

Prove :

$$\text{We know } \sum_{i=1}^N \hat{\alpha}_t(i) = 1$$

$$\text{and if } \hat{\alpha}_t(i) = \frac{1}{\pi} \eta_k \alpha_t(i)$$

$$\therefore \sum_{i=1}^N \frac{1}{\pi} \eta_k \alpha_t(i) = 1$$

$$\therefore \sum_{i=1}^N \alpha_t(i) \frac{1}{\pi} \eta_k = 1$$

$$\therefore \frac{1}{\pi} \eta_k = \frac{1}{\sum_{i=1}^N \alpha_t(i)} = \frac{1}{p(o(t)|\lambda)}$$

$$\text{in particular, } \frac{1}{\pi} \eta_k = \frac{1}{\sum_{i=1}^N \alpha_T(i)} = \frac{1}{p(o|\lambda)}$$

$$\therefore \hat{\alpha}_t(i) = p(q_t = s_i | o(t), \lambda)$$

$$\therefore \alpha_t(i) = p(o(t), q_t = s_i | \lambda)$$

$\therefore$  Prove (make  $\eta = c$ ,  $k = s$ ,  $\therefore$  Prove)

2. We know :  $\beta_T(j) = c_T$  and

$$\begin{aligned}\beta_t(i) &= \sum_{j=1}^N a_{ij} b_j(o_{t+1}) \beta_{t+1}(j) \\ &= P(o_{t+1} \dots o_T | x_t = q_i, \lambda)\end{aligned}$$

Prove  $\hat{\beta}_i(j) = \pi_{s=i}^T c_s \beta_t(j)$

Obviously, when  $t = T$ , Prove.

When  $t \neq T$ , Assume  $\hat{\beta}_t(j) = \pi_{s=t}^T c_s \beta_t(j)$

$$\sum_{j=1}^N \pi_{s=1}^T c_s \beta_1(j) = 1$$

$$\Rightarrow \sum_{j=1}^N \beta_T(j) \pi_{s=1}^T c_s = 1$$

$$\text{Cause } \pi_{s=1}^T c_s = \frac{1}{\sum_{j=1}^N \alpha_T(j)}$$

$$\Rightarrow \sum_{j=1}^N \beta_1(j)$$

$$\frac{\sum_{j=1}^N \beta_1(j)}{\sum_{j=1}^N \alpha_T(j)} = 1 \quad \text{So prove}$$



$$3. \quad P(o|\lambda) = \sum_i \alpha_T(i) \quad (\text{using formula in (1)(2)})$$

$$\Rightarrow \xi_t(i, j) = \frac{\alpha_t(i) \beta_{t+1}(j) a_{ij} b_j(o_{t+1})}{P(o|\lambda)}$$

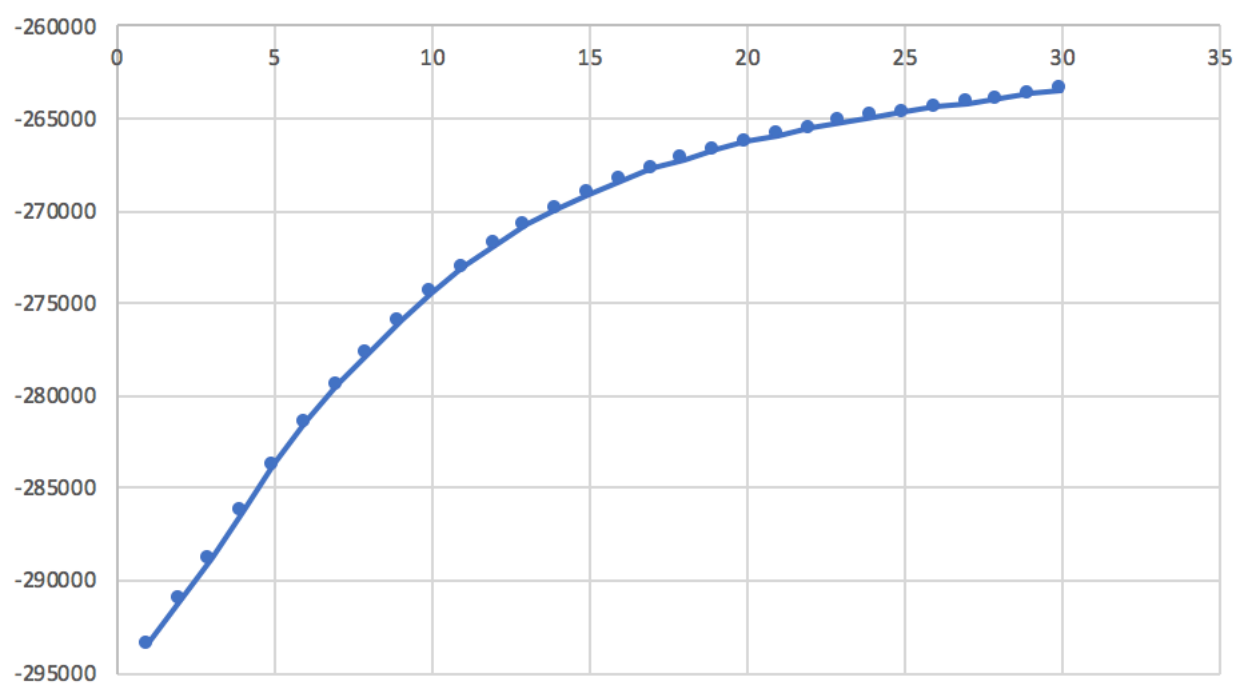
$$= \frac{\alpha_t(i) \beta_{t+1}(j) a_{ij} b_j(o_{t+1})}{\sum_j \alpha_T(j)}$$

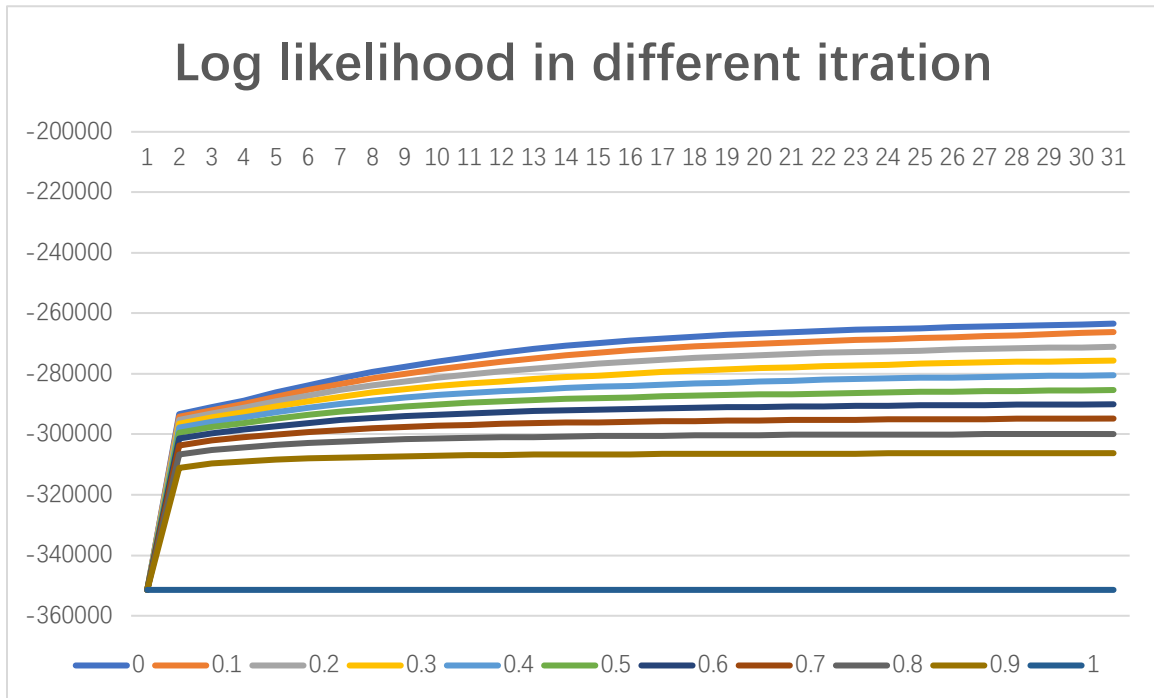
$$\sum_j \alpha_T(j) = \frac{1}{\pi_{s=1}^T c_s}$$

$$\Rightarrow \xi_t(i, j) = (\pi_{s=1}^T c_s \alpha_t(i)) (\pi_{s=t+1}^T c_s \beta_{t+1}(j)) \cdot a_{ij} b_j(o_{t+1})$$

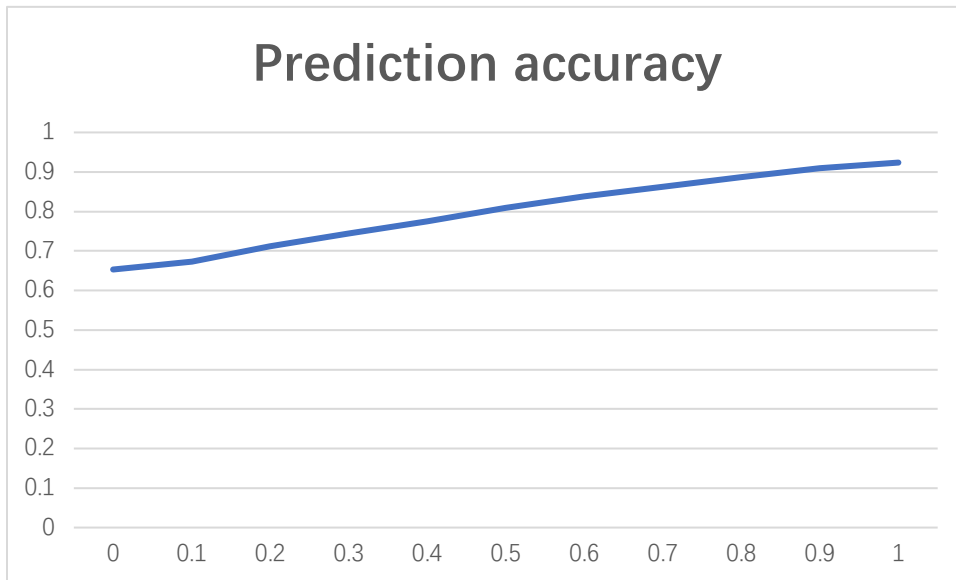
$$= \hat{\alpha}_t(i) \hat{\beta}_{t+1}(j) a_{ij} b_j(o_{t+1})$$

So we could prove that .





x-axis is the number of iterations and the y-axis is the log likelihoods  $P(D|\lambda)$ .



x-axis is different  $\mu$  values and the y-axis is the POS-tagging accuracies.

4,

Because  $A = \mu A_L + (1 - \mu) A_0$

for  $A_{ij}$  in  $A_L, A_0$

We know  $\sum_j A_{ij} = 1$  for all of  $i$ .

$$\text{So } \sum_j A_{ij} = \mu \sum_j A_{ij}^L + (1 - \mu) \sum_j A_{ij}^0$$

$$= \mu + 1 - \mu$$

$$= 1$$

And same with  $\beta, \pi$

So prove.