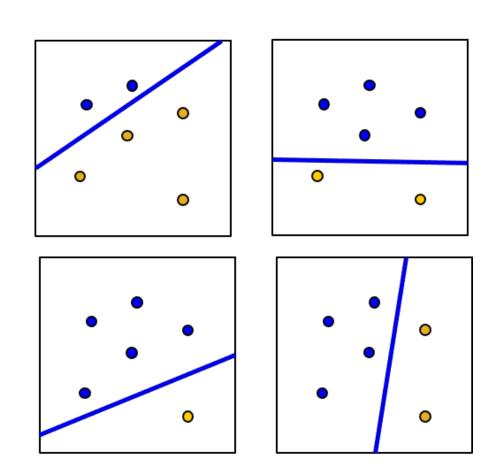
Instead of

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \le 2 \qquad M \qquad e^{-2N\epsilon^2}$$

seek to replace M with growth function

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \stackrel{?}{\leq} 2 \qquad m_{\mathcal{H}}(N) \qquad e^{-2N\epsilon^2}$$

Dichotomies



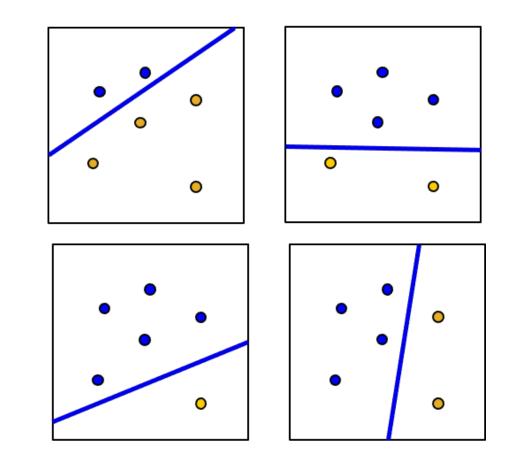
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$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \stackrel{?}{\leq} 2 \qquad m_{\mathcal{H}}(N) \qquad e^{-2N\epsilon^2}$$

Dichotomies



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

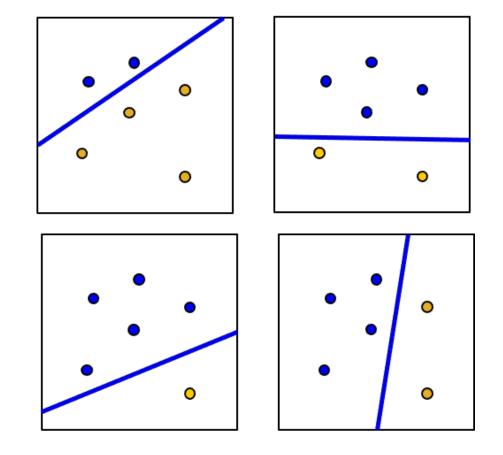
Instead of

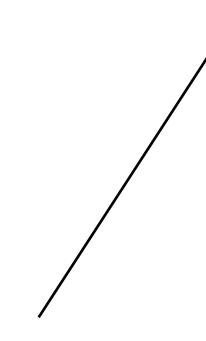
$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \le 2 \qquad M \qquad e^{-2N\epsilon^2}$$

seek to replace M with growth function

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \stackrel{?}{\leq} 2 \qquad m_{\mathcal{H}}(N) \qquad e^{-2N\epsilon^2}$$

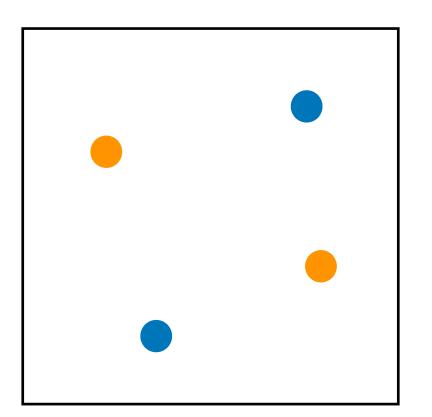
Dichotomies





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

• Break point k=4



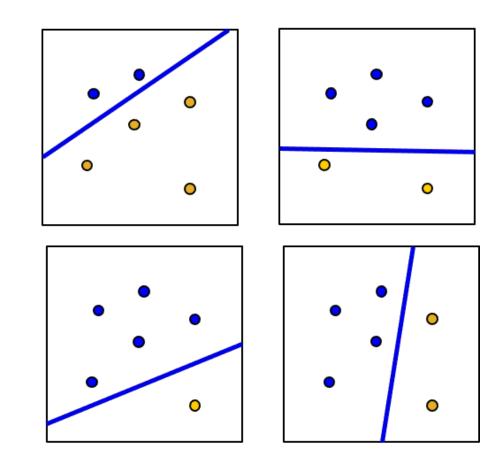
Instead of

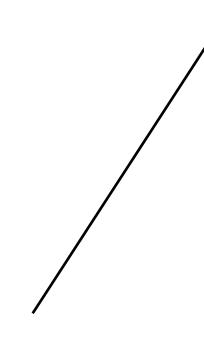
$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \le 2 \qquad M \qquad e^{-2N\epsilon^2}$$

seek to replace M with growth function

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \stackrel{?}{\leq} 2 \qquad m_{\mathcal{H}}(N) \qquad e^{-2N\epsilon^2}$$

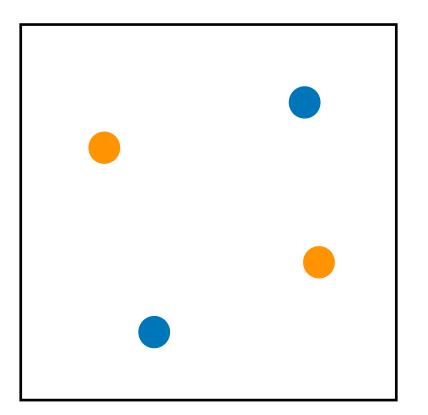
Dichotomies





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

• Break point k=4



Maximum # of dichotomies

$\underline{x_1}$	x_2	x_3
0	0	0



$$k = 2$$





ECE 6254 Statistical Machine Learning

Professor: Amirali Aghazadeh

Office: Coda S1209

Georgia Institute of Technology

Lecture 5: Theory of Generalization II



Outline

• Prove that $m_{\mathcal{H}}(N)$ is polynomial

• Prove that $m_{\mathcal{H}}(N)$ can replace M

Why do we like polynomial growth so much? (and dislike exponential)

A) Union Bound
$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \le 2Me^{-2N\epsilon^2}$$

B) With probability at least $1-\delta$: $R(h^*) \leq \hat{R}_N(h^*) + \sqrt{\frac{1}{2N}} \ln \frac{2M}{\delta}$

Assume M grows

- 1) exponential with N
- 2) polynomial with N

what happens when N goes to infinity?

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

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

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

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

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

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

Key quantity: B(N, k)

Maximum number of dichotomies on N points, with break point k

Recall the Puzzle from the last lecture

$$B(N, k)$$
 for $N = 3, k = 2$

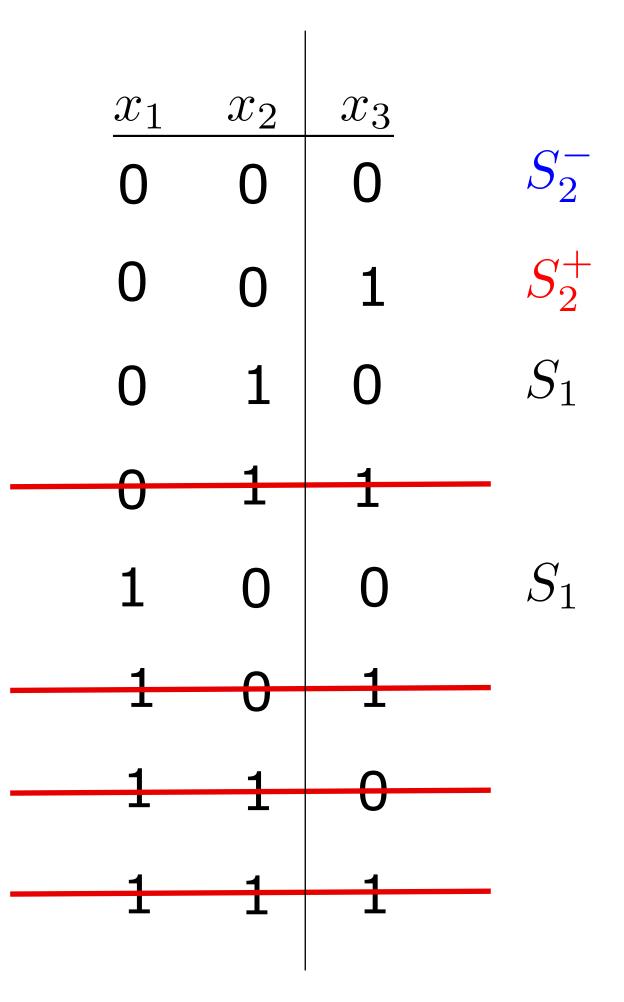
x_1	x_2	x_3		$\underline{x_1}$	x_2	x_3	
				0	0	0	
				0	0	1	
				0	1	0	
				0	1	1	
				1	0	0	
				1	0	1	
				1	1	-0 -	
					-		

Recall the Puzzle from the last lecture

$$B(N, k)$$
 for $N = 3, k = 2$

 $S_1 \triangleq \text{dichotomies appear only once on 1st N-1 columns}$

 $S_2 \triangleq \text{dichotomies appear twice on 1st N-1 columns}$



Let's expand this to larger N

 $x_1 \quad x_2 \quad \dots \quad x_{N-1} \quad x_N$

Let's expand this to larger N

	$ x_1 $	x_2	• • •	x_{N-1}	$ x_N $
	0	0	• • •	0	0
	1	0	• • •	0	1
S_1	•	•	•	• •	•
	0	1	• • •	1	1
	1	0	• • •	1	$\mid 0$

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

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	$ x_N $
		0	0	• • •	0	0
		1	0	• • •	0	1
S_1	α	•	•	•	•	•
		0	1	• • •	1	1
		1	0	• • •	1	0

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

	# of rows	$ \gamma_1 $	x_0		x_{N-1}	$ x_N $
		$\frac{x_1}{0}$	$\frac{x_2}{0}$	• • •	$\frac{w_N-1}{0}$	
		1		• • •	0	1
			0	• • •	U	T
S_1	α	•	•	•	• •	•
_		0	1	• • •	1	1
		1	0	• • •	1	0
		0	1		0	0
S_2^-						
		0	1	• • •	0	1
c+						
S_2^+						

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

	# of rows	$ \gamma_1 $	r_{2}		x_{N-1}	$\mid x_N \mid$
				• • •	$\frac{x_{N-1}}{0}$	
		$\begin{vmatrix} 0 \end{vmatrix}$	0	• • •	U	U
		1	0	• • •	O	
\boldsymbol{S} .		•	•	•	•	•
S_1	α	•	•	•	•	•
		0	1	• • •	1	
		1	0	• • •	1	0
		0	1	• • •	0	0
		1	1	• • •	0	0
S_2^-						
		0	1		0	1
		1	1	• • •	0	1
		<u>1</u>	1	• • •	U	1
S_2^+						
\sim_2						

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

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	$ x_N $
		0	0	• • •	0	0
		1	0	• • •	0	1
S_1	lpha	•	•	•	• •	•
		0	1	• • •	1	1
		1	0	• • •	1	0
		0	1		0	0
		1	1	• • •	0	0
S_2^-	β	•	•	•	• •	•
		0	1	• • •	0	0
		1	1	• • •	1	0
		0	1		0	1
		1	1	• • •	0	1
S_2^+	β	•	•	•	•	•
_		0	1	• • •	0	1
		1	1	• • •	1	1

Estimating α and β

Focus on x_1, \ldots, x_{N-1} columns

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	x_N
		0	0		0	0
		1	0	• • •	0	1
S_1	α	•	•	•	• •	•
		0	1	• • •	1	1
		1	0	• • •	1	
		0	1	• • •	0	0
		1	1	• • •	0	0
S_2^-	β	•	•	•	• •	•
		0	1	• • •	0	0
		1	1	• • •	1	0
		0	1	• • •		1
		1	1	• • •		1
S_2^+	B	•	•	•	•	•
_		0	1	• • •		1
		1	1	• • •	1	1

Estimating α and β

Focus on x_1, \ldots, x_{N-1} columns

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

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	x_N
		0	0	• • •	0	0
		1	0	• • •	0	1
S_1	α	•	•	•	• •	•
		0	1	• • •	1	1
		1	0	• • •	1	0
		0	1	• • •	0	0
		1	1	• • •	0	0
S_2^-	β	•	•	•	• •	•
		0	1	• • •	0	0
		1	1	• • •	1	0
		0	1	• • •	0	1
		1	1	• • •		1
S_2^+	B	•	•	•	•	0 0
		0	1	• • •		1
		1	1	• • •	1	1

Estimating \(\beta \) by itself

Focus on $S_2 = S_2^+ \cup S_2^-$ rows

	# of rows	x_1	x_2	• • •	x_{N-1}	x_N
		0	0		0	0
		1		• • •		1
S_1	α	•	•	•	•	•
		0	1		1	1
		1		• • •	1	0
		0	1	• • •	0	0
		1	1	• • •	0	0
S_2^-	eta	•	•	•	• •	•
		0	1	• • •	0	0
		1	1	• • •	1	0
		0	1		0	1
		1	1	• • •		1
S_2^+	B	•	•	•	•	0 0
		0	1	• • •		1
	_	1	1	• • •	1	1

Estimating \(\beta \) by itself

Focus on $S_2 = S_2^+ \cup S_2^-$ rows

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

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	x_N
		0	0	• • •		0
		1		• • •		1
S_1	α	•	•	•	•	•
		0	1	• • •	1	1
		1		• • •	1	0
		0	1		0	0
		1	1	• • •		0
S_2^-	β	•	•	•	•	•
		0	1			0
		1	1	• • •	1	0
		0	1		0	1
		1	1	• • •		1
S_2^+	B	•	•	•	•	0 0 0
		0	1	• • •		1
		1	1	• • •	1	1

Statistical Machine Learning - Lecture 5

Putting it all together

$$B(N, k) = \alpha + 2\beta$$
$$\alpha + \beta \le B(N - 1, k)$$
$$\beta \le B(N - 1, k - 1)$$

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

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

	# of rows	$ x_1 $	x_2	• • •	x_{N-1}	$ x_N $
		0	0	• • •	0	0
		1	0	• • •	0	1
S_1	α	•	•	•	•	•
		0	1	• • •	1	1
		1	0	• • •	1	0
		0	1	• • •	0	0
		1	1	• • •	0	0
S_2^-	β	•	•	•	• •	•
		0	1	• • •	0	0
		1	1	• • •	1	0
		0	1	• • •	0	1
		1	1	• • •	0	1
S_2^+	β	•	•	•	• •	•
		0	1	• • •	0	1
		1	1	• • •	1	1

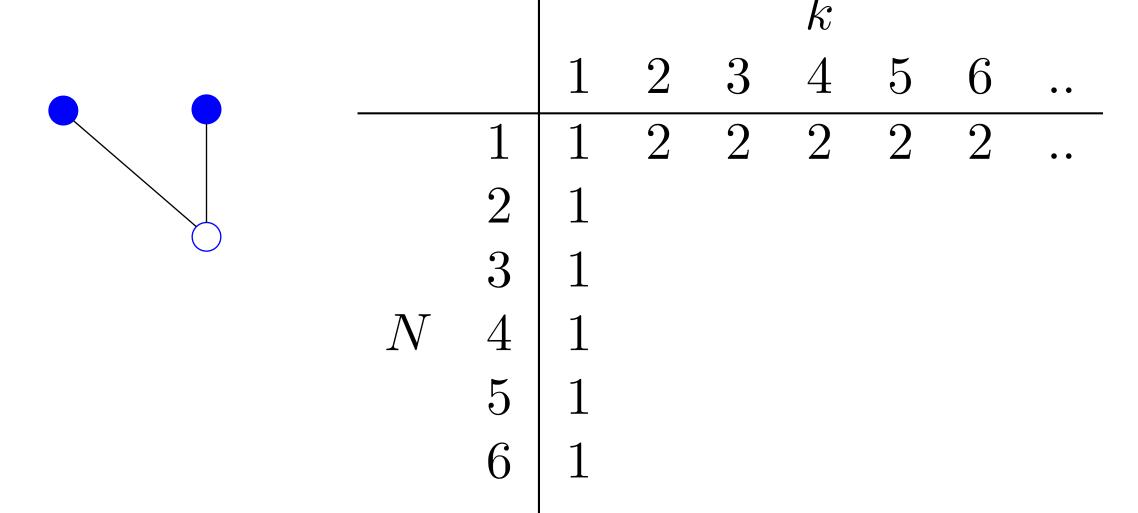
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$

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

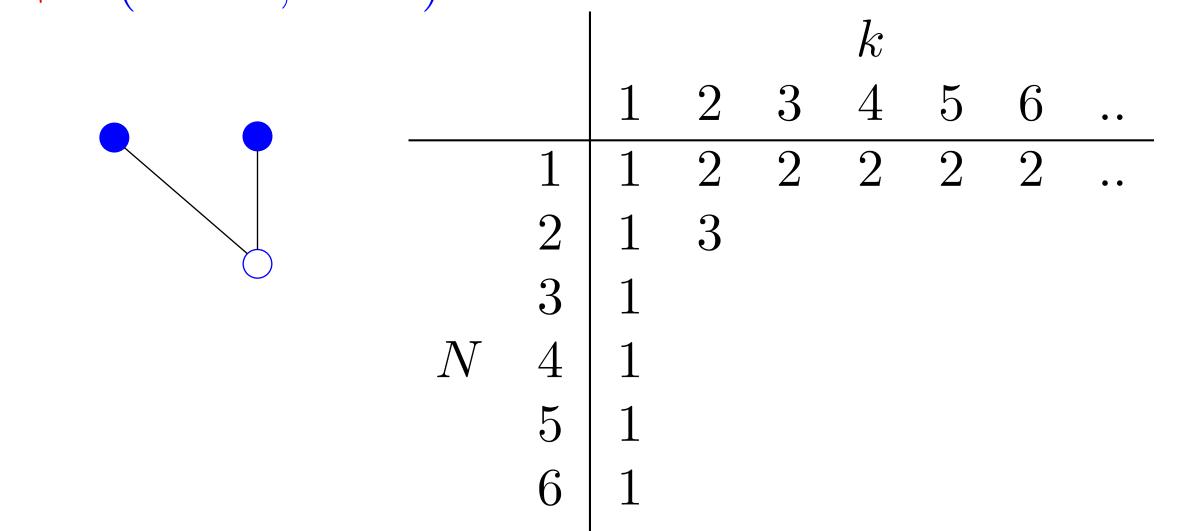
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$

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

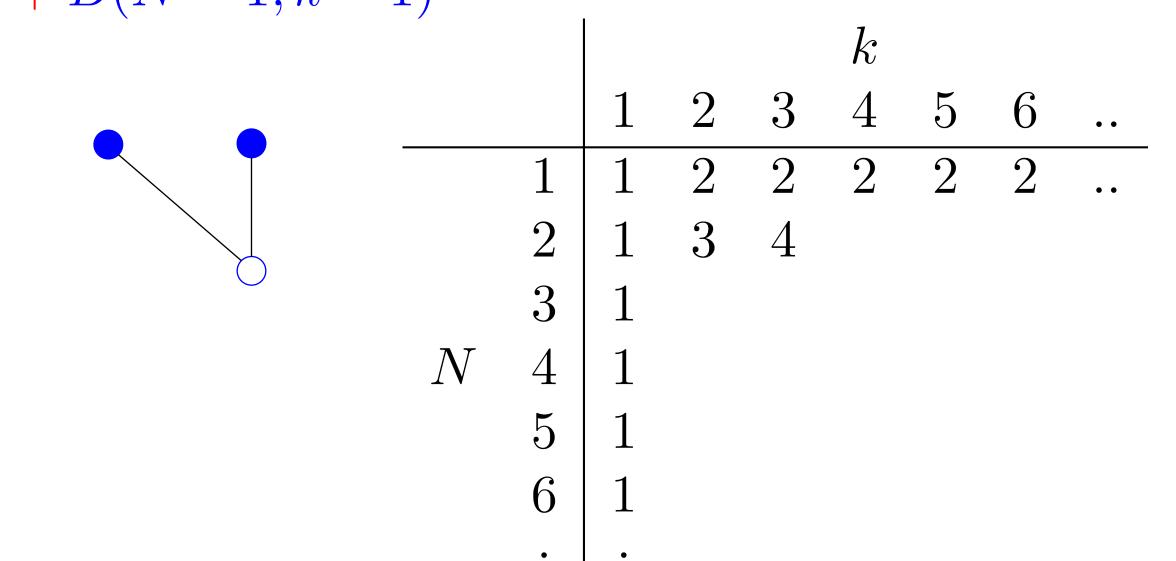
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



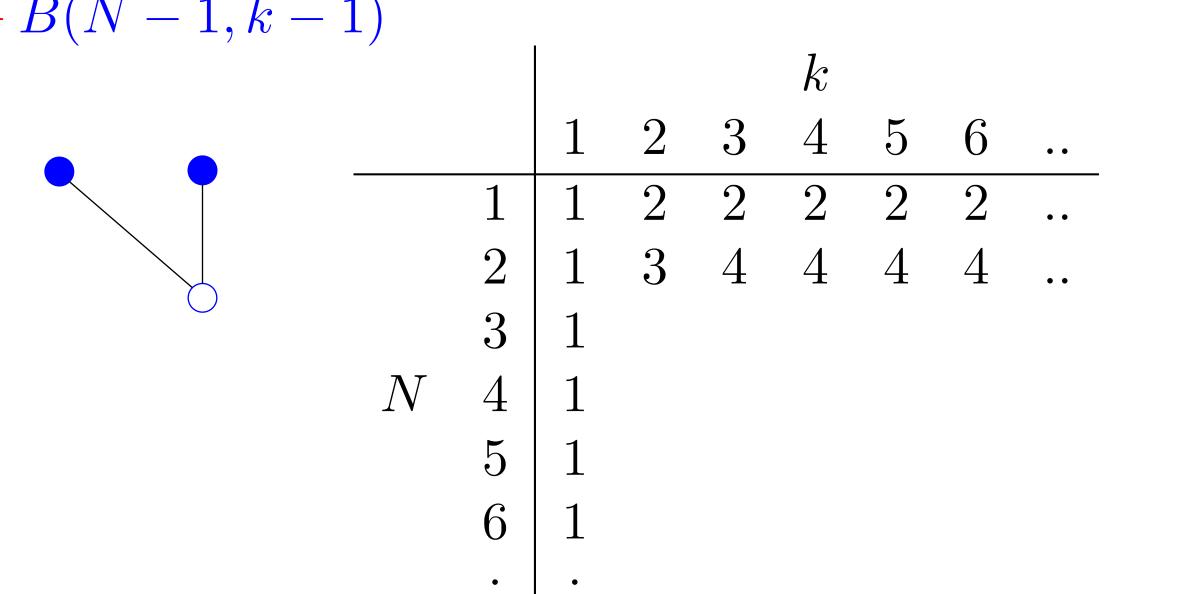
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



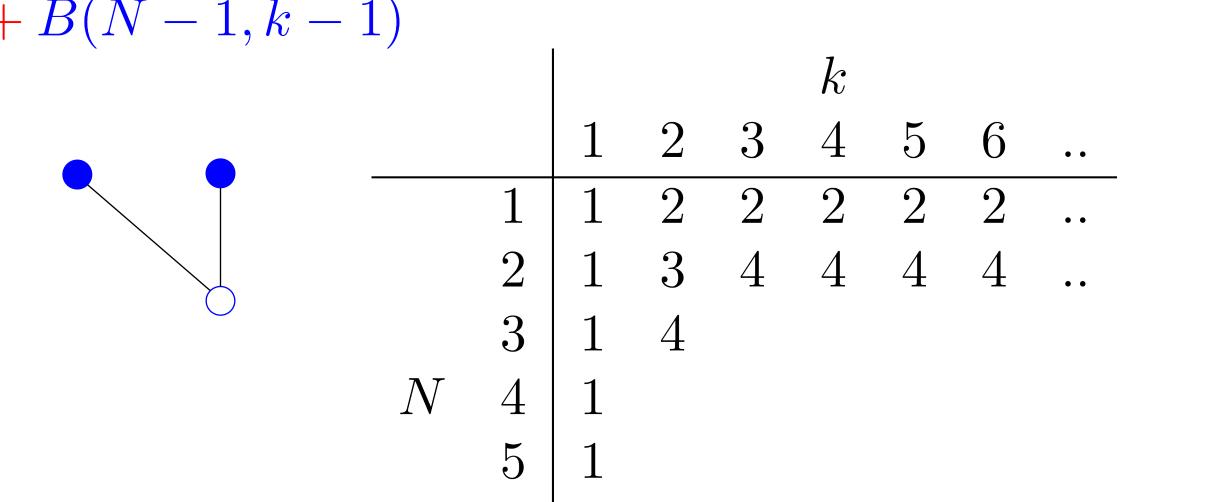
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



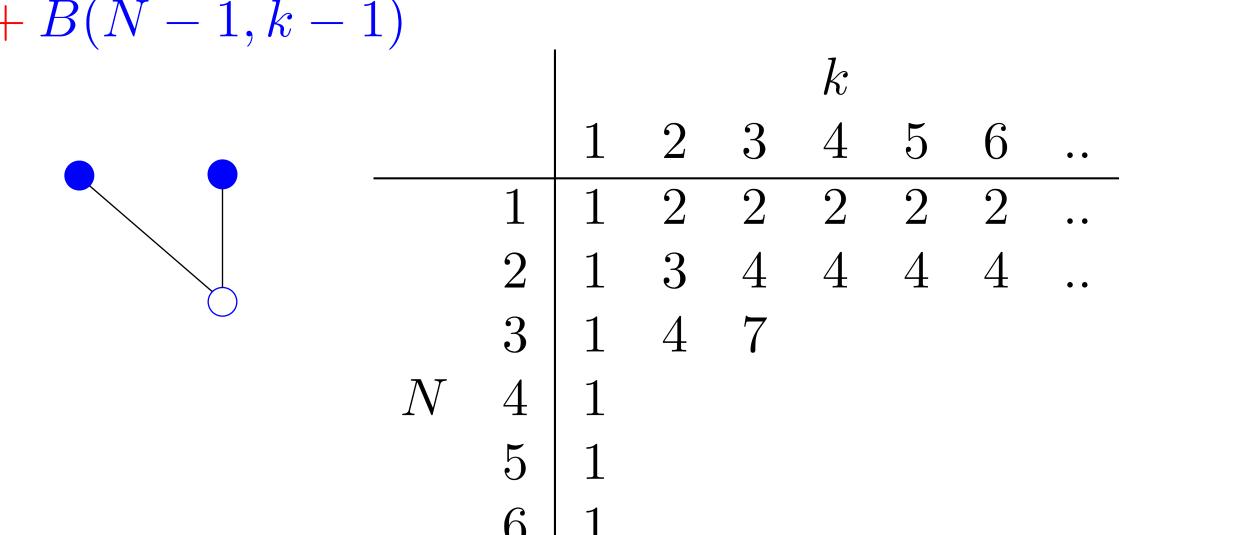
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



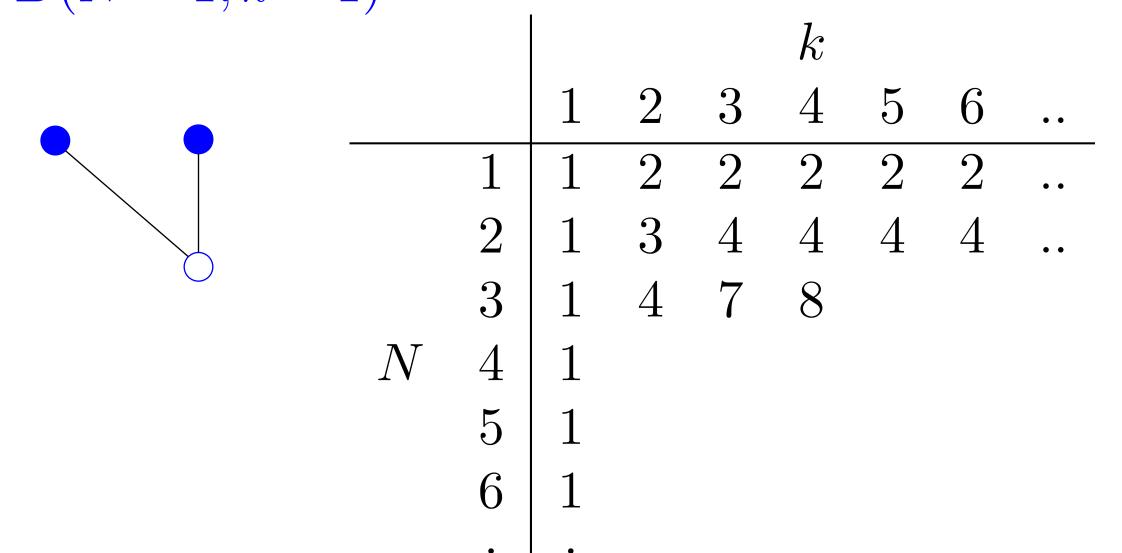
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



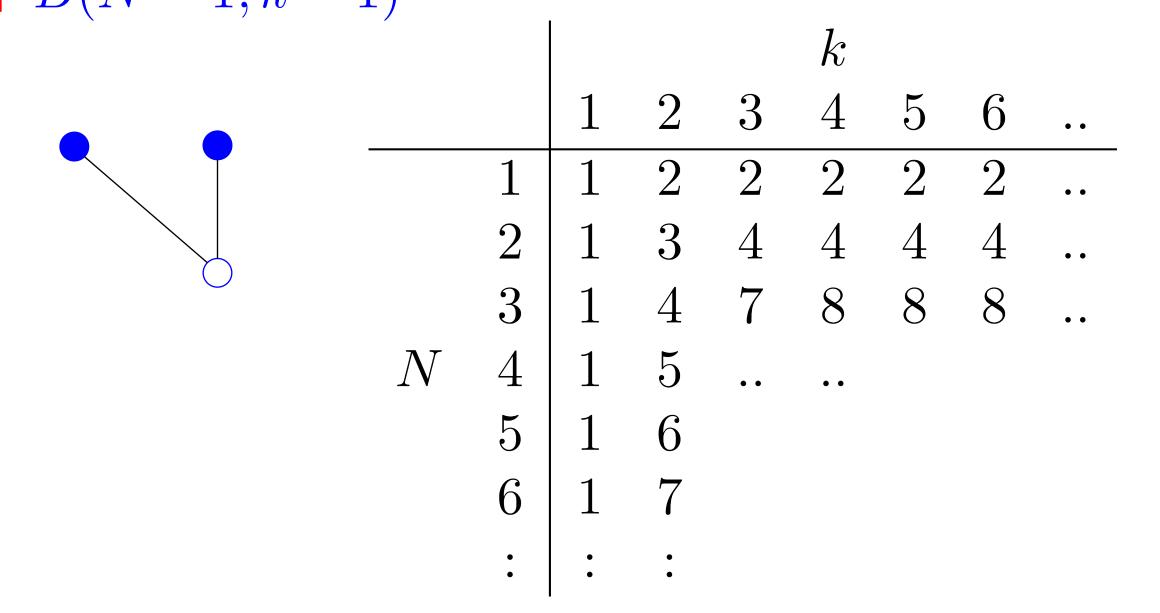
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



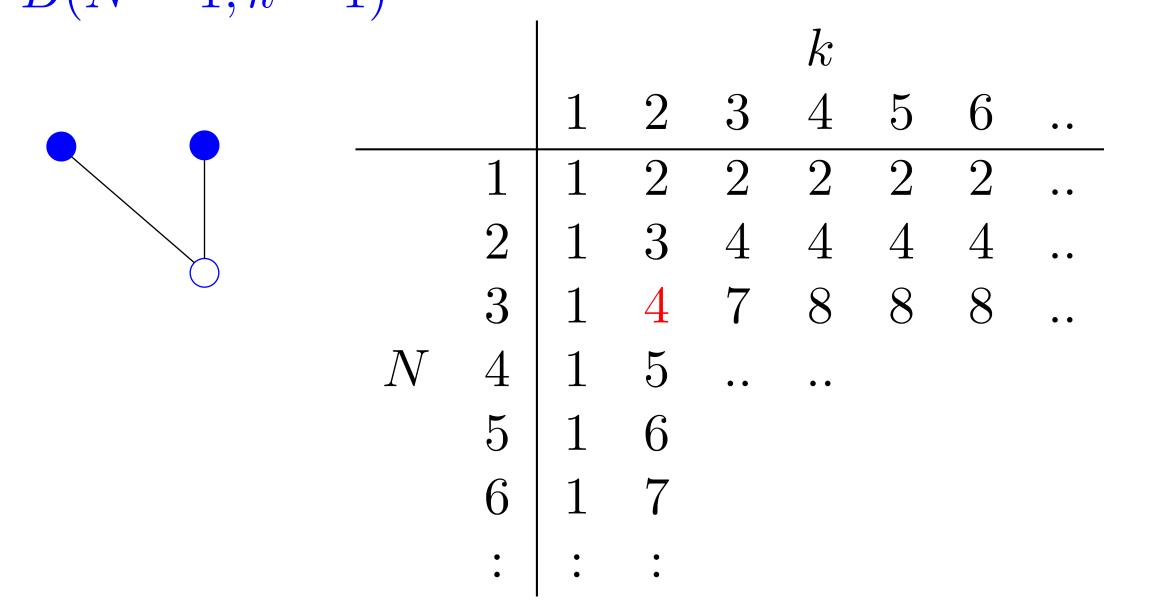
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



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



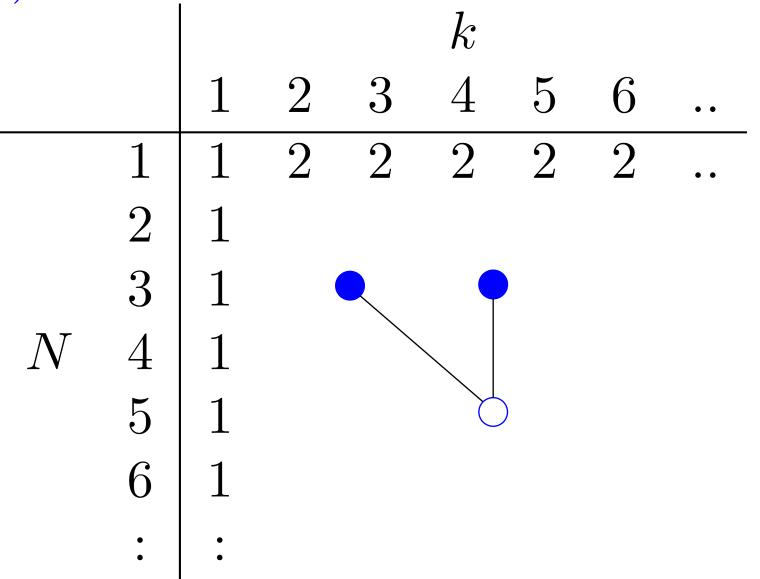
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



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

Theorem:

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

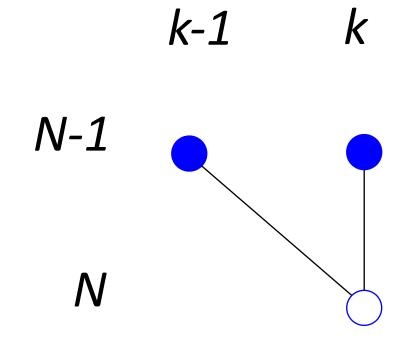


- 1. Boundary conditions: easy
- 2. Induction step

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

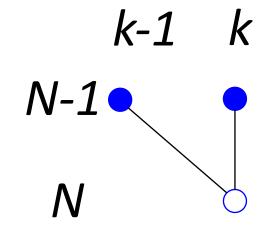
The induction step

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



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

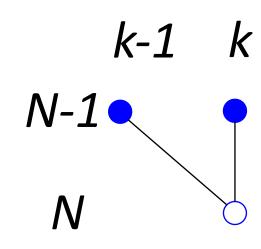
$$B(N,k) \le B(N-1,k) + B(N-1,k-1)$$



$$\left| \frac{B(N,k)}{E(N,k)} \le \sum_{i=0}^{k-1} \left(\begin{array}{c} N \\ i \end{array} \right) \right|$$

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

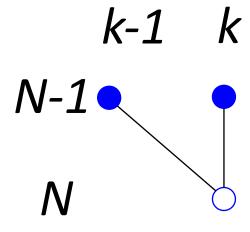
$$\sum_{i=0}^{k-1} \left(\begin{array}{c} N-1 \\ i \end{array} \right)$$



$$B(N,k) \le \sum_{i=0}^{k-1} \left(\begin{array}{c} N \\ i \end{array} \right)$$

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

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

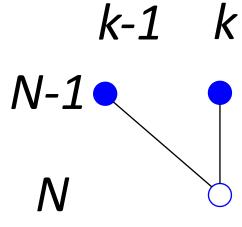


$$\sum_{i=0}^{k-1} \left(\begin{array}{c} N-1 \\ i \end{array}\right) + \sum_{i=0}^{k-2} \left(\begin{array}{c} N-1 \\ i \end{array}\right)$$

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

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

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

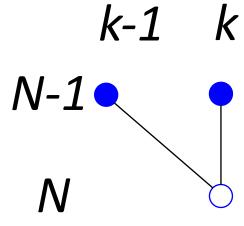


$$\sum_{i=0}^{k-1} \binom{N-1}{i} + \sum_{i=0}^{k-2} \binom{N-1}{i}$$

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

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

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



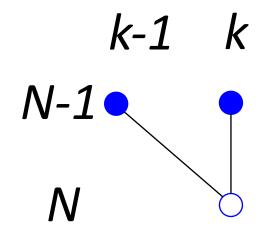
$$\sum_{i=0}^{k-1} \binom{N-1}{i} + \sum_{i=0}^{k-2} \binom{N-1}{i}$$

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

$$= 1 + \sum_{i=1}^{k-1} \left[\left(\begin{array}{c} N-1 \\ i \end{array} \right) + \left(\begin{array}{c} N-1 \\ i-1 \end{array} \right) \right]$$

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

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



$$\sum_{i=0}^{k-1} \left(\begin{array}{c} N-1\\ i\end{array}\right) + \sum_{i=0}^{k-2} \left(\begin{array}{c} N-1\\ i\end{array}\right)$$

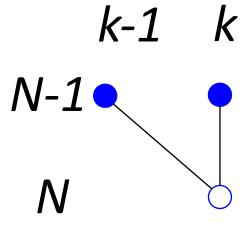
$$= 1 + \sum_{i=1}^{k-1} {N-1 \choose i} + \sum_{i=1}^{k-1} {N-1 \choose i-1}$$

$$= 1 + \sum_{i=1}^{k-1} \left[\left(\begin{array}{c} N-1 \\ i \end{array} \right) + \left(\begin{array}{c} N-1 \\ i-1 \end{array} \right) \right]$$

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

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

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



$$\sum_{i=0}^{k-1} \left(\begin{array}{c} N-1\\ i\end{array}\right) + \sum_{i=0}^{k-2} \left(\begin{array}{c} N-1\\ i\end{array}\right)$$

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

$$= 1 + \sum_{i=1}^{k-1} \left[\left(\begin{array}{c} N-1 \\ i \end{array} \right) + \left(\begin{array}{c} N-1 \\ i-1 \end{array} \right) \right]$$

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

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

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

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

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

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

$$m_{\mathcal{H}}(N) \leq \sum_{i=0}^{k-1} \begin{pmatrix} N \\ i \end{pmatrix}$$

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

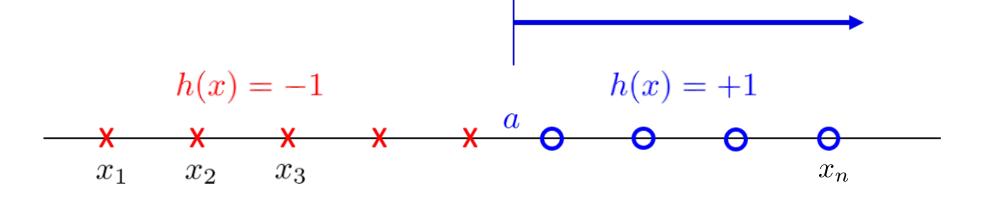
$$m_{\mathcal{H}}(N) \leq \sum_{i=0}^{k-1} \binom{N}{i}$$

maximum power is N^{k-1}

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

3 Examples

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



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

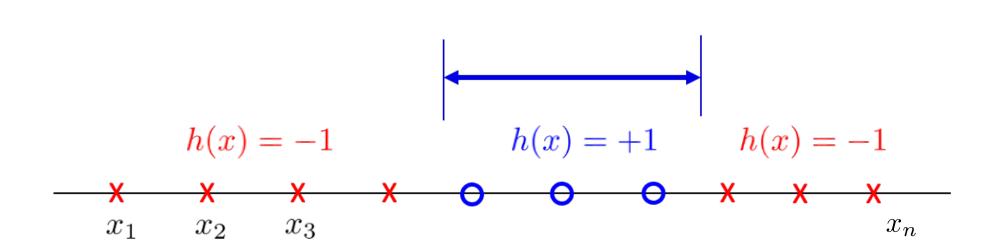
$$\sum_{i=0}^{k-1} \binom{N}{i}$$

3 Examples

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

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

• ${\cal H}$ is **positive interval** (break point k=3)



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

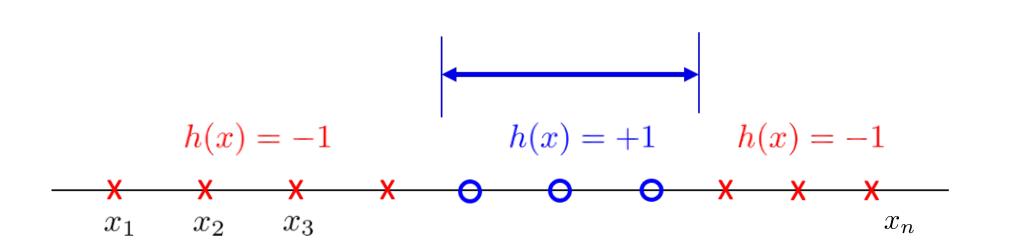
$$\sum_{i=0}^{k-1} \left(\begin{array}{c} N \\ i \end{array} \right)$$

3 Examples

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

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

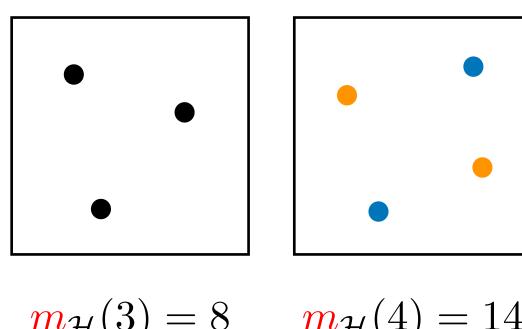
• \mathcal{H} is **positive interval** (break point k=3)



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

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

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



Recall: outline

• Prove that $m_{\mathcal{H}}(N)$ is polynomial

• Prove that $m_{\mathcal{H}}(N)$ can replace M

Statistical Machine Learning - Lecture 5

A (tighter) bound with the growth function

Instead of

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \le 2 \quad M \quad e^{-2N\epsilon^2}$$

we want

$$\mathbb{P}(|\hat{R}_N(h^*) - R(h^*)| > \epsilon) \stackrel{?}{\leq} 2 \qquad m_{\mathcal{H}}(N) \qquad e^{-2N\epsilon^2}$$

With probability at least $1-\delta$: $R(h^*) \stackrel{?}{\leq} \hat{R}_N(h^*) + \sqrt{\frac{1}{2N}} \ln \frac{2m_{\mathcal{H}}(N)}{\delta}$

Logistics

- Quiz on Thursday
- Based on HW1 and HW2
- 15 mins in-class
- Closed book