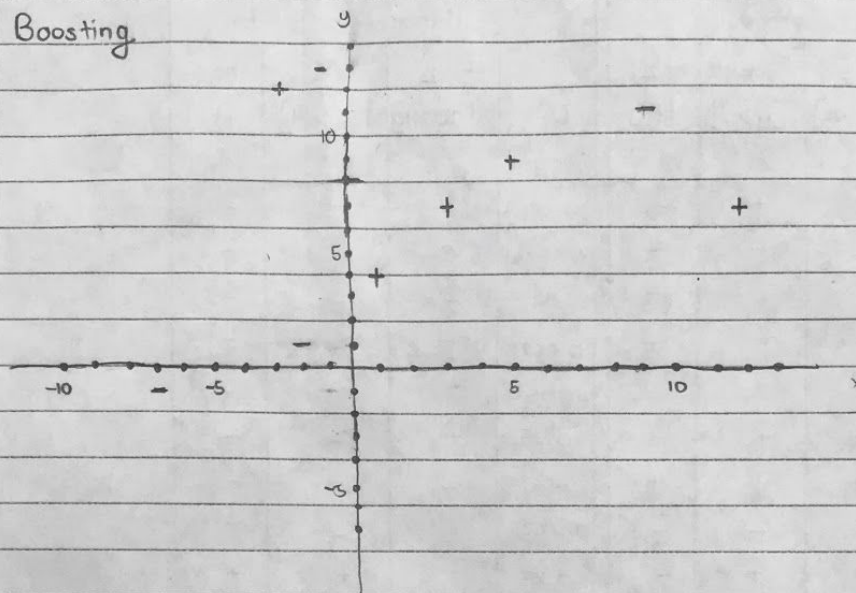


PSET 4  
1 Boosting



a.  $D_0 = 0.1$

Best learners  $\rightarrow f_1 = [x > 2]$  and  $f_2 = [y > 5]$

$$\epsilon_{x1} = \frac{2}{10} \quad \epsilon_{x2} = \frac{3}{10}$$

$$\alpha_0 = \frac{1}{2} \log_2 \frac{1 - \epsilon}{\epsilon} = \frac{1}{2} \log_2 \frac{0.8}{0.2} = 1$$

c. From the value of  $\alpha_0 = 1$  we get

$$D_{t+1}(i) = \frac{D_0(i)}{Z_0} \begin{cases} 2^{-\alpha_t} & \text{if } y_i = h_t(x_i) \\ 2^{\alpha_t} & \text{if } y_i \neq h_t(x_i) \end{cases}$$

$$\begin{aligned} D_1(i) &= \frac{0.1}{Z_0} \begin{cases} 2^{-1} & \text{if } y_i = h_1(x_i) \\ 2 & \text{if } y_i \neq h_1(x_i) \end{cases} \\ &= \begin{cases} \frac{1}{20Z_0} & \text{if } y_i = h_1(x_i) \\ \frac{1}{5Z_0} & \text{if } y_i \neq h_1(x_i) \end{cases} \end{aligned}$$

$$Z_0 = \frac{8}{20Z_0} + \frac{2}{5Z_0} = 1 \rightarrow \frac{16}{20Z_0} = 1 \rightarrow Z_0 = \frac{4}{5}$$

Thus,

$$D_1(i) = \begin{cases} 0.0625 & \text{if } y_i = h_1(x_i) \\ 0.25 & \text{if } y_i \neq h_1(x_i) \end{cases}$$

Best learners  $\rightarrow f_1 = [x > 10]$  and  $f_2 = [y > 11]$

( $\hookrightarrow$  continue below the table

		Hypothesis 1				Hypothesis 2			
			$f_1 \equiv$	$f_2 \equiv$	$h_1 \equiv$		$f_1 \equiv$	$f_2 \equiv$	$h_2 \equiv$
i	label	$D_0$	$[x > 2]$	$[y > 5]$	$[f_1]$	$D_1$	$[x > 10]$	$[y > 11]$	$[f_2]$
1	-	0.1	-	+	-	0.0625	-	-	-
2	-	0.1	-	-	-	0.0625	-	-	-
3	+	0.1	+	+	+	0.0625	-	-	-
4	-	0.1	-	-	-	0.0625	-	-	-
5	-	0.1	-	+	-	0.0625	-	+	+
6	-	0.1	+	+	+	0.25	-	-	-
7	+	0.1	+	+	+	0.0625	+	-	-
8	-	0.1	-	-	-	0.0625	-	-	-
9	+	0.1	-	+	-	0.25	-	+	+
10	+	0.1	+	+	+	0.0625	-	-	-

$$c. \quad E f_1 = 1 \times 0.25 + 2 \times 0.0625 \\ = 0.3825$$

$$E f_2 = 0 \times 0.25 + 4 \times 0.0625 \\ = 0.25$$

$$\alpha_1 = \frac{1}{2} \log_2 \frac{1 - E f_2}{E f_2} = \frac{1}{2} \log_2 \frac{0.75}{0.25} \\ = 0.79$$

$$d. \quad H(x) = \text{sgn} (1 \times [x > 2] + 0.79 \times [y > 11])$$

$$-\frac{m}{k} - \frac{km+m}{k} =$$

## 2 Multi-class classification

a) i. One vs All  $\rightarrow k$  classifiers

$$\text{All vs All} \rightarrow \binom{k}{2} = \frac{k(k-1)}{2}$$

ii. One vs All  $\rightarrow m$  examples

$$\text{All vs All} \rightarrow \frac{2m}{k} \text{ examples}$$

iii. One vs All  $\rightarrow$  the rule of winner takes all, or we choose the label that achieves highest score.

All vs All  $\rightarrow$  by vote. For ex: apply all vs all classifiers and let each classifier vote the label.

iv. One vs All  $\rightarrow O(mk) \sim m$  examples with  $k$  classifiers.

$$\text{All vs All} \rightarrow O\left(\frac{2m}{k} \times \frac{k(k-1)}{2}\right) = O(mk).$$

b). Even though both has the same time complexity, I will choose one vs all because practically it is easier to implement and only has  $k$  classifiers. While All vs All need at least  $k^2$ .

c). Complexity for KERNEL PERCEPTRON  $\rightarrow O(m^2)$

Thus, complexity of one vs all using this method,  $O(m^2k)$

$$\text{--- " --- all vs all } O\left(\frac{4m^2}{k^2} \times \frac{k(k-1)}{2}\right) = O(m^2)$$

Therefore, if using this method, all vs all is more preferable than one vs all since  $O(m^2) < O(m^2k)$

d) One vs all  $\rightarrow O(dm^2k)$

$$\text{All vs all} \rightarrow O\left(d \frac{4m^2}{k^2} \times \frac{k(k-1)}{2}\right) = O(dm^2)$$

Here, all vs all is better

e) One vs all  $\rightarrow O(d^2mk)$

$$\text{All vs all} \rightarrow O\left(d^2 \frac{4m}{k} \times \frac{k(k-1)}{2}\right) = O(d^2mk)$$

Since both has the same time complexity, and we don't know the exact



implementation of this magic box, I would assume they have the same efficiency.

f) Counting  $\rightarrow O(m^2)$

since we need to run on each classifier.

$$\frac{m(m-1)}{2} \rightarrow O(m^2)$$

Knockout  $\rightarrow O(m)$

Since we don't care about the loser class.