

Cover page for answers.pdf
CSE512 Fall 2018 - Machine Learning - Homework 5

Your Name: Saif Suleman Vazir

Solar ID: 112072061

NetID email address: saifsuleman.vazir@stonybroook.edu

Names of people whom you discussed the homework with:

HOMEWORK 5

Q1) 1)

Given:

$$H(x) = \text{sign}(f(x))$$

$$f(x) = \sum_{t=1}^T \alpha_t h_t(x)$$

$$\delta(H(x^j) \neq y^j) = 1$$

$$\delta(H(x^j) = y^j) = 0$$

To prove:

$$E_{\text{train}} = \frac{1}{N} \sum_{j=1}^N \delta(H(x^j) \neq y^j) \leq \frac{1}{N} \sum_{j=1}^N e^{-f(x^j)y^j}$$

we know that for a classification task,
training error is given by:

$$E_{\text{train}} = \frac{1}{N} \sum_{j=1}^N \delta(H(x^j) \neq y^j)$$

Now, from the definition of $H(x)$ we get:

$$H(x) = \text{sign}(f(x)) = \begin{cases} 1 & f(x) > 0 \\ 0 & f(x) = 0 \\ -1 & f(x) < 0 \end{cases}$$

\therefore cases when $H(x^j) \neq y^j$:

i) $y^j = +1$ $H(x^j) = 0, -1$ $\{ f(x^j) = 0 \text{ or } f(x^j) < 0 \}$

ii) $y^j = -1$ $H(x^j) = 0, 1$ $\{ f(x^j) = 0 \text{ or } f(x^j) > 0 \}$

we can see that for the above cases:

$$y^j \cdot H(x^j) \leq 0 \quad \text{or} \quad y^j \cdot f(x^j) \leq 0$$

Our new training error \Rightarrow

$$E_{\text{train}} = \frac{1}{N} \sum_{j=1}^N E(x) \quad \text{where } E(x) = \begin{cases} 1 & \text{when } y^j f(x^j) \leq 0 \\ 0 & y^j f(x^j) > 0 \end{cases}$$

\therefore

~~2) use map this function to:~~

~~$e^{-E(x)}$ we get:~~

~~$e^{-E(x)} \geq 1$ when $E(x) \leq 0$~~

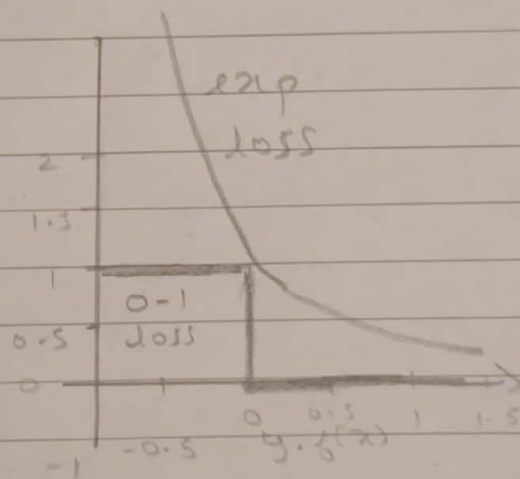
Now, considering $e^{-y_j^i f(x_j^i)}$ we get:

$$e^{-y_j^i f(x_j^i)} = \begin{cases} \geq 1 & y_j^i f(x_j^i) \leq 0 \\ 0 < z \leq 1 & y_j^i f(x_j^i) > 0 \end{cases} \quad \left[\begin{array}{l} \text{Proof of training} \\ \text{error in question} \\ 1.2 \end{array} \right]$$

Hence, from the above eqⁿs we get that:

$$\frac{1}{N} \sum_j \delta(H(x_j^i) \neq y_j^i) \leq \frac{1}{N} \sum_j e^{-y_j^i f(x_j^i)}$$

This can also be visualized graphically as left hand side is 0-1 loss and right hand side is exponential loss f^* . And we know that 0-1 loss is always less than or equal to exponential loss.



Q1) 2) we have:

$$w_j^{(t+1)} = \frac{w_j^{(t)} e^{-\alpha_t y_j^i h_t(x_j^i)}}{Z_t}$$

$$\therefore w_j^{(t)} = \frac{w_j^{(t+1)} e^{-\alpha_{t-1} y_j^i h_{t-1}(x_j^i)}}{Z_{t-1}}$$

$$w_j^{(k)} = \frac{w_j^{(k+1)} e^{-\alpha_{k+1} y_j^i h_{k+1}(x_j^i)}}{Z_{k+1}}$$

1

Also, we know that:

$$\omega_j^{(1)} = 1/N$$

From the above eqⁿs we get:

$$\begin{aligned}\omega_j^{(t+1)} &= \omega_j^{(1)} \cdot \frac{e^{-\alpha_1 y_j^{(1)} h_1(x_j^{(1)})}}{z_1} \cdot \frac{e^{-\alpha_2 y_j^{(2)} h_2(x_j^{(2)})}}{z_2} \cdots \frac{e^{-\alpha_t y_j^{(t)} h_t(x_j^{(t)})}}{z_t} \\ &= \frac{1}{N} \cdot \frac{1}{\prod_{i=1}^t z_i} \cdot e^{-y_j^{(1)} \alpha_1 h_1(x_j^{(1)}) - y_j^{(2)} \alpha_2 h_2(x_j^{(2)}) - \cdots - y_j^{(t)} \alpha_t h_t(x_j^{(t)})} \\ &= \frac{1}{N} \cdot \frac{1}{\prod_{i=1}^t z_i} \cdot e^{-y_j^{(1)} \sum_{t=1}^t \alpha_t h_t(x_j^{(t)})}\end{aligned}$$

$$\omega_j^{(t+1)} = \frac{1}{N} \cdot \frac{e^{-y_j^{(1)} \sum_{t=1}^t \alpha_t h_t(x_j^{(t)})}}{\prod_{i=1}^t z_i}$$

$$\text{As } \sum_{t=1}^t \alpha_t h_t(x_j^{(t)}) = b(x_j^{(1)})$$

$$\omega_j^{(t+1)} = \frac{1}{N} \cdot \frac{e^{-y_j^{(1)} b(x_j^{(1)})}}{\prod_{i=1}^t z_i}$$

$$\frac{1}{N} e^{-y_j^{(1)} b(x_j^{(1)})} = \omega_j^{(t+1)} \prod_{i=1}^t z_i$$

~~Summing~~ Summing for all values of $j=1$ to N

$$\frac{1}{N} \sum_{j=1}^N e^{-y_j^{(1)} b(x_j^{(1)})} = \sum_{j=1}^N \omega_j^{(t+1)} \prod_{i=1}^t z_i$$

$$\frac{1}{N} \sum_{j=1}^N e^{-y_j^{(1)} b(x_j^{(1)})} = \prod_{i=1}^t z_i \quad \left[\text{as } \sum_{j=1}^N \omega_j^{(t+1)} = 1 \right]$$

Q1) 3) Given $z_t = (1 - \epsilon_t) e^{-\alpha_t} + \epsilon_t e^{\alpha_t}$

Now, in order to minimize z_t :

a) $\frac{\partial z_t}{\partial \alpha_t} = \frac{\partial}{\partial \alpha_t} \left[(1 - \epsilon_t) e^{-\alpha_t} + \epsilon_t e^{\alpha_t} \right]$

$$= (1 - \epsilon_t) e^{-\alpha_t} (-1) + \epsilon_t e^{\alpha_t} = 0$$

$$\epsilon_t e^{\alpha_t} = (1 - \epsilon_t) e^{-\alpha_t}$$

$$e^{2\alpha_t} = \frac{1 - \epsilon_t}{\epsilon_t}$$

$$2\alpha_t = \ln \frac{1 - \epsilon_t}{\epsilon_t}$$

$$\alpha_t = \frac{1}{2} \ln \frac{1 - \epsilon_t}{\epsilon_t}$$

$$\begin{aligned}
 z_t^{opt} &= (1-\varepsilon_t) e^{-\frac{1}{2} \ln \frac{1-\varepsilon_t}{\varepsilon_t}} + \varepsilon_t e^{\frac{1}{2} \ln \frac{1-\varepsilon_t}{\varepsilon_t}} \\
 &= (1-\varepsilon_t) \cdot \sqrt{\frac{\varepsilon_t}{1-\varepsilon_t}} + \varepsilon_t \cdot \sqrt{\frac{1-\varepsilon_t}{\varepsilon_t}} \\
 &= \sqrt{(1-\varepsilon_t)\varepsilon_t} + \sqrt{\varepsilon_t(1-\varepsilon_t)} \\
 \therefore z_t^{opt} &= \underline{\underline{2\sqrt{(1-\varepsilon_t)\varepsilon_t}}}
 \end{aligned}$$

b) substituting $\varepsilon_t = 1/2 - \gamma t$ in the above eqⁿ we get:

$$z_t = 2\sqrt{(1-1/2+\gamma t)(1/2-\gamma t)}$$

$$\begin{aligned}
 &= 2\sqrt{(1/2+\gamma t)(1/2-\gamma t)} \\
 &= 2\sqrt{\frac{1}{4} - \gamma t^2}
 \end{aligned}$$

$$= 2\sqrt{\frac{1-4\gamma t^2}{4}} = \sqrt{1-4\gamma t^2}$$

Taking log we get:

$$\log z_t = \frac{1}{2} \{\log 1 - 4\gamma t^2\}$$

$$= \frac{1}{2} [\log 1 - 2\gamma t + \log 1 + 2\gamma t]$$

$$\leq \frac{1}{2} [-2\gamma t - 2\gamma t]$$

using $\log 1-x \leq -x$
 $\log 1+x \leq x$
 $x = -2\gamma t$

$$\log z_t \leq -2\gamma t$$

$$\log z_t \leq \frac{1}{2} [-4\gamma t^2]$$

using $\log 1-x \leq -x$
 $x = 4\gamma t^2$

$$\log z_t \leq -2\gamma t^2$$

$$z_t \leq \underline{\underline{e^{-2\gamma t^2}}}$$

$$c) \quad \epsilon_{\text{train}} \leq \prod_{t=1}^T z_t \leq \prod_{t=1}^T e^{-2\gamma t^2} \\ \leq e^{-2 \sum_{t=1}^T \gamma t^2}$$

As we have that:

$$\gamma_t \geq \gamma \quad (\gamma > 0)$$

squaring both sides:

$$\gamma_t^2 \geq \gamma^2$$

summing over all t :

$$\sum_{t=1}^T \gamma_t^2 \geq \sum_{t=1}^T \gamma^2$$

$$\sum_{t=1}^T \gamma_t^2 \geq T\gamma^2$$

Multiplying by -2 we get:

$$-2 \sum_{t=1}^T \gamma_t^2 \leq -2T\gamma^2$$

Exponentiation:

$$e^{-2 \sum_{t=1}^T \gamma_t^2} \leq e^{-2T\gamma^2}$$

From the eqⁿ for training error we get:

$$\epsilon_{\text{train}} \leq e^{-2 \sum_{t=1}^T \gamma_t^2} \leq e^{-2T\gamma^2}$$

Here proved.

2.5.1

Total sum within groups, [p1,p2,p3]:

K=2

$5.3648 \times 1.0e+08$, [79.82 54.81 67.31]

K=4

$4.6111 \times 1.0e+08$, [67.88 86.83 77.36]

K=6

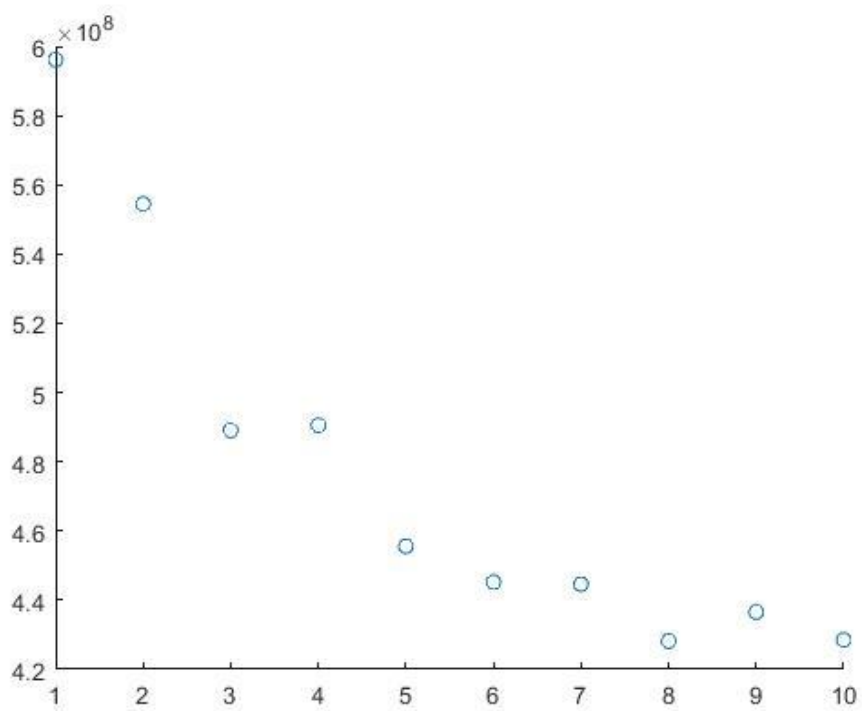
$4.3135 \times 1.0e+08$, [55.18 94.43 74.81]

2.5.2

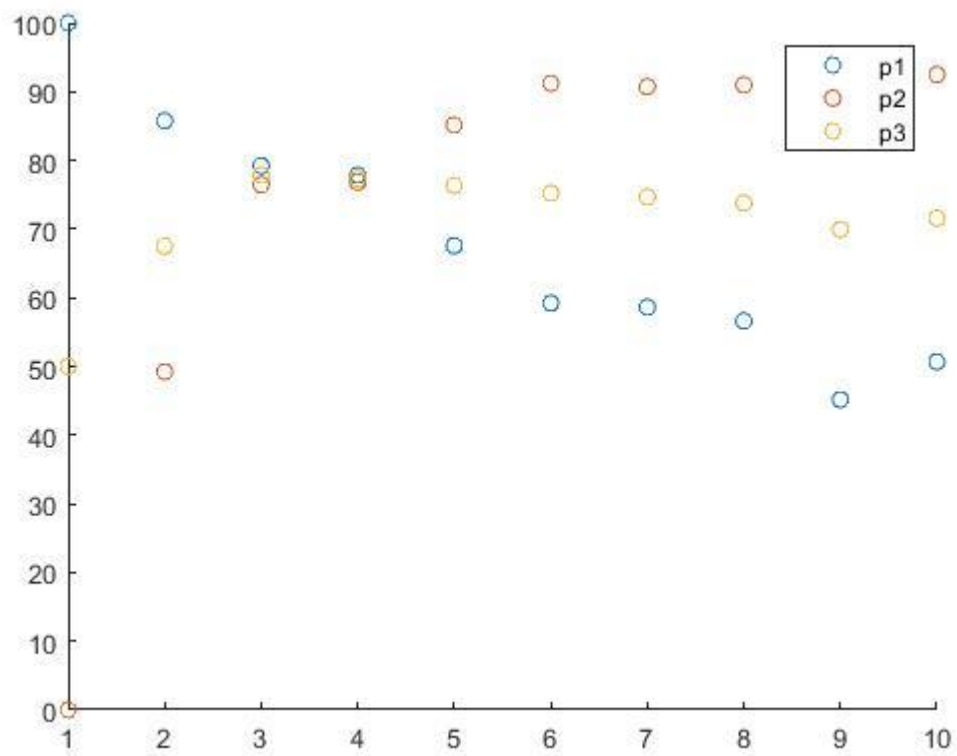
Number of iterations = 8

2.5.3

Sum of squares vs k



2.5.4



3.4.2

Accuracy with 5-fold CV = 15.6443

3.4.3

Accuracy with 5-fold CV = 84.018

C=100

Gamma=20

3.4.5

Accuracy with 5-fold CV=90.2082

C=200

Gamma=20