Simple Beamer Class

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Variational Inference

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Overview of Variational Inference

- Turns a complicated inference problems into an optimization problem
- ► Minimizes the KL divergence from the variational distribution to the posterior distribution
- ► EM is a special case

Model Image

put fig 2 here give gloss of variables: relate them to the input/output/nuissance ones Jason defines

- Key insight is the use of Jensen's inequality
- ightharpoonup We choose q from some family of distributions $\mathcal Q$

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$$= \mathcal{L}(q)$$

Why does maximizes the ELBO minimize the KL-Divergence?

$$\begin{aligned} \mathsf{KL}(q(z,\beta)||p(z,\beta|x) &= & \mathbb{E}_q \left[\log(q(z,\beta)] - \mathbb{E}_q \left[\log p(z,\beta|x) \right] \\ &= & \mathbb{E}_q \left[\log(q(z,\beta)] - \mathbb{E}_q \left[\log p(z,\beta,x) \right] + \log p(x) \right] \\ &= & -\mathcal{L}(q) + const. \end{aligned}$$

▶ Maximizing $\mathcal{L}(q)$ is just minimizing $-\mathcal{L}(q)$

How is EM a special case?

- ► How do we choose *Q*?
- We want it to be easily computable!
- ▶ What if $p(z, \beta|x) \in Q$?
- ► Then computing expectations under q is just inference in our model!
- Consider a standard HMM, our E-step involves direct computation of the marginals through Forward-Backwards
- Let $p_{\theta}(z|x)$ be our model and θ_1 be a setting of parameters where z is a latent variable (tags in an HMM) and x is an observed variable (words in an HMM)
- ▶ Since $p_{\theta} \in \mathcal{Q}$, $\forall \theta \in \Theta$, we simply need to maximize $\sum_{z} p(z|x; \theta_1) \log (p(z|x; \theta_2))$ with respect to θ_2
- blah

Variational $+ x, \forall x$

- ▶ Variational EM the process described above
- Variational Bayes approximate inference (no M-step)
- Variational Decoding approximation decoding

unnumbered lists

- ► Introduction to LATEX
- ► Course 2
- ► Termpapers and presentations with LATEX
- Beamer class

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numbered lists

- 1. Introduction to LATEX
- 2. Course 2
- 3. Termpapers and presentations with LATEX
- 4. Beamer class

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Tables

Date	Instructor	Title
WS 04/05	Sascha Frank	First steps with LATEX
SS 05	Sascha Frank	LATEX Course serial

Tables with pause

 $\mathsf{A} \quad \mathsf{B} \quad \mathsf{C}$

Tables with pause

A B C 1 2 3

Tables with pause

A B C 1 2 3 A B C

blocs

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