ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

UNIVERSITY OF PIRAEUS

DATA STORIES

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Mobility Data Science: Perspectives and Challenges

Mokbel, M., Sakr, M., Xiong, L., Züfle, A., et al.

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Mobility Data Science: Perspectives and Challenges

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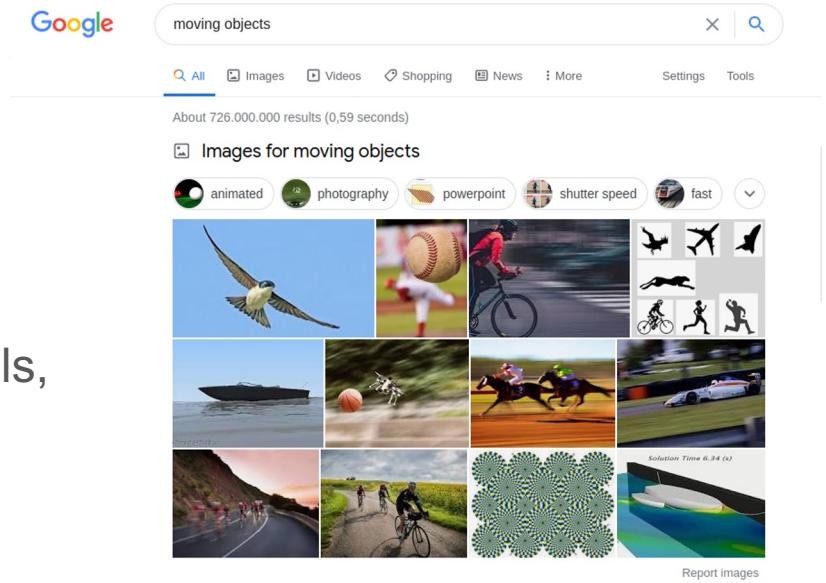
contributed equally to this research. The seminar was held in the week of January 9 - 14 , 202
topics: data management, mobility analysis, geography, privacy, urban computing, systems,
integration, and theory. Due to COVID-19, the seminar took place in hybrid mode, with 8
challenge of different time zones of the participants, all sessions were attended by at least 37

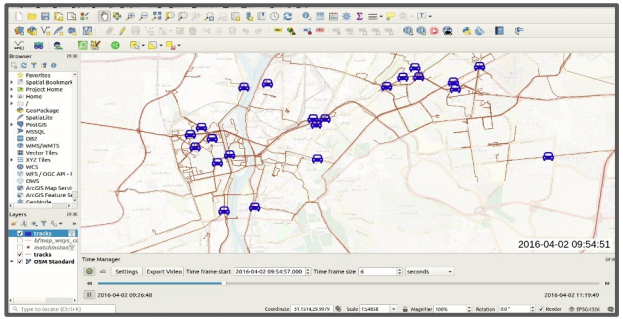
Moving Objects



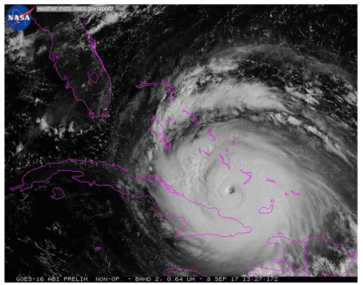
Informal definition: **Moving objects are objects that move in the space over time**

- **points** that change location (e.g., animals, sport players, vehicles, drones, …)
- **regions** that change location and, eventually, extent (hurricanes, etc.)

Most common sources: sensors (GPS), as well as radar, bluetooth, RFID, etc.



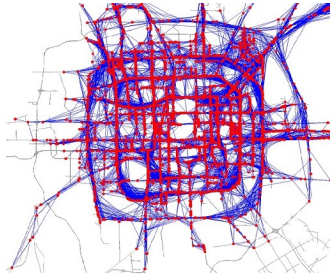
(source: mobilitydb.com)



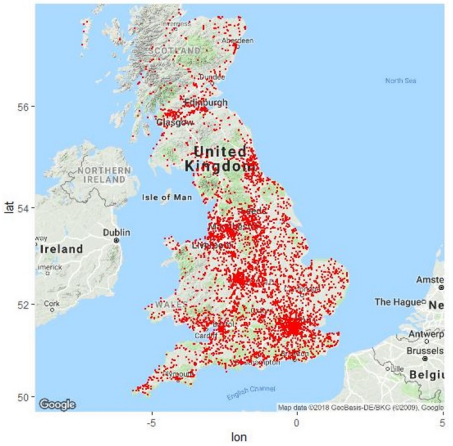
(source: giphy.com)

Examples of Mobility Data

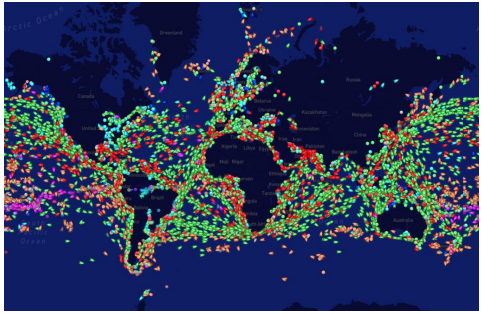
- ➔ Transportation (urban/maritime/aviation)
- ➔ Movement in indoor environments
- ➔ Location-Based Social Networking (LBSN), etc. etc.



T-Drive Urban traffic data
(source: research.microsoft.com)

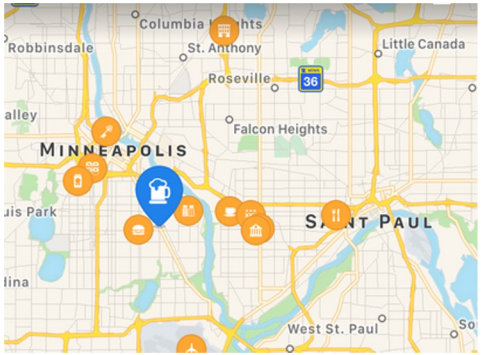


UK road accidents 2012-14
(source: kaggle.com)



Marine transportation data
(source: marinetraffic.com)

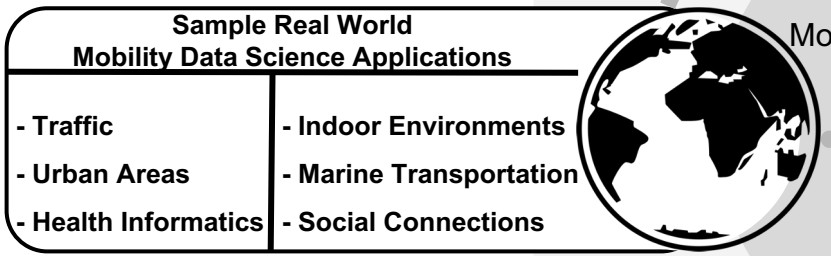
Aviation data
(source: flightradar24.com)

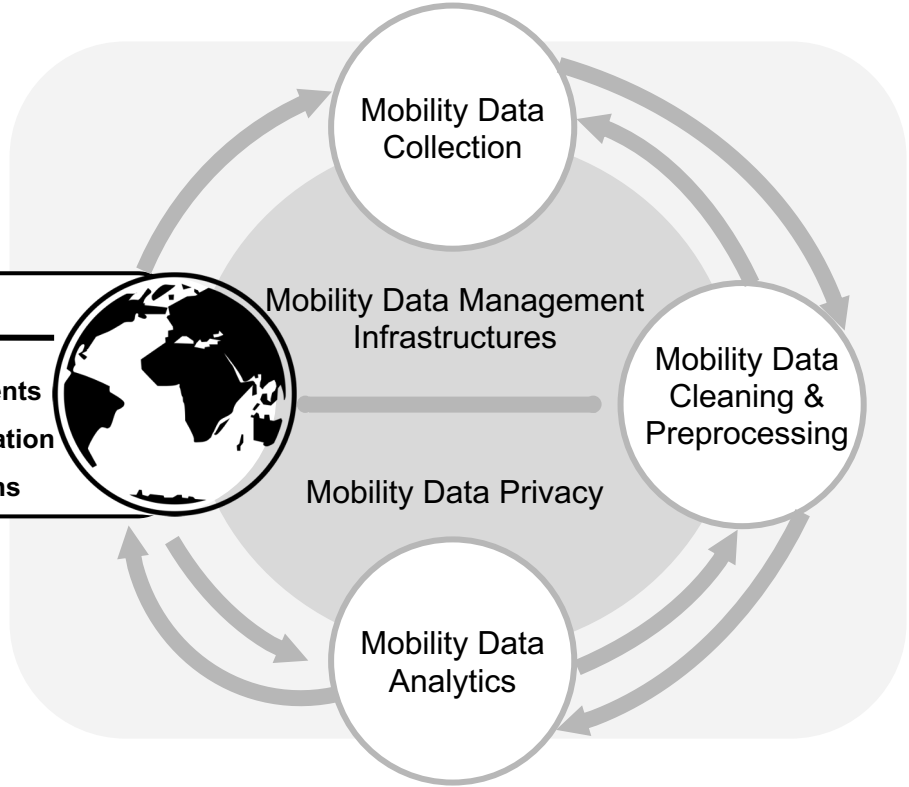


Foursquare check-ins
(source: foursquare.com)

“Mobility Data Science” Definition

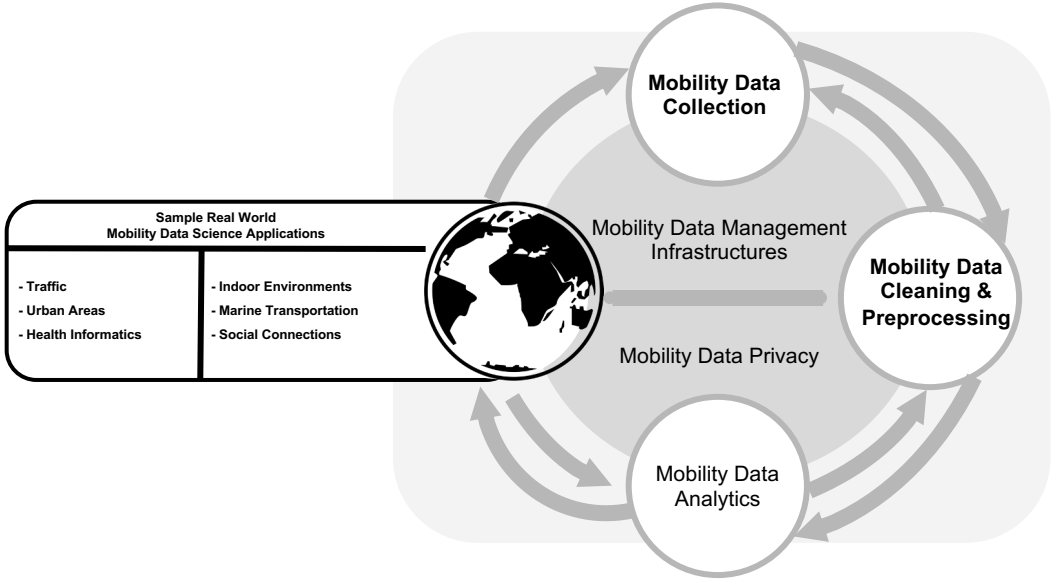
An **interdisciplinary** field that uses scientific **methods**, **processes**, **algorithms** and **systems** to extract or extrapolate **knowledge and insights** from potentially noisy, structured and unstructured **mobility data**, and apply knowledge from mobility data across a broad range of application domains





The Mobility Data Science pipeline

I. Mobility Data Collection, Cleaning & Preprocessing
II. Mobility Data Analytics and Data Management Infrastructures
III. Mobility Data Privacy



Open Mobility Data (1/2)

Trajectory datasets in the **urban domain** are limited to **small** size datasets, e.g.:

- **RioBuses** (Rio de Janeiro, Brazil): 12K trajectories (buses), 118M points, 1 month period, 1 min. sampling rate
- **Grab-Posisi** (Singapore): 84K trajectories (vehicles), 89M points, 1 month period, 1 sec. sampling rate
- **GeoLife** (Beijing, China): 17K trajectories (mixed), 26M points, 3 years period, 1-5 sec. sampling rate
- **RomaTaxi** (Rome, Italy): 320 trajectories (taxis), 21M points, 1 month period, 7 sec. sampling rate

Why do we call them “small”?

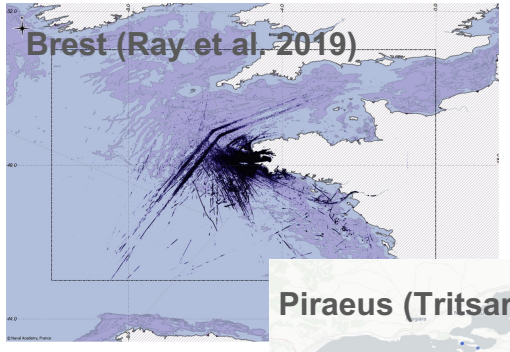
Other urban datasets only include **origin/destination** of each trajectory, e.g.,

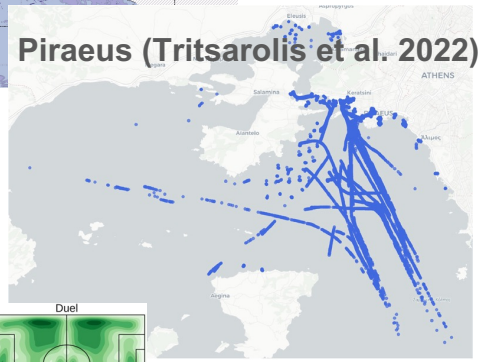
- **NYC Cabs** (New York City, NY, USA): 1.4 billion trips, 9 years period

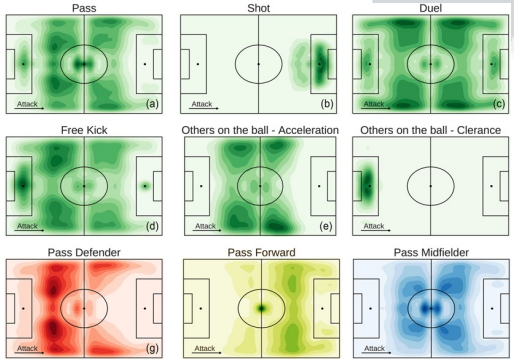
Open Mobility Data (2/2)

Other than road network- constrained datasets:

- **Maritime AIS data** (+metadata), e.g.:
  - Brest, France: 19M points (6 months)
  - Piraeus, Greece: 244M points (32 months)
- **Sport** (basketball, soccer, etc.) data
  - Wyscout soccer dataset: ~3M time-stamped and geo-positioned events during ~2K matches



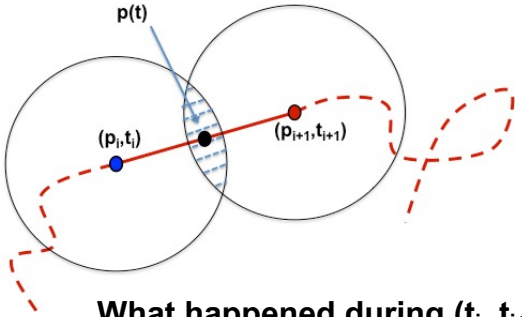




Soccer data (Pappalardo et al. 2019)

The Need for Mobility Data Preprocessing

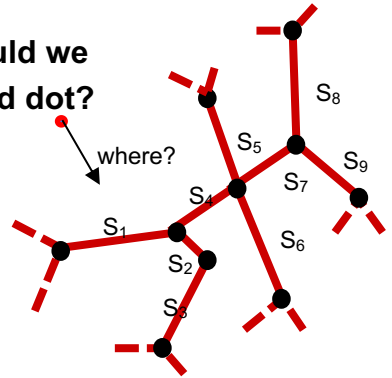
- GPS device inaccuracy; noise in data transmission; uncertainty of moving objects whereabouts between two recorded locations; etc.



What happened during (t_i, t_{i+1})?
Potential Area of Activity (PAA)

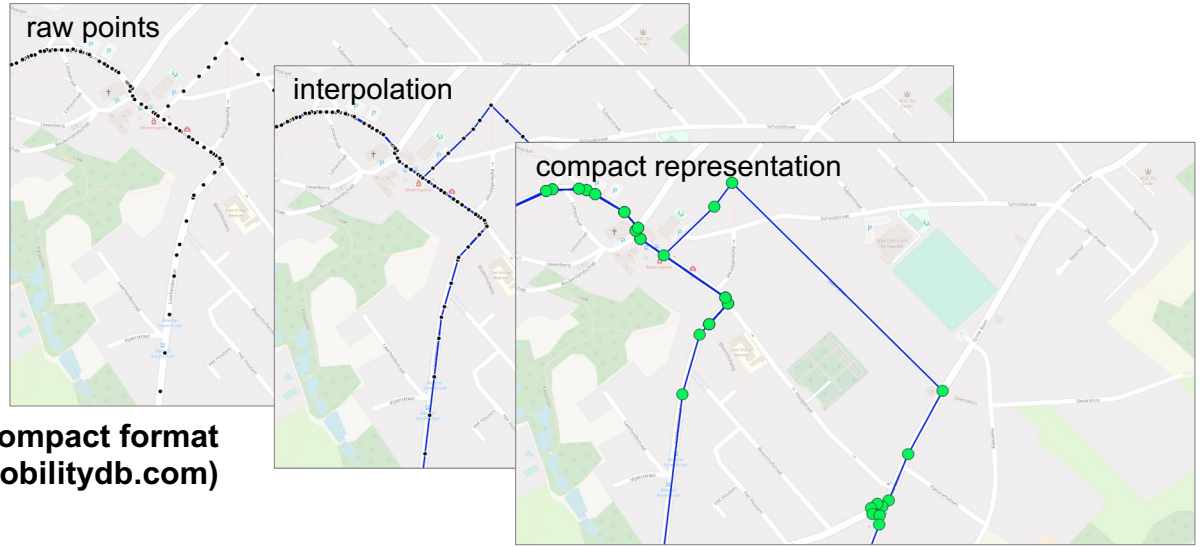
Noise in ADS-B Flight Aware positions during takeoff of an aircraft (examine the sequence of the timestamps)

Where should we place the red dot?



Typical Preprocessing Pipeline

1. Noise elimination
2. (if network-constrained data) Map matching
3. (if trajectory-oriented analysis) Gap filling, Trajectory segmentation
4. Data enrichment



From raw points to a compact format (source: mobilitydb.com)

Challenges in Mobility Data Collection & Prep.

1. **Mobility data privacy**
    - *tradeoff between fine granularity detailed mobility data and privacy*
2. **Mobility data bias**
    - *equitable, fair actions and policies based on mobility data science results*
3. **Incentives for data sharing**
    - *incentives to drivers to share their mobility traces, even for sporadic trips*
4. **Simulated mobility data**
    - *work with social scientists to create realistic individual-level human mobility data*
5. **Inaccuracy in the movement space infrastructure**
    - *map inference algorithms that go beyond inferring the map topology to inferring map metadata*
6. **Filling in temporal mobility gaps**
    - *scalable, fine-grained imputations that mimic a continuous trajectory data stream*

I. Mobility Data Collection, Cleaning & Preprocessing

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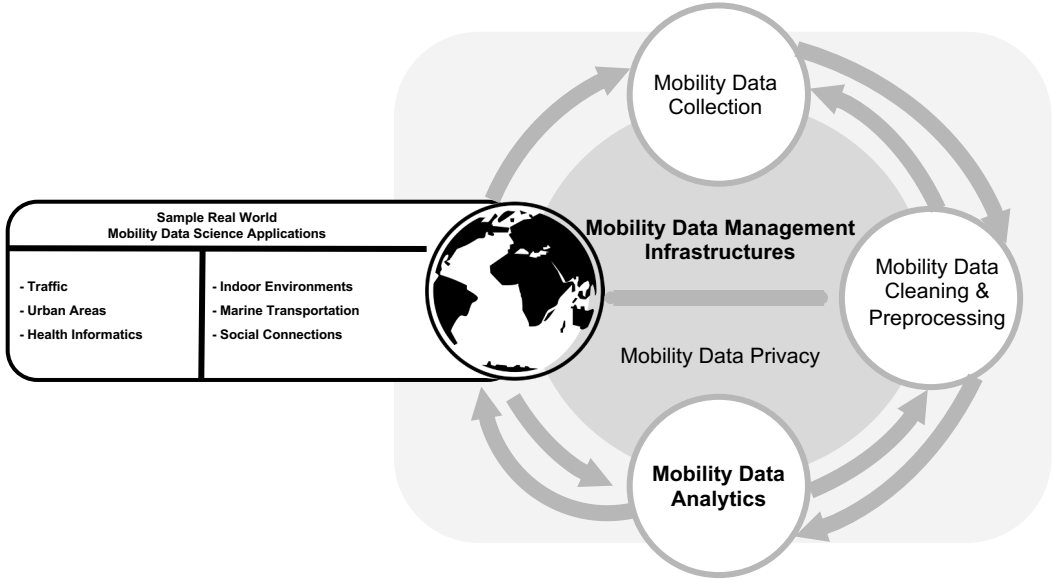
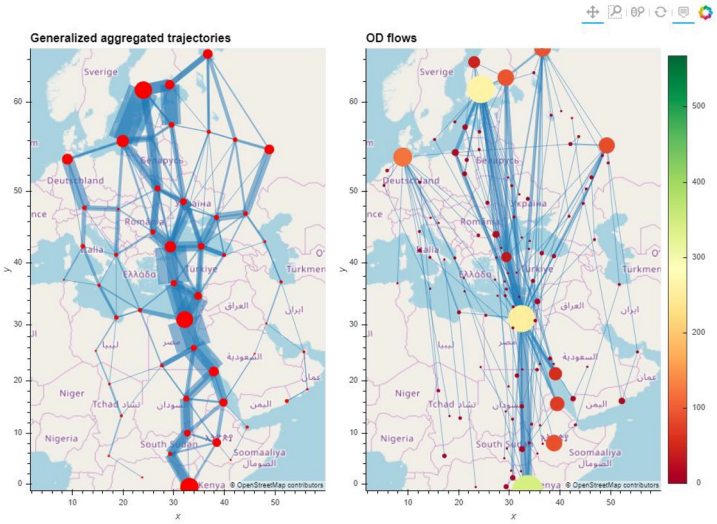


Goals of Mobility Data Analytics

A wide palette of analytics themes. To name but a few:

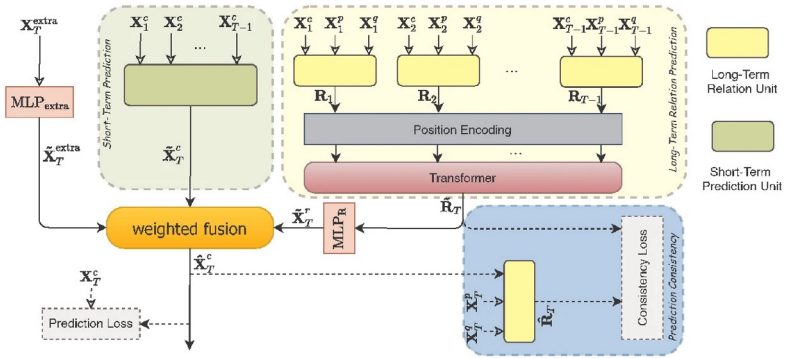
- **Urban mobility (traffic data)**: green routing, traffic anomaly detection, hot spot / path analysis, road traffic prediction, travel time estimation, update of road network
- **Public transportation (ticketing data)**: understanding passenger demand and movement patterns, strategic long-term planning of the network
- **Personal mobility of individuals (GPS and other sensor data)**: activity recognition, personalized routing, matching with ride-sharing services, crowd-sourcing



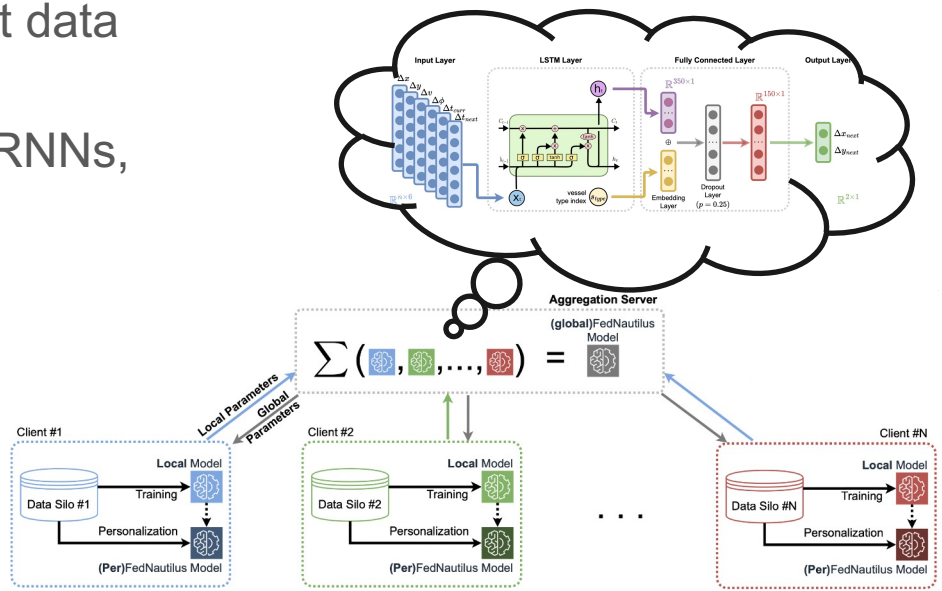
Analyzing aggregated trajectories and OD flows with MovingPandas (source: movingpandas.org)

Mobility Data Analytics Architectures

- from Python libraries for movement data analysis (e.g., MovingPandas)
- … to deep learning architectures (RNNs, GANs, Transformers, etc.)



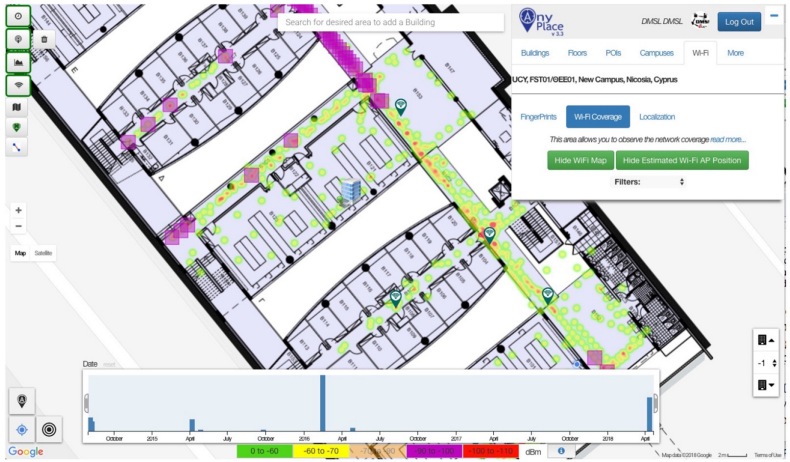
The TermCAST architecture for urban flow forecasting (Xue & Salim, 2021)



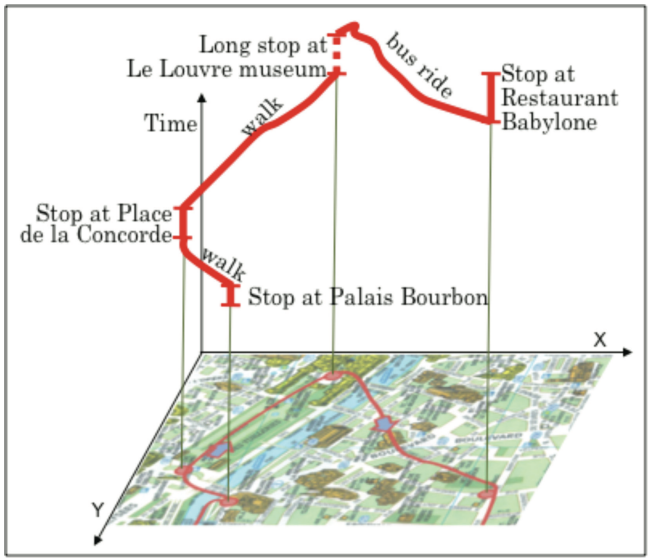
The FedNautilus architecture for (federated) maritime traffic forecasting (Tritsarolis et al. 2024)

Advances in Mobility Data Mgmt Infra. (1/2)

From models and complex data types to capture, e.g. **mobility semantics** or **indoor movement** …



Fingerprint management in indoor environments (Laoudias et al. 2021)

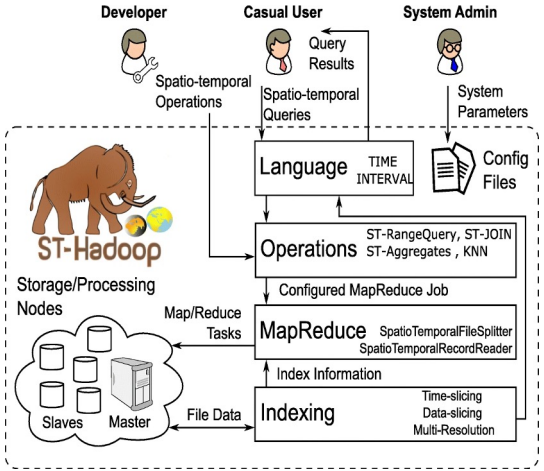


Semantic Trajectories (Parent et al. 2013)

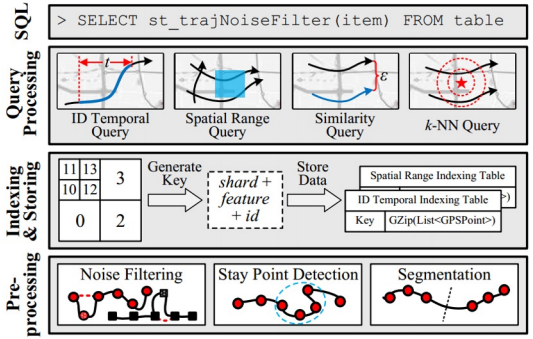
Advances in Mobility Data Mgmt Infra. (2/2)

…to **indexing** and **query processing** techniques, aiming to boost performance

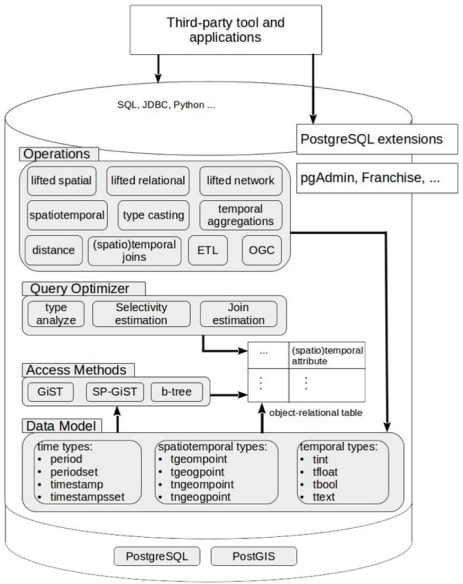
… to **systems** (all-in-one solutions)



ST-Hadoop (Alarabi et al. 2018)



TrajMesa (Li et al. 2020)



MobilityDB (Zimányi et al. 2020)

Challenges in Mobility Data Analytics & Data Mgmt Infra.

7. **ML for mobility data**
   - *build analysis primitives and common building blocks shaping a framework of ML-based mobility data analysis*
8. **Movement behavior understanding**
   - *modelling and understanding mobility behavior (using e.g., XAI), robust to changes due to societal events*
9. **Visual Analytics**
   - *develop VA techniques facilitating visual discovery of behavioral patterns*
10. **Building mobility-aware systems**
    - *native support for mobility data (from spatially- and temporally-aware DBMSs to scalable big data and NoSQL systems)*
11. **Location data as first-class citizens**
    - *support multi-models in one seamlessly integrated location+X system ("X" being keywords, graphs, relational data, click streams, document data, etc.)*
12. **Hybrid (streaming, batch) workloads**
    - *adopt the concepts behind HTAP (= OLTP + OLAP) systems to support the nature of mobility data*

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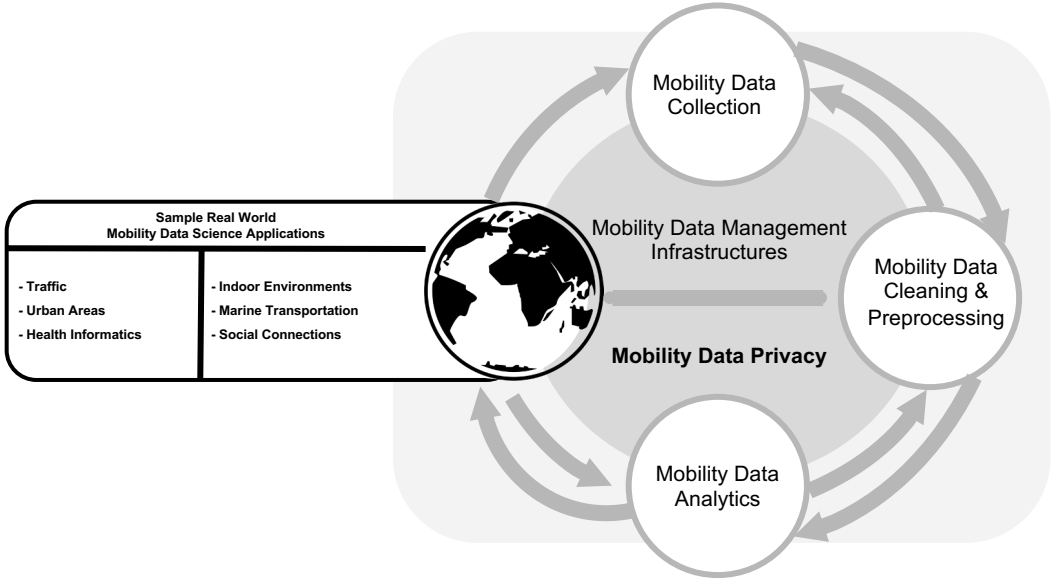


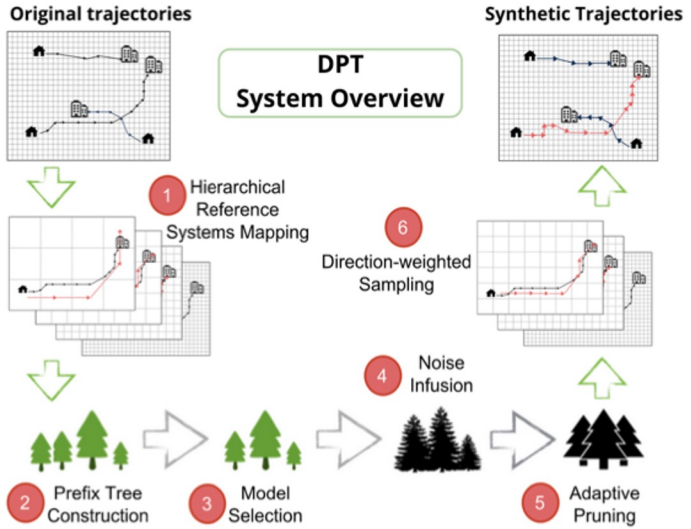
Efforts in Mobility Data Privacy

@ **data collection stage** (local setting):

- Applying Local Differential Privacy (LDP) schemes to location data
- Perturbation methods (e.g., GeoInd)

@ **data analysis stage** (central setting):

- Differential Privacy techniques for training ML models, e.g., Differential Private Trajectories (DPT)
- ML models for the assessment of privacy attacks (e.g., home-work attack) over raw mobility data



DPT overview (He et al. 2015)

Challenges in Mobility Data Privacy

13. **Threat models and privacy definitions**
    - *DP-relaxed versions may be needed given specific threat models to enhance the privacy and utility tradeoff*
    - *Better understanding on what sensitive information may be revealed and reconstructed from mobility data based models*
14. **Privacy and utility tradeoff and other factors**
    - *Designing realistic synthetic data generation methods for optimal privacy utility tradeoff (also, ensuring the fairness)*
15. **Explainability and societal education**
    - *Principles, design guidelines, and tools for explaining DP's protection and limitation to the society / stakeholders*

Geo-Indistinguishability (Andrés et al. 2013)

Conclusions

- **Mobility Data Science** is a distinct branch of (generic) Data Science
  - Space-time dimensions call for different methods of data acquisition, management, analysis, and privacy preservation

- We surveyed recent advances, described motivating applications, and identified major research questions ⇒ a list of **15 challenges** on
  - Mobility data collection & data preprocessing (6)
  - Mobility data analytics & data mgmt infra. (6)
  - Mobility data privacy (3)

1. **Mobility data privacy**
2. **Mobility data bias**
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MobiSpaces
new data spaces for green mobility

EMERALDS
Extreme-scale Urban Mobility Data Analytics as a Service

Thank you for your attention !!

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- **GeoLife**: https://www.microsoft.com/en-us/research/publication/geolife-gps-trajectory-dataset-user-guide/
- **RomaTaxi**: https://ieee-dataport.org/open-access/crawdad-romataxi
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Papers …

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