Experiment No. 2
Analyze the Titanic Survival Dataset and apply appropriate regression technique
Date of Performance:
Date of Submission:

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:

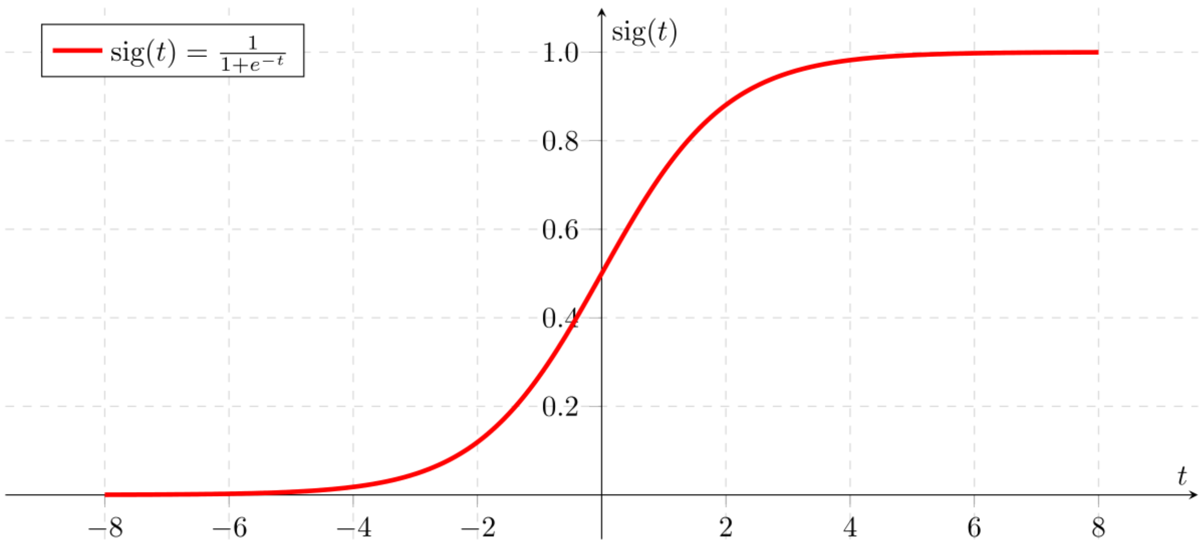
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

Code:

Conclusion:

The features chosen such as passenger class (Pclass) where Higher class passengers might have had higher chances of survival , gender (Sex) where Women might be given preference during the evacuation, age (Age) in this it might play a role, as children and elderly passengers might have given priority, number of siblings/spouses aboard (SibSp) and parch ie no of parents /children are considered for Family presence, fare feature sorting with Higher fare Embarked: Departure port correlated with socio-economic backgrounds. These features were chosen based on their potential correlation with survival and socio-economic factors.

The logistic regression model displayed the results, with an accuracy of about 0.81 on the training data and roughly 0.78 on the test data. The model learned well from the training data and performed respectively on unseen data and has captured essential features and relationships within the dataset.

```
import pandas as pd
import numpy as np
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
import warnings
```

```
df=pd.read_csv('train.csv')
print(df)
```

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 ...     ...   ...    ...
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     ...               ...      ...   ...      ...
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

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

```
# check the number of missing values in each column
df.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
```

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

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

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

```
0    S
Name: Embarked, dtype: object
```

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

```
S
```

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

```
# check the number of missing values in each column
df.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
```

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	F
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	13.002015	1.102743	0.806057	49.693
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000
25%	223.500000	0.000000	2.000000	22.000000	0.000000	0.000000	7.910
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

```
# finding the number of people survived and not survived
df['Survived'].value_counts()
```

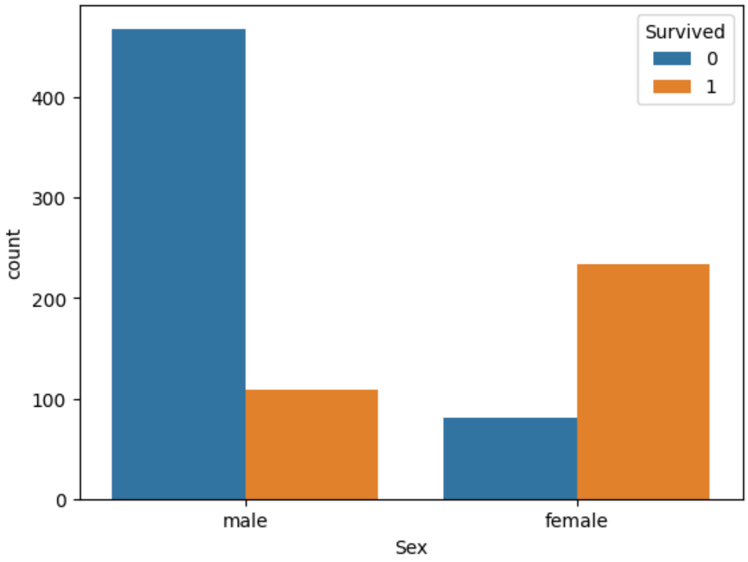
```
0    549
1    342
Name: Survived, dtype: int64
```

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

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

```
# number of survivors Gender wise
# 1st male and other female
# 0 are the one who did not survived
sns.countplot(x='Sex', hue='Survived', data=df)
```

```
<Axes: xlabel='Sex', ylabel='count'>
```




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

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

```
# converting categorical Columns
df.replace({'Sex':{'male':0,'female':1}, 'Embarked':{'S':0,'C':1,'Q':2}}, inplace=True)
```

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

```
print(X)
print(Y)
```

```
     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]
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
```

```
df.head()
```

PassengerId Survived Pclass Name Sex Age SibSp Parch Ticket Far

```
X.head()
```

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	0	22.0	1	0	7.2500	0
1	1	1	38.0	1	0	71.2833	1
2	3	1	26.0	0	0	7.9250	0
3	1	1	35.0	1	0	53.1000	0
4	3	0	35.0	0	0	8.0500	0

```
Y.head()
```

```
0    0
1    1
2    1
3    1
4    0
Name: Survived, 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 = LogisticRegression()
```

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

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: Conve
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
  n_iter_i = _check_optimize_result(
▾ LogisticRegression
LogisticRegression()
```

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

```
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
```

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

```
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
```

0s completed at 11:02 PM