In [1]:
```
# importing the dependencies
import pandas as pd
import numpy as np
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
```

In [6]:
```
# load the data
titanic_data = pd.read_csv('train.csv')
```

In [7]:
```
#print first five rows of data
titanic_data.head()
```

Out[7]:

	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

In [8]:
```
#print last five rows of the data
titanic_data.tail()
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

In [9]:
```
# finding no. of rows and columns
titanic_data.shape
```

Out[9]: (891, 12)

In [10]:
```
# getting some informatiom about data
titanic_data.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 [11]:
```
# checking the missing values in each column
titanic_data.isnull().sum()
```

Out[11]:
```
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 [13]:
```
#drop the Cabin column from data set as it has too many missing values
titanic_data = titanic_data.drop(columns = 'Cabin', axis = 1 )
```

In [14]:
```
titanic_data.isnull().sum()
```

Out[14]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         2
dtype: int64
```

In [16]:
```
# replacing value in the age column with the mean value
titanic_data['Age'].fillna(titanic_data['Age'].mean(), inplace = True)
```

In [17]:
```
titanic_data.isnull().sum()
```

Out[17]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       2
dtype: int64
```

In [21]:
```
# finding the mode value in Embarked column
print(titanic_data['Embarked'].mode())
print(titanic_data['Embarked'].mode()[0])
```

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

In [22]:
```
# replacing the missing values in Embarked column with mode value
titanic_data['Embarked'].fillna(titanic_data['Embarked'].mode()[0], inplace = True)
```

In [24]:
```
 titanic_data.isnull().sum()
```

Out[24]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

In [25]:
```
# now data analysis
#getting some statical measure about data
titanic_data.describe()
```

Out[25]:

	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

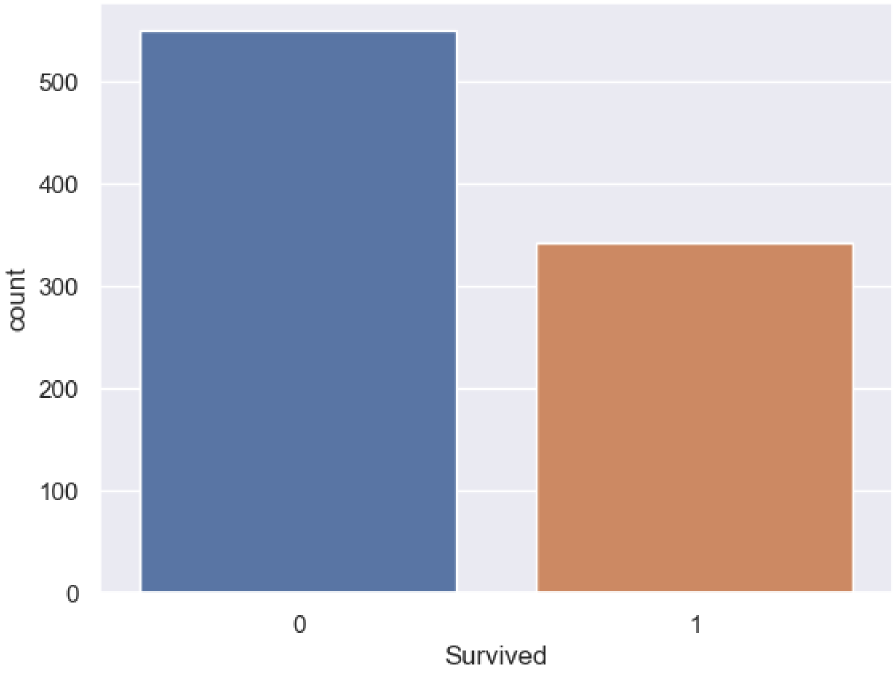
In [26]:
```
# finding tha no. of people survived and not survived
titanic_data['Survived'].value_counts()
```

Out[26]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

In [48]:
```
# data visualization
sns.set()
```

In [51]:
```
# making a count plot for survived column
sns.countplot(x = 'Survived', data = titanic_data)
```

Out[51]: <Axes: xlabel='Survived', ylabel='count'>

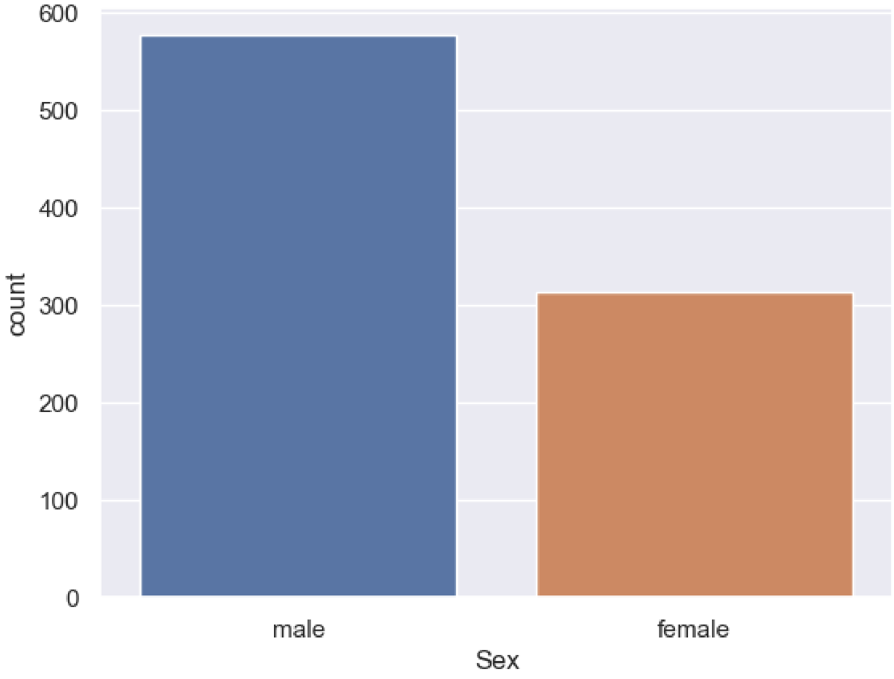


In [52]:
```
titanic_data['Sex'].value_counts()
```

Out[52]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

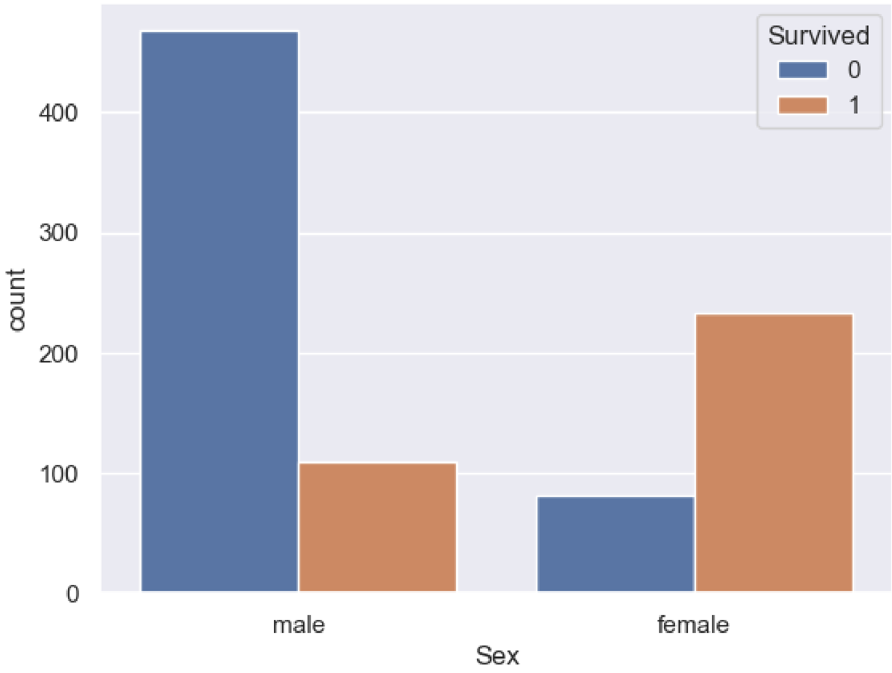
In [53]:
```
sns.countplot(x = 'Sex', data = titanic_data)
```

Out[53]: <Axes: xlabel='Sex', ylabel='count'>



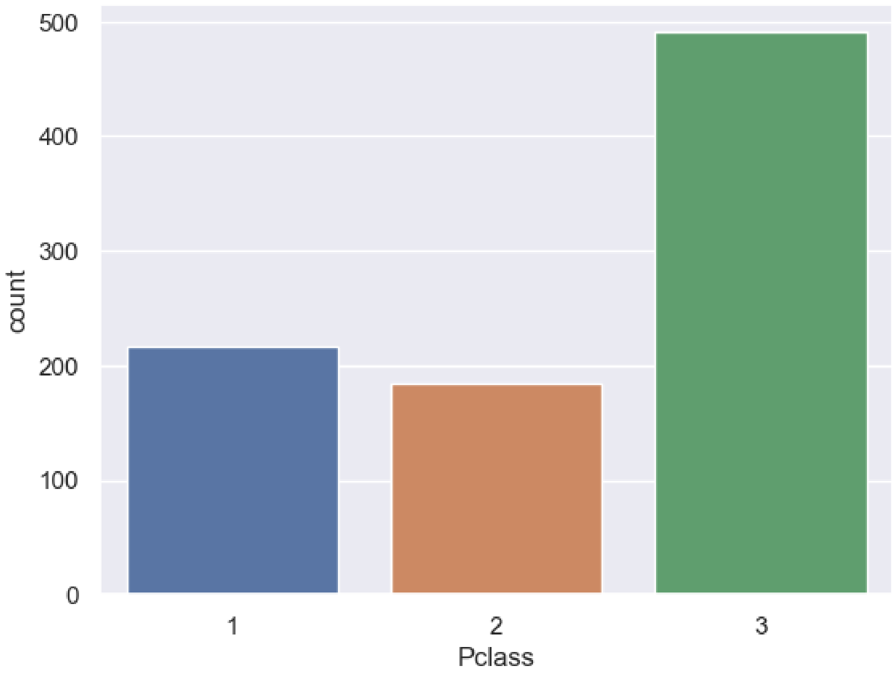
In [60]:
```
# no. of survivers gender wise
sns.countplot(x = 'Sex', hue = 'Survived', data = titanic_data)
```

Out[60]: <Axes: xlabel='Sex', ylabel='count'>



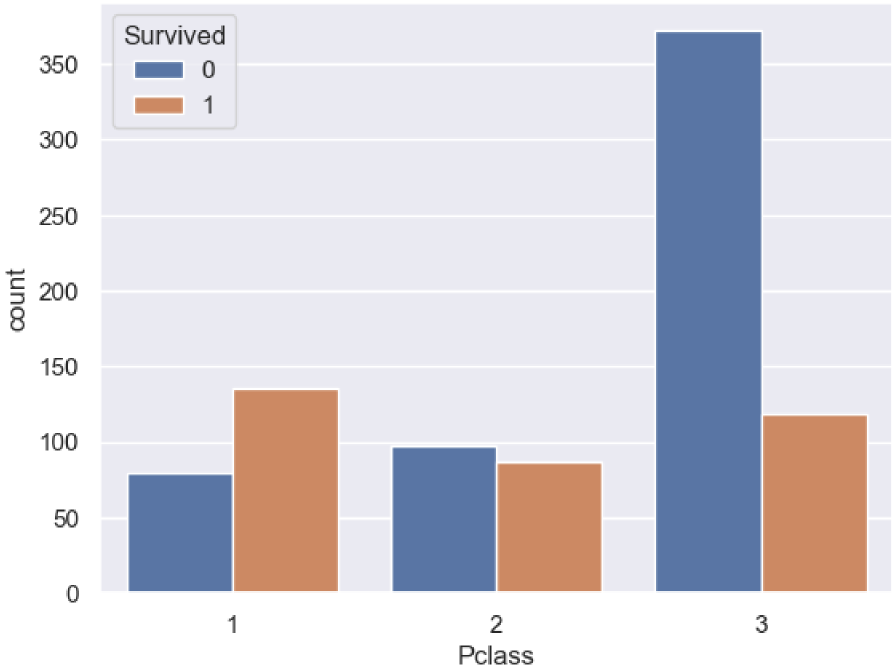
In [61]:
```
# making a countplot for Pclass
sns.countplot(x = 'Pclass', data = titanic_data)
```

Out[61]: <Axes: xlabel='Pclass', ylabel='count'>



In [63]:
```
# find the no of people survived based on Pclass
sns.countplot(x = 'Pclass', hue = 'Survived', data = titanic_data)
```

Out[63]: <Axes: xlabel='Pclass', ylabel='count'>



In [72]:
```
# encoding the categorical column
titanic_data['Sex'].value_counts()
```

Out[72]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

In [73]:
```
titanic_data['Embarked'].value_counts()
```

Out[73]:
```
Embarked
S    646
C    168
Q     77
Name: count, dtype: int64
```

In [80]:
```
# converting categorical column
titanic_data.replace({'Sex':{'male':0, 'female':1}, 'Embarked':{'S':0, 'C':1, 'Q':2}}, inplace = True
```

In [81]:
```
titanic_data.head()
```

Out[81]:

	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 [83]:
```
# seperating features and target
x = titanic_data.drop(columns = ['PassengerId', 'Name', 'Ticket', 'Survived'])
y = titanic_data['Survived']
```

In [84]:
```
print(x)
```

```
     Pclass  Sex        Age  SibSp  Parch     Fare  Embarked
0         3    0  22.000000      1      0   7.2500         0
1         1    1  38.000000      1      0  71.2833         1
2         3    1  26.000000      0      0   7.9250         0
3         1    1  35.000000      1      0  53.1000         0
4         3    0  35.000000      0      0   8.0500         0
..      ...  ...        ...    ...    ...      ...       ...
886       2    0  27.000000      0      0  13.0000         0
887       1    1  19.000000      0      0  30.0000         0
888       3    1  29.699118      1      2  23.4500         0
889       1    0  26.000000      0      0  30.0000         1
890       3    0  32.000000      0      0   7.7500         2

[891 rows x 7 columns]
```

In [85]:
```
print(y)
```

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

In [89]:
```
#spliting data into training data and test data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.2, random_state = 2)
```

In [90]:
```
print(x.shape, x_train.shape, x_test.shape)
```

```
(891, 7) (712, 7) (179, 7)
```

In [94]:
```
# model training - we are using LogisticRegression model
model = LogisticRegression()
```

In [96]:
```
#training the Logistic regression with training data
model.fit(x_train, y_train)
```

```
C:\Users\91993\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: ConvergenceWarnin
g: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modu
les/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-le
arn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[96]:
```
▾ LogisticRegression
LogisticRegression()
```

In [99]:
```
# model evaluation
# accuracy on training data
x_train_prediction = model.predict(x_train)
```

In [100]:
```
print(x_train_prediction)
```

```
[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]
```

In [106]:
```
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 [107]:
```
# accuracy on test data
x_test_prediction = model.predict(x_test)
print(x_test_prediction)
```

```
[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]
```

In [109]:
```
test_data_accuracy = accuracy_score(y_test, x_test_prediction)
print('Accuracy score of training data', test_data_accuracy)
```

```
Accuracy score of training data 0.7821229050279329
```

In [ ]: