In [ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer

sns.set_theme(style="darkgrid", palette= 'muted')
%matplotlib inline
```

Exploratory Data Analysis

Data overview

- PassengerId: Unique id for each passenger. No effect on the target feature.
- Survived: Whether or not the passenger survived. This is the target feature.
  - 0 = No, 1 = Yes
- Pclass: Reflects the socio-economic status of the passenger.
  - 1 = 1st, Upper Class
  - 2 = 2nd, Middle Class
  - 3 = 3rd, Lower Class
- Name: The name of the passenger. Includes the title of the passenger, such as "Mr.", "Mrs.", and "Master.".
- Sex: Gender of the passenger, either "male" or "female".
- Age: The age of the passenger in years.
- SibSp: # of siblings / spouses aboard the Titanic.
- Parch: # of parents / children aboard the Titanic.
- Ticket: The Ticket number.
- Fare: Passenger fare.
- Cabin: Cabin number of the passenger.
- Embarked: Which port the passenger embarked from.
  - C = Cherbourg
  - Q = Queenstown
  - S = Southampton

In [ ]:
```
path1 = '/content/drive/MyDrive/Datasets/Internship/Task-02/train.cs
v'
path2 = '/content/drive/MyDrive/Datasets/Internship/Task-02/test.csv'

train_data = pd.read_csv(path1)
test_data = pd.read_csv(path2)
```

In [ ]:
```
train_data.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Em
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

In [ ]:
```
test_data.head()
```

Out[ ]:

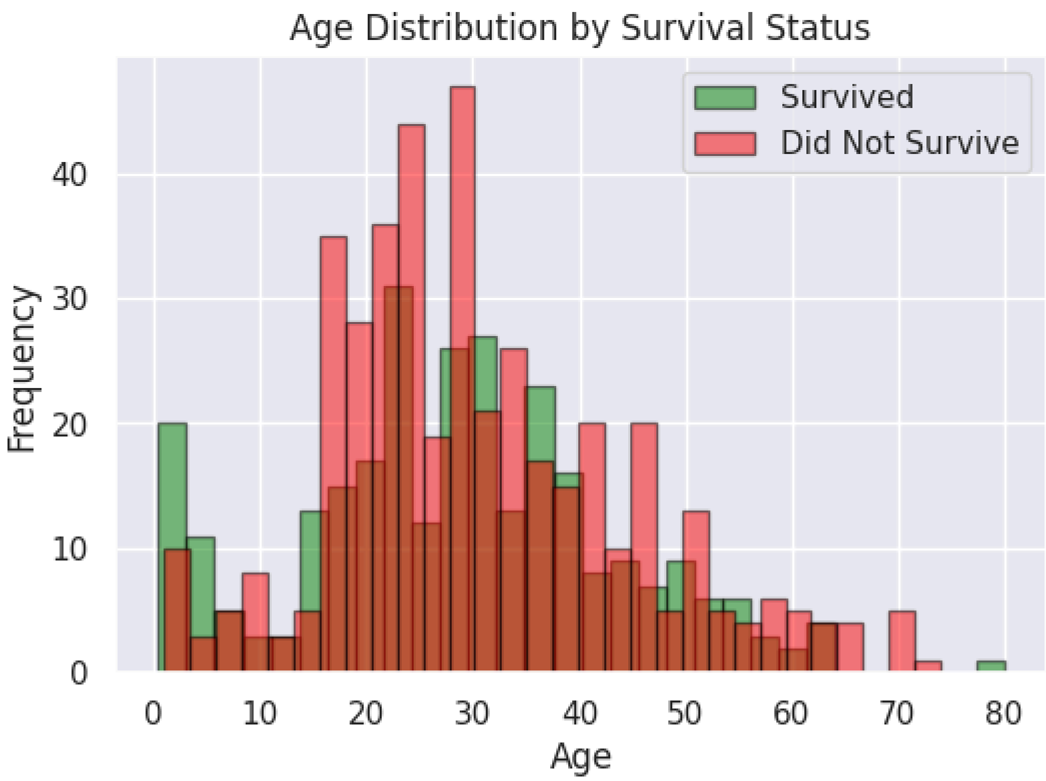
	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

Features and Survival

In [ ]:
```
plt.figure(figsize=(6, 4))

plt.hist(train_data[train_data['Survived'] == 1]['Age'], bins=30, alp
ha=0.5, label='Survived', color='green', edgecolor='black')
plt.hist(train_data[train_data['Survived'] == 0]['Age'], bins=30, alp
ha=0.5, label='Did Not Survive', color='red', edgecolor='black')

plt.title('Age Distribution by Survival Status')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.legend()
plt.grid(True)
```



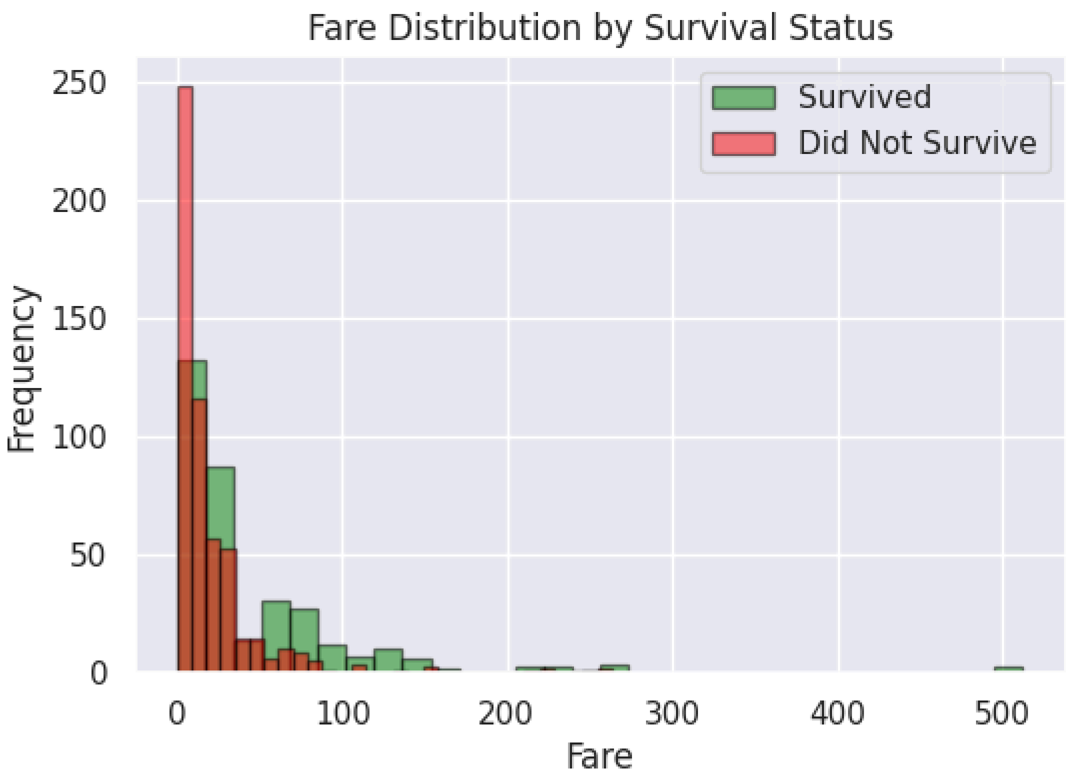
- Younger passengers, especially those < 5 years old, seem to survive at a higher rate.
- Older passengers seem to have a lower survival rate, especially around 40 - 75 years old.

In [ ]:

```
plt.figure(figsize=(6, 4))

plt.hist(train_data[train_data['Survived'] == 1]['Fare'], bins=30, alpha=0.5, label='Survived', color='green', edgecolor='black')
plt.hist(train_data[train_data['Survived'] == 0]['Fare'], bins=30, alpha=0.5, label='Did Not Survive', color='red', edgecolor='black')

plt.title('Fare Distribution by Survival Status')
plt.xlabel('Fare')
plt.ylabel('Frequency')
plt.legend()
plt.grid(True)
```



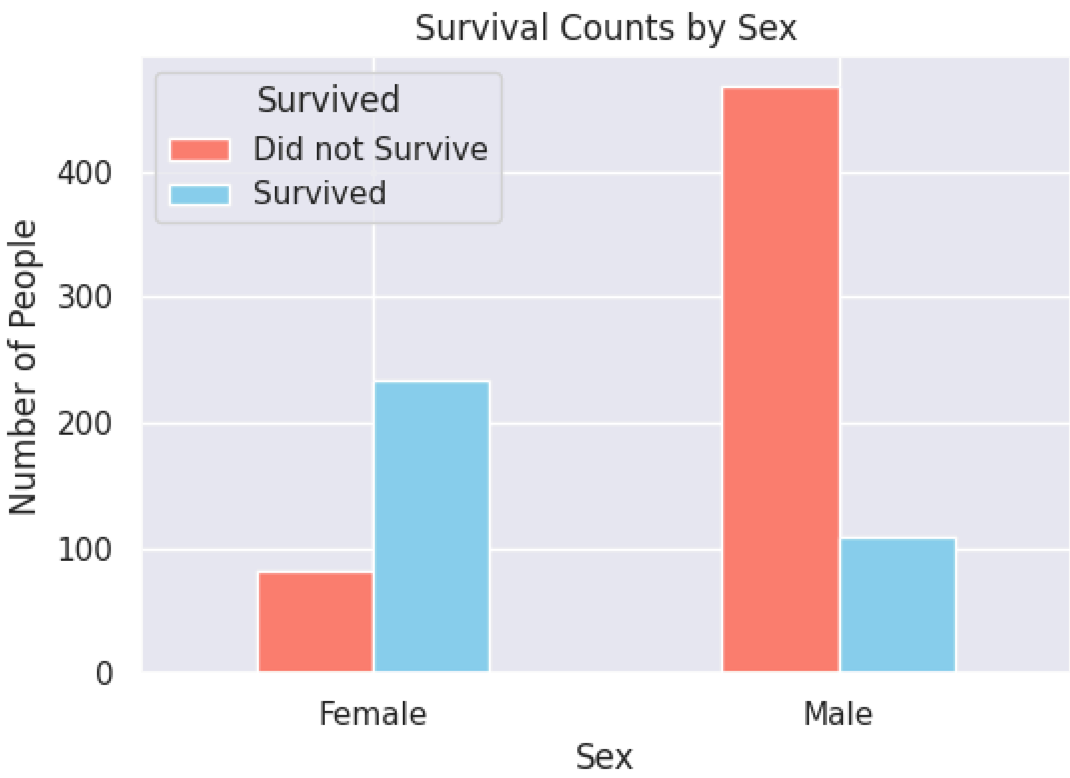
- Lower fares seemed to have survived less.
- Higher fares seemed to survive more.
- This can be correlated with the socio-economic status of the passenger.

In [ ]:

```
df = train_data.copy()
df['Sex_Label'] = df['Sex'].map({'male': 'Male', 'female': 'Female'})

survival_counts = df.groupby(['Sex_Label', 'Survived']).size().unstac
k()
survival_counts.plot(kind='bar', stacked=False, figsize=(6, 4), color
=['salmon', 'skyblue'])

plt.title('Survival Counts by Sex')
plt.xlabel('Sex')
plt.ylabel('Number of People')
plt.xticks(rotation=0)
plt.legend(title='Survived', labels=['Did not Survive', 'Survived'])
plt.grid(True)
```

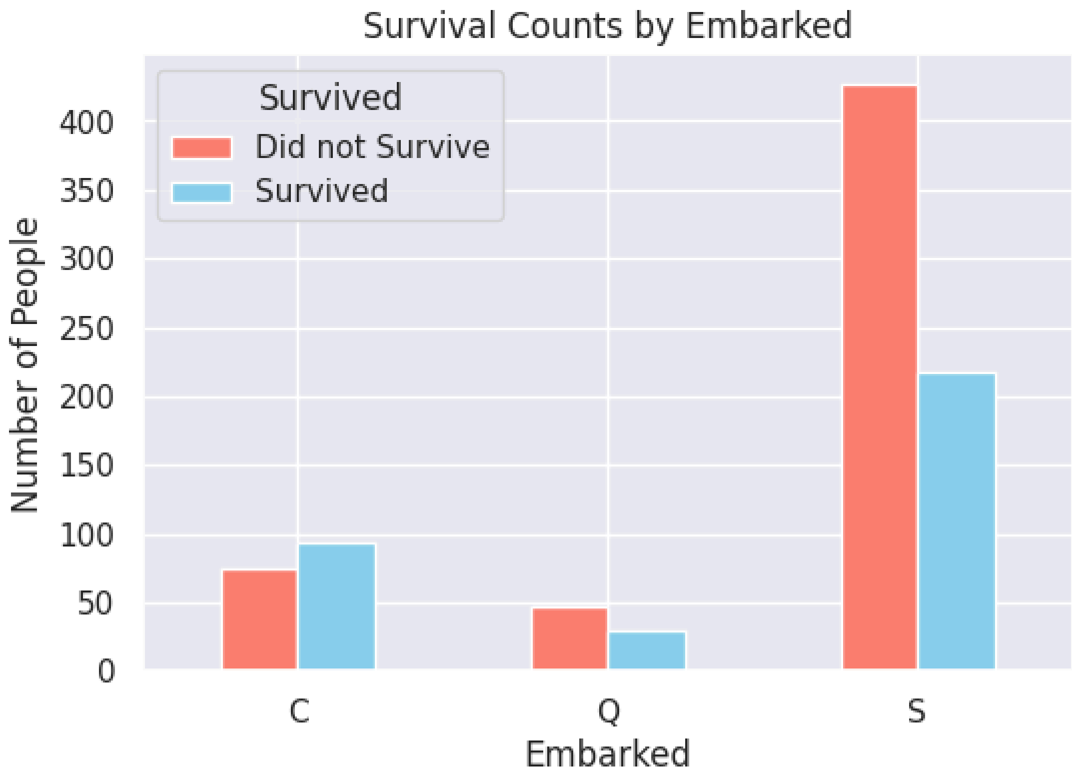


- Females have a higher rate of survival than Males.

In [ ]:
```
survival_counts = train_data.groupby(['Embarked', 'Survived']).size
().unstack()

survival_counts.plot(kind='bar', stacked=False, figsize=(6, 4), color
=['salmon', 'skyblue'])

plt.title('Survival Counts by Embarked')
plt.xlabel('Embarked')
plt.ylabel('Number of People')
plt.xticks(rotation=0)
plt.legend(title='Survived', labels=['Did not Survive', 'Survived'])
plt.grid(True)
```

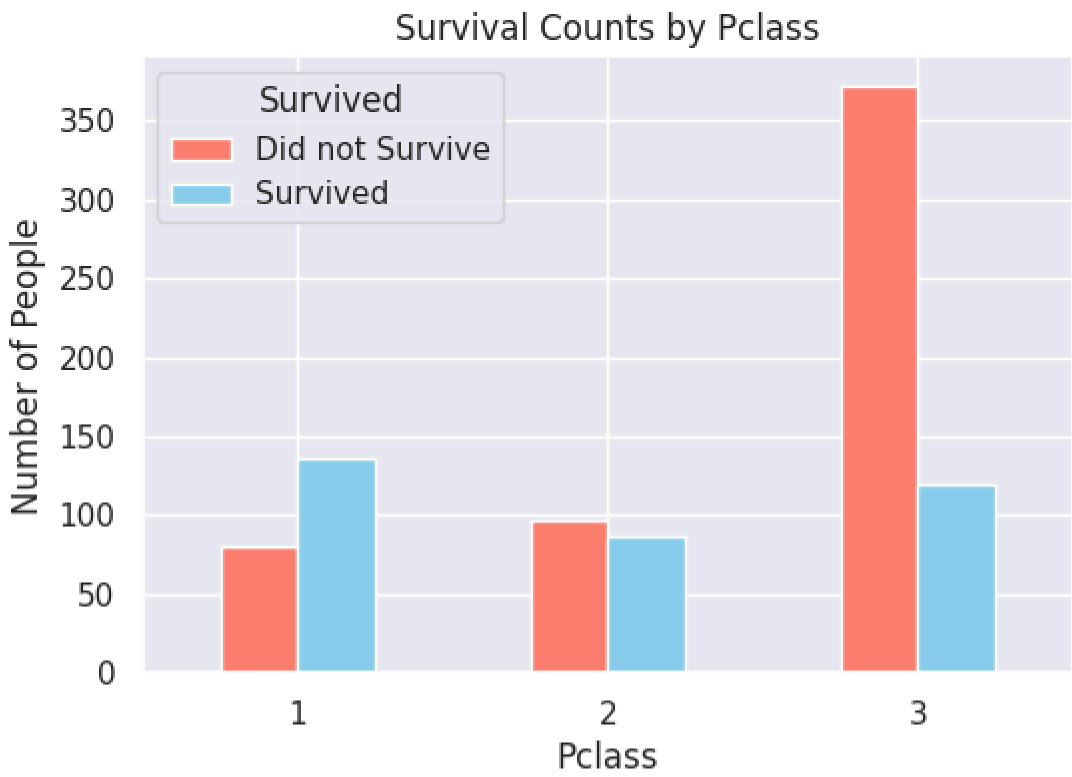


- Those who embarked from "S" had the lowest rate of survival.
- Those who embarked from "C" had the highest rate to survive.

In [ ]:
```
survival_counts = train_data.groupby(['Pclass', 'Survived']).size().u
nstack()

survival_counts.plot(kind='bar', stacked=False, figsize=(6, 4), color
=['salmon', 'skyblue'])

plt.title('Survival Counts by Pclass')
plt.xlabel('Pclass')
plt.ylabel('Number of People')
plt.xticks(rotation=0)
plt.legend(title='Survived', labels=['Did not Survive', 'Survived'])
plt.grid(True)
```



- 1st class passengers have a high chance of survival, while 3rd class passengers have a high chance of dying.
- Socio-economic status seems to play a part for survival.

Filling in missing values

In [ ]:
```
all_data = pd.concat([train_data, test_data])
```

In [ ]:
```
all_data.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Em
0	1	0.0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1.0	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0.0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

In [ ]:
```
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1309 entries, 0 to 417
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  1309 non-null   int64  
 1   Survived     891 non-null    float64
 2   Pclass       1309 non-null   int64  
 3   Name         1309 non-null   object 
 4   Sex          1309 non-null   int64  
 5   Age          1309 non-null   float64
 6   SibSp        1309 non-null   int64  
 7   Parch        1309 non-null   int64  
 8   Ticket       1309 non-null   object 
 9   Fare         1309 non-null   float64
 10  Cabin        295 non-null    object 
 11  Embarked     1309 non-null   object 
 12  Deck         1309 non-null   object 
 13  CabinMissing 1309 non-null   int64  
dtypes: float64(3), int64(6), object(5)
memory usage: 153.4+ KB
```

In [ ]:
```
all_data.isna().sum()
```

Out[ ]:

	0
PassengerId	0
Survived	418
Pclass	0
Name	0
Sex	0
Age	0
SibSp	0
Parch	0
Ticket	0
Fare	0
Cabin	1014
Embarked	0
Deck	0
CabinMissing	0

dtype: int64

- Missing values in all_data:
  - Survived (418 missing values)
  - Cabin (1014 missing values)

In [ ]:
```
all_data.loc[:,['Cabin', 'Survived']].dtypes
```

Out[ ]:

	0
Cabin	object
Survived	float64

dtype: object

In [ ]:
```
col = all_data.loc[:, ['Cabin', 'Survived']]
col.head()
```

Out[ ]:

	Cabin	Survived
0	NaN	0.0
1	C85	1.0
2	NaN	1.0
3	C123	1.0
4	NaN	0.0

In [ ]:
```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer


# Define the imputers for different data types
numeric_imputer = SimpleImputer(strategy='mean')
categorical_imputer = SimpleImputer(strategy='most_frequent')

# Define the column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_imputer, ['Survived']),
        ('cat', categorical_imputer, ['Cabin'])
    ])

# Apply the transformer to the DataFrame
imputed_data = preprocessor.fit_transform(col)

imputed_data
```

Out[ ]:
```
array([[0.0, 'C23 C25 C27'],
       [1.0, 'C85'],
       [1.0, 'C23 C25 C27'],
       ...,
       [0.3838383838383838, 'C23 C25 C27'],
       [0.3838383838383838, 'C23 C25 C27'],
       [0.3838383838383838, 'C23 C25 C27']], dtype=object)
```

In [ ]:
```
all_data['Survived'] = imputed_data[:,0].astype(float)
all_data['Cabin'] = imputed_data[:,1]
```

In [ ]:
```
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1309 entries, 0 to 417
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   PassengerId   1309 non-null   int64
 1   Survived      1309 non-null   float64
 2   Pclass        1309 non-null   int64
 3   Name          1309 non-null   object
 4   Sex           1309 non-null   int64
 5   Age           1309 non-null   float64
 6   SibSp         1309 non-null   int64
 7   Parch         1309 non-null   int64
 8   Ticket        1309 non-null   object
 9   Fare          1309 non-null   float64
 10  Cabin         1309 non-null   object
 11  Embarked      1309 non-null   object
 12  Deck          1309 non-null   object
 13  CabinMissing  1309 non-null   int64
dtypes: float64(3), int64(6), object(5)
memory usage: 153.4+ KB
```

- No Missing value

In [ ]: