

# Foundations of Data Science & Machine Learning

Summary — Week 05  
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## **Abstract**

In this week's lectures, we continue discussing PAC. Further, we define growth function and VC dimension of Hypothesis classes.

## 1 PAC (Cont'd.)

→ Examples for H:

- **Ex1.**  $H = \text{lines in } \mathbb{R}^2 \text{ passing through origin.}$
- **Ex2.** Any finite  $H$ .
- **Ex3.** Any finite  $X$ .
- **Ex4.**  $H = \text{lines in } \mathbb{R}^2$ .
- **Ex5.**  $H = \text{hyperplanes in } \mathbb{R}^n$ , where  $n$  is finite

→ **Ex3. Special Case:** The Hypothesis class of lines in  $\mathbb{R}^2$  separating a finite input space  $X$  is PAC-learnable with  $n \geq (1/\epsilon)(2\ln|x| + \ln(1/\delta))$  training examples. This is called "Smart Move".

→ **Ex3. - Smartest Move:**

- If  $E_{out}(h)$  is bad ( $> \epsilon$ ), then it's very likely (with prob.  $> 1/2$ ), that for another  $S' \sim D^n$ ,  $E_{S'}(h)$  is also bad ( $> \epsilon/2$ ).
- Hence instead of worrying about all  $X$ , we need to worry only about  $S \cup S'$ .

Let  $S \sim D^n$

Take  $h \in H : E_S(h) = 0 \wedge E_D(h) > \epsilon$

Then for some  $S' \sim D^n$ ,  $E_{S'}(h) > \epsilon/2$  (with high prob.  $\approx \geq 1/2$ )

**Proof:**

$$E_D(h) > \epsilon \Rightarrow P_D(h \Delta f) = p > \epsilon$$

$$\begin{aligned}
&\Rightarrow P_{x \sim D}(h(x) \neq f(x)) = p \\
&\Rightarrow P_{S' \sim D^n}(|S' \cap (h \Delta f)| = k) \sim \text{Binom}_p(n, k) \\
&\Rightarrow E_{S' \sim D^n} |S' \cap (h \Delta f)| = pn \\
&\Rightarrow P_{S' \sim D^n}(|S' \cap (h \Delta f)| = pn/2) < 1/2 \quad (\text{Using Chernoff bound, though very loose bound}) \\
&\Rightarrow P_{S' \sim D^n}[E_{S'}(h) < p/2] < 1/2 \\
&\Rightarrow P_{S' \sim D^n}[E_{S'}(h) \geq p/2] \geq 1/2 \\
&\Rightarrow P_{S' \sim D^n}[E_{S'}(h) \geq \epsilon/2] \geq 1/2
\end{aligned}$$

$\rightarrow$  Since in the last random experiment:  $S \sim D^n$ ,  $S' \sim D^n$

Event A::  $\exists h \in H : E_S(h) = 0 \wedge E_D(h) > \epsilon$

Event B::  $\exists h \in H : E_S(h) = 0 \wedge E_{S'}(h) > \epsilon/2$

We proved:  $P(B/A) \geq 1/2$

$$1/2 \leq P(B/A) = P(B \cap A)/P(A) \leq P(B)/P(A)$$

$$P(A) \leq 2P(B)$$

$\rightarrow$  Now we can forget X and just worry about  $S \cup S'$

**Model:**  $T = S \cup S' \sim D^{2n}$

$S$  and  $S'$  are obtained by uniform random equipartition.

**Lemma:** Let  $A \subseteq S \cup S'$ , then what is  $P(A \subseteq S)$  in a random equipartition.

$$\begin{aligned}
P(A \subseteq S) &= \binom{2n-k}{n-k}/\binom{2n}{n} \quad (n = |S| = |S'|, k = |A|) \\
&= ((n)(n-1)\dots(n-k+1))/((2n)(2n-1)\dots(2n-k+1)) \\
&< (1/2).(1/2)\dots(1/2) = (1/2)^k = (1/2)^{|A|}
\end{aligned}$$

So, for any  $h \in H$ ,

$$P_{S,S' \sim D^n}[(E_S(h, f) = 0) \wedge (E_{S'}(h, f) > \epsilon/2)] \leq (1/2)^{|A|} \leq (1/2)^{\epsilon n/2}$$

(Proof:  $A = \{x \in S \cup S' : h(x) \neq f(x)\}$ ,  $|A| > \epsilon n/2 = k$ )

$\rightarrow$  Now considering  $B_h := [(E_S(h, f) = 0) \wedge (E_{S'}(h, f) > \epsilon/2)]$ , so

$$P_{S,S' \sim D^n}[\exists h \in H : B_h] \leq (" \# distinct h") (1/2)^{\epsilon n/2}$$

$$\begin{aligned}
&\text{(considering } h_1 = h_2 \text{ (i.e. } h_1 \approx h_2 \sim f \text{) if } h_1|_{S \cup S'} = h_2|_{S \cup S'}) \\
&\leq |\{[h] : h \in H\}| (1/2)^{\epsilon n/2} \\
&\leq (2n)^2 (1/2)^{\epsilon n/2} \leq \delta/2 \text{ (required)}
\end{aligned}$$

## 2 Growth function & VC Dimension of Hypothesis Classes

→ Extending idea from **Ex4.** case to **Ex5.** case.

**Definition:** The **Growth Function** of a hypothesis class  $H$  on a domain  $X$  is defined as:

$g_H(n)$  = Maximum no. of distinct function that can be obtained by restricting the function in  $H$  to a set of  $n$  points in  $X$ .

For  $T \subseteq X$  let  $H|_T = \{h|_T : h \in H\}$ , where  $h : X \rightarrow \{+1, -1\}$  and  $h|_T : T \rightarrow \{+1, -1\}$ , then:

$$g_H(T) = |H|_T | << |H|$$

$$g_N(n) = \max\{g_H(T) : T \in \binom{X}{n}\}$$

→ If  $H$  = linear separators in  $\mathbb{R}^2$ , then  $g_N(n) = \binom{n+1}{2} + 1$

→ Let  $H$  be the hypothesis class with growth function  $g_H()$ . For any  $\epsilon, \delta \in (0, 1)$ , any distribution  $D$  on  $\mathbb{R}^2$  and any true labelling  $f : \mathbb{R}^2 \rightarrow \{+1, -1\}$ ,  $P_{S \sim D^n}[\exists h \in H : (E_S(h, f) = 0) \wedge (E_D(h, f) > \epsilon)] \leq \delta$  whenever  $n$  is large enough so that  $g_H(2n)(1/2)^{\epsilon n/2} \leq \delta/2$  (will work if  $g_H$  is polynomial).

→ When is  $g_H() \in O(n^d)$  i.e polynomial bounded?

ANS. When the VC dimension of  $N$  is finite. ( $g_H() \in O(n^d) \iff H$  has finite VC dimension)

**Definition:** A hypothesis class  $H$  over a domain  $X$  is said to **shatter** a set  $T \subseteq X$  if every binary function on  $T$  can be obtained as the restriction  $h|_T$  of some  $h \in H$ . The **VC Dimension** of  $H$  is the size of a largest set that is shattered by  $H$ .

→ Examples:

<b>H</b>	<b>VC-d(H)</b>
Intervals in $\mathbb{R}$	2
Lines in $\mathbb{R}^2$	3
Axis aligned rectangles in $\mathbb{R}^2$	4
Polygons in $\mathbb{R}^2$	$\infty$
Circles in $\mathbb{R}^2$	3
Half spaces in $\mathbb{R}^d$	$d+1$
Spheres in $\mathbb{R}^d$	$d+1$