

Fitting time series models

FORECASTING USING 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

```
=====
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Fit summary

```
=====
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```

Introduction to ARMAX models

- Exogenous ARMA
- Use external variables as well as time series
- $\text{ARMAX} = \text{ARMA} + \text{linear regression}$

ARMAX equation

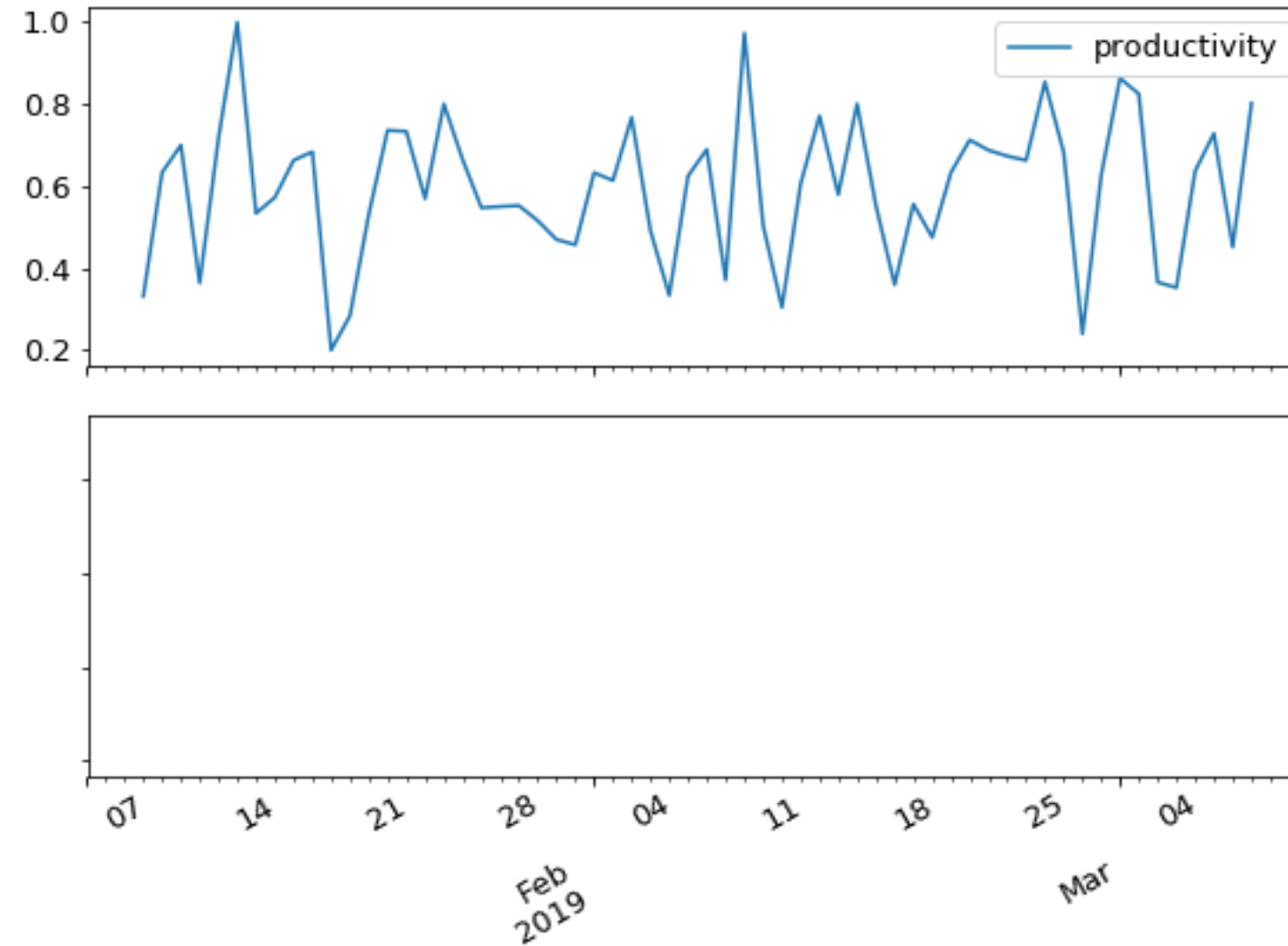
ARMA(1,1) model:

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

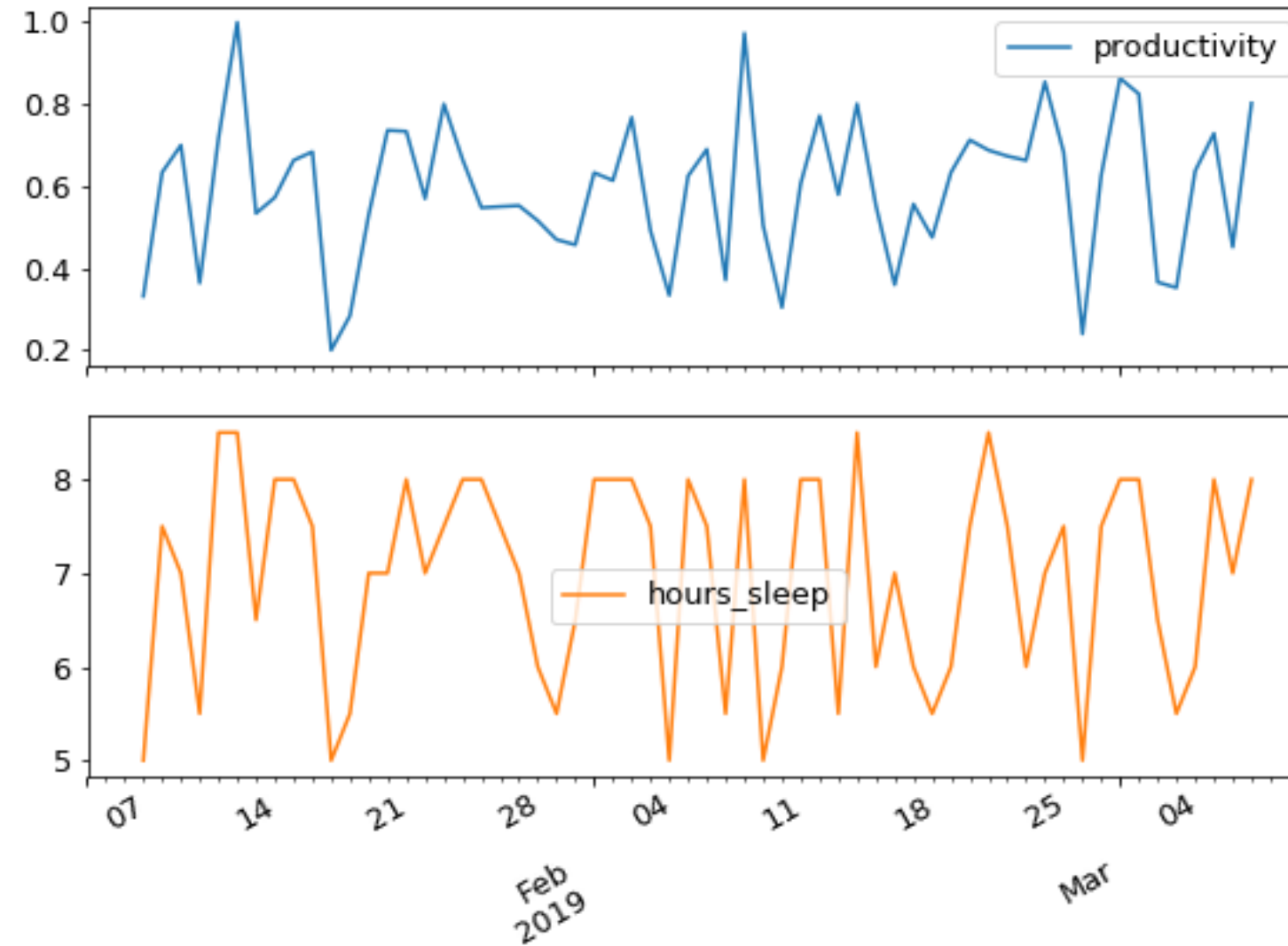
ARMAX(1,1) model:

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

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!

FORECASTING USING ARIMA MODELS IN PYTHON

Forecasting

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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

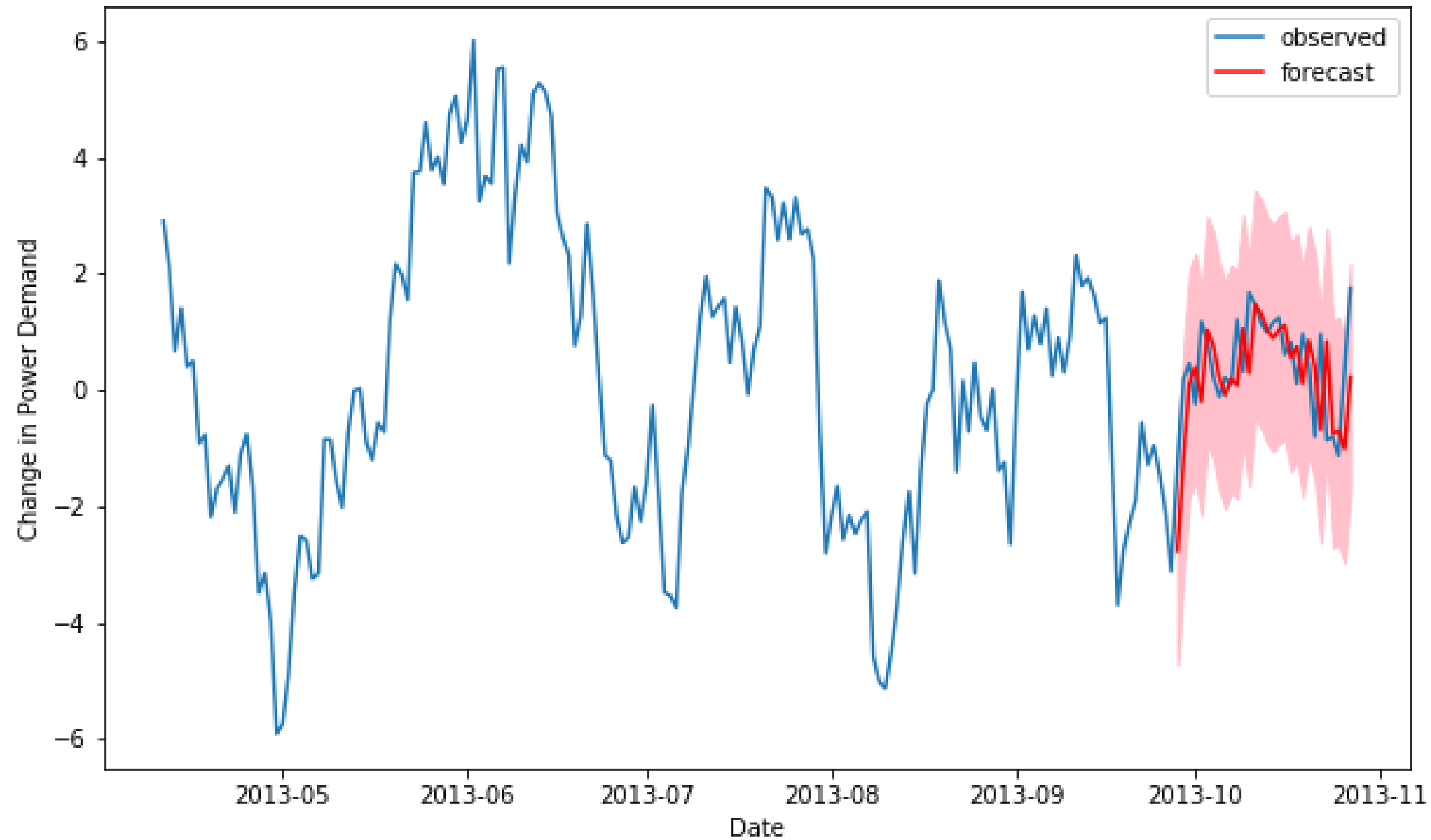
$$y_t = 0.6 \times 10 + \epsilon_t$$

$$y_t = 6.0 + \epsilon_t$$

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))
```

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')
```

Making one-step-ahead predictions

```
# Make predictions for last 25 values
results = model.fit()

# Make in-sample prediction
forecast = results.get_prediction(start=-25)
```

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

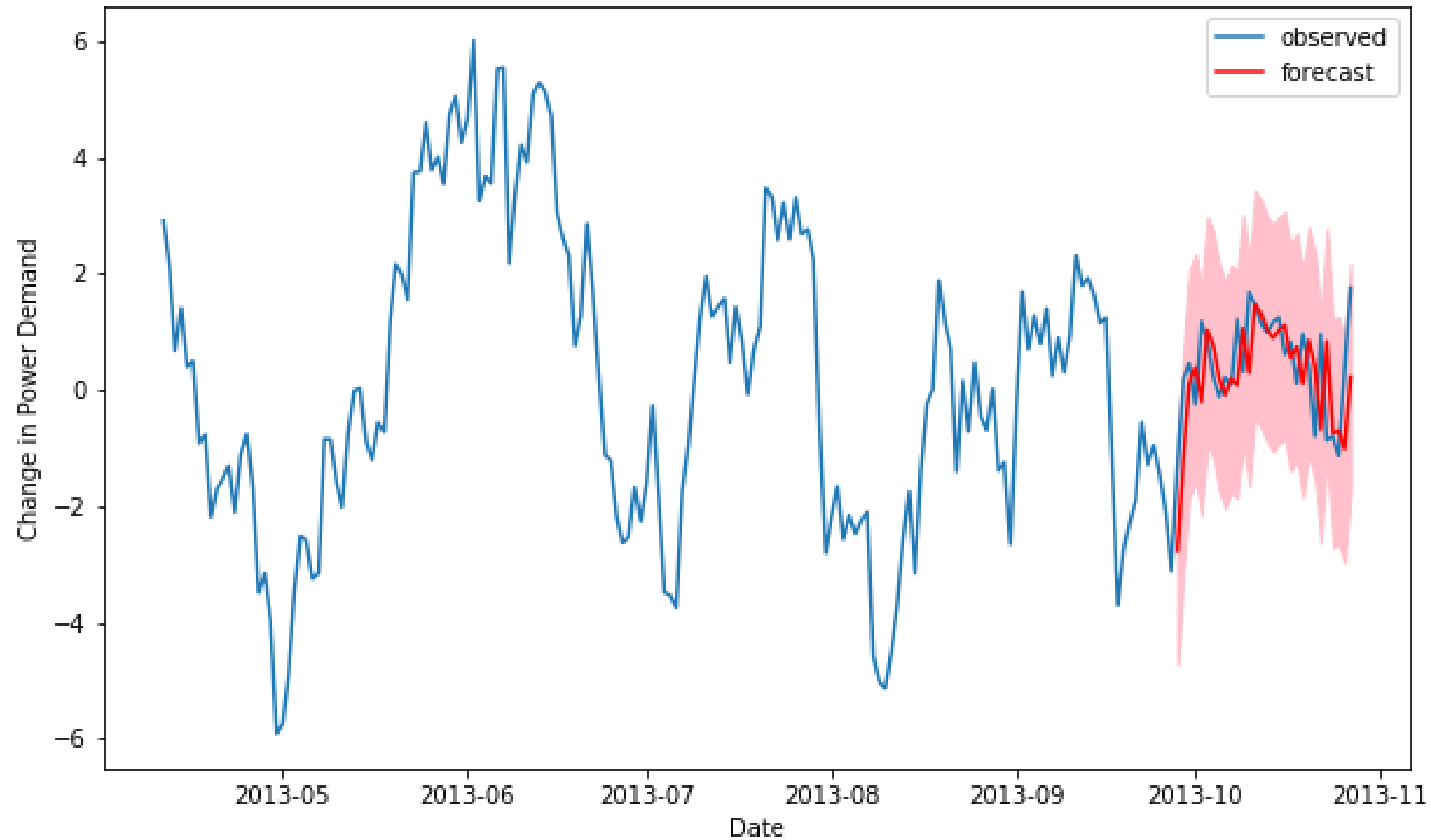
```
plt.figure()

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

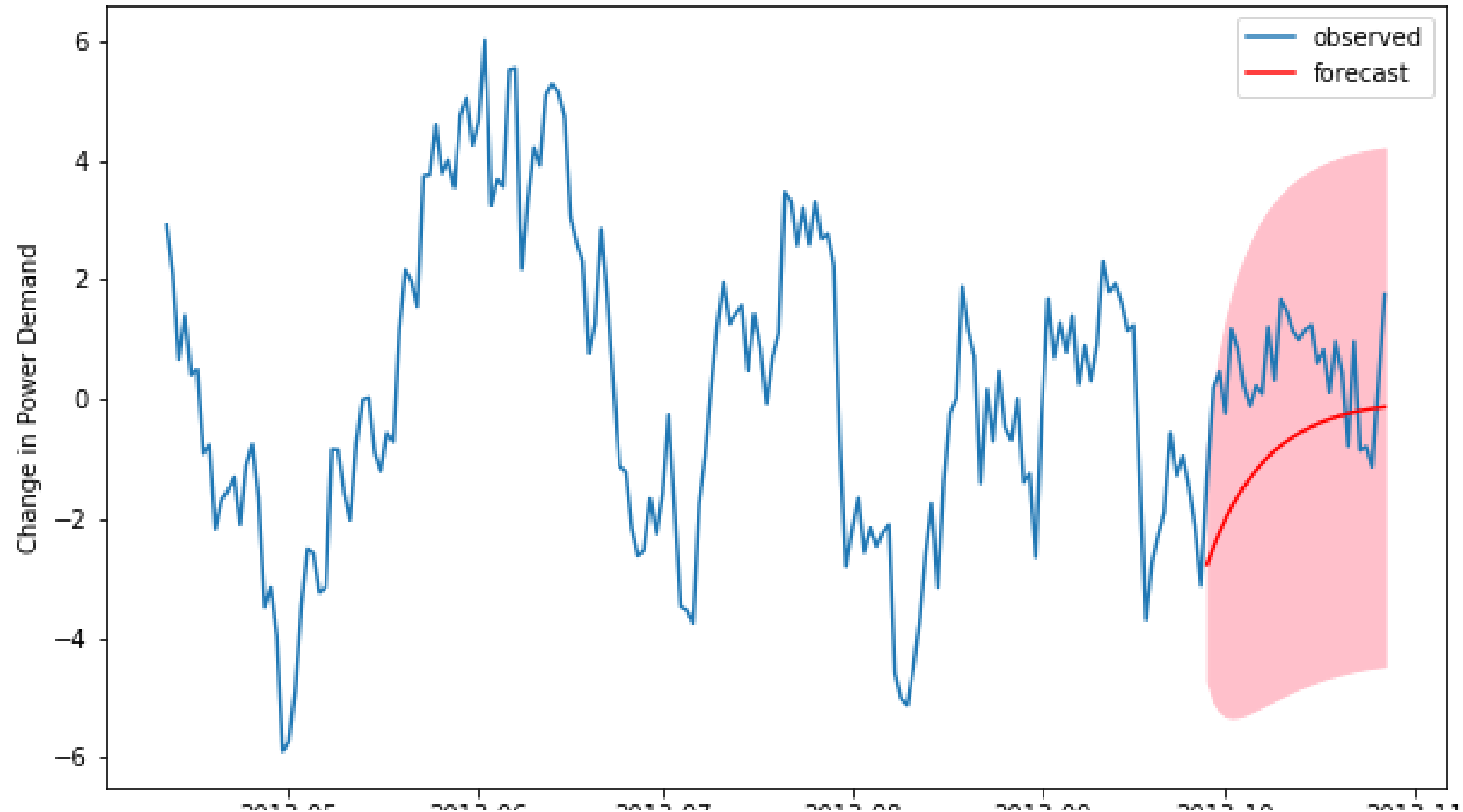
# Shade uncertainty area
plt.fill_between(dates, lower_limits, upper_limits, color='pink')

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
```

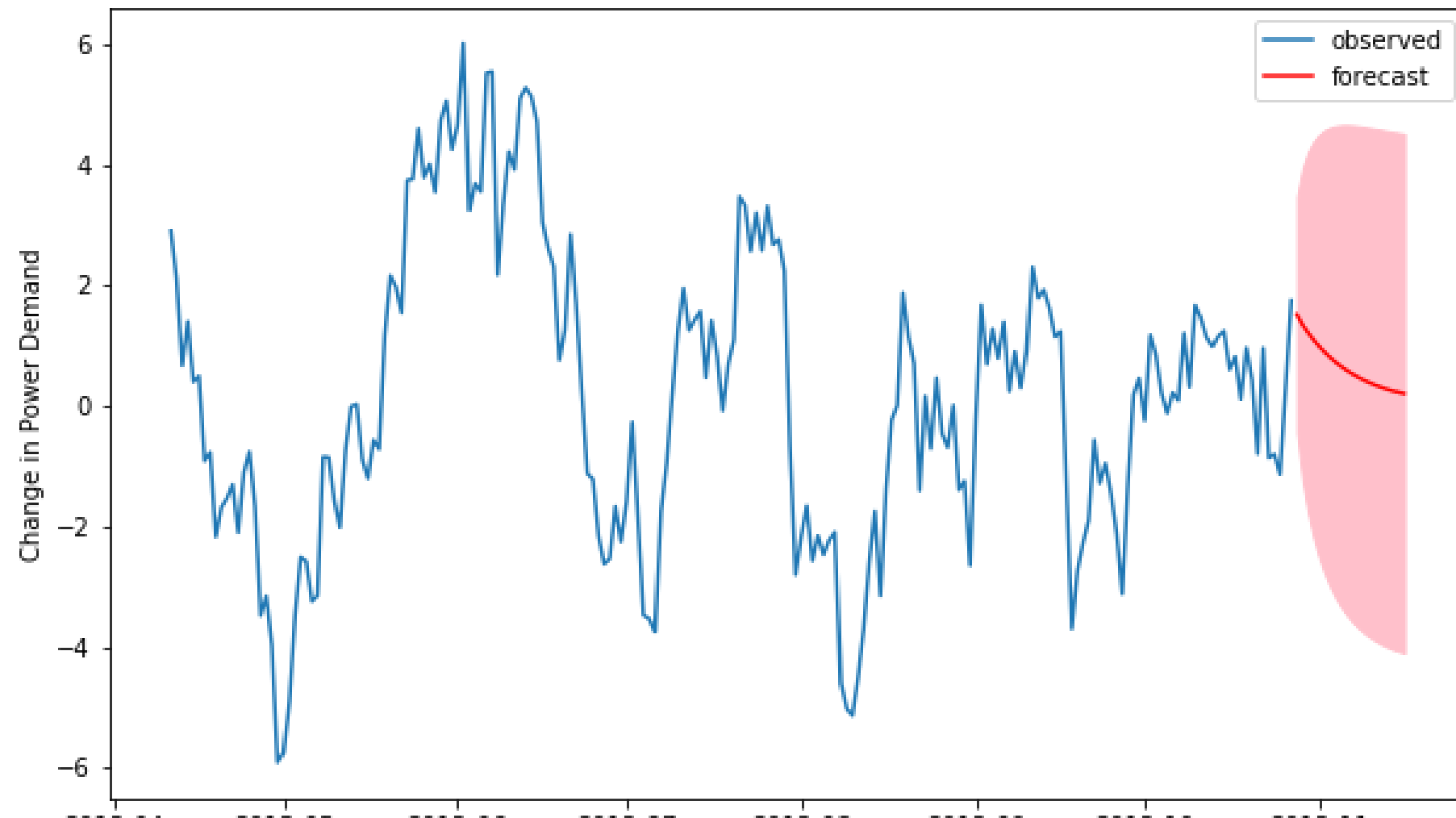
```
mean_forecast = forecast.predicted_mean
```

```
# Get confidence intervals of forecasts
```

```
confidence_intervals = forecast.conf_int()
```

Forecasting out of sample

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



Let's practice!

FORECASTING USING ARIMA MODELS IN PYTHON

Introduction to ARIMA models

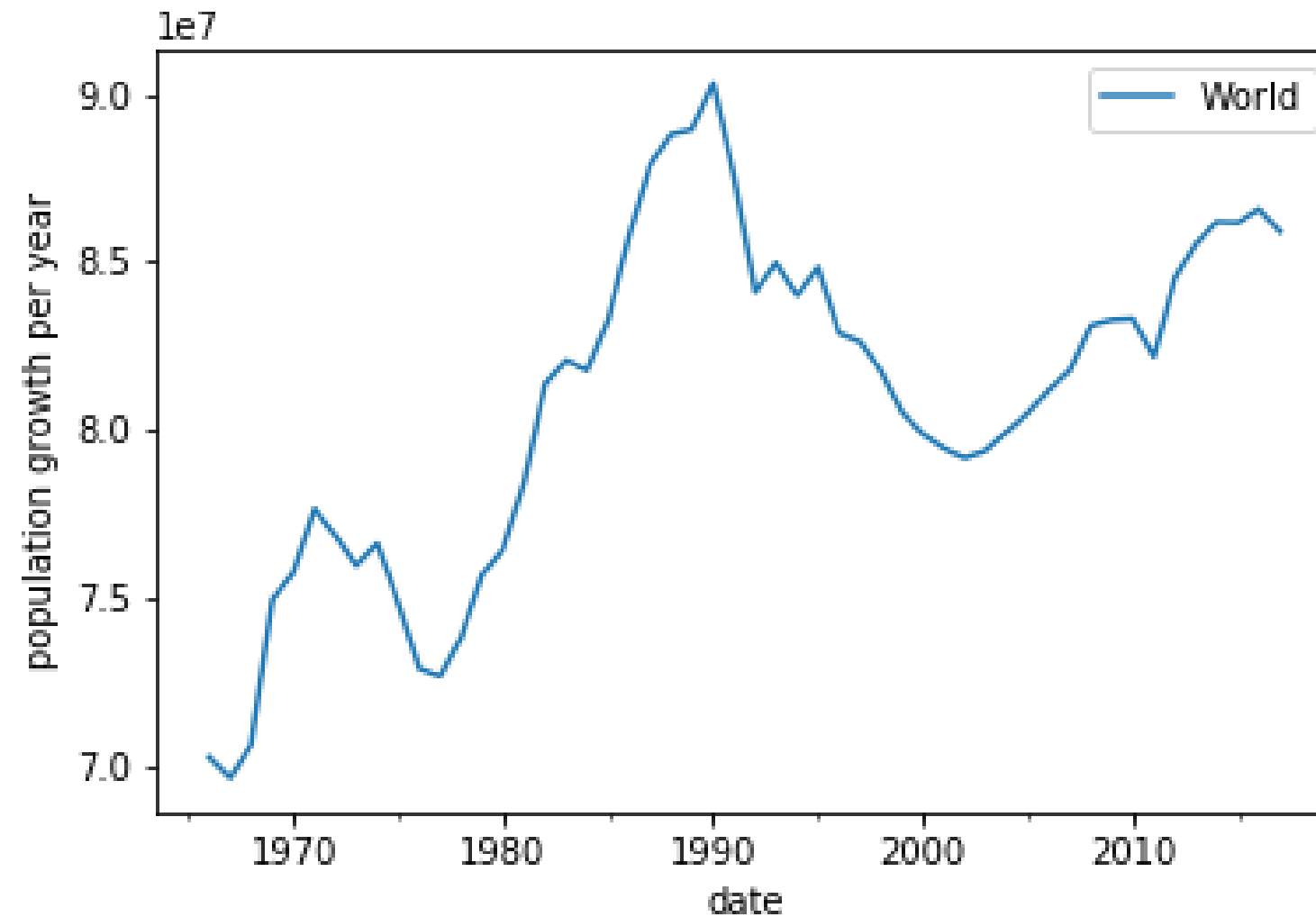
FORECASTING USING ARIMA MODELS IN PYTHON



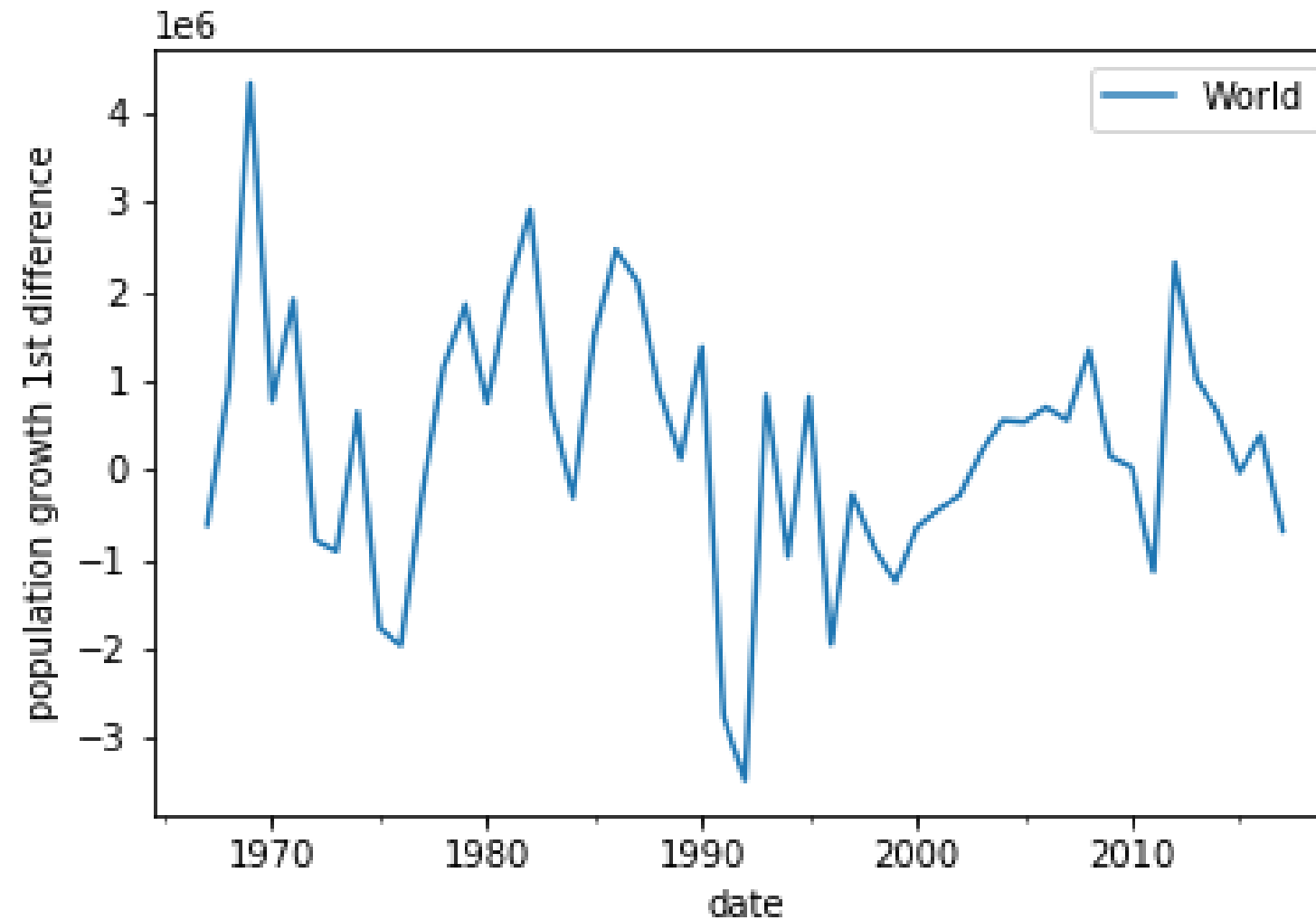
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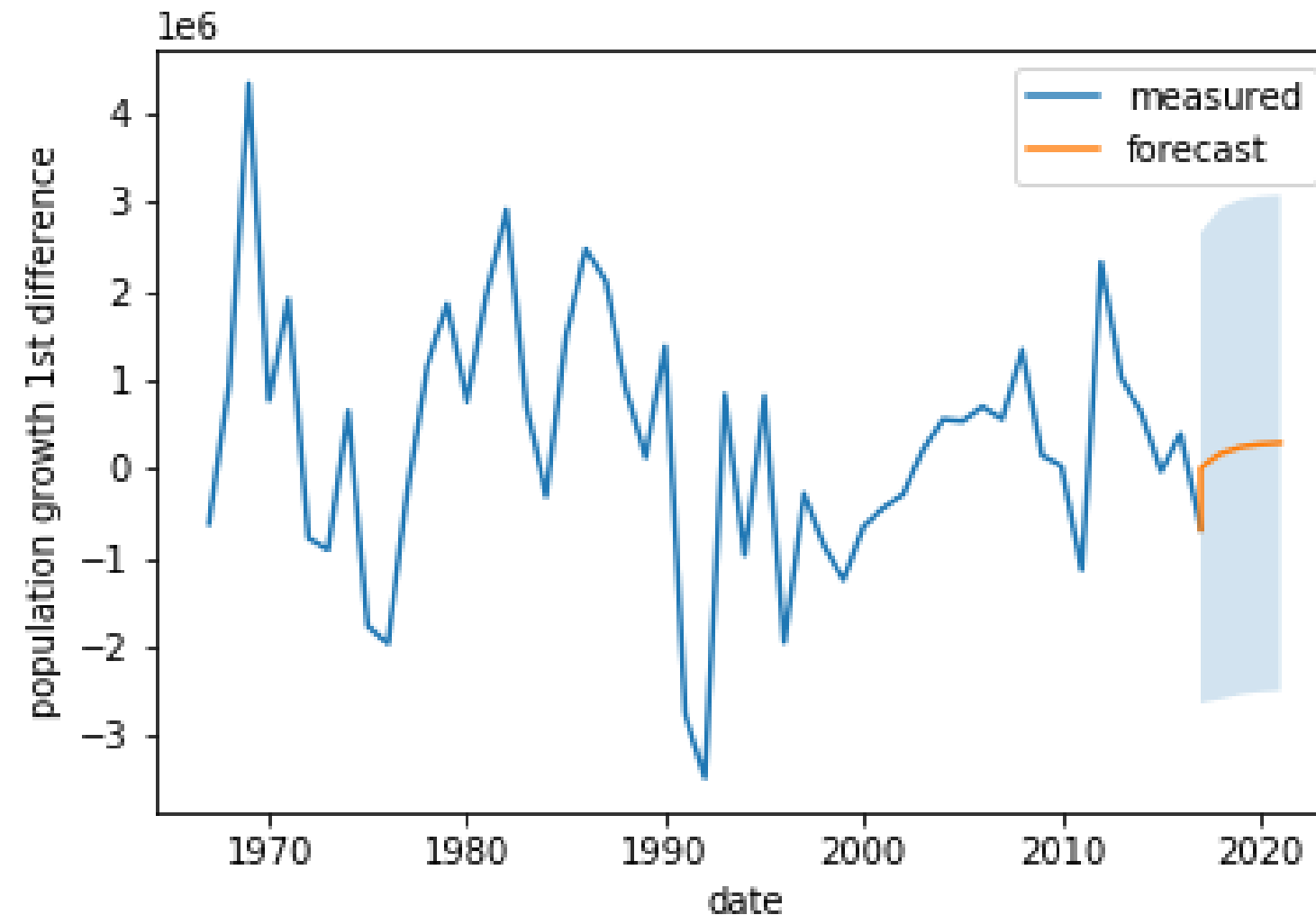
Non-stationary time series recap



Non-stationary time series recap



Forecast of differenced time series



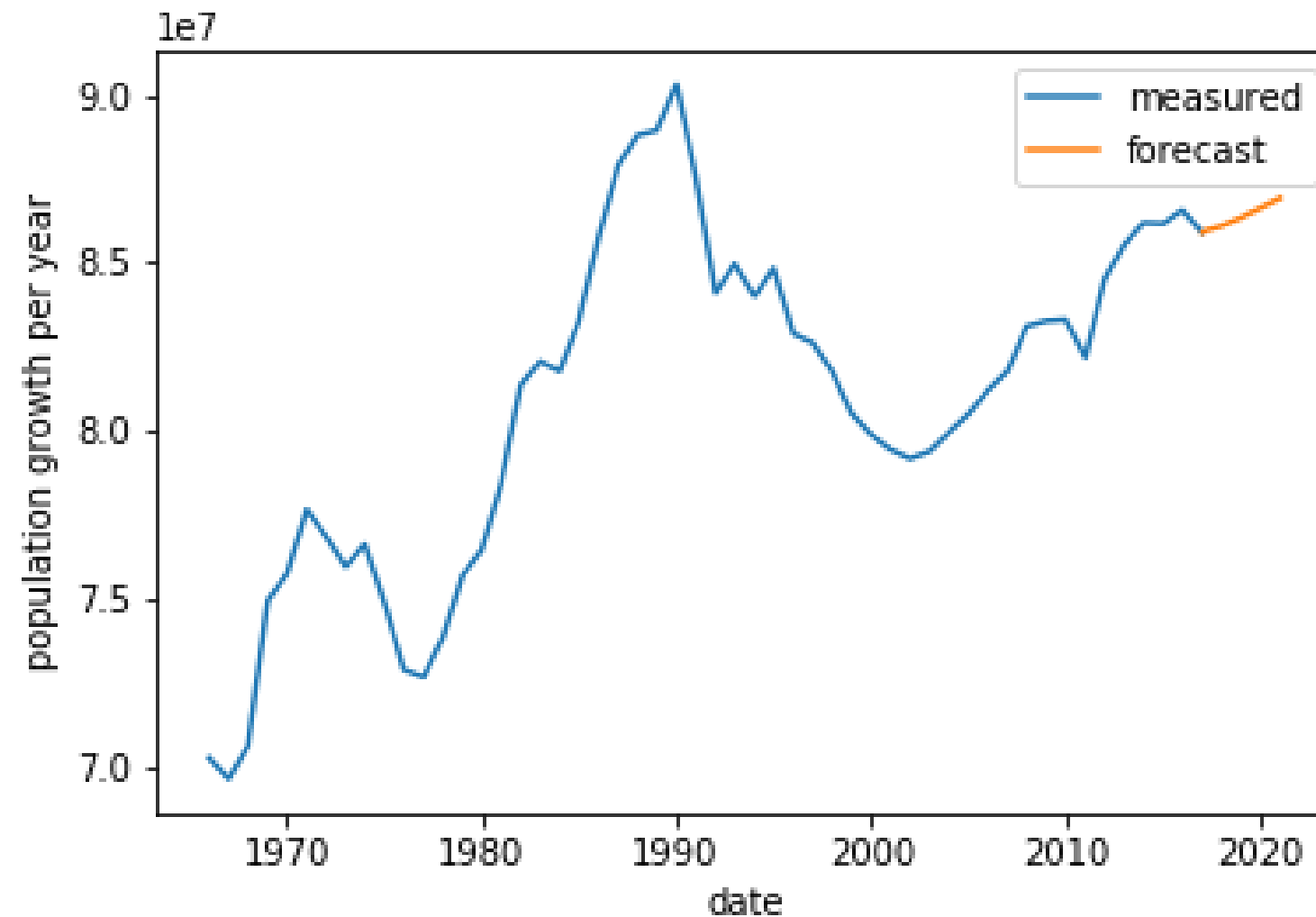
Reconstructing original time series after differencing

```
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]
```

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

$\text{ARMA}(p, 0, q) = \text{ARMA}(p, q)$

Using the ARIMA model

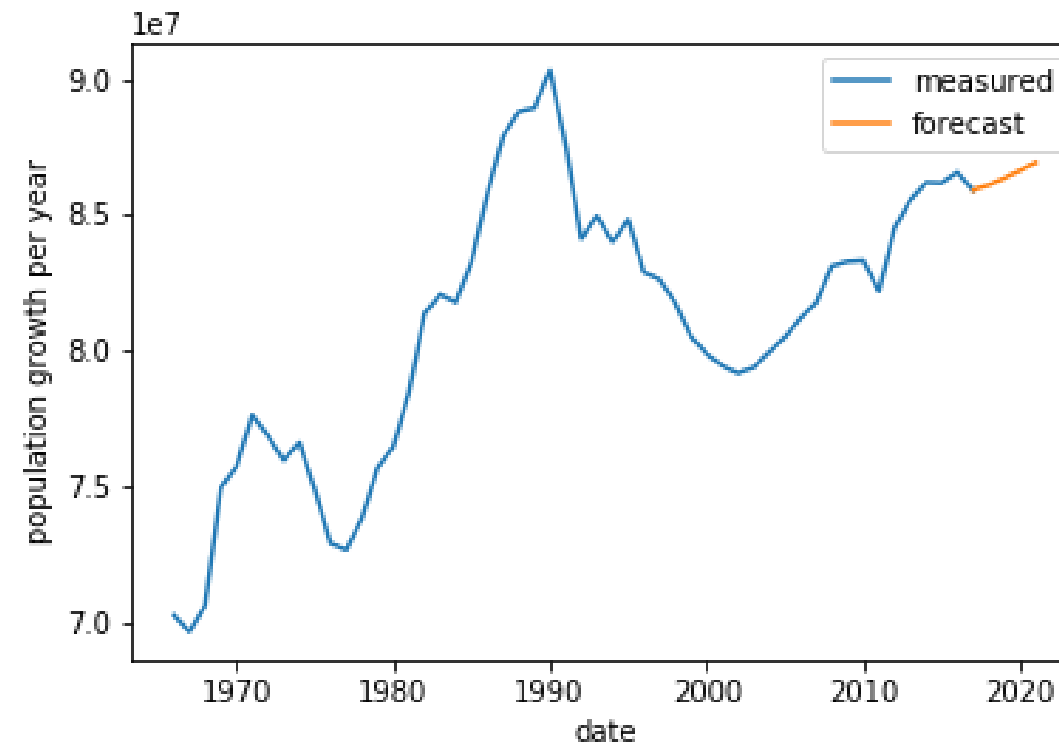
```
# Create model
model = SARIMAX(df, order=(2,1,1))

# 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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