index

April 30, 2022

1 ARMA Models in `statsmodels`

1.1 Introduction

In this lesson, you'll use your knowledge of the autoregressive (AR) and moving average (MA) models, along with the `statsmodels` library to model time series data.

1.2 Objectives

You will be able to:

- Fit an AR model using `statsmodels`
- Fit an MA model using `statsmodels`

1.3 Generate a first order AR model

Recall that the AR model has the following formula:

$$Y_t = \mu + \phi * Y_{t-1} + \epsilon_t$$

This means that:

$$Y_1 = \mu + \phi * Y_0 + \epsilon_1$$
$$Y_2 = \mu + \phi * (\text{mean-centered version of } Y_1) + \epsilon_2$$

and so on.

Let's assume a mean-zero white noise with a standard deviation of 2. We'll also create a daily datetime index ranging from January 2017 until the end of March 2018.

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

np.random.seed(11225)

# Create a series with the specified dates
dates = pd.date_range('2017-01-01', '2018-03-31')
```

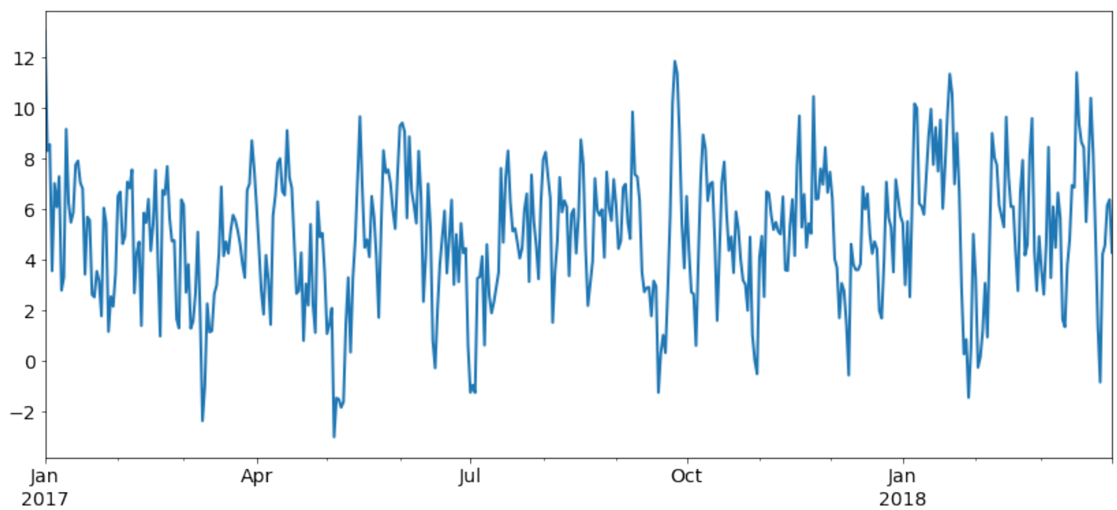
We will generate a first order AR model with $\phi = 0.7$, $\mu = 5$, and $Y_0 = 8$.

[2]:
```
error = np.random.normal(0, 2, len(dates))
Y_0 = 8
mu = 5
phi = 0.7
```

[3]:
```
TS = [None] * len(dates)
y = Y_0
for i, row in enumerate(dates):
    TS[i] = mu + y * phi + error[i]
    y = TS[i] - mu
```

Let's plot the time series to verify:

[4]:
```
series = pd.Series(TS, index=dates)

series.plot(figsize=(14,6), linewidth=2, fontsize=14);
```

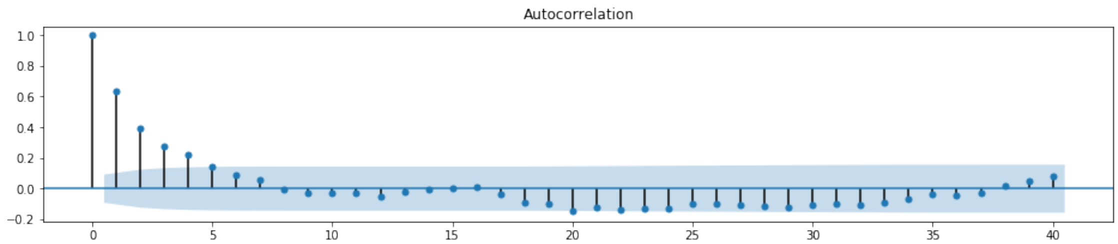


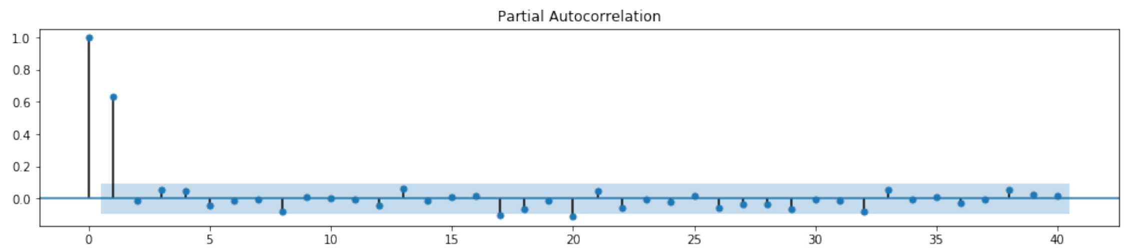
1.4 Look at the ACF and PACF of the model

Although we can use `pandas` to plot the ACF, we highly recommended that you use the `statsmodels` variant instead.

[6]:
```
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.graphics.tsaplots import plot_acf

fig, ax = plt.subplots(figsize=(16,3))
plot_acf(series, ax=ax, lags=40);

fig, ax = plt.subplots(figsize=(16,3))
```

```
plot_pacf(series, ax=ax, lags=40);
```





1.5 Check the model with ARMA in `statsmodels`

`statsmodels` also has a tool that fits ARMA models to time series. The only thing we have to do is provide the number of orders for AR and MA. Have a look at the code below, and the output of the code.

The `ARMA()` function requires two arguments: the first is the time series to which the model is fit, and the second is the `order` in the form `(p,q)` – where `p` refers to the order of AR and `q` refers to the order of MA. For example, a first order AR model would be represented as `(1,0)`.

[9]:
```
# Import ARMA
from statsmodels.tsa.arima_model import ARMA
import statsmodels.api as sm
import warnings

# Instantiate an AR(1) model to the simulated data
mod_arma = ARMA(series, order=(1,0))
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-
packages/statsmodels/tsa/arima_model.py:472: FutureWarning:
statsmodels.tsa.arima_model.ARMA and statsmodels.tsa.arima_model.ARIMA have
been deprecated in favor of statsmodels.tsa.arima.model.ARIMA (note the .
between arima and model) and
statsmodels.tsa.SARIMAX. These will be removed after the 0.12 release.

statsmodels.tsa.arima.model.ARIMA makes use of the statespace framework and
```

```
is both well tested and maintained.

To silence this warning and continue using ARMA and ARIMA until they are
removed, use:

import warnings
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARMA',
                        FutureWarning)
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARIMA',
                        FutureWarning)

  warnings.warn(ARIMA_DEPRECATION_WARN, FutureWarning)
```

Once you have instantiated the AR(1) model, you can call the `.fit()` method to the fit the model to the data.

[10]:
```python
# Fit the model to data
res_arma = mod_arma.fit()
```

Similar to other models, you can then call the `.summary()` method to print the information of the model.

[11]:
```python
# Print out summary information on the fit
print(res_arma.summary())
```

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  455
Model:                     ARMA(1, 0)   Log Likelihood                -968.698
Method:                       css-mle   S.D. of innovations              2.033
Date:                Sat, 30 Apr 2022   AIC                           1943.395
Time:                        01:59:38   BIC                           1955.756
Sample:                    01-01-2017   HQIC                          1948.265
                         - 03-31-2018
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          4.9664      0.269     18.444      0.000       4.439       5.494
ar.L1.y        0.6474      0.036     17.880      0.000       0.576       0.718
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.5446           +0.0000j            1.5446            0.0000
-----------------------------------------------------------------------------
```

Make sure that the output for the ϕ parameter and μ is as you'd expect. You can use the `.params` attribute to check these values.

[12]:
```
# Print out the estimate for the constant and for theta
print(res_arma.params)
```

```
const      4.966377
ar.L1.y    0.647429
dtype: float64
```

1.6 Generate a first order MA model

Recall that the MA model has the following formula:

$$Y_t = \mu + \epsilon_t + \theta * \epsilon_{t-1}$$

This means that:

$$Y_1 = \mu + \epsilon_1 + \theta * \epsilon_0$$
$$Y_2 = \mu + \epsilon_2 + \theta * \epsilon_1$$

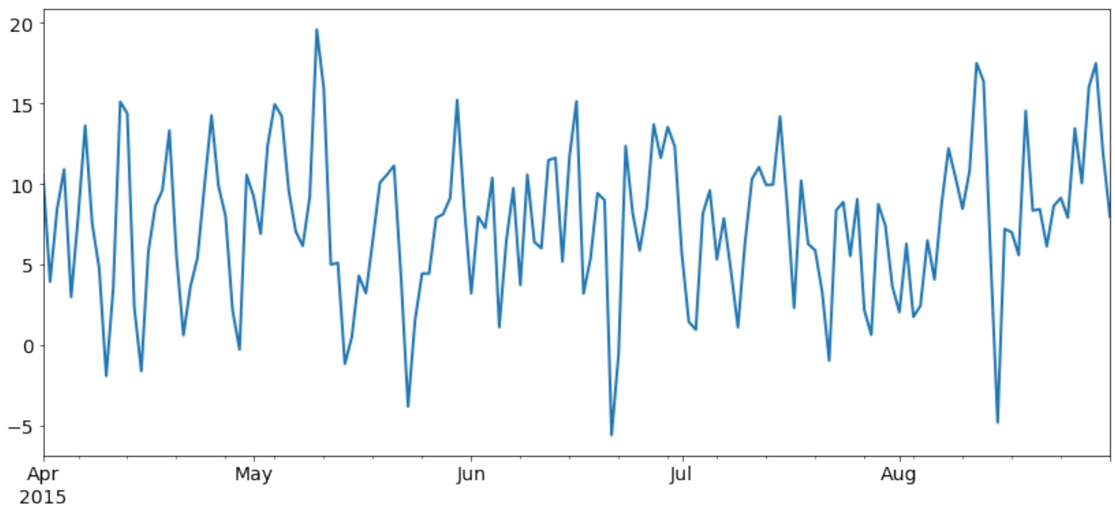
and so on.

Assume a mean-zero white noise with a standard deviation of 4. We'll also generate a daily datetime index ranging from April 2015 until the end of August 2015.

We will generate a first order MA model with $\theta = 0.9$ and $\mu = 7$.

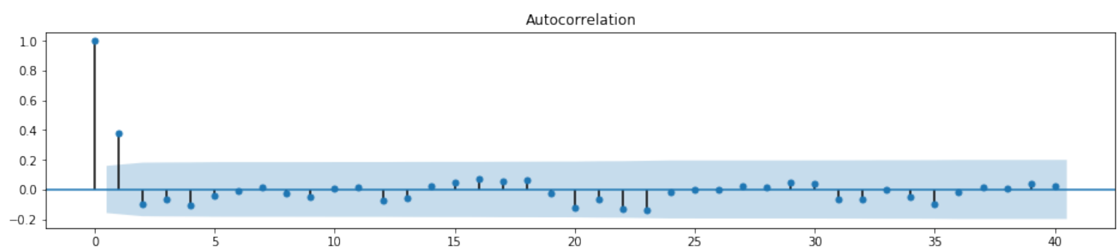
[13]:
```
np.random.seed(1234)

# Create a series with the specified dates
dates = pd.date_range('2015-04-01', '2015-08-31')

error = np.random.normal(0, 4, len(dates))
mu = 7
theta = 0.9

TS = [None] * len(dates)
error_prev = error[0]
for i, row in enumerate(dates):
    TS[i] = mu + theta * error_prev + error[i]
    error_prev = error[i]
```

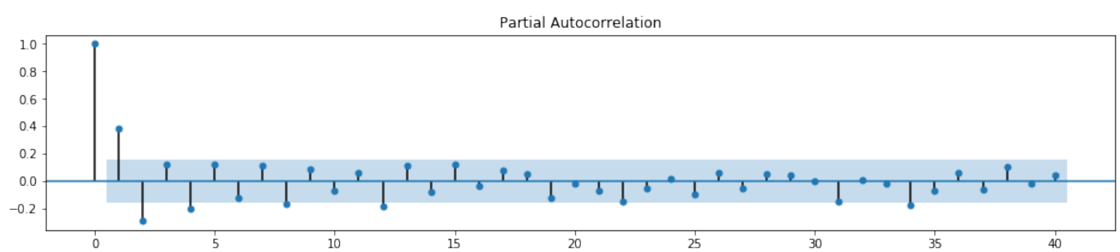
[14]:
```
series = pd.Series(TS, index=dates)

series.plot(figsize=(14,6), linewidth=2, fontsize=14);
```



1.7 Look at the ACF and PACF of the model

[15]:
```
fig, ax = plt.subplots(figsize=(16,3))
plot_acf(series, ax=ax, lags=40);

fig, ax = plt.subplots(figsize=(16,3))
plot_pacf(series, ax=ax, lags=40);
```





1.8 Check the model with ARMA in statsmodels

Let's fit an MA model to verify the parameters are estimated correctly. The first order MA model would be represented as (0,1).

[16]:
```
# Instantiate and fit an MA(1) model to the simulated data
mod_arma = ARMA(series, order=(0,1))
res_arma = mod_arma.fit()

# Print out summary information on the fit
print(res_arma.summary())
```

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  153
Model:                     ARMA(0, 1)   Log Likelihood                -426.378
Method:                       css-mle   S.D. of innovations              3.909
Date:                Sat, 30 Apr 2022   AIC                            858.757
Time:                        02:02:02   BIC                            867.848
Sample:                    04-01-2015   HQIC                           862.450
                         - 08-31-2015
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.5373      0.590     12.776      0.000       6.381       8.694
ma.L1.y        0.8727      0.051     17.165      0.000       0.773       0.972
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1           -1.1459           +0.0000j            1.1459            0.5000
-----------------------------------------------------------------------------

/opt/anaconda3/envs/learn-env/lib/python3.8/site-
packages/statsmodels/tsa/arima_model.py:472: FutureWarning:
statsmodels.tsa.arima_model.ARMA and statsmodels.tsa.arima_model.ARIMA have
been deprecated in favor of statsmodels.tsa.arima.model.ARIMA (note the .
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statsmodels.tsa.SARIMAX. These will be removed after the 0.12 release.

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removed, use:

import warnings
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARMA',
                        FutureWarning)
```

```
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARIMA',
                        FutureWarning)

  warnings.warn(ARIMA_DEPRECATION_WARN, FutureWarning)
```

[17]:
```
# Print out the estimate for the constant and for theta
print(res_arma.params)
```

```
const      7.537294
ma.L1.y    0.872683
dtype: float64
```

1.9 Summary

Great job! In this lesson, you saw how you can use the AR and MA models using the `ARMA()` function from `statsmodels` by specifying the order in the form of `(p,q)`, where at least one of `p` or `q` was zero depending on the kind of model fit. You can use `ARMA()` to fit a combined ARMA model as well – which you will do in the next lab!