## **Random Forest**

June 14, 2020

[49]: import pandas as pd

```
import numpy as np
     import matplotlib.pyplot as plt
     from statsmodels.tsa.seasonal import seasonal_decompose
[2]: import h2o
     from h2o.estimators import H2ORandomForestEstimator
[3]: h2o.init()
    Checking whether there is an H2O instance running at http://localhost:54321
    ... not found.
    Attempting to start a local H2O server...
    ; Picked up _JAVA_OPTIONS: -Xms1024M -Xmx6144M251-b08, mixed mode)
      Starting server from e:\documents\university\timeseries\venv\lib\site-
    packages\h2o\backend\bin\h2o.jar
      Ice root: C:\Users\babar\AppData\Local\Temp\tmpm1rsz501
      JVM stdout:
    C:\Users\babar\AppData\Local\Temp\tmpm1rsz501\h2o_babar_started_from_python.out
      JVM stderr:
    C:\Users\babar\AppData\Local\Temp\tmpm1rsz501\h2o_babar_started_from_python.err
      Server is running at http://127.0.0.1:54321
    Connecting to H2O server at http://127.0.0.1:54321 ... successful.
    H2O cluster uptime:
                                 03 secs
    H20_cluster_timezone:
                                Europe/Belgrade
    H2O_data_parsing_timezone: UTC
    H20_cluster_version:
                                3.30.0.4
    H20_cluster_version_age:
                                13 days
    H20_cluster_name:
                                H20_from_python_babar_n045b7
    H20_cluster_total_nodes:
    H2O_cluster_free_memory:
                                5.333 Gb
    H20_cluster_total_cores:
                                 4
    H20_cluster_allowed_cores:
    H20_cluster_status:
                                accepting new members, healthy
                                http://127.0.0.1:54321
    H20_connection_url:
                                {"http": null, "https": null}
    H20_connection_proxy:
```

H2O\_internal\_security: False

H2O\_API\_Extensions: Amazon S3, Algos, AutoML, Core V3, TargetEncoder, Core V4

Python\_version: 3.7.7 final

\_\_\_\_\_\_

[107]: # Load data from CSV
df = pd.read\_csv('TOTALNSA.csv', parse\_dates=True, index\_col='DATE')
df.index.freq = "MS"

[108]: df.tail()

[108]: TOTALNSA

DATE

2019-08-01 1685.339

2019-09-01 1315.678

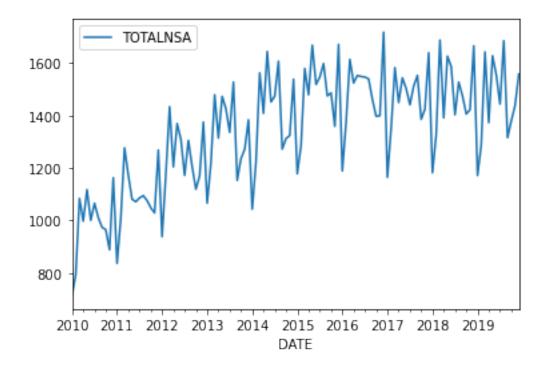
2019-10-01 1380.174

2019-11-01 1438.444

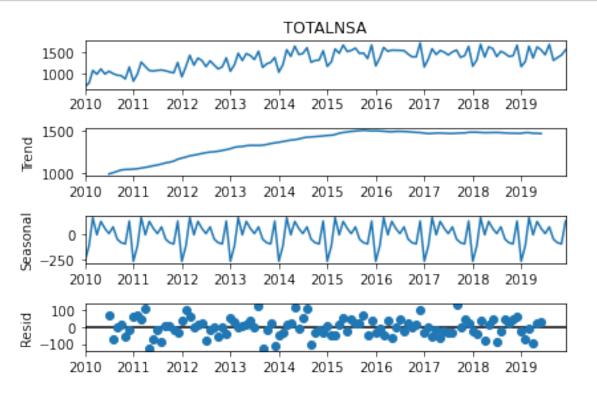
2019-12-01 1558.430

[109]: df.plot()

[109]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1ce3a5245c8>



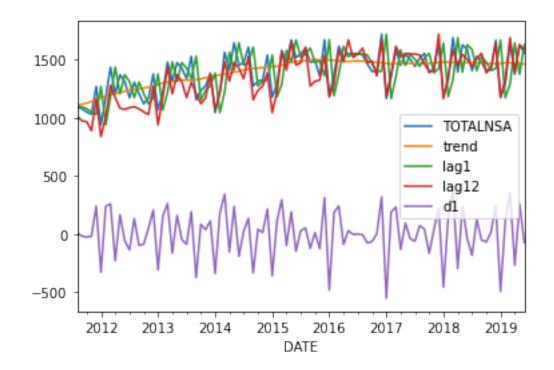
```
[110]: result_sd = seasonal_decompose(df.TOTALNSA)
result_sd.plot();
```



```
[111]: # add trend to variables
       df1=df.copy()
       df1['trend'] = result_sd.trend
       df1.tail()
[111]:
                   TOTALNSA trend
       DATE
       2019-08-01 1685.339
                               NaN
       2019-09-01 1315.678
                               NaN
       2019-10-01 1380.174
                               NaN
       2019-11-01 1438.444
                               NaN
       2019-12-01 1558.430
                               NaN
[112]: # add previous value to variables
       df1['lag1'] = df1.TOTALNSA.shift(1)
       df1.dropna(inplace=True)
       df1.tail()
[112]:
                   TOTALNSA
                                   trend
                                              lag1
```

```
1171.495
      2019-02-01 1288.278 1473.112208
      2019-03-01 1642.746 1473.054042
                                        1288.278
      2019-04-01 1372.696 1465.343500
                                        1642.746
      2019-05-01 1628.074 1464.947292
                                        1372.696
      2019-06-01 1554.747 1461.145167
                                        1628.074
[113]: # add seasonality 12 to variables
      df1['lag12'] = df1.TOTALNSA.shift(12)
      df1.dropna(inplace=True)
      df1.tail()
[113]:
                  TOTALNSA
                                 trend
                                            lag1
                                                     lag12
      DATE
      2019-02-01 1288.278 1473.112208 1171.495 1328.140
      2019-03-01 1642.746 1473.054042
                                        1288.278 1687.609
      2019-04-01 1372.696 1465.343500 1642.746 1391.226
      2019-05-01 1628.074 1464.947292
                                        1372.696 1626.484
      2019-06-01 1554.747 1461.145167 1628.074 1586.664
[114]: # add diff to variables
      df1['d1'] = df1.TOTALNSA.diff(1)
      df1.dropna(inplace=True)
      df1.tail()
[114]:
                  TOTALNSA
                                 trend
                                            lag1
                                                     lag12
                                                                d1
      DATE
      2019-02-01 1288.278 1473.112208 1171.495 1328.140
                                                           116.783
      2019-03-01 1642.746 1473.054042
                                        1288.278 1687.609
                                                           354.468
                                        1642.746 1391.226 -270.050
      2019-04-01 1372.696 1465.343500
      2019-05-01 1628.074 1464.947292 1372.696 1626.484
                                                           255.378
      2019-06-01 1554.747 1461.145167 1628.074 1586.664 -73.327
[115]: df1.plot()
```

[115]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1ce3bbbba08>



```
[116]: train=h2o.H2OFrame(df1.iloc[:-12])
       test=h2o.H2OFrame(df1.iloc[-12:])
                                                       | 100%
      Parse progress: |
      Parse progress: |
                                                       | 100%
[117]: x=['lag12', 'lag1', 'trend', 'd1']
       y='TOTALNSA'
[118]: model = H2ORandomForestEstimator(ntrees=100, max_depth=30, nfolds=15)
       model.train(x=x, y=y, training_frame=train)
      drf Model Build progress: |
                                                            | 100%
[119]: performance = model.model_performance(test_data=test)
       print(performance)
      ModelMetricsRegression: drf
      ** Reported on test data. **
```

MSE: 1811.9511771167126 RMSE: 42.56701982893227 MAE: 38.775986226399745 RMSLE: 0.029440548464803748 Mean Residual Deviance: 1811.9511771167126

## [120]: model.varimp\_plot()

