Statistical Models & Computing Methods

Lecture 8: Variational Inference

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▶ EM algorithm finds the MLE for latent variable model

$$\mathcal{L}(\theta) = \log p(x|\theta) = \log \sum_z p(x, z|\theta)$$

▶ EM update formula

$$\theta^{(t+1)} = \arg\max_\theta Q^{(t)}(\theta) = \arg\max_\theta \mathbb{E}_{p(z|x,\theta^{(t)})} \log p(x, z|\theta)$$

▶ EM requires the posterior $p(z|x, \theta^{(t)})$ is known. What if $p(z|x, \theta^{(t)})$ is unknown?
  ▶ If somehow we can sample from $p(z|x, \theta^{(t)})$, we can use Monte Carlo estimates, that is Monte Carlo EM.
  ▶ However, the associated computation may be expansive.

- Recall EM maximizes the lower bound

$$\mathcal{F}(q, \theta^{(t)}) = \mathbb{E}_{q(z)} \log \frac{p(x, z|\theta)}{q(z)} \leq \mathcal{L}(\theta), \quad \forall q(z)$$

- When the best $q(z) = p(z|x, \theta^{(t)})$ is not available, we can use approximate $q(z)$ instead.
- A widely used approximation is the mean-field approximation

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

► In that case, the lower bound is

$$\mathcal{F}(q(z), \theta^{(t)}) = \int \prod_{i=1}^{d} q_i(z_i) \log \frac{p(x, z|\theta^{(t)})}{\prod_{i=1}^{d} q_i(z_i)} \, dz_1 dz_2 \ldots dz_d$$

$$= \int \prod_{i=1}^{d} q_i(z_i) \log p(x, z|\theta^{(t)}) \, dz_1 dz_2 \ldots dz_d$$

$$- \sum_{i=1}^{d} \int q_i(z_i) \log q_i(z_i) \, dz_i$$

► Coordinate Ascent

$$q_i^{(t)}(z_i) \propto \exp\left(\mathbb{E}_{-q_i} \log p(x, z|\theta^{(t)})\right), i = 1, \ldots, d$$

Mean-Field Variational EM

- ▶ E-step. Run coordinate ascent several times to obtain good mean-field approximation

$$q^{(t)}(z) = \prod_{i=1}^{d} q_i^{(t)}(z_i)$$

compute the expected complete data log-likelihood

$$Q^{(t)}(\theta) = \mathbb{E}_{q^{(t)}(z)} \log p(x, z | \theta)$$

- ▶ M-step. Update θ to maximize $Q^{(t)}(\theta)$

$$\theta^{(t+1)} = \arg\max_{\theta} Q^{(t)}(\theta)$$

- Now let us consider Bayesian inference for latent variable models

$$p(z, \theta | x) \propto p(x, z | \theta) p(\theta)$$

- We can lower bound the marginal likelihood

$$
\begin{aligned}
\mathcal{L}(x) = \log p(x) &= \log \int p(x, z|\theta)p(\theta) \; dz d\theta \\
&= \log \int q(z, \theta) \frac{p(x, z|\theta)p(\theta)}{q(z, \theta)} \; dz d\theta \\
&\geq \int q(z, \theta) \log \frac{p(x, z|\theta)p(\theta)}{q(z, \theta)} \; dz d\theta \\
&= \mathcal{F}(q(z, \theta))
\end{aligned}
$$

- Maximizing this lower bound $\mathcal{F}$ is equivalent to minimizing $D_{\mathrm{KL}}(q(z, \theta) \| p(z, \theta | x))$

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Mean-Field Approximation

▶ Again, we consider a simple factorized approximation $q(z, \theta) = q_z(z)q_\theta(\theta)$

$$\mathcal{L}(x) \geq \int q_z(z)q_\theta(\theta) \log \frac{p(x, z|\theta)p(\theta)}{q_z(z)q_\theta(\theta)} \; dzd\theta$$
$$= \mathcal{F}(q_z(z), q_\theta(\theta))$$

▶ Maximizing this lower bound $\mathcal{F}$, leads to **EM**-like iterative updates

$$q_z^{(t+1)}(z) \propto \exp\left(\mathbb{E}_{q_\theta^{(t)}(\theta)} \log p(x, z|\theta)\right)$$
$$q_\theta^{(t+1)}(\theta) \propto p(\theta) \cdot \exp\left(\mathbb{E}_{q_z^{(t+1)}(z)} \log p(x, z|\theta)\right)$$

Let's focus on conjugate-exponential (CE) models, which satisfy

Condition 1
The joint probability over variables is in the exponential family

$$p(x, z|\theta) = h(x, z) \exp\left(\phi(\theta) \cdot T(x, z) - A(\theta)\right)$$

Condition 2
The prior over parameters is conjugate to this joint probability

$$p(\theta|\eta, \nu) \propto \exp\left(\phi(\theta) \cdot \nu - \eta A(\theta)\right)$$

Conjugate priors are computationally convenient and have an intuitive interpretation:

▶ η: number of pseudo-observations

▶ ν: values of pseudo-observations

Now suppose we have an iid data set $x = \{x_1, \ldots, x_n\}$

▶ VB E-step.

$$q_z^{(t+1)}(z) \propto \exp\left(\mathbb{E}_{q_\theta^{(t)}(\theta)} \log p(x, z|\theta)\right)$$
$$\propto \prod_{i=1}^{n} h(x_i, z_i) \exp\left(\bar{\phi} \cdot T(x_i, z_i)\right)$$

where $\bar{\phi} = \mathbb{E}_{q_\theta^{(t)}}(\phi(\theta))$

▶ VB M-step

$$q_\theta^{(t+1)}(\theta) \propto \exp\left(\phi(\theta) \cdot \left(\nu + \sum_{i=1}^{n} \overline{T}(x_i, z_i)\right) - (\eta + n)A(\theta)\right)$$

where $\overline{T}(x_i, z_i) = \mathbb{E}_{q_z^{(t+1)}}(T(x_i, z_i))$

EM for MAP

- Goal: maximize $p(x, \theta)$
- **E-step**: compute

$$q_z^{(t+1)}(z) = p(z|x, \theta^{(t)})$$

- **M-step**:

$$\theta^{(t+1)} = \arg\max_{\theta} Q^{(t)}(\theta)$$

$$Q^{(t)}(\theta) = \mathbb{E}_{q_z^{(t+1)}} \log p(x, z, \theta)$$

Variational Bayesian EM

- Goal: lower bound $p(x)$
- **VB E-step**: compute

$$q_z^{(t+1)}(z) = p(z|x, \bar{\phi})$$

- **VB M-step**:

$$q_\theta^{(t+1)}(\theta) \propto \exp\left(Q^{(t)}(\theta)\right)$$

$$Q^{(t)}(\theta) = \mathbb{E}_{q_z^{(t+1)}} \log p(x, z, \theta)$$

- ▶ Reduces to the EM algorithm if $q_\theta(\theta) = \delta(\theta - \theta^*)$.
- ▶ $\mathcal{F}$ increases monotonically, and incorporates the model complexity penalty.
- ▶ Analytical parameter distributions
- ▶ VB E-step has the same complexity as corresponding E step, and is almost identical except that it uses the expected natural parameters, $\bar{\phi}$.
- ▶ The lower bound given by VBEM can be used for model selection.

Bayesian Model Selection

► In Bayesian model selection, we want to select the model class with the highest marginal likelihood (evidence)

$$p(x|m) = \int p(x|\theta, m)p(\theta|m)d\theta$$

► Occam's Razor

All possible data sets
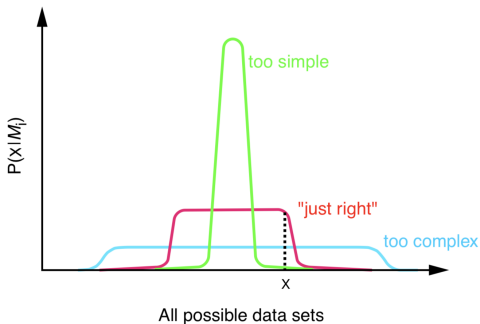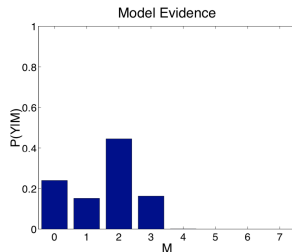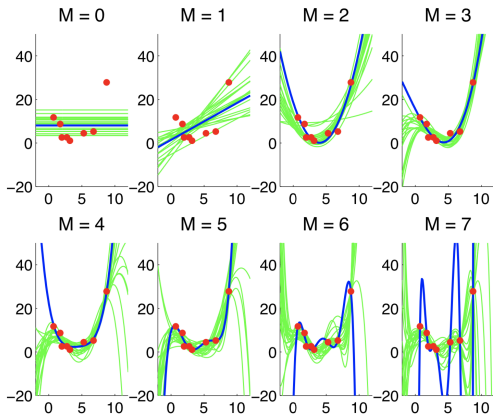
Adapted from Zoubin Ghahramani

- **Bayesian Information Criterion** (BIC):

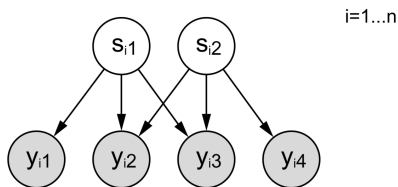$$\log p(x|m) \approx \log p(x|\hat{\theta}_{\mathrm{MAP}}, m) - \frac{d}{2}\log n$$

- **Annealed Importance Sampling** (AIS):

$$Z_k = \int p(x|\theta, m)^{\tau_k} p(\theta|m)d\theta, \quad 0 = \tau_0 < \cdots < \tau_K = 1$$

$$\log p(x|\theta) = Z_K = \prod_{k=0}^{K-1} \frac{Z_{k+1}}{Z_k}$$

  where $\frac{Z_{k+1}}{Z_k}$ can be estimated via importance sampling.

- **Variational Bayesian EM** (VB): use VBEM lower bound estimate

Example: A Bipartite Structured Model

▶ A simple bipartite graphical model: **two** binary hidden variables, and **four** five-valued discrete observed variables
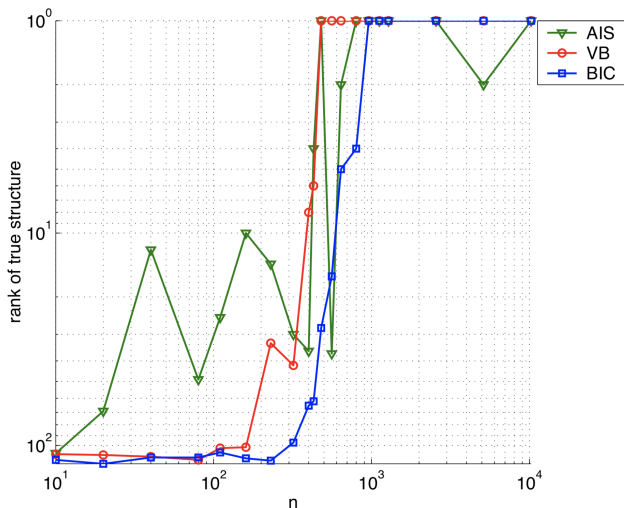

▶ Experiment: there are 136 distinict structures with 2 latent variables as potential parents of 4 conditionally independent observed variables

▶ Score each structure with 3 methods: BIC, VB and the gold standard AIS.

How Reliable is The AIS Gold Standard?
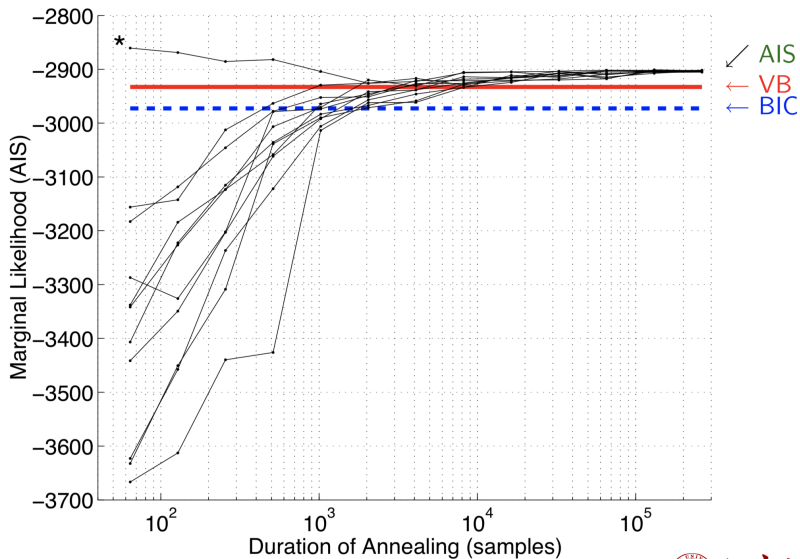
VB score finds correct structure earlier, and more reliably

- A Bayesian probabilistic model includes the conditional distribution $p(x|\theta)$ of observed variable x given the model parameter θ, and the prior $p(\theta)$, which gives a joint distribution

$$p(x, \theta) = p(x|\theta)p(\theta)$$

- Inference about the parameter θ is through the **posterior**, the conditional distribution of the parameters given the observations

$$p(\theta|x) = \frac{p(x, \theta)}{p(x)}$$

- For most interesting models, the denominator is not tractable. We appeal to approximate posterior inference.
  - **Markov chain Monte Carlo** – We've introduced before.
 - **Variational inference** – The topic for this lecture!

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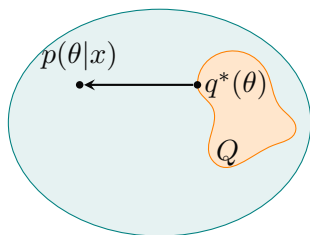
$$q^*(\theta) = \operatorname*{arg\,min}_{q \in Q} \mathrm{KL}\left(q(\theta) \| p(\theta|x)\right)$$
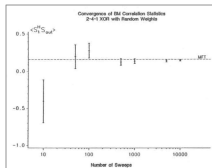
▶ VI turns inference into optimization

▶ Specify a variational family of distributions over the model parameters
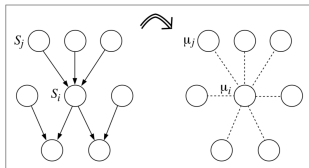
$$Q = \{q_\phi(\theta); \phi \in \Phi\}$$

▶ Fit the variational parameters ϕ to minimize the distance (often in terms of KL divergence) to the exact posterior
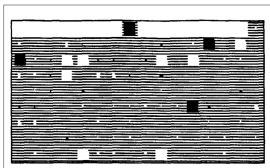
Example: Mixture of Gaussians

Adapted from David Blei

History
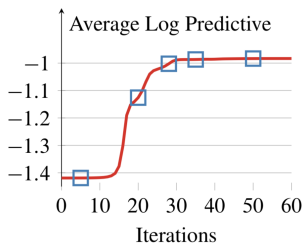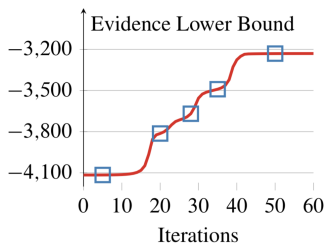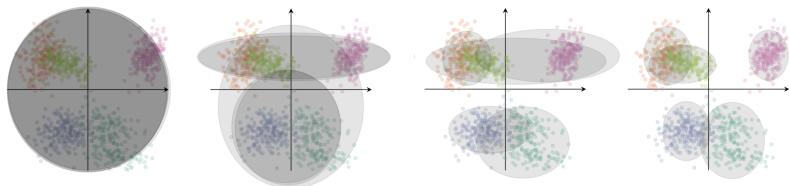
[Peterson and Anderson 1987]   [Jordan et al. 1999]   [Hinton and van Camp 1993]

▶ Idea adapted from statistical physics – mean-field methods to fit a neural network (Peterson and Anderson, 1987).

▶ Picked up by Jordan's lab in the early 1990s, generalized it to many probabilistic models. (see Jordan et al., 1999 for an overview)

▶ Contributions from Hinton's group: mean-field for neural networks (Hinton and Van Camp, 1993); connection to the EM algorithm (Neal and Hinton, 1993).

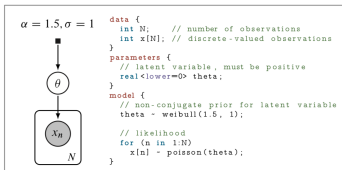[Kingma and Welling 2013] [Rezende et al. 2014] [Kucukelbir et al. 2015]
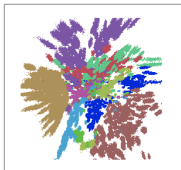
▶ More and more work on variational inference now, making it scalable, easier to derive, faster, more accurate, and applying it to more complicated models and applications.

▶ Modern VI touches many important areas: probabilistic programming, reinforcement learning, neural networks, convex optimization, Bayesian statistics, and myriad applications.

- We use Kullback-Leibler (KL) divergence to measure the distance between two distributions.
- This comes from **information theory**, a field that has deep links to statistics and machine learning.
- The KL divergence for variational inference is

$$\mathrm{KL}(q\|p) = \mathbb{E}_{q(\theta)}\left(\log \frac{q(\theta)}{p(\theta|x)}\right)$$

  - If q is high, p and q should be close
  - if q is low then we don't care
- We choose q that are tractable: easy to take expectations and compute the pdf.
- Reversing the arguments leads to a different kind of variational inference, i.e., expectation propagation, which is in general more computationally expensive.

- We actually can't minimize the KL divergence exactly, but we can find an equivalent formulation that is tractable – the **evidence lower bound** (ELBO)

- By Jensen's inequality

$$\log p(x) = \log \int p(x, \theta) d\theta$$
$$= \log \int q(\theta) \frac{p(x, \theta)}{q(\theta)} d\theta$$
$$\geq \int q(\theta) \log \frac{p(x, \theta)}{q(\theta)} d\theta$$
$$\geq \mathbb{E}_q(\log p(x, \theta)) - \mathbb{E}_q(\log q(\theta))$$

This is the ELBO. Note that this is the free-energy lower bound we derived for EM.

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- What does the ELBO have to do with the KL divergence to the posterior?
- Note that $p(\theta|x) = p(x,\theta)/p(x)$, use this in the KL divergence

$$
\begin{aligned}
\mathrm{KL}(q(\theta)\|p(\theta|x)) &= \mathbb{E}_q\left(\log\frac{q(\theta)}{p(\theta|x)}\right) \\
&= \mathbb{E}_q\left(\log\frac{q(\theta)}{p(x,\theta)}\right) + \log p(x) \\
&= \log p(x) - \mathbb{E}_q\left(\log\frac{p(x,\theta)}{q(\theta)}\right)
\end{aligned}
$$

- Therefore, the KL divergence is just the gap between the ELBO and the model evidence, and minimizing the KL divergence is equivalent to maximizing the ELBO.

$$\mathcal{L} = \mathbb{E}_q \left(\log \frac{p(x, \theta)}{q(\theta)} \right)$$
$$= \mathbb{E}_q(\log p(x, \theta)) - \mathbb{E}_q(\log q(\theta))$$

▶ $\mathcal{L}$ only requires the joint probability $p(x, \theta)$, which is computable.
▶ The ELBO trades off two terms
  ▶ The first term drives q towards the MAP estimate.
  ▶ The second term encourages q to be diffuse.
▶ Unfortunately, the ELBO is usually not convex, and VI may end up with local modes.

- A commonly used variational family is the mean field approximation, a variational family that factorizes

$$q(\theta) = \prod_{i=1}^{d} q_i(\theta_i)$$

  Each variable is independent. We can relax this constraint by using blockwise factorization.

- Note that this family is usually quite limited since the parameters in true posteriors are likely to be dependent.
  - E.g., in the Gaussian mixture model all of the cluster assignments z and the cluster locations μ are dependent on each other given the data x.
  - These dependencies often make the posterior difficult to work with.

► We now turn to optimizing the ELBO for the mean field approximation

$$\mathcal{L} = \mathbb{E}_q(\log p(x, \theta)) - \mathbb{E}_q \sum_{i=1}^{d} \log q_i(\theta_i)$$

$$= \mathbb{E}_q(\log p(x, \theta)) - \sum_{i=1}^{d} \mathbb{E}_{q_i} \log q_i(\theta_i)$$

► For each component $q_i(\theta_i)$

$$\mathcal{L} = \int \prod_{i=1}^{d} q_i(\theta_i) \log p(x, \theta) d\theta - \sum_{i=1}^{d} \mathbb{E}_{q_i} \log q_i(\theta_i)$$

$$= \mathbb{E}_{q_i} \mathbb{E}_{-q_i} (\log p(x, \theta)) - \mathbb{E}_{q_i} \log q_i(\theta_i) + \text{const}$$

▶ Take the derivative w.r.t. $q_i(\theta_i)$

$$\frac{\partial \mathcal{L}}{\partial q_i(\theta_i)} = \mathbb{E}_{-q_i}(\log p(x, \theta)) - \log q_i(\theta_i) - 1 = 0$$

▶ This leads to a coordinate ascent algorithm

$$q_i^*(\theta_i) \propto \exp\left(\mathbb{E}_{-q_i}\left(\log p(x, \theta)\right)\right)$$

  ▶ The RHS only depends on $q_j(\theta_j), j \neq i$.
  ▶ This determines the form of the optimal $q_i(\theta_i)$. We only specify the factorization before.
  ▶ While the optimal $q_i(\theta_i)$ might not be easy to compute (depending on the form), for many models it is.

▶ The ELBO converges to a *local minimum*. We use the resulting q as a proxy for the true posterior.

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There is a strong relationship between Mean-Field VI and Gibbs sampling

▶ In Gibbs sampling, we sample from the conditional

▶ In Mean-Field VI (via coordinate ascent), we iteratively set each factor to

$$q_i(\theta_i) \propto \exp\left(\mathbb{E}(\log(\text{conditional}))\right)$$

Example: Multinomial conditionals

▶ Suppose the conditional is multinomial

$$p(\theta_i | \theta_{-i}, x) \sim \text{Multinomial}(\pi(\theta_{-i}, x))$$

▶ Then the optimal $q_i(\theta_i)$ is also a multinomial

$$q^*(\theta_i) \propto \exp\left(\mathbb{E}(\log \pi(\theta_{-i}, x))\right)$$

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▶ Suppose each conditional is in the exponential family

$$p(\theta_i|\theta_{-i}, x) = h(\theta_i) \exp\left(\eta(\theta_{-i}, x) \cdot T(\theta_i) - A(\eta(\theta_{-i}, x))\right)$$

where $\eta(\theta_{-i}, x)$ is the natural parameters and $T(\theta_i)$ is the sufficient statistics.

▶ This includes a lot of complicated models
  ▶ Bayesian mixture of exponential families with conjugate priors
  ▶ Hierarchical HMMs
  ▶ Mixed-membership models of exponential families
  ▶ Bayesian linear regression

▶ Compute the log of the conditional

$$\log p(\theta_i|\theta_{-i}, x) = \log h(\theta_i) + \eta(\theta_{-i}, x) \cdot T(\theta_i) - A(\eta(\theta_{-i}, x))$$

▶ Compute the expectation w.r.t. $q(\theta_{-i})$

$$\mathbb{E}\left(\log p(\theta_i|\theta_{-i}, x)\right) = \log h(\theta_i) + \mathbb{E}\left(\eta(\theta_{-i}, x)\right) \cdot T(\theta_i) - \mathbb{E}\left(A(\eta(\theta_{-i}, x))\right)$$

▶ Note that the last term does not depend on θ_i, therefore

$$q_i^*(\theta_i) \propto h(\theta_i) \exp\left(\mathbb{E}\left(\eta(\theta_{-i}, x)\right) \cdot T(\theta_i)\right)$$

and the normalizing constant is $A(\mathbb{E}\left(\eta(\theta_{-i}, x)\right))$

▶ The optimal $q_i(\theta_i)$ is in the same exponential family as the conditional.

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- Consider the clustering of $x = \{x_1, \ldots, x_n\}$ using a finite mixture of Gaussians with generating variance one

$$z_i \sim \text{Discrete}(\pi), \quad x_i|z_i = k \sim \mathcal{N}(\mu_k, 1)$$
$$\mu_k \sim \mathcal{N}(\mu_0, \sigma_0), \quad k = 1, \ldots, K$$

- The joint probability is

$$\log p(x, z, \mu) = \sum_{i=1}^{n} \log p(x_i, z_i|\mu) + \sum_{k=1}^{K} \log \mathcal{N}(\mu_k|\mu_0, \sigma_0^2)$$
$$= \sum_{i=1}^{n} \sum_{k=1}^{K} 1_{z_i=k} \left(\log \pi_k + \log \mathcal{N}(x_i|\mu_k, 1)\right)$$
$$+ \sum_{k=1}^{K} \log \mathcal{N}(\mu_k|\mu_0, \sigma_0^2)$$

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- The mean field family is

$$q(\mu, z) = \prod_{k=1}^{K} \mathcal{N}(\mu_k | \tilde{\mu}_k, \tilde{\sigma}_k^2) \prod_{i=1}^{n} q(z_i | \phi_i)$$

- Coordinate ascent update for $q(z_i)$ is

$$q^*(z_i) \propto \exp\left(\mathbb{E}_{-q(z_i)}(\log p(x, z_i, z_{-i}, \mu))\right)$$

- Take expectation and restrict the terms relate to z_i

$$q^*(z_i) \propto \exp(\log \pi_{z_i} + \mathbb{E}(\log \mathcal{N}(x_i | \mu_{z_i}, 1)))$$
$$\propto \exp\left(\log \pi_{z_i} + x_i \tilde{\mu}_{z_i} - \frac{\tilde{\mu}_{z_i}^2 + \tilde{\sigma}_{z_i}^2}{2}\right)$$
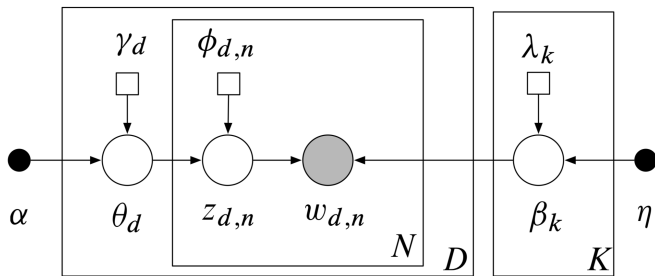
▶ Similarly, the coordinate ascent update for $q(\mu_k)$ is

$$
\begin{aligned}
q^*(\mu_k) &\propto \exp\left(\mathbb{E}_{-q(\mu_k)}(\log p(x, z, \mu_k, \mu_{-k}))\right) \\
&\propto \exp\left(\sum_{i=1}^{n} q(z_i = k) \log \mathcal{N}(x_i|\mu_k, 1) + \log \mathcal{N}(\mu_k|\mu_0, \sigma_0^2)\right) \\
&\propto \exp\left(\sum_{i=1}^{n} \phi_{i,k}\left(x_i\mu_k - \frac{1}{2}\mu_k^2\right) + \frac{\mu_0}{\sigma_0^2}\mu_k - \frac{1}{2\sigma_0^2}\mu_k^2\right) \\
&\propto \mathcal{N}\left(\hat{\mu}_k, \hat{\sigma}_k^2\right)
\end{aligned}
$$

where

$$
\hat{\mu}_k = \frac{\frac{\mu_0}{\sigma_0^2} + \sum_{i=1}^{n} \phi_{i,k} x_i}{\frac{1}{\sigma_0^2} + \sum_{i=1}^{n} \phi_{i,k}}, \quad \hat{\sigma}_k^2 = \frac{1}{\frac{1}{\sigma_0^2} + \sum_{i=1}^{n} \phi_{i,k}}
$$

- The local variables are θ_d and z_d.
- The global variables are the topics $\beta_1, \ldots, \beta_K$.
- The variational distribution is

$$q(\beta, \theta, z) = \prod_{k=1}^{K} q(\beta_k | \lambda_k) \prod_{d=1}^{D} q(\theta_d | \gamma_d) \prod_{n=1}^{N} q(z_{d,n} | \phi_{d,n})$$
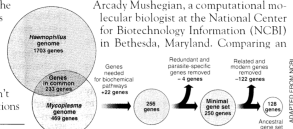
Adapted from David Blei

► The complete probability model

$$\theta_d \sim \text{Dirichlet}(\alpha), \quad \beta_k \sim \text{Dirichlet}(\eta)$$

$$z_{d,n}|\theta_d \sim \text{Discrete}(\theta_d), \quad w_{d,n}|z_{d,n},\beta \sim \text{Discrete}(\beta_{z_{d,n}})$$

► The joint probability is

$$p(w,z,\theta,\beta) = \prod_{k=1}^{K} p(\beta_k|\eta) \prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{n=1}^{N} p(z_{d,n}|\theta_d)p(w_{d,n}|z_{d,n},\beta)$$

► We set $q(\beta_k|\lambda_k), q(\theta_d|\gamma_d), q(z_{d,n}|\phi_{d,n})$ accordingly

$$q(\beta_k|\lambda_k) \sim \text{Dirichlet}(\lambda_k), \quad q(\theta_d|\gamma_d) \sim \text{Dirichlet}(\gamma_d)$$

$$q(z_{d,n}|\phi_{d,n}) \sim \text{Discrete}(\phi_{d,n})$$

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▶ **Update λ**

$$q(\beta_k|\lambda_k^*) \propto \exp\left(\mathbb{E}_{q(\beta_{-k},\theta,z)} \log p(w,z,\theta,\beta)\right)$$

$$\propto \exp\left(\sum_{j=1}^{V}(\eta_j - 1 + \sum_{d=1}^{D}\sum_{n=1}^{N} \phi_{d,n,k} w_{d,n}^j) \log \beta_{k,j}\right)$$

$$\boxed{\Rightarrow \lambda_{k,j}^* = \eta_j + \sum_{d=1}^{D}\sum_{n=1}^{N} \phi_{d,n,k} w_{d,n}^j}$$

▶ **Update γ**

$$q(\theta_d|\gamma_d^*) \propto \exp(\mathbb{E}_{q(\beta,\theta_{-d},z)} \log p(w,z,\theta,\beta))$$

$$\propto \exp\left(\sum_{k=1}^{K}(\alpha_k - 1 + \sum_{n=1}^{N} \phi_{d,n,k}) \log \theta_{d,k}\right)$$

$$\boxed{\Rightarrow \gamma_{d,k}^* = \alpha_k + \sum_{n=1}^{N} \phi_{d,n,k}}$$

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▶ **Update** ϕ

$$q(z_{d,n}|\phi^*_{d,n}) \propto \exp(\mathbb{E}_{q(\beta,\theta,z_{-(d,n)})} \log p(w,z,\theta,\beta))$$
$$\propto \exp(\mathbb{E}_{q(\beta,\theta,z_{-(d,n)})}(\log p(z_{d,n}|\theta_d)$$
$$+ \log p(w_{d,n}|z_{d,n},\beta)))$$
$$\propto \exp\left(\sum_{k=1}^{K} 1_{z_{d,n}=k}(\mathbb{E}_{\theta_d}(\log \theta_{d,k})\right.$$
$$\left.+ \sum_{j=1}^{V} w_{d,n}^j \mathbb{E}_{\beta_k}(\log \beta_{k,j}))\right)$$

$$\Rightarrow \phi^*_{d,n,k} \propto \exp\left(\mathbb{E}_{\theta_d}(\log \theta_{d,k}) + \sum_{j=1}^{V} w_{d,n}^j \mathbb{E}_{\beta_k}(\log \beta_{k,j})\right)$$

A Generic Class of Models

Global variables β

Local variables z_i x_i

n
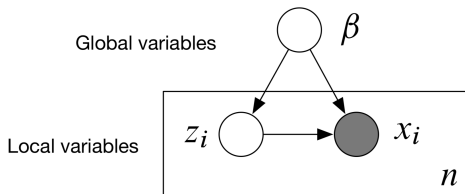
$$p(\beta, z, x) = p(\beta) \prod_{i=1}^{n} p(z_i, x_i | \beta)$$

- ▶ The observations are $x = \{x_1, \ldots, x_n\}$
- ▶ The **local** latent variables are $z = \{z_1, \ldots, z_n\}$
- ▶ The **global** variables are β
- ▶ The i-th data point x_i only depends on z_i and β

- **Goal**: compute $p(\beta, z | x)$
- Exponential family and conditional conjugacy

$$p(x_i, z_i | \beta) = h(x_i, z_i) \exp\left(\beta \cdot T(x_i, z_i) - A_\ell(\beta)\right)$$
$$p(\beta) = h(\beta) \exp\left(\alpha \cdot T(\beta) - A_g(\alpha)\right)$$
$$= h(\beta) \exp\left(\alpha_1 \cdot \beta - \alpha_2 A_\ell(\beta) - A_g(\alpha)\right)$$

- Complete conditionals

$$p(\beta | x, z) = h(\beta) \exp\left(\eta_g(x, z) \cdot T(\beta) - A_g(\eta_g(x, z))\right)$$
$$p(z_i | x_i, \beta) = h(z_i) \exp\left(\eta_\ell(x_i, \beta) \cdot T(z_i) - A_\ell(\eta_l(x_i, \beta))\right)$$

where $\eta_g(x, z) = (\alpha_1 + \sum_{i=1}^n T(x_i, z_i), \alpha_2 + n)$

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► The mean-field variational family

$$q(\beta, z) = q(\beta|\lambda) \prod_{i=1}^{n} q(z_i|\phi_i)$$

  ► The global parameters λ govern the global variables
  ► The local parameters ϕ_i govern the local variables
► Moreover, we set $q(\beta|\lambda), q(z_i|\phi_i)$ to be in the same exponential family

$$q(\beta|\lambda) = h(\beta) \exp(\lambda \cdot T(\beta) - A_g(\lambda))$$

$$q(z_i|\phi_i) = h(z_i) \exp(\phi_i \cdot T(z_i) - A_\ell(\phi_i))$$

▶ Update λ

$$q(\beta|\lambda^*) \propto \exp(\mathbb{E}_{q(z)}(\log p(x, z, \beta))$$
$$\propto \exp\left(\mathbb{E}_{q(z)}(\log p(\beta) + \sum_{i=1}^{n} \log p(x_i, z_i|\beta))\right)$$
$$\propto h(\beta) \exp(\mathbb{E}_{q(z)}(\eta_g(x, z)) \cdot T(\beta))$$

Therefore

$$\boxed{\lambda^* = \mathbb{E}_{q(z)}(\eta_g(x, z))}$$

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► Update ϕ_i

$$q(z_i|\phi_i^*) \propto \exp(\mathbb{E}_{q(\beta, z_{-i})}(\log p(x, z, \beta)))$$
$$\propto \exp(\mathbb{E}_{q(\beta)}(\log p(z_i|x_i, \beta)))$$
$$\propto \exp(\mathbb{E}_{q(\beta)}(\log h(z_i) + \eta_\ell(x_i, \beta) \cdot T(z_i)))$$
$$\propto h(z_i) \exp(\mathbb{E}_{q(\beta)}(\eta_\ell(x_i, \beta)) \cdot T(z_i))$$

Therefore

$$\boxed{\phi_i^* = \mathbb{E}_{q(\beta)}(\eta_\ell(x_i, \beta))}$$

► We then iteratively update each parameter, holding others fixed.

Classical Variational Inference

Input: data $\mathbf{x}$, model $p(\beta, \mathbf{z}, \mathbf{x})$.

Initialize λ randomly.

repeat

    for *each data point i* **do**

        Set local parameter $\phi_i \leftarrow \mathbb{E}_\lambda [\eta_\ell(\beta, x_i)]$.

    end

    Set global parameter

$$\lambda \leftarrow \alpha + \sum_{i=1}^n \mathbb{E}_{\phi_i} [t(Z_i, x_i)].$$

until *the ELBO has converged*

- We introduced **variational inference** (VI), an alternative method to MCMC for approximate Bayesian inference.
- For models with conditional conjugacy, a mean-field approximation can be learned via coordinate ascent.
- This strategy is applicable to a generic class of models, including Bayesian mixture models, time series models (e.g., HMM), factorial models, multilevel regression, and mixed-membership models (e.g., LDA), etc.

Pros and Cons for Mean-field VI

- can be fast to train (compared to MCMC).
- may provide poor approximation, depending on the complexity of the posterior.

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