Urban Computing

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Second Session: Urban Computing - Processing Time-series Data

Agenda for this session

- Part 1: Preliminaries on time-series data
  - What does time-series data look like?
  - How do we represent time-series data?
- Part 2: Techniques for processing time-series data
  - Forecasting
  - Classification
- Part 3: Assignment

Part 1: Preliminaries on time-series data

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
- Humidity
- Number of people, cars passing a road
- Price of houses
- Sensor measurements

How does this data look like?

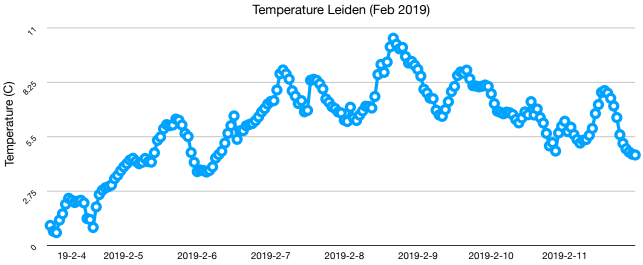

Figure: Temperature in Leiden during the month of February so far [1]

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

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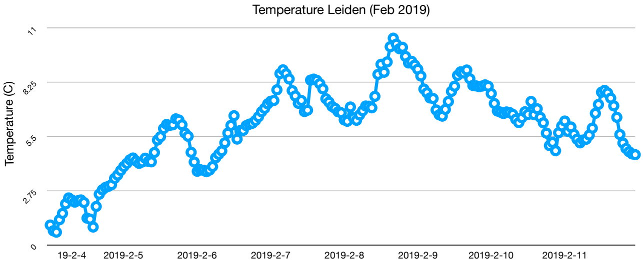

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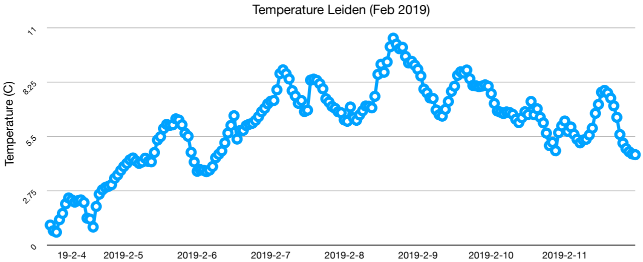

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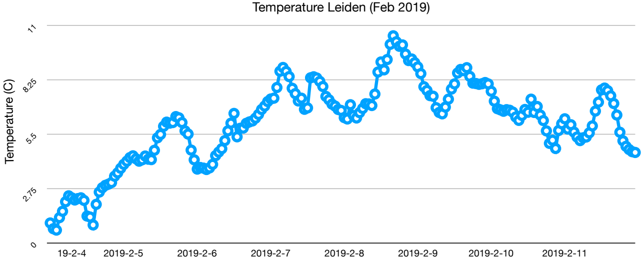

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How many dimensions the data have? Length over time defines the dimensions, $\rightarrow$ many (even infinite)

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

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

Time-series versus signal

- By nature all the data we get is discrete. We can make it continuous by interpolation.
- Time series data is a signal variation over time...

Who has so far developed methods, algorithms for working with such data?

- Signal processing experts
- Statisticians

What can we do with such data?

- Predict?

What can we do with such data?

- Predict? (Better say forecast)

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- Classify
- Find patterns, clusters, outliers
- Query

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.

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- **Approach 1**: Take it as it is.
  - Time domain.
  - Main issue (Time-series data is high dimensional very difficult to work with)

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- **Approach 2**: Represent it into a format that is more understandable or easier to work with. Representation techniques are designed to reduce dimensionality as much as possible.

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  - 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?

What is Fourier transform?

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)

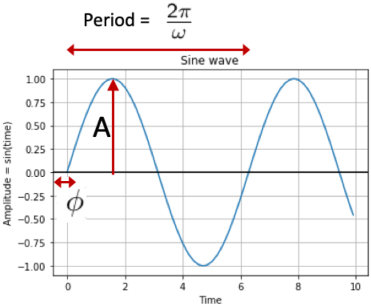


Figure: A sine wave, basic element of Fourier transform

$$Asin(\omega t + \phi)$$

Fourier transform in one image

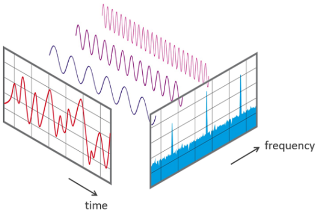


Figure: View of a signal in time and frequency domain[2]

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

Why is it useful?

The main intuition:

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

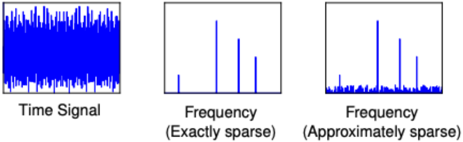


Figure: Different views of a signal and levels of sparsity. [3]

Question we should seek to answer before using a frequency domain transformation:

Does a transformation give us a sparser, thus, more understandable representation?

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

Why is it useful?

Intuition behind frequency

- **Change, speed of change**: If change has a repetitive pattern we see it better in the frequency domain
- Change in different contexts?
  - Image: Edges
  - Sound: Removing noise
  - Urban computing related data: Typically in understanding any phenomenon with a periodic pattern:
    - Periodicity from trajectory data (daily, weekly, seasonal, yearly patterns)
    - Detecting activities with periodic patterns from accelerometer data (walking, running, biking)
    - Forecasting
    - Compressing data

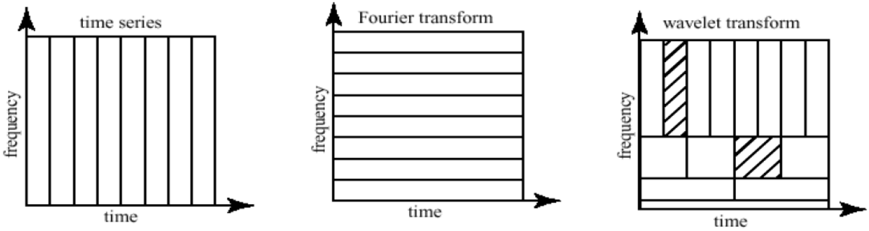
Approach 2-example 2

Wavelet transform

- Fourier tells you **what** frequency component are strong in a signal
- Wavelet tells you **what** frequency components and also **where** it happens (Time +frequency view) in a signal
- Useful for multi-resolution analysis

Time, Frequency, Frequency-time domains

[4]



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

[4] http://www.cerm.unifi.it/EUcourse2001/Gunther_lecturenotes.pdf

Example case

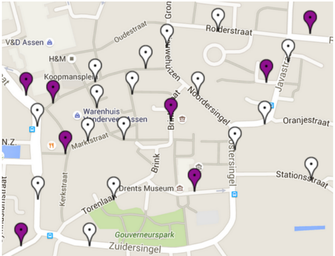


Figure: Assen sensor setup

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**?

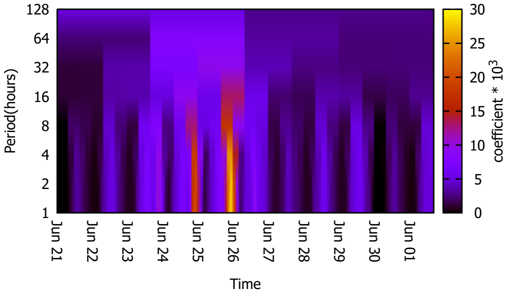


Figure: [PCB+17]

Example: Two approaches for dealing with the same problem

How do you find important periods from one person's trajectory data?

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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

$$ACF_{\tau} = \frac{1}{T}\sum_{t=1}^{t=T("orT-\tau")}(Y_t)(Y_{t+\tau}).,\tau = 0, 1, 2, ..., T$$

Circular autocorrelation function

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

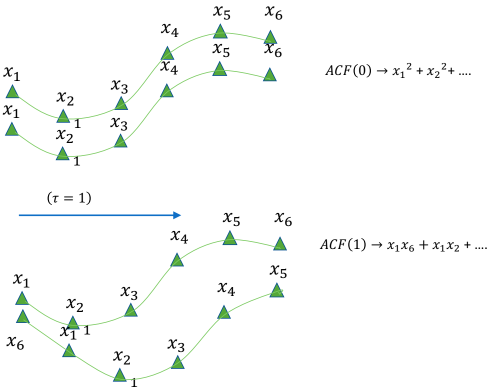


Figure: Calculating autocorrelation in different lags

Finding periodicity using autocorrelation function

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

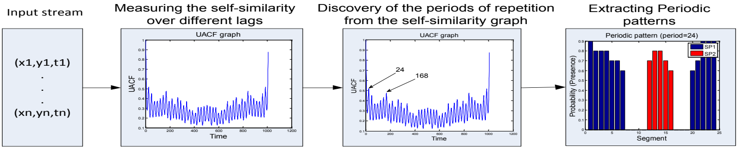


Figure: Finding periodic patterns using autocorrelation function [BMH14]

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 coefficinets in each period is used to create the periodogram

Periodogram

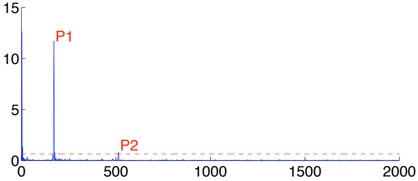


Figure: Periodogram

[LDH+10]

Why 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 important periods.

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

[WMD$^+$13]

- Discrete Cosine transform
- Discrete Fourier transform
- Discrete Wavelet transform
- Piecewise aggregate approximation
- Piecewise cloud approximation
- ...

What effects of time exist?

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 things **change**?

Part 2: Techniques for processing time-series data

Classical forecasting using time-series

Problem:

Given $y_1, y_2, y_3, ...y_t$ forecast the value of $y_{t+1}, y_{t+2}...y_{t+n}$

Forecast horizon depending on the value n:

- Short-term
- Medium-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 (an imperfectly predictable 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 probablity distribution of $Y_t, Y_{t+1}, ..., Y_{t+n}$ is equal to $Y_{t+k}, Y_{t+k+1}, ..., Y_{t+k+n}$
  - In a more strict sense, a stationary time series exhibits similar statistical behavior in time and this is often characterized as a constant probability distribution in time

Regression, Auto-regressive, Moving average

- **Regression**
  - $Y_i = c + \phi X_i + \epsilon_i$
- **Autoregressive**
  - $X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t$
- **Moving average**
  - $X_t = c + \sum_{i=1}^{q} \phi_i \epsilon_{t-i}$
  - It is not regression, literally moving average, (i.e.) average value of previous values of the time-series
- **Auto-Regressive Moving Average (ARMA)**
  - $X_t = c + \sum_{i=1}^{q} \phi_i \epsilon_{t-i} + \sum_{i=1}^{p} \phi_i X_{t-i}$

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

Typical patterns in time-series that should be considered

How far can you go ahead in time:

- Seasonality
- Periodicity
- Trends

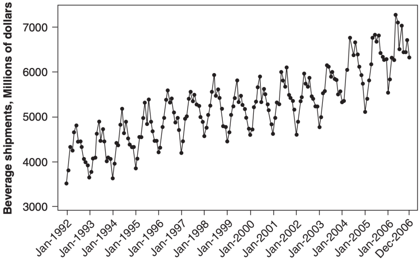


Figure: Time series with trend and periodicity [BJRL15]

Some other examples of time-series forecasting models [MJK15]

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

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

Time series classification

Problem: Assign class labels to $X_i....X_{i+n}$

Figure: Classification of timeseries data [LBKLT16]

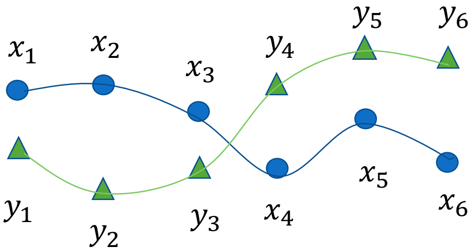
Time-series classification

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

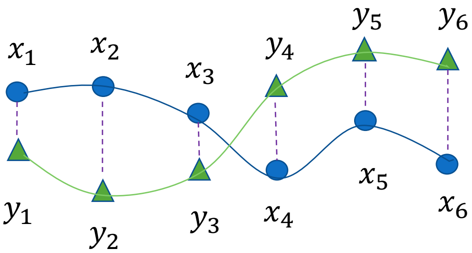
Representation and similarity measure go hand-in-hand and should be matched!

Similarity measure

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

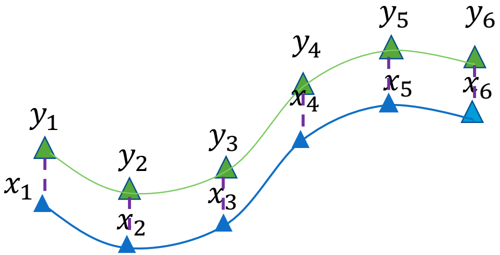


Euclidean distance



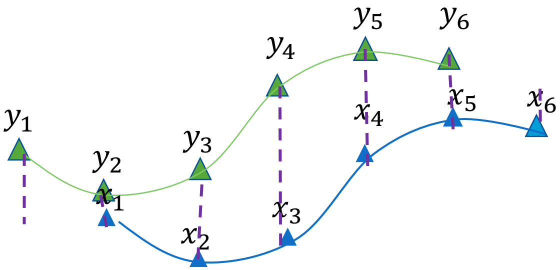
Euclidean distance

Very similar time-series



Euclidean distance

Very similar time-series (?)



What do we miss?

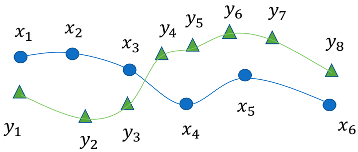
Euclidean distance:

- Sensitive to shifting, time or amplitude scaling

Dynamic time warping (DTW)

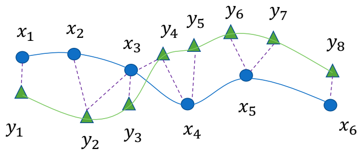
- DTW-algorithm is able to compare two curves in a way that makes sense to human. It maintains the importance of spots in curves that are important for humans when comparing curves.
- Elastic similarity measure
- The most used measure of similarity between time-series
- Works by finding the optimal alignment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

DTW [CB17]

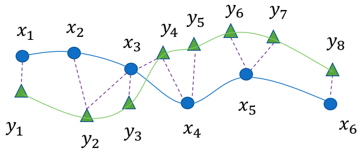


DTW

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	0	1	0	0	0
x_5	0	0	0	0	0	1	1	0
x_6	0	0	0	0	0	0	0	1

Finding the best alignment path

Pair-wise Distance matrix

$\Delta_{(i,j)}$ 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 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)
- ...

End of theory!

Part 3: Assignment

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