BML lecture #3: variational Bayes

http://github.com/rbardenet/bml-course

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Outline

1. Introduction
2. Variational inference
3. Back to LDA

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What comes to *your* mind when you hear "variational inference"?

Outline

When MCMC is intractable, variational inference comes to help

Turning integration into optimization over measures

Variational Bayesian inference (VB) consists in approximating

$$\int f(\theta)\pi(\theta)\mathrm{d}\theta \approx \int f(\theta)q^\star(\theta)\mathrm{d}\theta$$

with $q^\star \in \arg\min_{q\in\mathcal{Q}} \mathrm{distance}(\pi, q)$. Often we take

$$\mathrm{distance}(\pi, \tilde{q}) = \mathrm{KL}(\tilde{q}, \pi) := \int q(\theta)\log\frac{q(\theta)}{\pi(\theta)}\mathrm{d}\theta.$$

for computational convenience.

But remember we can only evaluate $\pi_u = Z\pi$...

- Show that $J(q) := \int q(\theta) \log \frac{q(\theta)}{\pi_u(\theta)} \mathrm{d}\theta = \mathrm{KL}(q, \pi) - \log Z$.

- In particular, $L(q) = -J(q) \leqslant \log Z$. For

$$\pi_u(\theta) = p(\text{data}|\theta)p(\theta),$$

$L(q)$ is thus a lower bound for the evidence $p(\text{data})$ (ELBO).

Choosing the approximating family $\mathcal{Q}$

- The most common approach is the mean-field approximation

$$\mathcal{Q} = \{\theta \mapsto \prod_{d=1}^{D} q_d(\theta_d)\}.$$

- Include all variables over which you integrate, e.g.

$$q(\theta, z_{1:n}) = \prod_{d=1}^{D} q_d(\theta_d) \prod_{i=1}^{N} q_i(z_i).$$

- Try to keep some dependence if it is key in your application.
- If your original model has NEF conditionals, coordinate-wise maximization of $q \mapsto L(q)$ is easy.

Mean-field yields closed-form updates

Outline

Back to LDA 1/2

$$
\begin{aligned}
&\log p(y, z, \pi, B) \\
&= \sum_{i=1}^{N} \left[\log p(\pi_i|\alpha) + \sum_{\ell=1}^{L_i} \Big(\log p(z_{i\ell}|\pi_i) + \log p(y_{i\ell}|z_{i\ell}, B) \Big) \right] + p(B|\gamma) \\
&\propto \sum_{i=1}^{N} \left[\sum_{k=1}^{K} \alpha_k \log \pi_{ik} + \sum_{\ell=1}^{L_i} \left(\sum_{k=1}^{K} 1_{z_{i\ell}=k} \log \pi_{ik} + \sum_{v=1}^{V} \sum_{k=1}^{K} 1_{y_{i\ell}=v} 1_{z_{i\ell}=k} \log b_{kv} \right) \right] \\
&\quad + \sum_{k=1}^{K} \sum_{v=1}^{V} \gamma_k \log b_{kv}.
\end{aligned}
$$

Lemma (exercise)

Let $\Psi(\cdot) := \Gamma'(\cdot)/\Gamma(\cdot)$ be the digamma function. Then

$$
\mathbb{E}_{\mathrm{Dir}(\theta|\alpha)} \log \theta_i = \Psi(\theta_i) - \Psi(\|\theta\|_1).
$$

Back to LDA 2/2

Using counts keeps space and time complexity low

- Storing $\tilde{z}_{i\ell k}$ requires $\mathcal{O}(NK \sum_i L_i)$ space. In practice, one works with (sparse) count data

  $$n_{iv} = \text{number of times word } v \text{ appears in document } i,$$

  and variables c_{ivk}, thus reducing storage costs (and the dimension of the underlying integral!) to $\mathcal{O}(NVK)$.

Reparametrization+SGD vs mean-field+closed updates

VB for deep networks

Lots of variants of VB exist (Murphy, 2012)

- For hidden variable models, EM is VB with

$$q(z, \theta) = \pi(z|\theta)\delta_{\tilde{\theta}}(\theta).$$

- Variational EM is VB with

$$q(z, \theta) = q(z)\delta_{\tilde{\theta}}(\theta).$$

- VB for any PGMs with NEF arrows is variational message passing.
- Rather approximating

$$\pi(\theta) \approx \prod_{f=1}^{F} q_f(\theta)$$

leads to expectation propagation.

- These days, ADVI with stochastic gradients is the default VI choice in probabilistic programming software like PyMC3, Stan, or PyRo.

References I

[1] A. Kucukelbir et al. "Automatic differentiation variational inference". In: *The Journal of Machine Learning Research* 18.1 (2017), pp. 430–474.

[2] K. Murphy. *Machine learning: a probabilistic perspective*. MIT Press, 2012.