In [1]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

from sklearn.naive_bayes import GaussianNB
```

In [2]:
```
data=pd.read_csv(r"C:\Users\DELL\Downloads\train.csv")
```

In [3]:
```
data.shape
```

Out[3]:
```
(891, 12)
```

In [4]:
```
data.head()
```

Out[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
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 [5]:
```
data.describe()
```

Out[5]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	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	14.526497	1.102743	0.806057	49.693429

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [6]:
```
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 [7]:
```
data[data.duplicated()]
```

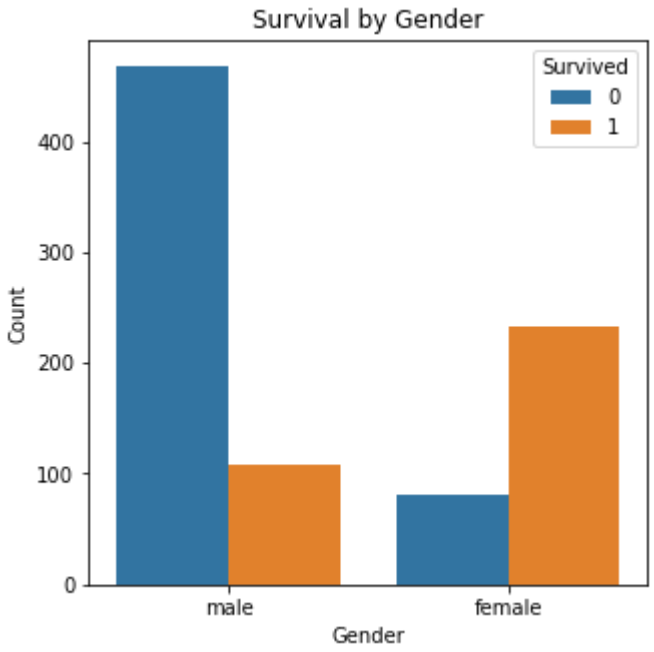
Out[7]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked

In [8]:
```
data.dtypes
```

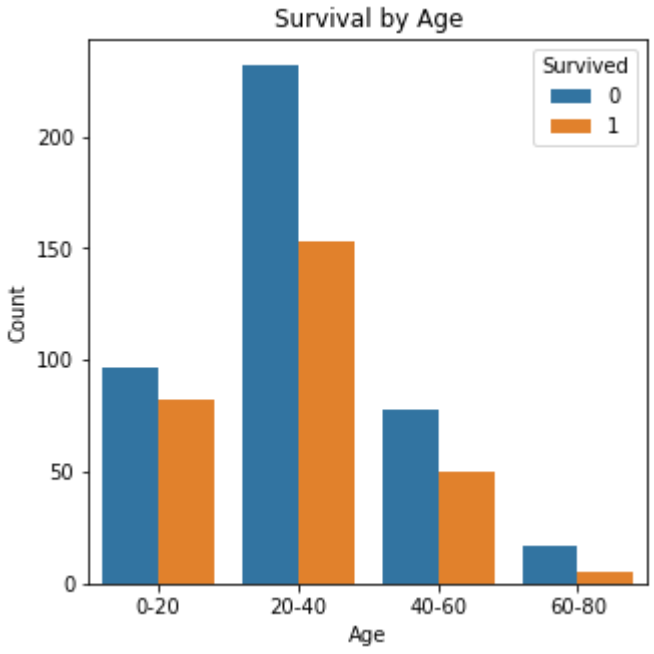
Out[8]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [9]:
```
plt.figure(figsize=(5,5))
sns.countplot(x='Sex',hue='Survived',data=data)
plt.title("Survival by Gender")
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



In [10]:
```
#Females are mostly survived than mens

data['Age_group']=pd.cut(data.Age,bins=[0,20,40,60,80],right=True,labels=['0-20','20
```

In [11]:
```
plt.figure(figsize=(5,5))
sns.countplot(x='Age_group',hue='Survived',data=data)
plt.title("Survival by Age")
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



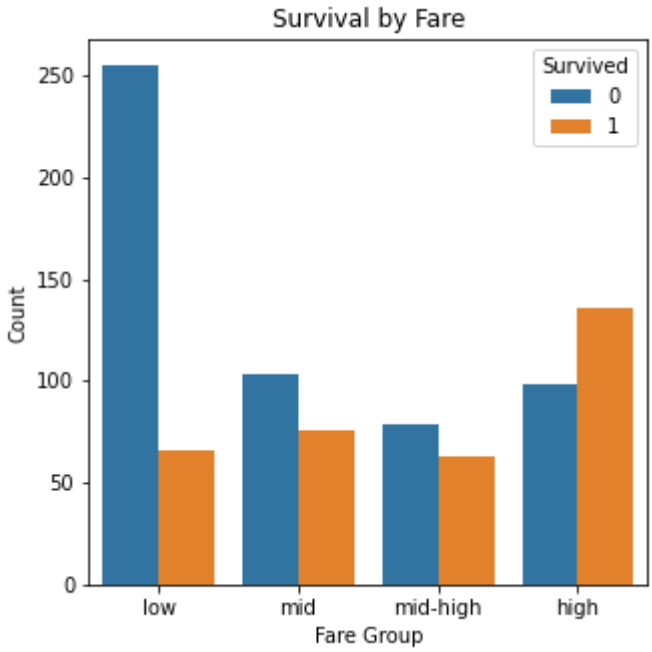
In [12]:
```
#Most of the passengers belongs to the 20-40 Age group. Survival rate of 20-40 is hi

data['Fare'].describe()
```

Out[12]:
```
count    891.000000
mean      32.204208
```

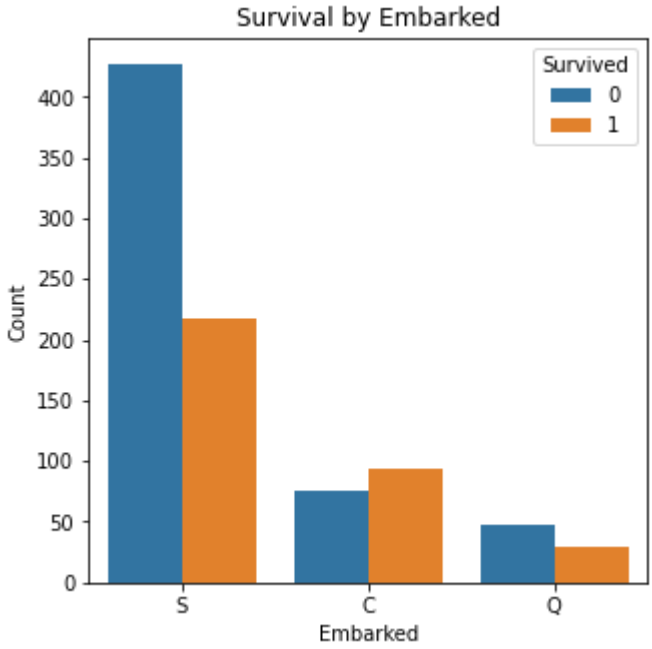
```
std       49.693429
min        0.000000
25%        7.910400
50%       14.454200
75%       31.000000
max      512.329200
Name: Fare, dtype: float64
```

In [13]:
```
data['Fare_group']=pd.cut(data.Fare,bins=[0,10,20,30,513],right=True,labels=['low','
```

In [14]:
```
plt.figure(figsize=(5,5))
sns.countplot(x='Fare_group',hue='Survived',data=data)
plt.title('Survival by Fare')
plt.xlabel('Fare Group')
plt.ylabel('Count')
plt.show()
```



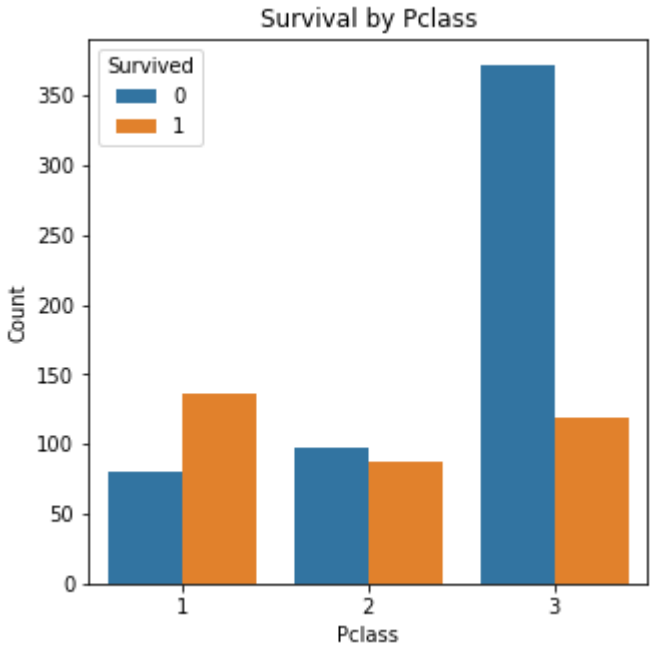
In [15]:
```
#Passengers belong to the High_class have the high survival count

plt.figure(figsize=(5,5))
sns.countplot(x='Embarked',hue='Survived',data=data)
plt.title('Survival by Embarked')
plt.xlabel('Embarked')
plt.ylabel('Count')
plt.show()
```



In [16]:
```
data.Pclass.unique()
```

Out[16]:
```
array([3, 1, 2], dtype=int64)
```

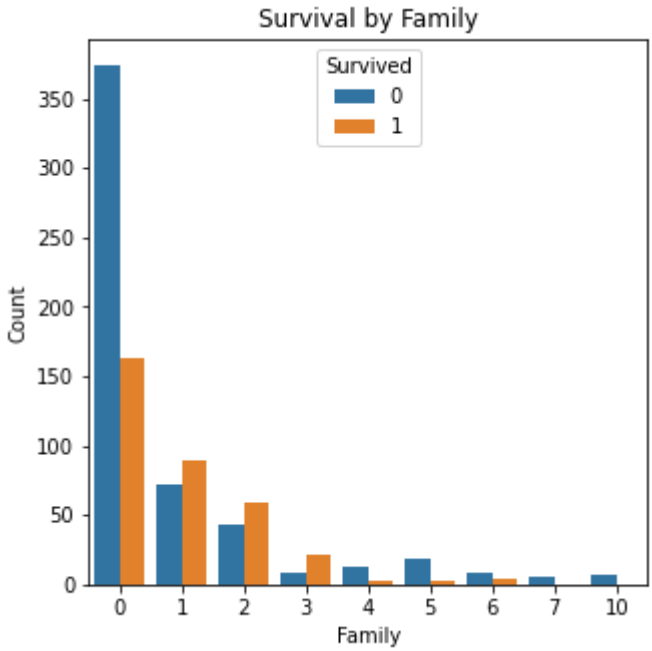
In [17]:
```
plt.figure(figsize=(5,5))
sns.countplot(x='Pclass',hue='Survived',data=data)
plt.title('Survival by Pclass')
plt.xlabel('Pclass')
plt.ylabel('Count')
plt.show()
```



In [18]:
```
#Passengers in 1st class have high survival count than 2nd class and 3rd class

data['Family']=data['Parch']+data['SibSp']
```

In [19]:
```
data['Family']=data['Family'].astype('object')
```

In [20]:
```
plt.figure(figsize=(5,5))
sns.countplot(x='Family',hue='Survived',data=data)
plt.title('Survival by Family')
plt.xlabel('Family')
plt.ylabel('Count')
plt.show()
```



In [21]:
```
#Passengers who are alone has high survival count

data.head()
```

Out[21]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
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 [22]:
```
data.drop(['Name','Ticket','Age_group','Fare_group','Family','PassengerId'],axis=1,i
```

In [23]:
```
data.head()
```

Out[23]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	0	3	male	22.0	1	0	7.2500	NaN	S
1	1	1	female	38.0	1	0	71.2833	C85	C
2	1	3	female	26.0	0	0	7.9250	NaN	S
3	1	1	female	35.0	1	0	53.1000	C123	S
4	0	3	male	35.0	0	0	8.0500	NaN	S

In [24]:
```
#Data Preprocessing

x=data.drop(['Survived'],axis=1)
y=data['Survived']
```

In [25]:
```
#Train Test Split

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.25,random_state=123)
```

In [26]:
```
xtrain.shape,xtest.shape
```

Out[26]:
```
((668, 8), (223, 8))
```

In [27]:
```
ytrain.shape,ytest.shape
```

Out[27]:
```
((668,), (223,))
```

In [28]:
```
#Missing values handling

xtrain.isnull().sum()
```

Out[28]:
```
Pclass        0
Sex           0
Age         139
SibSp         0
Parch         0
Fare          0
Cabin       522
Embarked      2
dtype: int64
```

In [29]:
```
xtrain.drop('Cabin',axis=1,inplace=True)
```

In [30]:
```
xtrain['Age'].fillna(xtrain['Age'].median(),inplace=True)
```

In [31]:
```
xtrain['Embarked'].value_counts()
```

Out[31]:
```
S    488
C    118
Q     60
Name: Embarked, dtype: int64
```

In [32]:
```
xtrain['Embarked'].fillna('Q',inplace=True)
```

In [33]:
```
xtest.isnull().sum()
```

Out[33]:
```
Pclass        0
Sex           0
Age          38
SibSp         0
Parch         0
Fare          0
Cabin       165
Embarked      0
dtype: int64
```

In [34]:
```
xtest.drop('Cabin',axis=1,inplace=True)
```

In [35]:
```
xtest['Age'].fillna(xtest['Age'].mean(),inplace=True)
```

In [36]:
```
#Label Encoding

xtrain['Sex']=xtrain['Sex'].replace({'male':1,'female':0})
```

In [37]:
```
xtest['Sex']=xtest['Sex'].replace({'male':1,'female':0})
```

In [38]:
```
xtrain=xtrain.reset_index(drop=True)
xtest=xtest.reset_index(drop=True)
ytrain=ytrain.reset_index(drop=True)
ytest=ytest.reset_index(drop=True)
```

In [39]:
```
#OneHotEncoding

from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown='ignore', sparse=True)
```

In [40]:
```
ohedata_train = ohe.fit_transform(xtrain[['Embarked']]).toarray()
ohedata_test = ohe.transform(xtest[['Embarked']]).toarray()
```

In [41]:
```
pip install -U scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\dell\anaconda3\lib\site-pack
ages (1.3.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\dell\anaconda3\lib\site-pac
kages (from scikit-learn) (1.22.4)
```

```
Requirement already satisfied: joblib>=1.1.1 in c:\users\dell\anaconda3\lib\site-pac
kages (from scikit-learn) (1.3.2)
Requirement already satisfied: scipy>=1.5.0 in c:\users\dell\anaconda3\lib\site-pack
ages (from scikit-learn) (1.7.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dell\anaconda3\lib\s
ite-packages (from scikit-learn) (2.2.0)
Note: you may need to restart the kernel to use updated packages.
```

In [42]:
```
ohedata_train = pd.DataFrame(ohedata_train, columns = ohe.get_feature_names_out())
ohedata_test = pd.DataFrame(ohedata_test, columns = ohe.get_feature_names_out())
```

In [43]:
```
xtrain=pd.concat([ohedata_train,xtrain],axis=1)
xtest=pd.concat([ohedata_test,xtest],axis=1)
```

In [44]:
```
xtrain.drop(['Embarked'],axis=1,inplace=True)
xtest.drop(['Embarked'],axis=1,inplace=True)
```

In [45]:
```
xtrain['Age']=xtrain['Age'].astype(int)
xtest['Age']=xtest['Age'].astype(int)
```

In [46]:
```
#Scaling

from sklearn.preprocessing import StandardScaler
```

In [47]:
```
sc=StandardScaler()
xtrain.iloc[:,[-1]]=sc.fit_transform(xtrain.iloc[:,[-1]])
xtest.iloc[:,[-1]]=sc.transform(xtest.iloc[:,[-1]])
```

In [48]:
```
#Model Defining

nb = GaussianNB()
```

In [49]:
```
#Model Fitting

nb.fit(xtrain, ytrain)
```

Out[49]:
```
▾ GaussianNB
GaussianNB()
```

In [50]:
```
#Predicting Values

ypred=nb.predict(xtest)
```

In [53]:
```
pip install --upgrade scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\dell\anaconda3\lib\site-pack
ages (1.3.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\dell\anaconda3\lib\site-pac
kages (from scikit-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dell\anaconda3\lib\s
```

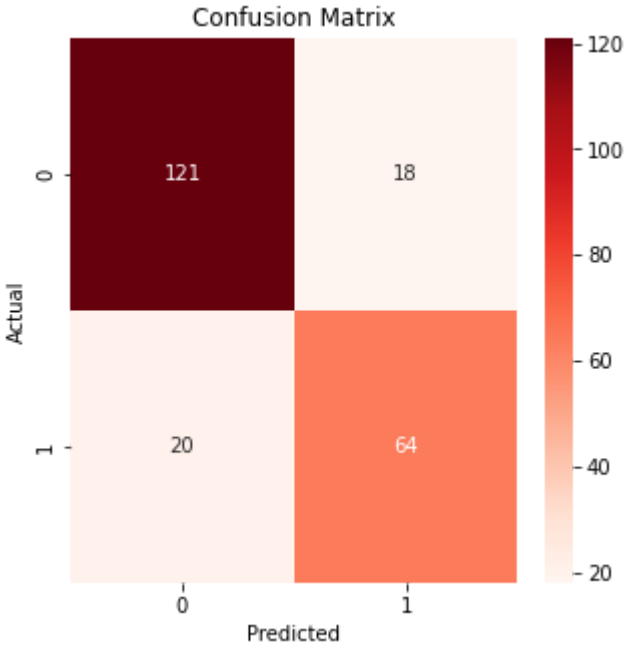
```
ite-packages (from scikit-learn) (2.2.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\dell\anaconda3\lib\site-pac
kages (from scikit-learn) (1.22.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\dell\anaconda3\lib\site-pack
ages (from scikit-learn) (1.7.1)
Note: you may need to restart the kernel to use updated packages.
```

In [55]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import  ConfusionMatrixDisplay, roc_curve, auc
from sklearn.model_selection import cross_val_score
```

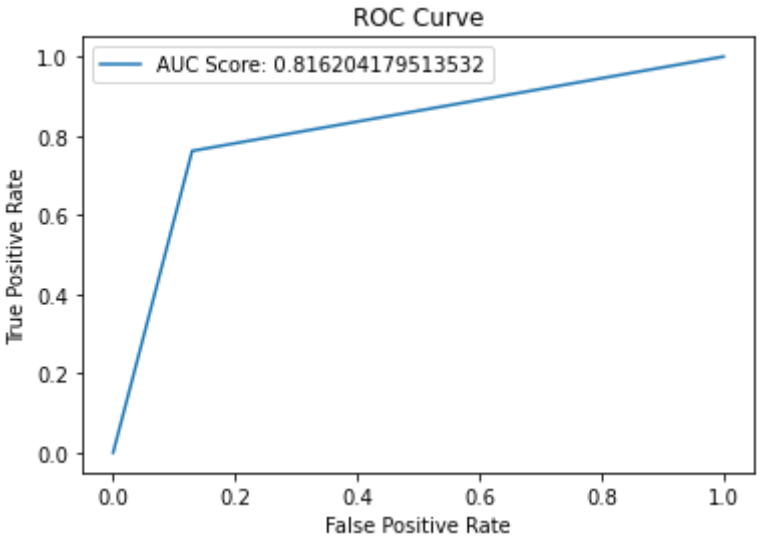
In [56]:
```
accuracy=accuracy_score(ytest,ypred)
print(f"accuracy:{accuracy:2f}")
```

```
accuracy:0.829596
```

In [57]:
```
conf_matrix=confusion_matrix(ytest,ypred)
plt.figure(figsize=(5,5))
sns.heatmap(conf_matrix,annot=True,fmt='d',cmap='Reds')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title("Confusion Matrix")
plt.show()
```



In [58]:
```
#Roc Curve

fpr, tpr, threshold = roc_curve(ytest, ypred)
auc_score = auc(fpr, tpr)
auc_str = "AUC Score: "+ str(auc_score)
plt.plot(fpr,tpr,label=auc_str)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```


ROC Curve
AUC Score: 0.816204179513532
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]: