Universiteit Leiden
The Netherlands

Urban Computing

Dr. Mitra Baratchi

7 September, 2020

Leiden Institute of Advanced Computer Science - Leiden University

Second Session: Urban Computing - Processing Time-series Data

Table of Contents

Preliminaries on time-series

Table of content

Why do we care about time-series data?

- Time-series data are ubiquitous ...
- What types of data do we have in form of time-series for urban computing research?
    - Temperature
    - Air pollutants
    - Number of people, cars passing a road
    - Price of houses
    - Sensor measurements
    - Number of infected people, deaths, ...

Peculiarities of time-series

Why analysis of time-series data is challenging? What qualities should algorithms for analysis of time-series data have?

Dimensionality?

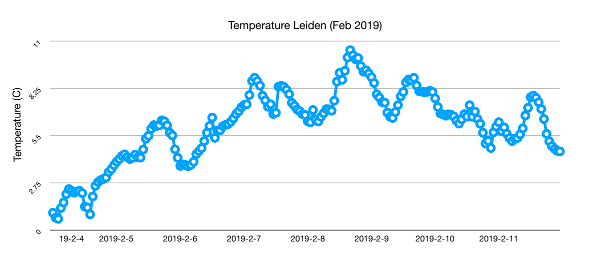


Figure 1: Temperature in Leiden during the month of February so far [1]

How many dimensions does the data have? Dimension is the number of attributes required to explain every instance of data Length over time defines the dimensions, → many (even infinite)

How would you use this data for predicting the temperature of the following days?

[1] data source: https://www.meteoblue.com

Non-stationarity

- **Non-stationarity:** Data points have means, variances and covariances that change over time

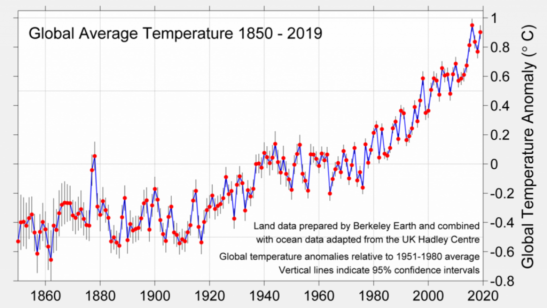


Figure 2: A non-stationary time-series [2]

[2] image source:http://berkeleyearth.org/2019-temperatures/

Peculiarities of time-series

- **High-dimensionality**: We hope to reduce dimensionality by finding a model $Temp_t = f(Temp_{(0 \ldots t-1)})$
- **Non-stationarity:** Data points have means, variances and covariances that change over time (related to concept drift)
- **Single versus multi-variate**: e.g., having time-series data of multiple different sensors
- **Distortions in time-series data**: Missing values, noises, etc. in real data create challenges for algorithms

What can we do with such data?

- Predict? (Better say forecast)
- Classify
- Find patterns, clusters, outliers
- Query

There are already algorithms available for these tasks suitable for non-time-series data. In order to use them we need to find a way to *represent* time-series data to them.

Table of content

Two approaches to deal with or represent data

How do we represent time-series data in order to process it?

- **Approach 1**: Take it as it is.
  - Represent it in the time domain.
  - Main issue: (Time-series data is high dimensional $\rightarrow$ very difficult to work with)
- **Approach 2**: Represent it in a format that is more understandable or easier to work with. **Time-series representation** techniques are designed to reduce the dimensionality of data as much as possible.
  - Frequency domain
  - Time-frequency domain
  - ...

Approach 2-example 1

Fourier transform

- What is Fourier transform?
- What does it do?
- Why is it useful (in math, in engineering, etc.)?
- How can it be useful in Urban Computing?

The basic elements:

Fourier theory shows that **all signals** (periodic and non-periodic) can be decomposed into a linear combination of sine waves defined based on their amplitude (A), period ($\frac{2\pi}{\omega}$), and phase (ϕ)

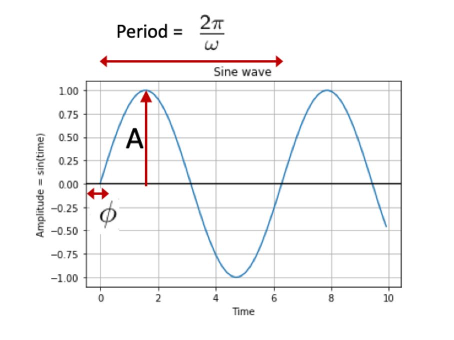


Figure 3: A sine wave, basic element of Fourier transform

Fourier transform in one image

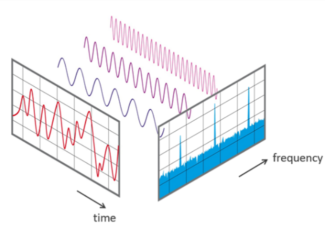


Figure 4: View of a signal in time and frequency domain[3]

[3] source: http://www.nti-audio.com/portals/0/pic/news/FFT-Time-Frequency-View-540.png

The main intuition:

If the frequency domain view is **sparse**, we can leverage the sparsity in different ways. (e.g., create new features for classification, compress the signal, ...)

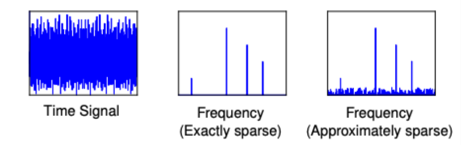


Figure 5: Different views of a signal and levels of sparsity. [4]

Question we should seek to answer before using a frequency domain transformation: **Does a transformation give us a sparser, thus, more understandable representation?**

[4] Source: https://groups.csail.mit.edu/netmit/sFFT/slidesEric.pdf

Why is it useful?

What is the intuition behind frequency?

- **Change, speed of change, repetitive patterns of change**: If change has a repetitive pattern we see it better in the frequency domain
- How can we use frequency analysis in urban computing?
  - Typically any phenomenon with a periodic pattern can be captured in the frequency domain
    - Periodicity in trajectory data (daily, weekly, seasonal, yearly patterns)
    - Activities with periodic patterns from accelerometer data (walking, running, biking)
    - Forecasting
    - Compressing data

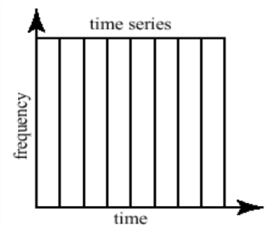
Approach 2-example 2

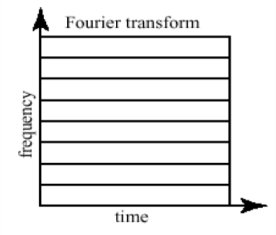
Wavelet transform

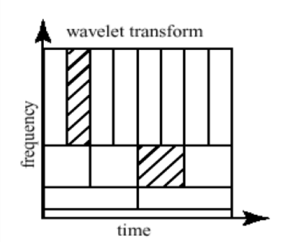
- Fourier analysis tells you **what** frequency components are strong in a signal, but not where in the signal (frequency view)
- Wavelet tells you **what** frequency components and also **where** they happen in a signal (time + frequency view)
- Useful for multi-resolution analysis

Time, Frequency, Frequency-time domains

[5]







- Lower frequency components take more time
- Higher frequency components take less time

[5] http://www.cerm.unifi.it/EUcourse2001/Guntherlecturenotes.pdf

Example case

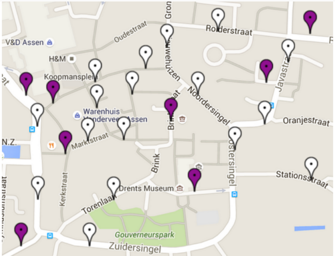


Figure 6: Assen sensor setup

We collected WiFi data from a city during TT festival.

- What would you do to see what happened in the city during the festival?
- How would you automate the process of detecting things that changed during the festival?

Multi-resolution analysis using Wavelets

Multiresolution analysis on visits of people to TT festival.

When and **how strongly** the number of visitors **changed**?

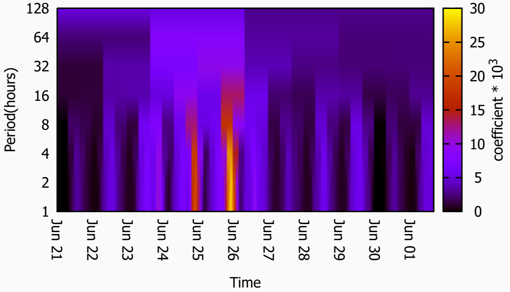


Figure 7: Multi-resolution view of crowd data[6]

[6] Andreea-Cristina Petre et al. "Chapter 14 - WiFi Tracking of Pedestrian Behavior". In: *Smart Sensors Networks*. Intelligent Data-Centric Systems. 2017, pp. 309–337. ISBN: 978-0-12-809859-2. DOI: https://doi.org/10.1016/B978-0-12-809859-2.00018-8. URL:

Example: Two approaches for dealing with the same problem

Let's see all an example

- How do you find important periods from one person's trajectory data?
  - **Method 1: Time domain analysis**
  - **Method 2: Frequency domain analysis**

Method 1: Autocorrelation function

- **Auto**-correlation function (correlation of data with **itself**)
- The value of the autocorrelation function in (τ) can be interpreted as the self-similarity score of a time-series when shifted (τ) timestamps

$$ACF_\tau = \frac{1}{T}\sum_{t=1}^{t=T-\tau(orT)} {}^{7}(x_t - \overline{x})(x_{t+\tau} - \overline{x}).,\tau = 0, 1, 2, ..., T\ ^{8}$$

[7] T is used in circular autocorrelation

[8] max value of τ can be smaller

Circular autocorrelation function

For implementing circular autocorrelation we use a shift operation from the end of time-series to its beginning

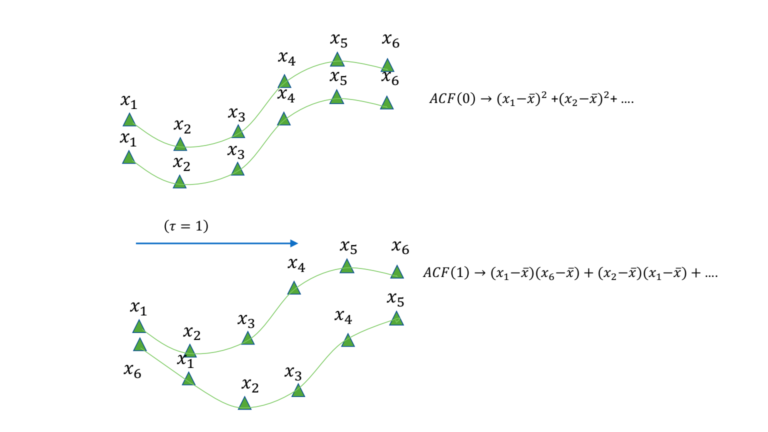


Figure 8: Calculating autocorrelation in different lags

Finding periodicity using autocorrelation function

Once ACF is visualized in a graph, the peaks on the autocorrelation graph can show the periods of repetitive behavior

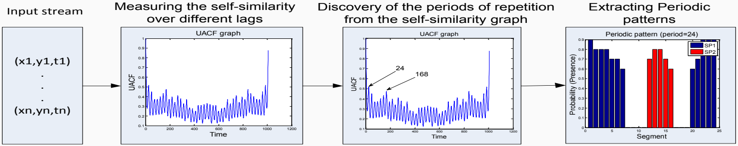


Figure 9: Finding periodic patterns using autocorrelation function[9]

[9] Mitra Baratchi, Nirvana Meratnia, and Paul J. M. Havinga. "Recognition of Periodic Behavioral Patterns from Streaming Mobility Data". In: *Mobile and Ubiquitous Systems: Computing, Networking, and Services*. Ed. by Ivan Stojmenovic, Zixue Cheng, and Song Guo. Cham: Springer International Publishing, 2014, pp. 102–115.

Method 2: Periodogram

- A periodogram is used to identify the dominant periods (or frequencies) of a time-series.
- After performing Fourier transform the sum of squared coefficients in each period is used to create the periodogram

Periodogram

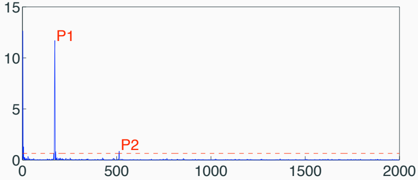


Figure 10: Periodogram[10]

[10] Zhenhui Li et al. "Mining periodic behaviors for moving objects". In: *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM. 2010, pp. 1099–1108.

Why do you need to know different methods?

Each method has its pros and cons (typically, they complement each other in some way)

- In practice, on real data both of them fail in someway
- Fourier transform often suffers from the low resolution problem in the low frequency region, hence it provides poor estimation of large periods. (this is referred to as the **spectral leakage** problem)
- False positives can appear in periodogram that are caused by noise
- Autocorrelation offers accurate estimation for both short and large periods. However, It is more difficult to set the significance threshold for finding important periods.

Many more different methods for representing time-series data in alternative domains[11]

- Discrete Cosine transform
- Discrete Fourier transform
- Discrete Wavelet transform
- Piece-wise linear approximation (PLA)
- Piecewise cloud approximation
- Symbolic approximation (SAX)
- Model based transformation (Average seasonal profile, Median seasonal profile)
- ...

[11] Xiaoyue Wang et al. "Experimental comparison of representation methods and distance measures for time series data". In: *Data Mining and Knowledge Discovery* 26.2 (Mar. 2013), pp. 275–309. ISSN: 1573-756X. DOI: 10.1007/s10618-012-0250-5. URL: https://doi.org/10.1007/s10618-012-0250-5.

What effects of time exist?

- Autocorrelation and periodogram both represent one aspect of time-series data (periodicity)
- Some effects we would like to capture in a representation based on the task we have in mind
    - **When** things happen?
    - **How long** do they last?
    - How do they **repeat**?
    - How do they **follow** each other?
    - When things start to **appear/disappear**?
    - When and how things **change**?

Techniques for processing time-series data

Classical forecasting using time-series

Problem:

Given $x_1, x_2, x_3, ...x_t$ forecast the value of $x_{t+1}, x_{t+2}...x_{t+n}$

Forecast horizon depending on the value n:

- Short-term
- Long-term

Autoregressive models

- Classical models widely used by statisticians
- The **auto**-regressive model specifies that the output variable depends linearly on its **own previous values** and on a stochastic term
- Assumption: Having a stationary process
  - Time-series is said to be strictly stationary if its properties are not affected by a change in the time origin. OR Joint probability distribution of $x_t, x_{t+1}, ..., x_{t+n}$ is equal to $x_{t+k}, x_{t+k+1}, ..., x_{t+k+n}$

Regression, Auto-regressive, Moving average

$\rightarrow$ c is constant, ϕ is model parameter, ϵ is white noise

- **Regression**
  - $Y_i = c + \phi X_i + \epsilon_i$
- **Auto-regressive**
  - $X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t$
- **Moving average**
  - $X_t = c + \sum_{i=1}^{q} \phi_i \epsilon_{t-i}$
  - Literally moving average, (i.e.) average value of previous values of the time-series
- **Auto-Regressive Moving Average (ARMA)**
  - $X_t = c + \sum_{i=1}^{q} \phi_i \epsilon_{t-i} + \sum_{i=1}^{p} \phi_i X_{t-i}$

Typical patterns in time-series that should be considered

How far can you go ahead in time:

- Seasonality (Periodicity)
- Trends

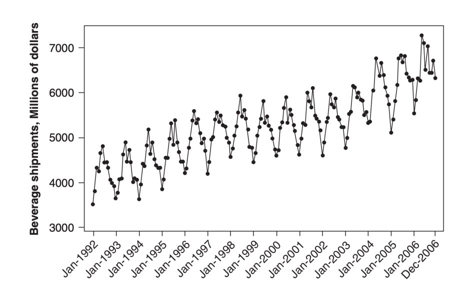


Figure 11: Time-series with trend and periodicity[12]

[12] George EP Box et al. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

Some other examples of time-series forecasting models[13]

- Autoregressive integrated moving average (ARIMA)
- Seasonal ARIMA (SARIMA)
- Fractional ARIMA (FARIMA)

[13] Douglas C Montgomery, Cheryl L Jennings, and Murat Kulahci. *Introduction to time series analysis and forecasting*. John Wiley & Sons, 2015.

Forecasting using frequency domain representation

- Transform the signal to the frequency domain (e.g. using Fourier transform)
- Remove insignificant high-frequency components
- Forecast for each remaining component
- Transform the signal back to the time domain

Table of content

Time-series classification

Problem: Assign class labels to $x_i \ldots x_{i+n}$

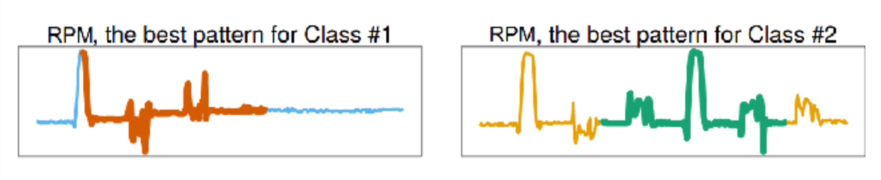


Figure 12: Classification of time-series data[14]

[14] Daoyuan Li et al. "Dsco-ng: A practical language modeling approach for time series classification". In: *International Symposium on Intelligent Data Analysis*. Springer. 2016, pp. 1–13.

Time-series classification

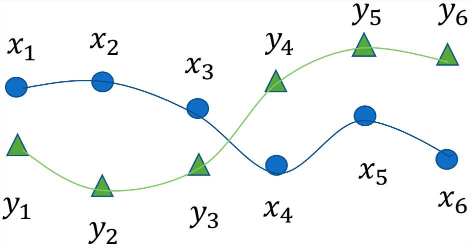
One approach in time-series classification:

- Represent time-series in a suitable domain
- Select a similarity measure
- Classification method (K-nearest neighbor is very popular)

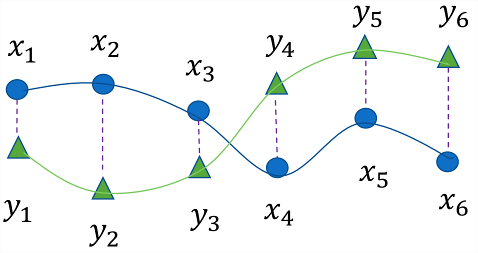
Representation and similarity measure go hand-in-hand and should be matched!

Similarity measure

How to measure similarity of two time-series to each other?

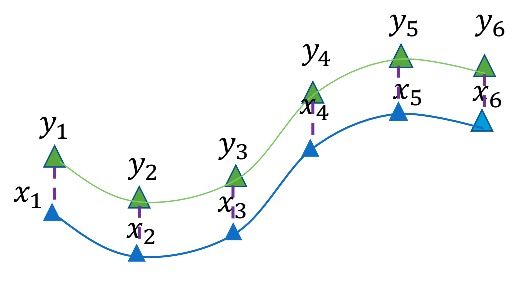


Euclidean distance



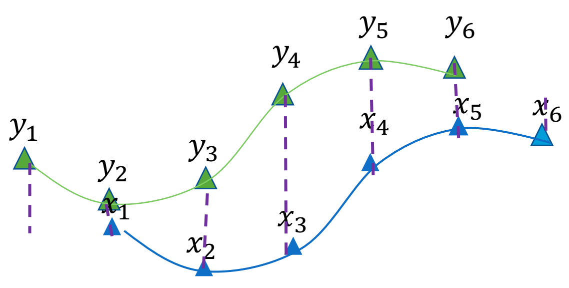
Euclidean distance

Very similar time-series



Euclidean distance

Very similar time-series (?)



What do we miss?

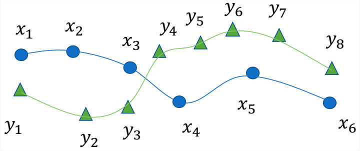
Euclidean distance:

- Sensitive to shifting, time or amplitude scaling

Dynamic time warping (DTW)

- DTW-algorithm is able to compare two curves in a way that makes sense to human. It maintains the importance of spots in curves that are important for humans when comparing curves.
- Elastic similarity measure
- The most used measure of similarity between time-series
- Works by finding the optimal **alignment** between two time-series
- Based on pair-wise distance matrix of time-series

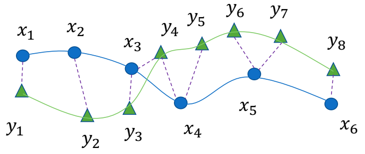
DTW[15]



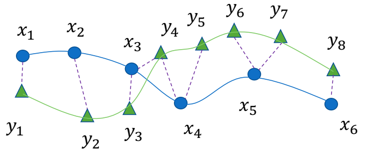
[15]Marco Cuturi and Mathieu Blondel. "Soft-DTW: a differentiable loss function for time-series". In: *arXiv preprint arXiv:1703.01541* (2017).

DTW

Intuition: finding the best matching pair of points on two time-series



DTW



	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8
x_1	1	0	0	0	0	0	0	0
x_2	0	1	0	0	0	0	0	0
x_3	0	0	1	1	0	0	0	0
x_4	0	0	0	1	1	0	0	0
x_5	0	0	0	0	0	1	1	0
x_6	0	0	0	0	0	0	0	1

The goal of DTW is finding the best alignment path

Pair-wise distance matrix

- The matrix can be initialized from data, through recursion we find the optimal alignment
- $\Delta_{(i,j)}$ is $|x_i - y_j|$

$\Delta_{(1,1)}$	$\Delta_{(1,2)}$	$\Delta_{(1,3)}$	$\Delta_{(1,4)}$	$\Delta_{(1,5)}$	$\Delta_{(1,6)}$	$\Delta_{(1,7)}$	$\Delta_{(1,8)}$
$\Delta_{(2,1)}$	$\Delta_{(2,2)}$	$\Delta_{(2,3)}$	$\Delta_{(2,4)}$	$\Delta_{(2,5)}$	$\Delta_{(2,6)}$	$\Delta_{(2,7)}$	$\Delta_{(2,8)}$
$\Delta_{(3,1)}$	$\Delta_{(3,2)}$	$\Delta_{(3,3)}$	$\Delta_{(3,4)}$	$\Delta_{(3,5)}$	$\Delta_{(3,6)}$	$\Delta_{(3,7)}$	$\Delta_{(3,8)}$
$\Delta_{(4,1)}$	$\Delta_{(4,2)}$	$\Delta_{(4,3)}$	$\Delta_{(4,4)}$	$\Delta_{(4,5)}$	$\Delta_{(4,6)}$	$\Delta_{(4,7)}$	$\Delta_{(4,8)}$
$\Delta_{(5,1)}$	$\Delta_{(5,2)}$	$\Delta_{(5,3)}$	$\Delta_{(5,4)}$	$\Delta_{(5,5)}$	$\Delta_{(5,6)}$	$\Delta_{(5,7)}$	$\Delta_{(5,8)}$
$\Delta_{(6,1)}$	$\Delta_{(6,2)}$	$\Delta_{(6,3)}$	$\Delta_{(6,4)}$	$\Delta_{(6,5)}$	$\Delta_{(6,6)}$	$\Delta_{(6,7)}$	$\Delta_{(6,8)}$

$$dtw(i,j) =$$
$$\Delta_{i,j} + min(dtw(i-1,j-1), dtw(i-1,j), dtw(i,j-1))$$

A recursive process

Finding the best alignment path is achieved through recursion using the pairwise distance matrix

$dtw(i, j) =$
$\Delta_{i,j} + min(dtw(i-1, j-1), dtw(i-1, j), dtw(i, j-1))$

Other similarity measures

- Least Common Subsequence (LCSS)
- Edit Distance on Real sequence (EDR)
- ...

Lessons learned

Lessons learned

- Peculiarities of time-series data creates extra challenges in designing algorithms for analysis of data (high-dimensionality, non-stationary nature, noise, missing data)
- Extra effort is needed to use available algorithms on time-series data
    - **Representing time-series data**: time, frequency, time-frequency, symbolic, ...
        - A similar problem (extraction of periodic patterns) can be addressed by two approaches, both might have difficulties on real data
    - **Forecasting tasks:** creating auto-regressive, moving average models
    - **Classification tasks:** defining robust similarity measures combined with a representation

Assignment

- Put into practice some of the techniques learned today
- Develop methods for finding periodicity of trajectories and apply it on simulated data as well as real Geolife data