Foundation of ML

Week 1

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Real-world applications of machine learning

- ML involves “computer algorithms” that learn how to perform different tasks
    - Robotics
    - Board Games
    - Voice Recognition
    - Digit Recognition

Examples - Robotics

- ML is a fundamental part of robotics for enabling robots to perform -
  - household work ranging from cleaning, cooking, reading and scheduling tasks
  - Simultaneous Localization and Mapping (SLAM)
  - walking patterns of humanoid robots
  - finding routes for rescue robots

Examples - Board Games

- one of the oldest applications of ML
- in March 2016, AlphaGo, the board-game-playing AI from Google’s DeepMind played Korean Go Champion Lee Sedol
- AlphaGo won the game 4 points to 1.

Examples - Voice Recognition

- benefited from advances in deep learning
- as well as big data
- Siri uses
  - speech recognizer,
  - natural language processing
  - text-to-speech techniques

Examples - Digit Recognition

- The task of reading in the images of handwritten numbers and letters
- Recognise the digits
  - output the machine-encoded equivalent
- ML methods (SVM and Deep Learning) have hit >99% accuracy for this task

Definitions of ML

- “Field of study that gives computers the ability to learn without being explicitly programmed,” (*Samuel 1959*)
- If not explicitly programmed can it learn to do things? How? Magic?
- “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E,” (*Mitchell 1997, p. 2*)

Steps in ML

- How do we learn to perform a task?
  - have access to data from which we can learn (**Data Manipulation**)
  - find patterns or build the model (**Analytics**)
  - finally, evaluate the model and visualise results (**Evaluation and Visualisation**)

Data representation

- Text data
  - Without tools, it’s difficult for humans to analyse and interpret larges volumes of data
  - ML requires data to be described by attributes or parameters prior to learning a model

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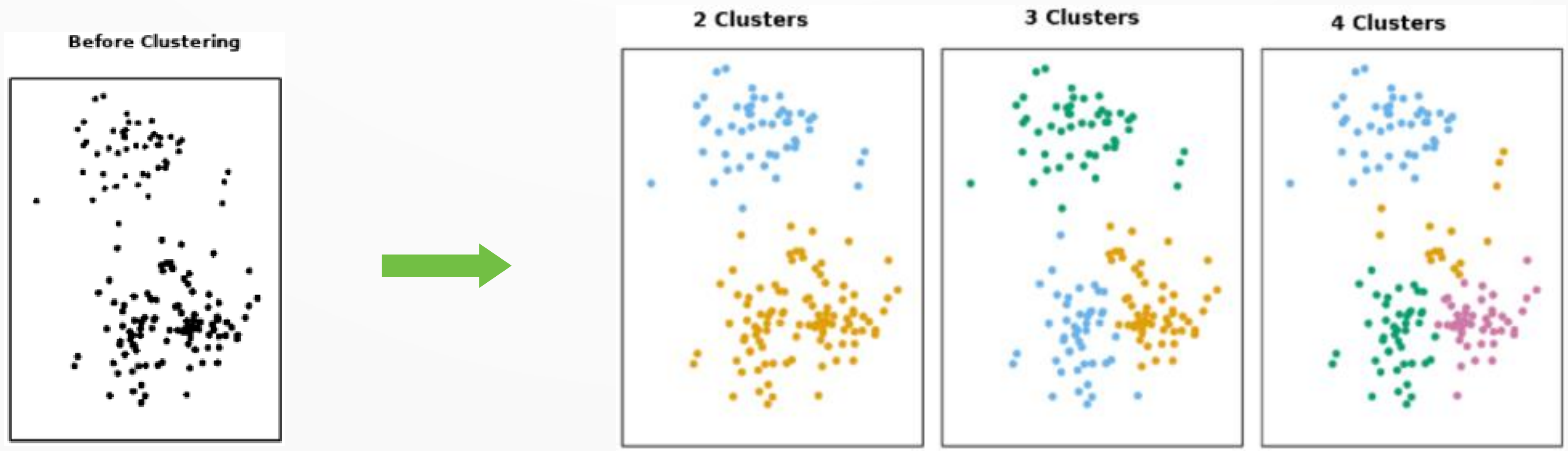
- Number of vowels
- Frequency of a given set of words
- Length of the document
- Set of repetitive words
- Frequency of words
- Number of sentences
- Number of adjectives
- Number of positive and negative words

Data representation...

- Image data
  - build a system able to identify if a given image is from outdoors or not
  - needs to be represented in a vector of features
  - consider a image divided into $9 \times 15 = 135$ blocks
  - For these blocks we can compute – Mean, Variance, radiant, other statistics
  - p features per block leads to
    - **135p** features per image
    - for n images, the size of Feature Matrix is **135p×n**

ML Type - Unsupervised learning

- How do you find the underlying structure of a dataset which is unlabelled?
- Popular approaches - **Clustering** (similarity-based)
  - the process of grouping similar points together
  - gives insight into underlying patterns of different groups



ML Type - Unsupervised learning...

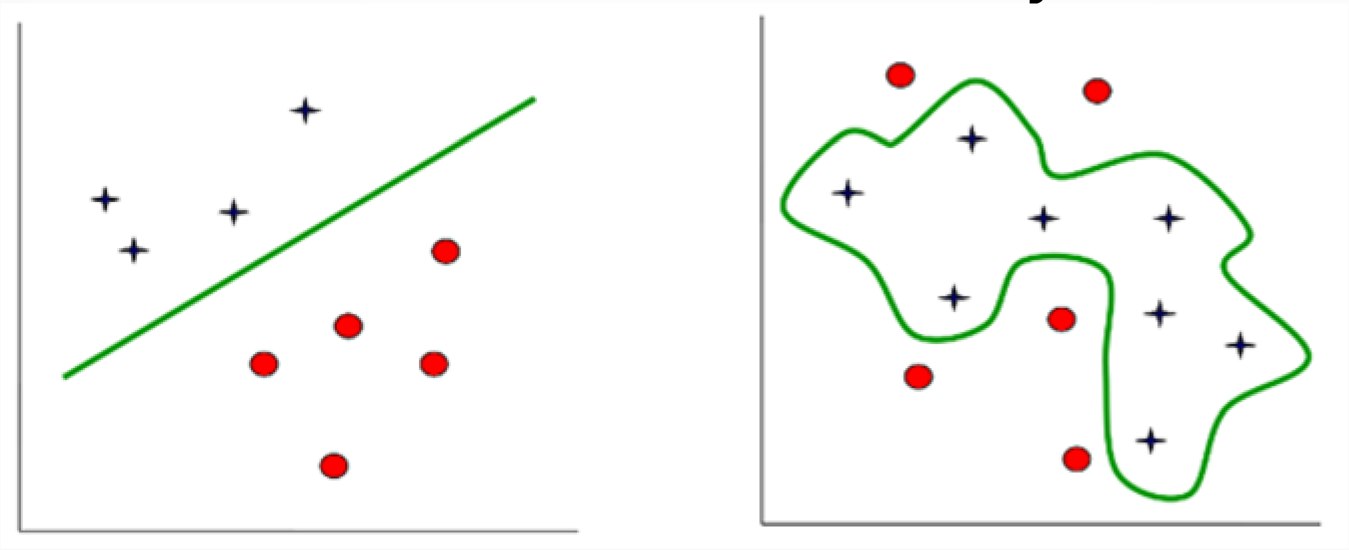
- Common examples -
  - Data understanding and visualization
  - Anomaly detection
  - Information retrieval
  - Data compression (reduction)

ML Type - Supervised learning

- "Learn a function (model) from data to relate the inputs with outputs."
- In supervised learning, the training data includes output information (labels/targets)
- **Target function**: $f: X \rightarrow Y$
- **Examples**: It is in the form of (x,y), denoted as $(x1,y1)$, ..., (xn,yn)
- **Hypothesis** $g: X \rightarrow Y$ such that $g(x)=f(x)$
  - x = set of attribute values
  - y = discrete label (*classification*), real valued number (*regression*)

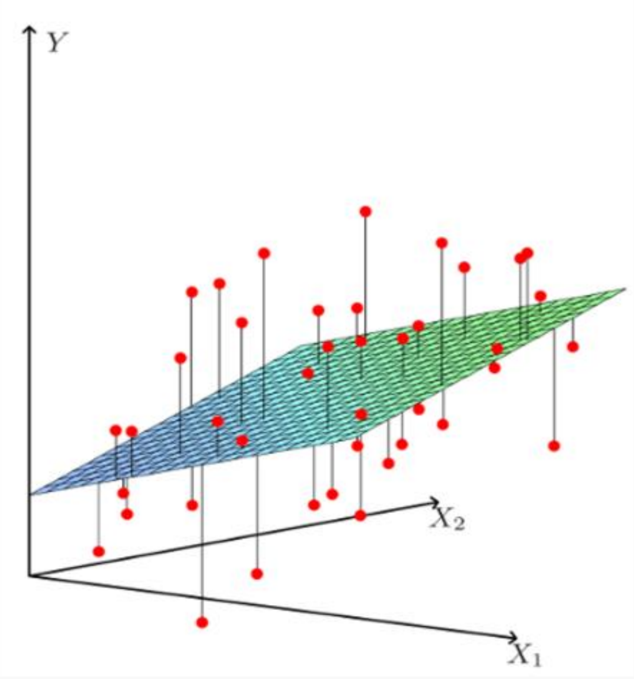
ML Type - Supervised learning..

- Classification problem
  - with two classes, decision boundaries are a hyper-surface that partitions data space into two sets
  - each of these sets represents one of the classes
  - linear vs non-linear decision boundary



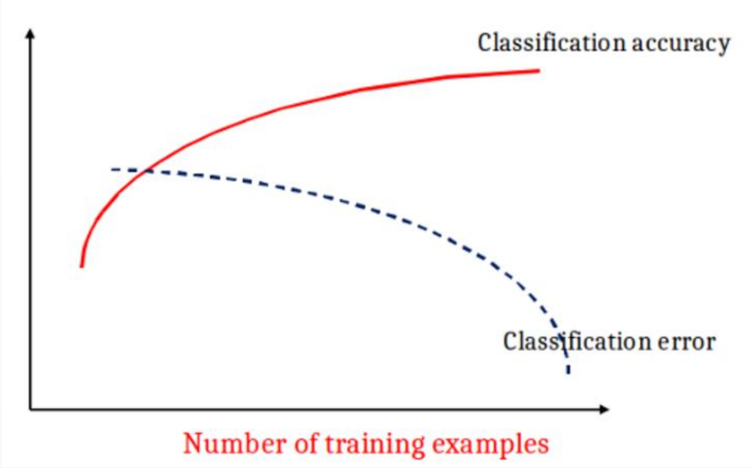
ML Type - Supervised learning...

- Regression problem
  - to examine the relationship between response variables and one or more predictor variables
  - examination can result in a hyperplane, representing the regression analysis
  - regression problem in 2 dimensions



Model assessment and adjustment

- Model evaluation
  - to determine if it will do a perfect job of predicting the labels on new and future test data
    - randomly split examples into a training set and test set
    - use training set to learn a model
    - evaluate the model using test set and a measurement (such as accuracy of prediction)
    - repeat for different random splits and average results
    - more training data, more accuracy



Model assessment and adjustment...

- Model selection
  - how to find the BEST model (hypothesis)?
  - There are often many knobs (parameters and hyper-parameters) that we can use to vary its fitness to the data
  - effective ways in which people approach this problem
    - look at averaged evaluation score on many random test sets
    - cross-validation (train using one set and test on the other, rotate them) etc.
  - be aware of *Over-fitting*

Summary

Data

Model

Decision

Thank You.