Task 5: Exploratory Data Analysis (EDA)

Objective: Extract insights using visual and statistical exploration.

Dataset Used: Titanic Dataset

Step 1: Import Libraries

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

Step 2: Data Loading & Initial Checks

In [2]:
```
df = pd.read_csv('Titanic.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Survived
0	1	3	Allison Hill	male	17	4	2	43d75413-a939-4bd1-a516-b0d47d3572cc	144.08	Q	1
1	2	1	Noah Rhodes	male	60	2	2	6334fa2a-8b4b-47e7-a451-5ae01754bf08	249.04	S	0
2	3	3	Angie Henderson	male	64	0	0	61a66444-e2af-4629-9efb-336e2f546033	50.31	Q	1
3	4	3	Daniel Wagner	male	35	4	0	0b6c03c8-721e-4419-afc3-e6495e911b91	235.20	C	1
4	5	1	Cristian Santos	female	70	0	3	436e3c49-770e-49db-b092-d40143675d58	160.17	C	1

a. Use .describe(), .info(), .value_counts()

In [4]:
```
print("Basic Statistics:")
df.describe()
```

```
Basic Statistics:
```

Out[4]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare	Survived
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	500.500000	1.964000	38.458000	2.032000	2.005000	247.968650	0.492000
std	288.819436	0.820596	23.103723	1.424431	1.410306	139.301211	0.500186
min	1.000000	1.000000	1.000000	0.000000	0.000000	10.020000	0.000000
25%	250.750000	1.000000	19.000000	1.000000	1.000000	126.295000	0.000000
50%	500.500000	2.000000	36.500000	2.000000	2.000000	246.500000	0.000000
75%	750.250000	3.000000	59.000000	3.000000	3.000000	365.662500	1.000000
max	1000.000000	3.000000	79.000000	4.000000	4.000000	499.780000	1.000000

Observation: Basic Statistics (Summary Table)

- Average passenger age is around 38 years, and the average fare paid is about ₹248.
- Most passengers belonged to Pclass 1 or 2, and the survival rate is close to 49%.
- Fare and age show wide variation (high standard deviation), while family members onboard (SibSp, Parch) mostly range between 0 and 4.

In [5]:
```python
print("Dataset Info:")
df.info()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  1000 non-null   int64
 1   Pclass       1000 non-null   int64
 2   Name         1000 non-null   object
 3   Sex          1000 non-null   object
 4   Age          1000 non-null   int64
 5   SibSp        1000 non-null   int64
 6   Parch        1000 non-null   int64
 7   Ticket       1000 non-null   object
 8   Fare         1000 non-null   float64
 9   Embarked     1000 non-null   object
 10  Survived     1000 non-null   int64
dtypes: float64(1), int64(6), object(4)
memory usage: 86.1+ KB
```

Observation: Dataset Info (Structure Overview)

- The dataset contains 1000 entries and 11 columns with no missing values.
- Features include a mix of numerical (int, float) and categorical (object) types.
- Major numerical columns are PassengerId, Pclass, Age, SibSp, Parch, Fare, Survived, while Name, Sex, Ticket, and Embarked are categorical.

In [6]:
```python
print("Categorical Value Counts:")
print("\n", df['Embarked'].value_counts(), sep='\n')
print("\n", df['Sex'].value_counts(), sep='\n')
```

```
Categorical Value Counts:


Embarked
Q    362
C    328
S    310
Name: count, dtype: int64


Sex
male      527
female    473
Name: count, dtype: int64
```

Observation: Categorical Value Counts

- Gender: Slightly more males (527) than females (473).
- Embarked: Most passengers boarded at Queenstown (Q: 362).

In [7]:
```python
# Check missing values
df.isnull().sum()
```

Out[7]:
```
PassengerId    0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
Survived       0
dtype: int64
```

In [8]:
```python
# Drop unncessary columns
df = df.drop(['PassengerId', 'Name', 'Ticket'], axis=1)
```

In [9]:
```
df.head()
```

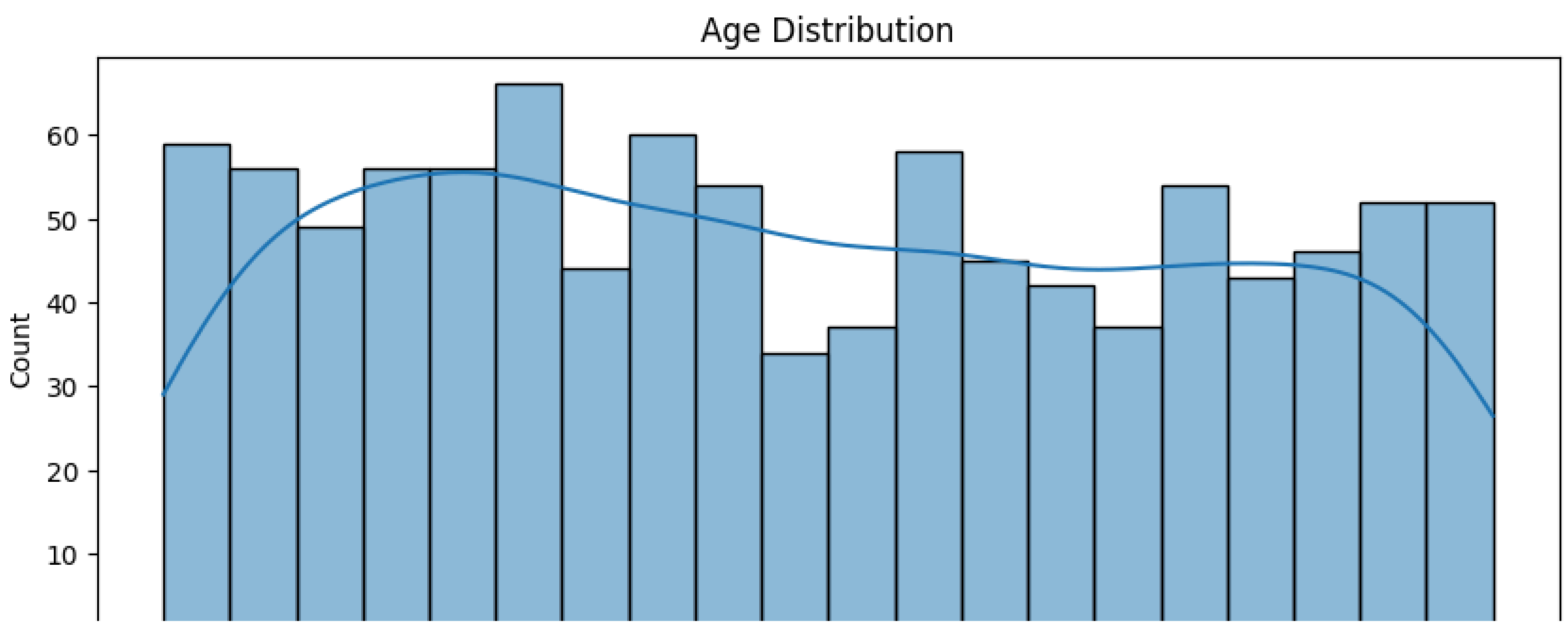
Out[9]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Survived
0	3	male	17	4	2	144.08	Q	1
1	1	male	60	2	2	249.04	S	0
2	3	male	64	0	0	50.31	Q	1
3	3	male	35	4	0	235.20	C	1
4	1	female	70	0	3	160.17	C	1

Step 3: Univariate Analysis

d. Plot histograms, boxplots, Scatter Plot

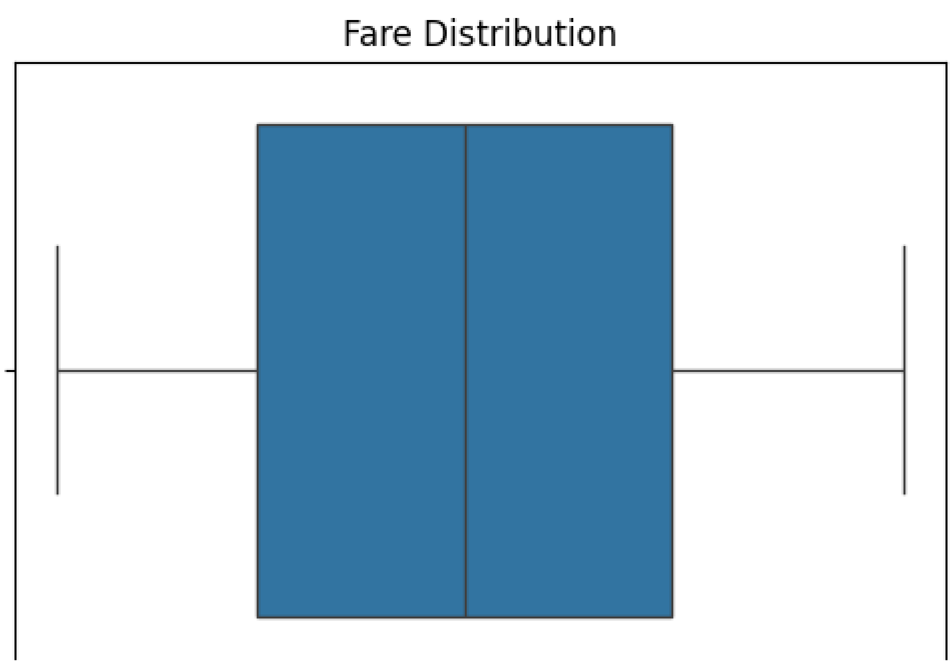
In [10]:
```
# Age Distribution (Histogram)
plt.figure(figsize=(10,4))
sns.histplot(df['Age'], bins=20, kde=True)
plt.title('Age Distribution')
plt.show()
```



Observation: Age Distribution (Histogram with KDE Line)

- The age distribution is fairly uniform across different age groups, with slight peaks around 0–10 years, 20–30 years, and 60–70 years.
- The density curve shows mild fluctuations but no sharp skew — indicating a balanced presence of young, middle-aged, and elderly passengers.

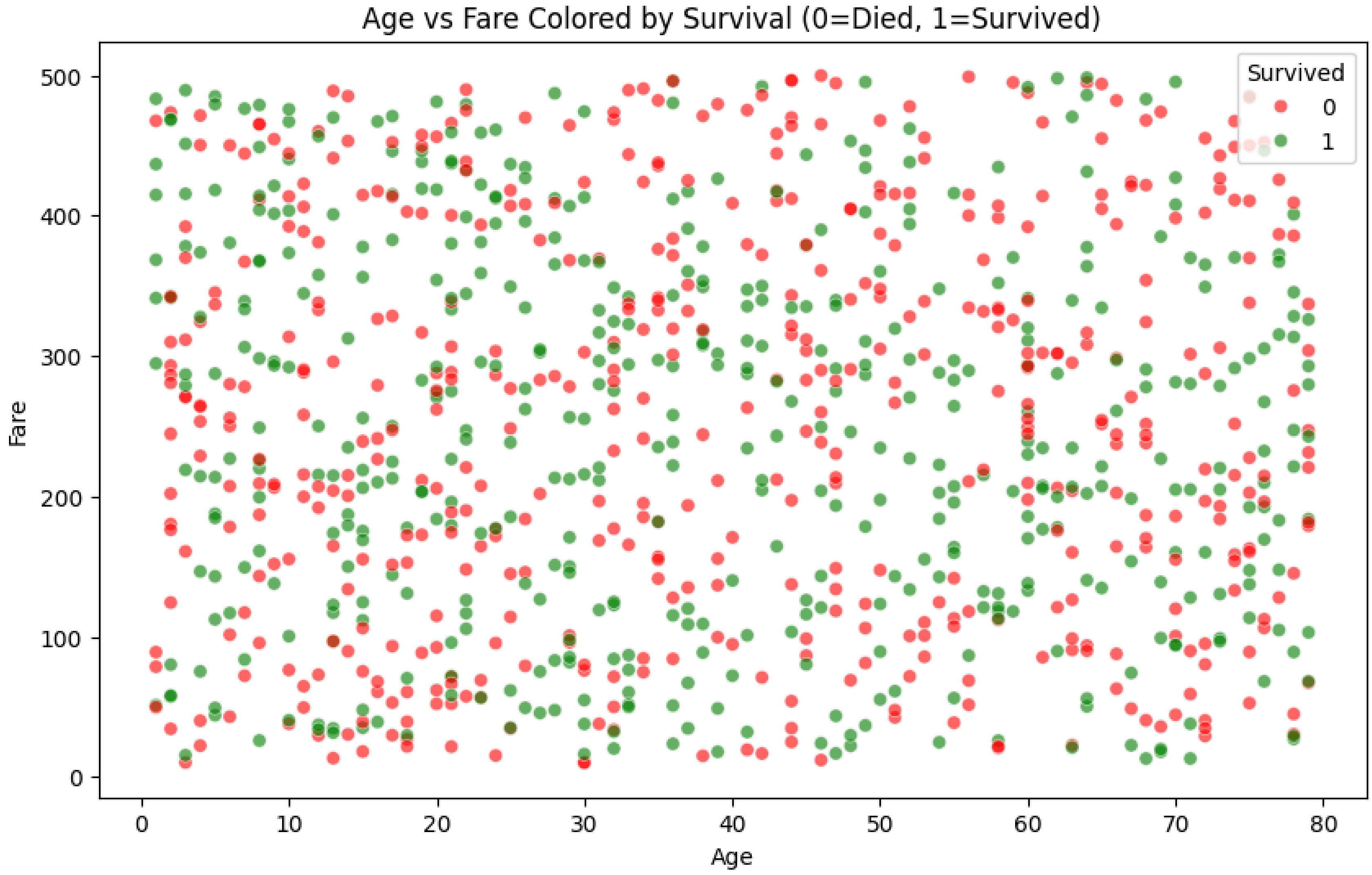
In [11]:
```
# Fare Distribution (Boxplot)
plt.figure(figsize=(6,4))
sns.boxplot(x=df['Fare'])
plt.title('Fare Distribution')
plt.show()
```



Observation: Fare Distribution (Boxplot)

- Fare values are widely spread between around ₹10 and ₹500.
- The median fare is close to ₹250, indicating many passengers paid moderate fares.
- No major outliers are visible, suggesting a fairly even distribution of ticket prices within the dataset.

In [12]:
```python
# Scatter Plot (Age vs Fare with Survival Hue)
plt.figure(figsize=(10,6))
sns.scatterplot(x='Age', y='Fare', hue='Survived',
                data=df, palette={0:'red', 1:'green'}, alpha=0.6)
plt.title('Age vs Fare Colored by Survival (0=Died, 1=Survived)')
plt.legend(title='Survived')
plt.show()
```



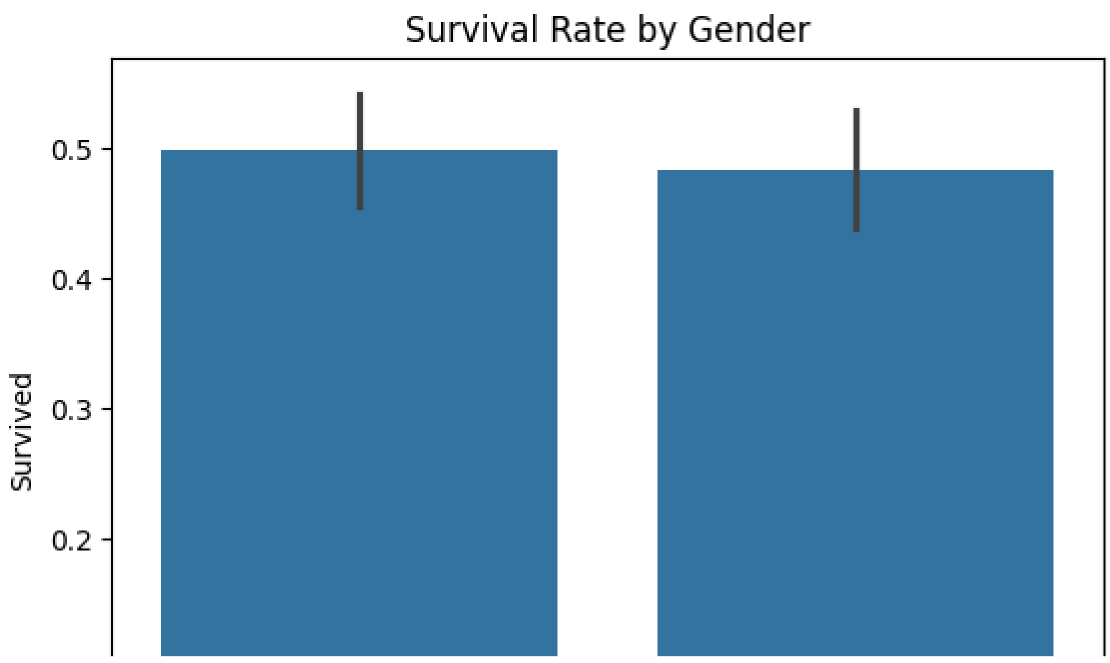
Observation: Scatter Plot (Age vs Fare Colored by Survival)

- Survivors (green) are relatively more concentrated in higher fare ranges.
- Non-survivors (red) are more evenly spread across all fare and age groups.
- Fare, rather than age, shows a stronger link to survival chances.

Step 4: Bivariate Analysis

c. Identify relationships and trends

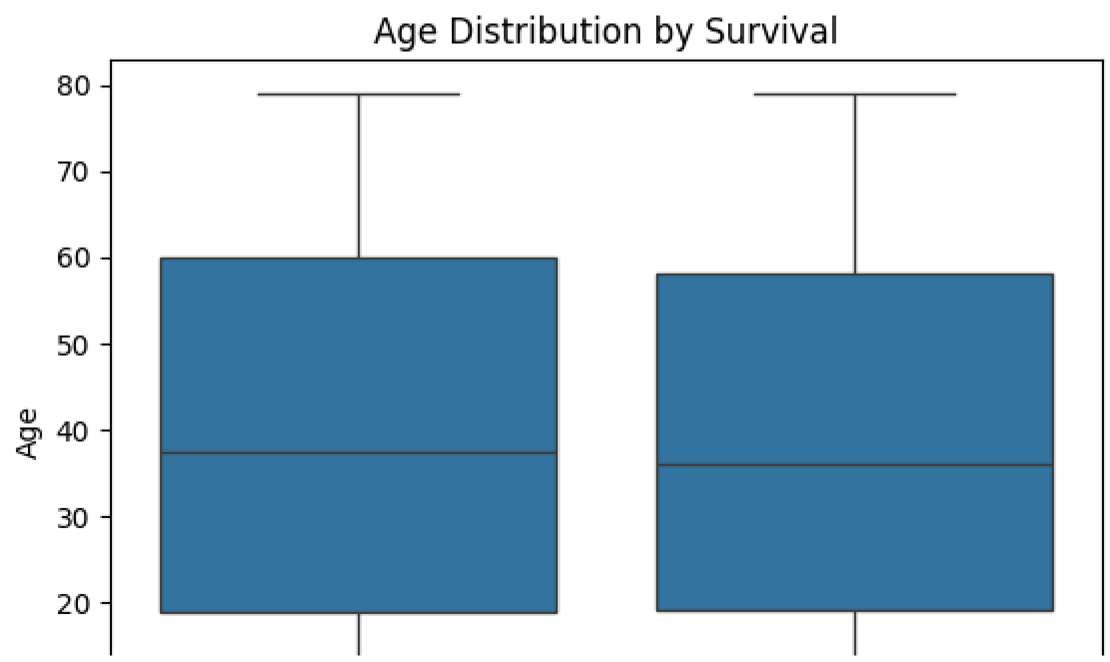
In [13]:
```python
# Survival vs Sex (Barplot)
sns.barplot(x='Sex', y='Survived', data=df)
plt.title('Survival Rate by Gender')
plt.show()
```



Observation: Survival Rate by Gender (Bar Plot)

- Male and female survival rates are very close, around 50% each.
- Slightly higher survival observed for males in this dataset, which is unusual compared to typical Titanic datasets.

In [14]:
```python
# Age vs Survival (Boxplot)
sns.boxplot(x='Survived', y='Age', data=df)
plt.title('Age Distribution by Survival')
plt.show()
```



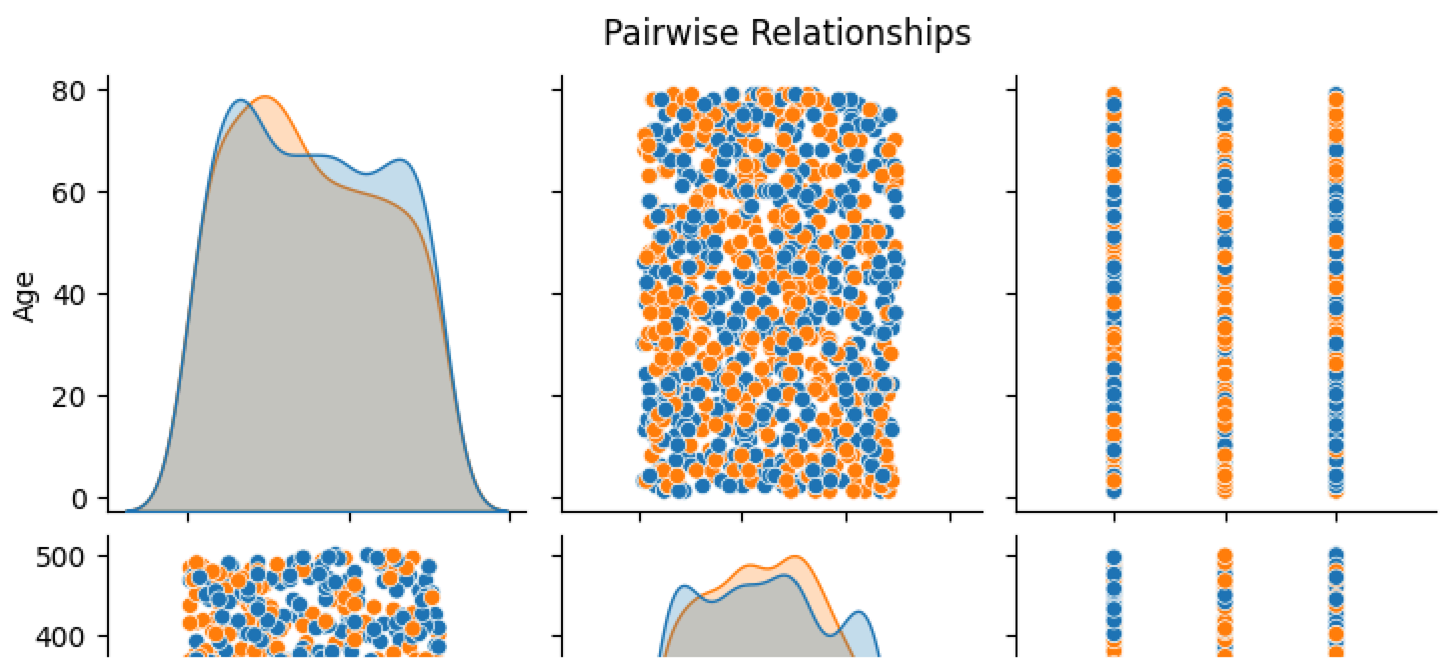
Observation: Age Distribution by Survival (Boxplot)

- Age distributions for survivors and non-survivors are very similar, covering a wide range (0–79 years).
- Median age of survivors is slightly lower than that of non-survivors, suggesting younger passengers had a small advantage in survival.

Step 5: Multivariate Analysis

b. Use sns.pairplot(), sns.heatmap()

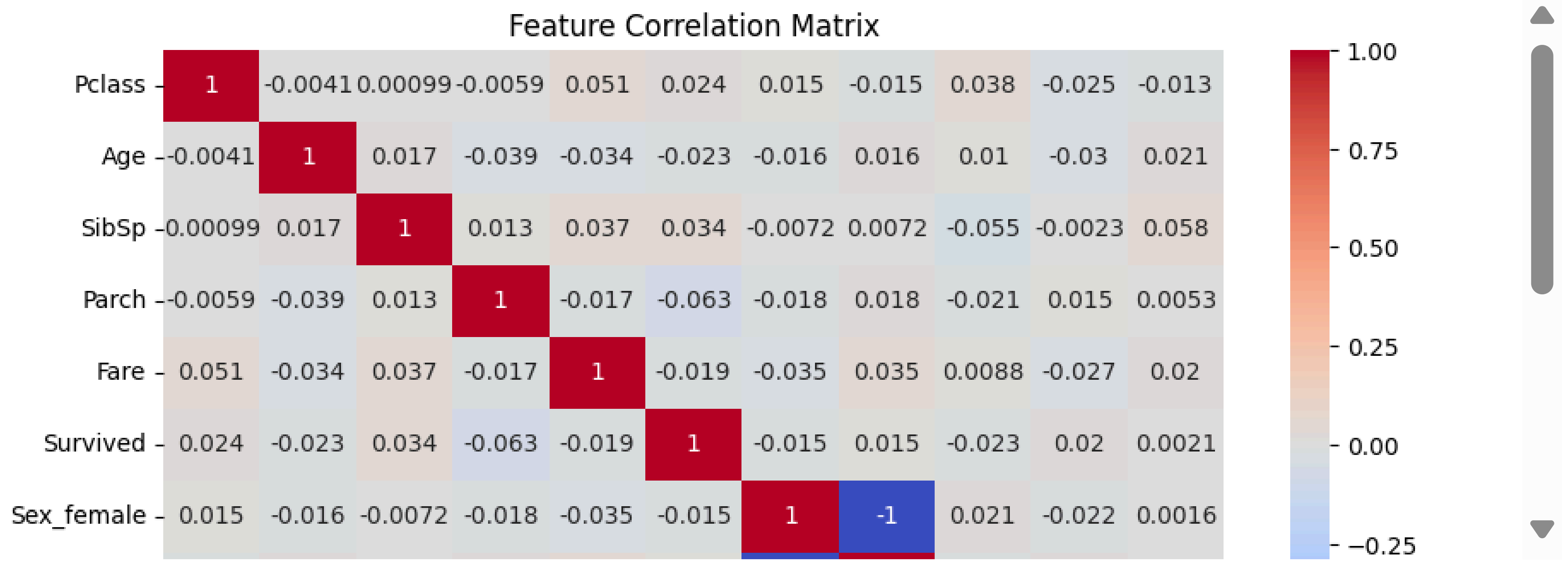
In [15]:
```python
# Pairplot for numerical features
sns.pairplot(df, vars=['Age', 'Fare', 'Pclass'], hue='Survived')
plt.suptitle('Pairwise Relationships', y=1.02)
plt.show()
```



Observation: Pairwise Relationships (Pairplot)

- Survivors (orange) are more frequent among lower Pclass (1st class) and higher fare groups.
- Age shows no strong separation between survived and non-survived.
- Pclass and Fare together show a clearer trend: higher class and higher fare passengers had better survival chances.

In [16]:
```python
# Correlation Heatmap
plt.figure(figsize=(10,6))
sns.heatmap(pd.get_dummies(df, columns=['Sex', 'Embarked']).corr(),
            annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Feature Correlation Matrix')
plt.show()
```



Observation: Feature Correlation Matrix (Heatmap)

- Features have very weak correlations overall with survival.
- Sex_female shows a positive link to survival, and Sex_male shows a negative link (perfect opposites).
- Strong negative correlations observed between different Embarked categories due to one-hot encoding.