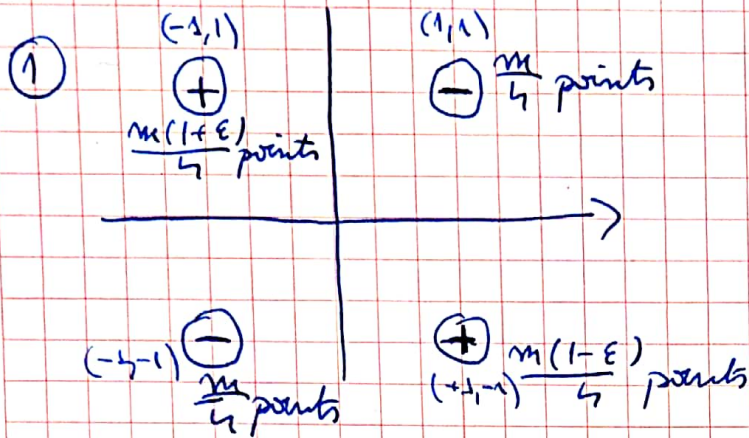


Similiar class C



$$\frac{m(1+\epsilon)}{4} + \frac{m(1-\epsilon)}{4} = \frac{m}{2} \text{ points with } + \text{ label}$$

$$\frac{m}{4} + \frac{m}{4} = \frac{m}{2} \text{ points with } - \text{ label}$$

The probability distribution of the training point $(-1, 1)$ with label $+$ is $\frac{\frac{m(1+\epsilon)}{4}}{m} = \frac{1+\epsilon}{4}$. For point $(1, -1)$ we obtain $\frac{1-\epsilon}{4}$, for points $(1, 1)$ and $(-1, -1)$ with label $-$ we obtain $\frac{1}{4}$.

The initial problem with m points in the training sample is similar with the problem with 4 points with the corresponding probabilities.

$$S = \left\{ \left(\underset{\substack{\downarrow \\ \text{point}}}{(-1, 1)}, \underset{\substack{\uparrow \\ \text{label}}}{+1} \right), \left((1, -1), +1 \right), \left((1, 1), -1 \right), \left((-1, -1), -1 \right) \right\}$$

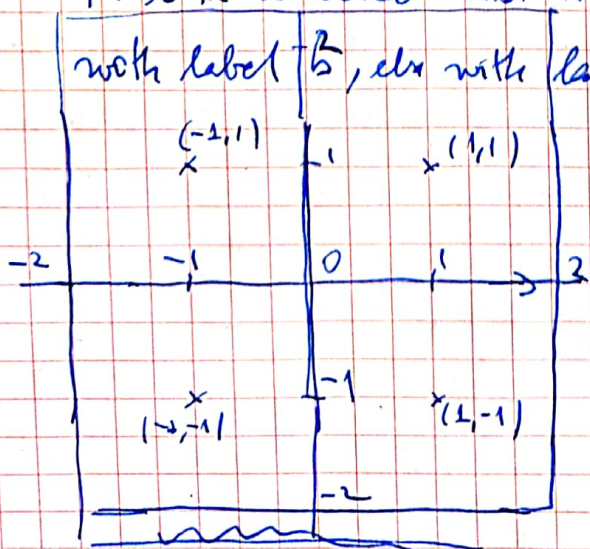
$$D^{(1)} = \begin{pmatrix} (-1, 1) & (1, -1) & (1, 1) & (-1, -1) \\ \frac{1+\epsilon}{4} & \frac{1-\epsilon}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$$

Base hypothesis class = decision stumps in \mathbb{R}^2

$$\mathcal{H}_{DS}^2 = \left\{ h_{i, \theta, b} : \mathbb{R}^2 \rightarrow \{-1, 1\}, h_{i, \theta, b}(x_1, x_2) = \text{sign}(\theta - x_i) * b, \begin{matrix} 1 \leq i \leq 2 \\ \theta \in \mathbb{R} \\ b \in \{+1, -1\} \end{matrix} \right\}$$

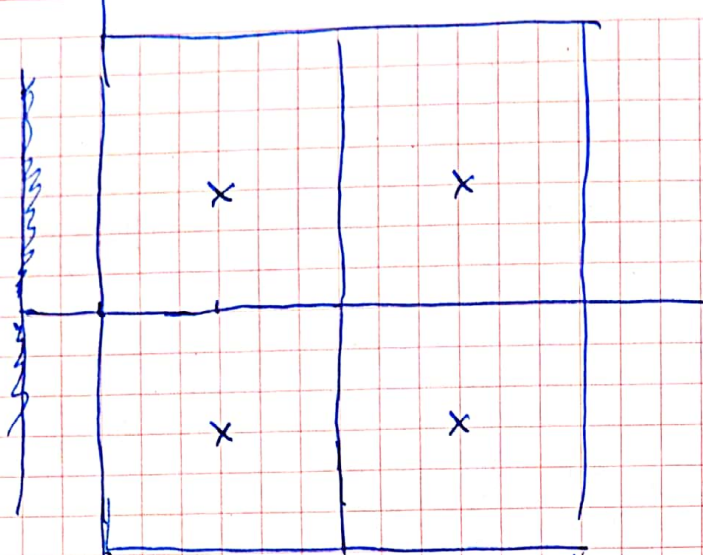
= pick a coordinate i (1 or 2), project the input $x = (x_1, x_2)$ on

the i -th coordinate and obtain x_i ; if $x_i \leq \theta$ label the example x_i with label $+b$, else with label $-b$.



For our problem we can see that we can take set of representative thresholds θ to be $\theta = \{-2, 0, 2\}$.

So we have at most 12 base classifiers $h_{1,-2,1}; h_{1,-2,-1} \dots h_{2,2,-1}$



+ | -

$h_{1,-2,+1} \rightarrow$ project on x_1 , compare to -2 , all points < -2 get label 1 , all other get label -1

$h_{1,-2,-1} \rightarrow$ project on x_1 , compare to -2 , all point < -2 get label -1 , all other get label $+1$

- | +

+ | -

$h_{1,+2,+1}$

project on x_1 , compare to 2 , all points < 2 get label $+1$, all other get label -1

So we see that as our training set $h_{1,-2,-1}$ and $h_{1,+2,+1}$ will have the same behavior (all points will receive label $+1$).

If we analyze the behavior of all 12 base classifiers (decision stumps in \mathbb{R}^2) we will see that in the end there are only 6 unique base classifiers.

| | |
|---|---|
| + | + |
| + | + |

h^1

| | |
|---|---|
| - | - |
| - | - |

h^2

| | |
|---|---|
| + | - |
| + | - |

h^3

| | |
|---|---|
| - | + |
| - | + |

h^4

| | |
|---|---|
| - | - |
| + | + |

h^5

| | |
|---|---|
| + | + |
| - | - |

h^6

So we have $B = \{h^1, h^2, h^3, h^4, h^5, h^6\}$

Round 1
- distribution $D^{(1)}: \begin{pmatrix} (-1,1) & (1,-1) & (1,1) & (-1,-1) \\ \frac{1+\epsilon}{4} & \frac{1-\epsilon}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$

- select the best classifier from \mathcal{H} , the one with minimum empirical risk

$$L_{D^{(1)}}(h^1) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

$$L_{D^{(1)}}(h^2) = \frac{1+\epsilon}{4} + \frac{1-\epsilon}{4} = \frac{1}{2}$$

$$L_{D^{(1)}}(h^3) = \frac{1}{4} + \frac{1-\epsilon}{4} = \frac{1}{2} - \frac{\epsilon}{4}$$

$$L_{D^{(1)}}(h^4) = \frac{1+\epsilon}{4} + \frac{1}{4} = \frac{1}{2} + \frac{\epsilon}{4}$$

$$L_{D^{(1)}}(h^5) = \frac{1+\epsilon}{4} + \frac{1}{4} = \frac{1}{2} + \frac{\epsilon}{4}$$

$$L_{D^{(1)}}(h^6) = \frac{1}{4} + \frac{1-\epsilon}{4} = \frac{1}{2} - \frac{\epsilon}{4}$$

So, the minimum achievable error is $\frac{1}{2} - \frac{\epsilon}{4}$ and it is attained by best classifiers h^3 and h^6 . Let's choose h^3 as our weak classifier

$$h^3 = h_{1,0,+1}$$

So, for $t=1$ (round 1) we have $h_t = h^3 = h_{1,0,+1}$

The error of the best classifier is $\epsilon_1 = \frac{1}{2} - \frac{\epsilon}{4}$

$$w_1 = \frac{1}{2} \ln\left(\frac{1}{\epsilon_1} - 1\right) = \frac{1}{2} \ln\left(\frac{1}{\frac{1}{2} - \frac{\epsilon}{4}} - 1\right) = \ln\left(\frac{2+\epsilon}{2-\epsilon}\right)^{\frac{1}{2}} = \ln\sqrt{\frac{2+\epsilon}{2-\epsilon}}$$

~~Based on~~ $D^{(1)}$ we will build $D^{(2)}$. Examples correctly classified at round 1 will have now the weight decreased, examples misclassified at round 1 will have their weight increased.

$$D^{(2)}((-1,1)) = \frac{1}{Z_2} D^{(1)}((-1,1)) \times \sqrt{\frac{\epsilon_1}{1-\epsilon_1}} = \frac{1}{Z_2} \cdot \left(\frac{1+\epsilon}{4}\right) \times \sqrt{\frac{2-\epsilon}{2+\epsilon}} \quad \downarrow$$

$$D^{(2)}((+1,-1)) = \frac{1}{Z_2} \cdot \left(\frac{1-\epsilon}{4}\right) \times \sqrt{\frac{2+\epsilon}{2-\epsilon}} \quad \uparrow$$

$$D^{(2)}((+1,+1)) = \frac{1}{Z_2} \cdot \frac{1}{4} \cdot \sqrt{\frac{2-\epsilon}{2+\epsilon}} \quad \downarrow$$

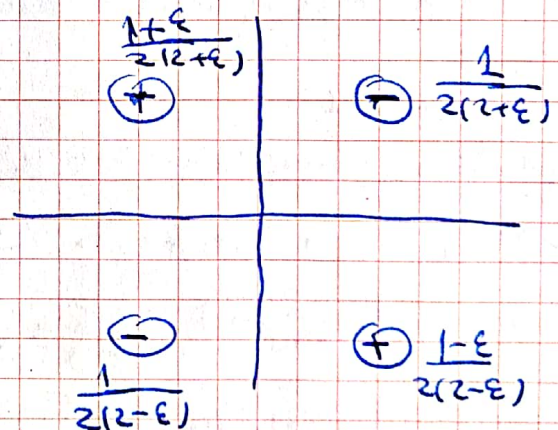
$$D^{(2)}((-1,-1)) = \frac{1}{Z_2} \cdot \frac{1}{4} \cdot \sqrt{\frac{2+\epsilon}{2-\epsilon}} \quad \uparrow$$

We can find the value of Z_2 such that $D^{(2)}$ is a probability distribution,

meaning that sum of probability masses should be equal to 1.

$$\begin{aligned}
 & D^{(2)}((-1, 1)) + D^{(2)}((+1, -1)) + D^{(2)}((-1, -1)) + D^{(2)}((+1, 1)) = 1 \\
 \Rightarrow Z_2 &= \left\{ \frac{1+\epsilon}{4} \cdot \sqrt{\frac{2-\epsilon}{2+\epsilon}} + \frac{1-\epsilon}{4} \cdot \sqrt{\frac{2+\epsilon}{2-\epsilon}} + \frac{1}{4} \cdot \sqrt{\frac{2-\epsilon}{2+\epsilon}} + \frac{1}{4} \cdot \sqrt{\frac{2+\epsilon}{2-\epsilon}} \right\} \\
 &= \frac{1}{4} \sqrt{\frac{2-\epsilon}{2+\epsilon}} \left((1+\epsilon) + (1-\epsilon) \cdot \left(\frac{2+\epsilon}{2-\epsilon} \right) + 1 + \frac{2+\epsilon}{2-\epsilon} \right) \\
 &= \frac{1}{4} \sqrt{\frac{2-\epsilon}{2+\epsilon}} \cdot \frac{(1+\epsilon)(2-\epsilon) + (1-\epsilon)(2+\epsilon) + (2-\epsilon) + 2+\epsilon}{2-\epsilon} \\
 &= \frac{1}{4} \sqrt{\frac{2-\epsilon}{2+\epsilon}} \cdot \frac{2+\epsilon-\epsilon^2 + 2-\epsilon-\epsilon^2 + 2-\epsilon + 2+\epsilon}{2-\epsilon} \\
 &= \frac{1}{4} \sqrt{\frac{2-\epsilon}{2+\epsilon}} \cdot \frac{8-2\epsilon^2}{2-\epsilon} = \frac{1}{4} \sqrt{\frac{2-\epsilon}{2+\epsilon}} \cdot \frac{2(2-\epsilon)(2+\epsilon)}{(2-\epsilon)} \\
 &= \frac{1}{2} \cdot \sqrt{(2-\epsilon)(2+\epsilon)}
 \end{aligned}$$

$$\begin{aligned}
 \Rightarrow D^{(2)}((-1, 1)) &= \frac{(1+\epsilon)}{2(2+\epsilon)} \\
 D^{(2)}((+1, -1)) &= \frac{(1-\epsilon)}{2(2-\epsilon)} \\
 D^{(2)}((-1, -1)) &= \frac{1}{2(2+\epsilon)} \\
 D^{(2)}((+1, 1)) &= \frac{1}{2(2-\epsilon)}
 \end{aligned}$$



What is the error of the best classifier $h^3 = h_{1,0,1,1}$ selected at round 1 or $D^{(2)}$? $\text{Loss}(h^3) = \frac{1}{2(2-\epsilon)} \times \frac{1-\epsilon}{2(2+\epsilon)} = \frac{2-\epsilon}{2(2-\epsilon)} = \frac{1}{2}$.

Round 2

- distribution $D^{(2)}$: $\begin{pmatrix} (1,1) & (1,-1) & (-1,1) & (-1,-1) \\ \frac{1+\epsilon}{2(2+\epsilon)} & \frac{1-\epsilon}{2(2-\epsilon)} & \frac{1}{2(2+\epsilon)} & \frac{1}{2(2-\epsilon)} \end{pmatrix}$

- select the best classifier from H , the one with the minimum

empirical risk

$$L_{D^{(2)}}(h^1) = \frac{1}{2(2-\epsilon)} + \frac{1}{2(2+\epsilon)} = \frac{2+\epsilon+2-\epsilon}{2(2-\epsilon)(2+\epsilon)} = \frac{2}{(2-\epsilon)(2+\epsilon)} = \frac{4}{2(2+\epsilon)(2-\epsilon)}$$

$$L_{D^{(2)}}(h^2) = \frac{(1+\epsilon)}{2(2+\epsilon)} + \frac{1-\epsilon}{2(2-\epsilon)} = \frac{(1+\epsilon)(2-\epsilon) + (1-\epsilon)(2+\epsilon)}{2(2-\epsilon)(2+\epsilon)} = \frac{4-2\epsilon^2}{2(2-\epsilon)(2+\epsilon)}$$

$$L_{D^{(2)}}(h^3) = \frac{1}{2} = \frac{4-\epsilon^2}{2(2-\epsilon)(2+\epsilon)}$$

$$L_{D^{(2)}}(h^4) = \frac{1}{2} = \frac{4-\epsilon^2}{2(2-\epsilon)(2+\epsilon)}$$

$$L_{D^{(2)}}(h^5) = \frac{(1+\epsilon)}{2(2+\epsilon)} + \frac{1}{2(2-\epsilon)} = \frac{(1+\epsilon)(2-\epsilon) + 2+\epsilon}{2(2+\epsilon)(2-\epsilon)} = \frac{4+2\epsilon-\epsilon^2}{2(2+\epsilon)(2-\epsilon)}$$

$$L_{D^{(2)}}(h^6) = \frac{1}{2(2+\epsilon)} + \frac{1-\epsilon}{2(2-\epsilon)} = \frac{(2-\epsilon) - (1-\epsilon)(2+\epsilon)}{2(2+\epsilon)(2-\epsilon)} = \frac{4-2\epsilon-\epsilon^2}{2(2+\epsilon)(2-\epsilon)}$$

The smallest error is attained by h^6 . Thus ~~is~~ the best classifier selected at the current round.

So, for $A=2$ (round 2) we have $h_2 = h^6 = h_{2,0,1,-1}$

$$\epsilon_2 = \frac{4-2\epsilon-\epsilon^2}{2(2+\epsilon)(2-\epsilon)}$$

$$w_2 = \frac{1}{2} \ln\left(\frac{1}{\epsilon_2} - 1\right) = \frac{1}{2} \ln\left(\frac{4-\epsilon^2+2\epsilon}{4-\epsilon^2-2\epsilon}\right)$$