Experiment No. 2
Analyze the Titanic Survival Dataset and apply appropriate regression technique
Date of Performance:24/7/2023
Date of Submission:11/08/2023

Aim: Analyze the Titanic Survival Dataset and apply appropriate Regression Technique.

Objective: Able to perform various feature engineering tasks, apply logistic regression on the given dataset and maximize the accuracy.

Theory:

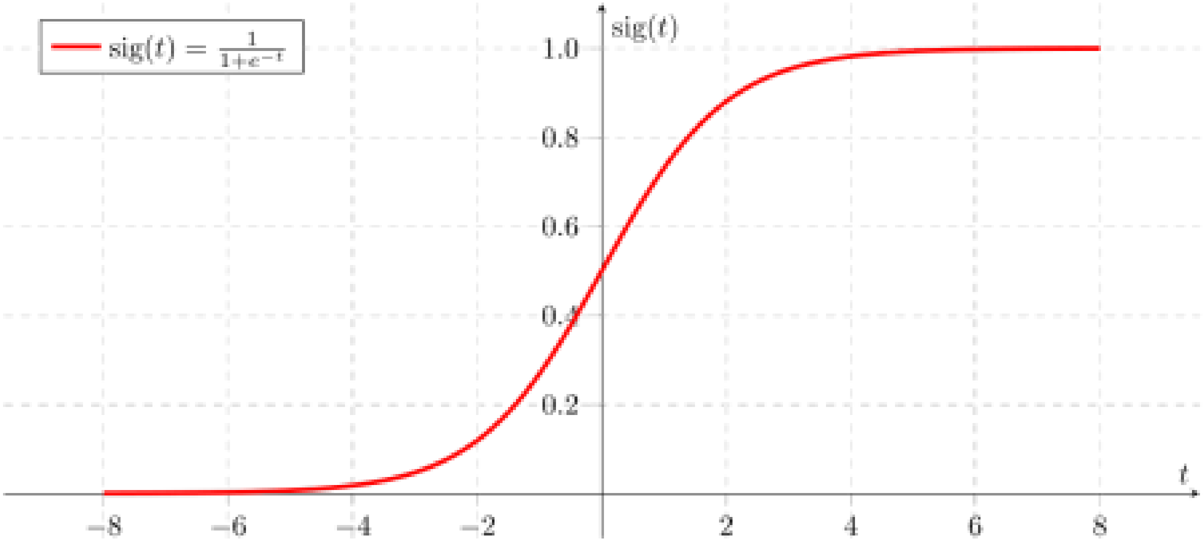
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression techniques makes use of Sigmoid function.

For example,

To predict whether an email is spam (1) or (0)

Whether the tumor is malignant (1) or not (0)

Consider a scenario where we need to classify whether an email is spam or not. If we use linear regression for this problem, there is a need for setting up a threshold based on which classification can be done. Say if the actual class is malignant, predicted continuous value 0.4 and the threshold value is 0.5, the data point will be classified as not malignant which can lead to serious consequence in real time.



From this example, it can be inferred that linear regression is not suitable for classification problem. Linear regression is unbounded, and this brings logistic regression into picture. Their value strictly ranges from 0 to 1.

Dataset:

The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered “unsinkable” RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren’t enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

In this challenge, we ask you to build a predictive model that answers the question: “what sorts of people were more likely to survive?” using passenger data (ie name, age, gender, socio-economic class, etc).

Variable	Definition Key
survival	Survival 0 = No, 1 = Yes
pclass	Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex
Age	Age in years
sibsp	# of siblings / spouses aboard the Titanic
parch ticket	# of parents / children aboard the Titanic Ticket number
fare cabin	Passenger fare Cabin number

C = Cherbourg, Q = Queenstown, S =
embarked Port of Embarkation

Variable Notes

pclass: A proxy for socio-economic status (SES) 1st = Upper, 2nd = Middle, 3rd = Lower

Southampton
age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

sibsp: The dataset defines family relations in this way...,

Sibling = brother, sister, stepbrother, stepsister

Spouse = husband, wife (mistresses and fiancés were ignored)

parch: The dataset defines family relations in this way...

Parent = mother, father

Child = daughter, son, stepdaughter, stepson

Some children travelled only with a nanny, therefore parch=0 for them.

Code:(ATTACHED)

Conclusion:

1. Here, we sought to forecast the Titanic incident's survivability rate using logistic regression. Therefore, we examined all of the values in the columns using the pandas library to identify any missing data.filling in the missing values after that. Additionally, using the seaborn library gives us a visual representation of the distribution of those who survived and those who did not, allowing us to take those factors into account when making the prediction.After taking into account all factors, we use logistic regression to determine the distribution of the number of passengers that survived.The accuracy of the model is then determined using Pandas' metrics tool.

2. Accuracy obtained:

```
AUC of the predictions: 0.7448377581120942

Accuracy score of the predictions: 0.7653631284916201
```

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

```
df = pd.DataFrame(pd.read_csv('./train (1).csv'))
test_data = pd.DataFrame(pd.read_csv('./test.csv'))
gender_df = pd.DataFrame(pd.read_csv('./gender_submission.csv'))
```

```
df.head()
```

PassengerId Survived Pclass Name Sex Age SibSp Parch Ticket Fare Cabin Embarke Braund,

0 1 0 3 Th
male 22.0 1 0 A/5 21171 7.2500 NaN

1 2 1 1 `for i in df.columns:`
female 38.0 1 0 PC 17599 71.2833 C85

Mr. Owen Harris

Cumings, Mrs. John Bradley (Florence
Briggs

```
  print(i,"\t-\t", df[i].isna().mean()*100)
```

```
PassengerId - 0.0
Survived - 0.0
Pclass - 0.0
Name - 0.0
Sex - 0.0
Age - 19.865319865319865
SibSp - 0.0
Parch - 0.0
Ticket - 0.0
Fare - 0.0
Cabin - 77.10437710437711
Embarked - 0.22446689113355783
```

```
df = df.drop(["Cabin"], axis=1)
```

```
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Embarked'].fillna(df['Embarked'].mode(), inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 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 891 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 Embarked 889 non-null object
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

```
df = df.drop(["PassengerId", "Fare", "Ticket", "Name"], axis = 1)
```

```
from sklearn.preprocessing import LabelEncoder

cat_col= df.drop(df.select_dtypes(exclude=['object']), axis=1).columns
print(cat_col)

enc1 = LabelEncoder()
df[cat_col[0]] = enc1.fit_transform(df[cat_col[0]].astype('str'))


enc2 = LabelEncoder()
df[cat_col[1]] = enc2.fit_transform(df[cat_col[1]].astype('str'))
```

```
Index(['Sex', 'Embarked'], dtype='object')
```

```
df.head()
```

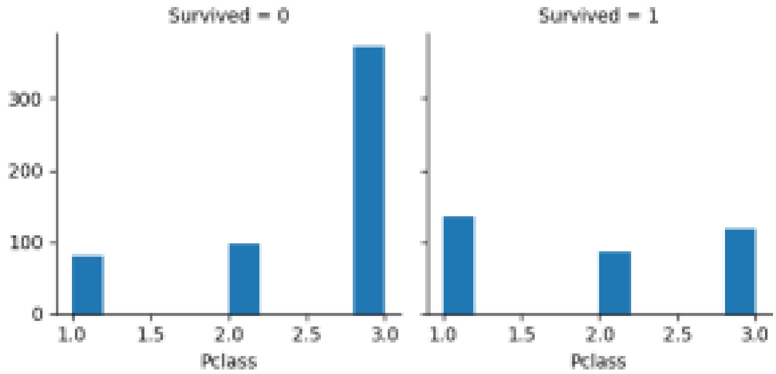
	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked
0	0	3	1	22.0	1	0	2
1	1	1	0	38.0	1	0	0
2	1	3	0	26.0	0	0	2
3	1	1	0	35.0	1	0	2
4	0	3	1	35.0	0	0	2

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 # Column Non-Null Count Dtype
--- ------ -------------- -----
 0 Survived 891 non-null int64
 1 Pclass 891 non-null int64
 2 Sex 891 non-null int64
 3 Age 891 non-null float64
 4 SibSp 891 non-null int64
 5 Parch 891 non-null int64
 6 Embarked 891 non-null int64
dtypes: float64(1), int64(6)
memory usage: 48.9 KB
```

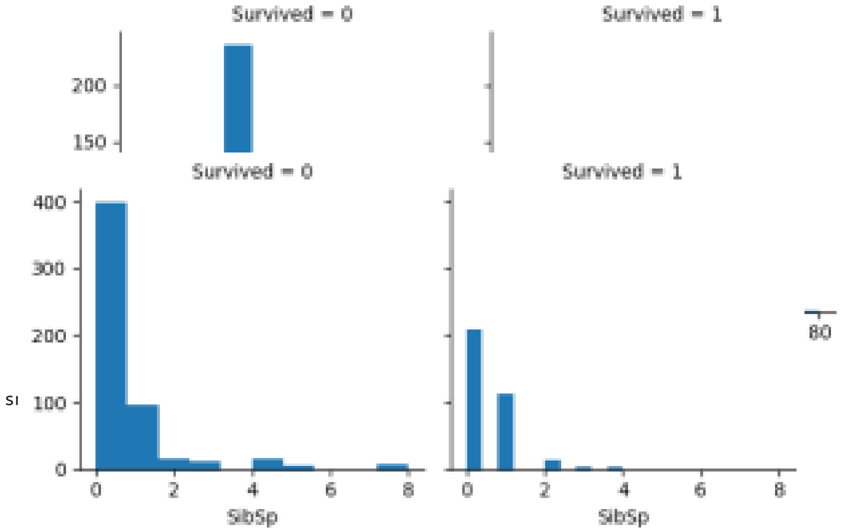
```
sns.FacetGrid(df, col= 'Survived').map(plt.hist,'Pclass')
```

```
<seaborn.axisgrid.FacetGrid at 0x79eb325ba050>
```



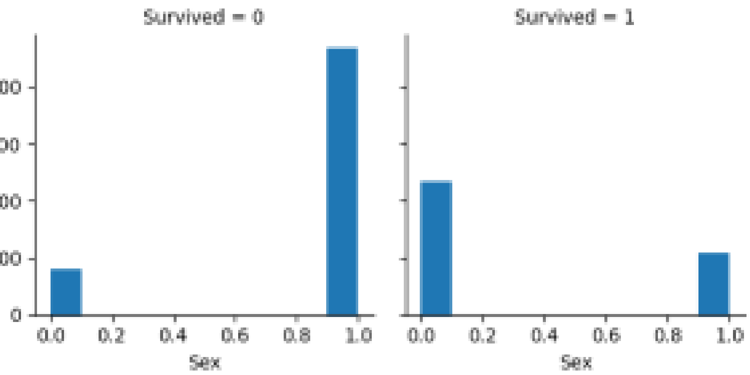

```
sns.FacetGrid(df, col='Survived').map(plt.hist, 'Age')
```

```
<seaborn.axisgrid.FacetGrid at 0x79eb325373d0>
```



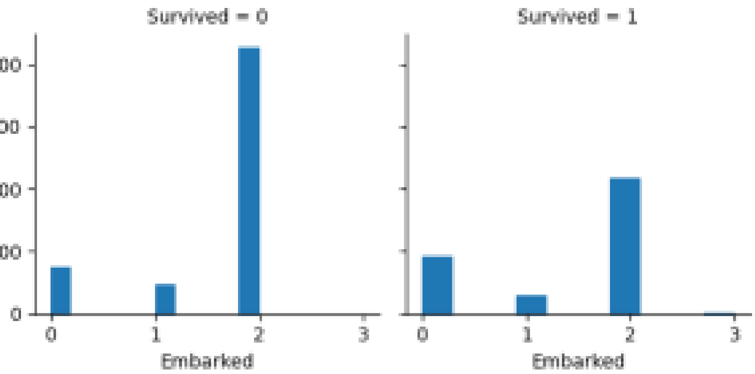

```
sns.FacetGrid(df, col='Survived').map(plt.hist, 'Sex')
```

    <seaborn.axisgrid.FacetGrid at 0x79eb2f3810c0>




```
sns.FacetGrid(df, col='Survived').map(plt.hist, 'Embarked')
```

    <seaborn.axisgrid.FacetGrid at 0x79eb329b82b0>




```
X = df.drop(['Survived'], axis=1)
y = df['Survived']

#now lets split data in test train pairs

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)


from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
```

```
model.fit(X_train, y_train)
```

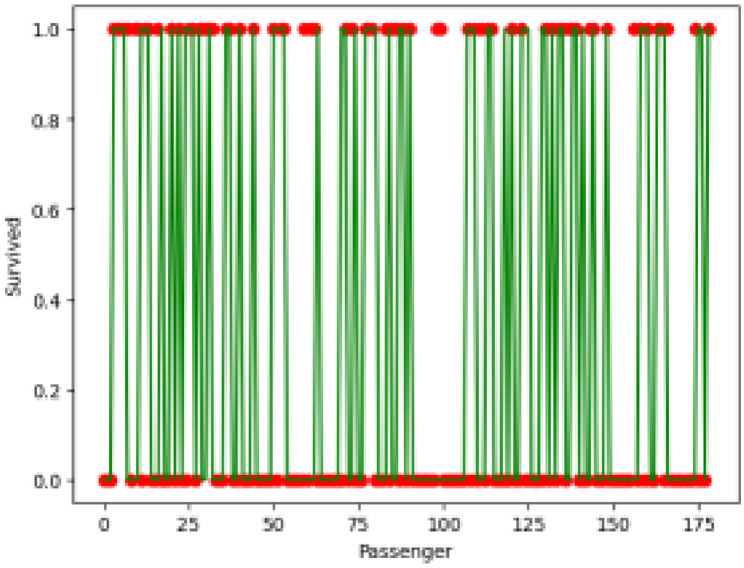
▾ LogisticRegression

LogisticRegression()

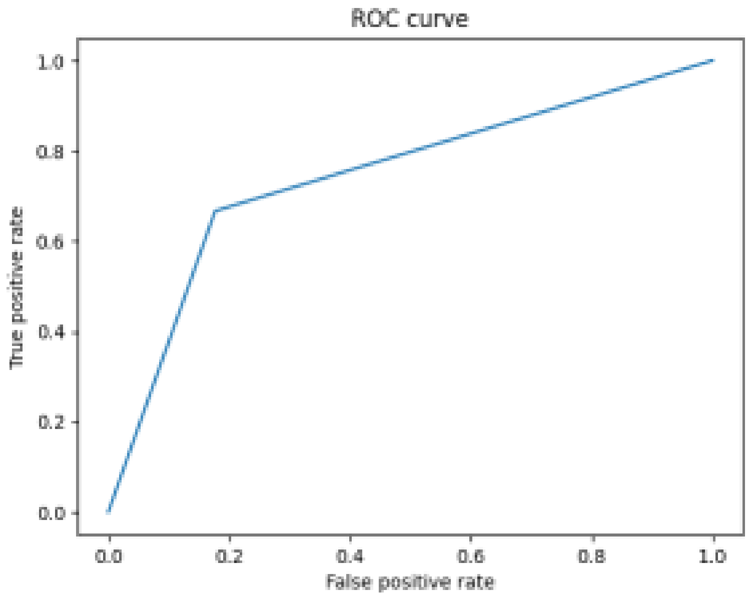
```
y_pred = model.predict(X_test)

pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
pred_df.head()
```

	Actual	Predicted
735	0	0
67	0	0
575	0	0
43	1	1
394	1	1

```
plt.scatter([i for i in range(len(X_test["Age"]))], y_test, color='red')
plt.plot([i for i in range(len(X_test["Age"]))], y_pred, color='green')

plt.ylabel('Survived')
plt.xlabel('Passenger')

plt.show()
```




```
from sklearn import metrics

fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred, pos_label=1)
plt.plot(fpr, tpr)
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.show()

print("AUC of the predictions: {0}".format(metrics.auc(fpr, tpr)))

print("Accuracy score of the predictions: {0}".format(metrics.accuracy_score(y_pred, y_test)))
```




```
AUC of the predictions: 0.7448377581120942
Accuracy score of the predictions: 0.7653631284916201
```

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