Titanic Dataset – Exploratory Data Analysis (EDA)

Author: *Garima Negi*
Dataset: Titanic - Machine Learning from Disaster (Kaggle)
Tools Used: Python, Pandas, Matplotlib, Seaborn

Objective

The goal of this EDA is to analyze the Titanic dataset to uncover patterns, trends, and anomalies that could help understand the survival outcomes of passengers.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

pd.set_option('display.max_columns', None)
sns.set_style("whitegrid")
```

```
from google.colab import files
uploaded = files.upload()

df = pd.read_csv('train.csv')
```

Choose files train.csv

- **train.csv**(text/csv) - 61194 bytes, last modified: 11/08/2025 - 100% done

```
Saving train.csv to train (1).csv
```

Step 1: Basic Data Exploration

We begin by checking:

- Structure of the dataset
- Summary statistics
- Missing values
- Category distributions

```
# Structure of dataset
df.info()

# Summary statistics
df.describe()

# Missing values
df.isnull().sum()
```

```
# Value counts for key categorical variables
print("\n--- Value Counts for 'Sex' ---")
print(df['Sex'].value_counts())

print("\n--- Value Counts for 'Pclass' ---")
print(df['Pclass'].value_counts())

print("\n--- Value Counts for 'Embarked' ---")
print(df['Embarked'].value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB

--- Value Counts for 'Sex' ---
Sex
male      577
female    314
Name: count, dtype: int64

--- Value Counts for 'Pclass' ---
Pclass
3    491
1    216
2    184
Name: count, dtype: int64

--- Value Counts for 'Embarked' ---
Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
```

Step 2: Univariate Analysis

This process helps in identifying:

- The central tendency and dispersion of numerical variables.

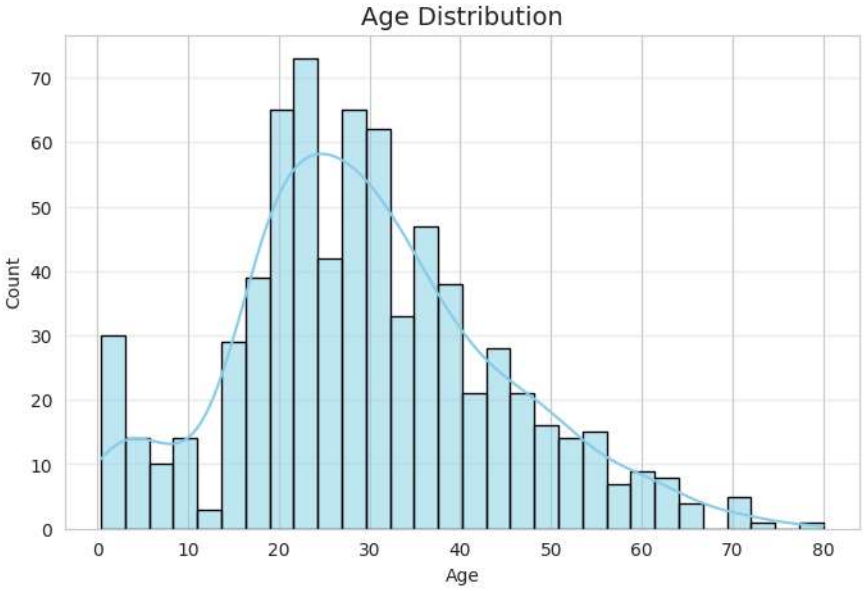
- The frequency distribution of categorical variables.
- The presence of outliers or unusual patterns.

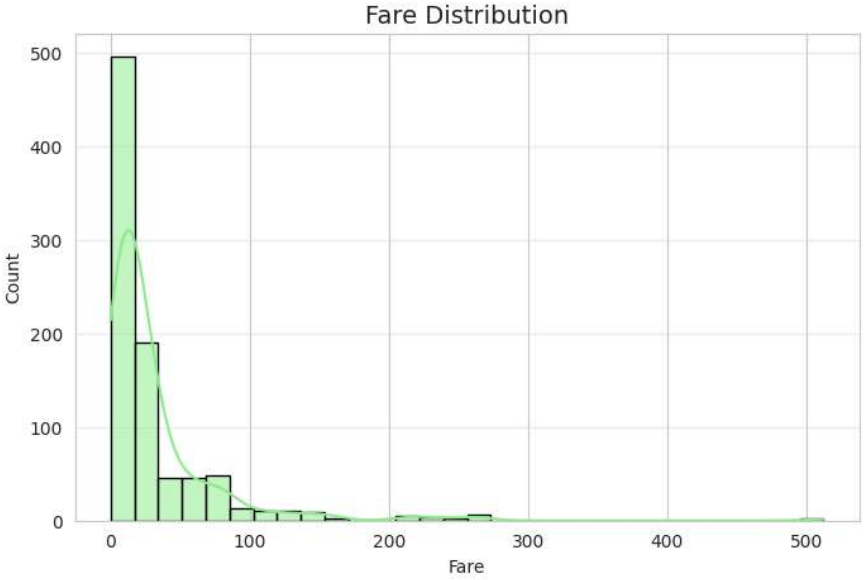
The following visualizations are used:

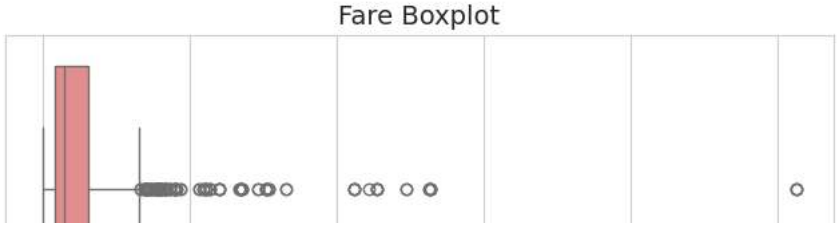
- **Histograms** for understanding the distribution of numerical features such as *Age* and *Fare*.
- **Boxplots** for detecting outliers and examining the spread of continuous variables.
- **Bar charts** for visualizing the frequency of categories such as *Sex* and *Pclass*.

This analysis forms the foundation for subsequent bivariate and multivariate explorations by highlighting important patterns and potential anomalies in individual features.

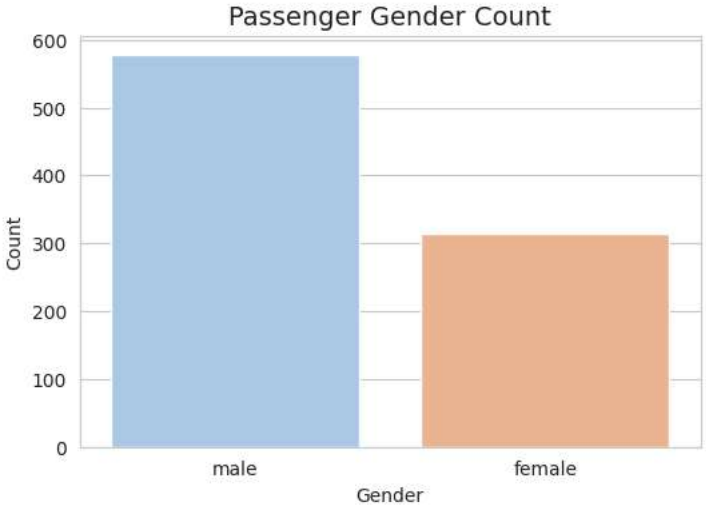
```
# Age distribution
plt.figure(figsize=(8,5))
sns.histplot(df['Age'], bins=30, kde=True, color='skyblue', edgecolor='black')
plt.title('Age Distribution', fontsize=14)
plt.xlabel('Age')
plt.ylabel('Count')
plt.grid(axis='y', alpha=0.3)
plt.show()

# Fare distribution
plt.figure(figsize=(8,5))
sns.histplot(df['Fare'], bins=30, kde=True, color='lightgreen', edgecolor='black')
plt.title('Fare Distribution', fontsize=14)
plt.xlabel('Fare')
plt.ylabel('Count')
plt.grid(axis='y', alpha=0.3)
plt.show()

# Fare boxplot
plt.figure(figsize=(8,3))
sns.boxplot(x=df['Fare'], color='lightcoral')
plt.title('Fare Boxplot', fontsize=14)
plt.show()

# Gender count
plt.figure(figsize=(6,4))
sns.countplot(x='Sex', data=df, palette='pastel')
plt.title('Passenger Gender Count', fontsize=14)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()

# Passenger class count
plt.figure(figsize=(6,4))
sns.countplot(x='Pclass', data=df, palette='Set2')
plt.title('Passenger Class Count', fontsize=14)
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```


Age Distribution
Count
Age
0
10
20
30
40
50
60
70
80

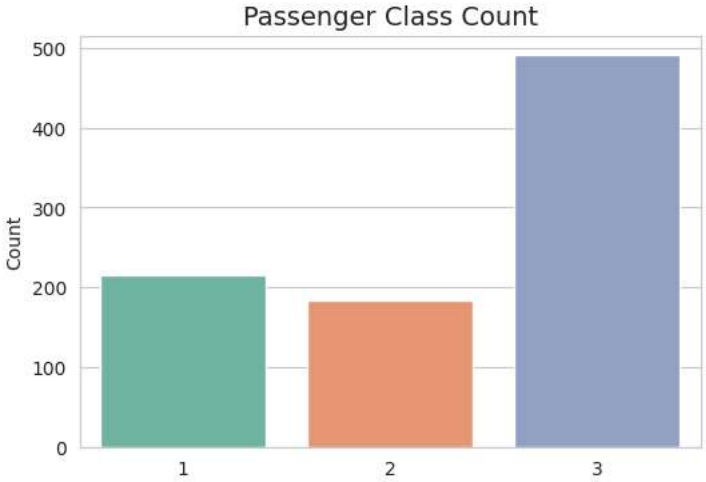

Fare Distribution
Count
Fare
0
100
200
300
400
500


Fare Boxplot


```
/tmp/ipython-input-2857684001.py:27: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1

  sns.countplot(x='Sex', data=df, palette='pastel')
```




```
/tmp/ipython-input-2857684001.py:35: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1

  sns.countplot(x='Pclass', data=df, palette='Set2')
```



Class

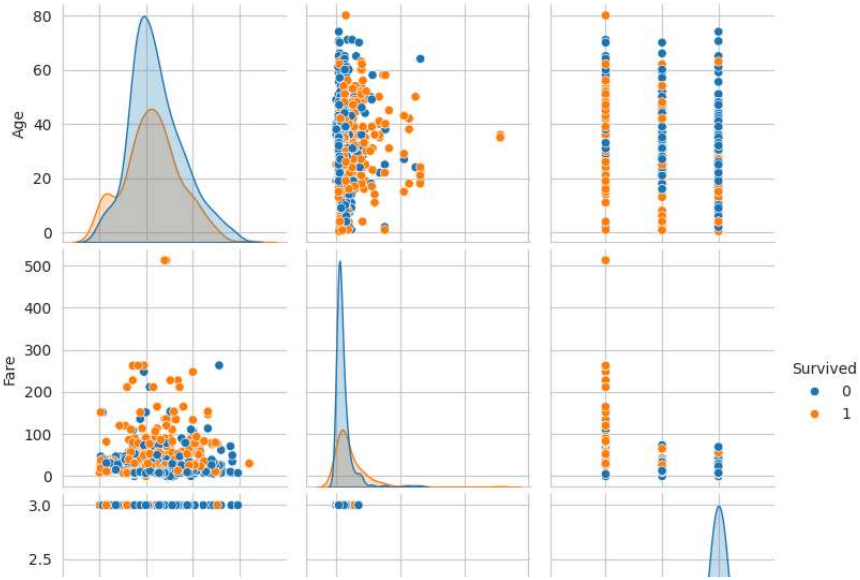
Observations, Univariate Analysis

1. **Age Distribution**
   - Most passengers were between 20 and 40 years old, with a clear peak in the mid-20s.
   - There were fewer elderly passengers who were over 60 years.
   - The distribution shows a moderate spread, indicating a mix of age groups on board.
2. **Fare Distribution**
   - Most ticket fares were in the lower range, suggesting that many passengers traveled in lower classes.
   - A small number of passengers paid much higher fares, indicating some premium ticket holders.
   - The fare distribution skews to the right because of these high-value outliers.
3. **Fare Boxplot**
   - Outliers are clearly visible on the higher end, confirming the skewness observed in the histogram.
   - The interquartile range (IQR) indicates that most fares fall within a narrow price band.
4. **Gender Count**
   - There were more male passengers than female passengers on board.
   - This imbalance is an important factor when looking at survival rates.
5. **Passenger Class Count**
   - Third-class passengers made up the largest group, followed by second and first class.
   - This shows the social and economic diversity of the passengers on the Titanic.

Step 4: Multivariate Analysis

Exploring patterns with more than two variables.

```
sns.pairplot(df[['Survived','Age','Fare','Pclass']], hue='Survived')
plt.show()
```


Age
Fare
Survived
0
1