Variational Inference: The Basics

Philip Schulz and Wilker Aziz

https: //github.com/philschulz/VITutorial

Generative Models

Examples

Variational Inference
    Deriving VI with Jensen's Inequality
    Deriving VI from KL Divergence
    Relationship to EM

Mean Field Inference

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Joint Distribution

Let X and Z be random variables. A generative model is any model that defines a joint distribution over these variables.

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3 Examples of Generative Models

- $p(x, z) = p(x)p(z|x)$
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- $p(x, z) = p(x)p(z)$

Likelihood and prior

From here on, x is our observed data. On the other
hand, z is an unobserved outcome.

- $p(x|z)$ is the **likelihood**
- $p(z)$ is the **prior** over Z

Notice: both distributions may depend on a
non-random quantity α (write e.g. $p(z|\alpha)$). In that
case, we call α a hyperparameter.

Bayes rule

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$$p(z|x) = \frac{\overbrace{p(x|z)}^{\text{likelihood}}\overbrace{p(z)}^{\textit{prior}}}{p(x)}$$

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$$\underbrace{p(z|x)}_{\text{posterior}} = \frac{\overbrace{p(x|z)}^{\text{likelihood}}\ \overbrace{p(z)}^{\textit{prior}}}{p(x)}$$

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We can *invert* a conditional probability distribution.

$$\underbrace{p(z|x)}_{\text{posterior}} = \frac{\overbrace{p(x|z)}^{\text{likelihood}} \overbrace{p(z)}^{\text{prior}}}{\underbrace{p(x)}_{\text{marginal likelihood/evidence}}}$$

The Basic Problem

We want to compute the posterior over latent variables $p(z|x)$. This involves computing the marginal likelihood

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

which is often **intractable**. This problem motivates the use of **approximate inference** techniques.

Generative Models

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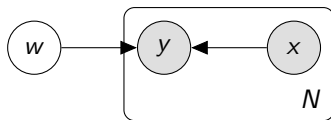   Relationship to EM

Mean Field Inference
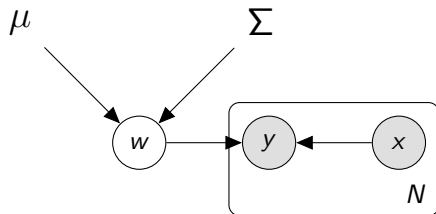
We cannot compute the posterior when

1. The functional form of the posterior is unknown (we don't know which parameters to infer)
2. The functional form is known but the computation is intractable

Bayesian Log-Linear POS Tagger

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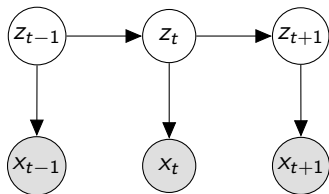# Bayesian Log-Linear POS Tagger

Intuition

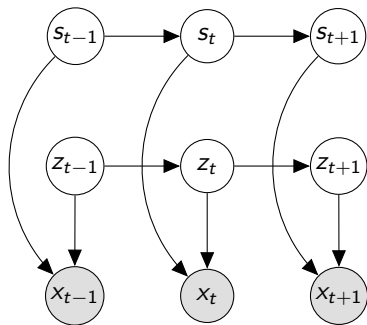Simply assume that the posterior is Gaussian.

Factorial HMMs

FHMMs have several Markov chains over latent variables.

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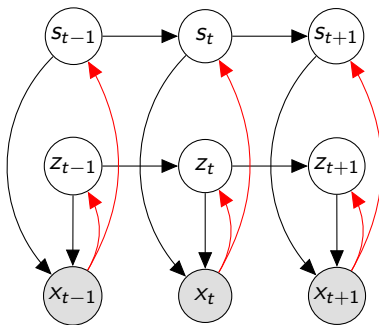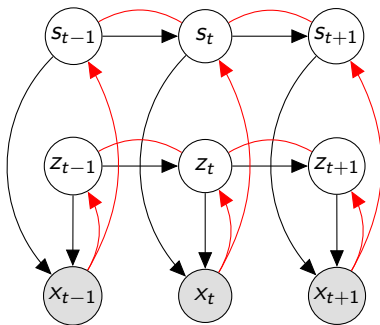FHMMs have several Markov chains over latent variables.
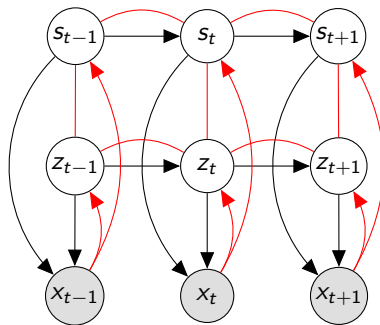
Factorial HMMs

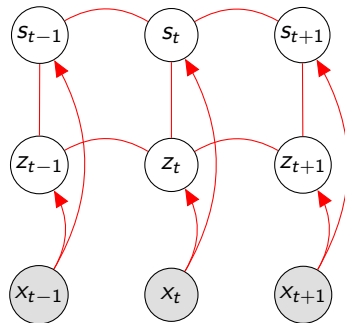FHMMs have several Markov chains over latent variables.

Factorial HMMs

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Factorial HMMs

Inference network for FHHMs.

Factorial HMMs

FHMMs have several Markov chains over latent variables.

- ▶ M Markov chains over latent variables.
- ▶ L outcomes per latent variable.
- ▶ Sequence of length T.
- ▶ Complexity of inference: $\mathcal{O}(L^{2M}T)$.

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Intractable
Exponential dependency on the number of hidden Markov chains.

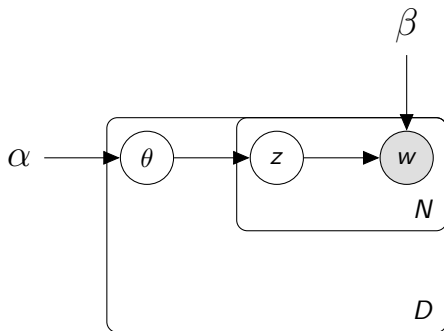# Factorial HMMs

Intuition

Simply assume that the posterior consists of independent Markov chains.

Latent Dirichlet Allocation

An admixture model that changes its mixture weights per document. We assume that the mixture components are fixed.

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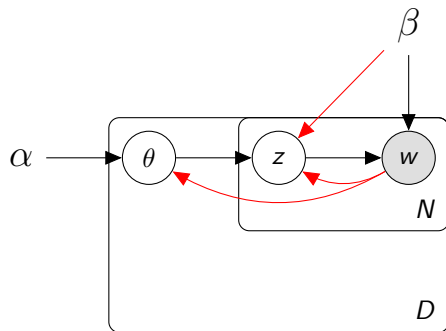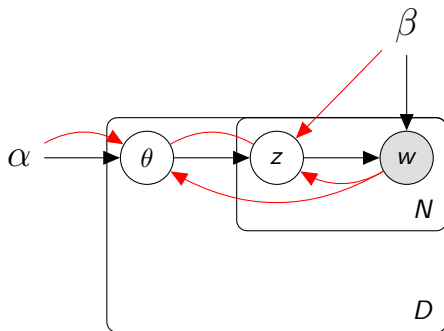
Inference network for LDA.
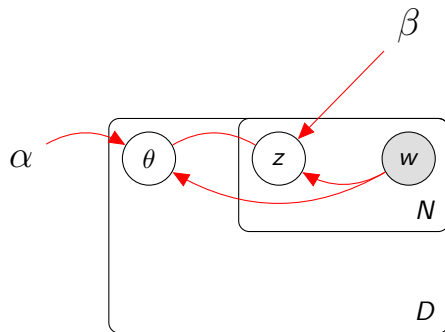
Latent Dirichlet Allocation

An admixture model that changes its mixture weights per document. Here we assume that the mixture components are fixed.

- D documents.
- N tokens and latent variables per document.
- L outcomes per latent variable.
- Complexity of inference: $\mathcal{O}(L^{DN})$.

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Rule of Thumb
Simply assume that the posterior is in the same family as the prior.

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The Goal

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Idea
Let's approximate it by an auxiliary distribution $q(z)$ that is computable!

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Requirement
Choose $q(z)$ as close as possible to $p(z|x)$ to obtain a faithful approximation.

Recap KL divergence

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- $\mathrm{KL}\left(q(z) \mid\mid p(z|x)\right) = \mathbb{E}_{q(z)}\left[\log\left(\frac{q(z)}{p(z|x)}\right)\right]$ (both)

Recap KL divergence

Properties

- KL $(q(z) \ || \ p(z|x)) \geq 0$ with equality iff $q(z) = p(z|x)$.

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- $\mathrm{KL}\left(q(z) \mid\mid p(z|x)\right) = \infty$ if $\exists z$ s.t. $p(z|x) = 0$ and $q(z) > 0$.

VI derivation I

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We have derived a lower bound on the log-evidence whose gap is exactly $\operatorname{KL}\left(q(z) \,\|\, p(z|x) \right)$.

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$$\min_{q(z)} \text{KL}\left(q(z) \,\|\, p(z|x)\right) = \max_{q(z)} - \text{KL}\left(q(z) \,\|\, p(z|x)\right)$$

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

As before, we have derived a lower bound on the log-evidence. This **evidence lower bound** or **ELBO** is our optimisation objective.

ELBO

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VI in its basic form can be performed via coordinate ascent. This can be done as a 2-step procedure.

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2. Optimise generative model.

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Recap: EM Algorithm

E-step   Compute: $\mathbb{E}_{p(z|x)}\left[\log\left(p(x,z)\right)\right]$.

          Same as: $\max\limits_{p(z|x)} \mathbb{E}_{p(z|x)}\left[\log p(x,z)\right]$

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M-step $\max\limits_{p(x,z)} \mathbb{E}_{p(z|x)}\left[\log p(x,z)\right] + \underbrace{\mathbb{H}\left(p(z|x)\right)}_{\text{constant}}$

EM is variational inference!

$$q(z) = p(z|x)$$
$$\mathrm{KL}\left(q(z) \,||\, p(z|x)\right) = 0$$

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Designing a tractable approximation

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This approximation strategy is commonly known as **mean field** approximation.

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- the categorical distribution in turn depends on Gaussian latent factors $z = (z_1, \ldots, z_K)$ which are also i.i.d.

$$z_j \sim \mathcal{N}(0, 1) \qquad (1 \leq j \leq K)$$
$$x_i \sim \text{Categorical}\,(f_\theta(z)) \quad (1 \leq i \leq N)$$

$f_\theta(\cdot)$ is computed by a NN with softmax output.

Example Model

Joint distribution: latent variables are marginally independent a priori
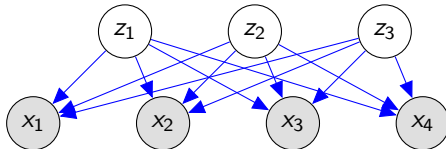
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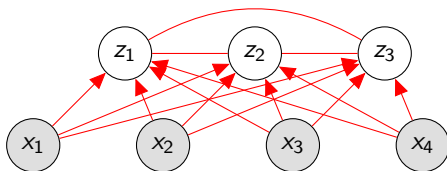
Posterior: latent variables are marginally dependent given observations

Mean field assumption

We have K latent variables

- assume the posterior factorises as K independent terms

$$q(z_1, \ldots, z_K) = \underbrace{\prod_{j=1}^{K} q_{\lambda_j}(z_j)}_{\text{mean field}}$$

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with independent sets of parameters $\lambda_j = \{u_j, s_j\}$

$$Z_j \sim \mathcal{N}(u_j, s_j^2)$$

Mean field: example
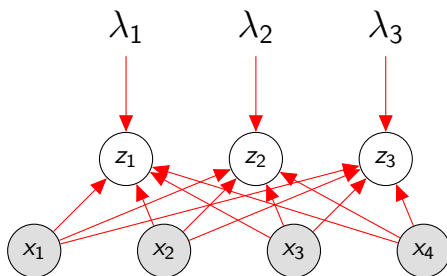
Amortised variational inference

Amortise the cost of inference using NNs
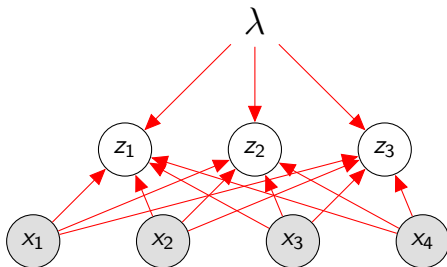
$$q(z_1, \ldots, z_K | x) = \prod_{j=1}^{K} q_\lambda(z_j | x)$$

Amortised variational inference

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still mean field

$$Z_j | x \sim \mathcal{N}(u_j, s_j^2)$$

Amortised variational inference
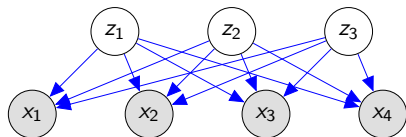
Amortise the cost of inference using NNs

$$q(z_1, \ldots, z_K | x) = \prod_{j=1}^{K} q_\lambda(z_j | x)$$

still mean field

$$Z_j | x \sim \mathcal{N}(u_j, s_j^2)$$

but with a shared set of parameters

- ▸ where $u_1^K = \mu_\lambda(x)$
- ▸ and $s_1^K = \sigma_\lambda(x)$
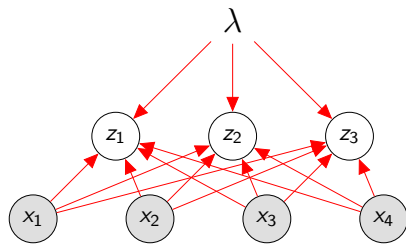
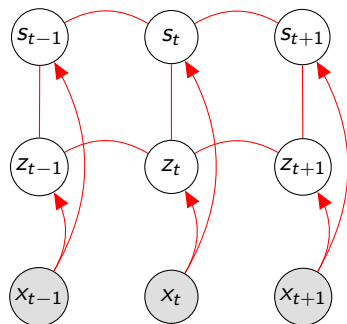# Amortised VI: example

Joint distribution
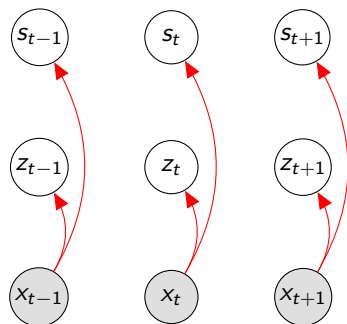
Posterior
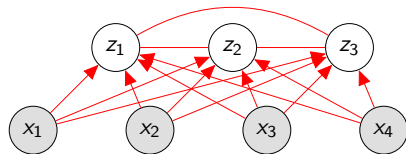
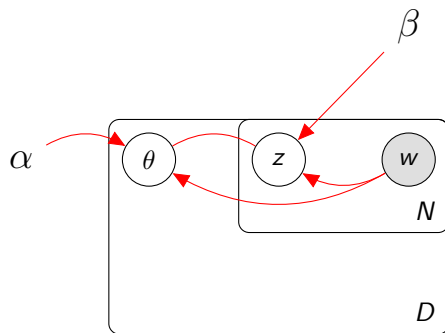Mean field
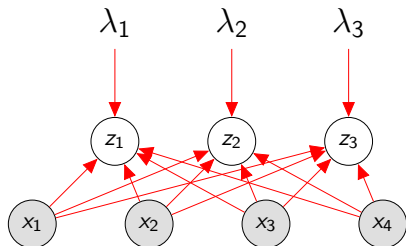
Amortised VI

Original FHHM Inference

Exact posterior $p(s, z|x)$
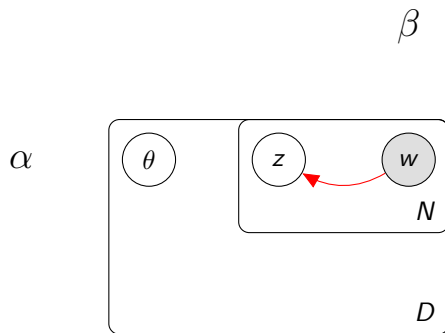
Mean field FHHM Inference

Approximate posterior $q(s, z) = \prod_{t=1}^{T} q(s_t) q(z_t)$

Original LDA Inference

Exact posterior $p(z, \theta | w, \alpha, \beta)$

Mean field LDA Inference

Approximate posterior
$$q(z, \theta | w, \alpha, \beta) = \prod_{d=1}^{D} q(\theta_d) \prod_{i=1}^{N} q(z_i | w)$$

Summary

- Posterior inference is often **intractable** because the marginal likelihood (or **evidence**) $p(x)$ cannot be computed efficiently.
- Variational inference approximates the posterior $p(z|x)$ with a simpler distribution $q(z)$.
- The variational objective is the **evidence lower bound (ELBO)**:

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

Summary

- The **ELBO** is a lower bound on the log-evidence.
- When $q(z) = p(z|x)$ we recover EM.
- A common approximation is the **mean field** approximation which assumes that all latent variables are independent:

$$q(z) = \prod_{i=1}^{N} q(z_i)$$

Literature I