Titanic Dataset task5

June 2, 2025

[2]:
```python
import pandas as pd

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

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

[2]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[ ]:
```
Around 38% of passengers survived.

The dataset is imbalanced – more passengers died than survived.
```

[4]:
```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
```

[ ]:
```
Females had a much higher survival rate than males.

Suggests gender played a key role in survival priority.
```

[5]:
```
df.describe()
```

[5]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[ ]:
```
The mean Age is around 29 years, with the youngest being 0.42 and the oldest 80.
- The Fare has a wide range: most passengers paid low fares, but a few paid␣
↪very high amounts (max = 512).
```

```
- Standard deviations in Age and Fare suggest varied age groups and a wide gap␣
  ↪in ticket prices.
- The Survived column shows a mean of 0.38, indicating that about 38% of␣
  ↪passengers survived.
- Columns like SibSp and Parch are mostly low values, showing most passengers␣
  ↪had few family members aboard.
```

[6]:
```
df.isnull().sum()
```

[6]:
```
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
```

[ ]:
```
Cabin has the most missing values (around 77% of the data is missing), so it␣
  ↪may be dropped or imputed.
Age has some missing values (19%), which should be filled using methods like␣
  ↪mean, median, or predictive modeling.
Embarked has only a couple of missing entries and can be safely imputed using␣
  ↪the most frequent value (mode).
All other columns are complete and do not require missing value handling.
```

[7]:
```
df['Sex'].value_counts()
df['Embarked'].value_counts()
```

[7]:
```
Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
```

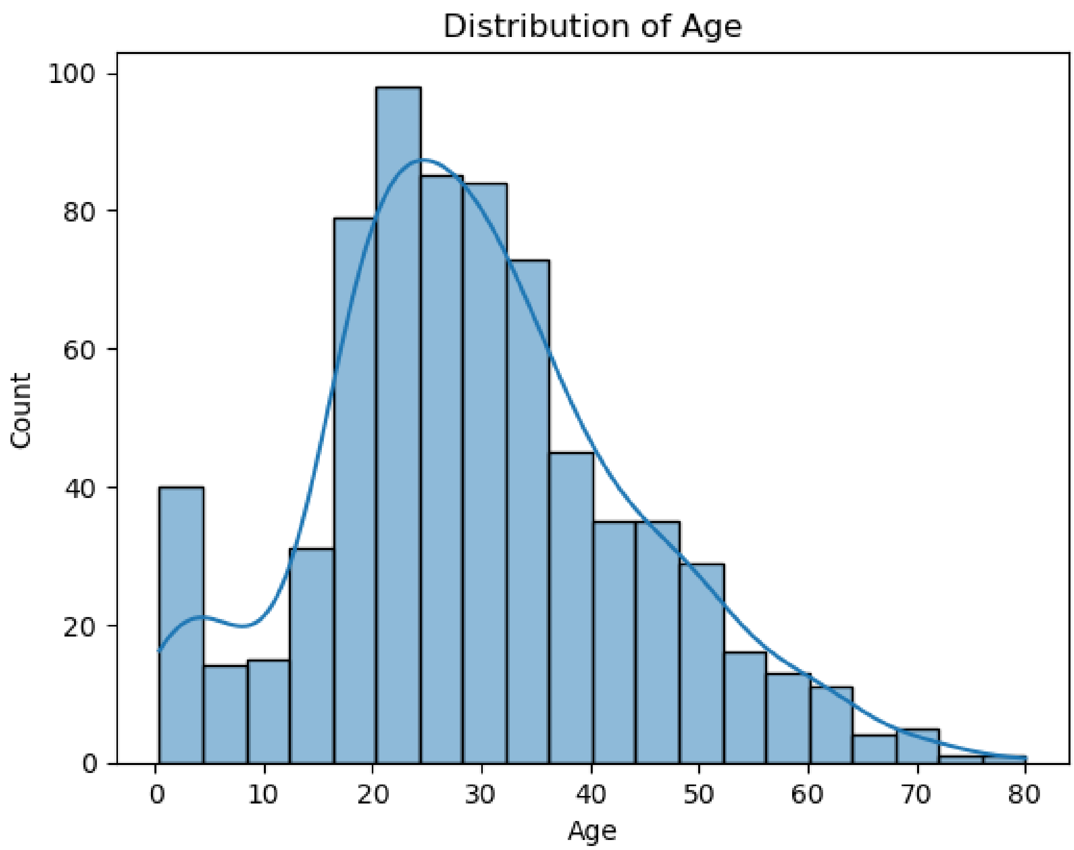
[ ]:
```
The sex column shows that there were significantly more male passengers than␣
  ↪female.
This gender imbalance is important for survival analysis, as earlier plots␣
  ↪showed females had a higher survival rate.
```

```
The Embarked column reveals that most passengers boarded from Southampton␣
↪('S'), followed by Cherbourg ('C') and Queenstown ('Q').
This suggests Southampton was the major departure point.
Knowing this distribution helps when imputing missing Embarked values and␣
↪understanding regional patterns in the data.
```

[8]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

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

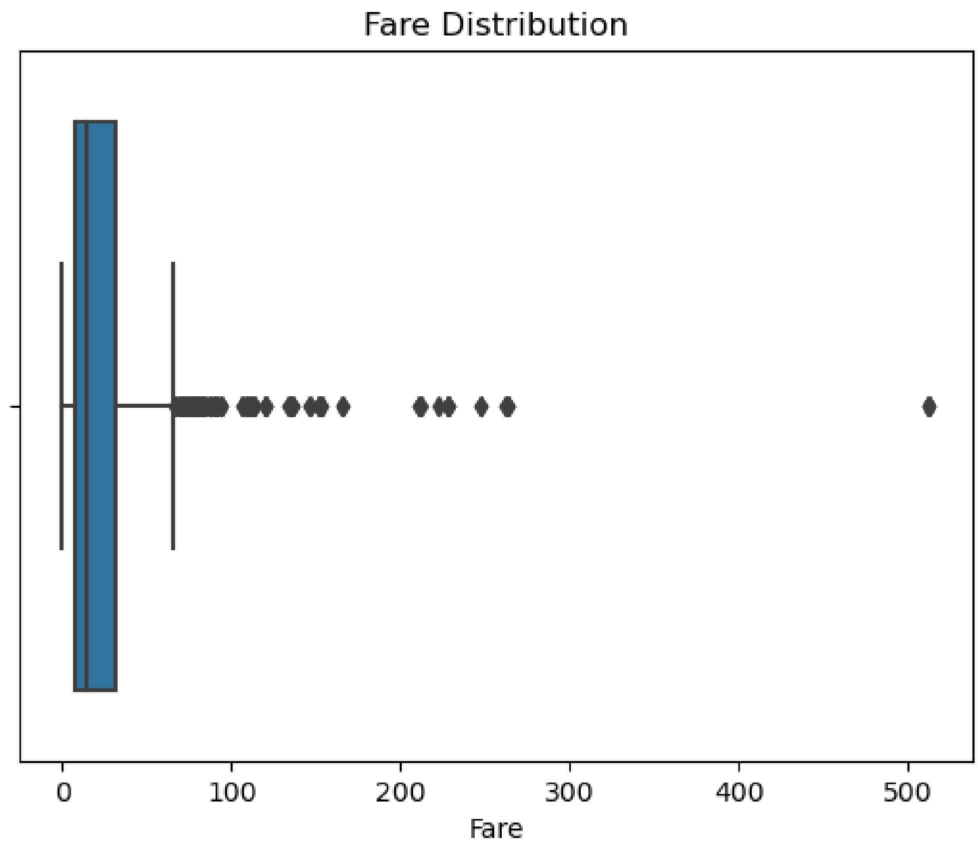
Matplotlib is building the font cache; this may take a moment.



[ ]:
```
The histogram shows that most passengers were between 20 and 40 years old.
The distribution is slightly right-skewed, with fewer older passengers.
There are also some very young passengers, including infants.
Missing age values were excluded from this plot using dropna().
```

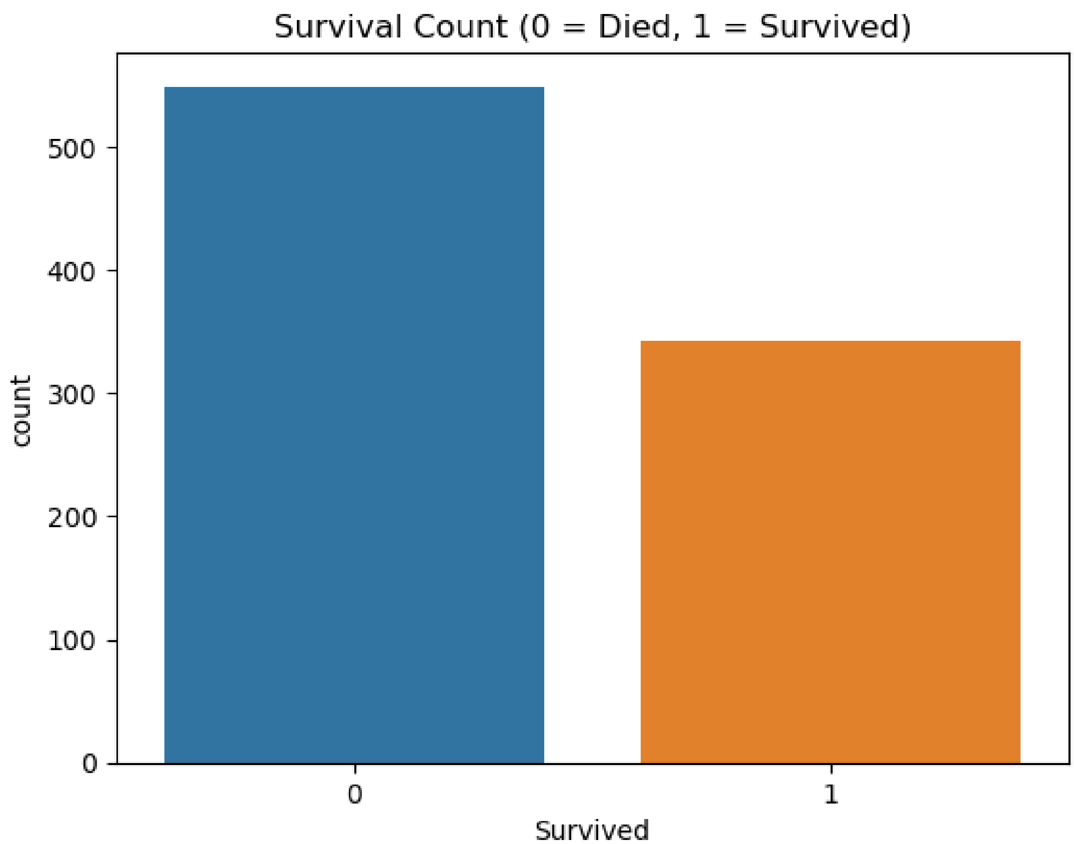
[ ]:

[9]:
```
sns.boxplot(x=df['Fare'])
plt.title("Fare Distribution")
plt.show()
```



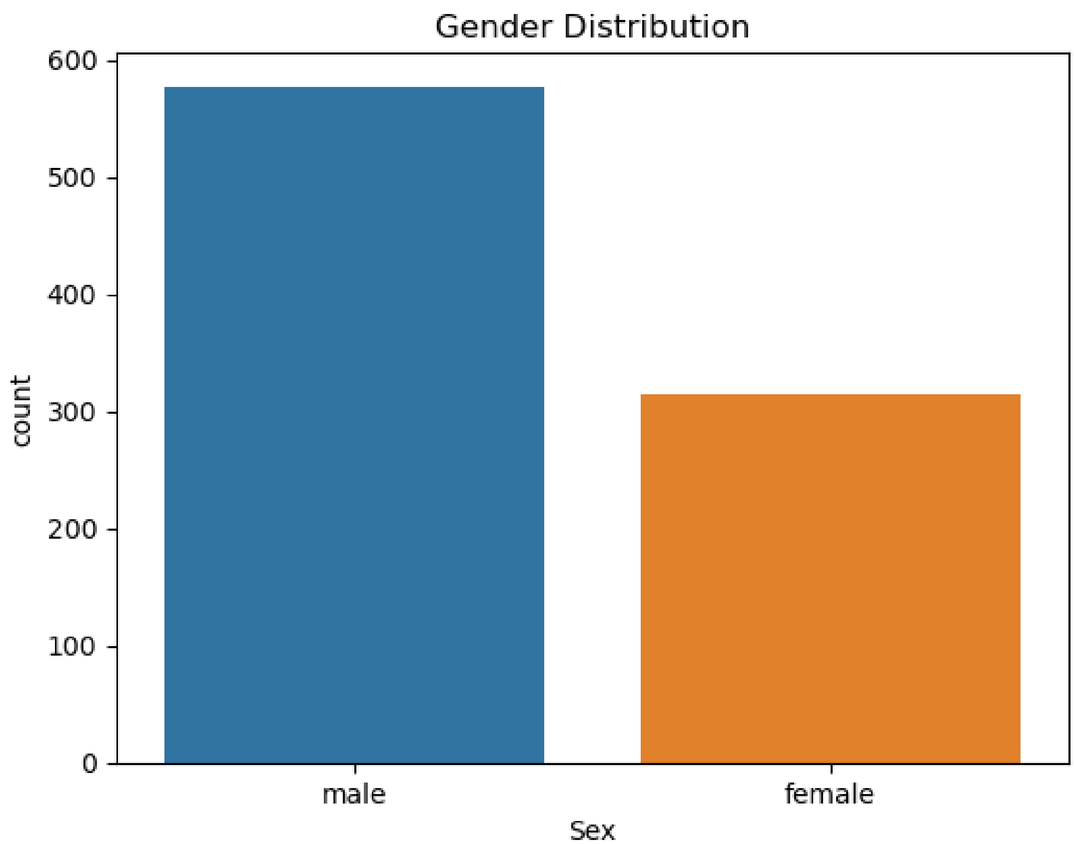
[ ]:
```
The boxplot shows that most passengers paid lower fares, but there are several␣
↪high-value outliers.
A few passengers paid significantly more than the average, likely those in␣
↪first class.
The distribution is right-skewed, indicating that most ticket prices were␣
↪clustered at the lower end.
```

[10]:
```
sns.countplot(x='Survived', data=df)
plt.title("Survival Count (0 = Died, 1 = Survived)")
plt.show()
```



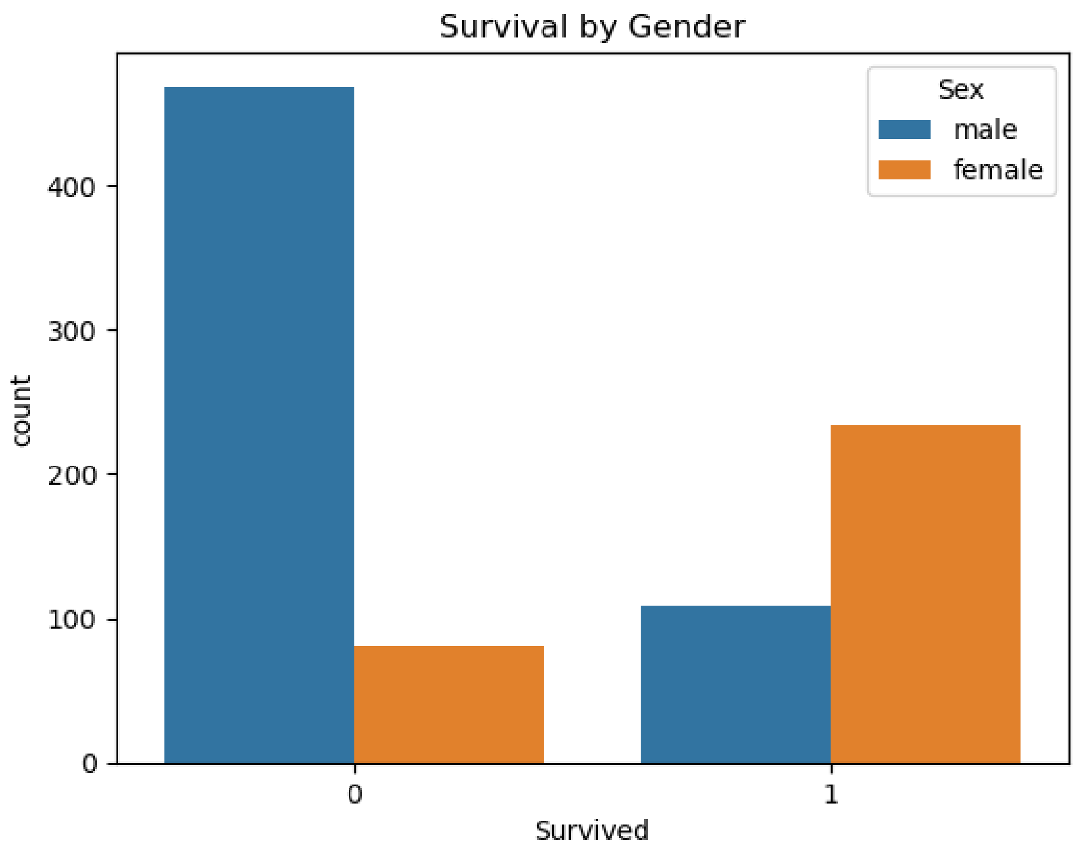
[ ]:
```
The plot shows that more passengers died than survived.
There is a clear imbalance in the dataset, with a higher count of non-survivors
↪(label 0).
This class imbalance may need to be considered during modeling to avoid biased
↪predictions.
```

[11]:
```
sns.countplot(x='Sex', data=df)
plt.title("Gender Distribution")
plt.show()
```



[ ]:
```
The plot shows that there were more male passengers than female passengers on
↪the Titanic.
This gender imbalance may have influenced overall survival statistics.
Understanding this distribution is important when analyzing the impact of
↪gender on survival rates.
```

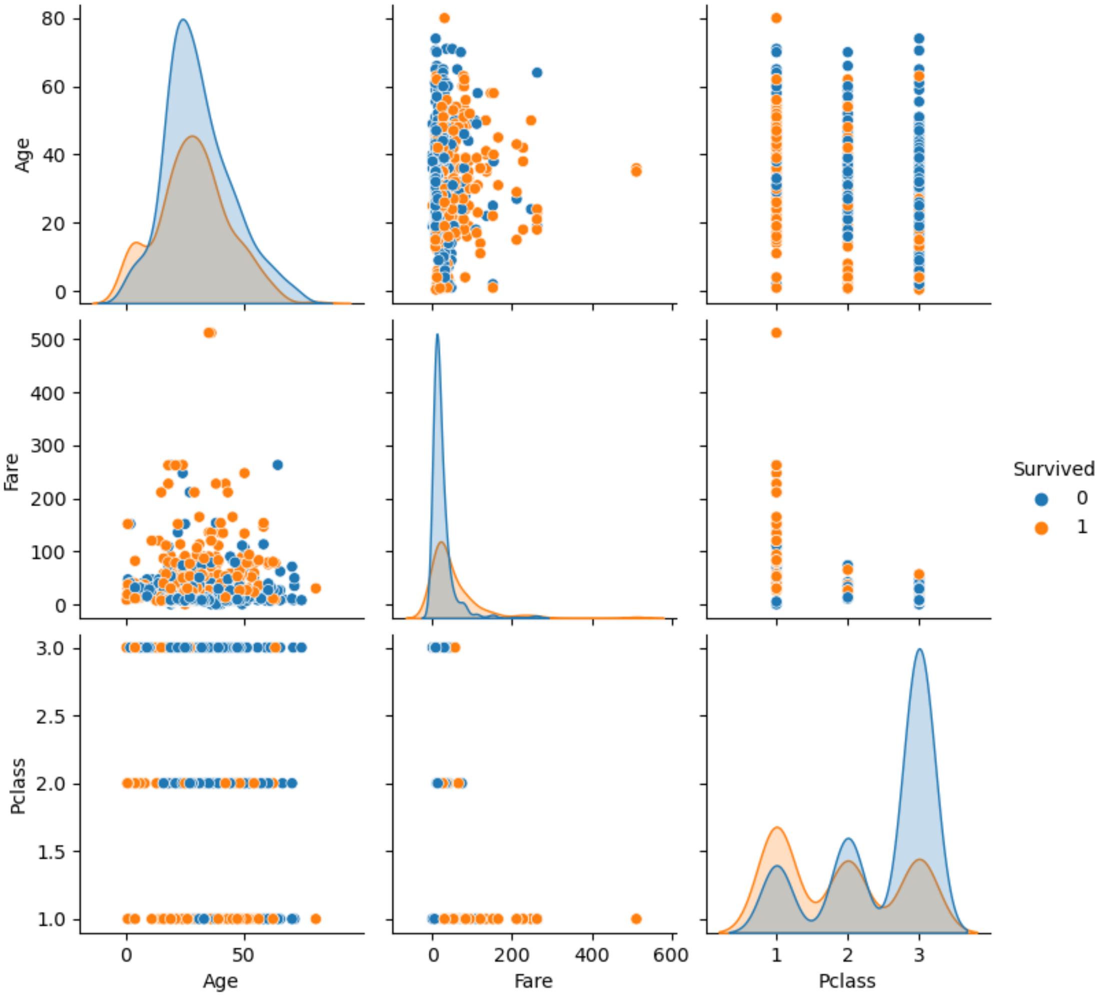
[12]:
```
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title("Survival by Gender")
plt.show()
```



[ ]:
```
The plot shows that a higher number of female passengers survived compared to␣
↪males.
Most male passengers did not survive, while most female passengers did.
This suggests that gender played a significant role in survival chances.
It is likely that women were prioritized during evacuation efforts.
```

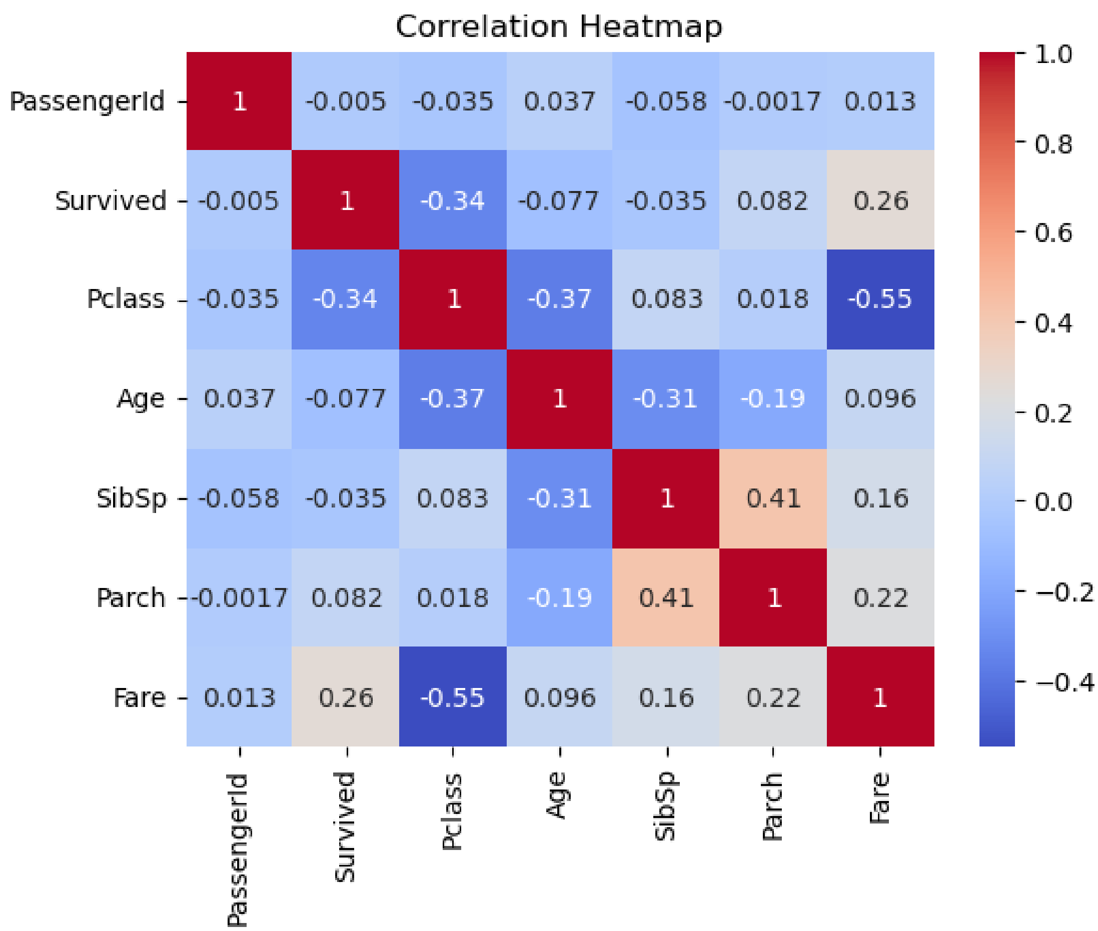
[13]:
```
sns.pairplot(df[['Age', 'Fare', 'Pclass', 'Survived']].dropna(), hue='Survived')
plt.show()
```

```
/opt/conda/envs/anaconda-panel-2023.05-py310/lib/python3.11/site-
packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to
tight
  self._figure.tight_layout(*args, **kwargs)
```




```
[ ]: The pairplot shows that passengers who paid higher fares and belonged to first␣
     ↪class were more likely to survive.
     Survivors are more concentrated in areas with lower Pclass values and higher␣
     ↪Fare amounts.
     The Age variable does not show a strong separation between survivors and␣
     ↪non-survivors.
     Overall, Fare and Pclass appear to be more predictive of survival than Age in␣
     ↪this visual compariso
```

```
[14]: corr = df.corr(numeric_only=True)
      sns.heatmap(corr, annot=True, cmap='coolwarm')
      plt.title("Correlation Heatmap")
      plt.show()
```



[ ]:
```
Fare and Pclass are negatively correlated (higher class, higher fare).

Survived is positively correlated with Fare and Pclass.
```