

$$P(X) = \frac{1}{Z} \tilde{P}(X) = \frac{1}{Z} e^{F(X)}$$

An "easy" distribution Q(X)

$$\begin{aligned} KL(Q \parallel P) &= \sum_x Q(x) \log \frac{Q(x)}{P(x)} \\ &= \sum_x Q(x) \log \frac{Q(x)}{\tilde{P}(x)} + \log Z \\ &= - \sum_x Q(x) \log \frac{\tilde{P}(x)}{Q(x)} + \log Z \end{aligned}$$

$$\sum_x Q(x) \log \frac{\tilde{P}(x)}{Q(x)} = \log Z - KL(Q \parallel P)$$

$L(Q, \tilde{P})$

variational lower bound

1. $L(Q, \tilde{P}) \leq \log Z$
2. $Q^* = \operatorname{argmin}_Q KL(Q \parallel P) = \operatorname{argmax}_Q L(Q, \tilde{P})$

$$P(X) = \frac{1}{Z} e^{F(X)}, \quad F(X) = \sum_{i=1}^n F_i(x_i) + \sum_{(i,j) \in E} F_{ij}(x_i, x_j)$$

$$\begin{aligned} -L(Q, \tilde{P}) &= \sum_i \sum_{x_i} Q_i(x_i) \log Q_i(x_i) - \sum_{i=1}^n \sum_{x_i} Q_i(x_i) F_i(x_i) \\ &\quad - \sum_{(i,j) \in E} \sum_{x_i, x_j} Q_i(x_i) Q_j(x_j) F_{ij}(x_i, x_j) \end{aligned}$$

$$\begin{aligned} L(Q, \tilde{P}) &= - \sum_i \sum_{x_i} Q_i(x_i) \log Q_i(x_i) + \sum_{i=1}^n \sum_{x_i} Q_i(x_i) F_i(x_i) \\ &\quad + \sum_{(i,j) \in E} \sum_{x_i, x_j} Q_i(x_i) Q_j(x_j) F_{ij}(x_i, x_j) \end{aligned}$$

$$Q(X) = Q(X_1, X_2, \dots, X_n) = \prod_{i=1}^n q_i(X_i) \quad \text{mean-field}$$

$$P(X) = \frac{1}{Z} \tilde{P}(X) = \frac{1}{Z} e^{F(X)} \quad \sum_{i=1}^n F_i(X_i) + \sum_{(i,j) \in E} F_{ij}(X_i, X_j)$$

$$L(Q, \tilde{P}) = - \sum_{i=1}^n \sum_{X_i} q_i(X_i) \log q_i(X_i) + \sum_{i=1}^n \sum_{X_i} q_i(X_i) F_i(X_i) + \sum_{(i,j) \in E} \sum_{X_i} \sum_{X_j} q_i(X_i) q_j(X_j) F_{ij}(X_i, X_j)$$

$$\max_Q L(Q, \tilde{P}) = \max_{q_1, q_2, \dots, q_n} L(Q, \tilde{P})$$

Discrete Case

$$q_i(X_i = k) = q_{ik} \quad q_i \xrightarrow{\text{parameterize}} (q_{i1}, q_{i2}, \dots, q_{iL})$$

$$k=1, 2, \dots, L \quad \sum_{k=1}^L q_{ik} = 1$$

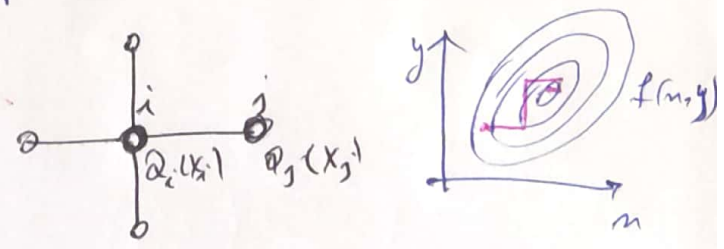
$$L(Q, \tilde{P}) = - \sum_{i=1}^n \sum_{k=1}^L q_{ik} \log q_{ik} + \sum_{i=1}^n \sum_{k=1}^L q_{ik} F_i(k) + \sum_{(i,j) \in E} \sum_{k=1}^L \sum_{k'=1}^L q_{ik} q_{jk'} F_{ij}(k, k')$$

$$\max_Q L(Q, P) \quad \text{subject to} \quad \sum_{k=1}^L q_{ik} = 1 \quad \text{for } i=1 \dots n$$

coordinate ascent

Loop for $i=1 \dots n$

$\max_{q_{il}}$



$$\max_{q_{i1}, q_{i2}, \dots, q_{iL}} L(Q, P) \Rightarrow \frac{\partial}{\partial q_{il}} L(Q, P) = + \lambda \left(\sum_{k=1}^L q_{ik} - 1 \right)$$

$$= -\log q_{il} - 1 + F_i(l) + \sum_{j \in N_i} \sum_{k=1}^L q_{jk'} F_{ij}(l, k') + \lambda = 0$$

for $l=1, 2, \dots, L$

$$\sum_{k=1}^L q_{ik} = 1$$

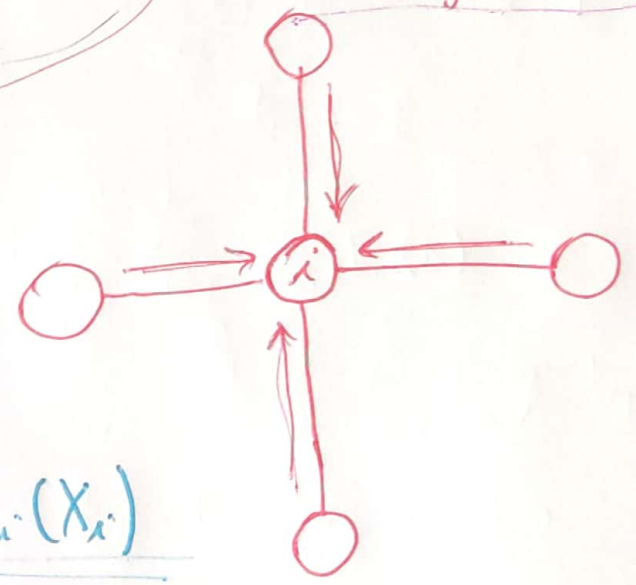
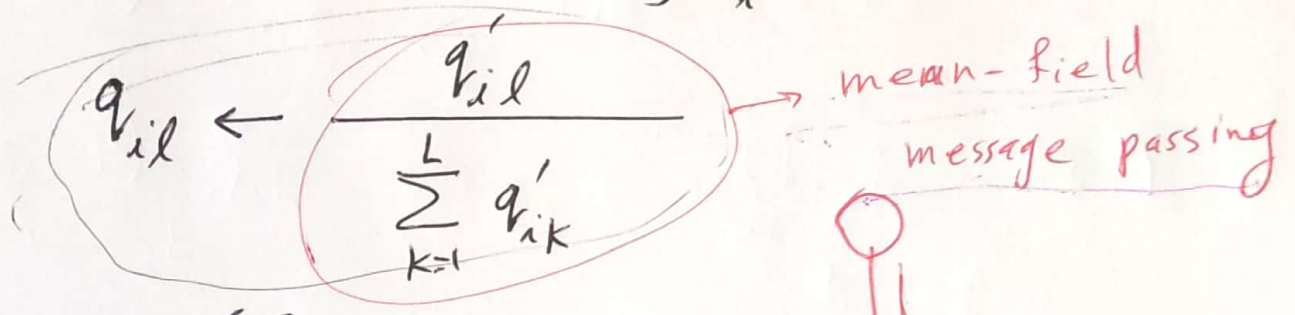
$$\Rightarrow \log q_{il} = F_i(l) + \sum_{j \in N_i} \sum_{k=1}^L q_{jk} F_{ij}(l, k) + \lambda - 1$$

$$q_{il} = \exp(F_i(l) + \sum_{j \in N_i} \sum_{k=1}^L q_{jk} F_{ij}(l, k)) e^{\lambda - 1}$$

$$l = 1, 2, \dots, L$$

$$\sum_{k=1}^L q_{il} = 1$$

$$q'_{il} = \exp(F_i(l) + \sum_{j \in N_i} \sum_{k=1}^L q_{jk} F_{ij}(l, k))$$



Case 2: Continuous $q_i(x_i)$

Among all $q_i(x)$ with $q_i(x) \geq 0$, $\int q_i(x) dx = 1$
 $i = 1, \dots, n$

find the one that maximizes $J(Q, \tilde{P})$
 minimizes $KL(Q || P)$

Variational Calculus $f: \mathbb{R}^m \rightarrow \mathbb{R}^n$ is a function
 optimize $J(f)$ s.t. so some constraint

Variational Learning

$$p_{\theta}(x) = \frac{1}{Z(\theta)} P_{\theta}(x) = \frac{1}{Z(\theta)} e^{F_{\theta}(x)}$$

Latent Variable Models

$$p_{\theta}(x) = \int p_{\theta}(x, z) dz$$

Data x^1, x^2, \dots, x^m

$$\max_{\theta} \sum_i \log P_{\theta}(x^i)$$

$$\max_{\theta} \ell(\theta) = \max_{\theta} \sum_{i=1}^m \log P_{\theta}(x^i)$$

$$= \max_{\theta} \sum_{i=1}^m \log \int P_{\theta}(x^i, z) dz$$

Solution 1

$$\frac{\partial \ell(\theta)}{\partial \theta_k} = \frac{\partial}{\partial \theta_k} \sum_{i=1}^m \log \int P_{\theta}(x^i, z) dz$$

$$= \sum_{i=1}^m \frac{\int \frac{\partial}{\partial \theta_k} P_{\theta}(x^i, z) dz}{\int P_{\theta}(x^i, z) dz}$$

hard to compute

Solution 2: Expectation - Maximization

⇒ Need $P_{\theta}(z|x^i)$ for $i=1, \dots, m$
 posterior

→ hard to compute