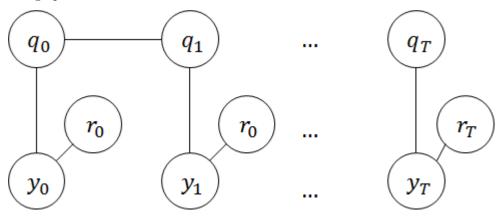
# CS281A/STAT241A Homework 5

Juanyan Li 11/13/2015

## HMMs with mixtures of Poissons

## a. Graphical model

The graphical model for HMM with mixtures of Poissons looks like this:



#### b. Expected complete log likelihood

$$\log p(q, r, y) = \sum_{i=1}^{m} q_0^i \log \pi_i + \sum_{t=0}^{T-1} \sum_{i=1}^{m} \sum_{j=1}^{m} q_t^i q_{t+1}^j \log a_{ij} + \sum_{t=0}^{T} \sum_{i=1}^{m} \sum_{j=1}^{k} y_t q_t^i r_t^j \log \lambda_{ij} + [\lambda_{ij}]^{q_t^i r_t^j} - \log y_t!$$

Sufficient statistic for  $a_{ij}$  is  $m_{ij} \stackrel{\Delta}{=} \sum_{t=0}^{T-1} q_t^i q_{t+1}^j$ ; sufficient statistic for  $\lambda_{ij}$  is  $n_{ij} \stackrel{\Delta}{=} \sum_{t=0}^{T} y_t q_t^i r_t^j$ ; sufficient statistic for  $\pi_i$  is  $q_0^i$ .

The maximum likelihood estimates for the case of complete data are therefore given by:

$$\hat{a_{ij}} = \frac{m_{ij}}{\sum_{s=1}^{m} m_{is}}$$

$$\hat{\pi_{ij}} = q_0^i$$

$$\hat{\lambda_{ij}} = \frac{n_{ij}}{\sum_{s=1}^{k} n_{is}}$$

Parameters of the model are defined as  $\theta \stackrel{\Delta}{=} (\pi, A, \lambda)$ . The expectations for E step is given by:

$$E(m_{ij}|y,\theta^{(p)}) = \sum_{t=0}^{T-1} p(q_t^i q_{t+1}^j | y, \theta^{(p)}) \stackrel{\Delta}{=} \sum_{t=0}^{T-1} \xi_{t,t+1}^{ij}$$
$$E(n_{ij}|y,\theta^{(p)}) = \sum_{t=0}^{T} y_t r_t^j p(q_t^i | y, \theta^{(p)}) \stackrel{\Delta}{=} \sum_{t=0}^{T} \gamma_t^i r_t^j y_t$$

### c. Algorithm for E step

• Forward recursion

$$\alpha(q_{t+1}) = \sum_{q_t} \alpha(q_t) a_{q_t, q_{t+1}} p(y_{t+1}|q_{t+1})$$

Initialization of  $\alpha(q_0)$  is given by:

$$\alpha(q_0) = p(y_0|q_0)\pi_{q_0}$$

• Backward recursion

$$\beta(q_t) = \sum_{q_{t+1}} \beta(q_{t+1}) a_{q_t, q_{t+1}} p(y_{t+1}|q_{t+1})$$

Initialization of  $\beta(q_T)$  is no more complex than a vector of ones.

Thus, we have everything we need for the E step:

$$\gamma(q_t) = \frac{\alpha(q_t)\beta(q_t)}{\sum_{q_t} \alpha(q_t)\beta(q_t)}$$
$$\xi(q_t, q_{t+1}) = \frac{\alpha(q_t)p(y_{t+1}|q_{t+1})\gamma(q_{t+1})a_{q_t, q_{t+1}}}{\alpha(q_{t+1})}$$

 $\gamma_t^i$  is equal to  $\gamma(q_t)$  evaluated at  $q_t^i=1$ ;  $\xi_{t,t+1}^{ij}$  is equal to  $\xi(q_t,q_{t+1})$  evaluated at  $q_t^i=1,q_{t+1}^j=1$ .

#### d. Algorithm for M step

After the calculation of E step, updates in M step are given by:

$$\hat{\lambda}_{ij}^{(p+1)} = \frac{\sum_{t=0}^{T} \gamma_t^i r_t^j y_t}{\sum_{t=0}^{T} \gamma_t^i y_t}$$

$$\hat{a}_{ij}^{(p+1)} = \frac{\sum_{t=0}^{T-1} \xi_{t,t+1}^{ij}}{\sum_{t=0}^{T-1} \gamma_t^i}$$

$$\hat{\pi}_i^{(p+1)} = \gamma_0^i$$