MAC 0460 / 5832 Introduction to Machine Learning

 $08 - Is learning feasible ? (Infinite <math>\mathcal{H}$)

dichotomy
 growth function
 break point

IME/USP (10/05/2021)

h: hypothesis

 $E_{in}(h)$: empirical error <-- computed on D

 $E_{out}(h)$: true error <-- unknown

Our question: Does $E_{in}(h)$ say anything about $E_{out}(h)$?



What is the probability that *h* is a "bad event"?

$$P(|E_{in}(h) - E_{out}(h)| > \epsilon) = ?$$

Probability of a "bad" event (fixed
$$h$$
)
$$P(|E_{in}(h) - E_{out}(h)| > \epsilon) \le 2e^{-2\epsilon^2 N}$$
(Hoeffding)

Probability of a "bad" event (g selected from a set of M hypothesis)

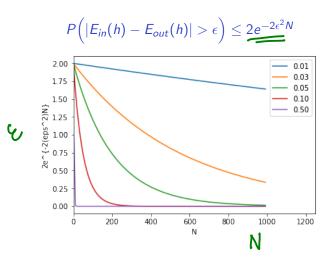
$$P(|E_{in}(g) - E_{out}(g)| > \epsilon) \le 2Me^{-2\epsilon^2N}$$

Compare the experiment of **tossing one coin** N **times** with the experiment of **tossing** M **coins,** N **times each**. The chance of a coin resulting in N heads is much larger for the second case.

Recall: Bound variation in function of N

The smaller is ϵ , the larger is the number of samples needed to keep the probability of "bad" events small

(Each color represents a different value of ϵ)



(verification scenario)

The good news: we can make the Hoeffding bound arbitrarily small



(learning scenario)

If M is infinite, the bound $2Me^{-2\epsilon^2N}$ will be large (meaningless)

$$P(|E_{in}(g) - E_{out}(g)| > \epsilon) \le 2 \frac{M}{\epsilon} e^{-2\epsilon^2 N}$$

Today's question: Can we replace M?

Where did the M come from?

The ${\mathcal B}$ ad events ${\mathcal B}_m$ are

C 👺 Creator: Yaser - Mostafa - LFD Lecture 5

$$||E_{\mathrm{in}}(h_m) - E_{\mathrm{out}}(h_m)| > \epsilon||$$
The union bound:
$$||E[\mathcal{B}_1 \text{ or } \mathcal{B}_2 \text{ or } \cdots \text{ or } \mathcal{B}_M]|$$

$$\leq ||E[\mathcal{B}_1]| + ||E[\mathcal{B}_2]| + \cdots + ||E[\mathcal{B}_M]||$$
no overlaps: M terms

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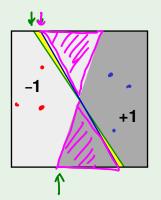
Can we improve on M?

Yes, bad events are very overlapping!

$$\Delta E_{
m out}$$
: change in $+1$ and -1 areas

 $\Delta E_{
m in}$: change in labels of data points

$$|E_{ ext{in}}(h_1) - E_{ ext{out}}(h_1)| pprox |E_{ ext{in}}(h_2) - E_{ ext{out}}(h_2)|$$



The choice of g from \mathcal{H} is affected by D (training data)

Usually there are many similar hypothesis h_j that classify samples in D in the exact same way

If in such a group of hypothesis, there is one that corresponds to a "bad" event, would it not be reasonable to think that other similar hypothesis also correspond to a "bad" event?

To improve the bound, we will replace the *Union bound* with one that takes the overlap into consideration

For that, we will define a "number" that characterizes the complexity of ${\cal H}$

Important definitions:

- dichotomy /
- growth function /
- break point (the "number")

What can we replace M with?

Instead of the whole input space,

we consider a finite set of input points,

and count the number of dichotomies









Let
$$X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$$
 (N points)



Let \mathcal{H} be a hypothesis space

Dichotomies generated by \mathcal{H} :

any bipartition of X as $X_{-1} \cup X_{+1}$ that agrees with some hypothesis $h \in \mathcal{H}$

$$\mathcal{H}(\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_N) = \left\{ \left(h(\mathbf{x}_1), h(\mathbf{x}_2),\ldots,h(\mathbf{x}_N) \right) \mid h \in \mathcal{H} \right\}$$

Dichotomies: mini-hypotheses

A hypothesis
$$h: \mathcal{X} \to \{-1, +1\}$$

A dichotomy
$$h:\{\mathbf{x}_1,\mathbf{x}_2,\cdots,\mathbf{x}_N\} o\{-1,+1\}$$

Number of hypotheses $|\mathcal{H}|$ can be infinite \checkmark

Number of dichotomies $|\mathcal{H}(\mathbf{x}_1,\mathbf{x}_2,\cdots,\mathbf{x}_N)|$ is at most 2^N

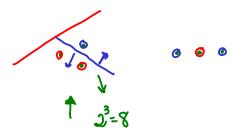
Candidate for replacing $oldsymbol{M}$

Why the number of dichotomies $|\mathcal{H}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N)|$ is at most 2^N ?

If you consider another set of points, say, $X' = \{\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_N\}$,

1. is
$$\mathcal{H}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N) = \mathcal{H}(\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_N)$$
 ?

2. is
$$|\mathcal{H}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N)| = |\mathcal{H}(\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_N)|$$
?



The growth function

The growth function counts the $\underline{\mathsf{most}}$ dichotomies on any N points

$$\underline{\boldsymbol{m}}_{\mathcal{H}}(N) = \max_{\mathbf{x}_1, \cdots, \mathbf{x}_N \in \mathcal{X}} |\mathcal{H}(\mathbf{x}_1, \cdots, \mathbf{x}_N)|$$

The growth function satisfies:

$$m_{\mathcal{H}}(N) \leq 2^N$$

Let's apply the definition.

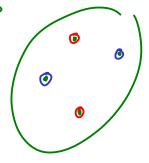
Growth function for the perceptron

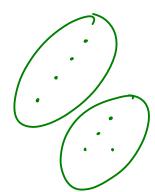
$$m_{\mathcal{H}}(N) = \max_{\mathbf{x}_1, \dots, \mathbf{x}_N \in \mathcal{X}} |\mathcal{H}(\mathbf{x}_1, \dots, \mathbf{x}_N)|$$

$$m_{\mathcal{H}}(3) = ?$$

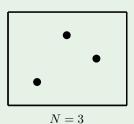
$$m_{\mathcal{H}}(3) = 8$$
?

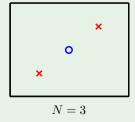
$$m_{H}(4) = ?$$

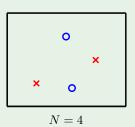




Applying $m_{\mathcal{H}}(N)$ definition - perceptrons







$$\frac{m_{\mathcal{H}}(3)}{=} = 8$$

 $m_{\mathcal{H}}(4) = 14$



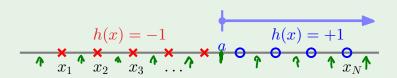
It may not be easy to compute the growth function for an arbitrary hypothesis set.

Imagine doing that for perceptrons, for each value of N!

There are, however some simple hypothesis set for which we can write down the growth function in terms of N

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Example 1: positive rays

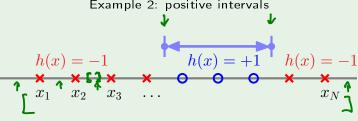


$$\mathcal{H} \text{ is set of } h \colon \mathbb{R} \to \{-1, +1\}$$

$$h(x) = \operatorname{sign}(x-a)$$

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





$$\mathcal{H}$$
 is set of $h \colon \mathbb{R} \to \{-1, +1\}$

Place interval ends in two of N+1 spots

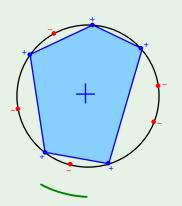
$$m_{\mathcal{H}}(N) = {N+1 \choose 2} + 1 = \frac{1}{2}N^2 + \frac{1}{2}N + 1$$

Example 3: convex sets

$$\mathcal{H}$$
 is set of $h \colon \mathbb{R}^2 \to \{-1, +1\}$

$$h(\mathbf{x}) = +1$$
 is convex

$$m_{\mathcal{H}}(N) = 2^N$$
 The N points are 'shattered' by convex sets



The 3 growth functions

$$ullet$$
 $\mathcal H$ is positive rays:

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

ullet $\mathcal H$ is positive intervals:

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

• \mathcal{H} is convex sets:

$$m_{\mathcal{H}}(N) = 2^N$$

Why are we discussing growth functions?

Back to the big picture

Remember this inequality?

$$\mathbb{P}\left[\left|E_{\text{in}} - E_{\text{out}}\right| > \epsilon\right] \le 2M e^{-2\epsilon^2 N}$$

What happens if $m_{\mathcal{H}}(N)$ replaces M?

$$m_{\mathcal{H}}(N)$$
 polynomial \implies Good!

Just prove that $m_{\mathcal{H}}(N)$ is polynomial?

If the growth function is polynomial, the bound could be made arbitrarily small by choosing an adequate value of N.

Do we need to compute the growth function value for each N?

Break point of
$$\mathcal{H}$$
 $\mathcal{D}=\{x_1,...,x_N\}$

Definition: If no data set of size k can be shattered by \mathcal{H} , then k is a $\underline{break\ point}$ for \mathcal{H} $m_{\mathcal{H}}(k)\ <\ 2^k$

For 2D perceptrons, k=4

A bigger data set cannot be shattered either

$$m_{\mathcal{H}}(3) = 2^3 = 8$$

 $m_{\mathcal{H}}(4) = 14 < 2^4$

Break point - the 3 examples

• Positive rays
$$m_{\mathcal{H}}(N) = N+1$$

break point $k=\,2$

$$ullet$$
 Positive intervals $m_{\mathcal{H}}(N) = rac{1}{2}N^2 + rac{1}{2}N + 1$

break point
$$k = 3$$



ullet Convex sets $m_{\mathcal{H}}(N)=2^N$ \bullet

break point
$$k=\infty$$

An exercise

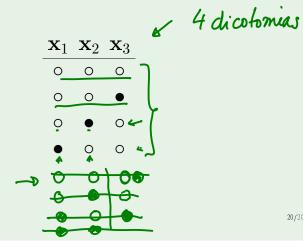
Assume that for a certain hypothesis set ${\mathcal H}$ the break-point is 2

This means that \mathcal{H} can not generate the $2^2=4$ possible dichotomies for any subset of two samples $\{x_1, x_2\}$.

Under such supposition, how many dichotomies are possible when we consider three samples $\{x_1, x_2, x_3\}$?



K=2 is a break point





Main result

No break point
$$\implies$$
 $m_{\mathcal{H}}(N)=2^N$

Any break point
$$\Longrightarrow$$
 $\underline{m}_{\mathcal{H}}(N)$ is **polynomial** in N

Summary

can generate

1. We started searching a replacement for M

$$P(|E_{in}(g) - E_{out}(g)| > \epsilon) \le 2 \underbrace{M}_{e} e^{-2\epsilon^2 N}$$

- 2. **Dichotomies**: to deal with the issue of overlapping "bad" events. The complexity of $\mathcal H$ is related to the number of dichotomies it
- 3. **Growth function**: number of dichotomies for each *N*
 - Polynomial growth functions are good candidate for replacing M
 - Not always possible to write this function

4. **Break-point**: if it is finite, it means that the growth function is polynomial (to be demonstrated)

5. Next meeting

- if there is a finite break-point, then the growth function is polynomial
- ullet it is valid to replace \underline{M} with the growth function