# Welcome to the CoGrammar Exploratory Data Analysis (EDA)

The session will start shortly...

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

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# 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]

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# **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

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# Exploratory Data Analysis

April 2024

# Learning objectives

**Understand and apply Exploratory Data Analysis (EDA) techniques to effectively analyse datasets.**

❖ Understand the importance of EDA in data science projects

❖ Apply EDA techniques to clean, preprocess, and explore data

❖ Use Python libraries for EDA tasks and data visualisation

# Introduction to EDA

- **Definition:** Exploratory Data Analysis (EDA) is the process of investigating and understanding a dataset through visual and statistical techniques.
- **Importance:** EDA is a crucial first step in any data science project as it helps uncover patterns, anomalies, and relationships in the data, guiding further analysis and decision-making.

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# Introduction to EDA

- **Role in the data science workflow:** EDA is performed after data collection and before model building and evaluation. It helps in understanding the data, identifying data quality issues, and selecting relevant features for modeling.

# Simple EDA Framework

- When performing exploratory data analysis, we typically follow most of these five key steps in some order:
  - **Understand the Data:**
    - Load the dataset and examine its structure
    - Check for missing values and data types
    - Get a feel for the data through basic statistics and visualisations

# Simple EDA Framework

- **Clean and Preprocess:**
  - Handle missing values and outliers
  - Encode categorical variables if necessary
  - Scale or normalise numerical features if required

# Simple EDA Framework

- **Explore Relationships:**
  - Analyse relationships between features and the target variable
  - Use visualisations like scatter plots, pair plots, and correlation matrices
  - Identify patterns, trends, and clusters in the data

# Simple EDA Framework

➢ **Assess Feature Importance:**

- Determine the significance of features using statistical tests
- Use techniques like Decision Trees or Random Forests to evaluate feature importance
- Select relevant features based on their importance and domain knowledge

# Simple EDA Framework

- **Iterate and Refine:**
  - Iterate on the analysis based on the insights gained
  - Refine the data cleaning and preprocessing steps if necessary
  - Consider additional visualisations or techniques to deepen the understanding of the data

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# Loading and Exploring the Dataset

- To demonstrate EDA techniques, we'll use the Iris dataset from scikit-learn.
- The Iris dataset consists of measurements of sepal length, sepal width, petal length, and petal width for three species of Iris flowers.
- We'll load the dataset using scikit-learn and create a pandas DataFrame to work with.

*Iris setosa*

*Iris versicolor*

*Iris virginica*

Source: [Wikipedia]

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```python
# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=iris.data, columns=iris.feature_names)
data['species'] = iris.target_names[iris.target]
```

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# Loading and Exploring the Dataset

- After loading the dataset, we'll explore its basic properties:
  - **Shape of the dataset:** number of rows and columns
  - **Features:** the independent variables in the dataset
  - **Target variable:** the dependent variable (depends on the features) we want to predict or analyse

```
Dataset shape: (150, 6)
Features: Index(['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
       'petal width (cm)', 'species'],
      dtype='object')
Target variable: Cluster
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

  species  Cluster
0  setosa        1
1  setosa        1
2  setosa        1
3  setosa        1
4  setosa        1
```

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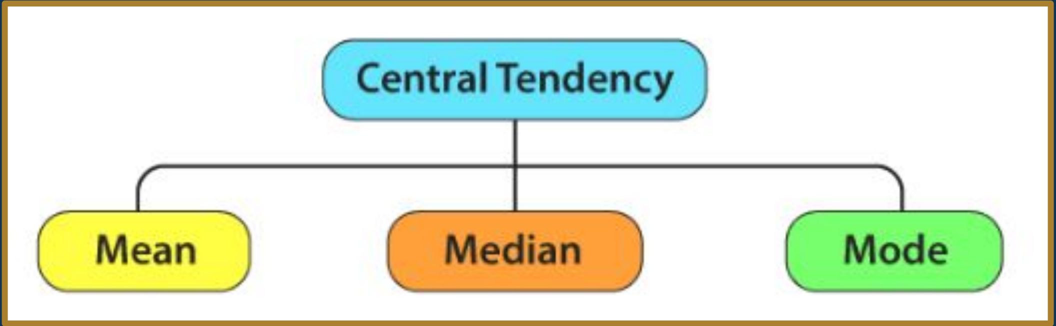
# Univariate Analysis

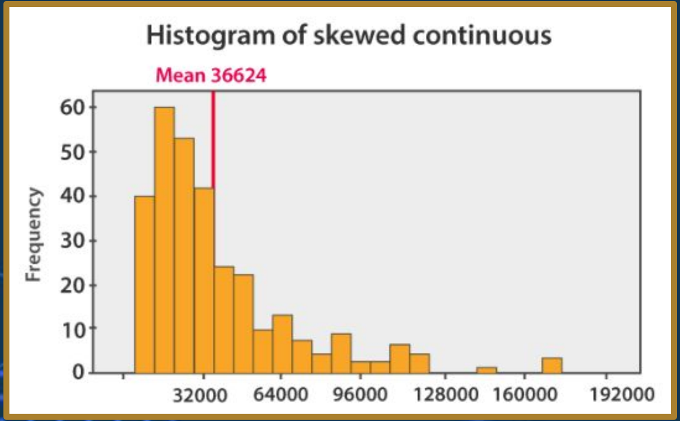
- Univariate analysis involves analysing each variable individually.
  - **Univariate:** involving one variate or variable quantity.
- We'll start by calculating descriptive statistics for the numeric variables using the describe() function.
- Descriptive statistics provide a summary of the central tendency, dispersion, and shape of the data.

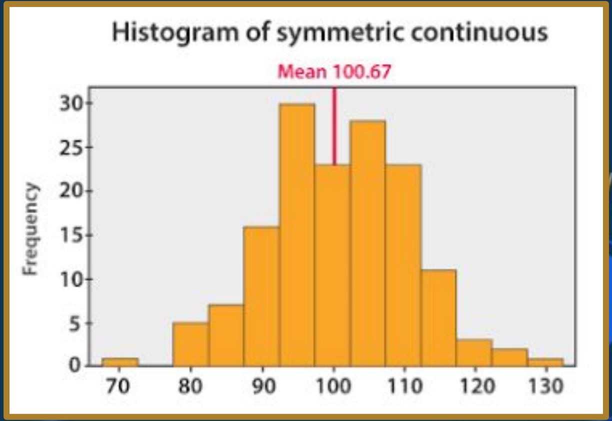
# Measures of Central Tendency



# Measures of Central Tendency

❖ **Mean** represents the average value of the dataset. It can be calculated as the sum of all the values in the dataset divided by the number of values.

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# Measures of Central Tendency

- **Median** is the middle value of the dataset in which the dataset is arranged in the ascending order or in descending order. When the dataset contains an even number of values, then the median value of the dataset can be found by taking the mean of the middle two values.

| Median odd |
|---|
| 23 |
| 21 |
| 18 |
| 16 |
| 15 |
| 13 |
| 12 |
| 10 |
| 9 |
| 7 |
| 6 |
| 5 |
| 2 |

| | Median even |
|---|---|
| | 40 |
| | 38 |
| | 35 |
| | 33 |
| | 32 |
| | 30 |
| 28 | 29 |
| | 27 |
| | 26 |
| | 24 |
| | 23 |
| | 22 |
| | 19 |
| | 17 |

# Measures of Central Tendency

- **Mode** represents the frequently occurring value in the dataset. Sometimes the dataset may contain multiple modes and in some cases, it does not contain any mode at all.

| Mode |
| --- |
| 5 |
| 5 |
| 5 |
| 4 |
| 4 |
| 3 |
| 2 |
| 2 |
| 1 |

# Univariate Analysis

```
# Univariate Analysis
data.describe()
```

✓ 0.0s

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | Cluster |
|---|---|---|---|---|---|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 5.843333 | 3.057333 | 3.758000 | 1.199333 | 0.333333 |
| std | 0.828066 | 0.435866 | 1.765298 | 0.762238 | 0.472984 |
| min | 4.300000 | 2.000000 | 1.000000 | 0.100000 | 0.000000 |
| 25% | 5.100000 | 2.800000 | 1.600000 | 0.300000 | 0.000000 |
| 50% | 5.800000 | 3.000000 | 4.350000 | 1.300000 | 0.000000 |
| 75% | 6.400000 | 3.300000 | 5.100000 | 1.800000 | 1.000000 |
| max | 7.900000 | 4.400000 | 6.900000 | 2.500000 | 1.000000 |

# Univariate Analysis

- Next, we'll visualise the distribution of each feature using histograms and box plots.
- **Histograms** show the frequency distribution of a variable, helping to identify the shape, central tendency, and spread of the data.
- **Box plots** provide a summary of the distribution, highlighting the median, quartiles, and outliers.

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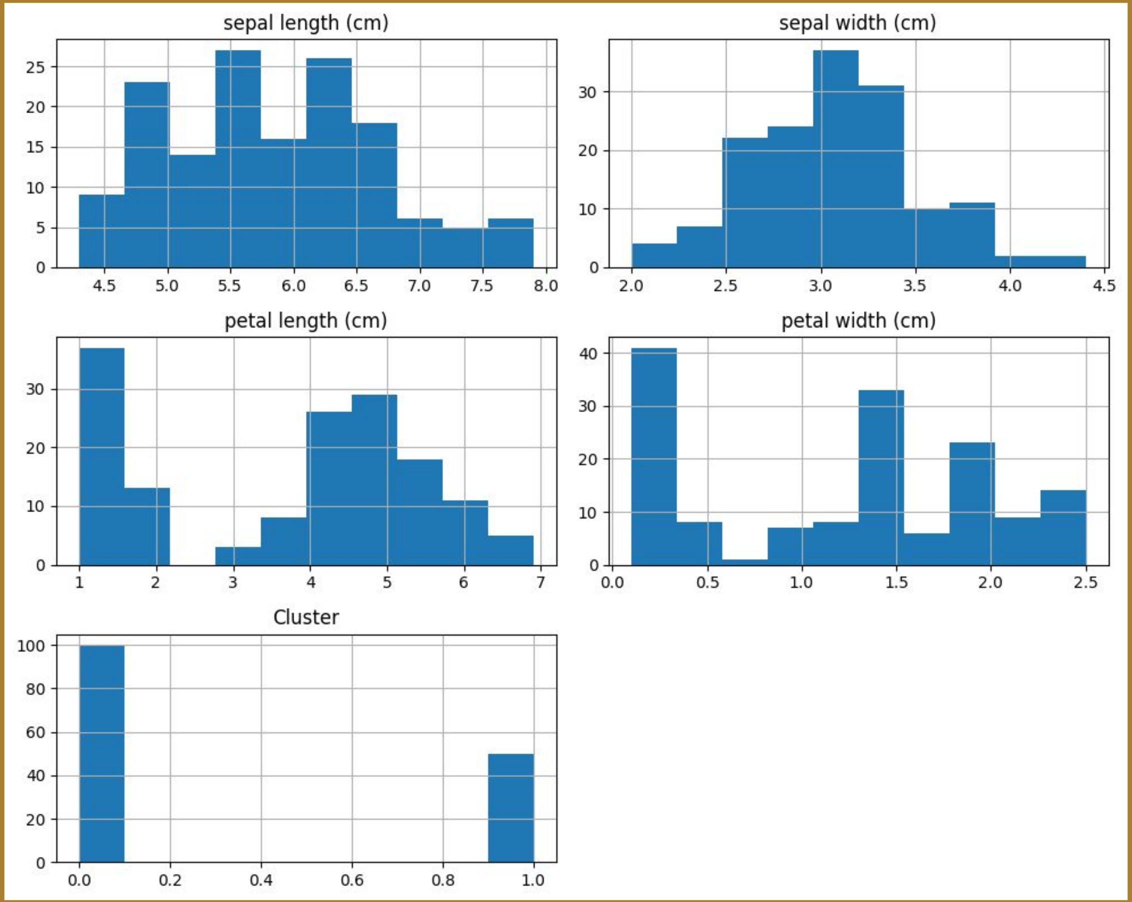
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
Cluster

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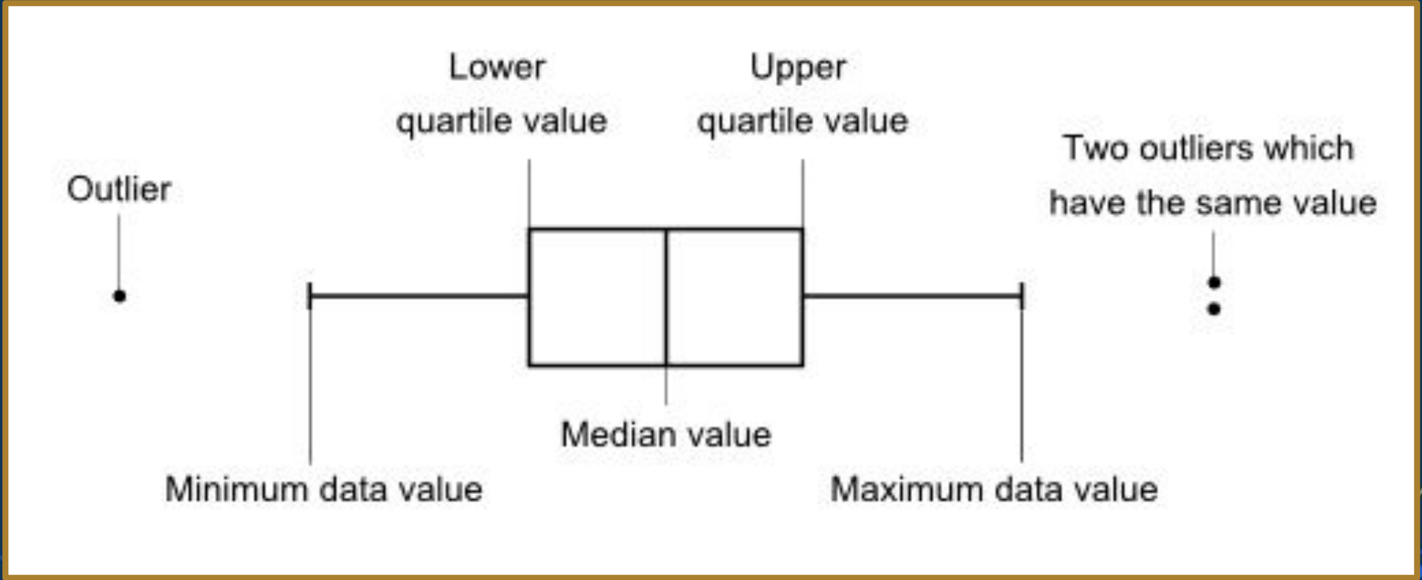
# Box Plots

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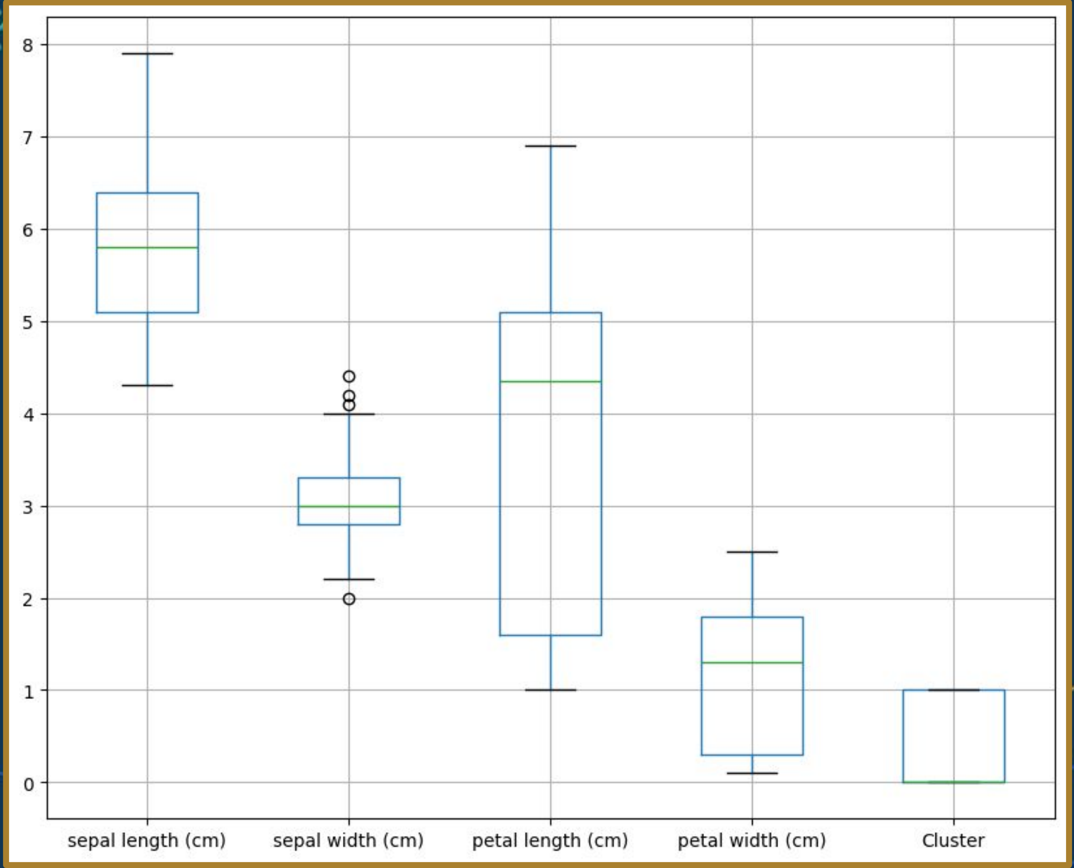
8
7
6
5
4
3
2
1
0
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
Cluster

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# Univariate Analysis

- We'll also check for missing values in the dataset using the isnull().sum() function.
- Missing values can impact the analysis and need to be handled appropriately.
  - Common strategies include filling missing values with the mean, median, or mode.
  - It’s usually not a good idea to just drop data, as this could skew the data and thus the results of prediction.

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```
Missing values: sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
species              0
Cluster              0
dtype: int64
```

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# Bivariate Analysis

- ❖ Bivariate analysis involves examining the relationship between two variables.
  - ➢ **Bivariate:** involving or depending on two variates.
- ❖ We'll use scatter plots to visualise the relationship between features and the target variable.
- ❖ **Scatter plots** help identify patterns, correlations, and clusters in the data.

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```python
# Bivariate Analysis
sns.pairplot(data, hue='species')
plt.show()
corr_matrix = data.iloc[:, :-1].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```

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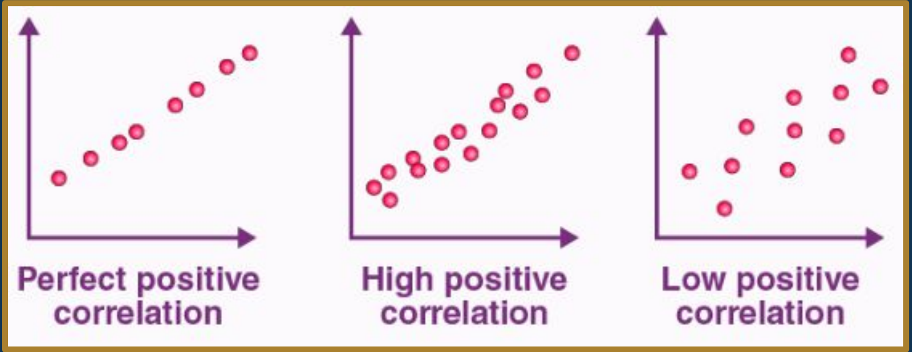
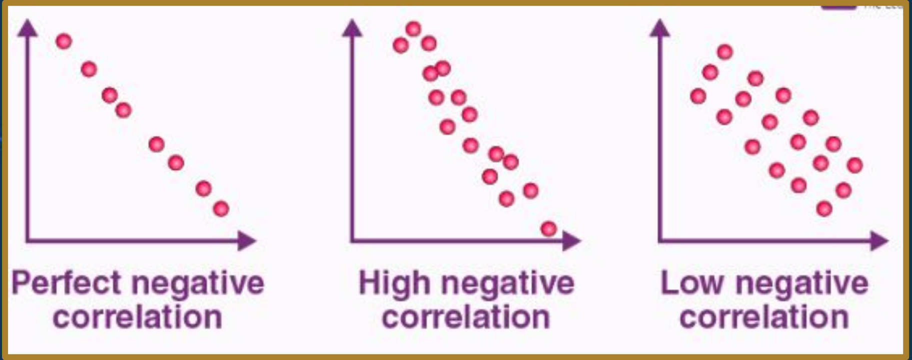
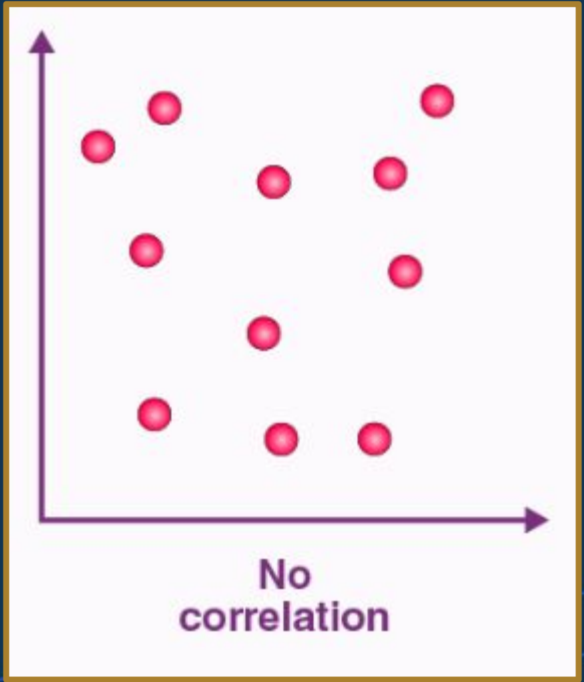
# Scatter Plot

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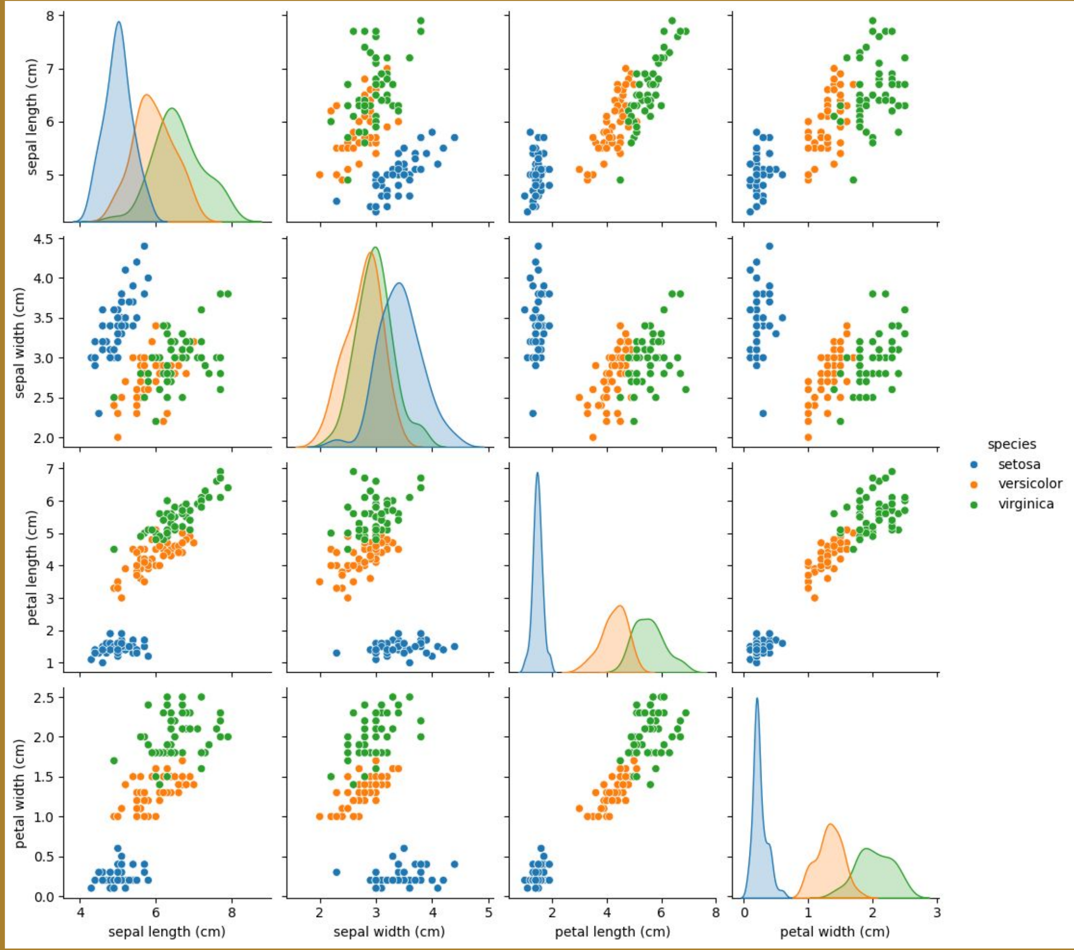
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
species
setosa
versicolor
virginica

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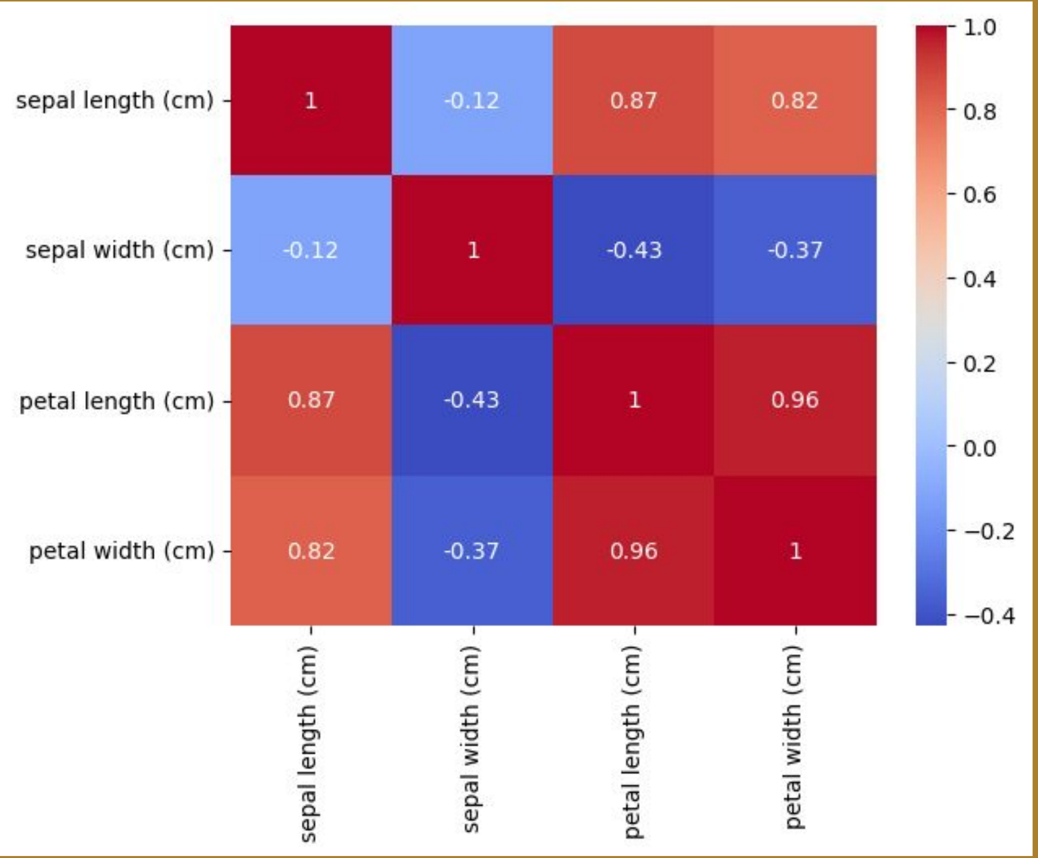
# Bivariate Analysis

- To quantify the relationship between numeric features, we'll calculate the correlation matrix.
- The correlation matrix shows the pairwise correlation coefficients between variables.
- We'll visualise the correlation matrix using a heatmap.


sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
1
-0.12
0.87
0.82
-0.12
1
-0.43
-0.37
0.87
-0.43
1
0.96
0.82
-0.37
0.96
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

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# Bivariate Analysis

- Interpreting the correlation matrix:
  - Correlation coefficients range from -1 to 1.
  - The high positive correlations between Petal Length and Petal Width (0.96) and between Sepal Length and Petal Length (0.87) suggest that these pairs of features are strongly related and may provide similar information.
  - The low correlations between Sepal Width and the other features indicate that Sepal Width provides relatively independent information compared to the other features.

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# What does a scatter plot help identify in bivariate analysis?

1. Frequency distribution of a variable
2. Patterns, correlations, and clusters in the data
3. Median, quartiles, and outliers
4. Missing values in the dataset

# What does a scatter plot help identify in bivariate analysis?

1. Frequency distribution of a variable
2. **Patterns, correlations, and clusters in the data**
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# What does a correlation coefficient of 1 indicate?

1. Perfect positive correlation
2. Perfect negative correlation
3. No correlation
4. Missing data

# What does a correlation coefficient of 1 indicate?

1. **Perfect positive correlation**
2. Perfect negative correlation
3. No correlation
4. Missing data

# What does the color intensity in a correlation matrix heatmap represent?

1. The number of variables
2. The strength and direction of correlations
3. The size of the dataset
4. The number of missing values

# What does the color intensity in a correlation matrix heatmap represent?

1. The number of variables
2. **The strength and direction of correlations**
3. The size of the dataset
4. The number of missing values

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# Multivariate Analysis - PCA

- Multivariate analysis involves examining relationships among multiple variables simultaneously.
- **Principal Component Analysis (PCA)** is a dimensionality reduction technique that transforms the original features into a new set of uncorrelated features called principal components.
- PCA helps identify patterns and structure in high-dimensional data by finding the directions of maximum variance.

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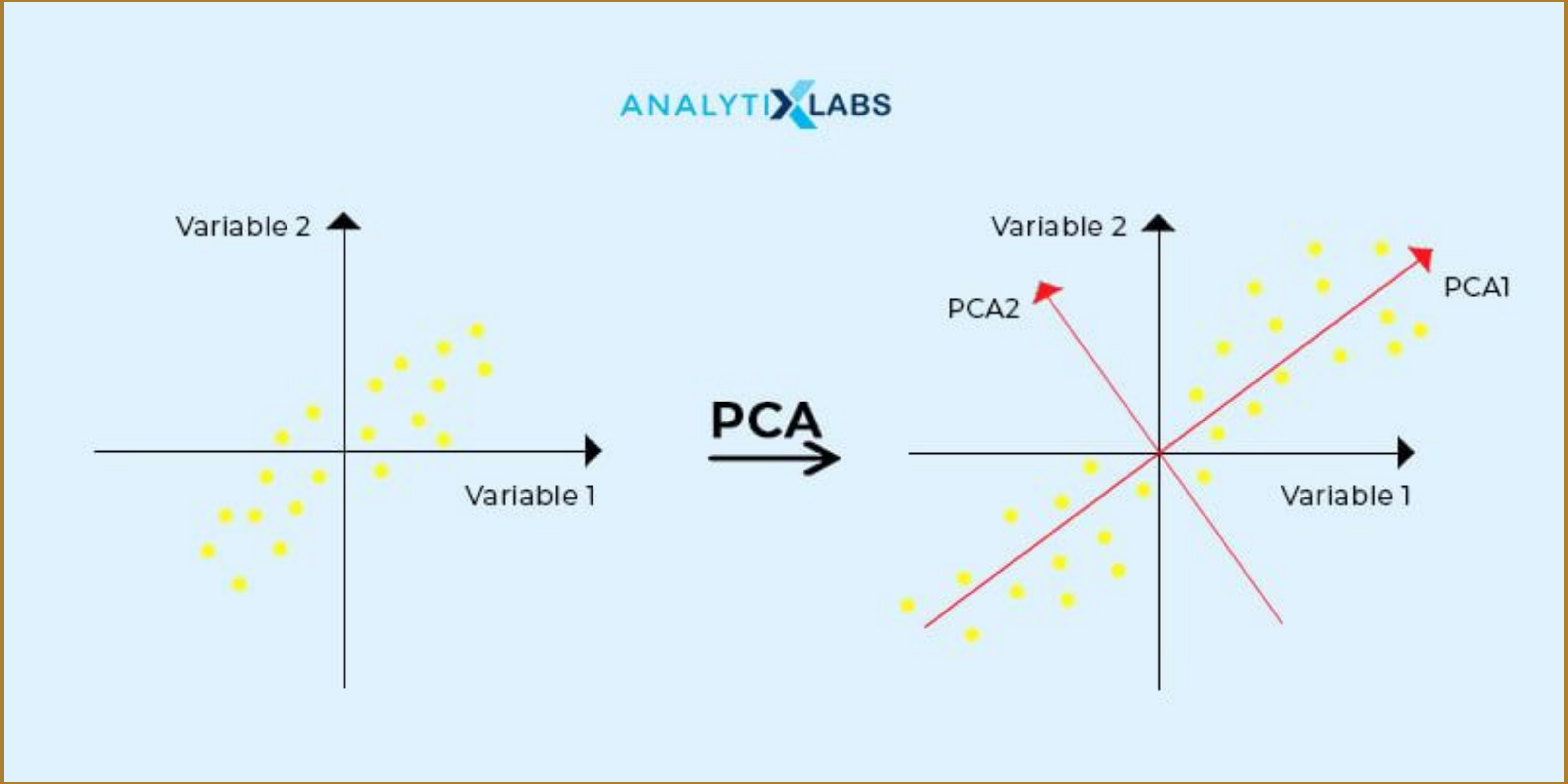


Source: [AnalytixLabs]

# PCA Steps (Python abstracts all the math)

1. Standardize the data to ensure all features have zero mean and unit variance.
2. Compute the covariance matrix of the standardized data.
3. Calculate the eigenvectors and eigenvalues of the covariance matrix.
4. Sort the eigenvectors in descending order of their corresponding eigenvalues.
5. Select the top k eigenvectors as the principal components.
6. Transform the original data into the new feature space defined by the principal components.

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```python
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

X = data.iloc[:, :-1]
y = data.iloc[:, -1]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA()
principalComponents = pca.fit_transform(X_scaled)
```

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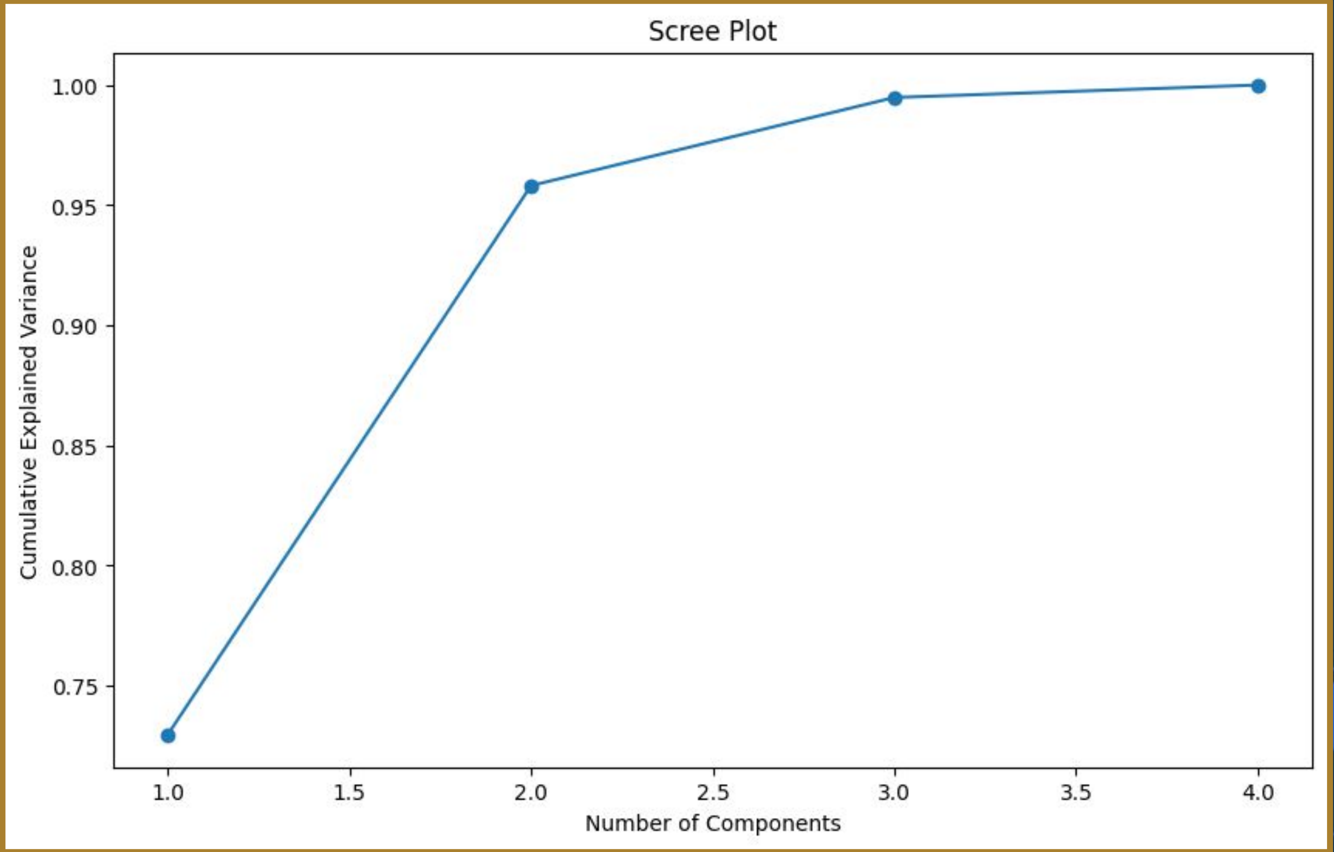
# PCA

- To determine the number of principal components to retain, we can analyse the explained variance ratio.
- The explained variance ratio represents the proportion of variance explained by each principal component.
- We can visualise the cumulative explained variance using a scree plot.


Scree Plot
1.00
0.95
0.90
0.85
0.80
0.75
Cumulative Explained Variance
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Number of Components

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# Scree Plot

- Interpreting the scree plot:
  - Look for an elbow point where the cumulative explained variance starts to plateau.
  - Choose the number of components that capture a significant portion of the total variance (e.g., 80-90%).
  - In our case it seems to be 2 components.

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# Multivariate Analysis - K-means Clustering

- K-means clustering is an unsupervised learning algorithm that partitions the data into K clusters based on similarity.
- It aims to minimize the within-cluster sum of squares (WCSS) or the Euclidean distance between data points and their cluster centroids.
- **More about this in later lectures.**

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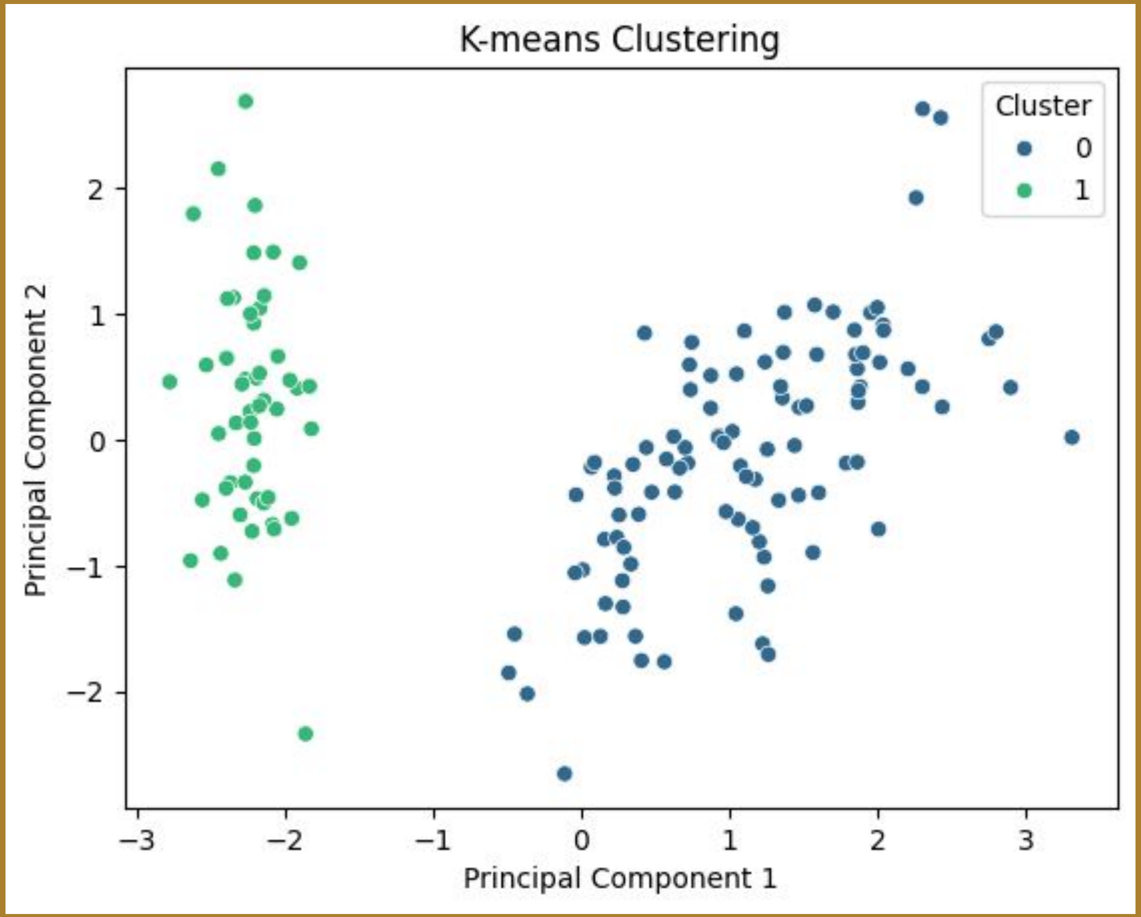
# K-means Clustering Steps (Python abstracts the math)

1. Choose the number of clusters K.
2. Initialize K cluster centroids randomly.
3. Assign each data point to the nearest centroid based on Euclidean distance.
4. Update the cluster centroids by taking the mean of the data points assigned to each cluster.
5. Repeat steps 3 and 4 until convergence or a maximum number of iterations is reached.


K-means Clustering
Cluster
0
1
Principal Component 2
Principal Component 1
2
1
0
−1
−2
−3
−2
−1
0
1
2
3

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# Multivariate Analysis - K-means Clustering

- Interpreting the clustering results:
  - Observe the separation and compactness of the clusters.
  - Analyse the characteristics of data points within each cluster.
  - Consider the domain knowledge and interpret the meaning of the clusters.
    - In our case it seems like 2 plant species are very alike and one is distinctly different (setosa).

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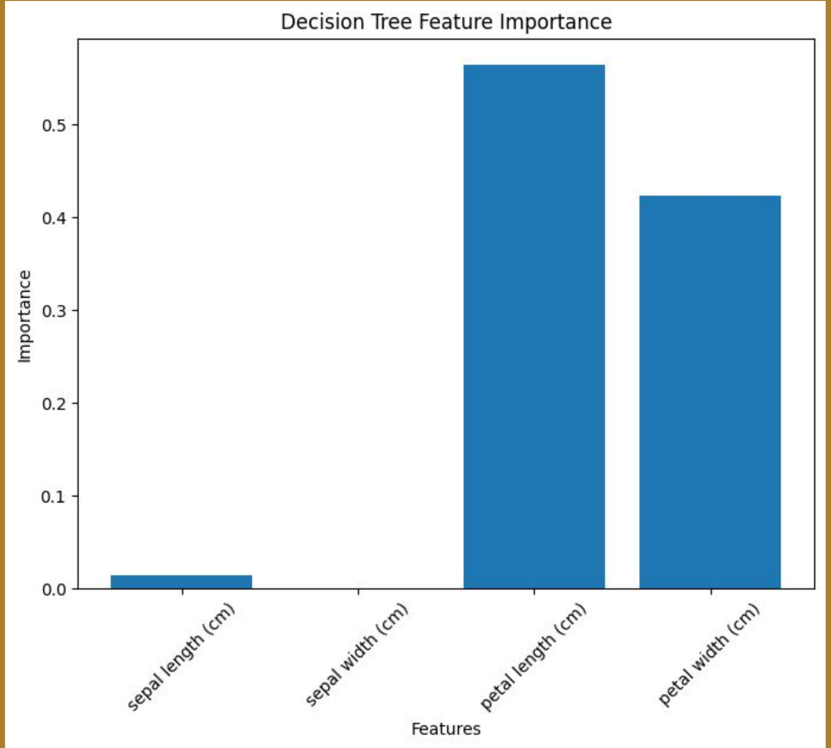
# Feature Importance

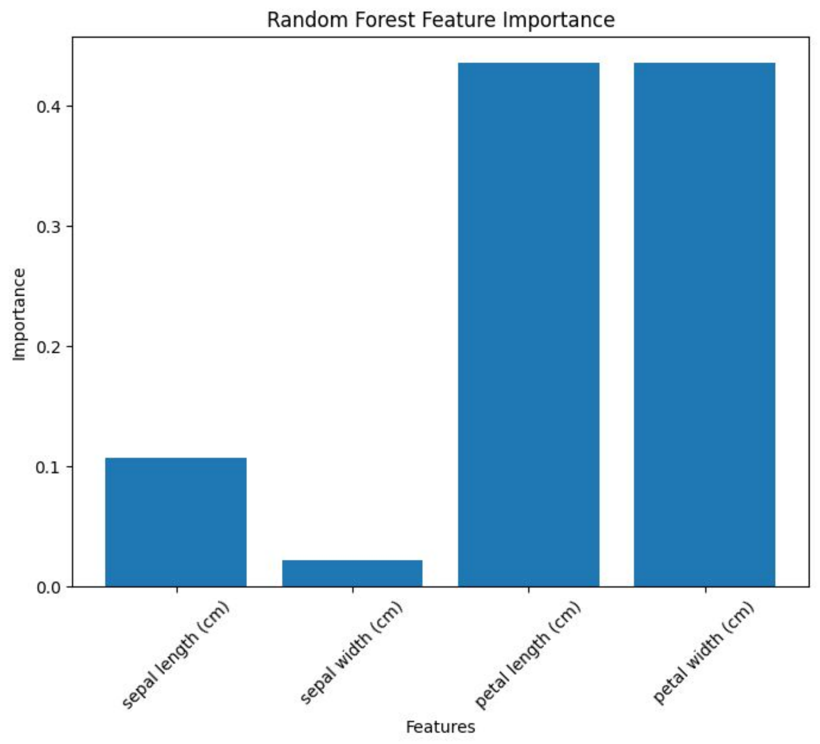
- Feature importance refers to the relative contribution of each feature in predicting the target variable.
- The prediction of a model is only as good as the features used to make the prediction, thus we want the most important predictors.
- We'll assess feature importance using statistical tests and machine learning techniques.

# Decision Trees and Random Forests

- Decision Trees and Random Forests are machine learning algorithms that can provide feature importance scores.
- The importance score represents the decrease in impurity or increase in information gain achieved by splitting on a particular feature.
- **More on these in dedicated lectures later on.**



Decision Tree Feature Importance
Importance
Features
0.0
0.1
0.2
0.3
0.4
0.5
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)

Random Forest Feature Importance
Importance
Features
0.0
0.1
0.2
0.3
0.4
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)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# What is the purpose of Principal Component Analysis (PCA)?

1. To partition the data into clusters
2. To test the significance of the difference in means between groups
3. To transform original features into a new set of uncorrelated features
4. To handle missing values in the dataset

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# What is the purpose of Principal Component Analysis (PCA)?

1. To partition the data into clusters
2. To test the significance of the difference in means between groups
3. **To transform original features into a new set of uncorrelated features**
4. To handle missing values in the dataset

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# In the K-means clustering algorithm, what does the "K" represent?

1. The number of iterations
2. The number of clusters
3. The number of features
4. The number of data points

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## In the K-means clustering algorithm, what does the "K" represent?

1. The number of iterations
2. **The number of clusters**
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# Questions and Answers

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# Thank you for attending

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