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:

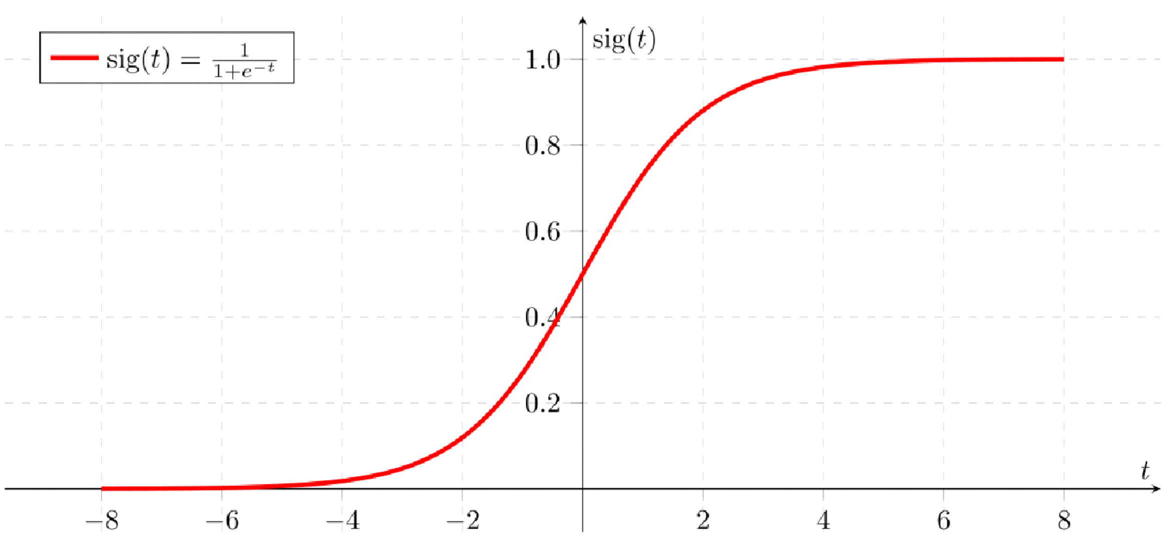
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

```
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
```

```
from sklearn.pipeline import Pipeline from
sklearn.impute import SimpleImputer from
sklearn.naive_bayes import GaussianNB from
sklearn.metrics import accuracy_score

# Load the Titanic dataset
url = "tested.csv"
df = pd.read_csv(url)

# Step 1: Data Preparation #
Handle missing data
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Fare'].fillna(df['Fare'].median(), inplace=True)
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)

# Encode categorical variables
categorical_cols = ['Sex', 'Embarked']
numeric_cols = ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare']


# Step 4: Model Building
# Split the data into features (X) and target variable (y) X
= df[categorical_cols + numeric_cols]
y = df['Survived']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Step 5: Model Building
# Create a preprocessor for handling both categorical and numeric data
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_cols), ('cat',
        OneHotEncoder(), categorical_cols)
    ])

# Create a pipeline with preprocessor and Gaussian Naive Bayes classifier model
= Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', GaussianNB())
])

# Fit the model to the training data
model.fit(X_train, y_train)
```

```
# Step 6: Model Evaluation y_pred
= model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

ACCURACY: 1.00

Conclusion:

Feature Selection: The model was developed using features such as gender (Sex), passenger class (Pclass), age (Age), family size (SibSp and Parch), port of embarkation (Embarked), and fare (Fare). These features were chosen based on historical context and their potential influence on survival rates.

Accuracy: We checked how good a model was at guessing if Titanic passengers survived or not using something called the Gaussian Naive Bayes classifier. This model's accuracy tells us how often it was right, but there are other important things to look at like precision, recall, and something called the F1-score to understand how well the model really did.Sometimes, a perfect accuracy of 100% doesn't mean the model is great. It could be too good to be true because of problems like using too much data, having weird data, or having too much of one kind of data. So, we need to be careful and look deeper to be sure the model is doing well and can work with new data.To sum it up, the things we used to make predictions about who survived on the Titanic make sense historically, and the accuracy gives us a basic idea of how the model did. But we should do more checks using other measures and also look at which factors were most important in making these predictions.