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:

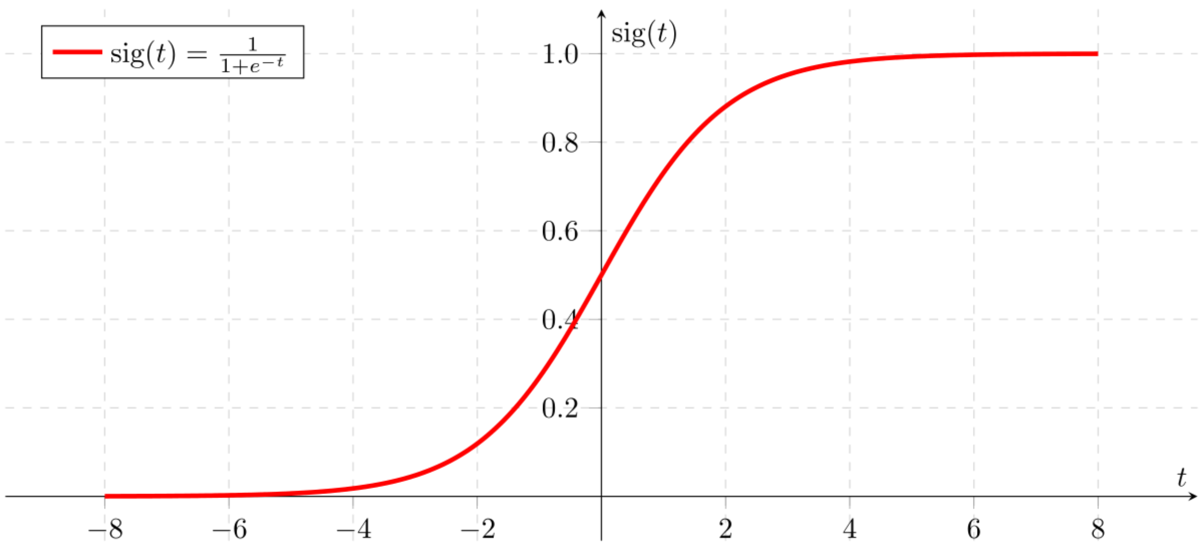
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification the logistic regression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

1. What are features have been chosen to develop the model? Justify the features chosen to determine the survival of a passenger.

   The attributes used for the Titanic Survival dataset are Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, and Embarked. These characteristics are based on historical information of the Titanic tragedy, an understanding of human behavior in emergency situations, and hypotheses regarding how specific elements may have affected the chance of survival.

2. Comment on the accuracy obtained.
   The accuracy value for the Titanic survival dataset is 0.84, or around 84 %, which indicates the percentage of accurate predictions generated by the model.

```python
import numpy as np
import pandas as pd
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
warnings.filterwarnings('ignore')
```

```python
df=sns.load_dataset("titanic")
```

```python
df.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adul
0	0	3	male	22.0	1	0	7.2500	S	Third	man	
1	1	1	female	38.0	1	0	71.2833	C	First	woman	
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	
3	1	1	female	35.0	1	0	53.1000	S	First	woman	
4	0	3	male	35.0	0	0	8.0500	S	Third	man	

```python
df.shape
```

```
(891, 15)
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

```python
df.isnull().sum()
```

```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

```python
df.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False

```
columns = ['alive', 'alone', 'embark_town', 'who', 'adult_male', 'deck']
data = df.drop(columns, axis=1)
```

```
data.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class
0	0	3	male	22.0	1	0	7.2500	S	Third
1	1	1	female	38.0	1	0	71.2833	C	First
2	1	3	female	26.0	0	0	7.9250	S	Third
3	1	1	female	35.0	1	0	53.1000	S	First
4	0	3	male	35.0	0	0	8.0500	S	Third

```
data
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class
0	0	3	male	22.0	1	0	7.2500	S	Third
1	1	1	female	38.0	1	0	71.2833	C	First
2	1	3	female	26.0	0	0	7.9250	S	Third
3	1	1	female	35.0	1	0	53.1000	S	First
4	0	3	male	35.0	0	0	8.0500	S	Third
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Second
887	1	1	female	19.0	0	0	30.0000	S	First
888	0	3	female	NaN	1	2	23.4500	S	Third
889	1	1	male	26.0	0	0	30.0000	C	First
890	0	3	male	32.0	0	0	7.7500	Q	Third

891 rows × 9 columns

```
df['age'].fillna(df['age'].mean(), inplace=True)
```

```
print(df['embarked'].mode())
```

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

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

```
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)
```

```
df.isnull().sum()
```

```
survived         0
pclass           0
sex              0
age              0
sibsp            0
parch            0
fare             0
embarked         0
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

Data Analysis

```
df.describe()
```

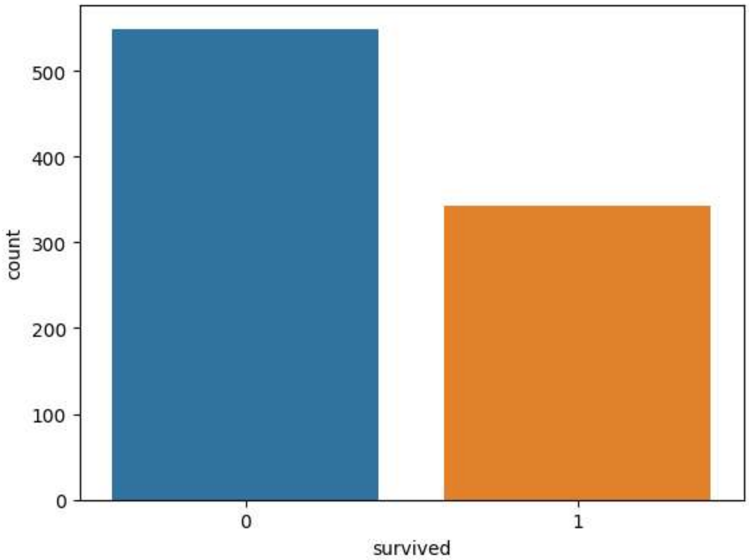
	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	13.002015	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

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

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

```
sns.countplot(x='survived', data=df)
```

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

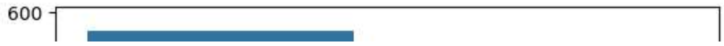



```
df['sex'].value_counts()
```

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

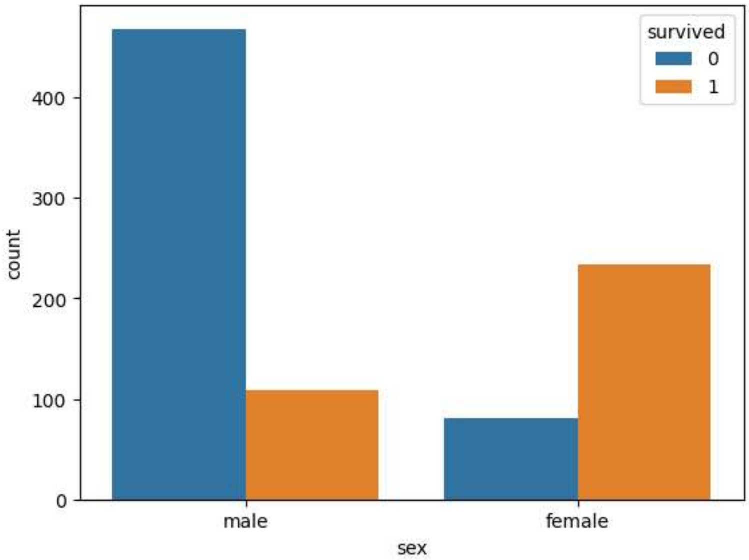
```
sns.countplot(x='sex', data=df)
```

<Axes: xlabel='sex', ylabel='count'>



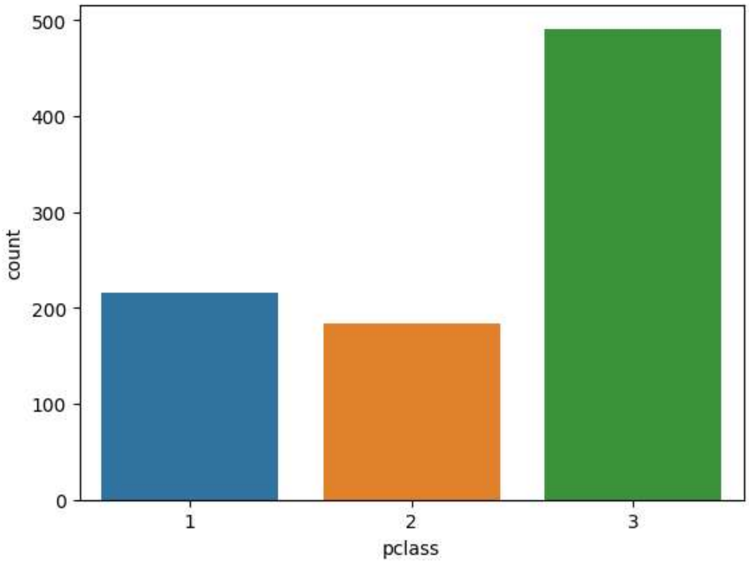

```
sns.countplot(x='sex', hue='survived', data=df)
```

<Axes: xlabel='sex', ylabel='count'>




```
sns.countplot(x='pclass', data=df)
```

<Axes: xlabel='pclass', ylabel='count'>




```
sns.countplot(x='pclass', hue='survived', data=df)
```

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

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

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

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

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

```
df.replace({'sex':{'male':0,'female':1}, 'embarked':{'S':0,'C':1,'Q':2}}, inplace=True)
```

```
df.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	0	22.0	1	0	7.2500	0	Third	man	True	NaN	Southampton	no	False
1	1	1	1	38.0	1	0	71.2833	1	First	woman	False	C	Cherbourg	yes	False
2	1	3	1	26.0	0	0	7.9250	0	Third	woman	False	NaN	Southampton	yes	True
3	1	1	1	35.0	1	0	53.1000	0	First	woman	False	C	Southampton	yes	False
4	0	3	0	35.0	0	0	8.0500	0	Third	man	True	NaN	Southampton	no	True

```
data[data['sex'].str.match("female")].count()
```

```
survived    314
pclass      314
sex         314
age         261
sibsp       314
parch       314
fare        314
embarked    312
class       314
dtype: int64
```

```
data[data['sex'].str.match("male")].count()
```

```
survived    577
pclass      577
sex         577
age         453
sibsp       577
parch       577
fare        577
embarked    577
class       577
dtype: int64
```

```
gender = pd.get_dummies(data['sex'], drop_first=True)
```

```
data['gender'] = gender
```

```
data.drop('sex', axis=1,inplace=True)
```

```
data.head()
```

	survived	pclass	age	sibsp	parch	fare	embarked	class	gender
0	0	3	22.0	1	0	7.2500	S	Third	1
1	1	1	38.0	1	0	71.2833	C	First	0
2	1	3	26.0	0	0	7.9250	S	Third	0
3	1	1	35.0	1	0	53.1000	S	First	0
4	0	3	35.0	0	0	8.0500	S	Third	1

```
change = {'First':1 ,'Second':2,'Third':3}
data['class'] = data['class'].replace(change)
```

```
change = {'C':1 ,'Q':2,'S':3}
data['embarked'] = data['embarked'].replace(change)
```

```
data.head()
```

	survived	pclass	age	sibsp	parch	fare	embarked	class	gender
0	0	3	22.0	1	0	7.2500	3.0	3	1
1	1	1	38.0	1	0	71.2833	1.0	1	0
2	1	3	26.0	0	0	7.9250	3.0	3	0
3	1	1	35.0	1	0	53.1000	3.0	1	0
4	0	3	35.0	0	0	8.0500	3.0	3	1

```
column_name = 'embarked'
data = data.dropna(subset = [column_name],axis = 0)
```

```
data['age'].fillna(data['age'].mean() , inplace=True)
```

```
x=data.iloc[:,1:]
y=data.iloc[:,0]
```

```
x
```

	pclass	age	sibsp	parch	fare	embarked	class	gender
0	3	22.000000	1	0	7.2500	3.0	3	1
1	1	38.000000	1	0	71.2833	1.0	1	0
2	3	26.000000	0	0	7.9250	3.0	3	0
3	1	35.000000	1	0	53.1000	3.0	1	0
4	3	35.000000	0	0	8.0500	3.0	3	1
...	...	...	...	...	...	...	...	...
886	2	27.000000	0	0	13.0000	3.0	2	1
887	1	19.000000	0	0	30.0000	3.0	1	0
888	3	29.642093	1	2	23.4500	3.0	3	0
889	1	26.000000	0	0	30.0000	1.0	1	1
890	3	32.000000	0	0	7.7500	2.0	3	1

889 rows × 8 columns

```
y
```

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: survived, Length: 889, dtype: int64
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
```

```
X_train, X_test, Y_train , Y_test = train_test_split(x , y,test_size = 0.2 , random_state=1)
```

```
model = LogisticRegression()
```

```
print(X_train.shape , Y_train.shape)
```

```
(711, 8) (711,)
```

```
model.fit(X_train , Y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
y_pred = model.predict(X_test)
```

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

```
Accuracy:0.84
```

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