```python
# ---------------------------------------------
# 1. Import Libraries
# ---------------------------------------------
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_theme(style="whitegrid")

# ---------------------------------------------
# 2. Upload & Load Data
# ---------------------------------------------
from google.colab import files

# Upload train.csv, test.csv, gender_submission.csv from Titanic
folder
uploaded = files.upload()

# Load datasets
train = pd.read_csv("train.csv")
test  = pd.read_csv("test.csv")
gender = pd.read_csv("gender_submission.csv")

print("Train shape:", train.shape)
print("Test shape:", test.shape)
print("Gender shape:", gender.shape)

train.head()
```

```
<IPython.core.display.HTML object>
```

```
Saving gender_submission.csv to gender_submission.csv
Saving test.csv to test.csv
Saving train.csv to train.csv
Train shape: (891, 12)
Test shape: (418, 11)
Gender shape: (418, 2)
```


```
{"summary":"{\n  \"name\": \"train\",\n  \"rows\": 891,\n  \"fields\": [\n    {\n      \"column\": \"PassengerId\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 257,\n        \"min\": 1,\n        \"max\": 891,\n        \"num_unique_values\": 891,\n        \"samples\": [\n          710,\n          440,\n          841\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"Survived\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n        \"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\": [\n          1,\n          0\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
```

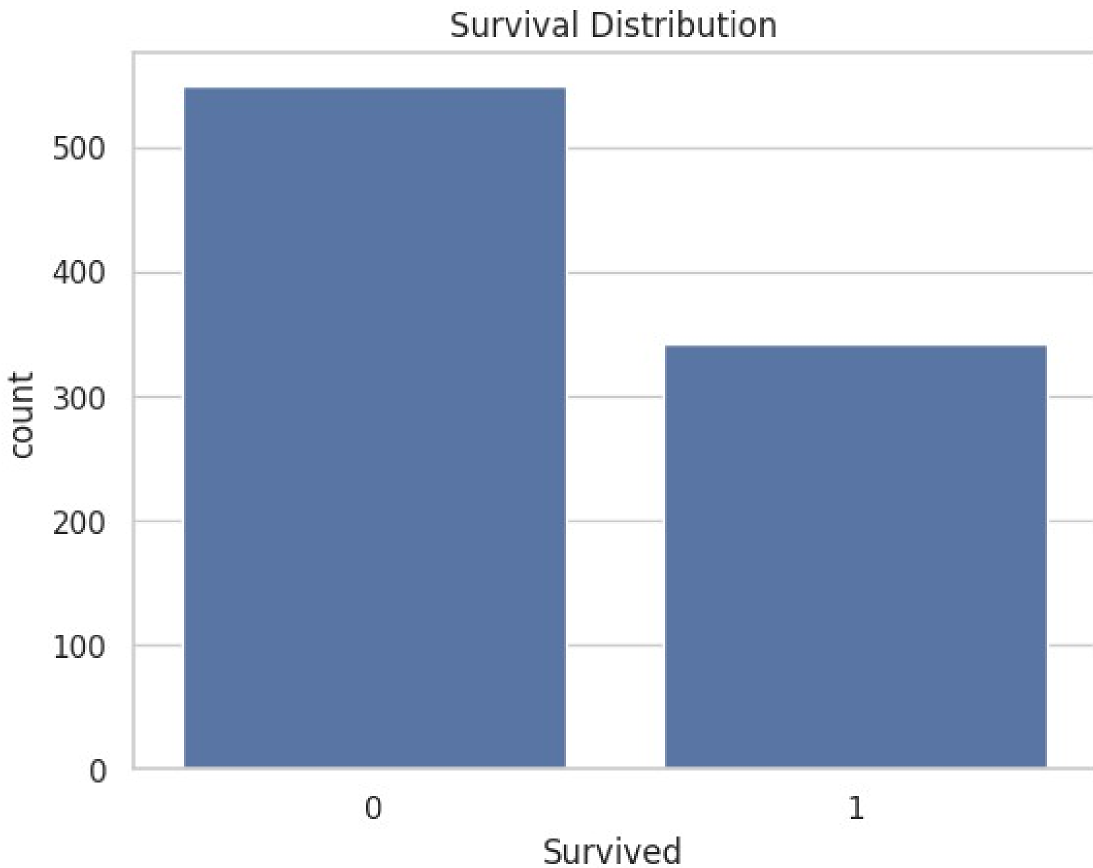
```
\"column\": \"Pclass\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 1,\n
\"max\": 3,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          3,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Name\",\n      \"properties\": {\n        \"dtype\":
\"string\",\n        \"num_unique_values\": 891,\n        \"samples\":
[\n          \"Moubarek, Master. Halim Gonios (\\\"William
George\\\")\",\n          \"Kvillner, Mr. Johan Henrik Johannesson\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"Sex\",\n      \"properties\": {\
n        \"dtype\": \"category\",\n        \"num_unique_values\": 2,\n
\"samples\": [\n          \"female\",\n          \"male\"\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"Age\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 14.526497332334044,\
n        \"min\": 0.42,\n        \"max\": 80.0,\n
\"num_unique_values\": 88,\n        \"samples\": [\n          0.75,\n
22.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"SibSp\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 1,\n        \"min\": 0,\n        \"max\": 8,\n
\"num_unique_values\": 7,\n        \"samples\": [\n          1,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Parch\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0,\n        \"min\": 0,\n        \"max\": 6,\n
\"num_unique_values\": 7,\n        \"samples\": [\n          0,\n
1\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Ticket\",\n      \"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 681,\n        \"samples\": [\n
\"11774\",\n          \"248740\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Fare\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 49.693428597180905,\n
\"min\": 0.0,\n        \"max\": 512.3292,\n
\"num_unique_values\": 248,\n        \"samples\": [\n
11.2417,\n          51.8625\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Cabin\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 147,\n
\"samples\": [\n          \"D45\",\n          \"B49\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Embarked\",\n      \"properties\":
{\n        \"dtype\": \"category\",\n        \"num_unique_values\":
3,\n        \"samples\": [\n          \"S\",\n          \"C\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"train"}
```

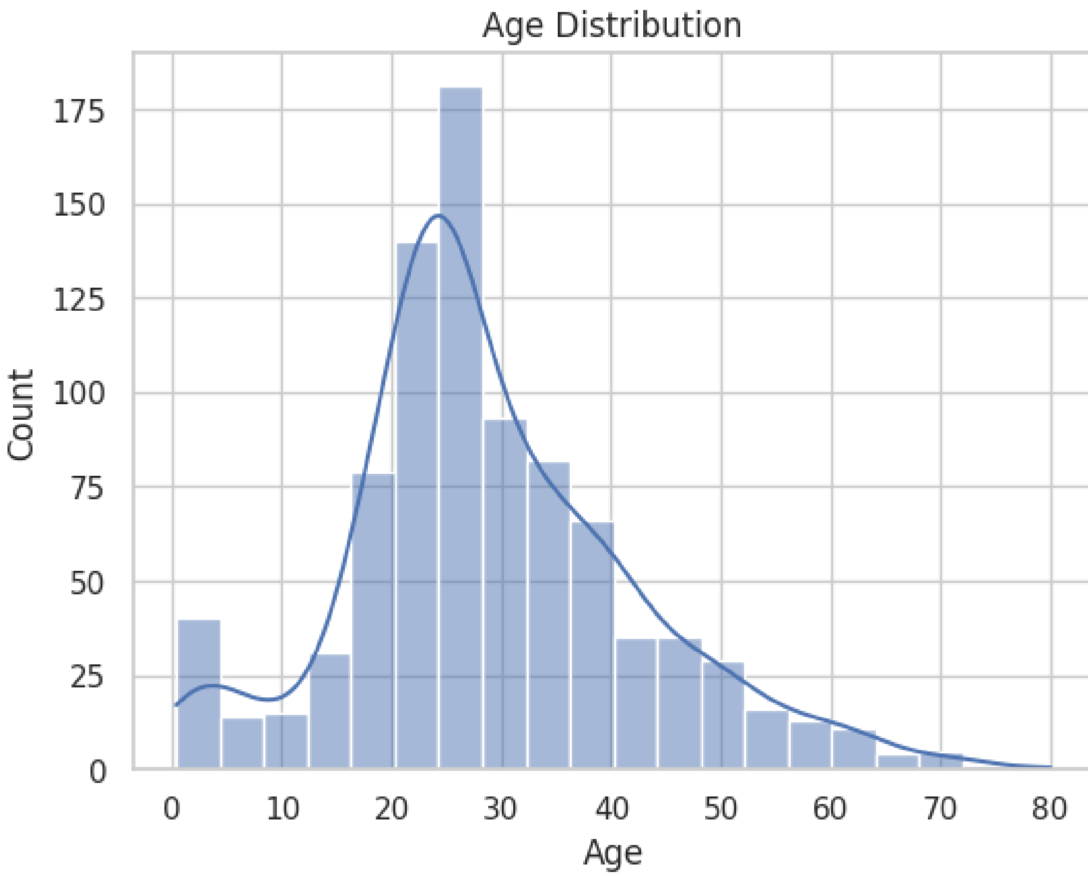
```python
# -----------------------------------------------
# 3. Check Data Info & Missing Values
# -----------------------------------------------
train.info()
print("\nMissing values in training set:\n", train.isna().sum())
```

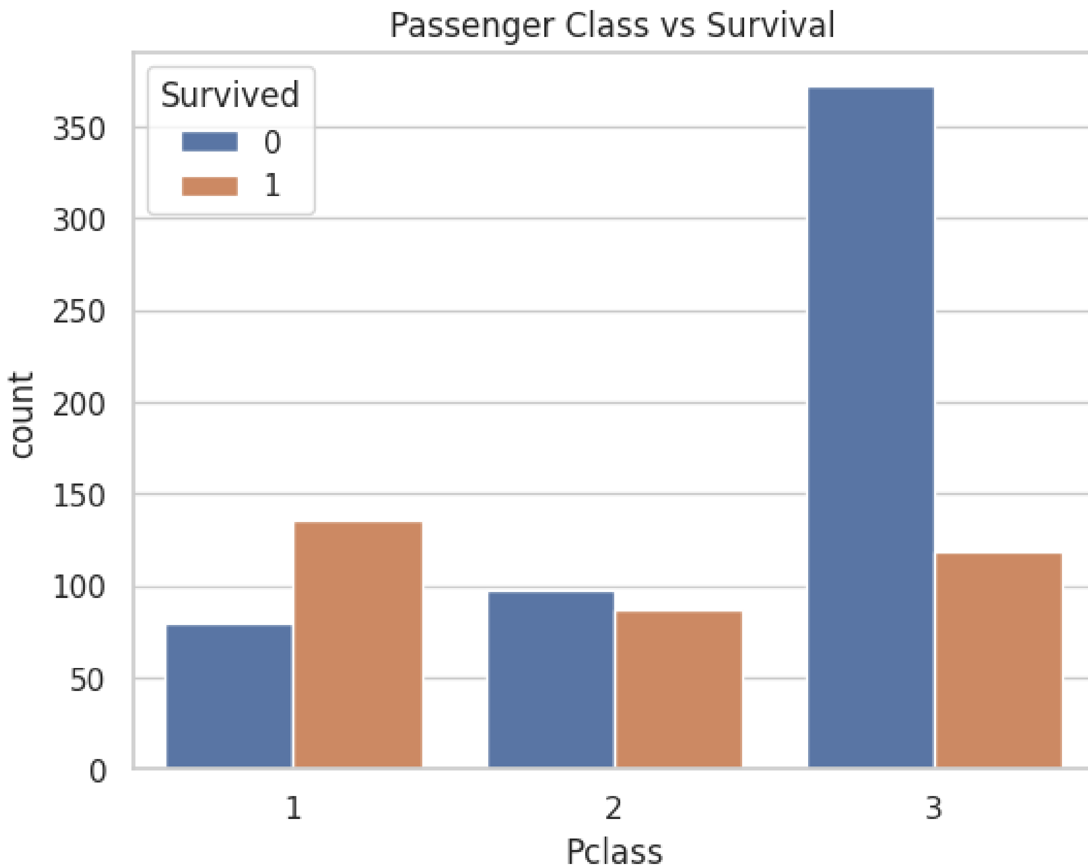
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    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

Missing values in training set:
 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
```

```python
# -----------------------------------------------
# 4. Handle Missing Values
# -----------------------------------------------
# Fill Embarked with mode (most common value)
train['Embarked'] = train['Embarked'].fillna(train['Embarked'].mode()
[0])

# Fill Age using median grouped by Sex & Pclass
age_medians = train.groupby(['Sex','Pclass'])['Age'].median()
```

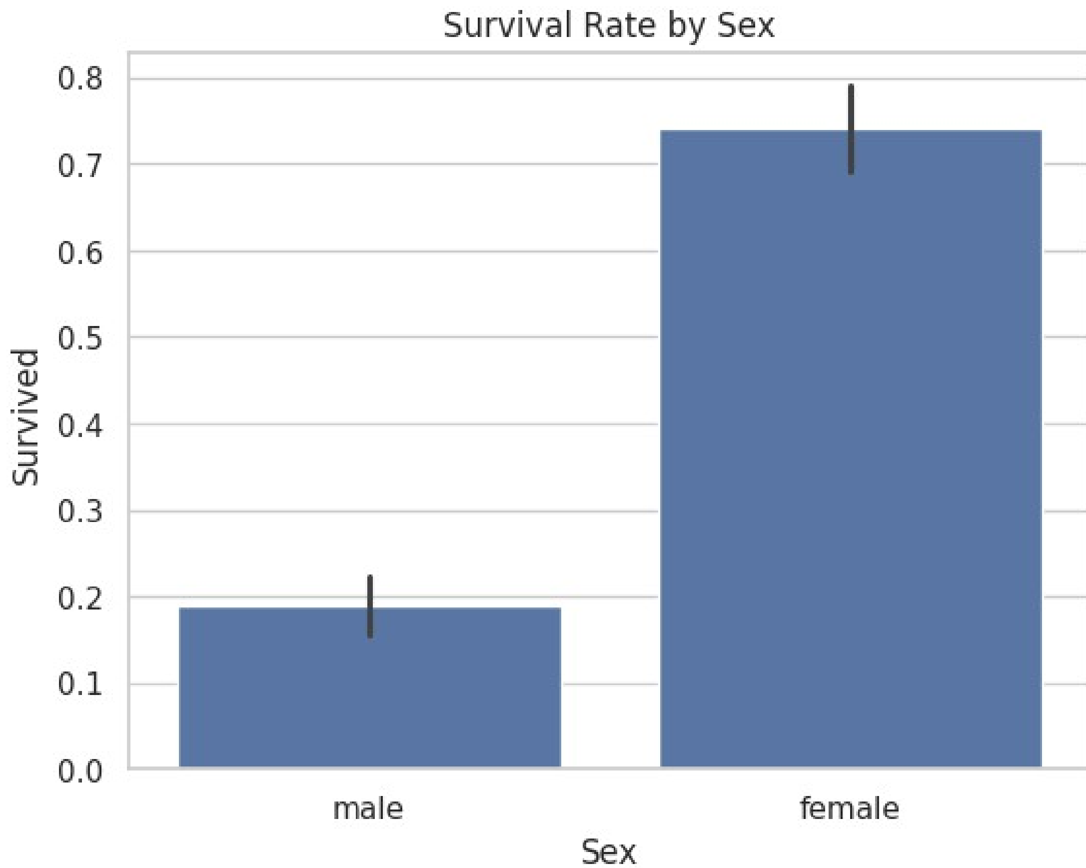
```python
def impute_age(row):
    if pd.isna(row['Age']):
        return age_medians.loc[row['Sex'], row['Pclass']]
    return row['Age']

train['Age'] = train.apply(impute_age, axis=1)

# Create a new feature: Cabin Available or Not
train['HasCabin'] = train['Cabin'].notna().astype(int)

# ----------------------------------------------
# 5. Feature Engineering for EDA
# ----------------------------------------------
# Family Size
train['FamilySize'] = train['SibSp'] + train['Parch'] + 1
train['IsAlone'] = (train['FamilySize'] == 1).astype(int)

# Extract title from Name
train['Title'] = train['Name'].str.extract(r',\s*([^\.]+)\.')
title_map = {
    'Mlle':'Miss','Ms':'Miss','Mme':'Mrs',

'Lady':'Rare','Countess':'Rare','Capt':'Rare','Col':'Rare','Don':'Rare
',

'Dr':'Rare','Major':'Rare','Rev':'Rare','Sir':'Rare','Jonkheer':'Rare'
,'Dona':'Rare'
}
train['Title'] = train['Title'].replace(title_map)

# ----------------------------------------------
# 6. Univariate Analysis
# ----------------------------------------------
# Target variable
sns.countplot(data=train, x="Survived")
plt.title("Survival Distribution")
plt.show()

# Age distribution
sns.histplot(train['Age'], bins=20, kde=True)
plt.title("Age Distribution")
plt.show()

# Passenger Class
sns.countplot(data=train, x="Pclass", hue="Survived")
plt.title("Passenger Class vs Survival")
plt.show()
```


Survival Distribution
500
400
300
200
100
0
count
0
1
Survived

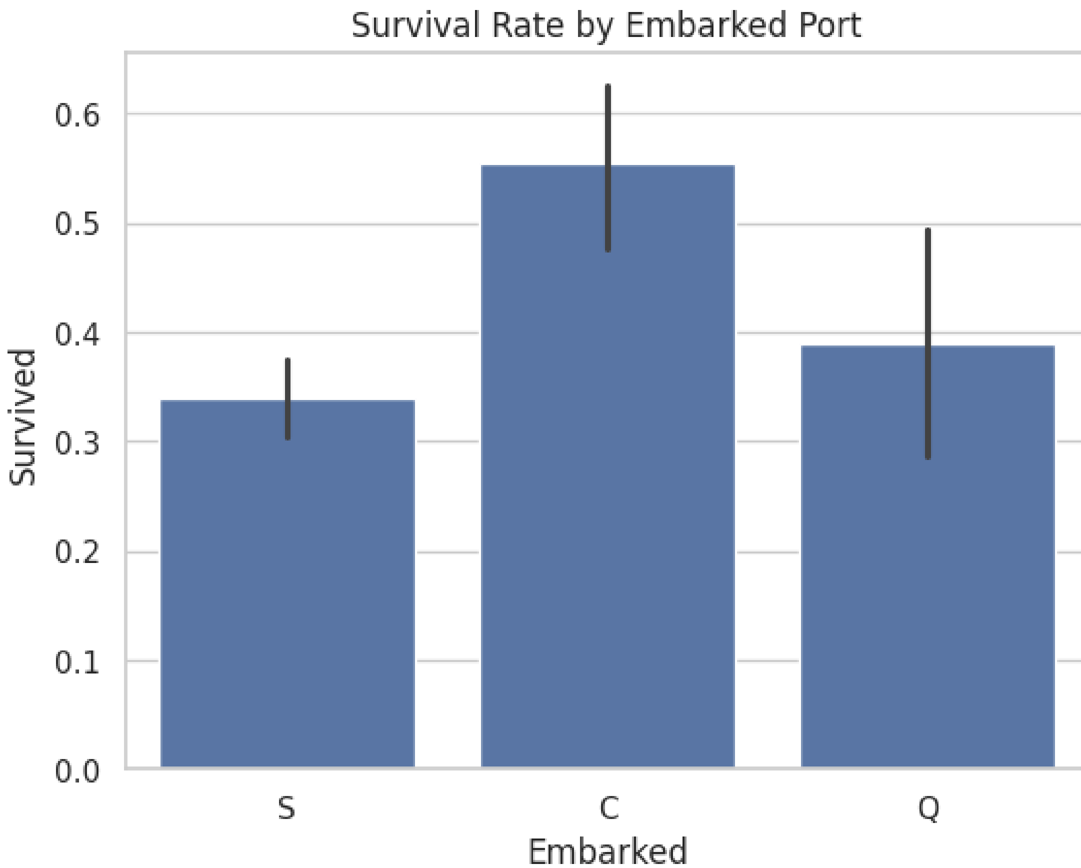

Age Distribution
Count
175
150
125
100
75
50
25
0
0
10
20
30
40
50
60
70
80
Age

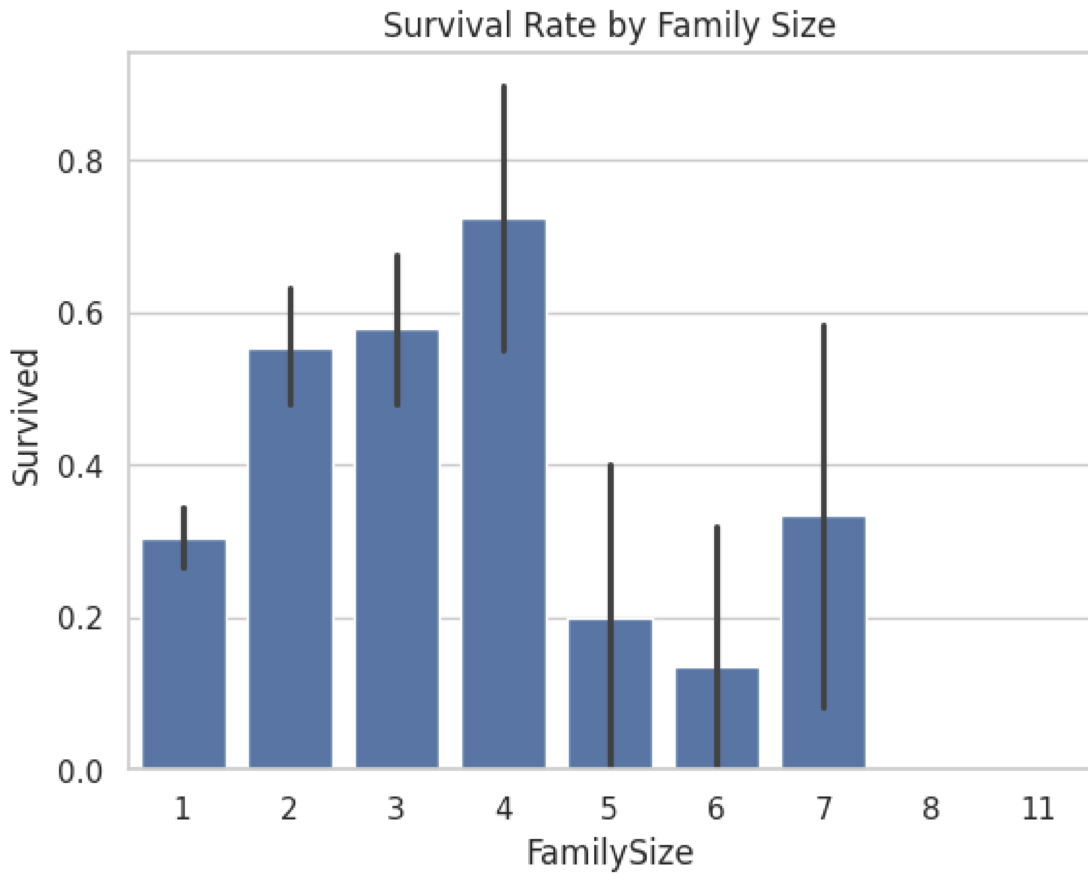


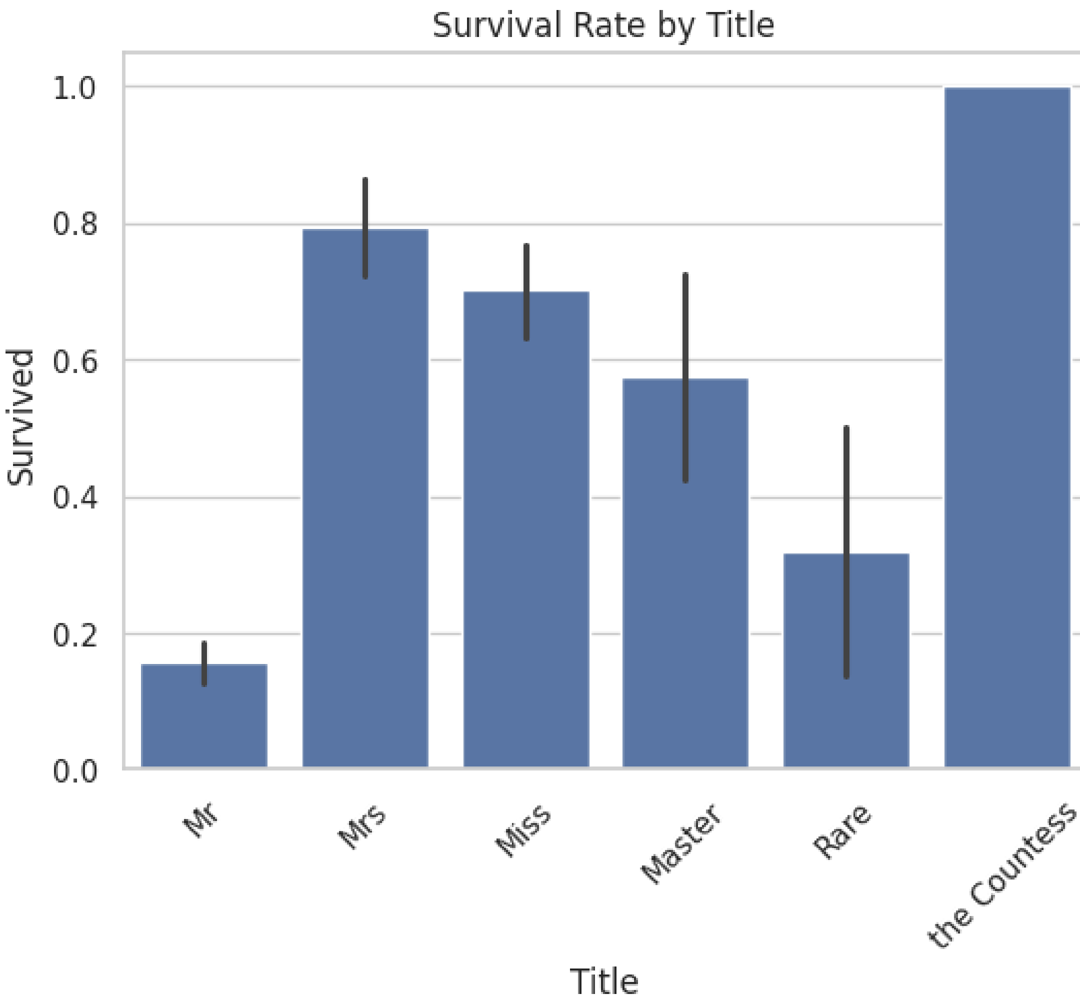

```python
# ---------------------------------------------
# 7. Bivariate Analysis: Who Survived?
# ---------------------------------------------
# Survival by Sex
sns.barplot(x="Sex", y="Survived", data=train)
plt.title("Survival Rate by Sex")
plt.show()

# Survival by Embarked
sns.barplot(x="Embarked", y="Survived", data=train)
plt.title("Survival Rate by Embarked Port")
plt.show()

# Survival by Family Size
sns.barplot(x="FamilySize", y="Survived", data=train)
plt.title("Survival Rate by Family Size")
plt.show()

# Survival by Title
sns.barplot(x="Title", y="Survived", data=train)
plt.title("Survival Rate by Title")
plt.xticks(rotation=45)
plt.show()
```



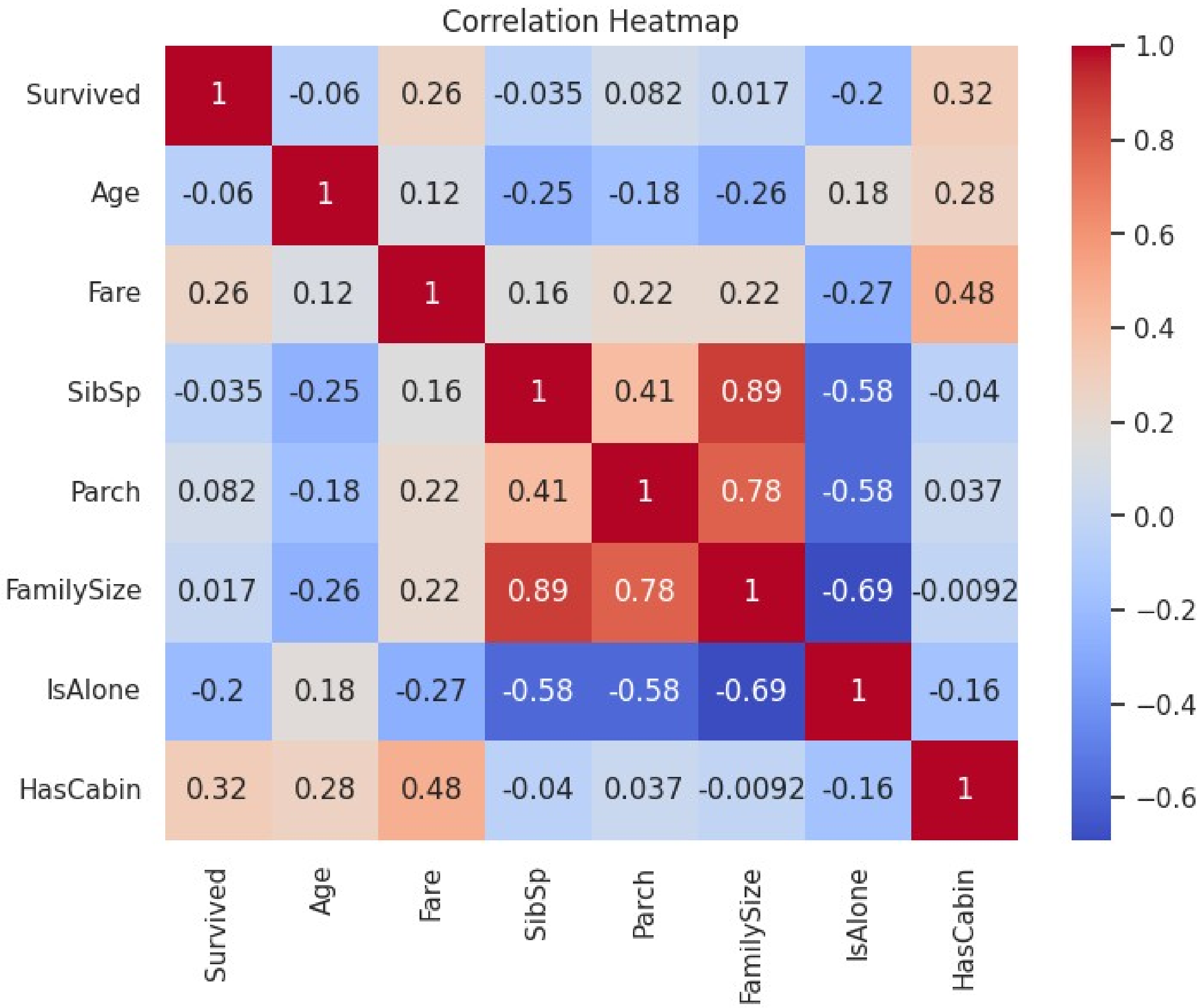
Survival Rate by Sex
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Survived
male
female
Sex


Survival Rate by Embarked Port
Survived
0.0
0.1
0.2
0.3
0.4
0.5
0.6
S
C
Q
Embarked

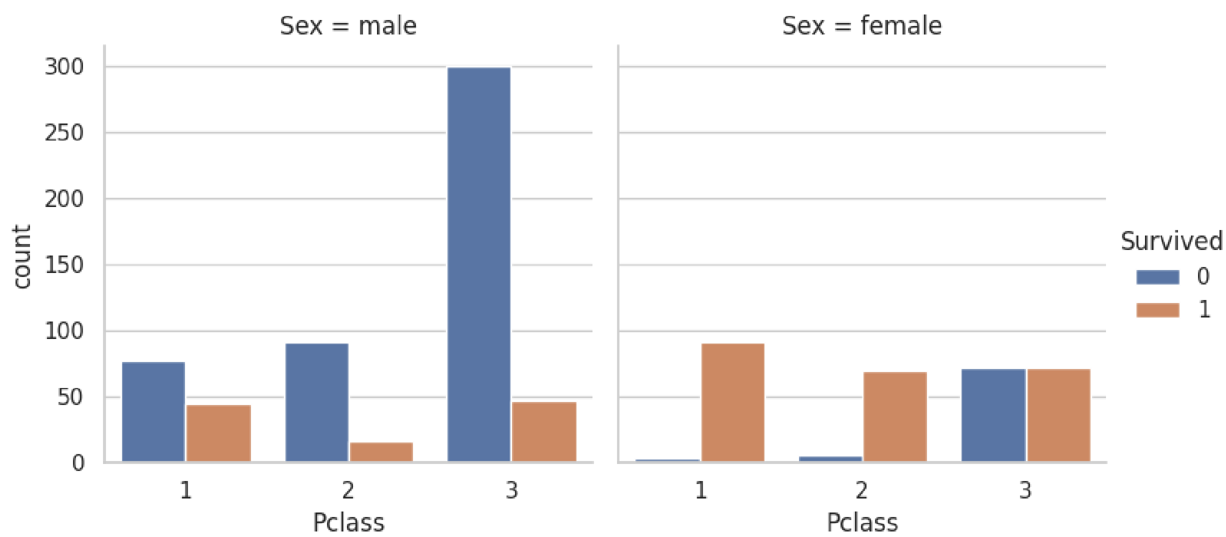

Survival Rate by Family Size
Survived
0.0
0.2
0.4
0.6
0.8
1
2
3
4
5
6
7
8
11
FamilySize




```
# ---------------------------------------------
# 8. Correlation Heatmap
# ---------------------------------------------
plt.figure(figsize=(8,6))
sns.heatmap(train[['Survived','Age','Fare','SibSp','Parch','FamilySize
','IsAlone','HasCabin']].corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```




```
# ----------------------------------------------
# 9. Multivariate Visualization
# ----------------------------------------------
sns.catplot(x="Pclass", hue="Survived", col="Sex", data=train,
kind="count", height=4)
plt.show()
```




**Titanic Dataset – EDA Summary & Conclusions**

1.Data Cleaning

- Missing Values:

  Age → Filled with group median (by Sex & Pclass).

  Embarked → Filled with mode (most common port).

  Cabin → Too many missing → created a binary feature HasCabin.

- New Features: FamilySize, IsAlone, Title extracted from Name

**Key Findings**

1.Survival Distribution:

- About 38% of passengers survived.
- Survival was highly imbalanced (more deaths than survivors).

2.Gender:

- Females had a survival rate of ~74% vs ~19% for males.
- This is the strongest predictor of survival.

3.Passenger Class (Pclass):

- 1st Class survival ≈ 63%,
- 2nd Class ≈ 47%,
- 3rd Class ≈ 24%.

- Wealth/status influenced survival chances.

4.Age:

- Children (<12 yrs) had higher survival rates.
- Elderly (>60 yrs) had very low survival rates.

5.Family Size / IsAlone:

- People traveling alone had lower survival rates (~30%).
- Small families (2–4 members) had better chances.
- Very large families (>5) again had worse survival.

6.Embarked Port:

- Passengers who boarded at Cherbourg (C) survived more often than those at Southampton (S) or Queenstown (Q).

7.Cabin Information:

- Having a recorded cabin number was associated with a much higher chance of survival.

8.Titles (from Names):

- Social titles like 'Mrs', 'Miss', 'Master' showed higher survival.
- Rare titles (like Dr, Col, Rev) mostly had low survival.

**Conclusion**

- The most important factors for survival were Sex, Pclass, and Age, followed by Family connections and Cabin availability.
- The results reflect the "Women and children first" policy during the Titanic disaster.
- Higher-class passengers had better access to lifeboats.
- Traveling with a small family group improved chances, likely due to mutual support.