

Improving MCMC sampling efficiency with normalizing flows

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- **Bayesian inference:**

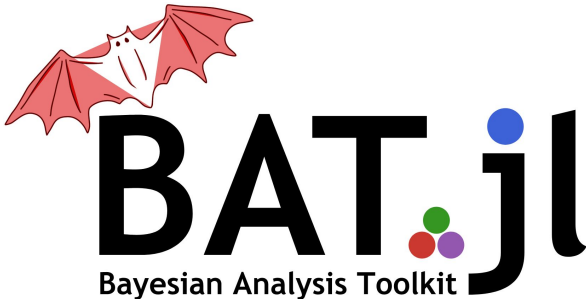


- Updating probabilities based on **Bayes Theorem**

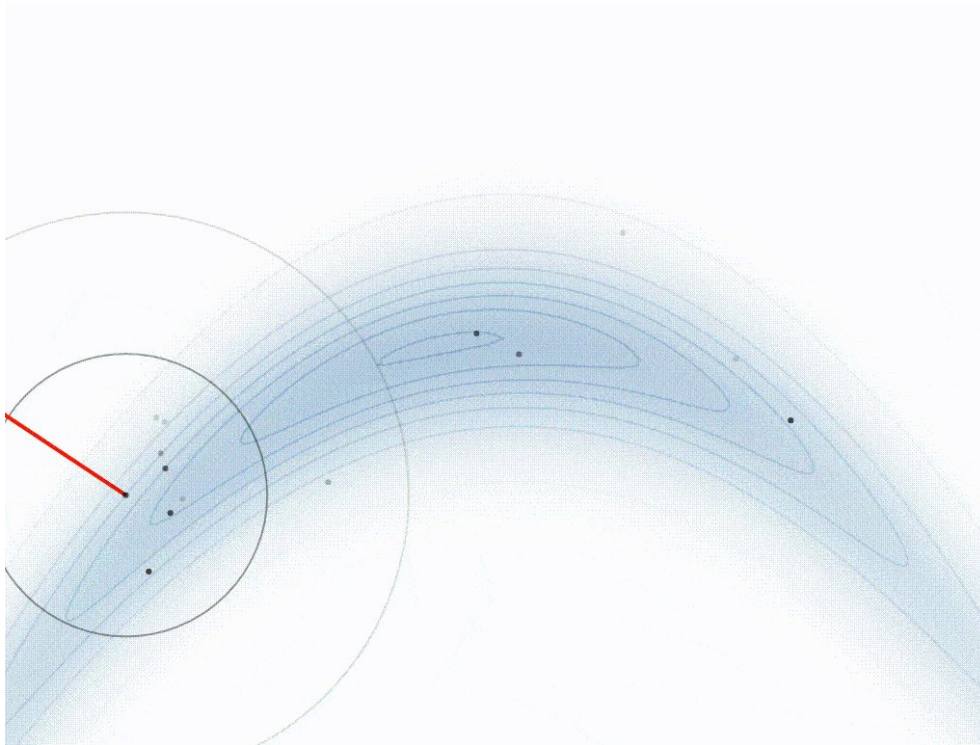
$$\text{posterior} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}$$

- Posterior distributions oftentimes complex

- **Bayesian Analysis Toolkit:**

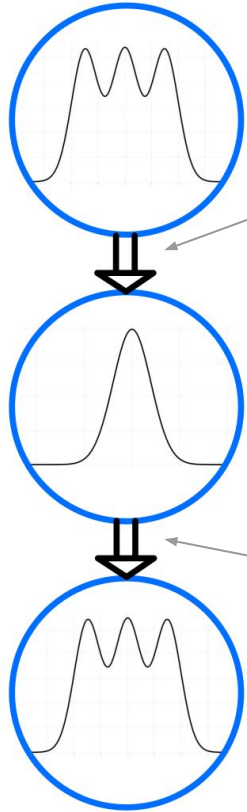


- Framework for the use of Bayesian inference written in julia
- **Monte Carlo Markov Chain sampling** methods are used



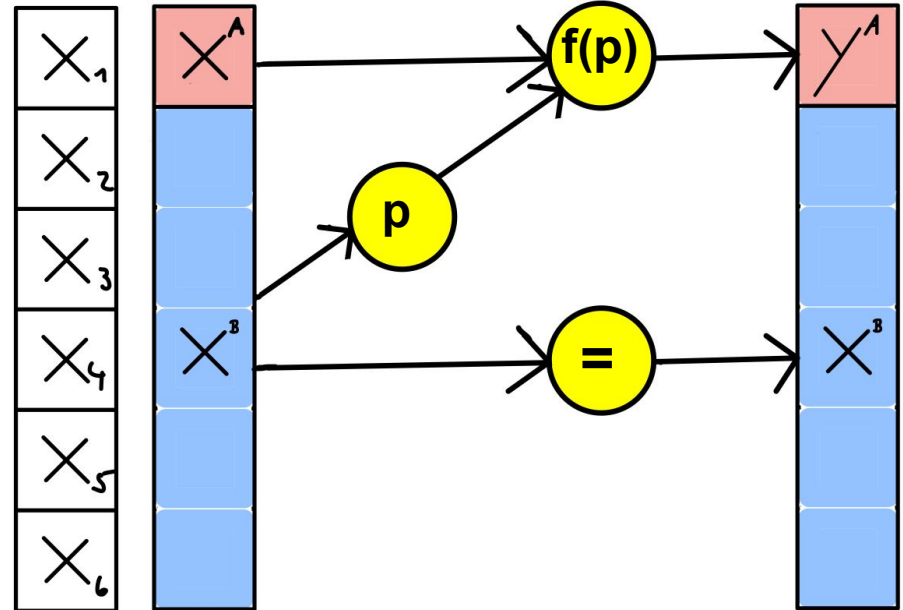
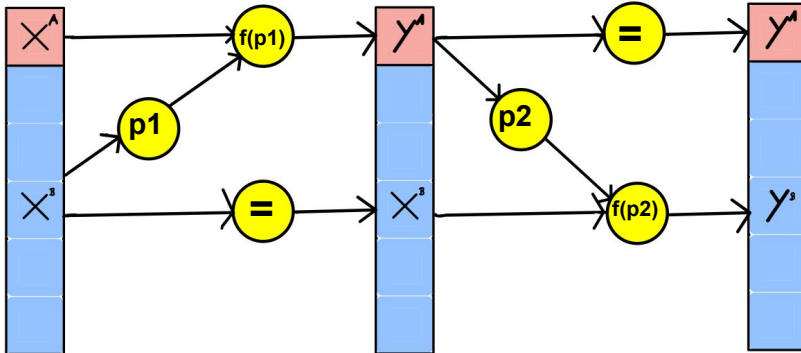
- Converges to the target distribution
- **Curse of dimensionality**
Parameter space of a distribution grows exponentially with the number of parameters
- **Efficient proposal function** needed
 - High dimensional spaces
 - Complex distributions

<https://github.com/chi-feng/mcmc-demo>



- **Transform** the target distribution into a simpler distribution (**Gaussian**)
- **Draw samples** in the simpler transformed space
- Apply the **inverse transformation** to obtain samples from the original target distribution

- **Blockwise transformation** is a good choice for high-dimensional and multimodal data
- **One part of data is transformed** taking into account the correlation to the other part



- The parameters p are learned in a way that **enables inversion**

Monotonous rational quadratic spline function:

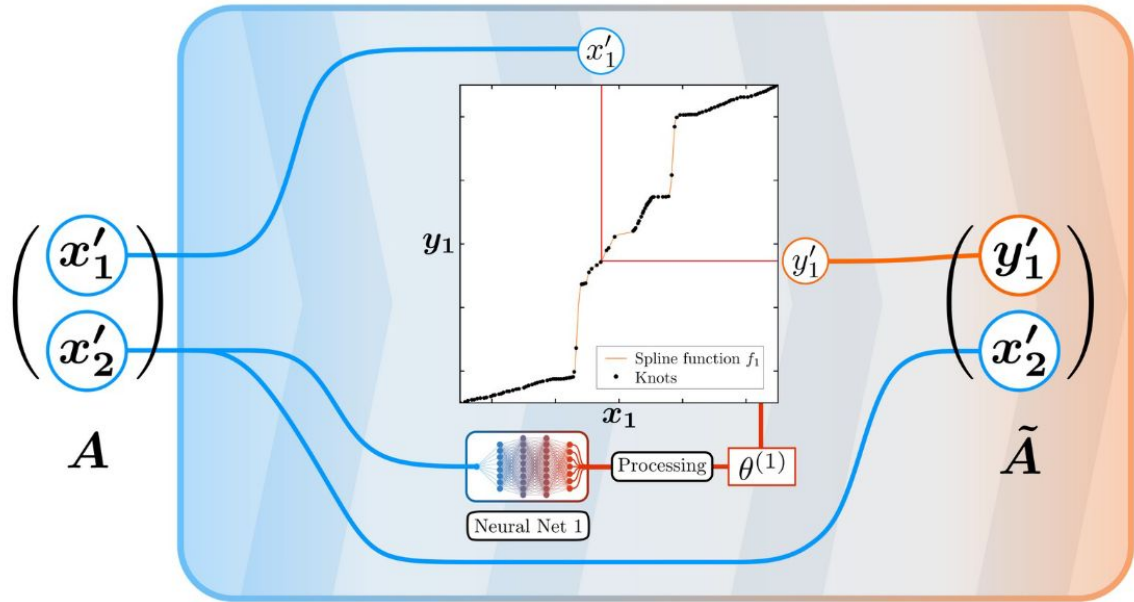
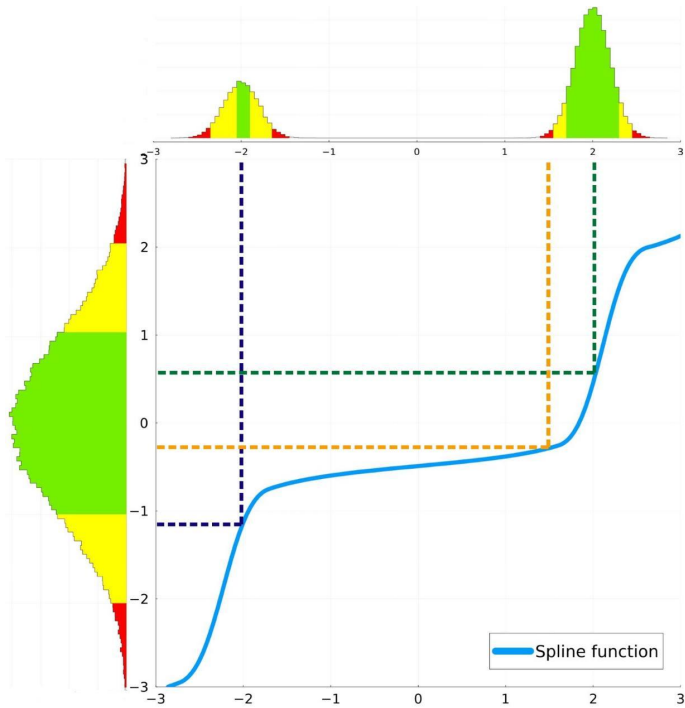
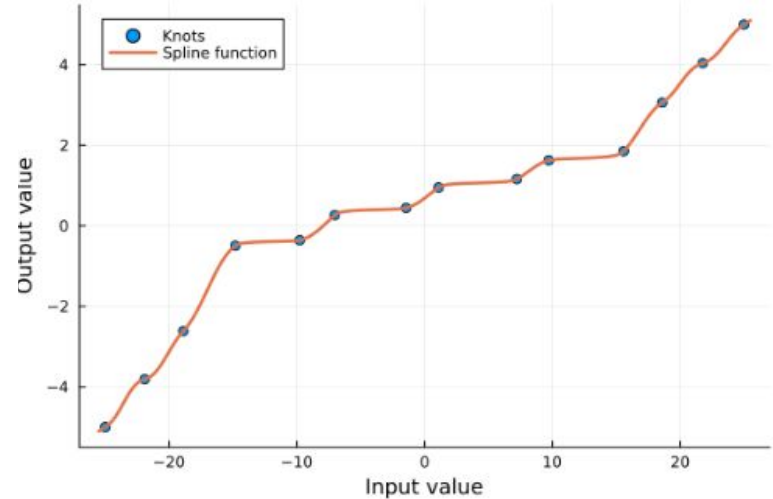
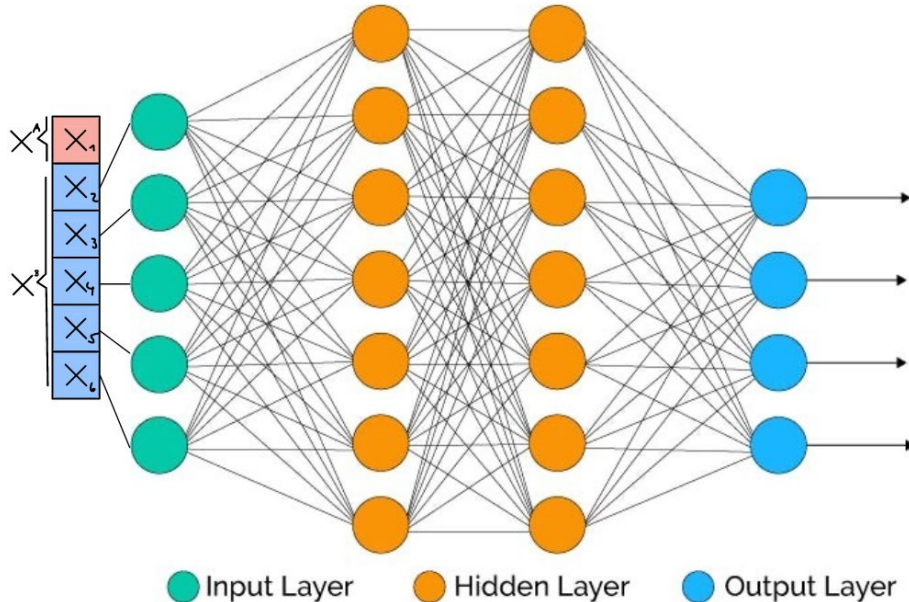


Image created by Michael Dudkowiak

Finding the best spline function

- With more **knots K** , a more complex spline function can be represented
- One **spline function** is defined by **$3(K-1)$** parameters



- Using a **dense neural network** to find an optimal spline function
- Input layer has (dimensions-1) neurons
- Output layer has $3(K-1)$ neurons

- Each step one component is transformed based on all others

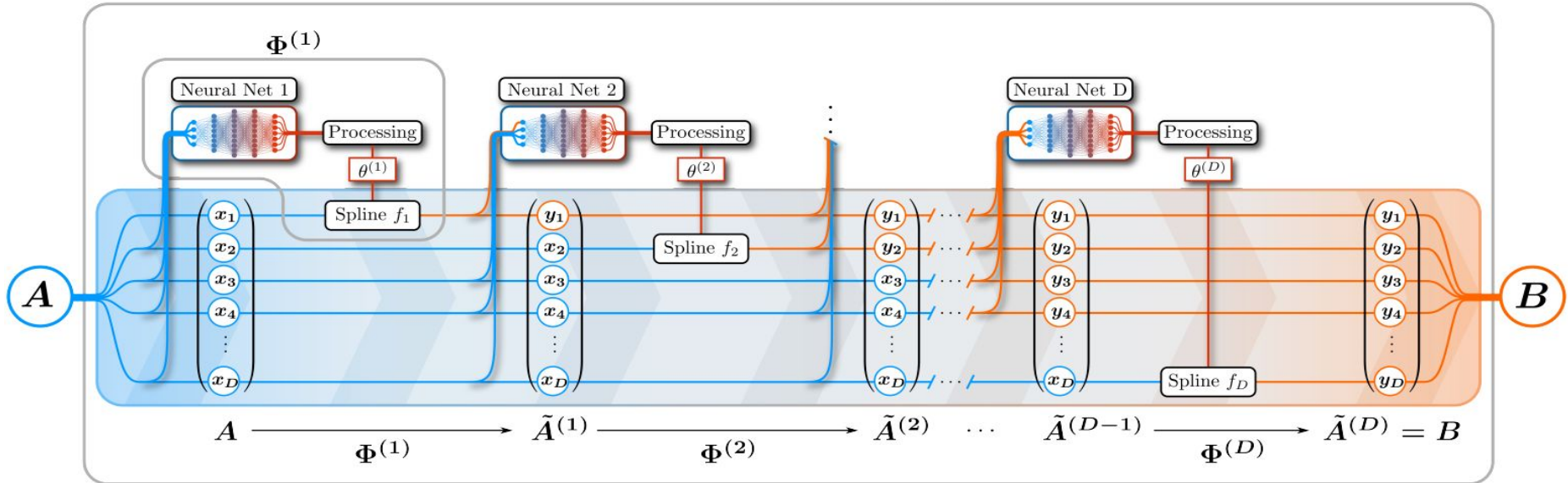
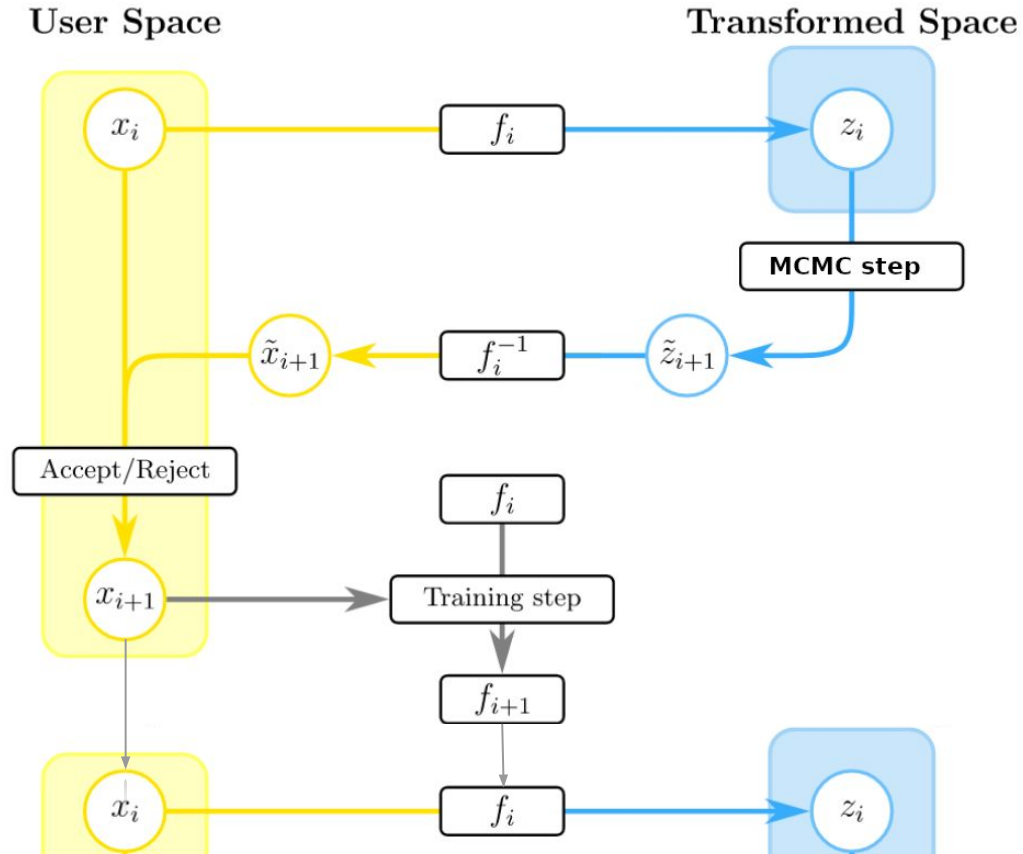


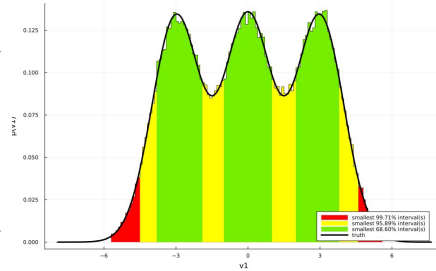
Image created by Michael Dudkowiak

- There is no pre-trained flow in reality
- **Train** a flow **during sampling** process
- Use every new sample to train the flow
- Draw **multiple samples in parallel** for efficiency

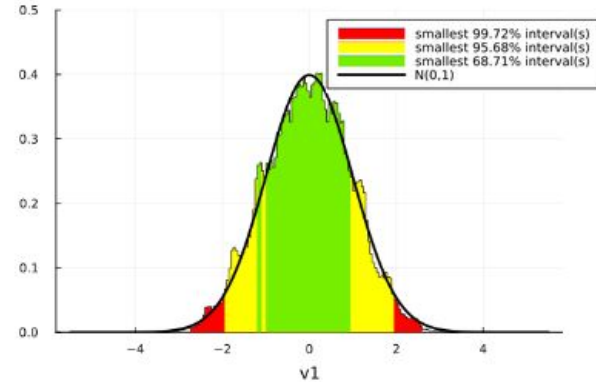


Train a normalizing flow during sampling

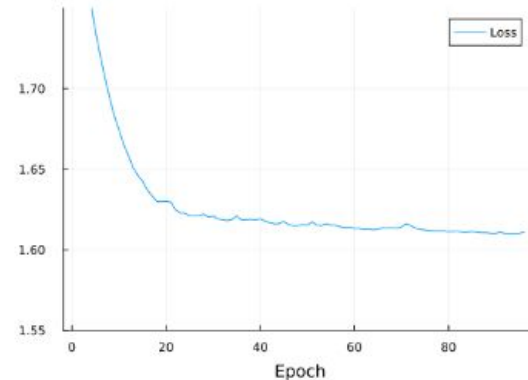
flow(




=



Loss, End=1.6103



- Flow improves over time
- Trained on MCMC samples during sampling
- 1000 new samples per epoch

- **Normalizing flows** are interesting for the **improvement of MCMC sampling** methods
- An implementation is in development for the toolkit 
- Initial toy experiments of training a flow during the sampling process were successful
- Next step is to study the potential for higher levels of complexity

Thank you for listening!

