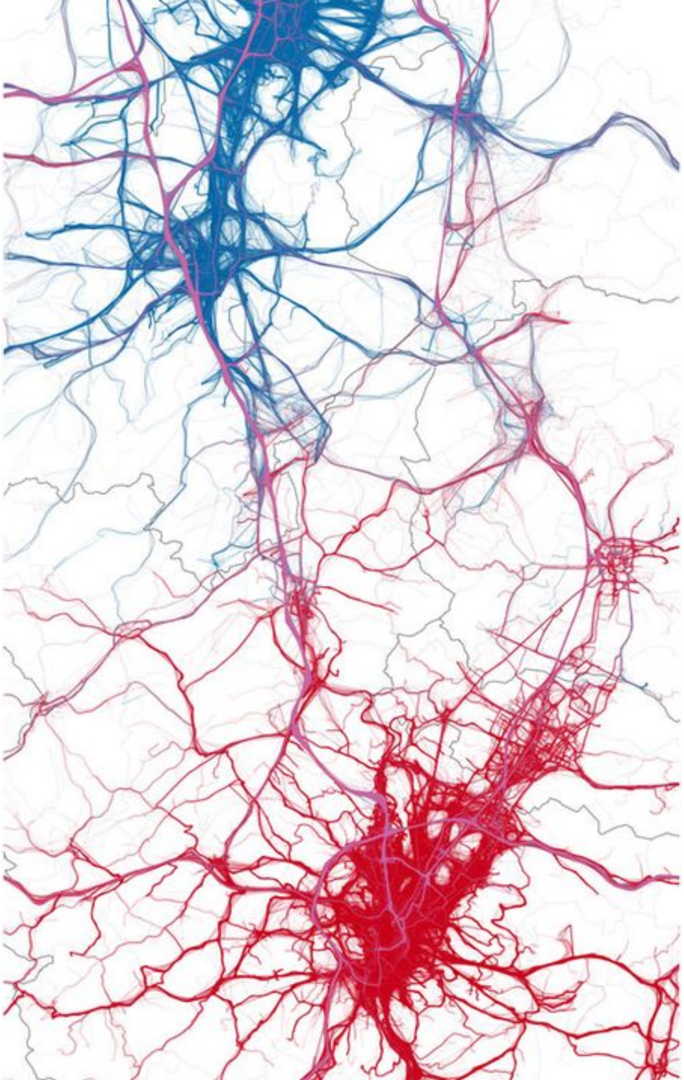

IN SUPREMÆ DIGNITATIS

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delle Ricerche

Mobility Patterns

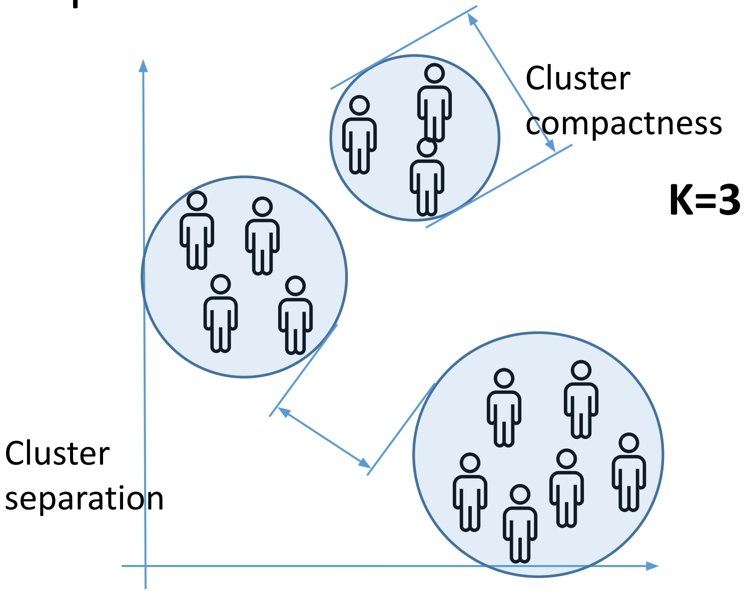
Content of this lesson

- Global patterns
  - Trajectory distances
  - Trajectory clustering
- Local patterns
  - Flocks, Convoys & Swarms
  - Moving clusters
  - T-Patterns

Global Patterns

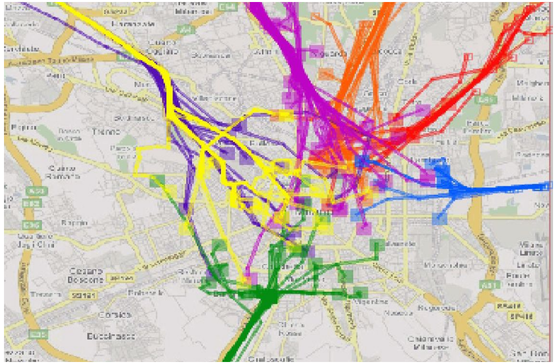
Clustering
(sample K-means family)

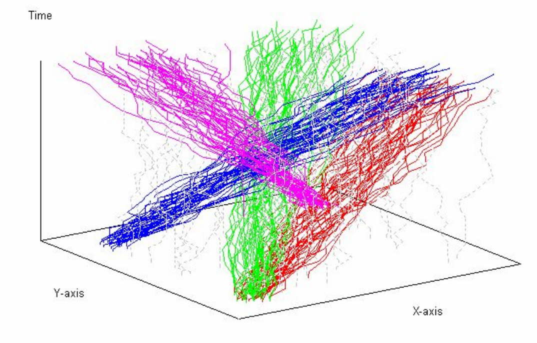
- Find k subgroups that form compact and well-separated clusters



Trajectory clustering

- Trajectories are grouped based on similarity



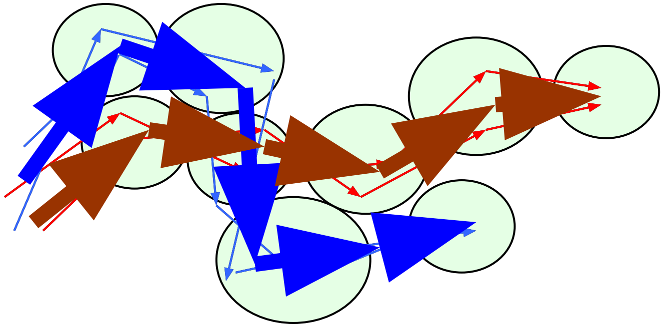


Nanni, Pedreschi. **Time-focused clustering of trajectories of moving objects**. J. of Intelligent Information Systems, 2006

Rinzivillo, Pedreschi, Nanni, Giannotti, Andrienko, Andrienko. **Visually-driven analysis of movement data by progressive clustering**. J. of Information Visualization, 2008

Trajectory Clustering

- Questions:
  - Which distance between trajectories?
  - Which kind of clustering?
  - What is a cluster ‘mean’ in our case?
    - A representative trajectory?



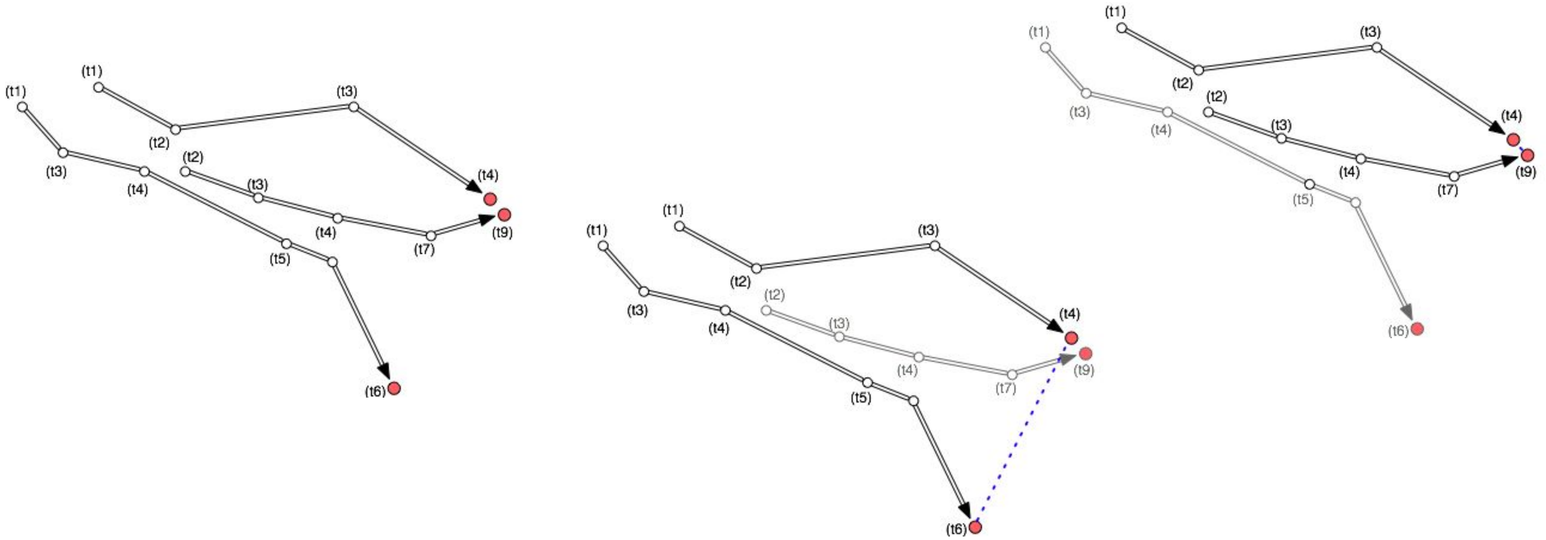
Trajectory Distances

Families of Trajectory Distances

- Trajectory as **set** of points
  - Single-point approaches
  - Hausdorff distance
- Trajectory as **sequence** of points
  - Fréchet distance
  - Time series distances: Euclidean, DTW & LCSS
- Trajectory as **time-stamped sequence** of points
  - Average Euclidean distance

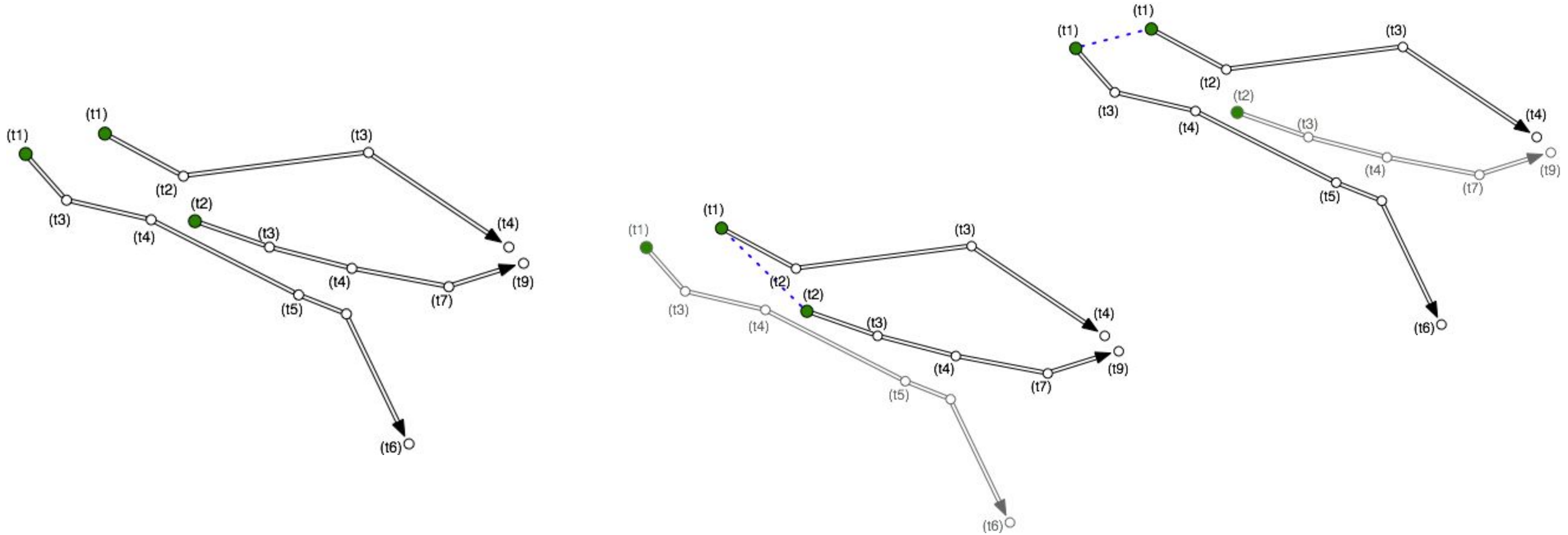
Trajectory as set of points
Common Destination

- Select last point *Plast* for each trajectory
- D(T,T’) = Euclidean(Plast, P’last)

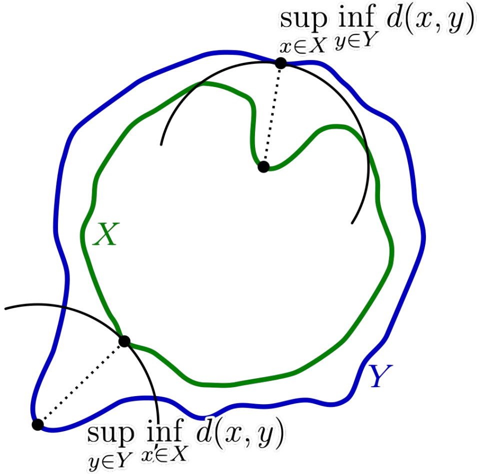


Trajectory as set of points
Common Origin

- Select first point *Pfirst* for each trajectory
- D(T,T') = Euclidean(Pfirst, P'first)

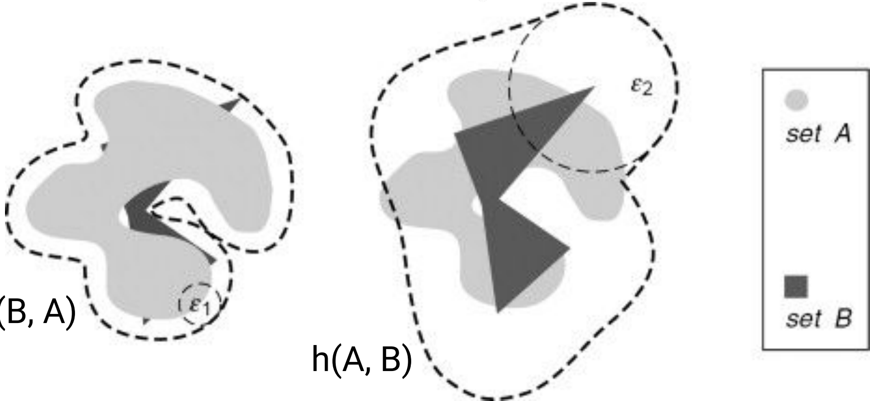


Trajectory as set of points
Hausdorff distance



- Intuition: two sets are close if every point of either set is close to some point of the other set
- Formally, given sets A and B: $d_H(X, Y) = \max\left\{\sup_{x \in X} \inf_{y \in Y} d(x, y), \sup_{y \in Y} \inf_{x \in X} d(x, y)\right\}.$
    - r (x , B) = inf {d(x , b) : b ∈ B}
    - h(A, B) = sup{r (a, B) : a ∈ A}
    - d_H(A, B) = max { h(A, B), h(B, A) }

- Equivalently:
    - h(A, B) = minimum buffer radius around B that fully contains A
    - d_H(A, B) = symmetric version of h()

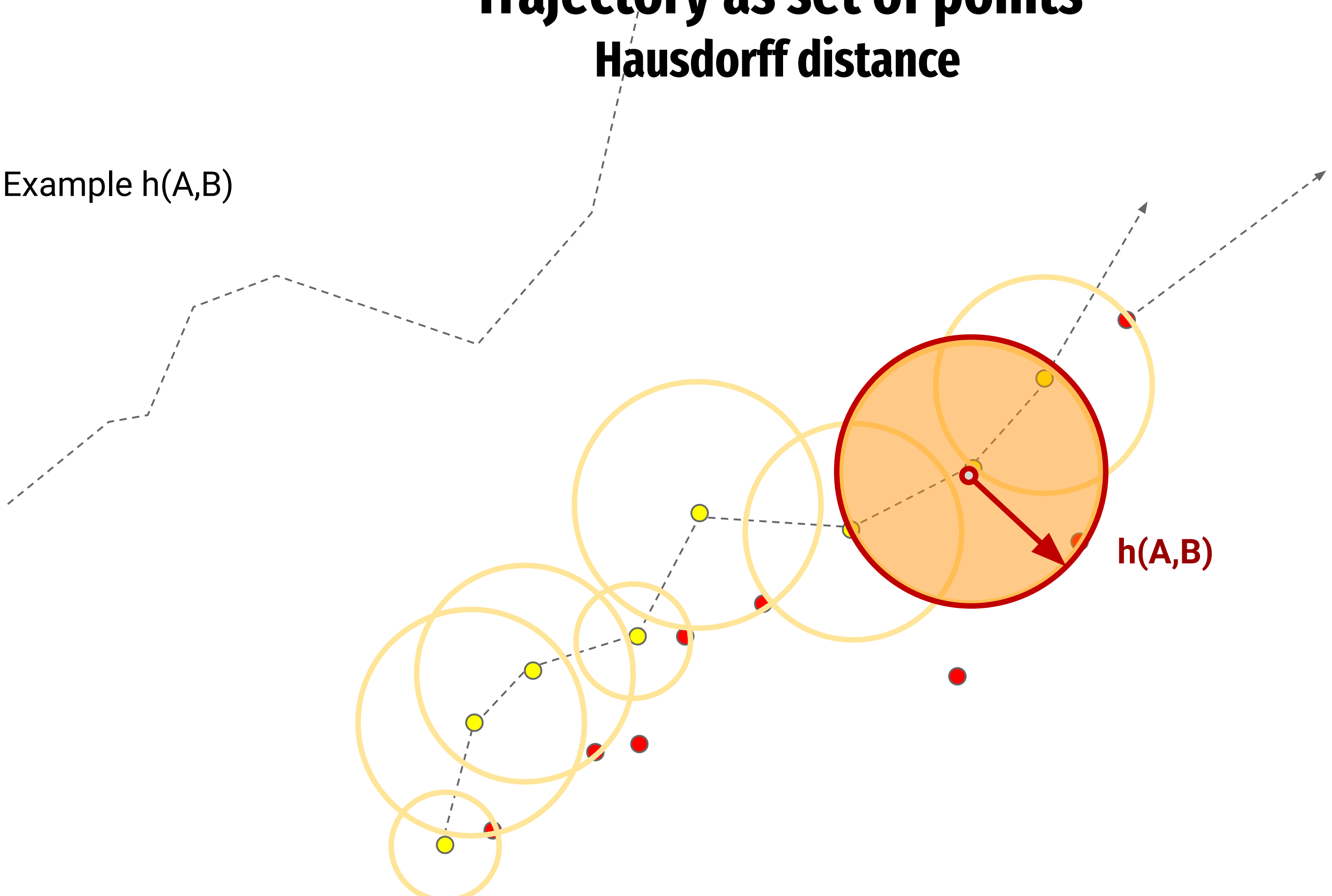


h(B, A)

h(A, B)

Trajectory as set of points
Hausdorff distance

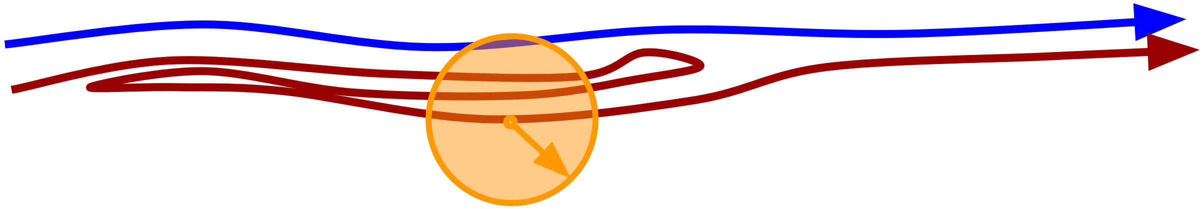
Example h(A,B)



Trajectory as sequence of points

From Hausdorff to Fréchet distance

- Applied to trajectories, sometimes Hausdorff distance yields counter-intuitive results
- How far are these?

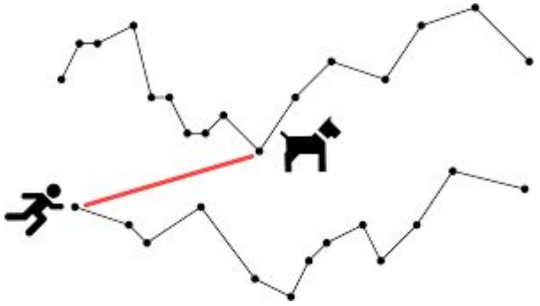


- Reasonable in a set-oriented view
- Wrong in terms of moving objects

Trajectory as sequence of points
Fréchet distance

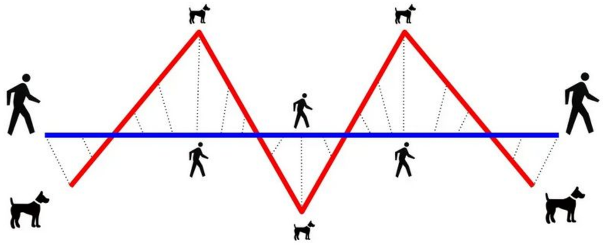
- Intuition: equivalent of Dynamic Time Warping on continuous curves
- Formally:

$$F(A,B) = \inf_{\alpha,\beta} \max_{t\in[0,1]} \left\{ d\Big(A(\alpha(t)),\, B(\beta(t)) \Big) \right\}$$



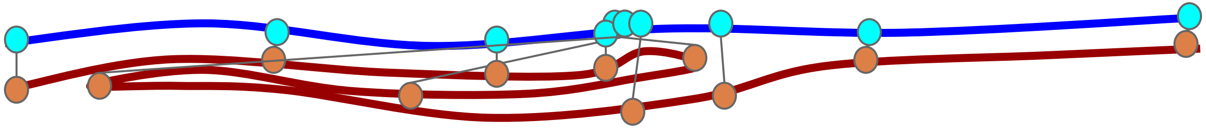
α and β are non-decreasing mappings from [0,1] to the points along A and B in forward order

- Also described as “minimum leash length”:
    - What is the minimum length of a leash needed to stroll around the dog, given the owner’s and the dog’s trajectories?



Trajectory as sequence of points
Fréchet distance

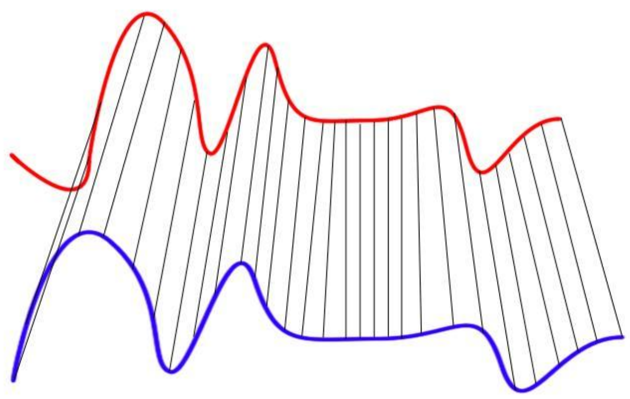
- Back to our example



Trajectory as sequence of points
Time series distances

- Just replace “difference of two values” with “spatial distance of two points”
- IMPORTANT: most methods in this class assume constant sampling rates

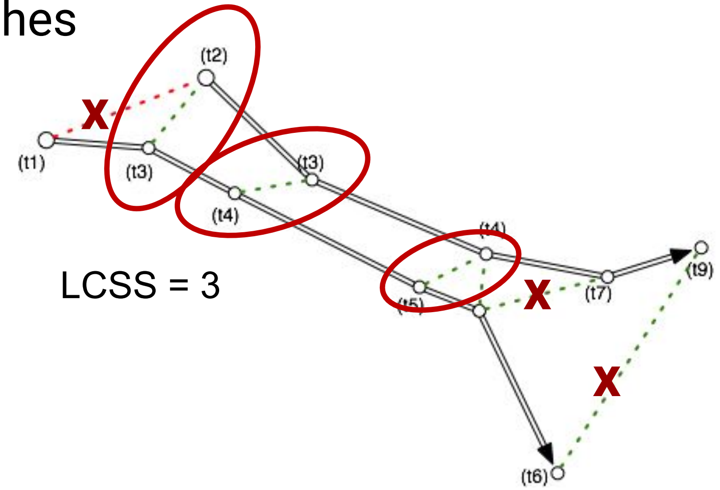
- Examples:
    - Dynamic Time Warping
    - Edit Distance with Real values
        - Similar to DTW, but can remove points



Dynamic Time Warping Matching

Trajectory as sequence of points
Time series distances

- Longest Common SubSequence
  - Define a maximum radius
  - Match points from the two trajectories if dist() < radius
  - Find contiguous subsequences of matches
  - LCSS = length of the best match



Trajectory as time-stamped sequence of points
Average Euclidean distance

- The trajectory is seen as a continuous spatio-temporal curve
- Positions between input points (the GPS fixes) linearly interpolated

$$D(\tau_1, \tau_2)|_T = \frac{\int_T \boxed{d(\tau_1(t), \tau_2(t))} dt}{|T|}$$

distance between moving objects τ_1 and τ_2 at time t

- “Synchronized” behaviour distance
  - Similar objects = almost always in the same place at the same time
- Computed on the whole trajectory

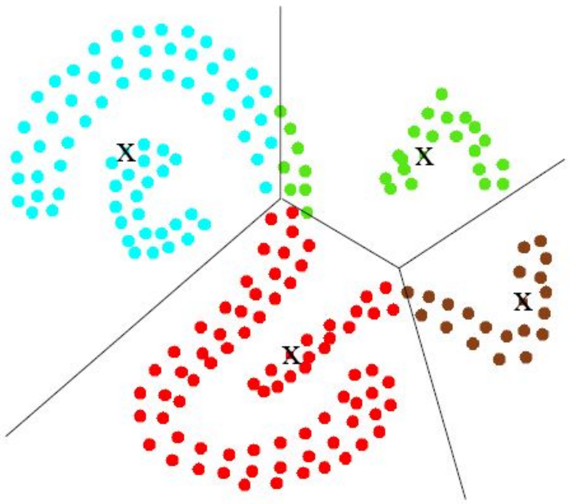
Clustering Algorithms

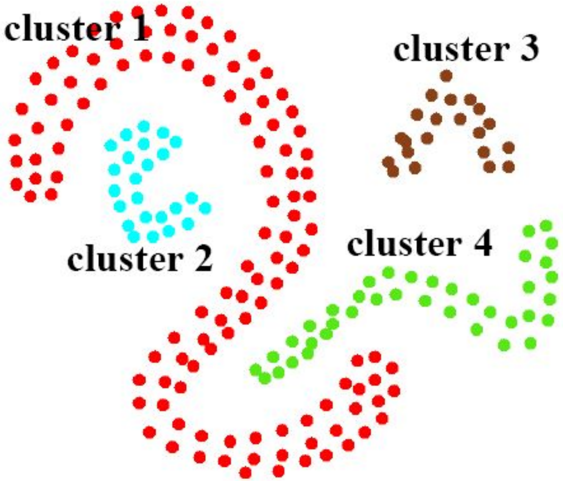
Which kind of clustering method?

- In principle, any distance-based algorithm
- General requirements:
  - Non-spherical clusters should be allowed
    - E.g.: A traffic jam along a road = “snake-shaped” cluster
  - Tolerance to noise
  - Low computational cost
  - Applicability to complex, possibly non-vectorial data
- A suitable candidate: Density-based clustering
  - OPTICS (Ankerst et al., 1999)
  - Evolution of standard DBSCAN

Density Based Clustering
A refresher

K-means	*Density-based*

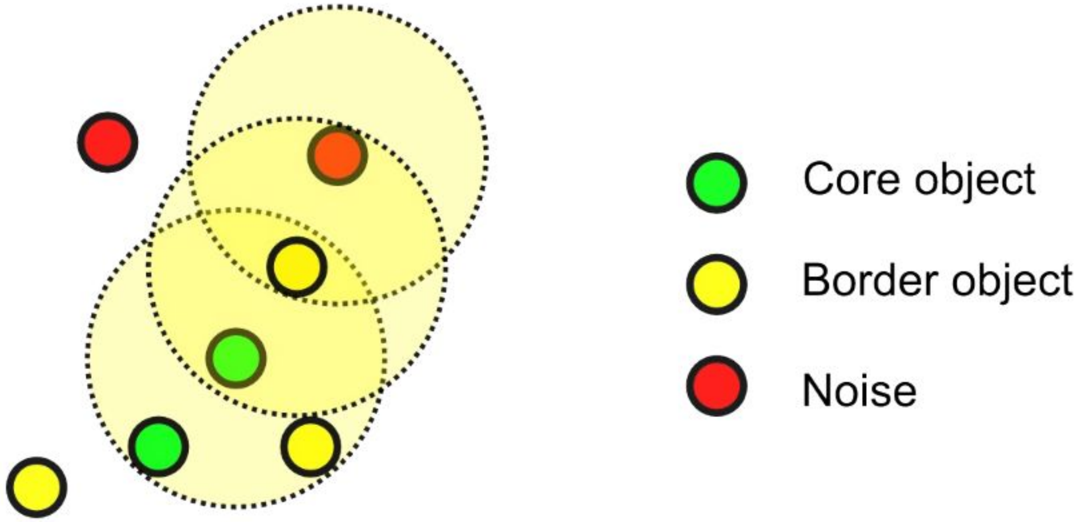




Density Based Clustering

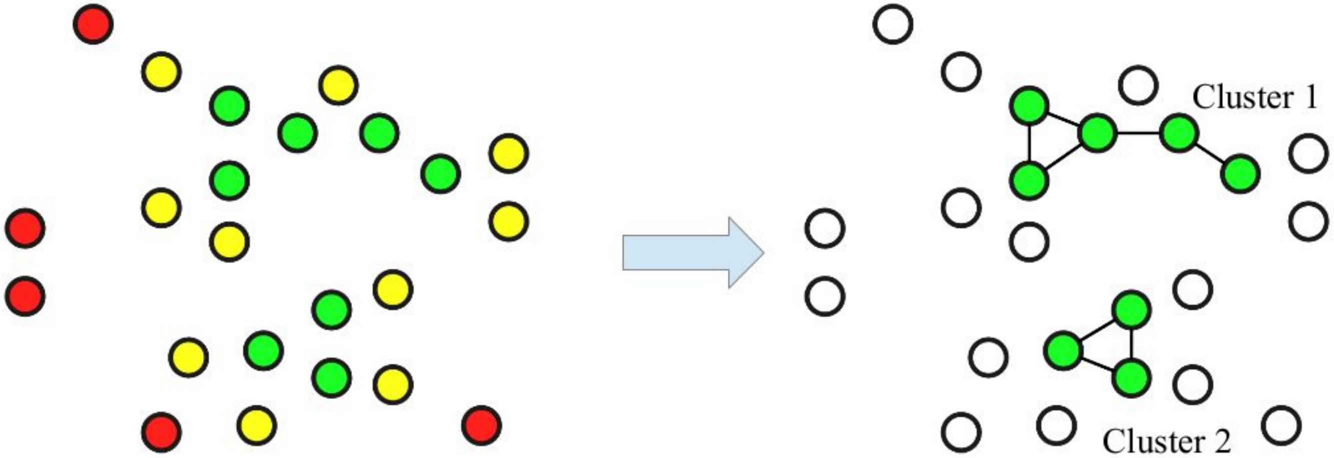
Step 1: label points as core (dense), border and noise

- Based on thresholds R (radius of neighborhood) and min_pts (min number of neighbors)



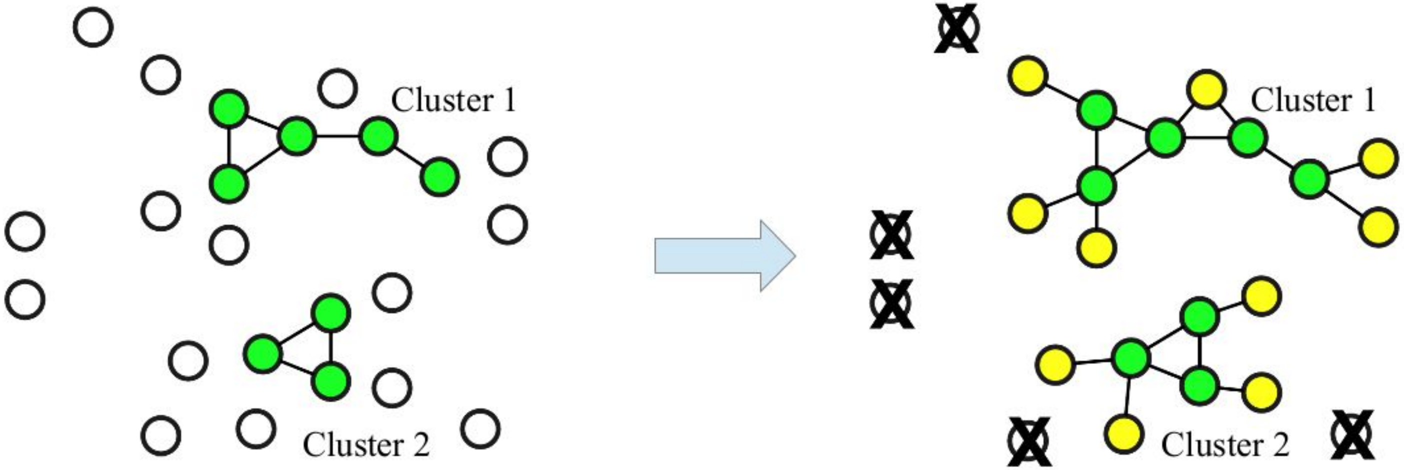
Density Based Clustering

Step 2: connect core objects that are neighbors, and put them in the same cluster



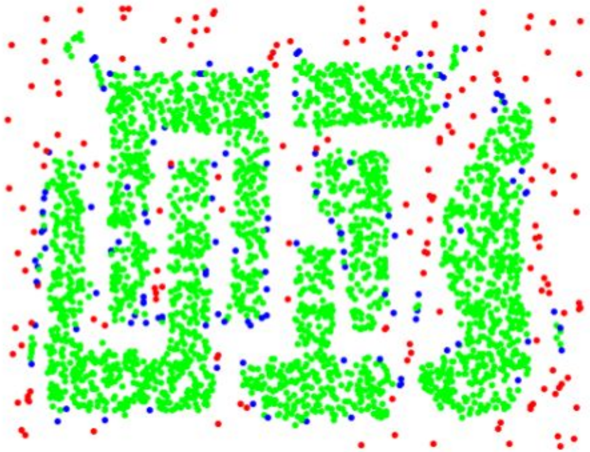
Density Based Clustering

Step 3: associate border objects to (one of) their core(s), and remove noise



Density Based Clustering

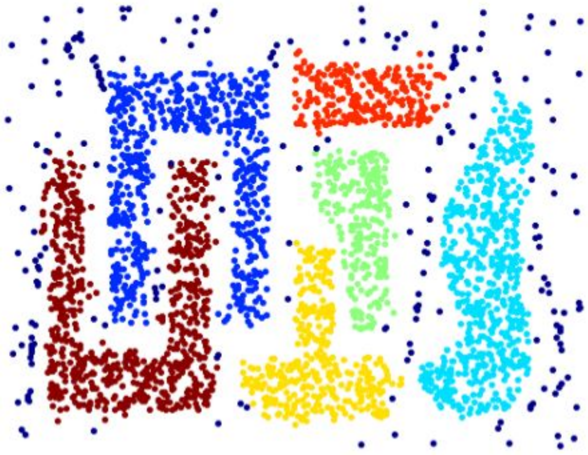
Original Points



Point types: core, border and noise

Density Based Clustering

Original Points

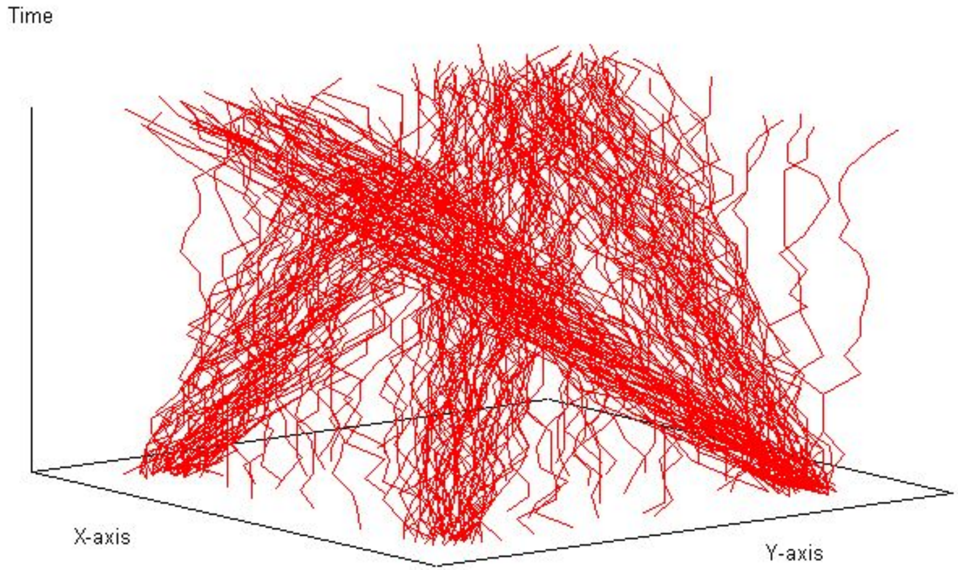


Clusters

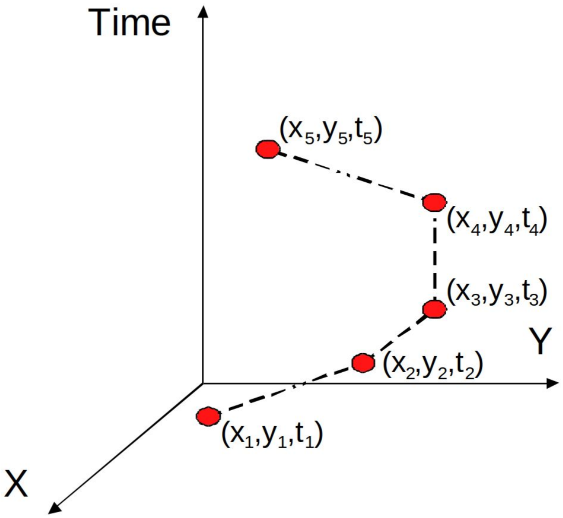
- Resistant to Noise
- Can handle clusters of different shapes and sizes

A sample dataset

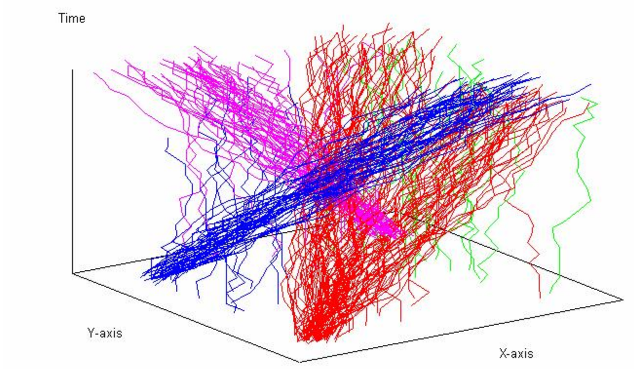
- A set of trajectories forming 4 clusters + noise (synthetic)

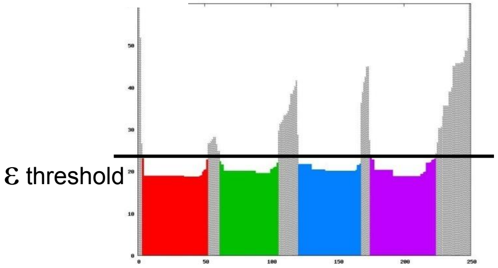


T-OPTICS vs. K-means

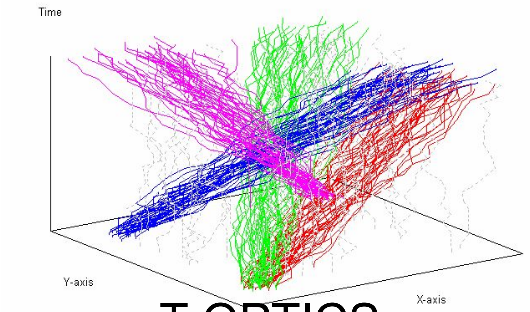


K-means





Reachability plot
(= objects reordering for distance distribution)

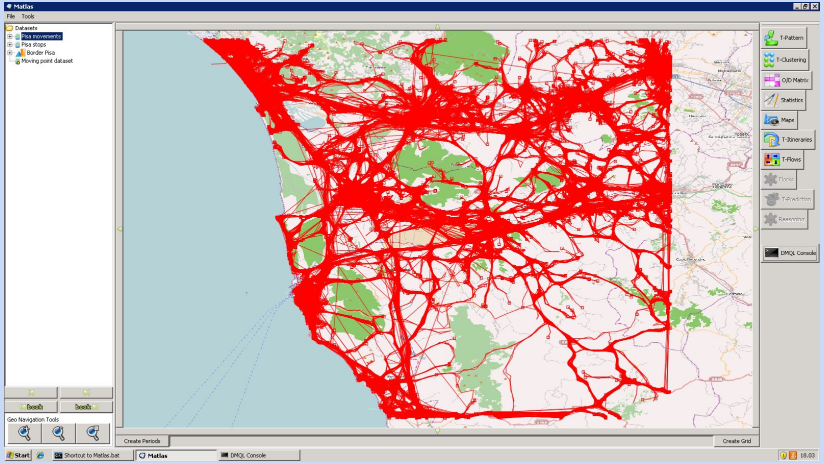


T-OPTICS

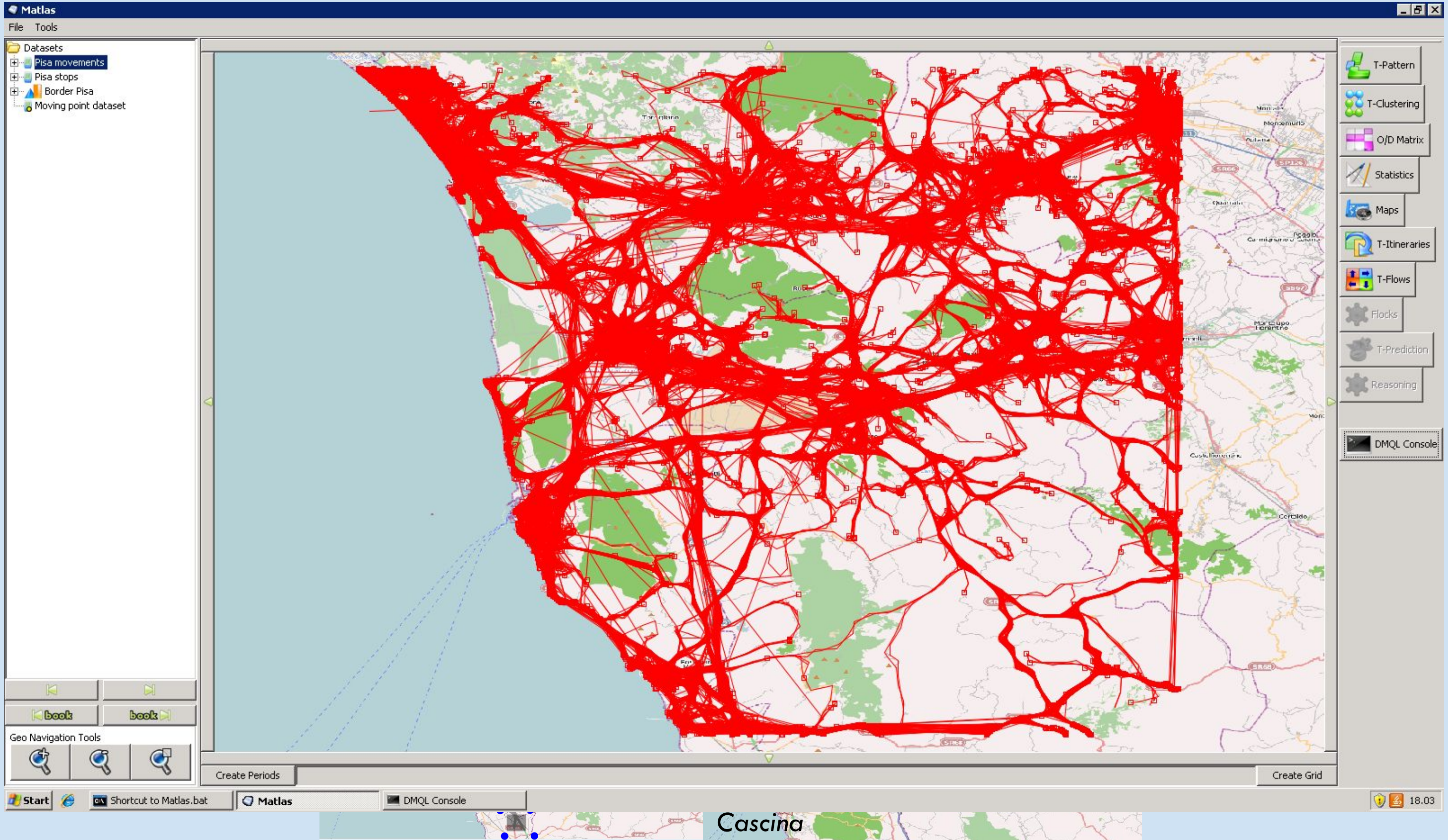
INTERVALLO

What's the source of traffic in Pisa?

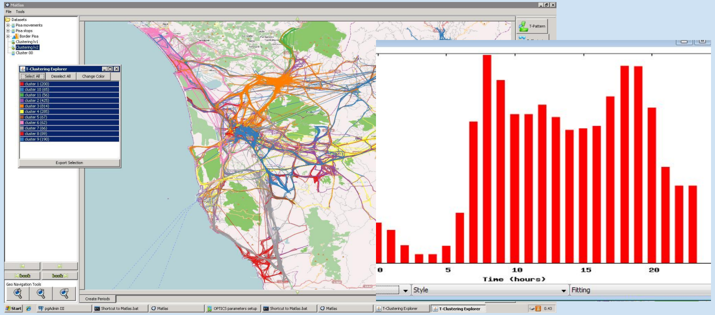
Trajectory clustering at work

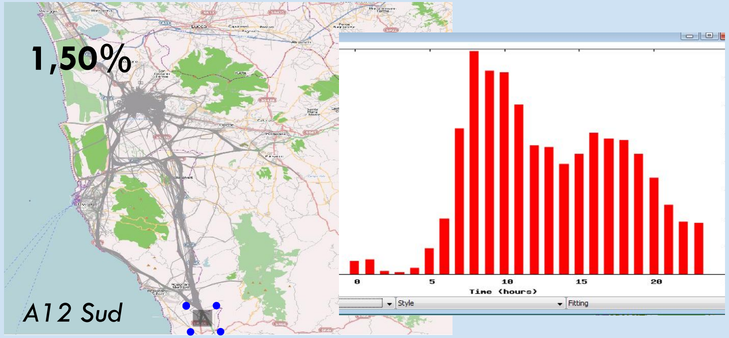


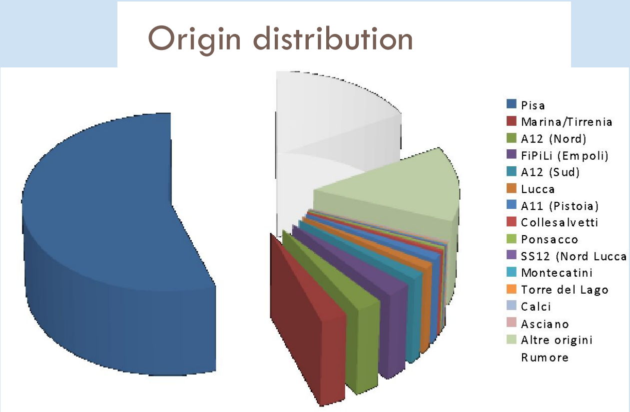
Access patterns using T-clustering

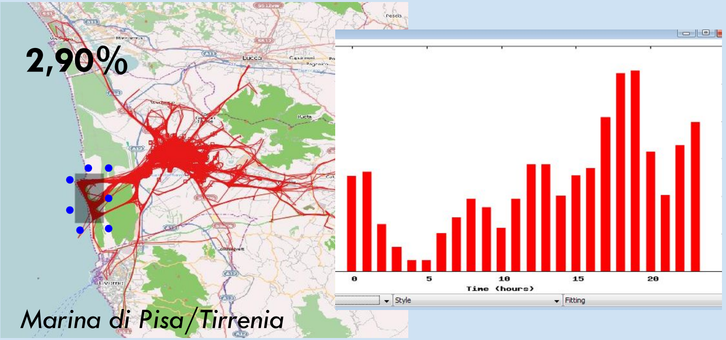


Characterizing the access patterns: origin & time





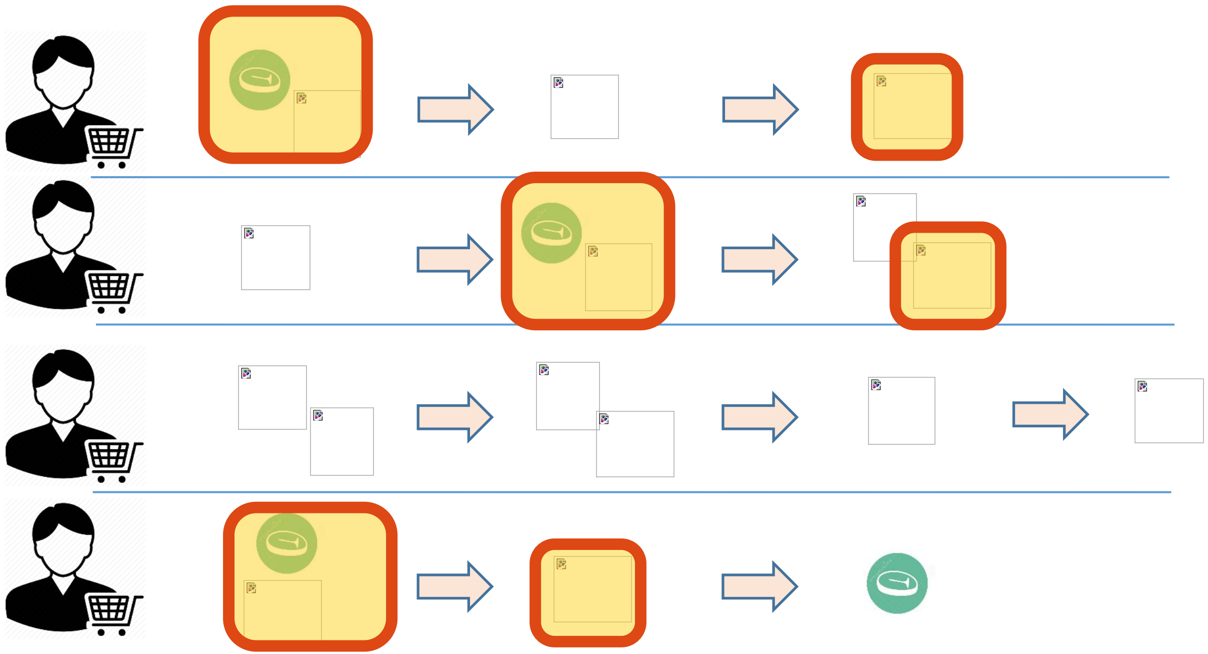




Local Trajectory Patterns

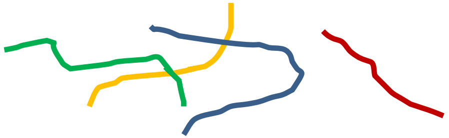
Frequent patterns in sequences

- Frequent sequences (a.k.a. Sequential patterns)
- Input: sequences of events (or of groups)



From trajectories to sequential patterns: the easy way

- Map each trajectory to a sequence of areas
  - Predefined or driven by data



+

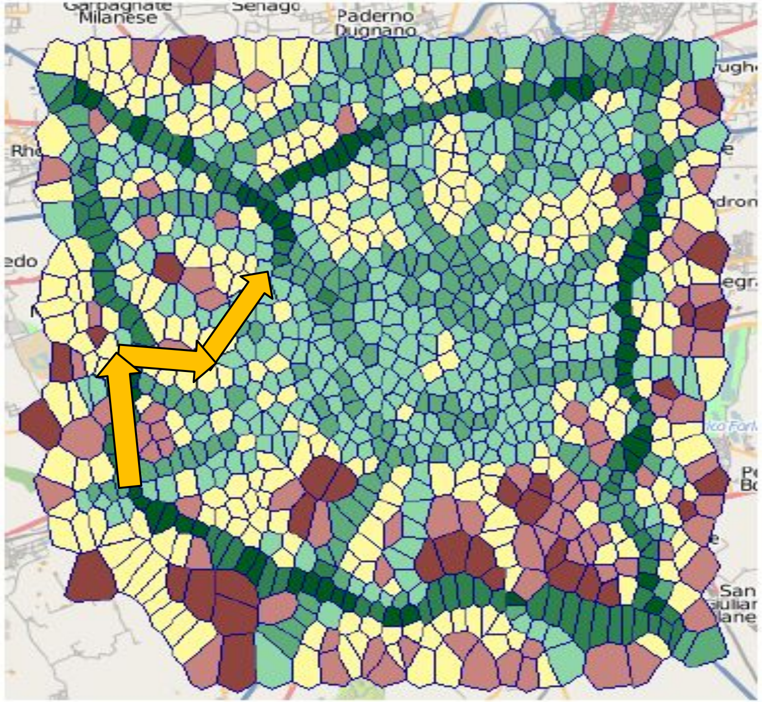
O	I	F	P	Q
A	B	E	H	M
N	D	C	G	L

=

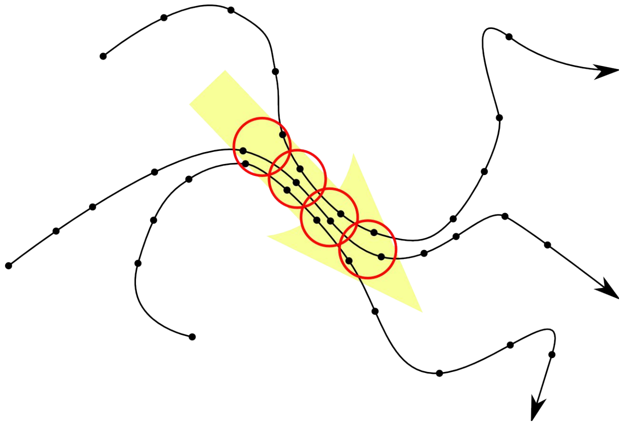
A → B → C
D → B → E → F
C → G → H → E → I
L → M → H

From trajectories to sequential patterns: the easy way

- A “Trajectory frequent pattern” can be defined as sequential pattern over traversed areas

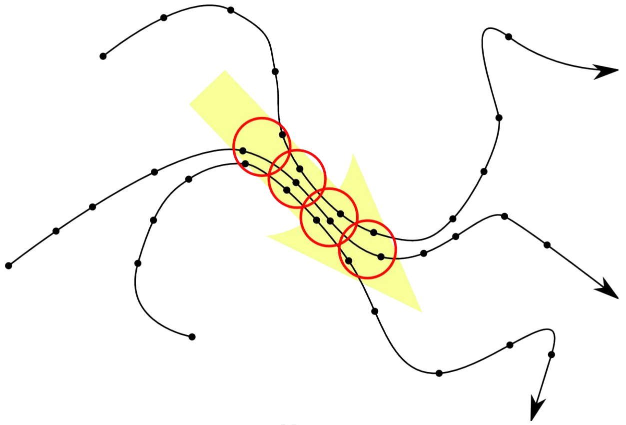


Moving Trajectory Flocks



- Group of objects that move together (close to each other) for a time interval

Moving Trajectory Flocks

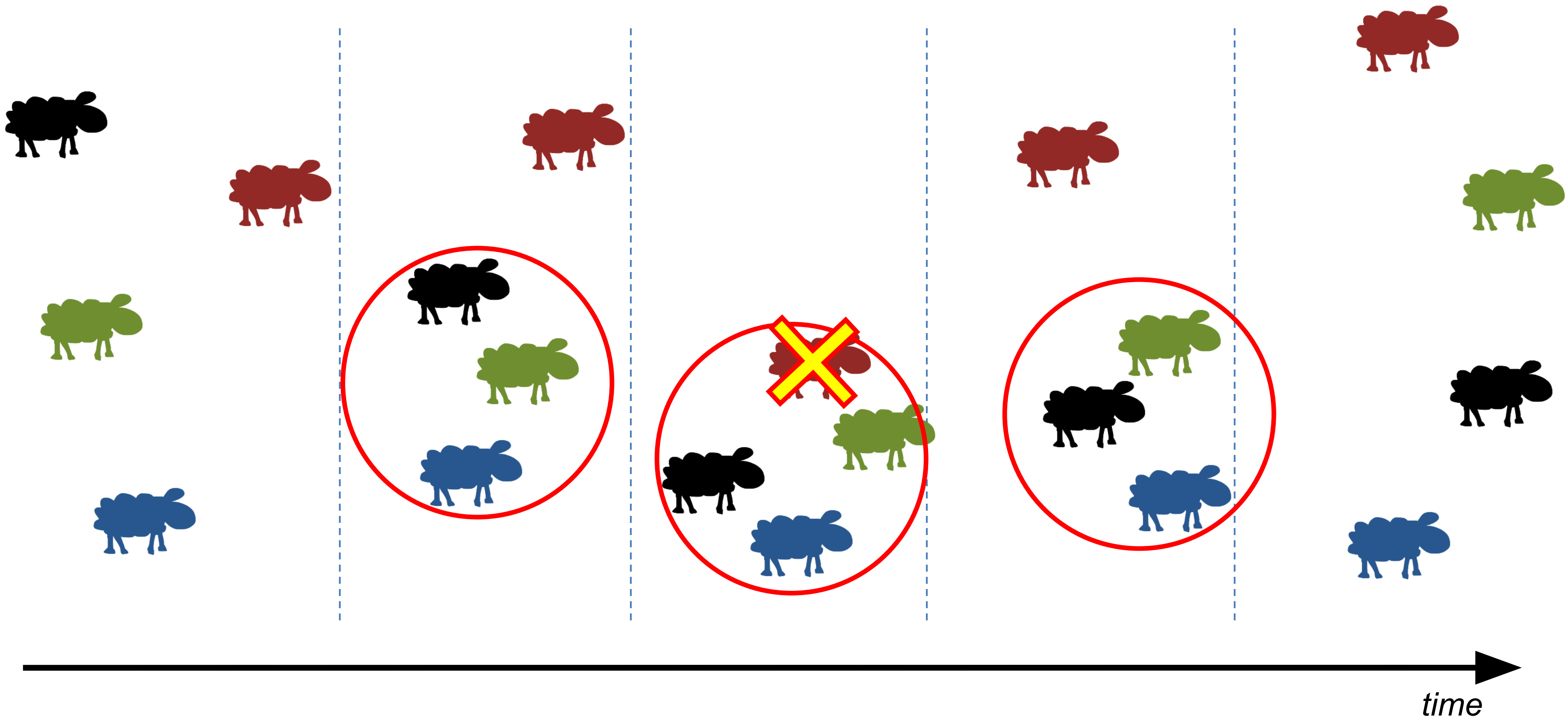


- Group of objects that move together (close to each other) for a time interval

- Discover all possible:
  - sets of objects O, with |O| > min_size and
  - time intervals T, with |T| > min_duration
- such that for all timestamps t ∈T the points in O|t are contained in a circle of radius *r*

M. Wachowicz, R. Ong, C. Renso, M. Nanni: ***Finding moving flock patterns among pedestrians through collective coherence.*** *IJGIS 25(11): 1849-1864 (2011)*

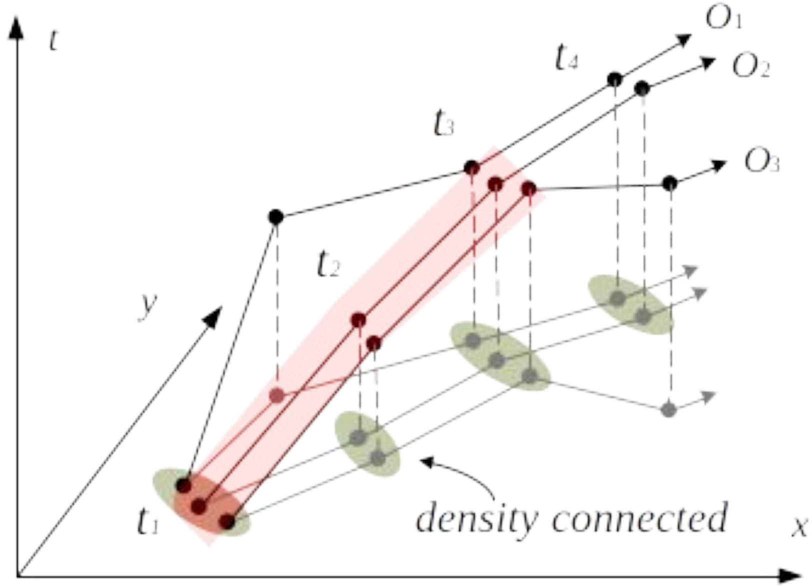
Moving Trajectory Flocks



From Flocks to Convoys

- Given radius r, size m, and time threshold k
  - find all groups of objects so that each group consists of **density-connected objects** w.r.t. r and m
  - during at least k consecutive time points

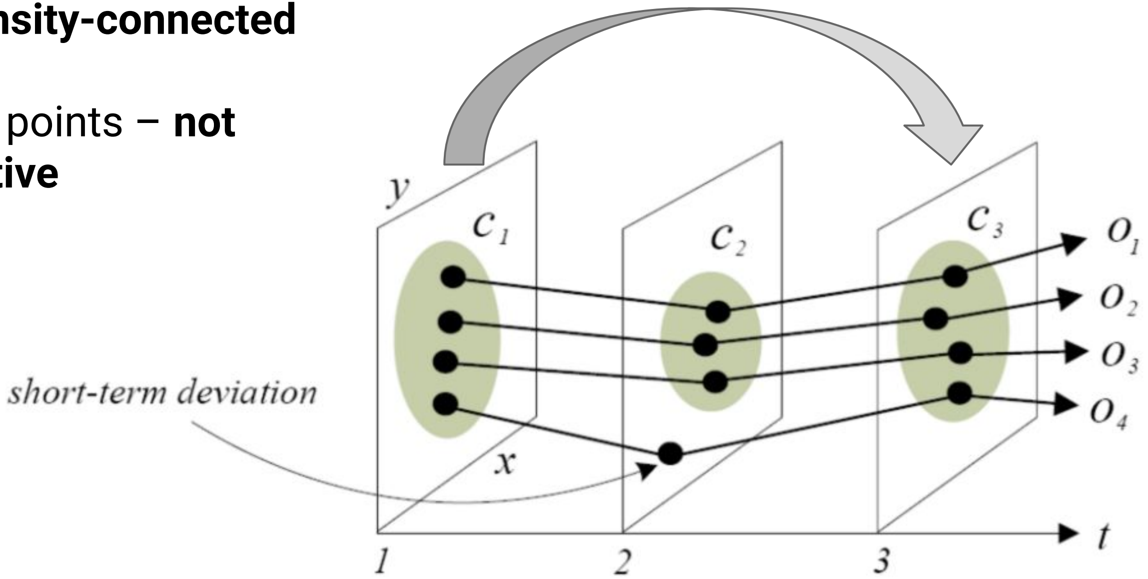
- Basically replace circles with DBSCAN clusters



From Convoys to Swarms

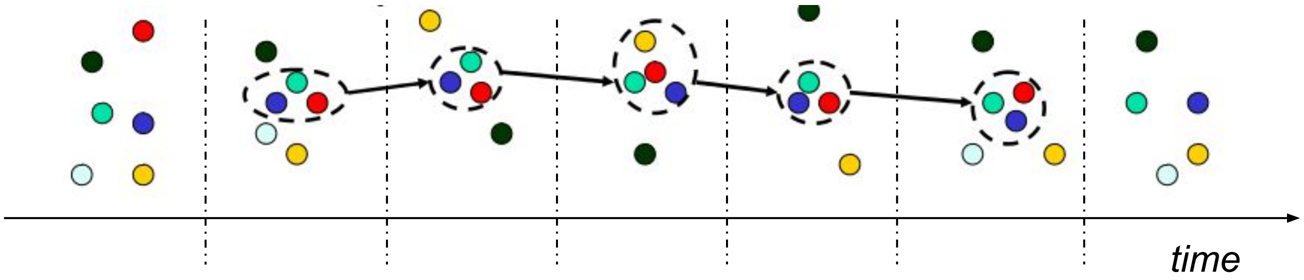
- Given radius r, size m, and time threshold k
  - find all groups of objects so that each group consists of **density-connected objects** w.r.t. r and m
  - during at least k time points – **not necessarily consecutive**

swarm pattern = $\{O_1, O_2, O_3, O_4\}$
over times <1,3>



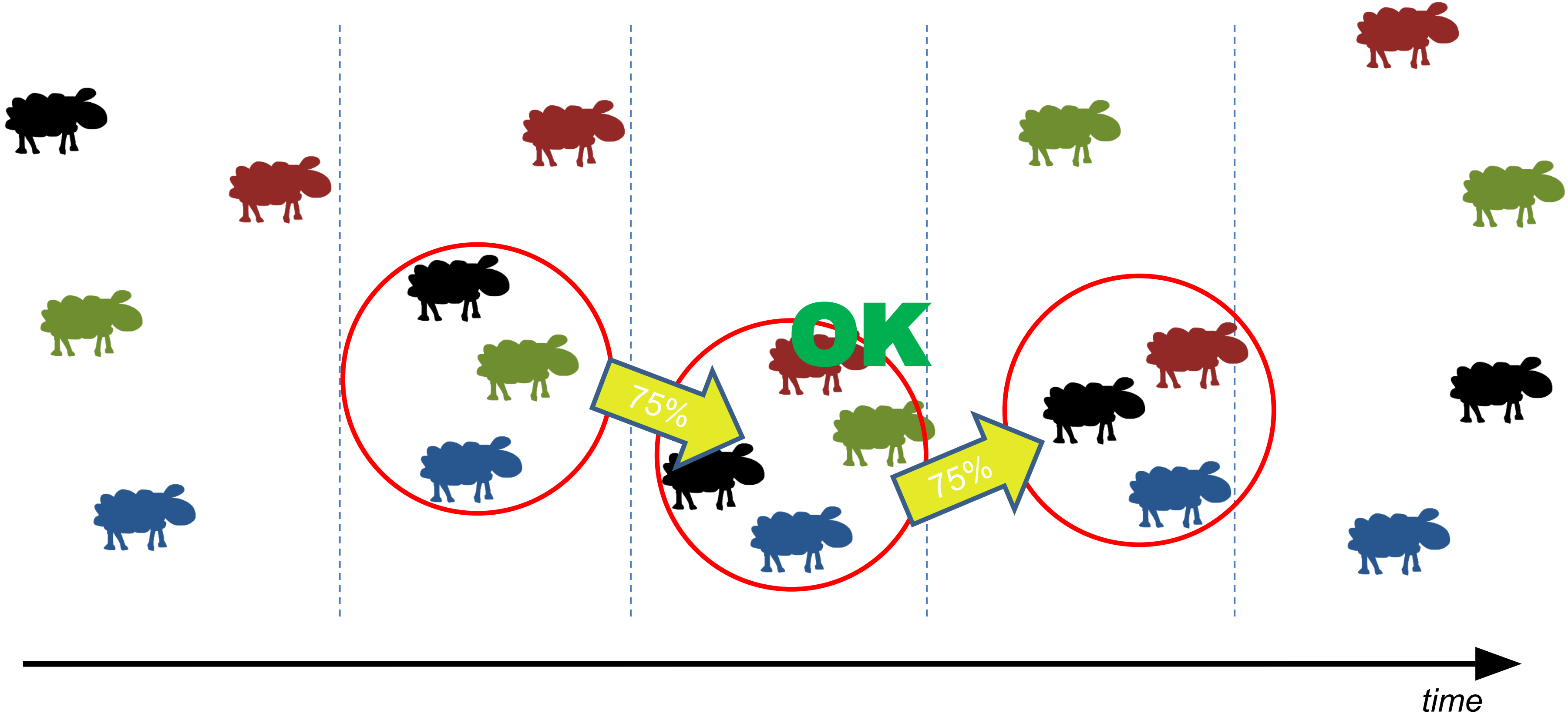
Moving Clusters

- A ***moving cluster*** is a set of objects that move close to each other for a long time interval



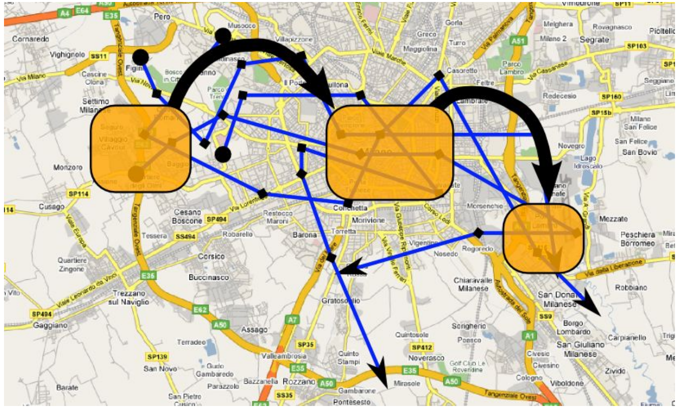
- Formal Definition [Kalnis et al., SSTD'05]:
  - A ***moving cluster*** is a sequence of (snapshot) clusters ***c1, c2, …, ck*** such that for each timestamp i ($1 \le i < k$): Jaccard(c_i, c_{i+1}) $\ge \theta$
    - Jaccard(c_i, c_{i+1}) = $|c_i \cap c_{i+1}| \;/\; |c_i \cup c_{i+1}|$
    - $0 < \theta \le 1$
  - Clustering computed with density-based method (DBSCAN)

Moving Clusters



T-Patterns

- A sequence of visited regions, **frequently** visited in the **specified order** with **similar transition times**

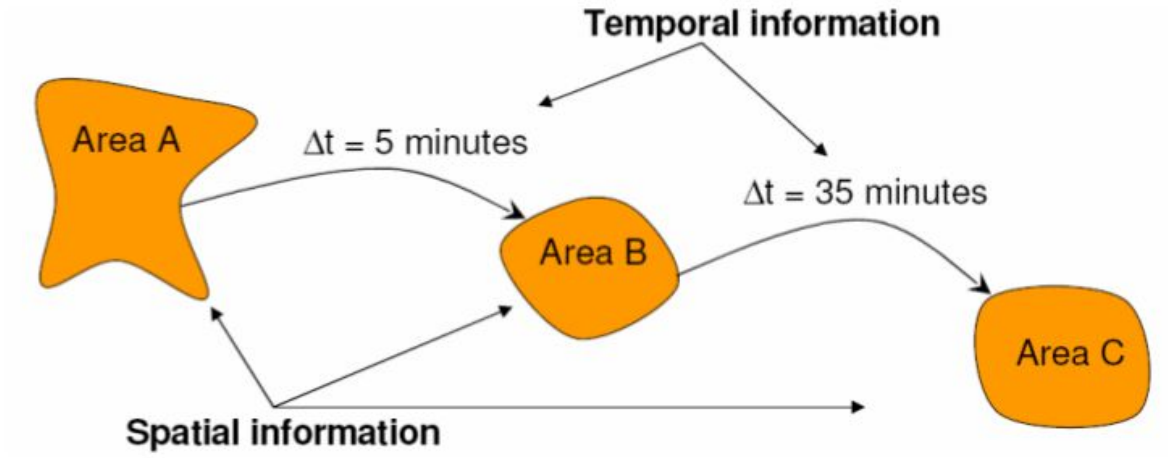


$$A_0 \xrightarrow{t_1} A_1 \xrightarrow{t_2} \ldots \; A_{n-1} \xrightarrow{t_n} A_n$$

$\boldsymbol{t_i}$ = transition time, $\boldsymbol{A_i}$ = spatial region

Giannotti, Nanni, Pedreschi, Pinelli. Trajectory pattern mining. Proc. ACM SIGKDD 2007

T-Patterns

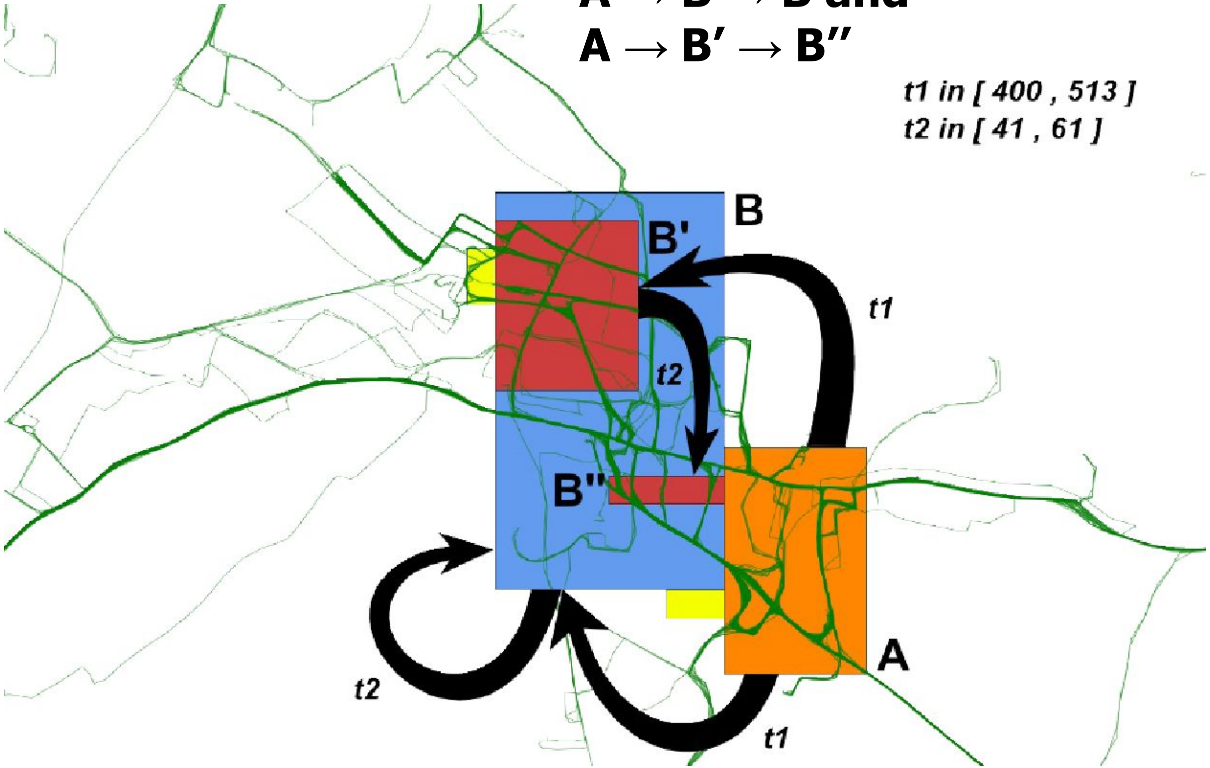


- Key features
  - Includes typical transition times in the output
  - Areas are automatically detected – not “the easy way”

Sample Trajectory Pattern

Data Source: Trucks in Athens (273 trajectories)

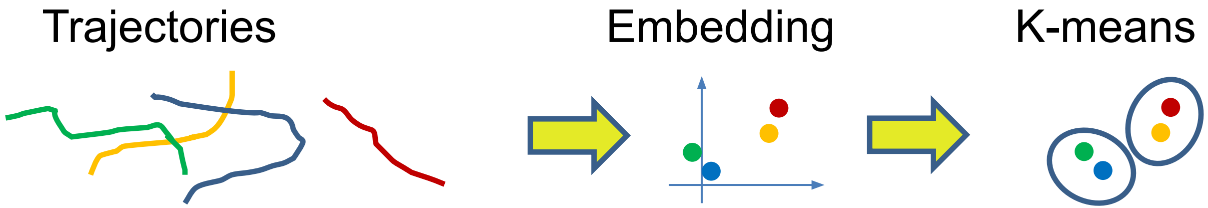
A → B → B and
A → B′ → B″



A quick peek into Deep Learning

Deep Learning approaches

- Sample approach: DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis
- Basic idea:

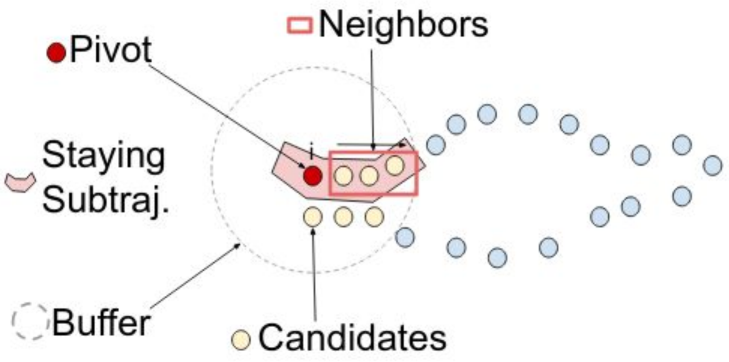


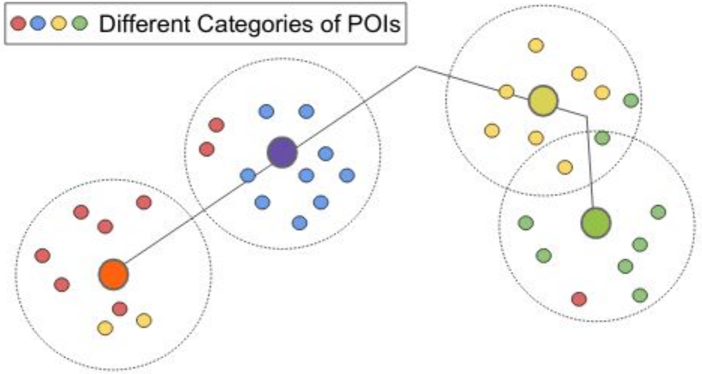
- Integrate the clustering step in the learning of embeddings
- Three steps:
  - Enrich trajectories with context
  - LSTM-based embedding of trajectories
  - Clustering on embeddings

M. Yue, Y. Li, H. Yang, R. Ahuja, Y. Chiang and C. Shahabi, "DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis," 2019 IEEE International Conference on Big Data (Big Data), 2019, pp. 988-997

DETECT / 1

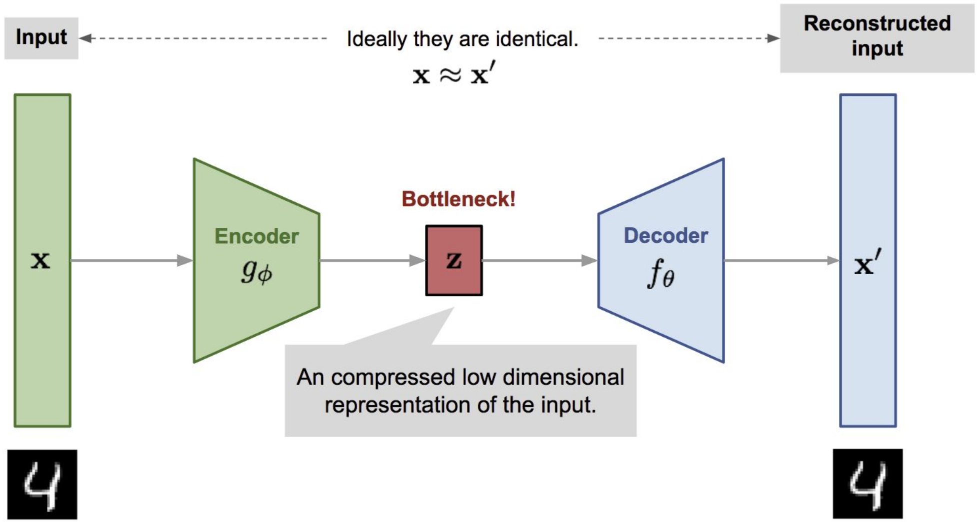
- Enrich trajectories with context
  - Identify stay areas = segment of trajectory where there is no movement, basically a stop
  - Create a buffer around the area
  - Select all points-of-interest located there (hotels, shops, etc.)
  - Compute a feature vector, one feature per PoI category
- Output
  - Traj = < $(x,y,[f_1,\ldots, f_n])$, $(x',y',[f'_1,\ldots, f'_n])$, … >





DETECT / 2

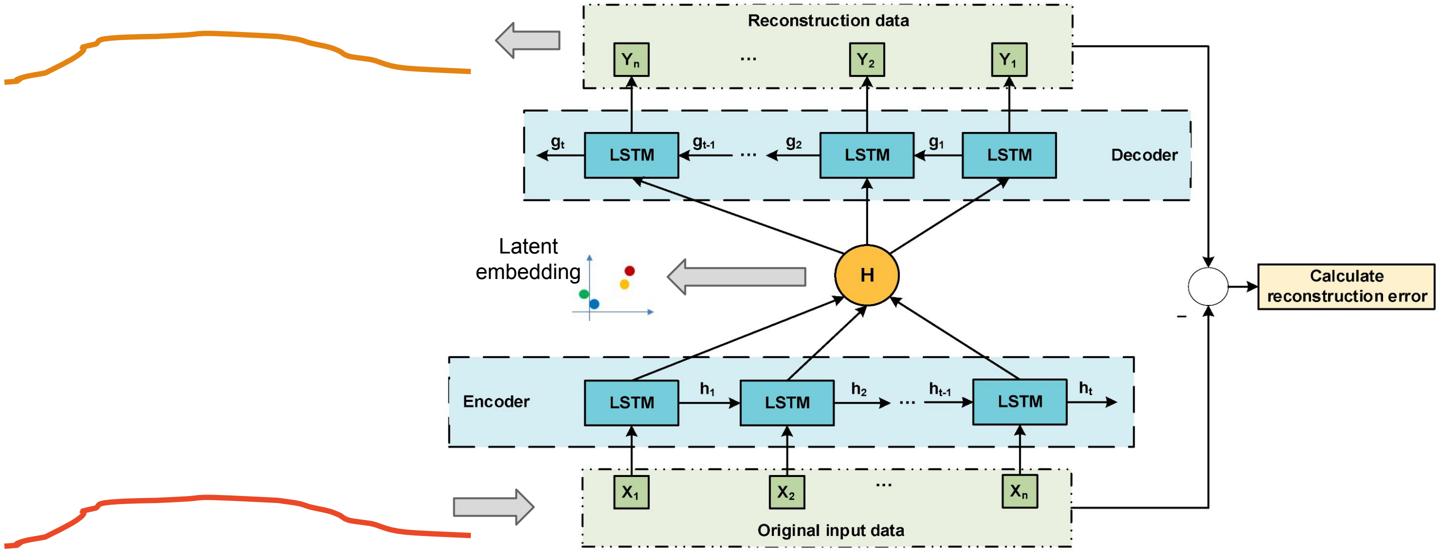
- LSTM-based embedding of trajectories
  - Apply a encoder-decoder schema to the enriched trajectories
  - Use LSTM as basic mechanism



- Objective: minimize the difference between the encoder input and the decoder output

DETECT / 2

- LSTM-based embedding of trajectories
    - Apply a encoder-decoder schema to the enriched trajectories
    - Use LSTM as basic mechanism

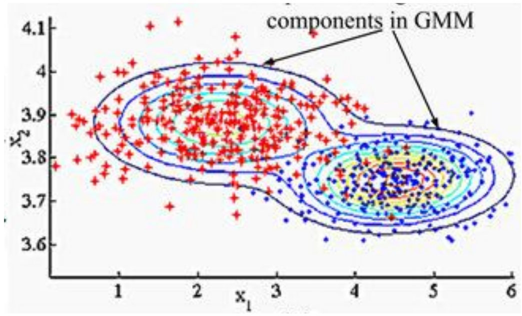


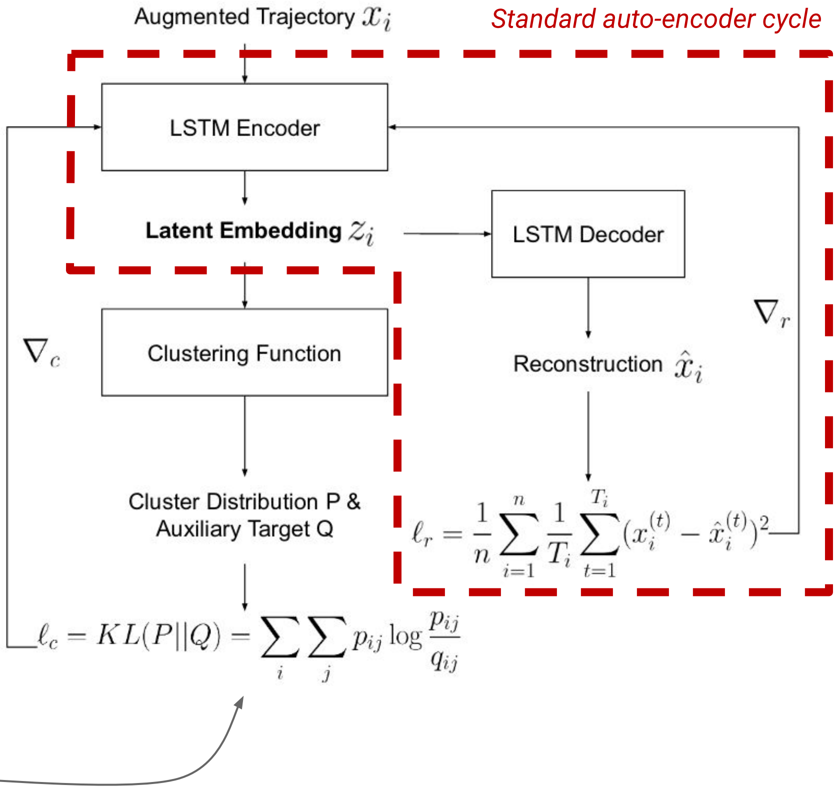
- Objective: minimize the difference between the encoder input and the decoder output

DETECT / 3

- Clustering on embeddings

- Clustering error becomes one term of the overall loss function
- P & Q = points distribution
  - P = real data (embedded)
  - Q = clusters (Student t-distribution around centers)

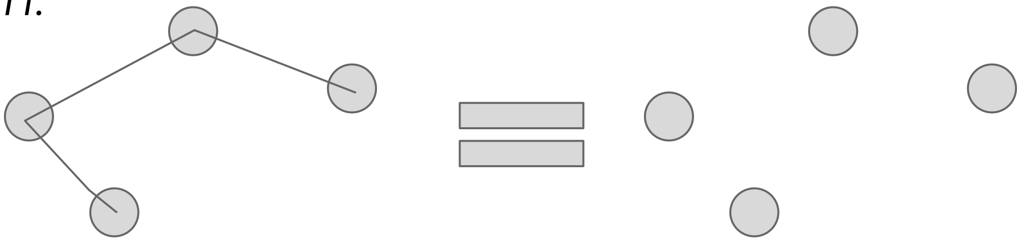




Homeworks

Homework 7.1

Implement a simple (non-optimized) discrete version of Hausdorff distance for trajectories, i.e. considering only the GPS points and not the segments connecting them:



- Apply it to a set of taxi trips: randomly pick 10 trajectories as "query objects"; find for each of them the trips of the dataset having $d_H(.)$ < 500 mt; show them (query + result) on the map.
- Write a (well commented) python notebook, where d_H is defined as a function

Homework 7.2

Define a simple "embedding" of trajectories, e.g. as trajectory length, main direction, average latitude, etc. (you decide the number of features to use); then cluster the embeddings (you decide the clustering algorithm); finally, show on a map the different clusters.

- Apply it to a (sub)set of taxi trips, e.g. SF.
- Write a (well commented) python notebook

Homework 7.3

Clustering trajectory segments (a.k.a. mimicking TraClus [1])

Strongly simplify a dataset D of trajectories (output = D’), then build a second dataset D” containing, for each trip in D’, all its segments. Then, cluster the segments in D” using the coordinates of start and end as attributes for clustering (4 attributes per segment), and show results on a map. You decide the clustering algorithm to use.

- Apply it to a (sub)set of taxi trips, e.g. SF.
- Write a (well commented) python notebook

[1] https://pypi.org/project/traclus-python/