TimeSeries2021_Python_state_space

March 23, 2021

[1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
```

[2]:
```
testseries = pd.Series([1, 2, 3, 4, 5, 6, 6, 6, 6, 7, 8])
```

[5]:
```
class LocalLevel(sm.tsa.statespace.MLEModel):
    def __init__(self, endog):
        # Initialize the statespace
        super().__init__(
            endog, k_states=1, k_posdef=1,
            initialization='approximate_diffuse')

        # Initialize the matrices
        self.ssm['design'] = np.array([1])
        self.ssm['transition'] = np.array([1])
        self.ssm['selection'] = np.eye(1)  # 1x1 identity matrix

    @property
    def param_names(self):
        return ['sigma2.measurement', 'sigma2.level']

    @property
    def start_params(self):
        return [np.std(self.endog), np.std(self.endog)]

    def transform_params(self, unconstrained):
        return unconstrained**2

    def untransform_params(self, constrained):
        return constrained**0.5

    def update(self, params, *args, **kwargs):
        params = super().update(params, *args, **kwargs)
```

```python
        # Observation covariance
        self.ssm['obs_cov',0,0] = params[0]

        # State covariance
        self.ssm['state_cov',0,0] = params[1]
```

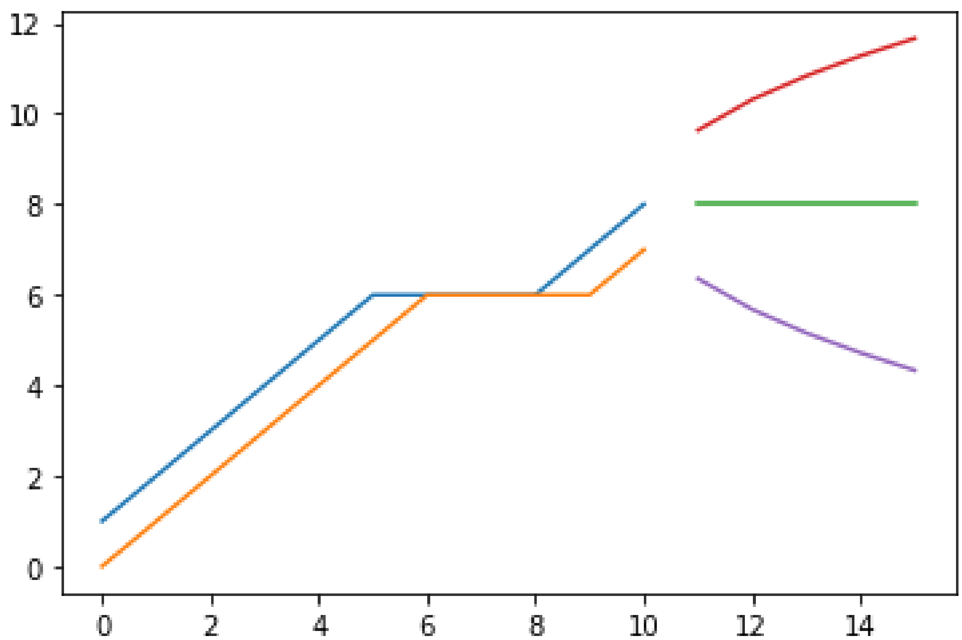
[6]:
```python
# Setup the model
mod = LocalLevel(testseries)

# Fit it using MLE (recall that we are fitting the two variance parameters)
res = mod.fit(disp=False)
print(res.summary())
```

```
                           Statespace Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   11
Model:                     LocalLevel   Log Likelihood                 -20.233
Date:                Tue, 07 Apr 2020   AIC                             44.465
Time:                        10:25:46   BIC                             45.261
Sample:                             0   HQIC                            43.964
                                 - 11
Covariance Type:                  opg
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
sigma2.measurement   1.38e-11      0.247   5.58e-11      1.000      -0.485
0.485
sigma2.level           0.7000      0.691      1.013      0.311      -0.654
2.054
================================================================================
===
Ljung-Box (Q):                       15.08   Jarque-Bera (JB):
1.88
Prob(Q):                              0.13   Prob(JB):
0.39
Heteroskedasticity (H):               0.67   Skew:
-0.57
Prob(H) (two-sided):                  0.70   Kurtosis:
1.32
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
```

step).

[225]:
```python
# Perform prediction and forecasting
predict = res.get_prediction()
forecast = res.get_forecast(5)
plt.figure()
testseries.plot()
predict.predicted_mean.plot()
forecast.predicted_mean.plot()
forecast.conf_int()["upper y"].plot()
forecast.conf_int()["lower y"].plot()
```

[225]: <matplotlib.axes._subplots.AxesSubplot at 0x11a4fa6a0>



[259]:
```python
class LocalLinearTrend(sm.tsa.statespace.MLEModel):
    def __init__(self, endog):
        # Initialize the statespace
        super().__init__(
            endog, k_states=2, k_posdef=2,
            initialization='approximate_diffuse')

        # Initialize the matrices
        self.ssm['design'] = np.array([1, 0])
        self.ssm['transition'] = np.array([[1, 1],
                                           [0, 1]])
        self.ssm['selection'] = np.eye(2)  # 2x2 identity matrix
```

```
    @property
    def param_names(self):
        return ['sigma2.measurement', 'sigma2.level', 'sigma2.trend']

    @property
    def start_params(self):
        return [np.std(self.endog), np.std(self.endog), np.std(self.endog)]

    def transform_params(self, unconstrained):
        return unconstrained**2

    def untransform_params(self, constrained):
        return constrained**0.5

    def update(self, params, *args, **kwargs):
        params = super().update(params, *args, **kwargs)

        # Observation covariance
        self.ssm['obs_cov',0,0] = params[0]

        # State covariance
        self.ssm['state_cov',0,0] = params[1]
        self.ssm['state_cov',1,1] = params[2]
```

[260]:
```
# Setup the model
mod = LocalLinearTrend(testseries)

# Fit it using MLE (recall that we are fitting the three variance parameters)
res = mod.fit(disp=False)
print(res.summary())
```

```
                           Statespace Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   11
Model:               LocalLinearTrend   Log Likelihood                 -21.655
Date:                Mon, 06 Apr 2020   AIC                             49.311
Time:                        20:35:42   BIC                             50.505
Sample:                             0   HQIC                            48.559
                                 - 11
Covariance Type:                  opg
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
```

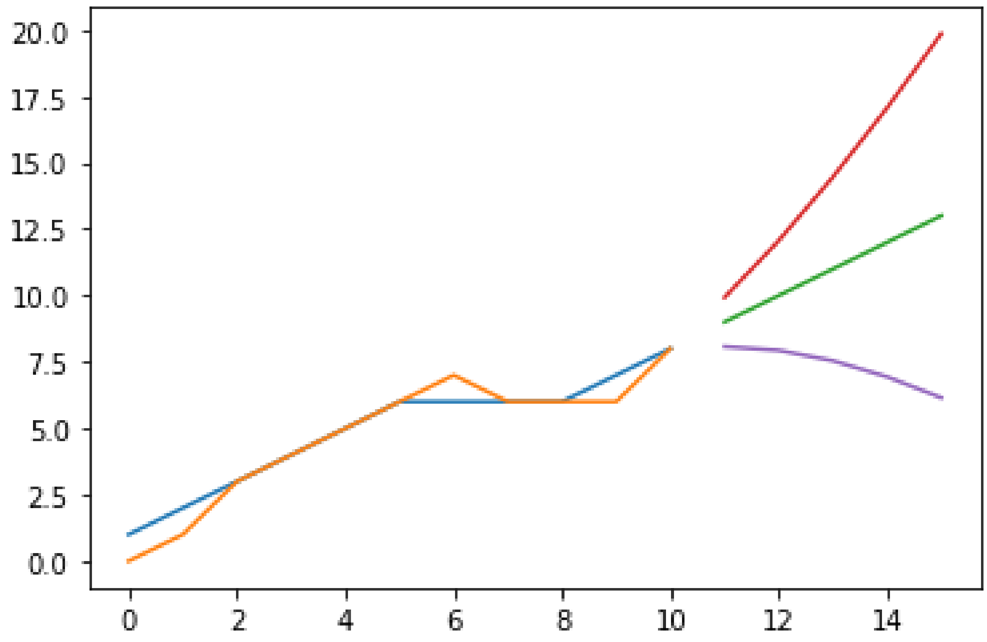
```
sigma2.measurement  4.425e-08    492.328   8.99e-11      1.000    -964.945
964.945
sigma2.level        1.448e-05   2168.668   6.68e-09      1.000   -4250.512
4250.512
sigma2.trend           0.2222   1653.108      0.000      1.000   -3239.810
3240.255
================================================================================
===
Ljung-Box (Q):                        4.47   Jarque-Bera (JB):
2.86
Prob(Q):                              0.92   Prob(JB):
0.24
Heteroskedasticity (H):         2249824.77   Skew:
-0.00
Prob(H) (two-sided):                  0.00   Kurtosis:
5.50
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[228]:

```python
# Perform prediction and forecasting
predict = res.get_prediction()
forecast = res.get_forecast(5)
plt.figure()
testseries.plot()
predict.predicted_mean.plot()
forecast.predicted_mean.plot()
forecast.conf_int()["upper y"].plot()
forecast.conf_int()["lower y"].plot()
```

[228]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11a5b9518>
```



[281]:
```
class LocalDampedTrend(sm.tsa.statespace.MLEModel):
    def __init__(self, endog):
        # Initialize the statespace
        super().__init__(
            endog, k_states=2, k_posdef=2,
            initialization='approximate_diffuse')

        # Initialize the matrices
        self.ssm['design'] = np.array([1, 0])
        self.ssm['selection'] = np.eye(2)  # 2x2 identity matrix

    @property
    def param_names(self):
        return ['sigma2.measurement', 'sigma2.level', 'sigma2.trend', 'damping']

    @property
    def start_params(self):
        return [np.std(self.endog), np.std(self.endog), np.std(self.endog), 0.5]

    def transform_params(self, unconstrained):
        return unconstrained**2

    def untransform_params(self, constrained):
        return constrained**0.5

    def update(self, params, *args, **kwargs):
```

```
        params = super().update(params, *args, **kwargs)

        # Observation covariance
        self.ssm['obs_cov',0,0] = params[0]

        # State covariance
        self.ssm['state_cov',0,0] = params[1]
        self.ssm['state_cov',1,1] = params[2]

        # Transition matrix
        self.ssm['transition'] = np.array([[1, 1],
                                          [0, params[3]]])
```

[282]:
```
# Setup the model
mod = LocalDampedTrend(testseries)

# Fit it using MLE (recall that we are fitting the three variance parameters)
res = mod.fit(disp=False)
print(res.summary())
```

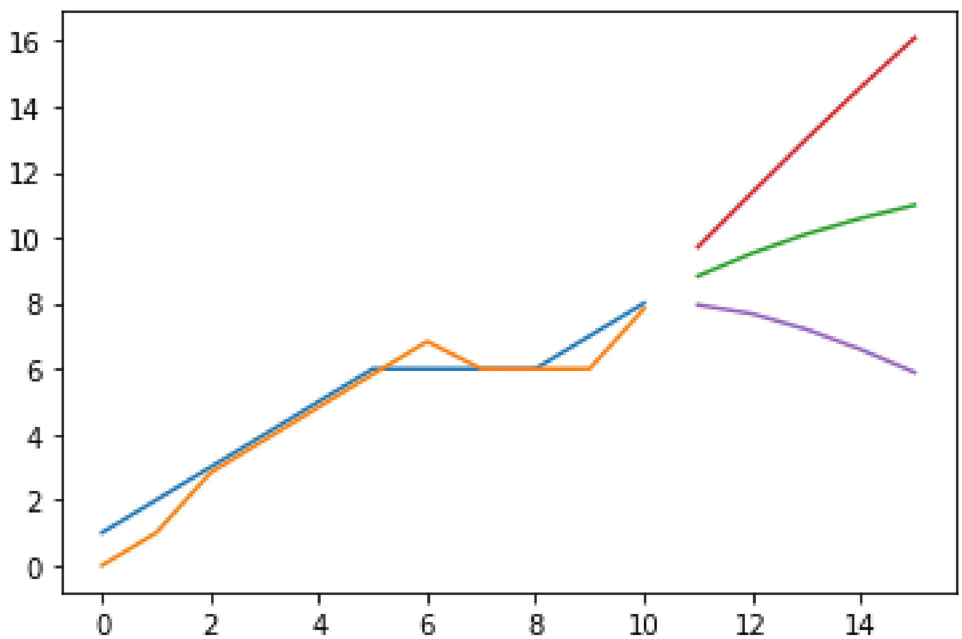
```
                           Statespace Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   11
Model:               LocalDampedTrend   Log Likelihood                 -21.264
Date:                Mon, 06 Apr 2020   AIC                             50.528
Time:                        20:40:14   BIC                             52.119
Sample:                             0   HQIC                            49.525
                                 - 11
Covariance Type:                  opg
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
sigma2.measurement  2.228e-10      1.221   1.83e-10      1.000      -2.392
2.392
sigma2.level        3.381e-10      5.105   6.62e-11      1.000     -10.006
10.006
sigma2.trend           0.2037      2.523      0.081      0.936      -4.742
5.149
damping                0.8333      0.977      0.853      0.394      -1.082
2.749
================================================================================
===
Ljung-Box (Q):                        6.04   Jarque-Bera (JB):
2.07
```

```
Prob(Q):                              0.81   Prob(JB):
0.36
Heteroskedasticity (H):              18.50   Skew:
-0.06
Prob(H) (two-sided):                  0.02   Kurtosis:
5.12
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[283]:

```
# Perform prediction and forecasting
predict = res.get_prediction()
forecast = res.get_forecast(5)
plt.figure()
testseries.plot()
predict.predicted_mean.plot()
forecast.predicted_mean.plot()
forecast.conf_int()["upper y"].plot()
forecast.conf_int()["lower y"].plot()
```

[283]: <matplotlib.axes._subplots.AxesSubplot at 0x11a6afe48>



[15]:
```
stockRtn = [1, 1, -3, 1, -2, -5, -1, 4]
marketRtn = [1, 1, -2, 0, -2, 1, 1, -1]
```

[21]:
```
class TVRegress(sm.tsa.statespace.MLEModel):
    def __init__(self, endog, exog):
        # Initialize the statespace
        super().__init__(
            endog, k_states=1, k_posdef=1,
            initialization='approximate_diffuse')

        # Initialize the matrices
        self.ssm['design'] = np.array([[exog]])
        self.ssm['transition'] = np.array([1])
        self.ssm['selection'] = np.eye(1)  # 1x1 identity matrix

    @property
    def param_names(self):
        return ['sigma2.measurement', 'sigma2.beta']

    @property
    def start_params(self):
        return [np.std(self.endog), np.std(self.endog)]

    def transform_params(self, unconstrained):
        return unconstrained**2

    def untransform_params(self, constrained):
        return constrained**0.5

    def update(self, params, *args, **kwargs):
        params = super().update(params, *args, **kwargs)

        # Observation covariance
        self.ssm['obs_cov',0,0] = params[0]

        # State covariance
        self.ssm['state_cov',0,0] = params[1]
```

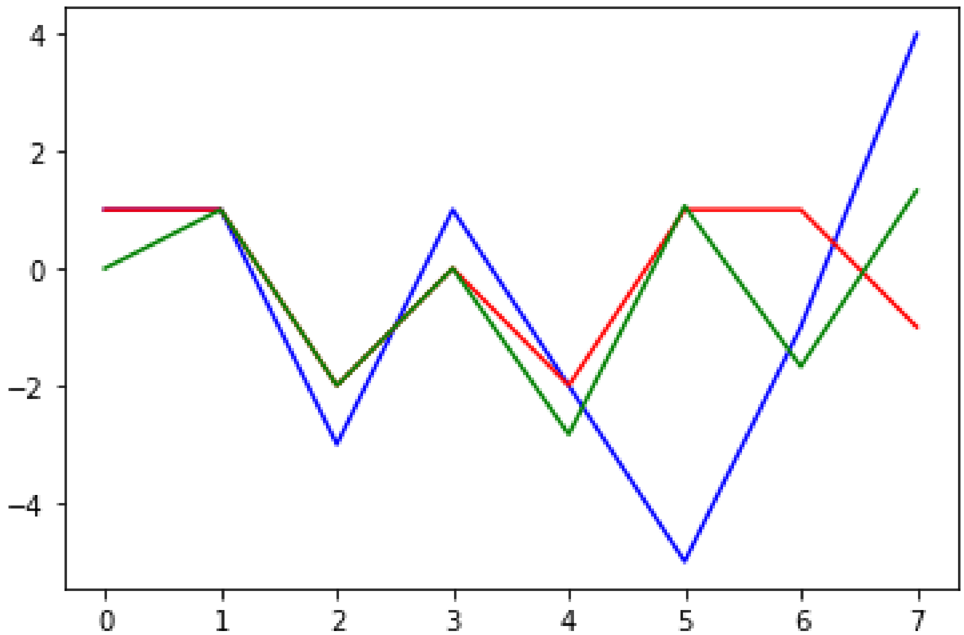
[22]:
```
# Setup the model
mod = TVRegress(stockRtn, marketRtn)

# Fit it using MLE (recall that we are fitting the two variance parameters)
res = mod.fit(disp=False)
print(res.summary())
```

```
                           Statespace Model Results
==============================================================================
```

```
Dep. Variable:                      y   No. Observations:                    8
Model:                      TVRegress   Log Likelihood                 -25.575
Date:                Tue, 07 Apr 2020   AIC                             55.150
Time:                        11:33:53   BIC                             55.309
Sample:                             0   HQIC                            54.079
                                  - 8
Covariance Type:                  opg
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
sigma2.measurement     3.5735      4.588      0.779      0.436      -5.419
12.566
sigma2.beta            2.1799      4.451      0.490      0.624      -6.544
10.904
================================================================================
===
Ljung-Box (Q):                        4.44   Jarque-Bera (JB):
4.64
Prob(Q):                              0.73   Prob(JB):
0.10
Heteroskedasticity (H):             140.26   Skew:
-1.63
Prob(H) (two-sided):                  0.00   Kurtosis:
4.80
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[23]:
```
# Perform prediction and forecasting
predict = res.get_prediction()
plt.figure()
plt.plot(stockRtn, "b-")
plt.plot(marketRtn, "r-")
plt.plot(predict.predicted_mean, "g-")
```

[23]:
```
[<matplotlib.lines.Line2D at 0x11a368fd0>]
```

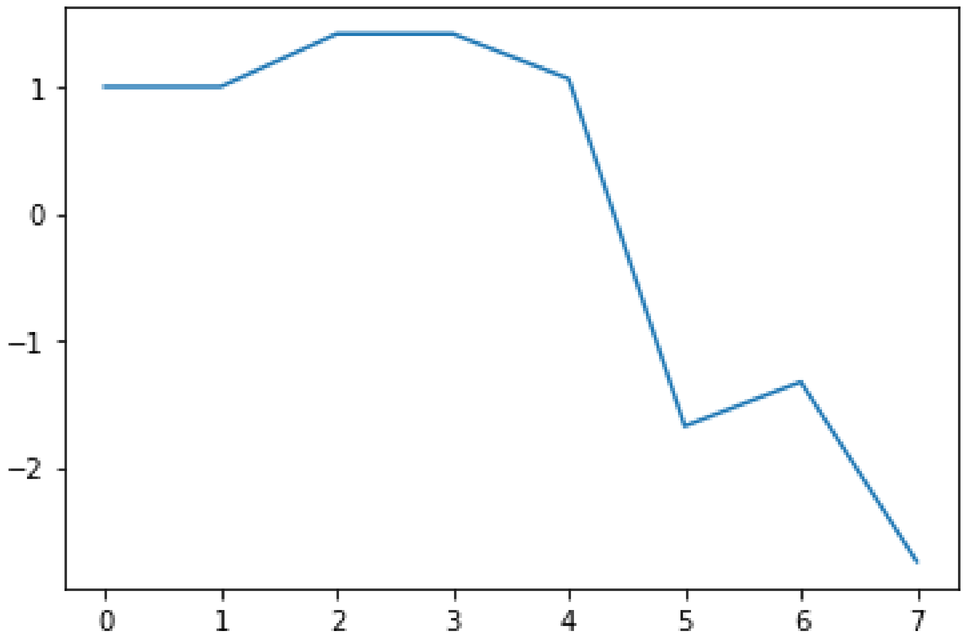


[24]:
```
res.states.filtered
```

[24]:
```
array([[ 0.99999643],
       [ 0.99999863],
       [ 1.41536261],
       [ 1.41536261],
       [ 1.06189308],
       [-1.67436589],
       [-1.32713699],
       [-2.74213916]])
```

[25]:
```
plt.plot(res.states.filtered)
```

[25]:
```
[<matplotlib.lines.Line2D at 0x11a3b5b38>]
```


1
0
−1
−2
0
1
2
3
4
5
6
7

```
[ ]:
```