

Week 1 Lecture 1

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What is Data Science?

Data Science is;

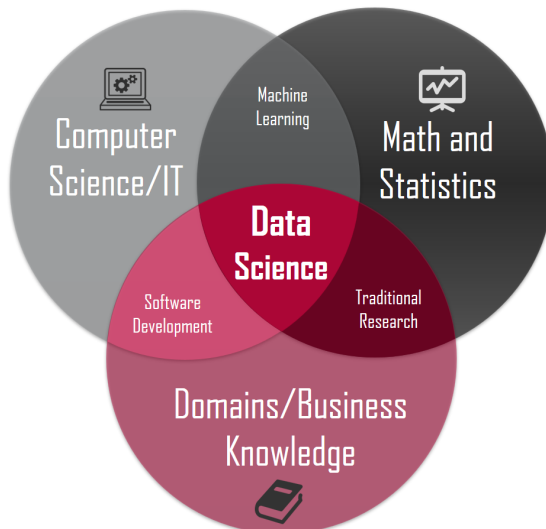
- Statistics?
- Machine Learning?
- Big Data?

Data Science is the extraction of knowledge from large volumes of *structured* or *unstructured data*. It has application in Science, Business, Social Science, wherever data is collected. . .

We will look at some areas of Data Science.

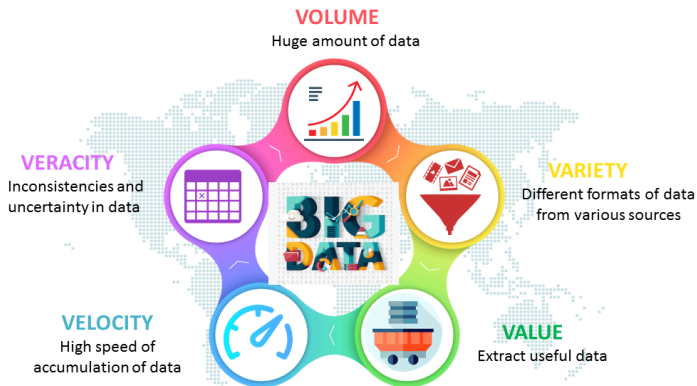
Data Science

From *towardsdatascience.com*



Big data

From *eureka.co*



Jobs in Data Science

From *indeed.com*

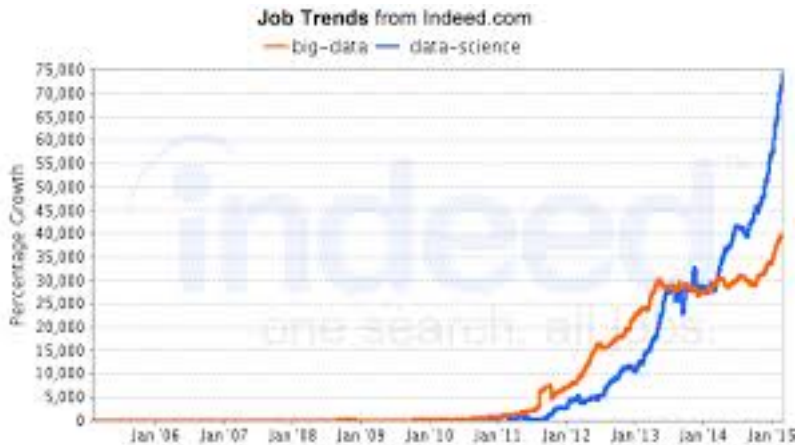


Figure 3:

Jobs in Big Data Analytics

From *indeed.com*



Figure 4:

Data Science or Statistics

Data Science uses a blend of methods from *statistics*, *computing* and *machine learning* to extract information from data. It is **LESS** concerned about *p-values* and *hypothesis testing*. But these have uses.

Typical data has multiple measurements (*variables*) on several *observations*.

For example, **Fisher's Iris data** - measured the species, sepal lengths and widths and petal lengths and widths for 150 iris flowers.

Types of Data

Structured data

- *Quantitative* or *Numeric data* - height, weight, salary, sales dollars
- *Qualitative* or *Factor/Categorical data* - Ethnicity, product code, hair colour

Structured data is usually a series of measurements on distinct observational units, and **can be arranged as a table**.

Unstructured data

- Images - Flickr
- Videos - Youtube
- Text - eg. Twitter

Unstructured data usually **DOES NOT** look like a nice table, but contains information non-the-less. Often the first step in analysing unstructured data is to extract information to make structured data.

Big Data

You've no doubt heard the hype around “*Big Data*”.

Data from multiple sources that can be linked to form a complete (or extensive) picture of an individual?

This is probably harder than it looks.

However, many areas now have access to large amounts of data or linked “big data”.

Examples of Data Science problems

- Predict the outcome of marketing campaigns
- Model (anticipate) demand for a product or service
- Model (understand) the relationship between stress and working conditions
- Recommend similar products to previous purchases
- Find likely fraudulent insurance claims
- Understand structures in groups or networks

Supervised versus Unsupervised

Data Science problems generally split into *supervised* and *unsupervised* problems.

Supervised learning involves data where each observational unit has one special variable - the *output/outcome*.

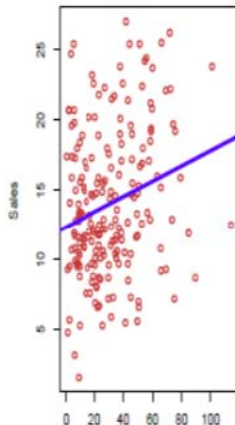
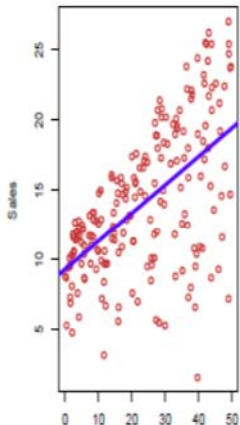
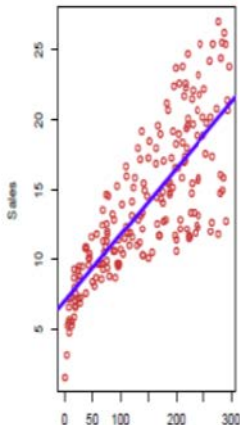
- Patients survive a treatment or not
- Customer spend on a certain product

Unsupervised learning **DOES NOT** have a special variable, we are interested in discovering patterns.

- **Fraud** - finding observations that don't fit the usual pattern
- **Segmentation** - grouping a market into more homogeneous groups

Supervised Learning

- In supervised learning, we have a *response* or *outcome*.
- We are interested in understanding or predicting the relationship between the output and several inputs.



Supervised Learning

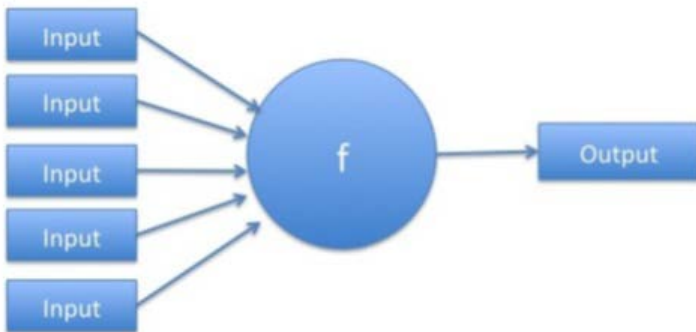


Figure 6:

We want to learn about f from a sample of inputs and outputs

Supervised Learning

Starting point:

- Outcome measurement Y (also called *dependent variable*, *response*, *target*).
- Vector of p predictor measurements X (also called *inputs*, *regressors*, *covariates*, *features*, *independent variables*).
- In the *regression problem*, Y is *quantitative* (e.g price, blood pressure).
- In the *classification problem*, Y takes values in a finite, unordered set (survived/died, digit 0-9, cancer class of tissue sample).
- We have *training data* $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$. These are *observations* (*examples*, *instances*) of these measurements.

Supervised Learning

- In Mathematical terms we would write;

$$E(Y) = f(X_1, X_2, \dots, X_p)$$

- y is the *output* and the x 's are the *inputs*.
- We **DO NOT** model y but its *expected value*.
- Even for the same set of inputs, the output may vary;
measurement error, random variation, etc.
- So, $E(y)$ is the expected value or average value, for a given set of inputs.
- Any difference between the expected value and an observed value is called *noise*.

Supervised Learning

The simplest form of supervised learning is *simple linear regression*

$$E(Y) = a + bX$$

There is one input (X) and one output, and two parameters, a and b . A sample of data; input/output pairs, would be used to estimate the parameters.

The results could then be used to;

- Make inferences about the relationship between input and output.
- Make prediction of future outputs for a given input value.

Bias and Variance

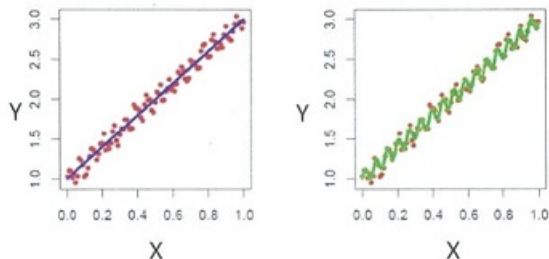


Figure 7:

Both graphs have the same Y and X . The left graph has a *very simple smooth* f , the right a *more complex* f . Modelling must choose the right form of f as well as fitting the actual f (*estimating parameters*).

Bias and Variance

Generally, fitting complex functions results in *more variance* - there is more uncertainty around the fitted parameters.

Fitting simple functions can result in *more bias* - there is systematic differences between the fitted and true functions.

Both bias and variance contribute to *prediction accuracy*.

Prediction Accuracy and Interpretation

Prediction Accuracy refers to how closely we can predict a future observation.

Often it must be estimated from the same sample that was used to fit the function (**Not good practice**).

- *Training data set* is used to build the model
- *Validation data set* is used to validate the model accuracy
- *Testing data set* is used to measure prediction accuracy.

More complex functions sometimes have better prediction accuracy but the results can be hard to interpret.

Regression vs. Classification

When the output is a *numeric variable*, supervised learning is sometimes referred to as *regression*. Some examples of regression methods are;

- (Simple) Linear Regression
- Generalised Linear Models
- Neural Networks

When the output is a *class* or *factor variable*, supervised learning is *classification*. Some examples of classification methods are;

- Nearest Neighbours
- Generalised Linear Models (Logistic Regression)
- Support Vector Machines

Unsupervised Learning

When there is **NO** variable that can be considered an output or special, then ***unsupervised learning*** may be appropriate. Unsupervised learning looks for patterns amongst the input variables.

Methods can range from;

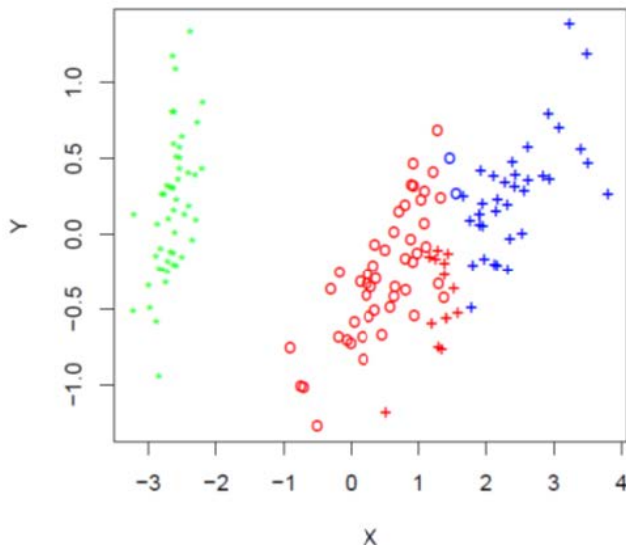
- **Visualisation and dimension reduction** (eg: PCA)

for a large number of inputs finding combinations of variables that can be plotted to display features in the data.

- **Clustering** (eg: kmeans, hierarchical clustering)

using automated techniques to find groups in the data.

Clustering the Iris data



Unsupervised Learning

- No outcome variable, just a set of predictors (features) measured on a set of samples.
- Objective is more fuzzy and groups of samples that behave similarly, and features that behave similarly, and linear combinations of features with the most variation.
- Difficult to know how well you are doing.
- Different from supervised learning, but can be useful as a *pre-processing step* for supervised learning.

This Unit

Supervised Learning:

- Linear models: Simple Linear Regression and Multiple Linear Regression
- Classification: Logistic Regression, Discrimination and kNN
- Classification and Regression Trees (Decision Trees)
- Support Vector Machines

Unsupervised Learning:

- Dimension reduction: Principal Component Analysis
- Clustering: K Means and Hierarchical

Unstructured Data:

- Text Mining (**NOT COVERED**)

Resampling and Error estimation

Visualisation

Objectives

On the basis of the training data, we would like to:

- Accurately *predict* unseen test cases.
- *Understand* which inputs affect the outcome, and how.
- *Assess* the quality of our predictions and inferences.

Philosophy

- It is important to understand the ideas behind the various techniques, in order to know how and when to use them.
- One has to understand the simpler methods first, in order to grasp the more sophisticated ones.
- It is important to accurately assess the performance of a method, to know how well or how badly it is working [**simpler methods often perform as well as fancier ones!**]
- This is an exciting research area, having important applications in science, industry and finance.
- *Statistical learning* is a fundamental ingredient in the training of a modern data scientist.

TEXTBOOK

Lecture notes are based on the textbook,
for further reference refer;

Prescribed Textbook

- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: with Applications in R Springer.