project2

June 14, 2020

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from pmdarima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tools.eval_measures import rmse
from sklearn.metrics import mean_squared_error
from fbprophet import Prophet
```

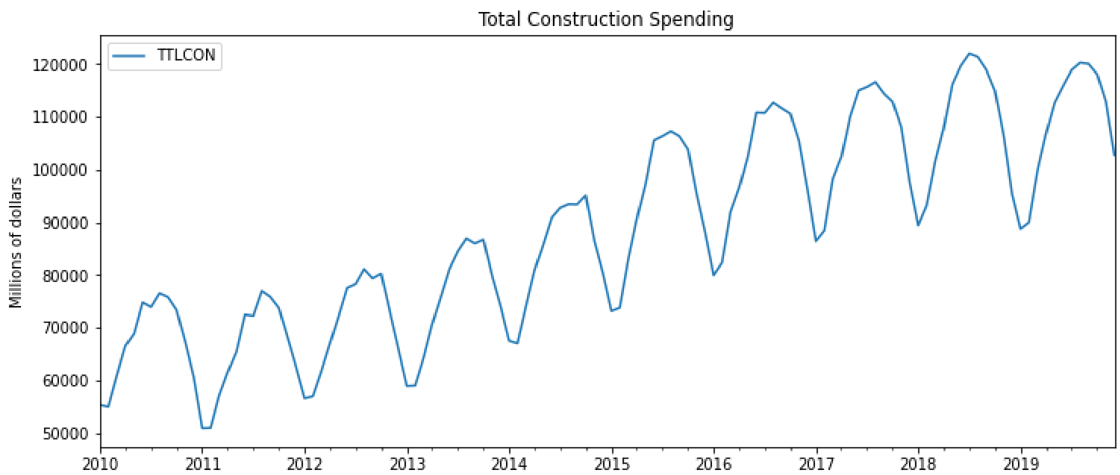
```
Importing plotly failed. Interactive plots will not work.
```

[2]:
```
df = pd.read_csv("TTLCON.csv", parse_dates=True, index_col="DATE")
df.index.freq="MS"
```

[3]:
```
df.describe()
```

[3]:
```
              TTLCON
count     120.000000
mean    88216.833333
std     19533.130602
min     50973.000000
25%     73332.250000
50%     86840.500000
75%    106361.750000
max    122010.000000
```

[5]:
```
ax = df.plot(figsize=(12,5))
plt.title("Total Construction Spending")
plt.ylabel("Millions of dollars")
plt.xlabel("")
plt.show()
```



Check if the data are stationary

[6]:
```
adfuller(df.TTLCON)
```

[6]:
```
(-1.0060633845743006,
 0.7510464016810172,
 13,
 106,
 {'1%': -3.4936021509366793,
  '5%': -2.8892174239808703,
  '10%': -2.58153320754717},
 1852.3576355439993)
```

[7]:
```
adfuller(df.TTLCON.diff(1).dropna())
```

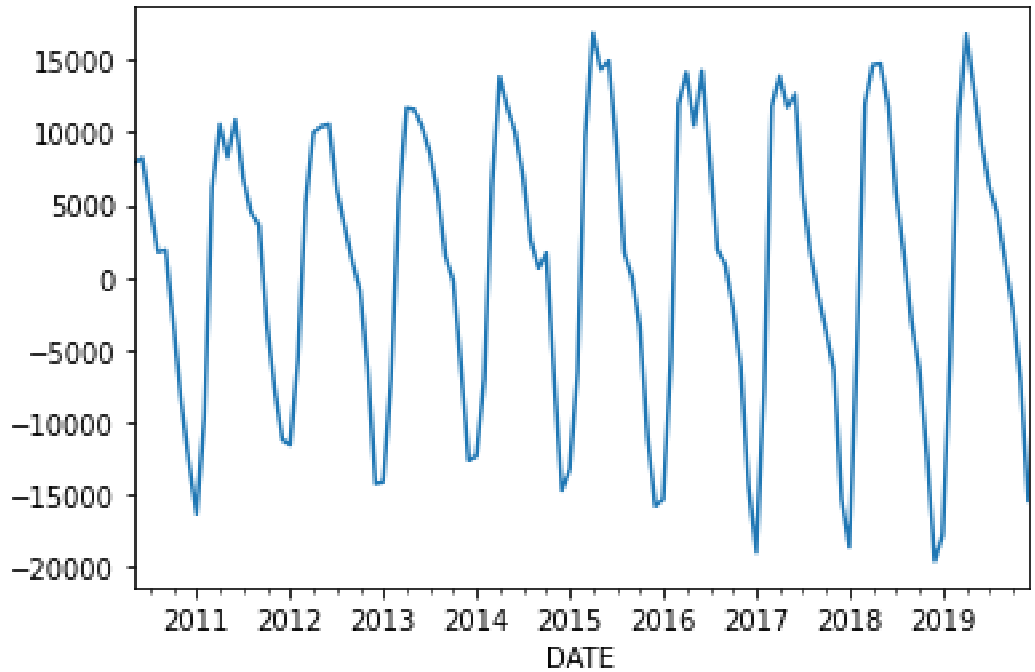
[7]:
```
(-2.642896744021171,
 0.08445145458921421,
 12,
 106,
 {'1%': -3.4936021509366793,
  '5%': -2.8892174239808703,
  '10%': -2.58153320754717},
 1835.3207631252785)
```

[8]:
```
adfuller(df.TTLCON.diff(2).dropna())
```

[8]:
```
(-3.2109969822637976,
 0.01935689015691865,
 13,
 104,
 {'1%': -3.4948504603223145,
```

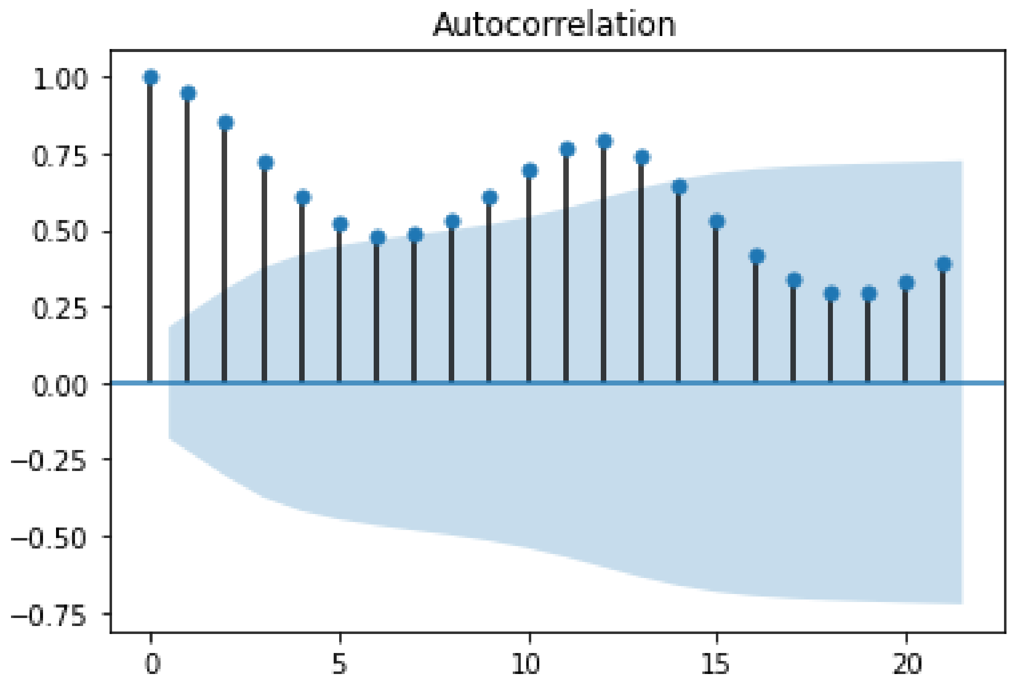
```
 '5%': -2.889758398668639,
 '10%': -2.5818220155325444},
1814.0888303127529)
```

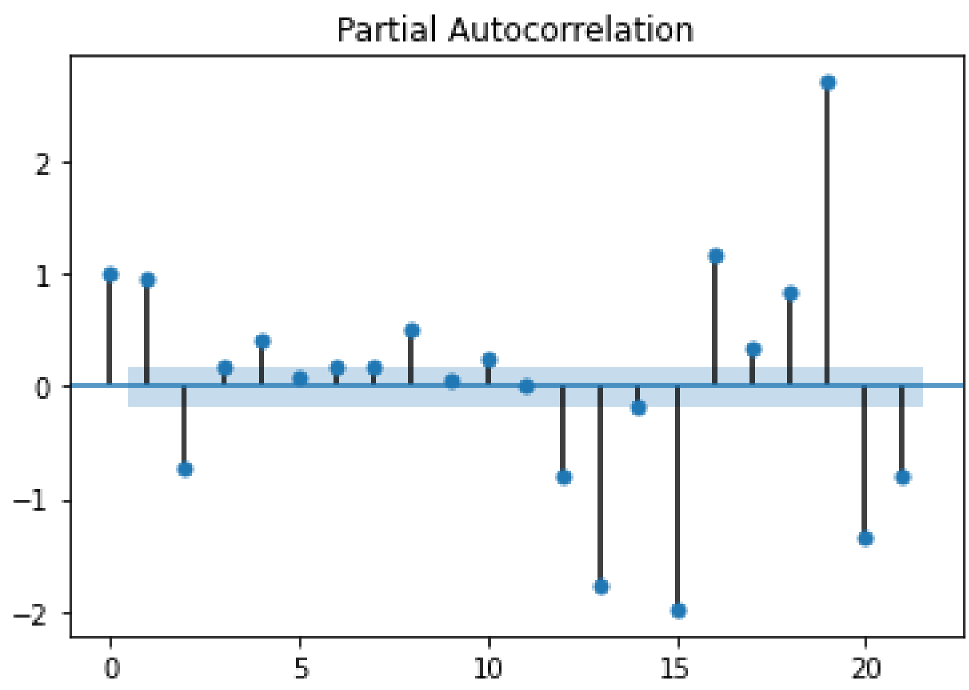
[14]:
```python
df['d2'] = df.TTLCON.diff(2)
df.dropna(inplace=True)
df.d2.plot();
```



[16]:
```python
plot_acf(df.TTLCON);
plot_pacf(df.TTLCON);
```

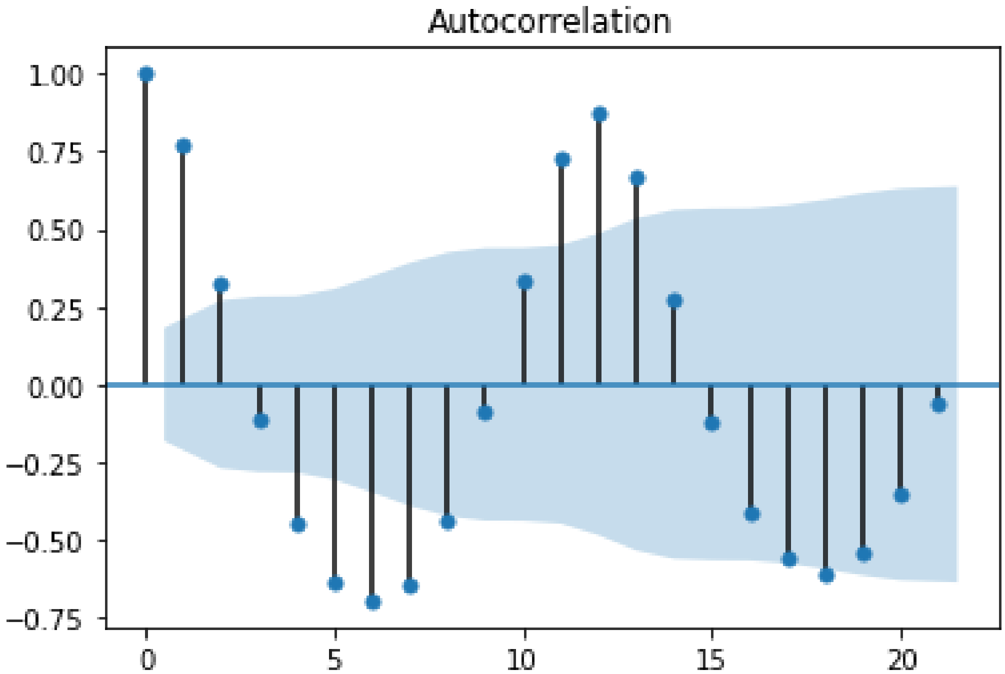
```
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/regression/linear_model.py:1406: RuntimeWarning: invalid
value encountered in sqrt
  return rho, np.sqrt(sigmasq)
```

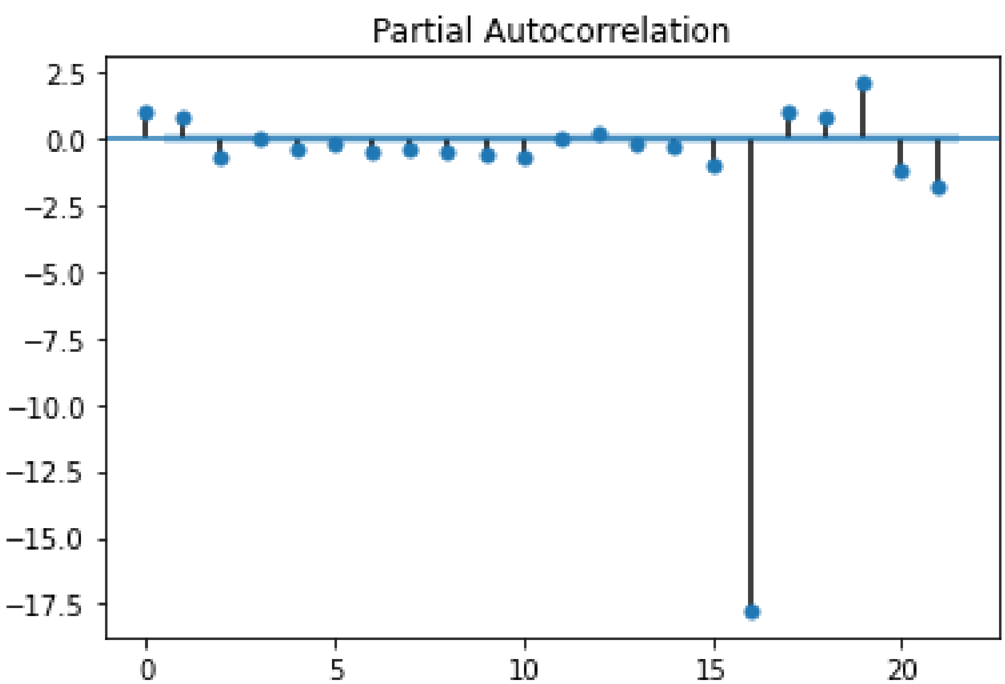




[17]:
```
plot_acf(df.d2);
plot_pacf(df.d2);
```

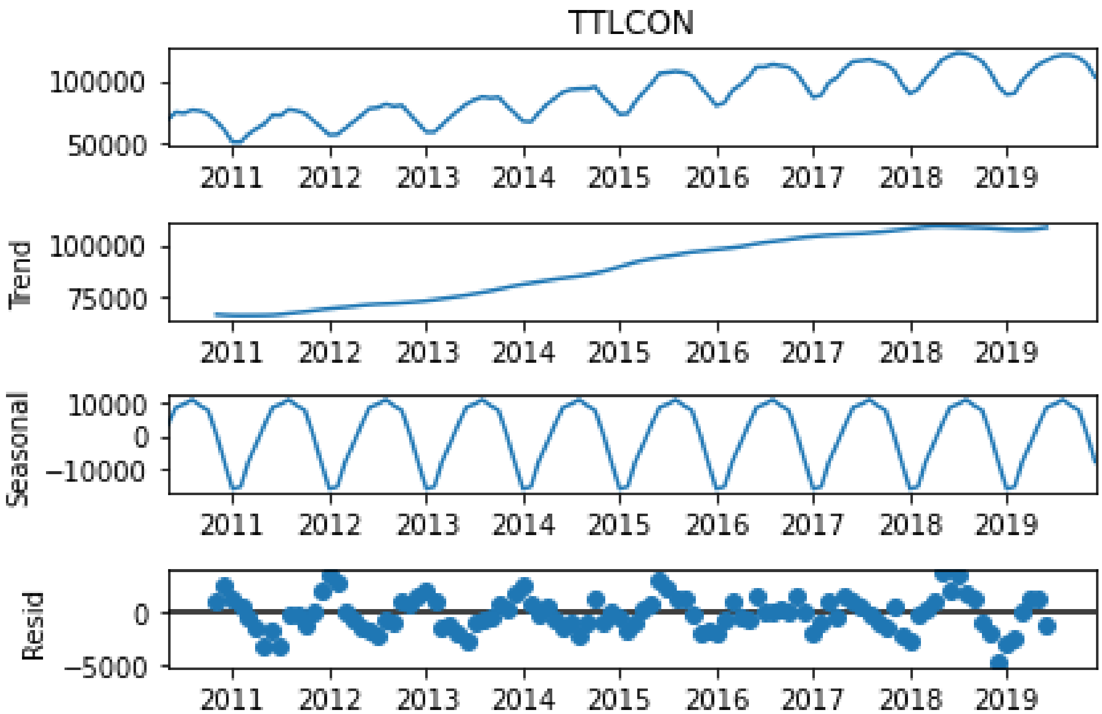
```
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/regression/linear_model.py:1406: RuntimeWarning: invalid
value encountered in sqrt
  return rho, np.sqrt(sigmasq)
```





Check for the seasonality

[18]:
```
res_season = seasonal_decompose(df.TTLCON)
res_season.plot();
```



[19]:
```
def evaluate_model(model, start, test, model_name, **kwargs):
    """ Function to evaluate predictions against test set.

    Args:
        model: model to produce predictions
        start: start index of prediction usually len(train)
        test: test data
        model_name: name to rename the model data
        **kwargs: additional parameters for predict function

    Returns:
        predictions
    """
    predictions = model.predict(start=start, end=start+len(test)-1,␣
 ↪dynamic=False, **kwargs).rename(model_name)
    print(f"MSE for {model_name}: \t{mean_squared_error(test, predictions)}")
```

```
    print(f"RMSE for {model_name}: \t{rmse(test, predictions)}")
    return predictions
```

[20]:
```
def plot_results(test, predictions):
    """ Plots the predicted data and test data to visualise the predictions.

    Args:
        test: test data
        prediction: predictions data
    """
    title = "Compare prediction with test set"
    xlabel = "date"
    ylabel="Millions of units"

    ax = test.plot(legend=True, figsize=(12,6), title=title, label="Test data")
    predictions.plot(legend=True)
    ax.autoscale(axis="x", tight=True)
    ax.set(xlabel=xlabel, ylabel=ylabel)
    plt.show()
```

Do not specify any parameters

[21]:
```
stepwise = auto_arima(
    df.TTLCON,
    m=12,
    d=None,
    D=None,
    start_p=1,
    start_q=1,
    max_p=4,
    max_d=4,
    max_q=4,
    max_P=4,
    max_D=4,
    max_Q=4,
    stepwise=False,
    trace=True,
    n_jobs=-1
)
stepwise.summary()
```

```
Total fit time: 100.280 seconds
```

[21]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                        SARIMAX Results
================================================================================
```

```
===============
Dep. Variable:                                   y   No. Observations:
116
Model:             SARIMAX(0, 0, 1)x(2, 1, [1, 2], 12)   Log Likelihood
-979.254
Date:                             Sun, 14 Jun 2020   AIC
1972.509
Time:                                     22:39:38   BIC
1991.019
Sample:                                          0   HQIC
1980.008
                                             - 116
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept   5044.7942   1242.834      4.059      0.000    2608.885    7480.704
ma.L1          0.1464      0.051      2.879      0.004       0.047       0.246
ar.S.L12       1.0567      0.134      7.861      0.000       0.793       1.320
ar.S.L24      -0.8850      0.144     -6.149      0.000      -1.167      -0.603
ma.S.L12      -1.1668      0.160     -7.276      0.000      -1.481      -0.852
ma.S.L24       0.9540      0.232      4.117      0.000       0.500       1.408
sigma2      1.319e+07      0.017   7.55e+08      0.000    1.32e+07    1.32e+07
================================================================================
===
Ljung-Box (Q):                      193.79   Jarque-Bera (JB):
34.11
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               1.41   Skew:
-0.97
Prob(H) (two-sided):                  0.31   Kurtosis:
5.03
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
1.43e+26. Standard errors may be unstable.
"""
```

Set $d = 2$

[22]:
```
stepwise = auto_arima(
    df.TTLCON,
```

```
    m=12,
    d=2,
    D=None,
    start_p=1,
    start_q=1,
    max_p=4,
    max_q=4,
    max_P=4,
    max_D=4,
    max_Q=4,
    stepwise=False,
    trace=True,
    n_jobs=-1
)
stepwise.summary()
```

```
Total fit time: 83.841 seconds
```

[22]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results
================================================================================
==========
Dep. Variable:                                  y   No. Observations:
116
Model:             SARIMAX(1, 2, 1)x(1, 1, 1, 12)   Log Likelihood
-915.768
Date:                            Sun, 14 Jun 2020   AIC
1843.537
Time:                                    22:41:02   BIC
1859.287
Sample:                                         0   HQIC
1849.914
                                            - 116
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      4.9294      4.461      1.105      0.269      -3.813      13.672
ar.L1          0.5930      0.076      7.854      0.000       0.445       0.741
ma.L1         -0.8864      0.072    -12.373      0.000      -1.027      -0.746
ar.S.L12       0.7608      0.081      9.412      0.000       0.602       0.919
ma.S.L12      -0.9998      0.172     -5.803      0.000      -1.337      -0.662
sigma2      3.322e+06   6.92e-08     4.8e+13      0.000    3.32e+06    3.32e+06
================================================================================
===
Ljung-Box (Q):                      255.68   Jarque-Bera (JB):
```

```
2.16
Prob(Q):                              0.00   Prob(JB):
0.34
Heteroskedasticity (H):               1.07   Skew:
-0.27
Prob(H) (two-sided):                  0.85   Kurtosis:
2.54
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
1.26e+31. Standard errors may be unstable.
"""
```

set $d = 1$

[23]:
```
stepwise = auto_arima(
    df.TTLCON,
    m=12,
    d=1,
    D=None,
    start_p=1,
    start_q=1,
    max_p=4,
    max_q=4,
    max_P=4,
    max_D=4,
    max_Q=4,
    stepwise=False,
    trace=True,
    n_jobs=-1
)
stepwise.summary()
```

```
Total fit time: 64.049 seconds
```

[23]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results
================================================================================
===========
Dep. Variable:                                   y   No. Observations:
116
Model:             SARIMAX(2, 1, 3)x(0, 1, [], 12)   Log Likelihood
-897.390
```

```
Date:                            Sun, 14 Jun 2020   AIC
1808.780
Time:                                    22:42:06   BIC
1827.223
Sample:                                         0   HQIC
1816.250
                                            - 116
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     16.1788    474.308      0.034      0.973    -913.448     945.806
ar.L1         -1.1264      0.020    -57.191      0.000      -1.165      -1.088
ar.L2         -0.9995      0.005   -212.532      0.000      -1.009      -0.990
ma.L1          1.1121      0.098     11.327      0.000       0.920       1.305
ma.L2          0.9779      0.147      6.643      0.000       0.689       1.266
ma.L3         -0.0190      0.069     -0.276      0.783      -0.154       0.116
sigma2      2.203e+06      0.002   1.01e+09      0.000     2.2e+06     2.2e+06
================================================================================
===
Ljung-Box (Q):                       73.03   Jarque-Bera (JB):
0.03
Prob(Q):                              0.00   Prob(JB):
0.98
Heteroskedasticity (H):               1.54   Skew:
-0.00
Prob(H) (two-sided):                  0.22   Kurtosis:
3.09
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
1.12e+27. Standard errors may be unstable.
"""
```

set $d = 1$ and $D = 1$

[24]:

```
stepwise = auto_arima(
    df.TTLCON,
    m=12,
    d=1,
    D=1,
    start_p=1,
    start_q=1,
```

```
    max_p=4,
    max_q=4,
    max_P=4,
    max_Q=4,
    stepwise=False,
    trace=True,
    n_jobs=-1
)
stepwise.summary()
```

```
Total fit time: 65.529 seconds
```

[24]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results
================================================================================
===========
Dep. Variable:                                    y   No. Observations:
116
Model:             SARIMAX(2, 1, 3)x(0, 1, [], 12)   Log Likelihood
-897.390
Date:                             Sun, 14 Jun 2020   AIC
1808.780
Time:                                     22:43:12   BIC
1827.223
Sample:                                          0   HQIC
1816.250
                                             - 116
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     16.1788    474.308      0.034      0.973    -913.448     945.806
ar.L1         -1.1264      0.020    -57.191      0.000      -1.165      -1.088
ar.L2         -0.9995      0.005   -212.532      0.000      -1.009      -0.990
ma.L1          1.1121      0.098     11.327      0.000       0.920       1.305
ma.L2          0.9779      0.147      6.643      0.000       0.689       1.266
ma.L3         -0.0190      0.069     -0.276      0.783      -0.154       0.116
sigma2      2.203e+06      0.002   1.01e+09      0.000     2.2e+06     2.2e+06
================================================================================
===
Ljung-Box (Q):                       73.03   Jarque-Bera (JB):
0.03
Prob(Q):                              0.00   Prob(JB):
0.98
Heteroskedasticity (H):               1.54   Skew:
-0.00
```

```
Prob(H) (two-sided):                  0.22   Kurtosis:
3.09
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
1.12e+27. Standard errors may be unstable.
"""
```

[25]:
```
s_index = -12
train = df.iloc[:s_index]
test = df.iloc[s_index:]
```

Create all the SARIMAX models

[29]:
```
sarimax_1 = SARIMAX(train.TTLCON, order=(0, 0, 1), seasonal_order=(2, 1, [1,␣
↪2], 12)).fit()
sarimax_2 = SARIMAX(train.TTLCON, order=(1, 2, 1), seasonal_order=(1, 1, 1,␣
↪12)).fit()
sarimax_3 = SARIMAX(train.TTLCON, order=(2, 1, 3), seasonal_order=(0, 1, [],␣
↪12)).fit()
# additional to test
sarimax_4 = SARIMAX(train.TTLCON, order=(2,0,1), seasonal_order=(0,1,1,12)).
↪fit()
sarimax_5 = SARIMAX(train.TTLCON, order=(2,1,1), seasonal_order=(0,1,1,12)).
↪fit()
```

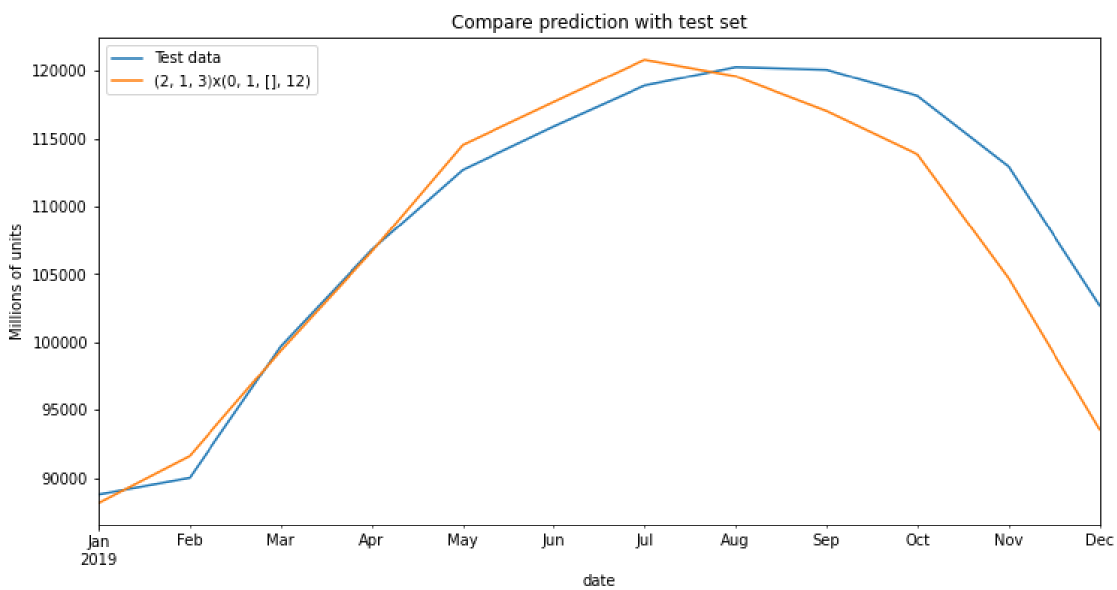
```
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/tsa/statespace/sarimax.py:1006: UserWarning: Non-invertible
starting seasonal moving average Using zeros as starting parameters.
  warn('Non-invertible starting seasonal moving average'
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/base/model.py:567: ConvergenceWarning: Maximum Likelihood
optimization failed to converge. Check mle_retvals
  warn("Maximum Likelihood optimization failed to converge. "
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/tsa/statespace/sarimax.py:963: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/statsmodels/tsa/statespace/sarimax.py:975: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

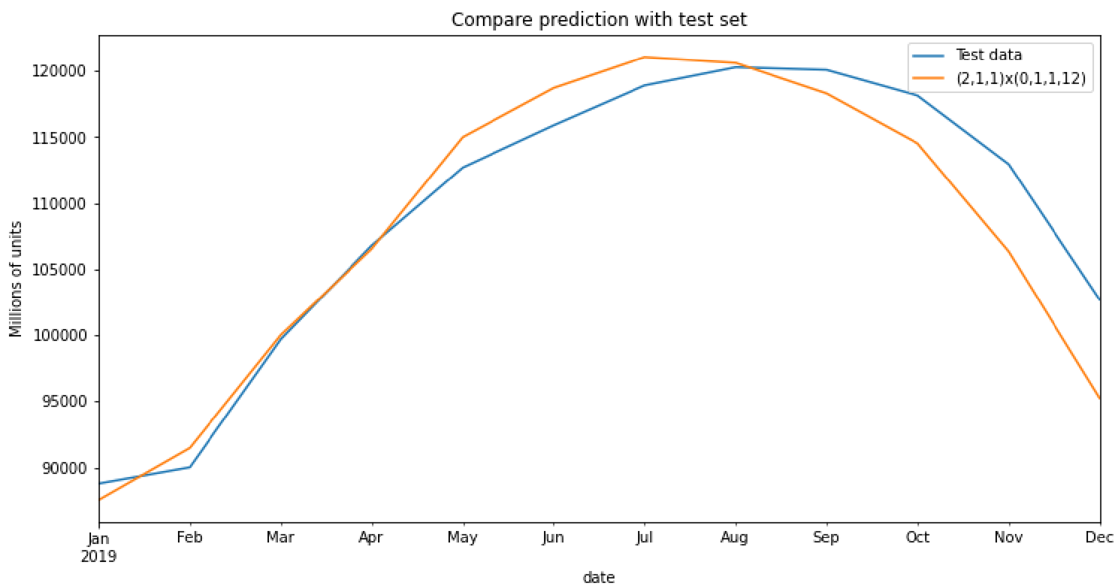
[30]:
```
res_sarimax_1 = evaluate_model(sarimax_1, len(train), test.TTLCON, "(0, 0,␣
↪1)x(2, 1, [1, 2], 12)")
res_sarimax_2 = evaluate_model(sarimax_2, len(train), test.TTLCON, "(1, 2,␣
↪1)x(1, 1, 1, 12)")
res_sarimax_3 = evaluate_model(sarimax_3, len(train), test.TTLCON, "(2, 1,␣
↪3)x(0, 1, [], 12)")
res_sarimax_4 = evaluate_model(sarimax_4, len(train), test.TTLCON,␣
↪"(2,0,1)x(0,1,1,12)")
res_sarimax_5 = evaluate_model(sarimax_5, len(train), test.TTLCON,␣
↪"(2,1,1)x(0,1,1,12)")
```

```
MSE for (0, 0, 1)x(2, 1, [1, 2], 12):   36409656.630913
RMSE for (0, 0, 1)x(2, 1, [1, 2], 12):  6034.041484023208
MSE for (1, 2, 1)x(1, 1, 1, 12):        246517961.62099406
RMSE for (1, 2, 1)x(1, 1, 1, 12):       15700.890472230996
MSE for (2, 1, 3)x(0, 1, [], 12):       16101919.083244847
RMSE for (2, 1, 3)x(0, 1, [], 12):      4012.7196616814444
MSE for (2,0,1)x(0,1,1,12):     43446948.46537794
RMSE for (2,0,1)x(0,1,1,12):    6591.429925697302
MSE for (2,1,1)x(0,1,1,12):     11428876.71968624
RMSE for (2,1,1)x(0,1,1,12):    3380.6621717773337
```

Plot 2 best results

[34]:
```
plot_results(test.TTLCON, res_sarimax_3)
plot_results(test.TTLCON, res_sarimax_5)
```



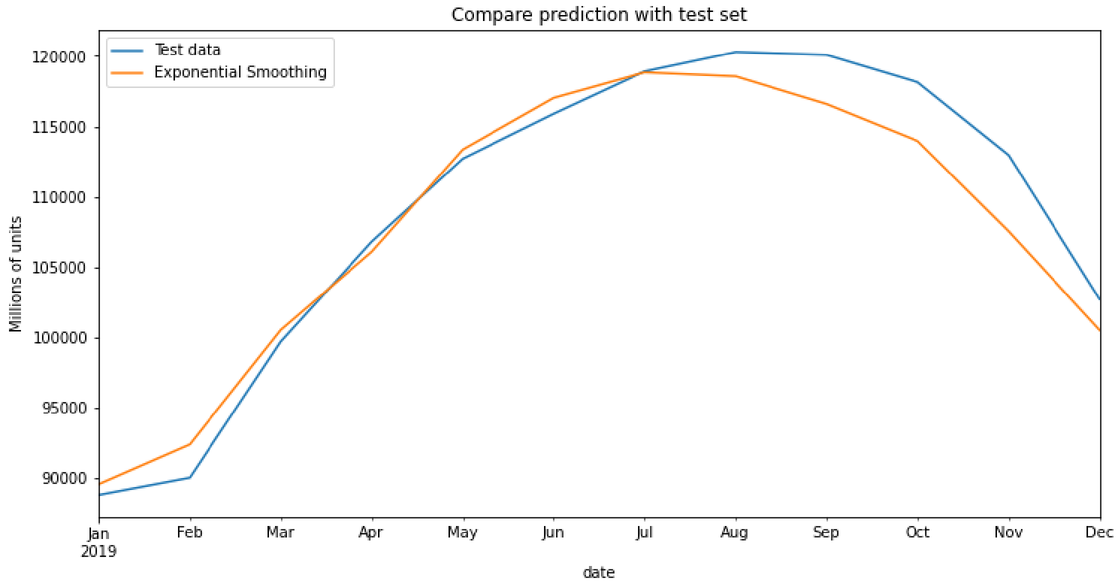


Let us check the Exponential Smoothing

[35]:
```
hw_es = ExponentialSmoothing(
    train.TTLCON,
    trend='mul',
    seasonal='mul',
    seasonal_periods=12
).fit()
res_hw_es = hw_es.forecast(12).rename("Exponential Smoothing")
print(f"MSE for Exponential Smoothing: \t{mean_squared_error(test.TTLCON,␣
 ↪res_hw_es)}")
print(f"RMSE for Exponential Smoothing: \t{rmse(test.TTLCON, res_hw_es)}")
```

```
MSE for Exponential Smoothing:  6327353.1897783615
RMSE for Exponential Smoothing:         2515.423063776422
```

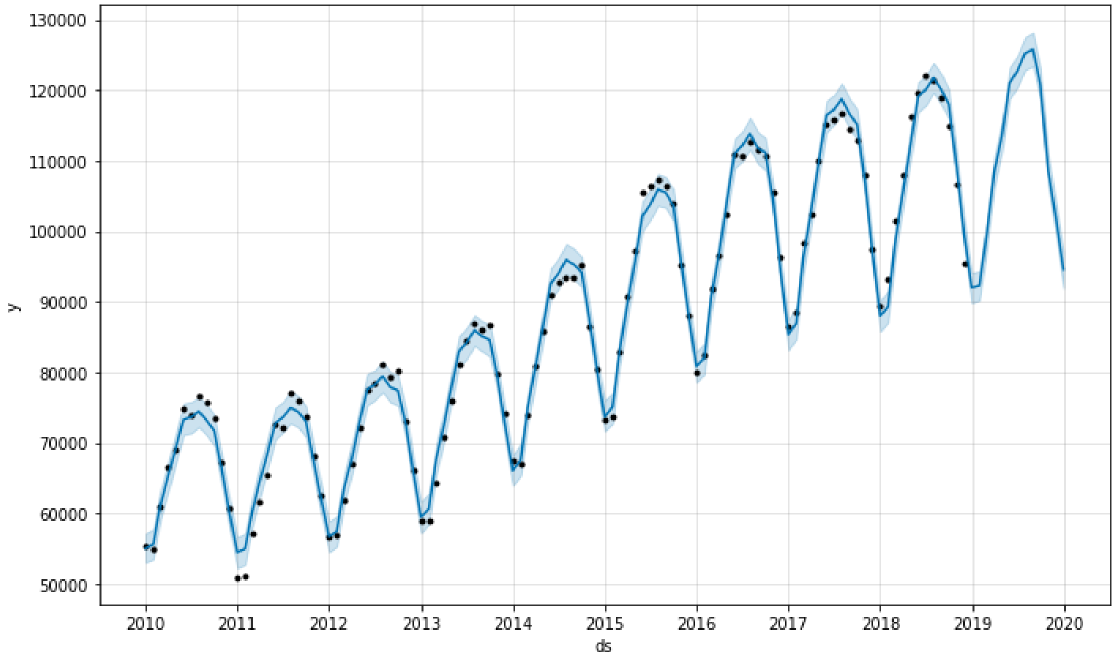
[36]:
```
plot_results(test.TTLCON, res_hw_es)
```



Let us check the Prophet from fbprophet module

[38]:
```
prop_data = pd.read_csv("TTLCON.csv", parse_dates=True)
prop_data.columns = ["ds", "y"]
prop_train = prop_data.iloc[:-12]
m = Prophet(seasonality_mode='multiplicative').fit(prop_train)
future = m.make_future_dataframe(periods=13, freq='M')
fcst = m.predict(future)
fig = m.plot(fcst)
```

```
INFO:fbprophet:Disabling weekly seasonality. Run prophet with
weekly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```



[39]:
```
fcst[["ds",'yhat']].iloc[-12:]
```

[39]:

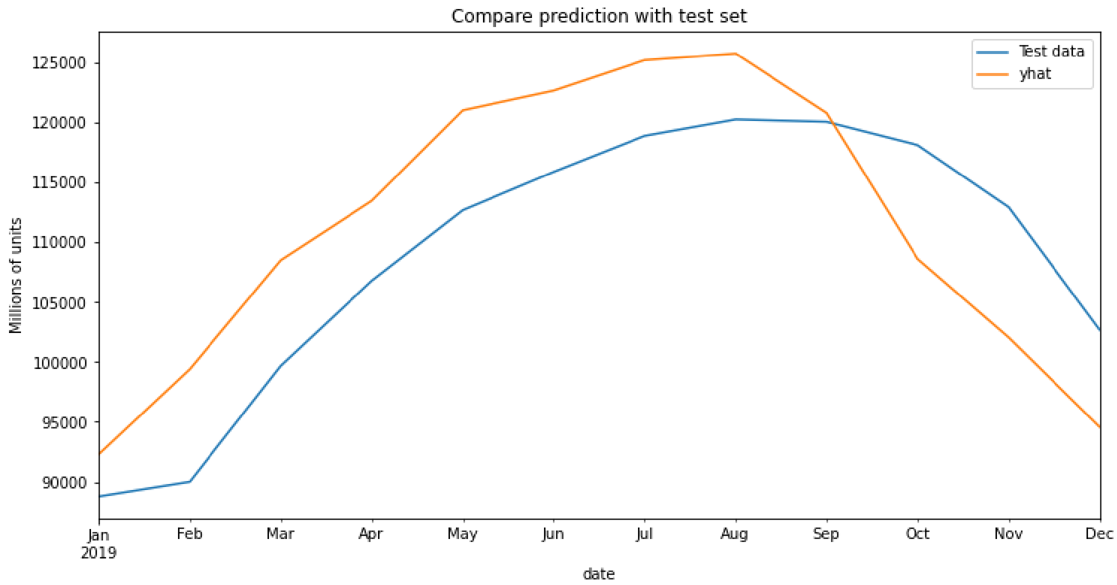
	ds	yhat
109	2019-01-31	92287.256960
110	2019-02-28	99409.009943
111	2019-03-31	108507.939186
112	2019-04-30	113468.256666
113	2019-05-31	121032.438876
114	2019-06-30	122677.707122
115	2019-07-31	125226.438199
116	2019-08-31	125776.792472
117	2019-09-30	120809.014583
118	2019-10-31	108628.248808
119	2019-11-30	102058.108034
120	2019-12-31	94585.917873

[40]:
```
fcst_test = fcst.set_index("ds")
```

[41]:
```
print(f"MSE for Prophet: \t{mean_squared_error(test.TTLCON,␣
↪fcst_test['yhat'][-12:])}")
print(f"RMSE for Prophet: \t{rmse(test.TTLCON, fcst_test['yhat'][-12:])}")
```

```
MSE for Prophet:        57048913.57835562
RMSE for Prophet:       7553.073121475498
```

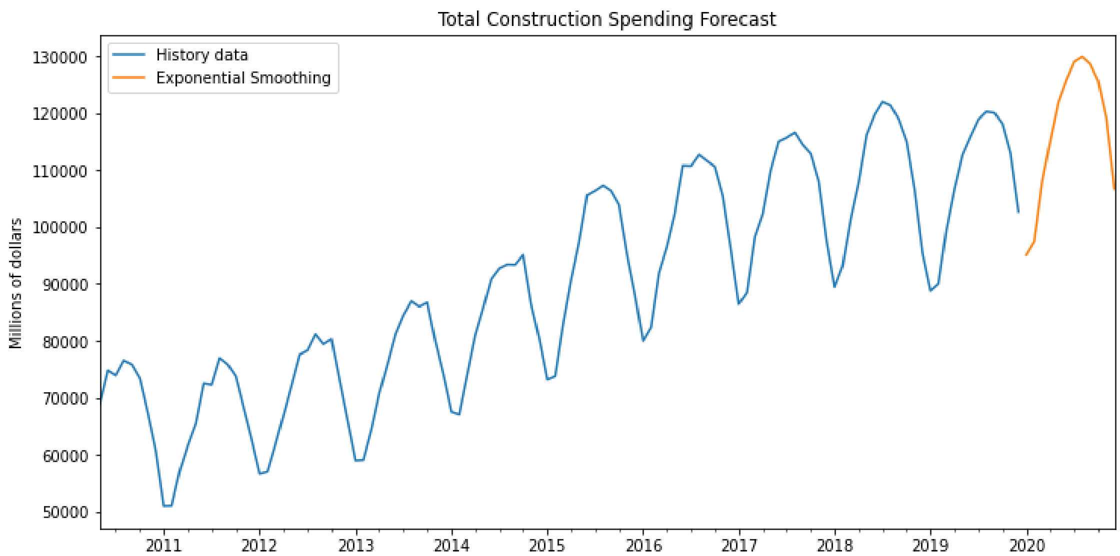
[42]:
```
plot_results(test.TTLCON, fcst_test['yhat'][-12:])
```



Again the Exponential Smoothing gives us the smallest error, we will use this one to predict the future data.

[43]:
```
hw_es = ExponentialSmoothing(
    df.TTLCON,
    trend='mul',
    seasonal='mul',
    seasonal_periods=12
).fit()
res_hw_es = hw_es.forecast(12).rename("Exponential Smoothing")
```

[44]:
```
title = "Total Construction Spending Forecast"
ylabel = "Millions of dollars"
ax = df.TTLCON.plot(legend=True, figsize=(12,6), title=title, label="History␣
↪data")
res_hw_es.plot(legend=True)
ax.autoscale(axis="x", tight=True)
ax.set(xlabel="", ylabel=ylabel)
plt.show()
```



Let us try RandomForest from H2o

[45]:
```python
import h2o
from h2o.estimators import H2ORandomForestEstimator
```

[46]:
```python
h2o.init()
```

```
Checking whether there is an H2O instance running at http://localhost:54321
… not found.
Attempting to start a local H2O server…
  Java Version: openjdk version "11.0.7" 2020-04-14; OpenJDK Runtime Environment
(build 11.0.7+10-post-Ubuntu-3ubuntu1); OpenJDK 64-Bit Server VM (build
11.0.7+10-post-Ubuntu-3ubuntu1, mixed mode, sharing)
  Starting server from
/home/sqauess/Documents/University/TimeSeries/venv/lib/python3.8/site-
packages/h2o/backend/bin/h2o.jar
  Ice root: /tmp/tmpva_42spc
  JVM stdout: /tmp/tmpva_42spc/h2o_sqauess_started_from_python.out
  JVM stderr: /tmp/tmpva_42spc/h2o_sqauess_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:         02 secs
H2O_cluster_timezone:       Europe/Warsaw
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.30.0.4
H2O_cluster_version_age:    13 days
H2O_cluster_name:           H2O_from_python_sqauess_vkjy44
```

```
H2O_cluster_total_nodes:     1
H2O_cluster_free_memory:     3.887 Gb
H2O_cluster_total_cores:     4
H2O_cluster_allowed_cores:   4
H2O_cluster_status:          accepting new members, healthy
H2O_connection_url:          http://127.0.0.1:54321
H2O_connection_proxy:        {"http": null, "https": null}
H2O_internal_security:       False
H2O_API_Extensions:          Amazon S3, XGBoost, Algos, AutoML, Core V3, TargetEncoder, Core V4
Python_version:              3.8.2 final
--------------------------   -----------------------------------------------------------------
```

[50]:
```
df = pd.read_csv("TTLCON.csv", parse_dates=True, index_col='DATE')
df.index.freq="MS"
df.tail()
```

[50]:
```
            TTLCON
DATE
2019-08-01  120278
2019-09-01  120078
2019-10-01  118134
2019-11-01  112942
2019-12-01  102703
```

[63]:
```
df1 = df.copy()

df1['lag1'] = df1.TTLCON.shift(1)
df1.dropna(inplace=True)

df1['lag2'] = df1.TTLCON.shift(2)
df1.dropna(inplace=True)

df1['lag12'] = df1.TTLCON.shift(12)
df1.dropna(inplace=True)

df1['d1'] = df1.TTLCON.diff(1)
df1.dropna(inplace=True)

df1['d2'] = df1.TTLCON.diff(2)
df1.dropna(inplace=True)
df1.tail()
```

[63]:
```
            TTLCON      lag1      lag2     lag12      d1      d2
DATE
2019-08-01  120278  118902.0  115887.0  121385.0   1376.0   4391.0
2019-09-01  120078  120278.0  118902.0  118968.0   -200.0   1176.0
2019-10-01  118134  120078.0  120278.0  115002.0  -1944.0  -2144.0
```

```
2019-11-01  112942  118134.0  120078.0  106590.0  -5192.0  -7136.0
2019-12-01  102703  112942.0  118134.0   95415.0 -10239.0 -15431.0
```

[64]:
```python
train=h2o.H2OFrame(df1.iloc[:-12])
test=h2o.H2OFrame(df1.iloc[-12:])
```

```
Parse progress: |                                         | 100%
Parse progress: |                                         | 100%
```

[66]:
```python
x=['lag1', 'lag2', 'lag12', 'd2', 'd1']
y='TTLCON'
model = H2ORandomForestEstimator(ntrees=100, max_depth=30, nfolds=15)
model.train(x=x, y=y, training_frame=train)
```

```
drf Model Build progress: |                                 | 100%
```

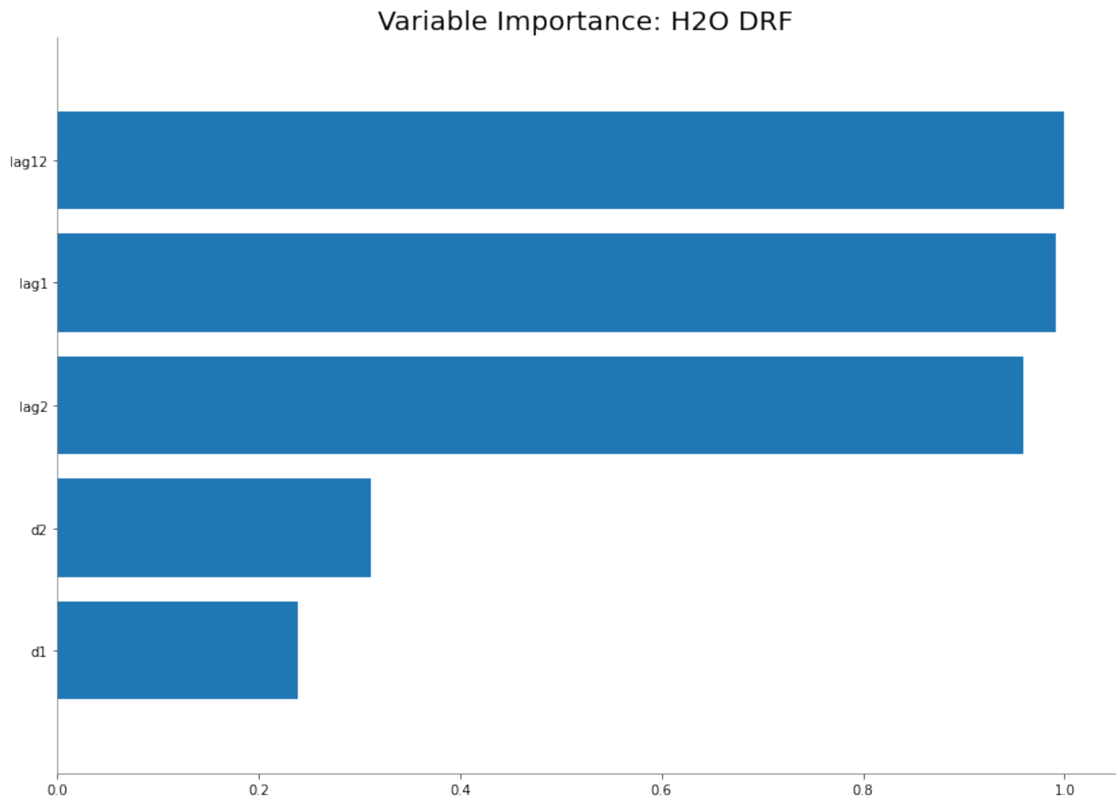
[67]:
```python
performance = model.model_performance(test_data=test)
print(performance)
```

```
ModelMetricsRegression: drf
** Reported on test data. **

MSE: 15497732.252277084
RMSE: 3936.7159222221107
MAE: 2572.877083333334
RMSLE: 0.03896676002131595
Mean Residual Deviance: 15497732.252277084
```

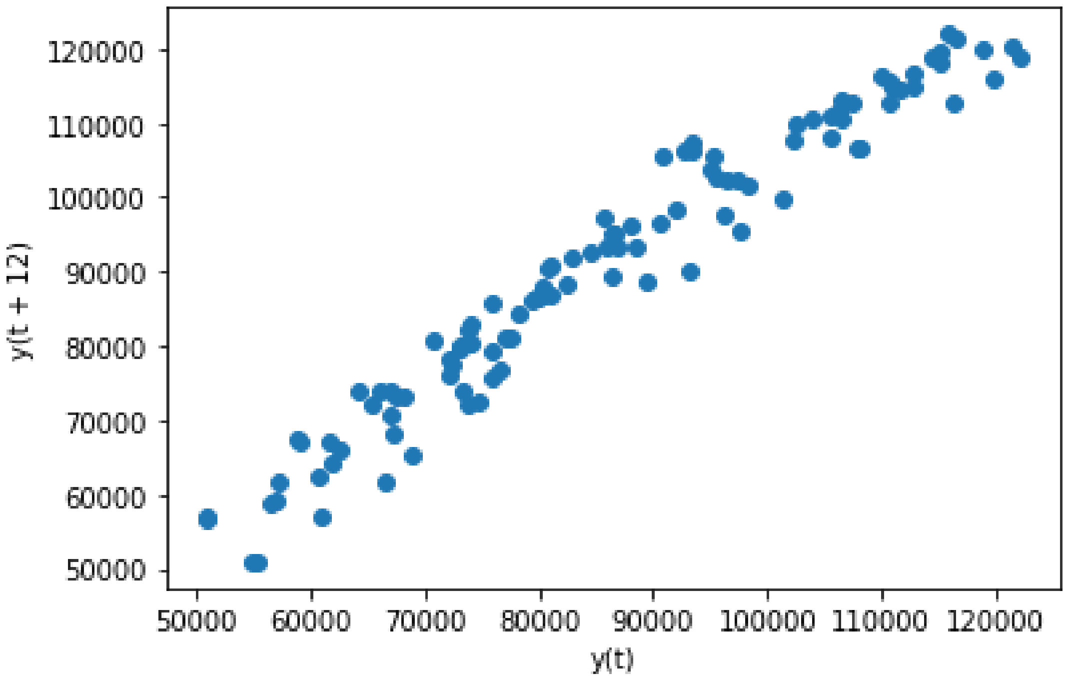
RMSE is worse than the Exponential Smoothing

[68]:
```python
model.varimp_plot()
```



[74]:
```
from pandas.plotting import lag_plot
lag_plot(df.TTLCON, lag=12)
```

[74]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb8426d76d0>



Summary: I was dealing with seasonal data of period 12 month. From all tested models the best one was ExponentialSmoothing with $RMSE \approx 2515$