Experiment No. 2
Analyze the Titanic Survival Dataset and apply appropriate regression technique
Date of Performance:31/07/2023
Date of Submission:10/08/2023

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:

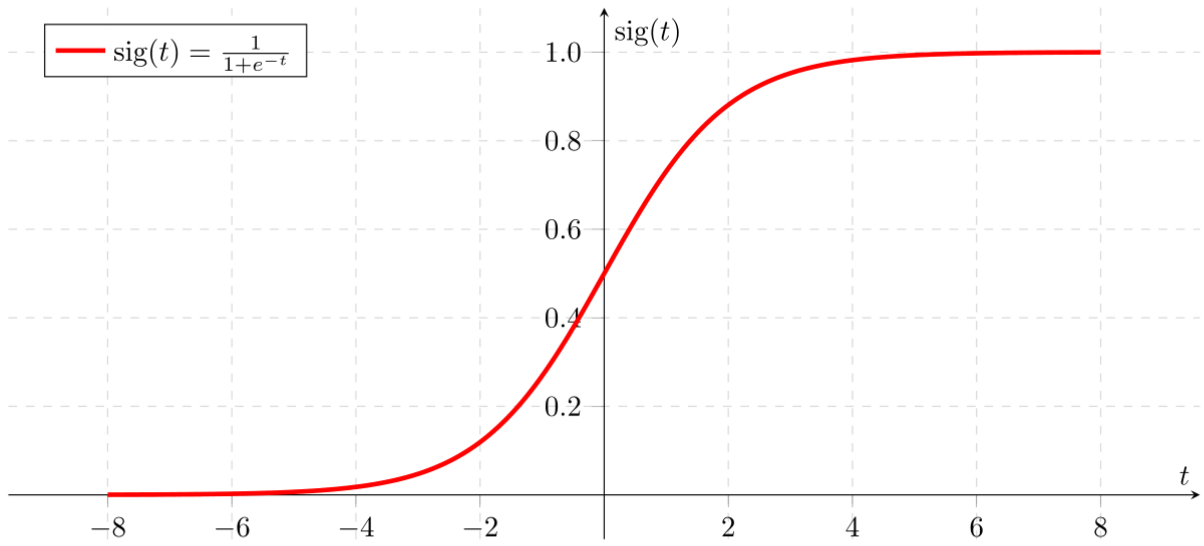
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

1. Pclass (Passenger Class): This refers to the ticket class (first, second, or third class). It may be a useful indication since upper classes may have received preference in times of need.

2. Sex: The passenger's gender is represented by this attribute. Gender may play a crucial role in predicting survival due to the "women and children first" strategy that was historically observed during the evacuation of the Titanic catastrophe.

3. Age: The passenger's age is an essential factor. It is known that young adults may have had a higher survival rate than children and seniors.

4. Number of Brothers/Spouses Aboard, or SibSp. This function lets passengers know if their siblings or spouses are traveling with them. It could affect the evacuation decision-making process. Number of Parents/Children Aboard.

5 Parch Similar to 'SibSp', this trait denotes the presence of parents or kids on board, which may affect survival choices.

6. Fare: The passenger's fare may be related to their accommodations or class, which may impact their ability to use lifeboats or other safety equipment.

7. Embarked: The port of embarkation is represented by this characteristic (S= Southampton, C = Cherbourg, Q = Queenstown). The socioeconomic effects of various embarkation places could have an impact on survival rates.

Accuracy:-

Test Accuracy (81.00%) : This shows that for about 81.00% of the test data, the model properly predicts the survival result. The model correctly predicted the survival result for around 81.00% of the occurrences in your test dataset.

```
import pandas as pd
```

```
data = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
test_ids = test["PassengerId"]

def clean(data):
    data = data.drop(["Ticket", "PassengerId", "Name", "Cabin"], axis=1)

    cols = ["SibSp", "Parch", "Fare", "Age"]
    for col in cols:
        data[col].fillna(data[col].median(), inplace=True)

    data.Embarked.fillna("U", inplace=True)
    return data

data = clean(data)
test = clean(test)
```

```
data.head(10)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S
5	0	3	male	28.0	0	0	8.4583	Q
6	0	1	male	54.0	0	0	51.8625	S
7	0	3	male	2.0	3	1	21.0750	S
8	1	3	female	27.0	0	2	11.1333	S
9	1	2	female	14.0	1	0	30.0708	C

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
columns = ["Sex", "Embarked"]

for col in columns:
    data[col] = le.fit_transform(data[col])
    test[col] = le.transform(test[col])
    print(le.classes_)

data.head(5)
```

```
['female' 'male']
['C' 'Q' 'S' 'U']
```

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

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LogisticRegression
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y = data["Survived"]
X = data.drop("Survived", axis=1)

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
clf = LogisticRegression(random_state=0, max_iter=1000).fit(X_train, y_train)
```

```
predictions = clf.predict(X_val)
from sklearn.metrics import accuracy_score
accuracy_score(y_val, predictions)
```

```
0.8100558659217877
```