

# Formulation of the Learning Problem

## I Concept and function learning (realizable case)

$\mathcal{X}$  - feature space

$\mathcal{C}$  - concept class (collection of subsets of  $\mathcal{X}$ )

... all images of lowercase 'a'

... negative examples

$x_1, \dots, x_n \stackrel{iid}{\sim} P$  (instances)  
 $P \in \mathcal{P}$  (class of distributions)

$C^* \in \mathcal{C}$  (unknown concept)

training data:  $(x_i, y_i)$   $i = 1, \dots, n$

$$y_i = \mathbb{1}_{\{x_i \in C^*\}}$$

$z_i = (x_i, y_i)$  - instance-label pair

learning algo:  $z^n = (z_1, \dots, z_n) \xrightarrow{A_n} \hat{C}_n \in \mathcal{C}$

$$\mathcal{A} = \{A_n\}_{n=1}^{\infty} \quad A_n: (\mathcal{X} \times \{0, 1\})^n \rightarrow \mathcal{C}$$

$\hat{C}_n = A_n(z_1, \dots, z_n)$  - hypothesis returned  
by  $\mathcal{A}$  on  $z^n$   
- training

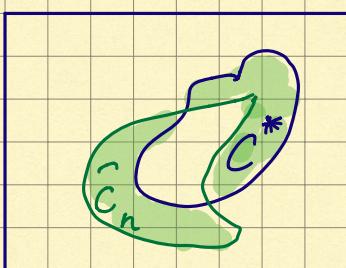
$X \sim P$  (indep. of  $X_1, \dots, X_n$ )

$$\hat{Y} = \mathbb{1}_{\{X \in \hat{C}_n\}}$$

Misclassification:  $X \notin C^*$ ,  $X \in \hat{C}_n$   
 $X \in C^*$ ,  $X \notin \hat{C}_n$

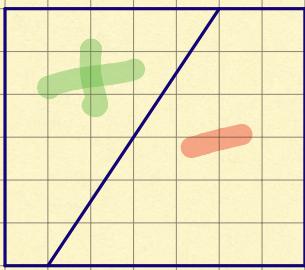
$$\left\{ x \in \mathcal{X} : x \in C^* \cap \hat{C}_n^c \text{ or } x \in (C^*)^c \cap \hat{C}_n \right\}$$

$\therefore \hat{C}_n \Delta C^* \text{ (sym. diff.)}$

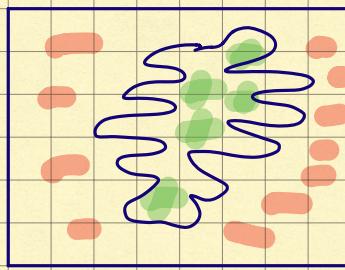


$P[\hat{C}_n \Delta C^*]$  - classification error  
(r.v. depends on  $\mathbf{z}^n$ )

"Learnability" ( $\rightarrow$  complexity/richness of concepts)



"Simple"



"Complex"

Probably Approximately Correct (PAC):

property of a learning algo for a given task

$$\text{data } (\mathbf{z}^n) \xrightarrow{\text{An}} \hat{C}_n$$

$$P_C^n \left[ \hat{C}_n \Delta C^* \leq \varepsilon \right] \leq \delta \quad (\text{approx. correct})$$

$P_C^n$  - dist. of  $n$  iid labeled pts when  $C^* = C$

$$P_{C^*}^n \left\{ z^n : P[\tilde{C}_n \Delta C^*] > \varepsilon \right\} < \delta$$

- probably approx. correct

(L. Valiant, D. Angluin 1980s)

Notation: fix  $C \in \mathcal{C}$

$$(x, y) : x \sim P, y = \mathbb{1}_{\{x \in C\}}$$

$P_C = \text{dist. of } (x, y)$

$P_C^n = \text{dist. of } (x_1, y_1), \dots, (x_n, y_n) \stackrel{iid}{\sim} P_C$

PAC learnability: property of a learning task  
 $(\mathcal{P}, \mathcal{C})$

PAC learnable  $\Rightarrow \exists$  a PAC learning algo  $A$   
 for  $(\mathcal{P}, \mathcal{C})$

$$\text{Fix } A : r_A(n, \varepsilon, P) := \sup_{C \in \mathcal{C}} P_C^n \left\{ P(\tilde{C}_n \Delta C) > \varepsilon \right\}$$

$$\bar{r}_A(n, \varepsilon, \mathcal{P}) := \sup_{P \in \mathcal{P}} r_A(n, \varepsilon, P)$$

if is PAC if  $\lim_{n \rightarrow \infty} \bar{r}_A(n, \varepsilon, \mathcal{P}) = 0$ .  
 (at accuracy  $\varepsilon$ )

To prove PAC learnability: produce PAC learning algo

Examples :

1) Any finite concept class is PAC-learnable

$$\mathcal{C} = \{C_1, C_2, \dots, C_M\} \quad M < \infty$$

Claim:  $\exists$  a learning. algo  $A$  s.t.

$$r_A(n, \varepsilon, \mathcal{P}) \leq M(1-\varepsilon)^n$$

where  $\mathcal{P}$  is the class of all distributions on  $\mathcal{X}$

$n \geq \frac{1}{\varepsilon} \log \frac{M}{\delta}$  examples suffices to give  
 $r_A(n, \varepsilon, \mathcal{P}) \leq \delta$ .

Proof sketch: data  $\mathcal{Z}^n$

$$\mathcal{F}(\mathcal{Z}^n) := \left\{ m \in [M] : Y_i = 1_{\{X_i \in C_m\}} \quad \forall i \right\}$$

$$\hat{m}_n := \min \{m : m \in \mathcal{F}(\mathcal{Z}^n)\}$$

$$\hat{C}_n = C_{\hat{m}_n}$$

"bad set":  $B := \{m : P(C_m \Delta C_{m^*}) > \varepsilon\}$

$$P_{C^*}^n [\hat{m}_n \in B] = \sum_{m \in B} P_{C^*}^n [\hat{m}_n = m]$$

$\hat{m}_n \in \mathcal{F}(\mathcal{Z}^n)$  :  $C_{\hat{m}_n}$  consistent w/ data

$\hat{m}_n \notin B$  :  $P[C_m \Delta C_{m^*}] > \varepsilon$

$$P_{C^*}^n [ \vec{m}_n = m ] \leq P [ X_i \notin C_m * \Delta C_m, \forall i ] \\ (m \in \mathcal{B}) \leq (1 - \varepsilon)^n$$

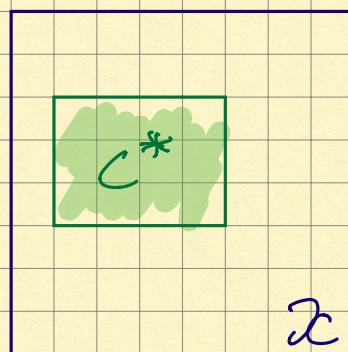
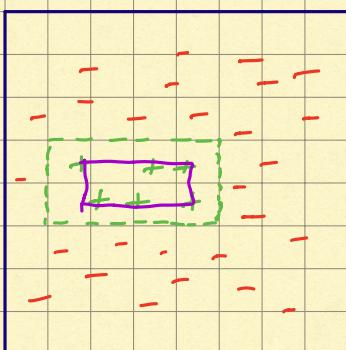
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2) Axis-aligned rectangles are PAC learnable

$$\mathcal{X} = [0, 1]^2 \quad (\text{unit square})$$

$$\mathcal{C} = \{ [a_1, b_1] \times [a_2, b_2] : a_1, b_1, a_2, b_2 \in [0, 1] \}$$

Algo:



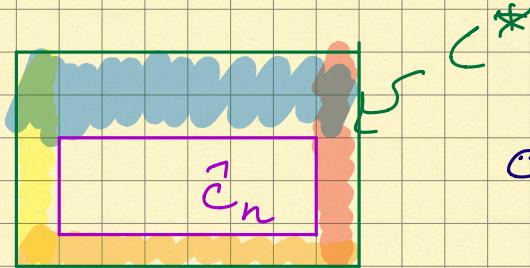
An: data  $\rightarrow C_u$ :  
smallest  $C \in \mathcal{C}$  that contains  
all positive examples

Claim:  $\bar{r}_{\mathcal{A}}(n, \varepsilon, \mathcal{P}) \leq 4(1 - \varepsilon/4)^n$

↓  
all dist.  
on  $[0, 1]^2$

(Blumer, Ehrenfeucht, Haussler, Warmuth, 1980s)

idea:



$$C^* \Delta C_n = \underbrace{\text{yellow}}_{\downarrow} \cup \underbrace{\text{orange}}_{\downarrow} \cup \underbrace{\text{red}}_{\downarrow} \cup \underbrace{\text{blue}}_{\downarrow}$$

random sets

show that, w.p.  $\geq 1 - 4(1 - \varepsilon/4)^n$

each of these random rectangles has  $P(\cdot) \leq \varepsilon/4$

■

$$\bar{r}_A(n, \varepsilon, P) \leq 4(1 - \varepsilon/4)^n \leq 4e^{-n\varepsilon/4} \leq \delta$$

$$\text{if } n \geq \frac{4}{\varepsilon} \log \frac{4}{\delta}$$