

# 清华大学实验报告

系别 \_\_\_\_\_ 班号 \_\_\_\_\_ 姓名 <sup>ZHANG</sup> NAIFU (同组姓名: \_\_\_\_\_)

作实验日期 \_\_\_\_\_ 年 \_\_\_\_\_ 月 \_\_\_\_\_ 日 2018280351 教师评定: \_\_\_\_\_

Q1.1

$$\begin{aligned} \ln l(\mu) &= \ln P(x|\mu) \\ &= \ln \left( \frac{n!}{\prod_{i=1}^d x_i!} \prod_{i=1}^d \mu_i^{x_i} \right) \\ &= \ln n! - \sum_{i=1}^d \ln x_i! + \sum_{i=1}^d x_i \ln \mu_i \end{aligned}$$

Constrained optimisation  $\Rightarrow$  Lagrange method

$$\begin{aligned} \mathcal{L}(\mu, \lambda) &= \ln n! - \sum_{i=1}^d \ln x_i! + \sum_{i=1}^d x_i \ln \mu_i \\ &\quad - \lambda_1 \left( \sum_{i=1}^d x_i - n \right) - \lambda_2 \left( \sum_{i=1}^d \mu_i - 1 \right) \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial \mu_i} \mathcal{L}(\mu, \lambda) &= \frac{x_i}{\mu_i} - \lambda_2 = 0 \\ \mu_i &= \frac{x_i}{\lambda_2} \end{aligned}$$

$$\sum \mu_i = \sum \frac{x_i}{\lambda_2}$$

$$1 = \frac{n}{\lambda_2}$$

$$\lambda_2 = n$$

$$\mu_i = \frac{x_i}{n}$$

$$\therefore \mu_i = \frac{x_i}{n}$$

$$\vec{\mu} = n^{-1} \vec{x} //$$

(科目: ) 数 学 作 业 纸

编号:

班级:

姓名:

第

页

$$Q1.2 \quad p(d) = \frac{n_d!}{\prod_w T_{dw}!} \sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}}$$

$$\ell(\pi, \mu) = \sum \ln p(d)$$

$$= \sum \left[ \ln \frac{n_d!}{\prod_w T_{dw}!} + \ln \left( \sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}} \right) \right]$$

$$\mathcal{L}(\pi, \mu, \lambda) = \ell(\pi, \mu) - \lambda_1 \left( \sum_k \pi_k - 1 \right) - \lambda_2 \left( \sum_w \mu_{wk} - 1 \right)$$

$$\frac{\partial \mathcal{L}}{\partial \mu_{wk}} = \sum_d \frac{\pi_k \prod_w \mu_{wk}^{T_{dw}}}{\sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}}} \frac{T_{dw}}{\mu_{wk}} - \lambda_2$$

Let  ~~$\pi_k$~~   $\gamma_{dk} = \frac{\pi_k \prod_w \mu_{wk}^{T_{dw}}}{\sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}}}$  be responsibility

$$\frac{\partial \mathcal{L}}{\partial \mu_{wk}} = \sum_d \gamma_{dk} \frac{T_{dw}}{\mu_{wk}} - \lambda_2$$

$$\sum_d \gamma_{dk} T_{dw} = \lambda_2 \mu_{wk}$$

$$\sum_w \sum_d \gamma_{dk} T_{dw} = \lambda_2 \sum_w \mu_{wk}$$

$$\lambda_2 = \sum_w \sum_d \gamma_{dk} T_{dw}$$

$$\mu_{wk} = \frac{\sum_d \gamma_{dk} T_{dw}}{\sum_w \sum_d \gamma_{dk} T_{dw}}$$

$$\frac{\partial \mathcal{L}}{\partial \pi_k} = \sum_d \frac{\pi_k \prod_w \mu_{wk}^{T_{dw}}}{\sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}}} \frac{1}{\pi_k} - \lambda_1 \dots$$

$$\sum_d \gamma_{dk} \frac{\cancel{\pi_k}}{\cancel{\pi_k}} = \lambda_1 \pi_k$$

$$\sum_k \sum_d \gamma_{dk} = \lambda_1 \sum_k \pi_k$$

$$\lambda_1 = \sum_k \sum_d \gamma_{dk}$$

$$\pi_k = \frac{\sum_d \gamma_{dk}}{\sum_k \sum_d \gamma_{dk}}$$

$$\pi_k = \frac{\sum_d \gamma_{dk}}{D} //$$

E step: For each document  $d$ , update the responsibility

$$\gamma_{dk}^{(t+1)} = \frac{\pi_k \prod_w \mu_{wk}^{T_{dw}}}{\sum_{k=1}^K \pi_k \prod_w \mu_{wk}^{T_{dw}}}$$

This corresponds to the ~~responsibility~~ posterior probability of topic  $C_d = k$  for generating the document.

M step: For each  $C_d = k$ , update parameter estimates

$$\pi_k^{(t+1)} = \frac{\sum_d \gamma_{dk}}{D}$$

$$\mu_{wk}^{(t+1)} = \frac{\sum_d \gamma_{dk} T_{dw}}{\sum_w \sum_d \gamma_{dk} T_{dw}}$$

(科目: ) 数 学 作 业 纸

编号:

班级:

姓名:

第

页

$T_{lk}^{(t+1)}$ : Numerator is no. of documents in topic  $C_d = k$   
Denominator is total number of documents  $D$

$T_{lk}$  represents the proportion of documents in each topic.

$M_{wk}^{(t+1)}$ : Numerator is expected times of ~~times~~ word  $w$   
in topic  $C_d = k$

Denominator is total number of words in topic  
 $C_d = k$ .

$M_{wk}$  represents proportion of word  $w$  in topic  $k$ .

# 清华大学实验报告

系别 \_\_\_\_\_ 班号 \_\_\_\_\_ 姓名 \_\_\_\_\_ (同组姓名: \_\_\_\_\_)

作实验日期 \_\_\_\_\_ 年 \_\_\_\_\_ 月 \_\_\_\_\_ 日 2018 28035 / 教师评定: \_\_\_\_\_

$$Q2 \quad J = \frac{1}{N} \sum_{n=1}^N \|X_n - \hat{X}_n\|^2$$

$$J = \frac{1}{N} \sum_{n=1}^N \left\| X_n - \sum_{i=1}^d z_{ni} \mu_i - \sum_{i=d+1}^p b_i \mu_i \right\|^2$$

$$\frac{\partial J}{\partial z_{ni}} = \frac{1}{N} \sum_{n=1}^N \frac{\partial}{\partial z_{ni}} \left\| X_n - \sum_{i=1}^d z_{ni} \mu_i - \sum_{i=d+1}^p b_i \mu_i \right\|^2$$

$$0 = \frac{2}{N} \sum_{n=1}^N \left( X_n - \sum_{i=1}^d z_{ni} \mu_i - \sum_{i=d+1}^p b_i \mu_i \right) (-\mu_i)$$

$$0 = \sum_{n=1}^N (X_n^T \mu_i - z_{ni}) \quad \text{for } i=1 \dots d$$

As  $z_{ni}$  is unique for each data point  $n$

so we can just look at each term in the summation

~~$$X_n^T \mu_i - z_{ni}$$~~

$$z_{ni} = X_n^T \mu_i \quad \forall i=1 \dots d$$

$$\frac{\partial J}{\partial b_i} = \frac{1}{N} \sum_{n=1}^N \frac{\partial}{\partial b_i} \left\| X_n - \sum_{i=1}^d z_{ni} \mu_i - \sum_{i=d+1}^p b_i \mu_i \right\|^2$$

$$0 = \frac{2}{N} \sum_{n=1}^N \left( X_n - \sum_{i=1}^d z_{ni} \mu_i - \sum_{i=d+1}^p b_i \mu_i \right) (-\mu_i)$$

$$0 = \sum_{n=1}^N (X_n^T \mu_i - b_i) \quad \text{for } i=d+1 \dots p$$

$$\sum_{n=1}^N b_i = \sum_{n=1}^N X_n^T \mu_i$$

$$b_i = \bar{X}_n^T \mu_i \quad \forall i=d+1 \dots p$$