In [49]:

```python
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

# Basic dataset info
df.head()
```

Out[49]:

	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 [50]:

```python
# Shape and data types
df.info()

# Summary statistics
df.describe()

# Check missing values
df.isnull().sum()

# Value counts for categorical features
df['Sex'].value_counts()
df['Embarked'].value_counts()
```

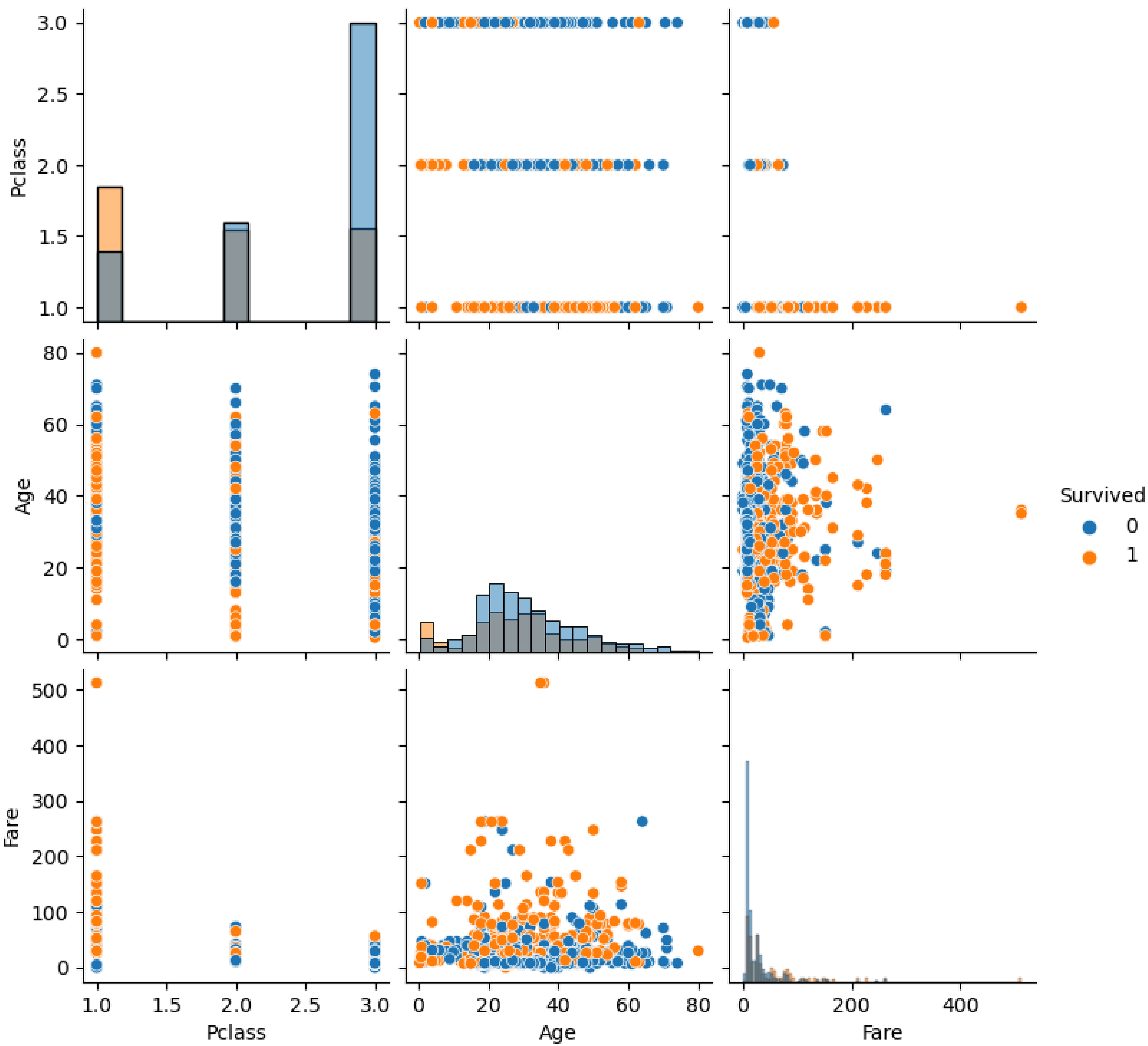
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    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[50]:

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [51]:

```python
# Pairplot
sns.pairplot(
    df[['Survived', 'Pclass', 'Age', 'Fare']].dropna(),
    hue='Survived', diag_kind='hist')
plt.show()
```

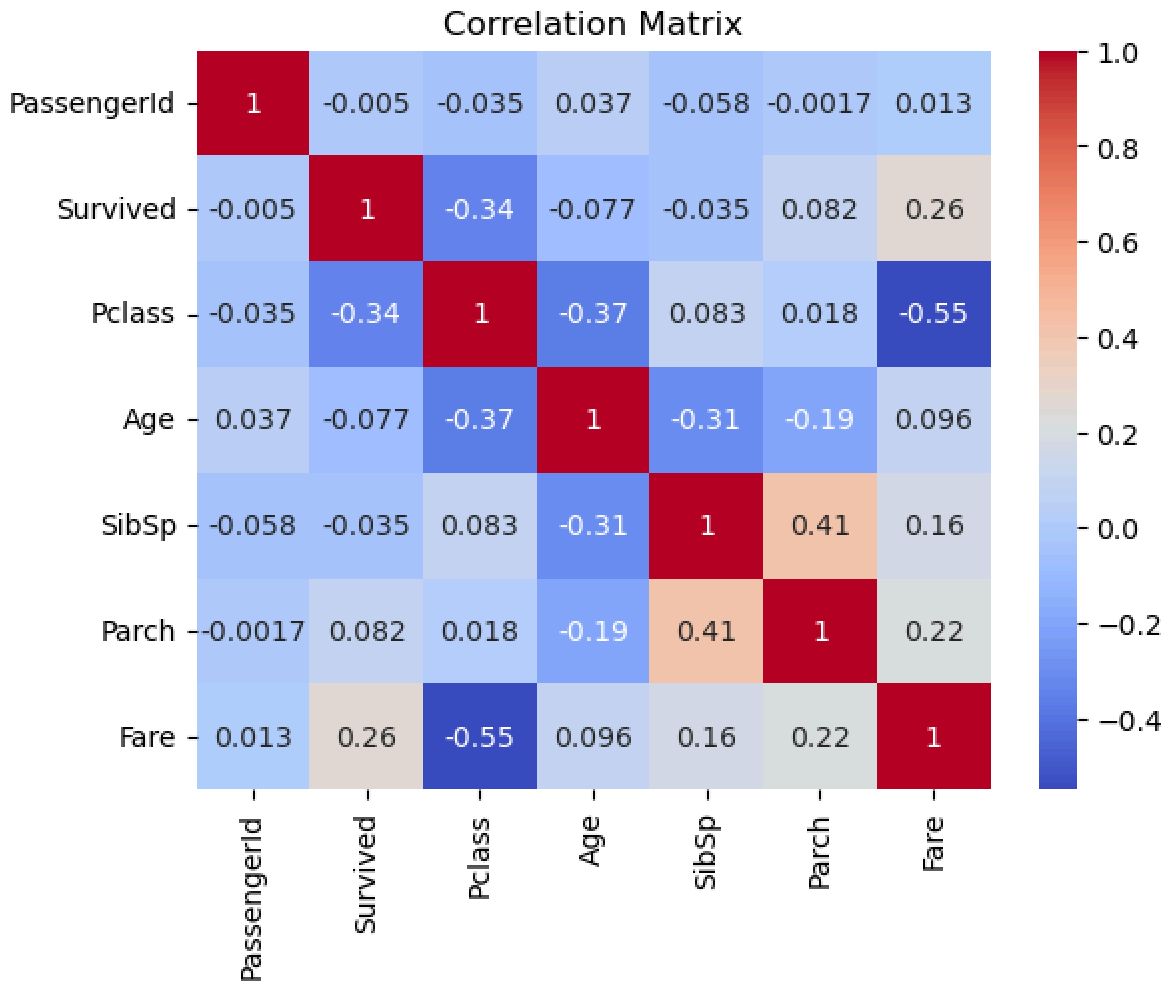


Pclass
Age
Fare
Survived
0
1

Observations

- **Pclass vs Fare**: Higher class → Higher fare.
- **Age vs Fare**: No clear trend, but older high-fare passengers seem to survive more.
- **Survival trends**: Survivors cluster in higher fare and lower Pclass zones.

In [52]:
```python
# Heatmap
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



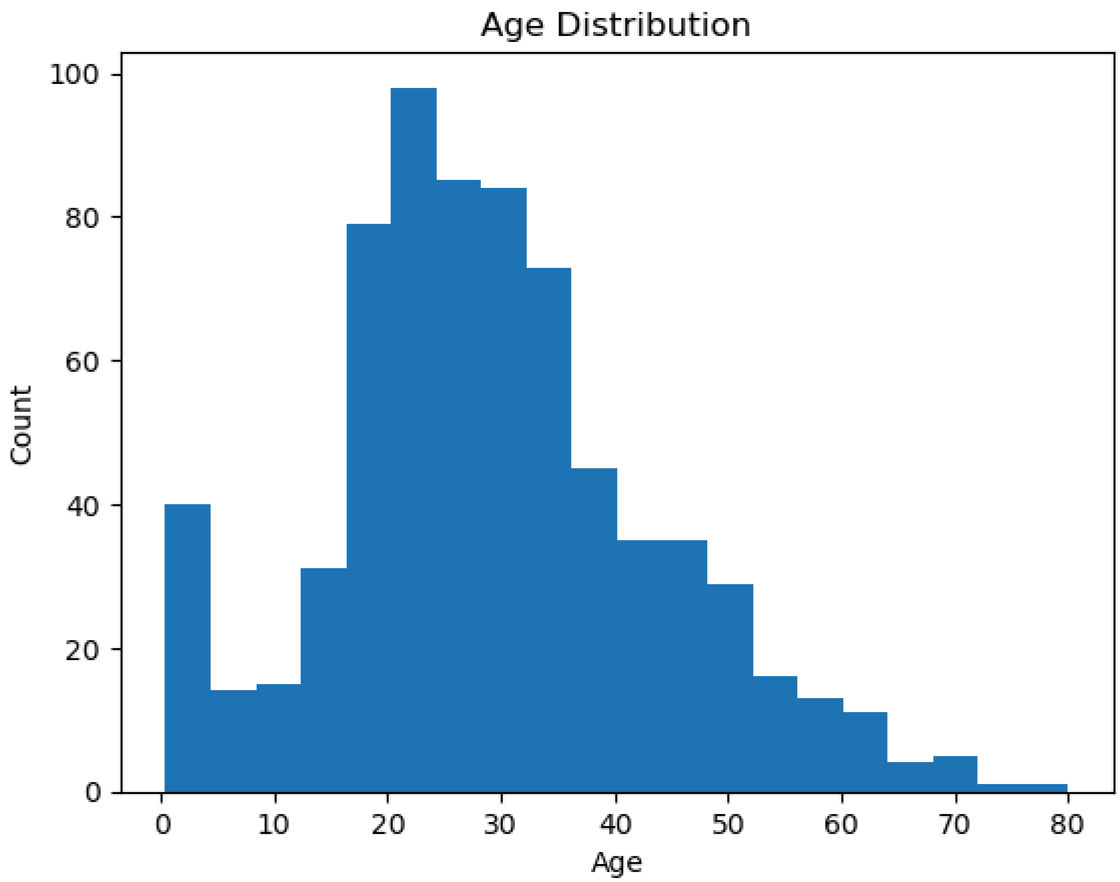
Observations

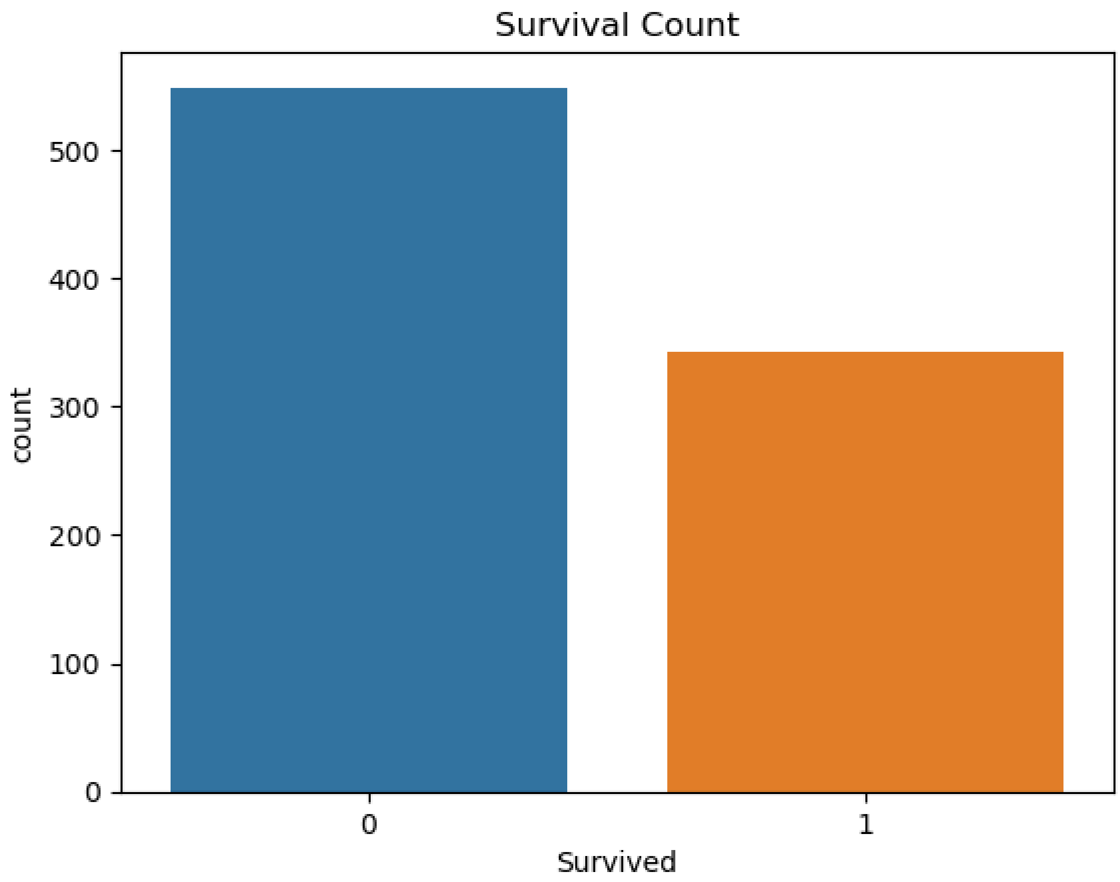
- **Pclass & Fare**: Strong negative correlation (-0.55).
- **Survived & Fare**: Positive correlation (0.26).
- **Survived & Pclass**: Negative correlation (-0.34).

In [53]:

```
# Histogram of Age
plt.hist(df['Age'].dropna(), bins=20)
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution')
plt.show()

# Countplot for Survival
sns.countplot(x='Survived', data=df)
plt.title('Survival Count')
plt.show()
```


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



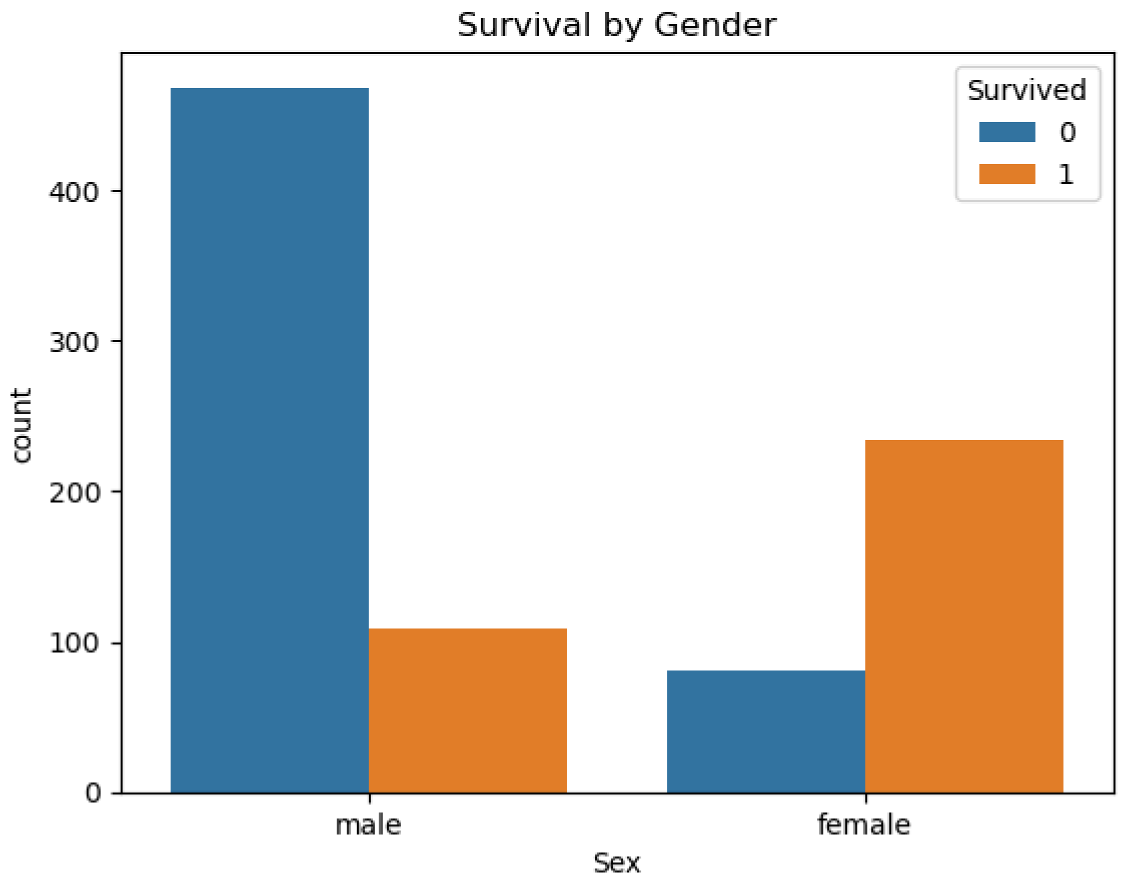
Observations

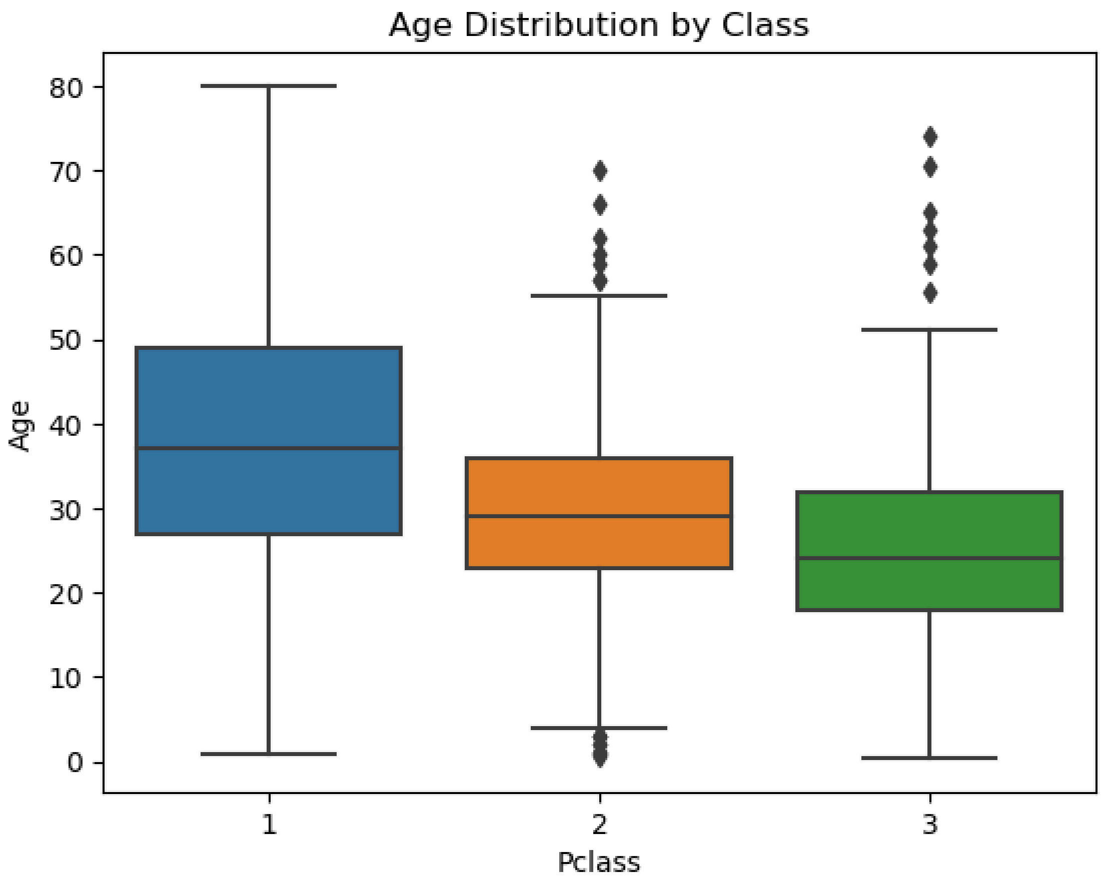
- **Age**: Most passengers are between 20–40 years old.
- **Fare**: Skewed distribution; most fares are low, with few very high.

In [54]:

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

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


Survival by Gender
Survived
0
1
400
300
200
100
0
count
male
female
Sex

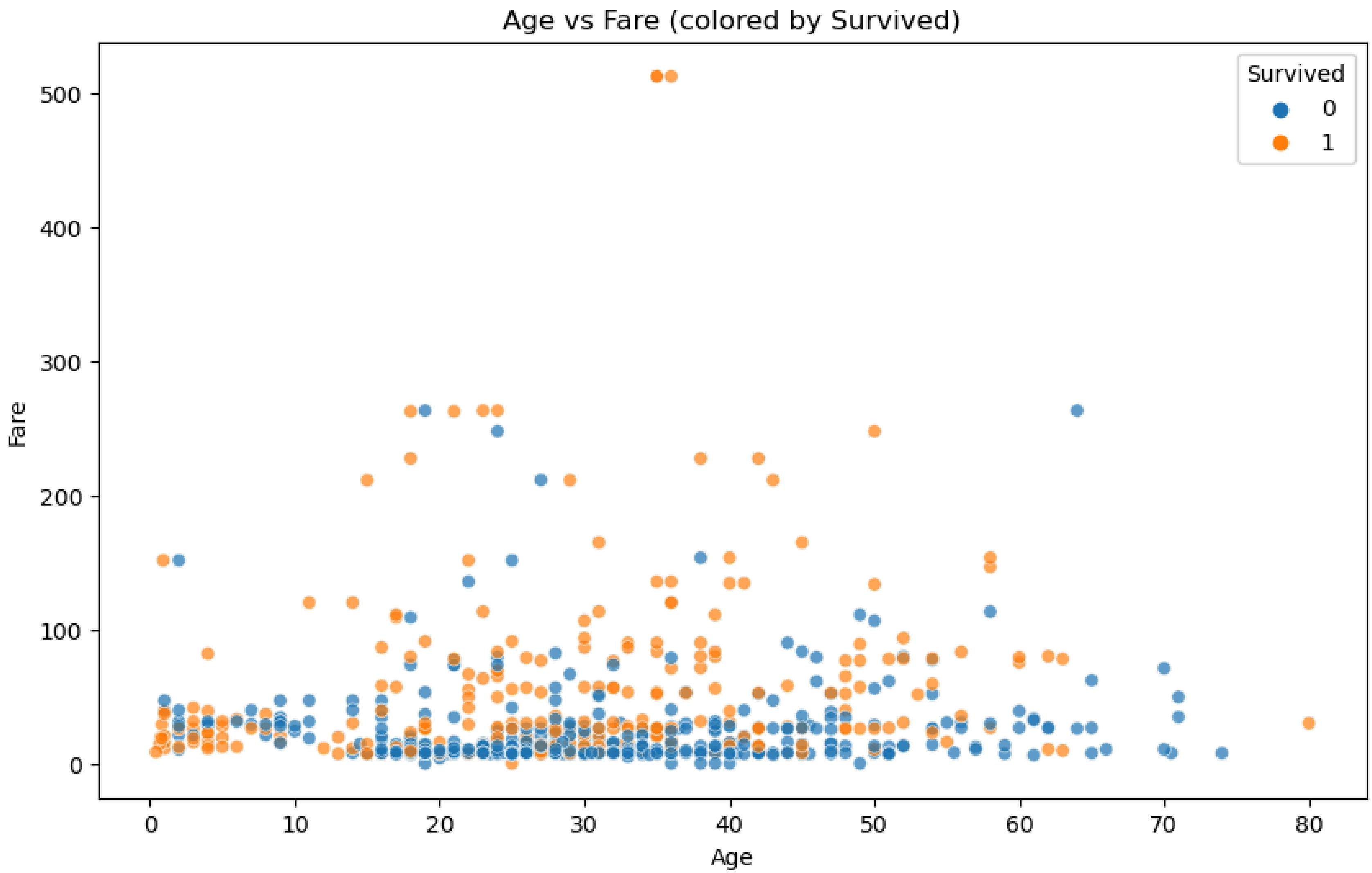


Observations

- **Age vs Survival**: Younger survivors more frequent; wide variation in non-survivors.
- **Fare vs Pclass**: Clear price differences by class.

In [55]:

```
# --- Scatter 1: Age vs Fare colored by Survival ---
plt.figure(figsize=(10,6))
sns.scatterplot(data=df.dropna(subset=['Age','Fare']), x='Age', y='Fare', hue='Survived', alpha=0.7)
plt.title('Age vs Fare (colored by Survived)')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```

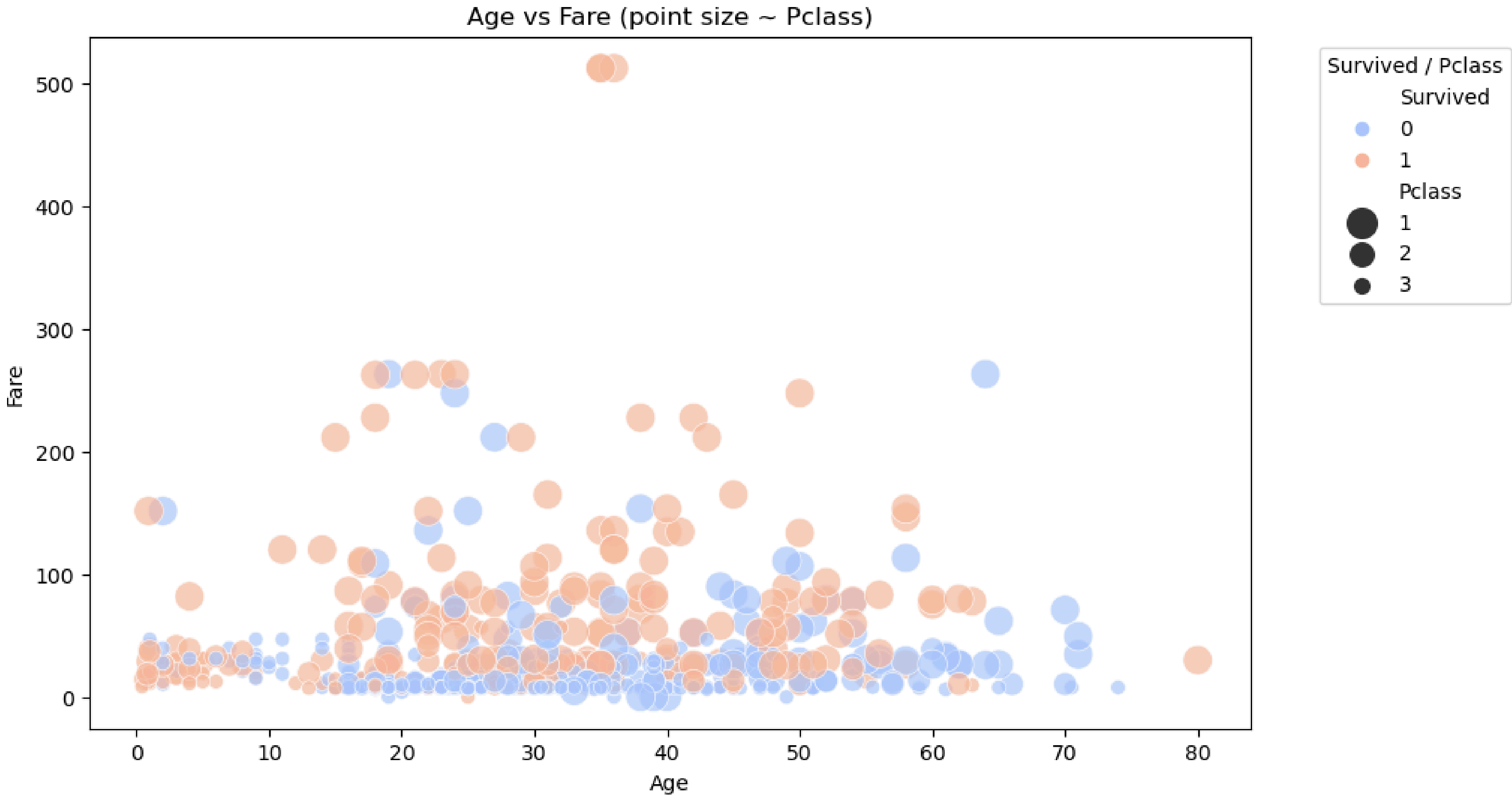


Observations

- Survivors are concentrated in higher fare ranges, particularly among passengers aged 20–40.
- Non-survivors dominate the low-fare and older-age groups.
- Extremely high fares (>200) are almost entirely survivors, hinting at a strong socio-economic advantage.

In [56]:
```
# --- Scatter 2: Age vs Fare, point size = Pclass ---
plt.figure(figsize=(10,6))
sns.scatterplot(data=df.dropna(subset=['Age','Fare','Pclass']), x='Age', y='Fare', hue='Survived', size='Pclass',
```

```
    sizes=(200, 50), alpha=0.7, palette='coolwarm')
plt.title('Age vs Fare (point size ~ Pclass)')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.legend(title='Survived / Pclass', bbox_to_anchor=(1.05,1), loc='upper left')
plt.show()
```

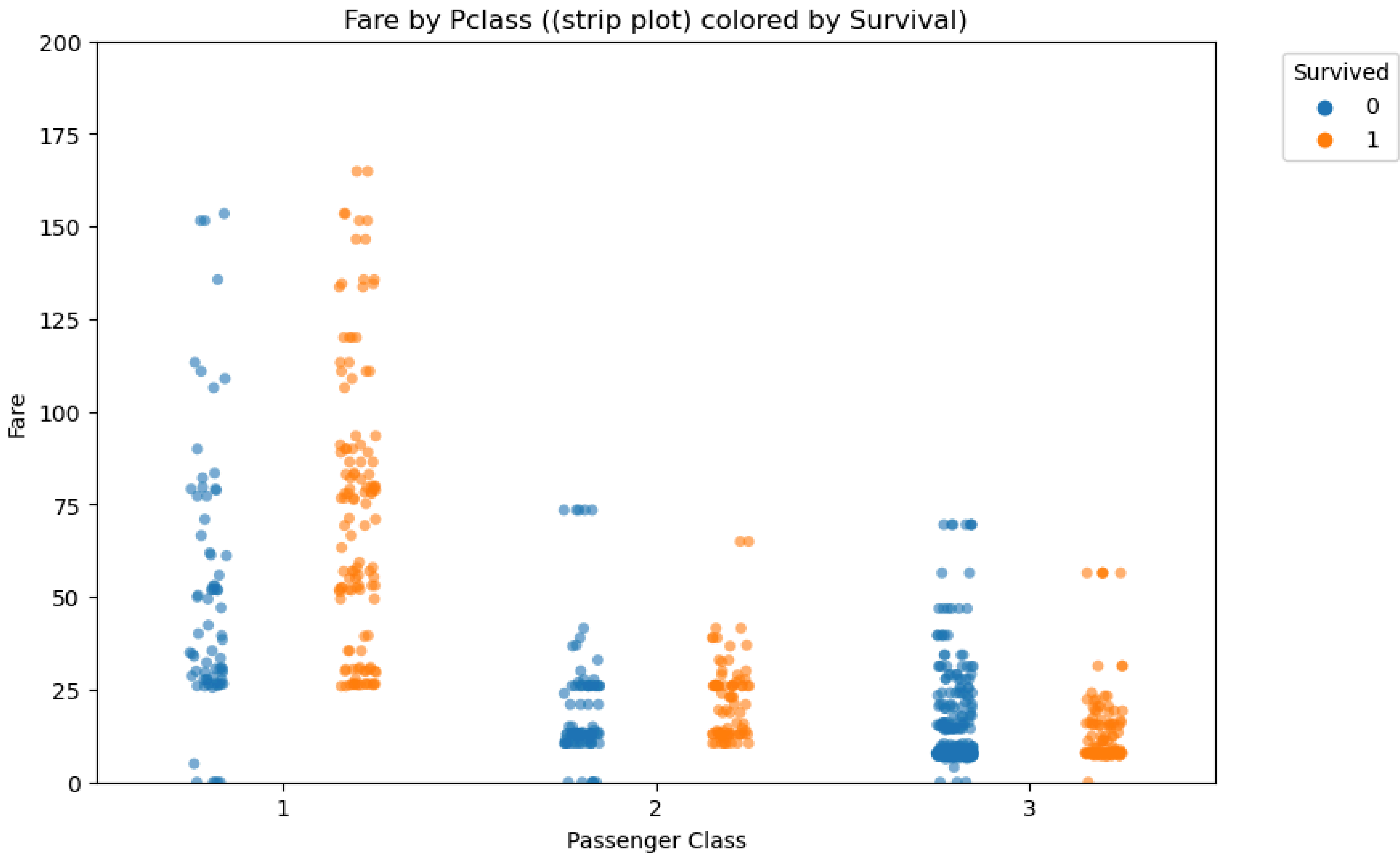


Observations

- Larger points (1st class) cluster in the high-fare zone and have a higher proportion of survivors.
- Smaller points (3rd class) mostly fall in the low-fare range and have lower survival rates.
- The visual separation confirms a strong interaction between class, fare, and survival.

In [57]:

```python
# --- Scatter 3: Fare vs Pclass (jittered) colored by Survival ---
plt.figure(figsize=(9,6))
sns.stripplot(
    data=df,
    x='Pclass', y='Fare',
    hue='Survived',
    jitter=True, dodge=True, alpha=0.6
)
plt.ylim(0, 200)
plt.title('Fare by Pclass ((strip plot) colored by Survival)')
plt.xlabel('Passenger Class')
plt.ylabel('Fare')
plt.legend(title='Survived', bbox_to_anchor=(1.05,1), loc='upper left')
plt.show()
```

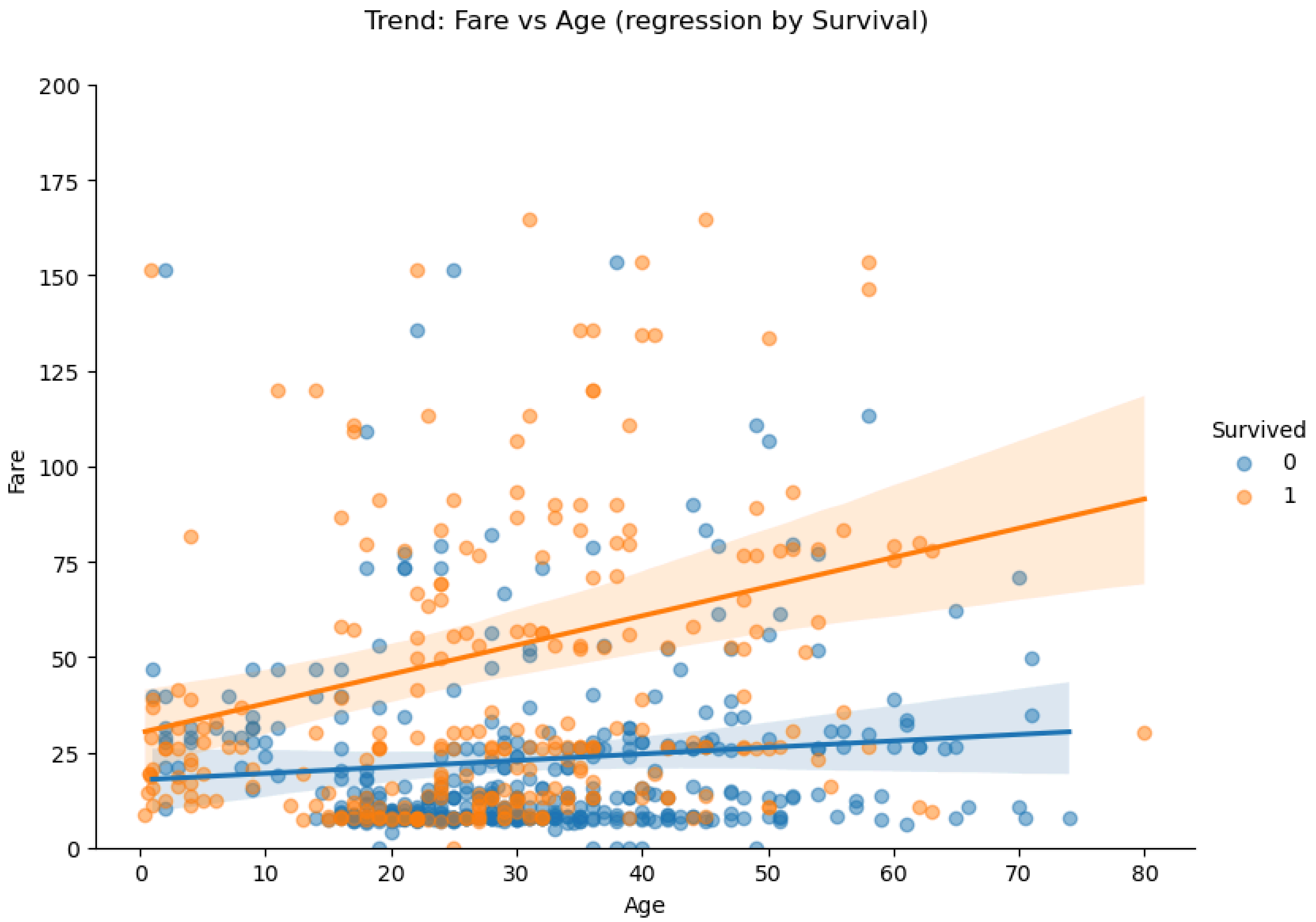


Observations

- 1st class passengers (Pclass=1) have a wide fare range but generally high survival rates.
- 3rd class passengers (Pclass=3) have low fares and the lowest survival rates.
- The overlap in fares within classes is minimal, making Pclass a clear proxy for socio-economic status.

In [58]:
```
# --- Scatter 4: Regression/trend plot — Fare vs Age split by Survival ---
sns.lmplot(
    data=df.dropna(subset=['Age','Fare']),
```

```
    x='Age', y='Fare', hue='Survived',
    height=6, aspect=1.3, scatter_kws={'alpha':0.5}
)
plt.subplots_adjust(top=0.9)
plt.suptitle('Trend: Fare vs Age (regression by Survival)')
plt.ylim(0, 200)
plt.show()
```



Observations

- For survivors, there’s a slight negative slope: younger survivors tend to have slightly higher fares.
- For non-survivors, fares are consistently low across ages, with no strong trend.
- This suggests that fare is more predictive of survival for certain age groups, especially younger ones.

Summary of Findings

- **Ticket Class**: Strongly affects survival; higher classes had better chances.
- **Fare**: Higher fares correlate with higher survival probability.
- **Age**: Younger passengers had a slightly higher survival rate.
- **Family Size**: Small families had better survival chances than large ones.
- **Correlations**: Pclass, Fare, and Survival have the strongest relationships.