6CS030 Big Data

Steps in the **Data Science Process**

- Acquiring data
- Exploring and pre-processing data
- Analyzing data
- Reporting insights and taking action

Data Science

- When handling Big Data you need “Process” or “Framework” to work with
- A data-handling lifecycle
- Various approaches exist:
  - ***Team Data Science Lifecycle*** *(TDSL)*
  - ***Cross-industry standard process for data mining*** *(CRISP-DM)*
  - ***Knowledge Discovery in Databases*** *(KDD)*
  - ***AWS Data Pipeline***

Team Data Science Lifecycle

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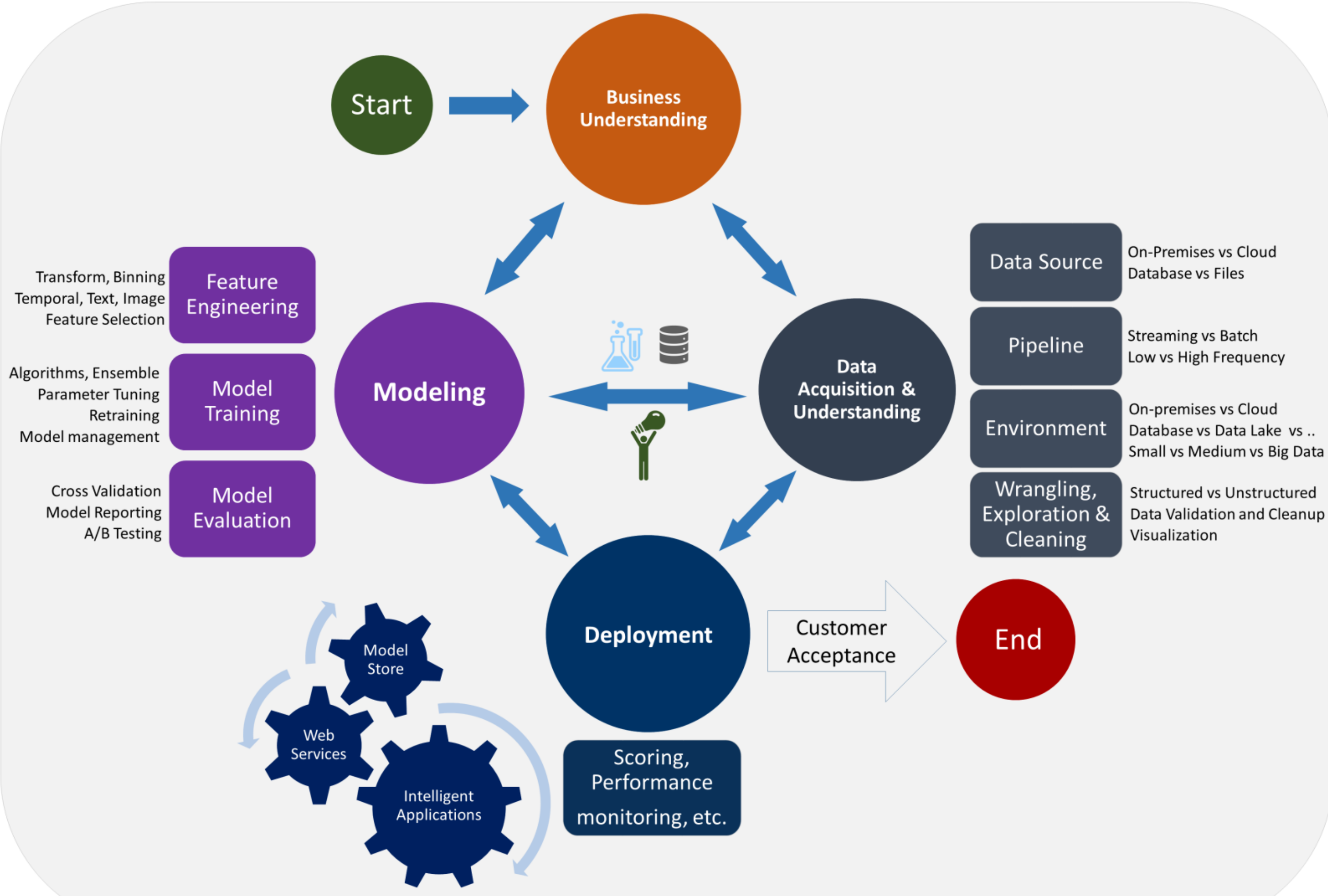
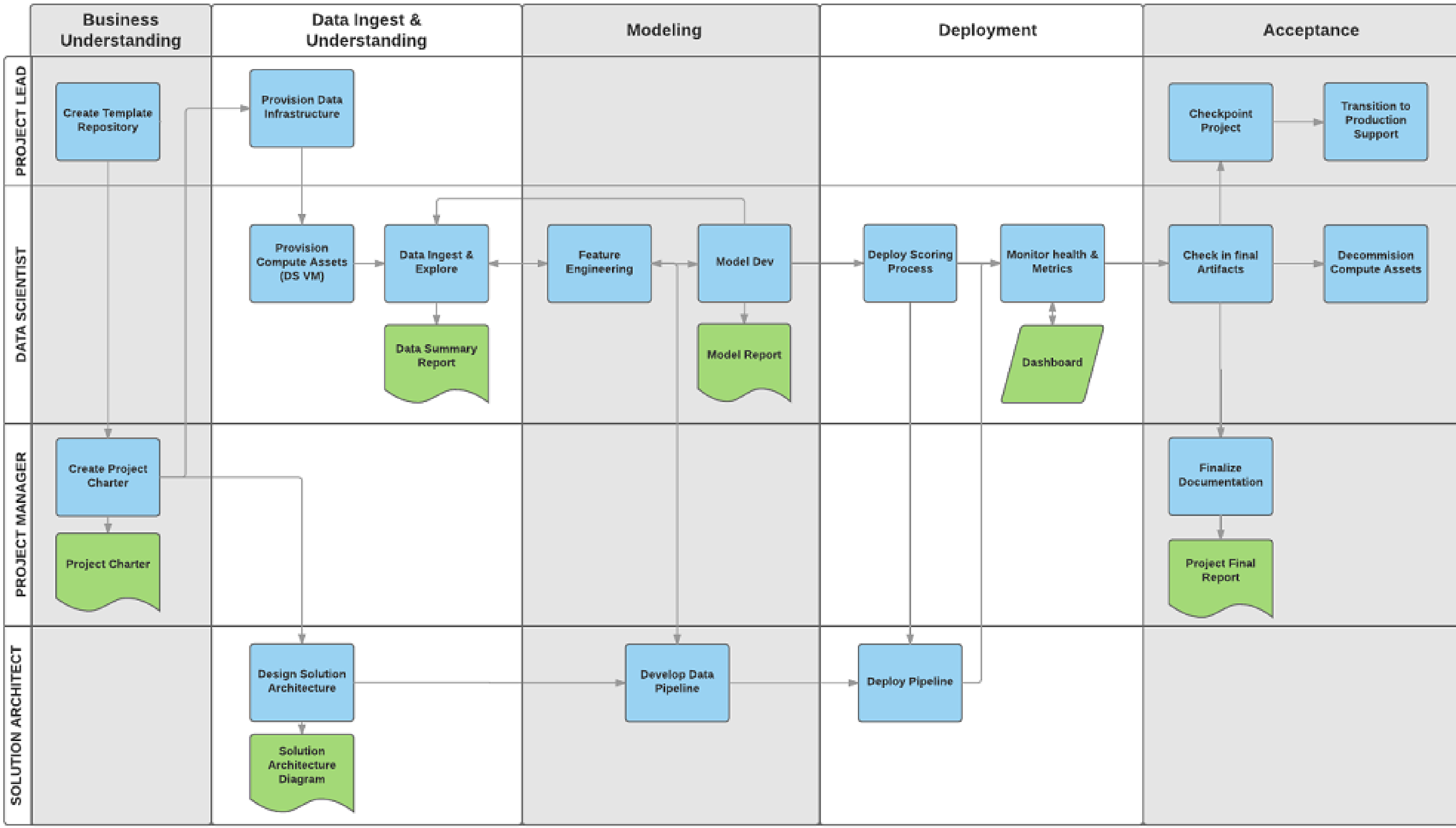


The following diagram provides a grid view of the tasks (in blue) and artifacts (in green) associated with each stage of the lifecycle (on the horizontal axis) for these roles (on the vertical axis).



Cross-industry standard process for data mining (CRISP-DM)

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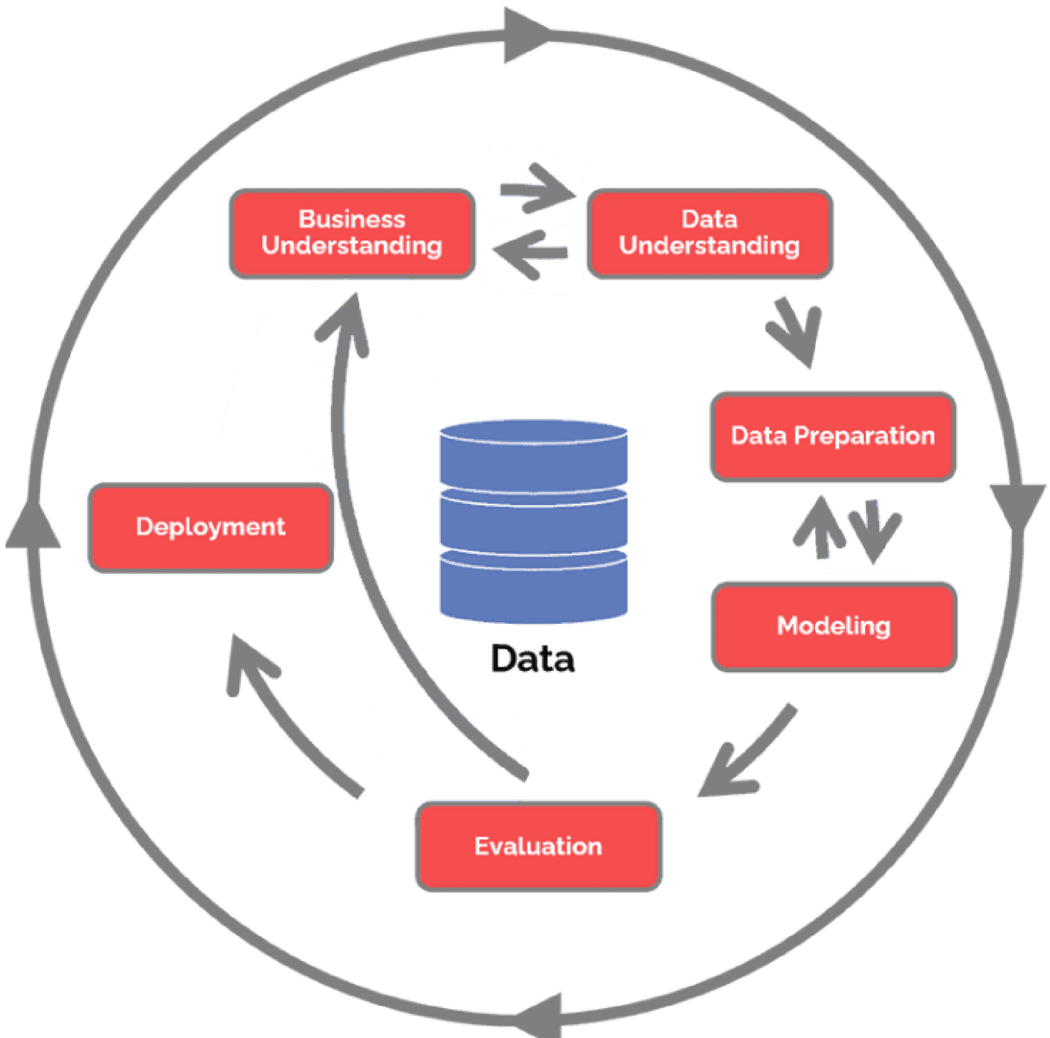

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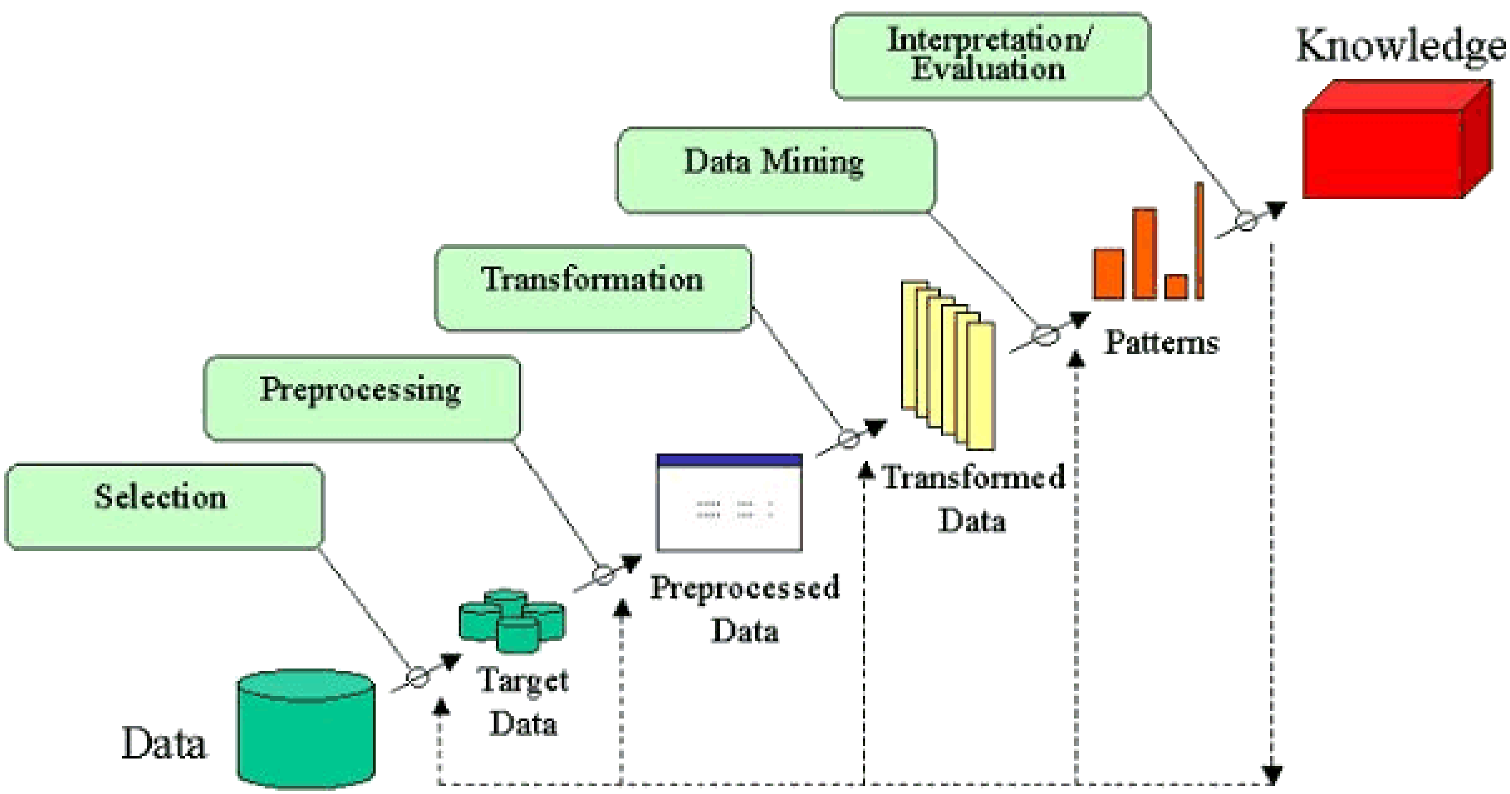
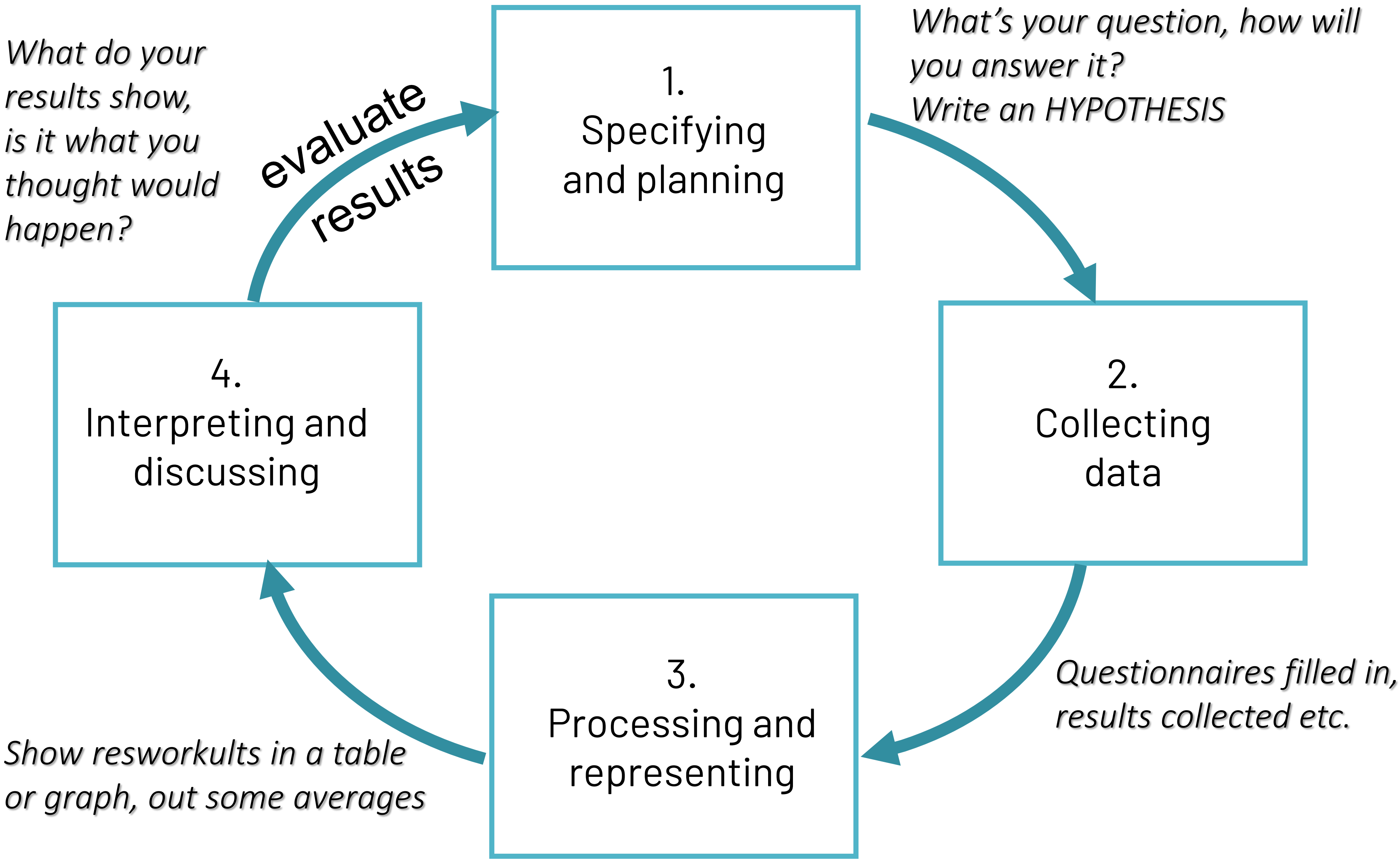
Knowledge Discovery in Database

The term **Knowledge Discovery in Databases**, or **KDD** for short, refers to the broad process of finding knowledge in data, and emphasizes the "high-level" application of particular data mining methods. It is of interest to researchers in machine learning, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition for expert systems, and data visualization.



The Data Handling Cycle – TES



Data Handling Framework

- Many big data analytics lifecycles or workflows can be found
- The following steps are fairly typical of what is suggested:
    - *Acquire data*
    - *Prepare or Process data*
    - *Analyse data*
    - *Report or visualise data*
    - *Act*
- All require some sort of question/business case to be answered
- Important to track the provenance throughout the workflow
- May have to justify decisions, so need to be able to reproduce the data processes undertaken.

Step 1: Acquiring the Data

This involves:

- Identifying suitable data sets
- Where is the data?
  - Can come from many places, local and remote
  - Can be many varieties: structured and unstructured
  - Can have different velocities
- Acquire all the available data

If some left out may lead to incorrect conclusions

- Querying the data

SQL and query browsers help examine the data

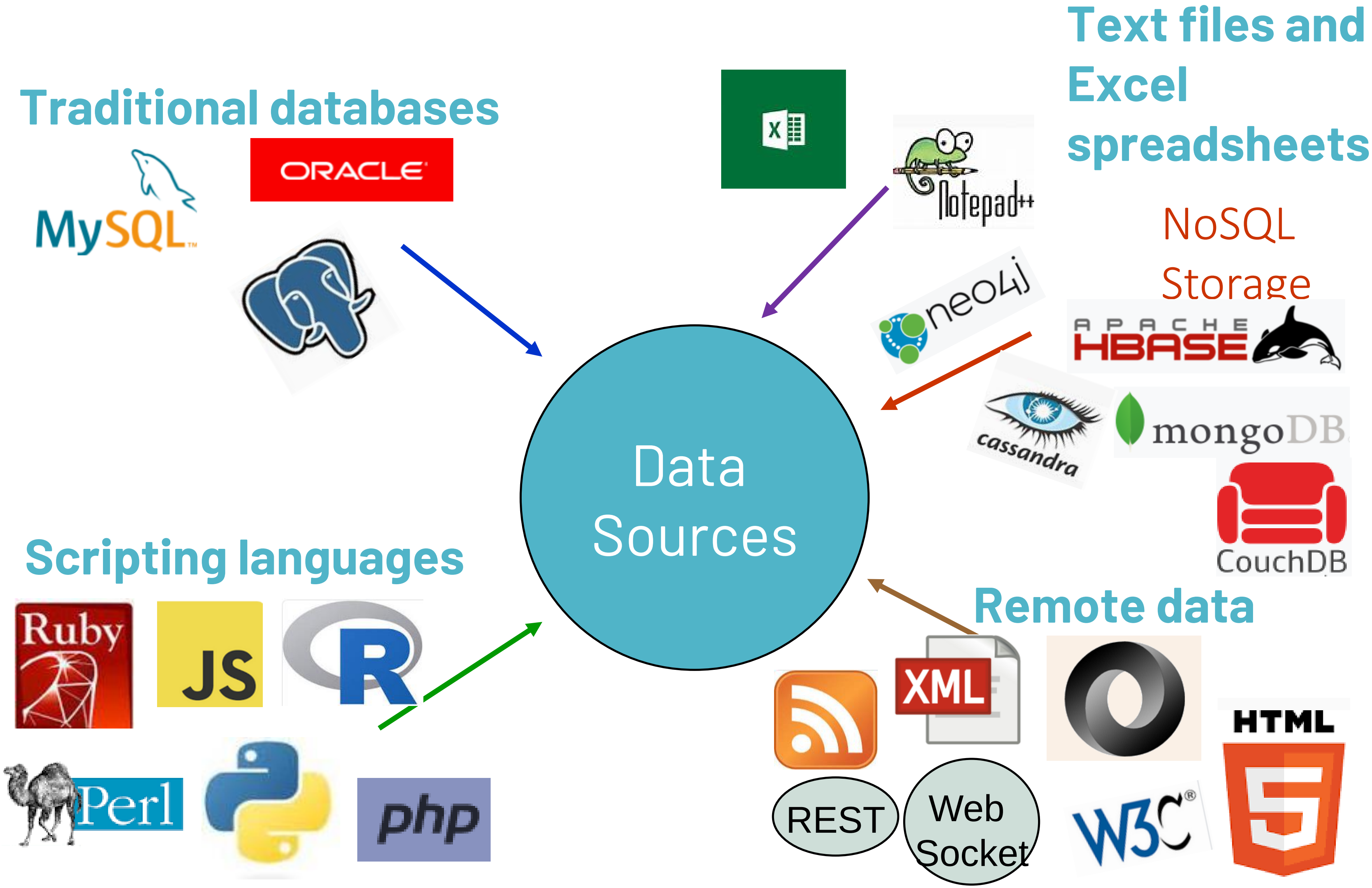
Data comes from many places

Every minute:

- *204 million emails are sent*
- *200,000 photos are uploaded and*
- *1.8 million likes are generated on Facebook.*
- *On YouTube, 1.3 million videos are viewed and 72 hours of video are uploaded*

24th Aug 2015 saw 1 billion users login on a single day!

And many ways to access it!


Traditional databases
ORACLE
MySQL
Text files and Excel spreadsheets
Notepad++
NoSQL Storage
neo4j
APACHE HBASE
cassandra
mongoDB
CouchDB
Data Sources
Scripting languages
Ruby
JS
R
Perl
php
Remote data
XML
REST
Web Socket
W3C
HTML

Found Data Examples

Name	URL
ONS	https://www.ons.gov.uk
EU Stats	http://ec.europa.eu/eurostat
European commission stats	http://ec.europa.eu/eurostat/data/statistics-a-z/abc
UK Government	https://www.gov.uk/government/statistics
US Government	https://www.usa.gov/statistics
Edinburgh University data share	http://datashare.is.ed.ac.uk/
List of high quality data sets	https://github.com/caesar0301/awesome-public-datasets
AW public data sets	https://aws.amazon.com/datasets/
Comparative political data set	www.cpds-data.org
Stanford – Computational Journalism lab	http://cjlab.stanford.edu/
KDNuggets – data sets for mining/discovery	www.kdnuggets.com/datasets/
UK Healthcare	http://www.hscic.gov.uk/datasets
Halifax house prices	http://www.lloydsbankinggroup.com/media/economic-insight/halifax-house-price-index/
Nationwide house prices	http://www.nationwide.co.uk/about/house-price-index/headlines
Historical weather	http://www.wunderground.com/history

House prices in the three months to October 2018 were 1.5% higher than in the same three months a year earlier

National Parks produce 22% price premium

Analysed Data Examples

Website	URL
Fact checking E.g., BBC QT Under 30s special	https://fullfact.org/ https://fullfact.org/election-2019/question-time-under-30s-fact-checked/
Mapping inequalities in England	https://theconversation.com/heres-what-we-learned-from-mapping-out-englands-inequalities-48562
How to know if where you live is "up and coming"	https://medium.com/@Sam_Floy/how-to-know-if-where-you-live-is-up-and-coming-fried-chicken-vs-coffee-shops-546080119f98
Find meaning in 40 years of UK political debate	https://thestack.com/iot/2015/10/14/big-data-40-years-uk-parliament-debate-complex-politics/
Evolution of US Girls Names over 100 years	https://youtu.be/qVh2Qw5KSFg
Evolution of US Boys names	https://www.youtube.com/watch?v=WQv99sEPDsw
Popular UK baby names	http://www.babycentre.co.uk/popular-baby-names
Nuclear Detonations from 1945	https://cdn.theguardian.tv/mainwebsite/2015/08/14/150813Detonations_FromGAus-16x9.mp4
World's best footballers (2015)	http://www.theguardian.com/football/datablog/2015/dec/24/worlds-best-footballers-and-where-they-play-the-numbers-crunched

Measurement Scales

Once the data is acquired you need to know what sort of data types it contains, since this will affect what analysis you can do

For any statistical analysis it is important to know about the different scales of measurement:

- INTERVAL
  Scale with a fixed and defined interval e.g. temperature or time.
- ORDINAL
  Scale for ordering observations from low to high, so has some kind of order. E.g. a questionnaire with a scale 1-5 of how happy you are with a product.
- Might not be a standardized value for the difference from one score to another. E.g., position in a running race(1st, 2nd, 3rd etc.). The difference between 1st and 2nd may be different to the difference between 2nd and 3rd
- **NOMINAL with order** : Scale for grouping into categories with order, e.g. mild, moderate or severe. This can be difficult to separate from ordinal.
- **NOMINAL without order:** Scale for grouping into unique categories, e.g. eye colour, or gender.
- **DICHOTOMOUS:** As for nominal but two categories only, e.g. driving test has pass/fail.

Measurement Scales

It is also important to know whether the data is:

CATEGORICAL (quantitative):

- Data that represent categories, such as dichotomous (two categories) and nominal (more than two categories)
- Observations are collectively called categorical.

NUMERICAL (qualitative):

- Data that are counted or measured using a numerically defined method are called numerical.

Step 2a: Prepare the Data

Once you have the data, you need to understand it before building a model with it.

Involves two sub-steps:

- Exploring the data : The goal is to understand your data
  - What it means
  - Its quality and format
- Carry out some preliminary analysis: Look at some samples of the data to try and understand it
  - Look for
    - Trends
    - Correlations
    - Outliers
  - Carry out some statistics

Step 2a: Prepare the Data

Statistics include:

- Mean: average score of the data
- Mode: values that occur most frequently in the data set
- Median: middle value in a data set
- Range: measures the difference between the largest and smallest values
- Standard deviation: a measure used to quantify the amount of variation in a set of data values
- Count: count number of values
- Sum: sum total of values in a dataset
- Min and Max: minimum and maximum values

✓ These can help identify if there is something wrong in the data.

✓ For example, negative numbers or percentages greater than 100 for exam scores

✓ Will be used later too for more complex analysis.

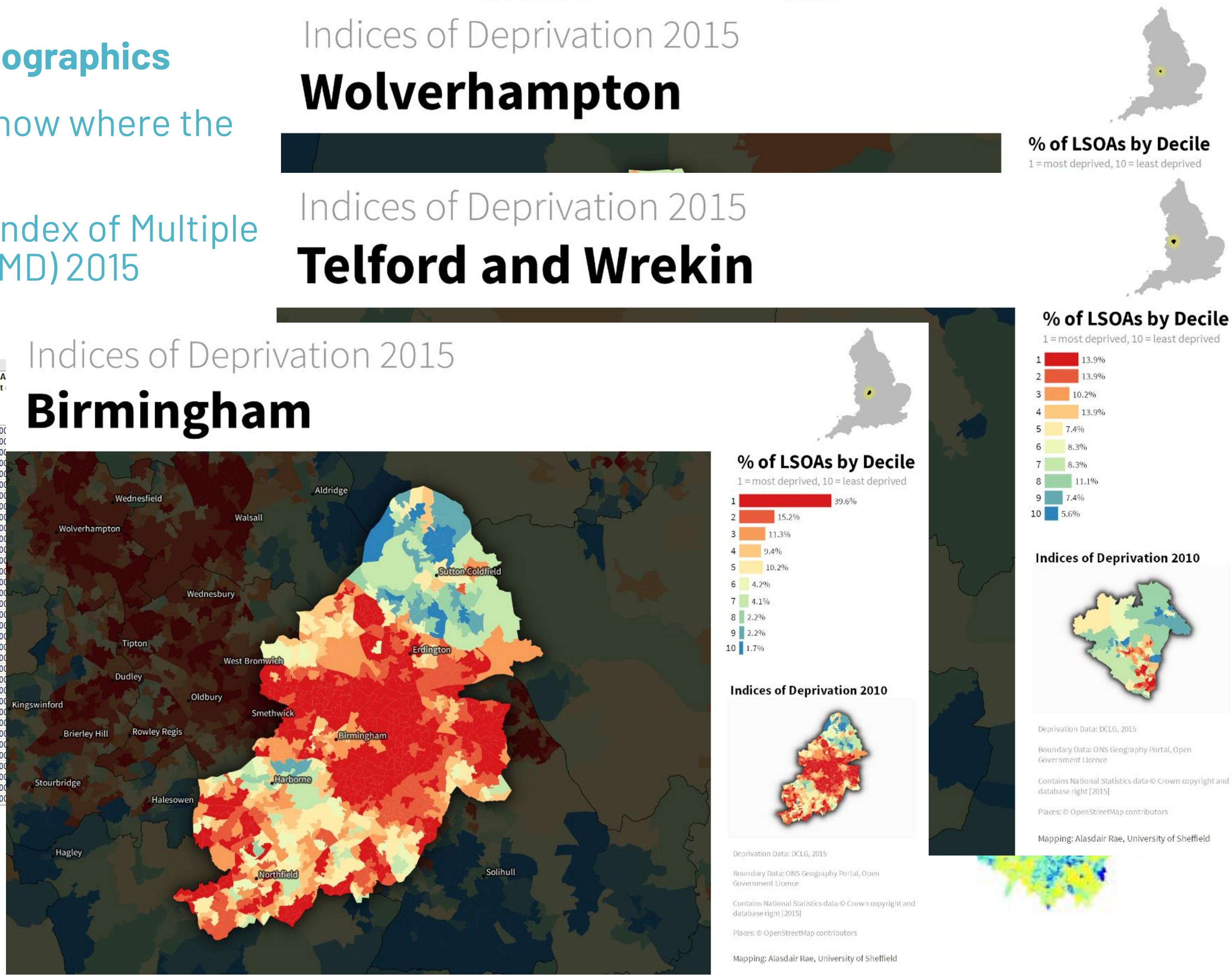
✓ Initial visualisations can help.

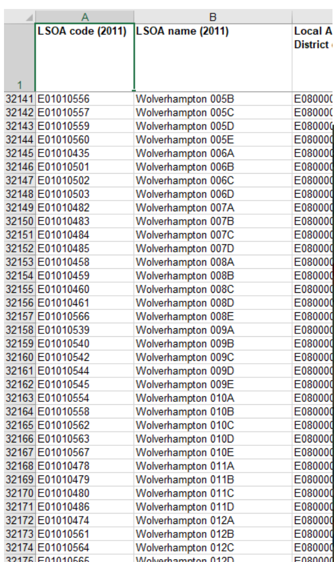
Step 2a: Visualisation Examples

Heat Maps/Infographics

Can quickly show where the hotspots are

E.g., English Index of Multiple Deprivation (IMD) 2015





	A	B	
1	LSOA code (2011)	LSOA name (2011)	Local A District
32141	E01010556	Wolverhampton 005B	E080000
32142	E01010557	Wolverhampton 005C	E080000
32143	E01010559	Wolverhampton 005D	E080000
32144	E01010560	Wolverhampton 005E	E080000
32145	E01010435	Wolverhampton 006A	E080000
32146	E01010501	Wolverhampton 006B	E080000
32147	E01010502	Wolverhampton 006C	E080000
32148	E01010503	Wolverhampton 006D	E080000
32149	E01010482	Wolverhampton 007A	E080000
32150	E01010483	Wolverhampton 007B	E080000
32151	E01010484	Wolverhampton 007C	E080000
32152	E01010485	Wolverhampton 007D	E080000
32153	E01010458	Wolverhampton 008A	E080000
32154	E01010459	Wolverhampton 008B	E080000
32155	E01010460	Wolverhampton 008C	E080000
32156	E01010461	Wolverhampton 008D	E080000
32157	E01010566	Wolverhampton 008E	E080000
32158	E01010539	Wolverhampton 009A	E080000
32159	E01010540	Wolverhampton 009B	E080000
32160	E01010542	Wolverhampton 009C	E080000
32161	E01010544	Wolverhampton 009D	E080000
32162	E01010545	Wolverhampton 009E	E080000
32163	E01010554	Wolverhampton 010A	E080000
32164	E01010558	Wolverhampton 010B	E080000
32165	E01010562	Wolverhampton 010C	E080000
32166	E01010563	Wolverhampton 010D	E080000
32167	E01010567	Wolverhampton 010E	E080000
32168	E01010478	Wolverhampton 011A	E080000
32169	E01010479	Wolverhampton 011B	E080000
32170	E01010480	Wolverhampton 011C	E080000
32171	E01010486	Wolverhampton 011D	E080000
32172	E01010474	Wolverhampton 012A	E080000
32173	E01010561	Wolverhampton 012B	E080000
32174	E01010564	Wolverhampton 012C	E080000
32175	E01010565	Wolverhampton 012D	E080000

Sample raw data

Step 2a: Visualisation Examples

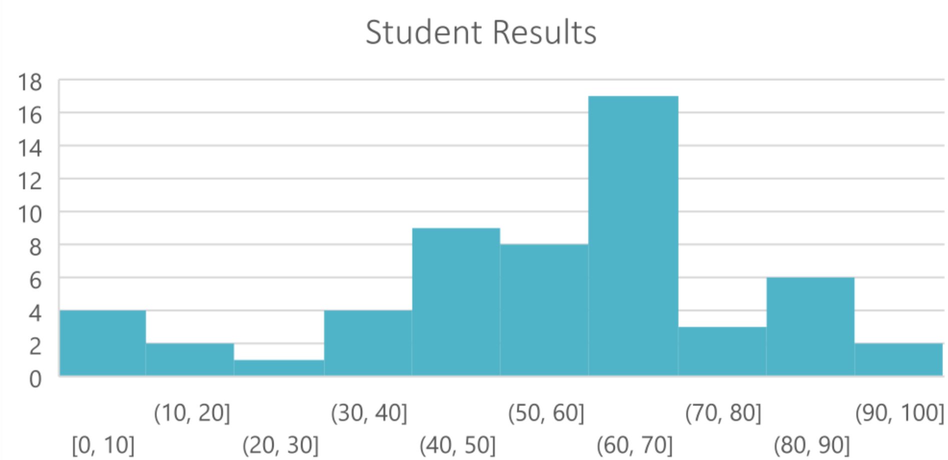
Histogram

Can show the distribution of the data and any skewness or unusual dispersion

Given this set of student results, can you predict their overall performance?

	A	B
1	**Student Name**	**Result**
2	Student1	0
3	Student2	50
4	Student3	72
5	Student4	78
6	Student5	22
7	Student6	81
8	Student7	40
9	Student8	40
10	Student9	62
11	Student10	62
12	Student11	54
13	Student12	90
14	Student13	53
15	Student14	60
16	Student15	90
17	Student16	54
18	Student17	57
19	Student18	0
20	Student19	17
21	Student20	48
22	Student21	0
23	Student22	86
24	Student23	83
25	Student24	70
26	Student25	45
27	Student26	67
28	Student27	61
29	Student28	40
30	Student30	67
31	Student31	67
32	Student32	65

Does this make it easier?



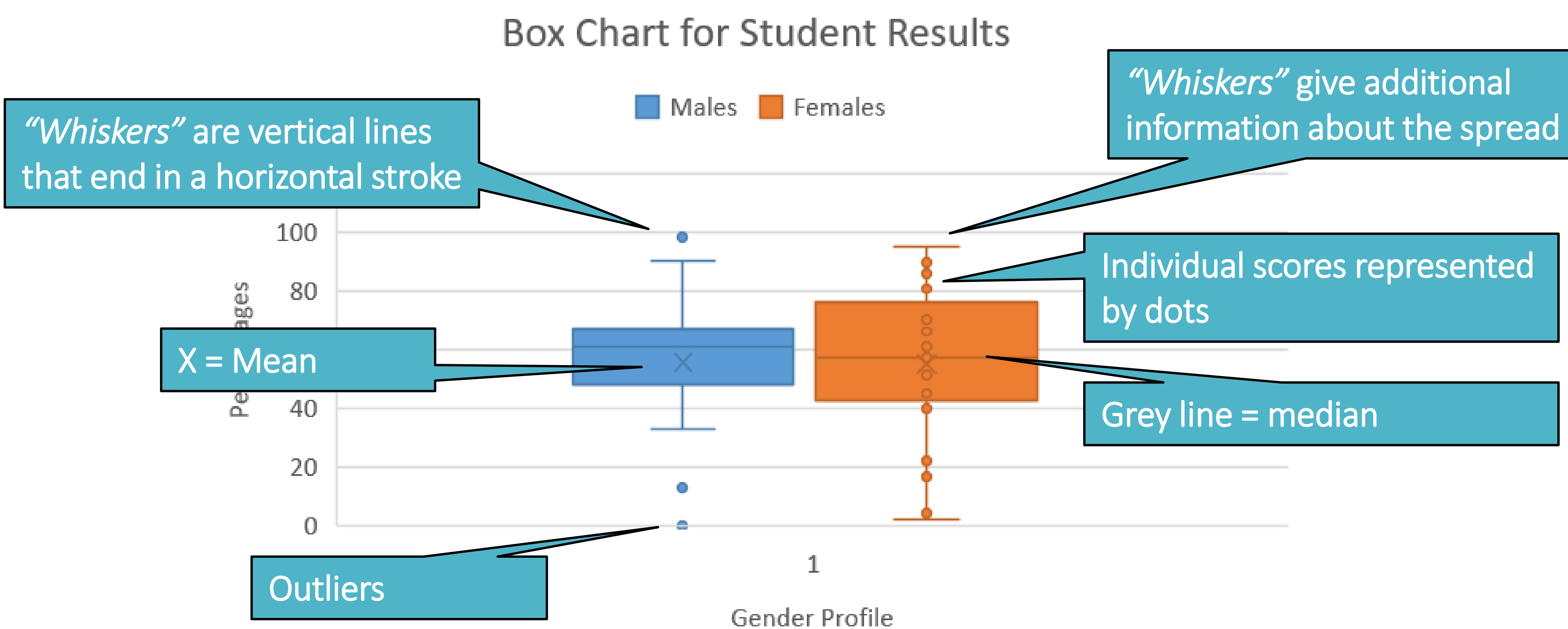
Step 2a: Visualisation Examples

Boxplots

Another type of plot for showing data distribution

Useful for identifying outliers and comparing distributions

Excel calls these *Box and Whisker* charts



Step 2a: Visualisation Examples

Line graphs

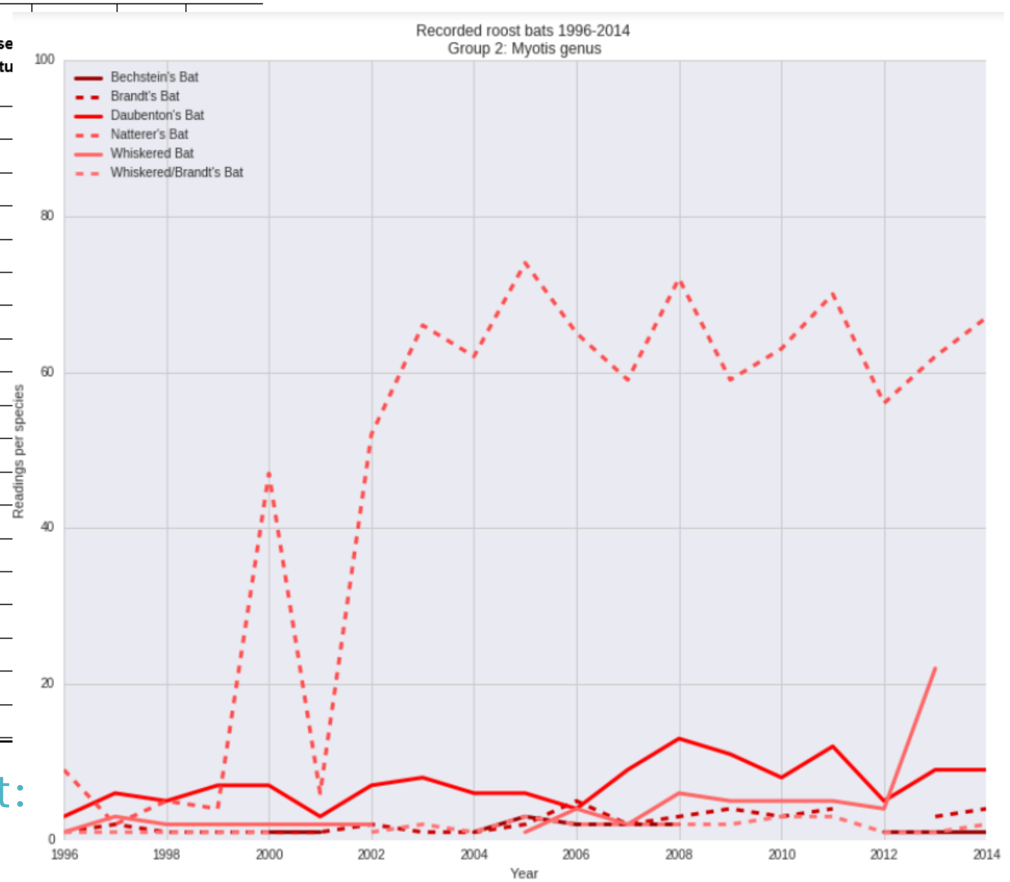
Useful for seeing how values in the data changes over time.

Spikes in the data are also easy to spot

For example data on bats:

Species	Year	Bat	Bechstein's Bat	Brandt's Bat	Brown Long-eared Bat	Common Pipistrelle	Daubenton's Bat	Greater Horseshoe Bat	Grey Long-eared Bat	Lesser Horseshoe Bat	Lesse Noctu
0	1996	NaN	NaN	1	10	28	3	NaN	NaN	149	NaN
1	1997	NaN	NaN	2	12	123	6	11	NaN	50	NaN
2	1998	1	NaN	1	9	195	5	10	NaN	63	NaN
3	1999	3	NaN	1	11	238	7	11	NaN	121	NaN
4	2000	1	1	1	14	210	7	12	NaN	105	NaN
5	2001	2	1	1	60	158	3	17	NaN	62	NaN
6	2002	3	NaN	2	85	257	7	20	NaN	126	NaN
7	2003	2	NaN	1	84	256	8	15	NaN	127	NaN
8	2004	2	1	1	94	309	6	16	NaN	140	NaN
9	2005	2	3	2	113	316	6	27	NaN	175	NaN
10	2006	2	2	5	110	392	4	31	NaN	160	NaN
11	2007	2	2	2	124	369	9	27	NaN	167	1
12	2008	1	2	3	146	365	13	26	NaN	151	3
13	2009	1	NaN	4	136	398	11	25	NaN	157	2
14	2010	2	NaN	3	142	394	8	31	NaN	185	2
15	2011	3	NaN	4	147	368	12	28	NaN	199	3
16	2012	6	1	NaN	109	347	5	36	NaN	175	NaN
17	2013	4	1	3	115	327	9	36	1	238	NaN
18	2014	12	1	4	107	285	9	38	3	233	NaN

Easier to visualise using line chart:

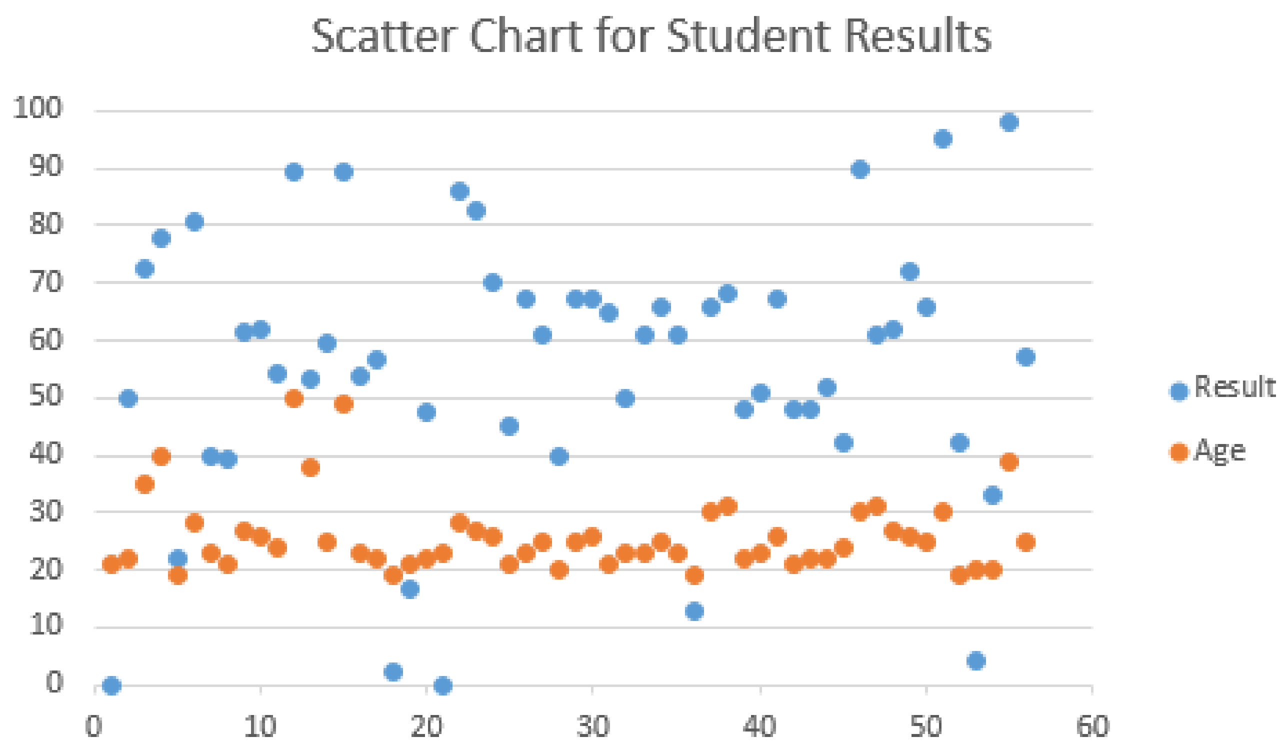


Step 2a: Visualisation Examples

Scatter plots

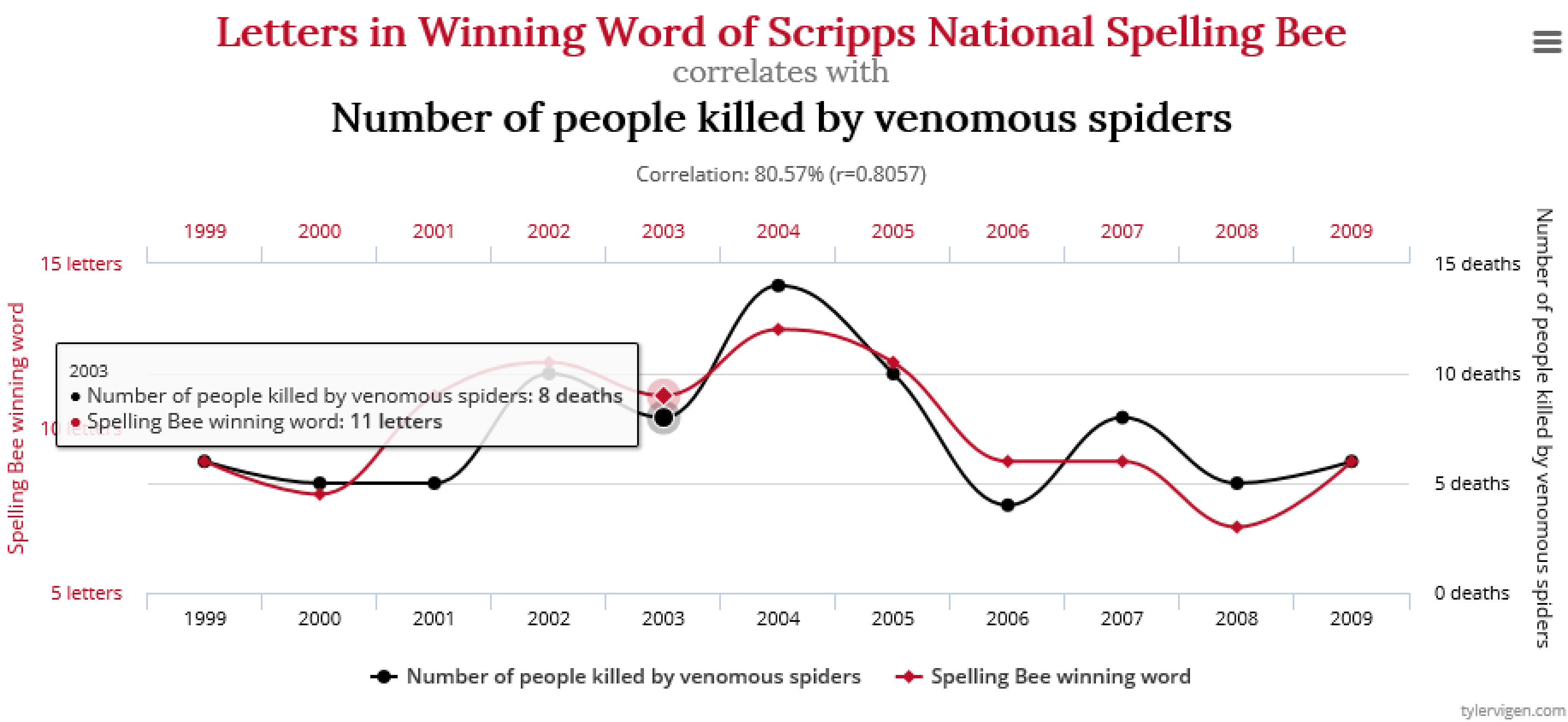
Can show correlation between two variables

Is there any correlation between results and a student's age?



Correlation

Beware: correlation does not always imply causation!



http://tylervigen.com/spurious-correlations

Step 2b: Prepare Data

After the exploratory analysis you need to prepare the data

The raw data acquired is not usually in the format you want

Integration

  You may need to merge data from multiple sources

  Are they all using the same formats, naming conventions?

  E.g., date formats can vary in DBMSs:

    Oracle's *DD-MON-YY* v's MySQL *YYYY-MM-DD*

Two main goals in data pre-processing:

- Clean the data to address data quality issues
- Transform the raw data to make it suitable for analysis

Step 2b: Pre-process the Data

- Clean the data
  - Garbage In Garbage Out
- Real-world data is messy!
  - Inconsistent values
    - *Customer with 2 different addresses*
  - Duplicate records
    - *Customer with more than one record*
  - Missing values
    - *E.g., missing a customer's age which is needed for a demographic study*
  - Invalid data
    - *Postcode in the wrong format*
  - Outliers
    - *Values that are much higher/lower than expected*

Step 2b: Prepare Data

You will have to decide and document whether to:

- Remove data with missing values
- Merge duplicate records

  Need to decide what to do if they have conflicting values?

  E.g., keep the latest value
- Generate best estimates for invalid values

  E.g., estimate a missing employee's age from their length of service
- Remove outliers

  Could be real values that were just extremes on occasions

Step 2b: Cleaning Data

Common types of data errors (Kim 2003):

Dirty data error	Description
Validity	Do values match constraints? Are values in range?
Accuracy	Are values accurate, e.g., compare to reference lookup? Correct spelling? Correct capitalisation?
Completeness	Are all mandatory fields present, that is, not null?
Consistency	Are the same type values in different cells in the same column, e.g., names, numbers?
Uniformity	Are formats the same for the same fields, e.g. dates? Is white space present? Are Units of Measurement the same?

Handling dirty data:

Approach	Outcome
Fix it	Replace incorrect value with correct value Insert missing values
Remove it	Delete value or group of values => impact?
Replace it	Put marker in dataset indicating it is an inappropriate value
Leave it	Note and accept any dirty data

Don’t forget to document what has been added/deleted/changed

Step 2b: Cleaning Data

Below is a sample student data set for the fictitious *Borchester University*.

What issues are there with this data?

studentNo	studentName	Gender	DOB	avgMark
1234	Johnny Rick Philips	b	12-Jan-08	59
2345	Sheila Hebden Lloyd	f	22/04/1957	85
3355	Perks, Jamie	m	09/25/05	
4455	will grundy	m	23-Feb-81	105
6541	Madikane, Kate	F	02/08/1978	-55

Mixed case, inconsistent first and surname order

Inconsistent case, b = boy?

Inconsistent date formats

Percentages? Minus or >100 ok?

Step 2b: Prepare Data

- Knowledge about the application the data came from is important
  - How the data was collected; intended use
  - Called the *domain knowledge*
- The domain knowledge helps make informed decisions on how to handle incomplete or incorrect data
- For example, if there were no integrity checks, there is more likely to be rogue data
- Getting data into shape is called many things:
  - Data munging
  - Data wrangling
  - Data pre-processing
  - Data manipulation

Step 2b: Prepare Data – Operations

Types of operations include:

- Dimensionality reduction
  - E.g., change 3D model to 2D
- Data manipulation
  - Shaping the data to fit new requirements
  - Filtering the data – may not need everything
- Transformation
  - To reduce noise and variability
  - One example is aggregation.
    - *This generally results in data with less variability.*
    - *For example, daily sales figures may have many peaks and troughs. Aggregating values to weekly or monthly sales figures will result in similar data*

Step 2b: Prepare Data – Operations

Feature selection

- Remove redundant or unnecessary features
  - Two features may be correlated, so one could be removed, such as VAT paid
- Combine features, such as adding salary and commission to create a total salary
- Creating new features, such as adding an applicant's education level to a loan approval

Scaling

- Involves changing the range of values to be between a specified range
- Done to avoid large values dominating the results

Step 3: Analyse the Data

Involves several steps

- Select analytical techniques
- Build models
  - *– This may need several iterations and involve going back to Steps 1 and 2*
    - E.g., if need further data or need to package the data using a specific format
  - *– This involves taking the input data from the previous steps and generating an output model*
- Validate Model

Step 3: Analyse the Data

Categories of Analysis Techniques

Classification

Goal: predict category

E.g., predict weather as sunny, rainy or cloudy

Regression

Goal: predict numerical value

E.g., predict price of a stock

Clustering

Goal: organise similar items into groups

E.g., organise customers to seniors, adults and teenagers

Association Analysis

Goal: find rules to capture associations between items

E.g., if you buy one item, what else might you buy

Graph Analytics

Goal: Use graph structures to find connections between entities

E.g., explore spread of a disease by analysing hospital records

Step 3: Analyse the Data

Before moving on you need to evaluate the results

For example,

- For classification and regression you could compare the predicted values against some correct values.
- For clustering do the groups make sense for the application?
- For association analysis and graph analysis, further investigation is needed to check whether the results are correct. E.g., does what your model predict actually happen?

Step 4: Communicate Results

- Evaluation of the analytical results
- Usually involves Visualisation techniques

  A picture is worth a 1000 words!
- Involves interpreting the results, summarising or visualising
- May need to acknowledge the source of data if the licence agreement requires this.

Various tools exists to help with the visualisation:

- Power BI
- Tableau
- Google Charts
- R and Python
- Many others.....

Step 5: Apply Results

There should be some purpose to the exercise

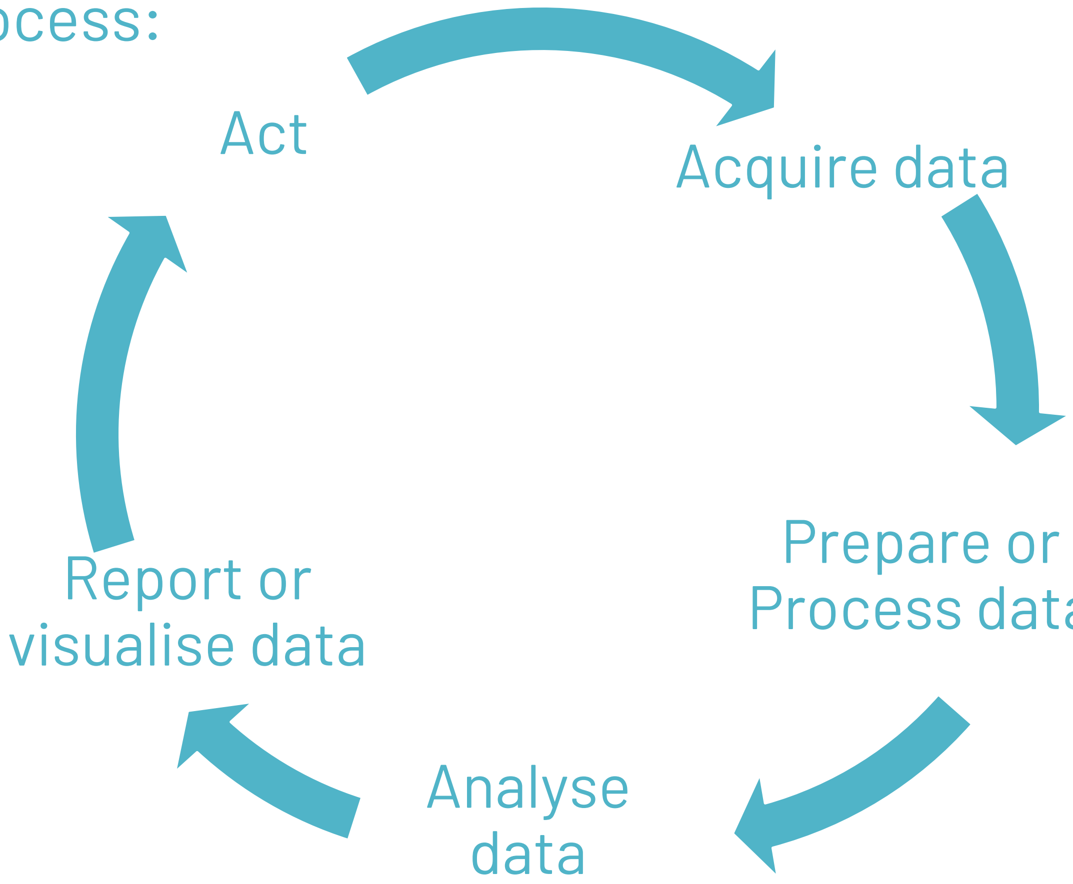
The main reason why data science is needed:

- Involves reporting insights from the analysis and determining actions
- May involve helping business needs
- Need to determine next steps:
  - *Is extra analysis needed to yield better results?*
  - *Any data needs revisiting?*
  - *Any further opportunities to explore?*

Remember: big data and data science are only useful if the insights can be turned into actions and the actions are carefully defined and evaluated.

Summary

This lecture has looked at a variety of techniques in the data science process:



Note: these steps should be an iterative process!