Theory of Statistical Learning

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Outline

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2. Introduction to Statistical Learning
   - General introduction
   - First concepts
   - Empirical risk minimization
   - Overfitting
   - PAC learning
   - Uniform convergence
3. Bias-complexity trade-off
   - No-free-lunch theorem
   - Error decomposition
4. VC dimension
   - Infinite classes can be PAC learnable
   - Examples
   - The fundamental theorem of learning

1. General presentation

Who am I?

- maître de conférence (= assistant professor) in LJAD (Laboratoire Jean Dieudonné)
- before that: postdoctoral researcher (Max Planck Institute, Tübingen, Germany)
- even before: PhD in Inria Paris
- teaching ($\approx$ 200 hours per year)
- **Rest of the time?** research!
- **Goal:** think about open problems whose solution could benefit society, solve them, publish papers with the answer
- examples of topics that interest me at the moment:
  - interpretability of machine learning algorithms
  - statistical tools for the study of deep neural networks

Who are you?

- online teaching is suboptimal :(
- speaking to a black screen is weird
- **Please introduce yourselves!** (with camera on if possible)
- I will call your name then you can briefly introduce yourself

Goal of the course

- **Goal i):** understand the *maths* behind the algorithms that you learn
- this can save a lot of time!
- one often works with limited resources
- **Goal ii):** learn about theoretical guarantees on existing algorithms
- a way to be reassured: under some assumptions, my method works
- see more clearly the *limitations* of the methods: if some assumption is not satisfied, we can prove that it will fail

Organization of the course

- all the information, documents $\rightarrow$ Slack
- (provisional) calendar:
  1. January 20, (today), 9am-12am
  2. January 27, 9am-12am
  3. February 3, 9am-12am
  4. February 10, 9am-12am
  5. February 17, 9am-12am
  6. February 24, 9am-12am (midterm)
  7. March 10, 9am-12am
  8. March 17, 9am-12am
  9. March 24, 9am-12am
  10. March 31, 9am-12am (exam)
- **Disclaimer:** midterm and exam may be online depending on the situation in the coming weeks
- final grade $=$ (midterm $+$ final)$/2$

Requirements

- **Elementary real analysis:** functions of a real variable, usual functions, continuity, Lipschitz continuity
- **Calculus:** derivative, partial derivatives, gradient, Taylor series
- **Basic probability theory:** measurable space, probability measure, random variable, expectation, conditional expectation, probability density function, cumulative density functions
- **Limit theorems:** law of large numbers, central limit theorem
- **Linear algebra:** vector space, matrix, norms, diagonalization of a matrix, singular value decomposition

If you feel like you are not up to date on one of these points, write me and I will point you towards some good books.

Useful resources

- **Main reference:** Shalev-Schwartz, Ben-David, *Understanding Machine Learning: from Theory to Algorithms*, Cambridge University Press, 2014
- **Also a good read:** Hastie, Tibshirani, Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer Series in Statistics, 2001 (second edition: 2009)
- **Wikipedia:** as good as ever.
- **Wolfram alpha:** if you have computations to make and you do not know want to use a proper language: `https://www.wolframalpha.com/`
- **Google scholar:** use it!

2. Introduction to Statistical Learning

2.1. General introduction

The goal of statistical learning

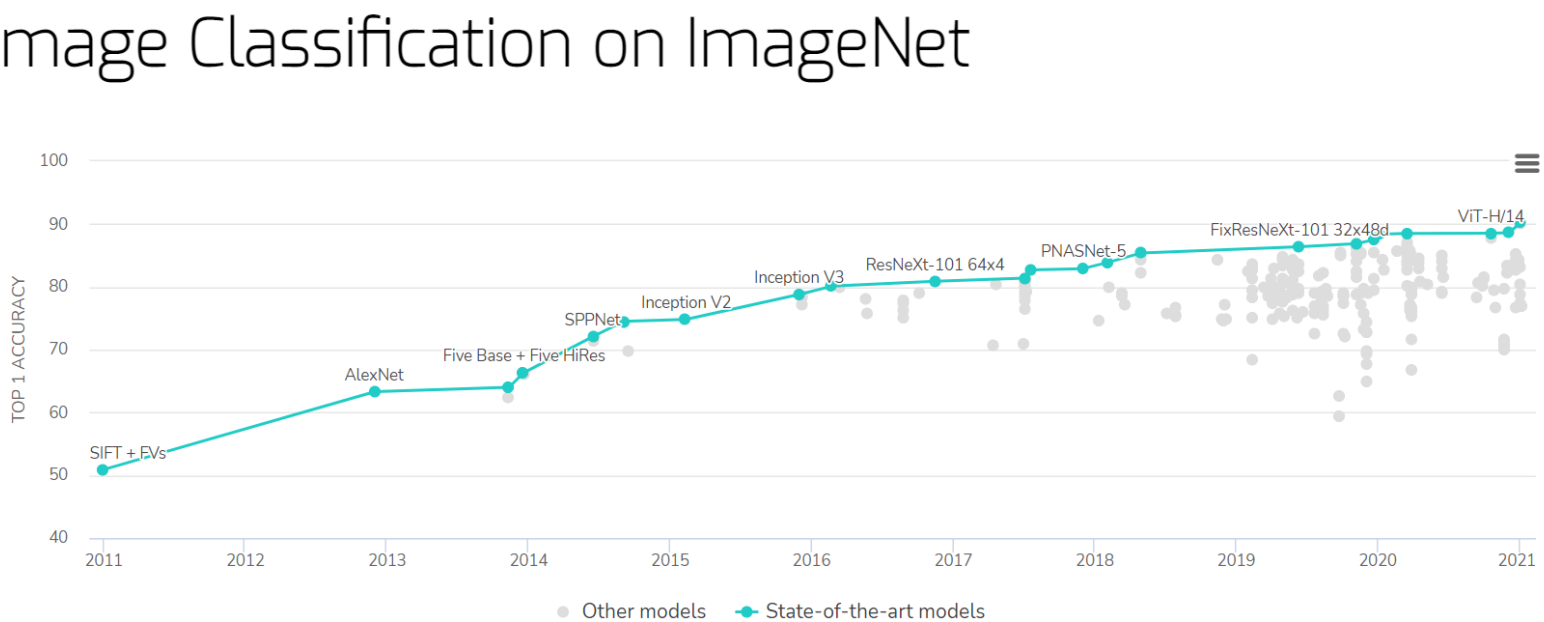
- **Fundamental example:** image classification
- **Goal:** given any image x, we want to predict which object / animal y is in the image

$\longmapsto$ "lion"

- **Main idea:** instead of defining the function f ourselves, we are going to *learn it* from data
- **Why?** no clear definition of a "lion"
- **Motivation:** industry (advertisement), healthcare (automated patient triage), military (automated defense systems)

How is this even possible?

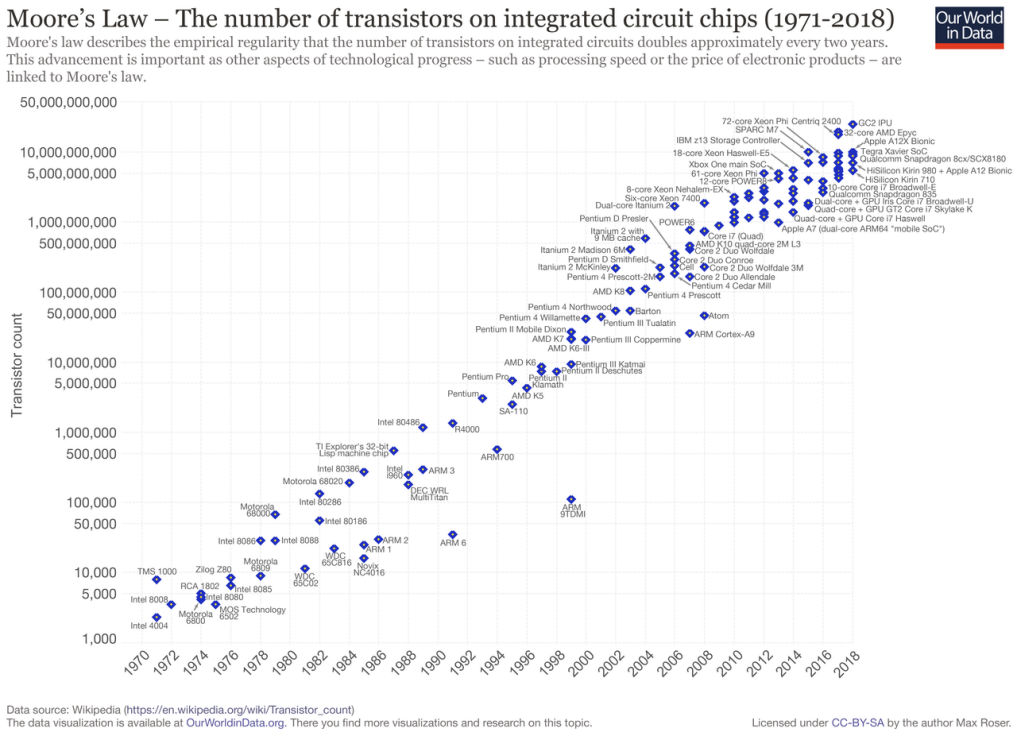
- four ingredients made statistical learning a viable paradigm:
- **Ingredient (i):** data to feed to the models
- previous example from ImageNet[1]: roughly 1 million images for training (150GB of data)



[1] Deng et al., *ImageNet: A large hierarchical image database*, CVPR, 2009

How is this even possible?

- **Ingredient (ii):** computing power
- we have the processing power to deal with these data

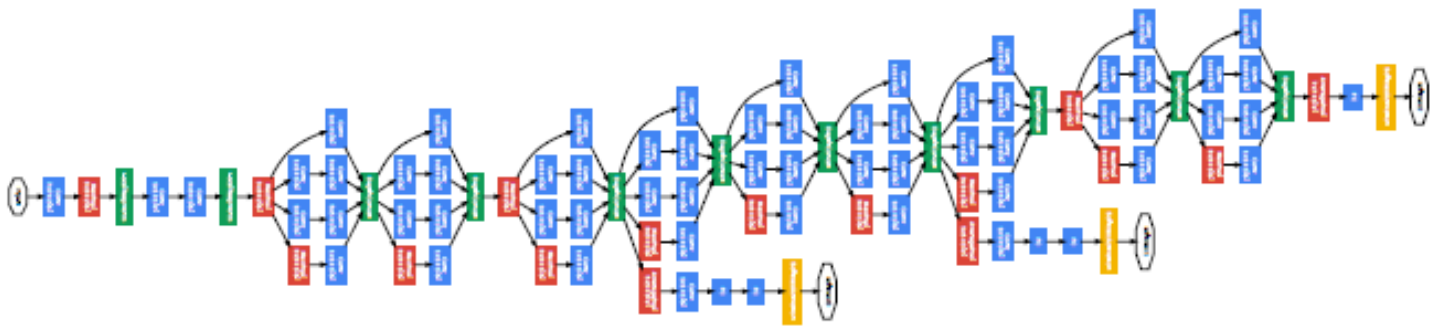


Data source: Wikipedia (https://en.wikipedia.org/wiki/Transistor_count)
The data visualization is available at OurWorldinData.org. There you find more visualizations and research on this topic.

Licensed under CC-BY-SA by the author Max Roser.

How is this even possible?

- **Ingredient (iii):** models that are complex enough
- sate-of-the-art today: (deep) neural networks (originating from much earlier research[2])
- Inception:[3] 24M parameters, GTP-3:[4] 175B



[2] Rosenblatt, *The perceptron, a perceiving and recognizing automaton*, tech report, 1957

[3] Szegedy et al., *Going deeper with convolutions*, CVPR, 2015

[4] Brown et al., *Language Models are Few-Shot Learners*, tech report, 2020

How is this even possible

SWITCH TRANSFORMERS: SCALING TO TRILLION PARAMETER MODELS WITH SIMPLE AND EFFICIENT SPARSITY

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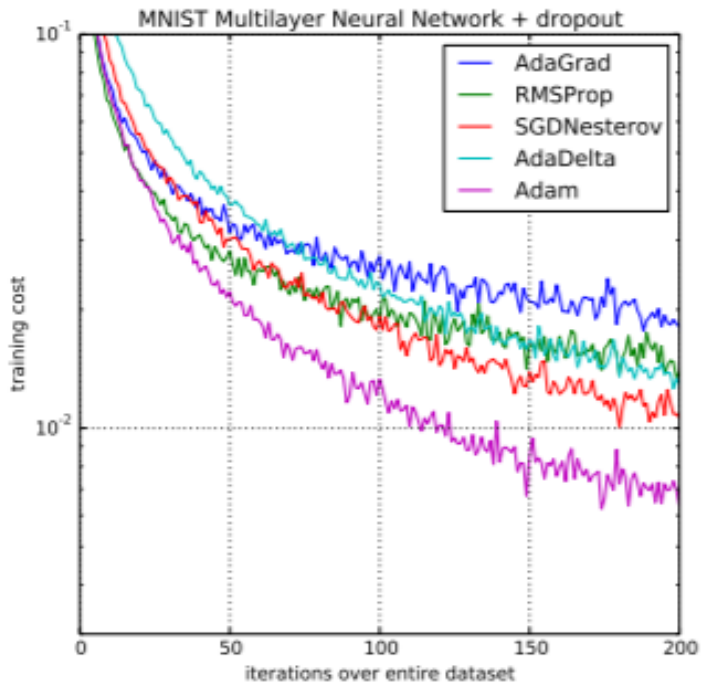
ABSTRACT

In deep learning, models typically reuse the same parameters for all inputs. Mixture of Experts (MoE) models defy this and instead select *different* parameters for each incoming example. The result is a sparsely-activated model – with an outrageous number of parameters – but a constant computational cost. However, despite several notable successes of MoE, widespread adoption has been hindered by complexity, communication costs, and training instability. We address these with the Switch Transformer. We simplify the MoE routing algorithm and design intuitive improved models with reduced communication and computational costs. Our proposed training techniques mitigate the instabilities, and we show large sparse models may be trained, for the first time, with lower precision (bfloat16) formats. We design models based off T5-Base and T5-Large (Raffel et al., 2019)

How is this even possible?

- **Ingredient (iv):** efficient algorithms to train the models
- gradient descent on steroids[5]
- efficient gradient computations[6]



[5] Kingma, Ba, *ADAM: A method for stochastic optimization*, ICLR, 2015

[6] Rumelhart et al., *Learning representations by back-propagating errors*, Nature, 1986

2.2. First concepts

Input space

- **Input space:** measurable space $\mathcal{X}$ containing all the objects that we want to label
- also called *domain*, or *domain set*
- elements $x \in \mathcal{X}$ are usually described as vectors
- coordinates of the vector $=$ *features*
- **Example:** ImageNet images: RGB images $\rightarrow$ 3 8-bits channels

$$\in [\![0, 255]\!]^{299 \times 299 \times 3}$$

- $\mathcal{X}$ can be very high-dimensional in modern applications (here $299 \times 299 \times 3 = 268,203$)

Labels and training data

- **Label set:** labels belong to a set $\mathcal{Y}$
- **Example:** $\mathcal{Y}$ is the set of names of object and animals of the dataset

```
{0: 'tench, Tinca tinca',
 1: 'goldfish, Carassius auratus',
 2: 'great white shark, white shark, man-eater, man-eating shark, Carcharodon carcharias',
 3: 'tiger shark, Galeocerdo cuvieri',
 4: 'hammerhead, hammerhead shark',
 5: 'electric ray, crampfish, numbfish, torpedo',
 6: 'stingray',
 7: 'cock',
 8: 'hen',
 9: 'ostrich, Struthio camelus',
```

- we restrict ourselves to $\mathcal{Y} = \{0, 1\}$ for the time being, but can be much larger in modern applications ($1,000$ for ImageNet)
- **Training data:** $S = ((x_1, y_1), \ldots, (x_n, y_n))$ *finite* sequence of points of $\mathcal{X} \times \mathcal{Y}$
- also called *training set*

Hypothesis class

- **Hypothesis:** $h : \mathcal{X} \to \mathcal{Y}$ a prediction rule. also called *predictor*, *classifier* (in the context of classification)
- we are looking for a good h
- **Hypothesis class:** $\mathcal{H}$ some space of functions. if no restrictions, set of all measurable functions
- **Example:** linear classifiers:

$$\mathcal{H} = \{h : \text{sign}(x) \mapsto w^\top x + b, w \in \mathbb{R}^d, b \in \mathbb{R}\},$$

  where $w^\top x$ denotes the scalar product between w and x
- given an algorithm A and a dataset S, we will write $h = A(S)$ the output of our algorithm on S

Data generation

- **Data generation:** for now, we assume that there is a true distribution $\mathcal{D}$ of the data on $\mathcal{X}$
- the training examples are i.i.d. samples from $\mathcal{D}$
- i.i.d.: *independent identically distributed*
- **Example:** sample images uniformly at random from a larger set (all the images on the internet)
- hard to satisfy: there is always a bias in the way your dataset is constructed

Assumption (noiseless setting): there exists a function $f : \mathcal{X} \to \mathcal{Y}$ such that $y = f(x)$ for any $x \in \mathcal{X}$.

- **Important:** we know neither $\mathcal{D}$ nor f! we only have access to S

Measure of success

- **Risk of a classifier:** probability that h does not return the correct label on a (new) random sample:

$$\mathcal{R}_{\mathcal{D},f}(h) = \mathbb{P}_{x\sim\mathcal{D}}\left(h(x) \neq f(x)\right) .$$

- **Intuition:** we want to be good, *on average*, for new samples of the same distribution
- subscript often omitted when clear from context
- also called *generalization error*, *true error* (notation L or $\mathcal{E}$)
- **Important:** we want to find h with small generalization error. Ideally,

$$\mathcal{R}_{\mathcal{D},f}(h) = 0 .$$

- **Question:** how to do this?

2.3. Empirical risk minimization

Empirical risk minimization

- as we have seen, what we would *like* to do is find

$$h \in \arg\min_{h \in \mathcal{H}} \mathcal{R}_{\mathcal{D},f}(h) = \arg\min_{h \in \mathcal{H}} \mathbb{P}_{x \sim \mathcal{D}} \left(h(x) \neq f(x) \right) .$$

- **Problem:** we know neither $\mathcal{D}$ nor f...
- ...and even if we did it would still be a very difficult problem (there are *a lot* of measurable functions!)
- **Idea:** replace $\mathcal{R}_{\mathcal{D},f}$ by an *empirical* version
- empirical risk (or training error):

$$\hat{\mathcal{R}}_S(h) = \frac{1}{n} \left| \{ i \in \{1, \ldots, n\} \text{ s.t. } h(x_i) \neq y_i \} \right| ,$$

  where $|E|$ denotes the cardinality of (finite) set E
- minimizing the empirical risk = empirical risk minimization[7] (ERM)

[7] Vapnik, *Principles of risk minimization for learning theory*, NIPS, 1992

Exercise

Exercise: set $h \in \mathcal{H}$. Let n be a fixed integer.

1. Show that
$$\mathbb{E}_S\left[\hat{\mathcal{R}}_S(h)\right] = \mathcal{R}_{\mathcal{D},f}(h)\,,$$
where the expectation is taken with respect to all i.i.d. draws of S.
2. Show that $\hat{\mathcal{R}}_S(h) \xrightarrow{\mathbb{P}} \mathcal{R}_{\mathcal{D},f}(h)$ when $n \to +\infty$.

Solution

1. First, we see that

$$|\{i \in \{1, \dots, n\} \text{ s.t. } h(x_i) \neq y_i\}| = \sum_{i=1}^{n} \mathbb{1}_{h(x_i) \neq y_i} .$$

Then we write

$$\begin{aligned}
\mathbb{E}\left[\hat{\mathcal{R}}_S(h)\right] &= \mathbb{E}\left[\frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{h(x_i) \neq y_i}\right] \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbb{E}\left[\mathbb{1}_{h(x_i) \neq y_i}\right] && \text{(linearity)} \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbb{P}\left(h(x_i) \neq y_i\right) && (\mathbb{E}\left[\mathbb{1}_A\right] = \mathbb{P}\left(A\right)) \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbb{P}\left(h(x_i) \neq f(x_i)\right) && \text{(noiseless assumption)}
\end{aligned}$$

Solution, ctd.

Further, since the x_i are i.i.d., for any $1 \leq i \leq n$,

$$\mathbb{P}\left(h(x_i) \neq f(x_i)\right) = \mathbb{P}\left(h(x) \neq f(x)\right) .$$

We recognize the definition of the true risk. Therefore,

$$\begin{aligned} \mathbb{E}\left[\hat{\mathcal{R}}_S(h)\right] &= \frac{1}{n}\sum_{i=1}^{n} \mathcal{R}_{\mathcal{D},f}(h) \\ &= \mathcal{R}_{\mathcal{D},f}(h) \qquad \text{(does not depend on } i\text{)} \end{aligned}$$

2. Since the x_i are i.i.d. random variables, so are the Z_i defined by

$$Z_i = \mathbb{1}_{h(x_i)\neq f(x_i)} .$$

Solution, ctd.

Moreover, the Z_is are bounded almost surely (by 1). In particular, they are integrable. There fore, we can use the law of large numbers and write

$$\frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{h(x_i)\neq y_i} \xrightarrow{\mathbb{P}} \mathbb{E}\left[\mathbb{1}_{h(x_1)\neq f(x_1)}\right] .$$

From question 1., we deduce that

$$\hat{\mathcal{R}}_S(h) \xrightarrow{\mathbb{P}} \mathcal{R}_{\mathcal{D},f}(h) .$$

□

Reminder: the law of large numbers

Theorem (Weak Law of Large Numbers = WLLN): Let $Z_1, Z_2, \ldots$ be a sequence of i.i.d. random variables. Assume that $\mathbb{E}[|Z_1|] < +\infty$ and set $\mu := \mathbb{E}[Z_1]$. Then

$$\frac{Z_1 + \cdots + Z_n}{n} \xrightarrow{\mathbb{P}} \mu\,.$$

- **Intuition:** average of measurements converges towards the true value
- stronger statement is true, *strong* law of large numbers, with almost sure convergence instead of in probability
- multivariate extension: coordinate-wise

Law of large numbers, in pictures

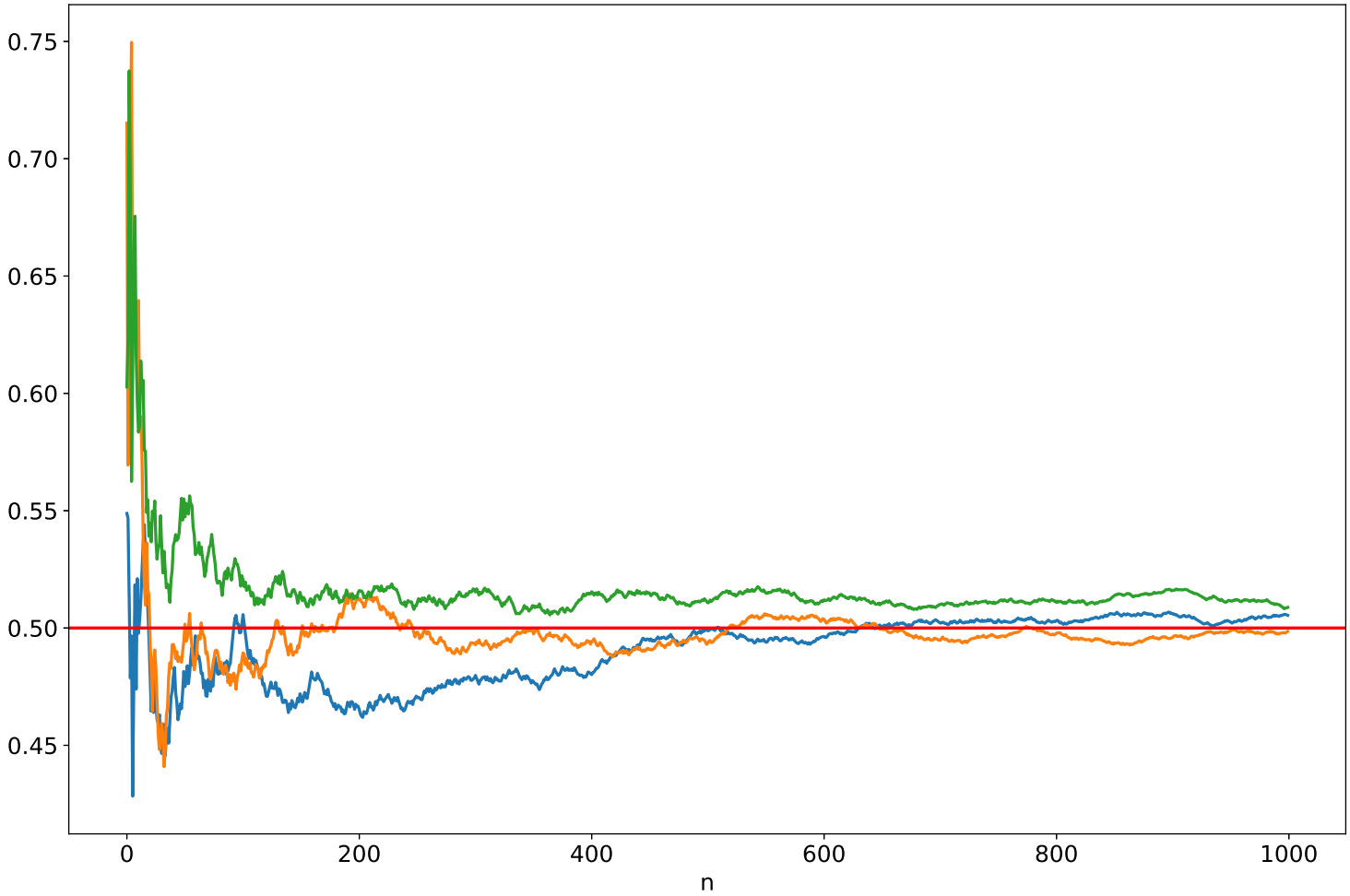


Figure: trajectories of the empirical mean for i.i.d. $\mathcal{B}(1/2)$

2.4. Overfitting

Overfitting

- **Problem:** is the hypotheses class $\mathcal{H}$ is too large, then we can bring the empirical risk to *zero*
- easy when $\mathcal{H}$ is the set of all measurable functions:

$$h(x) = \begin{cases} y_i & \text{if } \exists i \in \{1, \dots, n\} \text{ s.t. } x = x_i \\ 0 & \text{otherwise.} \end{cases}$$

- in particular,

$$\forall 1 \leq i \leq n, \quad h(x_i) = y_i \,.$$

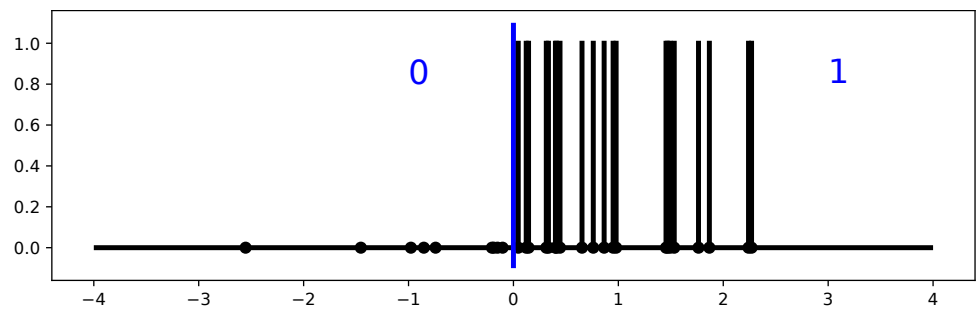
- in that case,

$$\hat{\mathcal{R}}_S(h) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}_{h(x_i) \neq y_i} = 0 \,.$$

- our predictor has *memorized* the examples, but cannot *generalize*

Overfitting: a simple example

- consider binary classification in $\mathcal{X} = \mathbb{R}$
- very simple problem: $f(x) = \mathbb{1}_{x>0}$ (examples have label 1 if they are positive, 0 otherwise)
- suppose that $\mathcal{D}$ is symmetric and has a density over $\mathbb{R}$ (for instance $\mathcal{D} = \mathcal{N}(0, 1)$)
- if $\mathcal{H}$ is the class of **all** functions $\mathcal{X} \to \{0, 1\}$, at training we will learn the following:



- since X has a density, $\mathbb{P}(X = x_i) = 0$: always predict 0
- thus the generalization error is equal to $1/2 \to$ not very good

One solution to overfitting

- one possible solution: **reduce the hypothesis class**
- in advance, choose a restricted $\mathcal{H}$ and solve

$$h \in \arg\min_{h \in \mathcal{H}} \hat{\mathcal{R}}_S(h)\,. \qquad (\star)$$

- by doing so, we *bias* the predictor
- **Example:** take $\mathcal{H}$ the class of linear predictor $\rightarrow$ much less functions
- but surely some problems are too complicated for linear classifiers!
- **One of the fundamental questions of statistical learning theory:** how to choose $\mathcal{H}$ for a given class of problems?
- **Notation:** we will write h_S the solution of $(\star)$

Finite hypothesis class

- as a starting point, let us investigate *finite* $\mathcal{H}$
- **Remark:** for a given class of algorithms, we are limited by our computer $\Rightarrow$ always finite in a sense
- let us analyze ERM for finite hypothesis classes

Assumption (realizability): there exists $h^\star \in \mathcal{H}$ such that

$$\mathcal{R}_{\mathcal{D},f}(h^\star) = 0\,.$$

- **Consequence:** in the noiseless setting, $\hat{\mathcal{R}}_S(h^\star) = 0$ with proba. 1 over the sampling of S and therefore $\hat{\mathcal{R}}_S(h_S) = 0$ (see next slide)
- but remember: we are interested in the *true* risk $\mathcal{R}_{\mathcal{D},f}(h_S)$

Consequence of realizability

- by assumption, there exists $h^\star \in \mathcal{H}$ such that $\mathcal{R}_{\mathcal{D},f}(h^\star) = 0$
- by definition of the risk,

$$\mathbb{P}\left(h^\star(x) \neq f(x)\right) = 0\,.$$

- that is, $h^\star(x) = f(x)$ almost surely when x is sampled according to $\mathcal{D}$
- in particular, since $x_1, \ldots, x_n$ is an i.i.d. sample from $\mathcal{D}$,

$$\forall 1 \leq i \leq n, \quad h^\star(x_i) = f(x_i)\,.$$

- we deduce that $\hat{\mathcal{R}}_S(h^\star) = 0$
- but remember: h_S **minimizes the empirical risk** over $\mathcal{H}$
- thus $\hat{\mathcal{R}}_S(h_S) \leq \hat{\mathcal{R}}_S(h^\star) = 0$

Randomness of the sample

- recall that S is an i.i.d. random sample from $\mathcal{D}$
- we could be unlucky!
- for instance, sample only images with a lion $\rightarrow$ this predictor will surely *fail* when presented with images of other animals
- $\Rightarrow$ in our analysis, we allow for a margin of error δ
- $1 - \delta =$ confidence parameter (you can imagine $\delta = 0.01$ if you want)
- **Typical statement:** Let $\delta \in (0, 1)$. With probability $1 - \delta$, it holds that h_S satisfies this property
- this means with probability $1 - \delta$ *on the sampling of* S
- sometimes abridged to "with high probability"

Probably Approximately Correct learning

- we can show our first result:

Proposition: Assume that $|\mathcal{H}|$ is finite. Let $\delta \in (0,1)$ and $\varepsilon \in (0,1)$, let n be an integer such that

$$n \geq \frac{\log\left(|\mathcal{H}|/\delta\right)}{\varepsilon}\,.$$

Then, in the **noiseless setting** for any labeling function f and any distribution $\mathcal{D}$ such that the **realizability** assumption holds, with probability at least $1-\delta$, it holds that

$$\mathcal{R}_{\mathcal{D},f}(h_S) \leq \varepsilon\,.$$

- *probably:* with probability $\geq 1-\delta$ over the sampling
- *approximately correct:* with tolerance ε on the test error

Proof of the proposition

- let us introduce the set of *bad hypotheses*

$$\mathcal{H}_B = \{h \in \mathcal{H} \text{ s.t. } \mathcal{R}_{\mathcal{D},f}(h) > \varepsilon\},$$

- and the set of *misleading examples*

$$M = \{S \text{ s.t. } \exists h \in \mathcal{H}_B, \hat{\mathcal{R}}_S(h) = 0\}.$$

- let S such that $\mathcal{R}_{\mathcal{D},f}(h_S) > \varepsilon$
- by definition, $h_S \in \mathcal{H}_B$
- by the realizability assumption, $\hat{\mathcal{R}}_S(h_S) = 0$
- we deduce that $S \in M$: we have showed that

$$\boxed{\{S \text{ s.t. } \mathcal{R}_{\mathcal{D},f}(h_S) > \varepsilon\} \subseteq M.}$$

- thus

$$\mathbb{P}\left(\mathcal{R}_{\mathcal{D},f}(h_S) > \varepsilon\right) \leq \mathbb{P}\left(\exists h \in \mathcal{H}_B, \hat{\mathcal{R}}_S(h) = 0\right).$$

Proof of the proposition, ctd.

- now we upper bound the right-hand side by the *union bound*:

$$\mathbb{P}\left(\exists h \in \mathcal{H}_B, \hat{\mathcal{R}}_S(h) = 0\right) \leq \sum_{h \in \mathcal{H}_B} \mathbb{P}\left(\hat{\mathcal{R}}_S(h) = 0\right) .$$

- **Reminder:** let A and B be two events, then

$$\mathbb{P}(A \cup B) \leq \mathbb{P}(A) + \mathbb{P}(B) .$$

- with our definition of the empirical risk,

$$\hat{\mathcal{R}}_S(h) = 0 \quad \Leftrightarrow \quad \forall 1 \leq i \leq n, \quad h(x_i) = y_i .$$

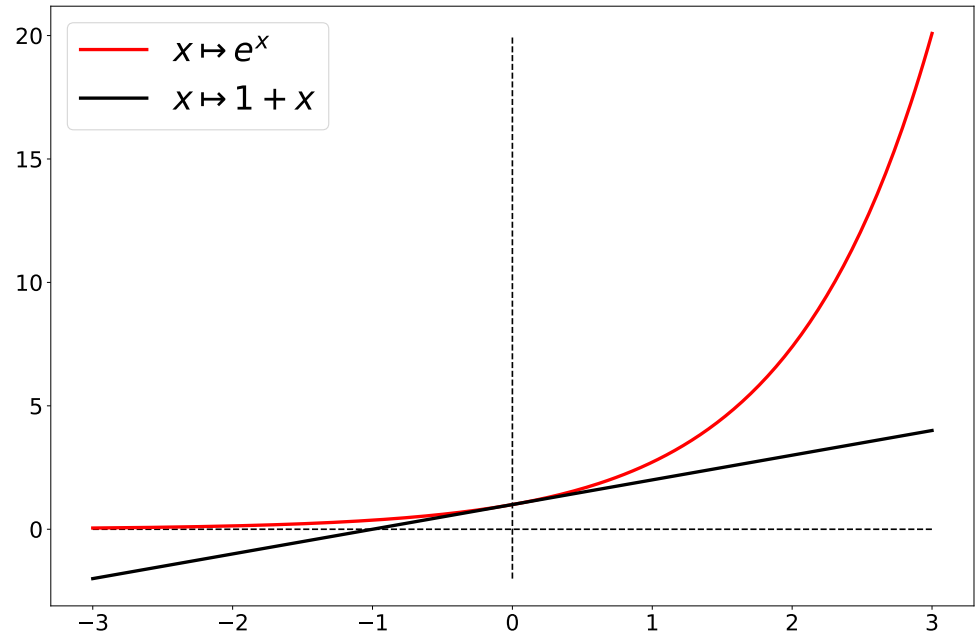
- since the sample is i.i.d. and $h \in \mathcal{H}_B$,

$$\begin{aligned} \mathbb{P}(h(x_1) = y_1, \ldots, h(x_n) = y_n) &= \mathbb{P}(h(x) = y)^n \\ &= (1 - \mathcal{R}_{\mathcal{D},f}(h))^n \\ &\leq (1 - \varepsilon)^n . \end{aligned}$$

Proof of the proposition, ctd.

- we notice that $\forall x \in \mathbb{R}$,

$$\mathrm{e}^x \geq 1 + x\,.$$



- thus $1 - \varepsilon \leq \mathrm{e}^{-\varepsilon}$
- we deduce that

$$(1 - \varepsilon)^n \leq \mathrm{e}^{-n\varepsilon}\,.$$

Proof of the proposition, ctd.

- let us put everything together:

$$\begin{aligned}
\mathbb{P}\left(\mathcal{R}_{\mathcal{D},f}(h_S) > \varepsilon\right) &\leq \mathbb{P}\left(\exists h \in \mathcal{H}_B, \hat{\mathcal{R}}_S(h) = 0\right) \\
&\qquad\qquad \text{(first part of the proof)} \\
&\leq |\mathcal{H}_B| \, (1-\varepsilon)^n \qquad\qquad \text{(union bound)} \\
&\leq |\mathcal{H}_B| \, \mathrm{e}^{-n\varepsilon} \qquad\qquad \text{(exponential bound)} \\
&\leq |\mathcal{H}| \, \mathrm{e}^{-n\varepsilon} \qquad\qquad (\mathcal{H}_B \subseteq \mathcal{H}) \\
&\leq |\mathcal{H}| \exp\left(-\varepsilon \cdot \frac{\log\left(|\mathcal{H}|/\delta\right)}{\varepsilon}\right) \qquad \text{(hyp. on } n\text{)} \\
\mathbb{P}\left(\mathcal{R}_{\mathcal{D},f}(h_S) > \varepsilon\right) &\leq \delta \,. \quad \square
\end{aligned}$$

2.5. PAC learning

PAC learning

- first definition:

Definition (PAC learnability): A hypothesis class $\mathcal{H}$ is *PAC learnable* if there exists a function $m_{\mathcal{H}} : (0,1)^2 \to \mathbb{N}$ and a learning algorithm A such that for every $\varepsilon, \delta \in (0,1)^2$, for every labeling function f and any distribution $\mathcal{D}$ such that the **realizability assumption** holds, then, if $h = A(S)$ with S a dataset containing more than $m_{\mathcal{H}}(\varepsilon, \delta)$ samples,

$$\mathbb{P}\left(\mathcal{R}_{\mathcal{D},f}(h) > \varepsilon\right) \leq \delta\,.$$

- $m_{\mathcal{H}}$ is called the *sample complexity* of learning $\mathcal{H}$
- many $m_{\mathcal{H}}$, we take the minimal one

A corollary

- we have already showed the following:

Corollary: Every finite hypothesis class is PAC learnable with sample complexity

$$m_{\mathcal{H}}(\varepsilon, \delta) \leq \left\lceil \frac{\log\left(|\mathcal{H}|/\delta\right)}{\varepsilon} \right\rceil .$$

- **Spoiler alert:** infinite class are also PAC learnable, but we need to define VC dimension
- first let us **generalize** our definition of PAC learning

Removing assumptions

- **Realizibility:** too restrictive!
- maybe there are no functions in our class mapping exactly examples to the label
- **Example:** consider $\mathcal{H}$ the set of functions defined by $h(x) = \mathbb{1}_{x \in A}$ where A are rectangles
- maybe examples labeled 1 are not contained in a rectangle
- $\Rightarrow$ *agnostic* PAC learning
- further, we now consider $\mathcal{D}$ a distribution on $\mathcal{X} \times \mathcal{Y}$, not only $\mathcal{X}$
- for a fixed x, y is now a random variable with distribution $\mathcal{D}_x$, there is no more f
- the definition of the risk is slightly modified:

$$\mathcal{R}_{\mathcal{D}}(h) = \mathbb{P}_{(x,y)\sim\mathcal{D}}\left(h(x) \neq y\right) .$$

Agnostic PAC learning

- our goal remains the same: find $h \in \mathcal{H}$ that minimizes $\mathcal{R}_{\mathcal{D}}(h)$
- we generalize slightly the definition:

Definition (agnostic PAC learnable): A hypothesis class $\mathcal{H}$ is *agnostic PAC learnable* if there exists a function $m_{\mathcal{H}} : (0,1)^2 \to \mathbb{N}$ and a learning algorithm A with the following properties: for every $\varepsilon, \delta \in (0,1)$, and for every distribution $\mathcal{D}$ over $\mathcal{X} \times \mathcal{Y}$, when running the algorithm on $n \geq m_{\mathcal{H}}(\varepsilon, \delta)$ examples i.i.d. generated from $\mathcal{D}$, $h = A(S)$ satisfies

$$\mathcal{R}_{\mathcal{D}}(h) \leq \min_{h' \in \mathcal{H}} \mathcal{R}_{\mathcal{D}}(h') + \varepsilon \,,$$

with probability $\geq 1 - \delta$.

Exercise

Exercise: Set $g(x) = \mathbb{P}(Y = 1 \,|\, X = x)$. We define the *Bayes optimal predictor* as

$$f_{\mathcal{D}}(x) = \begin{cases} 1 & \text{if } g(x) \geq 1/2 \\ 0 & \text{otherwise.} \end{cases}$$

1. let $h : \mathcal{X} \to \{0, 1\}$ be a classifier. Show that

$$\mathbb{P}(h(X) \neq Y \,|\, X = x) = g(x) \cdot \mathbb{P}(h(X) = 0 \,|\, X = x) + (1 - g(x)) \cdot \mathbb{P}(h(X) = 1 \,|\, X = x) \,.$$

2. deduce that

$$\mathbb{P}(f_{\mathcal{D}}(X) \neq Y \,|\, X = x) = \min(g(x), 1 - g(x)) \,.$$

3. show that

$$\mathbb{P}(h(X) \neq Y \,|\, X = x) \geq \mathbb{P}(f_{\mathcal{D}}(X) \neq Y \,|\, X = x) \,.$$

4. deduce that $f_{\mathcal{D}}$ is risk optimal, that is, for any predictor h,

$$\mathcal{R}_{\mathcal{D}}(f_{\mathcal{D}}) \leq \mathcal{R}_{\mathcal{D}}(h) \,.$$

Correction of the exercise

1. there are two mutually exclusive possibility for misclassifiction: either $h(X) = 0$ and $Y = 1$, or $h(X) = 1$ and $Y = 0$. Thus

$$\begin{aligned}
\mathbb{P}(h(X) \neq Y \,|\, X = x) &= \mathbb{P}(h(X) = 0 \text{ and } Y = 1 \,|\, X = x) \\
&\quad + \mathbb{P}(h(X) = 1 \text{ and } Y = 0 \,|\, X = x) \\
&= \mathbb{P}(h(X) = 0 \,|\, X = x) \cdot \mathbb{P}(Y = 1 \,|\, X = x) \\
&\quad + \mathbb{P}(h(X) = 1 \,|\, X = x) \cdot \mathbb{P}(Y = 0 \,|\, X = x) \\
&= \mathbb{P}(h(X) = 0 \,|\, X = x) \cdot g(x) \\
&\quad + \mathbb{P}(h(X) = 1 \,|\, X = x) \cdot (1 - g(x))
\end{aligned}$$

by definition of g. **Remark:** we keep the proba formulation since h maybe non-deterministic.

Correction of the exercise, ctd.

2. we specialize the result of the previous question to $h = f_{\mathcal{D}}$. We obtain:

$$\begin{aligned}\mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y \,|\, X = x\right) = g(x) \cdot \mathbb{P}\left(f_{\mathcal{D}}(X) = 0 \,|\, X = x\right) \\ + \left(1 - g(x)\right) \cdot \mathbb{P}\left(f_{\mathcal{D}}(X) = 1 \,|\, X = x\right) .\end{aligned}$$

By definition of $f_{\mathcal{D}}$, $\mathbb{P}\left(f_{\mathcal{D}}(X) = 0 \,|\, X = x\right)$ is a *deterministic* quantity depending only on $g(x)$. We find that

$$\begin{aligned}\mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y \,|\, X = x\right) &= g(x) \cdot \mathbb{1}_{g(x)<1/2} + \left(1 - g(x)\right) \cdot \mathbb{1}_{g(x)\geq 1/2} \\ &= \min(g(x), 1 - g(x)) ,\end{aligned}$$

where the last step is obtained after careful inspection of the two possible cases.

Correction of the exercise, ctd.

3. Starting from question 1., we know that

$$\begin{aligned}\mathbb{P}\left(h(X) \neq Y \,|\, X = x\right) &= \mathbb{P}\left(h(X) = 0 \,|\, X = x\right) \cdot g(x) \\ &\quad + \mathbb{P}\left(h(X) = 1 \,|\, X = x\right) \cdot (1 - g(x)) \\ &\geq \min(g(x), 1 - g(x)) \cdot \mathbb{P}\left(h(X) = 0 \,|\, X = x\right) \\ &\quad \min(g(x), 1 - g(x)) \cdot \mathbb{P}\left(h(X) = 1 \,|\, X = x\right) \\ &= \min(g(x), 1 - g(x)) \,,\end{aligned}$$

since $h(X) = 0$ and $h(X) = 1$ are mutually exclusive. According to question 2.,

$$\min(g(x), 1 - g(x)) = \mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y \,|\, X = x\right) \,,$$

and we deduce that

$$\mathbb{P}\left(h(X) \neq Y \,|\, X = x\right) \geq \mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y \,|\, X = x\right) \,.$$

Correction of the exercise, ctd.

4. Let $h \in \mathcal{H}$. We write

$$
\begin{aligned}
\mathcal{R}_{\mathcal{D}}(f_{\mathcal{D}}) &= \mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y\right) && \text{(definition)} \\
&= \mathbb{E}_{X,Y}\left[\mathbb{1}_{f_{\mathcal{D}}(X)\neq Y}\right] && \left(\mathbb{E}\left[\mathbb{1}_A\right] = \mathbb{P}(A)\right) \\
&= \mathbb{E}_{x\sim X}\left[\mathbb{E}\left[\mathbb{1}_{f_{\mathcal{D}}(X)\neq Y} \mid X = x\right]\right] && \text{(law of total expectation)} \\
&= \mathbb{E}_{x\sim X}[\mathbb{P}\left(f_{\mathcal{D}}(X) \neq Y \mid X = x\right)] \\
&\leq \mathbb{E}_{x\sim X}[\mathbb{P}\left(h(X) \neq Y \mid X = x\right)] && \text{(question 3.)} \\
&= \mathbb{P}\left(h(X) \neq Y\right) \\
&= \mathcal{R}_{\mathcal{D}}(h)\,. \quad \square
\end{aligned}
$$

Beyond binary classification

- **Multiclass classification:** $\mathcal{Y}$ is some (potentially large) finite set
- we have already encountered such examples ImageNet (1000 classes)
- **Important:** classes are not numbers: being in class 2 instead of 1 is equally bad as 53 instead of 1
- **Regression:** $\mathcal{Y} \subseteq \mathbb{R}^k$, we say *target set* instead of labels
- other notion of success:

$$\mathcal{R}_{\mathcal{D}}(h) = \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[(h(x) - y)^2\right] ,$$

  for instance
- **Other examples:** structured prediction, functional regression, etc.

Generalized loss functions

- to accommodate for these various settings, we consider arbitrary **loss functions** $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}_+$
- **Intuition:** $\ell(y, y') \approx 0$ means that y and y' are close
- we generalize the notions of risk and empirical risk:

$$\mathcal{R}_{\mathcal{D}}(h) = \mathbb{E}_{(x,y)\sim\mathcal{D}}[\ell(y, h(x))] \quad \text{and} \quad \hat{\mathcal{R}}_S(h) = \frac{1}{n}\sum_{i=1}^{n} \ell(y_i, h(x_i))\,.$$

- **Example (i):** $0-1$ loss:

$$\ell(y, y') = \begin{cases} 0 & \text{if } y = y' \\ 1 & \text{otherwise.} \end{cases}$$

- this is the loss we used for binary classification

Generalized loss functions, ctd.

- **Example (ii):** hinge loss:

$$\ell(y, y') = \max(0, 1 - yy') \,.$$

- **Example (iii):** square loss:

$$\ell(y, y') = (y - y')^2 \,.$$

  used for regression.

- **Example (iv):** ℓ_1 loss:

$$\ell(y, y') = |y - y'| \,.$$

  also used for regression.

- we will see more of them, generally symmetric and increasing at infinity

PAC learnability

- we can now give the general definition of PAC learnability:

Definition (PAC learnability): A hypothesis class $\mathcal{H}$ is *agnostic PAC learnable* for the loss ℓ if there exists a function $m_{\mathcal{H}} : (0,1)^2 \to \mathbb{N}$ and a learning algorithm A with the following properties: for every $\varepsilon, \delta \in (0,1)$, and for every distribution $\mathcal{D}$ over $\mathcal{X} \times \mathcal{Y}$, when running the algorithm on $n \geq m_{\mathcal{H}}(\varepsilon, \delta)$ examples i.i.d. generated from $\mathcal{D}$, $h = A(S)$ satisfies

$$\mathcal{R}_{\mathcal{D}}(h) \leq \min_{h' \in \mathcal{H}} \mathcal{R}_{\mathcal{D}}(h') + \varepsilon \,,$$

with probability $\geq 1 - \delta$.

- **Intuition:** running the algorithm on a sufficient number of examples gives a good predictor most of the time, *for any data distribution*

Example: least-square regression

- consider data $(x_i, y_i) \in \mathbb{R}^d \times \mathbb{R}$
- *regression* problem
- let us restrict ourselves to *linear* hypotheses:

$$\mathcal{H} = \{h : x \mapsto w^\top x + b, w \in \mathbb{R}^d, b \in \mathbb{R}\} .$$

- **Remark:** $w^\top x$ is the scalar product between w and x:

$$w^\top x = \sum_{j=1}^{d} w_j x_j .$$

- **Appropriate loss?** $\ell(y, y') = (y - y')^2$
- **ERM** $\Rightarrow$

$$(\hat{w}, \widehat{b}) \in \operatorname*{arg\,min}_{w,b \in \mathbb{R}^d, \mathbb{R}} \sum_{i=1}^{n} (y_i - w^\top x_i - b)^2 ,$$

ordinary least squares

Example: ridge regression

- we may want to **keep only solutions that have a small ℓ_2 norm**
- we can, for instance, restrict $\mathcal{H}$ even further
- take $\lambda > 0$ and set

$$\mathcal{H}_\lambda = \{h \text{ linear s.t. } \|h\| \leq \lambda\}\,.$$

- ridge regression solves

$$(\hat{w}, \widehat{b}) \in \underset{\substack{w,b\in\mathbb{R}^d,\mathbb{R} \\ \|w\|\leq\lambda}}{\arg\min} \sum_{i=1}^{n} (y_i - w^\top x_i - b)^2\,.$$

- equivalent to *regularization*:

$$(\hat{w}, \widehat{b}) \in \underset{w,b\in\mathbb{R}^d,\mathbb{R}}{\arg\min} \left\{ \sum_{i=1}^{n} (y_i - w^\top x_i - b)^2 + \lambda \|w\|^2 \right\}.$$

Example: LASSO

- maybe we want **a lot of coordinates to be zero**
- then ℓ_1 norm is appropriate
- take $\lambda > 0$ and set

$$\mathcal{H}_\lambda = \{h \text{ linear s.t. } \|h\|_1 \leq \lambda\}.$$

- the LASSO solves

$$(\hat{w}, \widehat{b}) \in \underset{\substack{w,b \in \mathbb{R}^d, \mathbb{R} \\ \|w\|_1 \leq \lambda}}{\arg\min} \sum_{i=1}^{n} (y_i - w^\top x_i - b)^2 .$$

- equivalent to the regularized version:

$$(\hat{w}, \widehat{b}) \in \underset{w,b \in \mathbb{R}^d, \mathbb{R}}{\arg\min} \left\{ \sum_{i=1}^{n} (y_i - w^\top x_i - b)^2 + \lambda \|w\|_1 \right\} .$$

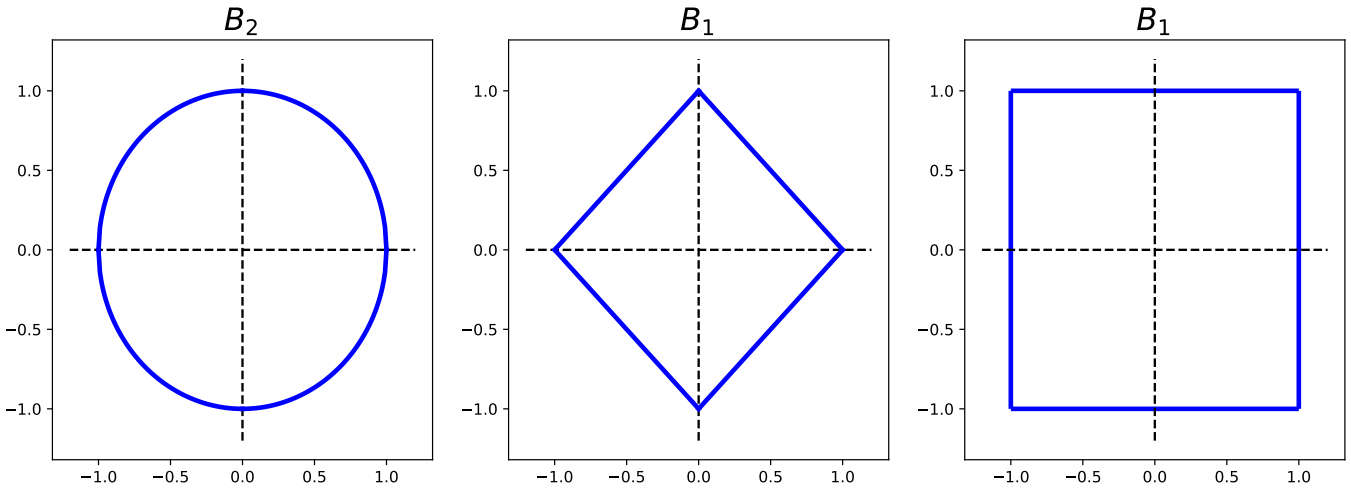
Reminder on norms

Definition: for any $p > 0$, we define the p-norm on $\mathbb{R}^d$ by

$$\forall u \in \mathbb{R}^d, \qquad \|u\|_p := \sqrt[p]{\sum_{j=1}^{d} |u_j|^p}\,.$$

When $p = +\infty$, we set $\|u\|_\infty := \max_k(|u_k|)$.

- most commonly used: 2-norm = Euclidean norm (Pythagoras)



2.6. Uniform convergence

Representative samples

- key idea in the proof of PAC learnability: large number of samples $\Rightarrow \hat{\mathcal{R}}_S$ is close from $\mathcal{R}_\mathcal{D} \Rightarrow$ minimizing either one is equivalent
- let us formalize this intuition:

Definition: A training set S is called ε-*representative* if

$$\forall h \in \mathcal{H}, \quad \left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_\mathcal{D}(h)\right| \leq \varepsilon \,.$$

- this is a very constraining property! must be true for all members of $\mathcal{H}$
- **Intuition:** if a sample if ε-representative, then ERM returns a good hypothesis

Representative samples, ctd.

- in fact, we have the following:

Lemma: Assume that the training set S is $\varepsilon/2$-representative. Then any ERM estimator given by $h_S \in \arg\min_{h\in\mathcal{H}} \hat{\mathcal{R}}_S(h)$ satisfies

$$\mathcal{R}_{\mathcal{D}}(h_S) \leq \min_{h\in\mathcal{H}} \mathcal{R}_{\mathcal{D}}(h) + \varepsilon\,.$$

- **Consequence:** to ensure that the ERM rule is agnostic PAC learnable, we only have to prove that the samples are representative with high probability

Proof of the lemma

- since S is $\varepsilon/2$-representative,

$$\mathcal{R}_{\mathcal{D}}(h_S) \leq \hat{\mathcal{R}}_S(h_S) + \varepsilon/2\,.$$

- since h_S is the ERM, for any $h \in \mathcal{H}$,

$$\hat{\mathcal{R}}_S(h_S) \leq \hat{\mathcal{R}}_S(h)\,.$$

- again, since S is $\varepsilon/2$-representative,

$$\hat{\mathcal{R}}_S(h) \leq \mathcal{R}_{\mathcal{D}}(h) + \varepsilon/2\,.$$

- putting everything together, we obtain:

$$\begin{aligned}\mathcal{R}_{\mathcal{D}}(h_S) &\leq \hat{\mathcal{R}}_S(h_S) + \varepsilon/2\\ &\leq \hat{\mathcal{R}}_S(h) + \varepsilon/2\\ &\leq \mathcal{R}_{\mathcal{D}}(h) + \varepsilon/2 + \varepsilon/2 \quad \square\end{aligned}$$

Uniform convergence property

- let us formalize the previous intuition:

Definition (uniform convergence): we say that $\mathcal{H}$ has the *uniform convergence property* if there exists $m_{\mathcal{H}}^{\mathsf{UC}} : (0,1)^2 \to \mathbb{N}$ such that for every ε, δ and for any $\mathcal{D}$, if S is a sample of size $\geq m_{\mathcal{H}}^{\mathsf{UC}}(\varepsilon, \delta)$, S is ε-representative with proba $\geq 1 - \delta$.

- **Why "uniform"?** *all* the hypotheses and *all* probability distributions

Corollary: if $\mathcal{H}$ has the uniform convergence property then it is agnostic PAC learnable with sample complexity

$$m_{\mathcal{H}}(\varepsilon, \delta) \leq m_{\mathcal{H}}^{\mathsf{UC}}(\varepsilon/2, \delta)\,.$$

In that case, ERM is an agnostic PAC learner for this class.

Back to finite classes

- let us use this formalism for $\mathcal{H}$ finite but arbitrary loss function and distribution on $\mathcal{X} \times \mathcal{Y}$
- let us fix ε, δ
- we need to find a sample size n such that for any $\mathcal{D}$ on $\mathcal{X} \times \mathcal{Y}$, we have

$$\mathbb{P}\left(\forall h \in \mathcal{H}, \left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| \leq \varepsilon\right) \geq 1 - \delta\,.$$

- equivalent statement:

$$\mathbb{P}\left(\exists h \in \mathcal{H}, \left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| > \varepsilon\right) < \delta\,.$$

- by the **union bound**, we just have to control

$$\mathbb{P}\left(\left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| > \varepsilon\right)$$

  for a fixed $h \in \mathcal{H}$
- we loose a factor $|\mathcal{H}|$

Concentration inequalities

- recall that

$$\hat{\mathcal{R}}_S(h) = \frac{1}{n}\sum_{i=1}^{n} \ell(y_i, h(x_i)) \quad \text{and} \quad \mathcal{R}_{\mathcal{D}}(h) = \mathbb{E}_{(x,y)\sim\mathcal{D}}[\ell(y, h(x))] \ .$$

- in particular, $\mathbb{E}\left[\hat{\mathcal{R}}_S(h)\right] = \mathcal{R}_{\mathcal{D}}(h)$
- we want to control the deviation of a random variable around its expectation
- we want to do this for fixed n: LLN is not enough (asymptotic result)
- **Basic inequality:** Chebyshev

$$\mathbb{P}\left(|Z - \mathbb{E}[Z]| > \varepsilon\right) \leq \frac{\mathrm{Var}\,(Z)}{\varepsilon^2} \ .$$

Exercise

Exercise: Let Z be a random variable with a second moment such that $\mathbb{E}[Z] = \mu$ and $\mathrm{Var}(Z) = \sigma^2$.

1. define $g : t \mapsto \mathbb{E}\left[(Z-t)^2\right]$. Show that g is minimum at $t = \mu$.
2. Suppose additionally that $Z \in [a, b]$ a.s. Use the previous question to show that $\mathrm{Var}(Z) \leq (b-a)^2/4$ (*Popoviciu's inequality*).
3. Let $Z_1, \ldots, Z_n$ be i.i.d. Z. Use Chebyshev inequality to obtain a concentration inequality for

$$Z := \frac{1}{n}\sum_{i=1}^{n} Z_i \,.$$

4. Show that

$$\mathbb{P}\left(\left|\frac{1}{n}\sum_{i=1}^{n} Z_i - \mu\right| > \varepsilon\right) \leq \frac{(b-a)^2}{4n\varepsilon^2} \,.$$

Correction of the exercise

1. Let $t \in \mathbb{R}$, we decompose $g(t)$ as

$$\begin{aligned} g(t) &= \mathbb{E}\left[(Z-t)^2\right] && \text{(definition)} \\ &= \mathbb{E}\left[(Z-\mu+\mu-t)^2\right] \\ &= \mathbb{E}\left[(Z-\mu)^2\right] + 2(\mu-t)\mathbb{E}\left[Z-\mu\right] + (\mu-t)^2 g(t) && = g(\mu) + (\mu-t)^2 . \end{aligned}$$

Since $(\mu-t)^2 \geq 0$, we deduce that $g(t) \geq g(\mu)$ for any $t \in \mathbb{R}$.
Remark: it is also possible to differentiate g with respect to t, solve $g'(t) = 0$ and check that $g''(\mu) > 0$.
2. We know that $g(\mu) = \mathrm{Var}\,(Z)$ is upper bounded by $g(t)$ for any t.
The idea is to take $t = (a+b)/2$:

$$\begin{aligned} g\left(\frac{a+b}{2}\right) &= \mathbb{E}\left[\left(Z - \frac{a+b}{2}\right)^2\right] \\ &= \frac{1}{4}\mathbb{E}\left[(Z-a+Z-b)^2\right] . \end{aligned}$$

Correction of the exercise, ctd.

Since $Z \in [a, b]$, we deduce that $|(Z - a + Z - b)| \leq b - a$. We have obtained:

$$\mathrm{Var}\,(Z) \leq \frac{(b-a)^2}{4}\,.$$

Remark: noticing that $Z \in [a, b]$ implies $\mu \in [a, b]$, we can see that $|Z - \mu| \leq b - a$ and deduce that

$$\mathrm{Var}\,(Z) \leq (b-a)^2\,,$$

which is a weaker result.

3. To apply Chebyshev, we only need to compute the variance of Z. We write

$$\begin{aligned}\mathrm{Var}\,(Z) &= \mathrm{Var}\left(\frac{1}{n}\sum_{i=1}^{n} Z_i\right)\\ &= \frac{1}{n^2}\sum_{i=1}^{n}\mathrm{Var}\,(Z_i)\end{aligned}$$

since the Z_i are independent.

Correction of the exercise

We deduce that $\mathrm{Var}(Z) = \frac{\sigma^2}{n}$, and therefore

$$\mathbb{P}\left(\left|\frac{1}{n}\sum_{i=1}^{n} Z_i - \mu\right| > \varepsilon\right) \leq \frac{\sigma^2}{n\varepsilon^2}\,.$$

4. Using the bound obtained in question 2. with the concentration given by question 3., we find that

$$\mathbb{P}\left(\left|\frac{1}{n}\sum_{i=1}^{n} Z_i - \mu\right| > \varepsilon\right) \leq \frac{(b_a)^2}{4n\varepsilon^2}\,.$$

Hoeffding's inequality

- we are going to use a better inequality, using the fact that $\hat{\mathcal{R}}_S(h)$ is a sum of i.i.d. random variables

Lemma (Hoeffding's inequality[8]): Let $Z_1, \ldots, Z_n$ be a sequence of i.i.d. random variables such that $Z_1 \in (a, b)$ almost surely and $\mathbb{E}[Z_1] = \mu$. Then, for any $\varepsilon > 0$,

$$\mathbb{P}\left(\left|\frac{1}{n}\sum_{i=1}^{n} Z_i - \mu\right| > \varepsilon\right) \leq 2 \cdot \exp\left(\frac{-2n\varepsilon^2}{(b-a)^2}\right) .$$

Question: why is this better than Chebyshev?

[8] Boucheron, Lugosi, Massart, *Concentration inequalities: a non-asymptotic theory of independence*, Oxford University Press, 2013

Application of Hoeffding's inequality

- let us go back to our problem
- we assume $\ell(y, y') \in (0, 1)$ almost surely
- then we obtain

$$\mathbb{P}\left(\left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| > \varepsilon\right) \leq 2 \cdot \exp\left(-2n\varepsilon^2\right) .$$

- we deduce that

$$\mathbb{P}\left(\exists h \in \mathcal{H}, \left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| > \varepsilon\right) \leq 2\,|\mathcal{H}| \exp\left(-2n\varepsilon^2\right) .$$

- hence choosing

$$n \geq \frac{\log(2\,|\mathcal{H}|\,/\delta)}{2\varepsilon^2}$$

ensures that

$$\mathbb{P}\left(\exists h \in \mathcal{H}, \left|\hat{\mathcal{R}}_S(h) - \mathcal{R}_{\mathcal{D}}(h)\right| > \varepsilon\right) \leq \delta .$$

Finite hypothesis class are PAC learnable

- we can state the main result of this section:

Corollary: Let $\mathcal{H}$ be a finite hypothesis class. Let $\ell : \mathcal{Y} \times \mathcal{Y} \to [0, 1]$ be a loss function. Then $\mathcal{H}$ enjoys the uniform convergence property with sample complexity function

$$m_{\mathcal{H}}^{\mathrm{UC}}(\varepsilon, \delta) \leq \left\lceil \frac{\log(2\left|\mathcal{H}\right|/\delta)}{2\varepsilon^2} \right\rceil .$$

Furthermore, the class is agnostic PAC learnable using the ERM with sample complexity

$$m_{\mathcal{H}}(\varepsilon, \delta) \leq m_{\mathcal{H}}^{\mathrm{UC}}(\varepsilon/2, \delta) \leq \left\lceil 2\frac{\log(2\left|\mathcal{H}\right|/\delta)}{\varepsilon^2} \right\rceil .$$

Exercise

Exercise: adapt the proof of the corollary when $\ell : \mathcal{Y} \times \mathcal{Y} \to [a, b]$. What happens when $|b - a| \to +\infty$?