Deep Generative Models: Discrete Latent Variables

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https://vitutorial.github.io/tour/ua2020

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Discrete Latent Variables

- Language is an inherently discrete structure.

Discrete Latent Variables

- Language is an inherently discrete structure.
- Many structures used to describe language are discrete, e.g. trees, graphs, tags, etc.

Generative Models

Joint distribution over observed data x and latent variables z.

$$p(x, z|\theta) = \underbrace{p(z)}_{\text{prior}} \underbrace{p(x|z, \theta)}_{\text{likelihood}}$$

The likelihood and prior are often standard distributions (Gaussian, Bernoulli) with simple dependence on conditioning information.

Deep generative models

Joint distribution with **deep observation model**

$$p(x, z|\theta) = \underbrace{p(z)}_{\text{prior}} \underbrace{p(x|z, \theta)}_{\text{likelihood}}$$

mapping from z to $p(x|z, \theta)$ is a neural network with parameters θ

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Marginal likelihood

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

intractable in general

Goals

We want

- richer probabilistic models

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We need approximate inference techniques!

ELBO recap

And we've developed the ELBO

$$\log p(x) = \log \int p(z, x)\mathrm{d}z$$

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ELBO recap

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$$\log p(x) = \log \int p(z,x)\mathrm{d}z \ = \log \int q(z|x)\frac{p(z,x)}{q(z|x)}\mathrm{d}z$$

$$\overset{\text{JI}}{\geq} \underbrace{\mathbb{E}_{q(z|x)}\left[\log \frac{p(z,x)}{q(z|x)}\right]}_{\text{ELBO}}$$

ELBO recap

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$$\log p(x) = \log \int p(z,x)\mathrm{d}z \;= \log \int q(z|x)\frac{p(z,x)}{q(z|x)}\mathrm{d}z$$

$$\overset{\text{JI}}{\geq} \underbrace{\mathbb{E}_{q(z|x)}\left[\log \frac{p(z,x)}{q(z|x)}\right]}_{\text{ELBO}}$$

$$\text{ELBO} = \mathbb{E}_{q(z|x)}\left[\log \frac{p(z|x)p(x)}{q(z|x)}\right]$$

$$= -\underbrace{\mathrm{KL}\left(q(z|x) \;||\; p(z|x)\right)}_{\text{gap}} + \log p(x)$$

1. First Attempt: Wake-Sleep
2. Neural Variational Inference and Learning
3. Score Function Estimator

Wake-Sleep Algorithm

- Generalise latent variables to neural networks.
- Train generative neural model.
- Use variational inference! (kind of)
- Hinton et al. (1995)

Wake-Sleep Architecture

2 neural networks:

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- A generation network to model the data (the one we want to optimise) – parameters: θ

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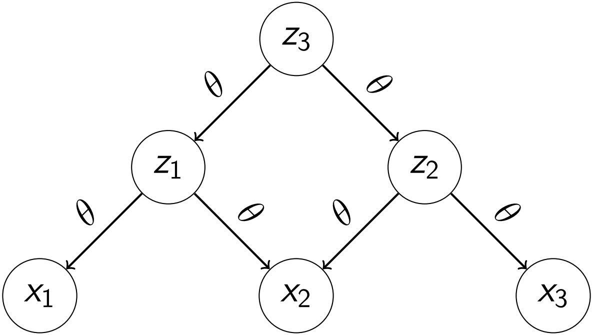
- Original setting: binary hidden units

Wake-Sleep Architecture

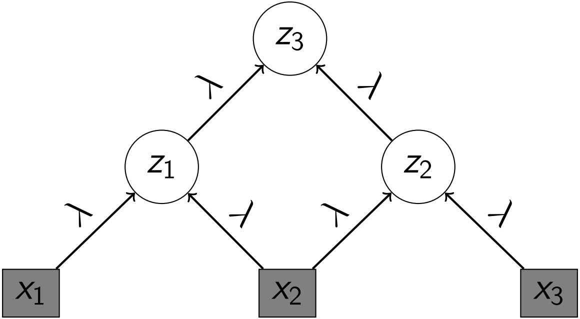
2 neural networks:

- A generation network to model the data (the one we want to optimise) – parameters: θ
- An inference (recognition) network (to model the latent variable) – parameters: λ
- Original setting: binary hidden units
- Training is performed in a "hard EM" fashion

Generator



Inference Network



Wake-sleep Training

Wake Phase

- Use inference network to sample hidden unit setting z from $q(z|x,\lambda)$
- Update generation parameters θ to maximize joint log-likelihood of data and latents $p(x,z|\theta)$

Wake-sleep Training

Wake Phase

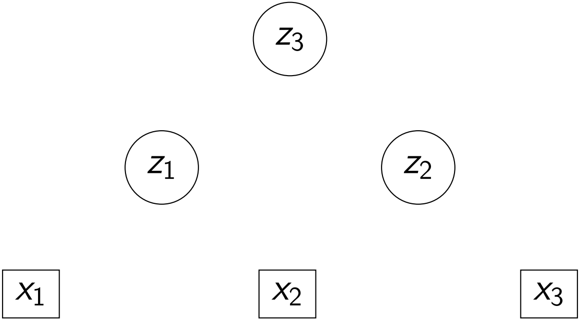
- Use inference network to sample hidden unit setting z from $q(z|x, \lambda)$
- Update generation parameters θ to maximize joint log-likelihood of data and latents $p(x, z|\theta)$

Sleep Phase

- Produce dream sample $\tilde{x}$ from random hidden unit z
- Update inference parameters λ to maximize probability of latent state $q(z|\tilde{x}, \lambda)$

Wake Phase Sampling

Sampling $z \sim q(z|x, \lambda)$



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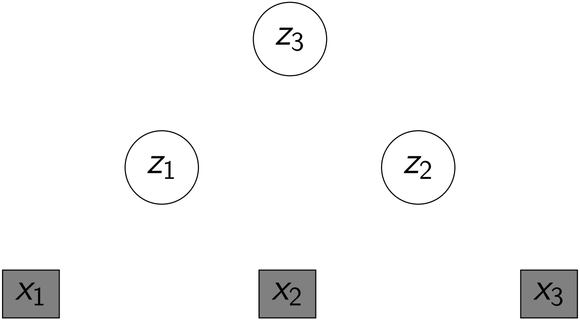

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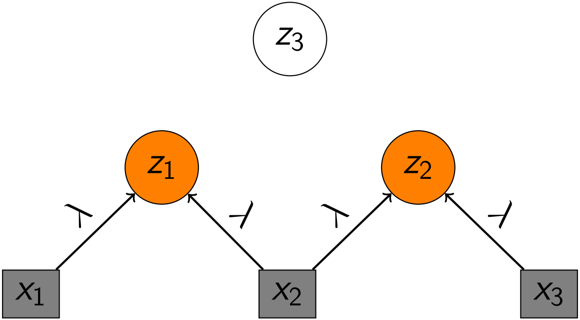

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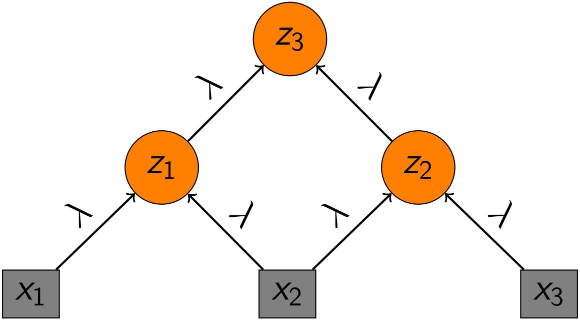
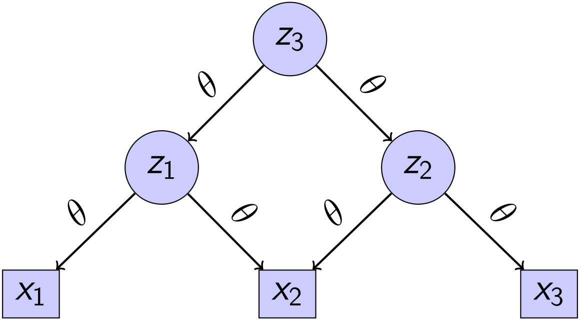


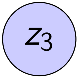
Wake Phase Update

Compute $\log p(x, z|\theta)$ and update θ



Sleep Phase Sampling

Sampling $(z, \tilde{x}) \sim p(x, z|\theta)$



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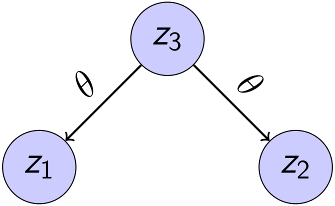

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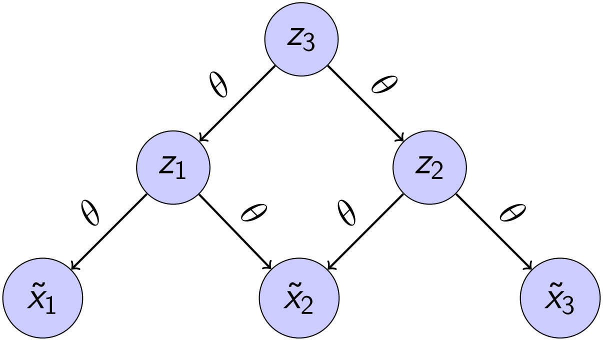
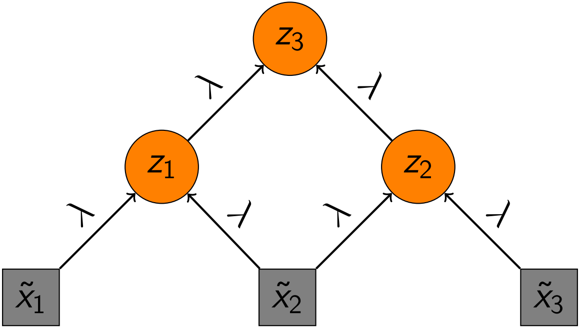


Sleep Phase Update

Compute $\log q(z|\tilde{x}, \lambda)$ and update λ



Wake Phase Objective

Objective

$$\arg\min_{\theta} \; \mathbb{E}_{p(x)} \left[\mathrm{KL} \left(q(z|x, \lambda) \; || \; p(z|x, \theta) \right) \right]$$

Wake Phase Objective

Objective

$$\begin{aligned} &\arg\min_{\theta} \; \mathbb{E}_{p(x)} \left[\mathrm{KL}\left(q(z|x,\lambda) \,||\, p(z|x,\theta) \right) \right] \\ =\, &\arg\max_{\theta} \mathbb{E}_{p(x)} \left[\mathrm{ELBO}(\theta,\lambda|x) - \log p(x|\theta) \right] \end{aligned}$$

Wake Phase Objective

Objective

$$\begin{aligned} &\arg\min_{\theta} \; \mathbb{E}_{p(x)} \left[\mathrm{KL}\left(q(z|x,\lambda) \;||\; p(z|x,\theta) \right) \right] \\ = &\arg\max_{\theta} \mathbb{E}_{p(x)} \left[\mathrm{ELBO}(\theta,\lambda|x) - \log p(x|\theta) \right] \end{aligned}$$

Approximation: optimize the lower-bound alone.

Wake Phase Objective

Objective

$$\arg\max_{\theta} \ \mathbb{E}_{p(x)}\left[\mathrm{ELBO}(\theta, \lambda|x)\right]$$

$$= \arg\max_{\theta} \ \mathbb{E}_{p(x)}\left[\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z, x|\theta)\right] + \mathbb{H}[q(z|x, \lambda)]\right]$$

Wake Phase Objective

Objective

$$\arg\max_{\theta} \; \mathbb{E}_{p(x)} \left[\text{ELBO}(\theta, \lambda | x) \right]$$
$$= \arg\max_{\theta} \; \mathbb{E}_{p(x)} \left[\mathbb{E}_{q(z|x,\lambda)} \left[\log p(z, x|\theta) \right] + \mathbb{H}[q(z|x, \lambda)] \right]$$

Gradient wrt θ for $x \sim p(x)$

$$\nabla_{\theta} \mathbb{E}_{q(z|x,\lambda)} \left[\log p(z, x|\theta) \right] + \nabla_{\theta} \mathbb{H}[q(z|x, \lambda)]$$

Wake Phase Objective

Objective

$$\arg\max_{\theta} \mathbb{E}_{p(x)}\left[\text{ELBO}(\theta, \lambda|x)\right]$$
$$= \arg\max_{\theta} \mathbb{E}_{p(x)}\left[\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z,x|\theta)\right] + \mathbb{H}[q(z|x,\lambda)]\right]$$

Gradient wrt θ for $x \sim p(x)$

$$\nabla_{\theta}\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z,x|\theta)\right] + \nabla_{\theta}\mathbb{H}[q(z|x,\lambda)]$$
$$= \mathbb{E}_{q(z|x,\lambda)}\left[\nabla_{\theta}\log p(z,x|\theta)\right]$$

Wake Phase Objective

Objective

$$\arg\max_{\theta} \; \mathbb{E}_{p(x)} \left[\text{ELBO}(\theta, \lambda|x)\right]$$
$$= \arg\max_{\theta} \; \mathbb{E}_{p(x)} \left[\mathbb{E}_{q(z|x,\lambda)} \left[\log p(z, x|\theta)\right] + \mathbb{H}[q(z|x, \lambda)]\right]$$

Gradient wrt θ for $x \sim p(x)$

$$\nabla_{\theta}\mathbb{E}_{q(z|x,\lambda)} \left[\log p(z, x|\theta)\right] + \nabla_{\theta}\mathbb{H}[q(z|x, \lambda)]$$
$$= \mathbb{E}_{q(z|x,\lambda)} \left[\nabla_{\theta} \log p(z, x|\theta)\right]$$
$$\overset{\text{MC}}{\approx} \nabla_{\theta} \log p(z, x|\theta) \quad \text{where } z \sim q(z|x, \lambda)$$

Wake Phase Objective

Assumes z to be fixed random draw from $q(z|x, \lambda)$ and maximises $\log p(z, x|\theta)$.

This is simply supervised learning with imputed latent data!

Sleep Phase Objective

Objective

$$\arg\max_{\lambda} \ \mathbb{E}_{p(x)}\left[\mathrm{ELBO}(\theta, \lambda | x)\right]$$
$$= \arg\max_{\lambda} \ \mathbb{E}_{p(x)}\left[\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z, x|\theta)\right] + \mathbb{H}[q(z|x,\lambda)]\right]$$

Sleep Phase Objective

Objective

$$\underset{\lambda}{\arg\max}\ \mathbb{E}_{p(x)}\left[\text{ELBO}(\theta, \lambda | x)\right]$$
$$= \underset{\lambda}{\arg\max}\ \mathbb{E}_{p(x)}\left[\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z, x|\theta)\right] + \mathbb{H}[q(z|x,\lambda)]\right]$$

Gradient wrt λ for $x \sim p(x)$

$$\nabla_{\lambda}\mathbb{E}_{q(z|x,\lambda)}\left[\log p(z, x|\theta)\right] + \nabla_{\lambda}\mathbb{H}[q(z|x,\lambda)]$$

Sleep Phase Objective

Objective

$$\arg\max_{\lambda} \; \mathbb{E}_{p(x)} [\text{ELBO}(\theta, \lambda | x)]$$
$$= \arg\max_{\lambda} \; \mathbb{E}_{p(x)} \left[\mathbb{E}_{q(z|x,\lambda)} [\log p(z, x|\theta)] + \mathbb{H}[q(z|x, \lambda)]\right]$$

Gradient wrt λ for $x \sim p(x)$

$$\nabla_{\lambda} \mathbb{E}_{q(z|x,\lambda)} [\log p(z, x|\theta)] + \nabla_{\lambda} \mathbb{H}[q(z|x, \lambda)]$$

Let's change the objective!

Sleep Phase (Convenient) Objective

Flip the direction of the KL

$$\arg\min_{\lambda} \mathbb{E}_{p(x)} \left[\mathrm{KL} \left(p(z|x, \theta) \mid\mid q(z|x, \lambda) \right) \right]$$

Sleep Phase (Convenient) Objective

Flip the direction of the KL

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\begin{aligned}
&\arg\min_{\lambda} \mathbb{E}_{p(x)} \left[\mathrm{KL}\left(p(z|x,\theta) \;||\; q(z|x,\lambda) \right) \right] \\
&= \arg\min_{\lambda} \mathbb{E}_{p(x)} \mathbb{E}_{p(z|x,\theta)} \left[\log p(z|x,\theta) - \log q(z|x,\lambda) \right]
\end{aligned}
$$

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&= \arg\max_{\lambda} \mathbb{E}_{p(x,z|\theta)} \left[\log q(z|x,\lambda)\right] - \underbrace{\mathbb{E}_{p(x,z|\theta)} \left[\log p(z|x,\theta)\right]}_{\text{constant}}
\end{aligned}
$$

Sleep Phase (Convenient) Objective

Flip the direction of the KL

$$\begin{aligned} &\arg\min_{\lambda} \mathbb{E}_{p(x)}\left[\mathrm{KL}\left(p(z|x,\theta) \,||\, q(z|x,\lambda)\right)\right] \\ &= \arg\min_{\lambda} \mathbb{E}_{p(x)}\mathbb{E}_{p(z|x,\theta)}\left[\log p(z|x,\theta) - \log q(z|x,\lambda)\right] \\ &= \arg\max_{\lambda} \mathbb{E}_{p(x,z|\theta)}\left[\log q(z|x,\lambda)\right] - \underbrace{\mathbb{E}_{p(x,z|\theta)}\left[\log p(z|x,\theta)\right]}_{\text{constant}} \end{aligned}$$

Gradient wrt λ

$$\nabla_{\lambda}\mathbb{E}_{p(x,z|\theta)}\left[\log q(z|x,\lambda)\right]$$

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Flip the direction of the KL

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Gradient wrt λ

$$\nabla_{\lambda} \mathbb{E}_{p(x,z|\theta)} \left[\log q(z|x,\lambda)\right]$$

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Sleep Phase (Convenient) Objective

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\end{aligned}$$

Gradient wrt λ

$$\begin{aligned}
&\nabla_{\lambda} \mathbb{E}_{p(x,z|\theta)} \left[\log q(z|x,\lambda)\right] \\
&= \mathbb{E}_{p(x,z|\theta)} \left[\nabla_{\lambda} \log q(z|x,\lambda)\right] \\
&\overset{\text{MC}}{\approx} \nabla_{\lambda} \log q(z|\tilde{x},\lambda) \quad \text{where } z \sim p(z|\theta) \\
&\qquad\qquad\qquad\qquad\qquad\qquad \tilde{x} \sim p(x|z,\theta)
\end{aligned}$$

Sleep Phase (Convenient) Objective

Assumes fake data $\tilde{x}$ and latent variables z to be fixed random draws from $p(x, z|\theta)$ via

$$z \sim p(z|\theta)$$
$$\tilde{x} \sim p(x|z, \theta)$$

and maximises $\log q(z|\tilde{x}, \lambda)$.

Wake-sleep Algorithm

Advantages

- Simple layer-wise updates
- Amortised inference: all latent variables are inferred from the same weights λ

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Drawbacks

- Inference and generative networks are trained on different objectives
- Inference weights λ are updated on fake data $\tilde{x}$
- Generative weights are bad initially, giving wrong signal to the updates of λ

Variational Inference Learning (NVIL)

Generative model with NN likelihood

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Generative model with NN likelihood

Let us consider a latent factor model for topic modelling:

Variational Inference Learning (NVIL)

Generative model with NN likelihood

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- a document $x = (x_1, \ldots, x_N)$ consists of n i.i.d. categorical draws from that model

Variational Inference Learning (NVIL)

Generative model with NN likelihood

Let us consider a latent factor model for topic modelling:

- a document $x = (x_1, \ldots, x_N)$ consists of n i.i.d. categorical draws from that model
- the categorical distribution in turn depends on binary latent factors $z = (z_1, \ldots, z_K)$ which are also i.i.d.

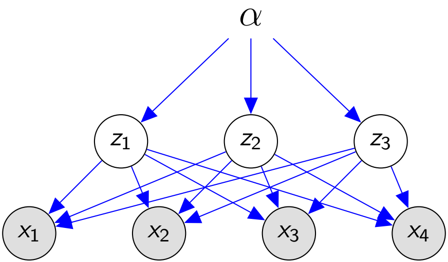
Latent factor model

$$\begin{aligned} Z_j &\sim \text{Bernoulli}\,(\alpha) & (1 \leq k \leq K) \\ X_i | z &\sim \text{Categorical}\,(f(z;\theta)) & (1 \leq i \leq N) \end{aligned}$$

Here $0 < \alpha < 1$ specifies a Bernoulli prior and $f(\cdot;\theta)$ is a function computed by a neural network with softmax output, e.g.

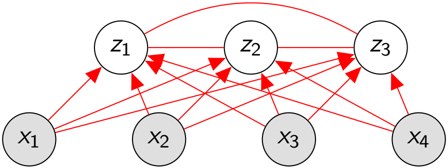
$$\begin{aligned} f(z;\theta) &= \text{softmax}(Wz + b) \\ \theta &= \{W, b\} \end{aligned}$$

Example Model



Joint distribution: independent latent variables

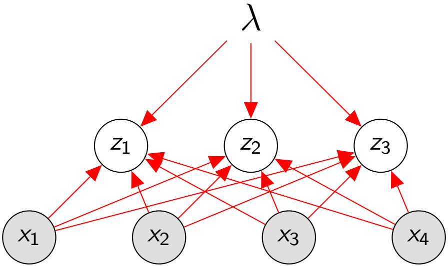
Example Model



Posterior: latent variables are marginally dependent.

For our variational distribution we are going to assume that they are not (recall: mean field assumption).

Mean Field Inference



The inference network needs to predict K Bernoulli parameters b_1^K. Any neural network with sigmoid output will do that job.

Inference Network

$$q(z|x,\lambda) = \prod_{k=1}^{K} \mathrm{Bern}(z_k|b_k)$$

$$\text{where } b_1^K = g(x;\lambda)$$

Example architecture

$$h = \frac{1}{N}\sum_{i=1}^{N} E_{x_i} \qquad b_1^K = \mathrm{sigmoid}(Mh + c)$$

$$\lambda = \{E, M, c\}$$

Objective

$$\mathrm{ELBO} = \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x, z|\theta)\right] + \mathbb{H}\left(q(z|x,\lambda)\right)$$

Objective

$$\begin{aligned}\mathrm{ELBO} &= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x,z|\theta)\right] + \mathbb{H}\left(q(z|x,\lambda)\right)\\ &= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \mathrm{KL}\left(q(z|x,\lambda)\;||\;p(z)\right)\end{aligned}$$

Objective

$$\begin{aligned}\text{ELBO} &= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x,z|\theta)\right] + \mathbb{H}\left(q(z|x,\lambda)\right) \\ &= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \text{KL}\left(q(z|x,\lambda) \mid\mid p(z)\right)\end{aligned}$$

Parameter estimation

$$\arg\max_{\theta,\lambda}\ \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \text{KL}\left(q(z|x,\lambda) \mid\mid p(z)\right)$$

KL

KL between K independent Bernoulli distributions is tractable

$$\mathrm{KL}\left(q(z|x,\lambda) \mid\mid p(z|\alpha)\right) = \sum_{k=1}^{K} \mathrm{KL}\left(q(z_k|x,\lambda) \mid\mid p(z_k|\alpha)\right)$$

KL

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$$= \sum_{k=1}^{K} \mathrm{KL}\left(\mathrm{Bernoulli}\left(b_k\right) \mid\mid \mathrm{Bernoulli}\left(\alpha\right)\right)$$

KL

KL between K independent Bernoulli distributions is tractable

$$\mathrm{KL}\left(q(z|x,\lambda)\;||\;p(z|\alpha)\right)=\sum_{k=1}^{K}\mathrm{KL}\left(q(z_k|x,\lambda)\;||\;p(z_k|\alpha)\right)$$

$$=\sum_{k=1}^{K}\mathrm{KL}\left(\mathrm{Bernoulli}\left(b_k\right)\right)\;||\;\mathrm{Bernoulli}\left(\alpha\right))$$

$$=\sum_{k=1}^{K} b_k \log\frac{b_k}{\alpha}+(1-b_k)\log\frac{1-b_k}{1-\alpha}$$

Generative Network Gradient

$$\frac{\partial}{\partial \theta}\left(\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \overbrace{\mathrm{KL}\left(q(z|x,\lambda) \mid\mid p(z)\right)}^{\text{constant wrt } \theta}\right)$$

Generative Network Gradient

$$\frac{\partial}{\partial\theta}\left(\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right]-\overbrace{\mathrm{KL}\left(q(z|x,\lambda)\;||\;p(z)\right)}^{\text{constant wrt }\theta}\right)$$

$$=\underbrace{\mathbb{E}_{q(z|x,\lambda)}\left[\frac{\partial}{\partial\theta}\log p(x|z,\theta)\right]}_{\text{expected gradient :)}}$$

Generative Network Gradient

$$\frac{\partial}{\partial\theta}\left(\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \overbrace{\mathrm{KL}\left(q(z|x,\lambda)\,||\,p(z)\right)}^{\text{constant wrt }\theta}\right)$$

$$= \underbrace{\mathbb{E}_{q(z|x,\lambda)}\left[\frac{\partial}{\partial\theta}\log p(x|z,\theta)\right]}_{\text{expected gradient :)}}$$

$$\overset{\text{MC}}{\approx} \frac{1}{S}\sum_{s=1}^{S}\frac{\partial}{\partial\theta}\log p(x|z^{(s)},\theta) \quad \text{where } z^{(s)} \sim q(z|x,\lambda)$$

Inference Network Gradient

$$\frac{\partial}{\partial \lambda}\left(\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \overbrace{\mathrm{KL}\left(q(z|x,\lambda)\ ||\ p(z)\right)}^{\text{analytical}}\right)$$

Inference Network Gradient

$$\frac{\partial}{\partial \lambda}\left(\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \overbrace{\mathrm{KL}\left(q(z|x,\lambda)\;||\;p(z)\right)}^{\text{analytical}}\right)$$

$$= \frac{\partial}{\partial \lambda}\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] - \underbrace{\frac{\partial}{\partial \lambda}\mathrm{KL}\left(q(z|x,\lambda)\;||\;p(z)\right)}_{\text{analytical computation}}$$

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The first term again requires approximation by sampling, but there is a problem

Inference Network Gradient

$$\frac{\partial}{\partial \lambda} \mathbb{E}_{q_\lambda(z|x)}\left[\log p_\theta(x|z)\right]$$

Inference Network Gradient

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$$= \frac{\partial}{\partial \lambda} \sum_{z} q(z|x,\lambda) \log p(x|z,\theta)$$

Inference Network Gradient

$$
\begin{aligned}
&\frac{\partial}{\partial \lambda} \mathbb{E}_{q_\lambda(z|x)} [\log p_\theta(x|z)] \\
&= \frac{\partial}{\partial \lambda} \sum_z q(z|x, \lambda) \log p(x|z, \theta) \\
&= \underbrace{\sum_z \frac{\partial}{\partial \lambda} (q(z|x, \lambda)) \log p(x|z, \theta)}_{\text{not an expectation}}
\end{aligned}
$$

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\end{aligned}
$$

- MC estimator is non-differentiable

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\end{aligned}
$$

- MC estimator is non-differentiable
- Differentiating the expression does not yield an expectation: cannot approximate via MC

Score Function Estimator

We can again use the log identity for derivatives

$$\frac{\partial}{\partial \lambda}\mathbb{E}_{q_\lambda(z|x)}\left[\log p_\theta(x|z)\right]$$
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$$= \underbrace{\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\frac{\partial}{\partial\lambda}\log q(z|x,\lambda)\right]}_{\text{expected gradient :)}}$$

Score Function Estimator

We can now build an MC estimator

$$\begin{aligned}
&\frac{\partial}{\partial \lambda}\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right] \\
&= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\frac{\partial}{\partial \lambda}\log q(z|x,\lambda)\right]
\end{aligned}$$

Score Function Estimator

We can now build an MC estimator

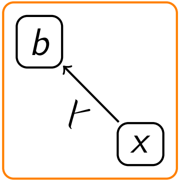
$$\frac{\partial}{\partial\lambda}\mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\right]$$

$$= \mathbb{E}_{q(z|x,\lambda)}\left[\log p(x|z,\theta)\frac{\partial}{\partial\lambda}\log q(z|x,\lambda)\right]$$

$$\overset{\text{MC}}{\approx} \frac{1}{S}\sum_{s=1}^{S}\log p(x|z^{(s)},\theta)\frac{\partial}{\partial\lambda}\log q(z^{(s)}|x,\lambda)$$

where $z^{(s)} \sim q(z|x,\lambda)$

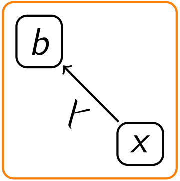
Computation Graph



inference model

Computation Graph

$$z \sim \text{Bernoulli}\,(b)$$



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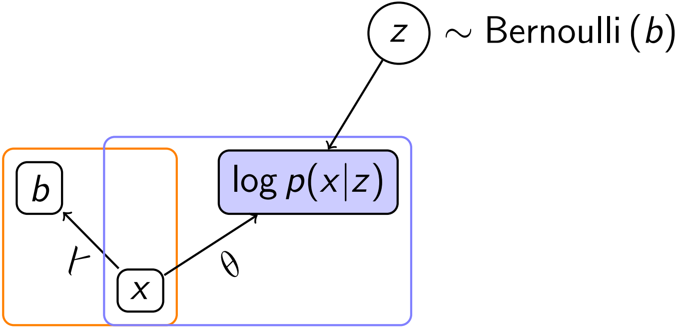
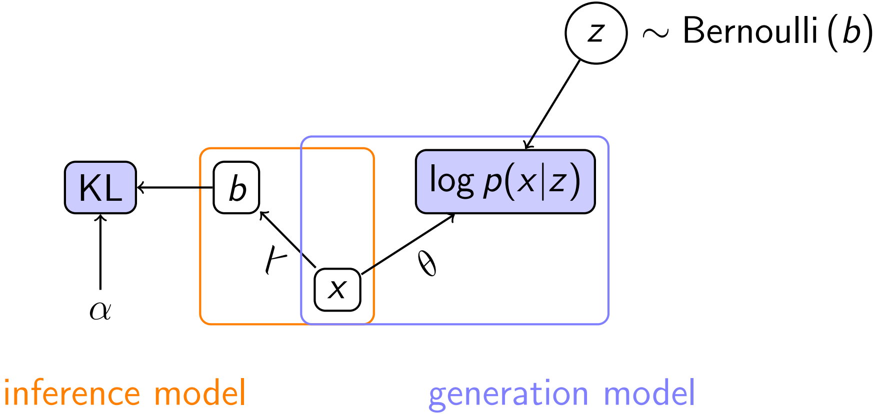
Computation Graph



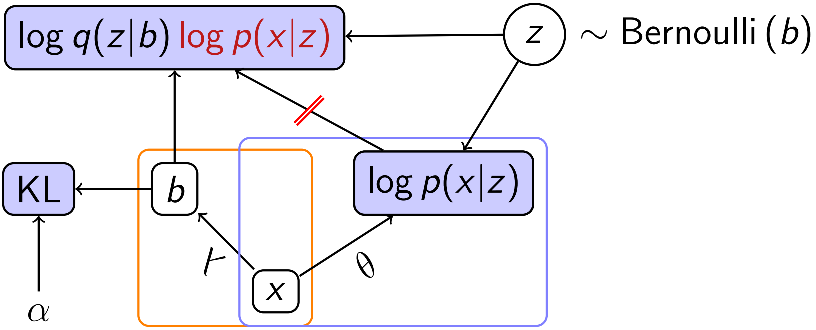
inference model

generation model

Computation Graph



Computation Graph



inference model

generation model

Score Function Estimator: Variance

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Empirically this estimator often exhibits high variance.

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Empirically this estimator often exhibits high variance.

- the magnitude of $\log p(x|z,\theta)$ varies widely
- the model likelihood does not contribute to direction of gradient

Score Function Estimator: Variance

We could:

Score Function Estimator: Variance

We could:

- sample more (better MC estimates)

Score Function Estimator: Variance

We could:

- sample more (better MC estimates)
- use variance reduction techniques (e.g. baselines and control variates)

Score Function Estimator: Variance

Idea: standardize the "reward" $\log p(x|z,\theta)$ to have a mean at 0 and a variance of 1

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$$\approx E_{q(z|x,\lambda)}\left[\hat{r}\frac{\partial}{\partial\lambda}\log q(z|x,\lambda)\right]$$

Score Function Estimator: Variance

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- More about this tomorrow!

Pros and Cons

Pros:

- Applicable to all distributions
- Many libraries come with samplers for common distributions

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Cons:

- High Variance!

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- Wake-Sleep: train inference and generation networks with separate objectives
- NVIL: a single objective (ELBO) for both models
- Use score function estimator
- Always use baselines for variance reduction!

Implementation

Check one of our notebooks, e.g.

- inducing rationales for sentiment classification
  github.com/vitutorial/exercises/tree/master/SST

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