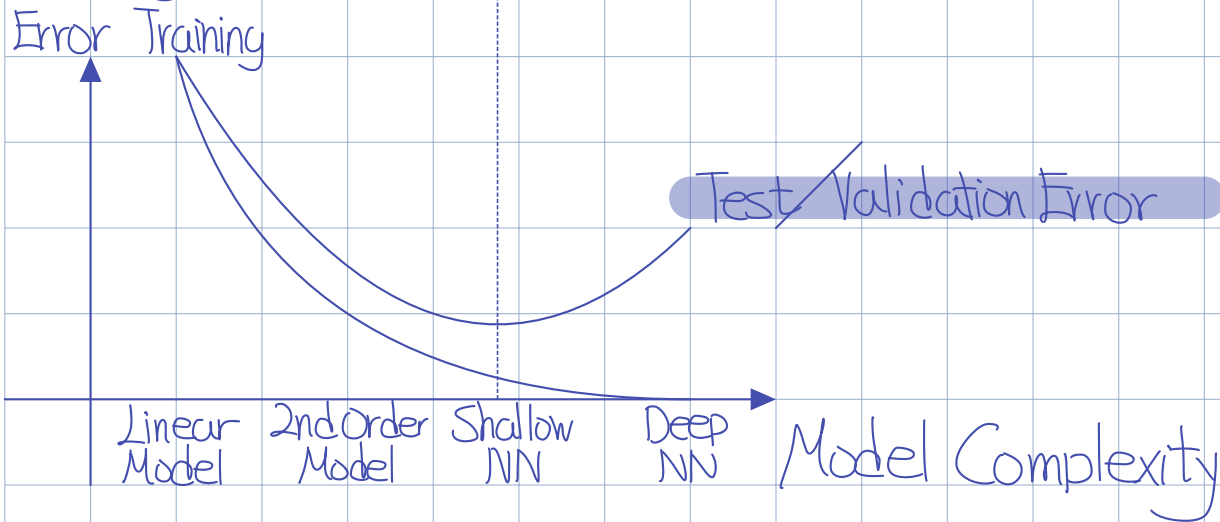


ECJ 324 → Machine Learning Courses

APS 360 →

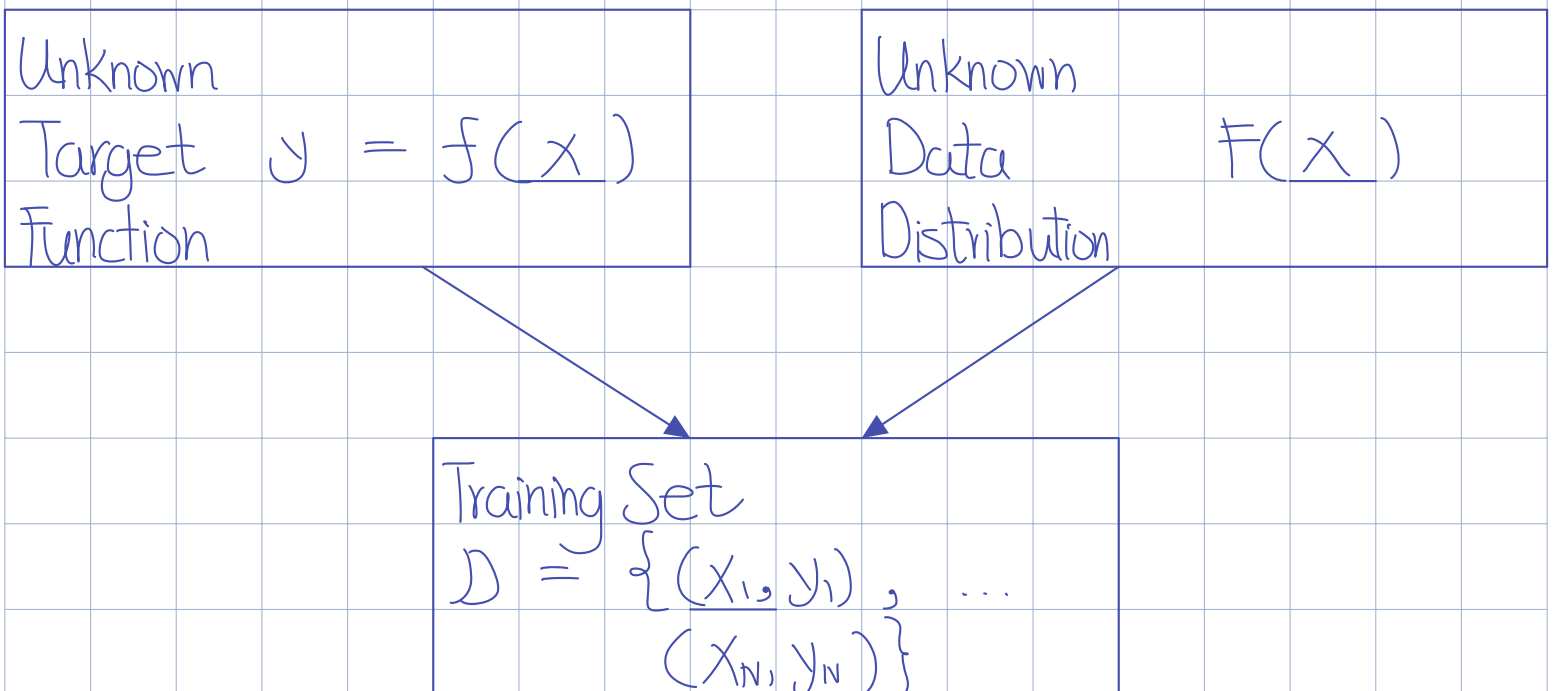
## Probability Approximately Correct (PAC)

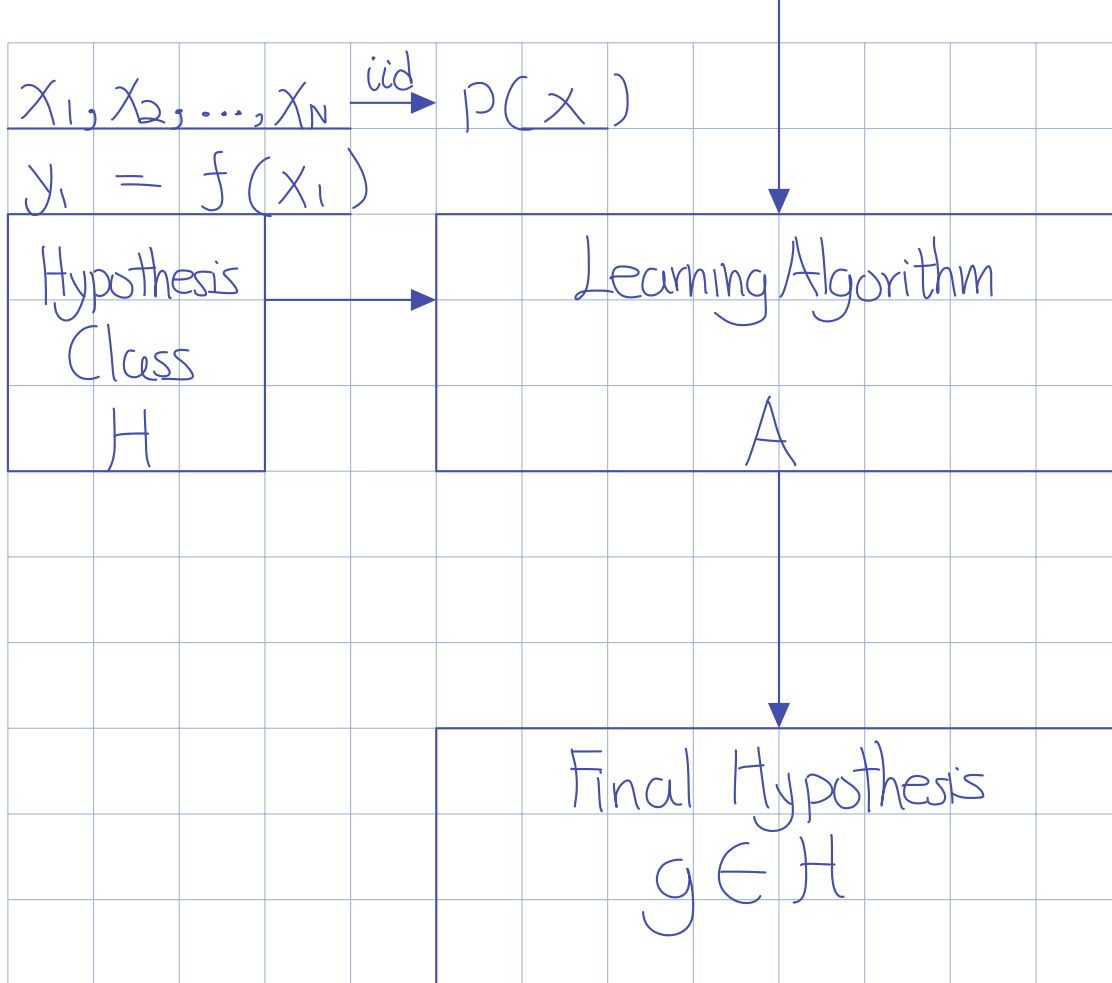
Given a training dataset which model should be selected for training?



## Mathematical Framework

Binary Classification  $x \in \mathbb{R}^d$ ,  $y \in \{-1, 1\}$





## Summary

1) Unknown Function  $f: \mathbb{R}^d \longrightarrow \{-1, +1\}$

2) Unknown Distribution  $p(x)$

$$x_1, x_2, \dots, x_N \xrightarrow{iid} p(x)$$

$$y_1 = f(x_1)$$

3) Hypothesis Class  $H = \{h_1, h_2, \dots, h_m\}$

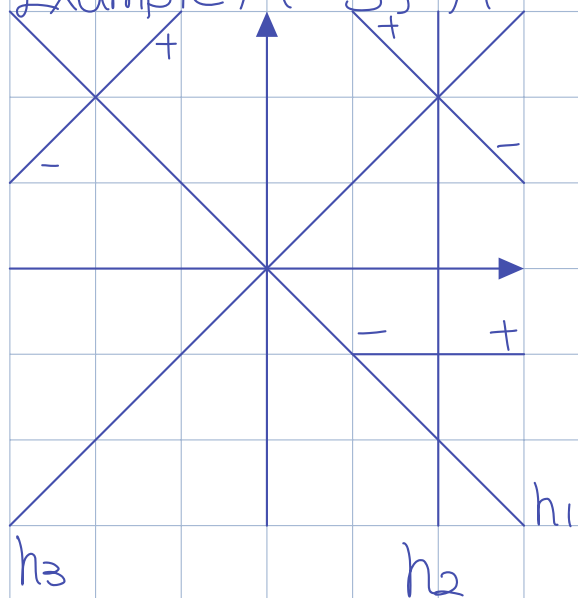
$$h_i: \mathbb{R}^d \longrightarrow \{-1, 1\}$$

Output hypothesis  $g \in H$

Chapter 1:  $M$  is finite

Chapter 2:  $M$  is infinite

Example  $M=3$ ,  $H = \{h_1, h_2, h_3\}$



A will output either

$g = h_1$   
or  $g = h_2$   
or  $g = h_3$

## Performance Metrics

### In Sample Training Errors

$$E_{in}(g) = \frac{1}{N} \sum_{i=1}^N e(y_i, g(x_i))$$

### Binary Classification

$$e(y_i, g(x_i)) = \begin{cases} 1, & y \neq g(x_i) \\ 0, & y = g(x_i) \end{cases}$$

$$= \mathbb{1}_{\{y \neq g(x_i)\}}$$

### Test Error

$$E_{out}(g) = \mathbb{E}_x[e(y, g(x))]$$

Integral  
In D-Dim  $\leftarrow \int_{x \in \mathbb{R}^d} e(y, g(x)) p(x) dx$

$$= \int_{x \in \mathbb{R}^d} \frac{1}{\{y \neq g(x_i)\}} p(x) dx$$

$$= \int_{x \in \mathbb{R}^d, y=g(x)} \frac{1}{\{y \neq g(x_i)\}} p(x) dx + \int_{x \in \mathbb{R}^d, y \neq g(x)} \frac{1}{\{y \neq g(x_i)\}} p(x) dx$$

Zero

Splitting into two integrals

$$= \int_{x \in \mathbb{R}^d, y \neq g(x)} \frac{1}{\{y \neq g(x_i)\}} p(x) dx$$

$$= \int_{x \in \mathbb{R}^d, y \neq g(x)} p(x) dx$$

$$= \Pr(y \neq g(x))$$

$$\text{Err}(g) = \Pr(y \neq g(x)) \quad (\text{What We Care About})$$

$X \equiv$  test data point (no access)

$X \sim P(X)$

also  $X$  is independent of  $X_1, X_2, \dots, X_N$

PAC Learning Guarantee Condition

## 2 Performance Metric

Training Error

Computable

Testing Error

Not Computable