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:

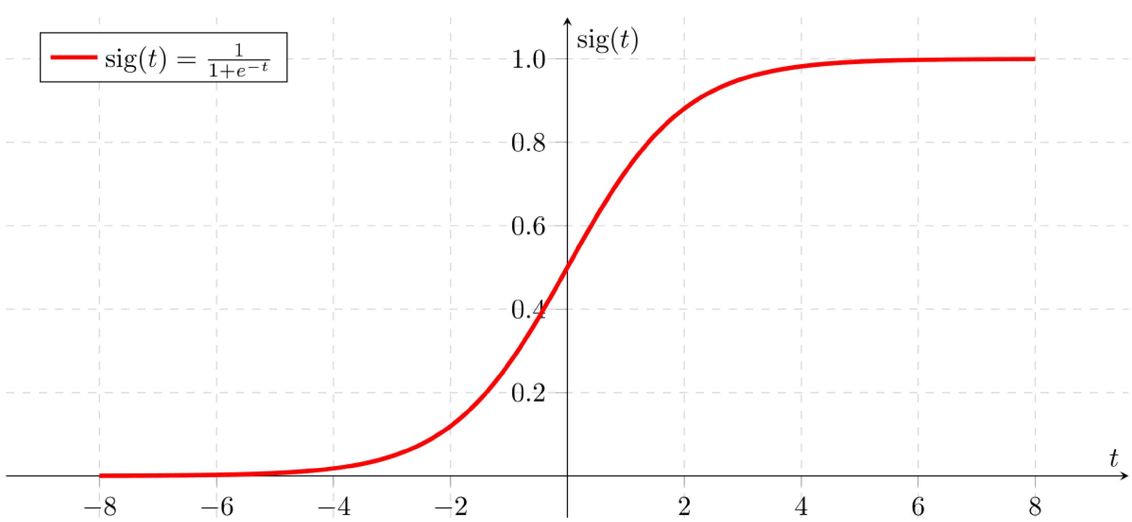
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

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 & Output:

```
import pandas as pd

df = pd.read_csv('TITANIC.csv')

df.head()
```

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

```
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
```

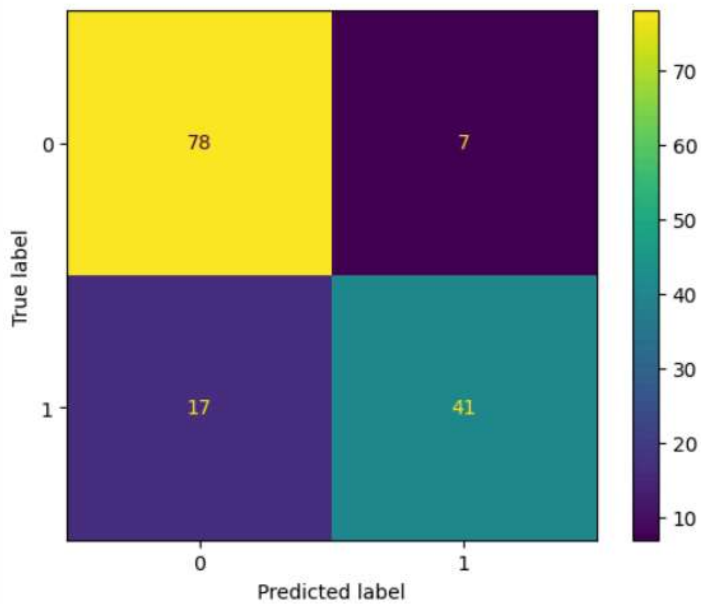
```
df = df[['Survived', 'Age', 'Sex', 'Pclass']]

df = pd.get_dummies(df, columns=['Sex', 'Pclass'])

df.dropna(inplace=True)

df.head()
```

	Survived	Age	Sex_female	Sex_male	Pclass_1	Pclass_2	Pclass_3
0	0	22.0	False	True	False	False	True
1	1	38.0	True	False	True	False	False
2	1	26.0	True	False	False	False	True
3	1	35.0	True	False	True	False	False
4	0	35.0	False	True	False	False	True

```
from sklearn.model_selection import train_test_split

x = df.drop('Survived', axis=1)

y = df['Survived']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
stratify=y, random_state=0)

from sklearn.linear_model import LogisticRegression

model = LogisticRegression(random_state=0)

model.fit(x_train, y_train)

LogisticRegression(random_state=0)

model.score(x_test, y_test)

0.8321678321678322

from sklearn.model_selection import cross_val_score
cross_val_score(model, x, y, cv=5).mean()

0.7857480547621394

from sklearn.metrics import confusion_matrix
y_predicted = model.predict(x_test)
confusion_matrix(y_test, y_predicted)
array([[78,  7],
       [17, 41]])
```

```
%matplotlib inline
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_estimator(model, x_test, y_test)
```

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7d9de7b43670>

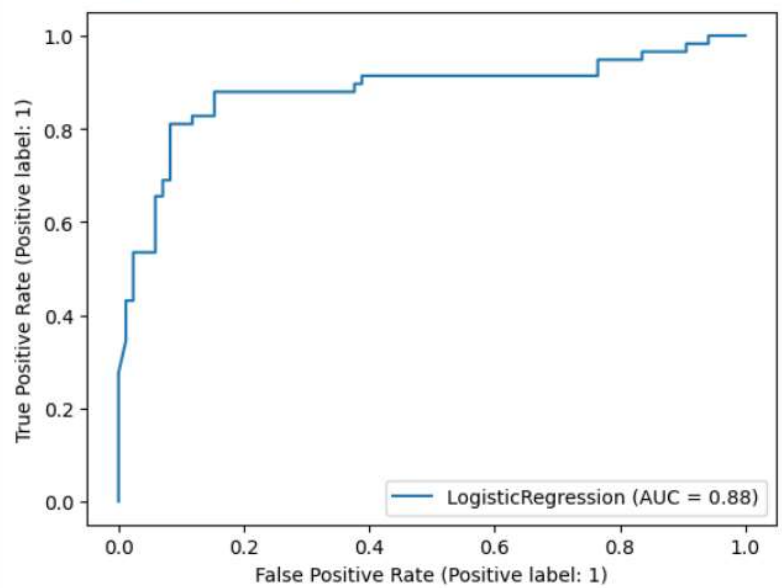



```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_predicted))
```

```
              precision    recall  f1-score   support

           0       0.82      0.92      0.87        85
           1       0.85      0.71      0.77        58
    accuracy                           0.83       143
   macro avg       0.84      0.81      0.82       143
weighted avg       0.83      0.83      0.83       143
```

```
from sklearn.metrics import RocCurveDisplay
RocCurveDisplay.from_estimator(model, x_test, y_test)
```

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7d9e273d2ef0>
```




```
female = [[30, 1, 0, 1, 0, 0]]
model.predict(female)[0]
1

probability = model.predict_proba(female)[0][1]
print(f'Probability of survival: {probability:.1%}')
Probability of survival: 91.6%

male = [[60, 0, 1, 0, 0, 1]]
probability = model.predict_proba(male)[0][1]
print(f'Probability of survival: {probability:.1%}')
Probability of survival: 2.9%
```

Conclusion: The logistic regression model achieved an accuracy of 83.22% on the test set, indicating strong performance in predicting Titanic survivors. The cross-validation score, around 78.57%, suggests consistent results across various data splits. The confusion matrix shows that the model has a higher rate of false negatives (incorrectly predicting survivors as non-survivors) compared to false positives. According to the classification report, the model exhibits better precision and recall for non-survivors (class 0) than for survivors (class 1), with overall balanced performance reflected in the F1-scores.