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

Probability of a "bad" event (fixed h) (Hoeffding)

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

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

$$\mathsf{P}\Big(ig| \mathsf{E}_{\mathit{in}}(g) - \mathsf{E}_{\mathit{out}}(g) ig| > \epsilon \Big) \leq 2 M e^{-2\epsilon^2 N}$$

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 ϵ , the larger the number of samples needed to keep the probability of "bad" events small (Each color represents a different value of ϵ)



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

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

Can we replace M?

Where did the M come from?

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

$$|E_{ ext{in}}(h_m) - E_{ ext{out}}(h_m)| > \epsilon''$$

The union bound:

$$\mathbb{P}[\mathcal{B}_1 \text{ or } \mathcal{B}_2 \text{ or } \cdots \text{ or } \mathcal{B}_M]$$

$$\leq \underbrace{\mathbb{P}[\mathcal{B}_1] + \mathbb{P}[\mathcal{B}_2] + \dots + \mathbb{P}[\mathcal{B}_M]}_{\text{no overlaps: } M \text{ terms}}$$



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 "bad" event ?

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

 $|E_{\rm in}(h_1) - E_{\rm out}(h_1)| \approx |E_{\rm in}(h_2) - E_{\rm out}(h_2)|$



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 $\ensuremath{\mathcal{H}}$

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*





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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 a hypothesis $h \in \mathcal{H}$

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

Dichotomies: mini-hypotheses

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

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

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

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

Candidate for replacing 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, $X' = \{\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_N\}$,

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

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

The growth function

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

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

The growth function satisfies:

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

Let's apply the definition.

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8/20

Growth function for the perceptron

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

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



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

Example 1: positive rays



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

 $\boldsymbol{m}_{\mathcal{H}}(N) = N + 1$

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11/20

Example 2: positive intervals



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

Place interval ends in two of N+1 spots

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

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Example 3: convex sets

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

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

 $\mathbf{m}_{\mathcal{H}}(N) = 2^N$

The N points are 'shattered' by convex sets



The 3 growth functions

• \mathcal{H} is positive rays:

$$\mathbf{m}_{\mathcal{H}}(N) = N + 1$$

 $\bullet \ensuremath{\mathcal{H}}$ is positive intervals:

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

 $\bullet \ \mathcal{H}$ is convex sets:

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

Why are we discussing growth functions ?

Back to the big picture

Remember this inequality?

$$\mathbb{P}\left[\left|E_{ ext{in}}-E_{ ext{out}}
ight|>\epsilon
ight]\leq 2Me^{-2\epsilon^2N}$$

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 ${\mathcal H}$

Definition:

If no data set of size k can be shattered by \mathcal{H} , then k is a *break point* for \mathcal{H}

 $m_{\mathcal{H}}(k) < 2^k$

For 2D perceptrons, k = 4

A bigger data set cannot be shattered either

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17/20

Break point - the 3 examples

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

break point k = 2 • •

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

break point k = 3 • • •

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

break point $k = \infty$ '

18/20

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 $\{x_1, x_2, x_3\}$?

Puzzle



Main result

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

Any break point $\implies m_{\mathcal{H}}(N)$ is **polynomial** in N

1. We started searching a replacement for M

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

- Dichotomies: to deal with the issue of overlapping "bad" events.
 The complexity of *H* is related to the number of dichotomies it can generate
- 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
 - it is valid to replace *M* with the growth function