

Teaching Dimension

COMS 6998-4 Learning Theory

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1 Introduction

- Learning model
- Generic bounds

2 Examples

- Least Teachable Class
- Axis Aligned Boxes

3 Teaching versus Learning

- Disparities
- Bounds

4 Recursive Teaching

- Almost maximal Classes
- Recursive Teaching Dimension

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Consistent learners and Helpful Directors

[Goldman, Rivest, & Shapire 1993]

Definition (Consistent learner)

A learner is *consistent* when for all t there is some $f \in \mathcal{C}$ such that

$$\forall i < t, f(x_i) = f^*(x_i) \quad \text{and} \quad f(x_t) = y_t$$

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In the online model, after inputs x_1, x_2, \dots, x_i :

No consistent learner will make a mistake at $t > i$

\Leftrightarrow

Exactly one consistent hypothesis is consistent with the $x_{<t}$

Teaching dimension

[Goldman & Kearns 1995]

Definition (Teaching Sequence)

Inputs x_1, \dots, x_m are a *teaching sequence* for f when there is no other function $g \in \mathcal{C}$ such that $g(x_i) = f(x_i)$ for all $i \leq m$.

Teaching dimension

[Goldman & Kearns 1995]

Definition (Teaching Sequence)

Inputs x_1, \dots, x_m are a *teaching sequence* for f when there is no other function $g \in \mathcal{C}$ such that $g(x_i) = f(x_i)$ for all $i \leq m$.

Definition (Teaching Dimension)

The class \mathcal{C} has *teaching dimension* of t when t is the smallest integer such that each $f \in \mathcal{C}$ has a teaching sequence of length at most t .

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Theorem (Teaching Upper Bound)

Any finite class has a teaching dimension at most

$$t \leq |\mathcal{C}| - 1.$$

Enumerate $\mathcal{C} = f, f_1, \dots, f_{|\mathcal{C}|-1}$.

To teach f , choose x_i such that $f(x_i) \neq f_i(x_i)$.

Theorem (Teaching Lower Bound)

Any finite class \mathcal{C} over X has a teaching dimension at least

$$t \leq \frac{\log |\mathcal{C}| - 1}{\log |X|}.$$

Each f uniquely identified by some x_1, \dots, x_t with $f(x_1), \dots, f(x_t)$.

$$|\mathcal{C}| \leq 2^t \binom{|X|}{t} \leq 2|X|^t.$$

Theorem (Teaching Bounds)

Any finite class \mathcal{C} over X has a teaching dimension t such that

$$|\mathcal{C}| - 1 \geq t \geq \frac{\log |\mathcal{C}| - 1}{\log |X|}.$$

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Example (Least Teachable Class)

Consider the following concept class over $\{1, 2, \dots, n\}$:

$$\mathcal{C} = \{X \setminus \{1\}, X \setminus \{2\}, \dots, X \setminus \{n\}\} \cup \{X\}.$$

To teach $X \setminus \{i\}$ use teaching sequence i .

To teach X need sequence $1, 2, \dots, n$.

So teaching dimension is $n = |\mathcal{C}| - 1$.

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Rectangles in the Plane

Example (Rectangles in \mathbb{Z}^2)

Two points \mathbf{x} , $\mathbf{y} \in \mathbb{Z}^2$ define a rectangle

$$R_{\mathbf{x},\mathbf{y}}(\mathbf{z}) = 1 \Leftrightarrow z_1 \in [x_1, y_1] \text{ and } z_2 \in [x_2, y_2].$$

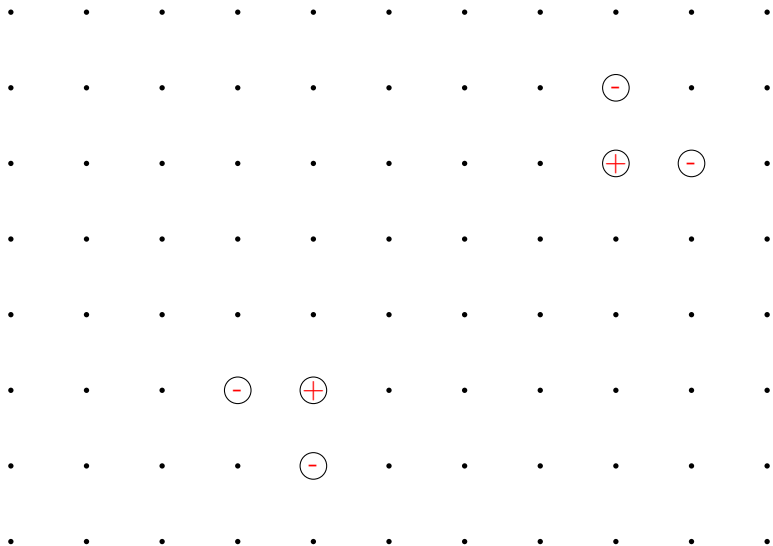
Teaching sequence

Positive examples: \mathbf{x} and \mathbf{y}

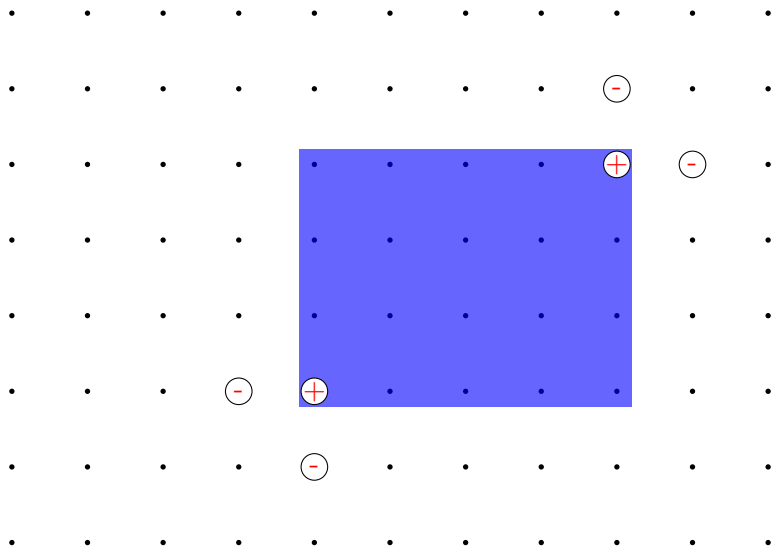
Negative examples: $\mathbf{x} - (1, 0)$, $\mathbf{x} - (0, 1)$, $\mathbf{y} + (1, 0)$, $\mathbf{y} + (0, 1)$

Teaching dimension 6

Rectangles in the Plane



Rectangles in the Plane



Example (Boxes in \mathbb{Z}^d)

Two points $\mathbf{x}, \mathbf{y} \in \mathbb{Z}^d$ define a box

$$R_{\mathbf{x},\mathbf{y}}(z) = 1 \Leftrightarrow \forall i \in [d] \quad z_i \in [x_i, y_i].$$

Teaching sequence

Positive examples: \mathbf{x} and \mathbf{y}

Negative examples for each $i \in [d]$: $\mathbf{x} - \mathbf{e}_i, \mathbf{y} + \mathbf{e}_i$

Teaching dimension $2(1 + d)$

Example (Union of Boxes)

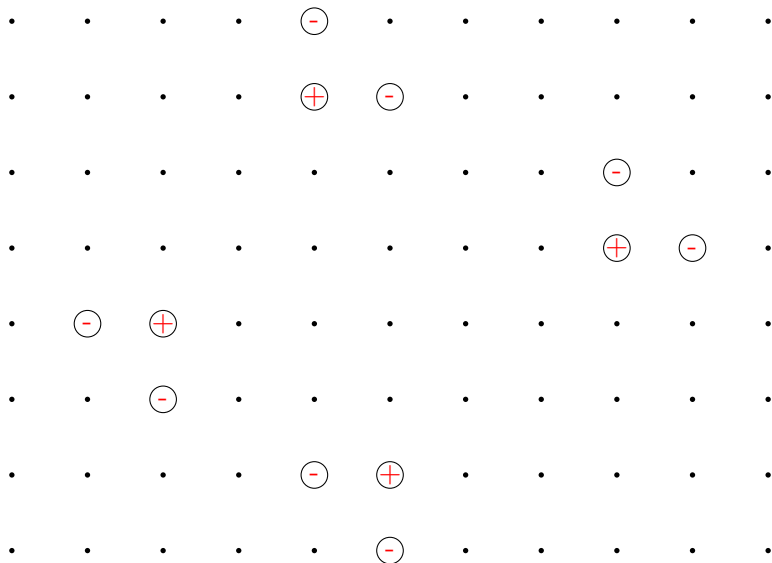
Fix k . For $R_{\mathbf{x}_1, \mathbf{y}_1}, \dots, R_{\mathbf{x}_k, \mathbf{y}_k}$ disjoint each in \mathbb{R}^d let

$$U_{\{\mathbf{x}_i, \mathbf{y}_i\}}(z) = \bigcup_{i=1}^k R_{\mathbf{x}_i, \mathbf{y}_i}.$$

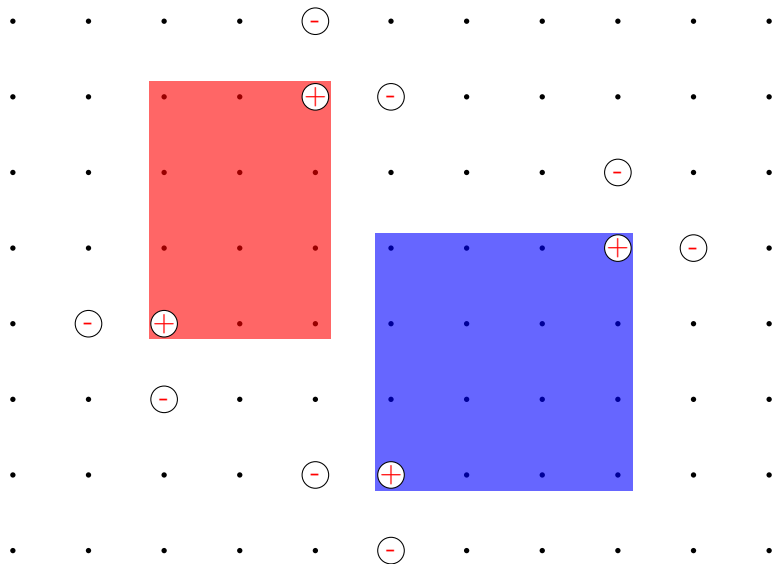
Use the union of the teaching sequences for each box
(with special case when boxes are adjacent)

Teaching dimension $2k(1 + d)$.

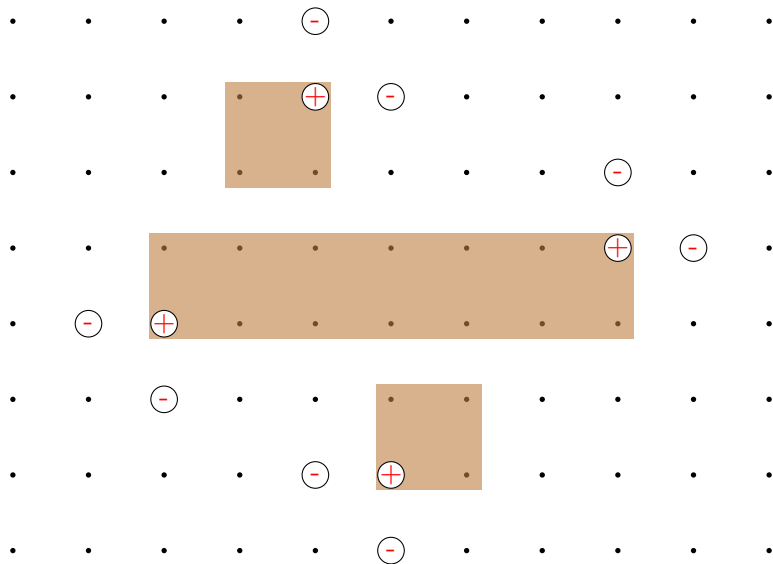
Union of boxes



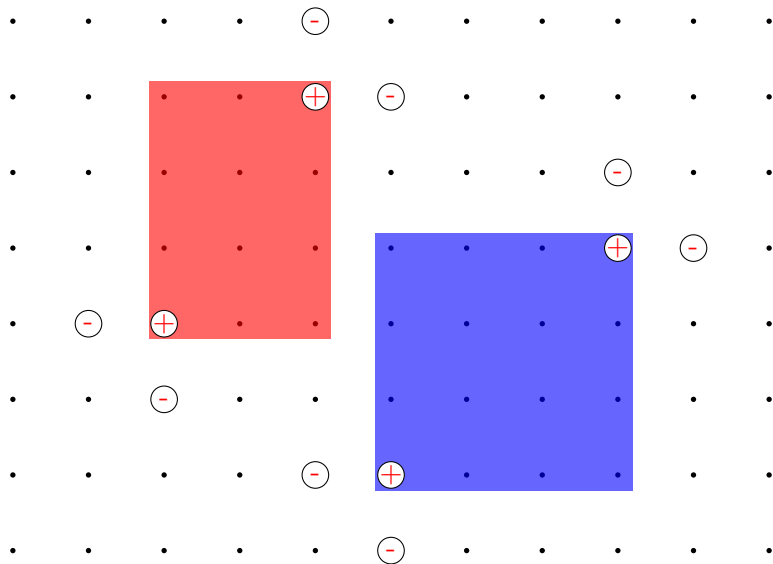
Union of boxes ($k = 2$)



Union of boxes ($k = ?$)



Union of boxes ($k = 2$)



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Definition (Shattered set)

The class \mathcal{C} *shatters* a set $S \subset X$ when

$$\{S \cap c : c \in \mathcal{C}\} = \mathbb{P}(S).$$

Definition (VC dimension)

The integer d is the *Vapnik-Chervonenkis dimension* of a class \mathcal{C} if it is the minimum d such that \mathcal{C} shatters no sets of $d + 1$ points.

Example (Least Teachable Class)

$$\mathcal{C} = \{X \setminus \{1\}, X \setminus \{2\}, \dots, X \setminus \{n\}\} \cup \{X\}.$$

Teaching Dimension n

VC Dimension 2 as no hypothesis induces $(1, 0, 0)$ on three points

Infinite Teaching Dimension

[Moran, Shpilka, Wigderson, Yehudayoff 2015]

Example (Dedekind cuts)

Consider the class of sets of rational numbers less than some real

$$\mathcal{C} = \{(-\infty, r) \cap \mathbb{Q} : r \in \mathbb{R}\}.$$

VC Dimension 2 as for $q_1 < q_2 < q_3$ cannot induce $(1, 0, 1)$

Teaching Dimension ∞

Easy to teach, hard to learn

Set of n easy to teach functions:

$$F = \{\{x\} : x \in [n]\}$$

Easy to teach, hard to learn

Set of n easy to teach functions:

$$F = \{\{x\} : x \in [n]\}$$

Set of 2^m hard to learn functions:

$$G = 2^{[m]}$$

Easy to teach, hard to learn

Set of n easy to teach functions:

$$F = \{\{x\} : x \in [n]\}$$

Set of 2^m hard to learn functions:

$$G = 2^{[m]}$$

Choose $2^m = n$ and construct class over $[n] \cup [m]$

Example (Hybrid Concept)

Enumerate $F = f_1, \dots, f_n$ and $G = g_1, \dots, g_m$ above. Define class

$$\mathcal{C} = \{h_i = f_i \cup g_i : i \in [n]\}.$$

Easy to teach, hard to learn

	x_1	x_2	x_3	\dots	x_{n-1}	x_n	y_1	\dots	y_{m-1}	y_m
h_1	+	-	-	\dots	-	-	-	\dots	-	-
h_2	-	+	-	\dots	-	-	-	\dots	-	+
h_3	-	-	+	\dots	-	-	-	\dots	+	-
\vdots										
h_{n-1}	-	-	-	\dots	+	-	+	\dots	+	-
h_n	-	-	-	\dots	-	+	+	\dots	+	+

Easy to teach, hard to learn

	x_1	x_2	x_3	\dots	x_{n-1}	x_n	y_1	\dots	y_{m-1}	y_m
h_1	+	-	-	\dots	-	-	-	\dots	-	-
h_2	-	+	-	\dots	-	-	-	\dots	-	+
h_3	-	-	+	\dots	-	-	-	\dots	+	-
\vdots										
h_{n-1}	-	-	-	\dots	+	-	+	\dots	+	-
h_n	-	-	-	\dots	-	+	+	\dots	+	+

Still easy to teach: h_i identified by positive example x_i

Still hard to learn: y_1, \dots, y_m is shattered

Teaching Dimension 1 but VC Dimension $\log n$

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Theorem (Lower bound)

$$t \geq \frac{d - 1}{\log |X|}.$$

Follows directly from previous:

$$t \geq \frac{\log |\mathcal{C}| - 1}{\log |X|} \quad \text{and} \quad \log |\mathcal{C}| \geq d.$$

Theorem (Upper bound)

$$t \leq |\mathcal{C}| - 2^d + d.$$

Learning sequence:

Shattered set of size d

One example to exclude each remaining hypothesis

First step removes $2^d - 1$ hypotheses with d examples

Second step removes $|\mathcal{C}| - (2^d - 1) - 1$ hypotheses, 1 example each

Theorem (Teaching versus Learning Bounds)

If \mathcal{C} has teaching dimension t and VC dimension d then

$$|\mathcal{C}| - 2^d + d \geq t \geq \frac{d-1}{\log |\mathcal{X}|}$$

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Theorem (Concentration of Teaching Dimension)

If the teaching dimension of \mathcal{C} is $t \geq |\mathcal{C}| - k$, then for some $f \in \mathcal{C}$ the class $\mathcal{C} \setminus \{f\}$ has teaching dimension at most k .

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If the teaching dimension of \mathcal{C} is $t \geq |\mathcal{C}| - k$, then for some $f \in \mathcal{C}$ the class $\mathcal{C} \setminus \{f\}$ has teaching dimension at most k .

Fix f requiring a teaching sequence x_1, x_2, \dots, x_t of length t .

To prove: fix some f_1 in the class $\mathcal{C} \setminus \{f\}$ and wlog take $f_1(x_1) \neq f(x_1)$.

Theorem (Concentration of Teaching Dimension)

If the teaching dimension of \mathcal{C} is $t \geq |\mathcal{C}| - k$, then for some $f \in \mathcal{C}$ the class $\mathcal{C} \setminus \{f\}$ has teaching dimension at most k .

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To prove: fix some f_1 in the class $\mathcal{C} \setminus \{f\}$ and wlog take $f_1(x_1) \neq f(x_1)$.

Idea: partition $\mathcal{C} \setminus \{f\}$ into

- S a large set that disagrees with f_1 on x_1
- T a small set

To teach f_1 , use sequence x_i plus one x to distinguish from each $g \in T$.

Concentration Theorem (proof)

Construct S and T inductively.

Let $C = \mathcal{C} \setminus (\{f\} \cup S \cup T)$ the remaining concepts.

Define $D(x)$ the set of $g \in C$ such that $g(x) \neq f(x)$.

Concentration Theorem (proof)

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Define $D(x)$ the set of $g \in C$ such that $g(x) \neq f(x)$.

First set $S = \{f_1\}$ and $T = D(x_1) \setminus \{f_1\}$.

Concentration Theorem (proof)

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First set $S = \{f_1\}$ and $T = D(x_1) \setminus \{f_1\}$.

Then for $i = 2, \dots, t$:

Pick an arbitrary $f_i \in D(x_i)$.

Add f_i to S .

Add any remaining $D(x_i) \setminus \{f_i\}$ to T .

Concentration Theorem (proof)

Construct S and T inductively.

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Then for $i = 2, \dots, t$:

Pick an arbitrary $f_i \in D(x_i)$.

Add f_i to S .

Add any remaining $D(x_i) \setminus \{f_i\}$ to T .

Claim 1: $f_i \in S$ disagrees with f_1 on x_1

Assume $f_i(x_1) = f_1(x_1)$.

$f_i(x_1) \neq f(x_1)$ by construction.

But then in first step $f_i \in D(x_1)$ so $f_i \in T$

T and S are disjoint, so $f_i \notin S$.

Concentration Theorem (proof)

First set $S = \{f_1\}$ and $T = D(x_1) \setminus \{f_1\}$.

Then for $i = 2, \dots, t$:

Pick an arbitrary $f_i \in D(x_i)$.

Add f_i to S .

Add any remaining $D(x_i) \setminus \{f_i\}$ to T .

Claim 2: $|T| = k - 1$:

$D(x_i)$ non-empty at each step, otherwise $\{x_j\} \setminus x_i$ a learning sequence

One f_i gets added to S each round, have $|S| = t$

$\mathcal{C} \setminus \{f\} = S \cup T$ implies $|T| = |\mathcal{C}| - 1 - |S|$

Assumed $t = |\mathcal{C}| - k$ so $|T| = k - 1$. □

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Recursive Teaching Dimension

[Zilles, Lange, Holte, Zinkevich 2011]

Let $\text{MinTD}(\mathcal{C})$ be the set of $f \in \mathcal{C}$ with the shortest teaching sequences.

Construct levels of \mathcal{C} as follows:

$$\mathcal{C}_i = \text{MinTD}\left(\mathcal{C} \setminus \bigcup_{j < i} \mathcal{C}_j\right).$$

Recursive Teaching Dimension

[Zilles, Lange, Holte, Zinkevich 2011]

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Construct levels of \mathcal{C} as follows:

$$\mathcal{C}_i = \text{MinTD}\left(\mathcal{C} \setminus \bigcup_{j < i} \mathcal{C}_j\right).$$

Then we can define a robust notion of teaching dimension.

Definition (Recursive Teaching Dimension)

The *recursive teaching dimension* of \mathcal{C} is the maximum of the teaching dimensions of the levels \mathcal{C}_i constructed above.