

# Time Series II

WS 2018/2019

22.11.2018

Dennis Kroll



# State of the art / Related work

- Scientifically contributions have to consider the “state of the art” (also called “related work”)
- State of the art focus on
  - Analyzation of papers which are related to your work
  - Description of these relations
  - Things to be learned from the listed work
  - Clear differentiation of listed work and your work

# State of the art / Related work

The screenshot shows the IEEE Xplore Digital Library homepage. At the top, there is a maintenance notice: "Scheduled System Maintenance on April 19th, 2016: IEEE Xplore will be upgraded between 1:00 and 6:00 PM ET. During this time there may be intermittent impact on performance. We apologize for any inconvenience." Below the notice, the IEEE Xplore logo is displayed, along with the text "Access provided by: University Kassel" and a "Sign Out" link. The main search bar displays "Search 3,921,494 items". A red box highlights this search bar, and three red arrows point from the right side of the slide towards it, the search button, and the "Other Search Options" dropdown. The search input field contains "Time ser|". Below the search bar, a dropdown menu lists "Time Series", "Time Series Analysis", and "Time Sharing Services". To the right of the search bar, there is a "Search" button with a magnifying glass icon and a "Other Search Options" dropdown. The main content area features a thumbnail of the "MOTION IMAGING JOURNAL" cover, which includes the title "IP & NETWORKING" and a subtitle "Recent Issue of the SMPTE Motion Imaging Journal explores IP and Networking". Below the journal cover, there is a brief description of the issue's topics and a "Browse this issue in IEEE Xplore" link. At the bottom of the page, there are five navigation links: "Journals & Magazines", "Conference Publications", "Standards", "Books & eBooks", and "Courses". There are also three sections at the bottom: "Just Published" (with a thumbnail of the IEEE Micro journal), "Most Popular" (with a thumbnail of the Internet of Things for Smart Cities article), and "Popular Search Terms" (listing "control", "power", and "network").

Scheduled System Maintenance on April 19th, 2016:  
IEEE Xplore will be upgraded between 1:00 and 6:00 PM ET. During this time there may be intermittent impact on performance. We apologize for any inconvenience.

IEEE.org | IEEE Xplore Digital Library | IEEE-SA | IEEE Spectrum | More Sites | Cart (0) | Create Account | Personal Sign In

IEEE Xplore®  
Digital Library

Access provided by:  
University Kassel  
» Sign Out

IEEE

BROWSE ▾

MY SETTINGS ▾

GET HELP ▾

WHAT CAN I ACCESS?

Search 3,921,494 items

Time ser|

Time Series

Time Series Analysis

Time Sharing Services

Search

Other Search Options ▾

MOTION IMAGING JOURNAL

IP & NETWORKING

INSIDE THIS ISSUE

Recent Issue of the SMPTE Motion Imaging Journal explores IP and Networking

This issue dives into topics such as Design Elements for Core IP Media Infrastructures, Elementary Flows for Live IP Production, Video Over LTE: Exploring Efficiency in Distribution, and more.

Browse this issue in IEEE Xplore

Journals & Magazines

Conference Publications

Standards

Books & eBooks

Courses

Just Published

Most Popular

Popular Search Terms

control

power

network

[IEEE]

# State of the art / Related work

dl.acm.org

IEEE ACM UbiComp Submit UbiComp comtec software private icons iCloud supervision

SIGN IN SIGN UP

Time series

**ACM DL DIGITAL LIBRARY**

Universitaetsbibliothek Kassel

**The ACM Digital Library** is a research, discovery and networking platform containing:

- The **Full-Text Collection** of all ACM publications, including journals, conference proceedings, technical magazines, newsletters and books.
- A collection of curated and **hosted full-text** publications from select publishers.
- **The ACM Guide to Computing Literature**, a comprehensive bibliographic database focused exclusively on the field of computing.
- A richly interlinked set of **connections** among authors, works, institutions, and specialized communities.
  - [Using the ACM Digital Library](#)
  - [For Consortia Administrators](#)

---

**Announcements**

**Digital Library Training Sessions**

Join us for our [DL Weekly Online Training Sessions](#)

 **ACM BOOKS** a dynamic new series of advanced level books in computer science, published by ACM in collaboration with Morgan & Claypool Publishers.  
[learn more about the program](#) | [check out the books](#)

**Advanced Search** 

**Browse the ACM Publications:**

- [Journals/Transactions](#)
- [Magazines](#)
- [Proceedings](#)
- [ACM Books](#)

**Browse the Special Interest Groups:**

- [Special Interest Groups \(SIGs\)](#)

**Browse the Conferences:**

- [Recent and Upcoming Conferences](#)
- [Conference Listing](#)

**Browse the Special Collections:**

- [eBooks](#) available to ACM Members 
- [ACM International Conference Proceeding Series \(ICPS\)](#)
- [Classic Book Series](#)
- [ACM Oral History interviews](#)
- [ACM Curricula Recommendations](#)
- [NSF Workshop Reports](#)

**Browse the Hosted Content**

**Browse all literature by type**

**Browse all literature by Publisher**

**Browse by the ACM Computing Classification System**

[ACM]

Revision of CT1 (SS-2017)

# **INTRODUCTION TO TIME SERIES**

# What are time series?

- Oxford dictionary says:

*“A series of values of a quantity obtained at successive times, often with equal intervals between them [OTS]”*

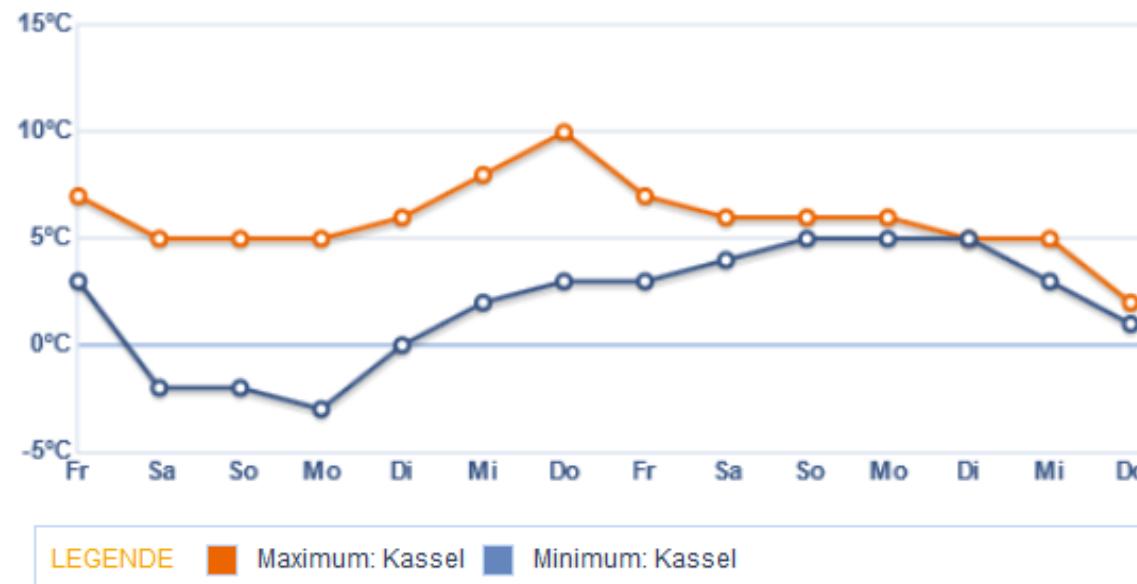
# What are time series?

- Some examples for time series



# What are time series?

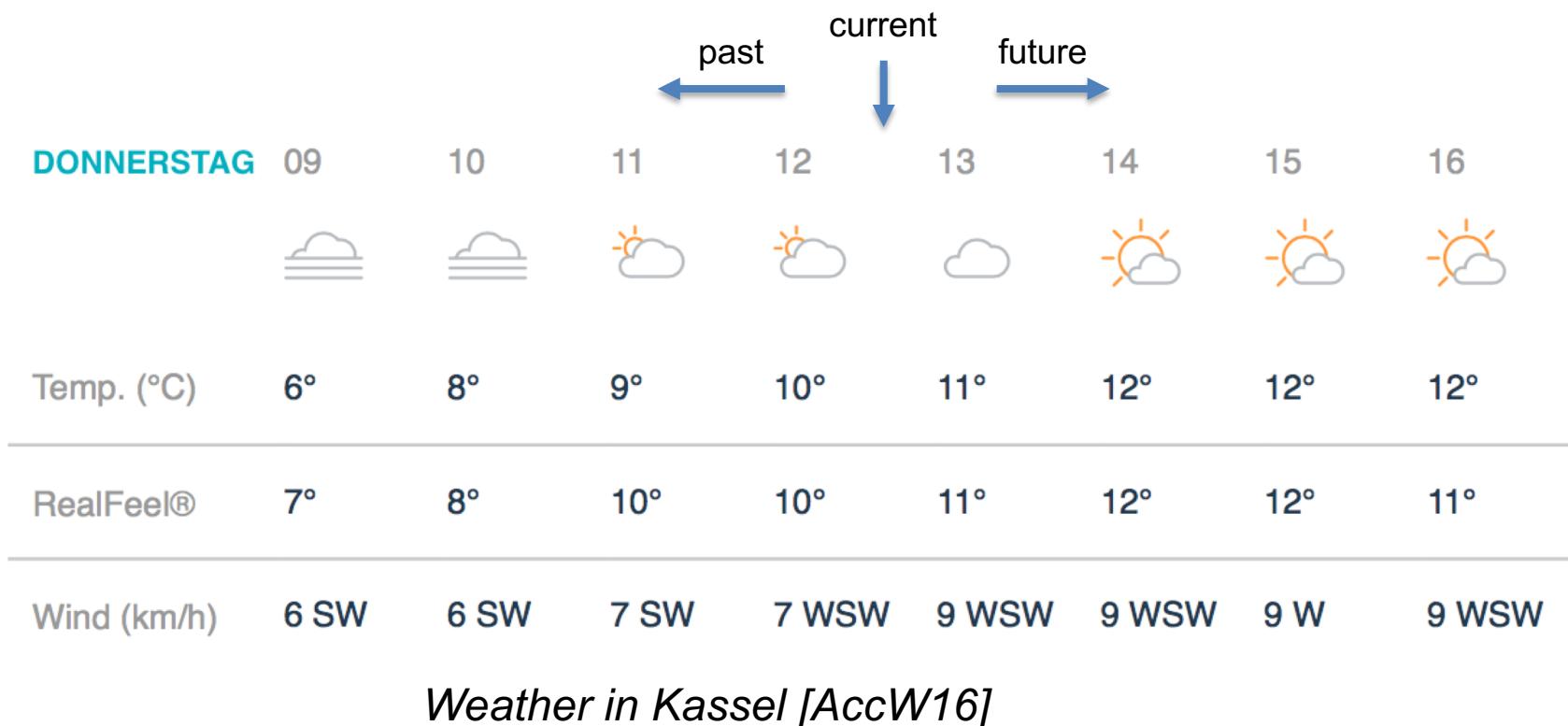
- Some examples for time series



*Weather (winter 2015) by wetter.com [WC]*

# What are time series?

- Some examples for time series



# Time series properties

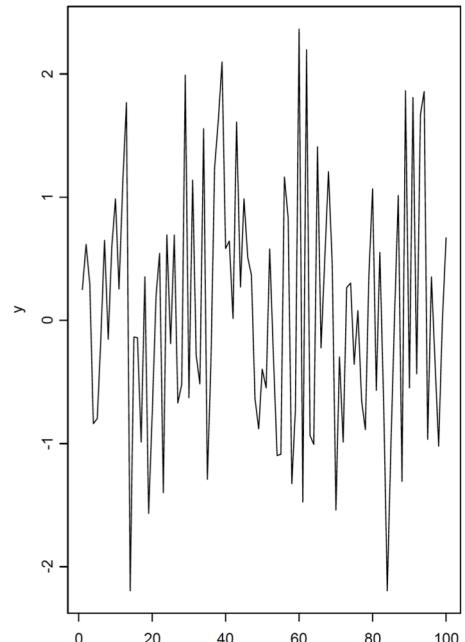
- Value
  - Numeric, text, binary, dates, ..
  - Missing values
- Time
  - Axis units often seconds, minutes, hours, ..
  - Equally spaced values
    - Specific sampling rate (Hz), seasonal, annual, ..
  - Unevenly spaced values
    - earthquakes, floods, astronomical observations (e.g. supernovas)

# Time series properties

- Noise
  - No noise, white noise, pink noise, ..
- Others
  - Trends, patterns
  - Complete / Continuous  
(also called “stream data”)
  - Nonstationarity / Stationarity

## [Noise]

- 2 [MASS NOUN] *technical* Irregular fluctuations that accompany a transmitted electrical signal but are not part of it and tend to obscure it:  
*‘the enhancer can improve the video signal quality, reducing noise and increasing image sharpness’*



*Example stationary time series:  
white noise [TSC]*

# Time series representation



- Reasons to change the representation of time series (TSs)
  - Save storage
  - Get time series “human readable”
  - Focus on important information
  - Data representation is key for applying context algorithms
    - Raw time series are rarely applicable for machine learning
    - Therefore, TSs are often divided into segments
    - On the segments, e.g. "Feature Extraction" is applied
    - Next, features are used to learn and recognize activities (see CT lectures about *activity recognition*)

# Time series representation

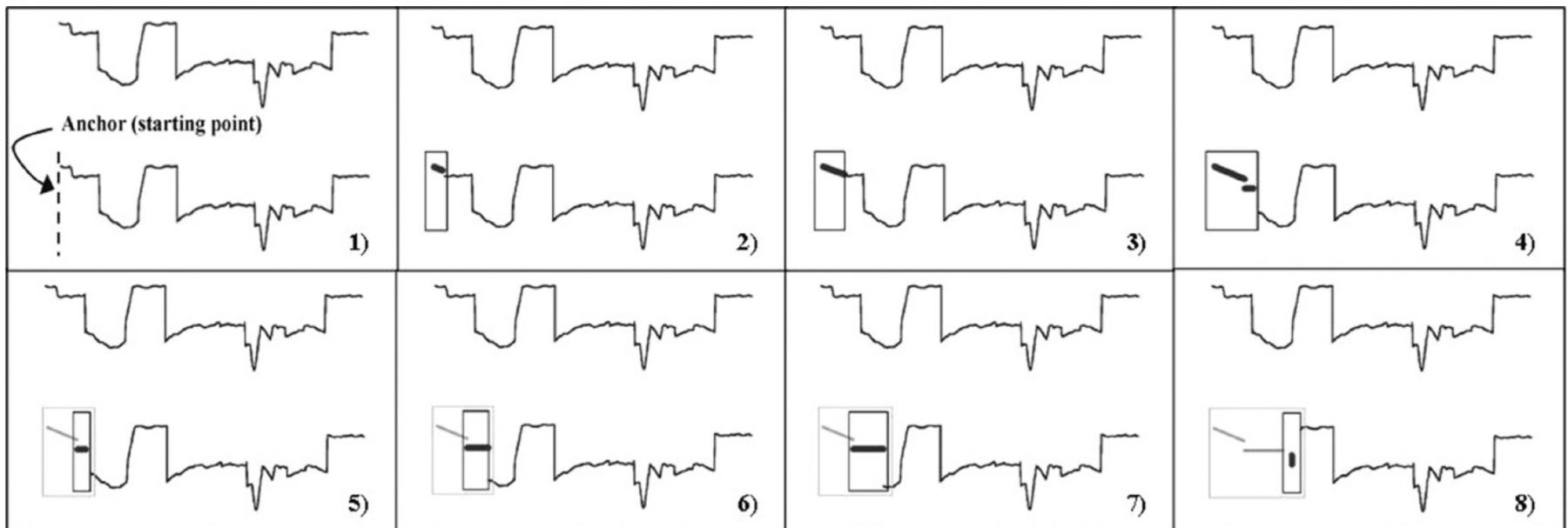
- Example representations
  - Piecewise Linear Approximation (PLA)
    - Segment time series [K01]
    - Approximate segments
  - Autoregressive Models (AR Models)
    - Use time series to parametrize a model
    - Models useful for predicting time series
    - A variety of models exist, in this lecture we focus on AR Models

# Time series representation

- Example representations
  - Piecewise Linear Approximation (PLA)
    - Segment time series [K01]
    - Approximate segments
  - Autoregressive Models (AR Models)
    - Use time series to parametrize a model
    - Models useful for predicting time series
    - A variety of models exist, in this lecture we focus on AR Models

# Time series segmentation

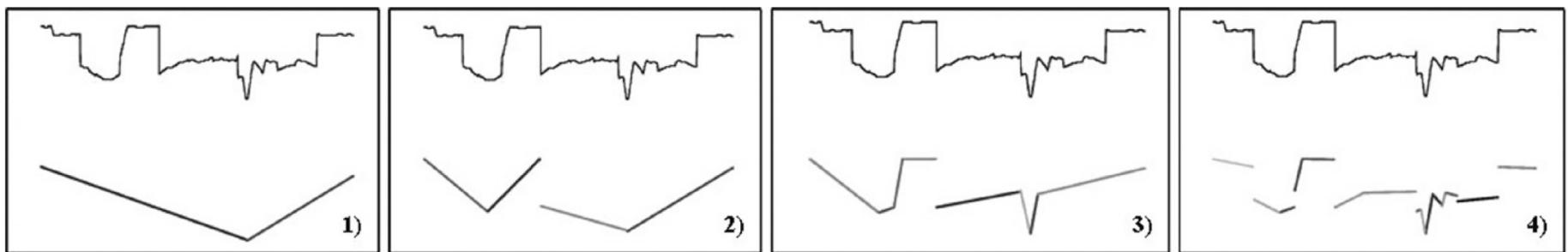
- Sliding Window Segmentation – Short example



[LMS14]

# Time series segmentation

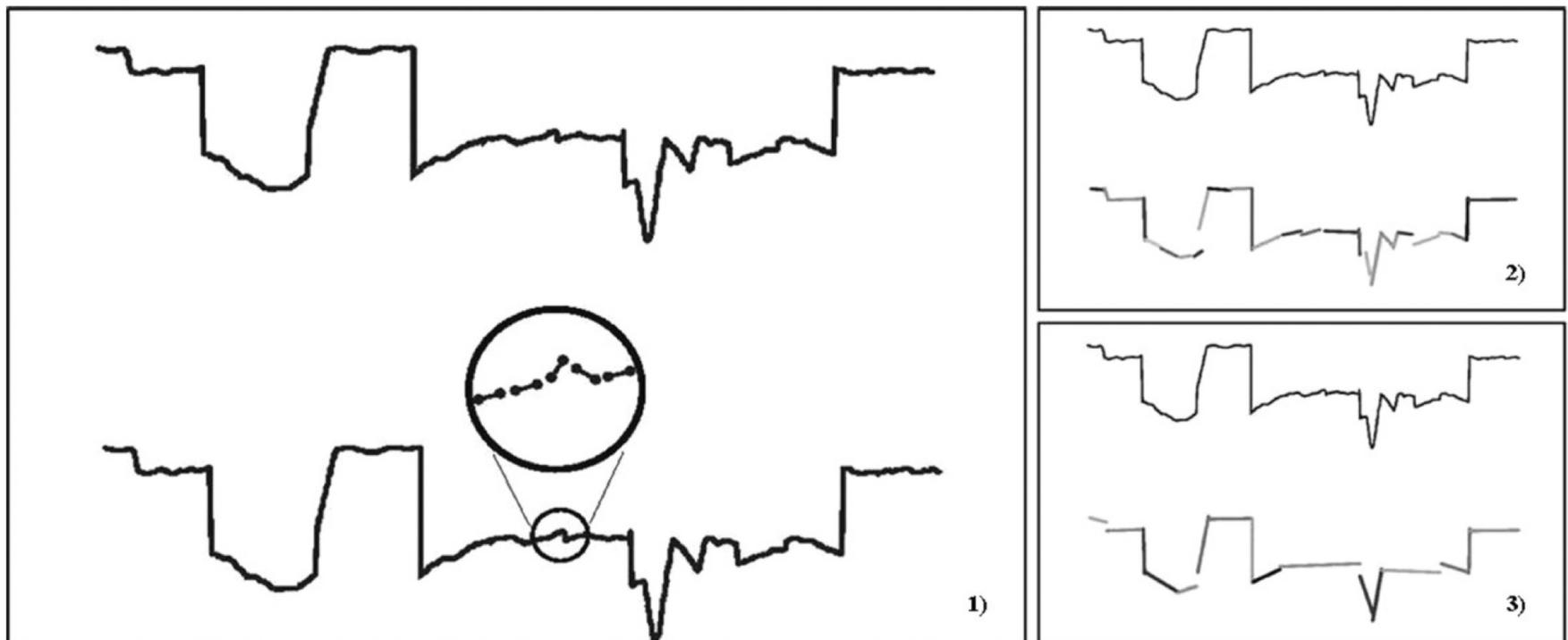
- Top Down Segmentation – Short example



[LMS14]

# Time series segmentation

- Bottom Up Segmentation – Short example



[LMS14]

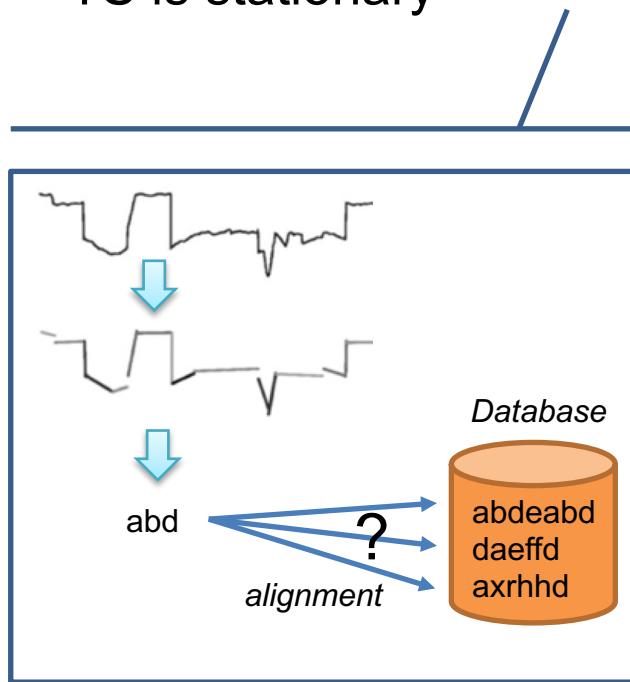
# Time series representation and prediction



- Some representations and models also support predicting time series
- In this lecture, two options for time series modelling and prediction are presented
  - A combination of algorithms which can be applied to both, stationary and nonstationary models
  - A model fit for stationary time series

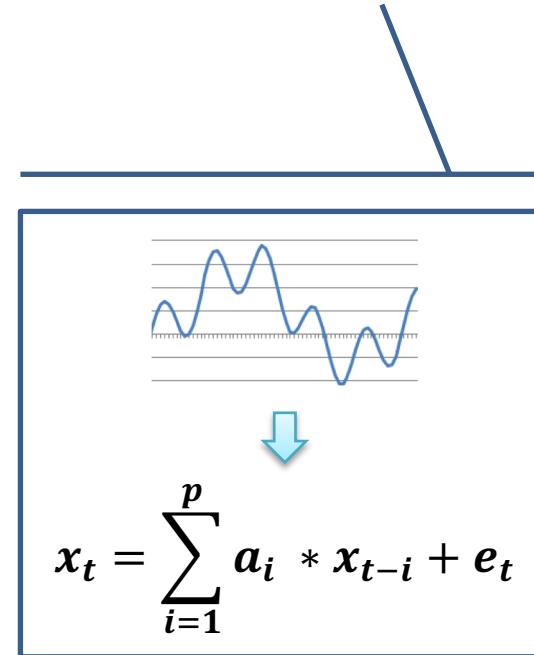
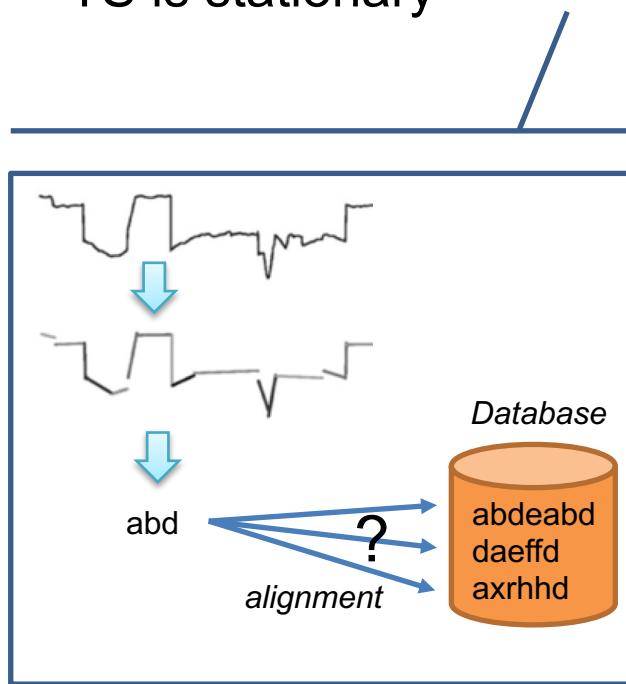
# Time series prediction

- Option for Nonstationary
  - Uses: *PLA*, label sequences, *alignment*
  - Usable, regardless whether TS is stationary



# Time series prediction

- Option for Nonstationary
  - Uses: *PLA*, label sequences, *alignment*
  - Usable, regardless whether TS is stationary
- Option for stationary
  - *Autoregressive models*
  - Parametrize (or train) models with raw TS

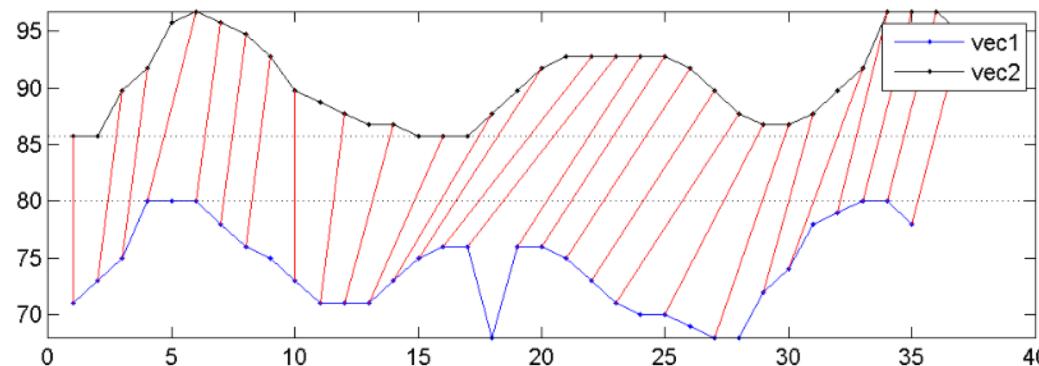


Segmentation, PLA, label sequences, and alignment

# TIME SERIES PREDICTION I

# Segment comparison

- What we have:
  - Segmentation algorithms and approximations
  - Distance measures to compare segments
    - E.g. euclidean distance
  - Techniques to compare segments with different length
    - E.g. Dynamic-Time-Warping

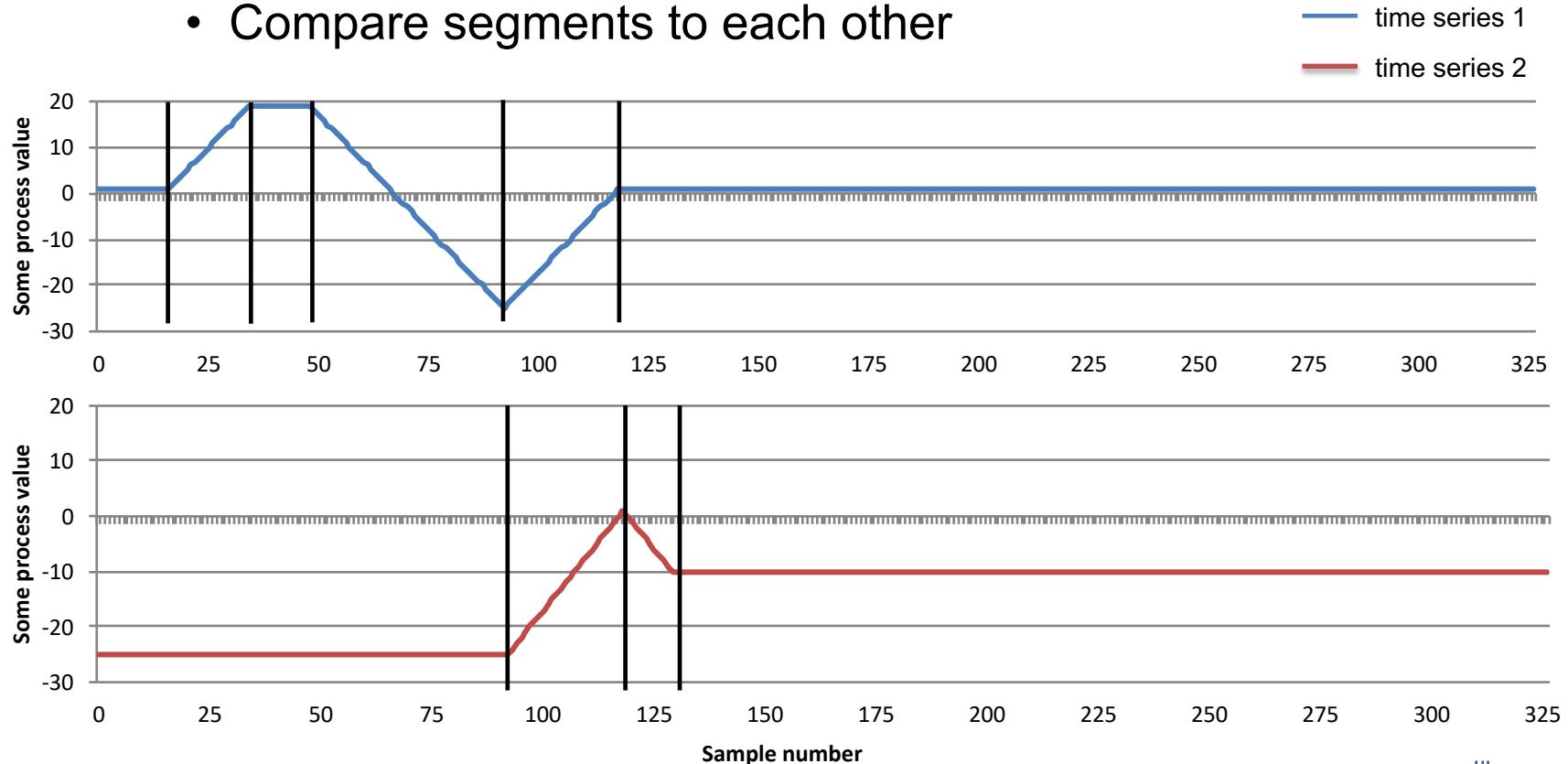


Example of aligning segments with unequal length

<http://mirlab.org/jang/books/dcpr/example/output/dtwBridgePlot02.png>

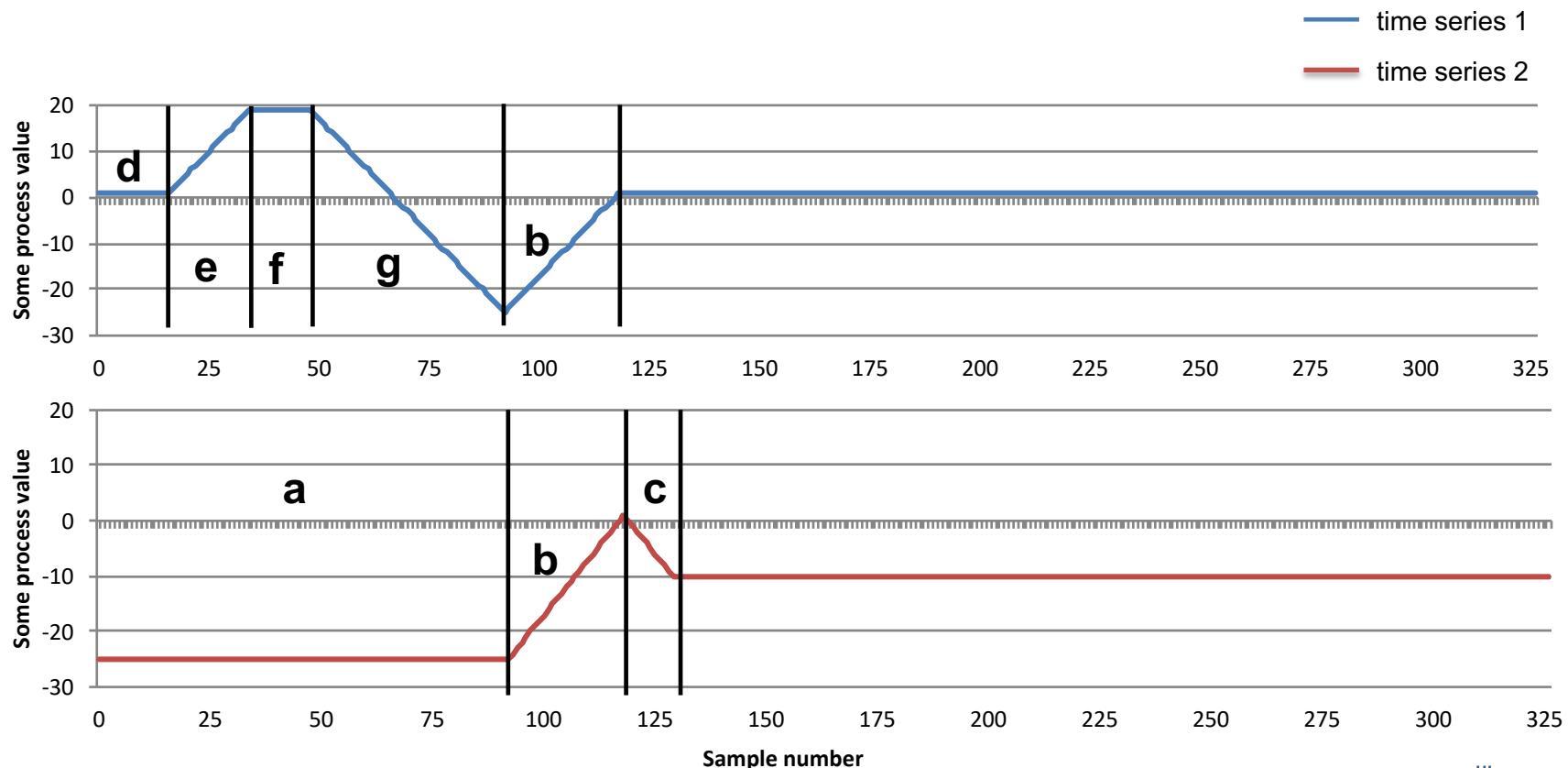
# Segment comparison

- What we need next:
  - A way to recognize and label segments
    - Compare segments to each other



# Segment comparison and labeling

- Similar segments get the same label



# Use alignment for prediction

- Now TSs are presented as a label sequence
  - Label sequence of time series 1 = “defgb”
  - Label sequence of time series 2 =“abc”
- This representation
  - enables several methods to go on (Markov, Rules)
  - Is input for ‘alignment’ [S07]

# Use alignment for prediction

- Need to identify the similarity of label sequences
  - Are two sequences similar?
  - Is a sequence similar to a part of another sequence?
  - If so, we can predict!
- Alignment algorithm supports this
  - Input: two label sequences
  - Tasks
    - align sequences to each other
    - calculate a distance (or cost) for the sequences
    - When sequences match, predict rest of the known sequence

Introduction to Autoregressive Models

# TIME SERIES PREDICTION II

# Forecast – Auto regressive models



- The auto regressive models (AR models)
  - “Regression”
    - A variable depends on others
    - Value of variable is regressed to others
  - “Auto”:
    - Regress values of series  $ts1$  from its own past (stationarity!)
  - “model”:
    - Mathematical description of a process
    - Approximates the process
    - Has parameters to optimize the approximation

# Forecast – Auto regressive models

ComTec

- Definition

*“An observation at time  $t$  is predictable from a weighted sum of the  $p$  previous observations (called an AR( $p$ ) process) [G10]”*

- The AR model order
  - AR(1) model: use weighted last observation
  - AR(2) model: use weighted sum of last two observations
  - AR(3) model: ...

# Forecast – Auto regressive models

- The first-order AR model (called AR(1))

$$x_t = a_1 * x_{t-1} + e_t$$

weight for last observation  
(*autocorrelation coefficient*)

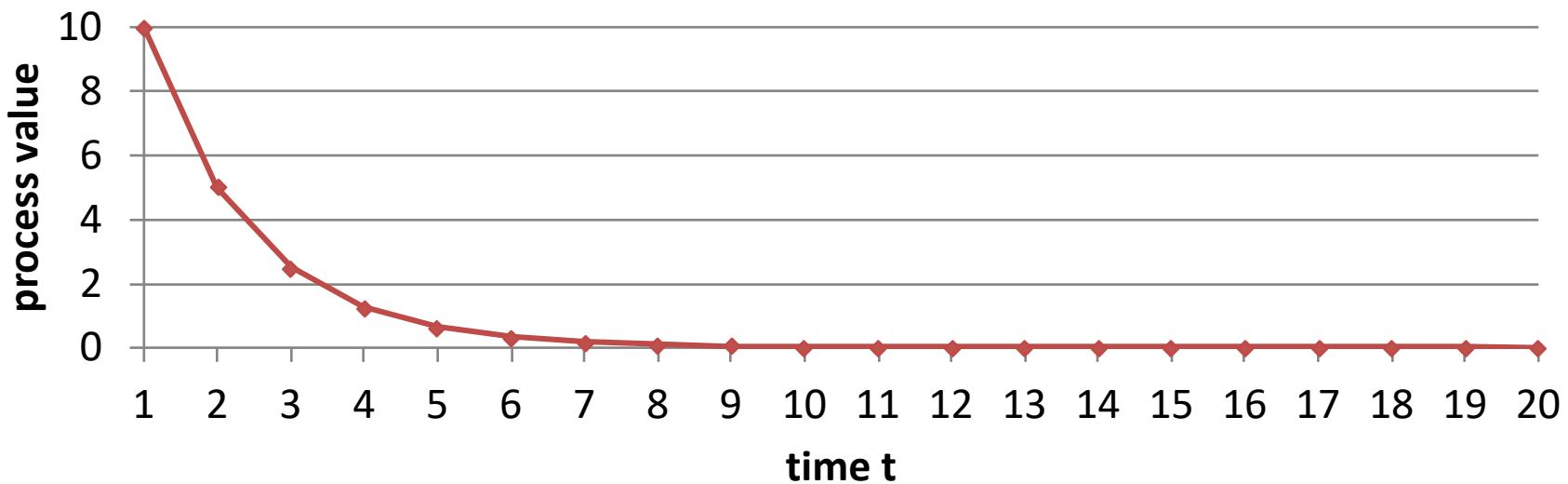
the last observation

the noise

# Forecast – Auto regressive models

- AR(1) model example. Observed  $x_0 = 10$ 
  - $a_1 = 0,5$
  - $e_t = 0$

$$x_t = 0,5 * x_{t-1} + e_t$$



# Forecast – Auto regressive models

- First-order AR(1) model

$$x_t = a_1 * x_{t-1} + e_t$$

- Second-order AR(2) model

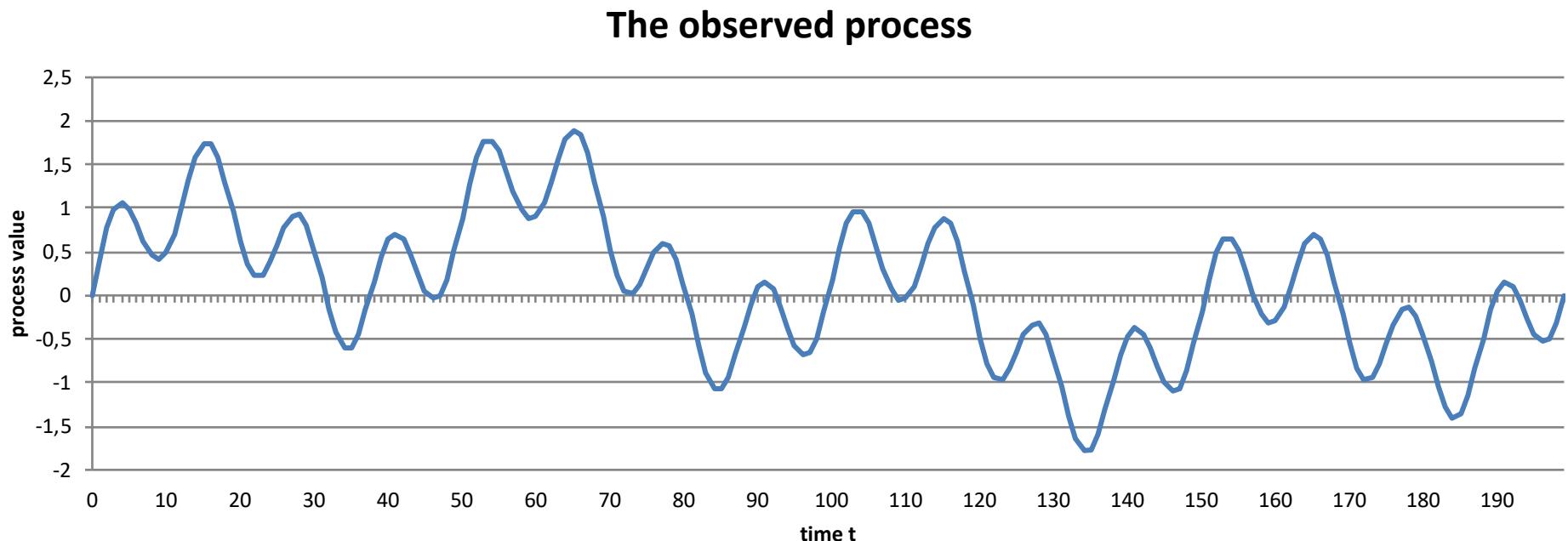
$$x_t = a_1 * x_{t-1} + a_2 * x_{t-2} + e_t$$

- General AR(p) model

$$x_t = \sum_{i=1}^p a_i * x_{t-i} + e_t$$

# Forecast – Auto regressive models

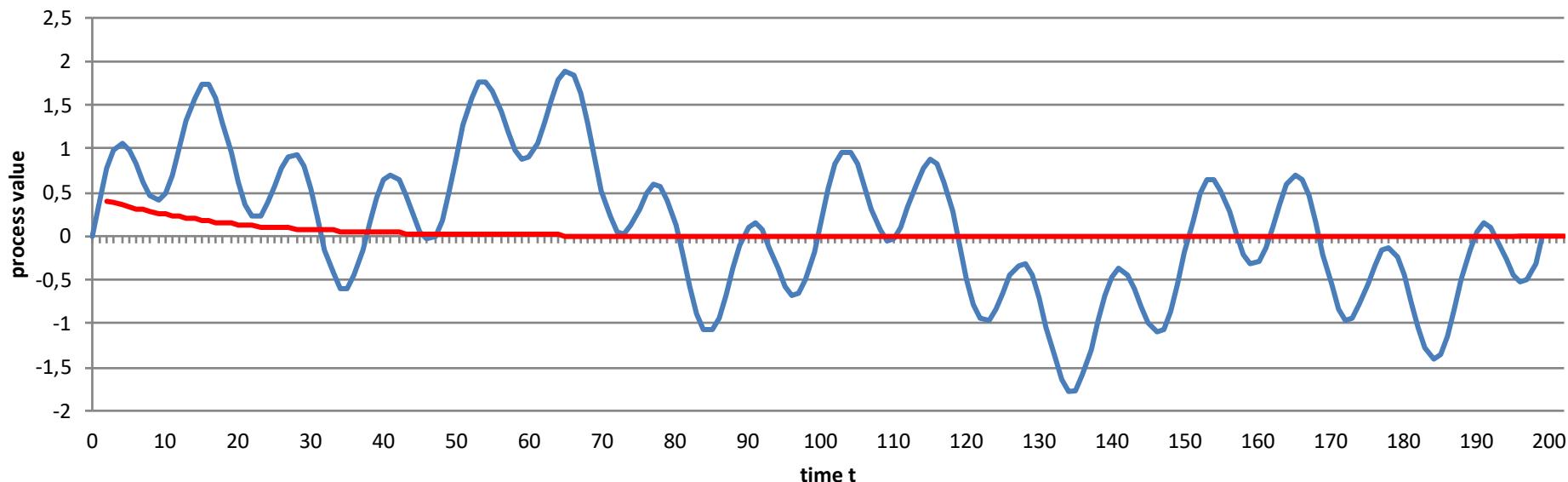
- Example process
  - first 200 Points of data available at [KBG04]



# Forecast – Auto regressive models

- Example process
  - first 200 Points of data available at [KBG04]

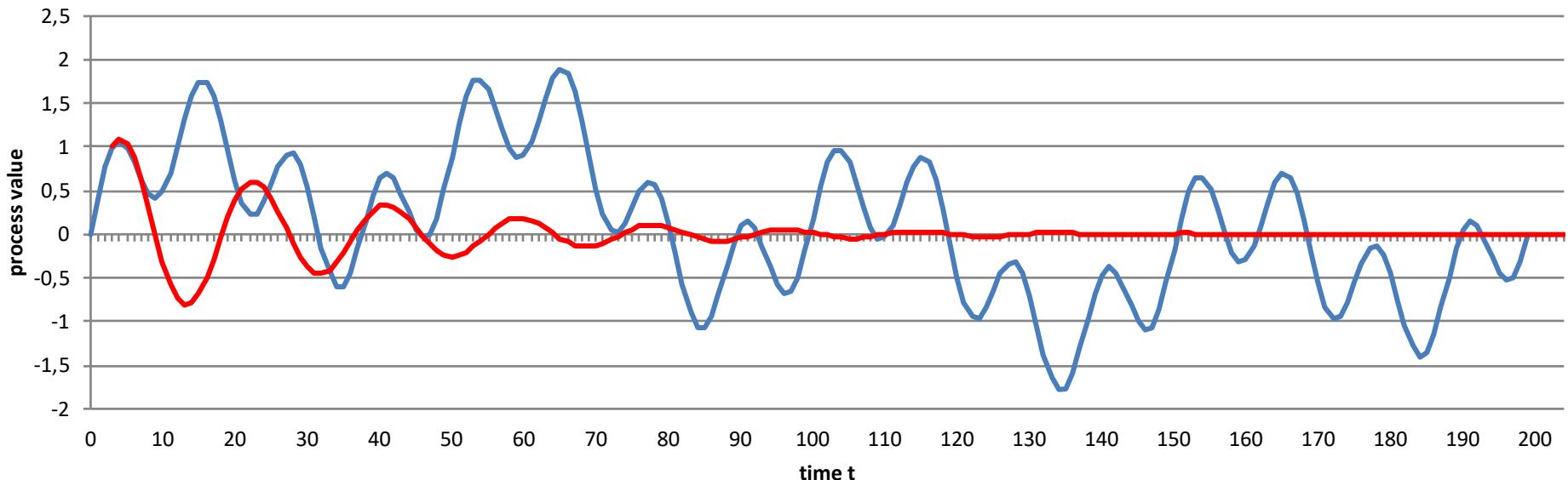
The observed process & AR(1) :  $a_1 = 0,94$



# Forecast – Auto regressive models

- Example process
  - first 200 Points of data available at [KBG04]

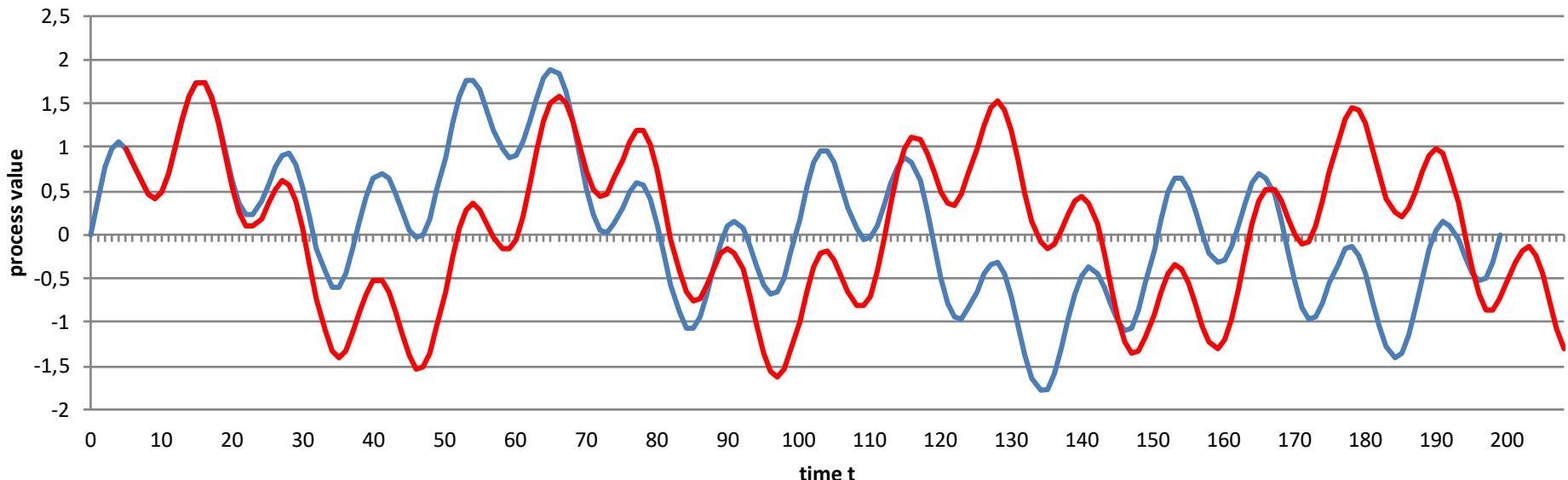
The observed process & AR(2) :  $a_1 = 1,82$ ;  $a_2 = -0,94$



# Forecast – Auto regressive models

- Example process
  - first 200 Points of data available at [KBG04]

The observed process & AR(4) :  $a_1 = 3,74$ ;  $a_2 = -5,47$ ;  $a_3 = 3,73$ ;  $a_4 = 0,998$



# Forecast – Auto regressive models



- To create an AR model
  - Choose order  $p$  of model
  - Use  $N$  observed past values to estimate  $p$  weights
- Example
  - Use data from [KBG04] ( $N = 1000$  points)
  - Choose order  $p = 1$
  - Calculate parameters of the AR(1) model

# Forecast – Auto regressive models

- Calculate  $a_1$  in AR(1) :  $x_t = a_1 * x_{t-1} + e_t$
- Therefore, use N observed points:

$$\begin{pmatrix} x_2 \\ x_3 \\ \dots \\ x_N \end{pmatrix} \approx \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_{N-1} \end{pmatrix} * a_1$$

# Forecast – Auto regressive models

- Calculate  $a_1$  in AR(1) :  $x_t = a_1 * x_{t-1} + e_t$
- Use *least squares method* [LSF] to get  $a_1$

$$\begin{pmatrix} x_2 \\ x_3 \\ \dots \\ x_N \end{pmatrix} \approx \underbrace{\begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_{N-1} \end{pmatrix}}_A * a_1$$

$$a_1 = (A^T A)^{-1} (A^T b)$$

# Forecast – Auto regressive models

- Simple for AR(1)

$$\begin{pmatrix} x_2 \\ x_3 \\ \dots \\ x_N \end{pmatrix} \approx \underbrace{\begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_{N-1} \end{pmatrix}}_A * a_1$$

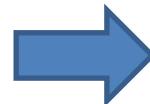
$$(A^T A)^{-1} (A^T b) = \dots = \frac{\sum_{i=1}^{n-1} x_i x_{i+1}}{\sum_{i=1}^{n-1} x_i^2} = a_1$$

# Forecast – Auto regressive models

- Simple for AR(1)

**Observed data  
about 1000 points**

0
0,423468
0,773358
0,994145
1,06138
0,987356
0,817725
0,619848
0,46583
0,414411
0,496197
1,59398
.....
.....



$$\frac{\sum_{i=1}^{1000-1} x_i x_{i+1}}{\sum_{i=1}^{1000-1} x_i^2} = a_1 = 0,94$$

# Forecast – Auto regressive models



- Least squares method (or *fitting*)
  - Expand matrix A for higher AR model order
  - Expand matrix A -> more complex calculations
- Yule-Walker equations [YW]
  - Suitable for general AR(p)
  - Out of scope of this lecture

Thanks for your attention

**END**

# References

- [IEEE] The IEEE Xplore Digital Library, last access 2016/10/27, <http://ieeexplore.ieee.org/Xplore/home.jsp>
- [ACM] The ACM Digital Library, last access 2016/10/27, <http://dl.acm.org>
- [OTS] Oxford dictionary. Definition of “time series”, last access 2016/10/27, [https://en.oxforddictionaries.com/definition/time\\_series](https://en.oxforddictionaries.com/definition/time_series)
- [AS] [Yahoo! Finances](#) – Apple stock, last access 2015/04/29
- [WC] [Wetter.com – Weather history / forecast Kassel](#), last access 2015/04/29

# References

- [AccW16] AccuWeather.com. Weather forecast for the 27<sup>th</sup> October 2016, last access 2016/10/25,  
<http://www.accuweather.com/de/de/kassel/34117/hourly-weather-forecast/168717?hour=57>
- [Noise] Oxford Dictionary, Definition of “noise”, last access 2016/04/19,  
<http://www.oxforddictionaries.com/definition/english/noise?q=noise>
- [TSC] Time Series Concepts, last access 2016/04/20,  
<http://faculty.washington.edu/ezivot/econ584/notes/timeSeriesConcepts.pdf>

# References

- [K01] Keogh E., Chu S., Hart D., Pazzani M. (2001). An Online Algorithm for Segmenting Time Series. *ICDM 2001*.
- [LMS14] M. Lovrić, M. Milanović, M. Stamenković, *Algorithmic Methods for Segmentation of Time Series: An Overview*, JCEBI, Vol.1 (2014) No.1, pp. 31 – 53.
- [S07] Sigg S. (2007). Development of a novel context prediction algorithm and analysis of context prediction schemes. *PhD in the ComTec department*.
- [G10] Gottman J. M. (2010). Time-Series Analysis. *Cambridge University Press*.

# References

- [KBG04] Bourke P., University of Western Australia. [AutoRegression Analyzis](#), last checked 2015/04/29
- [LSF] Wolfram Math World, Least Squares Fitting, last access 2016/04/19, <http://mathworld.wolfram.com/LeastSquaresFitting.html>
- [YW] G. Eshel, The Yule Walker Equations for the AR Coefficients, last access 2016/10/27, <http://www-stat.wharton.upenn.edu/~steele/Courses/956/Resource/YWSourceFiles/YW-Eshel.pdf>
- [GEN] GenTxWarper: Mining of gene expression time series with dynamic time warping techniques, last access 2016/10/27, <http://www.psb.ugent.be/cbd/papers/gentxwarper/index.htm>