

BML lecture #3: variational Bayes

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

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

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Turning integration into optimization over measures

Variational Bayesian inference (VB) consists in approximating

$$\int f(\theta)\pi(\theta)d\theta \approx \int f(\theta)q(\theta)d\theta$$

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

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

for computational convenience.

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

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

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

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

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

- ▶ 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.**

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

Lemma (exercise)

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

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

- ▶ 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.

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