Applied Data Science

Assignment 2

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1)

a) Univariate Analysis:

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()

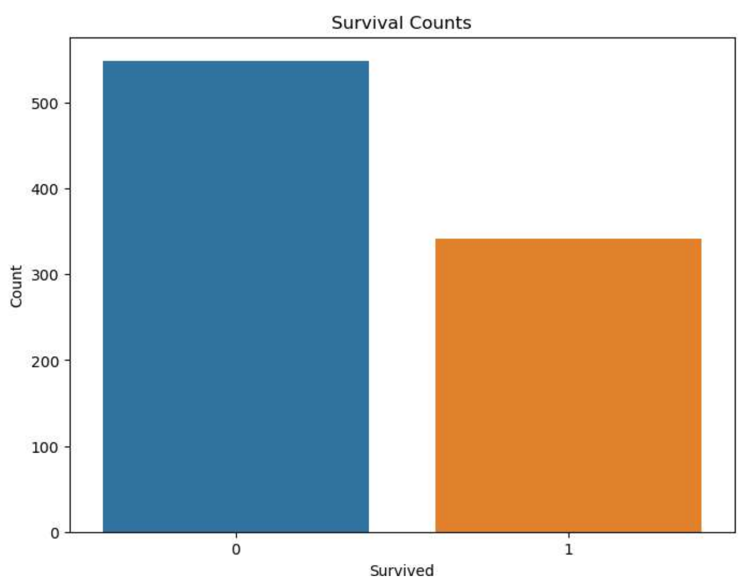
In [4]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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
```

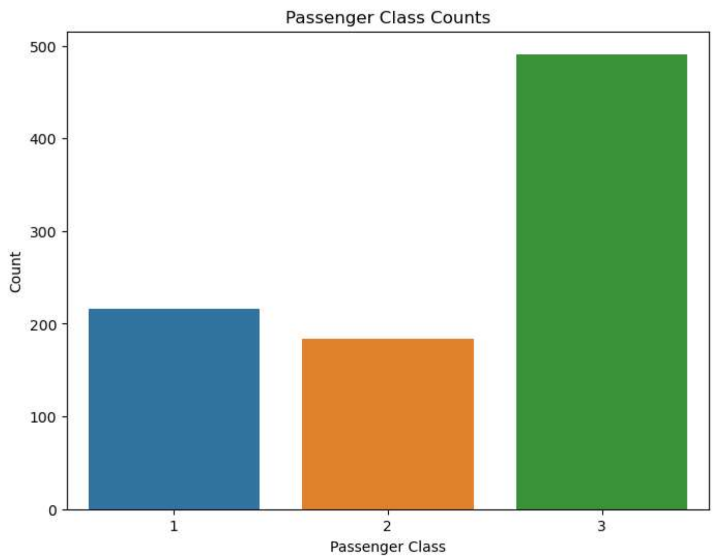
In [7]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='survived', data=df)
plt.title('Survival Counts')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```



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()
```

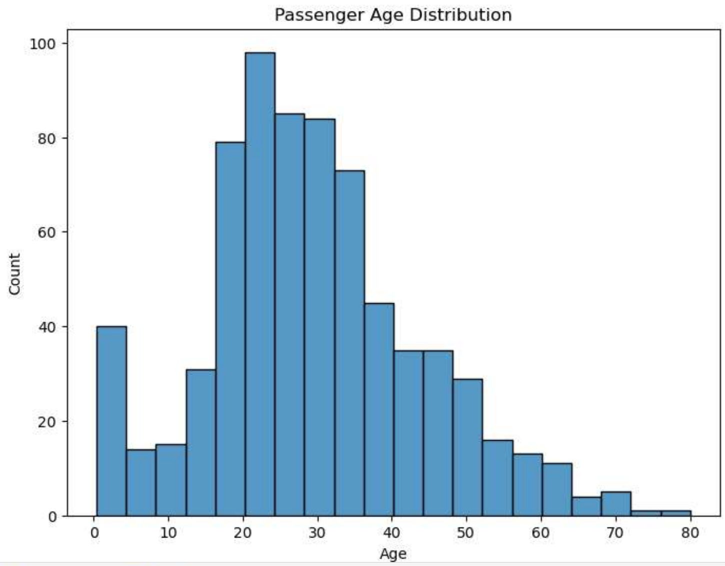


In [10]:
```
sex_counts = df['sex'].value_counts()
print('Sex counts:')
print(sex_counts)
```

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

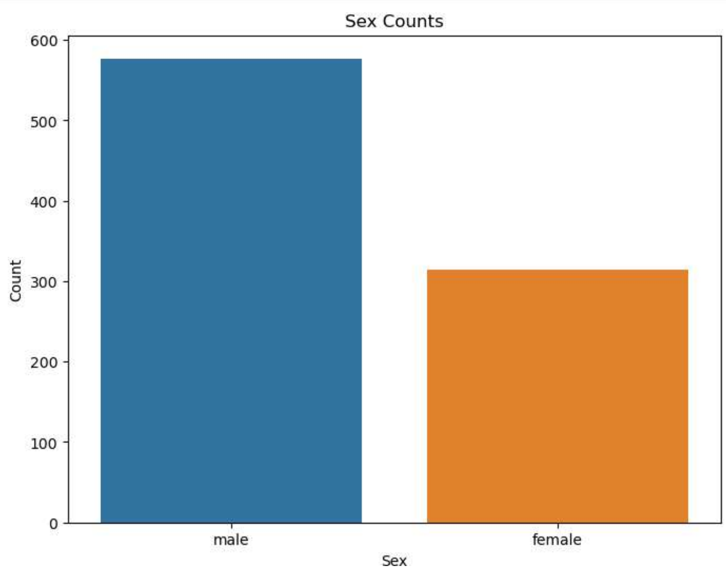
In [12]:

```
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()
```



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()
```



b) Bi - Variate Analysis:

```
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':

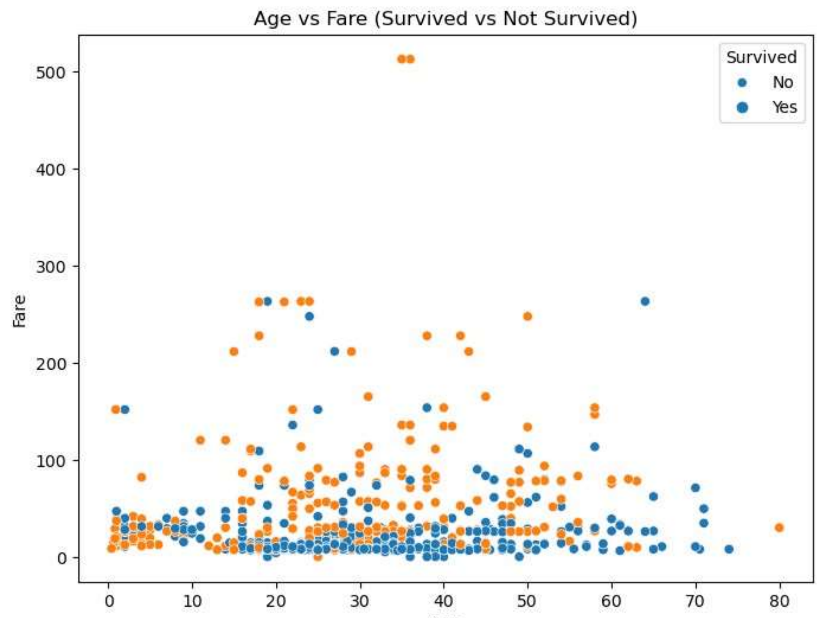
```
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', hue='survived', data=df)
plt.title('Survival Count by Sex') plt.xlabel('Sex')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes']) plt.show()
```

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()
```

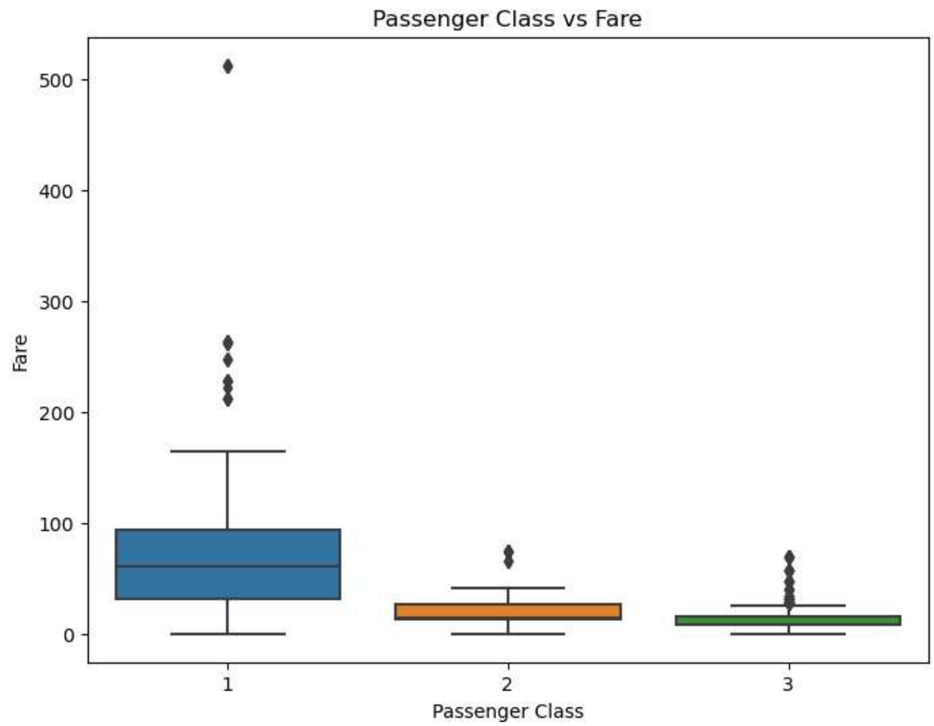
In [13]:

```
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()
```



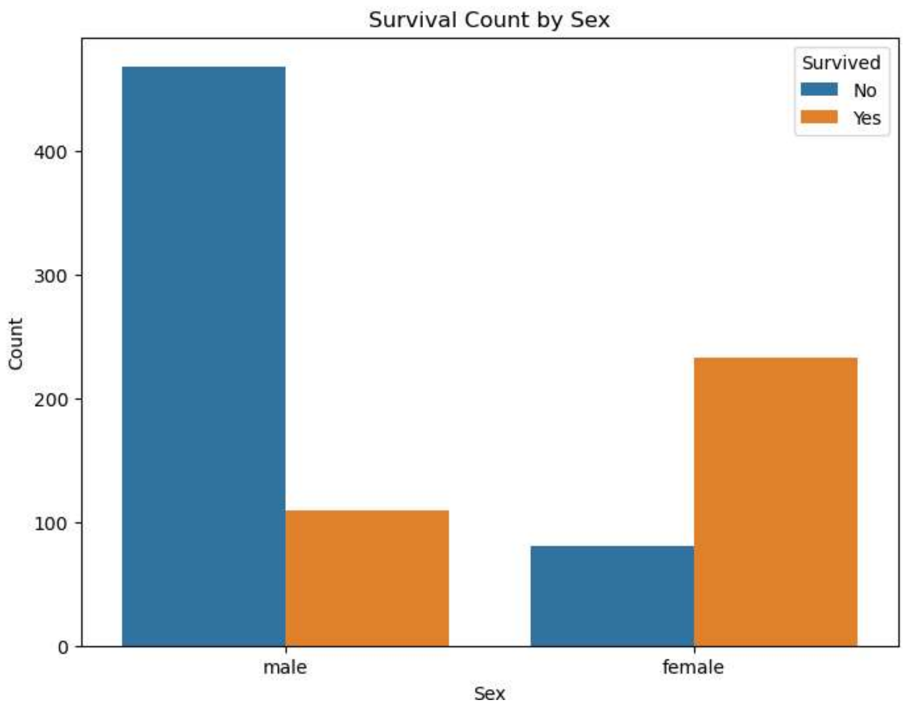
In [14]:

```
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()
```

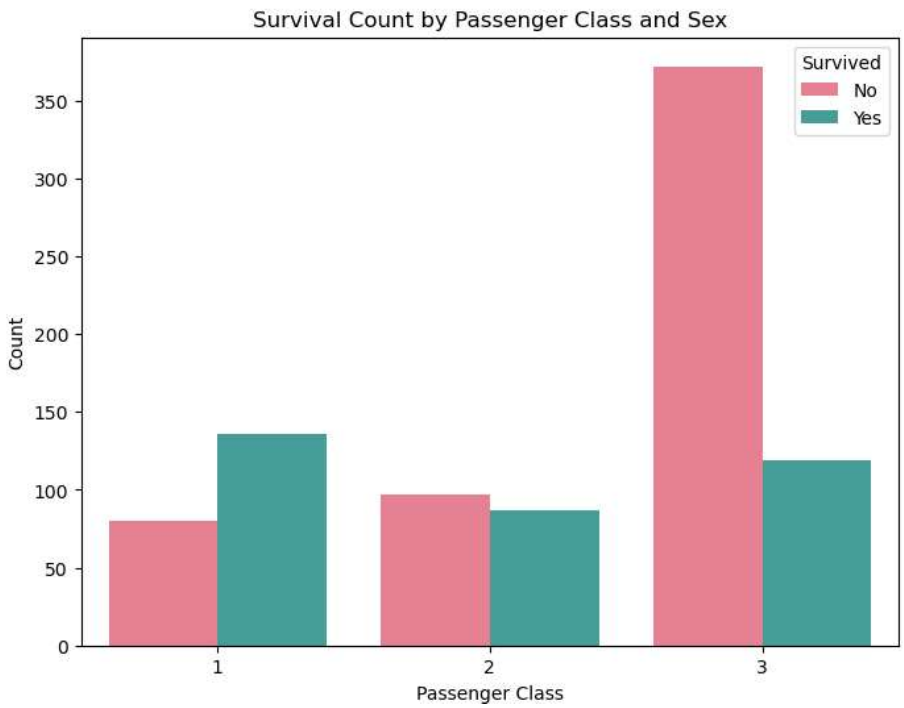


In [15]:

```
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()
```



c) Multi - Variate Analysis:

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:

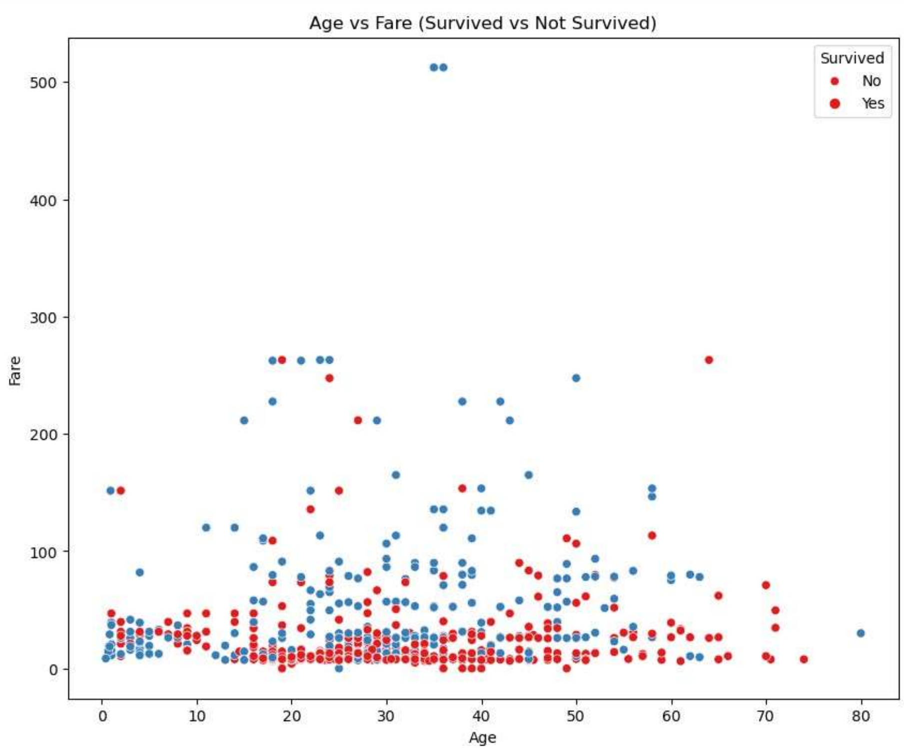
pivot_table = df.pivot_table(index='embarked', columns='pclass', values='survived', aggfunc='mean') plt.figure(figsize=(10, 8))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", cbar=True)
plt.title('Survival Rate by Embarked and Passenger Class')
plt.xlabel('Passenger Class') plt.ylabel('Embarked')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

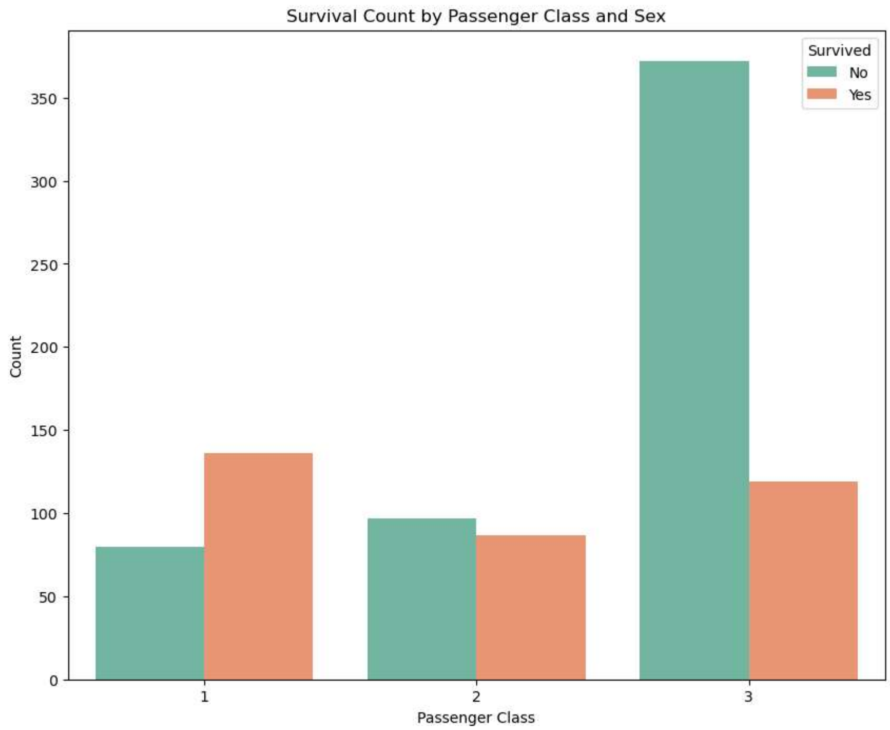
In [17]:

```
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()
```



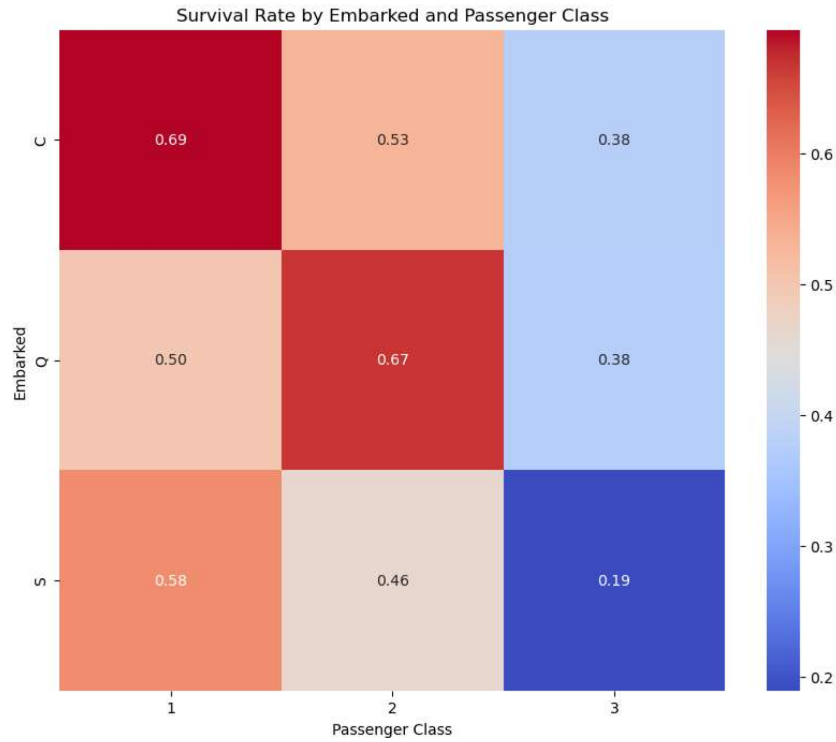
In [18]:

```
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()
```

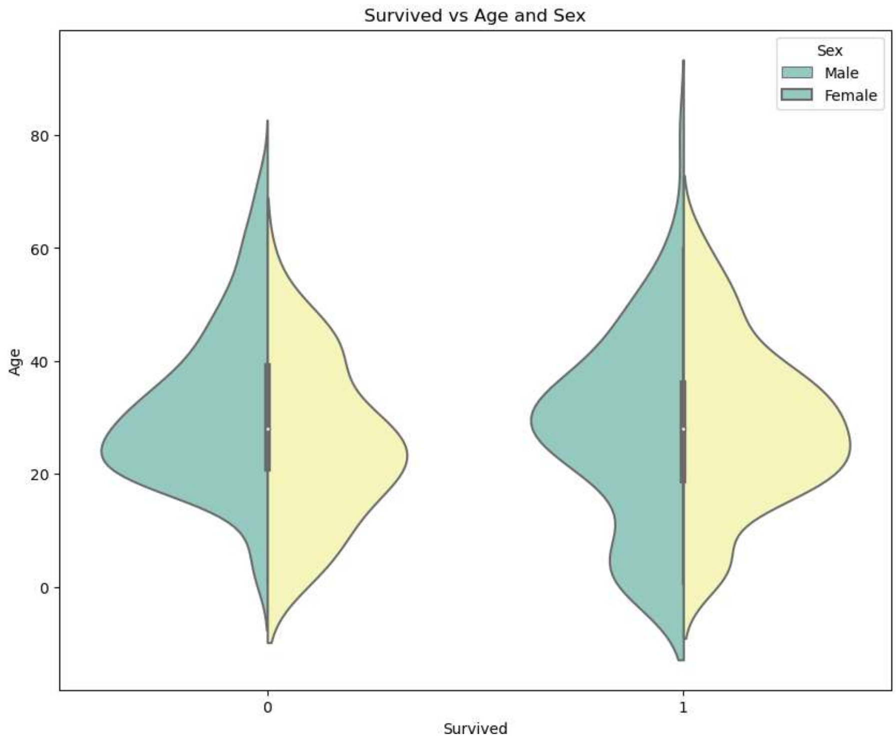


In [19]:

```
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()
```



2) Perform descriptive statistics on the dataset.
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

3) Handle the Missing values.
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]:
```python
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]:
```python
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]:
```python
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]:
```python
df['age'].fillna(df['age'].mean(), inplace=True)
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)
```

In [26]:
```python
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
```

4) Find the outliers and replace the outliers
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]
```

5) Check for Categorical columns and perform encoding.
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
```

6) Split the data into dependent and independent variables.
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
```

7) Scale the independent variables
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
```

8) Split the data into training and testing
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,)
```