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:

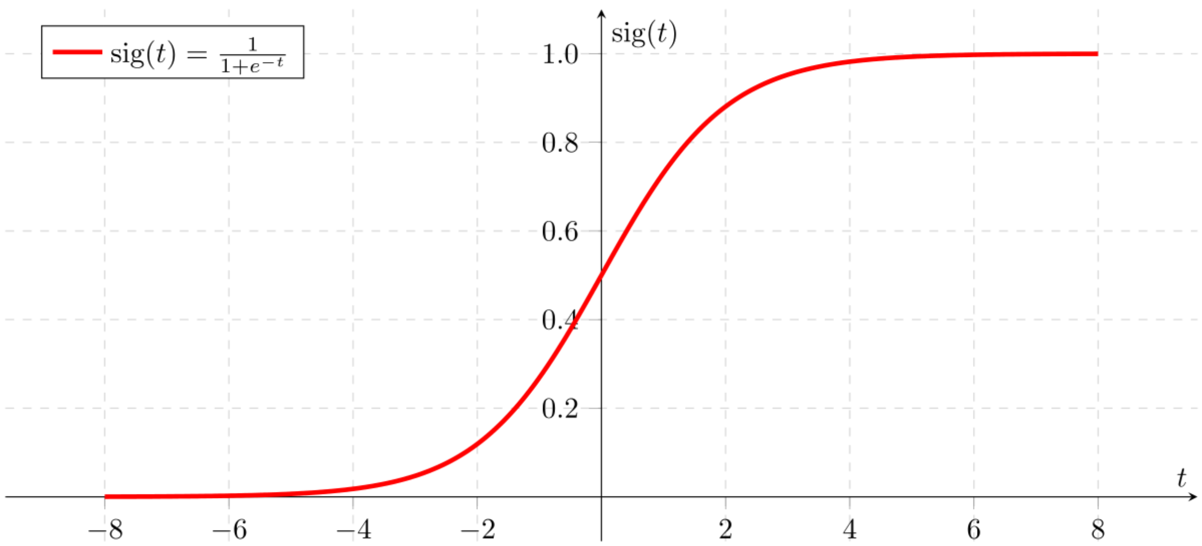
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         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


   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
```

```
print(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
None
```

```
df = df[['Survived', 'Age', 'Sex', 'Pclass']]
df = pd.get_dummies(df, columns=['Sex', 'Pclass'])
df.dropna(inplace=True)
print(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
```

```
print(df)
```

```
     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
..        ...   ...         ...       ...       ...       ...       ...
885         0  39.0        True     False     False     False      True
886         0  27.0       False      True     False      True     False
887         1  19.0        True     False      True     False     False
889         1  26.0       False      True      True     False     False
890         0  32.0       False      True     False     False      True

[714 rows x 7 columns]
```

```
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, s
tratify=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]])
```

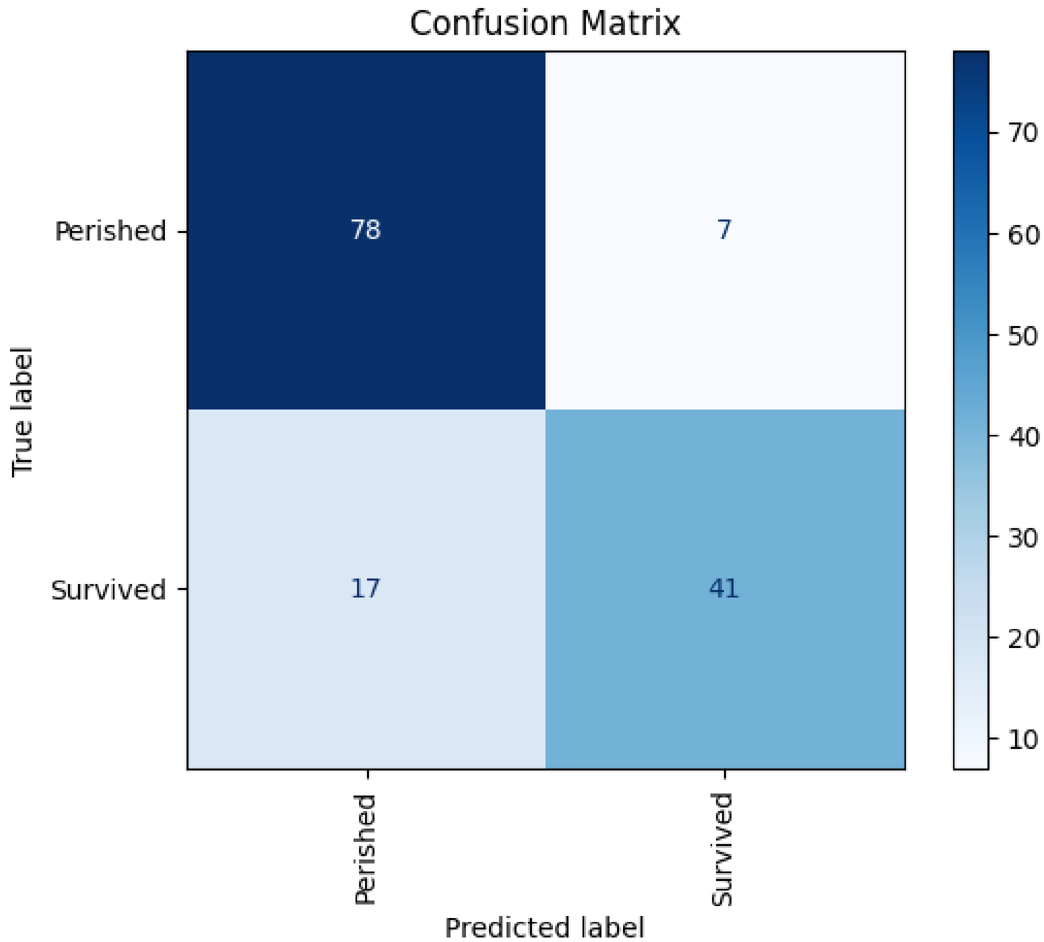
```
from sklearn.metrics import ConfusionMatrixDisplay, confusion_matrix
import matplotlib.pyplot as plt
```

```
y_pred = model.predict(x_test)

# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Display the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Perish
ed', 'Survived'])
disp.plot(cmap='Blues')

# Optional: customize the plot further
plt.xticks(rotation='vertical')
plt.title('Confusion Matrix')
plt.show()
```




```
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
```

```
accuracy = model.score(x_test, y_test)
print(f'Accuracy: {accuracy:.2f}')
```

```
Accuracy: 0.83
```

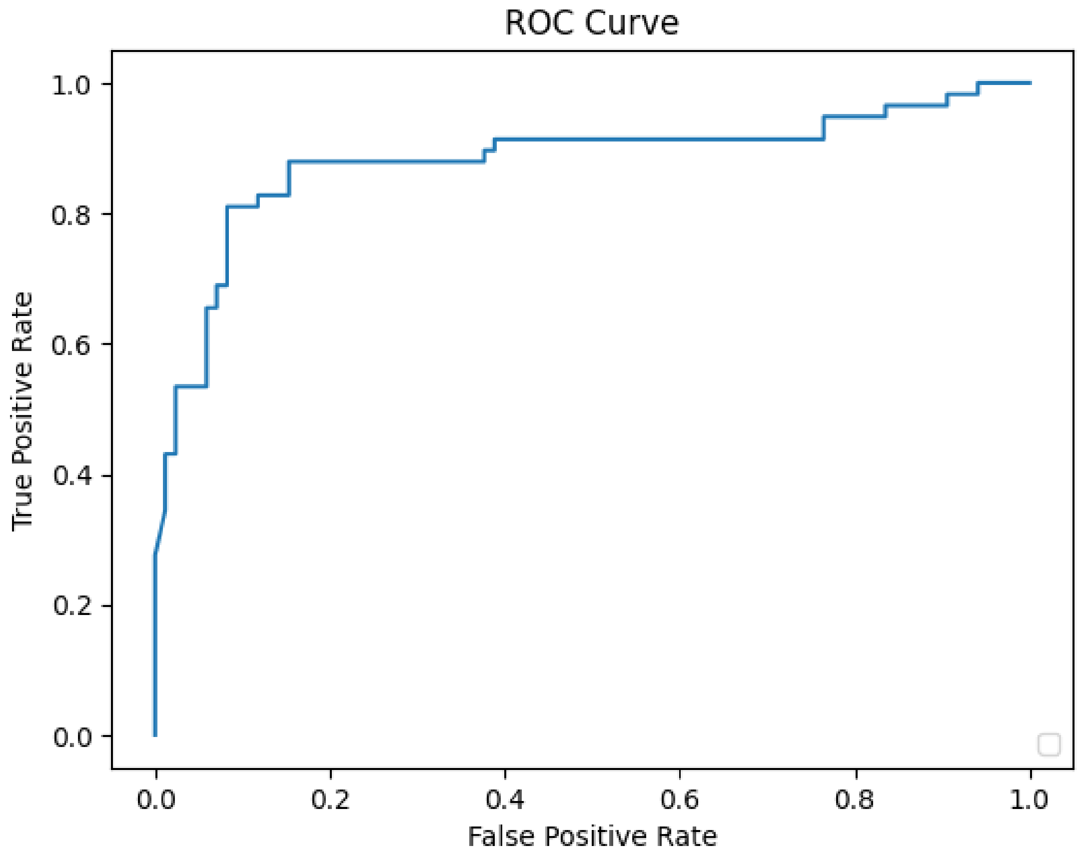
```
from sklearn.metrics import roc_curve, RocCurveDisplay
y_prob = model.predict_proba(x_test)[:,1]
fpr, tpr, _ = roc_curve(y_test, y_prob)

# Create the ROC curve display
disp = RocCurveDisplay(fpr=fpr, tpr=tpr)
disp.plot()

# Add labels and title if desired
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')

plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.
Note that artists whose label start with an underscore are ignored when le
gend() is called with no argument.
```



Conclusion:

The accuracy obtained from the Logistic Regression model on the Titanic dataset provides an overall measure of the model's performance, indicating the proportion of correct predictions out of the total instances. However, accuracy alone can be misleading, especially in the presence of imbalanced classes. For instance, if there are significantly more non-survivors than survivors, a high accuracy might still mean the model predominantly predicts the majority class. Therefore, while a high accuracy suggests good performance, it is essential to also consider other metrics like precision, recall, F1-score, and the ROC curve to comprehensively evaluate the model's ability to correctly predict both survivors and non-survivors. The provided script includes these additional metrics to ensure a more thorough assessment of the model.