World Happiness Report Project

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as MSE
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df= pd.read_csv("https://raw.githubusercontent.com/dsrscientist/DSData/master/happines
df
```

Out[2]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.6655
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.6287
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.6493
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.6697
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.6329
...	...	...	...	...	...	...	...	...	..
153	Rwanda	Sub-Saharan Africa	154	3.465	0.03464	0.22208	0.77370	0.42864	0.5920
154	Benin	Sub-Saharan Africa	155	3.340	0.03656	0.28665	0.35386	0.31910	0.4845
155	Syria	Middle East and Northern Africa	156	3.006	0.05015	0.66320	0.47489	0.72193	0.1568
156	Burundi	Sub-Saharan Africa	157	2.905	0.08658	0.01530	0.41587	0.22396	0.1185
157	Togo	Sub-Saharan Africa	158	2.839	0.06727	0.20868	0.13995	0.28443	0.3645

158 rows × 12 columns

In [3]:
```
df.head()
```

Out[3]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	(
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.66557	
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.62877	
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.64938	
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.66973	
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.63297	

In [4]:
```
df.shape
```

Out[4]:
```
(158, 12)
```

In [5]:
```
df.describe()
```

Out[5]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	T (Governn Corrupt
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.00
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615	0.14
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693	0.12
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000	0.00
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330	0.06
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515	0.10
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092	0.18
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730	0.55

In [6]:
```
df.drop(columns=["Happiness Rank","Standard Error","Dystopia Residual"],inplace= True)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['Country', 'Region', 'Happiness Score', 'Economy (GDP per Capita)',
       'Family', 'Health (Life Expectancy)', 'Freedom',
       'Trust (Government Corruption)', 'Generosity'],
      dtype='object')
```

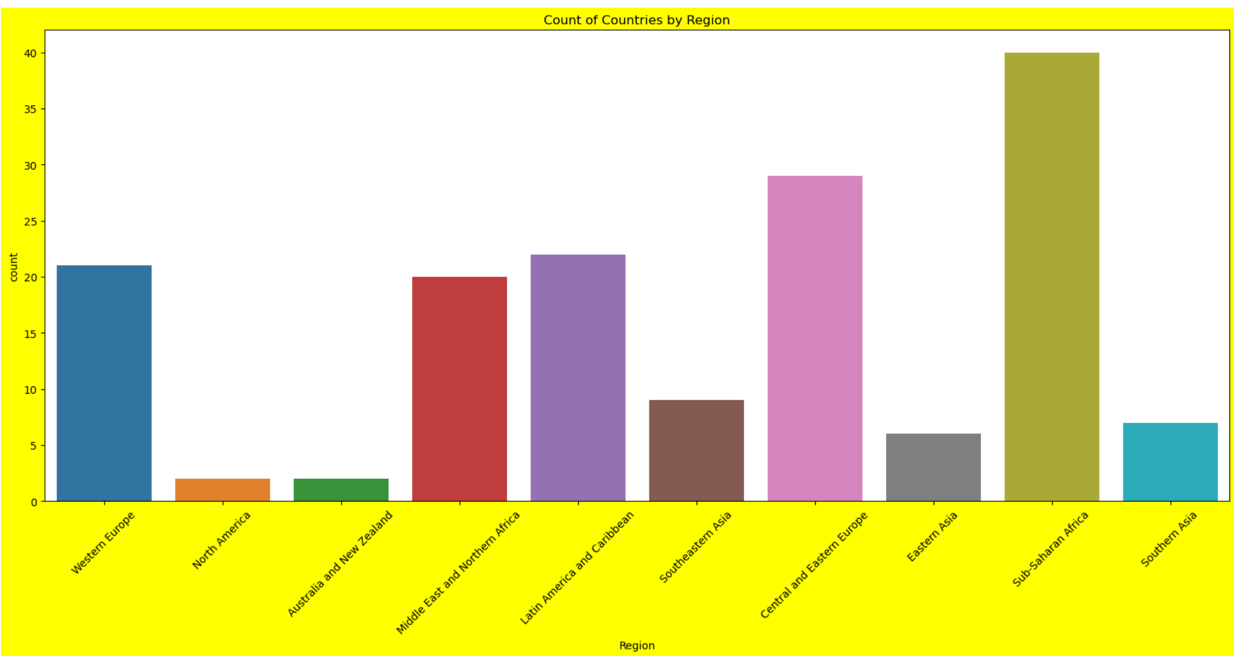
In [8]:
```
df.dtypes
```

Out[8]:
```
Country                          object
Region                           object
Happiness Score                 float64
Economy (GDP per Capita)        float64
Family                          float64
Health (Life Expectancy)        float64
Freedom                         float64
Trust (Government Corruption)   float64
Generosity                      float64
dtype: object
```

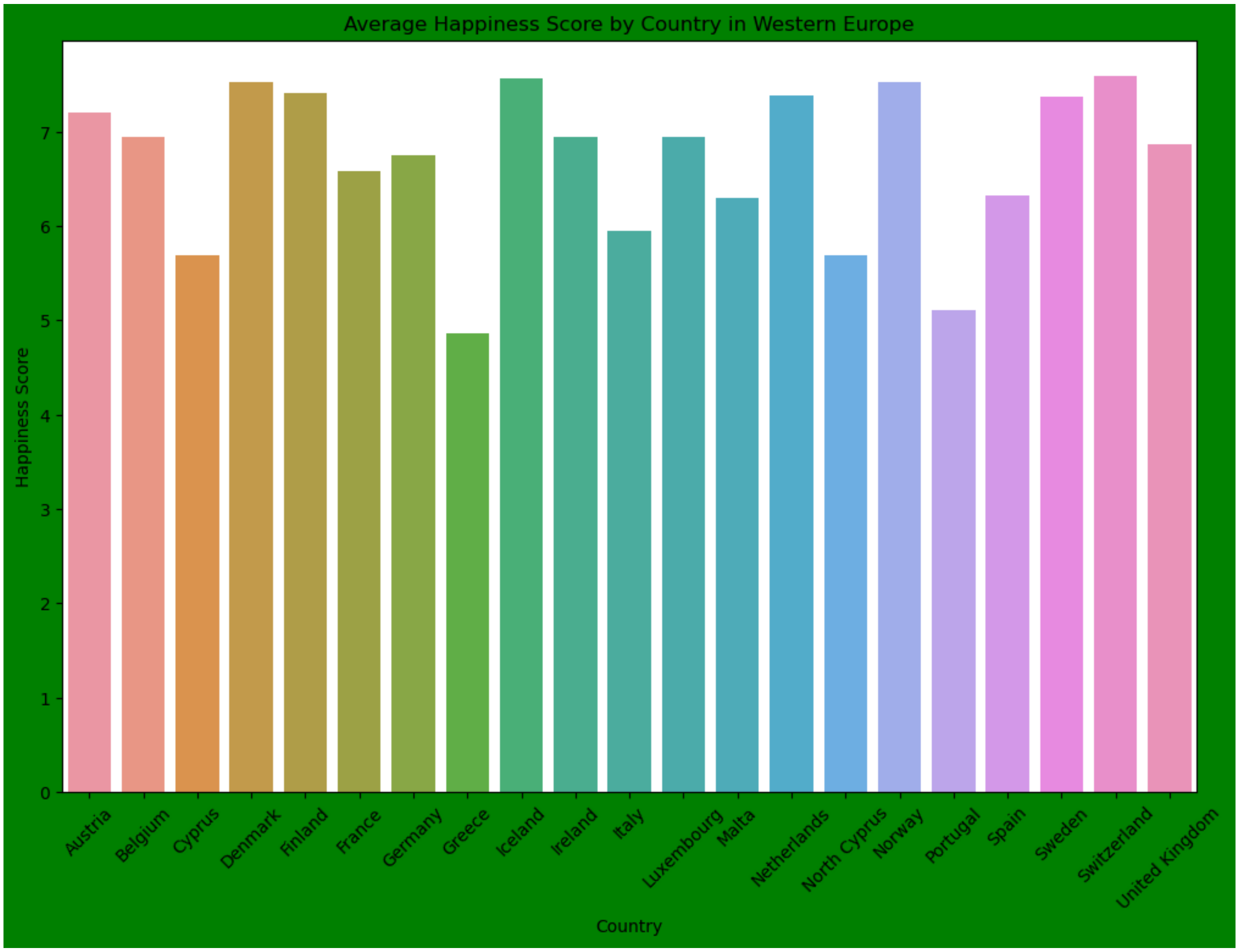
In [9]:
```
df.isnull().sum()
```

Out[9]:
```
Country                         0
Region                          0
Happiness Score                 0
Economy (GDP per Capita)        0
Family                          0
Health (Life Expectancy)        0
Freedom                         0
Trust (Government Corruption)   0
Generosity                      0
dtype: int64
```

In [10]:
```
plt.figure(figsize=(20,8),facecolor='yellow')
count_region= sns.countplot(data=df, x= "Region")
plt.xticks(rotation=45)
count_region.set_title("Count of Countries by Region")
plt.show()
```



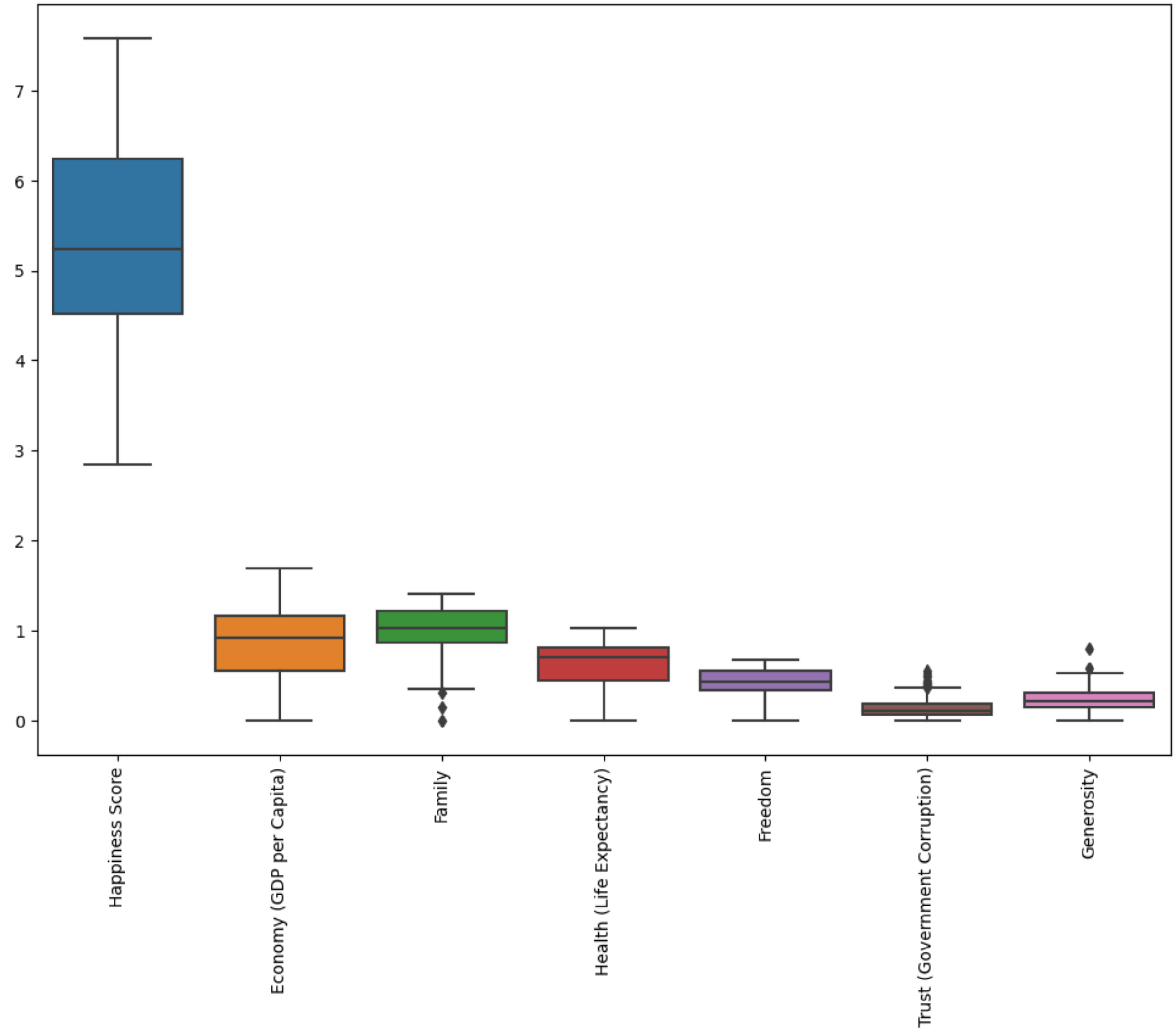
In [11]:
```
europe= df[df.Region== "Western Europe"]
by_country= europe.groupby("Country",as_index= False)
happiness_by_country= by_country["Happiness Score"].mean()
plt.figure(figsize=(12,8),facecolor='green')
barplot=sns.barplot(x="Country",y="Happiness Score", data=happiness_by_country)
barplot.set_title("Average Happiness Score by Country in Western Europe")
plt.xticks(rotation=45)
plt.show()
```



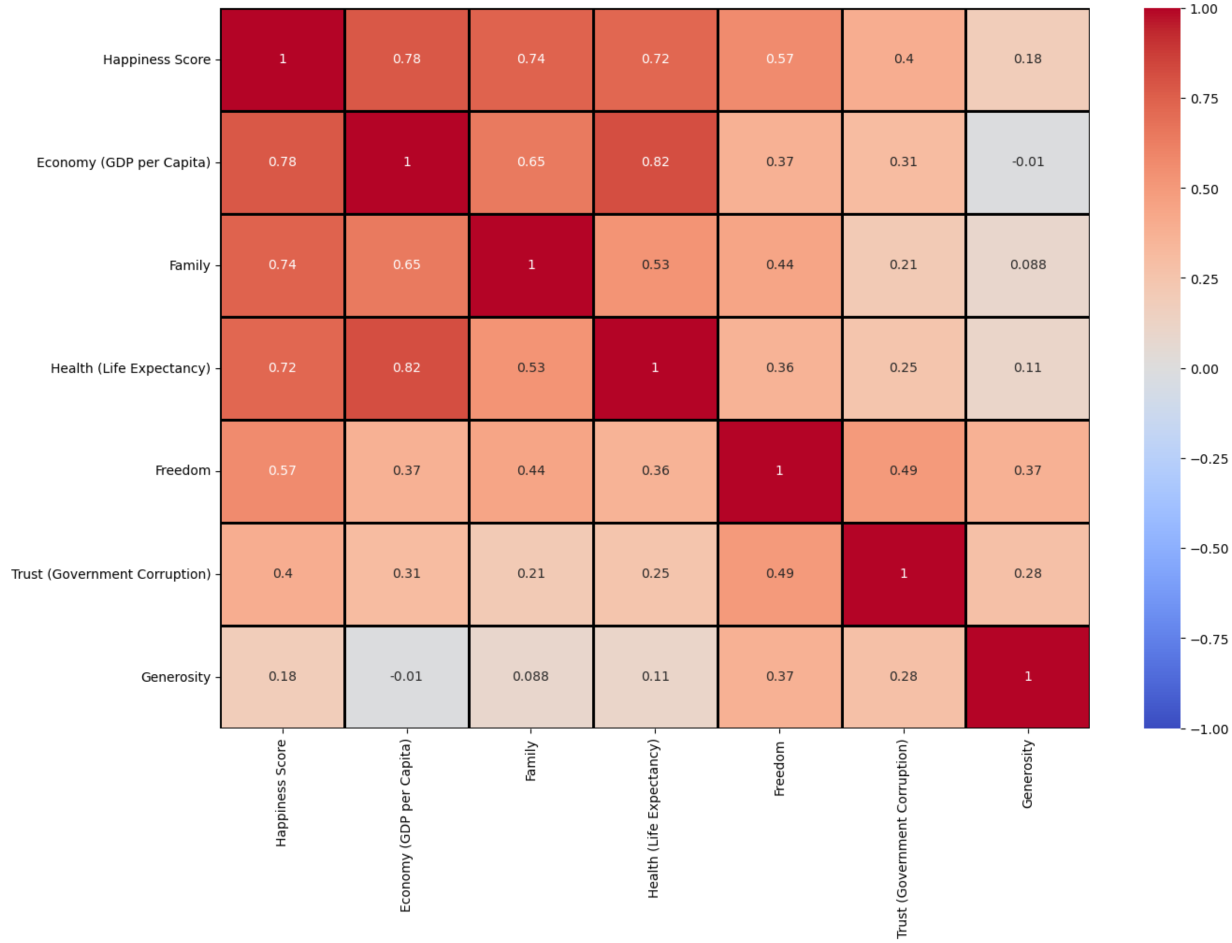
This visualization shows that the happiness score in switzerland,iceland and denmark has the highest happiness score in western europe

checking the outliers

In [12]:
```
plt.figure(figsize=(12,8))
ax= sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.show()
```

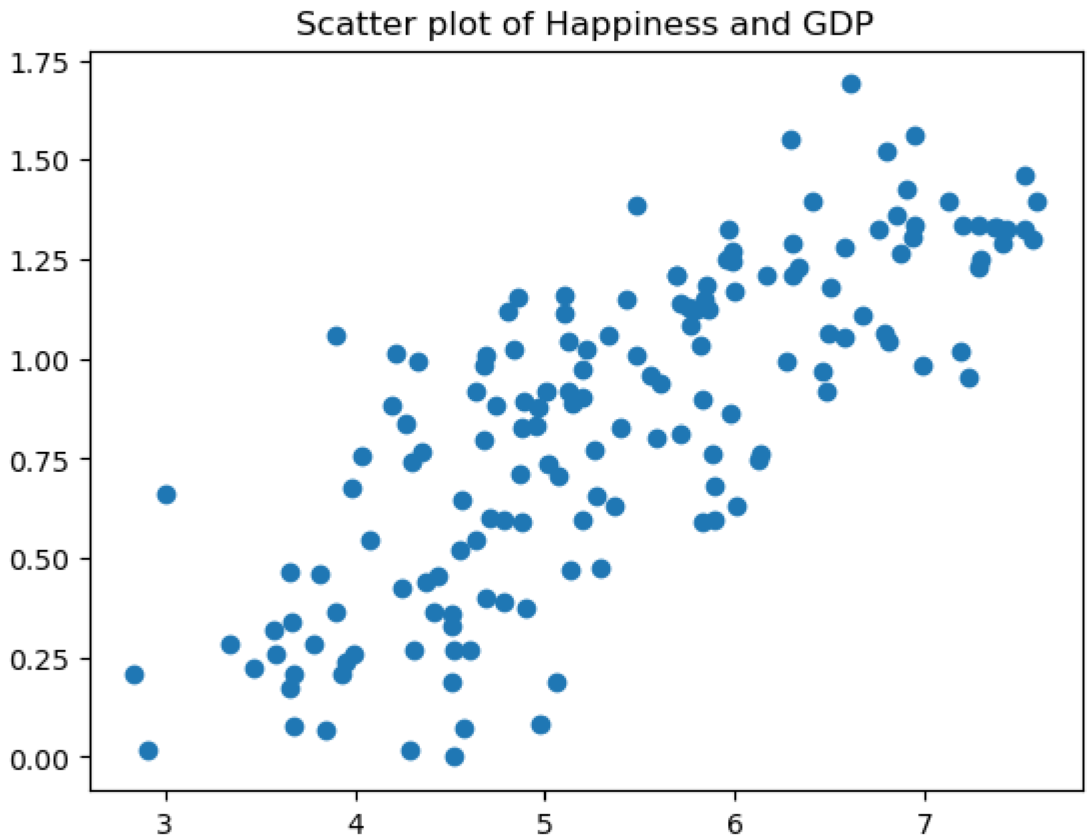


In [13]:
```
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(),annot= True,vmin=-1, vmax=1,cmap='coolwarm',linewidths=2,linecol
plt.show()
```



It shows the strong correlation between happiness score, Economy and health whereas it has a low correlation with trust and generosity.

In [14]:
```
happiness_score= df['Happiness Score']
gdp= df['Economy (GDP per Capita)']
plt.scatter(happiness_score,gdp)
plt.title("Scatter plot of Happiness and GDP")
plt.xlabel= ['Happiness Score']
plt.ylabel= ['Economy (GDP per Capita)']
plt.show()
```



It shows that the countries with high GDP are much happier.

In [15]:
```
rich_countries= df[['Country','Economy (GDP per Capita)']].groupby('Country').mean().s
rich_countries.head()
```

Out[15]:

Country	Economy (GDP per Capita)
Qatar	1.69042
Luxembourg	1.56391
Kuwait	1.55422
Singapore	1.52186
Norway	1.45900

In [16]:
```
Healthy_countries= df[['Country','Health (Life Expectancy)']].sort_values(by= 'Health
Healthy_countries.head()
```

Out[16]:

	Country	Health (Life Expectancy)
23	Singapore	1.02525
71	Hong Kong	1.01328
45	Japan	0.99111
46	South Korea	0.96538
35	Spain	0.95562

In [17]:
```
low_life_expectancy= df[['Country','Health (Life Expectancy)']].sort_values(by= 'Healt
low_life_expectancy.head()
```

Out[17]:

	Country	Health (Life Expectancy)
122	Sierra Leone	0.00000
127	Botswana	0.04776
147	Central African Republic	0.06699
100	Swaziland	0.07566
96	Lesotho	0.07612

In [18]:
```
X= df[['Economy (GDP per Capita)','Family', 'Health (Life Expectancy)', 'Freedom']]
y= df['Happiness Score']
X_train, X_test, y_train, y_test= train_test_split(X,y,test_size= 0.2, random_state= 0
```

The data is split into training and test sets.

In [19]:
```
scale= StandardScaler()
df= scale.fit_transform(X)
```

After standardization we can train the algorithm and make prediction on the test data to compare actual values with the predicted values.

In [20]:
```
lm= LinearRegression()
lm.fit(X_train,y_train)
```

Out[20]:
```
LinearRegression()
```

In [21]:
```
coefficient= lm.coef_
coefficient_df= pd.DataFrame(list(zip(X.columns,lm.coef_)),columns=['features','coeffi
coefficient_df
```

Out[21]:

	features	coefficients
0	Economy (GDP per Capita)	0.914757
1	Family	1.418679
2	Health (Life Expectancy)	0.902836
3	Freedom	1.934132

In [22]:
```
y_pred = lm.predict(X_test)
y_pred
```

Out[22]:
```
array([6.94977382, 6.00173856, 4.4486987 , 4.61392229, 5.91234477,
       4.2521346 , 4.07386374, 3.9187213 , 4.7106378 , 5.37757708,
       6.24515925, 4.62738208, 6.04105412, 6.03073952, 3.63518555,
       6.00483871, 4.4732444 , 5.03994486, 5.06730069, 5.71077711,
       6.60459724, 6.22682362, 6.37986186, 6.87685318, 6.22785414,
       6.07084913, 5.12373313, 6.67848402, 4.94850258, 4.11217429,
       4.98139199, 6.66097864])
```

Model Accuracy

In [26]:
```
accuracy= np.sqrt(MSE(y_test,y_pred))
accuracy
```

Out[26]:
```
0.5937109307075934
```

The model has a Root Mean Squared Error of 0.59. The lower the RMSE, the better the model is at making prediction.

Titanic Survived Project

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, mean_squared_error as MSE
```

In [2]:
```
df= pd.read_csv("https://raw.githubusercontent.com/dsrscientist/dataset1/master/titani
df
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
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
...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN

891 rows × 12 columns

In [3]:

```
df.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	E
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 [4]:

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

Out[4]:

```
array([0, 1], dtype=int64)
```

In [5]:

```
df.describe()
```

Out[5]:

	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

In [6]:

```
dd_sv_cnt= pd.crosstab(df['Survived'],df['Sex'],margins= True)
dd_sv_cnt
```

Out[6]:

Sex	female	male	All
Survived			
0	81	468	549
1	233	109	342
All	314	577	891

In [7]:
```
class_gen_cnt= pd.crosstab(df['Sex'],df['Pclass'],margins=True)
class_gen_cnt
```

Out[7]:

Pclass	1	2	3	All
Sex				
female	94	76	144	314
male	122	108	347	577
All	216	184	491	891

In [8]:
```
df.isna().sum()
```

Out[8]:
```
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 [9]:
```
age_missing= df[df['Age'].isna()]
age_missing
```

Out[9]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	NaN
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	NaN
26	27	0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250	NaN
28	29	1	3	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0	0	330959	7.8792	NaN
...	...	...	...	...	...	...	...	...	...	...	...
859	860	0	3	Razi, Mr. Raihed	male	NaN	0	0	2629	7.2292	NaN
863	864	0	3	Sage, Miss. Dorothy Edith "Dolly"	female	NaN	8	2	CA. 2343	69.5500	NaN
868	869	0	3	van Melkebeke, Mr. Philemon	male	NaN	0	0	345777	9.5000	NaN
878	879	0	3	Laleff, Mr. Kristo	male	NaN	0	0	349217	7.8958	NaN
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN

177 rows × 12 columns

In [10]:
```
with_age= df[df['Age'].notnull()]
with_age
```

Out[10]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
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
...	...	...	...	...	...	...	...	...	...	...	...
885	886	0	3	Rice, Mrs. William (Margaret Norton)	female	39.0	0	5	382652	29.1250	NaN
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN

714 rows × 12 columns

In [11]:
```
max(df['Fare'])
```

Out[11]:
```
512.3292
```

In [12]:
```
max_= df[df.Fare==max(df['Fare'])]
max_
```

Out[12]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Em
258	259	1	1	Ward, Miss. Anna	female	35.0	0	0	PC 17755	512.3292	NaN	
679	680	1	1	Cardeza, Mr. Thomas Drake Martinez	male	36.0	0	1	PC 17755	512.3292	B51 B53 B55	
737	738	1	1	Lesurer, Mr. Gustave J	male	35.0	0	0	PC 17755	512.3292	B101	

In [13]:

```
class1_female=df[df.Pclass.isin([1]) & df.Sex.isin(['female'])]
class1_female
```

Out[13]:

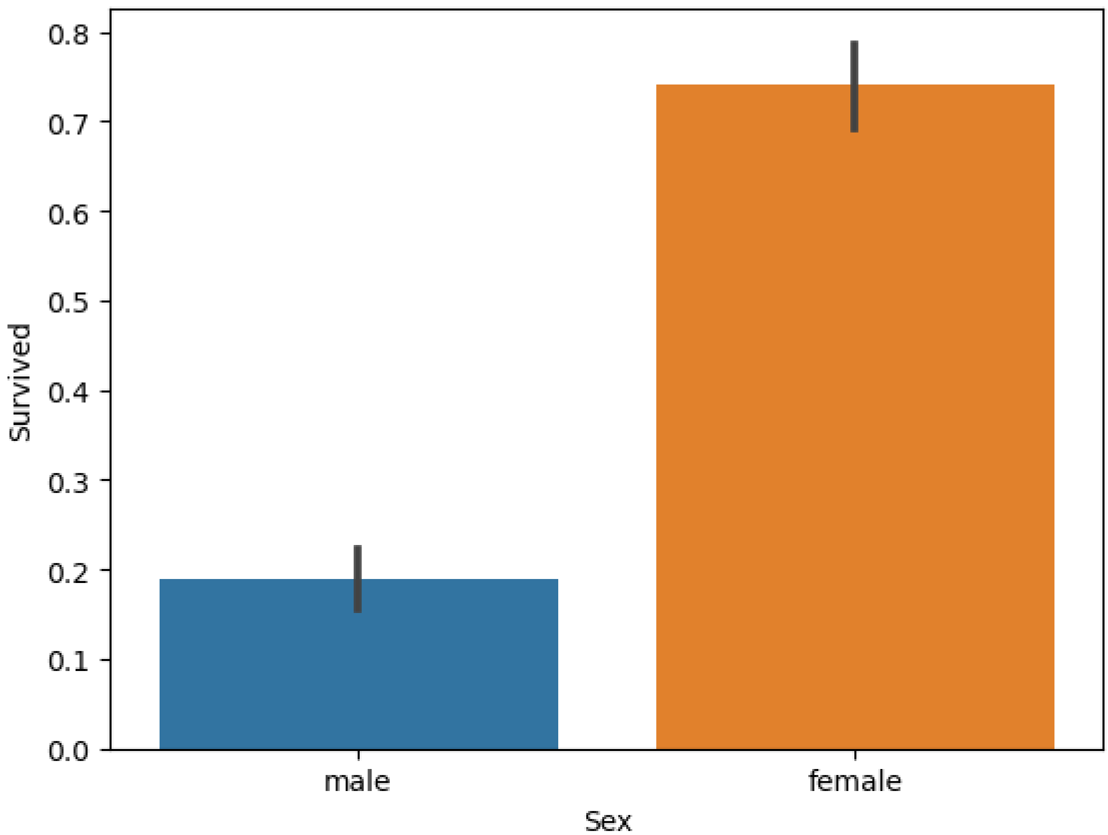
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	C103
31	32	1	1	Spencer, Mrs. William Augustus (Marie Eugenie)	female	NaN	1	0	PC 17569	146.5208	B78
52	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33
...	...	...	...	...	...	...	...	...	...	...	...
856	857	1	1	Wick, Mrs. George Dennick (Mary Hitchcock)	female	45.0	1	1	36928	164.8667	NaN
862	863	1	1	Swift, Mrs. Frederick Joel (Margaret Welles Ba...	female	48.0	0	0	17466	25.9292	D17
871	872	1	1	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	1	1	11751	52.5542	D35
879	880	1	1	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	0	1	11767	83.1583	C50
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42

94 rows × 12 columns

In [14]:
```
sns.barplot(x='Sex', y= 'Survived',data=df)
df.groupby('Sex',as_index= False).Survived.mean()
```

Out[14]:

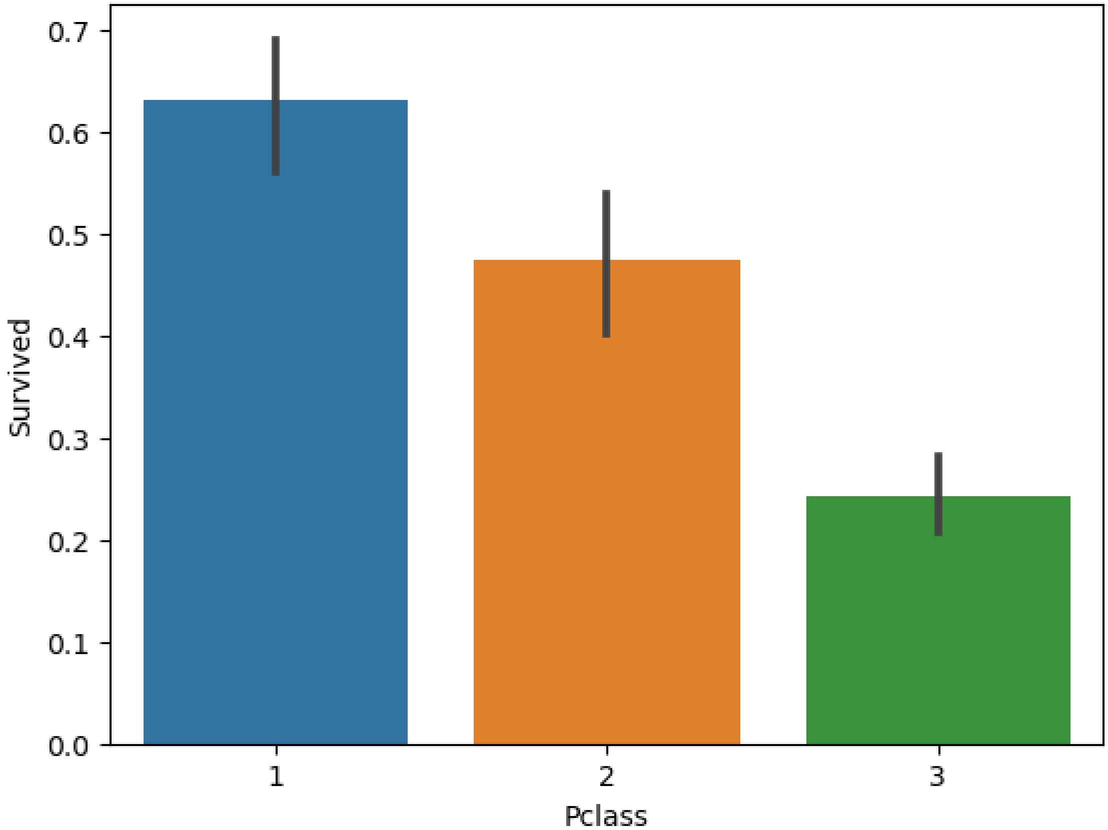
	Sex	Survived
0	female	0.742038
1	male	0.188908



In [15]:
```
sns.barplot(x='Pclass', y='Survived',data=df)
df[["Pclass", "Survived"]]. groupby(['Pclass'],as_index=False).mean().sort_values(by='
```

Out[15]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

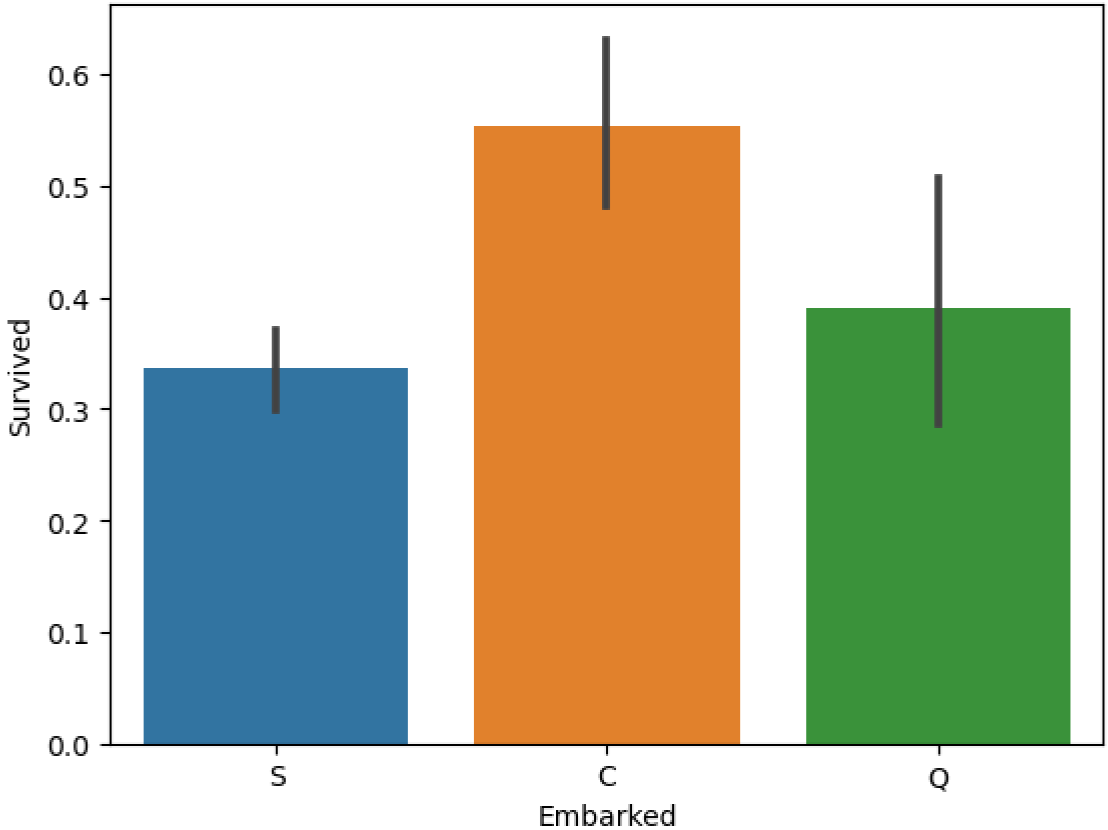


In [16]:

```
sns.barplot(x='Embarked',y='Survived',data=df)
df[['Embarked','Survived']].groupby(['Embarked'], as_index=False).mean().sort_values(b
```

Out[16]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.336957

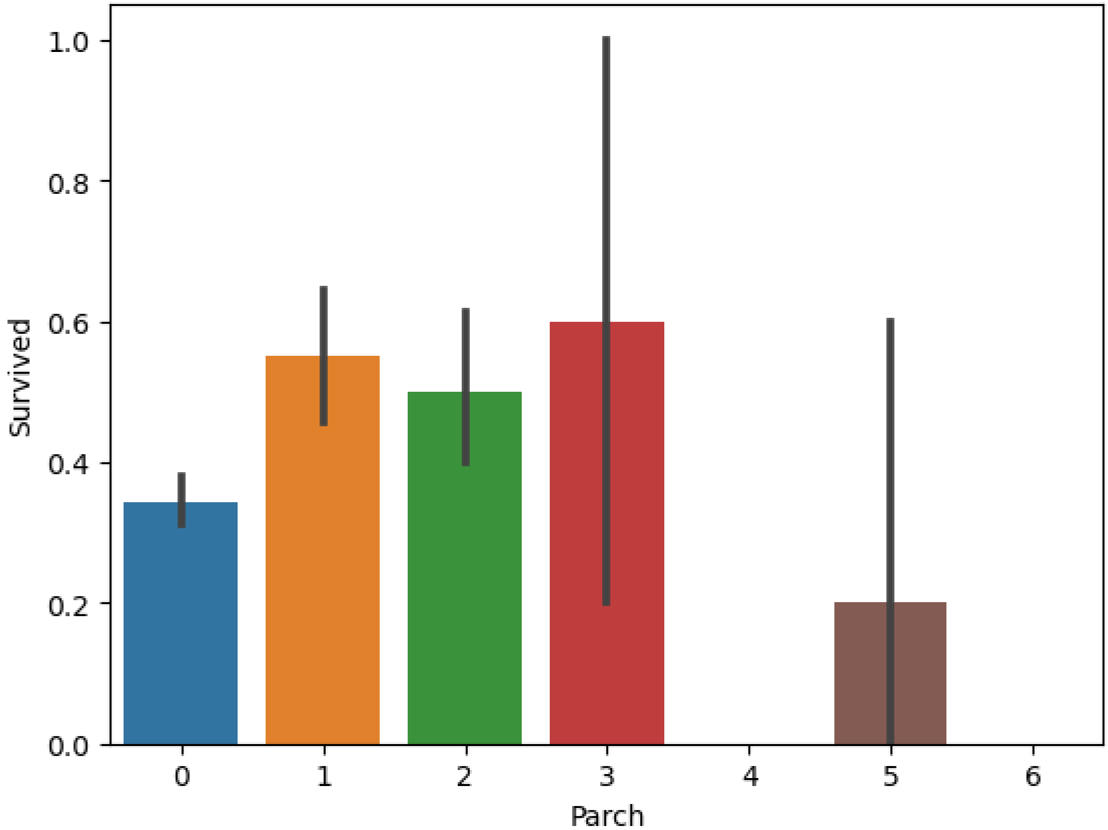


In [17]:

```
sns.barplot(x='Parch',y= 'Survived',data=df)
df[['Parch','Survived']].groupby(['Parch'], as_index=False).mean().sort_values(by='Sur
```

Out[17]:

	Parch	Survived
3	3	0.600000
1	1	0.550847
2	2	0.500000
0	0	0.343658
5	5	0.200000
4	4	0.000000
6	6	0.000000

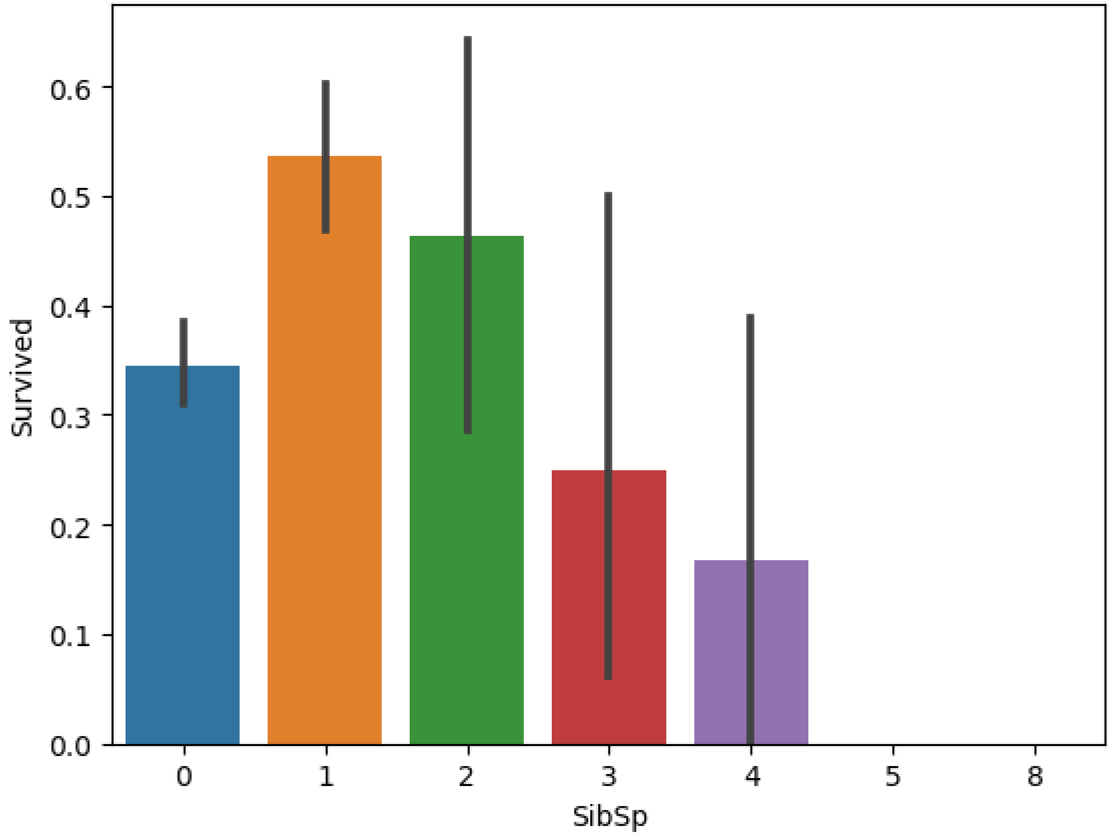


In [18]:

```
sns.barplot(x='SibSp',y='Survived',data=df)
df[['SibSp','Survived']].groupby(['SibSp'], as_index=False).mean().sort_values(by='Sur
```

Out[18]:

	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000



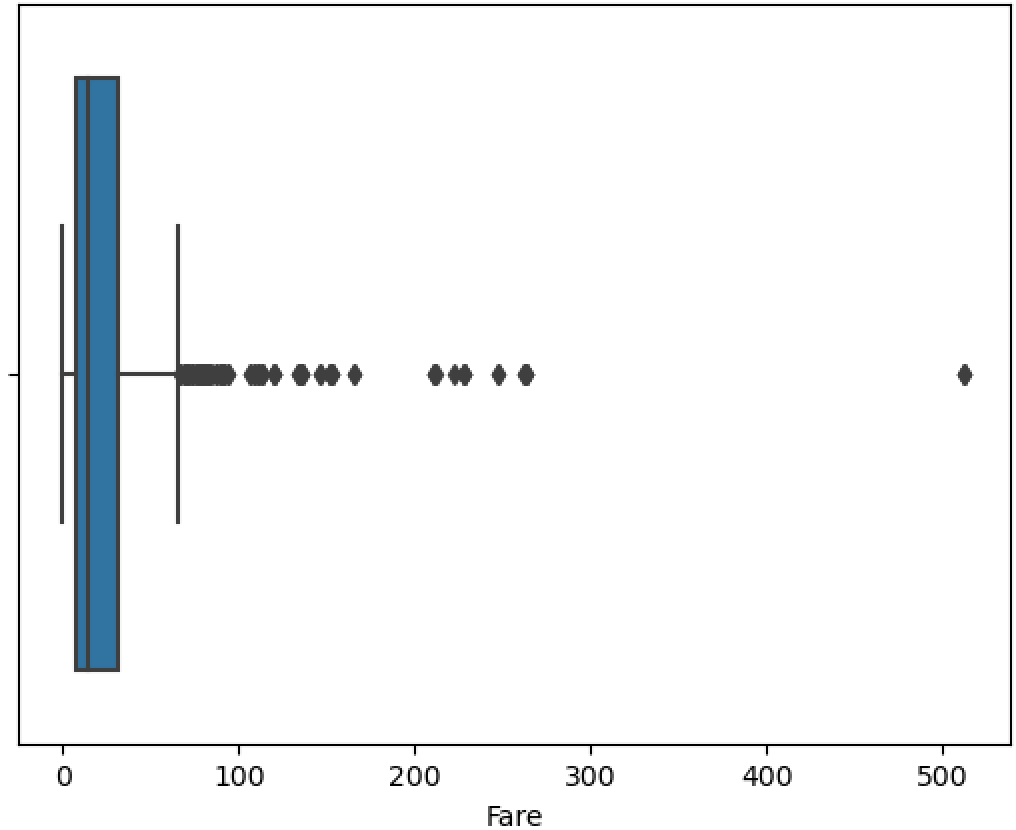
In [19]:
```
df.Embarked.fillna('S',inplace=True)
```

Most people embarked the journey from Southhampton port therefore filling S in the missing values.

In [20]:
```
sns.boxplot("Fare",data=df)
print('Mean is: ',df.Fare.mean())
print('Median is: ',df.Fare.median())
```

```
Mean is:  32.2042079685746
Median is:  14.4542
```

```
C:\Users\Sony\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: P
ass the following variable as a keyword arg: x. From version 0.12, the only valid pos
itional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```



In [21]:
```
df.Age.fillna(28, inplace=True)
```

In [22]:
```
df.drop(columns=['Cabin','Embarked','Name','Sex','Ticket'],inplace=True)
df.head()
```

Out[22]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
0	1	0	3	22.0	1	0	7.2500
1	2	1	1	38.0	1	0	71.2833
2	3	1	3	26.0	0	0	7.9250
3	4	1	1	35.0	1	0	53.1000
4	5	0	3	35.0	0	0	8.0500

In [23]:
```
X= df.drop(columns=["Survived"],axis=1)
y=df["Survived"]
X_train, X_test, y_train, y_test= train_test_split(X,y,test_size=0.3, random_state=42)
```

In [24]:
```
scale= StandardScaler()
df= scale.fit_transform(X)
```

In [25]:
```
lm= LinearRegression()
lm.fit(X_train, y_train)
```

Out[25]:
```
LinearRegression()
```

In [26]:
```
y_pred= lm.predict(X_test)
```

In [28]:
```
(f"accuracy Score: {np.sqrt(MSE(y_test,y_pred))*100: .2f}%")
```

Out[28]:
```
'accuracy Score:  44.11%'
```

In [ ]: