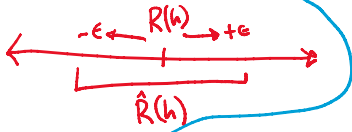


Def: PAC Criterion

$$\Pr(\forall h \in \mathcal{H}, |R(h) - \hat{R}(h)| < \epsilon) \geq (1 - \delta)$$

↖ small
↖ small



Q: What is 'random' here?

A: $\hat{R}(h)$ is based on a random sample of training data from $p^*(x)$

Def: sample complexity is the minimum number of training examples N s.t. the PAC criterion is satisfied for some ϵ and δ

Def: a hypothesis $h \in \mathcal{H}$ is consistent with the training data if $\hat{R}(h) = 0$

Thm 1: Realizable, Finite $|\mathcal{H}|$

$N \geq \frac{1}{\epsilon} [\ln(|\mathcal{H}|) + \ln(1/\delta)]$ labeled examples are sufficient to ensure that w/prob. $(1 - \delta)$ all $h \in \mathcal{H}$ with $\hat{R}(h) = 0$ have $R(h) < \epsilon$

Proof of Thm. 1

① Assume k bad hypotheses h_1, h_2, \dots, h_k with $R(h_i) > \epsilon$

② Pick bad h_i : prob. of h_i consistent w/first training example $\leq (1 - \epsilon)$
 prob. of h_i consistent w/first N training examples $\leq (1 - \epsilon)^N = \overbrace{(1 - \epsilon) \dots (1 - \epsilon)}^{N \text{ times}}$

③ Prob. that at least one bad h_i is consistent w/first N train examples $\leq k(1 - \epsilon)^N$

$\exists h \in \mathcal{H}$ s.t. $\hat{R}(h) = 0$ and $R(h) > \epsilon$

by Union Bound
 $P(A \cup B) \leq P(A) + P(B)$

$\leq |\mathcal{H}| (1 - \epsilon)^N$

④ Fact: $(1 - x) \leq \exp(-x)$
 $\Rightarrow |\mathcal{H}| (1 - \epsilon)^N \leq |\mathcal{H}| \exp(-\epsilon N) = |\mathcal{H}| \exp(-\epsilon N)$

Q: which is larger?
 A: $k \leq |\mathcal{H}|$

⑤ Choose δ s.t. $|\mathcal{H}| \exp(-\epsilon N) \leq \delta$

⑥ Solve for N : $\Rightarrow |\mathcal{H}| (1/\delta) \leq \exp(-\epsilon N)$

Statement 1
 $\Rightarrow \ln(|\mathcal{H}|) + \ln(1/\delta) \leq \ln(1) - \ln(\exp(-\epsilon N)) \rightarrow \epsilon N$
 $\Rightarrow \frac{1}{\epsilon} [\ln(|\mathcal{H}|) + \ln(1/\delta)] \leq N$

Assume Stat. 1 then:

$$\epsilon [\ln(1/\delta) + \ln(1/\delta)] \leq N$$

Assume Stat. 1, then:

w/prob δ

$\exists h \in \mathcal{H}$ s.t. $R(h) > \epsilon$ and $\hat{R}(h) = 0$] "bad"

w/prob. $(1-\delta)$

all $h \in \mathcal{H}$ with $R(h) > \epsilon$ have $\hat{R}(h) > 0$] "not bad"

\Rightarrow all $h \in \mathcal{H}$ with $\hat{R}(h) = 0$ have $R(h) \leq \epsilon$

\Rightarrow if the learner returns $h \in \mathcal{H}$ w/zero training error then w/prob. $(1-\delta)$ we know that h has $\leq \epsilon$ true error

Contrapositive
 $A \Rightarrow B$
 equiv.
 $\neg B \Rightarrow \neg A$

O H

x_1	x_2	x_3	h_i
e	i	i	h_1
e	i	n	h_2
i	n	i	h_3
i	i	i	\vdots
n	i	e	\vdots
i	i	i	\vdots
i	e	i	\vdots
e	i	i	\vdots
i	\vdots	\vdots	\vdots
e	e	e	h_{27}
e	e	e	

\mathbb{R}^k

$$\vec{b} = \beta \vec{z}$$

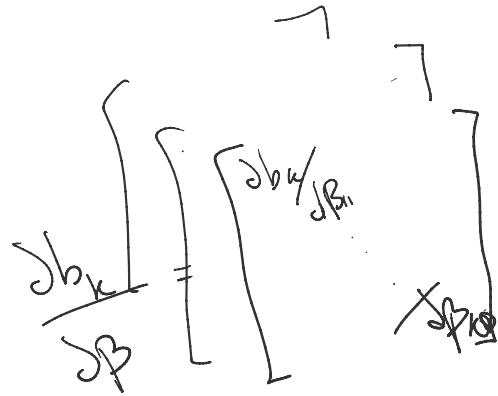
$$b \in \mathbb{R}^k$$

$$z \in \mathbb{R}^D$$

$$\beta \in \mathbb{R}^{k \times D}$$

$$\frac{dL}{d\beta} \in \mathbb{R}^k$$

$$\frac{dL}{d\beta} \in \mathbb{R}^{(k+D) \times k}$$



$$\frac{db_k}{d\beta_{ij}}$$

2D matrix
 $k \times D$

= 3D tensor
 $k \times D \times k$

$$\frac{dL}{d\beta_{ij}} = \square$$

1D vector
 k

$$\vec{y} = [0 \ 0 \ 1 \ 0 \ 0]$$

$$\sum y_x = 1$$

$$0.7 - 1 = 9$$

$$0.7 - 0 = 10$$