In [ ]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

In [ ]:

```
# Read the data..
df_train = pd.read_csv("train.csv")
df_test = pd.read_csv("test.csv")
```

Data Understanding

In [ ]:

```
# Check the top values of training data set.
df_train.head()
```

Out[ ]:

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

In [ ]:

```
# Check the lower values of training data set.
df_train.tail()
```

Out[ ]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
886	887	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S	0
887	888	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S	1
888	889	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S	0
889	890	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C	1
890	891	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q	0

In [ ]:

```
df_train.describe()
```

```
df_train.describe()
```

Out[ ]:

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

In [ ]:

```
df_train.shape
```

Out[ ]:

```
(891, 12)
```

In [ ]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
Survived       891 non-null int64
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [ ]:

```
df_train.columns
```

Out[ ]:

```
Index(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
       'Ticket', 'Fare', 'Cabin', 'Embarked', 'Survived'],
      dtype='object')
```

In [ ]:

```
df_train.corr()
```

Out[ ]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare	Survived
PassengerId	1.000000	-0.035144	0.036847	-0.057527	-0.001652	0.012658	-0.005007
Pclass	-0.035144	1.000000	-0.369226	0.083081	0.018443	-0.549500	-0.338481
Age	0.036847	-0.369226	1.000000	-0.308247	-0.189119	0.096067	-0.077221
SibSp	-0.057527	0.083081	-0.308247	1.000000	0.414838	0.159651	-0.035322

	PassengerId	Pclass	Age	SibSp	Parch	Fare	Survived
Parch	-0.001652	0.018443	-0.189119	0.414838	1.000000	0.216225	0.081629
Fare	0.012658	-0.549500	0.096067	0.159651	0.216225	1.000000	0.257307
Survived	-0.005007	-0.338481	-0.077221	-0.035322	0.081629	0.257307	1.000000

Data Cleaning

Some columns have a large number of missing values, let's first fix the missing values and then check for other types of data quality problems.

In [ ]:

```
# summarising number of missing values in each column
df_train.isnull().sum()
```

Out[ ]:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
Survived         0
dtype: int64
```

In [ ]:

```
# percentage of missing values in each column
round(df_train.isnull().sum()/len(df_train.index), 2)*100
```

Out[ ]:

```
PassengerId     0.0
Pclass          0.0
Name            0.0
Sex             0.0
Age            20.0
SibSp           0.0
Parch           0.0
Ticket          0.0
Fare            0.0
Cabin          77.0
Embarked        0.0
Survived        0.0
dtype: float64
```

In [ ]:

```
#Check the missing Columns
missing_columns = df_train.columns[100*(df_train.isnull().sum()/len(df_train.index)) > 7
0]
print(missing_columns)
```

```
Index(['Cabin'], dtype='object')
```

In [ ]:

```
# Drop the column which has large missing value
df_train = df_train.drop(missing_columns, axis=1)
print(df_train.shape)
```

```
(891, 11)
```

In [ ]:

```
# summarise number of missing values again
100*(df_train.isnull().sum()/len(df_train.index))
```

Out[ ]:

```
PassengerId     0.000000
Pclass          0.000000
Name            0.000000
Sex             0.000000
Age            19.865320
SibSp           0.000000
Parch           0.000000
Ticket          0.000000
Fare            0.000000
Embarked        0.224467
Survived        0.000000
dtype: float64
```

In [ ]:

```
# fill the empty places with mean or maximum used value
df_train.Age = df_train.Age.fillna(df_train.Age.mean())
df_train.Embarked = df_train.Embarked.fillna('S')
```

In [ ]:

```
# summarise number of missing values again
100*(df_train.isnull().sum()/len(df_train.index))
```

Out[ ]:

```
PassengerId    0.0
Pclass         0.0
Name           0.0
Sex            0.0
Age            0.0
SibSp          0.0
Parch          0.0
Ticket         0.0
Fare           0.0
Embarked       0.0
Survived       0.0
dtype: float64
```

In [ ]:

```
#now check the data again
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
PassengerId    891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            891 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Embarked       891 non-null object
Survived       891 non-null int64
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

In [ ]:

```
df_train.head()
```

Out[ ]:

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

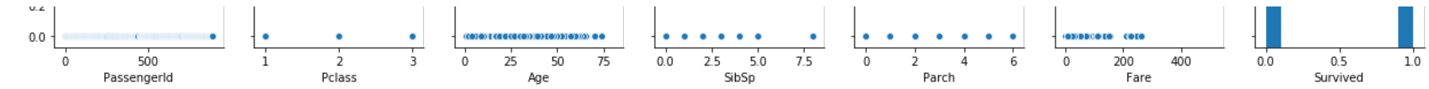
Now see there is no missing value in our data..so out data is cleaned

Data Analysis and Outlier Handling

Let's now move to data analysis

In [ ]:

```
sns.pairplot(df_train)
plt.show()
```



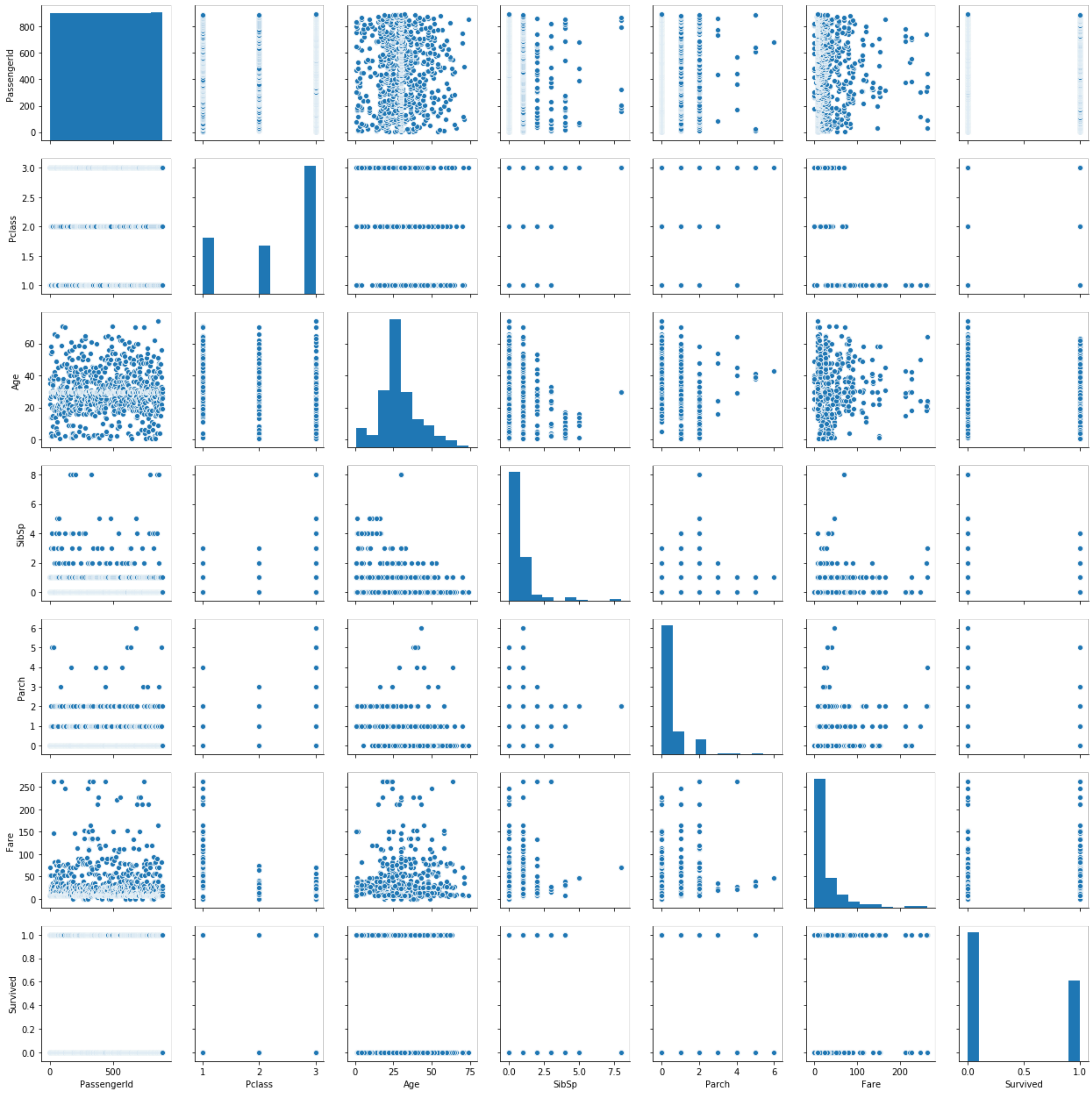
From the graph we see that there is lot of outtliers in the case of (fare,age)columns.

In [ ]:

```
#change outlier value with mean
# AGE
df_train.Age[(df_train.Age> 75)] = (df_train.Age.mean())
# FARE
df_train.Fare[(df_train.Fare> 500)] = (df_train.Fare.mean())
```

In [ ]:

```
#check the values again
sns.pairplot(df_train)
plt.show()
```



Analyze by pivoting features

TO CHECK HOW MUCH A PART OF COLUMN AFFECT THE MODEL

TO CHECK HOW MUCH A PART OF COLUMN AFFECT THE MODEL

In [ ]:

```
df_train[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean().sort_values(
by='Survived', ascending=False)
```

Out[ ]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [ ]:

```
df_train[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().sort_values(by='Su
rvived', ascending=False)
```

Out[ ]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

In [ ]:

```
df_train[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by
='Survived', ascending=False)
```

Out[ ]:

	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 [ ]:

```
df_train[["Parch", "Survived"]].groupby(['Parch'], as_index=False).mean().sort_values(by
='Survived', ascending=False)
```

Out[ ]:

	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 [ ]:

```
df_train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().sort_val
ues(by='Survived', ascending=False)
```

Out[ ]:

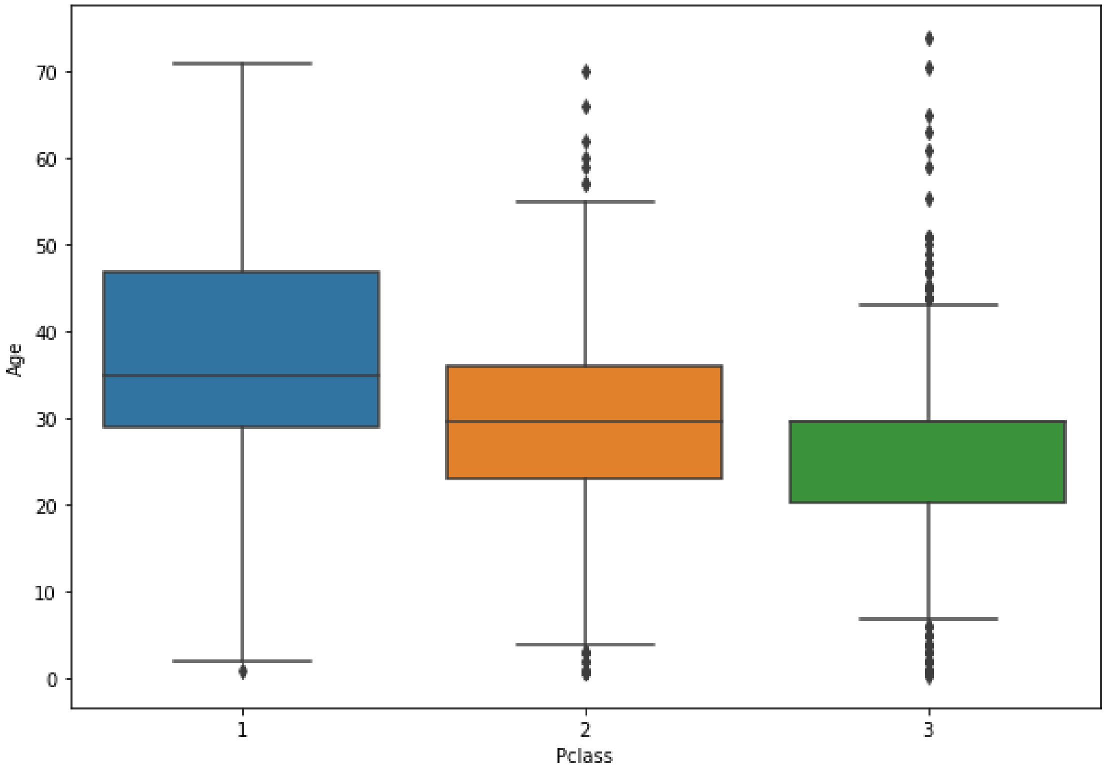
	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.339009

In [ ]:

```
# boxplot acc to age of passengers...
plt.figure(figsize=(10,7))
sns.boxplot(x='Pclass', y='Age', data=df_train)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x180aef17808>
```

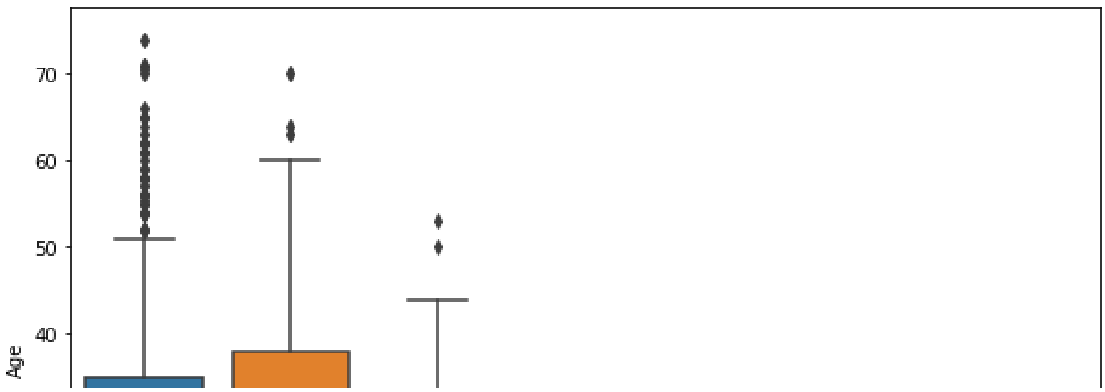


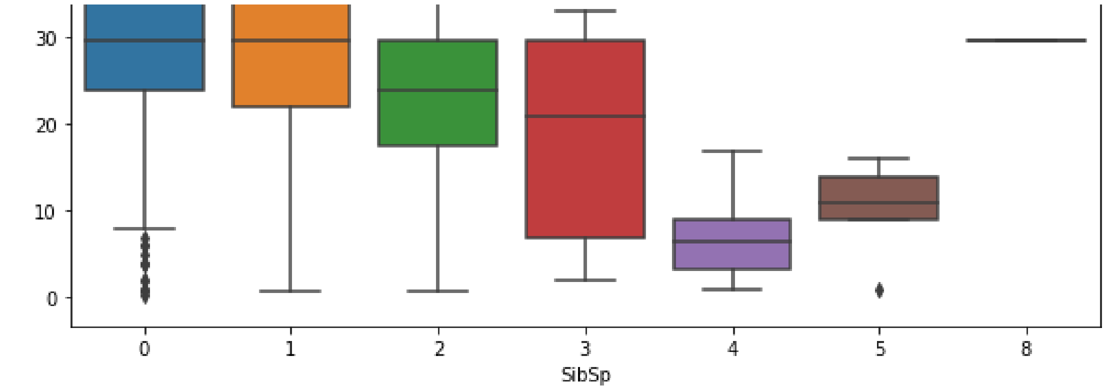
In [ ]:

```
# boxplot acc to SibSp of passengers...
plt.figure(figsize=(10,7))
sns.boxplot(x='SibSp', y='Age', data=df_train)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x180af8a4bc8>
```



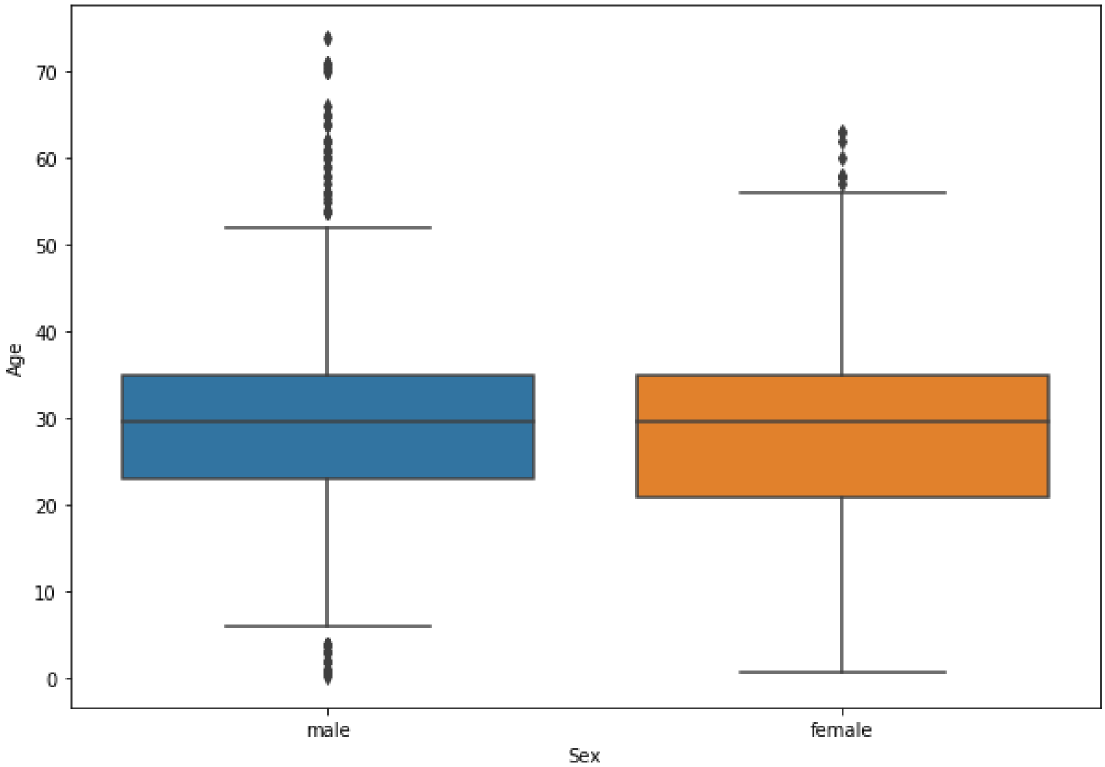


In [ ]:

```
# boxplot acc to Sex of passengers...
plt.figure(figsize=(10,7))
sns.boxplot(x='Sex', y='Age', data=df_train)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x180b3d32148>
```

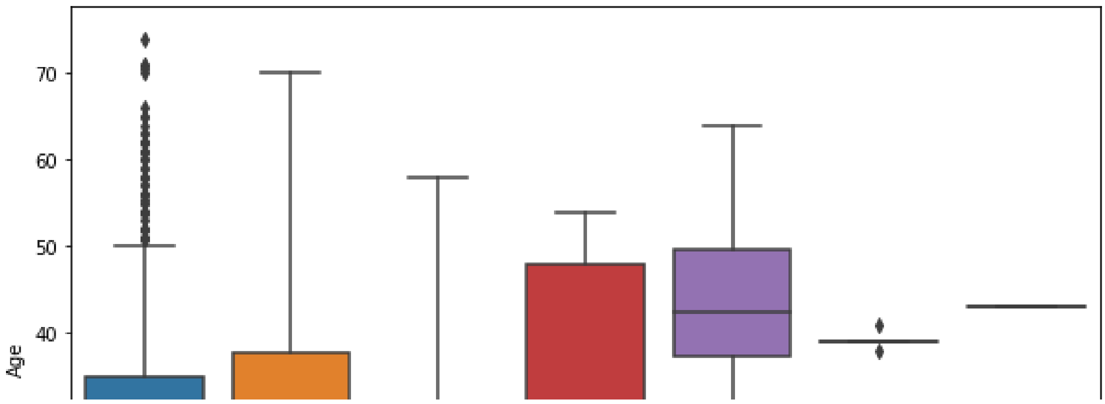


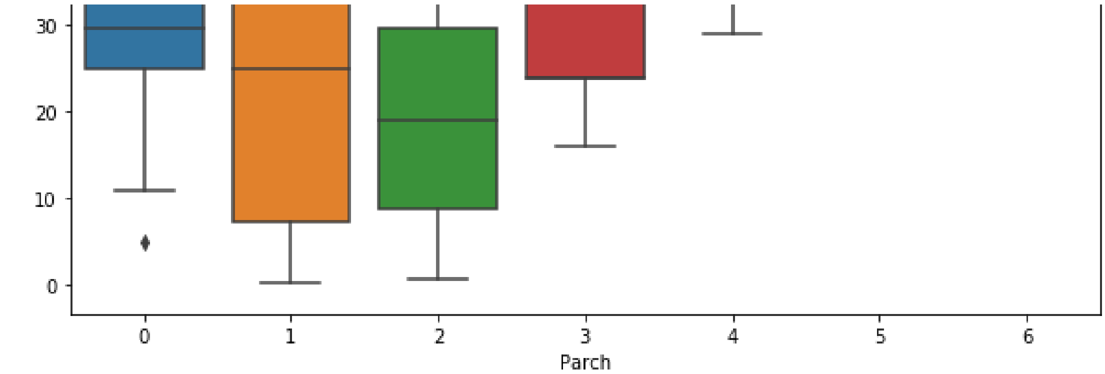
In [ ]:

```
# boxplot acc to Parch of passengers...
plt.figure(figsize=(10,7))
sns.boxplot(x='Parch', y='Age', data=df_train)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x180aeb05348>
```



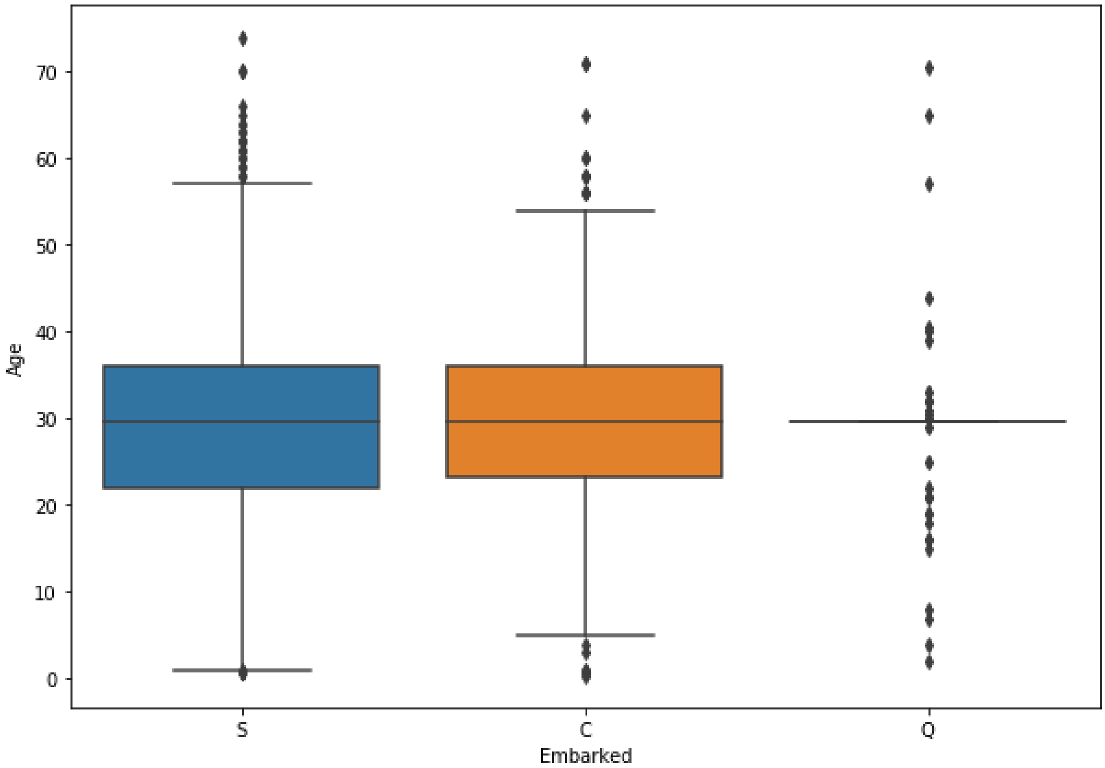


In [ ]:

```python
# boxplot acc to Embarked of passengers...
plt.figure(figsize=(10,7))
sns.boxplot(x='Embarked', y='Age', data=df_train)
```

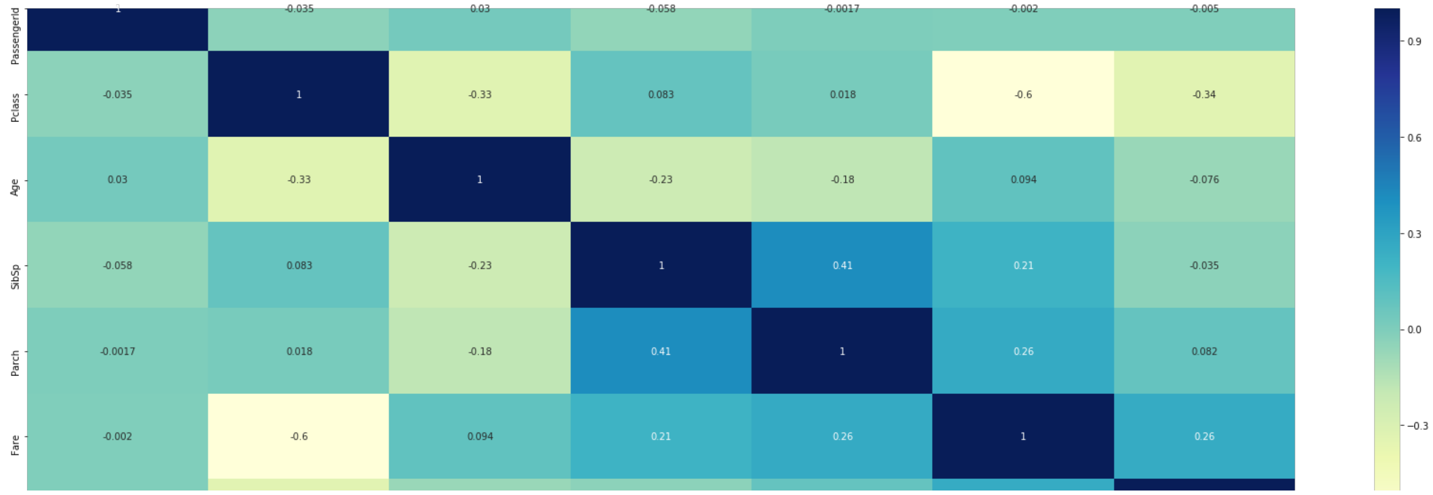
Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x180aeddfb48>
```



In [ ]:

```python
#plot a heat map
plt.figure(figsize=(30,10))
sns.heatmap(df_train.corr(),annot=True,cmap="YlGnBu")
plt.show()
```



In [ ]:

```
# Make the dummy variables for the feature 'Sex' and concat it with dataframe
# Let's drop the first column from status df using 'drop_first = True'
abc = pd.get_dummies(df_train['Sex'], drop_first = True)
df_train = pd.concat([df_train, abc], axis = 1)
df_train.head()
```

Out[ ]:

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

In [ ]:

```
# Make the dummy variables for the feature 'Embarked' and concat it with dataframe
# Let's drop the first column from status df using 'drop_first = True'
abc = pd.get_dummies(df_train['Embarked'], drop_first = True)
df_train = pd.concat([df_train, abc], axis = 1)
df_train.head()
```

Out[ ]:

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

In [ ]:

```
# Make the dummy variables for the feature 'Pclass' and concat it with dataframe
# Let's drop the first column from status df using 'drop_first = True'
abc = pd.get_dummies(df_train['Pclass'], drop_first = True)
df_train = pd.concat([df_train, abc], axis = 1)
df_train.head()
```

Out[ ]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Survived	male	Q	S	2	3
0	1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	0	1	0	1	0	1

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

In [ ]:

```
#Dropping the redundant features which were converted to dummies earlier
df_train.drop(['Sex', 'Embarked','Pclass','Name', 'Ticket'], axis=1, inplace=True)
```

Dividing into X and Y sets for the model building

In [ ]:

```
x_train = df_train.loc[:, df_train.columns != 'Survived']
y_train=  df_train['Survived']
```

Building our model Using RFE

Check RFE Value

In [ ]:

```
from sklearn.feature_selection import RFE
clf_lr = LogisticRegression()
clf_lr.fit(x_train,y_train)
rfe = RFE(clf_lr, 10)              # running RFE
rfe = rfe.fit(x_train, y_train)
```

In [ ]:

```
list(zip(x_train.columns,rfe.support_,rfe.ranking_))
```

Out[ ]:

```
[('PassengerId', True, 1),
 ('Age', True, 1),
 ('SibSp', True, 1),
 ('Parch', True, 1),
 ('Fare', True, 1),
 ('male', True, 1),
 ('Q', True, 1),
 ('S', True, 1),
 (2, True, 1),
 (3, True, 1)]
```

In [ ]:

```
col = x_train.columns[rfe.support_]
col
```

Out[ ]:

```
Index(['PassengerId', 'Age', 'SibSp', 'Parch', 'Fare', 'male', 'Q', 'S', 2, 3], dtype='ob
```

```
Index(['PassengerId', 'Age', 'SibSp', 'Parch', 'Fare', 'male', 'Q', 'S', 2, 3], dtype='object')
```

In [ ]:

```
# Creating X_test dataframe with RFE selected variables
x_train_new = x_train[col]
```

In [ ]:

```
x_train_new = sm.add_constant(x_train_new)
lm = sm.GLM(y_train,x_train_new,family = sm.families.Binomial())
res=lm.fit()
res.summary()
```

Out[ ]:

Generalized Linear Model Regression Results

Dep. Variable:	Survived	**No. Observations:**	891
Model:	GLM	**Df Residuals:**	880
Model Family:	Binomial	**Df Model:**	10
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-391.10
Date:	Tue, 18 Aug 2020	**Deviance:**	782.20
Time:	21:23:32	**Pearson chi2:**	913.
No. Iterations:	5		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	4.4046	0.526	8.368	0.000	3.373	5.436
PassengerId	8.276e-05	0.000	0.236	0.813	-0.001	0.001
Age	-0.0422	0.008	-5.289	0.000	-0.058	-0.027
SibSp	-0.3118	0.111	-2.805	0.005	-0.530	-0.094
Parch	-0.0726	0.121	-0.599	0.549	-0.310	0.165
Fare	-0.0004	0.003	-0.140	0.889	-0.007	0.006
male	-2.7388	0.202	-13.536	0.000	-3.135	-2.342
Q	-0.0495	0.382	-0.130	0.897	-0.799	0.700
S	-0.4836	0.238	-2.028	0.043	-0.951	-0.016
2	-1.0830	0.311	-3.484	0.000	-1.692	-0.474
3	-2.3515	0.319	-7.366	0.000	-2.977	-1.726

In [ ]:

```
y_train_pred = res.predict(x_train_new)
y_train_pred[:10]
```

Out[ ]:

```
0    0.082162
1    0.921013
2    0.614979
3    0.891644
4    0.065960
5    0.119973
6    0.245851
7    0.093578
8    0.569513
9    0.917272
dtype: float64
```

In [ ]:

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[ ]:

```
array([0.08216204, 0.92101288, 0.61497872, 0.89164368, 0.06595972,
       0.11997314, 0.24585131, 0.09357758, 0.56951279, 0.91727186])
```

Creating the dataframe with actual value and predicted value

In [ ]:

```
y_train_final =  pd.DataFrame({'Survived':y_train.values,"Survived_prob":y_train_pred})
y_train_final["Id"]= x_train_new.PassengerId
y_train_final.head()
```

Out[ ]:

	Survived	Survived_prob	Id
0	0	0.082162	1
1	1	0.921013	2
2	1	0.614979	3
3	1	0.891644	4
4	0	0.065960	5

In [ ]:

```
# create new column as predict which tell about the predicted value is 1 if prob>0.5 else
0
y_train_final['PredictedValue'] = y_train_final.Survived_prob.map(lambda x:1 if x>0.5 els
e 0)
y_train_final.head()
```

Out[ ]:

	Survived	Survived_prob	Id	PredictedValue
0	0	0.082162	1	0
1	1	0.921013	2	1
2	1	0.614979	3	1
3	1	0.891644	4	1
4	0	0.065960	5	0

In [ ]:

```
# make a confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(y_train, y_train_final.PredictedValue)
```

Out[ ]:

```
array([[475,  74],
       [100, 242]], dtype=int64)
```

In [ ]:

```
from sklearn.metrics import accuracy_score
accuracy_score(y_train, y_train_final.PredictedValue)
```

Out[ ]:

```
0.8047138047138047
```

Checking VIF Values

In [ ]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = x_train.columns
vif['VIF'] = [variance_inflation_factor(x_train.values, i) for i in range(x_train.shape[
1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[ ]:

	Features	VIF
1	Age	5.04
7	S	4.96
9	3	4.21
0	PassengerId	3.62
5	male	3.08
4	Fare	2.30
8	2	2.07
3	Parch	1.67
2	SibSp	1.61
6	Q	1.59

Drop the columns which has VIF greater than 5

In [ ]:

```
x_train = x_train.drop('Age',axis =1)
```

In [ ]:

```
# check vif again
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = x_train.columns
vif['VIF'] = [variance_inflation_factor(x_train.values, i) for i in range(x_train.shape[
1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[ ]:

	Features	VIF
6	S	4.56
8	3	4.15
0	PassengerId	3.39
4	male	2.86
7	2	2.01
3	Fare	1.94
2	Parch	1.66
1	SibSp	1.57

	Features	VIF
5	Q	1.51

In [ ]:

```
#fit the model again and check the accuracy again
x_train = sm.add_constant(x_train)
lm = sm.GLM(y_train,x_train,family = sm.families.Binomial())
res=lm.fit()
res.summary()
```

Out[ ]:

Generalized Linear Model Regression Results

Dep. Variable:	Survived	**No. Observations:**	891
Model:	GLM	**Df Residuals:**	881
Model Family:	Binomial	**Df Model:**	9
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-406.28
Date:	Tue, 18 Aug 2020	**Deviance:**	812.56
Time:	21:23:32	**Pearson chi2:**	919.
No. Iterations:	5		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	2.7085	0.390	6.944	0.000	1.944	3.473
PassengerId	7.867e-05	0.000	0.229	0.819	-0.001	0.001
SibSp	-0.2168	0.102	-2.115	0.034	-0.418	-0.016
Parch	-0.0546	0.116	-0.468	0.640	-0.283	0.174
Fare	0.0009	0.003	0.279	0.780	-0.005	0.007
male	-2.7252	0.199	-13.710	0.000	-3.115	-2.336
Q	-0.2160	0.371	-0.582	0.561	-0.944	0.512
S	-0.5450	0.230	-2.367	0.018	-0.996	-0.094
2	-0.6557	0.293	-2.239	0.025	-1.230	-0.082
3	-1.7487	0.288	-6.062	0.000	-2.314	-1.183

In [ ]:

```
# make a confusion matrix
from sklearn.metrics import confusion_matrix
confusion = confusion_matrix(y_train_final.Survived, y_train_final.PredictedValue)
confusion
```

Out[ ]:

```
array([[475,  74],
       [100, 242]], dtype=int64)
```

In [ ]:

```
from sklearn.metrics import accuracy_score
accuracy_score(y_train, y_train_final.PredictedValue)
```

Out[ ]:

```
0.8047138047138047
```

Now we see that there is not effect in accurracy score so age column do not effect our model.

Performance metrics

- **Precision**

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- **Recall**

$$\text{recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **AUC (ROC)**

In [ ]:

```
TP = confusion[1,1]
TN = confusion[0,0]
FP = confusion[0,1]
FN = confusion[1,0]
```

In [ ]:

```
#Check Senstivity
TP / float(TP+FN)
```

Out[ ]:

```
0.7076023391812866
```

In [ ]:

```
# Check Specificity
TN / float(TN+FP)
```

Out[ ]:

```
0.8652094717668488
```

In [ ]:

```
# False Positive Rate
FN / float(TN+FP)
```

Out[ ]:

```
0.18214936247723132
```

Plot Roc Curve

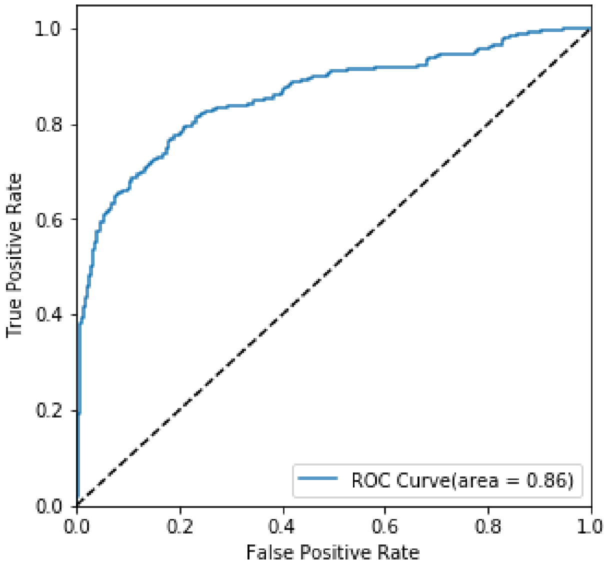
In [ ]:

```
def plt_roc(actual,probs):
    fpr,tpr,threshold = metrics.roc_curve(actual,probs,drop_intermediate=False)
    auc_score=metrics.roc_auc_score(actual,probs)
    plt.figure(figsize=(5,5))
    plt.plot(fpr,tpr,label='ROC Curve(area = %0.2f)' %auc_score)
    plt.plot([0,1],[0,1],'k--')
    plt.xlim([0.00,1.00])
    plt.ylim([0.00,1.05])
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc="lower right")
    plt.show()

    return None
```

In [ ]:

```
fpr,tpr,threshold = metrics.roc_curve(y_train_final.Survived,y_train_final.Survived_prob,
drop_intermediate=False)
plt_roc(y_train_final.Survived,y_train_final.Survived_prob)
```



Find Optimal Cuttoff Point

In [ ]:

```
# lets check for all points
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_final[i] = y_train_final.Survived_prob.map(lambda x:1 if x>i else 0)
y_train_final.head()
```

Out[ ]:

	Survived	Survived_prob	Id	PredictedValue	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.082162	1	0	1	0	0	0	0	0	0	0	0	0
1	1	0.921013	2	1	1	1	1	1	1	1	1	1	1	1
2	1	0.614979	3	1	1	1	1	1	1	1	1	0	0	0
3	1	0.891644	4	1	1	1	1	1	1	1	1	1	1	0
4	0	0.065960	5	0	1	0	0	0	0	0	0	0	0	0

In [ ]:

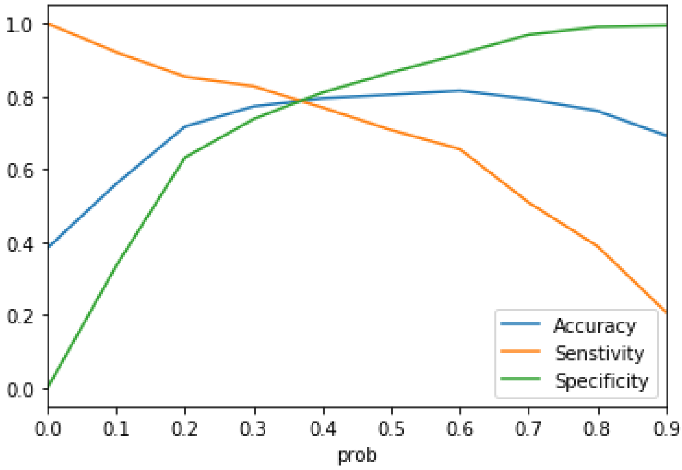
```
# Calculate accuracy,specificity and sensitivity for all d points...
df = pd.DataFrame(columns=['prob','Accuracy','Senstivity','Specificity'])
var = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in var:
    cm = confusion_matrix(y_train_final.Survived,y_train_final[i])
    total=sum(sum(cm))
    Accuracy = (cm[0,0]+cm[1,1])/total
    Specificity = cm[0,0]/(cm[0,0]+cm[0,1])
    Senstivity = cm[1,1]/(cm[1,1]+cm[1,0])
    df.loc[i]  = [i,Accuracy,Senstivity,Specificity]
print(df)
```

```
     prob  Accuracy  Senstivity  Specificity
0.0   0.0  0.383838    1.000000     0.000000
0.1   0.1  0.560045    0.921053     0.335155
0.2   0.2  0.717172    0.853801     0.632058
0.3   0.3  0.772166    0.827485     0.737705
0.4   0.4  0.794613    0.769006     0.810565
0.5   0.5  0.804714    0.707602     0.865209
0.6   0.6  0.815937    0.654971     0.916211
```

```
0.7    0.7   0.792368     0.508772      0.969035
0.8    0.8   0.759820     0.388889      0.990893
0.9    0.9   0.692480     0.207602      0.994536
```

In [ ]:

```
df.plot.line(x='prob',y=['Accuracy','Senstivity','Specificity'])
plt.show()
```



From the above graph we see that the cutoff point is approx 0.4

In [ ]:

```
y_train_final['FinalPredictedValue'] = y_train_final.Survived_prob.map(lambda x:1 if x>0
.4 else 0)
y_train_final.head()
```

Out[ ]:

	Survived	Survived_prob	Id	PredictedValue	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	FinalPredictedValue
0	0	0.082162	1	0	1	0	0	0	0	0	0	0	0	0	0
1	1	0.921013	2	1	1	1	1	1	1	1	1	1	1	1	1
2	1	0.614979	3	1	1	1	1	1	1	1	1	0	0	0	1
3	1	0.891644	4	1	1	1	1	1	1	1	1	1	1	0	1
4	0	0.065960	5	0	1	0	0	0	0	0	0	0	0	0	0

In [ ]:

```
accuracy_score(y_train_final.Survived,y_train_final.FinalPredictedValue)
```

Out[ ]:

```
0.7946127946127947
```

In [ ]:

```
cnfsn = confusion_matrix(y_train_final.Survived, y_train_final.FinalPredictedValue)
cnfsn
```

Out[ ]:

```
array([[445, 104],
       [ 79, 263]], dtype=int64)
```

In [ ]:

```
TP = cnfsn[1,1]
TN = cnfsn[0,0]
FP = cnfsn[0,1]
FN = cnfsn[1,0]
```

In [ ]:

```
#Check Senstivity
TP / float(TP+FN)
```

Out[ ]:

```
0.7690058479532164
```

In [ ]:

```
# Check Specificity
TN / float(TN+FP)
```

Out[ ]:

```
0.8105646630236795
```

In [ ]:

```
# False Positive Rate
FN / float(TN+FP)
```

Out[ ]:

```
0.14389799635701275
```

Precision and Recall

In [ ]:

```
cnfsn = confusion_matrix(y_train_final.Survived, y_train_final.FinalPredictedValue)
cnfsn
```

Out[ ]:

```
array([[445, 104],
       [ 79, 263]], dtype=int64)
```

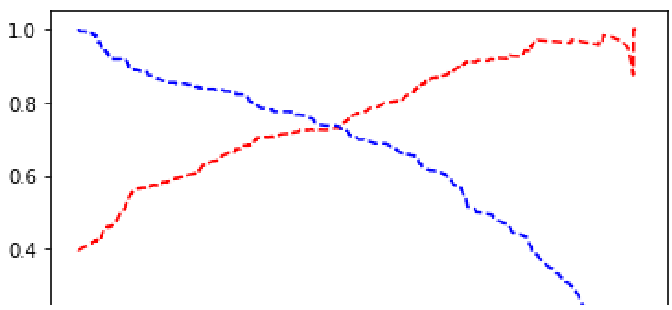
In [ ]:

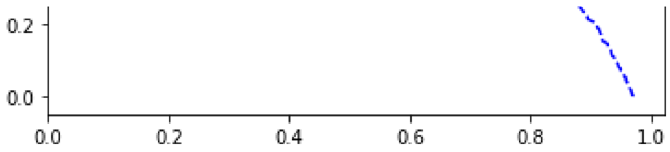
```
from sklearn.metrics import precision_score, recall_score
# Precision
print("Precision = ",precision_score(y_train_final.Survived, y_train_final.FinalPredicted
Value))
# Recall
print("Recall = ",recall_score(y_train_final.Survived, y_train_final.FinalPredictedValue)
)
```

```
Precision =  0.7166212534059946
Recall =  0.7690058479532164
```

In [ ]:

```
# plot graph
from sklearn.metrics import precision_recall_curve
p,r,threshold = precision_recall_curve(y_train_final.Survived, y_train_final.Survived_pro
b)
plt.plot(threshold,p[:-1],"r--")## Red in Colour
plt.plot(threshold,r[:-1],"b--")## Blue in Colour
plt.show()
```





Now make predictions on test data.

We firstly make test data according to out model

In [ ]:

```
abc = pd.get_dummies(df_test['Sex'], drop_first = True)
df_test = pd.concat([df_test, abc], axis = 1)
abc1 = pd.get_dummies(df_test['Embarked'], drop_first = True)
df_test = pd.concat([df_test, abc1], axis = 1)
abc2 = pd.get_dummies(df_test['Pclass'], drop_first = True)
df_test = pd.concat([df_test, abc2], axis = 1)
```

In [ ]:

```
# drop the columns
x_test = df_test.drop(['Pclass','Name','Age','Sex','Cabin','Ticket','Embarked','Survived
'],axis =1)
```

In [ ]:

```
y_test = df_test['Survived']
```

In [ ]:

```
x_test.head()
```

Out[ ]:

	PassengerId	SibSp	Parch	Fare	male	Q	S	2	3
0	892	0	0	7.8292	1	1	0	0	1
1	893	1	0	7.0000	0	0	1	0	1
2	894	0	0	9.6875	1	1	0	1	0
3	895	0	0	8.6625	1	0	1	0	1
4	896	1	1	12.2875	0	0	1	0	1

In [ ]:

```
x_test_sm = sm.add_constant(x_test)
```

Now we will make predictions with the help of trained model

In [ ]:

```
y_test_pred = res.predict(x_test_sm)
y_test_pred[:15]
```

Out[ ]:

```
0      0.129617
1      0.568170
2      0.307980
3      0.096880
4      0.555937
5      0.096937
6      0.694473
7      0.198984
8      0.738262
```

```
9     0.065869
10    0.096869
11    0.385108
12    0.889896
13    0.207469
14    0.888094
dtype: float64
```

In [ ]:

```
# make new dataframe
df_y = pd.DataFrame(y_test)
df_y['Id'] = x_test.PassengerId
df_y['Survived'] = df_test.Survived
df_y['Survived_Prob'] = y_test_pred
df_y.head()
```

Out[ ]:

	Survived	Id	Survived_Prob
0	0	892	0.129617
1	1	893	0.568170
2	0	894	0.307980
3	0	895	0.096880
4	1	896	0.555937

From the precision recall graph the optimal point = 0.5

In [ ]:

```
df_y['FinalPredicted'] = df_y.Survived_Prob.map(lambda x : 1 if x>0.5 else 0)
df_y.head()
```

Out[ ]:

	Survived	Id	Survived_Prob	FinalPredicted
0	0	892	0.129617	0
1	1	893	0.568170	1
2	0	894	0.307980	0
3	0	895	0.096880	0
4	1	896	0.555937	1

In [ ]:

```
accuracy_score(df_y.Survived,df_y.FinalPredicted)
```

Out[ ]:

```
0.9545454545454546
```

In [ ]:

```
# make a confusion matrix
from sklearn.metrics import confusion_matrix
confusion3 = confusion_matrix(df_y.Survived,df_y.FinalPredicted)
confusion3
```

Out[ ]:

```
array([[251,  15],
       [  4, 148]], dtype=int64)
```

In [ ]:

```
TP = confusion3[1,1]
TN = confusion3[0,0]
FP = confusion3[0,1]
FN = confusion3[1,0]
```

In [ ]:

```
#Check Senstivity
TP / float(TP+FN)
```

Out[ ]:

```
0.9736842105263158
```

In [ ]:

```
# Check Specificity
TN / float(TN+FP)
```

Out[ ]:

```
0.943609022556391
```

Thank You..........