CIT

COMP9033
DATA ANALYTICS

1/12

INTRODUCTION TO DATA ANALYTICS

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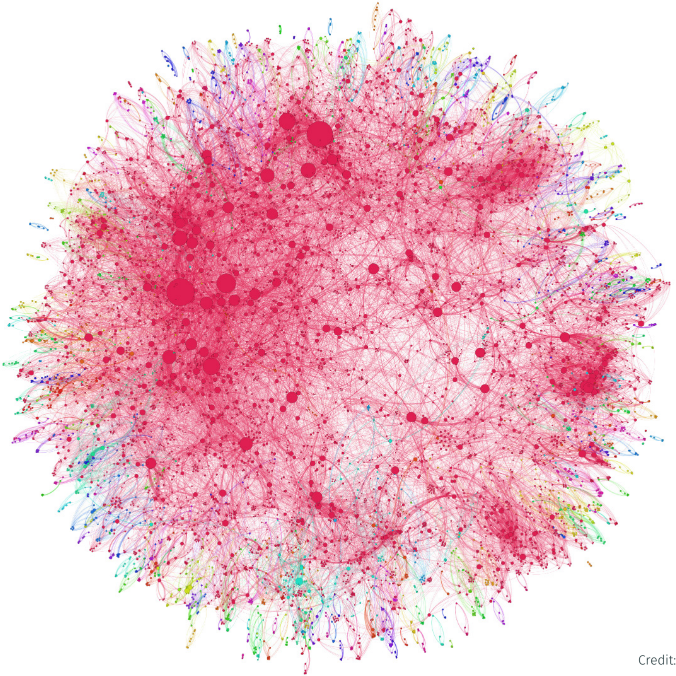


Credit: Andy Lamb

Overview

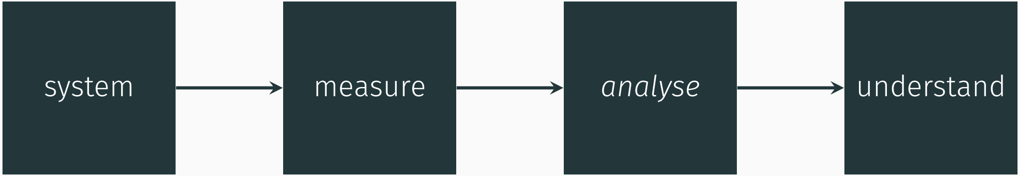
1. Introduction to data analysis:
    - What is it?
    - How does it work?
    - Real world examples.
2. Module outline:
    - Overview of topics.
    - Marking scheme.
    - Lab work.
    - Project work.
    - Contact information.
3. Data analysis processes:
    - What are they?
    - Why use them?
    - How do they work?
    - Which one to use?
4. Data sampling:
    - What is it?
    - Why is it important?
    - How to do it?

Introduction to data analysis

- Data analytics is an area of science concerned with the analysis and understanding of data.
- In recent years, it has become a hot topic, with notable uses in areas such as
    - Search engines: Google, Yahoo, DuckDuckGo.
    - Speech recognition: Siri, Alexa, Cortana.
    - Music fingerprinting: Shazam, SoundHound.
    - Customer intelligence: Tesco, Amazon.
    - Recommendation systems: Netflix, Spotify, Audible.
    - Spam detection: Gmail, Outlook, Yahoo.
- It encompasses concepts such as statistics, visualisation and machine learning, but it is these things and more!

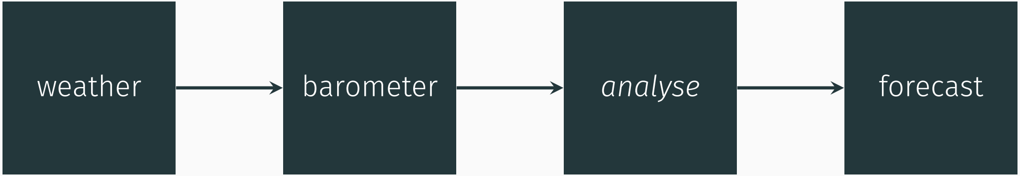
- Formally, data analytics is a systematic way of examining and manipulating data to discover new information.
- It is a *scientific* method, with defined steps and procedures:
    - Observations are made.
    - Hypotheses are formulated, refined, accepted and rejected.
    - Generally applicable conclusions are reached.
- It is also an *art*, often relying on subjective human judgement:
    - Should the data be manipulated and, if so, how?
    - Which technique or tool is best to use in a given situation?
    - What level of cost-performance trade off is acceptable?

1.3 / WHAT IS DATA ANALYTICS?



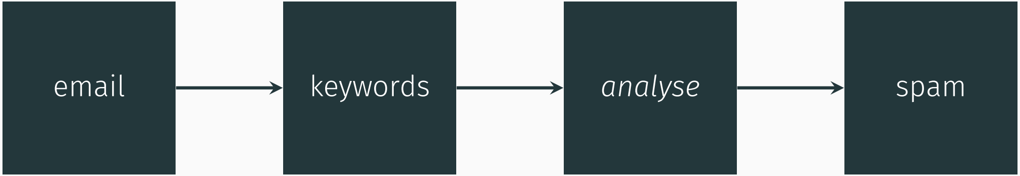
- We can think of data analysis as a step in a process:
  1. We have a system we want to understand.
  2. We measure some data related to the system.
  3. We *analyse* the data to better understand it.
  4. We gain understanding and draw conclusions.

1.4 / EXAMPLE: WEATHER FORECASTING



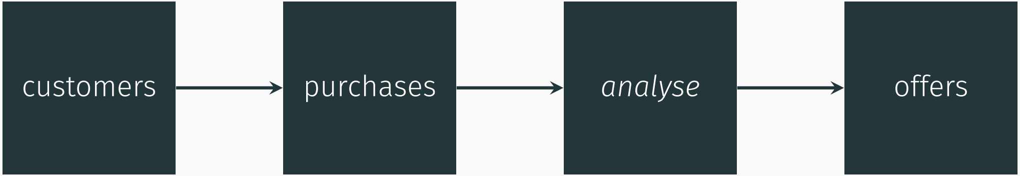
- Weather forecasting is a form of data analysis:
  1. We want to make predictions about the weather.
  2. We measure some data related to it, *e.g*. atmospheric pressure.
  3. We *analyse* the data to extract information about the relationship.
  4. We better understand how pressure affects weather, *e.g*. high pressure $\rightarrow$ sunshine!

1.5 / EXAMPLE: SPAM DETECTION



- Spam detection is a form of data analysis:
  1. We want to detect whether incoming emails are spam or not.
  2. We measure some data related to this, *e.g.* keywords in the email text.
  3. We *analyse* the data to extract information about the relationship.
  4. We better understand how certain keywords are good indicators of spam.

1.6 / EXAMPLE: DISCOUNT OFFERS



- Data analysis can be used to make offers to customers:
  1. We want to understand and/or predict customer behaviour.
  2. We measure some data related to this, *e.g.* purchase history.
  3. We *analyse* the data to extract information about the relationship.
  4. We better understand which items to offer discounts on to encourage purchases.

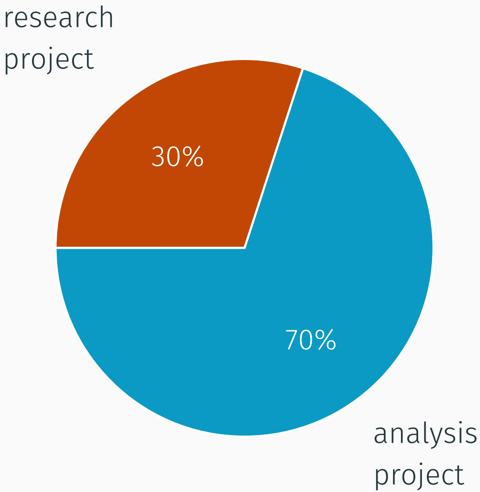
- So what does data analysis actually involve?
- It can take a variety of forms, including:
  - Examination of statistical measures, *e.g.* mean, median, standard deviation.
  - Visualisation of the data, *e.g.* histogram, scatter plot matrix.
  - Transformation of the data into a form that makes further analysis more convenient.
  - Building and testing models of the data.
- Typically, multiple forms are used in combination to solve a given problem.
- The key to solving problems effectively is to know which of these tools to use and in what order.

Module overview

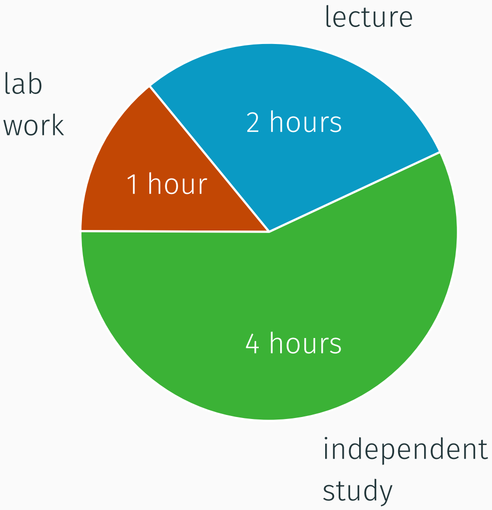
- My name is Donagh (pronounced *done-a*).
- I design algorithms to solve problems using data.
- Currently: Principal Data Scientist at Johnson Controls.
- Previously: Data Scientist and Software Engineer at Johnson Controls and IBM, PhD in Electrical Engineering.
- This is my fourth year teaching COMP9033.

- The aim of this module is to provide both a theoretical and a practical introduction to data analysis techniques.
- Over the coming weeks, we will cover a variety of topics:
  - Data analysis process models.
  - Exploratory data analysis.
  - Data visualisation.
  - Cleaning and transforming data.
  - Machine learning.
  - Linear regression.
  - Decision trees.
  - k-nearest neighbours.
  - Clustering algorithms.
  - Association rule mining.
  - Big data processing.
  - Data ethics.

- The course marks are divided between a research project and a data analysis project:
  - The research project will be set in week 1 and is due in week 8.
  - The analysis project will be set in week 6 and is due in week 12.
- For more information, see the module description at bit.ly/2mi9jNM.



- Each week, there will be a two hour lecture and a lab assignment.
- The lab work is *ungraded*, but you will need to understand it in order to do the projects.
- The course material is not hard, but there is a lot to cover — you should take time outside of class to study the material.



2.5 / LECTURES

- Lectures take place every week, on Tuesday, from 20:00-22:00:
  - Daylight saving time: Irish time zone changes from GMT to IST on 25th March.
  - No classes during Easter break: 26th March to 6th April.
  - Official CIT student calendar: bit.ly/2CUhA4a.
- Lecture notes will be posted to Blackboard in advance of class.
- Lecture audio and video are recorded with Adobe Connect and will be uploaded to Blackboard shortly after class.
- If you spot broken links, typos or other mistakes, please let me know!

2.6 / LECTURES

- Except where indicated otherwise, the notes for this course are licensed to you under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International license.
- You are free to share these notes with anyone you like, as long as you:
  1. Give appropriate credit for the material and indicate the license.
  2. Don’t use the material for commercial purposes.
  3. Don’t redistribute any modified version of the material.
- For more information, see bit.ly/1weyPUN.

2.7 / LABS

- Each week, there will be a lab assignment related to the lecture material.
- The lab assignments are *ungraded*, but you will need to understand them in order to complete the project work.
- Each lab involves the completion of data analysis exercises using Jupyter Notebook.
    - Already installed on your vDesktop environment.
    - Can run it on your personal computer too (more on this later).
- Lab assignments will also be posted to Blackboard.
- Again, please let me know if you spot broken links, typos or other mistakes.

- Except where indicated otherwise, the code for this course is licensed to you under the GNU General Public License (version 3).
- You are free to use, share and/or change this code however you like, as long as you:
    1. Give appropriate credit for the material and indicate the license.
    2. Make any modifications available under the same license.
- For more information, see bit.ly/2eXCFdY.

	R	Python
Algorithm support	Very large	Large
Difficulty	Moderate	Easy
Useful outside domain	No	Yes

- R and Python are commonly used for data analysis:
  - Both are useful and have their pros and cons.
  - However, Python is far more widely used for general computing.
  - To save having to learn a single purpose language, we will use Python.
- If you don't know Python or haven't used it in some time, Codecademy offer a free introduction course that covers the basics: bit.ly/1DCO2hj.

- To run the labs on your own computer, you will need to install the following software:

    - Python 2.7.x
    - IPython
    - Jupyter Notebook
    - NumPy
    - SciPy
    - pandas
    - matplotlib
    - scikit-learn

- Alternatively, you can use the *Jupyter Data Science Notebook* Docker image on GitHub: git.io/vDJb0.

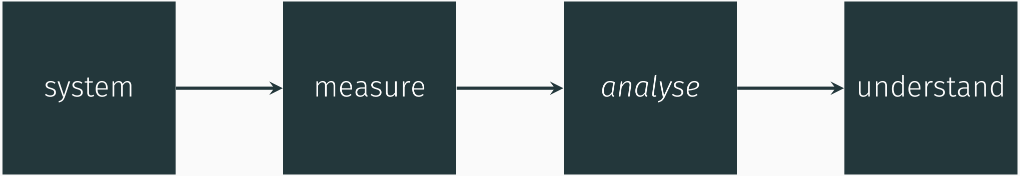
2.11 / PROJECT WORK

- For this module, you are required to complete two projects:
    - The first project is research-based and focuses on distributed file systems.
    - The second project is practical and requires you to analyse a complex data problem and produce your own solution.
- Project work will be managed using Blackboard:
    - Project briefs will be posted to the *Assessment* folder.
    - You can submit your reports using the built-in submission tool.
- Again, please let me know if you spot broken links, typos or other mistakes.

- If you have a question about lecture notes, lab work, project work, or even something not related specifically to course content (*e.g.* you want to share an interesting link or blog post), post it to the Blackboard forum.
    - Sharing information benefits everyone.
    - Someone else might answer your question faster than I will.
    - URL: blackboard.cit.ie.
- If you have a problem, send me an email.
    - Please don't send emails about course material — let's keep this on Blackboard.
    - Email: donagh.horgan@cit.ie.
- I will try to reply to Blackboard posts and emails within 48 hours, but sometimes it may take longer than this.

Data analysis processes

3.1 / DATA ANALYSIS PROCESSES



- Earlier, we discussed how data analysis is the *process* of manipulating data to discover new information.
- So what exactly is involved in this process? It depends on your goals!
    - Several standardised processes exist, each with their own area of speciality.
    - Some industries/organisations prefer one over the others.
    - However, *all* are driven by the same core principles.

- Knowledge Discovery in Databases (KDD) is an early data analysis paradigm.
    - Its main focus is on the extraction of knowledge from large enterprise databases.
    - While KDD was a popular paradigm initially, it has now largely been superseded by SEMMA and CRISP-DM.
- KDD consists of five stages: selection, preprocessing, transformation, data mining/modelling and interpretation/evaluation.

3.3 / KDD STEPS

1. Selection
   - This consists of gathering the data to be analysed.
   - Data may be sub-sampled to a more manageable level.
2. Preprocessing
   - Fix data quality issues (*e.g.* missing data, outliers).
3. Transformation
   - Select features for further analysis.
   - Transform data into forms more suitable for analysis.
4. Data mining/modelling
   - Application of a data modelling technique (*e.g.* a machine learning algorithm).
5. Interpretation/evaluation
   - Validate the model to ensure it works (*e.g.* testing a weather forecast).
   - Analyse the results and draw conclusions.

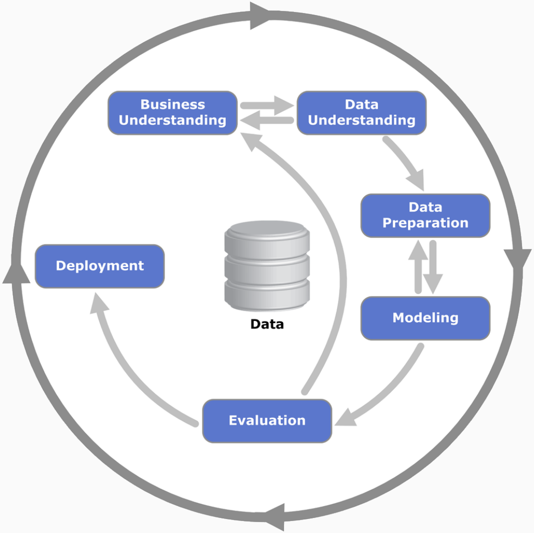
- SEMMA is an alternative process flow model for data mining.
    - It is an evolution of the KDD process, developed by SAS Institute.
    - More commonly used than KDD, but less than CRISP-DM.
- SEMMA is an acronym for the five steps involved: Sample, Explore, Modify, Model, Assess.

3.5 / SEMMA STEPS

1. Sample
    - If the total amount of data is large, then take a *representative* sample to speed up later analysis.
    - If the total amount of data is not large, then don't sample.
2. Explore
    - Explore the data to find patterns or trends.
    - Identify data quality problems.
    - Form hypotheses based on your findings.
3. Modify
    - Select the data to be analysed.
    - Fix data quality problems.
    - Transform the data, if necessary.
4. Model
    - Apply a data modelling technique to solve the problem.
5. Assess
    - Evaluate how useful and reliable the generated model is.
    - Estimate how well it will generalise to new situations.

3.6 / CRISP-DM

- CRISP-DM is the CRoss Industry Standard Process for Data Mining.
    - Developed by a consortium of industry partners, although mainly associated with IBM.
    - Currently, the most widely used data mining paradigm.
- CRISP-DM consists of six distinct phases, which are repeated if requirements are not met.
- At the end of the evaluation phase, the entire process may be restarted if requirements are not met.



Credit: Kenneth Jensen/Wikipedia

1. Business understanding
    - Define objectives based on business requirements.
    - Translate the objectives into data analysis problems.
    - Create a project plan.
2. Data understanding
    - Gather the data to be analysed.
    - Sample and explore the data to identity any problems and/or form hypotheses.
3. Data preparation
    - Select and clean/transform data before modelling.
4. Modelling
    - Apply data modelling or pattern matching techniques to solve the problem.
    - Optimise algorithm parameters to maximise performance.
5. Evaluation
    - Review the business requirements and determine whether the model meets them.
6. Deployment
    - Deploy the model in a production system.
    - Maintain the solution, if required.

3.8 / COMPARISON

<table>
<tr><th>KDD</th><th>SEMMA</th><th>CRISP-DM</th></tr>
<tr><td>-</td><td>-</td><td>Business understanding</td></tr>
<tr><td>Selection</td><td>Sample</td><td rowspan="2">Data understanding</td></tr>
<tr><td rowspan="2">Preprocessing and Transformation</td><td>Explore</td></tr>
<tr><td>Modify</td><td>Data preparation</td></tr>
<tr><td>Data mining/modelling</td><td>Model</td><td>Modelling</td></tr>
<tr><td>Interpretation/evaluation</td><td>Assess</td><td>Evaluation</td></tr>
<tr><td>-</td><td>-</td><td>Deployment</td></tr>
</table>

- SEMMA evolved from KDD and is more comprehensive in certain areas:
    - Greater emphasis on exploratory data analysis.
    - All data modification actions are grouped under one step (Modify).
- CRISP-DM also evolved from KDD, but has some distinctions from SEMMA:
    - Focuses on business requirements as well as data analysis.
    - Emphasises the iterative nature of data analysis more strongly.
    - Focuses on post-analysis model deployment and maintenance.
- All three paradigms are useful and, in a given situation, adopting one may be a better choice than adopting another.
- For the remainder of this course, however, we will focus on the core steps shared by all three.

Data structures

- The first stage in any analytics project is to gather the data to be analysed:
  - We might write a SQL query to extract it from a database.
  - We might parse the data from a CSV file.
  - We might extract features from an MP3 file (*e.g.* Shazam).
- Generally, data is classified as belonging to one of three categories:
  1. Structured data.
  2. Semi-structured data.
  3. Unstructured data.
- Usually, the techniques that we use to gather the data depend on which category it belongs to.

4.2 / STRUCTURED DATA

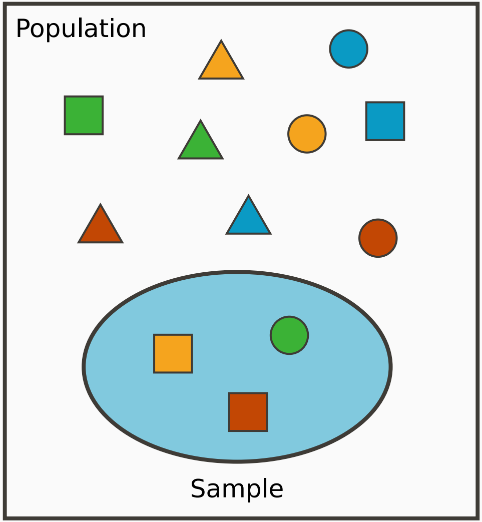
- The term *structured data* describes data that is highly organised.
- Typically, structured data follows a defined schema or data model (*e.g.* relational databases), which imposes strict organisational rules:
  - The organisation of data is strictly defined, *e.g.* the number of columns in a relational database table is generally fixed when the table is created.
  - The types of data are strictly defined, *e.g.* the data type of a column in a relational database table is generally fixed when the column is created.
- This has both advantages and disadvantages:
  - The strict order facilitates optimisation and predictability, allowing the data to be queried quickly and easily.
  - However, it is also inflexible, leading to major redesign effort in order to accommodate relatively small changes in the data structure.

- The term *semi-structured data* refers to data that is organised in a flexible structure, which generally does not impose restrictions on data organisation and types in as strict a manner as structured data.
    - File formats: CSV, JSON, XML and more.
    - NoSQL databases: MongoDB, InfluxDB, Redis and more.
- Because there is no schema or data model, semi-structured data is generally harder to query than structured data.
    - In a database schema, you might disallow null values in a column.
    - You can't do this in (schema-less) JSON — queries become more complicated.
- However, the flexible structure allows for variations in the structure of the data being stored, and so schema redesign is not required.
    - Adding a new field to a JSON object is easier than rewriting a database schema.

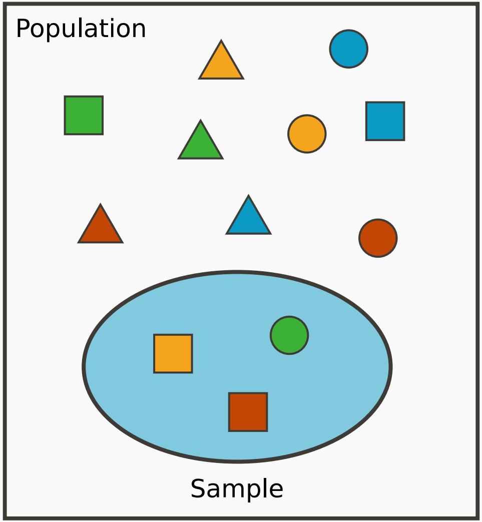
- The term *unstructured data* refers to data that does not follow any defined structure.
    - Text: documents, emails, tweets.
    - Audio: human speech, music.
    - Images: photographs, video.
- Generally, unstructured data cannot be queried directly and must be preprocessed in order to extract data in a form that we can analyse:
    - Natural language processing extracts linguistic features from text, so that we can analyse its meaning using standard techniques.
    - Fingerprinting allows us to extract summary details from audio, which we can then use to identify the track (*e.g.* Shazam).
    - Pattern matching enables computers to detect human faces in images and video, allowing us to work with concrete identifiers rather than raw bits.

Data sampling

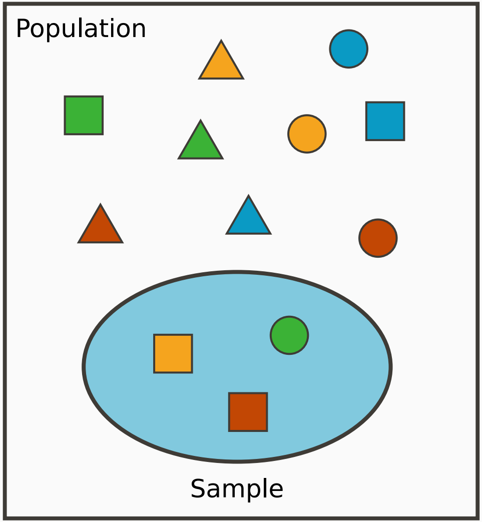
- A statistical *population* is a complete set, representing the entire space of possible outcomes.
- A statistical *sample* is a subset of a population and so represents a number of the possible outcomes, but not the total.



- Populations describe all possible outcomes, while samples describe only a few.
- By random chance, a sample may look extremely different from the population it was drawn from.
    - For instance, in the image on the right, the sample contains no blue shapes or triangles.
- While conclusions based on an analysis of a population will always generalise, conclusions based on a sample may not.



- For example, consider the population of a country:
    - A well chosen sample will reflect the general trends in the greater population: age, gender, income and so on.
    - A poorly chosen sample will not, *e.g.* if our sample contains only teenagers or criminals.



- In many cases, we want to understand the behaviour of a *large* population:
  - Voters in an election.
  - Customers of a business (*e.g.* Tesco).
  - Spam vs. non-spam emails.
- But generally we are constrained:
  - The financial cost of polling voters is high.
  - It's difficult to get customers to agree to let us analyse their data.
  - The computational effort involved in processing billions of emails is large.
- If we *sample* the population, then we can avoid these high costs — but we need to be careful to choose our sample well.

- The term *data sampling* refers to a concrete step in the analytics process, the aim of which is to reduce the *quantity* of data to be analysed, while maintaining the *quality*.
    - In KDD, sampling falls under the Selection stage.
    - In SEMMA, there is a step called Sample.
    - In CRISP-DM, sampling is a part of the Data Understanding phase.
- Sampling can be done during the data gathering process:
    - Selecting a subset of rows from a database table.
    - Selecting a subset from a collection of JSON objects.
    - Downsampling images to reduce their size.
- Sampling can also be done after data gathering, *e.g.* by selecting a subset of the gathered data.

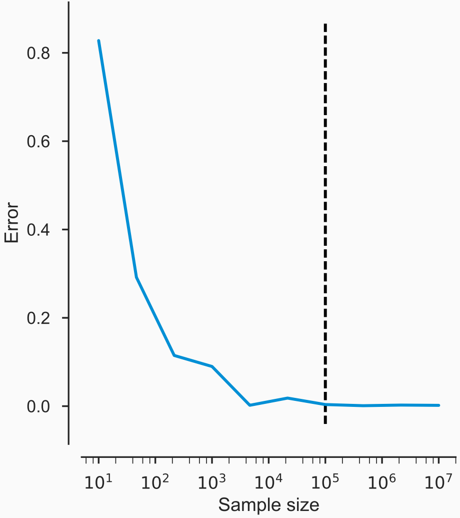
- Do we *have* to sample?
    - Sampling isn't mandatory, if the cost of analysis is small.
    - However, if analysing the whole population is not feasible, then we *must* sample.
- If we decide to sample, then we must do so carefully to avoid choosing subsets of the data that do not represent the population.
- The two most common causes of sampling error are:
    1. Lack of randomness.
    2. Small sample size.

- If we choose a sample in a way that isn't random, then it might not reflect the population that it was drawn from:
    - Polling voters in a single area to estimate national preferences.
    - Issuing discount offers in June based on sales information from December.
    - Deciding that all emails containing the phrase "online pharmacy" are spam.
- By choosing samples randomly, we can minimise the chance that our sample does not resemble the population it was drawn from.

- In general, larger randomly selected samples tend to reflect their populations better than smaller ones[1].
- However, larger samples are also more costly to analyse.
- Need to be able to choose a "Goldilocks" sample size, *i.e.* one that is large enough to be representative of its population, but small enough to be analysed cheaply.
- Choosing a specific number is often subjective! This is part of the *art* of data science.
- Generally, you should choose as large a sample size as possible, given the resources available to you (*e.g.* time, computing power).

[1] Due to law of large numbers — for mode information, see bit.ly/2hq7i0s.

- If you have a very large data sample, then it may be possible to determine a good sample size *experimentally*.
- The chart on the right shows the typical effect of increasing the sample size on the accuracy of a model.
- As can be seen, there is no real advantage to increasing the sample size beyond the dashed line.



Summary

- This week, we covered lots of the fundamentals of data analysis:
    - Formal processes for data analysis: KDD, SEMMA, CRISP-DM.
    - Data structures: structured, semi-structured and unstructured data.
    - Data sampling: populations and samples, randomness, sample size.
- Lab work:
    - This week's lab covers computing statistics and making basic plots in Python.
    - If you have questions, post on Blackboard!
- Next week, we'll look at
    - Exploratory data analysis.
    - Data visualisation.

1. Module information: bit.ly/2mi9jNM.
2. Blackboard: blackboard.cit.ie.
3. Codecademy introductory Python course: bit.ly/1DCO2hj.
4. Jupyter documentation: bit.ly/2gPFe7p.