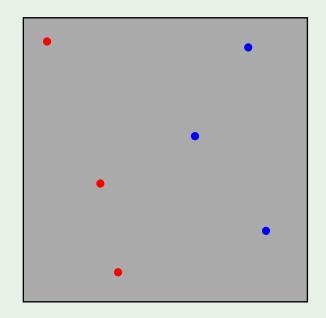
Review of Lecture 5

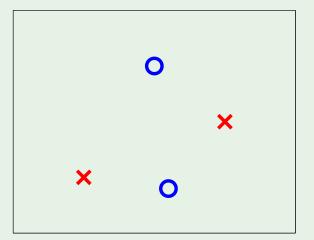
Dichotomies



Growth function

$$m_{\mathcal{H}}(N) = \max_{\mathbf{x}_1, \dots, \mathbf{x}_N \in \mathcal{X}} |\mathcal{H}(\mathbf{x}_1, \dots, \mathbf{x}_N)|$$

Break point



Maximum # of dichotomies

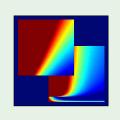
\mathbf{x}_1	\mathbf{x}_2	\mathbf{x}_3
0	0	0
0	0	•
0	•	0
•	0	0

Learning From Data

Yaser S. Abu-Mostafa California Institute of Technology

Lecture 6: Theory of Generalization





Outline

ullet Proof that $m_{\mathcal{H}}(N)$ is polynomial

ullet Proof that $m_{\mathcal{H}}(N)$ can replace M

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Bounding $m_{\mathcal{H}}(N)$

To show: $m_{\mathcal{H}}(N)$ is polynomial

We show: $m_{\mathcal{H}}(N) \leq \cdots \leq \cdots \leq$ a polynomial

Key quantity:

B(N,k): Maximum number of dichotomies on N points, with break point k

Recursive bound on B(N, k)

Consider the following table:

$$B(N,k) = \alpha + 2\beta$$

		# of rows	\mathbf{x}_1	\mathbf{x}_2		\mathbf{x}_{N-1}	\mathbf{x}_N
			+1	+1	• • •	+1	+1
	S_1	lpha	$\begin{vmatrix} -1 \\ \vdots \end{vmatrix}$	+1	• • • ÷	+1	−1 ∷
	1		+1	-1		-1	-1
			-1	+1		-1	+1
			+1	-1		+1	+1
			-1	-1		+1	+1
	S_{2}^{+}	eta	÷	:	i	:	÷
			+1	-1		+1	+1
S_2			-1	-1		-1	+1
$\mathcal{O}_{\mathcal{L}}$			+1	-1		+1	-1
			-1	-1		+1	-1
	S_2^-	eta	÷	÷	÷	÷	÷
			+1	-1		+1	-1
			-1	-1		-1	-1

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Estimating α and β

Focus on $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_{N-1}$ columns:

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

		# of rows	\mathbf{x}_1	\mathbf{x}_2		\mathbf{x}_{N-1}	\mathbf{x}_N
			+1	+1		+1	+1
			-1	+1		+1	-1
	S_1	α	i i	÷	÷	:	:
			+1	-1		-1	-1
			-1	+1		-1	+1
			+1	-1		+1	+1
			-1	-1		+1	+1
	S_2^+	eta	i	÷	÷	:	:
			+1	-1		+1	+1
S_2			-1	-1		-1	+1
			+1	-1		+1	-1
			-1	-1		+1	-1
	S_2^-	β	:		:	:	:
			+1	-1		+1	-1
			-1	-1		-1	-1

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Estimating β by itself

Now, focus on the $S_2 = S_2^+ \cup S_2^-$ rows:

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

		# of rows	\mathbf{x}_1	\mathbf{x}_2		\mathbf{x}_{N-1}	\mathbf{x}_N
			+1	+1		+1	+1
			-1	+1		+1	-1
	S_1	α	:	:	:	:	:
			+1	-1		-1	-1
			-1	+1		-1	+1
			+1	-1		+1	+1
			-1	-1		+1	+1
	S_2^+	eta	:	:	:	i:	:
			+1	-1		+1	+1
S_2			-1	-1		-1	+1
\mathcal{O}_2			+1	-1		+1	-1
			-1	-1		+1	-1
	S_2^-	β	:	:	:	:	:
			+1	-1		+1	-1
			-1	-1		-1	-1

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Putting it together

$$B(N,k) = \alpha + 2\beta$$

$$\alpha + \beta \le B(N-1,k)$$

$$\beta \le B(N-1,k-1)$$

$$B(N,k) \le$$

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

	ī		ı				
		# of rows	\mathbf{x}_1	\mathbf{x}_2	• • •	\mathbf{x}_{N-1}	\mathbf{x}_N
			+1	+1		+1	+1
			-1	+1		+1	-1
	S_1	lpha	÷	÷	÷	i.	÷
			+1	-1		-1	-1
			-1	+1		-1	+1
			+1	-1		+1	+1
			-1	-1		+1	+1
	S_{2}^{+}	eta	:	:	÷	÷	:
			+1	-1		+1	+1
S_2			-1	-1		-1	+1
$\mathcal{O}_{\mathcal{L}}$			+1	-1		+1	-1
			-1	-1		+1	-1
	S_{2}^{-}	eta	:	:	<u>:</u>	÷	:
			+1	-1		+1	-1
			-1	-1		-1	-1

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Numerical computation of B(N,k) bound

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Analytic solution for B(N, k) bound

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

Theorem:

$$B(N,k) \leq \sum_{i=0}^{k-1} {N \choose i}$$

1. Boundary conditions: easy

		k							
		1	2	3	4	5	6	• •	
	1		2	2	2	2	2	• •	
	2	1							
	3	1							
N	4	1							
	5	1							
	6	1							
	•	•							

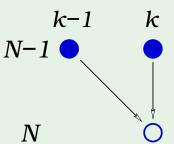
2. The induction step

$$\sum_{i=0}^{k-1} \binom{N}{i} = \sum_{i=0}^{k-1} \binom{N-1}{i} + \sum_{i=0}^{k-2} \binom{N-1}{i} ?$$

$$= 1 + \sum_{i=1}^{k-1} \binom{N-1}{i} + \sum_{i=1}^{k-1} \binom{N-1}{i-1}$$

$$= 1 + \sum_{i=1}^{k-1} \left[\binom{N-1}{i} + \binom{N-1}{i-1} \right]$$

$$= 1 + \sum_{i=1}^{k-1} \binom{N}{i} = \sum_{i=0}^{k-1} \binom{N}{i} \checkmark$$



It is polynomial!

For a given \mathcal{H} , the break point k is fixed

$$m_{\mathcal{H}}(N) \leq \sum_{i=0}^{k-1} \binom{N}{i}$$
 maximum power is N^{k-1}

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Three examples

$$\sum_{i=0}^{k-1} \binom{N}{i}$$

• \mathcal{H} is **positive rays**: (break point k=2)

$$m_{\mathcal{H}}(N) = N + 1 \leq N + 1$$

• \mathcal{H} is **positive intervals**: (break point k=3)

$$m_{\mathcal{H}}(N) = \frac{1}{2}N^2 + \frac{1}{2}N + 1 \le \frac{1}{2}N^2 + \frac{1}{2}N + 1$$

• \mathcal{H} is 2D perceptrons: (break point k=4)

$$m_{\mathcal{H}}(N) = ? \le \frac{1}{6}N^3 + \frac{5}{6}N + 1$$

Outline

ullet Proof that $m_{\mathcal{H}}(N)$ is polynomial

ullet Proof that $m_{\mathcal{H}}(N)$ can replace M

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What we want

Instead of:

$$\mathbb{P}[|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon] \le 2 \qquad \mathbf{M} \qquad e^{-2\epsilon^2 N}$$

We want:

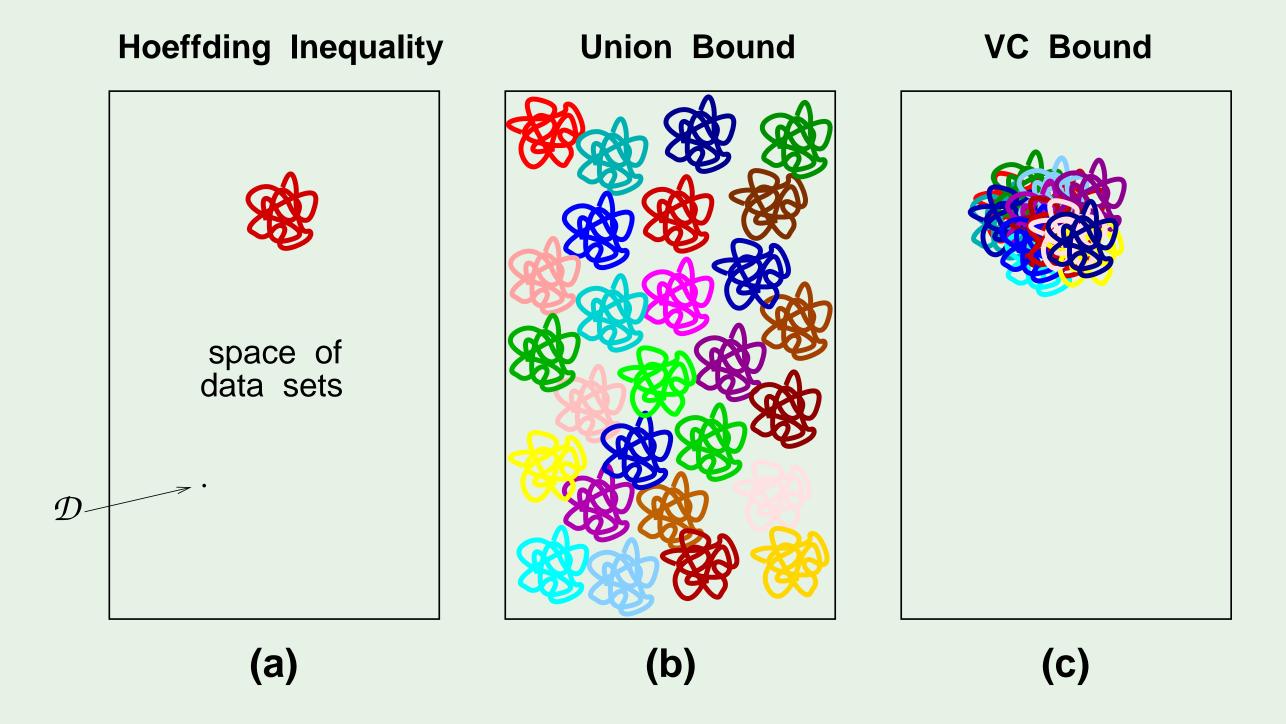
$$\mathbb{P}[|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon] \leq 2 \, m_{\mathcal{H}}(N) \, e^{-2\epsilon^2 N}$$

Pictorial proof ©

ullet How does $m_{\mathcal{H}}(N)$ relate to overlaps?

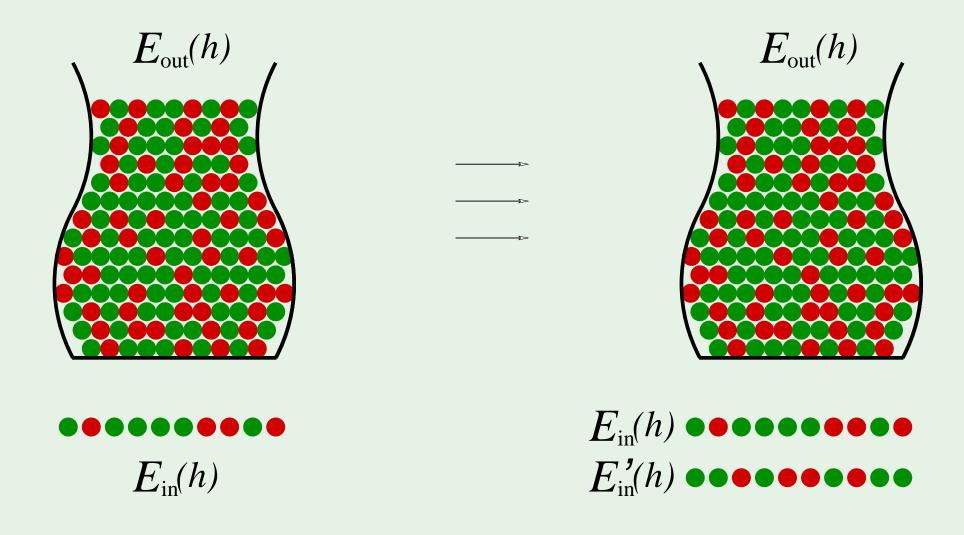
ullet What to do about $E_{
m out}$?

Putting it together



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What to do about $E_{\rm out}$



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Putting it together

Not quite:

$$\mathbb{P}[|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon] \le 2 m_{\mathcal{H}}(N) e^{-2\epsilon^2 N}$$

but rather:

$$\mathbb{P}[|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon] \le 4 m_{\mathcal{H}}(2N) e^{-\frac{1}{8}\epsilon^2 N}$$

The Vapnik-Chervonenkis Inequality