SCT_DS_02

December 14, 2024

[259]:
```python
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.0.1 Step 1: Load the Titanic dataset and display its first few rows to understand its structure.

[262]:
```python
# Load the dataset
data = pd.read_csv('task2.csv')

# Display the first few rows of the dataset
print("Dataset Preview:")
display(data.head())
```

```
Dataset Preview:

   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

0.0.2 Step 2: Use data.isnull().sum() to show the number of missing values in each column.

[265]:
```
# Check for missing values
print(data.isnull().sum())
```

```
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
```

0.0.3 step 3: Handle missing values

[175]:
```
# Fill missing 'Age' values with the median
data['Age'] = data['Age'].fillna(data['Age'].median())

# Fill missing 'Embarked' values with the most frequent value (mode)
data['Embarked'] = data['Embarked'].fillna(data['Embarked'].mode()[0])

# Drop the 'Cabin' column due to a high number of missing values
data_cleaned = data.drop(columns=['Cabin'])
```

0.0.4 Step 4: check for any other missing values

[178]:
```
# Check if there are any missing values remaining
missing_values_summary = data_cleaned.isnull().sum()
print(missing_values_summary)
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

0.0.5 step 5: Convert categorical variables to numeric values (if needed for analysis)

[181]:
```
# Convert 'Sex' column to numeric (Male=0, Female=1)
data_cleaned['Sex'] = data_cleaned['Sex'].map({'male': 0, 'female': 1})
```

0.0.6 Step 6: Exploratory Data Analysis (EDA)

[184]:
```
# 6.1 Descriptive Statistics
print("Descriptive Statistics:")
display(data.describe(include='all'))
```

```
Descriptive Statistics:

        PassengerId    Survived      Pclass                     Name   Sex  \
count    891.000000  891.000000  891.000000                      891   891
unique          NaN         NaN         NaN                      891     2
top             NaN         NaN         NaN  Braund, Mr. Owen Harris  male
freq            NaN         NaN         NaN                        1   577
mean     446.000000    0.383838    2.308642                      NaN   NaN
std      257.353842    0.486592    0.836071                      NaN   NaN
min        1.000000    0.000000    1.000000                      NaN   NaN
25%      223.500000    0.000000    2.000000                      NaN   NaN
50%      446.000000    0.000000    3.000000                      NaN   NaN
75%      668.500000    1.000000    3.000000                      NaN   NaN
max      891.000000    1.000000    3.000000                      NaN   NaN

               Age       SibSp       Parch  Ticket        Fare    Cabin  \
count   891.000000  891.000000  891.000000     891  891.000000      204
unique         NaN         NaN         NaN     681         NaN      147
top            NaN         NaN         NaN  347082         NaN  B96 B98
freq           NaN         NaN         NaN       7         NaN        4
mean     29.361582    0.523008    0.381594     NaN   32.204208      NaN
std      13.019697    1.102743    0.806057     NaN   49.693429      NaN
min       0.420000    0.000000    0.000000     NaN    0.000000      NaN
25%      22.000000    0.000000    0.000000     NaN    7.910400      NaN
50%      28.000000    0.000000    0.000000     NaN   14.454200      NaN
75%      35.000000    1.000000    0.000000     NaN   31.000000      NaN
max      80.000000    8.000000    6.000000     NaN  512.329200      NaN

       Embarked
count       891
unique        3
top           S
freq        646
mean        NaN
std         NaN
min         NaN
25%         NaN
```

```
50%          NaN
75%          NaN
max          NaN
```

[186]:
```
# 6.2 Survival Rate
survival_rate = data_cleaned['Survived'].mean()
print(f"Survival Rate: {survival_rate * 100:.2f}%")
```

```
Survival Rate: 38.38%
```

0.1 Conclusion:The overall survival rate was about 38%.

[234]:
```
# 6.3 Survival Rate by Gender
survival_by_gender = data_cleaned.groupby('Sex')['Survived'].mean()
print("Survival Rate by Gender:")
print(survival_by_gender)
```

```
Survival Rate by Gender:
Sex
0    0.188908
1    0.742038
Name: Survived, dtype: float64
```

[236]:
```
# 6.4 Survival Rate by Pclass (Ticket Class)
survival_by_class = data_cleaned.groupby('Pclass')['Survived'].mean()
print("Survival Rate by Ticket Class:")
print(survival_by_class)
```

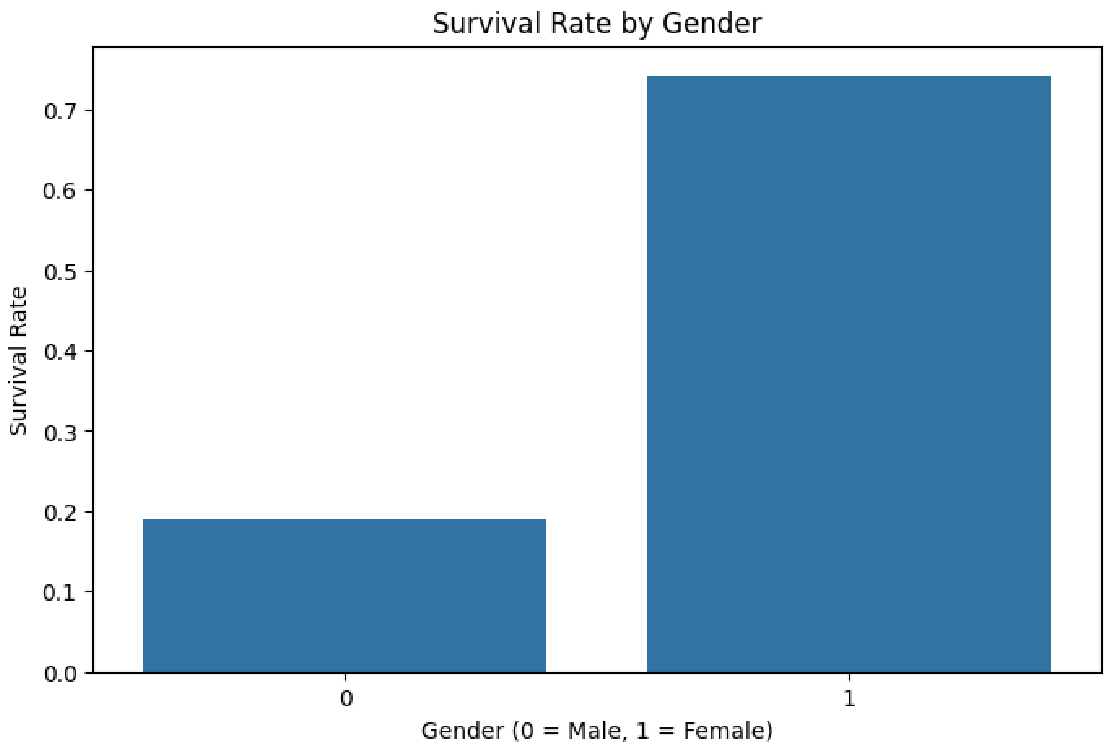
```
Survival Rate by Ticket Class:
Pclass
1    0.629630
2    0.472826
3    0.242363
Name: Survived, dtype: float64
```

[238]:
```
# 5.5 Survival Rate by Embarked (Port of Embarkation)
survival_by_embarked = data_cleaned.groupby('Embarked')['Survived'].mean()
print("Survival Rate by Embarked Port:")
print(survival_by_embarked)
```

```
Survival Rate by Embarked Port:
Embarked
C    0.553571
Q    0.389610
S    0.339009
Name: Survived, dtype: float64
```

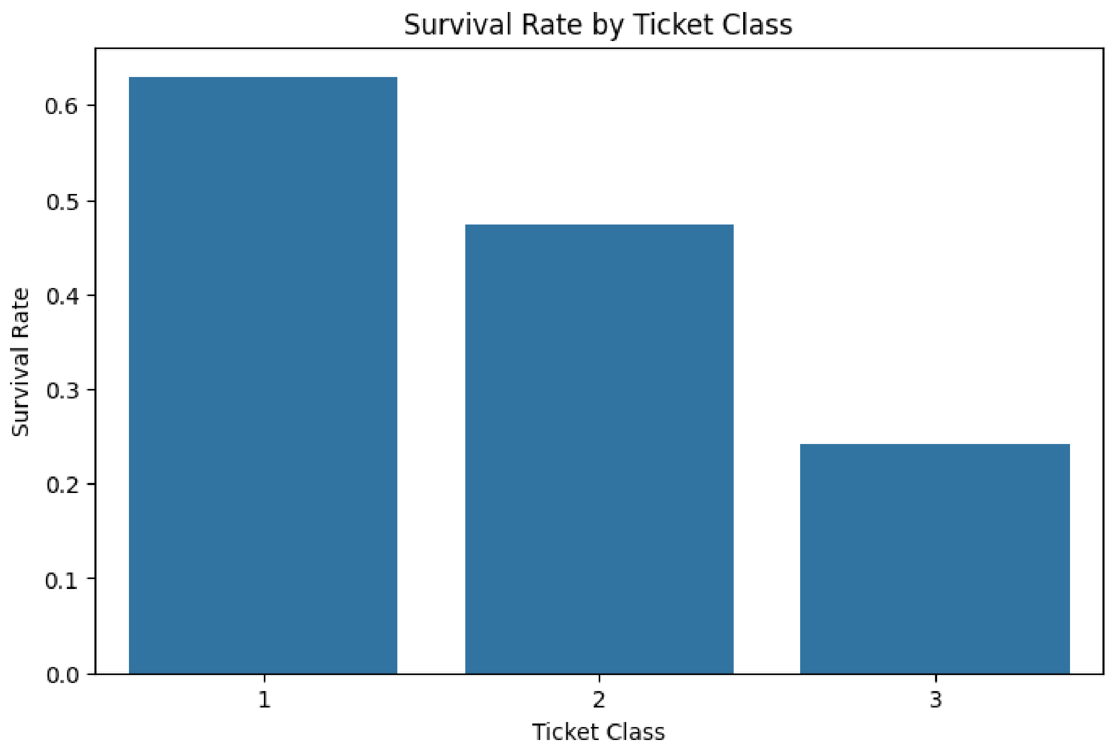
0.2 6.6 Visualizations

[241]:
```
# Plotting survival rate by gender
plt.figure(figsize=(8, 5))
sns.barplot(x=survival_by_gender.index, y=survival_by_gender.values)
plt.title('Survival Rate by Gender')
plt.xlabel('Gender (0 = Male, 1 = Female)')
plt.ylabel('Survival Rate')
plt.show()
```



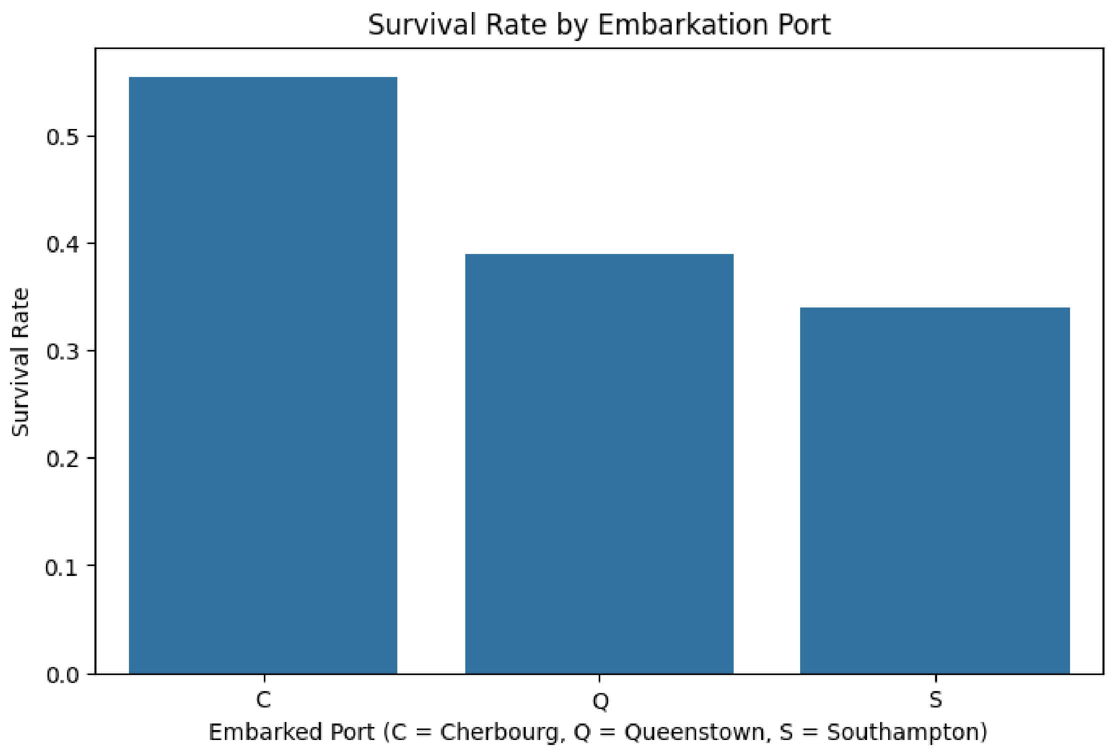
0.3 Conclusion: Female passengers had a much higher survival rate compared to male passengers.

[243]:
```
# Plotting survival rate by ticket class
plt.figure(figsize=(8, 5))
sns.barplot(x=survival_by_class.index, y=survival_by_class.values)
plt.title('Survival Rate by Ticket Class')
plt.xlabel('Ticket Class')
plt.ylabel('Survival Rate')
plt.show()
```



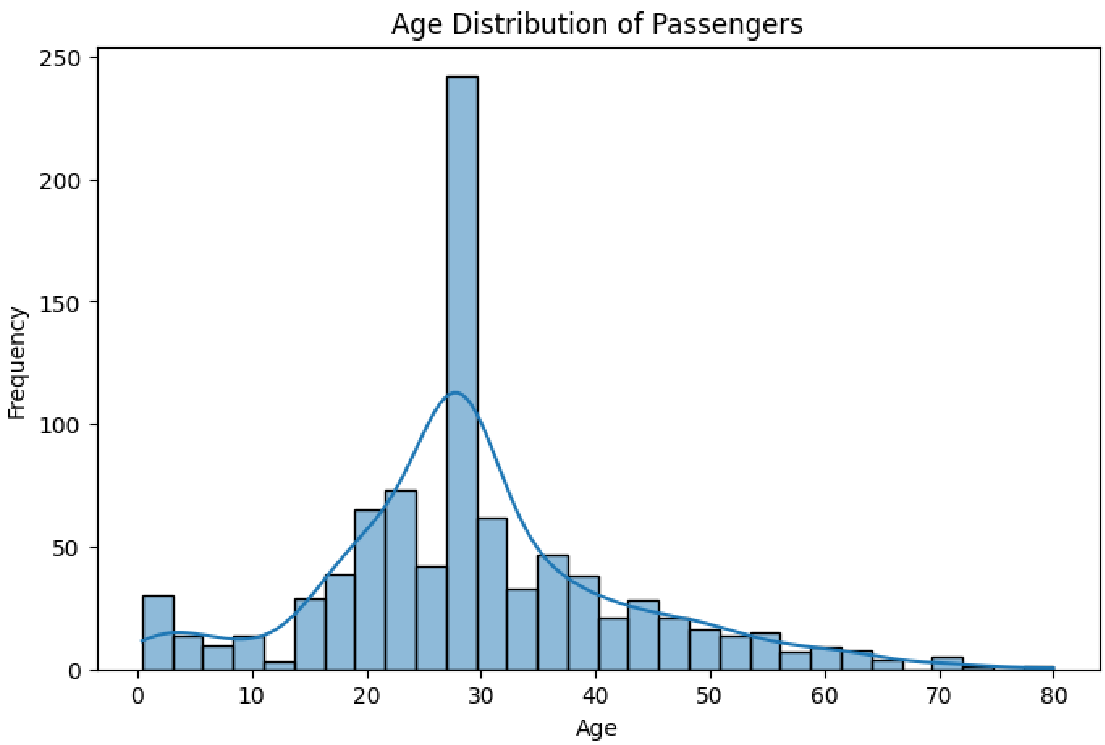
0.4 Conclusion: First-class passengers had the highest survival rates, followed by second and third-class passengers.

[245]:
```
# Plotting survival rate by embarkation port
plt.figure(figsize=(8, 5))
sns.barplot(x=survival_by_embarked.index, y=survival_by_embarked.values)
plt.title('Survival Rate by Embarkation Port')
plt.xlabel('Embarked Port (C = Cherbourg, Q = Queenstown, S = Southampton)')
plt.ylabel('Survival Rate')
plt.show()
```



0.5 Conclusion: Passengers who embarked from Cherbourg had the highest survival rates, while Southampton passengers had the lowest.

[209]:
```
# Age Distribution of Passengers
plt.figure(figsize=(8, 5))
sns.histplot(data_cleaned['Age'], kde=True, bins=30)
plt.title('Age Distribution of Passengers')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

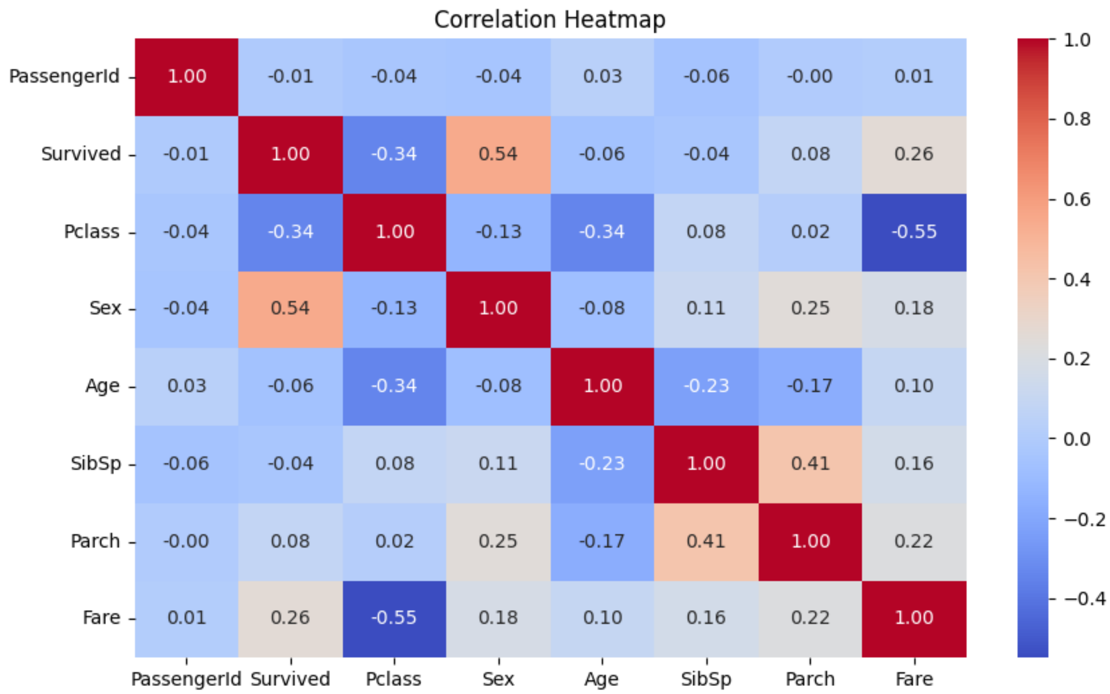


0.6 Conclusion: The majority of passengers were between 20-40 years old, with lower survival rates for older passengers.

[49]:
```
# Step 2.8 Correlation Heatmap (fixing the issue)
# Select only numeric columns for correlation
numeric_columns = data_cleaned.select_dtypes(include=[np.number])

# Calculate the correlation matrix
correlation_matrix = numeric_columns.corr()

# Plot the correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



0.7 Conclusion: There is a clear correlation between ticket class and survival: higher class (first class) passengers had higher survival rates.