Titanic Survival Patterns: An EDA Approach

"Exploring survival stories hidden beneath the numbers."

Objective

Perform detailed exploratory data analysis (EDA) on the Titanic dataset to identify trends and patterns related to passenger survival. This involves examining missing values, understanding feature distributions, and analyzing relationships between variables using basic visualizations.

Dataset Information

- Source: Kaggle Titanic: Machine Learning from Disaster
- Files Used: train.csv
- Target Variable: Survived (0 = Did not survive, 1 = Survived)
- Features:
- Pclass (Passenger class)
- Sex
- Age
- SibSp (Number of siblings/spouses aboard)
- Parch (Number of parents/children aboard)
- Fare
- Embarked (Port from boarded)

  Let's dive into the code and start with loading the dataset!

Step 1: Import Required Libraries

We'll begin by importing essential Python libraries for data analysis and visualization.

```
# Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Set Seaborn style
sns.set(style='whitegrid')
%matplotlib inline
```

Step 2: Load the Dataset

We'll use the training dataset from the Titanic - Machine Learning from Disaster challenge on Kaggle.

```
# Load the dataset
df = pd.read_csv('titanic.csv') # We begin by loading the Titanic
dataset into a pandas DataFrame.
```

Step 3: Basic Data Exploration

We will check the dataset's shape, data types, and get a basic statistical summary.

```
print("Shape of dataset:", df.shape)  # Shows Shape of dataset

Shape of dataset: (891, 12)

df.head() # Shows the first 5 rows by default

   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
```

```
1      0          PC 17599  71.2833   C85        C
2      0   STON/O2. 3101282   7.9250   NaN        S
3      0             113803  53.1000  C123        S
4      0             373450   8.0500   NaN        S

df.tail() # Shows the bottom 5 rows by default

     PassengerId  Survived  Pclass
Name  \
886          887         0       2                      Montvila, Rev.
Juozas
887          888         1       1               Graham, Miss. Margaret
Edith
888          889         0       3  Johnston, Miss. Catherine Helen
"Carrie"
889          890         1       1                      Behr, Mr. Karl
Howell
890          891         0       3                        Dooley, Mr.
Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

Step 4: Data Overview

We'll examine the dataset's structure, including number of entries, data types, and missing values.

```
# Basic info and missing values
df.info() # Quick Overview of DataFrame

<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
```

```
df.isnull() # Checks for Missing Values
```

```
     PassengerId  Survived  Pclass   Name    Sex    Age  SibSp  Parch
Ticket  \
0          False     False   False  False  False  False  False  False
False
1          False     False   False  False  False  False  False  False
False
2          False     False   False  False  False  False  False  False
False
3          False     False   False  False  False  False  False  False
False
4          False     False   False  False  False  False  False  False
False
..           ...       ...     ...    ...    ...    ...    ...    ...
...
886        False     False   False  False  False  False  False  False
False
887        False     False   False  False  False  False  False  False
False
888        False     False   False  False  False   True  False  False
False
889        False     False   False  False  False  False  False  False
False
890        False     False   False  False  False  False  False  False
False

      Fare  Cabin  Embarked
0    False   True     False
1    False  False     False
2    False   True     False
3    False  False     False
4    False   True     False
..     ...    ...       ...
886  False   True     False
887  False  False     False
888  False   True     False
889  False  False     False
890  False   True     False

[891 rows x 12 columns]
```

```
df.isnull().sum() #Count Missing Values Per Column
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

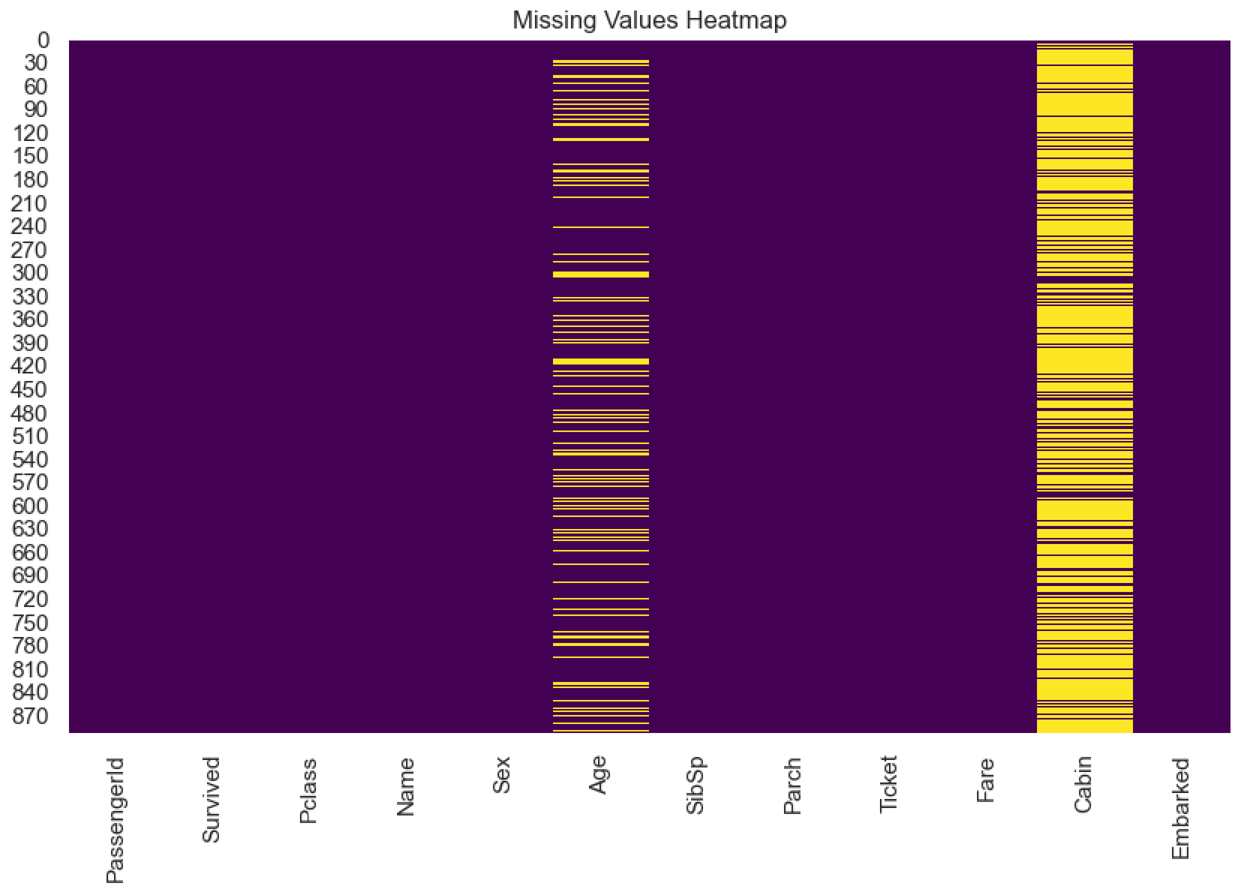
- It is clear to see that there is 177 missing values in the Age feature and the 2 values are missing in the Embarked.

```
# Summary statistics
df.describe() #Descriptive Statistics at a Glance for all numeric
columns

       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200

df.describe(include='object') #Summary Stats for
Categorical(text/string) Columns

                           Name   Sex  Ticket    Cabin Embarked
count                       891   891     891      204      889
unique                      891     2     681      147        3
top     Braund, Mr. Owen Harris  male  347082  B96 B98        S
freq                          1   577       7        4      644
```

Step 5: Visualize Missing Values- Heatmap

Let's visualize where data is missing to guide our cleaning strategy.

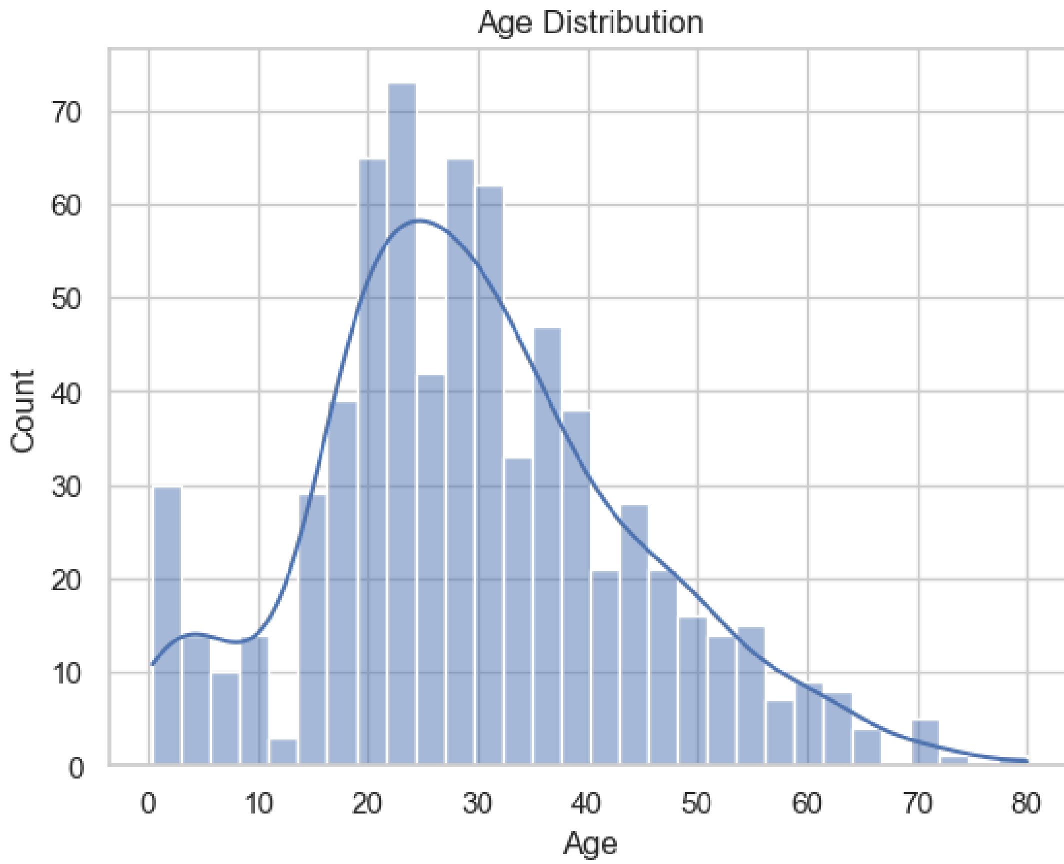
```
#creates a heatmap to visually inspect missing values
plt.figure(figsize=(10,6))
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.title("Missing Values Heatmap")
plt.show()
```



Step 6: Univariate Analysis

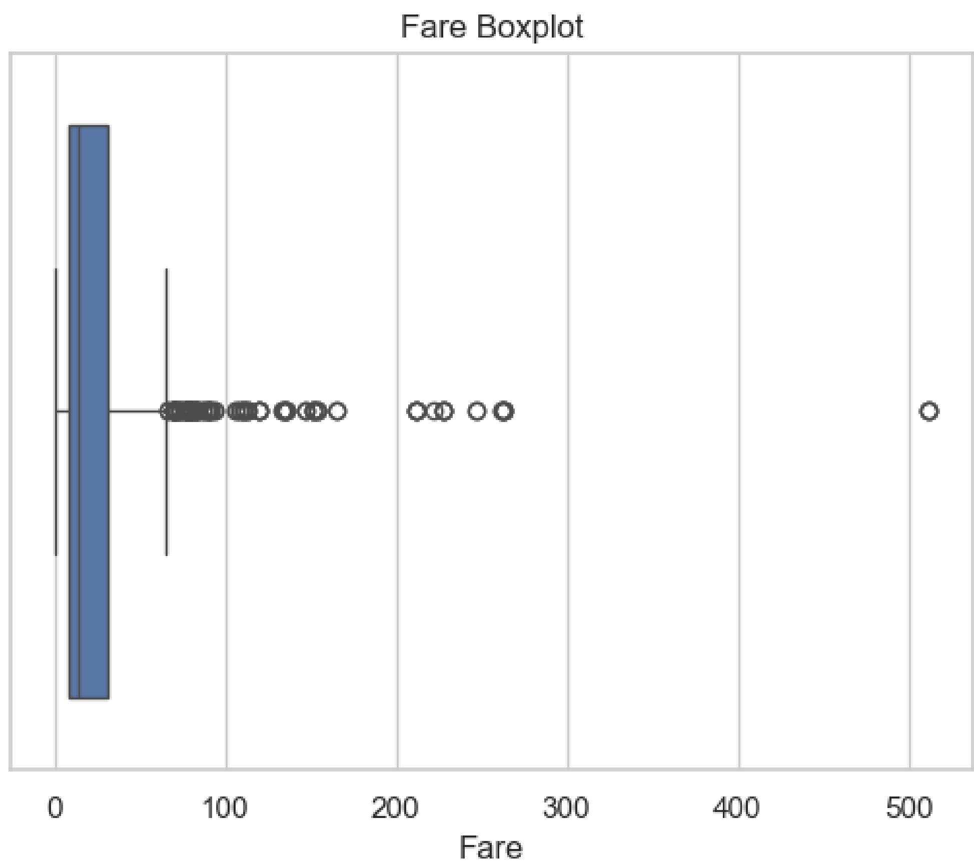
Numerical Features:

```
# Numerical Features - Age
sns.histplot(df['Age'].dropna(), kde=True, bins=30)  #creates a histogram of Age distribution
plt.title("Age Distribution")
plt.show()
```



- Most passengers were in their 20s and 30s. The distribution is right-skewed with fewer older passengers.

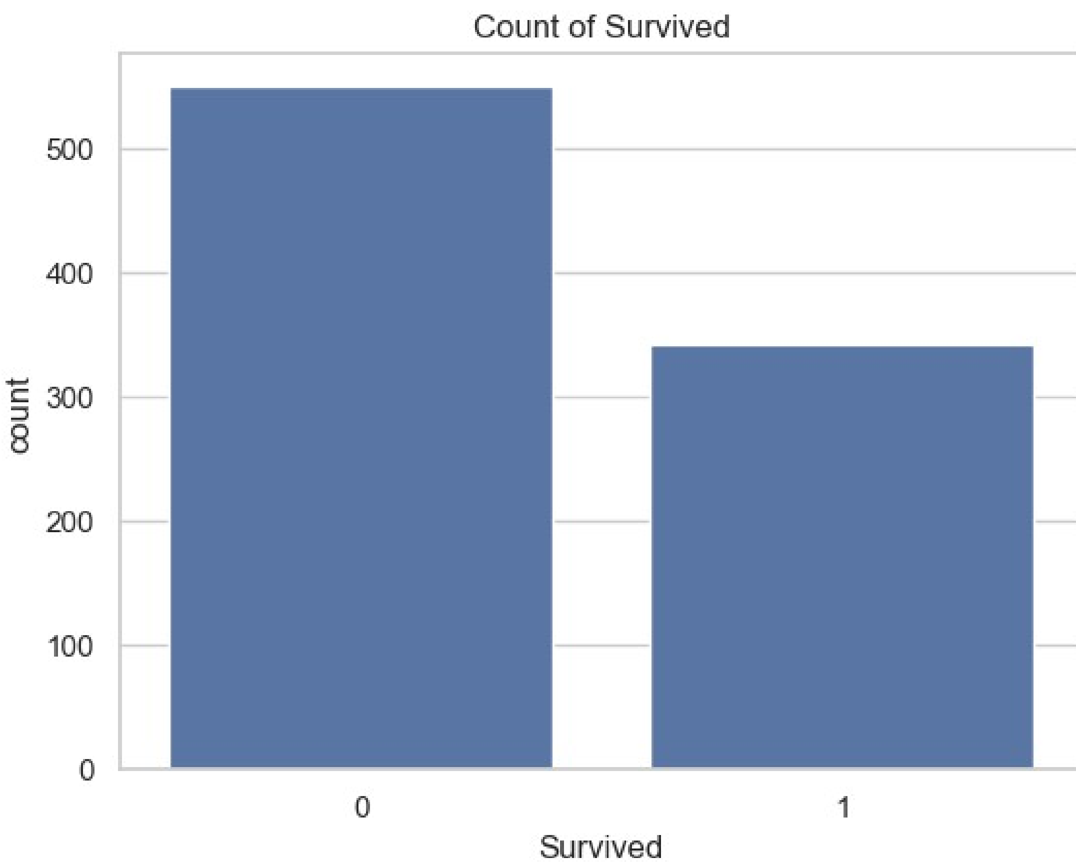
```
# Numerical Features - Fare
sns.boxplot(x=df['Fare']) # Spot outliers
plt.title("Fare Boxplot")
plt.show()
```



- Most fares are concentrated under $100, with a few high-value outliers.

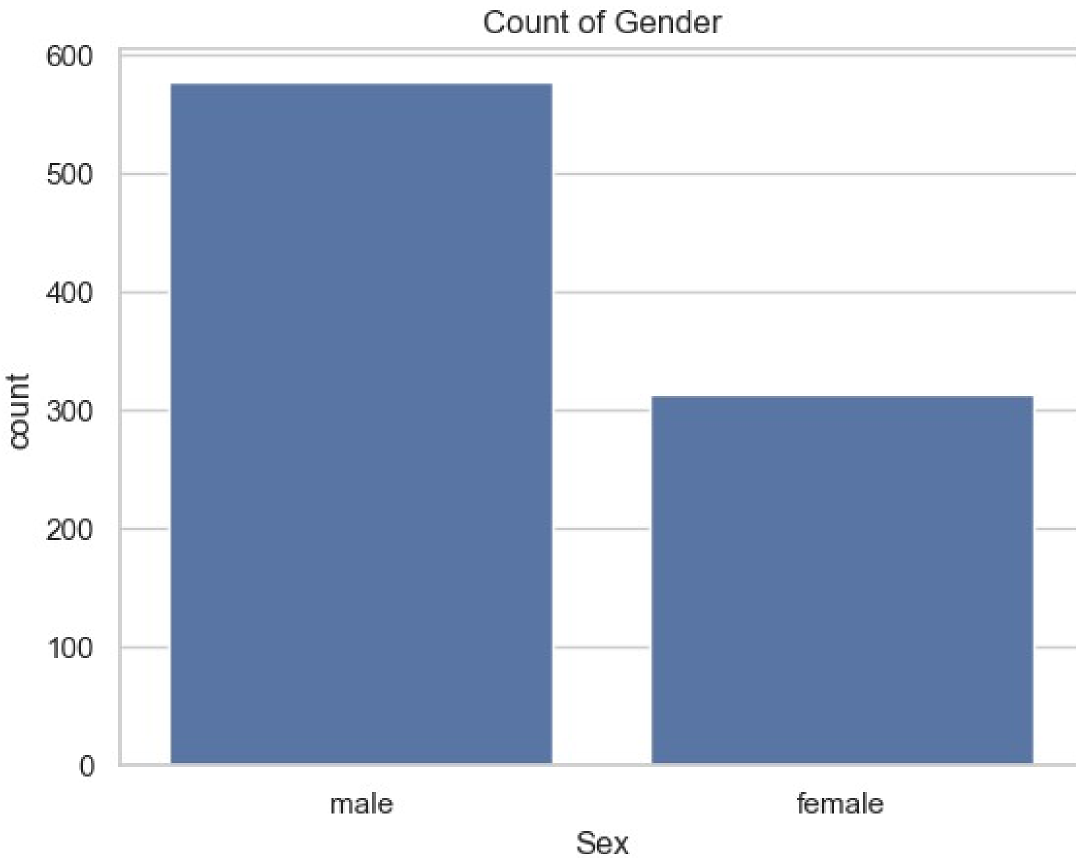
Categorical Features:

```
# Categorical Features - Survived
sns.countplot(x='Survived', data=df) #creates a bar chart for Survived count
plt.title("Count of Survived")
plt.show()
```



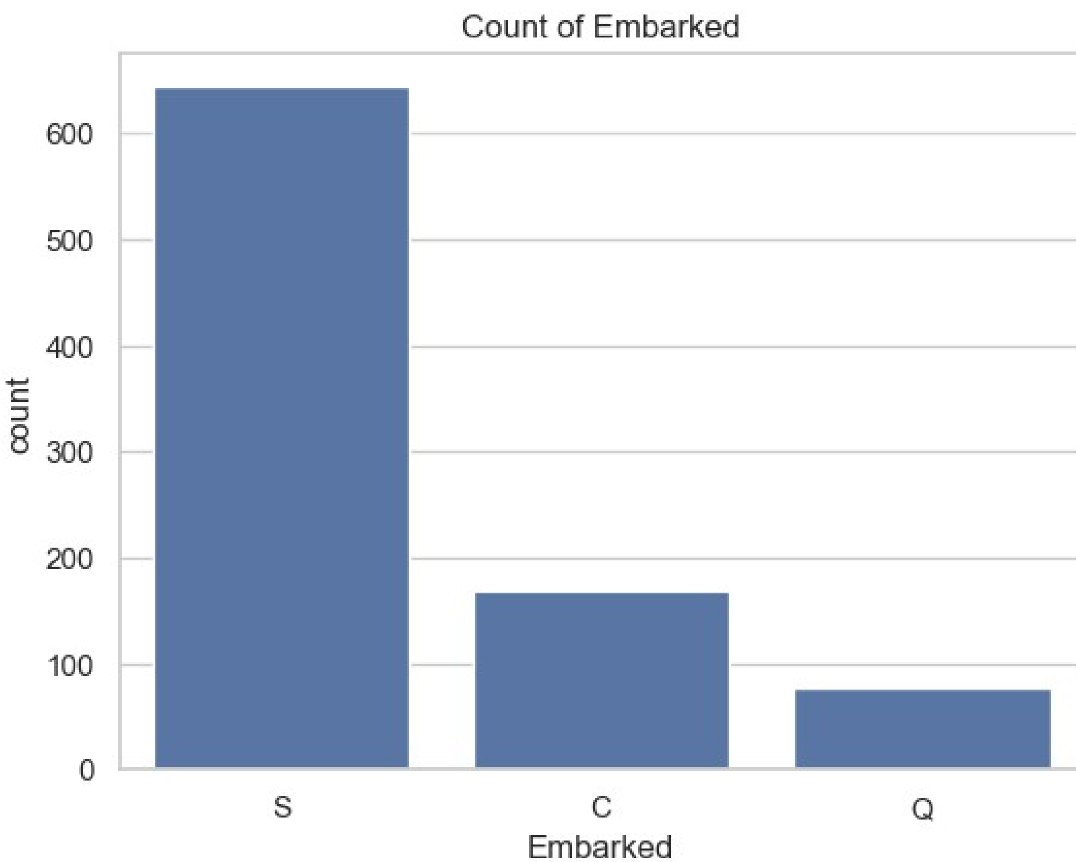
- Survival Count: More people died (0) than survived (1)

```
# Categorical Features - Sex
sns.countplot(x='Sex', data=df)
plt.title("Count of Gender")
plt.show()
```



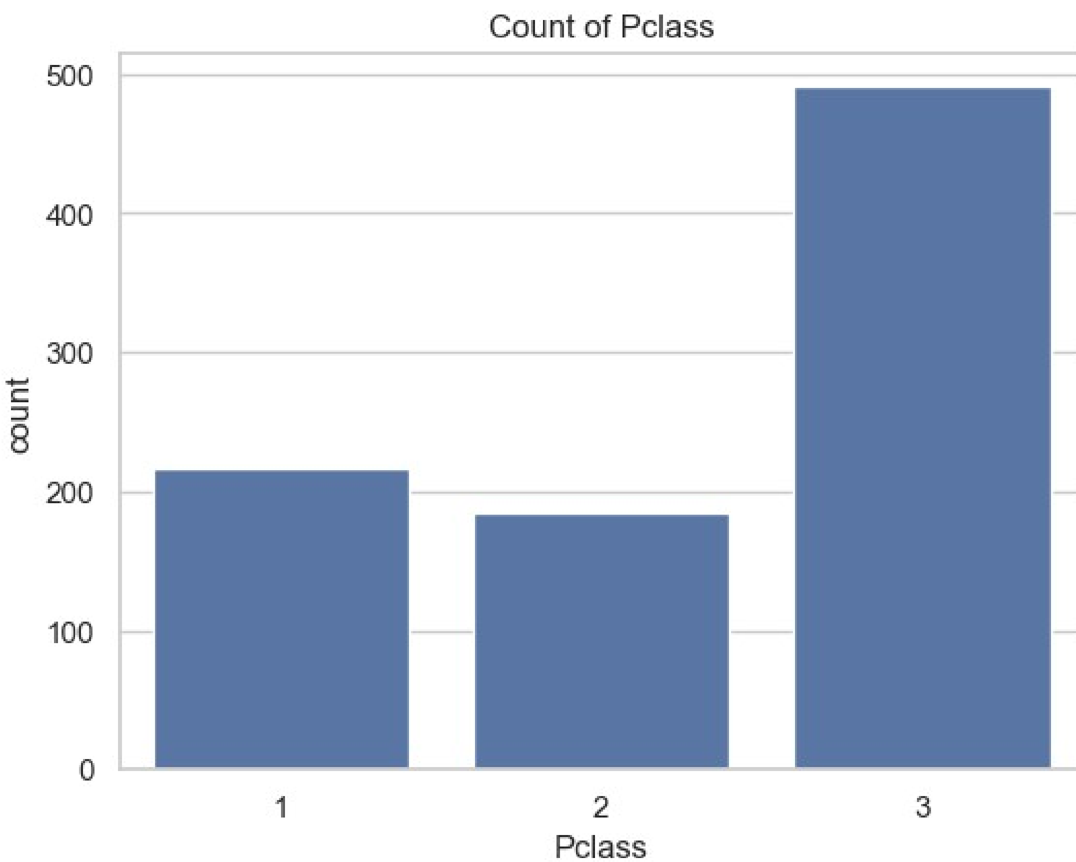
- More males than females on board.

```
# Categorical Features - Embarked
sns.countplot(x='Embarked', data=df)
plt.title("Count of Embarked")
plt.show()
```



- Most passengers boarded from port 'S' (Southampton).

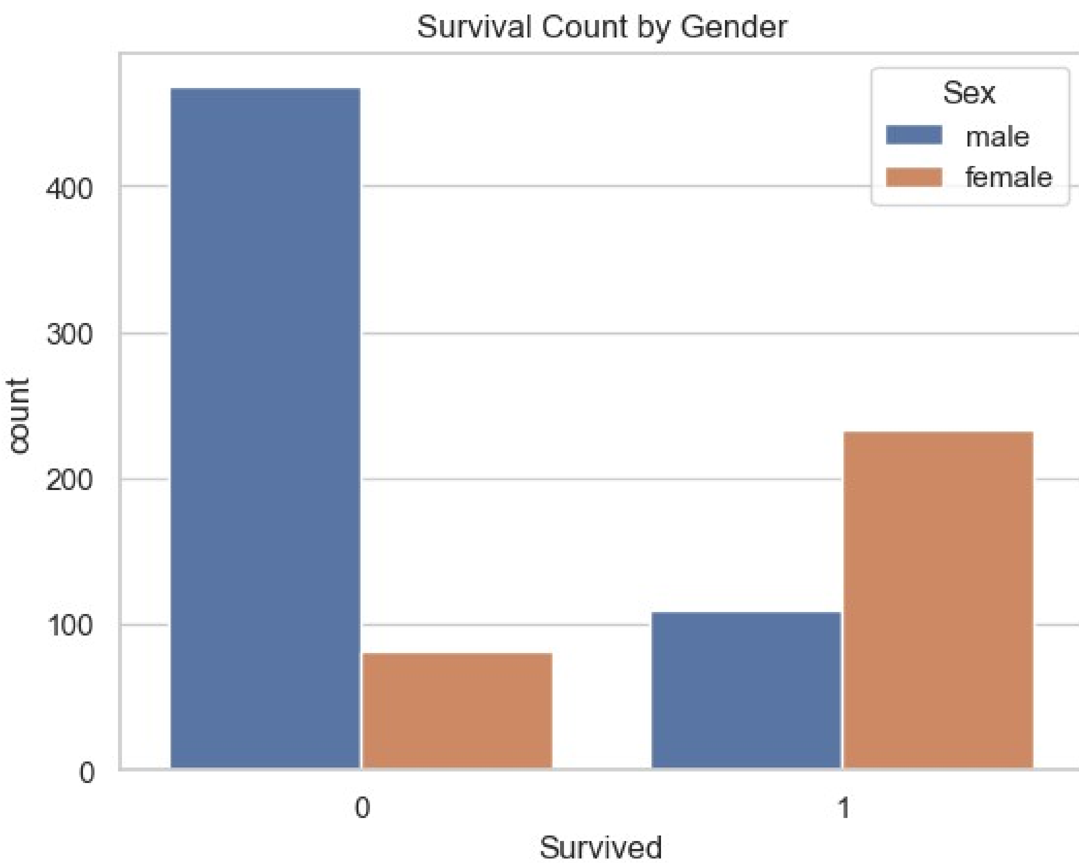
```
# Categorical Features - Pclass
sns.countplot(x='Pclass', data=df)  #creates a bar chart for Class
distribution
plt.title("Count of Pclass")
plt.show()
```



- Pclass: Most passengers were in 3rd class.

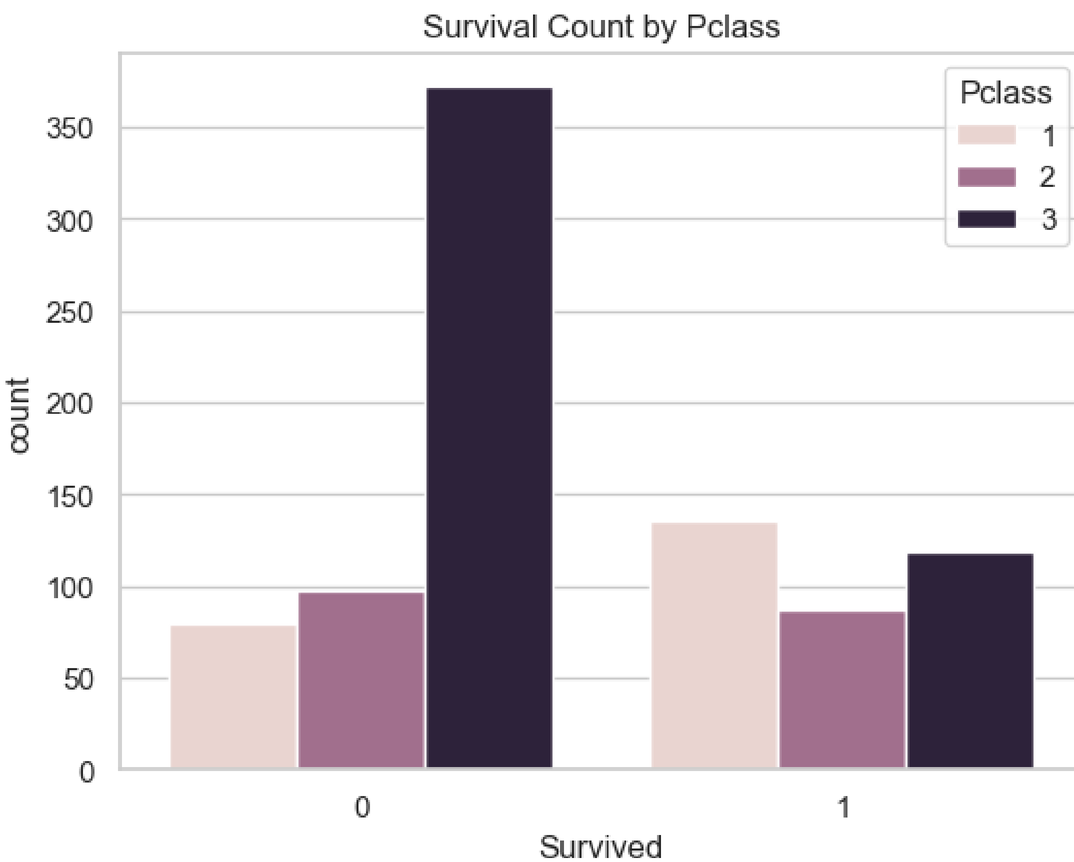
Step 7: Bivariate Analysis

```
# Bivariate Analysis
# Survival Count by Gender
sns.countplot(x='Survived', hue='Sex', data=df)  #creates a count plot
of Survival by gender
plt.title('Survival Count by Gender')
plt.show()
```



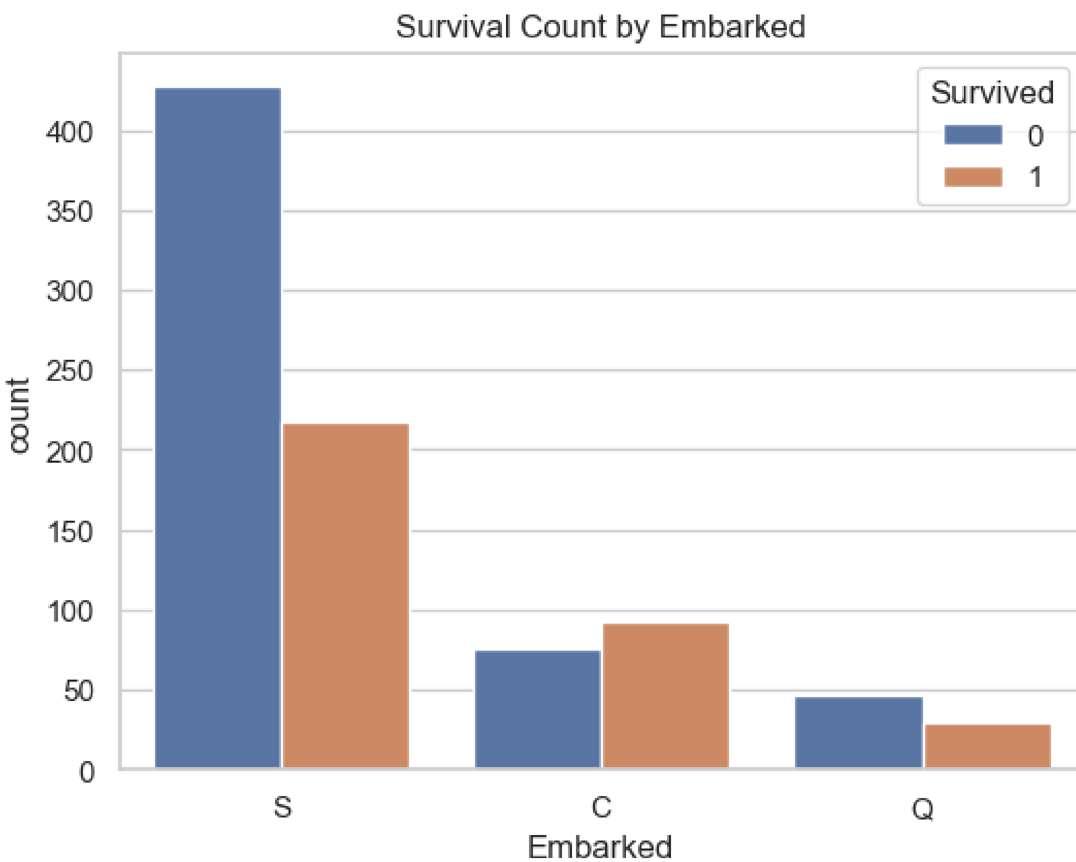
- Females had a significantly higher survival rate than males.

```
# Survival Count by Pclass
sns.countplot(x='Survived', hue='Pclass', data=df)  #creates a count plot of Survival by class
plt.title("Survival Count by Pclass")
plt.show()
```



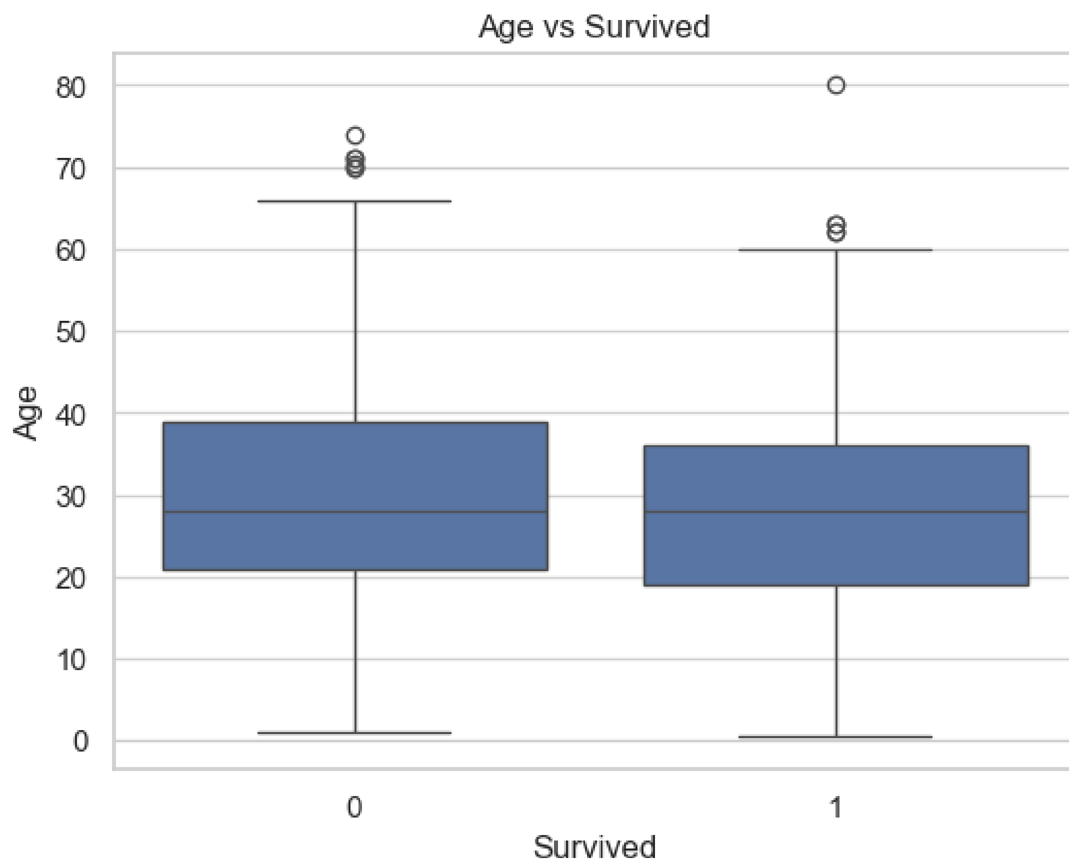
- 1st class passengers had better survival rates compared to 2nd and 3rd classes.

```
# Survival Count by Embarked
sns.countplot(x='Embarked', hue='Survived', data=df)  #creates a count plot of Survival by Embarked port
plt.title("Survival Count by Embarked")
plt.show()
```



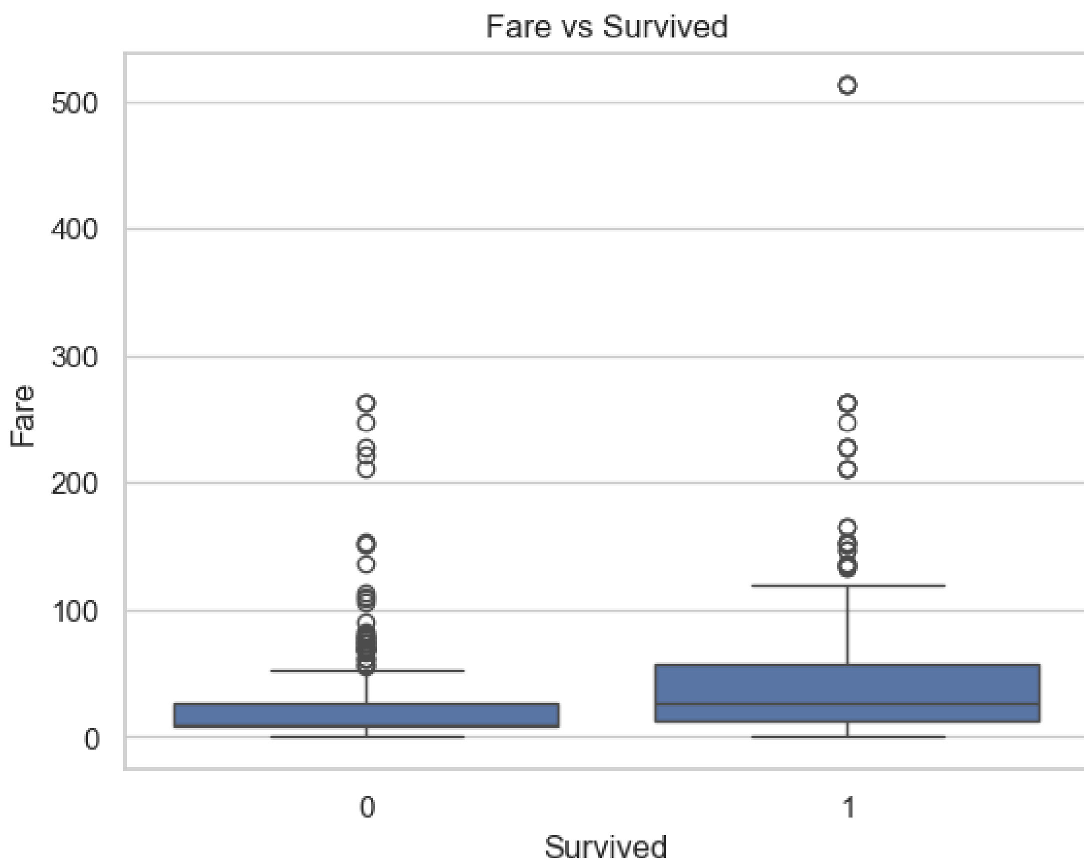
- Passengers who embarked from port 'C' had a higher survival rate.

```
# Age vs Survived
sns.boxplot(x='Survived', y='Age', data=df)  # Box plot of Survival by
Age
plt.title('Age vs Survived')
plt.show()
```



- Survivors had slightly lower average age than non-survivors. Some children survived more.

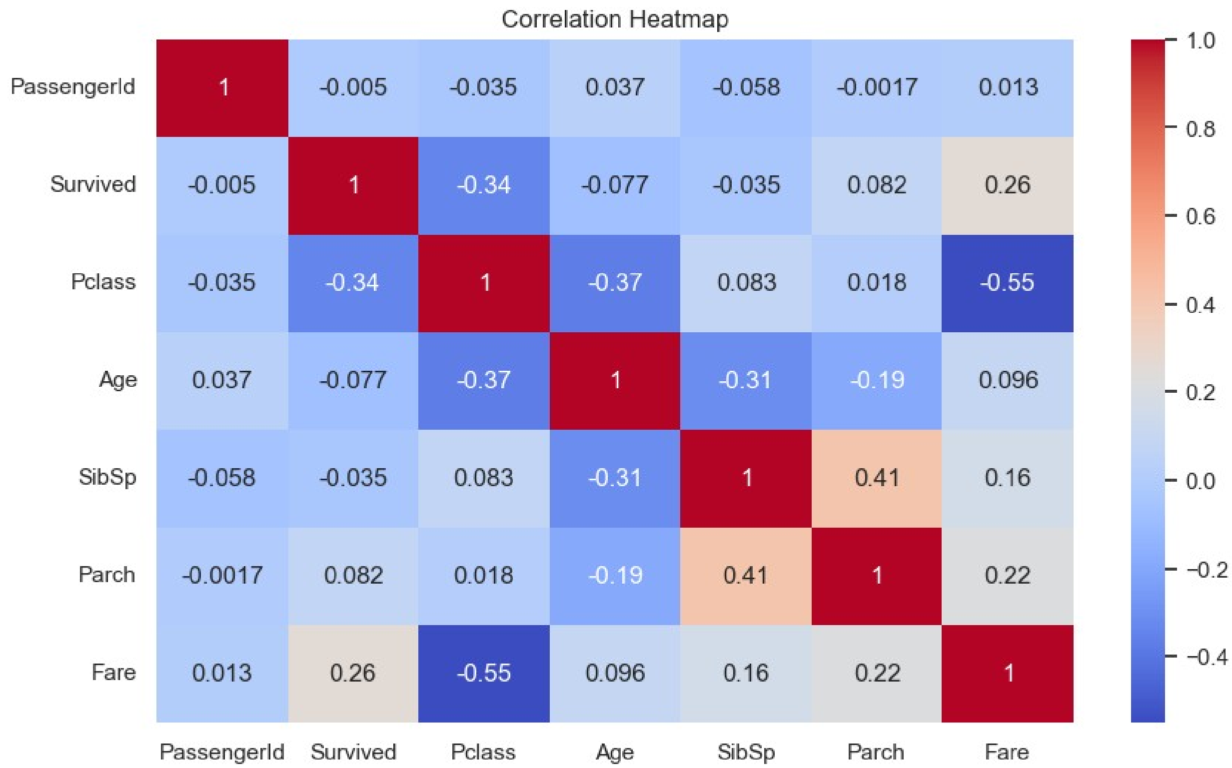
```python
# Fare vs Survived
sns.boxplot(x='Survived', y='Fare', data=df)
plt.title("Fare vs Survived")
plt.show()
```



- Survivors generally paid higher fares, suggesting more from higher classes survived.

Step 8: Multivariate Analysis- Correlation Heatmap

```
# Correlation Heatmap for Numerical Features
corr = df.corr(numeric_only=True) # Calculate correlation matrix
plt.figure(figsize=(10, 6))
sns.heatmap(corr, annot=True, cmap='coolwarm') # Plot heatmap
plt.title("Correlation Heatmap")
plt.show()
```



- Fare and Survived show moderate positive correlation (~0.26), indicating passengers who paid higher fares were more likely to survive.

- Pclass and Fare have moderate negative correlation (~ -0.55), meaning higher class (lower number) generally paid more.

- Age and Survived show a slight negative correlation (~ -0.08), suggesting younger passengers had slightly better chances of survival.

Step 9: Data Cleaning - Handling Missing Values

The dataset has missing values in the Age, Cabin, and Embarked columns. Here's how we'll handle them:

- **Drop Cabin** since it's mostly missing and not that informative.
- **Fill missing Age** with the median age.
- **Fill missing Embarked** with the most frequent value (mode).

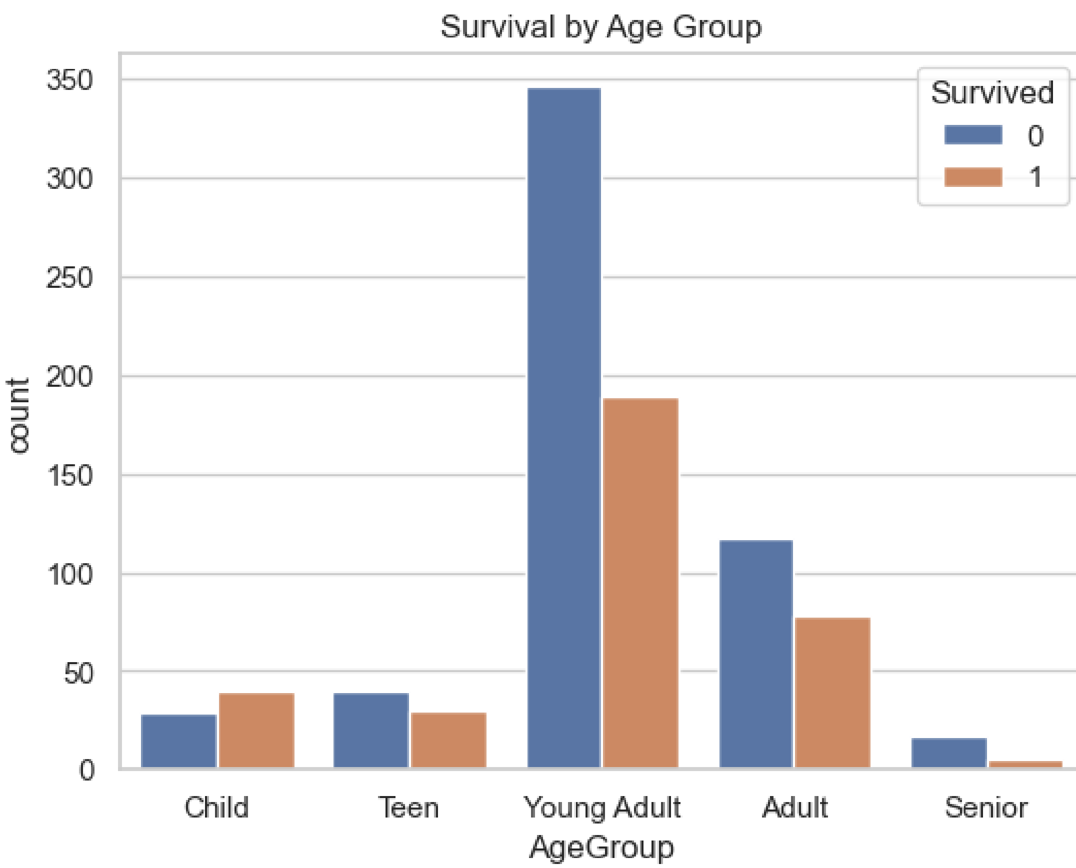
```
# Drop Cabin since it's mostly missing
df.drop(columns='Cabin', inplace=True)

# Replace missing Age with median — the safe way
df['Age'] = df['Age'].fillna(df['Age'].median())

# Replace missing Embarked with mode — the safe way
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

```python
# Final check for missing values
print("Missing values after cleaning:\n", df.isnull().sum())
```

```
Missing values after cleaning:
 PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

Step 10: Feature Engineering: Create Age Groups

```python
# Create Age Groups from Age for better interpretability and modeling
df['AgeGroup'] = pd.cut(df['Age'], bins=[0,12,18,35,60,80],
                        labels=['Child','Teen','Young
Adult','Adult','Senior'])

# Bivariate analysis to see how AgeGroup relates to survival
sns.countplot(x='AgeGroup', hue='Survived', data=df)
plt.title("Survival by Age Group")
plt.show()
```



- Children had the highest survival rate among all age groups.

Insights

Through this EDA, we observed:

- Females had a significantly higher survival rate than males
- Higher-class passengers (Pclass 1) were more likely to survive
- Fare and Age distributions suggest survival advantages for higher-paying and younger passengers (especially children), though age correlation is weaker.
- Sex, Pclass, and Fare are strong predictors of survival. Fare shows moderate positive correlation with Survived.

Recommendations

For Future Passenger Safety on Ships:

- Ensure equal access to lifeboats for all passengers, regardless of class.
- Conduct mandatory lifeboat training for all passengers.
- Develop special evacuation protocols for large families.

For the Travel & Cruise Industry:

- Safety procedures should be class-independent.
- Provide dedicated assistance for elderly and solo travelers.
- Implement better crowd management for efficient evacuations.

End of EDA