Experiment No. 2
Analyze the Titanic Survival Dataset and apply appropriate regression technique
Date of Performance:08/07/2023
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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.
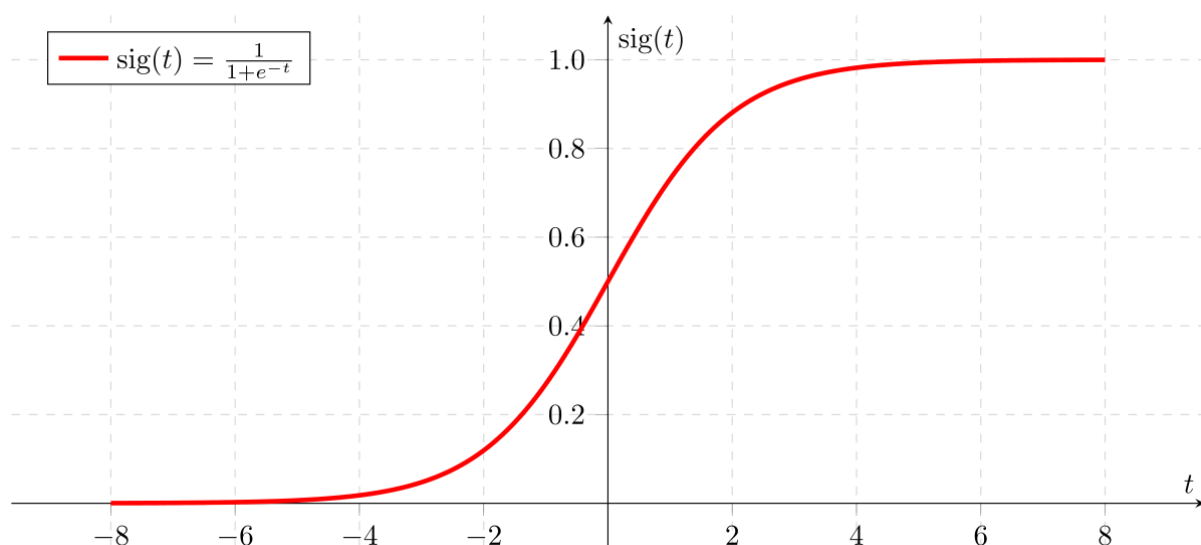
From this example, it can be inferred that linear regression is not suitable for classification problem. Linear regression is unbounded, and this brings logistic regression into picture. Their value strictly ranges from 0 to 1.

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	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

Variable Notes

pclass: A proxy for socio-economic status (SES)

1st = Upper, 2nd = Middle, 3rd = Lower

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.

Analyze the Titanic Survival Dataset and apply appropriate regression technique Code :
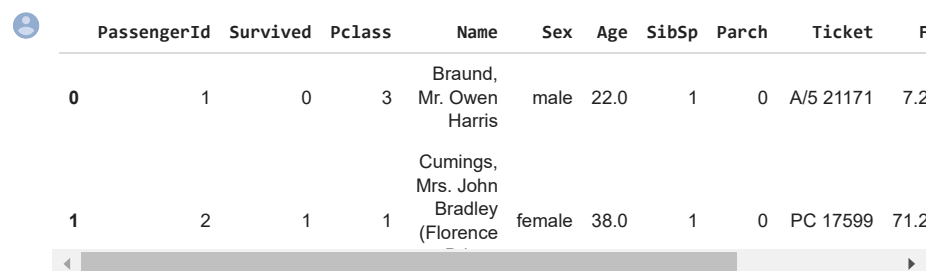
```
#Code

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

Data Collection & Processing

```
# load the data from csv file to Pandas DataFrame
titanic_data = pd.read_csv('/content/train.csv')
```

```
# printing the first 5 rows of the dataframe
titanic_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence	female	38.0	1	0	PC 17599	71.2

```
# number of rows and Columns
titanic_data.shape
```

```
(891, 12)
```

```
# getting some informations about the data
titanic_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
```

```
# check the number of missing values in each column
titanic_data.isnull().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
```

Handling the Missing values

```
# drop the "Cabin" column from the dataframe
titanic_data = titanic_data.drop(columns='Cabin', axis=1)
```

```
# replacing the missing values in "Age" column with mean value
titanic_data['Age'].fillna(titanic_data['Age'].mean(), inplace=True)
```

```
# finding the mode value of "Embarked" column
print(titanic_data['Embarked'].mode())
```

```
    0    S
    dtype: object
```

```
print(titanic_data['Embarked'].mode()[0])
```

```
    S
```

```
# replacing the missing values in "Embarked" column with mode value
titanic_data['Embarked'].fillna(titanic_data['Embarked'].mode()[0], inplace=True)
```

```
# check the number of missing values in each column
titanic_data.isnull().sum()
```

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

Data Analysis

```
# getting some statistical measures about the data
titanic_data.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	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	13.002015	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	22.000000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
# finding the number of people survived and not survived
titanic_data['Survived'].value_counts()
```
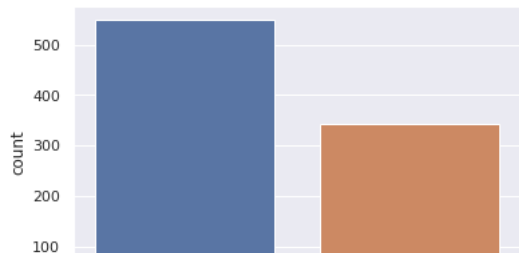
```
    0    549
    1    342
    Name: Survived, dtype: int64
```

Data Visualization

```
sns.set()
```

```
# making a count plot for "Survived" column
sns.countplot('Survived', data=titanic_data)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following var
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fd6c77f16d0>
```
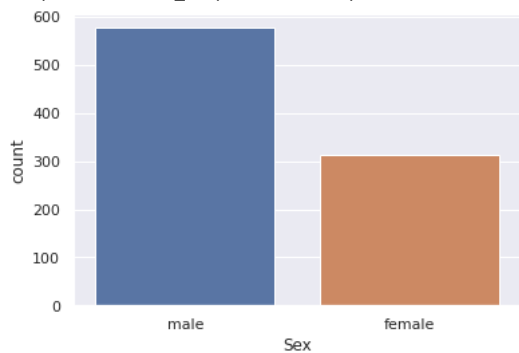


```
titanic_data['Sex'].value_counts()
```

```
male      577
female    314
Name: Sex, dtype: int64
```
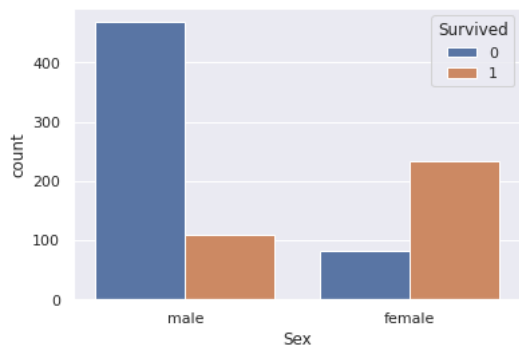
```
# making a count plot for "Sex" column
sns.countplot('Sex', data=titanic_data)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following var
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fd6cbeb1d90>
```



```
# number of survivors Gender wise
sns.countplot('Sex', hue='Survived', data=titanic_data)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fd6c77d0dd0>
```



```
# making a count plot for "Pclass" column
sns.countplot('Pclass', data=titanic_data)
```

```
usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
matplotlib.axes._subplots.AxesSubplot at 0x7fd6c5f7bfd0>
```

```
sns.countplot('Pclass', hue='Survived', data=titanic_data)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fd6c7286a90>
```
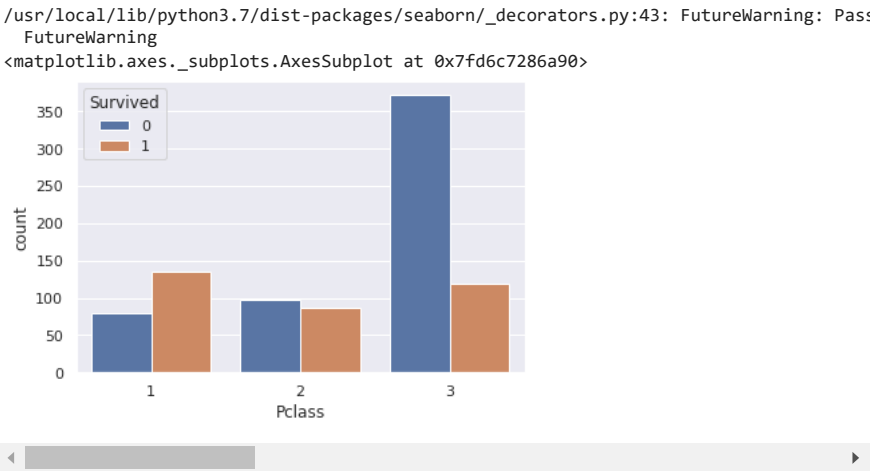

Encoding the Categorical Columns

```
titanic_data['Sex'].value_counts()
```

```
male      577
female    314
Name: Sex, dtype: int64
```

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

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

```
# converting categorical Columns
```

```
titanic_data.replace({'Sex':{'male':0,'female':1}, 'Embarked':{'S':0,'C':1,'Q':2}}, inplace=True)
```

```
titanic_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence	1	38.0	1	0	PC 17599	71.283

Separating features & Target

```
X = titanic_data.drop(columns = ['PassengerId','Name','Ticket','Survived'],axis=1)
Y = titanic_data['Survived']
```

```
print(X)
```

```
     Pclass  Sex        Age  SibSp  Parch     Fare  Embarked
0         3    0  22.000000      1      0   7.2500         0
1         1    1  38.000000      1      0  71.2833         1
2         3    1  26.000000      0      0   7.9250         0
3         1    1  35.000000      1      0  53.1000         0
4         3    0  35.000000      0      0   8.0500         0
..      ...  ...        ...    ...    ...      ...       ...
886       2    0  27.000000      0      0  13.0000         0
887       1    1  19.000000      0      0  30.0000         0
888       3    1  29.699118      1      2  23.4500         0
889       1    0  26.000000      0      0  30.0000         1
890       3    0  32.000000      0      0   7.7500         2
```

```
    [891 rows x 7 columns]
```

```
print(Y)
```

```
    0      0
    1      1
    2      1
    3      1
    4      0
          ..
    886    0
    887    1
    888    0
    889    1
    890    0
    Name: Survived, Length: 891, dtype: int64
```

Splitting the data into training data & Test data

```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2, random_state=2)
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
    (891, 7) (712, 7) (179, 7)
```

Model Training

Logistic Regression

```
model = LogisticRegression()
```

```
# training the Logistic Regression model with training data
model.fit(X_train, Y_train)
```

```
    /usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=
    STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

    Increase the number of iterations (max_iter) or scale the data as shown in:
        https://scikit-learn.org/stable/modules/preprocessing.html
    Please also refer to the documentation for alternative solver options:
        https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
      extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
    LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                       intercept_scaling=1, l1_ratio=None, max_iter=100,
                       multi_class='auto', n_jobs=None, penalty='l2',
                       random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                       warm_start=False)
```

Model Evaluation

Accuracy Score

```
# accuracy on training data
X_train_prediction = model.predict(X_train)
```

```
print(X_train_prediction)
```

```
    [0 1 0 0 0 0 0 1 0 0 0 1 0 0 1 0 1 0 0 0 0 0 1 0 0 1 0 0 1 0 1 1 0 0 1 0 1
     0 0 0 0 0 0 1 1 0 0 1 0 1 0 1 0 1 0 0 0 0 0 1 0 1 0 0 1 1 0 0 1 1 0 1 0 0 1
     0 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0 0 0 1 1 1 0 1 0 0 0 0 0 0 1 0 0 0
     1 1 0 0 1 0 0 1 0 0 1 0 0 1 0 1 0 1 0 1 0 1 1 1 1 1 1 0 0 1 1 1 0 0 1 0 0
     0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 1 0 1 0 1 1 1
     0 0 0 1 0 0 0 1 0 0 1 0 0 0 1 1 0 1 0 0 0 0 0 1 1 0 1 1 1 1 0 0 0 0 0
     0 1 0 0 1 1 1 0 0 1 0 1 1 1 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 1 0 0 0
     0 0 0 0 0 0 1 0 1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 1 0 1 0 0 1 0 0 0 1 0 0 0
     0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 1 1 0 0 0 1 0 1 0 0 0 0 0 0 1 1 0 1 1
     0 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 1 1 1 0 1 0 0 0 0 1 1 0 0 0 1 0 1 1 1 0 0
     0 0 1 0 0 0 1 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 1 1 1 0 1 1 0 1 1
     0 1 0 1 0 0 1 1 0 0 0 0 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 1 0 0
     1 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 1 1 0 1 0 0 1 0 0 0 1 1 0 1 0
     0 0 0 0 1 0 0 1 0 1 1 0 0 1 0 0 1 0 0 0 1 0 1 1 0 0 1 1 0 1 0 1 1 1 0 1 0
     0 1 0 0 1 0 0 1 0 0 0 0 1 1 0 0 1 0 1 0 1 0 0 0 0 0 0 1 1 1 0 0 1 1 0 0 0 0 0
     0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0
     0 0 1 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 1 1 1 0 0 0 1 0 1 0 0 0 1 1 1 0 0 1 1
     0 0 0 1 0 1 0 1 0 0 0 0 0 1 1 0 1 1 0 1 1 1 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0
```

```
 1 0 0 1 0 1 0 0 0 1 1 1 1 1 0 0 1 1 0 1 1 1 1 0 0 0 1 1 0 0 1 0 0 0 0 0 0
 0 0 0 1 1 0 0 1 0]
```

```python
training_data_accuracy = accuracy_score(Y_train, X_train_prediction)
print('Accuracy score of training data : ', training_data_accuracy)
```

```
Accuracy score of training data :  0.8075842696629213
```

```python
# accuracy on test data
X_test_prediction = model.predict(X_test)
```

```python
print(X_test_prediction)
```

```
[0 0 1 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 1 0 1 1 0 1 0 1 1 0 0 0 0 0 0 0 0 1 1
 0 0 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 0 0 1 0 1 0
 1 0 0 0 1 0 1 0 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 1 0 0 1 0 1 1 0 1 1 0 0 0 0
 0 0 0 1 1 0 1 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 1 1 1 1 0 1 0 0
 0 1 0 0 0 0 1 0 0 1 1 0 1 0 0 0 1 1 0 0 1 0 0 1 1 1 0 0 0 0 0]
```

```python
test_data_accuracy = accuracy_score(Y_test, X_test_prediction)
print('Accuracy score of test data : ', test_data_accuracy)
```

```
Accuracy score of test data :  0.7821229050279329
```

Conclusion:

1. What are features have been chosen to develop the model? Justify the features chosen to determine the survival of a passenger.
   - Features have been chosen based on the intuition that they could be significant factors influencing a passenger's survival. They represent a combination of socio-economic status, family relationships, gender, and age. The choices are justified by historical knowledge of the Titanic disaster and how different groups of passengers were treated during the evacuation

2. Comment on the accuracy obtained.
   - The accuracy obtained from the logistic regression model applied to the Titanic Survival Dataset. Training Data Accuracy: The accuracy score on the training data is approximately 80.76%. This means that the model correctly predicts the survival status of around 80.76% of the training data samples. Test Data Accuracy: The accuracy score on the test data is approximately 78.21%. This represents the model's ability to generalize its predictions to new, unseen data.