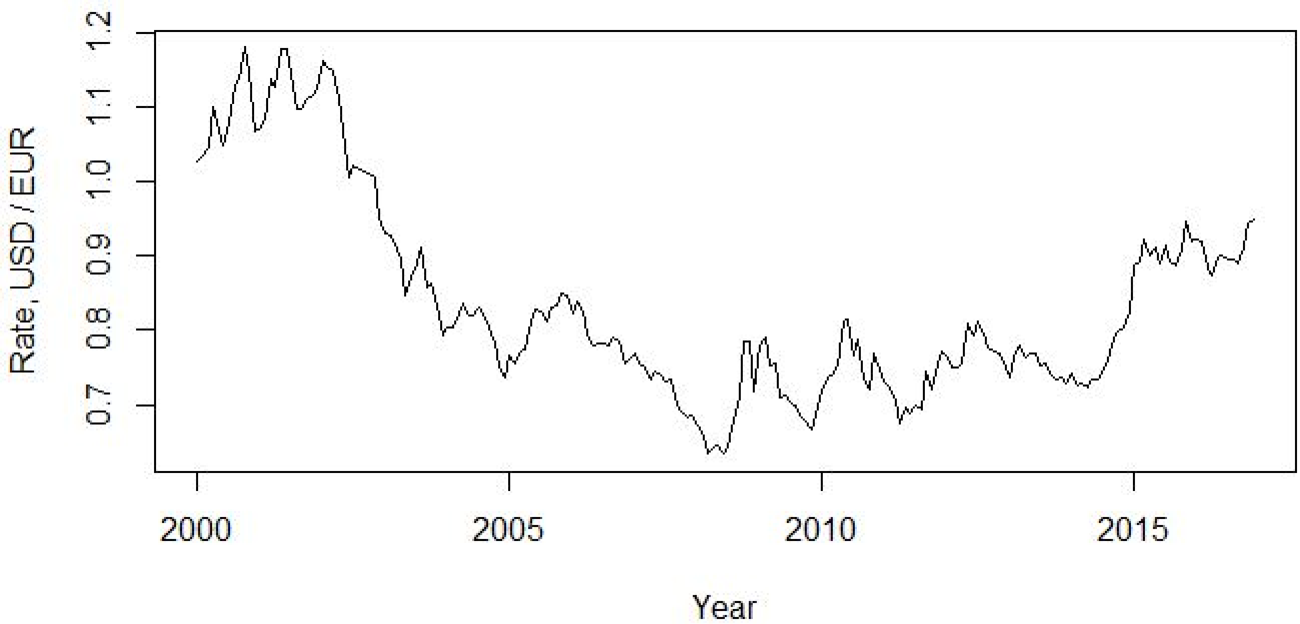
Home assignment on
Applied Time Series Econometrics

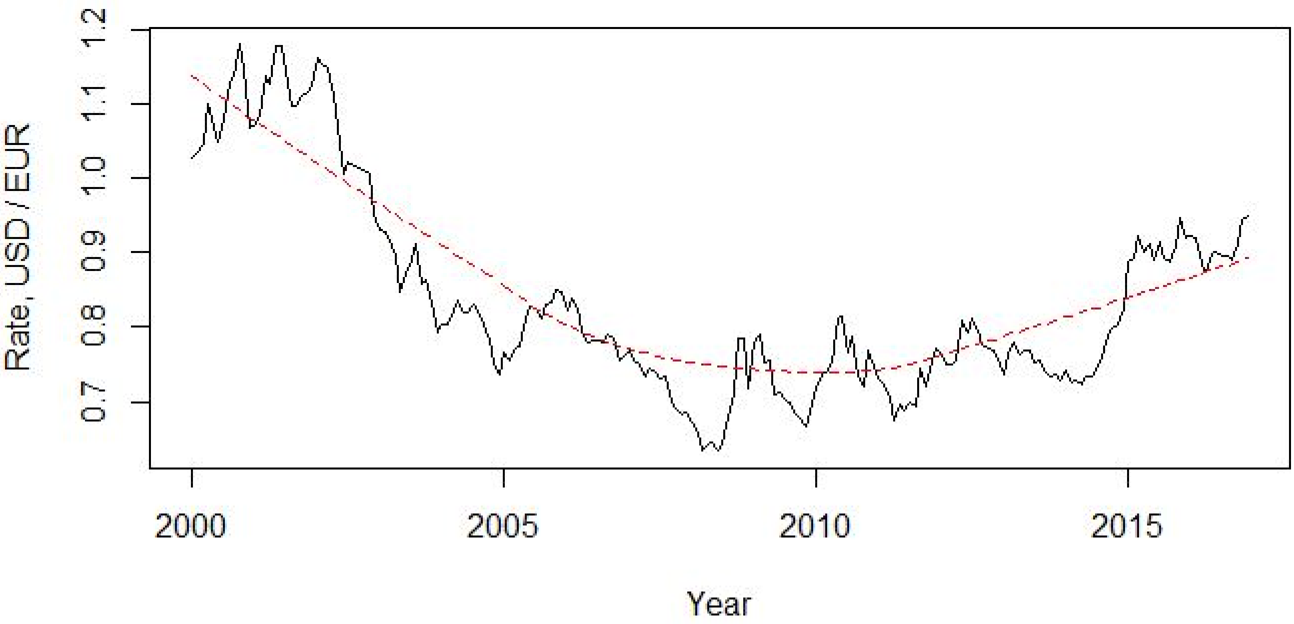
Lev Novikov

Introduction

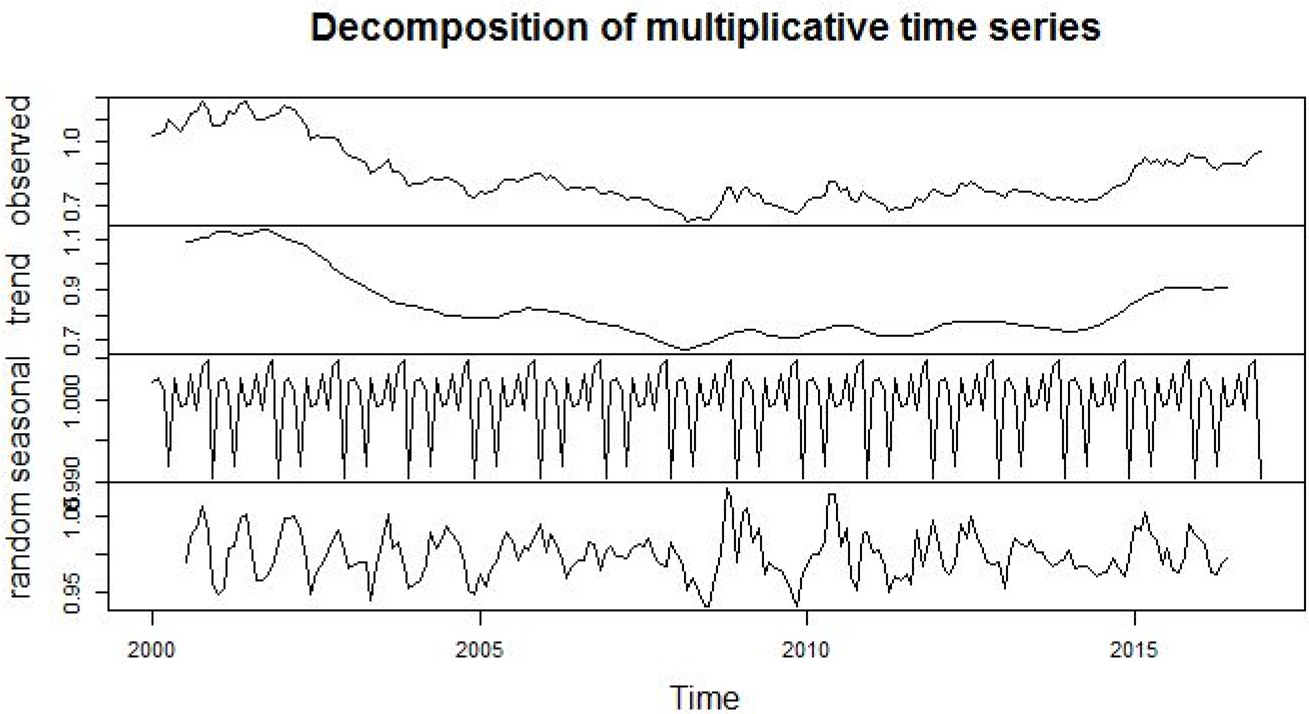
We will work with currency exchange rate from 2000 to 2016 for pair USD/EUR.
This data is taken from Quandl (Quandl("CUR/EUR") works fine here)
First of all, let's see how our data looks like:



As we can see, the series is likely not stationary: the exchange rate USD/EUR diminishes approximately till 2008, and after that continuously grows.



Let’s consider the components of the series and conduct augmented Dickey-Fuller test to check if the series really isn’t stationary.

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        Augmented Dickey-Fuller Test

data:  exrate
Dickey-Fuller = -0.73583, Lag order = 5, p-value = 0.9659
alternative hypothesis: stationary
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We reject the hypothesis of stationarity with p-value = 0.9659.

However, the first-order differences of the series are stationary, because augmented DF-test gives p-value ~ 0.01:

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        Augmented Dickey-Fuller Test

data:  diff(exrate)
Dickey-Fuller = -5.7956, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
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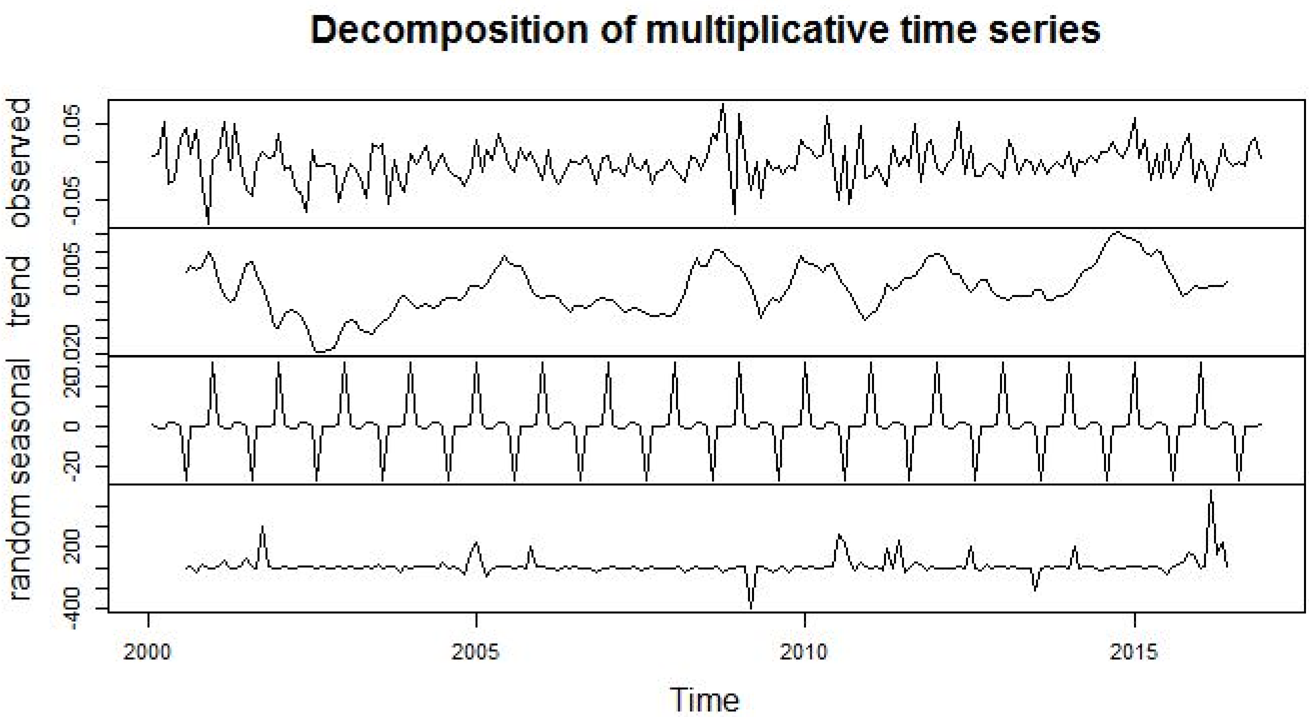
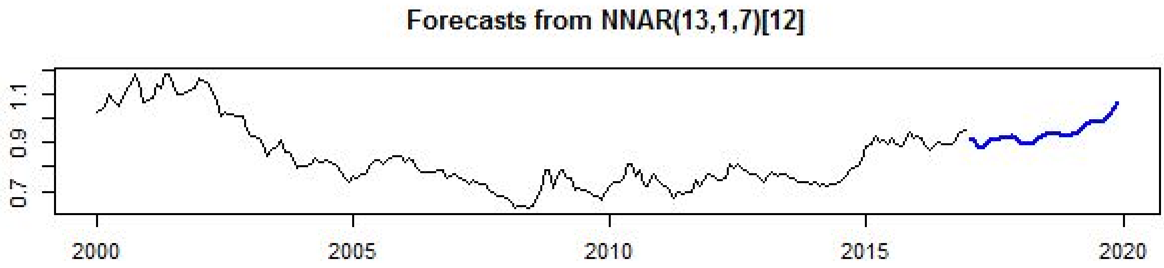
For series of first-order differences after decomposition we get the following:

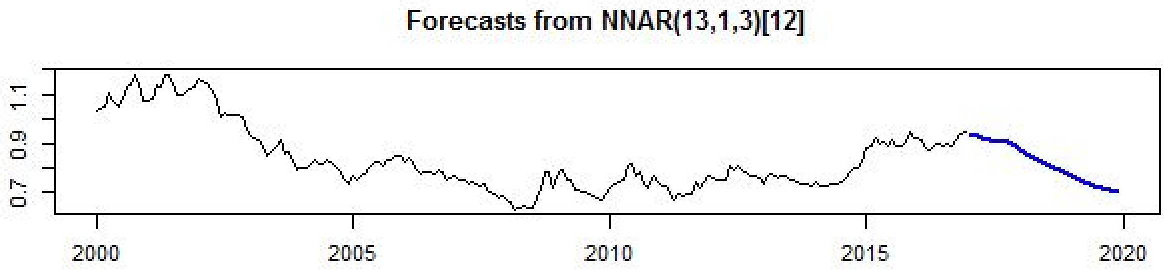


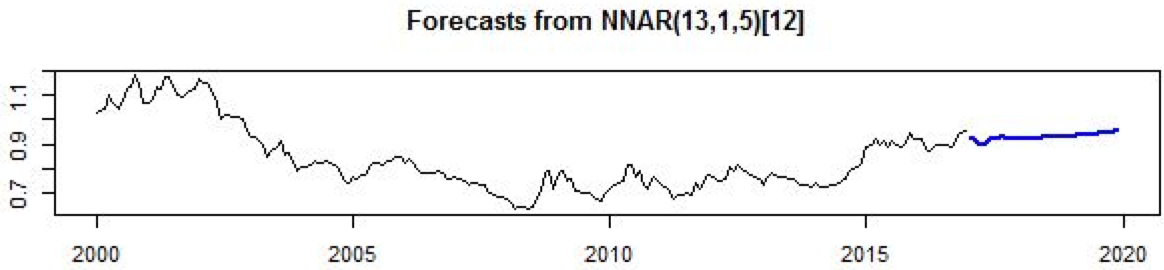
Here the line of trend obviously fluctuates. This means that we have integrated time series of the first order (ndiffs(exrate) = 1), what allows us to build an ARIMA(p, 1, q) model.

Neural networks

First of all we apply Box-Cox transformation, which stabilizes the dispersion and the data. Let's try to find the model without ARIMA, using only neural networks.





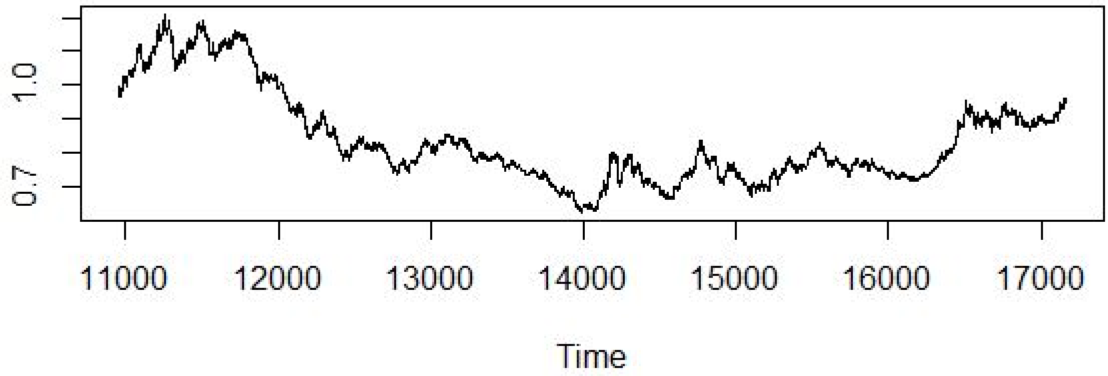


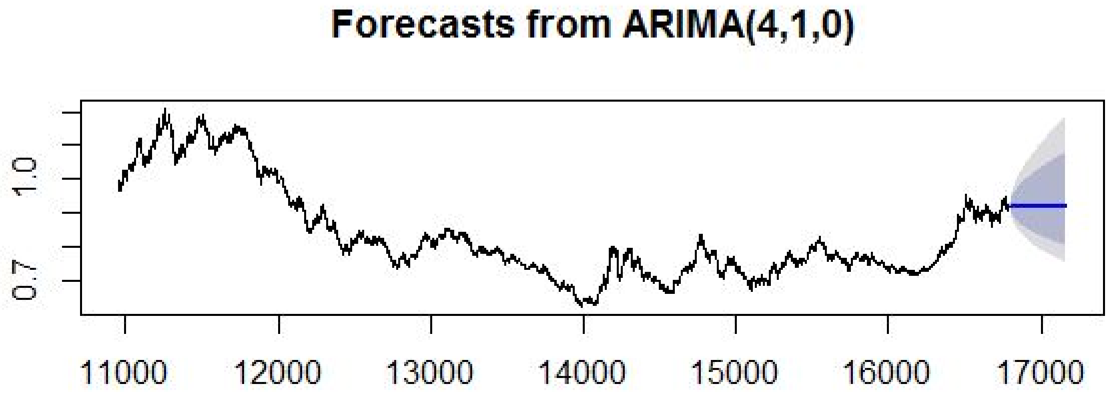
As we can see, the different methods give us absolutely different answers if we try to predict for more than a year in advance. So we will use ARIMA for daily data and we won't try to predict exchange rate for more than a year in advance.
We virtually already checked series for stationarity, so we don't need to do it the second time.

ARIMA model

We build ARIMA model based on the first 16 years (from 2000-01-01 to 2015-12-31) and make prediction for 2016-th year, so we can check if our model is pretty good when working with new data or not.

The result can be seen on the graph:





In the result, we get ARIMA(4, 1, 0) with constant forecast. It looks a little bit strange, but it predicts real values quite well (as they are close to it on the first graph).

Conclusion

We have found the appropriate autoregressive integrated moving average model with $p = 4$, $d = 1$, $q = 0$ that can predict approximate exchange rate USD/EUR for a year in advance, and showed that forecasting for longer periods for that data seems problematic even if we use neural networks, which should work better than ARIMA in the long-run.