



# **17. TIME SERIES MODELING AND FORECASTING**

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# PREVIOUSLY

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- Time series
- Smoothing
- Trending and seasonality
- Stationarity, Dickey-Fuller test
- Autocorrelation, partial autocorrelation
- Forecasting 101 & Metrics

## TODAY

- ARMA  
Modeling
- ARMA  
Modeling

# TYPES OF TS

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## Different types of TS

- White noise
- Trend
- Seasonality
- Cycle
- **Seasonality !=  
Cycle**

*Some cases can be confusing — a time series with cyclic behaviour (but not trend or seasonality) is NOT stationary. That is because the cycles are not of fixed length, so before we observe the series we cannot be sure where the peaks and troughs of the cycles will be.*

# STATIONARITY

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Required for most models.

- Mean is constant  $E[Y_t] = \mu$
- Variance is constant  $\text{Var}(Y_t) = E[(Y_t - \mu)^2] = \sigma^2$
- Autocorrelation is lag dependent

$$R(\tau) = \frac{E[(Y_t - \mu)(Y_{t+\tau} - \mu)]}{\sigma^2}$$

# TESTING FOR STATIONARITY

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## DICKEY-FULLER TEST

Null hypothesis: TS is NOT stationary

[Demo in Notebook](#)

- Dickey Fuller test does not test for seasonality  
stationarity

# (PARTIAL) AUTOCORRELATION

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## ACF

Correlation between  $Y_t$  and  $Y_{t-s}$

## PACF

Correlation between  $Y_t$  and  $Y_{t-s}$

- without the cumulative correlation between  $Y_t$  and  $Y_{t-1} \cdots Y_{t-s+1}$

# SIMPLE FORECASTING

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- next sample = last sample

$$\hat{Y}_{t+1} = Y_t$$

- Moving average

$$\hat{Y}_{t+1} = \frac{1}{n} \sum_{i=0}^n Y_{t-1-i}$$

- EWMA

$$\hat{Y}_t = \alpha \cdot Y_t + (1 - \alpha) \cdot \hat{Y}_{t-1}$$

- Linear Regression OLS

# TODAY

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- Transform TS into a Stationary TS
- Test is the TS predictable? Is it **white noise**?
- Decomposition: Trend, Seasonality, Residuals
- Is my forecast reliable?
- Is the Dow Jones a **Random Walk**?
- AutoRegressive modeling (AR) and Moving Average (MA)



# DIFFERENCING

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Create a new TS by taking the difference shifted by 1

$$X_t = Y_t - Y_{t-1}$$

! Try it out on the milk production ts

What happens to the seasonality? to the trend?

What is the result of the Dickey Fuller test on the difference? Is the difference series stationary?

# WHITE NOISE

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## WHAT IS WHITE NOISE?

Time series data that shows **no auto correlation** is called **white noise**.

Formally,  $X(t)$  is a white noise process if

- $E[X(t)] = 0$
- $E[X(t)^2] = \sigma^2$
- and  $E[X(t)X(h)] = 0$  for  $t \neq h$

The autocorrelation matrix of a white noise TS is a diagonal matrix

# HOW TO DETECT WHITE NOISE

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## 1. ACF AND PACF

Rule of thumb:

- A Time series is white noise if 95% of the spikes in the Auto-correlation Function lie within  $\pm \frac{2}{\sqrt{N}}$  with N the length of the time series.

=> Plot the PACF for the milk volume and difference TS and the tree rings series

Which one is a white noise?

# TESTING FOR WHITE NOISE: THE LJUNG-BOX TEST

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The Ljung–Box test may be defined as:

- $H_0$ : The data are independently distributed
- $H_a$ : The data are not independently distributed; they exhibit serial correlation.

The test statistic is

$$Q = n(n + 2) \sum_{k=1}^h \frac{\hat{\rho}_k^2}{n - k}$$

where

- $n$  is the sample size,
- $|\hat{\rho}_k|$  is the sample autocorrelation at lag  $k$ ,
- $h$  is the number of lags being tested.

# TESTING FOR WHITE NOISE: THE LJUNG-BOX TEST

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Rule of thumb for  $h$

- $h = 10$  for non-seasonal data
- $h = 2m$  for seasonal data, where  $m$  is the period of seasonality.

# RESIDUAL DIAGNOSTICS ON FORECASTING

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A good forecasting method will yield residuals with the following properties:

- The residuals are uncorrelated: *If there are correlations between residuals, then there is information left in the residuals which should be used in computing forecasts.*
- The residuals have zero mean : *If the residuals have a mean other than zero, then the forecasts are biased.*

It is useful to also have the following two properties which make the calculation of prediction intervals easier

- The residuals have constant variance.
- The residuals are normally distributed.

These two properties make the calculation of **prediction intervals** easier

# PREDICTION INTERVALS

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95% prediction interval:  $\hat{Y}_t \pm 1.96\sigma$  | with  $\sigma$  an estimate of the standard deviation of the forecast distribution.

When the residuals are **normally distributed and uncorrelated** and when **forecasting one-step ahead**

=> the standard deviation of the *forecast distribution* is almost the same as the standard deviation of the *residuals*.

When conditions are not met, there are more complex ways to estimate confidence intervals



# TS DECOMPOSITION

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## ADDITIVE MODEL

$$Y_t = S_t + T_t + E_t$$

where  $S_t$  is the seasonal component,  $T_t$  is the trend-cycle component and  $E_t$  is the residual

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```
import statsmodels.api as sm
res = sm.tsa.seasonal_decompose(milk_prod.volume, model = 'additive')
resplot = res.plot()
```

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## MULTIPLICATIVE MODEL

$$Y_t = S_t \cdot T_t \cdot E_t$$

# FORECAST WITH DECOMPOSITION

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- forecast seasonality, trend and residuals separately
- add back together

# LAB: IBM DATASET

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Consider the daily closing IBM stock prices (data set ibmclose).

<https://datamarket.com/data/set/2322/ibm-common-stock-closing-prices-daily-17th-may-1961-2nd-november-1962#!ds=2322&display=line>

- Produce some plots of the data in order to become familiar with it.
- Split the data into a training set of 300 observations and a test set of 69 observations.
- Try various simple methods to forecast the training set and compare the results on the test set.
- Which method did best?

# LAB: HOUSE SALES

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<https://datamarket.com/data/set/22q8/monthly-sales-of-new-one-family-houses-sold-in-th-e-usa-since-1973#!ds=22q8&display=line>

Consider the sales of new one-family houses in the USA, Jan 1973 – Nov 1995 (data set hsales).

- Produce some plots of the data in order to become familiar with it.
- Split the data into a training set of 300 observations and a test set of 69 observations.
- Try various simple methods to forecast the training set and compare the results on the test set.
- Which method did best?

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**BREAK 5MN**

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# NEXT SESSION

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- R
- SQL
- AWS Machine Learning
- ?

# LAB IS THE DJ A RANDOM WALK?

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Why you cannot beat the market

# WHAT'S A RANDOM WALK

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When the differenced series is white noise, the model for the original series can be written as

$$y_t - y_{t-1} = e_t \quad \text{or} \quad y_t = y_{t-1} + e_t$$

A random walk model is very widely used for non-stationary data, particularly finance and economic data. Random walks typically have:

- long periods of apparent trends up or down
- sudden and unpredictable changes in direction.

<http://python-for-signal-processing.blogspot.com/2014/04/random-walks-and-stumbles.html>



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# NOTEBOOK: THE DOW JONES IS A RANDOM WALK

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<http://www.johnwittenauer.net/a-simple-time-series-analysis-of-the-sp-500-index/>

- plot DJ
- plot diff
- transform with log
- plot rolling variance original + log
- plot diff of log => stationary time series model of daily changes to the S&P 500 index
- lag variables scatter plot => all centered and normal
- acf and pacf => no correlation => increment is white noise => we have a random walk
- decomposition of diff => look at the residuals white noise ?
- AR model, look at the residuals => much smaller values predicted than actual changes
- look at histogram of residuals
  - skewed => not great for confidence

- skewed  $\Rightarrow$  not great for confidence intervals
- autocorrelation plot of residuals
- test with Ljung-Box

# AR(P) MODEL

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In an autoregression model, we forecast the variable of interest using a linear combination of past values of the variable.

$$\begin{aligned} AR(1) : \quad X_t &= c + \varphi X_{t-1} + \varepsilon_t \\ AR(p) : \quad X_t &= c + \sum_{i=1}^p \varphi_i X_{t-i} + \varepsilon_t \end{aligned}$$

where

- $\varphi_i$  are the parameters of the model
- $\varepsilon_t$  is a white noise process with zero mean and constant variance  $\sigma_\varepsilon^2$
- $c$  is a constant

# SPECIAL CASES

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For an AR(1) model:

- When  $\varphi_1 = 0$ ,  $X_t$  is equivalent to white noise.
- When  $\varphi_1 = 1$ ,  $X_t$  is equivalent to a random walk.
- When  $\varphi_1 = 0, c \neq 0$   $X_t$  is equivalent to a random walk with drift
- When  $\varphi_1 < 0$   $X_t$  tends to oscillate between positive and negative values.

# MA(Q) MODELS

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Rather than use past values of the forecast variable in a regression, a moving average model uses past forecast errors in a regression-like model.

Moving Average model of order  $q$ :

$$X_t = c + \sum_{i=1}^p \varphi_i X_{t-i} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

where

- $\mu$  is the mean of the series
- $\theta_1 \cdots \theta_q$  are the parameters of the model
- $\varepsilon_t \cdots \varepsilon_{t-q}$  are white noise error terms

# ARIMA(P,D,Q) MODEL

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We combine the AR(p) and the MA(q) and add i<sup>th</sup> differencing

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}$$

We call this an ARIMA(p,d,q) model, where

- p: order of the autoregressive part;
- d: degree of first differencing involved;
- q: order of the moving average part.

# ESTIMATING P, D, Q

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The *squirrel* approach

<http://people.duke.edu/~rnau/411arim3.htm>

The ML approach: Brute Force and Grid Search



# CRITERIA FOR MODEL SELECTION

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- Akaike Information Criterion (AIC)
- Schwarz Bayesian Information Criterion (BIC)
- Hannan-Quinn Information Criterion (HQIC)

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# WHITE NOISE - NORMALITY TEST

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## THE DURBIN WATSON TEST

The Durbin-Watson statistic ranges in value from 0 to 4.

- A value near 2 indicates non-autocorrelation;
- A value toward 0 indicates positive autocorrelation;
- A value toward 4 indicates negative autocorrelation.

## AGOSTINO AND PEARSON FOR NORMALITY

Null hypothesis: the sample comes from a normal distribution

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```
scipy.stats.normaltest(ts)
```

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# LAB ON SUNSPOTS

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Wolf's Sunspot Numbers. 1700 – 1988

from <https://bicorner.com/2015/11/16/time-series-analysis-using-ipython/>

# TIME SERIES CLASSIFICATION AND CLUSTERING

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## Time Series Classification and Clustering

## DICKEY FULLER TEST

<http://stats.stackexchange.com/questions/44647/which-dickey-fuller-test-should-i-apply-to-a-time-series-with-an-underlying-mode>

<http://stats.stackexchange.com/questions/225087/seasonal-data-deemed-stationary-by-adf-and-kpss-tests>

## RANDOM WALK

<http://python-for-signal-processing.blogspot.com/2014/04/random-walks-and-stumbles.html> <http://fedc.wiwi.hu-berlin.de/xplore/tutorials/xegbohtmlnode39.html>

## LJUNG-BOX TEST

Thoughts on the Ljung-Box test

<http://stats.stackexchange.com/questions/18135/testing-normality-and-independence-of-time-series-residuals>

<https://www.otexts.org/fpp/2/6>

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# TRAIN TEST AND CROSS VALIDATION

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<https://www.otexts.org/fpp/2/5>