Overview

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

In this challenge, we target to complete the analysis of what sorts of people were likely to survive.

[https://www.kaggle.com/c/titanic/data (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data)

Import Libraries

In [222]:

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



from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC


# To ignore Warnings
import warnings
warnings.filterwarnings('ignore')
```

Loading Dataset

In [8]:

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

In [9]:

```
df.head()
```

Out[9]:

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

```
SibSp -> Denotes any siblings or spouse
Parch -> Denotes any Parents or childrens
emabarked -> Port of Embarkation
                c = Cherbourg
                Q = Queenstown
                S = Southhampton
Pclass -> Ticket Class [1: 1st, 2: 2nd, 3: 3rd]
Cabin -> Cabin Number
Survival -> Survived/Dead [0: Survived, 1: Died]
```

Type of Features :

- **Categorical** : Sex and Embarked
- **Continous** : Age, Fare
- **Discrete** : SibSP, ParCh
- **Alphanumeric** : Cabin

In [11]:

```
df.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
```

In [12]:

```
df.isnull().sum()
```

Out[12]:

```
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
```

In [15]:

```
df.shape
```

Out[15]:

```
(891, 12)
```

In [16]:

```
df.describe()
```

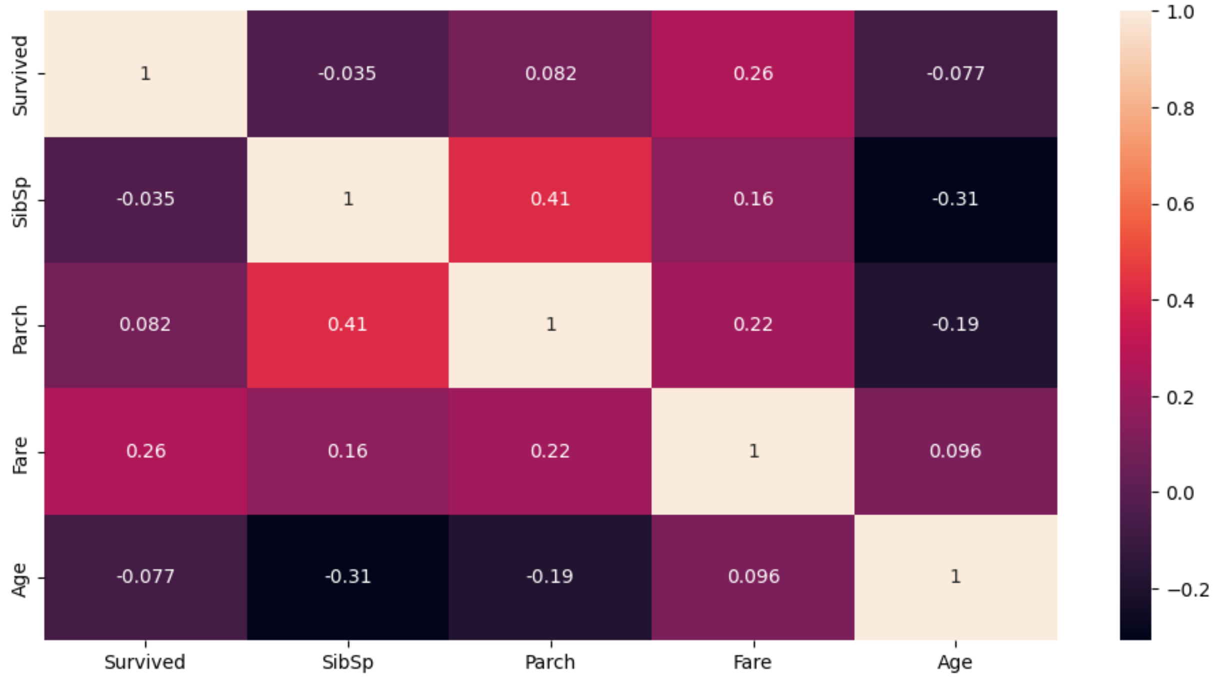
Out[16]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Numerical Value Analysis

In [19]:

```
plt.figure(figsize = (12,6))
heatmap = sns.heatmap(df[["Survived", "SibSp", "Parch", "Fare", "Age"]].corr(), annot = True)
```



SibSp - Number of siblings / Spouse aboard the Titanic :

In [22]:

```
df["SibSp"].nunique()
```

Out[22]:

```
7
```

In [23]:

```
df["SibSp"].unique()
```

Out[23]:

```
array([1, 0, 3, 4, 2, 5, 8])
```

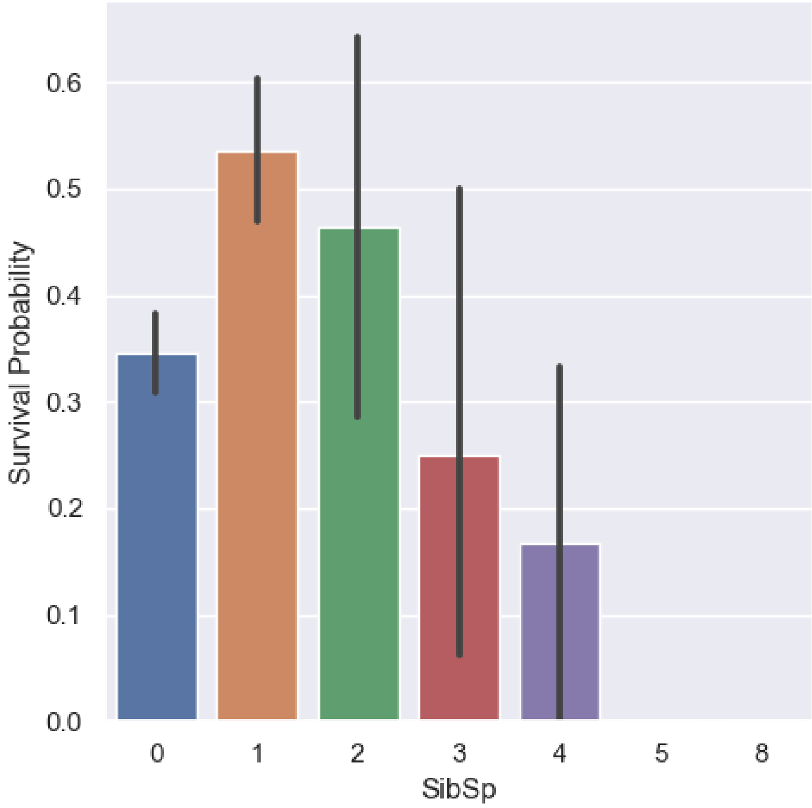
In [80]:

```
plt.figure(figsize = (12,6))
sns.catplot(x = 'SibSp', y = "Survived", data = df, kind = 'bar').set_ylabels('Survival Probabili
#Factorplot & Catplot are same
```

Out[80]:

```
<seaborn.axisgrid.FacetGrid at 0x7f9c180a76a0>
```

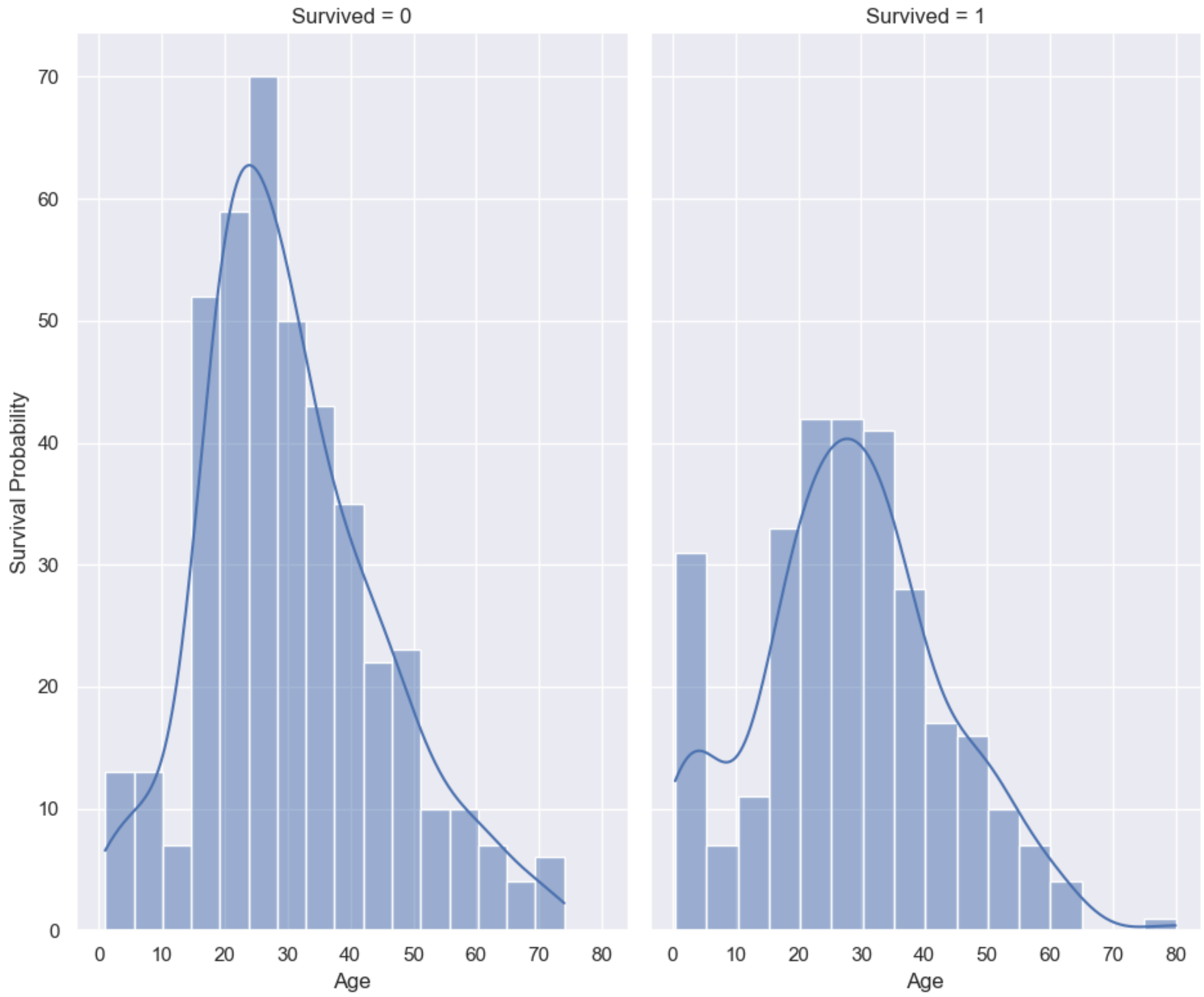
```
<Figure size 1200x600 with 0 Axes>
```



Age :

In [157]:

```
age_visual = sns.FacetGrid(df, col = 'Survived',height=8, aspect=.6)
age_visual = age_visual.map(sns.histplot, "Age", kde=True).set_ylabels('Survival Probability')
```

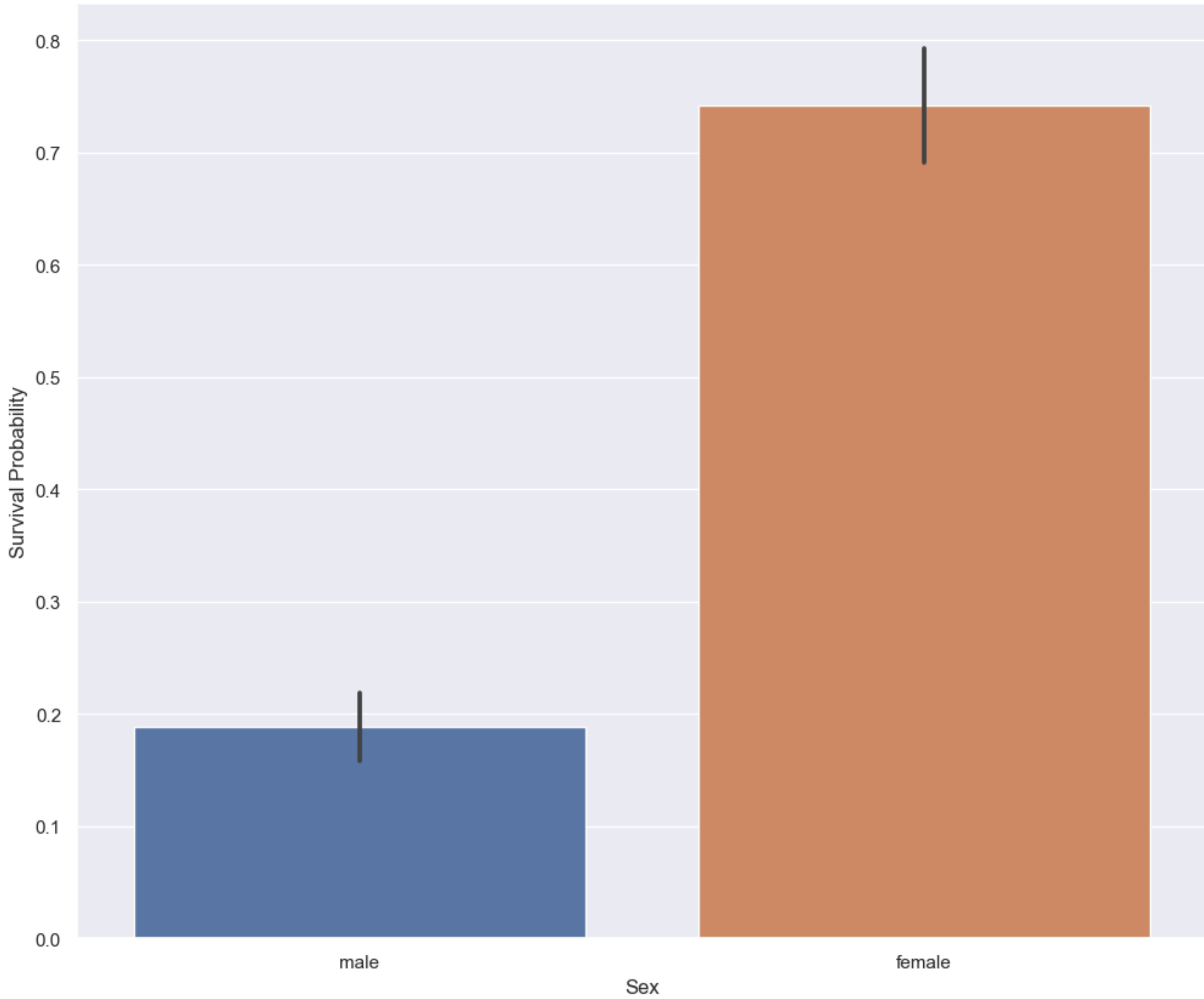



```
Age has no direct relation with survival but childrens had a high chance of survival
```

```
### <font color = "green">Gender :</font>
```

In [82]:

```
gender_plot = sns.barplot(x = 'Sex', y = 'Survived', data = df).set_ylabel('Survival Probability'
```



In [89]:

```
df[['Sex', 'Survived']].groupby('Sex').mean()
```

Out[89]:

	Survived
Sex	
female	0.742038
male	0.188908

```
Females have a huge chance of survival. By this we can Say Womens and childrens were given the
first priority to get on to the life boat.
```

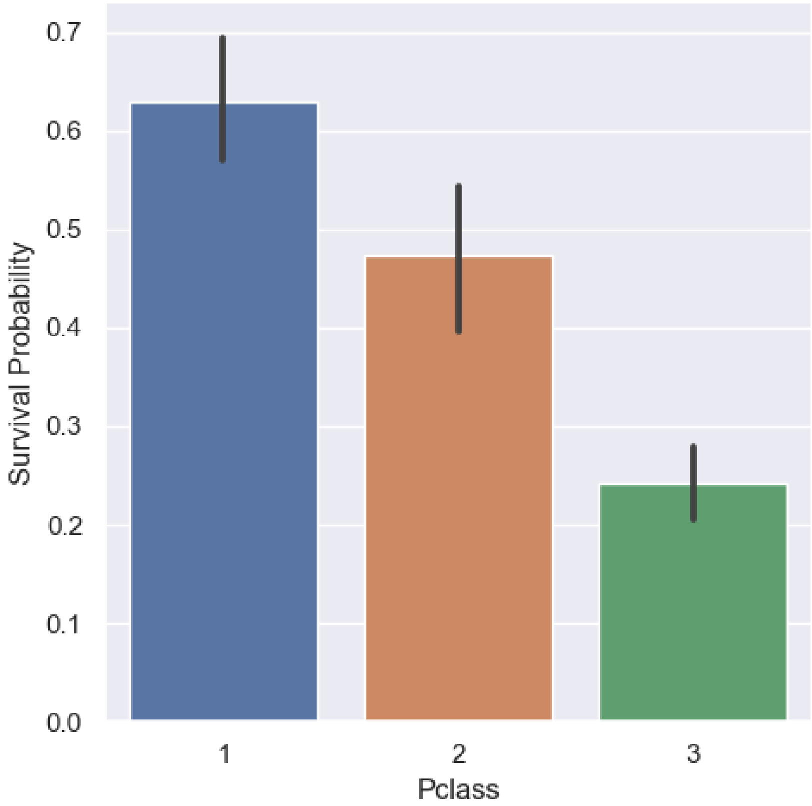
PClass :

In [101]:

```
sns.catplot(x = 'Pclass', y = "Survived", data = df, kind = 'bar').set_ylabels('Survival Probabil
```

Out[101]:

```
<seaborn.axisgrid.FacetGrid at 0x7f9c16e07c70>
```

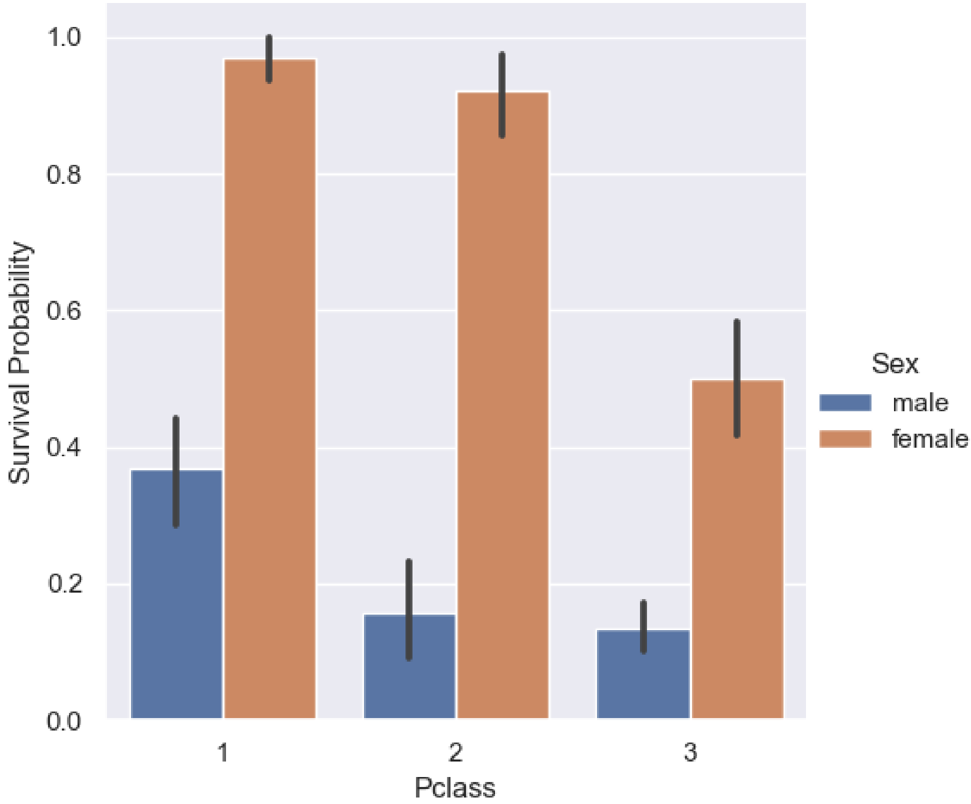


In [107]:

```
sns.catplot(x = 'Pclass', y = "Survived", data = df, kind = 'bar', hue = 'Sex').set_ylabels('Surv
```

Out[107]:

```
<seaborn.axisgrid.FacetGrid at 0x7f9c4ce88c70>
```




```
From this we can save people from the high class were saved first and high class females had
highest chance of survival.
```

Embarked :

In [109]:

```
df["Embarked"].isnull().sum()
```

Out[109]:

```
2
```

In [110]:

```
df['Embarked'].value_counts()
```

Out[110]:

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

In [111]:

```
df['Embarked'] = df['Embarked'].fillna('S')
```

In [112]:

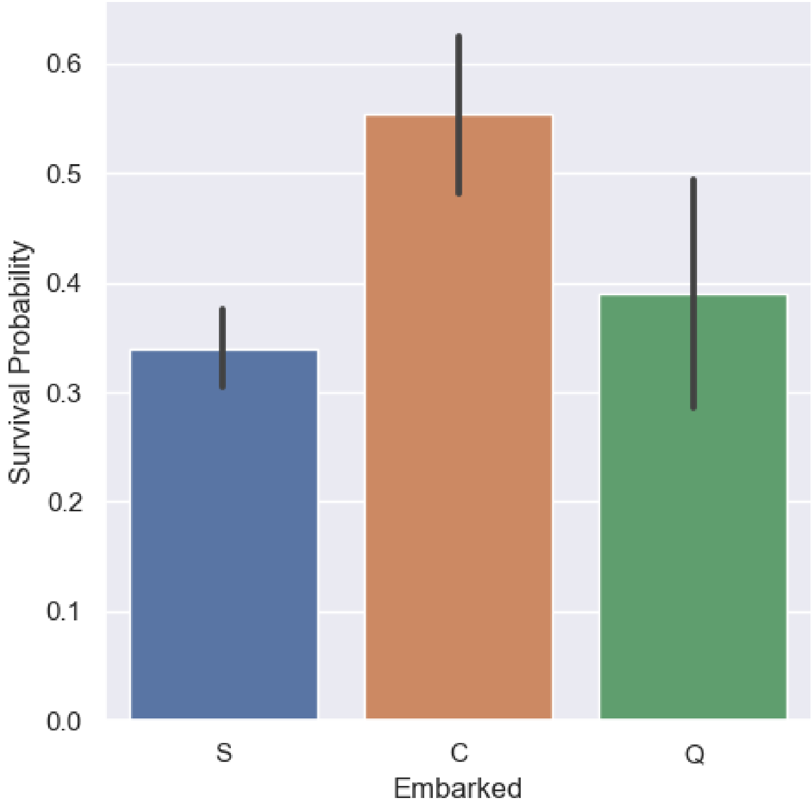
```
df['Embarked'].value_counts()
```

Out[112]:

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

In [113]:

```
q = sns.catplot(x ='Embarked', y = 'Survived', data = df, kind = 'bar').set_ylabels('Survival Prol
```



In [215]:

```
df[df['Embarked'] == 'C']['Sex'].value_counts()
```

Out[215]:

```
male      95
female    73
Name: Sex, dtype: int64
```

In [208]:

```
df[df['Embarked'] == 'S']['Sex'].value_counts()
```

Out[208]:

```
male      441
female    205
Name: Sex, dtype: int64
```

In [209]:

```
df[df['Embarked'] == 'Q']['Sex'].value_counts()
```

Out[209]:

```
male      41
female    36
Name: Sex, dtype: int64
```

In [216]:

```
df[df['Embarked'] == 'C']['Age'].describe()
```

Out[216]:

```
count    130.000000
mean      30.814769
std       15.434860
min        0.420000
25%       21.250000
50%       29.000000
75%       40.000000
max       71.000000
Name: Age, dtype: float64
```

In [217]:

```
df[df['Embarked'] == 'Q']['Age'].describe()
```

Out[217]:

```
count    28.000000
mean     28.089286
std      16.915396
min       2.000000
25%      17.500000
50%      27.000000
75%      34.500000
max      70.500000
Name: Age, dtype: float64
```

In [218]:

```
df[df['Embarked'] == 'S']['Age'].describe()
```

Out[218]:

```
count    556.000000
mean      29.519335
std       14.189608
min        0.670000
25%       21.000000
50%       28.000000
75%       38.000000
max       80.000000
Name: Age, dtype: float64
```

In [219]:

```
df[df['Embarked'] == 'C']['Pclass'].value_counts()
```

Out[219]:

```
1    85
3    66
2    17
Name: Pclass, dtype: int64
```

In [220]:

```
df[df['Embarked'] == 'Q']['Pclass'].value_counts()
```

Out[220]:

```
3    72
2     3
1     2
Name: Pclass, dtype: int64
```

In [221]:

```
df[df['Embarked'] == 'S']['Pclass'].value_counts()
```

Out[221]:

```
3    353
2    164
1    129
Name: Pclass, dtype: int64
```

By Above data we can say there were less crowd in C and Q and Ratio of Male / Female was nearly equal but as there were more number of people from first class in C so the Survival Probablity was higher for C.

So, We can assume Embarkment is not an important parameter as its biased by the class of passangers.

Preparing Data

In [223]:

```
df.shape
```

Out[223]:

```
(891, 12)
```

In [224]:

```
df.head()
```

Out[224]:

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

In [226]:

```
df.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     891 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [231]:

```
df.isnull().sum()
```

Out[231]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         0
dtype: int64
```

In [229]:

```
df.drop('Cabin', inplace = True, axis = 1)
```

now as per the normal distribution most of the data lies between mean + std and mean - std, so we will be randomly filling the null values of age with values between mean + std and mean - std

In [234]:

```
mean = df['Age'].mean()
std = df['Age'].std()
```

In [235]:

```
mean, std
```

Out[235]:

```
(29.69911764705882, 14.526497332334044)
```

In [237]:

```
is_null = df['Age'].isnull().sum()
```

In [238]:

```
is_null
```

Out[238]:

```
177
```

In [242]:

```
random_age = np.random.randint(mean-std, mean+std, size = is_null)
```

In [244]:

```
temp = df['Age'].copy()
```

In [249]:

```
temp[np.isnan(temp)] = random_age
```

In [250]:

```
df['Age'] = temp
```

In [251]:

```
df.isnull().sum()
```

Out[251]:

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

In [252]:

```
cols_to_drop = ['PassengerId', 'Name' , 'Ticket']
df.drop(cols_to_drop, inplace = True, axis = 1)
```

In [253]:

```
df
```

Out[253]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S
...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S
887	1	1	female	19.0	0	0	30.0000	S
888	0	3	female	26.0	1	2	23.4500	S
889	1	1	male	26.0	0	0	30.0000	C
890	0	3	male	32.0	0	0	7.7500	Q

891 rows × 8 columns

Treating Categorical Parameters

In [254]:

```
genders = {'male': 0, 'female' : 1}
df['Sex'] = df['Sex'].map(genders)
```

In [255]:

```
df
```

Out[255]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22.0	1	0	7.2500	S
1	1	1	1	38.0	1	0	71.2833	C
2	1	3	1	26.0	0	0	7.9250	S
3	1	1	1	35.0	1	0	53.1000	S
4	0	3	0	35.0	0	0	8.0500	S
...	...	...	...	...	...	...	...	...
886	0	2	0	27.0	0	0	13.0000	S
887	1	1	1	19.0	0	0	30.0000	S
888	0	3	1	26.0	1	2	23.4500	S
889	1	1	0	26.0	0	0	30.0000	C
890	0	3	0	32.0	0	0	7.7500	Q

891 rows × 8 columns

In [256]:

```
emabrk = {'S' : 0, 'C' : 1, 'Q' : 2}
df['Embarked'] = df['Embarked'].map(emabrk)
```

In [257]:

```
df
```

Out[257]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22.0	1	0	7.2500	0
1	1	1	1	38.0	1	0	71.2833	1
2	1	3	1	26.0	0	0	7.9250	0
3	1	1	1	35.0	1	0	53.1000	0
4	0	3	0	35.0	0	0	8.0500	0
...	...	...	...	...	...	...	...	...
886	0	2	0	27.0	0	0	13.0000	0
887	1	1	1	19.0	0	0	30.0000	0
888	0	3	1	26.0	1	2	23.4500	0
889	1	1	0	26.0	0	0	30.0000	1
890	0	3	0	32.0	0	0	7.7500	2

891 rows × 8 columns

Splitting the data

In [258]:

```
x = df.drop(df.columns[[0]], axis = 1)
```

In [259]:

```
y = df['Survived']
```

In [262]:

```
from sklearn.model_selection import train_test_split
```

In [263]:

```
xtrain, xtest, ytrain, ytest = train_test_split(x, y , test_size = 0.30, random_state = 10)
```

Scaling Data

In [264]:

```
from sklearn.preprocessing import StandardScaler
```

In [265]:

```
sc_x = StandardScaler()
xtrain = sc_x.fit_transform(xtrain)
xtest = sc_x.transform(xtest)
```

Classification

In [266]:

```
logistic_regression = LogisticRegression()
svc_classifier = SVC()
dc_classifier = DecisionTreeClassifier()
knn_classifier = KNeighborsClassifier(5)
rf_classifier = RandomForestClassifier(n_estimators=1000)
```

In [267]:

```
logistic_regression.fit(xtrain, ytrain)
svc_classifier.fit(xtrain, ytrain)
dc_classifier.fit(xtrain, ytrain)
knn_classifier.fit(xtrain, ytrain)
rf_classifier.fit(xtrain, ytrain)
```

Out[267]:

```
▾ RandomForestClassifier
RandomForestClassifier(n_estimators=1000)
```

In [268]:

```
logistic_regression_ypred = logistic_regression.predict(xtest)
svc_classifier_ypred = svc_classifier.predict(xtest)
dc_classifier_ypred = dc_classifier.predict(xtest)
knn_classifier_ypred = knn_classifier.predict(xtest)
rf_classifier_ypred = rf_classifier.predict(xtest)
```

Calculating Accuracy

In [269]:

```
from sklearn.metrics import accuracy_score
```

In [270]:

```
logistic_regression_acc = accuracy_score(ytest, logistic_regression_ypred)
svc_classifier_acc = accuracy_score(ytest, svc_classifier_ypred)
dc_classifier_acc = accuracy_score(ytest, dc_classifier_ypred)
knn_classifier_acc = accuracy_score(ytest, knn_classifier_ypred)
rf_classifier_acc = accuracy_score(ytest, rf_classifier_ypred)
```

In [273]:

```
print("Logistic Regression     :", round(logistic_regression_acc*100, 2))
print("Support Vector          :", round(svc_classifier_acc*100, 2))
print("Decision Tree           :", round(dc_classifier_acc*100, 2))
print("K-NN Classifier         :", round(knn_classifier_acc*100, 2))
print("Random Forest           :", round(rf_classifier_acc*100, 2))
```

```
Logistic Regression     : 80.97
Support Vector          : 82.09
Decision Tree           : 76.49
K-NN Classifier         : 80.97
Random Forest           : 81.34
```

```
As per the above data Support Vector has the highest Accuracy and beside that Random forest has
the second
```

```
highest accuracy
```