In [13]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [14]:
```
datanames=sns.get_dataset_names()
print(datanames)
```

```
['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diamonds',
'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp',
'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic', 'anagr
ams', 'anagrams', 'anscombe', 'anscombe', 'attention', 'attention', 'brain_network
s', 'brain_networks', 'car_crashes', 'car_crashes', 'diamonds', 'diamonds', 'dot
s', 'dots', 'dowjones', 'dowjones', 'exercise', 'exercise', 'flights', 'flights',
'fmri', 'fmri', 'geyser', 'geyser', 'glue', 'glue', 'healthexp', 'healthexp', 'iri
s', 'iris', 'mpg', 'mpg', 'penguins', 'penguins', 'planets', 'planets', 'seaice',
'seaice', 'taxis', 'taxis', 'tips', 'tips', 'titanic', 'titanic', 'anagrams', 'ans
combe', 'attention', 'brain_networks', 'car_crashes', 'diamonds', 'dots', 'dowjone
s', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp', 'iris', 'mpg',
'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic']
```

In [15]:
```
df=sns.load_dataset("titanic")
df
```

Out[15]:

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

891 rows × 15 columns

In [16]:
```
df=df.drop('alone',axis=1)
df
```

Out[16]:

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

891 rows × 14 columns

In [17]:

```
df['alive'].replace(['no','yes'],[0,1],inplace=True)
df
```

Out[17]:

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

891 rows × 14 columns

In [20]:

```
from sklearn import preprocessing
enc = preprocessing.OneHotEncoder()
enc_df = pd.DataFrame(enc.fit_transform(df[['sex']]).toarray())
enc_df
```

Out[20]:

	0	1
0	0.0	1.0
1	1.0	0.0
2	1.0	0.0
3	1.0	0.0
4	0.0	1.0
...	...	...
886	0.0	1.0
887	1.0	0.0
888	1.0	0.0
889	0.0	1.0
890	0.0	1.0

891 rows × 2 columns

In [21]:
```
df.head()
```

Out[21]:

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

In [22]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 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    int64
dtypes: bool(1), category(2), float64(2), int64(5), object(4)
memory usage: 79.8+ KB
```

In [23]:
```
df.describe()
```

Out[23]:

	survived	pclass	age	sibsp	parch	fare	alive
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208	0.383838
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429	0.486592
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400	0.000000
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200	0.000000
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000	1.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200	1.000000

In [24]:
```
df["sex"].value_counts(normalize=True)
```

Out[24]:
```
sex
male      0.647587
female    0.352413
Name: proportion, dtype: float64
```

In [25]:
```
df["deck"].value_counts(normalize=True)
```

Out[25]:
```
deck
C    0.290640
B    0.231527
D    0.162562
E    0.157635
A    0.073892
F    0.064039
G    0.019704
Name: proportion, dtype: float64
```

In [29]:
```
df1=df.drop(["embarked","class","who","deck","adult_male","embark_town"],axis=1)
```

In [30]:
```
df1
```

Out[30]:

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

891 rows × 8 columns

In [31]:
```
df1['sex'].mode()[0]
```
Out[31]:
```
'male'
```

In [32]:
```
df1['age'].mode()
```
Out[32]:
```
0    24.0
Name: age, dtype: float64
```

In [33]:
```
df1['age'].mean()
```
Out[33]:
```
29.69911764705882
```

In [34]:
```
df1.loc[:,"sex"].mode()
```
Out[34]:
```
0    male
Name: sex, dtype: object
```

In [35]:
```
df1.min()
```
Out[35]:
```
survived         0
pclass           1
sex         female
age           0.42
sibsp            0
parch            0
fare           0.0
alive            0
dtype: object
```

In [36]:
```
boll_series = pd.notnull(df1["sex"])
df1
```

Out[36]:

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

891 rows × 8 columns

In [37]:

```
df1.fillna(df1['age'].mean(),inplace=True)
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 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       891 non-null    float64
 4   sibsp     891 non-null    int64  
 5   parch     891 non-null    int64  
 6   fare      891 non-null    float64
 7   alive     891 non-null    int64  
dtypes: float64(2), int64(5), object(1)
memory usage: 55.8+ KB
```

In [38]:

```
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
label_encoder = preprocessing.LabelEncoder()
```

In [39]:

```
df1['sex']=label_encoder.fit_transform(df1['sex'])
df1['sex'].unique()
```

Out[39]:

```
array([1, 0])
```

In [40]:

```
df1
```

Out[40]:

	survived	pclass	sex	age	sibsp	parch	fare	alive
0	0	3	1	22.000000	1	0	7.2500	0
1	1	1	0	38.000000	1	0	71.2833	1
2	1	3	0	26.000000	0	0	7.9250	1
3	1	1	0	35.000000	1	0	53.1000	1
4	0	3	1	35.000000	0	0	8.0500	0
...	...	...	...	...	...	...	...	...
886	0	2	1	27.000000	0	0	13.0000	0
887	1	1	0	19.000000	0	0	30.0000	1
888	0	3	0	29.699118	1	2	23.4500	0
889	1	1	1	26.000000	0	0	30.0000	1
890	0	3	1	32.000000	0	0	7.7500	0

891 rows × 8 columns

In [41]:
```
df1['alive']=label_encoder.fit_transform(df1['alive'])
df1['alive'].unique()
```

Out[41]:
```
array([0, 1], dtype=int64)
```

In [42]:
```
df1
```

Out[42]:

	survived	pclass	sex	age	sibsp	parch	fare	alive
0	0	3	1	22.000000	1	0	7.2500	0
1	1	1	0	38.000000	1	0	71.2833	1
2	1	3	0	26.000000	0	0	7.9250	1
3	1	1	0	35.000000	1	0	53.1000	1
4	0	3	1	35.000000	0	0	8.0500	0
...	...	...	...	...	...	...	...	...
886	0	2	1	27.000000	0	0	13.0000	0
887	1	1	0	19.000000	0	0	30.0000	1
888	0	3	0	29.699118	1	2	23.4500	0
889	1	1	1	26.000000	0	0	30.0000	1
890	0	3	1	32.000000	0	0	7.7500	0

891 rows × 8 columns

In [43]:
```
x=df1.drop(['alive'],axis=1)
```

In [44]:
```
y=df1['alive']
```

In [45]:
```
x
```

Out[45]:

	survived	pclass	sex	age	sibsp	parch	fare
0	0	3	1	22.000000	1	0	7.2500
1	1	1	0	38.000000	1	0	71.2833
2	1	3	0	26.000000	0	0	7.9250
3	1	1	0	35.000000	1	0	53.1000
4	0	3	1	35.000000	0	0	8.0500
...	...	...	...	...	...	...	...
886	0	2	1	27.000000	0	0	13.0000
887	1	1	0	19.000000	0	0	30.0000
888	0	3	0	29.699118	1	2	23.4500
889	1	1	1	26.000000	0	0	30.0000
890	0	3	1	32.000000	0	0	7.7500

891 rows × 7 columns

In [46]:

```
y
```

Out[46]:

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

In [47]:

```
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(x,y,test_size=0.2,random_state=1)
train_x
```

Out[47]:

	survived	pclass	sex	age	sibsp	parch	fare
301	1	3	1	29.699118	2	0	23.2500
309	1	1	0	30.000000	0	0	56.9292
516	1	2	0	34.000000	0	0	10.5000
120	0	2	1	21.000000	2	0	73.5000
570	1	2	1	62.000000	0	0	10.5000
...	...	...	...	...	...	...	...
715	0	3	1	19.000000	0	0	7.6500
767	0	3	0	30.500000	0	0	7.7500
72	0	2	1	21.000000	0	0	73.5000
235	0	3	0	29.699118	0	0	7.5500
37	0	3	1	21.000000	0	0	8.0500

712 rows × 7 columns

In [48]:

```
train_y
```

Out[48]:

```
301    1
309    1
516    1
120    0
570    1
      ..
715    0
767    0
72     0
235    0
37     0
Name: alive, Length: 712, dtype: int64
```

In [49]:

```
test_x
```

Out[49]:

	survived	pclass	sex	age	sibsp	parch	fare
862	1	1	0	48.000000	0	0	25.9292
223	0	3	1	29.699118	0	0	7.8958
84	1	2	0	17.000000	0	0	10.5000
680	0	3	0	29.699118	0	0	8.1375
535	1	2	0	7.000000	0	2	26.2500
...	...	...	...	...	...	...	...
796	1	1	0	49.000000	0	0	25.9292
815	0	1	1	29.699118	0	0	0.0000
629	0	3	1	29.699118	0	0	7.7333
421	0	3	1	21.000000	0	0	7.7333
448	1	3	0	5.000000	2	1	19.2583

179 rows × 7 columns

In [50]:

```
test_y
```

Out[50]:

```
862    1
223    0
84     1
680    0
535    1
      ..
796    1
815    0
629    0
421    0
448    1
Name: alive, Length: 179, dtype: int64
```

In [51]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
scaler
```

Out[51]:

```
▾ MinMaxScaler
MinMaxScaler()
```

In [52]:

```
train_x_scaled=scaler.fit_transform(train_x)
train_x_scaled
```

Out[52]:
```
array([[1.        , 1.        , 1.        , ..., 0.25      , 0.        ,
        0.04538098],
       [1.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.1111184 ],
       [1.        , 0.5       , 0.        , ..., 0.        , 0.        ,
        0.02049464],
       ...,
       [0.        , 0.5       , 1.        , ..., 0.        , 0.        ,
        0.14346245],
       [0.        , 1.        , 0.        , ..., 0.        , 0.        ,
        0.01473662],
       [0.        , 1.        , 1.        , ..., 0.        , 0.        ,
        0.01571255]])
```

In [53]:
```
cols=train_x.columns
cols
```

Out[53]:
```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare'], dtype='objec
t')
```

In [54]:
```
train_x_scaled=scaler.fit_transform(train_x)
train_x_scaled
```

Out[54]:
```
array([[1.        , 1.        , 1.        , ..., 0.25      , 0.        ,
        0.04538098],
       [1.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.1111184 ],
       [1.        , 0.5       , 0.        , ..., 0.        , 0.        ,
        0.02049464],
       ...,
       [0.        , 0.5       , 1.        , ..., 0.        , 0.        ,
        0.14346245],
       [0.        , 1.        , 0.        , ..., 0.        , 0.        ,
        0.01473662],
       [0.        , 1.        , 1.        , ..., 0.        , 0.        ,
        0.01571255]])
```

In [55]:
```
train_x_scaled=pd.DataFrame(train_x_scaled,columns=cols)
train_x_scaled
```

Out[55]:

	survived	pclass	sex	age	sibsp	parch	fare
0	1.0	1.0	1.0	0.367921	0.25	0.0	0.045381
1	1.0	0.0	0.0	0.371701	0.00	0.0	0.111118
2	1.0	0.5	0.0	0.421965	0.00	0.0	0.020495
3	0.0	0.5	1.0	0.258608	0.25	0.0	0.143462
4	1.0	0.5	1.0	0.773813	0.00	0.0	0.020495
...	...	...	...	...	...	...	...
707	0.0	1.0	1.0	0.233476	0.00	0.0	0.014932
708	0.0	1.0	0.0	0.377984	0.00	0.0	0.015127
709	0.0	0.5	1.0	0.258608	0.00	0.0	0.143462
710	0.0	1.0	0.0	0.367921	0.00	0.0	0.014737
711	0.0	1.0	1.0	0.258608	0.00	0.0	0.015713

712 rows × 7 columns

In [56]:
```python
from sklearn.naive_bayes import GaussianNB
```

In [57]:
```python
gnb = GaussianNB()
gnb.fit(train_x,train_y)
```

Out[57]:
```
▾ GaussianNB
GaussianNB()
```

In [58]:
```python
train_predict=gnb.predict(train_x)
test_predict=gnb.predict(test_x)
```

In [59]:
```python
train_predict
```

Out[59]:
```
array([1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1,
       0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0,
       1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [60]:
```python
test_predict
```

Out[60]:
```
array([1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 1], dtype=int64)
```

In [75]:
```python
from mlxtend.plotting import plot_confusion_matrix
```

In [74]:
```
pip install mlxtend
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting mlxtend
  Obtaining dependency information for mlxtend from https://files.pythonhosted.or
g/packages/1c/07/512f6a780239ad6ce06ce2aa7b4067583f5ddcfc7703a964a082c706a070/mlxt
end-0.23.1-py3-none-any.whl.metadata
  Downloading mlxtend-0.23.1-py3-none-any.whl.metadata (7.3 kB)
Requirement already satisfied: scipy>=1.2.1 in c:\programdata\anaconda3\lib\site-p
ackages (from mlxtend) (1.11.1)
Requirement already satisfied: numpy>=1.16.2 in c:\programdata\anaconda3\lib\site-
packages (from mlxtend) (1.24.3)
Requirement already satisfied: pandas>=0.24.2 in c:\programdata\anaconda3\lib\site
-packages (from mlxtend) (2.0.3)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\programdata\anaconda3\lib
\site-packages (from mlxtend) (1.3.0)
Requirement already satisfied: matplotlib>=3.0.0 in c:\programdata\anaconda3\lib\s
ite-packages (from mlxtend) (3.7.2)
Requirement already satisfied: joblib>=0.13.2 in c:\programdata\anaconda3\lib\site
-packages (from mlxtend) (1.2.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\programdata\anaconda3\lib\si
te-packages (from matplotlib>=3.0.0->mlxtend) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3\lib\site-p
ackages (from matplotlib>=3.0.0->mlxtend) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\programdata\anaconda3\lib\s
ite-packages (from matplotlib>=3.0.0->mlxtend) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anaconda3\lib\s
ite-packages (from matplotlib>=3.0.0->mlxtend) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\programdata\anaconda3\lib\sit
e-packages (from matplotlib>=3.0.0->mlxtend) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3\lib\site-
packages (from matplotlib>=3.0.0->mlxtend) (9.4.0)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in c:\programdata\anaconda3\l
ib\site-packages (from matplotlib>=3.0.0->mlxtend) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\programdata\anaconda3\li
b\site-packages (from matplotlib>=3.0.0->mlxtend) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\programdata\anaconda3\lib\site-p
ackages (from pandas>=0.24.2->mlxtend) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\programdata\anaconda3\lib\site
-packages (from pandas>=0.24.2->mlxtend) (2023.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\anaconda3\li
b\site-packages (from scikit-learn>=1.0.2->mlxtend) (2.2.0)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-packa
ges (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.16.0)
Downloading mlxtend-0.23.1-py3-none-any.whl (1.4 MB)
   ---------------------------------------- 0.0/1.4 MB ? eta -:--:--
   ---------------------------------------- 0.0/1.4 MB ? eta -:--:--
   - -------------------------------------- 0.0/1.4 MB 653.6 kB/s eta 0:00:03
   ------------- -------------------------- 0.5/1.4 MB 4.4 MB/s eta 0:00:01
   -------------------------- ------------- 1.0/1.4 MB 7.0 MB/s eta 0:00:01
   ---------------------------------------  1.4/1.4 MB 7.6 MB/s eta 0:00:01
   ---------------------------------------- 1.4/1.4 MB 7.7 MB/s eta 0:00:00
Installing collected packages: mlxtend
Successfully installed mlxtend-0.23.1
Note: you may need to restart the kernel to use updated packages.
```

In [69]:
```
from sklearn.metrics import f1_score,confusion_matrix,roc_auc_score,roc_curve,clas
```

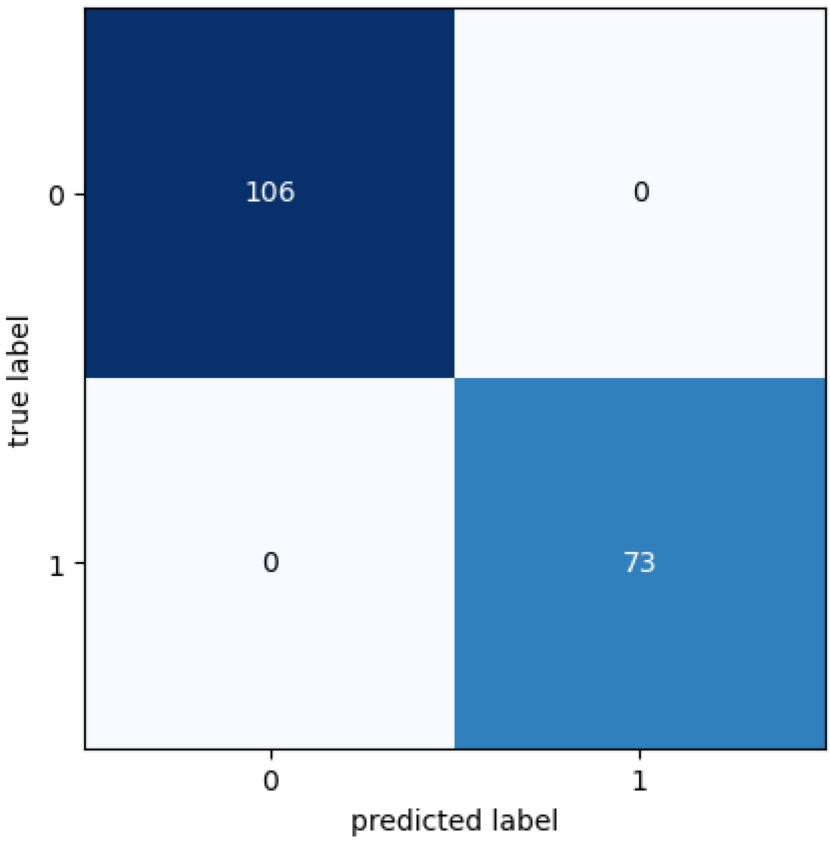
In [70]:
```
accuracy = accuracy_score(test_y,test_predict)
conf_matrix = confusion_matrix(test_y,test_predict)
accuracy
```

Out[70]:
```
1.0
```

In [71]:
```
print("Accuracy:",accuracy)
print("Confusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report(test_y,test_predict))
```

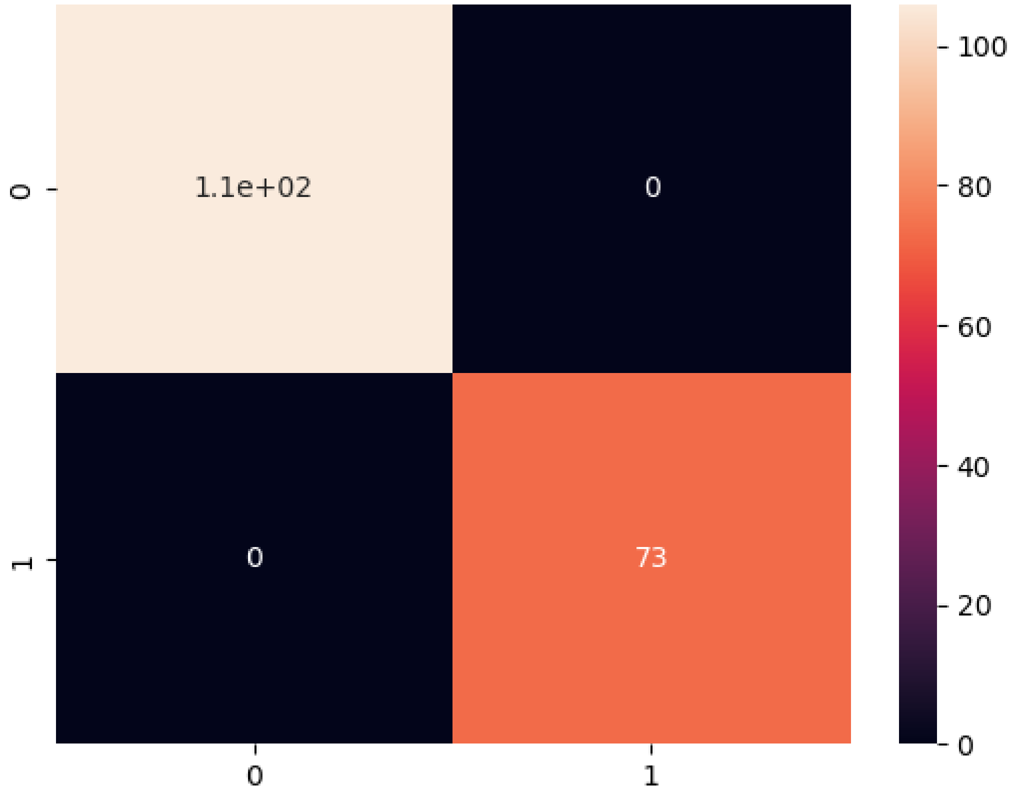
```
Accuracy: 1.0
Confusion Matrix:
[[106   0]
 [  0  73]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       106
           1       1.00      1.00      1.00        73

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

In [76]:
```
fig, ax = plot_confusion_matrix(conf_mat=conf_matrix)
plt.show()
```



In [77]:
```
import seaborn as sns
sns.heatmap(conf_matrix,annot=True)
```

Out[77]: <Axes: >



In [ ]: