Urban Computing

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Fourth Session: Urban Computing - Processing spatio–temporal data

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Preliminaries

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Examples

Real-world processes being studied in many domains are inherently spatio-temporal in nature including:

- Climate science
- Neuroscience
- Social sciences
- Transportation
- Earth sciences

Example

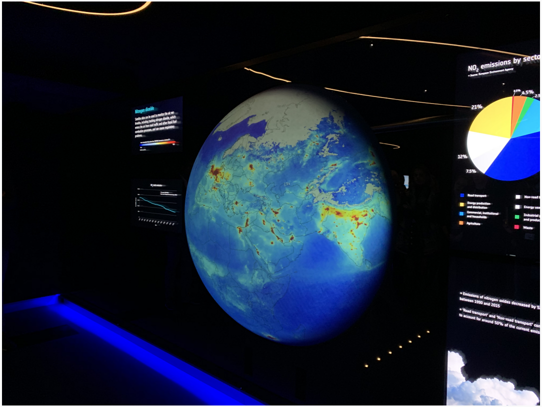

Figure 1: Example spatio-temporal data, NO2 emissions

Essence of spatio-temporal data

- **Temporal and spatial auto-correlation:** Nearby values in space and time tend to be alike
- **Spatial heterogeneity:** as we move away from a central point similarities decrease
- **Temporal non-stationarity:** as time passes similarities decrease
- **Multiple-scale patterns:** Daily (temporal scale 1) and seasonal (temporal scale 2) patterns within a patch of land (spatial scale 1) within a landscape (spatial scale 2)

What are spatio-temporal datasets?

- Spatio-temporal databases are an extension of spatial databases
- A spatio-temporal database embodies spatial, temporal, and spatio-temporal database concepts:
  - Geometry changing over time
  - Location of objects moving over invariant geometry

Spatio-temporal phenomena

1. **Spatio-temporal processes:** variables which are dependent on space and time $\leftarrow$
    - Weather
    - Population
2. **Moving object:** an object moving over space
    - People's trajectories
    - Cars' trajectories

How can we deal with spatio-temporal data?

- How did we deal with spatial data?
- Can we extend those methods to spatio-temporal data?

Spatio-temporal processes

Correspondence of spatial and spatio-temporal processes:

Spatial	Spatio-temporal
Geo-statistical	Spatio-temporal point referenced
Spatial point	Spatio-temporal event
Lattice	Spatio-temporal raster

Spatio-temporal processes

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Spatial	**Spatio-temporal**
Geo-statistical	**Spatio-temporal point referenced**
Spatial point	Spatio-temporal event
Lattice	Spatio-temporal raster

Spatio-temporal point reference data

- Measurements of a continuous spatio-temporal field over a set of fixed reference points in space and time
    - Meteorological variables
    - Temperature
    - Humidity

Spatio-temporal processes

Correspondence of spatial and spatio-temporal processes:

Spatial	**Spatio-temporal**
Geo-statistical	Spatio-temporal point referenced
Spatial point	**Spatio-temporal event**
Lattice	Spatio-temporal raster

Spatio-temporal event processes

- Random points in space and time denoting where and when the event occurred
  - Crime event
  - Road accidents

Spatio-temporal processes

Correspondence of spatial and spatio-temporal processes:

Spatial	**Spatio-temporal**
Geo-statistical	Spatio-temporal point referenced
Spatial point	Spatio-temporal event
Lattice	**Spatio-temporal raster**

Spatio-temporal raster processes

- Aggregated values over discrete regions of space and periods of time
  - Demographic information
  - Population increase in a city over a year

Spatio-temporal phenomena

1. **Spatio-temporal processes:** variables which are dependent on space and time
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Moving objects

- **Trajectories:** Multi-dimensional sequences containing a temporally ordered list of locations visited by the moving object
- What can we do by analysis of trajectory data?
  - **Studying moving objects:** Can we cluster a collection of trajectories into a small set of representative groups?
  - **Studying locations:** Are there frequent sequences of locations within the trajectories that are traversed by multiple moving bodies?

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Data types (processes) and data instances

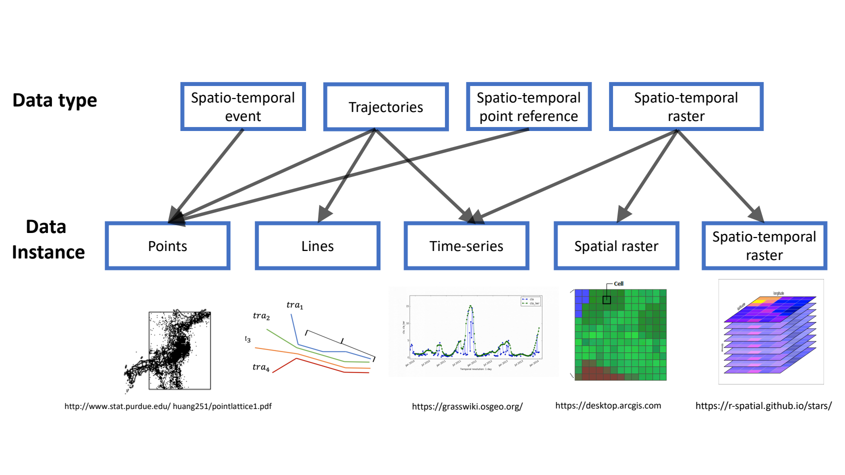

Figure 2: Spatio-temporal data instances and data types that can be used to represent them to algorithms as data instances

Methods for processing spatio-temporal data

Spatio-temporal statistics

Many statistical methods designed for spatial data can be extended to the spatio-temporal data:

- Spatio-temporal auto-correlation
- Space-time forecasting (auto-regressive models)
- Spatio-temporal kriging (interpolation)
- Spatio-temporal k-function (e.g., k-nearest neighbors)
- ...

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1. Preliminaries
   - What is spatio-temporal data?
   - How do we represent spatio-temporal data?
2. Methods for processing spatio-temporal data
   - Auto-regressive models for spatio-temporal data
3. Methods for processing moving object data (spatio-temporal trajectories)
   - Trajectory pre-processing
   - Trajectory pattern mining (next session)

Auto-regressive models for spatio-temporal data

Y_n , Y_t are vectors of dependent variables of size n. ϕ, λ, ρ are model parameters. c is a constant. ϵ represents the noise term. W_n is the spatial weights matrix

- **Auto-regressive**
  - $x_t = c + \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t$
- **Spatial Auto-Regressive model (SAR)**
  - $y_n = c + \lambda \sum_{m \neq n} w_{n,m} y_m + \epsilon_n,$
  - $w_{n,m} y_n$ is referred to as the spatial lag term in the models
  - How we use W determines global and local effect
- **Space-Time Autoregressive model (STAR)**
  - $y_{n,t} = c + \sum_{m \neq n} \sum_{\tau=1}^{p} \phi_\tau w_{n,m,\tau} y_{m,t-\tau} + \epsilon_{n,t}$

Exercise: try to derive the equivalent if a spatio-temporal moving average model

Methods for processing moving object data (spatio-temporal trajectories)

How does trajectory data look like?

Time

location

Mobile Entity ID, something else

Id	Timestamp	Location-long	Location-lat
2635	1997-07-24 20:50:00	− 149.007	63.809
2635	1997-07-24 21:23:35	− 148.897	63.766
2635	1997-07-27 22:30:23	− 148.967	63.824
2635	1997-07-31 02:52:48	− 149.026	63.803
2635	1997-08-03 01:47:04	− 149.046	63.795

GPS

	Scannerid	Time	DeviceAddress
2	1324	[illegible]	[illegible]
3	1324	1435505646	724290cde6af4645
4	1306	1435492293	6f1cf35f0bae2726
5	1293	1435513780	0c6185a840a4ee04
6	1293	1435513780	1eae7d8fde8dc50a
7	1297	1434550416	58884273fc450e86
8	1297	1434550412	6404531599f094e9
9	1297	1434550418	6e05f4edfdf08391
10	1297	1434550419	a04138e1aff48b03
11	1297	1434559015	6ea0d773c851ed56
12	1297	1434550018	58884273fc450e86

WiFi scans

Trajectory data, moving object data

- **Lagrangian motion data:** Allows collecting data of the movement of one entity globally
  - GPS
- **Eulerian motion data:** Allows collecting data of movement of many entities in restricted spaces
  - Wifi scanning
  - RFID
  - Video surveillance

What are different ways we can look at trajectory data?

We can query a trajectory dataset in different ways. Thus, we can study the data in different ways.

Query type	**Location**	**Entity**	**time**
1	**Fixed**	**Fixed**	Variable
2	**Fixed**	Variable	Variable
3	Variable	**Fixed**	Variable
4	Variable	Variable	Variable

Table 1: Different ways of looking at trajectory data

Patterns to extract from moving object data

Each type of query allows extracting a different type of pattern:

- **Individual**
    - Frequent
    - Periodic
    - Outliers
- **Social**
    - Flock
    - Leadership
    - Convergence
    - Encounter
- **Spatial**
    - Spatial interactions
    - Spatial functions

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Pre-processing trajectory data

- **In which ways** can we pre-process trajectory data?
  - Reduce the size of data → **Trajectory compression**
  - Remove noise → **Trajectory filtering**
  - Create workable instances → **Trajectory segmentation**

Trajectory compression

- **Goal:** reducing the dimensionality of the trajectory
- **Task:** Reducing the size of trajectory while preserving the precision
- **Good for:**
  - Efficiency (**computationally**) in pattern mining
  - Efficiency (**energy consumption**) in data collection procedure: the location of an object can be reported to the server when the precision reduces according to an error threshold.
  - Efficiency (**storage**)
- **Essence:** finding appropriate techniques and error measures for use in algorithms and performance evaluation.

Techniques for trajectory compression

- Uniform sampling
- Douglas-Peuker $\leftarrow$
- TD-TR
- Window-based algorithms (sliding window, open window, etc.)
- ...

Douglas-Peuker, Also known as Ramer-Douglas-Peucker

- Widely used in cartography and computer graphics
- Tries to estimate the original trajectory with one that has smaller number of points
- Iterative end-point fit algorithm
  - **Recursively** divides the line and approximates based on an error threshold
  - The **optimization** problem is formulated such that it minimizes the "area" between the original function and the approximate line segments
- Douglas-Peuker does not necessarily find a globally optimal solution

Douglas-Peuker approach

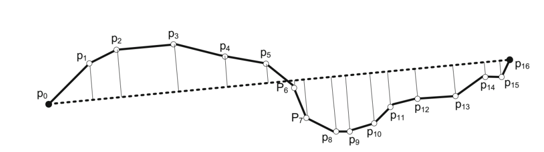


Figure 3: Step 1

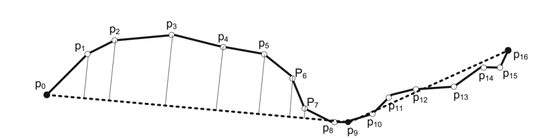


Figure 4: Step 2

Trajectory compression

Error metrics used for implementing trajectory compression:

- **Euclidean distance:** perpendicular distance between a point and a line
  - Only takes into account the geometric aspect of the trajectory representation without considering the temporal characteristics
- **Time synchronized euclidean distance:** Is a **time-distance** ratio metric
  - $SED(A, B, C) = \sqrt{(x'_B - x_B)^2 + (y'_B - y_B)^2}$
  - where $x'_B = x_A + \frac{x_c - x_A}{t_c - t_A}(t_B - t_A)$ and $y'_B = y_A + \frac{y_c - y_A}{t_c - t_A}(t_B - t_A)$

Trajectory compression: Mode of operation

- **Batch:**
  - Leads to high quality approximation due to access to full trajectories
  - It is not practical in many applications
- **Online:**
  - Typically limits the scope within a window
  - Certain trajectory properties can be preserved based on the application's needs
  - Intelligently select some negligible location points to retain a satisfactory approximated trajectory

Trajectory compression: Sliding window algorithm

- **Main idea:** Fitting the location points in a growing sliding window with a valid line segment
- Continues to grow the sliding window until the approximation error exceeds some threshold

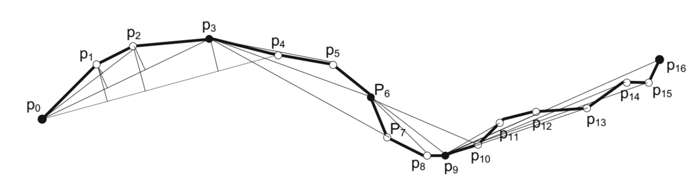


Figure 5: Sliding window algorithm

Trajectory filtering

- Spatial trajectories are often noisy because of the sensing technology
- Filtering techniques are used to smooth the noise and potentially decrease the error in the measurements
- This noise is different from the ϵ we had in the autoregressive models
- Trajectory model:
  - $\mathbf{z}_i = \mathbf{x_i} + \mathbf{v_i} \rightarrow$ Measurement
  - $\mathbf{x}_i = (x_i, y_i) \rightarrow$ True position
  - $\mathbf{v}_i \in N(0, R) \rightarrow$ Noise

Trajectory filtering

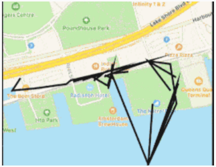


Figure 6: Raw noisy data, $\mathbf{Z}$

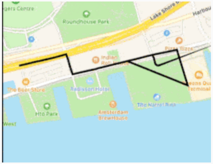


Figure 7: True position $\mathbf{X}$

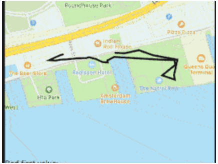


Figure 8: Estimated position $\hat{\mathbf{X}}$

Techniques for trajectory filtering

- Median filter
- Mean filter
- Kalman filter
- Particle filter
- ...

Filtering techniques

- Mean filter
  - $\hat{\mathbf{x}}_i = \frac{1}{n} \sum_{j=i-n+1}^{i} \mathbf{z}_j$
- Median filter
  - $\hat{\mathbf{x}}_i = median\{\mathbf{z}_{i-n+1}, \mathbf{z}_{i-n+2}, ..., \mathbf{z}_{i-1}, \mathbf{z}_i\}$

Mean and Median Filter

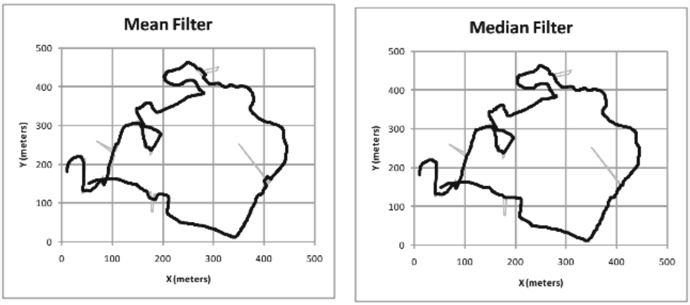


Figure 9: The result of applying the mean and the median filters

1

[1] Yu Zheng and Xiaofang Zhou. *Computing with spatial trajectories*. Springer Science & Business Media, 2011.

Properties of filters

- **Mean filter:**
  - Causal $\rightarrow$ depends on the values in the past
  - If the trajectory changes suddenly the effect on the trajectory is only gradually seen $\rightarrow$ It introduces a lag
  - Sensitive to outliers
- **Median filter:**
  - Not sensitive to outliers

Median and mean filters

- **Advantage:**
  - Simple and effective in smoothing trajectories
- **Disadvantages:**
  - Both suffer from the lag problem
  - They are not designed to help estimate higher order variables like speed and acceleration
  - In fact they might reduce the estimation accuracy of higher order variables

Advanced filters

- Advanced techniques that reduce lag and estimate the trajectory based on more than just location information
- **State-space models:**
    - Kalman filter
    - Particle filter

State and observations

- **States:** Things that you cannot measure directly but are interested in estimating
- Examples:
  - The true location
  - The true speed
- **Observations:** Noisy measurements from sensors
- Examples
  - GPS fixes
  - Acceleration

Kalman Filter

- **First use:** estimating trajectory of a space craft to the moon and back (There is no GPS trajectory in the space!)
- **General idea:** estimating the state variables from noisy observations by incorporating the physical domain knowledge $\rightarrow$ **Optimal estimation algorithm**
    - true location
    - speed
    - acceleration
- **Applications:**
    - Error correction
    - Data fusion: When measurements are available from various sensors but mixed with noise

Kalman filter

- Formulation of Kalman filter makes a distinction between what is **measured** as observations and what is **estimated** as states
    - **Measurement model:** How measurements are related to the states
    - **Dynamics model:** How previous states are related to future states

$$
\begin{aligned}
\mathbf{z}_i &= x_i + v_i \\
\mathbf{x}_i &= (x_i, y_i) \\
\mathbf{v}_i &\in N(0, R)
\end{aligned}
$$

Noise vector

Original trajectory model

$$
\mathbf{z}_i = \begin{bmatrix} z_i{}^{(x)} \\ z_i{}^{(y)} \end{bmatrix}
$$

Noisy measurements of the trajectory data

$$
\mathbf{x}_i = \begin{bmatrix} x_i \\ y_i \\ s_i{}^{(x)} \\ s_i{}^{(y)} \end{bmatrix}
$$

True unknown coordinates

True unknown velocity

State vector

$$
\mathbf{z}_i = H_i \mathbf{x}_i + \mathbf{v}_i
$$

Relationship between measurement and state vector

$$
H_i = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}
$$

Measurement matrix

- Kalman filter gives estimates for the state vector $\mathbf{x}_i$
- H_i is the measurement matrix translating between x_i and z_i and matching the dimensionality of z_i and v_i

Dynamics model

$$\mathbf{x}_i = \phi_{i-1}\mathbf{x}_{i-1} + \mathbf{w}_{i-1}$$

Change with time

$$\phi_{i-1} = \begin{bmatrix} 1 & 0 & \Delta t_i & 0 \\ 0 & 1 & 0 & \Delta t_i \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

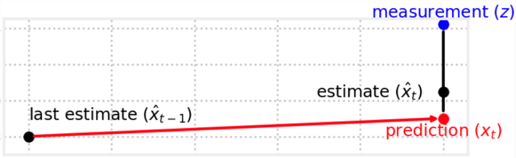
System matrix

- Approximates how the state vector $\mathbf{x}_i$ changes with time
- $\mathbf{w}_i$ is the Gaussian noise term

Kalman filter

A two-step algorithm that

- **Step 1:** Using the dynamics model extrapolates the current state to the next state
- **Step 2:** Incorporates the current measurement to make new estimates (weighted average of predicted state and the measurement)



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[2] image source: (Roger R. Labbe. *Kalman and Bayesian Filters in Python*. Available: `https://github.com/rlabbe/Kalman-and-Bayesian-Filters-in-Python`. 2015)

Kalman filter

Advantages:

- No lag effect
- Richer state vector (velocity and location)
- It can incorporate more **physical knowledge** explaining how speed, time and displacement are related to each other
- It can be used to incorporate input from **other sensors**
- It can be used to incorporate **uncertainty** (using a covariance matrix)

Kalman filter

Limitations:

- To initialize the filter we need to have assumptions about the initial state and the uncertainty of the initial state
- The requirement is having a linear dynamic model
- It uses continuous variables without having a way to represent discrete variables like:
    - The mode of transportation
    - Activity

Particle filter

- Also makes disctinction between **measurement** and **dynamics model**
- To formulate these models it does not limit itself to physical movement parameters
- Has less strict assumptions about the linearity of equations and the noise model
- More **general** and **less efficient**

Particle filter

- **Measurement model:**
  - A conditional Gaussian distribution with covariance matrix R_i
  - $p(\mathbf{z}_i|\mathbf{x}_i) = N((x_i, y_i), R_i)$,
- **Dynamics model:**
  - Probability distribution $p(\mathbf{x}_i|\mathbf{x}_{i-1})$
  - It samples from the dynamics models
  - Instead of formalizing it we generate random samples of $\mathbf{x}_{i+1}$ from $\mathbf{x}_i$
  - Each generated sample is referred to as a **particle**
- Computation time and accuracy both depend on the number of particles

Stops and Moves

- Trajectories are considered as a collection of stops and moves[3]
- For many applications semantics of points in trajectories are more important than shapes
- Interest regions
  - Stay points
  - Activity regions
  - The path between two points of interest

[3] Andrey Tietbohl Palma et al. "A clustering-based approach for discovering interesting places in trajectories". In: *Proceedings of the 2008 ACM symposium on Applied computing*. ACM. 2008, pp. 863–868.

Stops and moves

Figure 10: Stops and moves in a trajectory[4]

[4]Image source: (Palma et al., "A clustering-based approach for discovering interesting places in trajectories")

Not only a spatial clustering task

- **Challenge:**
  - We cannot only look at where point are clustered spatially
  - We want to find places that one trajectory has stopped but not only the overlap of a lot of trajectories
  - We want to find meaningful stops where a lot of trajectories stop and not any random stop
- Example approach: based on DBSCAN clustering[5]

[5] Palma et al., "A clustering-based approach for discovering interesting places in trajectories".

Lessons learned

- **Spatio-temporal processes:**
  - Extension of spatial process (geo-statistic, point, lattice processes)
  - Spatio-temporal auto-regressive as a combination of auto-regressive and spatial auto-regressive
- **Moving objects:**
  - Technology allows collection of trajectory data of moving object data in different ways:
    - **Lagrangian:** One individual visiting many locations
    - **Eulerian:** Many individuals passing one location
  - Different patterns can be extracted from data based on how we query the ID of moving objects and locations

Lessons learned (continued)

- **Trajectory pre-processing:**
  - **Trajectory compression:** summarize the trajectory data to key points, save space, save communication, efficient processing
    - Douglas-peuker (batch mode)
    - Window-based (online)
  - **Trajectory filtering:** GPS sensors produce noisy and only approximate location data
    - **Mean, Median filters:** simple, lag problem
    - **State-space filters:** defining a measurement (measurement, state relation) and dynamics model (past state, future state relation)
    - Kalman filter (physics laws, inflexible), Particle filter (flexible, slow)
  - **Trajectory segmentation:** Extracting region of interest by extending DBSCAN clustering

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End of theory!