Fitting time series models

ARIMA MODELS IN PYTHON

James Fulton
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Creating a model

```
from statsmodels.tsa.arima_model import ARMA
```

```
model = ARMA(timeseries, order=(p,q))
```

Creating AR and MA models

```
ar_model = ARMA(timeseries, order=(p,0))
```

```
ma_model = ARMA(timeseries, order=(0,q))
```

Fitting the model and fit summary

```
model = ARMA(timeseries, order=(2,1))

results = model.fit()
```

```
print(results.summary())
```

Fit summary

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1000
Model:                     ARMA(2, 1)   Log Likelihood                 148.580
Method:                       css-mle   S.D. of innovations              0.208
Date:                Thu, 25 Apr 2019   AIC                           -287.159
Time:                        22:57:00   BIC                           -262.621
Sample:                             0   HQIC                          -277.833


==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0017      0.012     -0.147      0.883      -0.025       0.021
ar.L1.y        0.5253      0.054      9.807      0.000       0.420       0.630
ar.L2.y       -0.2909      0.042     -6.850      0.000      -0.374      -0.208
ma.L1.y        0.3679      0.052      7.100      0.000       0.266       0.469
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            0.9029           -1.6194j            1.8541           -0.1690
AR.2            0.9029           +1.6194j            1.8541            0.1690
MA.1           -2.7184           +0.0000j            2.7184            0.5000
-----------------------------------------------------------------------------
```

Fit summary

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1000
Model:                     ARMA(2, 1)   Log Likelihood                 148.580
Method:                       css-mle   S.D. of innovations              0.208
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```

Fit summary

```
==================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
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```

Introduction to ARMAX models

- Exogenous ARMA
- Use external variables as well as time series
- ARMAX = ARMA + linear regression

We model the time series using other independent variables as well as the time series itself.

ARMAX equation

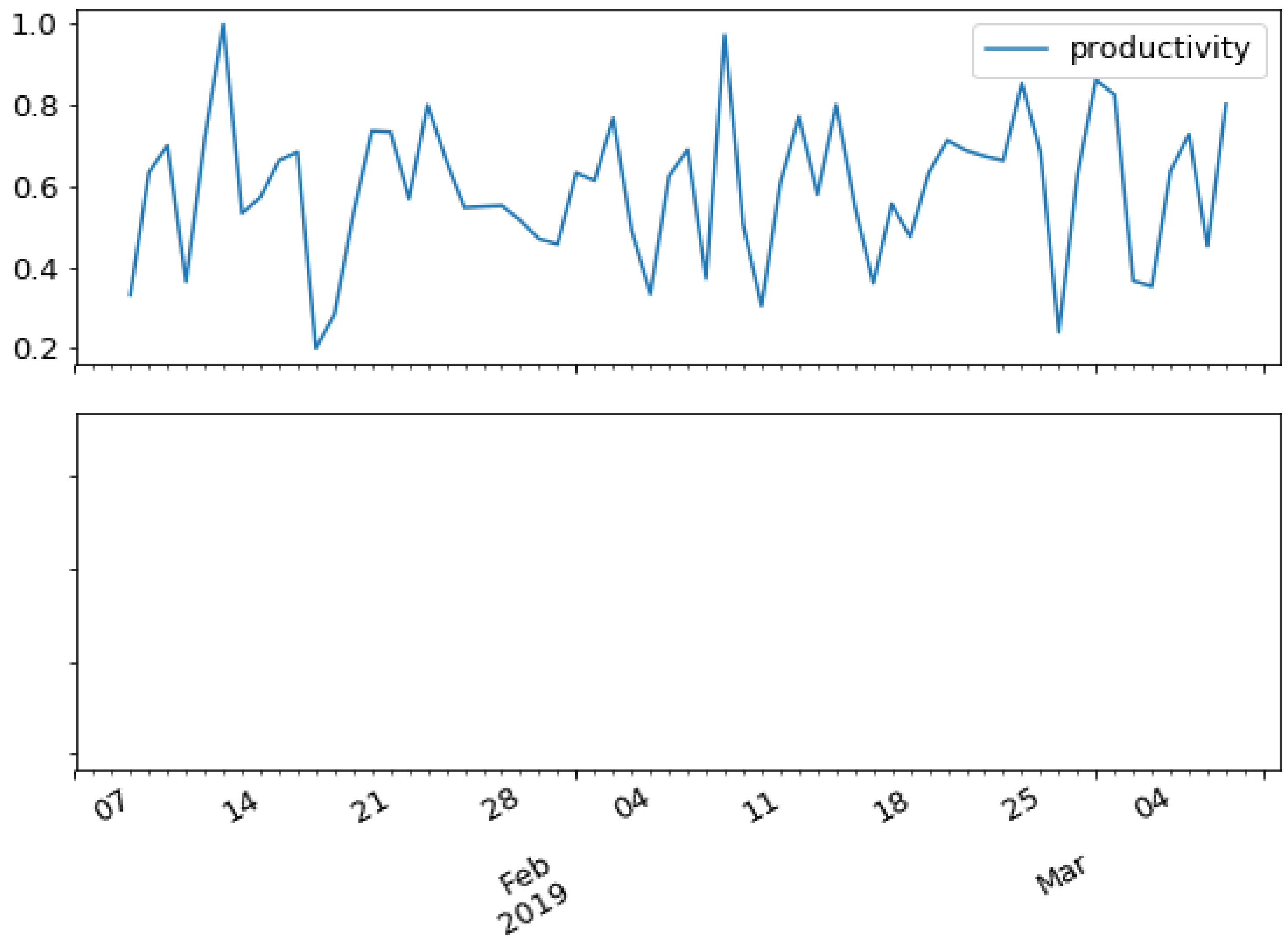
ARMA(1,1) model :

$$y_t = a_1 y_{t-1} + m_1 \epsilon_{t-1} + \epsilon_t$$

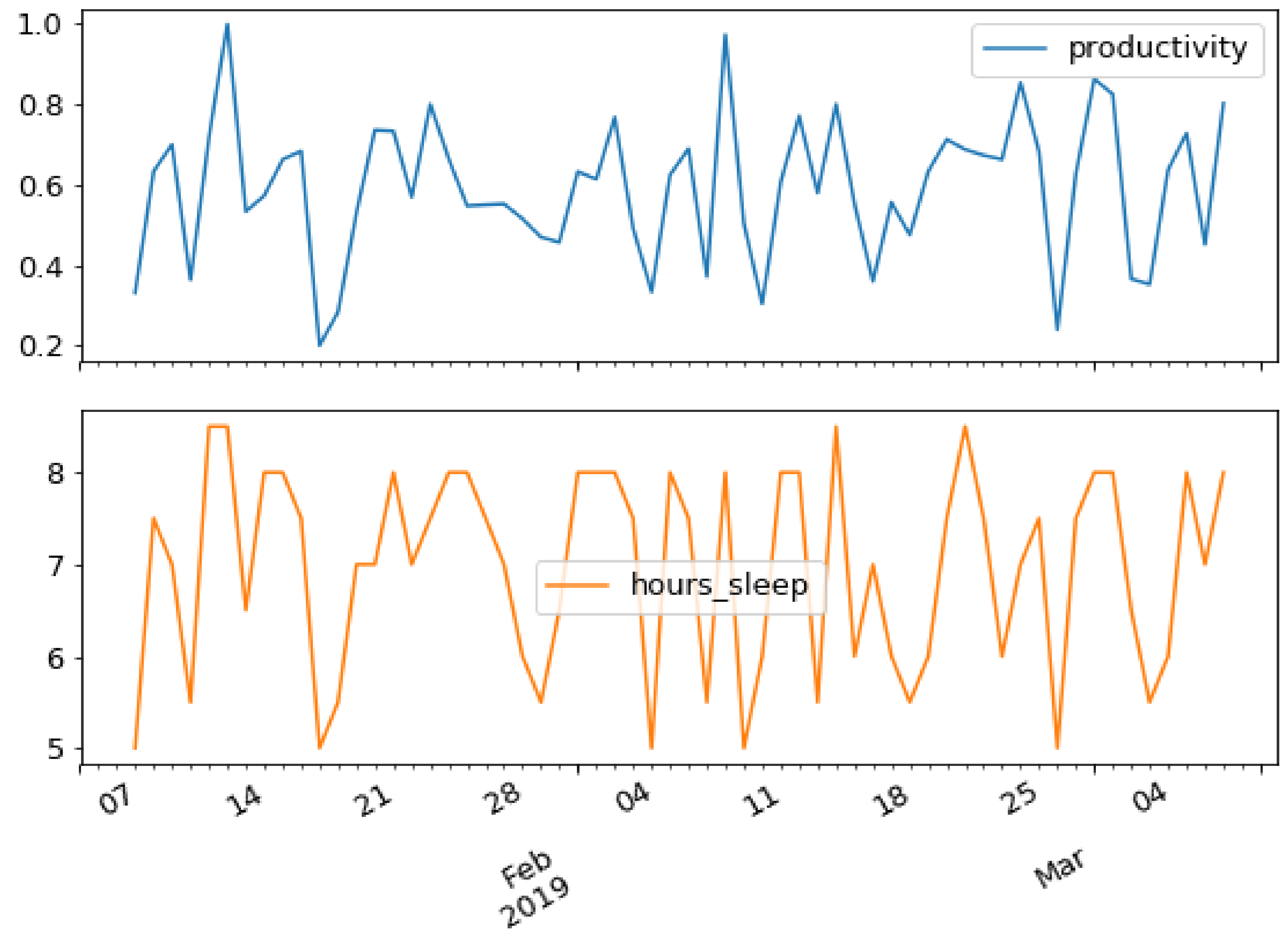
ARMAX(1,1) model :

$$y_t = x_1 z_t + a_1 y_{t-1} + m_1 \epsilon_{t-1} + \epsilon_t$$

ARMAX example



ARMAX example



Fitting ARMAX

```
# Instantiate the model
model = ARMA(df['productivity'], order=(2,1), exog=df['hours_sleep'])


# Fit the model
results = model.fit()
```

ARMAX summary

```
==================================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
const          -0.1936      0.092     -2.098      0.041      -0.375      -0.013
x1              0.1131      0.013      8.602      0.000       0.087       0.139
ar.L1.y         0.1917      0.252      0.760      0.450      -0.302       0.686
ar.L2.y        -0.3740      0.121     -3.079      0.003      -0.612      -0.136
ma.L1.y        -0.0740      0.259     -0.286      0.776      -0.581       0.433
```

Let's practice!

ARIMA MODELS IN PYTHON

Forecasting

ARIMA MODELS IN PYTHON

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Predicting the next value

Take an AR(1) model

$$y_t = a_1 y_{t-1} + \epsilon_t$$

Predict next value

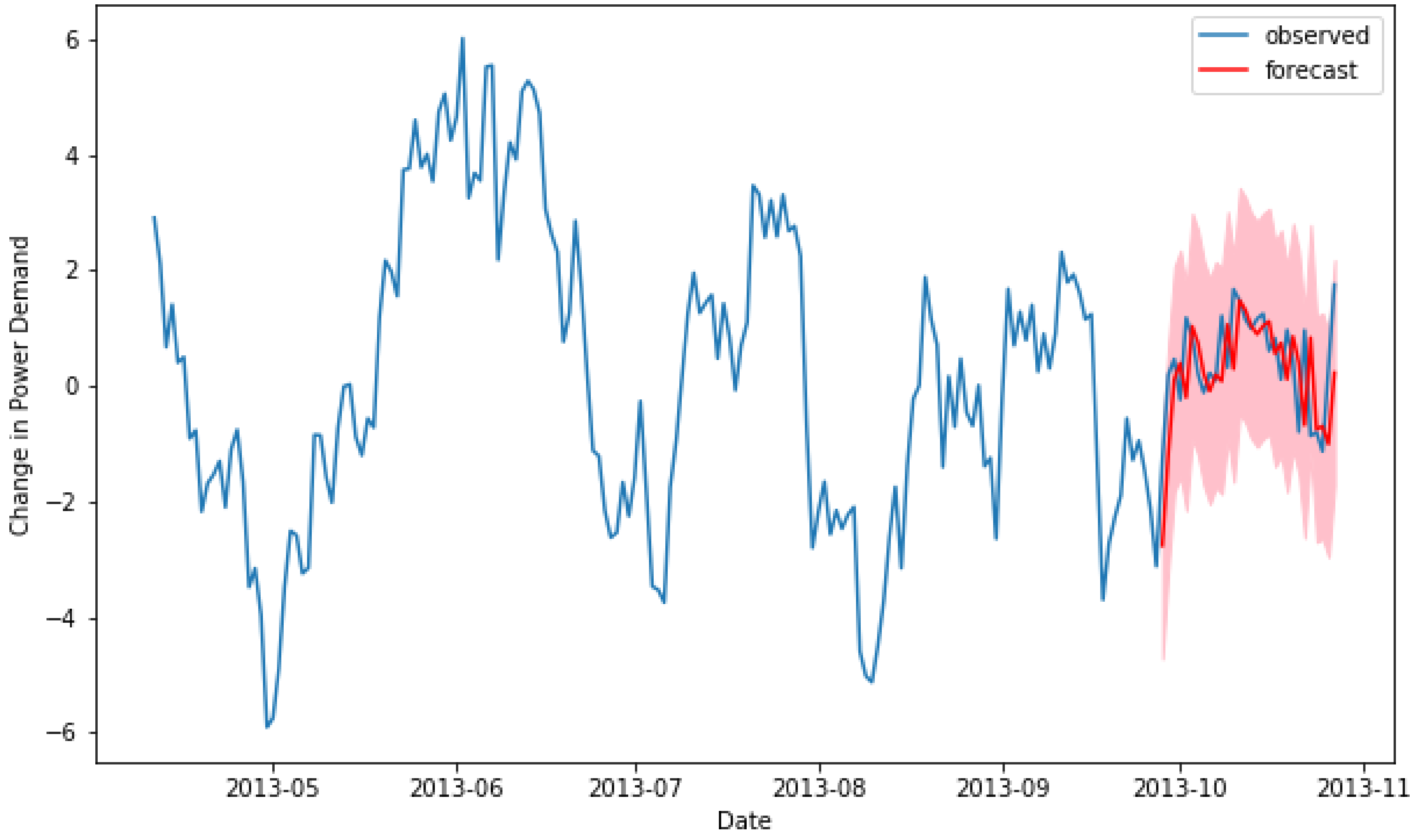
$$y_t = 0.6 \text{ x } 10 + \epsilon_t$$

$$y_t = 6.0 + \epsilon_t$$

Uncertainty on prediction

$$5.0 < y_t < 7.0$$

One-step-ahead predictions



Statsmodels SARIMAX class

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Just an ARMA(p,q) model
model = SARIMAX(df, order=(p,0,q))
```

an additional model order

Statsmodels SARIMAX class

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

# An ARMA(p,q) + constant model
model = SARIMAX(df, order=(p,0,q), trend='c')
```

If the time series isn't centered around zero this is a must.

Making one-step-ahead predictions

```
# Make predictions for last 25 values
results = model.fit()
# Make in-sample prediction
forecast = results.get_prediction(start=-25)
```

how many steps back to begin the forecast

Making one-step-ahead predictions

```
# Make predictions for last 25 values
results = model.fit()
# Make in-sample prediction
forecast = results.get_prediction(start=-25)
# forecast mean
mean_forecast = forecast.predicted_mean
```

Predicted mean is a pandas series

```
2013-10-28    1.519368
2013-10-29    1.351082
2013-10-30    1.218016
```

Confidence intervals

```
# Get confidence intervals of forecasts
confidence_intervals = forecast.conf_int()
```

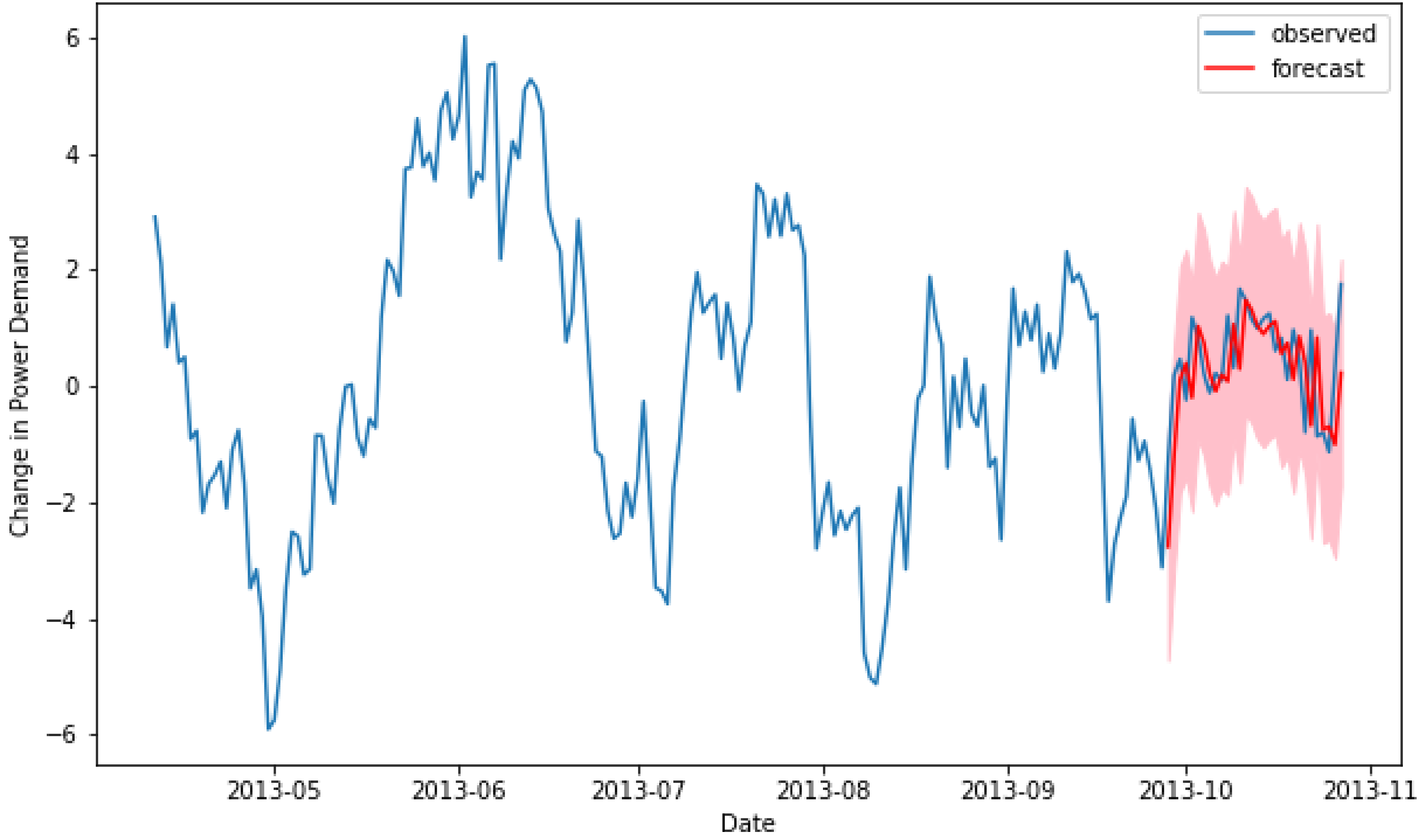
Confidence interval method returns `pandas` DataFrame

```
                lower y         upper y
2013-09-28    -4.720471       -0.815384
2013-09-29    -5.069875        0.112505
2013-09-30    -5.232837        0.766300
2013-10-01    -5.305814        1.282935
2013-10-02    -5.326956        1.703974
```

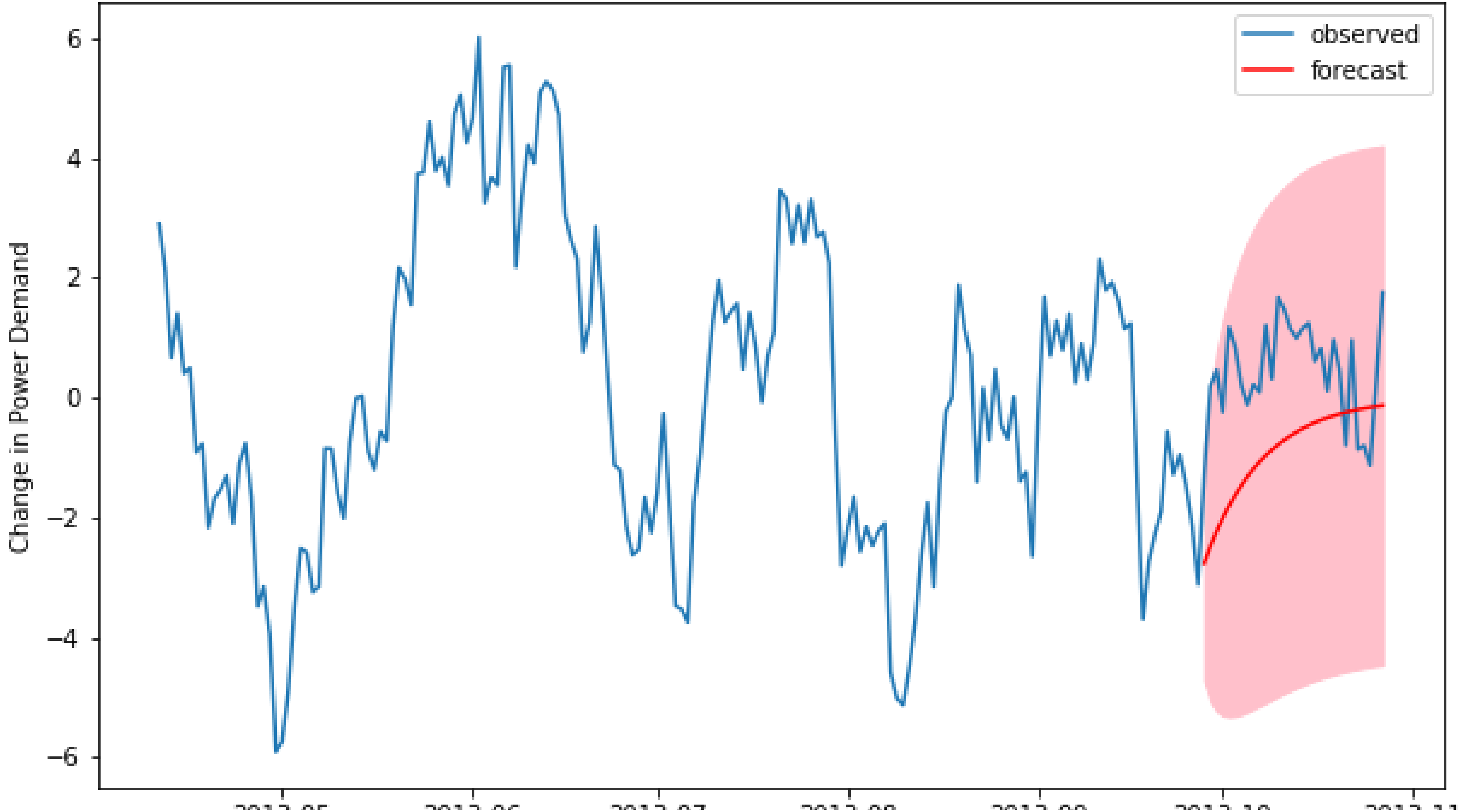
Plotting predictions

```
plt.figure()

# Plot prediction
plt.plot(dates,
         mean_forecast.values,
         color='red',
         label='forecast')

# Shade uncertainty area
plt.fill_between(dates, lower_limits, upper_limits, color='pink')

plt.show()
```

Plotting predictions



Dynamic predictions



Making dynamic predictions

```
results = model.fit()
forecast = results.get_prediction(start=-25, dynamic=True)
```

```
# forecast mean
mean_forecast = forecast.predicted_mean


# Get confidence intervals of forecasts
confidence_intervals = forecast.conf_int()
```

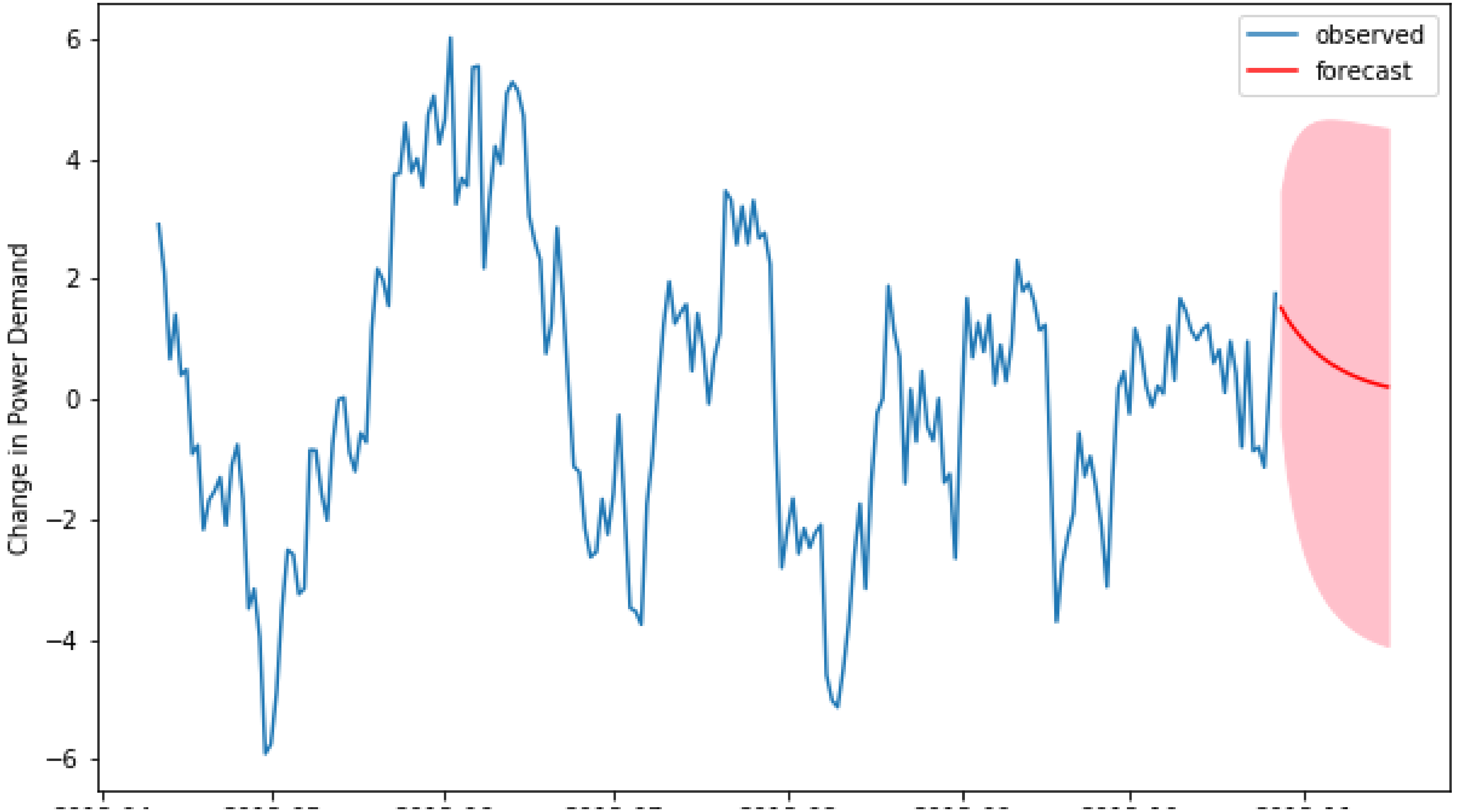
Forecasting out of sample

```
forecast = results.get_forecast(steps=20)
```

```
# forecast mean
mean_forecast = forecast.predicted_mean

# Get confidence intervals of forecasts
confidence_intervals = forecast.conf_int()
```

Forecasting out of sample

```
forecast = results.get_forecast(steps=20)
```



Let's practice!

ARIMA MODELS IN PYTHON

Introduction to ARIMA models

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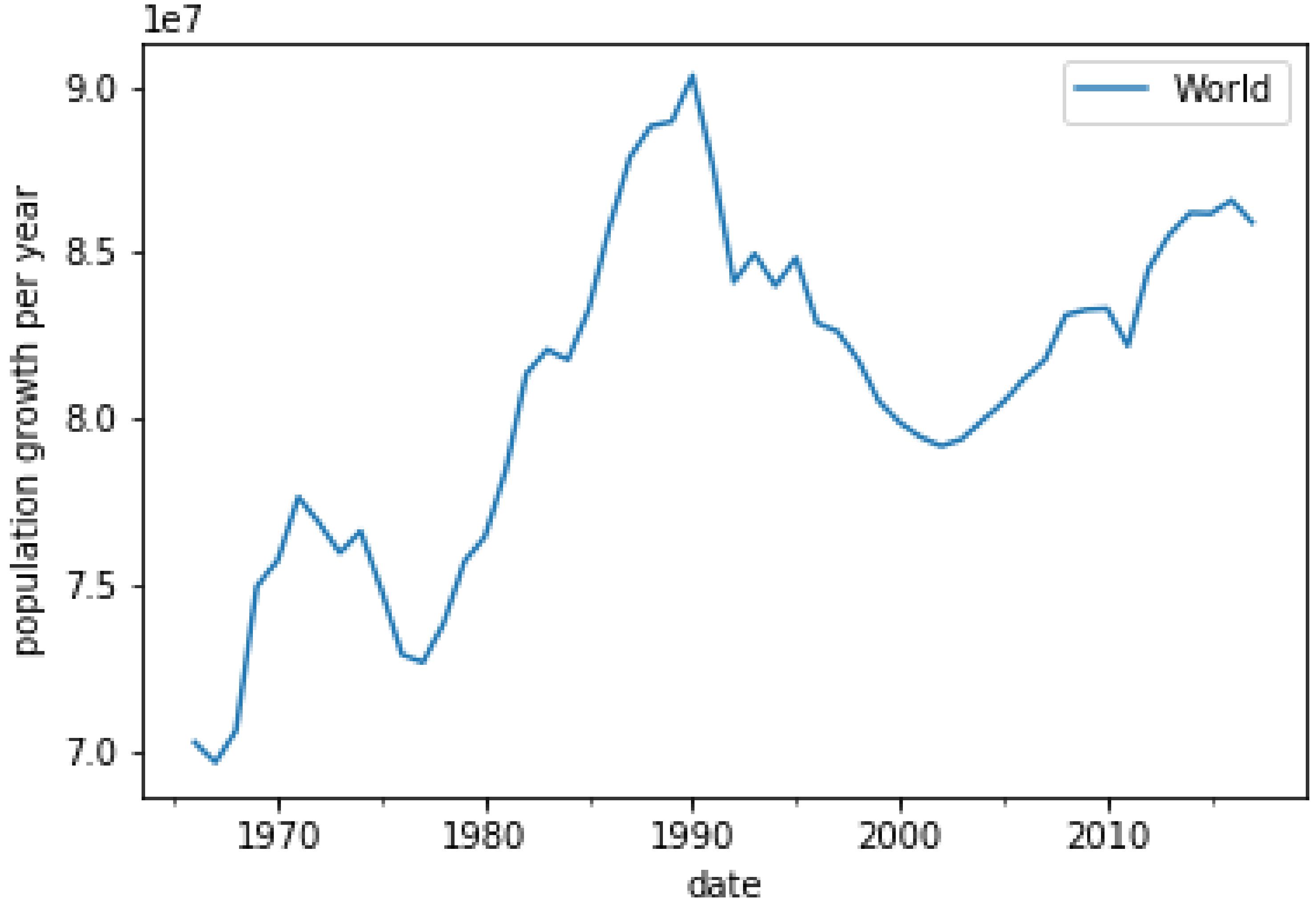
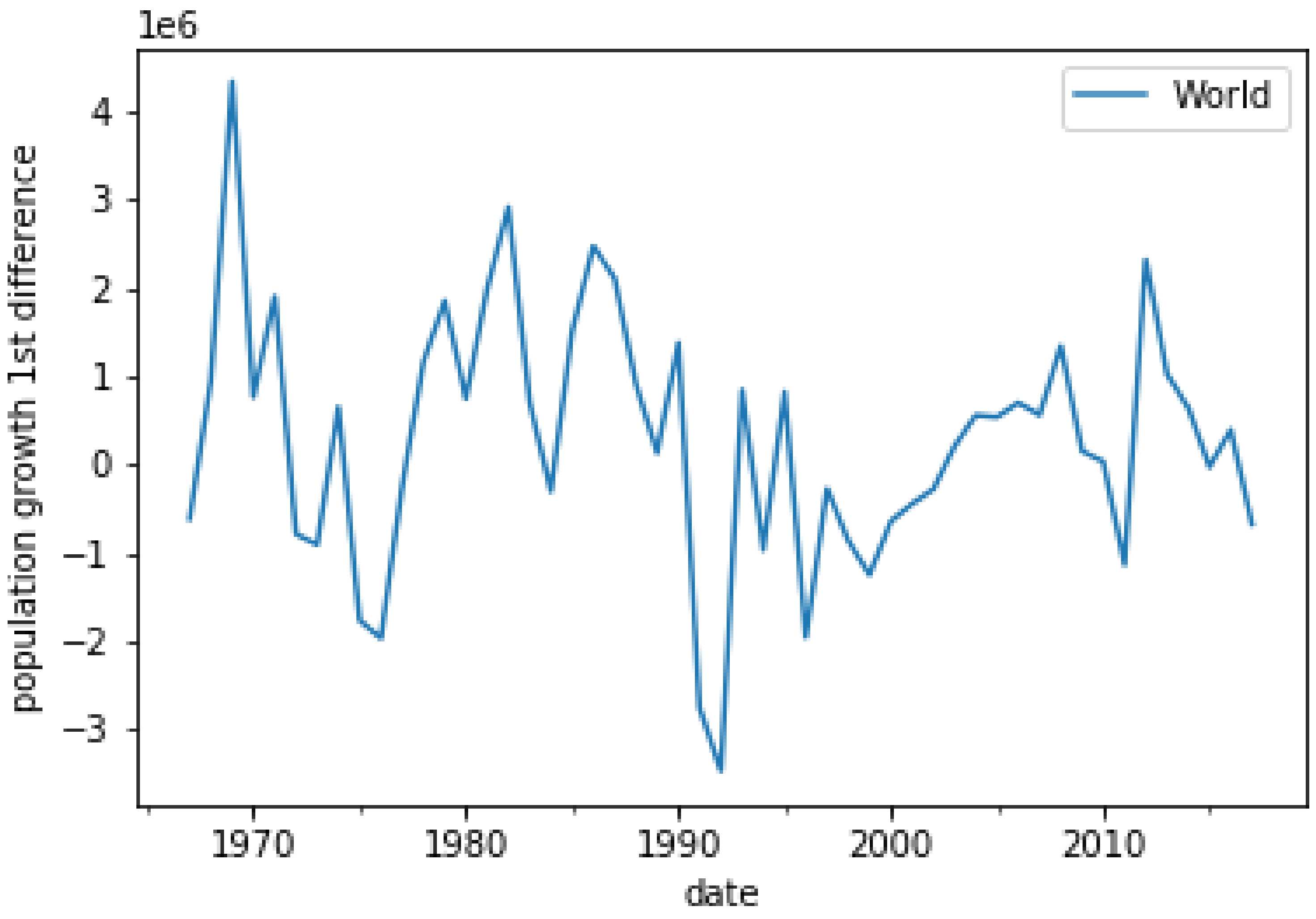
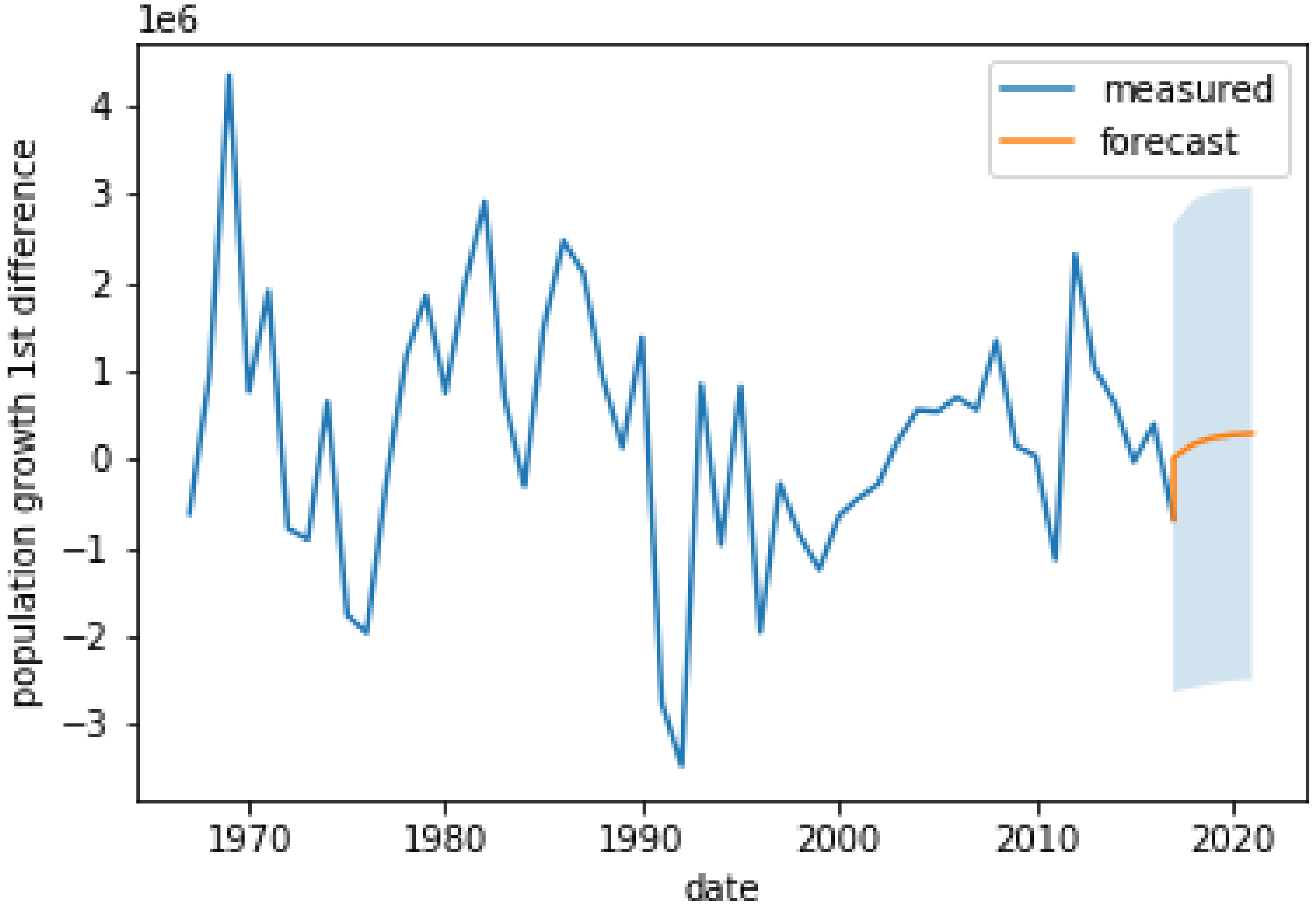
Non-stationary time series recap



Non-stationary time series recap



Forecast of differenced time series



Reconstructing original time series after differencing

```
diff_forecast = results.get_forecast(steps=10).predicted_mean

from numpy import cumsum

mean_forecast = cumsum(diff_forecast)
```

Reconstructing original time series after differencing

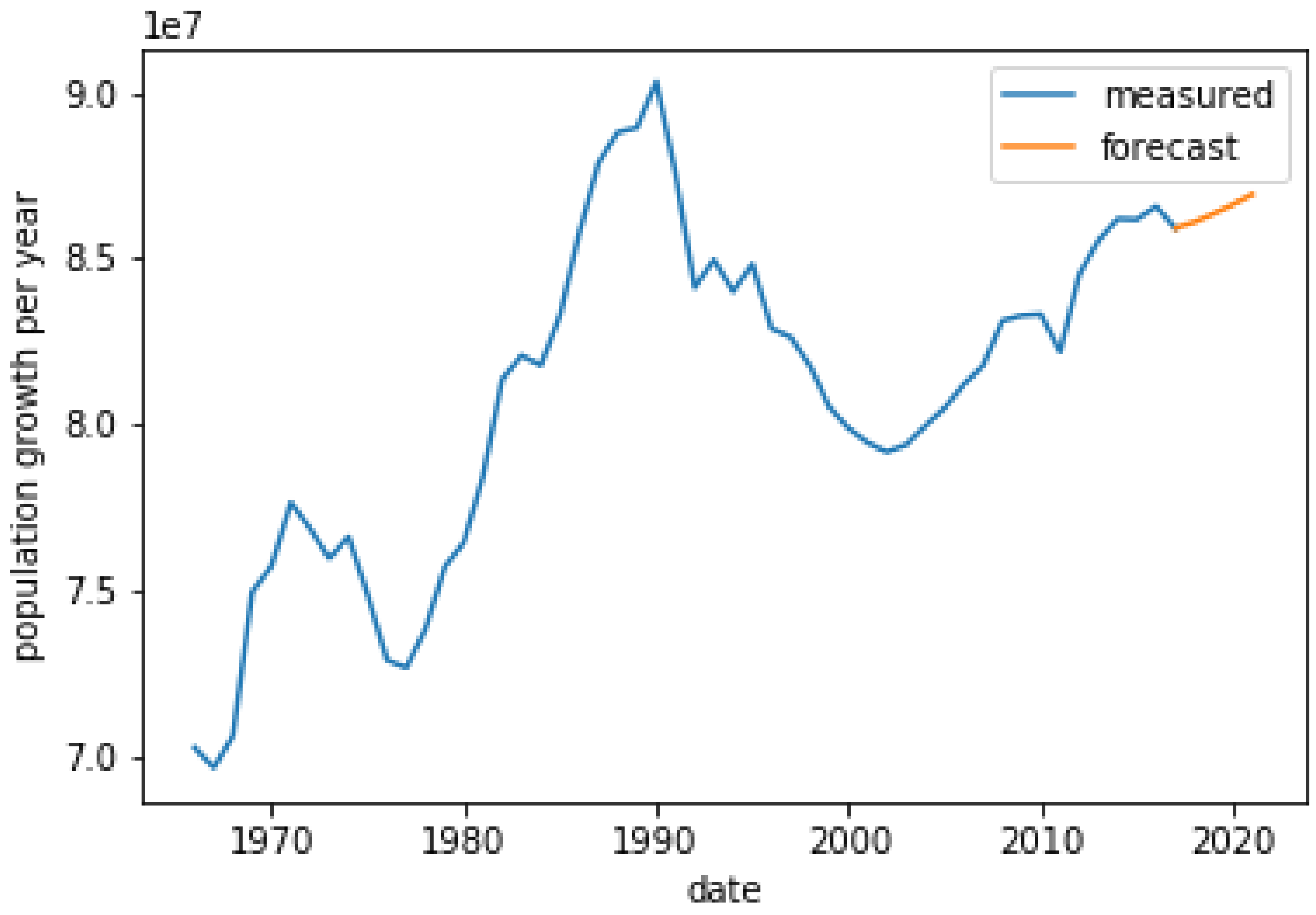
```
diff_forecast = results.get_forecast(steps=10).predicted_mean

from numpy import cumsum

mean_forecast = cumsum(diff_forecast) + df.iloc[-1,0]
```

The opposite of taking the difference is taking the cumulative sum or integral of the difference values to predictions of the absolute values.

Reconstructing original time series after differencing



The ARIMA model

- Take the difference
- Fit ARMA model
- Integrate forecast

Can we avoid doing so much work?

Yes!

ARIMA - Autoregressive Integrated Moving Average

Using the ARIMA model

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

model = SARIMAX(df, order =(p,d,q))
```

- p - number of autoregressive lags
- d - order of differencing
- q - number of moving average lags

ARMA$(p, 0, q)$ = ARMA(p, q)

Using the ARIMA model

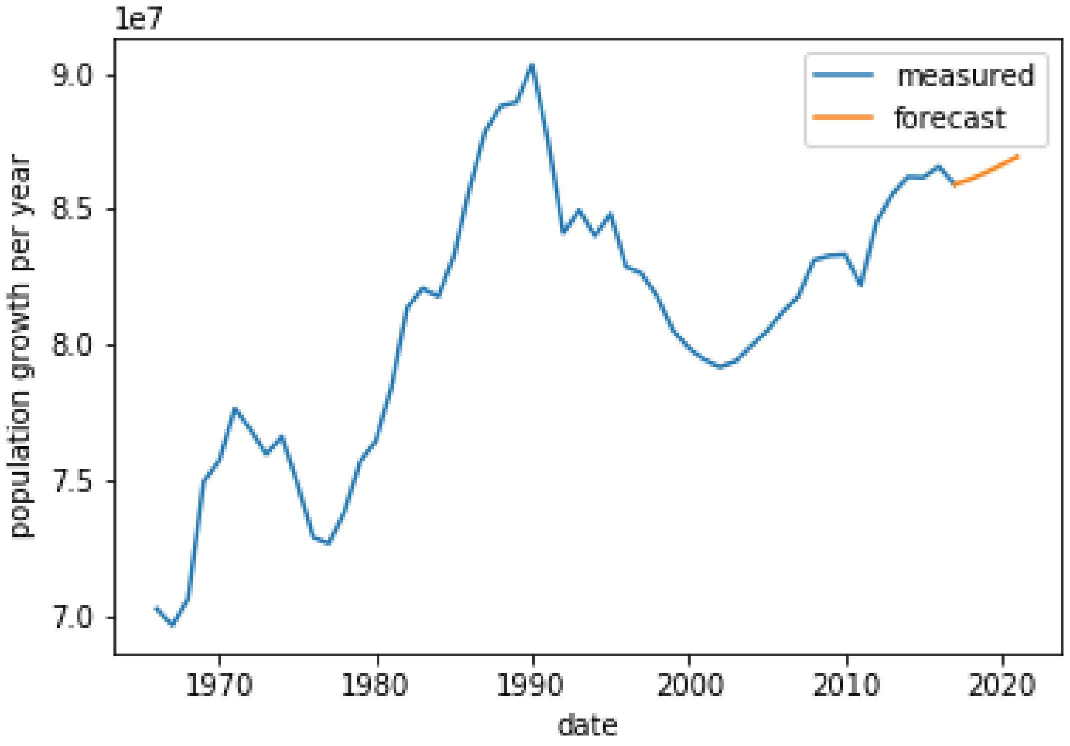
```
# Create model
model = SARIMAX(df, order=(2,1,1))

# Fit model
model.fit()

# Make forecast
mean_forecast = results.get_forecast(steps=10).predicted_mean
```

Using the ARIMA model

```
# Make forecast
mean_forecast = results.get_forecast(steps=steps).predicted_mean
```



Picking the difference order

```
adf = adfuller(df.iloc[:,0])
print('ADF Statistic:', adf[0])
print('p-value:', adf[1])
```

```
ADF Statistic: -2.674
p-value: 0.0784
```

```
adf = adfuller(df.diff().dropna().iloc[:,0])
print('ADF Statistic:', adf[0])
print('p-value:', adf[1])
```

```
ADF Statistic: -4.978
p-value: 2.44e-05
```

Picking the difference order

```
model = SARIMAX(df, order=(p,1,q))
```

Let's practice!

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