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
Example:

- Patients in hospital
- Collect data: O_2, CO_2 in blood, glucose reaction (silly example)
- Measure outcomes: end up on respirator, live/die, recover 95% of capacity prior at 2 years, etc.

How do we model this. Talk about tuples and vector spaces and functions that map from one space to another.

Types of ML

1. $\boxed{\text{Supervised}}$
   (a) Training data: input and correct responses
   (b) Regression (continuous) (example: home prices)
   (c) Classification (discrete) (example: medical outcome (alive/dead))
2. $\boxed{\text{Unsupervised}}$
   (a) Clustering
   (b) Deep neural networks
   (c) Associative (example: human experience, e.g. from a career)
   (d) Dimensionality reduction
3. $\boxed{\text{Reinforcement}}$
   (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

- Three sessions
- In class: mostly theory, no code, no math

$\boxed{\text{Curse of Dimensionality}}$

1. *Fléau (ou : malédiction) de la dimension*
2. Volume of unit cube $\pm\epsilon$
3. Distance from $(0, 0, \ldots, 0)$ to $(1, 1, \ldots, 1)$
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. $\boxed{\text{addition } (\times 2), \text{ multiplication } \times 2)}$

6. $\boxed{\text{Conditional probability}}$

7. Marginal probability

8. Joint probability

Statistics

1. Goal for a bit: think like a statistician (use hospital example)

2. $\boxed{\text{What is statistics? } (\times 3)}$

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. $\boxed{\text{What is data science } (\times 5)}$

Study design

1. $\boxed{\text{Anecdote}}$

2. $\boxed{\text{Study types } (\times 2)}$

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. $\boxed{\text{Variable types}}$
    - 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. $\boxed{\text{Population statistics } (\times 5)}$
    - sample mean vs population $\boxed{\text{mean } (\times 5)}$
    - Sample standard deviation and variance: divide by $n - 1$
3. Distributions
    - $\boxed{\text{Important: pdf (pmf), cdf, ppf } (\times 5)}$
        - pdf = densité de probabilité
        - pmf = fonction de masse
        - cdf = fonction de répartition
        - ppf = ?
    - The rest: just so you've heard of them
    - $\boxed{\text{Boxplot } (\times 2)}$
4. $\boxed{\text{Normal distributions } (\times 2)}$
    - 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. $\boxed{\text{Sampling distributions } (\times 3)}$
   - 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. $\boxed{\text{Confidence intervals } (\times 3)}$
   - 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

- Setting up an environment
- Jupyter notebook
- Titanic