

Variational Message Passing (VMP)

Univariate Gaussian Distribution

Lets define the likelihood for N i.i.d samples each following a uniform distribution:

$$P(\mathbf{x}|\Omega) = \prod_{n=1}^N \mathcal{N}(x_n|\mu, \gamma^{-1})$$

where μ corresponds to the mean parameter and γ corresponds to the precision parameter ($\gamma = \sigma^{-2}$)

We rewrite the Normal in exponential family form

$$\begin{aligned} \ln \mathcal{N}(x_n|\mu, \gamma^{-1}) &= \begin{bmatrix} \gamma\mu & -\gamma/2 \end{bmatrix} \begin{bmatrix} x_n \\ x_n^2 \end{bmatrix} + \frac{1}{2} (\ln \gamma - \gamma\mu^2 - \ln 2\pi) \\ &= \begin{bmatrix} \gamma x_n & -\gamma/2 \end{bmatrix} \begin{bmatrix} \mu \\ \mu^2 \end{bmatrix} + \frac{1}{2} (\ln \gamma - \gamma x_n^2 - \ln 2\pi) \\ &= \begin{bmatrix} -\frac{1}{2}(x_n - \mu)^2 & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \gamma \\ \ln \gamma \end{bmatrix} - \ln 2\pi \end{aligned}$$

We impose a Normal prior for the mean parameter and a Gamma prior for the precision parameter

$$\begin{aligned} \ln P(\mu|m, \beta) &= \begin{bmatrix} \beta m & \beta/2 \end{bmatrix} \begin{bmatrix} \mu \\ \mu^2 \end{bmatrix} + \frac{1}{2} (\ln \beta - \beta m^2 - \ln 2\pi) \\ \ln P(\gamma|a, b) &= \begin{bmatrix} -b & a-1 \end{bmatrix} \begin{bmatrix} \gamma \\ \ln \gamma \end{bmatrix} + a \ln b - \ln \Gamma(a) \end{aligned}$$

Variational Approximation

$$Q(\mu, \gamma) = Q_\mu(\mu)Q_\gamma(\gamma)$$

$$\ln Q_\mu^*(\mu) = \left[\beta m + \mathbb{E}_{q_\gamma}(\gamma) \sum_{n=1}^N x_n \quad -\beta/2 - \mathbb{E}_{q_\gamma}(\gamma) N/2 \right] \begin{bmatrix} \mu \\ \mu^2 \end{bmatrix} + f_\mu(\mu) + \text{const}$$

$$\ln Q_\gamma^*(\gamma) = \left[-b - 1/2 \sum_{n=1}^N (x_n^2 - 2x_n \mathbb{E}_{q_\mu}(\mu) + \mathbb{E}_{q_\mu}(\mu^2)) \quad a-1-1/2 \right] \begin{bmatrix} \gamma \\ \ln \gamma \end{bmatrix} + f_\gamma(\gamma) + \text{const}$$

Therefore,

$$\begin{aligned}
\ln Q_\mu^*(\mu) &= \begin{bmatrix} \beta_\mu m_\mu & -\beta_\mu/2 \end{bmatrix} \begin{bmatrix} \mu \\ \mu^2 \end{bmatrix} + \frac{1}{2} (\ln \beta_\mu - \beta_\mu m_\mu^2 - \ln 2\pi) \\
\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} &= \begin{bmatrix} \beta_\mu m_\mu \\ -\beta_\mu/2 \end{bmatrix} \\
f_\mu(\mu) &= \frac{1}{2} \ln 2\pi \\
A(m_\mu, \beta_\mu) &= \frac{1}{2} (-\ln \beta_\mu + \beta_\mu m_\mu^2) \\
A(\theta_1, \theta_2) &= \frac{1}{2} \left(-\ln(-2\theta_2) - 2\theta_2 \left(\frac{\theta_1}{-2\theta_2} \right)^2 \right) = \frac{1}{2} \left(-\ln(-2\theta_2) - \frac{\theta_1^2}{2\theta_2} \right) \\
\nabla A(\theta_1, \theta_2) &= \begin{bmatrix} -\frac{\theta_1}{2\theta_2} \\ -\frac{1}{2\theta_2} + \frac{\theta_1^2}{4\theta_2^2} \end{bmatrix} \rightarrow \mathbb{E}_{q_\mu}(\mathbf{u}(\mu)) = \begin{bmatrix} m_\mu \\ \frac{1}{\beta_\mu} + m_\mu^2 \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\ln Q_\gamma^*(\gamma) &= \begin{bmatrix} -b_\gamma & a_\gamma - 1 \end{bmatrix} \begin{bmatrix} \gamma \\ \ln \gamma \end{bmatrix} + a_\gamma \ln b_\gamma - \ln \Gamma(a_\gamma) \\
\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} &= \begin{bmatrix} -b_\gamma \\ a_\gamma - 1 \end{bmatrix} \\
f_\gamma(\gamma) &= 1 \\
A(a_\gamma, b_\gamma) &= -a_\gamma \ln b_\gamma + \ln \Gamma(a_\gamma) \\
A(\theta_1, \theta_2) &= -(\theta_2 + 1) \ln(-\theta_1) + \ln \Gamma(\theta_2 + 1) \\
\nabla A(\theta_1, \theta_2) &= \begin{bmatrix} \frac{-(\theta_2+1)}{\theta_1} \\ -\ln(-\theta_1) + \Psi(\theta_2 + 1) \end{bmatrix} \rightarrow \mathbb{E}_{q_\gamma}(\mathbf{u}(\gamma)) = \begin{bmatrix} \frac{a_\gamma}{b_\gamma} \\ \Psi(a_\gamma) - \ln(b_\gamma) \end{bmatrix}
\end{aligned}$$

Variational Message Passing

$$\begin{aligned}
\mathbf{m}_{\gamma \rightarrow x_n} &= \mathbb{E}_{q_\gamma(\gamma|a_\gamma, b_\gamma)}(\mathbf{u}_\gamma(\gamma)) = \begin{bmatrix} \mathbb{E}_{q_\gamma}(\gamma) \\ \mathbb{E}_{q_\gamma}(\ln \gamma) \end{bmatrix} = \begin{bmatrix} -\frac{\delta g(a_\gamma b_\gamma)}{\delta a_\gamma} \\ -\frac{\delta g(a_\gamma b_\gamma)}{\delta b_\gamma} \end{bmatrix} = \begin{bmatrix} \frac{a_\gamma}{b_\gamma} \\ \Psi(a_\gamma) - \ln(b_\gamma) \end{bmatrix}^T \\
\mathbf{m}_{x_n \rightarrow \mu} &= \begin{bmatrix} \mathbb{E}_{q_\gamma}(\gamma) x_n \\ -\mathbb{E}_{q_\gamma}(\gamma)/2 \end{bmatrix} = \begin{bmatrix} \frac{a_\gamma}{b_\gamma} x_n \\ -\frac{a_\gamma}{2b_\gamma} \end{bmatrix} \\
\phi_\mu^* &= \begin{bmatrix} \beta m \\ -\beta/2 \end{bmatrix} + \sum_{n=1}^N \mathbf{m}_{x_n \rightarrow \mu} \\
\mathbf{m}_{\mu \rightarrow x_n} &= \mathbb{E}_{q_\mu(\mu|m_\mu, \beta_\mu)}(\mathbf{u}_\mu(\mu)) = \begin{bmatrix} \mathbb{E}_{q_\mu}(\mu) \\ \mathbb{E}_{q_\mu}(\mu^2) \end{bmatrix} = \begin{bmatrix} -\frac{\delta g(m_\mu, \beta_\mu)}{\delta m_\mu} \\ -\frac{\delta g(m_\mu, \beta_\mu)}{\delta \beta_\mu} \end{bmatrix} = \begin{bmatrix} m_\mu \\ \frac{1}{\beta_\mu} + m_\mu^2 \end{bmatrix} \\
\mathbf{m}_{x_n \rightarrow \gamma} &= \begin{bmatrix} -\frac{1}{2} (x_n^2 - 2x_n \mathbb{E}_{q_\mu}(\mu) + \mathbb{E}_{q_\mu}(\mu^2)) \\ \frac{1}{2} \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} (x_n^2 - 2x_n m_\mu + \frac{1}{\beta_\mu} + m_\mu^2) \\ \frac{1}{2} \end{bmatrix} \\
\phi_\gamma^* &= \begin{bmatrix} -b \\ a-1 \end{bmatrix} + \sum_{n=1}^N \mathbf{m}_{x_n \rightarrow \gamma}
\end{aligned}$$

LowerBound

$$\begin{aligned}
\mathcal{L}(Q) &= \sum_i \mathcal{L}_i \\
\mathcal{L}_{x_n} &= \begin{bmatrix} \mathbb{E}_{q_\gamma}(\gamma) \mathbb{E}_{q_\mu}(\mu) \\ -\mathbb{E}_{q_\gamma}(\gamma)/2 \end{bmatrix}^T \begin{bmatrix} x_n \\ x_n^2 \end{bmatrix} + \frac{1}{2} (\mathbb{E}_{q_\gamma}(\ln \gamma) - \mathbb{E}_{q_\gamma}(\gamma) \mathbb{E}_{q_\mu}(\mu^2) - \ln 2\pi) \\
\mathcal{L}_\mu &= \begin{bmatrix} \beta m - \beta_\mu m_\mu \\ -\beta/2 + \beta_\mu/2 \end{bmatrix}^T \begin{bmatrix} \mathbb{E}_{q_\mu}(\mu) \\ \mathbb{E}_{q_\mu}(\mu^2) \end{bmatrix} + \frac{1}{2} (\ln \beta - \beta m^2 - \ln \beta_\mu + \beta_\mu m_\mu^2) \\
\mathcal{L}_\gamma &= \begin{bmatrix} -b + b_\gamma \\ a - a_\gamma \end{bmatrix}^T \begin{bmatrix} \mathbb{E}_{q_\gamma}(\gamma) \\ \mathbb{E}_{q_\gamma}(\ln \gamma) \end{bmatrix} + a \log b - \log \Gamma(a) - a_\gamma \log b_\gamma + \log \Gamma(a_\gamma)
\end{aligned}$$