


Consistency,
Compression,
and
Learning:
The Finite \mathcal{H} Case

Recipe for (PAC) Learning:

1. Design algo L that finds $h \in \mathcal{H}$ consistent with sample S
($\hat{\epsilon}_S(L(h)) = 0$)
2. Analyze how big $m = |S|$ must be s.t. $\epsilon(h) \leq \epsilon$.

We will show:

- This recipe **always works**
- Answer to 2. is **independent*** of L -consistency is all that matters.

Let's warm up with
the case of
finite \mathcal{H} .

Notation

$$\varepsilon(h) \stackrel{\text{a}}{=} P_{x \sim p} [h(x) \neq c(x)]$$

true error

$$\hat{\varepsilon}_S(h) \stackrel{\text{a}}{=} \frac{1}{m} \sum_i I[h(x_i) \neq y_i]$$

where $S = \{ \langle x_0, y_0 \rangle, \dots, \langle x_m, y_m \rangle \}$

training error

~~Q: When does $\hat{\varepsilon}_S(h) = 0$~~
imply $\varepsilon(h)$ small?

• Fix $\epsilon > 0$

• Call $h \in \mathcal{H}$ ϵ -bad
if $\epsilon(h) \geq \epsilon$

• \forall fixed ϵ -bad h :

$$P_{r_S}[\hat{\epsilon}_S(h) = 0] \leq (1-\epsilon)^m$$



indep.

$$P_{r_S}[\text{any } \epsilon\text{-bad } h \in \mathcal{H} \\ \text{has } \hat{\epsilon}(h) = 0]$$

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

union
bound

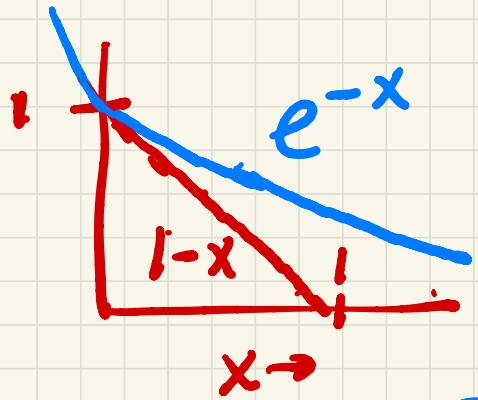
Algebra:

$$|H|(1-\varepsilon)^m \leq$$

$$|H|e^{-\varepsilon m} \Rightarrow$$

set $\leq \delta$ & solve:

$$m \geq \frac{1}{\varepsilon} \ln \frac{|H|}{\delta}$$



$$\therefore 1-x \leq e^{-x}$$

"complexity"

of \mathcal{H}

$$: \ln |H|$$

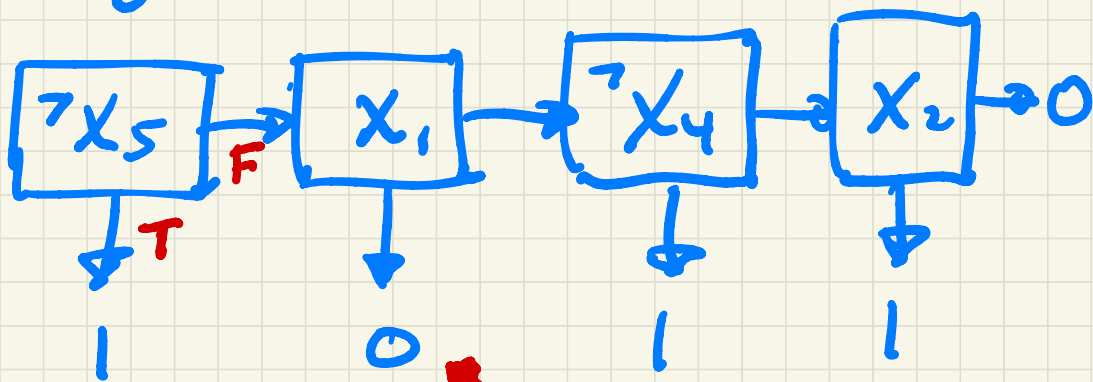
bits ^{ss} needed
to describe $h \in \mathcal{H}$

- Immediately applies to & simplifies PAC analyses for rectangles, conjunctions, 3CNF

- Any consistent $h \in \mathcal{H}$ suffices

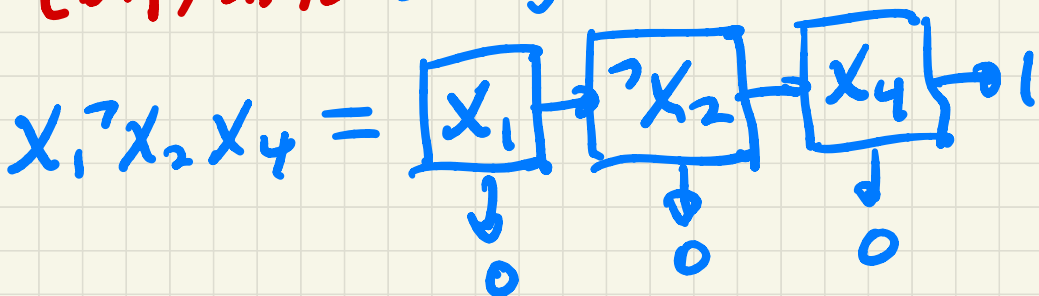
Another application:
decision lists over $\{0,1\}^n$.

e.g. $C \in \mathcal{C}$ given by:



$$C(01101) = 1$$
$$C(10011) = 0$$

Contains conjunctions:



Consistent algo:

- $S \leftarrow$ all examples
- $h \leftarrow$ empty list
- while ($S \neq \emptyset$):

- $\forall z, b$:

$$S_{z,b} \leftarrow \{ \langle x, y \rangle \in S : z = 1 \wedge x \text{ and } y = b \}$$

- find $\max |S_{z,b}|$ s.t.

$$S_{z,\neg b} = \emptyset$$

- append $\rightarrow \boxed{z}$ to h

\downarrow
 b

- $S \leftarrow S - S_{z,b}$

Theorem Decision lists
are PAC learnable
(by \mathcal{H} =decision lists).

Learning & Compression

- For $h \in \mathcal{H}$, let $l(h)$ be the # bits needed to describe h .
- In general, $l(h) \approx \text{poly}(n)$
(dim. of X)
 $\Rightarrow |\mathcal{H}| \approx 2^{\text{poly}(n)}$

- Suppose we allow

$$l(h) \approx \text{poly}(n, m)$$

$|S| \nearrow$

Good or bad idea?

If we allow

$l(h) \sim n \cdot m$ (linear
in both)

then we can just

encode/memorize S !

(\mathcal{H} = lists of $\langle x, y \rangle$)

~~—————~~

So linear dependence
on m goes too far.

Let's try $l(h) = c \cdot m^\alpha$

includes \nearrow
dep. on n $\alpha \neq 1$

$$|Z| e^{-\epsilon m} = 2^{c m^\alpha} e^{-\epsilon m}$$

$$\leq e^{c m^\alpha - \epsilon m}, \text{ set } \leq \delta:$$

$$c m^\alpha - \epsilon m \leq \ln(\delta)$$

$$\epsilon m \geq \ln(1/\delta) + c m^\alpha$$

Satisfied if:

$$m \geq \frac{2}{\epsilon} \ln(1/\delta) \quad \&$$

$$m \geq \frac{2 c m^\alpha}{\epsilon}$$

$$m \geq \frac{2cm^\alpha}{\varepsilon}$$

$$m^{1-\alpha} \geq \frac{2c}{\varepsilon}$$

$$m \geq \left(\frac{2c}{\varepsilon}\right)^{\frac{1}{1-\alpha}} \quad \leftarrow \text{blows up as } \alpha \rightarrow 1!$$

$\alpha = 0$: $m \sim 2c/\varepsilon$, original bound

$\alpha = 1/2$: $m \sim \left(\frac{2c}{\varepsilon}\right)^2$

$\alpha = 1$: $m \sim \infty$

So not just consistency
but even the slightest

compression of S

yields PAC learning
(with larger m).

One more variation.

So far we have
shown (for n large)

$$|\hat{\epsilon}_S(h) - \epsilon(h)| =$$

$$|0 - \epsilon(h)| = \epsilon(h) \leq \epsilon$$

for all consistent h .

What about all
the other $h \in \mathcal{H}$?

Chernoff bounds

- Consider biased coin with $\Pr[\text{heads}] = p$
- Flip n times, let $\tilde{p} =$ fraction of heads

Then $\forall \gamma > 0$:

$$\Pr[|\tilde{p} - p| \geq \gamma] \leq 2e^{-n\gamma^2/3}$$

→ 0 exponentially fast

- A "concentration inequality"

- \forall fixed $h \in \mathcal{H}$:

$$\Pr[|\hat{\mathbb{E}}_S(h) - \mathbb{E}(h)| \geq \varepsilon] \leq \text{blah}$$

- Prob. any

$$h \in \mathcal{H} \text{ has } \leq |\mathcal{H}| \cdot \text{blah}$$

$$| \cdot | \geq \varepsilon$$

- $\leq \delta$ if

$$m \sim \frac{1}{\varepsilon^2} \ln \frac{|\mathcal{H}|}{\delta}$$

"uniform convergence"

WYSIWYG

Fine.

But what if

H is

infinite ???