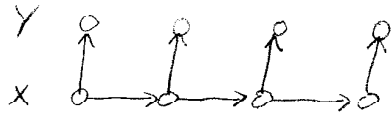


Extension



$$P\{x_0 = i\} = \pi_i \quad i = 1, \dots, M$$

$$p(y_s | x_s) \sim N(\mu_{x_s}, \sigma_{x_s}^2)$$

$$p(y | x) = \prod_{s=1}^n p(y_s | x_s)$$

$$P_{ij} = P\{x_s = j | x_{s-1} = i\}$$

Each element is a vector

$$\theta = [\pi, P, \mu, \gamma]$$

↑
matrix

$$\hat{\theta} = \operatorname{argmax}_{\theta \in \Omega} P\{Y=y | \theta\}$$

$$\Omega = \left\{ \theta : \sum_{i=1}^M \pi_i = 1, \sum_{j=1}^M P_{ij} = 1 \quad \forall i \right\}$$

Lecture 31

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

$$Q(\theta', \theta) = E[\log p(Y, x|\theta) | Y=y, \theta]$$

$$= E[\log p(Y|x|\theta') | Y=y, \theta] \quad 1^{st} \text{ term}$$

$$+ E[\log p(x|\theta') | Y=y, \theta] \quad 2^{nd} \text{ term}$$

1st term same as previous example

$$= \sum_{j=1}^M \sum_{s=1}^N \left\{ \frac{1}{2\sigma_j^2} (y_s - \mu_j')^2 + \frac{1}{2} \log(2\pi\sigma_j^2) \right\} P\{X_s = j' | Y=y, \theta\}$$

$$f_s(j|\theta) \triangleq P\{X_s = j' | Y=y, \theta\}$$

2nd term = ?

$$\log p(x|\theta') = \log \left\{ \pi_{x_1}' \prod_{s=1}^{N-1} \rho_{x_s x_{s+1}}' \right\}$$

Define

$$\begin{aligned} \tau_i &= \delta(x_1 - i) \\ &= \# \text{ of } x_1's = i \end{aligned}$$

$$K_{i,j} = \# \text{ of } (X_s = i, X_{s+1} = j) \text{ pairs}$$

$$\log p(x|\theta') = \log \left(\left(\prod_{i=1}^M \pi_i' \tau_i \right) \left(\prod_{i=1}^M \prod_{j=1}^M p_{ij}'^{K_{ij}} \right) \right)$$

$$= \sum_{i=1}^M \tau_i \log \pi_i' + \sum_{i=1}^M \sum_{j=1}^M K_{ij} \log p_{ij}'$$

$$E[\log p(X|\theta') | Y=y, \theta]$$

$$= \sum_{i=1}^M \bar{\tau}_i \log \pi_i' + \sum_{i=1}^M \sum_{j=1}^M \bar{K}_{ij} \log p_{ij}'$$

$$\bar{\tau}_i = P\{X_1=i | Y=y, \theta\} = f_1(i|\theta)$$

$$\bar{K}_{ij} = E[K(i,j) | Y=y, \theta]$$

$$= \sum_{s=1}^{N-1} \underbrace{P\{X_s=i, X_{s+1}=j | Y=y, \theta\}}_{g_s(i,j|\theta)}$$

M-step

$$Q(\theta', \theta) =$$

$$\sum_{s=1}^N \sum_{j=1}^M \left\{ \frac{1}{2\delta_j'} (y_s - \mu_j')^2 + \frac{1}{2} \log(2\pi\delta_j') \right\} f_s(j|\theta)$$

$$+ \sum_{i=1}^M \bar{v}_i \log \pi_i' + \sum_{i,j=1}^M \bar{K}_{i,j'} \log P_{i,j'}$$

maximize with respect to π, P, μ, δ

1) From previous example

$$\text{for } j=1, \dots, M \quad \bar{N}_j' = \sum_{s=1}^N f_s(j|\theta)$$

$$\hat{\mu}_j' = \frac{1}{\bar{N}_j'} \sum_{s=1}^N y_s f_s(j|\theta)$$

$$\hat{\delta}_j' = \frac{1}{\bar{N}_j'} \sum_{s=1}^N (y_s - \hat{\mu}_j')^2 f_s(j|\theta)$$

2) Maximize P_{ij} subject to $\sum_{j=1}^M P_{ij} = 1$
constraint

Use Lagrange Multipliers λ_i

$$\frac{2}{2P_{m,n}} \left\{ \sum_{i,j} \bar{K}_{i,j} \log P_{ij} + \sum_{i=1}^M \lambda_i \sum_{j=1}^M P_{ij} \right\} \bigg|_{P=\hat{P}} = 0$$

$$\frac{\bar{K}_{m,n}}{\hat{P}_{m,n}} + \lambda_m = 0$$

$$\hat{P}_{m,n} = \frac{\bar{K}_{m,n}}{-\lambda_m}$$

$$\sum_{n=1}^N \hat{P}_{mn} = 1 \Rightarrow$$

$$\hat{P}_{mn} = \frac{\bar{K}_{m,n}}{\sum_{n=1}^M \bar{K}_{m,n}}$$

3) Maximize π_i subject to $\sum_{i=1}^M \pi_i = 1$

$$\hat{\pi}_i = \frac{\bar{\tau}_i}{\sum_{i=1}^M \bar{\tau}_i}$$

E steps

(Details in HMM paper by Rabiner + Juang)

How do we compute

$$f_s(i|\theta), R(i, j), \hat{c}(i)$$

$$\text{note } \hat{c}(i) = f_2(i|\theta)$$

First we must compute the following constants

$$\alpha_s(i) = P\{Y_r = y_r \ r \leq s, x_s = i | \theta\}$$

$$\beta_s(i) = P\{Y_r = y_r \ r > s \mid x_s = i, \theta\}$$

Exercise: show that $\alpha_s(i)$ and $\beta_s(i)$ can be computed using the following recursions

$$\begin{aligned} \text{Define } p(y_s | j') &\triangleq P(y_s | x_s = j') \\ &\sim N(\mu_{j'}, \sigma_{j'}^2) \end{aligned}$$

$$\alpha_1(i) = \pi_i p(y_1 | i)$$

$$\alpha_{s+1}(i) = \left[\sum_{j'=1}^M \alpha_s(j') p_{ij'} \right] p(y_{s+1} | j')$$

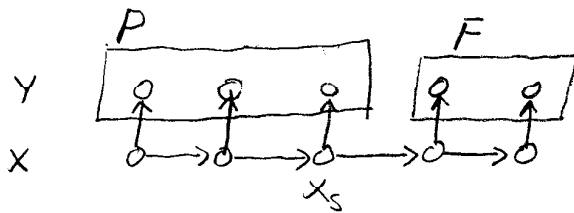
forward recursion

$$\beta_N(i) = 1$$

$$\beta_s(i) = \sum_{j=1}^M P_{ij} p(y_{s+2}|j) \beta_{s+2}(j)$$

backward recursion

Intuition



present +
P - past observations
F - future observations

$$\alpha_s(i) = P\{P, x_s=i | \theta\}$$

$$\beta_s(i) = P\{F | x_s=i, \theta\}$$

$$\xi_s(i|\theta) = p(x_s=i | y, \theta)$$

$$= \frac{p(x_s, F, P | \theta)}{p(F, P | \theta)}$$

$$p(F, P | \theta) = p(y | \theta) \leftarrow \text{constant}$$

$$\xi_s(i|\theta) = \frac{\beta_s(i) \alpha_s(i)}{\sum_{i=1}^M \beta_s(i) \alpha_s(i)}$$

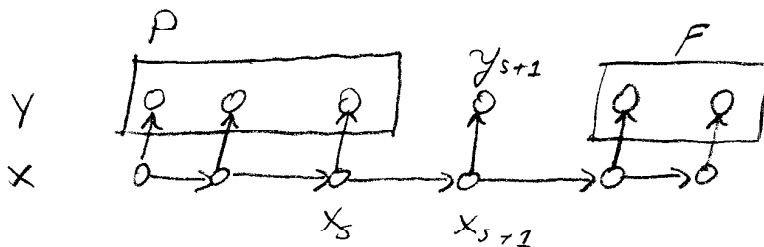
notice: $p(y|\theta) = \sum_{i=1}^M \beta_s(i) \alpha_s(i)$

$$\hat{R}(i, j) = \sum_{S=1}^N P\{X_S = i, X_{S+1} = j \mid Y = y, \theta\}$$

$$= \sum_{S=1}^N \frac{P\{X_S = i, X_{S+1} = j, Y = y\}}{P(y) \leftarrow \text{constant}}$$

↑ drop θ
for convenience

$$= \sum_{S=1}^N \frac{P\{F \mid X_{S+1} = j\} P(y_{S+1} \mid j) P_{X_S X_{S+1}} P\{X_S = i, P\}}{P(y)}$$



$$= \sum_{S=1}^N \frac{B_{S+1}(j) P(y_{S+1} \mid j) P_{ij} \alpha_S(i)}{P(y)} = \hat{R}(i, j)$$

Exercise: Write all update equations together

Summary of EM for HMM

M step

$$N_j^{(k+1)} = \sum_{s=1}^N f_s(j | \theta^{(k)})$$

$$\mu_j^{(k+1)} = \frac{1}{N_j^{(k+1)}} \sum_{s=1}^N y_s f_s(j | \theta^{(k)})$$

$$\sigma_j^{(k+1)} = \frac{1}{N_j^{(k+1)}} \sum_{s=1}^N (y_s - \mu_j^{(k+1)})^2 f_s(j | \theta^{(k)})$$

$$\pi_j^{(k+1)} = f_0(j | \theta^{(k)})$$

$$p_{ij}^{(k+1)} = \frac{g(i, j | \theta^{(k)})}{\sum_{e=1}^M g(i, e | \theta^{(k)})}$$

E step

$$\alpha_1^{(k)}(i) = p(y_1 | i, \theta^{(k)}) \pi_i^{(k)}$$

$$\alpha_{s+1}^{(k)} = \left[\sum_{i=1}^M \alpha_s^{(k)}(i) p_{ij}^{(k)} \right] p(y_{s+1} | j, \theta^{(k)})$$

$$\beta_N^{(k)}(i) = 1$$

$$\beta_{s+1}^{(k)}(i) = \sum_{j=1}^M p_{ij}^{(k)} p(y_s | j, \theta^{(k)}) \beta_s^{(k)}(j)$$

$$f_s(i | \theta^{(k)}) = \frac{\beta_s^{(k)}(i) \alpha_s^{(k)}(i)}{\sum_{l=1}^M \beta_s^{(k)}(l) \alpha_s^{(k)}(l)}$$

$$g(i, j | \theta^{(k)}) = \sum_{s=1}^{N-1} \alpha_s^{(k)}(i) P_{ij}^{(k)} p(y_{s+1} | j, \theta^{(k)}) \beta_{s+1}^{(k)}(j)$$