

Q1.

(d) 收集網站用戶過往的消費紀錄和點擊、流覽的頻率，通常來說越常消費於此網站的人，在往後也比較容易在此網站重複進行消費，並推測其可能的消費頻率，便可預測其於接下來  $\eta$  天內進行消費的可能性並進行排序。

Q3.

(E)

Dataset is linear separable

Exists perfect  $W_f$  such that  $y_n = \text{sign}(W_f^T X_n)$ 

① inner product grows fast.

$$\frac{W_f^T W_{t+1}}{\|W_f\|} \geq \frac{W_f^T W_t}{\|W_f\|} + \underbrace{\min_n \left( \frac{y_n W_f^T X_n}{\|W_f\|} \right)}_f \cdot \eta_t$$

② length<sup>2</sup> grows slowly

$$\|W_{t+1}\|^2 \leq \|W_t\|^2 + \underbrace{\max_n (y_n^2 \|X_n\|^2)}_{R^2} \cdot \eta_t^2$$

starts from  $W_0 = 0$ , after  $T$  mistake corrections

$$1 \geq \frac{W_f^T W_t}{\|W_f\| \|W_t\|} \geq \frac{\sum_{t=0}^{T-1} (\eta_t \cdot f)}{\sqrt{\sum_{t=0}^{T-1} \eta_t^2} \cdot R} \Rightarrow 1^2 \geq \left( \frac{\sum_{t=0}^{T-1} (\eta_t \cdot f)}{\sqrt{\sum_{t=0}^{T-1} \eta_t^2} \cdot R} \right)^2 = f(T) \cdot \frac{f^2}{R^2}$$

而若  $f(T) = \frac{(\sum_{t=0}^{T-1} \eta_t)^2}{\sum_{t=0}^{T-1} \eta_t^2}$  為 monotonically increasing 而  $f(T) \cdot \frac{f^2}{R^2} = 1$  則在  $T$  夠大時成立，即  $\text{Perfect Halt}$ .

$$(a) \lim_{T \rightarrow \infty} f(T) = \frac{\left( \sum_{t=0}^{\infty} (2^{-t}) \right)^2}{\sum_{t=0}^{\infty} (2^{-2t})} = \frac{2}{\frac{4}{3}} = 1.5$$

$$(b) \lim_{T \rightarrow \infty} f(T) = \frac{\left( \sum_{t=0}^{\infty} 0.6211 \right)^2}{\sum_{t=0}^{\infty} (0.6211)^2} = \infty$$

$$(d) \lim_{T \rightarrow \infty} f(T) = \frac{\left( \sum_{t=0}^{\infty} \left( \frac{1}{1+t} \right)^2 \right)^2}{\sum_{t=0}^{\infty} \left( \frac{1}{1+t} \right)^2} = \frac{8}{6} = \infty$$

(C)(E)在下一頁

Q2.

$$(e) \cdot y_{n(t)} \cdot W_{t+1}^T \cdot X_{n(t)} > 0, \quad y_{n(t)} \in \{+1, -1\}$$

$$\text{let } W_{t+1} = W_t + y_{n(t)} X_{n(t)} \cdot \eta_t$$

$$\cdot y_{n(t)} \cdot (W_t^T + y_{n(t)} \cdot \eta_t \cdot X_{n(t)}^T) \cdot X_{n(t)} > 0$$

$$\cdot y_{n(t)} \cdot W_t^T X_{n(t)} + y_{n(t)}^2 \cdot \eta_t \cdot X_{n(t)}^T X_{n(t)} > 0$$

$$\therefore y_{n(t)}^2 = (+1)^2 = (-1)^2 = 1$$

$$\therefore \eta_t \cdot \|X_{n(t)}\|^2 > -y_{n(t)} \cdot W_t^T \cdot X_{n(t)}$$

$$\text{又 } \because y_{n(t)} \cdot W_t^T \cdot X_{n(t)} \leq 0$$

$$\therefore \eta_t \cdot \|X_{n(t)}\|^2 > -y_{n(t)} \cdot W_t^T \cdot X_{n(t)} \geq 0$$

$$\Rightarrow \eta_t > \left( \frac{-y_{n(t)} \cdot W_t^T \cdot X_{n(t)}}{\|X_{n(t)}\|^2} \right) \geq 0$$

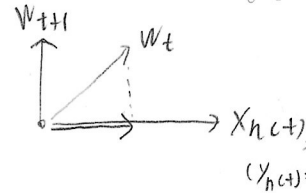
$$\text{而 } \left[ \frac{-y_{n(t)} \cdot W_t^T \cdot X_{n(t)}}{\|X_{n(t)}\|^2} + 1 \right] \geq \frac{-y_{n(t)} \cdot W_t^T \cdot X_{n(t)}}{\|X_{n(t)}\|^2} \geq 0$$

(c)

$$W_{t+1} = W_t + y_{n(t)} X_{n(t)} \cdot \left( \frac{-y_{n(t)} W_t^T X_{n(t)}}{\|X_{n(t)}\|^2} \right)$$

$$= W_t - X_{n(t)} \left( \frac{W_t^T X_{n(t)}}{\|X_{n(t)}\|} \right)$$

$W_t \text{ project on } X_{n(t)}$



$\Rightarrow$  由於  $W_{t+1}$  永遠是  $X_{n(t)}$  之法向量，  
假若  $\text{sign}(0) = +1$ ，且  $y_{n(t)} = -1$

而  $X_{n(t+1)} = X_{n(t)}$  (即在下車輪中又用

同樣的  $X$  來更新)，此時  $W_{t+1} = W_t$

即  $W_t$  停止更新，但  $\text{sign}(W_{t+1}^T X_{n(t+1)}) = \text{sign}(0) = 1 \neq -1 = y_{n(t+1)}$

故 (c) 不保證 halt with a perfect line.

$$(e) \quad W_{t+1} = W_t + y_{n(t)} X_{n(t)} \cdot \left[ \frac{-y_{n(t)} W_t^T X_{n(t)}}{\|X_{n(t)}\|^2} + 1 \right]$$

$$= W_t + y_{n(t)} X_{n(t)} \left[ \frac{-y_{n(t)} W_t^T X_{n(t)}}{\|X_{n(t)}\|^2} + 1 \right] + y_{n(t)} X_{n(t)}$$

$$= W_t + y_{n(t)} X_{n(t)} (\alpha + 1), \quad \alpha = \text{非負整數}$$

$\because -y_{n(t)} W_t^T X_{n(t)} \geq 0$

故  $\lim_{T \rightarrow \infty} f(T) = \frac{\left( \sum_{t=0}^{\infty} (\alpha + 1) \right)^2}{\sum_{t=0}^{\infty} (\alpha + 1)^2} = \infty \quad (*, \alpha + 1 \geq 1)$

故前題之 (b)(d)(e) 之  $f(T)$  為 monotonically increasing

即有了者可 ensure halting with a perfect line.

Q4, 根據題述:

- (c)  $X$  為一維度為  $(d+1) \times 1$  之向量, 且  $X_0 = 1, X_1 \sim d \in \{0, 1\}$  且同時  $X_1 \sim d$  中最多存在  $m$  個 1,  $m \leq d$

另

$$f(x) = \text{sign}(z_+(x) - z_-(x) - 0.5) = \text{sign}(W_f^T X)$$

$$\text{而 } W_f^T \text{ 為 } \begin{cases} W_{f_0}^T = -0.5 \\ W_{f_{1 \sim d}}^T = \{+1, -1\} \end{cases}$$

其中  $W_{f_{1 \sim d}}^T$  中存在  $d_+$  個 1 和  $d_-$  個 -1  
此做法是由於  $(z_+(x) - z_-(x))$  相當於在計算 spam-like word 和 less spam-like 的個數差, 因  $X$  中的值  $\in \{0, 1\}$ , 故  $W_{f_{1 \sim d}} = \{+1, -1\}$  和  $X_{1 \sim d}$  的內積和即等於  $(z_+(x) - z_-(x))$ 。

而

$$\rho = \min_n \left( \frac{y_n W_f^T X_n}{\|W_f\|} \right) = \frac{0.5}{\sqrt{(0.25 + 1^2 \times d)}}$$

$$R^2 = \max_n (y_n^2 \cdot \|X_n\|^2) = 1 + 1^2 \times m = 1 + m$$

(∵  $X_{1 \sim d}$  中最多存在  $m$  個 1)

故

$$T \text{ 之 upper bound} = \left( \frac{R}{\rho} \right)^2 = \frac{R^2}{\rho^2} = \frac{m+1}{\frac{0.25}{0.25+d}}$$

$$= 4(d+0.25)(m+1)$$

$$= (4d+1)(m+1) \quad \#$$

Q5.

(b) Consider binary PLA

$$W_{t+1} \leftarrow W_t + y_{n(t)} X_{n(t)}$$

考慮兩種 mistake

① 若  $y_{n(t)} = -1 \neq \text{sign}(W_t^T X_{n(t)})$ , 則  $W_{t+1} \leftarrow W_t - X_{n(t)}$

$$\text{而 Multi-class PLA 會 } \begin{cases} W_1^{(t+1)} \leftarrow W_1^{(t)} + X_{n(t)} \\ W_2^{(t+1)} \leftarrow W_2^{(t)} - X_{n(t)} \end{cases}$$

$$\text{即 } W_T = \sum_{t=0}^{T-1} y_{n(t)} X_{n(t)}$$

② 若  $y_{n(t)} = 1 \neq \text{sign}(W_t^T X_{n(t)})$ , 則  $W_{t+1} \leftarrow W_t + X_{n(t)}$

$$\text{而 Multi-class PLA 會 } \begin{cases} W_1^{(t+1)} \leftarrow W_1^{(t)} - X_{n(t)} \\ W_2^{(t+1)} \leftarrow W_2^{(t)} + X_{n(t)} \end{cases}$$

$$W_1^{(T)} = \sum_{t=0}^{T-1} (-y_{n(t)} X_{n(t)})$$

$$W_2^{(T)} = \sum_{t=0}^{T-1} (y_{n(t)} X_{n(t)})$$

$$\text{故 } W_{\text{PLA}} = -W_1^* = W_2^*$$

Q6.

(d)

(a) Train 的過程並無任何向外界的主動探詢, 不符 X

(b) 訓練過程中並無明顯的 feedback of goodness 來調整訓練參數, X

(c) 分類結果不為有限數量類別, 不符 X

(e) 訓練之輸入為預先錄製的完整資料集, 不符 X

(d) 訓練之產出為自我定義的 label, 且可結尾後續工程, 產生更具物理/實際意義之資料, 符合 ✓

參考  
Q3之  
說明

Q7.

(c) 由於訓練時的 input, 總數 (1126566 + 1126) 筆的資料中, 僅有 1126 筆有 target multi-label (事先由專家上好的, label 有總數上限, 每一筆 data 有不等數量的 label) 而分類目標也為 multi-label 每個 Article 會被分類到複數個 tag 故屬於 semi-supervised learning 和 multi-label classification。

透過刪去法, 僅有 (c) 符合。

Q9.

(c)

$$\begin{aligned} (a) E[\hat{\theta}] &= E\left[\frac{1}{N} \sum_{n=1}^N [h(x_n) \neq y_n]\right] \\ &= \frac{1}{N} \sum_{n=1}^N E([h(x_n) \neq y_n]) = E([h(x_n) \neq y_n]) = \theta \end{aligned}$$

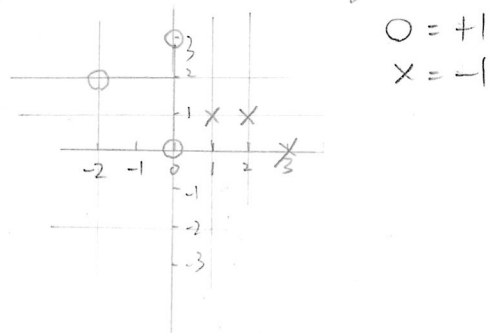
( $\because p$  is fixed)

$$\begin{aligned} (b) E[\hat{\theta}] &= \frac{1}{N} \sum_{n=1}^N E[x_n] = \frac{1}{N} \sum_{n=1}^N (0 \times (1-\theta) + 1 \times (\theta)) \\ &= \frac{1}{N} \sum_{n=1}^N (\theta) = \theta \end{aligned}$$

$$\begin{aligned} (d) E[\hat{\theta}] &= \frac{1}{N} \sum_{n=1}^N E[x_n^2] \quad \left( \because \text{Var}[x] = E[x_n^2] - (E[x_n])^2 \right) \\ &= \frac{1}{N} \sum_{n=1}^N (\text{Var}[x] + (E[x_n])^2) \\ &= \frac{1}{N} \sum_{n=1}^N (\theta + (\theta^2)) \quad (\because \text{zero-mean}) \\ &= \theta \end{aligned}$$

Q8.

(b) 採用 Human-learning:



若欲以 (0, 3), (0, 0), (1, 1) 三點進行 PLA,

則可能得出使兩 label 完美分割的  $w_f$

例  $w_f^T = [-1, 0, 0.5]$ , 其中  $w_{f2}$  是對應常數項

以 (0, 3) 為例  $\text{sign}(w_f^T \cdot \begin{bmatrix} 0 \\ 3 \\ 1 \end{bmatrix}) = \text{sign}(0.5) = +1$

而若抽選到都是相同 label (此處以 +1 為例), 則可能得到

如  $w^T = [1, 0, -3]$ , 其中  $w_2$  對應常數項

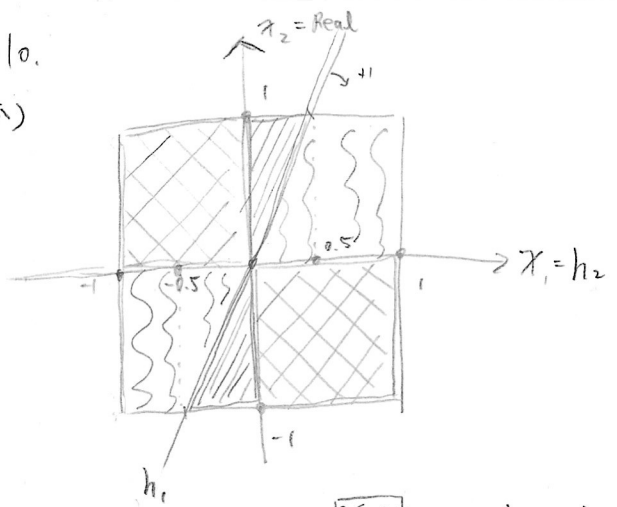
對 +1 label 會全為正確, 但對 out-of-test 的 -1 例而言則是錯誤

故  $(\min E_{\text{ots}}, \max E_{\text{ots}}) = (\frac{1}{3} \times 0, \frac{1}{3} \times 3) = (0, 1)$

$$\begin{aligned} (c) P(\hat{\theta} \leq x) &= P(X_1 \leq x, X_2 \leq x, \dots, X_N \leq x) = \prod_{i=1}^n P(X_i \leq x) = \left(\frac{x}{m}\right)^n \\ \text{PDF}(x) &= P'(\hat{\theta} \leq x) = \frac{n x^{n-1}}{m^n} \\ E(\hat{\theta}) &= \frac{1}{m^n} \int_0^m x \cdot n x^{n-1} dx \\ &= \frac{1}{m^n} \int_0^m n x^n dx = \frac{1}{m^n} \cdot \frac{n}{n+1} \cdot m^{n+1} \\ &= \frac{n}{n+1} \cdot m \neq m = \theta \end{aligned}$$

✗

Q10.  
(a)



$\begin{matrix} \text{diagonal lines} \\ \text{cross-hatch} \end{matrix} : \begin{cases} h_1(x) \neq f(x) \\ h_2(x) = f(x) \end{cases}$   
 $\begin{matrix} \text{wavy lines} \\ \text{diagonal lines} \end{matrix} : \begin{cases} h_1(x) = f(x) \\ h_2(x) \neq f(x) \end{cases}$   
 $\begin{matrix} \text{wavy lines} \\ \text{cross-hatch} \end{matrix} : h_1(x) = h_2(x) = f(x)$   
 $\text{diagonal lines} + \text{cross-hatch} + \text{wavy lines} = [-1, 1] \times [-1, 1]$

故  $E_{out}(h_1) = \frac{\text{area of diagonal lines}}{2 \times 2} = \frac{(1 \times 0.5/2) \times 2}{2 \times 2} = \frac{1}{8}$   
 $E_{out}(h_2) = \frac{\text{area of cross-hatch}}{2 \times 2} = \frac{(1 \times 1) \times 2}{2 \times 2} = \frac{1}{2}$

Q11 根據 Q10 圖之結果得

(b)

$h_1(x) = f(x)$	$h_2(x) = f(x)$	
T	T	$\frac{\text{diagonal lines}}{2 \times 2} = \frac{1.5}{4} = \frac{3}{8}$
T	F	$\frac{\text{cross-hatch}}{2 \times 2} = \frac{2}{4} = \frac{4}{8}$
F	T	$\frac{\text{wavy lines}}{2 \times 2} = \frac{0.5}{4} = \frac{1}{8}$
F	F	$\frac{0}{2 \times 2} = 0$

若  $E_{in}(h_2) = E_{in}(h_1)$ , 則僅有以下三種組合 (單組內順序不拘)

$h_1: \begin{bmatrix} T \\ T \\ T \\ T \end{bmatrix}, h_2: \begin{bmatrix} T \\ T \\ T \\ T \end{bmatrix}, E_{in}(h_1) = E_{in}(h_2) = 1$   
 $h_1: \begin{bmatrix} T \\ T \\ T \\ F \end{bmatrix}, h_2: \begin{bmatrix} T \\ T \\ T \\ T \end{bmatrix}, E_{in}(h_1) = E_{in}(h_2) = \frac{3}{4}$   
 $h_1: \begin{bmatrix} T \\ T \\ F \\ F \end{bmatrix}, h_2: \begin{bmatrix} T \\ T \\ T \\ T \end{bmatrix}, E_{in}(h_1) = E_{in}(h_2) = \frac{1}{2}$

故  $\left(\frac{3}{8}\right)^4 \times \frac{4!}{4!} + \frac{4}{8} \times \left(\frac{3}{8}\right)^2 \times \frac{1}{8} \times \frac{4!}{2!} + \left(\frac{4}{8}\right)^2 \times \left(\frac{1}{8}\right)^2 \times \frac{4!}{2! \times 2!} = \frac{8!}{4096} + \frac{36 \times 12}{4096} + \frac{16 \times 6}{4096} = \frac{609}{4096}$

Q12.

(b)

	1	2	3	4	5	6
A		G		G		G
B	G	G				G
C						G
D		G	G		G	

1 types only:  $(5) \times (A), (B), (C), (D) \quad \left(\frac{5!}{5!}\right) \times 4 = 4$   
 2 types:  $(4, 1) \times (A, B), (A, C), (A, D), (B, C), (B, D) \quad \left(\frac{5!}{4!} \times 2 + \frac{5!}{3!2!} \times 2\right) \times 5 = 150$   
 3 types:  $(3, 1, 1) \times (A, B, D), (A, B, C) \quad \left(\frac{5!}{3!} \times \frac{3!}{2!} + \frac{5!}{2!2!} \times \frac{3!}{2!}\right) \times 2 = 300$   
 $\therefore$  The probability that we got some number that is purely green is:  $\left(\frac{1}{4}\right)^5 \times (4 + 150 + 300) = \frac{454}{1024}$