W3-ML&DM

October 23, 2021

0.1 Week 3: Machine Learning and Data Mining

[2]:
```
import pandas as pd
import numpy as np
from mlxtend.classifier import OneRClassifier
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from tabulate import tabulate
```

Load Titanic dataset

[3]:
```
pd.set_option('display.max_colwidth',None)
titanic = pd.read_csv('./titanic.csv')
print("Number of samples in original data: {}\n".format(len(titanic.index)))
print("Features present in dataset: \n", titanic.columns)
print(titanic.head(10))
```

```
Number of samples in original data: 887

Features present in dataset:
 Index(['Survived', 'Pclass', 'Name', 'Sex', 'Age', 'Siblings/Spouses Aboard',
       'Parents/Children Aboard', 'Fare'],
      dtype='object')
   Survived  Pclass                                               Name  \
0         0       3                             Mr. Owen Harris Braund
1         1       1  Mrs. John Bradley (Florence Briggs Thayer) Cumings
2         1       3                              Miss. Laina Heikkinen
3         1       1        Mrs. Jacques Heath (Lily May Peel) Futrelle
4         0       3                            Mr. William Henry Allen
5         0       3                                    Mr. James Moran
6         0       1                             Mr. Timothy J McCarthy
7         0       3                      Master. Gosta Leonard Palsson
8         1       3    Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson
9         1       2                  Mrs. Nicholas (Adele Achem) Nasser
```

```
     Sex   Age  Siblings/Spouses Aboard  Parents/Children Aboard     Fare
0    male  22.0                       1                        0   7.2500
1  female  38.0                       1                        0  71.2833
2  female  26.0                       0                        0   7.9250
3  female  35.0                       1                        0  53.1000
4    male  35.0                       0                        0   8.0500
5    male  27.0                       0                        0   8.4583
6    male  54.0                       0                        0  51.8625
7    male   2.0                       3                        1  21.0750
8  female  27.0                       0                        2  11.1333
9  female  14.0                       1                        0  30.0708
```

0.1.1 Problem 1:

Q1. Default rule for the titanic Dataset

Ans. Since most number of the people are not survived i.e., 545 out of 887 as compared to 342 survided. So, naturally, the default rule for this is "not survived."

[15]:
```
survived_in_titanic = titanic.loc[titanic['Survived'] == 1]
not_survived_in_titanic = titanic.loc[titanic['Survived'] == 0]


print("Total number of people            : {}".format(len(titanic)))
print("Total number people survived      : {}\nTotal number people not survived␣
↪ : {} \n"
      .format(len(survived_in_titanic),len(not_survived_in_titanic)))
```

```
Total number of people            : 887
Total number people survived      : 342
Total number people not survived  : 545
```

0.1.2 Q2. Best 1R for Titanic dataset

0.1.3 Best Selected feature based on 1R is Feature 1, Name.

Please find analysis below.

[16]:
```
titanic.describe(include='all')
```

[16]:
```
          Survived      Pclass                        Name   Sex         Age  \
count   887.000000  887.000000                         887   887  887.000000
unique         NaN         NaN                         887     2         NaN
top            NaN         NaN  Mr. Antti Gustaf Leinonen  male         NaN
freq           NaN         NaN                           1   573         NaN
```

```
mean      0.385569    2.305524                          NaN    NaN    29.471443
std       0.487004    0.836662                          NaN    NaN    14.121908
min       0.000000    1.000000                          NaN    NaN     0.420000
25%       0.000000    2.000000                          NaN    NaN    20.250000
50%       0.000000    3.000000                          NaN    NaN    28.000000
75%       1.000000    3.000000                          NaN    NaN    38.000000
max       1.000000    3.000000                          NaN    NaN    80.000000

        Siblings/Spouses Aboard  Parents/Children Aboard       Fare
count                887.000000               887.000000  887.00000
unique                      NaN                      NaN        NaN
top                         NaN                      NaN        NaN
freq                        NaN                      NaN        NaN
mean                   0.525366                 0.383315   32.30542
std                    1.104669                 0.807466   49.78204
min                    0.000000                 0.000000    0.00000
25%                    0.000000                 0.000000    7.92500
50%                    0.000000                 0.000000   14.45420
75%                    1.000000                 0.000000   31.13750
max                    8.000000                 6.000000  512.32920
```

Split dataset into train and test

[21]:
```
le = preprocessing.LabelEncoder()
x_d = titanic[["Pclass","Name","Sex","Age","Siblings/Spouses Aboard","Parents/
 ↪Children Aboard","Fare"]]
y = le.fit(titanic["Survived"])
y = le.transform(titanic["Survived"])

xd_train, xd_test, y_train, y_test = train_test_split(x_d, y, test_size = 0.20)
print("No of training samples: {}".format(len(xd_train)))
print("No of test samples: {}".format(len(xd_test)))
```

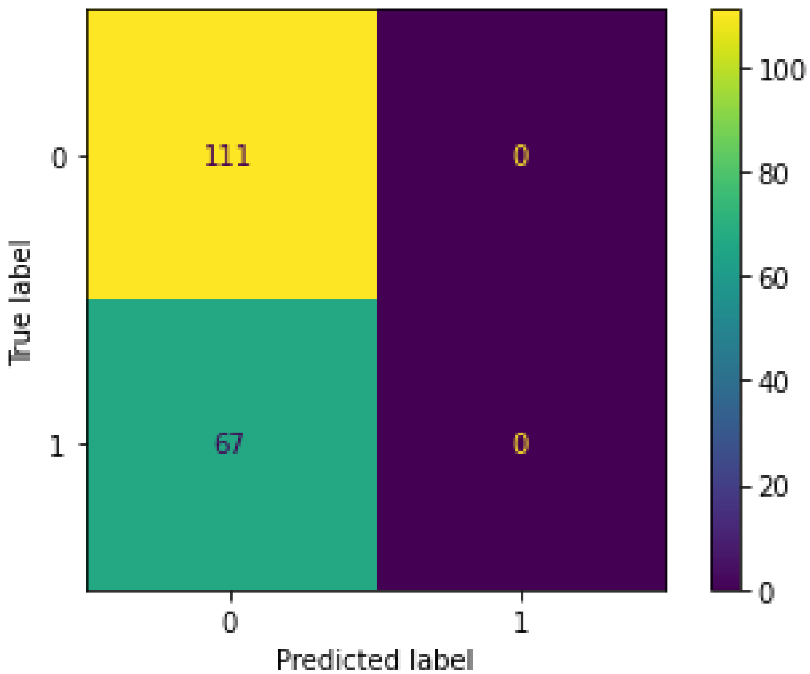
```
No of training samples: 709
No of test samples: 178
```

Train OneR Classifier

[22]:
```
oner = OneRClassifier()
oner.fit(xd_train.to_numpy(),y_train)
y_pred = oner.predict(xd_test.to_numpy())

accuracy = accuracy_score(y_train, oner.predict(xd_train.to_numpy()))
print("Accuracy on training examples : {:.2f}%".format(100*accuracy))


accuracy = accuracy_score(y_test, y_pred)
```

```
print("Accuracy on test examples     : {:.2f}%\n".format(100*accuracy))
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
print("Best Selected feature based on 1R is {}, {}".format(oner.feature_idx_,
                                                              xd_train.
 ↪columns[oner.feature_idx_]))
```

```
Accuracy on training examples : 100.00%
Accuracy on test examples     : 62.36%

Best Selected feature based on 1R is 1, Name
```



0.1.4 Q3. Can you produce a second rule based on a single attribute with a good effectiveness?

0.1.5 Yes, by using 'Sex' Attribute only, the 1R classifier achieves 76.40% accuracy on test set of 178.

Analysis as below.

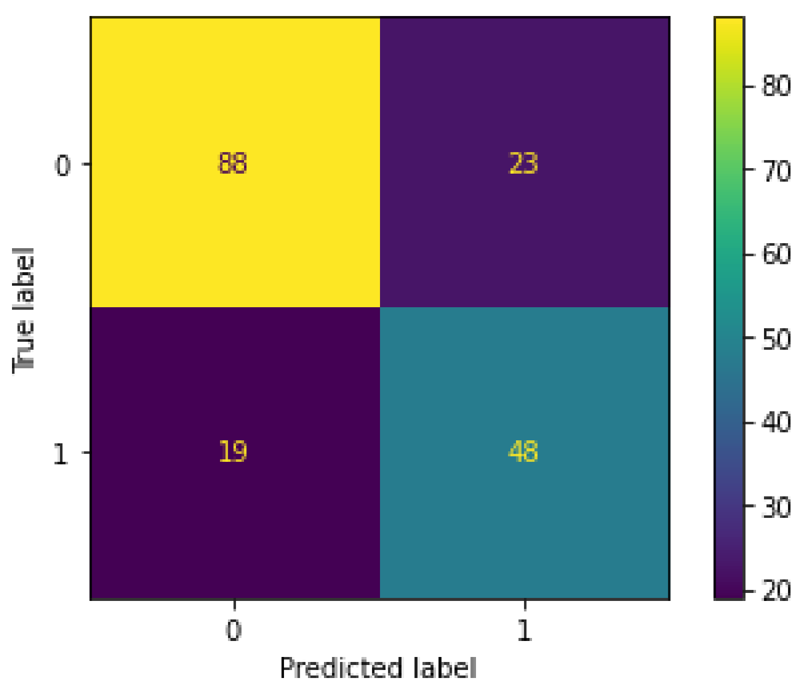
[42]:
```
## Exclude 'Name' attributes and additional 'Fare' attributes seem to be␣
 ↪optimal
x_d_new = titanic[["Sex","Age","Siblings/Spouses Aboard","Parents/Children␣
 ↪Aboard", "Pclass"]]
y_new = le.fit(titanic["Survived"])
```

```
y_new = le.transform(titanic["Survived"])
```

[43]:
```
xd_train_new, xd_test_new, y_train_new, y_test_new = train_test_split(x_d_new,␣
 ↪y_new, test_size = 0.20)
```

[41]:
```
oner = OneRClassifier()
oner.fit(xd_train_new.to_numpy(),y_train_new)
y_pred_new = oner.predict(xd_test_new.to_numpy())



accuracy = accuracy_score(y_train_new, oner.predict(xd_train_new.to_numpy()))
print("Accuracy on training examples : {:.2f}%".format(100*accuracy))


accuracy = accuracy_score(y_test_new, y_pred_new)
print("Accuracy on test examples     : {:.2f}%\n".format(100*accuracy))
ConfusionMatrixDisplay.from_predictions(y_test_new, y_pred_new)
print("Best Selected feature based on 1R is {}, {}".format(oner.feature_idx_,
                                                              xd_train_new.
 ↪columns[oner.feature_idx_]))
```

```
Accuracy on training examples : 79.13%
Accuracy on test examples     : 76.40%

Best Selected feature based on 1R is 0, Sex
```



1 Problem 2.

1.0.1 Producing 1R with selected stock IBM

Loading data

[44]:
```
df = pd.read_csv('./IBM.txt', delimiter = " ")
df_raw = df
print("Number of rows in original data: {}".format(len(df.index)))
print("Features: ", df.columns)
df.head(5)
```

```
Number of rows in original data: 3692
Features:  Index(['Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'Adjusted'],
dtype='object')
```

[44]:

	Date	Open	High	Low	Close	Volume	\
0	2007-01-03	97.180000	98.400002	96.260002	97.269997	9196800	
1	2007-01-04	97.250000	98.790001	96.879997	98.309998	10524500	
2	2007-01-05	97.599998	97.949997	96.910004	97.419998	7221300	
3	2007-01-08	98.500000	99.500000	98.349998	98.900002	10340000	
4	2007-01-09	99.080002	100.330002	99.070000	100.070000	11108200	

	Adjusted
0	63.127567
1	63.802544
2	63.224930
3	64.185463
4	64.944771

1.0.2 A. Calculate daily returns using previous day's close price

[45]:
```
df['Daily_returns'] = 100*((df['Close'] - df['Close'].shift())/ df['Close'].
 ↪shift())
conditions = [(df['Daily_returns'] >= 0.0),(df['Daily_returns'] < 0.0)]
values = ['Up', 'Down']
df['Decision'] = np.select(conditions, values)

# remove the first row, since it is not possible to calculate daily return
df_new = df[1:]
print("Number of rows in processed data: {}".format(len(df_new.index)))
df_new.head(8)
```

```
Number of rows in processed data: 3691
```

[45]:
```
         Date       Open        High        Low       Close    Volume  \
1  2007-01-04  97.250000   98.790001  96.879997   98.309998  10524500
2  2007-01-05  97.599998   97.949997  96.910004   97.419998   7221300
3  2007-01-08  98.500000   99.500000  98.349998   98.900002  10340000
4  2007-01-09  99.080002  100.330002  99.070000  100.070000  11108200
5  2007-01-10  98.500000   99.050003  97.930000   98.889999   8744800
6  2007-01-11  99.000000   99.900002  98.500000   98.650002   8000700
7  2007-01-12  98.989998   99.690002  98.500000   99.339996   6636500
8  2007-01-16  99.400002  100.839996  99.300003  100.820000   9602200

    Adjusted  Daily_returns Decision
1  63.802544       1.069190       Up
2  63.224930      -0.905300     Down
3  64.185463       1.519199       Up
4  64.944771       1.183011       Up
5  64.178978      -1.179176     Down
6  64.023201      -0.242691     Down
7  64.471024       0.699436       Up
8  65.431503       1.489837       Up
```

1.0.3 Train 1R Classifier to predict daily returns of 'NEXT DAY' using shift(-1) operation.

[46]:
```
x = df_new[["Open", "High", "Low", "Close", "Volume",␣
↪"Adjusted","Daily_returns"]]
le = preprocessing.LabelEncoder()
decision = le.fit(df_new["Decision"].shift(-1))
decision = le.transform(df_new["Decision"].shift(-1))

print("Label for Returns of Next Day: ",decision[:10])
print("\nNext day returns are :\n ")
df_new["Decision"].shift(-1).head(10)
```

```
Label for Returns of Next Day:  [0 1 1 0 0 1 1 0 0 0]

Next day returns are :
```

[46]:
```
1      Down
2        Up
3        Up
4      Down
5      Down
6        Up
7        Up
8      Down
```

```
9     Down
10    Down
Name: Decision, dtype: object
```

[47]:
```
xd_train_IBM =  x[:-102]
xd_test_IBM  =  x[-102:-2]

y_train_IBM =  decision[:-102]
y_test_IBM  =  decision[-102:-2]

print("No of training samples : {}".format(len(xd_train_IBM)))
print("No of test samples     : {}\n".format(len(xd_test_IBM)))
print("Training data:")
xd_train_IBM.head()
```

```
No of training samples : 3589
No of test samples     : 100

Training data:
```

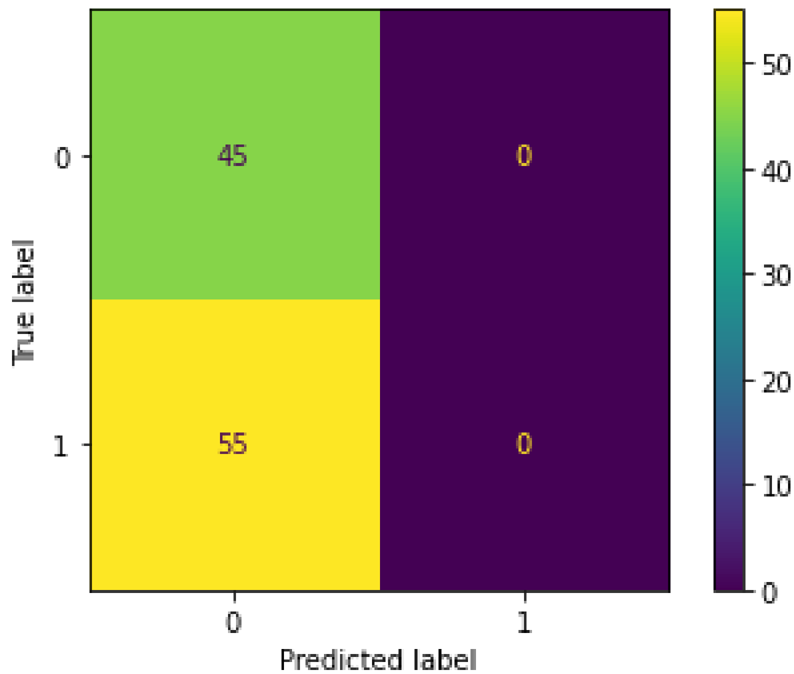
[47]:
```
        Open        High        Low       Close    Volume   Adjusted  \
1  97.250000   98.790001  96.879997   98.309998  10524500  63.802544
2  97.599998   97.949997  96.910004   97.419998   7221300  63.224930
3  98.500000   99.500000  98.349998   98.900002  10340000  64.185463
4  99.080002  100.330002  99.070000  100.070000  11108200  64.944771
5  98.500000   99.050003  97.930000   98.889999   8744800  64.178978

   Daily_returns
1       1.069190
2      -0.905300
3       1.519199
4       1.183011
5      -1.179176
```

1.0.4 Accuracy on test examples : 45.00% to predict the Next day's trend using attribute 'Daily_returns' of current day

[48]:
```
oner = OneRClassifier()
oner.fit(xd_train_IBM.to_numpy(),y_train_IBM)

accuracy = accuracy_score(y_train_IBM, oner.predict(xd_train_IBM.to_numpy()))
print("Accuracy on training examples : {:.2f}%".format(100*accuracy))

y_pred_ibm = oner.predict(xd_test_IBM.to_numpy())
accuracy = accuracy_score(y_test_IBM, y_pred_ibm)
print("Accuracy on test examples     : {:.2f}%\n".format(100*accuracy))
```

```
ConfusionMatrixDisplay.from_predictions(y_test_IBM, y_pred_ibm)
print("Best Selected feature based on 1R is {}, {}".format(oner.feature_idx_,
                                                          x.columns[oner.
 ↪feature_idx_]))
```

```
Accuracy on training examples : 99.86%
Accuracy on test examples     : 45.00%

Best Selected feature based on 1R is 6, Daily_returns
```



1.0.5 B. Moving Average of 5,10,20,50 and 200 days

Denote moving average of close price of MA_i

[4]:
```
df_raw = pd.read_csv('./IBM.txt', delimiter = " ")

for i in [5,10, 20, 50,200]:
    df_raw['MA_{}'.format(i)] = df_raw['Close'].rolling(window=i).mean()
```

[7]:
```
df_raw.head(25)
```

[7]:
```
         Date       Open       High        Low      Close    Volume  \
0  2007-01-03  97.180000  98.400002  96.260002  97.269997   9196800
1  2007-01-04  97.250000  98.790001  96.879997  98.309998  10524500
```

2	2007-01-05	97.599998	97.949997	96.910004	97.419998	7221300
3	2007-01-08	98.500000	99.500000	98.349998	98.900002	10340000
4	2007-01-09	99.080002	100.330002	99.070000	100.070000	11108200
5	2007-01-10	98.500000	99.050003	97.930000	98.889999	8744800
6	2007-01-11	99.000000	99.900002	98.500000	98.650002	8000700
7	2007-01-12	98.989998	99.690002	98.500000	99.339996	6636500
8	2007-01-16	99.400002	100.839996	99.300003	100.820000	9602200
9	2007-01-17	100.690002	100.900002	99.900002	100.019997	8200700
10	2007-01-18	99.800003	99.949997	98.910004	99.449997	14636100
11	2007-01-19	95.000000	96.849998	94.550003	96.169998	26035800
12	2007-01-22	96.419998	97.230003	96.120003	97.110001	13539300
13	2007-01-23	96.910004	97.379997	96.199997	97.080002	10337400
14	2007-01-24	97.080002	97.580002	96.580002	97.400002	5700000
15	2007-01-25	97.220001	97.919998	97.220001	97.510002	6201300
16	2007-01-26	97.519997	97.830002	96.839996	97.449997	5771100
17	2007-01-29	97.699997	98.660004	97.449997	98.540001	7294800
18	2007-01-30	98.570000	99.449997	98.500000	99.370003	7177900
19	2007-01-31	98.800003	99.480003	98.349998	99.150002	6432600
20	2007-02-01	98.970001	99.180000	97.959999	99.000000	6610700
21	2007-02-02	99.099998	99.730003	98.879997	99.169998	6656300
22	2007-02-05	99.169998	100.440002	98.900002	100.379997	8184800
23	2007-02-06	100.000000	100.400002	99.540001	99.849998	6532800
24	2007-02-07	99.800003	100.360001	99.120003	99.540001	7698200

	Adjusted	MA_5	MA_10	MA_20	MA_50	MA_200
0	63.127567	NaN	NaN	NaN	NaN	NaN
1	63.802544	NaN	NaN	NaN	NaN	NaN
2	63.224930	NaN	NaN	NaN	NaN	NaN
3	64.185463	NaN	NaN	NaN	NaN	NaN
4	64.944771	98.393999	NaN	NaN	NaN	NaN
5	64.178978	98.717999	NaN	NaN	NaN	NaN
6	64.023201	98.786000	NaN	NaN	NaN	NaN
7	64.471024	99.170000	NaN	NaN	NaN	NaN
8	65.431503	99.553999	NaN	NaN	NaN	NaN
9	64.912323	99.543999	98.968999	NaN	NaN	NaN
10	64.542397	99.655998	99.186999	NaN	NaN	NaN
11	62.413712	99.159998	98.972999	NaN	NaN	NaN
12	63.023762	98.713999	98.941999	NaN	NaN	NaN
13	63.004272	97.965999	98.759999	NaN	NaN	NaN
14	63.211952	97.442000	98.492999	NaN	NaN	NaN
15	63.283344	97.054001	98.355000	NaN	NaN	NaN
16	63.244381	97.310001	98.234999	NaN	NaN	NaN
17	63.951797	97.596001	98.155000	NaN	NaN	NaN
18	64.490479	98.054001	98.010000	NaN	NaN	NaN
19	64.347694	98.404001	97.923001	98.4460	NaN	NaN
20	64.250343	98.702001	97.878001	98.5325	NaN	NaN
21	64.360657	99.046001	98.178001	98.5755	NaN	NaN

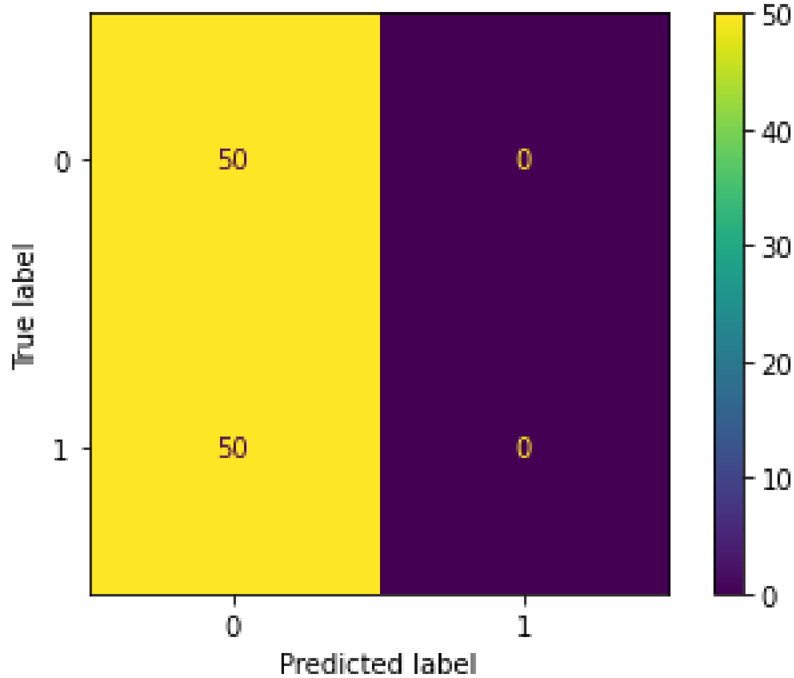
```
22  65.145950  99.414000  98.505000  98.7235    NaN     NaN
23  64.801994  99.509999  98.782000  98.7710    NaN     NaN
24  64.795479  99.587999  98.996000  98.7445    NaN     NaN
```

[6]:

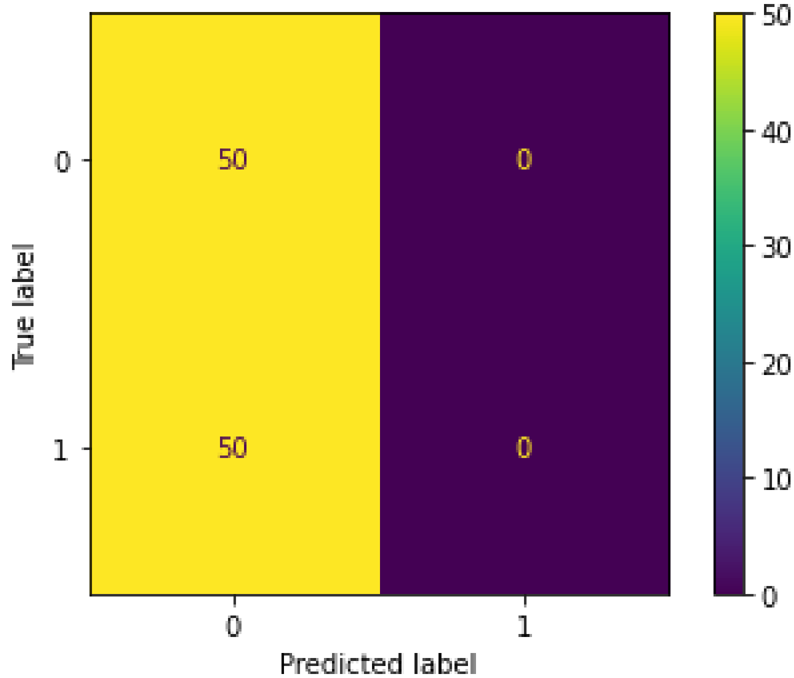
```
pd.set_option('mode.chained_assignment',None)
import matplotlib.pyplot as plt
Windows = [5, 10, 20, 50, 200]
for i, Window in enumerate(Windows):

    print("********* Performing experiment [{}]/[{}] with Moving average window␣
↪size:"
          "{} *******".format(i, len(Windows), Window))
    feat = 'MA_{}'.format(Window)
    df_new_MA = df_raw[["Open", "High", "Low",  "Volume", "Adjusted", feat]]
    df_new_MA['Daily_returns'] = 100*((df_new_MA[feat] - df_new_MA[feat].
↪shift())/ df_new_MA[feat].shift())

    conditions = [(df_new_MA['Daily_returns'] >= 0.
↪0),(df_new_MA['Daily_returns'] < 0.0)]
    values = ['Up', 'Down']
    df_new_MA['Decision'] = np.select(conditions, values)

    # remove the fews row, since it is not possible to calculate
    # daily return with moving average of initial days
    df_new_MA = df_new_MA[Window:]
    df_new_MA.head(8)
    le = preprocessing.LabelEncoder()
    decision_MA = le.fit(df_new_MA["Decision"].shift(-1))
    decision_MA = le.transform(df_new_MA["Decision"].shift(-1))
    #print(tabulate(df_new_MA.head(10), headers='keys', tablefmt='psql'))

    xd_train_IBM_MA =  df_new_MA[:-102]
    xd_test_IBM_MA  =  df_new_MA[-102:-2]

    y_train_IBM_MA =  decision_MA[:-102]
    y_test_IBM_MA  =  decision_MA[-102:-2]

    print("No of training samples with moving average {} days : {}".
↪format(Window,len(xd_train_IBM_MA)))
    print("No of test samples  with moving average {} days    : {}\n".
↪format(Window, len(xd_test_IBM_MA)))

    oner = OneRClassifier()
    oner.fit(xd_train_IBM_MA.to_numpy(),y_train_IBM_MA)

    accuracy = accuracy_score(y_train_IBM_MA, oner.predict(xd_train_IBM_MA.
↪to_numpy()))
```

```
    print("Accuracy on training examples with moving average {} days: {:.2f}%".
↪format(Window,100*accuracy))

    y_pred_ibm_MA = oner.predict(xd_test_IBM_MA.to_numpy())
    accuracy = accuracy_score(y_test_IBM_MA, y_pred_ibm_MA)
    print("Accuracy on test examples  with moving average {} days    : {:.2f}%".
↪format(Window,100*accuracy))
    cmp = ConfusionMatrixDisplay.from_predictions(y_test_IBM_MA, y_pred_ibm_MA)
    #cmp.plot()
    #cmp.show()

    print("Best Selected feature based on 1R is {}, {}\n".format(oner.
↪feature_idx_,
                                                                  df_new_MA.
↪columns[oner.feature_idx_]))



    plt.show()
```

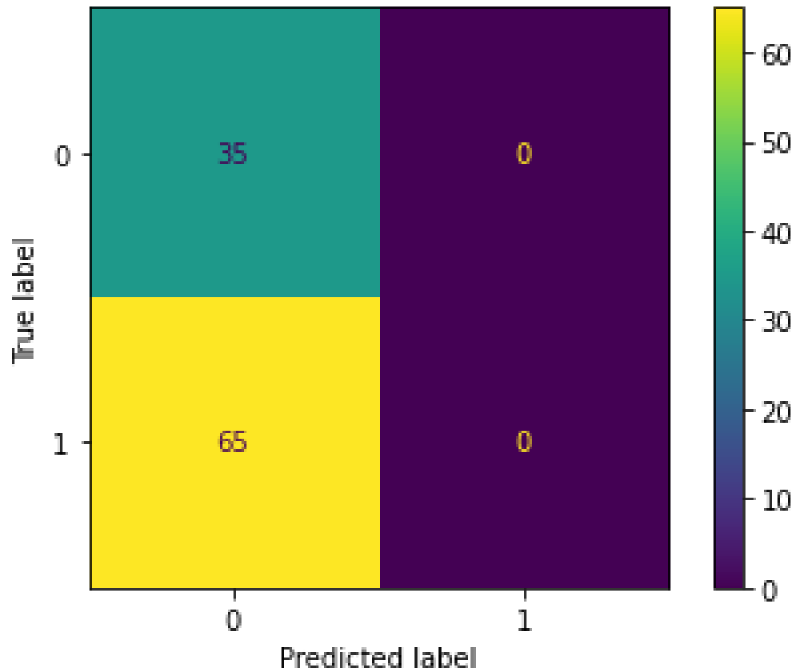
```
********* Performing experiment [0]/[5] with Moving average window size:5
*******
No of training samples with moving average 5 days : 3585
No of test samples  with moving average 5 days    : 100

Accuracy on training examples with moving average 5 days: 99.97%
Accuracy on test examples  with moving average 5 days    : 50.00%
Best Selected feature based on 1R is 5, MA_5
```



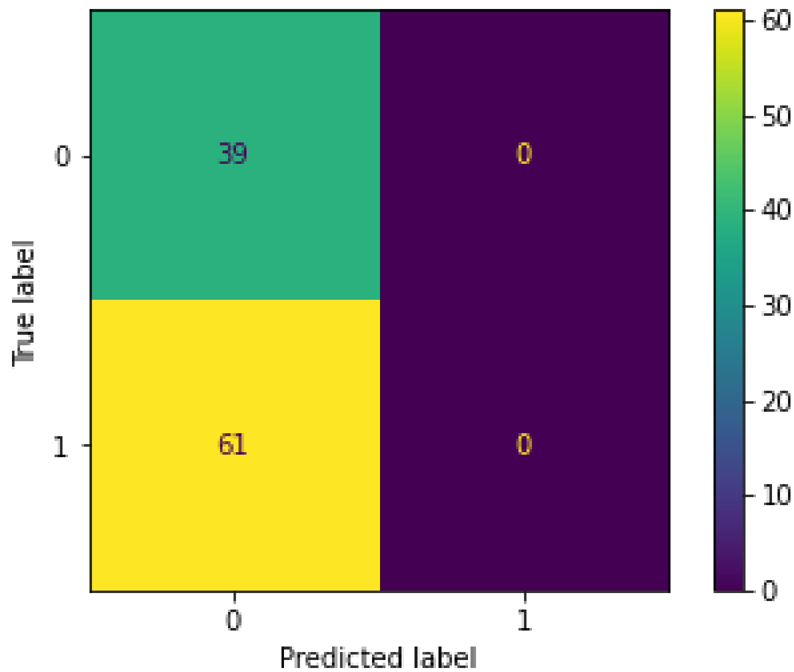

```
********* Performing experiment [1]/[5] with Moving average window size:10
*******
No of training samples with moving average 10 days : 3580
No of test samples  with moving average 10 days    : 100

Accuracy on training examples with moving average 10 days: 99.97%
Accuracy on test examples  with moving average 10 days    : 50.00%
Best Selected feature based on 1R is 6, Daily_returns
```



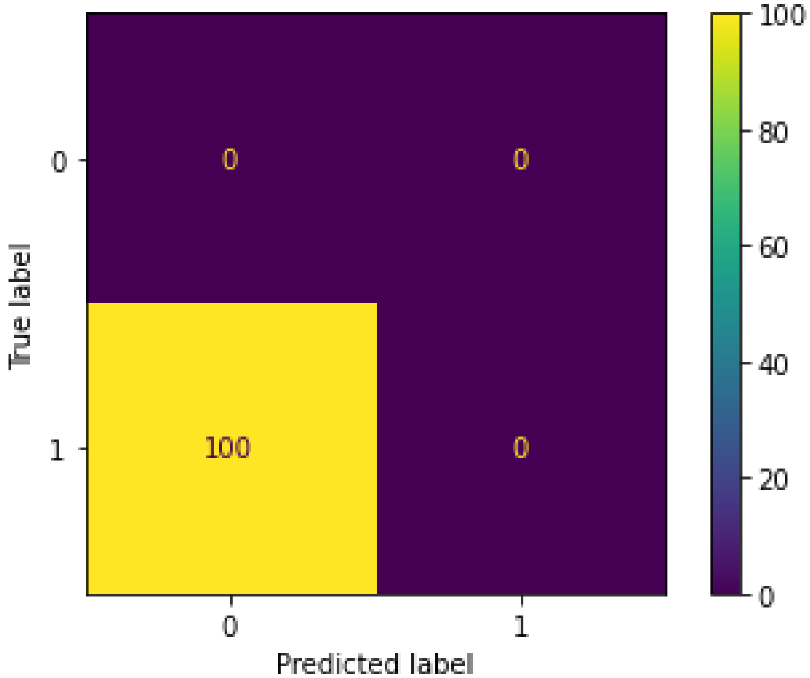

```
********* Performing experiment [2]/[5] with Moving average window size:20
*******
No of training samples with moving average 20 days : 3570
No of test samples  with moving average 20 days    : 100

Accuracy on training examples with moving average 20 days: 99.97%
Accuracy on test examples  with moving average 20 days    : 35.00%
Best Selected feature based on 1R is 5, MA_20
```




```
********* Performing experiment [3]/[5] with Moving average window size:50
*******
No of training samples with moving average 50 days : 3540
No of test samples  with moving average 50 days    : 100

Accuracy on training examples with moving average 50 days: 100.00%
Accuracy on test examples  with moving average 50 days    : 39.00%
Best Selected feature based on 1R is 6, Daily_returns
```




```
********* Performing experiment [4]/[5] with Moving average window size:200
*******
No of training samples with moving average 200 days : 3390
No of test samples  with moving average 200 days    : 100

Accuracy on training examples with moving average 200 days: 100.00%
Accuracy on test examples  with moving average 200 days    : 0.00%
Best Selected feature based on 1R is 5, MA_200
```



1.1 As observed from above plots, the test accuracy is high of 50% for moving average of 5 and 10 days.

[ ]:

```

```