

$\frac{1}{1+e^{-\eta(\bar{x})}}$   
 $\frac{e^{\eta(\bar{x})}}{1+e^{\eta(\bar{x})}}$

$\sigma(\eta(\bar{x})) = p(y=1|\bar{x})$

features      topology      bias/variance

$S=1$   
 $S=0$

$\pi = p(y=1)$

$\delta_0 = p(S=1|y=0) = \frac{p(S=1, y=0)}{p(y=0)} = \frac{n_0/N}{(1-\pi)N/N} = \frac{n_0}{(1-\pi)N}$

$\delta_1 = p(S=1|y=1) = \frac{n_1}{\pi N}$

$1 - \sigma(\eta(\bar{x})) = \frac{1}{1+e^{\eta(\bar{x})}}$

$p(y=1|\bar{x}, S=1) = \frac{p(S=1|y=1, \bar{x}) p(y=1|\bar{x})}{p(S=1|y=1, \bar{x}) p(y=1|\bar{x}) + p(S=1|y=0, \bar{x}) p(y=0|\bar{x})}$

$= \frac{\delta_1 \sigma(\eta(\bar{x}))}{\delta_1 \sigma(\eta(\bar{x})) + \delta_0 (1 - \sigma(\eta(\bar{x})))}$

$= \frac{\delta_1 / \delta_0 e^{\eta(\bar{x})}}{\frac{\delta_1}{\delta_0} e^{\eta(\bar{x})} + \delta_0 \cdot 1} = \sigma\left(\log \frac{\delta_1}{\delta_0} + \eta(\bar{x})\right)$

$\frac{n_0, n_1}{N}$        $\sigma(\eta^*(\bar{x})) = p(y=1|\bar{x}, S=1)$

$\eta(\bar{x}) = \eta^*(\bar{x}) - \log \frac{\delta_1}{\delta_0} = \eta^*(\bar{x}) - \log \frac{n_1}{n_0} + \log \frac{\pi}{1-\pi}$

Presence-only:       $n_p$  - positive       $z=1, y=1$   
                           $n_u$  - unknown       $z=0, y=?$

$p(y=1|s=1) = \frac{p(y=1, s=1)}{p(s=1)} = \frac{(n_p + \pi n_u)/N}{(n_p + n_u)/N} = \frac{n_p + \pi n_u}{n_p + n_u}$

$p(y=0|s=1) = \frac{(1-\pi)n_u}{n_p + n_u}$

$\delta_1 = p(S=1|y=1) = \frac{p(y=1|s=1) p(s=1)}{p(y=1)} = \frac{n_p + \pi n_u}{\pi(n_p + n_u)} \cdot p(s=1)$

$\delta_0 = p(S=1|y=0) = \frac{(1-\pi)n_u}{(1-\pi)(n_p + n_u)} p(s=1) = \frac{n_u}{n_p + n_u} p(s=1)$

$\sigma(\eta_{naive}^*(\bar{x})) = p(\underline{z}=1|\bar{x}, s=1)$

$\eta_{naive}^*(\bar{x}) = \eta_{naive}^*(\bar{x}) - \log \frac{n_p + \pi n_u}{\pi n_u}$

$$z, y \quad L(\bar{y} | \bar{y}_1, \bar{z}, X) = \prod_i p(y_i | s_i=1, \bar{x}_i) = \prod_i \sigma(\eta^*(\bar{x}_i))^{y_i} (1 - \sigma(\eta^*(\bar{x}_i)))^{1-y_i}$$

$$L(\bar{\eta} | \bar{z}, X) = \prod_i p(z_i | s_i=1, \bar{x}_i) = \prod_i p(z_i=1 | s_i=1, \bar{x}_i)^{z_i} (1 - p(z_i=1 | s_i=1, \bar{x}_i))^{1-z_i} = \text{---} \times$$

$$p(z=1 | s=1, \bar{x}) = p(z=1 | y=1, s=1) p(y=1 | s=1, \bar{x}) + p(z=1 | y=0, s=1, \bar{x}) p(y=0 | s=1, \bar{x}) = \frac{\sigma(\eta^*(\bar{x}))}{1 - \eta^*(\bar{x})}$$

$$\frac{\sigma(\eta^*(\bar{x}))}{1 - \eta^*(\bar{x})} \cdot \frac{p(z=1, y=1 | s=1)}{p(y=1 | s=1)} = \sigma(\eta^*(\bar{x})) \cdot \frac{n_p / n_{p+n_u}}{(n_p + \pi n_u) / n} = \frac{n_p}{n_p + \pi n_u} \eta^*(\bar{x})$$

$$\text{---} \times = \prod_i \left( \frac{n_p}{n_p + \pi n_u} \cdot \frac{\frac{n_p + \pi n_u}{\pi n_u} \cdot e^{\eta(\bar{x}_i)}}{1 + \frac{n_p + \pi n_u}{\pi n_u} \cdot e^{\eta(\bar{x}_i)}} \right)^{z_i} \left( 1 - \frac{\dots}{\dots} \right)^{1-z_i} \xrightarrow{\bar{z}} \max$$

E-var:  $\sigma(\eta^{*(t+1)}(\bar{x}_i)) = E_{(t)}[y_i] = \sigma(\eta^{(t)}(\bar{x}_i))$

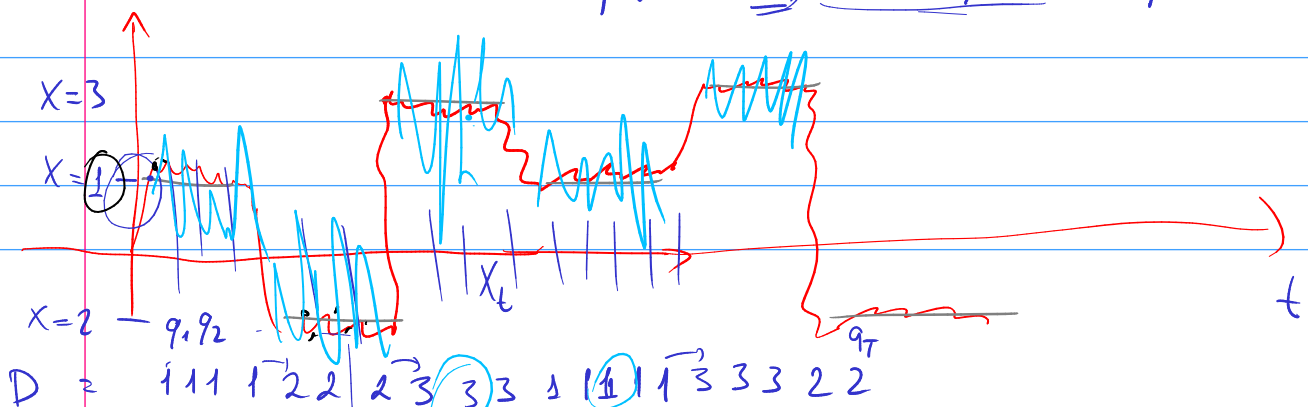
M-var:  $\eta^{(t+1)} = \eta^{*(t+1)} - \log \frac{n_p}{n_p + \pi n_u}$

### Markov chains



$X_1, X_2, \dots, X_{t-1}, X_t, X_{t+1}, \dots$

$$p(X_{t+1} | X_t, X_{t-1}, X_{t-2}, \dots, X_1) = p(X_{t+1} | X_t)$$



$$a_{ij} = p(X_t = j | X_{t-1} = i)$$

$$\pi_i = p(X_1 = i)$$

$$A = (a_{ij})_{i,j=1}^n$$

n - rows  
columns

$$p(D | A, \pi) = \prod_{n=1}^N p(X_1 = q_{1N}) p(X_2 = q_{2N} | X_1 = q_{1N}) p(X_3 = q_{3N} | X_2 = q_{2N}) \dots p(X_T = q_{TN} | X_{T-1} = q_{(T-1)N})$$

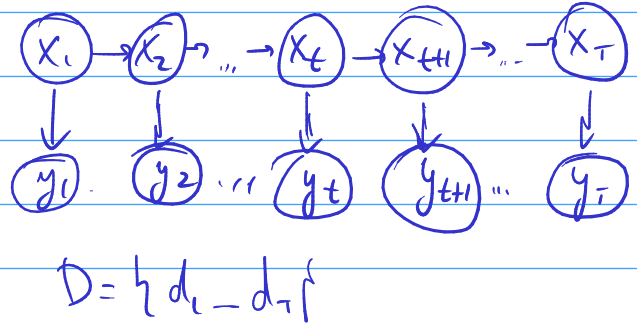
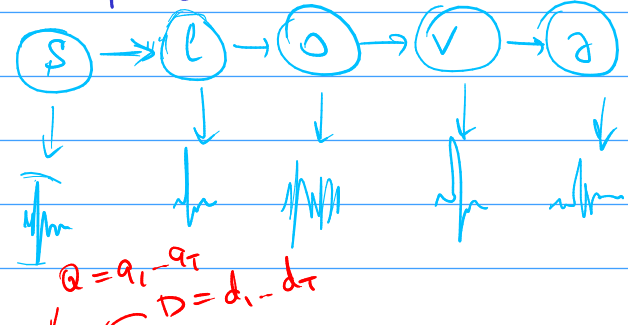
$$= \prod_{n=1}^N \pi_{q_{1N}} a_{q_{1N} q_{2N}} a_{q_{2N} q_{3N}} \dots a_{q_{(T-1)N} q_{TN}} \xrightarrow{\pi, A} \max$$

$$q_{1N} q_{2N} \dots q_{TN}$$

$$\ln p(D | A, \pi) = \sum_n \left( \log \pi_{q_{1N}} + \sum_t \log a_{q_{nt}, q_{n,t+1}} \right)$$

$$\pi_i^* = \frac{\#\{q_{1N} = i\}}{N}; a_{ij}^* = \frac{\#\{q_{nt} = i, q_{n,t+1} = j\}}{\#\{q_{nt} = i\}}$$

### Hidden Markov Model



$$p(X, Y) = p(x_1) p(y_1 | x_1) p(x_2 | x_1) p(y_2 | x_2) p(x_3 | x_2) \dots p(x_T | x_{T-1}) p(y_T | x_T)$$

$$\lambda = (\pi, A, B)$$

$$\pi_i = p(x_1 = i)$$

$$a_{ij} = p(x_{t+1} = j | x_t = i)$$

$$b_i(k) = p(y_t = v_k | x_t = i)$$

emission probabilities  $v_1, \dots, v_m$

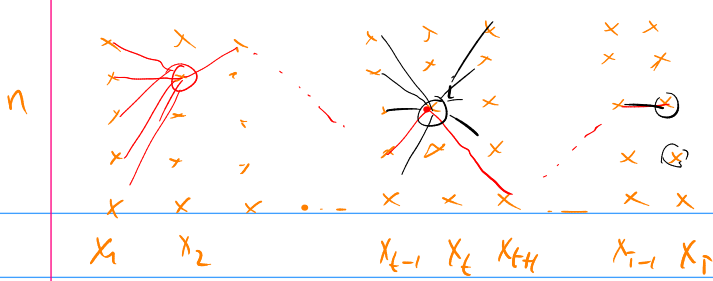
$$p(Q, D | X) = \frac{\pi_{q_1} b_{q_1}(d_1) a_{q_1 q_2} b_{q_2}(d_2) a_{q_2 q_3} \dots a_{q_{T-1} q_T} b_{q_T}(d_T)}{\#\{q_{nt} = i, d_{nt} = v_k\} / \#\{q_{nt} = i\}}$$

$$b_i^*(v_k) = \frac{\#\{q_{nt} = i, d_{nt} = v_k\}}{\#\{q_{nt} = i\}}$$

$$p(D | X) = \sum_Q p(Q, D | \lambda) =$$

$$= \sum_{q_1, \dots, q_T} (\pi_{q_1} \dots b_{q_T}(d_T))$$

- ①  $p(D | X) = ?$   $d_t(i) \checkmark$   
 $\beta_t(i)$
- ②  $Q^* = \underset{Q}{\operatorname{argmax}} p(Q | D, X)$
- $q_t^* = \underset{q_t}{\operatorname{argmax}} p(q_t | D, X)$
- ③  $p(D | X) \xrightarrow{\pi, A, B} \max$



Q - najsve enaka konjunktio  
 $p(D|\lambda) = \sum_Q p(Q, D|\lambda)$

$x_t \in \{1, \dots, n\}$

$\alpha_t(i) = p(x_t = i, d_1, d_2, \dots, d_t | \lambda)$   
 $\alpha_1(i) = p(x_1 = i, d_1 | \lambda) = \pi_i \cdot b_i(d_1)$   
 $\alpha_{t+1}(i) = \left( \sum_{j=1}^n \alpha_t(j) \cdot a_{ji} \right) \cdot b_i(d_{t+1})$   
 $p(D|\lambda) = \sum_i p(x_T = i, D|\lambda) = \sum_{i=1}^n \alpha_T(i)$

$\beta_t(i) = p(d_{t+1}, d_{t+2}, \dots, d_T | x_t = i, \lambda)$   
 $\beta_T(i) = 1$   
 $\beta_t(i) = \sum_{j=1}^n \beta_{t+1}(j) \cdot a_{ij} \cdot b_j(d_{t+1})$   
 $p(D|\lambda) = \sum_i p(x_1 = i, D|\lambda) = \sum_i \pi_i \cdot \beta_1(i)$

②  $\delta_t(i) = p(x_t = i | D, \lambda)$   
 $\delta_t(i) \propto \alpha_t(i) \beta_t(i)$

$\alpha_{t+1}(i) = p(x_{t+1} = i, d_1, \dots, d_{t+1} | \lambda) =$   
 $= \sum_{j=1}^n p(x_{t+1} = i, x_t = j, d_1, \dots, d_{t+1} | \lambda) =$   
 $= \sum_{j=1}^n p(x_t = j, d_1, \dots, d_t | \lambda) p(x_{t+1} = i | x_t = j, d) =$   
 $p(x_{t+1} = i | x_t = i, \lambda) =$

$\beta_t(i) = \sum_{j=1}^n p(x_{t+1} = j, d_{t+1}, \dots, d_T | x_t = i, \lambda) =$   
 $= \sum_{j=1}^n p(d_{t+2}, \dots, d_T | x_{t+1} = j, \lambda) \cdot p(d_{t+1} | x_{t+1} = j, \lambda) p(x_{t+1} = j | x_t = i, \lambda)$

$\delta_t(i) = \frac{p(x_t = i, D | \lambda)}{p(D | \lambda)} = \frac{p(x_t = i, d_1, \dots, d_t, d_{t+1}, \dots, d_T | \lambda)}{p(D | \lambda)}$   
 $= \frac{p(x_t = i, d_1, \dots, d_t | \lambda) \cdot p(d_{t+1}, \dots, d_T | x_t = i, \lambda)}{p(D | \lambda)}$

$Q^* = \operatorname{argmax}_{q_1, \dots, q_T} p(Q | D, \lambda)$   
 $\delta_t(i) = \max_{q_1, \dots, q_{t-1}} p(q_t = i, q_1, \dots, q_{t-1}, d_1, \dots, d_t | \lambda)$   
 $\delta_{t+1}(i) = \max_j [\delta_t(j) \cdot a_{ji} \cdot b_i(d_{t+1})]$

$\delta_t(i) = \max_{q_1, \dots, q_{t-1}} p(q_t = i, d_1, \dots, d_t | \lambda) =$   
 $= \max_{q_1, \dots, q_{t-2}} \max_j p(q_t = i, q_{t-1} = j, q_1, \dots, q_{t-2}, d_1, \dots, d_t | \lambda)$   
 $= p(q_{t-1} = j, q_1, \dots, q_{t-2}, d_1, \dots, d_{t-1} | \lambda) \cdot p(q_t = i | q_{t-1} = j, \lambda) p(d_t | q_t = i, \lambda)$

Baum-Welch algorithm

③  $p(D|\lambda) \xrightarrow{\lambda} \max$  E-war!  $\lambda, D \rightsquigarrow [\alpha_t(i), \beta_t(i), \delta_t(i), \zeta_t(i, j)]$   
 $p(Q, D|\lambda) \xrightarrow{\lambda} \max$   $\zeta_t(i, j) = p(q_t = i, q_{t+1} = j | D, \lambda) \propto \alpha_t(i) a_{ij} b_j(d_{t+1}) \beta_{t+1}(j)$

M-war:  $\pi_i^* = \frac{E[\#\{q_{nt} = i\}]}{N} = \frac{\sum_n \delta_{nt}(i)}{N}$   
 $a_{ij}^* = \frac{E[\#\{q_{nt} = i, q_{nt+1} = j\}]}{E[\#\{q_{nt} = i\}]} = \frac{\sum_n \sum_t \zeta_t(i, j)}{\sum_n \sum_t \delta_t(i)}$   
 $b_j(v_k) = \frac{E[\#\{q_{nt} = i, d_{nt} = v_k\}]}{E[\#\{q_{nt} = i\}]} = \frac{\sum_{n, t: d_{nt} = v_k} \delta_t(i)}{\sum_n \sum_t \delta_t(i)}$

Непрерывные наблюдения:

$\beta \rightsquigarrow p(y|\bar{x}, \bar{\theta})$

$b_i(d_t) \rightsquigarrow p(d_t|x=i, \theta)$

$\mu_i, \Sigma_i$

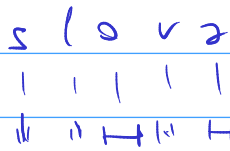
$\Rightarrow \bar{\mu}_i^*$

$\frac{\sum_{n,t} \delta_{nt}(i) d_{nt}}{\sum_{n,t} \delta_{nt}(i)}$

Оценки  $\theta^*$  по формуле с весами  $\delta_{nt}(i)$

Время наблюдения

$A \quad p(\text{в оср. } i \text{ } k \text{ раз}) = \frac{k-1}{a_{ii}} (1-a_{ii})$



$p(\dots k \text{ раз}) = \text{Gam}(k|\dots) \quad C_i(k) = p(\text{в оср. } i \text{ } k \text{ раз})$   
 $\uparrow$   
 $d_t^+(i), d_t^-(i)$