```python

import os
import zipfile

# Ensure Kaggle directory exists
os.makedirs(os.path.expanduser("~/.kaggle"), exist_ok=True)

```

```python

# Move the Kaggle JSON file to the Kaggle directory
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json  # Secure the Kaggle API token file

print("Kaggle API configured successfully.")

# Step 2: Define a function to download and extract datasets from Kaggle
def download_kaggle_dataset(dataset_name, download_path='/content'):
    """
    Downloads a dataset from Kaggle and extracts it to the specified directory.

    Args:
    - dataset_name (str): The Kaggle dataset identifier (e.g., 'markmedhat/titanic'
    - download_path (str): The directory where the dataset should be extracted.

    """
    # Download the dataset
    print(f"Downloading {dataset_name} dataset...")
    !kaggle datasets download -d {dataset_name} -p {download_path}

    # Extract the dataset if it's in zip format
    zip_path = os.path.join(download_path, f"{dataset_name.split('/')[-1]}.zip")
    if os.path.exists(zip_path):
        with zipfile.ZipFile(zip_path, 'r') as zip_ref:
            zip_ref.extractall(download_path)
        print(f"Dataset {dataset_name} extracted successfully.")
        os.remove(zip_path)  # Clean up the zip file
    else:
        print("Download completed. No extraction needed.")

# Example usage
download_kaggle_dataset('markmedhat/titanic')
print("Data source import complete.")

# Step 3: List the files in the download directory
for dirname, _, filenames in os.walk('/content'):
    for filename in filenames:
```

```
        print(os.path.join(dirname, filename))
```

Show hidden output

Univariate Data Analysis in Machine Learning

Understanding Exploratory Data Analysis (EDA)

What Is EDA?

- **Definition**: EDA is the process of analyzing datasets to summarize their main characteristics, often using visual methods.
- **Purpose**: To understand the data better, detect patterns, anomalies, and test hypotheses.

Types of EDA

1. **Univariate Analysis**: Examination of one variable at a time.
2. **Bivariate Analysis**: Examination of two variables simultaneously to understand the relationship between them.
3. **Multivariate Analysis**: Examination of more than two variables to understand complex interactions.

Univariate Analysis

What Does "Univariate" Mean?

- **Breakdown**:
    - **Uni**: Single.
    - **Variate**: Variable.
- **Definition**: Analysis of a single variable to understand its distribution and characteristics.

Importance

- **Foundation**: Univariate analysis is the first step in EDA, providing a basic understanding of each variable.
- **Guidance**: Helps in choosing appropriate statistical methods and models for further analysis.

Data Types in Univariate Analysis

Numerical Data

- **Definition**: Variables that represent quantities and can be measured.
- **Examples**:
    - Height.
    - Weight.
    - Age.
    - Price of a product.
    - Battery capacity of a phone.

Categorical Data

- **Definition**: Variables that represent categories or groups.
- **Examples**:
    - Country of residence.
    - Gender.
    - College or university attended.
    - Field of study.

Identifying Data Types

- **Process**: For each column in your dataset, determine whether it is numerical or categorical.
- **Why It Matters**: The type of data influences the choice of visualization and statistical methods.

Applying Univariate Analysis to the Titanic Dataset

About the Dataset

- **Description**: Contains information about passengers on the Titanic, including whether they survived the shipwreck.
- **Objective**: Use univariate analysis to understand each variable in the dataset.

Steps

1. **Import the Dataset**
    - Use pandas to read the CSV file into a DataFrame.
2. **Understand the Columns**
    - Identify which columns are numerical and which are categorical.

- Examples:
    - `Survived`: Categorical (0 = No, 1 = Yes).
    - `Pclass`: Categorical (Passenger class).
    - `Age`: Numerical.
    - `Fare`: Numerical.
    - `Sex`: Categorical.

```
import pandas as pd
import seaborn as sns
```

```
df = pd.read_csv("/content/titanic.csv")
```

Analyzing Categorical Variables

Techniques

1. **Frequency Count**
    - **Method**: Use `value_counts()` to count the occurrences of each category.
    - **Visualization**: Bar plots or pie charts.
    - **Example**:

      ```
      df['Survived'].value_counts()
      ```

        - Shows how many passengers survived and how many did not.
2. **Bar Plots**
    - **Purpose**: Visualize the frequency of categories.
    - **Method**: Use seaborn's `countplot()` function.
    - **Example**:

      ```
      sns.countplot(x='Pclass', data=df)
      ```

        - Visualizes the number of passengers in each class.
3. **Pie Charts**
    - **Purpose**: Show the proportion of categories as parts of a whole.
    - **Method**: Use matplotlib's `pie()` function.

- **Example**:

```
df['Sex'].value_counts().plot.pie(autopct='%1.1f%%')
```

  - Displays the percentage of male and female passengers.

Adding Analogies

- **Analogy for Frequency Counts**:
  - Counting the number of students in each class to understand class sizes.
- **Analogy for Bar Plots**:
  - Visualizing sales of different product categories in a store to see which sells the most.

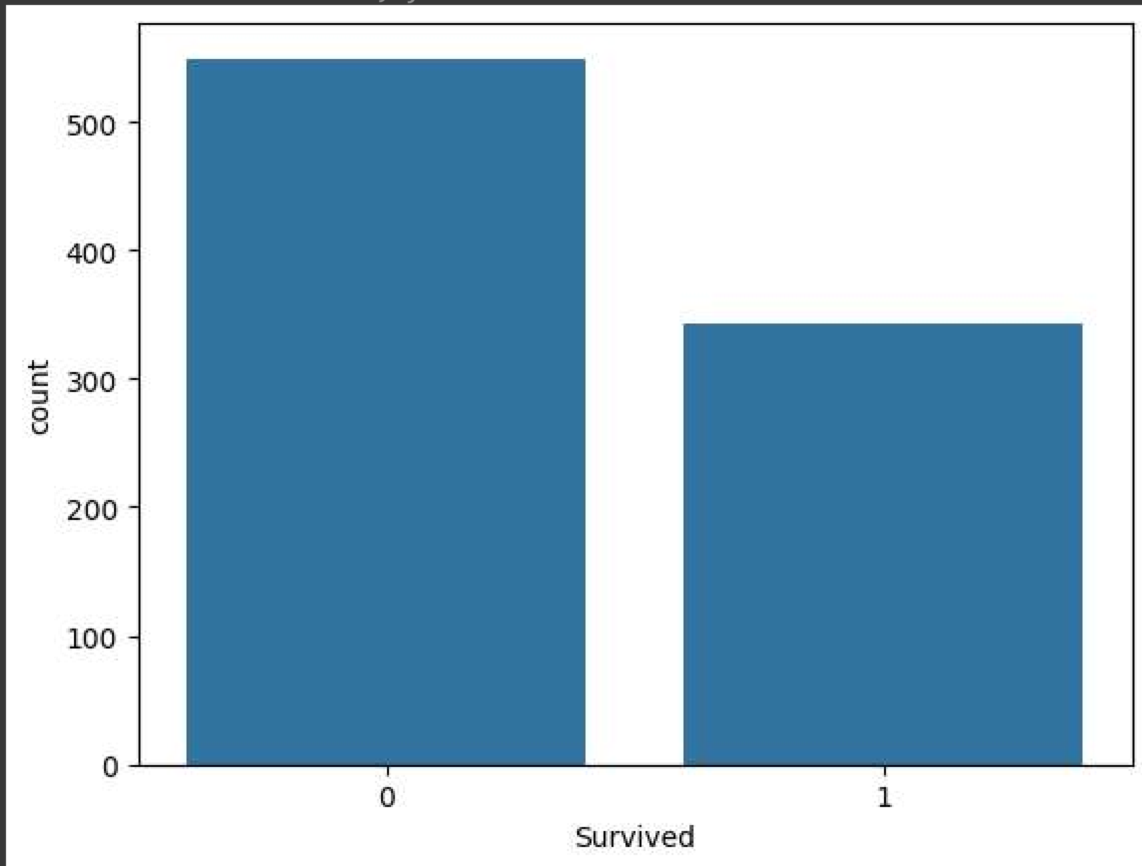
```
1 df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence	female	38.0	1	0	PC 17599	71.2833

Next steps: View recommended plots New interactive sheet

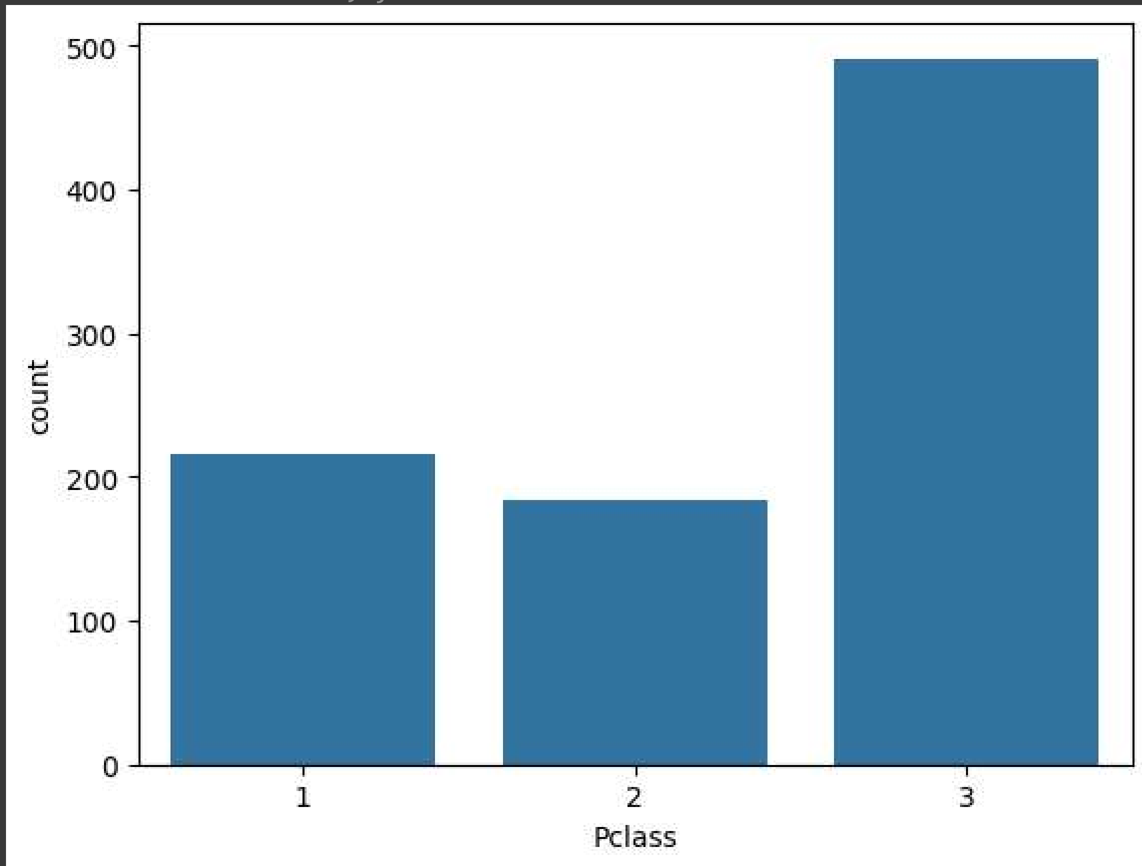
```
1 sns.countplot(x="Survived", data=df)
```

```
<Axes: xlabel='Survived', ylabel='count'>
```



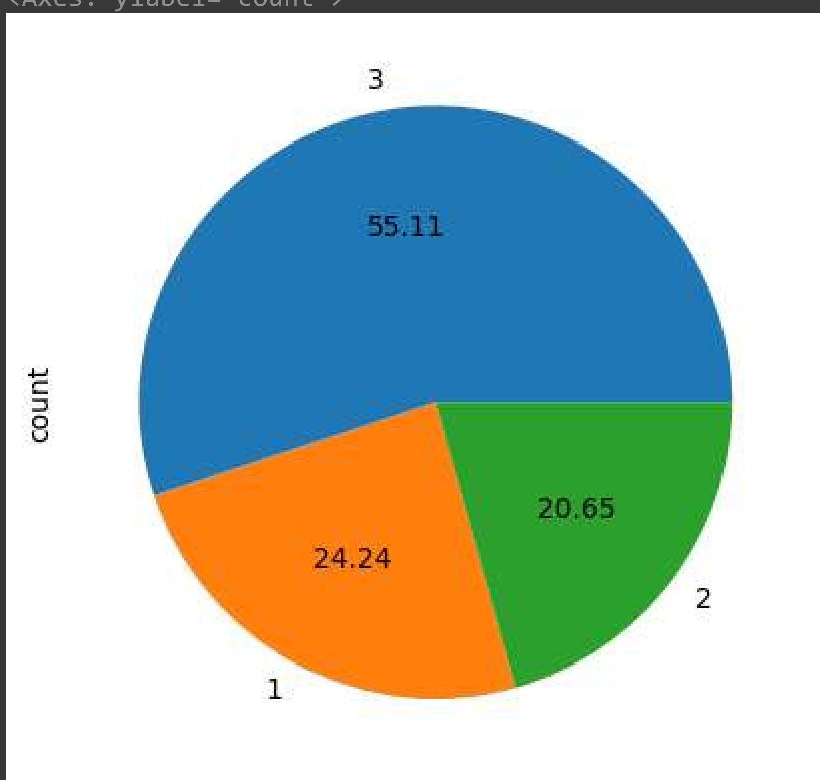

```
sns.countplot(x='Pclass', data=df)
```

<Axes: xlabel='Pclass', ylabel='count'>




```
1 df['Pclass'].value_counts().plot(kind='pie', autopct='%.2f')
```

<Axes: ylabel='count'>



Analyzing Numerical Variables

Techniques

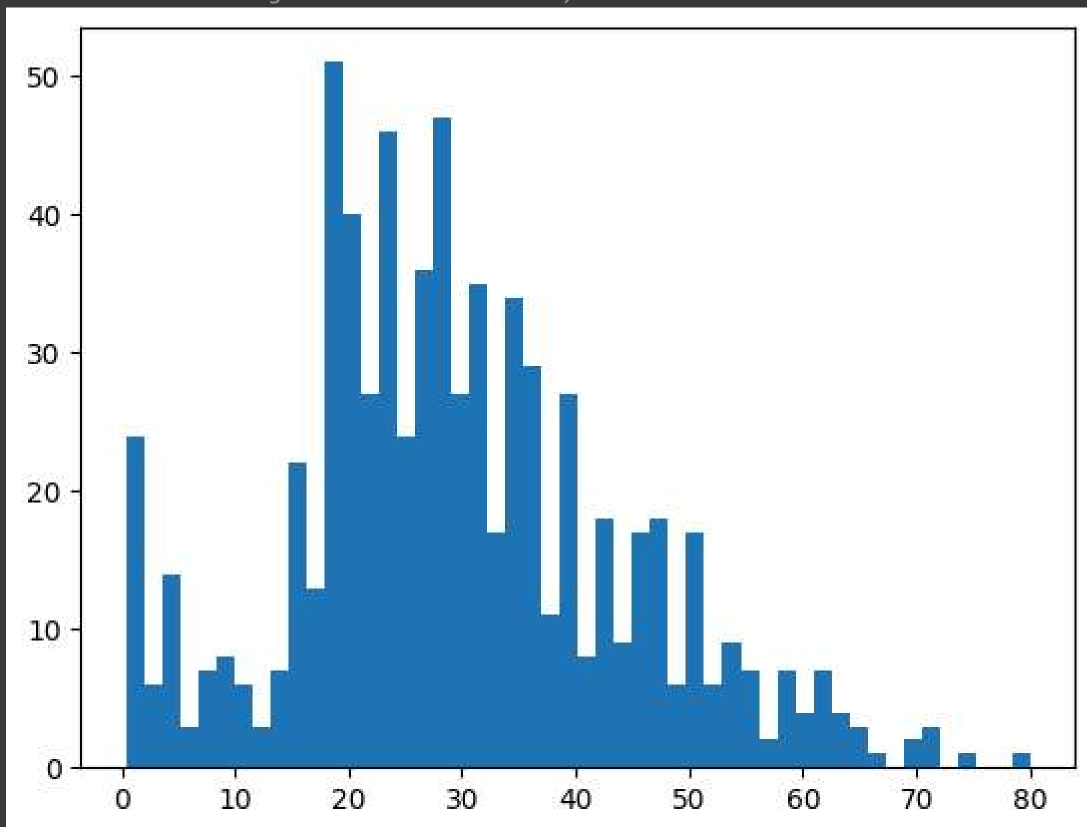
1. **Histograms**
    - **Purpose**: Understand the distribution of numerical data.
    - **Method**: Use matplotlib or seaborn's `histplot()` function.
    - **Example**:

      ```
      sns.histplot(df['Age'], bins=10)
      ```

        - Shows the age distribution of passengers.
    - **Interpretation**:
        - See which age groups had more passengers.
    - **Analogy**:
        - Like creating bins for heights of students to see how many fall into each height range.

```
import matplotlib.pyplot as plt
plt.hist(df['Age'], bins = 50)
```

```
(array([24.,  6., 14.,  3.,  7.,  8.,  6.,  3.,  7., 22., 13., 51., 40.,
        27., 46., 24., 36., 47., 27., 35., 17., 34., 29., 11., 27.,  8.,
        18.,  9., 17., 18.,  6., 17.,  6.,  9.,  7.,  2.,  7.,  4.,  7.,
         4.,  3.,  1.,  0.,  2.,  3.,  0.,  1.,  0.,  0.,  1.]),
 array([ 0.42  ,  2.0116,  3.6032,  5.1948,  6.7864,  8.378 ,  9.9696,
        11.5612, 13.1528, 14.7444, 16.336 , 17.9276, 19.5192, 21.1108,
        22.7024, 24.294 , 25.8856, 27.4772, 29.0688, 30.6604, 32.252 ,
        33.8436, 35.4352, 37.0268, 38.6184, 40.21  , 41.8016, 43.3932,
        44.9848, 46.5764, 48.168 , 49.7596, 51.3512, 52.9428, 54.5344,
        56.126 , 57.7176, 59.3092, 60.9008, 62.4924, 64.084 , 65.6756,
        67.2672, 68.8588, 70.4504, 72.042 , 73.6336, 75.2252, 76.8168,
        78.4084, 80.    ]),
 <BarContainer object of 50 artists>)
```



2. **Density Plots**
   - **Purpose**: Show the probability density of the variable.
   - **Method**: Use seaborn's `kdeplot()`.
   - **Example**:

     ```
     sns.kdeplot(df['Fare'])
     ```

     - Visualizes the distribution of fares paid.
   - **Analogy**:
     - Similar to smoothing out a histogram to see the overall trend.

```
1 sns.distplot(df['Age'])
```

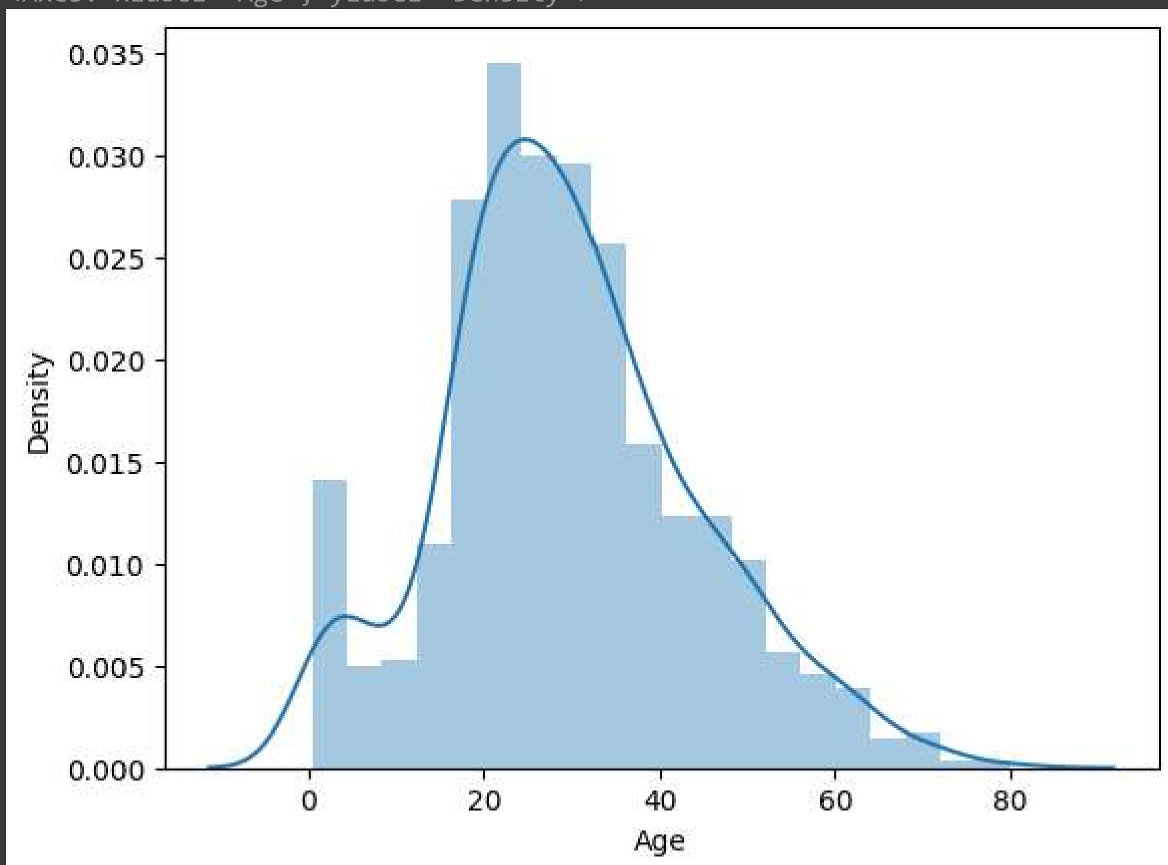
```
<ipython-input-22-0fafe04ea3f6>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Age'])
<Axes: xlabel='Age', ylabel='Density'>
```



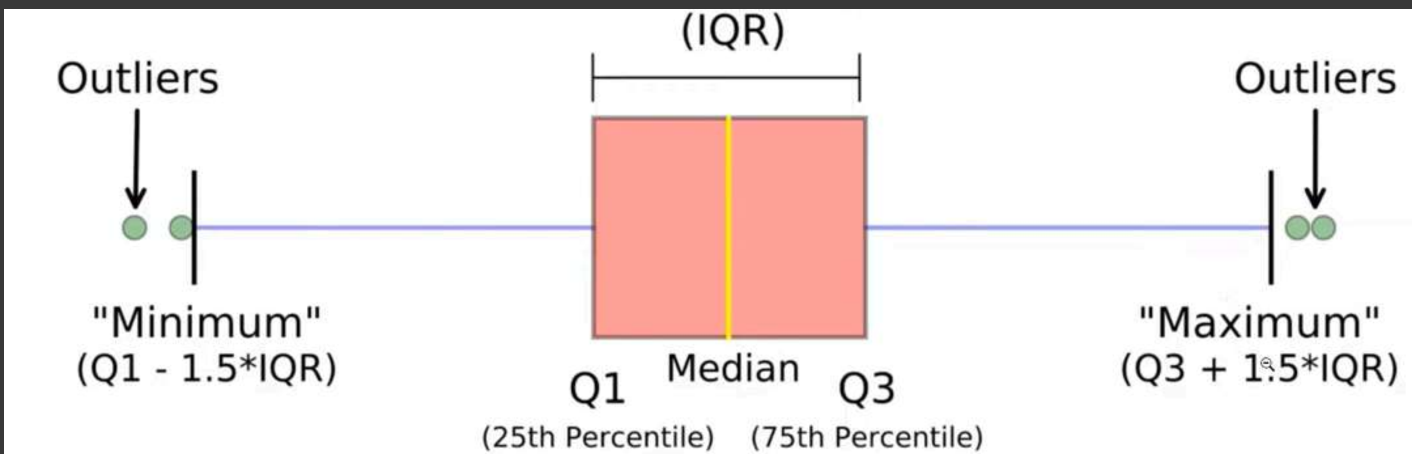
3. **Box Plots**
    - **Purpose**: Summarize data using quartiles and identify outliers.
    - **Method**: Use seaborn's `boxplot()`.
    - **Example**:

    ```
    sns.boxplot(y='Age', data=df)
    ```

        - Shows median, quartiles, and potential outliers in age.

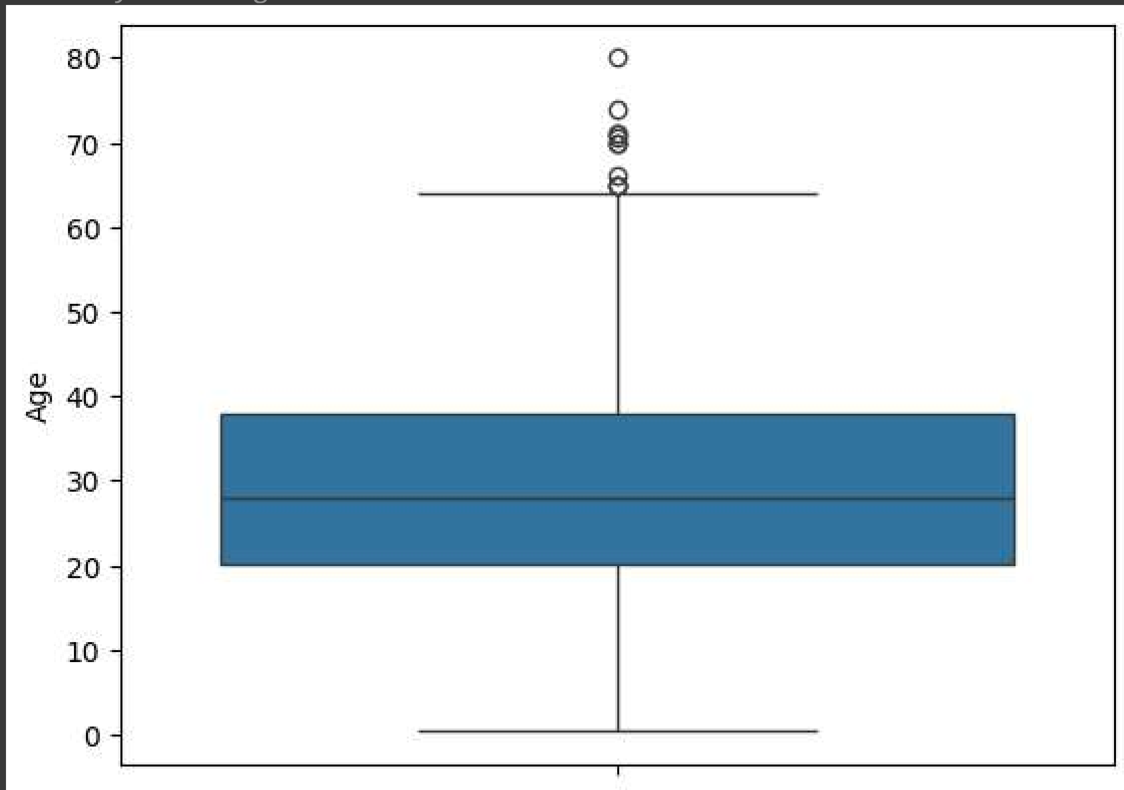
- **Interpretation**:
    - **Median**: The middle value.
    - **Quartiles**: Divides data into four equal parts.
    - **Outliers**: Data points that fall outside the typical range.
- **Analogy**:
    - Like a summary of test scores showing the middle score, spread, and any unusually high or low scores.

IQR- interquartile range




```
sns.boxplot(df['Age'])
```

<Axes: ylabel='Age'>



4. **Statistical Measures**

   - **Mean**: Average value.
   - **Median**: Middle value when data is sorted.
   - **Mode**: Most frequent value.
   - **Standard Deviation**: Measures the spread of data.
   - **Example**:

     ```
     df['Age'].mean()
     df['Age'].median()
     df['Age'].std()
     ```

   - **Analogy**:
     - Understanding the average and variability of students' test scores in a class.

```
df['Age'].describe()
```

	Age
count	714.000000
mean	29.699118
std	14.526497
min	0.420000
25%	20.125000
50%	28.000000
75%	38.000000

Understanding Data Distribution

Skewness

- **Definition**: Measures the asymmetry of the distribution.
- **Types**:
  - **Positive Skew (Right-Skewed)**: Tail on the right side.
  - **Negative Skew (Left-Skewed)**: Tail on the left side.
- **Method**:

```
df['Fare'].skew()
```

- **Interpretation**:
  - A high positive skew indicates a long tail on the right.
- **Analogy**: