

(MSc) Data Mining

Topic 01 : Module Overview

Part 03 : Module Introduction

Dr Bernard Butler and Dr Kieran Murphy

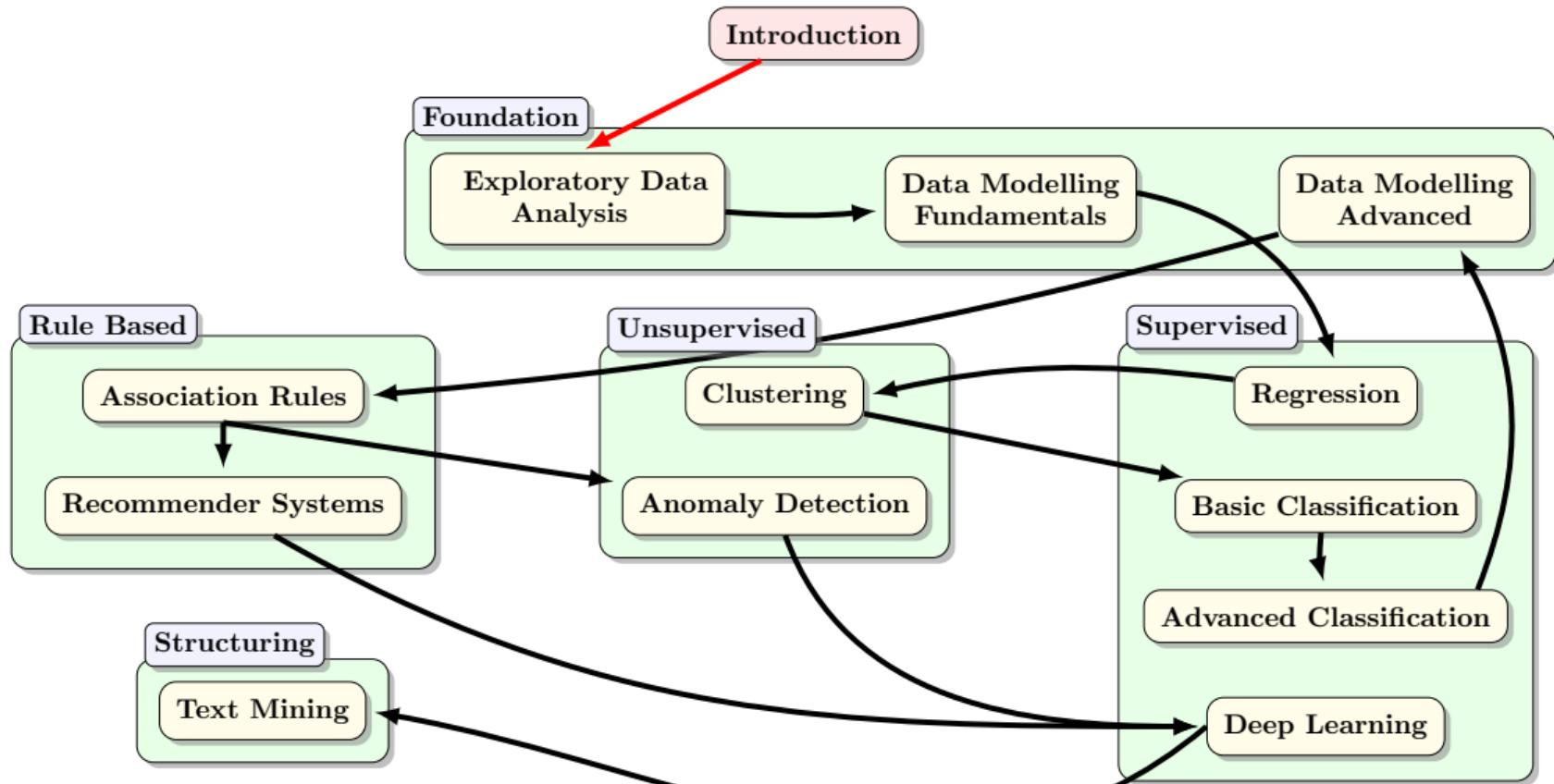
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Spring Semester, 2026

Outline

- Introduction, definitions and context
- Roles, expertise and ethics
- Workflow and process models
- Overview of Machine Learning Algorithms
- Delivery and Assessment
- Resources

Data Mining (Week 1)



How? — Delivery

➤ Contact hours

- One 2-hour lecture per week.
 - Friday 14:15 (GMT/IST; online over zoom)
 - Presented by Bernard and Kieran, generally on alternate weeks.
 - We cover concepts, definitions, examples, etc.
 - Lecture objective is to improve understanding of the topic.
 - Lab is used to develop practical experience of an integrated set of topics
 - Feel free to stop us and ask questions (raise your hand and/or put message in chat) at any point.
- One 2-hour practical session per week on Monday afternoons from 15:15 onwards.
 - Labs use python workbooks to define and implement data mining *workflows*.

➤ (Hardware) Requirements

- Use of own (moderately powerful: multi-core CPU, min 8GB RAM, but ideally 16GB or more) laptop is recommended!

How? — Assessment Structure

100% Continuous Assessment

- ① Issued Week 1, submitted end Week 4 (Data Mining Proposal, 20%)
- ② Issued Week 3, submitted end Week 6 (Initial Data Investigation, 30%)
- ③ Issued Week 4, submitted end Week 14 (Private Kaggle Competition, 30%)
- ④ Week 11 (In-class (Moodle) Quiz, 20%)

What is the AIM of the module?

➤ Aim, as per Module Descriptor*...

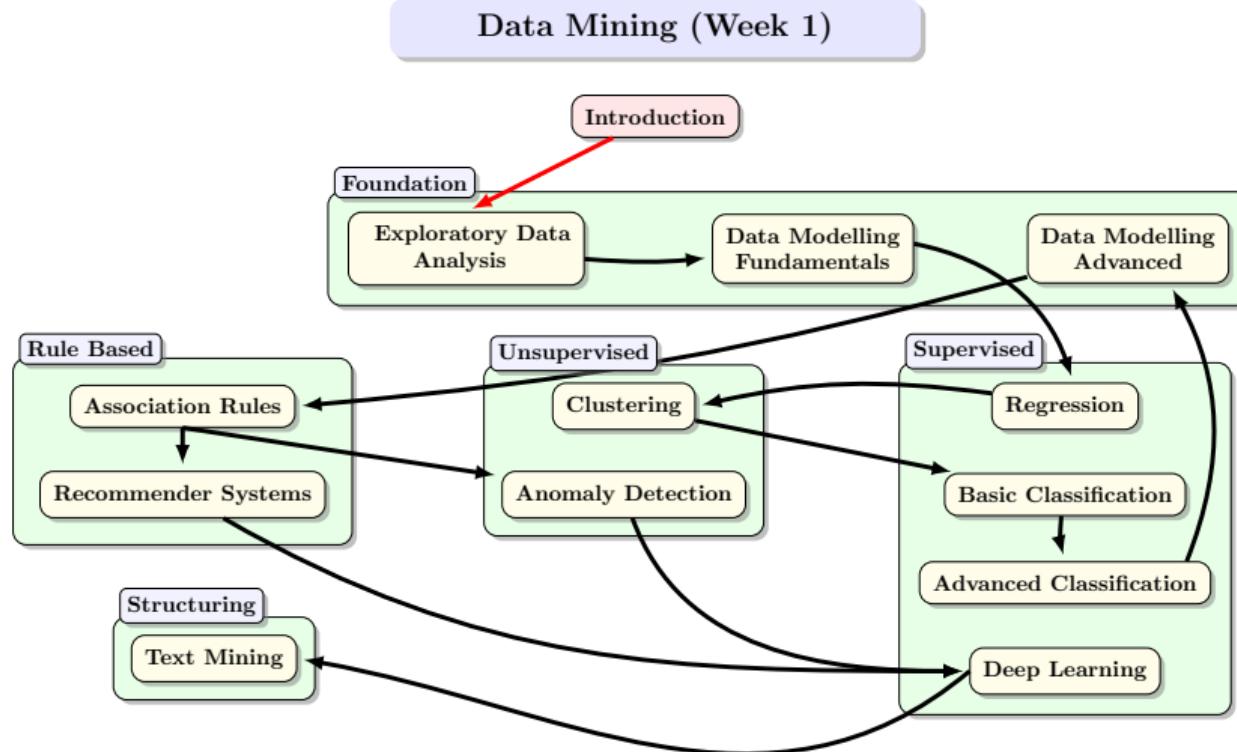
The student will be introduced to the fundamental concepts and techniques of Data Mining. The student will learn the data mining process and experience the steps involved; including data pre-processing, modelling, optimisation, result interpretation and validation...

➤ Translation (Informal Aims)

- ① Collect observations from a variety of processes, yielding large amounts of data.
- ② Preprocess this data, selecting relevant features only.
- ③ Use data-intensive analysis techniques to obtain insights.
- ④ Postprocess analysis results, validate, visualise and refine the process.

* Also, see the [module descriptor](#) for the learning outcomes for a more formal description of this module.

What topics does it contain?



Why study Data Mining?

Selected definitions

Data Scientist: can ask the right questions, generate and consume the results of analysis of Big Data effectively.

(McKinsey 2011)

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Generative AI: AI that creates *instances* of new data that resemble or extend the training data (Restack 2025).

More definitions...

Large Language Models: LLMs are a category of deep learning models trained on immense amounts of data, making them capable of understanding and generating natural language and other types of content to perform a wide range of tasks. LLMs are built on a type of neural network architecture called a transformer which excels at handling sequences of words and capturing patterns in text. (IBM, 2026)

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Agentic AI: Agentic AI is an autonomous AI system that can act independently to achieve pre-determined goals. Traditional software follows pre-defined rules, and traditional artificial intelligence also requires prompting and step-by-step guidance. ... Agentic AI is proactive and can perform complex tasks without constant human oversight. (AWS, 2026)

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➤ This module focuses on fundamental concepts and understanding, so it just touches upon these topics.

What is data mining and how does it relate to similar terms?

Operational Definitions

- deriving knowledge from large and/or complex datasets, with *guidance* from the data scientist
- “Data mining is the study of efficiently finding structures and patterns in large data sets. It draws from and influences the disciplines of programming, mathematics/statistics, database management and machine learning.”

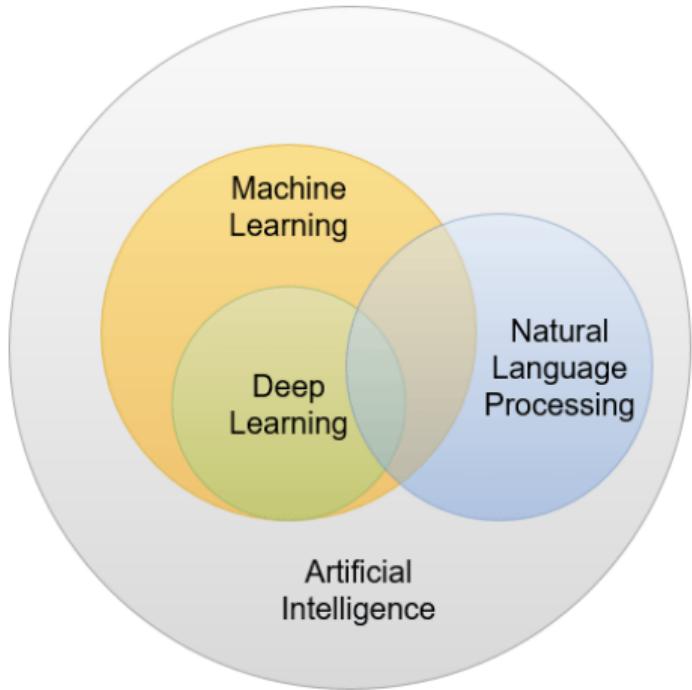
Primary goals

- From messy and noisy raw data, deriving structure and context
- Applying scalable learning algorithms to these higher value data sets

Secondary goals

- Modelling and understanding the error and other consequences of the modelling process.
- Building data-driven processes, architectures & frameworks: *Big Data*

AI vs ML vs DL



- Note the AI > ML > DL hierarchy
- Generative AI (cf., ChatGPT) is very active at the moment, and goes beyond ML and DL.

Interlude: Examples of Data Mining

Exercise

Please consider (real world) challenges where *Data Mining* might help..
Can you come up with 3 examples in 3 minutes?

Analytics and Classical ML

Data Generation

- Financial transactions (bank, retail, ...)
- Social engagement (texts, comments, likes, shares, ...)
- Machine-to-machine (IoT, cyberphysical systems, ...)
- Content curation and recommendation

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Data Processing

- From Relational to NoSQL, to Multi-model databases
- From stored procedures to microservices and serverless computing
- From in-database to Apache Hadoop and Spark
- From proprietary statistical software to R and to python
- From consultants, to data scientists to machine learning engineers

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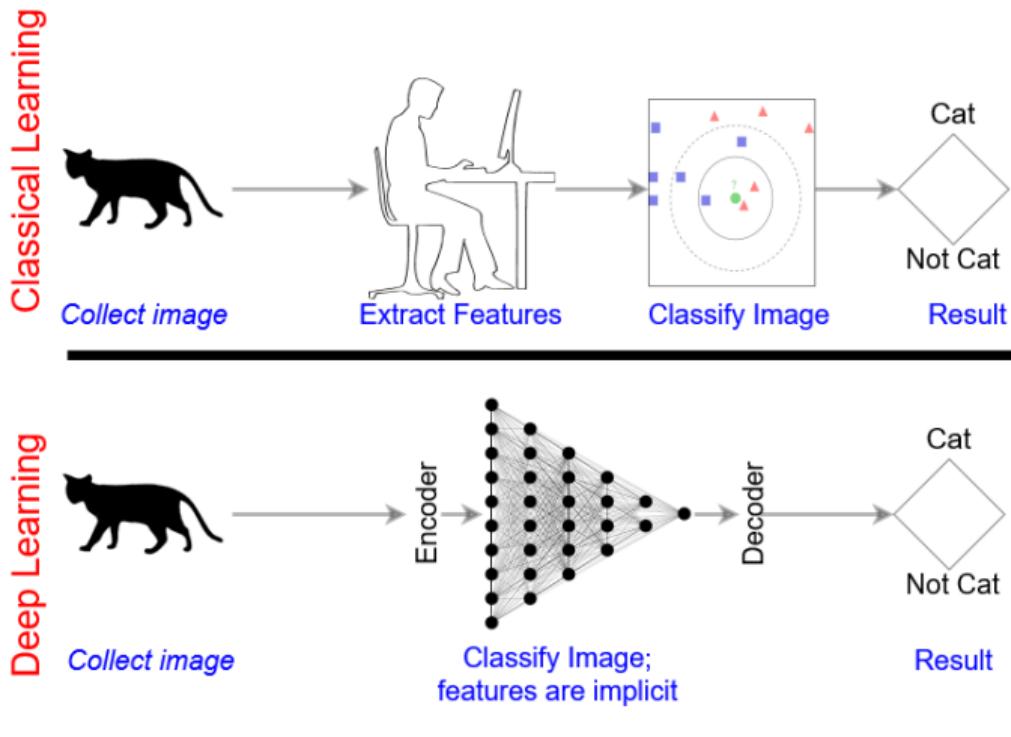
Data Analysis

- Reporting with descriptive statistics and simple plots, to classical ML with predictive analytics
- From predictive accuracy, to robustness vs fragility, to data understanding and visualisation
- Traditional chatbots are limited to specific contexts

The generative wave: 2022–date

- Traditional ML (big data processing for predicting labels or numbers) becomes mainstream
 - ML skills become expected
 - ML is operationalised by incorporating it in other practices (ML + DevOps = MLOps)
- *Generative AI* becomes practical
 - Large Language Models for generating textual responses to prompts, e.g., ChatGPT
 - Generate images, e.g., DALL-E and video, e.g., Sora given textual descriptions.
 - Rise of the **Prompt Engineer**, now **Context Engineer**, going from all-knowing chatbots to autonomous agents
- AI is beginning to deliver on the promise identified by Alan Turing and others in the 1950s.

Classical versus Deep Learning - overview



➤ Classical learning requires extensive setup before training.

Classical versus Deep Learning - pros and cons

Classical Learning	Deep Learning
Can work well with less data (< 10^6 rows, say)	More training data gives more accuracy (within reason!)
Easier to interpret/explain models	Model is opaque and can be fragile
Training is relatively fast	Training can require many epochs
Training requires fewer resources	Training requires massive resources
Accuracy improvement falls off	Accuracy can improve with more training data
Features engineering is performed by humans	Features are encoded implicitly in layers during training
Complex prediction requires complex model	With enough nodes, DL can represent any function

Classical versus Deep Learning - pros and cons

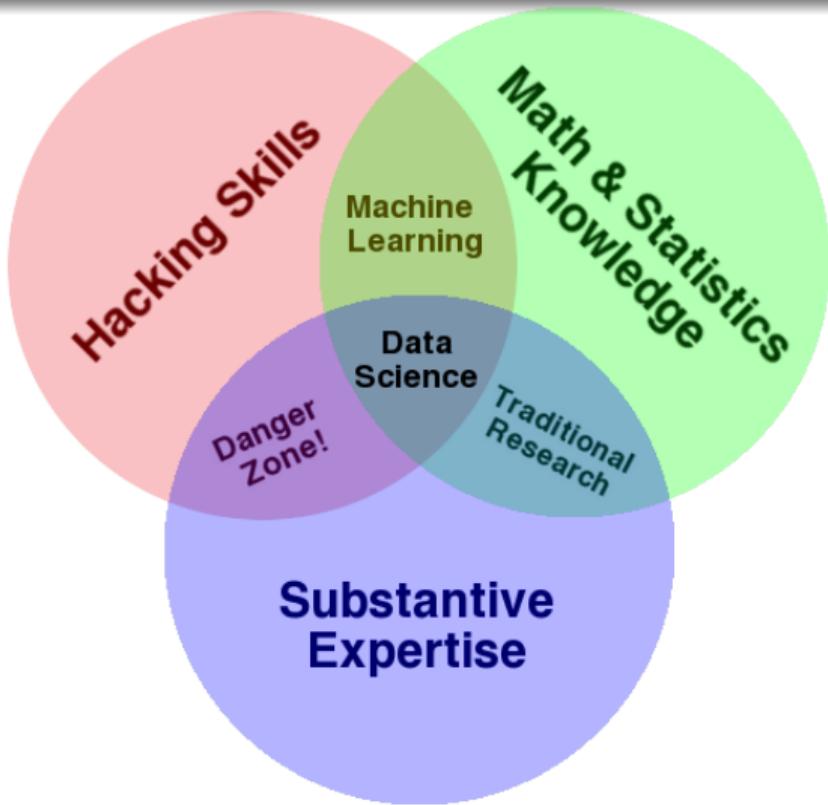
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In conditions where one type of learning is weak, the other is often strong.

Emphasis of this module

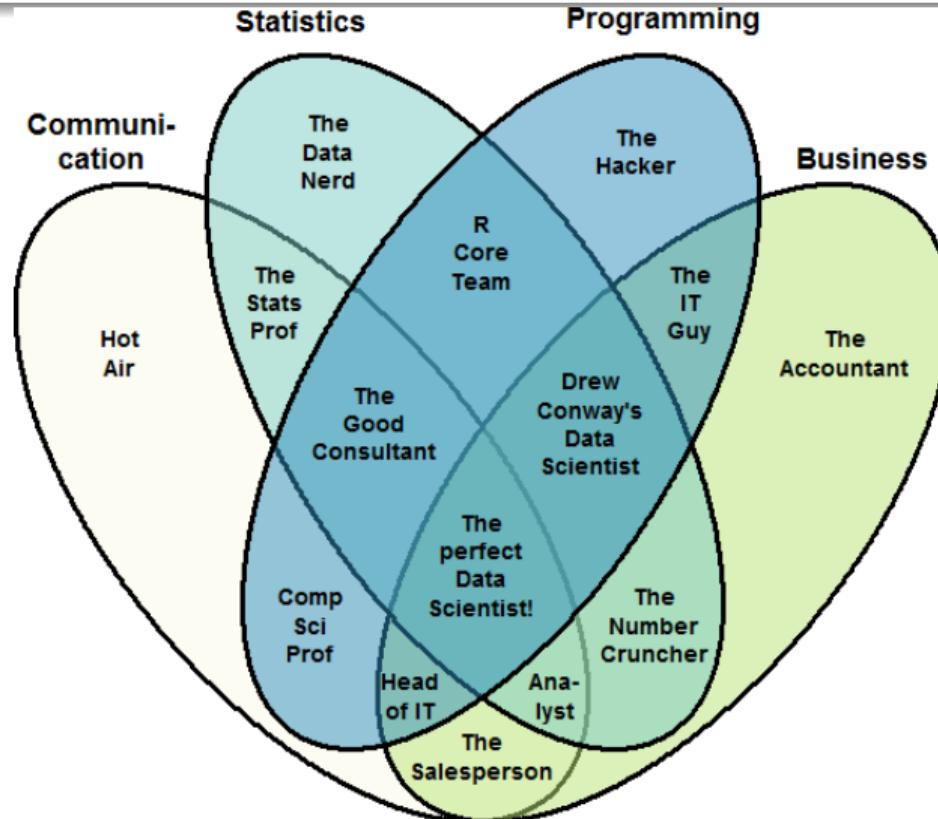
- This module covers foundations, classical models, some deep learning
- Foundations include EDA, notions of error and variance, training vs test data, ...
- Classical modelling includes feature selection and classical approaches to learning from data
- Neural network and Deep learning go straight to predicting based on (encoded) data
- Foundations are shared by both classical and deep learning
- Deep learning is ideal for learning from **labeled, web-scale** big data. Specialised deep-learning models are the basis of LLMs.
- Day-to-day, classical machine learning is often more suitable for predicting from relatively small datasets.

Drew Conway's 3-set Venn Diagram of Data Science Expertise



Source: <http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram>

Stephan Kolassa's 4-set Venn Diagram of Data Science Expertise



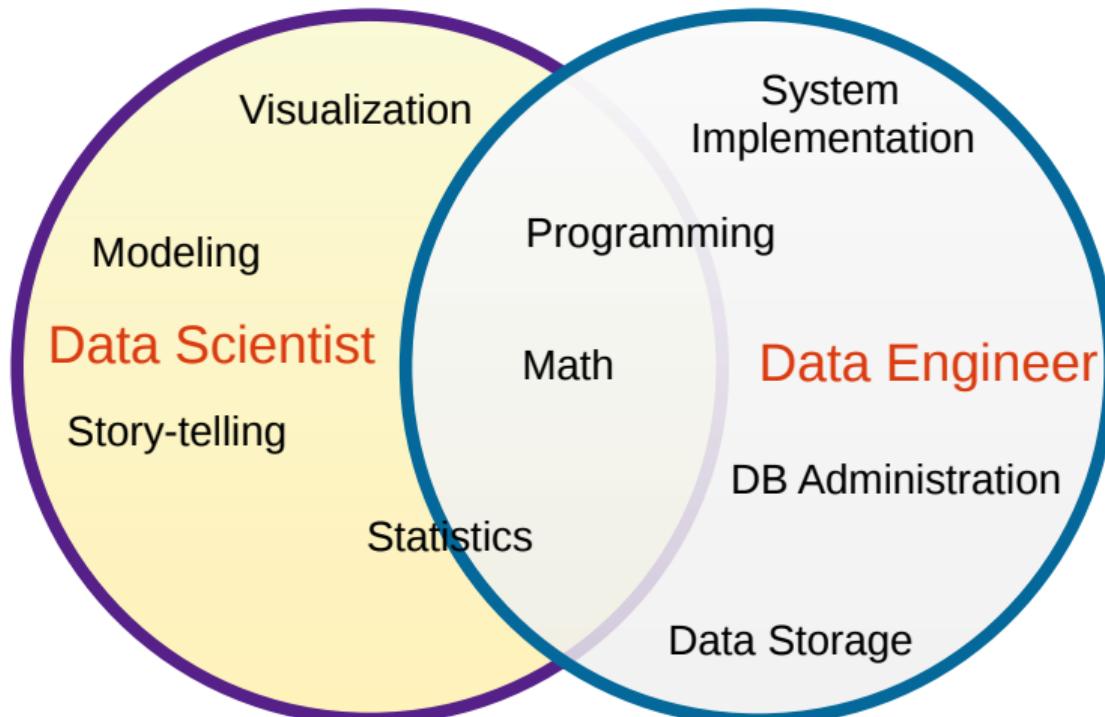
Source: <https://datascience.stackexchange.com/a/2406>

Gartner suggests the need for a *Citizen Data Scientist*



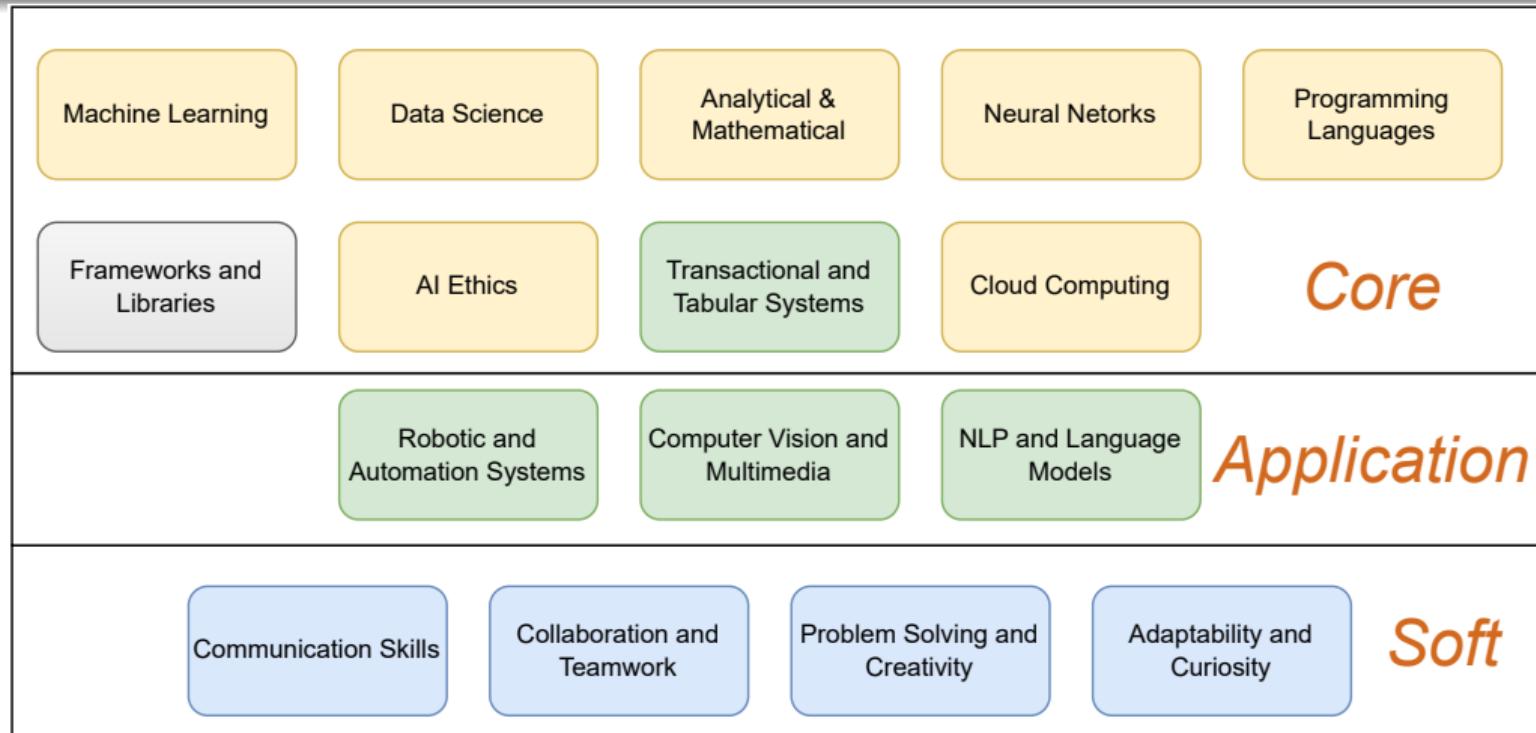
Source: <http://www.kdnuggets.com/2016/03/cartoon-citizen-data-scientist.html>

Data Scientist vs Data Engineer



Source: <https://ryanswanstrom.com/2014/07/08/data-scientist-vs-data-engineer/>
Also the traditional roles of *Data Analyst* and *Software Engineer*...

AI Engineer Skills 2025



Source: Based on <https://dmletterstudio.com/ai-engineer-skills-needed>

➤ This module touches on most of the core skills and some of the soft skills

Ethical Concerns

- protecting privacy
 - obtain informed consent for training data
 - pseudonymisation can be insufficient

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 - Biased training data leads to biased outputs from models
 - Diverse and representative training data gives more reliable predictions

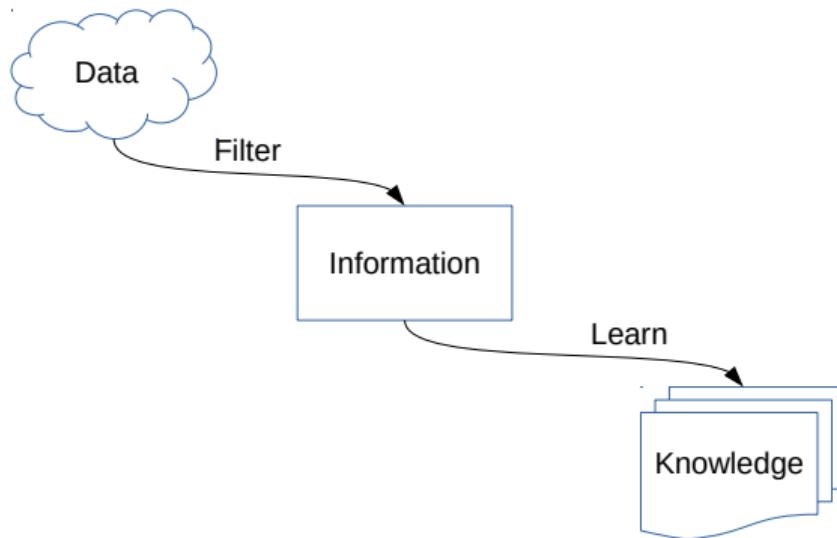
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 - Poor choice of techniques, settings and model parameters can harm prediction quality
 - Careful validation can assess whether predictions are as good as expected

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 - Poor choice of techniques, settings and model parameters can harm prediction quality
 - Careful validation can assess whether predictions are as good as expected
- enabling decisions to be challenged
 - Related to interpretability, predictions without understanding can be misleading
 - Need to support an audit trail, validation procedure and due process

The Data to Knowledge Pipeline



Data Filtering

- Clean (drop unwanted observations)
- Summarise (remove observation detail)
- Reduce (remove/transform variables)

Learning

- Derive models
- Validate models
- Analyse discordance

Data - Information - Knowledge - Wisdom

Example of the DIKW chain

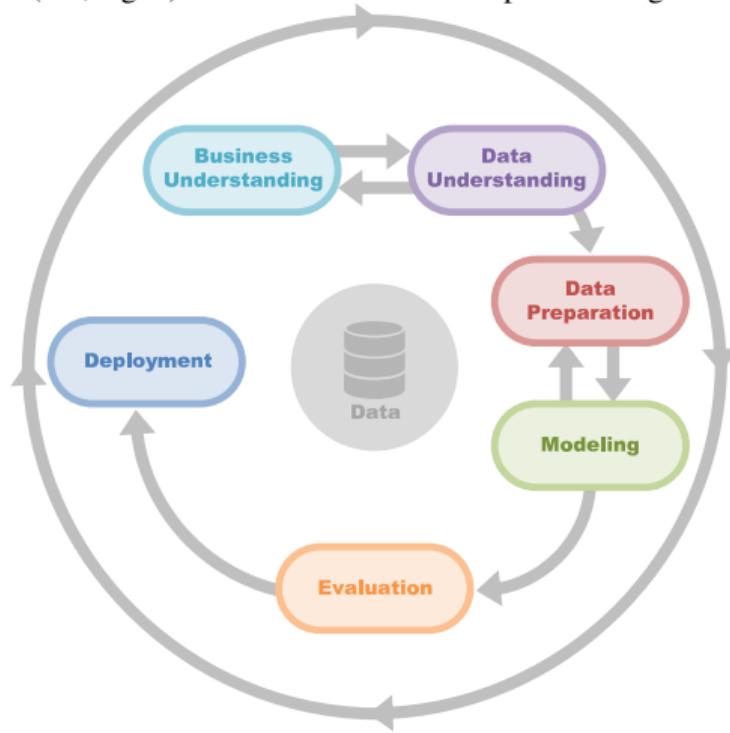
- Servers and applications log events in files and/or databases [DATA]
- *Collector* agents select specific events, in context [INFORMATION]
- Machine learning *classifiers* learn system behaviour and identify anomalies [KNOWLEDGE]
- Humans and software use this knowledge to prevent future problems [WISDOM]

Note that the DIKW chain is often represented as a pyramid.

Cross Industry Standard Process (for) Data Mining

CRISP-DM

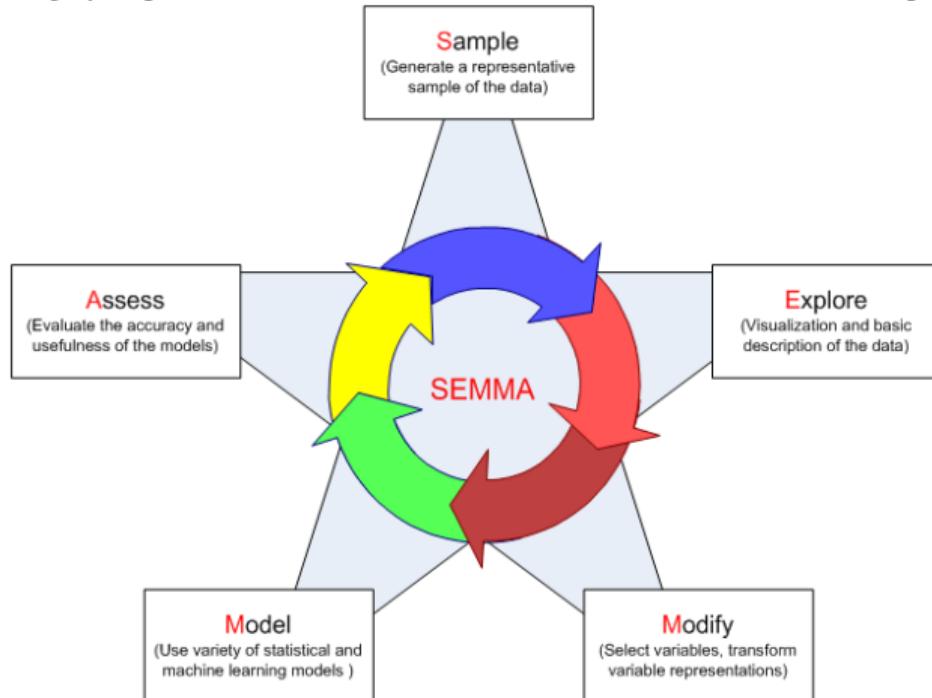
CRISP-DM is a high-level iterative process model. It gives much weight to data understanding and preprocessing and involves the data and problem owners from the start (c.f., Agile). It is the best known but predates Big Data, etc.



Sample, Explore, Model, Modify, Assess

SEMMA

SEMMA is promoted by SAS and takes a more operational view of data mining, using a (statistical) *model-building* metaphor. Business input is essential but largely implicit. It is more concrete than CRISP-DM so it tends to map well to DM tool workflows.

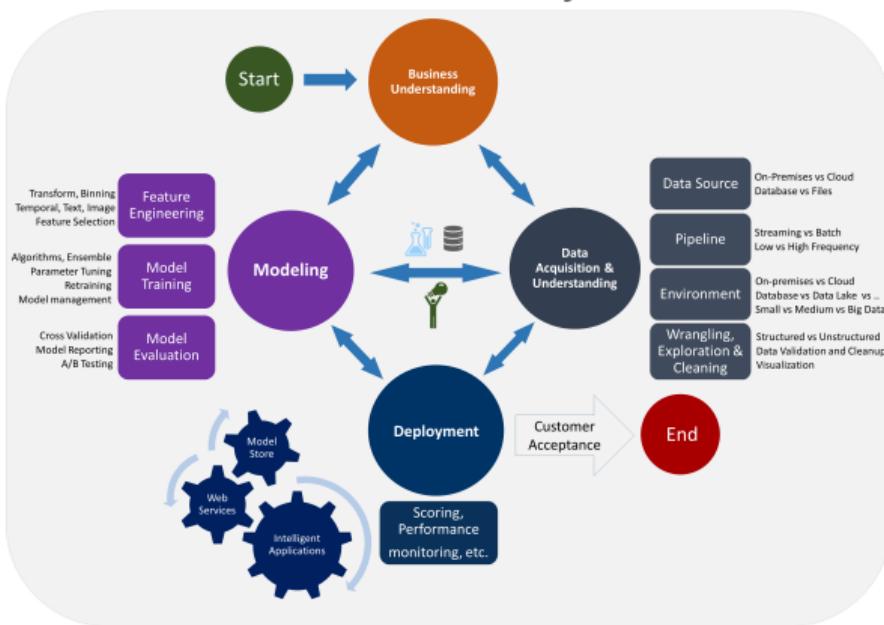


Microsoft Team Data Science Process



TDSP is the most detailed process model of the 3. It is much more recent. It is cloud-aware and directly references Azure and other Microsoft technologies. Typically there are two main cycles, one involving the Business, the other involving Deployment. Interestingly, there is a Start and End, so it is more project-focused.

Data Science Lifecycle



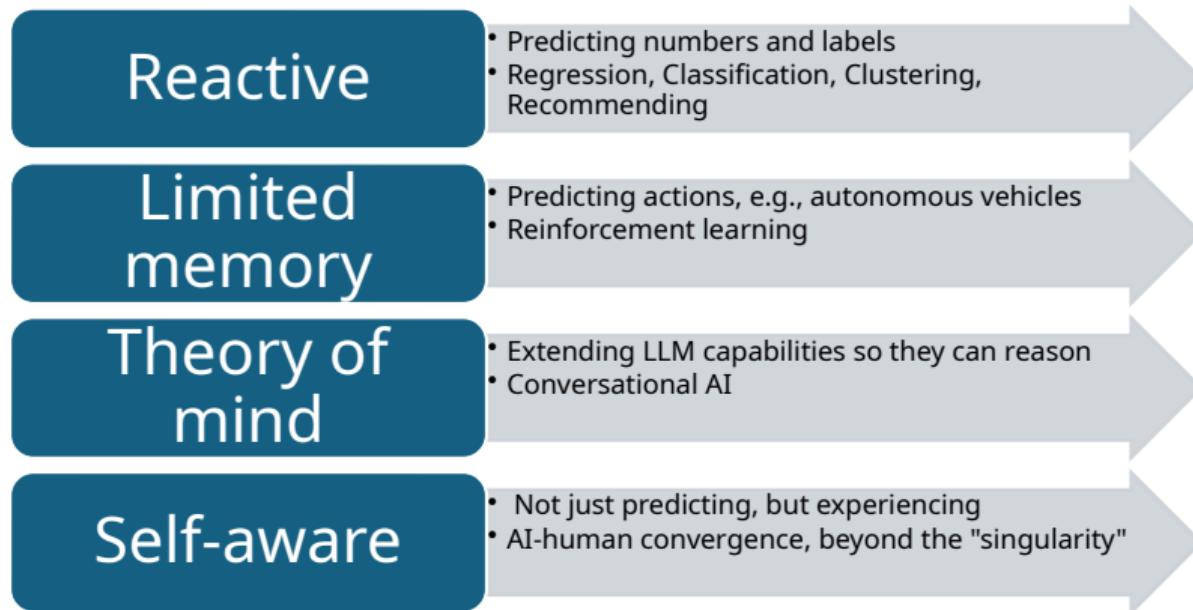
The “5 Tribes of Machine Learning”

Tribe	Origins	Learning Algorithm
Symbolists	Logic, Philosophy	Inverse Deduction
Connectionists	Neuroscience	Backpropagation
Evolutionaries	Mathematical Biology	Genetic Programming
Bayesians	Statistics	Probabilistic Inference
Analogizers	Psychology	Kernel Machines

Summarised from Domingos (2015) “The Master Algorithm”

Each approach works well in specific contexts - there is no “master algorithm” yet...

Bernard Marr's 4 Types of AI

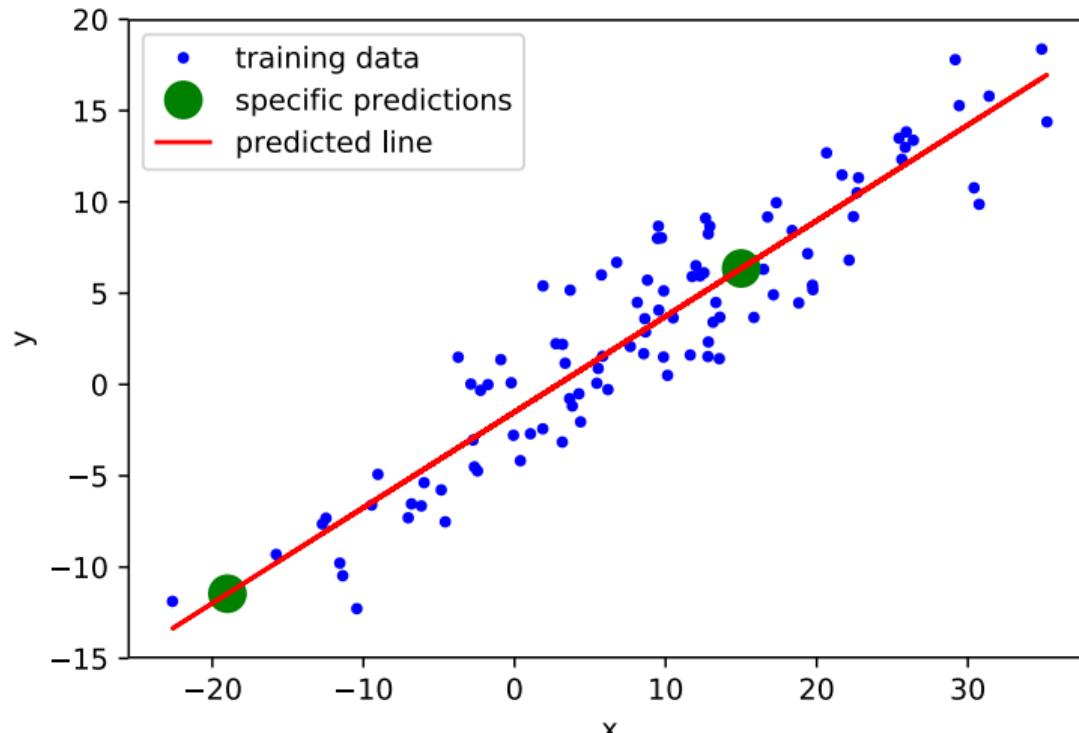


- This module focuses on Reactive AI (models, tools, techniques, interpretation, ...)
- Limited memory AI is gaining increasing adoption.
- Theory of Mind AI has been partially achieved (conversational AI can *mimic* a human's responses).
- Self-Aware AI is still science fiction.

Regression

Definition

Given data comprising a set of independent variables (of any type \mathbf{x}) with a set of dependent variables (numeric only \mathbf{y}), find the relationship $\mathbf{y} = f(\mathbf{x})$ having the maximum likelihood given the available observations $\{\mathbf{x}_i, \mathbf{y}_i\}$.



Classification

Definition

Given data comprising a set of independent variables (of any type x) with a set of dependent variables (categorical y (labels)), find the relationship $y = f(x)$ having the maximum likelihood given the available observations $\{x_i, y_i\}$.

There are many ways of representing f : a classification tree is shown here.

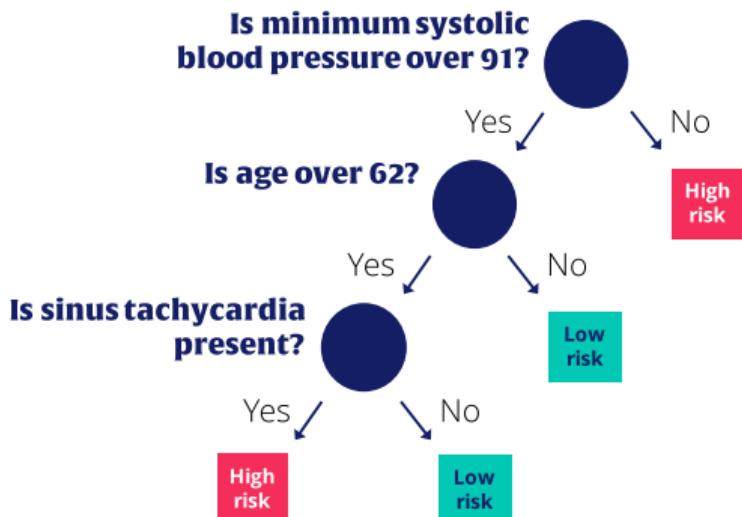
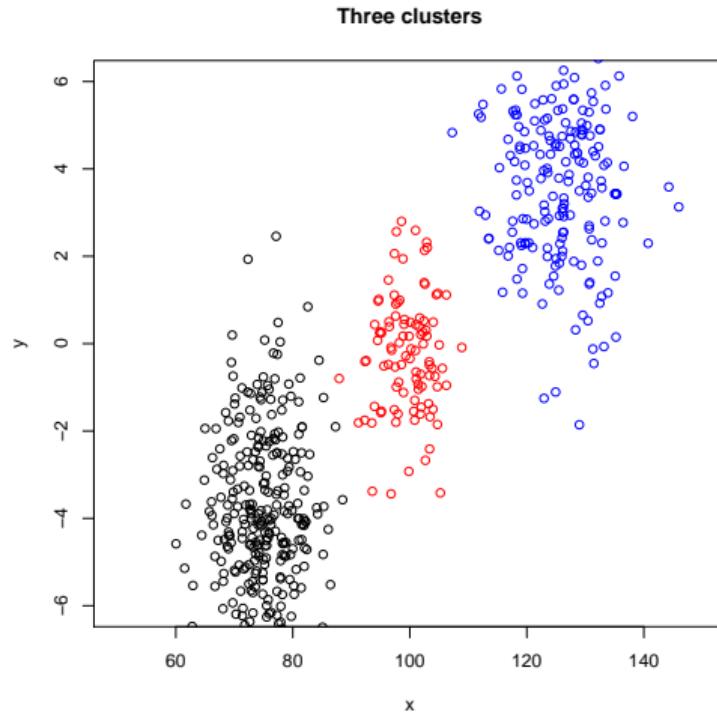
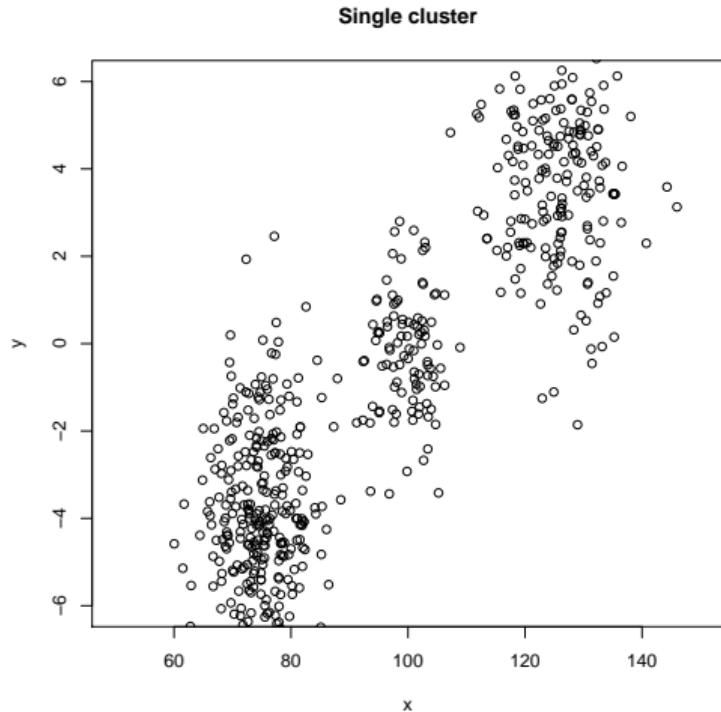


Diagram taken from the book Classification and Regression Trees, by Breiman L., Friedman J., Stone C. and Olshen R. 1984.

Clustering

Definition

Clustering is the process of grouping data into classes or clusters, so that objects within a cluster have high similarity with each other but are dissimilar to objects in other clusters. Different similarity measures and/or algorithms result in different cluster arrangements.



Clustering Example 2: Image Analysis

Le et al (2012)

- Google Brain simulator crawled the web, looking for patterns in photographs on the web.
- **It was *not* looking for anything in particular!**
- One pattern came up strongly...

Supervised learning question: what does this represent?

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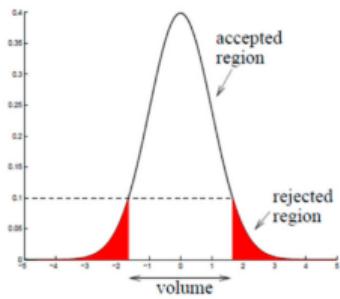
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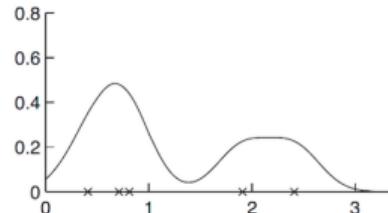
Anomaly Detection

Definition

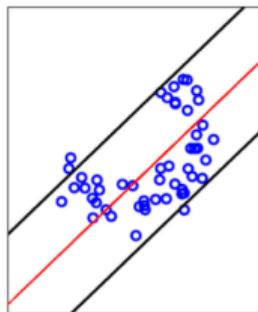
Anomaly detection identifies data points, events, and/or observations that depart from a dataset's normal behavior. Anomalous data can indicate problems, such as fraud, or opportunities, like a surge in demand for a product.



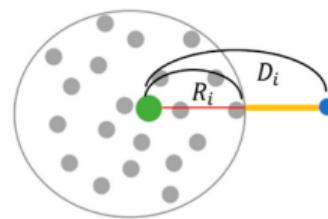
(a)



(b)



(c)



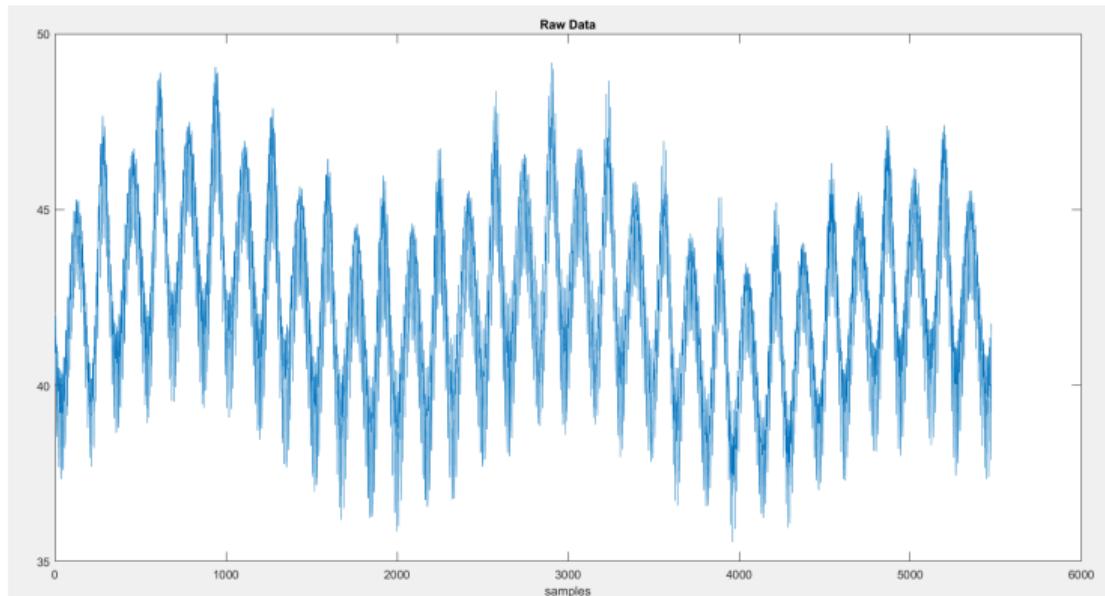
(d)

Source: Appl. Sci. 2019, 9, 4018; doi:10.3390/app9194018

Time Series Analysis

Definition

Time series data is a sequence of observations on the values that a variable taken at regularly-spaced time intervals. This data is sequentially correlated and techniques are needed to determine seasonality, trends, anomalies etc.



Source: <https://stats.stackexchange.com/q/458491>

Association Rules Mining

Definition

Frequent itemset mining looks for associations and correlations among items in large data sets. Associations are expressed as rules and quantified in terms of their *support* and *confidence*. The classical example is market basket analysis and the famous rule about buying diapers and beer together. See example transaction data below

TID	Items
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke



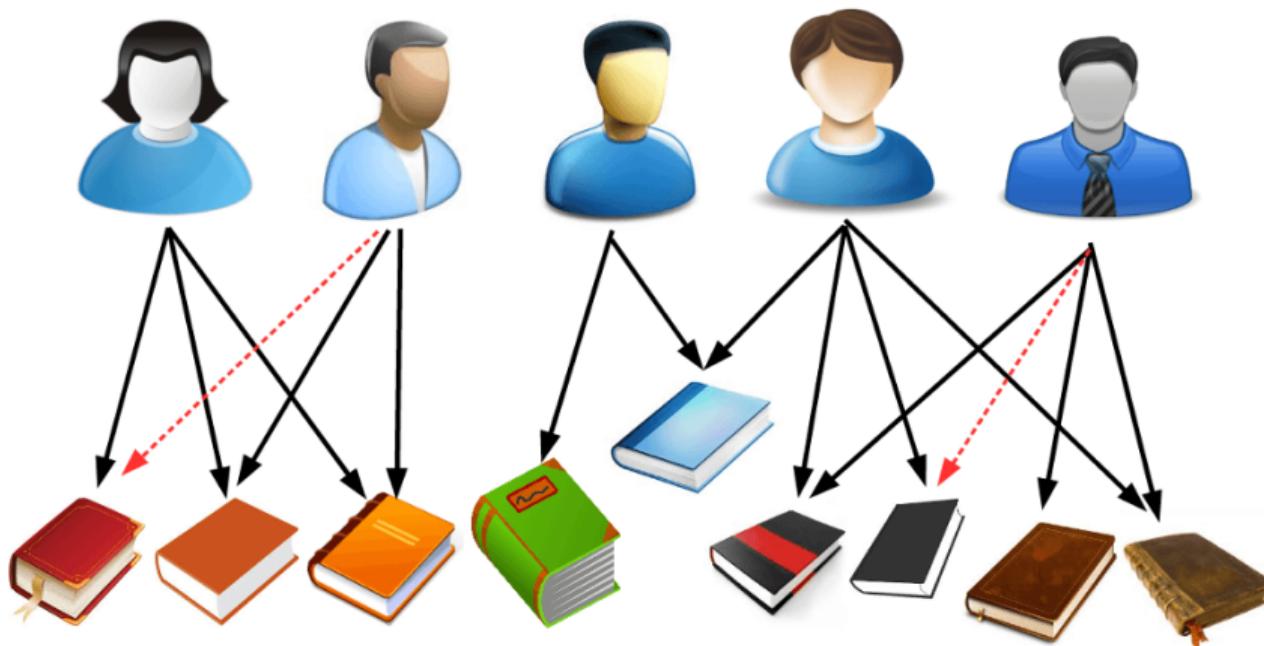
	Beer	Bread	Milk	Diaper	Eggs	Coke
T_1	0	1	1	0	0	0
T_2	1	1	0	1	1	0
T_3	1	0	1	1	0	1
T_4	1	1	1	1	0	0
T_5	0	1	1	1	0	1

ARM is a special case of structure mining, which includes graph mining, molecular and DNA nucleotide analysis

Recommender Systems

Definition

Collaborative filtering is an extension of item-based association rules mining to consider relationships between users and items. Generally, if two users have similar behaviour and/or preferences, items favoured by one user will also be favoured by the other. This can be used to recommend “new” items to users. Used very commonly on ecommerce websites for cross-selling.



Sample rows from auto-mpg dataset

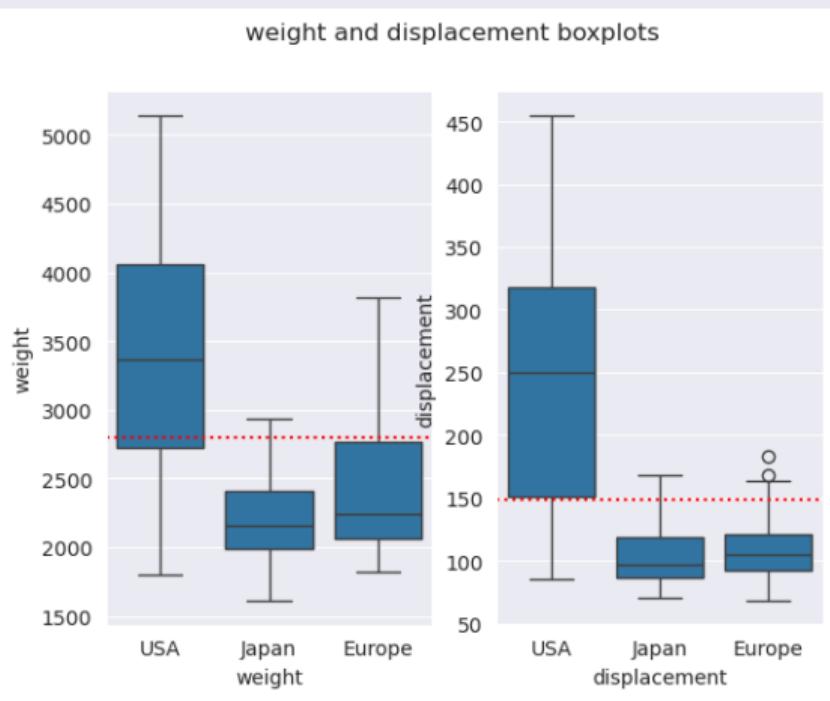
Pandas dataframe: sample rows used for training data

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
<u>32</u>	25.0	4	98.0	?	2046	19.0	71	1	ford pinto
<u>112</u>	19.0	4	122.0	85	2310	18.5	73	1	ford pinto
<u>130</u>	26.0	4	122.0	80	2451	16.5	74	1	ford pinto
<u>168</u>	23.0	4	140.0	83	2639	17.0	75	1	ford pinto
<u>174</u>	18.0	6	171.0	97	2984	14.5	75	1	ford pinto
<u>206</u>	26.5	4	140.0	72	2565	13.6	76	1	ford pinto

- The first (unnamed) “column” is the *dataframe index*; the values are like rowids in a database table.
- The rows contain data about automobiles in the US market in the early 1970s.
- The data is used to train models to predict “mpg” (*target*) given the other columns (features).

Example plot to develop an understanding of the data

Boxplot showing how manufacturer country affects weight and engine size



- Boxplot is one of many plot types available in plotting libraries
- Generated by a few lines of python code
- Side-by-side placement can help comparison
- What do the plots tell us?

Resources



- URL: [Moodle: Data Mining-28115-\[2025-2026\]](#)
- Used for all notices, assignment briefs and practical work submissions.



- URL: [Data Mining 2025-2026 pages on github.io](#)
- Used for content delivery (lecture notes and labs).



All software used during this module is open source or freely available for non-commercial use (full details given in notes). Primarily

- Anaconda (**Python 3.13, 64 bit**) www.anaconda.com
- scikit-learn scikit-learn.org
- pandas pandas.pydata.org

Further Reading

Please note that the notes and labs we provide should be sufficient to pass to pass this module, so the books below are intended as *further reading*, not *recommended reading*.

Data Mining, Concepts and Techniques

by *Jiawei Han, Micheline Kamber and Jian Pei*

Broad selection of topics, looks at the entire data mining process including how to collect and preprocess data, discusses selected algorithms in depth.

Mining of Massive Data Sets

by *Jure Leskovec, Anand Rajaraman and Jeffrey David Ullman*

Good mix of mathematical rigour and a treatment of the *Big Data* aspects for data mining at scale.

Python Data Science Handbook

by *Jake VanderPlas*, is both a textbook and a set of freely-available Jupyter notebooks that go into more detail on implementing some of the material in this module.

Neural Networks and Deep Learning

by *Michael Nielsen*, is a free online textbook that demystifies deep learning and is the basis of our treatment of deep learning later in this module.