COMS30035, Machine learning: Introduction

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Disclaimer

This is an unusual year. COVID-19 means that we had to change our teaching processes. So please bear with us – we are trying our best.

Agenda

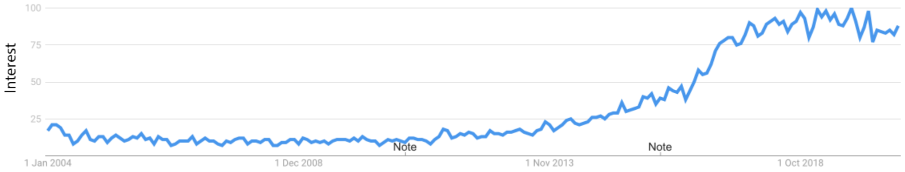
- What is machine learning?
- Examples
- How does it relate to other units?
- What will we cover?
- Unit outline
- Assessments/coursework
- Labs

What is machine learning?

- Machine Learning (ML) is the study of computer **algorithms** that **learn** a **model** of **data**. These models are then used to make **predictions** and better **understand** the problem at hand.
- It is typically grounded on statistical science[1] and seen as a subfield of Artificial Intelligence.

[1] Remember to review some key statistical concepts. See Iain Murray's crib-sheet with a revision of math commonly used in ML here.

Machine learning interest [Google trends]



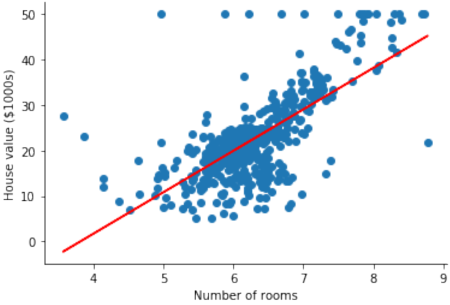
Machine learning interest [Google trends]

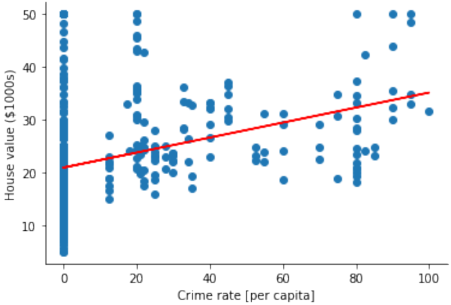
In contrast to Computer Science, Machine Learning is increasing in popularity.

Examples: Linear regression

When we regress one variable against another using a linear model.
Pros: Simple model **Cons**: Simple model

Example: Can we predict property prices in Boston?





Examples: Classification

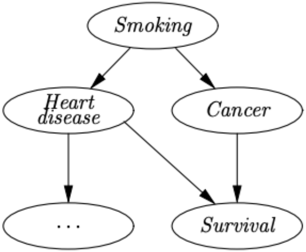
When we want to automatically separate data into classes.
Pros: A wide range of methods that work well (e.g. ANNs or SVMs).
Cons: Needs labelled data (i.e. sample X is an example of a dog).

Example: Is it a dog or a bagel?

Examples: Graphical models

When we use a graphical model to represent an explicit probabilistic model.
Pros: Easy to interpret and explicit notion of uncertainty. **Cons**: Can be hard to estimate.

Example: What are the changes of survival for a smoker?

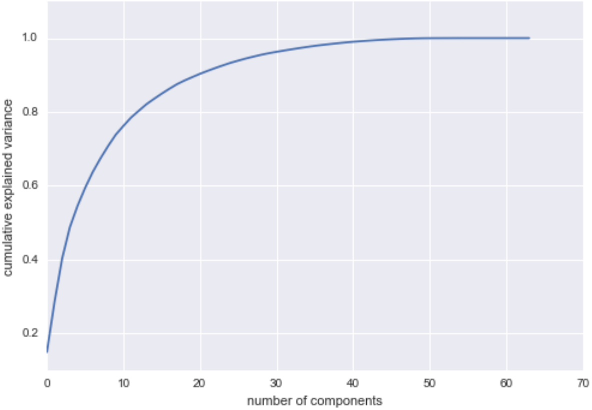


$\Pr(cancer \mid smoking)$	$\Pr(cancer \mid \neg smoking)$
$\Pr(\neg cancer \mid smoking)$	$\Pr(\neg cancer \mid \neg smoking)$

Examples: Dimensionality reduction

Used to compress data to a much smaller number of dimentions.
Pros: Easy to compute (e.g. using PCA). **Cons**: Loss of features semantics.

Example: How many features/components are enough to explain 80% of the variance in a given dataset? More here.



Examples: Generating text in natural language

Pros: Can give impressive results (e.g. using deep learning).
Cons: Models can be hard to interpret.

Example using a Transformer (a type of neural network):

Input: "Machine Learning is the study of computer algorithms that learn a model of data."

Output/completion: "Traditional AI, such as natural language processing, machine translation, image recognition, and machine translation relies heavily on well-defined data, and can perform well without much further manipulation of the data. Typically, a machine learning system recognizes patterns of data and then uses those patterns to predict outcomes of a given scenario. (see prediction)"

Try it out **app.inferkit.com/demo**!

How does it relate to other units

- This unit builds directly on previous units
  - Data Science for CS (previously known as SPS) [introduction to data science in **Python**]
  - Algorithms I and II [design/analyse algorithms, and data structures]
  - Math for CS I and II [algebra and statistics]
- And is a building block for more advanced units (4th year):
  - Advanced ML
  - Applied Deep Learning (neural networks)
  - Information Processing & the Brain (ML and neuroscience)
  - Cloud Computing and Big Data (ML on the cloud)
  - Advanced Computer Vision (ML for vision)
  - Applied Data Science (ML and data management)

What we will cover

We will focus on the following textbook

- **Bishop, C. M., Pattern recognition and machine learning (2006). Available for free here.**

With some sections from:

- Murphy, K., Machine learning a probabilistic perspective (2012). The book is also freely available here.

What we will cover

1. Part 1: Overview, ML concepts, revisiting regression and neural networks [» Rui Ponte Costa, unit director]
2. Part 2: Graphical models, mixture models, EM, Continuous latent models (PCA, ICA) [» James Cussens]
3. Part 3: Sequential data (RNNs, HMMs), model ensembles [» Edwin Simpson]



Unit Outline

On the unit BB page; and uob-coms30035.github.io

Weeks	*First lecture*	*Second lecture*	*Labs*	*Q&A class*
1	Introduction	Machine learning concepts	L1: Revision of Jupiter Notebook and ML libraries	General questions about the unit
2	Linear models and neural networks	Kernel machines	L2: Linear models, nnets and SVMs	ML concepts, linear models and nnets
3	Introduction to graphical models	Bayesian ML using graphical models	L3: Probabilistic graphical models	Probabilistic graphical models
4	k-means and mixtures of Gaussians	The EM algorithm	L4: k-means and EM	The k-means and EM
5	PCA	kernel PCA and ICA	L5: PCA and ICA	PCA and ICA
6	Seqential data and hidden Markov models	Sequential data and linear dynamical systems	L6: Hidden Markov Models	Modelling sequential data
7	Ensemble methods	Probabilistic model combination	L7: Ensemble methods	Combining models using ensembles and probabilistic methods
Coursework weeks				
11	Review/QA part I (Rui)	Review/QA part II (James)	-	Review/QA Part III (Edwin)
12	**Review week**			

Online teaching

Every week you will get two teaching components:

1. **Asynchronous/during your own time**:
   - 2 recorded lectures (available on BB>Recordings)
   - Pointers to textbook (Bishop book)

2. **Synchronous/during the time set in your timetable**:
   - 1 live lecture (QA/problem class) [1 hour; **Tue 9-10am**]
   - 1 lab on the lectures taught on that week [three hours; about 10-12 people per online room/bubble]

Microsoft Teams

All our synchronous activities will be run on Microsoft Teams:
grp-COMS30035-ML-teaching

How to join?

1. Install Microsoft Teams.
2. Go to the unit BB (teaching unit version) page.
3. Click on the link 'Join Teams'.

[Run BB/Teams demo]

Assessments

- **Option 1, 100% Coursework**[2]: A small project involving a ML challenge [fulltime in weeks 8-10]

  Coursework released at beginning of week 8.

  Discussion with others is encouraged, but submissions need to be unique [**plagiarism is taken seriously!**]

- **Option 2, 100% Exam** [multiple choice]

- Labs are only formative, but we highly encourage you to finish all of them, as it will massively help you preparing for either option.

[2] It is possible to change options until end of Week 2, but remember that you can only do 2 units via Option 1.

Labs

- Thursday 10am - 1pm [as in timetable]: Online groups of 10-12 each
- Lab Environment [Jupyter + Python] [3]
- **Lab Work:**
  - Work proactively together online (and offline if possible) with your bubble.

[3] For those doing the CS undergrad, we will follow a similar setup to Signals, Patterns and Symbols (SPS) last year.

Labs: Important!!

- Main source of 1:1 support will be from the TAs in the labs!
- Go to your Bubble (see lab/Bubble allocation in BB).
- How to ask questions? In the current meeting or use the [labs] QA > Ask Question tab.
- Labs are <u>essential</u> for a good understanding of ML!

Your TAs

That you will interact with through Teams:

- Stefan Radic Webster
- Will Greedy
- Dabal Pedamonti
- Dan Whettam
- Amirhossein Dadashzadeh
- Abanoub Ghobrial

Tasks

- Live lecture (Tue 9-10): Questions about the structure of the unit
  - You can use the Teams QA>Ask Question system to ask question before hand.

- Next Lab (Week 1): Jupyter Notebook and intro to Python-Sklearn
  1. Find out your lab Bubble allocation (its on BB)
  2. Join Teams
  3. Join meeting on that Bubble [from 10am on Thu]
  4. See link to lab 1 on BB