):
...     x = numpyro.sample("x", dist.Normal(0, 1))
...     with numpyro.plate("N", data.shape[0], subsample_size=100):
...         batch = numpyro.subsample(data, event_dim=0)
...         numpyro.sample("obs", dist.Normal(x, 1), obs=batch)
...
>>> data = random.normal(random.PRNGKey(0), (10000,)) + 1
>>> kernel = HMCECS(NUTS(model), num_blocks=10)
>>> mcmc = MCMC(kernel, 1000, 1000)
>>> mcmc.run(random.PRNGKey(0), data)
>>> samples = mcmc.get_samples()["x"]
>>> assert abs(jnp.mean(samples) - 1.) < 0.1
```

postprocess_fn (*args*, *kwargs*)

Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

init (*rng_key*, *num_warmup*, *init_params*, *model_args*, *model_kwargs*)

Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample(*state*, *model_args*, *model_kwargs*)

Given the current *state*, return the next *state* using the given transition kernel.

Parameters

- **state** – A pytree class representing the state for the kernel. For HMC, this is given by *HMCState*. In general, this could be any class that supports *getattr*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state*.

static taylor_proxy(*reference_params*)

class SA(*model=None*, *potential_fn=None*, *adapt_state_size=None*, *dense_mass=True*, *init_strategy=<function init_to_uniform>*)

Bases: *numpyro.infer.mcmc.MCMCKernel*

Sample Adaptive MCMC, a gradient-free sampler.

This is a very fast (in term of n_eff / s) sampler but requires many warmup (burn-in) steps. In each MCMC step, we only need to evaluate potential function at one point.

Note that unlike in reference [1], we return a randomly selected (i.e. thinned) subset of approximate posterior samples of size num_chains x num_samples instead of num_chains x num_samples x adapt_state_size.

Note: We recommend to use this kernel with *progress_bar=False* in MCMC to reduce JAX's dispatch overhead.

References:

1. *Sample Adaptive MCMC* (https://papers.nips.cc/paper/9107-sample-adaptive-mcmc), Michael Zhu

Parameters

- **model** – Python callable containing Pyro *primitives*. If model is provided, *potential_fn* will be inferred using the model.
- **potential_fn** – Python callable that computes the potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to *init()* has the same type.
- **adapt_state_size** (*int*) – The number of points to generate proposal distribution. Defaults to 2 times latent size.

- **dense_mass** (*bool*) – A flag to decide if mass matrix is dense or diagonal (default to `dense_mass=True`)
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.

init(*rng_key*, *num_warmup*, *init_params=None*, *model_args=()*, *model_kwargs={}*)
Initialize the *MCMCKernel* and return an initial state to begin sampling from.

Parameters

- **rng_key** (*random.PRNGKey*) – Random number generator key to initialize the kernel.
- **num_warmup** (*int*) – Number of warmup steps. This can be useful when doing adaptation during warmup.
- **init_params** (*tuple*) – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns

The initial state representing the state of the kernel. This can be any class that is registered as a pytree.

sample_field
The attribute of the *state* object passed to *sample()* that denotes the MCMC sample. This is used by *postprocess_fn()* and for reporting results in *MCMC.print_summary()*.

default_fields
The attributes of the *state* object to be collected by default during the MCMC run (when `MCMC.run()` is called).

get_diagnostics_str(*state*)
Given the current *state*, returns the diagnostics string to be added to progress bar for diagnostics purpose.

postprocess_fn(*args*, *kwargs*)
Get a function that transforms unconstrained values at sample sites to values constrained to the site's support, in addition to returning deterministic sites in the model.

Parameters

- **model_args** – Arguments to the model.
- **model_kwargs** – Keyword arguments to the model.

sample(*state*, *model_args*, *model_kwargs*)
Run SA from the given `SAState` and return the resulting `SAState`.

Parameters

- **state** (*SAState*) – Represents the current state.
- **model_args** – Arguments provided to the model.
- **model_kwargs** – Keyword arguments provided to the model.

Returns Next *state* after running SA.

hmc(*potential_fn=None*, *potential_fn_gen=None*, *kinetic_fn=None*, *algo='NUTS'*)
Hamiltonian Monte Carlo inference, using either fixed number of steps or the No U-Turn Sampler (NUTS) with adaptive path length.

References:

1. *MCMC Using Hamiltonian Dynamics*, Radford M. Neal
2. *The No-U-turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo*, Matthew D. Hoffman, and Andrew Gelman.
3. *A Conceptual Introduction to Hamiltonian Monte Carlo'*, Michael Betancourt

Parameters

- **potential_fn** – Python callable that computes the potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to *init_kernel* has the same type.
- **potential_fn_gen** – Python callable that when provided with model arguments / keyword arguments returns *potential_fn*. This may be provided to do inference on the same model with changing data. If the data shape remains the same, we can compile *sample_kernel* once, and use the same for multiple inference runs.
- **kinetic_fn** – Python callable that returns the kinetic energy given inverse mass matrix and momentum. If not provided, the default is euclidean kinetic energy.
- **algo** (*str*) – Whether to run `HMC` with fixed number of steps or `NUTS` with adaptive path length. Default is `NUTS`.

Returns a tuple of callables (*init_kernel*, *sample_kernel*), the first one to initialize the sampler, and the second one to generate samples given an existing one.

Warning: Instead of using this interface directly, we would highly recommend you to use the higher level `numpyro.infer.MCMC` API instead.

Example

```
>>> import jax
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer.hmc import hmc
>>> from numpyro.infer.util import initialize_model
>>> from numpyro.util import fori_collect

>>> true_coefs = jnp.array([1., 2., 3.])
>>> data = random.normal(random.PRNGKey(2), (2000, 3))
>>> labels = dist.Bernoulli(logits=(true_coefs * data).sum(-1)).sample(random.
↪PRNGKey(3))
>>>
>>> def model(data, labels):
...     coefs = numpyro.sample('coefs', dist.Normal(jnp.zeros(3), jnp.ones(3)))
...     intercept = numpyro.sample('intercept', dist.Normal(0., 10.))
...     return numpyro.sample('y', dist.Bernoulli(logits=(coefs * data +␣
↪intercept).sum(-1)), obs=labels)
>>>
>>> model_info = initialize_model(random.PRNGKey(0), model, model_args=(data,␣
↪labels,))
>>> init_kernel, sample_kernel = hmc(model_info.potential_fn, algo='NUTS')
```

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```
>>> hmc_state = init_kernel(model_info.param_info,
...                         trajectory_length=10,
...                         num_warmup=300)
>>> samples = fori_collect(0, 500, sample_kernel, hmc_state,
...                        transform=lambda state: model_info.postprocess_
↪fn(state.z))
>>> print(jnp.mean(samples['coefs'], axis=0))
[0.9153987 2.0754058 2.9621222]
```

init_kernel(*init_params, num_warmup, step_size=1.0, inverse_mass_matrix=None, adapt_step_size=True, adapt_mass_matrix=True, dense_mass=False, target_accept_prob=0.8, trajectory_length=6.283185307179586, max_tree_depth=10, find_heuristic_step_size=False, forward_mode_differentiation=False, model_args=(), model_kwargs=None, rng_key=DeviceArray([0, 0], dtype=uint32)*)

Initializes the HMC sampler.

Parameters

- **init_params** – Initial parameters to begin sampling. The type must be consistent with the input type to *potential_fn*.
- **num_warmup** (*int*) – Number of warmup steps; samples generated during warmup are discarded.
- **step_size** (*float*) – Determines the size of a single step taken by the verlet integrator while computing the trajectory using Hamiltonian dynamics. If not specified, it will be set to 1.
- **inverse_mass_matrix** (*numpy.ndarray*) – Initial value for inverse mass matrix. This may be adapted during warmup if adapt_mass_matrix = True. If no value is specified, then it is initialized to the identity matrix.
- **adapt_step_size** (*bool*) – A flag to decide if we want to adapt step_size during warm-up phase using Dual Averaging scheme.
- **adapt_mass_matrix** (*bool*) – A flag to decide if we want to adapt mass matrix during warm-up phase using Welford scheme.
- **dense_mass** (*bool*) – A flag to decide if mass matrix is dense or diagonal (default when `dense_mass=False`)
- **target_accept_prob** (*float*) – Target acceptance probability for step size adaptation using Dual Averaging. Increasing this value will lead to a smaller step size, hence the sampling will be slower but more robust. Default to 0.8.
- **trajectory_length** (*float*) – Length of a MCMC trajectory for HMC. Default value is 2π.
- **max_tree_depth** (*int*) – Max depth of the binary tree created during the doubling scheme of NUTS sampler. Defaults to 10.
- **find_heuristic_step_size** (*bool*) – whether to a heuristic function to adjust the step size at the beginning of each adaptation window. Defaults to False.
- **model_args** (*tuple*) – Model arguments if *potential_fn_gen* is specified.
- **model_kwargs** (*dict*) – Model keyword arguments if *potential_fn_gen* is specified.
- **rng_key** (*jax.random.PRNGKey*) – random key to be used as the source of randomness.

sample_kernel (*hmc_state*, *model_args=()*, *model_kwargs=None*)
Given an existing HMCState, run HMC with fixed (possibly adapted) step size and return a new HMCState.

Parameters

- **hmc_state** – Current sample (and associated state).
- **model_args** (*tuple*) – Model arguments if *potential_fn_gen* is specified.
- **model_kwargs** (*dict*) – Model keyword arguments if *potential_fn_gen* is specified.

Returns new proposed HMCState from simulating Hamiltonian dynamics given existing state.

taylor_proxy (*reference_params*)
Control variate for unbiased log likelihood estimation using a Taylor expansion around a reference parameter. Suggest for subsampling in [1].

Parameters **reference_params** (*dict*) – Model parameterization at MLE or MAP-estimate.

** References: **

[1] Towards scaling up Markov chainMonte Carlo: an adaptive subsampling approach Bardenet., R., Doucet, A., Holmes, C. (2014)

BarkerMHState = <class 'numpyro.infer.barker.BarkerMHState'>
A namedtuple() consisting of the following fields:

- **i** - iteration. This is reset to 0 after warmup.
- **z** - Python collection representing values (unconstrained samples from the posterior) at latent sites.
- **potential_energy** - Potential energy computed at the given value of z.
- **z_grad** - Gradient of potential energy w.r.t. latent sample sites.
- **accept_prob** - Acceptance probability of the proposal. Note that z does not correspond to the proposal if it is rejected.
- **mean_accept_prob** - Mean acceptance probability until current iteration during warmup adaptation or sampling (for diagnostics).
- **adapt_state** - A HMCAdaptState namedtuple which contains adaptation information during warmup:
  - **step_size** - Step size to be used by the integrator in the next iteration.
  - **inverse_mass_matrix** - The inverse mass matrix to be used for the next iteration.
  - **mass_matrix_sqrt** - The square root of mass matrix to be used for the next iteration. In case of dense mass, this is the Cholesky factorization of the mass matrix.
- **rng_key** - random number generator seed used for generating proposals, etc.

HMCState = <class 'numpyro.infer.hmc.HMCState'>
A namedtuple() consisting of the following fields:

- **i** - iteration. This is reset to 0 after warmup.
- **z** - Python collection representing values (unconstrained samples from the posterior) at latent sites.
- **z_grad** - Gradient of potential energy w.r.t. latent sample sites.
- **potential_energy** - Potential energy computed at the given value of z.
- **energy** - Sum of potential energy and kinetic energy of the current state.
- **r** - The current momentum variable. If this is None, a new momentum variable will be drawn at the beginning of each sampling step.

- **trajectory_length** - The amount of time to run HMC dynamics in each sampling step. This field is not used in NUTS.
- **num_steps** - Number of steps in the Hamiltonian trajectory (for diagnostics). In NUTS sampler, the tree depth of a trajectory can be computed from this field with *tree_depth = np.log2(num_steps).astype(int) + 1*.
- **accept_prob** - Acceptance probability of the proposal. Note that `z` does not correspond to the proposal if it is rejected.
- **mean_accept_prob** - Mean acceptance probability until current iteration during warmup adaptation or sampling (for diagnostics).
- **diverging** - A boolean value to indicate whether the current trajectory is diverging.
- **adapt_state** - A `HMCAdaptState` namedtuple which contains adaptation information during warmup:
  - **step_size** - Step size to be used by the integrator in the next iteration.
  - **inverse_mass_matrix** - The inverse mass matrix to be used for the next iteration.
  - **mass_matrix_sqrt** - The square root of mass matrix to be used for the next iteration. In case of dense mass, this is the Cholesky factorization of the mass matrix.
- **rng_key** - random number generator seed used for the iteration.

HMCGibbsState = <class 'numpyro.infer.hmc_gibbs.HMCGibbsState'>

- **z** - a dict of the current latent values (both HMC and Gibbs sites)
- **hmc_state** - current hmc_state
- **rng_key** - random key for the current step

SAState = <class 'numpyro.infer.sa.SAState'>

A `namedtuple()` used in Sample Adaptive MCMC. This consists of the following fields:

- **i** - iteration. This is reset to 0 after warmup.
- **z** - Python collection representing values (unconstrained samples from the posterior) at latent sites.
- **potential_energy** - Potential energy computed at the given value of `z`.
- **accept_prob** - Acceptance probability of the proposal. Note that `z` does not correspond to the proposal if it is rejected.
- **mean_accept_prob** - Mean acceptance probability until current iteration during warmup or sampling (for diagnostics).
- **diverging** - A boolean value to indicate whether the new sample potential energy is diverging from the current one.
- **adapt_state** - A `SAAdaptState` namedtuple which contains adaptation information:
  - **zs** - Step size to be used by the integrator in the next iteration.
  - **pes** - Potential energies of *zs*.
  - **loc** - Mean of those *zs*.
  - **inv_mass_matrix_sqrt** - If using dense mass matrix, this is Cholesky of the covariance of *zs*. Otherwise, this is standard deviation of those *zs*.
- **rng_key** - random number generator seed used for the iteration.

TensorFlow Kernels

Thin wrappers around TensorFlow Probability (TFP) distributions. For details on the TFP distribution interface, see its TransitionKernel docs.

TFPKernel

class TFPKernel(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

A thin wrapper for TensorFlow Probability (TFP) MCMC transition kernels. The argument *target_log_prob_fn* in TFP is replaced by either *model* or *potential_fn* (which is the negative of *target_log_prob_fn*).

This class can be used to convert a TFP kernel to a NumPyro-compatible one as follows:

```
kernel = TFPKernel[tfp.mcmc.NoUTurnSampler](model, step_size=1.)
```

Note: By default, uncalibrated kernels will be inner kernels of the `MetropolisHastings` kernel.

Note: For *ReplicaExchangeMC*, TFP requires that the shape of *step_size* of the inner kernel must be *[len(inverse_temperatures), 1]* or *[len(inverse_temperatures), latent_size]*.

Parameters

- **model** – Python callable containing Pyro *primitives*. If model is provided, *potential_fn* will be inferred using the model.
- **potential_fn** – Python callable that computes the target potential energy given input parameters. The input parameters to *potential_fn* can be any python collection type, provided that *init_params* argument to `init()` has the same type.
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.
- **kernel_kwargs** – other arguments to be passed to TFP kernel constructor.

HamiltonianMonteCarlo

class HamiltonianMonteCarlo(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.hmc.HamiltonianMonteCarlo with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

MetropolisAdjustedLangevinAlgorithm

class MetropolisAdjustedLangevinAlgorithm(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.langevin.MetropolisAdjustedLangevinAlgorithm with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

NoUTurnSampler

class NoUTurnSampler(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.nuts.NoUTurnSampler with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

RandomWalkMetropolis

class RandomWalkMetropolis(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.random_walk_metropolis.RandomWalkMetropolis with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

ReplicaExchangeMC

class ReplicaExchangeMC(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.replica_exchange_mc.ReplicaExchangeMC with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

SliceSampler

class SliceSampler(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.slice_sampler_kernel.SliceSampler with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

UncalibratedHamiltonianMonteCarlo

class UncalibratedHamiltonianMonteCarlo(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.hmc.UncalibratedHamiltonianMonteCarlo with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

UncalibratedLangevin

class UncalibratedLangevin(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.langevin.UncalibratedLangevin with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

UncalibratedRandomWalk

class UncalibratedRandomWalk(*model=None*, *potential_fn=None*, *init_strategy=<function init_to_uniform>*, ***kernel_kwargs*)

Wraps tensorflow_probability.substrates.jax.mcmc.random_walk_metropolis.UncalibratedRandomWalk with *TFPKernel*. The first argument *target_log_prob_fn* in TFP kernel construction is replaced by either *model* or *potential_fn*.

MCMC Utilities

initialize_model(*rng_key*, *model*, *init_strategy=<function init_to_uniform>*, *dynamic_args=False*, *model_args=()*, *model_kwargs=None*, *forward_mode_differentiation=False*)

(EXPERIMENTAL INTERFACE) Helper function that calls `get_potential_fn()` and *find_valid_initial_params()* under the hood to return a tuple of (*init_params_info*, *potential_fn*, *postprocess_fn*, *model_trace*).

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed to sample from the prior. The returned *init_params* will have the batch shape `rng_key.shape[:-1]`.
- **model** – Python callable containing Pyro primitives.
- **init_strategy** (*callable*) – a per-site initialization function. See *Initialization Strategies* section for available functions.
- **dynamic_args** (*bool*) – if *True*, the *potential_fn* and *constraints_fn* are themselves dependent on model arguments. When provided a **model_args, **model_kwargs*, they return *potential_fn* and *constraints_fn* callables, respectively.
- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **forward_mode_differentiation** (*bool*) – whether to use forward-mode differentiation or reverse-mode differentiation. By default, we use reverse mode but the forward mode can be useful in some cases to improve the performance. In addition, some control flow utility on JAX such as *jax.lax.while_loop* or *jax.lax.fori_loop* only supports forward-mode differentiation. See JAX's The Autodiff Cookbook for more information.

Returns a namedtupe *ModelInfo* which contains the fields (*param_info*, *potential_fn*, *postprocess_fn*, *model_trace*), where *param_info* is a namedtuple *ParamInfo* containing values from the prior used to initiate MCMC, their corresponding potential energy, and their gradients; *postprocess_fn* is a callable that uses inverse transforms to convert unconstrained HMC samples to constrained values that lie within the site's support, in addition to returning values at *deterministic* sites in the model.

fori_collect(*lower*, *upper*, *body_fun*, *init_val*, *transform=<function identity>*, *progbar=True*, *return_last_val=False*, *collection_size=None*, *thinning=1*, ***progbar_opts*)

This looping construct works like `fori_loop()` but with the additional effect of collecting values from the loop body. In addition, this allows for post-processing of these samples via *transform*, and progress bar updates. Note that, *progbar=False* will be faster, especially when collecting a lot of samples. Refer to example usage in `hmc()`.

Parameters

- **lower** (*int*) – the index to start the collective work. In other words, we will skip collecting the first *lower* values.
- **upper** (*int*) – number of times to run the loop body.

- **body_fun** – a callable that takes a collection of *np.ndarray* and returns a collection with the same shape and *dtype*.
- **init_val** – initial value to pass as argument to *body_fun*. Can be any Python collection type containing *np.ndarray* objects.
- **transform** – a callable to post-process the values returned by *body_fn*.
- **progbar** – whether to post progress bar updates.
- **return_last_val** (*bool*) – If *True*, the last value is also returned. This has the same type as *init_val*.
- **thinning** – Positive integer that controls the thinning ratio for retained values. Defaults to 1, i.e. no thinning.
- **collection_size** (*int*) – Size of the returned collection. If not specified, the size will be `(upper - lower) // thinning`. If the size is larger than `(upper - lower) // thinning`, only the top `(upper - lower) // thinning` entries will be non-zero.
- ****progbar_opts** – optional additional progress bar arguments. A *diagnostics_fn* can be supplied which when passed the current value from *body_fun* returns a string that is used to update the progress bar postfix. Also a *progbar_desc* keyword argument can be supplied which is used to label the progress bar.

Returns collection with the same type as *init_val* with values collected along the leading axis of *np.ndarray* objects.

consensus(*subposteriors*, *num_draws=None*, *diagonal=False*, *rng_key=None*)

Merges subposteriors following consensus Monte Carlo algorithm.

References:

1. *Bayes and big data: The consensus Monte Carlo algorithm*, Steven L. Scott, Alexander W. Blocker, Fernando V. Bonassi, Hugh A. Chipman, Edward I. George, Robert E. McCulloch

Parameters

- **subposteriors** (*list*) – a list in which each element is a collection of samples.
- **num_draws** (*int*) – number of draws from the merged posterior.
- **diagonal** (*bool*) – whether to compute weights using variance or covariance, defaults to *False* (using covariance).
- **rng_key** (*jax.random.PRNGKey*) – source of the randomness, defaults to *jax.random.PRNGKey(0)*.

Returns if *num_draws* is None, merges subposteriors without resampling; otherwise, returns a collection of *num_draws* samples with the same data structure as each subposterior.

parametric(*subposteriors*, *diagonal=False*)

Merges subposteriors following (embarrassingly parallel) parametric Monte Carlo algorithm.

References:

1. *Asymptotically Exact, Embarrassingly Parallel MCMC*, Willie Neiswanger, Chong Wang, Eric Xing

Parameters

- **subposteriors** (*list*) – a list in which each element is a collection of samples.

- **diagonal** (*bool*) – whether to compute weights using variance or covariance, defaults to *False* (using covariance).

Returns the estimated mean and variance/covariance parameters of the joined posterior

parametric_draws(*subposteriors*, *num_draws*, *diagonal=False*, *rng_key=None*)

Merges subposteriors following (embarrassingly parallel) parametric Monte Carlo algorithm.

References:

1. *Asymptotically Exact, Embarrassingly Parallel MCMC*, Willie Neiswanger, Chong Wang, Eric Xing

Parameters

- **subposteriors** (*list*) – a list in which each element is a collection of samples.
- **num_draws** (*int*) – number of draws from the merged posterior.
- **diagonal** (*bool*) – whether to compute weights using variance or covariance, defaults to *False* (using covariance).
- **rng_key** (*jax.random.PRNGKey*) – source of the randomness, defaults to *jax.random.PRNGKey(0)*.

Returns a collection of *num_draws* samples with the same data structure as each subposterior.

2.3.2 Stochastic Variational Inference (SVI)

class SVI(*model*, *guide*, *optim*, *loss*, ***static_kwargs*)

Bases: object

Stochastic Variational Inference given an ELBO loss objective.

References

1. *SVI Part I: An Introduction to Stochastic Variational Inference in Pyro*, (http://pyro.ai/examples/svi_part_i.html)

Example:

```
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.distributions import constraints
>>> from numpyro.infer import SVI, Trace_ELBO

>>> def model(data):
...     f = numpyro.sample("latent_fairness", dist.Beta(10, 10))
...     with numpyro.plate("N", data.shape[0]):
...         numpyro.sample("obs", dist.Bernoulli(f), obs=data)

>>> def guide(data):
...     alpha_q = numpyro.param("alpha_q", 15., constraint=constraints.positive)
...     beta_q = numpyro.param("beta_q", lambda rng_key: random.exponential(rng_
↪key),
...                            constraint=constraints.positive)
...     numpyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))

>>> data = jnp.concatenate([jnp.ones(6), jnp.zeros(4)])
```

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```
>>> optimizer = numpyro.optim.Adam(step_size=0.0005)
>>> svi = SVI(model, guide, optimizer, loss=Trace_ELBO())
>>> svi_result = svi.run(random.PRNGKey(0), 2000, data)
>>> params = svi_result.params
>>> inferred_mean = params["alpha_q"] / (params["alpha_q"] + params["beta_q"])
```

Parameters

- **model** – Python callable with Pyro primitives for the model.
- **guide** – Python callable with Pyro primitives for the guide (recognition network).
- **optim** – an instance of _NumpyroOptim.
- **loss** – ELBO loss, i.e. negative Evidence Lower Bound, to minimize.
- **static_kwargs** – static arguments for the model / guide, i.e. arguments that remain constant during fitting.

Returns tuple of *(init_fn, update_fn, evaluate)*.

init(*rng_key*, **args*, ***kwargs*)
Gets the initial SVI state.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns the initial SVIState

get_params(*svi_state*)
Gets values at *param* sites of the *model* and *guide*.

Parameters **svi_state** – current state of SVI.

Returns the corresponding parameters

update(*svi_state*, **args*, ***kwargs*)
Take a single step of SVI (possibly on a batch / minibatch of data), using the optimizer.

Parameters

- **svi_state** – current state of SVI.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns tuple of *(svi_state, loss)*.

stable_update(*svi_state*, **args*, ***kwargs*)
Similar to *update()* but returns the current state if the the loss or the new state contains invalid values.

Parameters

- **svi_state** – current state of SVI.

- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns tuple of *(svi_state, loss)*.

run(*rng_key*, *num_steps*, **args*, *progress_bar=True*, *stable_update=False*, ***kwargs*)
(EXPERIMENTAL INTERFACE) Run SVI with *num_steps* iterations, then return the optimized parameters and the stacked losses at every step. If *num_steps* is large, setting *progress_bar=False* can make the run faster.

Note: For a complex training process (e.g. the one requires early stopping, epoch training, varying args/kwargs,...), we recommend to use the more flexible methods *init()*, *update()*, *evaluate()* to customize your training procedure.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed.
- **num_steps** (*int*) – the number of optimization steps.
- **args** – arguments to the model / guide
- **progress_bar** (*bool*) – Whether to enable progress bar updates. Defaults to `True`.
- **stable_update** (*bool*) – whether to use *stable_update()* to update the state. Defaults to False.
- **kwargs** – keyword arguments to the model / guide

Returns a namedtuple with fields *params* and *losses* where *params* holds the optimized values at `numpyro.param` sites, and *losses* is the collected loss during the process.

Return type SVIRunResult

evaluate(*svi_state*, **args*, ***kwargs*)
Take a single step of SVI (possibly on a batch / minibatch of data).

Parameters

- **svi_state** – current state of SVI.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide.

Returns evaluate ELBO loss given the current parameter values (held within *svi_state.optim_state*).

ELBO

class ELBO(*num_particles=1*)
Bases: *numpyro.infer.elbo.Trace_ELBO*

Trace_ELBO

class Trace_ELBO(*num_particles=1*)
Bases: object

A trace implementation of ELBO-based SVI. The estimator is constructed along the lines of references [1] and [2]. There are no restrictions on the dependency structure of the model or the guide.

This is the most basic implementation of the Evidence Lower Bound, which is the fundamental objective in Variational Inference. This implementation has various limitations (for example it only supports random variables with reparameterized samplers) but can be used as a template to build more sophisticated loss objectives.

For more details, refer to http://pyro.ai/examples/svi_part_i.html.

References:

1. *Automated Variational Inference in Probabilistic Programming*, David Wingate, Theo Weber
2. *Black Box Variational Inference*, Rajesh Ranganath, Sean Gerrish, David M. Blei

Parameters **num_particles** – The number of particles/samples used to form the ELBO (gradient) estimators.

loss(*rng_key*, *param_map*, *model*, *guide*, **args*, ***kwargs*)
Evaluates the ELBO with an estimator that uses num_particles many samples/particles.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed.
- **param_map** (*dict*) – dictionary of current parameter values keyed by site name.
- **model** – Python callable with NumPyro primitives for the model.
- **guide** – Python callable with NumPyro primitives for the guide.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns negative of the Evidence Lower Bound (ELBO) to be minimized.

TraceMeanField_ELBO

class TraceMeanField_ELBO(*num_particles=1*)
Bases: *numpyro.infer.elbo.Trace_ELBO*

A trace implementation of ELBO-based SVI. This is currently the only ELBO estimator in NumPyro that uses analytic KL divergences when those are available.

Warning: This estimator may give incorrect results if the mean-field condition is not satisfied. The mean field condition is a sufficient but not necessary condition for this estimator to be correct. The precise condition is that for every latent variable z in the guide, its parents in the model must not include any latent variables that are descendants of z in the guide. Here 'parents in the model' and 'descendants in the guide' is with respect to the corresponding (statistical) dependency structure. For example, this condition is always satisfied if the model and guide have identical dependency structures.

loss (*rng_key*, *param_map*, *model*, *guide*, **args*, ***kwargs*)
Evaluates the ELBO with an estimator that uses num_particles many samples/particles.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed.
- **param_map** (*dict*) – dictionary of current parameter values keyed by site name.
- **model** – Python callable with NumPyro primitives for the model.
- **guide** – Python callable with NumPyro primitives for the guide.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).
- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns negative of the Evidence Lower Bound (ELBO) to be minimized.

RenyiELBO

class RenyiELBO (*alpha=0*, *num_particles=2*)
Bases: *numpyro.infer.elbo.Trace_ELBO*

An implementation of Renyi's α-divergence variational inference following reference [1]. In order for the objective to be a strict lower bound, we require $\alpha \geq 0$. Note, however, that according to reference [1], depending on the dataset $\alpha < 0$ might give better results. In the special case $\alpha = 0$, the objective function is that of the important weighted autoencoder derived in reference [2].

Note: Setting $\alpha < 1$ gives a better bound than the usual ELBO.

Parameters

- **alpha** (*float*) – The order of α-divergence. Here $\alpha \neq 1$. Default is 0.
- **num_particles** – The number of particles/samples used to form the objective (gradient) estimator. Default is 2.

References:

1. *Renyi Divergence Variational Inference*, Yingzhen Li, Richard E. Turner
2. *Importance Weighted Autoencoders*, Yuri Burda, Roger Grosse, Ruslan Salakhutdinov

loss (*rng_key*, *param_map*, *model*, *guide*, **args*, ***kwargs*)
Evaluates the Renyi ELBO with an estimator that uses num_particles many samples/particles.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed.
- **param_map** (*dict*) – dictionary of current parameter values keyed by site name.
- **model** – Python callable with NumPyro primitives for the model.
- **guide** – Python callable with NumPyro primitives for the guide.
- **args** – arguments to the model / guide (these can possibly vary during the course of fitting).

- **kwargs** – keyword arguments to the model / guide (these can possibly vary during the course of fitting).

Returns negative of the Renyi Evidence Lower Bound (ELBO) to be minimized.

2.3.3 Automatic Guide Generation

AutoContinuous

class AutoContinuous(*model*, ***, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *create_plates=None*)

Bases: `numpyro.infer.autoguide.AutoGuide`

Base class for implementations of continuous-valued Automatic Differentiation Variational Inference [1].

Each derived class implements its own `_get_posterior()` method.

Assumes model structure and latent dimension are fixed, and all latent variables are continuous.

Reference:

1. *Automatic Differentiation Variational Inference*, Alp Kucukelbir, Dustin Tran, Rajesh Ranganath, Andrew Gelman, David M. Blei

Parameters

- **model** (*callable*) – A NumPyro model.
- **prefix** (*str*) – a prefix that will be prefixed to all param internal sites.
- **init_loc_fn** (*callable*) – A per-site initialization function. See *Initialization Strategies* section for available functions.

get_base_dist()

Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

get_transform(*params*)

Returns the transformation learned by the guide to generate samples from the unconstrained (approximate) posterior.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

Returns the transform of posterior distribution

Return type *Transform*

get_posterior(*params*)

Returns the posterior distribution.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

sample_posterior(*rng_key*, *params*, *sample_shape=()*)

Get samples from the learned posterior.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random key to be used draw samples.
- **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

- **sample_shape** (*tuple*) – batch shape of each latent sample, defaults to ().

Returns a dict containing samples drawn the this guide.

Return type dict

median(*params*)

Returns the posterior median value of each latent variable.

Parameters **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

Returns A dict mapping sample site name to median tensor.

Return type dict

quantiles(*params*, *quantiles*)

Returns posterior quantiles each latent variable. Example:

```
print(guide.quantiles(opt_state, [0.05, 0.5, 0.95]))
```

Parameters

- **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.
- **quantiles** (*list*) – A list of requested quantiles between 0 and 1.

Returns A dict mapping sample site name to a list of quantile values.

Return type dict

AutoBNAFNormal

class AutoBNAFNormal(*model*, ***, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *num_flows=1*, *hidden_factors=[8, 8]*, *init_strategy=None*)

Bases: *numpyro.infer.autoguide.AutoContinuous*

This implementation of *AutoContinuous* uses a Diagonal Normal distribution transformed via a *BlockNeuralAutoregressiveTransform* to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Usage:

```
guide = AutoBNAFNormal(model, num_flows=1, hidden_factors=[50, 50], ...)
svi = SVI(model, guide, ...)
```

References

1. *Block Neural Autoregressive Flow*, Nicola De Cao, Ivan Titov, Wilker Aziz

Parameters

- **model** (*callable*) – a generative model.
- **prefix** (*str*) – a prefix that will be prefixed to all param internal sites.
- **init_loc_fn** (*callable*) – A per-site initialization function.
- **num_flows** (*int*) – the number of flows to be used, defaults to 3.

- **hidden_factors** (*list*) – Hidden layer i has `hidden_factors[i]` hidden units per input dimension. This corresponds to both a and b in reference [1]. The elements of hidden_factors must be integers.

get_base_dist()
Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

AutoDiagonalNormal

class AutoDiagonalNormal(*model*, ***, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *init_scale=0.1*, *init_strategy=None*)
Bases: *numpyro.infer.autoguide.AutoContinuous*

This implementation of *AutoContinuous* uses a Normal distribution with a diagonal covariance matrix to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Usage:

```
guide = AutoDiagonalNormal(model, ...)
svi = SVI(model, guide, ...)
```

scale_constraint = <numpyro.distributions.constraints._GreaterThan object>

get_base_dist()
Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

get_transform(*params*)
Returns the transformation learned by the guide to generate samples from the unconstrained (approximate) posterior.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

Returns the transform of posterior distribution

Return type *Transform*

get_posterior(*params*)
Returns a diagonal Normal posterior distribution.

median(*params*)
Returns the posterior median value of each latent variable.

Parameters **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

Returns A dict mapping sample site name to median tensor.

Return type dict

quantiles(*params*, *quantiles*)
Returns posterior quantiles each latent variable. Example:

```
print(guide.quantiles(opt_state, [0.05, 0.5, 0.95]))
```

Parameters

- **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

- **quantiles** (*list*) – A list of requested quantiles between 0 and 1.

Returns A dict mapping sample site name to a list of quantile values.

Return type dict

AutoMultivariateNormal

class AutoMultivariateNormal(*model*, ***, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *init_scale=0.1*, *init_strategy=None*)

Bases: *numpyro.infer.autoguide.AutoContinuous*

This implementation of *AutoContinuous* uses a MultivariateNormal distribution to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Usage:

```
guide = AutoMultivariateNormal(model, ...)
svi = SVI(model, guide, ...)
```

scale_tril_constraint = <numpyro.distributions.constraints._LowerCholesky object>

get_base_dist()

Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

get_transform(*params*)

Returns the transformation learned by the guide to generate samples from the unconstrained (approximate) posterior.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

Returns the transform of posterior distribution

Return type *Transform*

get_posterior(*params*)

Returns a multivariate Normal posterior distribution.

median(*params*)

Returns the posterior median value of each latent variable.

Parameters **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

Returns A dict mapping sample site name to median tensor.

Return type dict

quantiles(*params*, *quantiles*)

Returns posterior quantiles each latent variable. Example:

```
print(guide.quantiles(opt_state, [0.05, 0.5, 0.95]))
```

Parameters

- **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.
- **quantiles** (*list*) – A list of requested quantiles between 0 and 1.

Returns A dict mapping sample site name to a list of quantile values.

Return type dict

AutoIAFNormal

class AutoIAFNormal(*model*, *, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *num_flows=3*, *hidden_dims=None*, *skip_connections=False*, *nonlinearity=(<function elementwise.<locals>.<lambda>>*, *<function elementwise.<locals>.<lambda>>)*, *init_strategy=None*)

Bases: *numpyro.infer.autoguide.AutoContinuous*

This implementation of *AutoContinuous* uses a Diagonal Normal distribution transformed via a *InverseAutoregressiveTransform* to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Usage:

```
guide = AutoIAFNormal(model, hidden_dims=[20], skip_connections=True, ...)
svi = SVI(model, guide, ...)
```

Parameters

- **model** (*callable*) – a generative model.
- **prefix** (*str*) – a prefix that will be prefixed to all param internal sites.
- **init_loc_fn** (*callable*) – A per-site initialization function.
- **num_flows** (*int*) – the number of flows to be used, defaults to 3.
- **hidden_dims** (*list*) – the dimensionality of the hidden units per layer. Defaults to `[latent_dim, latent_dim]`.
- **skip_connections** (*bool*) – whether to add skip connections from the input to the output of each flow. Defaults to False.
- **nonlinearity** (*callable*) – the nonlinearity to use in the feedforward network. Defaults to `jax.experimental.stax.Elu()`.

get_base_dist()

Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

AutoLaplaceApproximation

class AutoLaplaceApproximation(*model*, *, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *create_plates=None*)

Bases: *numpyro.infer.autoguide.AutoContinuous*

Laplace approximation (quadratic approximation) approximates the posterior $\log p(z|x)$ by a multivariate normal distribution in the unconstrained space. Under the hood, it uses Delta distributions to construct a MAP guide over the entire (unconstrained) latent space. Its covariance is given by the inverse of the hessian of $-\log p(x, z)$ at the MAP point of z.

Usage:

```
guide = AutoLaplaceApproximation(model, ...)
svi = SVI(model, guide, ...)
```

get_base_dist()
Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

get_transform(*params*)
Returns the transformation learned by the guide to generate samples from the unconstrained (approximate) posterior.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

Returns the transform of posterior distribution

Return type *Transform*

get_posterior(*params*)
Returns a multivariate Normal posterior distribution.

sample_posterior(*rng_key*, *params*, *sample_shape=()*)
Get samples from the learned posterior.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random key to be used draw samples.
- **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.
- **sample_shape** (*tuple*) – batch shape of each latent sample, defaults to ().

Returns a dict containing samples drawn the this guide.

Return type dict

median(*params*)
Returns the posterior median value of each latent variable.

Parameters **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

Returns A dict mapping sample site name to median tensor.

Return type dict

quantiles(*params*, *quantiles*)
Returns posterior quantiles each latent variable. Example:

```
print(guide.quantiles(opt_state, [0.05, 0.5, 0.95]))
```

Parameters

- **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.
- **quantiles** (*list*) – A list of requested quantiles between 0 and 1.

Returns A dict mapping sample site name to a list of quantile values.

Return type dict

AutoLowRankMultivariateNormal

class AutoLowRankMultivariateNormal(*model*, ***, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *init_scale=0.1*, *rank=None*, *init_strategy=None*)

Bases: *numpyro.infer.autoguide.AutoContinuous*

This implementation of *AutoContinuous* uses a LowRankMultivariateNormal distribution to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Usage:

```
guide = AutoLowRankMultivariateNormal(model, rank=2, ...)
svi = SVI(model, guide, ...)
```

scale_constraint = <numpyro.distributions.constraints._GreaterThan object>

get_base_dist()

Returns the base distribution of the posterior when reparameterized as a *TransformedDistribution*. This should not depend on the model's **args, **kwargs*.

get_transform(*params*)

Returns the transformation learned by the guide to generate samples from the unconstrained (approximate) posterior.

Parameters **params** (*dict*) – Current parameters of model and autoguide. The parameters can be obtained using *get_params()* method from *SVI*.

Returns the transform of posterior distribution

Return type *Transform*

get_posterior(*params*)

Returns a lowrank multivariate Normal posterior distribution.

median(*params*)

Returns the posterior median value of each latent variable.

Parameters **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.

Returns A dict mapping sample site name to median tensor.

Return type dict

quantiles(*params*, *quantiles*)

Returns posterior quantiles each latent variable. Example:

```
print(guide.quantiles(opt_state, [0.05, 0.5, 0.95]))
```

Parameters

- **params** (*dict*) – A dict containing parameter values. The parameters can be obtained using *get_params()* method from *SVI*.
- **quantiles** (*list*) – A list of requested quantiles between 0 and 1.

Returns A dict mapping sample site name to a list of quantile values.

Return type dict

AutoNormal

class AutoNormal(*model*, *, *prefix='auto'*, *init_loc_fn=<function init_to_uniform>*, *init_scale=0.1*, *create_plates=None*)

Bases: `numpyro.infer.autoguide.AutoGuide`

This implementation of `AutoGuide` uses Normal distributions to construct a guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

This should be equivalent to :class: *AutoDiagonalNormal* , but with more convenient site names and with better support for mean field ELBO.

Usage:

```
guide = AutoNormal(model)
svi = SVI(model, guide, ...)
```

Parameters

- **model** (*callable*) – A NumPyro model.
- **prefix** (*str*) – a prefix that will be prefixed to all param internal sites.
- **init_loc_fn** (*callable*) – A per-site initialization function. See *Initialization Strategies* section for available functions.
- **init_scale** (*float*) – Initial scale for the standard deviation of each (unconstrained transformed) latent variable.
- **create_plates** (*callable*) – An optional function inputing the same `*args, **kwargs` as `model()` and returning a `numpyro.plate` or iterable of plates. Plates not returned will be created automatically as usual. This is useful for data subsampling.

scale_constraint = <numpyro.distributions.constraints._GreaterThan object>

sample_posterior(*rng_key*, *params*, *sample_shape=()*)

Generate samples from the approximate posterior over the latent sites in the model.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – PRNG seed.
- **params** – Current parameters of model and autoguide.
- **sample_shape** – (keyword argument) shape of samples to be drawn.

Returns batch of samples from the approximate posterior.

median(*params*)

quantiles(*params*, *quantiles*)

AutoDelta

class AutoDelta(*model*, *, *prefix='auto'*, *init_loc_fn=<function init_to_median>*, *create_plates=None*)

Bases: `numpyro.infer.autoguide.AutoGuide`

This implementation of `AutoGuide` uses Delta distributions to construct a MAP guide over the entire latent space. The guide does not depend on the model's `*args, **kwargs`.

Note: This class does MAP inference in constrained space.

Usage:

```
guide = AutoDelta(model)
svi = SVI(model, guide, ...)
```

Parameters

- **model** (*callable*) – A NumPyro model.
- **prefix** (*str*) – a prefix that will be prefixed to all param internal sites.
- **init_loc_fn** (*callable*) – A per-site initialization function. See *Initialization Strategies* section for available functions.
- **create_plates** (*callable*) – An optional function inputing the same `*args, **kwargs` as `model()` and returning a `numpyro.plate` or iterable of plates. Plates not returned will be created automatically as usual. This is useful for data subsampling.

sample_posterior(*rng_key*, *params*, *sample_shape=()*)
Generate samples from the approximate posterior over the latent sites in the model.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – PRNG seed.
- **params** – Current parameters of model and autoguide.
- **sample_shape** – (keyword argument) shape of samples to be drawn.

Returns batch of samples from the approximate posterior.

median(*params*)
Returns the posterior median value of each latent variable.

Returns A dict mapping sample site name to median tensor.

Return type dict

2.3.4 Reparameterizers

The *numpyro.infer.reparam* module contains reparameterization strategies for the *numpyro.handlers.reparam* effect. These are useful for altering geometry of a poorly-conditioned parameter space to make the posterior better shaped. These can be used with a variety of inference algorithms, e.g. `Auto*Normal` guides and MCMC.

class Reparam
Bases: `abc.ABC`

Base class for reparameterizers.

Loc-Scale Decentering

class LocScaleReparam(*centered=None*, *shape_params=()*)
Bases: *numpyro.infer.reparam.Reparam*

Generic decentering reparameterizer [1] for latent variables parameterized by `loc` and `scale` (and possibly additional `shape_params`).

This reparameterization works only for latent variables, not likelihoods.

References:

1. *Automatic Reparameterisation of Probabilistic Programs*, Maria I. Gorinova, Dave Moore, Matthew D. Hoffman (2019)

Parameters

- **centered** (*float*) – optional centered parameter. If None (default) learn a per-site per-element centering parameter in `[0,1]`. If 0, fully decenter the distribution; if 1, preserve the centered distribution unchanged.
- **shape_params** (*tuple or list*) – list of additional parameter names to copy unchanged from the centered to decentered distribution.

__call__(*name*, *fn*, *obs*)

Parameters

- **name** (*str*) – A sample site name.
- **fn** (*Distribution*) – A distribution.
- **obs** (*numpy.ndarray*) – Observed value or None.

Returns A pair (`new_fn`, `value`).

Neural Transport

class NeuTraReparam(*guide*, *params*)

Bases: *numpyro.infer.reparam.Reparam*

Neural Transport reparameterizer [1] of multiple latent variables.

This uses a trained `AutoContinuous` guide to alter the geometry of a model, typically for use e.g. in MCMC. Example usage:

```
# Step 1. Train a guide
guide = AutoIAFNormal(model)
svi = SVI(model, guide, ...)
# ...train the guide...

# Step 2. Use trained guide in NeuTra MCMC
neutra = NeuTraReparam(guide)
model = netra.reparam(model)
nuts = NUTS(model)
# ...now use the model in HMC or NUTS...
```

This reparameterization works only for latent variables, not likelihoods. Note that all sites must share a single common *NeuTraReparam* instance, and that the model must have static structure.

[1] Hoffman, M. et al. (2019) "NeuTra-lizing Bad Geometry in Hamiltonian Monte Carlo Using Neural Transport" https://arxiv.org/abs/1903.03704

Parameters

- **guide** (`AutoContinuous`) – A guide.
- **params** – trained parameters of the guide.

reparam(*fn=None*)

__call__(*name*, *fn*, *obs*)

Parameters

- **name** (*str*) – A sample site name.
- **fn** (*Distribution*) – A distribution.
- **obs** (*numpy.ndarray*) – Observed value or None.

Returns A pair (`new_fn`, `value`).

transform_sample(*latent*)

Given latent samples from the warped posterior (with possible batch dimensions), return a *dict* of samples from the latent sites in the model.

Parameters **latent** – sample from the warped posterior (possibly batched).

Returns a *dict* of samples keyed by latent sites in the model.

Return type dict

Transformed Distributions

class TransformReparam

Bases: *numpyro.infer.reparam.Reparam*

Reparameterizer for `TransformedDistribution` latent variables.

This is useful for transformed distributions with complex, geometry-changing transforms, where the posterior has simple shape in the space of `base_dist`.

This reparameterization works only for latent variables, not likelihoods.

__call__(*name*, *fn*, *obs*)

Parameters

- **name** (*str*) – A sample site name.
- **fn** (*Distribution*) – A distribution.
- **obs** (*numpy.ndarray*) – Observed value or None.

Returns A pair (`new_fn`, `value`).

Projected Normal Distributions

class ProjectedNormalReparam

Bases: *numpyro.infer.reparam.Reparam*

Reparametrizer for `ProjectedNormal` latent variables.

This reparameterization works only for latent variables, not likelihoods.

__call__(*name*, *fn*, *obs*)

Parameters

- **name** (*str*) – A sample site name.
- **fn** (*Distribution*) – A distribution.
- **obs** (*numpy.ndarray*) – Observed value or None.

Returns A pair (`new_fn`, `value`).

2.3.5 Funsor-based NumPyro

Effect handlers

class enum (*fn=None*, *first_available_dim=None*)
Bases: `numpyro.contrib.funsor.enum_messenger.BaseEnumMessenger`

Enumerates in parallel over discrete sample sites marked `infer={"enumerate": "parallel"}`.

Parameters

- **fn** (*callable*) – Python callable with NumPyro primitives.
- **first_available_dim** (*int*) – The first tensor dimension (counting from the right) that is available for parallel enumeration. This dimension and all dimensions left may be used internally by Pyro. This should be a negative integer or None.

process_message (*msg*)

class infer_config (*fn=None*, *config_fn=None*)
Bases: `numpyro.primitives.Messenger`

Given a callable *fn* that contains NumPyro primitive calls and a callable *config_fn* taking a trace site and returning a dictionary, updates the value of the infer kwarg at a sample site to config_fn(site).

Parameters

- **fn** – a stochastic function (callable containing NumPyro primitive calls)
- **config_fn** – a callable taking a site and returning an infer dict

process_message (*msg*)

markov (*fn=None*, *history=1*, *keep=False*)
Markov dependency declaration.

This is a statistical equivalent of a memory management arena.

Parameters

- **fn** (*callable*) – Python callable with NumPyro primitives.
- **history** (*int*) – The number of previous contexts visible from the current context. Defaults to 1. If zero, this is similar to *numpyro.primitives.plate*.
- **keep** (*bool*) – If true, frames are replayable. This is important when branching: if `keep=True`, neighboring branches at the same level can depend on each other; if `keep=False`, neighboring branches are independent (conditioned on their shared ancestors).

class plate (*name*, *size*, *subsample_size=None*, *dim=None*)
Bases: `numpyro.contrib.funsor.enum_messenger.GlobalNamedMessenger`

An alternative implementation of *numpyro.primitives.plate* primitive. Note that only this version is compatible with enumeration.

There is also a context manager *plate_to_enum_plate()* which converts *numpyro.plate* statements to this version.

Parameters

- **name** (*str*) – Name of the plate.

- **size** (*int*) – Size of the plate.
- **subsample_size** (*int*) – Optional argument denoting the size of the mini-batch. This can be used to apply a scaling factor by inference algorithms. e.g. when computing ELBO using a mini-batch.
- **dim** (*int*) – Optional argument to specify which dimension in the tensor is used as the plate dim. If *None* (default), the leftmost available dim is allocated.

process_message(*msg*)

postprocess_message(*msg*)

to_data(*x*, *name_to_dim=None*, *dim_type=<DimType.LOCAL: 0>*)
A primitive to extract a python object from a `Funsor`.

Parameters

- **x** (*Funsor*) – A funsor object
- **name_to_dim** (*OrderedDict*) – An optional inputs hint which maps dimension names from *x* to dimension positions of the returned value.
- **dim_type** (*int*) – Either 0, 1, or 2. This optional argument indicates a dimension should be treated as 'local', 'global', or 'visible', which can be used to interact with the global `DimStack`.

Returns A non-funsor equivalent to *x*.

to_funsor(*x*, *output=None*, *dim_to_name=None*, *dim_type=<DimType.LOCAL: 0>*)
A primitive to convert a Python object to a `Funsor`.

Parameters

- **x** – An object.
- **output** (*funsor.domains.Domain*) – An optional output hint to uniquely convert a data to a Funsor (e.g. when *x* is a string).
- **dim_to_name** (*OrderedDict*) – An optional mapping from negative batch dimensions to name strings.
- **dim_type** (*int*) – Either 0, 1, or 2. This optional argument indicates a dimension should be treated as 'local', 'global', or 'visible', which can be used to interact with the global `DimStack`.

Returns A Funsor equivalent to *x*.

Return type funsor.terms.Funsor

class trace(*fn=None*)
Bases: *numpyro.handlers.trace*

This version of *trace* handler records information necessary to do packing after execution.

Each sample site is annotated with a "dim_to_name" dictionary, which can be passed directly to *to_funsor()*.

postprocess_message(*msg*)

Inference Utilities

config_enumerate(*fn*, *default='parallel'*)
Configures enumeration for all relevant sites in a NumPyro model.

When configuring for exhaustive enumeration of discrete variables, this configures all sample sites whose distribution satisfies `.has_enumerate_support == True`.

This can be used as either a function:

```
model = config_enumerate(model)
```

or as a decorator:

```
@config_enumerate
def model(*args, **kwargs):
    ...
```

Note: Currently, only `default='parallel'` is supported.

Parameters

- **fn** (*callable*) – Python callable with NumPyro primitives.
- **default** (*str*) – Which enumerate strategy to use, one of "sequential", "parallel", or None. Defaults to "parallel".

log_density(*model*, *model_args*, *model_kwargs*, *params*)

Similar to *numpyro.infer.util.log_density()* but works for models with discrete latent variables. Internally, this uses `funsor` to marginalize discrete latent sites and evaluate the joint log probability.

Parameters

- **model** – Python callable containing NumPyro primitives. Typically, the model has been enumerated by using *enum* handler:

```
def model(*args, **kwargs):
    ...

log_joint = log_density(enum(config_enumerate(model)), args,␣
↪kwargs, params)
```

- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **params** (*dict*) – dictionary of current parameter values keyed by site name.

Returns log of joint density and a corresponding model trace

plate_to_enum_plate()

A context manager to replace *numpyro.plate* statement by a funsor-based *plate*.

This is useful when doing inference for the usual NumPyro programs with *numpyro.plate* statements. For example, to get trace of a *model* whose discrete latent sites are enumerated, we can use:

```
enum_model = numpyro.contrib.funsor.enum(model)
with plate_to_enum_plate():
    model_trace = numpyro.contrib.funsor.trace(enum_model).get_trace(
        *model_args, **model_kwargs)
```

2.3.6 Optimizers

Optimizer classes defined here are light wrappers over the corresponding optimizers sourced from `jax.experimental.optimizers` with an interface that is better suited for working with NumPyro inference algorithms.

Adam

class Adam(**args*, ***kwargs*)

Wrapper class for the JAX optimizer: `adam()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params

Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]

Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

Adagrad

class Adagrad(**args*, ***kwargs*)
Wrapper class for the JAX optimizer: `adagrad()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like `eval_and_update()` but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as `Minimize`, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

ClippedAdam

class ClippedAdam(**args*, *clip_norm=10.0*, ***kwargs*)
`Adam` optimizer with gradient clipping.

Parameters **clip_norm** (`float`) – All gradient values will be clipped between *[-clip_norm, clip_norm]*.

Reference:

A Method for Stochastic Optimization, Diederik P. Kingma, Jimmy Ba https://arxiv.org/abs/1412.6980

eval_and_stable_update (*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update (*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params (*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init (*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update (*g*, *state*)
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

Minimize

class Minimize (*method='BFGS'*, ***kwargs*)
Wrapper class for the JAX minimizer: *minimize()*.

Example:

```
>>> from numpy.testing import assert_allclose
>>> from jax import random
>>> import jax.numpy as jnp
>>> import numpyro
>>> import numpyro.distributions as dist
>>> from numpyro.infer import SVI, Trace_ELBO
>>> from numpyro.infer.autoguide import AutoLaplaceApproximation

>>> def model(x, y):
...     a = numpyro.sample("a", dist.Normal(0, 1))
...     b = numpyro.sample("b", dist.Normal(0, 1))
...     with numpyro.plate("N", y.shape[0]):
...         numpyro.sample("obs", dist.Normal(a + b * x, 0.1), obs=y)

>>> x = jnp.linspace(0, 10, 100)
>>> y = 3 * x + 2
>>> optimizer = numpyro.optim.Minimize()
>>> guide = AutoLaplaceApproximation(model)
>>> svi = SVI(model, guide, optimizer, loss=Trace_ELBO())
>>> init_state = svi.init(random.PRNGKey(0), x, y)
>>> optimal_state, loss = svi.update(init_state, x, y)
>>> params = svi.get_params(optimal_state)  # get guide's parameters
>>> quantiles = guide.quantiles(params, 0.5)  # get means of posterior samples
>>> assert_allclose(quantiles["a"], 2., atol=1e-3)
>>> assert_allclose(quantiles["b"], 3., atol=1e-3)
```

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

Momentum

class Momentum(**args*, ***kwargs*)
Wrapper class for the JAX optimizer: `momentum()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.

- **state** – current optimizer state.

Returns new optimizer state after the update.

RMSProp

class RMSProp(**args*, ***kwargs*)

Wrapper class for the JAX optimizer: `rmsprop()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Like `eval_and_update()` but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as `Minimize`, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params

Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]

Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]

Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

RMSPropMomentum

class **RMSPropMomentum**(**args*, ***kwargs*)
Wrapper class for the JAX optimizer: `rmsprop_momentum()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params(*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init(*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update(*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

SGD

class **SGD**(**args*, ***kwargs*)
Wrapper class for the JAX optimizer: `sgd()`

eval_and_stable_update(*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update (*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params (*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init (*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update (*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

SM3

class SM3 (**args*, ***kwargs*)
Wrapper class for the JAX optimizer: *sm3()*

eval_and_stable_update (*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Like *eval_and_update()* but when the value of the objective function or the gradients are not finite, we will not update the input *state* and will set the objective output to *nan*.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

eval_and_update (*fn: Callable, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Performs an optimization step for the objective function *fn*. For most optimizers, the update is performed based on the gradient of the objective function w.r.t. the current state. However, for some optimizers such as *Minimize*, the update is performed by reevaluating the function multiple times to get optimal parameters.

Parameters

- **fn** – objective function.
- **state** – current optimizer state.

Returns a pair of the output of objective function and the new optimizer state.

get_params (*state: Tuple[int, _OptState]*) → _Params
Get current parameter values.

Parameters **state** – current optimizer state.

Returns collection with current value for parameters.

init (*params: _Params*) → Tuple[int, _OptState]
Initialize the optimizer with parameters designated to be optimized.

Parameters **params** – a collection of numpy arrays.

Returns initial optimizer state.

update (*g: _Params, state: Tuple[int, _OptState]*) → Tuple[int, _OptState]
Gradient update for the optimizer.

Parameters

- **g** – gradient information for parameters.
- **state** – current optimizer state.

Returns new optimizer state after the update.

2.3.7 Diagnostics

This provides a small set of utilities in NumPyro that are used to diagnose posterior samples.

Autocorrelation

autocorrelation (*x*, *axis=0*)
Computes the autocorrelation of samples at dimension `axis`.

Parameters

- **x** (*numpy.ndarray*) – the input array.
- **axis** (*int*) – the dimension to calculate autocorrelation.

Returns autocorrelation of `x`.

Return type numpy.ndarray

Autocovariance

autocovariance(*x*, *axis=0*)

Computes the autocovariance of samples at dimension `axis`.

Parameters

- **x** (*numpy.ndarray*) – the input array.
- **axis** (*int*) – the dimension to calculate autocovariance.

Returns autocovariance of `x`.

Return type numpy.ndarray

Effective Sample Size

effective_sample_size(*x*)

Computes effective sample size of input `x`, where the first dimension of `x` is chain dimension and the second dimension of `x` is draw dimension.

References:

1. *Introduction to Markov Chain Monte Carlo*, Charles J. Geyer
2. *Stan Reference Manual version 2.18*, Stan Development Team

Parameters **x** (*numpy.ndarray*) – the input array.

Returns effective sample size of `x`.

Return type numpy.ndarray

Gelman Rubin

gelman_rubin(*x*)

Computes R-hat over chains of samples `x`, where the first dimension of `x` is chain dimension and the second dimension of `x` is draw dimension. It is required that `x.shape[0] >= 2` and `x.shape[1] >= 2`.

Parameters **x** (*numpy.ndarray*) – the input array.

Returns R-hat of `x`.

Return type numpy.ndarray

Split Gelman Rubin

split_gelman_rubin(*x*)

Computes split R-hat over chains of samples `x`, where the first dimension of `x` is chain dimension and the second dimension of `x` is draw dimension. It is required that `x.shape[1] >= 4`.

Parameters **x** (*numpy.ndarray*) – the input array.

Returns split R-hat of `x`.

Return type numpy.ndarray

HPDI

hpdi (*x*, *prob=0.9*, *axis=0*)
Computes "highest posterior density interval" (HPDI) which is the narrowest interval with probability mass `prob`.

Parameters

- **x** (*numpy.ndarray*) – the input array.
- **prob** (*float*) – the probability mass of samples within the interval.
- **axis** (*int*) – the dimension to calculate hpdi.

Returns quantiles of `x` at `(1 - prob) / 2` and `(1 + prob) / 2`.

Return type numpy.ndarray

Summary

summary (*samples*, *prob=0.9*, *group_by_chain=True*)
Returns a summary table displaying diagnostics of `samples` from the posterior. The diagnostics displayed are mean, standard deviation, median, the 90% Credibility Interval *hpdi()*, *effective_sample_size()*, and *split_gelman_rubin()*.

Parameters

- **samples** (*dict or numpy.ndarray*) – a collection of input samples with left most dimension is chain dimension and second to left most dimension is draw dimension.
- **prob** (*float*) – the probability mass of samples within the HPDI interval.
- **group_by_chain** (*bool*) – If True, each variable in *samples* will be treated as having shape *num_chains x num_samples x sample_shape*. Otherwise, the corresponding shape will be *num_samples x sample_shape* (i.e. without chain dimension).

print_summary (*samples*, *prob=0.9*, *group_by_chain=True*)
Prints a summary table displaying diagnostics of `samples` from the posterior. The diagnostics displayed are mean, standard deviation, median, the 90% Credibility Interval *hpdi()*, *effective_sample_size()*, and *split_gelman_rubin()*.

Parameters

- **samples** (*dict or numpy.ndarray*) – a collection of input samples with left most dimension is chain dimension and second to left most dimension is draw dimension.
- **prob** (*float*) – the probability mass of samples within the HPDI interval.
- **group_by_chain** (*bool*) – If True, each variable in *samples* will be treated as having shape *num_chains x num_samples x sample_shape*. Otherwise, the corresponding shape will be *num_samples x sample_shape* (i.e. without chain dimension).

2.3.8 Runtime Utilities

enable_validation

enable_validation (*is_validate=True*)
Enable or disable validation checks in NumPyro. Validation checks provide useful warnings and errors, e.g. NaN checks, validating distribution arguments and support values, etc. which is useful for debugging.

Note: This utility does not take effect under JAX's JIT compilation or vectorized transformation `jax.vmap()`.

Parameters **is_validate** (*bool*) – whether to enable validation checks.

validation_enabled

validation_enabled(*is_validate=True*)
Context manager that is useful when temporarily enabling/disabling validation checks.

Parameters **is_validate** (*bool*) – whether to enable validation checks.

enable_x64

enable_x64(*use_x64=True*)
Changes the default array type to use 64 bit precision as in NumPy.

Parameters **use_x64** (*bool*) – when *True*, JAX arrays will use 64 bits by default; else 32 bits.

set_platform

set_platform(*platform=None*)
Changes platform to CPU, GPU, or TPU. This utility only takes effect at the beginning of your program.

Parameters **platform** (*str*) – either 'cpu', 'gpu', or 'tpu'.

set_host_device_count

set_host_device_count(*n*)
By default, XLA considers all CPU cores as one device. This utility tells XLA that there are *n* host (CPU) devices available to use. As a consequence, this allows parallel mapping in JAX `jax.pmap()` to work in CPU platform.

Note: This utility only takes effect at the beginning of your program. Under the hood, this sets the environment variable *XLA_FLAGS=–xla_force_host_platform_device_count=[num_devices]*, where *[num_device]* is the desired number of CPU devices *n*.

Warning: Our understanding of the side effects of using the *xla_force_host_platform_device_count* flag in XLA is incomplete. If you observe some strange phenomenon when using this utility, please let us know through our issue or forum page. More information is available in this JAX issue.

Parameters **n** (*int*) – number of CPU devices to use.

2.3.9 Inference Utilities

Predictive

class Predictive(*model*, *posterior_samples=None*, *guide=None*, *params=None*, *num_samples=None*, *return_sites=None*, *parallel=False*, *batch_ndims=1*)

Bases: `object`

This class is used to construct predictive distribution. The predictive distribution is obtained by running model conditioned on latent samples from *posterior_samples*.

> **Warning:** The interface for the *Predictive* class is experimental, and might change in the future.

Parameters

- **model** – Python callable containing Pyro primitives.
- **posterior_samples** (*dict*) – dictionary of samples from the posterior.
- **guide** (*callable*) – optional guide to get posterior samples of sites not present in *posterior_samples*.
- **params** (*dict*) – dictionary of values for param sites of model/guide.
- **num_samples** (*int*) – number of samples
- **return_sites** (*list*) – sites to return; by default only sample sites not present in *posterior_samples* are returned.
- **parallel** (*bool*) – whether to predict in parallel using JAX vectorized map `jax.vmap()`. Defaults to False.
- **batch_ndims** – the number of batch dimensions in posterior samples. Some usages:
  - set *batch_ndims=0* to get prediction for 1 single sample
  - set *batch_ndims=1* to get prediction for *posterior_samples* with shapes *(num_samples x ...)*
  - set *batch_ndims=2* to get prediction for *posterior_samples* with shapes *(num_chains x N x ...)*. Note that if *num_samples* argument is not None, its value should be equal to *num_chains x N*.

Returns dict of samples from the predictive distribution.

log_density

log_density(*model*, *model_args*, *model_kwargs*, *params*)

(EXPERIMENTAL INTERFACE) Computes log of joint density for the model given latent values `params`.

Parameters

- **model** – Python callable containing NumPyro primitives.
- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **params** (*dict*) – dictionary of current parameter values keyed by site name.

Returns log of joint density and a corresponding model trace

transform_fn

transform_fn(*transforms*, *params*, *invert=False*)
(EXPERIMENTAL INTERFACE) Callable that applies a transformation from the *transforms* dict to values in the *params* dict and returns the transformed values keyed on the same names.

Parameters

- **transforms** – Dictionary of transforms keyed by names. Names in *transforms* and *params* should align.
- **params** – Dictionary of arrays keyed by names.
- **invert** – Whether to apply the inverse of the transforms.

Returns *dict* of transformed params.

constrain_fn

constrain_fn(*model*, *model_args*, *model_kwargs*, *params*, *return_deterministic=False*)
(EXPERIMENTAL INTERFACE) Gets value at each latent site in *model* given unconstrained parameters *params*. The *transforms* is used to transform these unconstrained parameters to base values of the corresponding priors in *model*. If a prior is a transformed distribution, the corresponding base value lies in the support of base distribution. Otherwise, the base value lies in the support of the distribution.

Parameters

- **model** – a callable containing NumPyro primitives.
- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **params** (*dict*) – dictionary of unconstrained values keyed by site names.
- **return_deterministic** (*bool*) – whether to return the value of *deterministic* sites from the model. Defaults to *False*.

Returns *dict* of transformed params.

potential_energy

potential_energy(*model*, *model_args*, *model_kwargs*, *params*, *enum=False*)
(EXPERIMENTAL INTERFACE) Computes potential energy of a model given unconstrained params. Under the hood, we will transform these unconstrained parameters to the values belong to the supports of the corresponding priors in *model*.

Parameters

- **model** – a callable containing NumPyro primitives.
- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **params** (*dict*) – unconstrained parameters of *model*.
- **enum** (*bool*) – whether to enumerate over discrete latent sites.

Returns potential energy given unconstrained parameters.

log_likelihood

log_likelihood(*model*, *posterior_samples*, **args*, *parallel=False*, *batch_ndims=1*, ***kwargs*)
(EXPERIMENTAL INTERFACE) Returns log likelihood at observation nodes of model, given samples of all latent variables.

Parameters

- **model** – Python callable containing Pyro primitives.
- **posterior_samples** (*dict*) – dictionary of samples from the posterior.
- **args** – model arguments.
- **batch_ndims** – the number of batch dimensions in posterior samples. Some usages:
  - set *batch_ndims=0* to get log likelihoods for 1 single sample
  - set *batch_ndims=1* to get log likelihoods for *posterior_samples* with shapes *(num_samples x . . .)*
  - set *batch_ndims=2* to get log likelihoods for *posterior_samples* with shapes *(num_chains x num_samples x . . .)*
- **kwargs** – model kwargs.

Returns dict of log likelihoods at observation sites.

find_valid_initial_params

find_valid_initial_params(*rng_key*, *model*, *init_strategy=<function init_to_uniform>*, *enum=False*, *model_args=()*, *model_kwargs=None*, *prototype_params=None*, *forward_mode_differentiation=False*)
(EXPERIMENTAL INTERFACE) Given a model with Pyro primitives, returns an initial valid unconstrained value for all the parameters. This function also returns the corresponding potential energy, the gradients, and an *is_valid* flag to say whether the initial parameters are valid. Parameter values are considered valid if the values and the gradients for the log density have finite values.

Parameters

- **rng_key** (*jax.random.PRNGKey*) – random number generator seed to sample from the prior. The returned *init_params* will have the batch shape `rng_key.shape[:-1]`.
- **model** – Python callable containing Pyro primitives.
- **init_strategy** (*callable*) – a per-site initialization function.
- **enum** (*bool*) – whether to enumerate over discrete latent sites.
- **model_args** (*tuple*) – args provided to the model.
- **model_kwargs** (*dict*) – kwargs provided to the model.
- **prototype_params** (*dict*) – an optional prototype parameters, which is used to define the shape for initial parameters.

Returns tuple of *init_params_info* and *is_valid*, where *init_params_info* is the tuple containing the initial params, their potential energy, and their gradients.

Initialization Strategies

init_to_feasible

init_to_feasible(*site=None*)
Initialize to an arbitrary feasible point, ignoring distribution parameters.

init_to_median

init_to_median(*site=None*, *num_samples=15*)
Initialize to the prior median. For priors with no *.sample* method implemented, we defer to the *init_to_uniform()* strategy.

Parameters **num_samples** (*int*) – number of prior points to calculate median.

init_to_sample

init_to_sample(*site=None*)
Initialize to a prior sample. For priors with no *.sample* method implemented, we defer to the *init_to_uniform()* strategy.

init_to_uniform

init_to_uniform(*site=None*, *radius=2*)
Initialize to a random point in the area *(-radius, radius)* of unconstrained domain.

Parameters **radius** (*float*) – specifies the range to draw an initial point in the unconstrained domain.

init_to_value

init_to_value(*site=None*, *values={}*)
Initialize to the value specified in *values*. We defer to *init_to_uniform()* strategy for sites which do not appear in *values*.

Parameters **values** (*dict*) – dictionary of initial values keyed by site name.

Tensor Indexing

vindex(*tensor*, *args*)
Vectorized advanced indexing with broadcasting semantics.

See also the convenience wrapper *Vindex*.

This is useful for writing indexing code that is compatible with batching and enumeration, especially for selecting mixture components with discrete random variables.

For example suppose `x` is a parameter with `len(x.shape) == 3` and we wish to generalize the expression `x[i, :, j]` from integer `i,j` to tensors `i,j` with batch dims and enum dims (but no event dims). Then we can write the generalize version using *Vindex*

```
xij = Vindex(x)[i, :, j]

batch_shape = broadcast_shape(i.shape, j.shape)
event_shape = (x.size(1),)
assert xij.shape == batch_shape + event_shape
```

To handle the case when `x` may also contain batch dimensions (e.g. if `x` was sampled in a plated context as when using vectorized particles), *`vindex()`* uses the special convention that `Ellipsis` denotes batch dimensions (hence `...` can appear only on the left, never in the middle or in the right). Suppose `x` has event dim 3. Then we can write:

```
old_batch_shape = x.shape[:-3]
old_event_shape = x.shape[-3:]

xij = Vindex(x)[..., i, :, j]   # The ... denotes unknown batch shape.

new_batch_shape = broadcast_shape(old_batch_shape, i.shape, j.shape)
new_event_shape = (x.size(1),)
assert xij.shape = new_batch_shape + new_event_shape
```

Note that this special handling of `Ellipsis` differs from the NEP [1].

Formally, this function assumes:

1. Each arg is either `Ellipsis`, `slice(None)`, an integer, or a batched integer tensor (i.e. with empty event shape). This function does not support Nontrivial slices or boolean tensor masks. `Ellipsis` can only appear on the left as `args[0]`.
2. If `args[0] is not Ellipsis` then `tensor` is not batched, and its event dim is equal to `len(args)`.
3. If `args[0] is Ellipsis` then `tensor` is batched and its event dim is equal to `len(args[1:])`. Dims of `tensor` to the left of the event dims are considered batch dims and will be broadcasted with dims of tensor args.

Note that if none of the args is a tensor with `len(shape) > 0`, then this function behaves like standard indexing:

```
if not any(isinstance(a, jnp.ndarray) and len(a.shape) > 0 for a in args):
    assert Vindex(x)[args] == x[args]
```

References

[1] https://www.numpy.org/neps/nep-0021-advanced-indexing.html introduces `vindex` as a helper for vectorized indexing. This implementation is similar to the proposed notation `x.vindex[]` except for slightly different handling of `Ellipsis`.

Parameters

- **`tensor`** (*`jnp.ndarray`*) – A tensor to be indexed.
- **`args`** (*`tuple`*) – An index, as args to `__getitem__`.

Returns A nonstandard interpetation of `tensor[args]`.

Return type jnp.ndarray

`class Vindex`(*tensor*)

Bases: `object`

Convenience wrapper around *vindex()*.

The following are equivalent:

```
Vindex(x)[..., i, j, :]
vindex(x, (Ellipsis, i, j, slice(None)))
```

Parameters **tensor** (*jnp.ndarray*) – A tensor to be indexed.

Returns An object with a special `__getitem__()` method.

github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/bayesian_regression.ipynb

CHAPTER 3

Bayesian Regression Using NumPyro

In this tutorial, we will explore how to do bayesian regression in NumPyro, using a simple example adapted from Statistical Rethinking [*1*]. In particular, we would like to explore the following:

- Write a simple model using the `sample` NumPyro primitive.
- Run inference using MCMC in NumPyro, in particular, using the No U-Turn Sampler (NUTS) to get a posterior distribution over our regression parameters of interest.
- Learn about inference utilities such as `Predictive` and `log_likelihood`.
- Learn how we can use effect-handlers in NumPyro to generate execution traces from the model, condition on sample statements, seed models with RNG seeds, etc., and use this to implement various utilities that will be useful for MCMC. e.g. computing model log likelihood, generating empirical distribution over the posterior predictive, etc.

3.1 Tutorial Outline:

[ ]:
```
%reset -s -f
```

[2]:
```
import os

from IPython.display import set_matplotlib_formats
import jax.numpy as jnp
from jax import random, vmap
from jax.scipy.special import logsumexp
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

import numpyro
from numpyro.diagnostics import hpdi
import numpyro.distributions as dist
from numpyro import handlers
from numpyro.infer import MCMC, NUTS

plt.style.use('bmh')
if "NUMPYRO_SPHINXBUILD" in os.environ:
    set_matplotlib_formats('svg')

assert numpyro.__version__.startswith('0.6.0')
```

3.2 Dataset

For this example, we will use the `WaffleDivorce` dataset from Chapter 05, Statistical Rethinking [*1*]. The dataset contains divorce rates in each of the 50 states in the USA, along with predictors such as population, median age of marriage, whether it is a Southern state and, curiously, number of Waffle Houses.

[3]:
```
DATASET_URL = 'https://raw.githubusercontent.com/rmcelreath/rethinking/master/data/
↪WaffleDivorce.csv'
dset = pd.read_csv(DATASET_URL, sep=';')
dset
```

[3]:

	Location	Loc	Population	MedianAgeMarriage	Marriage	\
0	Alabama	AL	4.78	25.3	20.2	
1	Alaska	AK	0.71	25.2	26.0	
2	Arizona	AZ	6.33	25.8	20.3	
3	Arkansas	AR	2.92	24.3	26.4	
4	California	CA	37.25	26.8	19.1	
5	Colorado	CO	5.03	25.7	23.5	
6	Connecticut	CT	3.57	27.6	17.1	
7	Delaware	DE	0.90	26.6	23.1	
8	District of Columbia	DC	0.60	29.7	17.7	
9	Florida	FL	18.80	26.4	17.0	
10	Georgia	GA	9.69	25.9	22.1	
11	Hawaii	HI	1.36	26.9	24.9	
12	Idaho	ID	1.57	23.2	25.8	

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```
13              Illinois  IL       12.83               27.0      17.9
14               Indiana  IN        6.48               25.7      19.8
15                  Iowa  IA        3.05               25.4      21.5
16                Kansas  KS        2.85               25.0      22.1
17              Kentucky  KY        4.34               24.8      22.2
18             Louisiana  LA        4.53               25.9      20.6
19                 Maine  ME        1.33               26.4      13.5
20              Maryland  MD        5.77               27.3      18.3
21         Massachusetts  MA        6.55               28.5      15.8
22              Michigan  MI        9.88               26.4      16.5
23             Minnesota  MN        5.30               26.3      15.3
24           Mississippi  MS        2.97               25.8      19.3
25              Missouri  MO        5.99               25.6      18.6
26               Montana  MT        0.99               25.7      18.5
27              Nebraska  NE        1.83               25.4      19.6
28         New Hampshire  NH        1.32               26.8      16.7
29            New Jersey  NJ        8.79               27.7      14.8
30            New Mexico  NM        2.06               25.8      20.4
31              New York  NY       19.38               28.4      16.8
32        North Carolina  NC        9.54               25.7      20.4
33          North Dakota  ND        0.67               25.3      26.7
34                  Ohio  OH       11.54               26.3      16.9
35              Oklahoma  OK        3.75               24.4      23.8
36                Oregon  OR        3.83               26.0      18.9
37          Pennsylvania  PA       12.70               27.1      15.5
38          Rhode Island  RI        1.05               28.2      15.0
39        South Carolina  SC        4.63               26.4      18.1
40          South Dakota  SD        0.81               25.6      20.1
41             Tennessee  TN        6.35               25.2      19.4
42                 Texas  TX       25.15               25.2      21.5
43                  Utah  UT        2.76               23.3      29.6
44               Vermont  VT        0.63               26.9      16.4
45              Virginia  VA        8.00               26.4      20.5
46            Washington  WA        6.72               25.9      21.4
47         West Virginia  WV        1.85               25.0      22.2
48             Wisconsin  WI        5.69               26.3      17.2
49               Wyoming  WY        0.56               24.2      30.7

    Marriage SE  Divorce  Divorce SE  WaffleHouses  South  Slaves1860  \
0          1.27     12.7        0.79           128      1      435080
1          2.93     12.5        2.05             0      0           0
2          0.98     10.8        0.74            18      0           0
3          1.70     13.5        1.22            41      1      111115
4          0.39      8.0        0.24             0      0           0
5          1.24     11.6        0.94            11      0           0
6          1.06      6.7        0.77             0      0           0
7          2.89      8.9        1.39             3      0        1798
8          2.53      6.3        1.89             0      0           0
9          0.58      8.5        0.32           133      1       61745
10         0.81     11.5        0.58           381      1      462198
11         2.54      8.3        1.27             0      0           0
12         1.84      7.7        1.05             0      0           0
13         0.58      8.0        0.45             2      0           0
14         0.81     11.0        0.63            17      0           0
15         1.46     10.2        0.91             0      0           0
16         1.48     10.6        1.09             6      0           2
17         1.11     12.6        0.75            64      1      225483
```

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```
18          1.19     11.0        0.89             66      1      331726
19          1.40     13.0        1.48              0      0           0
20          1.02      8.8        0.69             11      0       87189
21          0.70      7.8        0.52              0      0           0
22          0.69      9.2        0.53              0      0           0
23          0.77      7.4        0.60              0      0           0
24          1.54     11.1        1.01             72      1      436631
25          0.81      9.5        0.67             39      1      114931
26          2.31      9.1        1.71              0      0           0
27          1.44      8.8        0.94              0      0          15
28          1.76     10.1        1.61              0      0           0
29          0.59      6.1        0.46              0      0          18
30          1.90     10.2        1.11              2      0           0
31          0.47      6.6        0.31              0      0           0
32          0.98      9.9        0.48            142      1      331059
33          2.93      8.0        1.44              0      0           0
34          0.61      9.5        0.45             64      0           0
35          1.29     12.8        1.01             16      0           0
36          1.10     10.4        0.80              0      0           0
37          0.48      7.7        0.43             11      0           0
38          2.11      9.4        1.79              0      0           0
39          1.18      8.1        0.70            144      1      402406
40          2.64     10.9        2.50              0      0           0
41          0.85     11.4        0.75            103      1      275719
42          0.61     10.0        0.35             99      1      182566
43          1.77     10.2        0.93              0      0           0
44          2.40      9.6        1.87              0      0           0
45          0.83      8.9        0.52             40      1      490865
46          1.00     10.0        0.65              0      0           0
47          1.69     10.9        1.34              4      1       18371
48          0.79      8.3        0.57              0      0           0
49          3.92     10.3        1.90              0      0           0

    Population1860  PropSlaves1860
0           964201        0.450000
1                0        0.000000
2                0        0.000000
3           435450        0.260000
4           379994        0.000000
5            34277        0.000000
6           460147        0.000000
7           112216        0.016000
8            75080        0.000000
9           140424        0.440000
10         1057286        0.440000
11               0        0.000000
12               0        0.000000
13         1711951        0.000000
14         1350428        0.000000
15          674913        0.000000
16          107206        0.000019
17         1155684        0.000000
18          708002        0.470000
19          628279        0.000000
20          687049        0.130000
21         1231066        0.000000
22          749113        0.000000
```

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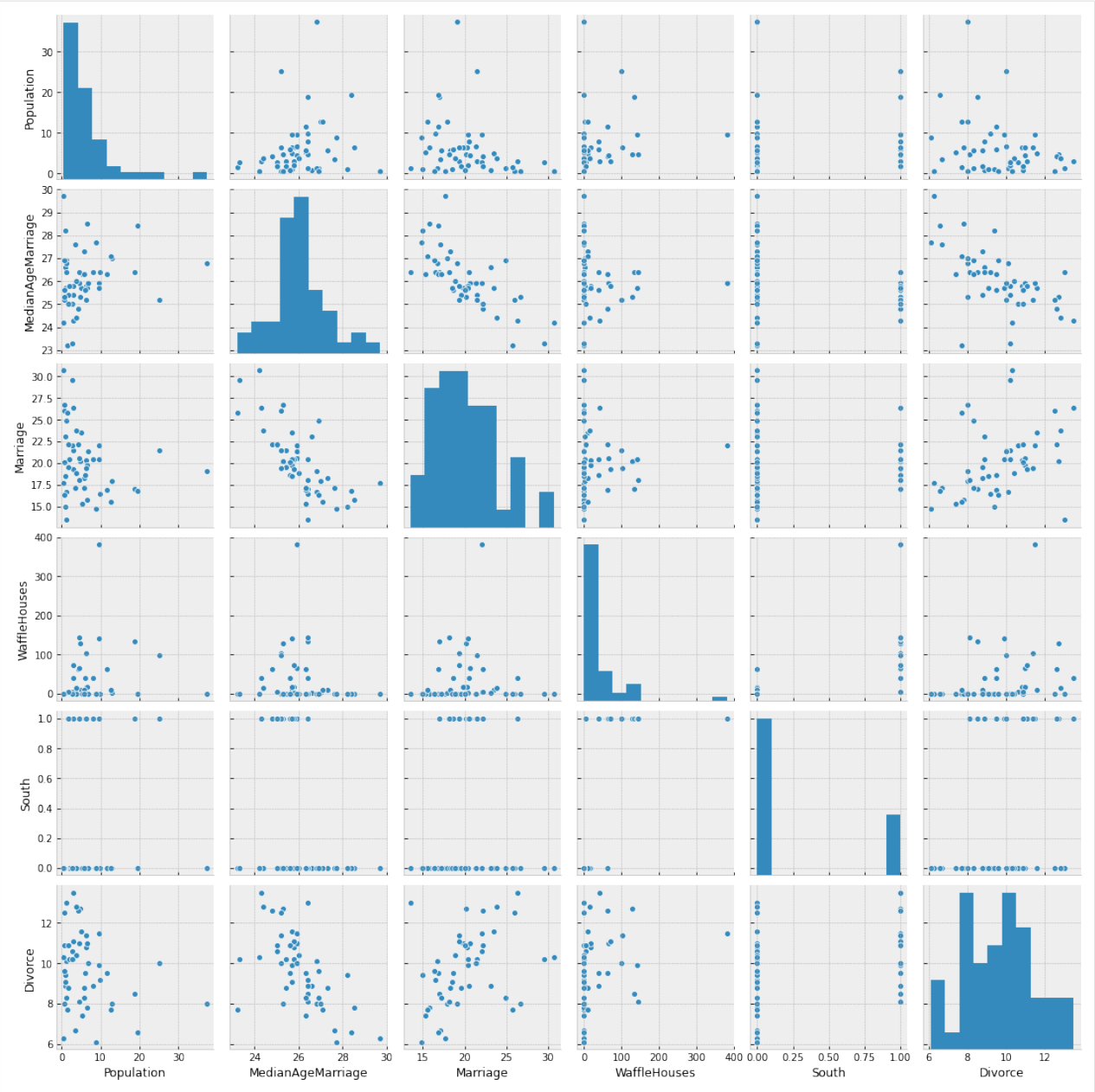
```
23          172023        0.000000
24          791305        0.550000
25         1182012        0.097000
26               0        0.000000
27           28841        0.000520
28          326073        0.000000
29          672035        0.000027
30           93516        0.000000
31         3880735        0.000000
32          992622        0.330000
33               0        0.000000
34         2339511        0.000000
35               0        0.000000
36           52465        0.000000
37         2906215        0.000000
38          174620        0.000000
39          703708        0.570000
40            4837        0.000000
41         1109801        0.200000
42          604215        0.300000
43           40273        0.000000
44          315098        0.000000
45         1219630        0.400000
46           11594        0.000000
47          376688        0.049000
48          775881        0.000000
49               0        0.000000
```

Let us plot the pair-wise relationship amongst the main variables in the dataset, using `seaborn.pairplot`.

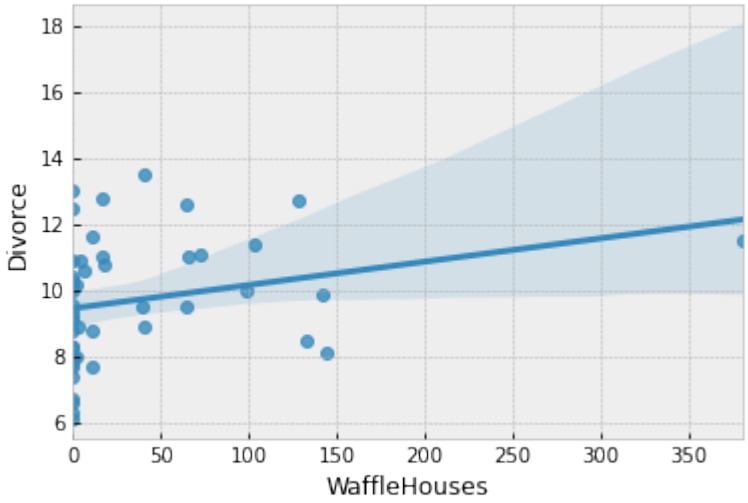
[4]:
```
vars = ['Population', 'MedianAgeMarriage', 'Marriage', 'WaffleHouses', 'South',
↪'Divorce']
sns.pairplot(dset, x_vars=vars, y_vars=vars, palette='husl');
```



From the plots above, we can clearly observe that there is a relationship between divorce rates and marriage rates in a state (as might be expected), and also between divorce rates and median age of marriage.

There is also a weak relationship between number of Waffle Houses and divorce rates, which is not obvious from the plot above, but will be clearer if we regress `Divorce` against `WaffleHouse` and plot the results.

[5]:
```
sns.regplot('WaffleHouses', 'Divorce', dset);
```



This is an example of a spurious association. We do not expect the number of Waffle Houses in a state to affect the divorce rate, but it is likely correlated with other factors that have an effect on the divorce rate. We will not delve into this spurious association in this tutorial, but the interested reader is encouraged to read Chapters 5 and 6 of [*1*] which explores the problem of causal association in the presence of multiple predictors.

For simplicity, we will primarily focus on marriage rate and the median age of marriage as our predictors for divorce rate throughout the remaining tutorial.

3.3 Regression Model to Predict Divorce Rate

Let us now write a regressionn model in *NumPyro* to predict the divorce rate as a linear function of marriage rate and median age of marriage in each of the states.

First, note that our predictor variables have somewhat different scales. It is a good practice to standardize our predictors and response variables to mean `0` and standard deviation `1`, which should result in faster inference.

[6]:
```
standardize = lambda x: (x - x.mean()) / x.std()

dset['AgeScaled'] = dset.MedianAgeMarriage.pipe(standardize)
dset['MarriageScaled'] = dset.Marriage.pipe(standardize)
dset['DivorceScaled'] = dset.Divorce.pipe(standardize)
```

We write the NumPyro model as follows. While the code should largely be self-explanatory, take note of the following:

- In NumPyro, *model* code is any Python callable which can optionally accept additional arguments and keywords. For HMC which we will be using for this tutorial, these arguments and keywords remain static during inference, but we can reuse the same model to generate *predictions* on new data.
- In addition to regular Python statements, the model code also contains primitives like `sample`. These primitives can be interpreted with various side-effects using effect handlers. For more on effect handlers, refer to [*3*], [*4*]. For now, just remember that a `sample` statement makes this a stochastic function that samples some latent parameters from a *prior distribution*. Our goal is to infer the *posterior distribution* of these parameters conditioned on observed data.
- The reason why we have kept our predictors as optional keyword arguments is to be able to reuse the same model as we vary the set of predictors. Likewise, the reason why the response variable is optional is that we

would like to reuse this model to sample from the posterior predictive distribution. See the *section* on plotting the posterior predictive distribution, as an example.

[7]:
```
def model(marriage=None, age=None, divorce=None):
    a = numpyro.sample('a', dist.Normal(0., 0.2))
    M, A = 0., 0.
    if marriage is not None:
        bM = numpyro.sample('bM', dist.Normal(0., 0.5))
        M = bM * marriage
    if age is not None:
        bA = numpyro.sample('bA', dist.Normal(0., 0.5))
        A = bA * age
    sigma = numpyro.sample('sigma', dist.Exponential(1.))
    mu = a + M + A
    numpyro.sample('obs', dist.Normal(mu, sigma), obs=divorce)
```

3.3.1 Model 1: Predictor - Marriage Rate

We first try to model the divorce rate as depending on a single variable, marriage rate. As mentioned above, we can use the same `model` code as earlier, but only pass values for `marriage` and `divorce` keyword arguments. We will use the No U-Turn Sampler (see [5] for more details on the NUTS algorithm) to run inference on this simple model.

The Hamiltonian Monte Carlo (or, the NUTS) implementation in NumPyro takes in a potential energy function. This is the negative log joint density for the model. Therefore, for our model description above, we need to construct a function which given the parameter values returns the potential energy (or negative log joint density). Additionally, the verlet integrator in HMC (or, NUTS) returns sample values simulated using Hamiltonian dynamics in the unconstrained space. As such, continuous variables with bounded support need to be transformed into unconstrained space using bijective transforms. We also need to transform these samples back to their constrained support before returning these values to the user. Thankfully, this is handled on the backend for us, within a convenience class for doing MCMC inference that has the following methods:

- `run(...)`: runs warmup, adapts steps size and mass matrix, and does sampling using the sample from the warmup phase.
- `print_summary()`: print diagnostic information like quantiles, effective sample size, and the Gelman-Rubin diagnostic.
- `get_samples()`: gets samples from the posterior distribution.

Note the following:

- JAX uses functional PRNGs. Unlike other languages / frameworks which maintain a global random state, in JAX, every call to a sampler requires an explicit PRNGKey. We will split our initial random seed for subsequent operations, so that we do not accidentally reuse the same seed.
- We run inference with the `NUTS` sampler. To run vanilla HMC, we can instead use the HMC class.

[8]:
```
# Start from this source of randomness. We will split keys for subsequent operations.
rng_key = random.PRNGKey(0)
rng_key, rng_key_ = random.split(rng_key)

num_warmup, num_samples = 1000, 2000

# Run NUTS.
kernel = NUTS(model)
mcmc = MCMC(kernel, num_warmup, num_samples)
mcmc.run(rng_key_, marriage=dset.MarriageScaled.values, divorce=dset.DivorceScaled.
↪values)
```

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```
mcmc.print_summary()
samples_1 = mcmc.get_samples()
```

```
sample: 100%|| 3000/3000 [00:06<00:00, 429.13it/s, 3 steps of size 7.48e-01. acc. prob=0.91]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
         a     -0.00      0.11     -0.00     -0.17      0.18   1804.63      1.00
        bM      0.35      0.13      0.35      0.13      0.56   1556.49      1.00
     sigma      0.94      0.10      0.94      0.78      1.08   1916.15      1.00

Number of divergences: 0
```

Posterior Distribution over the Regression Parameters

We notice that the progress bar gives us online statistics on the acceptance probability, step size and number of steps taken per sample while running NUTS. In particular, during warmup, we adapt the step size and mass matrix to achieve a certain target acceptance probability which is 0.8, by default. We were able to successfully adapt our step size to achieve this target in the warmup phase.

During warmup, the aim is to adapt hyper-parameters such as step size and mass matrix (the HMC algorithm is very sensitive to these hyper-parameters), and to reach the typical set (see [6] for more details). If there are any issues in the model specification, the first signal to notice would be low acceptance probabilities or very high number of steps. We use the sample from the end of the warmup phase to seed the MCMC chain (denoted by the second `sample` progress bar) from which we generate the desired number of samples from our target distribution.

At the end of inference, NumPyro prints the mean, std and 90% CI values for each of the latent parameters. Note that since we standardized our predictors and response variable, we would expect the intercept to have mean 0, as can be seen here. It also prints other convergence diagnostics on the latent parameters in the model, including effective sample size and the gelman rubin diagnostic ($\hat{R}$). The value for these diagnostics indicates that the chain has converged to the target distribution. In our case, the "target distribution" is the posterior distribution over the latent parameters that we are interested in. Note that this is often worth verifying with multiple chains for more complicated models. In the end, `samples_1` is a collection (in our case, a `dict` since `init_samples` was a `dict`) containing samples from the posterior distribution for each of the latent parameters in the model.

To look at our regression fit, let us plot the regression line using our posterior estimates for the regression parameters, along with the 90% Credibility Interval (CI). Note that the hpdi function in NumPyro's diagnostics module can be used to compute CI. In the functions below, note that the collected samples from the posterior are all along the leading axis.

[9]:
```
def plot_regression(x, y_mean, y_hpdi):
    # Sort values for plotting by x axis
    idx = jnp.argsort(x)
    marriage = x[idx]
    mean = y_mean[idx]
    hpdi = y_hpdi[:, idx]
    divorce = dset.DivorceScaled.values[idx]

    # Plot
    fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(6, 6))
    ax.plot(marriage, mean)
    ax.plot(marriage, divorce, 'o')
    ax.fill_between(marriage, hpdi[0], hpdi[1], alpha=0.3, interpolate=True)
    return ax
```

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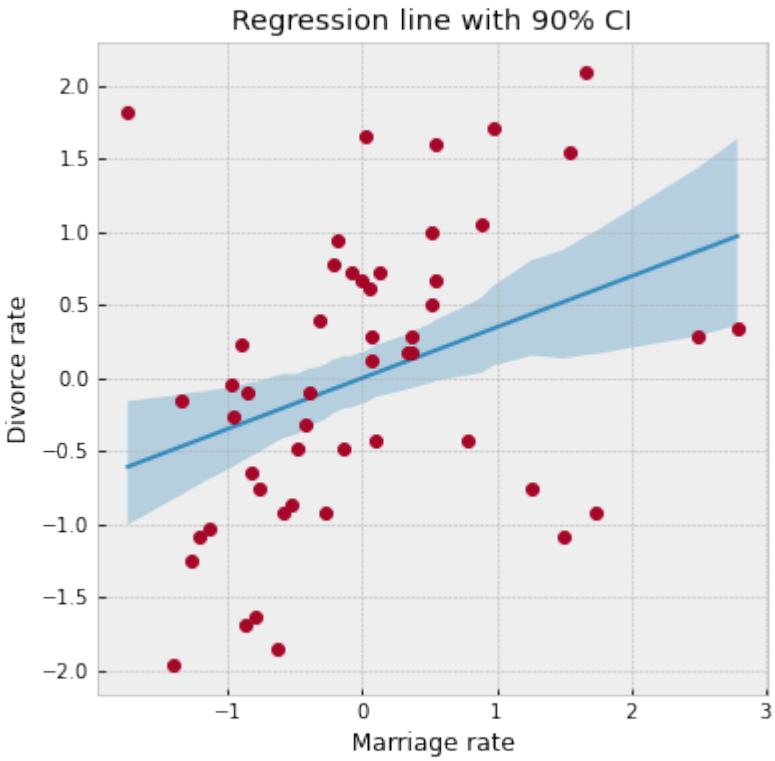
```
# Compute empirical posterior distribution over mu
posterior_mu = jnp.expand_dims(samples_1['a'], -1) + \
               jnp.expand_dims(samples_1['bM'], -1) * dset.MarriageScaled.values

mean_mu = jnp.mean(posterior_mu, axis=0)
hpdi_mu = hpdi(posterior_mu, 0.9)
ax = plot_regression(dset.MarriageScaled.values, mean_mu, hpdi_mu)
ax.set(xlabel='Marriage rate', ylabel='Divorce rate', title='Regression line with 90%␣
↪CI');
```



We can see from the plot, that the CI broadens towards the tails where the data is relatively sparse, as can be expected.

Posterior Predictive Distribution

Let us now look at the posterior predictive distribution to see how our predictive distribution looks with respect to the observed divorce rates. To get samples from the posterior predictive distribution, we need to run the model by substituting the latent parameters with samples from the posterior. NumPyro provides a handy Predictive utility for this purpose. Note that by default we generate a single prediction for each sample from the joint posterior distribution, but this can be controlled using the `num_samples` argument.

[10]:
```
from numpyro.infer import Predictive

rng_key, rng_key_ = random.split(rng_key)
predictive = Predictive(model, samples_1)
predictions = predictive(rng_key_, marriage=dset.MarriageScaled.values)['obs']
df = dset.filter(['Location'])
df['Mean Predictions'] = jnp.mean(predictions, axis=0)
df.head()
```

[10]:
```
     Location  Mean Predictions
0     Alabama          0.003563
1      Alaska          0.559501
2     Arizona          0.007107
3    Arkansas          0.539909
4  California         -0.077508
```

Predictive Utility With Effect Handlers

To remove the magic behind `Predictive`, let us see how we can combine effect handlers with the vmap JAX primitive to implement our own simplified predictive utility function that can do vectorized predictions.

[11]:
```
def predict(rng_key, post_samples, model, *args, **kwargs):
    model = handlers.seed(handlers.condition(model, post_samples), rng_key)
    model_trace = handlers.trace(model).get_trace(*args, **kwargs)
    return model_trace['obs']['value']

# vectorize predictions via vmap
predict_fn = vmap(lambda rng_key, samples: predict(rng_key, samples, model,␣
↪marriage=dset.MarriageScaled.values))
```

Note the use of the `condition`, `seed` and `trace` effect handlers in the `predict` function.

- The `seed` effect-handler is used to wrap a stochastic function with an initial `PRNGKey` seed. When a sample statement inside the model is called, it uses the existing seed to sample from a distribution but this effect-handler also splits the existing key to ensure that future `sample` calls in the model use the newly split key instead. This is to prevent us from having to explicitly pass in a `PRNGKey` to each `sample` statement in the model.
- The `condition` effect handler conditions the latent sample sites to certain values. In our case, we are conditioning on values from the posterior distribution returned by MCMC.
- The `trace` effect handler runs the model and records the execution trace within an `OrderedDict`. This trace object contains execution metadata that is useful for computing quantities such as the log joint density.

It should be clear now that the `predict` function simply runs the model by substituting the latent parameters with samples from the posterior (generated by the `mcmc` function) to generate predictions. Note the use of JAX's auto-vectorization transform called vmap to vectorize predictions. Note that if we didn't use `vmap`, we would have to use a native for loop which for each sample which is much slower. Each draw from the posterior can be used to get predictions over all the 50 states. When we vectorize this over all the samples from the posterior using `vmap`, we will get a `predictions_1` array of shape `(num_samples, 50)`. We can then compute the mean and 90% CI of these samples to plot the posterior predictive distribution. We note that our mean predictions match those obtained from the `Predictive` utility class.

[12]:
```
# Using the same key as we used for Predictive - note that the results are identical.

predictions_1 = predict_fn(random.split(rng_key_, num_samples), samples_1)

mean_pred = jnp.mean(predictions_1, axis=0)
df = dset.filter(['Location'])
df['Mean Predictions'] = mean_pred
df.head()
```

[12]:
```
     Location  Mean Predictions
0     Alabama          0.003563
1      Alaska          0.559501
2     Arizona          0.007107
```

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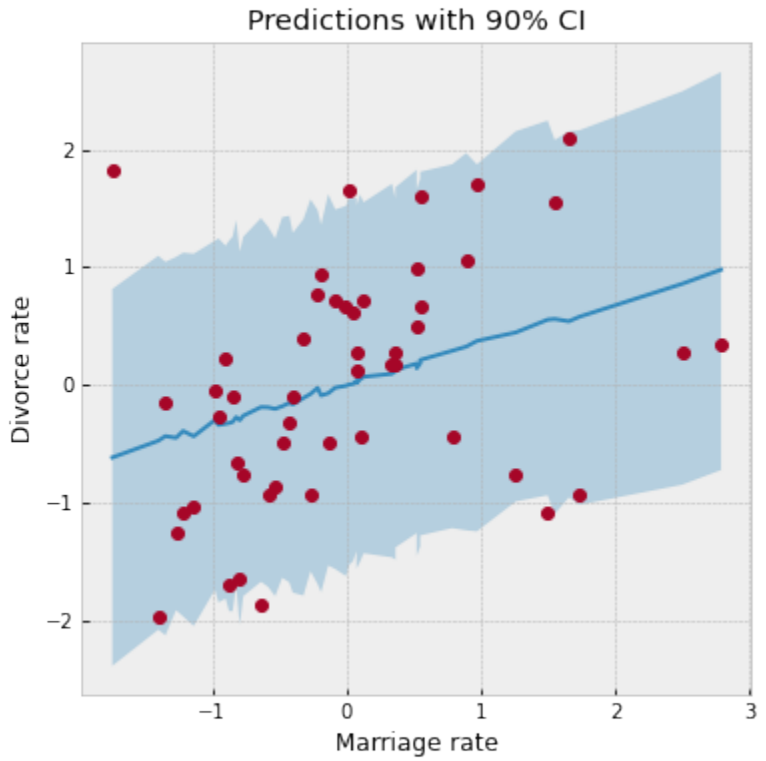
```
3    Arkansas          0.539909
4  California         -0.077508
```

[13]:
```
hpdi_pred = hpdi(predictions_1, 0.9)

ax = plot_regression(dset.MarriageScaled.values, mean_pred, hpdi_pred)
ax.set(xlabel='Marriage rate', ylabel='Divorce rate', title='Predictions with 90% CI
↪');
```



We have used the same `plot_regression` function as earlier. We notice that our CI for the predictive distribution is much broader as compared to the last plot due to the additional noise introduced by the `sigma` parameter. Most data points lie well within the 90% CI, which indicates a good fit.

Posterior Predictive Density

Likewise, making use of effect-handlers and `vmap`, we can also compute the log likelihood for this model given the dataset, and the log posterior predictive density [6] which is given by

$$log \prod_{i=1}^{n} \int p(y_i|\theta) p_{post}(\theta) d\theta \approx \sum_{i=1}^{n} log \frac{\sum_s p(\theta^s)}{S}$$
$$= \sum_{i=1}^{n} (log \sum_s p(\theta^s) - log(S))$$

.

Here, i indexes the observed data points y and s indexes the posterior samples over the latent parameters θ. If the posterior predictive density for a model has a comparatively high value, it indicates that the observed data-points have higher probability under the given model.

[14]:
```
def log_likelihood(rng_key, params, model, *args, **kwargs):
    model = handlers.condition(model, params)
    model_trace = handlers.trace(model).get_trace(*args, **kwargs)
    obs_node = model_trace['obs']
    return obs_node['fn'].log_prob(obs_node['value'])

def log_pred_density(rng_key, params, model, *args, **kwargs):
    n = list(params.values())[0].shape[0]
    log_lk_fn = vmap(lambda rng_key, params: log_likelihood(rng_key, params, model,␣
↪*args, **kwargs))
    log_lk_vals = log_lk_fn(random.split(rng_key, n), params)
    return (logsumexp(log_lk_vals, 0) - jnp.log(n)).sum()
```

Note that NumPyro provides the log_likelihood utility function that can be used directly for computing `log likelihood` as in the first function for any general model. In this tutorial, we would like to emphasize that there is nothing magical about such utility functions, and you can roll out your own inference utilities using NumPyro's effect handling stack.

[15]:
```
rng_key, rng_key_ = random.split(rng_key)
print('Log posterior predictive density: {}'.format(log_pred_density(rng_key_,
                                                                     samples_1,
                                                                     model,
                                                                     marriage=dset.
↪MarriageScaled.values,
                                                                     divorce=dset.
↪DivorceScaled.values)))
```

```
Log posterior predictive density: -66.65252685546875
```

3.3.2 Model 2: Predictor - Median Age of Marriage

We will now model the divorce rate as a function of the median age of marriage. The computations are mostly a reproduction of what we did for Model 1. Notice the following:

- Divorce rate is inversely related to the age of marriage. Hence states where the median age of marriage is low will likely have a higher divorce rate.
- We get a higher log likelihood as compared to Model 2, indicating that median age of marriage is likely a much better predictor of divorce rate.

[16]:
```
rng_key, rng_key_ = random.split(rng_key)

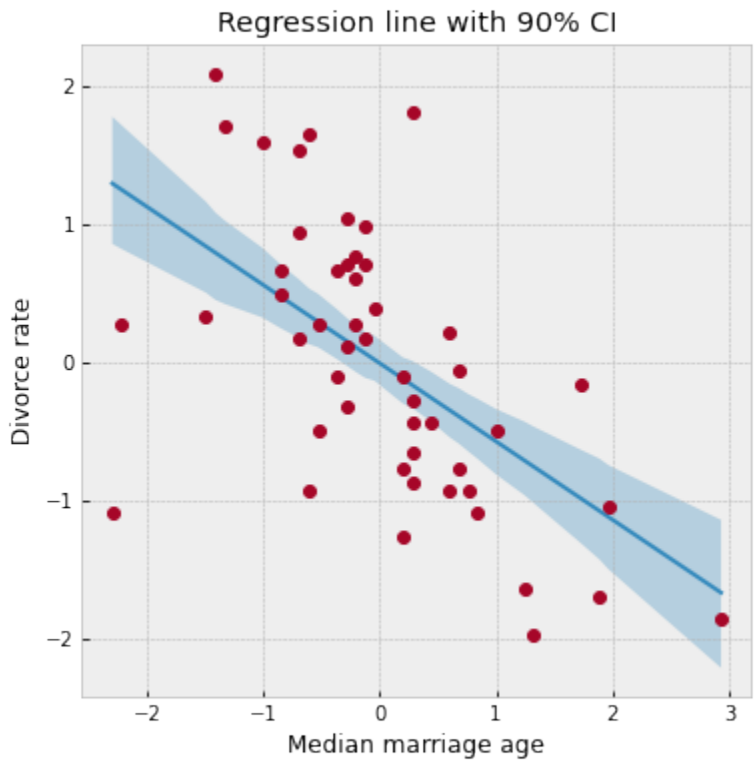
mcmc.run(rng_key_, age=dset.AgeScaled.values, divorce=dset.DivorceScaled.values)
mcmc.print_summary()
samples_2 = mcmc.get_samples()
```

```
sample: 100%|| 3000/3000 [00:07<00:00, 425.30it/s, 3 steps of␣
↪size 7.68e-01. acc. prob=0.92]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
         a     -0.00      0.10     -0.00     -0.16      0.16   1862.10      1.00
        bA     -0.57      0.11     -0.57     -0.75     -0.39   1962.83      1.00
     sigma      0.82      0.08      0.81      0.68      0.95   1544.86      1.00

Number of divergences: 0
```

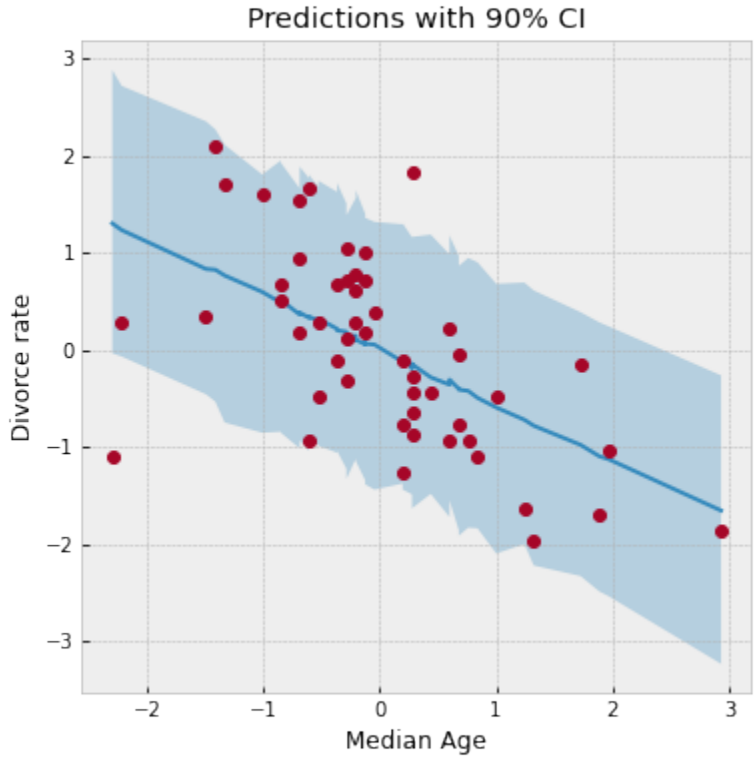
[17]:
```
posterior_mu = jnp.expand_dims(samples_2['a'], -1) + \
               jnp.expand_dims(samples_2['bA'], -1) * dset.AgeScaled.values
mean_mu = jnp.mean(posterior_mu, axis=0)
hpdi_mu = hpdi(posterior_mu, 0.9)
ax = plot_regression(dset.AgeScaled.values, mean_mu, hpdi_mu)
ax.set(xlabel='Median marriage age', ylabel='Divorce rate', title='Regression line␣
↪with 90% CI');
```



[18]:
```
rng_key, rng_key_ = random.split(rng_key)
predictions_2 = Predictive(model, samples_2)(rng_key_,
                                              age=dset.AgeScaled.values)['obs']

mean_pred = jnp.mean(predictions_2, axis=0)
hpdi_pred = hpdi(predictions_2, 0.9)

ax = plot_regression(dset.AgeScaled.values, mean_pred, hpdi_pred)
ax.set(xlabel='Median Age', ylabel='Divorce rate', title='Predictions with 90% CI');
```



[19]:
```
rng_key, rng_key_ = random.split(rng_key)
print('Log posterior predictive density: {}'.format(log_pred_density(rng_key_,
                                                     samples_2,
                                                     model,
                                                     age=dset.AgeScaled.values,
                                                     divorce=dset.DivorceScaled.
↪values)))
```

```
Log posterior predictive density: -59.238067626953125
```

3.3.3 Model 3: Predictor - Marriage Rate and Median Age of Marriage

Finally, we will also model divorce rate as depending on both marriage rate as well as the median age of marriage. Note that the model's posterior predictive density is similar to Model 2 which likely indicates that the marginal information from marriage rate in predicting divorce rate is low when the median age of marriage is already known.

[20]:
```
rng_key, rng_key_ = random.split(rng_key)

mcmc.run(rng_key_, marriage=dset.MarriageScaled.values,
         age=dset.AgeScaled.values, divorce=dset.DivorceScaled.values)
mcmc.print_summary()
samples_3 = mcmc.get_samples()
```

```
sample: 100%|| 3000/3000 [00:07<00:00, 389.02it/s, 7 steps of␣
↪size 5.15e-01. acc. prob=0.92]
```

```
             mean       std    median      5.0%     95.0%     n_eff     r_hat
         a      0.00      0.10      0.00     -0.17      0.16   1731.49      1.00
```

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```
        bA     -0.61      0.16     -0.61     -0.88     -0.36   1446.05      1.00
        bM     -0.06      0.16     -0.07     -0.32      0.20   1432.76      1.00
     sigma      0.82      0.08      0.82      0.69      0.96   1654.31      1.00

Number of divergences: 0
```

[21]:
```
rng_key, rng_key_ = random.split(rng_key)
print('Log posterior predictive density: {}'.format(
    log_pred_density(rng_key_,
                     samples_3,
                     model,
                     marriage=dset.MarriageScaled.values,
                     age=dset.AgeScaled.values,
                     divorce=dset.DivorceScaled.values)
))
```

```
Log posterior predictive density: -59.06075668334961
```

3.3.4 Divorce Rate Residuals by State

The regression plots above shows that the observed divorce rates for many states differs considerably from the mean regression line. To dig deeper into how the last model (Model 3) under-predicts or over-predicts for each of the states, we will plot the posterior predictive and residuals (`Observed divorce rate - Predicted divorce rate`) for each of the states.

[22]:
```
# Predictions for Model 3.
rng_key, rng_key_ = random.split(rng_key)
predictions_3 = Predictive(model, samples_3)(rng_key_,
                                             marriage=dset.MarriageScaled.values,
                                             age=dset.AgeScaled.values)['obs']
y = jnp.arange(50)


fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 16))
pred_mean = jnp.mean(predictions_3, axis=0)
pred_hpdi = hpdi(predictions_3, 0.9)
residuals_3 = dset.DivorceScaled.values - predictions_3
residuals_mean = jnp.mean(residuals_3, axis=0)
residuals_hpdi = hpdi(residuals_3, 0.9)
idx = jnp.argsort(residuals_mean)

# Plot posterior predictive
ax[0].plot(jnp.zeros(50), y, '--')
ax[0].errorbar(pred_mean[idx], y, xerr=pred_hpdi[1, idx] - pred_mean[idx],
               marker='o', ms=5, mew=4, ls='none', alpha=0.8)
ax[0].plot(dset.DivorceScaled.values[idx], y, marker='o',
           ls='none', color='gray')
ax[0].set(xlabel='Posterior Predictive (red) vs. Actuals (gray)', ylabel='State',
          title='Posterior Predictive with 90% CI')
ax[0].set_yticks(y)
ax[0].set_yticklabels(dset.Loc.values[idx], fontsize=10);

# Plot residuals
residuals_3 = dset.DivorceScaled.values - predictions_3
residuals_mean = jnp.mean(residuals_3, axis=0)
```

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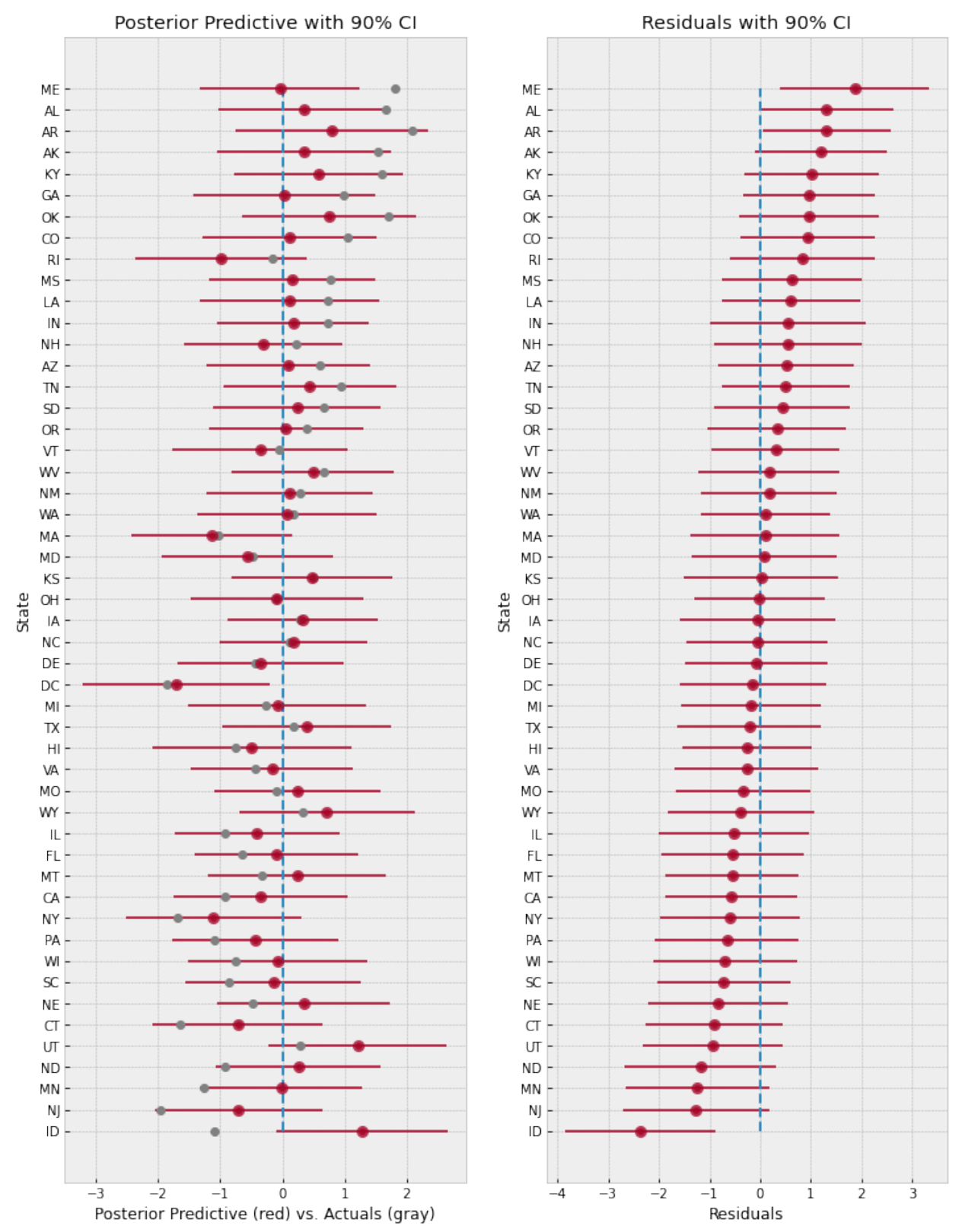
```
residuals_hpdi = hpdi(residuals_3, 0.9)
err = residuals_hpdi[1] - residuals_mean

ax[1].plot(jnp.zeros(50), y, '--')
ax[1].errorbar(residuals_mean[idx], y, xerr=err[idx],
               marker='o', ms=5, mew=4, ls='none', alpha=0.8)
ax[1].set(xlabel='Residuals', ylabel='State', title='Residuals with 90% CI')
ax[1].set_yticks(y)
ax[1].set_yticklabels(dset.Loc.values[idx], fontsize=10);
```



The plot on the left shows the mean predictions with 90% CI for each of the states using Model 3. The gray markers indicate the actual observed divorce rates. The right plot shows the residuals for each of the states, and both these plots

are sorted by the residuals, i.e. at the bottom, we are looking at states where the model predictions are higher than the observed rates, whereas at the top, the reverse is true.

Overall, the model fit seems good because most observed data points like within a 90% CI around the mean predictions. However, notice how the model over-predicts by a large margin for states like Idaho (bottom left), and on the other end under-predicts for states like Maine (top right). This is likely indicative of other factors that we are missing out in our model that affect divorce rate across different states. Even ignoring other socio-political variables, one such factor that we have not yet modeled is the measurement noise given by `Divorce SE` in the dataset. We will explore this in the next section.

3.4 Regression Model with Measurement Error

Note that in our previous models, each data point influences the regression line equally. Is this well justified? We will build on the previous model to incorporate measurement error given by `Divorce SE` variable in the dataset. Incorporating measurement noise will be useful in ensuring that observations that have higher confidence (i.e. lower measurement noise) have a greater impact on the regression line. On the other hand, this will also help us better model outliers with high measurement errors. For more details on modeling errors due to measurement noise, refer to Chapter 14 of [*1*].

To do this, we will reuse Model 3, with the only change that the final observed value has a measurement error given by `divorce_sd` (notice that this has to be standardized since the `divorce` variable itself has been standardized to mean 0 and std 1).

[23]:
```
def model_se(marriage, age, divorce_sd, divorce=None):
    a = numpyro.sample('a', dist.Normal(0., 0.2))
    bM = numpyro.sample('bM', dist.Normal(0., 0.5))
    M = bM * marriage
    bA = numpyro.sample('bA', dist.Normal(0., 0.5))
    A = bA * age
    sigma = numpyro.sample('sigma', dist.Exponential(1.))
    mu = a + M + A
    divorce_rate = numpyro.sample('divorce_rate', dist.Normal(mu, sigma))
    numpyro.sample('obs', dist.Normal(divorce_rate, divorce_sd), obs=divorce)
```

[24]:
```
# Standardize
dset['DivorceScaledSD'] = dset['Divorce SE'] / jnp.std(dset.Divorce.values)
```

[25]:
```
rng_key, rng_key_ = random.split(rng_key)

kernel = NUTS(model_se, target_accept_prob=0.9)
mcmc = MCMC(kernel, num_warmup=1000, num_samples=3000)
mcmc.run(rng_key_, marriage=dset.MarriageScaled.values, age=dset.AgeScaled.values,
         divorce_sd=dset.DivorceScaledSD.values, divorce=dset.DivorceScaled.values)
mcmc.print_summary()
samples_4 = mcmc.get_samples()
```

```
sample: 100%|██████████| 4000/4000 [00:09<00:00, 408.70it/s, 15 steps of␣
↪size 3.00e-01. acc. prob=0.91]
```

```
                     mean       std    median      5.0%     95.0%     n_eff     r_hat
              a     -0.06      0.09     -0.06     -0.21      0.10   3381.24      1.00
             bA     -0.61      0.16     -0.61     -0.86     -0.32   2457.71      1.00
             bM      0.06      0.17      0.06     -0.19      0.35   2384.97      1.00
 divorce_rate[0]      1.14      0.37      1.14      0.54      1.74   4196.29      1.00
```

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divorce_rate[1]	0.69	0.55	0.68	-0.24	1.54	4457.97	1.00
divorce_rate[2]	0.43	0.34	0.43	-0.12	0.97	4692.82	1.00
divorce_rate[3]	1.41	0.47	1.41	0.71	2.21	5338.40	1.00
divorce_rate[4]	-0.90	0.13	-0.90	-1.12	-0.69	6373.86	1.00
divorce_rate[5]	0.65	0.39	0.64	0.00	1.29	5890.75	1.00
divorce_rate[6]	-1.36	0.35	-1.35	-1.90	-0.74	6029.70	1.00
divorce_rate[7]	-0.33	0.48	-0.32	-1.13	0.42	6226.93	1.00
divorce_rate[8]	-1.88	0.61	-1.89	-2.84	-0.86	3797.97	1.00
divorce_rate[9]	-0.62	0.16	-0.62	-0.88	-0.33	7313.05	1.00
divorce_rate[10]	0.76	0.28	0.75	0.31	1.24	5122.44	1.00
divorce_rate[11]	-0.54	0.47	-0.55	-1.32	0.22	4301.37	1.00
divorce_rate[12]	0.20	0.51	0.21	-0.60	1.07	2646.56	1.00
divorce_rate[13]	-0.87	0.23	-0.86	-1.24	-0.49	6676.11	1.00
divorce_rate[14]	0.55	0.31	0.55	0.04	1.03	5340.67	1.00
divorce_rate[15]	0.29	0.38	0.29	-0.35	0.89	7546.96	1.00
divorce_rate[16]	0.51	0.43	0.50	-0.23	1.17	4965.65	1.00
divorce_rate[17]	1.24	0.34	1.25	0.69	1.82	4936.42	1.00
divorce_rate[18]	0.42	0.38	0.42	-0.15	1.11	5954.93	1.00
divorce_rate[19]	0.38	0.56	0.37	-0.53	1.28	2854.65	1.00
divorce_rate[20]	-0.56	0.32	-0.55	-1.09	-0.05	5861.17	1.00
divorce_rate[21]	-1.10	0.26	-1.10	-1.53	-0.66	5929.05	1.00
divorce_rate[22]	-0.28	0.27	-0.28	-0.70	0.16	6215.17	1.00
divorce_rate[23]	-0.99	0.30	-1.00	-1.44	-0.45	4756.94	1.00
divorce_rate[24]	0.42	0.42	0.41	-0.25	1.10	6284.63	1.00
divorce_rate[25]	-0.03	0.32	-0.03	-0.53	0.53	6587.60	1.00
divorce_rate[26]	-0.02	0.50	-0.02	-0.88	0.75	5119.31	1.00
divorce_rate[27]	-0.15	0.38	-0.14	-0.78	0.44	4868.48	1.00
divorce_rate[28]	-0.26	0.50	-0.27	-1.06	0.61	4898.44	1.00
divorce_rate[29]	-1.79	0.24	-1.80	-2.19	-1.40	5940.81	1.00
divorce_rate[30]	0.18	0.43	0.17	-0.60	0.80	6070.03	1.00
divorce_rate[31]	-1.66	0.16	-1.66	-1.92	-1.38	7048.38	1.00
divorce_rate[32]	0.12	0.24	0.11	-0.24	0.52	6550.93	1.00
divorce_rate[33]	-0.03	0.53	-0.01	-0.92	0.81	4108.95	1.00
divorce_rate[34]	-0.13	0.22	-0.13	-0.51	0.21	7752.43	1.00
divorce_rate[35]	1.27	0.40	1.27	0.66	1.99	5621.12	1.00
divorce_rate[36]	0.23	0.36	0.22	-0.36	0.81	7705.96	1.00
divorce_rate[37]	-1.02	0.22	-1.02	-1.40	-0.68	5115.13	1.00
divorce_rate[38]	-0.93	0.54	-0.93	-1.84	-0.10	3426.71	1.00
divorce_rate[39]	-0.67	0.32	-0.67	-1.23	-0.17	6310.21	1.00
divorce_rate[40]	0.25	0.54	0.25	-0.60	1.15	4844.06	1.00
divorce_rate[41]	0.73	0.35	0.74	0.12	1.27	5814.62	1.00
divorce_rate[42]	0.20	0.18	0.20	-0.12	0.48	8983.24	1.00
divorce_rate[43]	0.82	0.42	0.84	0.13	1.52	3795.81	1.00
divorce_rate[44]	-0.42	0.52	-0.43	-1.25	0.48	4979.32	1.00
divorce_rate[45]	-0.38	0.25	-0.38	-0.80	0.02	6811.34	1.00
divorce_rate[46]	0.13	0.31	0.14	-0.38	0.64	6527.01	1.00
divorce_rate[47]	0.57	0.48	0.56	-0.22	1.33	6760.92	1.00
divorce_rate[48]	-0.63	0.27	-0.63	-1.08	-0.20	6560.02	1.00
divorce_rate[49]	0.86	0.59	0.87	-0.13	1.78	4066.94	1.00
sigma	0.58	0.11	0.57	0.41	0.76	1067.58	1.00

```
Number of divergences: 0
```

3.4.1 Effect of Incorporating Measurement Noise on Residuals

Notice that our values for the regression coefficients is very similar to Model 3. However, introducing measurement noise allows us to more closely match our predictive distribution to the observed values. We can see this if we plot the residuals as earlier.

[26]:
```
rng_key, rng_key_ = random.split(rng_key)
predictions_4 = Predictive(model_se, samples_4)(rng_key_,
                                                marriage=dset.MarriageScaled.values,
                                                age=dset.AgeScaled.values,
                                                divorce_sd=dset.DivorceScaledSD.
↪values)['obs']
```

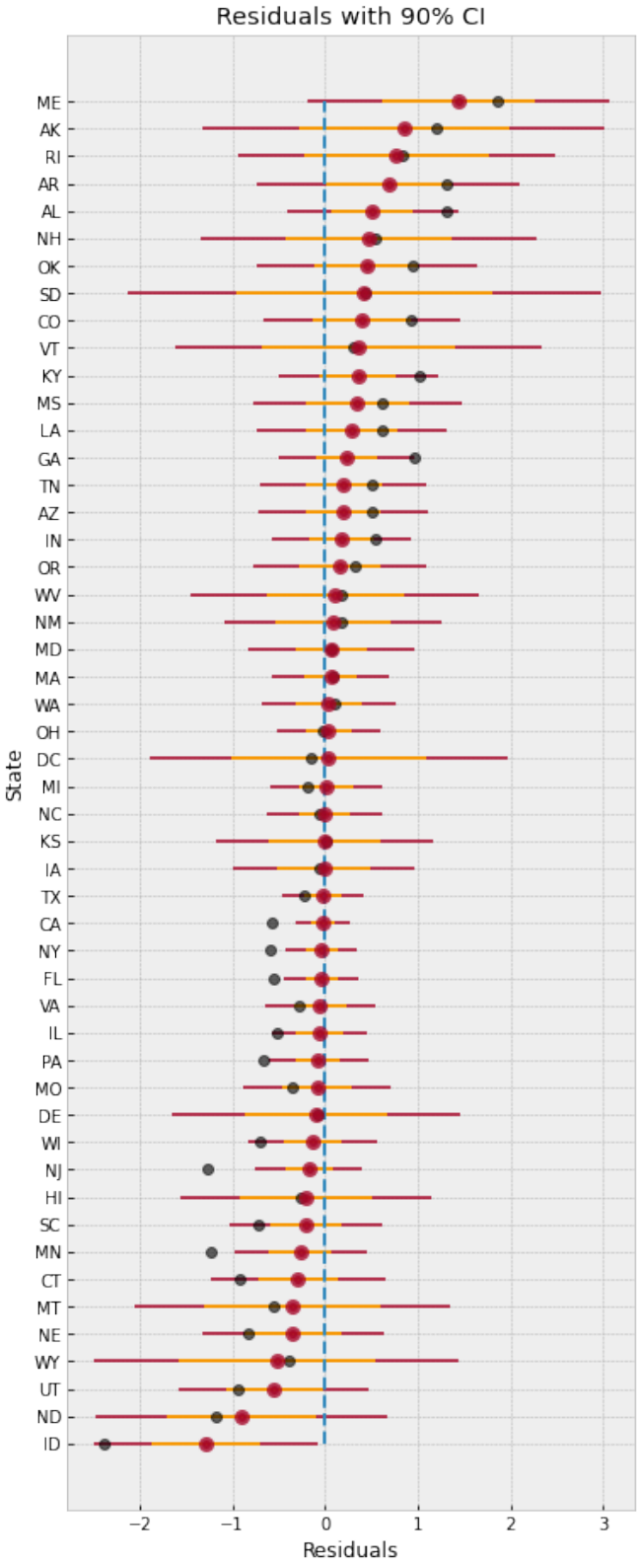
[27]:
```
sd = dset.DivorceScaledSD.values
residuals_4 = dset.DivorceScaled.values - predictions_4
residuals_mean = jnp.mean(residuals_4, axis=0)
residuals_hpdi = hpdi(residuals_4, 0.9)
err = residuals_hpdi[1] - residuals_mean
idx = jnp.argsort(residuals_mean)
y = jnp.arange(50)
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(6, 16))


# Plot Residuals
ax.plot(jnp.zeros(50), y, '--')
ax.errorbar(residuals_mean[idx], y, xerr=err[idx],
            marker='o', ms=5, mew=4, ls='none', alpha=0.8)

# Plot SD
ax.errorbar(residuals_mean[idx], y, xerr=sd[idx],
            ls='none', color='orange', alpha=0.9)

# Plot earlier mean residual
ax.plot(jnp.mean(dset.DivorceScaled.values - predictions_3, 0)[idx], y,
        ls='none', marker='o', ms=6, color='black', alpha=0.6)

ax.set(xlabel='Residuals', ylabel='State', title='Residuals with 90% CI')
ax.set_yticks(y)
ax.set_yticklabels(dset.Loc.values[idx], fontsize=10);
ax.text(-2.8, -7, 'Residuals (with error-bars) from current model (in red). '
                  'Black marker \nshows residuals from the previous model (Model 3). '
                  'Measurement \nerror is indicated by orange bar.');
```



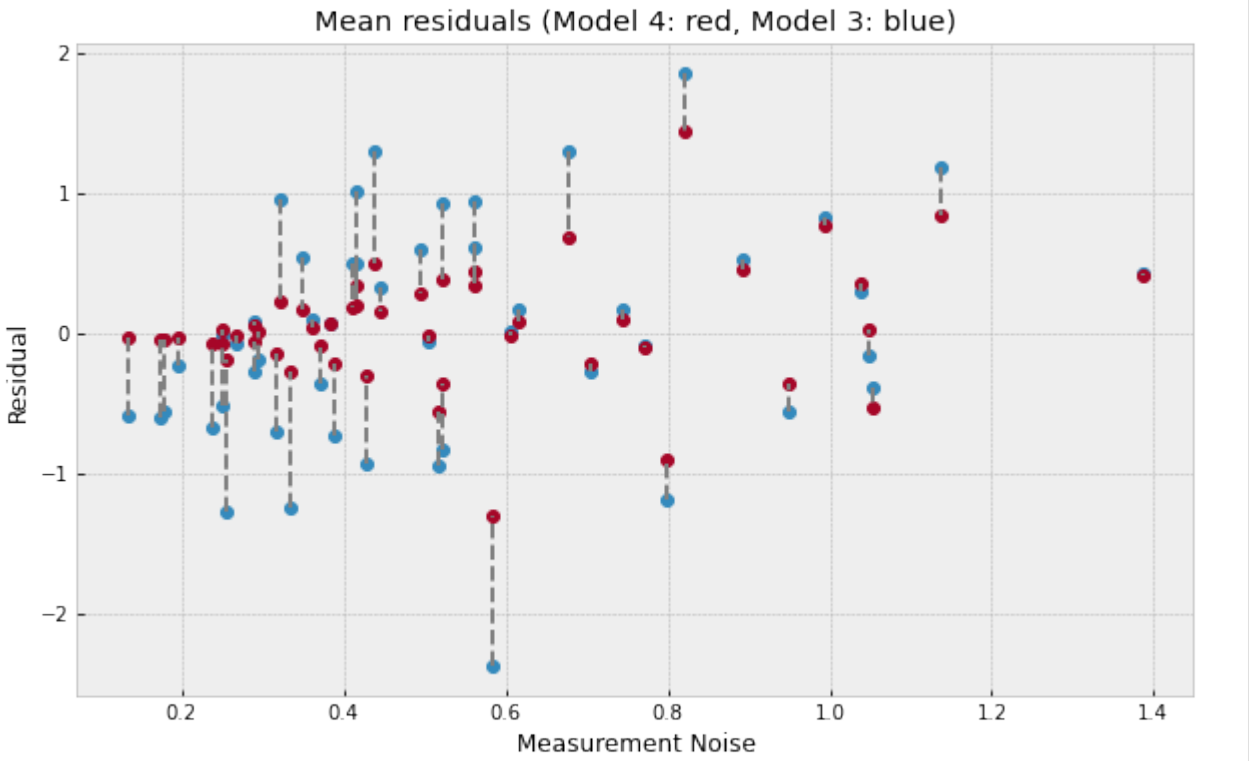
Residuals (with error-bars) from current model (in red). Black marker shows residuals from the previous model (Model 3). Measurement error is indicated by orange bar.

The plot above shows the residuals for each of the states, along with the measurement noise given by inner error bar. The gray dots are the mean residuals from our earlier Model 3. Notice how having an additional degree of freedom to model the measurement noise has shrunk the residuals. In particular, for Idaho and Maine, our predictions are now much closer to the observed values after incorporating measurement noise in the model.

To better see how measurement noise affects the movement of the regression line, let us plot the residuals with respect to the measurement noise.

[28]:
```
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(10, 6))
x = dset.DivorceScaledSD.values
y1 = jnp.mean(residuals_3, 0)
y2 = jnp.mean(residuals_4, 0)
ax.plot(x, y1, ls='none', marker='o')
ax.plot(x, y2, ls='none', marker='o')
for i, (j, k)  in enumerate(zip(y1, y2)):
    ax.plot([x[i], x[i]], [j, k], '--', color='gray');

ax.set(xlabel='Measurement Noise', ylabel='Residual', title='Mean residuals (Model 4:␣
↪red, Model 3: blue)');
```



The plot above shows what has happend in more detail - the regression line itself has moved to ensure a better fit for observations with low measurement noise (left of the plot) where the residuals have shrunk very close to 0. That is to say that data points with low measurement error have a concomitantly higher contribution in determining the regression line. On the other hand, for states with high measurement error (right of the plot), incorporating measurement noise allows us to move our posterior distribution mass closer to the observations resulting in a shrinkage of residuals as well.

3.5 References

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4. Pyro Development Team. Poutine: A Guide to Programming with Effect Handlers in Pyro
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github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/bayesian_hierarchical_linear_regression.ipynb

CHAPTER 4

Bayesian Hierarchical Linear Regression

Author: Carlos Souza

Probabilistic Machine Learning models can not only make predictions about future data, but also **model uncertainty**. In areas such as **personalized medicine**, there might be a large amount of data, but there is still a relatively **small amount of data for each patient**. To customize predictions for each person it becomes necessary to **build a model for each person** — with its inherent **uncertainties** — and to couple these models together in a **hierarchy** so that information can be borrowed from other **similar people** [1].

The purpose of this tutorial is to demonstrate how to **implement a Bayesian Hierarchical Linear Regression model using NumPyro**. To motivate the tutorial, I will use OSIC Pulmonary Fibrosis Progression competition, hosted at Kaggle.

4.1 1. Understanding the task

Pulmonary fibrosis is a disorder with no known cause and no known cure, created by scarring of the lungs. In this competition, we were asked to predict a patient's severity of decline in lung function. Lung function is assessed based on output from a spirometer, which measures the forced vital capacity (FVC), i.e. the volume of air exhaled.

In medical applications, it is useful to **evaluate a model's confidence in its decisions**. Accordingly, the metric used to rank the teams was designed to reflect **both the accuracy and certainty of each prediction**. It's a modified version of the Laplace Log Likelihood (more details on that later).

Let's explore the data and see what's that all about:

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
train = pd.read_csv('https://gist.githubusercontent.com/ucals/'
                    '2cf9d101992cb1b78c2cdd6e3bac6a4b/raw/'
                    '43034c39052dcf97d4b894d2ec1bc3f90f3623d9/'
```

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```
                    'osic_pulmonary_fibrosis.csv')
train.head()
```

[2]:

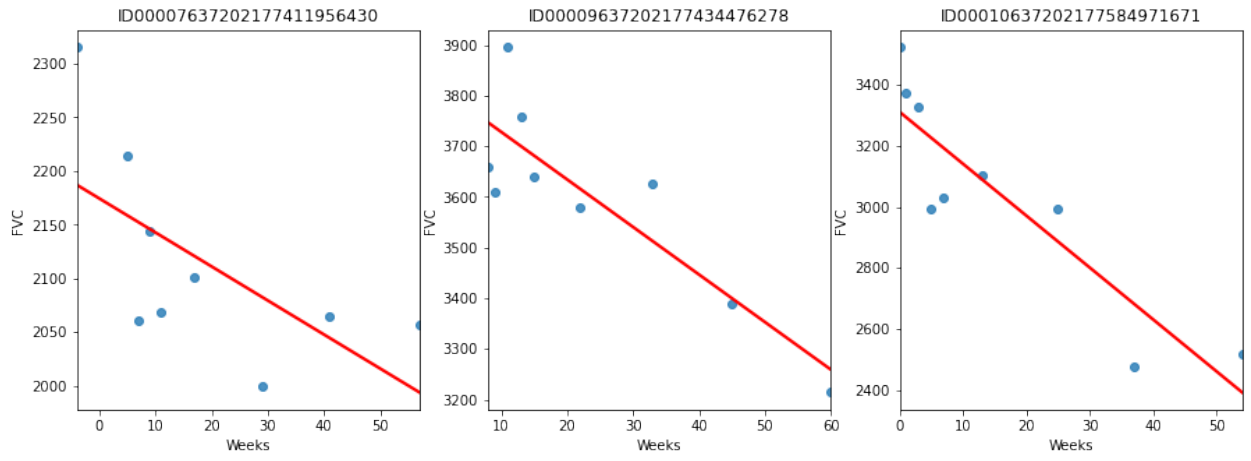
	Patient	Weeks	FVC	Percent	Age	Sex	SmokingStatus
0	ID00007637202177411956430	-4	2315	58.253649	79	Male	Ex-smoker
1	ID00007637202177411956430	5	2214	55.712129	79	Male	Ex-smoker
2	ID00007637202177411956430	7	2061	51.862104	79	Male	Ex-smoker
3	ID00007637202177411956430	9	2144	53.950679	79	Male	Ex-smoker
4	ID00007637202177411956430	11	2069	52.063412	79	Male	Ex-smoker

In the dataset, we were provided with a baseline chest CT scan and associated clinical information for a set of patients. A patient has an image acquired at time Week = 0 and has numerous follow up visits over the course of approximately 1-2 years, at which time their FVC is measured. For this tutorial, I will use only the Patient ID, the weeks and the FVC measurements, discarding all the rest. Using only these columns enabled our team to achieve a competitive score, which shows the power of Bayesian hierarchical linear regression models especially when gauging uncertainty is an important part of the problem.

Since this is real medical data, the relative timing of FVC measurements varies widely, as shown in the 3 sample patients below:

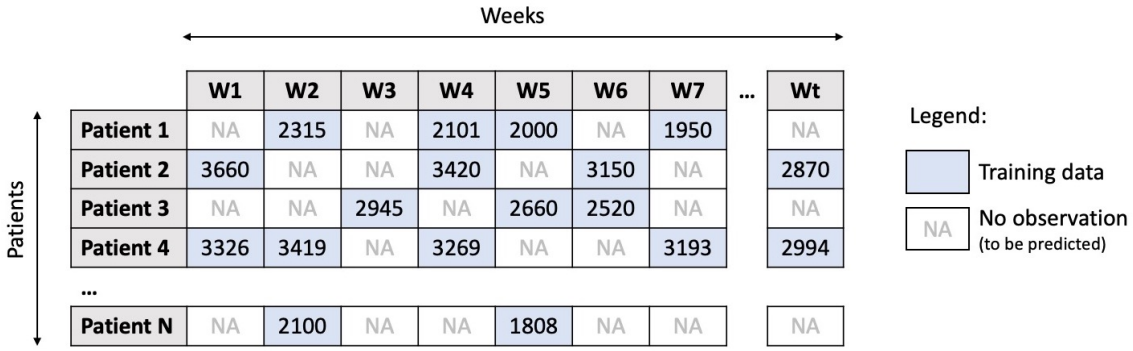
[3]:
```
def chart(patient_id, ax):
    data = train[train['Patient'] == patient_id]
    x = data['Weeks']
    y = data['FVC']
    ax.set_title(patient_id)
    ax = sns.regplot(x, y, ax=ax, ci=None, line_kws={'color':'red'})


f, axes = plt.subplots(1, 3, figsize=(15, 5))
chart('ID00007637202177411956430', axes[0])
chart('ID00009637202177434476278', axes[1])
chart('ID00010637202177584971671', axes[2])
```



On average, each of the 176 provided patients made 9 visits, when FVC was measured. The visits happened in specific weeks in the [-12, 133] interval. The decline in lung capacity is very clear. We see, though, they are very different from patient to patient.

We were are asked to predict every patient's FVC measurement for every possible week in the [-12, 133] interval, and the confidence for each prediction. In other words: we were asked fill a matrix like the one below, and provide a confidence score for each prediction:

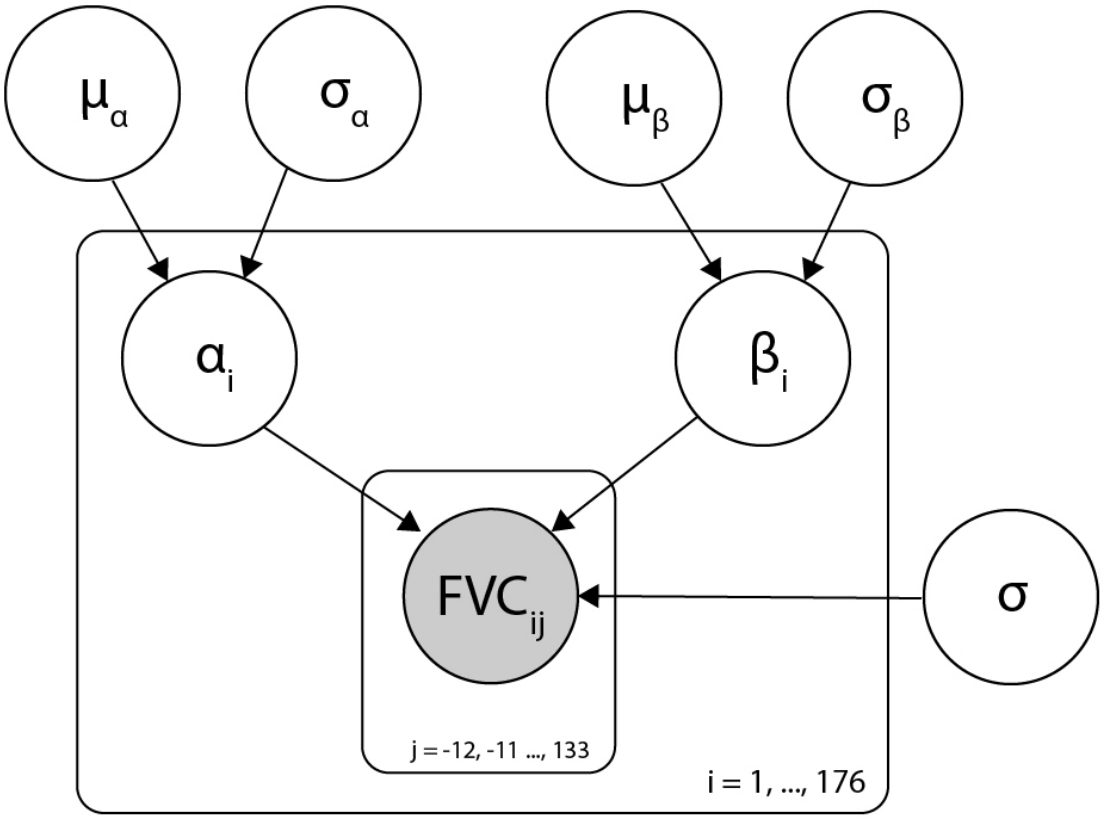


The task was perfect to apply Bayesian inference. However, the vast majority of solutions shared by Kaggle community used discriminative machine learning models, disconsidering the fact that most discriminative methods are very poor at providing realistic uncertainty estimates. Because they are typically trained in a manner that optimizes the parameters to minimize some loss criterion (e.g. the predictive error), they do not, in general, encode any uncertainty in either their parameters or the subsequent predictions. Though many methods can produce uncertainty estimates either as a by-product or from a post-processing step, these are typically heuristic based, rather than stemming naturally from a statistically principled estimate of the target uncertainty distribution [2].

4.2 2. Modelling: Bayesian Hierarchical Linear Regression with Partial Pooling

The simplest possible linear regression, not hierarchical, would assume all FVC decline curves have the same α and β. That's the **pooled model**. In the other extreme, we could assume a model where each patient has a personalized FVC decline curve, and **these curves are completely unrelated**. That's the **unpooled model**, where each patient has completely separate regressions.

Here, I'll use the middle ground: **Partial pooling**. Specifically, I'll assume that while α's and β's are different for each patient as in the unpooled case, **the coefficients all share similarity**. We can model this by assuming that each individual coefficient comes from a common group distribution. The image below represents this model graphically:



Mathematically, the model is described by the following equations:

$$\mu_\alpha \sim \mathcal{N}(0, 100) \tag{4.1}$$
$$\sigma_\alpha \sim |\mathcal{N}(0, 100)| \tag{4.2}$$
$$\mu_\beta \sim \mathcal{N}(0, 100) \tag{4.3}$$
$$\sigma_\beta \sim |\mathcal{N}(0, 100)| \tag{4.4}$$
$$\alpha_i \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha) \tag{4.5}$$
$$\beta_i \sim \mathcal{N}(\mu_\beta, \sigma_\beta) \tag{4.6}$$
$$\sigma \sim \mathcal{N}(0, 100) \tag{4.7}$$
$$FVC_{ij} \sim \mathcal{N}(\alpha_i + t\beta_i, \sigma) \tag{4.8}$$

where *t* is the time in weeks. Those are very uninformative priors, but that's ok: our model will converge!

Implementing this model in NumPyro is pretty straightforward:

[4]:
```
import numpyro
from numpyro.infer import MCMC, NUTS, Predictive
import numpyro.distributions as dist
from jax import random
```

[5]:
```
def model(PatientID, Weeks, FVC_obs=None):
    μ_α = numpyro.sample("μ_α", dist.Normal(0., 100.))
    σ_α = numpyro.sample("σ_α", dist.HalfNormal(100.))
    μ_β = numpyro.sample("μ_β", dist.Normal(0., 100.))
```

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```
    σ_β = numpyro.sample("σ_β", dist.HalfNormal(100.))

    unique_patient_IDs = np.unique(PatientID)
    n_patients = len(unique_patient_IDs)

    with numpyro.plate("plate_i", n_patients):
        α = numpyro.sample("α", dist.Normal(μ_α, σ_α))
        β = numpyro.sample("β", dist.Normal(μ_β, σ_β))

    σ = numpyro.sample("σ", dist.HalfNormal(100.))
    FVC_est = α[PatientID] + β[PatientID] * Weeks

    with numpyro.plate("data", len(PatientID)):
        numpyro.sample("obs", dist.Normal(FVC_est, σ), obs=FVC_obs)
```

That's all for modelling!

4.3 3. Fitting the model

A great achievement of Probabilistic Programming Languages such as NumPyro is to decouple model specification and inference. After specifying my generative model, with priors, condition statements and data likelihood, I can leave the hard work to NumPyro's inference engine.

Calling it requires just a few lines. Before we do it, let's add a numerical Patient ID for each patient code. That can be easily done with scikit-learn's LabelEncoder:

[6]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
train['PatientID'] = le.fit_transform(train['Patient'].values)

FVC_obs = train['FVC'].values
Weeks = train['Weeks'].values
PatientID = train['PatientID'].values
```

Now, calling NumPyro's inference engine:

[7]:
```
nuts_kernel = NUTS(model)

mcmc = MCMC(nuts_kernel, num_samples=2000, num_warmup=2000)
rng_key = random.PRNGKey(0)
mcmc.run(rng_key, PatientID, Weeks, FVC_obs=FVC_obs)

posterior_samples = mcmc.get_samples()
```

```
sample: 100%|| 4000/4000 [00:20<00:00, 195.69it/s, 63 steps of␣
↪size 1.06e-01. acc. prob=0.89]
```

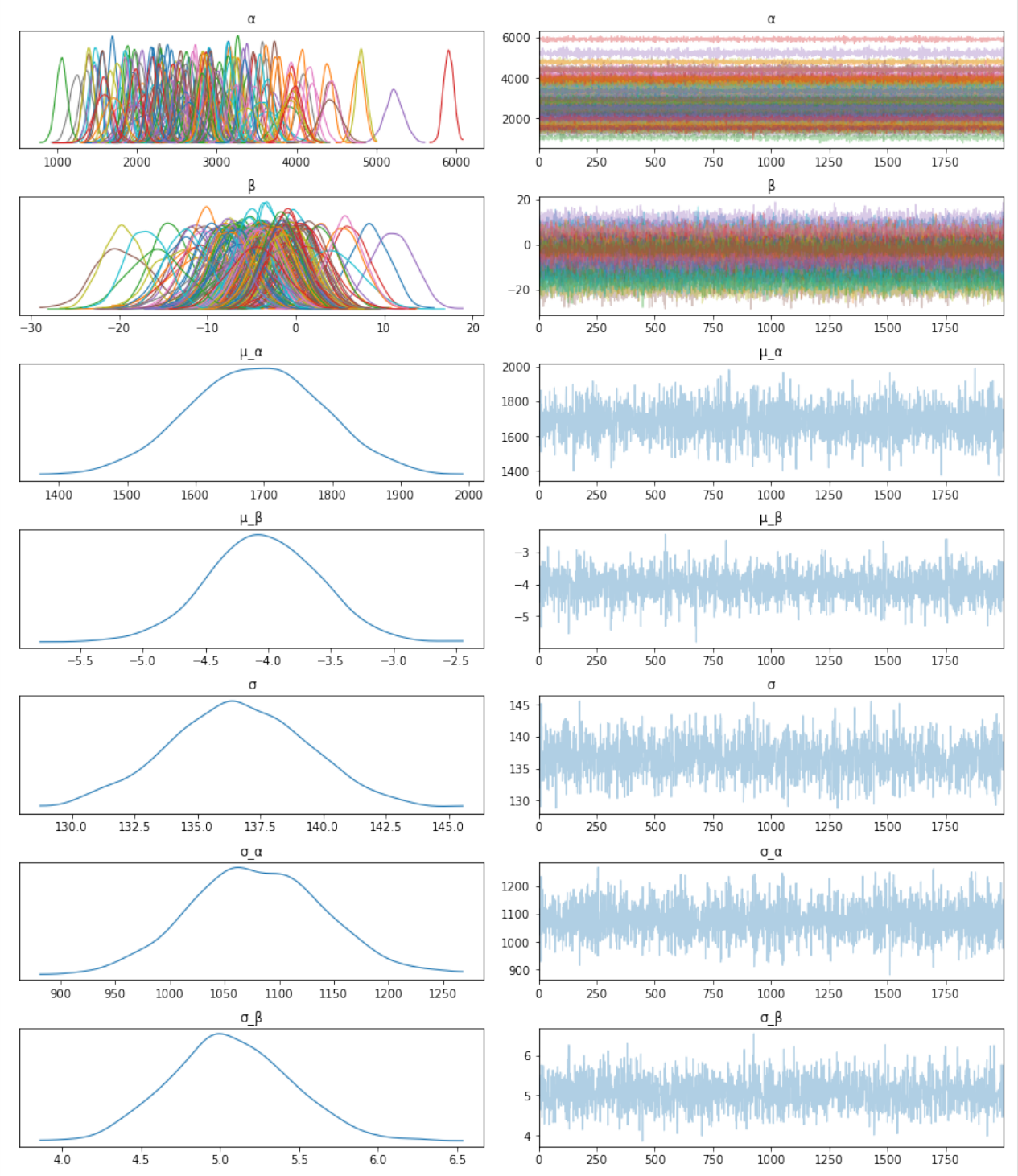
4.4 4. Checking the model

4.4.1 4.1. Inspecting the learned parameters

First, let's inspect the parameters learned. To do that, I will use ArviZ, which perfectly integrates with NumPyro:

[8]:
```
import arviz as az

data = az.from_numpyro(mcmc)
az.plot_trace(data, compact=True);
```



Looks like our model learned personalized alphas and betas for each patient!

4.4.2 4.2. Visualizing FVC decline curves for some patients

Now, let's visually inspect FVC decline curves predicted by our model. We will completely fill in the FVC table, predicting all missing values. The first step is to create a table to fill:

[9]:
```
pred_template = []
for i in range(train['Patient'].nunique()):
    df = pd.DataFrame(columns=['PatientID', 'Weeks'])
    df['Weeks'] = np.arange(-12, 134)
    df['PatientID'] = i
    pred_template.append(df)
pred_template = pd.concat(pred_template, ignore_index=True)
```

Predicting the missing values in the FVC table and confidence (sigma) for each value becomes really easy:

[10]:
```
PatientID = pred_template['PatientID'].values
Weeks = pred_template['Weeks'].values
predictive = Predictive(model, posterior_samples,
                        return_sites=['σ', 'obs'])
samples_predictive = predictive(random.PRNGKey(0),
                                PatientID, Weeks, None)
```

Let's now put the predictions together with the true values, to visualize them:

[11]:
```
df = pd.DataFrame(columns=['Patient', 'Weeks', 'FVC_pred', 'sigma'])
df['Patient'] = le.inverse_transform(pred_template['PatientID'])
df['Weeks'] = pred_template['Weeks']
df['FVC_pred'] = samples_predictive['obs'].T.mean(axis=1)
df['sigma'] = samples_predictive['obs'].T.std(axis=1)
df['FVC_inf'] = df['FVC_pred'] - df['sigma']
df['FVC_sup'] = df['FVC_pred'] + df['sigma']
df = pd.merge(df, train[['Patient', 'Weeks', 'FVC']],
              how='left', on=['Patient', 'Weeks'])
df = df.rename(columns={'FVC': 'FVC_true'})
df.head()
```

[11]:

	Patient	Weeks	FVC_pred	sigma	FVC_inf	FVC_sup	FVC_true
0	ID00007637202177411956430	-12	2219.361084	159.272430	2060.088623	2378.633545	NaN
1	ID00007637202177411956430	-11	2209.278076	157.698868	2051.579102	2366.977051	NaN
2	ID00007637202177411956430	-10	2212.443115	154.503906	2057.939209	2366.947021	NaN
3	ID00007637202177411956430	-9	2208.173096	153.068268	2055.104736	2361.241455	NaN
4	ID00007637202177411956430	-8	2202.373047	157.185608	2045.187500	2359.558594	NaN

Finally, let's see our predictions for 3 patients:

[12]:
```
def chart(patient_id, ax):
    data = df[df['Patient'] == patient_id]
    x = data['Weeks']
    ax.set_title(patient_id)
    ax.plot(x, data['FVC_true'], 'o')
    ax.plot(x, data['FVC_pred'])
```

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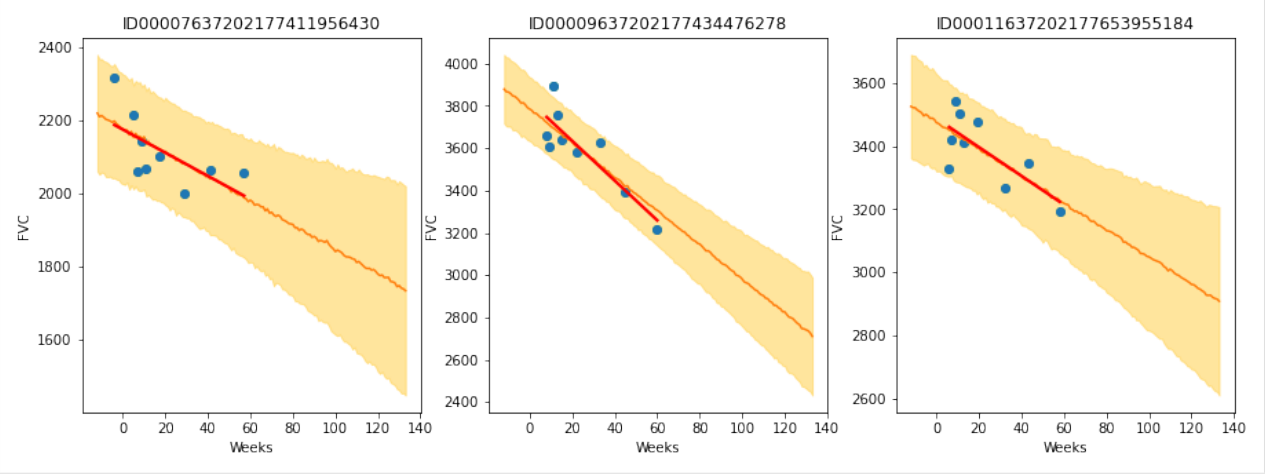
```
    ax = sns.regplot(x, data['FVC_true'], ax=ax, ci=None,
                     line_kws={'color':'red'})
    ax.fill_between(x, data["FVC_inf"], data["FVC_sup"],
                    alpha=0.5, color='#ffcd3c')
    ax.set_ylabel('FVC')

f, axes = plt.subplots(1, 3, figsize=(15, 5))
chart('ID00007637202177411956430', axes[0])
chart('ID00009637202177434476278', axes[1])
chart('ID00011637202177653955184', axes[2])
```



The results are exactly what we expected to see! Highlight observations:

- The model adequately learned Bayesian Linear Regressions! The orange line (learned predicted FVC mean) is very inline with the red line (deterministic linear regression). But most important: it learned to predict uncertainty, showed in the light orange region (one sigma above and below the mean FVC line)
- The model predicts a higher uncertainty where the data points are more disperse (1st and 3rd patients). Conversely, where the points are closely grouped together (2nd patient), the model predicts a higher confidence (narrower light orange region)
- Finally, in all patients, we can see that the uncertainty grows as the look more into the future: the light orange region widens as the # of weeks grow!

4.4.3 4.3. Computing the modified Laplace Log Likelihood and RMSE

As mentioned earlier, the competition was evaluated on a modified version of the Laplace Log Likelihood. In medical applications, it is useful to evaluate a model's confidence in its decisions. Accordingly, the metric is designed to reflect both the accuracy and certainty of each prediction.

For each true FVC measurement, we predicted both an FVC and a confidence measure (standard deviation σ). The metric was computed as:

$$\sigma_{clipped} = max(\sigma, 70) \tag{4.9}$$

$$\delta = min(|FVC_{true} - FVC_{pred}|, 1000) \tag{4.10}$$

$$metric = -\frac{\sqrt{2}\delta}{\sigma_{clipped}} - \ln(\sqrt{2}\sigma_{clipped}) \tag{4.11}$$

The error was thresholded at 1000 ml to avoid large errors adversely penalizing results, while the confidence values were clipped at 70 ml to reflect the approximate measurement uncertainty in FVC. The final score was calculated by

averaging the metric across all (Patient, Week) pairs. Note that metric values will be negative and higher is better.

Next, we calculate the metric and RMSE:

[13]:
```
y = df.dropna()
rmse = ((y['FVC_pred'] - y['FVC_true']) ** 2).mean() ** (1/2)
print(f'RMSE: {rmse:.1f} ml')

sigma_c = y['sigma'].values
sigma_c[sigma_c < 70] = 70
delta = (y['FVC_pred'] - y['FVC_true']).abs()
delta[delta > 1000] = 1000
lll = - np.sqrt(2) * delta / sigma_c - np.log(np.sqrt(2) * sigma_c)
print(f'Laplace Log Likelihood: {lll.mean():.4f}')
```

```
RMSE: 122.1 ml
Laplace Log Likelihood: -6.1376
```

What do these numbers mean? It means if you adopted this approach, you would **outperform most of the public solutions** in the competition. Curiously, the vast majority of public solutions adopt a standard deterministic Neural Network, modelling uncertainty through a quantile loss. **Most of the people still adopt a frequentist approach**.

Uncertainty for single predictions becomes more and more important in machine learning and is often a requirement. **Especially when the consequenses of a wrong prediction are high**, we need to know what the probability distribution of an individual prediction is. For perspective, Kaggle just launched a new competition sponsored by Lyft, to build motion prediction models for self-driving vehicles. "We ask that you predict a few trajectories for every agent **and provide a confidence score for each of them**."

Finally, I hope the great work done by Pyro/NumPyro developers help democratize Bayesian methods, empowering an ever growing community of researchers and practitioners to create models that can not only generate predictions, but also assess uncertainty in their predictions.

4.5 References

1. Ghahramani, Z. Probabilistic machine learning and artificial intelligence. Nature 521, 452–459 (2015). https://doi.org/10.1038/nature14541
2. Rainforth, Thomas William Gamlen. Automating Inference, Learning, and Design Using Probabilistic Programming. University of Oxford, 2017.

CHAPTER 5

Example: Baseball Batting Average

Original example from Pyro: https://github.com/pyro-ppl/pyro/blob/dev/examples/baseball.py

Example has been adapted from [1]. It demonstrates how to do Bayesian inference using various MCMC kernels in Pyro (HMC, NUTS, SA), and use of some common inference utilities.

As in the Stan tutorial, this uses the small baseball dataset of Efron and Morris [2] to estimate players' batting average which is the fraction of times a player got a base hit out of the number of times they went up at bat.

The dataset separates the initial 45 at-bats statistics from the remaining season. We use the hits data from the initial 45 at-bats to estimate the batting average for each player. We then use the remaining season's data to validate the predictions from our models.

Three models are evaluated:

- Complete pooling model: The success probability of scoring a hit is shared amongst all players.
- No pooling model: Each individual player's success probability is distinct and there is no data sharing amongst players.
- Partial pooling model: A hierarchical model with partial data sharing.

We recommend Radford Neal's tutorial on HMC ([3]) to users who would like to get a more comprehensive understanding of HMC and its variants, and to [4] for details on the No U-Turn Sampler, which provides an efficient and automated way (i.e. limited hyper-parameters) of running HMC on different problems.

Note that the Sample Adaptive (SA) kernel, which is implemented based on [5], requires large *num_warmup* and *num_samples* (e.g. 15,000 and 300,000). So it is better to disable progress bar to avoid dispatching overhead.

References:

1. Carpenter B. (2016), "Hierarchical Partial Pooling for Repeated Binary Trials".
2. Efron B., Morris C. (1975), "Data analysis using Stein's estimator and its generalizations", J. Amer. Statist. Assoc., 70, 311-319.
3. Neal, R. (2012), "MCMC using Hamiltonian Dynamics", (https://arxiv.org/pdf/1206.1901.pdf)
4. Hoffman, M. D. and Gelman, A. (2014), "The No-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo", (https://arxiv.org/abs/1111.4246)

5. Michael Zhu (2019), "Sample Adaptive MCMC", (https://papers.nips.cc/paper/9107-sample-adaptive-mcmc)

```
import argparse
import os

import jax.numpy as jnp
import jax.random as random
from jax.scipy.special import logsumexp

import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import BASEBALL, load_dataset
from numpyro.infer import HMC, MCMC, NUTS, SA, Predictive, log_likelihood


def fully_pooled(at_bats, hits=None):
    r"""
    Number of hits in $K$ at bats for each player has a Binomial
    distribution with a common probability of success, $\phi$.

    :param (jnp.DeviceArray) at_bats: Number of at bats for each player.
    :param (jnp.DeviceArray) hits: Number of hits for the given at bats.
    :return: Number of hits predicted by the model.
    """
    phi_prior = dist.Uniform(0, 1)
    phi = numpyro.sample("phi", phi_prior)
    num_players = at_bats.shape[0]
    with numpyro.plate("num_players", num_players):
        return numpyro.sample("obs", dist.Binomial(at_bats, probs=phi), obs=hits)


def not_pooled(at_bats, hits=None):
    r"""
    Number of hits in $K$ at bats for each player has a Binomial
    distribution with independent probability of success, $\phi_i$.

    :param (jnp.DeviceArray) at_bats: Number of at bats for each player.
    :param (jnp.DeviceArray) hits: Number of hits for the given at bats.
    :return: Number of hits predicted by the model.
    """
    num_players = at_bats.shape[0]
    with numpyro.plate("num_players", num_players):
        phi_prior = dist.Uniform(0, 1)
        phi = numpyro.sample("phi", phi_prior)
        return numpyro.sample("obs", dist.Binomial(at_bats, probs=phi), obs=hits)


def partially_pooled(at_bats, hits=None):
    r"""
    Number of hits has a Binomial distribution with independent
    probability of success, $\phi_i$. Each $\phi_i$ follows a Beta
    distribution with concentration parameters $c_1$ and $c_2$, where
    $c_1 = m * kappa$, $c_2 = (1 - m) * kappa$, $m ~ Uniform(0, 1)$,
    and $kappa ~ Pareto(1, 1.5)$.

    :param (jnp.DeviceArray) at_bats: Number of at bats for each player.
    :param (jnp.DeviceArray) hits: Number of hits for the given at bats.
    :return: Number of hits predicted by the model.
```

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```
    """
    m = numpyro.sample("m", dist.Uniform(0, 1))
    kappa = numpyro.sample("kappa", dist.Pareto(1, 1.5))
    num_players = at_bats.shape[0]
    with numpyro.plate("num_players", num_players):
        phi_prior = dist.Beta(m * kappa, (1 - m) * kappa)
        phi = numpyro.sample("phi", phi_prior)
        return numpyro.sample("obs", dist.Binomial(at_bats, probs=phi), obs=hits)


def partially_pooled_with_logit(at_bats, hits=None):
    r"""
    Number of hits has a Binomial distribution with a logit link function.
    The logits $\alpha$ for each player is normally distributed with the
    mean and scale parameters sharing a common prior.

    :param (jnp.DeviceArray) at_bats: Number of at bats for each player.
    :param (jnp.DeviceArray) hits: Number of hits for the given at bats.
    :return: Number of hits predicted by the model.
    """
    loc = numpyro.sample("loc", dist.Normal(-1, 1))
    scale = numpyro.sample("scale", dist.HalfCauchy(1))
    num_players = at_bats.shape[0]
    with numpyro.plate("num_players", num_players):
        alpha = numpyro.sample("alpha", dist.Normal(loc, scale))
        return numpyro.sample("obs", dist.Binomial(at_bats, logits=alpha), obs=hits)


def run_inference(model, at_bats, hits, rng_key, args):
    if args.algo == "NUTS":
        kernel = NUTS(model)
    elif args.algo == "HMC":
        kernel = HMC(model)
    elif args.algo == "SA":
        kernel = SA(model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if (
                    "NUMPYRO_SPHINXBUILD" in os.environ or args.disable_progbar) else␣
↪True)
    mcmc.run(rng_key, at_bats, hits)
    return mcmc.get_samples()


def predict(model, at_bats, hits, z, rng_key, player_names, train=True):
    header = model.__name__ + (' - TRAIN' if train else ' - TEST')
    predictions = Predictive(model, posterior_samples=z)(rng_key, at_bats)['obs']
    print_results('=' * 30 + header + '=' * 30,
                  predictions,
                  player_names,
                  at_bats,
                  hits)
    if not train:
        post_loglik = log_likelihood(model, z, at_bats, hits)['obs']
        # computes expected log predictive density at each data point
        exp_log_density = logsumexp(post_loglik, axis=0) - jnp.log(jnp.shape(post_
↪loglik)[0])
        # reports log predictive density of all test points
```

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```
        print('\nLog pointwise predictive density: {:.2f}\n'.format(exp_log_density.
↪sum()))


def print_results(header, preds, player_names, at_bats, hits):
    columns = ['', 'At-bats', 'ActualHits', 'Pred(p25)', 'Pred(p50)', 'Pred(p75)']
    header_format = '{:>20} {:>10} {:>10} {:>10} {:>10} {:>10}'
    row_format = '{:>20} {:>10.0f} {:>10.0f} {:>10.2f} {:>10.2f} {:>10.2f}'
    quantiles = jnp.quantile(preds, jnp.array([0.25, 0.5, 0.75]), axis=0)
    print('\n', header, '\n')
    print(header_format.format(*columns))
    for i, p in enumerate(player_names):
        print(row_format.format(p, at_bats[i], hits[i], *quantiles[:, i]), '\n')


def main(args):
    _, fetch_train = load_dataset(BASEBALL, split='train', shuffle=False)
    train, player_names = fetch_train()
    _, fetch_test = load_dataset(BASEBALL, split='test', shuffle=False)
    test, _ = fetch_test()
    at_bats, hits = train[:, 0], train[:, 1]
    season_at_bats, season_hits = test[:, 0], test[:, 1]
    for i, model in enumerate((fully_pooled,
                               not_pooled,
                               partially_pooled,
                               partially_pooled_with_logit,
                               )):
        rng_key, rng_key_predict = random.split(random.PRNGKey(i + 1))
        zs = run_inference(model, at_bats, hits, rng_key, args)
        predict(model, at_bats, hits, zs, rng_key_predict, player_names)
        predict(model, season_at_bats, season_hits, zs, rng_key_predict, player_names,
↪ train=False)


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Baseball batting average using MCMC
↪")
    parser.add_argument("-n", "--num-samples", nargs="?", default=3000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=1500, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument('--algo', default='NUTS', type=str,
                        help='whether to run "HMC", "NUTS", or "SA"')
    parser.add_argument('-dp', '--disable-progbar', action="store_true",␣
↪default=False,
                        help="whether to disable progress bar")
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 6

Example: Variational Autoencoder

```
import argparse
import inspect
import os
import time

import matplotlib.pyplot as plt

from jax import jit, lax, random
from jax.experimental import stax
import jax.numpy as jnp
from jax.random import PRNGKey

import numpyro
from numpyro import optim
import numpyro.distributions as dist
from numpyro.examples.datasets import MNIST, load_dataset
from numpyro.infer import SVI, Trace_ELBO

RESULTS_DIR = os.path.abspath(os.path.join(os.path.dirname(inspect.getfile(lambda:␣
↪None)),
                              '.results'))
os.makedirs(RESULTS_DIR, exist_ok=True)


def encoder(hidden_dim, z_dim):
    return stax.serial(
        stax.Dense(hidden_dim, W_init=stax.randn()), stax.Softplus,
        stax.FanOut(2),
        stax.parallel(stax.Dense(z_dim, W_init=stax.randn()),
                      stax.serial(stax.Dense(z_dim, W_init=stax.randn()), stax.Exp)),
    )


def decoder(hidden_dim, out_dim):
```

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```
    return stax.serial(
        stax.Dense(hidden_dim, W_init=stax.randn()), stax.Softplus,
        stax.Dense(out_dim, W_init=stax.randn()), stax.Sigmoid,
    )


def model(batch, hidden_dim=400, z_dim=100):
    batch = jnp.reshape(batch, (batch.shape[0], -1))
    batch_dim, out_dim = jnp.shape(batch)
    decode = numpyro.module('decoder', decoder(hidden_dim, out_dim), (batch_dim, z_
↪dim))
    z = numpyro.sample('z', dist.Normal(jnp.zeros((z_dim,)), jnp.ones((z_dim,))))
    img_loc = decode(z)
    return numpyro.sample('obs', dist.Bernoulli(img_loc), obs=batch)


def guide(batch, hidden_dim=400, z_dim=100):
    batch = jnp.reshape(batch, (batch.shape[0], -1))
    batch_dim, out_dim = jnp.shape(batch)
    encode = numpyro.module('encoder', encoder(hidden_dim, z_dim), (batch_dim, out_
↪dim))
    z_loc, z_std = encode(batch)
    z = numpyro.sample('z', dist.Normal(z_loc, z_std))
    return z


@jit
def binarize(rng_key, batch):
    return random.bernoulli(rng_key, batch).astype(batch.dtype)


def main(args):
    encoder_nn = encoder(args.hidden_dim, args.z_dim)
    decoder_nn = decoder(args.hidden_dim, 28 * 28)
    adam = optim.Adam(args.learning_rate)
    svi = SVI(model, guide, adam, Trace_ELBO(), hidden_dim=args.hidden_dim, z_
↪dim=args.z_dim)
    rng_key = PRNGKey(0)
    train_init, train_fetch = load_dataset(MNIST, batch_size=args.batch_size, split=
↪'train')
    test_init, test_fetch = load_dataset(MNIST, batch_size=args.batch_size, split=
↪'test')
    num_train, train_idx = train_init()
    rng_key, rng_key_binarize, rng_key_init = random.split(rng_key, 3)
    sample_batch = binarize(rng_key_binarize, train_fetch(0, train_idx)[0])
    svi_state = svi.init(rng_key_init, sample_batch)

    @jit
    def epoch_train(svi_state, rng_key):
        def body_fn(i, val):
            loss_sum, svi_state = val
            rng_key_binarize = random.fold_in(rng_key, i)
            batch = binarize(rng_key_binarize, train_fetch(i, train_idx)[0])
            svi_state, loss = svi.update(svi_state, batch)
            loss_sum += loss
            return loss_sum, svi_state
```

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```
        return lax.fori_loop(0, num_train, body_fn, (0., svi_state))

    @jit
    def eval_test(svi_state, rng_key):
        def body_fun(i, loss_sum):
            rng_key_binarize = random.fold_in(rng_key, i)
            batch = binarize(rng_key_binarize, test_fetch(i, test_idx)[0])
            # FIXME: does this lead to a requirement for an rng_key arg in svi_eval?
            loss = svi.evaluate(svi_state, batch) / len(batch)
            loss_sum += loss
            return loss_sum

        loss = lax.fori_loop(0, num_test, body_fun, 0.)
        loss = loss / num_test
        return loss

    def reconstruct_img(epoch, rng_key):
        img = test_fetch(0, test_idx)[0][0]
        plt.imsave(os.path.join(RESULTS_DIR, 'original_epoch={}.png'.format(epoch)),␣
↪img, cmap='gray')
        rng_key_binarize, rng_key_sample = random.split(rng_key)
        test_sample = binarize(rng_key_binarize, img)
        params = svi.get_params(svi_state)
        z_mean, z_var = encoder_nn[1](params['encoder$params'], test_sample.
↪reshape([1, -1]))
        z = dist.Normal(z_mean, z_var).sample(rng_key_sample)
        img_loc = decoder_nn[1](params['decoder$params'], z).reshape([28, 28])
        plt.imsave(os.path.join(RESULTS_DIR, 'recons_epoch={}.png'.format(epoch)),␣
↪img_loc, cmap='gray')

    for i in range(args.num_epochs):
        rng_key, rng_key_train, rng_key_test, rng_key_reconstruct = random.split(rng_
↪key, 4)
        t_start = time.time()
        num_train, train_idx = train_init()
        _, svi_state = epoch_train(svi_state, rng_key_train)
        rng_key, rng_key_test, rng_key_reconstruct = random.split(rng_key, 3)
        num_test, test_idx = test_init()
        test_loss = eval_test(svi_state, rng_key_test)
        reconstruct_img(i, rng_key_reconstruct)
        print("Epoch {}: loss = {} ({:.2f} s.)".format(i, test_loss, time.time() - t_
↪start))


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="parse args")
    parser.add_argument('-n', '--num-epochs', default=15, type=int, help='number of␣
↪training epochs')
    parser.add_argument('-lr', '--learning-rate', default=1.0e-3, type=float, help=
↪'learning rate')
    parser.add_argument('-batch-size', default=128, type=int, help='batch size')
    parser.add_argument('-z-dim', default=50, type=int, help='size of latent')
    parser.add_argument('-hidden-dim', default=400, type=int, help='size of hidden␣
↪layer in encoder/decoder networks')
    args = parser.parse_args()
    main(args)
```

CHAPTER 7

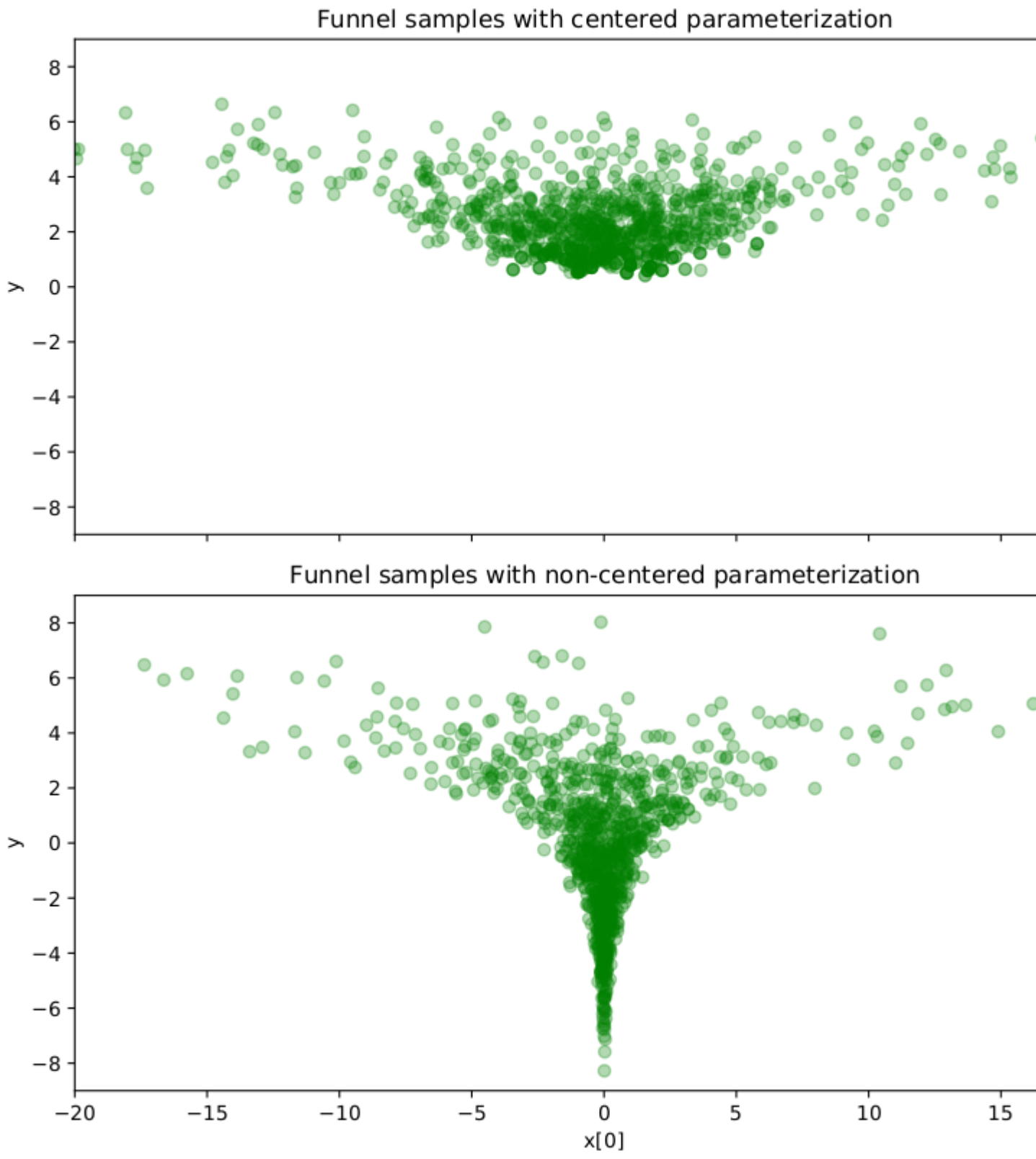
Example: Neal's Funnel

This example, which is adapted from [1], illustrates how to leverage non-centered parameterization using the `reparam` handler. We will examine the difference between two types of parameterizations on the 10-dimensional Neal's funnel distribution. As we will see, HMC gets trouble at the neck of the funnel if centered parameterization is used. On the contrary, the problem can be solved by using non-centered parameterization.

Using non-centered parameterization through `LocScaleReparam` or `TransformReparam` in NumPyro has the same effect as the automatic reparameterisation technique introduced in [2].

References:

1. *Stan User's Guide*, https://mc-stan.org/docs/2_19/stan-users-guide/reparameterization-section.html
2. Maria I. Gorinova, Dave Moore, Matthew D. Hoffman (2019), "Automatic Reparameterisation of Probabilistic Programs", (https://arxiv.org/abs/1906.03028)




```
import argparse
import os
```

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```
import matplotlib.pyplot as plt

from jax import random
import jax.numpy as jnp

import numpyro
import numpyro.distributions as dist
from numpyro.handlers import reparam
from numpyro.infer import MCMC, NUTS, Predictive
from numpyro.infer.reparam import LocScaleReparam


def model(dim=10):
    y = numpyro.sample('y', dist.Normal(0, 3))
    numpyro.sample('x', dist.Normal(jnp.zeros(dim - 1), jnp.exp(y / 2)))


reparam_model = reparam(model, config={'x': LocScaleReparam(0)})


def run_inference(model, args, rng_key):
    kernel = NUTS(model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key)
    mcmc.print_summary(exclude_deterministic=False)
    return mcmc.get_samples()


def main(args):
    rng_key = random.PRNGKey(0)

    # do inference with centered parameterization
    print("============================ Centered Parameterization␣
↪============================")
    samples = run_inference(model, args, rng_key)

    # do inference with non-centered parameterization
    print("\n========================== Non-centered Parameterization␣
↪==========================")
    reparam_samples = run_inference(reparam_model, args, rng_key)
    # collect deterministic sites
    reparam_samples = Predictive(reparam_model, reparam_samples, return_sites=['x', 'y
↪'])(
        random.PRNGKey(1))

    # make plots
    fig, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(8, 8), constrained_
↪layout=True)

    ax1.plot(samples['x'][:, 0], samples['y'], "go", alpha=0.3)
    ax1.set(xlim=(-20, 20), ylim=(-9, 9), ylabel='y',
            title='Funnel samples with centered parameterization')

    ax2.plot(reparam_samples['x'][:, 0], reparam_samples['y'], "go", alpha=0.3)
    ax2.set(xlim=(-20, 20), ylim=(-9, 9), xlabel='x[0]', ylabel='y',
```

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```
            title='Funnel samples with non-centered parameterization')

    plt.savefig('funnel_plot.pdf')


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Non-centered reparameterization␣
↪example")
    parser.add_argument("-n", "--num-samples", nargs="?", default=1000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument("--device", default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 8

Example: Stochastic Volatility

Generative model:

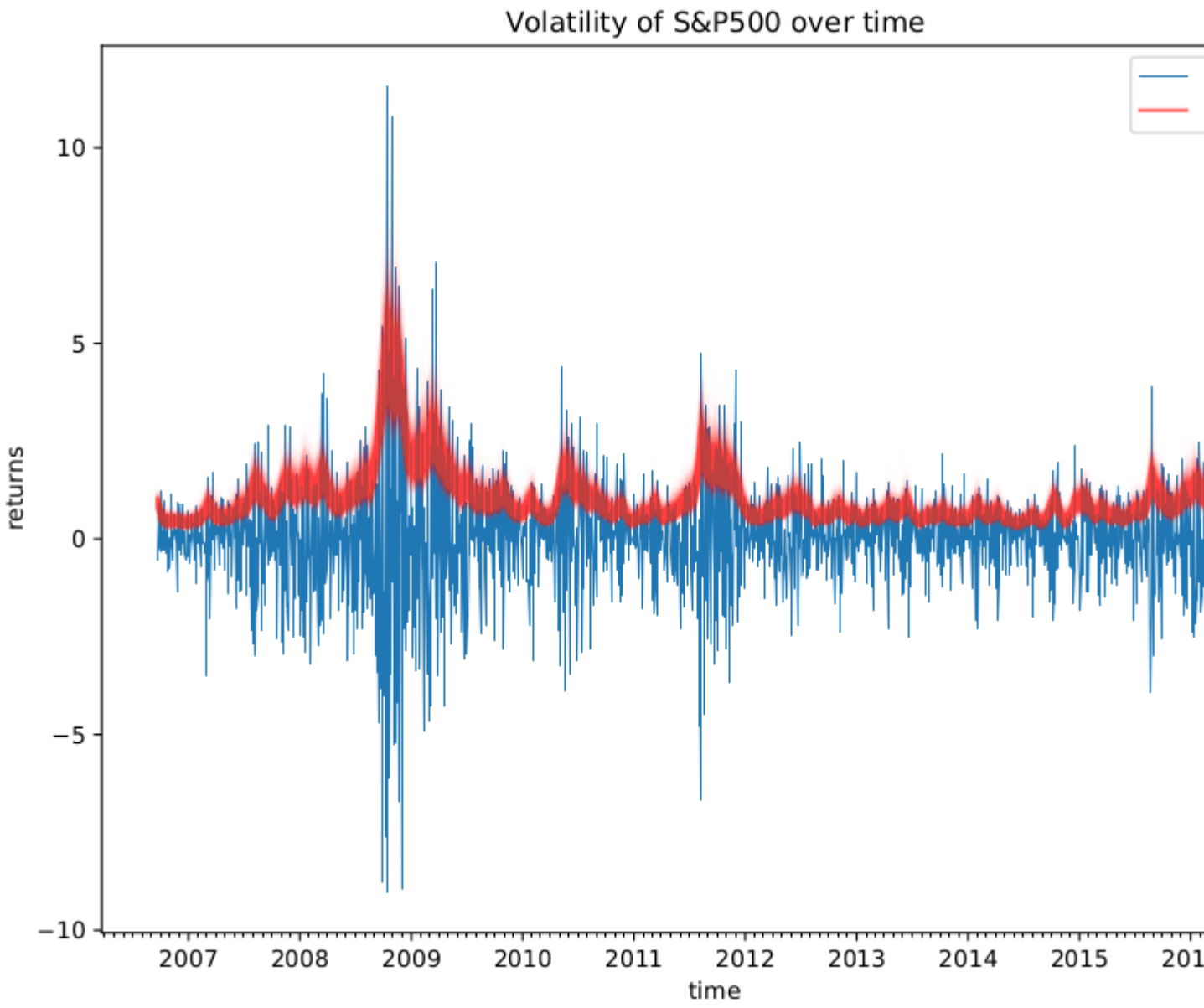
$$\sigma \sim \text{Exponential}(50) \tag{8.1}$$
$$\nu \sim \text{Exponential}(.1) \tag{8.2}$$
$$s_i \sim \text{Normal}(s_{i-1}, \sigma^{-2}) \tag{8.3}$$
$$r_i \sim \text{StudentT}(\nu, 0, \exp(s_i)) \tag{8.4}$$

This example is from PyMC3 [1], which itself is adapted from the original experiment from [2]. A discussion about translating this in Pyro appears in [3].

We take this example to illustrate how to use the functional interface *hmc*. However, we recommend readers to use *MCMC* class as in other examples because it is more stable and has more features supported.

References:

1. *Stochastic Volatility Model*, https://docs.pymc.io/notebooks/stochastic_volatility.html
2. *The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo*, https://arxiv.org/pdf/1111.4246.pdf
3. Pyro forum discussion, https://forum.pyro.ai/t/problems-transforming-a-pymc3-model-to-pyro-mcmc/208/14




```
import argparse
import os

import matplotlib
import matplotlib.dates as mdates
import matplotlib.pyplot as plt

import jax.numpy as jnp
import jax.random as random

import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import SP500, load_dataset
from numpyro.infer.hmc import hmc
from numpyro.infer.util import initialize_model
from numpyro.util import fori_collect
```

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```
matplotlib.use('Agg')  # noqa: E402


def model(returns):
    step_size = numpyro.sample('sigma', dist.Exponential(50.))
    s = numpyro.sample('s', dist.GaussianRandomWalk(scale=step_size, num_steps=jnp.
↪shape(returns)[0]))
    nu = numpyro.sample('nu', dist.Exponential(.1))
    return numpyro.sample('r', dist.StudentT(df=nu, loc=0., scale=jnp.exp(s)),
                          obs=returns)


def print_results(posterior, dates):
    def _print_row(values, row_name=''):
        quantiles = jnp.array([0.2, 0.4, 0.5, 0.6, 0.8])
        row_name_fmt = '{:>8}'
        header_format = row_name_fmt + '{:>12}' * 5
        row_format = row_name_fmt + '{:>12.3f}' * 5
        columns = ['(p{})'.format(q * 100) for q in quantiles]
        q_values = jnp.quantile(values, quantiles, axis=0)
        print(header_format.format('', *columns))
        print(row_format.format(row_name, *q_values))
        print('\n')

    print('=' * 20, 'sigma', '=' * 20)
    _print_row(posterior['sigma'])
    print('=' * 20, 'nu', '=' * 20)
    _print_row(posterior['nu'])
    print('=' * 20, 'volatility', '=' * 20)
    for i in range(0, len(dates), 180):
        _print_row(jnp.exp(posterior['s'][:, i]), dates[i])


def main(args):
    _, fetch = load_dataset(SP500, shuffle=False)
    dates, returns = fetch()
    init_rng_key, sample_rng_key = random.split(random.PRNGKey(args.rng_seed))
    model_info = initialize_model(init_rng_key, model, model_args=(returns,))
    init_kernel, sample_kernel = hmc(model_info.potential_fn, algo='NUTS')
    hmc_state = init_kernel(model_info.param_info, args.num_warmup, rng_key=sample_
↪rng_key)
    hmc_states = fori_collect(args.num_warmup, args.num_warmup + args.num_samples,␣
↪sample_kernel, hmc_state,
                              transform=lambda hmc_state: model_info.postprocess_
↪fn(hmc_state.z),
                              progbar=False if "NUMPYRO_SPHINXBUILD" in os.environ␣
↪else True)
    print_results(hmc_states, dates)

    fig, ax = plt.subplots(figsize=(8, 6), constrained_layout=True)
    dates = mdates.num2date(mdates.datestr2num(dates))
    ax.plot(dates, returns, lw=0.5)
    # format the ticks
    ax.xaxis.set_major_locator(mdates.YearLocator())
    ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))
    ax.xaxis.set_minor_locator(mdates.MonthLocator())
```

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```
    ax.plot(dates, jnp.exp(hmc_states['s'].T), 'r', alpha=0.01)
    legend = ax.legend(['returns', 'volatility'], loc='upper right')
    legend.legendHandles[1].set_alpha(0.6)
    ax.set(xlabel='time', ylabel='returns', title='Volatility of S&P500 over time')

    plt.savefig("stochastic_volatility_plot.pdf")


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Stochastic Volatility Model")
    parser.add_argument('-n', '--num-samples', nargs='?', default=600, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=600, type=int)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    parser.add_argument('--rng_seed', default=21, type=int, help='random number␣
↪generator seed')
    args = parser.parse_args()

    numpyro.set_platform(args.device)

    main(args)
```

CHAPTER 9

Example: Bayesian Models of Annotation

In this example, we run MCMC for various crowdsourced annotation models in [1].

All models have discrete latent variables. Under the hood, we enumerate over (marginalize out) those discrete latent sites in inference. Those models have different complexity so they are great refererences for those who are new to Pyro/NumPyro enumeration mechanism. We recommend readers compare the implementations with the corresponding plate diagrams in [1] to see how concise a Pyro/NumPyro program is.

The interested readers can also refer to [3] for more explanation about enumeration.

The data is taken from Table 1 of reference [2].

Currently, this example does not include postprocessing steps to deal with "Label Switching" issue (mentioned in section 6.2 of [1]).

References:

1. Paun, S., Carpenter, B., Chamberlain, J., Hovy, D., Kruschwitz, U., and Poesio, M. (2018). "Comparing bayesian models of annotation" (https://www.aclweb.org/anthology/Q18-1040/)
2. Dawid, A. P., and Skene, A. M. (1979). "Maximum likelihood estimation of observer error-rates using the EM algorithm"
3. "Inference with Discrete Latent Variables" (http://pyro.ai/examples/enumeration.html)


```
import argparse
import os

import numpy as np

from jax import nn, random
import jax.numpy as jnp

import numpyro
from numpyro import handlers
from numpyro.contrib.indexing import Vindex
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS
```

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```
from numpyro.infer.reparam import LocScaleReparam


def get_data():
    """
    :return: a tuple of annotator indices and class indices. The first term has shape
        `num_positions` whose entries take values from `0` to `num_annotators - 1`.
        The second term has shape `num_items x num_positions` whose entries take values
        from `0` to `num_classes - 1`.
    """
    # NB: the first annotator assessed each item 3 times
    positions = np.array([1, 1, 1, 2, 3, 4, 5])
    annotations = np.array([
        [1, 3, 1, 2, 2, 2, 1, 3, 2, 2, 4, 2, 1, 2, 1,
         1, 1, 1, 2, 2, 2, 2, 2, 2, 1, 1, 2, 1, 1, 1,
         1, 3, 1, 2, 2, 4, 2, 2, 3, 1, 1, 1, 2, 1, 2],
        [1, 3, 1, 2, 2, 2, 2, 3, 2, 3, 4, 2, 1, 2, 2,
         1, 1, 1, 2, 2, 2, 2, 2, 2, 1, 1, 3, 1, 1, 1,
         1, 3, 1, 2, 2, 3, 2, 3, 3, 1, 1, 2, 3, 2, 2],
        [1, 3, 2, 2, 2, 2, 2, 3, 2, 2, 4, 2, 1, 2, 1,
         1, 1, 1, 2, 2, 2, 2, 2, 1, 1, 1, 2, 1, 1, 2,
         1, 3, 1, 2, 2, 3, 1, 2, 3, 1, 1, 1, 2, 1, 2],
        [1, 4, 2, 3, 3, 3, 2, 3, 2, 2, 4, 3, 1, 3, 1,
         2, 1, 1, 2, 1, 2, 2, 3, 2, 1, 1, 2, 1, 1, 1,
         1, 3, 1, 2, 3, 4, 2, 3, 3, 1, 1, 2, 2, 1, 2],
        [1, 3, 1, 1, 2, 3, 1, 4, 2, 2, 4, 3, 1, 2, 1,
         1, 1, 1, 2, 3, 2, 2, 2, 2, 1, 1, 2, 1, 1, 1,
         1, 2, 1, 2, 2, 3, 2, 2, 4, 1, 1, 1, 2, 1, 2],
        [1, 3, 2, 2, 2, 2, 1, 3, 2, 2, 4, 4, 1, 1, 1,
         1, 1, 1, 2, 2, 2, 2, 2, 2, 1, 1, 2, 1, 1, 2,
         1, 3, 1, 2, 3, 4, 3, 3, 3, 1, 1, 1, 2, 1, 2],
        [1, 4, 2, 1, 2, 2, 1, 3, 3, 3, 4, 3, 1, 2, 1,
         1, 1, 1, 1, 2, 2, 1, 2, 2, 1, 1, 2, 1, 1, 1,
         1, 3, 1, 2, 2, 3, 2, 3, 2, 1, 1, 1, 2, 1, 2],
    ]).T
    # we minus 1 because in Python, the first index is 0
    return positions - 1, annotations - 1


def multinomial(annotations):
    """
    This model corresponds to the plate diagram in Figure 1 of reference [1].
    """
    num_classes = int(np.max(annotations)) + 1
    num_items, num_positions = annotations.shape

    with numpyro.plate("class", num_classes):
        zeta = numpyro.sample("zeta", dist.Dirichlet(jnp.ones(num_classes)))

    pi = numpyro.sample("pi", dist.Dirichlet(jnp.ones(num_classes)))

    with numpyro.plate("item", num_items, dim=-2):
        c = numpyro.sample("c", dist.Categorical(pi))

        with numpyro.plate("position", num_positions):
            numpyro.sample("y", dist.Categorical(zeta[c]), obs=annotations)
```

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```
def dawid_skene(positions, annotations):
    """
    This model corresponds to the plate diagram in Figure 2 of reference [1].
    """
    num_annotators = int(np.max(positions)) + 1
    num_classes = int(np.max(annotations)) + 1
    num_items, num_positions = annotations.shape

    with numpyro.plate("annotator", num_annotators, dim=-2):
        with numpyro.plate("class", num_classes):
            beta = numpyro.sample("beta", dist.Dirichlet(jnp.ones(num_classes)))

    pi = numpyro.sample("pi", dist.Dirichlet(jnp.ones(num_classes)))

    with numpyro.plate("item", num_items, dim=-2):
        c = numpyro.sample("c", dist.Categorical(pi))

        # here we use Vindex to allow broadcasting for the second index `c`
        # ref: http://num.pyro.ai/en/latest/utilities.html#numpyro.contrib.indexing.
↪vindex
        with numpyro.plate("position", num_positions):
            numpyro.sample("y", dist.Categorical(Vindex(beta)[positions, c, :]),␣
↪obs=annotations)


def mace(positions, annotations):
    """
    This model corresponds to the plate diagram in Figure 3 of reference [1].
    """
    num_annotators = int(np.max(positions)) + 1
    num_classes = int(np.max(annotations)) + 1
    num_items, num_positions = annotations.shape

    with numpyro.plate("annotator", num_annotators):
        epsilon = numpyro.sample("epsilon", dist.Dirichlet(jnp.full(num_classes, 10)))
        theta = numpyro.sample("theta", dist.Beta(0.5, 0.5))

    with numpyro.plate("item", num_items, dim=-2):
        # NB: using constant logits for discrete uniform prior
        # (NumPyro does not have DiscreteUniform distribution yet)
        c = numpyro.sample("c", dist.Categorical(logits=jnp.zeros(num_classes)))

        with numpyro.plate("position", num_positions):
            s = numpyro.sample("s", dist.Bernoulli(1 - theta[positions]))
            probs = jnp.where(s[..., None] == 0, nn.one_hot(c, num_classes),␣
↪epsilon[positions])
            numpyro.sample("y", dist.Categorical(probs), obs=annotations)


def hierarchical_dawid_skene(positions, annotations):
    """
    This model corresponds to the plate diagram in Figure 4 of reference [1].
    """
    num_annotators = int(np.max(positions)) + 1
    num_classes = int(np.max(annotations)) + 1
```

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```
    num_items, num_positions = annotations.shape

    with numpyro.plate("class", num_classes):
        # NB: we define `beta` as the `logits` of `y` likelihood; but `logits` is
        # invariant up to a constant, so we'll follow [1]: fix the last term of `beta`
        # to 0 and only define hyperpriors for the first `num_classes - 1` terms.
        zeta = numpyro.sample("zeta", dist.Normal(0, 1).expand([num_classes - 1]).to_
↪event(1))
        omega = numpyro.sample("Omega", dist.HalfNormal(1).expand([num_classes - 1]).
↪to_event(1))

    with numpyro.plate("annotator", num_annotators, dim=-2):
        with numpyro.plate("class", num_classes):
            # non-centered parameterization
            with handlers.reparam(config={"beta": LocScaleReparam(0)}):
                beta = numpyro.sample("beta", dist.Normal(zeta, omega).to_event(1))
            # pad 0 to the last item
            beta = jnp.pad(beta, [(0, 0)] * (jnp.ndim(beta) - 1) + [(0, 1)])

    pi = numpyro.sample("pi", dist.Dirichlet(jnp.ones(num_classes)))

    with numpyro.plate("item", num_items, dim=-2):
        c = numpyro.sample("c", dist.Categorical(pi))

        with numpyro.plate("position", num_positions):
            logits = Vindex(beta)[positions, c, :]
            numpyro.sample("y", dist.Categorical(logits=logits), obs=annotations)


def item_difficulty(annotations):
    """
    This model corresponds to the plate diagram in Figure 5 of reference [1].
    """
    num_classes = int(np.max(annotations)) + 1
    num_items, num_positions = annotations.shape

    with numpyro.plate("class", num_classes):
        eta = numpyro.sample("eta", dist.Normal(0, 1).expand([num_classes - 1]).to_
↪event(1))
        chi = numpyro.sample("Chi", dist.HalfNormal(1).expand([num_classes - 1]).to_
↪event(1))

    pi = numpyro.sample("pi", dist.Dirichlet(jnp.ones(num_classes)))

    with numpyro.plate("item", num_items, dim=-2):
        c = numpyro.sample("c", dist.Categorical(pi))

        with handlers.reparam(config={"theta": LocScaleReparam(0)}):
            theta = numpyro.sample("theta", dist.Normal(eta[c], chi[c]).to_event(1))
            theta = jnp.pad(theta, [(0, 0)] * (jnp.ndim(theta) - 1) + [(0, 1)])

        with numpyro.plate("position", annotations.shape[-1]):
            numpyro.sample("y", dist.Categorical(logits=theta), obs=annotations)


def logistic_random_effects(positions, annotations):
    """
```

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```
    This model corresponds to the plate diagram in Figure 5 of reference [1].
    """
    num_annotators = int(np.max(positions)) + 1
    num_classes = int(np.max(annotations)) + 1
    num_items, num_positions = annotations.shape

    with numpyro.plate("class", num_classes):
        zeta = numpyro.sample("zeta", dist.Normal(0, 1).expand([num_classes - 1]).to_
↪event(1))
        omega = numpyro.sample("Omega", dist.HalfNormal(1).expand([num_classes - 1]).
↪to_event(1))
        chi = numpyro.sample("Chi", dist.HalfNormal(1).expand([num_classes - 1]).to_
↪event(1))

    with numpyro.plate("annotator", num_annotators, dim=-2):
        with numpyro.plate("class", num_classes):
            with handlers.reparam(config={"beta": LocScaleReparam(0)}):
                beta = numpyro.sample("beta", dist.Normal(zeta, omega).to_event(1))
                beta = jnp.pad(beta, [(0, 0)] * (jnp.ndim(beta) - 1) + [(0, 1)])

    pi = numpyro.sample("pi", dist.Dirichlet(jnp.ones(num_classes)))

    with numpyro.plate("item", num_items, dim=-2):
        c = numpyro.sample("c", dist.Categorical(pi))

        with handlers.reparam(config={"theta": LocScaleReparam(0)}):
            theta = numpyro.sample("theta", dist.Normal(0, chi[c]).to_event(1))
            theta = jnp.pad(theta, [(0, 0)] * (jnp.ndim(theta) - 1) + [(0, 1)])

        with numpyro.plate("position", num_positions):
            logits = Vindex(beta)[positions, c, :] - theta
            numpyro.sample("y", dist.Categorical(logits=logits), obs=annotations)


NAME_TO_MODEL = {
    "mn": multinomial,
    "ds": dawid_skene,
    "mace": mace,
    "hds": hierarchical_dawid_skene,
    "id": item_difficulty,
    "lre": logistic_random_effects,
}


def main(args):
    annotators, annotations = get_data()
    model = NAME_TO_MODEL[args.model]
    data = (annotations,) if model in [multinomial, item_difficulty] else (annotators,
↪ annotations)

    mcmc = MCMC(
        NUTS(model),
        args.num_warmup,
        args.num_samples,
        num_chains=args.num_chains,
        progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True,
    )
```

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```
    mcmc.run(random.PRNGKey(0), *data)
    mcmc.print_summary()


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Bayesian Models of Annotation")
    parser.add_argument("-n", "--num-samples", nargs="?", default=1000, type=int)
    parser.add_argument("--num-warmup", nargs="?", default=1000, type=int)
    parser.add_argument("--num-chains", nargs="?", default=1, type=int)
    parser.add_argument(
        "--model",
        nargs="?",
        default="ds",
        help='one of "mn" (multinomial), "ds" (dawid_skene), "mace",'
        ' "hds" (hierarchical_dawid_skene),'
        ' "id" (item_difficulty), "lre" (logistic_random_effects)',
    )
    parser.add_argument("--device", default="cpu", type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 10

Example: Enumerate Hidden Markov Model

This example is ported from [1], which shows how to marginalize out discrete model variables in Pyro.

This combines MCMC with a variable elimination algorithm, where we use enumeration to exactly marginalize out some variables from the joint density.

To marginalize out discrete variables `x`:

1. Verify that the variable dependency structure in your model admits tractable inference, i.e. the dependency graph among enumerated variables should have narrow treewidth.
2. Ensure your model can handle broadcasting of the sample values of those variables.

Note that difference from [1], which uses Python loop, here we use `scan()` to reduce compilation times (only one step needs to be compiled) of the model. Under the hood, *scan* stacks all the priors' parameters and values into an additional time dimension. This allows us computing the joint density in parallel. In addition, the stacked form allows us to use the parallel-scan algorithm in [2], which reduces parallel complexity from O(length) to O(log(length)).

Data are taken from [3]. However, the original source of the data seems to be the Institut fuer Algorithmen und Kognitive Systeme at Universitaet Karlsruhe.

References:

1. *Pyro's Hidden Markov Model example*, (https://pyro.ai/examples/hmm.html)
2. *Temporal Parallelization of Bayesian Smoothers*, Simo Sarkka, Angel F. Garcia-Fernandez (https://arxiv.org/abs/1905.13002)
3. *Modeling Temporal Dependencies in High-Dimensional Sequences: Application to Polyphonic Music Generation and Transcription*, Boulanger-Lewandowski, N., Bengio, Y. and Vincent, P.
4. *Tensor Variable Elimination for Plated Factor Graphs*, Fritz Obermeyer, Eli Bingham, Martin Jankowiak, Justin Chiu, Neeraj Pradhan, Alexander Rush, Noah Goodman (https://arxiv.org/abs/1902.03210)


```
import argparse
import logging
import os
import time
```

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```
from jax import random
import jax.numpy as jnp

import numpyro
from numpyro.contrib.control_flow import scan
from numpyro.contrib.indexing import Vindex
import numpyro.distributions as dist
from numpyro.examples.datasets import JSB_CHORALES, load_dataset
from numpyro.handlers import mask
from numpyro.infer import HMC, MCMC, NUTS

logger = logging.getLogger(__name__)
logger.setLevel(logging.INFO)
```

Let's start with a simple Hidden Markov Model.

```
#     x[t-1] --> x[t] --> x[t+1]
#        |         |         |
#        V         V         V
#     y[t-1]     y[t]     y[t+1]
#
# This model includes a plate for the data_dim = 44 keys on the piano. This
# model has two "style" parameters probs_x and probs_y that we'll draw from a
# prior. The latent state is x, and the observed state is y.
def model_1(sequences, lengths, args, include_prior=True):
    num_sequences, max_length, data_dim = sequences.shape
    with mask(mask=include_prior):
        probs_x = numpyro.sample("probs_x",
                                 dist.Dirichlet(0.9 * jnp.eye(args.hidden_dim) + 0.1)
                                     .to_event(1))
        probs_y = numpyro.sample("probs_y",
                                 dist.Beta(0.1, 0.9)
                                     .expand([args.hidden_dim, data_dim])
                                     .to_event(2))

    def transition_fn(carry, y):
        x_prev, t = carry
        with numpyro.plate("sequences", num_sequences, dim=-2):
            with mask(mask=(t < lengths)[..., None]):
                x = numpyro.sample("x", dist.Categorical(probs_x[x_prev]))
                with numpyro.plate("tones", data_dim, dim=-1):
                    numpyro.sample("y", dist.Bernoulli(probs_y[x.squeeze(-1)]), obs=y)
        return (x, t + 1), None

    x_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    # NB swapaxes: we move time dimension of `sequences` to the front to scan over it
    scan(transition_fn, (x_init, 0), jnp.swapaxes(sequences, 0, 1))
```

Next let's add a dependency of y[t] on y[t-1].

```
#     x[t-1] --> x[t] --> x[t+1]
#        |         |         |
#        V         V         V
#     y[t-1] --> y[t] --> y[t+1]
def model_2(sequences, lengths, args, include_prior=True):
    num_sequences, max_length, data_dim = sequences.shape
```

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```
    with mask(mask=include_prior):
        probs_x = numpyro.sample("probs_x",
                                 dist.Dirichlet(0.9 * jnp.eye(args.hidden_dim) + 0.1)
                                     .to_event(1))

        probs_y = numpyro.sample("probs_y",
                                 dist.Beta(0.1, 0.9)
                                     .expand([args.hidden_dim, 2, data_dim])
                                     .to_event(3))

    def transition_fn(carry, y):
        x_prev, y_prev, t = carry
        with numpyro.plate("sequences", num_sequences, dim=-2):
            with mask(mask=(t < lengths)[..., None]):
                x = numpyro.sample("x", dist.Categorical(probs_x[x_prev]))
                # Note the broadcasting tricks here: to index probs_y on tensors x␣
↪and y,
                # we also need a final tensor for the tones dimension. This is␣
↪conveniently
                # provided by the plate associated with that dimension.
                with numpyro.plate("tones", data_dim, dim=-1) as tones:
                    y = numpyro.sample("y",
                                       dist.Bernoulli(probs_y[x, y_prev, tones]),
                                       obs=y)
        return (x, y, t + 1), None

    x_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    y_init = jnp.zeros((num_sequences, data_dim), dtype=jnp.int32)
    scan(transition_fn, (x_init, y_init, 0), jnp.swapaxes(sequences, 0, 1))
```

Next consider a Factorial HMM with two hidden states.

```
#    w[t-1] ----> w[t] ---> w[t+1]
#        \ x[t-1] --\-> x[t] --\-> x[t+1]
#         \  /       \  /       \  /
#          \/         \/         \/
#        y[t-1]      y[t]      y[t+1]
#
# Note that since the joint distribution of each y[t] depends on two variables,
# those two variables become dependent. Therefore during enumeration, the
# entire joint space of these variables w[t],x[t] needs to be enumerated.
# For that reason, we set the dimension of each to the square root of the
# target hidden dimension.
def model_3(sequences, lengths, args, include_prior=True):
    num_sequences, max_length, data_dim = sequences.shape
    hidden_dim = int(args.hidden_dim ** 0.5)  # split between w and x
    with mask(mask=include_prior):
        probs_w = numpyro.sample("probs_w",
                                 dist.Dirichlet(0.9 * jnp.eye(hidden_dim) + 0.1)
                                     .to_event(1))
        probs_x = numpyro.sample("probs_x",
                                 dist.Dirichlet(0.9 * jnp.eye(hidden_dim) + 0.1)
                                     .to_event(1))
        probs_y = numpyro.sample("probs_y",
                                 dist.Beta(0.1, 0.9)
                                     .expand([args.hidden_dim, 2, data_dim])
                                     .to_event(3))
```

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```
    def transition_fn(carry, y):
        w_prev, x_prev, t = carry
        with numpyro.plate("sequences", num_sequences, dim=-2):
            with mask(mask=(t < lengths)[..., None]):
                w = numpyro.sample("w", dist.Categorical(probs_w[w_prev]))
                x = numpyro.sample("x", dist.Categorical(probs_x[x_prev]))
                # Note the broadcasting tricks here: to index probs_y on tensors x␣
↪and y,
                # we also need a final tensor for the tones dimension. This is␣
↪conveniently
                # provided by the plate associated with that dimension.
                with numpyro.plate("tones", data_dim, dim=-1) as tones:
                    numpyro.sample("y",
                                   dist.Bernoulli(probs_y[w, x, tones]),
                                   obs=y)
        return (w, x, t + 1), None

    w_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    x_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    scan(transition_fn, (w_init, x_init, 0), jnp.swapaxes(sequences, 0, 1))
```

By adding a dependency of x on w, we generalize to a Dynamic Bayesian Network.

```
#     w[t-1] ----> w[t] ---> w[t+1]
#        |  \        |  \        |   \
#        | x[t-1] ----> x[t] ----> x[t+1]
#        |   /       |   /       |   /
#        V  /        V  /        V  /
#     y[t-1]       y[t]      y[t+1]
#
# Note that message passing here has roughly the same cost as with the
# Factorial HMM, but this model has more parameters.
def model_4(sequences, lengths, args, include_prior=True):
    num_sequences, max_length, data_dim = sequences.shape
    hidden_dim = int(args.hidden_dim ** 0.5)  # split between w and x
    with mask(mask=include_prior):
        probs_w = numpyro.sample("probs_w",
                                 dist.Dirichlet(0.9 * jnp.eye(hidden_dim) + 0.1)
                                     .to_event(1))
        probs_x = numpyro.sample("probs_x",
                                 dist.Dirichlet(0.9 * jnp.eye(hidden_dim) + 0.1)
                                     .expand_by([hidden_dim])
                                     .to_event(2))
        probs_y = numpyro.sample("probs_y",
                                 dist.Beta(0.1, 0.9)
                                     .expand([hidden_dim, hidden_dim, data_dim])
                                     .to_event(3))

    def transition_fn(carry, y):
        w_prev, x_prev, t = carry
        with numpyro.plate("sequences", num_sequences, dim=-2):
            with mask(mask=(t < lengths)[..., None]):
                w = numpyro.sample("w", dist.Categorical(probs_w[w_prev]))
                x = numpyro.sample("x", dist.Categorical(Vindex(probs_x)[w, x_prev]))
                with numpyro.plate("tones", data_dim, dim=-1) as tones:
                    numpyro.sample("y",
```

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```
                                    dist.Bernoulli(probs_y[w, x, tones]),
                                    obs=y)
        return (w, x, t + 1), None

    w_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    x_init = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    scan(transition_fn, (w_init, x_init, 0), jnp.swapaxes(sequences, 0, 1))
```

Next let's consider a second-order HMM model in which x[t+1] depends on both x[t] and x[t-1].

```
#                       _______>______
#          _____>_____/______          \
#         /          /        \         \
#      x[t-1] --> x[t] --> x[t+1] --> x[t+2]
#         |         |          |          |
#         V         V          V          V
#      y[t-1]     y[t]      y[t+1]     y[t+2]
#
#  Note that in this model (in contrast to the previous model) we treat
#  the transition and emission probabilities as parameters (so they have no prior).
#
# Note that this is the "2HMM" model in reference [4].
def model_6(sequences, lengths, args, include_prior=False):
    num_sequences, max_length, data_dim = sequences.shape

    with mask(mask=include_prior):
        # Explicitly parameterize the full tensor of transition probabilities, which
        # has hidden_dim cubed entries.
        probs_x = numpyro.sample("probs_x",
                                 dist.Dirichlet(0.9 * jnp.eye(args.hidden_dim) + 0.1)
                                     .expand([args.hidden_dim, args.hidden_dim])
                                     .to_event(2))

        probs_y = numpyro.sample("probs_y",
                                 dist.Beta(0.1, 0.9)
                                     .expand([args.hidden_dim, data_dim])
                                     .to_event(2))

    def transition_fn(carry, y):
        x_prev, x_curr, t = carry
        with numpyro.plate("sequences", num_sequences, dim=-2):
            with mask(mask=(t < lengths)[..., None]):
                probs_x_t = Vindex(probs_x)[x_prev, x_curr]
                x_prev, x_curr = x_curr, numpyro.sample("x", dist.Categorical(probs_x_
↪t))
                with numpyro.plate("tones", data_dim, dim=-1):
                    probs_y_t = probs_y[x_curr.squeeze(-1)]
                    numpyro.sample("y",
                                   dist.Bernoulli(probs_y_t),
                                   obs=y)
        return (x_prev, x_curr, t + 1), None

    x_prev = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    x_curr = jnp.zeros((num_sequences, 1), dtype=jnp.int32)
    scan(transition_fn, (x_prev, x_curr, 0), jnp.swapaxes(sequences, 0, 1), history=2)
```

Do inference

```
models = {name[len('model_'):]: model
          for name, model in globals().items()
          if name.startswith('model_')}


def main(args):

    model = models[args.model]

    _, fetch = load_dataset(JSB_CHORALES, split='train', shuffle=False)
    lengths, sequences = fetch()
    if args.num_sequences:
        sequences = sequences[0:args.num_sequences]
        lengths = lengths[0:args.num_sequences]

    logger.info('-' * 40)
    logger.info('Training {} on {} sequences'.format(
        model.__name__, len(sequences)))

    # find all the notes that are present at least once in the training set
    present_notes = ((sequences == 1).sum(0).sum(0) > 0)
    # remove notes that are never played (we remove 37/88 notes with default args)
    sequences = sequences[..., present_notes]

    if args.truncate:
        lengths = lengths.clip(0, args.truncate)
        sequences = sequences[:, :args.truncate]

    logger.info('Each sequence has shape {}'.format(sequences[0].shape))
    logger.info('Starting inference...')
    rng_key = random.PRNGKey(2)
    start = time.time()
    kernel = {'nuts': NUTS, 'hmc': HMC}[args.kernel](model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, sequences, lengths, args=args)
    mcmc.print_summary()
    logger.info('\nMCMC elapsed time: {}'.format(time.time() - start))


if __name__ == '__main__':
    parser = argparse.ArgumentParser(description="HMC for HMMs")
    parser.add_argument("-m", "--model", default="1", type=str,
                        help="one of: {}".format(", ".join(sorted(models.keys()))))
    parser.add_argument('-n', '--num-samples', nargs='?', default=1000, type=int)
    parser.add_argument("-d", "--hidden-dim", default=16, type=int)
    parser.add_argument('-t', "--truncate", type=int)
    parser.add_argument("--num-sequences", type=int)
    parser.add_argument("--kernel", default='nuts', type=str)
    parser.add_argument('--num-warmup', nargs='?', default=500, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')

    args = parser.parse_args()

    numpyro.set_platform(args.device)
```

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```
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 11

Example: CJS Capture-Recapture Model for Ecological Data

This example is ported from [8].

We show how to implement several variants of the Cormack-Jolly-Seber (CJS) [4, 5, 6] model used in ecology to analyze animal capture-recapture data. For a discussion of these models see reference [1].

We make use of two datasets:

- the European Dipper (Cinclus cinclus) data from reference [2] (this is Norway's national bird).
- the meadow voles data from reference [3].

Compare to the Stan implementations in [7].

References

1. Kery, M., & Schaub, M. (2011). Bayesian population analysis using WinBUGS: a hierarchical perspective. Academic Press.
2. Lebreton, J.D., Burnham, K.P., Clobert, J., & Anderson, D.R. (1992). Modeling survival and testing biological hypotheses using marked animals: a unified approach with case studies. Ecological monographs, 62(1), 67-118.
3. Nichols, Pollock, Hines (1984) The use of a robust capture-recapture design in small mammal population studies: A field example with Microtus pennsylvanicus. Acta Theriologica 29:357-365.
4. Cormack, R.M., 1964. Estimates of survival from the sighting of marked animals. Biometrika 51, 429-438.
5. Jolly, G.M., 1965. Explicit estimates from capture-recapture data with both death and immigration-stochastic model. Biometrika 52, 225-247.
6. Seber, G.A.F., 1965. A note on the multiple recapture census. Biometrika 52, 249-259.
7. https://github.com/stan-dev/example-models/tree/master/BPA/Ch.07
8. http://pyro.ai/examples/capture_recapture.html


```
import argparse
import os

from jax import random
```

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```
import jax.numpy as jnp
from jax.scipy.special import expit, logit

import numpyro
from numpyro import handlers
from numpyro.contrib.control_flow import scan
import numpyro.distributions as dist
from numpyro.examples.datasets import DIPPER_VOLE, load_dataset
from numpyro.infer import HMC, MCMC, NUTS
from numpyro.infer.reparam import LocScaleReparam
```

Our first and simplest CJS model variant only has two continuous (scalar) latent random variables: i) the survival probability phi; and ii) the recapture probability rho. These are treated as fixed effects with no temporal or individual/group variation.

```
def model_1(capture_history, sex):
    N, T = capture_history.shape
    phi = numpyro.sample("phi", dist.Uniform(0.0, 1.0))  # survival probability
    rho = numpyro.sample("rho", dist.Uniform(0.0, 1.0))  # recapture probability

    def transition_fn(carry, y):
        first_capture_mask, z = carry
        with numpyro.plate("animals", N, dim=-1):
            with handlers.mask(mask=first_capture_mask):
                mu_z_t = first_capture_mask * phi * z + (1 - first_capture_mask)
                # NumPyro exactly sums out the discrete states z_t.
                z = numpyro.sample("z", dist.Bernoulli(dist.util.clamp_probs(mu_z_t)))
                mu_y_t = rho * z
                numpyro.sample("y", dist.Bernoulli(dist.util.clamp_probs(mu_y_t)),␣
↪obs=y)

        first_capture_mask = first_capture_mask | y.astype(bool)
        return (first_capture_mask, z), None

    z = jnp.ones(N, dtype=jnp.int32)
    # we use this mask to eliminate extraneous log probabilities
    # that arise for a given individual before its first capture.
    first_capture_mask = capture_history[:, 0].astype(bool)
    # NB swapaxes: we move time dimension of `capture_history` to the front to scan␣
↪over it
    scan(transition_fn, (first_capture_mask, z), jnp.swapaxes(capture_history[:, 1:],␣
↪0, 1))
```

In our second model variant there is a time-varying survival probability phi_t for T-1 of the T time periods of the capture data; each phi_t is treated as a fixed effect.

```
def model_2(capture_history, sex):
    N, T = capture_history.shape
    rho = numpyro.sample("rho", dist.Uniform(0.0, 1.0))  # recapture probability

    def transition_fn(carry, y):
        first_capture_mask, z = carry
        # note that phi_t needs to be outside the plate, since
        # phi_t is shared across all N individuals
        phi_t = numpyro.sample("phi", dist.Uniform(0.0, 1.0))
```

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```
        with numpyro.plate("animals", N, dim=-1):
            with handlers.mask(mask=first_capture_mask):
                mu_z_t = first_capture_mask * phi_t * z + (1 - first_capture_mask)
                # NumPyro exactly sums out the discrete states z_t.
                z = numpyro.sample("z", dist.Bernoulli(dist.util.clamp_probs(mu_z_t)))
                mu_y_t = rho * z
                numpyro.sample("y", dist.Bernoulli(dist.util.clamp_probs(mu_y_t)),␣
↪obs=y)

        first_capture_mask = first_capture_mask | y.astype(bool)
        return (first_capture_mask, z), None

    z = jnp.ones(N, dtype=jnp.int32)
    # we use this mask to eliminate extraneous log probabilities
    # that arise for a given individual before its first capture.
    first_capture_mask = capture_history[:, 0].astype(bool)
    # NB swapaxes: we move time dimension of `capture_history` to the front to scan␣
↪over it
    scan(transition_fn, (first_capture_mask, z), jnp.swapaxes(capture_history[:, 1:],␣
↪0, 1))
```

In our third model variant there is a survival probability phi_t for T-1 of the T time periods of the capture data (just like in model_2), but here each phi_t is treated as a random effect.

```
def model_3(capture_history, sex):
    N, T = capture_history.shape
    phi_mean = numpyro.sample("phi_mean", dist.Uniform(0.0, 1.0))  # mean survival␣
↪probability
    phi_logit_mean = logit(phi_mean)
    # controls temporal variability of survival probability
    phi_sigma = numpyro.sample("phi_sigma", dist.Uniform(0.0, 10.0))
    rho = numpyro.sample("rho", dist.Uniform(0.0, 1.0))  # recapture probability

    def transition_fn(carry, y):
        first_capture_mask, z = carry
        with handlers.reparam(config={"phi_logit": LocScaleReparam(0)}):
            phi_logit_t = numpyro.sample("phi_logit", dist.Normal(phi_logit_mean, phi_
↪sigma))
        phi_t = expit(phi_logit_t)
        with numpyro.plate("animals", N, dim=-1):
            with handlers.mask(mask=first_capture_mask):
                mu_z_t = first_capture_mask * phi_t * z + (1 - first_capture_mask)
                # NumPyro exactly sums out the discrete states z_t.
                z = numpyro.sample("z", dist.Bernoulli(dist.util.clamp_probs(mu_z_t)))
                mu_y_t = rho * z
                numpyro.sample("y", dist.Bernoulli(dist.util.clamp_probs(mu_y_t)),␣
↪obs=y)

        first_capture_mask = first_capture_mask | y.astype(bool)
        return (first_capture_mask, z), None

    z = jnp.ones(N, dtype=jnp.int32)
    # we use this mask to eliminate extraneous log probabilities
    # that arise for a given individual before its first capture.
    first_capture_mask = capture_history[:, 0].astype(bool)
    # NB swapaxes: we move time dimension of `capture_history` to the front to scan␣
↪over it
```

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```
    scan(transition_fn, (first_capture_mask, z), jnp.swapaxes(capture_history[:, 1:],␣
↪0, 1))
```

In our fourth model variant we include group-level fixed effects for sex (male, female).

```
def model_4(capture_history, sex):
    N, T = capture_history.shape
    # survival probabilities for males/females
    phi_male = numpyro.sample("phi_male", dist.Uniform(0.0, 1.0))
    phi_female = numpyro.sample("phi_female", dist.Uniform(0.0, 1.0))
    # we construct a N-dimensional vector that contains the appropriate
    # phi for each individual given its sex (female = 0, male = 1)
    phi = sex * phi_male + (1.0 - sex) * phi_female
    rho = numpyro.sample("rho", dist.Uniform(0.0, 1.0))  # recapture probability

    def transition_fn(carry, y):
        first_capture_mask, z = carry
        with numpyro.plate("animals", N, dim=-1):
            with handlers.mask(mask=first_capture_mask):
                mu_z_t = first_capture_mask * phi * z + (1 - first_capture_mask)
                # NumPyro exactly sums out the discrete states z_t.
                z = numpyro.sample("z", dist.Bernoulli(dist.util.clamp_probs(mu_z_t)))
                mu_y_t = rho * z
                numpyro.sample("y", dist.Bernoulli(dist.util.clamp_probs(mu_y_t)),␣
↪obs=y)

        first_capture_mask = first_capture_mask | y.astype(bool)
        return (first_capture_mask, z), None

    z = jnp.ones(N, dtype=jnp.int32)
    # we use this mask to eliminate extraneous log probabilities
    # that arise for a given individual before its first capture.
    first_capture_mask = capture_history[:, 0].astype(bool)
    # NB swapaxes: we move time dimension of `capture_history` to the front to scan␣
↪over it
    scan(transition_fn, (first_capture_mask, z), jnp.swapaxes(capture_history[:, 1:],␣
↪0, 1))
```

In our final model variant we include both fixed group effects and fixed time effects for the survival probability phi: logit(phi_t) = beta_group + gamma_t We need to take care that the model is not overparameterized; to do this we effectively let a single scalar beta encode the difference in male and female survival probabilities.

```
def model_5(capture_history, sex):
    N, T = capture_history.shape

    # phi_beta controls the survival probability differential
    # for males versus females (in logit space)
    phi_beta = numpyro.sample("phi_beta", dist.Normal(0.0, 10.0))
    phi_beta = sex * phi_beta
    rho = numpyro.sample("rho", dist.Uniform(0.0, 1.0))  # recapture probability

    def transition_fn(carry, y):
        first_capture_mask, z = carry
        phi_gamma_t = numpyro.sample("phi_gamma", dist.Normal(0.0, 10.0))
        phi_t = expit(phi_beta + phi_gamma_t)
        with numpyro.plate("animals", N, dim=-1):
```

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```
            with handlers.mask(mask=first_capture_mask):
                mu_z_t = first_capture_mask * phi_t * z + (1 - first_capture_mask)
                # NumPyro exactly sums out the discrete states z_t.
                z = numpyro.sample("z", dist.Bernoulli(dist.util.clamp_probs(mu_z_t)))
                mu_y_t = rho * z
                numpyro.sample("y", dist.Bernoulli(dist.util.clamp_probs(mu_y_t)),␣
↪obs=y)

        first_capture_mask = first_capture_mask | y.astype(bool)
        return (first_capture_mask, z), None

    z = jnp.ones(N, dtype=jnp.int32)
    # we use this mask to eliminate extraneous log probabilities
    # that arise for a given individual before its first capture.
    first_capture_mask = capture_history[:, 0].astype(bool)
    # NB swapaxes: we move time dimension of `capture_history` to the front to scan␣
↪over it
    scan(transition_fn, (first_capture_mask, z), jnp.swapaxes(capture_history[:, 1:],␣
↪0, 1))
```

Do inference

```
models = {name[len('model_'):]: model
          for name, model in globals().items()
          if name.startswith('model_')}


def run_inference(model, capture_history, sex, rng_key, args):
    if args.algo == "NUTS":
        kernel = NUTS(model)
    elif args.algo == "HMC":
        kernel = HMC(model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, capture_history, sex)
    mcmc.print_summary()
    return mcmc.get_samples()


def main(args):
    # load data
    if args.dataset == "dipper":
        capture_history, sex = load_dataset(DIPPER_VOLE, split='dipper',␣
↪shuffle=False)[1]()
    elif args.dataset == "vole":
        if args.model in ["4", "5"]:
            raise ValueError("Cannot run model_{} on meadow voles data, since we lack␣
↪sex "
                             "information for these animals.".format(args.model))
        capture_history, = load_dataset(DIPPER_VOLE, split='vole', shuffle=False)[1]()
        sex = None
    else:
        raise ValueError("Available datasets are \'dipper\' and \'vole\'.")

    N, T = capture_history.shape
    print("Loaded {} capture history for {} individuals collected over {} time␣
↪periods.".format(
```

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```
          args.dataset, N, T))

    model = models[args.model]
    rng_key = random.PRNGKey(args.rng_seed)
    run_inference(model, capture_history, sex, rng_key, args)


if __name__ == '__main__':
    parser = argparse.ArgumentParser(description="CJS capture-recapture model for␣
↪ecological data")
    parser.add_argument("-m", "--model", default="1", type=str,
                        help="one of: {}".format(", ".join(sorted(models.keys()))))
    parser.add_argument("-d", "--dataset", default="dipper", type=str)
    parser.add_argument("-n", "--num-samples", nargs="?", default=1000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument('--rng_seed', default=0, type=int, help='random number␣
↪generator seed')
    parser.add_argument('--algo', default='NUTS', type=str,
                        help='whether to run "NUTS" or "HMC"')
    args = parser.parse_args()
    main(args)
```

github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/discrete_imputation.ipynb

CHAPTER 12

Bayesian Imputation for Missing Values in Discrete Covariates

Missing data is a very widespread problem in practical applications, both in covariates ('explanatory variables') and outcomes. When performing bayesian inference with MCMC, imputing discrete missing values is not possible using Hamiltonian Monte Carlo techniques. One way around this problem is to create a new model that enumerates the discrete variables and does inference over the new model, which, for a single discrete variable, is a mixture model. (see e.g. Stan's user guide on Latent Discrete Parameters) Enumerating the discrete latent sites requires some manual math work that can get tedious for complex models. Inference by automatic enumeration of discrete variables is implemented in numpyro and allows for a very convenient way of dealing with missing discrete data.

[1]:
```
import numpyro
from jax import numpy as jnp, random, ops
from jax.scipy.special import expit
from numpyro import distributions as dist, sample
from numpyro.infer.mcmc import MCMC
from numpyro.infer.hmc import NUTS
from math import inf
from graphviz import Digraph

simkeys = random.split(random.PRNGKey(0), 10)
nsim    = 5000
mcmc_key = random.PRNGKey(1)
```

First we will simulate data with correlated binary covariates. The assumption is that we wish to estimate parameter for some parametric model without bias (e.g. for inferring a causal effect). For several different missing data patterns we will see how to impute the values to lead to unbiased models.

The basic data structure is as follows. Z is a latent variable that gives rise to the marginal dependence between A and B, the observed covariates. We will consider different missing data mechanisms for variable A, where variable B and Y are fully observed. The effects of A and B on Y are the effects of interest.

[2]:
```
dot = Digraph()
dot.node('A')
dot.node('B')
dot.node('Z')
dot.node('Y')
```

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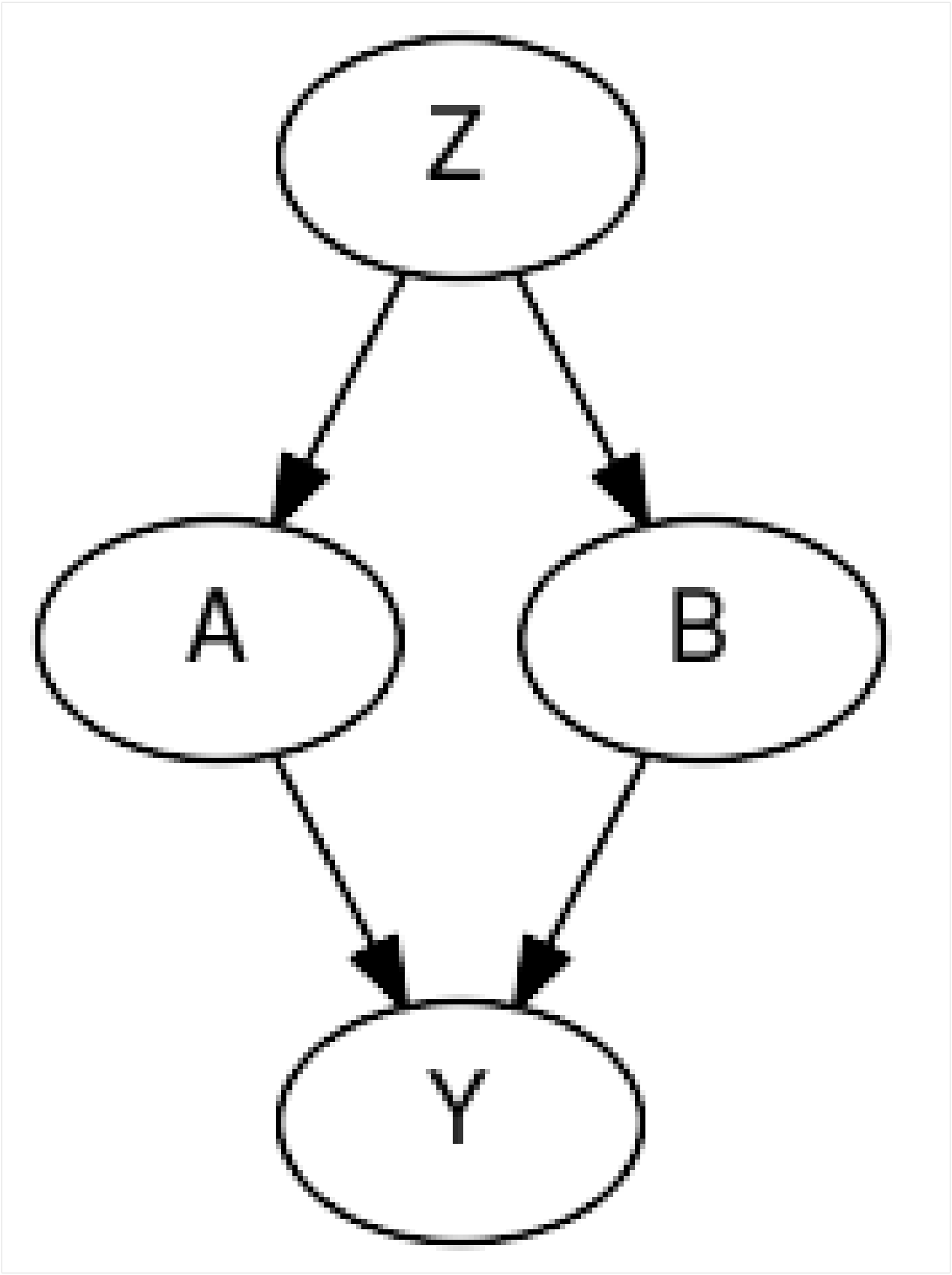
```
dot.edges(['ZA', 'ZB', 'AY', 'BY'])
dot
```

[2]:



[3]:
```
b_A = 0.25
b_B = 0.25
s_Y = 0.25
Z = random.normal(simkeys[0], (nsim, ))
A = random.bernoulli(simkeys[1], expit(Z))
B = random.bernoulli(simkeys[2], expit(Z))
Y = A * b_A + B * b_B + s_Y * random.normal(simkeys[3], (nsim,))
```

12.1 MAR conditional on outcome

According to Rubin's classic definitions there are 3 distinct of missing data mechanisms:

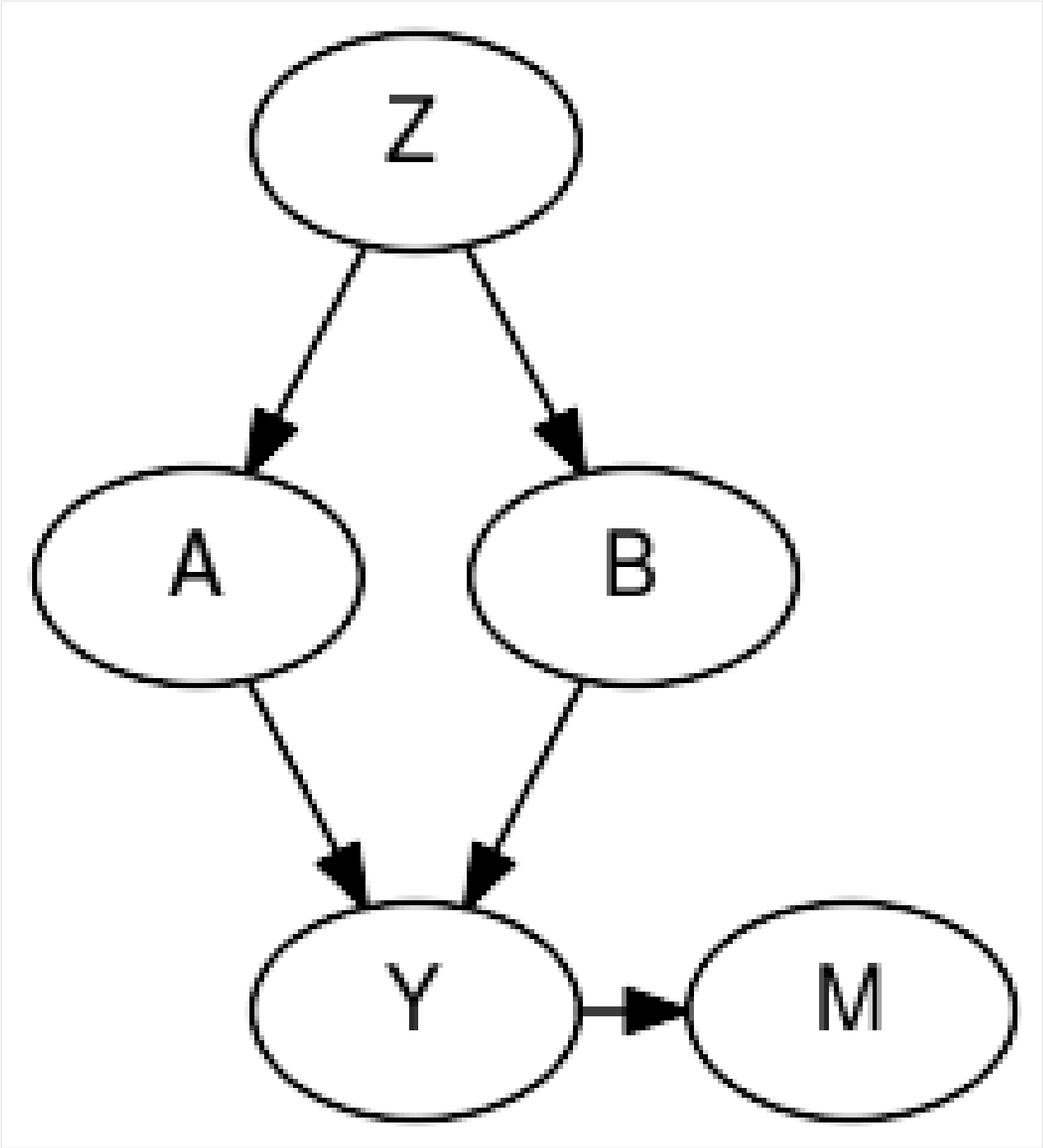
1. missing completely at random (MCAR)
2. missing at random, conditional on observed data (MAR)
3. missing not at random, even after conditioning on observed data (MNAR)

Missing data mechanisms 1. and 2. are 'easy' to handle as they depend on observed data only. Mechanism 3. (MNAR) is trickier as it depends on data that is not observed, but may still be relevant to the outcome you are modeling (see below for a concrete example).

First we will generate missing values in A, conditional on the value of Y (thus it is a MAR mechanism).

[4]:
```
dot_mnar_y = Digraph()
with dot_mnar_y.subgraph() as s:
    s.attr(rank='same')
    s.node('Y')
    s.node('M')
dot_mnar_y.node('A')
dot_mnar_y.node('B')
dot_mnar_y.node('Z')
dot_mnar_y.node('M')
dot_mnar_y.edges(['YM', 'ZA', 'ZB', 'AY', 'BY'])
dot_mnar_y
```

[4]:



This graph depicts the datagenerating mechanism, where Y is the only cause of missingness in A, denoted M. This means that the missingness in M is random, conditional on Y.

As an example consider this simplified scenario:

- A represents a history of heart illness
- B represents the age of a patient
- Y represents whether or not the patient will visit the general practitioner

A general practitioner wants to find out why patients that are assigned to her clinic will visit the clinic or not. She

thinks that having a history of heart illness and age are potential causes of doctor visits. Data on patient ages are available through their registration forms, but information on prior heart illness may be availalbe only after they have visited the clinic. This makes the missingness in A (history of heart disease), dependent on the outcome (visiting the clinic).

[5]:
```
A_isobs = random.bernoulli(simkeys[4], expit(3*(Y - Y.mean())))
Aobs = jnp.where(A_isobs, A, -1)
A_obsidx = jnp.where(A_isobs)

# generate complete case arrays
Acc = Aobs[A_obsidx]
Bcc = B[A_obsidx]
Ycc = Y[A_obsidx]
```

We will evaluate 2 approaches:

1. complete case analysis (which will lead to biased inferences)
2. with imputation (conditional on B)

Note that explicitly including Y in the imputation model for A is unneccesary. The sampled imputations for A will condition on Y indirectly as the likelihood of Y is conditional on A. So values of A that give high likelihood to Y will be sampled more often than other values.

[6]:
```
def ccmodel(A, B, Y):
    ntotal = A.shape[0]
    # get parameters of outcome model
    b_A = sample('b_A', dist.Normal(0, 2.5))
    b_B = sample('b_B', dist.Normal(0, 2.5))
    s_Y = sample('s_Y', dist.HalfCauchy(2.5))

    with numpyro.plate('obs', ntotal):
        ### outcome model
        eta_Y = b_A * A + b_B * B
        sample("obs_Y", dist.Normal(eta_Y, s_Y), obs=Y)
```

[7]:
```
cckernel = NUTS(ccmodel)
ccmcmc   = MCMC(cckernel, num_warmup=250, num_samples=750)
ccmcmc.run(mcmc_key, Acc, Bcc, Ycc)
ccmcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:02<00:00, 348.50it/s, 3 steps of␣
↪size 4.27e-01. acc. prob=0.94]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
       b_A      0.30      0.01      0.30      0.29      0.31    500.83      1.00
       b_B      0.28      0.01      0.28      0.27      0.29    546.34      1.00
       s_Y      0.25      0.00      0.25      0.24      0.25    559.55      1.00

Number of divergences: 0
```

[8]:
```
def impmodel(A, B, Y):
    ntotal = A.shape[0]
    A_isobs = A >= 0

    # get parameters of imputation model
    mu_A = sample("mu_A", dist.Normal(0, 2.5))
    b_B_A = sample("b_B_A", dist.Normal(0, 2.5))
```

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```
    # get parameters of outcome model
    b_A = sample('b_A', dist.Normal(0, 2.5))
    b_B = sample('b_B', dist.Normal(0, 2.5))
    s_Y = sample('s_Y', dist.HalfCauchy(2.5))

    with numpyro.plate('obs', ntotal):
        ### imputation model
        # get linear predictor for missing values
        eta_A = mu_A + B * b_B_A

        # sample imputation values for A
        # mask out to not add log_prob to total likelihood right now
        Aimp = sample("A", dist.Bernoulli(logits=eta_A).mask(False))

        # 'manually' calculate the log_prob
        log_prob = dist.Bernoulli(logits=eta_A).log_prob(Aimp)

        # cancel out enumerated values that are not equal to observed values
        log_prob = jnp.where(A_isobs & (Aimp != A), -inf, log_prob)

        # add to total likelihood for sampler
        numpyro.factor('A_obs', log_prob)

        ### outcome model
        eta_Y = b_A * Aimp + b_B * B
        sample("obs_Y", dist.Normal(eta_Y, s_Y), obs=Y)
```

[9]:
```
impkernel = NUTS(impmodel)
impmcmc   = MCMC(impkernel, num_warmup=250, num_samples=750)
impmcmc.run(mcmc_key, Aobs, B, Y)
impmcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:05<00:00, 174.83it/s, 7 steps of␣
↪size 4.41e-01. acc. prob=0.91]
```

	mean	std	median	5.0%	95.0%	n_eff	r_hat
b_A	0.25	0.01	0.25	0.24	0.27	447.79	1.01
b_B	0.25	0.01	0.25	0.24	0.26	570.66	1.01
b_B_A	0.74	0.08	0.74	0.60	0.86	316.36	1.00
mu_A	-0.39	0.06	-0.39	-0.48	-0.29	290.86	1.00
s_Y	0.25	0.00	0.25	0.25	0.25	527.97	1.00

```
Number of divergences: 0
```

As we can see, when data are missing conditionally on Y, imputation leads to consistent estimation of the parameter of interest (b_A and b_B).

12.2 MNAR conditional on covariate

When data are missing conditional on unobserved data, things get more tricky. Here we will generate missing values in A, conditional on the value of A itself (missing not at random (MNAR), but missing at random conditional on A).

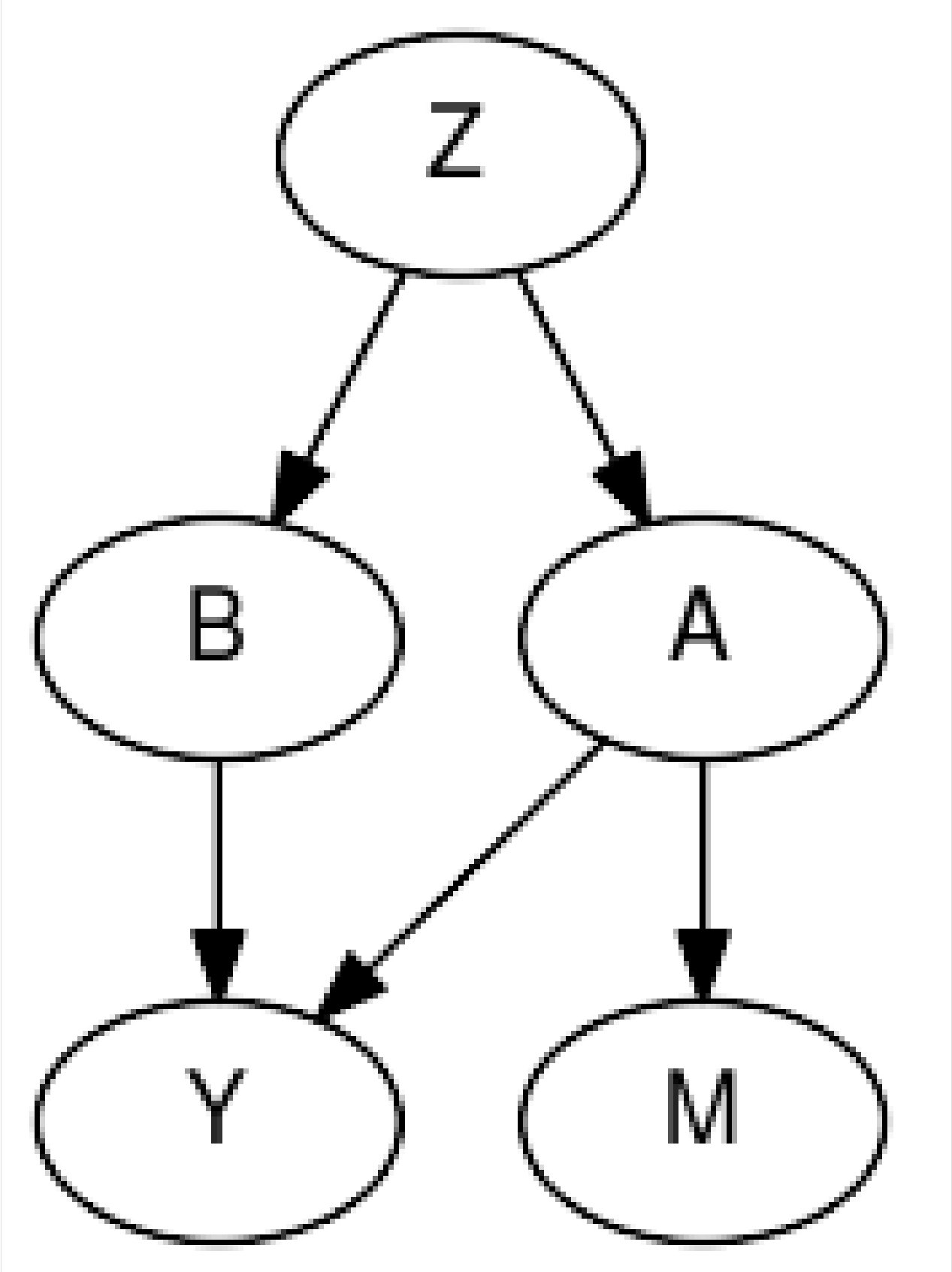
As an example consider patients who have cancer:

- A represents weight loss
- B represents age
- Y represents overall survival time

Both A and B can be related to survival time in cancer patients. For patients who have extreme weight loss, it is more likely that this will be noted by the doctor and registered in the electronic health record. For patients with no weight loss or little weight loss, it may be that the doctor forgets to ask about it and therefore does not register it in the records.

[10]:
```
dot_mnar_x = Digraph()
with dot_mnar_y.subgraph() as s:
    s.attr(rank='same')
    s.node('A')
    s.node('M')
dot_mnar_x.node('B')
dot_mnar_x.node('Z')
dot_mnar_x.node('Y')
dot_mnar_x.edges(['AM', 'ZA', 'ZB', 'AY', 'BY'])
dot_mnar_x
```

[10]:



[11]:
```
A_isobs = random.bernoulli(simkeys[5], 0.9 - 0.8 * A)
Aobs = jnp.where(A_isobs, A, -1)
A_obsidx = jnp.where(A_isobs)

# generate complete case arrays
Acc = Aobs[A_obsidx]
Bcc = B[A_obsidx]
Ycc = Y[A_obsidx]
```

[12]:
```
cckernel = NUTS(ccmodel)
ccmcmc   = MCMC(cckernel, num_warmup=250, num_samples=750)
ccmcmc.run(mcmc_key, Acc, Bcc, Ycc)
ccmcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:02<00:00, 342.07it/s, 3 steps of␣
↪size 5.97e-01. acc. prob=0.92]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
       b_A      0.27      0.02      0.26      0.24      0.29    667.08      1.01
       b_B      0.25      0.01      0.25      0.24      0.26    811.49      1.00
       s_Y      0.25      0.00      0.25      0.24      0.25    547.51      1.00

Number of divergences: 0
```

[13]:
```
impkernel = NUTS(impmodel)
impmcmc   = MCMC(impkernel, num_warmup=250, num_samples=750)
impmcmc.run(mcmc_key, Aobs, B, Y)
impmcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:06<00:00, 166.36it/s, 7 steps of␣
↪size 4.10e-01. acc. prob=0.94]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
       b_A      0.34      0.01      0.34      0.32      0.35    576.15      1.00
       b_B      0.33      0.01      0.33      0.32      0.34    800.58      1.00
     b_B_A      0.32      0.12      0.32      0.12      0.51    342.21      1.01
      mu_A     -1.81      0.09     -1.81     -1.95     -1.67    288.57      1.00
       s_Y      0.26      0.00      0.26      0.25      0.26    820.20      1.00

Number of divergences: 0
```

Perhaps surprisingly, imputing missing values when the missingness mechanism depends on the variable itself will actually lead to bias, while complete case analysis is unbiased! See e.g. Bias and efficiency of multiple imputation compared with complete-case analysis for missing covariate values.

However, complete case analysis may be undesirable as well. E.g. due to leading to lower precision in estimating the parameter from B to Y, or maybe when there is an expected difference interaction between the value of A and the parameter from A to Y. To deal with this situation, an explicit model for the reason of missingness (/observation) is required. We will add one below.

[14]:
```
def impmissmodel(A, B, Y):
    ntotal = A.shape[0]
    A_isobs = A >= 0

    # get parameters of imputation model
```

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```
    mu_A = sample("mu_A", dist.Normal(0, 2.5))
    b_B_A = sample("b_B_A", dist.Normal(0, 2.5))

    # get parameters of outcome model
    b_A = sample('b_A', dist.Normal(0, 2.5))
    b_B = sample('b_B', dist.Normal(0, 2.5))
    s_Y = sample('s_Y', dist.HalfCauchy(2.5))

    # get parameter of model of missingness
    with numpyro.plate('obsmodel', 2):
        p_Aobs = sample('p_Aobs', dist.Beta(1,1))

    with numpyro.plate('obs', ntotal):
        ### imputation model
        # get linear predictor for missing values
        eta_A = mu_A + B * b_B_A

        # sample imputation values for A
        # mask out to not add log_prob to total likelihood right now
        Aimp = sample("A", dist.Bernoulli(logits=eta_A).mask(False))

        # 'manually' calculate the log_prob
        log_prob = dist.Bernoulli(logits=eta_A).log_prob(Aimp)

        # cancel out enumerated values that are not equal to observed values
        log_prob = jnp.where(A_isobs & (Aimp != A), -inf, log_prob)

        # add to total likelihood for sampler
        numpyro.factor('obs_A', log_prob)

        ### outcome model
        eta_Y = b_A * Aimp + b_B * B
        sample("obs_Y", dist.Normal(eta_Y, s_Y), obs=Y)

        ### missingness / observationmodel
        eta_Aobs = jnp.where(Aimp, p_Aobs[0], p_Aobs[1])
        sample('obs_Aobs', dist.Bernoulli(probs=eta_Aobs), obs=A_isobs)
```

[15]:
```
impmisskernel = NUTS(impmissmodel)
impmissmcmc   = MCMC(impmisskernel, num_warmup=250, num_samples=750)
impmissmcmc.run(mcmc_key, Aobs, B, Y)
impmissmcmc.print_summary()
```

```
sample: 100%|██████████| 1000/1000 [00:09<00:00, 106.81it/s, 7 steps of␣
↪size 2.86e-01. acc. prob=0.91]
```

	mean	std	median	5.0%	95.0%	n_eff	r_hat
b_A	0.26	0.01	0.26	0.24	0.27	267.57	1.00
b_B	0.25	0.01	0.25	0.24	0.26	537.10	1.00
b_B_A	0.74	0.07	0.74	0.62	0.84	421.54	1.00
mu_A	-0.45	0.08	-0.45	-0.58	-0.31	241.11	1.00
p_Aobs[0]	0.10	0.01	0.10	0.09	0.11	451.90	1.00
p_Aobs[1]	0.86	0.03	0.86	0.82	0.91	244.47	1.00
s_Y	0.25	0.00	0.25	0.24	0.25	375.51	1.00

```
Number of divergences: 0
```

We can now estimate the parameters b_A and b_B without bias, while still utilizing all observations. Obviously, modeling the missingness mechanism relies on assumptions that need either be substantiated with prior evidence, or possibly analyzed through sensitivity analysis.

For more reading on missing data in bayesian inference, see:

- Presentation Bayesian Methods for missing data (pdf)
- Bayesian Approaches for Missing Not at Random Outcome Data: The Role of Identifying Restrictions (doi:10.1214/17-STS630)

github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/time_series_forecasting.ipynb

CHAPTER 13

Time Series Forecasting

In this tutorial, we will demonstrate how to build a model for time series forecasting in NumPyro. Specifically, we will replicate the **Seasonal, Global Trend (SGT)** model from the Rlgt: Bayesian Exponential Smoothing Models with Trend Modifications package. The time series data that we will use for this tutorial is the **lynx** dataset, which contains annual numbers of lynx trappings from 1821 to 1934 in Canada.

[1]:
```
import os

import matplotlib.pyplot as plt
import pandas as pd
from IPython.display import set_matplotlib_formats

import jax.numpy as jnp
from jax import random

import numpyro
import numpyro.distributions as dist
from numpyro.contrib.control_flow import scan
from numpyro.diagnostics import autocorrelation, hpdi
from numpyro.infer import MCMC, NUTS, Predictive

if "NUMPYRO_SPHINXBUILD" in os.environ:
    set_matplotlib_formats("svg")

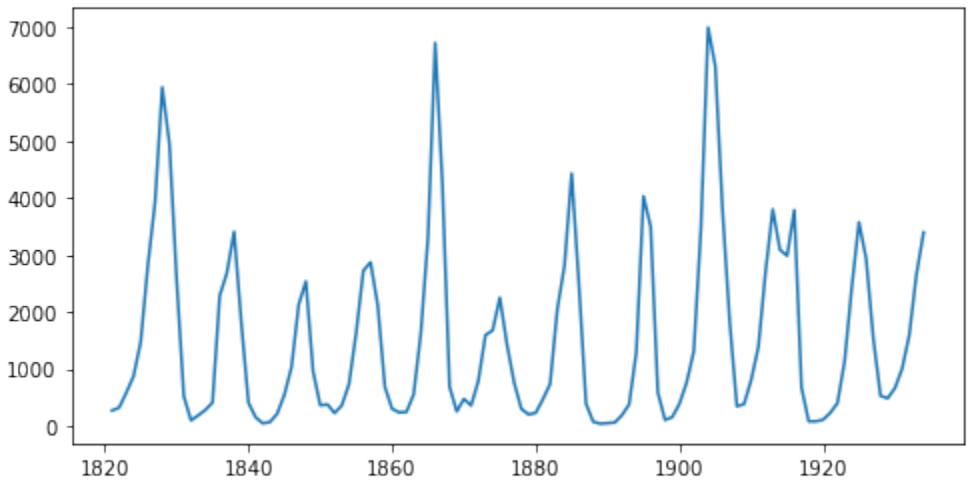
numpyro.set_host_device_count(4)
assert numpyro.__version__.startswith("0.5.0")
```

13.1 Data

First, lets import and take a look at the dataset.

[2]:
```
URL = "https://raw.githubusercontent.com/vincentarelbundock/Rdatasets/master/csv/
↪datasets/lynx.csv"
lynx = pd.read_csv(URL, index_col=0)
data = lynx["value"].values
print("Length of time series:", data.shape[0])
plt.figure(figsize=(8, 4))
plt.plot(lynx["time"], data)
plt.show()
```

```
Length of time series: 114
```



The time series has a length of 114 (a data point for each year), and by looking at the plot, we can observe seasonality in this dataset, which is the recurrence of similar patterns at specific time periods. e.g. in this dataset, we observe a cyclical pattern every 10 years, but there is also a less obvious but clear spike in the number of trappings every 40 years. Let us see if we can model this effect in NumPyro.

In this tutorial, we will use the first 80 values for training and the last 34 values for testing.

[3]:
```
y_train, y_test = jnp.array(data[:80], dtype=jnp.float32), data[80:]
```

13.2 Model

The model we are going to use is called **Seasonal, Global Trend**, which when tested on 3003 time series of the M-3 competition, has been known to outperform other models originally participating in the competition:

$$\text{exp-val}_t = \text{level}_{t-1} + \text{coef-trend} \times \text{level}_{t-1}^{\text{pow-trend}} + \text{s}_t \times \text{level}_{t-1}^{\text{pow-season}}, \tag{13.1}$$

$$\sigma_t = \sigma \times \text{exp-val}_t^{\text{powx}} + \text{offset}, \tag{13.2}$$

$$y_t \sim \text{StudentT}(\nu, \text{exp-val}_t, \sigma_t) \tag{13.3}$$

, where `level` and `s` follows the following recursion rules:

$$\text{level-p} = \begin{cases} y_t - \text{s}_t \times \text{level}_{t-1}^{\text{pow-season}} & \text{if } t \le \text{seasonality}, \\ \text{Average}\left[y(t - \text{seasonality} + 1), \ldots, y(t)\right] & \text{otherwise}, \end{cases} \tag{13.4}$$

$$\text{level}_t = \text{level-sm} \times \text{level-p} + (1 - \text{level-sm}) \times \text{level}_{t-1}, \tag{13.5}$$

$$\text{s}_{t+\text{seasonality}} = \text{s-sm} \times \frac{y_t - \text{level}_t}{\text{level}_{t-1}^{\text{pow-trend}}} + (1 - \text{s-sm}) \times \text{s}_t. \tag{13.6}$$

A more detailed explanation for SGT model can be found in this vignette from the authors of the Rlgt package. Here we summarize the core ideas of this model:

- Student's t-distribution, which has heavier tails than normal distribution, is used for the likelihood.
- The expected value `exp_val` consists of a trending component and a seasonal component:
- The trend is governed by the map $x \mapsto x + ax^b$, where x is `level`, a is `coef_trend`, and b is `pow_trend`. Note that when $b \sim 0$, the trend is linear with a is the slope, and when $b \sim 1$, the trend is exponential with a is the rate. So that function can cover a large family of trend.
- When time changes, `level` and `s` are updated to new values. Coefficients `level_sm` and `s_sm` are used to make the transition smoothly.
- When `powx` is near 0, the error σ_t will be nearly constant while when `powx` is near 1, the error will be propotional to the expected value.
- There are several varieties of SGT. In this tutorial, we use generalized seasonality and seasonal average method.

We are ready to specify the model using *NumPyro* primitives. In NumPyro, we use the primitive `sample(name, prior)` to declare a latent random variable with a corresponding `prior`. These primitives can have custom interpretations depending on the effect handlers that are used by NumPyro inference algorithms in the backend. e.g. we can condition on specific values using the `condition` handler, or record values at these sample sites in the execution trace using the `trace` handler. Note that these details are not important for specifying the model, or running inference, but curious readers are encouraged to read the tutorial on effect handlers in Pyro.

[4]:
```
def sgt(y, seasonality, future=0):
    # heuristically, standard derivation of Cauchy prior depends on
    # the max value of data
    cauchy_sd = jnp.max(y) / 150

    # NB: priors' parameters are taken from
    # https://github.com/cbergmeir/Rlgt/blob/master/Rlgt/R/rlgtcontrol.R
    nu = numpyro.sample("nu", dist.Uniform(2, 20))
    powx = numpyro.sample("powx", dist.Uniform(0, 1))
    sigma = numpyro.sample("sigma", dist.HalfCauchy(cauchy_sd))
    offset_sigma = numpyro.sample(
        "offset_sigma", dist.TruncatedCauchy(low=1e-10, loc=1e-10, scale=cauchy_sd)
    )

    coef_trend = numpyro.sample("coef_trend", dist.Cauchy(0, cauchy_sd))
    pow_trend_beta = numpyro.sample("pow_trend_beta", dist.Beta(1, 1))
    # pow_trend takes values from -0.5 to 1
    pow_trend = 1.5 * pow_trend_beta - 0.5
    pow_season = numpyro.sample("pow_season", dist.Beta(1, 1))

    level_sm = numpyro.sample("level_sm", dist.Beta(1, 2))
    s_sm = numpyro.sample("s_sm", dist.Uniform(0, 1))
    init_s = numpyro.sample("init_s", dist.Cauchy(0, y[:seasonality] * 0.3))

    def transition_fn(carry, t):
        level, s, moving_sum = carry
        season = s[0] * level ** pow_season
        exp_val = level + coef_trend * level ** pow_trend + season
        exp_val = jnp.clip(exp_val, a_min=0)
        # use expected vale when forecasting
        y_t = jnp.where(t >= N, exp_val, y[t])

        moving_sum = (
            moving_sum + y[t] - jnp.where(t >= seasonality, y[t - seasonality], 0.0)
```

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```
        )
        level_p = jnp.where(t >= seasonality, moving_sum / seasonality, y_t - season)
        level = level_sm * level_p + (1 - level_sm) * level
        level = jnp.clip(level, a_min=0)

        new_s = (s_sm * (y_t - level) / season + (1 - s_sm)) * s[0]
        # repeat s when forecasting
        new_s = jnp.where(t >= N, s[0], new_s)
        s = jnp.concatenate([s[1:], new_s[None]], axis=0)

        omega = sigma * exp_val ** powx + offset_sigma
        y_ = numpyro.sample("y", dist.StudentT(nu, exp_val, omega))

        return (level, s, moving_sum), y_

    N = y.shape[0]
    level_init = y[0]
    s_init = jnp.concatenate([init_s[1:], init_s[:1]], axis=0)
    moving_sum = level_init
    with numpyro.handlers.condition(data={"y": y[1:]}):
        _, ys = scan(
            transition_fn, (level_init, s_init, moving_sum), jnp.arange(1, N + future)
        )
    if future > 0:
        numpyro.deterministic("y_forecast", ys[-future:])
```

Note that `level` and `s` are updated recursively while we collect the expected value at each time step. NumPyro uses JAX in the backend to JIT compile many critical parts of the NUTS algorithm, including the verlet integrator and the tree building process. However, doing so using Python's `for` loop in the model will result in a long compilation time for the model, so we use `scan` - which is a wrapper of lax.scan with supports for NumPyro primitives and handlers. A detailed explanation for using this utility can be found in NumPyro documentation. Here we use it to collect `y` values while the triple `(level, s, moving_sum)` plays the role of carrying state.

Another note is that instead of declaring the observation site `y` in `transition_fn`

```
numpyro.sample("y", dist.StudentT(nu, exp_val, omega), obs=y[t])
```

, we have used condition handler here. The reason is we also want to use this model for forecasting. In forecasting, future values of `y` are non-observable, so `obs=y[t]` does not make sense when `t >= len(y)` (caution: index out-of-bound errors do not get raised in JAX, e.g. `jnp.arange(3)[10] == 2`). Using `condition`, when the length of `scan` is larger than the length of the conditioned/observed site, unobserved values will be sampled from the distribution of that site.

13.3 Inference

First, we want to choose a good value for `seasonality`. Following the demo in Rlgt, we will set `seasonality=38`. Indeed, this value can be guessed by looking at the plot of the training data, where the second order seasonality effect has a periodicity around 40 years. Note that 38 is also one of the highest-autocorrelation lags.

[5]:
```
print("Lag values sorted according to their autocorrelation values:\n")
print(jnp.argsort(autocorrelation(y_train))[::-1])
```

```
Lag values sorted according to their autocorrelation values:

[ 0 67 57 38 68  1 29 58 37 56 28 10 19 39 66 78 47 77  9 79 48 76 30 18
 20 11 46 59 69 27 55 36  2  8 40 49 17 21 75 12 65 45 31 26  7 54 35 41
 50  3 22 60 70 16 44 13  6 25 74 53 42 32 23 43 51  4 15 14 34 24  5 52
 73 64 33 71 72 61 63 62]
```

Now, let us run 4 MCMC chains (using the No-U-Turn Sampler algorithm) with 5000 warmup steps and 5000 sampling steps per each chain. The returned value will be a collection of 20000 samples.

[6]:
```
%%time
kernel = NUTS(sgt)
mcmc = MCMC(kernel, num_warmup=5000, num_samples=5000, num_chains=4)
mcmc.run(random.PRNGKey(0), y_train, seasonality=38)
mcmc.print_summary()
samples = mcmc.get_samples()
```

```
                  mean       std    median      5.0%     95.0%     n_eff     r_hat
     coef_trend     32.33    123.99     12.07    -91.43    157.37   1307.74      1.00
      init_s[0]     84.35    105.16     61.08    -59.71    232.37   4053.35      1.00
      init_s[1]    -21.48     72.05    -26.11   -130.13     94.34   1038.51      1.01
      init_s[2]     26.08     92.13     13.57   -114.83    156.16   1559.02      1.00
      init_s[3]    122.52    123.56    102.67    -59.39    305.43   4317.17      1.00
      init_s[4]    443.91    254.12    395.89     69.08    789.27   3090.34      1.00
      init_s[5]   1163.56    491.37   1079.23    481.92   1861.90   1562.40      1.00
      init_s[6]   1968.70    649.68   1860.04    902.00   2910.49   1974.42      1.00
      init_s[7]   3652.34   1107.27   3505.37   1967.67   5383.26   1669.91      1.00
      init_s[8]   2593.04    831.42   2452.27   1317.67   3858.55   1805.87      1.00
      init_s[9]    947.28    422.29    885.72    311.39   1589.56   3355.27      1.00
     init_s[10]     44.09    102.92     28.38   -105.25    203.73   1367.99      1.00
     init_s[11]     -2.25     52.92     -2.71    -86.51     72.90    611.35      1.01
     init_s[12]    -12.22     64.98    -13.67   -110.07     85.65    892.13      1.01
     init_s[13]     74.43    106.48     53.13    -79.73    225.92    658.08      1.01
     init_s[14]    332.98    255.28    281.72    -11.18    697.96   3685.55      1.00
     init_s[15]    965.80    389.00    893.29    373.98   1521.59   2575.80      1.00
     init_s[16]   1261.12    469.99   1191.83    557.98   1937.38   2300.48      1.00
     init_s[17]   1372.34    559.14   1274.21    483.96   2151.94   2007.79      1.00
     init_s[18]    611.20    313.13    546.56    167.97   1087.74   2854.06      1.00
     init_s[19]     17.81     87.79      8.93   -118.64    143.96   5689.95      1.00
     init_s[20]    -31.84     66.70    -25.15   -146.89     58.97   3083.09      1.00
     init_s[21]    -14.01     44.74     -5.80    -86.03     42.99   2118.09      1.00
     init_s[22]     -2.26     42.99     -2.39    -61.40     66.34   3022.51      1.00
     init_s[23]     43.53     90.60     29.14    -82.56    167.89   3230.17      1.00
     init_s[24]    509.69    326.73    453.22     44.04    975.15   2087.02      1.00
     init_s[25]    919.23    431.15    837.03    284.54   1563.05   3257.27      1.00
     init_s[26]   1783.39    697.15   1660.09    720.83   2811.83   1730.70      1.00
     init_s[27]   1247.60    461.26   1172.88    544.44   1922.68   1573.09      1.00
     init_s[28]    217.92    169.08    191.38    -29.78    456.65   4899.06      1.00
     init_s[29]     -7.43     82.23    -12.99   -133.20    118.31   7588.25      1.00
     init_s[30]     -6.69     86.99    -17.03   -130.99    125.43   1687.37      1.00
     init_s[31]    -35.24     71.31    -35.75   -148.09     76.96   5462.22      1.00
     init_s[32]     -8.63     80.39    -14.95   -138.34    113.89   6626.25      1.00
     init_s[33]    117.38    148.71     91.69    -78.12    316.69   2424.57      1.00
     init_s[34]    502.79    297.08    448.55     87.88    909.45   1863.99      1.00
     init_s[35]   1064.57    445.88    984.10    391.61   1710.35   2584.45      1.00
     init_s[36]   1849.48    632.44   1763.31    861.63   2800.25   1866.47      1.00
     init_s[37]   1452.62    546.57   1382.62    635.28   2257.04   2343.09      1.00
```

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```
        level_sm      0.00      0.00      0.00      0.00      0.00   7829.05      1.00
              nu     12.17      4.73     12.31      5.49     19.99   4979.84      1.00
     offset_sigma     31.82     31.84     22.43      0.01     73.13   1442.32      1.00
       pow_season      0.09      0.04      0.09      0.01      0.15   1091.99      1.00
   pow_trend_beta      0.26      0.18      0.24      0.00      0.52    199.20      1.01
             powx      0.62      0.13      0.62      0.40      0.84   2476.16      1.00
             s_sm      0.08      0.09      0.05      0.00      0.18   5866.57      1.00
            sigma      9.67      9.87      6.61      0.35     20.60   2376.07      1.00

Number of divergences: 4568
CPU times: user 1min 17s, sys: 108 ms, total: 1min 18s
Wall time: 41.2 s
```

13.4 Forecasting

Given `samples` from `mcmc`, we want to do forecasting for the testing dataset `y_test`. NumPyro provides a convenient utility Predictive to get predictive distribution. Let's see how to use it to get forecasting values.

Notice that in the `sgt` model defined above, there is a keyword `future` which controls the execution of the model - depending on whether `future > 0` or `future == 0`. The following code predicts the last 34 values from the original time-series.

[7]:
```
predictive = Predictive(sgt, samples, return_sites=["y_forecast"])
forecast_marginal = predictive(random.PRNGKey(1), y_train, seasonality=38, future=34)[
    "y_forecast"
]
```

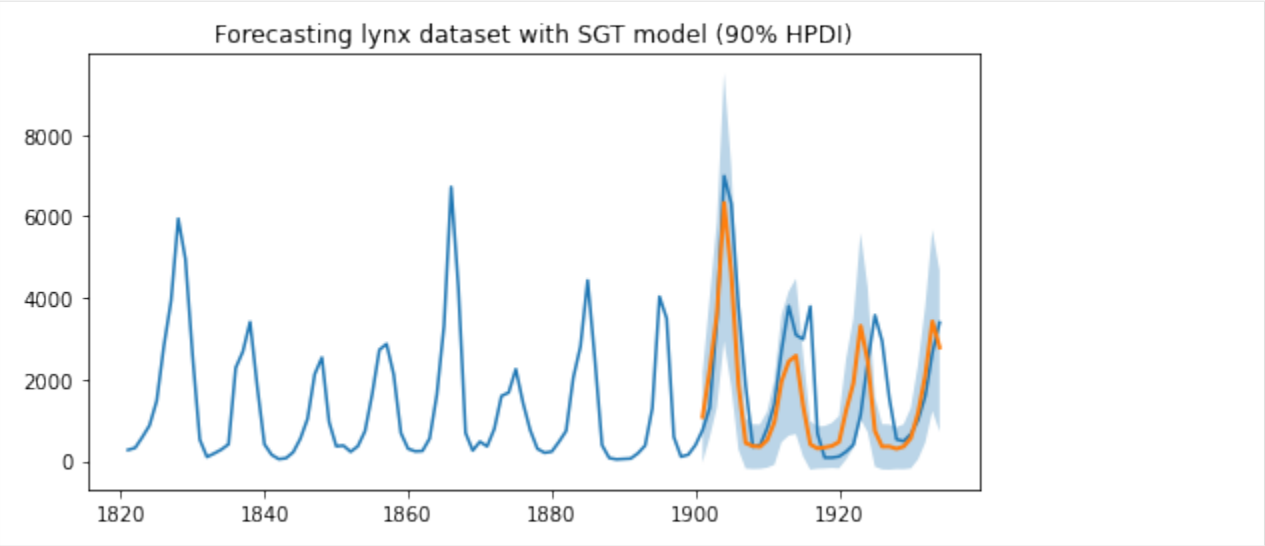
Let's get sMAPE, root mean square error of the prediction, and visualize the result with the mean prediction and the 90% highest posterior density interval (HPDI).

[8]:
```
y_pred = jnp.mean(forecast_marginal, axis=0)
sMAPE = jnp.mean(jnp.abs(y_pred - y_test) / (y_pred + y_test)) * 200
msqrt = jnp.sqrt(jnp.mean((y_pred - y_test) ** 2))
print("sMAPE: {:.2f}, rmse: {:.2f}".format(sMAPE, msqrt))
```

```
sMAPE: 63.93, rmse: 1249.29
```

Finally, let's plot the result to verify that we get the expected one.

[9]:
```
plt.figure(figsize=(8, 4))
plt.plot(lynx["time"], data)
t_future = lynx["time"][80:]
hpd_low, hpd_high = hpdi(forecast_marginal)
plt.plot(t_future, y_pred, lw=2)
plt.fill_between(t_future, hpd_low, hpd_high, alpha=0.3)
plt.title("Forecasting lynx dataset with SGT model (90% HPDI)")
plt.show()
```



As we can observe, the model has been able to learn both the first and second order seasonality effects, i.e. a cyclical pattern with a periodicity of around 10, as well as spikes that can be seen once every 40 or so years. Moreover, we not only have point estimates for the forecast but can also use the uncertainty estimates from the model to bound our forecasts.

13.5 Acknowledgements

We would like to thank Slawek Smyl for many helpful resources and suggestions. Fast inference would not have been possible without the support of JAX and the XLA teams, so we would like to thank them for providing such a great open-source platform for us to build on, and for their responsiveness in dealing with our feature requests and bug reports.

13.6 References

[1] `Rlgt: Bayesian Exponential Smoothing Models with Trend Modifications`, Slawek Smyl, Christoph Bergmeir, Erwin Wibowo, To Wang Ng, Trustees of Columbia University

github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/ordinal_regression.ipynb

CHAPTER 14

Ordinal Regression

Some data are discrete but instrinsically **ordered**, these are called **ordinal** data. One example is the likert scale for questionairs ("this is an informative tutorial": 1. strongly disagree / 2. disagree / 3. neither agree nor disagree / 4. agree / 5. strongly agree). Ordinal data is also ubiquitous in the medical world (e.g. the Glasgow Coma Scale for measuring neurological disfunctioning).

This poses a challenge for statistical modeling as the data do not fit the most well known modelling approaches (e.g. linear regression). Modeling the data as categorical is one possibility, but it disregards the inherent ordering in the data, and may be less statistically efficient. There are multiple appoaches for modeling ordered data. Here we will show how to use the OrderedLogistic distribution using cutpoints that are sampled from a Normal distribution with as additional constrain that the cutpoints they are ordered. For a more in-depth discussion of Bayesian modeling of ordinal data, see e.g. Michael Betancour's blog

[1]:
```
from jax import numpy as np, random
import numpyro
from numpyro import sample
from numpyro.distributions import (Categorical, ImproperUniform, Normal,␣
↪OrderedLogistic,
                                   TransformedDistribution, constraints, transforms)
from numpyro.infer import MCMC, NUTS
import pandas as pd
import seaborn as sns
assert numpyro.__version__.startswith('0.6.0')
```

First, generate some data with ordinal structure

[2]:
```
simkeys  = random.split(random.PRNGKey(1), 2)
nsim     = 50
nclasses = 3
Y        = Categorical(logits=np.zeros(nclasses)).sample(simkeys[0], sample_
↪shape=(nsim,))
X        = Normal().sample(simkeys[1], sample_shape = (nsim,))
X       += Y

print("value counts of Y:")
```

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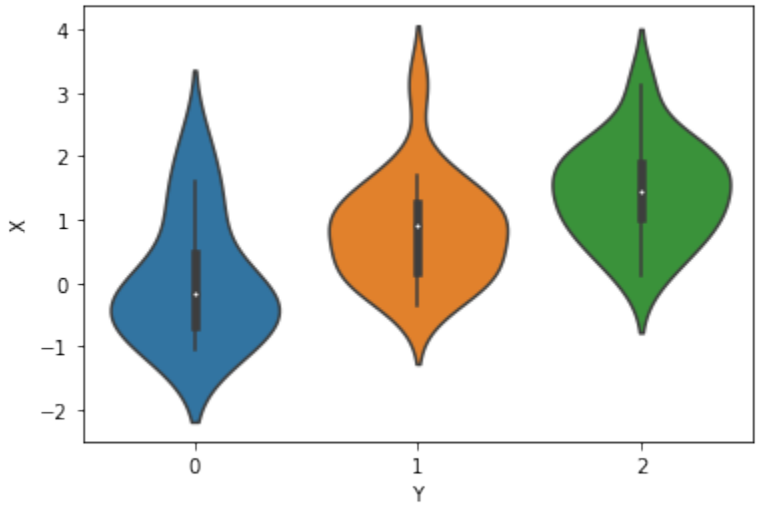
```
df = pd.DataFrame({'X': X, 'Y': Y})
print(df.Y.value_counts())

for i in range(nclasses):
    print(f"mean(X) for Y == {i}: {X[np.where(Y==i)].mean():.3f}")
```

```
value counts of Y:
1    19
2    16
0    15
Name: Y, dtype: int64
mean(X) for Y == 0: 0.042
mean(X) for Y == 1: 0.832
mean(X) for Y == 2: 1.448
```

[3]:
```
sns.violinplot(x='Y', y='X', data=df);
```



We will model the outcomes Y as coming from an OrderedLogistic distribution, conditional on X. The `OrderedLogistic` distribution in numpyro requires ordered cutpoints. We can use the `ImproperUnifrom` distribution to introduce a parameter with an arbitrary support that is otherwise completely uninformative, and then add an `ordered_vector` constraint.

[4]:
```
def model1(X, Y, nclasses=3):
    b_X_eta = sample('b_X_eta', Normal(0, 5))
    c_y     = sample('c_y',     ImproperUniform(support=constraints.ordered_vector,
                                                batch_shape=(),
                                                event_shape=(nclasses-1,)))
    with numpyro.plate('obs', X.shape[0]):
        eta = X * b_X_eta
        sample('Y', OrderedLogistic(eta, c_y), obs=Y)

mcmc_key = random.PRNGKey(1234)
kernel = NUTS(model1)
mcmc   = MCMC(kernel, num_warmup=250, num_samples=750)
mcmc.run(mcmc_key, X,Y, nclasses)
mcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:07<00:00, 126.55it/s, 7 steps of␣
↪size 4.34e-01. acc. prob=0.95]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
   b_X_eta      1.43      0.35      1.42      0.82      1.96    352.72      1.00
    c_y[0]     -0.11      0.41     -0.11     -0.78      0.55    505.85      1.00
    c_y[1]      2.18      0.52      2.15      1.35      2.95    415.22      1.00

Number of divergences: 0
```

The `ImproperUniform` distribution allows us to use parameters with constraints on their domain, without adding any additional information e.g. about the location or scale of the prior distribution on that parameter.

If we want to incorporate such information, for instance that the values of the cut-points should not be too far from zero, we can add an additional `sample` statement that uses another prior, coupled with an `obs` argument. In the example below we first sample cutpoints `c_y` from the `ImproperUniform` distribution with `constraints.ordered_vector` as before, and then `sample` a dummy parameter from a `Normal` distribution while conditioning on `c_y` using `obs=c_y`. Effectively, we've created an improper / unnormalized prior that results from restricting the support of a `Normal` distribution to the ordered domain

[5]:
```
def model2(X, Y, nclasses=3):
    b_X_eta = sample('b_X_eta', Normal(0, 5))
    c_y     = sample('c_y',     ImproperUniform(support=constraints.ordered_vector,
                                                batch_shape=(),
                                                event_shape=(nclasses-1,)))
    sample('c_y_smp', Normal(0,1), obs=c_y)
    with numpyro.plate('obs', X.shape[0]):
        eta = X * b_X_eta
        sample('Y', OrderedLogistic(eta, c_y), obs=Y)

kernel = NUTS(model2)
mcmc   = MCMC(kernel, num_warmup=250, num_samples=750)
mcmc.run(mcmc_key, X,Y, nclasses)
mcmc.print_summary()
```

```
sample: 100%|██████████| 1000/1000 [00:03<00:00, 315.02it/s, 7 steps of␣
↪size 4.80e-01. acc. prob=0.94]

                mean       std    median      5.0%     95.0%     n_eff     r_hat
   b_X_eta      1.23      0.30      1.23      0.69      1.65    535.41      1.00
    c_y[0]     -0.25      0.33     -0.25     -0.82      0.27    461.96      1.00
    c_y[1]      1.76      0.38      1.75      1.10      2.33    588.10      1.00

Number of divergences: 0
```

If having a proper prior for those cutpoints `c_y` is desirable (e.g. to sample from that prior and get prior predictive), we can use TransformedDistribution with an OrderedTransform transform as follows.

[6]:
```
def model3(X, Y, nclasses=3):
    b_X_eta = sample('b_X_eta', Normal(0, 5))
    c_y     = sample("c_y",     TransformedDistribution(Normal(0, 1).expand([nclasses␣
↪- 1]),
                                                        transforms.
↪OrderedTransform()))
    with numpyro.plate('obs', X.shape[0]):
        eta = X * b_X_eta
        sample('Y', OrderedLogistic(eta, c_y), obs=Y)

kernel = NUTS(model3)
```

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```
mcmc   = MCMC(kernel, num_warmup=250, num_samples=750)
mcmc.run(mcmc_key, X,Y, nclasses)
mcmc.print_summary()
```

```
sample: 100%|| 1000/1000 [00:03<00:00, 282.20it/s, 7 steps of␣
↪size 4.84e-01. acc. prob=0.94]
```

```
                mean       std    median      5.0%     95.0%     n_eff     r_hat
   b_X_eta      1.41      0.34      1.40      0.88      2.00    444.42      1.00
    c_y[0]     -0.05      0.36     -0.05     -0.58      0.54    591.60      1.00
    c_y[1]      2.08      0.47      2.07      1.37      2.87    429.27      1.00

Number of divergences: 0
```

github_url https://github.com/pyro-ppl/numpyro/blob/master/notebooks/source/bayesian_imputation.ipynb

CHAPTER 15

Bayesian Imputation

Real-world datasets often contain many missing values. In those situations, we have to either remove those missing data (also known as "complete case") or replace them by some values. Though using complete case is pretty straightforward, it is only applicable when the number of missing entries is so small that throwing away those entries would not affect much the power of the analysis we are conducting on the data. The second strategy, also known as imputation, is more applicable and will be our focus in this tutorial.

Probably the most popular way to perform imputation is to fill a missing value with the mean, median, or mode of its corresponding feature. In that case, we implicitly assume that the feature containing missing values has no correlation with the remaining features of our dataset. This is a pretty strong assumption and might not be true in general. In addition, it does not encode any uncertainty that we might put on those values. Below, we will construct a *Bayesian* setting to resolve those issues. In particular, given a model on the dataset, we will

- create a generative model for the feature with missing value
- and consider missing values as unobserved latent variables.

[1]:
```
# first, we need some imports
import os

from IPython.display import set_matplotlib_formats
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd

from jax import numpy as jnp
from jax import ops, random
from jax.scipy.special import expit

import numpyro
from numpyro import distributions as dist
from numpyro.distributions import constraints
from numpyro.infer import MCMC, NUTS, Predictive

plt.style.use("seaborn")
if "NUMPYRO_SPHINXBUILD" in os.environ:
```

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```
    set_matplotlib_formats("svg")

assert numpyro.__version__.startswith("0.5.0")
```

15.1 Dataset

The data is taken from the competition Titanic: Machine Learning from Disaster hosted on kaggle. It contains information of passengers in the Titanic accident such as name, age, gender,... And our target is to predict if a person is more likely to survive.

[2]:
```
train_df = pd.read_csv(
    "https://raw.githubusercontent.com/agconti/kaggle-titanic/master/data/train.csv"
)
train_df.info()
train_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[2]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
```

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```
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

Look at the data info, we know that there are missing data at `Age`, `Cabin`, and `Embarked` columns. Although `Cabin` is an important feature (because the position of a cabin in the ship can affect the chance of people in that cabin to survive), we will skip it in this tutorial for simplicity. In the dataset, there are many categorical columns and two numerical columns `Age` and `Fare`. Let's first look at the distribution of those categorical columns:

[3]:
```
for col in ["Survived", "Pclass", "Sex", "SibSp", "Parch", "Embarked"]:
    print(train_df[col].value_counts(), end="\n\n")
```

```
0    549
1    342
Name: Survived, dtype: int64

3    491
1    216
2    184
Name: Pclass, dtype: int64

male      577
female    314
Name: Sex, dtype: int64

0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: SibSp, dtype: int64

0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: Parch, dtype: int64

S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

15.2 Prepare data

First, we will merge rare groups in `SibSp` and `Parch` columns together. In addition, we'll fill 2 missing entries in `Embarked` by the mode `S`. Note that we can make a generative model for those missing entries in `Embarked` but let's skip doing so for simplicity.

[4]:
```
train_df.SibSp.clip(0, 1, inplace=True)
train_df.Parch.clip(0, 2, inplace=True)
train_df.Embarked.fillna("S", inplace=True)
```

Looking closer at the data, we can observe that each name contains a title. We know that age is correlated with the title of the name: e.g. those with Mrs. would be older than those with `Miss.` (on average) so it might be good to create that feature. The distribution of titles is:

[5]:
```
train_df.Name.str.split(", ").str.get(1).str.split(" ").str.get(0).value_counts()
```

[5]:
```
Mr.          517
Miss.        182
Mrs.         125
Master.       40
Dr.            7
Rev.           6
Mlle.          2
Major.         2
Col.           2
Ms.            1
Don.           1
the            1
Sir.           1
Lady.          1
Capt.          1
Jonkheer.      1
Mme.           1
Name: Name, dtype: int64
```

We will make a new column `Title`, where rare titles are merged into one group `Misc.`.

[6]:
```
train_df["Title"] = (
    train_df.Name.str.split(", ")
    .str.get(1)
    .str.split(" ")
    .str.get(0)
    .apply(lambda x: x if x in ["Mr.", "Miss.", "Mrs.", "Master."] else "Misc.")
)
```

Now, it is ready to turn the dataframe, which includes categorical values, into numpy arrays. We also perform standardization (a good practice for regression models) for `Age` column.

[7]:
```
title_cat = pd.CategoricalDtype(
    categories=["Mr.", "Miss.", "Mrs.", "Master.", "Misc."], ordered=True
)
embarked_cat = pd.CategoricalDtype(categories=["S", "C", "Q"], ordered=True)
age_mean, age_std = train_df.Age.mean(), train_df.Age.std()
data = dict(
    age=train_df.Age.pipe(lambda x: (x - age_mean) / age_std).values,
    pclass=train_df.Pclass.values - 1,
    title=train_df.Title.astype(title_cat).cat.codes.values,
    sex=(train_df.Sex == "male").astype(int).values,
    sibsp=train_df.SibSp.values,
    parch=train_df.Parch.values,
    embarked=train_df.Embarked.astype(embarked_cat).cat.codes.values,
)
survived = train_df.Survived.values
```

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```
# compute the age mean for each title
age_notnan = data["age"][jnp.isfinite(data["age"])]
title_notnan = data["title"][jnp.isfinite(data["age"])]
age_mean_by_title = jnp.stack([age_notnan[title_notnan == i].mean() for i in␣
↪range(5)])
```

15.3 Modelling

First, we want to note that in NumPyro, the following models

```
def model1a():
    x = numpyro.sample("x", dist.Normal(0, 1).expand([10]))
```

and

```
def model1b():
    x = numpyro.sample("x", dist.Normal(0, 1).expand([10].mask(False))
    numpyro.sample("x_obs", dist.Normal(0, 1).expand([10]), obs=x)
```

are equivalent in the sense that both of them have

- the same latent sites `x` drawn from `dist.Normal(0, 1)` prior,
- and the same log densities `dist.Normal(0, 1).log_prob(x)`.

Now, assume that we observed the last 6 values of `x` (non-observed entries take value `NaN`), the typical model will be

```
def model2a(x):
    x_impute = numpyro.sample("x_impute", dist.Normal(0, 1).expand([4]))
    x_obs = numpyro.sample("x_obs", dist.Normal(0, 1).expand([6]), obs=x[4:])
    x_imputed = jnp.concatenate([x_impute, x_obs])
```

or with the usage of `mask`,

```
def model2b(x):
    x_impute = numpyro.sample("x_impute", dist.Normal(0, 1).expand([4]).mask(False))
    x_imputed = jnp.concatenate([x_impute, x[4:]])
    numpyro.sample("x", dist.Normal(0, 1).expand([10]), obs=x_imputed)
```

Both approaches to model the partial observed data `x` are equivalent. For the model below, we will use the latter method.

[8]:
```
def model(age, pclass, title, sex, sibsp, parch, embarked, survived=None, bayesian_
↪impute=True):
    b_pclass = numpyro.sample("b_Pclass", dist.Normal(0, 1).expand([3]))
    b_title = numpyro.sample("b_Title", dist.Normal(0, 1).expand([5]))
    b_sex = numpyro.sample("b_Sex", dist.Normal(0, 1).expand([2]))
    b_sibsp = numpyro.sample("b_SibSp", dist.Normal(0, 1).expand([2]))
    b_parch = numpyro.sample("b_Parch", dist.Normal(0, 1).expand([3]))
    b_embarked = numpyro.sample("b_Embarked", dist.Normal(0, 1).expand([3]))

    # impute age by Title
    isnan = np.isnan(age)
    age_nanidx = np.nonzero(isnan)[0]
    if bayesian_impute:
```

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```
        age_mu = numpyro.sample("age_mu", dist.Normal(0, 1).expand([5]))
        age_mu = age_mu[title]
        age_sigma = numpyro.sample("age_sigma", dist.Normal(0, 1).expand([5]))
        age_sigma = age_sigma[title]
        age_impute = numpyro.sample(
            "age_impute", dist.Normal(age_mu[age_nanidx], age_sigma[age_nanidx]).
↪mask(False)
        )
        age = ops.index_update(age, age_nanidx, age_impute)
        numpyro.sample("age", dist.Normal(age_mu, age_sigma), obs=age)
    else:
        # fill missing data by the mean of ages for each title
        age_impute = age_mean_by_title[title][age_nanidx]
        age = ops.index_update(age, age_nanidx, age_impute)

    a = numpyro.sample("a", dist.Normal(0, 1))
    b_age = numpyro.sample("b_Age", dist.Normal(0, 1))
    logits = a + b_age * age
    logits = logits + b_title[title] + b_pclass[pclass] + b_sex[sex]
    logits = logits + b_sibsp[sibsp] + b_parch[parch] + b_embarked[embarked]
    numpyro.sample("survived", dist.Bernoulli(logits=logits), obs=survived)
```

Note that in the model, the prior for `age` is `dist.Normal(age_mu, age_sigma)`, where the values of `age_mu` and `age_sigma` depend on `title`. Because there are missing values in `age`, we will encode those missing values in the latent parameter `age_impute`. Then we can replace `NaN` entries in `age` with the vector `age_impute`.

15.4 Sampling

We will use MCMC with NUTS kernel to sample both regression coefficients and imputed values.

[9]:
```
mcmc = MCMC(NUTS(model), 1000, 1000)
mcmc.run(random.PRNGKey(0), **data, survived=survived)
mcmc.print_summary()
```

```
sample: 100%|| 2000/2000 [00:18<00:00, 110.91it/s, 63 steps of␣
↪size 6.48e-02. acc. prob=0.94]
```

```
                   mean       std    median      5.0%     95.0%     n_eff     r_hat
              a      0.18      0.80      0.20     -1.14      1.50   1078.98      1.00
  age_impute[0]      0.23      0.82      0.27     -1.09      1.54   2412.70      1.00
  age_impute[1]     -0.09      0.83     -0.10     -1.34      1.39   1956.25      1.00
  age_impute[2]      0.36      0.80      0.33     -1.01      1.60   1558.35      1.00
  age_impute[3]      0.23      0.90      0.24     -1.23      1.70   2134.81      1.00
  age_impute[4]     -0.65      0.89     -0.61     -2.06      0.82   2027.61      1.00
  age_impute[5]      0.23      0.87      0.23     -1.26      1.50   1777.25      1.00
  age_impute[6]      0.45      0.78      0.45     -0.78      1.66   1428.74      1.00
  age_impute[7]     -0.66      0.91     -0.64     -2.01      0.91   2021.78      1.00
  age_impute[8]     -0.09      0.87     -0.08     -1.41      1.42   1630.14      1.00
  age_impute[9]      0.22      0.89      0.24     -1.42      1.56   1404.25      1.00
 age_impute[10]      0.20      0.87      0.20     -1.16      1.66   2489.31      1.00
 age_impute[11]      0.17      0.85      0.17     -1.28      1.51   2063.14      1.00
 age_impute[12]     -0.66      0.89     -0.62     -2.18      0.72   1632.65      1.00
 age_impute[13]      0.19      0.91      0.17     -1.34      1.64   2394.35      1.00
 age_impute[14]     -0.02      0.85     -0.01     -1.38      1.33   1809.29      1.00
```

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age_impute[15]	0.37	0.84	0.40	-1.04	1.66	1443.69	1.00
age_impute[16]	-1.73	0.25	-1.73	-2.11	-1.30	2062.38	1.00
age_impute[17]	0.22	0.86	0.22	-1.23	1.55	1565.91	1.00
age_impute[18]	0.23	0.90	0.23	-1.28	1.72	1483.35	1.00
age_impute[19]	-0.68	0.86	-0.66	-2.13	0.67	2069.45	1.00
age_impute[20]	0.21	0.89	0.27	-1.39	1.59	1675.83	1.00
age_impute[21]	0.19	0.89	0.22	-1.28	1.56	1984.23	1.00
age_impute[22]	0.19	0.92	0.20	-1.37	1.57	1608.50	1.00
age_impute[23]	-0.14	0.86	-0.13	-1.59	1.26	1890.99	1.00
age_impute[24]	-0.67	0.88	-0.66	-2.14	0.74	1530.94	1.00
age_impute[25]	0.17	0.89	0.19	-1.34	1.55	1767.90	1.00
age_impute[26]	0.19	0.84	0.22	-1.11	1.56	1617.58	1.00
age_impute[27]	-0.70	0.89	-0.68	-2.02	0.89	1761.35	1.00
age_impute[28]	0.60	0.76	0.62	-0.72	1.75	1645.46	1.00
age_impute[29]	0.24	0.85	0.24	-1.13	1.56	2126.36	1.00
age_impute[30]	0.22	0.84	0.23	-1.03	1.69	2796.85	1.00
age_impute[31]	-1.72	0.27	-1.72	-2.15	-1.28	2433.69	1.00
age_impute[32]	0.43	0.86	0.43	-0.93	1.81	1458.56	1.00
age_impute[33]	0.32	0.87	0.33	-1.08	1.70	1583.13	1.00
age_impute[34]	-1.72	0.28	-1.72	-2.19	-1.28	2429.56	1.00
age_impute[35]	-0.43	0.86	-0.42	-1.88	0.90	1451.65	1.00
age_impute[36]	0.30	0.87	0.29	-1.09	1.72	2084.66	1.00
age_impute[37]	0.30	0.83	0.33	-0.98	1.74	1924.58	1.00
age_impute[38]	0.35	0.79	0.33	-0.82	1.73	1980.63	1.00
age_impute[39]	0.19	0.93	0.19	-1.33	1.75	1463.15	1.00
age_impute[40]	-0.65	0.90	-0.67	-2.04	0.85	1548.78	1.00
age_impute[41]	0.20	0.86	0.21	-1.19	1.56	1889.65	1.00
age_impute[42]	0.22	0.88	0.22	-1.39	1.54	1785.76	1.00
age_impute[43]	0.21	0.82	0.23	-1.35	1.36	1663.29	1.00
age_impute[44]	-0.40	0.92	-0.40	-1.96	1.15	1745.40	1.00
age_impute[45]	-0.34	0.86	-0.33	-1.75	1.05	1380.72	1.00
age_impute[46]	-0.30	0.90	-0.30	-1.87	1.10	1237.61	1.00
age_impute[47]	-0.73	0.91	-0.73	-2.13	0.78	1467.82	1.00
age_impute[48]	0.22	0.89	0.22	-1.15	1.84	2169.66	1.00
age_impute[49]	0.43	0.77	0.43	-0.79	1.65	1839.23	1.00
age_impute[50]	0.23	0.86	0.24	-1.30	1.49	1579.39	1.00
age_impute[51]	-0.29	0.88	-0.35	-1.58	1.23	2247.95	1.00
age_impute[52]	0.36	0.82	0.38	-1.13	1.57	1606.92	1.00
age_impute[53]	-0.67	0.94	-0.65	-2.08	0.94	1587.69	1.00
age_impute[54]	0.25	0.90	0.25	-1.07	1.77	2455.98	1.00
age_impute[55]	0.33	0.88	0.33	-0.94	1.88	1593.76	1.00
age_impute[56]	0.39	0.78	0.39	-0.81	1.65	1101.71	1.00
age_impute[57]	-0.01	0.82	-0.03	-1.40	1.25	1532.71	1.00
age_impute[58]	-0.69	0.90	-0.68	-2.09	0.77	1614.68	1.00
age_impute[59]	-0.12	0.88	-0.13	-1.52	1.33	1384.61	1.00
age_impute[60]	-0.62	0.89	-0.61	-2.08	0.77	2116.31	1.00
age_impute[61]	0.22	0.83	0.24	-1.11	1.58	1581.98	1.00
age_impute[62]	-0.59	0.93	-0.60	-2.17	0.88	1528.18	1.00
age_impute[63]	0.20	0.87	0.20	-1.35	1.48	1677.96	1.00
age_impute[64]	-0.69	0.89	-0.67	-2.22	0.70	1877.18	1.00
age_impute[65]	0.41	0.75	0.42	-0.80	1.67	1501.98	1.00
age_impute[66]	0.24	0.96	0.25	-1.25	1.86	2558.45	1.00
age_impute[67]	0.32	0.73	0.34	-0.82	1.55	1678.01	1.00
age_impute[68]	0.34	0.88	0.34	-1.05	1.83	1712.65	1.00
age_impute[69]	0.24	0.92	0.24	-1.15	1.88	1170.47	1.00
age_impute[70]	-0.65	0.89	-0.64	-2.13	0.76	2018.98	1.00
age_impute[71]	-0.67	0.86	-0.69	-2.12	0.64	1625.09	1.00

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age_impute[72]	0.18	0.84	0.17	-1.14	1.53	1929.52	1.00
age_impute[73]	0.38	0.77	0.37	-0.92	1.63	1696.03	1.00
age_impute[74]	-0.67	0.90	-0.66	-2.14	0.81	1683.08	1.00
age_impute[75]	0.44	0.84	0.40	-0.84	1.88	1215.51	1.00
age_impute[76]	0.20	0.86	0.22	-1.24	1.61	1899.12	1.00
age_impute[77]	0.18	0.86	0.16	-1.38	1.44	1809.40	1.00
age_impute[78]	-0.42	0.87	-0.44	-1.79	1.05	2265.80	1.00
age_impute[79]	0.20	0.84	0.20	-1.27	1.50	2009.37	1.00
age_impute[80]	0.25	0.84	0.23	-1.15	1.64	1561.96	1.00
age_impute[81]	0.26	0.88	0.29	-1.20	1.68	2251.52	1.00
age_impute[82]	0.62	0.83	0.62	-0.70	1.98	1502.80	1.00
age_impute[83]	0.21	0.86	0.20	-1.07	1.63	2044.48	1.00
age_impute[84]	0.20	0.86	0.18	-1.30	1.54	1497.56	1.00
age_impute[85]	0.25	0.88	0.24	-1.23	1.72	2379.66	1.00
age_impute[86]	0.31	0.75	0.32	-1.07	1.43	1543.45	1.00
age_impute[87]	-0.13	0.90	-0.10	-1.61	1.41	2132.30	1.00
age_impute[88]	0.21	0.90	0.25	-1.40	1.53	1824.99	1.00
age_impute[89]	0.23	0.93	0.23	-1.29	1.70	2859.52	1.00
age_impute[90]	0.40	0.82	0.39	-1.00	1.73	1416.46	1.00
age_impute[91]	0.24	0.92	0.24	-1.17	1.84	1843.64	1.00
age_impute[92]	0.20	0.83	0.19	-1.18	1.47	1970.14	1.00
age_impute[93]	0.24	0.89	0.26	-1.24	1.66	1831.49	1.00
age_impute[94]	0.21	0.90	0.17	-1.24	1.69	1975.06	1.00
age_impute[95]	0.21	0.88	0.22	-1.22	1.67	1904.83	1.00
age_impute[96]	0.34	0.90	0.33	-1.05	1.81	2090.87	1.00
age_impute[97]	0.27	0.88	0.24	-1.26	1.61	1768.14	1.00
age_impute[98]	-0.40	0.92	-0.40	-1.83	1.12	1787.86	1.00
age_impute[99]	0.16	0.91	0.14	-1.22	1.70	1518.86	1.00
age_impute[100]	0.24	0.86	0.22	-1.21	1.61	1856.56	1.00
age_impute[101]	0.20	0.88	0.21	-1.14	1.76	1967.24	1.00
age_impute[102]	-0.30	0.89	-0.28	-1.76	1.12	1795.47	1.00
age_impute[103]	0.01	0.86	0.01	-1.37	1.38	1416.70	1.00
age_impute[104]	0.25	0.92	0.26	-1.13	1.87	1643.05	1.00
age_impute[105]	0.25	0.85	0.29	-1.24	1.55	1831.86	1.00
age_impute[106]	0.25	0.87	0.24	-1.17	1.72	2185.41	1.00
age_impute[107]	0.21	0.87	0.21	-1.07	1.70	1945.87	1.00
age_impute[108]	0.34	0.86	0.35	-1.03	1.78	1666.87	1.00
age_impute[109]	0.27	0.88	0.22	-0.95	1.93	1470.86	1.00
age_impute[110]	0.32	0.76	0.35	-0.96	1.41	1737.45	1.00
age_impute[111]	0.22	0.86	0.22	-1.25	1.59	2439.65	1.00
age_impute[112]	-0.03	0.86	-0.03	-1.41	1.44	1737.27	1.00
age_impute[113]	0.22	0.87	0.23	-1.32	1.56	1211.30	1.00
age_impute[114]	0.38	0.79	0.36	-0.90	1.65	1416.21	1.00
age_impute[115]	0.20	0.88	0.19	-1.12	1.78	1437.63	1.00
age_impute[116]	0.25	0.86	0.20	-1.26	1.53	1336.80	1.00
age_impute[117]	-0.35	0.91	-0.36	-1.91	1.10	1737.09	1.00
age_impute[118]	0.23	0.94	0.23	-1.18	1.95	2347.76	1.00
age_impute[119]	-0.63	0.93	-0.66	-2.09	0.94	1681.58	1.00
age_impute[120]	0.60	0.80	0.59	-0.54	2.06	1437.89	1.00
age_impute[121]	0.21	0.85	0.23	-1.06	1.69	2152.47	1.00
age_impute[122]	0.22	0.82	0.20	-1.07	1.65	2296.29	1.00
age_impute[123]	-0.38	0.94	-0.39	-2.01	1.03	1557.61	1.00
age_impute[124]	-0.61	0.92	-0.63	-2.13	0.86	1450.41	1.00
age_impute[125]	0.24	0.93	0.23	-1.16	1.74	2397.23	1.00
age_impute[126]	0.21	0.84	0.21	-1.06	1.72	2248.42	1.00
age_impute[127]	0.36	0.87	0.36	-0.96	1.81	1663.20	1.00
age_impute[128]	0.24	0.90	0.25	-1.34	1.62	1790.40	1.00

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age_impute[129]	-0.71	0.88	-0.67	-2.07	0.84	2155.52	1.00
age_impute[130]	0.19	0.85	0.17	-1.29	1.50	1766.80	1.00
age_impute[131]	0.25	0.88	0.25	-1.12	1.76	1891.41	1.00
age_impute[132]	0.32	0.88	0.32	-1.21	1.70	2209.15	1.00
age_impute[133]	0.22	0.89	0.20	-1.21	1.66	1656.09	1.00
age_impute[134]	-0.10	0.91	-0.14	-1.51	1.46	2255.33	1.00
age_impute[135]	0.22	0.85	0.23	-1.04	1.66	1534.46	1.00
age_impute[136]	0.18	0.84	0.17	-1.21	1.55	2292.26	1.00
age_impute[137]	-0.69	0.88	-0.68	-2.29	0.63	2473.01	1.00
age_impute[138]	0.19	0.93	0.18	-1.36	1.65	2256.20	1.00
age_impute[139]	0.20	0.85	0.19	-1.16	1.59	1589.73	1.00
age_impute[140]	0.40	0.79	0.41	-0.90	1.66	2200.96	1.00
age_impute[141]	0.24	0.90	0.22	-1.14	1.73	1805.79	1.00
age_impute[142]	-0.32	0.92	-0.32	-1.82	1.19	1755.92	1.00
age_impute[143]	-0.15	0.86	-0.14	-1.58	1.22	1850.64	1.00
age_impute[144]	-0.67	0.94	-0.66	-2.21	0.80	1812.97	1.00
age_impute[145]	-1.75	0.25	-1.75	-2.17	-1.36	1786.83	1.00
age_impute[146]	0.35	0.84	0.34	-1.02	1.66	2006.44	1.00
age_impute[147]	0.26	0.89	0.27	-1.27	1.61	1800.77	1.00
age_impute[148]	-0.67	0.88	-0.65	-2.13	0.68	1832.48	1.00
age_impute[149]	0.29	0.83	0.29	-1.07	1.59	2181.78	1.00
age_impute[150]	0.22	0.87	0.23	-1.20	1.63	1788.63	1.00
age_impute[151]	0.20	0.87	0.17	-1.19	1.62	1561.13	1.00
age_impute[152]	0.01	0.83	-0.01	-1.35	1.38	2966.42	1.00
age_impute[153]	0.19	0.91	0.22	-1.44	1.55	2302.81	1.00
age_impute[154]	1.06	0.96	1.07	-0.53	2.59	1612.33	1.00
age_impute[155]	0.22	0.81	0.22	-1.08	1.51	1460.31	1.00
age_impute[156]	0.27	0.94	0.25	-1.40	1.75	1409.05	1.00
age_impute[157]	0.22	0.92	0.21	-1.26	1.70	1705.55	1.00
age_impute[158]	0.22	0.87	0.22	-1.08	1.72	1561.10	1.00
age_impute[159]	0.21	0.90	0.22	-1.30	1.56	1366.89	1.00
age_impute[160]	0.18	0.84	0.14	-1.15	1.46	1437.73	1.00
age_impute[161]	-0.49	0.92	-0.52	-1.91	1.09	1357.29	1.00
age_impute[162]	0.37	0.84	0.37	-0.98	1.72	1971.90	1.00
age_impute[163]	0.31	0.84	0.28	-1.05	1.71	1541.32	1.00
age_impute[164]	0.22	0.85	0.21	-1.23	1.60	2056.93	1.00
age_impute[165]	0.23	0.88	0.22	-1.12	1.65	2037.07	1.00
age_impute[166]	-0.11	0.87	-0.11	-1.49	1.33	1851.82	1.00
age_impute[167]	0.21	0.89	0.21	-1.10	1.73	1777.15	1.00
age_impute[168]	0.20	0.83	0.21	-1.12	1.56	1793.28	1.00
age_impute[169]	0.02	0.88	0.01	-1.40	1.43	2410.48	1.00
age_impute[170]	0.16	0.88	0.16	-1.29	1.60	2230.68	1.00
age_impute[171]	0.41	0.83	0.40	-0.96	1.75	1846.52	1.00
age_impute[172]	0.24	0.89	0.22	-1.32	1.54	1852.66	1.00
age_impute[173]	-0.44	0.87	-0.45	-1.92	0.92	2089.83	1.00
age_impute[174]	0.22	0.82	0.23	-1.12	1.55	2427.19	1.00
age_impute[175]	0.22	0.96	0.26	-1.45	1.79	2380.77	1.00
age_impute[176]	-0.43	0.89	-0.41	-1.84	1.06	1803.21	1.00
age_mu[0]	0.19	0.04	0.19	0.12	0.27	1509.52	1.00
age_mu[1]	-0.55	0.08	-0.55	-0.67	-0.43	1224.77	1.00
age_mu[2]	0.42	0.08	0.42	0.30	0.56	1212.38	1.00
age_mu[3]	-1.73	0.04	-1.73	-1.79	-1.64	1274.40	1.00
age_mu[4]	0.85	0.19	0.85	0.55	1.16	1387.85	1.00
age_sigma[0]	0.88	0.03	0.88	0.83	0.93	646.28	1.00
age_sigma[1]	0.90	0.05	0.90	0.82	0.98	1120.20	1.00
age_sigma[2]	0.79	0.05	0.79	0.71	0.88	1113.02	1.00
age_sigma[3]	0.26	0.03	0.25	0.20	0.31	1443.42	1.00

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   age_sigma[4]      0.94      0.13      0.92      0.74      1.16   1106.42      1.00
          b_Age     -0.44      0.13     -0.44     -0.66     -0.24    832.14      1.00
  b_Embarked[0]     -0.30      0.53     -0.30     -1.14      0.59    525.77      1.00
  b_Embarked[1]      0.27      0.54      0.28     -0.65      1.08    572.29      1.00
  b_Embarked[2]      0.02      0.55      0.02     -1.00      0.78    524.41      1.00
     b_Parch[0]      0.44      0.57      0.46     -0.52      1.35    484.44      1.00
     b_Parch[1]      0.10      0.57      0.10     -0.76      1.11    494.90      1.00
     b_Parch[2]     -0.49      0.56     -0.48     -1.42      0.38    498.59      1.00
    b_Pclass[0]      1.16      0.56      1.17      0.32      2.15    475.02      1.00
    b_Pclass[1]      0.02      0.55      0.04     -0.87      0.94    496.89      1.00
    b_Pclass[2]     -1.23      0.56     -1.20     -2.20     -0.37    477.51      1.00
       b_Sex[0]      1.18      0.70      1.16     -0.05      2.24    691.88      1.00
       b_Sex[1]     -1.00      0.69     -1.01     -2.12      0.11    802.26      1.00
     b_SibSp[0]      0.26      0.63      0.28     -0.78      1.25    779.73      1.00
     b_SibSp[1]     -0.19      0.64     -0.18     -1.15      0.91    775.18      1.00
     b_Title[0]     -0.96      0.57     -0.96     -1.85      0.02    521.30      1.00
     b_Title[1]     -0.34      0.62     -0.33     -1.40      0.62    695.62      1.00
     b_Title[2]      0.54      0.63      0.54     -0.42      1.58    672.71      1.00
     b_Title[3]      1.46      0.64      1.46      0.32      2.39    708.52      1.00
     b_Title[4]     -0.66      0.62     -0.68     -1.61      0.49    635.26      1.00

Number of divergences: 0
```

To double check that the assumption "age is correlated with title" is reasonable, let's look at the infered age by title. Recall that we performed standarization on `age`, so here we need to scale back to original domain.

[10]:
```
age_by_title = age_mean + age_std * mcmc.get_samples()["age_mu"].mean(axis=0)
dict(zip(title_cat.categories, age_by_title))
```

[10]:
```
{'Mr.': 32.434227,
 'Miss.': 21.763992,
 'Mrs.': 35.852997,
 'Master.': 4.6297398,
 'Misc.': 42.081936}
```

The infered result confirms our assumption that `Age` is correlated with `Title`:

- those with `Master.` title has pretty small age (in other words, they are children in the ship) comparing to the other groups,
- those with `Mrs.` title have larger age than those with `Miss.` title (in average).

We can also see that the result is similar to the actual statistical mean of `Age` given `Title` in our training dataset:

[11]:
```
train_df.groupby("Title")["Age"].mean()
```

[11]:
```
Title
Master.     4.574167
Misc.      42.384615
Miss.      21.773973
Mr.        32.368090
Mrs.       35.898148
Name: Age, dtype: float64
```

So far so good, we have many information about the regression coefficients together with imputed values and their uncertainties. Let's inspect those results a bit:

- The mean value `-0.44` of `b_Age` implies that those with smaller ages have better chance to survive.

- The mean value `(1.11, -1.07)` of `b_Sex` implies that female passengers have higher chance to survive than male passengers.

15.5 Prediction

In NumPyro, we can use Predictive utility for making predictions from posterior samples. Let's check how well the model performs on the training dataset. For simplicity, we will get a `survived` prediction for each posterior sample and perform the majority rule on the predictions.

[12]:
```
posterior = mcmc.get_samples()
survived_pred = Predictive(model, posterior)(random.PRNGKey(1), **data)["survived"]
survived_pred = (survived_pred.mean(axis=0) >= 0.5).astype(jnp.uint8)
print("Accuracy:", (survived_pred == survived).sum() / survived.shape[0])
confusion_matrix = pd.crosstab(
    pd.Series(survived, name="actual"), pd.Series(survived_pred, name="predict")
)
confusion_matrix / confusion_matrix.sum(axis=1)
```

```
Accuracy: 0.8271605
```

[12]:
```
predict         0         1
actual
0        0.876138  0.198830
1        0.156648  0.748538
```

This is a pretty good result using a simple logistic regression model. Let's see how the model performs if we don't use Bayesian imputation here.

[13]:
```
mcmc.run(random.PRNGKey(2), **data, survived=survived, bayesian_impute=False)
posterior_1 = mcmc.get_samples()
survived_pred_1 = Predictive(model, posterior_1)(random.PRNGKey(2), **data)["survived
↪"]
survived_pred_1 = (survived_pred_1.mean(axis=0) >= 0.5).astype(jnp.uint8)
print("Accuracy:", (survived_pred_1 == survived).sum() / survived.shape[0])
confusion_matrix = pd.crosstab(
    pd.Series(survived, name="actual"), pd.Series(survived_pred_1, name="predict")
)
confusion_matrix / confusion_matrix.sum(axis=1)
confusion_matrix = pd.crosstab(
    pd.Series(survived, name="actual"), pd.Series(survived_pred_1, name="predict")
)
confusion_matrix / confusion_matrix.sum(axis=1)
```

```
sample: 100%|[redacted]| 2000/2000 [00:11<00:00, 166.79it/s, 63 steps of␣
↪size 7.18e-02. acc. prob=0.93]
```

```
Accuracy: 0.82042646
```

[13]:
```
predict         0         1
actual
0        0.872495  0.204678
1        0.163934  0.736842
```

We can see that Bayesian imputation does a little bit better here.

Remark. When using `posterior` samples to perform prediction on the new data, we need to marginalize out `age_impute` because those imputing values are specific to the training data:

```
posterior.pop("age_impute")
survived_pred = Predictive(model, posterior)(random.PRNGKey(3), **new_data)
```

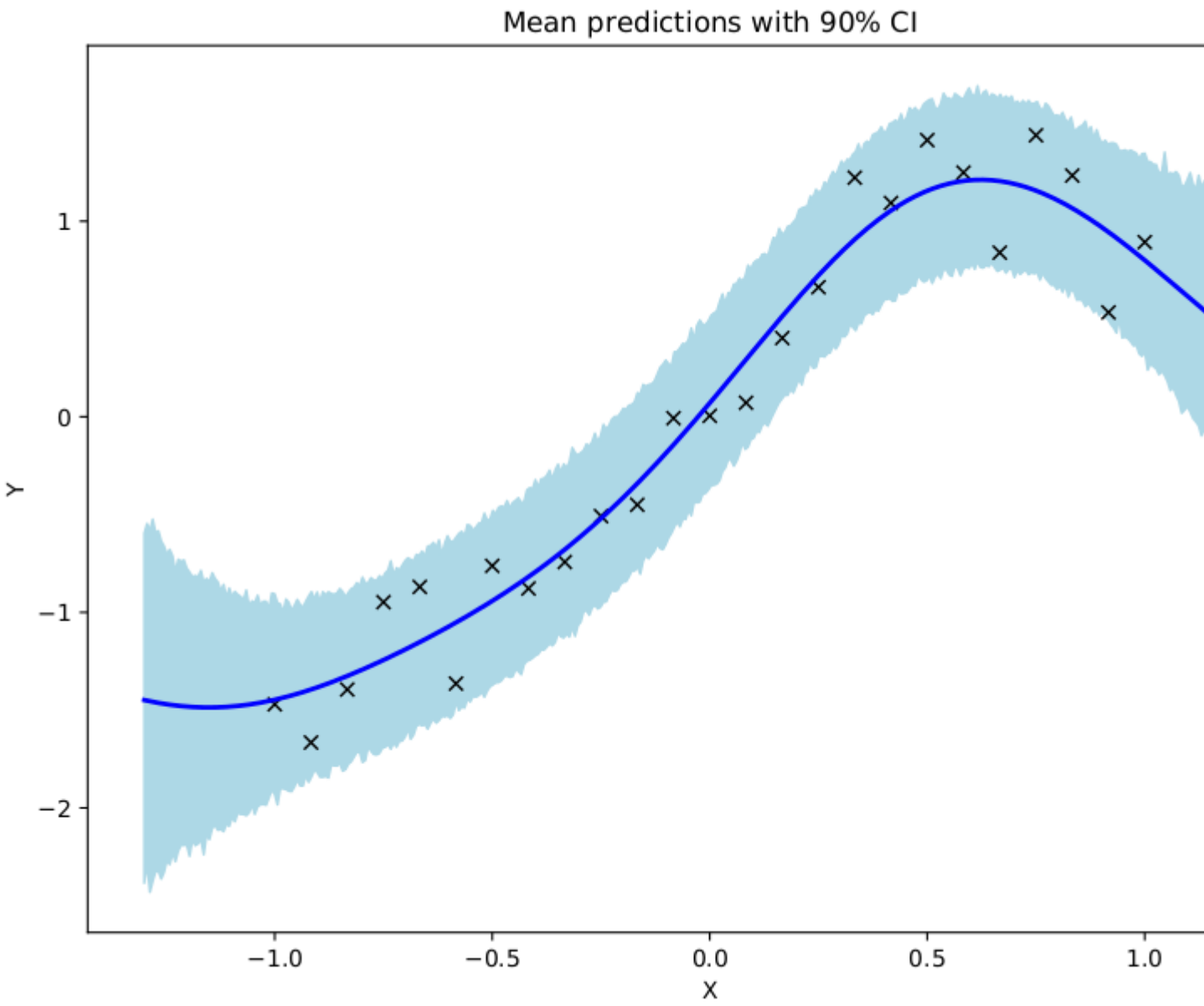
15.6 References

1. McElreath, R. (2016). Statistical Rethinking: A Bayesian Course with Examples in R and Stan.
2. Kaggle competition: Titanic: Machine Learning from Disaster

CHAPTER 16

Example: Gaussian Process

In this example we show how to use NUTS to sample from the posterior over the hyperparameters of a gaussian process.




```
import argparse
import os
import time

import matplotlib
import matplotlib.pyplot as plt
import numpy as np

import jax
from jax import vmap
import jax.numpy as jnp
import jax.random as random

import numpyro
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS, init_to_feasible, init_to_median, init_to_
↪sample, init_to_uniform, init_to_value
```

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```
matplotlib.use('Agg')  # noqa: E402


# squared exponential kernel with diagonal noise term
def kernel(X, Z, var, length, noise, jitter=1.0e-6, include_noise=True):
    deltaXsq = jnp.power((X[:, None] - Z) / length, 2.0)
    k = var * jnp.exp(-0.5 * deltaXsq)
    if include_noise:
        k += (noise + jitter) * jnp.eye(X.shape[0])
    return k


def model(X, Y):
    # set uninformative log-normal priors on our three kernel hyperparameters
    var = numpyro.sample("kernel_var", dist.LogNormal(0.0, 10.0))
    noise = numpyro.sample("kernel_noise", dist.LogNormal(0.0, 10.0))
    length = numpyro.sample("kernel_length", dist.LogNormal(0.0, 10.0))

    # compute kernel
    k = kernel(X, X, var, length, noise)

    # sample Y according to the standard gaussian process formula
    numpyro.sample("Y", dist.MultivariateNormal(loc=jnp.zeros(X.shape[0]), covariance_
↪matrix=k),
                   obs=Y)


# helper function for doing hmc inference
def run_inference(model, args, rng_key, X, Y):
    start = time.time()
    # demonstrate how to use different HMC initialization strategies
    if args.init_strategy == "value":
        init_strategy = init_to_value(values={"kernel_var": 1.0, "kernel_noise": 0.05,
↪ "kernel_length": 0.5})
    elif args.init_strategy == "median":
        init_strategy = init_to_median(num_samples=10)
    elif args.init_strategy == "feasible":
        init_strategy = init_to_feasible()
    elif args.init_strategy == "sample":
        init_strategy = init_to_sample()
    elif args.init_strategy == "uniform":
        init_strategy = init_to_uniform(radius=1)
    kernel = NUTS(model, init_strategy=init_strategy)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
↪ thinning=args.thinning,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, X, Y)
    mcmc.print_summary()
    print('\nMCMC elapsed time:', time.time() - start)
    return mcmc.get_samples()


# do GP prediction for a given set of hyperparameters. this makes use of the well-
↪known
# formula for gaussian process predictions
def predict(rng_key, X, Y, X_test, var, length, noise):
```

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```
    # compute kernels between train and test data, etc.
    k_pp = kernel(X_test, X_test, var, length, noise, include_noise=True)
    k_pX = kernel(X_test, X, var, length, noise, include_noise=False)
    k_XX = kernel(X, X, var, length, noise, include_noise=True)
    K_xx_inv = jnp.linalg.inv(k_XX)
    K = k_pp - jnp.matmul(k_pX, jnp.matmul(K_xx_inv, jnp.transpose(k_pX)))
    sigma_noise = jnp.sqrt(jnp.clip(jnp.diag(K), a_min=0.)) * jax.random.normal(rng_
↪key, X_test.shape[:1])
    mean = jnp.matmul(k_pX, jnp.matmul(K_xx_inv, Y))
    # we return both the mean function and a sample from the posterior predictive for␣
↪the
    # given set of hyperparameters
    return mean, mean + sigma_noise


# create artificial regression dataset
def get_data(N=30, sigma_obs=0.15, N_test=400):
    np.random.seed(0)
    X = jnp.linspace(-1, 1, N)
    Y = X + 0.2 * jnp.power(X, 3.0) + 0.5 * jnp.power(0.5 + X, 2.0) * jnp.sin(4.0 * X)
    Y += sigma_obs * np.random.randn(N)
    Y -= jnp.mean(Y)
    Y /= jnp.std(Y)

    assert X.shape == (N,)
    assert Y.shape == (N,)

    X_test = jnp.linspace(-1.3, 1.3, N_test)

    return X, Y, X_test


def main(args):
    X, Y, X_test = get_data(N=args.num_data)

    # do inference
    rng_key, rng_key_predict = random.split(random.PRNGKey(0))
    samples = run_inference(model, args, rng_key, X, Y)

    # do prediction
    vmap_args = (random.split(rng_key_predict, samples['kernel_var'].shape[0]),
                 samples['kernel_var'], samples['kernel_length'], samples['kernel_
↪noise'])
    means, predictions = vmap(lambda rng_key, var, length, noise:
                              predict(rng_key, X, Y, X_test, var, length,␣
↪noise))(*vmap_args)

    mean_prediction = np.mean(means, axis=0)
    percentiles = np.percentile(predictions, [5.0, 95.0], axis=0)

    # make plots
    fig, ax = plt.subplots(figsize=(8, 6), constrained_layout=True)

    # plot training data
    ax.plot(X, Y, 'kx')
    # plot 90% confidence level of predictions
    ax.fill_between(X_test, percentiles[0, :], percentiles[1, :], color='lightblue')
```

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```
    # plot mean prediction
    ax.plot(X_test, mean_prediction, 'blue', ls='solid', lw=2.0)
    ax.set(xlabel="X", ylabel="Y", title="Mean predictions with 90% CI")

    plt.savefig("gp_plot.pdf")


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Gaussian Process example")
    parser.add_argument("-n", "--num-samples", nargs="?", default=1000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument("--thinning", nargs='?', default=2, type=int)
    parser.add_argument("--num-data", nargs='?', default=25, type=int)
    parser.add_argument("--device", default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    parser.add_argument("--init-strategy", default='median', type=str,
                        choices=['median', 'feasible', 'value', 'uniform', 'sample'])
    args = parser.parse_args()

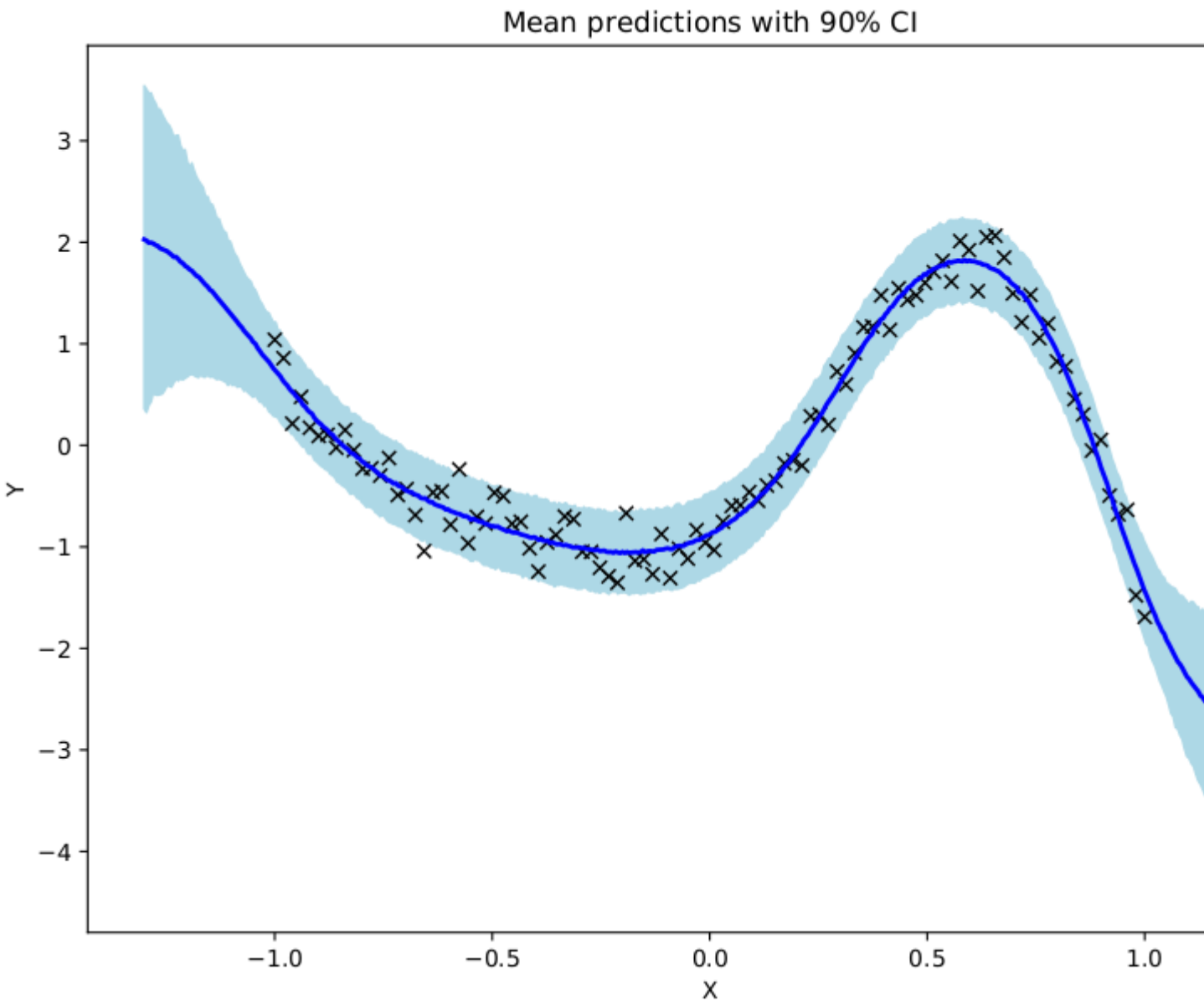
    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 17

Example: Bayesian Neural Network

We demonstrate how to use NUTS to do inference on a simple (small) Bayesian neural network with two hidden layers.




```
import argparse
import os
import time

import matplotlib
import matplotlib.pyplot as plt
import numpy as np

from jax import vmap
import jax.numpy as jnp
import jax.random as random

import numpyro
from numpyro import handlers
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS
```

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```
matplotlib.use('Agg')  # noqa: E402


# the non-linearity we use in our neural network
def nonlin(x):
    return jnp.tanh(x)


# a two-layer bayesian neural network with computational flow
# given by D_X => D_H => D_H => D_Y where D_H is the number of
# hidden units. (note we indicate tensor dimensions in the comments)
def model(X, Y, D_H):

    D_X, D_Y = X.shape[1], 1

    # sample first layer (we put unit normal priors on all weights)
    w1 = numpyro.sample("w1", dist.Normal(jnp.zeros((D_X, D_H)), jnp.ones((D_X, D_
↪H))))  # D_X D_H
    z1 = nonlin(jnp.matmul(X, w1))   # N D_H  <= first layer of activations

    # sample second layer
    w2 = numpyro.sample("w2", dist.Normal(jnp.zeros((D_H, D_H)), jnp.ones((D_H, D_
↪H))))  # D_H D_H
    z2 = nonlin(jnp.matmul(z1, w2))  # N D_H  <= second layer of activations

    # sample final layer of weights and neural network output
    w3 = numpyro.sample("w3", dist.Normal(jnp.zeros((D_H, D_Y)), jnp.ones((D_H, D_
↪Y))))  # D_H D_Y
    z3 = jnp.matmul(z2, w3)  # N D_Y  <= output of the neural network

    # we put a prior on the observation noise
    prec_obs = numpyro.sample("prec_obs", dist.Gamma(3.0, 1.0))
    sigma_obs = 1.0 / jnp.sqrt(prec_obs)

    # observe data
    numpyro.sample("Y", dist.Normal(z3, sigma_obs), obs=Y)


# helper function for HMC inference
def run_inference(model, args, rng_key, X, Y, D_H):
    start = time.time()
    kernel = NUTS(model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, X, Y, D_H)
    mcmc.print_summary()
    print('\nMCMC elapsed time:', time.time() - start)
    return mcmc.get_samples()


# helper function for prediction
def predict(model, rng_key, samples, X, D_H):
    model = handlers.substitute(handlers.seed(model, rng_key), samples)
    # note that Y will be sampled in the model because we pass Y=None here
    model_trace = handlers.trace(model).get_trace(X=X, Y=None, D_H=D_H)
    return model_trace['Y']['value']
```

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```
# create artificial regression dataset
def get_data(N=50, D_X=3, sigma_obs=0.05, N_test=500):
    D_Y = 1  # create 1d outputs
    np.random.seed(0)
    X = jnp.linspace(-1, 1, N)
    X = jnp.power(X[:, np.newaxis], jnp.arange(D_X))
    W = 0.5 * np.random.randn(D_X)
    Y = jnp.dot(X, W) + 0.5 * jnp.power(0.5 + X[:, 1], 2.0) * jnp.sin(4.0 * X[:, 1])
    Y += sigma_obs * np.random.randn(N)
    Y = Y[:, np.newaxis]
    Y -= jnp.mean(Y)
    Y /= jnp.std(Y)

    assert X.shape == (N, D_X)
    assert Y.shape == (N, D_Y)

    X_test = jnp.linspace(-1.3, 1.3, N_test)
    X_test = jnp.power(X_test[:, np.newaxis], jnp.arange(D_X))

    return X, Y, X_test


def main(args):
    N, D_X, D_H = args.num_data, 3, args.num_hidden
    X, Y, X_test = get_data(N=N, D_X=D_X)

    # do inference
    rng_key, rng_key_predict = random.split(random.PRNGKey(0))
    samples = run_inference(model, args, rng_key, X, Y, D_H)

    # predict Y_test at inputs X_test
    vmap_args = (samples, random.split(rng_key_predict, args.num_samples * args.num_
↪chains))
    predictions = vmap(lambda samples, rng_key: predict(model, rng_key, samples, X_
↪test, D_H))(*vmap_args)
    predictions = predictions[..., 0]

    # compute mean prediction and confidence interval around median
    mean_prediction = jnp.mean(predictions, axis=0)
    percentiles = np.percentile(predictions, [5.0, 95.0], axis=0)

    # make plots
    fig, ax = plt.subplots(figsize=(8, 6), constrained_layout=True)

    # plot training data
    ax.plot(X[:, 1], Y[:, 0], 'kx')
    # plot 90% confidence level of predictions
    ax.fill_between(X_test[:, 1], percentiles[0, :], percentiles[1, :], color=
↪'lightblue')
    # plot mean prediction
    ax.plot(X_test[:, 1], mean_prediction, 'blue', ls='solid', lw=2.0)
    ax.set(xlabel="X", ylabel="Y", title="Mean predictions with 90% CI")

    plt.savefig('bnn_plot.pdf')
```

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```
if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Bayesian neural network example")
    parser.add_argument("-n", "--num-samples", nargs="?", default=2000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument("--num-data", nargs='?', default=100, type=int)
    parser.add_argument("--num-hidden", nargs='?', default=5, type=int)
    parser.add_argument("--device", default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 18

Example: Sparse Regression

We demonstrate how to do (fully Bayesian) sparse linear regression using the approach described in [1]. This approach is particularly suitable for situations with many feature dimensions (large P) but not too many datapoints (small N). In particular we consider a quadratic regressor of the form:

$$f(X) = \text{constant} + \sum_i \theta_i X_i + \sum_{i<j} \theta_{ij} X_i X_j + \text{observation noise}$$

References:

1. Raj Agrawal, Jonathan H. Huggins, Brian Trippe, Tamara Broderick (2019), "The Kernel Interaction Trick: Fast Bayesian Discovery of Pairwise Interactions in High Dimensions", (https://arxiv.org/abs/1905.06501)


```
import argparse
import itertools
import os
import time

import numpy as np

import jax
from jax import vmap
import jax.numpy as jnp
import jax.random as random
from jax.scipy.linalg import cho_factor, cho_solve, solve_triangular

import numpyro
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS


def dot(X, Z):
    return jnp.dot(X, Z[..., None])[..., 0]


# The kernel that corresponds to our quadratic regressor.
```

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```
def kernel(X, Z, eta1, eta2, c, jitter=1.0e-4):
    eta1sq = jnp.square(eta1)
    eta2sq = jnp.square(eta2)
    k1 = 0.5 * eta2sq * jnp.square(1.0 + dot(X, Z))
    k2 = -0.5 * eta2sq * dot(jnp.square(X), jnp.square(Z))
    k3 = (eta1sq - eta2sq) * dot(X, Z)
    k4 = jnp.square(c) - 0.5 * eta2sq
    if X.shape == Z.shape:
        k4 += jitter * jnp.eye(X.shape[0])
    return k1 + k2 + k3 + k4


# Most of the model code is concerned with constructing the sparsity inducing prior.
def model(X, Y, hypers):
    S, P, N = hypers['expected_sparsity'], X.shape[1], X.shape[0]

    sigma = numpyro.sample("sigma", dist.HalfNormal(hypers['alpha3']))
    phi = sigma * (S / jnp.sqrt(N)) / (P - S)
    eta1 = numpyro.sample("eta1", dist.HalfCauchy(phi))

    msq = numpyro.sample("msq", dist.InverseGamma(hypers['alpha1'], hypers['beta1']))
    xisq = numpyro.sample("xisq", dist.InverseGamma(hypers['alpha2'], hypers['beta2
↪']))

    eta2 = jnp.square(eta1) * jnp.sqrt(xisq) / msq

    lam = numpyro.sample("lambda", dist.HalfCauchy(jnp.ones(P)))
    kappa = jnp.sqrt(msq) * lam / jnp.sqrt(msq + jnp.square(eta1 * lam))

    # compute kernel
    kX = kappa * X
    k = kernel(kX, kX, eta1, eta2, hypers['c']) + sigma ** 2 * jnp.eye(N)
    assert k.shape == (N, N)

    # sample Y according to the standard gaussian process formula
    numpyro.sample("Y", dist.MultivariateNormal(loc=jnp.zeros(X.shape[0]), covariance_
↪matrix=k),
                   obs=Y)


# Compute the mean and variance of coefficient theta_i (where i = dimension) for a
# MCMC sample of the kernel hyperparameters (eta1, xisq, ...).
# Compare to theorem 5.1 in reference [1].
def compute_singleton_mean_variance(X, Y, dimension, msq, lam, eta1, xisq, c, sigma):
    P, N = X.shape[1], X.shape[0]

    probe = jnp.zeros((2, P))
    probe = jax.ops.index_update(probe, jax.ops.index[:, dimension], jnp.array([1.0, -
↪1.0]))

    eta2 = jnp.square(eta1) * jnp.sqrt(xisq) / msq
    kappa = jnp.sqrt(msq) * lam / jnp.sqrt(msq + jnp.square(eta1 * lam))

    kX = kappa * X
    kprobe = kappa * probe

    k_xx = kernel(kX, kX, eta1, eta2, c) + sigma ** 2 * jnp.eye(N)
```

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```
    k_xx_inv = jnp.linalg.inv(k_xx)
    k_probeX = kernel(kprobe, kX, eta1, eta2, c)
    k_prbprb = kernel(kprobe, kprobe, eta1, eta2, c)

    vec = jnp.array([0.50, -0.50])
    mu = jnp.matmul(k_probeX, jnp.matmul(k_xx_inv, Y))
    mu = jnp.dot(mu, vec)

    var = k_prbprb - jnp.matmul(k_probeX, jnp.matmul(k_xx_inv, jnp.transpose(k_
↪probeX)))
    var = jnp.matmul(var, vec)
    var = jnp.dot(var, vec)

    return mu, var


# Compute the mean and variance of coefficient theta_ij for a MCMC sample of the
# kernel hyperparameters (eta1, xisq, ...). Compare to theorem 5.1 in reference [1].
def compute_pairwise_mean_variance(X, Y, dim1, dim2, msq, lam, eta1, xisq, c, sigma):
    P, N = X.shape[1], X.shape[0]

    probe = jnp.zeros((4, P))
    probe = jax.ops.index_update(probe, jax.ops.index[:, dim1], jnp.array([1.0, 1.0, -
↪1.0, -1.0]))
    probe = jax.ops.index_update(probe, jax.ops.index[:, dim2], jnp.array([1.0, -1.0,␣
↪1.0, -1.0]))

    eta2 = jnp.square(eta1) * jnp.sqrt(xisq) / msq
    kappa = jnp.sqrt(msq) * lam / jnp.sqrt(msq + jnp.square(eta1 * lam))

    kX = kappa * X
    kprobe = kappa * probe

    k_xx = kernel(kX, kX, eta1, eta2, c) + sigma ** 2 * jnp.eye(N)
    k_xx_inv = jnp.linalg.inv(k_xx)
    k_probeX = kernel(kprobe, kX, eta1, eta2, c)
    k_prbprb = kernel(kprobe, kprobe, eta1, eta2, c)

    vec = jnp.array([0.25, -0.25, -0.25, 0.25])
    mu = jnp.matmul(k_probeX, jnp.matmul(k_xx_inv, Y))
    mu = jnp.dot(mu, vec)

    var = k_prbprb - jnp.matmul(k_probeX, jnp.matmul(k_xx_inv, jnp.transpose(k_
↪probeX)))
    var = jnp.matmul(var, vec)
    var = jnp.dot(var, vec)

    return mu, var


# Sample coefficients theta from the posterior for a given MCMC sample.
# The first P returned values are {theta_1, theta_2, ...., theta_P}, while
# the remaining values are {theta_ij} for i,j in the list `active_dims`,
# sorted so that i < j.
def sample_theta_space(X, Y, active_dims, msq, lam, eta1, xisq, c, sigma):
    P, N, M = X.shape[1], X.shape[0], len(active_dims)
    # the total number of coefficients we return
```

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```
    num_coefficients = P + M * (M - 1) // 2

    probe = jnp.zeros((2 * P + 2 * M * (M - 1), P))
    vec = jnp.zeros((num_coefficients, 2 * P + 2 * M * (M - 1)))
    start1 = 0
    start2 = 0

    for dim in range(P):
        probe = jax.ops.index_update(probe, jax.ops.index[start1:start1 + 2, dim],␣
↪jnp.array([1.0, -1.0]))
        vec = jax.ops.index_update(vec, jax.ops.index[start2, start1:start1 + 2], jnp.
↪array([0.5, -0.5]))
        start1 += 2
        start2 += 1

    for dim1 in active_dims:
        for dim2 in active_dims:
            if dim1 >= dim2:
                continue
            probe = jax.ops.index_update(probe, jax.ops.index[start1:start1 + 4,␣
↪dim1],
                                         jnp.array([1.0, 1.0, -1.0, -1.0]))
            probe = jax.ops.index_update(probe, jax.ops.index[start1:start1 + 4,␣
↪dim2],
                                         jnp.array([1.0, -1.0, 1.0, -1.0]))
            vec = jax.ops.index_update(vec, jax.ops.index[start2, start1:start1 + 4],
                                       jnp.array([0.25, -0.25, -0.25, 0.25]))
            start1 += 4
            start2 += 1

    eta2 = jnp.square(eta1) * jnp.sqrt(xisq) / msq
    kappa = jnp.sqrt(msq) * lam / jnp.sqrt(msq + jnp.square(eta1 * lam))

    kX = kappa * X
    kprobe = kappa * probe

    k_xx = kernel(kX, kX, eta1, eta2, c) + sigma ** 2 * jnp.eye(N)
    L = cho_factor(k_xx, lower=True)[0]
    k_probeX = kernel(kprobe, kX, eta1, eta2, c)
    k_prbprb = kernel(kprobe, kprobe, eta1, eta2, c)

    mu = jnp.matmul(k_probeX, cho_solve((L, True), Y))
    mu = jnp.sum(mu * vec, axis=-1)

    Linv_k_probeX = solve_triangular(L, jnp.transpose(k_probeX), lower=True)
    covar = k_prbprb - jnp.matmul(jnp.transpose(Linv_k_probeX), Linv_k_probeX)
    covar = jnp.matmul(vec, jnp.matmul(covar, jnp.transpose(vec)))

    # sample from N(mu, covar)
    L = jnp.linalg.cholesky(covar)
    sample = mu + jnp.matmul(L, np.random.randn(num_coefficients))

    return sample


# Helper function for doing HMC inference
def run_inference(model, args, rng_key, X, Y, hypers):
```

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```
    start = time.time()
    kernel = NUTS(model)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, X, Y, hypers)
    mcmc.print_summary()
    print('\nMCMC elapsed time:', time.time() - start)
    return mcmc.get_samples()


# Get the mean and variance of a gaussian mixture
def gaussian_mixture_stats(mus, variances):
    mean_mu = jnp.mean(mus)
    mean_var = jnp.mean(variances) + jnp.mean(jnp.square(mus)) - jnp.square(mean_mu)
    return mean_mu, mean_var


# Create artificial regression dataset where only S out of P feature
# dimensions contain signal and where there is a single pairwise interaction
# between the first and second dimensions.
def get_data(N=20, S=2, P=10, sigma_obs=0.05):
    assert S < P and P > 1 and S > 0
    np.random.seed(0)

    X = np.random.randn(N, P)
    # generate S coefficients with non-negligible magnitude
    W = 0.5 + 2.5 * np.random.rand(S)
    # generate data using the S coefficients and a single pairwise interaction
    Y = np.sum(X[:, 0:S] * W, axis=-1) + X[:, 0] * X[:, 1] + sigma_obs * np.random.
↪randn(N)
    Y -= jnp.mean(Y)
    Y_std = jnp.std(Y)

    assert X.shape == (N, P)
    assert Y.shape == (N,)

    return X, Y / Y_std, W / Y_std, 1.0 / Y_std


# Helper function for analyzing the posterior statistics for coefficient theta_i
def analyze_dimension(samples, X, Y, dimension, hypers):
    vmap_args = (samples['msq'], samples['lambda'], samples['eta1'], samples['xisq'],␣
↪samples['sigma'])
    mus, variances = vmap(lambda msq, lam, eta1, xisq, sigma:
                          compute_singleton_mean_variance(X, Y, dimension, msq, lam,
                                                          eta1, xisq, hypers['c'],␣
↪sigma))(*vmap_args)
    mean, variance = gaussian_mixture_stats(mus, variances)
    std = jnp.sqrt(variance)
    return mean, std


# Helper function for analyzing the posterior statistics for coefficient theta_ij
def analyze_pair_of_dimensions(samples, X, Y, dim1, dim2, hypers):
    vmap_args = (samples['msq'], samples['lambda'], samples['eta1'], samples['xisq'],␣
↪samples['sigma'])
    mus, variances = vmap(lambda msq, lam, eta1, xisq, sigma:
```

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```
                            compute_pairwise_mean_variance(X, Y, dim1, dim2, msq, lam,
                                                           eta1, xisq, hypers['c'],␣
↪sigma))(*vmap_args)
    mean, variance = gaussian_mixture_stats(mus, variances)
    std = jnp.sqrt(variance)
    return mean, std


def main(args):
    X, Y, expected_thetas, expected_pairwise = get_data(N=args.num_data, P=args.num_
↪dimensions,
                                                        S=args.active_dimensions)

    # setup hyperparameters
    hypers = {'expected_sparsity': max(1.0, args.num_dimensions / 10),
              'alpha1': 3.0, 'beta1': 1.0,
              'alpha2': 3.0, 'beta2': 1.0,
              'alpha3': 1.0, 'c': 1.0}

    # do inference
    rng_key = random.PRNGKey(0)
    samples = run_inference(model, args, rng_key, X, Y, hypers)

    # compute the mean and square root variance of each coefficient theta_i
    means, stds = vmap(lambda dim: analyze_dimension(samples, X, Y, dim, hypers))(jnp.
↪arange(args.num_dimensions))

    print("Coefficients theta_1 to theta_%d used to generate the data:" % args.active_
↪dimensions, expected_thetas)
    print("The single quadratic coefficient theta_{1,2} used to generate the data:",␣
↪expected_pairwise)
    active_dimensions = []

    for dim, (mean, std) in enumerate(zip(means, stds)):
        # we mark the dimension as inactive if the interval [mean - 3 * std, mean + 3␣
↪* std] contains zero
        lower, upper = mean - 3.0 * std, mean + 3.0 * std
        inactive = "inactive" if lower < 0.0 and upper > 0.0 else "active"
        if inactive == "active":
            active_dimensions.append(dim)
        print("[dimension %02d/%02d]  %s:\t%.2e +- %.2e" % (dim + 1, args.num_
↪dimensions, inactive, mean, std))

    print("Identified a total of %d active dimensions; expected %d." % (len(active_
↪dimensions),
                                                                        args.active_
↪dimensions))

    # Compute the mean and square root variance of coefficients theta_ij for i,j␣
↪active dimensions.
    # Note that the resulting numbers are only meaningful for i != j.
    if len(active_dimensions) > 0:
        dim_pairs = jnp.array(list(itertools.product(active_dimensions, active_
↪dimensions)))
        means, stds = vmap(lambda dim_pair: analyze_pair_of_dimensions(samples, X, Y,
                                                                       dim_pair[0],␣
↪dim_pair[1], hypers))(dim_pairs)
```

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```
        for dim_pair, mean, std in zip(dim_pairs, means, stds):
            dim1, dim2 = dim_pair
            if dim1 >= dim2:
                continue
            lower, upper = mean - 3.0 * std, mean + 3.0 * std
            if not (lower < 0.0 and upper > 0.0):
                format_str = "Identified pairwise interaction between dimensions %d␣
↪and %d: %.2e +- %.2e"
                print(format_str % (dim1 + 1, dim2 + 1, mean, std))

        # Draw a single sample of coefficients theta from the posterior, where we␣
↪return all singleton
        # coefficients theta_i and pairwise coefficients theta_ij for i, j active␣
↪dimensions. We use the
        # final MCMC sample obtained from the HMC sampler.
        thetas = sample_theta_space(X, Y, active_dimensions, samples['msq'][-1],␣
↪samples['lambda'][-1],
                                    samples['eta1'][-1], samples['xisq'][-1], hypers[
↪'c'], samples['sigma'][-1])
        print("Single posterior sample theta:\n", thetas)


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="Gaussian Process example")
    parser.add_argument("-n", "--num-samples", nargs="?", default=1000, type=int)
    parser.add_argument("--num-warmup", nargs='?', default=500, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument("--num-data", nargs='?', default=100, type=int)
    parser.add_argument("--num-dimensions", nargs='?', default=20, type=int)
    parser.add_argument("--active-dimensions", nargs='?', default=3, type=int)
    parser.add_argument("--device", default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 19

Example: Proportion Test

You are managing a business and want to test if calling your customers will increase their chance of making a purchase. You get 100,000 customer records and call roughly half of them and record if they make a purchase in the next three months. You do the same for the half that did not get called. After three months, the data is in - did calling help?

This example answers this question by estimating a logistic regression model where the covariates are whether the customer got called and their gender. We place a multivariate normal prior on the regression coefficients. We report the 95% highest posterior density interval for the effect of making a call.

```
import argparse
import os
from typing import Tuple

from jax import random
import jax.numpy as jnp
from jax.scipy.special import expit

import numpyro
from numpyro.diagnostics import hpdi
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS


def make_dataset(rng_key) -> Tuple[jnp.ndarray, jnp.ndarray]:
    """
    Make simulated dataset where potential customers who get a
    sales calls have ~2% higher chance of making another purchase.
    """
    key1, key2, key3 = random.split(rng_key, 3)

    num_calls = 51342
    num_no_calls = 48658

    made_purchase_got_called = dist.Bernoulli(0.084).sample(key1, sample_shape=(num_
↪calls,))
```

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```
    made_purchase_no_calls = dist.Bernoulli(0.061).sample(key2, sample_shape=(num_no_
↪calls,))

    made_purchase = jnp.concatenate([made_purchase_got_called, made_purchase_no_
↪calls])

    is_female = dist.Bernoulli(0.5).sample(key3, sample_shape=(num_calls + num_no_
↪calls,))
    got_called = jnp.concatenate([jnp.ones(num_calls), jnp.zeros(num_no_calls)])
    design_matrix = jnp.hstack([jnp.ones((num_no_calls + num_calls, 1)),
                                got_called.reshape(-1, 1),
                                is_female.reshape(-1, 1)])

    return design_matrix, made_purchase


def model(design_matrix: jnp.ndarray, outcome: jnp.ndarray = None) -> None:
    """
    Model definition: Log odds of making a purchase is a linear combination
    of covariates. Specify a Normal prior over regression coefficients.
    :param design_matrix: Covariates. All categorical variables have been one-hot
        encoded.
    :param outcome: Binary response variable. In this case, whether or not the
        customer made a purchase.
    """

    beta = numpyro.sample('coefficients', dist.MultivariateNormal(loc=0.,
                                                                  covariance_
↪matrix=jnp.eye(design_matrix.shape[1])))
    logits = design_matrix.dot(beta)

    with numpyro.plate('data', design_matrix.shape[0]):
        numpyro.sample('obs', dist.Bernoulli(logits=logits), obs=outcome)


def print_results(coef: jnp.ndarray, interval_size: float = 0.95) -> None:
    """
    Print the confidence interval for the effect size with interval_size
    probability mass.
    """

    baseline_response = expit(coef[:, 0])
    response_with_calls = expit(coef[:, 0] + coef[:, 1])

    impact_on_probability = hpdi(response_with_calls - baseline_response,␣
↪prob=interval_size)

    effect_of_gender = hpdi(coef[:, 2], prob=interval_size)

    print(f"There is a {interval_size * 100}% probability that calling customers "
          "increases the chance they'll make a purchase by "
          f"{(100 * impact_on_probability[0]):.2} to {(100 * impact_on_
↪probability[1]):.2} percentage points."
          )

    print(f"There is a {interval_size * 100}% probability the effect of gender on the␣
↪log odds of conversion "
```

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```
          f"lies in the interval ({effect_of_gender[0]:.2}, {effect_of_gender[1]:.2f}
↪)."
          " Since this interval contains 0, we can conclude gender does not impact␣
↪the conversion rate.")


def run_inference(design_matrix: jnp.ndarray, outcome: jnp.ndarray,
                  rng_key: jnp.ndarray,
                  num_warmup: int,
                  num_samples: int, num_chains: int,
                  interval_size: float = 0.95) -> None:
    """
    Estimate the effect size.
    """

    kernel = NUTS(model)
    mcmc = MCMC(kernel, num_warmup, num_samples, num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, design_matrix, outcome)

    # 0th column is intercept (not getting called)
    # 1st column is effect of getting called
    # 2nd column is effect of gender (should be none since assigned at random)
    coef = mcmc.get_samples()['coefficients']
    print_results(coef, interval_size)


def main(args):
    rng_key, _ = random.split(random.PRNGKey(3))
    design_matrix, response = make_dataset(rng_key)
    run_inference(design_matrix, response, rng_key,
                  args.num_warmup,
                  args.num_samples,
                  args.num_chains,
                  args.interval_size)


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description='Testing whether  ')
    parser.add_argument('-n', '--num-samples', nargs='?', default=500, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=1500, type=int)
    parser.add_argument('--num-chains', nargs='?', default=1, type=int)
    parser.add_argument('--interval-size', nargs='?', default=0.95, type=float)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 20

Example: Generalized Linear Mixed Models

The UCBadmit data is sourced from the study [1] of gender biased in graduate admissions at UC Berkeley in Fall 1973:

Table 1: UCBadmit dataset

dept	male	applications	admit
0	1	825	512
0	0	108	89
1	1	560	353
1	0	25	17
2	1	325	120
2	0	593	202
3	1	417	138
3	0	375	131
4	1	191	53
4	0	393	94
5	1	373	22
5	0	341	24

This example replicates the multilevel model *m_glmm5* at [3], which is used to evaluate whether the data contain evidence of gender biased in admissions accross departments. This is a form of Generalized Linear Mixed Models for binomial regression problem, which models

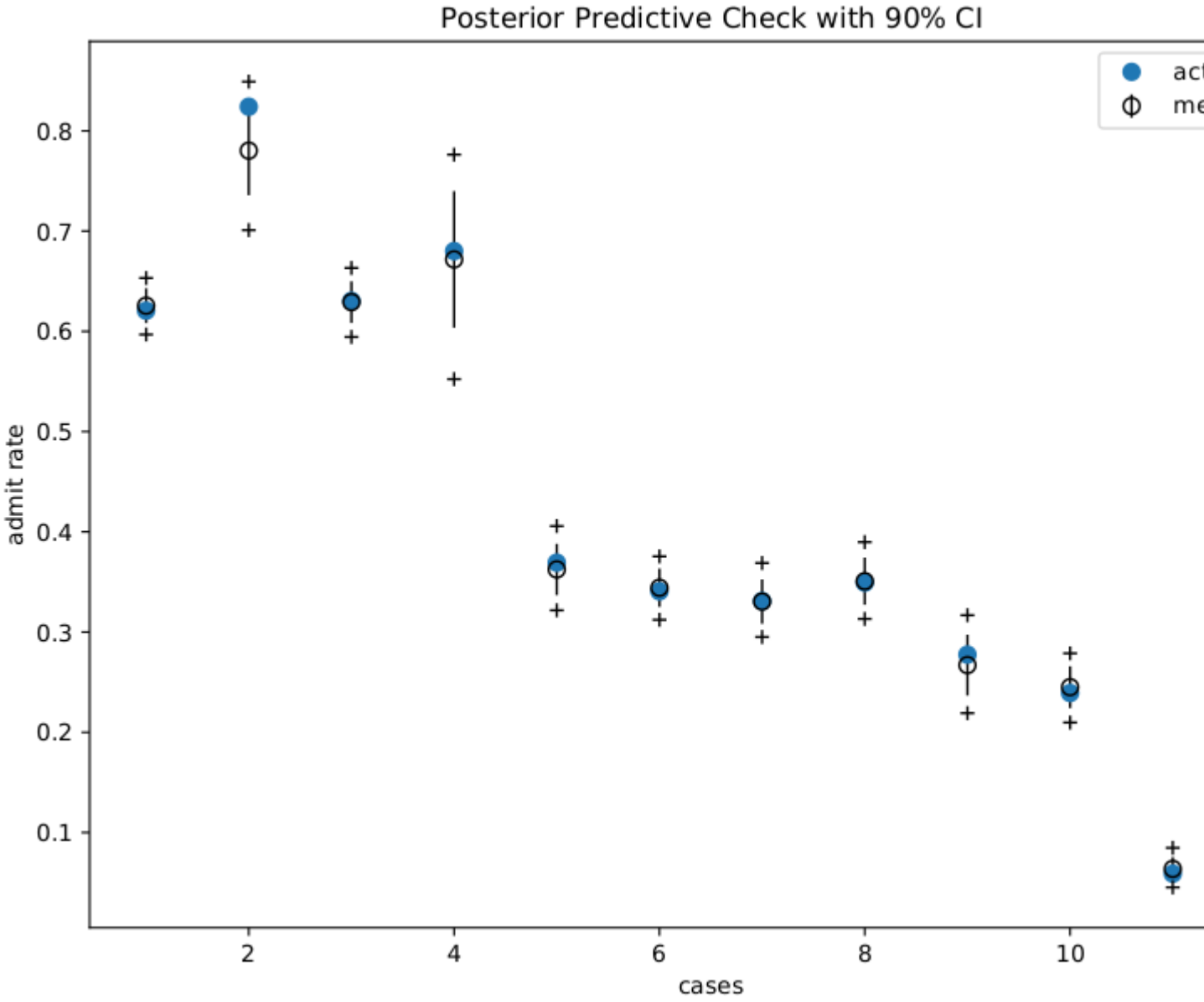
- varying intercepts accross departments,
- varying slopes (or the effects of being male) accross departments,
- correlation between intercepts and slopes,

and uses non-centered parameterization (or whitening).

A more comprehensive explanation for binomial regression and non-centered parameterization can be found in Chapter 10 (Counting and Classification) and Chapter 13 (Adventures in Covariance) of [2].

References:

1. Bickel, P. J., Hammel, E. A., and O'Connell, J. W. (1975), "Sex Bias in Graduate Admissions: Data from Berkeley", Science, 187(4175), 398-404.
2. McElreath, R. (2018), "Statistical Rethinking: A Bayesian Course with Examples in R and Stan", Chapman and Hall/CRC.
3. https://github.com/rmcelreath/rethinking/tree/Experimental#multilevel-model-formulas




```
import argparse
import os

import matplotlib.pyplot as plt
import numpy as np

from jax import random
import jax.numpy as jnp
from jax.scipy.special import expit
```

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```
import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import UCBADMIT, load_dataset
from numpyro.infer import MCMC, NUTS, Predictive


def glmm(dept, male, applications, admit=None):
    v_mu = numpyro.sample('v_mu', dist.Normal(0, jnp.array([4., 1.])))

    sigma = numpyro.sample('sigma', dist.HalfNormal(jnp.ones(2)))
    L_Rho = numpyro.sample('L_Rho', dist.LKJCholesky(2, concentration=2))
    scale_tril = sigma[..., jnp.newaxis] * L_Rho
    # non-centered parameterization
    num_dept = len(np.unique(dept))
    z = numpyro.sample('z', dist.Normal(jnp.zeros((num_dept, 2)), 1))
    v = jnp.dot(scale_tril, z.T).T

    logits = v_mu[0] + v[dept, 0] + (v_mu[1] + v[dept, 1]) * male
    if admit is None:
        # we use a Delta site to record probs for predictive distribution
        probs = expit(logits)
        numpyro.sample('probs', dist.Delta(probs), obs=probs)
    numpyro.sample('admit', dist.Binomial(applications, logits=logits), obs=admit)


def run_inference(dept, male, applications, admit, rng_key, args):
    kernel = NUTS(glmm)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, dept, male, applications, admit)
    return mcmc.get_samples()


def print_results(header, preds, dept, male, probs):
    columns = ['Dept', 'Male', 'ActualProb', 'Pred(p25)', 'Pred(p50)', 'Pred(p75)']
    header_format = '{:>10} {:>10} {:>10} {:>10} {:>10} {:>10}'
    row_format = '{:>10.0f} {:>10.0f} {:>10.2f} {:>10.2f} {:>10.2f} {:>10.2f}'
    quantiles = jnp.quantile(preds, jnp.array([0.25, 0.5, 0.75]), axis=0)
    print('\n', header, '\n')
    print(header_format.format(*columns))
    for i in range(len(dept)):
        print(row_format.format(dept[i], male[i], probs[i], *quantiles[:, i]), '\n')


def main(args):
    _, fetch_train = load_dataset(UCBADMIT, split='train', shuffle=False)
    dept, male, applications, admit = fetch_train()
    rng_key, rng_key_predict = random.split(random.PRNGKey(1))
    zs = run_inference(dept, male, applications, admit, rng_key, args)
    pred_probs = Predictive(glmm, zs)(rng_key_predict, dept, male, applications)[
↪'probs']
    header = '=' * 30 + 'glmm - TRAIN' + '=' * 30
    print_results(header, pred_probs, dept, male, admit / applications)

    # make plots
    fig, ax = plt.subplots(figsize=(8, 6), constrained_layout=True)
```

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```
    ax.plot(range(1, 13), admit / applications, "o", ms=7, label="actual rate")
    ax.errorbar(range(1, 13), jnp.mean(pred_probs, 0), jnp.std(pred_probs, 0),
                fmt="o", c="k", mfc="none", ms=7, elinewidth=1, label=r"mean $\pm$ std
↪")
    ax.plot(range(1, 13), jnp.percentile(pred_probs, 5, 0), "k+")
    ax.plot(range(1, 13), jnp.percentile(pred_probs, 95, 0), "k+")
    ax.set(xlabel="cases", ylabel="admit rate", title="Posterior Predictive Check␣
↪with 90% CI")
    ax.legend()

    plt.savefig("ucbadmit_plot.pdf")


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description='UCBadmit gender discrimination␣
↪using HMC')
    parser.add_argument('-n', '--num-samples', nargs='?', default=2000, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=500, type=int)
    parser.add_argument('--num-chains', nargs='?', default=1, type=int)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

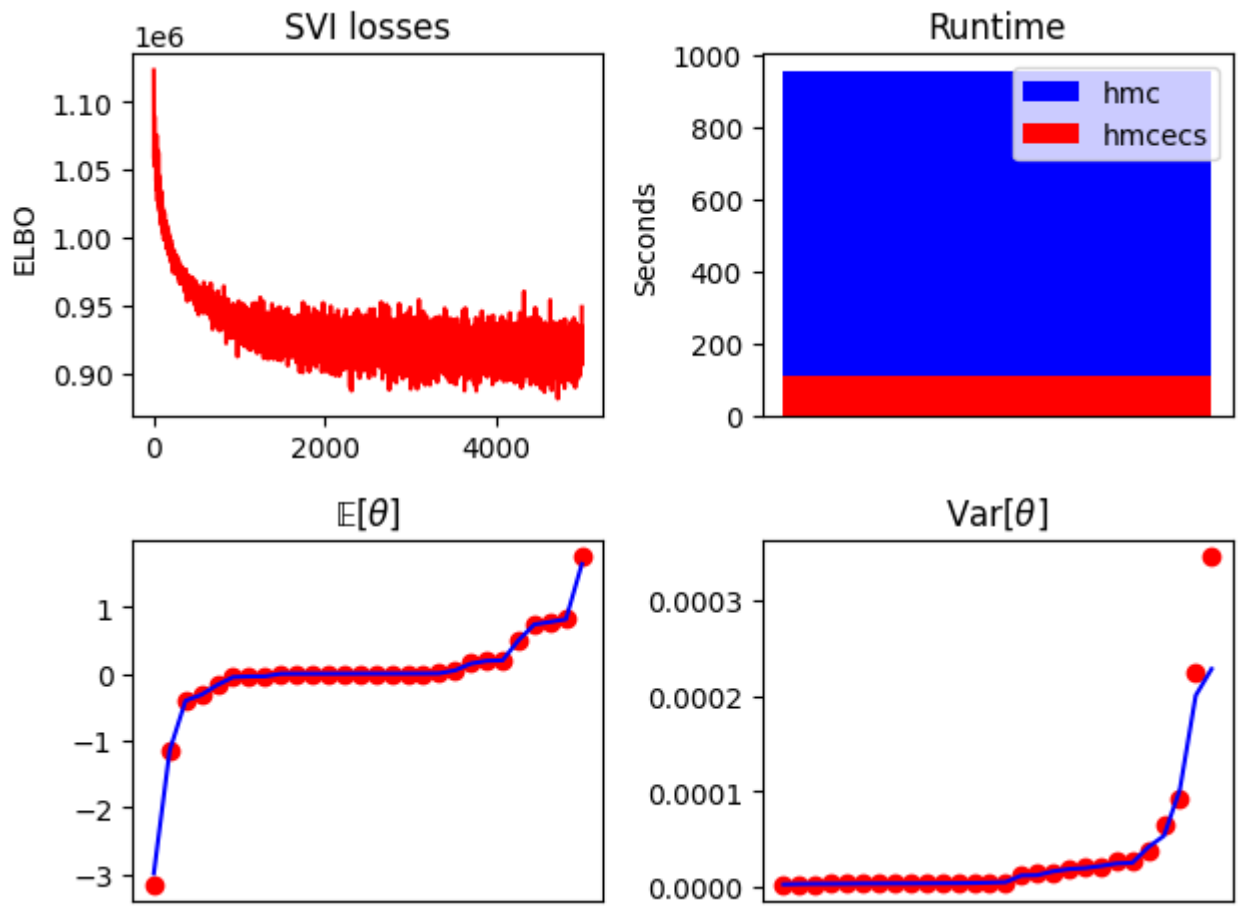
CHAPTER 21

Example: Hamiltonian Monte Carlo with Energy Conserving Subsampling

This example illustrates the use of data subsampling in HMC using Energy Conserving Subsampling. Data subsampling is applicable when the likelihood factorizes as a product of N terms.

References:

1. *Hamiltonian Monte Carlo with energy conserving subsampling*, Dang, K. D., Quiroz, M., Kohn, R., Minh-Ngoc, T., & Villani, M. (2019)




```
import argparse
import time

import matplotlib.pyplot as plt
import numpy as np

from jax import random
import jax.numpy as jnp

import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import HIGGS, load_dataset
from numpyro.infer import HMC, HMCECS, MCMC, NUTS, SVI, Trace_ELBO, autoguide


def model(data, obs, subsample_size):
    n, m = data.shape
    theta = numpyro.sample('theta', dist.Normal(jnp.zeros(m), .5 * jnp.ones(m)))
    with numpyro.plate('N', n, subsample_size=subsample_size):
        batch_feats = numpyro.subsample(data, event_dim=1)
        batch_obs = numpyro.subsample(obs, event_dim=0)
        numpyro.sample('obs', dist.Bernoulli(logits=theta @ batch_feats.T), obs=batch_
↪obs)
```

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```
def run_hmcecs(hmcecs_key, args, data, obs, inner_kernel):
    svi_key, mcmc_key = random.split(hmcecs_key)

    # find reference parameters for second order taylor expansion to estimate␣
↪likelihood (taylor_proxy)
    optimizer = numpyro.optim.Adam(step_size=1e-3)
    guide = autoguide.AutoDelta(model)
    svi = SVI(model, guide, optimizer, loss=Trace_ELBO())
    params, losses = svi.run(svi_key, args.num_svi_steps, data, obs, args.subsample_
↪size)
    ref_params = {'theta': params['theta_auto_loc']}

    # taylor proxy estimates log likelihood (ll) by
    # taylor_expansion(ll, theta_curr) +
    #     sum_{i in subsample} ll_i(theta_curr) - taylor_expansion(ll_i, theta_curr)␣
↪around ref_params
    proxy = HMCECS.taylor_proxy(ref_params)

    kernel = HMCECS(inner_kernel, num_blocks=args.num_blocks, proxy=proxy)
    mcmc = MCMC(kernel, num_warmup=args.num_warmup, num_samples=args.num_samples)

    mcmc.run(mcmc_key, data, obs, args.subsample_size)
    mcmc.print_summary()
    return losses, mcmc.get_samples()


def run_hmc(mcmc_key, args, data, obs, kernel):
    mcmc = MCMC(kernel, num_warmup=args.num_warmup, num_samples=args.num_samples)
    mcmc.run(mcmc_key, data, obs, None)
    mcmc.print_summary()
    return mcmc.get_samples()


def main(args):
    assert 11_000_000 >= args.num_datapoints, "11,000,000 data points in the Higgs␣
↪dataset"
    # full dataset takes hours for plain hmc!
    if args.dataset == 'higgs':
        _, fetch = load_dataset(HIGGS, shuffle=False, num_datapoints=args.num_
↪datapoints)
        data, obs = fetch()
    else:
        data, obs = (np.random.normal(size=(10, 28)), np.ones(10))

    hmcecs_key, hmc_key = random.split(random.PRNGKey(args.rng_seed))

    # choose inner_kernel
    if args.inner_kernel == 'hmc':
        inner_kernel = HMC(model)
    else:
        inner_kernel = NUTS(model)

    start = time.time()
    losses, hmcecs_samples = run_hmcecs(hmcecs_key, args, data, obs, inner_kernel)
    hmcecs_runtime = time.time() - start

    start = time.time()
```

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```
    hmc_samples = run_hmc(hmc_key, args, data, obs, inner_kernel)
    hmc_runtime = time.time() - start

    summary_plot(losses, hmc_samples, hmcecs_samples, hmc_runtime, hmcecs_runtime)


def summary_plot(losses, hmc_samples, hmcecs_samples, hmc_runtime, hmcecs_runtime):
    fig, ax = plt.subplots(2, 2)
    ax[0, 0].plot(losses, 'r')
    ax[0, 0].set_title('SVI losses')
    ax[0, 0].set_ylabel('ELBO')

    if hmc_runtime > hmcecs_runtime:
        ax[0, 1].bar([0], hmc_runtime, label='hmc', color='b')
        ax[0, 1].bar([0], hmcecs_runtime, label='hmcecs', color='r')
    else:
        ax[0, 1].bar([0], hmcecs_runtime, label='hmcecs', color='r')
        ax[0, 1].bar([0], hmc_runtime, label='hmc', color='b')
    ax[0, 1].set_title('Runtime')
    ax[0, 1].set_ylabel('Seconds')
    ax[0, 1].legend()
    ax[0, 1].set_xticks([])

    ax[1, 0].plot(jnp.sort(hmc_samples['theta'].mean(0)), 'or')
    ax[1, 0].plot(jnp.sort(hmcecs_samples['theta'].mean(0)), 'b')
    ax[1, 0].set_title(r'$\mathrm{\mathbb{E}}[\theta]$')

    ax[1, 1].plot(jnp.sort(hmc_samples['theta'].var(0)), 'or')
    ax[1, 1].plot(jnp.sort(hmcecs_samples['theta'].var(0)), 'b')
    ax[1, 1].set_title(r'Var$[\theta]$')

    for a in ax[1, :]:
        a.set_xticks([])

    fig.tight_layout()
    fig.savefig('hmcecs_plot.pdf', bbox_inches='tight')


if __name__ == '__main__':
    parser = argparse.ArgumentParser("Hamiltonian Monte Carlo with Energy Conserving␣
↪Subsampling")
    parser.add_argument('--subsample_size', type=int, default=1300)
    parser.add_argument('--num_svi_steps', type=int, default=5000)
    parser.add_argument('--num_blocks', type=int, default=100)
    parser.add_argument('--num_warmup', type=int, default=500)
    parser.add_argument('--num_samples', type=int, default=500)
    parser.add_argument('--num_datapoints', type=int, default=1_500_000)
    parser.add_argument('--dataset', type=str, choices=['higgs', 'mock'], default=
↪'higgs')
    parser.add_argument('--inner_kernel', type=str, choices=['nuts', 'hmc'], default=
↪'nuts')
    parser.add_argument('--device', default='cpu', type=str, choices=['cpu', 'gpu'])
    parser.add_argument('--rng_seed', default=37, type=int, help='random number␣
↪generator seed')

    args = parser.parse_args()
```

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```
    numpyro.set_platform(args.device)

    main(args)
```

CHAPTER 22

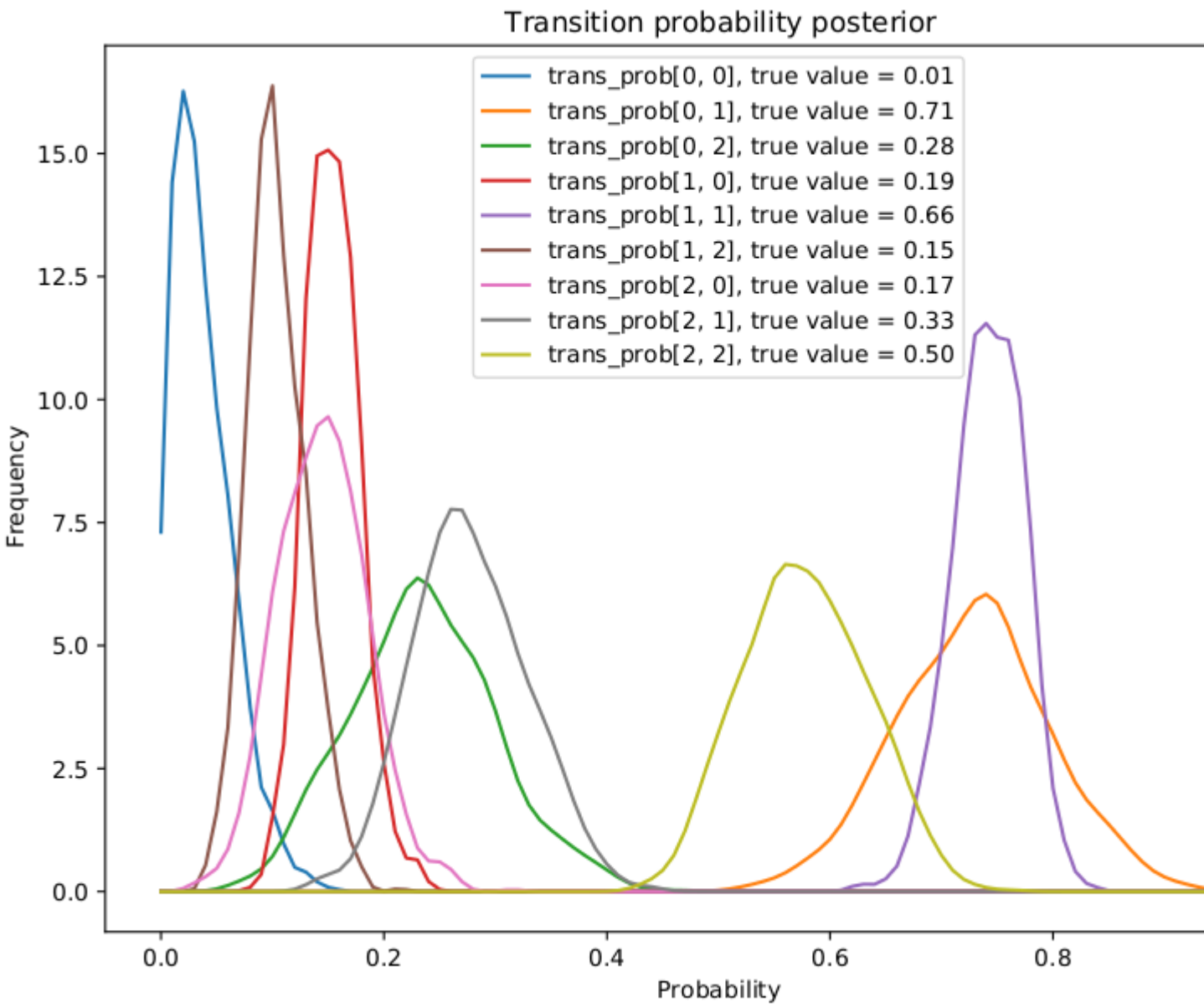
Example: Hidden Markov Model

In this example, we will follow [1] to construct a semi-supervised Hidden Markov Model for a generative model with observations are words and latent variables are categories. Instead of automatically marginalizing all discrete latent variables (as in [2]), we will use the "forward algorithm" (which exploits the conditional independent of a Markov model - see [3]) to iteratively do this marginalization.

The semi-supervised problem is chosen instead of an unsupervised one because it is hard to make the inference works for an unsupervised model (see the discussion [4]). On the other hand, this example also illustrates the usage of JAX's *lax.scan* primitive. The primitive will greatly improve compiling for the model.

References:

1. https://mc-stan.org/docs/2_19/stan-users-guide/hmms-section.html
2. http://pyro.ai/examples/hmm.html
3. https://en.wikipedia.org/wiki/Forward_algorithm
4. https://discourse.pymc.io/t/how-to-marginalized-markov-chain-with-categorical/2230




```
import argparse
import os
import time

import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import gaussian_kde

from jax import lax, random
import jax.numpy as jnp
from jax.scipy.special import logsumexp

import numpyro
import numpyro.distributions as dist
from numpyro.infer import MCMC, NUTS
```

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```
def simulate_data(rng_key, num_categories, num_words, num_supervised_data, num_
↪unsupervised_data):
    rng_key, rng_key_transition, rng_key_emission = random.split(rng_key, 3)

    transition_prior = jnp.ones(num_categories)
    emission_prior = jnp.repeat(0.1, num_words)

    transition_prob = dist.Dirichlet(transition_prior).sample(key=rng_key_transition,
                                                              sample_shape=(num_
↪categories,))
    emission_prob = dist.Dirichlet(emission_prior).sample(key=rng_key_emission,
                                                          sample_shape=(num_
↪categories,))

    start_prob = jnp.repeat(1. / num_categories, num_categories)
    categories, words = [], []
    for t in range(num_supervised_data + num_unsupervised_data):
        rng_key, rng_key_transition, rng_key_emission = random.split(rng_key, 3)
        if t == 0 or t == num_supervised_data:
            category = dist.Categorical(start_prob).sample(key=rng_key_transition)
        else:
            category = dist.Categorical(transition_prob[category]).sample(key=rng_key_
↪transition)
        word = dist.Categorical(emission_prob[category]).sample(key=rng_key_emission)
        categories.append(category)
        words.append(word)

    # split into supervised data and unsupervised data
    categories, words = jnp.stack(categories), jnp.stack(words)
    supervised_categories = categories[:num_supervised_data]
    supervised_words = words[:num_supervised_data]
    unsupervised_words = words[num_supervised_data:]
    return (transition_prior, emission_prior, transition_prob, emission_prob,
            supervised_categories, supervised_words, unsupervised_words)


def forward_one_step(prev_log_prob, curr_word, transition_log_prob, emission_log_
↪prob):
    log_prob_tmp = jnp.expand_dims(prev_log_prob, axis=1) + transition_log_prob
    log_prob = log_prob_tmp + emission_log_prob[:, curr_word]
    return logsumexp(log_prob, axis=0)


def forward_log_prob(init_log_prob, words, transition_log_prob, emission_log_prob,␣
↪unroll_loop=False):
    # Note: The following naive implementation will make it very slow to compile
    # and do inference. So we use lax.scan instead.
    #
    # >>> log_prob = init_log_prob
    # >>> for word in words:
    # ...     log_prob = forward_one_step(log_prob, word, transition_log_prob,␣
↪emission_log_prob)
    def scan_fn(log_prob, word):
        return forward_one_step(log_prob, word, transition_log_prob, emission_log_
↪prob), jnp.zeros((0,))
```

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```
    if unroll_loop:
        log_prob = init_log_prob
        for word in words:
            log_prob = forward_one_step(log_prob, word, transition_log_prob, emission_
↪log_prob)
    else:
        log_prob, _ = lax.scan(scan_fn, init_log_prob, words)
    return log_prob


def semi_supervised_hmm(transition_prior, emission_prior,
                        supervised_categories, supervised_words,
                        unsupervised_words, unroll_loop=False):
    num_categories, num_words = transition_prior.shape[0], emission_prior.shape[0]
    transition_prob = numpyro.sample('transition_prob', dist.Dirichlet(
        jnp.broadcast_to(transition_prior, (num_categories, num_categories))))
    emission_prob = numpyro.sample('emission_prob', dist.Dirichlet(
        jnp.broadcast_to(emission_prior, (num_categories, num_words))))

    # models supervised data;
    # here we don't make any assumption about the first supervised category, in other␣
↪words,
    # we place a flat/uniform prior on it.
    numpyro.sample('supervised_categories', dist.Categorical(transition_
↪prob[supervised_categories[:-1]]),
                   obs=supervised_categories[1:])
    numpyro.sample('supervised_words', dist.Categorical(emission_prob[supervised_
↪categories]),
                   obs=supervised_words)

    # computes log prob of unsupervised data
    transition_log_prob = jnp.log(transition_prob)
    emission_log_prob = jnp.log(emission_prob)
    init_log_prob = emission_log_prob[:, unsupervised_words[0]]
    log_prob = forward_log_prob(init_log_prob, unsupervised_words[1:],
                                transition_log_prob, emission_log_prob, unroll_loop)
    log_prob = logsumexp(log_prob, axis=0, keepdims=True)
    # inject log_prob to potential function
    numpyro.factor('forward_log_prob', log_prob)


def print_results(posterior, transition_prob, emission_prob):
    header = semi_supervised_hmm.__name__ + ' - TRAIN'
    columns = ['', 'ActualProb', 'Pred(p25)', 'Pred(p50)', 'Pred(p75)']
    header_format = '{:>20} {:>10} {:>10} {:>10} {:>10}'
    row_format = '{:>20} {:>10.2f} {:>10.2f} {:>10.2f} {:>10.2f}'
    print('\n', '=' * 20 + header + '=' * 20, '\n')
    print(header_format.format(*columns))

    quantiles = np.quantile(posterior['transition_prob'], [0.25, 0.5, 0.75], axis=0)
    for i in range(transition_prob.shape[0]):
        for j in range(transition_prob.shape[1]):
            idx = 'transition[{},{}]'.format(i, j)
            print(row_format.format(idx, transition_prob[i, j], *quantiles[:, i, j]),
↪'\n')

    quantiles = np.quantile(posterior['emission_prob'], [0.25, 0.5, 0.75], axis=0)
```

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```
    for i in range(emission_prob.shape[0]):
        for j in range(emission_prob.shape[1]):
            idx = 'emission[{},{}]'.format(i, j)
            print(row_format.format(idx, emission_prob[i, j], *quantiles[:, i, j]),
↪'\n')


def main(args):
    print('Simulating data...')
    (transition_prior, emission_prior, transition_prob, emission_prob,
     supervised_categories, supervised_words, unsupervised_words) = simulate_data(
        random.PRNGKey(1),
        num_categories=args.num_categories,
        num_words=args.num_words,
        num_supervised_data=args.num_supervised,
        num_unsupervised_data=args.num_unsupervised,
    )
    print('Starting inference...')
    rng_key = random.PRNGKey(2)
    start = time.time()
    kernel = NUTS(semi_supervised_hmm)
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(rng_key, transition_prior, emission_prior, supervised_categories,
             supervised_words, unsupervised_words, args.unroll_loop)
    samples = mcmc.get_samples()
    print_results(samples, transition_prob, emission_prob)
    print('\nMCMC elapsed time:', time.time() - start)

    # make plots
    fig, ax = plt.subplots(figsize=(8, 6), constrained_layout=True)

    x = np.linspace(0, 1, 101)
    for i in range(transition_prob.shape[0]):
        for j in range(transition_prob.shape[1]):
            ax.plot(x, gaussian_kde(samples['transition_prob'][:, i, j])(x),
                    label="trans_prob[{}, {}], true value = {:.2f}"
                    .format(i, j, transition_prob[i, j]))
    ax.set(xlabel="Probability", ylabel="Frequency",
           title="Transition probability posterior")
    ax.legend()

    plt.savefig("hmm_plot.pdf")


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description='Semi-supervised Hidden Markov Model
↪')
    parser.add_argument('--num-categories', default=3, type=int)
    parser.add_argument('--num-words', default=10, type=int)
    parser.add_argument('--num-supervised', default=100, type=int)
    parser.add_argument('--num-unsupervised', default=500, type=int)
    parser.add_argument('-n', '--num-samples', nargs='?', default=1000, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=500, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument("--unroll-loop", action='store_true')
```

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```
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

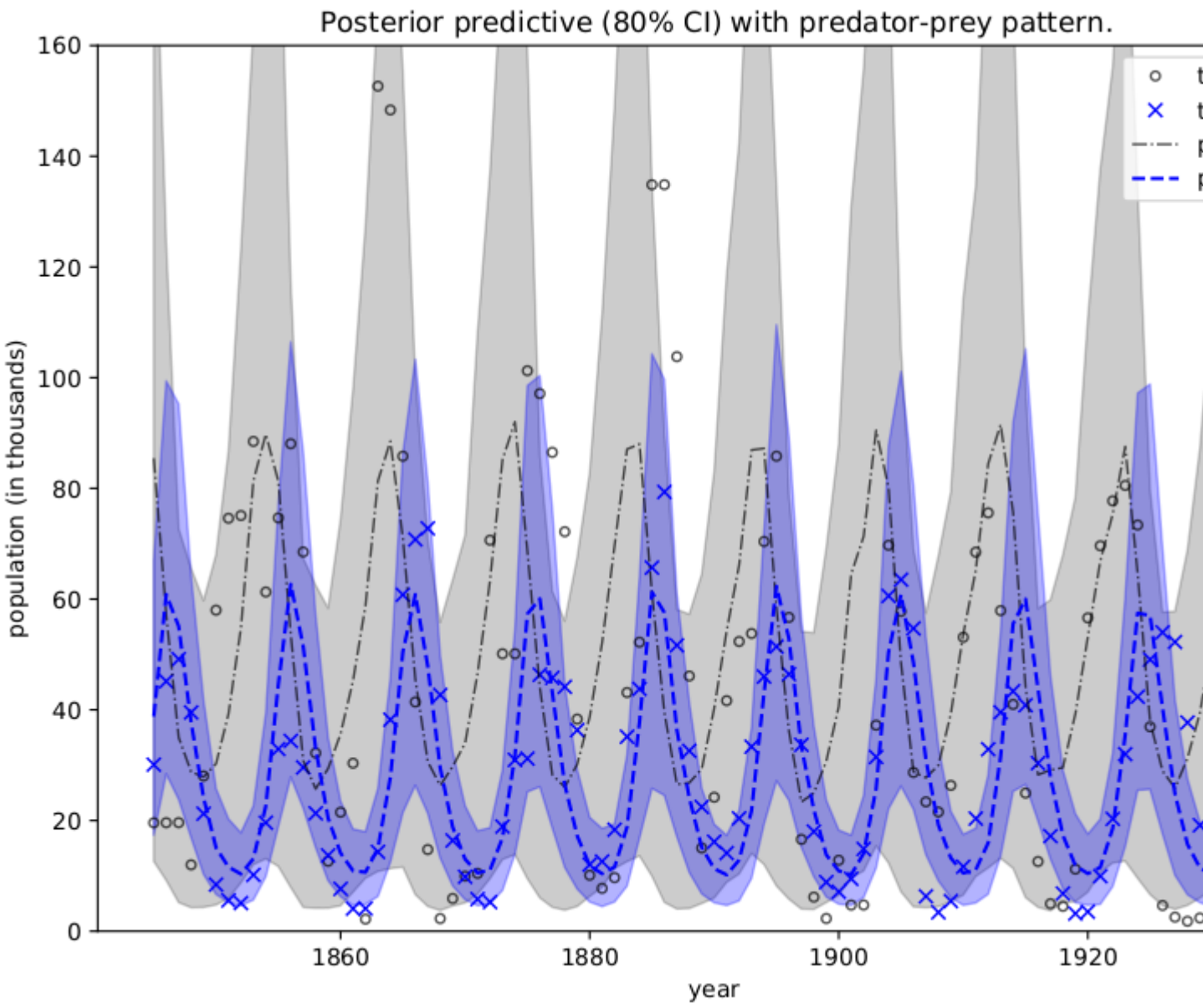
CHAPTER 23

Example: Predator-Prey Model

This example replicates the great case study [1], which leverages the Lotka-Volterra equation [2] to describe the dynamics of Canada lynx (predator) and snowshoe hare (prey) populations. We will use the dataset obtained from [3] and run MCMC to get inferences about parameters of the differential equation governing the dynamics.

References:

1. Bob Carpenter (2018), "Predator-Prey Population Dynamics: the Lotka-Volterra model in Stan".
2. https://en.wikipedia.org/wiki/Lotka-Volterra_equations
3. http://people.whitman.edu/~hundledr/courses/M250F03/M250.html




```
import argparse
import os

import matplotlib
import matplotlib.pyplot as plt

from jax.experimental.ode import odeint
import jax.numpy as jnp
from jax.random import PRNGKey

import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import LYNXHARE, load_dataset
from numpyro.infer import MCMC, NUTS, Predictive

matplotlib.use('Agg')  # noqa: E402
```

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```
def dz_dt(z, t, theta):
    """
    Lotka-Volterra equations. Real positive parameters `alpha`, `beta`, `gamma`,␣
↪`delta`
    describes the interaction of two species.
    """
    u = z[0]
    v = z[1]
    alpha, beta, gamma, delta = theta[..., 0], theta[..., 1], theta[..., 2], theta[...
↪, 3]
    du_dt = (alpha - beta * v) * u
    dv_dt = (-gamma + delta * u) * v
    return jnp.stack([du_dt, dv_dt])


def model(N, y=None):
    """
    :param int N: number of measurement times
    :param numpy.ndarray y: measured populations with shape (N, 2)
    """
    # initial population
    z_init = numpyro.sample("z_init", dist.LogNormal(jnp.log(10), 1).expand([2]))
    # measurement times
    ts = jnp.arange(float(N))
    # parameters alpha, beta, gamma, delta of dz_dt
    theta = numpyro.sample(
        "theta",
        dist.TruncatedNormal(low=0., loc=jnp.array([1.0, 0.05, 1.0, 0.05]),
                             scale=jnp.array([0.5, 0.05, 0.5, 0.05])))
    # integrate dz/dt, the result will have shape N x 2
    z = odeint(dz_dt, z_init, ts, theta, rtol=1e-6, atol=1e-5, mxstep=1000)
    # measurement errors
    sigma = numpyro.sample("sigma", dist.LogNormal(-1, 1).expand([2]))
    # measured populations
    numpyro.sample("y", dist.LogNormal(jnp.log(z), sigma), obs=y)


def main(args):
    _, fetch = load_dataset(LYNXHARE, shuffle=False)
    year, data = fetch()  # data is in hare -> lynx order

    # use dense_mass for better mixing rate
    mcmc = MCMC(NUTS(model, dense_mass=True),
                args.num_warmup, args.num_samples, num_chains=args.num_chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(PRNGKey(1), N=data.shape[0], y=data)
    mcmc.print_summary()

    # predict populations
    pop_pred = Predictive(model, mcmc.get_samples())(PRNGKey(2), data.shape[0])["y"]
    mu, pi = jnp.mean(pop_pred, 0), jnp.percentile(pop_pred, (10, 90), 0)
    plt.figure(figsize=(8, 6), constrained_layout=True)
    plt.plot(year, data[:, 0], "ko", mfc="none", ms=4, label="true hare", alpha=0.67)
    plt.plot(year, data[:, 1], "bx", label="true lynx")
    plt.plot(year, mu[:, 0], "k-.", label="pred hare", lw=1, alpha=0.67)
```

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```
    plt.plot(year, mu[:, 1], "b--", label="pred lynx")
    plt.fill_between(year, pi[0, :, 0], pi[1, :, 0], color="k", alpha=0.2)
    plt.fill_between(year, pi[0, :, 1], pi[1, :, 1], color="b", alpha=0.3)
    plt.gca().set(ylim=(0, 160), xlabel="year", ylabel="population (in thousands)")
    plt.title("Posterior predictive (80% CI) with predator-prey pattern.")
    plt.legend()

    plt.savefig("ode_plot.pdf")


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description='Predator-Prey Model')
    parser.add_argument('-n', '--num-samples', nargs='?', default=1000, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

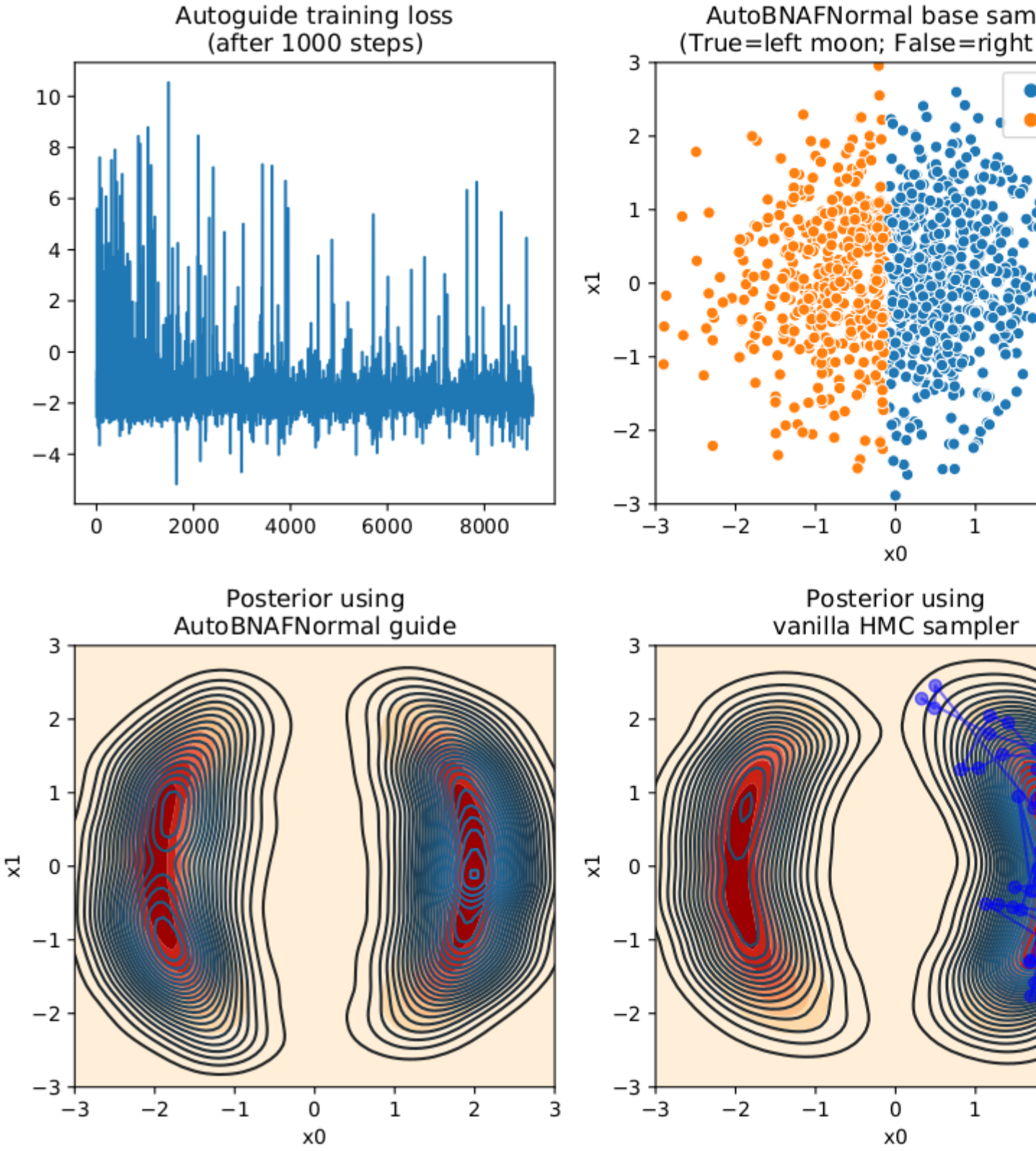
CHAPTER 24

Example: Neural Transport

This example illustrates how to use a trained AutoBNAFNormal autoguide to transform a posterior to a Gaussian-like one. The transform will be used to get better mixing rate for NUTS sampler.

References:

1. Hoffman, M. et al. (2019), "NeuTra-lizing Bad Geometry in Hamiltonian Monte Carlo Using Neural Transport", (https://arxiv.org/abs/1903.03704)




```
import argparse
import os
```

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```
from matplotlib.gridspec import GridSpec
import matplotlib.pyplot as plt
import seaborn as sns

from jax import random
import jax.numpy as jnp
from jax.scipy.special import logsumexp

import numpyro
from numpyro import optim
from numpyro.diagnostics import print_summary
import numpyro.distributions as dist
from numpyro.distributions import constraints
from numpyro.infer import MCMC, NUTS, SVI, Trace_ELBO
from numpyro.infer.autoguide import AutoBNAFNormal
from numpyro.infer.reparam import NeuTraReparam


class DualMoonDistribution(dist.Distribution):
    support = constraints.real_vector

    def __init__(self):
        super(DualMoonDistribution, self).__init__(event_shape=(2,))

    def sample(self, key, sample_shape=()):
        # it is enough to return an arbitrary sample with correct shape
        return jnp.zeros(sample_shape + self.event_shape)

    def log_prob(self, x):
        term1 = 0.5 * ((jnp.linalg.norm(x, axis=-1) - 2) / 0.4) ** 2
        term2 = -0.5 * ((x[..., :1] + jnp.array([-2., 2.])) / 0.6) ** 2
        pe = term1 - logsumexp(term2, axis=-1)
        return -pe


def dual_moon_model():
    numpyro.sample('x', DualMoonDistribution())


def main(args):
    print("Start vanilla HMC...")
    nuts_kernel = NUTS(dual_moon_model)
    mcmc = MCMC(nuts_kernel, args.num_warmup, args.num_samples, num_chains=args.num_
↪chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(random.PRNGKey(0))
    mcmc.print_summary()
    vanilla_samples = mcmc.get_samples()['x'].copy()

    guide = AutoBNAFNormal(dual_moon_model, hidden_factors=[args.hidden_factor, args.
↪hidden_factor])
    svi = SVI(dual_moon_model, guide, optim.Adam(0.003), Trace_ELBO())

    print("Start training guide...")
    svi_result = svi.run(random.PRNGKey(1), args.num_iters)
    print("Finish training guide. Extract samples...")
```

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```
    guide_samples = guide.sample_posterior(random.PRNGKey(2), svi_result.params,
                                           sample_shape=(args.num_samples,))['x'].
↪copy()

    print("\nStart NeuTra HMC...")
    neutra = NeuTraReparam(guide, svi_result.params)
    neutra_model = neutra.reparam(dual_moon_model)
    nuts_kernel = NUTS(neutra_model)
    mcmc = MCMC(nuts_kernel, args.num_warmup, args.num_samples, num_chains=args.num_
↪chains,
                progress_bar=False if "NUMPYRO_SPHINXBUILD" in os.environ else True)
    mcmc.run(random.PRNGKey(3))
    mcmc.print_summary()
    zs = mcmc.get_samples(group_by_chain=True)["auto_shared_latent"]
    print("Transform samples into unwarped space...")
    samples = neutra.transform_sample(zs)
    print_summary(samples)
    zs = zs.reshape(-1, 2)
    samples = samples['x'].reshape(-1, 2).copy()

    # make plots

    # guide samples (for plotting)
    guide_base_samples = dist.Normal(jnp.zeros(2), 1.).sample(random.PRNGKey(4),␣
↪(1000,))
    guide_trans_samples = neutra.transform_sample(guide_base_samples)['x']

    x1 = jnp.linspace(-3, 3, 100)
    x2 = jnp.linspace(-3, 3, 100)
    X1, X2 = jnp.meshgrid(x1, x2)
    P = jnp.exp(DualMoonDistribution().log_prob(jnp.stack([X1, X2], axis=-1)))

    fig = plt.figure(figsize=(12, 8), constrained_layout=True)
    gs = GridSpec(2, 3, figure=fig)
    ax1 = fig.add_subplot(gs[0, 0])
    ax2 = fig.add_subplot(gs[1, 0])
    ax3 = fig.add_subplot(gs[0, 1])
    ax4 = fig.add_subplot(gs[1, 1])
    ax5 = fig.add_subplot(gs[0, 2])
    ax6 = fig.add_subplot(gs[1, 2])

    ax1.plot(svi_result.losses[1000:])
    ax1.set_title('Autoguide training loss\n(after 1000 steps)')

    ax2.contourf(X1, X2, P, cmap='OrRd')
    sns.kdeplot(x=guide_samples[:, 0], y=guide_samples[:, 1], n_levels=30, ax=ax2)
    ax2.set(xlim=[-3, 3], ylim=[-3, 3],
            xlabel='x0', ylabel='x1', title='Posterior using\nAutoBNAFNormal guide')

    sns.scatterplot(x=guide_base_samples[:, 0], y=guide_base_samples[:, 1], ax=ax3,
                    hue=guide_trans_samples[:, 0] < 0.)
    ax3.set(xlim=[-3, 3], ylim=[-3, 3],
            xlabel='x0', ylabel='x1', title='AutoBNAFNormal base samples\n(True=left␣
↪moon; False=right moon)')

    ax4.contourf(X1, X2, P, cmap='OrRd')
    sns.kdeplot(x=vanilla_samples[:, 0], y=vanilla_samples[:, 1], n_levels=30, ax=ax4)
```

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```
    ax4.plot(vanilla_samples[-50:, 0], vanilla_samples[-50:, 1], 'bo-', alpha=0.5)
    ax4.set(xlim=[-3, 3], ylim=[-3, 3],
            xlabel='x0', ylabel='x1', title='Posterior using\nvanilla HMC sampler')

    sns.scatterplot(x=zs[:, 0], y=zs[:, 1], ax=ax5, hue=samples[:, 0] < 0.,
                    s=30, alpha=0.5, edgecolor="none")
    ax5.set(xlim=[-5, 5], ylim=[-5, 5],
            xlabel='x0', ylabel='x1', title='Samples from the\nwarped posterior - p(z)
↪')

    ax6.contourf(X1, X2, P, cmap='OrRd')
    sns.kdeplot(x=samples[:, 0], y=samples[:, 1], n_levels=30, ax=ax6)
    ax6.plot(samples[-50:, 0], samples[-50:, 1], 'bo-', alpha=0.2)
    ax6.set(xlim=[-3, 3], ylim=[-3, 3],
            xlabel='x0', ylabel='x1', title='Posterior using\nNeuTra HMC sampler')

    plt.savefig("neutra.pdf")


if __name__ == "__main__":
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="NeuTra HMC")
    parser.add_argument('-n', '--num-samples', nargs='?', default=4000, type=int)
    parser.add_argument('--num-warmup', nargs='?', default=1000, type=int)
    parser.add_argument("--num-chains", nargs='?', default=1, type=int)
    parser.add_argument('--hidden-factor', nargs='?', default=8, type=int)
    parser.add_argument('--num-iters', nargs='?', default=10000, type=int)
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)

    main(args)
```

CHAPTER 25

Example: MCMC Methods for Tall Data

This example illustrates the usages of various MCMC methods which are suitable for tall data:

- *algo="SA"* uses the sample adaptive MCMC method in [1]
- *algo="HMCECS"* uses the energy conserving subsampling method in [2]
- *algo="FlowHMCECS"* utilizes a normalizing flow to neutralize the posterior geometry into a Gaussian-like one. Then HMCECS is used to draw the posterior samples. Currently, this method gives the best mixing rate among those methods.

References:

1. *Sample Adaptive MCMC*, Michael Zhu (2019)
2. *Hamiltonian Monte Carlo with energy conserving subsampling*, Dang, K. D., Quiroz, M., Kohn, R., Minh-Ngoc, T., & Villani, M. (2019)
3. *NeuTra-lizing Bad Geometry in Hamiltonian Monte Carlo Using Neural Transport*, Hoffman, M. et al. (2019)


```
import argparse
import time

import matplotlib.pyplot as plt

from jax import random
import jax.numpy as jnp

import numpyro
import numpyro.distributions as dist
from numpyro.examples.datasets import COVTYPE, load_dataset
from numpyro.infer import HMC, HMCECS, MCMC, NUTS, SA, SVI, Trace_ELBO, init_to_value
from numpyro.infer.autoguide import AutoBNAFNormal
from numpyro.infer.reparam import NeuTraReparam


def _load_dataset():
    _, fetch = load_dataset(COVTYPE, shuffle=False)
```

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```
    features, labels = fetch()

    # normalize features and add intercept
    features = (features - features.mean(0)) / features.std(0)
    features = jnp.hstack([features, jnp.ones((features.shape[0], 1))])

    # make binary feature
    _, counts = jnp.unique(labels, return_counts=True)
    specific_category = jnp.argmax(counts)
    labels = (labels == specific_category)

    N, dim = features.shape
    print("Data shape:", features.shape)
    print("Label distribution: {} has label 1, {} has label 0"
          .format(labels.sum(), N - labels.sum()))
    return features, labels


def model(data, labels, subsample_size=None):
    dim = data.shape[1]
    coefs = numpyro.sample('coefs', dist.Normal(jnp.zeros(dim), jnp.ones(dim)))
    with numpyro.plate("N", data.shape[0], subsample_size=subsample_size) as idx:
        logits = jnp.dot(data[idx], coefs)
        return numpyro.sample('obs', dist.Bernoulli(logits=logits), obs=labels[idx])


def benchmark_hmc(args, features, labels):
    rng_key = random.PRNGKey(1)
    start = time.time()
    # a MAP estimate at the following source
    # https://github.com/google/edward2/blob/master/examples/no_u_turn_sampler/
↪logistic_regression.py#L117
    ref_params = {"coefs": jnp.array([
        +2.03420663e+00, -3.53567265e-02, -1.49223924e-01, -3.07049364e-01,
        -1.00028366e-01, -1.46827862e-01, -1.64167881e-01, -4.20344204e-01,
        +9.47479829e-02, -1.12681836e-02, +2.64442056e-01, -1.22087866e-01,
        -6.00568838e-02, -3.79419506e-01, -1.06668741e-01, -2.97053963e-01,
        -2.05253899e-01, -4.69537191e-02, -2.78072730e-02, -1.43250525e-01,
        -6.77954629e-02, -4.34899796e-03, +5.90927452e-02, +7.23133609e-02,
        +1.38526391e-02, -1.24497898e-01, -1.50733739e-02, -2.68872194e-02,
        -1.80925727e-02, +3.47936489e-02, +4.03552800e-02, -9.98773426e-03,
        +6.20188080e-02, +1.15002751e-01, +1.32145107e-01, +2.69109547e-01,
        +2.45785132e-01, +1.19035013e-01, -2.59744357e-02, +9.94279515e-04,
        +3.39266285e-02, -1.44057125e-02, -6.95222765e-02, -7.52013028e-02,
        +1.21171586e-01, +2.29205526e-02, +1.47308692e-01, -8.34354162e-02,
        -9.34122875e-02, -2.97472421e-02, -3.03937674e-01, -1.70958012e-01,
        -1.59496680e-01, -1.88516974e-01, -1.20889175e+00])}
    if args.algo == "HMC":
        step_size = jnp.sqrt(0.5 / features.shape[0])
        trajectory_length = step_size * args.num_steps
        kernel = HMC(model, step_size=step_size, trajectory_length=trajectory_length,␣
↪adapt_step_size=False,
                     dense_mass=args.dense_mass)
        subsample_size = None
    elif args.algo == "NUTS":
        kernel = NUTS(model, dense_mass=args.dense_mass)
        subsample_size = None
```

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```
    elif args.algo == "HMCECS":
        subsample_size = 1000
        inner_kernel = NUTS(model, init_strategy=init_to_value(values=ref_params),
                            dense_mass=args.dense_mass)
        # note: if num_blocks=100, we'll update 10 index at each MCMC step
        # so it took 50000 MCMC steps to iterative the whole dataset
        kernel = HMCECS(inner_kernel, num_blocks=100, proxy=HMCECS.taylor_proxy(ref_
↪params))
    elif args.algo == "SA":
        # NB: this kernel requires large num_warmup and num_samples
        # and running on GPU is much faster than on CPU
        kernel = SA(model, adapt_state_size=1000, init_strategy=init_to_
↪value(values=ref_params))
        subsample_size = None
    elif args.algo == "FlowHMCECS":
        subsample_size = 1000
        guide = AutoBNAFNormal(model, num_flows=1, hidden_factors=[8])
        svi = SVI(model, guide, numpyro.optim.Adam(0.01), Trace_ELBO())
        params, losses = svi.run(random.PRNGKey(2), 2000, features, labels)
        plt.plot(losses)
        plt.show()

        neutra = NeuTraReparam(guide, params)
        neutra_model = neutra.reparam(model)
        neutra_ref_params = {"auto_shared_latent": jnp.zeros(55)}
        # no need to adapt mass matrix if the flow does a good job
        inner_kernel = NUTS(neutra_model, init_strategy=init_to_value(values=neutra_
↪ref_params),
                            adapt_mass_matrix=False)
        kernel = HMCECS(inner_kernel, num_blocks=100, proxy=HMCECS.taylor_
↪proxy(neutra_ref_params))
    else:
        raise ValueError("Invalid algorithm, either 'HMC', 'NUTS', or 'HMCECS'.")
    mcmc = MCMC(kernel, args.num_warmup, args.num_samples)
    mcmc.run(rng_key, features, labels, subsample_size, extra_fields=("accept_prob",))
    print("Mean accept prob:", jnp.mean(mcmc.get_extra_fields()["accept_prob"]))
    mcmc.print_summary(exclude_deterministic=False)
    print('\nMCMC elapsed time:', time.time() - start)


def main(args):
    features, labels = _load_dataset()
    benchmark_hmc(args, features, labels)


if __name__ == '__main__':
    assert numpyro.__version__.startswith('0.6.0')
    parser = argparse.ArgumentParser(description="parse args")
    parser.add_argument('-n', '--num-samples', default=1000, type=int, help='number␣
↪of samples')
    parser.add_argument('--num-warmup', default=1000, type=int, help='number of␣
↪warmup steps')
    parser.add_argument('--num-steps', default=10, type=int, help='number of steps␣
↪(for "HMC")')
    parser.add_argument('--num-chains', nargs='?', default=1, type=int)
    parser.add_argument('--algo', default='HMCECS', type=str,
                        help='whether to run "HMC", "NUTS", "HMCECS", "SA" or
↪"FlowHMCECS"')
```

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```
    parser.add_argument('--dense-mass', action="store_true")
    parser.add_argument('--x64', action="store_true")
    parser.add_argument('--device', default='cpu', type=str, help='use "cpu" or "gpu".
↪')
    args = parser.parse_args()

    numpyro.set_platform(args.device)
    numpyro.set_host_device_count(args.num_chains)
    if args.x64:
        numpyro.enable_x64()

    main(args)
```

CHAPTER 26

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Python Module Index

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