Assignment 2

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VIT Applied Data Science 2023

1.Univariate Analysis:

1.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


df = pd.read_csv('titanic.csv')
```

Counting the number of survivors:

```
survived_counts = df['survived'].value_counts()
print('Survived counts:')
print(survived_counts)
```

Bar chart of survival counts:

```
plt.figure(figsize=(8, 6))
sns.countplot(x='survived', data=df)
plt.title('Survival Counts')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```

Number of passengers in each class:

```
pclass_counts = df['pclass'].value_counts()
print('Passenger Class counts:')
print(pclass_counts)
```

Bar chart of passenger class counts:

```
plt.figure(figsize=(8, 6))
sns.countplot(x='pclass', data=df)
plt.title('Passenger Class Counts')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.show()
```

Number of male and female passengers:

```
sex_counts = df['sex'].value_counts()
print('Sex counts:')
print(sex_counts)
```

Bar chart of sex counts:

```
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', data=df)
plt.title('Sex Counts')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.show()
```

Histogram of passenger ages:

```
plt.figure(figsize=(8, 6))
sns.histplot(df['age'].dropna(), bins=20)
plt.title('Passenger Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```

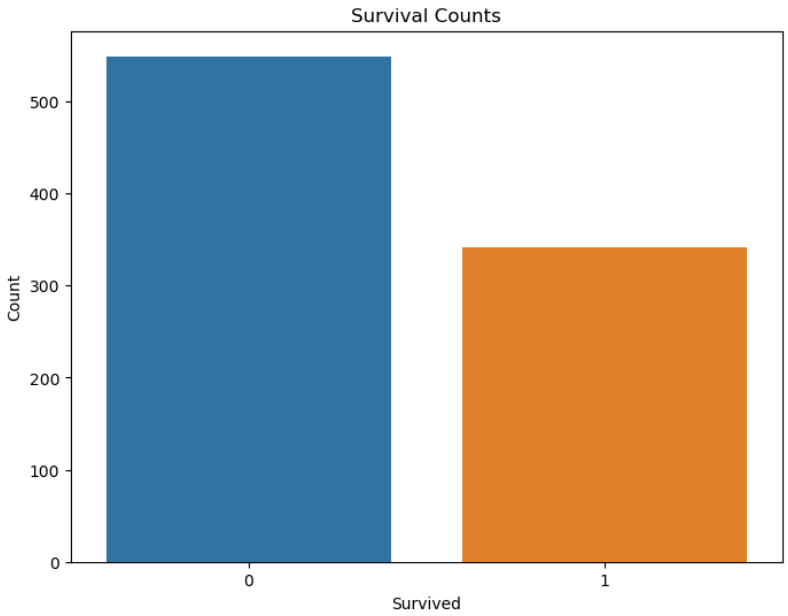
In [4]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [5]:
```
df = pd.read_csv('titanic.csv')
```

In [6]:
```
survived_counts = df['survived'].value_counts()
print('Survived counts:')
print(survived_counts)
```

```
Survived counts:
0    549
1    342
Name: survived, dtype: int64
```

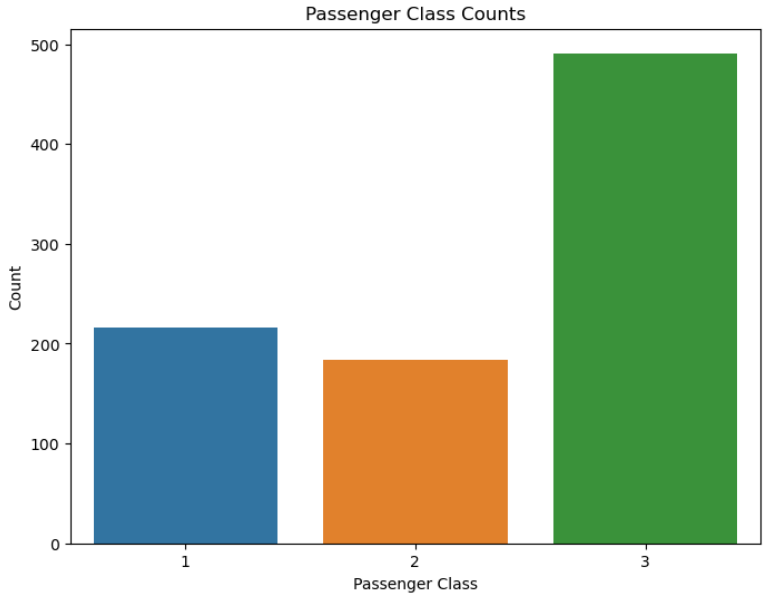
In [7]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='survived', data=df)
plt.title('Survival Counts')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```



In [8]:
```
pclass_counts = df['pclass'].value_counts()
print('Passenger Class counts:')
print(pclass_counts)
```

```
Passenger Class counts:
3    491
1    216
2    184
Name: pclass, dtype: int64
```

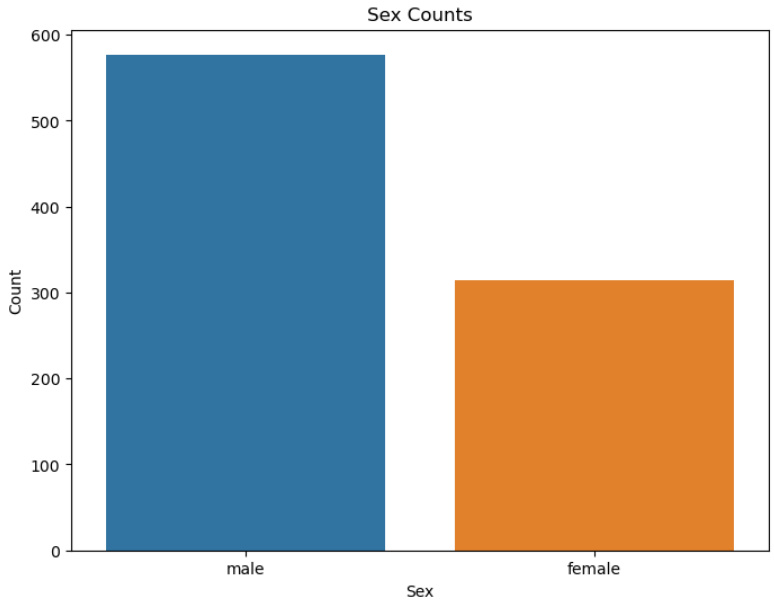
In [9]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='pclass', data=df)
plt.title('Passenger Class Counts')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.show()
```



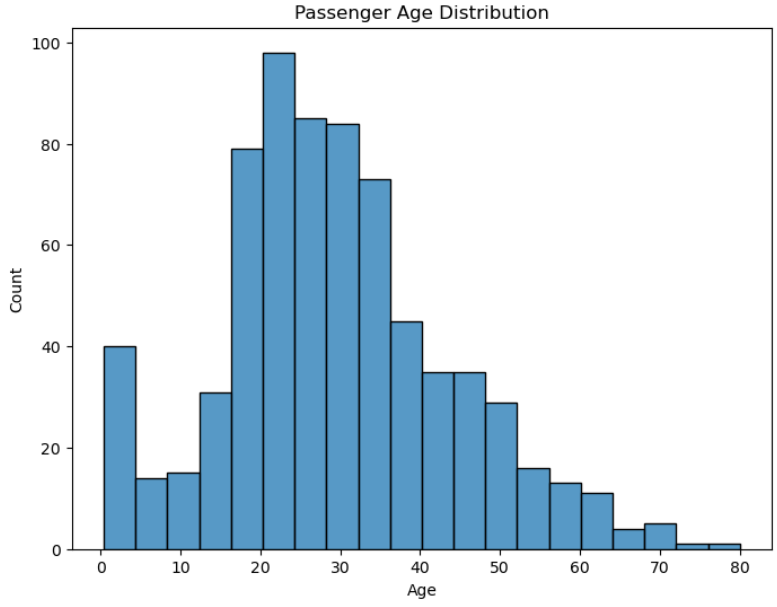
In [10]:
```
sex_counts = df['sex'].value_counts()
print('Sex counts:')
print(sex_counts)
```

```
Sex counts:
male      577
female    314
Name: sex, dtype: int64
```

In [11]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', data=df)
plt.title('Sex Counts')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.show()
```



In [12]:
```
plt.figure(figsize=(8, 6))
sns.histplot(df['age'].dropna(), bins=20)
plt.title('Passenger Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



2. Bi - Variate Analysis:

2.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('titanic.csv')
```

Relationship between 'age' and 'fare':

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='age', y='fare', data=df, hue='survived')
plt.title('Age vs Fare (Survived vs Not Survived)')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

Relationship between 'pclass' and 'fare':

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='pclass', y='fare', data=df)
plt.title('Passenger Class vs Fare')
plt.xlabel('Passenger Class')
plt.ylabel('Fare')
plt.show()
```

Relationship between 'sex' and 'survived':

```
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', hue='survived', data=df)
```

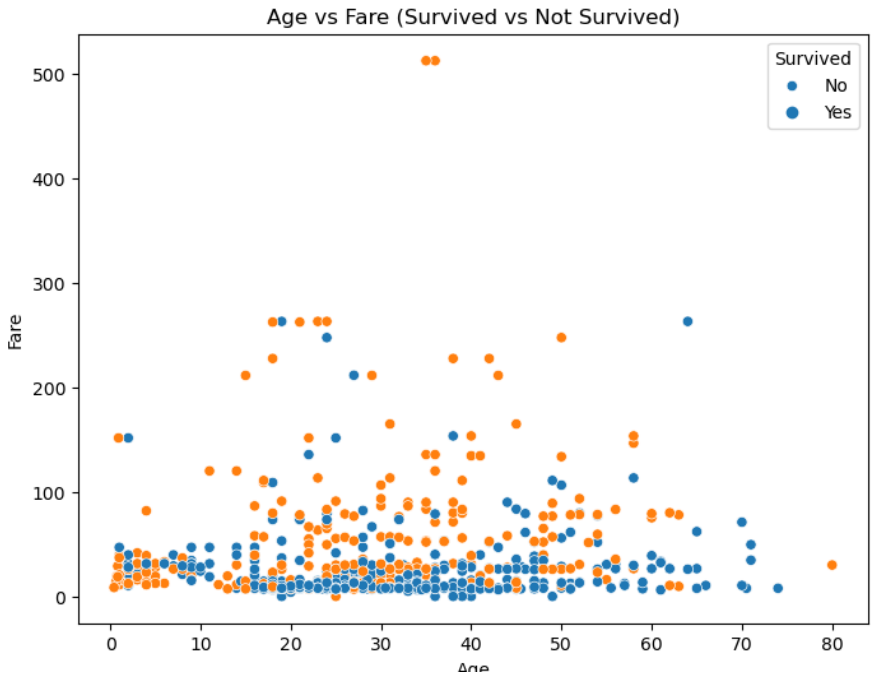
```
plt.title('Survival Count by Sex')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

Relationship between 'pclass', 'sex', and 'survived':

```
plt.figure(figsize=(8, 6))
sns.countplot(x='pclass', hue='survived', data=df, palette='husl')
plt.title('Survival Count by Passenger Class and Sex')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

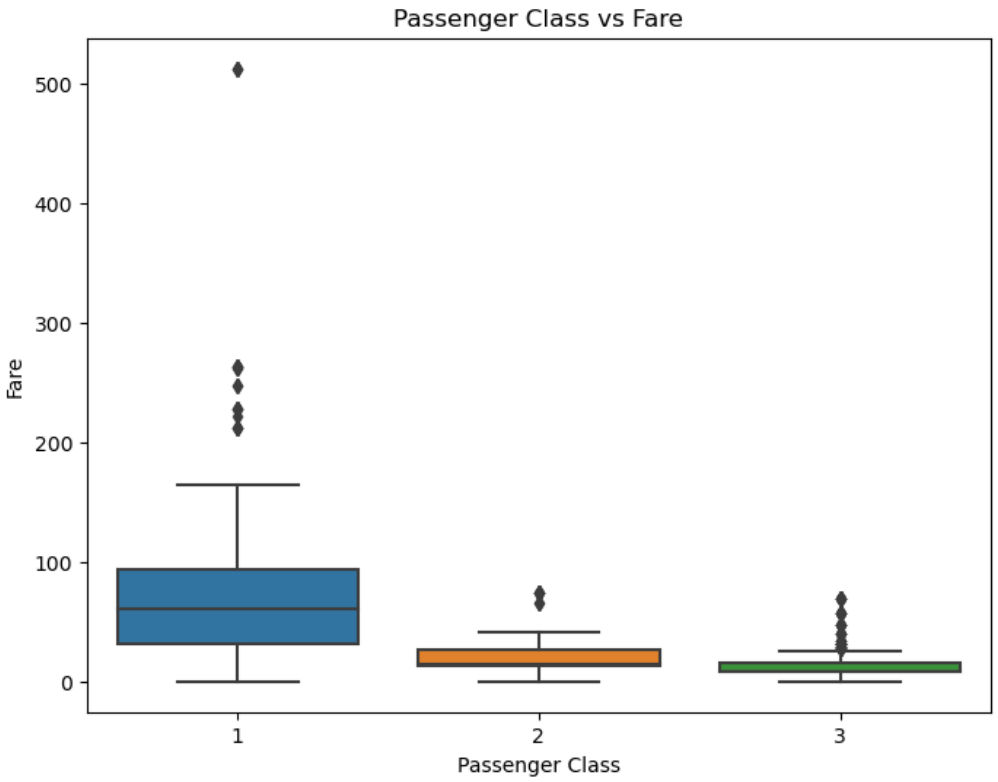
In [13]:

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='age', y='fare', data=df, hue='survived')
plt.title('Age vs Fare (Survived vs Not Survived)')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



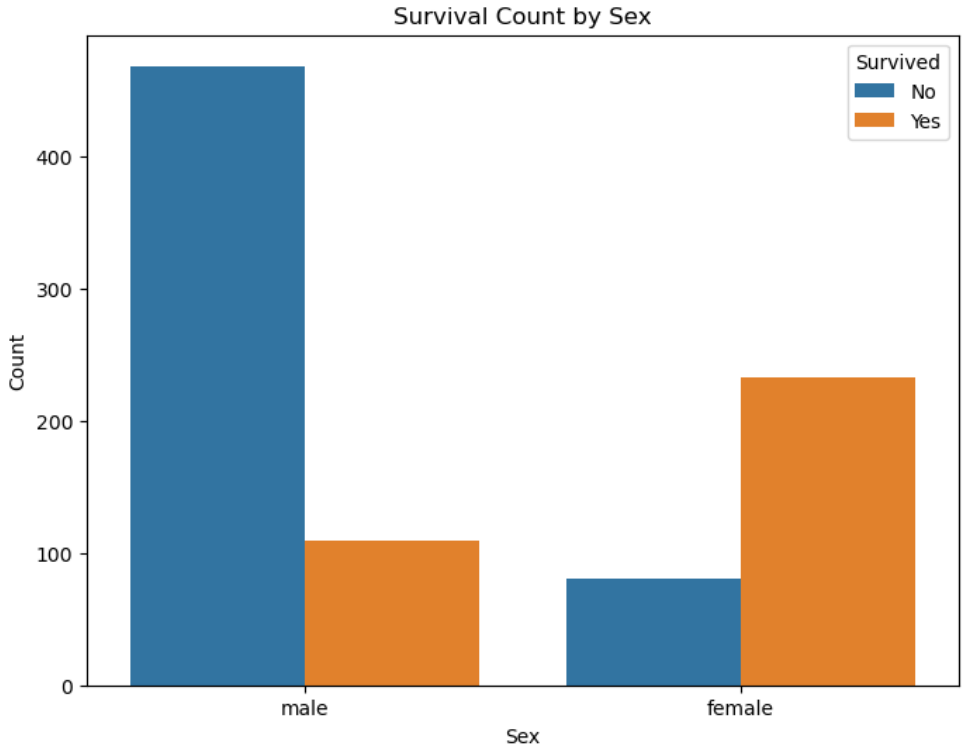
In [14]:

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='pclass', y='fare', data=df)
plt.title('Passenger Class vs Fare')
plt.xlabel('Passenger Class')
plt.ylabel('Fare')
plt.show()
```

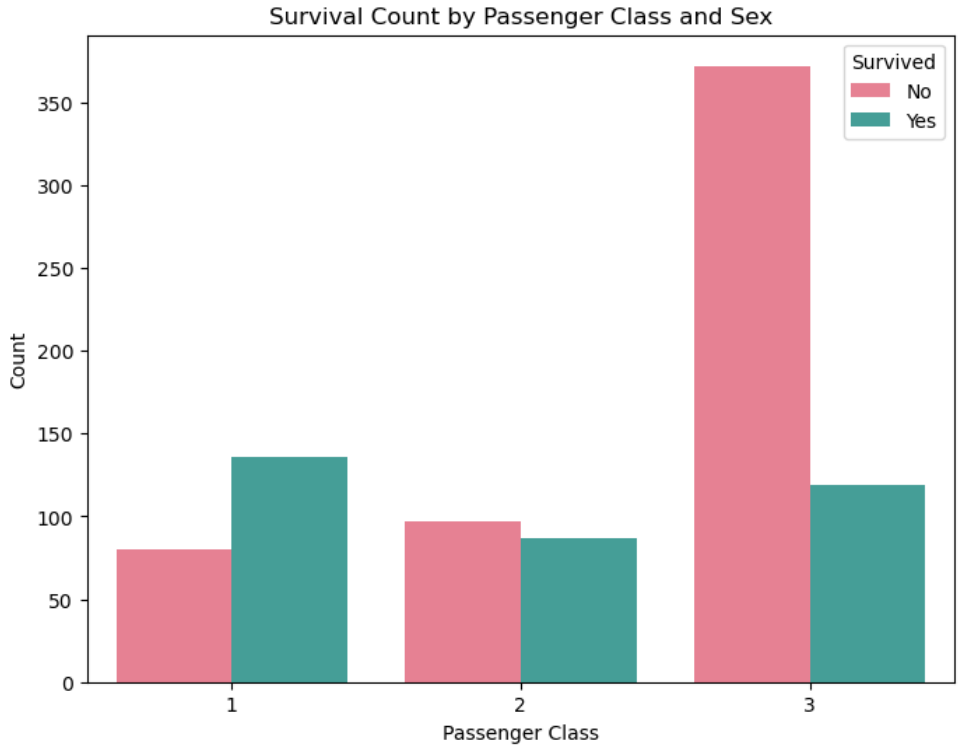


In [15]:

```
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', hue='survived', data=df)
plt.title('Survival Count by Sex')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



In [16]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='pclass', hue='survived', data=df, palette='husl')
plt.title('Survival Count by Passenger Class and Sex')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



3. Multi - Variate Analysis:

3.

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

df = pd.read_csv('titanic_dataset.csv')

Relationship between 'age', 'fare', and 'survived' using scatterplot:

plt.figure(figsize=(10, 8))

sns.scatterplot(x='age', y='fare', hue='survived', data=df, palette='Set1')

plt.title('Age vs Fare (Survived vs Not Survived)')

```
plt.xlabel('Age')
plt.ylabel('Fare')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

Relationship between 'pclass', 'sex', and 'survived' using countplot:

```
plt.figure(figsize=(10, 8))
sns.countplot(x='pclass', hue='survived', data=df, palette='Set2', hue_order=[0, 1])
plt.title('Survival Count by Passenger Class and Sex')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

Relationship between 'embarked', 'pclass', and 'survived' using heatmap:

```
pivot_table = df.pivot_table(index='embarked', columns='pclass', values='survived', aggfunc='mean')
plt.figure(figsize=(10, 8))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", cbar=True)
plt.title('Survival Rate by Embarked and Passenger Class')
plt.xlabel('Passenger Class')
plt.ylabel('Embarked')
plt.show()
```

Relationship between 'age', 'fare', and 'survived' using violinplot:

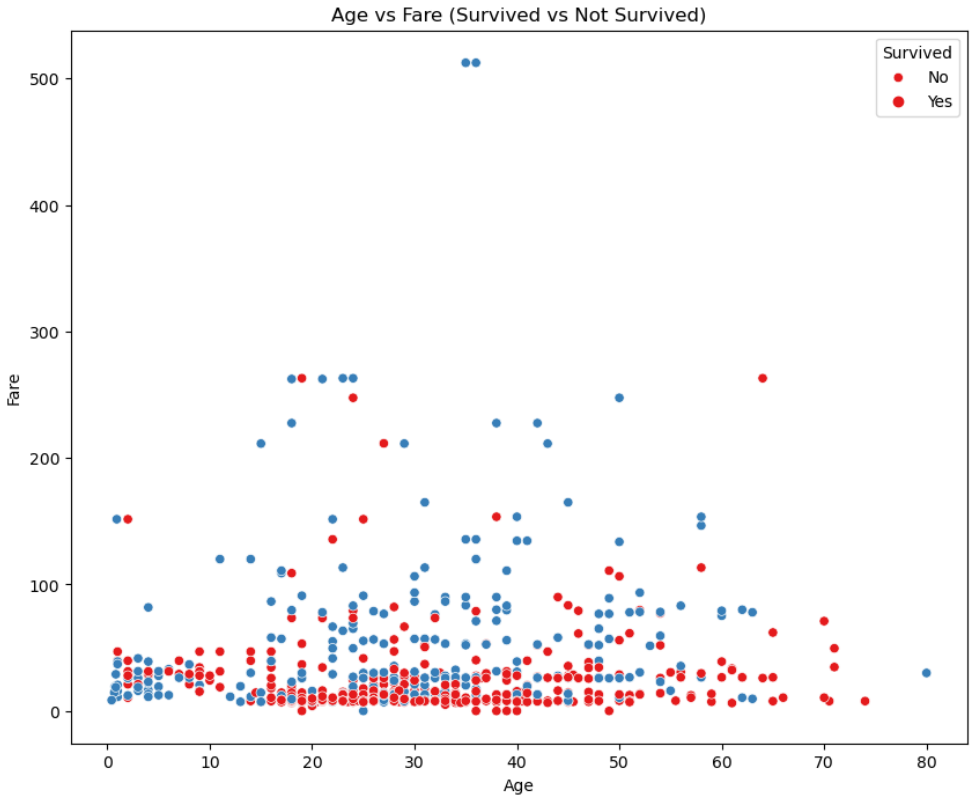
```
plt.figure(figsize=(10, 8))
sns.violinplot(x='survived', y='age', hue='sex', data=df, palette='Set3', split=True)
plt.title('Survived vs Age and Sex')
plt.xlabel('Survived')
```

plt.ylabel('Age')

plt.legend(title='Sex', labels=['Male', 'Female'])

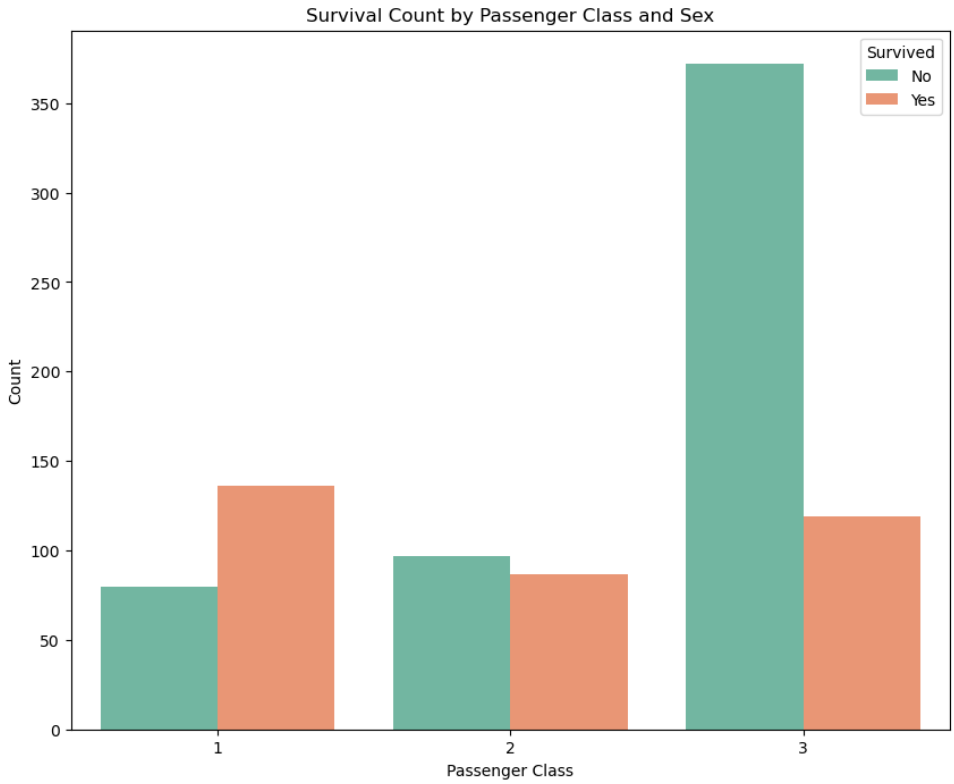
plt.show()

In [17]:
```
plt.figure(figsize=(10, 8))
sns.scatterplot(x='age', y='fare', hue='survived', data=df, palette='Set1')
plt.title('Age vs Fare (Survived vs Not Survived)')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



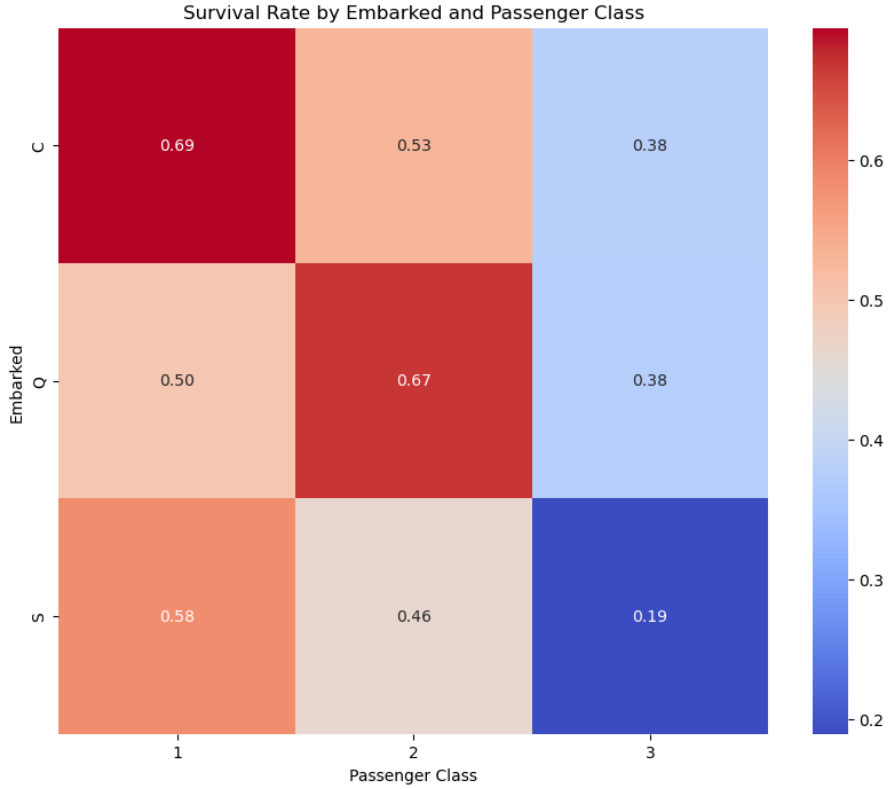
In [18]:

```
plt.figure(figsize=(10, 8))
sns.countplot(x='pclass', hue='survived', data=df, palette='Set2', hue_order=[0, 1])
plt.title('Survival Count by Passenger Class and Sex')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```

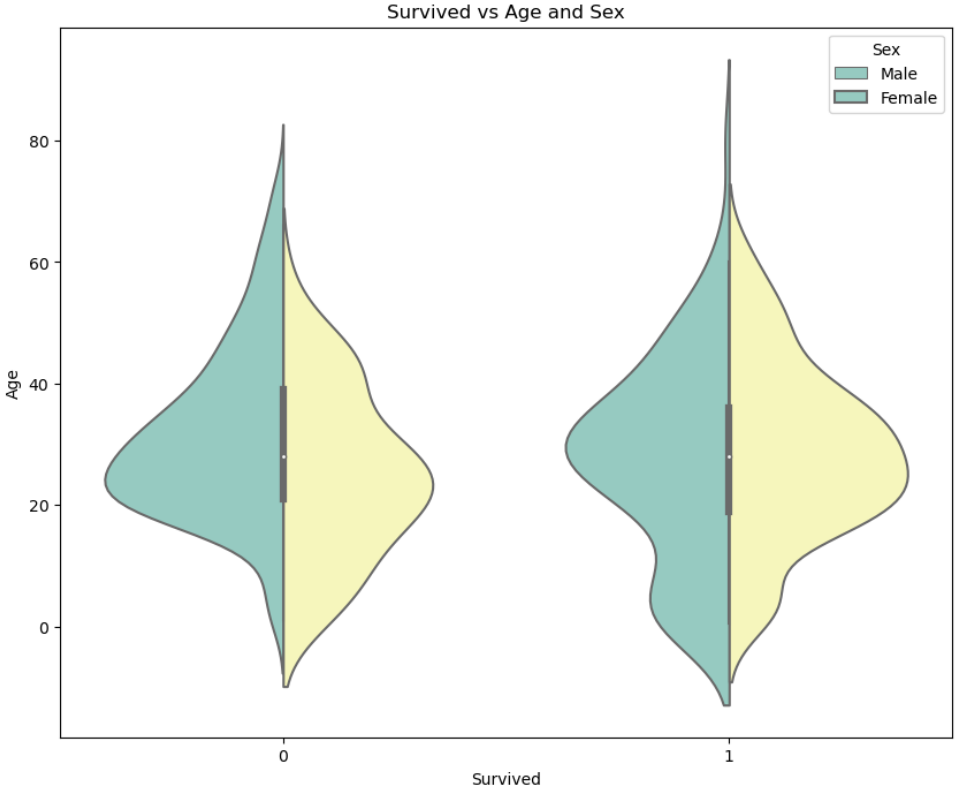


In [19]:

```
pivot_table = df.pivot_table(index='embarked', columns='pclass', values='survived', aggfunc='mean')
plt.figure(figsize=(10, 8))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", cbar=True)
plt.title('Survival Rate by Embarked and Passenger Class')
plt.xlabel('Passenger Class')
plt.ylabel('Embarked')
plt.show()
```



In [20]:
```
plt.figure(figsize=(10, 8))
sns.violinplot(x='survived', y='age', hue='sex', data=df, palette='Set3', split=True)
plt.title('Survived vs Age and Sex')
plt.xlabel('Survived')
plt.ylabel('Age')
plt.legend(title='Sex', labels=['Male', 'Female'])
plt.show()
```



4. Perform descriptive statistics on the dataset.

4.

df = pd.read_csv('titanic.csv')

descriptive_stats = df.describe()

print(descriptive_stats)

In [21]:
```
df = pd.read_csv('titanic.csv')

descriptive_stats = df.describe()
print(descriptive_stats)
```

```
         survived      pclass         age       sibsp       parch        fare
count  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
mean     0.383838    2.308642   29.699118    0.523008    0.381594   32.204208
std      0.486592    0.836071   14.526497    1.102743    0.806057   49.693429
min      0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
25%      0.000000    2.000000   20.125000    0.000000    0.000000    7.910400
50%      0.000000    3.000000   28.000000    0.000000    0.000000   14.454200
75%      1.000000    3.000000   38.000000    1.000000    0.000000   31.000000
max      1.000000    3.000000   80.000000    8.000000    6.000000  512.329200
```

5. Handle the Missing values.

5.

Checking for missing values:

```
missing_values = df.isnull().sum()
print("Missing Values:")
print(missing_values)
```

Dropping the columns with high missing value ratio:

```
missing_ratio = missing_values / len(df)
high_missing_cols = missing_ratio[missing_ratio > 0.5].index
df = df.drop(columns=high_missing_cols)
print("Columns dropped due to high missing value ratio:")
print(high_missing_cols)
```

Dropping the rows with missing values in specific columns:

```
columns_with_missing = ['age', 'embarked']
df = df.dropna(subset=columns_with_missing)
print("Rows dropped with missing values in columns:", columns_with_missing)
```

Filling the missing values with mean or mode:

```
df['age'].fillna(df['age'].mean(), inplace=True)
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)
```

Checking if the missing values are handled:

```
missing_values_after = df.isnull().sum()
print("Missing Values After Handling:")
```

print(missing_values_after)

In [22]:
```
missing_values = df.isnull().sum()
print("Missing Values:")
print(missing_values)
```

```
Missing Values:
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [23]:
```
missing_ratio = missing_values / len(df)
high_missing_cols = missing_ratio[missing_ratio > 0.5].index
df = df.drop(columns=high_missing_cols)
print("Columns dropped due to high missing value ratio:")
print(high_missing_cols)
```

```
Columns dropped due to high missing value ratio:
Index(['deck'], dtype='object')
```

In [24]:
```
columns_with_missing = ['age', 'embarked']
df = df.dropna(subset=columns_with_missing)
print("Rows dropped with missing values in columns:", columns_with_missing)
```

```
Rows dropped with missing values in columns: ['age', 'embarked']
```

In [25]:
```
df['age'].fillna(df['age'].mean(), inplace=True)
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)
```

In [26]:
```
missing_values_after = df.isnull().sum()
print("Missing Values After Handling:")
print(missing_values_after)
```

```
Missing Values After Handling:
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64
```

---

6. Find the outliers and replace the outliers

6.

Selecting the numeric columns for outlier detection and replacement:

```
numeric_cols = ['age', 'fare']
```

Calculating the IQR for the selected columns:

```
Q1 = df[numeric_cols].quantile(0.25)
Q3 = df[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
```

Defining a threshold for identifying outliers:

```
threshold = 1.5
```

Finding the indices of outliers:

```
outlier_indices = ((df[numeric_cols] < (Q1 - threshold * IQR)) | (df[numeric_cols] > (Q3 + threshold * IQR))).any(axis=1)
```

Replacing outliers with the median value of the corresponding column:

```
for col in numeric_cols:
    median = df[col].median()
    df.loc[outlier_indices, col] = median
```

Verifying if the outliers have been replaced:

```
replaced_values = df[outlier_indices][numeric_cols]
print("Replaced Outlier Values:")
print(replaced_values)
```

```
In [27]: numeric_cols = ['age', 'fare']

In [28]: Q1 = df[numeric_cols].quantile(0.25)
         Q3 = df[numeric_cols].quantile(0.75)
         IQR = Q3 - Q1

In [29]: threshold = 1.5

In [30]: utlier_indices = ((df[numeric_cols] < (Q1 - threshold * IQR)) | (df[numeric_cols] > (Q3 + threshold * IQR))).any(axis=1)

In [31]: for col in numeric_cols:
             median = df[col].median()
             df.loc[outlier_indices, col] = median

In [32]: replaced_values = df[outlier_indices][numeric_cols]
         print("Replaced Outlier Values:")
         print(replaced_values)

Replaced Outlier Values:
      age      fare
1    28.0  15.64585
27   28.0  15.64585
33   28.0  15.64585
34   28.0  15.64585
52   28.0  15.64585
..    ...       ...
820  28.0  15.64585
835  28.0  15.64585
851  28.0  15.64585
856  28.0  15.64585
879  28.0  15.64585

[102 rows x 2 columns]
```

7. Check for Categorical columns and perform encoding.

7.

Checking for categorical columns:

```
categorical_cols = df.select_dtypes(include=['object', 'category']).columns
print("Categorical Columns:")
print(categorical_cols)
```

Performing the encoding for categorical columns:

```
for col in categorical_cols:
    if len(df[col].unique()) == 2:
        df[col] = df[col].astype('category').cat.codes
    else:
        df = pd.get_dummies(df, columns=[col], drop_first=True)
```

Verifying the encoding results:

print("Encoded DataFrame:")

print(df.head())

In [33]:
```
categorical_cols = df.select_dtypes(include=['object', 'category']).columns
print("Categorical Columns:")
print(categorical_cols)
```

```
Categorical Columns:
Index(['sex', 'embarked', 'class', 'who', 'embark_town', 'alive'], dtype='object
```

In [34]:
```
for col in categorical_cols:
    if len(df[col].unique()) == 2:
        df[col] = df[col].astype('category').cat.codes
    else:
        df = pd.get_dummies(df, columns=[col], drop_first=True)
```

In [35]:
```
print("Encoded DataFrame:")
print(df.head())
```

```
Encoded DataFrame:
   survived  pclass  sex   age  sibsp  parch      fare  adult_male  alive  \
0         0       3    1  22.0      1      0   7.25000        True      0
1         1       1    0  28.0      1      0  15.64585       False      1
2         1       3    0  26.0      0      0   7.92500       False      1
3         1       1    0  35.0      1      0  53.10000       False      1
4         0       3    1  35.0      0      0   8.05000        True      0

   alone  embarked_Q  embarked_S  class_Second  class_Third  who_man  \
0  False           0           1             0            1        1
1  False           0           0             0            0        0
2   True           0           1             0            1        0
3  False           0           1             0            0        0
4   True           0           1             0            1        1

   who_woman  embark_town_Queenstown  embark_town_Southampton
0          0                       0                       1
1          1                       0                       0
2          1                       0                       1
3          1                       0                       1
4          0                       0                       1
```

8. Split the data into dependent and independent variables.

8.

Splitting the data into dependent and independent variables:

X = df.drop('survived', axis=1) # Independent variables (all columns except 'survived')

y = df['survived'] # Dependent variable

Verifying if the data has been split successfully:

print("Independent Variables (X):")

print(X.head())

print("\nDependent Variable (y):")

print(y.head())

In [36]:
```
X = df.drop('survived', axis=1)  # Independent variables (all columns except 'survived')
y = df['survived']  # Dependent variable
```

In [37]:
```
print("Independent Variables (X):")
print(X.head())

print("\nDependent Variable (y):")
print(y.head())
```

```
Independent Variables (X):
   pclass  sex   age  sibsp  parch      fare  adult_male  alive  alone  \
0       3    1  22.0      1      0   7.25000        True      0  False
1       1    0  28.0      1      0  15.64585       False      1  False
2       3    0  26.0      0      0   7.92500       False      1   True
3       1    0  35.0      1      0  53.10000       False      1  False
4       3    1  35.0      0      0   8.05000        True      0   True

   embarked_Q  embarked_S  class_Second  class_Third  who_man  who_woman  \
0           0           1             0            1        1          0
1           0           0             0            0        0          1
2           0           1             0            1        0          1
3           0           1             0            0        0          1
4           0           1             0            1        1          0

   embark_town_Queenstown  embark_town_Southampton
0                       0                       1
1                       0                       0
2                       0                       1
3                       0                       1
4                       0                       1

Dependent Variable (y):
0    0
1    1
2    1
3    1
4    0
Name: survived, dtype: int64
```

9. Scale the independent variables

9.

import pandas as pd

from sklearn.preprocessing import StandardScaler

Splitting the data into dependent and independent variables:

X = df.drop('survived', axis=1)

Scaling the independent variables:

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)

Converting the scaled array back to a DataFrame:

X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

Verifying the scaled independent variables

print("Scaled Independent Variables:")

print(X_scaled_df.head())

In [40]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
```

In [41]:
```
X = df.drop('survived', axis=1)
```

In [42]:
```

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [43]:
```

X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
```

In [44]:
```
print("Scaled Independent Variables:")
print(X_scaled_df.head())
```

```
Scaled Independent Variables:
     pclass       sex       age     sibsp     parch      fare  adult_male  \
0  0.908600  0.756138 -0.504594  0.522511 -0.506787 -0.850611    0.850865
1 -1.482983 -1.322511 -0.029027  0.522511 -0.506787 -0.216809   -1.175275
2  0.908600 -1.322511 -0.187549 -0.552714 -0.506787 -0.799655   -1.175275
3 -1.482983 -1.322511  0.525801  0.522511 -0.506787  2.610599   -1.175275
4  0.908600  0.756138  0.525801 -0.552714 -0.506787 -0.790219    0.850865

      alive     alone  embarked_Q  embarked_S  class_Second  class_Third  \
0 -0.824163 -1.138760   -0.202326    0.534040     -0.566538     1.002813
1  1.213352 -1.138760   -0.202326   -1.872519     -0.566538    -0.997195
2  1.213352  0.878148   -0.202326    0.534040     -0.566538     1.002813
3  1.213352 -1.138760   -0.202326    0.534040     -0.566538    -0.997195
4 -0.824163  0.878148   -0.202326    0.534040     -0.566538     1.002813

    who_man  who_woman  embark_town_Queenstown  embark_town_Southampton
0  0.850865  -0.659912               -0.202326                 0.534040
1 -1.175275   1.515354               -0.202326                -1.872519
2 -1.175275   1.515354               -0.202326                 0.534040
3 -1.175275   1.515354               -0.202326                 0.534040
4  0.850865  -0.659912               -0.202326                 0.534040
```

10. Split the data into training and testing

10.

import pandas as pd

from sklearn.model_selection import train_test_split

Splitting the data into independent and dependent variables:

X = df.drop('survived', axis=1)

y = df['survived']

Splitting the data into training and testing sets:

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Verifying the split:

print("Training set shape:", X_train.shape, y_train.shape)

print("Testing set shape:", X_test.shape, y_test.shape)

```
In [45]: import pandas as pd
         from sklearn.model_selection import train_test_split

In [46]: X = df.drop('survived', axis=1)
         y = df['survived']

In [47]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

In [48]:
         print("Training set shape:", X_train.shape, y_train.shape)
         print("Testing set shape:", X_test.shape, y_test.shape)

         Training set shape: (569, 17) (569,)
         Testing set shape: (143, 17) (143,)
```