

CSE 417T

# Introduction to Machine Learning

Lecture 5

Instructor: Chien-Ju (CJ) Ho

# Logistics: Homework 1

- Due: **Feb 14 (Monday), 2022**
  - <http://chienjuho.com/courses/cse417t/hw1.pdf>
  - Intended deadline: Feb 10.
    - Recommend to work on it early to spare time for homework 2
- Two submission links: Report and Code
  - Report: Answer all questions, including the implementation question
    - **Grades are based on the report**
  - Code: Complete and submit **hw1.py** for Problem 2
    - The code will only be used for correctness checking (when in doubts) and plagiarism checking
- Reserve time if you never used Gradescope.
  - Make sure to **specify the pages for each problem**. You **won't get points** otherwise

# Logistics: Office Hours

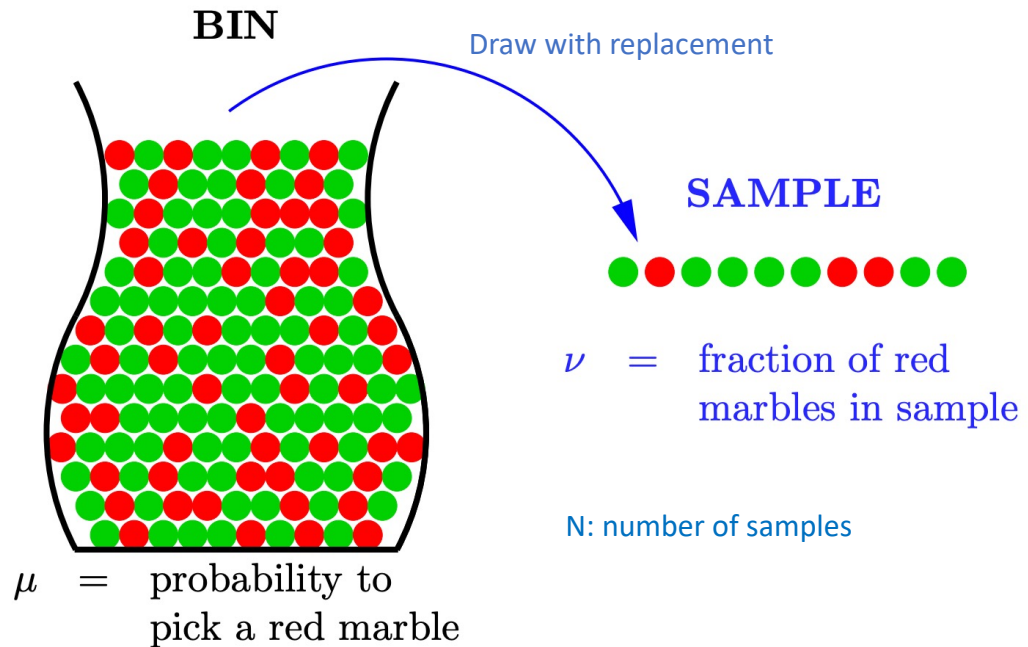
- TA Office Hours

Monday	11:30am (Herbert Zhou)	4pm (Dean Yu)	
Tuesday	1pm (Ziqi Xu)	3:30pm (Neal Huang)	
Wednesday	1pm (Eddie Choi)	4:30pm (Weiwei Ma)	
Thursday	10am (Jackie Zhong)	3pm (Fankun Zeng)	
Friday	8am (Shohaib Shaffiey)	1pm (Yunfan Wang)	7pm (Hao Qin)
Sunday	1pm (Jonathan Ma)		

- 60 minutes per session
- Please follow **Piazza** for additional information
- Recommendation: Try to utilize the office hour early (way ahead of deadlines), you are likely to get more of TAs' time this way

Recap

# Hoeffding's Inequality



$$\Pr[|\mu - \nu| > \epsilon] \leq 2e^{-2\epsilon^2 N}$$

Define  $\delta = \Pr[|\mu - \nu| > \epsilon]$

- Fix  $\delta$ ,  $\epsilon$  decreases as  $N$  increases
- Fix  $\epsilon$ ,  $\delta$  decreases as  $N$  increases
- Fix  $N$ ,  $\delta$  decreases as  $\epsilon$  increases

Informal intuitions of notations  
 $N$ : # sample  
 $\delta$ : probability of "bad" event  
 $\epsilon$ : error of estimation

# Connection to Learning

- Given dataset  $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)\}$ 
  - $E_{in}(h) \stackrel{\text{def}}{=} \frac{1}{N} \sum_{n=1}^N \mathbb{I}[h(\vec{x}_n) \neq f(\vec{x}_n)]$  [In-sample error, analogy to  $v$ ]
  - $E_{out}(h) \stackrel{\text{def}}{=} \Pr_{\vec{x} \sim P(\vec{x})} [h(\vec{x}) \neq f(\vec{x})]$  [Out-of-sample error, analogy to  $\mu$ ]

- Learning bounds

- Fixed  $h$  (verification)

$$\Pr[|E_{out}(h) - E_{in}(h)| > \epsilon] \leq 2e^{-2\epsilon^2 N}$$

- Finite hypothesis set: learn  $g \in \{h_1, \dots, h_M\}$

$$\Pr[|E_{out}(g) - E_{in}(g)| > \epsilon] \leq 2Me^{-2\epsilon^2 N}$$

# Dealing with Infinite Hypothesis Set: $M \rightarrow \infty$

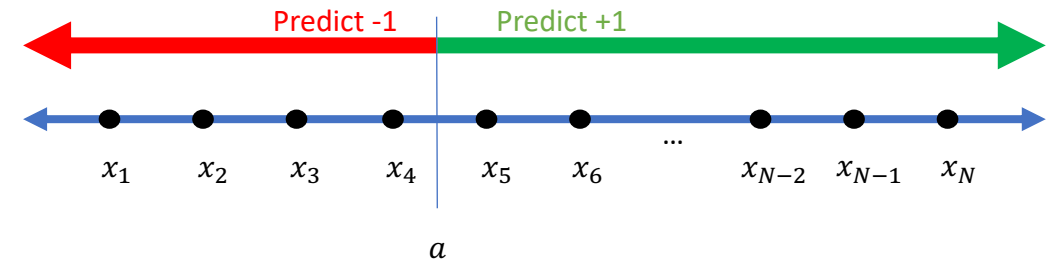
- Most of the practical cases involve  $M \rightarrow \infty$
- Instead of # hypothesis, counting “effective” # hypothesis
- Dichotomies
  - Informally, consider a dichotomy as “data-dependent” hypothesis
  - Characterized by both  $H$  and  $N$  data points  $(\vec{x}_1, \dots, \vec{x}_N)$ 
$$H(\vec{x}_1, \dots, \vec{x}_N) = \{(h(\vec{x}_1), \dots, h(\vec{x}_N)) | h \in H\}$$
  - The set of possible prediction combinations  $h \in H$  can induce on  $\vec{x}_1, \dots, \vec{x}_N$
- Growth function
  - Largest number of dichotomies  $H$  can induce across all possible data sets of size  $N$

$$m_H(N) = \max_{(\vec{x}_1, \dots, \vec{x}_N)} |H(\vec{x}_1, \dots, \vec{x}_N)|$$

# Examples on Growth Functions

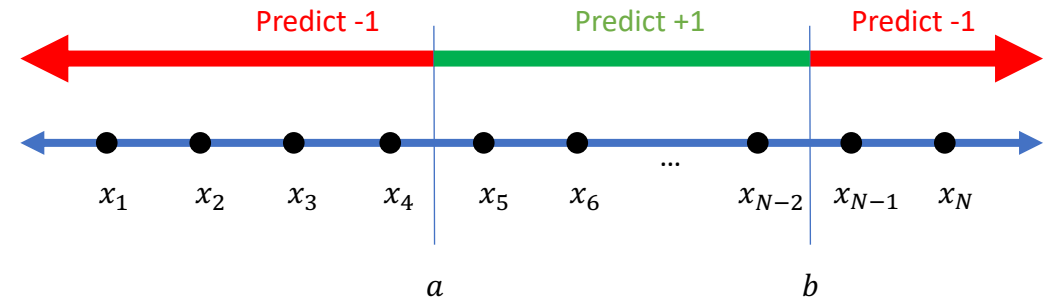
- $H$  = Positive rays

- $m_H(N) = N + 1$



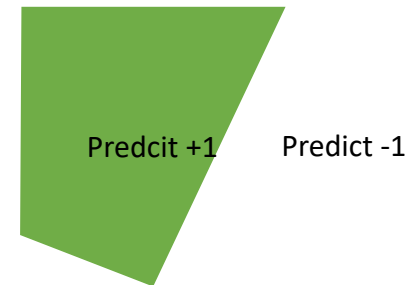
- $H$  = Positive intervals

- $m_H(N) = \binom{N+1}{2} + 1 = \frac{N^2}{2} + \frac{N}{2} + 1$



- $H$  = Convex sets

- $m_H(N) = 2^N$



- For all  $H$  and for all  $N$

- $m_H(N) \leq 2^N$



# Why Growth Function?

- Growth function  $m_H(N)$ 
  - Largest number of “effective” hypothesis  $H$  can induce on  $N$  data points
  - A more precise “complexity” measure for  $H$
  - Goal: Replace  $M$  in finite-hypothesis analysis with  $m_H(N)$ 
    - With prob at least  $1 - \delta$ ,  $E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{1}{2N} \ln \frac{2M}{\delta}}$
- VC Generalization Bound (VC Inequality, 1971)  
With prob at least  $1 - \delta$

$$E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{8}{N} \ln \frac{4m_H(2N)}{\delta}}$$

# Today's Lecture

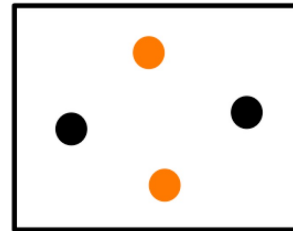
The notes are not intended to be comprehensive. They should be accompanied by lectures and/or textbook.  
Let me know if you spot errors.

# Bounding Growth Function

- What we know so far
  - $H$  = Positive rays:  $m_H(N) = N + 1$
  - $H$  = Positive intervals:  $m_H(N) = \binom{N+1}{2} + 1$
  - $H$  = Convex sets:  $m_H(N) = 2^N$


- What about  $H$  = 2-D Perceptron?

- $m_H(3) = 8$
- $m_H(4) = 14$
- $m_H(5) = ?$



- Generally hard to write down the growth function exactly
  - Goal: “bound” the growth function using some proxy

# Bounding Growth Function

- More definitions....
  - Shatter:
    - $H$  **shatters**  $(\vec{x}_1, \dots, \vec{x}_N)$  if  $|H(\vec{x}_1, \dots, \vec{x}_N)| = 2^N$
    - $H$  can induce all label combinations for  $(\vec{x}_1, \dots, \vec{x}_N)$
  - Break point
    - $k$  is a **break point** for  $H$  if no data set of size  $k$  can be shattered by  $H$
- A peek at the key result (take this as a fact for now)
  - If there are no break points for  $H$ ,  $m_H(N) = 2^N$
  - If  $k$  is a break point for  $H$ ,  $m_H(N)$  is polynomial in  $N$ .  
In particular,  $m_H(N) = O(N^{k-1})$  

A bit more accurately:

- $m_H(N) \leq \sum_{i=1}^{k-1} \binom{N}{i}$ , or
- $m_H(N) \leq N^{k-1} + 1$

# Practice

## • Dichotomies

- Informally, consider a dichotomy as a “data-dependent” hypothesis
- Characterized by both hypothesis set  $H$  and  $N$  data points  $(\vec{x}_1, \dots, \vec{x}_N)$

$$H(\vec{x}_1, \dots, \vec{x}_N) = \{(h(\vec{x}_1), \dots, h(\vec{x}_N)) | h \in H\}$$

- The set of possible prediction combinations  $h \in H$  can induce on  $\vec{x}_1, \dots, \vec{x}_N$

## • Growth function

- Largest number of dichotomies  $H$  can induce across all possible data sets of size  $N$

$$m_H(N) = \max_{(\vec{x}_1, \dots, \vec{x}_N)} |H(\vec{x}_1, \dots, \vec{x}_N)|$$

## • Shatter:

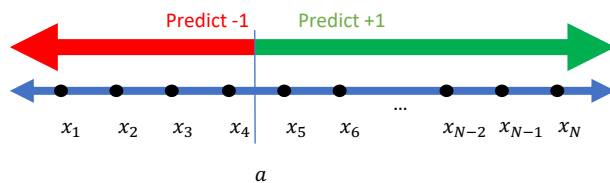
- $H$  **shatters**  $(\vec{x}_1, \dots, \vec{x}_N)$  if  $|H(\vec{x}_1, \dots, \vec{x}_N)| = 2^N$
- $H$  can induce all label combinations for  $(\vec{x}_1, \dots, \vec{x}_N)$

## • Break point

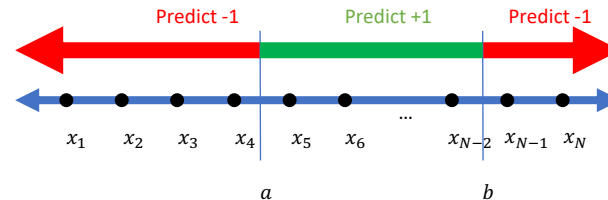
- $k$  is a **break point** for  $H$  if no data set of size  $k$  can be shattered by  $H$

## • What is the break point for

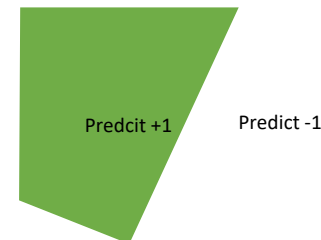
### 1. Positive Rays



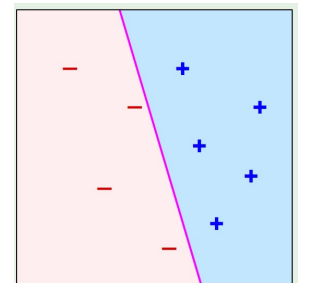
### 2. Positive Intervals



### 3. Convex Sets



### 4. 2-D Perceptron



# Practice

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  - Largest number of dichotomies  $H$  can induce across all possible data sets of size  $N$ 

$$m_H(N) = \max_{(\vec{x}_1, \dots, \vec{x}_N)} |H(\vec{x}_1, \dots, \vec{x}_N)|$$

- Shatter:
  - $H$  **shatters**  $(\vec{x}_1, \dots, \vec{x}_N)$  if  $|H(\vec{x}_1, \dots, \vec{x}_N)| = 2^N$
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- Break point
  - $k$  is a **break point** for  $H$  if no data set of size  $k$  can be shattered by  $H$

	$m_H(N)$					
$m_H(N)$	N=1	N=2	N=3	N=4	N=5	Break Points
$N + 1$	Positive Rays					
$\frac{N^2}{2} + \frac{N}{2} + 1$	Positive Intervals					
$N^2$	Convex Sets					
	2D Perceptron					

# Practice

- Dichotomies

- Informally, consider a dichotomy as a “data-dependent” hypothesis
- Characterized by both hypothesis set  $H$  and  $N$  data points  $(\vec{x}_1, \dots, \vec{x}_N)$

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- The set of possible prediction combinations  $h \in H$  can induce on  $\vec{x}_1, \dots, \vec{x}_N$

- Growth function

- Largest number of dichotomies  $H$  can induce across all possible data sets of size  $N$

$$m_H(N) = \max_{(\vec{x}_1, \dots, \vec{x}_N)} |H(\vec{x}_1, \dots, \vec{x}_N)|$$

- Shatter:

- $H$  **shatters**  $(\vec{x}_1, \dots, \vec{x}_N)$  if  $|H(\vec{x}_1, \dots, \vec{x}_N)| = 2^N$
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- Break point

- $k$  is a **break point** for  $H$  if no data set of size  $k$  can be shattered by  $H$

$m_H(N)$

	N=1	N=2	N=3	N=4	N=5	Break Points
Positive Rays	2	3	4	5	6	$k = 2, 3, 4, \dots$
Positive Intervals	2	4	7	11	16	$k = 3, 4, 5, \dots$
Convex Sets	2	4	8	16	32	None
2D Perceptron	2	4	8	14	?	$k = 4, 5, 6, \dots$

# Why Break Points?

- Theorem statement (Again, take it as a fact for now)
  - If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
  - If  $k$  is a break point for  $H$ , i.e., if  $m_H(k) < 2^k$  for some value  $k$ , then

$$m_H(N) \leq \sum_{i=0}^{k-1} \binom{N}{i}$$

- Rephrase the above theorem
  - If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
  - If  $k$  is a break point for  $H$ , the following statements are true
    - $m_H(N) \leq N^{k-1} + 1$  [Can be proven using induction. See LFD Problem 2.5]
    - $m_H(N) = O(N^{k-1})$
    - $m_H(N)$  is polynomial in  $N$
- We can “bound” the growth function without knowing it exactly.
  - Find break point!



# Why Break Points?

- VC Generalization Bound

With prob  $1 - \delta$

$$E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{8}{N} \ln \frac{4m_H(2N)}{\delta}}$$

- In the following discussion, we treat  $\delta$  as a constant [i.e., with high probability, the following is true]

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{\frac{1}{N} \ln m_H(N)}\right)$$

- Rephrase the above theorem

- If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
- If  $k$  is a break point for  $H$ , the following statements are true
  - $m_H(N) \leq N^{k-1} + 1$  [Can be proven using induction. See LFD Problem 2.5]
  - $m_H(N) = O(N^{k-1})$
  - $m_H(N)$  is polynomial in  $N$

[For example, we can set  $\delta$  to be a small constant, say 0.01. Then every time we wrote the above inequality, we mean that it is true with probability at least 99%.]

# Applying Break Points in VC Bound

- VC Bound:

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{\frac{1}{N} \ln m_H(N)}\right)$$



- Rephrase the above theorem

- If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
- If  $k$  is a break point for  $H$ , the following statements are true
  - $m_H(N) \leq N^{k-1} + 1$  [Can be proven using induction. See LFD Problem 2.5]
  - $m_H(N) = O(N^{k-1})$
  - $m_H(N)$  is polynomial in  $N$

- If there are no break point ( $m_H(N) = 2^N$ )

$$E_{out}(g) \leq E_{in}(g) + \text{Constant}$$

(This implies that we can't infer  $E_{out}$  from  $E_{in}$  even when  $N \rightarrow \infty$ )

- If  $k$  is a break point for  $H$ , i.e.,  $m_H(N) = O(N^{k-1})$

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{(k-1) \frac{\ln N}{N}}\right)$$

# $H$ is Either Good or Bad

- Rephrase the above theorem
  - If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
  - If  $k$  is a break point for  $H$ , the following statements are true
    - $m_H(N) \leq N^{k-1} + 1$  [Can be proven using induction. See LFD Problem 2.5]
    - $m_H(N) = O(N^{k-1})$
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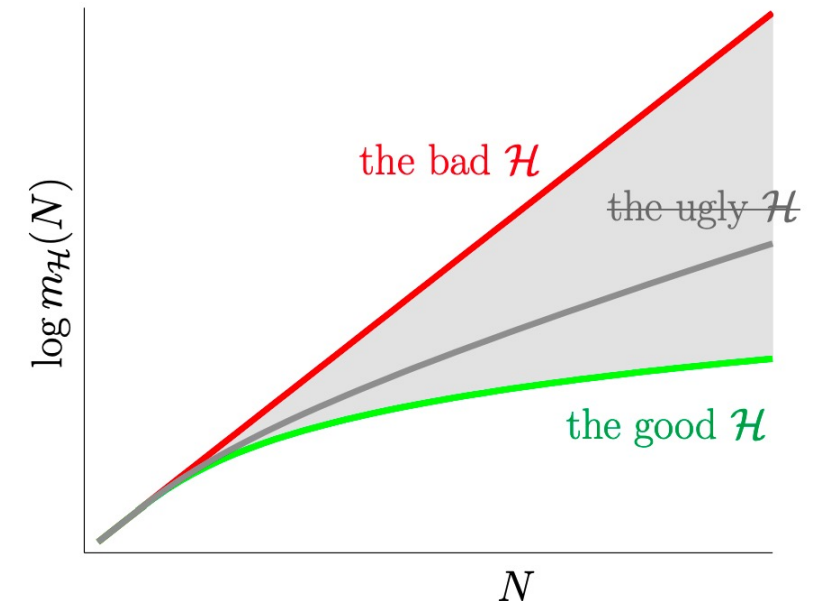
- The growth function of  $H$  is either one of the two
  - Without break points,  $m_H(N) = 2^N$
  - With some break point,  $m_H(N)$  is polynomial in  $N$  (it can be bounded more tightly using the theorem)
  - There is nothing in between!

- **Bad** hypothesis set

$$E_{out}(g) \leq E_{in}(g) + \text{Constant}$$

- **Good** hypothesis set  $m_H(N) = O(N^{k-1})$

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{(k-1)\frac{\ln N}{N}}\right)$$



# VC Dimension

- VC Dimension of  $H$ :  $d_{vc}(H)$  or  $d_{vc}$ 
  - The VC dimension of  $H$  is the **largest  $N$  such that  $m_H(N) = 2^N$** .
    - $d_{vc}(H) = \infty$  if  $m_H(N) = 2^N$  for all  $N$ .
  - Or, let  $k^*$  be the smallest break point for  $H$ , the VC dimension of  $H$  is  $k^* - 1$

	$m_H(N)$					Break Points	VC Dimension
	N=1	N=2	N=3	N=4	N=5		
Positive Rays	2	3	4	5	6	$k = 2, 3, 4, \dots$	
Positive Intervals	2	4	7	11	16	$k = 3, 4, 5, \dots$	
Convex Sets	2	4	8	16	32	None	
2D Perceptron	2	4	8	14	?	$k = 4, 5, 6, \dots$	

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	$m_H(N)$					Break Points	VC Dimension
	N=1	N=2	N=3	N=4	N=5		
Positive Rays	2	3	4	5	6	$k = 2, 3, 4, \dots$	1
Positive Intervals	2	4	7	11	16	$k = 3, 4, 5, \dots$	2
Convex Sets	2	4	8	16	32	None	$\infty$
2D Perceptron	2	4	8	14	?	$k = 4, 5, 6, \dots$	3

# VC Dimension

- VC Dimension of  $H$ :  $d_{vc}(H)$  or  $d_{vc}$

- The VC dimension of  $H$  is the **largest  $N$  such that  $m_H(N) = 2^N$** .

- $d_{vc}(H) = \infty$  if  $m_H(N) = 2^N$  for all  $N$ .

- Or, let  $k^*$  be the smallest break point for  $H$ , the VC dimension of  $H$  is  $k^* - 1$

- Plug the definition into VC Generalization Bound

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$$

- If there are no break point ( $m_H(N) = 2^N$ )

$$E_{out}(g) \leq E_{in}(g) + \text{Constant}$$

- If  $k$  is a break point for  $H$ , i.e.,  $m_H(N) = O(N^{k-1})$

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{(k-1) \frac{\ln N}{N}}\right)$$

# Discussion on the VC Theory

*All models are wrong  
but some are useful*



George E.P. Box



# Discussion on the VC Theory

- VC Bound

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{VC} \frac{\ln N}{N}}\right)$$

- Built on top of the i.i.d. data assumption
- The bound is “loose”
  - Depends only on  $H$  and  $N$
  - The analysis is loose in many places
- However, it qualitatively characterizes the practice reasonably well
  - (the bound is roughly equally loose for every  $H$ )

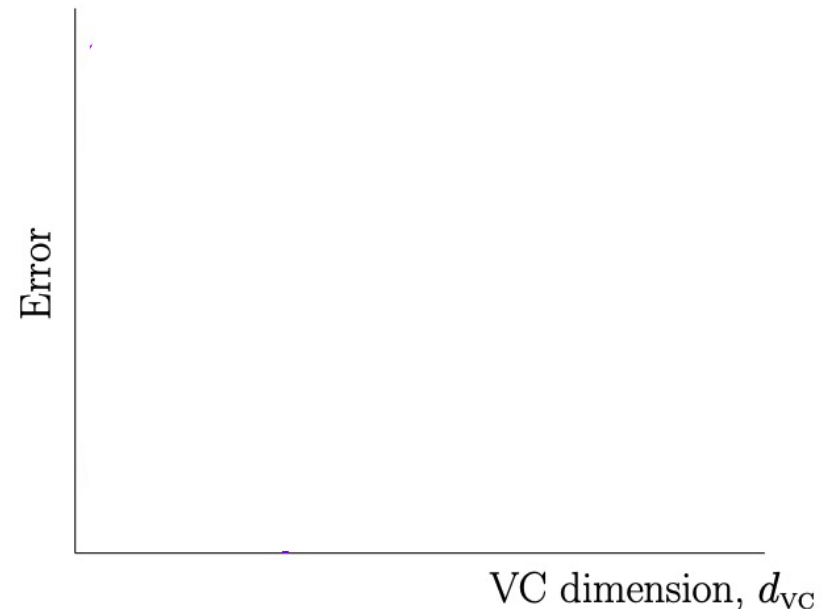
$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{VC} \frac{\ln N}{N}}\right)$$

- Goal of learning: Minimize  $E_{out}(g)$
- How to achieve that
  - Minimize  $E_{in}(g)$ 
    - Choose a hypothesis set with large  $d_{VC}$  (complex hypothesis likely fit data better)
  - Minimize **generalization error**
    - Choose a hypothesis with small  $d_{VC}$
    - Have a lot of data points to train on ( $N$  is large)
- Think about the high-level tradeoff of choosing  $d_{VC}$  and its dependency on  $N$

# Discussion on the VC Theory

- It establishes the feasibility of learning for infinite hypothesis set
- It provides nice intuitions on what's happening underneath ML
  - A single parameter to characterize complexity of  $H$

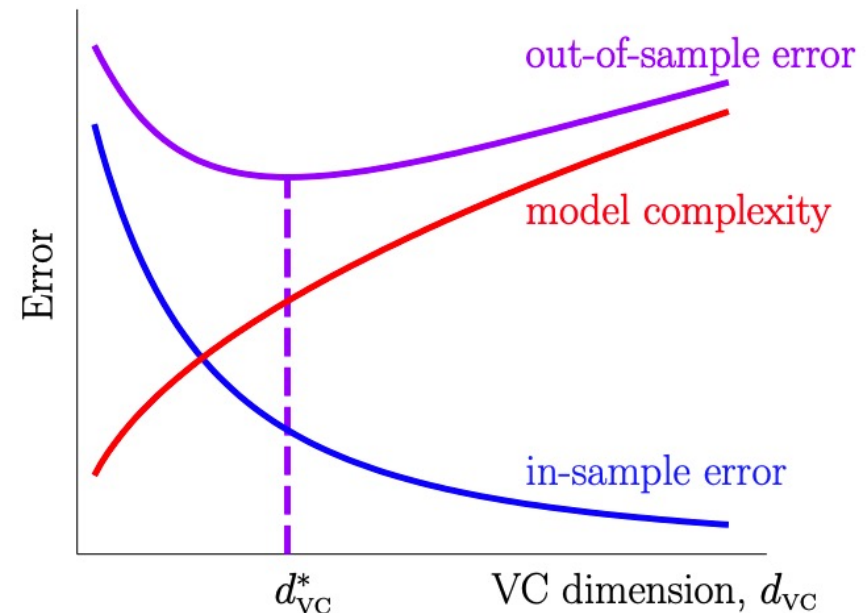
$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{VC} \frac{\ln N}{N}}\right)$$



# Discussion on the VC Theory

- It establishes the feasibility of learning for infinite hypothesis set.
- It provides nice intuitions on what's happening underneath ML.
  - A single parameter to characterize complexity of  $H$

$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{VC} \frac{\ln N}{N}}\right)$$



# Sample Complexity

- Sample complexity:
  - Analogy to time/space complexity
  - How many data points do we need to achieve generalization error less than  $\epsilon$  with prob  $1 - \delta$ ?

- Recall the (full) VC Bound:

$$\text{With prob at least } 1 - \delta, E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{8}{N} \ln \frac{4((2N)^{d_{vc}} + 1)}{\delta}}$$

- How to determine the sample complexity?

- Set  $\sqrt{\frac{8}{N} \ln \frac{4((2N)^{d_{vc}} + 1)}{\delta}} \leq \epsilon$
- We get  $N \geq \frac{8}{\epsilon^2} \ln \left( \frac{4(1 + (2N)^{d_{vc}})}{\delta} \right)$

- $N \propto 1/\epsilon^2$
- $N = O(d_{vc} \ln N)$ 
  - In practice, roughly,  $N \propto d_{vc}$

# Test Set

- Goal of learning: Minimize  $E_{out}(g)$
- Can we estimate  $E_{out}$  directly?
  - Reserve a test set ( $D_{test}$ ) before learning
  - Ensure  $D_{test}$  is **not used at all** in any way for learning
  - For  $D_{test}$ ,  $g$  is a “fixed” hypothesis and standard Hoeffding’s inequality is valid
  - Let  $E_{test}(g)$  be the error in the test set

$$P\{|E_{test}(g) - E_{out}(g)| > \epsilon\} \leq 2e^{-2\epsilon^2 N_{test}} \text{ where } N_{test} = |D_{test}|$$

# Test Set

- Test set is great: we can obtain an unbiased estimate of  $E_{out}$
- At what cost?
  - We have a finite amount of data
  - Data points in test set cannot be involved in learning at all
  - More points in test set
    - Better estimate of  $E_{out}$
    - Less data points in training set -> often leads to worse learned hypothesis
- Practical rule of thumb (i.e., a common heuristic, not really a gold rule)
  - 80% for training, 20% for testing

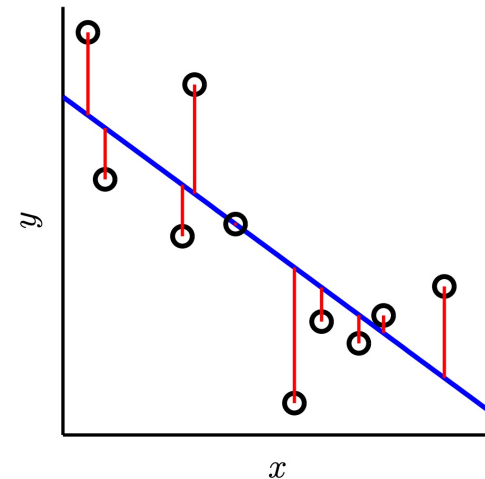
# Bias-Variance Decomposition

Another theory of generalization



# Real-Value Target and Squared Error

- So far, we focus on binary target function and binary error
  - Binary target function  $f(\vec{x}) \in \{-1, 1\}$
  - Binary error  $e(h(\vec{x}), f(\vec{x})) = \mathbb{I}[h(\vec{x}) \neq f(\vec{x})]$
- Real-value functions [“**regression**”] and squared error?
  - Real-value target function  $f(\vec{x}) \in \mathbb{R}$
  - Square error  $e(h(\vec{x}), f(\vec{x})) = (h(\vec{x}) - f(\vec{x}))^2$



# Real-Value Target and Square Error

- Real-value functions [called "**regression**"] and squared error?
  - Real-value target function  $f(\vec{x}) \in \mathbb{R}$
  - Square error  $e(h(\vec{x}), f(\vec{x})) = (h(\vec{x}) - f(\vec{x}))^2$
- Errors:
  - In-sample error:  $E_{in}(g) = \frac{1}{N} \sum_{n=1}^N e(h(\vec{x}_n), f(\vec{x}_n)) = \frac{1}{N} \sum_{n=1}^N (h(\vec{x}_n) - f(\vec{x}_n))^2$
  - Out-of-sample error:  $E_{out}(g) = \mathbb{E}_{\vec{x}}[e(h(\vec{x}), f(\vec{x}))] = \mathbb{E}_{\vec{x}}[(g(\vec{x}) - f(\vec{x}))^2]$
- Theory of generalization: What can we say about  $E_{out}(g)$ ?

- Note that  $g$  is learned by some algorithm on the dataset  $D$ 
  - We'll make the dependency on  $D$  explicit and write it as  $g^{(D)}$  here.
  - [In VC theory, we consider the worst-case  $D$  through the definition of growth function  $m_H(N)$ ]

- $E_{out}(g^{(D)}) = \mathbb{E}_{\vec{x}}[(g^{(D)}(\vec{x}) - f(\vec{x}))^2]$

- $\mathbb{E}_D[E_{out}(g^{(D)})]$

$$= \mathbb{E}_D \left[ \mathbb{E}_{\vec{x}} \left[ (g^{(D)}(\vec{x}) - f(\vec{x}))^2 \right] \right]$$

$$= \mathbb{E}_{\vec{x}} \left[ \mathbb{E}_D \left[ (g^{(D)}(\vec{x}) - \bar{g}(\vec{x}) + \bar{g}(\vec{x}) - f(\vec{x}))^2 \right] \right]$$

$$= \mathbb{E}_{\vec{x}} \left[ \mathbb{E}_D \left[ (g^{(D)}(\vec{x}) - \bar{g}(\vec{x}) + \bar{g}(\vec{x}) - f(\vec{x}))^2 \right] \right]$$

$$= \mathbb{E}_{\vec{x}} \left[ \mathbb{E}_D \left[ (g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))^2 + (\bar{g}(\vec{x}) - f(\vec{x}))^2 + 2(g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))(\bar{g}(\vec{x}) - f(\vec{x})) \right] \right]$$

- Note that  $\mathbb{E}_D \left[ (g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))(\bar{g}(\vec{x}) - f(\vec{x})) \right] = (\bar{g}(\vec{x}) - f(\vec{x})) \mathbb{E}_D \left[ (g^{(D)}(\vec{x}) - \bar{g}(\vec{x})) \right] = 0$

Define “expected” hypothesis  
 $\bar{g}(\vec{x}) = \mathbb{E}_D[g^{(D)}(\vec{x})]$

$$\bar{g}(\vec{x}) = \mathbb{E}_D[g^{(D)}(\vec{x})]$$

# Finishing Up

- $$\begin{aligned} & \mathbb{E}_D[E_{out}(g^{(D)})] \\ &= \mathbb{E}_{\vec{x}} \left[ \mathbb{E}_D \left[ \left( g^{(D)}(\vec{x}) - \bar{g}(\vec{x}) \right)^2 + \left( \bar{g}(\vec{x}) - f(\vec{x}) \right)^2 \right] \right] \\ &= \mathbb{E}_{\vec{x}} \left[ \mathbb{E}_D \left[ \left( g^{(D)}(\vec{x}) - \bar{g}(\vec{x}) \right)^2 \right] \right] + \mathbb{E}_{\vec{x}} \left[ \left( \bar{g}(\vec{x}) - f(\vec{x}) \right)^2 \right] \\ &= \mathbb{E}_{\vec{x}} [\text{Variance of } g^{(D)}(\vec{x}) + \text{Bias of } \bar{g}(\vec{x})] \\ &= \text{Variance} + \text{Bias} \end{aligned}$$

$X$ : a random variable  
 $\mu$ : the mean of  $X$

Variance of  $X$ :  
 $Var(X) = \mathbb{E}[(X - \mu)^2]$

- Bias-Variance Decomposition

# Discussion

$$\bullet \mathbb{E}_D[E_{out}(g^{(D)})] = \mathbb{E}_{\vec{x}} \left[ \overset{\text{Bias}(\vec{x})}{\left( \bar{g}(\vec{x}) - f(\vec{x}) \right)^2} \right] + \mathbb{E}_{\vec{x}} \left[ \overset{\text{Var}(\vec{x})}{\mathbb{E}_D \left[ \left( g^{(D)}(\vec{x}) - \bar{g}(\vec{x}) \right)^2 \right]} \right]$$

- This is a **conceptual** decomposition
  - Both  $\bar{g}$  and  $f$  are unknown
  - We can't really calculate bias and variance in practice
- However, it provides a conceptual guideline in decreasing  $E_{out}$

# Proof: Bounding Growth Functions

# Recall: Theorem in Bounding Growth Function

- Theorem statement:
  - If there is no break point for  $H$ , then  $m_H(N) = 2^N$  for all  $N$ .
  - If  $k$  is a break point for  $H$ , i.e., if  $m_H(k) < 2^k$  for some value  $k$ , then

$$m_H(N) \leq \sum_{i=0}^{k-1} \binom{N}{i}$$

- You were asked to take this as a fact
- Will provide proof sketch now

# Proof Sketch

[See LFD Section 2.1.2 for the formal proof]

[Safe to Skip] (This proof won't appear in exams/homework)



## [Safe to Skip]

### Key Intuitions

- When there exist a break point  $k$ 
  - No datasets of size  $k$  can be shattered
  - It also imposes strong constraints on dataset of size  $k' > k$ 
    - No subset of data with size  $k$  can be shattered
- This leads to the bound  $m_H(N) = O(N^{k-1})$

[Safe to Skip]

## Proof Intuitions

- Max # dichotomies can you list on **2 points** when **no 2 points can be shattered**

$\vec{x}_1$	$\vec{x}_2$
+1	+1
+1	-1
-1	+1

[Safe to Skip]

## Proof Intuitions

- Max # dichotomies can you list on **4 points** when **no 2 points can be shattered**

$\vec{x}_1$	$\vec{x}_2$	$\vec{x}_3$	$\vec{x}_4$
+1	+1	+1	+1
+1	+1	+1	-1
+1	+1	-1	+1
+1	-1	+1	+1
-1	+1	+1	+1

Can you add an additional dichotomy?

# [Safe to Skip]

## Proof Intuitions

- How “no 2 points can be shattered” impacts the scenario with **4 points**?

$\vec{x}_1$	$\vec{x}_2$	$\vec{x}_3$	$\vec{x}_4$
+1	+1	+1	+1
+1	+1	+1	-1
+1	+1	-1	+1
+1	-1	+1	+1
-1	+1	+1	+1

$(\vec{x}_1, \vec{x}_2, \vec{x}_3)$  appear twice, with different  $\vec{x}_4$

No 1 points can be shattered

$(\vec{x}_1, \vec{x}_2, \vec{x}_3)$  appear once (including one in each of the pair above)

No 2 points can be shattered

# [Safe to Skip]

## Proof Intuitions

- Max # dichotomies you can list on **4 points** when **no 2 points can be shattered**

No 1 point can be shattered

$\vec{x}_1$	$\vec{x}_2$	$\vec{x}_3$	$\vec{x}_4$
+1	+1	+1	+1
+1	+1	+1	-1
+1	+1	-1	+1
+1	-1	+1	+1
-1	+1	+1	+1

No 2 points can be shattered

$B(N, k)$ : max # dichotomies on  $N$  points when no  $k$  points are shattered

A recursive definition:

$$B(N, k) \leq B(N - 1, k) + B(N - 1, k - 1)$$

Sauer's Lemma:  $B(N, k) \leq \sum_{i=0}^{k-1} \binom{N}{i}$

Can be proved by induction

$B(N, k) \leq \sum_{i=0}^{k-1} \binom{N}{i}$  is the bound of  $m_H(N)$  for  $H$  with break point  $k$