

# HW02

EECS 6770

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Problem 1:

Setup:  $X = \{x_0, x_1, \dots, x_n\}$ ,  $Z = \{z_1, \dots, z_n\}$   
 $x_n \sim N(Wz_n, \sigma^2 I)$      $z_n \sim N(0, 1)$

$$p(W) = \left(\frac{\lambda}{2\pi}\right)^{dk/2} \exp \left\{ -\frac{\lambda}{2} \text{trace}(W^T W) \right\}$$

Find:  $W' = \arg\max \ln p(x_1, \dots, x_n, W)$

Steps:

① use  $z$  as  $q(\phi)$  in class example to set up "E" step.

$$\ln p(X, W) = \underbrace{\int q(z) \ln \frac{p(W, X, z)}{q(z)} dz}_{= \mathcal{L}(W)} + \underbrace{\int q(z) \ln \frac{q(z)}{p(z|W, X)} dz}_{= KL(q||p)}$$

E-Step at iteration t:

$$\text{set } q_t(z) = p(z|X, W_{t-1}) = \prod_{i=1}^n p(z_i | x_i, W_{t-1})$$

$$\mathcal{L}_t(W) = \int q_t(z) \ln p(X, W, z) dz - \int q_t(z) \ln q_t(z) dz$$

for every  $i$ :

$$p(z_i | x_i, W_{t-1}) = \frac{p(x_i | z_i, W_{t-1}) p(z_i | W_{t-1}) p(W_{t-1})}{p(x_i, W_{t-1})}$$

since  $z$  doesn't depend on  $W$  and we don't want depend on  $p(W_{t-1})$   
 we have:

$$= \frac{p(x_i | z_i, W_{t-1}) p(z_i)}{\int p(x_i | W, z_i) p(z_i) dz_i}$$

$$\text{we look at } p(x_i | z_i, W_{t-1}) p(z_i) = N(z_i; \mu_i, \Sigma_i)$$

$$\begin{aligned}
& p(x_i | w, z_i) p(z_i) \\
&= (2\pi)^{-\frac{d}{2}} (|\sigma^2 I|)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (x_i - w z_i)^T (\sigma^2 I)^{-1} (x_i - w z_i) \right\} \cdot (2\pi)^{-\frac{k}{2}} (|I|)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (z_i)^T (I)^{-1} z_i \right\} \\
&= 2\pi^{-\frac{d+k}{2}} (|\sigma^2 I|)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} [(x_i - w z_i)^T (\sigma^2 I)^{-1} (x_i - w z_i) + z_i^T z_i] \right\} \\
&\quad \bar{\Sigma} = (I + \frac{1}{\sigma^2} W_{t-1}^T W_{t-1})^{-1}, \quad \mu_i = \bar{\Sigma}_i \cdot W_{t-1}^T x_i / \sigma^2
\end{aligned}$$

M-step:

$$L_t(w) = \int q_t(z) \ln p(x, w_{t-1}, z) dz - \int q_t(z) \ln q_t(z) dz$$

where  $q_t(z) = p(z | x, w_{t-1})$   
sub it in, we have

$$L_t(w) = \sum_{i=1}^n \int p(z_i | x_i, w_{t-1}) \ln p(x_i | w_{t-1}, z_i) p(w_{t-1}) p(z_i) dz_i$$

$$- \sum_{i=1}^n \int p(z_i | x_i, w) \ln p(z_i | x_i, w) dz_i$$

$$\Rightarrow \sum_{i=1}^n \int p(z_i | x_i, w_{t-1}) \ln p(x_i | w_{t-1}, z_i) p(w_{t-1}) p(z_i) dz_i + \text{constant}$$

$$= \sum_{i=1}^n \mathbb{E}_{q_t} [\ln p(x_i | w_{t-1}, z_i) p(w_{t-1}) p(z_i)] + \text{constant}$$

$$= \sum_{i=1}^n \mathbb{E}_{q_t} [\ln p(x_i | w_{t-1}, z_i)] + \mathbb{E}_{q_t} [\ln p(w_{t-1})] + \mathbb{E}_{q_t} [\ln p(z_i)] + \text{constant}$$

$$= \sum_{i=1}^n \mathbb{E}_{q_t} [\ln p(x_i | w_{t-1}, z_i)] + \mathbb{E}_{q_t} [\ln p(w_{t-1})] + \text{constant}$$

for simplification,  
w now denotes

$w_{t-1}$

$$= \sum_{i=1}^n \mathbb{E}_{q_t} \left[ -\frac{1}{2\sigma^2} (x_i - w z_i)^T (x_i - w z_i) \right] + \left( -\frac{\lambda}{2} \text{tr}(w^T w) \right) + \text{constant}$$

$$= \sum_{i=1}^n -\frac{1}{2\sigma^2} \left\{ -2 \text{tr}(\mu_i x_i^T w) + \text{tr}(w^T w (\mu_i \mu_i^T + \Sigma)) \right\} + \left( -\frac{\lambda}{2} \text{tr}(w^T w) \right) + \text{constant}$$

exclude every term not involving  $W$  and absorb into constant, use linear expansion, take derivative of  $L(W)$ :

$$\sum \nabla W = 0 = \sum_i \frac{1}{\sigma^2} x_i \mu_i^T - \sum_i \frac{1}{2\sigma^2} \mathbb{E}_{q_i} [2(Wz_i)z_i^T] - \frac{\lambda}{2} \cdot 2W$$

$$\sum_{i=1}^n x_i \mu_i^T = W \left[ \sum_{i=1}^n (\Sigma_i + \mu_i \mu_i^T) + \sigma^2 \lambda \cdot I \right]$$

$$W = \left( \sum_{i=1}^n x_i \mu_i^T \right) \left( \sum_{i=1}^n \mu_i \mu_i^T + \Sigma \cdot n + \sigma^2 \lambda \cdot I \right)^{-1}$$

Algorithm Steps:

First, we set  $q(z_i) = p(z_i | x_i, W_t)$  and get  $L(W)$

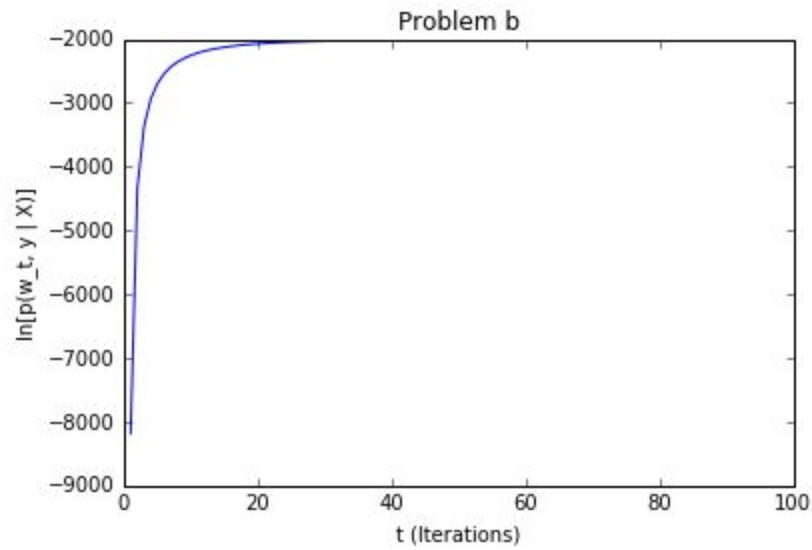
and then we take derivative of  $L(W)$  and get  $W_{t+1}$  which maximizes  $L_{W_t}(W)$

After we get new  $W$ , we get the new  $L(W)$ .

Repeat the process to find better and better  $W$ .

## Problem 2

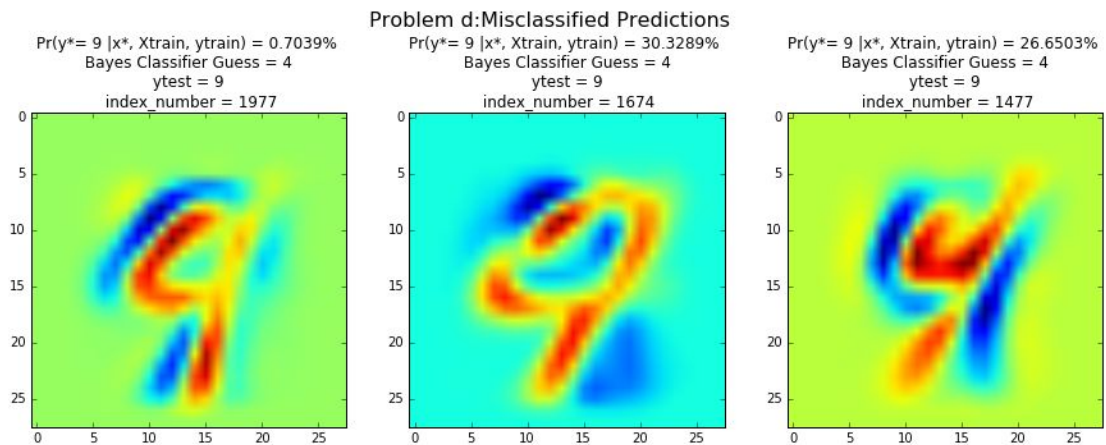
a) Just run iteration for 100 times



b)

	Classified as 4	Classified as 9
ytest= 4	930	52
ytest= 9	77	932

c)



d)

