DATA STORIES
Data Science Lab. @ University of Piraeus

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
UNIVERSITY OF PIRAEUS

Mobility Data Analytics

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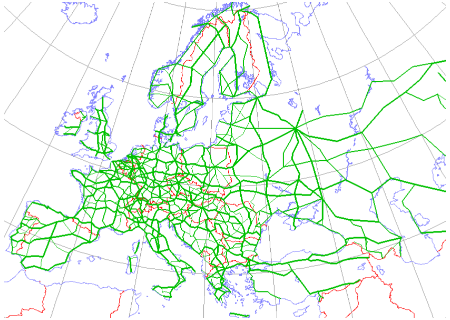
Outline

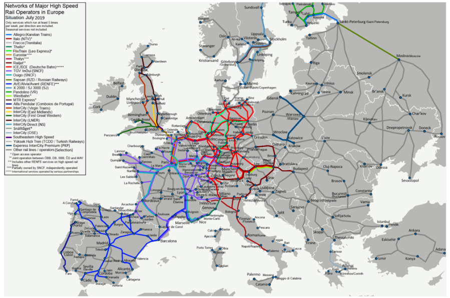
1. **Introduction - Getting familiar with mobility data**
2. **Pre-processing mobility data**
   - Cleansing, Simplification, Enrichment, Sampling, etc.
3. **Analyzing mobility data**
   - Cluster analysis (group behavior) and outlier detection
   - Collective behavior discovery
   - Trajectory prediction
4. **Summary**

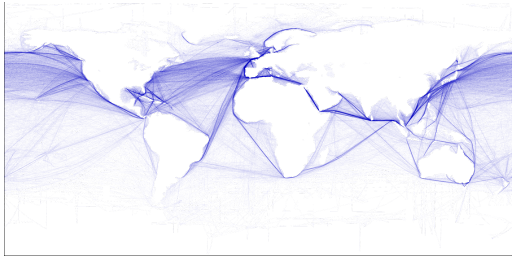
1.
Introduction –
Getting to know mobility data

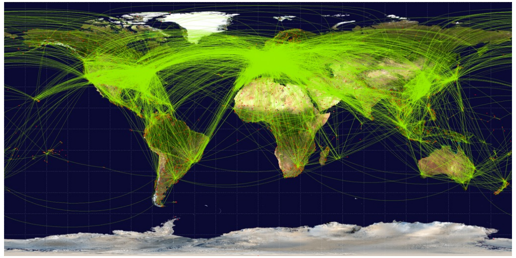
Application domains

- **Road network**: Find shortest path from location A to location B; Which points of interest (POIs) are found in a range of 5 km from A?
- **Railway network**: Find the number of stops on the stop A to stop B route; Which stops that are reachable from stop A in 2 hrs. time horizon?
- **Air (sea) path network**: Find the flights from airport (seaport) A to airport (seaport) B with direct connection (or at most 1 intermediate stop)









All images source: Wikipedia.org

Examples of datasets @ land

- **GeoLife** (source: Microsoft Research Asia)
  - 182 user movements (under various transportation means) organized in 17,621 trajectories;
  - 68 Km in 2,7 hrs. per trajectory, avg.;
  - dense sampling (1 sample every ~5 sec)
- **T-Drive** (source: Microsoft Research Asia):
  - 2,357 taxis in Beijing for 1 week (15 million points, in total);
  - 869 Km per taxi, avg.;
  - sparse sampling (1 sample every ~3 min)

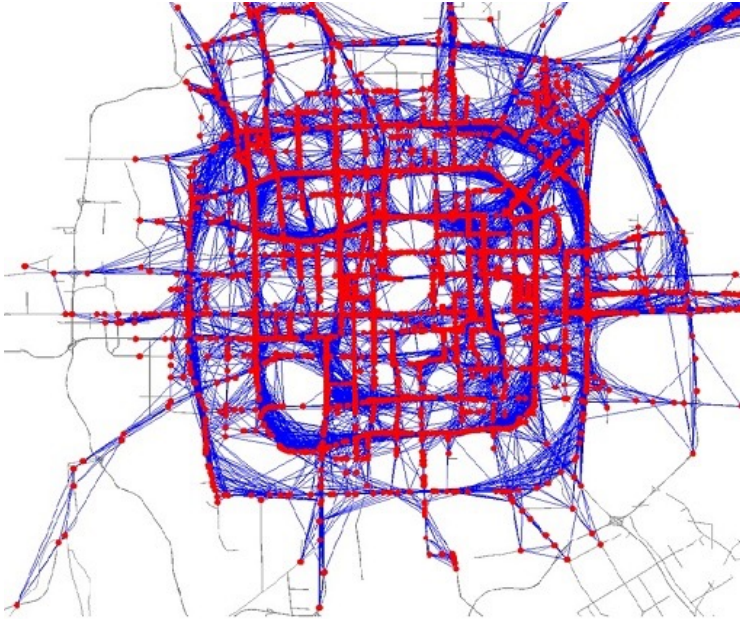
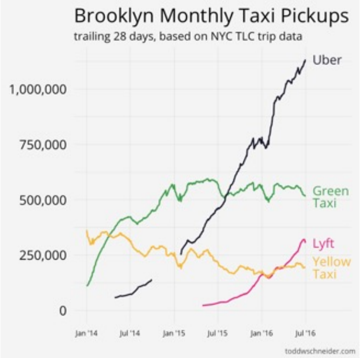


image source: research.microsoft.com

Examples of datasets @ land (cont.)

- **NYC taxis** (source: NYC Taxi & Limousine Commission): 1.4 billion trips, Jan. 09 – Dec.17.
  - **Ride-hailing apps** data are also provided
  - Attention: pickup – drop-off locations are only available



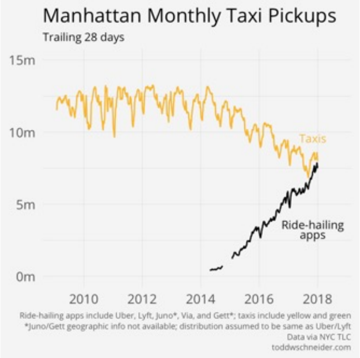
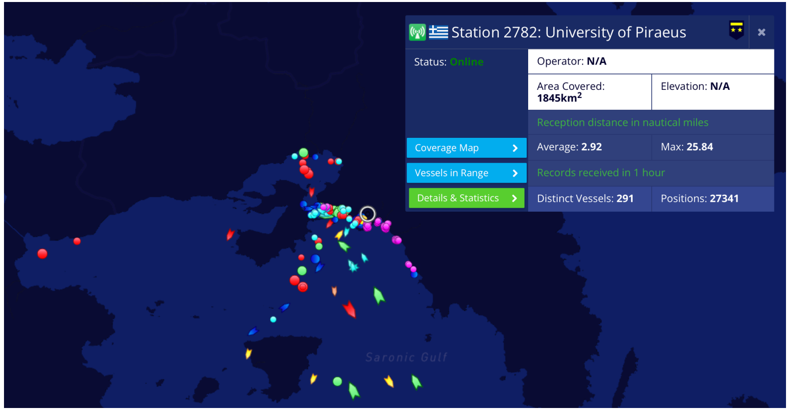


image source: toddwschneider.com

Examples of datasets @ sea

- **AIS** (Automatic Identification System)
  - >250,000 vessels tracked daily (source: marinetraffic.com)
  - AIS signal transmitted: every 2 to 10 sec depending on speed while underway; every 3 min while at anchor



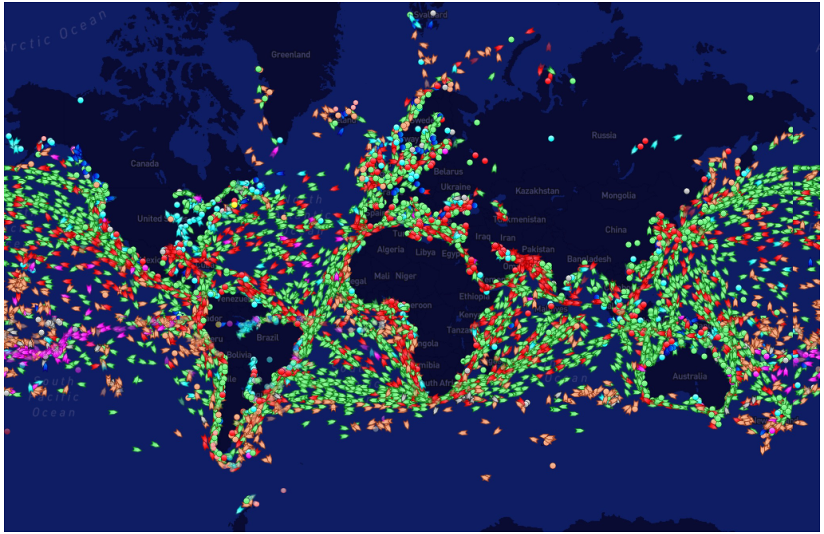


image source: marinetraffic.com

- top: global snapshot on May 26th, 2022; vessel colors correspond to different vessel types (e.g., cargo is green, tanker is red)
- left: vessels tracked by the Univ. Piraeus' AIS station

Examples of datasets @ air

- **ADS-B** (Automatic Detection System - Broadcast)
  - >15,000 aircrafts flying at the same time worldwide (source: flightradar24.com)
  - ADS-B signal transmitted: every 1 sec while on air; not transmitted while on the ground

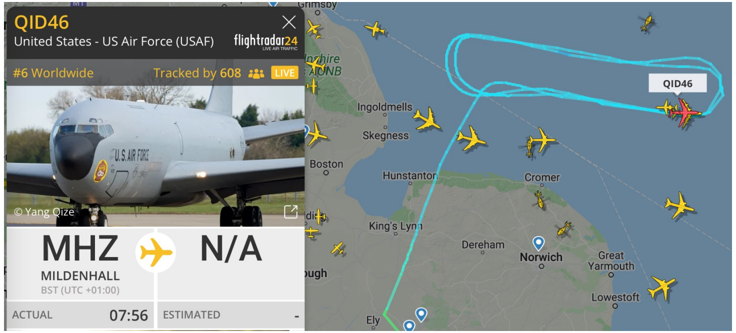


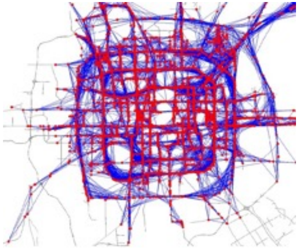
image source: flightradar24.com

- top: global snapshot on May 25th, 2022; yellow vs. blue planes if located by terrestrial vs. satellite stations
- left: the route of a military aircraft

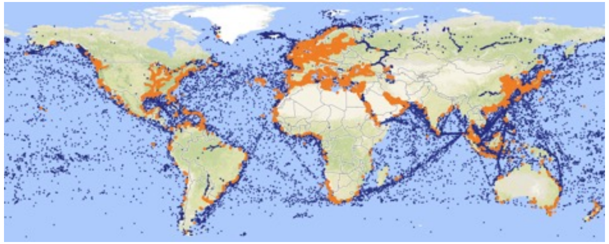
Learning from mobility data

- Examples:
  - Find objects that **move together** (for long time)
  - Find the **most typical** among objects' routes as well as the <u>outliers</u>
  - Find the **most crowded** places or routes
  - **Forecast** the anticipated route of an object or traffic in an area,

  etc.



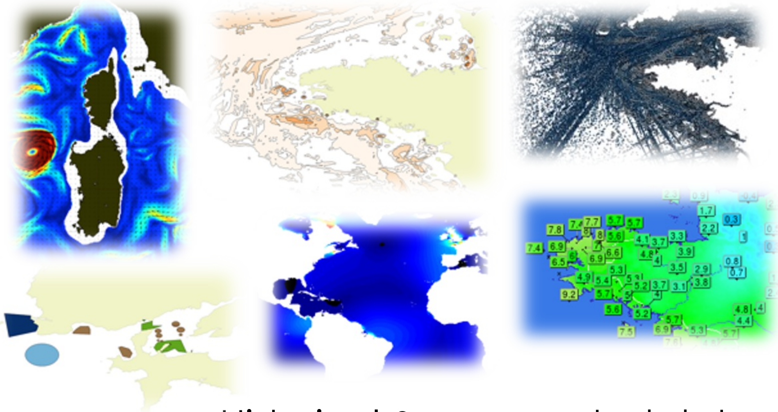
- Big Data problem!



Big Data challenges

Volume
Velocity

12K distinct ships/day, 200M AIS signals/month in EU waters



Variety

Historical & aggregated data, geographical & environmental data, contextual data, etc.

Veracity

Noisy and error-prone data due to receivers limited coverage, positioning devices switch-off

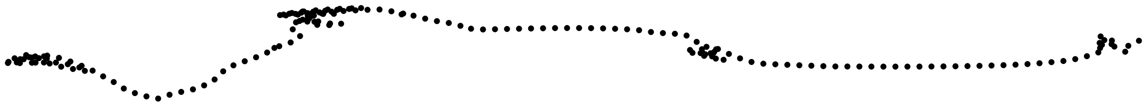
Image source: (Claramunt et al. 2017)

2.
Pre-processing mobility data

Data pre-processing

- Definition: **preparing data for analytics purposes**

$$T = \{ <p_1, t_1>, <p_2, t_2>, \ldots, <p_n, t_n> \}$$

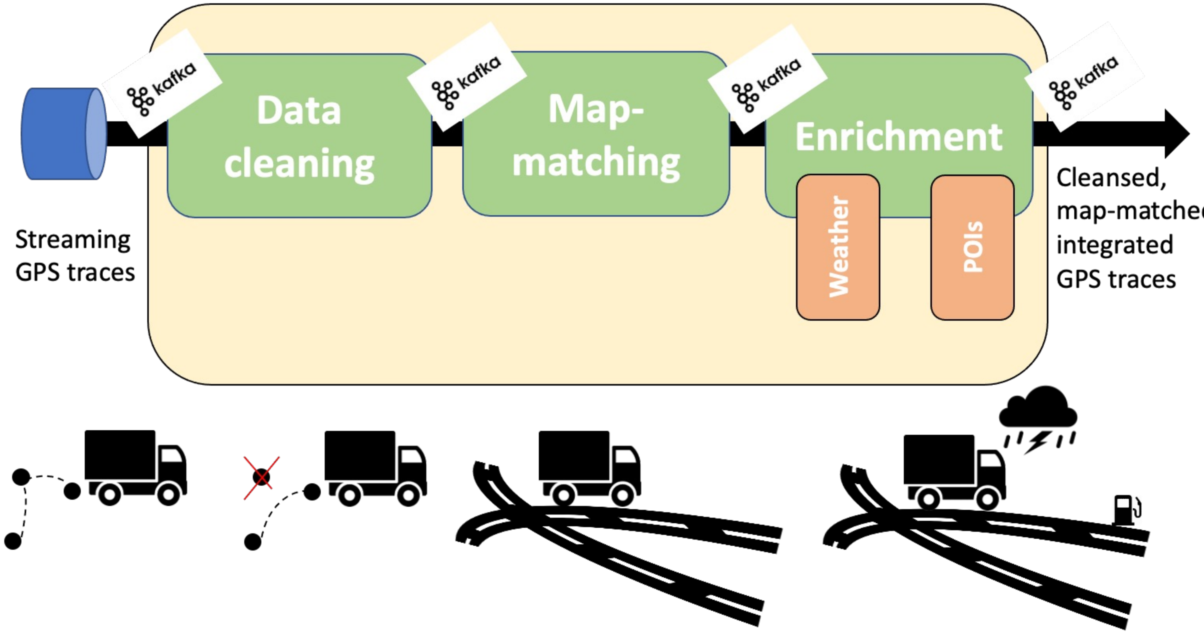


- Data pre-processing includes:
  - **Cleansing** (noise removal, smoothing, map matching, etc.)
  - **Transformation** (trajectory segmentation, simplification, etc.)
  - **Enrichment** (semantic annotation, data fusion, etc.)

  etc.

Data pre-processing (cont.)

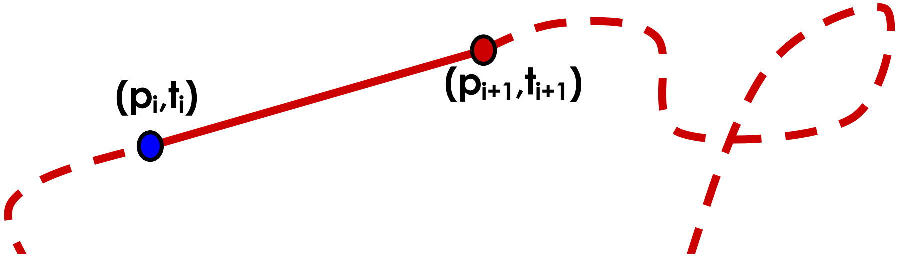
- An example: **data pre-processing pipeline (urban traffic)**



Source: Track & Know EU project

From GPS locations to trajectories

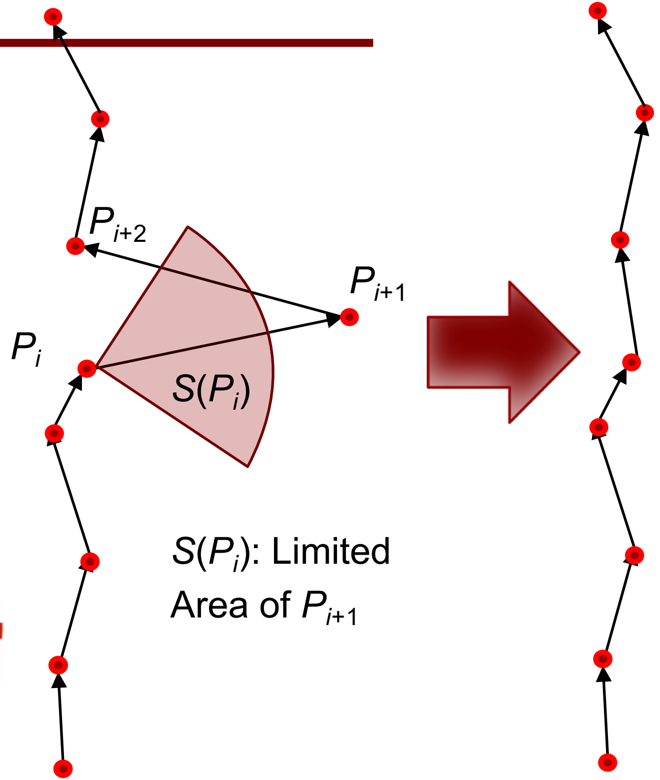
- GPS records correspond to **samples** (p_i, t_i) of our movement – inferring 'continuous' movement is not trivial.
- A typical representation of a moving object's trajectory is a **polyline** (in 4D space; x-, y-, z-, t-) – vertices correspond to (p_i, t_i)
- Typically, **linear interpolation** is assumed between (p_i, t_i) and (p_{i+1}, t_{i+1})



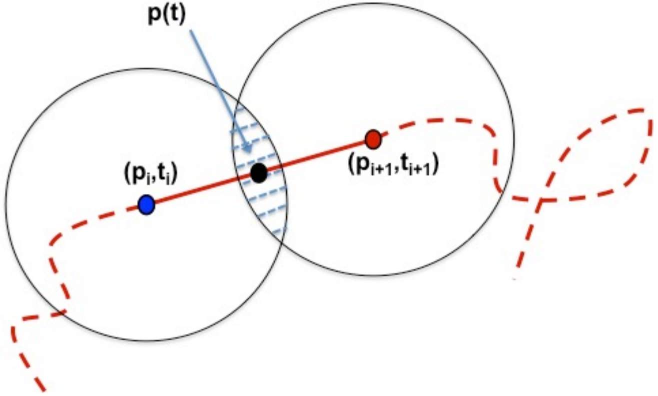
$$p(t) = \left(x_i + \frac{t - t_i}{t_{i+1} - t_i}(x_{i+1} - x_i), y_i + \frac{t - t_i}{t_{i+1} - t_i}(y_{i+1} - y_i) \right)$$

GPS Data Cleansing

- Erroneous recordings: noise vs. random errors
- **Noise** corresponds to values that are 'impossible' to appear
- Can be detected and removed using appropriate filters
  - e.g., maximum speed

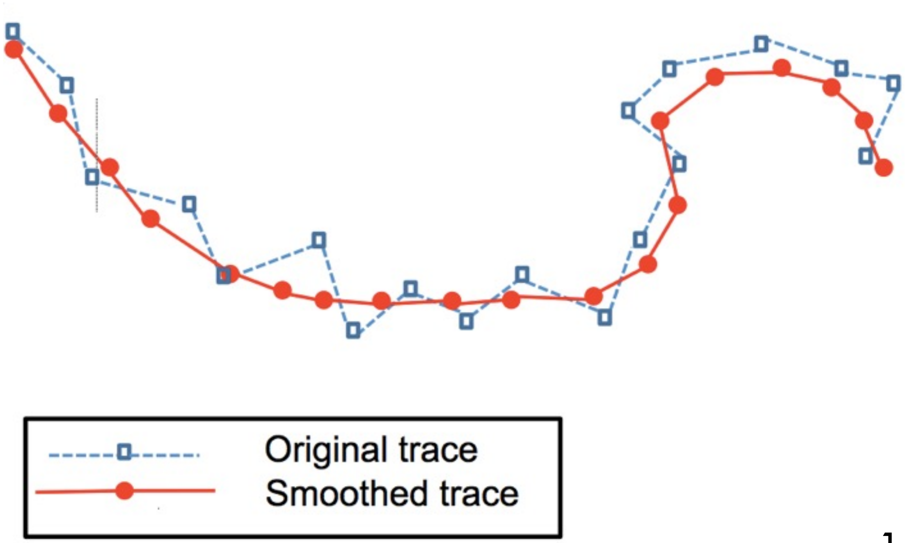


- **Potential Area of Activity** (PAA)



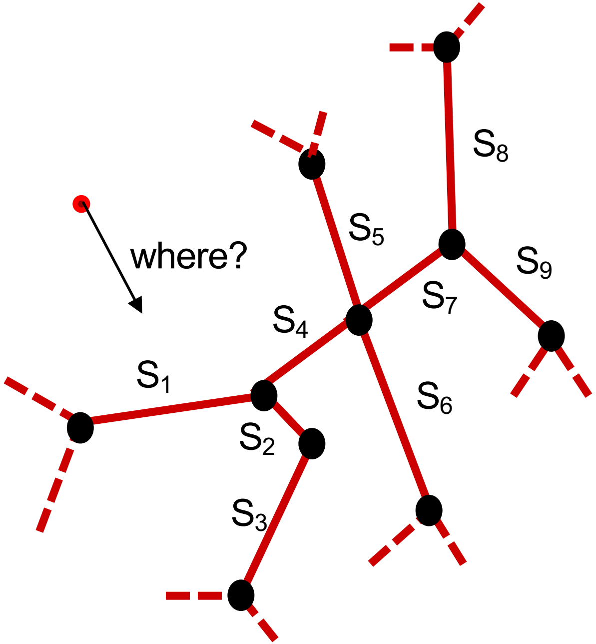
GPS Data Cleansing (cont.)

- Erroneous recordings: noise vs. random errors
- **Random errors** correspond to ‘possible’ values that appear to be small deviations from actual ones
- Can be smoothed using a plethora of statistical methods
  - e.g., least squares spline approximation (de Boor, 1978)



GPS Data Cleansing (cont.)

- Special case: network-constrained movement
- Requires an additional step: **map-matching**
- Several techniques (Quddus et al. 2003; 2007):
  - Geometric map-matching
  - Topological map-matching
  - Probabilistic map-matching
  - Hybrid map-matching



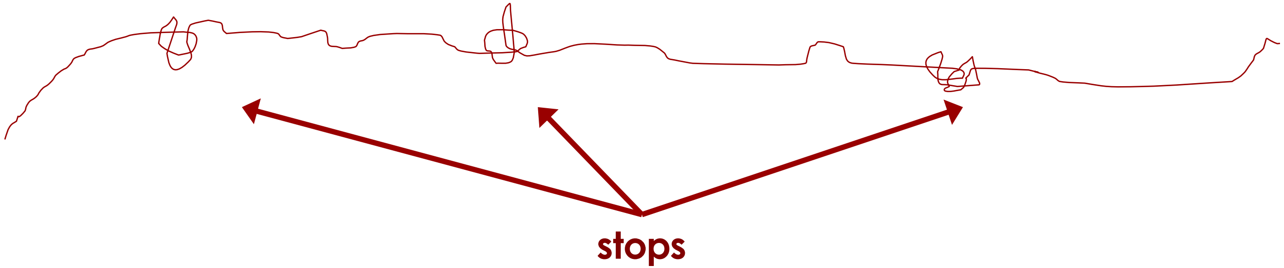
Trajectory segmentation

- Goal: **Segment sequences of points** in homogeneous sub-sequences (called **trajectories**)

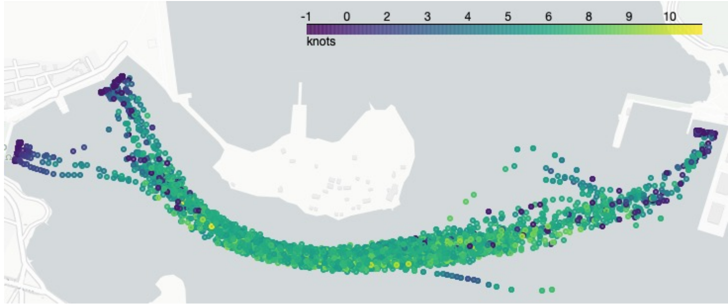
- Various approaches:
  - Segmentation via raw (spatial / temporal) gap
  - Segmentation via stop discovery
  - Segmentation via prior knowledge (e.g., office / sleeping hours, arrival at ports)
  - etc.

Trajectory segmentation (cont.)

- One possible solution: Segmentation via stop discovery (Alvares et al. 2007)



- Technical issue (when stop places are not given): **how to 'learn' stop places from trajectories?**
  - A typical approach: extract stationary points (i.e., those with speed close to zero) and then, perform density-based clustering



Example: speed of ferry boats serving the line connecting Salamis island (left) and Piraeus/Perama port (right)

Trajectory simplification

- The need for simplification: efficiency in storage, processing time, etc.
  - Actually, simplification is a form of data compression
- Goal: maintain the original 'signature' as much as possible by keeping a set of **critical points** only
- Approaches
  - Offline, i.e., multi-pass, vs.
  - Online, i.e., 1-pass

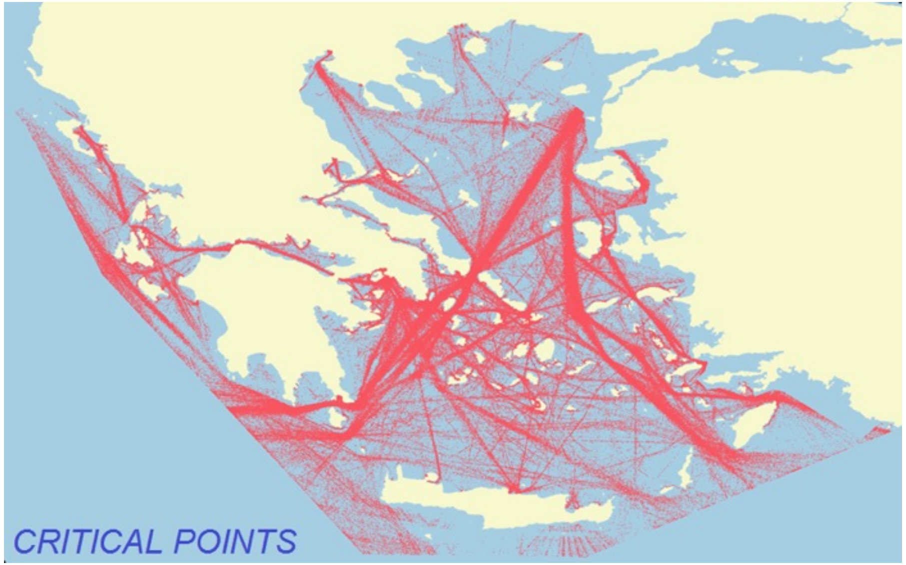


image source: aminess.eu

Trajectory simplification (cont.)

- Offline approaches:
  - top-down vs. bottom-up vs. sliding window vs. opening window
- e.g., **Synchronous Euclidean Distance – SED** (Meratnia & de By, 2004)
  - Adapts the popular Douglas & Peucker polyline simplification (1973) to the mobility domain

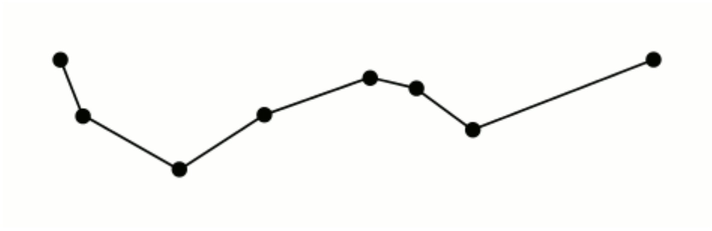
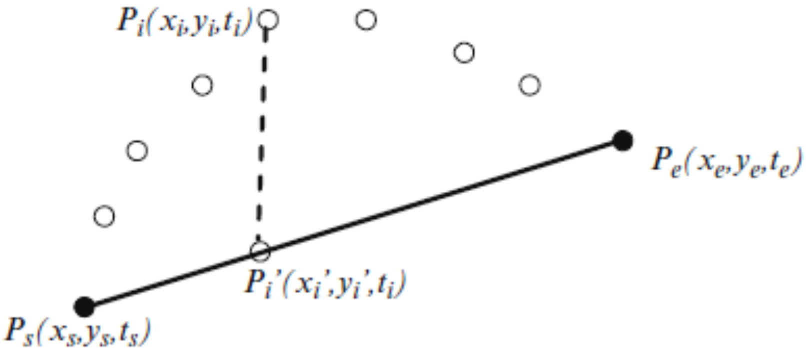
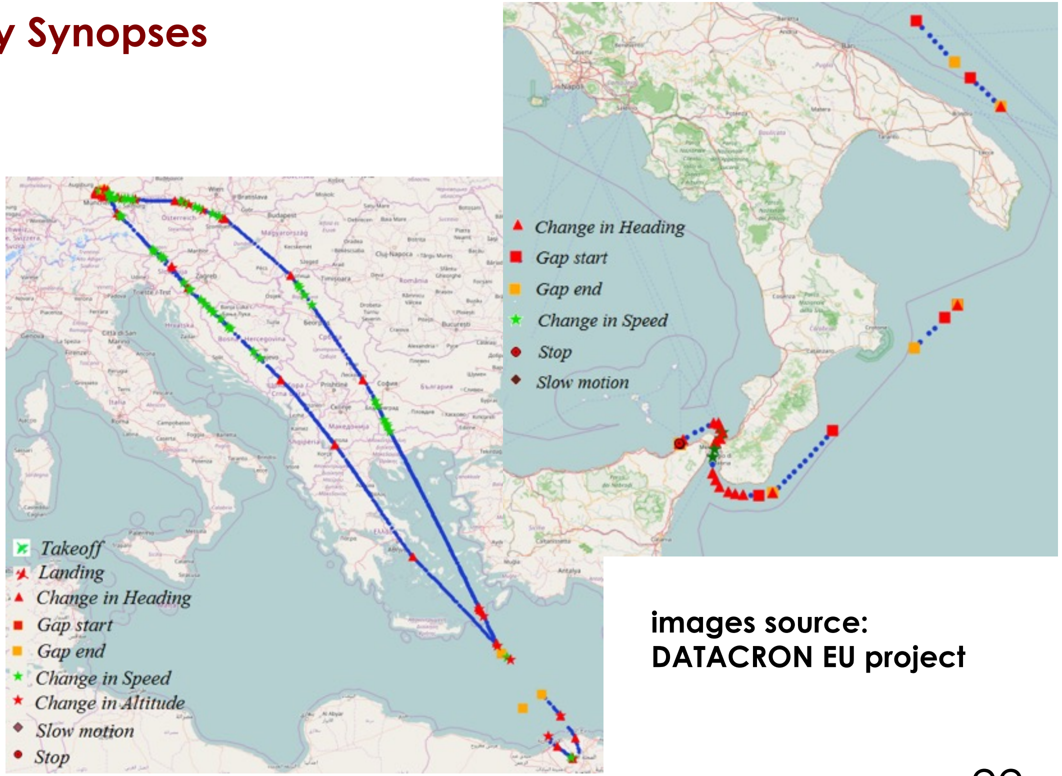


image source: https://commons.wikimedia.org/wiki/File:Douglas-Peucker_animated.gif



Trajectory simplification (cont.)

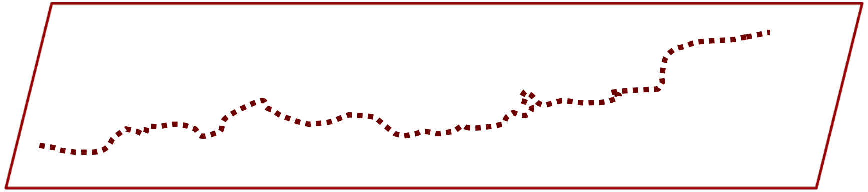
- Online approaches, e.g., **Trajectory Synopses** (Patroumpas et al. 2015; 2017)
- Maintains a **velocity vector** per moving object in order to detect **instantaneous events**
  - stop; change in velocity vector; etc.
- Tradeoff: degree of compression vs. quality of approximation



images source: DATACRON EU project

Trajectory enrichment

- From “raw” sequences (p,t) of time-stamped locations
- … to meaningful mobility tuples <where, when, what/how/why>
- **Semantic trajectory** (Yan et al. 2011; 2012, Parent et al. 2015)
  - semantically-annotated representation of the motion path of a moving object
  - **sequence of episodes (stops/moves)** along with appropriate **tags**



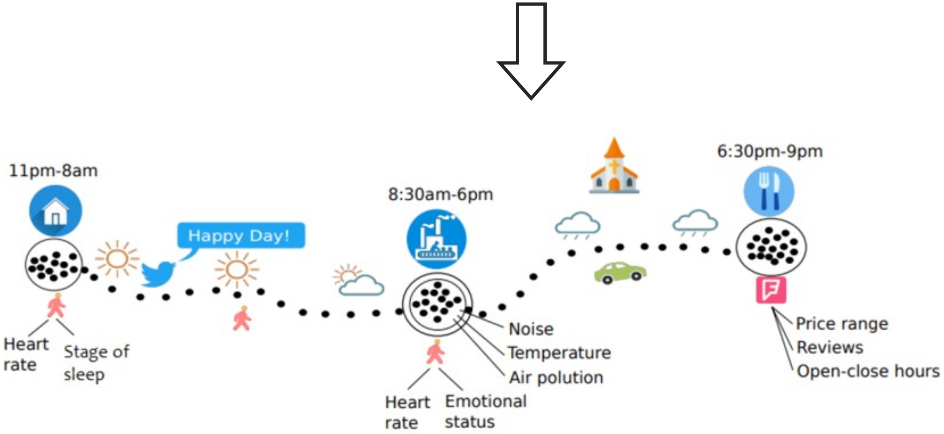
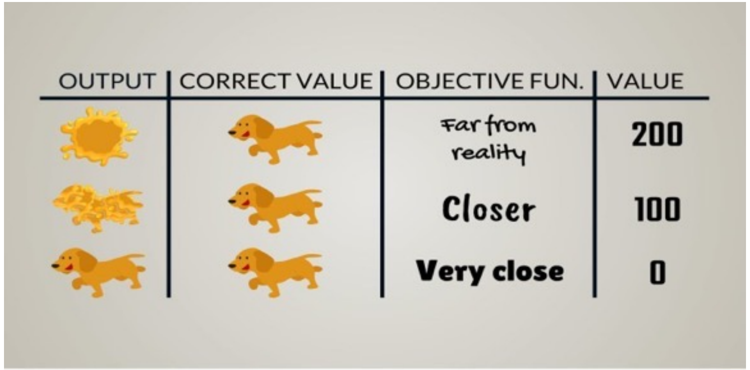


Image source: MASTER EU project

3.
Analyzing mobility data

Types of mobility data analytics

- Discovering **groups** and **outliers**
- Discovering **frequent routes** (hot paths) and **frequent locations** (hot spots)
- **Trajectory prediction** tasks, etc.



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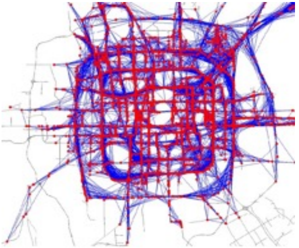
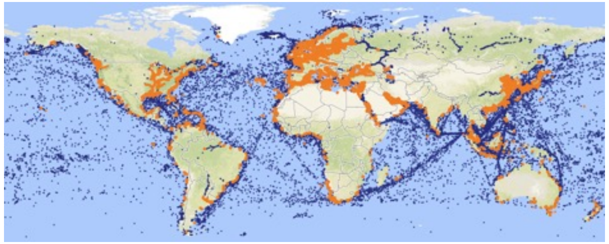
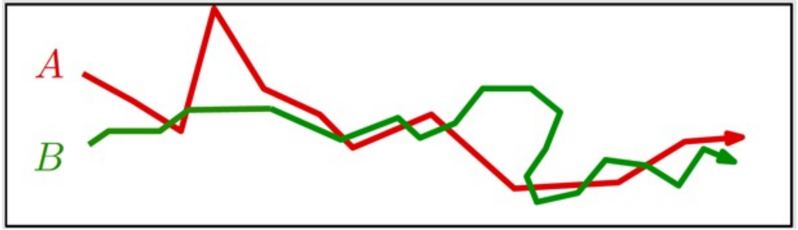




Orthogonal issue: Trajectory similarity

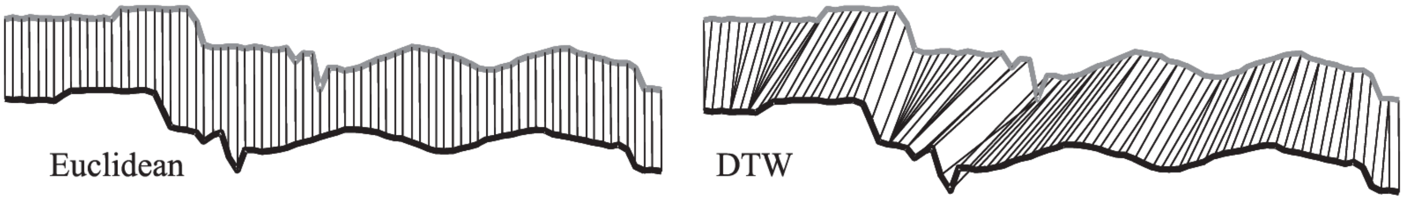
- How do we measure **similarity** between two trajectories A, B?
  - not so trivial as it sounds



- Alternative approaches:
  - Trajectory as a 2D time-series
  - Trajectory as a 2D polyline
  - Trajectory as a movement function

Trajectory as a time series

- Time series similarity has been studied extensively (e.g., Vlachos et al. 2002; Chen et al. 2005). Examples:
  - Euclidean distance, Chebyshev distance, Dynamic Time Warping (DTW),
  - Longest Common SubSequence (LCSS),
  - Edit Distance on Real sequences (EDR),
  - Edit distance with Real Penalty (ERP), etc.



Trajectory as a polyline

- **DISSIM** (Nanni & Pedreschi, 2006; Frentzos et al. 2007)
  - Extension of Euclidean distance:

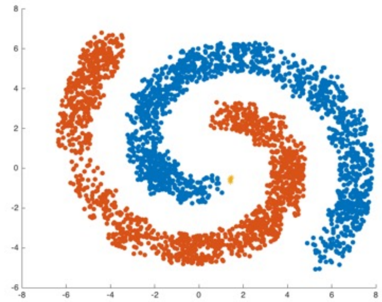
$$DISSIM(R,S) = \int_{t_1}^{t_n} L_2\big(R(t), S(t)\big)dt$$

$$DISSIM(R,S) \approx \frac{1}{2}\sum_{k=1}^{n-1}\Big(\Big(L_2\big(R(t_k), S(t_k)\big) + L_2\big(R(t_{k+1}), S(t_{k+1})\big)\Big) \cdot (t_{k+1} - t_k)\Big)$$

  - DISSIM function is a metric
    - Conditions: (1) non-negativity; (2) identity of indiscernibles; (3) symmetry; (4) triangle inequality

1. $d(x,y) \geq 0$
2. $d(x,y) = 0 \Leftrightarrow x = y$
3. $d(x,y) = d(y,x)$
4. $d(x,z) \leq d(x,y) + d(y,z)$

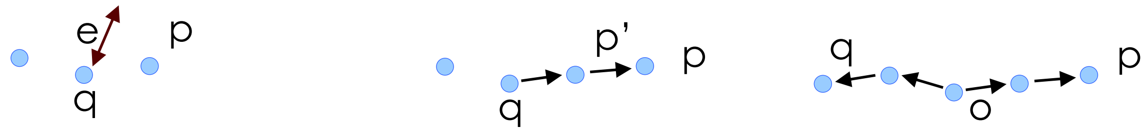
Point clustering



- **DBSCAN** (Ester et al. 1996): A density-based algorithm for discovering clusters in large spatial databases with noise
- Method parameters:
  - radius of an object's neighborhood (e)
  - minimum population within an object's neighborhood (m)
- Cores (build clusters) vs. Borders (assigned to their cores' clusters) vs. Noise

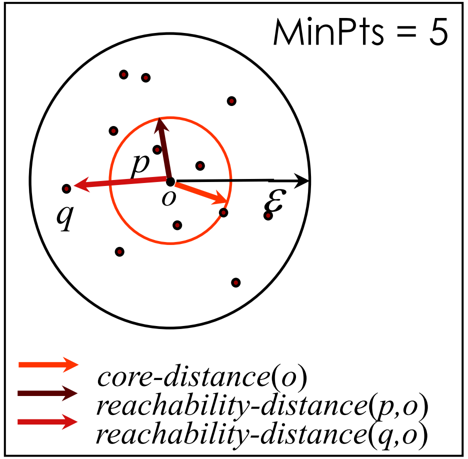
- The notion of **density reachability**
  - Directly Density-Reachable vs. Density-Reachable vs. Density Connected

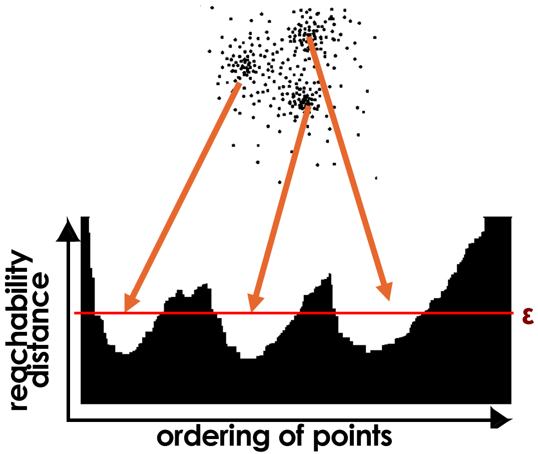
m = 3

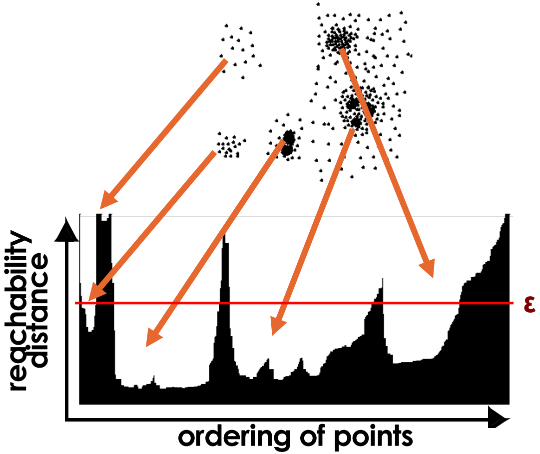


Point clustering (cont.)

- **OPTICS** (Ankerst et al. 1996): ordering points to identify the clustering structure
- The notions of **core distance** and **reachability distance**
- **Reachability plot**: partitions the dataset in a sequence of '**valleys**' (==> clusters) and '**hills**' (==> outliers)







Trajectory clustering

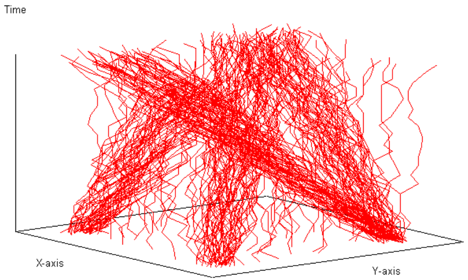
- Objectives:
  - Cluster trajectories w.r.t. similarity
  - Eventually, detect outliers
- Issues:
  - Which similarity function?
  - Upon the entire trajectories or portions (sub-trajectories?

- State-of-the-art:
  - Clustering on the entire trajectories: **T-OPTICS** (Nanni & Pedreschi, 2006)
  - Clustering on sub-trajectories: **TraClus** (Lee et al. 2007); **S²T-Clustering** (Pelekis et al. 2017a; 2017b), **DSC** (Tampakis et al. 2019)

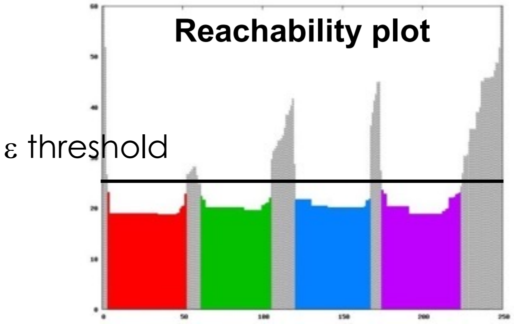
Clustering on the entire trajectories

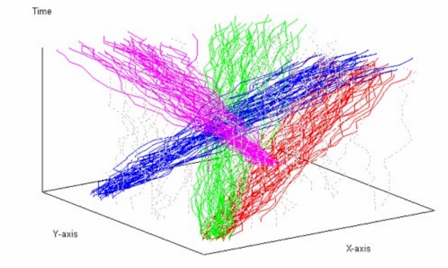
- T-OPTICS (Trajectory OPTICS) (Nanni & Pedreschi, 2006)
  - Builds upon OPTICS (Ankerst et al, 1999) and DISSIM distance function

$$DISSIM(R,S) = \int_{t_1}^{t_n} L_2(R(t), S(t))dt$$



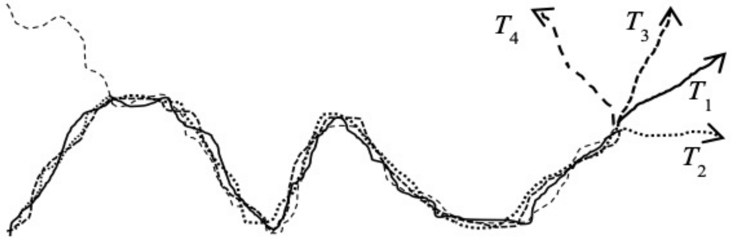
  - The **reachability plot** produces "valleys" and "hills"
    - Valleys → clusters; Hills → outliers (noise)
    - Recall that DISSIM is a metric → indexing is allowed



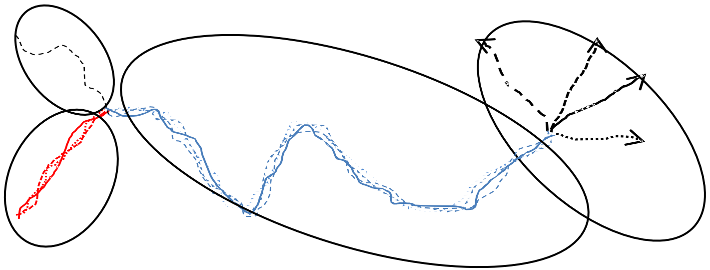


Clustering on the sub-trajectories

- Motivation: how many clusters are formed by these four trajectories? zero? one?
  - What if we consider sub-trajectories?



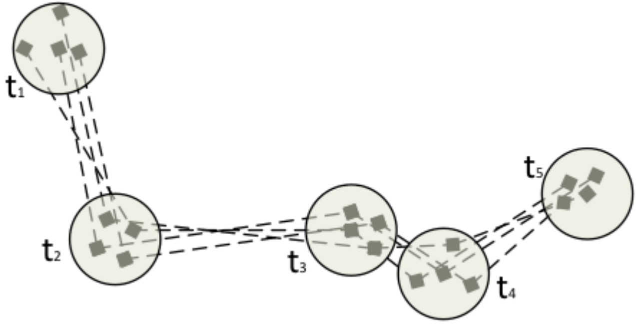
- Two recent solutions:
  - **S²T-Clustering** (Sampling-based Sub-Trajectory Clustering) (Pelekis et al. 2017a; 2017b)
  - **Distributed Subtrajectory Join** (Tampakis et al. 2020) and **Clustering** (Tampakis et al. 2019)

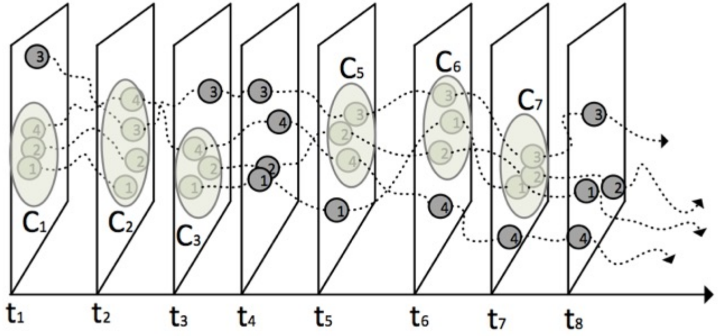


Discovering collective mobility behavior

- Detecting a large enough subset of objects moving along paths close to each other for a certain time. Main approaches:
  - Spherical-like clustering: **Flocks** (Laube et al. 2005; Gudmundsson & van Kreveld, 2006) vs.
  - Density-based clustering: **Convoys** (Jeung et al. 2008); **Swarms** (Li et al. 2010), etc.
  - Hybrid: **Evolving Clusters** (Tritsarolis et al. 2021)

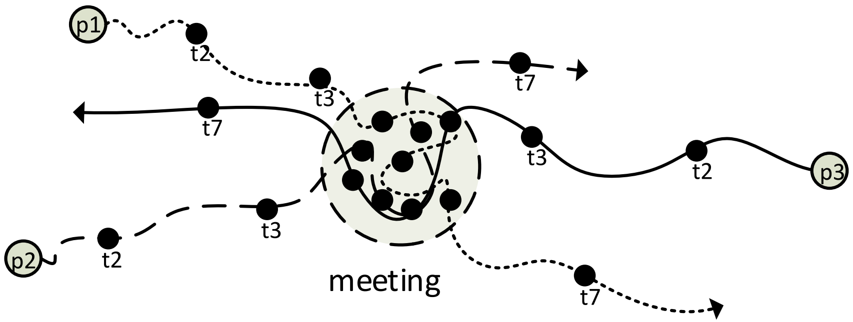
- Note: these methods work on time-aligned location sequences → need for fixed re-sampling

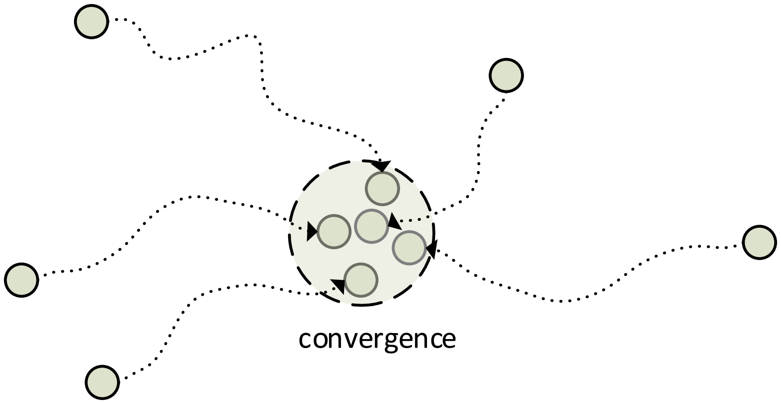




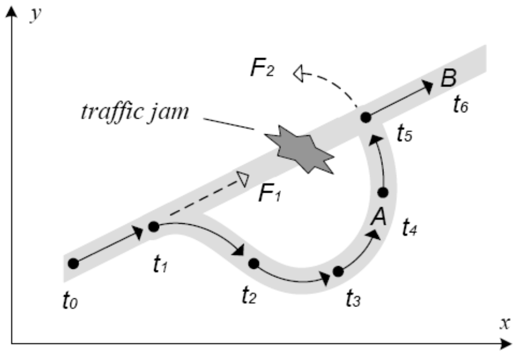
Flocks and variants

- Interesting applications of the flock/convoy pattern discovery:
  - Identify long flock patterns (**top-k longest flock pattern discovery**)
  - Discover **meetings** (fixed- vs. varying- versions)
  - Discover **convergences**
  - Discover **leaders** and **followers**

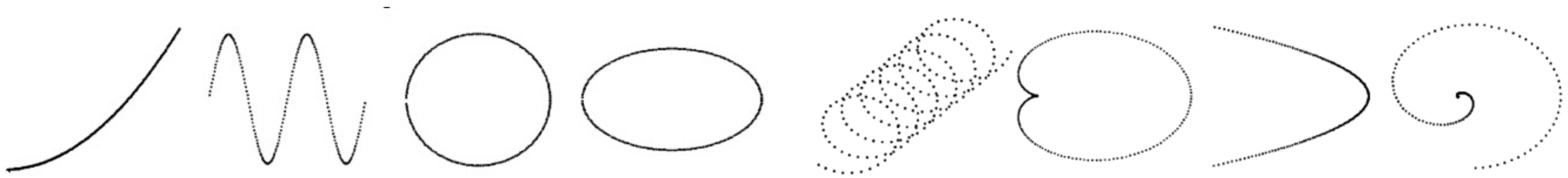




Location / Trajectory prediction



- **Prediction** aims to predict the future location(s) of (or even the entire trajectory to be followed by) a moving object.
- Two main approaches: **Formula-** vs. **Pattern-based** prediction
  - Motion function models, e.g., RMF (Tao et al. 2004)
  - vs. patterns built upon the history, e.g., Personal profiles (Trasarti et al. 2017)
  - A survey of 50+ methods: (Georgiou et al. 2018)



Location / Trajectory prediction (cont.)

- **MyWay** (Trasarti et al. 2017) maintains a Personal Mobility Data Store (PMDS) per participating person
  - How is a person moving?
    - According to his/her past movement patterns
  - What if the personal datastore is not adequate?
    - Look into the collective knowledge base
- 3 predictors: personal (red), collective (blue), hybrid (green)

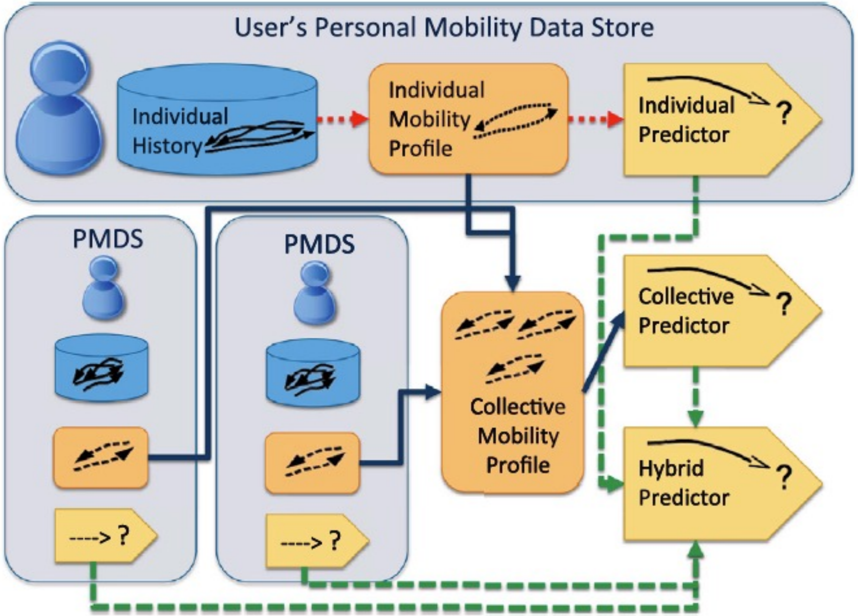
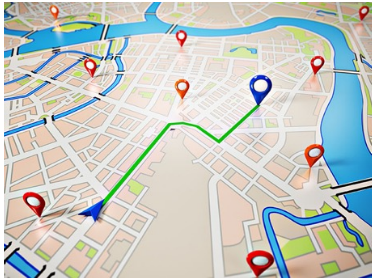


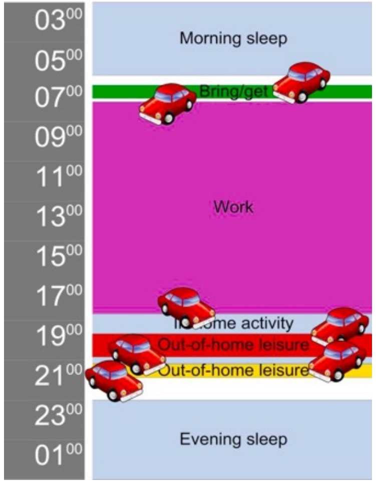
image source: kdd.isti.cnr.it

5.
Summary

Summary

- The **Mobility Data Analytics** field (Pelekis & Theodoridis 2014) includes many success stories on:
  - **Data management** - access methods & query processing techniques, DBMS extensions (the so-called, Moving Object Databases), etc.
  - **Data mining** – clusters, flocks, convoys, hot spots, etc.
- The new era that has emerged this decade is around two keywords:
  - **Semantically-enriched trajectories** (Parent et al. 2013): information about when, where, what, how, why
  - **Extreme-scale mobility data processing** (Vouros et al. 2018): voluminous, streaming, disperse information about objects' movement





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- **Track & Know** – Big Data for Mobility Tracking Knowledge Extraction in Urban Areas. 2018-20 [trackandknowproject.eu]
- **MASTER** – Multiple Aspect Trajectory Management and Analysis, 2018-22 [master-project-h2020.eu]
- **datAcron** – Big Data Analytics for Time Critical Mobility Forecasting, 2016-18 [datacron-project.eu]
- **DART** – Data-Driven Aircraft Trajectory Prediction Research. 2016-18 [dart-research.eu]

The Data Science Lab @ UniPi.GR

Our research agenda:

- Extreme-scale mobility data processing
- Mobility data analytics at the (edge/fog/cloud) compute continuum
- Time series analytics & forecasting
- Data fusion & semantic integration
- etc.

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