

$$x_1, \dots, x_n \sim p(x|\theta), \ln p(x|\theta) \rightarrow \max_{\theta}$$

$t_1, \dots, t_n, p(x, t|\theta)$  экспоненциальный класс

латентные переменные

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

ЕМ-алгоритм

$$\begin{aligned} \ln p(x|\theta) &= \int q(T) \ln p(x|\theta) dT = \int q(T) \ln \frac{p(x, T|\theta)}{p(T|x, \theta)} dT = \\ &= \int q(T) \ln \frac{p(x, T|\theta)}{p(T|x, \theta)} \frac{q(T)}{q(T)} dT = \int q(T) \ln \frac{p(x, T|\theta)}{q(T)} dT + \\ &+ \int q(T) \ln \frac{q(T)}{p(T|x, \theta)} dT \end{aligned}$$

$$\uparrow \mathcal{L}(q, \theta)$$

$$\geq \mathcal{L}(q, \theta)$$

$$KL(p||q) = \int p(x) \ln \frac{p(x)}{q(x)} dx$$

$$KL \geq 0, = 0 \Leftrightarrow p(x) = q(x) \text{ н.в.}$$

оптимизация вариационной нижней оценки  $\mathcal{L}(q, \theta)$

по  $q$  и по  $\theta$

$$E\text{-step: } \mathcal{L}(q, \theta) \rightarrow \max_q, M\text{-step: } \mathcal{L}(q, \theta) \rightarrow \max_{\theta}$$

оптимизация в функциональном пр-ве

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

$$\mathcal{L}(q|\theta) \rightarrow \max_q \Leftrightarrow KL(q(T)||p(T|x, \theta)) \rightarrow \min_q \Leftrightarrow q(T) = p(T|x, \theta)$$

$$\mathcal{L}(q|\theta) = \int q(T) \ln \frac{p(x, T|\theta)}{q(T)} dT \rightarrow \max_{\theta}$$

$$\Leftrightarrow \mathbb{E}_q \underbrace{\ln p(x, T|\theta)}_{\text{возмущающая ф-ия}} \rightarrow \max_{\theta}$$

вариационная комбинация возмущающих ф-ий.

$$\theta x_1 + (1-\theta)x_2 \quad \text{взвешенная комбинация}$$

$$\sum_{j=1}^n \theta_j x_j, \quad \theta_j \geq 0, \quad \sum_{j=1}^n \theta_j = 1$$

$$\int \theta(j) x(j) dj = \mathbb{E}_{\theta(j)} x(j), \quad \theta(j) \geq 0, \quad \int \theta(j) dj = 1$$

$$q(T) = p(T|x, \theta) = \frac{p(x, T|\theta)}{\int p(x, T|\theta) dT} = \frac{p(x|T, \theta)p(T|\theta)}{\int p(x|T, \theta)p(T|\theta) dT}$$

$$KL(q(T) || p(T|x, \theta)) \xrightarrow[\boxed{q \in Q}]{\min} \Leftrightarrow q(T) \approx p(T|x, \theta)$$

вариационный вывод

$$Q = \Delta \quad \text{пр-во } \delta\text{-ф-ий}$$

$$KL(\delta(x-x_0) || p(x)) = \int \delta(x-x_0) \ln \frac{\delta(x-x_0)}{p(x)} dx =$$

$$= - \int \delta(x-x_0) \ln p(x) dx + \int \delta(x-x_0) \ln \delta(x-x_0) dx =$$

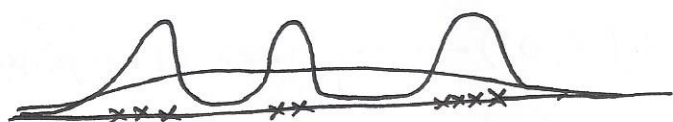
$$= \text{const} - \ln p(x_0) \xrightarrow{x_0} \min, \quad x_0 = \arg \max_x p(x)$$

$$\text{mod } p(x) = p(x_0)$$

$$T_{\text{mp}} = \arg \max_T p(T|x, \theta) = \arg \max_T p(x, T|\theta)$$

$$\mathbb{E}_q \ln p(x, T|\theta) = \mathbb{E}_{\delta(T-T_{\text{mp}})} \ln p(x, T|\theta) = \ln p(x, T_{\text{mp}}|\theta)$$

местный. EM-алгоритм.



$$p(x|\theta) \rightarrow p(x, t|\theta) = p(x|t, \theta)p(t|\theta) =$$

$$= \mathcal{N}(x|\mu_t, \sigma_t^2) \cdot \prod_{k=1}^K \pi_k^{[t=k]}$$

$$\pi_k > 0, \quad \sum \pi_k = 1$$

$$\theta = \{\mu_k\}, \{\sigma_k^2\}, \pi_k$$

$$\begin{aligned}
 \text{- step: } q(T) &= p(T | X, \theta) = \frac{p(X, T | \theta)}{\sum_T p(X, T | \theta)} = \\
 &= \frac{\prod_{i=1}^n p(x_i, t_i | \theta)}{\sum_T \prod_{i=1}^n p(x_i, t_i | \theta)} = \frac{\prod_{i=1}^n p(x_i, t_i | \theta)}{\prod_{i=1}^n \sum_{t_i=1}^K p(x_i, t_i | \theta)} = \prod_{i=1}^n \frac{p(x_i, t_i | \theta)}{\sum_{t_i=1}^K p(x_i, t_i | \theta)} = \\
 &= \prod_{i=1}^n q(t_i) \\
 q(t_i = l) &= \frac{p(x_i, l | \theta)}{\sum_{t_i=1}^K p(x_i, t_i | \theta)} = \frac{N(x_i | \mu_l, \sigma_l^2) \cdot \pi_l}{\sum_{k=1}^K N(x_i | \mu_k, \sigma_k^2) \pi_k} = \delta_{il} = \\
 &= p(t_i = l | x_i, \theta)
 \end{aligned}$$

$\mathcal{M}$ -max

$$\begin{aligned}
 \mathbb{E}_q \ln p(X, T | \theta) &= \mathbb{E}_q \sum_{i=1}^n \ln p(x_i, t_i | \theta) = \sum_{i=1}^n \mathbb{E}_{q(t_i)} \ln p(x_i, t_i | \theta) = \\
 &= \sum_{i=1}^n \mathbb{E}_{q(t_i)} \left( \ln N(x_i | \mu_{t_i}, \sigma_{t_i}^2) + \sum_{k=1}^K [t_i = k] \ln \pi_k \right) = \\
 &= \sum_{i=1}^n \sum_{k=1}^K (\delta_{ik} \ln N(x_i | \mu_{t_i}, \sigma_{t_i}^2) + \delta_{ik} \ln \pi_k) \rightarrow \max_{\mu, \sigma^2, \pi}
 \end{aligned}$$

PCA

$$p(x, t | \theta) = p(x | t, \theta) p(t) = N(x | \mu + w t, \sigma^2 I) N(t | 0, I)$$

$$x \in \mathbb{R}^D, t \in \mathbb{R}^d, X = (x_1, \dots, x_n), p(X | \theta) \rightarrow \max_{\theta}$$

$$p(X | \theta) = \prod_{i=1}^n p(x_i | t_i, \theta) = \prod_{i=1}^n \int p(x_i, t_i | \theta) dt_i = \prod_{i=1}^n \int p(x_i | t_i, \theta) \cdot$$

$$p(t_i) dt_i$$

$$\text{E-step: } p(T | X, \theta) = \frac{\prod_{i=1}^n p(x_i | t_i, \theta) p(t_i)}{\int \prod_{i=1}^n p(x_i | t_i, \theta) p(t_i) dt_i} = \prod_{i=1}^n \frac{p(x_i | t_i, \theta) p(t_i)}{\int p(x_i | t_i, \theta) p(t_i) dt_i}$$

$$\text{M-step: } \mathbb{E}_{p(T | X, \theta)} \ln p(X, T | \theta) \rightarrow \max_{\theta}$$



$$\odot \prod_{i=1}^n \frac{N(x_i | \mu + w t_i, \sigma^2 I) N(t_i | 0, I)}{\int N(x_i | \mu + w t_i, \sigma^2 I) N(t_i | 0, I) dt_i} =$$

$$= \prod_{i=1}^n \frac{N(x_i | \mu + w t_i, \sigma^2 I) N(t_i | 0, I)}{N(x_i | \mu, \sigma^2 I + w w^T)} =$$

$$= \prod_{i=1}^n N(t_i | (\sigma^2 I + w^T w)^{-1} w^T (x_i - \mu), (I + \sigma^{-2} w^T w)^{-1})$$

M-step

$$\mathbb{E}_{T|x,\theta} p(x, T | \theta) = \sum_{i=1}^n \mathbb{E}_{t_i | x_i, \theta} (\ln p(x_i | t_i, \theta) - \ln p(t_i)) =$$

$$= \sum_{i=1}^n \mathbb{E} \left( -\frac{d}{2} \ln 2\pi - d \ln \sigma - \frac{1}{2\sigma^2} (x_i - \mu - w t_i)^T (x_i - \mu - w t_i) - \frac{d}{2} \ln 2\pi - \frac{1}{2} t_i^T t_i \right) = \sum_{i=1}^n \left( -d \ln \sigma - \frac{1}{2\sigma^2} (x - \mu)^T (x - \mu) + \right. \\ \left. + \frac{1}{\sigma^2} (x_i - \mu)^T w \mathbb{E} t_i - \frac{1}{2\sigma^2} \mathbb{E} t_i^T w^T w t_i \right) + \text{const} \neq$$

$$\neq \frac{\partial}{\partial w} \mathbb{E} \ln p(x, T | \theta) = \sum_{i=1}^n \left( \frac{1}{\sigma^2} (x_i - \mu) (\mathbb{E} t_i)^T - \frac{1}{\sigma^2} w \mathbb{E} t_i t_i^T \right) = 0$$

$$\sum_{i=1}^n w \mathbb{E} t_i t_i^T = \sum_{i=1}^n (x_i - \mu) (\mathbb{E} t_i)^T$$

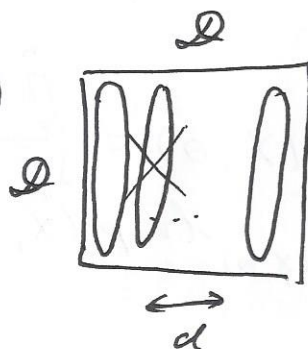
$$w = \left( \sum_{i=1}^n (x_i - \mu) (\mathbb{E} t_i)^T \right) \left( \sum_{i=1}^n \mathbb{E} t_i t_i^T \right)^{-1}$$

$$PCA \quad O(nD^2 + D^3) \sim O(nD^2) \Rightarrow O(nDd)$$

$$t \in \mathbb{R}^D, w \in \mathbb{R}^{D \times D}$$

$$p(w | d) = \prod_{i=1}^D N(w_i | 0, d_i^{-1} I)$$

Эксперимент A M D



07.10.16 думно сеп

$$p(x) = \sum_{n=1}^K \pi_n p_n(x|\theta), \quad \sum_{i=1}^K \pi_i = 1, \quad \pi_i \geq 0 \quad \forall i$$

$$p(x, t) = \prod_{n=1}^K [\pi_n p_n(x|\theta)]^{t_n}, \quad t \in \{0, 1\}^K, \quad \sum_{i=1}^K t_i = 1$$

$$x_1, \dots, x_n \sim p(x)$$

$$\mu, \pi : \pi_{\mu}, \theta_{\mu} ?$$

$$p(x, T | \pi, \theta) = \prod_{n=1}^K \prod_{k=1}^K [\pi_n p_n(x_n | \theta)]^{t_{nk}}$$

$$E\text{-step: } q(T) = p(T | x, \pi, \theta) = \prod_n q_n(t_n)$$

$$q_n(t_n) \propto \prod_k [\pi_k p_k(x_n | \theta)]^{t_{nk}}$$

$$q_n(t_{nk}=1) = \frac{\pi_k p_k(x_n | \theta)}{\sum_k \pi_k p_k(x_n | \theta)} = \delta_{nk}$$

$$M\text{-step: } \mathbb{E}_q \ln p(x, T | \pi, \theta) = \mathbb{E}_q \sum_n \sum_k t_{nk} (\ln p_k(x_n | \theta) + \ln \pi_k)$$

$$= \sum_{n,k} (\mathbb{E}_q t_{nk}) (\ln \pi_k + \ln p_k(x_n | \theta)) =$$

$$= \sum_{n,k} \delta_{nk} (\ln \pi_k + \ln p_k(x_n | \theta)) \rightarrow \max_{\pi, \theta}$$

$$\pi_k = \frac{\sum_n \delta_{nk}}{N}$$

$$\# x_1, \dots, x_n \sim \delta p_1(x) + (1-\delta) p_2(x)$$

$$p_1 \propto (1-\alpha)\alpha \quad \alpha_0 = \beta_0 = \delta_0 = \frac{1}{2} \quad N_1 = 30, N_2 = 20, N_3 = 60$$

$$p_2 \propto (1-\beta)\beta \quad \delta, \alpha, \beta ?$$

$$t \in [x \in p_2], \quad \theta = (\alpha, \beta, \delta)$$

$$p(x, t | \theta) = \delta^{1-t} p_1(x)^{1-t} (1-\delta)^t p_2(x)^t = \delta p_1(x) \left( \frac{p_2(x)(1-\delta)}{p_1(x)\delta} \right)^t$$

$$p(X, T | \theta) = \prod_n p(x_n, t_n | \theta) = \prod_n \delta p_1(x_n) \left( \frac{p_2(x_n)(1-\delta)}{p_1(x_n)\delta} \right)^{t_n}$$

$$\delta_{n+1} = \frac{\delta p_1(x_n | \theta)}{\delta p_1(x_n | \theta) + (1-\delta) p_2(x_n | \theta)} = q_n(t_n=0)$$

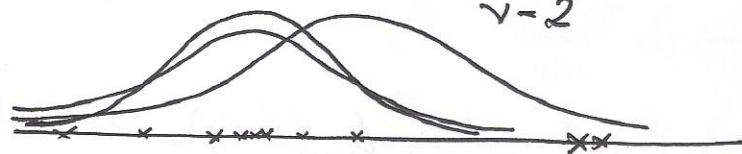
$$q_n(t_n=0) \Big|_{x_n=1} = \frac{\delta d}{\delta \alpha} = 1$$

$$\begin{aligned} \mathbb{E}_q \ln p(x, T | \theta) &= \mathbb{E}_q \sum_n \ln \delta p_1(x_n) + t_n (\ln p_2(x_n) + 1 - \delta) + \\ &+ \ln(1-\delta) - \ln p_1(x_n) - \ln \delta = \sum_n (\mathbb{E}_q t_n (\ln p_2(x_n) + \\ &+ \ln(1-\delta) - \ln p_1(x_n) - \ln \delta) + \ln \delta p_1(x_n)) \rightarrow \max_{\alpha, \beta, \delta} \end{aligned}$$

Распределение Стьюдента  $\sim$

$$x \in \mathbb{R}, \tau(x | \mu, \sigma^2, \gamma) \propto \left(1 + \frac{1}{\gamma} \left(\frac{x-\mu}{\sigma}\right)^2\right)^{-\frac{\gamma+1}{2}}$$

$$\mathbb{E}x = \mu, \mathbb{D}x = \sigma^2 \frac{\gamma}{\gamma-2}$$



устойчивость  
Стьюдента.

$$x \in \mathbb{R}^{dD}, \tau \propto \left(1 + \frac{1}{\gamma} (x-\mu)^T \Sigma^{-1} (x-\mu)\right)^{-\frac{\gamma+D}{2}}$$

$$\tau(x | \mu, \Sigma, \gamma) = \int_0^\infty N(x | \mu, \frac{1}{z} \Sigma) G(z | \frac{\gamma}{2}, \frac{\gamma}{2}) dz, z \in \mathbb{R}^+$$

$$x_1 \dots x_N \sim \tau(x | \mu, \Sigma, \gamma) \left\{ G(x | a, b) = \frac{b^a}{\Gamma(a)} x^{a-1} \exp(-bx) \right\}$$

$$p(x, z | \mu, \Sigma, \gamma) = N(x | \mu, \frac{1}{z} \Sigma) G(z | \frac{\gamma}{2}, \frac{\gamma}{2})$$

$$\underline{\Rightarrow}: q(z) = p(z | X, \theta) = \prod_n q_n(z_n)$$

$$q_n(z_n) = N(x_n | \mu, \frac{1}{z_n} \Sigma) G(z_n | \frac{\gamma}{2}, \frac{\gamma}{2}) \neq$$

$$\begin{aligned} &= \frac{1}{(2\pi)^{\frac{dD}{2}} \det \frac{1}{z_n} \Sigma} \exp\left(-\frac{1}{2} (x_n - \mu)^T \left(\frac{1}{z_n} \Sigma\right)^{-1} (x_n - \mu)\right) \cdot \\ &\quad \cdot \frac{\left(\frac{\gamma}{2}\right)^{\frac{\gamma}{2}}}{\Gamma(\frac{\gamma}{2})} z_n^{\frac{\gamma}{2}-1} \exp\left(-\frac{\gamma}{2} z_n\right) \quad (\Rightarrow) \end{aligned}$$



$$\frac{z_n^{\frac{D}{2} + \frac{\gamma}{2} - 1}}{(2\pi)^{\frac{W}{2}} \frac{1}{\Gamma(\frac{\gamma}{2})} \det \Sigma} \cdot \exp\left(-\frac{z_n}{2} (\gamma + (x_n - \mu)^T \Sigma^{-1} (x_n - \mu))\right) =$$

$$= G(z_n | \frac{D}{2} + \frac{\gamma}{2}, \frac{\gamma}{2} (\gamma + (x_n - \mu)^T \Sigma^{-1} (x_n - \mu)))$$

$$\begin{aligned} \mathcal{L}: \mathbb{E}_q \ln p(x, z | \theta) &= \mathbb{E}_q \sum_n \left( \frac{D}{2} \ln z_n - \frac{\gamma}{2} \ln \det \Sigma - \right. \\ &\quad \left. - \frac{z_n}{2} (x_n - \mu)^T \Sigma^{-1} (x_n - \mu) + \left(\frac{\gamma}{2} - 1\right) \ln z_n - \frac{\gamma z_n}{2} + \right. \\ &\quad \left. + \frac{\gamma}{2} \ln \frac{\gamma}{2} - \ln \Gamma\left(\frac{\gamma}{2}\right) \right) \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial \mu} \sum_n \mathbb{E}_q \left( -\frac{z_n}{2} (x_n - \mu)^T \Sigma^{-1} (x_n - \mu) \right) &= -\sum_n \mathbb{E}_q z_n \Sigma^{-1} (x_n - \mu) = 0 \\ -\sum_n \mathbb{E}_q z_n \Sigma^{-1} x_n + \sum_n \mathbb{E}_q z_n \Sigma^{-1} \mu &= 0, \quad \mu = \frac{\sum_n x_n \mathbb{E}_q z_n}{\sum_n \mathbb{E}_q z_n} \end{aligned}$$

13.10.16

$$p(x_k | d_k, \theta) = \prod_{i,j} \begin{cases} N(x_k(i,j) | F(i - d_k^h, j - d_k^w), s^2) & \text{если } (i,j) \in \text{faceArea}(d_k) \\ N(x_k(i,j) | B(i,j), s^2) & \text{иначе} \end{cases}$$

$$\theta = \{B, F, s^2\}, \quad \text{faceArea} = \{(i,j) | d_k^h \leq i \leq d_k^h + h - 1, d_k^w \leq j \leq d_k^w + w - 1\}$$

$x_k(i,j)$  - пиксель  $k$ -го изображения

$B \in \mathbb{R}^{h \times w}$  - маска чистого фона без лица преступника

$B(i,j)$  - пиксель маски

$F \in \mathbb{R}^{h \times w}$  - маска лица преступника,  $F(i,j)$  - пиксель маски

$d_k = (d_k^h, d_k^w)$  - координаты верхнего левого угла маски лица на  $k$ -ом изображении,  $d = (d_1, \dots, d_K)$  для всех.

Распределение на неизвестные координаты лица:

$$A \in \mathbb{R}^{h-h+1, w-w+1}, \quad p(d_k | A) = A(d_k^h, d_k^w)$$

$$\sum_{i,j} A(i,j) = 1$$

$$p(X, d | \theta, A) = \prod_k p(x_k | d_k, \theta) p(d_k | A)$$

$$p(X | \theta, A) \rightarrow \max_{\theta, A}$$

$$\mathcal{L}(q, \theta, A) = \mathbb{E}_{q(d)} \ln p(X, d | \theta, A) - \mathbb{E}_{q(d)} \ln q(d) \rightarrow \max_{q, \theta, A}$$

$$\mathbb{E}: q(d) = p(d | X, \theta, A) = \prod_k p(d_k | x_k, \theta, A)$$

$$\mathcal{U}: \mathbb{E}_{q(d)} \ln p(X, d | \theta, A) =$$

$$= \mathbb{E}_{q(d_k)} \sum_k \ln p(x_k, d_k | \theta, A) =$$

$$= \sum_k \mathbb{E}_{q(d_k)} \ln p(x_k, d_k | \theta, A) \rightarrow \max_{\theta, A}$$

$$1) / p(d_k | x_k, \theta, A) = \frac{p(x_k | d_k, \theta, A) \cdot p(d_k | \theta, A)}{p(x_k | \theta, A)} =$$

$$\frac{A(d_k^h, d_k^w)}{p(x_k | d_k, \theta, A) \cdot p(d_k | \theta, A)}$$

$$q(d_k) \frac{\sum_k p(x_k, d_k | \theta, A)}{p(x_k | \theta, A)}$$

$$p(d_k | x_k, \theta, A) = \frac{p(d_k, x_k | \theta, A)}{p(x_k | \theta, A)} = \frac{p(x_k | d_k, \theta) p(d_k | A)}{p(x_k | \theta, A)}$$

$$= \frac{p(x_k | d_k, \theta) p(d_k | A)}{\sum_{i,j} p(x_k | d_k, \theta) p(d_k | A)}$$

$$\sum_{i,j} p(x_k | d_k, \theta) p(d_k | A)$$

$$\begin{matrix} 0 \leq i \leq H-h \\ 0 \leq j \leq W-w \end{matrix}$$

$$\{i, j \in \text{face Area}(d_k)\}$$

$$2) \mathbb{E}_{q(d_k)} \ln p(x_k, d_k | \theta, A) \rightarrow \max_{\theta, A}$$

$$\mathbb{E}_{q(d_k)} (\ln p(x_k | d_k, \theta) + \ln p(d_k | A)) =$$

$$= \mathbb{E}_{q(d_k)} \ln p(x_k | d_k, \theta) + \mathbb{E}_{q(d_k)} \ln p(d_k | A)$$

$$\mathbb{E}_{q(d_k)} \ln p(x_k | d_k, \theta) \rightarrow \max_{\theta}$$

$$\mathbb{E}_{q(d_k)} \ln A(d_k^h, d_k^w) \rightarrow \max_A$$

$$\mathbb{E}_{q(d_k)} \ln p(d_k | A) \rightarrow \max_A$$

$$\sum_{i,j} q(d_k) \ln A(d_k^h, d_k^w) \rightarrow \max_A$$