

$$\ell(x|\theta) \rightarrow \max_{\theta}; \hat{\theta}_{ML}$$

z - латентная (ненабл.) переменная.
 $(1 \dots K)$

$$\underbrace{\ell(x|\theta)}_{\text{неполное}} \rightarrow \underbrace{\ell(x, z|\theta)}_{\text{полное}} \quad p(x) \begin{matrix} \nearrow P\{x=x\} \\ \searrow f_x(z) \end{matrix}$$

$$\begin{aligned} \ell(x|\theta) &= \sum_i \ln p(x_i|\theta) = \sum_i \sum_j P\{z=j\} \ln p(x_i|\theta) = \\ &= \sum_i \sum_j P\{z=j\} \ln \frac{p(z=j, x_i|\theta) \cdot P\{z=j\}}{p(z=j|x_i, \theta) \cdot P\{z=j\}} = \end{aligned}$$

$$= \sum_i \sum_j P\{z=j\} \ln \frac{p(z=j, x_i|\theta)}{P\{z=j\}} + \quad M(p(z), p(z, x|\theta))$$

$$+ \sum_i \sum_j P\{z=j\} \ln \frac{P\{z=j\}}{p(z=j|x_i, \theta)}$$

$$\underbrace{\hspace{10em}}_{KL(\underbrace{p(z)}_{\text{prior}} \parallel \underbrace{p(z|x, \theta)}_{\text{posterior}})}$$

$$\ell(x|\Theta) = \underbrace{M(p(z), p(z, x|\Theta))}_{\text{мнимая оценка на } \ell(x|\Theta)} + \underbrace{KL(p(z) \parallel p(z|x, \Theta))}_{\approx 0}$$

$$\begin{matrix} z_1 & z_2 & \dots & z_k \\ p_1 & p_2 & \dots & p_k \end{matrix}$$

$$\underline{E\text{-max}} : M(p(z), p(z, x|\Theta)) \rightarrow \max_{p(z)}$$

\Leftrightarrow

$$KL(p(z) \parallel p(z|x, \Theta)) \rightarrow \min_{p(z)}$$

$$\Rightarrow p(z)^* = p(z|x, \Theta_{old}) = q$$

$$\underline{M\text{-max}} : M(\dots, \dots) \rightarrow \max_{\Theta}$$

$$M = \sum_i \sum_j \underbrace{P\{z=j\}}_{p(z)^* = g_{ij}} \ln \underbrace{p(z=j, x_i|\Theta)}_{p(z)^* = g_{ij}} \sim$$

$$\sim \sum_i \sum_j \underbrace{P\{z=j\}}_{g_{ij}} \ln p(z=j, x_i|\Theta) \rightarrow \max_{\Theta}$$

$= Q(\Theta, \Theta_{old})$

EM-алгоритм

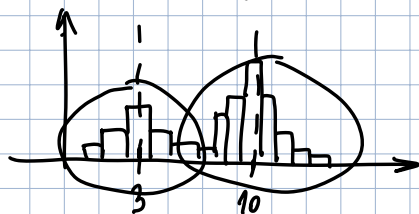
Init: $\Theta_{old} = \left[\underbrace{\text{--- } \Theta \text{ ---}}_{\text{парам. модели}}, \underbrace{p_1 \dots p_k}_{p(z)} \right]$

E-шаг: $p(z)^* = p(z | X, \Theta_{old}) \rightarrow \begin{matrix} p(z=1)^* \\ \vdots \\ p(z=k)^* \end{matrix}$

M-шаг: $Q(\Theta, \Theta_{old}) \rightarrow \Theta$

Разделение смеси норм. распрег.

$X_1 \dots X_n \xrightarrow{z=1} N(\mu_1, \sigma_1^2) \quad z \in \{1, 2\}$
 $\xrightarrow{z=2} N(\mu_2, \sigma_2^2)$



$$\begin{aligned} p_1 &:= P\{z=1\} \\ p_2 &:= P\{z=2\} = 1 - p_1 \end{aligned}$$

Init: $\Theta_{old} := \left[\underbrace{\mu_1; \sigma_1^2}_3; \underbrace{\mu_2; \sigma_2^2}_{10}; \underbrace{p_1}_{0.5} \right]$

E-шаг: $p(z=1)^* := p(z=1 | X, \Theta)$

$$p(z_i=1 | x_i, \Theta) = \frac{p(z_i=1, x_i | \Theta)}{p(x_i | \Theta)}$$

$$\begin{aligned}
&= \frac{p(x_i | z_i=1, \Theta) \cdot p(z_i=1)}{p(x_i | z_i=1, \Theta) \cdot p(z_i=1) + p(x_i | z_i=2, \Theta) p(z_i=2)} \\
&= \frac{\frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2}\left(\frac{x_i - \mu_1}{\sigma_1}\right)^2} \cdot p_1}{\left[\frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2}\left(\frac{x_i - \mu_1}{\sigma_1}\right)^2} \cdot p_1 \right. \\
&\quad \left. + \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{1}{2}\left(\frac{x_i - \mu_2}{\sigma_2}\right)^2} \cdot (1-p_1) \right]} \\
&= g_i
\end{aligned}$$

M-max: $Q(\Theta, \Theta_{old})$

$$Q(\Theta, \Theta_{old}) = \sum_i \sum_j g_{ij} \times \ln p(z=j, x_i | \Theta) \rightarrow \max_{\Theta}$$

$$\begin{aligned}
Q &= \sum_i \overset{P\{z=1\}}{g_i} \ln \left(p(x_i | z=1, \Theta) \cdot p_1 \right) + \\
&+ (1-g_i) \ln \left(p(x_i | z=2, \Theta) \cdot p_2 \right) = \\
&\quad \uparrow \text{" } P\{z=2\} = 1 - P\{z=1\} \text{ " }
\end{aligned}$$

$$= \sum_i g_i \left(\ln \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{1}{2}\left(\frac{x_i - \mu_1}{\sigma_1}\right)^2} + \ln p_1 \right) +$$

$$+ (1 - g_i) \left(\ln \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2}\left(\frac{x_i - \mu_2}{\sigma_2}\right)^2} + \ln (1 - p_1) \right).$$

$$\rightarrow \max_{\Theta} \equiv \max_{\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, p_1}$$

$$Q'_{\mu_1} = \left[\sum_i g_i \left(-\frac{1}{2} \ln(2\pi\sigma_1^2) - \frac{1}{2} \left(\frac{x_i - \mu_1}{\sigma_1} \right)^2 \right) \right]_{\mu_1}' =$$

$$= \sum_i g_i \frac{(x_i - \mu_1)}{\sigma_1^2}$$

$$\sum_i g_i \frac{(x_i - \hat{\mu}_1)}{\hat{\sigma}_1^2} = 0 \Rightarrow \sum_i g_i x_i - \sum_i g_i \hat{\mu}_1 = 0$$

$$\hat{\mu}_1 = \frac{\sum_i g_i x_i}{\sum_i g_i}$$

$$\Theta_{\text{new}} := (\hat{\mu}_1, \hat{\sigma}_1^2, \hat{\mu}_2, \hat{\sigma}_2^2, \hat{p}_1)$$

↪ E-max

$$\hat{\mu}_2 = \frac{\sum_i (1 - g_i) x_i}{\sum_i (1 - g_i)}$$

$$\hat{\sigma}_1^2 = \dots, \hat{\sigma}_2^2 = \dots$$

$$\hat{p}_1 = \dots$$