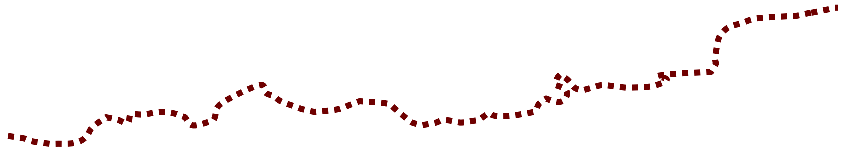
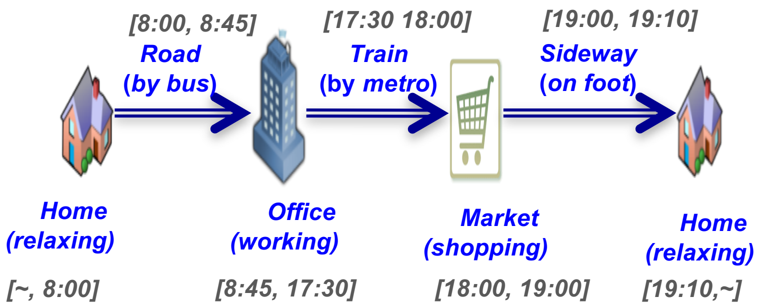
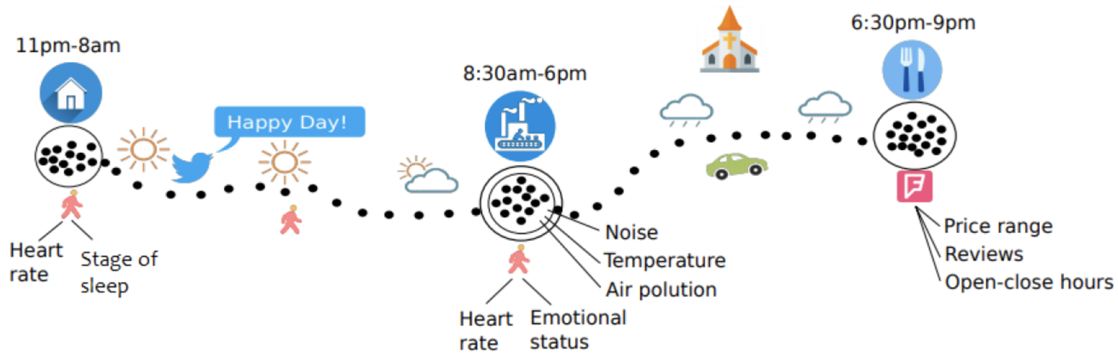
Trajectory enrichment

- From “raw” …
  - sequences of time-stamped locations (p,t)



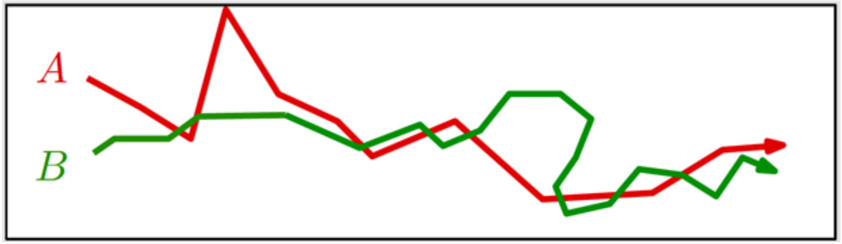
- … to context-enriched trajectories, i.e. meaningful mobility tuples about where, when, what, how, why, etc.
  - **Semantic trajectories** (Yan et al. 2011; 2012, Parent et al. 2015)
  - **Multi-aspect / holistic trajectories** (Mello et al. 2019, Soares at al. 2019)



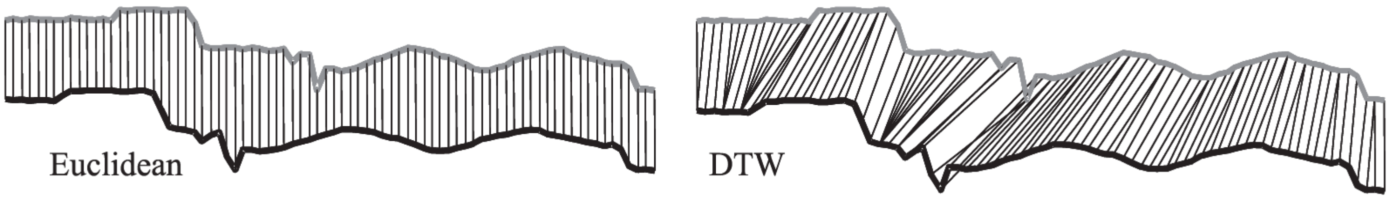


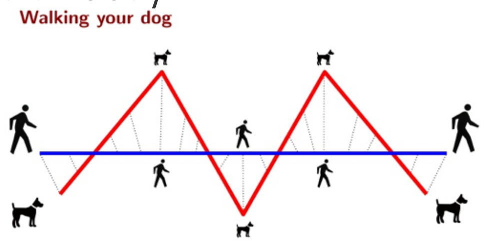
Trajectory Similarity

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



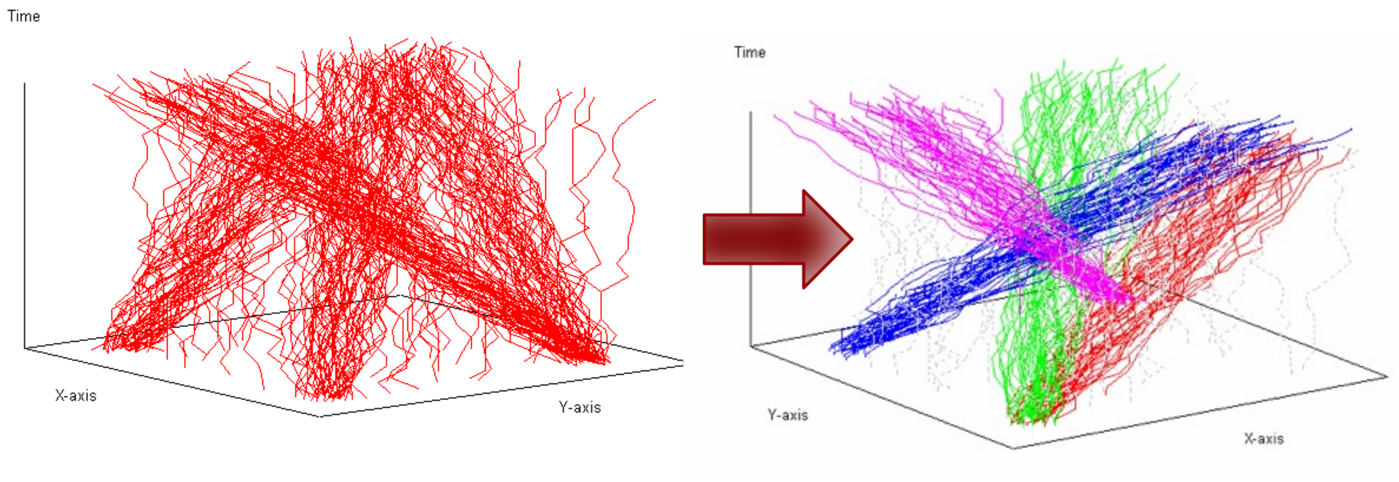
- Various approaches:
  - Trajectory as a **k-D time-series**, e.g. DTW, LCSS, EDR, ERP (Vlachos et al. 2002; Chen et al. 2005)
  - Trajectory as a **k-D polyline**, e.g. DISSIM distance function (Nanni & Pedreschi, 2006; Frentzos et al. 2007)
  - Trajectory as a **movement function**, e.g. Fréchet distance (Buchin et al. 2009)





Trajectory clustering

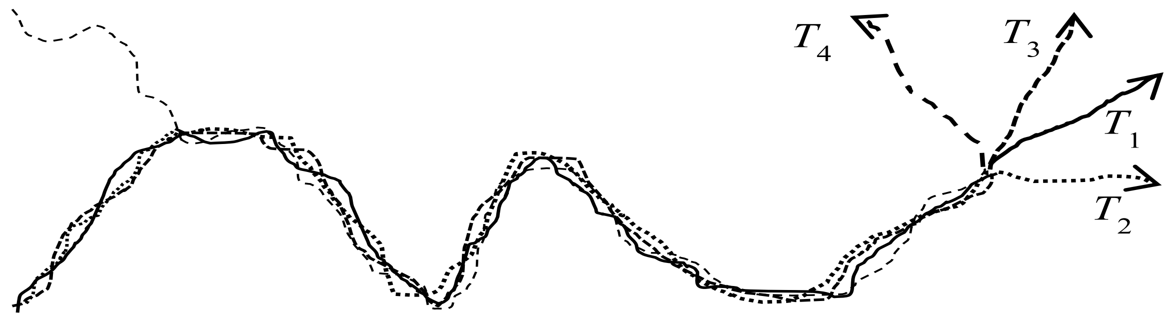
- Objectives: Cluster trajectories w.r.t. similarity; eventually, detect outliers

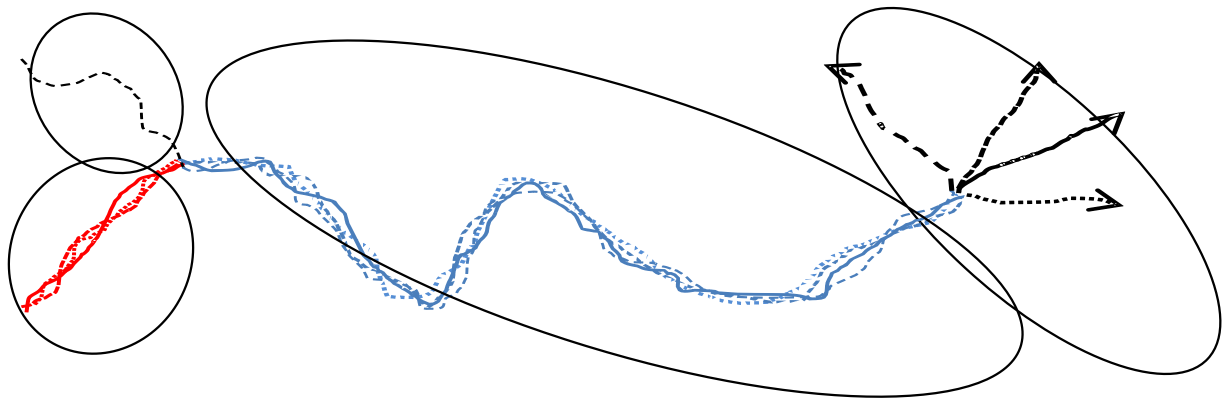


- Examples:
  - Clustering on entire trajectories: **T-OPTICS** (Nanni & Pedreschi, 2006)
  - Clustering on sub-trajectories: **TraClus / TraOD** (Lee et al. 2007; 2008); **S²T-Clustering** (Pelekis et al. 2017a; 2017b)

Sub-trajectory clustering

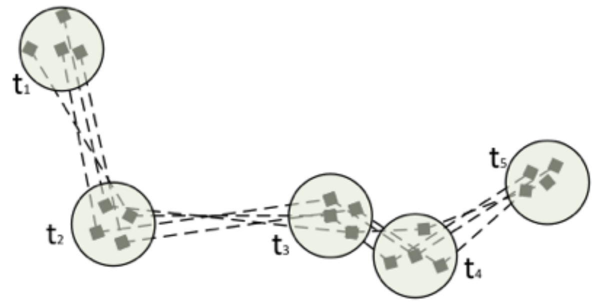
- Motivation: how many clusters (and outliers) are formed by trajectories $T_1 \ldots T_4$?
  - 1 cluster (0 outliers)?
  - 0 clusters (4 outliers)?
- What if we work at sub-trajectory level?
- Challenge: how can we detect the appropriate sub-trajectories?

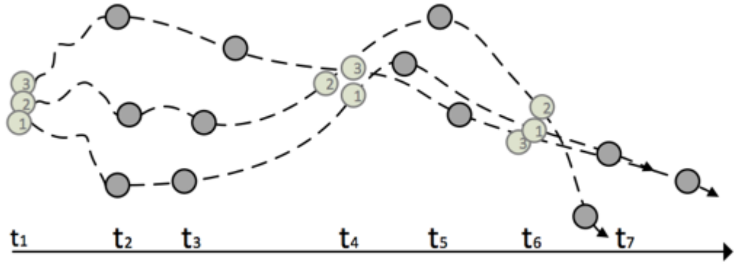




Detecting group movement behavior

- Several variants
  - Spherical-like clustering: **Flocks** (Laube et al. 2005; Gudmundsson & van Kreveld, 2006)
  - Density-based clustering: **Convoys** (Jeung et al. 2008); **Swarms** (Li et al. 2010), etc.
  - Generic solutions: **Co-movement patterns** (Fan et al. 2016; Chen et al. 2019)

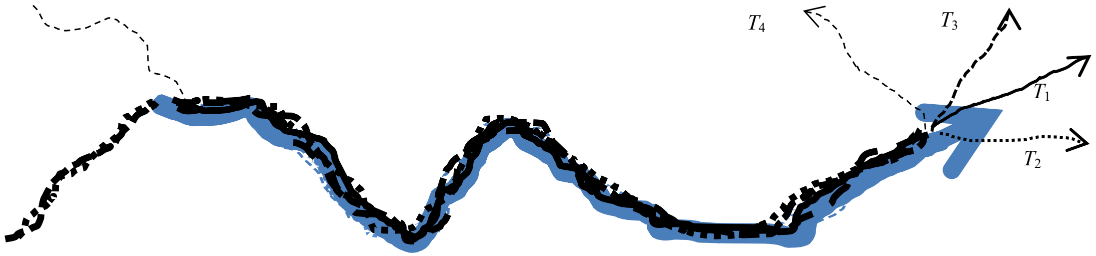




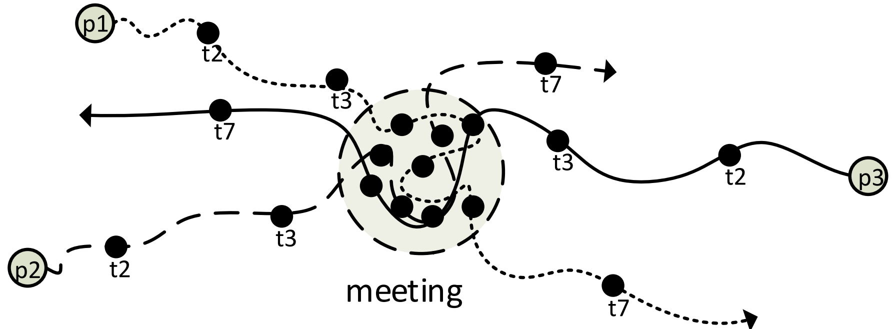
- Note: they work on time-aligned location sequences
  - recall fixed re-sampling preprocessing task

Frequent pattern mining

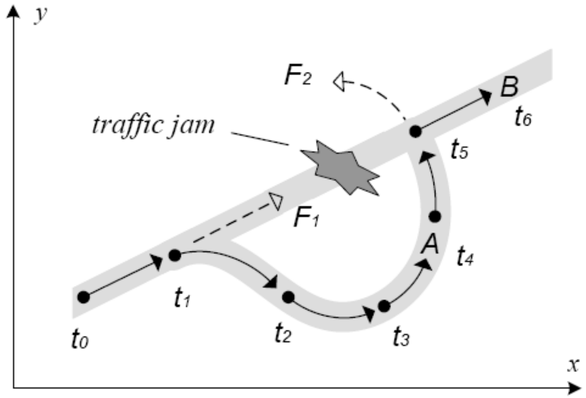
- Technical objective: identify 'frequent' or 'popular' patterns
  - Patterns could be routes (hot paths, etc.) or places (hot spots, etc.)



- Approaches:
  - techniques that identify regularities in the behavior of a single user, e.g. **Periodic patterns** (Cao et al. 2007)
  - techniques that reveal collective sequential behavior of a set of users, e.g. **T-Patterns** (Giannotti et al. 2007)

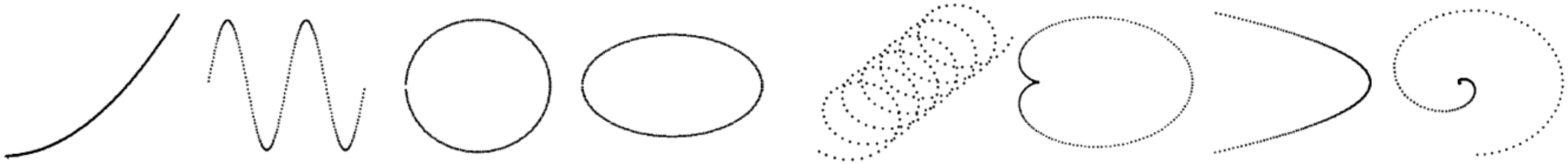


Trajectory Prediction



- **Predict** the future location(s) or even the entire trajectory of a moving object (Georgiou et al. 2018)

- **Formula-based** prediction: linear, polynomial, etc. extrapolation
  - Motion function models, e.g. RMF (Tao et al. 2004)



- **Pattern-based** prediction: patterns built upon historical information
  - e.g. Sequential patterns (Monreale et al. 2009), Personal profiles (Trasarti et al. 2017)

1. About movement data

2. A flashback to the past

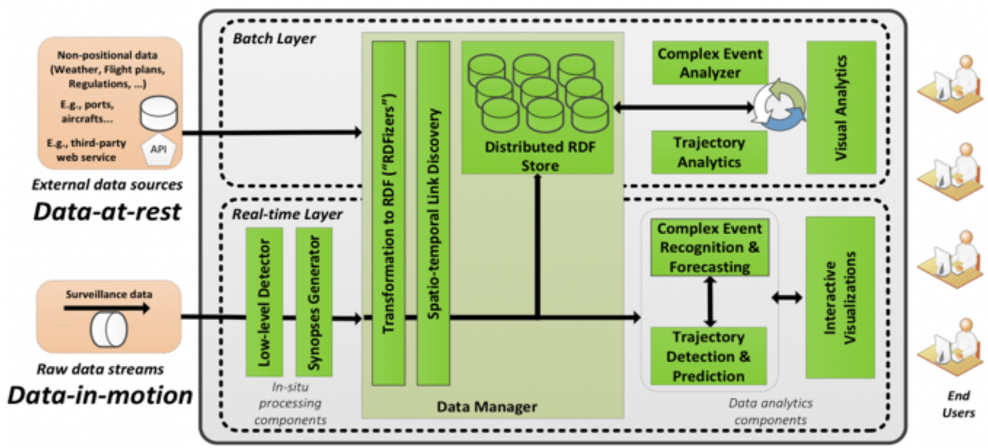
3. Mobility data analytics pipeline

4. A real-world use case

A real-world MDA example

- The problem: **data-driven aircraft trajectory prediction** *
  - … instead of model-based prediction
  - Data sources available include aircraft surveillance data (from multiple sources), flight plans, air space zones, weather info, etc.
- **H2020 project datAcron** system architecture (Claramunt et al. 2017; Vouros et al. 2018)

* For the following slides, credits to all datAcron partners, especially BRTE and CRIDA (aviation use case)



Data-driven aircraft trajectory prediction

- a flight is on the way; **when** and **where** is it expected to reach a specific **status** (e.g. 'top of climb', 'top of descent', 'touch down')?
- Ultimate goal: perform this operation for **every flight** in the globe at **real-time**