TITANIC MACHINE LEARNING FROM DISASTER

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Introduction

The Challenge

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 (i.e., name, age, gender, socio-economic class, etc).

Data-overview

Dataset Description

Overview

The data has been split into two groups:

- training set (train.csv)
- test set (test.csv)

- **The training set** should be used to build your machine learning models. For the training set, we provide the outcome (also known as the “ground truth”) for each passenger. Your model will be based on “features” like passengers’ gender and class. You can also use feature engineering to create new features.

- **The test set** should be used to see how well your model performs on unseen data. For the test set, we do not provide the ground truth for each passenger. It is your job to predict these outcomes. For each passenger in the test set, use the model you trained to predict whether or not they survived the sinking of the Titanic.

- We also include `gender_submission.csv` , a set of predictions that assume all and only female passengers survive, as an example of what a submission file should look like.

Data-dictionary

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, it is 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 traveled only with a nanny, therefore parch=0 for them.

IMPORT LIBRARY

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

In [2]:
```
data=pd.read_csv('data\\train.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	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 [4]:
```
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
```

NOTES

- AGE has missing values
- cabin has only 204 values
- Embarkded has 2 missing values

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
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
```

- Age Null values has been filled with Median values

In [6]:
```
data['Age'].median()
data['Age']=data['Age'].fillna(data['Age'].median())
```

In [7]:
```
data['Cabin'].unique()
```

Out[7]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

- For Now will drop the Cabin column as we can see 687 nan values
- Also we will remove PassangeID , Name , Ticket columns

In [8]:
```python
data1=data.drop(columns=['PassengerId','Name','Ticket', 'Cabin'], axis=1)
```

In [9]:
```python
data1.head(1)
```

Out[9]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.25	S

In [10]:
```python
data1.isnull().sum()
```

Out[10]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    2
dtype: int64
```

In [11]:
```python
data1['Embarked'].value_counts()
```

Out[11]:
```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [12]:
```python
data1['Embarked'].dropna(inplace=True)
```

In [13]:
```python
data1 = data1.dropna(subset=['Embarked'])
```

In [14]:
```python
data1.isnull().sum()
```

Out[14]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

In [15]:
```python
data1.head()
```

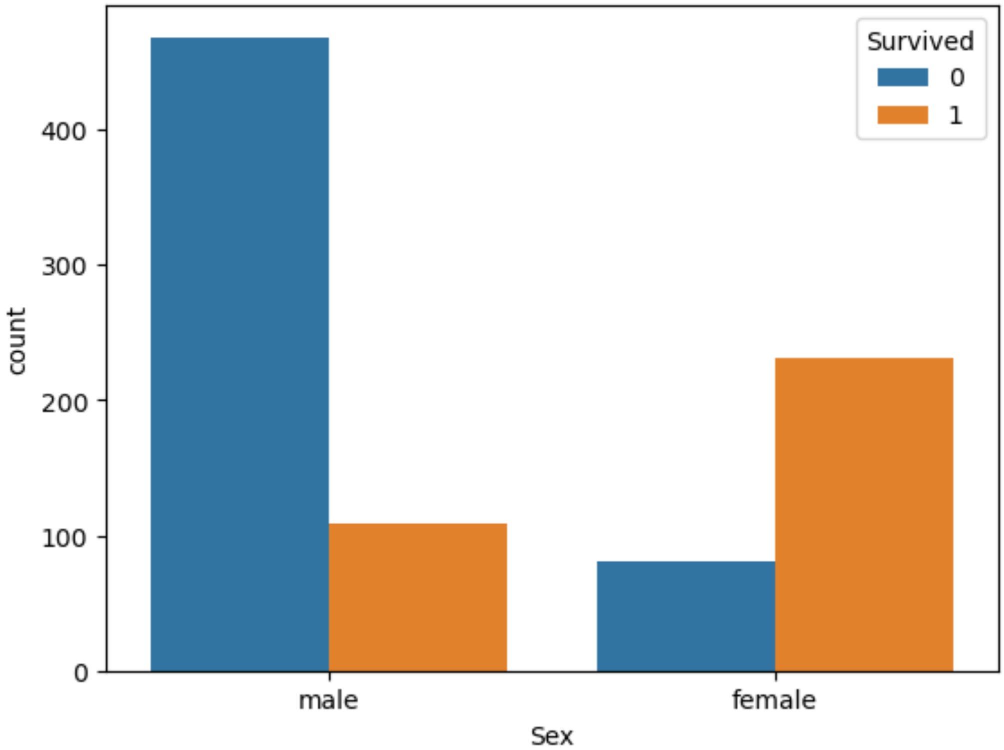
Out[15]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

EXPLORATORY DATA ANALYSIS

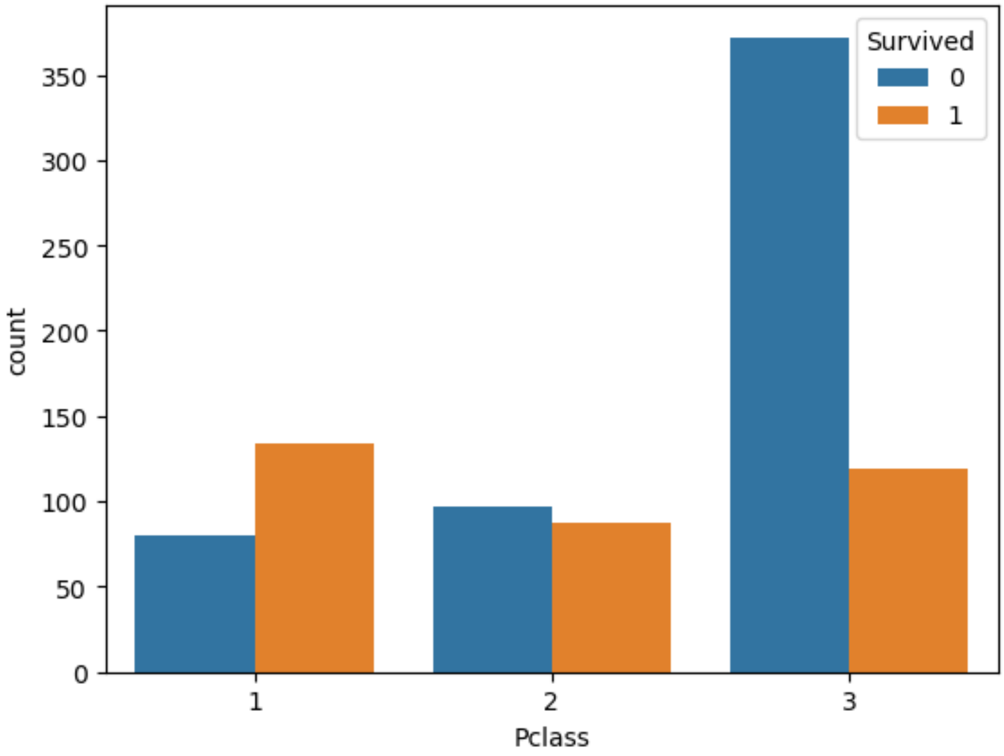
In [16]:
```
sns.countplot(data=data1, x='Sex', hue='Survived')
```

Out[16]:
```
<AxesSubplot:xlabel='Sex', ylabel='count'>
```



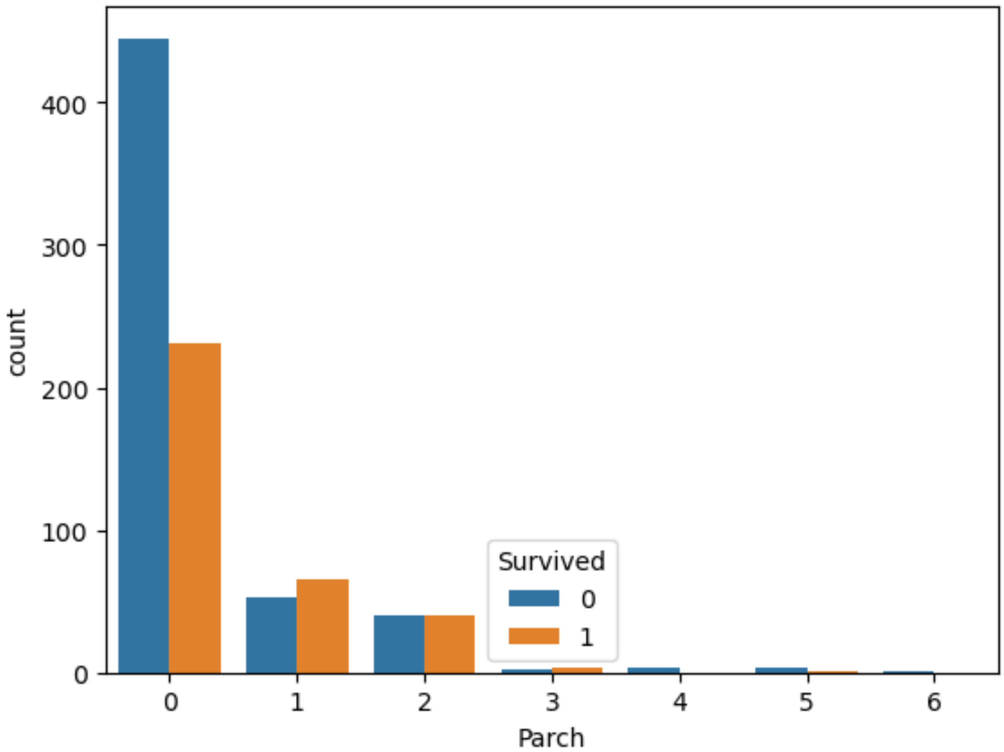
In [17]:
```
sns.countplot(data=data1, x='Pclass', hue='Survived')
```

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



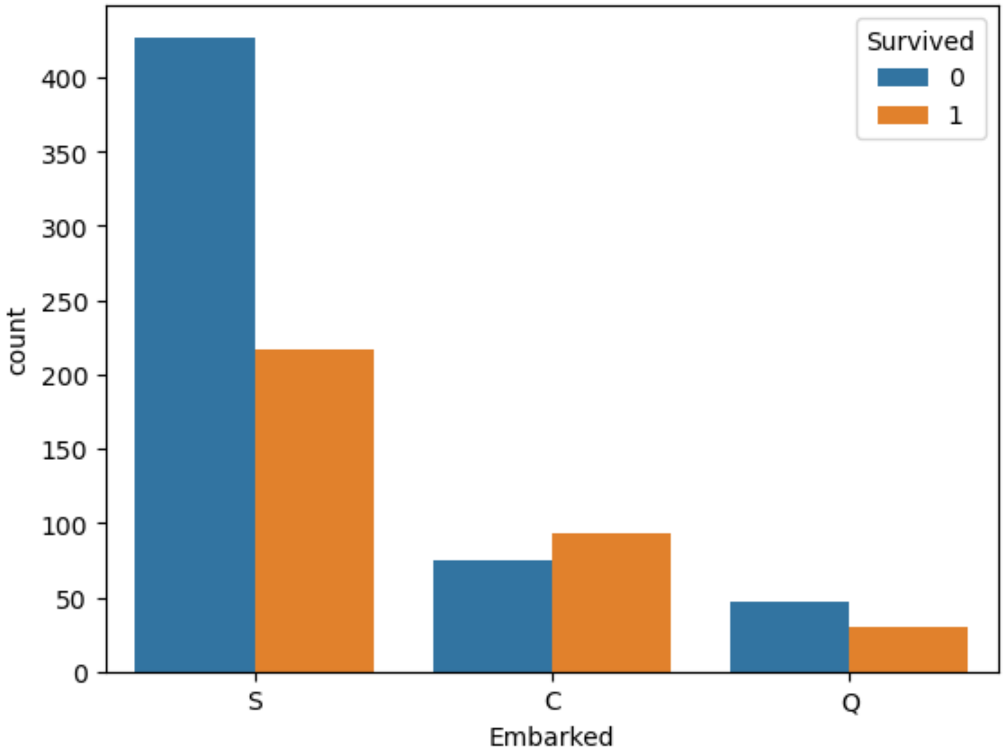
In [18]:
```
sns.countplot(data=data1, x='Parch', hue='Survived')
```

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



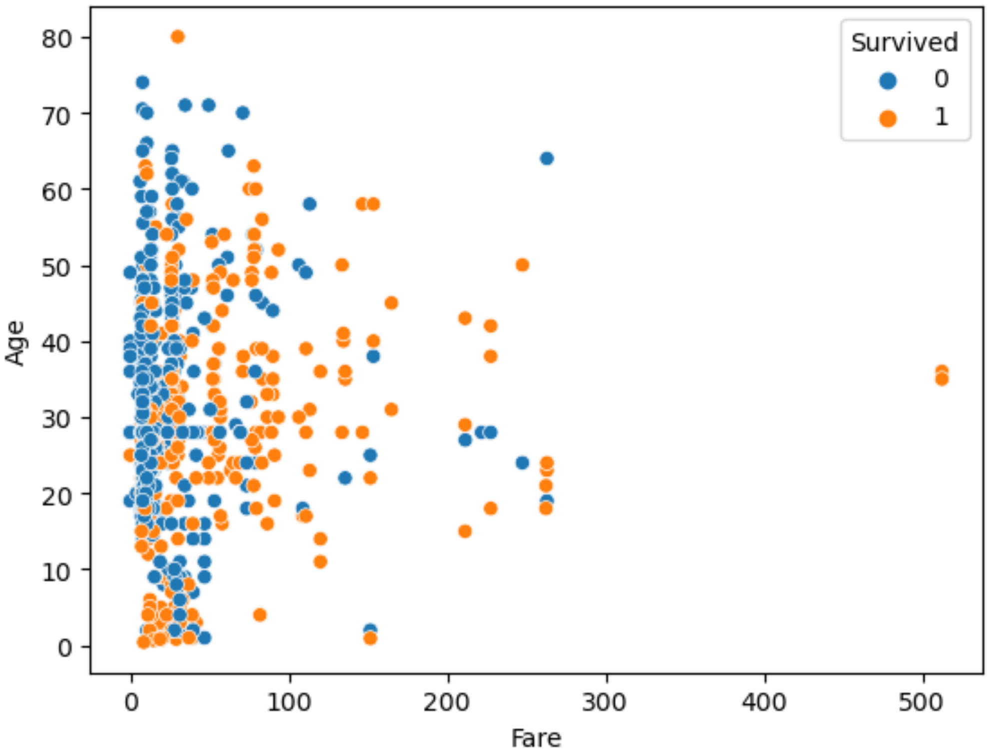
In [19]:
```
sns.countplot(data=data1, x='Embarked', hue='Survived')
```

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



In [20]:
```
sns.scatterplot(data=data1, x='Fare', y='Age',hue='Survived')
```

Out[20]: <AxesSubplot:xlabel='Fare', ylabel='Age'>



In [21]:
```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  889 non-null    int64
 1   Pclass    889 non-null    int64
 2   Sex       889 non-null    object
 3   Age       889 non-null    float64
 4   SibSp     889 non-null    int64
 5   Parch     889 non-null    int64
 6   Fare      889 non-null    float64
 7   Embarked  889 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 62.5+ KB
```

In [22]:
```
data1['Sex'].replace({'male':1, 'female':0}, inplace=True)
```

In [23]:
```
data1['Embarked'].unique()
```

Out[23]:
```
array(['S', 'C', 'Q'], dtype=object)
```

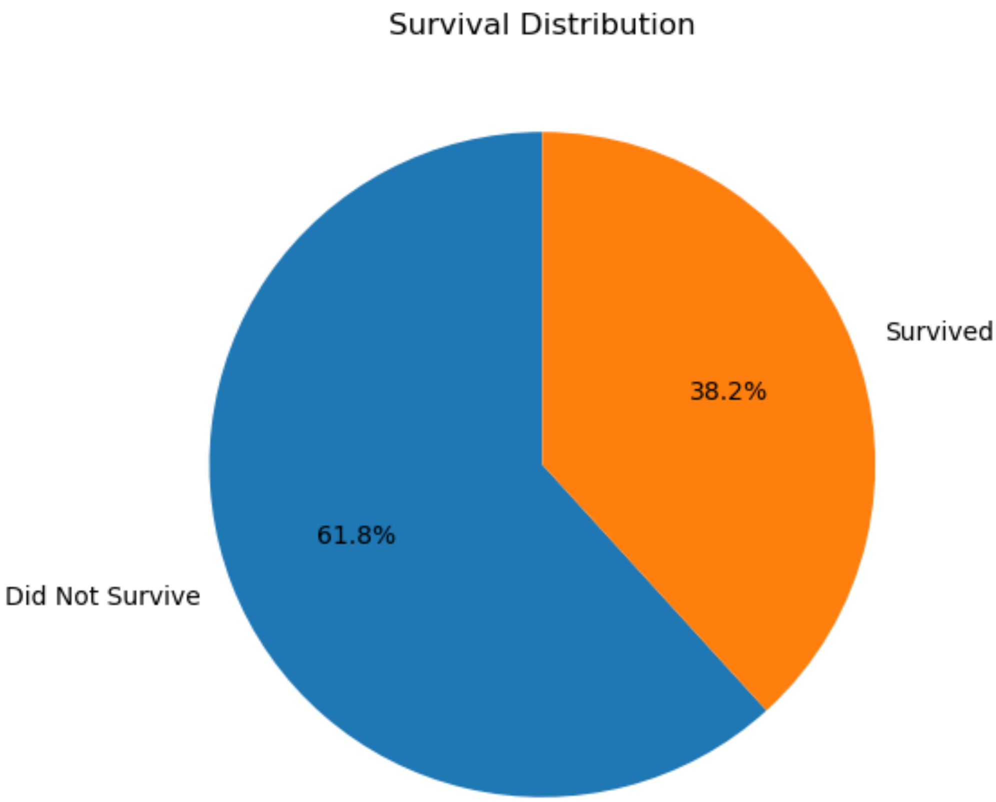
In [24]:
```
data1 = pd.get_dummies(data1, columns=['Embarked'], prefix=['Embarked'])
```

In [25]:
```
data1.corr()
```

Out[25]:

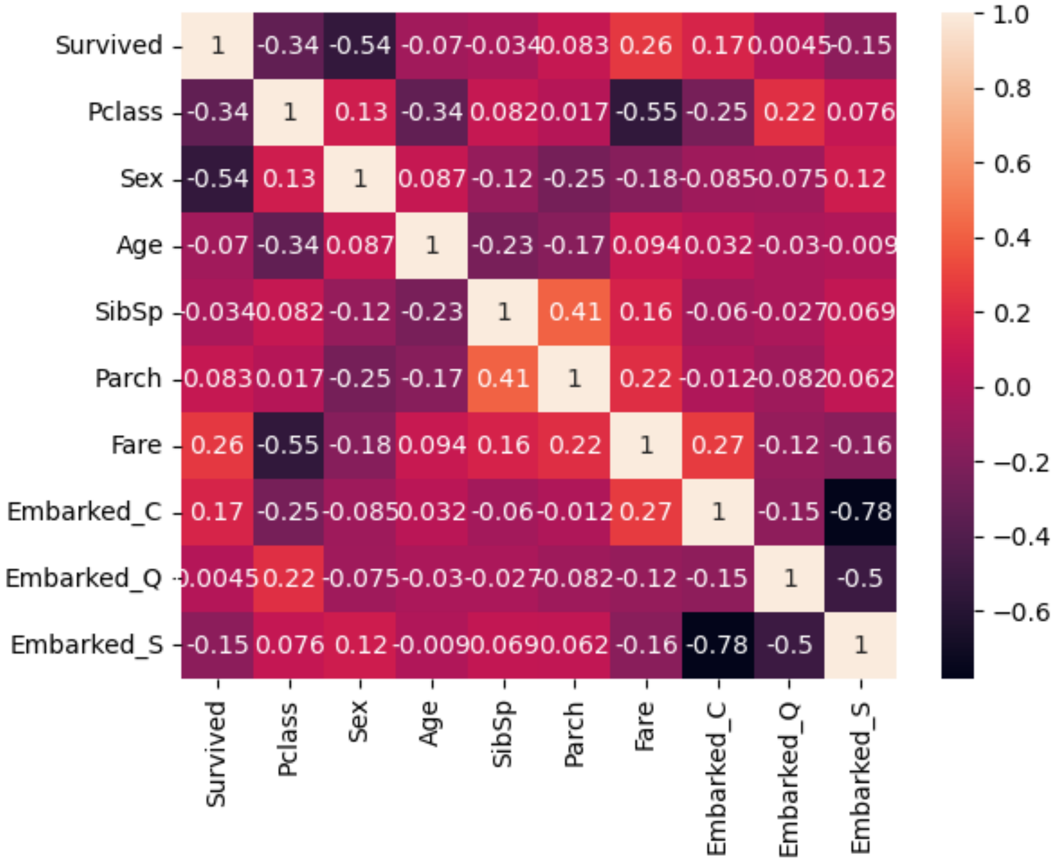
	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_
Survived	1.000000	-0.335549	-0.541585	-0.069822	-0.034040	0.083151	0.255290	0.169966	0.004536	-0.1517
Pclass	-0.335549	1.000000	0.127741	-0.336512	0.081656	0.016824	-0.548193	-0.245733	0.220558	0.0764
Sex	-0.541585	0.127741	1.000000	0.086506	-0.116348	-0.247508	-0.179958	-0.084520	-0.075217	0.1214
Age	-0.069822	-0.336512	0.086506	1.000000	-0.232543	-0.171485	0.093707	0.032098	-0.030436	-0.0089
SibSp	-0.034040	0.081656	-0.116348	-0.232543	1.000000	0.414542	0.160887	-0.060074	-0.026692	0.0694
Parch	0.083151	0.016824	-0.247508	-0.171485	0.414542	1.000000	0.217532	-0.011588	-0.081585	0.0615
Fare	0.255290	-0.548193	-0.179958	0.093707	0.160887	0.217532	1.000000	0.270731	-0.116684	-0.1637
Embarked_C	0.169966	-0.245733	-0.084520	0.032098	-0.060074	-0.011588	0.270731	1.000000	-0.148646	-0.7826
Embarked_Q	0.004536	0.220558	-0.075217	-0.030436	-0.026692	-0.081585	-0.116684	-0.148646	1.000000	-0.4992
Embarked_S	-0.151777	0.076466	0.121405	-0.008964	0.069438	0.061512	-0.163758	-0.782613	-0.499261	1.0000

In [26]:
```
survived_count = data1['Survived'].value_counts()

plt.figure(figsize=(6, 6))
plt.pie(survived_count, labels=['Did Not Survive', 'Survived'], autopct='%1.1f%%', startangle=90)
plt.title('Survival Distribution')

plt.show()
```



In [27]:
```
sns.heatmap(data1.corr(), annot=True,)
```

Out[27]:
```
<AxesSubplot:>
```



In [28]:
```
data1.head()
```

Out[28]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	0	3	1	22.0	1	0	7.2500	0	0	1
1	1	1	0	38.0	1	0	71.2833	1	0	0
2	1	3	0	26.0	0	0	7.9250	0	0	1
3	1	1	0	35.0	1	0	53.1000	0	0	1
4	0	3	1	35.0	0	0	8.0500	0	0	1

TRAIN TEST SPLIT

In [29]:
```
y=data1['Survived']
```

In [30]:
```
X=data1.drop('Survived', axis=1)
```

In [31]:
```
X.head()
```

Out[31]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	3	1	22.0	1	0	7.2500	0	0	1
1	1	0	38.0	1	0	71.2833	1	0	0
2	3	0	26.0	0	0	7.9250	0	0	1
3	1	0	35.0	1	0	53.1000	0	0	1
4	3	1	35.0	0	0	8.0500	0	0	1

STANDARD SCALER

In [32]:
```
scale=StandardScaler()
```

In [33]:
```
X_scaled =scale.fit_transform(X)
```

In [34]:
```
X=pd.DataFrame(X_scaled)
```

In [35]:
```
X_train, X_test, y_train, y_test=train_test_split(X,y, test_size=0.30, random_state=123)
```

NAIVE BAYES MODEL

In [36]:
```
gnb=GaussianNB()
```

In [37]:
```
gnb.fit(X_train, y_train)
```

Out[37]:
```
▾ GaussianNB
GaussianNB()
```

In [38]:
```
y_pred=gnb.predict(X_test)
```

In [39]:
```
print("Number of mislabeled points out of a total %d points : %d"       % (X_test.shape[0], (y_test != y_p
```

```
Number of mislabeled points out of a total 267 points : 60
```

ACCURECY

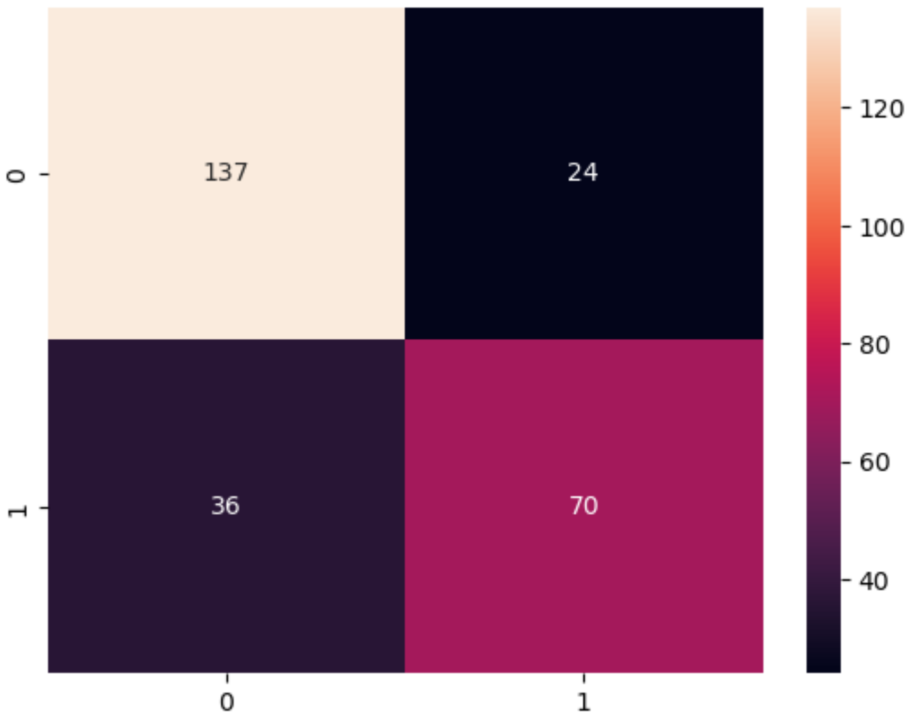
In [40]:
```
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
```

```
Accuracy: 0.7752808988764045
```

In [41]:
```
confusion=confusion_matrix(y_test, y_pred)
print(confusion)
sns.heatmap(confusion, annot=True, fmt='d')
```

```
[[137  24]
 [ 36  70]]
```

Out[41]:
```
<AxesSubplot:>
```



In [42]:
```
classification=classification_report(y_test, y_pred)
print("Classification Report")
print(classification)
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.79      0.85      0.82       161
           1       0.74      0.66      0.70       106

    accuracy                           0.78       267
   macro avg       0.77      0.76      0.76       267
weighted avg       0.77      0.78      0.77       267
```

DECISION TREE

In [43]:
```
data1.head()
```

Out[43]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	0	3	1	22.0	1	0	7.2500	0	0	1
1	1	1	0	38.0	1	0	71.2833	1	0	0
2	1	3	0	26.0	0	0	7.9250	0	0	1
3	1	1	0	35.0	1	0	53.1000	0	0	1
4	0	3	1	35.0	0	0	8.0500	0	0	1

In [44]:
```
selected_col=['Survived', 'Pclass','Sex','Age','SibSp', 'Parch', 'Fare']
```

In [45]:
```
df=data1[selected_col]
```

In [46]:
```
df.head()
```

Out[46]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	1	22.0	1	0	7.2500
1	1	1	0	38.0	1	0	71.2833
2	1	3	0	26.0	0	0	7.9250
3	1	1	0	35.0	1	0	53.1000
4	0	3	1	35.0	0	0	8.0500

In [47]:
```
y=df['Survived']
```

In [48]:
```
X=df.drop('Survived', axis=1)
```

In [49]:
```
scaler=StandardScaler()
```

In [50]:
```
X_df=scaler.fit_transform(X)
```

In [51]:
```
X=pd.DataFrame(X_df)
```

In [52]:
```
X
```

Out[52]:

	0	1	2	3	4	5
0	0.825209	0.735342	-0.563674	0.431350	-0.474326	-0.500240
1	-1.572211	-1.359911	0.669217	0.431350	-0.474326	0.788947
2	0.825209	-1.359911	-0.255451	-0.475199	-0.474326	-0.486650
3	-1.572211	-1.359911	0.438050	0.431350	-0.474326	0.422861
4	0.825209	0.735342	0.438050	-0.475199	-0.474326	-0.484133
...	...	...	...	...	...	...
884	-0.373501	0.735342	-0.178396	-0.475199	-0.474326	-0.384475
885	-1.572211	-1.359911	-0.794841	-0.475199	-0.474326	-0.042213
886	0.825209	-1.359911	-0.101340	0.431350	2.006119	-0.174084
887	-1.572211	0.735342	-0.255451	-0.475199	-0.474326	-0.042213
888	0.825209	0.735342	0.206883	-0.475199	-0.474326	-0.490173

889 rows × 6 columns

In [53]:
```
x_train, x_test,y_train, y_test=train_test_split(X,y, test_size=0.33,random_state=123)
```

In [54]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [55]:
```
model=DecisionTreeClassifier()
```

In [56]:
```
model.fit(x_train,y_train)
```

Out[56]:

▾ DecisionTreeClassifier

DecisionTreeClassifier()

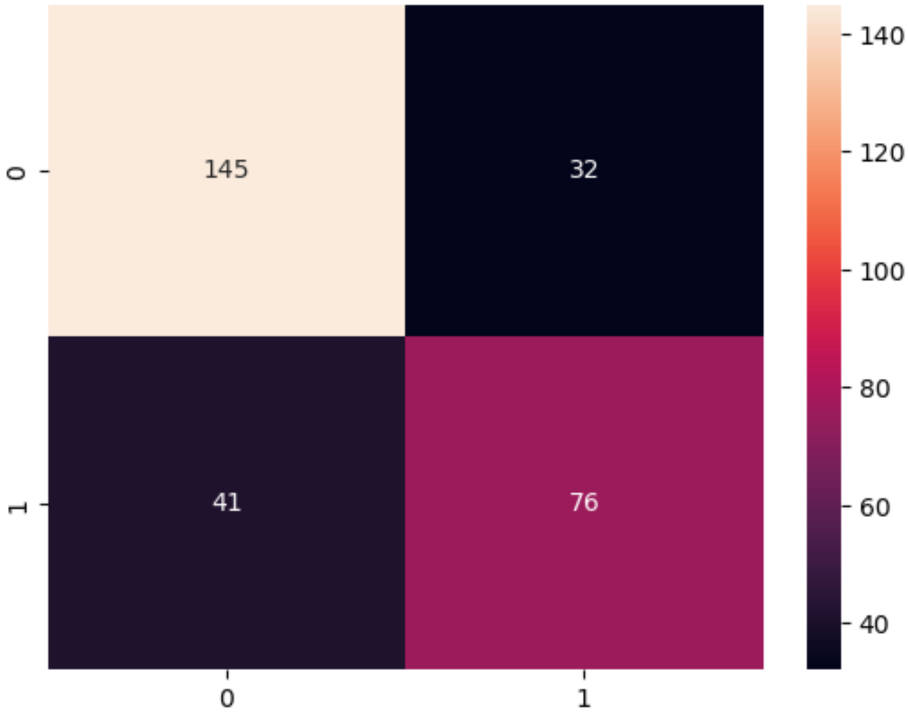
In [57]:
```
y_pred=model.predict(x_test)
```

In [58]:
```
accurecy=accuracy_score(y_test,y_pred)
print(accurecy)
```

```
0.7517006802721088
```

In [59]:
```
confusion=confusion_matrix(y_test,y_pred)
sns.heatmap(confusion, annot=True, fmt='d')
classification=classification_report(y_test, y_pred)
print(classification)
```

```
              precision    recall  f1-score   support

           0       0.78      0.82      0.80       177
           1       0.70      0.65      0.68       117

    accuracy                           0.75       294
   macro avg       0.74      0.73      0.74       294
weighted avg       0.75      0.75      0.75       294
```



RANDOM FOREST

In [60]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [61]:
```
rfc=RandomForestClassifier(n_estimators=100)
```

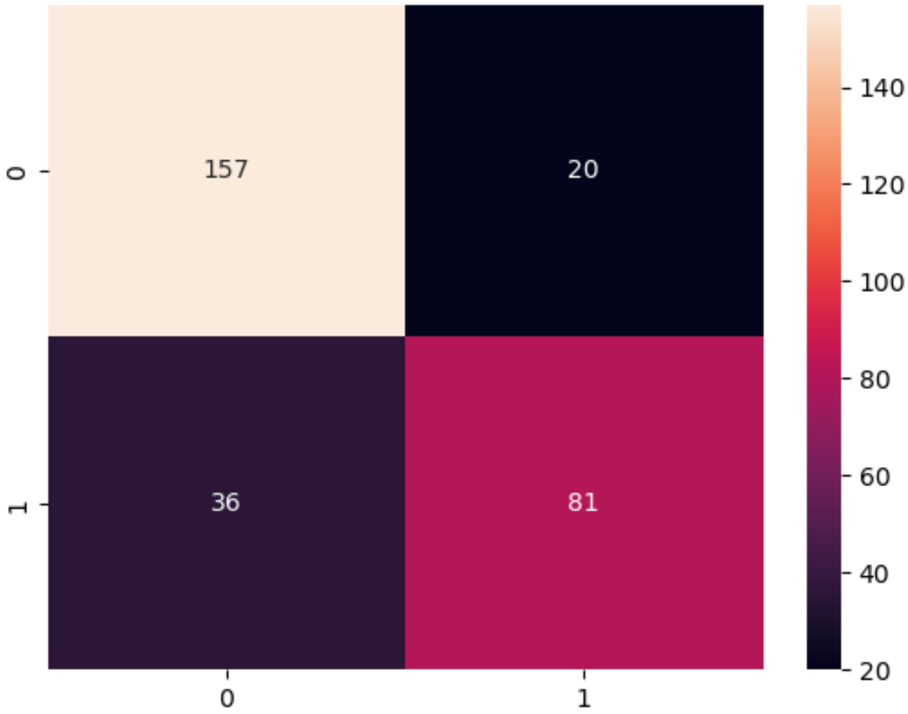
In [62]:
```
rfc.fit(x_train,y_train)
```

Out[62]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [63]:
```
Y_pred=rfc.predict(x_test)
```

In [64]:
```
rfc_acc=accuracy_score(y_test, Y_pred)
print(f"Accurecy: {rfc_acc}")
rfc_report=classification_report(y_test, Y_pred)
print(f"Classification Report for Random Forest Model{rfc_report}")
rfc_conf=confusion_matrix(y_test, Y_pred)
sns.heatmap(rfc_conf, annot=True, fmt='d')
plt.show()
```

```
Accurecy: 0.8095238095238095
Classification Report for Random Forest Model              precision    recall  f1-score   support

           0       0.81      0.89      0.85       177
           1       0.80      0.69      0.74       117

    accuracy                           0.81       294
   macro avg       0.81      0.79      0.80       294
weighted avg       0.81      0.81      0.81       294
```



TEST DATA

In [107…
```
test1=pd.read_csv('data/test.csv')
```

In [108…
```
test1.head()
```

Out[108]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

In [109…
```
test1=test1.drop(['PassengerId','Name','Ticket'], axis=1)
```

In [110…
```
test1.isnull().sum()
```

Out[110]:
```
Pclass        0
Sex           0
Age          86
SibSp         0
Parch         0
Fare          1
Cabin       327
Embarked      0
dtype: int64
```

In [111…
```
test1=test1.drop(['Cabin'], axis=1)
```

In [112…
```
test1.isnull().sum()
```

Out[112]:
```
Pclass       0
Sex          0
Age         86
SibSp        0
Parch        0
Fare         1
Embarked     0
dtype: int64
```

In [113…
```
test1['Age']=test1['Age'].fillna(test1['Age'].median())
```

In [114…
```
test1.isnull().sum()
```
Out[114]:
```
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        1
Embarked    0
dtype: int64
```
In [115…
```
test1['Fare']=test1['Fare'].fillna(test1['Fare'].median())
```
In [116…
```
test1.isnull().sum()
```
Out[116]:
```
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```
In [117…
```
test1.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    418 non-null    int64  
 1   Sex       418 non-null    object 
 2   Age       418 non-null    float64
 3   SibSp     418 non-null    int64  
 4   Parch     418 non-null    int64  
 5   Fare      418 non-null    float64
 6   Embarked  418 non-null    object 
dtypes: float64(2), int64(3), object(2)
memory usage: 23.0+ KB
```
In [128…
```
test_dummy=pd.get_dummies(test1,columns=(['Embarked']))
test_dummy
```
Out[128]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	3	1	34.5	0	0	7.8292	0	1	0
1	3	0	47.0	1	0	7.0000	0	0	1
2	2	1	62.0	0	0	9.6875	0	1	0
3	3	1	27.0	0	0	8.6625	0	0	1
4	3	0	22.0	1	1	12.2875	0	0	1
...	...	...	...	...	...	...	...	...	...
413	3	1	27.0	0	0	8.0500	0	0	1
414	1	0	39.0	0	0	108.9000	1	0	0
415	3	1	38.5	0	0	7.2500	0	0	1
416	3	1	27.0	0	0	8.0500	0	0	1
417	3	1	27.0	1	1	22.3583	1	0	0

418 rows × 9 columns

In [126…
```
test1['Sex']=test1['Sex'].replace({'male':1,'female':0})
```
Standarad Scaler

In [129…
```
test_scale=StandardScaler()
```

In [130…
```
test_scaler=test_scale.fit_transform(test_dummy)
```

In [131…
```
x_test=pd.DataFrame(test_scaler)
```

In [132…
```
xtest_pred=gnb.predict(x_test)
```

Gender_submmission

In [134…
```
submission=pd.read_csv('data/gender_submission.csv')
```

In [135…
```
submission
```

Out[135]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	0

418 rows × 2 columns

In [137…
```
test_accu=accuracy_score(submission['Survived'], xtest_pred)
print(f'Test Accurecy Score :{test_accu}')
```

```
Test Accurecy Score :0.8373205741626795
```

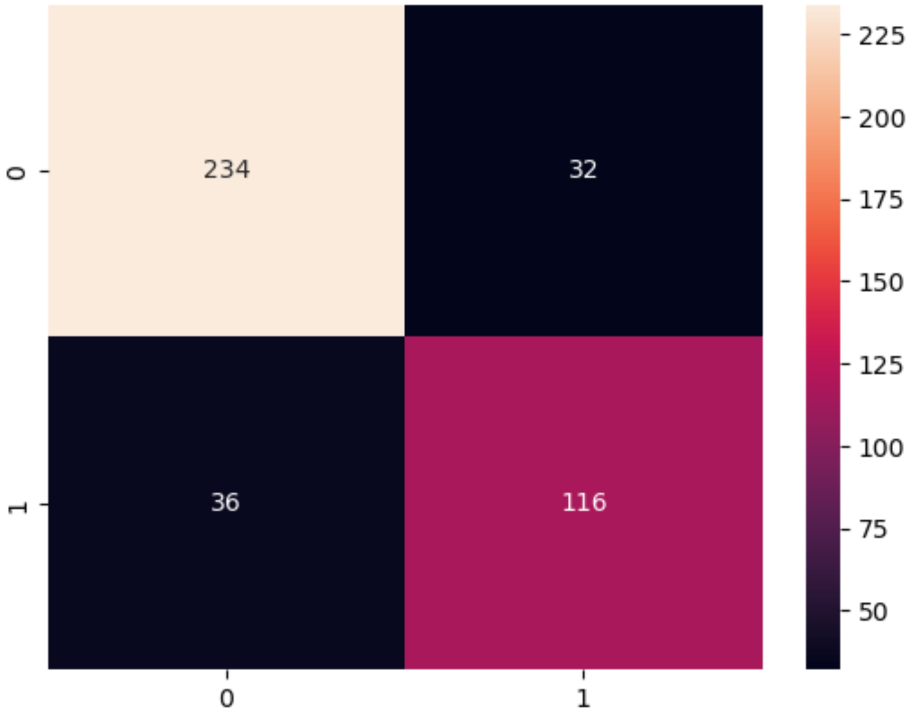
In [140…
```
test_reports=classification_report(submission['Survived'], xtest_pred)
print(f'Classification Reports : {test_reports}')
```

```
Classification Reports :                precision    recall  f1-score   support

           0       0.87      0.88      0.87       266
           1       0.78      0.76      0.77       152

    accuracy                           0.84       418
   macro avg       0.83      0.82      0.82       418
weighted avg       0.84      0.84      0.84       418
```

In [142…
```
test_conf=confusion_matrix(submission['Survived'], xtest_pred)
print(f"Confusion Metrics : {test_conf}")
sns.heatmap(test_conf, annot= True, fmt='d')
```

```
Confusion Metrics : [[234  32]
 [ 36 116]]
```

Out[142]:
```
<AxesSubplot:>
```



234
32
36
116
0
1
0
1
225
200
175
150
125
100
75
50