

Sample complexity of PAC learning

- We will deal with PAC model first.
 - We deal with agnostic model later.
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- Upper bound on sample complexity
 - Lower bound on sample complexity
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- Upper bound: If ERM is given $m \gtrsim \frac{VC(H) + \log(1/\delta)}{\epsilon}$ samples then it ϵ (ϵ, δ) -learns any target under any distribution

- Lower bound: Any algorithm requires at least $m \gtrsim \frac{VC(H) + \log(1/\delta)}{\epsilon}$ samples to learn some target under some distribution.

- lower bound $\leq m(H, \epsilon, \delta) \leq$ upper bound

- Similar results will hold for agnostic PAC model instead of $\frac{1}{\epsilon}$ the sample complexity will be $\frac{1}{\epsilon^2}$.
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Upper bounds

- We define notions of

ϵ -net and ϵ -approximation
(ϵ -sample)

Definition Let S be a finite subset of a domain X . Let $H \subseteq \mathcal{P}(X)$ and D be probability distribution over X . Let $\epsilon \in [0, 1]$.

- S is called ϵ -net for D, H iff

$$\forall h \in H \quad D(h) > \epsilon \Rightarrow S \cap h \neq \emptyset$$

- S is called ϵ -approximation (or ϵ -sample) for \mathcal{D}, H iff

$$\forall h \in H \left| D(h) - \frac{|S \cap h|}{|S|} \right| \leq \epsilon$$

- ($S \cap h$ is interpreted as a multi-set.)
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- If S is an ϵ -approximation then S is an ϵ -net.

- The reverse implication is not true.
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If $X = \mathbb{R}$ and D is uniform distribution over $[0, 1)$ then

$S = \left\{ \frac{1}{n}, \frac{2}{n}, \dots, \frac{n}{n} \right\}$ is $\frac{1}{n}$ -approximation with respect to the class of all intervals.



0 $\frac{1}{5}$ $\frac{2}{5}$. . .

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- For given $h: X \rightarrow Y$ and distribution D over X , consider the distribution D_h over $X \times Y$ defined as

$$D_h(x, y) = \begin{cases} D(x) & \text{if } y = h(x) \\ 0 & \text{if } y \neq h(x) \end{cases}$$

- Graph $h: X \rightarrow Y$ is $g(h) = \{(x, y) \in X \times Y : h(x) = y\}$
- $g^c(h)$ is the complement of $g(h)$
- $G(H) = \{g(h) : h \in H\}$
- $G^c(H) = \{g^c(h) : h \in H\}$

Lemma: Let X be a domain.

Let D be a distribution over X .

Let $H \subseteq \forall X$ and let $h^* \in H$

If $S \subseteq X \times Y$ is an ϵ -net for $D_{h^*}, G^S(H)$ and $\widehat{\text{err}}_S(h^*) = 0$ then

$$\text{err}_{D_{h^*}}(\text{ERM}(S)) \leq \epsilon.$$

Proof:

$$\text{err}_{D_{h^*}}(h) = \Pr_{x \sim D} [h^*(x) \neq h(x)]$$

$$= \Pr_{(x,y) \sim D_{h^*}} [h(x) \neq y]$$

$$= D_{h^*}(\{(x,y) \in X \times Y : h(x) \neq y\})$$

$$= D_{h^*}(g_h^c)$$

Consider any $h \in H$.

• If $\text{err}_{D_{h^*}}(h) > \epsilon$ then

$$D_{h^*}(g_h^c) > \epsilon.$$

• If $D_{h^*}(g_h^c) > \epsilon$ then

$$g_h^c \cap S \neq \emptyset$$

• If $g_h^c \cap S \neq \emptyset$ then

$$\widehat{\text{err}}_S(h) > 0.$$

• If $\widehat{\text{err}}_S(h) > 0$ then ERM will not output h .

So if $\text{err}_{D, h^*}(h) > \epsilon$, ERM will NOT output h .

Thus ERM outputs $h \in H$ such that $\text{err}_{D, h^*}(h) \leq \epsilon$.



Lemma: If $H \subseteq Y^X$ and $F \subseteq \mathcal{P}(X)$

• $VC(H) = VC(G(H))$

• $VC(F) = VC(F^c)$

Proof:

• If $(x, 0), (x, 1) \in S$ then $G(H)$ cannot shatter S .

• $S \subseteq X \times Y$ is shattered iff

$S|_X$ is shattered

• The second part is trivial



Theorem: Let $H \subseteq \mathcal{P}(X)$ with

$\overline{d} = VC(\overline{H})$ where $1 \leq d < \infty$.

Let $\epsilon \in (0, \frac{1}{4})$, $\delta \in (0, 1)$.

Let S be an i.i.d sample from a distribution D over X of size

$$m \geq \max\left(\frac{4}{\epsilon} \log_2 \frac{2}{\delta}, \frac{8d}{\epsilon} \log_2 \frac{8d}{\epsilon}\right).$$

Then, with probability at least $1 - \delta$,

S is an ϵ -net for H, D .

Proof:

Let's define event

$$E = \{S \in X^m : \exists h \in H \text{ s.t.}$$

$$D(h) > \epsilon \text{ and } S \cap h = \emptyset\}$$

We need to prove $\Pr[E] \leq \delta$.

- Consider an i.i.d. sample T from D of size m , independent of S .
- Sample T is called ghost sample

Let's define event

$$F = \left\{ (S, T) \in X^{2m} : \exists h \in H \text{ s.t.}, \right. \\ \left. D(h) > \varepsilon, h \cap S = \emptyset, |h \cap T| \geq \frac{\varepsilon m}{2} \right\}$$

- Clearly $F \subseteq E$, thus $P_{\tau}[F] \leq P_{\tau}[E]$

Claim 1 :

$$\Pr[F] \geq \frac{1}{2} \Pr[E]$$

Proof:

- It suffices to prove $\Pr[F|E] \geq \frac{1}{2}$.
- If E occurs, there is $h \in H$ s.t. $D(h) \geq \epsilon$ and $S \cap h = \emptyset$.

$$\Pr[F|E] \geq \Pr[|h \cap T| \geq \frac{\epsilon m}{2}]$$

- $|h \cap T|$ is a binomial random variable $B(p, m)$ where $p = D(h) \geq \epsilon$.

$$\Pr[|h \cap T| \geq \frac{\epsilon m}{2}]$$

$$\bullet \Pr[|h_n T| < \frac{pm}{2}]$$

$$\leq \Pr\left[|h_n T| < \frac{pm}{2}\right]$$

$$\leq \Pr\left[| |h_n T| - pm | > \frac{pm}{2}\right]$$

$$\leq \frac{\text{Var}(|h_n T|)}{\frac{1}{4} p^2 m^2} \quad (\text{Chebyshev})$$

$$\leq \frac{p(1-p)m}{\frac{1}{4} p^2 m^2}$$

$$= \frac{4(1-p)}{pm}$$

$$\leq \frac{4}{pm}$$

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$$1-p \leq 1$$

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$$\leq \frac{4}{\epsilon m}$$

$$\boxed{\epsilon \leq \rho}$$

$$\leq \frac{1}{2d \log_2\left(\frac{8d}{\epsilon}\right)}$$

$$\leq \frac{1}{2}$$

$$\boxed{d \geq 1}$$

• So $\Pr[E] \leq 2\Pr[F]$

Claim 2:

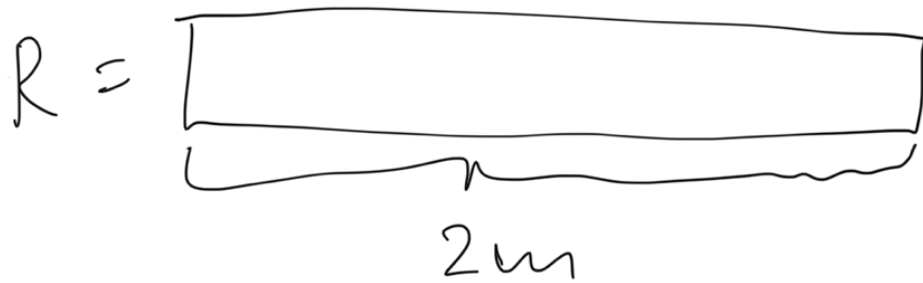
$$\Pr[F] \leq \pi_H(2m) \cdot 2^{-\frac{\epsilon m}{2}}$$

Proof:

• We can think of drawing samples S, T as follows:

n ... samples D at time t

How sample n w/ size cm .



Flip an fair coins.

- If i -th coin falls heads, put x_i into S and x_{i+m} into T .
 - If i -th coin falls tails, put x_i into T and x_{i+m} into S .
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• We condition on the choice of R .

• It suffices to prove

$$\mathbb{P}(T = 1) \rightarrow \dots - \text{E}_k$$

$$\{F \mid R\} \leq \| \cdot \|_H(2m) \cdot 2^{\frac{m}{2}}$$

- Note there are only finitely many behaviors of H on R !
- $F = \bigcup_{\substack{h \in H \\ D(h) > \varepsilon}} \{S, \text{TEX}^m : S \cap h = \emptyset, |T \cap h| \geq \frac{\varepsilon m}{2}\}$

$$H' = \{h \in \Pi_H(R) : \exists h' \in H \text{ s.t. } D(h') > \varepsilon, h' \cap R = h \cap R\}$$

$$\text{Note that } H' \subseteq \Pi_H(R)$$

• For $h \in H'$ define

$$F_h = \left\{ S, T \in X^m : S \cap h = \emptyset, |T \cap h| \geq \frac{\epsilon m}{2} \right\}$$

- $\Pr[F | R]$

$$= \Pr \left[\bigcup_{h \in H'} F_h \mid R \right]$$

$$\leq \sum_{h \in H'} \Pr[F_h \mid R]$$

- It suffices to show

$$\Pr[F_h \mid R] \leq 2^{-\frac{\epsilon m}{2}}$$

since $|H'| \leq |\Pi_H(R)| \leq \Pi_H(2m)$

- If $|h \cap R| < \frac{\epsilon M}{2}$

$$\Pr[F_h | R] = 0$$

- Suppose $|h \cap R| \geq \frac{\epsilon M}{2}$

- Let $a = |h \cap R|$

$$\Pr[F_h | R] \leq \Pr[S \cap h = \emptyset | R]$$

$$= 2^{-a}$$

$$\leq 2^{-\frac{\epsilon M}{2}}$$

We have

$$\begin{aligned} \Pr[E] &\leq 2 \Pr[F] \\ &\leq 2 \Pi_H(2m) \cdot 2^{-\frac{\epsilon m}{2}} \\ &\leq 2 \left(\frac{2em}{d} \right)^d \cdot 2^{-\frac{\epsilon m}{2}} \end{aligned}$$

We need to show

$$2 \left(\frac{2em}{d} \right)^d \cdot 2^{-\frac{\epsilon m}{2}} \leq \delta$$

It suffices to show

$$\frac{2}{\delta} (2em)^d \leq 2^{\frac{\epsilon m}{2}}$$

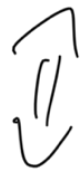
⇔

$$\log_2\left(\frac{2}{\varepsilon}\right) + d \log_2(2em) \leq \frac{2em}{2}$$

By assumption $\log_2\left(\frac{2}{\varepsilon}\right) \leq \frac{\varepsilon m}{4}$.

It suffices to prove

$$d \log_2(2em) \leq \frac{\varepsilon m}{4} \quad (*)$$



$$\frac{m}{\log_2(2em)} \geq \frac{4d}{\varepsilon}$$

Since left-hand side is increasing in m , it suffices to check (*) for

$$m = \frac{8d}{\varepsilon} \log_2 \frac{8d}{\varepsilon}$$

$$d \log_2(2em) \leq \frac{\epsilon}{4} m$$

$$\Leftrightarrow$$

$$d \log_2\left(\frac{16ed}{\epsilon} \log \frac{8d}{\epsilon}\right) \leq \frac{\epsilon}{4} \cdot \frac{8d}{\epsilon} \cdot \log_2\left(\frac{8d}{\epsilon}\right)$$

$$\Leftrightarrow$$

$$\log_2\left(\frac{16ed}{\epsilon} \log_2 \frac{8d}{\epsilon}\right) \leq 2 \log_2\left(\frac{8d}{\epsilon}\right)$$

$$\Leftrightarrow$$

$$\frac{16ed}{\epsilon} \log_2 \frac{8d}{\epsilon} \leq \left(\frac{8d}{\epsilon}\right)^2$$

$$\Leftrightarrow$$

$$2e \log_2 \frac{8d}{\epsilon} \leq \frac{8d}{\epsilon}$$

$$\Leftrightarrow$$

$$2e \log_2 A \leq A$$

which is true for $A \geq 32$
and clearly $A = \frac{8d}{\epsilon} \geq \frac{8}{\frac{1}{4}} = 32$

