Titanic EDA - Task 5: Data Analyst Internship

This notebook performs Exploratory Data Analysis (EDA) on the Titanic dataset to uncover patterns related to survival.

1. Import Libraries

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

2. Load Dataset

```python
train = pd.read_csv("train.csv")
train.head()
```

```
   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
```

3. Understand the Data

```
train.info()

<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
```

Observations:

- Dataset contains 891 passengers with 12 features
- Significant missing values in Age (177) and Cabin (687)
- Embarked has 2 missing values

```
train.describe()

       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
```

```
train.isnull().sum()
```

```
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
```

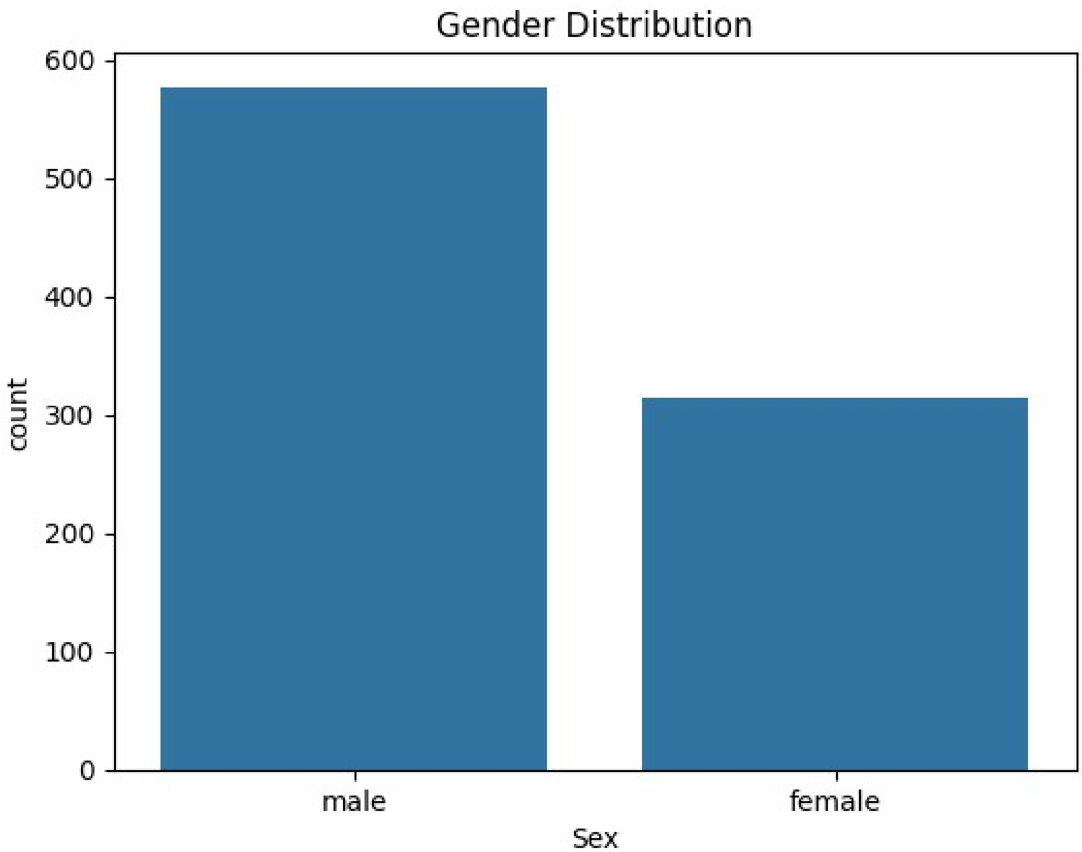
```
train.nunique()
```

```
PassengerId    891
Survived         2
Pclass           3
Name           891
Sex              2
Age             88
SibSp            7
Parch            7
Ticket         681
Fare           248
Cabin          147
Embarked         3
dtype: int64
```

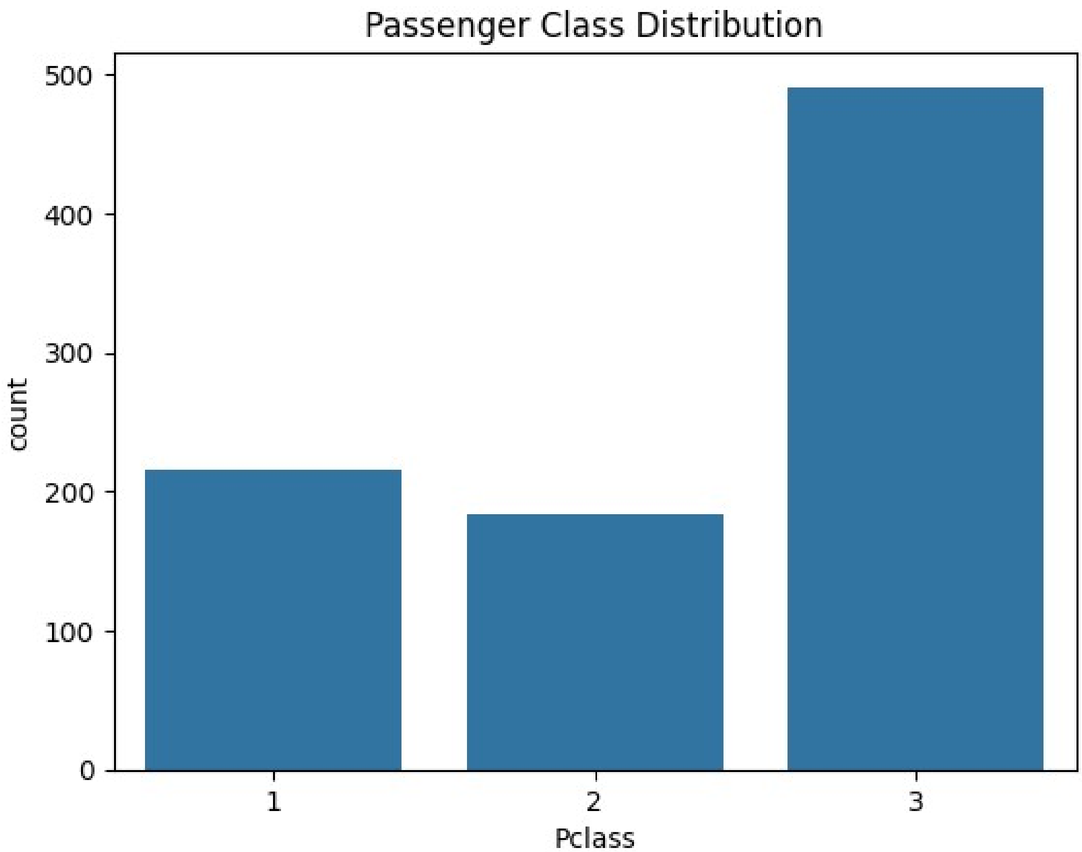
4. Univariate Analysis

Categorical Features

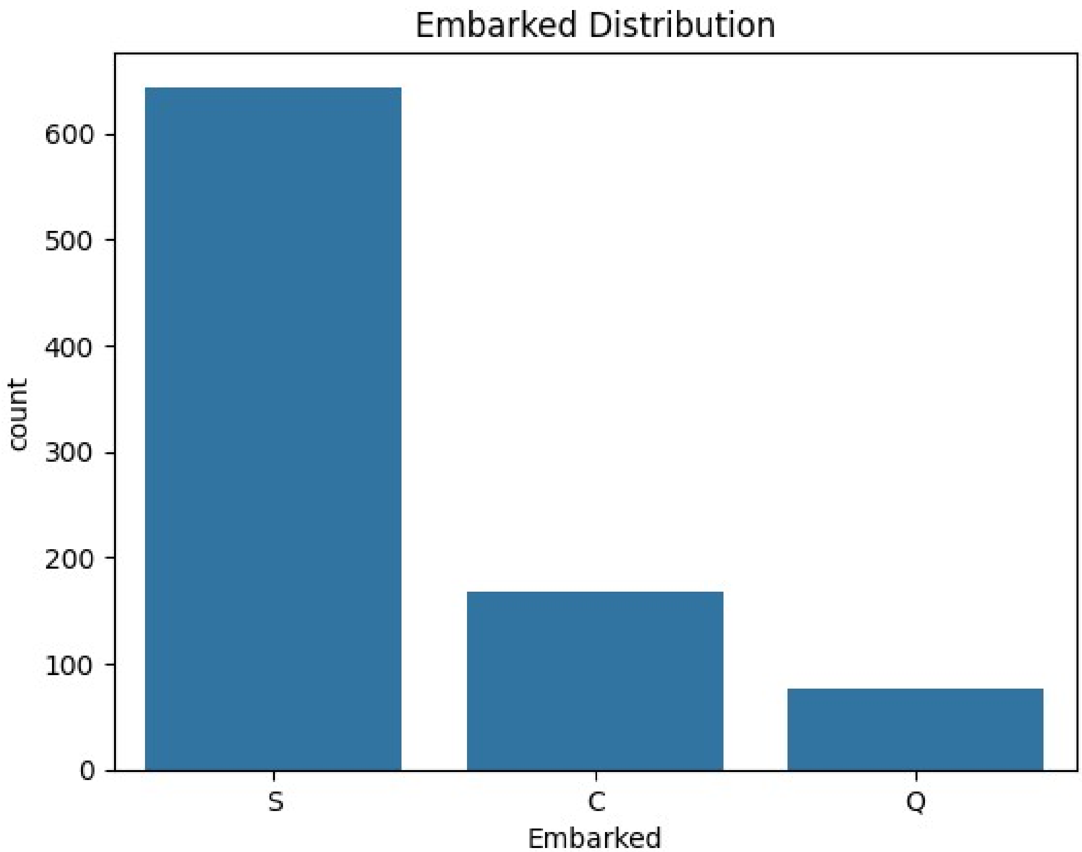
```
sns.countplot(x='Sex', data=train)
plt.title('Gender Distribution')
plt.show()
```




```
sns.countplot(x='Pclass', data=train)
plt.title('Passenger Class Distribution')
plt.show()
```

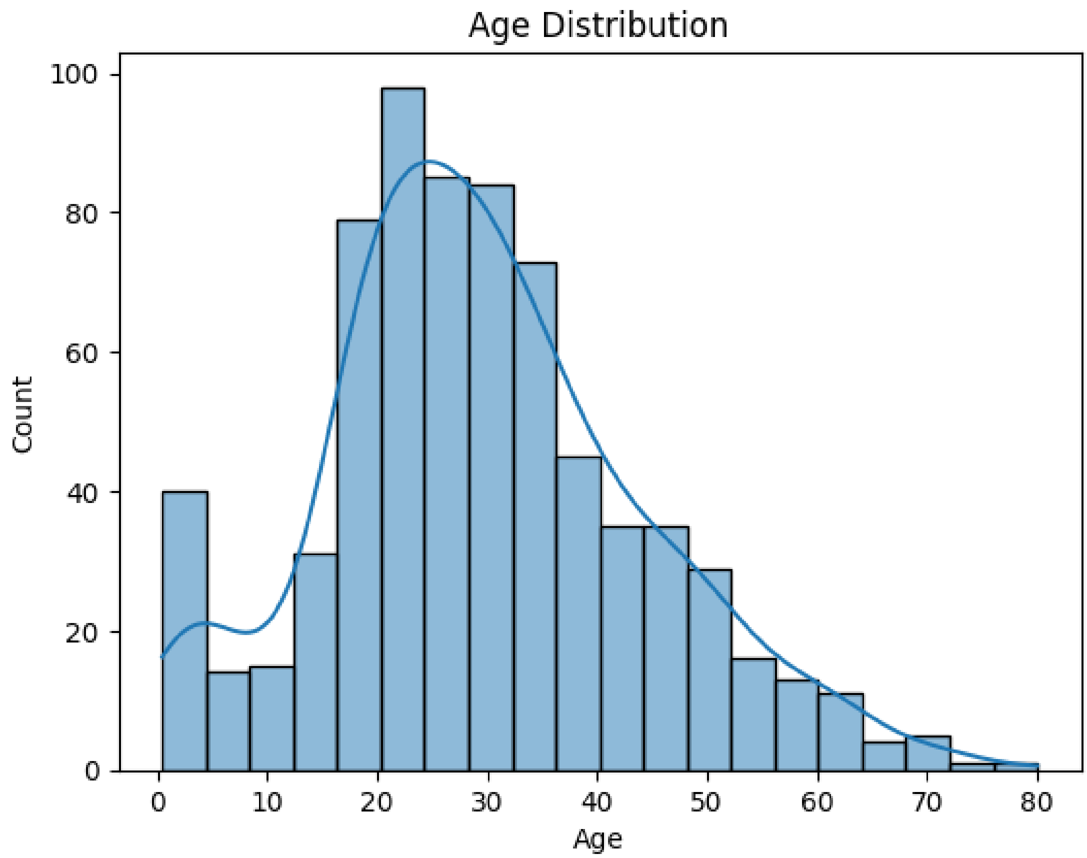



```
sns.countplot(x='Embarked', data=train)
plt.title('Embarked Distribution')
plt.show()
```

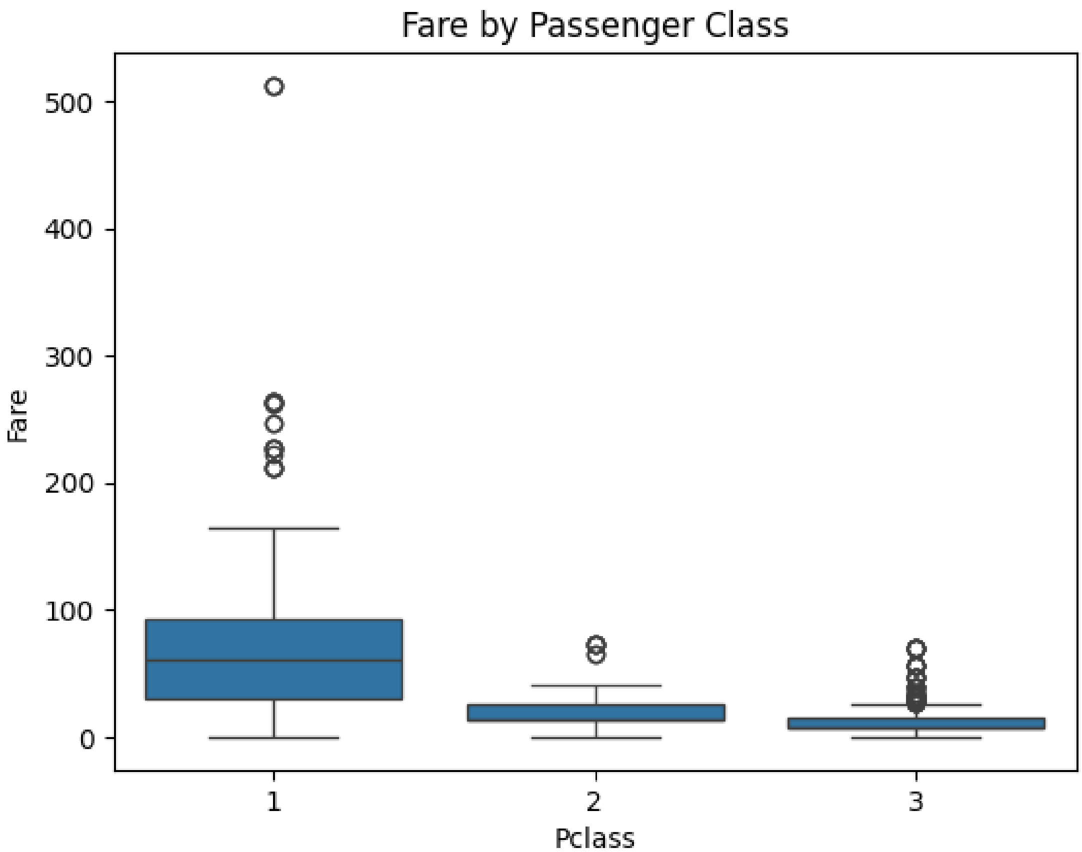


Numerical Features

```
sns.histplot(train['Age'].dropna(), kde=True)
plt.title('Age Distribution')
plt.show()
```




```
sns.boxplot(x='Pclass', y='Fare', data=train)
plt.title('Fare by Passenger Class')
plt.show()
```

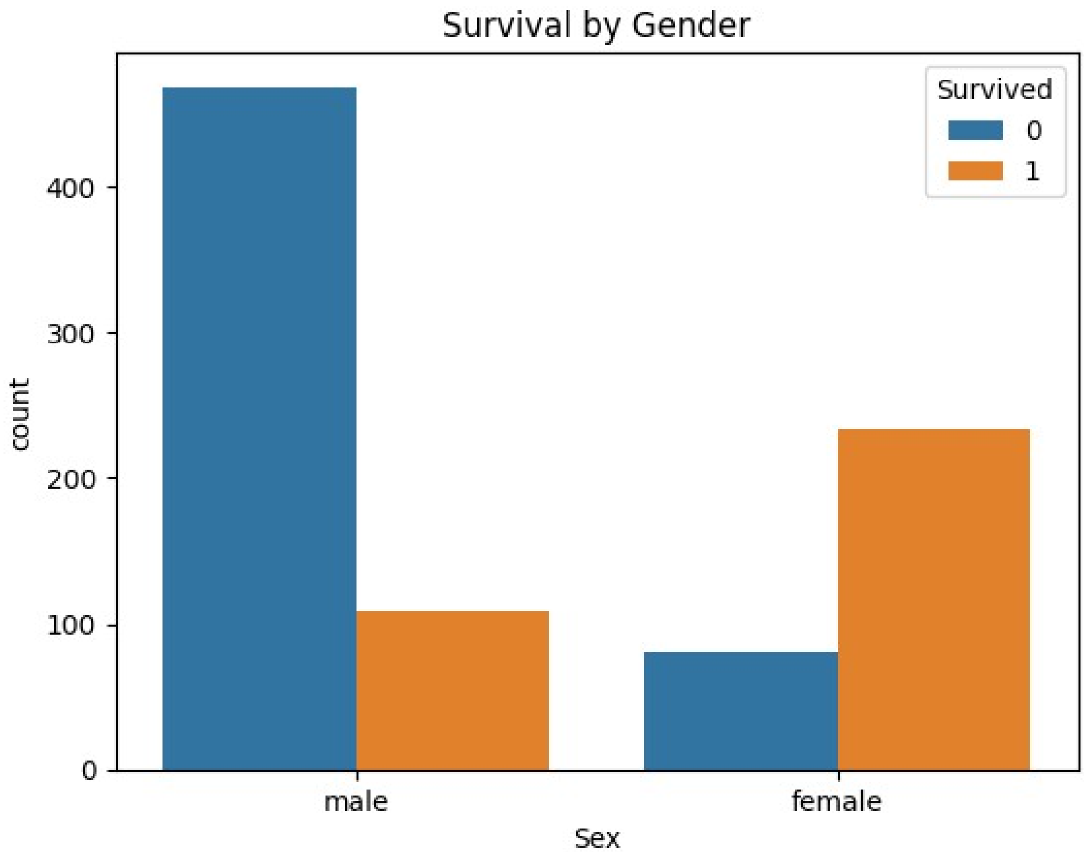


Observations:

- Majority of passengers are male.
- Most passengers are in 3rd class.,
- Age distribution is right-skewed with some older passengers.
- Fare varies significantly by passenger class.

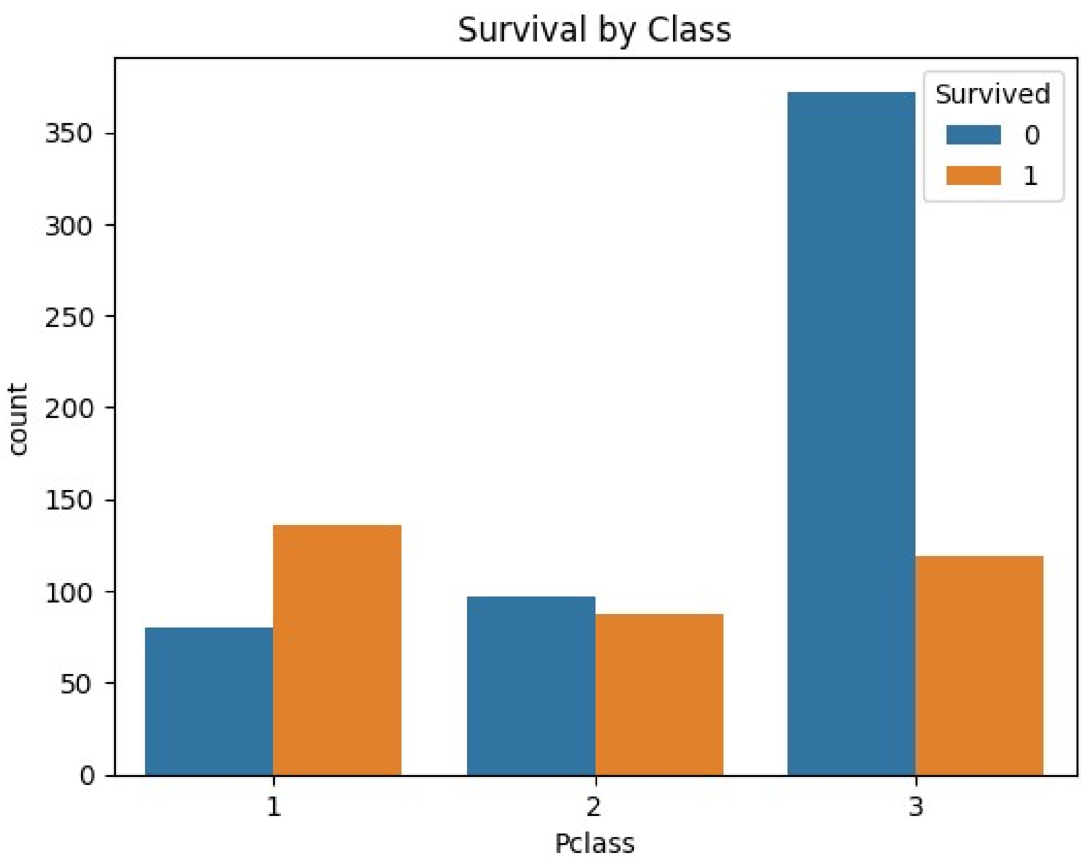
5. Bivariate Analysis

```
sns.countplot(x='Sex', hue='Survived', data=train)
plt.title('Survival by Gender')
plt.show()
```



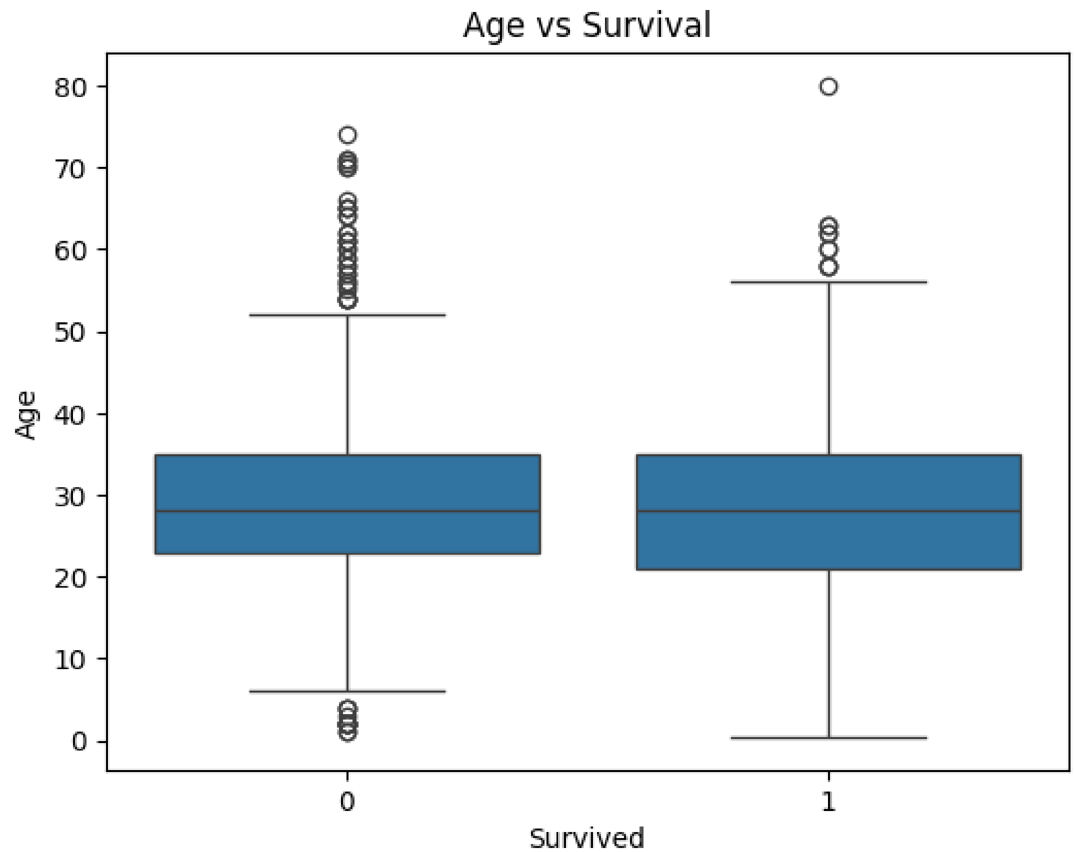
Observation: Females had a much higher survival rate than males.

```
sns.countplot(x='Pclass', hue='Survived', data=train)
plt.title('Survival by Class')
plt.show()
```



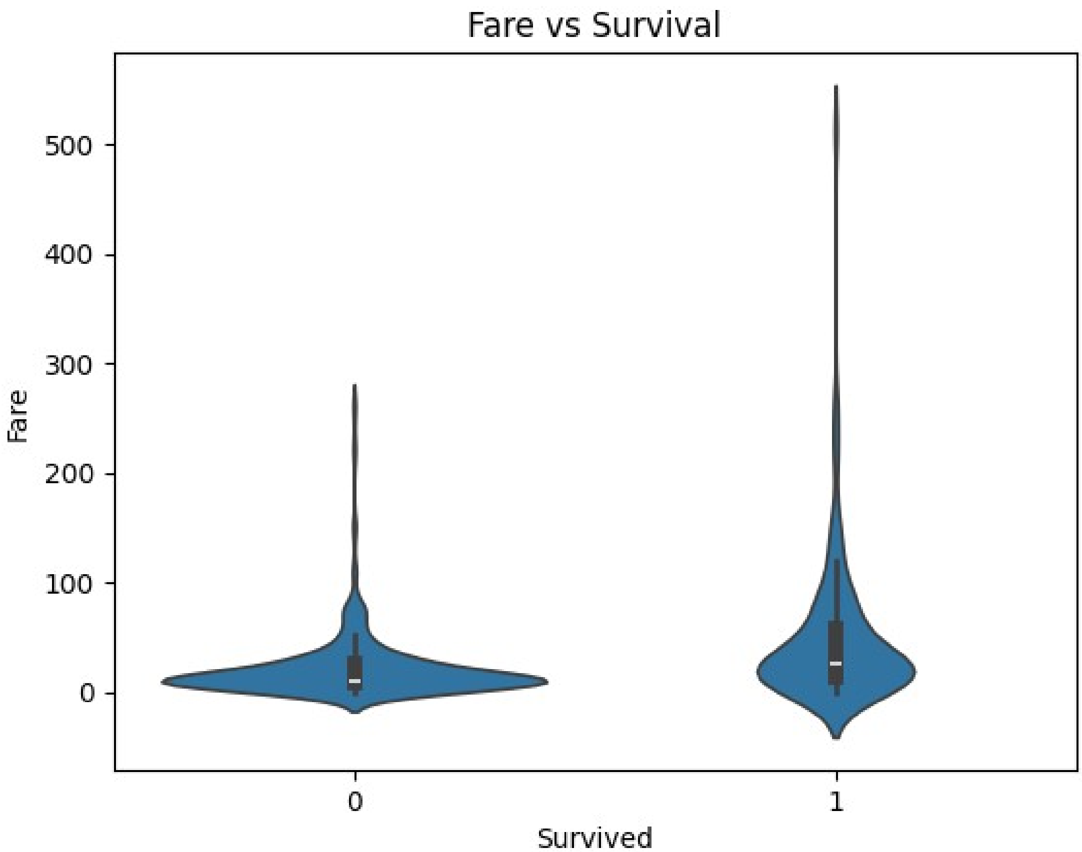
Observation: Survival rate was highest for 1st class passengers and lowest for 3rd class.

```
sns.boxplot(x='Survived', y='Age', data=train)
plt.title('Age vs Survival')
plt.show()
```



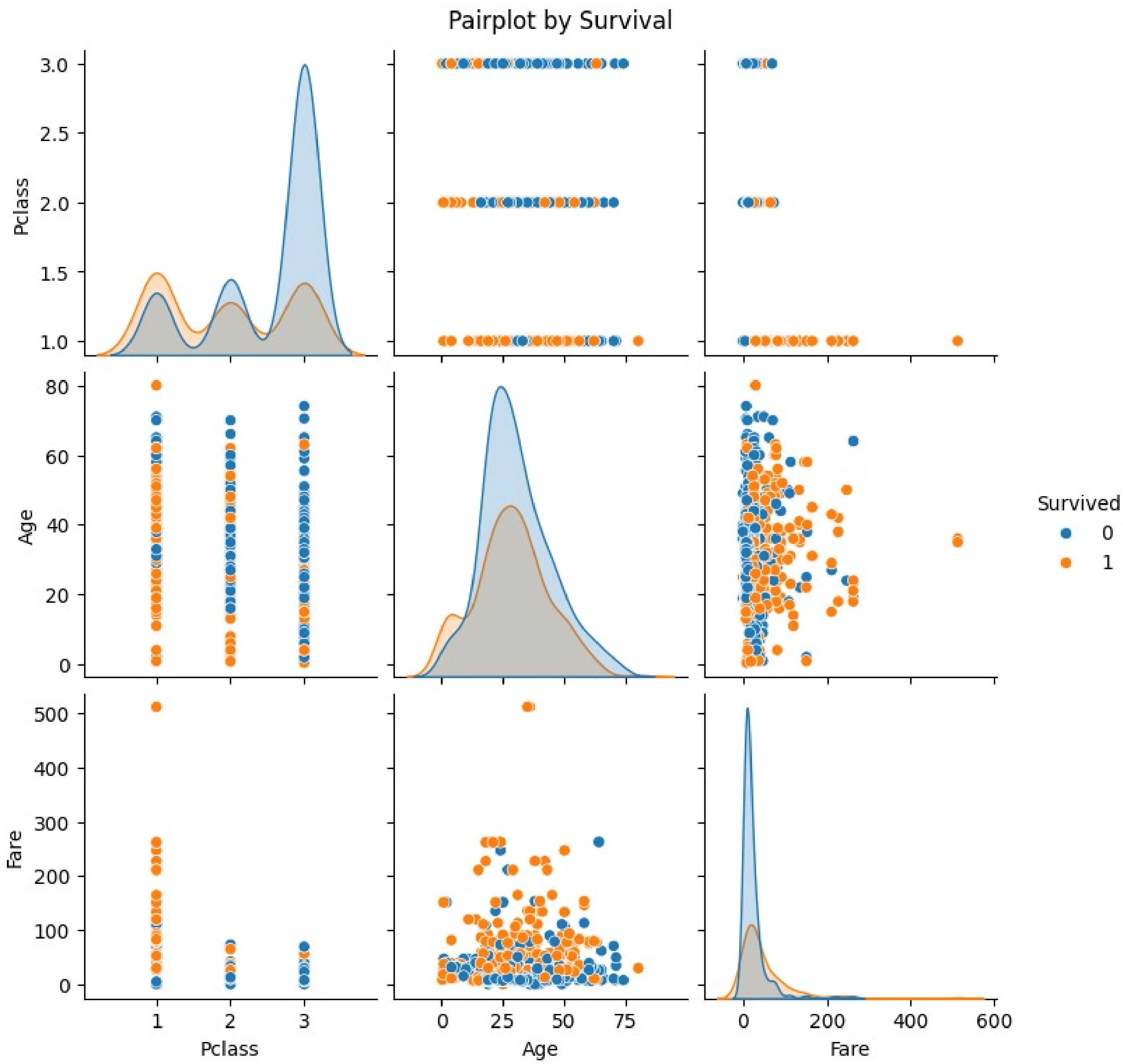
Observation: Younger passengers had a higher survival rate.

```
sns.violinplot(x='Survived', y='Fare', data=train)
plt.title('Fare vs Survival')
plt.show()
```



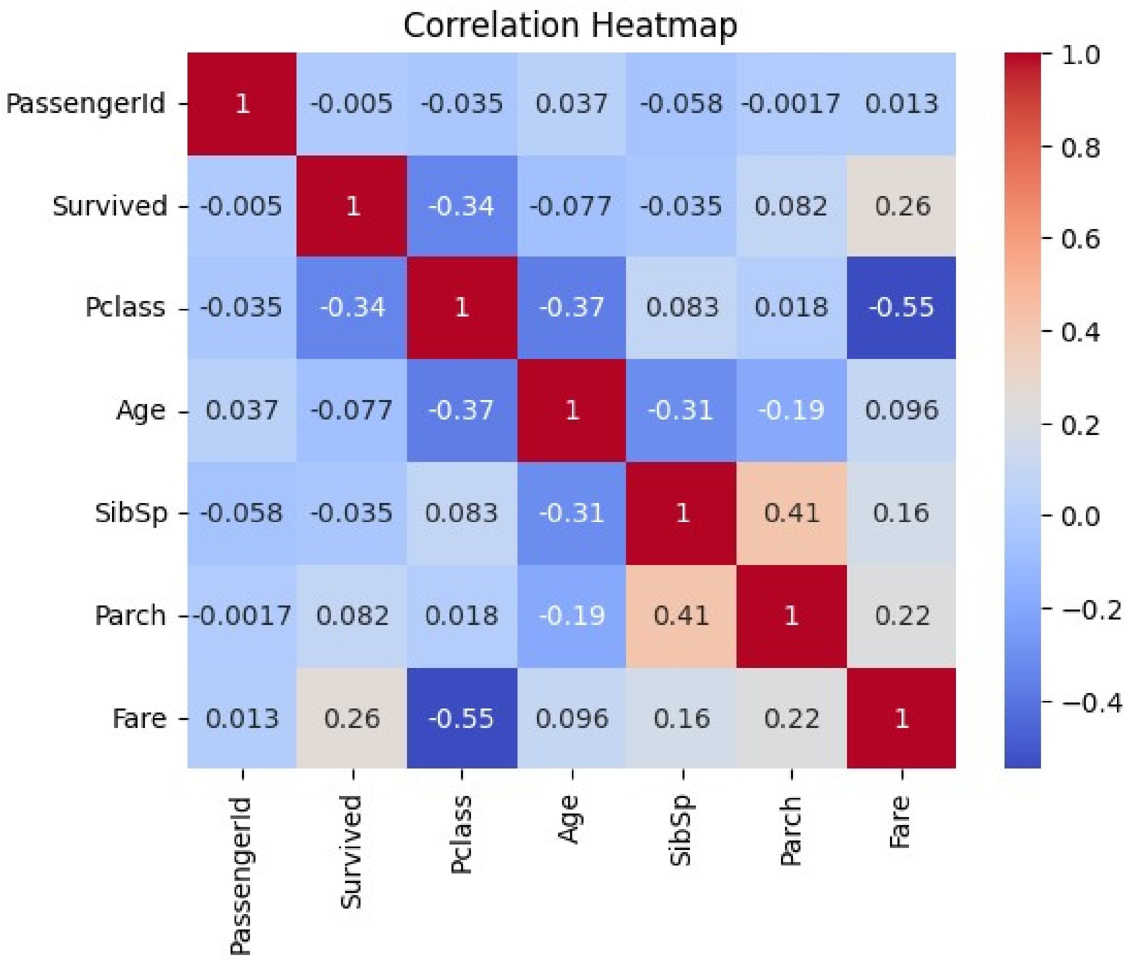
6. Multivariate Analysis

```
sns.pairplot(train[['Survived', 'Pclass', 'Age', 'Fare']],
hue='Survived')
plt.suptitle('Pairplot by Survival', y=1.02)
plt.show()
```



Observation: Some correlation between fare and class, and survival clusters visible.

```
sns.heatmap(train.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



Observation: Strong negative correlation between Pclass and Fare, moderate positive correlation between Fare and Survived.

7. Handle Missing Values

```
train['Age'].fillna(train['Age'].median(), inplace=True)
train['Embarked'].fillna(train['Embarked'].mode()[0], inplace=True)
```

Observations:

- Most passengers are in 3rd class.
- Passengers in 1st class had the highest survival rate, while 3rd class had the lowest.
- Females had higher survival rates than males.
- Younger passengers had higher survival probability.
- Passengers with higher fare had better survival odds.
- Age and Fare distributions are slightly skewed.
- There is a strong negative correlation between passenger class and fare, and a moderate positive correlation between fare and survival.