```
import pandas as pd

# Load your dataset (replace 'train.csv' with your file name if different)
df = pd.read_csv('train.csv')

# Display the first few rows of the dataset
df.head()
```

	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

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
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
```

```
df.describe()
```

	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

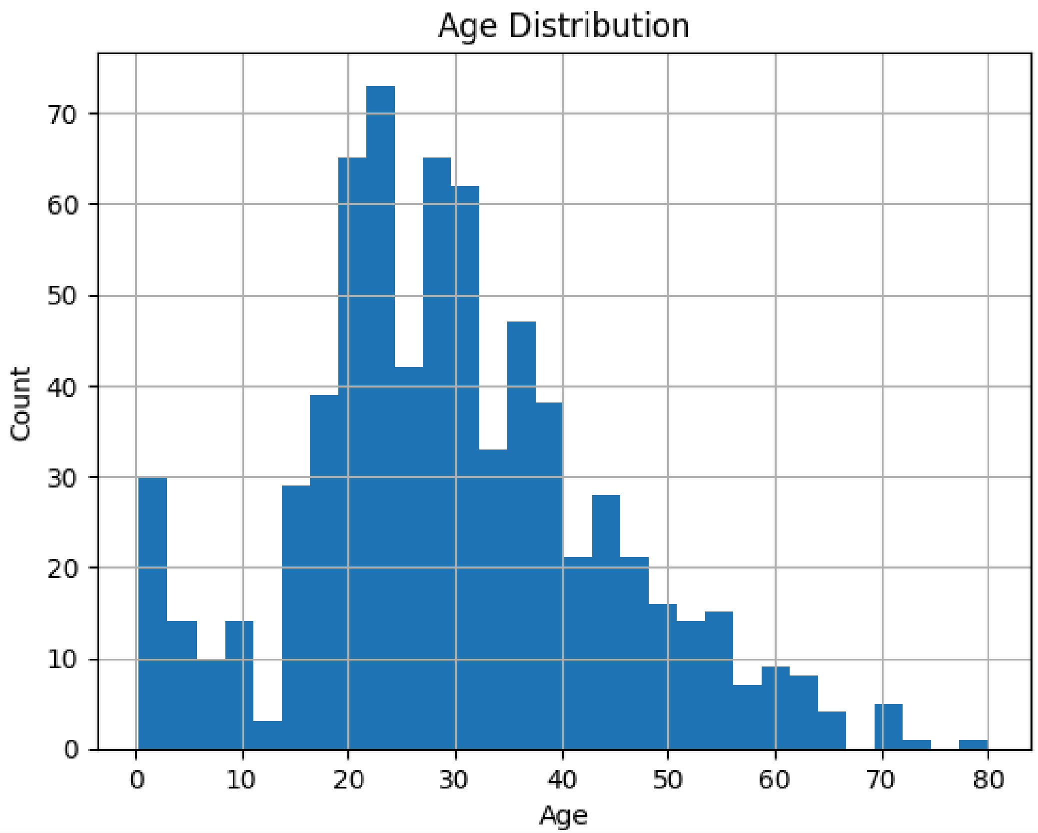
```
df.isnull().sum()
```

	0
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

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt  # Make sure you have this line to import pyplot
```

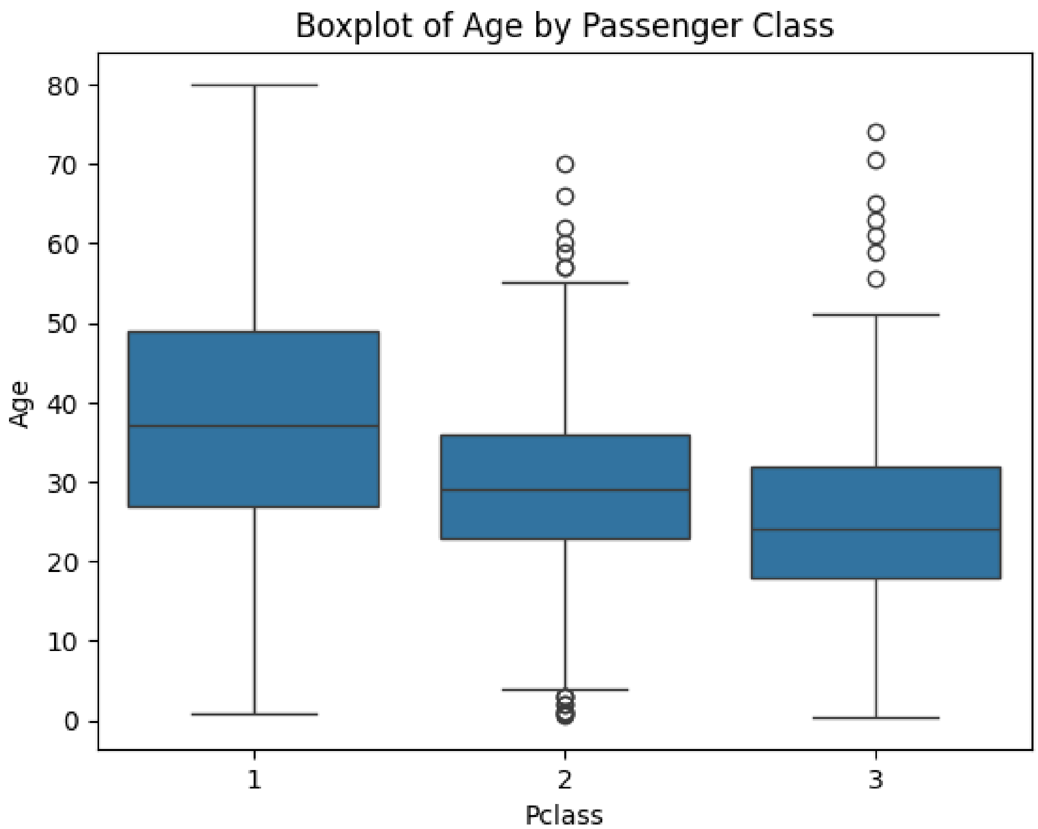
```
df['Age'].hist(bins=30)
plt.title("Age Distribution")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()
```



Observations on Age Distribution:

- The **age distribution** of passengers is **right-skewed**, with most passengers being relatively younger.
- There is a noticeable peak in the **20-30 age range**, indicating that this is the most common age group among passengers.
- A few **outliers** (older passengers) are visible, with ages over 70 years old.
- Most passengers are between the ages of **20 and 40**, and the number of very young passengers (children) is relatively low.

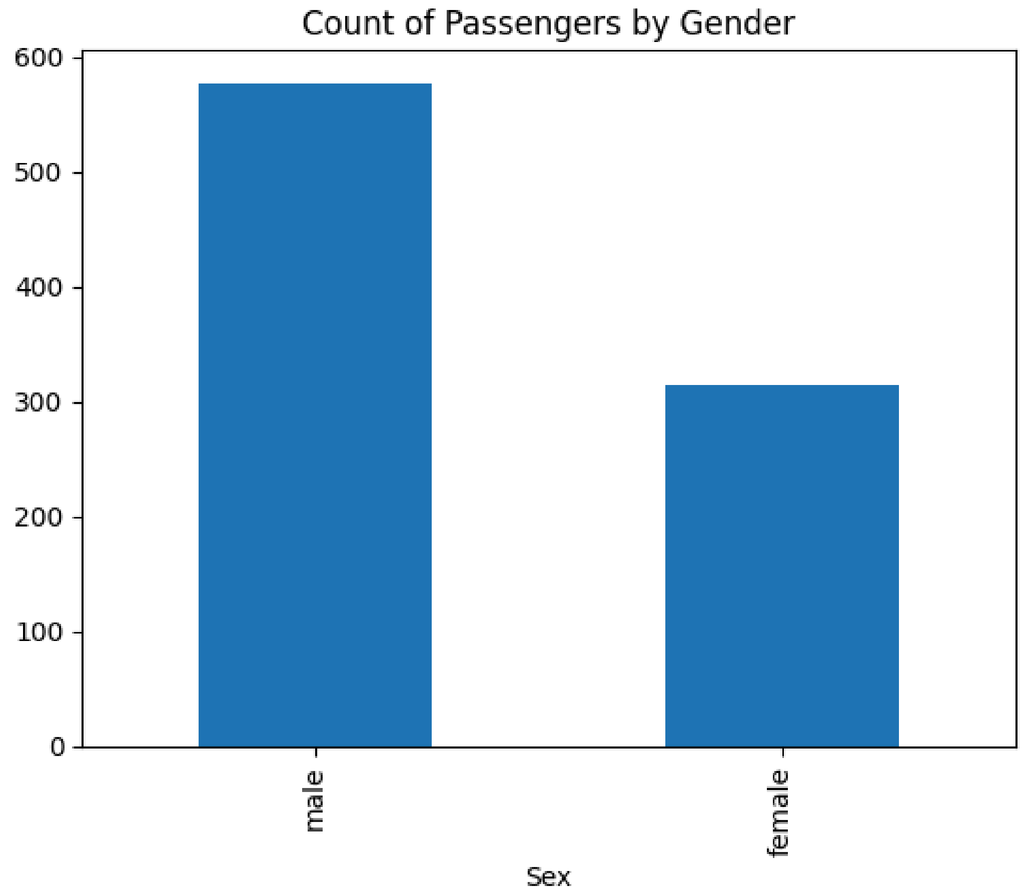
```
sns.boxplot(x='Pclass', y='Age', data=df)
plt.title("Boxplot of Age by Passenger Class")
plt.show()
```



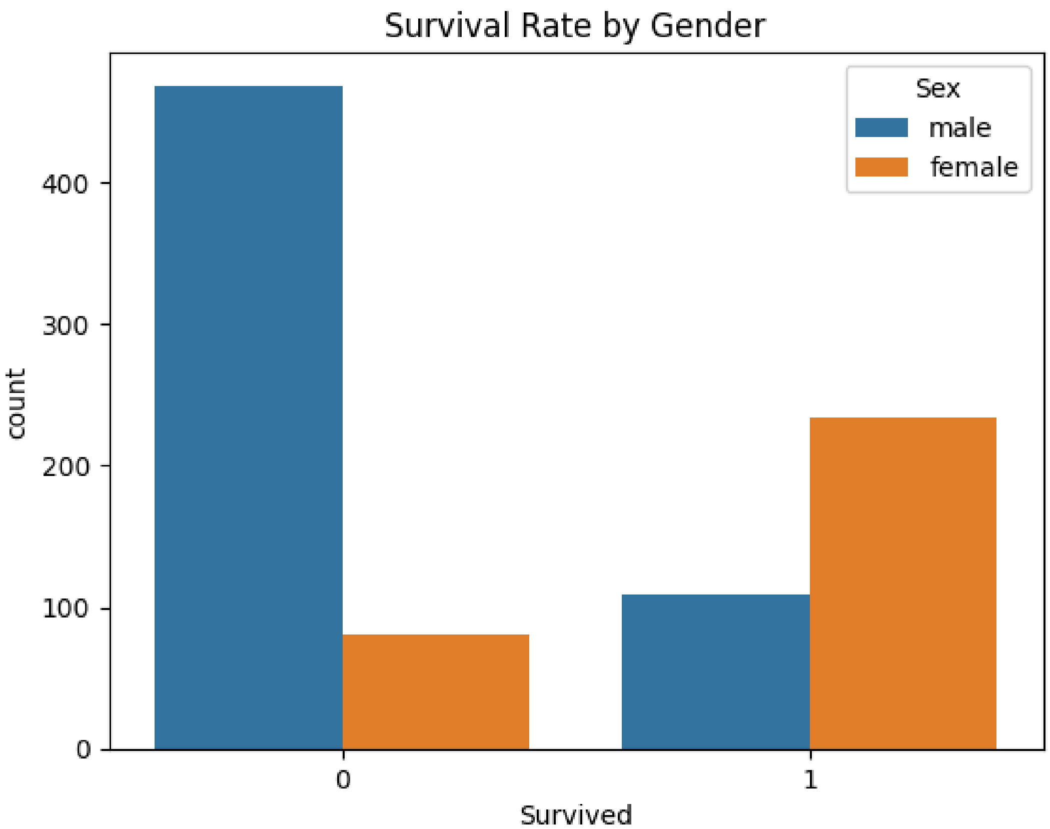
Observations on Age by Passenger Class:

- The **median age** of passengers in **1st class** is higher than in **2nd and 3rd classes**.
- The **interquartile range (IQR)** for age in **3rd class** is wider, meaning passengers in 3rd class span a broader age range.
- There are several **outliers** in **3rd class**, particularly among younger passengers, with ages below 10.
- **1st class** passengers are generally older, and **3rd class** passengers have a larger spread of ages, including more younger passengers.

```
df['Sex'].value_counts().plot(kind='bar')
plt.title("Count of Passengers by Gender")
plt.show()
```



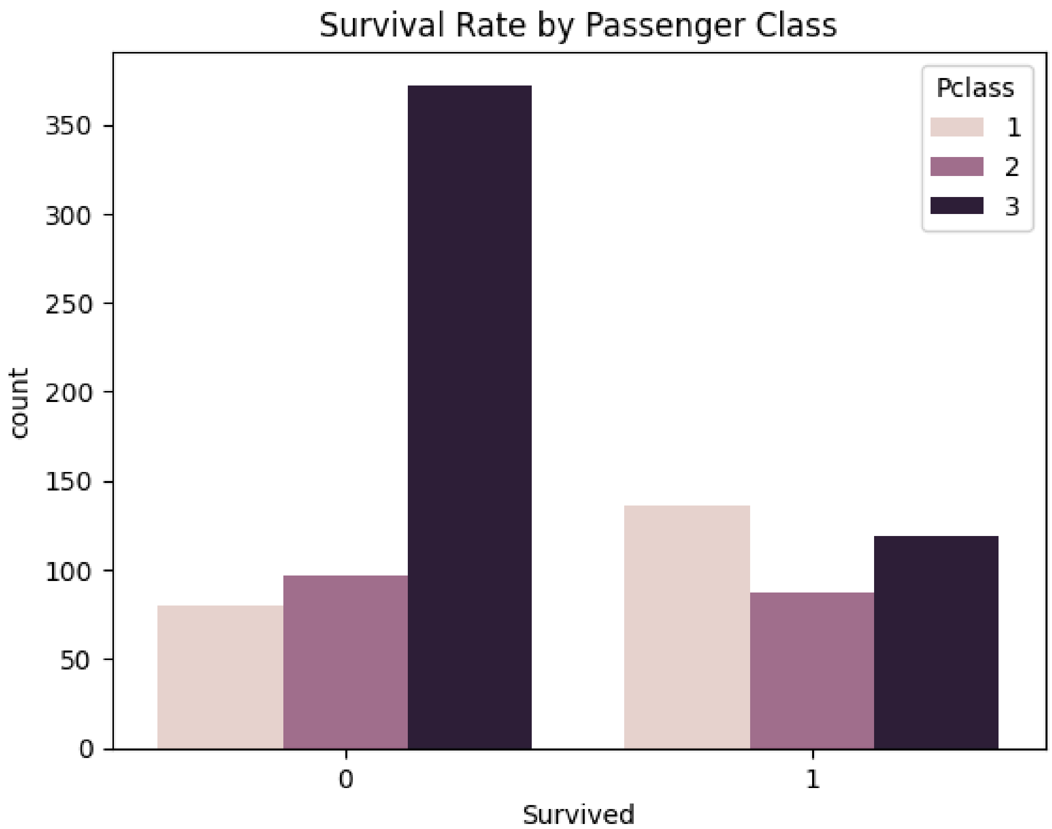

```
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title("Survival Rate by Gender")
plt.show()
```



Observations on Survival by Gender:

- **Females** had a significantly higher survival rate than **males**. The number of females who survived is clearly larger than the number of males who survived.
- The survival rate for **males** is much lower, with a large proportion of male passengers not surviving.
- This suggests that **gender may have played a role** in the survival chances of passengers, with women being prioritized for survival.

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



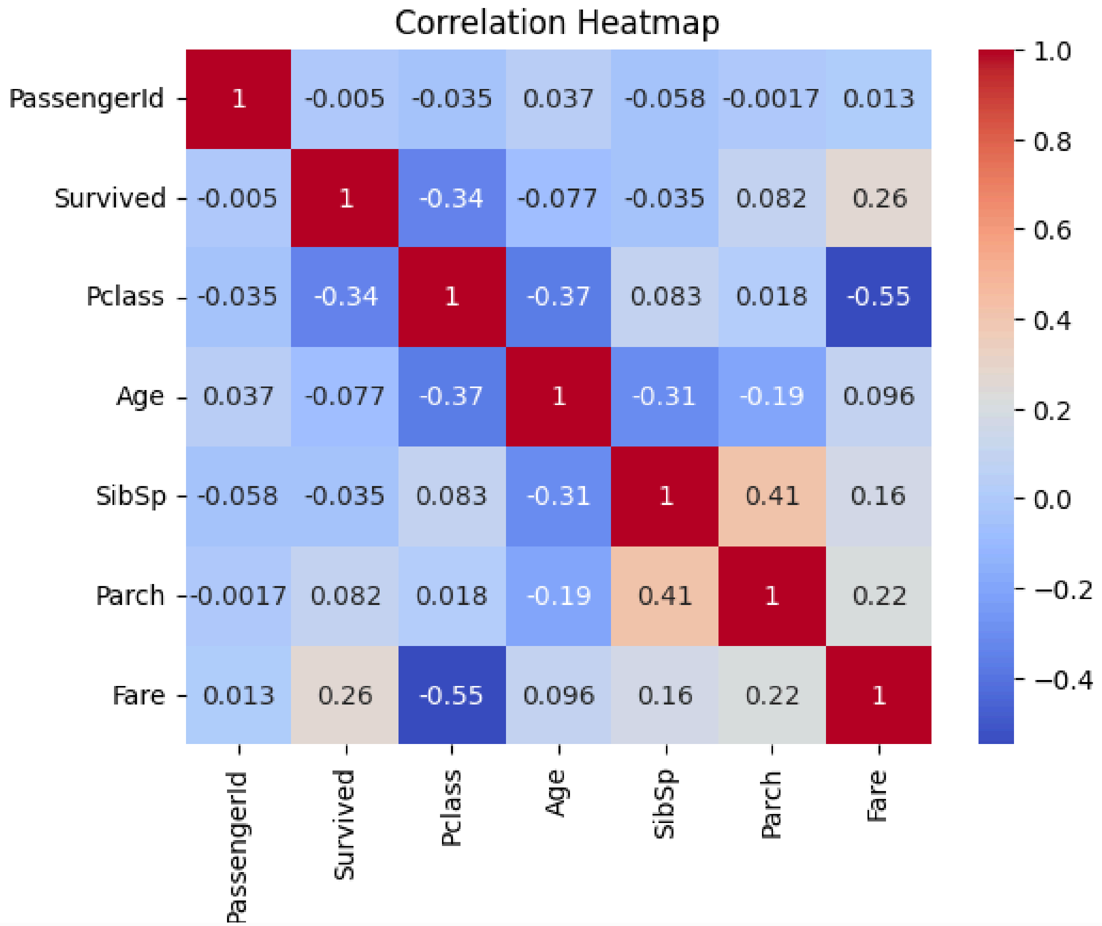
Observations on Survival by Passenger Class:

- **1st-class passengers** had the highest survival rate, with a much larger proportion of them surviving compared to **2nd** and **3rd-class passengers**.
- **3rd-class passengers** had the lowest survival rate, which may suggest the lack of resources or being located in lower decks.
- **2nd-class passengers** had a survival rate between the other two classes, though lower than 1st-class.

- This indicates that **passenger class** strongly influenced survival chances, with **higher-class passengers** being more likely to survive.

```
# Select only numeric columns
numeric_cols = df.select_dtypes(include=[np.number])

# Calculate the correlation matrix only for numeric columns
sns.heatmap(numeric_cols.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```

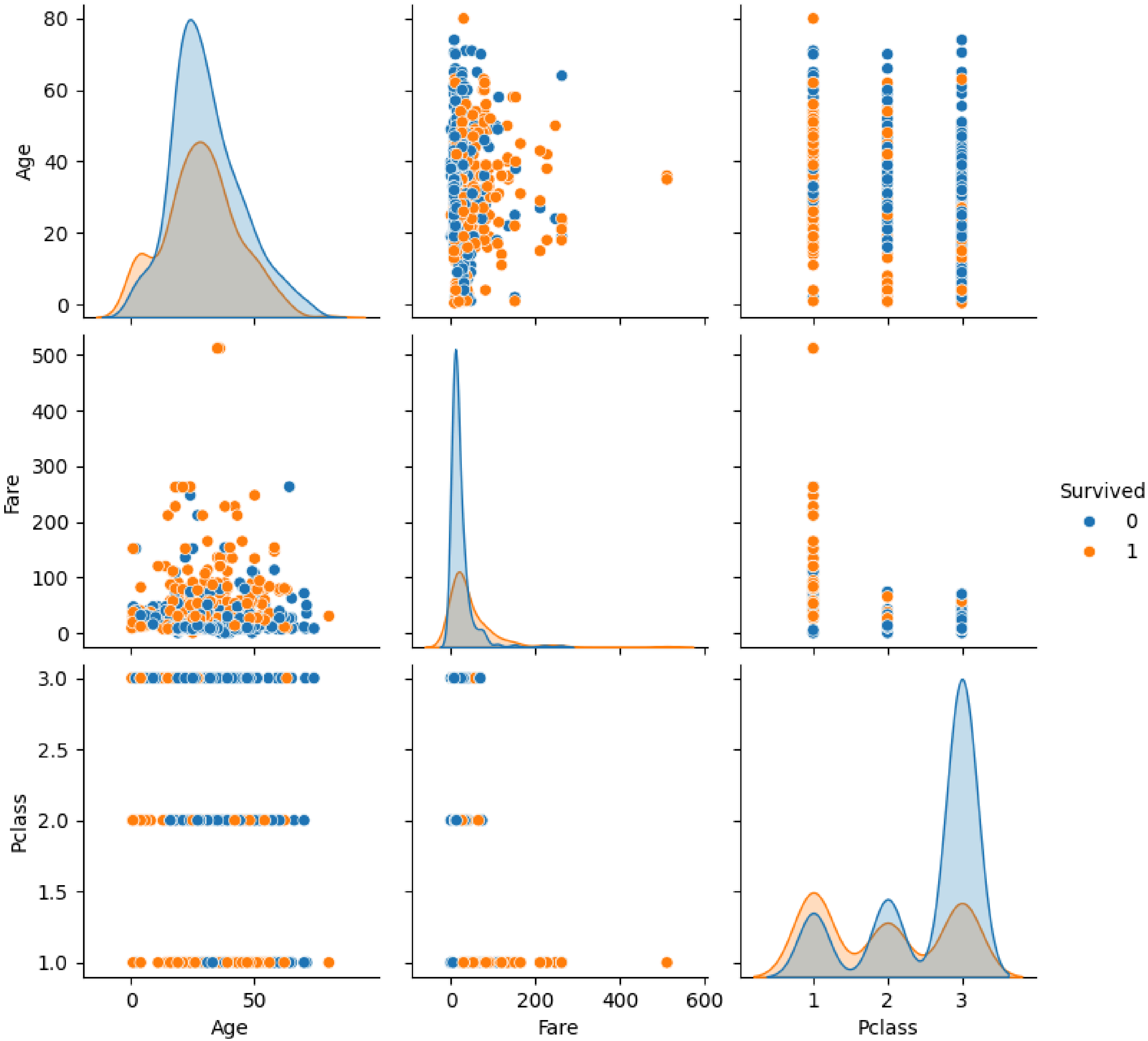


	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1	-0.005	-0.035	0.037	-0.058	-0.0017	0.013
Survived	-0.005	1	-0.34	-0.077	-0.035	0.082	0.26
Pclass	-0.035	-0.34	1	-0.37	0.083	0.018	-0.55
Age	0.037	-0.077	-0.37	1	-0.31	-0.19	0.096
SibSp	-0.058	-0.035	0.083	-0.31	1	0.41	0.16
Parch	-0.0017	0.082	0.018	-0.19	0.41	1	0.22
Fare	0.013	0.26	-0.55	0.096	0.16	0.22	1

Observations on Correlation Heatmap:

- There is a **strong negative correlation** between `Pclass` and `Fare` (r = -0.55). This suggests that passengers in **lower classes** (3rd class) paid **lower fares**, while passengers in **higher classes** (1st class) paid significantly more for their tickets.
- **Survived** is negatively correlated with `Pclass` (r = -0.34), indicating that passengers in **higher classes** had a better chance of survival.
- The correlation between `Age` and `Fare` is very **weak** (r = 0.09), suggesting that there is no strong relationship between passengers' ages and the fare they paid.
- **Fare** has a slightly **positive correlation** with `Age` (r = 0.1), meaning that older passengers tend to have slightly higher fares, but the correlation is not very strong.
- The correlation between `Age` and `Survived` is almost non-existent, indicating **age** had a weaker effect on **survival** compared to **class** and **gender**.

```
sns.pairplot(df[['Survived', 'Age', 'Fare', 'Pclass']], hue='Survived')
plt.show()
```


80
60
40
20
0
Age
500
400
300
200
100
0
Fare
3.0
2.5
2.0
1.5
1.0
Pclass
0
50
Age
0
200
400
600
Fare
1
2
3
Pclass
Survived
0
1

Observations on Pairplot (Survival, Age, Fare, Pclass):

- There is a clear separation between **survived and not survived** passengers. Those who survived (marked in blue) tend to be in **higher classes** (Pclass 1) and **tend to be younger** compared to those who did not survive.