

CS 6375

ASSIGNMENT 3

Names of students in your group:

Nimrat Bedi

Net ID: nxb200004

Number of free late days used: 1

Note: You are allowed a **total** of 4 free late days for the **entire semester**. You can use at most 2 for each assignment. After that, there will be a penalty of 10% for each late day.

Please list clearly all the sources/references that you have used in this assignment.

<https://towardsdatascience.com/understanding-k-means-clustering-in-machine-learning-6a6e67336aa1>

# Report : Part I

## Theory Questions

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<u>PART 1</u>		
$\text{Ans 1. } E_{\text{avg}} = \frac{1}{M} \sum_{i=1}^M E(\epsilon_i(x)^2)$ $h_{\text{agg}}(x) = \frac{1}{M} \sum_{i=1}^M h_i(x)$ $\text{Aggregated model } E_{\text{agg}}(u) = E \left[ \left\{ \frac{1}{M} \sum_{i=1}^M \epsilon_i(u) \right\}^2 \right]$		
To prove $E_{\text{agg}} = \frac{1}{M} E_{\text{avg}}$		
$E_{\text{agg}}(u) = E \left[ \left\{ \frac{1}{M} \sum_{i=1}^M \epsilon_i(u) \right\}^2 \right]$ $= \frac{1}{M^2} E \left[ \left( \sum_{i=1}^M \epsilon_i(u) \right)^2 \right]$ $= \frac{1}{M^2} E \left[ \epsilon_1(u)^2 + \epsilon_2(u)^2 + \epsilon_3(u)^2 + \dots + \epsilon_M(u)^2 \right.$ $\quad \left. + 2 \epsilon_1(u) \epsilon_2(u) + 2 \epsilon_1(u) \epsilon_3(u) + \dots \right]$ $= \frac{1}{M^2} E \left[ \epsilon_1(u)^2 + \epsilon_2(u)^2 + \dots + \epsilon_M(u)^2 \right]$ <p style="text-align: center;">as <math>\epsilon_i(u) \cdot \epsilon_j(u) = 0</math></p> <p style="text-align: right;">(given in assumption)</p> $= \frac{1}{M^2} \left[ E(\epsilon_1^2(u)) + E(\epsilon_2^2(u)) + \dots \right]$ $= \frac{1}{M} \cdot \frac{1}{M} \sum_{i=1}^M E(\epsilon_i(u))^2$ $E_{\text{agg}} = \frac{1}{M} E_{\text{avg}}$ <p style="text-align: center;">Hence Proved.</p>		

Aus 2.

Jensen's inequality states that for any convex function  $f$ :

$$f\left(\sum_{i=1}^m \lambda_i x_i\right) \leq \sum_{i=1}^m \lambda_i f(x_i)$$

Using Jensen's inequality, to prove  
 $E_{\text{agg}} \leq E_{\text{avg}}$

→ From quadratic inequality, we have:-

$$\frac{(x_1 + x_2 + x_3 + \dots + x_n)^2}{n} \leq x_1^2 + x_2^2 + x_3^2 + \dots + x_n^2$$

Using this in our error function:-

$$\frac{1}{m} \left\{ E_1(x) + E_2(x) + \dots + E_m(x) \right\}^2 \leq E_2(x)$$
$$E_2(x)^2 + \dots + E_n(x)^2$$

$$\Rightarrow \frac{1}{m} \left\{ \sum_{i=1}^m E_i(x) y_i^2 \right\} \leq \sum_{i=1}^m \{ E_i(x) y_i^2 \}$$

Putting estimate value equation above:-

$$E \left[ \frac{1}{m} \left\{ \sum_{i=1}^m E_i(x) y_i^2 \right\} \right] \leq E \left[ \sum_{i=1}^m \{ E_i(x) y_i^2 \} \right]$$

Dividing L.H.S & RHS by M

$$\frac{1}{M} \times E \left[ \frac{1}{m} \left\{ \sum_{i=1}^m E_i(x) y_i^2 \right\} \right] \leq \frac{1}{M} \times E \left[ \sum_{i=1}^m \{ E_i(x) y_i^2 \} \right]$$

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E is a linear function i.e

$$E\left[\sum_{i=1}^m x_i\right] = \sum_{i=1}^m E(x_i)$$

Therefore :-

$$E\left[\left(\frac{1}{m} \sum_{i=1}^m g_i(u)\right)^2\right] \leq \frac{1}{m} \sum_{i=1}^m E\left[\left(g_i(u)\right)^2\right]$$

$$\because E_{avg} = E\left[\left(\frac{1}{m} \sum_{i=1}^m g_i(u)\right)^2\right]$$

$$\text{Hence } E_{avg} \leq E_{avg}$$

$$+ \quad E_{avg} = \frac{1}{m} \sum_{i=1}^m E\left[\left(g_i(u)\right)^2\right]$$

Am 3

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### Defining the training error for AdaBoost

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right)$$

Weight for point  $i$  at step  $t+1$  is given by:-

$$D_{t+1}(i) = \frac{D_t(i) e^{-\alpha_t h_t(x_i) y(i)}}{Z_t}$$

$$D_1 = \frac{1}{N}$$

$N$  = total no. of data points

$$\varepsilon_t = \frac{1}{2} - \gamma_t = \text{total error}$$

→ Step 1 : The first step is to show that

$$D_{t+1}(i) = \frac{1}{N} \frac{e^{-y_i f(x)}}{\prod_t Z_t} \quad \dots \textcircled{1}$$

$$\text{where } f(x) = \sum_t \alpha_t h_t(x)$$

Eq \textcircled{1} can be rewritten as:-

$$D_{t+1}(i) = D_t(i) \frac{e^{-\alpha_t y_i h_t(x_i)}}{Z_t}$$

Suppose  $y_i$  and  $h_t(x_i)$  are both in  $\{-1, +1\}$

Recursive

$$\text{definition} \Rightarrow D_{t+1}(i) = D_t(i) \cdot \frac{e^{-\alpha_1 y_1 h_1(x_1)}}{Z_1} \cdots \frac{e^{-\alpha_T y_T h_T(x_T)}}{Z_T}$$

$$= \frac{1}{N} \cdot e^{-y_i \sum_t \alpha_t h_t(x_i)} \\ = \frac{1}{N} \cdot \frac{e^{-y_i f(x_i)}}{\prod_t z_t} \quad \text{as } D_1 = \frac{1}{N}$$

Step 2: Next, we show that the training error of the final classifier  $H$  is at most  $\prod_t z_t$

Proof:-

$$\text{training error}(H) = \frac{1}{N} \sum_i \begin{cases} 1 & \text{if } y_i \neq h(x_i) \\ 0 & \text{else} \end{cases}$$

by definition of training error

$$= \frac{1}{N} \sum_i \begin{cases} 1 & \text{if } y_i \neq f(x_i) \leq 0 \\ 0 & \text{else} \end{cases}$$

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

$$y_i \in \{-1, 1\}$$

$$\leq \frac{1}{N} \sum_i e^{(-y_i f(x_i))} \quad \text{since } e^{-z} \geq 1 \quad \text{if } z \leq 0$$

$$= \sum_t D_{T+1}(x_i) \prod_t z_t \quad \text{by step 1 above}$$

Training error =  $\prod_t z_t$  since  $D_{T+1}$  is a distribution

Step 3 : The last step is to compute  $Z_t$   
 we can compute this normalization  
 constant as follows:-

$$Z_t = \sum_i D_t(i) \times \begin{cases} e^{-\alpha_t} & \text{if } h(x_i) = y_i \\ e^{\alpha_t} & \text{if } h(x_i) \neq y_i \end{cases}$$

$$= \sum_{i: h_t(x_i) = y_i} D_t(i) e^{-\alpha_t} + \sum_{i: h_t(x_i) \neq y_i} D_t(i) e^{\alpha_t}$$

$$= e^{\alpha_t} \sum_{i: h_t(x_i) = y_i} D_t(i) + e^{-\alpha_t} \sum_{i: h_t(x_i) \neq y_i} D_t(i)$$

$$= e^{-\alpha_t} (1 - \varepsilon_t) + e^{\alpha_t} \varepsilon_t \quad (\text{by definition of } \varepsilon_t)$$

$$= 2 \sqrt{\varepsilon_t (1 - \varepsilon_t)} \quad (\text{by our choice of } \alpha_t \rightarrow \text{which was chosen to minimize this expression})$$

$$= \sqrt{1 - 4 \varepsilon_t^2} \quad \text{plugging in } \varepsilon_t = \frac{1 - \gamma_t}{2}$$

$$Z_t \leq e^{-2\alpha_t^2} \quad \text{using } 1 + x \leq e^x \text{ for all real } x$$

Combining with step 2 gives the claimed upper bound on training error of  $H$

$$\therefore E_{\text{training}} \leq \frac{1}{t} Z_t \leq \exp \left( -2 \frac{\sum \gamma_t^2}{t} \right)$$

# **Report : Part II**

## **Tweets Clustering using k-means**

### **Dataset used : gdnhealthcare**

<b>Value of K</b>	<b>SSE</b>	<b>Size of each cluster</b>
5	2284	1 : 171 2 : 358 3 : 1260 4 : 433 5 : 773
10	2186	1 : 93 2 : 168 3 : 296 4 : 106 5 : 354 6 : 257 7 : 795 8 : 231 9 : 213 10 : 482
15	2181	1 : 85 2 : 75 3 : 38 4 : 201 5 : 52 6 : 390 7 : 349 8 : 497 9 : 271 10 : 108 11 : 108 12 : 280 13 : 59 14 : 385 15 : 97
20	2146	1 : 32 2 : 159 3 : 38 4 : 116 5 : 203

		6 : 123 7 : 29 8 : 299 9 : 214 10 : 148 11 : 199 12 : 71 13 : 64 14 : 182 15 : 168 16 : 136 17 : 307 18 : 309 19 : 153 20 : 45
25	2039.0037	1 : 78 2 : 27 3 : 199 4 : 101 5 : 127 6 : 144 7 : 80 8 : 170 9 : 114 10 : 106 11 : 69 12 : 123 13 : 140 14 : 144 15 : 34 16 : 125 17 : 30 18 : 57 19 : 231 20 : 181 21 : 470 22 : 76 23 : 88 24 : 61 25 : 20