

Deep Generative Models

Lecture 4

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Bayesian framework

Bayes theorem

$$p(\mathbf{t}|\mathbf{x}) = \frac{p(\mathbf{x}|\mathbf{t})p(\mathbf{t})}{p(\mathbf{x})} = \frac{p(\mathbf{x}|\mathbf{t})p(\mathbf{t})}{\int p(\mathbf{x}|\mathbf{t})p(\mathbf{t})d\mathbf{t}}$$

- ▶ \mathbf{x} – observed variables, \mathbf{t} – unobserved variables (latent variables/parameters);
- ▶ $p(\mathbf{x}|\mathbf{t})$ – likelihood;
- ▶ $p(\mathbf{x}) = \int p(\mathbf{x}|\mathbf{t})p(\mathbf{t})d\mathbf{t}$ – evidence;
- ▶ $p(\mathbf{t})$ – prior distribution, $p(\mathbf{t}|\mathbf{x})$ – posterior distribution.

Meaning

We have unobserved variables \mathbf{t} and some prior knowledge about them $p(\mathbf{t})$. Then, the data \mathbf{x} has been observed. Posterior distribution $p(\mathbf{t}|\mathbf{x})$ summarizes the knoweldge after the observations.

Variational Lower Bound

We have set of objects $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^n$. The goal is to perform Bayesian inference on the unobserved variables $\mathbf{T} = \{\mathbf{t}_i\}_{i=1}^n$.

Evidence Lower Bound (ELBO)

$$\begin{aligned}\log p(\mathbf{X}) &= \log \frac{p(\mathbf{X}, \mathbf{T})}{p(\mathbf{T}|\mathbf{X})} = \\&= \int q(\mathbf{T}) \log \frac{p(\mathbf{X}, \mathbf{T})}{p(\mathbf{T}|\mathbf{X})} d\mathbf{T} = \int q(\mathbf{T}) \log \frac{p(\mathbf{X}, \mathbf{T})q(\mathbf{T})}{p(\mathbf{T}|\mathbf{X})q(\mathbf{T})} d\mathbf{T} = \\&= \int q(\mathbf{T}) \log \frac{p(\mathbf{X}, \mathbf{T})}{q(\mathbf{T})} d\mathbf{T} + \int q(\mathbf{T}) \log \frac{q(\mathbf{T})}{p(\mathbf{T}|\mathbf{X})} d\mathbf{T} = \\&= \mathcal{L}(q) + KL(q(\mathbf{T})||p(\mathbf{T}|\mathbf{X})) \geq \mathcal{L}(q).\end{aligned}$$

We would like to maximize lower bound $\mathcal{L}(q)$.

Mean field approximation

Independence assumption

$$q(\mathbf{T}) = \prod_{i=1}^k q_i(\mathbf{T}_i), \quad \mathbf{T} = [\mathbf{T}_1, \dots, \mathbf{T}_k], \quad \mathbf{T}_j = \{\mathbf{t}_{ij}\}_{i=1}^n, \quad \mathbf{t}_i = \{\mathbf{T}_{ij}\}_{j=1}^k.$$

Block coordinate optimization of ELBO for $q_j(\mathbf{T}_j)$

$$\begin{aligned} \mathcal{L}(q) &= \int q(\mathbf{T}) \log \frac{p(\mathbf{X}, \mathbf{T})}{q(\mathbf{T})} d\mathbf{T} = \int \left[\prod_{i=1}^k q_i(\mathbf{T}_i) \right] \log \frac{p(\mathbf{X}, \mathbf{T})}{\left[\prod_{i=1}^k q_i(\mathbf{T}_i) \right]} \prod_{i=1}^k d\mathbf{T}_i = \\ &= \int \left[\prod_{i=1}^k q_i \right] \log p(\mathbf{X}, \mathbf{T}) \prod_{i=1}^k d\mathbf{T}_i - \sum_{i=1}^k \int \left[\prod_{j=1}^k q_j \right] \log q_i \prod_{j=1}^k d\mathbf{T}_j = \\ &= \int q_j \left[\int \log p(\mathbf{X}, \mathbf{T}) \prod_{i \neq j} q_i d\mathbf{T}_i \right] d\mathbf{T}_j - \\ &\quad - \int q_j \log q_j d\mathbf{T}_j + \text{const}(q_j) \rightarrow \max_{q_j} \end{aligned}$$

Mean field approximation

Block coordinate optimization of ELBO for $q_j(\mathbf{T}_j)$

$$\begin{aligned}\mathcal{L}(q) &= \int q_j \left[\int \log p(\mathbf{X}, \mathbf{T}) \prod_{i \neq j} q_i d\mathbf{T}_i \right] d\mathbf{T}_j - \int q_j \log q_j d\mathbf{T}_j + \text{const}(q_j) = \\ &= \int q_j \log \hat{p}(\mathbf{X}, \mathbf{T}_j) d\mathbf{T}_j - \int q_j \log q_j d\mathbf{T}_j + \text{const}(q_j) \rightarrow \max_{q_j}.\end{aligned}$$

Here we introduce

$$\log \hat{p}(\mathbf{X}, \mathbf{T}_j) = \int \log p(\mathbf{X}, \mathbf{T}) \prod_{i \neq j} q_i d\mathbf{T}_i = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}(q_j)$$

Final ELBO derivation for $q_j(\mathbf{T}_j)$

$$\begin{aligned}\mathcal{L}(q) &= \int q_j(\mathbf{T}_j) \log \hat{p}(\mathbf{X}, \mathbf{T}_j) d\mathbf{T}_j - \int q_j(\mathbf{T}_j) \log q_j(\mathbf{T}_j) d\mathbf{T}_j + \text{const}(q_j) = \\ &\quad \int q_j(\mathbf{T}_j) \log \frac{\hat{p}(\mathbf{X}, \mathbf{T}_j)}{q_j(\mathbf{T}_j)} d\mathbf{T}_j + \text{const}(q_j) = \\ &= -KL(q_j(\mathbf{T}_j) || \hat{p}(\mathbf{X}, \mathbf{T}_j)) + \text{const}(q_j) \rightarrow \max_{q_j}.\end{aligned}$$

Mean field approximation

Independence assumption

$$q(\mathbf{T}) = \prod_{i=1}^k q_i(\mathbf{T}_i), \quad \mathbf{T} = [\mathbf{T}_1, \dots, \mathbf{T}_k], \quad \mathbf{T}_j = \{\mathbf{t}_{ij}\}_{i=1}^n.$$

ELBO

$$\mathcal{L}(q) = -KL(q_j(\mathbf{T}_j) || \hat{p}(\mathbf{X}, \mathbf{T}_j)) + \text{const}(q_j) \rightarrow \max_{q_j}.$$

Solution

$$q_j(\mathbf{T}_j) = \text{const} \cdot \hat{p}(\mathbf{X}, \mathbf{T}_j)$$

$$\log \hat{p}(\mathbf{X}, \mathbf{T}_j) = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}$$

$$\log q_j(\mathbf{T}_j) = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}$$

Mean field approximation

ELBO

$$\mathcal{L}(q) = -KL(q_j(\mathbf{T}_j) || \hat{p}(\mathbf{X}, \mathbf{T}_j)) + \text{const}(q_j) \rightarrow \max_{q_j}.$$

Solution

$$\log q_j(\mathbf{T}_j) = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}$$

Assumptions:

- ▶ $\mathbf{T} = [\mathbf{T}_1, \mathbf{T}_2] = [\mathbf{Z}, \boldsymbol{\theta}]$, $q(\mathbf{T}) = q(\mathbf{T}_1) \cdot q(\mathbf{T}_2) = q(\mathbf{Z}) \cdot q(\boldsymbol{\theta})$.
- ▶ restrict a class of probability distributions for $\boldsymbol{\theta}$ to Dirac delta functions:

$$q_2 = q(\mathbf{T}_2) = q(\boldsymbol{\theta}) = \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^*).$$

Under the restrictions the exact solution for q_2 is not reached (KL can be greater than 0).

Mean field approximation

General solution

$$\log q_j(\mathbf{T}_j) = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}$$

Solution for $q_1 = q(\mathbf{Z})$

$$\begin{aligned}\log q(\mathbf{Z}) &= \int q(\boldsymbol{\theta}) \log p(\mathbf{X}, \mathbf{Z}, \boldsymbol{\theta}) d\boldsymbol{\theta} + \text{const} = \\ &= \int \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^*) \log p(\mathbf{X}, \mathbf{Z}, \boldsymbol{\theta}) d\boldsymbol{\theta} + \text{const} = \\ &= \log p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^*) + \text{const.}\end{aligned}$$

EM-algorithm (E-step)

$$q(\mathbf{Z}) = \arg \max_q \mathcal{L}(q, \boldsymbol{\theta}^*) = \arg \min_q KL(q||p) = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^*).$$

Mean field approximation

ELBO

$$\mathcal{L}(q) = -KL(q_j(\mathbf{T}_j) || \hat{p}(\mathbf{X}, \mathbf{T}_j)) + \text{const}(q_j) \rightarrow \max_{q_j}.$$

ELBO maximization w.r.t. $q_2 = q(\boldsymbol{\theta}) = \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^*)$

$$\begin{aligned}\mathcal{L}(q_1, q_2) &= -KL(q(\boldsymbol{\theta}) || \hat{p}(\mathbf{X}, \boldsymbol{\theta})) + \text{const}(\boldsymbol{\theta}^*) \\ &= \int q(\boldsymbol{\theta}) \log \frac{\hat{p}(\mathbf{X}, \boldsymbol{\theta})}{q(\boldsymbol{\theta})} d\boldsymbol{\theta} + \text{const}(\boldsymbol{\theta}^*) \\ &= \int q(\boldsymbol{\theta}) \log \hat{p}(\mathbf{X}, \boldsymbol{\theta}) d\boldsymbol{\theta} - \int q(\boldsymbol{\theta}) \log q(\boldsymbol{\theta}) d\boldsymbol{\theta} + \text{const}(\boldsymbol{\theta}^*) \\ &= \int \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^*) \log \hat{p}(\mathbf{X}, \boldsymbol{\theta}) d\boldsymbol{\theta} + \text{const}(\boldsymbol{\theta}^*) \rightarrow \max_{\boldsymbol{\theta}^*}\end{aligned}$$

Mean field approximation

ELBO maximization w.r.t. $q_2 = q(\theta) = \delta(\theta - \theta^*)$

$$\begin{aligned}\mathcal{L}(q_1, q_2) &= \int \delta(\theta - \theta^*) \log \hat{p}(\mathbf{X}, \theta) d\theta + \text{const} = \log \hat{p}(\mathbf{X}, \theta^*) + \text{const} \\ &= \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const} = \mathbb{E}_{q_1} \log p(\mathbf{X}, \mathbf{Z}, \theta^*) + \text{const} \\ &= \int q(\mathbf{Z}) \log p(\mathbf{X}, \mathbf{Z} | \theta^*) d\mathbf{Z} + \log p(\theta^*) + \text{const} \rightarrow \max_{\theta^*}\end{aligned}$$

EM-algorithm (M-step)

$$\begin{aligned}\mathcal{L}(q, \theta) &= \int q(\mathbf{Z}) \log \frac{p(\mathbf{X}, \mathbf{Z} | \theta)}{q(\mathbf{Z})} d\mathbf{Z} \\ &= \int q(\mathbf{Z}) \log p(\mathbf{X}, \mathbf{Z} | \theta) d\mathbf{Z} + \text{const} \rightarrow \max_{\theta}\end{aligned}$$

Mean field approximation

Solution

$$\log q_j(\mathbf{T}_j) = \mathbb{E}_{i \neq j} \log p(\mathbf{X}, \mathbf{T}) + \text{const}$$

EM algorithm (special case)

- ▶ Initialize θ^* ;
- ▶ E-step

$$q(\mathbf{Z}) = \arg \max_q \mathcal{L}(q, \theta^*) = \arg \min_q KL(q||p) = p(\mathbf{Z}|\mathbf{X}, \theta^*);$$

- ▶ M-step
$$\theta^* = \arg \max_{\theta} \mathcal{L}(q, \theta);$$
- ▶ Repeat E-step and M-step until convergence.

Likelihood-based models so far...

Autoregressive models

$$p(\mathbf{x}|\boldsymbol{\theta}) = \prod_{i=1}^m p(x_i|\mathbf{x}_{1:i-1}, \boldsymbol{\theta})$$

- ▶ tractable likelihood,
- ▶ no inferred latent factors.

Latent variable models

$$p(\mathbf{x}|\boldsymbol{\theta}) = \int p(\mathbf{x}, \mathbf{z}|\boldsymbol{\theta}) d\mathbf{z}$$

- ▶ latent feature representation,
- ▶ intractable likelihood.

How to build model with latent variables and tractable likelihood?

Flows intuition

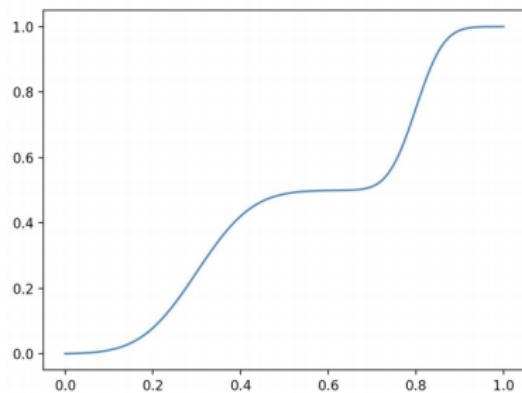
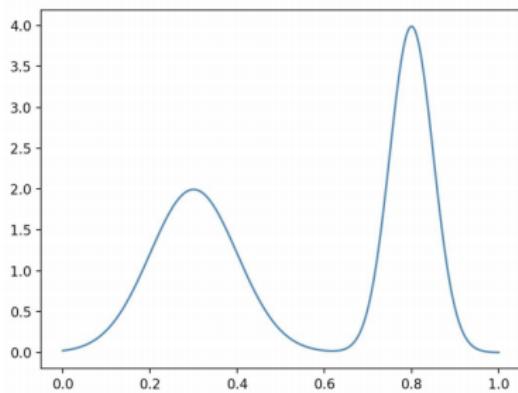
Let ξ be a random variable with density $p(\xi)$. Then

$$\eta = F(\xi) = P(\xi < x) = \int_{-\infty}^{\xi} p(t)dt \sim U[0, 1].$$

$$P(\eta < y) = P(F(\xi) < y) = P(\xi < F^{-1}(y)) = F(F^{-1}(y)) = y$$

Hence

$$\eta \sim U[0, 1]; \quad \xi = F^{-1}(\eta) \quad \xi \sim p(\xi).$$



Flows intuition

- ▶ Let $\mathbf{z} \sim p(\mathbf{z})$ is a random variable with base distribution $p(\mathbf{z}) = U[0, 1]^m$.
- ▶ Let $\mathbf{x} \sim p(\mathbf{x})$ is a random variable with complex distribution $p(\mathbf{x})$ and cdf $F(\mathbf{x})$.
- ▶ Then noise variable \mathbf{z} can be transformed to \mathbf{x} using inverse cdf F^{-1} ($\mathbf{x} = F^{-1}(\mathbf{z})$).

How to transform random variable \mathbf{z} which has a distribution different from uniform to \mathbf{x} ?

- ▶ Let $\mathbf{z} \sim p(\mathbf{z})$ is a random variable with base distribution $p(\mathbf{z})$ and cdf $G(\mathbf{z})$.
- ▶ Then $\mathbf{z}_0 = G(\mathbf{z})$ has base distribution $p(\mathbf{z}_0) = U[0, 1]^m$.
- ▶ Let $\mathbf{x} \sim p(\mathbf{x})$ is a random variable with complex distribution $p(\mathbf{x})$ and cdf $F(\mathbf{x})$.
- ▶ Then noise variable \mathbf{z} can be transformed to \mathbf{x} using cdf G and inverse cdf F^{-1} ($\mathbf{x} = F^{-1}(\mathbf{z}_0) = F^{-1}(G(\mathbf{z}))$).

Change of variables

Theorem

- ▶ \mathbf{x} is a random variable with density function $p(\mathbf{x})$;
- ▶ $f : \mathbb{R}^m \rightarrow \mathbb{R}^m$ is a differentiable, invertible function (diffeomorphism);
- ▶ $\mathbf{z} = f(\mathbf{x})$, $\mathbf{x} = f^{-1}(\mathbf{z}) = g(\mathbf{z})$ (here $g = f^{-1}$).

Then

$$p(\mathbf{x}) = p(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) \right| = p(f(\mathbf{x})) \left| \det \left(\frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} \right) \right|$$
$$p(\mathbf{z}) = p(\mathbf{x}) \left| \det \left(\frac{\partial \mathbf{x}}{\partial \mathbf{z}} \right) \right| = p(g(\mathbf{z})) \left| \det \left(\frac{\partial g(\mathbf{z})}{\partial \mathbf{z}} \right) \right|.$$

- ▶ \mathbf{x} and \mathbf{z} have the same dimensionality (lies in \mathbb{R}^m);
- ▶ $\left| \det \left(\frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = \left| \det \left(\frac{\partial g^{-1}(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = \left| \det \left(\frac{\partial g(\mathbf{z})}{\partial \mathbf{z}} \right) \right|^{-1}$;
- ▶ $f(\mathbf{x}, \theta)$ could be parametric function.

Fitting flows

MLE problem

$$\theta^* = \arg \max_{\theta} p(\mathbf{X}|\theta) = \arg \max_{\theta} \prod_{i=1}^n p(\mathbf{x}_i|\theta) = \arg \max_{\theta} \sum_{i=1}^n \log p(\mathbf{x}_i|\theta).$$

Challenge

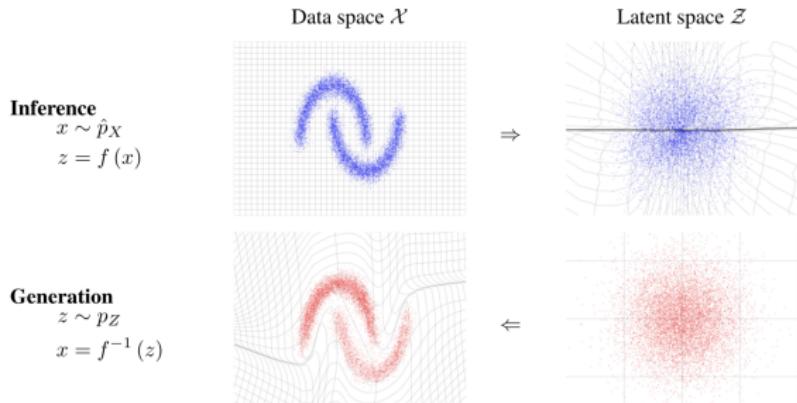
$p(\mathbf{x}|\theta)$ can be intractable.

Fitting flow to solve MLE

$$p(\mathbf{x}|\theta) = p(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) \right| = p(f(\mathbf{x}, \theta)) \left| \det \left(\frac{\partial f(\mathbf{x}, \theta)}{\partial \mathbf{x}} \right) \right|$$

$$\log p(\mathbf{x}|\theta) = \log p(f(\mathbf{x}, \theta)) + \log \left| \det \left(\frac{\partial f(\mathbf{x}, \theta)}{\partial \mathbf{x}} \right) \right|$$

Flows



Computational requirement

- ▶ Evaluating model density $p(\mathbf{x}|\boldsymbol{\theta})$ requires computing the transformation $\mathbf{z} = f(\mathbf{x}, \boldsymbol{\theta})$ and its Jacobian determinant $\left| \det \left(\frac{\partial f(\mathbf{x}, \boldsymbol{\theta})}{\partial \mathbf{x}} \right) \right|$, and evaluating the density $p(\mathbf{z})$.
- ▶ Sampling \mathbf{x} from the model requires the ability to sample from $p(\mathbf{z})$ and to compute the transformation $\mathbf{x} = g(\mathbf{z}, \boldsymbol{\theta}) = f^{-1}(\mathbf{z}, \boldsymbol{\theta})$.

Forward KL vs Reverse KL

Fix probabilistic model $p(\mathbf{x}|\theta)$ – the set of parameterized distributions .

Instead of searching true $\pi(\mathbf{x})$ over all probability distributions, learn function approximation $p(\mathbf{x}|\theta) \approx \pi(\mathbf{x})$.

Forward KL

$$KL(\pi||p) = \int \pi(\mathbf{x}) \log \frac{\pi(\mathbf{x})}{p(\mathbf{x}|\theta)} d\mathbf{x} \rightarrow \min_{\theta}$$

Reverse KL

$$KL(p||\pi) = \int p(\mathbf{x}|\theta) \log \frac{p(\mathbf{x}|\theta)}{\pi(\mathbf{x})} d\mathbf{x} \rightarrow \min_{\theta}$$

- ▶ What is the difference between these two formulations?
- ▶ What do we get in these two cases if $p(\mathbf{x}|\theta)$ is a flow model?

Forward KL vs Reverse KL

Forward KL

$$\begin{aligned} KL(\pi || p) &= \int \pi(\mathbf{x}) \log \frac{\pi(\mathbf{x})}{p(\mathbf{x}|\theta)} d\mathbf{x} \\ &= \int \pi(\mathbf{x}) \log \pi(\mathbf{x}) d\mathbf{x} - \int \pi(\mathbf{x}) \log p(\mathbf{x}|\theta) d\mathbf{x} \\ &= -\mathbb{E}_{\pi(\mathbf{x})} \log p(\mathbf{x}|\theta) + \text{const} \rightarrow \min_{\theta} \end{aligned}$$

Monte-Carlo estimation

$$KL(\pi || p) = -\mathbb{E}_{\pi(\mathbf{x})} \log p(\mathbf{x}|\theta) + \text{const} \approx -\sum_{i=1}^n \log p(\mathbf{x}_i|\theta) \rightarrow \min_{\theta}.$$

MLE problem

$$\theta^* = \arg \max_{\theta} p(\mathbf{X}|\theta) = \arg \max_{\theta} \prod_{i=1}^n p(\mathbf{x}_i|\theta) = \arg \max_{\theta} \sum_{i=1}^n \log p(\mathbf{x}_i|\theta).$$

Forward KL vs Reverse KL

Forward KL

$$\boldsymbol{\theta}^* = \arg \max_{\boldsymbol{\theta}} \sum_{i=1}^n \log p(\mathbf{x}_i | \boldsymbol{\theta}) \approx \arg \min_{\boldsymbol{\theta}} KL(\pi || p)$$

Maximum likelihood estimation is equivalent to minimization of the Monte-Carlo estimation of forward KL.

Forward KL for flow model

$$\log p(\mathbf{x} | \boldsymbol{\theta}) = \log p(f(\mathbf{x}, \boldsymbol{\theta})) + \log \left| \det \left(\frac{\partial f(\mathbf{x}, \boldsymbol{\theta})}{\partial \mathbf{x}} \right) \right|$$

- ▶ We need to be able to compute $f(\mathbf{x}, \boldsymbol{\theta})$ and its Jacobian.
- ▶ We need to be able to compute the density $p(\mathbf{z})$.
- ▶ We don't need to think about computing the function $g(\mathbf{z}, \boldsymbol{\theta}) = f^{-1}(\mathbf{z}, \boldsymbol{\theta})$ until we want to sample from the flow.

Forward KL vs Reverse KL

Reverse KL

$$\begin{aligned} KL(p||\pi) &= \int p(\mathbf{x}|\boldsymbol{\theta}) \log \frac{p(\mathbf{x}|\boldsymbol{\theta})}{\pi(\mathbf{x})} d\mathbf{x} \\ &= \mathbb{E}_{p(\mathbf{x}|\boldsymbol{\theta})} [\log p(\mathbf{x}|\boldsymbol{\theta}) - \log \pi(\mathbf{x})] \rightarrow \min_{\boldsymbol{\theta}} \end{aligned}$$

Reverse KL for flow model

$$\begin{aligned} \log p(\mathbf{z}) &= \log p(\mathbf{x}|\boldsymbol{\theta}) + \log \left| \det \left(\frac{\partial g(\mathbf{z}, \boldsymbol{\theta})}{\partial \mathbf{z}} \right) \right| \\ KL(p||\pi) &= \mathbb{E}_{p(\mathbf{z})} \left[\log p(\mathbf{z}) - \log \left| \det \left(\frac{\partial g(\mathbf{z}, \boldsymbol{\theta})}{\partial \mathbf{z}} \right) \right| - \log \pi(g(\mathbf{z}, \boldsymbol{\theta})) \right] \end{aligned}$$

- ▶ We need to be able to compute $g(\mathbf{z}, \boldsymbol{\theta})$ and its Jacobian.
- ▶ We need to be able to sample from the density $p(\mathbf{z})$ (do not need to evaluate it).
- ▶ We don't need to think about computing the function $f(\mathbf{x}, \boldsymbol{\theta})$.

Composition of flows

Theorem

Diffeomorphisms are **composable** (If f_1, f_2 satisfy conditions of the change of variable theorem (differentiable and invertible), then $\mathbf{z} = f(\mathbf{x}) = f_2 \circ f_1(\mathbf{x})$ also satisfies it).

$$\begin{aligned} p(\mathbf{x}) &= p(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) \right| = p(f(\mathbf{x})) \left| \det \left(\frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = \\ &= p(f(\mathbf{x})) \left| \det \left(\frac{\partial f_2 \circ f_1(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = p(f(\mathbf{x})) \left| \det \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{f}_1} \cdot \frac{\partial \mathbf{f}_1}{\partial \mathbf{x}} \right) \right| = \\ &= p(f(\mathbf{x})) \left| \det \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{f}_1} \right) \right| \cdot \left| \det \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}} \right) \right| \end{aligned}$$

What will we get in the case $\mathbf{z} = f(\mathbf{x}) = f_n \circ \dots \circ f_1(\mathbf{x})$?

Flows

$$\log p(\mathbf{x}|\theta) = \log p(f(\mathbf{x}, \theta)) + \log \left| \det \left(\frac{\partial f(\mathbf{x}, \theta)}{\partial \mathbf{x}} \right) \right|$$

Definition

Normalizing flow is a *differentiable, invertible* mapping from data \mathbf{x} to the noise \mathbf{z} .

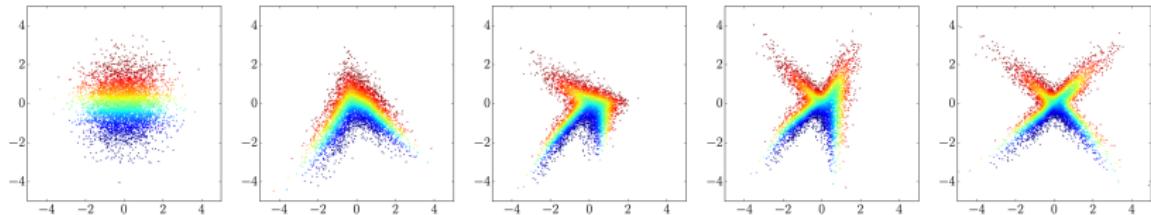
- ▶ "Normalizing" means that the inverse flow takes samples from $p(\mathbf{x})$ and normalizes them into samples from density $p(\mathbf{z})$.
- ▶ "Flow" refers to the trajectory that samples from $p(\mathbf{z})$ follow as they are transformed by the sequence of transformations

$$\mathbf{z} = f_K \circ \cdots \circ f_1(\mathbf{x}); \quad \mathbf{x} = f_1^{-1} \circ \cdots \circ f_K^{-1}(\mathbf{z}) = g_1 \circ \cdots \circ g_K(\mathbf{z})$$

$$\begin{aligned} p(\mathbf{x}) &= p(f_K \circ \cdots \circ f_1(\mathbf{x})) \left| \det \left(\frac{\partial f_K \circ \cdots \circ f_1(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = \\ &= p(f_K \circ \cdots \circ f_1(\mathbf{x})) \prod_{k=1}^K \left| \det \left(\frac{\partial \mathbf{f}_k}{\partial \mathbf{f}_{k-1}} \right) \right|. \end{aligned}$$

Flows

Example of a 4-step flow



Flow likelihood

$$\log p(\mathbf{x}|\theta) = \log p(f(\mathbf{x}, \theta)) + \log \left| \det \left(\frac{\partial f(\mathbf{x}, \theta)}{\partial \mathbf{x}} \right) \right|$$

What is the complexity of the determinant computation?

What we want

- ▶ Efficient computation of Jacobian $\frac{\partial f(\mathbf{x}, \theta)}{\partial \mathbf{x}}$;
- ▶ Efficient sampling from the base distribution $p(\mathbf{z})$;
- ▶ Efficient inversion of $f(\mathbf{x}, \theta)$.

Planar Flows

$$g(\mathbf{z}, \theta) = \mathbf{z} + \mathbf{u} h(\mathbf{w}^T \mathbf{z} + b).$$

- ▶ $\theta = \{\mathbf{u}, \mathbf{w}, b\}$;
- ▶ h is a smooth element-wise non-linearity.

$$\begin{aligned}\left| \det \left(\frac{\partial g(\mathbf{z}, \theta)}{\partial \mathbf{z}} \right) \right| &= \left| \det \left(\mathbf{I} + h'(\mathbf{w}^T \mathbf{z} + b) \mathbf{w} \mathbf{u}^T \right) \right| \\ &= \left| 1 + h'(\mathbf{w}^T \mathbf{z} + b) \mathbf{w}^T \mathbf{u} \right|\end{aligned}$$

The transformation is invertible, for example, if

$$h = \tanh; \quad h'(\mathbf{w}^T \mathbf{z} + b) \mathbf{u}^T \mathbf{w} \geq -1.$$

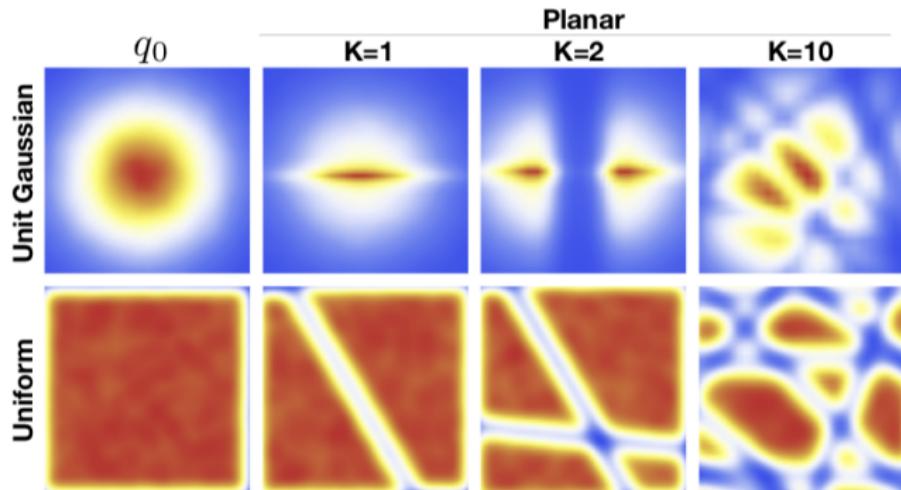
Sylvester flow: planar flow extension

$$g(\mathbf{z}, \theta) = \mathbf{z} + \mathbf{A} h(\mathbf{B} \mathbf{z} + \mathbf{b}).$$

Planar Flows

$$\mathbf{z}_K = g_1 \circ \cdots \circ g_K(\mathbf{z}); \quad g_k = g(\mathbf{z}_k, \theta_k).$$

Expressiveness of planar flows



Jacobian structure

Flow likelihood

$$\log p(\mathbf{x}|\boldsymbol{\theta}) = \log p(f(\mathbf{x}, \boldsymbol{\theta})) + \log \left| \det \left(\frac{\partial f(\mathbf{x}, \boldsymbol{\theta})}{\partial \mathbf{x}} \right) \right|$$

- ▶ What is a determinant of a diagonal matrix?

$$\mathbf{z} = f(\mathbf{x}, \boldsymbol{\theta}) = (f_1(x_1, \boldsymbol{\theta}), \dots, f_m(x_m, \boldsymbol{\theta})).$$

$$\log \left| \det \left(\frac{\partial f(\mathbf{x}, \boldsymbol{\theta})}{\partial \mathbf{x}} \right) \right| = \log \left| \prod_{i=1}^m f'_i(x_i, \boldsymbol{\theta}) \right| = \sum_{i=1}^m \log |f'_i(x_i, \boldsymbol{\theta})|.$$

- ▶ What is a determinant of a triangular matrix?

Let z_i depends only on $\mathbf{x}_{1:i}$ (or without loss of generality x_i depends on $\mathbf{z}_{1:i}$).

What is the Jacobian of such a transformation?

Coupling layer

$$\begin{cases} \mathbf{z}_{1:d} = \mathbf{x}_{1:d} \\ \mathbf{z}_{d:m} = \tau(\mathbf{x}_{d:m}, c(\mathbf{x}_{1:d})) \end{cases} \quad \begin{cases} \mathbf{x}_{1:d} = \mathbf{z}_{1:d} \\ \mathbf{x}_{d:m} = \tau^{-1}(\mathbf{z}_{d:m}, c(\mathbf{z}_{1:d})) \end{cases}$$

- ▶ $c : \mathbb{R}^d \rightarrow \mathbb{R}^k$ – coupling function (do not need to be invertible);
- ▶ $\tau : \mathbb{R}^{m-d} \times c(\mathbb{R}^d) \rightarrow \mathbb{R}^{m-d}$ – coupling law.
- ▶

$$\det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) = \det \begin{pmatrix} \mathbf{I}_d & \mathbf{0}_{d \times m-d} \\ \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{1:d}} & \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{d:m}} \end{pmatrix} = \det \left(\frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{d:m}} \right)$$

Coupling layer

$$\begin{cases} \mathbf{z}_{1:d} = \mathbf{x}_{1:d}; \\ \mathbf{z}_{d:m} = \tau(\mathbf{x}_{d:m}, c(\mathbf{x}_{1:d})); \end{cases} \Rightarrow \begin{cases} \mathbf{x}_{1:d} = \mathbf{z}_{1:d}; \\ \mathbf{x}_{d:m} = \tau^{-1}(\mathbf{z}_{d:m}, c(\mathbf{z}_{1:d})). \end{cases}$$

Coupling function $c(\cdot)$

Any complex function (without restrictions). For example, neural network.

Coupling law $\tau(\cdot, \cdot)$

- ▶ $\tau(x, c) = x + c$ – additive;
- ▶ $\tau(x, c) = x \odot c, c \neq 0$ – multiplicative;
- ▶ $\tau(x, c) = x \odot c_1 + c_2, c_1 \neq 0$ – affine.

To obtain more flexible class of distributions, stack more coupling layers (with different ordering of components!).

Coupling layer

$$\begin{cases} \mathbf{z}_{1:d} = \mathbf{x}_{1:d}; \\ \mathbf{z}_{d:m} = \tau(\mathbf{x}_{d:m}, c(\mathbf{x}_{1:d})); \end{cases} \Rightarrow \begin{cases} \mathbf{x}_{1:d} = \mathbf{z}_{1:d}; \\ \mathbf{x}_{d:m} = \tau^{-1}(\mathbf{z}_{d:m}, c(\mathbf{z}_{1:d})). \end{cases}$$

Jacobian

$$\det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) = \det \begin{pmatrix} \mathbf{I}_d & \mathbf{0}_{d \times m-d} \\ \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{1:d}} & \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{d:m}} \end{pmatrix} = \det \left(\frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{d:m}} \right)$$

What is the Jacobian for the additive coupling law

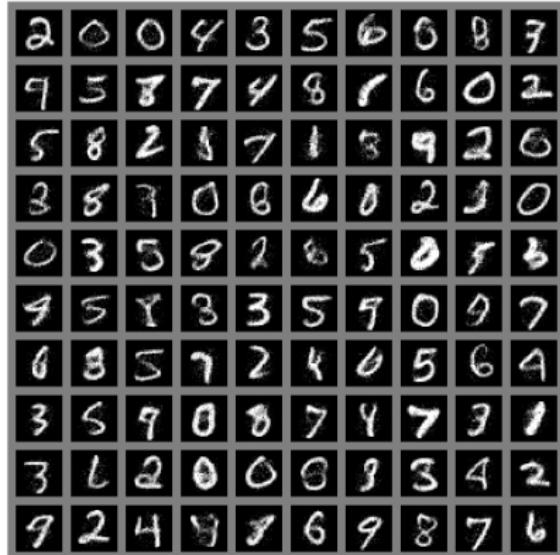
$$\tau(x + c) = x + c?$$

In this case the transformation is *volume preserving*.

The last layer is rescaling $z_i = s_i x_i$ ($x_i = z_i / s_i$).

What is the Jacobian of the last layer?

NICE



(a) Model trained on MNIST



(b) Model trained on TFD

RealNVP

Affine coupling law

$$\begin{cases} \mathbf{z}_{1:d} = \mathbf{x}_{1:d}; \\ \mathbf{z}_{d:m} = \mathbf{x}_{d:m} \odot \exp(c_1(\mathbf{x}_{1:d}, \theta)) + c_2(\mathbf{x}_{1:d}, \theta). \end{cases}$$

$$\begin{cases} \mathbf{x}_{1:d} = \mathbf{z}_{1:d}; \\ \mathbf{x}_{d:m} = (\mathbf{z}_{d:m} - c_2(\mathbf{x}_{1:d}, \theta)) \odot \exp(-c_1(\mathbf{x}_{1:d}, \theta)). \end{cases}$$

Jacobian

$$\det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) = \det \begin{pmatrix} \mathbf{I}_d & 0_{d \times m-d} \\ \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{1:d}} & \frac{\partial \mathbf{z}_{d:m}}{\partial \mathbf{x}_{d:m}} \end{pmatrix} = \prod_{i=1}^{m-d} \exp(c_1(\mathbf{x}_{1:d}, \theta)_i).$$

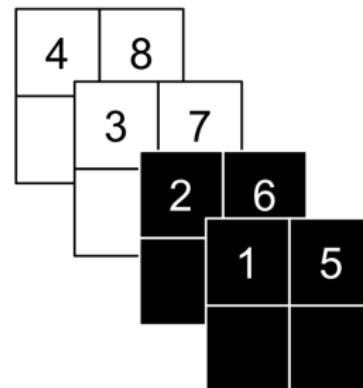
Non-Volume Preserving.

RealNVP

Affine coupling law

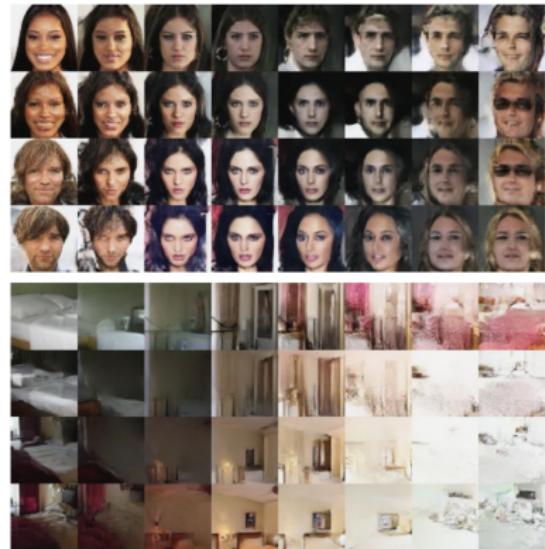
$$\begin{cases} \mathbf{z}_{1:d} = \mathbf{x}_{1:d}; \\ \mathbf{z}_{d:m} = \mathbf{x}_{d:m} \odot \exp(c_1(\mathbf{x}_{1:d}, \theta)) + c_2(\mathbf{x}_{1:d}, \theta). \end{cases}$$

How to choose variable partitioning for images?



Masked convolutions are used to define ordering.

RealNVP



Summary

- ▶ Mean-field approximation is a general form of approximate variational inference.
- ▶ The EM-algorithm and VAE model can be presented as a special case of the mean-field approximation.
- ▶ Forward KL minimization is equivalent to MLE. Reverse KL is used in variational inference.
- ▶ Flow models transform a simple base distribution to a complex one via a sequence of invertible transformations.
- ▶ Flow models have a tractable likelihood that is given by the change of variable theorem.
- ▶ Planar flows is a simple form of an invertible flow model (Sylvester flows are their extension). The NICE model is a more powerful type of flow.