Titanic Dataset Analysis

Using Python (Pandas, Matplotlib, Seaborn)

Objective: Explore the Titanic dataset to identify meaningful insights using data cleaning, feature engineering, and statistical/visual analysis.

1. Data Loading

In [1]:

```
import pandas as pd

# Load dataset
df = pd.read_csv("train.csv")

# Show first 5 rows
df.head()
```

Out[1]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

2. Data Cleaning (Handling Missing Values)

In [2]:
```python
df.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
```

In [3]:
```python
df.describe(include='all').T
```

Out[3]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
PassengerId	891.0	NaN	NaN	NaN	446.0	257.353842	1.0	223.5	446.0	668.5	891.0
Survived	891.0	NaN	NaN	NaN	0.383838	0.486592	0.0	0.0	0.0	1.0	1.0
Pclass	891.0	NaN	NaN	NaN	2.308642	0.836071	1.0	2.0	3.0	3.0	3.0
Name	891	891	Dooley, Mr. Patrick	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Sex	891	2	male	577	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Age	714.0	NaN	NaN	NaN	29.699118	14.526497	0.42	20.125	28.0	38.0	80.0
SibSp	891.0	NaN	NaN	NaN	0.523008	1.102743	0.0	0.0	0.0	1.0	8.0
Parch	891.0	NaN	NaN	NaN	0.381594	0.806057	0.0	0.0	0.0	0.0	6.0
Ticket	891	681	347082	7	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Fare	891.0	NaN	NaN	NaN	32.204208	49.693429	0.0	7.9104	14.4542	31.0	512.3292
Cabin	204	147	G6	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Embarked	889	3	S	644	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [4]:

```
cols = ['Survived', 'Pclass', 'Sex', 'Embarked', 'SibSp', 'Parch']

for col in cols:
    print("\n---", col, "---")
    print(df[col].value_counts(dropna=False))
```

```
--- Survived ---
Survived
0    549
1    342
Name: count, dtype: int64

--- Pclass ---
Pclass
3    491
1    216
2    184
Name: count, dtype: int64

--- Sex ---
Sex
male      577
female    314
Name: count, dtype: int64

--- Embarked ---
Embarked
S      644
C      168
Q       77
NaN      2
Name: count, dtype: int64

--- SibSp ---
SibSp
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: count, dtype: int64

--- Parch ---
Parch
0    678
```

```
1    118
2     80
5      5
3      5
4      4
6      1
Name: count, dtype: int64
```

In [5]:
```python
# Fill missing Embarked with mode
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

```
C:\Users\PIYUSH\AppData\Local\Temp\ipykernel_15928\2757060897.py:2: FutureWarning: A value is trying to be set on a copy of a D
ataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are set
ting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = d
f[col].method(value) instead, to perform the operation inplace on the original object.


  df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

In [6]:
```python
# safer way to fill Embarked missing values
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])

# confirm
print("Missing values after filling:\n", df[['Embarked']].isnull().sum())
```

```
Missing values after filling:
 Embarked    0
dtype: int64
```

In [8]:
```python
df['HasCabin'] = df['Cabin'].notnull().astype(int)
```

In [9]:
```python
df['Deck'] = df['Cabin'].astype(str).str[0]
df['Deck'] = df['Deck'].replace('n', 'Unknown')  # 'n' appears for NaN converted to 'nan'
```

In [10]:
```python
df['Age'] = df.groupby(['Sex', 'Pclass'])['Age'].transform(lambda x: x.fillna(x.median()))
```

In [11]:
```python
df.isnull().sum()
```

Out[11]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
HasCabin         0
Deck             0
dtype: int64
```

3. Feature Engineering

In [12]:
```
df['Title'] = df['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)

# Combine rare titles into a single group
rare_titles = ['Lady', 'Countess', 'Capt', 'Col', 'Don', 'Dr', 'Major',
               'Rev', 'Sir', 'Jonkheer', 'Dona']
df['Title'] = df['Title'].replace(rare_titles, 'Rare')
df['Title'] = df['Title'].replace({'Mlle': 'Miss', 'Ms': 'Miss', 'Mme': 'Mrs'})
```

In [13]:
```
df['FamilySize'] = df['SibSp'] + df['Parch'] + 1
```

In [14]:
```
df['IsAlone'] = (df['FamilySize'] == 1).astype(int)
```

In [15]:
```
df[['Title', 'FamilySize', 'IsAlone']].head()
```

Out[15]:

	Title	FamilySize	IsAlone
0	Mr	2	0
1	Mrs	2	0
2	Miss	1	1
3	Mrs	2	0
4	Mr	1	1

In [16]:

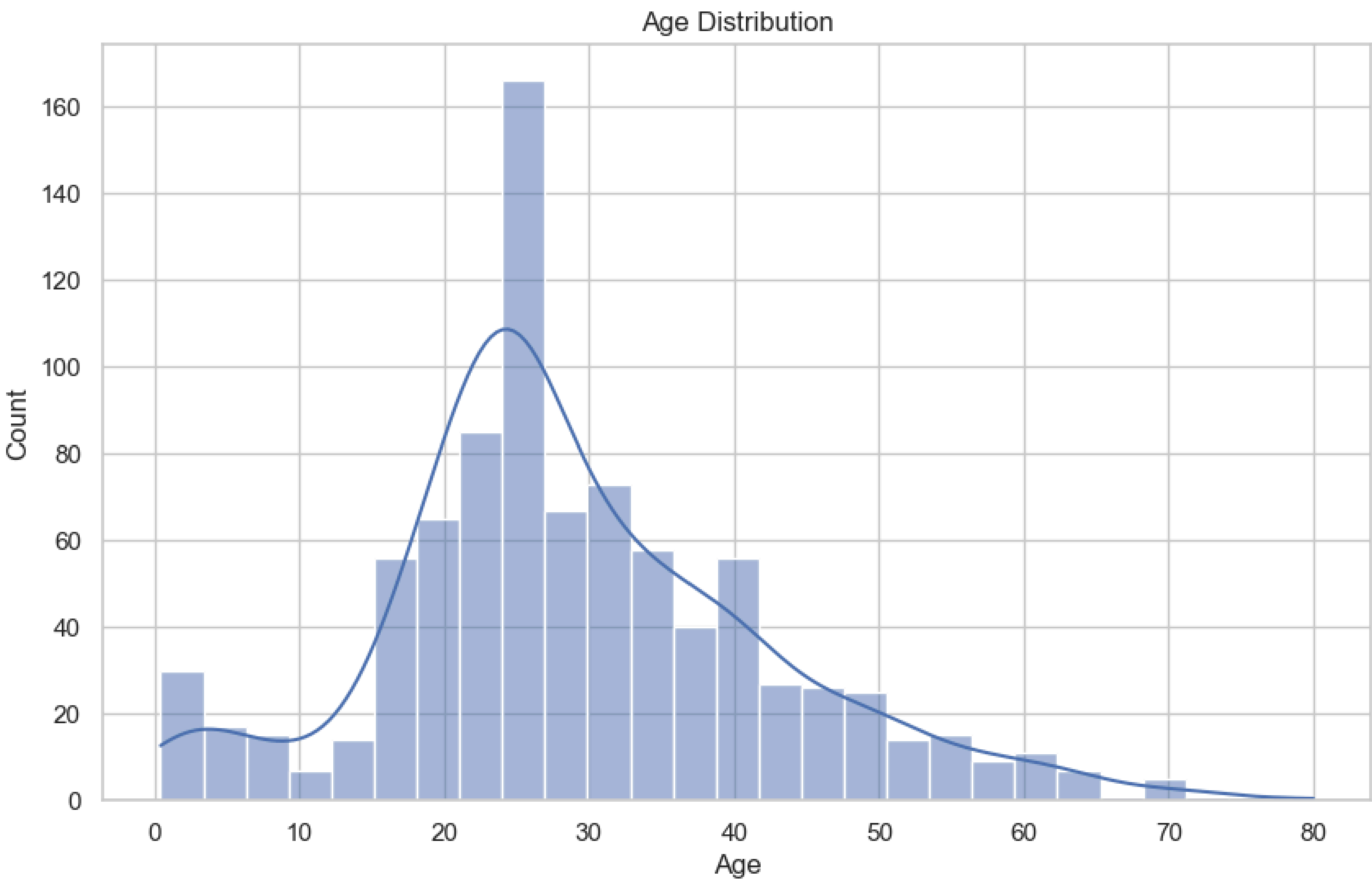
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
plt.rcParams['figure.figsize'] = (10,6)
```

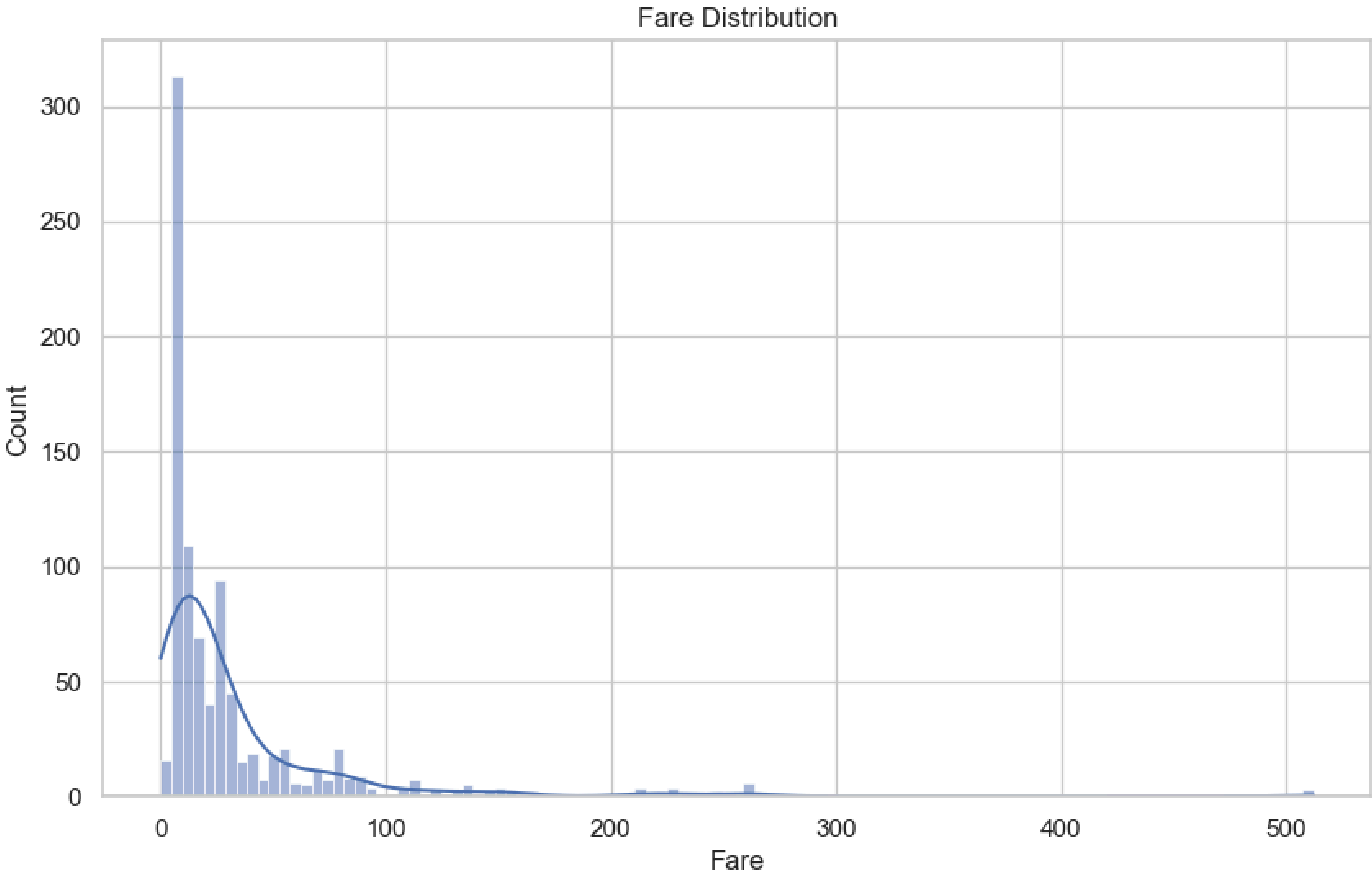
4. Univariate Analysis

In [17]:

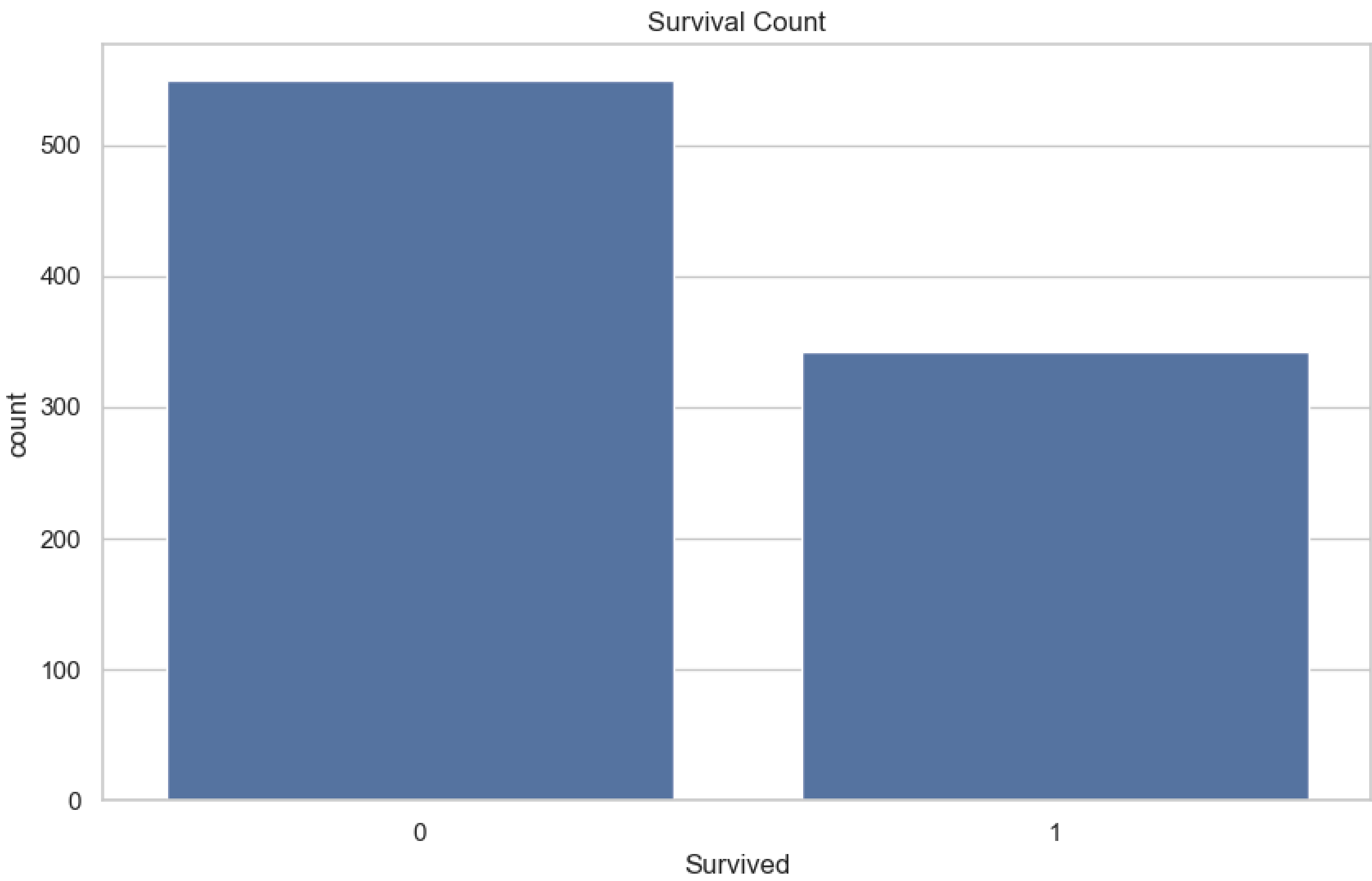
```
sns.histplot(df['Age'], kde=True)
plt.title("Age Distribution")
plt.show()
```



In [18]:
```
sns.histplot(df['Fare'], kde=True)
plt.title("Fare Distribution")
plt.show()
```

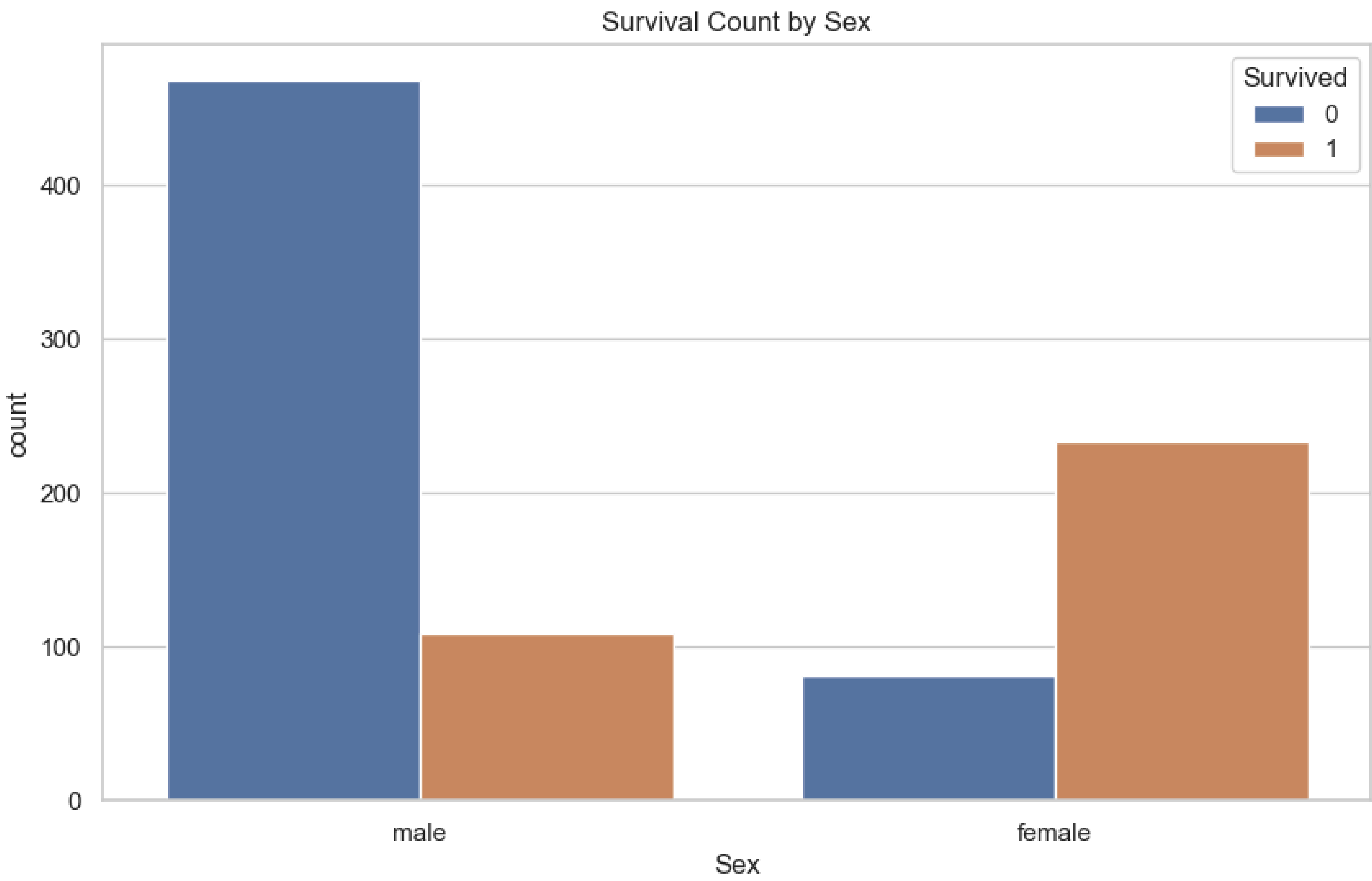


In [19]:
```
sns.countplot(data=df, x='Survived')
plt.title("Survival Count")
plt.show()
```

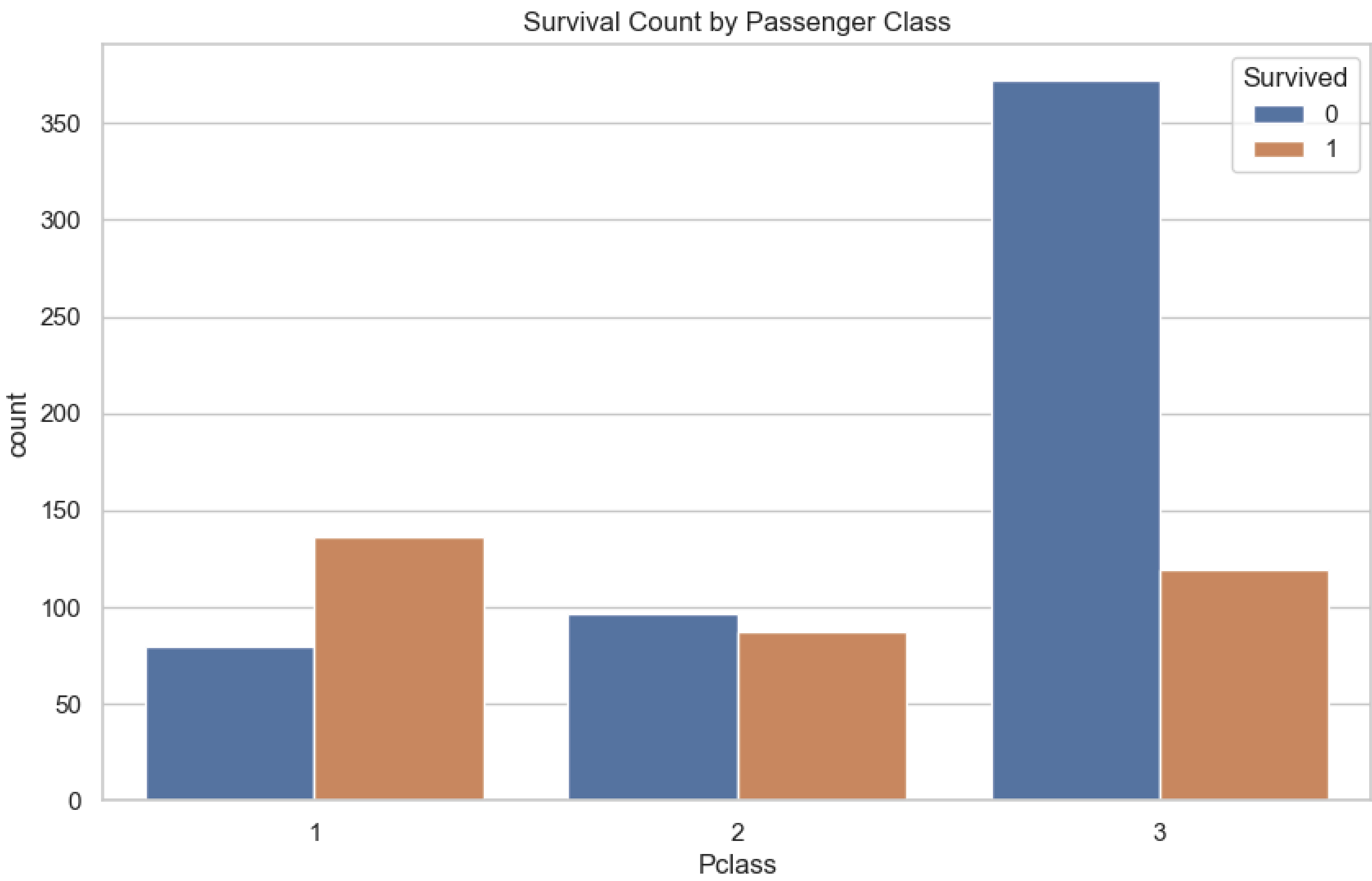


5. Bivariate Analysis

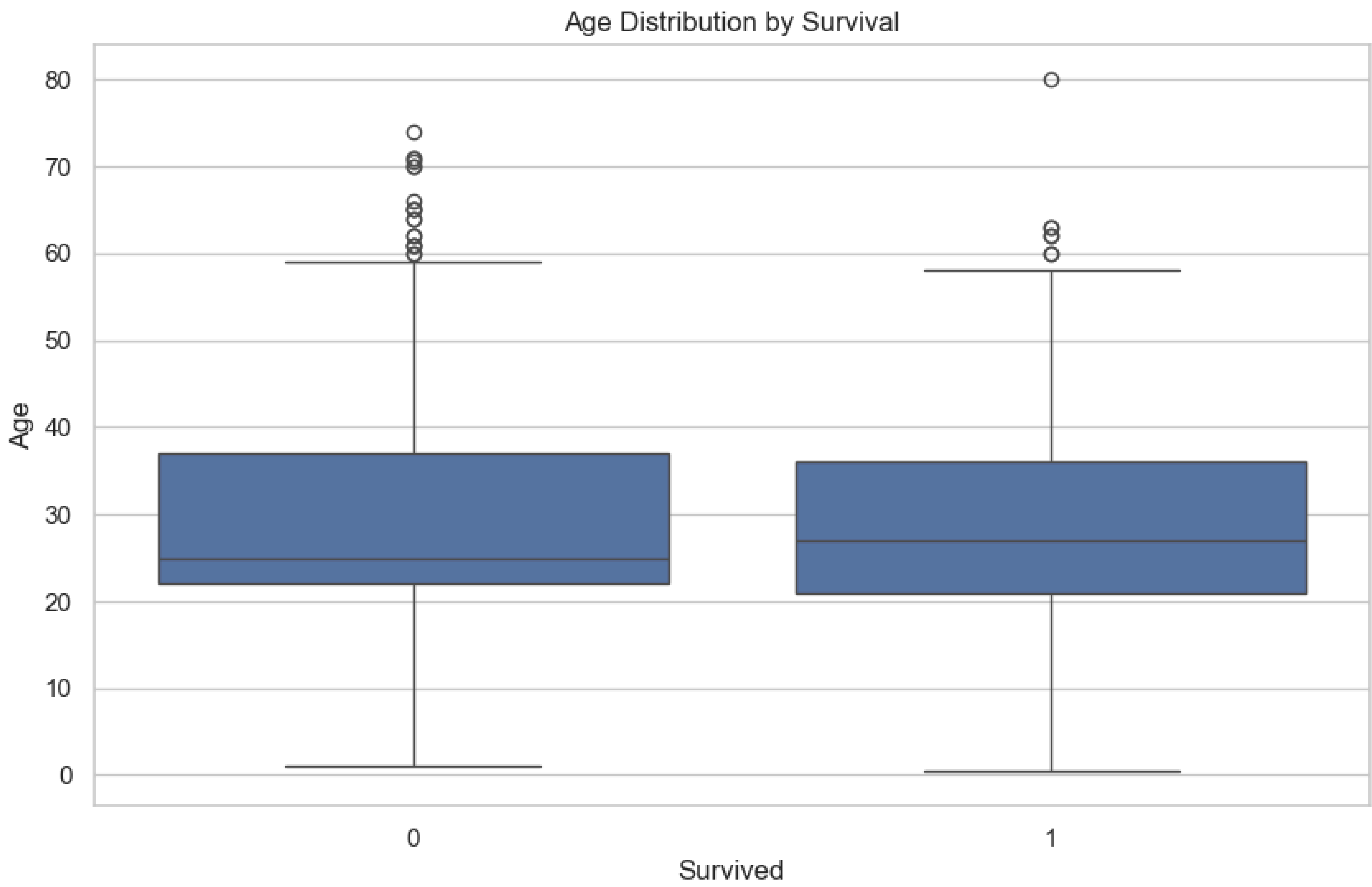
In [20]:
```
sns.countplot(data=df, x='Sex', hue='Survived')
plt.title("Survival Count by Sex")
plt.show()
```



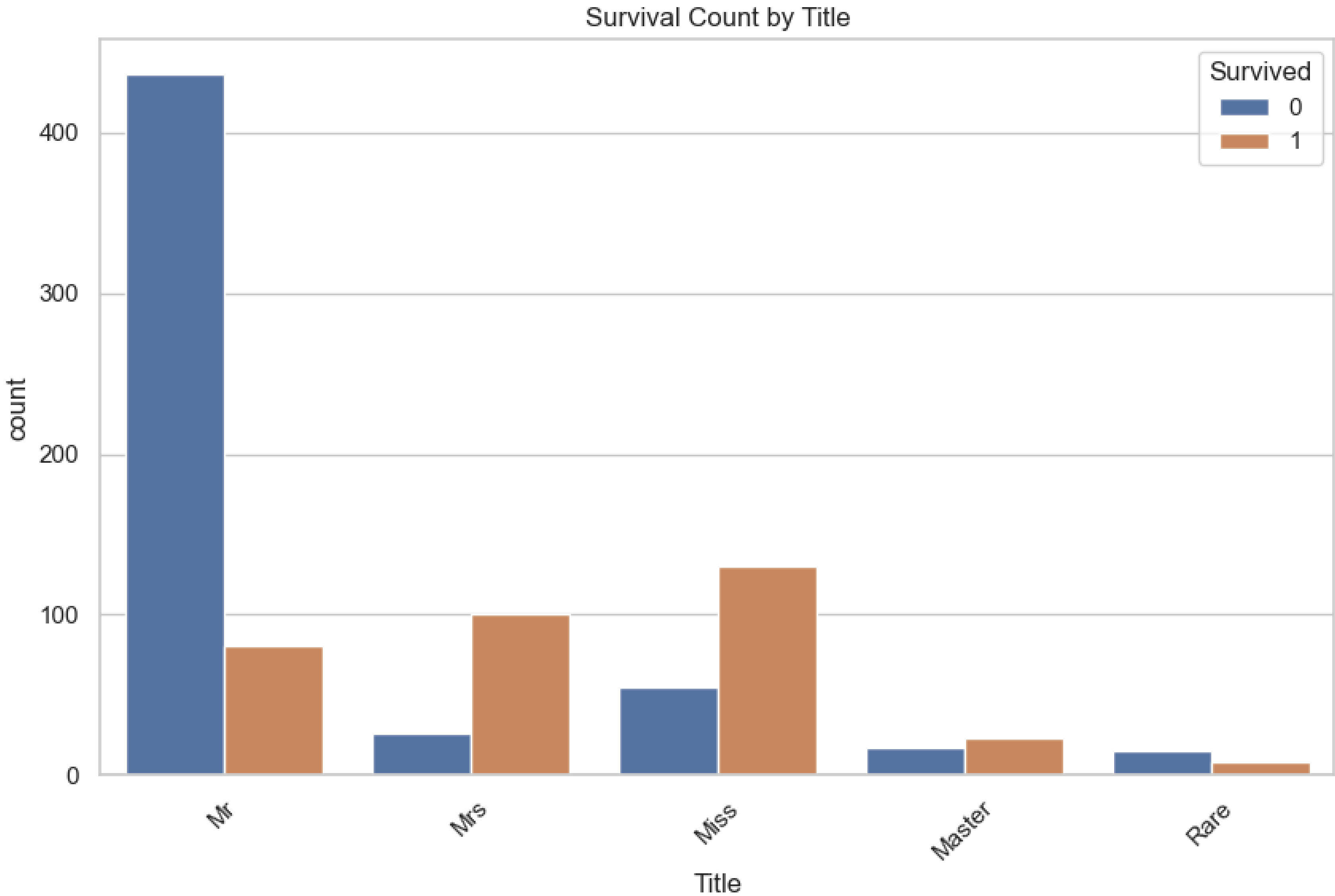
In [21]:
```
sns.countplot(data=df, x='Pclass', hue='Survived')
plt.title("Survival Count by Passenger Class")
plt.show()
```



In [22]:
```
sns.boxplot(data=df, x='Survived', y='Age')
plt.title("Age Distribution by Survival")
plt.show()
```



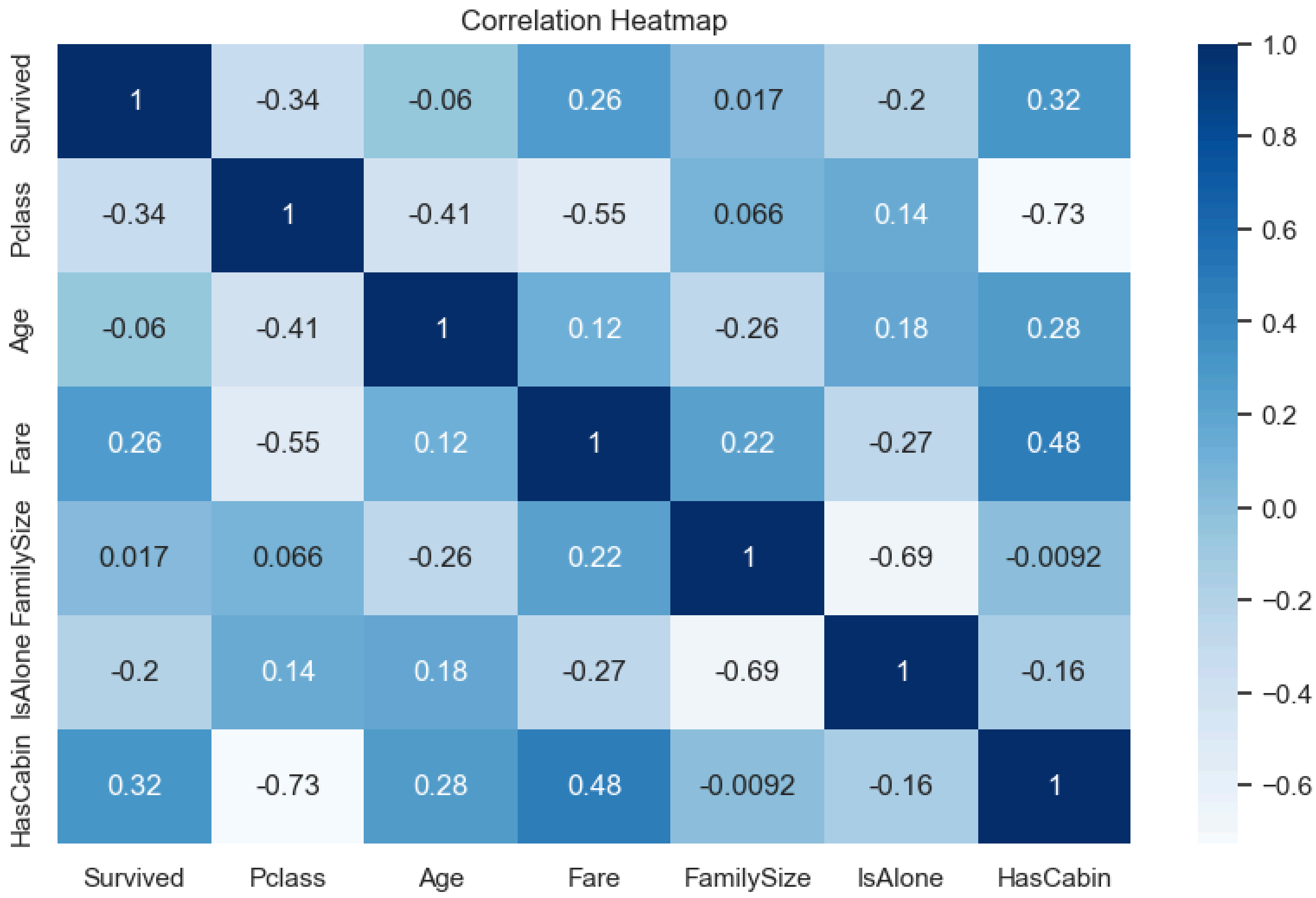
In [23]:
```
sns.countplot(data=df, x='Title', hue='Survived')
plt.title("Survival Count by Title")
plt.xticks(rotation=45)
plt.show()
```



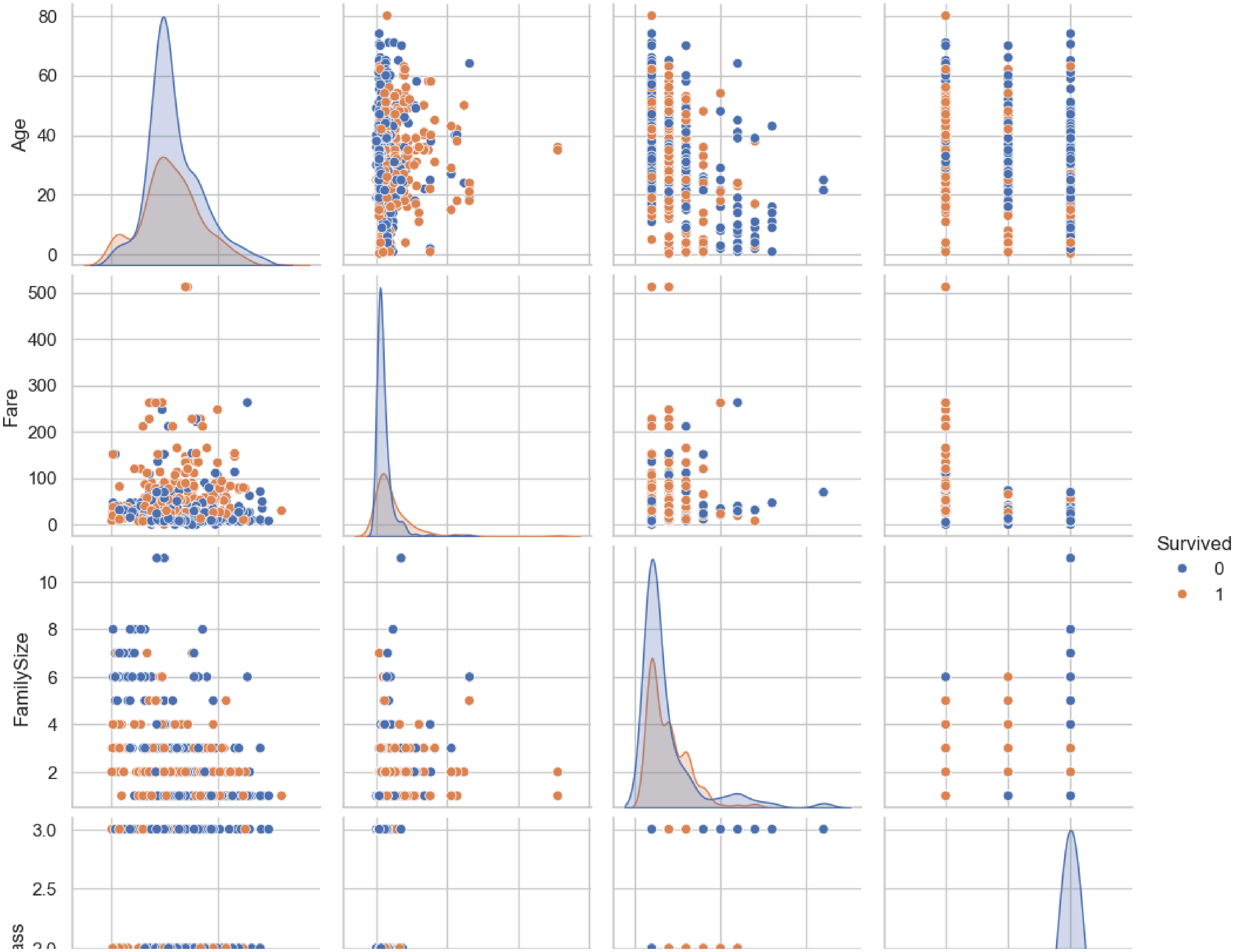
6. Multivariate Analysis

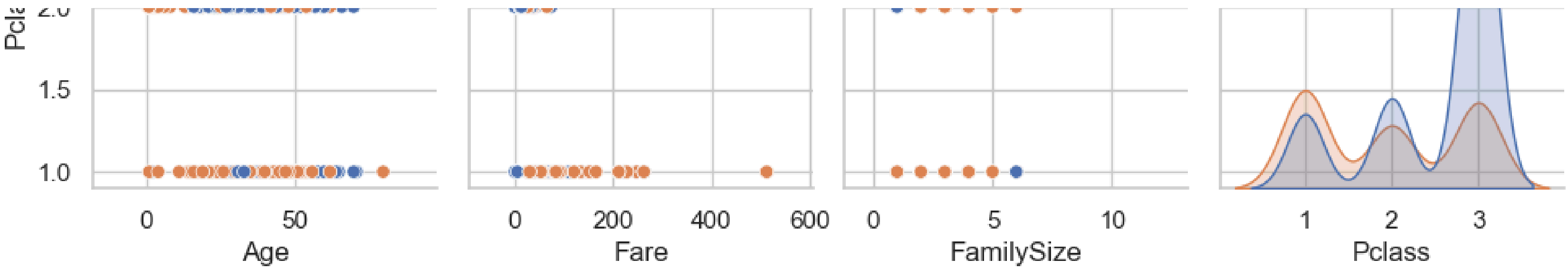
In [24]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df[['Survived','Pclass','Age','Fare','FamilySize','IsAlone','HasCabin']]
```

```
            .corr(), annot=True, cmap='Blues')
plt.title("Correlation Heatmap")
plt.show()
```



In [25]:
```
sns.pairplot(df[['Survived','Age','Fare','FamilySize','Pclass']],
             hue='Survived', diag_kind='kde')
plt.show()
```


Age
Fare
FamilySize
ass
Survived
0
1



7. Summary of Insights

Key Insights from the Titanic Dataset

- Approximately 38% of passengers survived, indicating low overall survival.
- Females had a significantly higher survival rate than males, showing “women and children first” behavior.
- Passenger Class strongly influenced survival: 1st class passengers survived more, while 3rd class had the lowest survival.
- Younger passengers, especially children, had higher survival rates.
- Higher fare correlates with better survival chances, suggesting wealthier passengers were safer.
- Titles extracted from passenger names showed strong patterns: “Miss” and “Mrs” had higher survival than “Mr”.
- Passengers traveling alone had lower survival compared to those with family.
- Presence of a cabin (HasCabin = 1) was associated with higher survival, likely because cabin information was more complete for higher-class passengers.

In [ ]:

```

```