

$\{\bar{x}_1, \dots, \bar{x}_N\} = X$  - данные

$p(x|\theta) \rightarrow \max$  трудно

$\{\bar{z}_1, \dots, \bar{z}_N\} = Z$  - скрытые перемен.

$p(x, z|\theta) \rightarrow \max$  легко

$$\log p(x|\theta) - \log p(x|\theta^{(m)}) =$$

$$= \log \int p(x, z|\theta) dz - \ell^{(m)} = \log \int p(x|z, \theta) p(z|\theta) dz - \ell^{(m)}$$

$$= \log \int \left( \frac{p(x|z, \theta) p(z|\theta)}{p(z|x, \theta^{(m)})} \right) p(z|x, \theta^{(m)}) dz - \ell^{(m)} \geq \mathbb{E}_{p(z|x, \theta^{(m)})} [\dots]$$

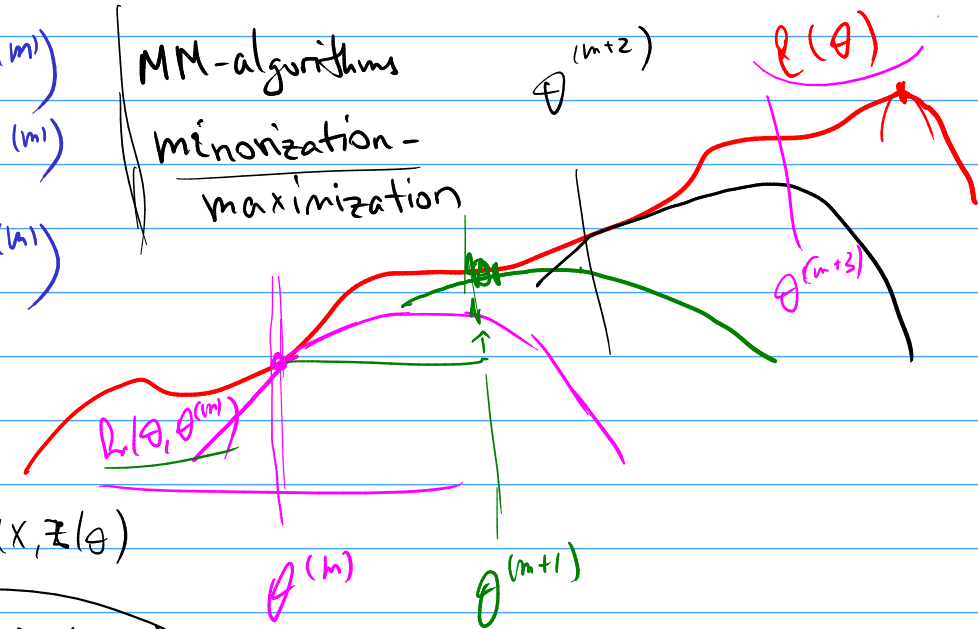
$$\geq \int p(z|x, \theta^{(m)}) \log \frac{p(x|z, \theta) p(z|\theta)}{p(z|x, \theta^{(m)})} dz - \log p(x|\theta^{(m)})$$

$$= \int \log \frac{p(x|z, \theta) p(z|\theta)}{p(z|x, \theta^{(m)}) p(x|\theta^{(m)})} p(z|x, \theta^{(m)}) dz$$

$$\log p(x|\theta) \geq \log p(x|\theta^{(m)}) + \int \dots dz = \ell(\theta, \theta^{(m)})$$

$\forall \theta \quad \ell(\theta) \geq \ell(\theta, \theta^{(m)})$   
 $\ell(\theta^{(m)}) = \ell(\theta^{(m)}, \theta^{(m)})$   
 $\theta^{(m+1)} = \arg \max_{\theta} \ell(\theta, \theta^{(m)})$

MM-algorithms  
 minorization-maximization

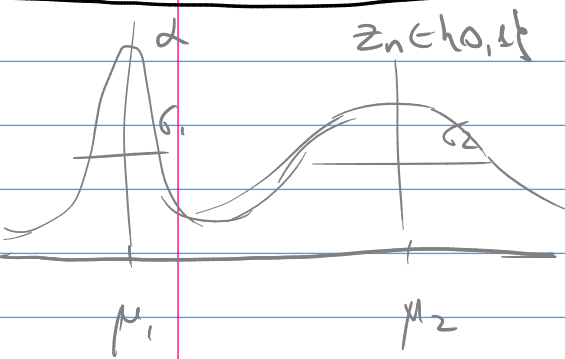


$\nearrow \max_{\theta}$

$$\ell(\theta, \theta^{(m)}) = \int \log \frac{p(x|z, \theta) p(z|\theta)}{p(z|x, \theta^{(m)}) p(x|\theta^{(m)})} p(z|x, \theta^{(m)}) dz$$

EM-algorithm:  $m$ -var:  $\theta^{(m+1)} := \arg \max_{\theta} Q(\theta, \theta^{(m)})$ , see

E-war:  $Q(\theta, \theta^{(m)}) = \int \log p(x, z | \theta) p(z | x, \theta^{(m)}) dz$



$p(x_n | \theta) = \alpha N(x_n | \mu_1, \sigma_1) + (1-\alpha) N(x_n | \mu_2, \sigma_2)$   
 $p(x_n, z_n | \theta) = \left[ \alpha N(x_n | \mu_1, \sigma_1) \right]^{z_n} \left[ (1-\alpha) N(x_n | \mu_2, \sigma_2) \right]^{1-z_n}$

$\log p(x, z | \theta) = \log \prod_n p(x_n, z_n | \theta) =$

$= \sum_n \left[ z_n \log \alpha N(x_n | \mu_1, \sigma_1) + (1-z_n) \log \left[ (1-\alpha) N(x_n | \mu_2, \sigma_2) \right] \right]$

$Q(\theta, \theta^{(m)}) = \int \sum_n \left[ \dots \right] p(z | x, \theta^{(m)}) dz =$

$E_{\theta^{(m)}} [z_n^2]$

$= \sum_n \left( \log \alpha N(x_n | \mu_1, \sigma_1) \cdot E_{z|x, \theta^{(m)}} [z_n] + \log \left[ (1-\alpha) N(x_n | \mu_2, \sigma_2) \right] \cdot \left( 1 - E_{z|x, \theta^{(m)}} [z_n] \right) \right)$

E-war:  $E_{z|x, \theta^{(m)}} [z_n] = p(z_n=1 | x, \theta^{(m)}) = \frac{\alpha N_1(x_n)}{\alpha N_1(x_n) + (1-\alpha) N_2(x_n)}$

1)  $Q(\theta, \theta^{(m)}) \rightarrow \max$

$y = (x, z) \quad \int \log p(y | \theta) p(z | x, \theta^{(m)}) dz$

$y = f(x, z)$

$y_n = f(x_n, z_n)$

$\int \log p(f(x, z) | \theta) p(z | x, \theta^{(m)}) dz$

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

$Q(\theta, \theta^{(m)}) = E_{z|x, \theta^{(m)}} \left[ \log p(x, z | \theta) \right]$

2)  $E_{\theta^{(m)}} z = \{ \bar{z}_1, \dots, \bar{z}_n \}$   
 $X = \{ \bar{x}_1, \dots, \bar{x}_n \}$

$= \sum_{n=1}^N E_{\bar{z}_n | \bar{x}_n, \theta^{(m)}} \left[ \log p(\bar{x}_n, \bar{z}_n | \theta) \right]$

### 3) Generalized EM



$$l(\theta) \approx l(\theta, \theta^{(m)})$$

$$\theta': l(\theta', \theta^{(m)}) > l(\theta^{(m)}, \theta^{(m)})$$

$$\underline{l(\theta') > l(\theta)}$$

### 4) Stochastic EM $Q(\theta, \theta^{(m)}) = \mathbb{E}_{z|X, \theta^{(m)}} [\log p(X, z | \theta)]$

Monte Carlo EM  $z_1^{(m)}, \dots, z_R^{(m)} \sim p(z | X, \theta^{(m)})$

$$\hat{Q}(\theta, \theta^{(m)}) = \frac{1}{R} \sum_{z=1}^R \log p(X, z_z^{(m)} | \theta) \xrightarrow{\theta} \max$$

$$p(X, z | \theta) = \prod_n (\alpha N_1(\bar{x}_n))^{z_n} ((1-\alpha) N_2(\bar{x}_n))^{1-z_n}$$

$\bar{x}_n: z_{n1}, z_{n2}, \dots, z_{nR}$

$$\sum_n \sum_z [z_{nz} \log(-) + (1-z_{nz}) \log(-)]$$

### 5) $\theta_{MAP} = \underset{\theta}{\operatorname{argmax}} \log p(\theta | X) = \underset{\theta}{\operatorname{argmax}} [\log p(X | \theta) + \log p(\theta)]$

$$Q(\theta, \theta^{(m)}) = \mathbb{E}_{z|X, \theta^{(m)}} [\log p(X, z | \theta)] \leq \log p(X | \theta)$$

$$\theta^{(m+1)} = \underset{\theta}{\operatorname{argmax}} [Q(\theta, \theta^{(m)}) + \log p(\theta)]$$

### 6) Semi-supervised learning

- fix  $z_n$

