

J-0x01 - Introduction

child block image

Why ML?

- Playing with blocks vs doing maths
- Sometimes we know how to solve problems (e.g., sorting)
- Sometimes we don't (e.g., recognise a cat, read handwriting on envelopes)
- Not magic

What is ML?

1. Some algorithms we know how to write
 - (a) Sort numbers
 - (b) Fly a plane
2. Some algorithms we don't know how to write (example: drive a car)
 - (a) Drive a car
 - (b) Read addresses on envelopes
 - (c) Detect spam
3. Maybe we can write programs to write programs when we can't
4. Some terms we used to use for ML
 - Artificial intelligence
 - Expert systems

fist image

Disclaimers

- The literature is overwhelmingly in English
- Time is short

tree image

Types of ML

1.

 - (a) Training data: input and correct responses
 - (b) Regression (continuous) (example: home prices)
 - (c) Classification (discrete) (example: medical outcome (alive/dead))
2.

- (a) Clustering
- (b) Deep neural networks
- (c) Associative (example: human experience, e.g. from a career)
- (d) Dimensionality reduction

3. Reinforcement

- (a) Make a choice, get feedback
- (b) Online
- (c) Can be stochastic (example: predicting weather from local clues)

high five image

Talk about course structure

- Ten afternoon sessions
- In class: mostly theory, some code, not much maths
- Between classes: coding assignments (python)
- Communication: github, mailing list
- Ask questions via mail, eventually github issues
- Help each other via same
- Don't copy. Learn.

Curse of Dimensionality

1. *Fléau (ou : malédiction) de la dimension*
2. Volume of unit cube $\pm \epsilon$
3. Distance from $(0, 0, \dots, 0)$ to $(1, 1, \dots, 1)$
4. Physics: $1/r^{d-1}$
5. It's easy to get lost...
6. Richard Ernest Bellman, Dynamic programming, Princeton University Press, 1957.

Probability

1. Event
2. Complement of an event
3. Disjoint (mutually exclusive)
4. Independent events — knowing one outcome gives no information about other

5. addition ($\times 2$), multiplication ($\times 2$)

6. Conditional probability

7. Marginal probability

8. Joint probability

Statistics

1. Goal for a bit: think like a statistician

2. What is statistics? ($\times 3$)

3. Said differently: goal is to compare reality to a model

4. Or to find a model and then compare.

5. Good statistical models are often relatively simple.

6. What is data science ($\times 5$)

Study design

1. Anecdote

2. Study types ($\times 2$)

3. Observational studies can't conclude causality

4. Observational studies can be

- prospective: identify individuals, collect information
- retrospective
- we can combine them

5. Experimental studies

- We do stuff
- Can conclude causation if properly designed
 - controlling: hold other variables constant (e.g., drink pill with full glass of water even if we don't care)
 - randomization: cancel out effects we can't control
 - replication: enough participants

6. Study types example

- Sunscreen use correlated to skin cancer rates.
- Confounding variable

7. Random sampling hazards

- Not actually random
- Convenience sample
- Non-response bias

Statistical concepts

1. Variable types

- Input: Features
- Input variables measure: Explanatory variable
- Output: Response variable
- Training set
- Test set (tune parameters) (compare model parameters)
- Validation set (tune hyperparameters) (measure performance of model)
- Cross validation
- Bias - same errors regardless of input (inflexible)
- Variance - different errors with same input (too flexible)

2. Population statistics ($\times 6$)

- sample mean vs population mean ($\times 7$)
- Sample standard deviation and variance: divide by $n - 1$

3. Distributions

- Important: pdf (pmf), cdf, ppf ($\times 5$)
 - pdf = densité de probabilité
 - pmf = fonction de masse
 - cdf = fonction de répartition
 - ppf = ?
- The rest: just so you've heard of them
- Boxplot ($\times 2$)

4. Normal distributions ($\times 2$)

- Sample mean vs population mean
- How close are they?
- Point estimate: if you have to guess, this is it
- Correction: if I want to be on average weighted right as much possible

5. Sampling distributions ($\times 3$)

- Sampling mean is unimodal and approximately symmetric
- It is centred at population mean.
- The standard deviation of the sample mean tells us how far a point sample's mean is likely to be from the population mean. In other words, how much error we are likely to have in the point estimate's mean. **Standard error.**
- TODO: Generate uniform population, sample, and plot sampling distribution
- TODO Generate highly skewed population, sample, and plot sampling distribution
- In real life, we don't have access to the population parameters. We have to *estimate* them from samples. So we can't *know* the standard error (erreur type).

6. Confidence intervals ($\times 3$)

- Sampling is usually expensive.
- Reminder: Independent random samples!
- Correct language: "We are 95% confident that the population parameter is between..."
- Incorrect language: describe the confidence interval as capturing the population parameter with a certain probability.
- This is one of the most common errors: while it might be useful to think of it as a probability, the confidence level only quantifies how plausible it is that the parameter is in the interval.
- Another especially important consideration of confidence intervals is that they only try to capture the population parameter. Our intervals say *nothing* about the confidence of
 - capturing individual observations
 - a proportion of the observations
 - about capturing point estimates

Confidence intervals only attempt to capture population parameters.

J-0x01 - Features and Modeling

J-0x01 - Practicum

- Setting up an environment
- Jupyter notebook
- Titanic