Birkbeck
UNIVERSITY OF LONDON

Big Data Analytics

Session 1a

Big Data and Data Analytics

Contact details

- Teacher: Tingting Han
  - Email: tingting@dcs.bbk.ac.uk
  - Room: MAL155
  - Office hours: By appointment
- Teaching Assistants:
  - Muawya Eldaw, Alan Mosca, Manni Singh
- Moodle
  - Course materials
  - Coursework submission dropboxes
  - Announcements
  - Discussions

To pass module

- Coursework (20%)
  - 2 coursework with 10% each
  - Deadlines see next slides
  - Don’t wait till the last minute

- In-class test (80%)
  - In term 3
  - 3 hours

- Pass mark: 50%

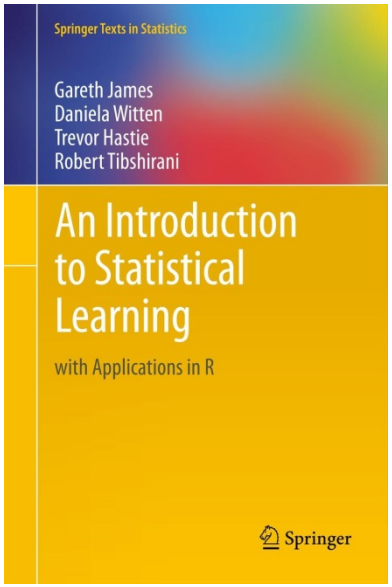
Tentative Schedule

Birkbeck UNIVERSITY OF LONDON

Session	Content	Coursework
1 (02/10)	Introduction	1st CW due: 18/11 Sunday 9pm Cut-off deadline: 02/11 Sunday 9pm Getting to know R Basic Statistics Linear Regression Logistic Regression Cross Validation
2 (09/10)	Basic Statistics + Linear Regression	
3 (16/10)	Linear Regression	
4 (23/10)	Logistic Regression	
5 (30/10)	Cross Validation	
6 (06/11)	Decision Trees	
7 (13/11)	Ensemble Methods	2nd CW due: 6/1 Sunday 9pm Cut-off deadline: 20/01 Sunday 9pm Decision trees Ensemble Methods SVM Clustering Model Evaluation
8 (20/11)	SVM	
9 (27/11)	Clustering	
10 (04/12)	Dimension Reduction	
11 (11/12)	Applications	

Textbook

- An Introduction to Statistical Learning: with Applications in R



- Available at http://www-bcf.usc.edu/~gareth/ISL/
  - Book, datasets and R code
- A previous more advanced book:
  - The Elements of Statistical Learning (Hastie, Tibshirani and Friedman, 2nd edition)

Birkbeck
UNIVERSITY OF LONDON

Dan Ariely

Professor of Psychology and Behavioral Economics
Duke University

Big data is like teenage sex:

everyone talks about it,
nobody really knows how to do it,
everyone thinks everyone else is doing it,
so everyone claims they are doing it…

Outline

- Big Data
  - Big
  - Data

- Data Analytics

Outline

- Big Data
  - Big
  - Data
- Data Analytics

Big Data Everywhere!

Birkbeck
UNIVERSITY OF LONDON

- The world is creating ever more data, and it's a mainstream problem.

Where does the data come from?

Big Data Everywhere!

Birkbeck UNIVERSITY OF LONDON

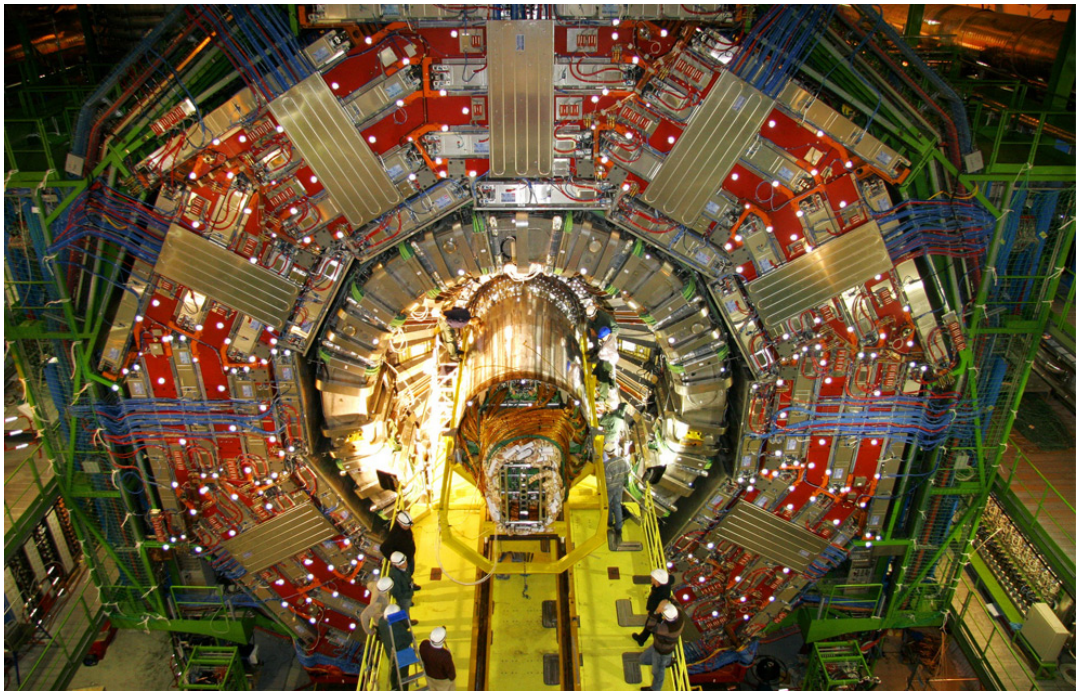
- The world is creating ever more data, and it's a mainstream problem.
  - Science
    - Databases from astronomy, genomics, environmental data, transportation data, …
  - Humanities and Social Sciences
    - Scanned books, historical documents, social interactions data, new technology like GPS, …
  - Business & Commerce
    - Corporate sales, stock market transactions, airline traffic, amazon, ebay…
  - Entertainment
    - Internet images, Hollywood movies, MP3 files, …
  - Medicine
    - MRI & CT scans, patient records, …

Example

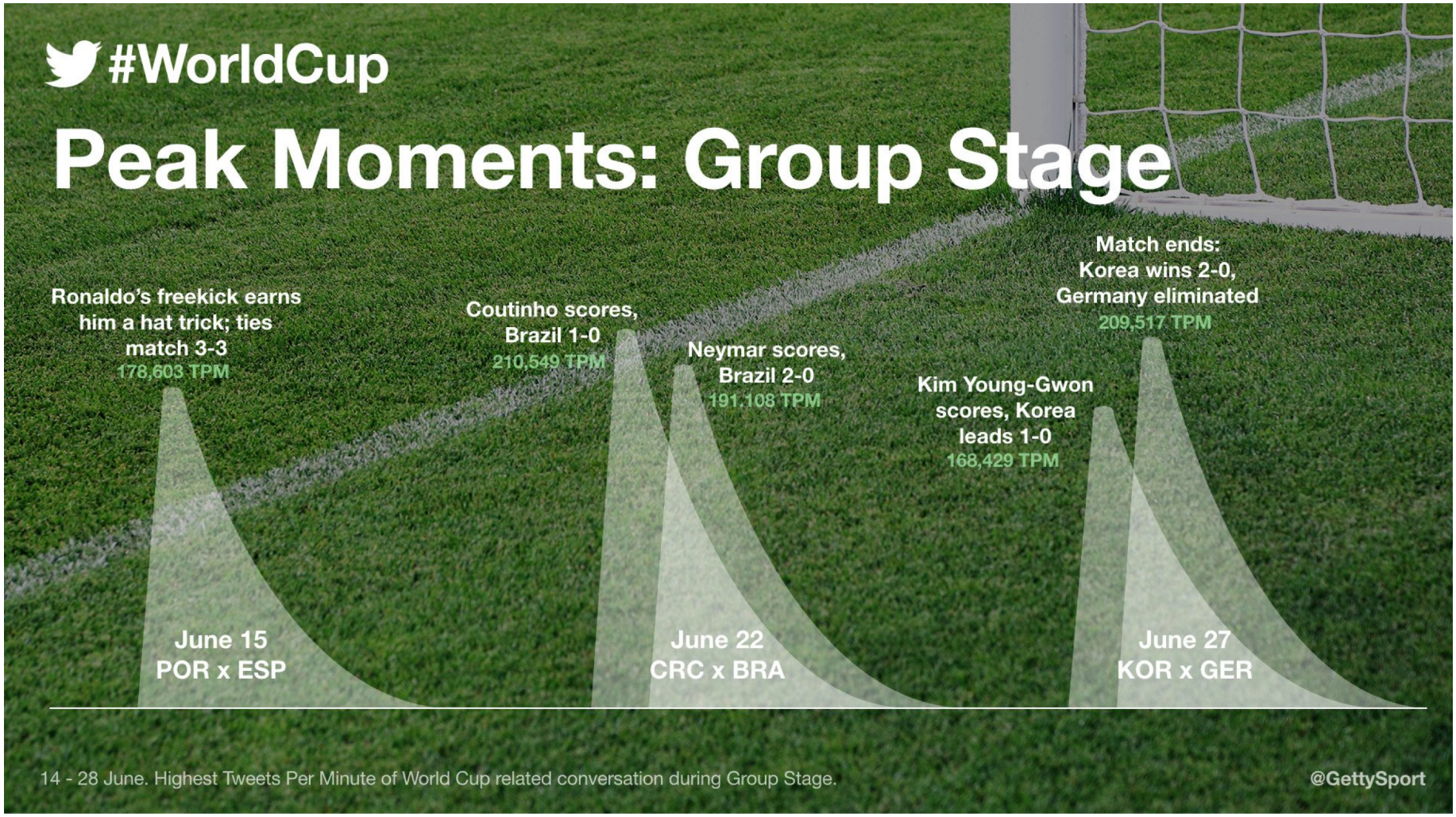
- US drone aircraft sent back 24 years worth of video footage in 2009

Example

- CERN's Large Hadron Collider (LHC) generates 40 terabytes/second
  - CERN: The European Organisation for Nuclear Research (Switzerland)
  - LHC: World's largest and most powerful particle accelerator
  - Terabytes (TB): all the catalogued books in America's library of Congress total 15TB



Example


#WorldCup
Peak Moments: Group Stage
Ronaldo's freekick earns him a hat trick; ties match 3-3
178,603 TPM
Coutinho scores, Brazil 1-0
210,549 TPM
Neymar scores, Brazil 2-0
191,108 TPM
Kim Young-Gwon scores, Korea leads 1-0
168,429 TPM
Match ends: Korea wins 2-0, Germany eliminated
209,517 TPM
June 15
POR x ESP
June 22
CRC x BRA
June 27
KOR x GER
14 - 28 June. Highest Tweets Per Minute of World Cup related conversation during Group Stage.
@GettySport

Example

- Around 30 billion RFID tags produced per year
  - RFID: radio frequency identification

A Quick Primer on Data Sizes

Birkbeck
UNIVERSITY OF LONDON

Data inflation

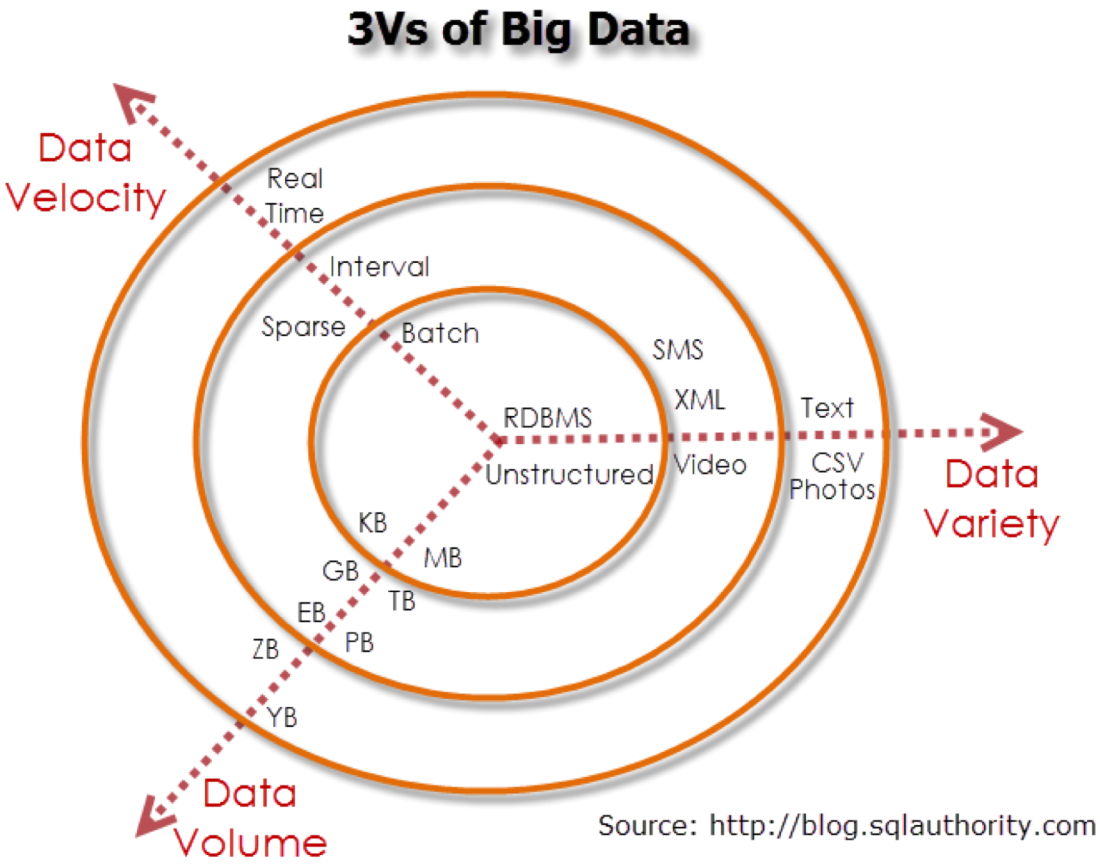
Unit	Size	What it means
Bit (b)	1 or 0	Short for "binary digit", after the binary code (1 or 0) computers use to store and process data
Byte (B)	8 bits	Enough information to create an English letter or number in computer code. It is the basic unit of computing
Kilobyte (KB)	1,000, or 2^{10}, bytes	From "thousand" in Greek. One page of typed text is 2KB
Megabyte (MB)	1,000KB; 2^{20} bytes	From "large" in Greek. The complete works of Shakespeare total 5MB. A typical pop song is about 4MB
Gigabyte (GB)	1,000MB; 2^{30} bytes	From "giant" in Greek. A two-hour film can be compressed into 1-2GB
Terabyte (TB)	1,000GB; 2^{40} bytes	From "monster" in Greek. All the catalogued books in America's Library of Congress total 15TB
Petabyte (PB)	1,000TB; 2^{50} bytes	All letters delivered by America's postal service this year will amount to around 5PB. Google processes around 1PB every hour
Exabyte (EB)	1,000PB; 2^{60} bytes	Equivalent to 10 billion copies of *The Economist*
Zettabyte (ZB)	1,000EB; 2^{70} bytes	The total amount of information in existence this year is forecast to be around 1.2ZB
Yottabyte (YB)	1,000ZB; 2^{80} bytes	Currently too big to imagine

Source: *The Economist*

The prefixes are set by an intergovernmental group, the International Bureau of Weights and Measures. Yotta and Zetta were added in 1991; terms for larger amounts have yet to be established.

Characteristics of Big Data

- Big data spans four dimensions:
  - Volume, Velocity, Variety, and Veracity
- The first 3 Vs definition is widely used in much of the industry.
- The new V 'Veracity' is introduced by some organisations



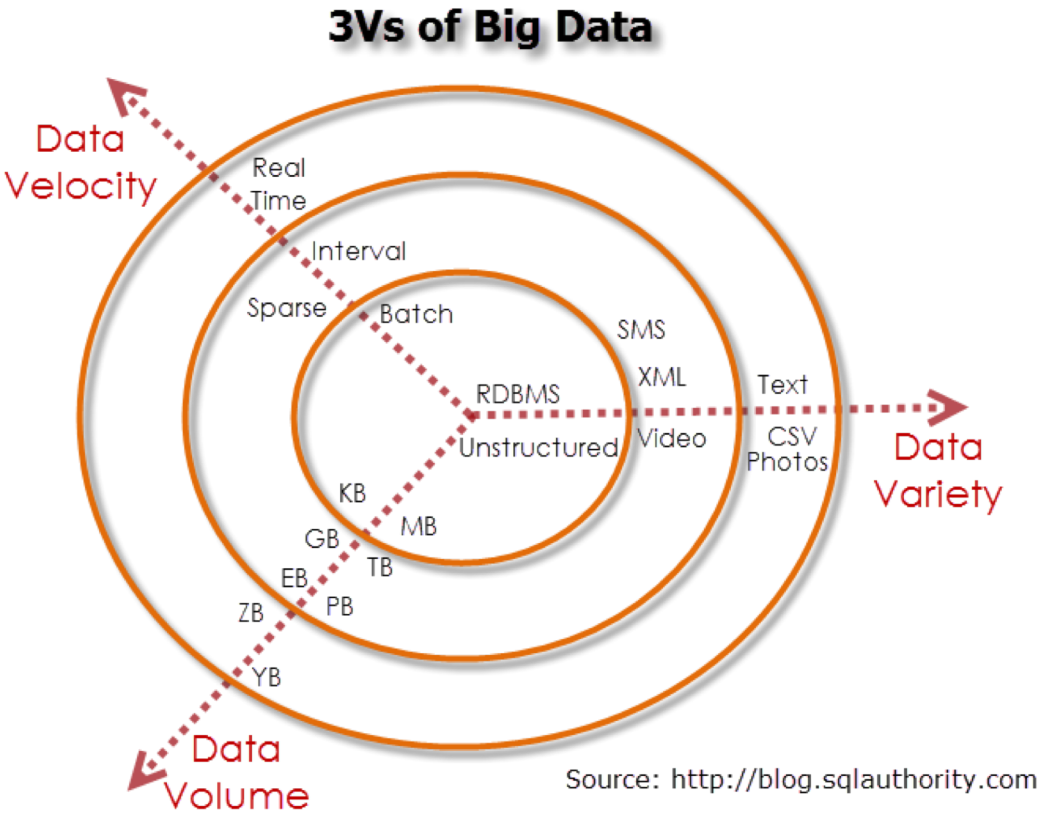
Volume

- **Volume**:

  "Data size."

  – Enormous volumes of data

  – The volume of data is not as much the problem as other V's.



Velocity

- **Velocity**:

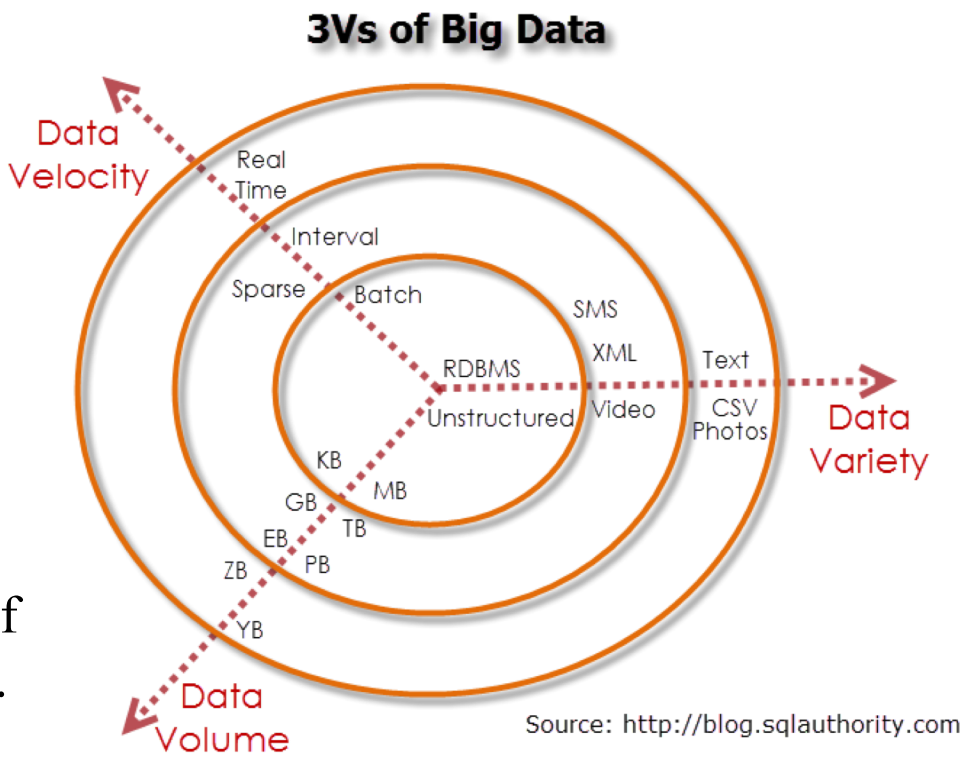
  "Speed of change."

  – The flow of data is massive and continuous.

  – There are time-sensitive processes such as
    - Stock trading
    - Fraud catching

  – Make valuable real-time decision if you are able to handle the velocity.

  – Sampling data can help deal with velocity



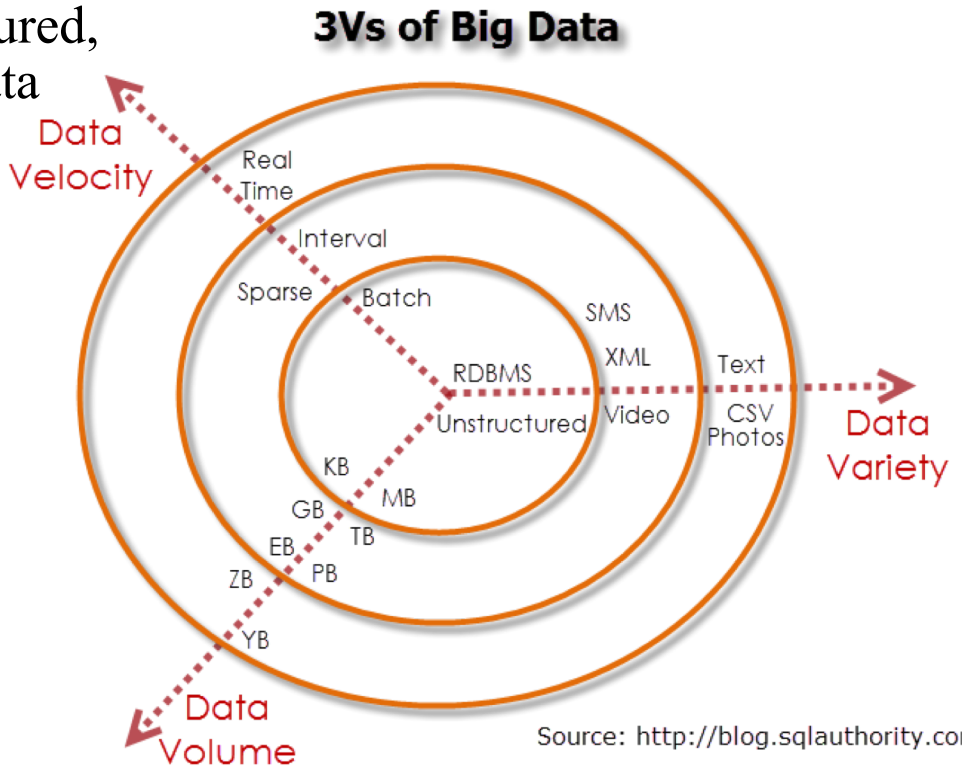
Variety

- **Variety**:

  "Different forms of data sources"

  – Big data is any type of data – structured, semi-structured and unstructured data such as

    - Relational Data
      - Tables/Transaction/Legacy Data
    - Text Data (Web)
    - Semi-structured Data (XML)
    - Graph Data
      - Social Network
      - Semantic Web (RDF)
      - …
    - Streaming Data
      - You can only scan the data once



Veracity

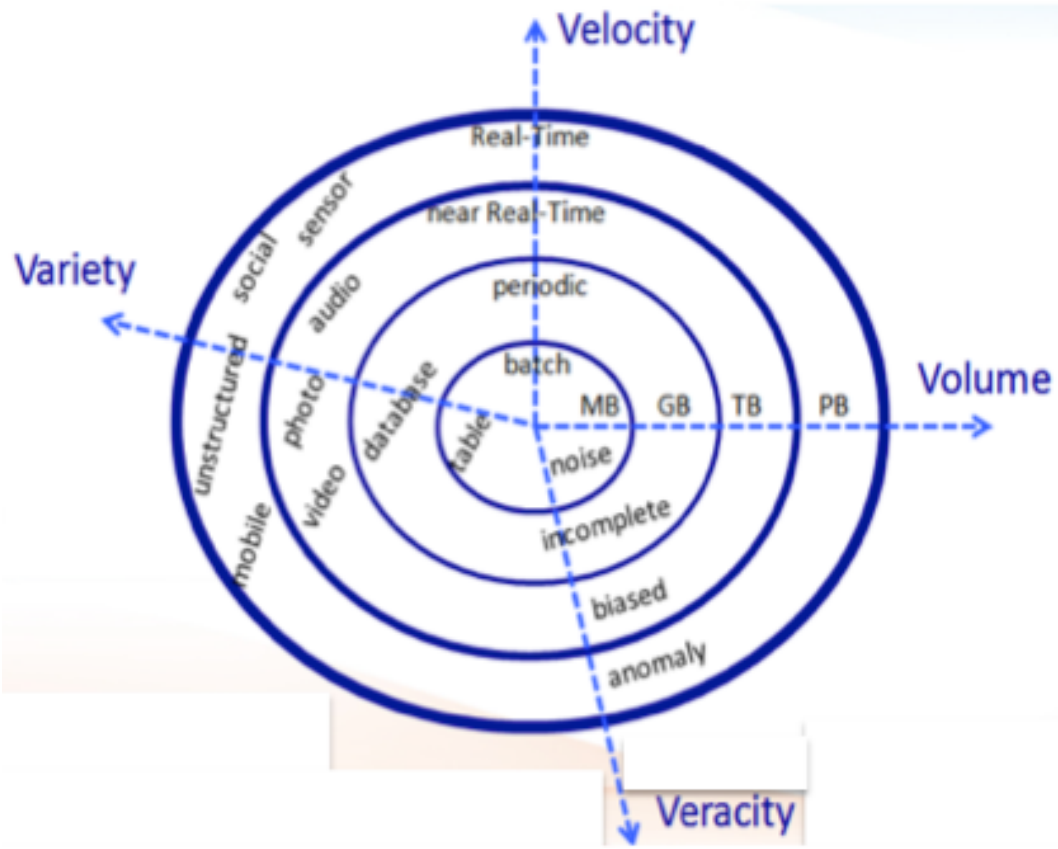
- **Veracity:**

  "Uncertainty of data"

–Refers to the biases, noise, uncertainty, incompleteness and abnormality in data.

–Is the data that is being stored, and mined meaningful to the problem being analysed?

–The biggest challenge in data analysis: to keep data clean



Outline

- Big Data
  - Big
  - Data

Data is getting larger and more diverse.

- Data Analytics

Goal of Data Science

Birkbeck
UNIVERSITY OF LONDON

Turn data into data products

Data Product -- Twitter

- Text Analysis – Spam Filter/Similarity Search
- User Sentiment/Satisfaction/Feedback
- News Breakout
- Trend and Topics

335 million users as of 2018, generating over 500 million tweets and handling over 2.1 billion search queries per day

Data Product -- Netflix

- Personalised movie ratings
- Movie recommendations
- Similar movies

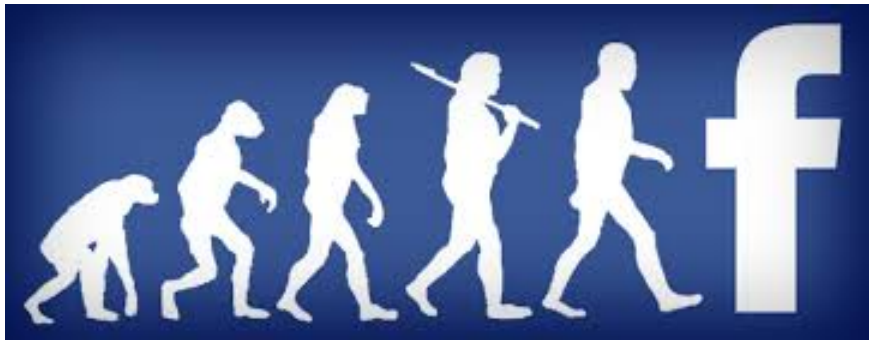
- Movie categories
  - e.g., 80's movie with a strong female lead, Kung Fu movies

BlockBuster is out of the business …

Data Product – LinkedIn/Facebook

- People you may know
- Applications you may like
- Jobs/Events you might be interested
- Classifier for bad users and bad content
- With high accuracy, Facebook can guess whether you are single or married

Who does not have LinkedIn or Facebook Account?



Data Product -- Google

- Web search (40,000 search queries per second)
- News recommendation engine
- Google map
- Google ads
- Google analytics

Still the hottest IT company to work for now –
Microsoft of the 90's, IBM of the 70's

The Sexiest Job of the Century?

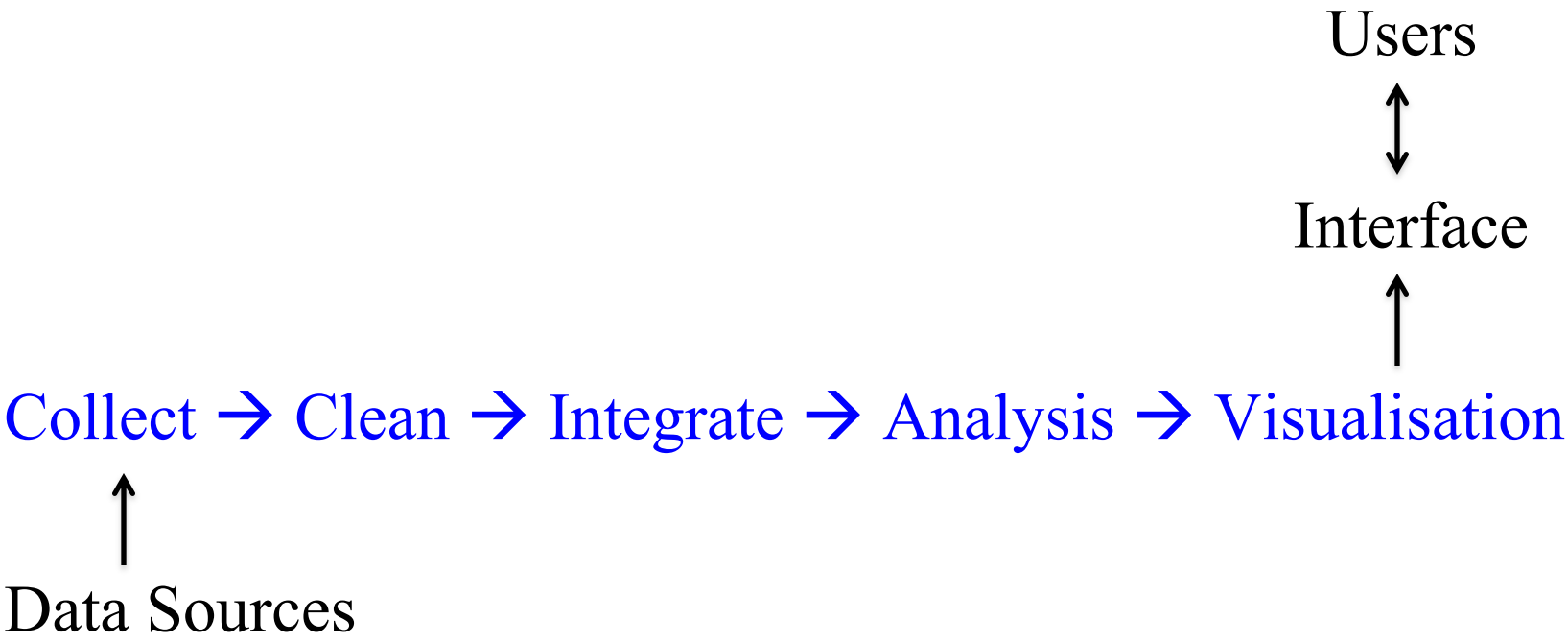
Birkbeck UNIVERSITY OF LONDON

- Data Scientist!

But…

- This job title has almost as much ambiguity as the term “big data”.

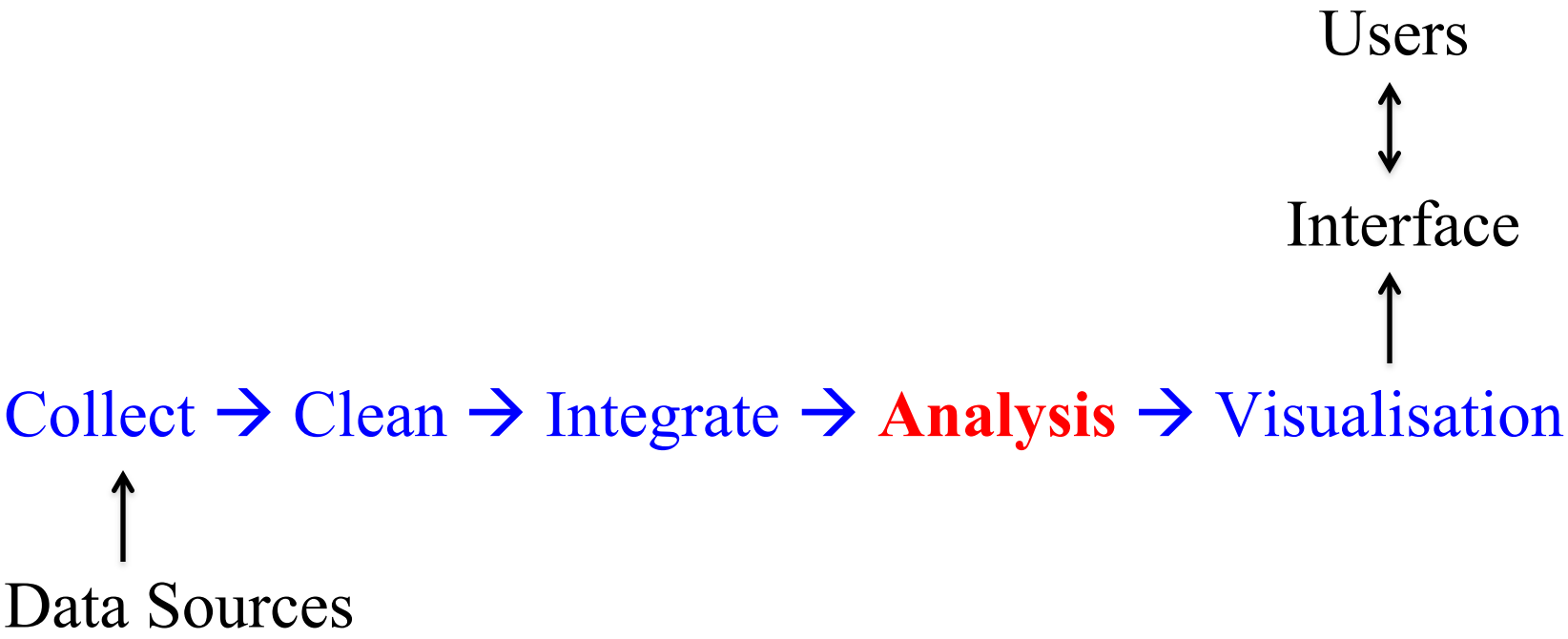
The Life of Data



But...

- This job title has almost as much ambiguity as the term “big data”.
- In job descriptions, a “data scientist” might do
  - Statistical analysis
  - Query and reporting
  - Database administration
  - Data warehouse management
  - Data integration
- The kind of tools a “data scientist” might need to know:
  - Hadoop, Pig, Hive, Python (typical big data manipulation tools);
  - SAS, SPSS, R (typical statistical analysis tools);
  - SQL, Business Objects, Cognos (typical query and reporting tools);
  - Excel (capable of a lot, but typically used for small-scale reporting & financial analysis);
  - Teradata, Informatica (data warehouse and loading tools).

The Life of Data



But…

Birkbeck UNIVERSITY OF LONDON

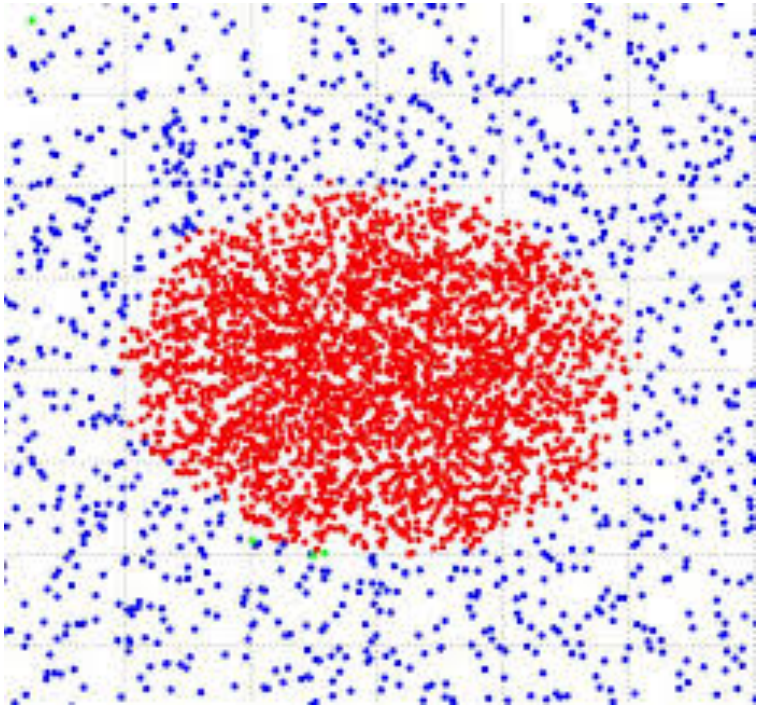
- This job title has almost as much ambiguity as the term “big data”.
- In a job description, a “data scientist” might do
  - **Statistical analysis**
  - Query and reporting
  - Database administration
  - Data warehouse management
  - Data integration
- The kind of tools the “data scientist” might need to know:
  - Hadoop, Pig, Hive, Python (typical big data manipulation tools);
  - SAS, SPSS, **R (typical statistical analysis tools)**;
  - SQL, Business Objects, Cognos (typical query and reporting tools)
  - Excel (capable of a lot, but typically used for small-scale reporting & financial analysis)
  - Teradata, Informatica (data warehouse and loading tools).

Techniques in Data Analysis

Birkbeck
UNIVERSITY OF LONDON

- Statistics and Machine Learning
  - Data modeling
  - Inference
  - Prediction
  - Pattern recognition
  - …

- In this module, we will focus on statistical learning.



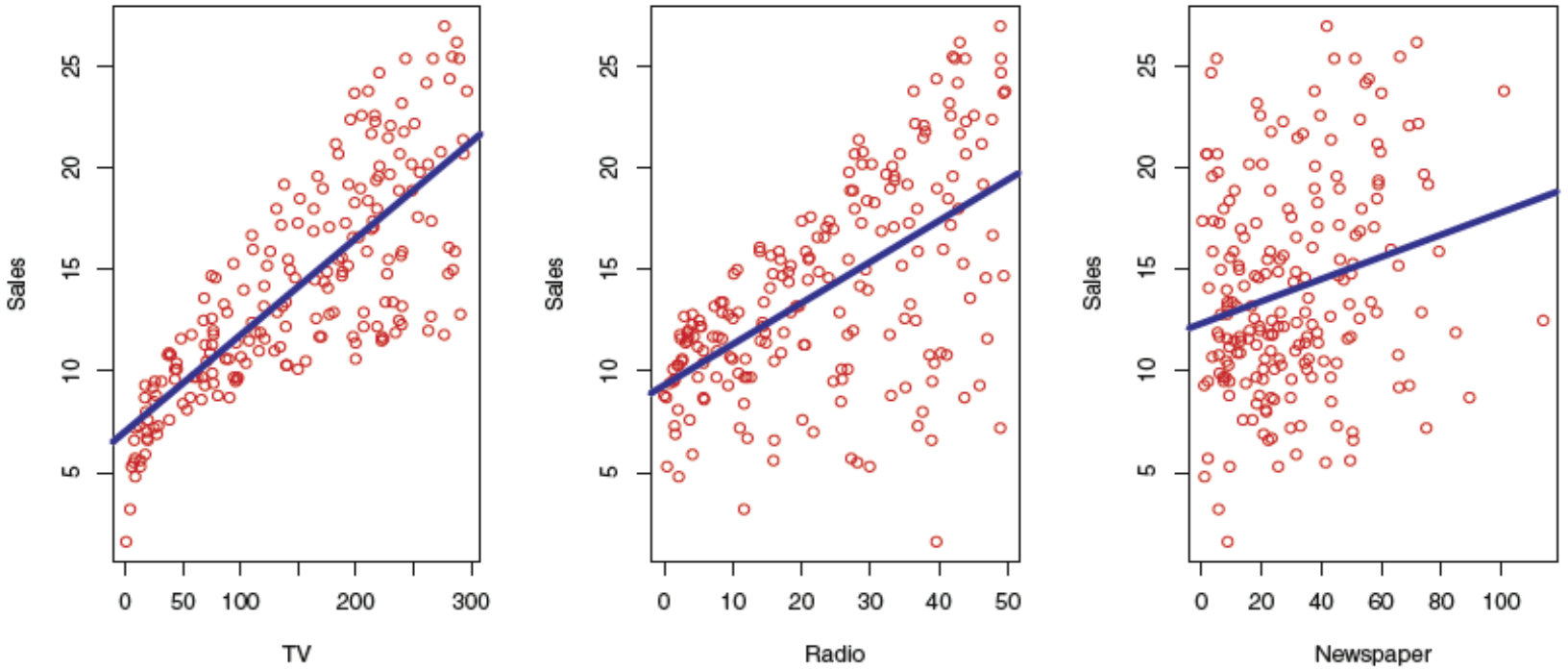
Outline

- Big Data
  - Big
  - Data
- Data Analytics
  - Statistical learning

Outline

- What is Statistical Learning?
  - Why estimate f?
  - How do we estimate f?
  - The trade-off between prediction accuracy and model interpretability
  - Supervised vs. unsupervised learning
  - Regression vs. classification problems

Advertising vs. Sales



- Is there an association between advertising and sales so that the company can adjust advertising budgets to increase sales?
  - Dataset:
    - sales in 200 markets
    - advertising budgets for 3 media in each market

What is Statistical Learning?

- Input variables $\mathbf{X} = (X_1, X_2, \ldots, X_p)$
  - Examples: TV budget, radio budget, newspaper budget
  - Predictors, independent variables, features, variables
- Output variable Y
  - Example: Sales
  - Response, dependent variables
- We believe there is a relationship between Y and at least one of the $\mathbf{X}$'s.
- We can model the relationship as

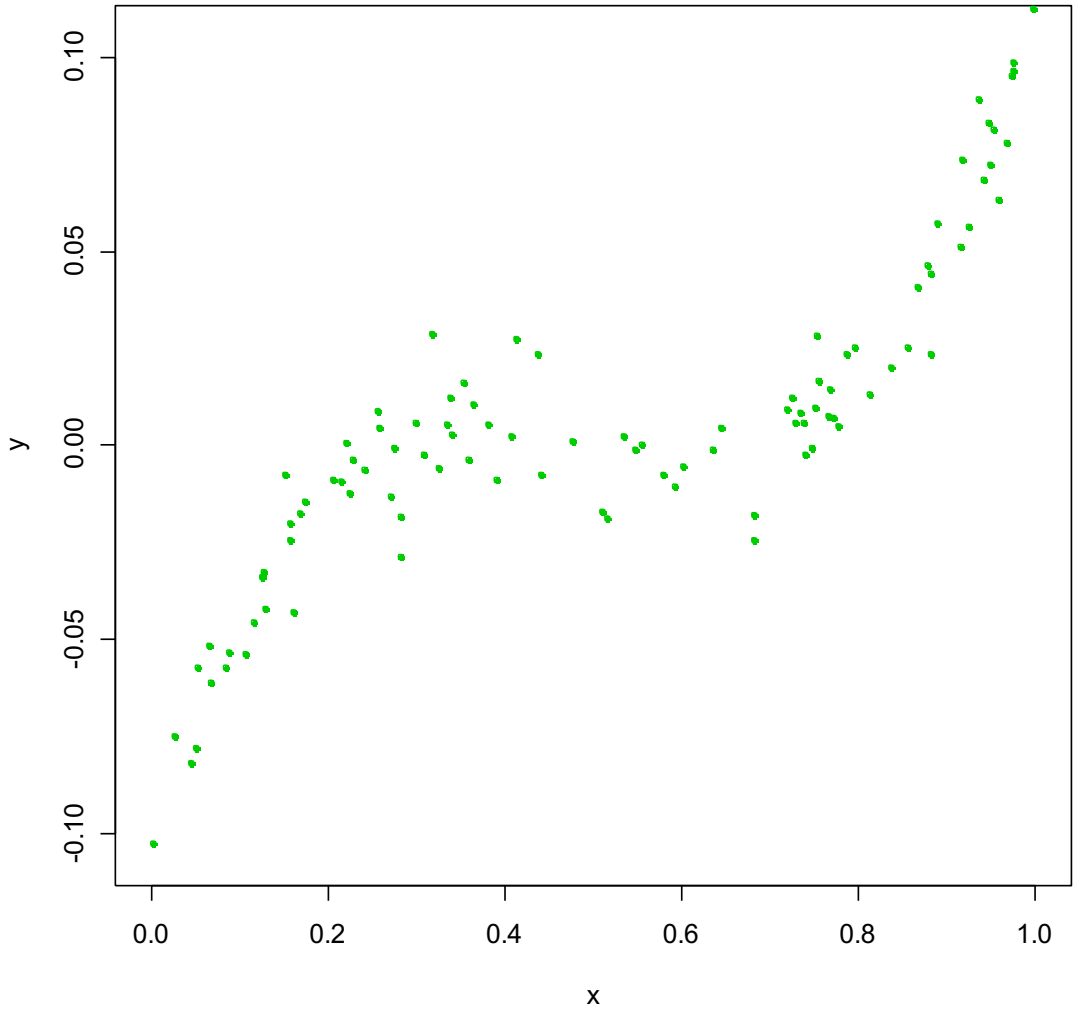
$$Y = f(\mathbf{X}) + \varepsilon$$

where f is an unknown function, and

ε is a random error that cannot be measured and is independent of $\mathbf{X}$.

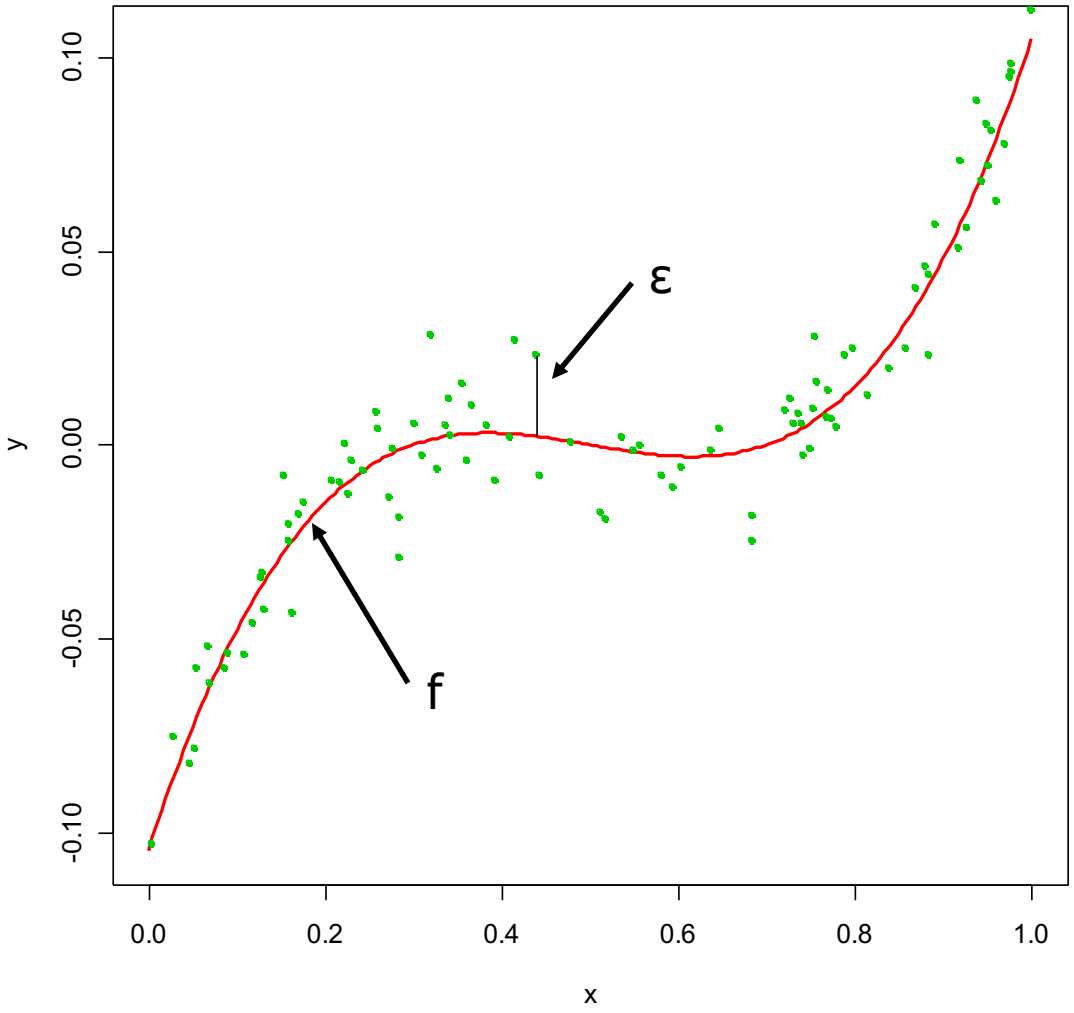
Irreducible error: no matter how well we estimate f, we cannot reduce the error introduced by ε.

A Simple Example



Green dots:
Observed values of x and y

A Simple Example



Green dots:
Observed values of x and y

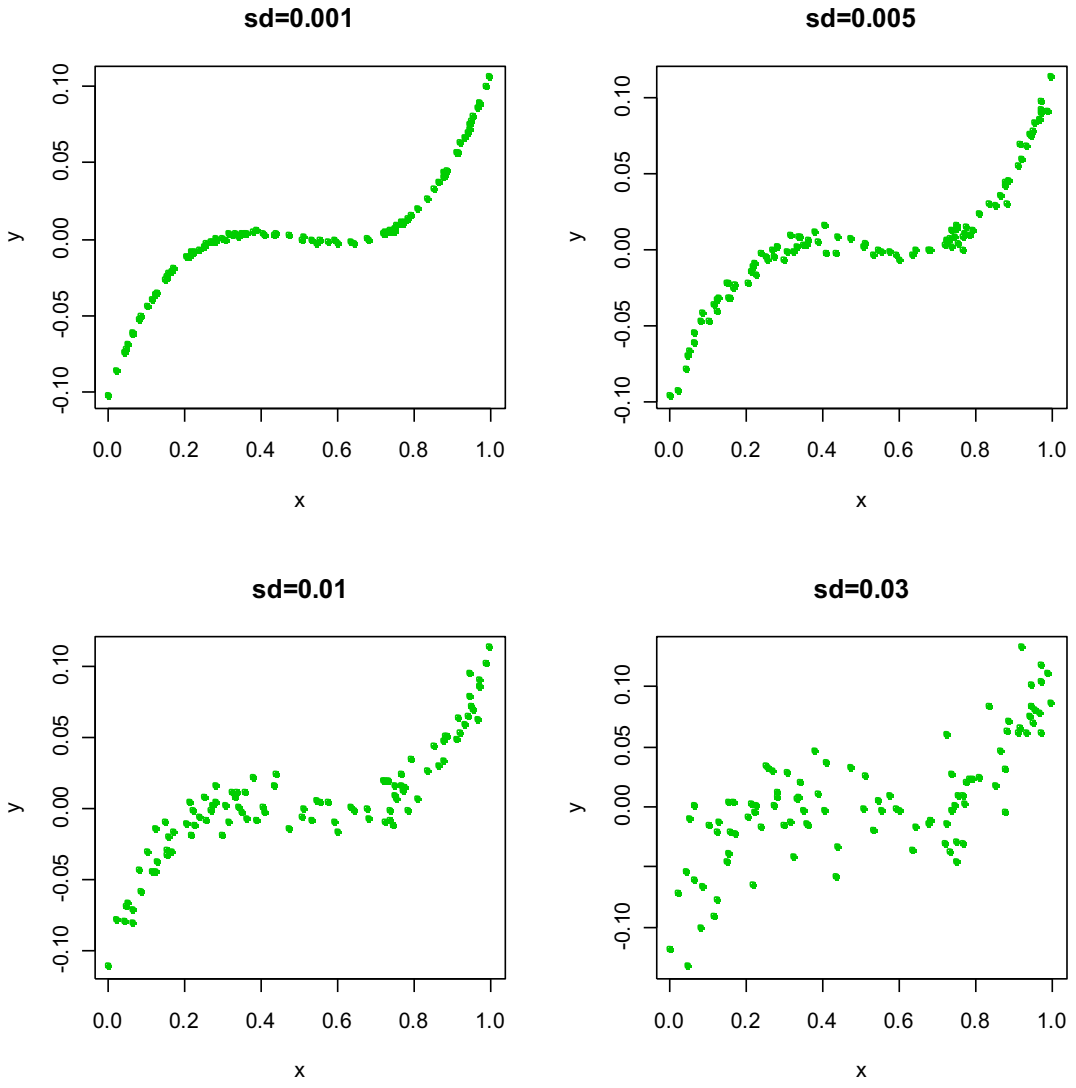
Red curve:
True underlying relationship between x and y

Black line:
The error ε associated with each observation

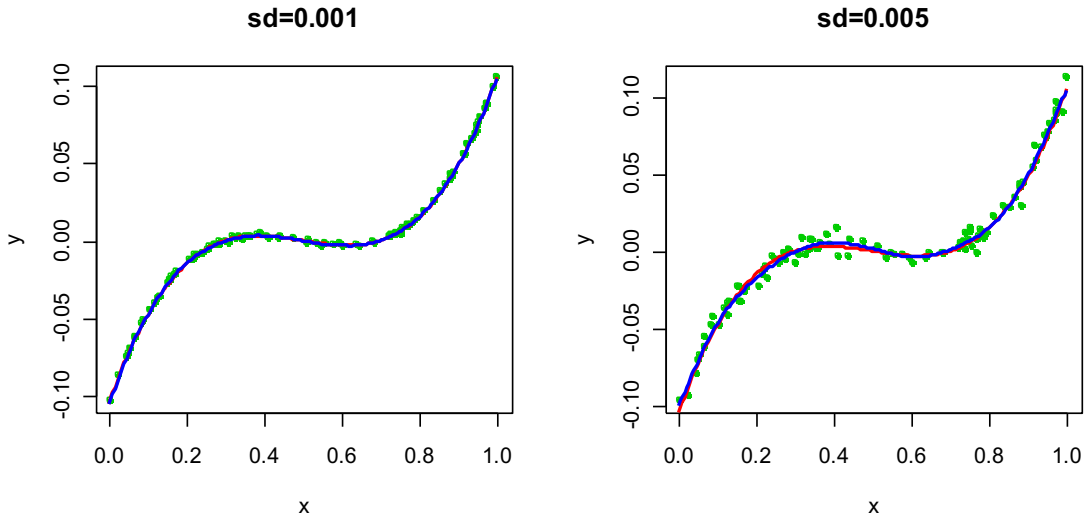
ε has a mean 0!

Different Standard Deviations

- Standard deviation measures the amount of variation from the average.
- The difficulty of estimating *f* will depend on the standard deviation of the ε's.



Different Estimates For *f*



Green dots:
Observed values of x and y

Red curve:
True underlying relationship between x and y

Blue curve:
Estimated relationship between x and y

Why Do We Estimate *f*?

- Statistical learning is all about how to estimate *f*.
  - The term refers to using the data to "learn" *f*.

- Why do we care about estimating *f*?
  - There are 2 reasons for estimating *f*
    - **Prediction**
    - **Inference**

Prediction

Birkbeck
UNIVERSITY OF LONDON

- If we can produce a good estimate for f (and the variance of ε is not too large) we can make accurate predictions for the response, Y, based on a new value of $\mathbf{X}$.

- Example: Direct Mailing Prediction
  - Interested in predicting how much money an individual will donate when receiving a mailing based on observations from 90,000 people on which we have recorded over 400 different characteristics.
  - Don't care too much about each individual characteristic.
  - Just want to know: For a given individual should I send out a mailing?

Inference

- Alternatively, we may also be interested in the type of relationship between Y and the $\mathbf{X}$'s.
  - Which particular predictors actually affect the response?
  - Is the relationship positive or negative?
  - Is the relationship a simple linear one or is it more complicated etc.?

- Example: Housing inference
  - Wish to predict median house price based on 14 variables.
  - Probably want to understand which factors have the biggest effect on the response and how big the effect is.
  - For example how much impact does a river view have on the house value etc.

How Do We Estimate *f*?

- We will assume we have observed a set of **training data**

$$\{(\mathbf{X}_1, Y_1), (\mathbf{X}_2, Y_2), \ldots, (\mathbf{X}_n, Y_n)\}$$

- We must then use the training data and a statistical learning method to estimate *f*.

- Statistical Learning Methods:
  - Parametric Methods
  - Non-parametric Methods

Parametric Methods

- Make explicit assumption about the functional form of *f*.
- It reduces the problem of estimating *f* down to one of estimating a set of parameters.
- They involve a two-step model based approach
  - STEP 1:

    Make some assumption about the functional form of *f*, i.e. come up with a model. The most common example is a linear model i.e.

$$f(\mathbf{X}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

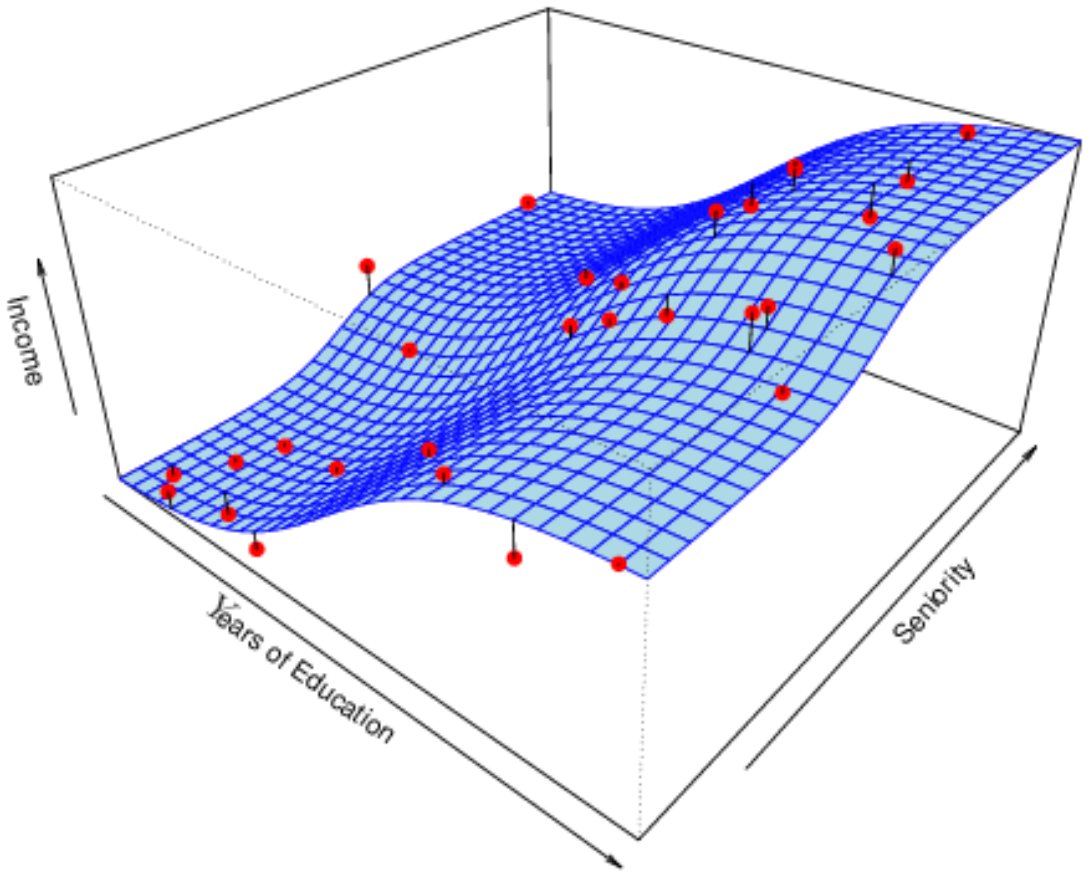
    where $\beta_0, \beta_1, \ldots, \beta_p$ are parameters to be fitted.

  - STEP 2:

    Use the training data to fit the model i.e. estimate *f* or equivalently the unknown parameters such as $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$.

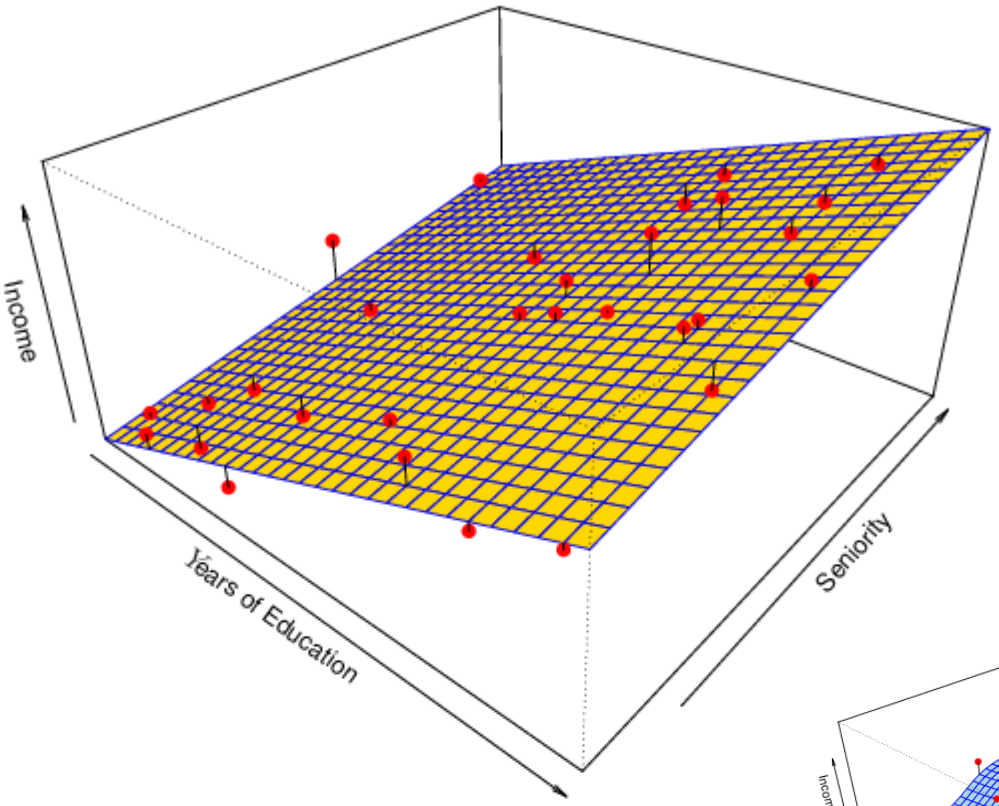
Income, Education, Seniority

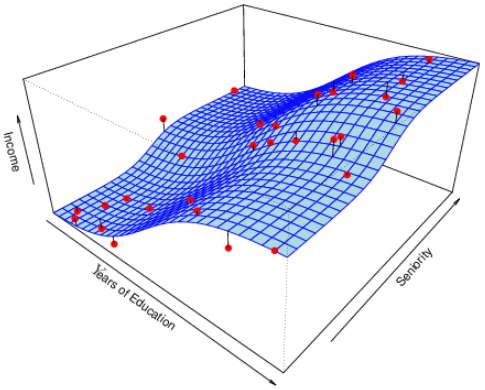
- Y: Income
- **X**: Year of Education,
  Seniority
- #observations: 30 (red points)
- f: the blue surface
- ε: the vertical lines



Example:
A Linear Regression Estimate

- Even if the standard deviation is low we will still get a bad answer if we use the wrong model.





$$f = \beta_0 + \beta_1 \times Education + \beta_2 \times Seniority$$

Non-parametric Methods

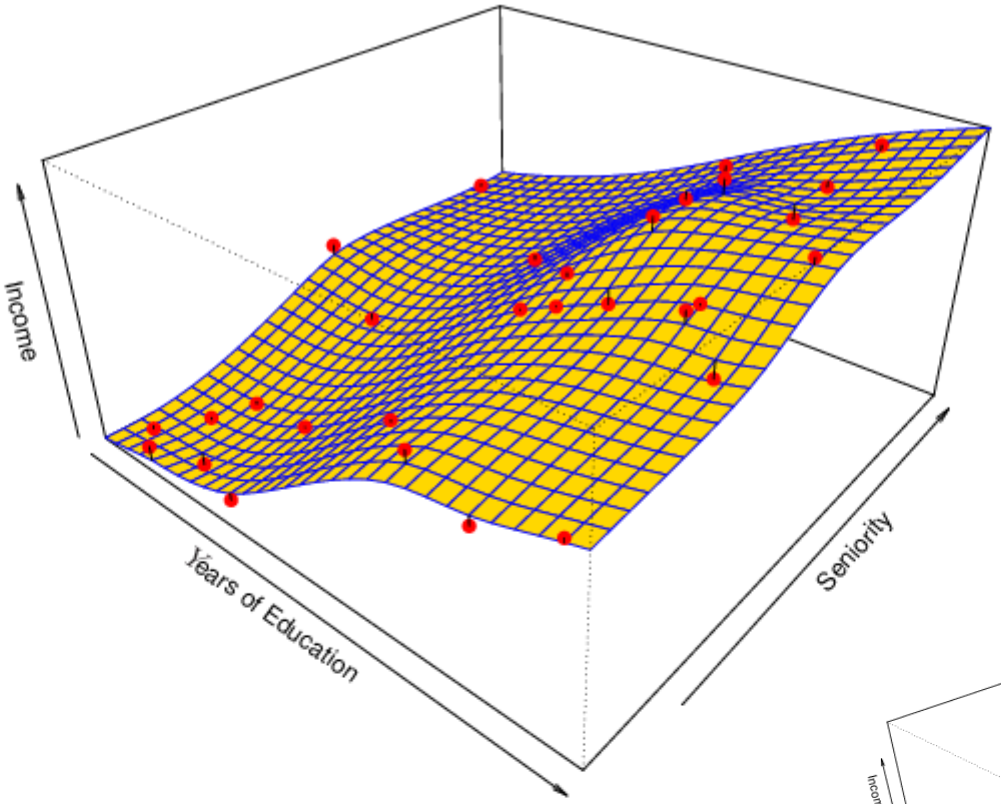
- They do not make explicit assumptions about the functional form of *f*.

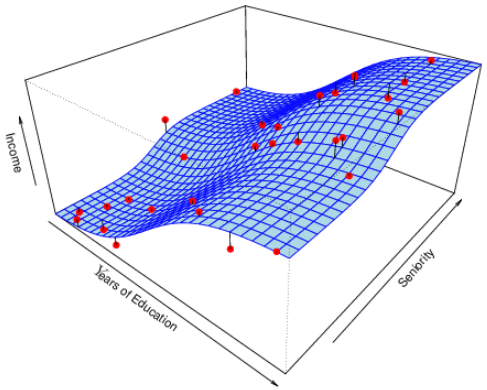
- Advantages:
  - They accurately fit a wider range of possible shapes of *f*.

- Disadvantages:
  - A very large number of observations is required to obtain an accurate estimate of *f*.

Example:
A Thin-Plate Spline Estimate

- Non-linear regression methods are more flexible and can potentially provide more accurate estimates.





Prediction Accuracy vs. Model Interpretability

- Why not just use a more flexible method if it is more realistic?
- There are two reasons
  - Reason 1: (interpretability)
    - A simple method such as linear regression produces a model which is much easier to interpret (the Inference part is better).
  - Reason 2: (overfitting)
    - Even if you are only interested in prediction, so the first reason is not relevant, it is often possible to get more accurate predictions with a simple, instead of a complicated, model.
    - This seems counter intuitive but has to do with the potential for overfitting in highly flexible methods.

Overfitting

Birkbeck
UNIVERSITY OF LONDON

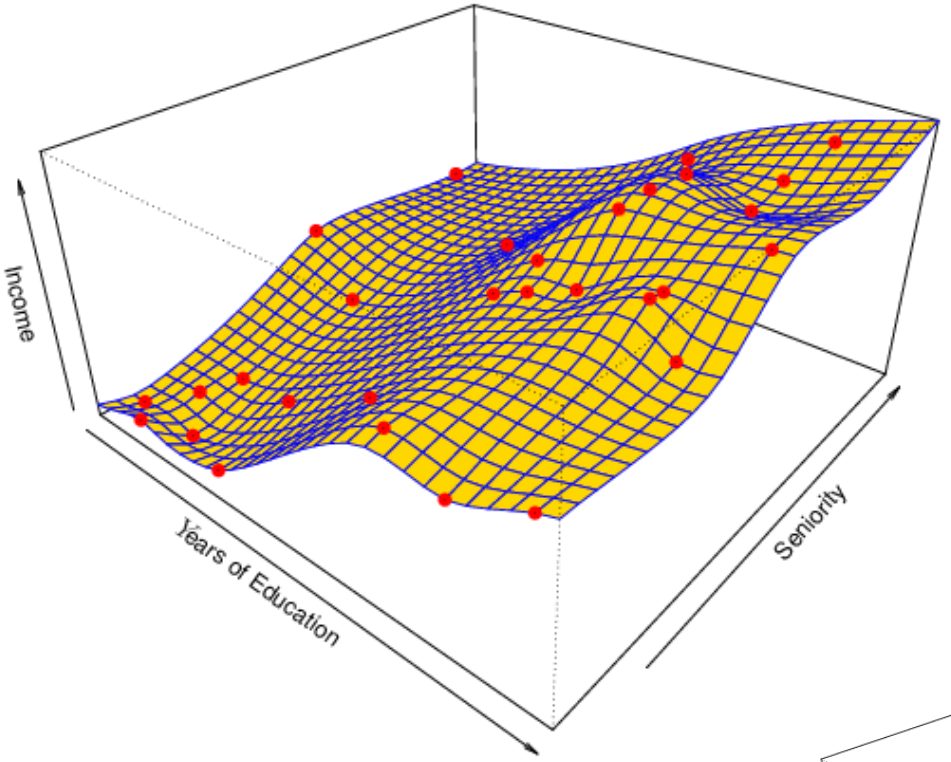
- In overfitting, a statistical model describes random error or noise instead of the underlying relationship.

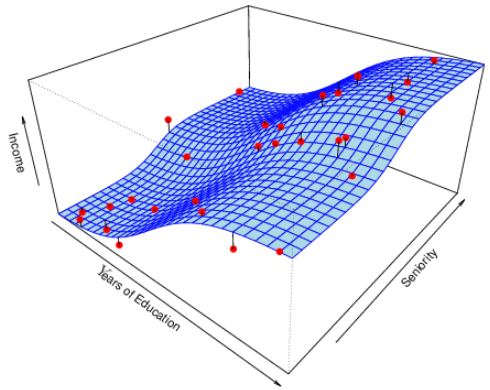
- Overfitting occurs when a model is excessively complex, such as having too many parameters relative to the number of observations.

- A model that has been overfit has poor predictive performance, as it overreacts to minor fluctuations in the training data.

A Poor Estimate

- Non-linear regression methods can also be too flexible and produce poor estimates for f.



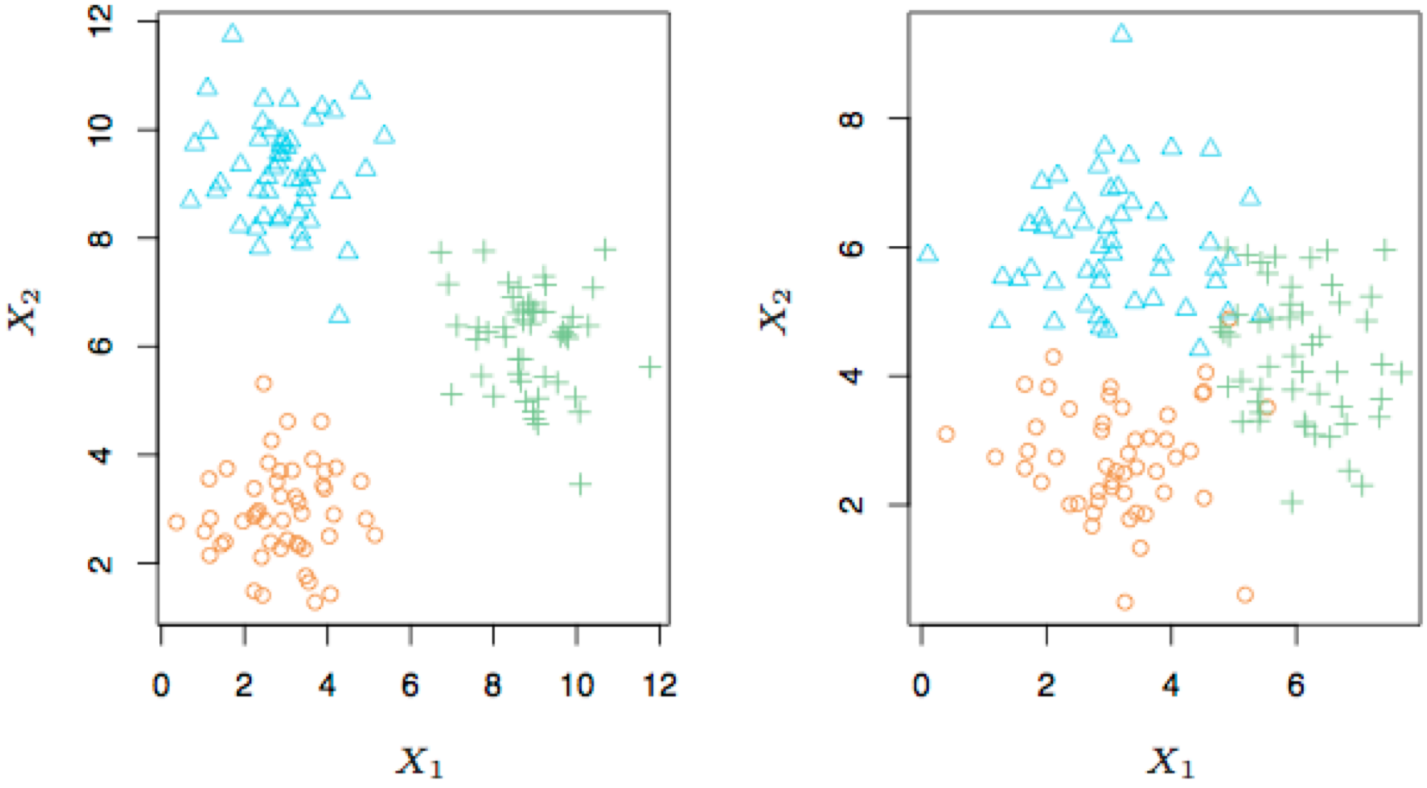


Supervised vs. Unsupervised Learning

- We can divide all learning problems into Supervised and Unsupervised situations
  - Supervised Learning:
    - Supervised Learning is where both the predictors, **X**, and the response, *Y*, are observed.
    - Example: linear regression, logistic regression, boosting, SVM
  - Unsupervised Learning:
    - In this situation only the **X**'s are observed.
    - We lack a response variable that can supervise our analysis. We need to use the **X**'s to guess what *Y* would have been and build a model from there.
    - Example: Clustering

A Simple Clustering Example

- 150 observations, 2 variables: X_1, X_2, 3 distinct groups



Regression vs. Classification

- Supervised learning problems can be further divided into regression and classification problems.
- Regression covers situations where Y is continuous/numerical
  - Examples
    - Predicting the value of the Dow in 6 months.
    - Predicting the value of a given house based on various inputs.
- Classification covers situations where Y is categorical
  - Examples
    - Will the Dow Jones index be up (U) or down (D) in 6 months?
    - Is this email a SPAM or not?

Course Syllabus Overview