

# Pattern Recognition and Machine Learning:

## Homework 2, Zhengzuo Liu

### Problem 1

Answer:

The distance of point  $v$  to  $H$  is

$$d(v, H) = \frac{|w^T v + b|}{\|w\|_2}$$

### Problem 2

Answer:

$$\begin{aligned}
 L(f(x_i; w, b), y_i) &= \frac{1}{2} \sum (w^T x + b - y)^2 \\
 \frac{\partial L}{\partial w} = 0 &\Rightarrow \sum [(w^T x + b - y) \cdot x] = 0 \Leftrightarrow \sum [x \cdot (x^T w + b - y)] = 0 \quad (1) \\
 \frac{\partial L}{\partial b} = 0 &\Rightarrow \sum (w^T x + b - y) = 0, \text{ since } \sum y = N_1 \cdot \left(\frac{N}{N_1}\right) + N_2 \cdot \left(-\frac{N}{N_2}\right) = 0 \\
 &\Rightarrow b = -\frac{1}{N} \sum w^T x = -\frac{1}{N} \sum x^T w = -\frac{1}{N} (N_1 m_1^T + N_2 m_2^T) w \\
 (1) &\Leftrightarrow \sum (x \cdot x^T - \frac{x}{N} \sum x^T) w = \sum x \cdot y = N_1 m_1 \cdot \left(\frac{N}{N_1}\right) + N_2 m_2 \cdot \left(-\frac{N}{N_2}\right) = N(m_1 - m_2) \\
 S_w &= \sum (x - m)(x - m)^T = \sum_{x \in X_1} (x - m_1)(x - m_1)^T + \sum_{x \in X_2} (x - m_2)(x - m_2)^T \\
 &= \sum x x^T - N_1 m_1 m_1^T - N_2 m_2 m_2^T \\
 (1) \text{ left} &= \left[ \sum x x^T - \sum \frac{x}{N} \cdot (N_1 m_1^T + N_2 m_2^T) \right] w \\
 &= \left[ \sum x x^T - \frac{1}{N} (N_1 m_1 + N_2 m_2) (N_1 m_1 + N_2 m_2)^T \right] w \\
 &= \left[ \sum x x^T - \frac{1}{N} (N_1^2 m_1 m_1^T + N_2^2 m_2 m_2^T + N_1 N_2 (m_1 m_2^T + m_2 m_1^T)) \right] w \\
 &= \left[ \sum x x^T - \frac{1}{N} (N_1^2 m_1 m_1^T + N_1 N_2 m_1 m_1^T + N_1 N_2 m_2 m_2^T + N_2^2 m_2 m_2^T \right. \\
 &\quad \left. - N_1 N_2 (m_1 - m_2)(m_1 - m_2)^T) \right] w \\
 &= \left[ S_w + \frac{N_1 N_2}{N} (m_1 - m_2)(m_1 - m_2)^T \right] w = N(m_1 - m_2) \\
 \Leftrightarrow S_w \cdot w &= \left[ N - \frac{N_1 N_2}{N} (m_1 - m_2)^T w \right] (m_1 - m_2) \\
 \text{given that } &\left[ N - \frac{N_1 N_2}{N} (m_1 - m_2)^T w \right] \text{ is scalar, and we only care about} \\
 \text{the direction of } &w, \text{ we get:} \\
 w^* &= S_w^{-1} (m_1 - m_2) = w^* \quad \square
 \end{aligned}$$

## Problem 3

Answer:

- $\sigma(x) + \sigma(-x) = 1$   

$$\sigma(x) + \sigma(-x) = \frac{1}{1+e^{-x}} + \frac{1}{1+e^x} = \frac{e^x}{e^x+1} + \frac{1}{1+e^x} = 1.$$
- $\sigma'(x) = \sigma(x)(1-\sigma(x))$   

$$\sigma'(x) = \frac{1}{(1+e^{-x})^2} \cdot (-e^{-x}) = \frac{1}{(1+e^{-x})} \cdot \frac{e^{-x}}{1+e^{-x}} = \sigma(x)(1-\sigma(x)).$$
- $\tanh(x) = 2\sigma(2x) - 1$   

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{1 - e^{-2x}}{1 + e^{-2x}} = \frac{2}{1 + e^{-2x}} - 1 = 2\sigma(2x) - 1.$$

$$\begin{aligned} \frac{\partial L}{\partial w} &= \frac{\partial (\sigma(w^T x + b) - \hat{y})^2}{\partial w} \\ &= 2(\sigma(w^T x + b) - \hat{y}) \cdot \frac{\partial \sigma(w^T x + b)}{\partial w} \\ &= 2(\sigma(w^T x + b) - \hat{y}) \cdot \sigma(w^T x + b) \sigma(-w^T x - b) \cdot x \\ \frac{\partial L}{\partial b} &= 2(\sigma(w^T x + b) - \hat{y}) \cdot \frac{\partial \sigma(w^T x + b)}{\partial b} \\ &= 2(\sigma(w^T x + b) - \hat{y}) \cdot \sigma(w^T x + b) \sigma(-w^T x - b) \end{aligned}$$

## Problem 4

Answer:

1

$$w^* = [-0.0013, -0.0009, -0.0006, -0.0003, -0.0004, -0.0019, -0.0008, -0.0005]^T$$

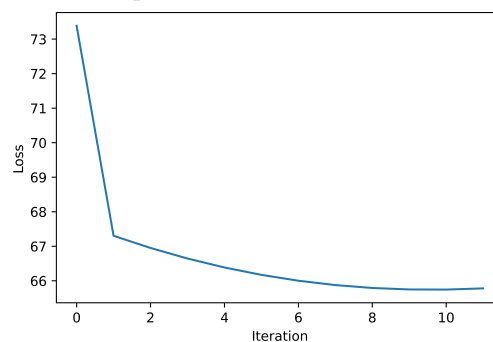
The classification accuracy on the dataset is 96.33%.

Program see "PRML\_H2\_4.1.py".

2

For all processes and results see "PRML\_H2\_4.2.py"

The the loss value against iterations plot is as follow:



Final accuracy is 100% (tested on the last 100 samples, trained on others), with a modified threshold value 0.64.

**3**

The cosine between two  $w$  in section 1 and 2 is -0.91. It means that the two  $w$  are almost in the exact reverse direction—very similar as far as we concern. The explanation should be similar to that of Problem 2.

The sixth component of both  $w$  has the largest absolute value. Hence, single epithelial cell size the most indicative feature that implies one gets breast cancer.