Lab7 - Jackson Nahom

October 13, 2021

[1]:
```
import pandas as pd
import numpy as np
from datetime import datetime, timedelta
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
```

[2]:
```
weather = pd.read_csv('data/last_ten_alb.csv')


weather['YEARMODA'] = pd.to_datetime(weather['YEARMODA'])
print("Most recent date in data:", weather['YEARMODA'].max())
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[3]:
```
weather['SLP1'] = weather['SLP'].shift(1)
weather['SLP2'] = weather['SLP'].shift(2)
weather['SLP3'] = weather['SLP'].shift(3)
```

[4]:
```
display(weather[['YEARMODA', 'SLP', 'SLP1', 'SLP2', 'SLP3']].head())
```

	YEARMODA	SLP	SLP1	SLP2	SLP3
0	2011-01-01	1017.7	NaN	NaN	NaN
1	2011-01-02	1014.2	1017.7	NaN	NaN
2	2011-01-03	1018.5	1014.2	1017.7	NaN
3	2011-01-04	1015.2	1018.5	1014.2	1017.7
4	2011-01-05	1009.0	1015.2	1018.5	1014.2

[5]:
```
pred_vars = ['YDAY', 'SLP1']

# make list of all variables required to generate a forecast
model_vars = pred_vars + ['I_PRCP']

weather.dropna(subset=model_vars, inplace=True)
```

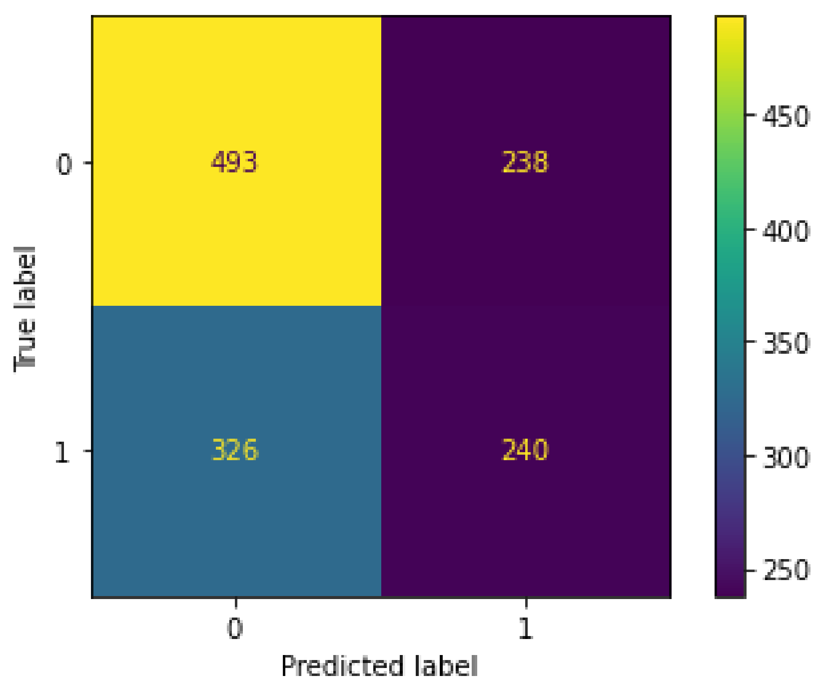
[6]:
```
train, test= np.split(weather, [int(.67 *len(weather))])
```

[7]:
```
rf = RandomForestClassifier()

rf.fit(train[pred_vars], train['I_PRCP'])
```

[7]: RandomForestClassifier()

[8]:
```
# get predictions
pred_p_prcp = rf.predict_proba(test.loc[:, pred_vars])
pred_i_prcp = rf.predict(test.loc[:, pred_vars])

# evaluation

metrics.plot_confusion_matrix(rf, test.loc[:, pred_vars], test['I_PRCP'])
print(metrics.classification_report(test['I_PRCP'], pred_i_prcp, digits=5))
```

```
              precision    recall  f1-score   support

           0    0.60195   0.67442   0.63613       731
           1    0.50209   0.42403   0.45977       566

    accuracy                        0.56515      1297
   macro avg    0.55202   0.54922   0.54795      1297
weighted avg    0.55837   0.56515   0.55917      1297
```



[9]:
```
#https://machinelearningmastery.com/
↪save-load-machine-learning-models-python-scikit-learn/
import pickle
file_name = 'rf_1day_prcp.sav'
```

```
pickle.dump(rf, open(file_name, 'wb'))
```

[10]:
```
weather = pd.read_csv('data/last_ten_alb.csv')


weather['YEARMODA'] = pd.to_datetime(weather['YEARMODA'])
print("Most recent date in data:", weather['YEARMODA'].max())
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[11]:
```
most_recent_data = weather['YEARMODA'].max()
# https://stackoverflow.com/questions/39964558/pandas-max-value-index
most_recent_yday = weather.loc[weather['YEARMODA'].idxmax(), 'YDAY']
print("Most recent date in data:", weather['YEARMODA'].max())


# figure out starting dates for predictions
prediction_start = most_recent_data + timedelta(days=1)
prediction_start_yday = list(most_recent_yday + range(1,2))

# generate list of dates for predictions
eval_dates = pd.date_range(prediction_start, periods=1).tolist()
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[12]:
```
predictions_df = pd.DataFrame(eval_dates, columns=['YEARMODA'])
predictions_df['YDAY'] = prediction_start_yday


# add these to the main dataframe
weather = weather.append(predictions_df, ignore_index=True)
weather[['YEARMODA', 'YDAY', 'SLP', 'I_PRCP']].tail()
```

[12]:

	YEARMODA	YDAY	SLP	I_PRCP
3926	2021-10-01	274	1022.8	0.0
3927	2021-10-02	275	1020.0	0.0
3928	2021-10-03	276	1015.1	0.0
3929	2021-10-04	277	1015.2	1.0
3930	2021-10-05	278	NaN	NaN

[13]:
```
weather['SLP1'] = weather['SLP'].shift(1)
weather['SLP2'] = weather['SLP'].shift(2)
weather['SLP3'] = weather['SLP'].shift(3)
```

[14]:
```
prediction_set = weather[(weather['YEARMODA'] >= prediction_start)].copy()
```

[15]:
```
prediction_set.head() # see the lagged columns on the end?
```

[15]:
```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3930         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_HAIL  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP  \
3930        NaN  …     NaN        NaN               NaN NaN NaN NaN     NaN

        SLP1    SLP2    SLP3
3930  1015.2  1015.1  1020.0

[1 rows x 52 columns]
```

[16]:
```
rf = pickle.load(open(file_name, 'rb'))
```

[17]:
```
prediction_set['P_PRCP'] = rf.predict_proba(prediction_set[pred_vars])[:,1]
```

[18]:
```
prediction_set.head() # now  we have a probability of  rain for a date not yet␣
↪in the data!
```

[18]:
```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3930         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP    SLP1  \
3930        NaN  …        NaN               NaN NaN NaN NaN     NaN  1015.2

        SLP2    SLP3  P_PRCP
3930  1015.1  1020.0    0.61

[1 rows x 53 columns]
```

1 Tasks

1. How would you go about building a model that predicts more than a day ahead? Implement a model that can predict precipitation three days in the future. Evaluation statistics.
2. Try using at least one other data type (rather than SLP (sea-level pressure) to predict the probability of rain. Does your model improve? Evaluation statistics.

[22]:
```
weather_2 = pd.read_csv('data/last_ten_alb.csv')



weather_2['YEARMODA'] = pd.to_datetime(weather_2['YEARMODA'])
print("Most recent date in data:", weather_2['YEARMODA'].max())
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[23]:
```
weather_2['SLP1'] = weather_2['SLP'].shift(1)
weather_2['SLP2'] = weather_2['SLP'].shift(2)
weather_2['SLP3'] = weather_2['SLP'].shift(3)
```

[24]:
```
display(weather_2[['YEARMODA', 'SLP', 'SLP1', 'SLP2', 'SLP3']].head())
```

```
    YEARMODA     SLP    SLP1    SLP2    SLP3
0 2011-01-01  1017.7     NaN     NaN     NaN
1 2011-01-02  1014.2  1017.7     NaN     NaN
2 2011-01-03  1018.5  1014.2  1017.7     NaN
3 2011-01-04  1015.2  1018.5  1014.2  1017.7
4 2011-01-05  1009.0  1015.2  1018.5  1014.2
```

[25]:
```
pred_vars_2 = ['YDAY', 'SLP3']

# make list of all variables required to generate a forecast
model_vars = pred_vars_2 + ['I_PRCP']

weather_2.dropna(subset=model_vars, inplace=True)
```

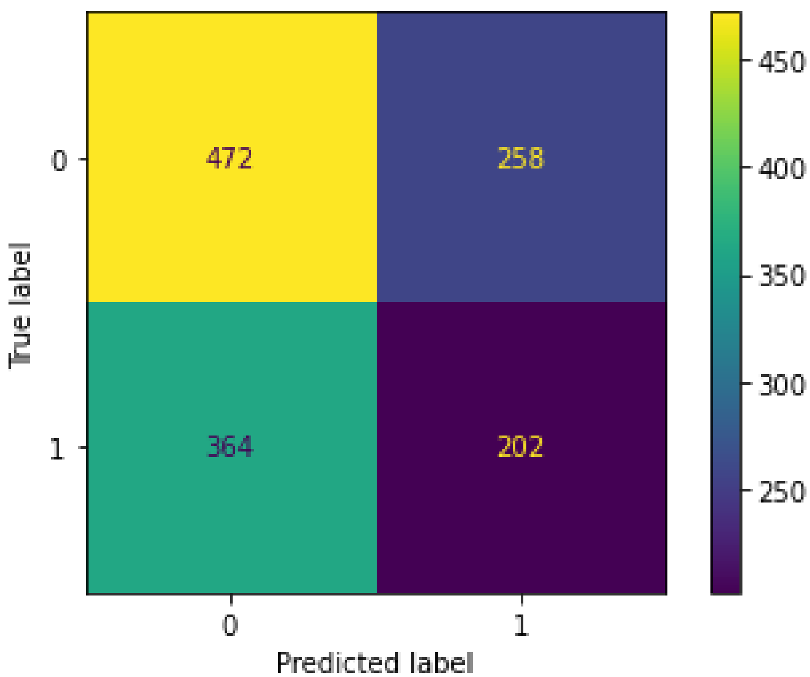
[26]:
```
train, test_2= np.split(weather_2, [int(.67 *len(weather_2))])
```

[27]:
```
rf_2 = RandomForestClassifier()

rf_2.fit(train[pred_vars], train['I_PRCP'])
```

[27]:
```
RandomForestClassifier()
```

[28]:
```
# get predictions
pred_p_prcp = rf_2.predict_proba(test_2.loc[:, pred_vars_2])
pred_i_prcp = rf_2.predict(test_2.loc[:, pred_vars_2])

# evaluation

metrics.plot_confusion_matrix(rf_2, test_2.loc[:, pred_vars_2],␣
 ↪test_2['I_PRCP'])
print(metrics.classification_report(test_2['I_PRCP'], pred_i_prcp, digits=5))
```

```
              precision    recall  f1-score   support

           0    0.56459   0.64658   0.60281       730
           1    0.43913   0.35689   0.39376       566

    accuracy                        0.52006      1296
   macro avg    0.50186   0.50173   0.49829      1296
weighted avg    0.50980   0.52006   0.51151      1296
```



[29]:
```
#https://machinelearningmastery.com/
↪save-load-machine-learning-models-python-scikit-learn/
import pickle
file_name = 'rf_3day_prcp.sav'
pickle.dump(rf_2, open(file_name, 'wb'))
```

[30]:
```
weather_test = pd.read_csv('data/last_ten_alb.csv')


weather_test['YEARMODA'] = pd.to_datetime(weather_test['YEARMODA'])
print("Most recent date in data:", weather_test['YEARMODA'].max())
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[31]:
```
most_recent_data = weather['YEARMODA'].max()
# https://stackoverflow.com/questions/39964558/pandas-max-value-index
most_recent_yday = weather_test.loc[weather_test['YEARMODA'].idxmax(), 'YDAY']
print("Most recent date in data:", weather_test['YEARMODA'].max())


# figure out starting dates for predictions
prediction_start = most_recent_data + timedelta(days=1)
prediction_start_yday = list(most_recent_yday + range(1,4))

# generate list of dates for predictions
```

```
eval_dates = pd.date_range(prediction_start, periods=3).tolist()
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[32]:
```
prediction_start_yday
```

[32]:
```
[278, 279, 280]
```

[33]:
```
predictions_df = pd.DataFrame(eval_dates, columns=['YEARMODA'])
predictions_df['YDAY'] = prediction_start_yday


# add these to the main dataframe
weather_test = weather_test.append(predictions_df, ignore_index=True)
weather_test[['YEARMODA', 'YDAY', 'SLP', 'I_PRCP']].tail()
```

[33]:
```
       YEARMODA  YDAY     SLP  I_PRCP
3928 2021-10-03   276  1015.1     0.0
3929 2021-10-04   277  1015.2     1.0
3930 2021-10-06   278     NaN     NaN
3931 2021-10-07   279     NaN     NaN
3932 2021-10-08   280     NaN     NaN
```

[34]:
```
weather_test['SLP1'] = weather_test['SLP'].shift(1)
weather_test['SLP2'] = weather_test['SLP'].shift(2)
weather_test['SLP3'] = weather_test['SLP'].shift(3)
```

[35]:
```
prediction_set = weather_test[(weather_test['YEARMODA'] >= prediction_start)].
 ↪copy()
```

[36]:
```
prediction_set.head()
```

[36]:
```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3930         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN
3931         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN
3932         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_HAIL  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP  \
3930        NaN  …     NaN        NaN               NaN NaN NaN NaN     NaN
3931        NaN  …     NaN        NaN               NaN NaN NaN NaN     NaN
3932        NaN  …     NaN        NaN               NaN NaN NaN NaN     NaN

        SLP1    SLP2    SLP3
3930  1015.2  1015.1  1020.0
3931     NaN  1015.2  1015.1
3932     NaN     NaN  1015.2

[3 rows x 52 columns]
```

[37]:
```
rf_2 = pickle.load(open(file_name, 'rb'))
```

[38]:
```
prediction_set['P_PRCP'] = rf_2.predict_proba(prediction_set[pred_vars_2])[:,1]
```

[39]:
```
prediction_set.head() # now  we have a probability of  rain for a date not yet␣
↪in the data!
```

[39]:
```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3930         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN
3931         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN
3932         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP   SLP1  \
3930        NaN  …        NaN               NaN NaN NaN NaN     NaN 1015.2
3931        NaN  …        NaN               NaN NaN NaN NaN     NaN    NaN
3932        NaN  …        NaN               NaN NaN NaN NaN     NaN    NaN

        SLP2    SLP3  P_PRCP
3930  1015.1  1020.0    0.25
3931  1015.2  1015.1    0.69
3932     NaN  1015.2    0.73

[3 rows x 53 columns]
```

[40]:
```
prediction_set.to_csv('3dayPred.csv')
```

2 Task 2

Try using at least one other data type (rather than SLP (sea-level pressure) to predict the probability of rain. Does your model improve? Evaluation statistics.

[41]:
```
weather_3 = pd.read_csv('data/last_ten_alb.csv')


weather_3['YEARMODA'] = pd.to_datetime(weather_3['YEARMODA'])
print("Most recent date in data:", weather_3['YEARMODA'].max())
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[42]:
```
weather_3
```

[42]:
```
      Unnamed: 0         STNID                           NAME CTRY  \
0              1  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
1              2  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
2              3  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
3              4  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
4              5  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
…            …           …                            …  …
```

```
3925        3926  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
3926        3927  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
3927        3928  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
3928        3929  725180-14735  ALBANY INTERNATIONAL AIRPORT   US
3929        3930  725180-14735  ALBANY INTERNATIONAL AIRPORT   US

       COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  LONGITUDE  …  I_FOG  \
0     UNITED STATES    US   USA    NY    42.747    -73.799  …      0
1     UNITED STATES    US   USA    NY    42.747    -73.799  …      1
2     UNITED STATES    US   USA    NY    42.747    -73.799  …      1
3     UNITED STATES    US   USA    NY    42.747    -73.799  …      1
4     UNITED STATES    US   USA    NY    42.747    -73.799  …      0
…               …   …   …   …       …         …   …    …
3925  UNITED STATES    US   USA    NY    42.747    -73.799  …      1
3926  UNITED STATES    US   USA    NY    42.747    -73.799  …      1
3927  UNITED STATES    US   USA    NY    42.747    -73.799  …      0
3928  UNITED STATES    US   USA    NY    42.747    -73.799  …      1
3929  UNITED STATES    US   USA    NY    42.747    -73.799  …      1

      I_RAIN_DRIZZLE  I_SNOW_ICE I_HAIL  I_THUNDER  I_TORNADO_FUNNEL   EA  \
0                  0         0.0    0.0        0.0               0.0  0.6
1                  0         0.0    0.0        0.0               NaN  0.7
2                  0         0.0    0.0        NaN               NaN  0.3
3                  0         0.0    0.0        NaN               NaN  0.3
4                  0         0.0    0.0        0.0               0.0  0.3
…                …          …    …         …                …   …
3925               0         0.0    0.0        0.0               NaN  1.1
3926               0         0.0    0.0        0.0               0.0  1.0
3927               0         0.0    0.0        0.0               0.0  1.2
3928               0         0.0    0.0        0.0               NaN  1.5
3929               0         0.0    0.0        0.0               NaN  1.7

       ES    RH  I_PRCP
0     0.9  67.1       0
1     0.9  75.4       1
2     0.5  59.7       1
3     0.5  67.7       0
4     0.5  68.0       0
…   …   …     …
3925  1.5  75.6       0
3926  1.3  72.8       0
3927  1.6  74.3       0
3928  1.8  83.0       0
3929  1.8  92.6       1

[3930 rows x 49 columns]
```

[43]:
```
weather_3['STP1'] = weather_3['STP'].shift(1)
weather_3['STP2'] = weather_3['STP'].shift(2)
weather_3['STP3'] = weather_3['STP'].shift(3)
```

[44]:
```
display(weather_3[['YEARMODA', 'STP', 'STP1', 'STP2', 'STP3']].head())
```

```
     YEARMODA    STP  STP1  STP2  STP3
0  2011-01-01    7.0   NaN   NaN   NaN
1  2011-01-02    3.4   7.0   NaN   NaN
2  2011-01-03    7.6   3.4   7.0   NaN
3  2011-01-04    4.2   7.6   3.4   7.0
4  2011-01-05  998.1   4.2   7.6   3.4
```

[45]:
```
pred_vars_3 = ['YDAY', 'STP1']

# make list of all variables required to generate a forecast
model_vars = pred_vars_3 + ['I_PRCP']

weather_3.dropna(subset=model_vars, inplace=True)
```

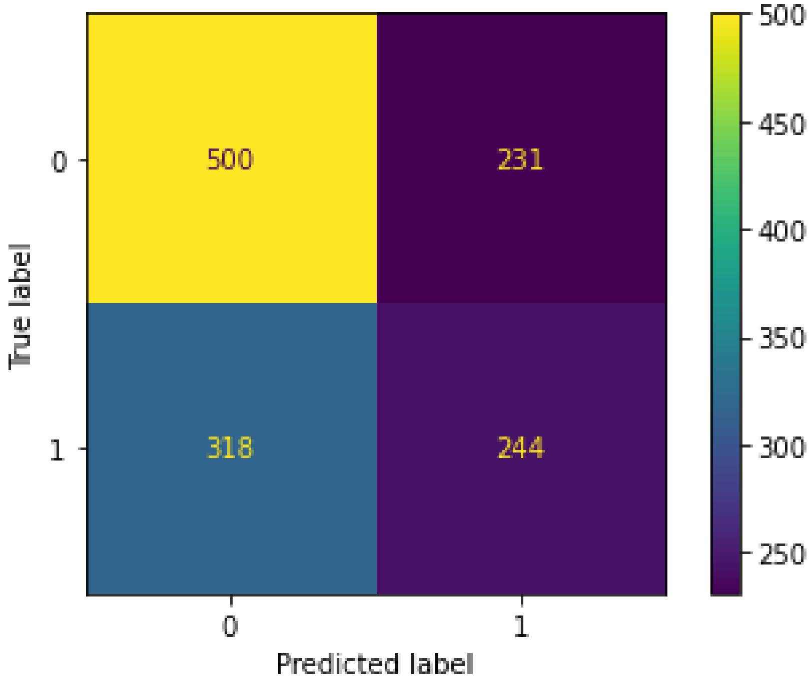
[46]:
```
train, test_3= np.split(weather_3, [int(.67 *len(weather_3))])
```

[49]:
```
rf_3 = RandomForestClassifier()

rf_3.fit(train[pred_vars_3], train['I_PRCP'])
```

[49]:
```
RandomForestClassifier()
```

[50]:
```
# get predictions
pred_p_prcp = rf_3.predict_proba(test_3.loc[:, pred_vars_3])
pred_i_prcp = rf_3.predict(test_3.loc[:, pred_vars_3])

# evaluation

metrics.plot_confusion_matrix(rf_3, test_3.loc[:, pred_vars_3],␣
↪test_3['I_PRCP'])
print(metrics.classification_report(test_3['I_PRCP'], pred_i_prcp, digits=5))
```

```
              precision    recall  f1-score   support

           0    0.61125   0.68399   0.64558       731
           1    0.51368   0.43416   0.47059       562

    accuracy                        0.57541      1293
   macro avg    0.56247   0.55908   0.55808      1293
weighted avg    0.56884   0.57541   0.56952      1293
```



[51]:
```
most_recent_data = weather_3['YEARMODA'].max()
# https://stackoverflow.com/questions/39964558/pandas-max-value-index
most_recent_yday = weather_3.loc[weather_3['YEARMODA'].idxmax(), 'YDAY']
print("Most recent date in data:", weather_3['YEARMODA'].max())


# figure out starting dates for predictions
prediction_start = most_recent_data + timedelta(days=1)
prediction_start_yday = list(most_recent_yday + range(1,2))

# generate list of dates for predictions
eval_dates = pd.date_range(prediction_start, periods=1).tolist()
```

```
Most recent date in data: 2021-10-04 00:00:00
```

[52]:
```
prediction_start_yday
```

[52]:
```
[278]
```

[53]:
```
predictions_df = pd.DataFrame(eval_dates, columns=['YEARMODA'])
predictions_df['YDAY'] = prediction_start_yday


# add these to the main dataframe
weather_3 = weather_3.append(predictions_df, ignore_index=True)
```

```
weather_3[['YEARMODA', 'YDAY', 'STP', 'STP1', 'I_PRCP', ]].tail()
```

[53]:

```
        YEARMODA  YDAY   STP  STP1  I_PRCP
3912 2021-10-01   274  12.0   7.9     0.0
3913 2021-10-02   275   9.3  12.0     0.0
3914 2021-10-03   276   4.5   9.3     0.0
3915 2021-10-04   277   3.5   4.5     1.0
3916 2021-10-05   278   NaN   NaN     NaN
```

[54]:

```
weather_3['STP1'] = weather_3['STP'].shift(1)
weather_3['STP2'] = weather_3['STP'].shift(2)
weather_3['STP3'] = weather_3['STP'].shift(3)
```

[55]:

```
prediction_set = weather_3[(weather_3['YEARMODA'] >= prediction_start)].copy()
```

[56]:

```
prediction_set
```

[56]:

```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3916         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_HAIL  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP  \
3916        NaN  …     NaN        NaN               NaN NaN NaN NaN     NaN

      STP1  STP2  STP3
3916   3.5   4.5   9.3

[1 rows x 52 columns]
```

[57]:

```
prediction_set['P_PRCP'] = rf_3.predict_proba(prediction_set[pred_vars_3])[:,1]
```

[58]:

```
prediction_set.head()
```

[58]:

```
      Unnamed: 0 STNID NAME CTRY COUNTRY_NAME ISO2C ISO3C STATE  LATITUDE  \
3916         NaN   NaN  NaN  NaN          NaN   NaN   NaN   NaN       NaN

      LONGITUDE  …  I_THUNDER  I_TORNADO_FUNNEL  EA  ES  RH  I_PRCP  STP1  \
3916        NaN  …        NaN               NaN NaN NaN NaN     NaN   3.5

      STP2  STP3  P_PRCP
3916   4.5   9.3     0.2

[1 rows x 53 columns]
```

2.0.1 Results

In all cases the new model using STP shifted once outperformed the previous two models using SLP shifted once and three times. STP outperformed the other two in precision, recall, f1-score and accuracy.

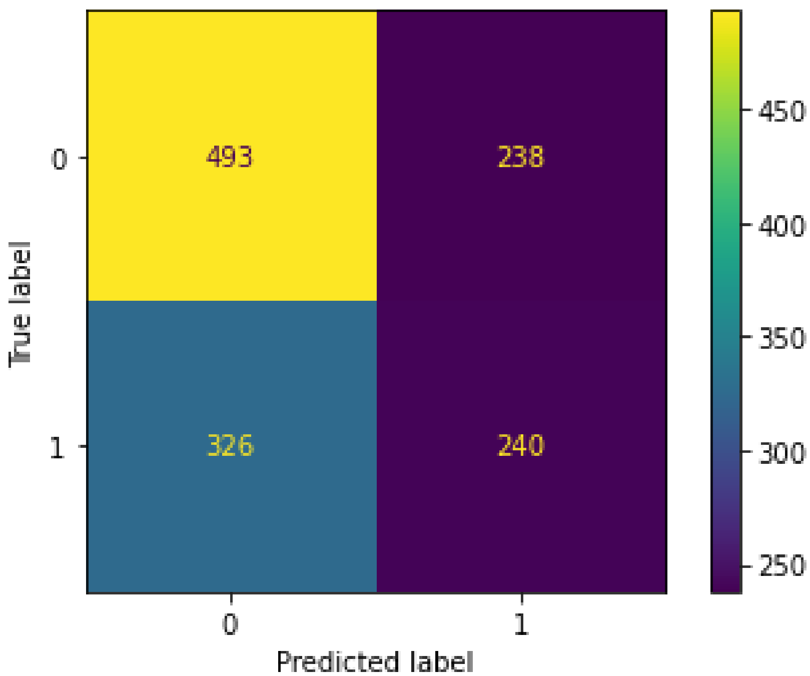
```
[60]: # get predictions
pred_p_prcp = rf.predict_proba(test.loc[:, pred_vars])
pred_i_prcp = rf.predict(test.loc[:, pred_vars])

# evaluation

metrics.plot_confusion_matrix(rf, test.loc[:, pred_vars], test['I_PRCP'])
print('SLP1')
print(metrics.classification_report(test['I_PRCP'], pred_i_prcp, digits=5))

# get predictions
pred_p_prcp = rf_2.predict_proba(test_2.loc[:, pred_vars_2])
pred_i_prcp = rf_2.predict(test_2.loc[:, pred_vars_2])

# evaluation

metrics.plot_confusion_matrix(rf_2, test_2.loc[:, pred_vars_2],␣
 ↪test_2['I_PRCP'])
print('SLP3')
print(metrics.classification_report(test_2['I_PRCP'], pred_i_prcp, digits=5))

# get predictions
pred_p_prcp = rf_3.predict_proba(test_3.loc[:, pred_vars_3])
pred_i_prcp = rf_3.predict(test_3.loc[:, pred_vars_3])

# evaluation

metrics.plot_confusion_matrix(rf_3, test_3.loc[:, pred_vars_3],␣
 ↪test_3['I_PRCP'])
print('STP1')
print(metrics.classification_report(test_3['I_PRCP'], pred_i_prcp, digits=5))
```

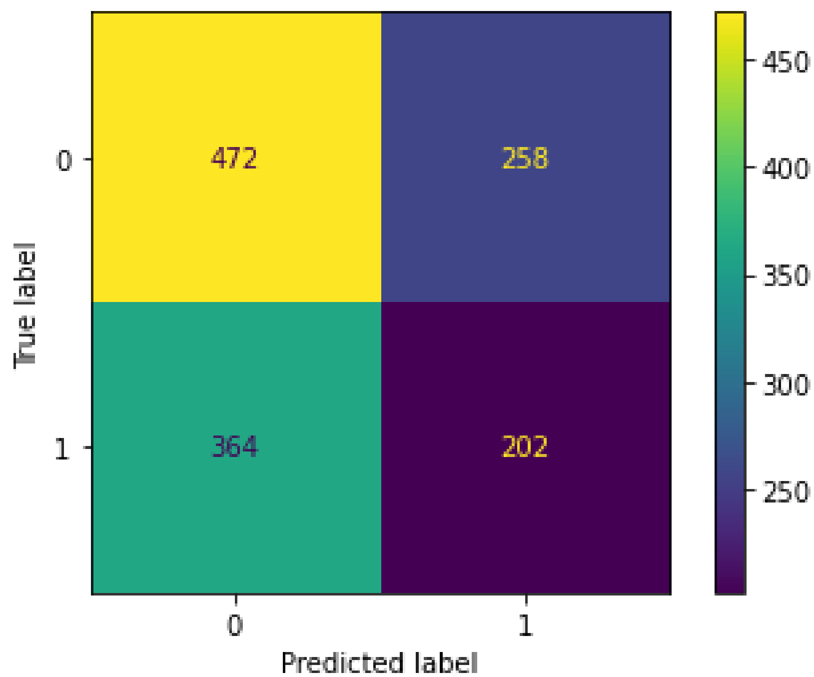
```
SLP1
              precision    recall  f1-score   support

           0    0.60195   0.67442   0.63613       731
           1    0.50209   0.42403   0.45977       566

    accuracy                        0.56515      1297
   macro avg    0.55202   0.54922   0.54795      1297
weighted avg    0.55837   0.56515   0.55917      1297

SLP3
              precision    recall  f1-score   support

           0    0.56459   0.64658   0.60281       730
           1    0.43913   0.35689   0.39376       566
```

	precision	recall	f1-score	support
accuracy			0.52006	1296
macro avg	0.50186	0.50173	0.49829	1296
weighted avg	0.50980	0.52006	0.51151	1296

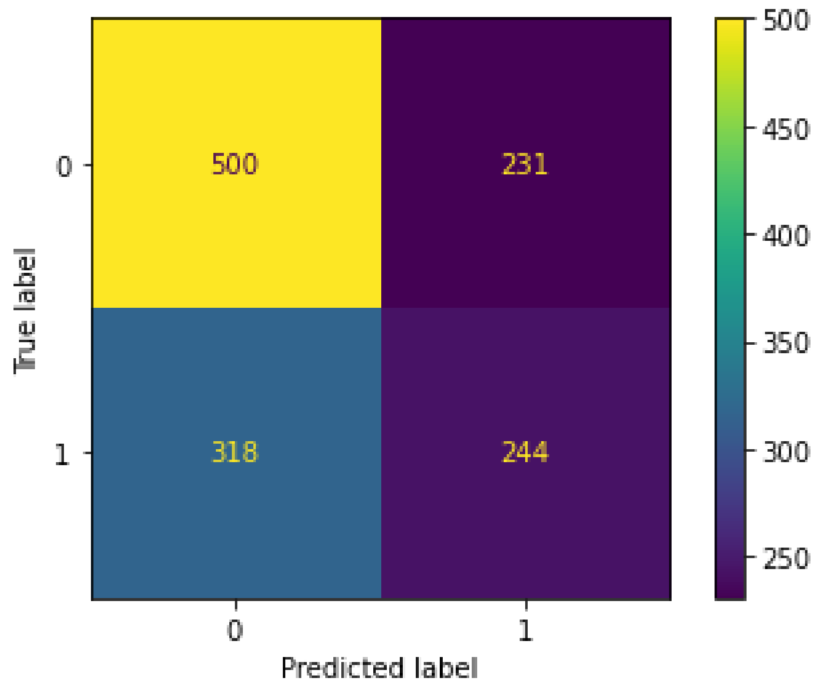
STP1

	precision	recall	f1-score	support
0	0.61125	0.68399	0.64558	731
1	0.51368	0.43416	0.47059	562
accuracy			0.57541	1293
macro avg	0.56247	0.55908	0.55808	1293
weighted avg	0.56884	0.57541	0.56952	1293





472
258
364
202
0
1
True label
0
1
Predicted label
450
400
350
300
250



500
231
318
244
0
1
True label
0
1
Predicted label
500
450
400
350
300
250