```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# to ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

```
train_data = pd.read_csv("train.csv")
test_data = pd.read_csv("test.csv")
```

```
train_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.:
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.:
2	3	1	3	Heikkinen, Miss.	female	26.0	0	0	STON/O2.	7.!

```
train_data.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0

```
train_data.shape
```

```
(891, 12)
```

```
train_data.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
```

```
train_data.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	F
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

```
train_data.nunique()
```

```
PassengerId    891
Survived         2
Pclass           3
Name           891
Sex              2
Age             88
SibSp            7
Parch            7
Ticket         681
Fare           248
Cabin          147
Embarked         3
dtype: int64
```

```
test_data.head()
```

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN

```
test_data.shape
```

```
(418, 11)
```

```
print(train_data.duplicated().sum())
print(test_data.duplicated().sum())
```

```
0
0
```

```
train_data.isna().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
```

```
test_data.isna().sum()
```

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

```
test_data['Fare'].fillna(test_data['Fare'].median(), inplace=True)
```

```
test_data.isna().sum()
```

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          327
Embarked         0
dtype: int64
```

```
train_data["Embarked"].value_counts()
```

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

```
train_data["Embarked"].fillna("S", inplace= True)
```

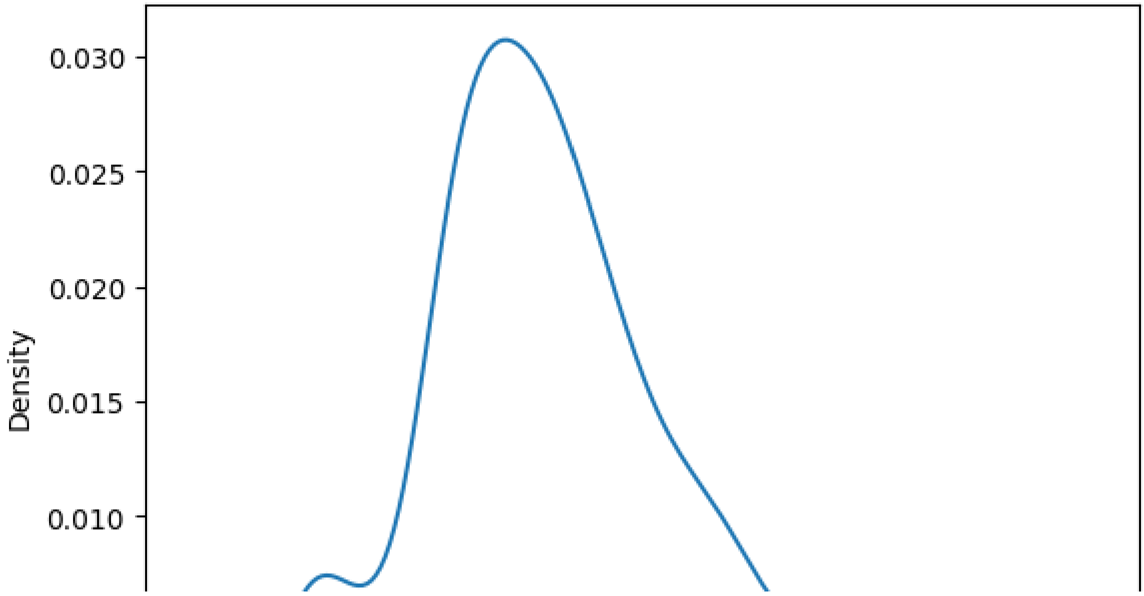
```
train_data["Embarked"].value_counts()
```

```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

```
train_data.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0

```
sns.kdeplot(data=train_data, x="Age");
```




```
age_median = train_data["Age"].median()
train_data["Age"].fillna(age_median, inplace=True)

age_median2 = test_data["Age"].median()
test_data["Age"].fillna(age_median2, inplace=True)
```

```
train_data.isna().sum()
```

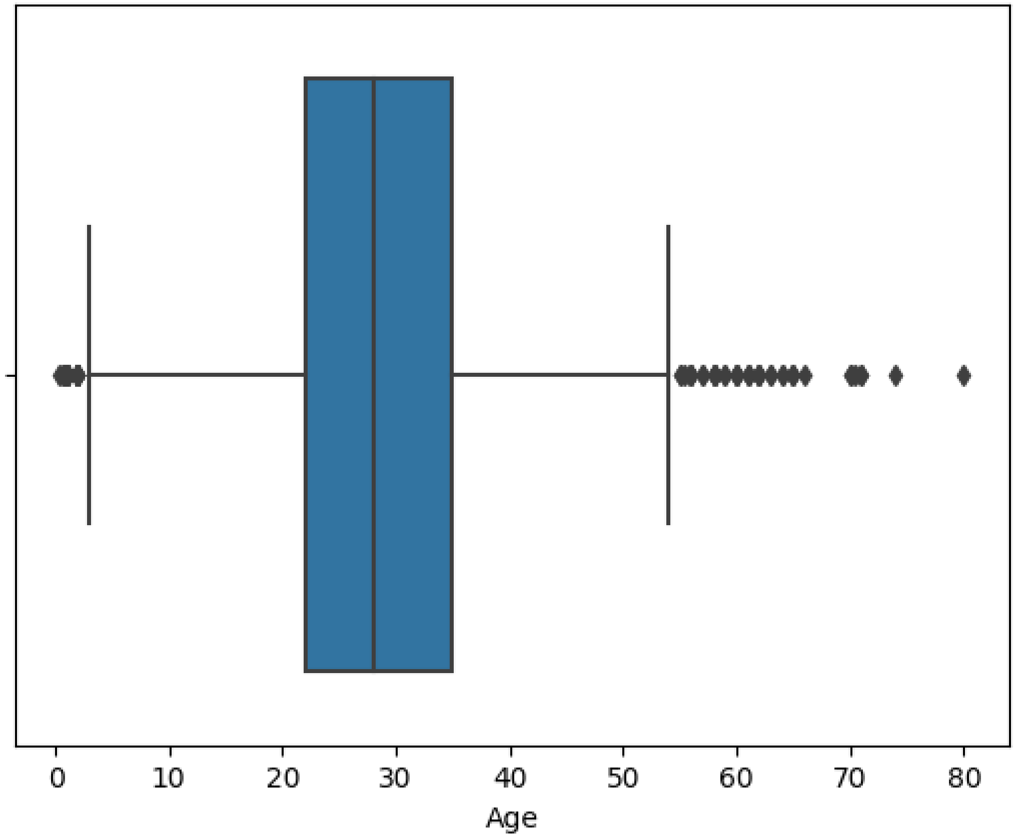
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
dtype: int64
```

```
train_data["Cabin"].value_counts()
```

```
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
```

```
train_data['Cabin'] = train_data['Cabin'].fillna('N/A')
test_data['Cabin'] = test_data['Cabin'].fillna('N/A')
```

```
sns.boxplot(data=train_data,x="Age");
```




```
train_data["SibSp"].value_counts()
```

```
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: SibSp, dtype: int64
```

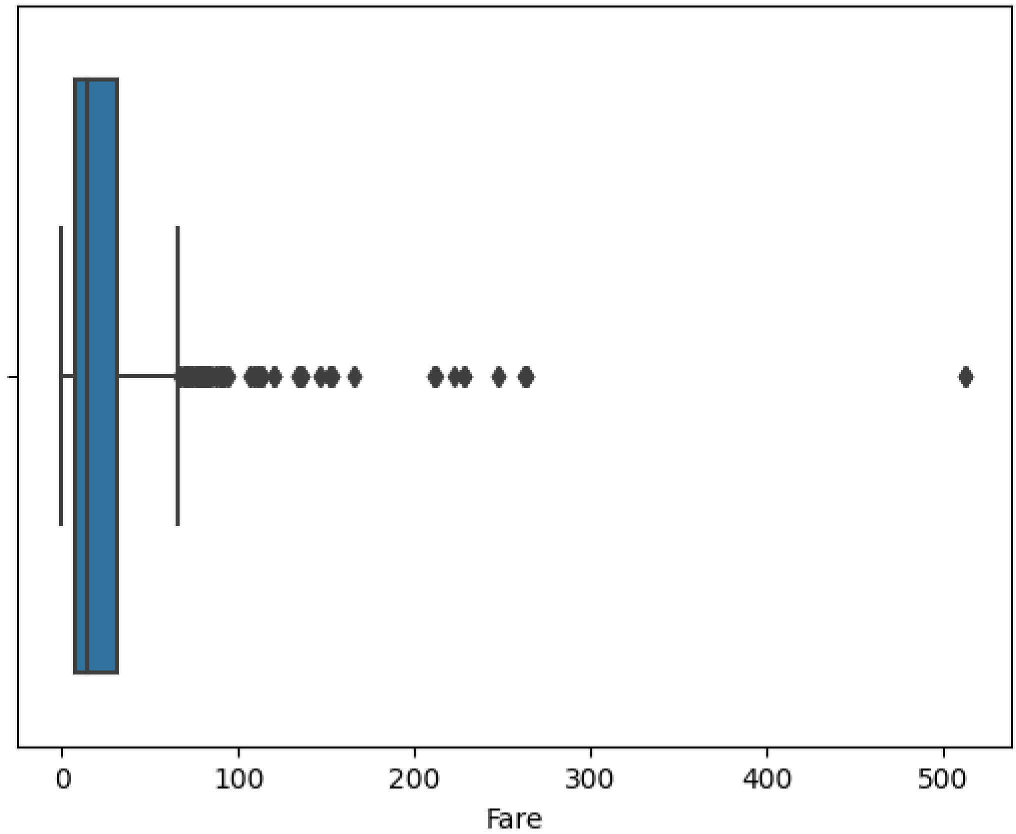
```
train_data["Parch"].value_counts()
```

```
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: Parch, dtype: int64
```

```
train_data["Ticket"].value_counts()
```

```
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
```

```
sns.boxplot(data=train_data,x="Fare");
```



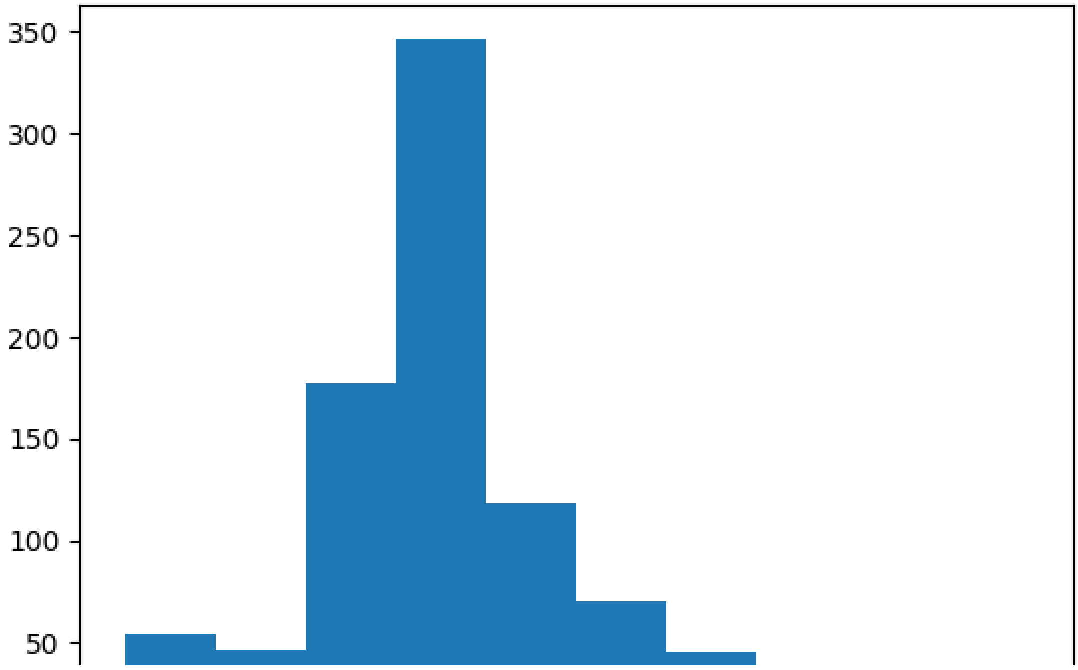

```
test_data["Age"].max()
```

```
76.0
```

```
test_data["Age"].max()
```

```
76.0
```

```
plt.hist(train_data["Age"]);
```




```
bins = [0, 12, 18, 30, 50, 100]
labels = ['Child', 'Teenager', 'Young Adult', 'Adult', 'Senior']
train_data['AgeGroup'] = pd.cut(train_data['Age'], bins=bins, labels=labels)
test_data["AgeGroup"] = pd.cut(test_data["Age"], bins=bins, labels = labels)
```

```
train_data["AgeGroup"].value_counts()
```

```
Young Adult    447
Adult          241
Teenager        70
Child           69
Senior          64
Name: AgeGroup, dtype: int64
```

```
# create title column
train_data["Title"] = [name.split(',')[1].split('.')[0].strip() for name in train_data['Na
test_data["Title"] = [name.split(',')[1].split('.')[0].strip() for name in test_data['Name
```

```
train_data["Title"].value_counts()
```

```
Mr              517
Miss            182
Mrs             125
Master           40
Dr                7
Rev               6
Mlle              2
Major             2
Col               2
the Countess      1
Capt              1
Ms                1
Sir               1
Lady              1
Mme               1
```

```
Don                1
Jonkheer           1
Name: Title, dtype: int64
```

```
test_data["Title"].value_counts()
```

```
Mr        240
Miss       78
Mrs        72
Master     21
Col         2
Rev         2
Ms          1
Dr          1
Dona        1
Name: Title, dtype: int64
```

```
train_data['Title'] = train_data['Title'].replace(['Dr', 'Rev', 'Major', 'Col', 'Capt', 'S
test_data['Title'] = test_data['Title'].replace(['Dr', 'Rev', 'Major', 'Col', 'Capt', 'Sir
```

```
train_data["Title"].value_counts()
```

```
Mr        517
Miss      182
Mrs       125
Master     40
Other      27
Name: Title, dtype: int64
```

```
test_data["Title"].value_counts()
```

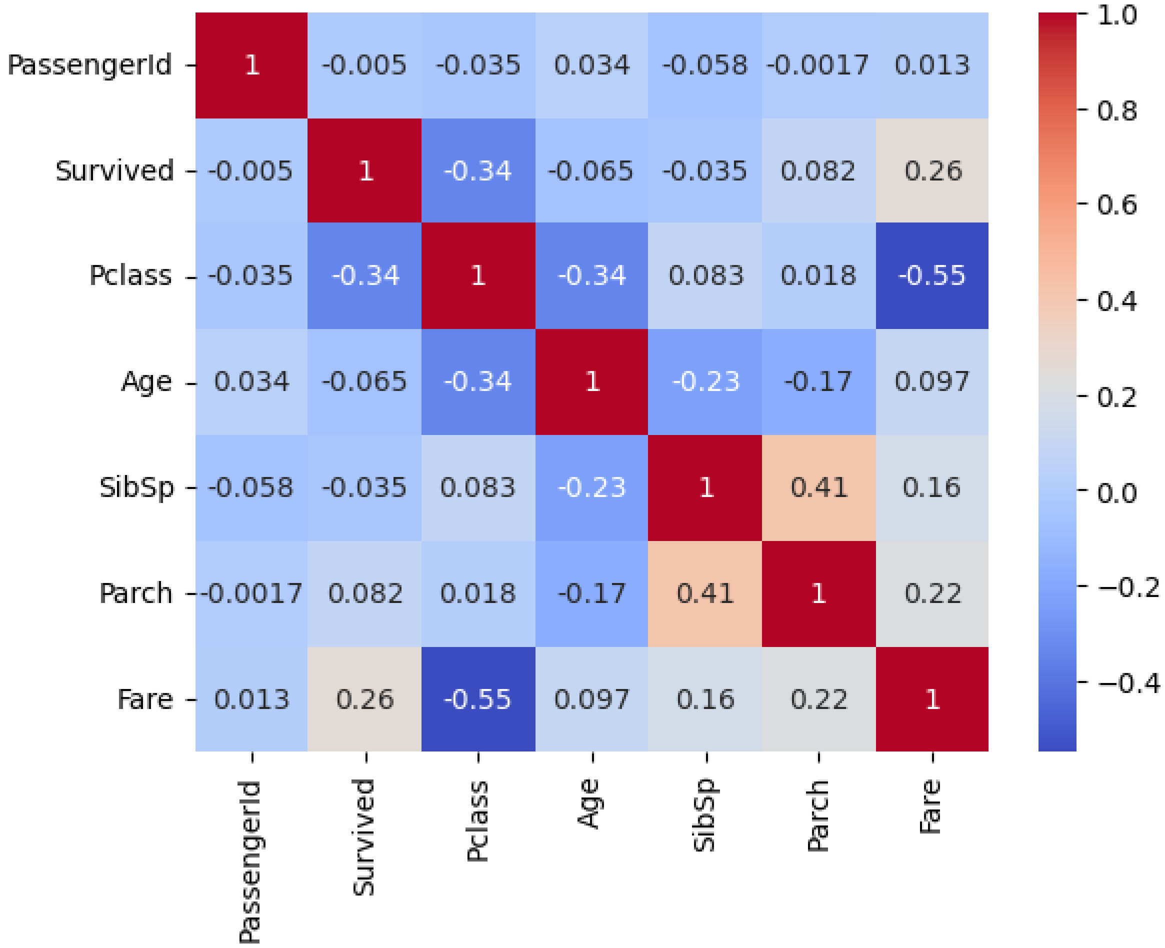
```
Mr        240
Miss       78
Mrs        72
Master     21
Other       7
Name: Title, dtype: int64
```

```
train_data.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
				Montvila						

EDA

```
# Create a correlation matrix
corr = train_data.corr()

# Create a heatmap using seaborn
sns.heatmap(corr, cmap="coolwarm", annot=True);
```



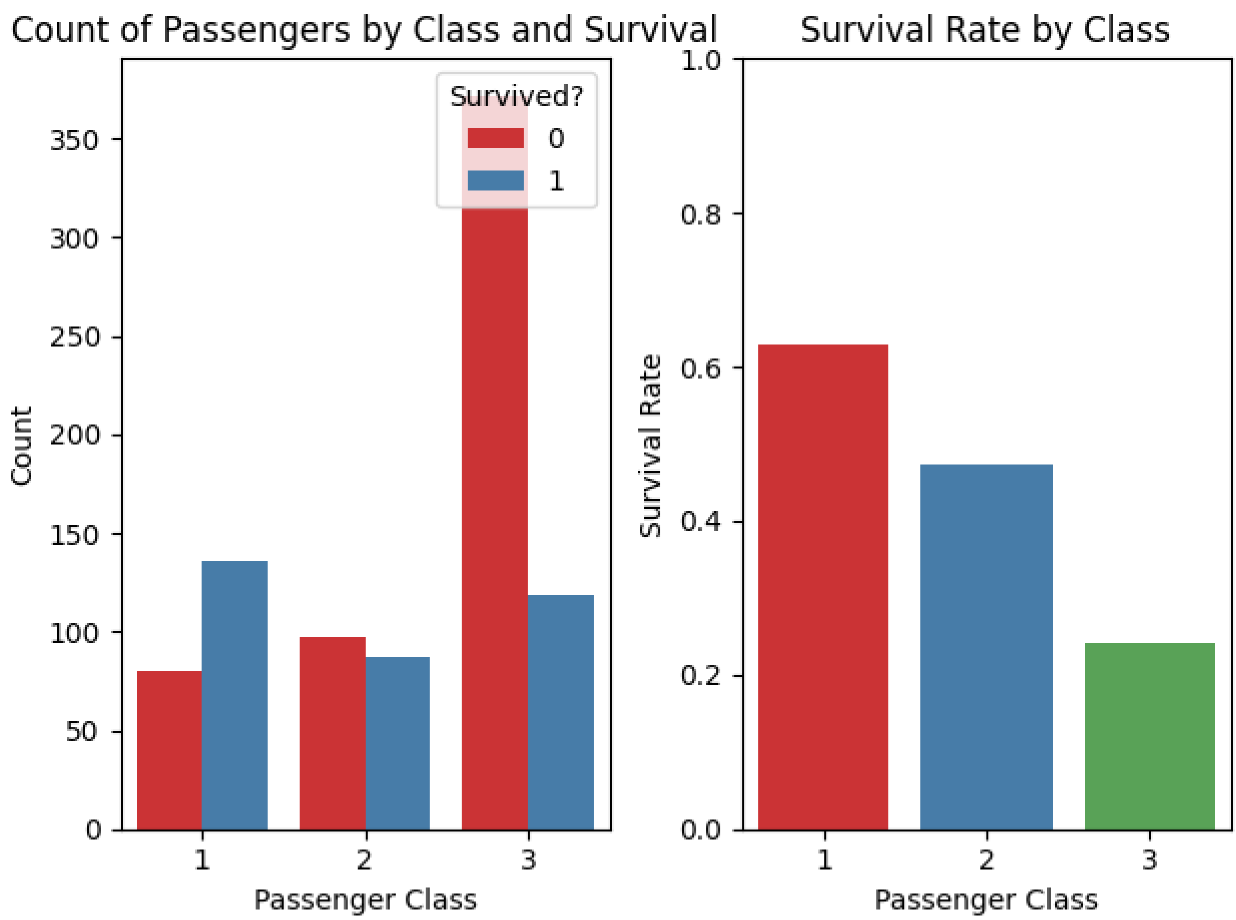
What is the Overall Survival Rate ?

```
# Count the number of survivors
num_survivors = train_data["Survived"].sum()

# Calculate the overall survival rate
total_passengers = len(train_data)
survival_rate = (num_survivors / total_passengers) * 100

print("The overall survival rate was: {:.2f}%".format(survival_rate))
```

```
The overall survival rate was: 38.38%
```

Does passenger class after Survival Rates ?

```
# Count plot
plt.subplot(1, 2, 1) # 1 row, 2 columns, first plot
sns.countplot(x='Pclass', hue='Survived', data=train_data, palette='Set1')
plt.title('Count of Passengers by Class and Survival')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived?', loc='upper right')

# Bar plot
plt.subplot(1, 2, 2) # 1 row, 2 columns, second plot
survival_rate_by_class = train_data.groupby('Pclass')['Survived'].mean().reset_index()
sns.barplot(x='Pclass', y='Survived', data=survival_rate_by_class, palette='Set1')
plt.title('Survival Rate by Class')
plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.ylim(0, 1) # Set y-axis limit from 0 to 1

plt.tight_layout() # Adjust the layout of the plots
plt.show()
```

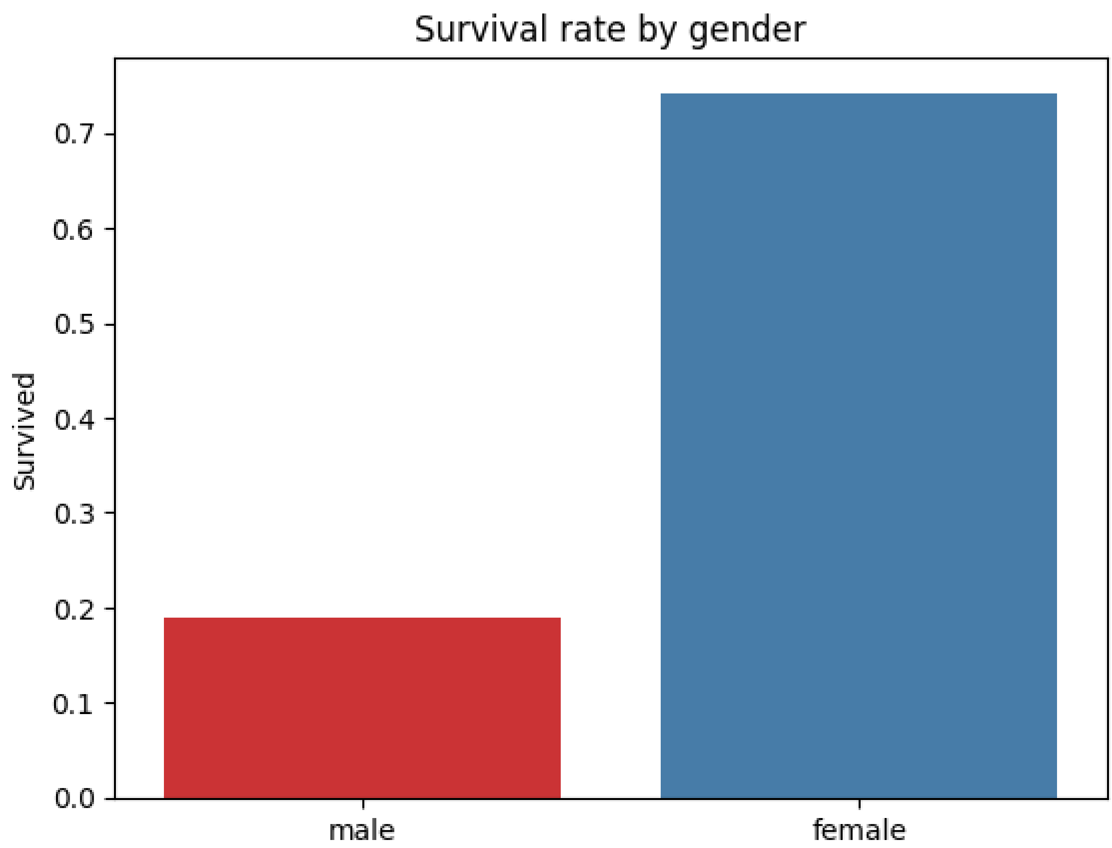


> Passengers in 1st class are more likely to survive.

> Passengers in 3d class are more likely to die.

How does the survival rate differ by gender ?

```
# Calculate survival rate based on gender
survival_rate = (train_data.groupby('Sex')['Survived'].mean()*100).round(1)

# Plot survival rate by gender
sns.barplot(x='Sex', y='Survived', data=train_data, ci=None, palette='Set1')
plt.title("Survival rate by gender")
plt.show()

# Select only the passengers who survived
survived = train_data[train_data['Survived'] == 1]

# Count the number of males and females
gender_counts = survived['Sex'].value_counts()

# Plot the gender pie chart
palette = "Set1"
colors = sns.color_palette(palette)

labels = ['Female','Male']
plt.pie(gender_counts, labels=labels, autopct='%1.1f%%', colors=colors)
plt.title('Gender of Survivors')
plt.show()
```



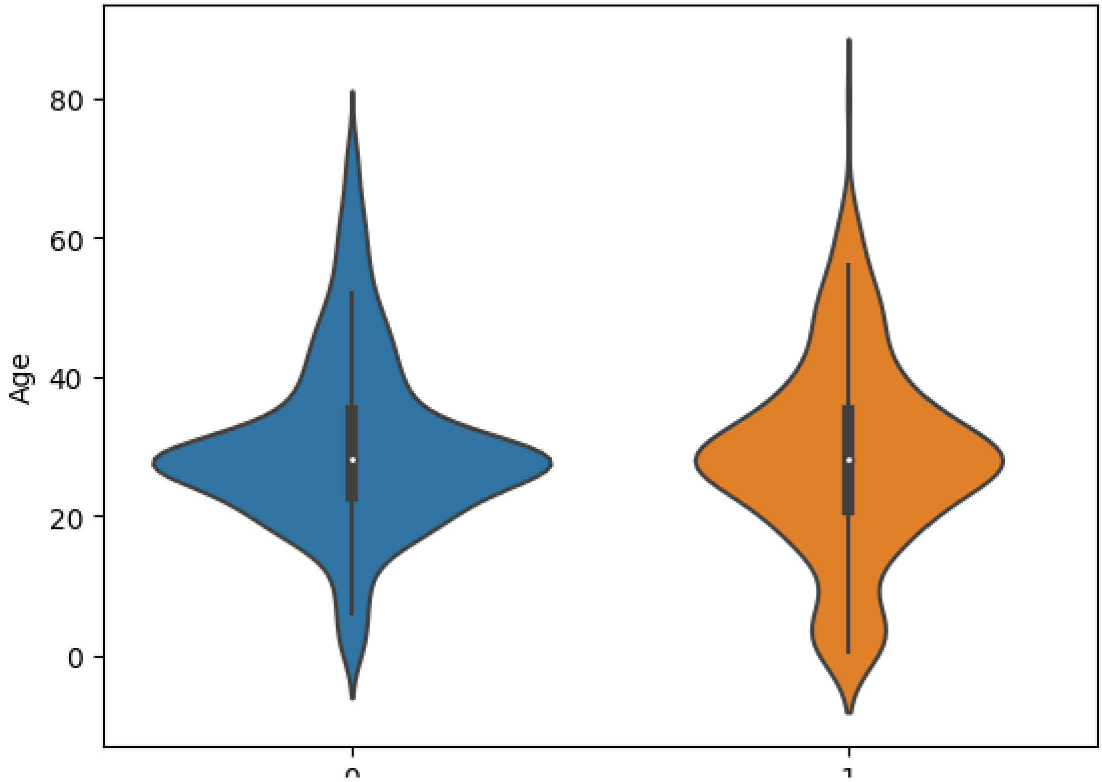
Women have a greater chance of survival than Men.

```
train_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.

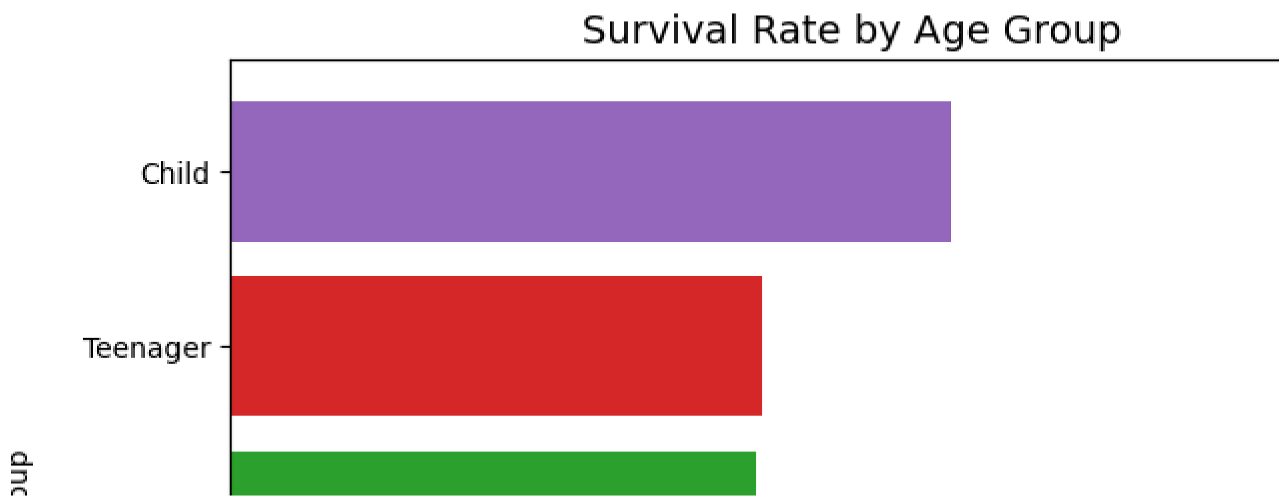
Any relationship between Age and Survival?

```
sns.violinplot(x='Survived', y='Age', data=train_data);
```



Were children more likely to survive compared to adults?

```
agegroup_survival_rate = train_data.groupby('AgeGroup')['Survived'].mean().sort_values()

colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd', '#8c564b', '#e377c2']

plt.figure(figsize=(8,6))
plt.barh(agegroup_survival_rate.index, agegroup_survival_rate.values, color = colors)
plt.title('Survival Rate by Age Group', fontsize=14)
plt.xlabel('Survival Rate')
plt.ylabel('Age Group')
plt.xticks(np.arange(0, 1.1, 0.1))
plt.show()
```



> Children have a greater chance of survival.

```
train_data.head()
```

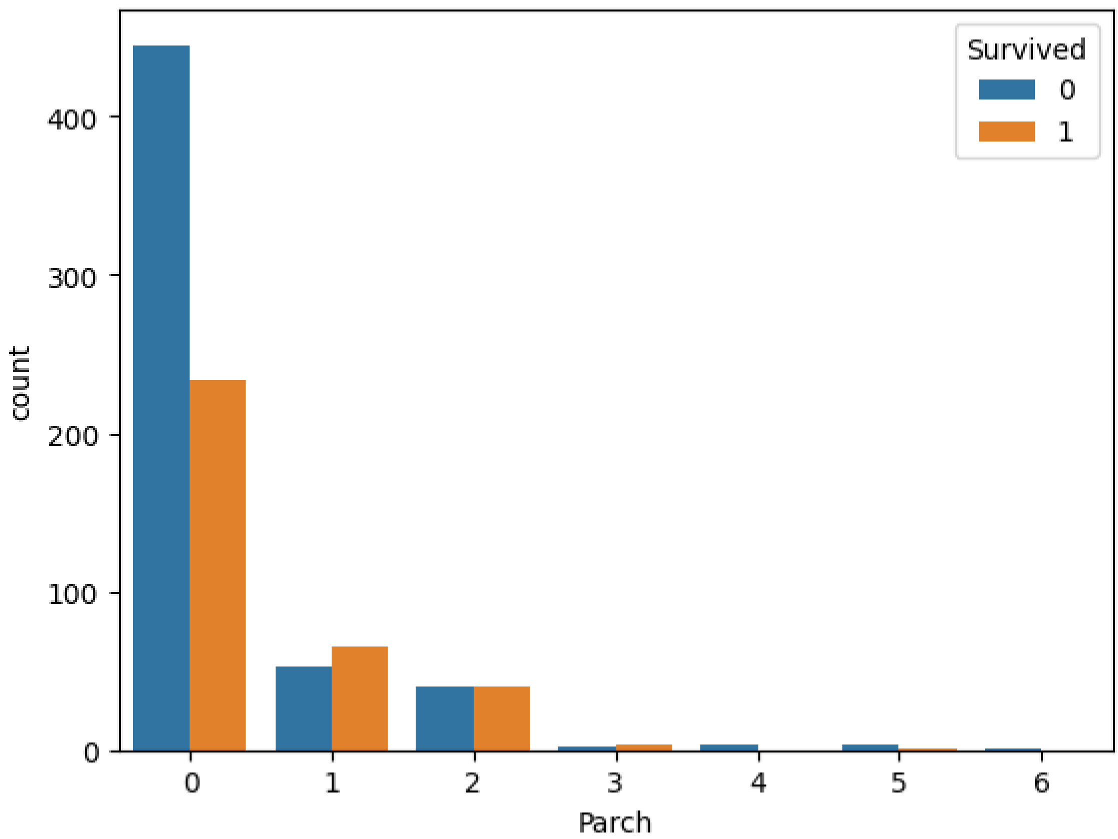
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.

Any relationship between Family on board and survival rates?

```
sns.countplot(x="SibSp", hue="Survived", data=train_data)
plt.show()
```

> The count of survived people having only one siblings/spouses is greater than who died.

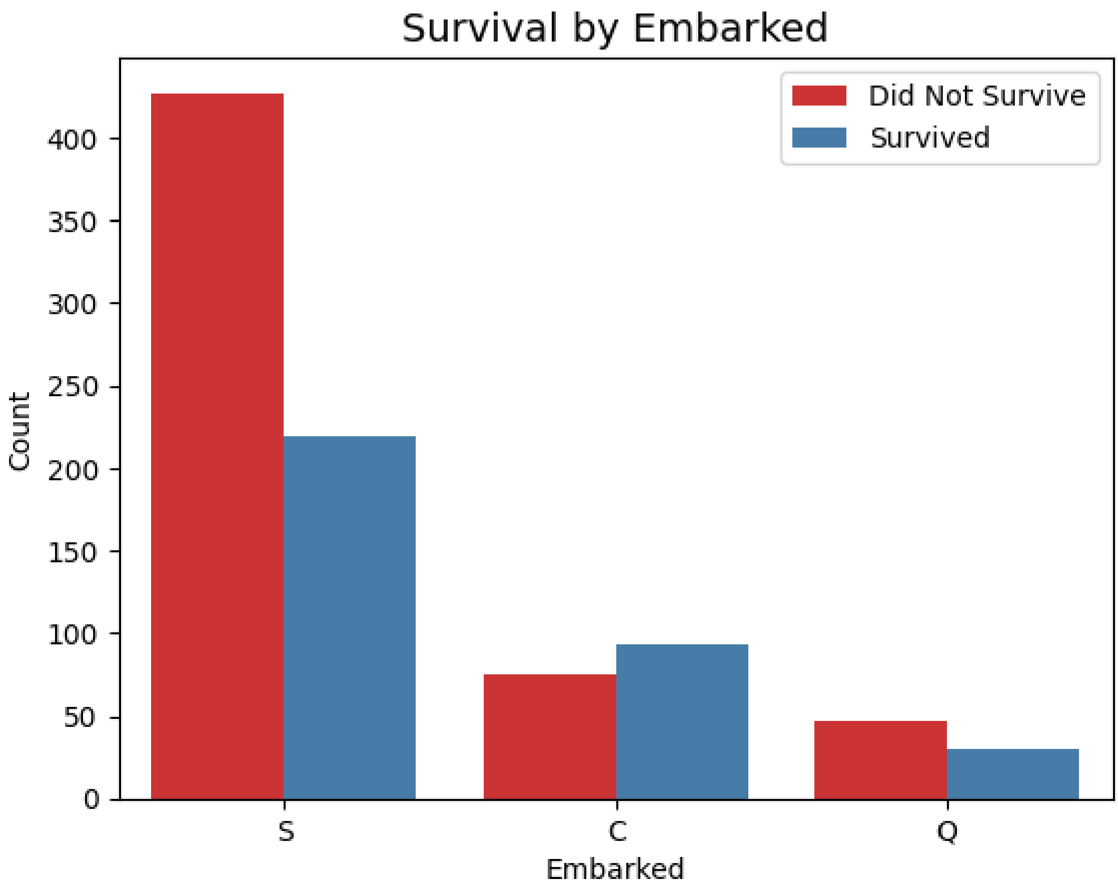

```
sns.countplot(x="Parch", hue="Survived", data=train_data)
plt.show()
```



> The count of survived people having only one parents/children is greater than who died.

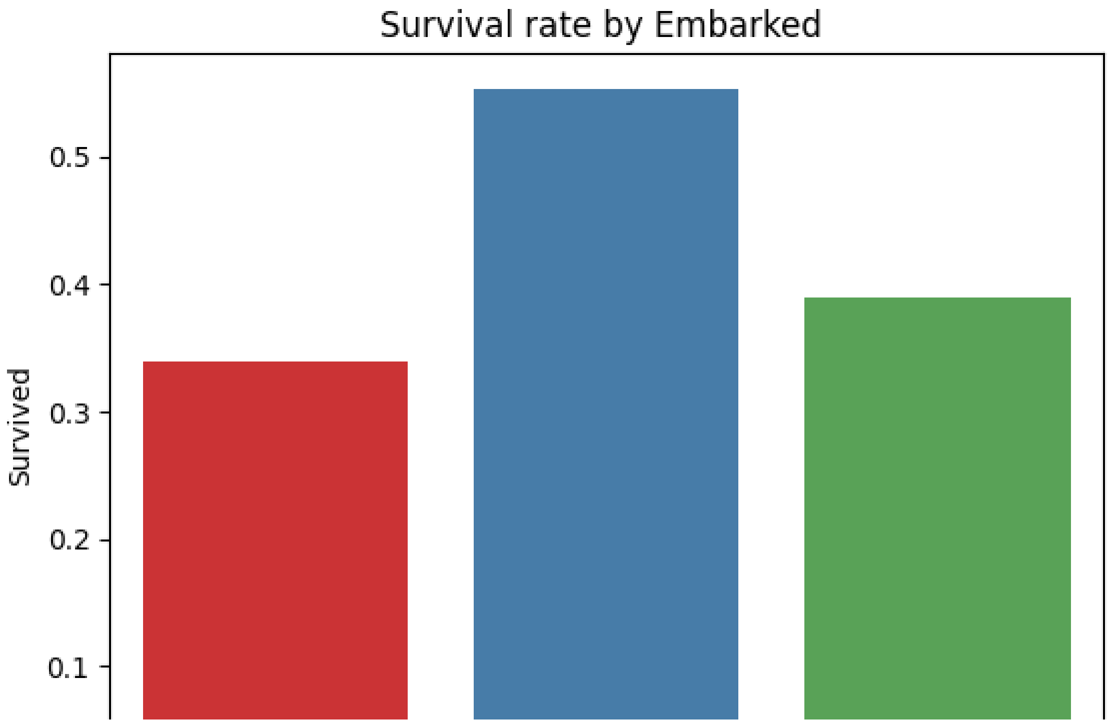
Did the embarkation location affect survival rates??

```
sns.countplot(x='Embarked', hue='Survived', data=train_data, palette='Set1')

plt.title('Survival by Embarked', fontsize=14)
plt.xlabel('Embarked')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.legend(['Did Not Survive', 'Survived'], loc='upper right')
plt.show()
```



> The number of embarked survivals from Cherbourg is > than who number of who died.

```
sns.barplot(x='Embarked', y='Survived', data=train_data, ci=None, palette='Set1');
plt.title("Survival rate by Embarked ")
plt.show()
```

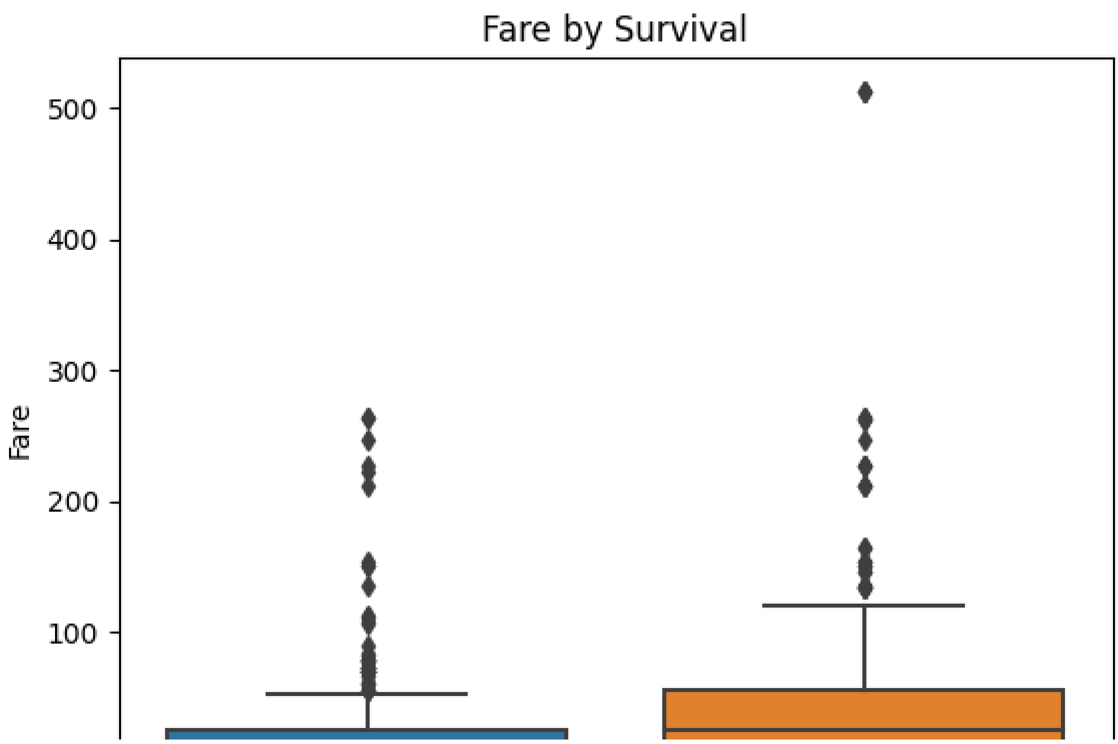



```
train_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.:
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.:
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.!

Any relationship between the fare and survival rates?

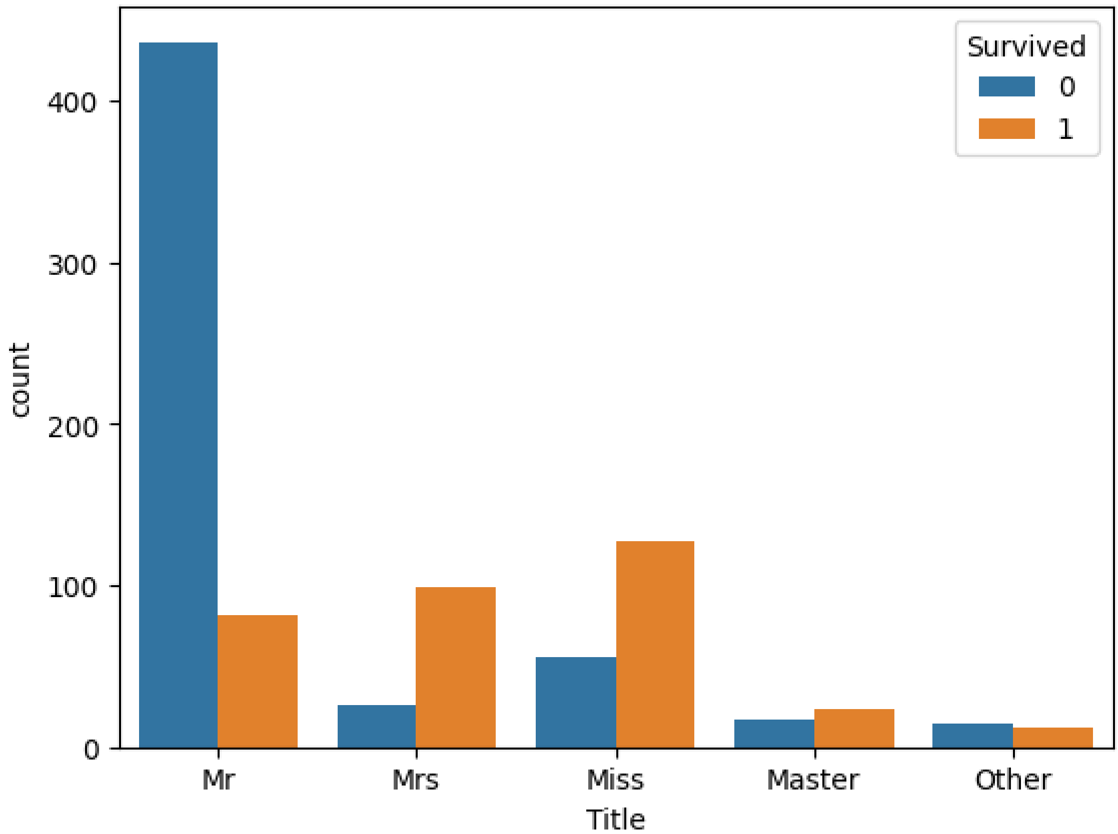
```
sns.boxplot(x='Survived', y='Fare', data=train_data)
plt.title('Fare by Survival')
plt.xlabel('Survived')
plt.ylabel('Fare')
plt.show()
```



> Survived passengers paid more.

Survived

```
sns.countplot(x='Title', hue='Survived', data=train_data)
plt.show()
```



> It is clear that Mrs,Miss and Master are more likely to survive.

```
train_data.shape
```

```
(891, 14)
```

```
train_data["Title"].value_counts()
```

```
Mr        517
Miss      182
Mrs       125
Master     40
Other      27
Name: Title, dtype: int64
```

```
train_data[train_data["Title"] == "Dona"]
```

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	E

```
test_data[train_data["Title"] == "Dona"]
```

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	A

```
test_data["Title"].value_counts()
```

```
Mr        240
Miss       78
Mrs        72
Master     21
Other       7
Name: Title, dtype: int64
```

Model building

```
train_data["FamilySize"] = train_data["SibSp"] + train_data["Parch"] + 1
test_data["FamilySize"] = test_data["SibSp"] + test_data["Parch"] + 1
```

```
# Create a new feature called IsAlone
train_data['IsAlone'] = 0
train_data.loc[(train_data["FamilySize"]) == 0, 'IsAlone'] = 1

test_data['IsAlone'] = 0
test_data.loc[(test_data["FamilySize"]) == 0, 'IsAlone'] = 1
```

```
# Create the Deck feature
train_data['Deck'] = train_data['Cabin'].apply(lambda x: x[0])
test_data['Deck'] = test_data['Cabin'].apply(lambda x: x[0])
```

```
# Combine Age and Pclass into a new feature called AgeClass
train_data['AgeClass'] = train_data['Age'] * train_data['Pclass']
test_data['AgeClass'] = test_data['Age'] * test_data['Pclass']
```

```
train_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.:
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.:
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.!
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.(

```
test_data.head()
```

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	N/A
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	N/A

```
Passenger_Id  = test_data["PassengerId"]
```

2	894	2	Mr.	male	62.0	0	0	240276	9.6875	N/A

Support Vector Machine

Albert

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectFromModel

# Define the features and target variable
features = ["Pclass","Sex","Fare","Embarked","AgeGroup","FamilySize","IsAlone","Title","De
target = "Survived"

# Split the data into train, validation, and test sets
X_train, X_val_test, y_train, y_val_test = train_test_split(train_data[features], train_da
X_val, X_test, y_val, y_test = train_test_split(X_val_test, y_val_test, test_size=0.5, rar

# Prepare the training data
X_train = pd.get_dummies(X_train)
X_val = pd.get_dummies(X_val)
test_data = pd.get_dummies(test_data[features])

# Align columns in training and test data
X_train, test_data = X_train.align(test_data, join='outer', axis=1, fill_value=0)
X_val, test_data = X_val.align(test_data, join='outer', axis=1, fill_value=0)

# Scale numerical columns
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
num_cols = ["Fare","FamilySize","AgeClass"]
X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_val[num_cols] = scaler.transform(X_val[num_cols])
test_data[num_cols] = scaler.transform(test_data[num_cols])
# Fit and evaluate Support Vector Classifier model
svc_model = SVC(kernel='linear')
svc_model.fit(X_train, y_train)

# Use feature selection to identify the most important features
```

```
selector = SelectFromModel(svc_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

svc_y_pred_val = svc_model.predict(X_val)
svc_acc_val = accuracy_score(y_val, svc_y_pred_val)
svc_cm_val = confusion_matrix(y_val, svc_y_pred_val)
svc_report_val = classification_report(y_val, svc_y_pred_val)

print("Support Vector Classifier Accuracy on validation data: ", round(svc_acc_val*100, 2)
print("Support Vector Classifier Confusion Matrix on validation data:\n", svc_cm_val)
print("Support Vector Classifier Classification Report on validation data:\n", svc_report_

# Make predictions on test data using the trained model
y_pred_svc = svc_model.predict(test_data)
```

```
Important features: Index(['Deck_E', 'Deck_G', 'FamilySize', 'Fare', 'Sex_female', '
       'Title_Master', 'Title_Mr'],
      dtype='object')
Support Vector Classifier Accuracy on validation data:  79.21 %
Support Vector Classifier Confusion Matrix on validation data:
 [[94 19]
 [18 47]]
Support Vector Classifier Classification Report on validation data:
               precision    recall  f1-score   support

           0       0.84      0.83      0.84       113
           1       0.71      0.72      0.72        65

    accuracy                           0.79       178
   macro avg       0.78      0.78      0.78       178
weighted avg       0.79      0.79      0.79       178
```

Random Classifier

```
# Random Forest Classifier
rfc_model = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=42)
rfc_model.fit(X_train, y_train)

# Use feature selection to identify the most important features
selector = SelectFromModel(rfc_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

# Make predictions on validation data
y_pred_val = rfc_model.predict(X_val)
```

```
# Evaluate model on validation data
acc_val = round(accuracy_score(y_val, y_pred_val) * 100, 2)
print("Random Forest Classifier accuracy on validation data:", acc_val)
print("Random Forest Classifier confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_val))
print("Random Forest Classifier classification report on validation data:")
print(classification_report(y_val, y_pred_val))

# Make predictions on test data using the trained model
y_pred_rfc = rfc_model.predict(test_data)
```

```
Important features: Index(['AgeClass', 'FamilySize', 'Fare', 'Pclass', 'Sex_female',
       'Title_Miss', 'Title_Mr', 'Title_Mrs'],
      dtype='object')
Random Forest Classifier accuracy on validation data: 80.9
Random Forest Classifier confusion matrix on validation data:
[[99 14]
 [20 45]]
Random Forest Classifier classification report on validation data:
              precision    recall  f1-score   support

           0       0.83      0.88      0.85       113
           1       0.76      0.69      0.73        65

    accuracy                           0.81       178
   macro avg       0.80      0.78      0.79       178
weighted avg       0.81      0.81      0.81       178
```

K - Neatest Neighbour

```
# K-Nearest Neighbors Classifier
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
```

```
# Make predictions on validation data
y_pred_knn_val = knn_model.predict(X_val)
acc_knn_val = round(accuracy_score(y_val, y_pred_knn_val) * 100, 2)
print("K-Nearest Neighbors Classifier accuracy on validation data:", acc_knn_val)
print("K-Nearest Neighbors Classifier confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_knn_val))
print("K-Nearest Neighbors Classifier classification report on validation data:")
print(classification_report(y_val, y_pred_knn_val))

# Make predictions on test data using the trained model
y_pred_knn = knn_model.predict(test_data)
```

```
K-Nearest Neighbors Classifier accuracy on validation data: 77.53
K-Nearest Neighbors Classifier confusion matrix on validation data:
[[98 15]
```

```
 [25 40]]
K-Nearest Neighbors Classifier classification report on validation data:
              precision    recall  f1-score   support

           0       0.80      0.87      0.83       113
           1       0.73      0.62      0.67        65

    accuracy                           0.78       178
   macro avg       0.76      0.74      0.75       178
weighted avg       0.77      0.78      0.77       178
```

Decision Tree Model

```
# Fit decision tree model
dt_model = DecisionTreeClassifier(random_state=0)
dt_model.fit(X_train, y_train)

# Use feature selection to identify the most important features
selector = SelectFromModel(dt_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

# Make predictions on validation data
y_pred_val = dt_model.predict(X_val)

# Evaluate model on validation data
acc_val = round(accuracy_score(y_val, y_pred_val) * 100, 2)
print("Decision Tree Classifier accuracy on validation data:", acc_val)
print("Decision Tree Classifier confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_val))
print("Decision Tree Classifier classification report on validation data:")
print(classification_report(y_val, y_pred_val))
# Make predictions on test data using the trained model
y_pred_dt = dt_model.predict(test_data)
```

```
Important features: Index(['AgeClass', 'FamilySize', 'Fare', 'Pclass', 'Sex_female']
Decision Tree Classifier accuracy on validation data: 75.84
Decision Tree Classifier confusion matrix on validation data:
[[87 26]
 [17 48]]
Decision Tree Classifier classification report on validation data:
              precision    recall  f1-score   support

           0       0.84      0.77      0.80       113
           1       0.65      0.74      0.69        65

    accuracy                           0.76       178
   macro avg       0.74      0.75      0.75       178
weighted avg       0.77      0.76      0.76       178
```

Logistic Regression

```
# Fit and evaluate Logistic Regression model
lr_model = LogisticRegression(random_state=0)
lr_model.fit(X_train, y_train)


# Use feature selection to identify the most important features
selector = SelectFromModel(lr_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

# Make predictions on validation data
y_pred_val = lr_model.predict(X_val)

# Evaluate model on validation data
acc_val = round(accuracy_score(y_val, y_pred_val) * 100, 2)
print("Logistic Regression Model accuracy on validation data:", acc_val)
print("Logistic Regression Model confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_val))
print("Logistic Regression Model classification report on validation data:")
print(classification_report(y_val, y_pred_val))

# Make predictions on test data using the trained model
y_pred_lr = lr_model.predict(test_data)
```

```
Important features: Index(['AgeClass', 'Deck_C', 'Deck_E', 'Deck_G', 'FamilySize', '
       'Sex_female', 'Sex_male', 'Title_Master', 'Title_Mr', 'Title_Mrs'],
      dtype='object')
Logistic Regression Model accuracy on validation data: 80.34
Logistic Regression Model confusion matrix on validation data:
[[96 17]
 [18 47]]
Logistic Regression Model classification report on validation data:
              precision    recall  f1-score   support

           0       0.84      0.85      0.85       113
           1       0.73      0.72      0.73        65

    accuracy                           0.80       178
   macro avg       0.79      0.79      0.79       178
weighted avg       0.80      0.80      0.80       178
```

XGBoost as XGB

```
import xgboost as xgb

# Define the XGBoost model
xgb_model = xgb.XGBClassifier(n_estimators=100, learning_rate=0.05, max_depth=3, random_st

# Fit the XGBoost model on the training data
xgb_model.fit(X_train, y_train)

# Use feature selection to identify the most important features
selector = SelectFromModel(xgb_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

# Make predictions on validation data
y_pred_val = xgb_model.predict(X_val)

# Evaluate model on validation data
acc_val = round(accuracy_score(y_val, y_pred_val) * 100, 2)
print("XGBoost Model accuracy on validation data:", acc_val)
print("XGBoost Model confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_val))
print("XGBoost Model classification report on validation data:")
print(classification_report(y_val, y_pred_val))

# Make predictions on test data using the trained model
y_pred_xgb = xgb_model.predict(test_data)
```

```
Important features: Index(['Pclass', 'Sex_female', 'Title_Mr', 'Title_Other'], dtype
XGBoost Model accuracy on validation data: 82.02
XGBoost Model confusion matrix on validation data:
[[98 15]
 [17 48]]
XGBoost Model classification report on validation data:
              precision    recall  f1-score   support

           0       0.85      0.87      0.86       113
           1       0.76      0.74      0.75        65

    accuracy                           0.82       178
   macro avg       0.81      0.80      0.80       178
weighted avg       0.82      0.82      0.82       178
```

Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier

# Define the Gradient Boosting model
gbm_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, r
```

```
# Fit the Gradient Boosting model on the training data
gbm_model.fit(X_train, y_train)

# Use feature selection to identify the most important features
selector = SelectFromModel(gbm_model, prefit=True)
important_features = X_train.columns[selector.get_support()]

# Print the important features
print("Important features:", important_features)

# Make predictions on validation data
y_pred_val = gbm_model.predict(X_val)
# Evaluate model on validation data
acc_val = round(accuracy_score(y_val, y_pred_val) * 100, 2)
print("Gradient Boosting Model accuracy on validation data:", acc_val)
print("Gradient Boosting Model confusion matrix on validation data:")
print(confusion_matrix(y_val, y_pred_val))
print("Gradient Boosting Model classification report on validation data:")
print(classification_report(y_val, y_pred_val))

# Make predictions on test data using the trained model
y_pred_gbm = gbm_model.predict(test_data)
```

```
Important features: Index(['AgeClass', 'Fare', 'Pclass', 'Sex_male', 'Title_Mr'], dt
Gradient Boosting Model accuracy on validation data: 82.02
Gradient Boosting Model confusion matrix on validation data:
[[99 14]
 [18 47]]
Gradient Boosting Model classification report on validation data:
              precision    recall  f1-score   support

           0       0.85      0.88      0.86       113
           1       0.77      0.72      0.75        65

    accuracy                           0.82       178
   macro avg       0.81      0.80      0.80       178
weighted avg       0.82      0.82      0.82       178
```

We will submit using RFC model

```
# Create submission file
submission = pd.DataFrame({
    "PassengerId": Passenger_Id,
    "Survived": y_pred_gbm
})
submission.to_csv("submission.csv", index=False)
```

My score is : 0.79186 = Top 6%

0s completed at 9:34 PM