

Consider a dataset given in the following:

x	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
y	1	1	1	-1	-1	-1	-1	1	1	1

Similar to Bagging, we can pick different training examples to obtain a new training set in AdaBoost. Supposed we have three rounds of boosting and each round has the following training record respectively:

Round 1

x	0.1	0.4	0.5	0.6	0.6	0.7	0.7	0.7	0.8	1
y	1	-1	-1	-1	-1	-1	-1	-1	1	1

Round 2

x	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3
y	1	1	1	1	1	1	1	1	1	1

Round 3

x	0.2	0.2	0.4	0.4	0.4	0.4	0.5	0.6	0.6	0.7
y	1	1	-1	-1	-1	-1	-1	-1	-1	-1

The best split point for each round is:

Round	Split Point	Left Class	Right Class
1	0.75	-1	1
2	0.05	1	1
3	0.3	1	-1

Use AdaBoost and follow what we have covered in the toy example to compute  $\varepsilon_i$ ,  $\alpha_i$  and the updated weights. Finally find the combined classifier  $H$ .

從 3 個 boosting round 以及題目所指定的 best split point 可以得到下表的結果，與題目所給的 dataset 相比，可以看出每個 round 都有被分錯的地方，以紅色去標記：

	Original Data	x	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
		y	1	1	1	-1	-1	-1	-1	1	1	1
Round	1		-1	-1	-1	-1	-1	-1	-1	1	1	1
	2		1	1	1	1	1	1	1	1	1	1
	3		1	1	1	-1	-1	-1	-1	-1	-1	-1

$$a_j = \frac{1}{2} \ln\left(\frac{1 - \varepsilon_j}{\varepsilon_j}\right)$$

### Round 1

On round 1, AdaBoost assigns equal weight to all of the examples. Given examples with these weights, the base learner chooses the base hypothesis indicated by  $h_1$ , this hypothesis incorrectly classifies three points so its error  $\varepsilon_1$  is 0.30  $\cdot \alpha_1 \approx 0.42 \cdot Z_1 \approx 0.92$  .

	1	2	3	4	5	6	7	8	9	10
$D_1(i)$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
$e^{-\alpha_1 y_i h_1(x_i)}$	1.53	1.53	1.53	0.66	0.66	0.66	0.66	0.66	0.66	0.66
$D_1(i)e^{-\alpha_1 y_i h_1(x_i)}$	0.15	0.15	0.15	0.07	0.07	0.07	0.07	0.07	0.07	0.07
$D_2(i)$	0.17	0.17	0.17	0.07	0.07	0.07	0.07	0.07	0.07	0.07

### Round 2

On round 2, the base learner pays special attention on the three relatively high-weight points missed by  $h_1$  and chooses  $h_2$ , under distribution  $D_2$ , these four points have weight only around 0.07143, so the error of  $h_2$  with respect to  $D_2$ ,  $\varepsilon_2 \approx 0.29 \cdot \alpha_2 \approx 0.46$  and  $Z_2 \approx 0.90$ .

	1	2	3	4	5	6	7	8	9	10
$D_1(i)$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
$e^{-\alpha_1 y_i h_1(x_i)}$	1.53	1.53	1.53	0.66	0.66	0.66	0.66	0.66	0.66	0.66
$D_1(i)e^{-\alpha_1 y_i h_1(x_i)}$	0.15	0.15	0.15	0.07	0.07	0.07	0.07	0.07	0.07	0.07
$D_2(i)$	0.17	0.17	0.17	0.07	0.07	0.07	0.07	0.07	0.07	0.07
$e^{-\alpha_2 y_i h_2(x_i)}$	0.63	0.63	0.63	1.58	1.58	1.58	1.58	0.63	0.63	0.63
$D_2(i)e^{-\alpha_2 y_i h_2(x_i)}$	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.05	0.05	0.05
$D_3(i)$	0.12	0.12	0.12	0.16	0.16	0.16	0.16	0.05	0.05	0.05

### Round 3

On round 3, this classifier misses none of the points misclassified by  $h_1$  and  $h_2$  since these points have relatively high weight under  $D_3$ . Instead, it misclassifies three points, they were not misclassified by  $h_1$  or  $h_2$ , so they have very low weight under  $D_3$ . On round 3,  $\varepsilon_3 \approx 0.15 \cdot \alpha_3 \approx 0.87$  and  $Z_3 \approx 0.71$ .

	1	2	3	4	5	6	7	8	9	10	
$D_1(i)$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	$\varepsilon_1 \approx 0.30$ $\alpha_1 \approx 0.42$ $Z_1 \approx 0.92$
$e^{-\alpha_1 y_i h_1(x_i)}$	1.53	1.53	1.53	0.66	0.66	0.66	0.66	0.66	0.66	0.66	
$D_1(i)e^{-\alpha_1 y_i h_1(x_i)}$	0.15	0.15	0.15	0.07	0.07	0.07	0.07	0.07	0.07	0.07	
$D_2(i)$	0.17	0.17	0.17	0.07	0.07	0.07	0.07	0.07	0.07	0.07	$\varepsilon_2 \approx 0.29$ $\alpha_2 \approx 0.46$ $Z_2 \approx 0.90$
$e^{-\alpha_2 y_i h_2(x_i)}$	0.63	0.63	0.63	1.58	1.58	1.58	1.58	0.63	0.63	0.63	
$D_2(i)e^{-\alpha_2 y_i h_2(x_i)}$	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.05	0.05	0.05	
$D_3(i)$	0.12	0.12	0.12	0.16	0.16	0.16	0.16	0.05	0.05	0.05	$\varepsilon_3 \approx 0.15$ $\alpha_3 \approx 0.87$ $Z_3 \approx 0.71$
$e^{-\alpha_3 y_i h_3(x_i)}$	0.42	0.42	0.42	0.42	0.42	0.42	0.42	2.38	2.38	2.38	
$D_3(i)e^{-\alpha_3 y_i h_3(x_i)}$	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.12	0.12	0.12	

Compute  $\varepsilon_i, \alpha_i$

	$\varepsilon_i$	$\alpha_i$
Round1	0.30	0.42
Round2	0.29	0.46
Round3	0.15	0.87

Combined classifier  $H$

Original Data	x	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	y	1	1	1	-1	-1	-1	-1	1	1	1
1		-1	-1	-1	-1	-1	-1	-1	1	1	1
2		1	1	1	1	1	1	1	1	1	1
3		1	1	1	-1	-1	-1	-1	-1	-1	-1
$\alpha_i y_{\text{round}_i}$		0.90	0.90	0.90	-0.83	-0.83	-0.83	-0.83	0.01	0.01	0.01

$\alpha_1 y_{\text{round}_1} + \alpha_2 y_{\text{round}_2} + \alpha_3 y_{\text{round}_3} > 0, y_n = 1$

$\alpha_1 y_{\text{round}_1} + \alpha_2 y_{\text{round}_2} + \alpha_3 y_{\text{round}_3} < 0, y_n = -1$

Combined classifier  $H$  :

$H = \text{sign}(\alpha_1 y_{\text{round}_1} + \alpha_2 y_{\text{round}_2} + \alpha_3 y_{\text{round}_3})$

藉由3個round所得出的權重 $\alpha_1$ 、 $\alpha_2$ 、 $\alpha_3$ ，可以得到最後每個x所對應的值，若所算出的數字大於0，則y就會是1相反地，若數字小於0，y就為-1。與原始資料相比二者相同。

$\sum_{n=1}^3 \alpha_i y_n$	0.90	0.90	0.90	-0.83	-0.83	-0.83	-0.83	0.01	0.01	0.01
y(Adaboost)	1	1	1	-1	-1	-1	-1	1	1	1