📊 Task 5 — Exploratory Data Analysis on Titanic Dataset

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Course: Data Analysis Internship
Toolset: Python, Pandas, Matplotlib, Seaborn

📝 Introduction

The Titanic dataset is one of the most well-known datasets in data science.
It contains information about passengers aboard the RMS Titanic, including whether they survived or not, their age, gender, passenger class, and other details.

The goal of this Exploratory Data Analysis (EDA) is to:

1. Understand the structure of the dataset.
2. Identify missing values and handle them.
3. Perform univariate and bivariate analysis.
4. Draw meaningful insights from visualizations.
5. Prepare the dataset for further modeling.

📂 Dataset Information

- **Source:** Titanic - Machine Learning from Disaster (Kaggle)
- **File Used:** `train.csv` — 891 rows × 12 columns
- **Target Variable:** `Survived` (0 = Did not survive, 1 = Survived)
- **Feature Variables:** Passenger demographics, ticket class, fare, cabin, etc.

Import & Load

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

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

Data Summary

In [3]:
```
df.info()
df.isnull().sum()
df.describe()
```

```
<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
```

Out[3]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Observation:

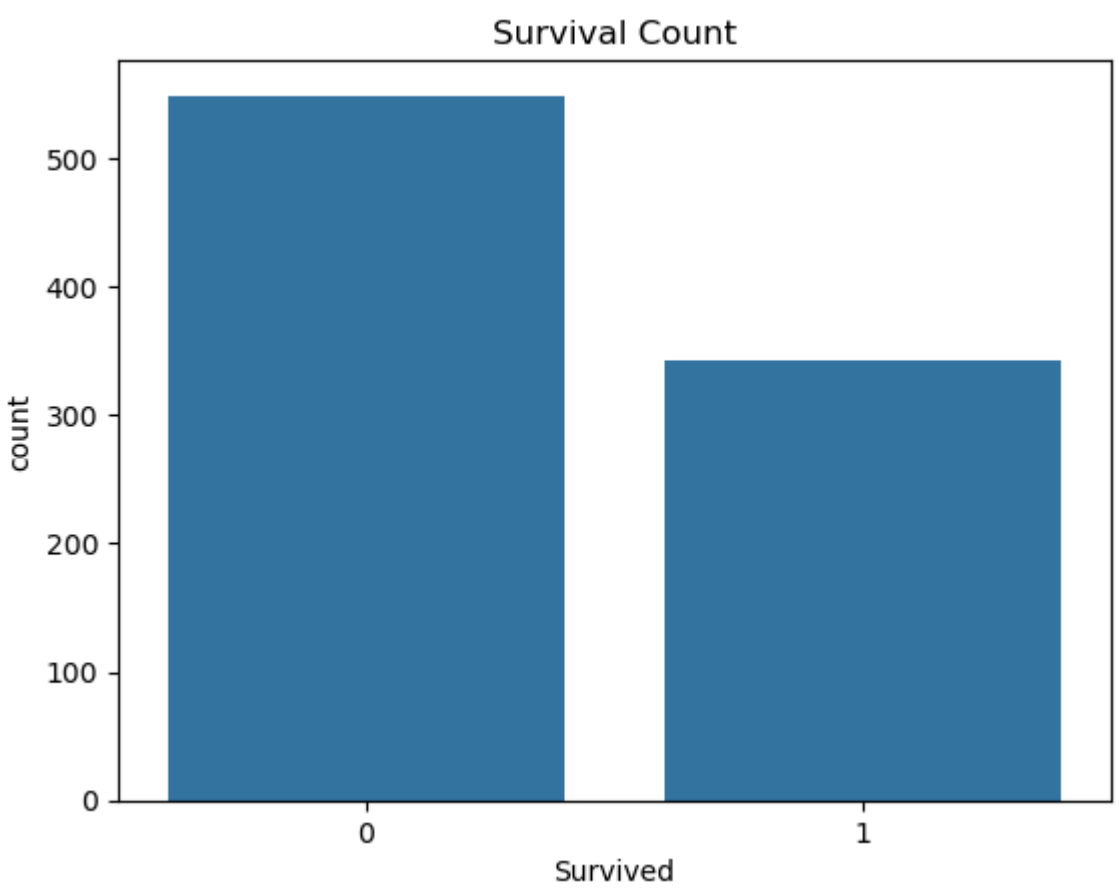
891 rows × 12 columns

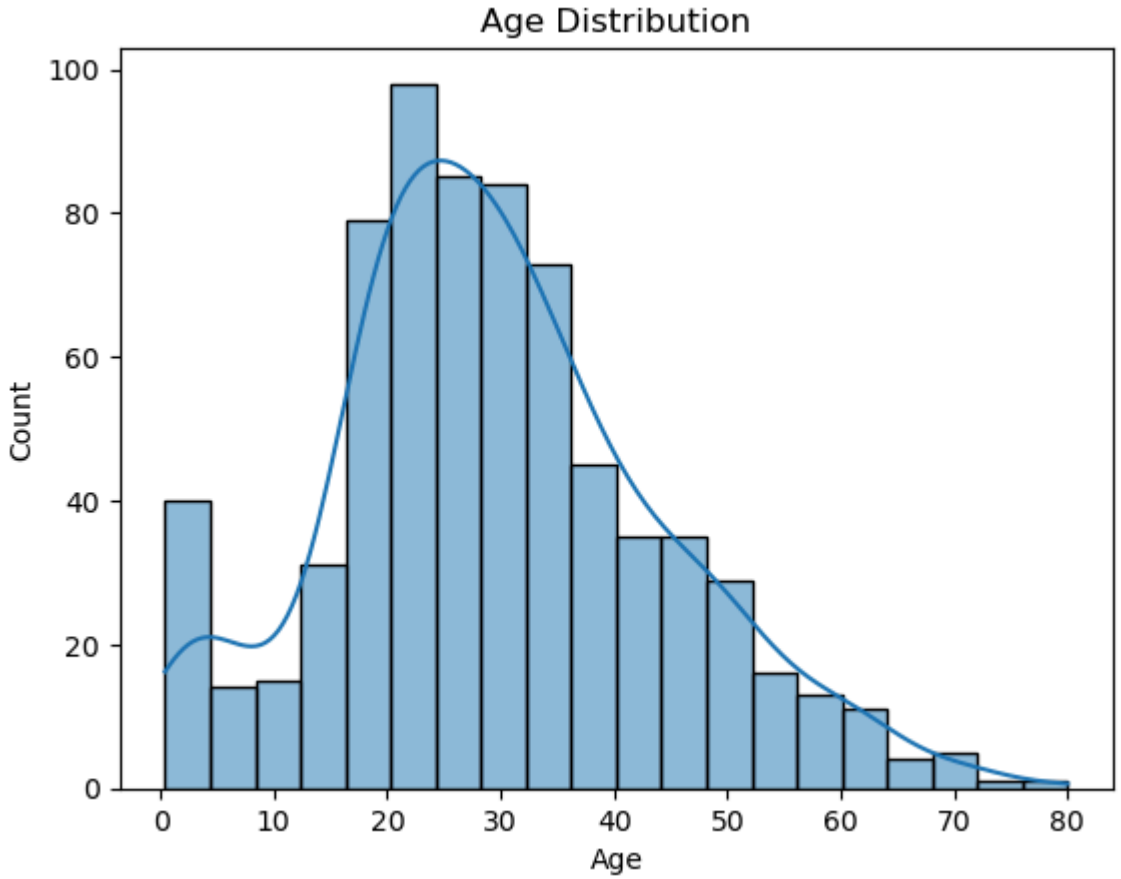
Missing: Cabin (687), Age (177), Embarked (2)

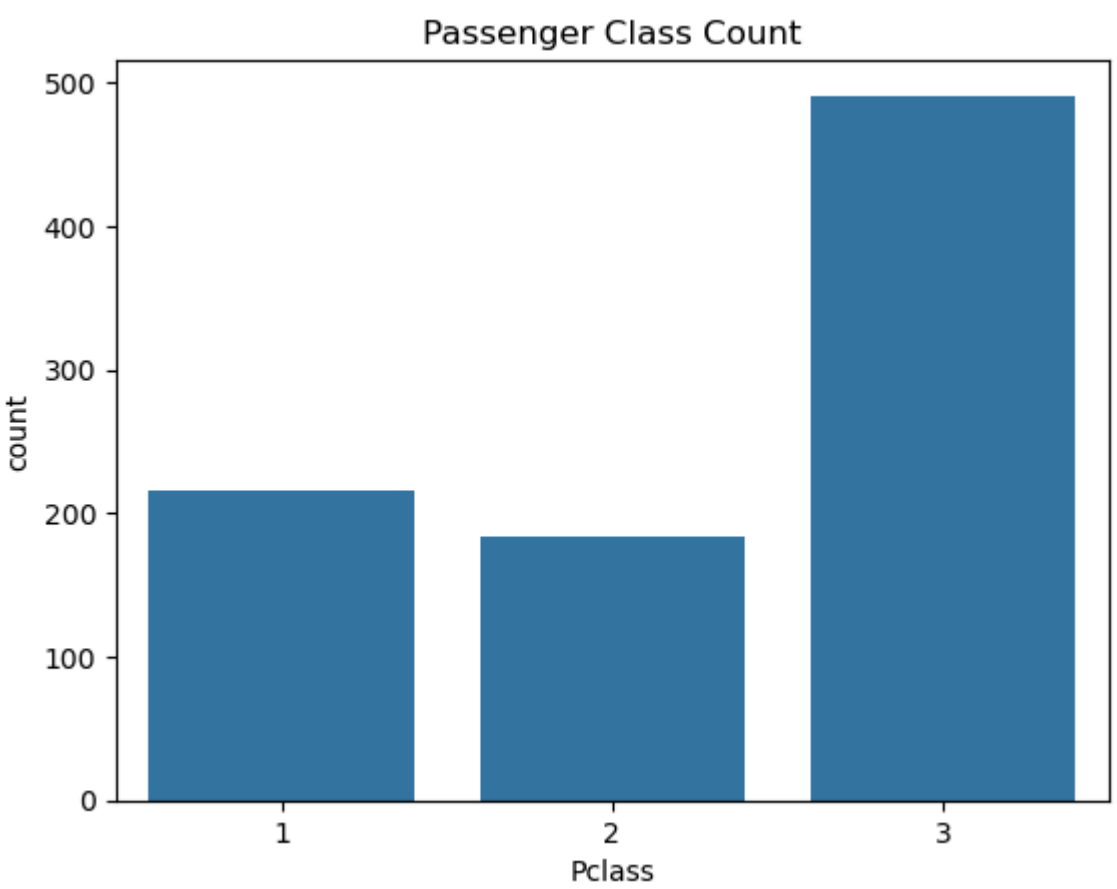
Avg Age ≈ 29, Avg Fare ≈ 32, Most passengers in Pclass 3.

Univariate Visualizations

In [4]:
```
sns.countplot(x='Survived', data=df)
plt.title('Survival Count')
plt.show()

sns.histplot(df['Age'].dropna(), bins=20, kde=True)
plt.title('Age Distribution')
plt.show()

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


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


Age Distribution
Count
Age
0
20
40
60
80
100
0
10
20
30
40
50
60
70
80



Observation:

More deaths than survivals.

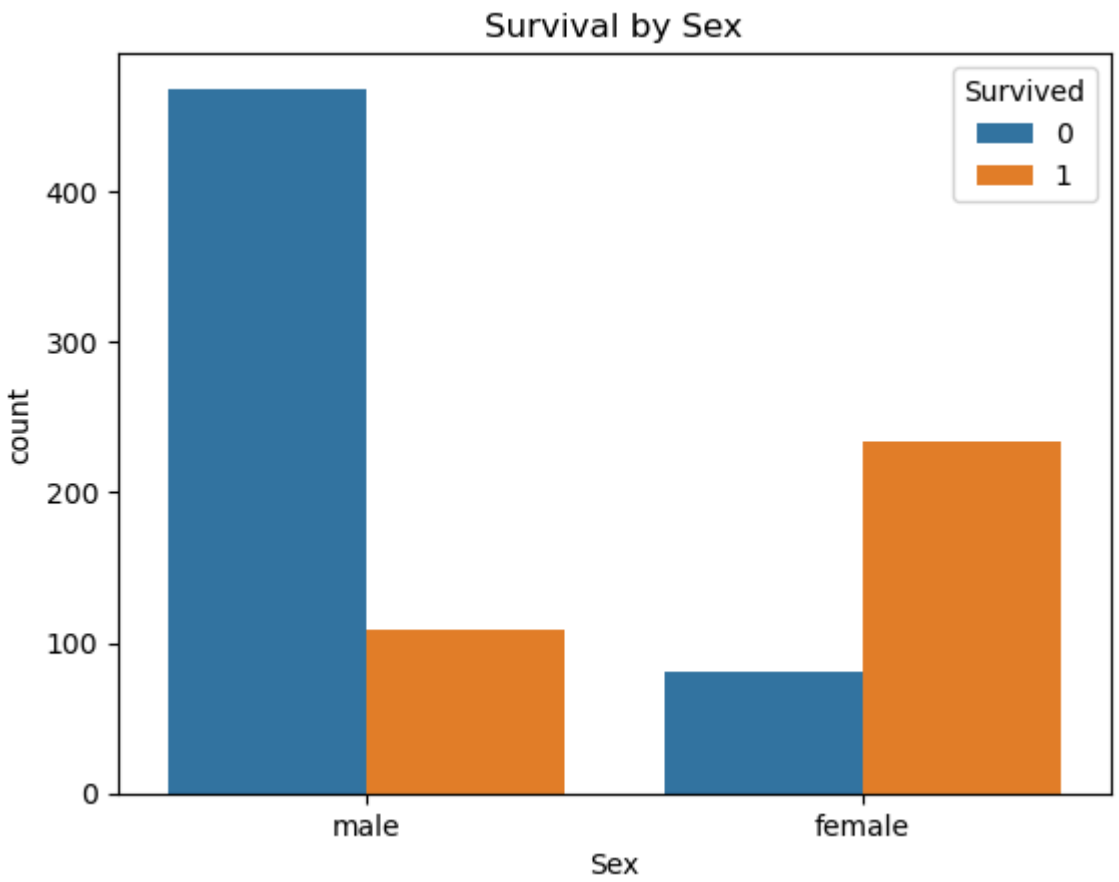
Most passengers 20–40 years old.

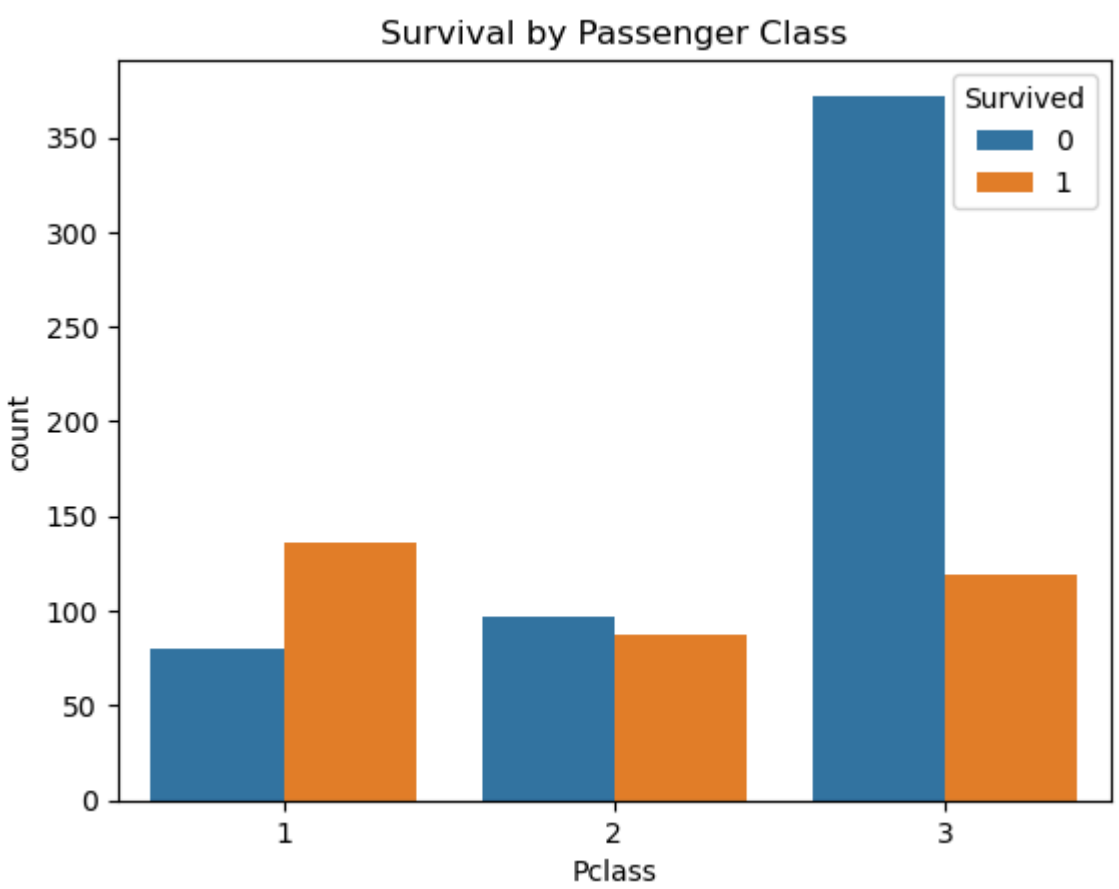
Most passengers in 3rd class.

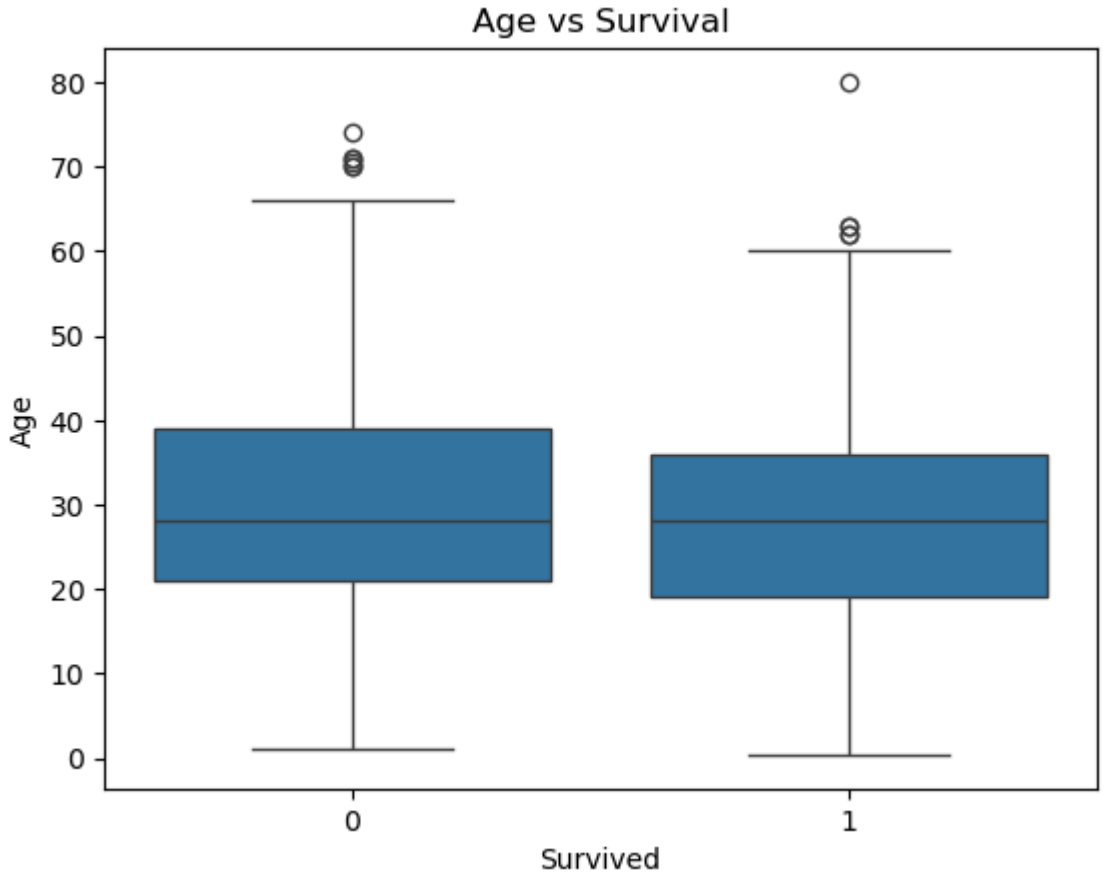
Bivariate Visualizations

In [5]:
```
sns.countplot(x='Sex', hue='Survived', data=df)
plt.title('Survival by Sex')
plt.show()

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

```
plt.show()

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




Survival by Passenger Class
Survived
0
1
count
350
300
250
200
150
100
50
0
1
2
3
Pclass



Observation:

Females survived more than males.

First-class passengers had better survival rates.

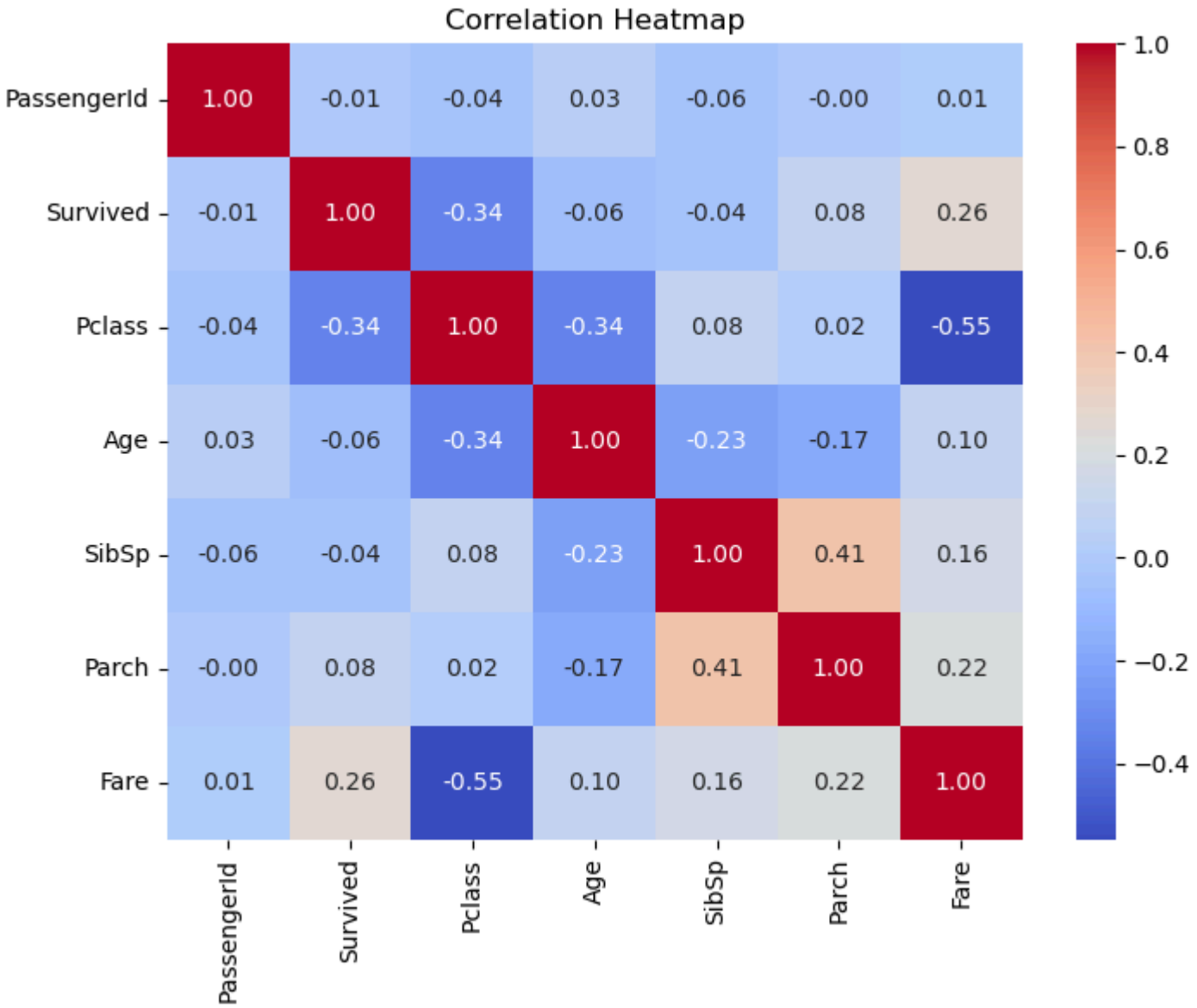
Younger passengers survived more.

Missing Value Handling

In [10]:
```
df.fillna({'Age': df['Age'].median(),
           'Embarked': df['Embarked'].mode()[0]}, inplace=True)
```

Correlation Heatmap

In [13]:
```
plt.figure(figsize=(8,6))
sns.heatmap(df.select_dtypes(include=['int64','float64']).corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



Observation:

Pclass shows a strong negative correlation with Survived (passengers in higher classes — 1st class — had better survival chances than those in 3rd class).

Fare has a positive correlation with Survived (higher ticket prices were linked to higher survival rates).

SibSp (siblings/spouses aboard) and Parch (parents/children aboard) show weak correlations with survival, meaning family size had only a small impact.

Age has a slight negative correlation with survival (younger passengers survived slightly more often).

Final Conclusion:

1. Females had a much higher survival rate than males.
2. Passengers in 1st class had better chances of survival compared to 2nd and 3rd classes.
3. Higher fares were associated with higher survival chances.
4. Younger passengers had a slightly better survival rate than older ones.
5. Missing values in Age and Embarked were handled; Cabin was dropped due to excessive missing data.