Connecting the (mobile) Dots: Mining User Mobility Patterns from Networks and Social Media

Jörg Ott
Ljubica Kärkkäinen
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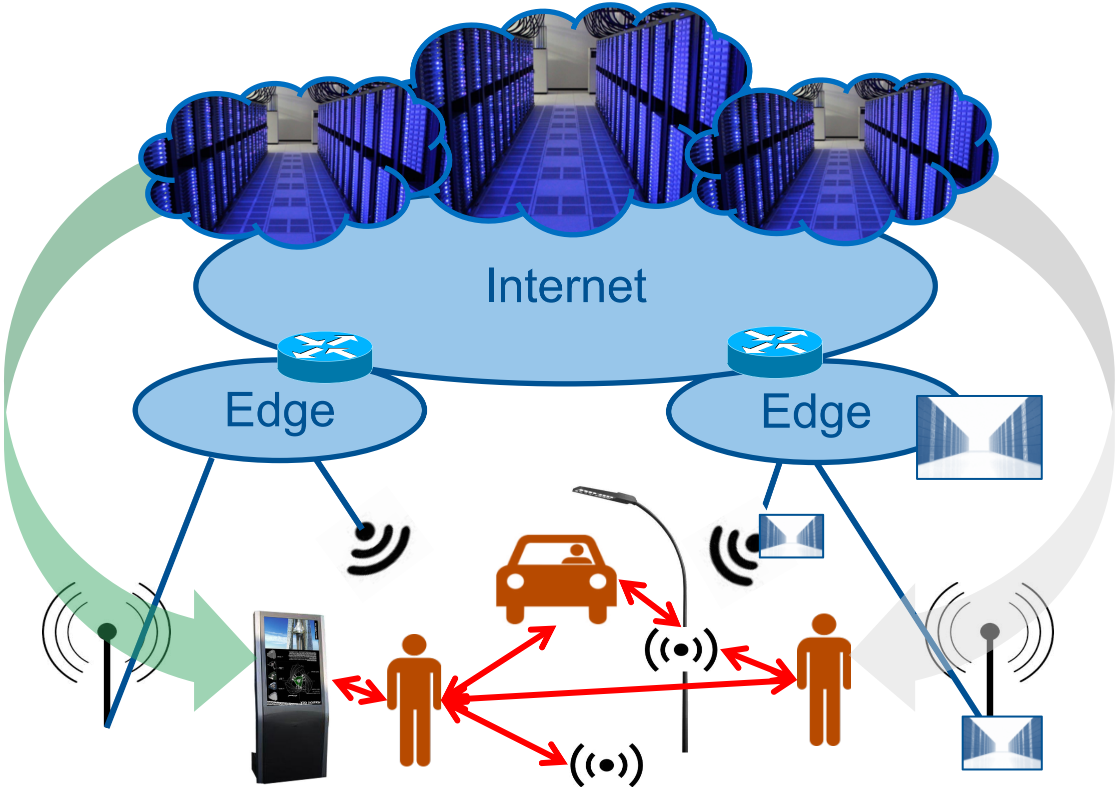
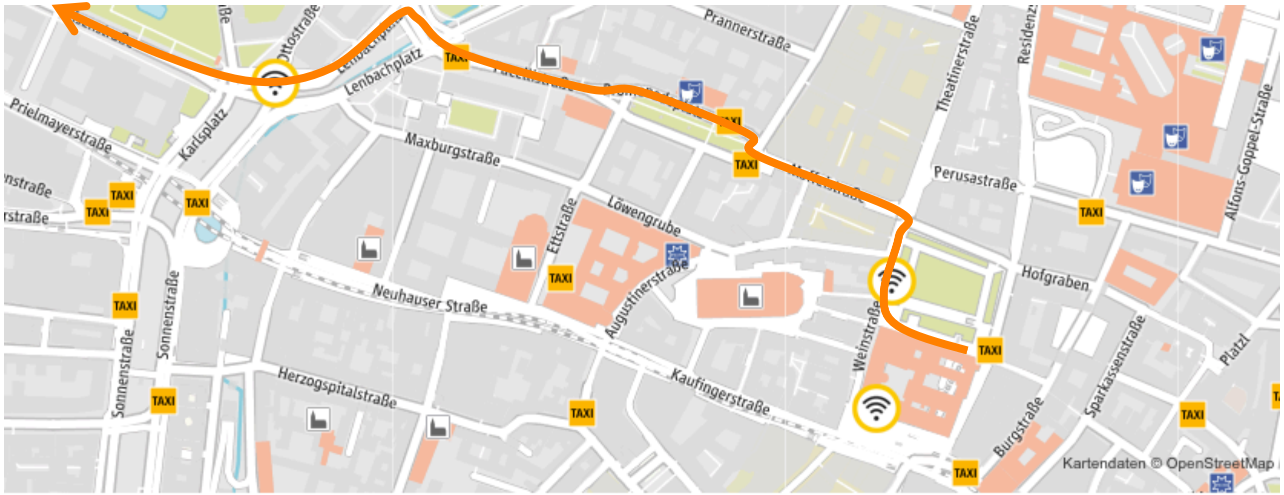
www.cm.in.tum.de

15 December 2017

Why do we care? (1)

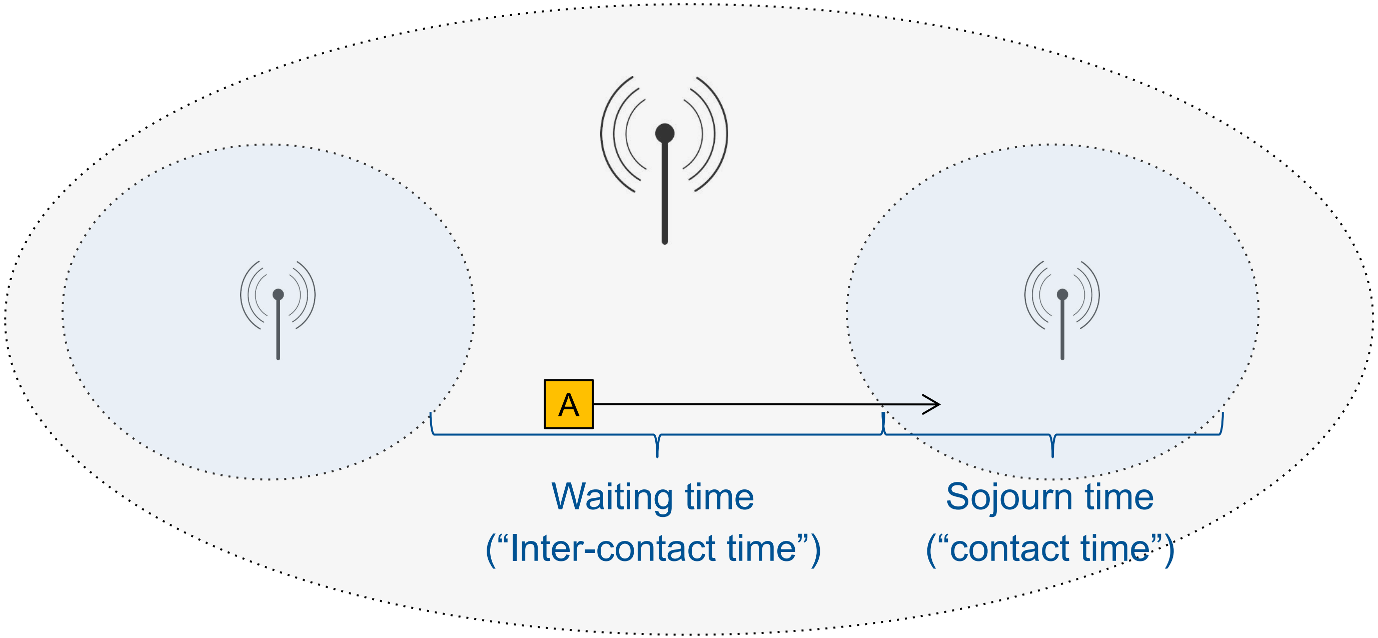


Why do we care? (2)

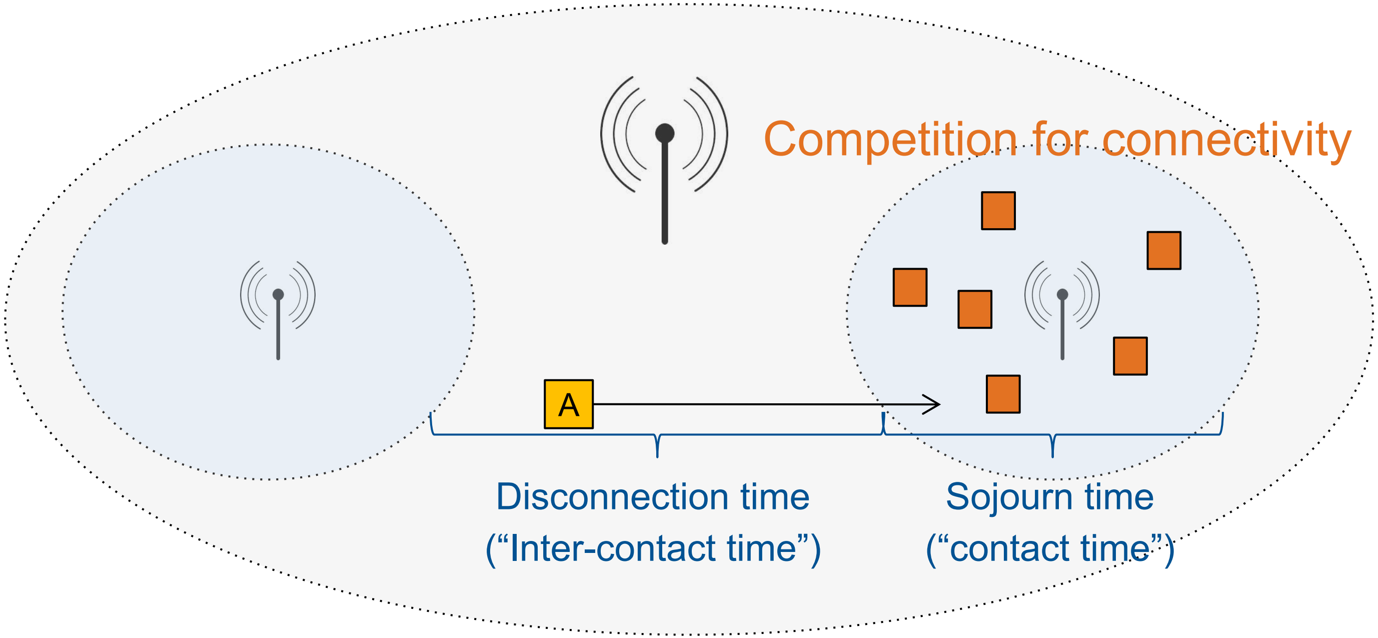


http://www.muenchen.de/leben/wlan-hotspot.html

Why do we care? (3)



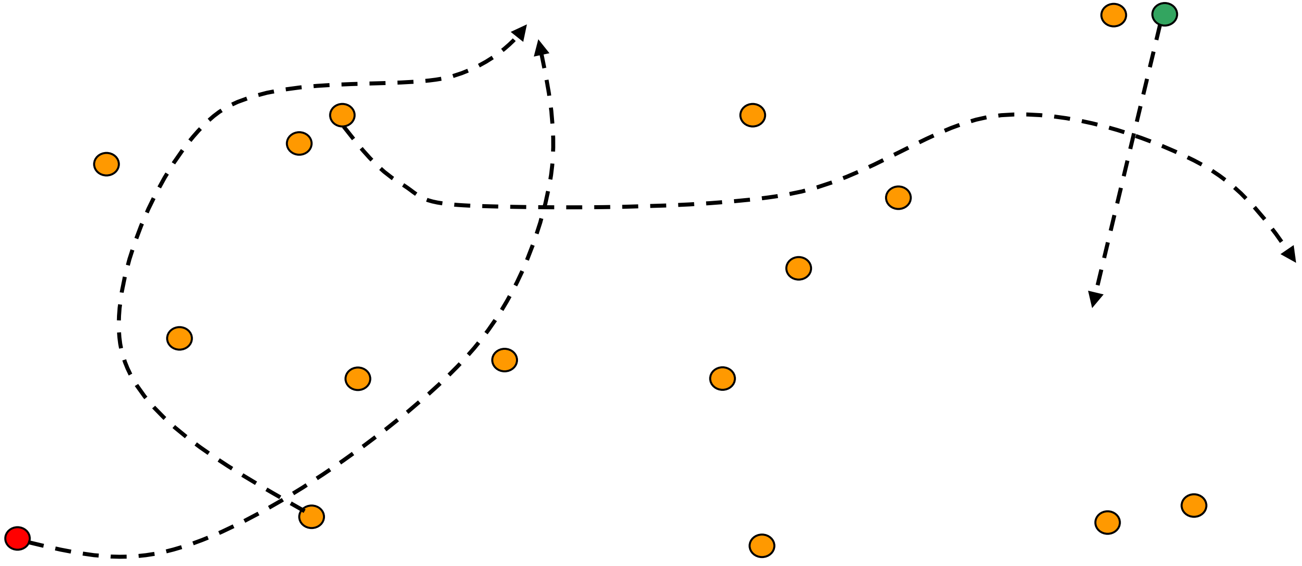
Why do we care? (3)



Network connectivity
(Availability, data rate, disruptions)

Why do we care? (4)

Contact time (duration) Inter-contact time Inter-encounter time Node density



Content spreading performance
(infection rate, coverage, latency)

Content delivery performance
(delivery probability, latency)

Sample application areas

Assessing (cellular) Internet access performance
- Example: complementing cellular networks by Wi-Fi or others

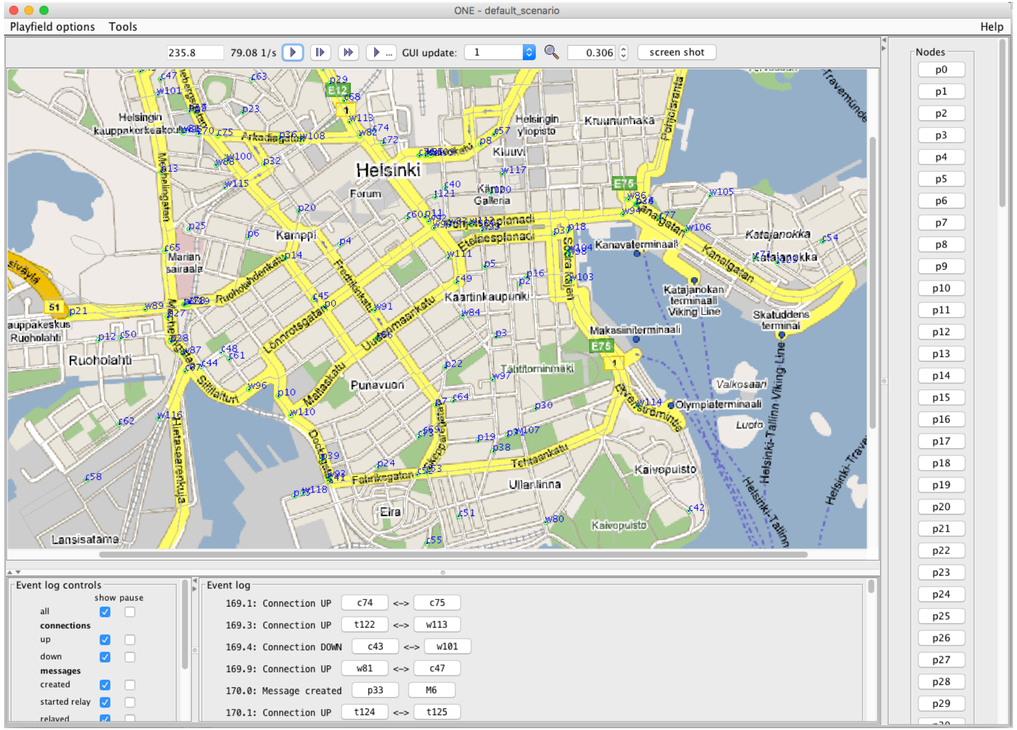
Local content dissemination
- Example: neighborhood networks for content sharing without the cloud

Censorship-resistant information exchange
- Example: Firechat during the Hong Kong protests

Enabling communication in rural or remote areas
- Example: Interconnecting villages through “messengers”

…

The ONE Simulator: mobility & apps



http://akeranen.github.io/the-one/

Working Day Movement Model

Synthetic model for daily routines
- Defines home, work places, favorite locations
  - Map-based movement with different regions
- Considers social groups for evening activities

Multi-modal transportation
- Submodels for walking, cars, trams/buses
- Simple schedules for public transportation
  (can also support real schedules)

Activity models
- Shortest path routing from/to places
- Not much movement at home
- Random movement at work
- Evening activities
- Variable parameters for daily routines (wake time, workday length, etc.)

City Square Model

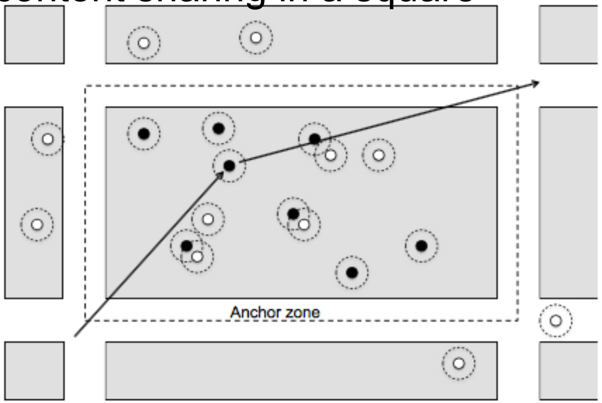
Observation-based model: web cams as sources

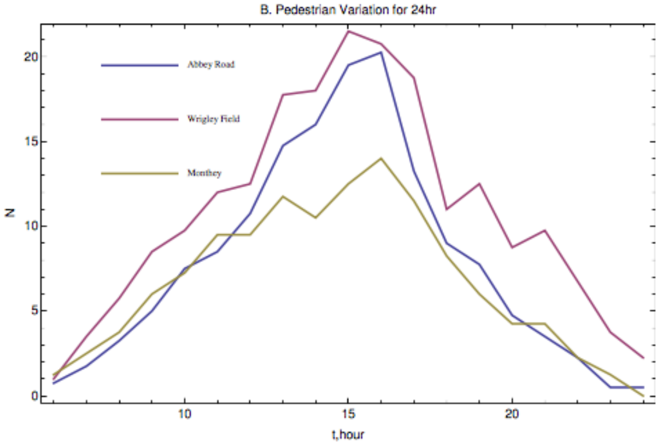
- Manual interpretation (no usable automated algorithms at the time)
- Shown to be automatable for vehicle density)

Computing arrival patterns and sojourn times

- Deriving a simple model with a few parameters

Application: content sharing in a square





More on mobility models

Trace-driven modeling and analysis

- for movement patterns
- for communication and interaction patterns
- how these influence each other

Mobility modeling using traces from the network

Mobility modeling using traces from social media

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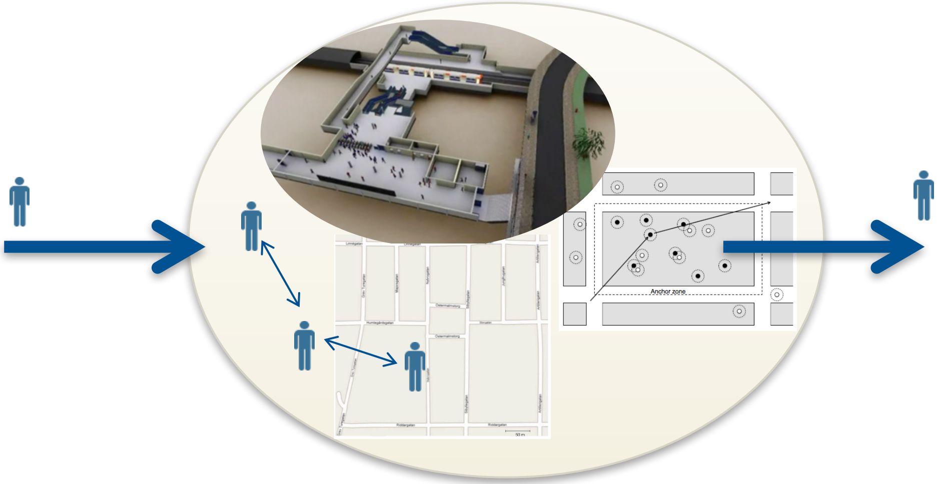
Outline

- Analytic mobility models
- Mobility modeling from wireless network records
- Modeling user association patterns in a university campus network
- Ongoing work: Mobility prediction

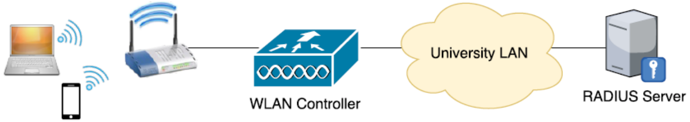
Analytic Mobility Modeling

- Queueing model for mobility of users and their interaction
- Black-box model for (small) urban areas: city square, subway stations, grid of streets, buildings
- Application: infrastructureless content sharing and ephemeral networks



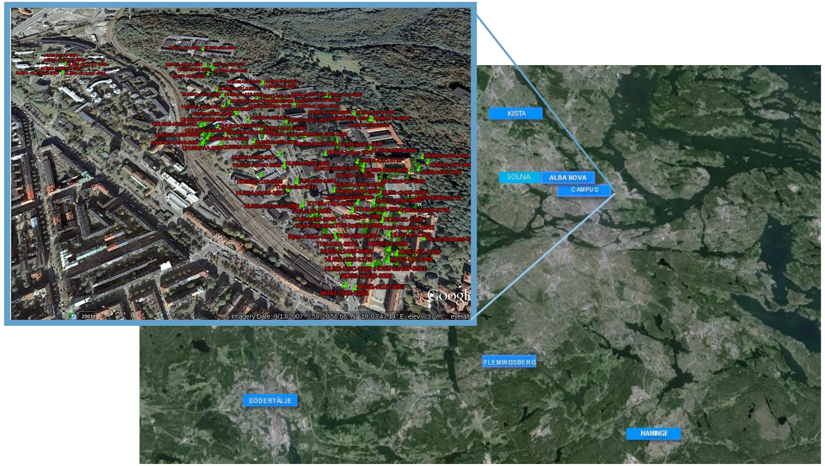
Trace-driven Mobility Modeling

- Objective: extract mobility traces from wireless network traces
- Wireless network records: Eduroam association events
- Trace obtained from the authentication server



- Description:
  - Trace duration: 16 months (January 2014—April 2015)
  - 250-300K associations from 13-15K users per day
  - ~1000 access points, located in 54 buildings on 5 sites
  - Not really big data, but…

has some challenges!

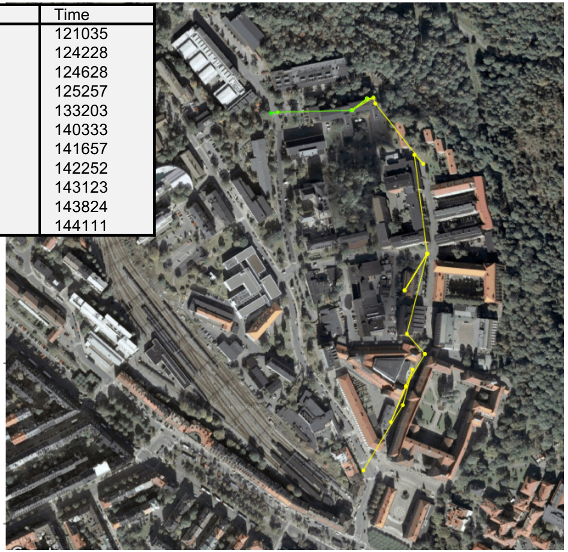


Trace-driven Mobility Modeling

- Objective: extract mobility traces from wireless network traces (location, duration of visiting time)
- Challenges: no accounting information, user devices are anonymized, access points labeling inconsistent, ping-pong effects, filtering short associations…

- Approach
  - Data cleaning
  - Capturing ground truth (*warwalking*, syslog)
  - Deriving heuristics: utilizing wireless coverage map, authentication state machine, infrastructure/device timers

Access Point	Time
KTHB-r1201-0915	121035
KTHB-r1209-0917	124228
KTHB-r1209-0917	124628
KTHB-r1209-0917	125257
KTHB-r1209-0917	133203
KTHB-r1201-0607	140333
HUS20-r4055-0307	141657
QHUS15-kApl4-0285	142252
KTHB-r4212-0894	143123
KTHB-r4212-0894	143824
KTHB-r4212-0894	144111



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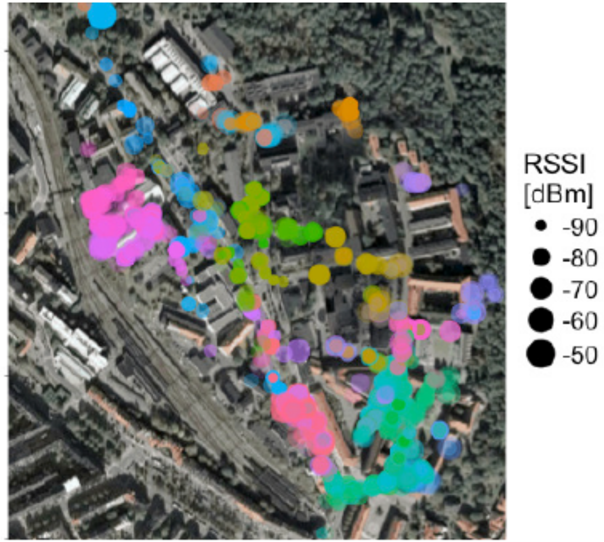
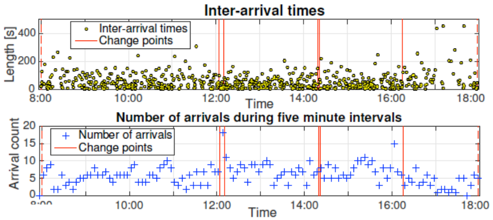
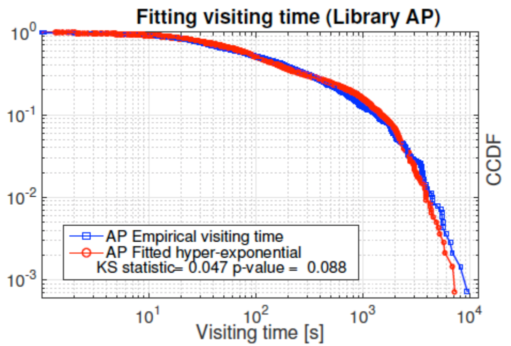
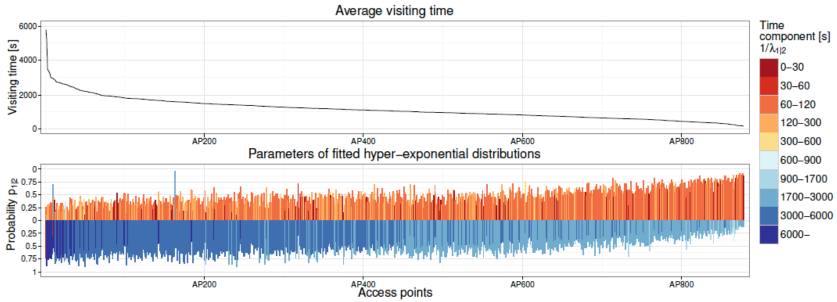


Modeling User Association Patterns

- Analysis and modeling of users' arrival patterns and visiting time at network access points
- Application: resource allocation, wireless protocol design, network dimensioning, abnormality detection
- Findings: Nonhomogeneous Poisson arrivals, two-stage hyper-exponential visiting time
- Tractable (and simple!) models, but time-varying and location-specific

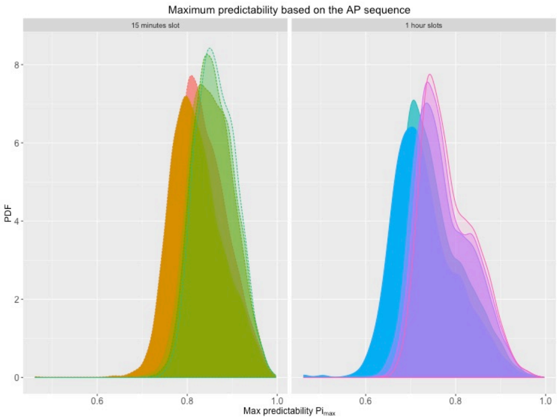


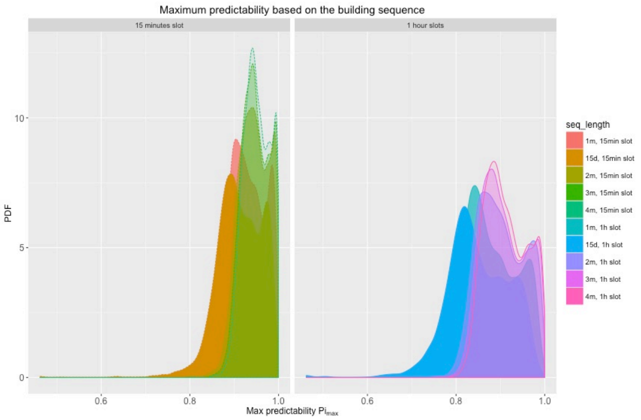


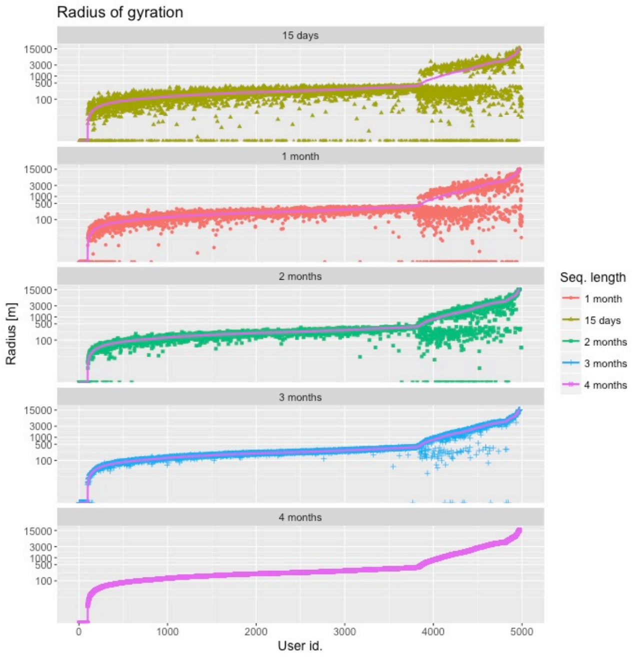


Ongoing Work: Mobility Prediction

- Estimating achievable predictability of the user's location based on entropy







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Pervasive Games and Human Mobility

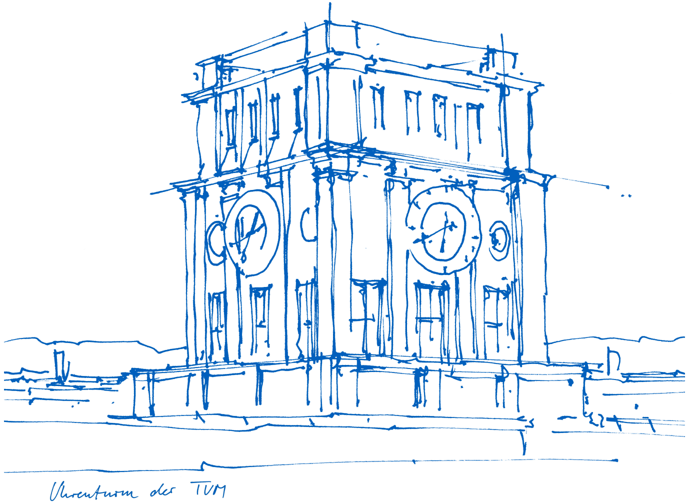
Leonardo Tonetto

Technical University of Munich

Department of Computer Science

Chair of Connected Mobility

Munich, 15. December 2017



What we found

- Increase of up to **2 km** in daily displacements, persistent after the game
- Gamers visit new **locations**, close to their past trajectories
- Gamers play for up **20 days** longer when playing often on cellular network

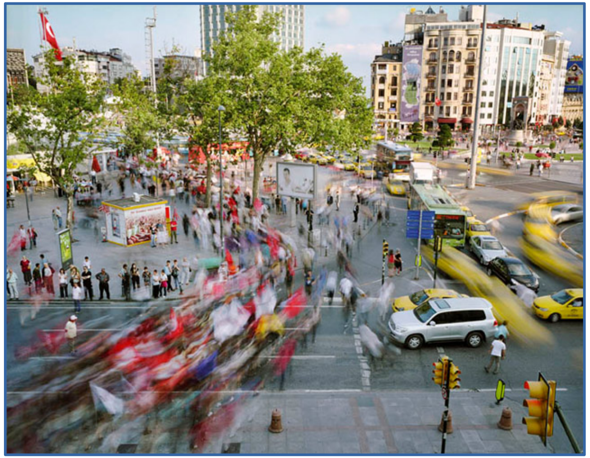
Background

- **Pervasive Games**

- Augmented Reality and Location Aware
- *Virtual*-world & *Real*-world
- Examples:

- **Human Mobility**

- Data driven modeling
- Understanding and prediction of users behavior
- Wireless network deployment, urban planning, ...



Our Datasets

- **Twitter**

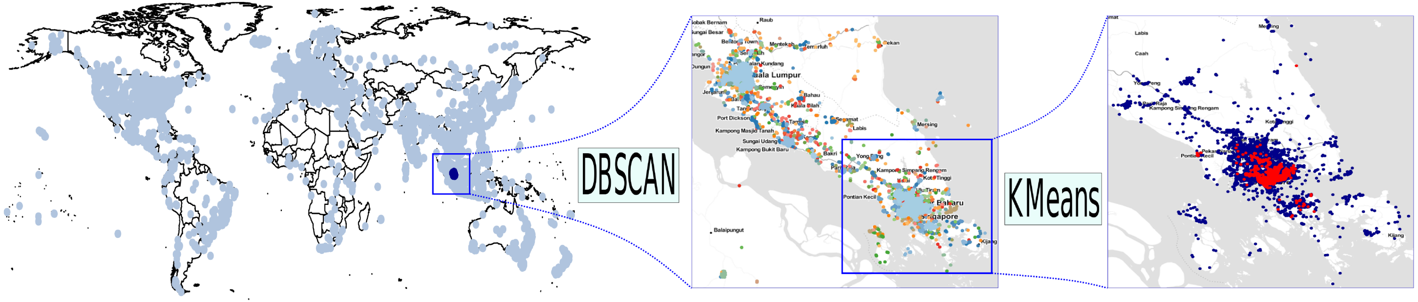
- 8.7M tweets from 21500 users
- 15 countries (18 cities)
- 8900 gamers with "#pokemongo"
- Bot detection with Botometer* (~3.1%)
- Spatial granularity: Fine
- Time granularity: Coarse

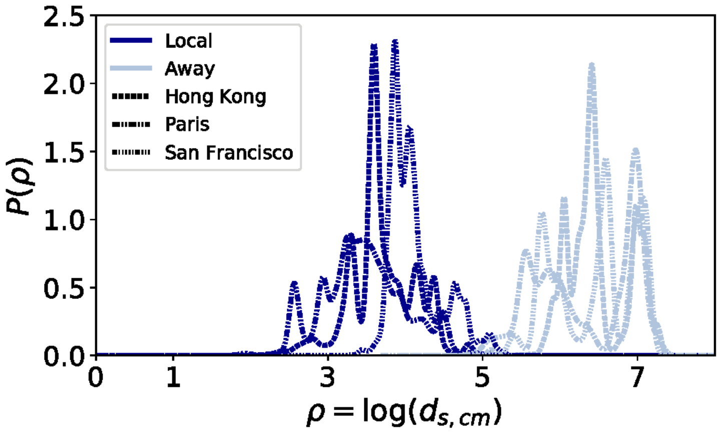
- **Carat**

- 62.8M records 58000 users
- +100 countries
- 3392 gamers
- Info about phone status/behavior
- Spatial granularity: 1D
- Time granularity: Fine (1% battery change)

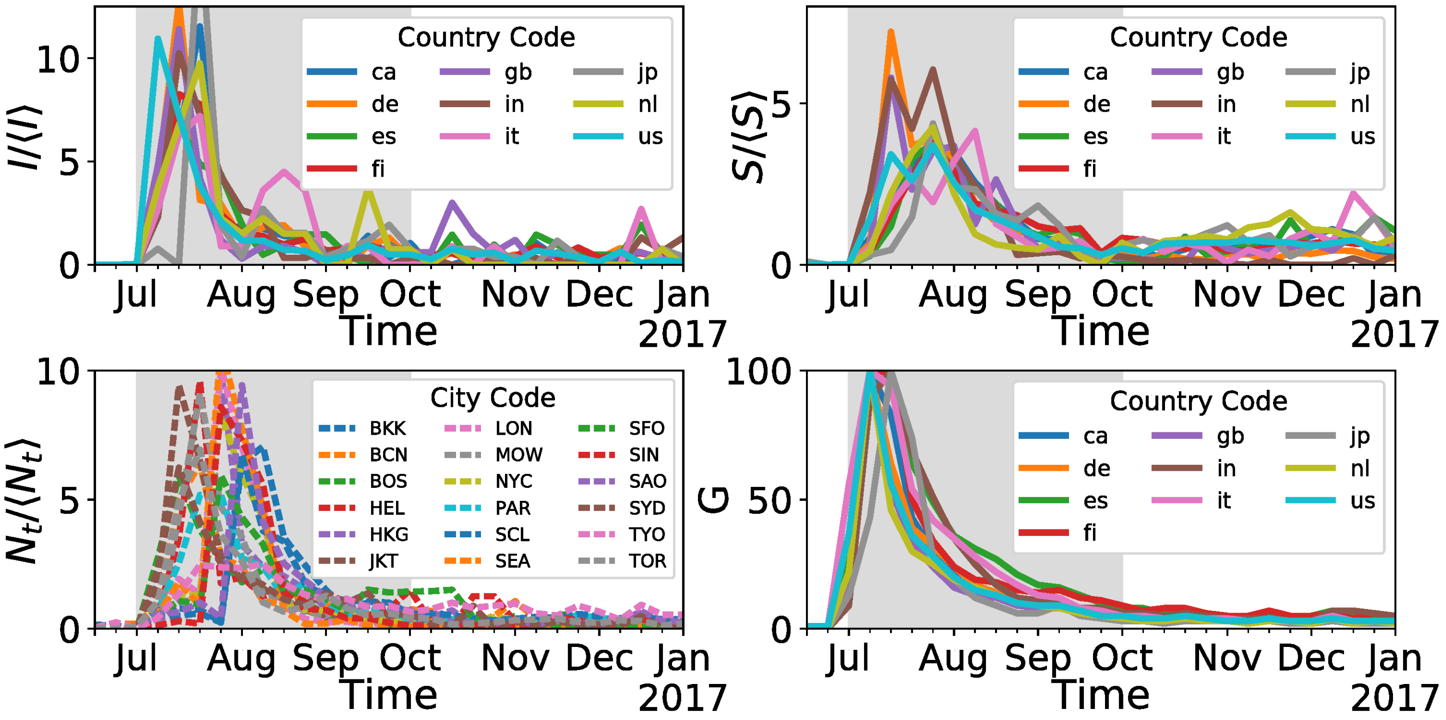
* https://botometer.iuni.iu.edu/

Spatial Clustering: Local vs. Away





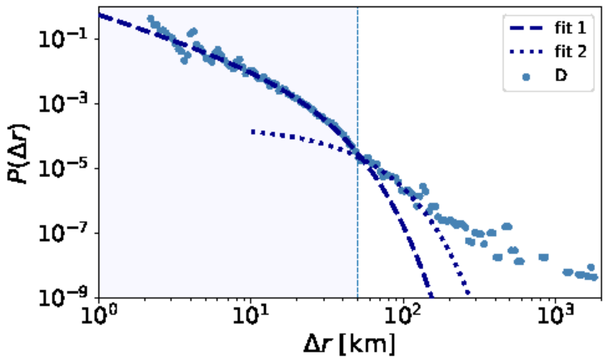
When was it trendy?



How each dataset was studied?

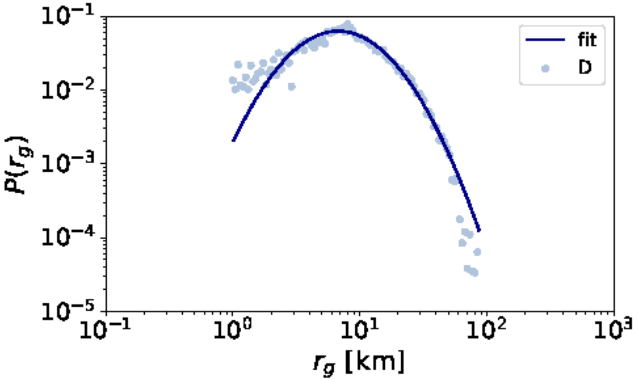
- **Carat**

- Displacements of consecutive records (Δr)
- Gaming sessions & installations
  - Average 2.3 km per session



- **Twitter**

- Radius of Gyration (r_g)
- Isotropy ratio
- *<u>Location</u>* visitation
- Displacements of consecutive records (Δr)



Combined Analysis (Carat & Twitter)

- Consistent scale between active days
  - Twitter: 59.2 days
  - Carat: 83.8 days
- Increase in daily mobility observed on Twitter
  - Supporting the observation in Carat

Conclusion

- Flow of people → Flow of information
- Synthetic Models vs. Real-World Data
- Mobility might be affected by exterior factors (Mobile Games)