Probabilistic Programming and AI: Lecture 5

Advanced Topics in Probabilistic Programming

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Recap

- Probabilistic programs can describe any probabilistic model
- Underlying models can be difficult to describe mathematically
    - Unbounded number of random variables
    - Stochastic branching
    - Dynamic distributions allowed (non-static support)
- Efficient general-purpose inference is hard

Recap

- General-purpose inference algorithms exist
  - importance sampling
  - single-site MH
  - Can be inefficient
- Imposing restrictions on the probabilistic program allows us to optimise inference
  - fixed, finite number of continuous variables
  - gradient-based inference: HMC, ADVI
  - Still work for a large class of models

Outlook

- We can **optimise inference for individual models**
- **Custom Inference**: manually exploit structure of model
- **Data-Driven Inference**: use observed data to improve proposals
- **Probabilistic Programs as Proposals**: convenient way to customise inference
- **Deep Probabilistic Programming**: learning proposals (and models) from data

Custom Inference

Infinite Mixture Models: Where single-site MH fails

- **Number of clusters:**

  $$K \sim \text{Poisson}(5)$$

- Probability of being in cluster k, p_k:

  $$p \sim \text{Dirichlet}(1/\text{K})$$

- Cluster centers, $k = 0, \ldots, K$:

  $$\mu_k^x \sim \text{Uniform(-3,3)},$$
  $$\mu_k^y \sim \text{Uniform(-3,3)}$$

- Cluster spread, $k = 0, \ldots, K$:

  $$\sigma_k^2 \sim \text{InverseGamma(1,1)}$$

- Cluster membership, $i = 1, \ldots, N$:

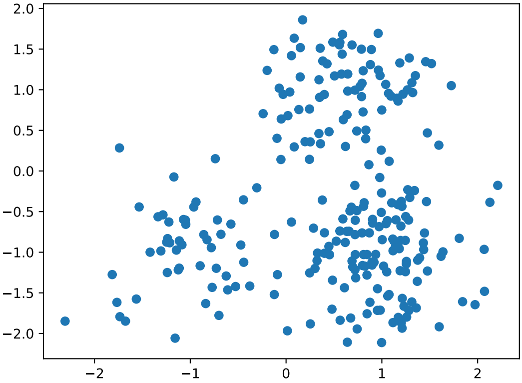
  $$z_i \sim \text{Categorical(p)}$$

- Observed data, , $i = 1, \ldots, N$:

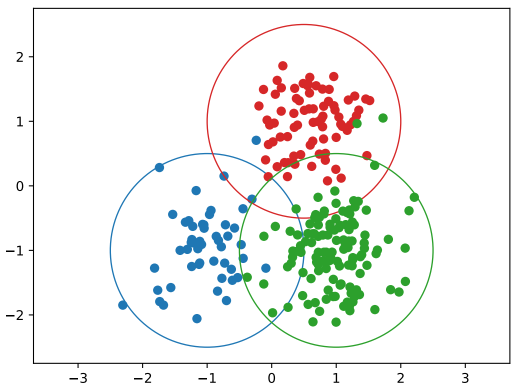
  $$x_i \sim \text{Normal}(\mu_{z_i}, \sigma_{z_i})$$

- Unbounded number of random variables
- Discrete variables
- $\implies$ no HMC / ADVI
- High-dimensional
- $\implies$ no IS / LW
- but single-site MH is applicable in principle

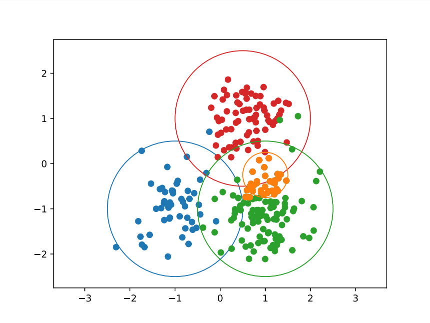
Data set



Ground truth



Single-site update



Updating the number of clusters K

- Adding clusters is easy: sample new cluster center and deviation
- How can we **remove the orange cluster?**
- Change K from 4 to 3 (single-site)
- Changes dimension of p (so current p has 0 log-prob?)
- Fix: sample p_k individually
- All memberships $z_i = 4$ have log-prob 0.

In theory, this update can happen, but is very low probability. All $z_i = 4$ have to be changed before setting $K = 3$.

Designing a Custom Inference Algorithm

In each iteration, we **pick one type of move at random**

1. Updating cluster centers μ_k and deviations σ_k
2. Reweighting clusters – updating p
3. Updating the memberships z_i
4. Merging two randomly selected clusters.
5. Splitting one random cluster

Designing a Custom Inference Algorithm - 1

Updating cluster centers μ_k and deviations σ_k

We can simply do random walk Metropolis Hastings updates.

Slightly perturbing the current values.

Designing a Custom Inference Algorithm - 2

Reweighting clusters – updating p

Let n_k be the number of data points allocated to cluster k.

We expect that

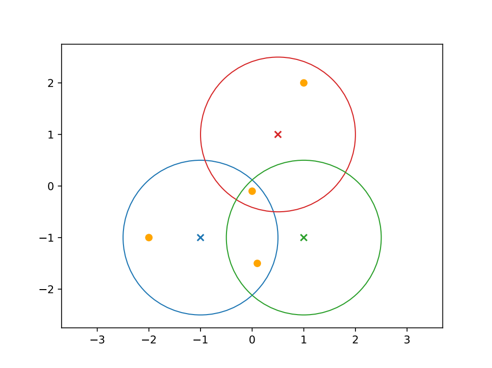
$$\frac{n_k}{N} \approx p_k.$$

We can update p reflecting this relationship:

$$p \sim \mathrm{Dirichlet}(n_1, \ldots, n_K)$$

Designing a Custom Inference Algorithm - 3

Updating the memberships z_i



$$\tilde{w}_k := \mathcal{N}(x_i; \mu_k, \sigma_k) \propto \exp\left(-\frac{1}{2\sigma_k}(x_i - \mu_k)^\top (x_i - \mu_k)\right), \quad w_k := \frac{\tilde{w}_k}{\sum_{k=1}^{K} \tilde{w}_k}$$

$$z_i \sim \text{Categorical}(w_1, \ldots, w_k)$$

Merging two randomly selected clusters

Choose two "neighbouring" clusters with weights p_i, means μ_i and deviations σ_i at random, such that

$$\|\mu_1 - \mu_2\|_2 \leq \|\mu_1 - \mu_j\|_2, \quad \text{for } j = 1, \ldots, K.$$

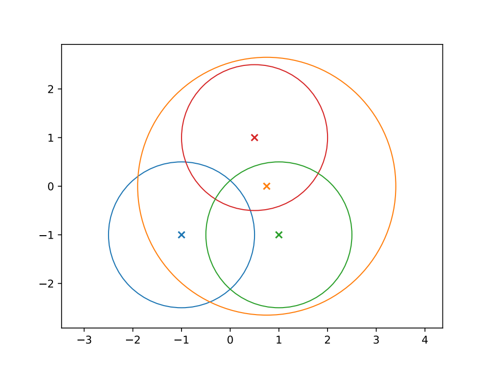
Match moments for isotropic Normals of dimension d:

$$\begin{aligned} p_* &= p_1 + p_2 && (1) \\ p_* \mu_* &= p_1 \mu_1 + p_2 \mu_2 && (2) \\ p_*(\mu_*^\top \mu_* + d\sigma_*^2) &= p_1(\mu_1^\top \mu_1 + d\sigma_1^2) + p_2(\mu_2^\top \mu_2 + d\sigma_2^2) && (3) \end{aligned}$$

and update memberships z_i.

Designing a Custom Inference Algorithm - 4

Merging two randomly selected clusters



Merge red and green cluster to orange.

Designing a Custom Inference Algorithm - 5

Splitting one random cluster

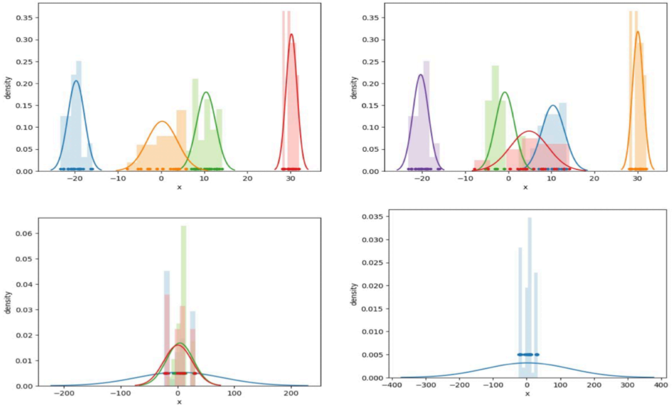
Select cluster at random with weight p_*, mean μ_* and deviation σ_*.

Draw auxiliary variables:
$u_1 \sim \mathrm{Beta}(2,2)$, $\boldsymbol{u}_2 \sim \mathrm{Dirichlet}(2,\ldots,2) \in \mathbb{R}^d$, $u_3 \sim \mathrm{Beta}(1,1)$

$$
\begin{aligned}
w_1 &= w_* u_1, && (4)\\
w_2 &= w_*(1-u_1) && (5)\\
\mu_1 &= \mu_* - \boldsymbol{u}_2 \sigma_* \sqrt{d \frac{w_2}{w_1}} && (6)\\
\mu_2 &= \mu_* + \boldsymbol{u}_2 \sigma_* \sqrt{d \frac{w_1}{w_2}} && (7)\\
\sigma_1 &= u_3(1-\boldsymbol{u}_2^\top \boldsymbol{u}_2)\sigma_*^2 \frac{w_*}{w_1} && (8)\\
\sigma_2 &= (1-u_3)(1-\boldsymbol{u}_2^\top \boldsymbol{u}_2)\sigma_*^2 \frac{w_*}{w_2} && (9)
\end{aligned}
$$

These variables satisfy equations (1) - (3). Thus, merging the two randomly created clusters results in the original cluster (p_*, μ_*, σ_*).

Designing a Custom Inference Algorithm - Results



(b) Two Samples from the Inferred Posterior: Richardson & Green's Data-driven MCMC (top), BLOG Ancestral Sampling (bottom)

Designing a Custom Inference Algorithm

- In the proposal, we make use of **auxiliary random variables**
- This makes **computing the acceptance probability non-trivial**
- It is key to be able to ”undo” moves, e.g. merge – join
- This is called **reversible-jump MCMC**
- It is a special case of **involutive MCMC**
- More details in: On Bayesian Analysis of Mixtures with an Unknown Number of Components (with discussion) *https://academic.oup.com/jrsssb/article-pdf/59/4/731/49588858/jrsssb_59_4_731.pdf*

Data-Driven Inference

Data-Driven Proposals = Biased Inference?

- It is often good practice to chose *uninformative* priors, i.e. we do not prefer any values for the latent variables *a-priori*
- However, with the proposals, we want to stir inference towards high probability areas of the *posterior*
- We can **use the observed data to construct proposals as close to the posterior as possible**

Data-Driven Proposals

However, to ensure convergence to the true posterior proposals have to satisfy following properties:

- **Unconditional proposals** $Q(x)$: if a state x is possible according to the model $P(x) > 0$, then it has to be possible according to the proposal $Q(x) > 0$
- **Conditional proposals** $Q(x'|x)$: any state should be reachable from any other state in any number of steps less or equal to a fixed number N.

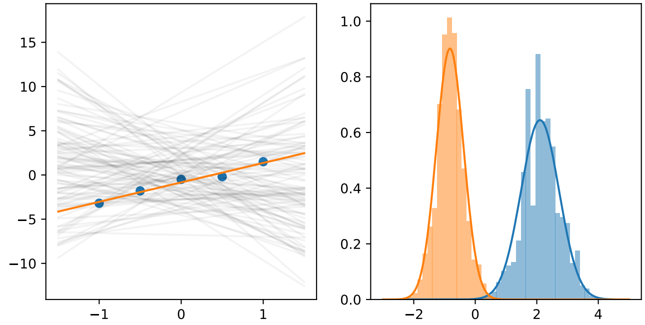
Data-Driven Inference

Common strategy:

One way of constructing data-driven proposals is to use a **heuristic to estimate the mode** of the target distribution (or one of its conditional distributions) and to sample values near the estimate of the mode, but with **noise added**.

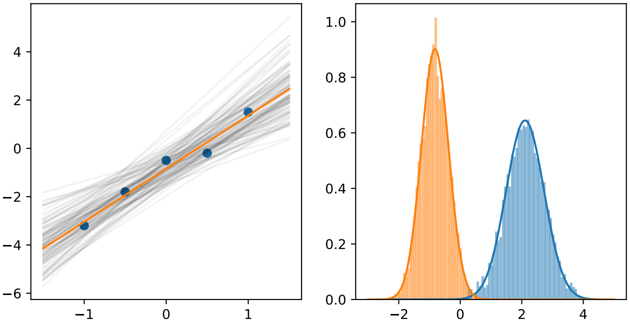
With enough data:
mode of posterior $\approx$ maximum likelihood estimator

Linear regression:
propose from prior



Data-Driven Inference

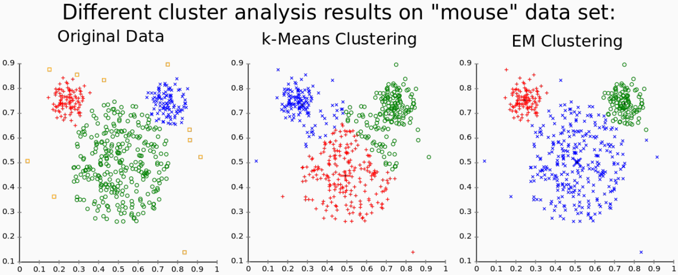
Linear regression: propose from Normals centered at ordinary least squares (OLS) solution



GMM:

Sample number of clusters $K \sim$ Poisson(5)

Run k-means clustering and perturb the result.



Probabilistic Programs as Proposals

Probabilistic Programs as Proposals

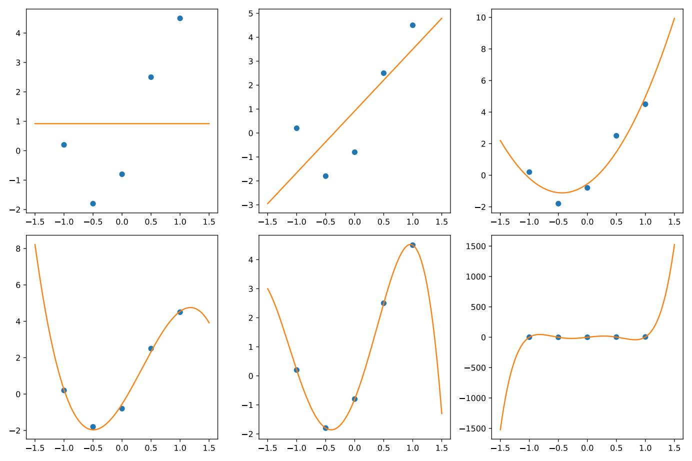
As proposals get more complex it is more convenient to write them programmatically.

Key idea: We can write a probabilistic program and use it for generating proposal in the inference for another program.

These programs are called *guides*.

Gen (and Pyro): programmable inference

Example: Polynomial Regression in Gen.jl



Example: Polynomial Regression in Gen.jl

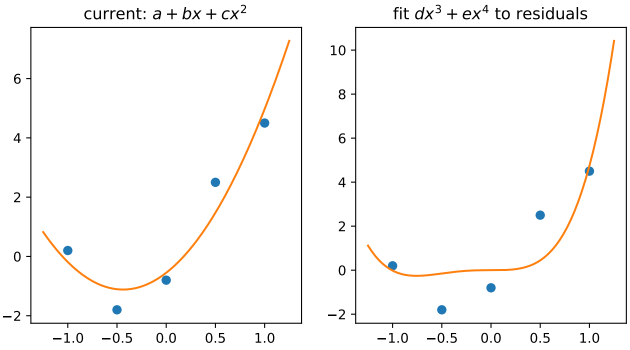
```
@gen function poly_model(x_coordinates)
    degree ~ uniform_discrete(0,4)
    var ~ inv_gamma(1,1)
    coefficients = [({(:c,i)} ~ normal(0,1)) for i in 0:degree]
    for i=1:length(x_coordinates)
        x = x_coordinates[i]
        mu = 'coefficients * x.^(0:degree)
        {(:y,i)} ~ normal(mu, sqrt(var))
    end
end
```

```
@gen function poly_proposal_prior(x_coordinates)
    degree ~ uniform_discrete(0,4)
    var ~ inv_gamma(1,1)
    coefficients = [({(:c,i)} ~ normal(0,1)) for i in 0:degree]
end
```

Example: Polynomial Regression in Gen.jl

Idea: Iteratively sampling coefficients.

We have currently polynomial of 2nd degree.



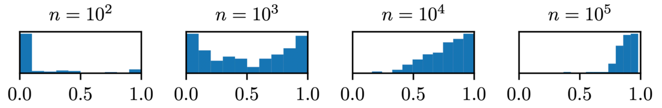
Sample value centered around OLS solution for d.

Example: Polynomial Regression in Gen.jl

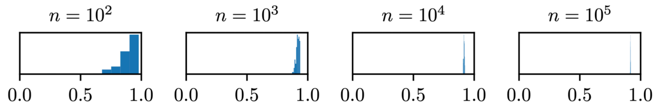
```julia
@gen function poly_proposal_data_driven(x_coords, y_coords)
    # noise for each coefficient
    scales = [0.395, 0.242, 0.088, 0.020, 0.007]
    n = length(x_coords)
    degree ~ uniform_discrete(0,4)
    coeffs = [NaN for i in 0:degree]
    predicted = zeros(n)
    for i in 0:degree
        residuals = y_coords .- predicted # elementwise subtraction
        # fit a polynomial to residuals with coefficients 0..i-1 fixed to zero
        est_coeffs = least_squares(x_coords, residuals, degree, min_degree=i)
        coeffs[i+1] = ({(:c,i)} ~ cauchy(est_coeffs[1], scales[i+1]))
        predicted = [dot(coeffs, x.^(0:i)) for x in x_coords]
    end
    # use variance of residuals to get estimate for model noise
    residuals = y_coords .- predicted
    var ~ inv_gamma(1 + n/2, 1 + 0.5 * dot(residuals, residuals))
end
```

Example: Polynomial Regression in Gen.jl

Estimate for the probability of degree = 3



(a) Estimates from self-normalized importance sampling with a prior proposal.



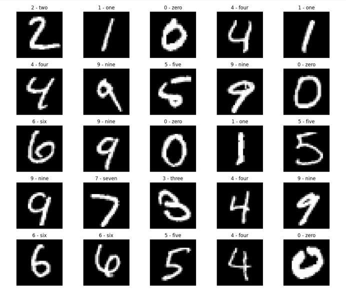
(b) Estimates from self-normalized importance sampling with a data-driven proposal.

Deep Probabilistic Programming

Deep Probabilistic Programming: Motivation

- **Non-programmability**: For many data modalities that are commonly considered in ML and AI, including images and natural language, it is **near-impossible to fully specify a probabilistic program** that defines a sufficiently realistic distribution over data.
- **Scalability**: Models in ML and AI are routinely trained on **very large datasets**. Most inference methods that we have considered so far do not scale to such large datasets without additional modifications.
- These challenges can be addressed by combining inference methods from probabilistic programming with differentiable programming techniques from deep learning research.

Deep Probabilistic Programming: Non-programmability



Non-programmability:

How to implement a probabilistic program that generates 28×28 px images of hand-written digits?

Sample digit $\sim \text{DiscreteUniform}(0, 9)$,

and then … ??

Deep Probabilistic Programming: Neural Networks

- **Neural networks** are universal function approximators
- Use neural network η_λ with parameters λ in the program to flexibly model relationship between latents and observes
- latent: digit; observed: image
- image[x,y] $\sim$ Bernoulli(η_λ(digit)[x, y])
- probability of pixel being white $\cong$ gray scale value
- Learn λ to fit our data set

Deep Probabilistic Programming: Neural Networks

How to learn λ (model parameters)?

- Fully Bayesian treatment: λ are additional latent variables, set prior $P(\lambda)$ and take maximum a-posteriori (MAP)
  $$\mathrm{argmax}_\lambda \, P(\lambda | x_1, \ldots, x_n)?$$
- $\rightarrow$ **Bayesian deep learning**
- Challenges: very high-dimensional posterior + choice of prior
- Instead maximise marginal likelihood of training data
  $$\mathrm{argmax}_\lambda \, P(x_1, \ldots, x_n | \lambda)$$
- $\rightarrow$ **Maximum likelihood estimation (MLE)**
- $P(\lambda | x_1, \ldots, x_n) \propto P(x_1, \ldots, x_n | \lambda) P(\lambda)$
- When there is a lot of data, the likelihood $P(X|\lambda)$ numerically dominates the prior $P(\lambda)$ so effectively the prior can be ignored (formally: Bernstein von Mises theorem)
- **MLE $\approx$ MAP if we have a lot of data**

Deep Probabilistic Programming: MLE

Find MLE of λ with stochastic gradient ascent

$$\nabla_\lambda \log P(X|\lambda) = \mathbb{E}_{\theta \sim P(.|X,\lambda)} \left[\nabla_\lambda \log P(X, \theta|\lambda)\right]$$

because

$$\begin{aligned}
& \mathbb{E}_{\theta \sim P(.|X,\lambda)} \left[\nabla_\lambda \log P(X, \theta|\lambda)\right] \\
= \; & \mathbb{E}_{\theta \sim P(.|X,\lambda)} \left[\nabla_\lambda \log P(X|\lambda) + \nabla_\lambda \log P(\theta|X, \lambda)\right] \\
= \; & \nabla_\lambda \log P(X|\lambda) + \underbrace{\mathbb{E}_{\theta \sim P(.|X,\lambda)} \left[\nabla_\lambda \log P(\theta|X, \lambda)\right]}_{=0}
\end{aligned}$$

How to compute $\mathbb{E}_{\theta \sim P(.|X,\lambda)} \left[\nabla_\lambda \log P(X, \theta|\lambda)\right]$?

Bayesian inference!

Deep Probabilistic Programming

- We do not only want to learn the model parameters
- We also want to perform posterior inference over latent variables
- E.g. what is the digit of an unlabeled image?
- How to combine model learning and posterior inference?

Variational guide programs

- If we cannot fully specify the model, then we probably also want to specify the proposals with neural networks η_ϕ.
- E.g. mapping images to their digit.
- Thus, we write a variational proposal distribution as a guide program.
- As in ADVI, we can differentiate through the neural networks and maximise the ELBO to minimise the KL-divergence.

Scalability: Amortised Inference

Instead of learning N variational distributions separately like in ADVI with mean-field approximation,

$$Q(\theta_i|x_i, \phi) = Q(\theta_i|\phi_i),$$

we use the neural network η_ϕ to predict the variational parameters for each observation x_i,

$$Q(\theta_i|x_i, \phi) = Q(\theta_i|\eta_\phi(x_i)).$$

E.g. for N images of hand-written digits x_i:
Learning N separate distributions over the true latent digits θ_i of x_i versus learning to predict the digit of each image $\eta_\phi(x_i)$ and then build a distribution around it.

Combining model learning and posterior inference

- Maximising the ELBO w.r.t to ϕ *and* λ

$$\begin{aligned} \mathrm{ELBO}(X;\lambda,\phi) &= \mathbb{E}_{\theta\sim Q(.|\phi)}\left[\log P(\theta,X|\lambda) - \log Q(\theta|\phi)\right] \\ &= \log P(X|\lambda) - D_{\mathrm{KL}}(Q(\Theta|\phi) \parallel P(\Theta|X,\lambda)) \end{aligned}$$

- Justification: assume we have variational distribution with an "infinity capacity" (it can fit every distribution perfectly), then

$$\min_{\phi} D_{\mathrm{KL}}(Q(\Theta|\phi) \parallel P(\Theta|X,\lambda)) = 0 \text{ and } \max_{\phi} \mathrm{ELBO}(X;\lambda,\phi) = \log P(X|\lambda)$$

- Thus, maximising the ELBO w.r.t to ϕ *and* λ is equivalent to maximum likelihood estimation,

$$\max_{\lambda}\max_{\phi} \mathrm{ELBO}(X;\lambda,\phi) = \max_{\lambda} \log P(X|\lambda)$$

Maximising the ELBO w.r.t to ϕ *and* λ

$$\max_{\lambda} \max_{\phi} \mathrm{ELBO}(X; \lambda, \phi) = \max_{\lambda} \log P(X|\lambda)$$

- In practice, we **will not have an infinite capacity variational distribution**, and we will typically **not fully solve the inner optimization problem** for ϕ at every gradient step for λ.
- We take gradient steps in both λ and ϕ space simultaneously so that the guide and model play chase, with the guide tracking a moving posterior $\log P(\Theta|X, \lambda)$.
- There will be a difference between maximizing the ELBO and maximizing the marginal likelihood. This difference manifests itself as an extra term in the gradient

$$\nabla_{\lambda} ELBO(X; \lambda, \phi) = \nabla_{\lambda} \log P(X|\lambda) + \nabla_{\lambda} D_{\mathrm{KL}}(Q(\Theta|\phi) \parallel P(\Theta|X, \lambda))$$

Maximising the ELBO w.r.t to ϕ *and* λ

$$\nabla_\lambda \mathrm{ELBO}(X; \lambda, \phi) = \nabla_\lambda \log P(X|\lambda) + \nabla_\lambda D_{\mathrm{KL}}(Q(\Theta|\phi) \parallel P(\Theta|X, \lambda))$$

In this gradient, the second term prevents gradient updates to λ from making changes to the model that strongly increase the KL relative to the variational approximation. This is sometimes argued to be beneficial, in the sense that it **acts as a form of regularization that prevents overfitting** in the generative model, or in the sense that it **stabilizes the optimizer**. However, it can also lead to **approximation errors in the learned generative model**.

Optimizing the ELBO will balance maximizing $\log P(X|\lambda)$ against minimizing $D_{\mathrm{KL}}(Q(\Theta|\phi) \parallel P(\Theta|X, \lambda))$. This can be seen as a bias towards learned $P(\Theta|X, \lambda)$ that are ”compatible” with performing variational inference in using the variational family $Q(\Theta|\phi)$.

Maximising the ELBO w.r.t to ϕ *and* λ - Computing Gradients

As

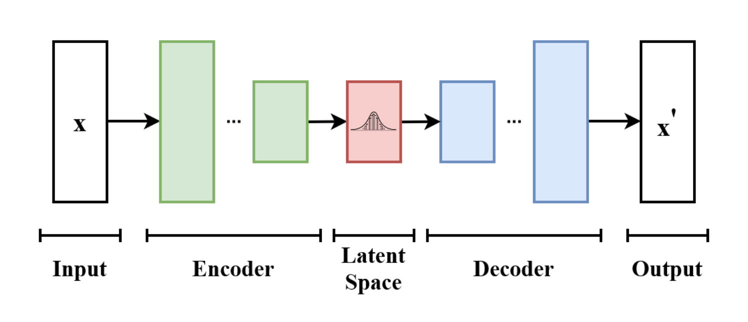
$$\mathrm{ELBO}(X;\lambda,\phi) = \mathbb{E}_{\theta\sim Q(.|\phi)}\left[\log P(X,\theta|\lambda) - \log Q(\theta|\phi)\right]$$

is an expectation w.r.t to $Q(.|\phi)$, we can pull ∇_ϕ inside the expectation if we can apply the reparametrisation trick as in ADVI. This allows us to use unbiased lower-variance Monte-Carlo estimates for the gradient.

∇_λ can always be pulled inside the expectation.

Deep Probabilistic Programming - Example

Semi-Supervised Variational Auto-Encoders (SSVAE) in Pyro



Objective: Learn generative distribution of hand-written digits and be able to predict the digit of unlabeled images.

Only a fraction of the images are assumed to be labeled.

Deep Probabilistic Programming - SSVAE

```python
# observation likelihood p(x|z)
class Decoder(nn.Module):
    def __init__(self, input_dim, output_dim, hidden_dims):
        super().__init__()
        self.fc1 = nn.Linear(input_dim, hidden_dims[0])
        self.fc2 = nn.Linear(hidden_dims[0], hidden_dims[1])
        self.fc3 = nn.Linear(hidden_dims[1], output_dim)

        self.softplus = nn.Softplus()

    def forward(self, z):
        z = self.softplus(self.fc1(z))
        z = self.softplus(self.fc2(z))
        loc_img = torch.sigmoid(self.fc3(z))
        return loc_img # probabilities of pixels being white
```

Deep Probabilistic Programming - SSVAE

```python
def model(self, x, y=None):
    pyro.module("decoder", self.decoder)
    with pyro.plate("data", x.shape[0]):
        # setup hyperparameters for prior p(z)
        z_loc = torch.zeros(x.shape[0], self.z_dim)
        z_scale = torch.ones(x.shape[0], self.z_dim)
        # sample from prior p(z)
        z = pyro.sample("latent", dist.Normal(z_loc, z_scale).to_event(1))
        # setup hyperparameters for prior p(y)
        alpha = torch.full(x.shape[0], 1/self.output_size)
        # sample from prior p(y)
        y = pyro.sample("y", dist.OneHotCategorical(alpha), obs=y)
        # sample from p(x|y,z)
        loc_img = self.decoder.forward(self.concat.forward(z, y))
        # sample image
        pyro.sample(
            "obs",
            dist.Bernoulli(loc_img, validate_args=False).to_event(1),
            obs=x,
        )
        return loc_img
```

Deep Probabilistic Programming - SSVAE

```python
# diagonal gaussian distribution q(z|x,y)
class EncoderZ(nn.Module):
    def __init__(self, input_dim, output_dim, hidden_dims):
        super().__init__()
        self.input_dim = input_dim

        self.fc1 = nn.Linear(input_dim, hidden_dims[1])
        self.fc2 = nn.Linear(hidden_dims[1], hidden_dims[0])

        # two heads for mean and std
        self.fc31 = nn.Linear(hidden_dims[0], output_dim)
        self.fc32 = nn.Linear(hidden_dims[0], output_dim)

        self.softplus = nn.Softplus()

    def forward(self, x):
        x = self.softplus(self.fc1(x))
        x = self.softplus(self.fc2(x))

        z_loc = self.fc31(x)
        z_scale = torch.exp(self.fc32(x))
        return z_loc, z_scale
```

Deep Probabilistic Programming - SSVAE

```python
# diagonal gaussian distribution q(y|x)
class EncoderY(nn.Module):
    def __init__(self, input_dim, output_dim, hidden_dims):
        super().__init__()
        self.input_dim = input_dim

        self.fc1 = nn.Linear(input_dim, hidden_dims[1])
        self.fc2 = nn.Linear(hidden_dims[1], hidden_dims[0])
        self.fc3 = nn.Linear(hidden_dims[0], output_dim)

        self.softplus = nn.Softplus()
        self.softmax = nn.Softmax(dim=1)

    def forward(self, x):
        x = self.softplus(self.fc1(x))
        x = self.softplus(self.fc2(x))

        y = self.softmax(self.fc3(x)) # returns class probabilities
        return y
```

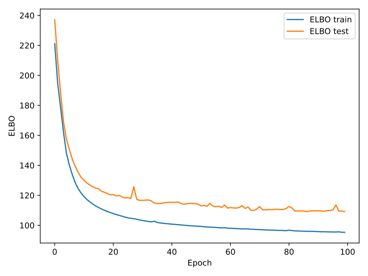
```python
# define the guide (variational distribution) q(z|x,y) q(y|x)
def guide(self, x, y=None):
    pyro.module("encoder_z", self.encoder_z)
    pyro.module("encoder_y", self.encoder_y)
    with pyro.plate("data", x.shape[0]):
        if y is None:
            # use the encoder to get the parameters used to define q(y|x)
            alpha = self.encoder_y.forward(x)
            # sample q(y|x)
            y = pyro.sample("y", dist.OneHotCategorical(alpha))

        # amortised inference
        # use the encoder to get the parameters used to define q(z|x,y)
        z_loc, z_scale = self.encoder_z.forward(self.concat.forward(x, y))

        # sample q(z|x,y)
        z = pyro.sample("latent", dist.Normal(z_loc, z_scale).to_event(1))
```

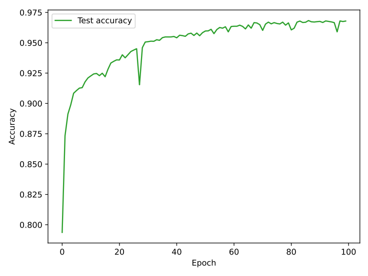
```python
# auxiliary model
def model_classify(self, x, y):
    pyro.module("encoder_y", self.encoder_y)
    assert y is not None
    with pyro.plate("data", x.shape[0]):
        alpha = self.encoder_y.forward(x)
        with pyro.poutine.scale(scale=self.aux_loss_multiplier):
            pyro.sample("y_aux", dist.OneHotCategorical(alpha), obs=y)

def guide_classify(self, x, y=None):
    pass
```

Deep Probabilistic Programming - SSVAE

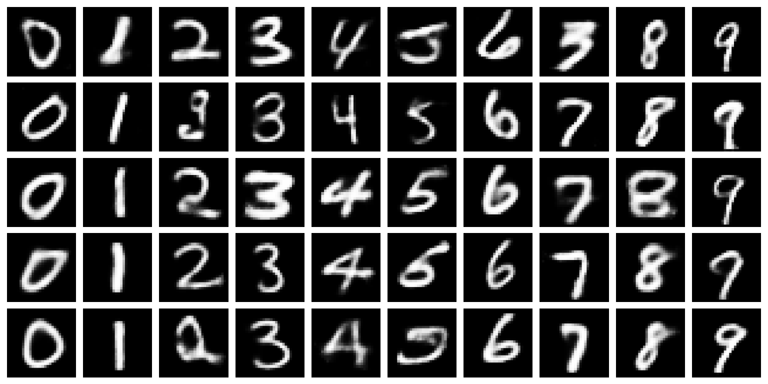
```python
for epoch in range(1, epochs+1):
    # perform svi steps on train loader
    epoch_loss = 0.0
    # batches are not shuffled
    for i, (x, y) in enumerate(loaders['train']):
        x = x.reshape(-1, ssvae.input_size).to(device)

        # alternate between supervised and unsupervised batches
        if nth_supervised and (i % nth_supervised == 0):
            y = F.one_hot(y, ssvae.output_size).to(device)

            # perform step on auxiliary model
            if aux_loss:
                epoch_loss += svi_aux.step(x, y)
        else:
            y = None

        epoch_loss += svi.step(x, y)
```

ELBO + classification accuracy for data set with 10% labeled





Newly generated digits



Resources

Probabilistic Graphical Models - D Koller, N Friedman - 2009: Chapter 2.1.4 and 3

Paper: On Bayesian Analysis of Mixtures with an Unknown Number of Components (with discussion) *https://academic.oup.com/jrsssb/article-pdf/59/4/731/49588858/jrsssb_59_4_731.pdf*

RJMCMC / Involutive MCMC in Gen Tutorial *https://www.gen.dev/tutorials/rj/tutorial*

Paper: Transforming Worlds: Automated Involutive MCMC for Open-Universe Probabilistic Models *https://people.eecs.berkeley.edu/~russell/papers/aabi21-oupm.pdf*

Data-Driven Proposals in Gen Tutorial *https://www.gen.dev/tutorials/data-driven-proposals/tutorial*

Resources

Paper: Using probabilistic programs as proposals
https://arxiv.org/pdf/1801.03612.pdf

Paper: Pyro: Deep Universal Probabilistic Programming
https://arxiv.org/pdf/1810.09538.pdf

An Introduction to Probabilistic Programming: Chapter 8 Deep Probabilistic Programming
https://arxiv.org/pdf/1809.10756.pdf

Pyro ELBO Gradients Estimators
https://pyro.ai/examples/svi_part_iii.html

Paper: Auto-Encoding Variational Bayes
https://arxiv.org/pdf/1312.6114.pdf

Pyro Semi-Supervised Variational Auto-Encoder
https://pyro.ai/examples/ss-vae.html

Organisation

- Today was last lecture
- 29.11. A4 Deadline
- 04.12. Assignment Discussion Session
- 06.12. Project Proposal Deadline
- 08.01. Project Milestone
- 28.01. & 29.01. Project Presentations