| |
|---|
| Experiment No. 2 |
| Analyze the Titanic Survival Dataset and apply appropriate regression technique |
| Date of Performance: 17/08/2023 |
| Date of Submission: 24/08/2023 |

**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:**

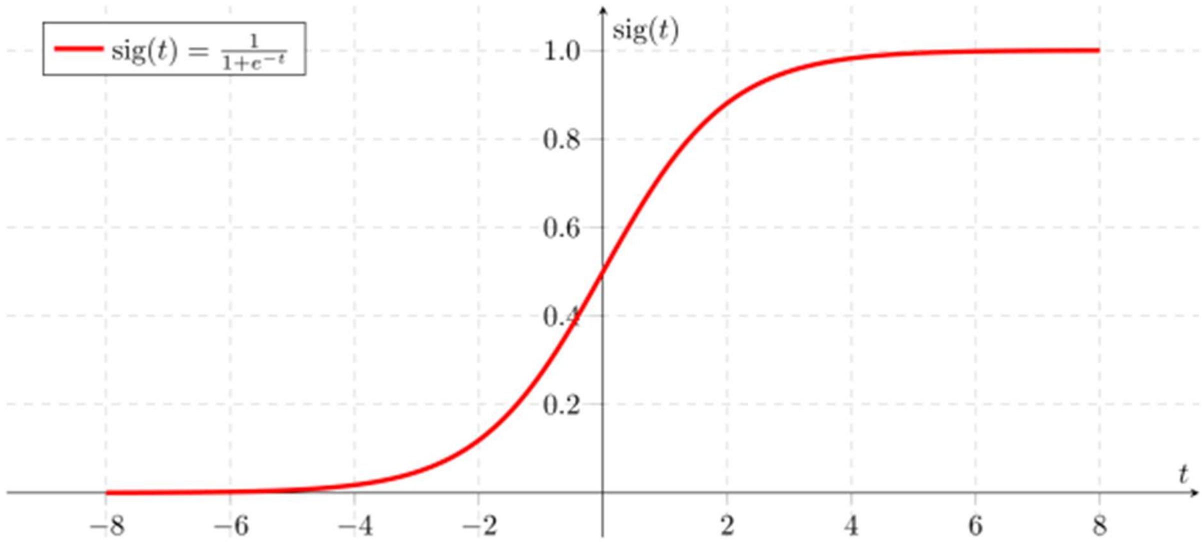
Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical and is binary in nature. In order to perform binary classification, the logistic regression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

In [40]:
```
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, confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# load the data from csv file to Pandas DataFrame
df = pd.read_csv('train.csv')
```

In [3]:
```
# printing the first 5 rows of the dataframe
df.head()
```

Out[3]:

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

In [4]:
```
# number of rows and Columns
df.shape
```

Out[4]: (891, 12)

```
]: #
```

```
In [5   getting some informations about the data
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
```

In [6]:
```
# check the number of missing values in each column
df.isnull().sum()
```

Out[6]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [7]:
```
# drop the "Cabin" column from the dataframe
df = df.drop(columns='Cabin', axis=1)
```

In [8]:
```
# replacing the missing values in "Age" column with mean value
df['Age'].fillna(df['Age'].mean(), inplace=True)
```

In [9]:
```
# finding the mode value of "Embarked" column
print(df['Embarked'].mode())
```

```
0    S
dtype: object
```

In [10]:
```
print(df['Embarked'].mode()[0])
```

```
S
```

In [1 ]:
```
#
```

```
  replacing the missing values in "Embarked" column with mode value
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

In [12]:
```
# check the number of missing values in each column
df.isnull().sum()
```

Out[12]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

Data Analysis

In [13]:
```
# getting some statistical measures about the data
df.describe()
```

Out[13]:

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|---|
| **count** | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 |
| **mean** | 446.000000 | 0.383838 | 2.308642 | 29.699118 | 0.523008 | 0.381594 | 32.204208 |
| **std** | 257.353842 | 0.486592 | 0.836071 | 13.002015 | 1.102743 | 0.806057 | 49.693429 |
| **min** | 1.000000 | 0.000000 | 1.000000 | 0.420000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 223.500000 | 0.000000 | 2.000000 | 22.000000 | 0.000000 | 0.000000 | 7.910400 |
| **50%** | 446.000000 | 0.000000 | 3.000000 | 29.699118 | 0.000000 | 0.000000 | 14.454200 |
| **75%** | 668.500000 | 1.000000 | 3.000000 | 35.000000 | 1.000000 | 0.000000 | 31.000000 |
| **max** | 891.000000 | 1.000000 | 3.000000 | 80.000000 | 8.000000 | 6.000000 | 512.329200 |

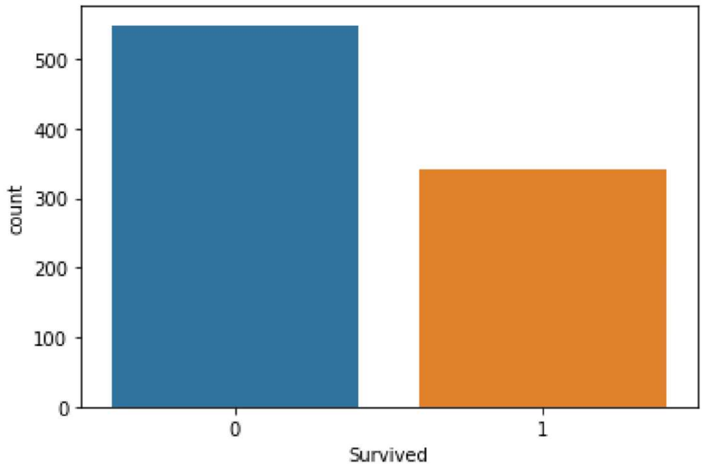
In [14]:
```
# finding the number of people survived and not survived
df['Survived'].value_counts()
```

Out[14]:
```
0    549
1    342
Name: Survived, dtype: int64
```

```
In [1 ]: #
```

```
5     making a count plot for "Survived" column
sns.countplot(x='Survived', data=df)
```

Out[15]: <AxesSubplot:xlabel='Survived', ylabel='count'>

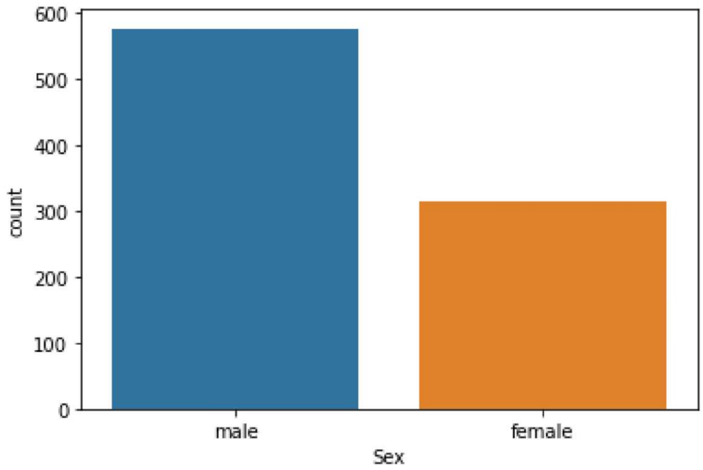



```
In [16]: df['Sex'].value_counts()
```

```
Out[16]: male      577
         female    314
         Name: Sex, dtype: int64
```

```
In [17]: # making a count plot for "Sex" column
         sns.countplot(x='Sex', data=df)
```

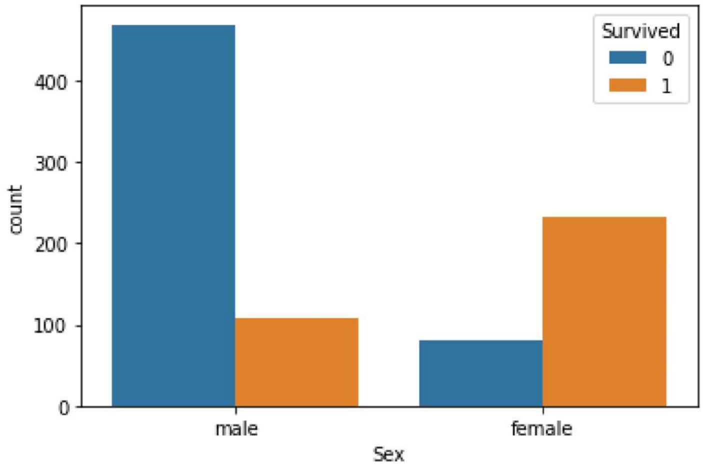
Out[17]: <AxesSubplot:xlabel='Sex', ylabel='count'>



In [1 ]:
```
#
```

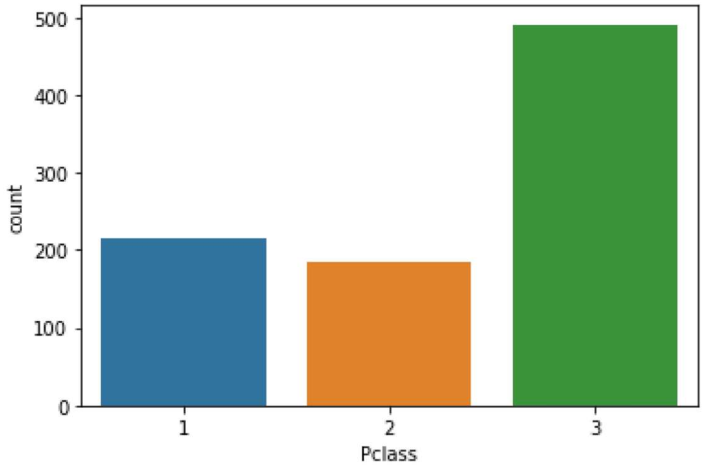
8
```
  number of survivors Gender wise
sns.countplot(x='Sex', hue='Survived', data=df)
```

Out[18]: <AxesSubplot:xlabel='Sex', ylabel='count'>




In [19]:
```
# making a count plot for "Pclass" column
sns.countplot(x='Pclass', data=df)
```

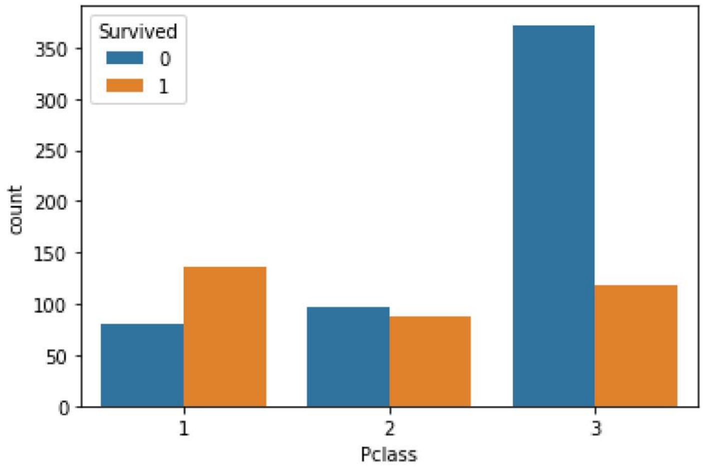
Out[19]: <AxesSubplot:xlabel='Pclass', ylabel='count'>



In [ ]:

20
```
sns.countplot(x='Pclass', hue='Survived', data=df)
```

Out[20]: <AxesSubplot:xlabel='Pclass', ylabel='count'>




In [21]:
```
df['Sex'].value_counts()
```

Out[21]:
```
male      577
female    314
Name: Sex, dtype: int64
```

In [22]:
```
df['Embarked'].value_counts()
```

Out[22]:
```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

In [23]:
```
# converting categorical Columns
df.replace({'Sex':{'male':0,'female':1}, 'Embarked':{'S':0,'C':1,'Q':2}}, inplace=True
```

In [24]:
```
df.head()
```

Out[24]:

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

In [ ]:

```

```

25

```
X = df.drop(columns = ['PassengerId','Name','Ticket','Survived'],axis=1)
Y = df['Survived']
```

In [26]:

```
X.head(3)
```

Out[26]:

| | Pclass | Sex | Age | SibSp | Parch | Fare | Embarked |
|---|---|---|---|---|---|---|---|
| **0** | 3 | 0 | 22.0 | 1 | 0 | 7.2500 | 0 |
| **1** | 1 | 1 | 38.0 | 1 | 0 | 71.2833 | 1 |
| **2** | 3 | 1 | 26.0 | 0 | 0 | 7.9250 | 0 |

In [27]:

```
Y.head(3)
```

Out[27]:

```
0    0
1    1
2    1
Name: Survived, dtype: int64
```

In [28]:

```
#Splitting the data into training data & Test data
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2, random_state=2
```

In [30]:

```
model = LogisticRegression()
```

In [31]:

```
# training the Logistic Regression model with training data
model.fit(X_train, Y_train)
```

Out[31]:

```
▾ LogisticRegression
LogisticRegression()
```

In [32]:

```
# accuracy on training data
X_train_prediction = model.predict(X_train)
```

In [ ]:

```
33  X_train_prediction
```

Out[33]:
```
array([0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1,
       0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0], dtype=int64)
```

In [34]:
```
training_data_accuracy = accuracy_score(Y_train, X_train_prediction)
print('Accuracy score of training data : ', training_data_accuracy)
```

```
Accuracy score of training data :  0.8075842696629213
```

In [36]:
```
# accuracy on test data
X_test_prediction = model.predict(X_test)
```

In [37]:
```
X_test_prediction
```

Out[37]:
```
array([0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1,
       0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0,
       0, 0, 0], dtype=int64)
```

In [ ]:

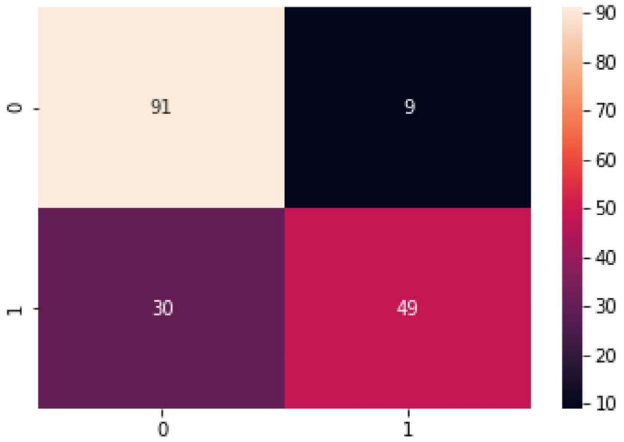
39
```python
test_data_accuracy = accuracy_score(Y_test, X_test_prediction)
print('Accuracy score of test data : ', test_data_accuracy)
```

```
Accuracy score of test data :  0.7821229050279329
```

In [48]:
```python
print("Confusion matrix :-")
sns.heatmap(confusion_matrix(Y_test, X_test_prediction), annot=True)
```

```
Confusion matrix :-
```

Out[48]: <AxesSubplot:>




In [44]:
```python
from sklearn.metrics import classification_report
print(classification_report(Y_test, X_test_prediction))
```

```
              precision    recall  f1-score   support

           0       0.75      0.91      0.82       100
           1       0.84      0.62      0.72        79

    accuracy                           0.78       179
   macro avg       0.80      0.77      0.77       179
weighted avg       0.79      0.78      0.78       179
```

**Conclusion:**

1. The Features chosen to develop the model are as follows: -
   a. Pclass – Ticket class
   b. Sex - sex
   c. Age – Age in years
   d. Sibsp – No. of siblings/spouses abord the titanic
   e. Parch – No. of parents/children aboard the titanic
   f. Fare - Passenger fare
   g. Embarked – Port of Embarkation

These features were chosen after performing appropriate feature engineering on the dataset such as handling missing values and converting categorical columns such as the attributes Sex and Embarked. These features also contributed in the prediction of the final outcome

2. The Accuracy score obtained by our logistic regression model on the training data is 0.80 which means our model is 80% accurate on the given training data.
3. The Accuracy score obtained by our logistic regression model on the testing data is 0.78 which means our model is 78% accurate on the testing data.