Machine learning: a hands-off introduction

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Filippo in one slide

- **Roma** (*born*)
- **Perugia** (*MSc degree*)
- **Cork, ICBF** (*Web-design & Database*)
- **Cremona, ANAFI** (*Quantitative Genetics*)
- **Guelph, CGIL** (*Visiting Scientist*)
- **Wageningen, WUR** (*PhD*)
- **Göttingen University** (*post-doctoral researcher*)
- **Lodi, PTP** (*'omics in animals, plants, humans*)
- **Milan** - **CNR** (*tenured researcher*)
- **Cardiff University** (*biostatistician*)
- **Milan** - **CNR** (*senior researcher*)
- **Bruxelles** - **ERC** (*seconded national expert*)
- **Milan** - **CNR** (*senior researcher*)

Overview

Day 1

- Introduction to data mining, ‘omics data and machine learning
- Experimental design
- Advanced R libraries

Day 2

- Multivariate data generalities
- Unsupervised statistical problems
- Principal Component Analysis (PCA) etc.
- Introduction to supervised learning

Overview

Day 3

- Machine learning for regression
- Overfitting and resampling techniques
- Classification problems
- p >> n problems and model regularization (Lasso)

Day 4

- Lasso and model tuning
- Bagging and Random Forest for regression and classification
- Multiclass classification with RF
- Slow learning: the boosting approach

Overview

Day 5

- Advanced data visualization
- Final interactive exercise
- Model and variable selection: the machine learning paradigm
- Quiz!

[timetable]

[repo]

[website]

It’s been a long way to machine learning

- 1925: Ronald Fisher’s “*Statistical Methods for Research Workers*” (he later regretted the 0.05 p-value threshold) ⟶ **frequentist statistics**

- **Bayesian** resurgence: 1980s → **MCMC** (1986: Gibbs sampling by Geman & Geman)

- Non-parametric statistics & resampling methods

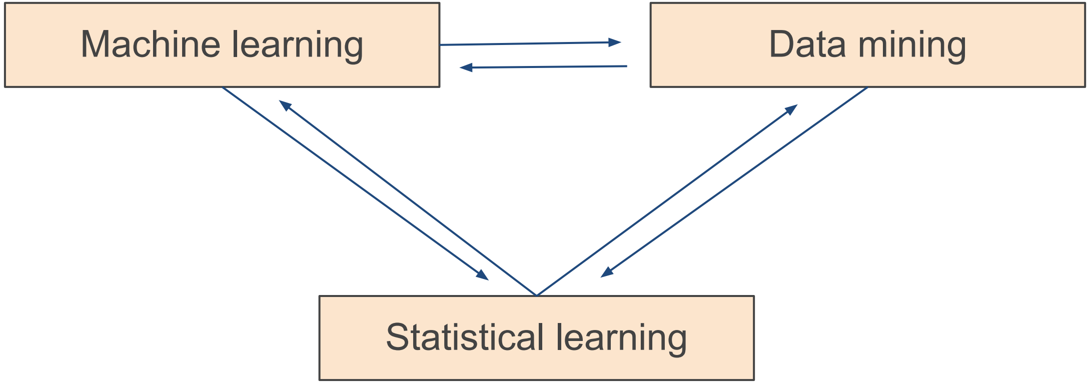
- The **machine** (statistical) **learning** paradigm

A lot of math!

Increasing computer power

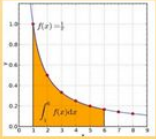
Big data

A bit of terminology



- **closely related terms** (very much so)
- **data mining** more for **unsupervised learning** (finding patterns in the data, novel insights) → but uses machine/statistical learning methods
- statistical and machine learning are quasi synonyms (approach from **different directions**: **statistics** or **computer science**)

A bit of terminology

	 Statistics	+  Machine Learning	= $\sum_{i=1}^{n}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \lvert\beta_j\rvert$ Statistical Learning
Subfield of...	Mathematics	Computer Science (AI)	Statistics & Machine Learning
Focus on...	Building models with explicitly programmed instructions	Creating systems that learn from data	Sets of tools for modeling and understanding complex data
Purpose	Inferences; Relationships between variables	Optimization; Prediction accuracy	Building statistical models for prediction; understanding data
Prior assumptions about data	Some knowledge about population usually required	None	Some knowledge about population may be required
Dimensionality of data	Usually applied to low-dimensional data	Usually applied to high dimensional data; ML learns from data	Usually applied to high dimensional data
Knowledge overlap	No ML knowledge required	Some stats knowledge usually needed: stats is basis for algorithms	Knowledge of statistics and ML required

Machine learning

- Concerned with the analysis of **complex data** to identify patterns that can be used to:
    - **predict** the outcomes of elections
    - **identify** and filter spam messages from e-mail
    - **foresee** criminal activity
    - automate traffic signals according to road conditions
    - produce financial estimates of storms and natural disasters
    - **identify** disease outbreaks (e.g. SoundsTalk)
    - **predict** when patients get sick
    - determine credit worthiness
    - target advertising to specific types of consumers
    - and many more ...

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many terms related to predictions (one of the main tasks in ML)

Machine learning - between legend and reality

1. US retailer used machine learning to identify pregnant women (customers) and predict due date
2. based on this, targeted promotional offers were sent via mail (e.g. maternity clothes, baby clothes, baby food etc.)
3. father reacted angrily to her daughter receiving such offers for maternity items
4. manger from the retailer called to apologise for the error in their ML system
5. ultimately, the father returned the apologies because his daughter was indeed pregnant

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May be true or not, yet:

- retailers indeed use ML to analyse purchase data
- ML can be surprisingly effective (know us better than ourselves)
- ethical implications! (“don’t be evil!” @google)

Machine learning - definition

- A. Samuel (1959): giving computers the **ability to learn without being explicitly programmed**
- T. Mitchell (1998): a computer program **learns** from **experience E** with respect to **task T** with **performance P**, **if P on T improves with E**

Machine learning - definition: a task for you!

Which is **E**, **T**, **P**?

- diagnosing patients as sick or healthy
- watching the clinician making the diagnosis (sick/healthy)
- number of patients correctly diagnosed

Data (knowledge) representation

Source: http://collections.lacma.org/node/239578

- not a real pipe
  (picture of a pipe)
- idea of a pipe
  (concept)
- actual pipe (object)

Abstract connections, knowledge representation

Data (knowledge) representation

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Abstract connections, knowledge representation

Data (knowledge) representation → learning

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Abstract connections, knowledge representation

model

generalization

(we want the machine to be able to learn from experience and generalise to new cases, just like we humans do)

Data representation: example from genomics

Let’s work this out together!

<u>Genomic variants for diabetes</u>

- raw data:
    - 0s and 1s stored in memory
- what the data mean (data representation):
    -
    -
- natural phenomenon (what we want to study):
    -
    -
    -
- model:
    -
    -

Data representation: example from genomics

Genomic variants for diabetes

- raw data:
    - 0s and 1s stored in memory
- what the data mean (data representation):
    - some 0/1 are genomic variants, others are disease labels
    - n. copies minor allele, presence/absence etc.
- natural phenomenon (what we want to study):
    - genetic predisposition to diabetes
    - predict diabetes based on genome
    - identify genomic variants linked to diabetes
- model:
    - knowledge that genes (co)determine phenotypes
    - $P(\text{diabetes}|x) = \text{variant}_1 + \text{variant}_2 + \ldots + \text{variant}_m + e$