timeserieslab8-rohramehak-251524

April 24, 2024

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:
```
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

[5]:
```
!pip install pmdarima
```

```
Collecting pmdarima
  Downloading pmdarima-2.0.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86
_64.manylinux_2_28_x86_64.whl (2.1 MB)
                           2.1/2.1 MB
10.2 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.4.0)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.10)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.25.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.3)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.11.4)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (24.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
```

```
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2024.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.4.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels>=0.13.2->pmdarima) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels>=0.13.2->pmdarima) (1.16.0)
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.4
```

Sliding window for training and testing over multiple iterations

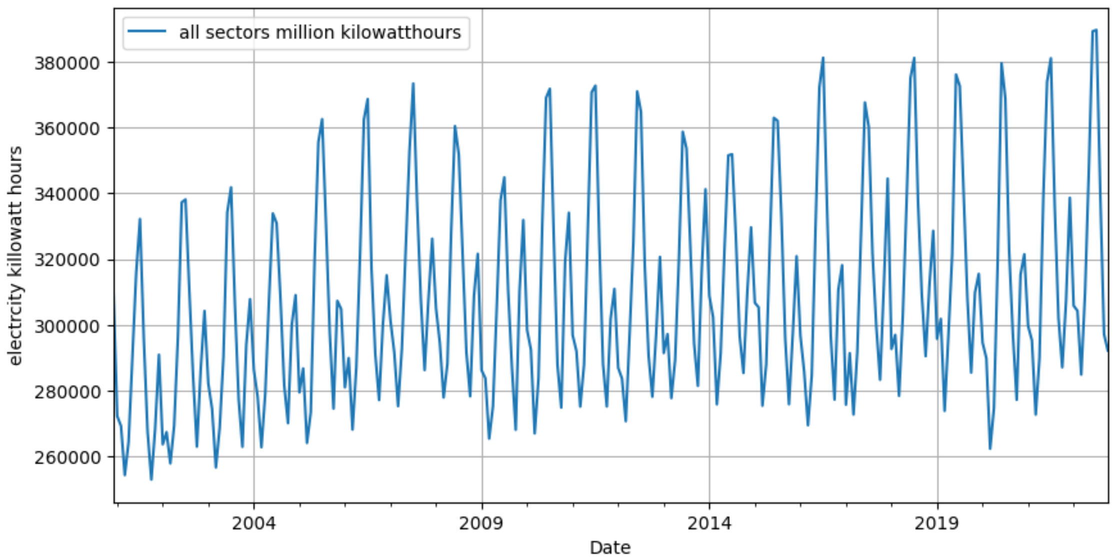
[68]:
```
from pmdarima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_absolute_percentage_error
```

[69]:
```
data = pd.read_csv('/content/drive/MyDrive/TSA_BDA_2024/Lab4/
 ↪Retail_sales_of_electricity_United_States_monthly.csv', skiprows=4)
```

[70]:
```
data.dropna(inplace=True)
data['DatePart'] = pd.to_datetime(data['Month'], format='%b %Y',␣
 ↪errors='coerce')
data.rename(columns = {"DatePart" : "Date"}, inplace=True)
data.set_index("Date", inplace=True)
data.drop(columns=["Month"], inplace=True)
```

All sectors electricity data:

[71]:
```
data.plot(figsize=(10,5), grid=True)
plt.ylabel("electrcity killowatt hours")
plt.show()
```



[72]:
```
data.sort_index(inplace=True)
data
```

[72]:
```
            all sectors million kilowatthours
Date
2000-12-01                     310816.06880
2001-01-01                     272334.73804
2001-02-01                     269298.40142
2001-03-01                     254390.93545
2001-04-01                     264490.49166
…                                         …
2022-06-01                     389214.17473
2022-07-01                     389626.28230
2022-08-01                     340543.84071
2022-09-01                     297195.94414
2022-10-01                     292257.74617

[263 rows x 1 columns]
```

using auto_arima for automatically selecting the optimal ARIMA model parameters for a given time series dataset

[73]:
```
auto_arima(data["all sectors million kilowatthours"], seasonal=True,m=12).
↪summary()
```

[73]:

Dep. Variable:	y	**No. Observations:**	263
Model:	SARIMAX(0, 0, 1)x(0, 1, [], 12)	**Log Likelihood**	-2675.909
Date:	Tue, 23 Apr 2024	**AIC**	5357.818
Time:	22:20:25	**BIC**	5368.395
Sample:	12-01-2000	**HQIC**	5362.074
	- 10-01-2022		
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
intercept	1707.6753	634.656	2.691	0.007	463.773	2951.577
ma.L1	0.1343	0.008	16.693	0.000	0.119	0.150
sigma2	8.528e+07	0.001	1.54e+11	0.000	8.53e+07	8.53e+07

Ljung-Box (L1) (Q):	52.99	**Jarque-Bera (JB):**	76.45
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.87	**Skew:**	-0.56
Prob(H) (two-sided):	0.54	**Kurtosis:**	5.46

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 9.71e+27. Standard errors may be unstable.

Using autoarima we see that are model to be used is a purely moving average model with auto regressive and diff paramters are 0

so we will move forard with that in our sliding window iterations

[76]:
```
data.index.freq='MS'
```

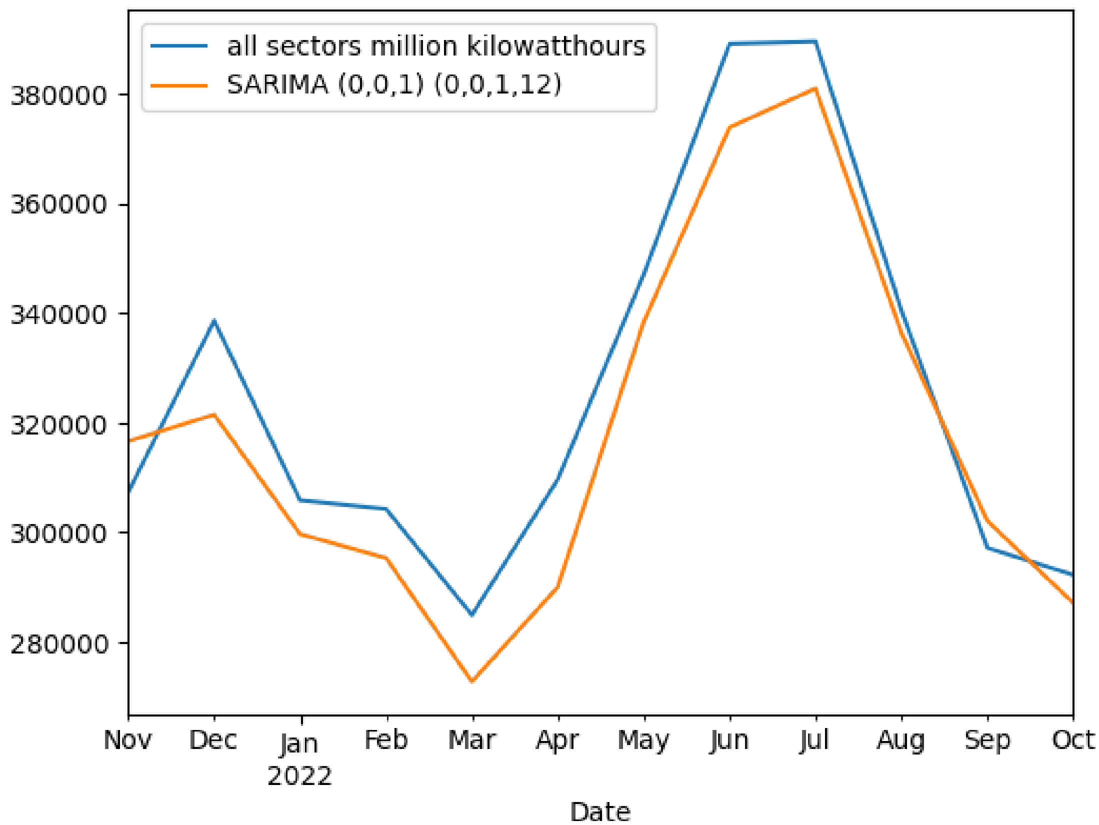
single iteration, training on entire data and testing on last 12 months

[77]:
```
X_train= data.iloc[:-12]
X_test= data.iloc[-12:]
start = len(X_train)
end = start + len(X_test) -1
```

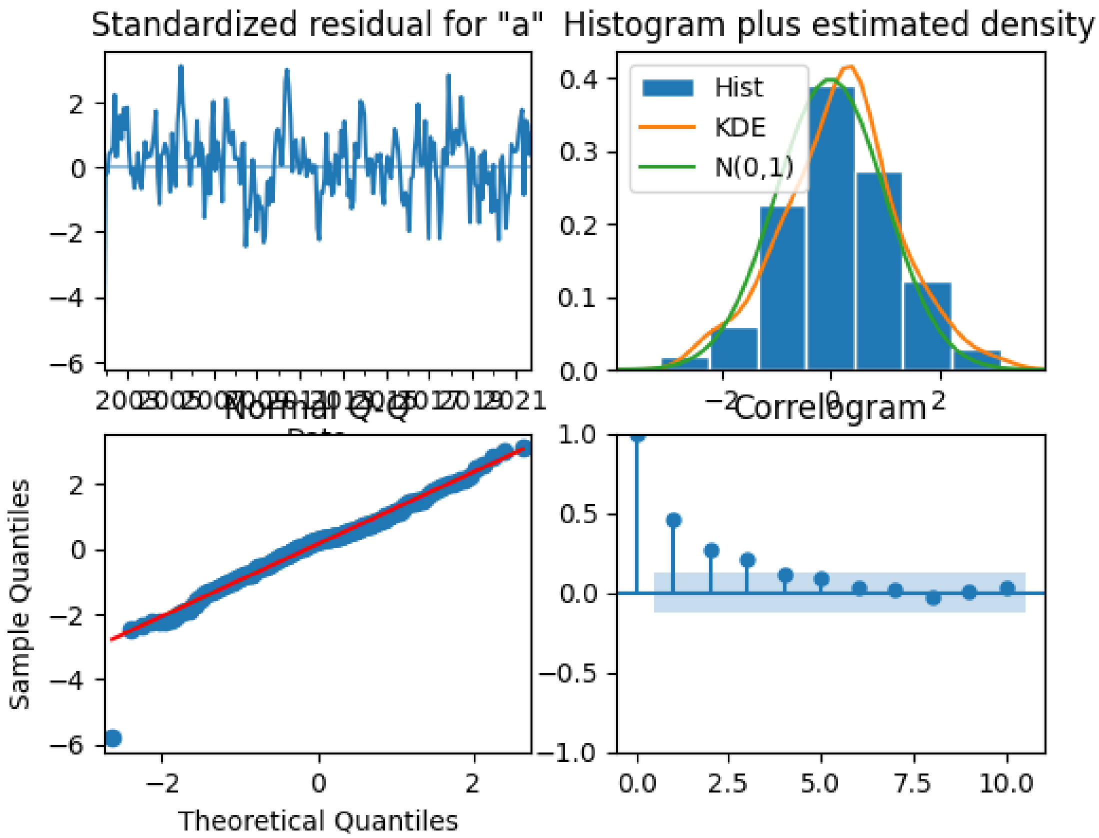
[78]:
```
model = SARIMAX(X_train["all sectors million kilowatthours"], order=(0,0,1),␣
 ↪seasonal_order=(0,1,0,12))
fit = model.fit()
pred = fit.predict(start, end).rename("SARIMA (0,0,1) (0,0,1,12)")
map = mean_absolute_percentage_error(X_test, pred) * 100
```

[79]:
```
ax=X_test.plot(legend=True, label="Test")
pred.plot(legend=True)
```

[79]: <Axes: xlabel='Date'>



[80]:
```
fit.plot_diagnostics();
```



[67]:
```
print(f"Mean absolute percentage error : {map}")
```

```
Mean absolute percentage error : 3.074995032564922
```

From the plot diagnostics we see we still have some corelations

Sliding window iterations

[81]:
```
from statsmodels.tools.sm_exceptions import ConvergenceWarning
import warnings
warnings.simplefilter('ignore', ConvergenceWarning)
```

[82]:
```
num_repeats = 30
length = len(data)
min_train_points = 70
move_window_by = 6
```

[102]:
```
min_map = float('inf')
best_fit = None
preds = None
test = None
```

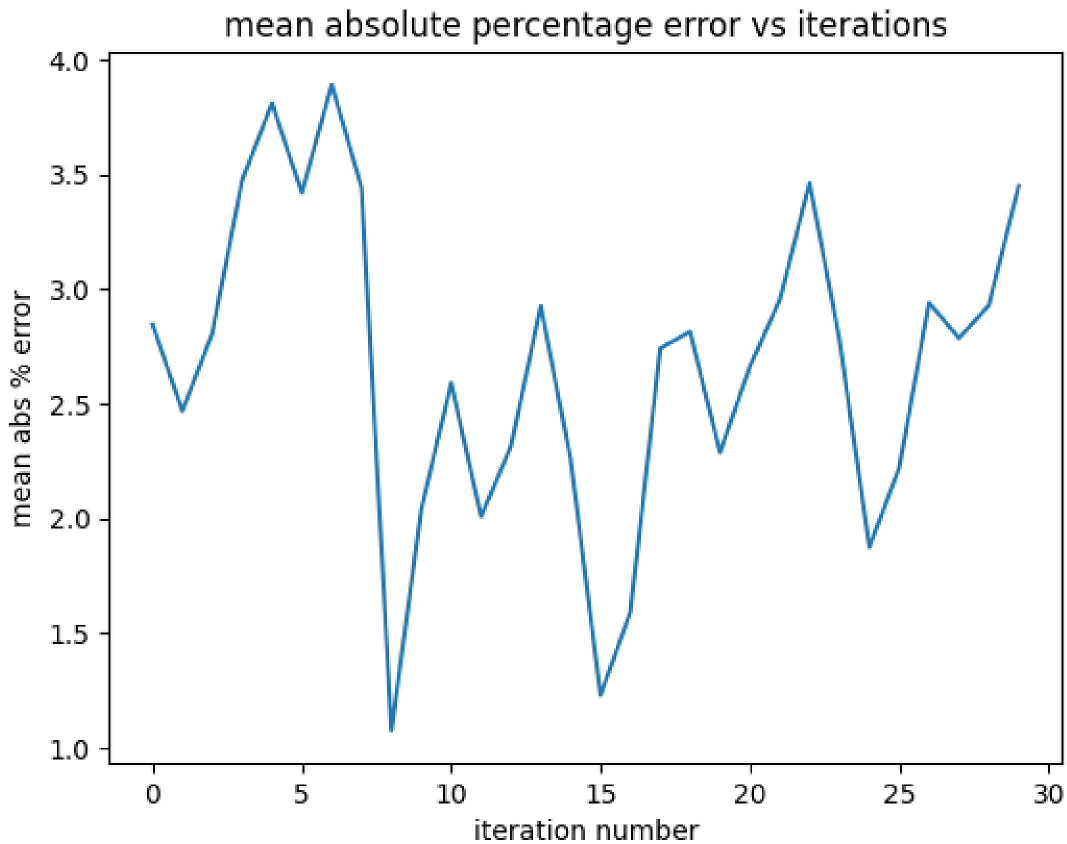
```
maps = []
```

[103]:
```
for j in range(num_repeats):
    train_window_start = j * move_window_by
    train_window_end = min(train_window_start + min_train_points, length)
    test_window_start = train_window_end
    test_window_end = min(test_window_start + 12, length)
    X_train = data[train_window_start:train_window_end]
    X_test = data[test_window_start:test_window_end]
    start = len(X_train)
    end = start + len(X_test) - 1
    model = SARIMAX(X_train["all sectors million kilowatthours"],␣
 ↪order=(0,0,1), seasonal_order=(0,1,0,12))
    fit = model.fit()
    pred = fit.predict(start, end).rename("SARIMA (0,0,1) (0,0,1,12)")
    map = mean_absolute_percentage_error(X_test, pred) * 100
    maps.append(map)
    if map < min_map:
        min_map = map
        best_fit = fit

print(f"Minimum Mean Absolte Percentage Error in {num_repeats} repitions:␣
 ↪{min_map} \n\n")
print(f"Average Mean Absolte Percentage Error over {num_repeats} repitions: {np.
 ↪mean(maps)} \n\n")
print("Best Fit Model:", best_fit.summary())
```

```
Minimum Mean Absolte Percentage Error in 30 repitions: 1.076937412196792


Average Mean Absolte Percentage Error over 30 repitions: 2.670455567882387


Best Fit Model:                                        SARIMAX Results
================================================================================
=============
Dep. Variable:     all sectors million kilowatthours   No. Observations:
70
Model:               SARIMAX(0, 0, 1)x(0, 1, [], 12)   Log Likelihood
-628.443
Date:                               Tue, 23 Apr 2024   AIC
1260.886
Time:                                       22:31:17   BIC
1265.007
Sample:                                   12-01-2004   HQIC
1262.491
                                        - 09-01-2010
```

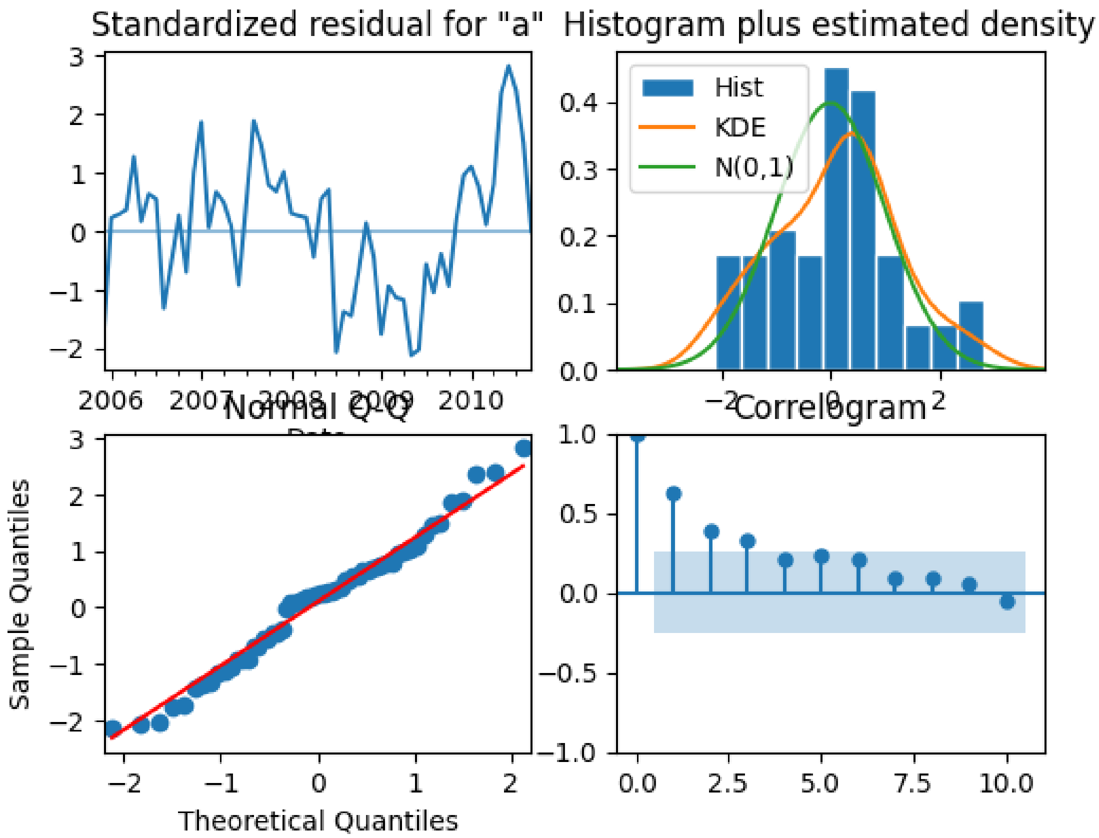
```
Covariance Type:                                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1          0.0486      0.021      2.326      0.020       0.008       0.090
sigma2      1.119e+08   1.21e-12   9.22e+19      0.000    1.12e+08    1.12e+08
================================================================================
===
Ljung-Box (L1) (Q):                  24.14   Jarque-Bera (JB):
0.24
Prob(Q):                              0.00   Prob(JB):
0.89
Heteroskedasticity (H):               2.71   Skew:
0.04
Prob(H) (two-sided):                  0.04   Kurtosis:
2.70
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
2.38e+36. Standard errors may be unstable.
```

[106]:
```
plt.plot(range(num_repeats),maps)
plt.title("mean absolute percentage error vs iterations")
plt.xlabel("iteration number")
plt.ylabel("mean abs % error")
plt.show()
```



PLOT DIAGNOSTICS OF THE BEST FIT: (best fit according to lowest mean abs% error value)

[92]:
```
best_fit.plot_diagnostics();
```



samples vs theoretical Quantiles plot is a straight line . nearing origin Ideally, the points should fall along the diagonal line, indicating that the residuals are normally distributed.

Significant autocorrelation at certain lags here may suggest that the model is not fully capturing our dependencies in the data

The sliding window model is more like the the real-world scenario where the model needs to make predictions sequentially over time. It provides a better evaluation of the model's performance compared to training on all data at once