Data Science Internship

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TITANIC EXPLORATORY DATA ANALYSIS

Objective: Clean and explore the Titanic dataset with the aim of investigating relationships between variables. Uncover patterns and trends to gain insights into the factors influencing passenger survival on the Titanic.

DATA UNDERSTANDING

The datasets is obtained from Kaggle: [Titanic (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data)

The dataset contains 891 rows (entries) and 12 columns
The columns are:

`PassengerId` : Unique identifier for each passenger.
`Survived` : Binary variable indicating survival (1 = Survived, 0 = Did Not Survive).
`Pclass` : Ticket class (1st, 2nd, 3rd class).
`Name` : Passenger's name.
`Sex` : Gender of the passenger.
`Age` : Age of the passenger.
`SibSp` : Number of siblings/spouses aboard.
`Parch` : Number of parents/children aboard.

`Ticket` : Ticket number.

`Fare` : Passenger fare.

`Cabin` : Cabin number.

`Embarked` : Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

In [11]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
import plotly.express as px
from scipy import stats
```

In [12]:
```
class DataUnderstanding:
    def __init__(self,df):
        self.df = df

    def get_summary_statistics(self):
        summary_stats = self.df.describe()
        return summary_stats

    def get_missing_values(self):
        missing_values = self.df.isnull().sum()
        return missing_values

    def get_info(self):
        info = self.df.info()
        return info

    def get_dtypes(self):
        dtypes = self.df.dtypes
        return dtypes

    def get_value_counts(self):
        value_counts = {} # Initialize an empty dictionary to store the res
        for column in self.df.columns:
            value_counts[column] = self.df[column].value_counts()
        return value_counts
```

In [13]:
```python
#Preview the dataset
df = pd.read_csv('D:/Prodigy/Task 2/train.csv')
df.head()
```

Out[13]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [14]:
```python
#Initialising the DataUnderstanding class
du = DataUnderstanding(df)
```

In [15]:
```python
# Getting the summary statistics
summary_stats = du.get_summary_statistics()
print("Summary Statistics: ")
summary_stats
```

```
Summary Statistics:
```

Out[15]:

	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 [16]:
```
# get summary of the data
du.get_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 [17]:
```
# get data types
du.get_dtypes()
```

Out[17]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [18]:
```
# Those who survived
df['Survived'].value_counts()
```

Out[18]:
```
0    549
1    342
Name: Survived, dtype: int64
```

DATA PREPARATION

Check for missing values

In [19]:
```
# Check for missing values
du.get_missing_values()
```

Out[19]:
```
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
```

Dealing with missing values

Since the column named 'Cabin' contains more than 50% of missing values, I choose to drop off that particular column.

In [20]:
```
# Drop the cabin column
df = df.drop('Cabin', axis=1)
```

For the 'embarked' column, We can impute missing values with the most frequent port

In [21]:
```
# finding the most frequent port (mode) in the embarked column
most_frequent_port = df['Embarked'].mode()[0]
print(most_frequent_port)

# Filling missing values with the most frequent values in the embarked colu
df['Embarked'].fillna(most_frequent_port, inplace=True)
```

```
S
```

In [22]:
```
# Removing rows with missing ages
df.dropna(subset=['Age'], inplace=True)
```

In [23]:
```
df
```

Out[23]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fa
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25(
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.28:
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.92!
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.10(
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05(
...	...	...	...	...	...	...	...	...	...	
885	886	0	3	Rice, Mrs. William (Margaret Norton)	female	39.0	0	5	382652	29.12!
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00(
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00(
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00(
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75(

714 rows × 11 columns

Value counts

In [24]:
```
# get value counts
du.get_value_counts()
```

Out[24]:
```
{'PassengerId': 1      1
 599    1
 588    1
 589    1
 590    1
       ..
 301    1
 302    1
 303    1
 304    1
 891    1
 Name: PassengerId, Length: 891, dtype: int64,
 'Survived': 0    549
 1    342
 Name: Survived, dtype: int64,
 'Pclass': 3    491
 1    216
 2    184
 Name: Pclass, dtype: int64,
 'Name': Braund, Mr. Owen Harris                        1
 Boulos, Mr. Hanna                              1
 Frolicher-Stehli, Mr. Maxmillian               1
 Gilinski, Mr. Eliezer                          1
 Murdlin, Mr. Joseph                            1
                                               ..
 Kelly, Miss. Anna Katherine "Annie Kate"       1
 McCoy, Mr. Bernard                             1
 Johnson, Mr. William Cahoone Jr                1
 Keane, Miss. Nora A                            1
 Dooley, Mr. Patrick                            1
 Name: Name, Length: 891, dtype: int64,
 'Sex': male      577
 female    314
 Name: Sex, dtype: int64,
 'Age': 24.00    30
 22.00    27
 18.00    26
 19.00    25
 28.00    25
          ..
 36.50     1
 55.50     1
 0.92      1
 23.50     1
 74.00     1
 Name: Age, Length: 88, dtype: int64,
 'SibSp': 0    608
 1    209
 2     28
 4     18
 3     16
 8      7
 5      5
 Name: SibSp, dtype: int64,
 'Parch': 0    678
 1    118
 2     80
 5      5
 3      5
 4      4
 6      1
```

```
Name: Parch, dtype: int64,
'Ticket': 347082      7
CA. 2343    7
1601        7
3101295     6
CA 2144     6
           ..
9234        1
19988       1
2693        1
PC 17612    1
370376      1
Name: Ticket, Length: 681, dtype: int64,
'Fare': 8.0500     43
13.0000    42
7.8958     38
7.7500     34
26.0000    31
           ..
35.0000     1
28.5000     1
6.2375      1
14.0000     1
10.5167     1
Name: Fare, Length: 248, dtype: int64,
'Cabin': B96 B98        4
G6             4
C23 C25 C27    4
C22 C26        3
F33            3
              ..
E34            1
C7             1
C54            1
E36            1
C148           1
Name: Cabin, Length: 147, dtype: int64,
'Embarked': S    644
C    168
Q     77
Name: Embarked, dtype: int64}
```

Checking for duplicates

passengerID is used here since it is a unique identifier

In [25]:
```
# Convert 'PassengerId' column to int64
df['PassengerId'] = df['PassengerId'].astype('int64')
```

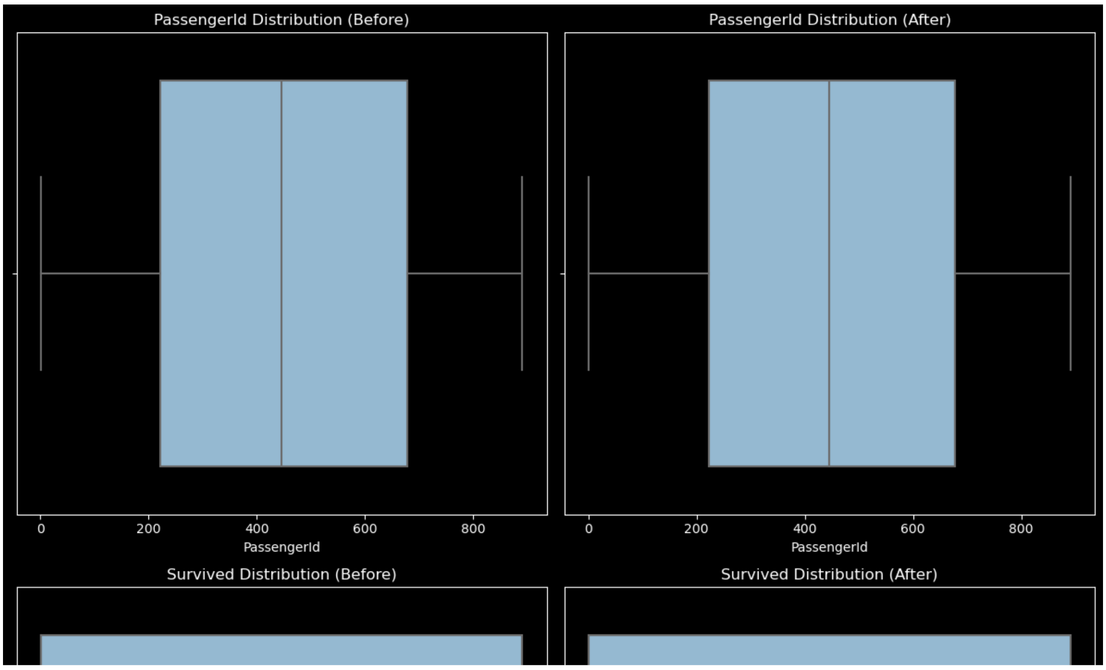
In [26]:
```
# checking for duplicates
df.duplicated(subset='PassengerId').sum()
```

Out[26]: 0

Checking for outliers and removing them

In [27]:
```
numerical_columns = ['PassengerId', 'Survived', 'Pclass', 'Age', 'SibSp', '
```

In [28]:
```
# Setting the plot style to a dark theme
plt.style.use('dark_background')
# Define a custom color palette with darker shades of blue
custom_palette = sns.color_palette("Blues_d")
sns.set_palette(custom_palette)
# Function to check for outliers by plotting
def outlier_plot_box(df, column_name, ax=None):
    sns.boxplot(x=df[column_name], ax=ax)

# Function to remove outliers
def remove_outliers(data, cols, threshold=3):
    for col in cols:
        z_scores = np.abs(stats.zscore(data[col]))
        data = data[(z_scores < threshold)]
    return data

# Function to plot outliers before and after removal
def plot_outliers_before_and_after(df, numerical_columns, threshold=3):
    fig, axes = plt.subplots(len(numerical_columns), 2, figsize=(12, len(nu

    for i, column in enumerate(numerical_columns):
        ax1 = axes[i][0]
        ax2 = axes[i][1]

        # Plot boxplot before removing outliers
        outlier_plot_box(df, column, ax=ax1)
        ax1.set_title(f"{column} Distribution (Before)")

        # Remove outliers
        df_cleaned = remove_outliers(df, [column], threshold=threshold)

        # Plot boxplot after removing outliers
        outlier_plot_box(df_cleaned, column, ax=ax2)
        ax2.set_title(f"{column} Distribution (After)")

    plt.tight_layout()
    plt.show()

# Call the function to plot outliers before and after removal
plot_outliers_before_and_after(df, numerical_columns)
```



EXPLORATORY DATA ANALYSIS

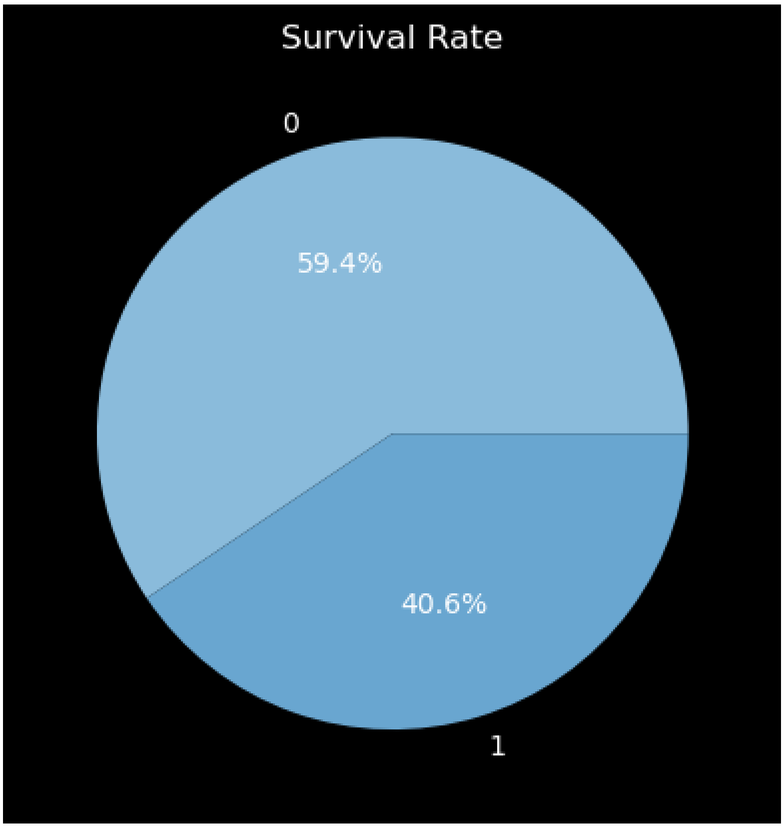
Univariate Analysis

This is a data analysis technique that focuses on examining and describing the characteristics and distribution of a single variable in a dataset

Survival Rate

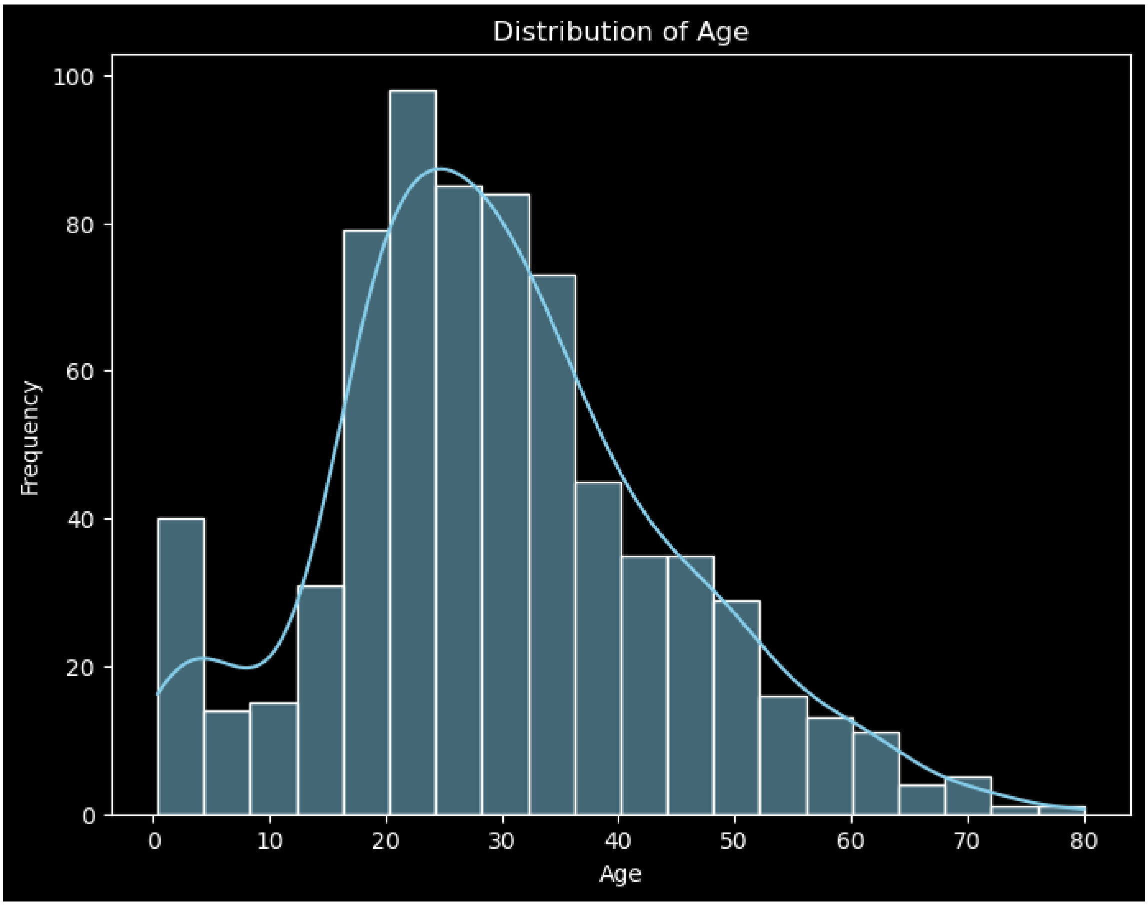
In [29]:

```
# Plot of Survival Rate
def plot_survival_rate(df):
    #Create a figure
    fig, ax = plt.subplots()

    # Plot the churn rate
    ax.pie(df['Survived'].value_counts(), labels=df['Survived'].value_count

    # Add a title
    ax.set_title('Survival Rate')

    # Show the plot
    plt.show()
plot_survival_rate(df)
```



- This pie chart gives a visual representation of the survival rate among passengers in the dataset, highlighting the proportion of survivors and non-survivors
- 59.4 % of people did not survive while 40.6 % percent survived.

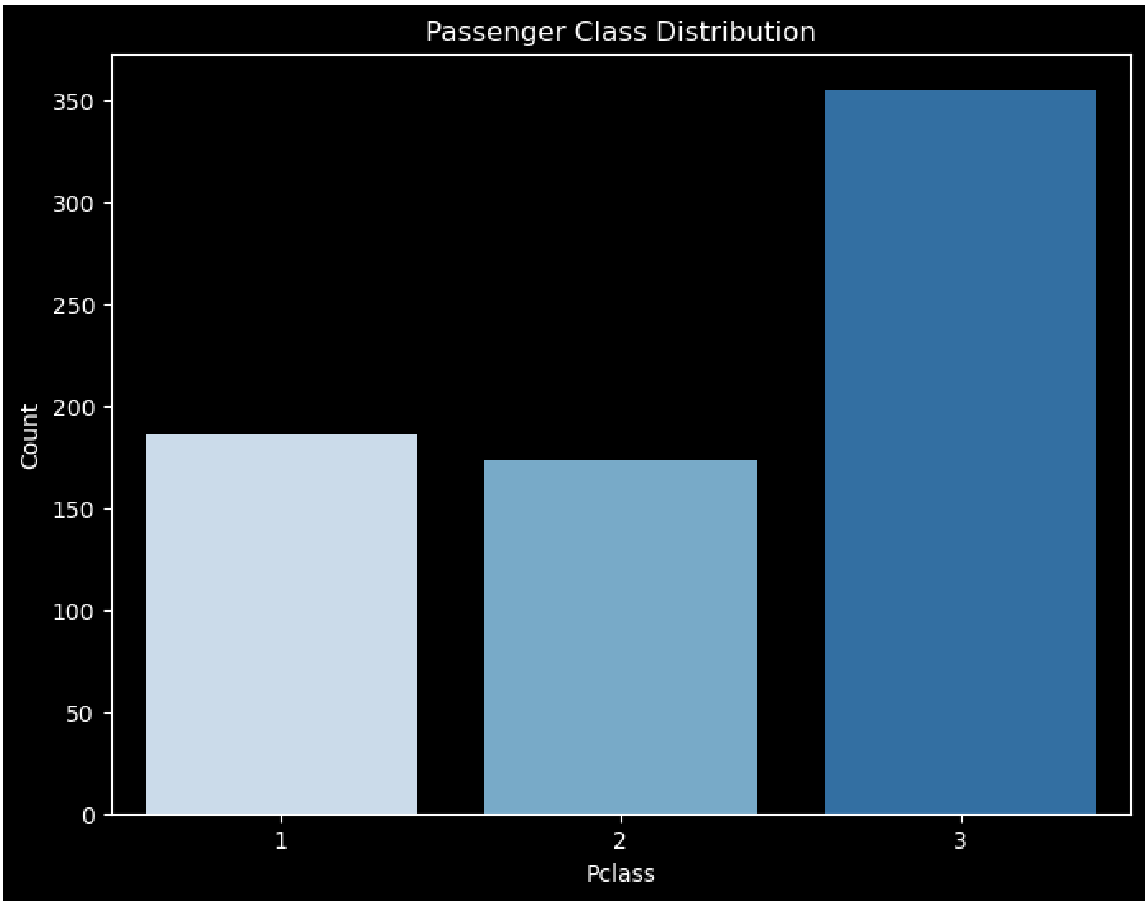
In [30]:
```
# Histogram for Age
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='Age', bins=20, kde=True, color='skyblue')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Distribution of Age')
plt.show()
```



- The histogram provides valuable insights into the age distribution among passengers, with the majority falling within the 15 to 35 age range
- The histogram shows a peak in the age range between approximately 20 and 25 years. This suggests that a significant portion of passengers falls within this age group
- The histogram's shape is somewhat right-skewed, indicating that there are more passengers in younger age groups compared to older age groups
- There is a relatively smaller number of children (around 5-15 years old) and elderly passengers (above 60 years old) on the Titanic

Passenger Class Distribution

In [31]:
```
# Bar plot for Pclass
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='Pclass', palette='Blues')
plt.xlabel('Pclass')
plt.ylabel('Count')
plt.title('Passenger Class Distribution')
plt.show()
```



- The bar plot for passenger class (Pclass) displays the distribution of passengers across different classes
- Class Distribution: Class 3 has the highest count, followed by Class 1, and then Class 2
- Class 3 has significantly more passengers than the other two classes, suggesting that it might be the most common class among the passengers.

Bivariate Analysis

Bivariate analysis involves exploring relationships between two variables

Age vs. Fare with Survival Hue

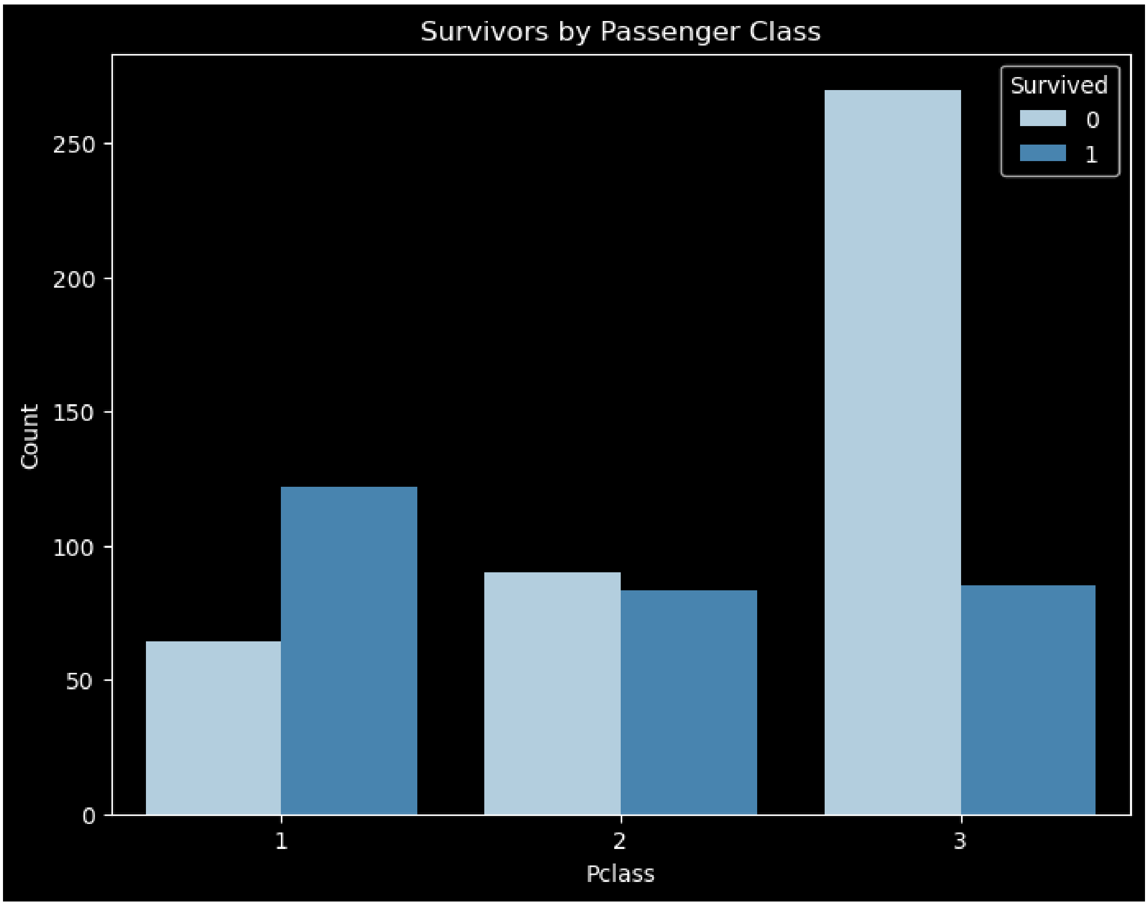
In [32]:
```
from plotly.offline import init_notebook_mode
init_notebook_mode(connected=True)
```

In [7]:
```
# Create scatter plot
import plotly.express as px
import pandas as pd

# Assuming df is your DataFrame
df = pd.DataFrame({
    'Age': [25, 30, 22, 35, 28],
    'Fare': [50.5, 23.8, 45.2, 67.9, 30.4],
    'Survived': [1, 0, 1, 0, 1]
})

# Create scatter plot
fig = px.scatter(df, x='Age', y='Fare', color='Survived', title='Scatter Pl
fig.show()
```

- The scatter plot shows the distribution of passengers based on their age and fare paid for the ticket.
- There is no strong relationship between age and fare. The scattered distribution suggests that passengers of various ages paid different fares for their tickets

survivors by Pclass

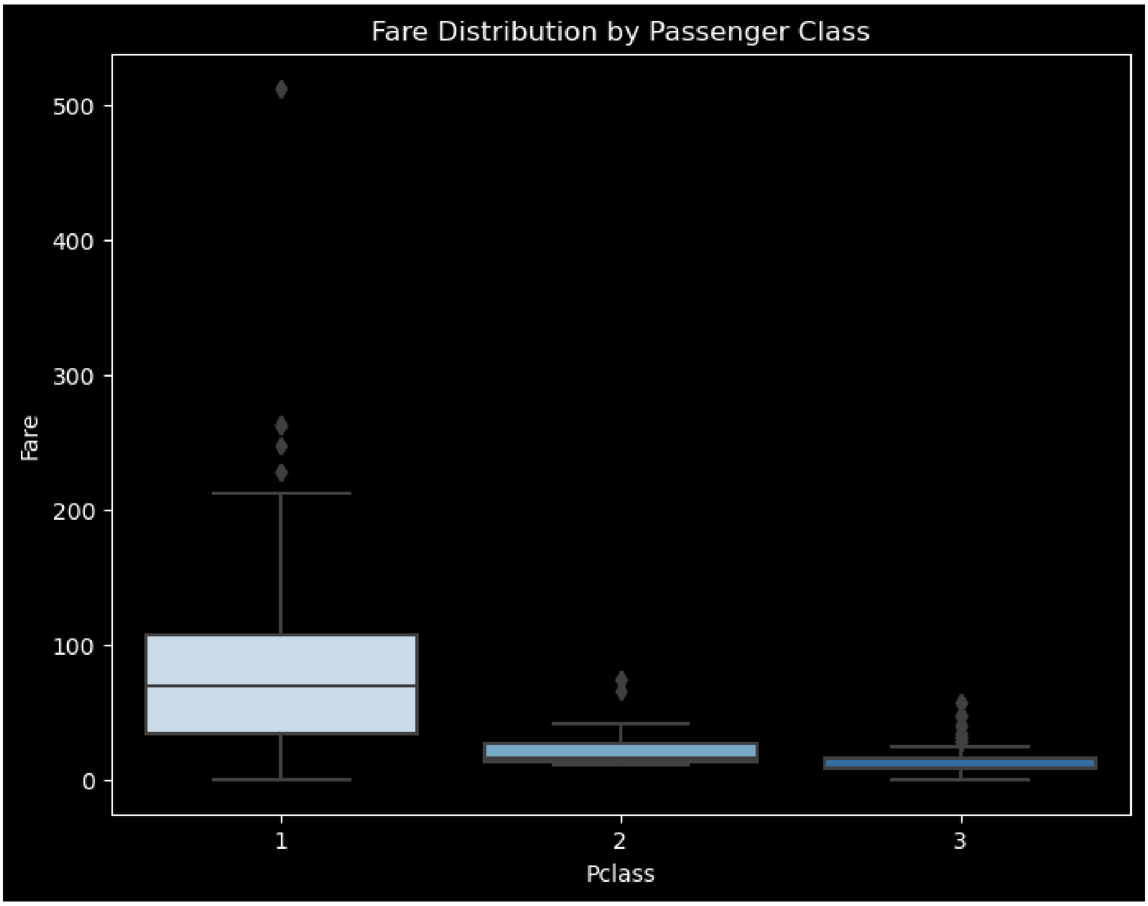
In [34]:
```
# Bar plot comparing the number of survivors by Pclass
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='Pclass', hue='Survived', palette='Blues')
plt.xlabel('Pclass')
plt.ylabel('Count')
plt.title('Survivors by Passenger Class')
plt.show()
```



- Class 1 (First Class): A larger number of passengers in first class survived compared to those who did not. This indicates a higher survival rate among first-class passengers
- Class 2 (Second Class): While there is a relatively close distribution, slightly more passengers in second class did not survive compared to those who survived. This suggests a lower survival rate in second class compared to first class
- Class 3 (Third Class): The bar plot shows a significant difference in the number of survivors between third class and non-survivors. Fewer passengers in third class survived, and a larger number did not survive, indicating a lower survival rate in third class
- Passengers in Class 1 had a higher chance of survival compared to those in Class 2 and Class 3. This suggests that the passenger class might have influenced the survival rate
- Class 3 had the highest number of passengers but the lowest survival rate, indicating a potential class-based hierarchy in rescue efforts

Fare Distribution by Passenger Class

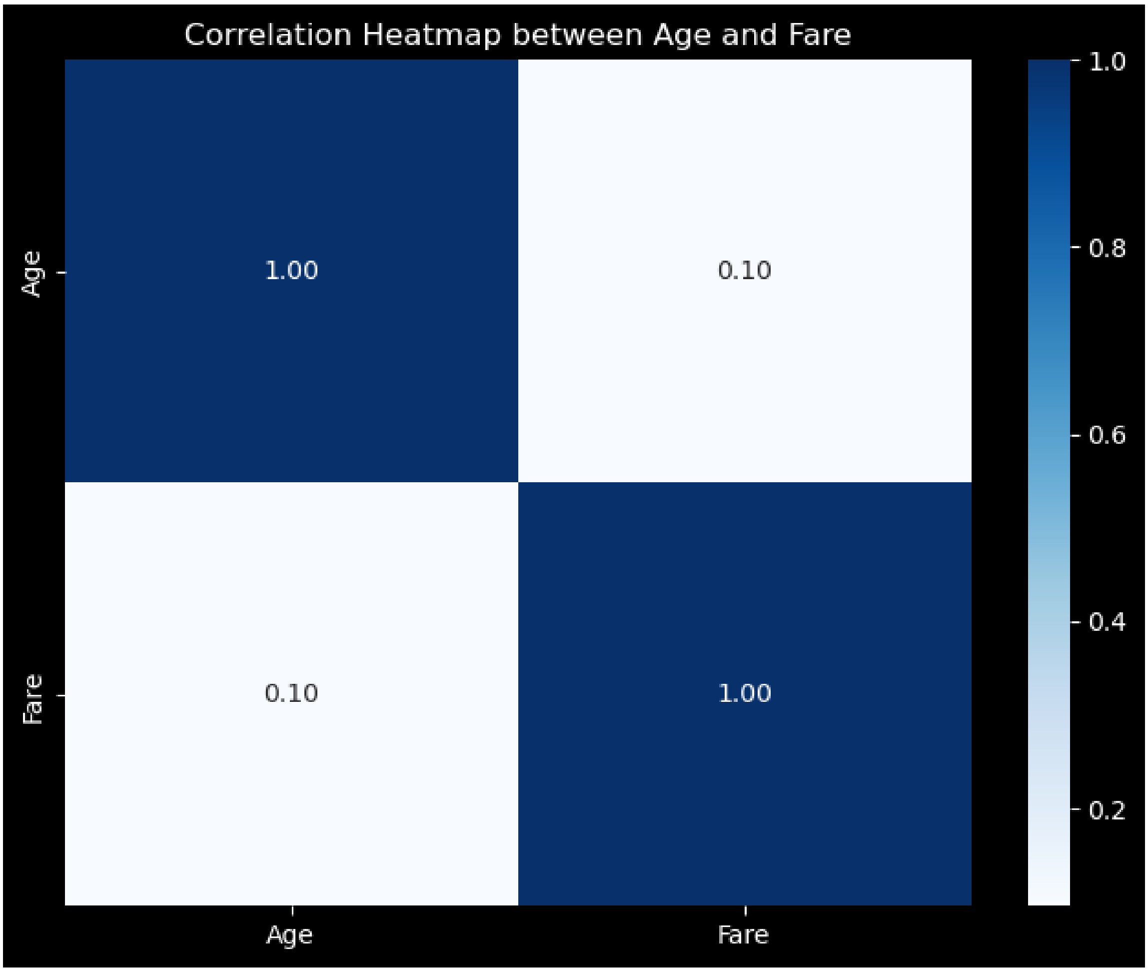
In [35]:
```
# Box plot comparing fares by passenger class
plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='Pclass', y='Fare', palette='Blues')
plt.xlabel('Pclass')
plt.ylabel('Fare')
plt.title('Fare Distribution by Passenger Class')
plt.show()
```



- Class 1 (First Class): The first-class passengers have the widest range of fares, with some paying significantly higher fares than others. There are a few outliers on the higher end, indicating that some first-class passengers paid exceptionally high fares.
- Class 2 (Second Class): Second-class fares have a narrower range compared to first-class, with generally lower fares. There are some outliers with relatively higher fares compared to the majority of second-class passengers.
- Class 3 (Third Class): Third-class fares have the narrowest range, and the majority of passengers paid lower fares. There are very few outliers on the higher end, suggesting that most third-class passengers paid lower fares
- This plot illustrates that first-class passengers paid a wide range of fares, including some very high fares. In contrast, second and third-class passengers generally paid lower fares, with fewer outliers indicating exceptionally high payments.

Correlation heatmap between Age and Fare

In [36]:
```
# Correlation heatmap between Age and Fare
correlation_matrix = df[['Age', 'Fare']].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='Blues', fmt='.2f')
plt.title('Correlation Heatmap between Age and Fare')
plt.show()
```



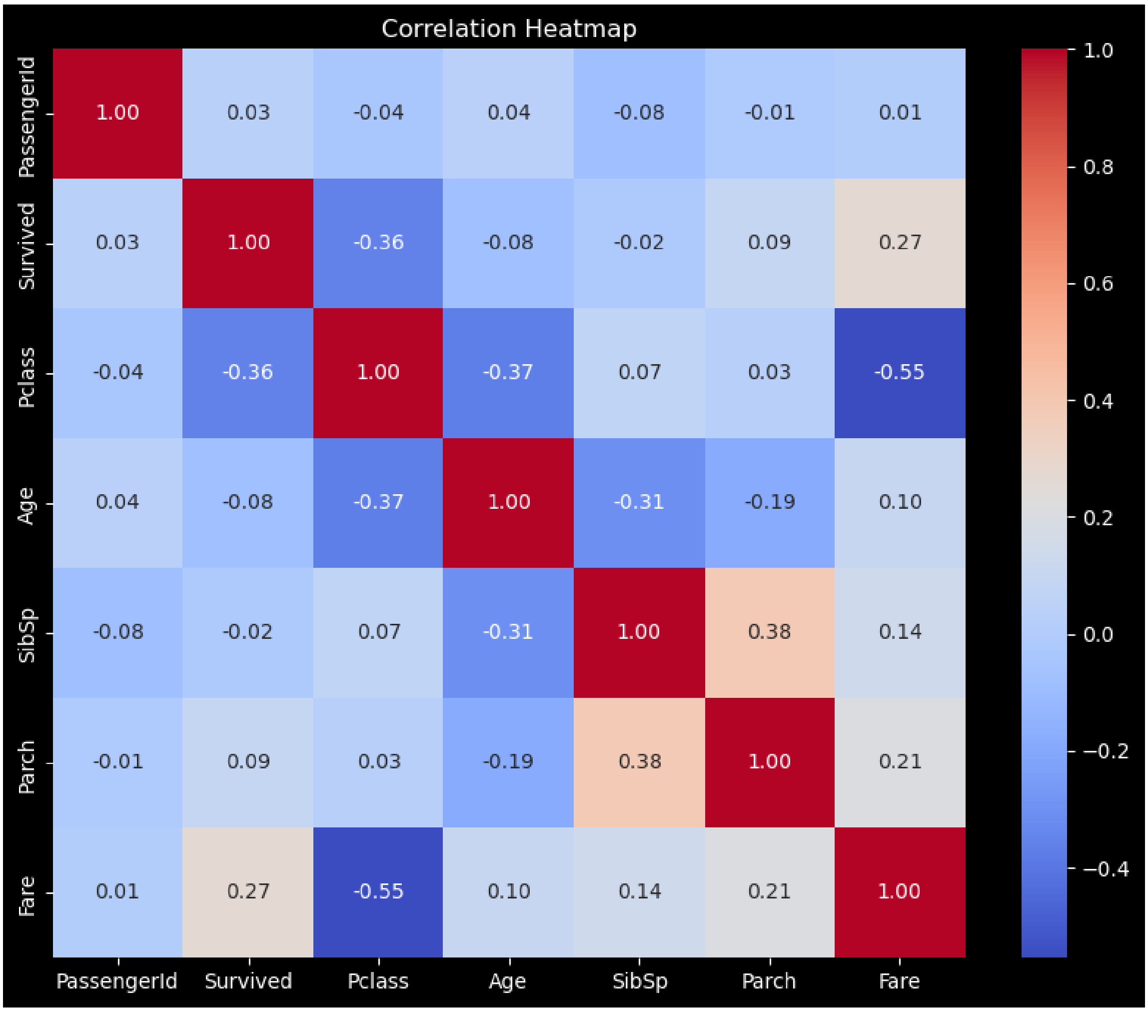
- Age vs. Fare (Age to Fare = 0.1):The correlation coefficient of 0.1 suggests a very weak positive linear relationship between a passenger's age and the fare they paid
- This implies that, on average, there is a slight tendency for older passengers to pay slightly higher fares, but the correlation is not strong enough to draw significant conclusions.

Multivariate Analysis

Multivariate analysis involves the exploration and analysis of relationships between three or more variables simultaneously

Correlation Heatmap

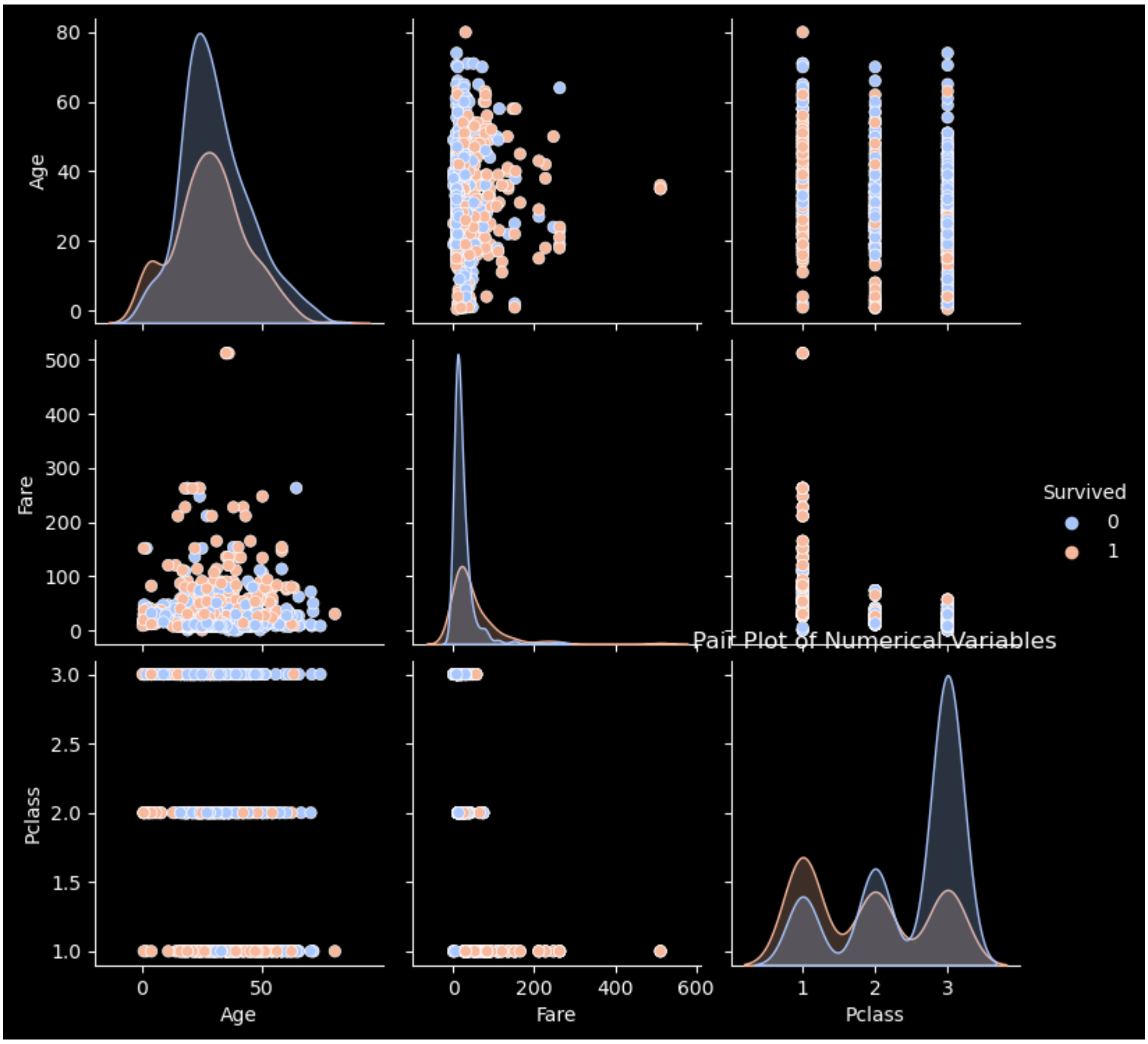
In [37]:
```
# Correlation heatmap
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



- Survived and Pclass: There is a noticeable negative correlation between "Survived" and "Pclass," indicating that passengers in higher classes (lower Pclass values) were more likely to survive.
- Survived and Fare: There is a positive correlation between "Survived" and "Fare," suggesting that passengers who paid higher fares had a higher chance of survival.
- Pclass and Fare: There is a negative correlation between "Pclass" and "Fare," which is expected since lower passenger classes typically paid lower fares.
- Age and Pclass: There is a negative correlation between "Age" and "Pclass," indicating that older passengers were more likely to be in higher classes.
- SibSp and Parch: There is a positive correlation between "SibSp" (number of siblings/spouses) and "Parch" (number of parents/children), suggesting that passengers with more siblings/spouses were more likely to have more parents/children aboard

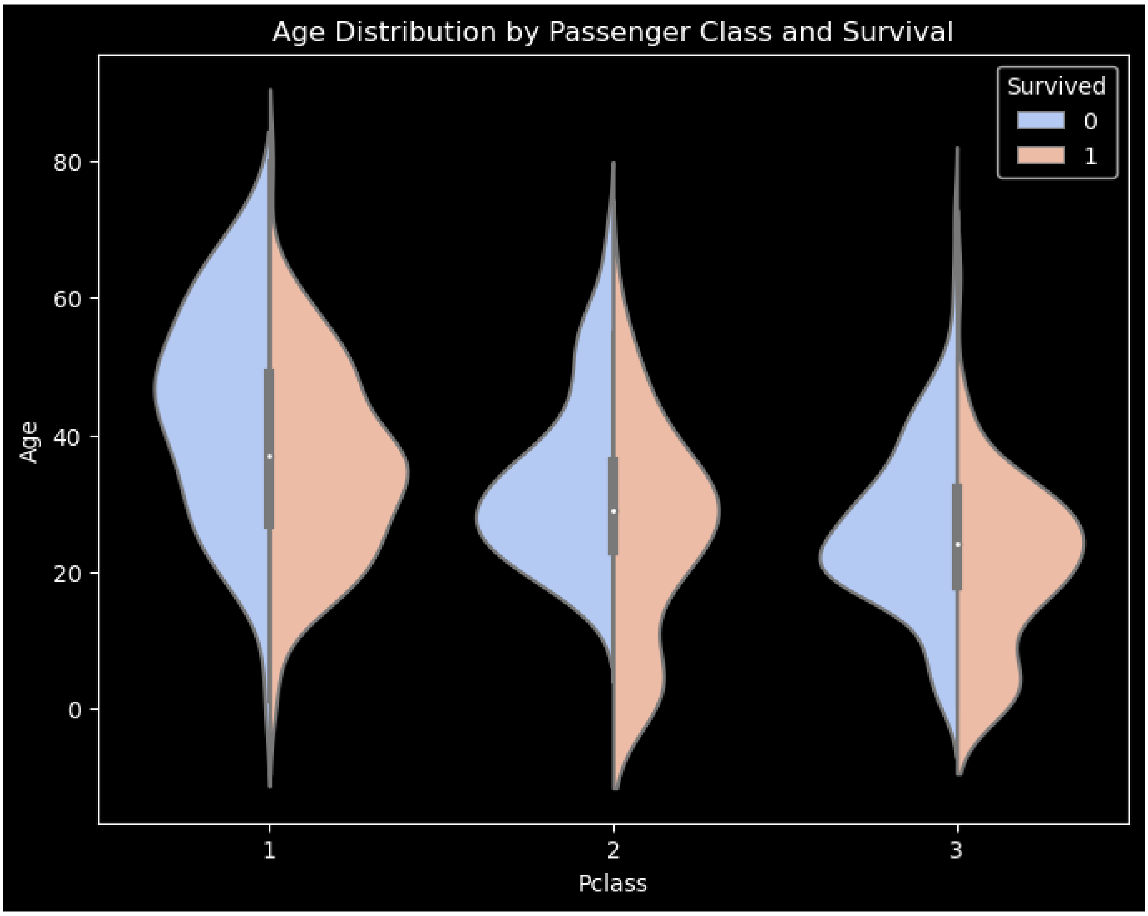
Pair Plot

In [38]:
```
# Pair plot for numerical variables
sns.pairplot(df[['Age', 'Fare', 'Pclass', 'Survived']], hue='Survived', pal
plt.title('Pair Plot of Numerical Variables')
plt.show()
```



- The pair plot generated provides a visual representation of the relationships between numerical variables in the dataset
- Age vs. Fare: The scatter plots between Age and Fare show a cluster of data points in the lower Fare range, including both non-survivors (blue) and survivors (orange). This suggests that Fare alone may not be a strong indicator of survival
- Fare vs. Pclass: The scatter plots between Fare and Pclass show that passengers in Pclass 1 (orange) paid significantly higher fares compared to those in Pclass 2 and 3 (blue). There is some overlap in fares between Pclass 2 and 3.
- Survived vs. Age: The histograms along the diagonal of the pair plot show the distribution of Age for survivors (orange) and non-survivors (blue). It appears that a higher proportion of younger passengers survived (orange), while older passengers have a more balanced distribution between survivors and non-survivors (blue)

In [39]:
```
# Violin plot for Age distribution by passenger class
plt.figure(figsize=(8, 6))
sns.violinplot(data=df, x='Pclass', y='Age', hue='Survived', palette='coolw
plt.xlabel('Pclass')
plt.ylabel('Age')
plt.title('Age Distribution by Passenger Class and Survival')
plt.show()
```



- Violin Plot: A violin plot combines a box plot with a kernel density estimation to visualize the distribution of a numerical variable across different categories of a categorical variable
- This plot highlights that age played a more significant role in survival for passengers in Pclass 3, where younger passengers had a better chance of surviving. In Pclass 1 and 2, the impact of age on survival is less pronounced.

In [6]:
```
# Multivariate Parallel Coordinates Plot
import plotly.express as px
import pandas as pd

# Assuming df is your DataFrame
df = pd.DataFrame({
    'Age': [25, 30, 22, 35, 28],
    'Fare': [50.5, 23.8, 45.2, 67.9, 30.4],
    'Pclass': [1, 2, 1, 3, 2],
    'Survived': [1, 0, 1, 0, 1]
})

# Multivariate Parallel Coordinates Plot
fig = px.parallel_coordinates(df, dimensions=['Age', 'Fare', 'Pclass', 'Sur
fig.show()
```

- Plot above created using Plotly Express visualizes the relationships between the variables 'Age', 'Fare', 'Pclass', and 'Survived' while color-coding the lines based on the 'Survived' status (0 for non-survivors and 1 for survivors)
- Age vs. Fare: It appears that survivors and non-survivors have a wide range of ages and fares. However, there isn't a clear separation between the two groups based on these two variables alone.
- Pclass vs. Age: In general, passengers in Pclass 1 tend to be older, while those in Pclass 3 are younger. This aligns with the expectation that higher-class passengers were typically older and wealthier.

- Pclass vs. Fare: As expected, passengers in Pclass 1 paid higher fares on average compared to those in Pclass 2 and Pclass 3.
- Age vs. Survived: While the age distribution is similar for both survivors and non-survivors, there might be a slight concentration of younger survivors.

In [ ]:

```

```