

$$p(x, \theta) = p(x|\theta)p(\theta) \quad X = (x_1, \dots, x_n)$$

$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{\int p(X|\theta)p(\theta)d\theta} = \frac{\prod_{i=1}^n p(x_i|\theta)p(\theta)}{\int \prod_{i=1}^n p(x_i|\theta)p(\theta)d\theta}$$

$$\theta_{\text{nb}} = \arg \max_{\theta} p(\theta|X) = \arg \max_{\theta} \prod_{i=1}^n p(x_i|\theta)p(\theta) =$$

$$= \arg \max_{\theta} \left[ \sum_{i=1}^n \log p(x_i|\theta) + \log p(\theta) \right] \quad \text{— Poor man's Bayes}$$

$$\left. \begin{array}{l} p(x|\theta) \in \mathcal{M}(\theta) \\ p(\theta) \in \mathcal{B}(\alpha) \end{array} \right\} \text{Conjugate} \iff \underline{p(\theta|X) \in \mathcal{B}(\alpha')}$$

$$\alpha \rightarrow \alpha'$$

$$p(x|\mu) = \mathcal{N}(x|\mu, 1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(x-\mu)^2\right)$$

$$p(\mu) = \mathcal{N}(\mu|m, s^2)$$

$$p(x|\gamma) = \mathcal{N}(x|0, \gamma^{-1}) = \sqrt{\frac{\gamma}{2\pi}} \exp\left(-\frac{\gamma}{2}x^2\right)$$

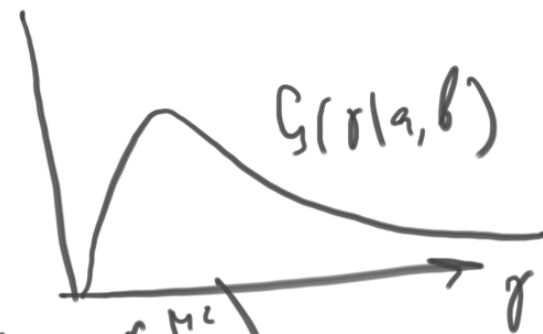
$$\gamma > 0$$

$$p(\gamma) = \mathcal{G}(\gamma|a, b) = \frac{b^a}{\Gamma(a)} \gamma^{a-1} \exp(-b\gamma) \quad a, b > 0$$

$$p(x|\mu, \gamma) = \mathcal{N}(x|\mu, \gamma^{-1}) \quad \textcircled{=}$$

$$p(\mu, \gamma) = p(\mu)p(\gamma)$$

$$\textcircled{=} \sqrt{\frac{\gamma}{2\pi}} \exp\left(-\frac{\gamma}{2}(x-\mu)^2\right) = \sqrt{\frac{\gamma}{2\pi}} \exp\left(-\frac{\gamma}{2}x^2 + \gamma\mu x - \gamma\frac{\mu^2}{2}\right)$$



$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{\int p(X|\theta)p(\theta)d\theta} \approx q(\theta) = \arg \min_{q \in Q} D(p(\theta|X), q(\theta))$$

↳ intractable

$$\text{KL}(q(\theta) \| p(\theta|X)) \stackrel{\text{def}}{=} \int q(\theta) \log \frac{q(\theta)}{p(\theta|X)} d\theta \geq 0$$

$$\underbrace{\log p(x)}_{\text{we get this or } q} = \underbrace{\int q(\theta) \log \frac{p(x, \theta)}{q(\theta)} d\theta}_{\mathcal{L}(q)} + \underbrace{\int q(\theta) \log \frac{q(\theta)}{p(\theta|X)} d\theta}_{\text{KL}(q(\theta) \| p(\theta|X))} \quad \Leftrightarrow q(\theta) = p(\theta|x)$$

$$q(\theta) = \arg \max_{q \in Q} \mathcal{L}(q)$$

1) Mean-field

$$q(\theta) = \prod_{j=1}^m q_j(\theta_j)$$

$$\theta = \bigcup_{j=1}^m \theta_j$$

2) Parametric VI

$$q(\theta) = q(\theta | \lambda)$$

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Conditional Conjugacy :  $\theta = \theta_1 \cup \dots \cup \theta_m$

$$p(x | \theta_{-j}, \theta_j) \sim p(\theta_j) - \text{conjugate}$$

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$$\log q_j(\theta_j) = \underbrace{E_{\theta_{-j}}}_{\text{tractable}} \log p(x, \theta) + \text{Const}$$

$$p(x|\mu, \sigma) = \mathcal{N}(x|\mu, \sigma^{-1})$$

$$p(\mu, \sigma) = p(\mu)p(\sigma) = \mathcal{N}(\mu|m, \beta^{-1})G(\sigma|a, b)$$

$$X = (x_1, \dots, x_n) \quad p(\mu, \sigma|X) \approx \underline{q(\mu)q(\sigma)}$$

$$\underline{\log q(\mu)} = \mathbb{E}_{q(\sigma)} \log p(X, \mu, \sigma) = \mathbb{E}_{\sigma} [\log p(X|\mu, \sigma) + \log p(\mu) + \log p(\sigma)] =$$

$$= \text{Count} - \underbrace{\frac{d}{2} \log 2\pi - \frac{b}{2} (\mu - m)^2}_{\log p(\mu)} + \mathbb{E}_{\sigma} \left[ \underbrace{\frac{n}{2} \log \sigma - \frac{n}{2} \log 2\pi}_{\text{Count}} - \underbrace{\frac{n}{2} \log \sigma^2}_{\text{in values or } \mu} \right]$$

$$- \frac{\sigma}{2} \sum_{i=1}^n (x_i - \mu)^2 \Big] \underline{\underline{= \text{Count} - \frac{b}{2} (\mu - m)^2 - \frac{1}{2} \mathbb{E} \sigma \cdot \sum_{i=1}^n (x_i - \mu)^2}}$$

$$= \text{Count} - \frac{b}{2} \mu^2 + b\mu m - \frac{b}{2} m^2 - \frac{1}{2} \mathbb{E} \sigma \left( \sum_i x_i^2 - 2\mu \sum x_i + \underline{n\mu^2} \right) =$$

$$= -\mu^2 \left( \frac{b}{2} + n \mathbb{E} \sigma \right) + \mu (bm + \mathbb{E} \sigma \sum x_i) + \text{Count} \quad p(\mu) = \mathcal{N}(\mu | m', \beta')$$

$$\mu' = \frac{\mu n + \sum x_i}{n + u}$$

$$b' = b + u$$

$$p(\gamma) = \frac{b^a}{\Gamma(a)} \gamma^{a-1} \exp(-b\gamma)$$

$$\log q(\gamma) = \mathbb{E}_{q(\mu)} \log p(X, \mu, \gamma) = \mathbb{E}_{q(\mu)} [\log p(X|\mu, \gamma) + \log p(\mu) + \log \gamma]$$

$$= a \log b - \log \Gamma(a) + (a-1) \log \gamma - b\gamma + \text{Count} +$$

$$+ \mathbb{E}_{q(\mu)} \left[ \frac{1}{2} \log \gamma - \frac{1}{2} \log 2\pi - \frac{r}{2} (x_i - \mu)^2 \right]$$

$$= (a+u-1) \log \gamma - r \left[ b + \frac{1}{2} \sum_{i=1}^n \mathbb{E}_{q(\mu)} (x_i - \mu)^2 \right] + \text{Count}$$

$$q(\gamma) = G(\gamma | a', b')$$

$$a' = a + u$$

$$b' = b + \frac{1}{2} \left( \sum_{i=1}^n x_i^2 - 2 \mathbb{E}_{q(\mu)} \sum_{i=1}^n x_i + \mathbb{E}_{q(\mu)} \right)$$

$$(a')^2 + (b')^{-1}$$

$$p(x|\theta) \rightarrow \max_{\theta}$$

$$p(x|\theta) = \int p(x, z|\theta) dz = \int p(x|z, \theta) p(z|\theta) dz$$

EM - algorithm

E - step

$$q(z) = \arg \max_q \mathcal{L}(q, \theta) = \arg \min_{q \in \mathcal{Q}} KL(q(z) \| p(z|x, \theta))$$

$$\stackrel{\text{①}}{=} p(z|x, \theta) \approx \prod_{j=1}^m q_j(z_j)$$

M - step

$$\theta = \arg \max_{\theta} \mathcal{L}(q, \theta) = \arg \max_{\theta} \mathbb{E}_{q(z)} \log p(x, z|\theta)$$

$$p(x, z, \theta) = p(x, z|\theta) p(\theta) = p(x|z, \theta) p(z|\theta) p(\theta)$$

$$\theta_{\text{new}} = \arg \max_{\theta} p(\theta|x) = \arg \max_{\theta} p(x|\theta) p(\theta) = \arg \max_{\theta} \left[ \log p(x|\theta) + \log p(\theta) \right]$$

$$\log p(x|\theta) \geq \mathcal{L}(q, \theta)$$

M' - step

$$\theta = \arg \max_{\theta} \left[ \mathbb{E}_{q(z)} \log p(x, z|\theta) + \log p(\theta) \right]$$



$$p(x, z, \theta) = p(x|z, \theta) p(z|\theta) p(\theta)$$

Каждое из

$$X = (x_1, \dots, x_n)$$

Свойств можем

Анализировать

Вид информации

Полное совместное  
распредел.  $z, \theta$

Условное совместное  
на  $z|\theta$  и на  $\theta|z$

Условное совместное  
на  $z|\theta$

Условное совместное  
на  $\theta|z$

Условное совместное  
на  $z_j|z_{-j}, \theta$

Нет совместности

Байесовский вывод

Mean-field

EM'

$\eta' E$

MF EM'

Байес и не-Байесовский

$p(z, \theta|X)$

$q(z) q(\theta) = \arg \min_{KL} (\dots)$

$p(z|x, \theta) \delta(\theta - \theta_{MP})$

$\delta(z - z_{MP}) p(\theta|x, z)$

$\prod_{j=1}^n q_j(z_j) \delta(\theta - \theta_{MP})$

$\delta(z - z_{MP}) \delta(\theta - \theta_{MP})$

$q(\theta) \in \Delta(\theta)$