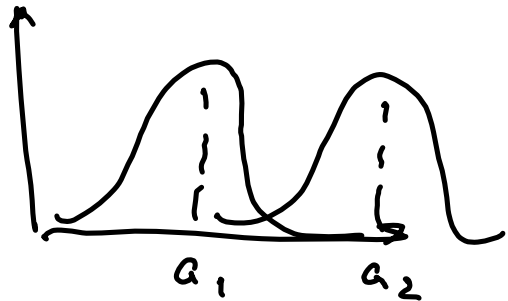


Bayes methods

$$KL(p \parallel q) = \int_{\mathbb{R}} p(x) \log \frac{p(x)}{q(x)} dx$$

$$N(x|a, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-a)^2}{2\sigma^2}}$$

$$KL(N(x|a_1, \sigma^2) \parallel N(x|a_2, \sigma^2)) = \frac{(a_1 - a_2)^2}{2\sigma^2}$$



$$p(x) = \int p(x, y) dy$$

$$p(x, y) = p(x|y) \cdot p(y)$$

EM - algorithm.

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

$$\log p(x|\theta) \cdot 1 = \log p(x|\theta) \cdot \int q(z) dz =$$

$$= \int q(z) \cdot \log p(x|\theta) dz =$$

$$= \int q(z) \cdot \log \frac{p(x, z|\theta)}{p(z|x, \theta)} dz \quad \Leftrightarrow$$

$$\left\{ p(x, z|\theta) = p(z|x, \theta) \cdot p(x|\theta) \right\}$$

$$\Leftrightarrow \int q(z) \log \frac{p(x, z|\theta) \cancel{q(z)}}{\cancel{q(z)} p(z|x, \theta)} dz =$$

$$= \underbrace{\int q(z) \log \frac{p(x, z|\theta)}{q(z)} dz}_{L(q, \theta)} + \underbrace{\int q(z) \log \frac{q(z)}{p(z|x, \theta)} dz}_{KL(q(z) || p(z|x, \theta))}$$

ELBO

$$\log p(x|\theta) = \mathcal{L}(q, \theta) + \underbrace{KL(q||p)}_{\geq 0}$$

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

$$\text{E-max: } \mathcal{L} \rightarrow \max_q$$

$$\text{M-max: } \mathcal{L} \rightarrow \max_{\theta}$$

$$\mathcal{L} = \log p(x|\theta) - KL(q(z)||p(z|x, \theta))$$

$$\mathcal{L} \rightarrow \max_q \sim KL(q||p) \rightarrow \min_q$$

$$KL(q||p) = 0 \Leftrightarrow q = p$$

$$\mathcal{L} \rightarrow \max_q \Rightarrow \boxed{q^*(z) = p(z|x, \theta^{\text{old}})}$$

$$\underline{\text{M-max: } \mathcal{L} \rightarrow \max_{\theta}}$$

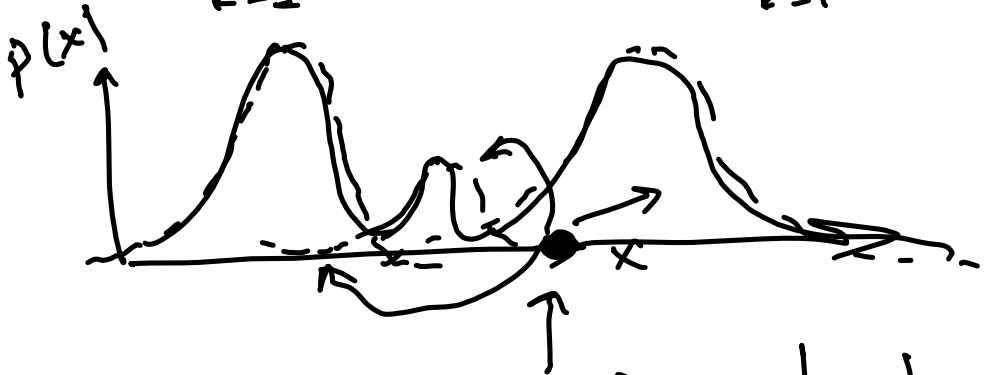
$$\mathcal{L}(q^*, \theta) = \int q^*(z) \cdot \log \frac{p(x, z|\theta)}{q^*(z)} dz =$$

$$= \underbrace{\int q^*(z) \log p(x, z | \theta) dz}_{\mathbb{E}_{q^*} \log p(x, z | \theta)} - \underbrace{\int q^*(z) \log q^*(z) dz}_{H(q^*)}$$

$$\theta^{\text{new}} = \underset{\theta}{\operatorname{argmax}} \mathbb{E}_{q^*} \log p(x, z | \theta)$$

Разложение смеси компонент.

$$p(x) = \sum_{k=1}^K \pi_k \cdot p_k(x) \quad \begin{array}{l} \pi_k \geq 0 \\ \sum_{k=1}^K \pi_k = 1 \end{array}$$



$$p_k(x) = \mathcal{N}(x | a_k, \sigma_k^2) \quad \begin{array}{c} | \quad | \quad | \\ \pi_1 \quad \pi_2 \quad \pi_K \end{array}$$

$$p(x) = \sum_{k=1}^K p(x | H_k = 1) p(H_k = 1)$$

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

$$= \prod_{i=1}^n \sum_{k=1}^K \pi_k \cdot \mathcal{N}(x_i | a_k, b_k^2)$$

$$\log p(x|\theta) = \sum_{i=1}^n \log \left(\sum_{k=1}^K \pi_k \cdot \mathcal{N}(x_i | a_k, b_k^2) \right)$$

$z_{ik} = \begin{cases} 1, & \text{i-ий объект из } k\text{-ой группы.} \\ 0, & \text{иначе.} \end{cases}$

$$P(x, z|\theta) = P(x|z, \theta) \cdot \underbrace{P(z|\theta)}$$

$$\underbrace{P(z_{ik} = 1)}_{\pi_k} = \pi_k \Rightarrow P(z_i = 1) = \prod_{k=1}^K \pi_k^{z_{ik}}$$

$$P(x|z, \theta) = \prod_{i=1}^n p(x_i | z_i, \theta) =$$

$$= \prod_{i=1}^n \mathcal{N}(x_i | a_k, b_k^2)$$

$$p(x_i | z_i, \theta) = \prod_{k=1}^K \mathcal{N}(x_i | a_k, b_k^2)^{z_{ik}}$$

$$P(x, z | \theta) = \underbrace{P(x | z, \theta)}_{\prod_{i=1}^n \prod_{k=1}^K N(\dots)} \cdot \underbrace{P(z | \theta)}_{\prod_{i=1}^n \prod_{k=1}^K \pi_k^{z_{ik}}} =$$

$$P(x, z | \theta) = \prod_{i=1}^n \prod_{k=1}^K \left(\pi_k \cdot N(x_i | a_k, \sigma_k^2) \right)^{z_{ik}}$$

$$\log P(x, z | \theta) = \sum_{i=1}^n \sum_{k=1}^K z_{ik} (\log \pi_k + \log N(\dots))$$

E-мод: $f^*(z) = P(z | x, \theta)$

$$P(z_{ik} = 1 | x_i, \theta) = \frac{\pi_k \cdot N(x_i | a_k, \sigma_k^2)}{\sum_{j=1}^K \pi_j \cdot N(x_i | a_j, \sigma_j^2)}$$

$$P(z | x) \propto P(x, z)$$

$$P(z | x) = \frac{P(x, z)}{P(x)} \rightarrow \text{не забыть } \sigma^2 z.$$

M-мод:

$$\theta^* = \underset{\theta}{\operatorname{argmax}} \mathbb{E}_{f^*} \log P(x, z | \theta)$$

$$\mathbb{E}_{\mathbf{z}} \log p(\mathbf{x}, \mathbf{z} | \theta) = \mathbb{E}_{\mathbf{z}} \sum_i \sum_k z_{ik} \{ \log \pi_k + \log \mathcal{N}(x_i | a_k, b_k^2) \} =$$

$$= \sum_i \sum_k \mathbb{E}(z_{ik}) \{ \log \pi_k + \log \mathcal{N}(\cdot) \} + \lambda \left(\sum_{k=1}^K \pi_k - 1 \right)$$

$$\mathbb{E}_{\mathbf{z}}(z_{ik}) = 1 \cdot p(z_{ik}=1 | x_i, \theta) + 0 \cdot$$

$$p(z_{ik}=0 | x_i, \theta) = p(z_{ik}=1 | x_i, \theta) =$$

$$= \boxed{f_{ik}}$$

$$Q = \sum_{i=1}^n \sum_{k=1}^K f_{ik} \left\{ \log \pi_k - \frac{1}{2} \log 2\pi - \log b_k - \frac{(x_i - a_k)^2}{2b_k^2} \right\} + \lambda \left(\sum_{k=1}^K \pi_k - 1 \right)$$

$$Q'_{\pi_k} = \dots = 0 \quad \pi_k^{\text{new}} = \dots$$

$$Q'_{a_k} = \dots = 0 \quad a_k^{\text{new}} = \dots$$

Lemma

$\Theta_{old} \dots \Theta_{new}$.

$$\log p(X|\Theta_{old}) = L(f, \Theta_{old}) + KL(f||p)$$

$$\begin{aligned} \text{E-max: } f^* &= p(z|X, \Theta_{old}) \Rightarrow \\ \Rightarrow KL(f^*||p) &= 0 \Rightarrow \log p(X|\Theta_{old}) = \\ &= L(f^*, \Theta_{old}) \end{aligned}$$

$$\text{M-max: } \Theta = \underset{\Theta}{\operatorname{argmax}} L(f^*, \Theta)$$

$$L(f^*, \Theta^{new}) > L(f^*, \Theta_{old})$$

$$\log p(X|\Theta_{new}) = L(f^*, \Theta^{new}) +$$

$$+ KL(f^*||p(z|X, \Theta^{new})) >$$

$$\begin{aligned} &\stackrel{\geq 0}{>} L(f^*, \Theta_{old}) = \log p(X|\Theta_{old}) \end{aligned}$$

$$\textcircled{1} p_{km} = \frac{1}{|R_m|} \sum_{i: x_i \in R_m} [y_i = k]$$

$$G(R_m) = \sum_{k=1}^K p_{km} (1 - p_{km})$$

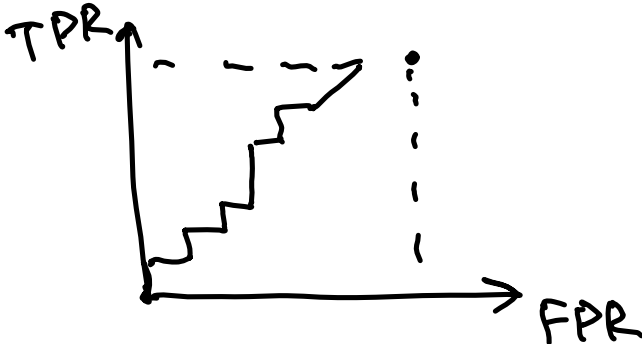
$$Q = G(R_m) - \frac{|R_e|}{|R_m|} \cdot G(R_e) - \frac{|R_v|}{|R_m|} \cdot G(R_v)$$

$$\textcircled{2} Pr = \frac{TP}{TP + FP} \quad Rec = \frac{TP}{TP + FN}$$

$a_i \backslash y_i$	1	0
1	TP	FP
0	FN	TN

	0	1
	0.5	0.5

$$\textcircled{3} AUC =$$



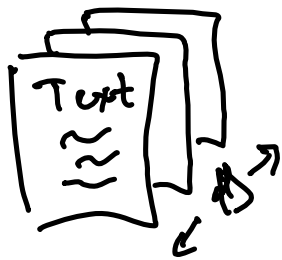
$$\textcircled{4.} \quad Q = \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(\underbrace{-y_i \langle w, x_i \rangle}_{\text{margin}_i})) \\ + \lambda \cdot \|w\|^2$$

$$\textcircled{5.} \quad \mathcal{L} = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} \mathbb{P}(w_{t+j} | w_j)$$

$$\mathbb{P}(\text{out} | \text{center}) = \frac{\exp(u_{\text{out}}^T \cdot v_{\text{center}})}{\sum_{u \in \mathcal{U}} \exp(u^T v_{\text{center}})}$$

$$U = \begin{array}{|c|} \hline \square \\ \hline |V_{oc}| \times h \end{array}$$

$$V = \begin{array}{|c|} \hline \square \\ \hline |V_{oc}| \times h \end{array}$$



(d_i, w_i)

$$P(D, W) = \prod_{d \in D} \prod_{w \in d} P(d, w)$$

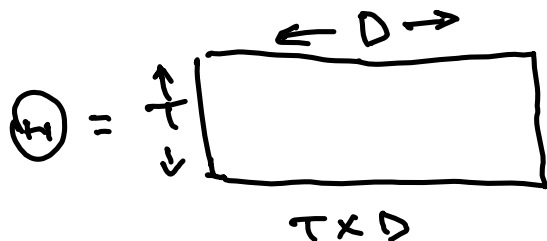
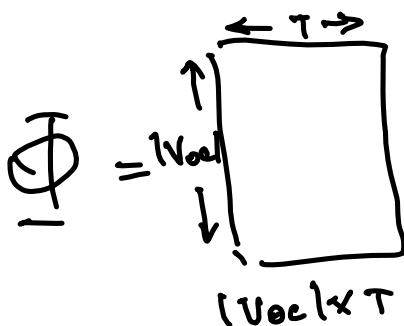
$$P(d, w) = P(w|d) \cdot P(d) \quad \textcircled{=}$$

$$P(w|t, d) = P(w|t) \quad \textcircled{=}$$

$$\textcircled{=} P(d) \cdot \sum_{t=1}^T P(w, t|d) \quad \textcircled{=}$$

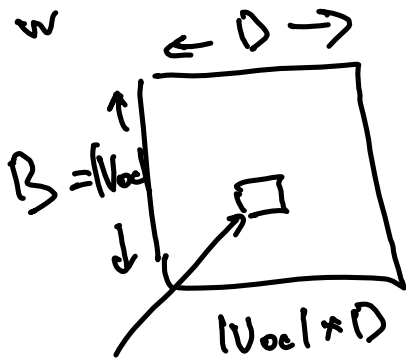
$$\left\{ P(A) = \sum_B P(A, B) \right\} \quad P(A, B) = P(A|B)P(B)$$

$$\textcircled{=} P(d) \cdot \sum_{t=1}^T \underbrace{P(w|t, d)}_{\psi_{wt}} \cdot \underbrace{P(t|d)}_{\theta_{td}}$$



$$\sum_w p(w|t) = 1$$

$$\sum_t p(w|t) \neq 1$$



$$\approx \Phi \cdot \Theta$$

$$p(w|d)$$

$$P(D, w) = \prod_{d=1}^D \prod_{w \in d} p(d, w) =$$

$$= \prod_{d=1}^D \prod_{w \in d} p(d) \cdot p(w|d) =$$

$$= \prod_{d=1}^D \prod_{w \in d} p(d) \cdot \sum_{t=1}^T p(w|t) \cdot p(t|d)$$

$$\log P(D, w) = \sum_{d=1}^D \sum_{w \in d} \log \left(\sum_{t=1}^T \varphi_{wt} \cdot \theta_{td} \right) \rightarrow$$

$$\rightarrow \max_{\Phi, \Theta}$$

$$P(D, w | T) = \prod_{d=1}^D \prod_{w \in d} \prod_{t=1}^T (p(w|t) \cdot p(t|d))^{[t=t_d]}$$

$$= \prod_{d=1}^D \prod_{w \in d} \prod_{t=1}^T (p(w|t) \cdot p(t|d))^{[t=t_d]}$$

$$P(D, w, T) \propto P(D, w | T)$$

$$\log P(D, w, T) = \sum_{d=1}^D \sum_{w \in d} \sum_{t=1}^T [t=t_d] \cdot \log(\psi_{wt} \cdot \theta_{td})$$

IE - max:

$$q(T) = p(t_d = t | w, d) \propto p(d, w, t) =$$

$$= \frac{p(w|t) \cdot p(t|d)}{\sum_{t=1}^T p(w|t) \cdot p(t|d)} = \boxed{\frac{\psi_{wt} \cdot \theta_{td}}{\sum_{j=1}^T \psi_{wj} \cdot \theta_{jd}}} =$$

$$= \gamma_{dwt}$$

$$\boxed{M - \text{word}} \mathbb{E}_{q(t)} \log P(D, w, T) \rightarrow \max_{\Phi, \Theta}$$

$$Q = \mathbb{E}_q \sum_{d=1}^D \sum_{w \in V_{\text{vec}}} \sum_{t=1}^T [t_d = t] \cdot \log(\varphi_{wt} \cdot \theta_{td}) +$$

$$+ \sum_{t=1}^T \lambda_t \left(\sum_{w \in V_{\text{vec}}} \varphi_{wt} - 1 \right) +$$

$$+ \sum_{d=1}^D \mu_d \left(\sum_{t=1}^T \theta_{td} - 1 \right) \rightarrow \max_{\varphi_{wt}, \theta_{td}}$$

$$\mathbb{E}_q([t_d = t]) = P(t_d = t | w, d) = f_{dwt}$$

$$Q = \sum_{d=1}^D \sum_{w \in V_{\text{vec}}} \sum_{t=1}^T f_{dwt} \cdot \log(\varphi_{wt} \cdot \theta_{td}) +$$

$$+ \sum_{t=1}^T \lambda_t \left(\sum_{w \in V_{\text{vec}}} \varphi_{wt} - 1 \right) + \sum_{d=1}^D \mu_d \left(\sum_{t=1}^T \theta_{td} - 1 \right)$$

$$Q'_{\varphi_{wt}} = \sum_{d=1}^D f_{dwt} \cdot n_{dw} \cdot \frac{1}{\varphi_{wt}} + \lambda_t = 0$$

$$\varphi_{wt} = - \frac{1}{\lambda_t} \sum_d f_{dwt} \cdot n_{dw} = \frac{\sum_{d=1}^D f_{dwt} \cdot n_{dw}}{\sum_{d=1}^D \sum_w f_{dwt} \cdot n_{dw}}$$

$$\sum_{w \in V_{\text{vec}}} \varphi_{wt} = 1 = - \frac{1}{\lambda_t} \cdot \sum_{d=1}^D \sum_{w \in V_{\text{vec}}} f_{dwt} \cdot n_{dw} \Rightarrow$$

$$\Rightarrow -\lambda_t = \sum_{d=1}^D \sum_{w \in V_{\text{vec}}} f_{dwt} \cdot n_{dw}$$

$$\begin{aligned}
 P(t|w) &= \frac{P(w|t)P(t)}{\sum_t P(w|t) \cdot P(t)} = \\
 &= \frac{P(w|t) \sum_d P(t|d) \cdot P(d)}{\sum_t (P(w|t) \cdot \sum_d P(t|d) \cdot P(d))}
 \end{aligned}$$

PLSA