Machine Learning primer

***Machine learning** is a method of data analysis that automates analytical model building. Using algorithms that iteratively learn from data, **machine learning** allows computers to find hidden insights without being explicitly programmed where to look (source: SAS)*

A word about myself

- My name is Gilles, I was born in France, spend my time between the US, France and Japan
- I hold M.Sc, B.Sc in Applied Mathematics and a Business degree
- I'm using mainly: Python, Scikit-Learn, R, Keras, Theano (for Neural networks) – although C++ was a long time favorite of mine
- Been doing Machine Learning and Analytics for more than 5 years – mainly in Finance and Marketing
- I am currently working on connected services for a large manufacturer
- My favorite games so far are Uncharted 3 and Last of Us, I like reading about history during my free time and to make a mess in my kitchen for the purpose of cooking nice food. Last dish was grilled salmon in mango salsa.

Overview

Objective:
- Develop an intuition of what Machine Learning is and does

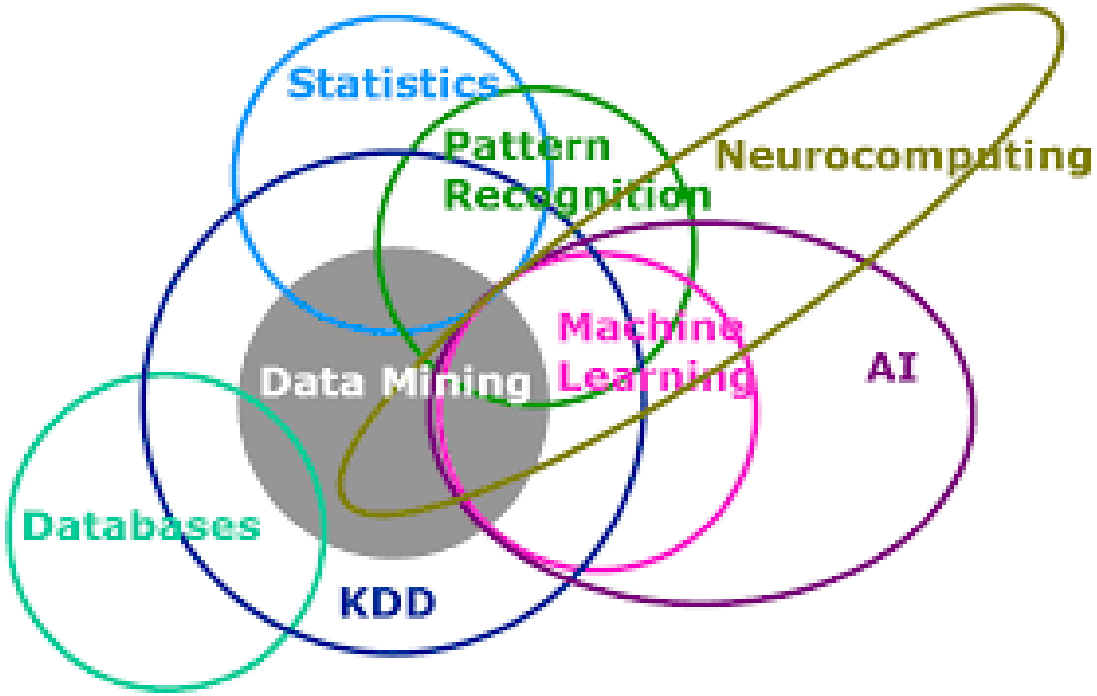
Audience:
- Interest in understanding the underlying mechanisms
- Interest in using and practicing Machine Learning
- Interest in exploring the potential of Machine Learning

Content:
- Intro some comparison
- Math part:
  - Conventions
  - How it works at the core
- What it can do
- What it takes
- Challenges

What do they say on the internet: Very different way of thinking

	MACHINE LEARNERS	STATISTICIANS
Network/Graphs vs. Models	Network/Graphs to train and test data	Models to create predictive power
Weights vs. Parameters	Weights used to maximize accuracy scoring and hand tuning	Parameters used to interpret real-world phenomena - stress on magnitude
Confidence Interval	There is no notion of uncertainty	Capturing the variability and uncertainty of parameters
Assumptions	No prior assumption (we learn from the data)	Explicit a-priori assumptions
Distribution	Unknown a priori	A-priori well-defined distribution
Fit	Best fit to learning models (generalization)	Fit to the distribution

What do they say on the internet:
Very different techniques



What do they say on the internet:
How is it done?

Supervised Machine Learning v. Econometrics/Statistics Lit. on Causality

Supervised ML

- Well-developed and widely used nonparametric prediction methods that work well with big data
  - Used in technology companies, computer science, statistics, genomics, neuroscience, etc.
  - Rapidly growing in influence
- Cross-validation for model selection
- Focus on prediction and applications of prediction
- Weaknesses
  - Causality (with notable exceptions, e.g. Pearl, but not much on data analysis)

Econometrics/Soc Sci/Statistics

- Formal theory of causality
  - Potential outcomes method (Rubin) maps onto economic approaches
- "Structural models" that predict what happens when world changes
  - Used for auctions, anti-trust (e.g. mergers) and business decision-making (e.g. pricing)
- Well-developed and widely used tools for estimation and inference of causal effects in exp. and observational studies
  - Used by social science, policy-makers, development organizations, medicine, business, experimentation
- Weaknesses
  - Non-parametric approaches fail with many covariates
  - Model selection unprincipled

What do they (still say) on the internet: Very briefly

Machine learning	Statistics
network, graphs	model
weights	parameters
learning	fitting
generalization	test set performance
supervised learning	regression/classification
unsupervised learning	density estimation, clustering

Vocabulary 1/3

- X : observations, they can have k features (parameters)

- Y : observed outcomes for observations

- Example:
  - X (average km per day,
    #days since installation,
    #maintenance days)

  - Y (useful life of part)

Vocabulary 2/3

- X : Data
- $X_{.,j}$: $X_{.,1}$ $X_{.,2}$ … $X_{.,k}$ k Features that describe each data point
- $$X \rightarrow \left.\begin{array}{l} X_{1,.} \\ X_{2,.} \\ X_{3,.} \\ \ldots \\ X_{n,.} \end{array}\right\} \text{N observations}$$

Vocabulary 3/3

- F : Model
- Θ : Weights of the model
- Y' : output of the Model

- Example:
  - Y'(useful life of part) =

$$12 + \boldsymbol{\Theta_1} \times \#Km/day + \boldsymbol{\Theta_2} \times \#days + \boldsymbol{\Theta_3} \times \#maintenance$$

What is Machine learning all about?

- We want to build a model F, such as Y' = F(X) so we can generalize for any new entry X an expected outcome Y'

- For this, we are going to train the model F by using all the outcomes Y we know about for observations X

- We will look for the Weights **Θi** of the model such that given Y and X, we have $Y \sim F_{\Theta i}(X)$

In other words

- We want to minimize the expression:

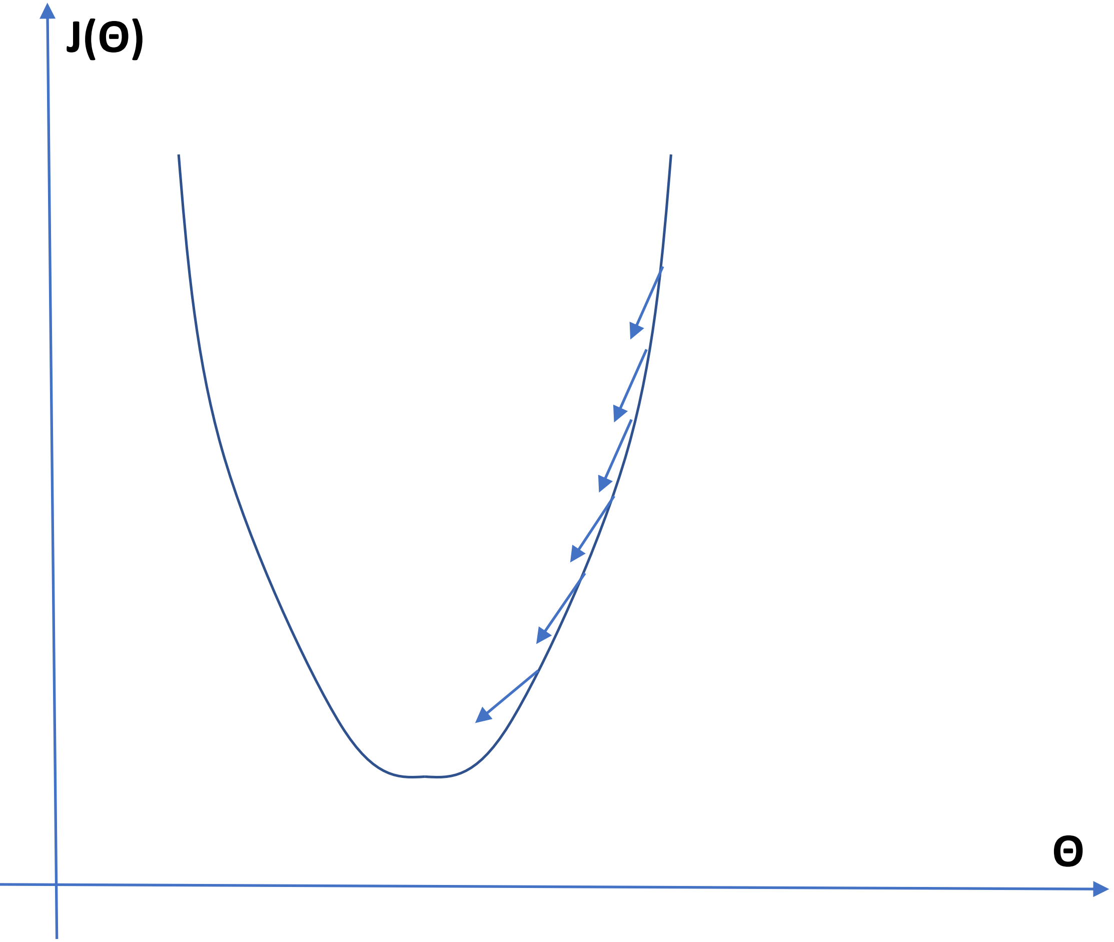
$$\underbrace{||Y - F_{\Theta i}(X)||}\leq \text{Epsilon}$$

- Given that we know X and Y while we train the model and that we are trying to determine the parameters **Θi** of F, this is equivalent to a minimization problem on **Θ**

$$\mathbf{J(\Theta) \leq Epsilon}$$

solved by **gradient descent** algorithm

Gradient descent



Here, the Θ values minimize J(Θ)

Repeat until convergence {

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

By iterating the algorithm on all the data points X and known outcomes Y, <u>we can determine the model</u>

Why is it (really) state of the art now?

- We have the ability to collect a lot of data

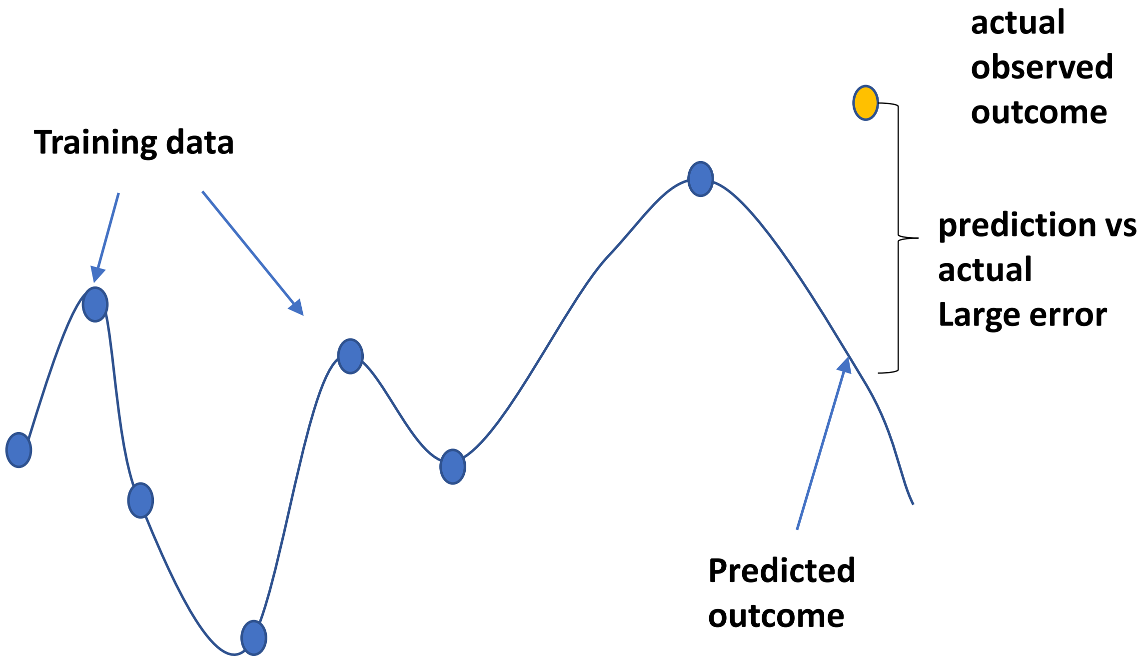
- We have computing power

- It is a mathematical solution that can extract information quickly, elegantly, optimally without (too much) prior knowledge of the underlying phenomena

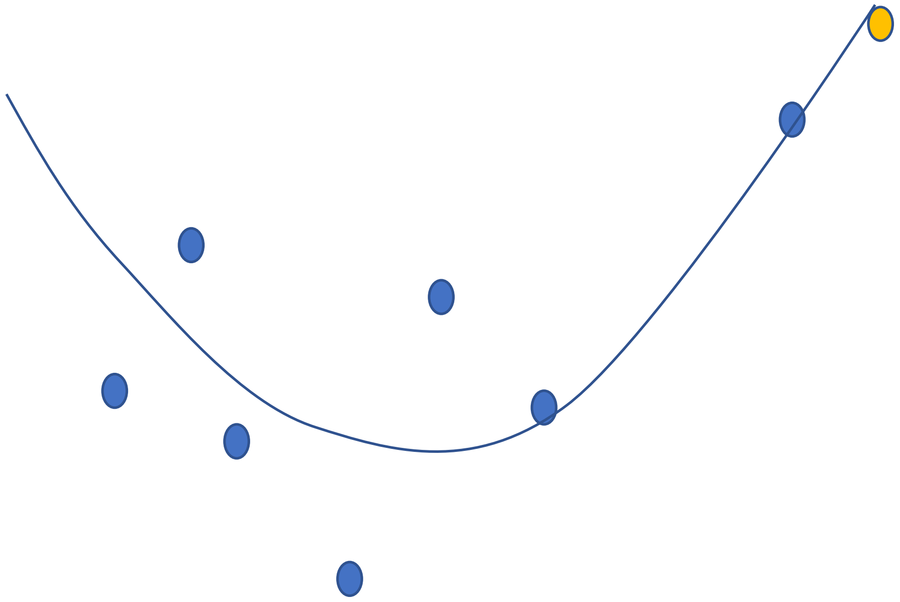
In short, this is big data

Pitfalls

- Overfitting (model is too sophisticated and doesn't generalize well)



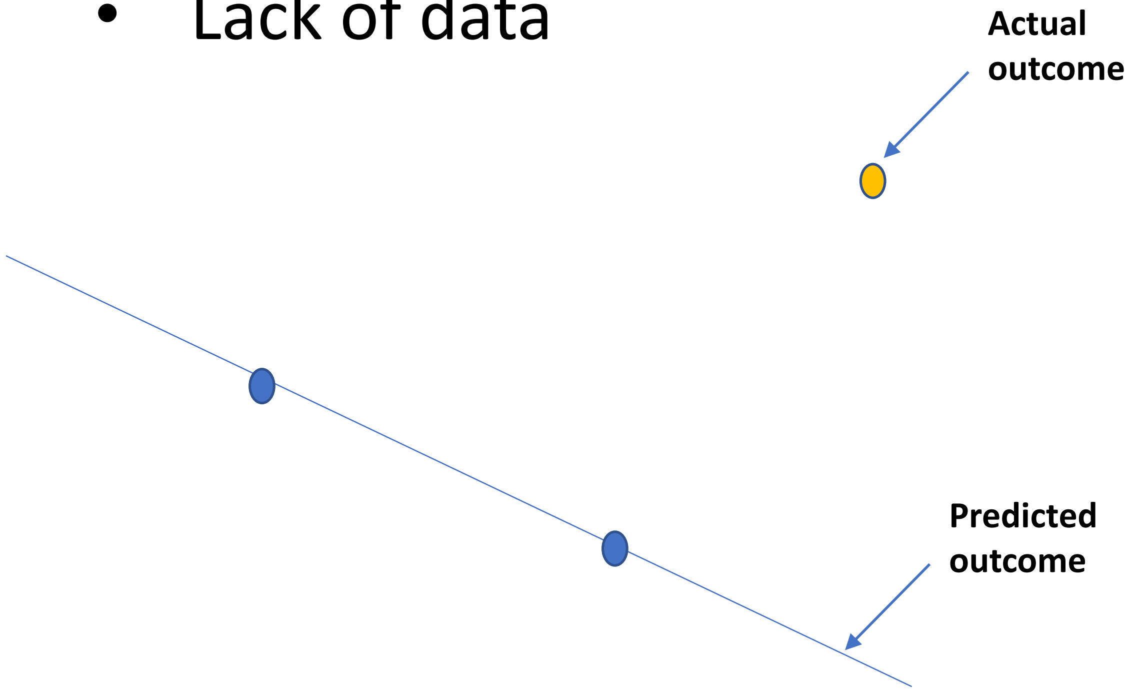
Overfitting: model very sophisticated and fits too well the training data

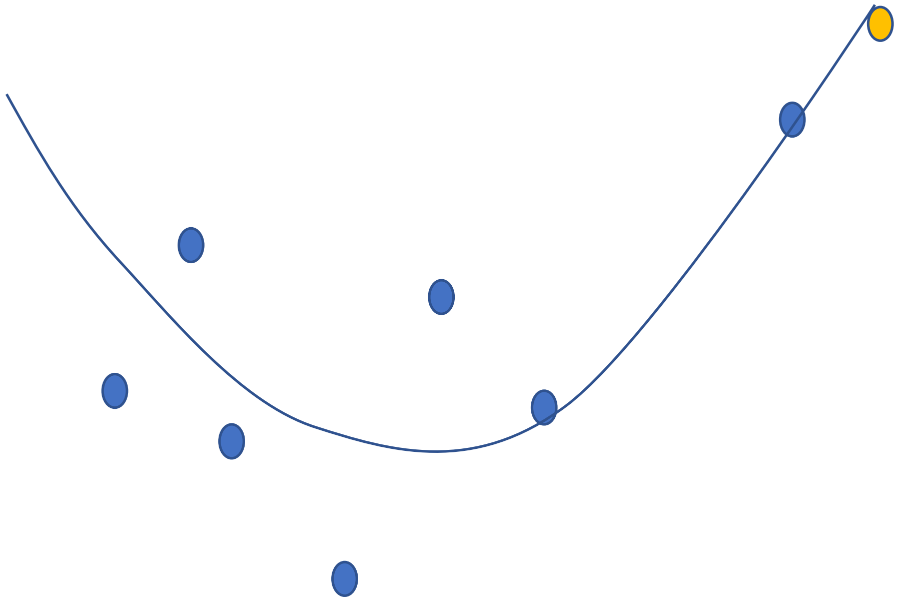


Model has a larger training error but generalize better the prediction of new observations

Pitfalls

- Lack of data





Not enough data, models can be poor

Good amount of data, models are better
(5,000 pts can be nice, 1,000 starts to be challenging)

In practice

- We use 70% of the data to train the model and 30% to test its validity (confirm we do not have overfitting and model can generalize well to new data)

- Machine learners *cannot* accept overfitting and fortunately a few techniques exist to avoid it

We constantly check the training error vs generalization error

A few points

- Preferable to have numerical data (most algorithms are mathematical)
- Preferable to have lots of data (law of big numbers)
- Very important work of pre-processing the data (scaling, cleaning, missing values, handling of categorical data, dimension reduction)

L2 regularization

- We are trying to determine the Θs so that:

J(Θ) is minimum

- With an L2 regularization term, we are trying to find the J(Θ) to minimize $J(\Theta) + \lambda/2 \times ||\Theta||^2$

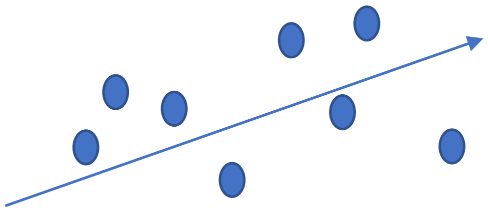
- If $\lambda = 0$, then it is the same as normal minimization of J(Θ) , if not, it will force the Θs not to have large values (the only way to minimize the formula above because all terms are positive)

- In practice, the parameters of the model will not take values that have too much importance, thus reducing the

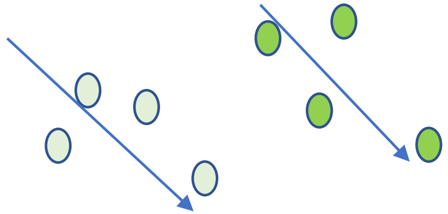
Where's the game?

- Being able to formulate the objective (it is not trivial at all!)
- Picking the most appropriate model
- Feature engineering, if we have X:
  - we may use also X, sin(X), X^2,...
  - Momentum, velocity, filters, pre-training, etc...
- Constantly keep in check and reduce the model error

- And be careful



Demand is increasing in total population...



Same data, if we look at females and males separately demand is actually decreasing!

Models are used (mainly) for

- Classification (sort data according to classes)
  - customer C will be more interested in owning a car
  - customer D will be more interested in sharing a car
- Regression (predict a value)
  - Number of cars a highway restaurant is likely to receive between 6pm and 9pm the first week of August
- Clustering (automatically group customers with same underlying characteristics)
  - Customers who purchased white Leaf cars are likely to subscribe to infant service media programs
  - Automated segmentation through underlying similarities among people who showed interest in mini cars

Keep in mind the words “supervised” and “unsupervised” (basically does the training requires a Y or not? Typically clusters don’t) that are used in Machine Learning (question of costs. Labeled data is generally more expansive).

A word about Neural networks

- A very nice set of tools to have:
  - It is *not* “standard Machine Learning” vs NN
  - Again best model should be chosen for the task at hand

- Can do (best of range and my favorites)
  - Image recognition (CNN convolutional network) – it works
  - Time series and prediction (LSTM – Long short term memory) – it works
  - Dimension reduction, anomaly detection (SOM, Auto-encoders) – it works

- Can do also
  - NLP (Natural language processing) – great field for automated human machine communication (chatbots), requires a lot of expertise, still a lot of research is being done but I will wait for the libraries
  - Generative networks: create new digital material from past data (not much experience on this)

Challenges

- Models can be (painfully) <u>more accurate</u> and <u>faster</u> than humans

- Mathematics and AI are difficult to explain, especially why they work (if you have temperature, you are sick. It is the same with ML,… it measures the symptoms of a system to understand a situation)

- Focus of ML is on the outcome, the why is complex and not primary – keeping in mind that the "real" human why cannot but be biased (by experience and education in the best cases) and is actually not always super accurate

Big Data is challenging, many possibilities but requires a different way of thinking

Cultural difference

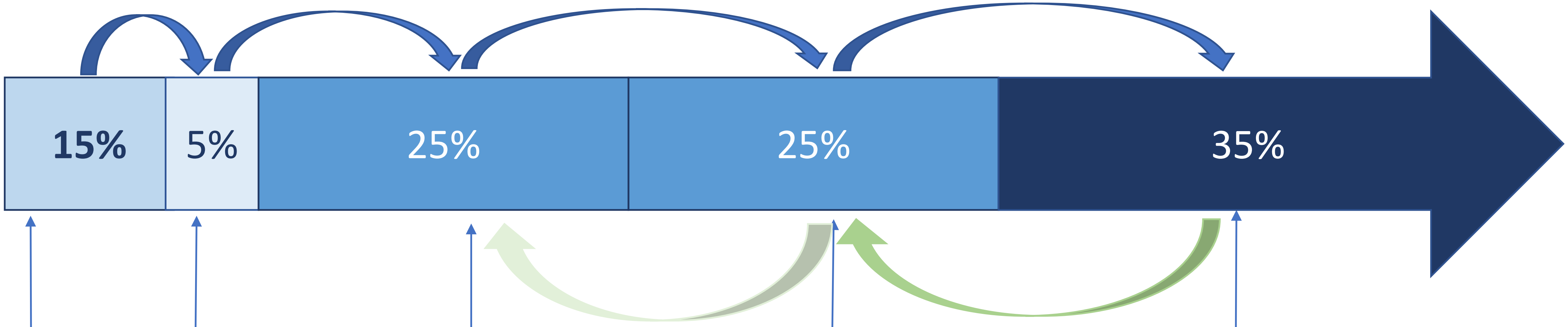
Traditional Statistics | **Machine Learning**

A Data Science Continuum

White-box modelling
simpler computation, emphasis on introspection, form, causal effects and processes, finding a ‘correct’ model

Black-box modelling
high computational complexity, emphasis on speed and quality of prediction, finding a ‘performant’ model

Machine Learner mental workload



Inferential statistics
-intuit "interesting" features

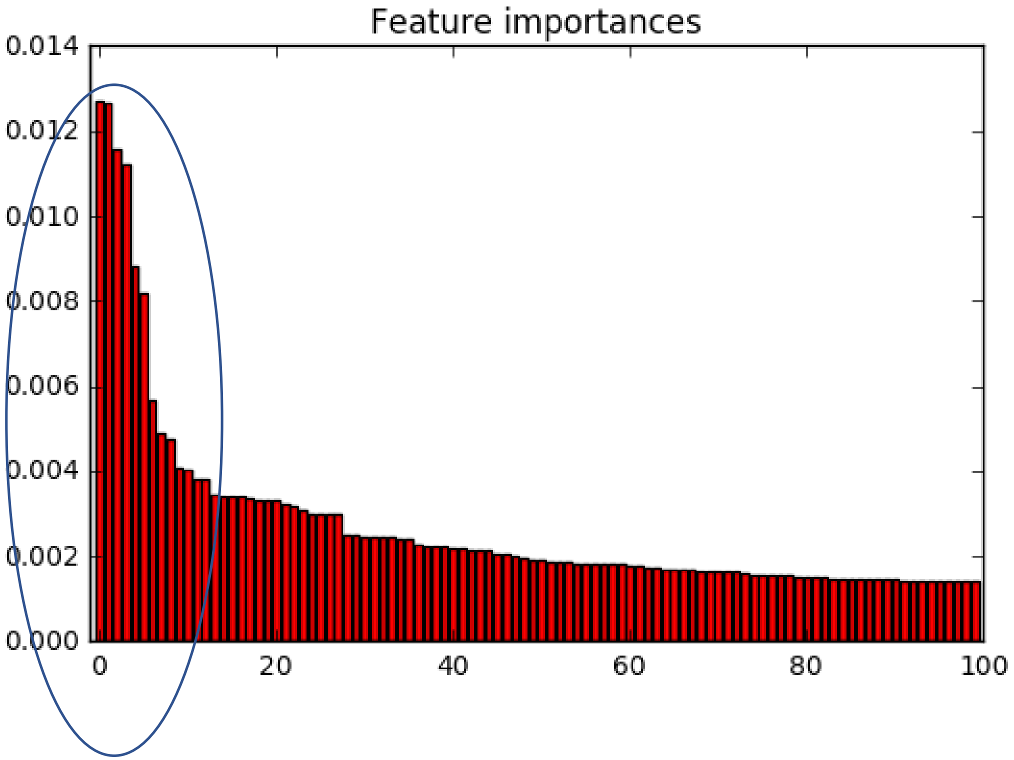
Model selection and training
-set-up models
-fine tune hyper-parameters

Descriptive statistics
-Quartiles
-Boxplots
-Histograms
-Variance / mean
-...

Feature engineering
-missing values
-categorical data
-dimension reduction
-data augmentation

Testing
-check prediction vs test data
-research more performing approach

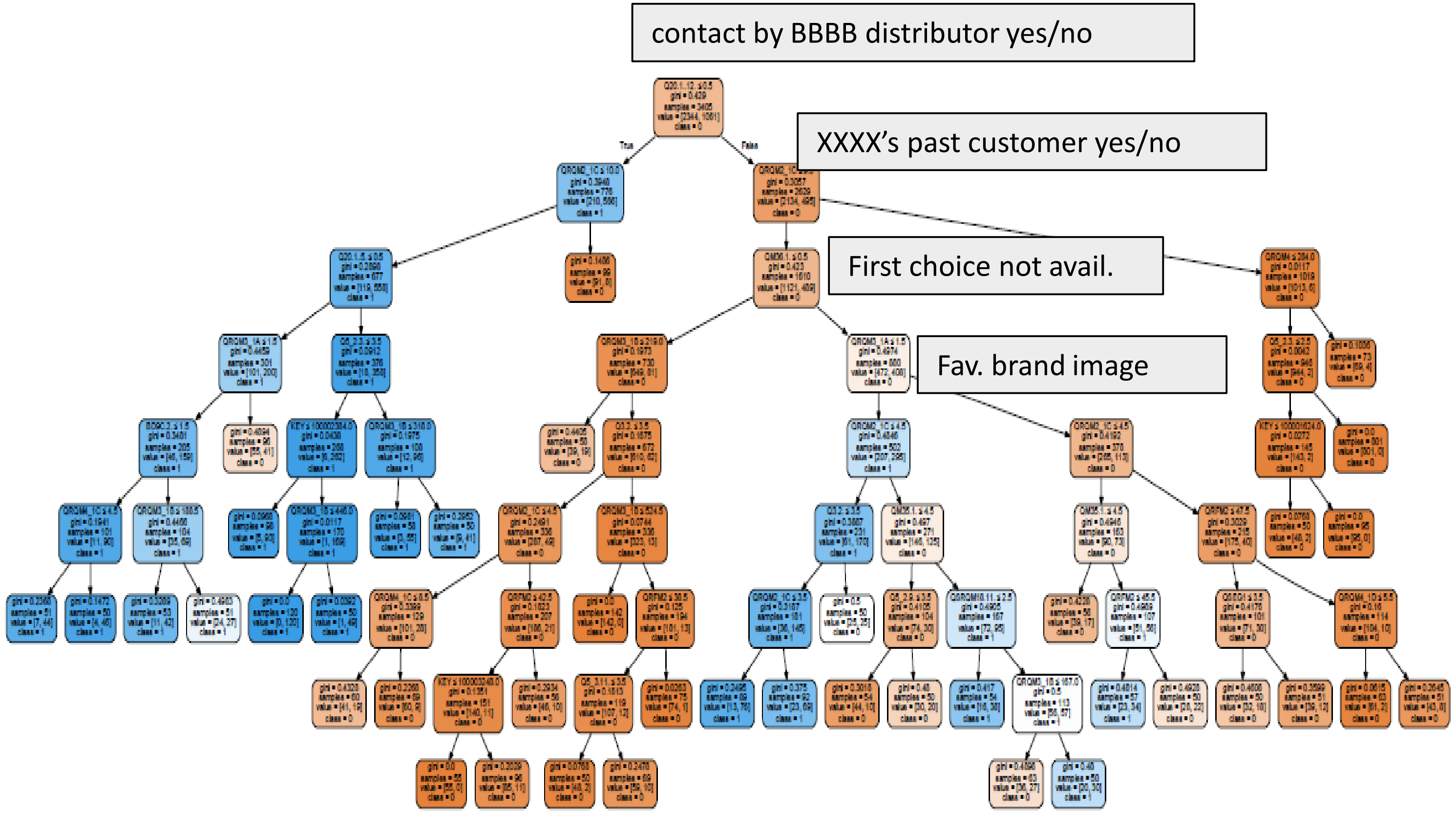
Purchase prediction of XXXX product



- Possible to predict purchase of XXXX product with **84% accuracy**
  (random tree forest algorithm used)

- Less than 20 parameters really significant for prediction
  (dimension reduction algorithm)

Main determining factors



(Blue likelihood to purchase XXXXX product)

<u>Determining factors*:</u>

-Contact by BBBB distributor

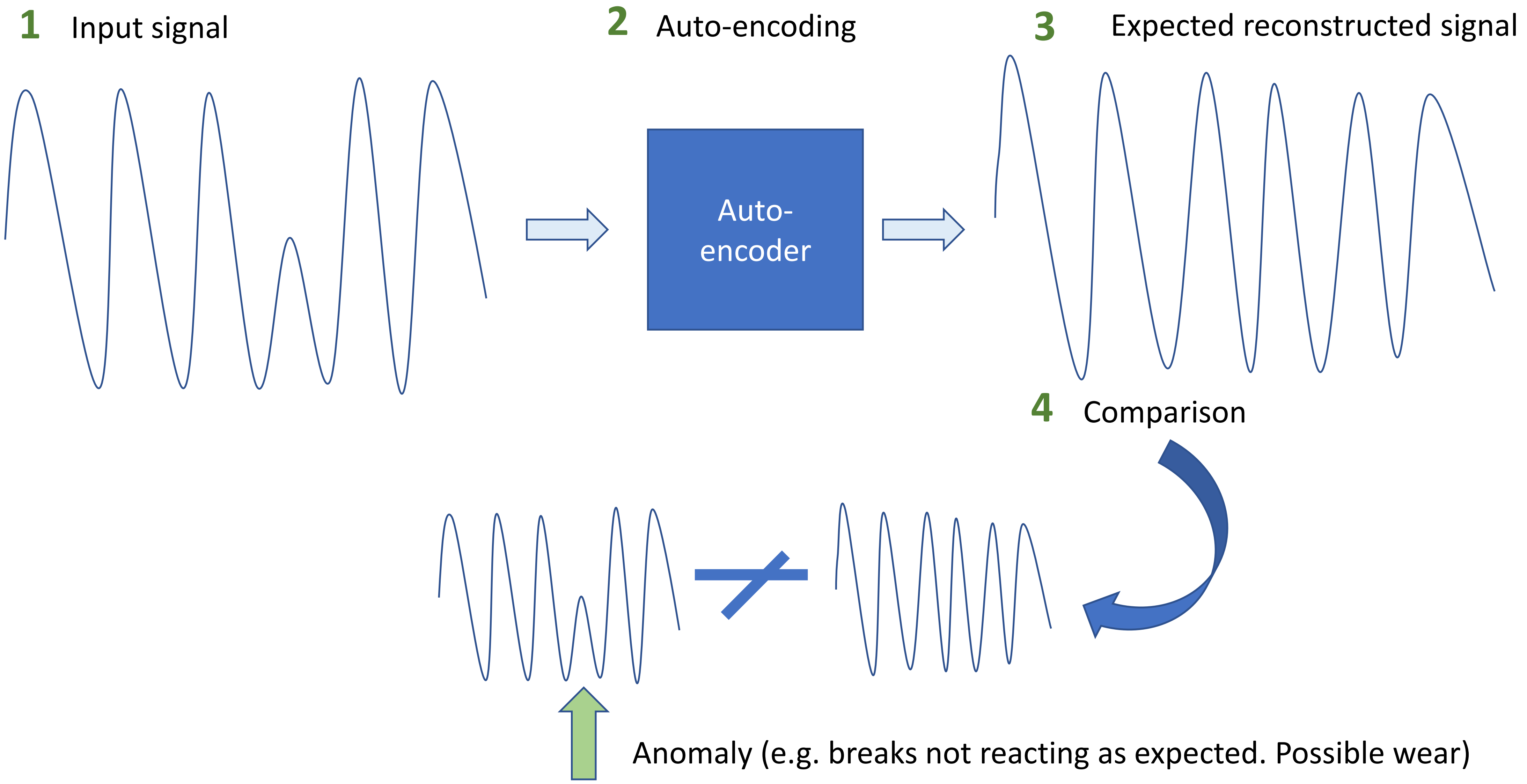
-XXXX's past customer

-First choice of product not available

-Favorable brand image

*data may actually be misleading (strong warning!!! questionnaire needs clarification)

Anomaly detections



Many terms (view from SAS)