In [3]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
```

In [4]:
```python
df = pd.read_csv("train.csv")    # or your dataset name
df.head()
```

Out[4]:

	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

In [5]:
```python
df.shape
```

Out[5]:
```
(891, 12)
```

In [6]:
```python
df.columns
```

Out[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [7]:
```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
```

In [15]:
```python
df.isnull().sum()
```

Out[15]:
```
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
```

In [16]:
```python
df.describe()
```

Out[16]:

	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

In [17]:
```python
df['Sex'].value_counts()
```

Out[17]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

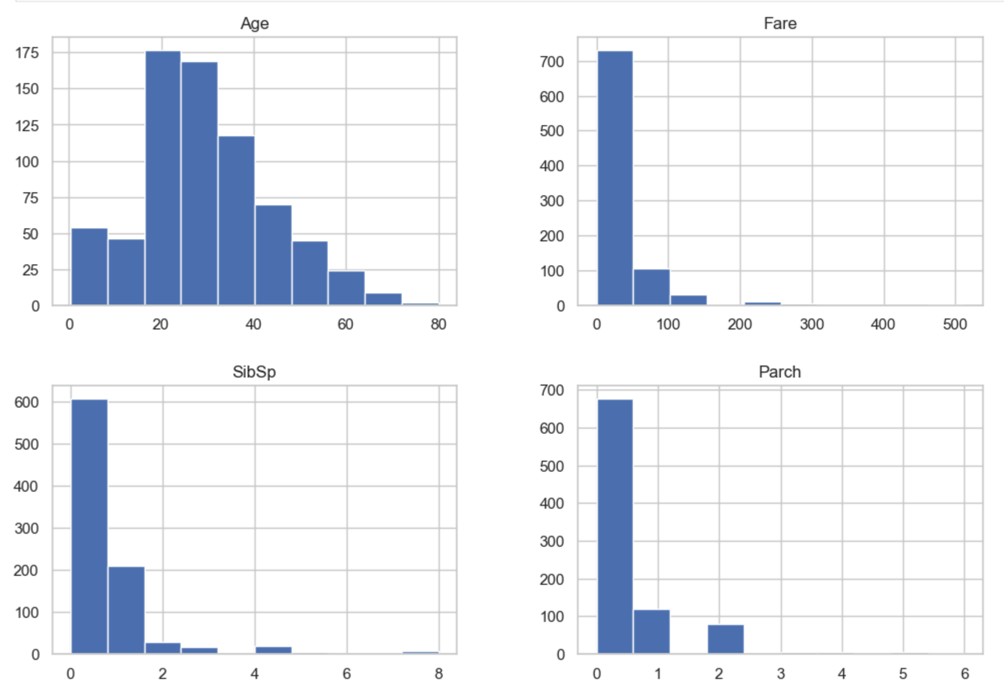
In [18]:
```python
df['Embarked'].value_counts()
```

Out[18]:
```
Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
```

In [19]:
```python
df['Pclass'].value_counts()
```

Out[19]:
```
Pclass
3    491
1    216
2    184
Name: count, dtype: int64
```

In [20]:
```python
df[['Age','Fare','SibSp','Parch']].hist(figsize=(12,8))
plt.show()
```



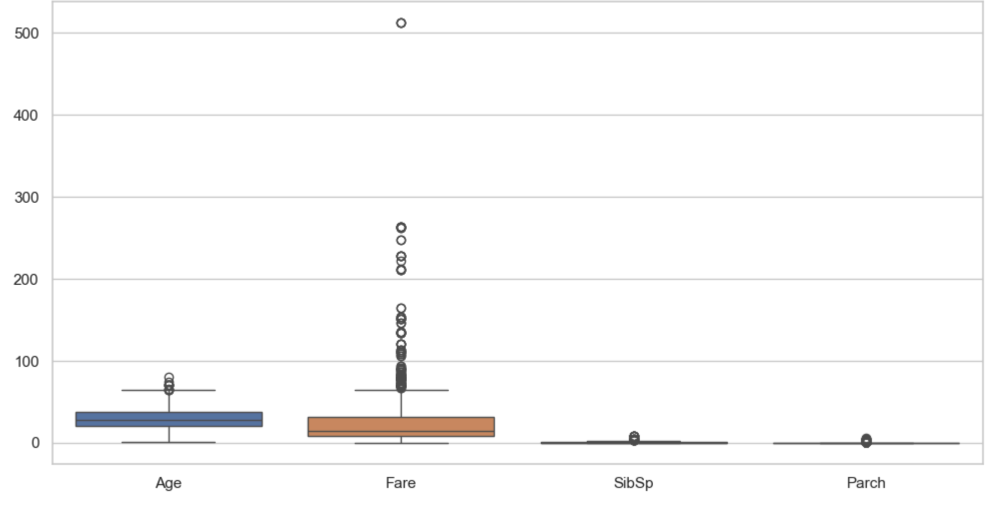
In [ ]:
```python
# - Histogram Observations — Age, Fare, SibSp, Parch
# 1) Age :
# Most passengers are between 20–40 years old.
# Very few children and elderly passengers.
# Missing values exist, which is typical for Titanic data.

# 2) Fare :
# Highly right-skewed distribution.
# Majority paid less than 100.
# A few very high fares indicate 1st class luxury tickets.

# 3) SibSp :
# Most passengers traveled alone or with 1 sibling/spouse.
# Very few had more than 3.

# 4) Parch :
# Most passengers traveled without parents/children.
# Some traveled with small families but rare.
```

In [21]:
```python
plt.figure(figsize=(12,6))
sns.boxplot(data=df[['Age','Fare','SibSp','Parch']])
plt.show()
```

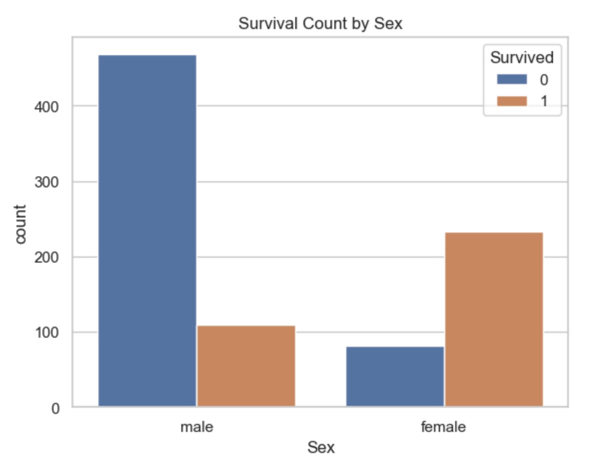


In [ ]:
```python
# - Boxplot Observations — Age, Fare, SibSp, Parch

# 1) Fare has many outliers → first-class passengers.
# 2) Age shows moderate outliers (infants + elderly).
# 3) SibSp and Parch are heavily skewed → most values are near 0.
```

In [22]:
```python
sns.countplot(data=df, x='Sex', hue='Survived')
plt.title("Survival Count by Sex")
```

Out[22]:
```
Text(0.5, 1.0, 'Survival Count by Sex')
```

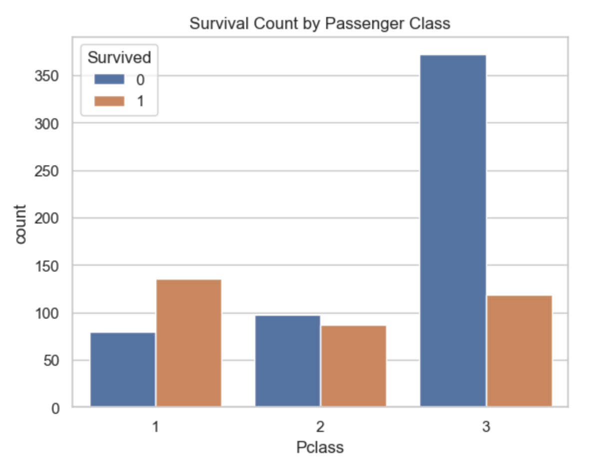


In [ ]:
```python
# - Survived vs Sex (Countplot)

# 1) Females survived at much higher rates than males.
# 2) Strong gender-based survival advantage.
# 3) A key predictor for the model.
```

In [23]:
```python
sns.countplot(data=df, x='Pclass', hue='Survived')
plt.title("Survival Count by Passenger Class")
```

Out[23]:
```
Text(0.5, 1.0, 'Survival Count by Passenger Class')
```

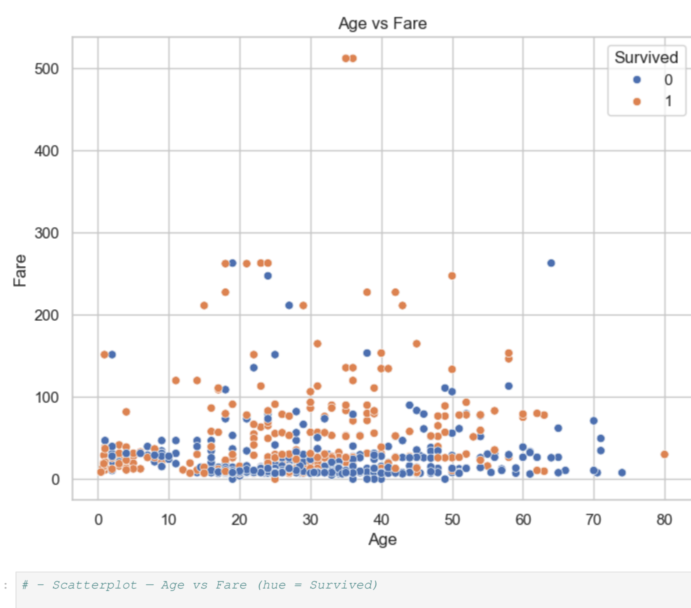


In [ ]:
```python
# - Survived vs Pclass (Countplot)

# 1) 1st class passengers survived the most.
# 2) 3rd class passengers survived the least.
# 3) Socioeconomic status strongly influenced survival.
```

In [24]:
```python
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x='Age', y='Fare', hue='Survived')
plt.title("Age vs Fare")
```

Out[24]:
```
Text(0.5, 1.0, 'Age vs Fare')
```

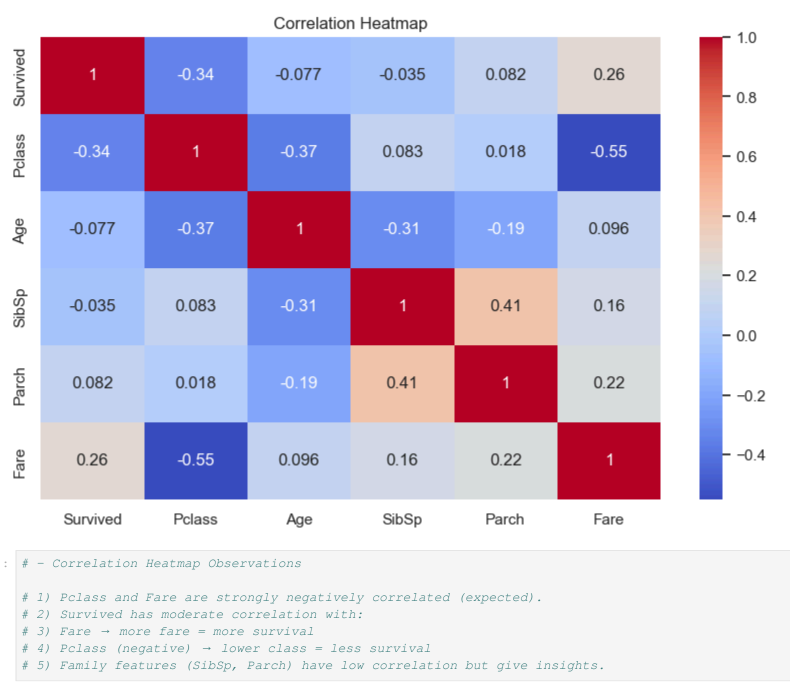


In [ ]:
```python
# - Scatterplot — Age vs Fare (hue = Survived)

# 1) Many high-fare individuals survived → mostly first class.
# 2) Survivors cluster around low to mid ages but visible across all ages.
# 3) Younger passengers slightly more likely to survive.
```

In [25]:
```python
plt.figure(figsize=(10,6))
sns.heatmap(df[['Survived','Pclass','Age','SibSp','Parch','Fare']].corr(),
            annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
```

Out[25]:
```
Text(0.5, 1.0, 'Correlation Heatmap')
```



In [ ]:
```python
# - Correlation Heatmap Observations

# 1) Pclass and Fare are strongly negatively correlated (expected).
# 2) Survived has moderate correlation with:
# 3) Fare → more fare = more survival
# 4) Pclass (negative) → lower class = less survival
# 5) Family features (SibSp, Parch) have low correlation but give insights.
```

In [26]:
```python
sns.pairplot(df[['Survived','Pclass','Age','SibSp','Parch','Fare']],
             hue='Survived')
```

Out[26]:
```
<seaborn.axisgrid.PairGrid at 0x1ce53af17f0>
```

In [ ]:
```python
# - Pairplot Observations:

# 1) Survivors appear more among:
#     Lower Pclass (1st class)
#     Higher Fare
#     Moderate age groups

# 2) Many non-survivors cluster in:
#     3rd class
#     Low fare zone
```

In [34]:
```python
df['Age'] = df['Age'].fillna(df['Age'].median())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

In [ ]:
```python
# - Missing Value Treatment Observations

# 1) Filling Age with median is appropriate for skewed data.
# 2) Filling Embarked with mode is standard since missing values are very few.
```

In [37]:
```python
# - Final Summary:
# The Titanic dataset provides demographic, travel, and survival information for 891 passengers. A detailed EDA reveals several importa
# 1) Gender played a major role: Females had a significantly higher survival rate than males.

# 2) Class mattered: First-class passengers survived more than second and third class.

# 3) Fare displayed strong influence: Higher fare amounts were linked to higher survival rates, suggesting priority evacuation for weal

# 4) Age distribution: Majority were young adults. Children had a slightly better chance of survival.

# 5) Family size: Most passengers traveled alone. Large families had lower survival probabilities.

# 6) Missing data: Age had considerable missing values, while Cabin had the most and was mostly unusable.

# Overall, socioeconomic status (Pclass), fare paid, and gender were the strongest determinants of survival.
```