Welcome to the CoGrammar

Lecture: Theory Summary I

The session will start shortly...

Questions? Drop them in the chat. We'll have dedicated moderators answering questions.

Data Science Session Housekeeping

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly. **(Fundamental British Values: Mutual Respect and Tolerance)**
- No question is daft or silly - **ask them!**
- There are **Q&A sessions** midway and at the end of the session, should you wish to ask any follow-up questions. Moderators are going to be answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Academic Sessions. You can submit these questions here: **Questions**

Data Science Session Housekeeping cont.

- For all **non-academic questions**, please submit a query: **www.hyperiondev.com/support**
- Report a **safeguarding** incident: **www.hyperiondev.com/safeguardreporting**
- We would love your **feedback** on lectures: **Feedback on Lectures**

Skills Bootcamp
8-Week Progression Overview

Fulfil 4 Criteria to Graduation

✅ Criterion 1: Initial Requirements

Timeframe: First 2 Weeks
Guided Learning Hours (GLH): Minimum of 15 hours
Task Completion: First four tasks

Due Date: 24 March 2024

✅ Criterion 2: Mid-Course Progress

60 Guided Learning Hours

Data Science - **13 tasks**
Software Engineering - **13 tasks**
Web Development - **13 tasks**

Due Date: 28 April 2024

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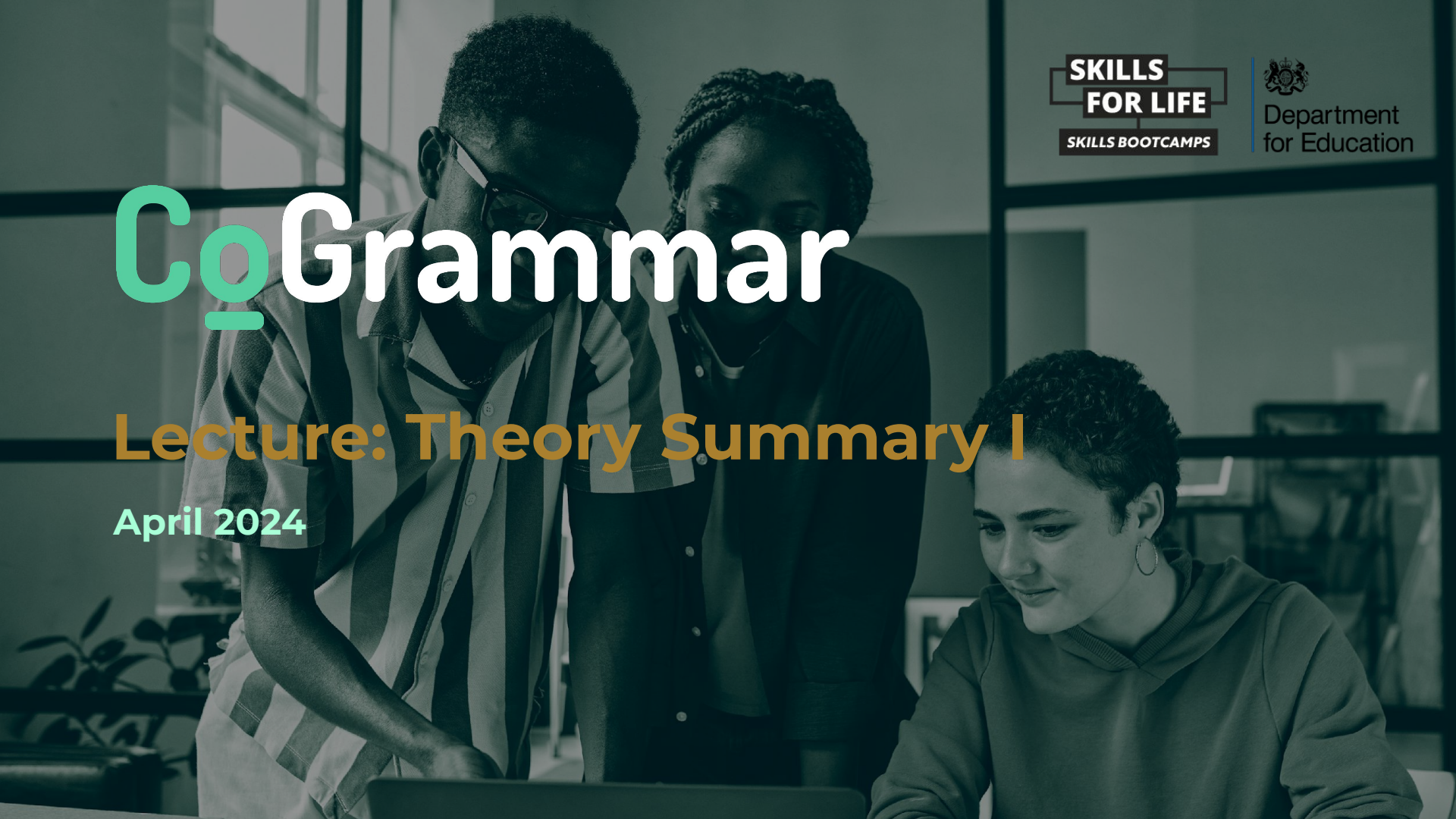
Skills Bootcamp Progression Overview

✅ Criterion 3: Course Progress

Completion: All mandatory tasks, including Build Your Brand and resubmissions by study period end
Interview Invitation: Within 4 weeks post-course
Guided Learning Hours: Minimum of 112 hours by support end date (10.5 hours average, each week)

✅ Criterion 4: Demonstrating Employability

Final Job or Apprenticeship Outcome: Document within 12 weeks post-graduation
Relevance: Progression to employment or related opportunity



SKILLS FOR LIFE
SKILLS BOOTCAMPS

Department for Education

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Lecture: Theory Summary I

April 2024

Learning objectives

- Understand the essential Python libraries for data science
- Develop a comprehensive understanding of data visualisation techniques and tools
- Consolidate knowledge of the various steps in data exploration and preparation
- Understand fundamental concepts of the learning algorithms covered

Python packages for data science

NumPy & Pandas

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Python packages for data science: NumPy

- **NumPy** - stands for **Num**erical **Py**thon
- Numpy arrays differ from python lists
  - Elements of same datatype
  - Can handle arithmetic operations
  - Preferred for larger chunks of data
  - Requires proper modules to perform operations on them
- Array oriented programming, NumPy has smaller memory consumption, better runtime, and ease of data manipulation

```
pip install numpy
```

```
import numpy as np

#Define a list
distances = [1, 13.1, 26.2, 100]
print(type(distances))
print(distances)
#Output: <class 'list'>
#Output: [1, 13.1, 26.2, 100]

#Convert to numpy array
numpy_dist = np.array(distances)
print(type(numpy_dist))
print(numpy_dist)
#Output: <class 'numpy.ndarray'>
#Output: [  1.   13.1  26.2 100. ]
```

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Python packages for data science: Pandas

- **Pandas**, built on NumPy, is a Python module that contains high-level data structures and tools designed for fast and easy data analysis.

```
pip install pandas
```

```
import pandas as pd
```

- Fundamental pandas data structures
  - Series (1-dimensional labelled array, can hold any data type)
  - DataFrame (2-dimensional)
  - Panel (pandas -> **pan**el **da**ta)

	Name	Age	Marks
0	Asha	12	96
1	Ben	12	92
2	Candice	13	94
3	Derek	12	96
4	Miriam	12	95
5	Seth	13	93
6	Zara	12	95

Pandas DataFrames

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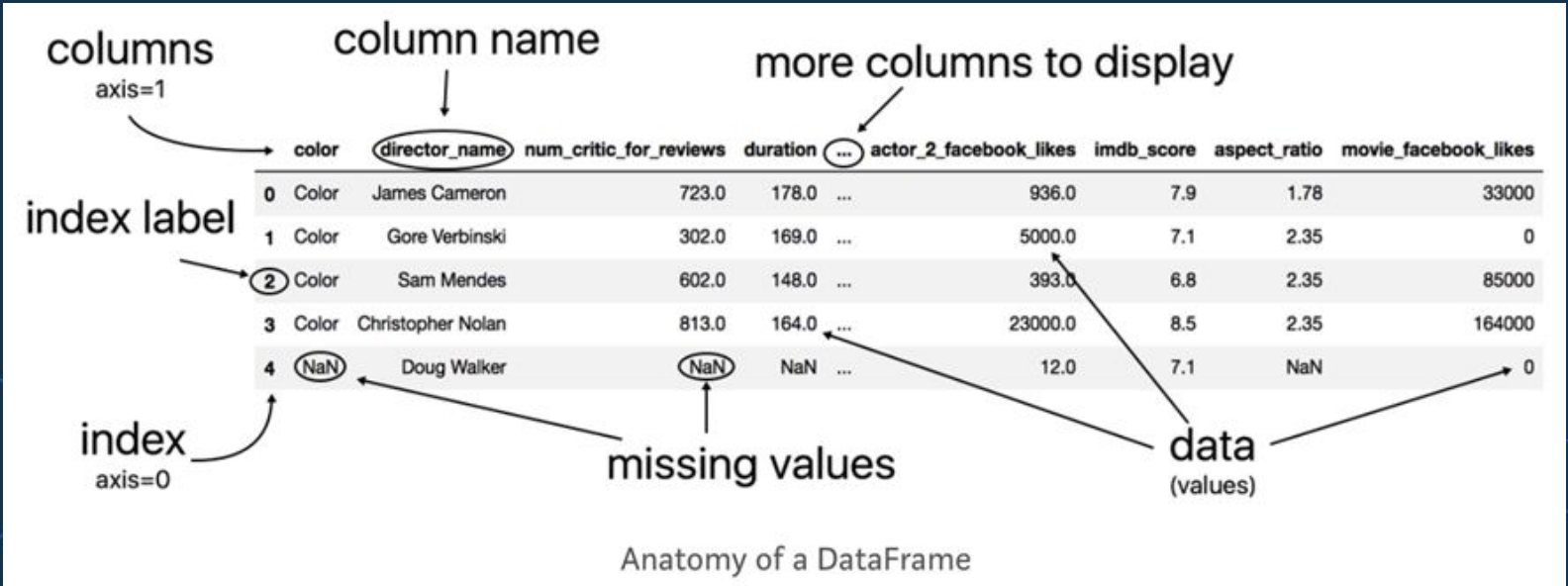
Pandas DataFrames

- A DataFrame is the way the Pandas library in Python represents tabular data. It's like a powerful *spreadsheet* within your code.
- The pandas' library documentation defines a DataFrame as a "two-dimensional, size-mutable, with labelled rows and columns."



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1	Color	Gore Verbinski	302.0	169.0	...	5000.0	7.1	2.35	0
2	Color	Sam Mendes	602.0	148.0	...	393.0	6.8	2.35	85000
3	Color	Christopher Nolan	813.0	164.0	...	23000.0	8.5	2.35	164000
4	NaN	Doug Walker	NaN	NaN	...	12.0	7.1	NaN	0

Anatomy of a DataFrame

Pandas cheat sheet

IMPORTING DATA

- `pd.read_csv(filename)` - From a CSV file
- `pd.read_table(filename)` - From a delimited text file (like TSV)
- `pd.read_excel(filename)` - From an Excel file
- `pd.read_sql(query, connection_object)` - Reads from a SQL table/database
- `pd.read_json(json_string)` - Reads from a JSON formatted string, URL or file.
- `pd.read_html(url)` - Parses an html URL, string or file and extracts tables to a list of dataframes
- `pd.read_clipboard()` - Takes the contents of your clipboard and passes it to `read_table()`
- `pd.DataFrame(dict)` - From a dict, keys for columns names, values for data as lists

EXPORTING DATA

- `df.to_csv(filename)` - Writes to a CSV file
- `df.to_excel(filename)` - Writes to an Excel file
- `df.to_sql(table_name, connection_object)` - Writes to a SQL table
- `df.to_json(filename)` - Writes to a file in JSON format
- `df.to_html(filename)` - Saves as an HTML table
- `df.to_clipboard()` - Writes to the clipboard

SELECTION

- `df[col]` - Returns column with label **col** as Series
- `df[[col1, col2]]` - Returns Columns as a new DataFrame
- `s.iloc[0]` - Selection by position
- `s.loc[0]` - Selection by index
- `df.iloc[0,:]` - First row
- `df.iloc[0,0]` - First element of first column

VIEWING/INSPECTING DATA

- `df.head(n)` - First **n** rows of the DataFrame
- `df.tail(n)` - Last **n** rows of the DataFrame
- `df.shape()` - Number of rows and columns
- `df.info()` - Index, Datatype and Memory information
- `df.describe()` - Summary statistics for numerical columns

DATA CLEANING

- `df.columns = ['a','b','c']` - Renames columns
- `pd.isnull()` - Checks for null Values, Returns Boolean Array
- `df.rename(columns={'old_name': 'new_name'})` - Selective renaming

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Data Visualisation

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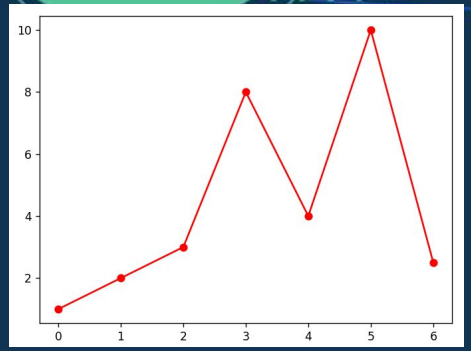
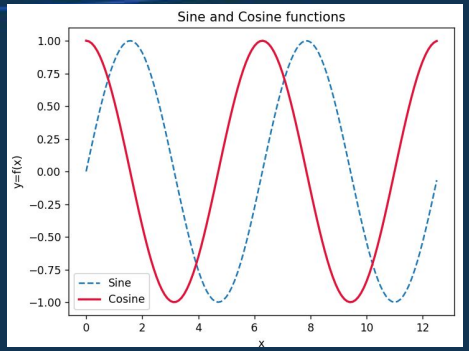
Data Visualisation

- Understanding the type of data you are working with can inform what kinds of visualisations you can create:
  - Barplots are good for plotting Categorical data vs. Continuous/Discrete data
  - Pie charts are good for plotting Categorical data vs. Discrete data. Also great for getting a sense of proportions
  - Scatterplots: Great for plotting Discrete vs. Discrete data or Continuous vs. Continuous data. Useful for finding relationships between variables.
  - Line graphs: Good for plotting Discrete / Continuous vs. Discrete / Continuous data or comparing with a Time Series.
- Matplotlib and Seaborn are two useful libraries for creating visualisations.

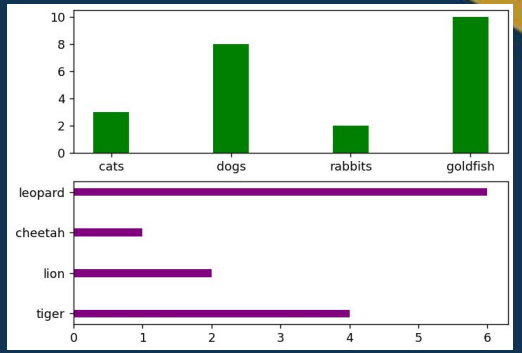
Matplotlib examples



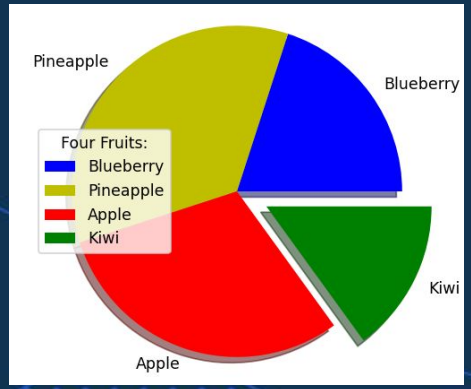
Line graph



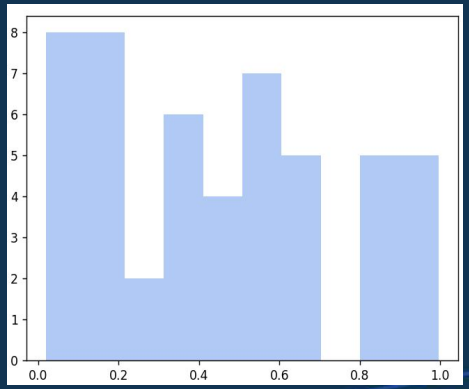
Line graph



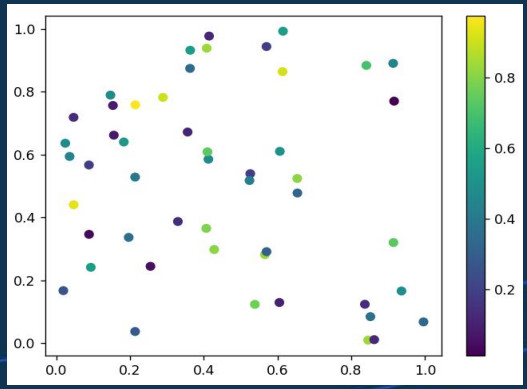
Bar plot



Pie chart



Histogram



Scatterplot

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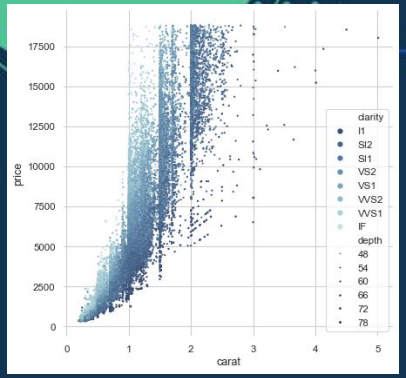
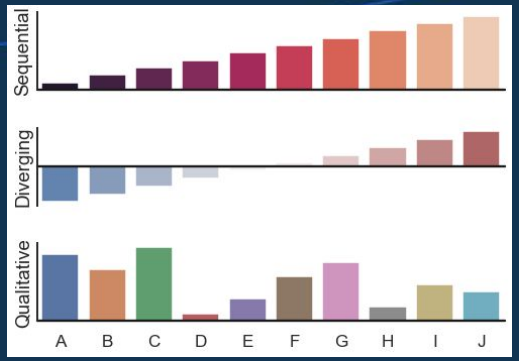
Seaborn examples



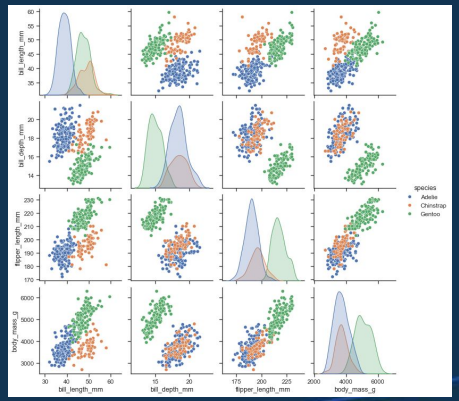
Scatterplot



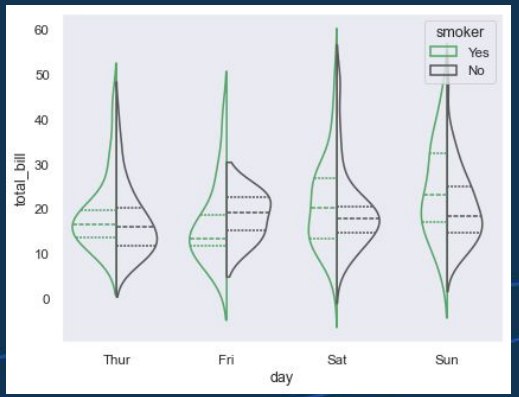
Bar plot

Line graph

Heatmap



Pairplot



Violin plot

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Exploratory Data Analysis

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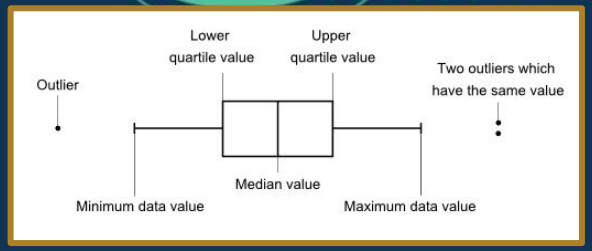
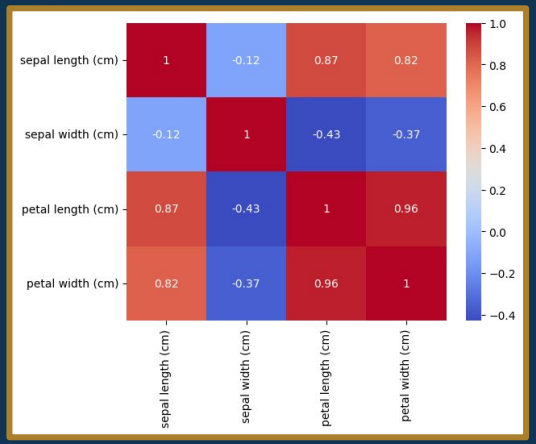
Exploratory Data Analysis

- **Definition:** Exploratory Data Analysis (EDA) is the process of investigating and understanding a dataset through visual and statistical techniques.
- Simple EDA framework:
  - Understand the data - dataset structure, check for missing values, basic statistics
  - Clean and preprocess - handle missing values, encode categorical variables, feature scaling
  - Explore relationships - analyse relationships between features and target variable, scatterplots, heatmaps, identify clusters
  - Assess feature importance - significance of features using statistical tests, Random Forests to evaluate feature importance
  - Iterate and refine - consider additional visualisations and techniques, refine data cleaning and preprocessing

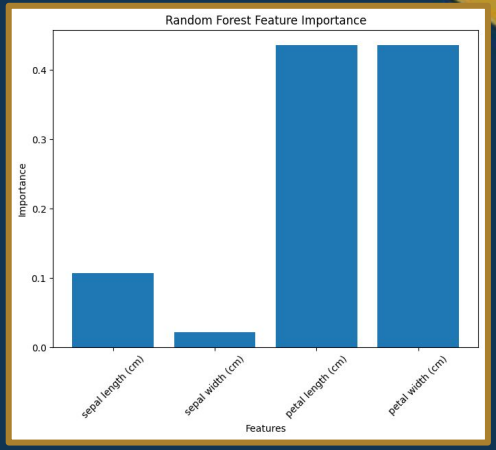
Useful visualisations for EDA



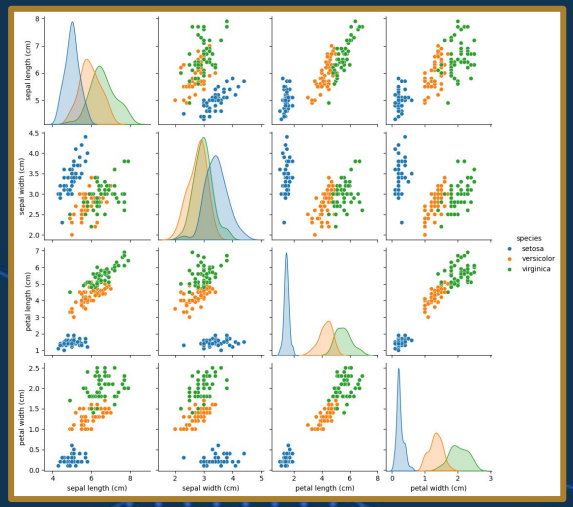
Box plot



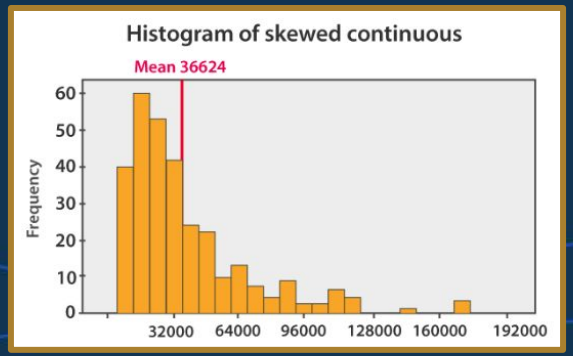
Heatmap

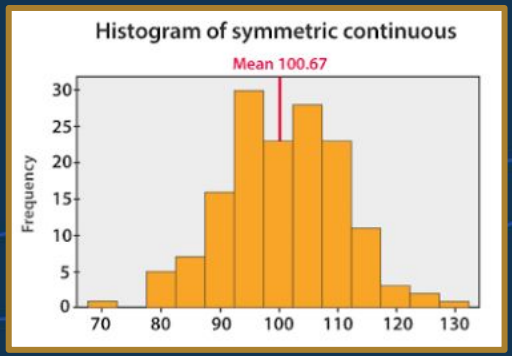


RF Feature Importance



Pairplot





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Feature Scaling

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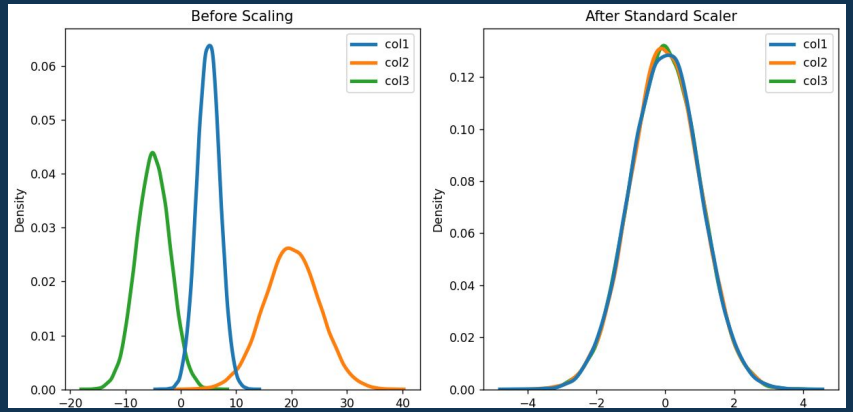
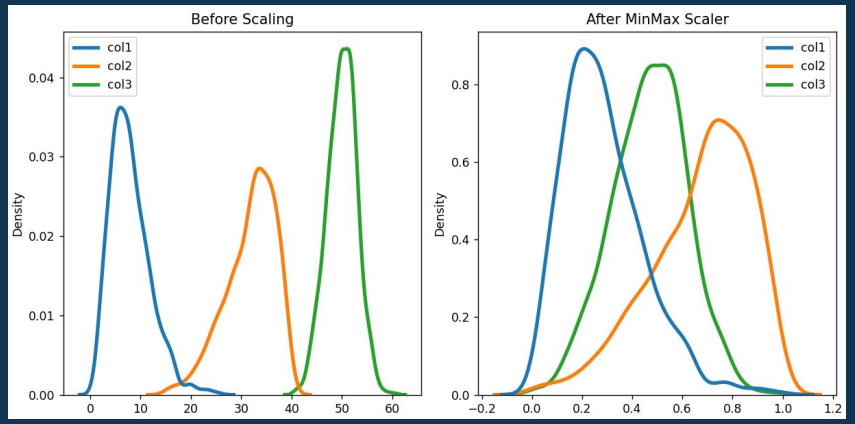
Feature Scaling

- Data columns have different values and measurement units, difficult to compare, e.g. What is kgs compared to metres? Or altitude compared to time?
- **Feature scaling - normalisation** and **standardisation**, involves transforming the data on the same scale
  - to compare easily,
  - more suitable for modeling,
  - to build accurate and effective machine learning models,
  - help improve model performance,
  - reduce the impact of outliers.

Normalisation	Standardisation
Rescales values to a range between 0 and 1	Centers data around mean and scales to standard deviation of 1
Useful when data distribution is unknown or **not Gaussian**	Useful with **Gaussian** data distribution
Sensitive to outliers	**Less sensitive to outliers**
Retains shape of original distribution	Changes shape of original distribution
May not preserve relationships between data points	Preserves relationships between data points
MinMaxScaler() (x – min)/(max – min)	**StandardScaler()** (x – mean)/standard deviation

Feature Scaling





StandardScaler
Gaussian distributions

MinMaxScaler
Non-Gaussian distribution

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Machine Learning Overview

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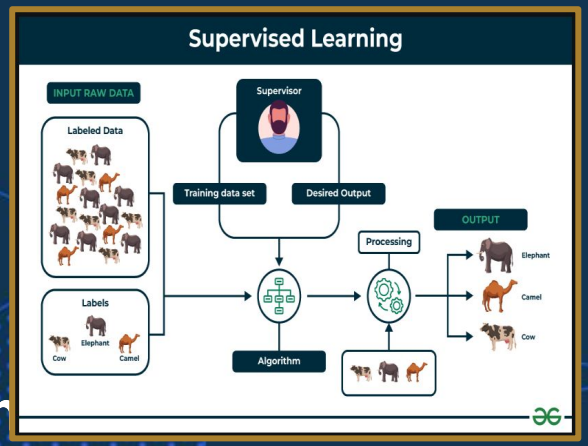
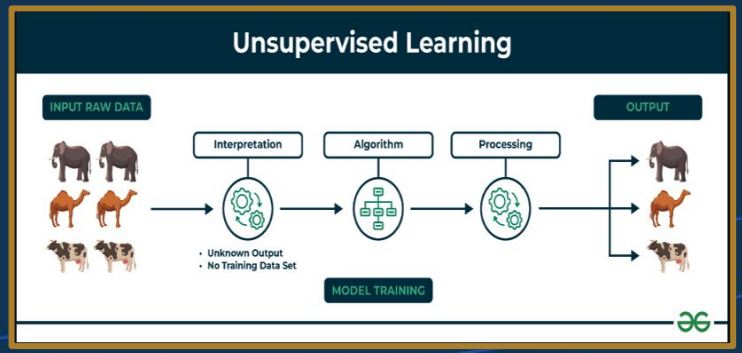
Machine Learning Introduction

- Machine learning is a way of teaching computers to learn and improve from experience without being explicitly programmed.
- 2 types of machine learning:
  - **Supervised learning** - The computer learns from labelled data, where both input and output data are provided e.g., linear regression, logistic regression
  - **Unsupervised learning:** The computer learns from unlabeled data, discovering hidden patterns or structures on its own e.g., clustering





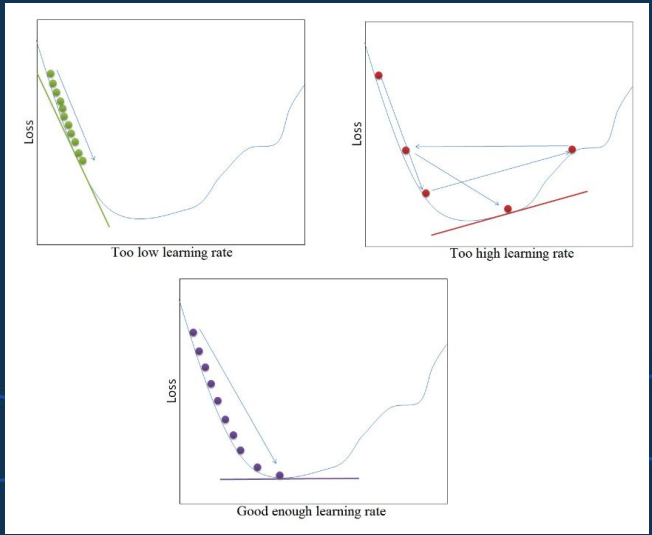
Evaluation Metrics

- It is important to evaluate the performance of your Machine Learning algorithm. The choice of evaluation metric is dependent on whether you have a **regression model** (predicting continuous numerical values, such as house prices or stock prices) or **classification model** (predicting discrete categories or classes, such as whether an email is spam or not).
- Regression model evaluation metrics:
  - **Mean Squared Error (MSE)** - measures the average squared difference between the predicted and actual values. A lower MSE indicates a better model performance.
  - **R-squared (R^2) score** - represents the proportion of variance in the target variable that can be explained by the model. An R^2 value closer to 1 indicates a better fit of the model to the data.
- Classification model evaluation metric:
  - **Accuracy** is a commonly used metric for evaluating the performance of model in classification models.

Accuracy = (Number of correct predictions) / (Total number of predictions) * 100%

Parameter Tuning

- **Parameter tuning** is the process of finding the optimal values for a model's hyperparameters to improve its performance.
- **Hyperparameters are settings** that are not learned from the data but are set before training the model.
  - Examples of hyperparameters in linear regression include the **learning rate**, **regularisation strength**, and the **number of iterations**.



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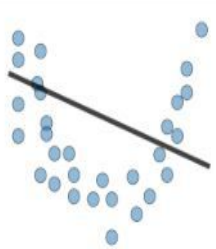
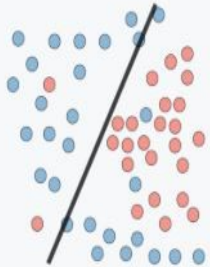
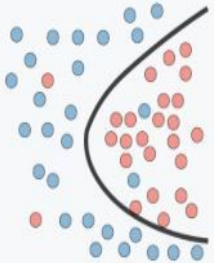
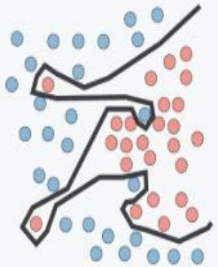
Bias-Variance Tradeoff

- Sometimes the models we choose can be too complex for our problem (overfitting) or too simple for our problem (underfitting). We want to find the sweet-spot or the balance between underfitting and overfitting.

	Underfitting	Just right	Overfitting
Symptoms	• High training error • Training error close to test error • High bias	• Training error slightly lower than test error	• Very low training error • Training error much lower than test error • High variance
Regression illustration			
Classification illustration			
Possible remedies	• Complexify model • Add more features • Train longer		• Perform regularization • Get more data

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Simple & Multiple Linear Regression

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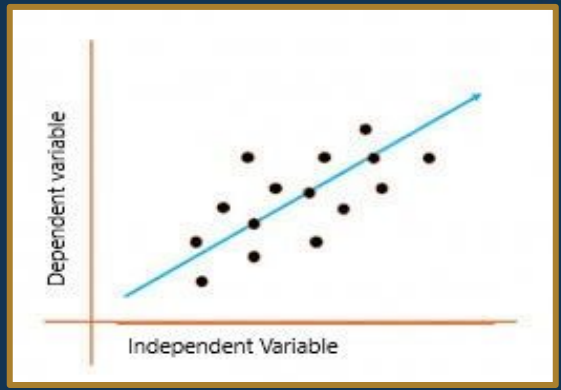
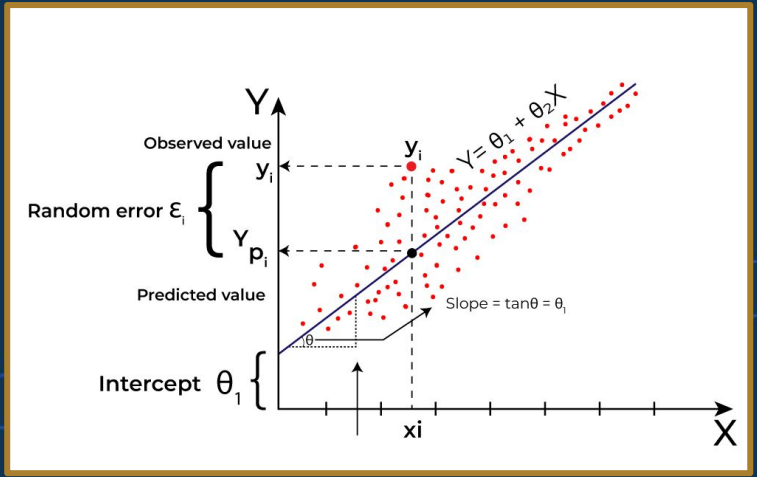
Simple Linear Regression

- The purpose of Simple Linear Regression is to find the best-fitting line that describes the relationship between the independent variable (x) and the dependent variable (y).
- This line can be used to make predictions about the dependent variable based on new values of the independent variable.
- The equation is written as: $y = \beta_0 + \beta_1 x + \varepsilon$
- Assumptions and limitations:
  - Linearity, independence, homoscedasticity, the errors should be normally distributed





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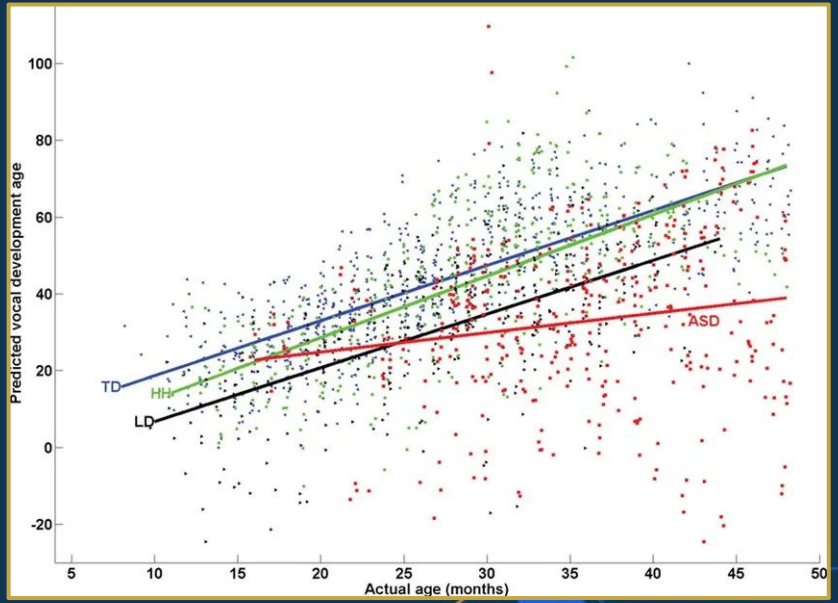
Multiple Linear Regression

- Multiple Linear Regression (MLR) algorithm is used which models the linear relationship between a single dependent continuous variable and more than one independent variable.
- The equation is written as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \varepsilon$$

- Assumptions and limitations:
  - Little or no multicollinearity, homogeneity of variance, residuals must be normally distributed



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Logistic Regression

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Logistic Regression

- Logistic Regression is a supervised learning algorithm which predicts the probability of categorical variables for a given observation and assigns the observation to the category with the highest probability.
- It is a **classification algorithm** so the dependent variables must be distinct, non-continuous, categorical.
- Types of logistic regression models:
  - **Binary (Binomial) logistic regression**: Response or dependent variable has only two possible outcomes (e.g. 0 or 1, True or False, Malignant or Benign tumour, Spam or Not Spam email).
  - **Multinomial logistic regression**: Dependent variable has three or more possible outcomes; but values have no specified order (e.g., movie studios predicting film genres depending on person's age, gender, family status).
  - **Ordinal logistic regression**: Response variable has three or more possible outcome, and values have a defined order (e.g. grading scales from A to F or rating scales from 1 to 5).

Logistic function

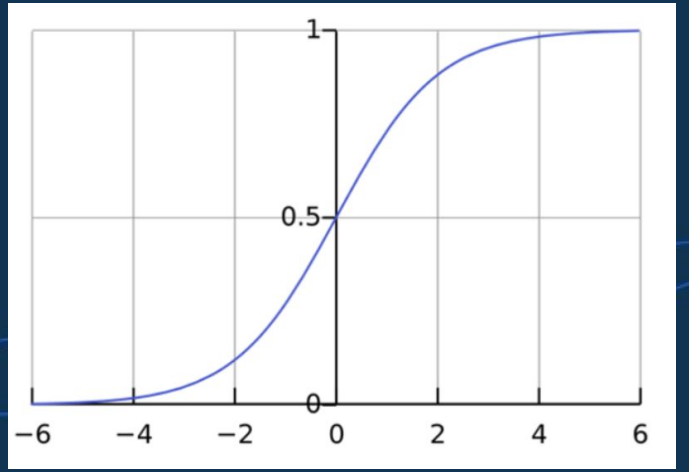
- Logistic regression: statistical model that uses the **logistic (logit) function**, as the equation between x and y (also called **sigmoid function** or **S-shaped curve**).

- Returns only values between 0 and 1 for the dependent variable, irrespective of the values of the independent variable.

- Also model equations between **multiple independent variables** and **one dependent variable.**

Sigmoid function

$$p = \frac{1}{(1 + e^{-y})}$$



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Decision Trees

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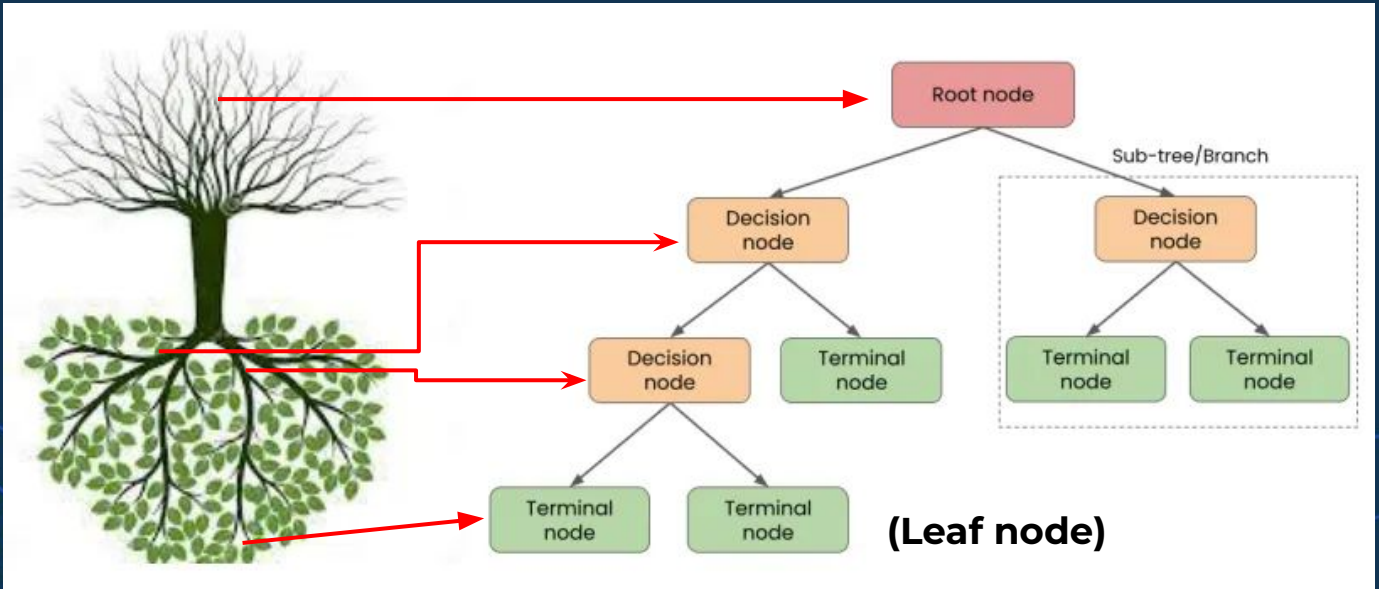
Decision Trees

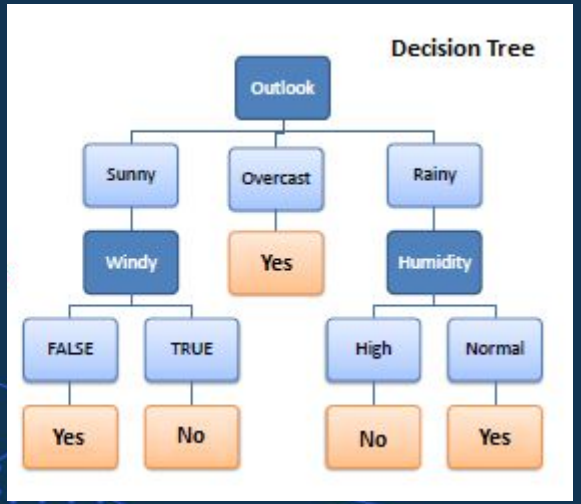
- **Supervised** learning algorithm for **regression** and **classification.**
- **Decision Trees:** (*upside down*) **tree-like** machine learning models.



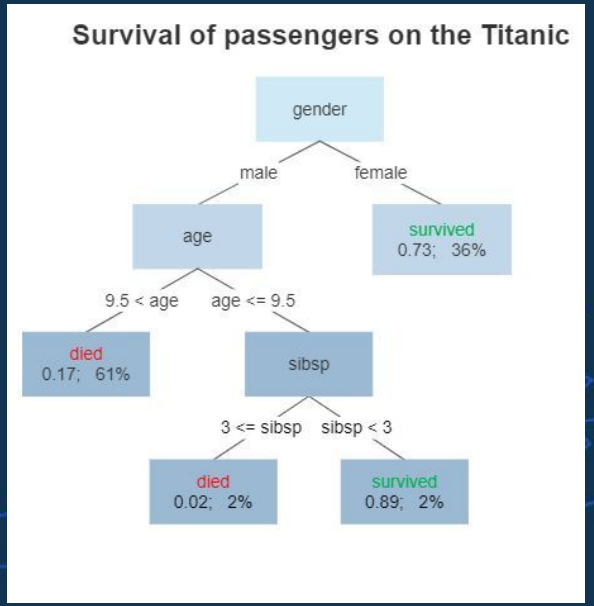
Decision Trees

- Represent data by **partitioning** it into different **smaller subsets** based on questions asked of predictive variable in the data.

Classification Tree



Regression Tree



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Optimising Trees: Pruning

- A **Decision tree** that is trained to its **full depth** will highly likely lead to **overfitting** the training data.
- **Pruning** avoids **overfitting**, **removes** parts of the Decision Tree that have little or **no significance** in the **decision-making process** and **prevent** it from growing to its **full depth**.
- **Pre-pruning** is done while growing the tree while **post-pruning** prunes nodes after it is built to depth.

Pre-pruning

- Tunes hyperparameters (**max_depth**, **min_samples_leaf**, **min_samples_split**) prior to the training
- 'Early stopping' - stops the growth of the **decision tree** to to reach its **full depth**
- Cross-validation error monitored at each step, if it is constant, stops growth.

Post-pruning

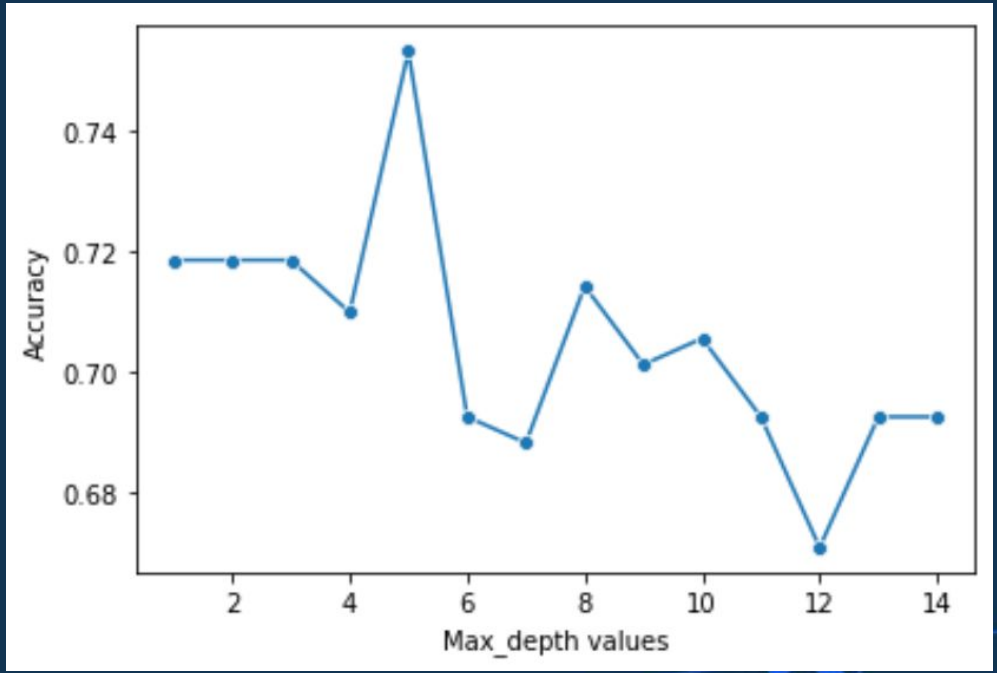
- **Decision Tree** model grows to its **full depth**, **tree branches** are **removed** to prevent the model from overfitting.
- Tune hyperparameter (**ccp_alpha - Cost Complexity Pruning**) to control the size of a tree, higher value leads to an increase in the number of nodes pruned.

Example: Pre-Pruning

We will choose **max_depth = 5** (default = None)

We will also choose **min_samples_leaf = 2,** (default=1), the minimum number of samples required to be at a leaf node.

We will also change the **splitting criterion** (the function to measure the quality of a split) to **'entropy'** instead of the default 'gini'.



How **accuracy** changes with the **max_depth** values. (The tree has a maximum depth of 14).

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Random Forests

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Ensemble Methods

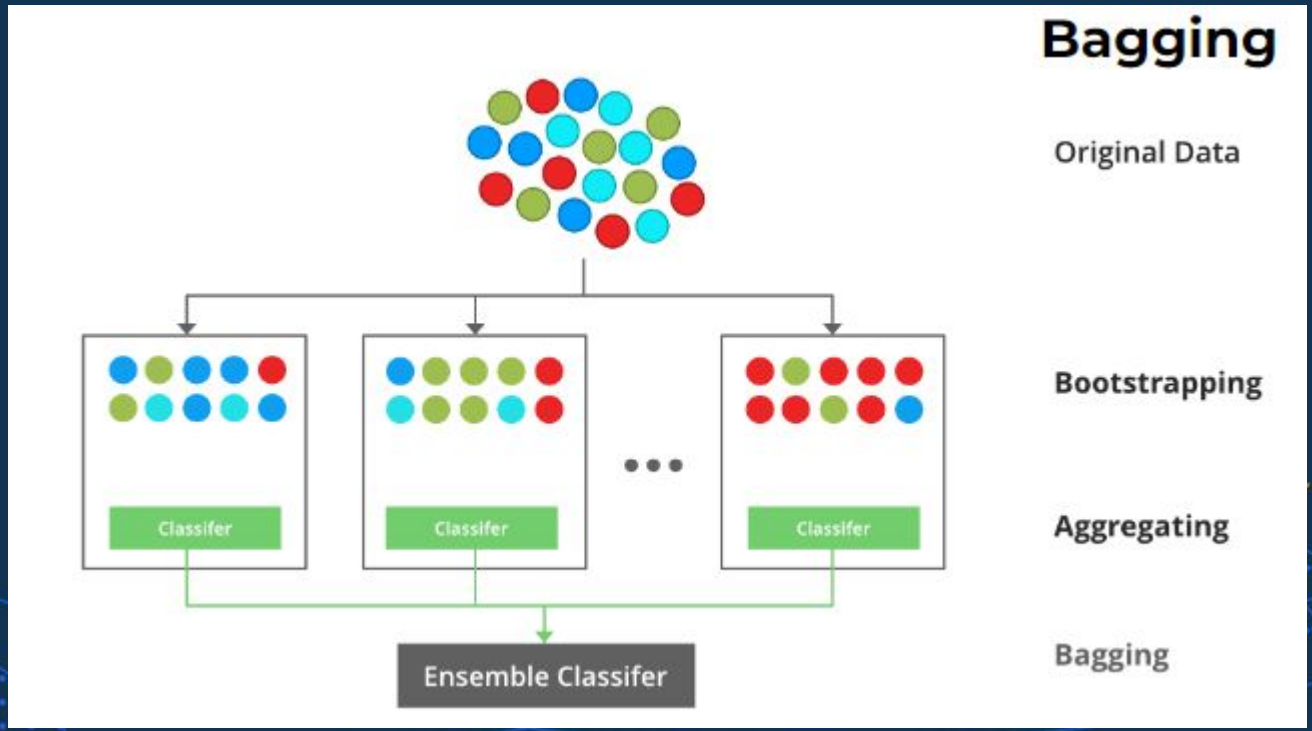
- **Decision Trees** are easy to understand, apply, interpret and visualise. However, they are **not very robust**, **small perturbations in the training data** could give rise to **substantially different predictions** at test time.

- Predictions of decision trees have very **high variance.** Ideally, we'd like our models to capture general patterns, not to be **so dependent on the data** they have trained on that a bit of noise or a different sample changes predictions entirely.

- Ensemble methods **aggregate the predictions of multiple classifiers/regressors** into a single, improved prediction.

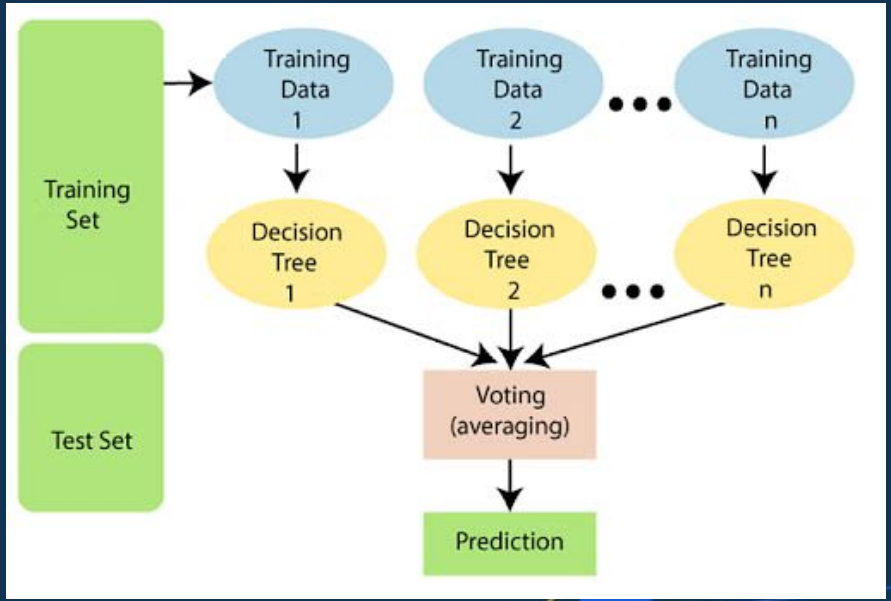
- **Ensemble techniques** work like a group of diverse experts teaming up to make decisions, and create a more robust solution than any individual could achieve alone.

Bagging: Bootstrap Aggregation



Random Forests

- **Random Forests:** created from **many decision trees** during training phase using **random subset of the dataset** to measure a **random subset of features** in each partition.
- Randomness introduces **variability** among individual trees, **reducing** the risk of **overfitting** and **improving** overall **prediction performance**.
- Aggregates predictions of all trees, either by **voting** (**classification problems**) or by **averaging** (**regression problems**).
- **Collaborative decision-making process**, supported by **multiple trees** with their insights, gives **stable** and **precise results.**



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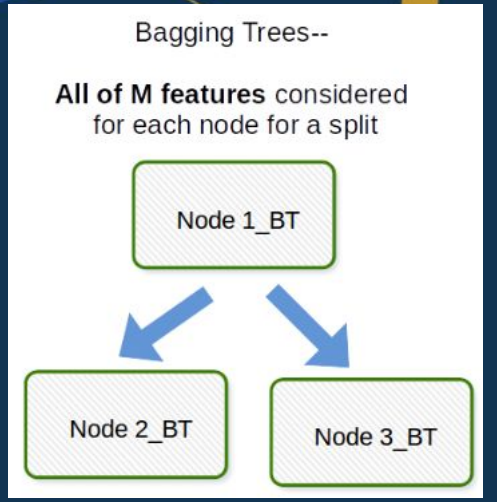
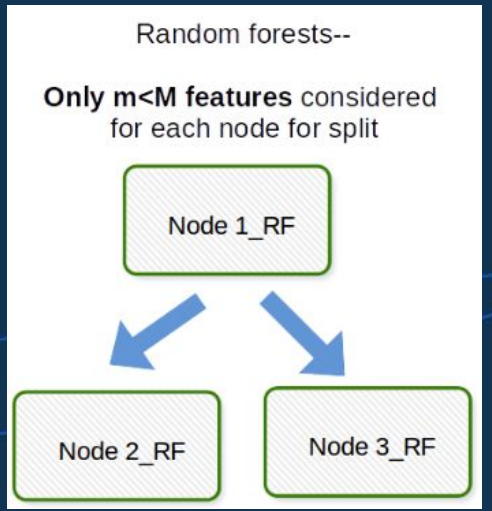
Differences with Decision Trees

Decision Trees	Random Forests
Can suffer from **overfitting** if allowed to grow without any control.	Created from subsets of data, and final output is based on average or majority ranking; **overfitting is mitigated.** Better **bias-variance trade-off.**
When a data set with features is taken as input by a decision tree, some **rules formulated to make predictions.**	**Randomly** selects observations, builds a decision tree, and takes the average result. Does not use any set of rules.
A single decision tree is **faster** in computation.	Comparatively **slower**.

Differences with Bagged Trees

Bagged Trees	Random Forests
All features are selected.	**Randomly selected features.**
Highly correlated trees, can **reduce diversity** of model. More prone to **overfitting**.	**Randomness lowers correlation** between trees, results in **diverse set** of trees, **improving** model **accuracy** by **reducing overfitting** and increasing the **diversity** of the model.
Less computationally expensive.	More computationally expensive.

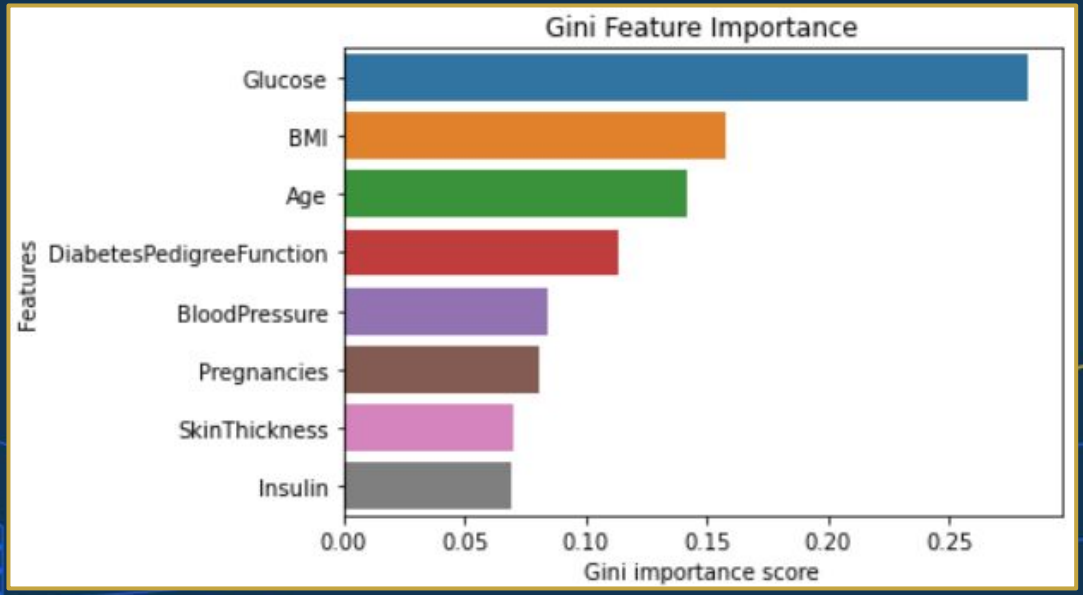




m = √M is a good place to start

Feature importance

- **Feature importance** calculates a **score** for all the input features for a given model to establish the "**importance**" of each feature in the decision-making process. The **higher the score for a feature**, the **larger effect** it has on the model to predict a certain variable.



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Hyperparameter Tuning

Hyperparameter to increase the Predictive Power

- **n_estimators:** number of trees the algorithm builds before taking the maximum voting or taking the averages of predictions. In general, a higher number of trees increases the performance and makes the predictions more stable, but it also slows down the computation.
- **max_features**: maximum number of features RF considers to split a node.
- **min_sample_leaf**: minimum number of leafs to split an internal node.

Hyperparameters to increase the RF model's speed

- **n_jobs, random_stat, oob_score** (out-of-bag sampling).

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https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

Image Processing

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Image Processing

- Image processing refers to the **manipulation and analysis of digital images** to **extract meaningful information** and enhance visual content.
- Enables computers to **interpret and understand visual data**.
- **Digital Image:** A digital image is represented as a two-dimensional array of pixels, where each pixel contains intensity or colour values.

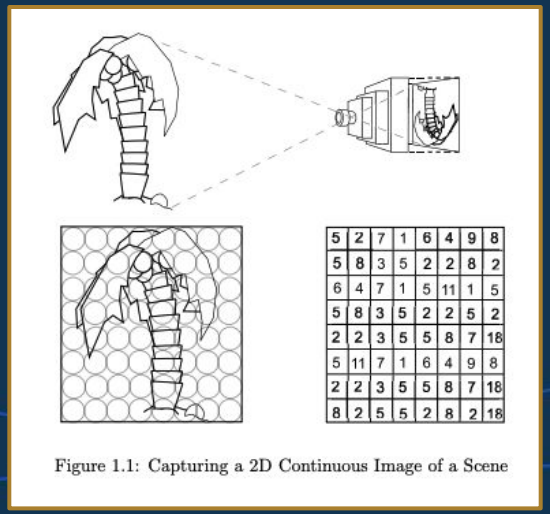
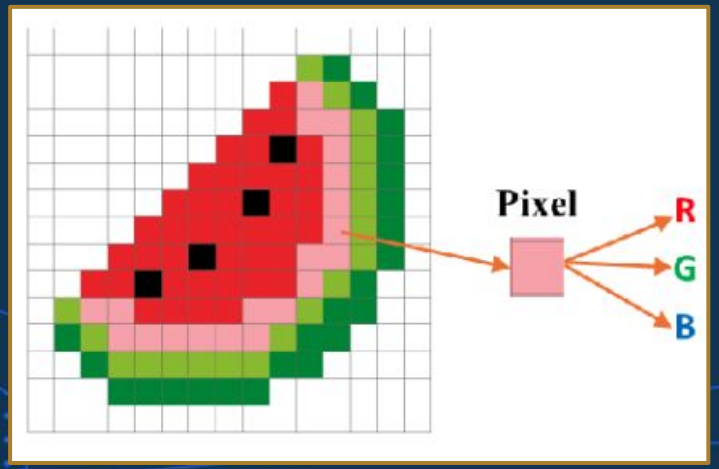


Figure 1.1: Capturing a 2D Continuous Image of a Scene

Source: Clemson University

Key Concepts: Pixel

- **Pixel:** A pixel is the smallest unit of a digital image and is represented by **one or more numerical values**. In grayscale images, each pixel has a single intensity value, while in colour images, pixels typically have three values corresponding to the **red, green, and blue** colour channels.



Source: ResearchGate

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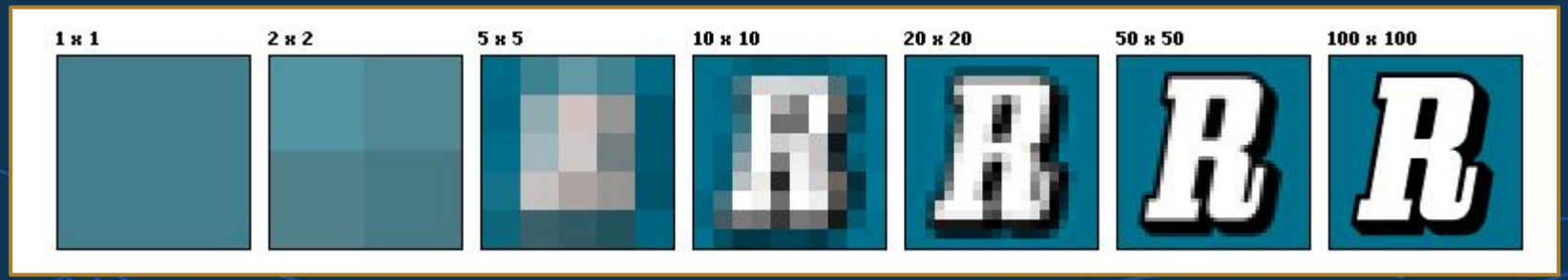
Key Concepts: Image resolution

- **Image Resolution:** Image resolution refers to the number of pixels in an image, usually expressed in terms of **width and height** (e.g., 1024x768). Higher resolution images contain more pixels and provide **more detailed and clearer representations** of the visual content.



Source: Wikipedia

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K-means Clustering

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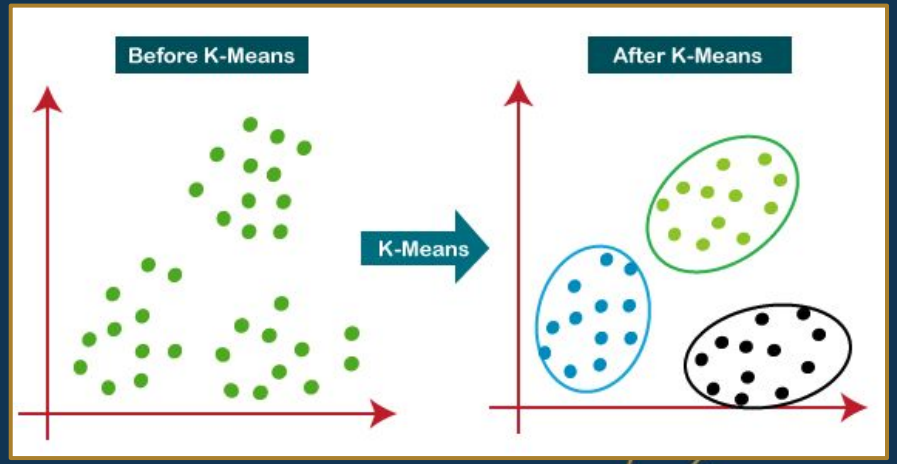
K-means Clustering

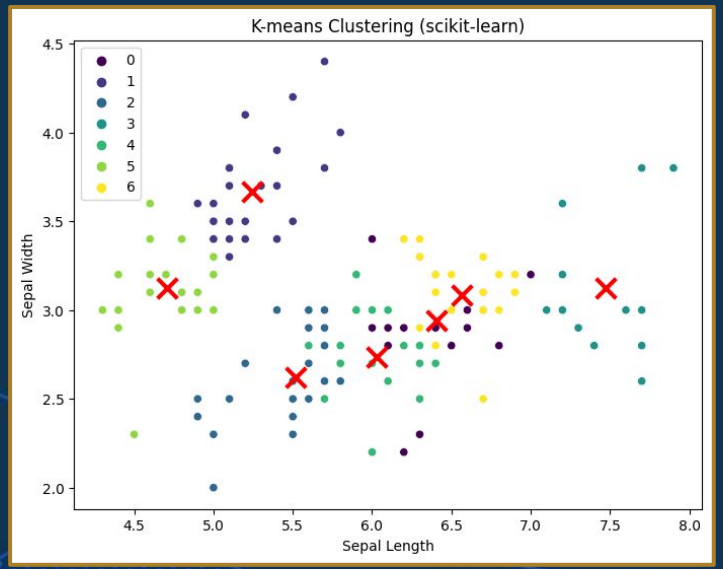
- K-means clustering is an **unsupervised learning algorithm used to partition a dataset into K distinct clusters.**
- The goal is to **minimise the within-cluster variation** and **maximise the separation between clusters**.
- It is a popular technique for **exploratory data analysis** and **pattern discovery**.



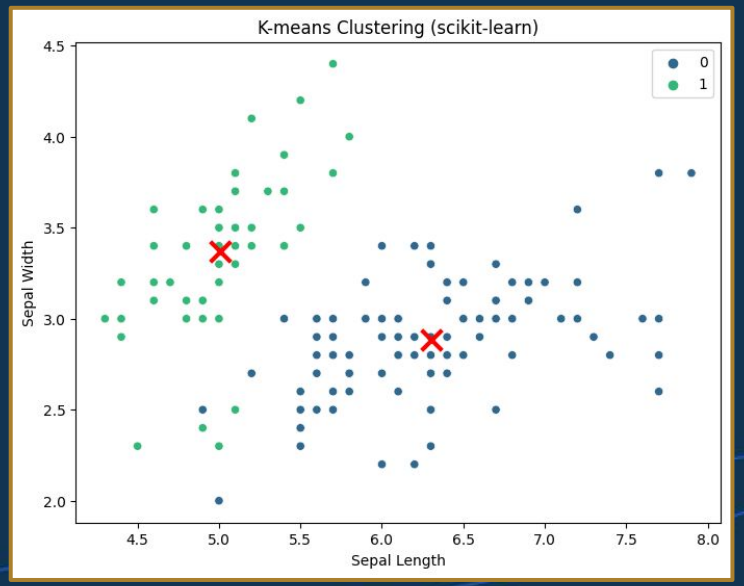
Source: Javapoint

Choosing K

Selecting an appropriate number of clusters (K) is crucial for effective clustering.



VS



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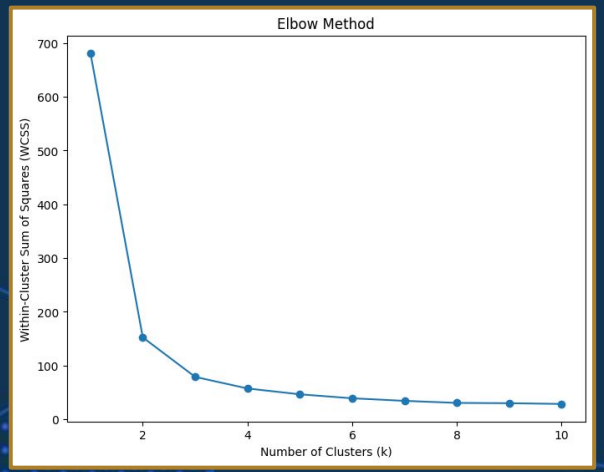
Techniques for choosing K

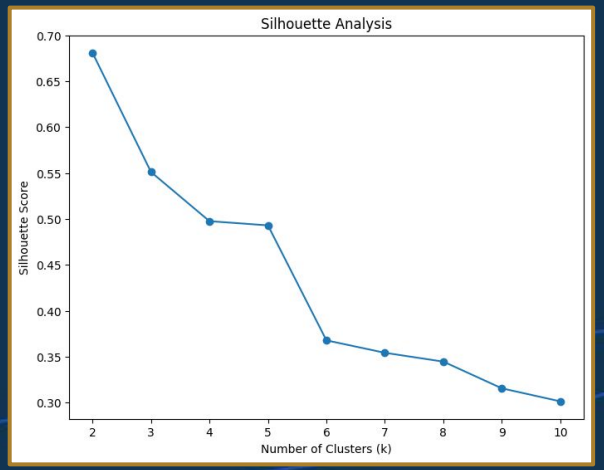
Elbow Method:

- Plot the within-cluster sum of squares (WCSS) against different values of K.
- Look for the **"elbow point"** where the rate of decrease in WCSS slows down significantly.



Silhouette Analysis:

- Calculate the silhouette score for each data point and average them for different values of K.
- Choose the K value that **maximises the average silhouette score.**



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Cluster Profiling

- After obtaining the clustering results, it's important to **interpret and analyse the clusters.**
- Examine the characteristics and centroids of each cluster to **understand their distinguishing features.**
- Assign **meaningful labels or descriptions** to the clusters based on domain knowledge and the patterns observed in the data.

Neural Networks

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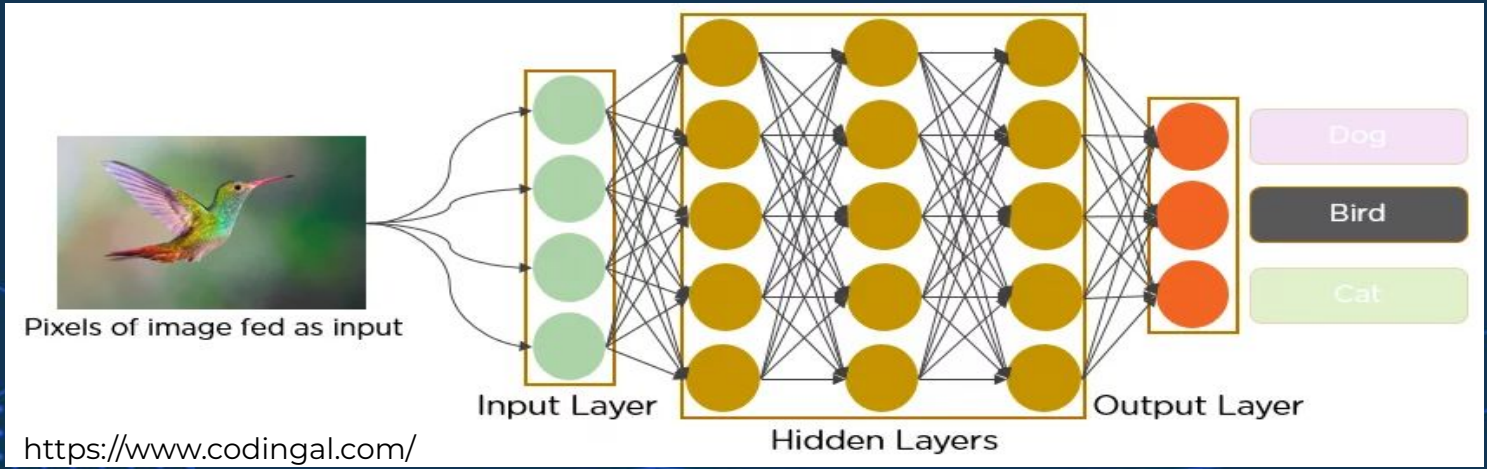
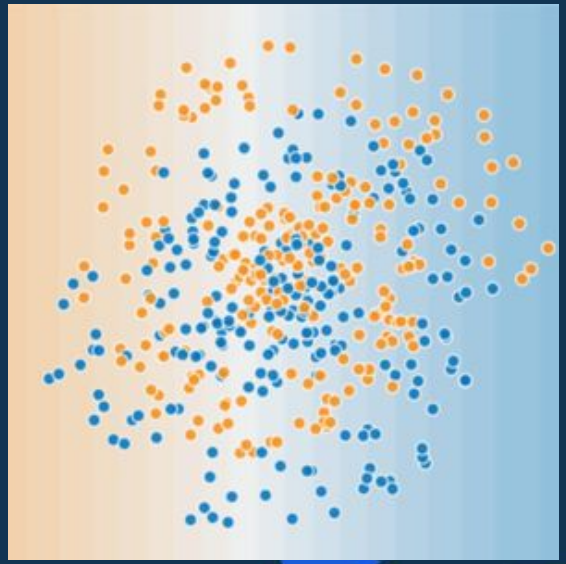
Neural Networks

- A **neural network (NN)** is a machine learning model inspired by the structure and function of the central nervous system in a human body.
- Consist of interconnected **nodes or neurons,** processing units that pass data to each other, like in the brain, biological neurons pass electrical impulses to each other.
- Enable tasks such as **pattern recognition** and **decision making** in machine learning.



Importance of Neural Networks

- Ideally suited to solve **complex and nonlinear** problems
- Make generalisations and inferences
- Reveal **hidden relationships, patterns** and **predictions**
- Model **highly volatile data** (financial time series data) and variances needed to **predict rare events** (fraud detection).

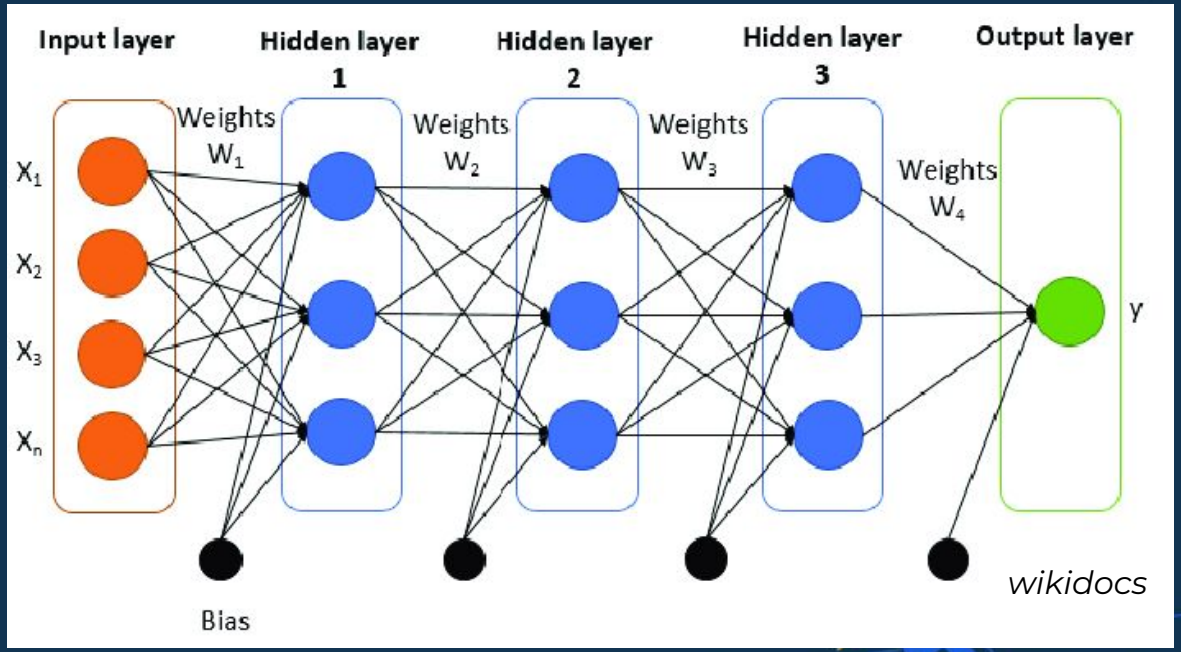


Non-linear classification

Neural Network Layers

Input layer: sends the data to subsequent layers, no. of nodes depend on features

Hidden layer/s: weighted inputs fed into these intermediate layers for computations; extracts features from the data.



Output layer: takes input from preceding hidden layers and comes to a final prediction based on the model's learnings

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Neural Network Layers

- **Input layer:** number of neurons in the input layer is equal to the number of features in the data, sometimes one additional for bias.

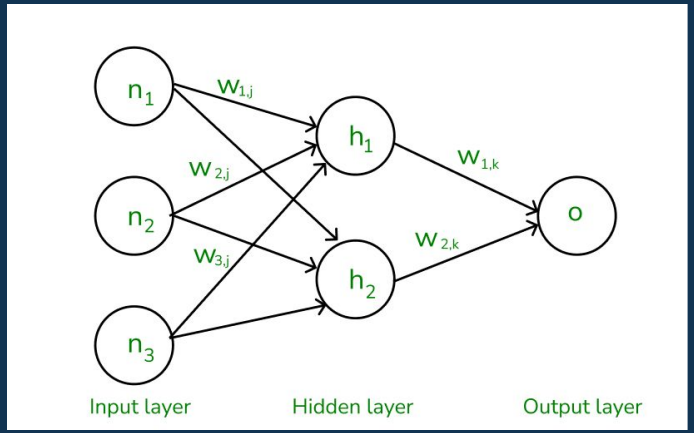
- **Hidden layer/s:** intermediate layer/s between input and output layer where all the computation is done. If number of layers is
  - 0: Only capable of representing linearly separable data
  - **1 - 2:** Data is less complex and have fewer dimensions or features
  - More layers for optimum solution in large dimensions/many features

Most common

- **Output layer:** number of neurons depends on whether the model is a regressor (only one neuron) or classifier (one neuron for each class label).

Neural Network Components

- Components include **neurons, connections, weights, biases, activation functions**.
- **Neurons** receive inputs, governed by **thresholds** and **activation functions.**

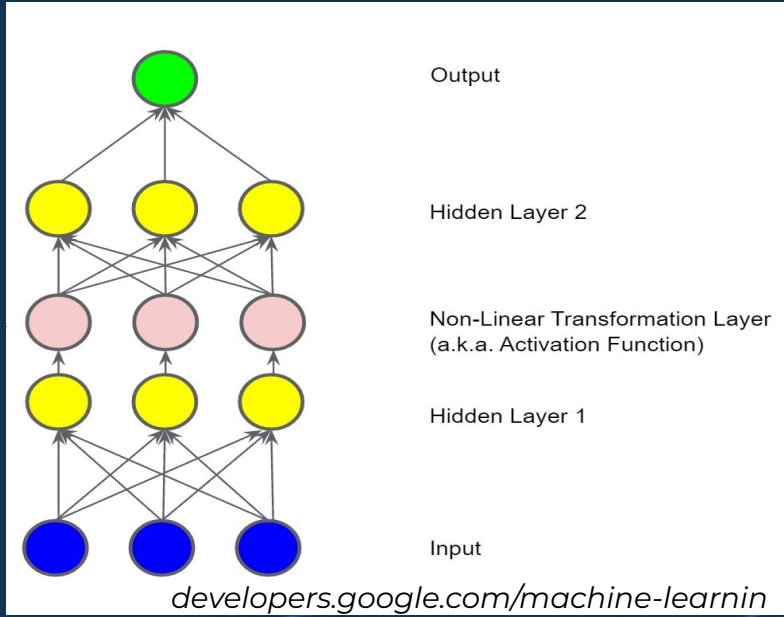


- **Connections** involve **weights** and **biases** regulating information transfer.
- Learning, adjusting weights and biases, occurs in **three stages: input computation, output generation, and iterative refinement** enhancing the network's proficiency in diverse tasks.

Activation Functions

To introduce **non-linearity** to model **non-linear problems**

- Pipe each hidden layer node through a nonlinear function.
- The value of each node in Hidden Layer 1 is transformed by a nonlinear function before being passed on to the weighted sums of the next layer.
- This nonlinear function is called the **activation function.**



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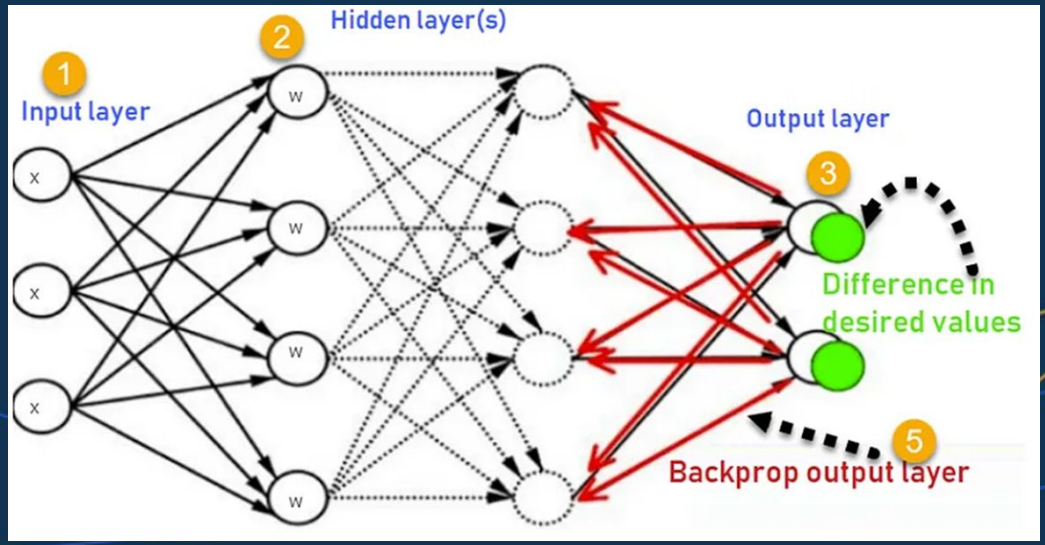
Backpropagation

- Backpropagation algorithm widely used to train feedforward NNs. It **minimises the cost function** by adjusting network's **weights** and **biases**.
- The level of adjustment is determined by the **gradients of the cost function** with respect to those parameters.

- **Gradient descent** or **stochastic gradient descent** estimation method used by the optimisation algorithm to compute the network parameter updates and train neural network models.



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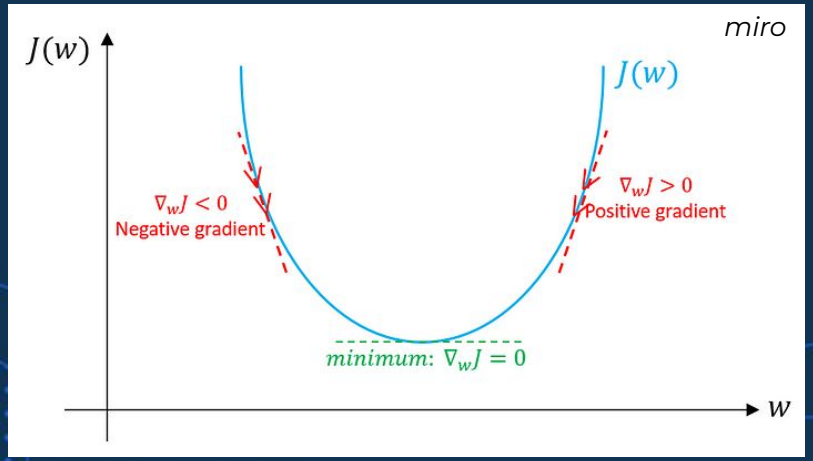
Gradient Descent

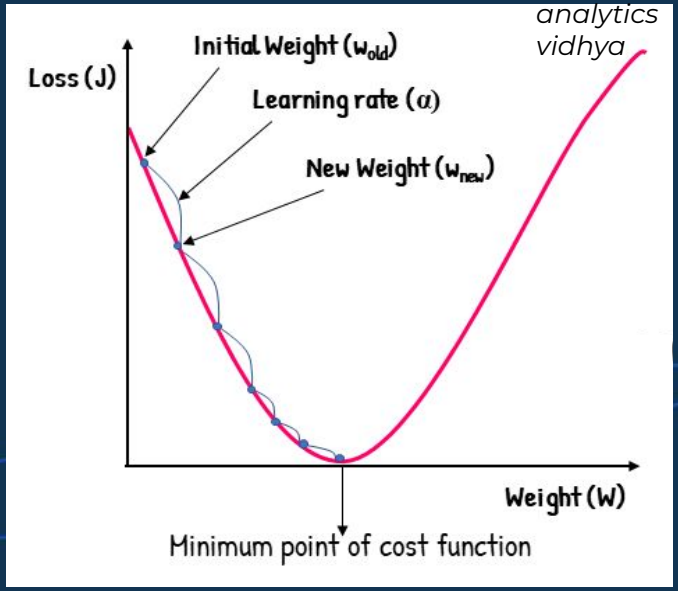
Updating the weights

$$w_{new} = w_{old} - \alpha \frac{\delta J}{\delta w}$$

α = Learning rate
$\delta J/\delta w$ = partial derivative of the loss function for each weight w (rate of change of the loss function to the change in weight.)

Gradient of J = ∇ J has all the partial derivatives (**∇ = Del / nabla operator)**





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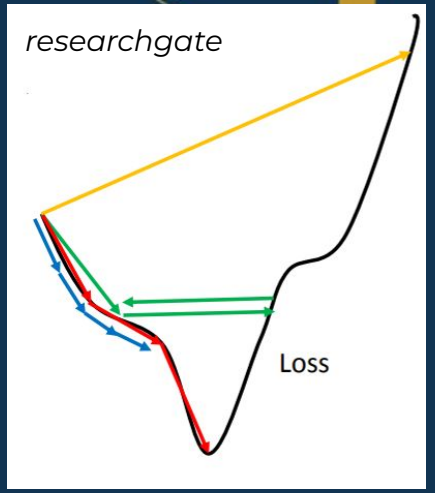
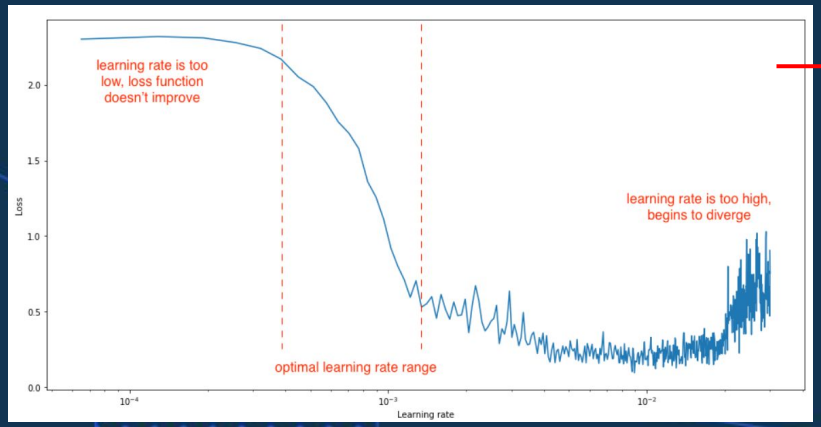
Learning Rates

High learning rates: result in larger steps but risks overshooting the minimum. (yellow and green lines)

Low learning rate: small step sizes, more precision, but compromises overall efficiency, more iterations takes more time and computations to reach the minimum (blue lines)





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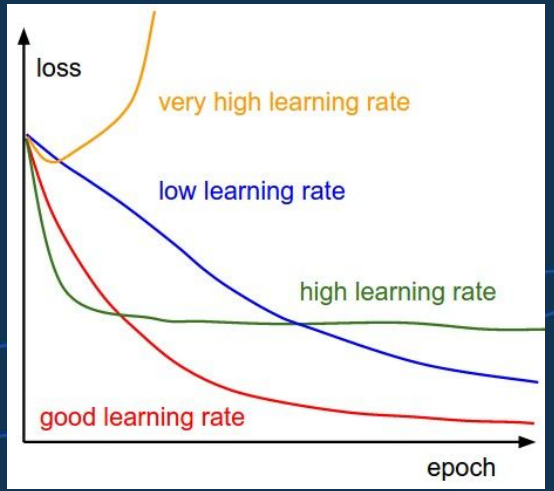
Set learning rate bounds to observe all three phases, making the optimal range trivial to identify.



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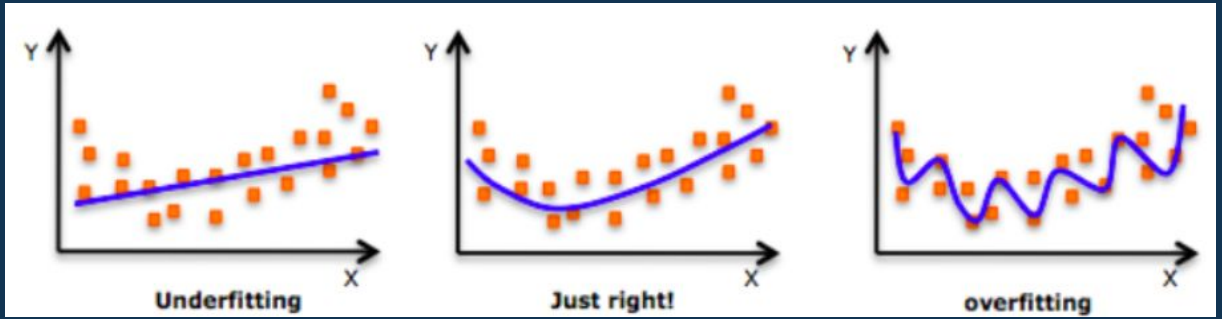
Loss Function

- A **loss function or cost function** measures how good a neural network model is in performing a regression or classification task.
- Minimise the loss function value during the backpropagation step to make the neural network perform better.
- The kind of loss function used depends on the problem:
  - **Binary cross-entropy** is used when performing binary classification, and **categorical cross-entropy** is used for multi-class classification.
  - **MSE loss function** used for **regression** tasks, when we want the network to predict continuous numbers.
  - **MAPE loss function** used during **demand forecasting** to check network performance during training time, **regression** tasks.

Regularisation Techniques

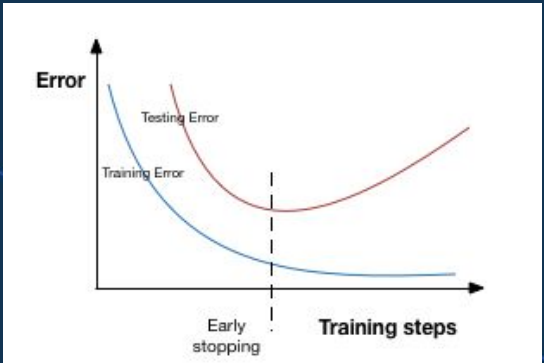
Regularisation techniques improve neural network's generalisation ability by reducing overfitting.



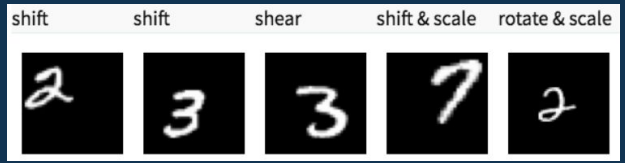
- Done by minimising complexity, exposing network to more diverse data.
- Can add a penalty term to the loss function during training which discourages the model from becoming too complex or having large parameter values.
- Models become more robust and better at making accurate predictions on unseen data.

Regularisation Techniques

Early stopping: Prevent training loss from becoming arbitrarily low, model is less likely to overfit on training dataset, and will generalise better.



Data augmentation: e.g. applies transformations to **images** (rotating the image, flipping, scaling, shifting) to create a larger dataset.



L1 and L2 regularisation prevent overfitting by adding a penalty term to the loss function.

$$\lambda \sum_{i=1}^{N} |\theta_i|$$

$$\lambda \sum_{i=1}^{N} \theta_i^2$$

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Questions and Answers

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Thank you for attending

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