

Lecture 10, 11: Variational Approximations

4F13: Machine Learning

Zoubin Ghahramani and Carl Edward Rasmussen

Department of Engineering, University of Cambridge

February 17th, 18th, 2010

Motivation

Many statistical inference problems result in **intractable computations...**

- Bayesian posterior over model parameters:

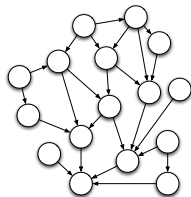
$$P(\theta|\mathcal{D}) = \frac{P(\mathcal{D}|\theta)P(\theta)}{P(\mathcal{D})}$$

- Computing posterior over hidden variables (e.g. for E step of EM):

$$P(H|V, \theta) = \frac{P(V|H, \theta)P(H|\theta)}{P(V|\theta)}$$

- Computing marginals in a multiply-connected graphical models:

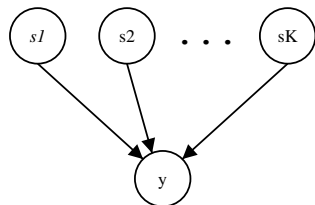
$$P(x_i|x_j = e) = \sum_{\mathbf{x} \setminus \{x_i, x_j\}} P(\mathbf{x}|x_j = e)$$



Solutions:

Markov chain Monte Carlo, variational approximations

Example: Binary latent factor model



Model with K binary latent variables, $s_i \in \{0, 1\}$,
organised into a vector $\mathbf{s} = (s_1, \dots, s_K)$
real-valued observation vector \mathbf{y}
parameters $\theta = \{\{\boldsymbol{\mu}_i, \pi_i\}_{i=1}^K, \sigma^2\}$

$\mathbf{s} \sim \text{Bernoulli}$
 $\mathbf{y}|\mathbf{s} \sim \text{Gaussian}$

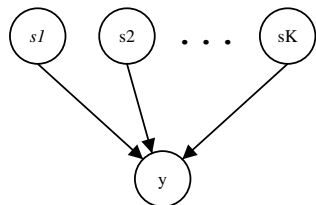
$$p(\mathbf{s}|\boldsymbol{\pi}) = p(s_1, \dots, s_K|\boldsymbol{\pi}) = \prod_{i=1}^K p(s_i|\pi_i) = \prod_{i=1}^K \pi_i^{s_i} (1 - \pi_i)^{(1-s_i)}$$

$$p(\mathbf{y}|\mathbf{s}_1, \dots, \mathbf{s}_K, \boldsymbol{\mu}, \sigma^2) = \mathcal{N}\left(\sum_{i=1}^K s_i \boldsymbol{\mu}_i, \sigma^2 \mathbf{I}\right)$$

EM optimizes bound on likelihood: $\mathcal{F}(q, \theta) = \langle \log p(\mathbf{s}, \mathbf{y}|\theta) \rangle_{q(\mathbf{s})} - \langle \log q(\mathbf{s}) \rangle_{q(\mathbf{s})}$
where $\langle \cdot \rangle_q$ is expectation under q : $\langle f(\mathbf{s}) \rangle_q \stackrel{\text{def}}{=} \sum_{\mathbf{s}} f(\mathbf{s}) q(\mathbf{s})$

Exact E step: $q(\mathbf{s}) = p(\mathbf{s}|\mathbf{y}, \theta)$ distribution over 2^K states: **intractable** for large K

Example: Binary latent factor model



Model with K binary latent variables, $s_i \in \{0, 1\}$,
organised into a vector $\mathbf{s} = (s_1, \dots, s_K)$
real-valued observation vector y
parameters $\theta = \{\{\mu_i, \pi_i\}_{i=1}^K, \sigma^2\}$

$\mathbf{s} \sim \text{Bernoulli}$
 $y|\mathbf{s} \sim \text{Gaussian}$

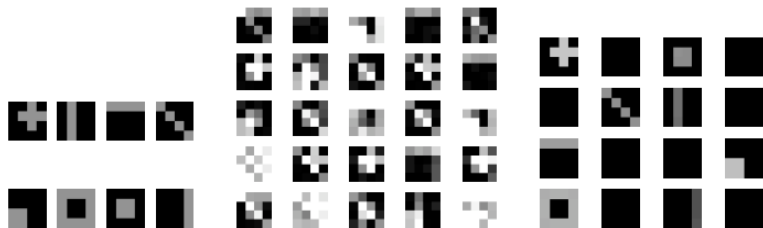


Figure 2: **Left panel:** Original source images used to generate data. **Middle panel:** Observed images resulting from mixture of sources. **Right panel:** Recovered sources

from Lu et al (2004)

Review: The EM algorithm

Given a set of observed (visible) variables V , a set of unobserved (hidden / latent / missing) variables H , and model parameters θ , optimize the log likelihood:

$$\mathcal{L}(\theta) = \log p(V|\theta) = \log \int p(H, V|\theta) dH,$$

Using Jensen's inequality, for **any distribution** of hidden variables $q(H)$ we have:

$$\mathcal{L}(\theta) = \log \int q(H) \frac{p(H, V|\theta)}{q(H)} dH \geq \int q(H) \log \frac{p(H, V|\theta)}{q(H)} dH = \mathcal{F}(q, \theta),$$

defining the $\mathcal{F}(q, \theta)$ functional, which is a lower bound on the log likelihood. In the EM algorithm, we alternately optimize $\mathcal{F}(q, \theta)$ wrt q and θ , and we can prove that this will never decrease \mathcal{L} .

The E and M steps of EM

The lower bound on the log likelihood:

$$\mathcal{F}(\mathbf{q}, \boldsymbol{\theta}) = \int \mathbf{q}(\mathbf{H}) \log \frac{p(\mathbf{H}, \mathbf{V}|\boldsymbol{\theta})}{\mathbf{q}(\mathbf{H})} d\mathbf{H} = \int \mathbf{q}(\mathbf{H}) \log p(\mathbf{H}, \mathbf{V}|\boldsymbol{\theta}) d\mathbf{H} + \mathcal{H}(\mathbf{q}),$$

where $\mathcal{H}(\mathbf{q}) = - \int \mathbf{q}(\mathbf{H}) \log \mathbf{q}(\mathbf{H}) d\mathbf{H}$ is the **entropy** of \mathbf{q} . We iteratively alternate:

E step: maximize $\mathcal{F}(\mathbf{q}, \boldsymbol{\theta})$ wrt the distribution over hidden variables given the parameters:

$$\mathbf{q}^{[k]}(\mathbf{H}) := \operatorname{argmax}_{\mathbf{q}(\mathbf{H})} \mathcal{F}(\mathbf{q}(\mathbf{H}), \boldsymbol{\theta}^{[k-1]}) = p(\mathbf{H}|\mathbf{V}, \boldsymbol{\theta}^{[k-1]}).$$

M step: maximize $\mathcal{F}(\mathbf{q}, \boldsymbol{\theta})$ wrt the parameters given the hidden distribution:

$$\boldsymbol{\theta}^{[k]} := \operatorname{argmax}_{\boldsymbol{\theta}} \mathcal{F}(\mathbf{q}^{[k]}(\mathbf{H}), \boldsymbol{\theta}) = \operatorname{argmax}_{\boldsymbol{\theta}} \int \mathbf{q}^{[k]}(\mathbf{H}) \log p(\mathbf{H}, \mathbf{V}|\boldsymbol{\theta}) d\mathbf{H},$$

which is equivalent to optimizing the expected complete-data log likelihood $\log p(\mathbf{H}, \mathbf{V}|\boldsymbol{\theta})$, since the **entropy of $\mathbf{q}(\mathbf{H})$** does not depend on $\boldsymbol{\theta}$.

Variational Approximations to the EM algorithm

Often $p(H|V, \theta)$ is computationally **intractable**, so an exact E step is out of the question.

Assume some simpler form for $q(H)$, e.g. $q \in \mathcal{Q}$, the set of fully-factorized distributions over the hidden variables: $q(H) = \prod_i q(H_i)$

E step (approximate): maximize $\mathcal{F}(q, \theta)$ wrt the distribution over hidden variables given the parameters:

$$q^{[k]}(H) := \underset{q(H) \in \mathcal{Q}}{\operatorname{argmax}} \mathcal{F}(q(H), \theta^{[k-1]}).$$

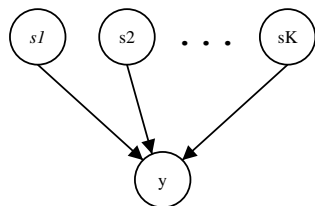
M step : maximize $\mathcal{F}(q, \theta)$ wrt the parameters given the hidden distribution:

$$\theta^{[k]} := \underset{\theta}{\operatorname{argmax}} \mathcal{F}(q^{[k]}(H), \theta) = \underset{\theta}{\operatorname{argmax}} \int q^{[k]}(H) \log p(H, V|\theta) dH,$$

This maximizes a lower bound on the log likelihood.

Using the fully-factorized q is sometimes called a **mean-field approximation**.

Example: Binary latent factor model



Model with K binary latent variables, $s_i \in \{0, 1\}$,
organised into a vector $\mathbf{s} = (s_1, \dots, s_K)$
real-valued observation vector \mathbf{y}
parameters $\theta = \{\{\boldsymbol{\mu}_i, \pi_i\}_{i=1}^K, \sigma^2\}$

$\mathbf{s} \sim \text{Bernoulli}$
 $\mathbf{y}|\mathbf{s} \sim \text{Gaussian}$

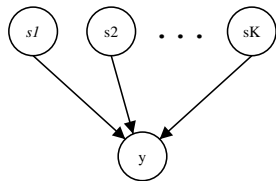
$$p(\mathbf{s}|\boldsymbol{\pi}) = p(s_1, \dots, s_K|\boldsymbol{\pi}) = \prod_{i=1}^K p(s_i|\pi_i) = \prod_{i=1}^K \pi_i^{s_i} (1 - \pi_i)^{(1-s_i)}$$

$$p(\mathbf{y}|\mathbf{s}_1, \dots, \mathbf{s}_K, \boldsymbol{\mu}, \sigma^2) = \mathcal{N}\left(\sum_{i=1}^K s_i \boldsymbol{\mu}_i, \sigma^2 \mathbf{I}\right)$$

EM optimizes bound on likelihood: $\mathcal{F}(q, \theta) = \langle \log p(\mathbf{s}, \mathbf{y}|\theta) \rangle_{q(\mathbf{s})} - \langle \log q(\mathbf{s}) \rangle_{q(\mathbf{s})}$
where $\langle \cdot \rangle_q$ is expectation under q : $\langle f(\mathbf{s}) \rangle_q \stackrel{\text{def}}{=} \sum_{\mathbf{s}} f(\mathbf{s}) q(\mathbf{s})$

Exact E step: $q(\mathbf{s}) = p(\mathbf{s}|\mathbf{y}, \theta)$ distribution over 2^K states: **intractable** for large K

Example: Binary latent factors model (cont.)



$$\mathcal{F}(\mathbf{q}, \boldsymbol{\theta}) = \langle \log p(\mathbf{s}, \mathbf{y} | \boldsymbol{\theta}) \rangle_{\mathbf{q}(\mathbf{s})} - \langle \log q(\mathbf{s}) \rangle_{\mathbf{q}(\mathbf{s})}$$

$$\log p(\mathbf{s}, \mathbf{y} | \boldsymbol{\theta}) + c$$

$$= \sum_{i=1}^K s_i \log \pi_i + (1 - s_i) \log(1 - \pi_i) - D \log \sigma - \frac{1}{2\sigma^2} \left(\mathbf{y} - \sum_i s_i \boldsymbol{\mu}_i \right)^\top \left(\mathbf{y} - \sum_i s_i \boldsymbol{\mu}_i \right)$$

$$= \sum_{i=1}^K s_i \log \pi_i + (1 - s_i) \log(1 - \pi_i) - D \log \sigma - \frac{1}{2\sigma^2} \left(\mathbf{y}^\top \mathbf{y} - 2 \sum_i s_i \boldsymbol{\mu}_i^\top \mathbf{y} + \sum_i \sum_j s_i s_j \boldsymbol{\mu}_i^\top \boldsymbol{\mu}_j \right)$$

we therefore need $\langle s_i \rangle$ and $\langle s_i s_j \rangle$ to compute \mathcal{F} .

These are the expected *sufficient statistics* of the hidden variables.

Example: Binary latent factors model (cont.)

Variational approximation:

$$q(\mathbf{s}) = \prod_i q_i(s_i) = \prod_{i=1}^K \lambda_i^{s_i} (1 - \lambda_i)^{(1-s_i)}$$

where λ_i is a parameter of the variational approximation modelling the posterior mean of s_i (compare to π_i which models the *prior* mean of s_i).

Under this approximation we know $\langle \mathbf{s}_i \rangle = \lambda_i$ and $\langle \mathbf{s}_i \mathbf{s}_j \rangle = \lambda_i \lambda_j + \delta_{ij} (\lambda_i - \lambda_i^2)$.

$$\begin{aligned} \mathcal{F}(\boldsymbol{\lambda}, \boldsymbol{\theta}) &= \sum_i \lambda_i \log \frac{\pi_i}{\lambda_i} + (1 - \lambda_i) \log \frac{(1 - \pi_i)}{(1 - \lambda_i)} \\ &\quad - D \log \sigma - \frac{1}{2\sigma^2} (\mathbf{y} - \sum_i \lambda_i \boldsymbol{\mu}_i)^\top (\mathbf{y} - \sum_i \lambda_i \boldsymbol{\mu}_i) \\ &\quad - \frac{1}{2\sigma^2} \sum_i (\lambda_i - \lambda_i^2) \boldsymbol{\mu}_i^\top \boldsymbol{\mu}_i - \frac{D}{2} \log(2\pi) \end{aligned}$$

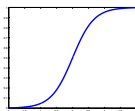
Fixed point equations for the binary latent factor model

Taking derivatives w.r.t. λ_i :

$$\frac{\partial \mathcal{F}}{\partial \lambda_i} = \log \frac{\pi_i}{1 - \pi_i} - \log \frac{\lambda_i}{1 - \lambda_i} + \frac{1}{\sigma^2} (\mathbf{y} - \sum_{j \neq i} \lambda_j \boldsymbol{\mu}_j)^\top \boldsymbol{\mu}_i - \frac{1}{2\sigma^2} \boldsymbol{\mu}_i^\top \boldsymbol{\mu}_i$$

Setting to zero we get fixed point equations:

$$\lambda_i = f \left(\log \frac{\pi_i}{1 - \pi_i} + \frac{1}{\sigma^2} (\mathbf{y} - \sum_{j \neq i} \lambda_j \boldsymbol{\mu}_j)^\top \boldsymbol{\mu}_i - \frac{1}{2\sigma^2} \boldsymbol{\mu}_i^\top \boldsymbol{\mu}_i \right)$$



where $f(x) = 1/(1 + \exp(-x))$ is the logistic (sigmoid) function.

Learning algorithm:

E step: run fixed point equations until convergence of λ for each data point.

M step: re-estimate θ given λ s.

KL divergence

Note that

E step maximize $\mathcal{F}(q, \theta)$ wrt the distribution over hidden variables, given the parameters:

$$q^{[k]}(H) := \operatorname{argmax}_{q(H) \in \mathcal{Q}} \mathcal{F}(q(H), \theta^{[k-1]}).$$

is equivalent to:

E step minimize $\mathcal{KL}(q \| p(H|V, \theta))$ wrt the distribution over hidden variables, given the parameters:

$$q^{[k]}(H) := \operatorname{argmin}_{q(H) \in \mathcal{Q}} \int q(H) \log \frac{q(H)}{p(H|V, \theta^{[k-1]})} dH$$

So, in each E step, the algorithm tries to find the best approximation to p in \mathcal{Q} .

This is related to ideas in *information geometry*.

Variational Approximations to Bayesian Learning

$$\begin{aligned}\log p(\mathbf{V}) &= \log \iint p(\mathbf{V}, \mathbf{H} | \boldsymbol{\theta}) p(\boldsymbol{\theta}) \, d\mathbf{H} \, d\boldsymbol{\theta} \\ &\geq \iint q(\mathbf{H}, \boldsymbol{\theta}) \log \frac{p(\mathbf{V}, \mathbf{H}, \boldsymbol{\theta})}{q(\mathbf{H}, \boldsymbol{\theta})} \, d\mathbf{H} \, d\boldsymbol{\theta}\end{aligned}$$

Constrain $q \in \mathcal{Q}$ s.t. $q(\mathbf{H}, \boldsymbol{\theta}) = q(\mathbf{H})q(\boldsymbol{\theta})$.

This results in the **variational Bayesian EM algorithm**.

More about this later (when we study model selection).

Variational Approximations and Graphical Models I

Let $q(\mathbf{H}) = \prod_i q_i(\mathbf{H}_i)$.

Variational approximation maximises \mathcal{F} :

$$\mathcal{F}(q) = \int q(\mathbf{H}) \log p(\mathbf{H}, \mathbf{V}) d\mathbf{H} - \int q(\mathbf{H}) \log q(\mathbf{H}) d\mathbf{H}$$

Focusing on one term, q_j , we can write this as:

$$\mathcal{F}(q_j) = \int q_j(\mathbf{H}_j) \left\langle \log p(\mathbf{H}, \mathbf{V}) \right\rangle_{\sim q_j(\mathbf{H}_j)} d\mathbf{H}_j - \int q_j(\mathbf{H}_j) \log q_j(\mathbf{H}_j) d\mathbf{H}_j + \text{const}$$

Where $\langle \cdot \rangle_{\sim q_j(\mathbf{H}_j)}$ denotes averaging w.r.t. $q_i(\mathbf{H}_i)$ for all $i \neq j$

Optimum occurs when:

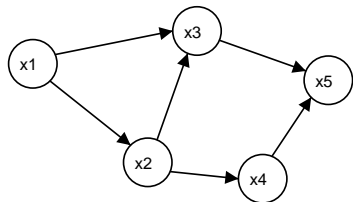
$$q_j^*(\mathbf{H}_j) = \frac{1}{Z} \exp \langle \log p(\mathbf{H}, \mathbf{V}) \rangle_{\sim q_j(\mathbf{H}_j)}$$

Variational Approximations and Graphical Models II

Optimum occurs when:

$$q_j^*(H_j) = \frac{1}{Z} \exp \langle \log p(H, V) \rangle_{\sim q_j(H_j)}$$

Assume graphical model: $p(H, V) = \prod_i p(X_i | pa_i)$



$$\begin{aligned} \log q_j^*(H_j) &= \left\langle \sum_i \log p(X_i | pa_i) \right\rangle_{\sim q_j(H_j)} + \text{const} \\ &= \left\langle \log p(H_j | pa_j) \right\rangle_{\sim q_j(H_j)} + \sum_{k \in \text{ch}_j} \left\langle \log p(X_k | pa_k) \right\rangle_{\sim q_j(H_j)} + \text{const} \end{aligned}$$

This defines messages that get passed between nodes in the graph. Each node receives messages from its **Markov boundary**: parents, children and parents of children.

Variational Message Passing (Winn and Bishop, 2004)

Expectation Propagation (EP)

Data (iid) $\mathcal{D} = \{\mathbf{x}^{(1)} \dots, \mathbf{x}^{(N)}\}$, model $p(\mathbf{x}|\boldsymbol{\theta})$, with parameter prior $p(\boldsymbol{\theta})$.

The parameter posterior is:

$$p(\boldsymbol{\theta}|\mathcal{D}) = \frac{1}{p(\mathcal{D})} p(\boldsymbol{\theta}) \prod_{i=1}^N p(\mathbf{x}^{(i)}|\boldsymbol{\theta})$$

We can write this as product of factors over $\boldsymbol{\theta}$:

$$p(\boldsymbol{\theta}) \prod_{i=1}^N p(\mathbf{x}^{(i)}|\boldsymbol{\theta}) = \prod_{i=0}^N f_i(\boldsymbol{\theta})$$

where $f_0(\boldsymbol{\theta}) \stackrel{\text{def}}{=} p(\boldsymbol{\theta})$ and $f_i(\boldsymbol{\theta}) \stackrel{\text{def}}{=} p(\mathbf{x}^{(i)}|\boldsymbol{\theta})$ and we will ignore the constants.

We wish to approximate this by a product of *simpler* terms:

$$q(\boldsymbol{\theta}) \stackrel{\text{def}}{=} \prod_{i=0}^N \tilde{f}_i(\boldsymbol{\theta})$$

$$\min_{q(\boldsymbol{\theta})} \mathcal{KL} \left(\prod_{i=0}^N f_i(\boldsymbol{\theta}) \parallel \prod_{i=0}^N \tilde{f}_i(\boldsymbol{\theta}) \right) \quad (\text{intractable})$$

$$\min_{\tilde{f}_i(\boldsymbol{\theta})} \mathcal{KL} (f_i(\boldsymbol{\theta}) \parallel \tilde{f}_i(\boldsymbol{\theta})) \quad (\text{simple, non-iterative, inaccurate})$$

$$\min_{\tilde{f}_i(\boldsymbol{\theta})} \mathcal{KL} \left(f_i(\boldsymbol{\theta}) \prod_{j \neq i} \tilde{f}_j(\boldsymbol{\theta}) \parallel \tilde{f}_i(\boldsymbol{\theta}) \prod_{j \neq i} \tilde{f}_j(\boldsymbol{\theta}) \right) \quad (\text{simple, iterative, accurate}) \leftarrow \text{EP}$$

Expectation Propagation II

```
Input  $f_0(\boldsymbol{\theta}) \dots f_N(\boldsymbol{\theta})$ 
Initialize  $\tilde{f}_0(\boldsymbol{\theta}) = f_0(\boldsymbol{\theta})$ ,  $\tilde{f}_i(\boldsymbol{\theta}) = 1$  for  $i > 0$ ,  $q(\boldsymbol{\theta}) = \prod_i \tilde{f}_i(\boldsymbol{\theta})$ 
repeat
  for  $i = 0 \dots N$  do
    Deletion:  $q_{\setminus i}(\boldsymbol{\theta}) \leftarrow \frac{q(\boldsymbol{\theta})}{\tilde{f}_i(\boldsymbol{\theta})} = \prod_{j \neq i} \tilde{f}_j(\boldsymbol{\theta})$ 
    Projection:  $\tilde{f}_i^{\text{new}}(\boldsymbol{\theta}) \leftarrow \arg \min_{f(\boldsymbol{\theta})} \mathcal{KL}(f_i(\boldsymbol{\theta})q_{\setminus i}(\boldsymbol{\theta}) \| f(\boldsymbol{\theta})q_{\setminus i}(\boldsymbol{\theta}))$ 
    Inclusion:  $q(\boldsymbol{\theta}) \leftarrow \tilde{f}_i^{\text{new}}(\boldsymbol{\theta}) q_{\setminus i}(\boldsymbol{\theta})$ 
  end for
until convergence
```

The EP algorithm. Some variations are possible: here we assumed that f_0 is in the exponential family, and we updated sequentially over i .

- Tries to minimize the opposite KL to variational methods
- $\tilde{f}_i(\boldsymbol{\theta})$ in exponential family \rightarrow projection step is **moment matching**
- No convergence guarantee (although convergent forms can be developed)

Some Further Readings

- MacKay, D.J.C. (2003) Information Theory, Inference, and Learning Algorithms. Chapter 33.
- Bishop, C.M. (2006) Pattern Recognition and Machine Learning.
- Winn, J. and Bishop, C.M. (2005) Variational Message Passing. *J. Machine Learning Research*. <http://johnwinn.org/Publications/papers/VMP2005.pdf>
- Lu, X., Hauskrecht, M., and Day, R.S. (2004) Modeling cellular processes with variational Bayesian cooperative vector quantizer. In the Proceedings of the Pacific Symposium on Biocomputing (PSB) 9:533-544.
<http://psb.stanford.edu/psb-online/proceedings/psb04/lu.pdf>
- Minka, T.P. (2004) Roadmap to EP:
<http://research.microsoft.com/~minka/papers/ep/roadmap.html>
- Ghahramani, Z. (1995) Factorial learning and the EM algorithm. In Adv Neur Info Proc Syst 7.
<http://learning.eng.cam.ac.uk/zoubin/zoubin/factorial.abstract.html>
- Jordan, M.I., Ghahramani, Z., Jaakkola, T.S. and Saul, L.K. (1999) An Introduction to Variational Methods for Graphical Models. *Machine Learning* 37:183-233.
Available at: <http://learning.eng.cam.ac.uk/zoubin/papers/varintro.pdf>

Appendix: Binary latent factor model for i.i.d. data

Assume data set $\mathcal{D} = \{\mathbf{y}^{(1)} \dots, \mathbf{y}^{(N)}\}$ of N points and params $\theta = \{\{\boldsymbol{\mu}_i, \pi_i\}_{i=1}^K, \sigma^2\}$. Use a factorised distribution:

$$q(\mathbf{s}) = \prod_{n=1}^N q_n(\mathbf{s}^{(n)}) = \prod_{n=1}^N \prod_{i=1}^K q_n(s_i^{(n)}) = \prod_n \prod_i (\lambda_i^{(n)})^{s_i^{(n)}} (1 - \lambda_i^{(n)})^{(1-s_i^{(n)})}$$

$$p(\mathcal{D}|\theta) = \prod_{n=1}^N p(\mathbf{y}^{(n)}|\theta)$$

$$p(\mathbf{y}^{(n)}|\theta) = \sum_{\mathbf{s}} p(\mathbf{y}^{(n)}|\mathbf{s}, \boldsymbol{\mu}, \sigma) p(\mathbf{s}|\boldsymbol{\pi})$$

$$\mathcal{F}(q(\mathbf{s}), \theta) = \sum_n \mathcal{F}_n(q_n(\mathbf{s}^{(n)}), \theta) \leq \log p(\mathcal{D}|\theta)$$

$$\mathcal{F}_n(q_n(\mathbf{s}^{(n)}), \theta) = \left\langle \log p(\mathbf{s}^{(n)}, \mathbf{y}^{(n)}|\theta) \right\rangle_{q_n(\mathbf{s}^{(n)})} - \left\langle \log q_n(\mathbf{s}^{(n)}) \right\rangle_{q_n(\mathbf{s}^{(n)})}$$

We need to optimise w.r.t. $q_n(\mathbf{s}^{(n)})$ for *each data point*, so

E step: optimize $q_n(\mathbf{s}^{(n)})$ (i.e. $\boldsymbol{\lambda}^{(n)}$) for each n .

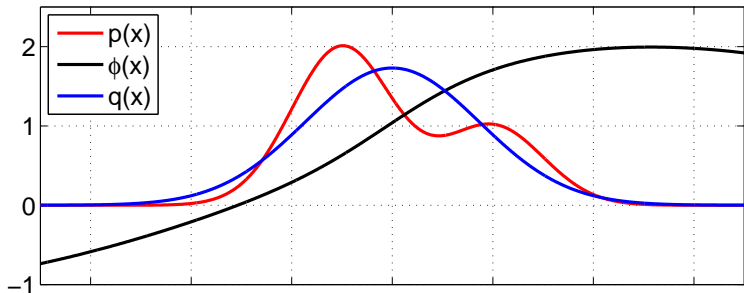
M step: re-estimate θ given $q_n(\mathbf{s}^{(n)})$'s.

Appendix: How tight is the lower bound?

It is hard to compute a nontrivial general upper bound.

To determine how tight the bound is, one can approximate the true likelihood by a variety of other methods.

One approach is to use the variational approximation as a proposal distribution for **importance sampling**.



But this will generally not work well. See exercise 33.6 in David MacKay's textbook.