Human mobility information extracted from mobile phone metadata

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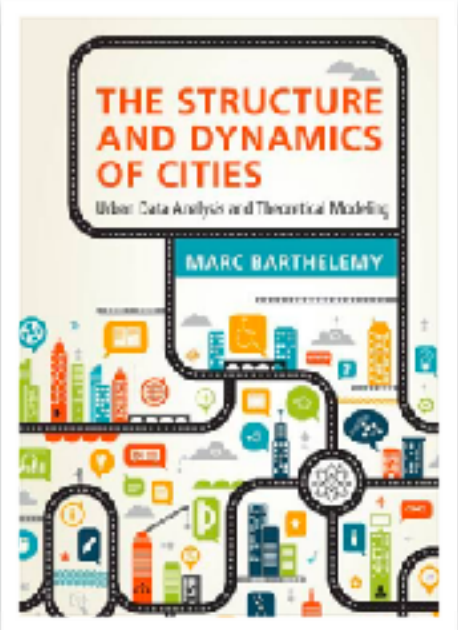
Outline

- Introduction
- Trajectories mapping using mobile phone metadata
- Dynamic population estimation using mobile phone metadata
- Travel mode extraction using mobile phone metadata
- Conclusion

Mobility is a challenge for cities



With the rise of urbanization, cities all around the world are facing scaling and design issues.

Cities are not only a physical space, but a place that fosters people interactions

"In The New Science of Cities, **Michael Batty** suggests that to understand cities we must view them not simply as places in space but as systems of networks and flows."

Empirical studies point to a systematic acceleration of social and economic life with city size (superlinear scale-invariant $Y \propto N^{\beta}$ when $\beta > 1$**)**

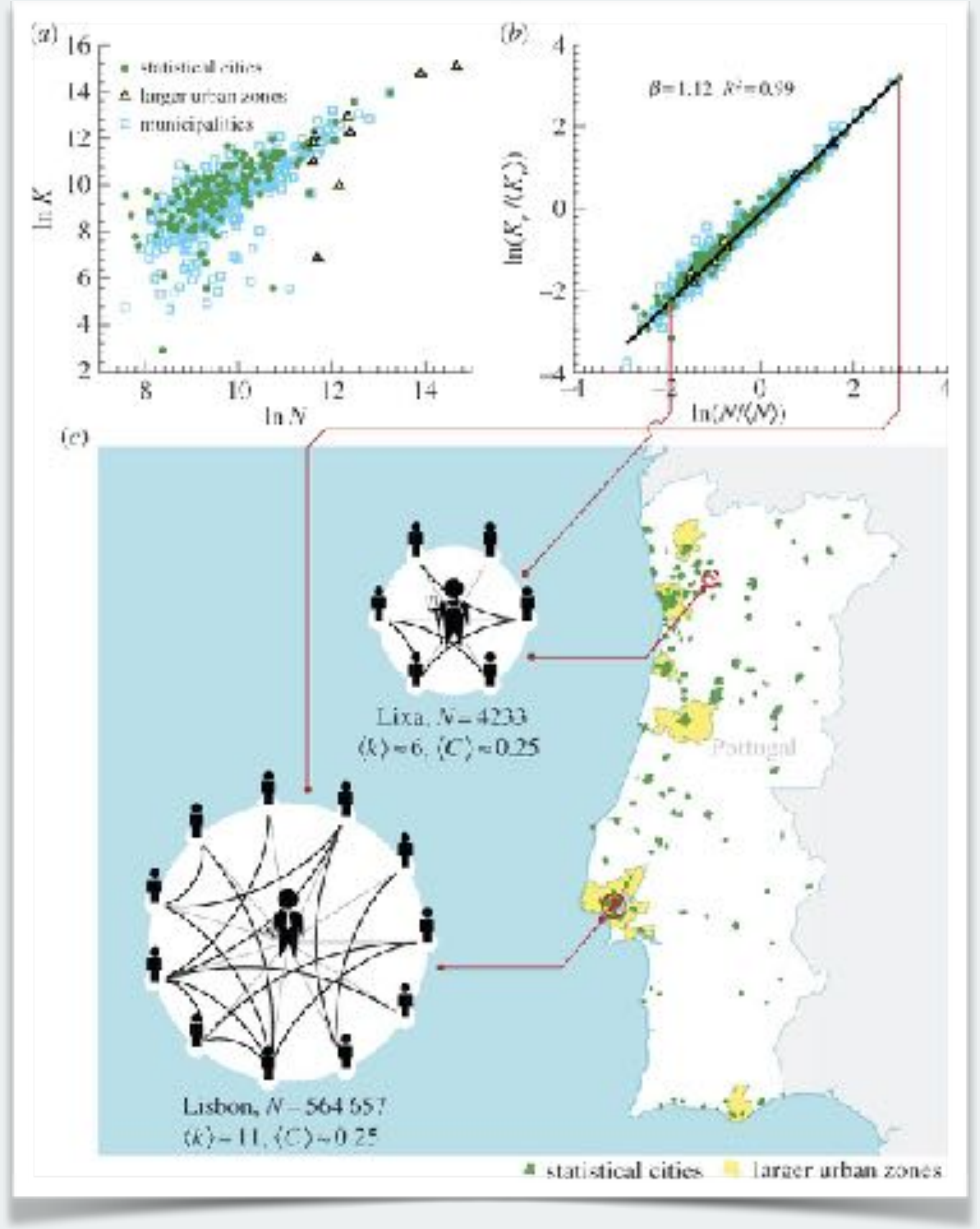
- Economic output, wages, patents, violent crime and the prevalence of certain contagious diseases.

A functioning transport system is the mean that enables interactions inside cities.

- As a city grows, the number of interactions also increases:

👉 as consequence the mobility demand increases and puts enormous strain on the transport infrastructures of all sorts.

Information about the mobility at the macro level of a city enables us characterize and understand how a city is functioning.

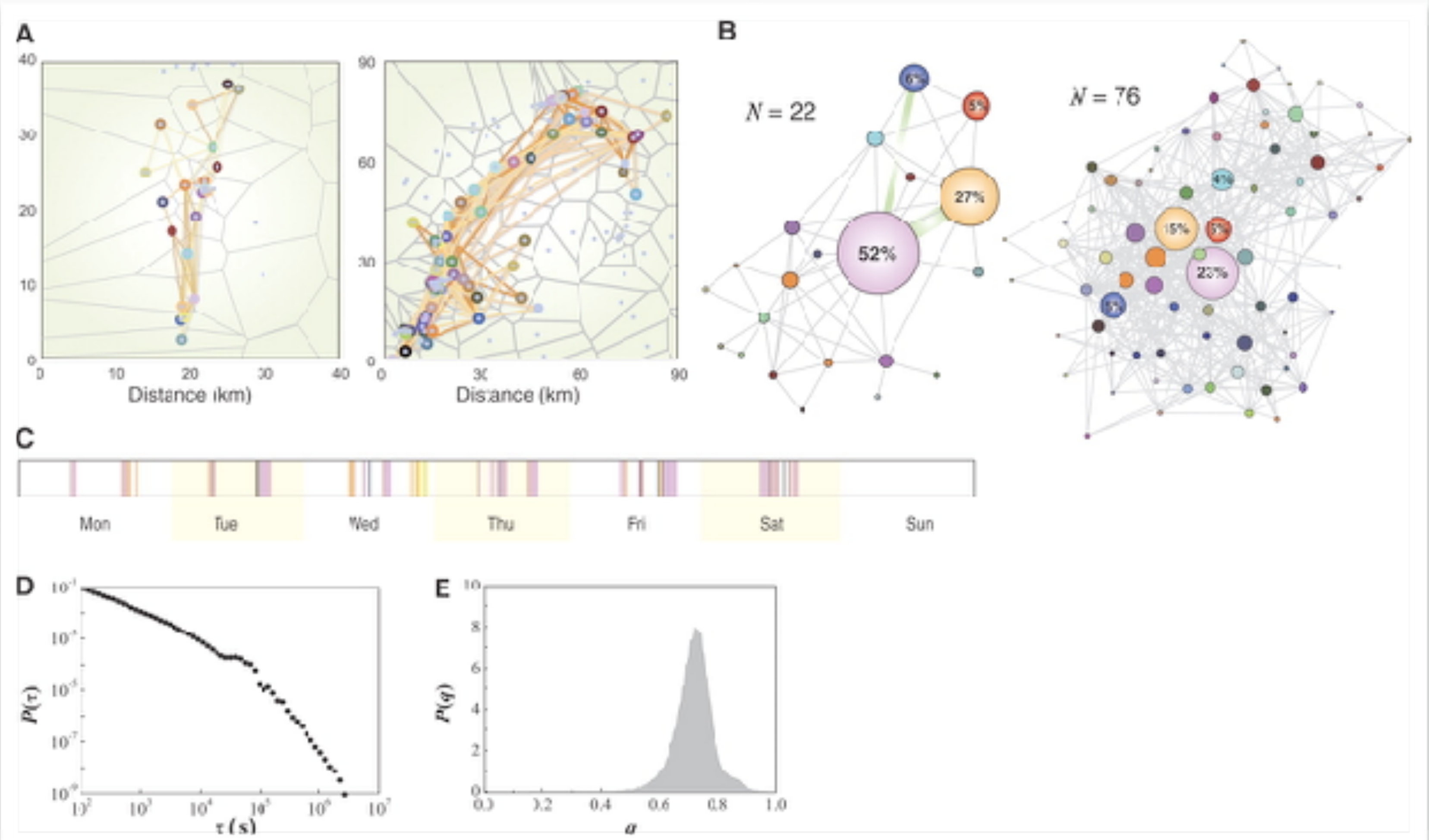


📘 **The origins of scaling in cities**
Louis M.A. Bettencourt
science 340 (6139), 1438-1441, 2013.

📘 **The scaling of human interactions with city size**
Markus Schläpfer, et al
J. R. Soc. Interface 2014.

Literature review

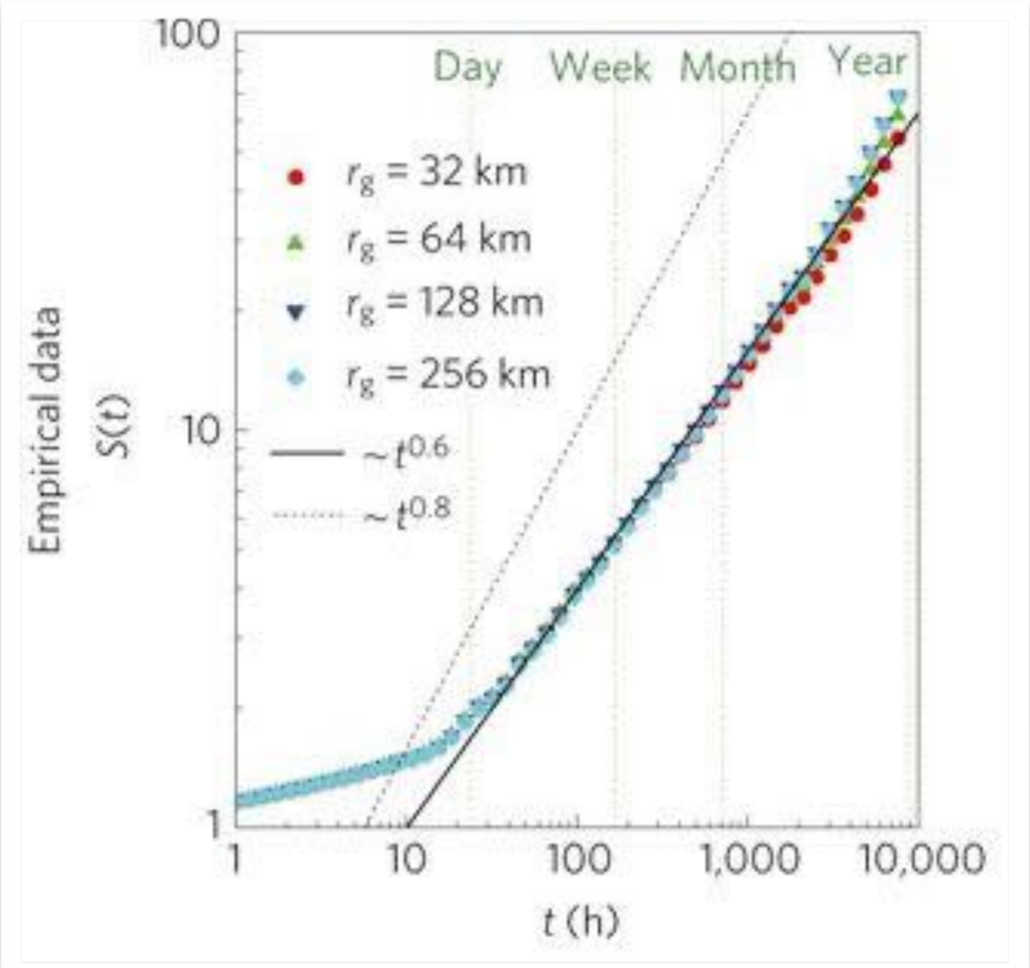
Predictable



📘 Song, Chaoming, et al.
"Limits of predictability in human mobility."
Science 327.5968 (2010): 1018-1021.

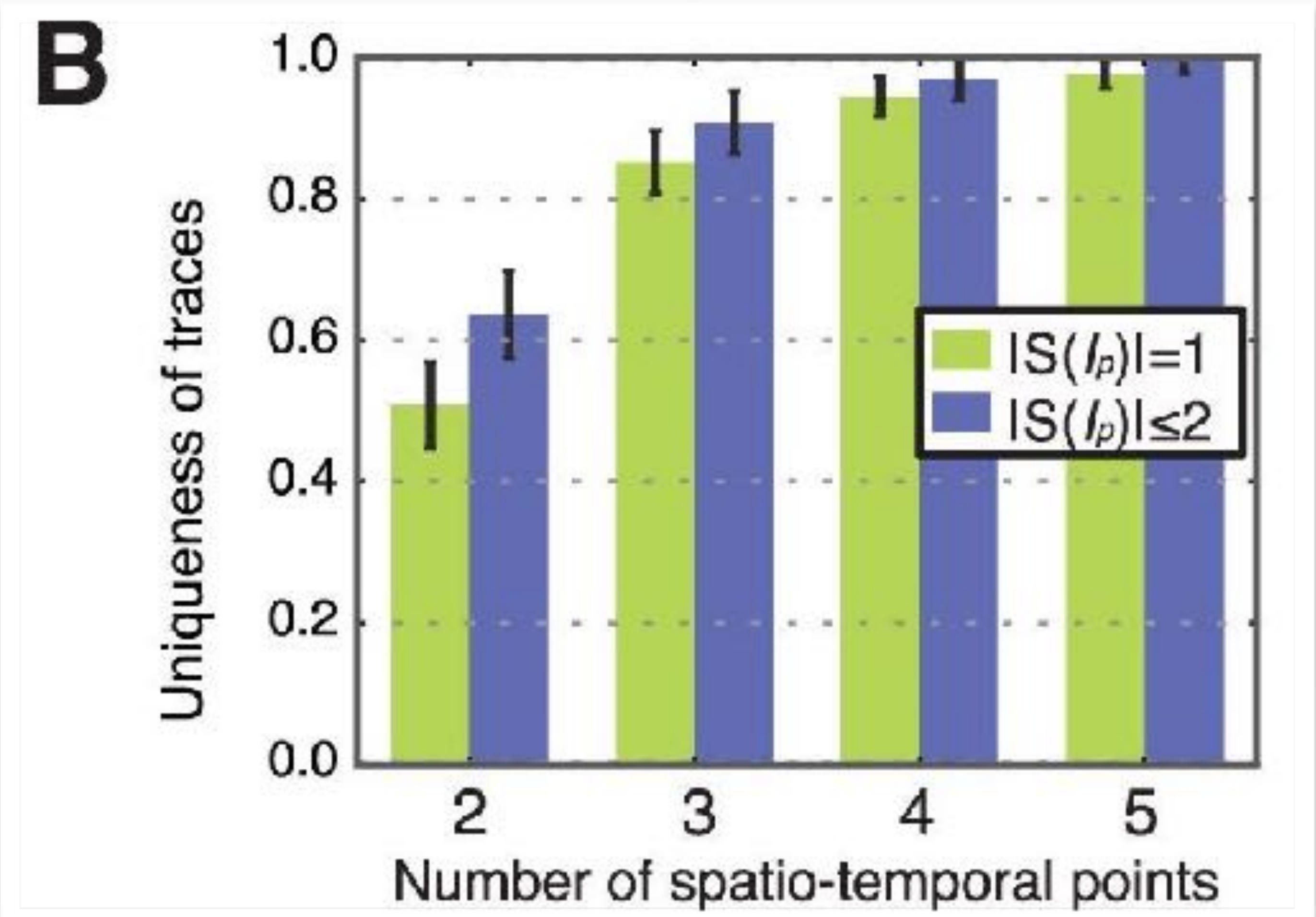
📘 Wang, Pu, et al.
"Understanding road usage patterns in urban areas."
Scientific reports 2 (2012).

Slow Explores



📘 Song, Chaoming, et al.
"Modelling the scaling properties of human mobility."
Nature Physics 6.10 (2010): 818-823.

Unique



📘 de Montjoye, Yves-Alexandre, et al.
"Unique in the Crowd: The privacy bounds of human mobility."
Scientific reports 3 (2013).

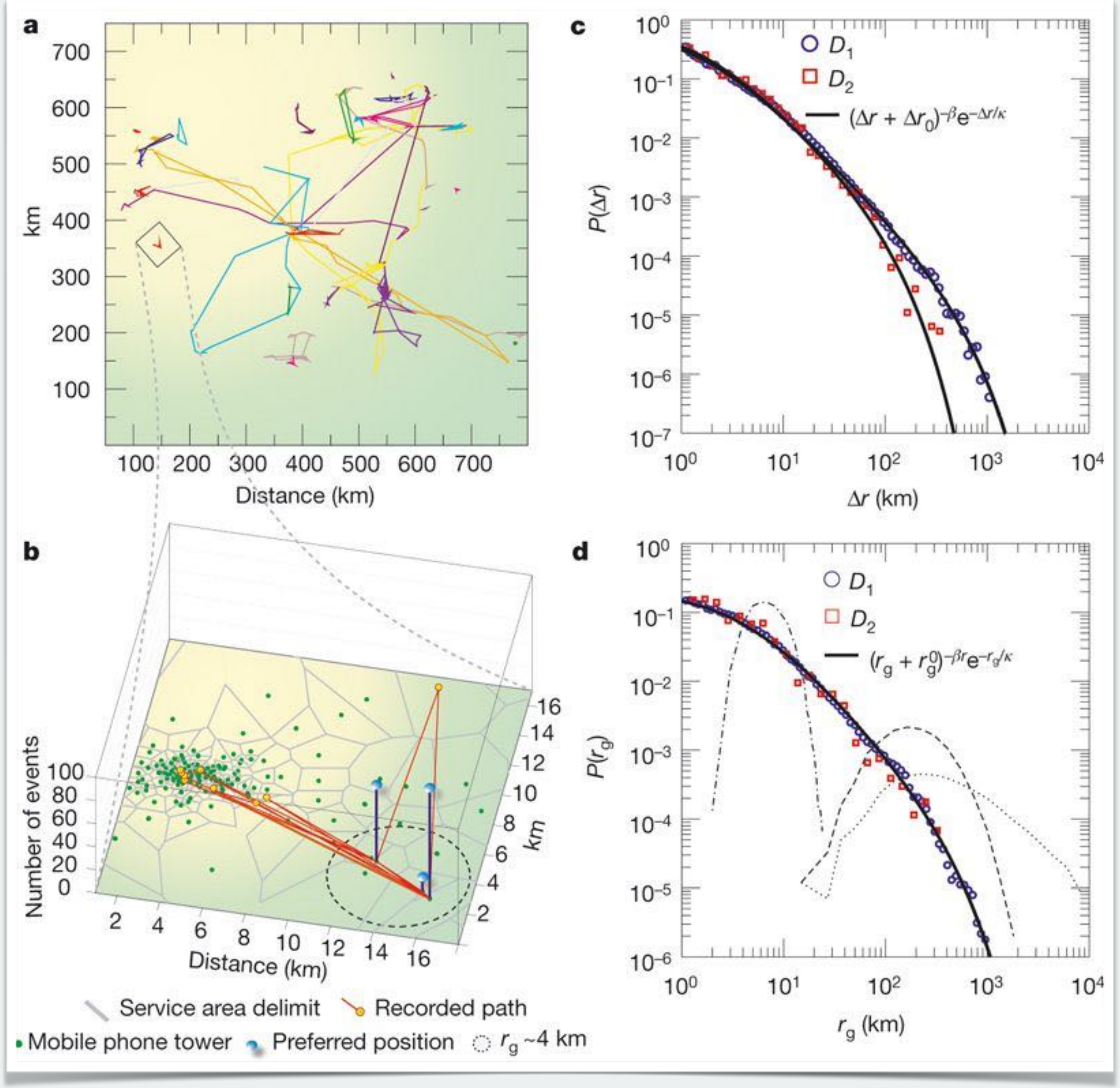
Literature review: Slow Exploration

Radius of Gyration:

$$R_g(t) = \sqrt{\frac{1}{N(t)} \sum_{i=1}^{N(t)} (\mathbf{r} - \mathbf{r_{cm}})^2}$$

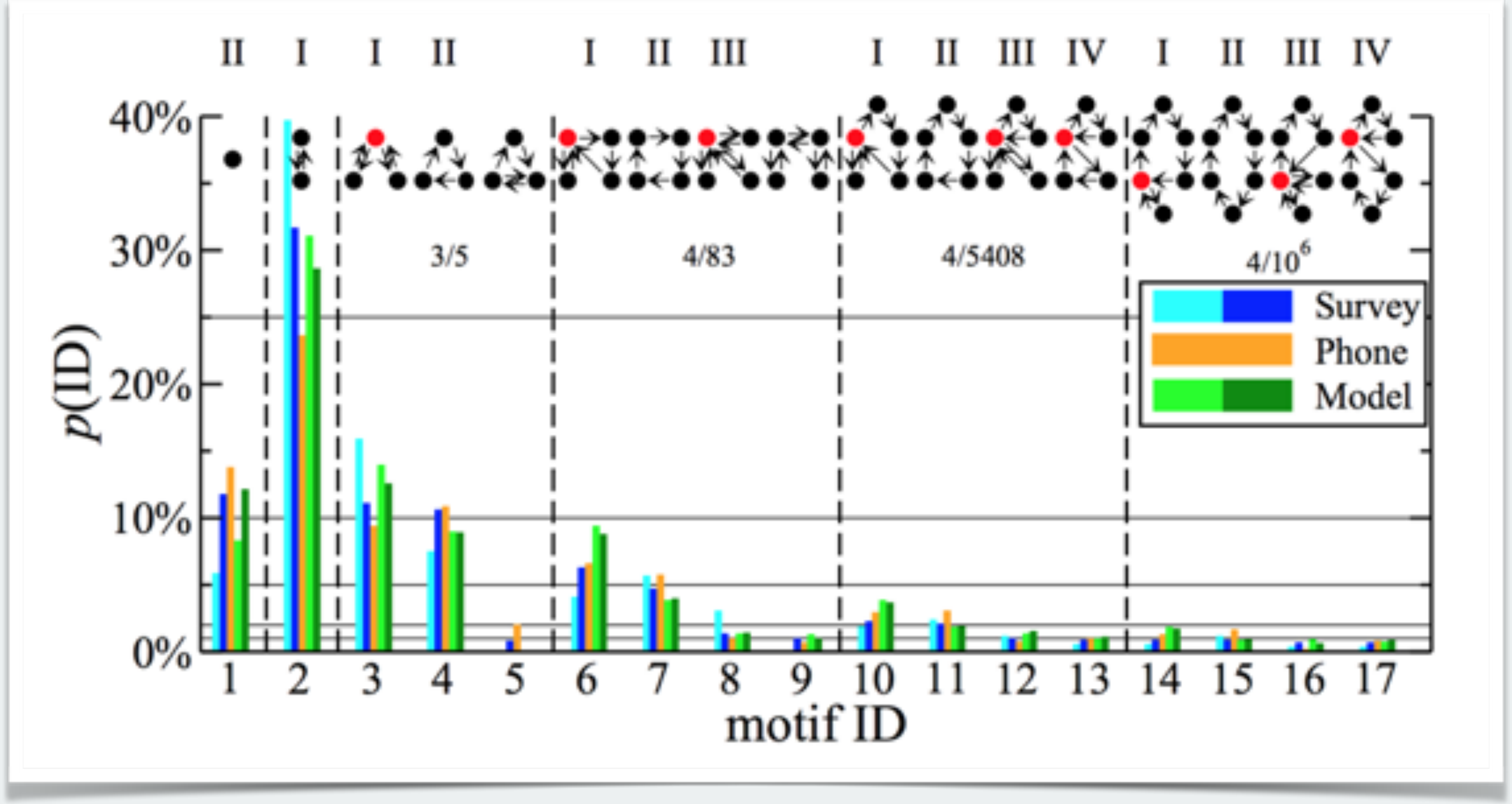
Conclusion:

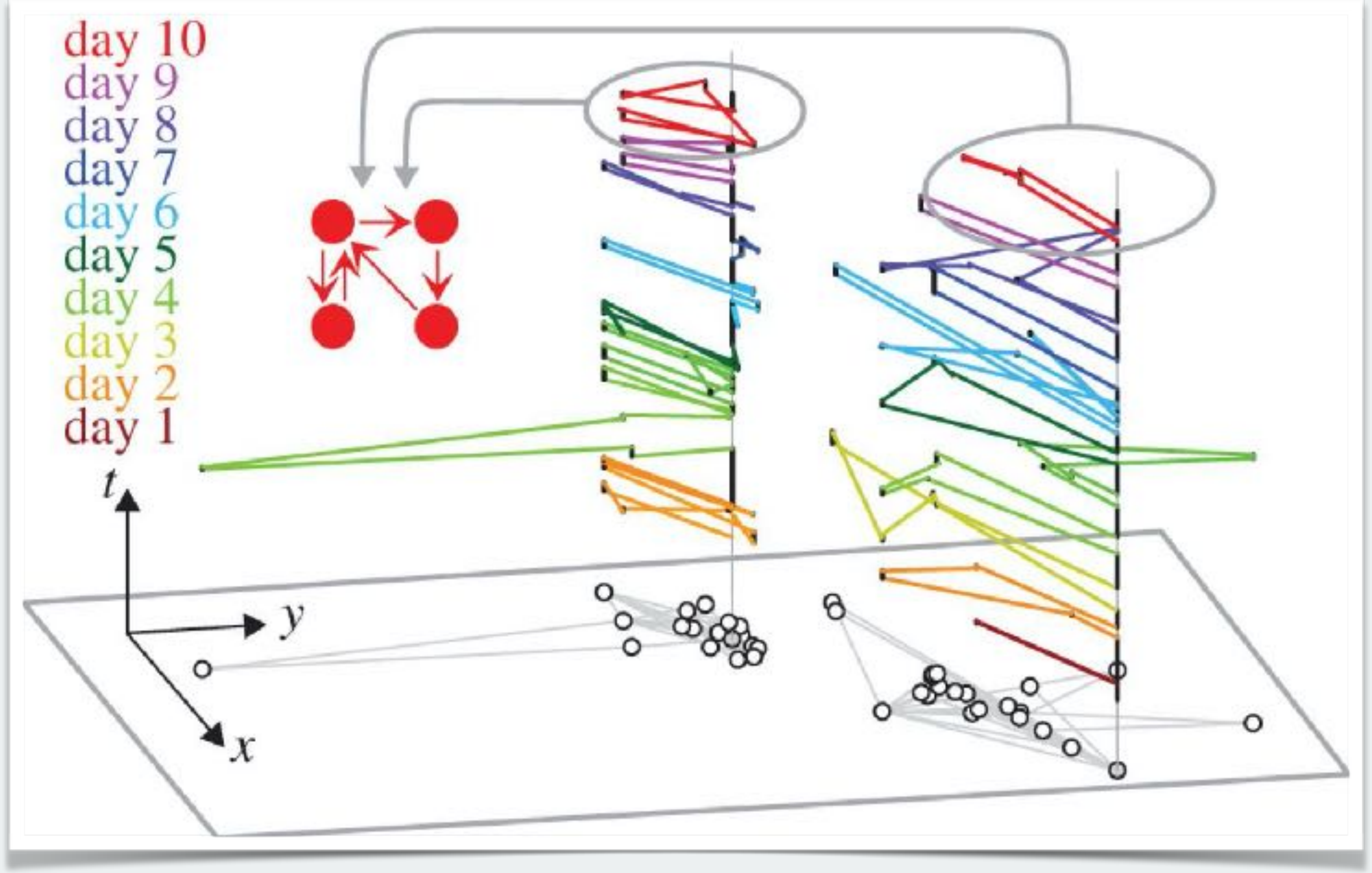
The human mobility can be easily model by a Levy Walk



Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns." Nature 453.7196 (2008): 779-782.

Literature review: Network motif





Daily Mobility Motif

- N distinct locations
- Directed edges mark trips between locations
- Must start and end at the same location
- Physical location no longer important

Schneider, Christian M., et al.
"Unravelling daily human mobility motifs."
Journal of The Royal Society Interface 10.84 (2013): 20130246.

Could mobile phone metadata be useful to derive human mobility ?

Human mobility information is of prime interest for:

- public safety authorities (large event management e.g. Olympic games)
- public transport authorities, transportation network companies (Uber, Lyft), bike sharing compagnies
- Public policies: the dynamic evolution of the mobility demand may affect cities policy such urban access regulations in case of pollution pic, low emission zones
- Up-to-date mobility information is a key element of a Mobility-as-a-Service (MaaS) system.

Questions to answer:

- Can we mesure the mobility at scale in realtime ?
- Can we measure the mode of transport ?
- can we measure precisely the delays in public transports ?

Pro and Cons

👍 capture mobility information at very lare scale and at relatively low price

👍 a tool that aims toward the studies of events of meso/macro scale

👎 poor geospatial accuracy compared with GPS dataset

👎 privacy issues (GDPR in EU)

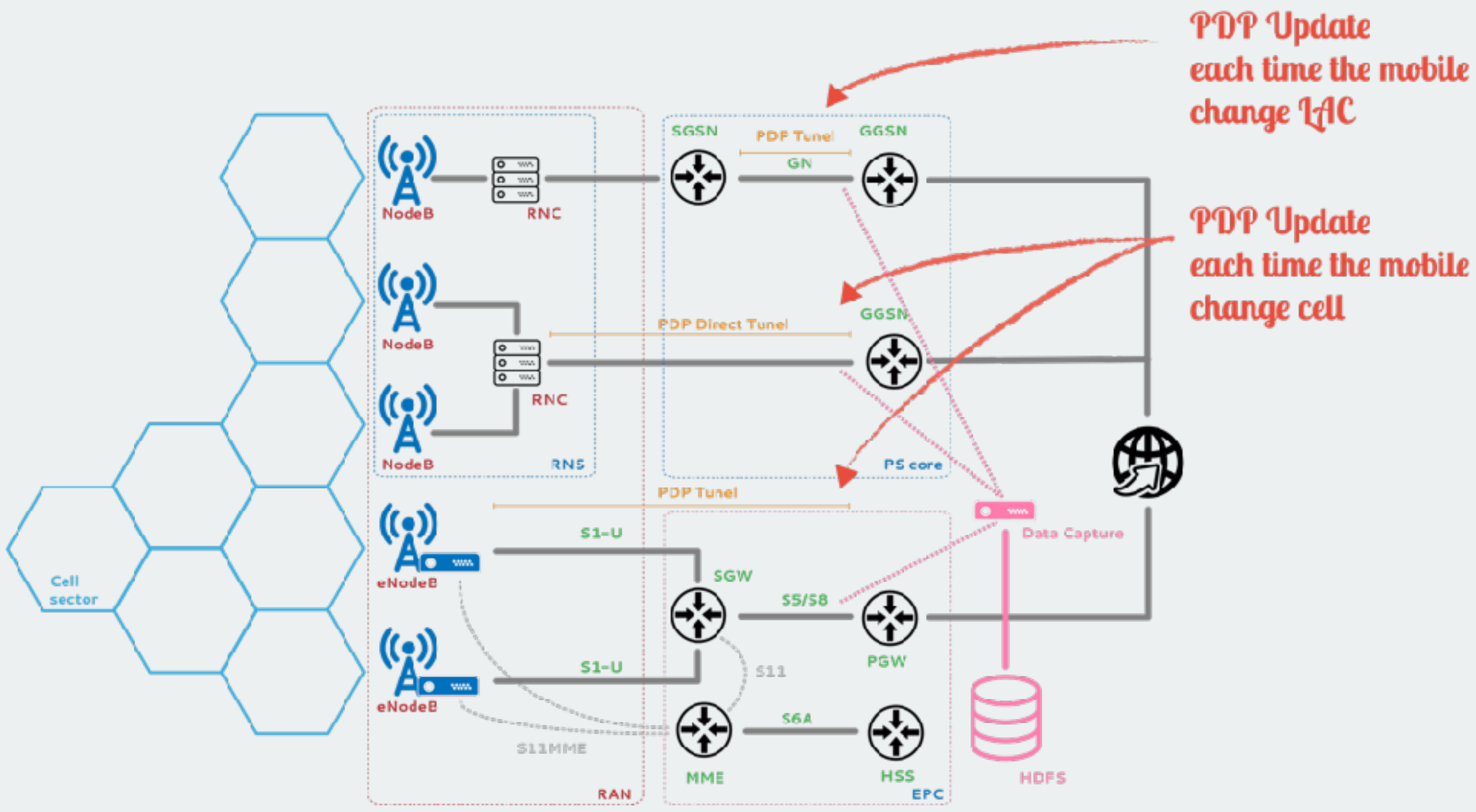
Mobile phone network signalization

What is GTP ?

A tunneling protocol that carries the data traffic between NodeB/ eNodeB to the point of presence (POP) toward internet.

What is the PDP context ?

GTP-C the signalization protocol for GTP. Each time a network event triggers a GTP-C message, this information is stored inside a specific PDP-context at the GGSN.



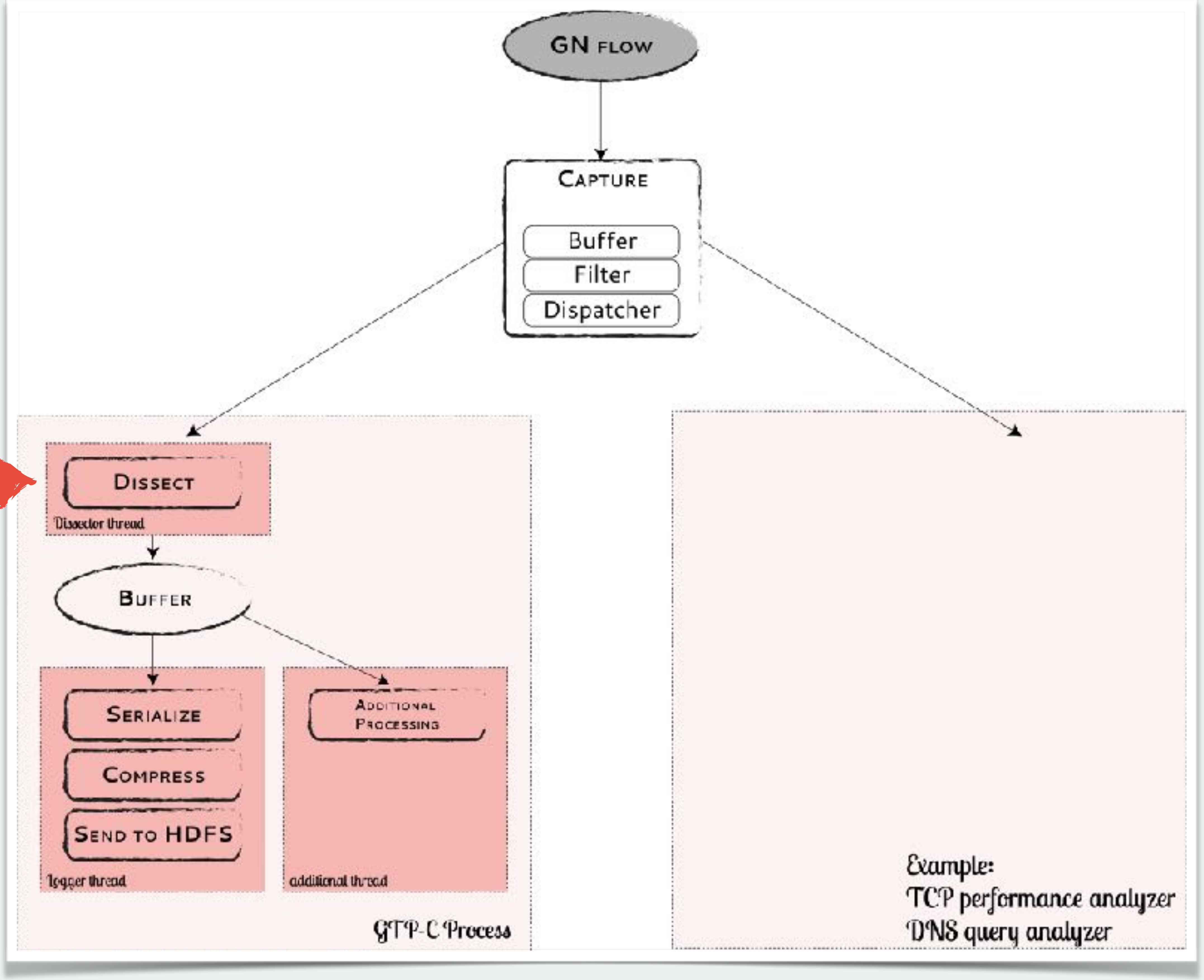
PDP context:

- IMEI
- IMSI
- MSISDN
- RAT (radio access technology)
- ULI (user location information)
- APN (access point name)

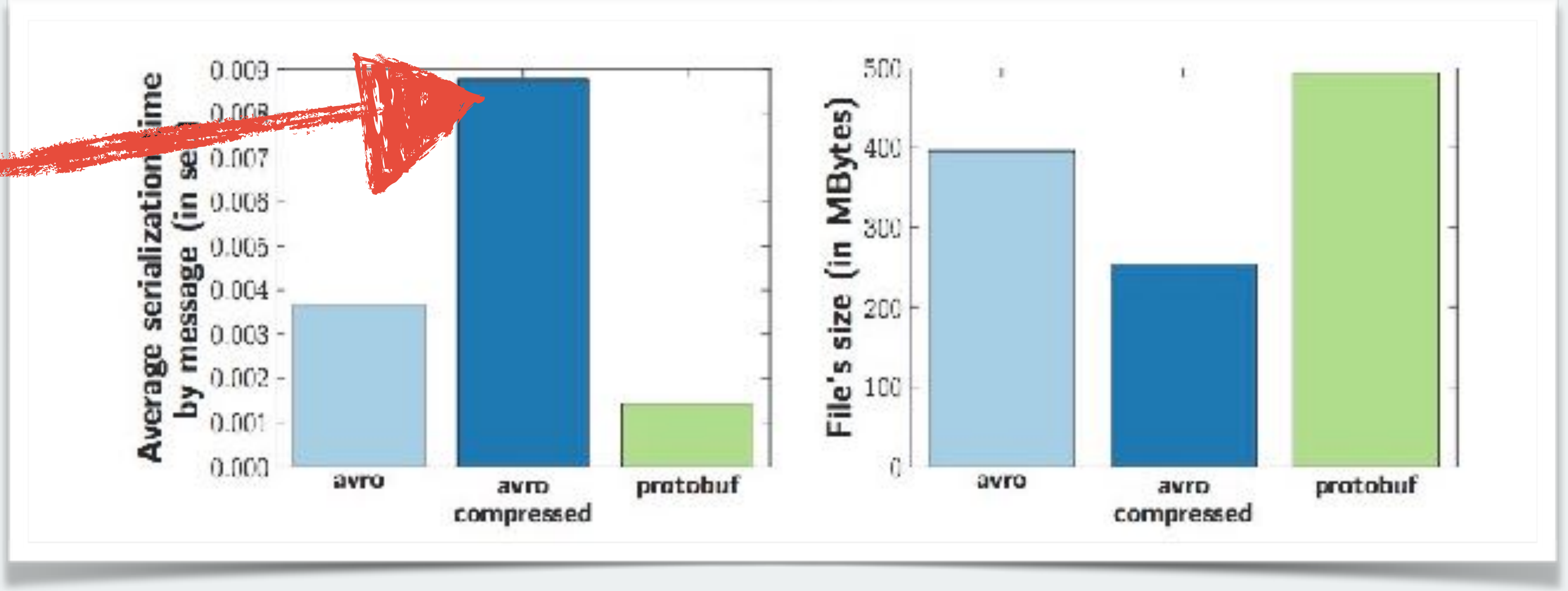
	GTP-C		
Network event	GTPv1	GTPv1 direct tunnel	GTPv2
Change LAC	✓	✓	✓
Create/destruct tunnel	✓	✓	✓
Switch Technologie (2G/3G/4G)	✓	✓	✓
Change RNC		✓	
Change TA			✓

Platform for data capture

Data	Description
Timestamp	Packet's timestamp in micro
Anonymous ID	Randomly generated ID
Tunnel ID	tunnel ID carrying the traffic
Message Type	Create / update / delete
Sequence Number	GTP-C number
Mobile's IP address	IP address
TAC	Brand & manufacturer of the device
QoS	3GPP QoS information
Radio Access Technology	GPRS, EDGE, EUTRAN

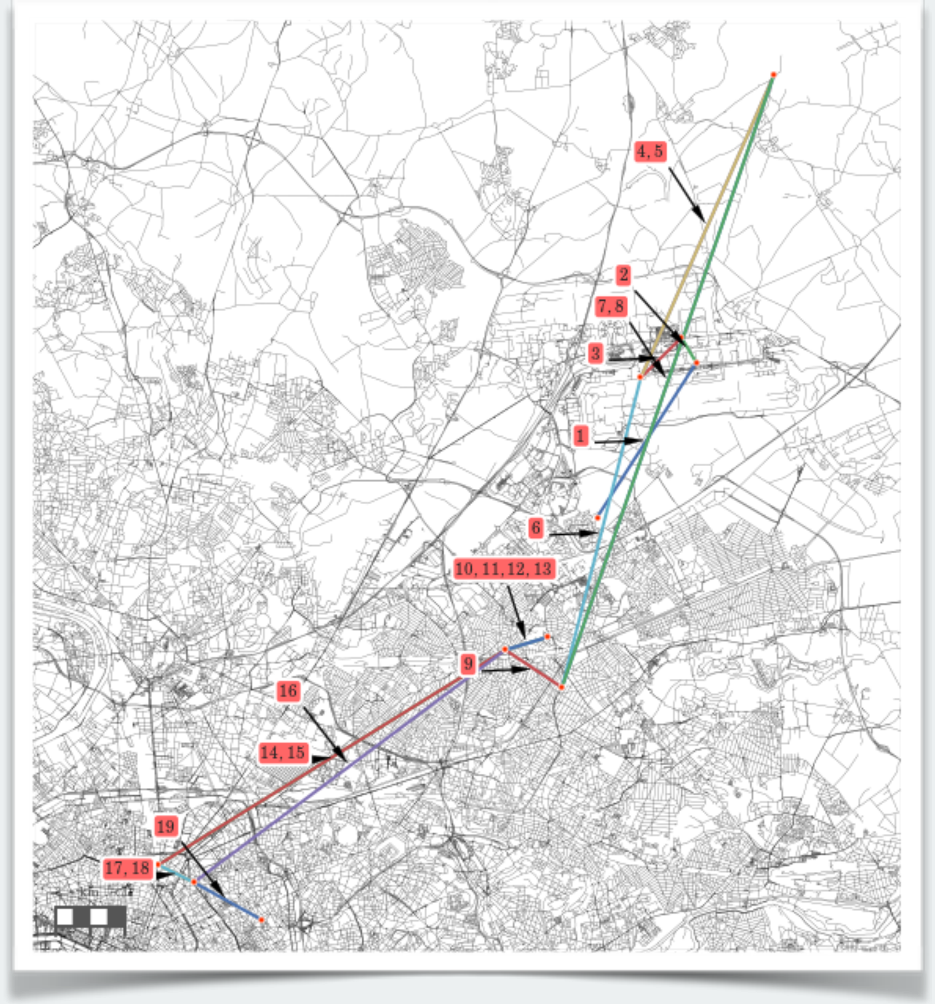


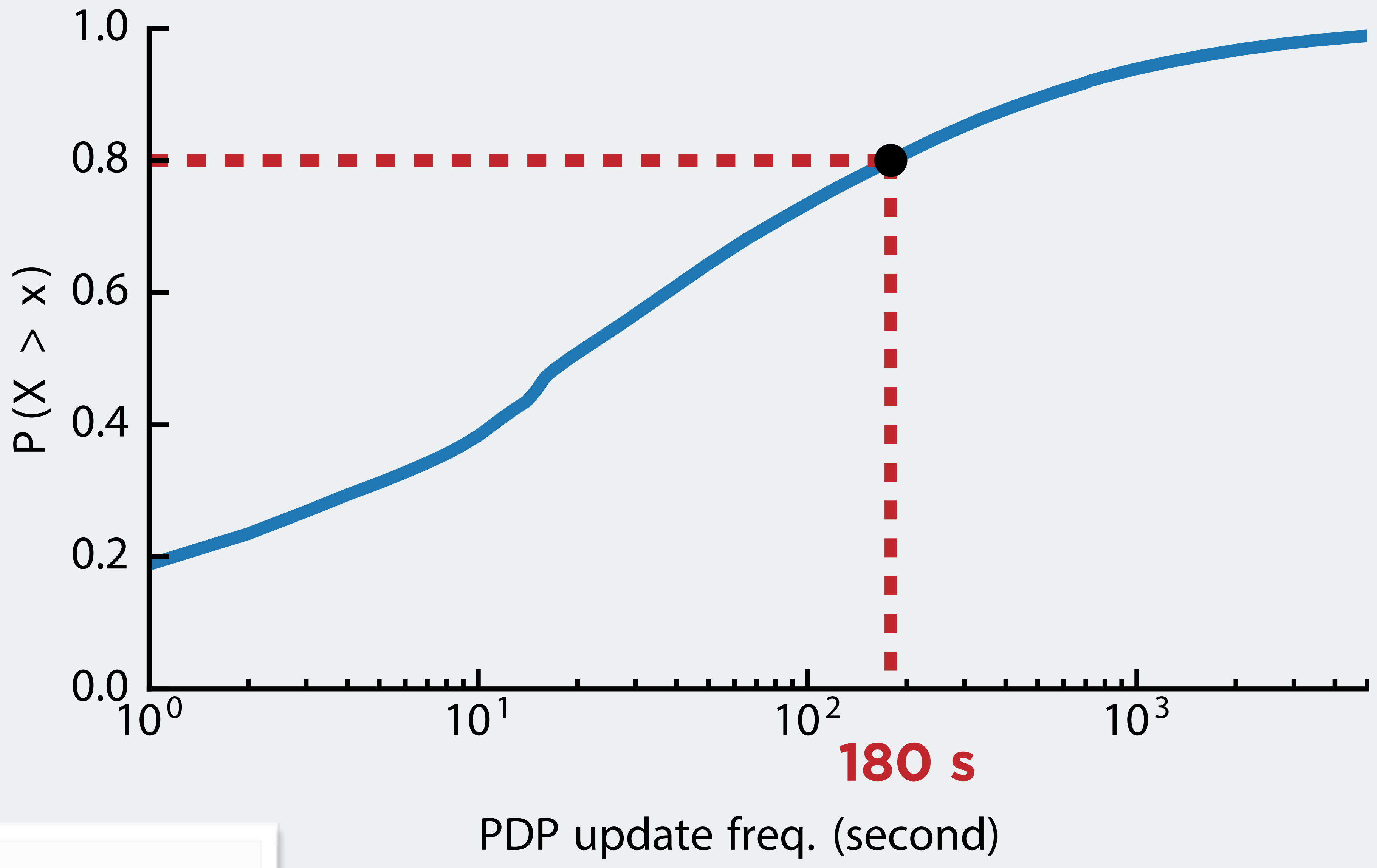
high serialization time

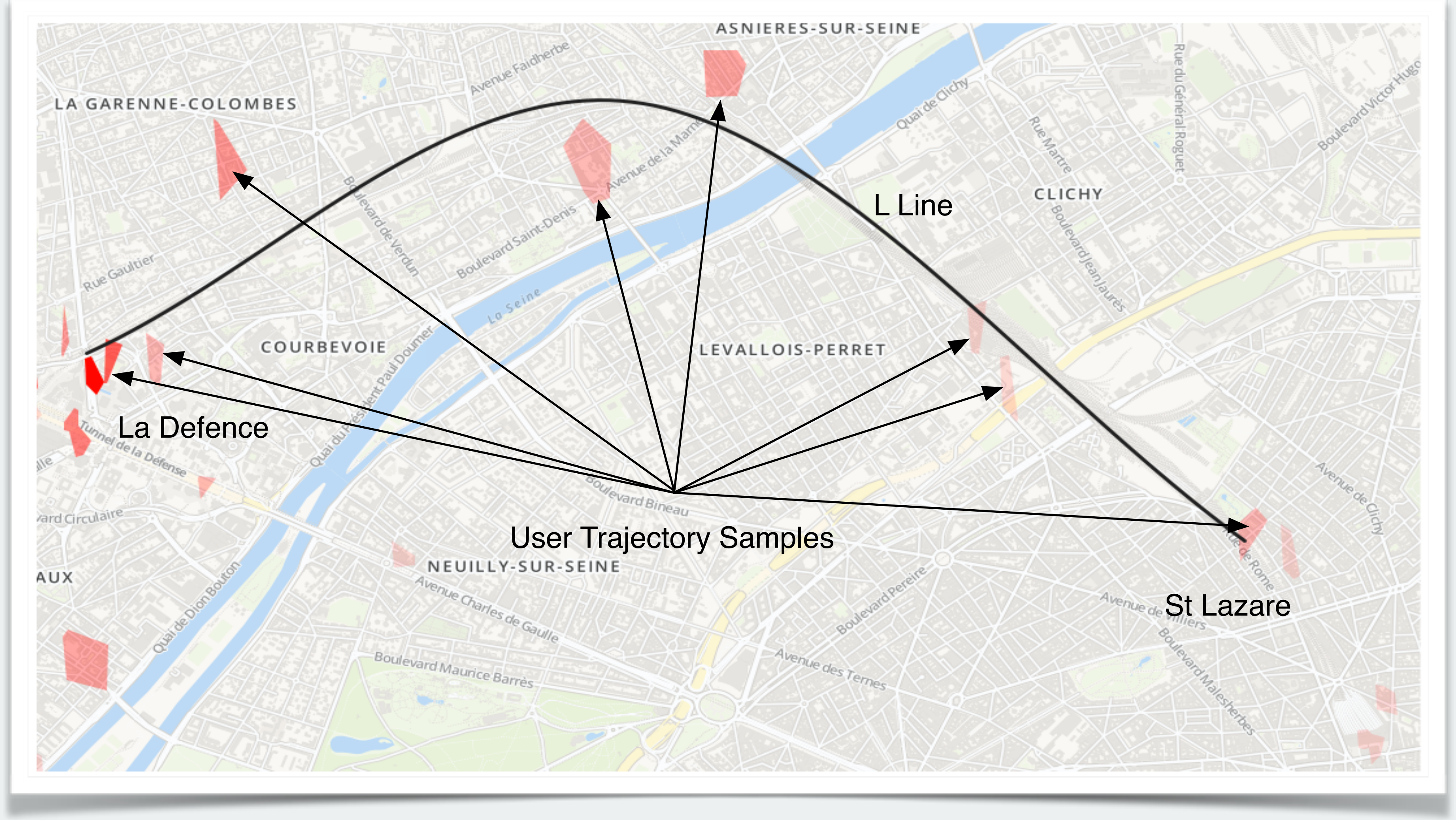


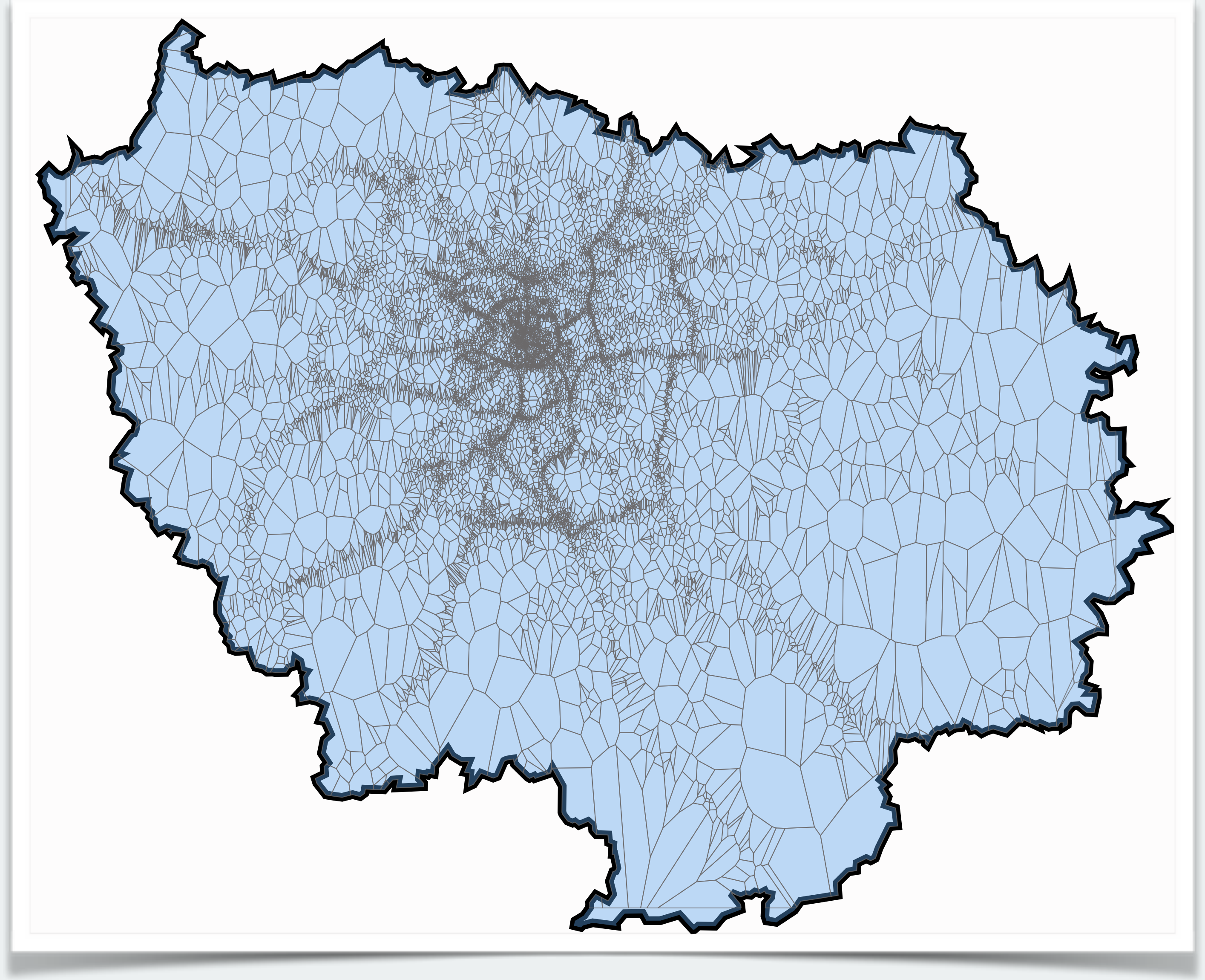
Mobile Data Network Analysis Platform
A. Sultan, F. Benbadis, V. Gauthier, H. Afifi
Proceedings of the 6th International Workshop on Hot Topics in Planet-Scale Measurement, 2015.

Mobile phone metadata (data channel)







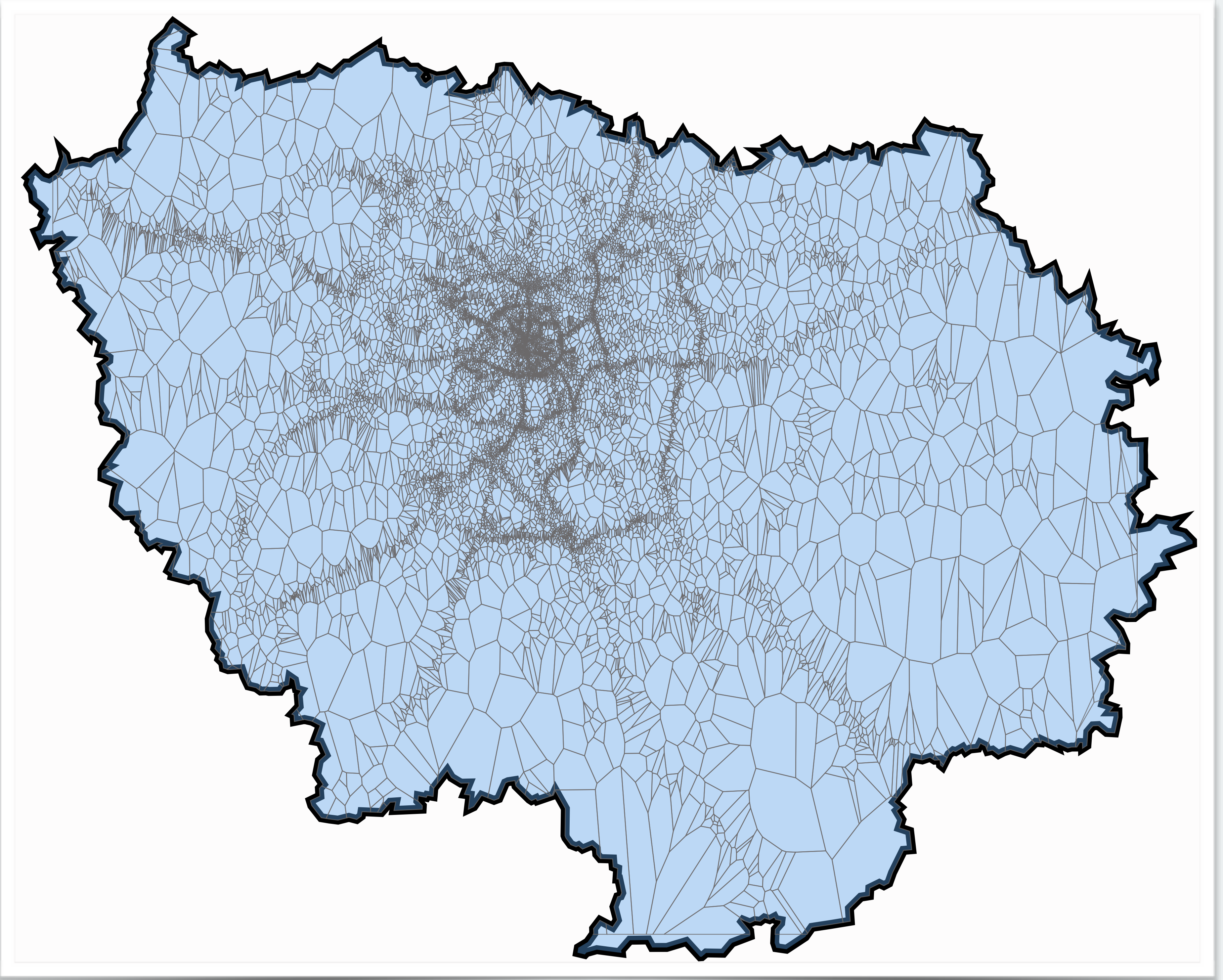


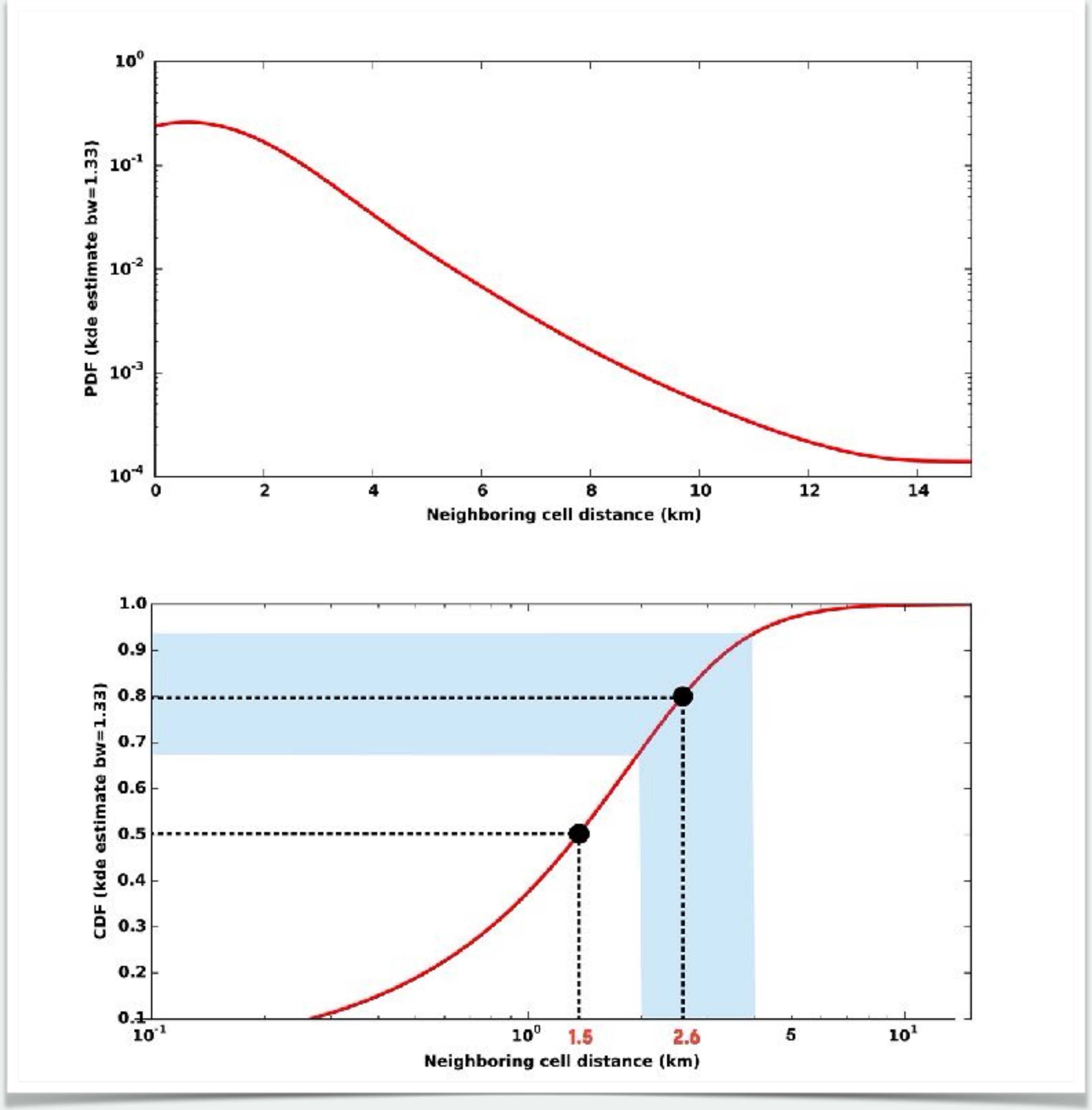
The sampling of mobile position is a complex spatio-temporal process:

1. The PDP update interval depends on the mobile phone activity: e.g. call (vertical handover), data channel standby
2. The distribution of BS (base station) in space is regular but non uniform

Spatial sampling
filter threshold

Compute the distance distribution of all the pair of BS.





Experimentation 1: SFR Dataset

Some experimentations

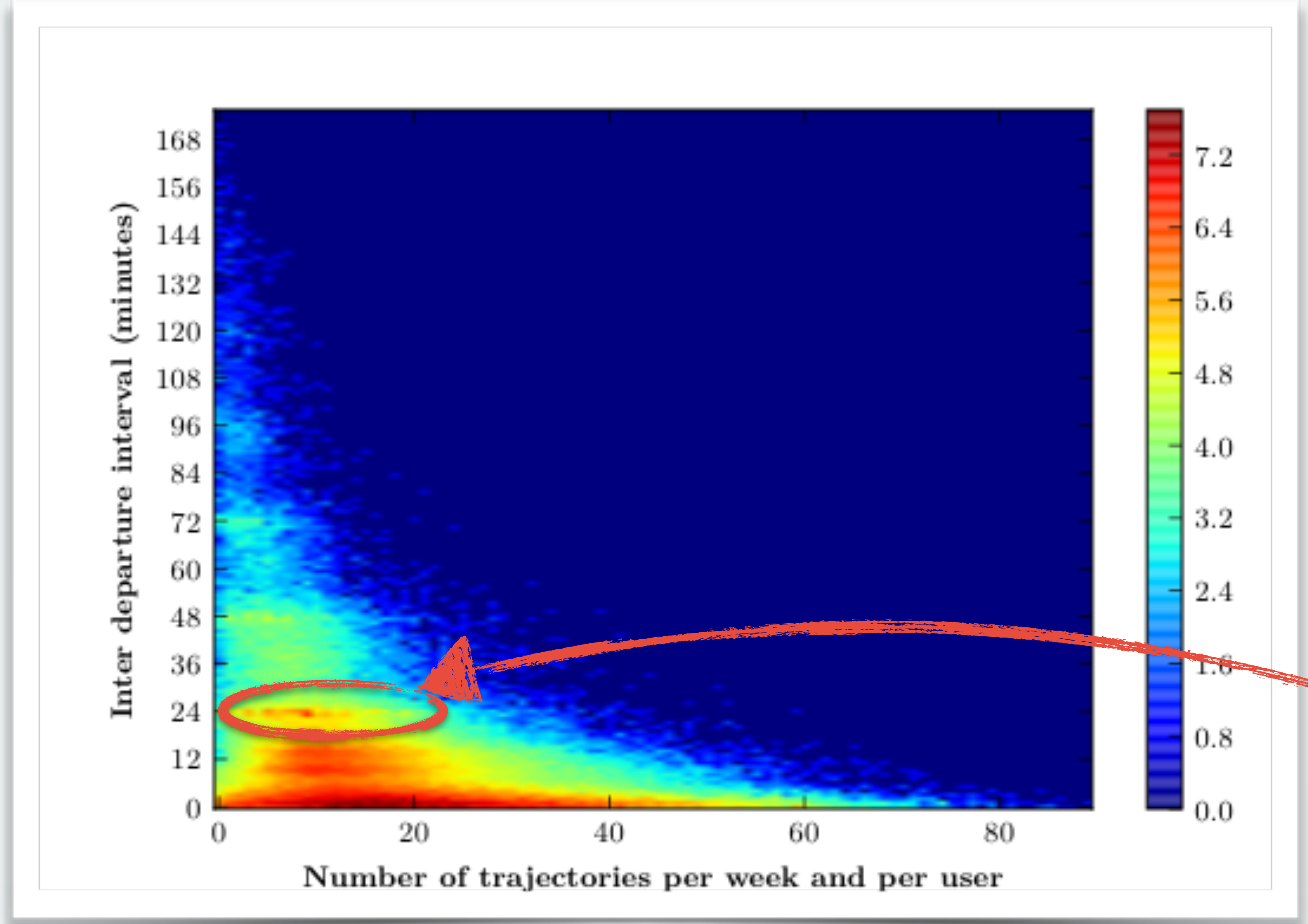


Fig 1.: Experimentation done over one week period in April 2015 in Paris vicinity. Inter-Departure rate of 4 million persons in Ile-de-France gathered over one week. inter departure distribution is represented by the color.

Spike at typical inter-departure time

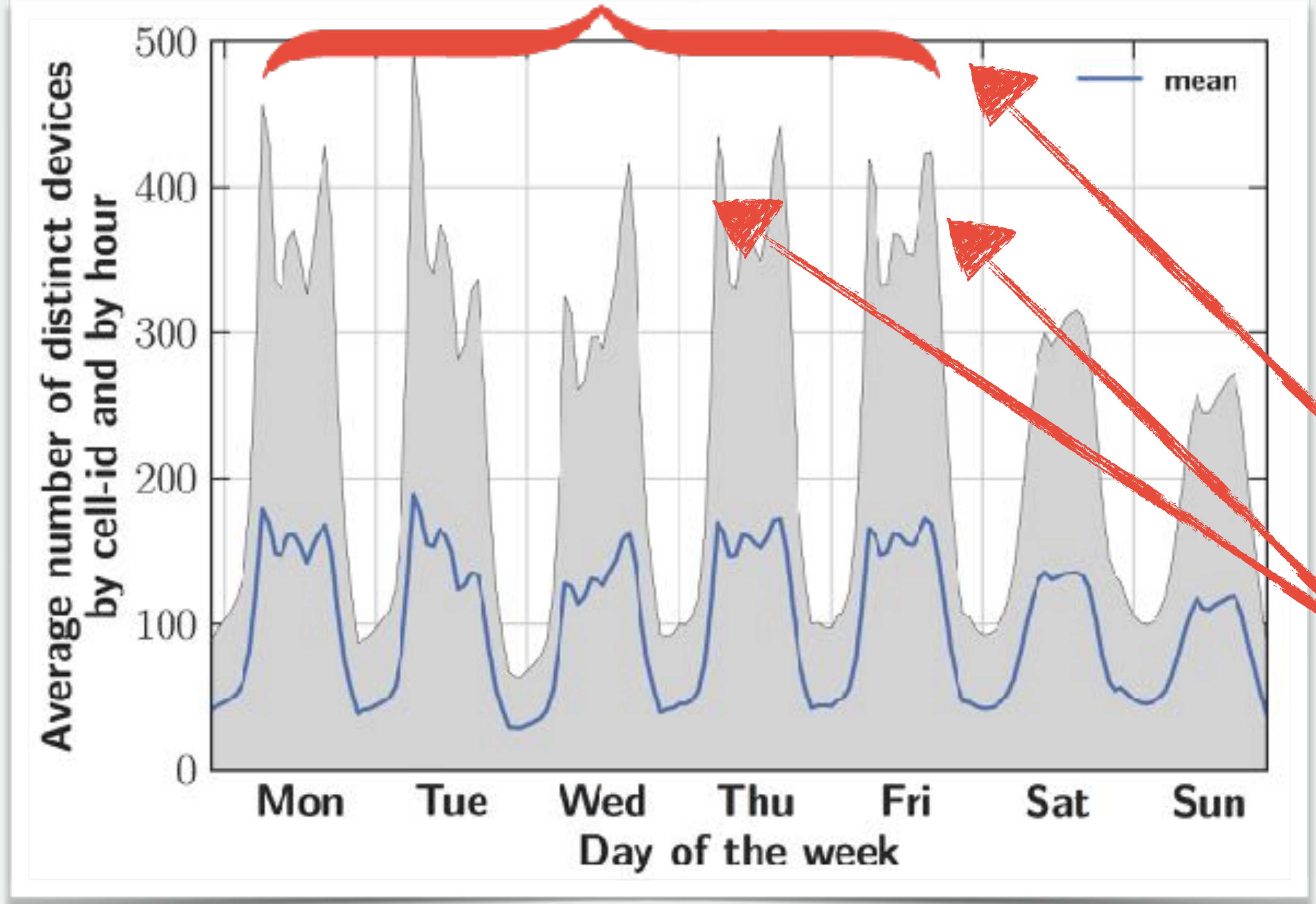


Fig 2.: Experimentation done over one week period in April 2015 in Paris vicinity. Number of distinct device x 10000 over time.

Weekday pike

Morning & afternoon pike

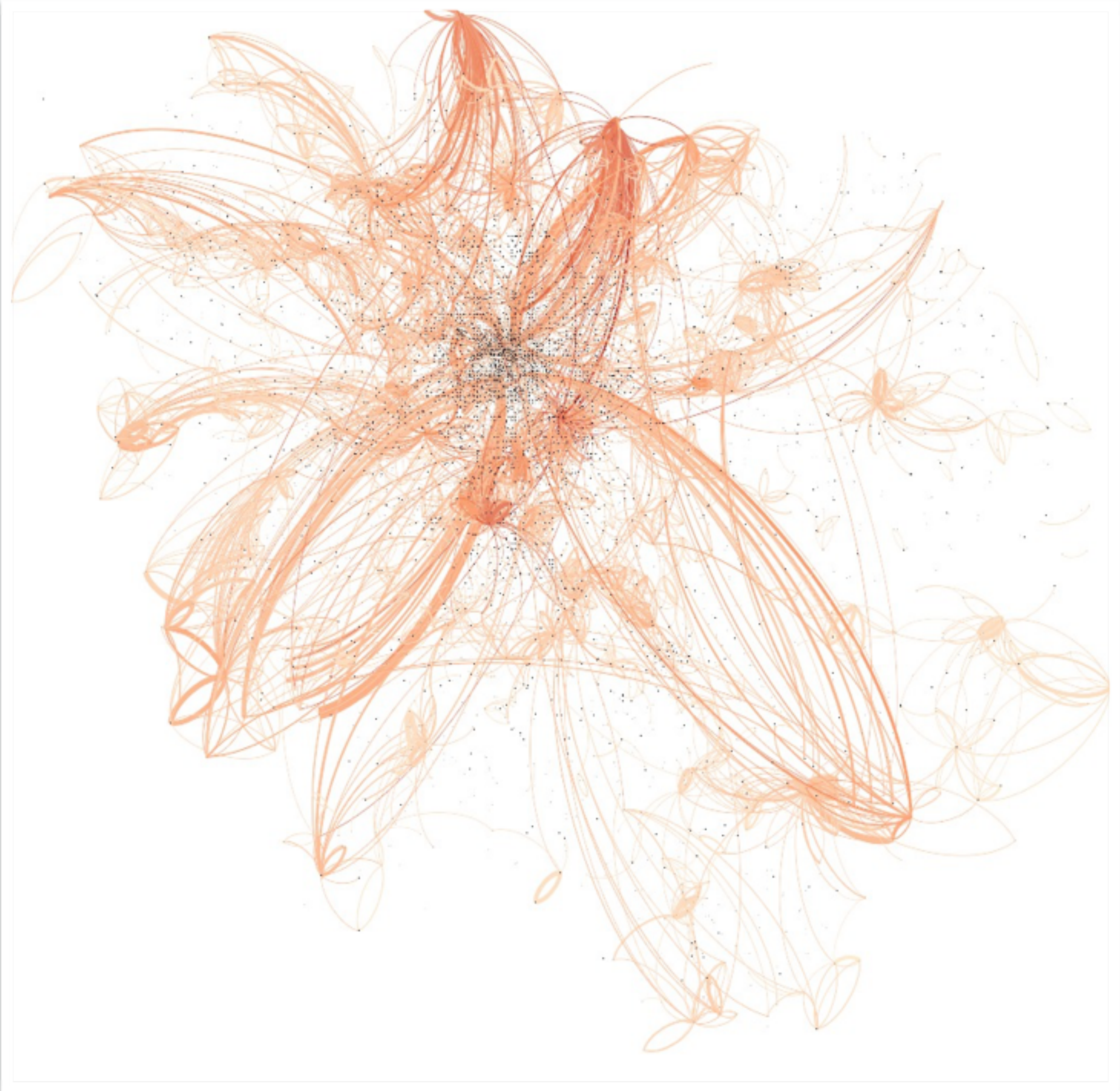


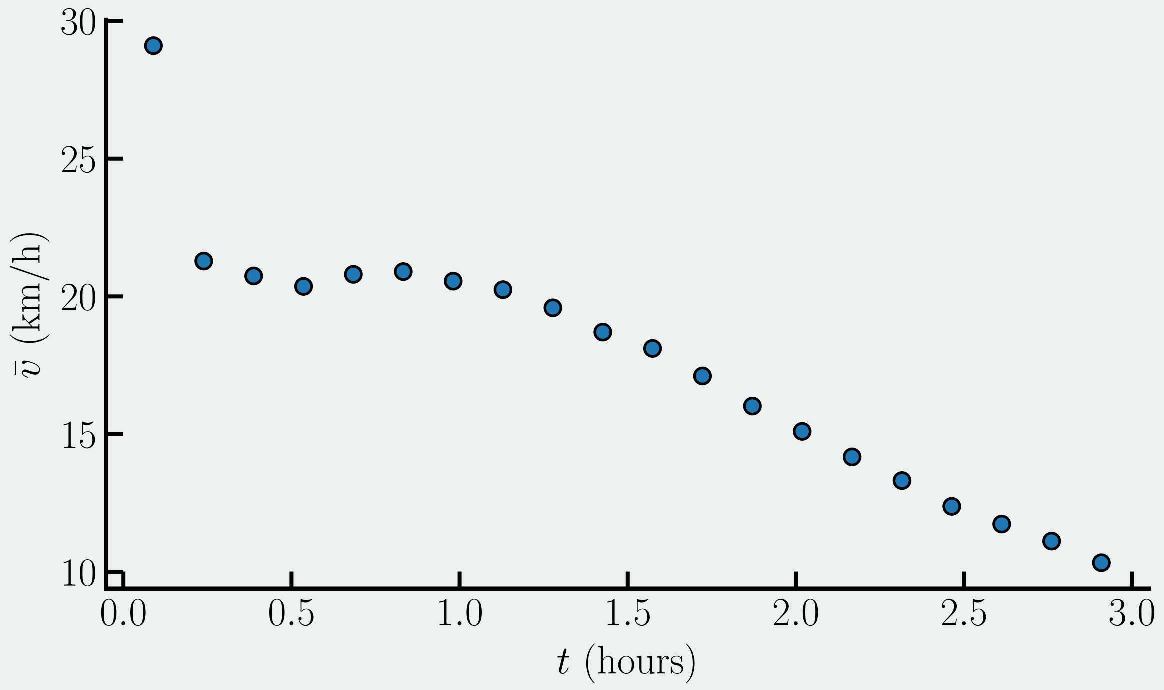
Fig. 3.: Aggregated representation 1 020 645 trajectories over half day period (04H00 to 12H00) for 784 699 users moving inside the Paris region, France. The transitions represent the beginning and the end of a trajectory. The end of a trajectory is defined when a user remains more than 30 minutes in the same spot. (the graph density is 0.0055 for 11980 Base Station, we filtered the trajectory radius of gyration under 2km)

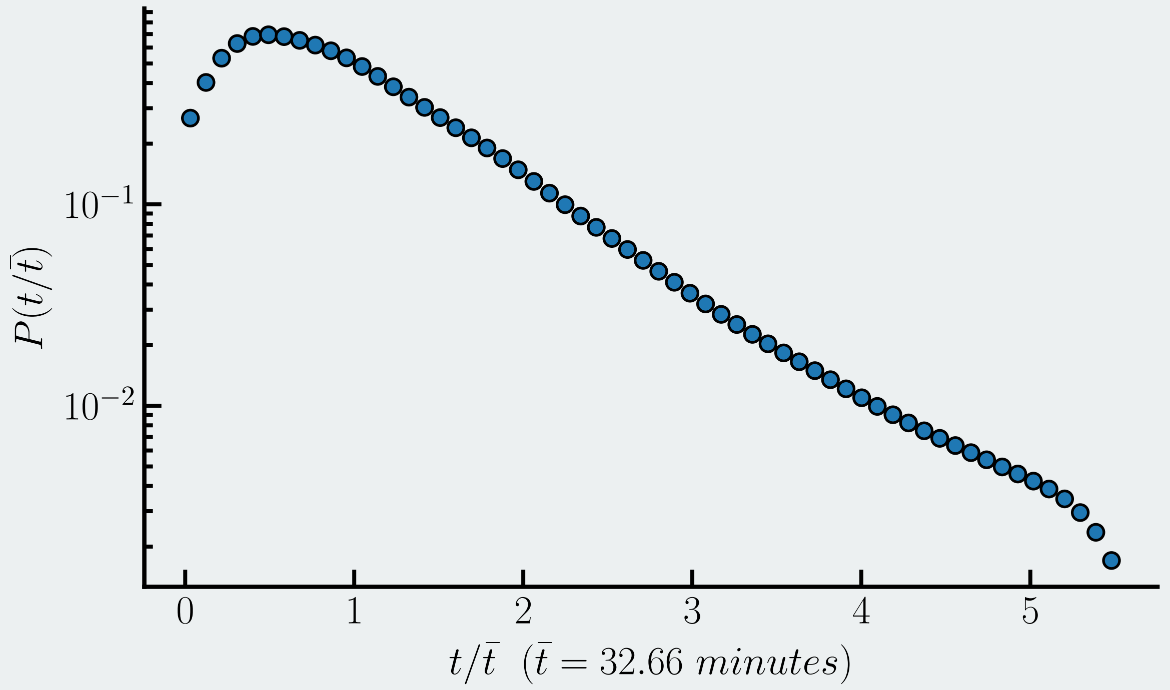
Experimentation 2: Bouygues Dataset

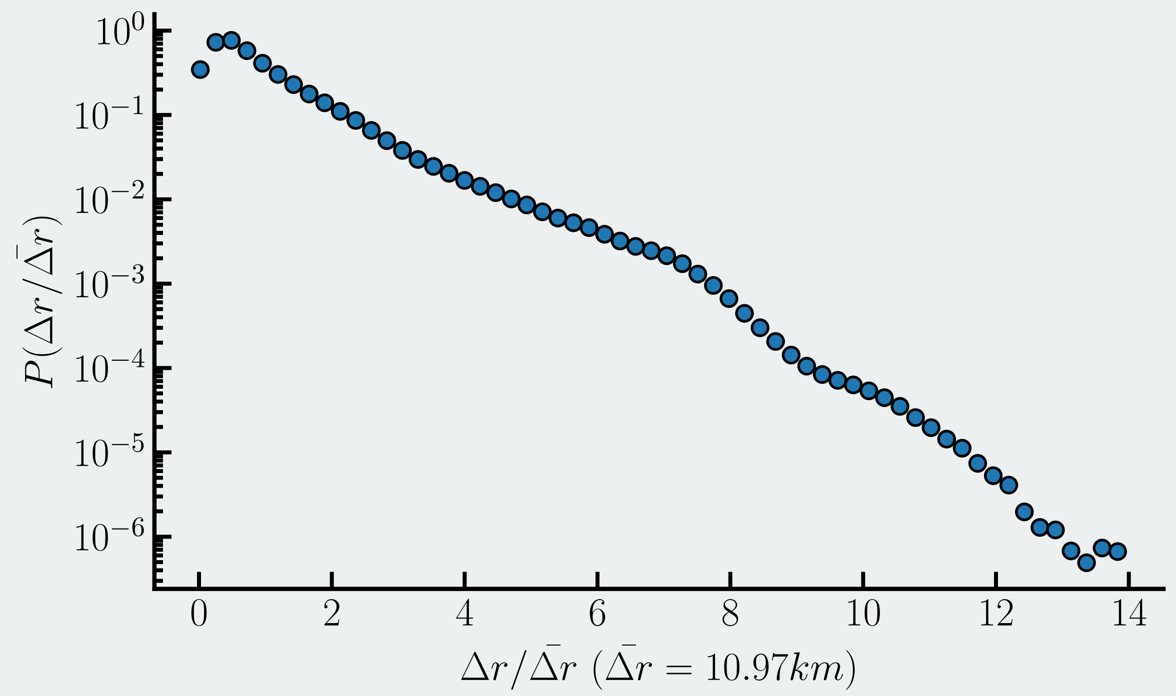
Travel Time, Jump Length, Speed

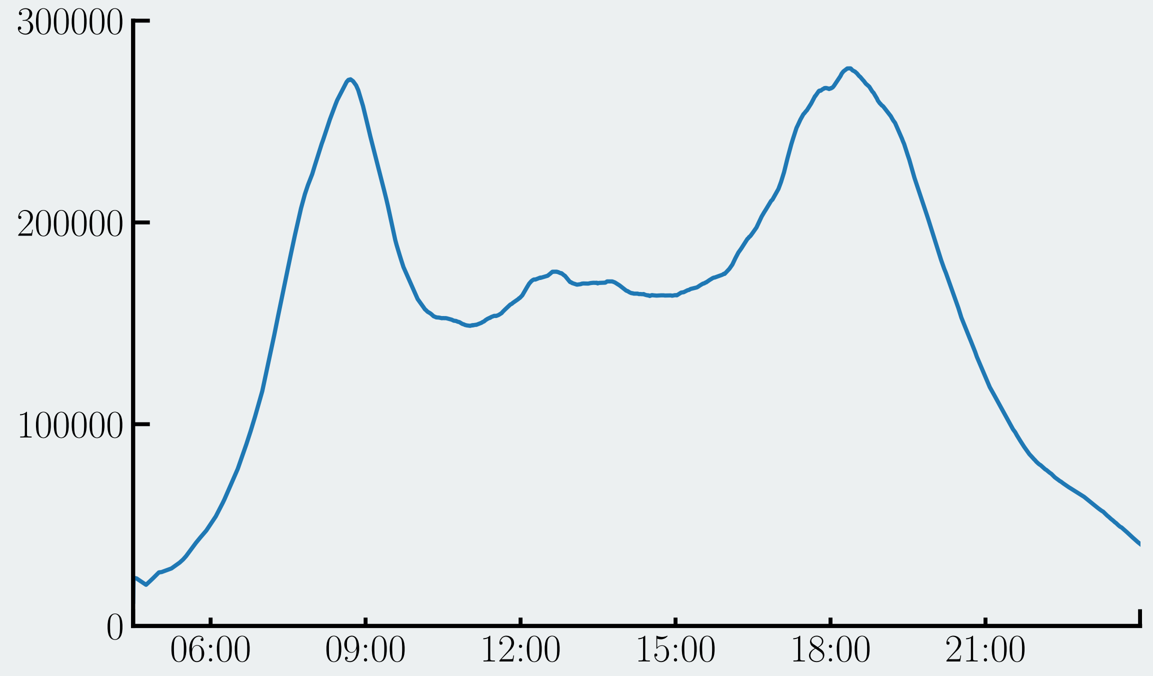
1. Travel time
2. Travel duration
3. Travel distance
4. Speed vs distance

DATASET:
- One couples of days of cellular network signalizations 30 GB (call, sms, PDP context)
- Geographic area : Île-de-France
- 3.5 Millions of distinct IMSI, approx. 1/3 of the pop of IDF
- 1.6 Millions usable trajectories (real mobility)
- 40 000 cells sectors, 5000 BTSs
- Preprocessing tool: Amazon Redshift

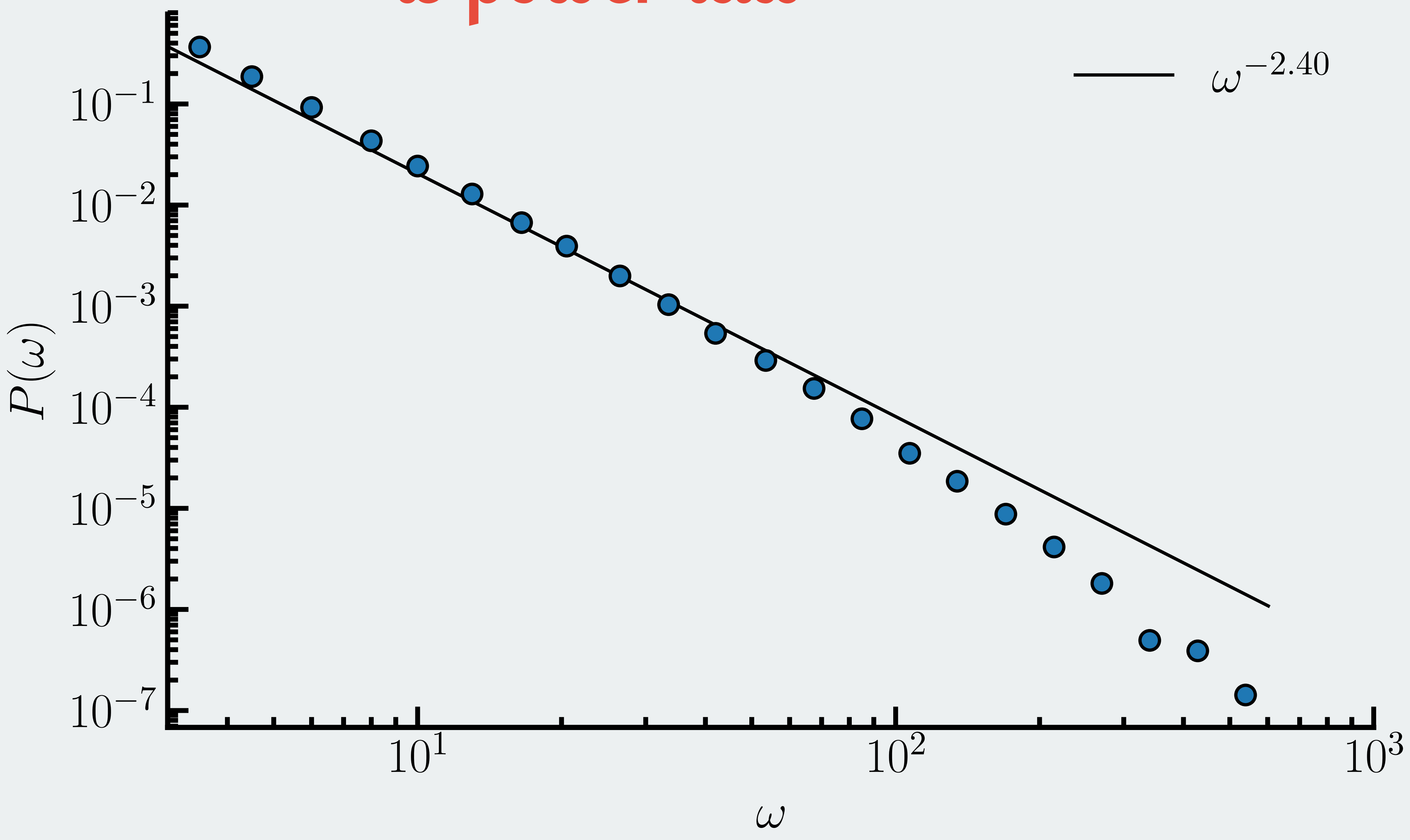






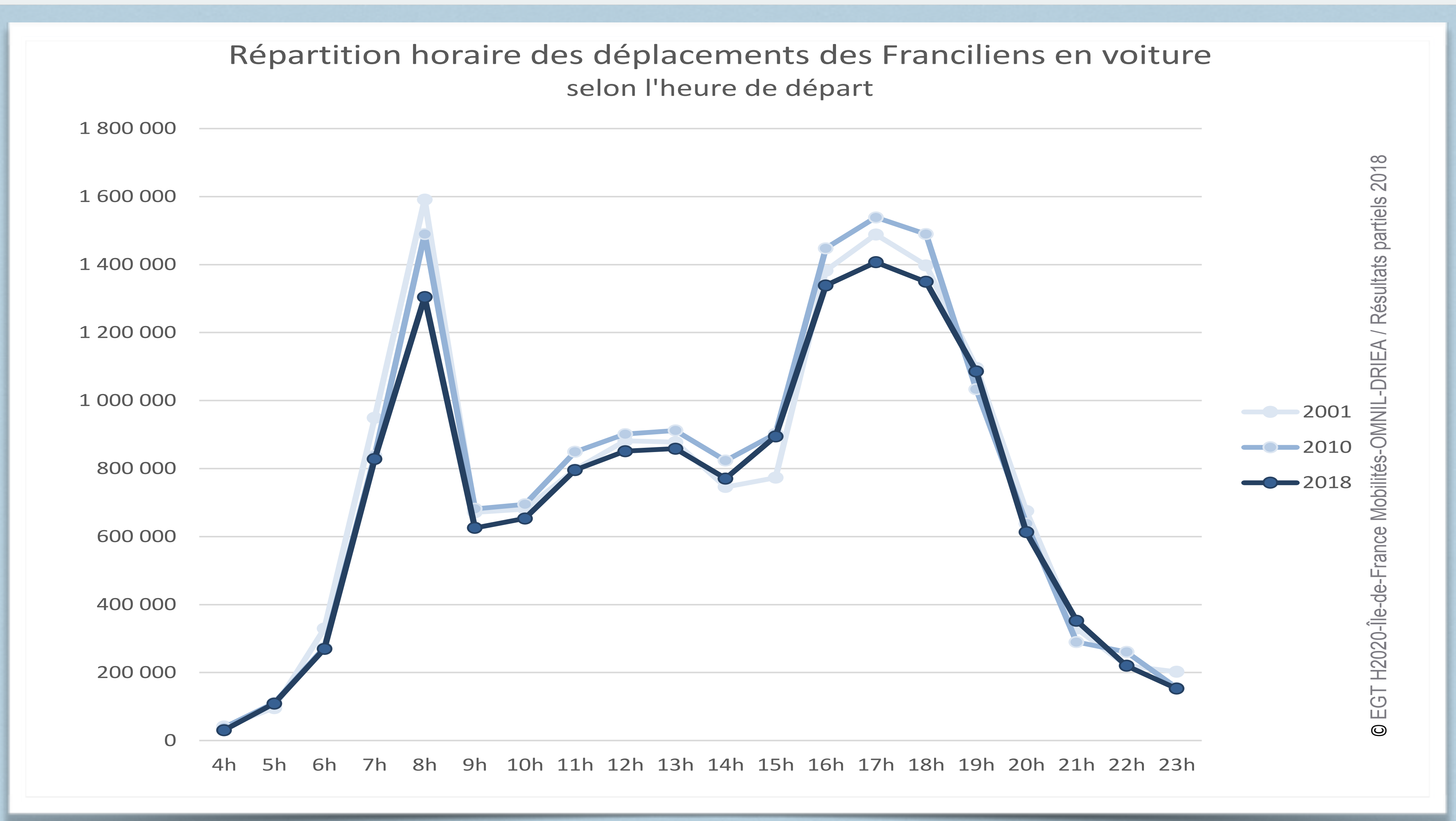


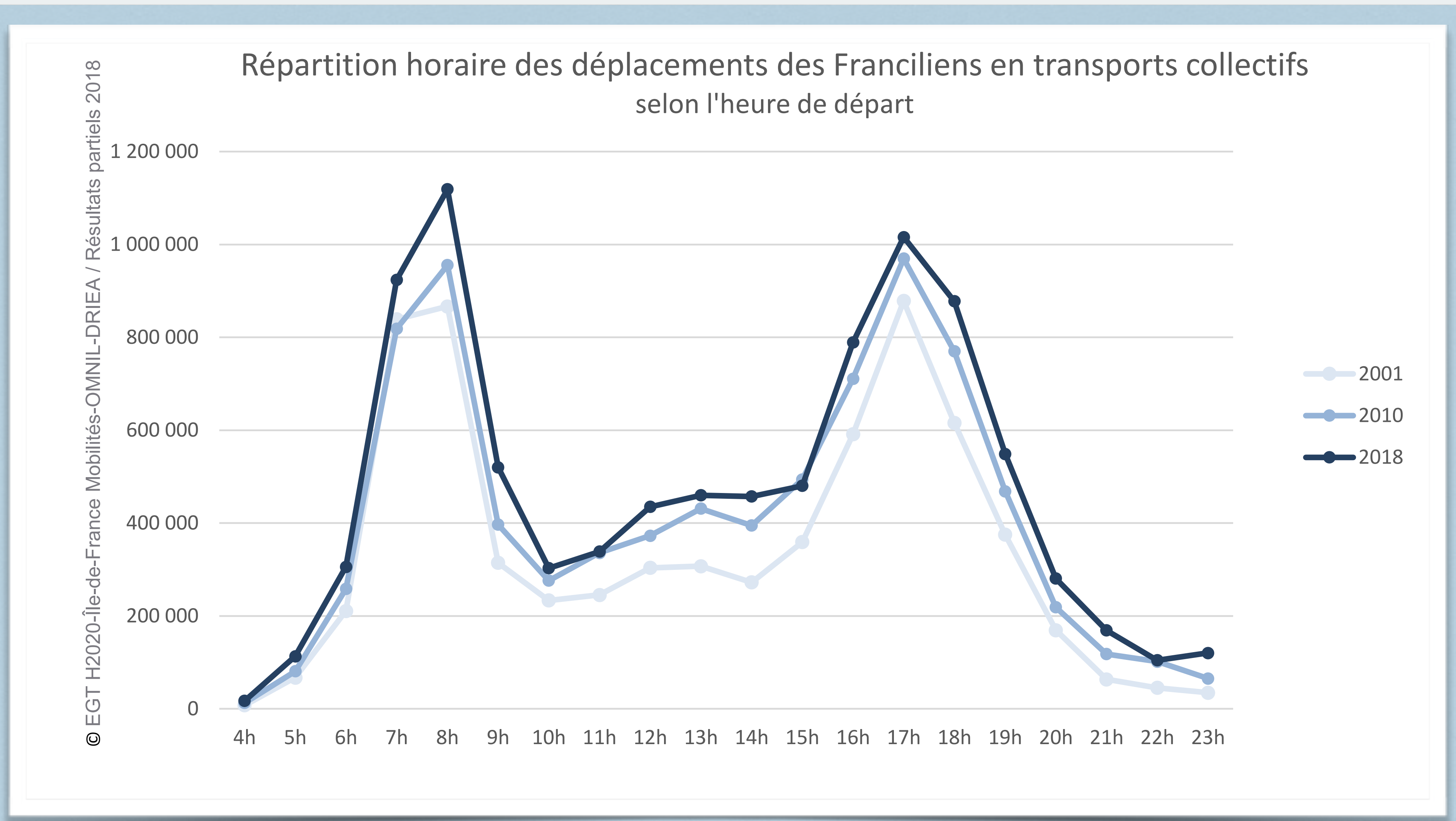
The flow distribution is power law



Comparison with the EGT-H2020

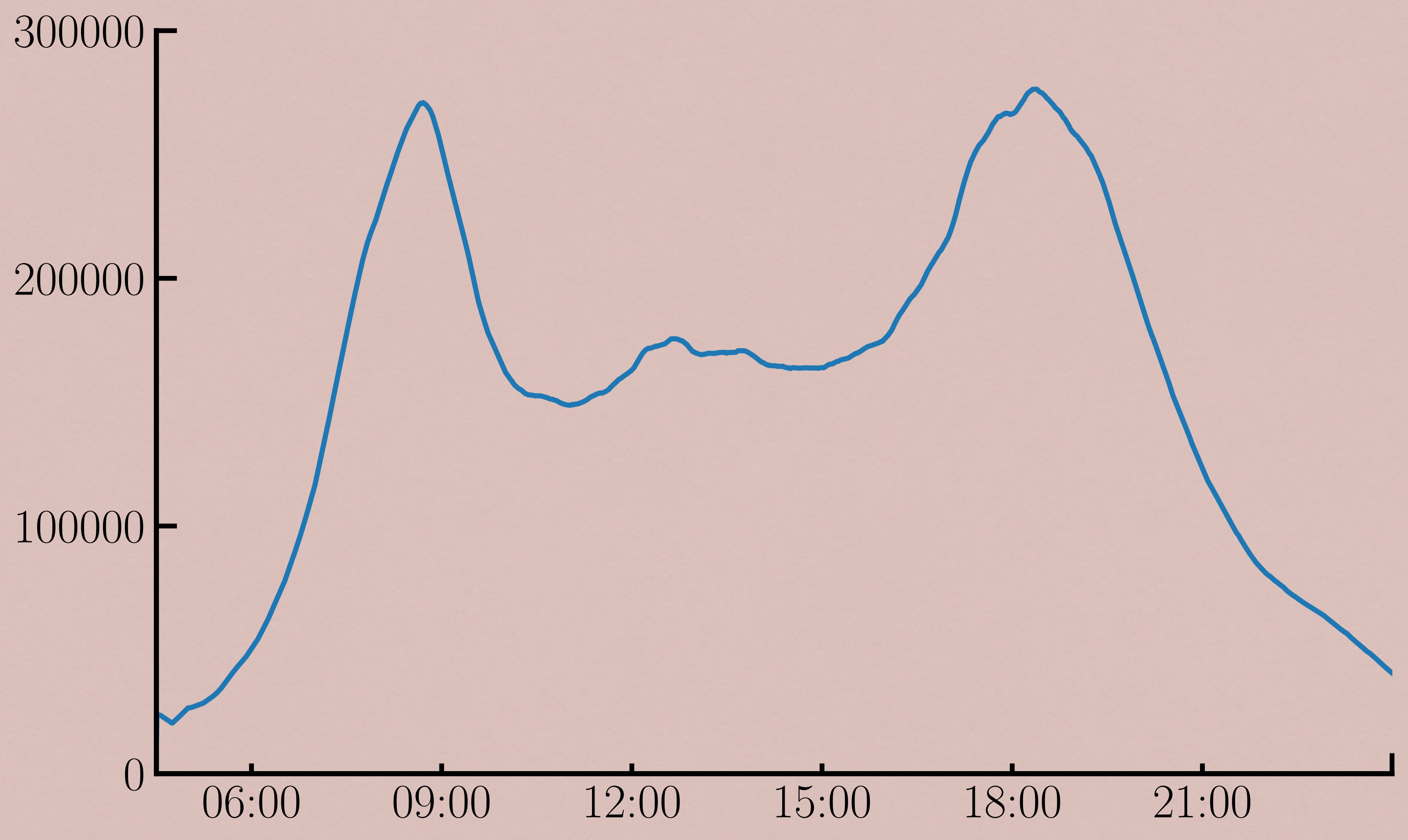
EGT-H2020





Bouygue Tel Dataset

$\approx \times 10$



Trajectories Mapping of Cellphone Metadata

Create a mapping algorithm for cellular trajectories

Goals

- Study the human mobility with a large dataset
- Map cellular user trajectories on a transport network
- Guess what is the transport mode used by a given mobile carrier

Issues

- Use an unsupervised method (large coverage area)
- The transport network is multimodal (road, train, subway)

Dataset

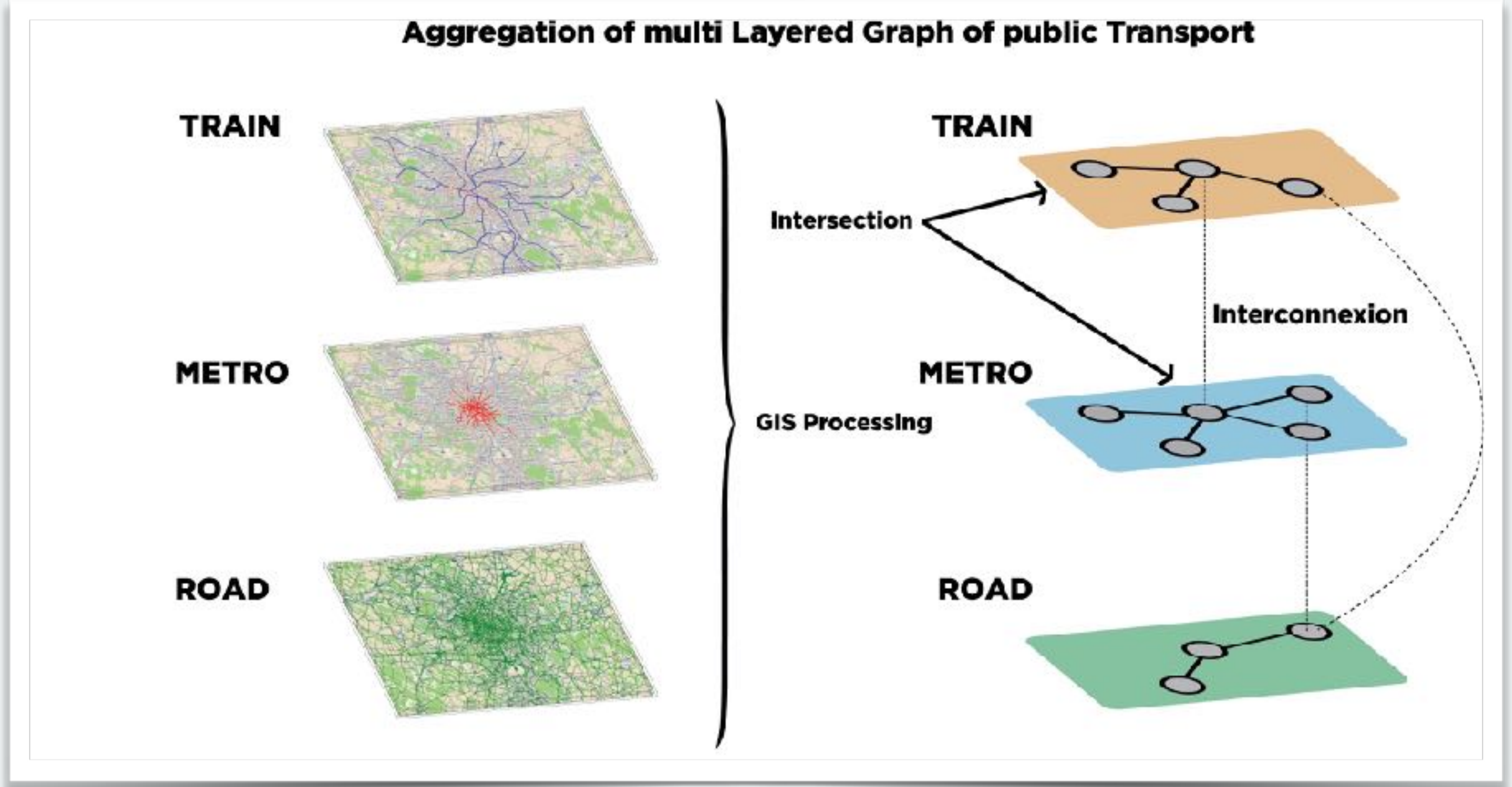
- GTP signalization data

Application for public transport authorities
Public safety: large event, i.e. olympic games
Human mobility applications: e.g. volumetry of transport modes
And many other applications

Trajectories inference: GIS

GIS processing

1. Process each layer separately and form a graph
   - each road intersection is a node
   - each metro station is a node
2. Add cross layer links where it's needed, i.e.: between a road intersection close to a metro station
3. Collapse all the layers into one graph



$$\mathbf{G} = (V, E, L, \Psi)$$

V : vertices

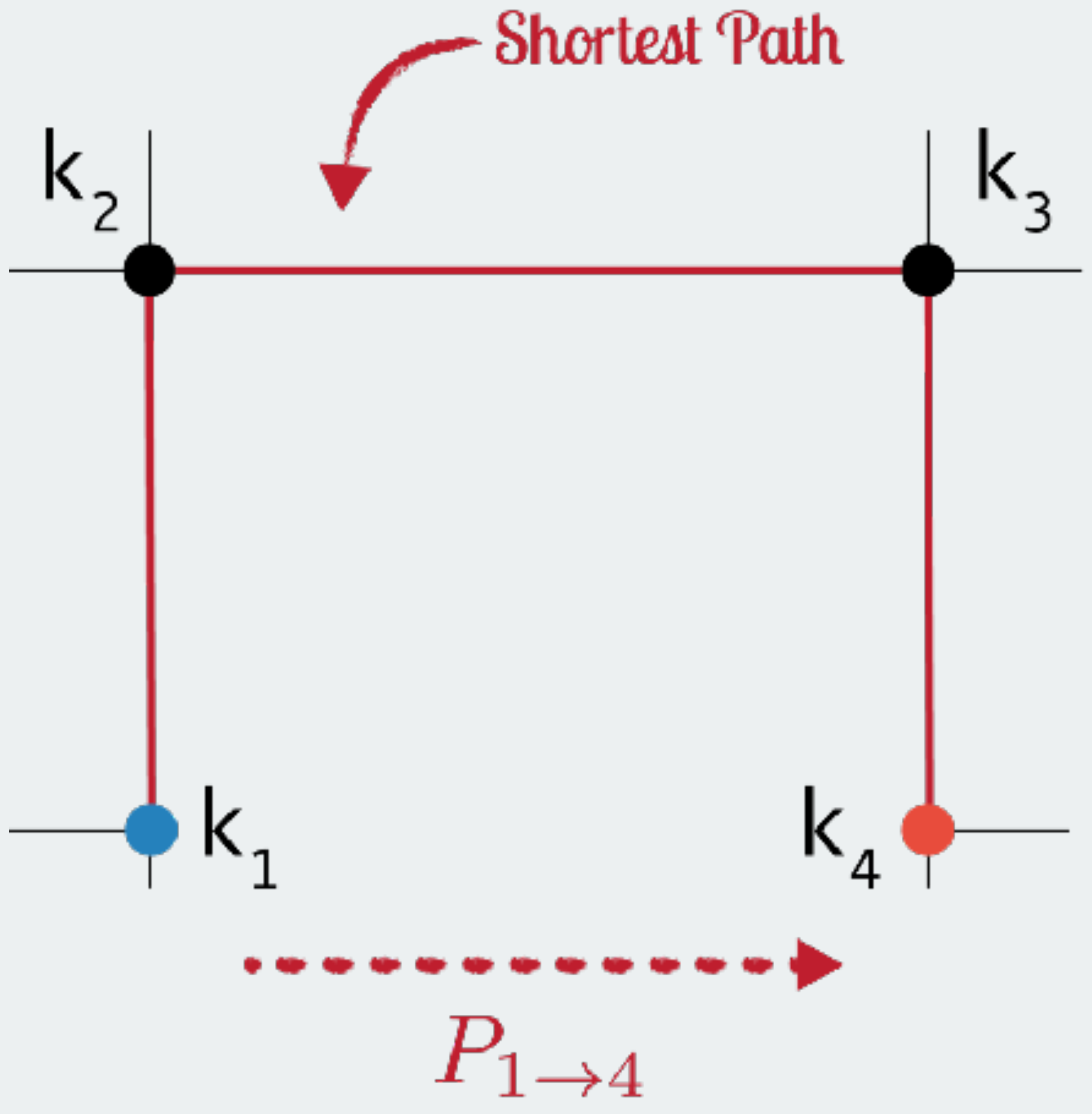
E : edges

L : layers

Ψ : fonction that associates a layer to a vertex

Quantifying the search complexity in graph

Complexity of searching on a graph[1,2]



$$P_{i\to j} = \frac{1}{k_i} \prod_{l\in SP(i,j)} \frac{1}{k_l - 1}$$

Probability for a random walker starting at node i to reach node j along the shortest path

	Number		Avg.		
	Node	Edge	Degree	Length	Reference
Subway	303	356	2.35	0.757	OSM
Train	241	244	2.025	3.07	OSM
Road	14798	22276	3.01	1.34	IGN

Table: Different transportation networks with their properties

The average length between two consecutive intersections is rather heterogeneous across different transportation layers. As well as the number of nodes in each layer.

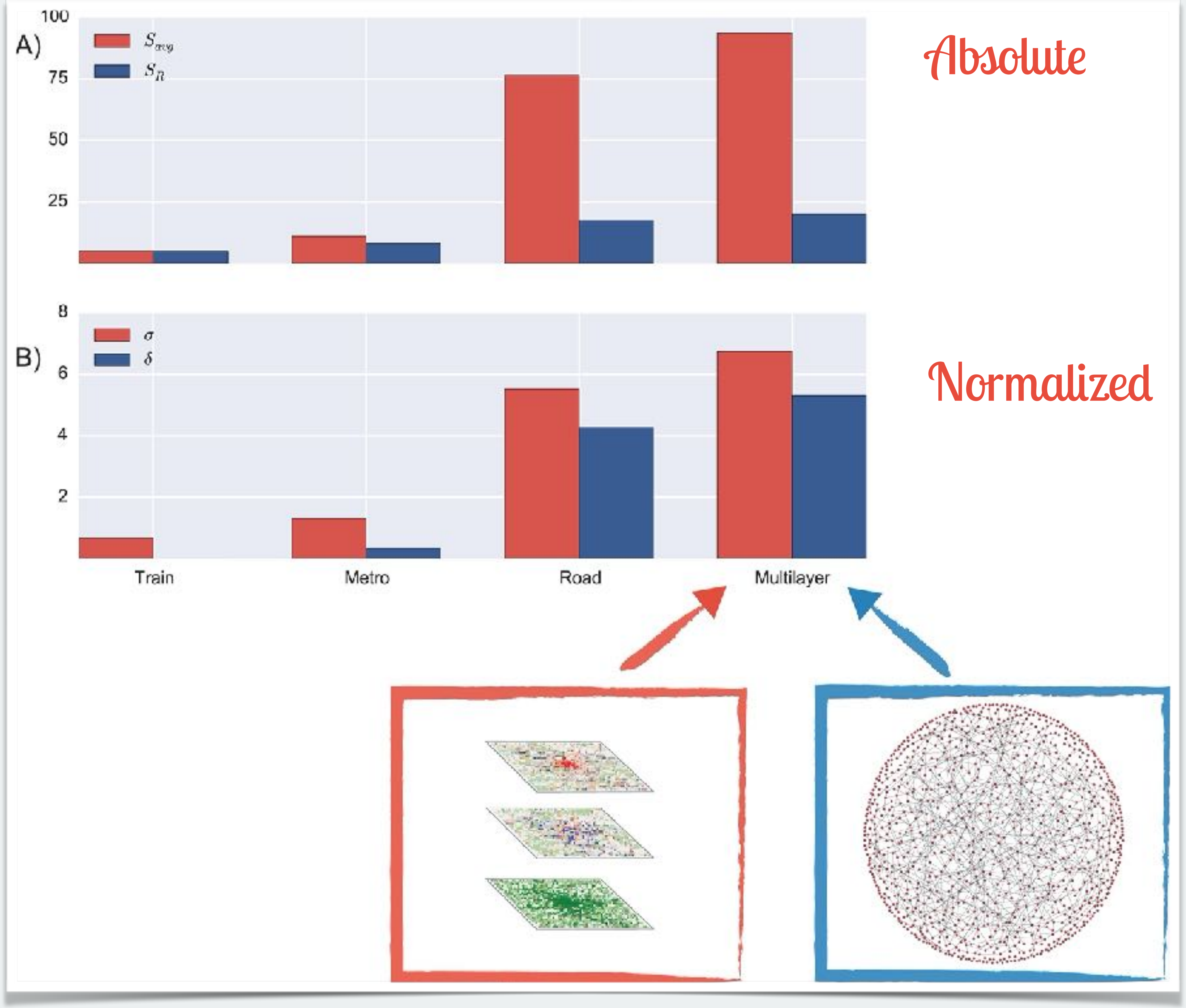
1. K. Sneppen, A. Trusina, M. Rosvall, Hide-and-seek on complex networks, Europhysics Letters (EPL) 69 (2005) 853–859.
2. M. Rosvall, A. Trusina, P. Minnhagen, K. Sneppen, Networks and cities: An information perspective, Phys. Rev. Lett. 94 (2005).

SEARCH COMPLEXITY OF THE MULTILAYER GRAPH

Continued

Compute the search entropy: the average probability for a random walker to reach a given destination.

$$S_{avg} = \frac{1}{N(N-1)} \underbrace{\sum_{i=1}^{N}\sum_{j=1}^{N}}_{\text{For all combination of sources and destinations}} \left[-\log_2 \underbrace{\sum_{\{SP\}} P_{i\to j}}_{\text{for all degenerate paths}} \right]$$



Conclusion

- Various level of complexity at each layer
- Searching in a multilayer graph is more complex than the sum of the search complexity of each layer

Design of the HMM

Given a user trajectory

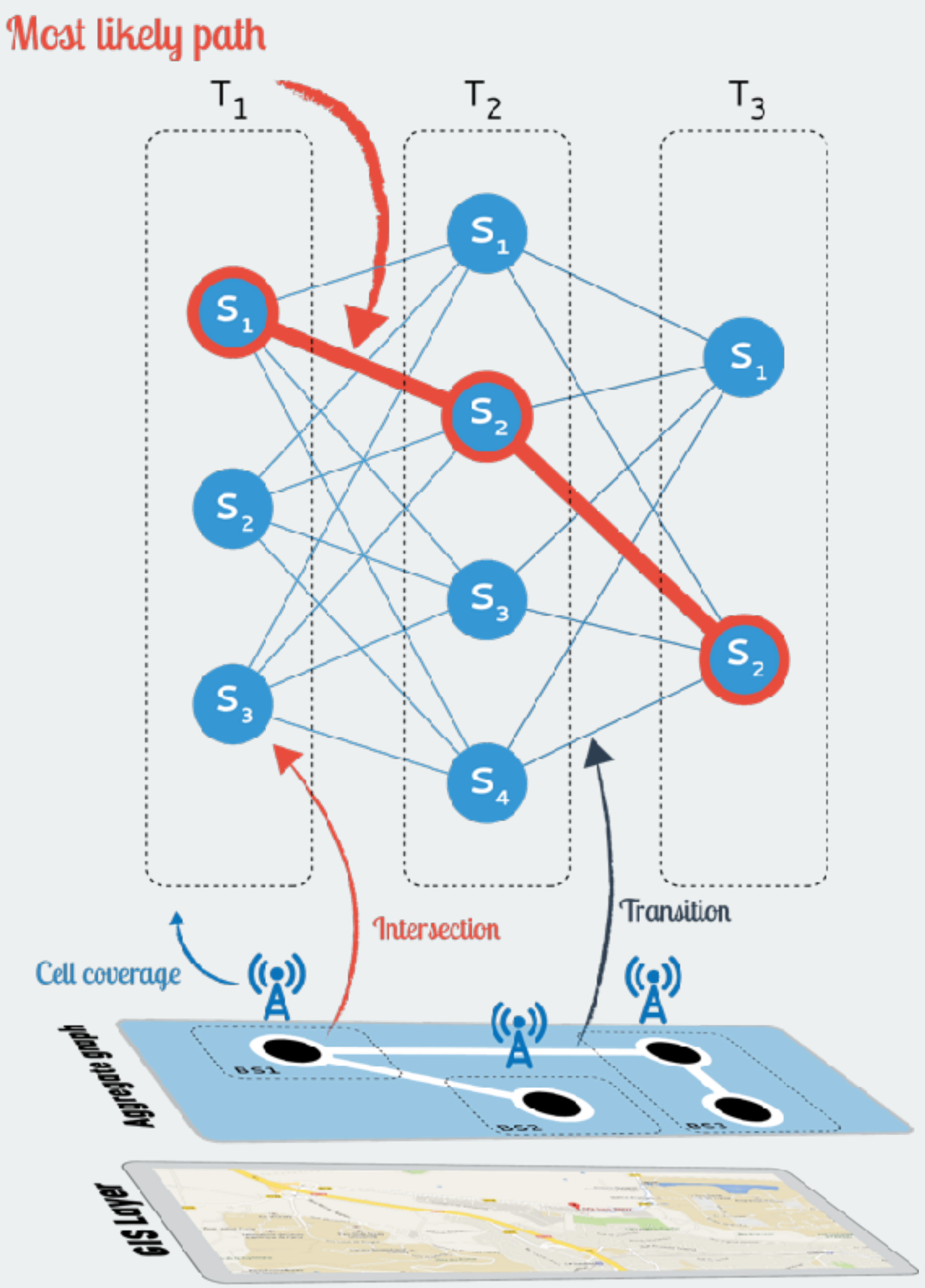
$$UT_i = \{(BS_1, t_1), (BS_2, t_1), \ldots, (BS_n, t_n)\}$$

Discretize the problem, a given user can only be in a:

- Road intersection
- Train or metro station

Use the Viterbi algorithm to compute the most likely path

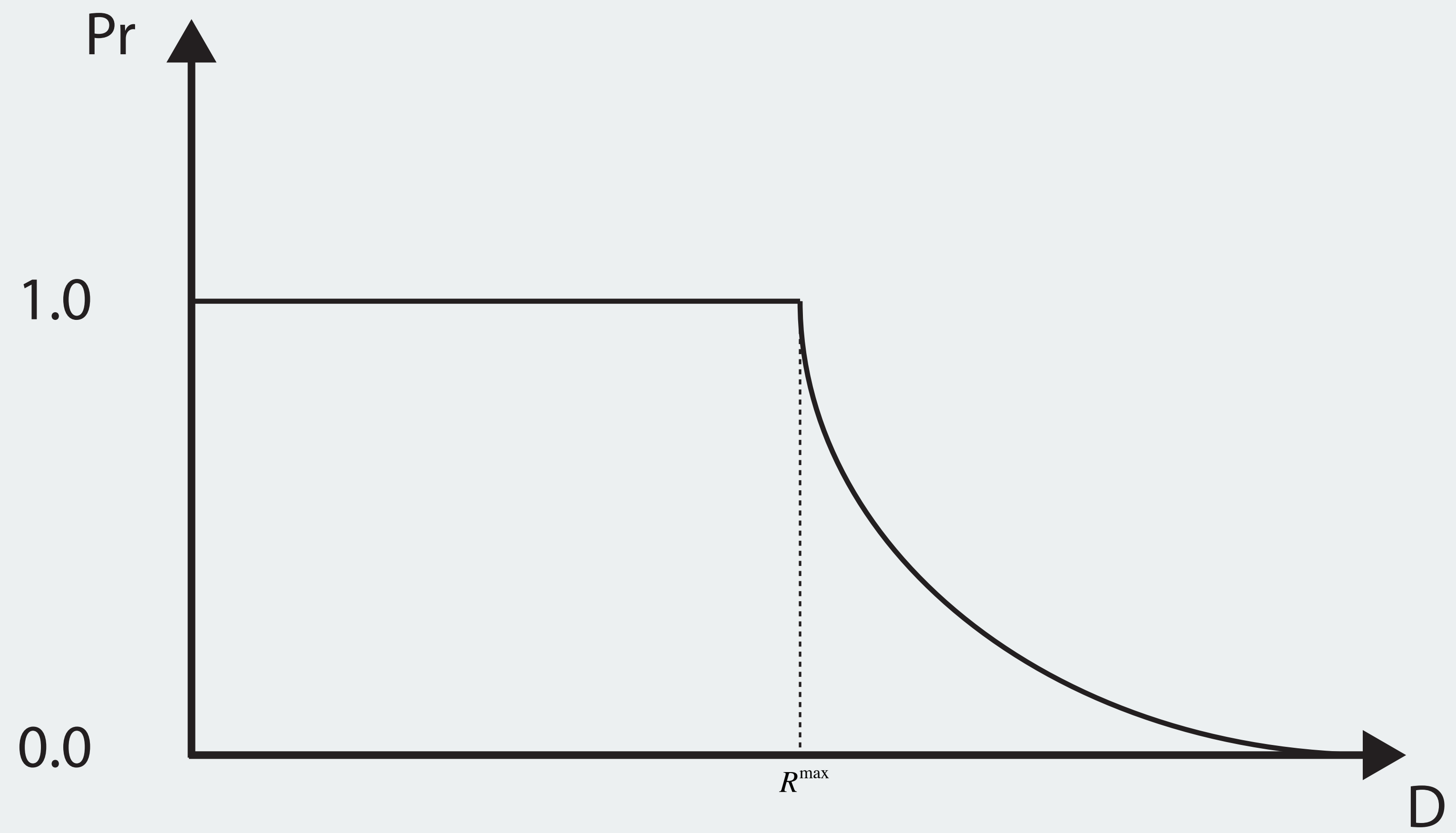
1. Associate a probability to each possible position (e.g. road intersection)
2. Define all possible transitions between all the possible states of the system



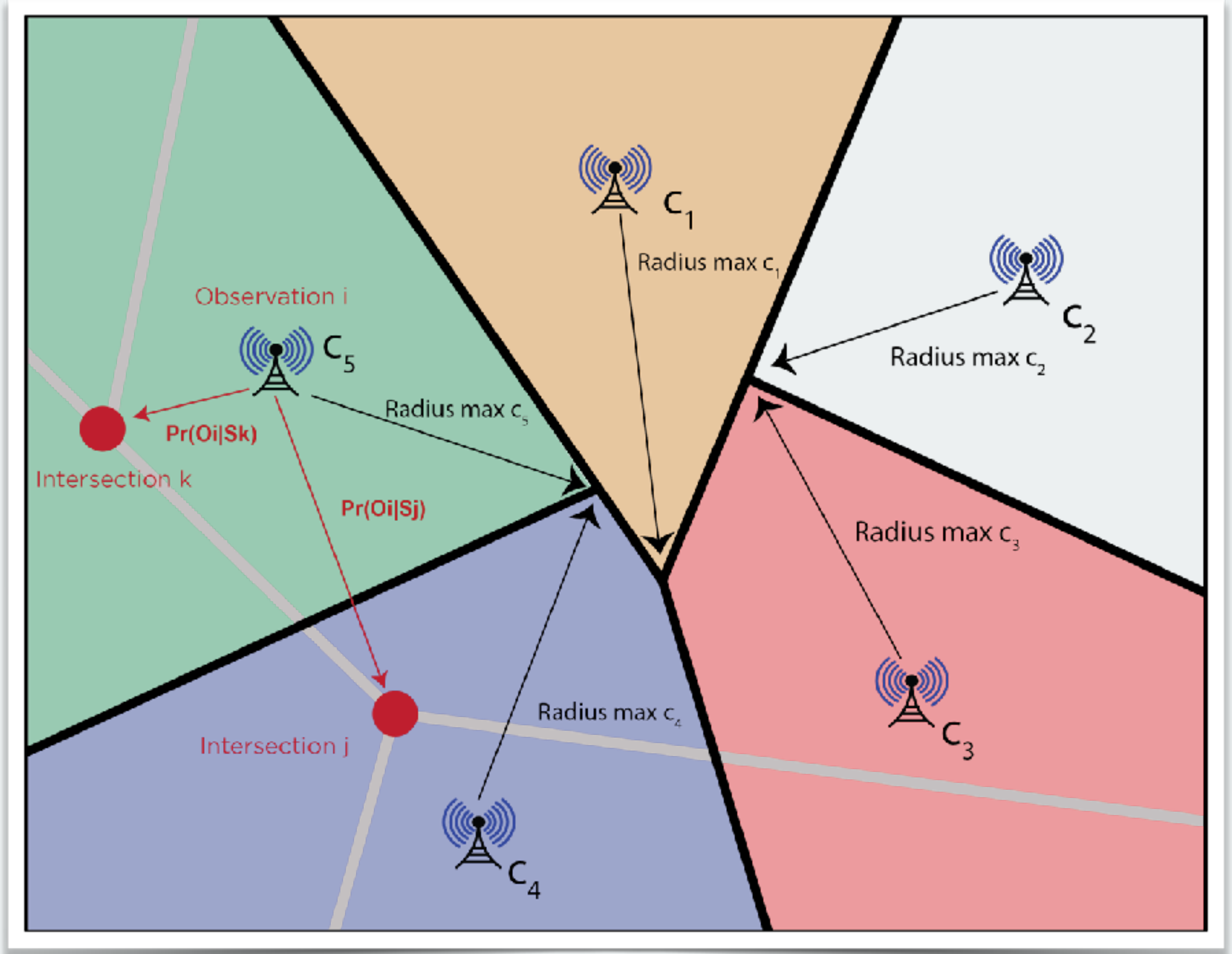
Emission probability

Many different kernels can be used to model the emission probability, such as ray tracing technic to account for the terrain elevation for instance.

$R_{O_t}^{max}$: is the maximum transmission radius of the base station that recorded the observation



$$Pr\left(O_t|S_j\right)=\begin{cases}1 & \text{if } D_{O_t,S_j}\leq R_{O_t}^{max}\\ \left(\frac{R_{O_t}^{max}}{D_{O_t,S_j}}\right)^{\alpha} & \text{if } D_{O_t,S_j}>R_{O_t}^{max}\end{cases}$$



Transition probability

Find the shortest path between any two nodes in the network

w_{ij}	Condition
80	$\Psi(v_i) = \Psi(v_j) =$ metro
90	$\Psi(v_i) = \Psi(v_j) =$ road (highway)
60	$\Psi(v_i) = \Psi(v_j) =$ road (principale)
40	$\Psi(v_i) = \Psi(v_j) =$ road (regional)
30	$\Psi(v_i) = \Psi(v_j) =$ road (local)
10	$\Psi(v_i) \neq \Psi(v_j) =$ crosslayer
100	$\Psi(v_i) = \Psi(v_j) =$ train

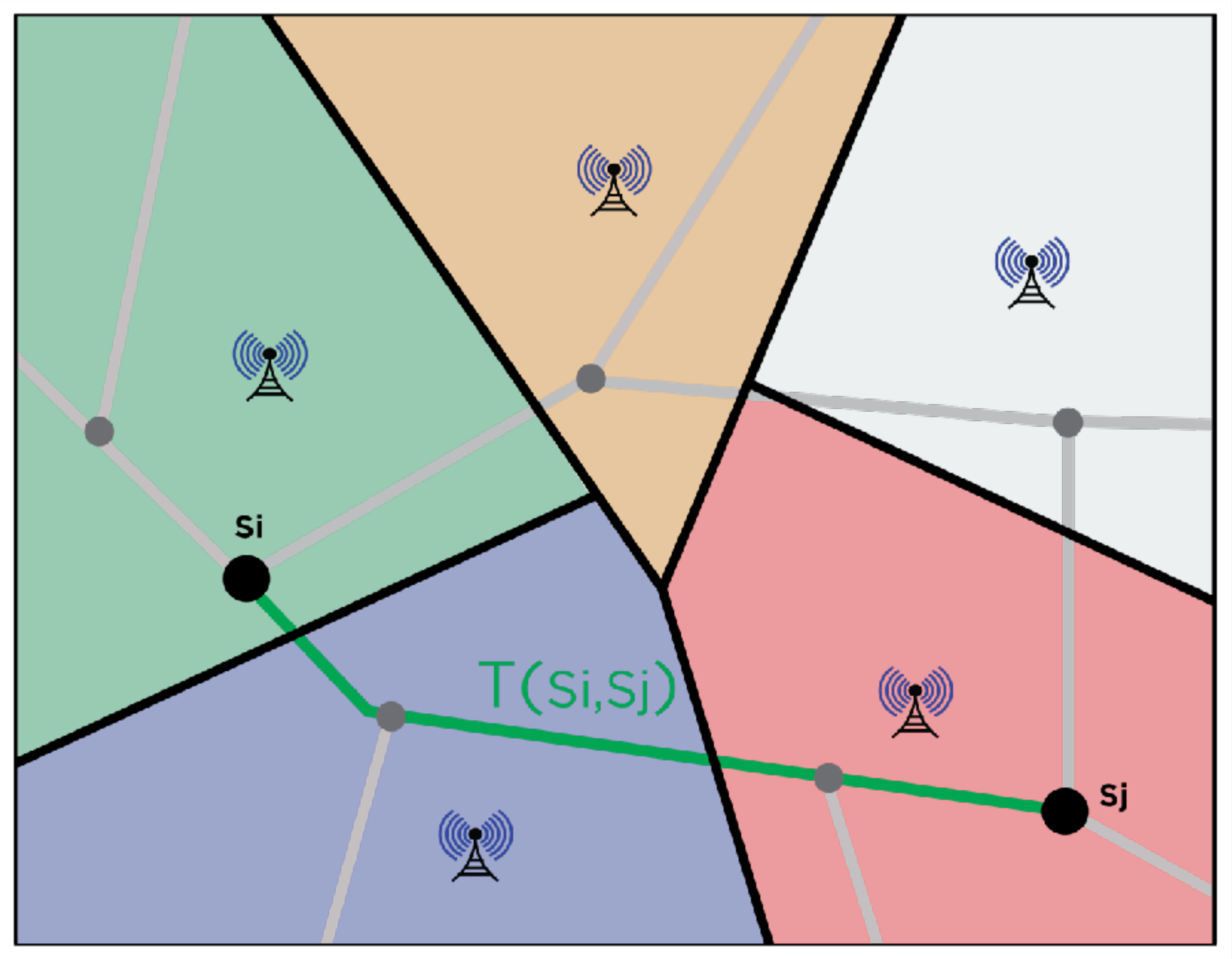
Table: Edge classification and weights for multilayer transportation network

$$T(S_i, S_J) = \left(\sum_{e \in SP(S_i, S_j)} (w_e)^{-1} l_e \right)^{-1}$$

$SP(S_i, S_j)$: shortest path between node Si and Sj

w_e : average speed on the link ***e***

l_e : geodesic distance of the link ***e***



Validation

Validation with a small sample of 10 people over a 1 month duration

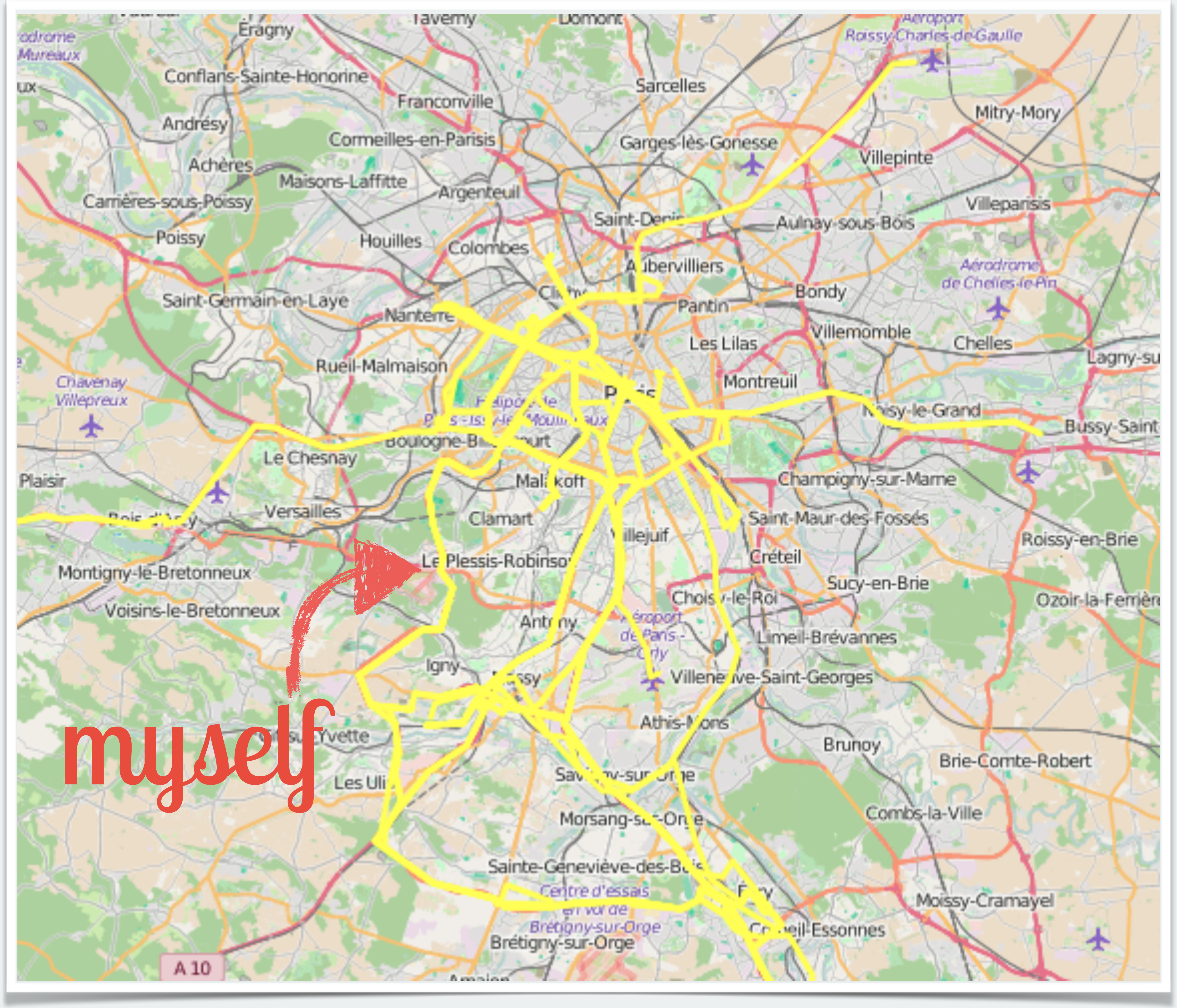
- **Experimentation 1**: Sampling Frequency of the mobile position (BS) every **15 mins**
- **Experimentation 2**: Sampling Frequency of the mobile position (BS) every **5 mins**

Each person was equipped with a GPS logger for ground truth

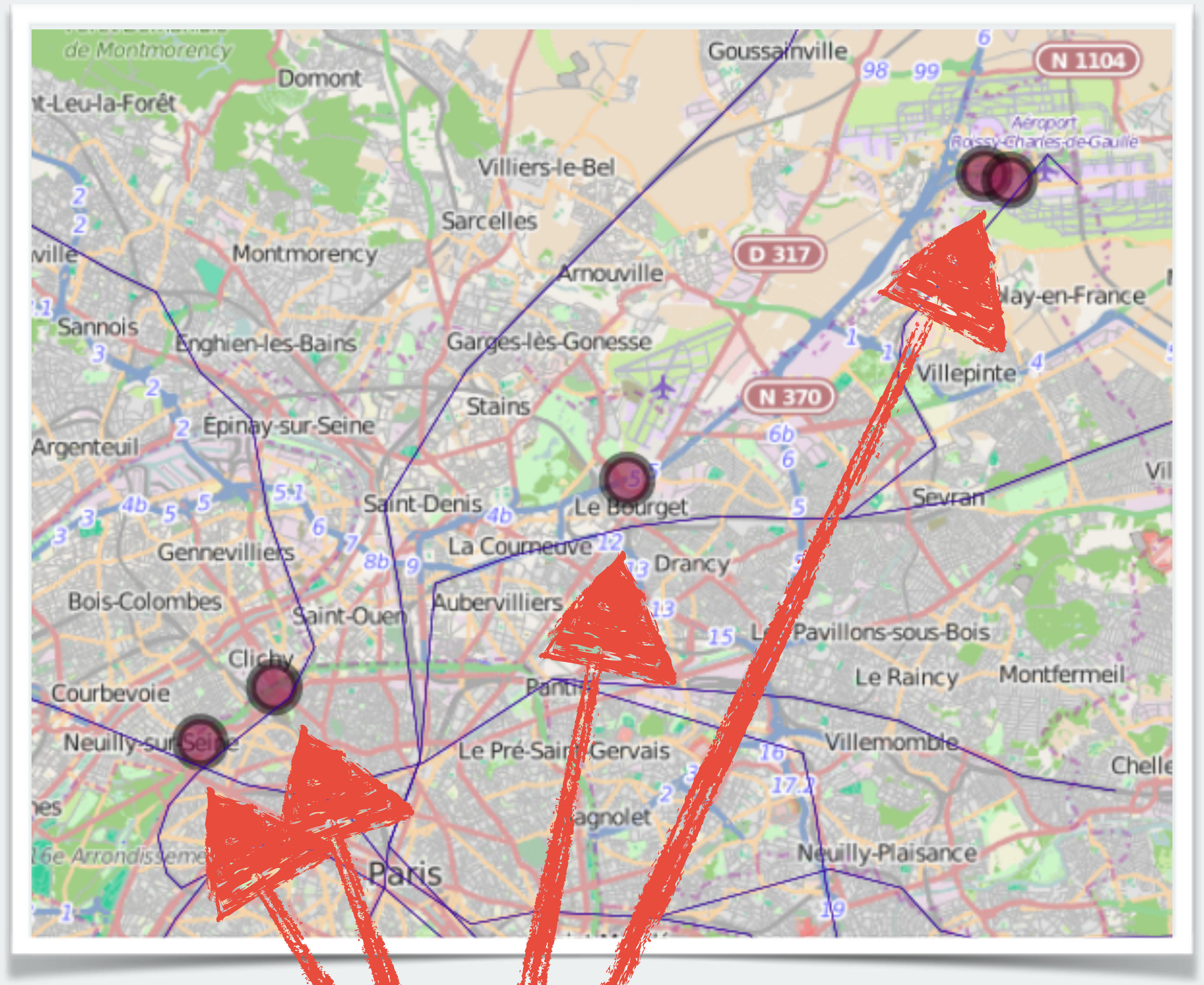
Move App
https://www.moves-app.com/

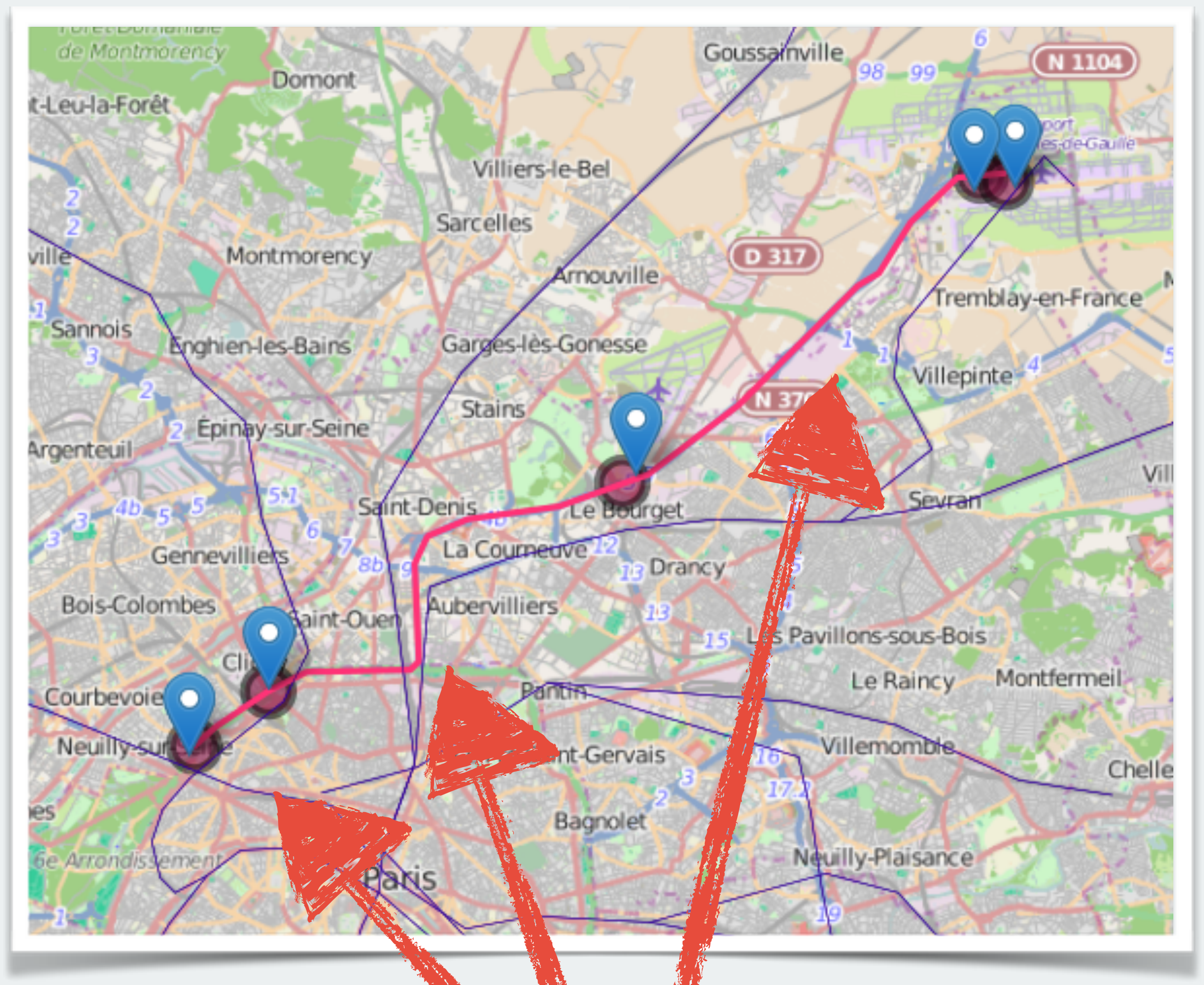
Around 1000 trajectories available that cover Ile-de-France (Paris area):

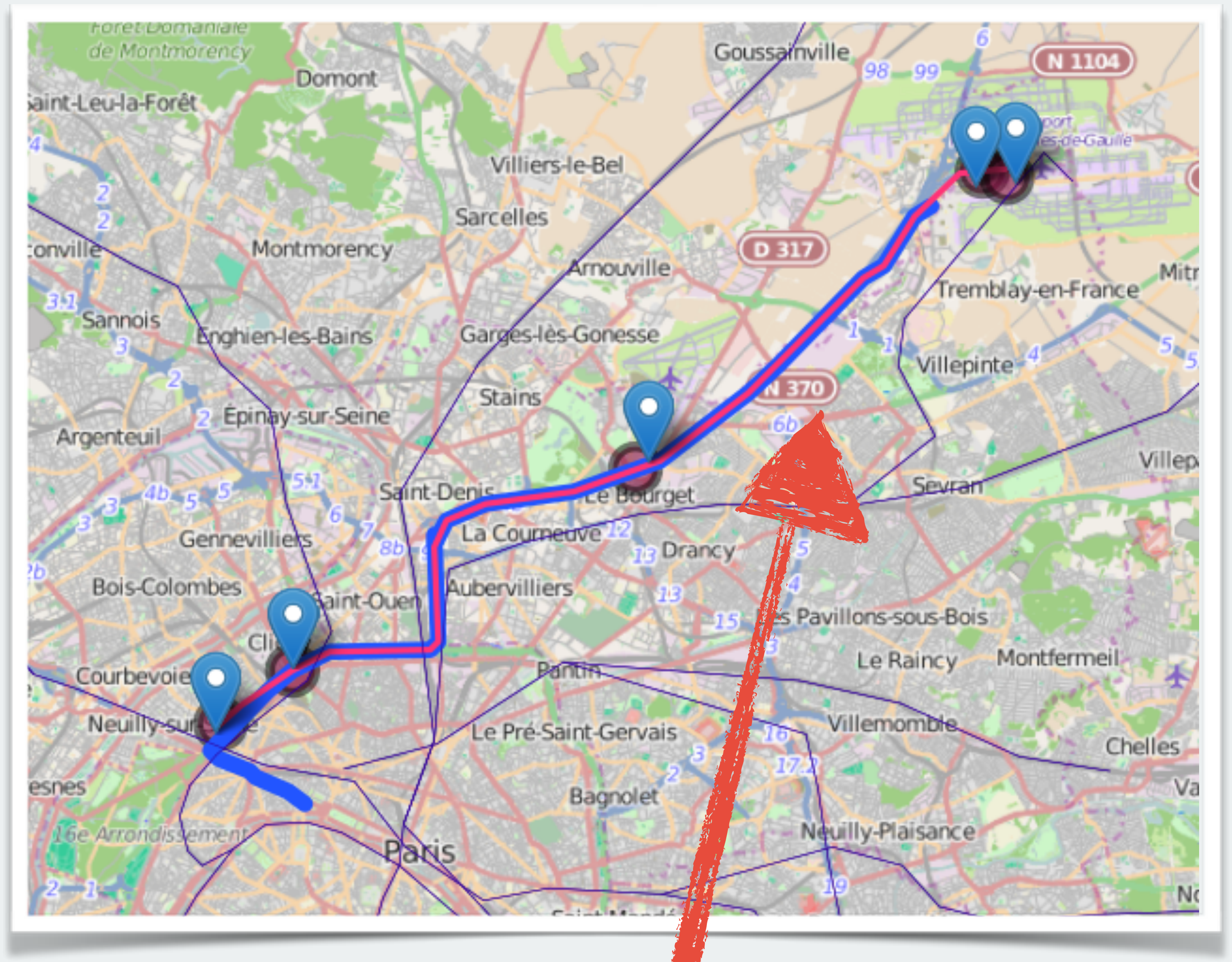
- 70% are using road only
- 30% subway + train



Algorithm







① Compute
the emission probabilities

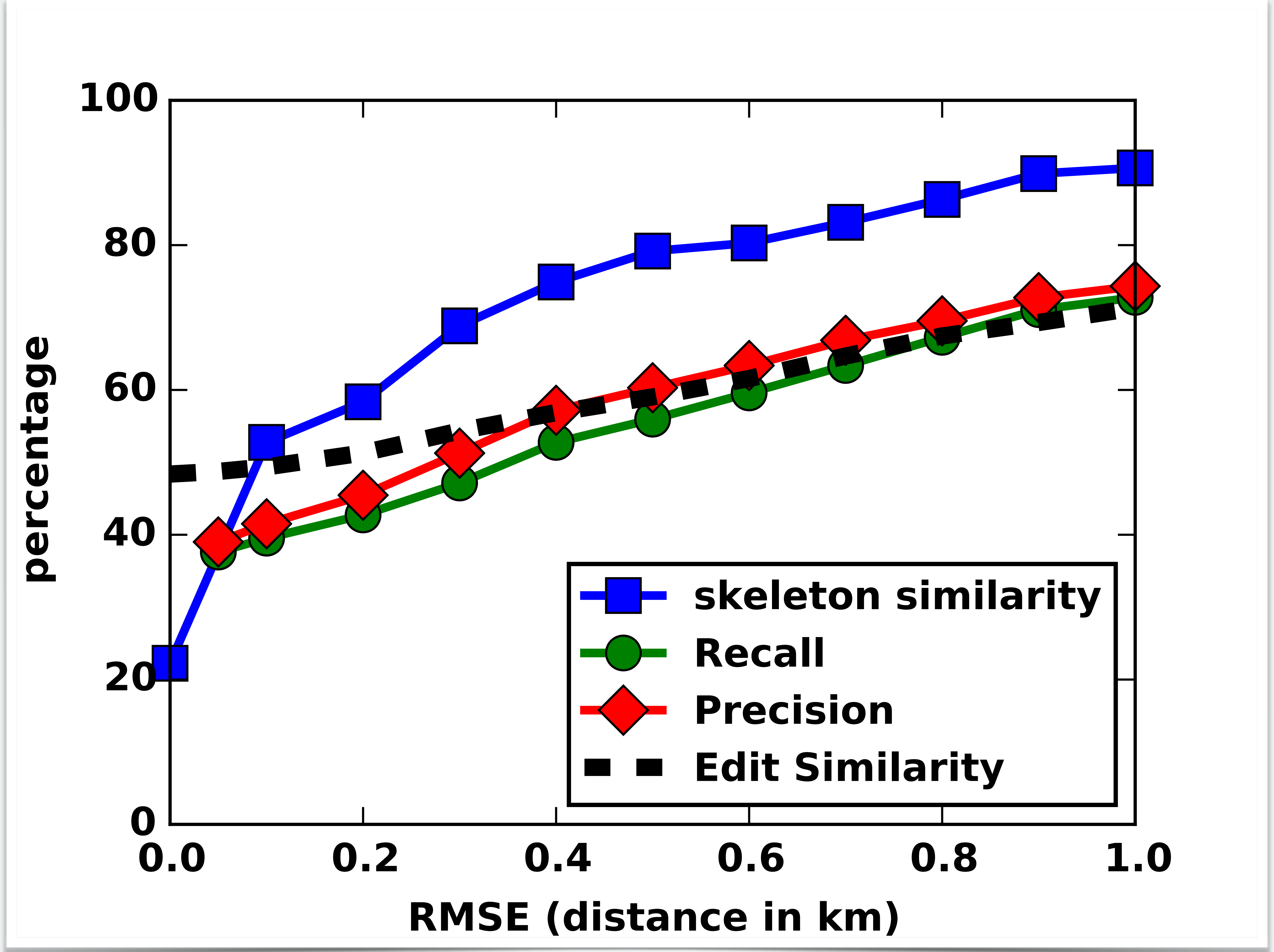
② Compute
the transition probabilities

③ Compute the most
likely path

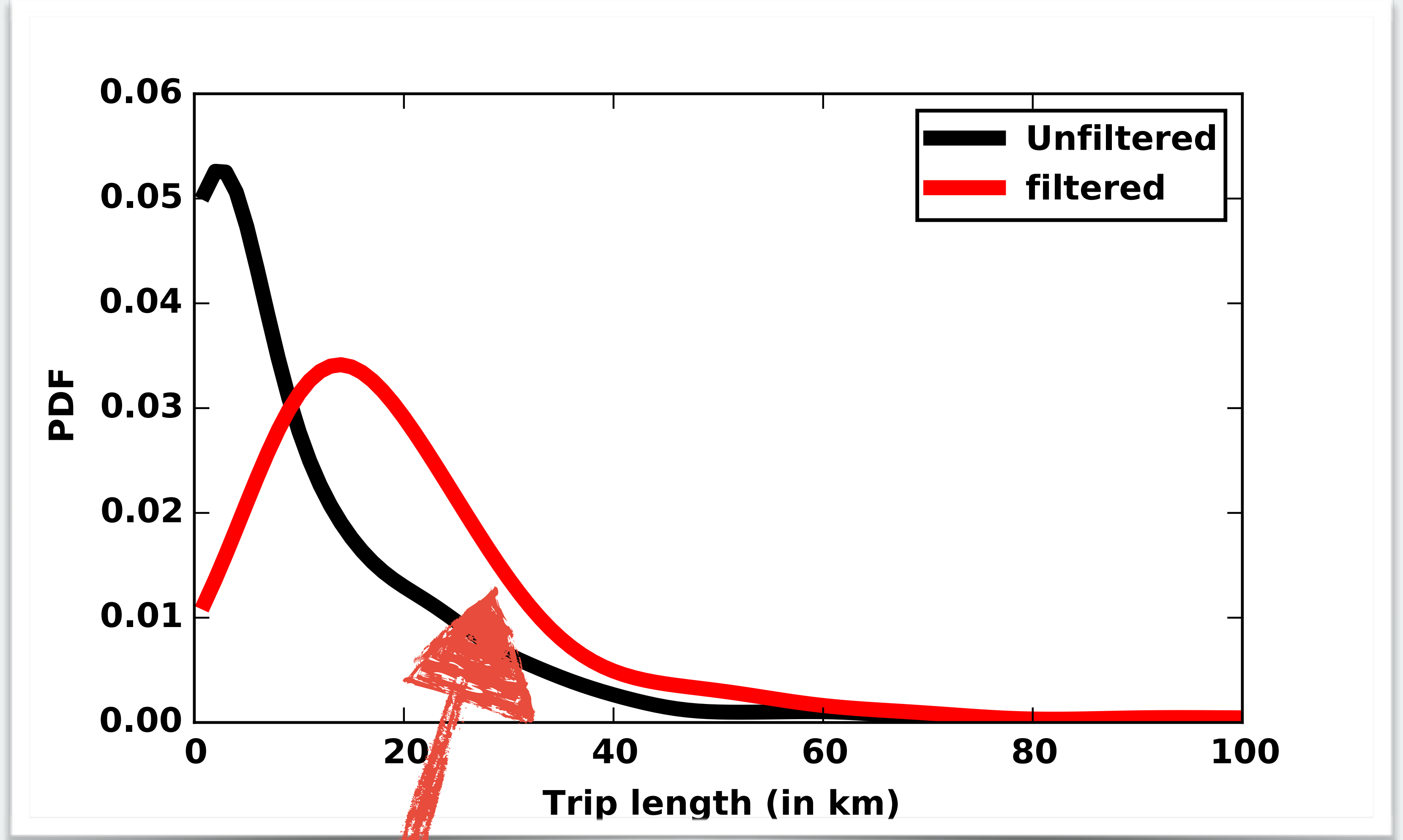
Results

continued

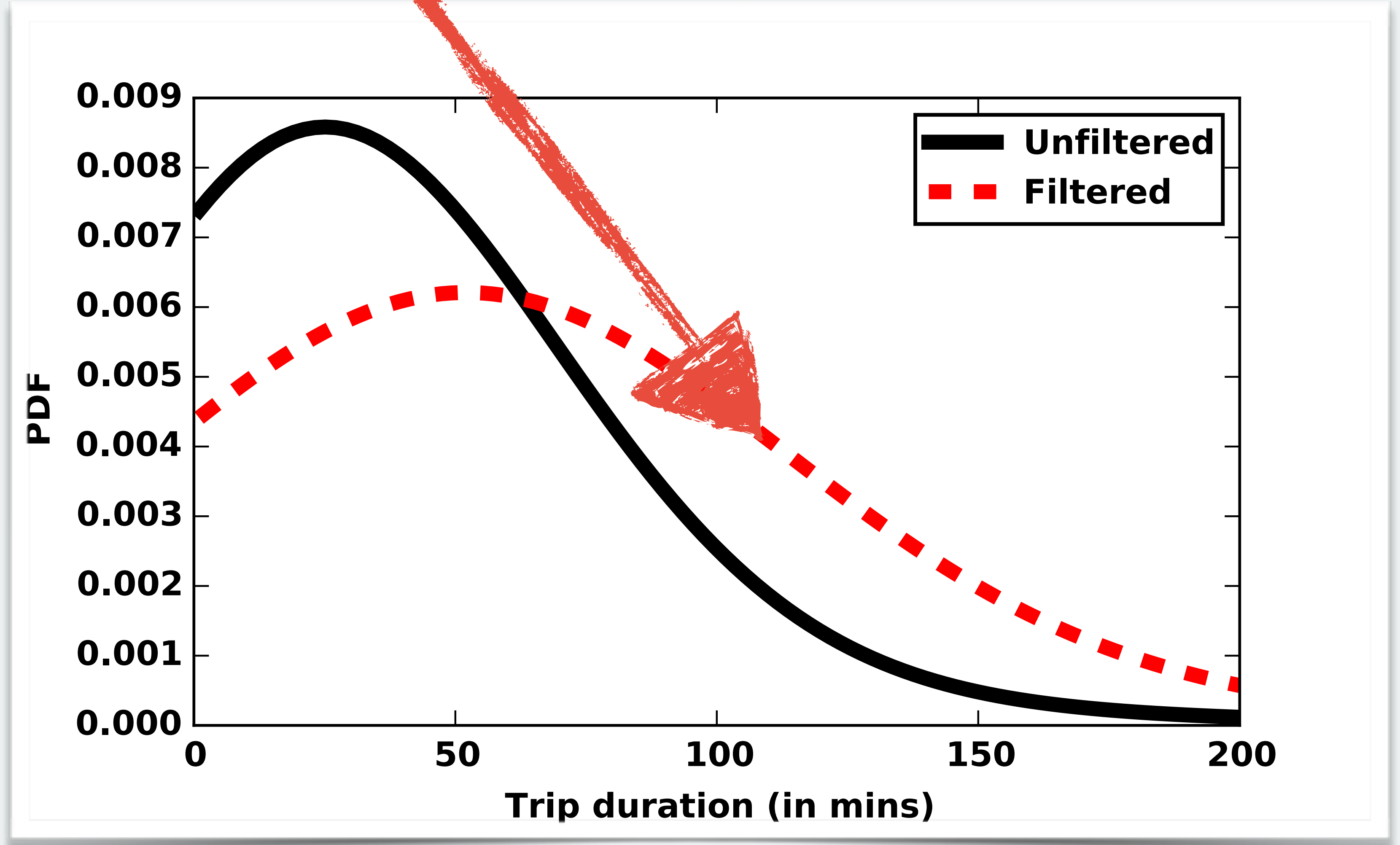
increase the goodness of the mapping



increase mapping error



usable trips
for mapping



Future work

1. Simplify the underlining map complexity by using a multiplex representation of the transport network as opposed to a multi-layer graph

2. Develop a more robust framework for computing the transition probability, including the travel time (e.g. measured travel time vs estimated travel time)

3. Develop more robust algorithms than the Viterbi algorithm. However there is a trade off between the scalability of the solution and the quality of the mapping

Dynamic population estimation using mobile phone metadata

Studies of the dynamic of population density

Goals:

1. New approach to infer population density, overcoming censuses and surveys limitations (cost, scalability, time)

2. Automatic and real-time estimation of population density

Dataset: Telecom Italia Challenge Datasets

Locations (regions):

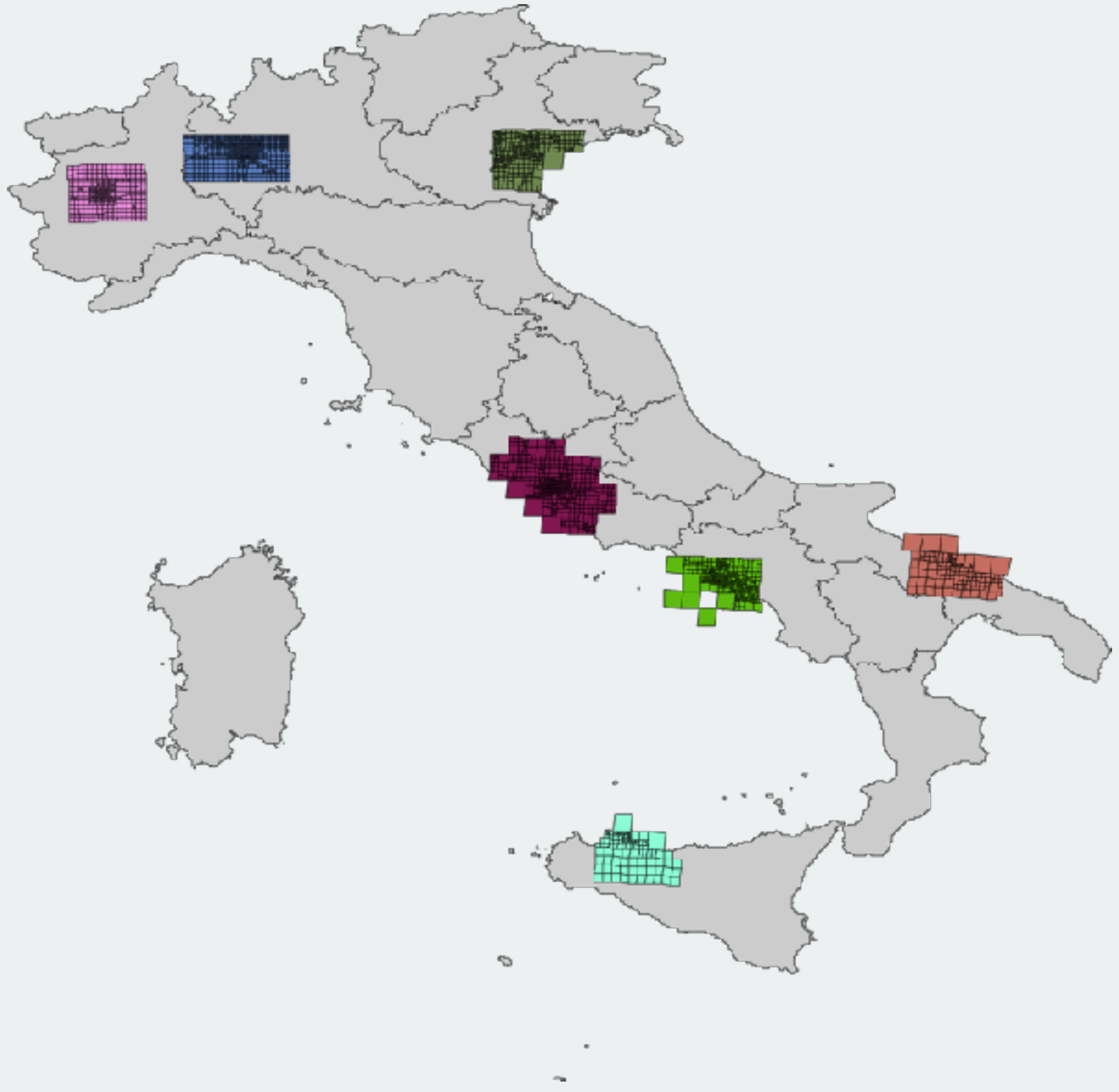
- Roma
- Turino
- Bari
- Palerno
- Milano
- Venizia

Datasets:

- Population data
- Callin/callout
- Cars traffic
- Cars Trajectories

Duration:

- 2 months

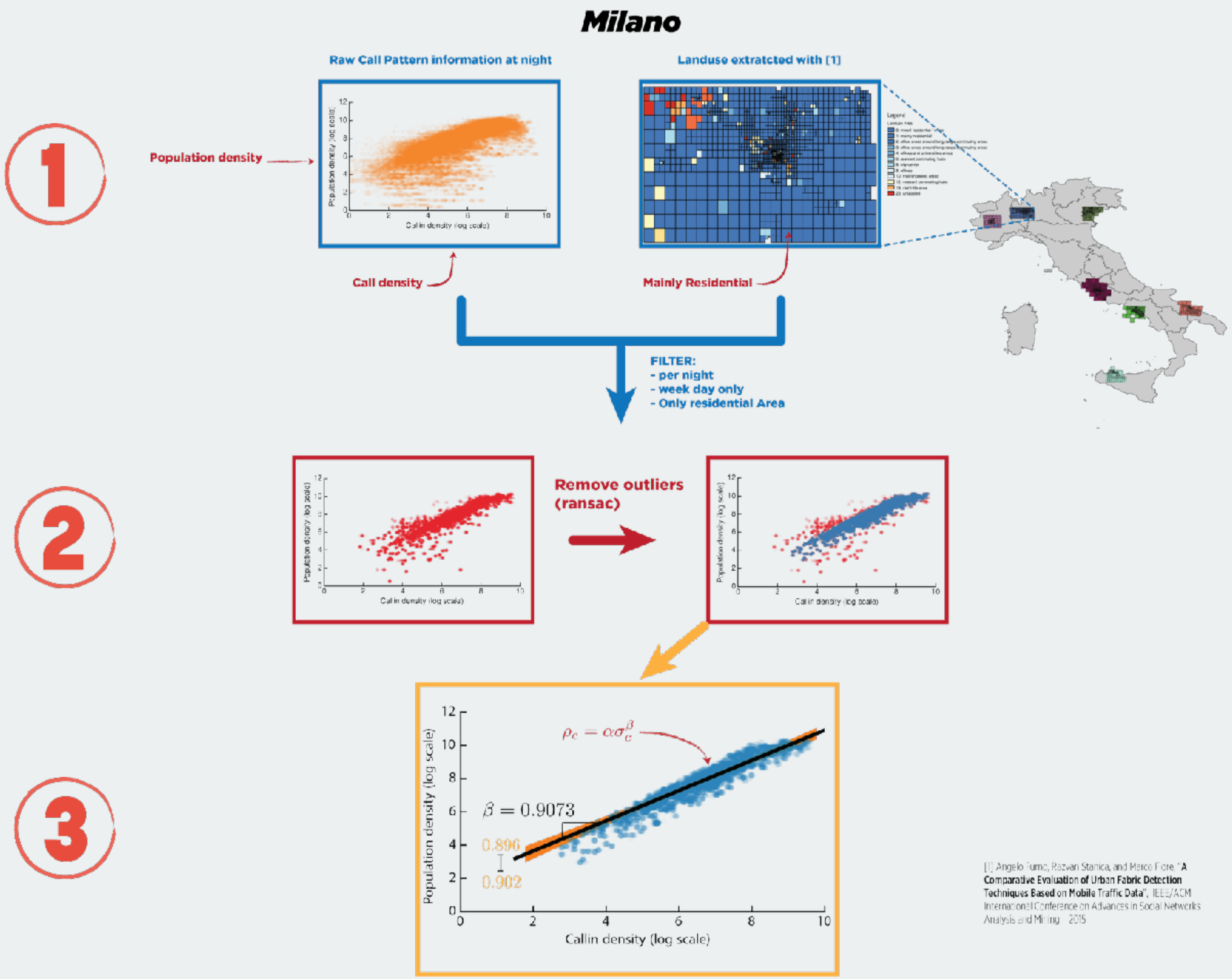


BIGDATACHALLENGE2015

TELECOM ITALIA

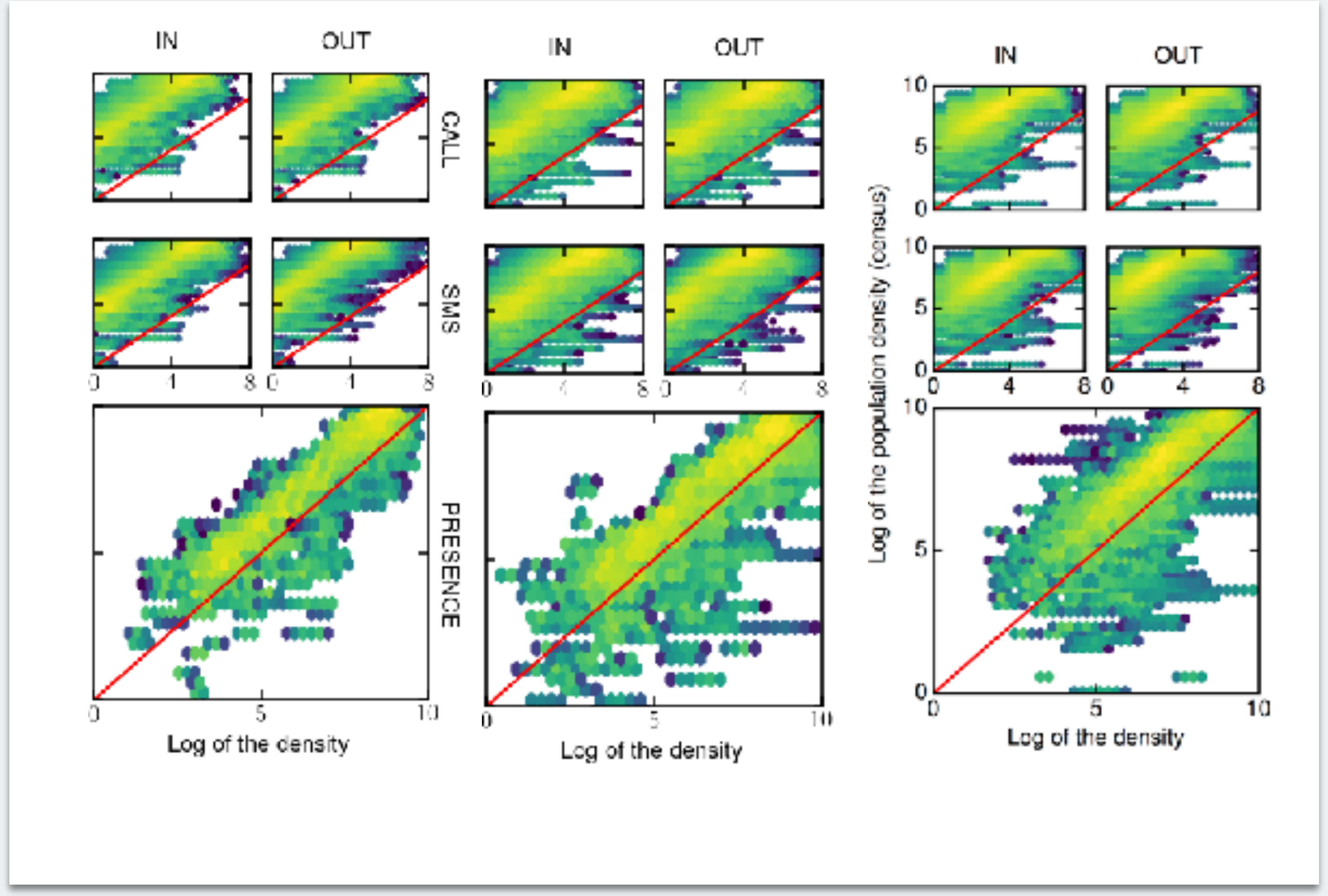
Model

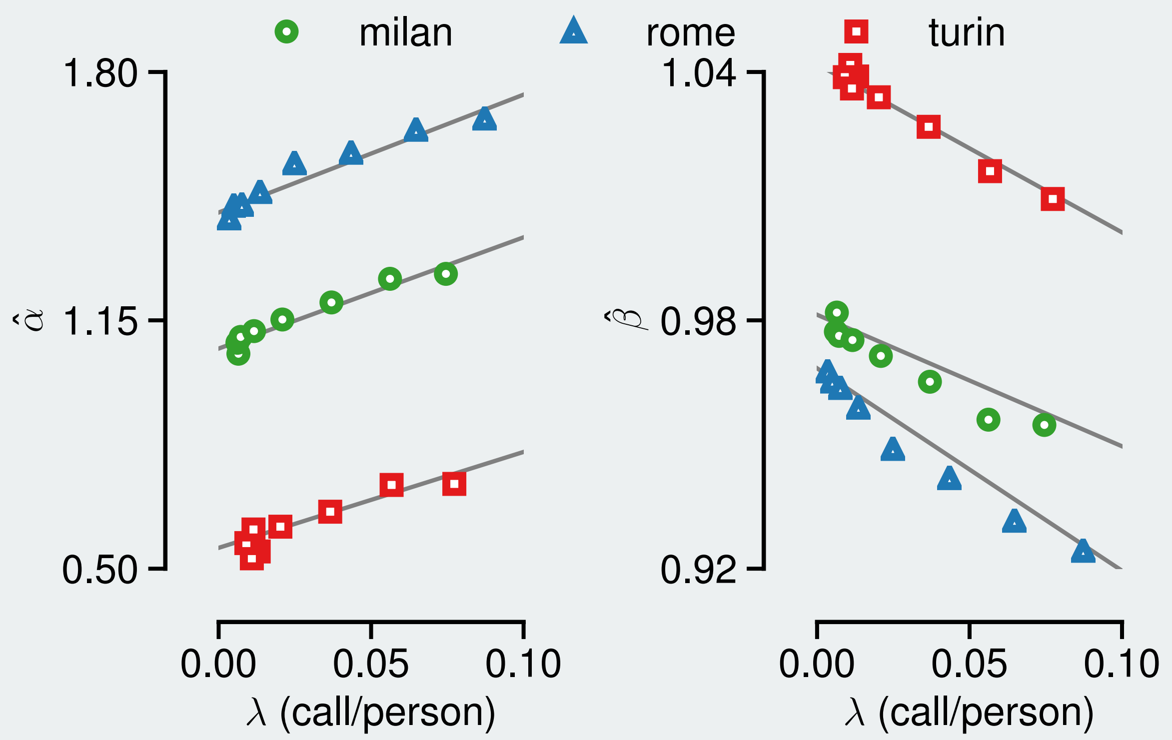
- Analysis of the telecommunication metadata for inference of the dynamic of the population density
- The landuse information is extracted through clustering of the call-patterns of each cells

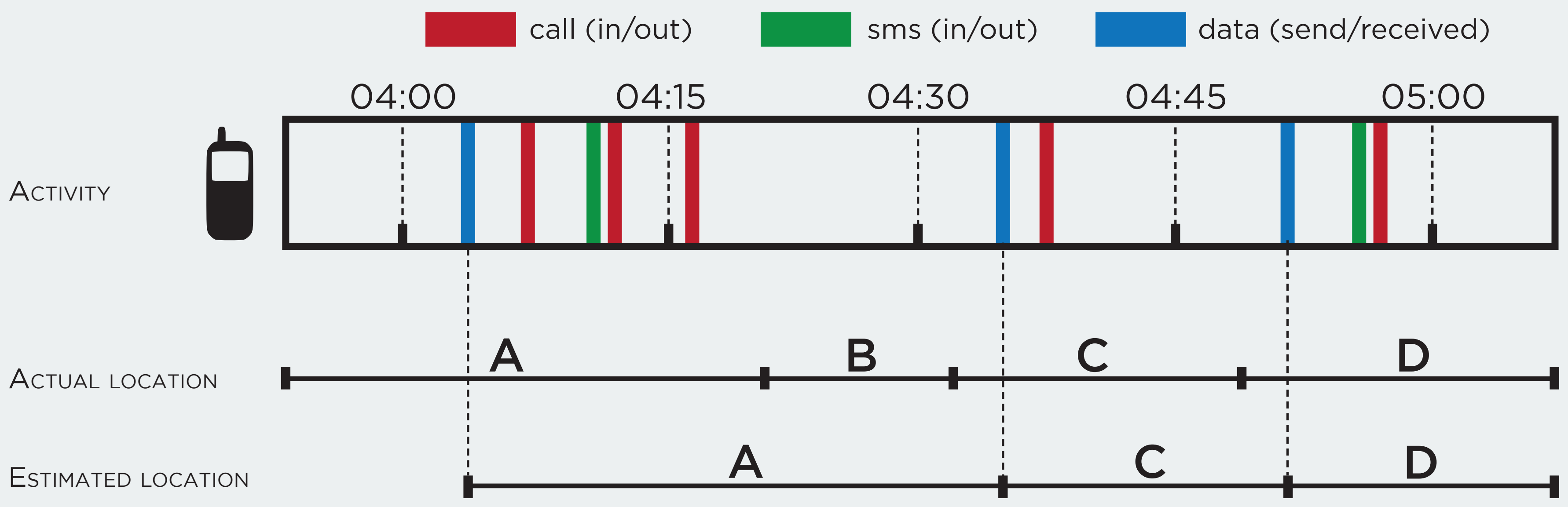


[1] Angelo Furno, Razvan Stanica, and Marco Fiore, "**A Comparative Evaluation of Urban Fabric Detection Techniques Based on Mobile Traffic Data**", IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015

Dynamic of the population density



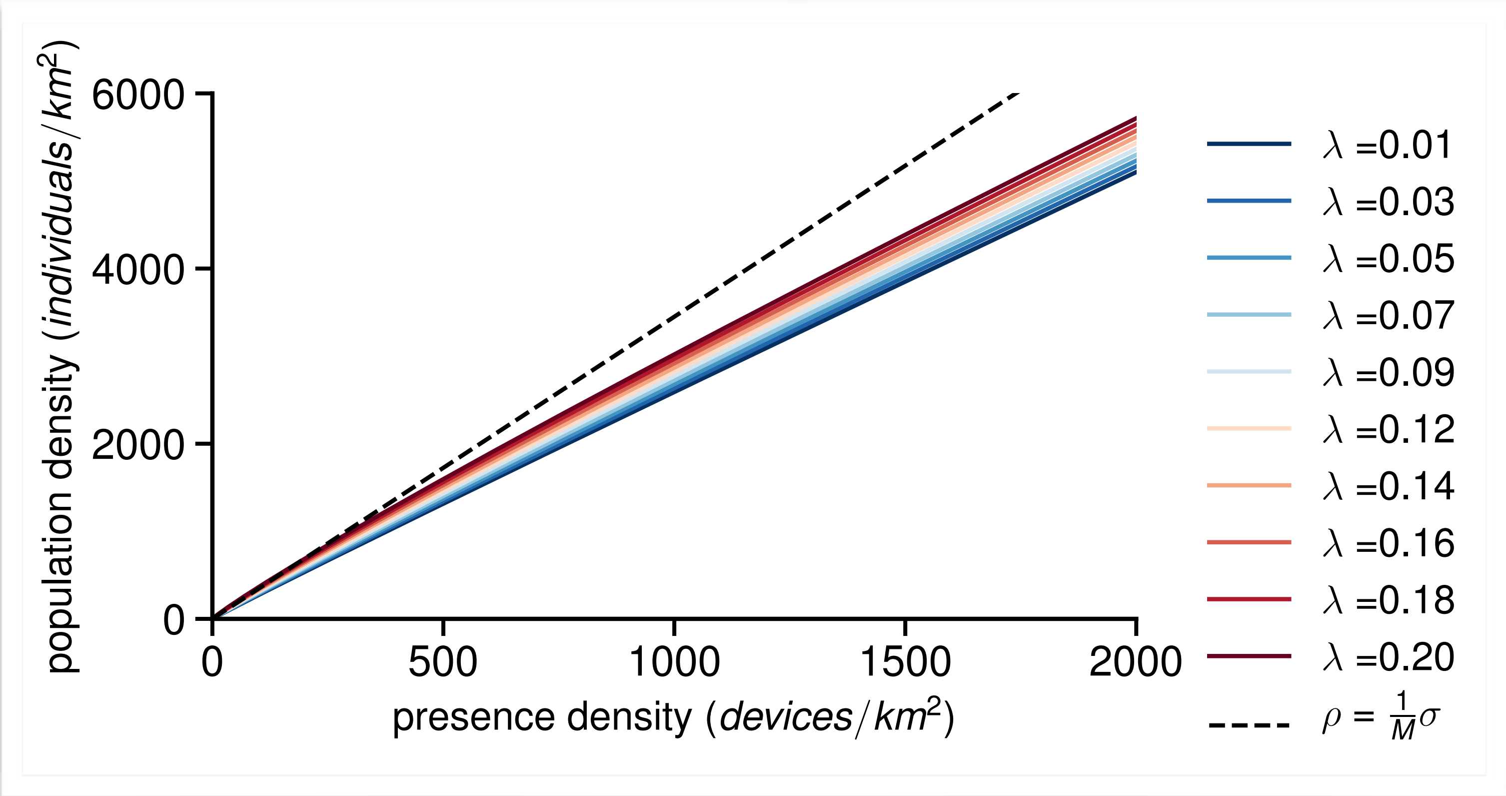




Population Density

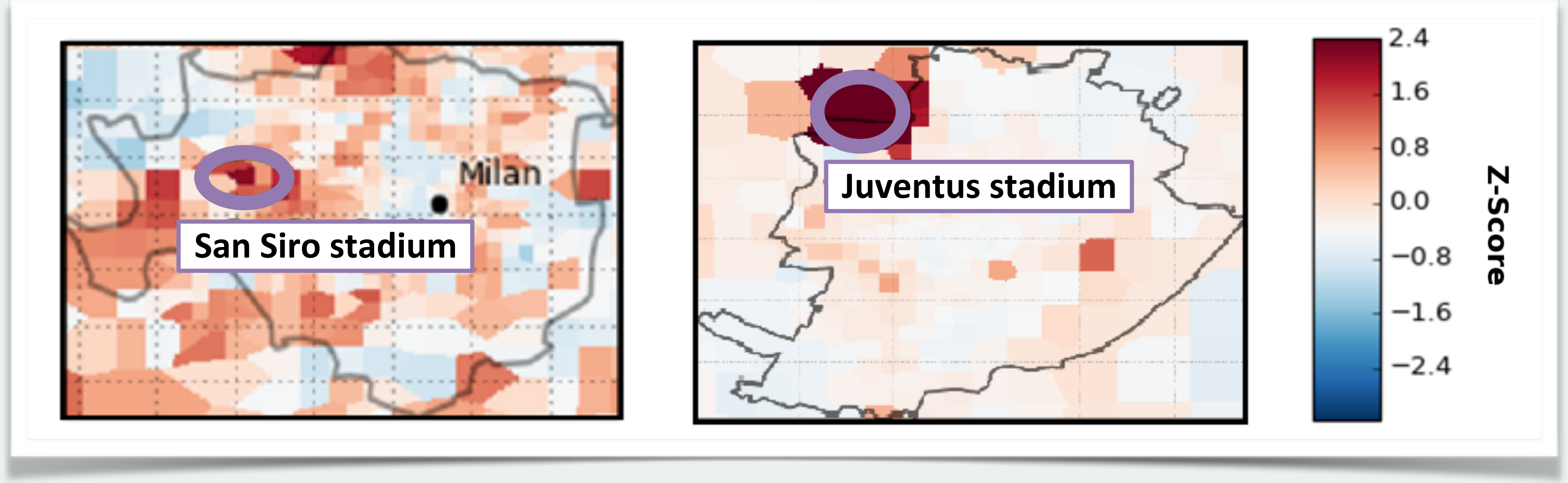
$$\rho_i = \alpha \sigma_i^{\beta}$$

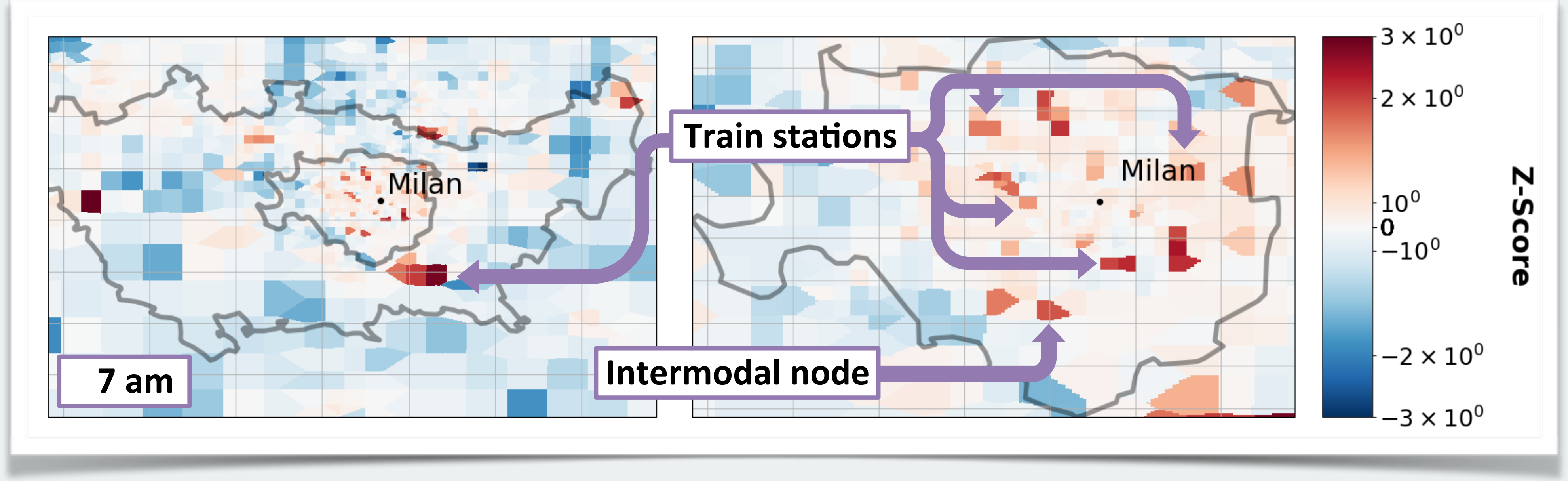
presence density
(mobile network metadata)

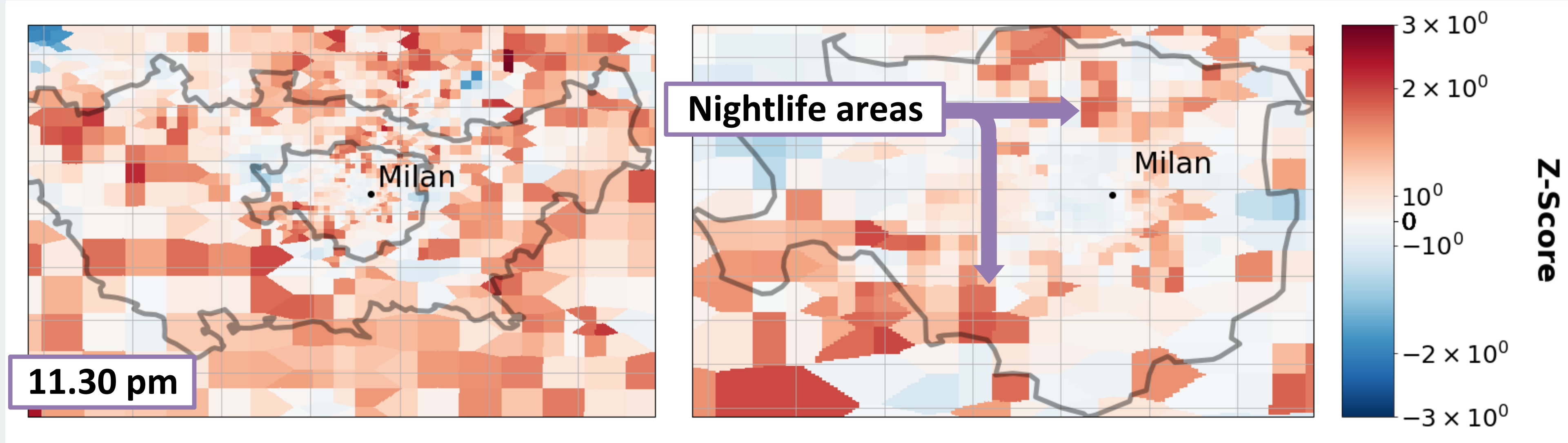


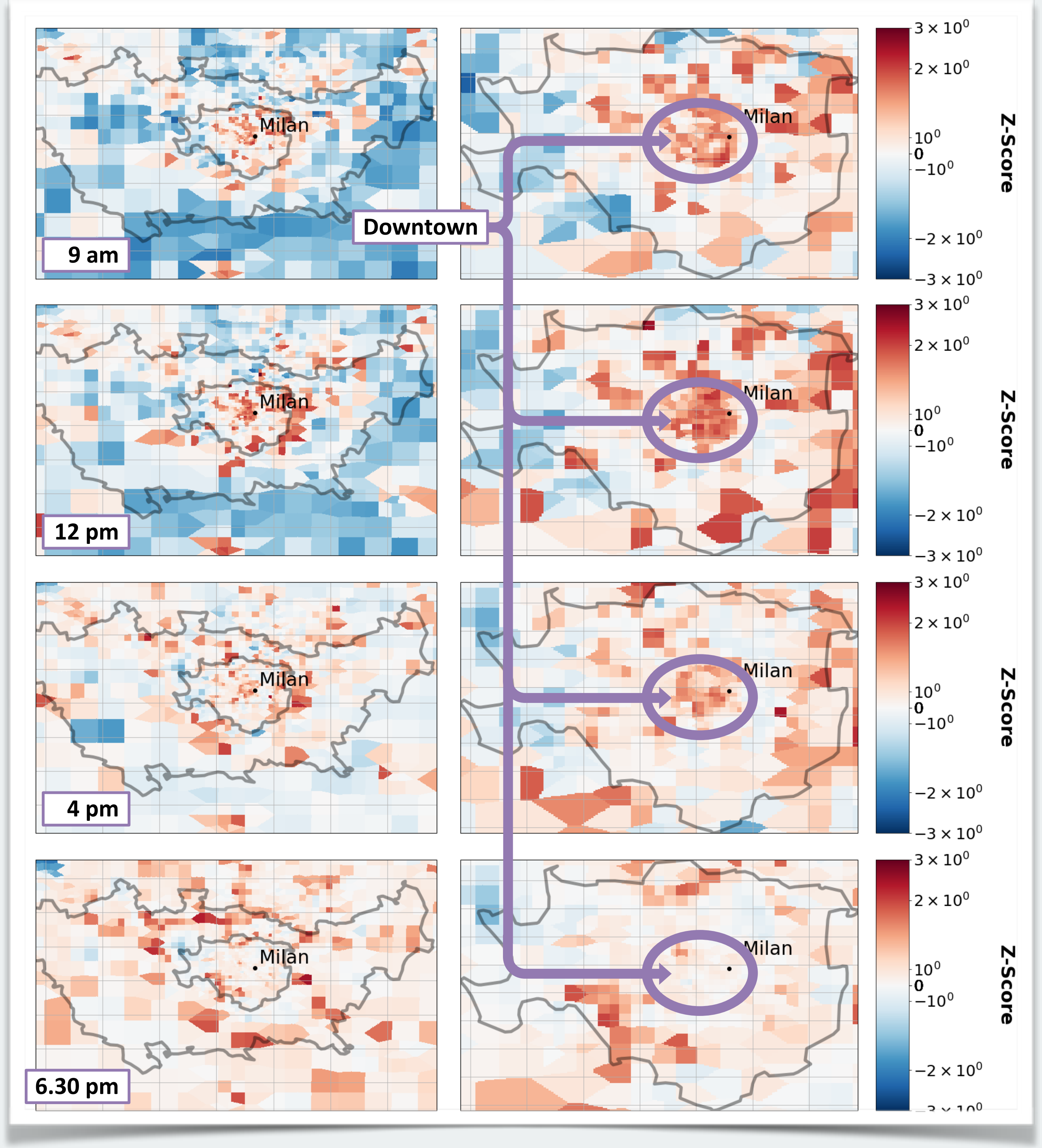
$$\hat{\rho}_i(\lambda_i(t)) = e^{(\hat{a}_\alpha \lambda_i(t) + \hat{b}_\alpha)} \cdot \sigma_i^{(\hat{a}_\beta \lambda_i(t) + \hat{b}_\beta)}$$

One day in Milan...

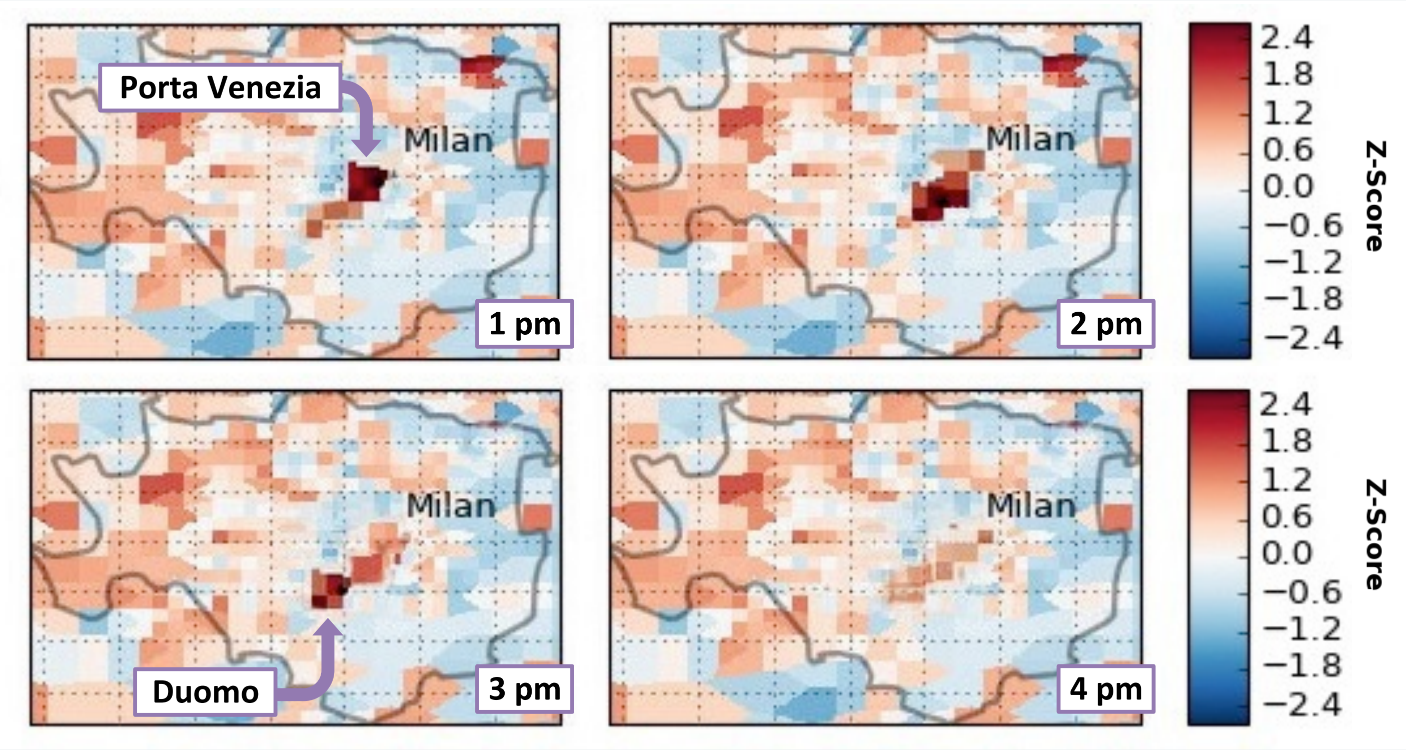




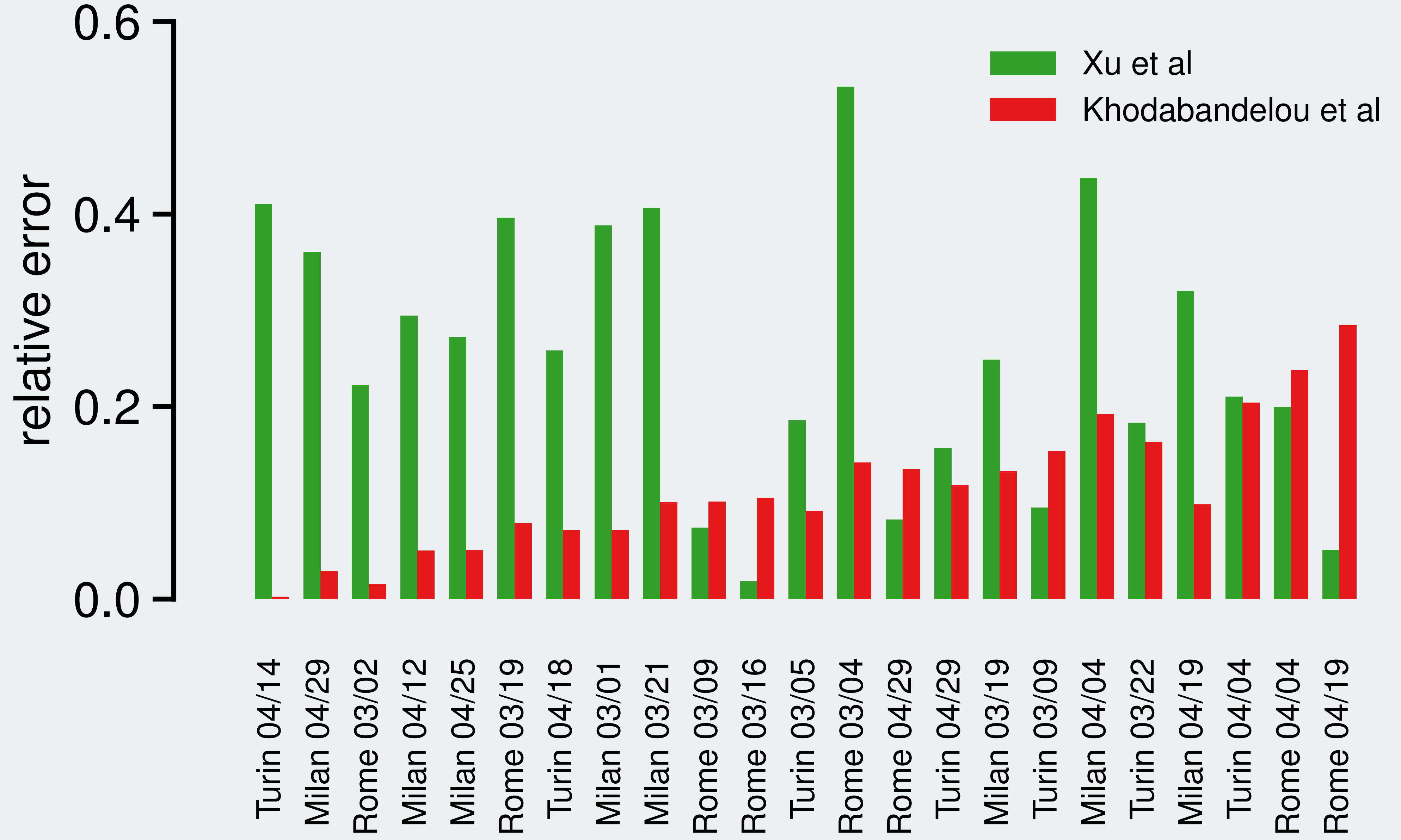


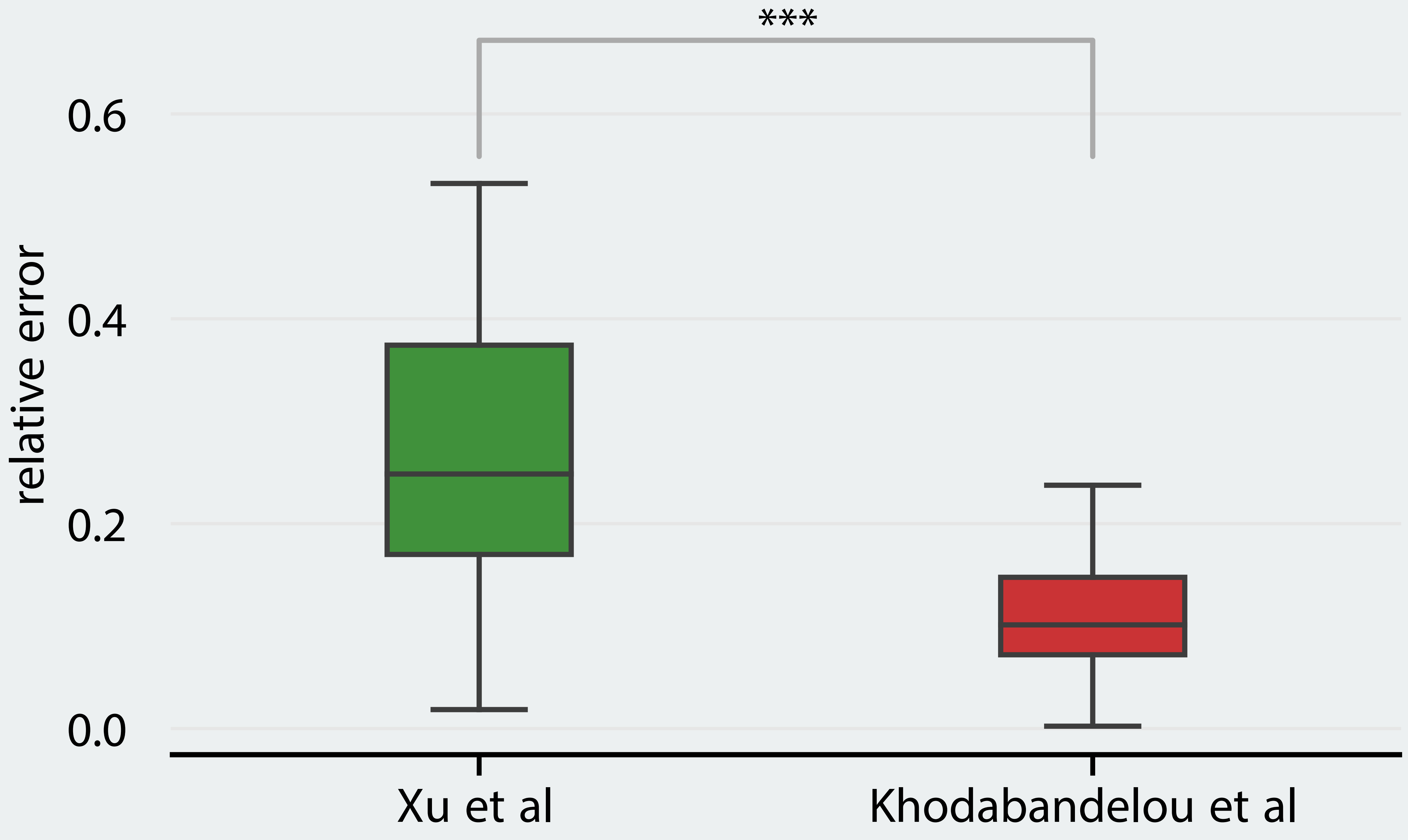


Dynamic distribution of population during a public march in Milan on April 25. Z-scores of the estimated population densities from 1 pm to 4 pm.



Validation of the method with football matches





- Estimation of football matches attendance compared with ticketing information
- Better result has been obtain with Bouygues Datasets for the UEFA European soccer cup in France in 2016 (euro2016)

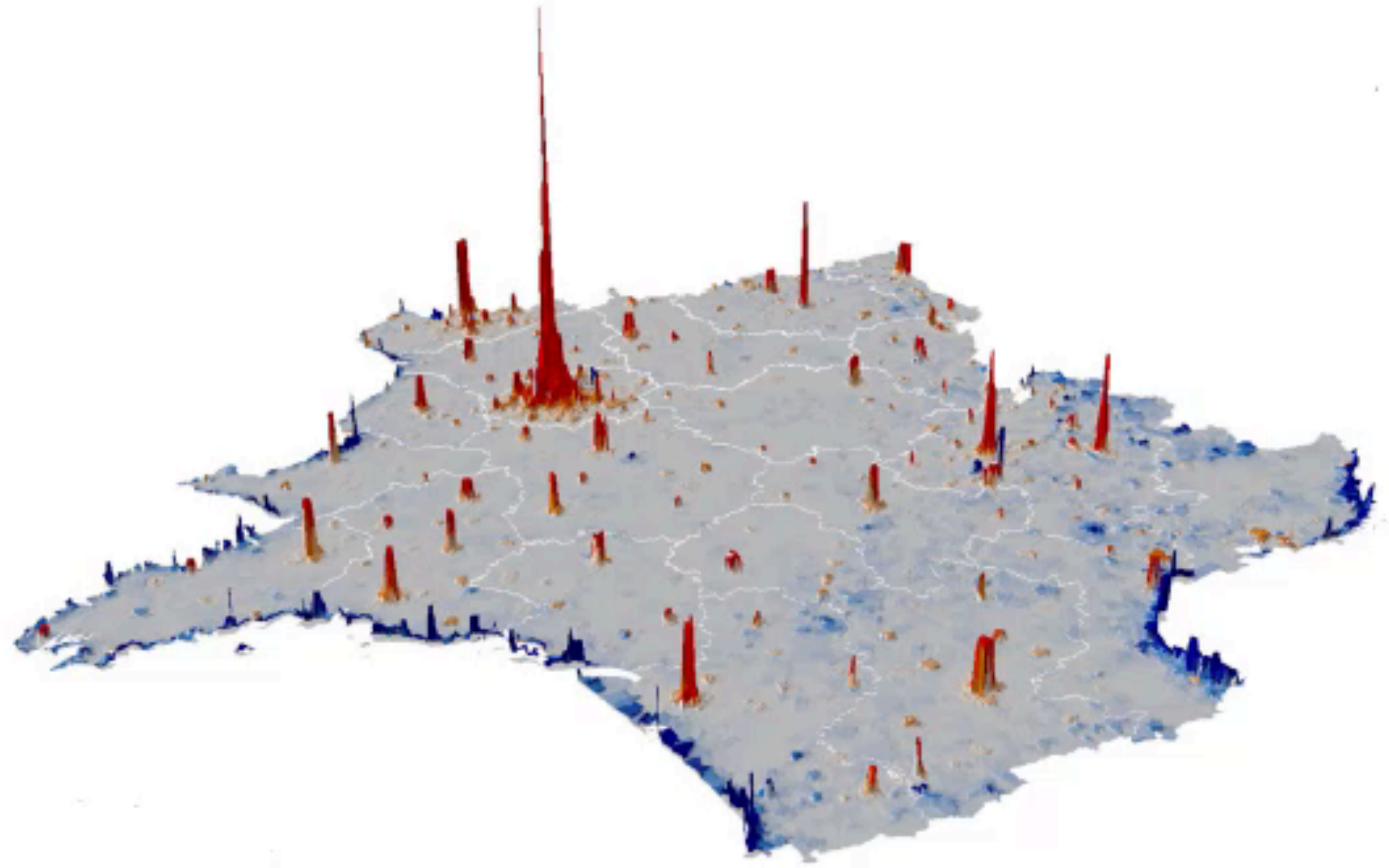
Population Estimation from Mobile Network Traffic Metadata

Ghazaleh Khodabandelou*, Vincent Gauthier*, Mounim El Yacoubi*, Marco Fiore‡

* SAMOVAR, Telecom SudParis, CNRS, University Paris Saclay, France

‡ CNR-IEIIT, Italy

Novel approach to infer population densities



Paris region's study (BT dataset)

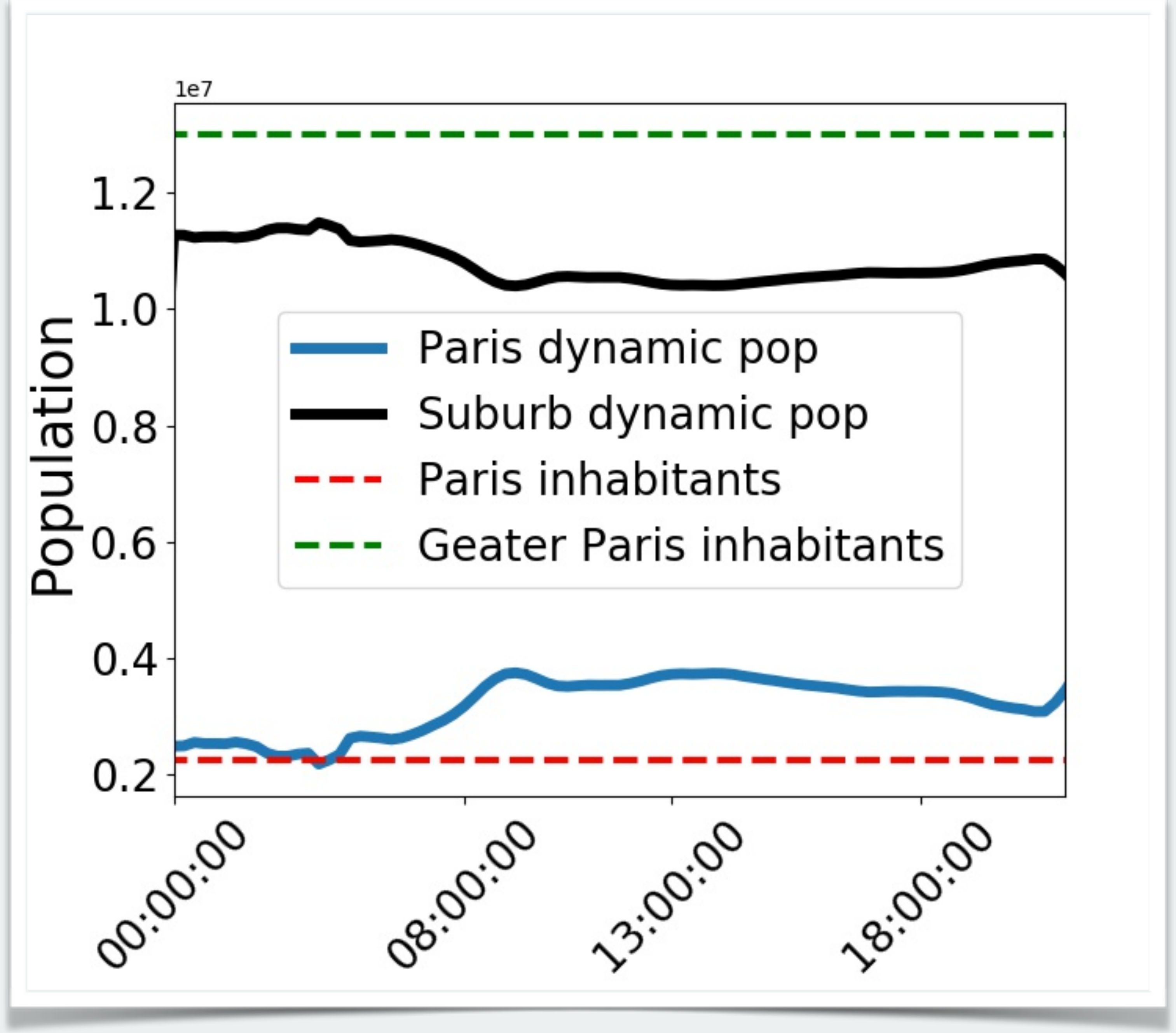


Table V: *Results on Stadiums Attendances*

Day	T_{start}	Sport	International	σ_{Med}	σ_{Max}	$\hat{\rho}_{Med}$	$\hat{\rho}_{Max}$	ρ
06 – 11 – 2016	08 : 45pm	Football	NO	2097	3242	39289	46734	42002
11 – 11 – 2016	09 : 00pm	Football	YES	3307	5135	61301	79374	78000
19 – 11 – 2016	05 : 00pm	Football	NO	2474	3859	30266	42754	44258
19 – 11 – 2016	09 : 00pm	Rugby	YES	2871	4412	65463	79558	73700
26 – 11 – 2016	09 : 00pm	Rugby	YES	3620	5824	81952	96622	78500
30 – 11 – 2016	09 : 00pm	Football	NO	1996	2827	39282	44235	40597
06 – 12 – 2016	08 : 45pm	Football	NO	2743	3658	40155	46387	42650
11 – 12 – 2016	08 : 45pm	Football	NO	3662	4466	46152	59302	47665
14 – 12 – 2016	09 : 00pm	Football	NO	2788	3314	40544	47305	45183

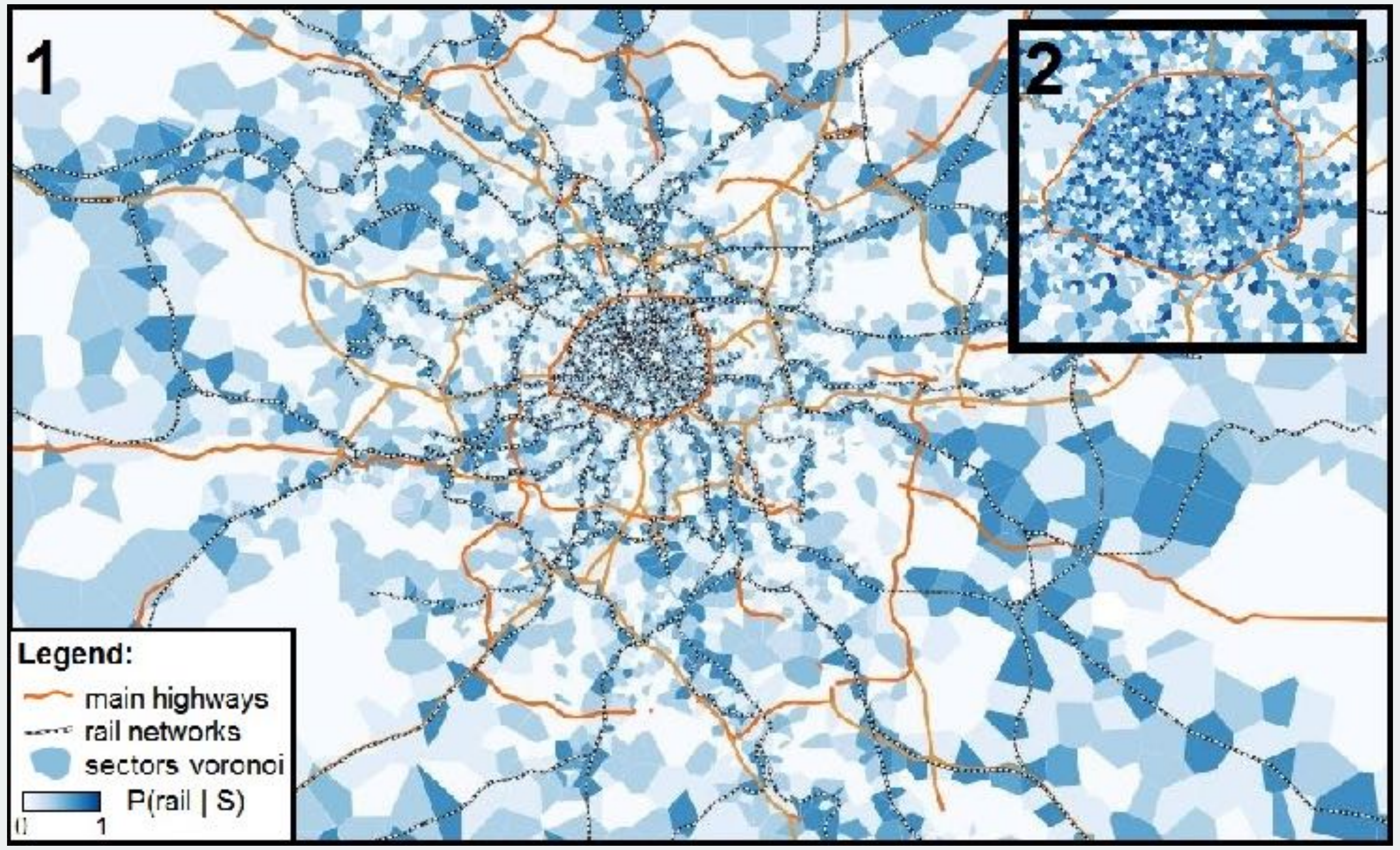
In order to validate our dynamic model during day time we estimated the population attending sport events. We collected spectators numbers hosted in two stadiums, Stade de France and Parc des Princes. Network antennas located inside both stadiums have long range signals with hypothetical circular areas. In this case, cells areas are erroneous as they cover several blocks surrounding the stadium. Consequently a substantial part of attendees is mapped over stadium neighboring blocks. The stadium blocks population was therefore largely underestimated. To overcome mapping bias, MPs presence was this time calculated at cellular resolution instead of blocks.

Inferring Dynamic Origin-Destination Flows by Transport Mode using Mobile Phone Data

Extraction of the travel mode in the Paris area

bayesian inference of travel mode:

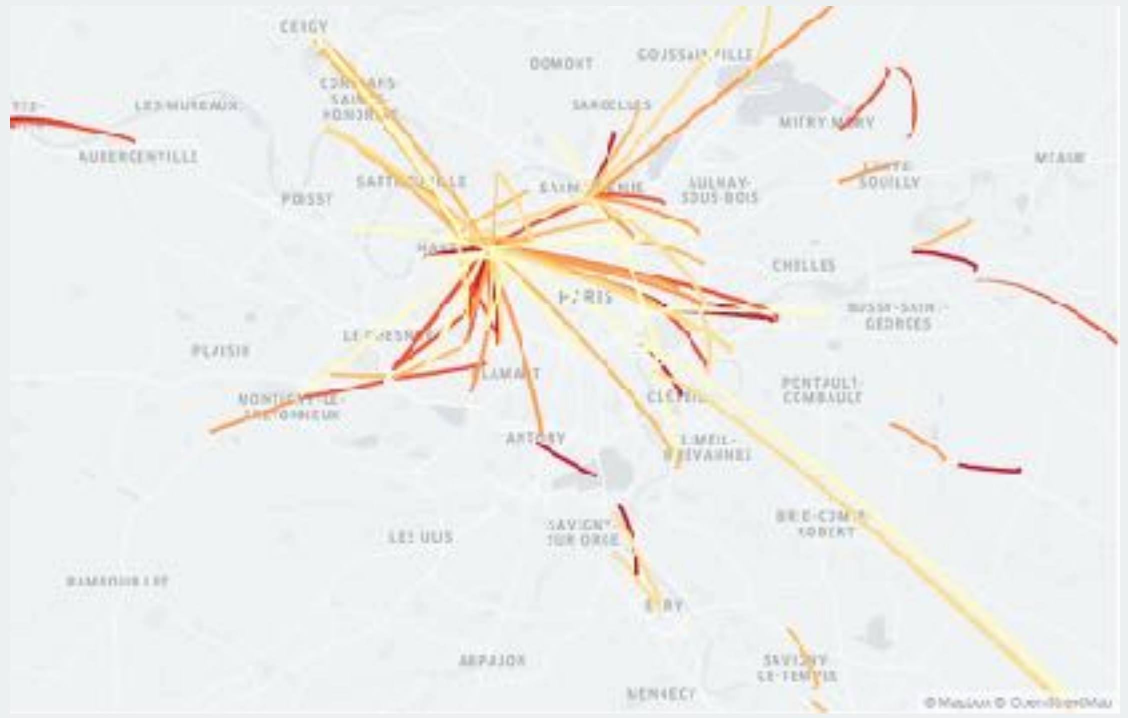
- we compute the landuse of each mobile network cell sector (subway, train, road), ***semi-semi-supervised learning***
- We use Bayesian inference to compute the transport mode of a given cellular trajectory

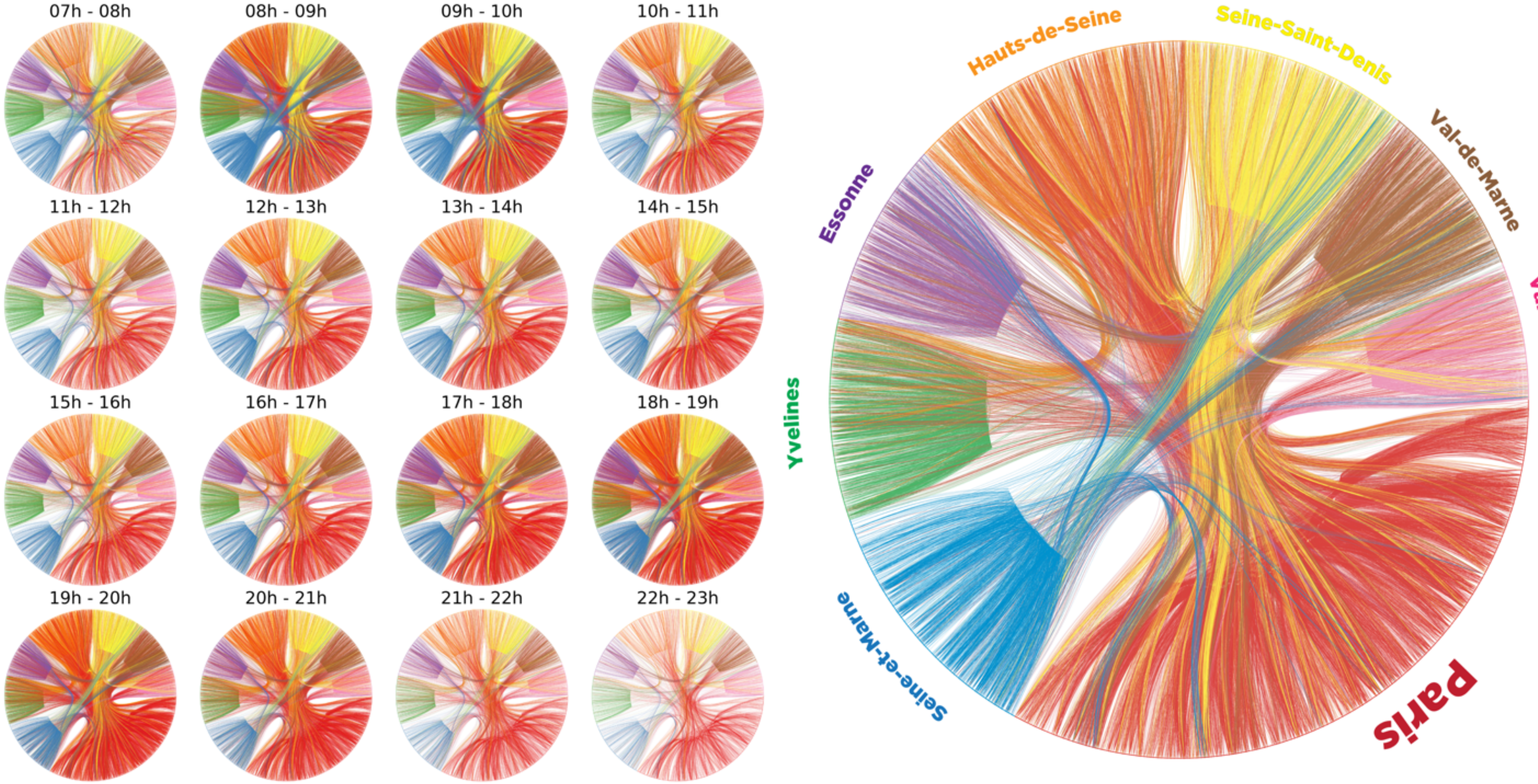


Major road
Traveled
In Paris region

Major
Subway line
In Paris region

Major
train line
In Paris region




07h - 08h
08h - 09h
09h - 10h
10h - 11h
11h - 12h
12h - 13h
13h - 14h
14h - 15h
15h - 16h
16h - 17h
17h - 18h
18h - 19h
19h - 20h
20h - 21h
21h - 22h
22h - 23h
Hauts-de-Seine
Seine-Saint-Denis
Val-de-Marne
Essonne
Val-d'Oise
Yvelines
Seine-et-Marne
Paris

OD from Paris area extracted from mobile phone data

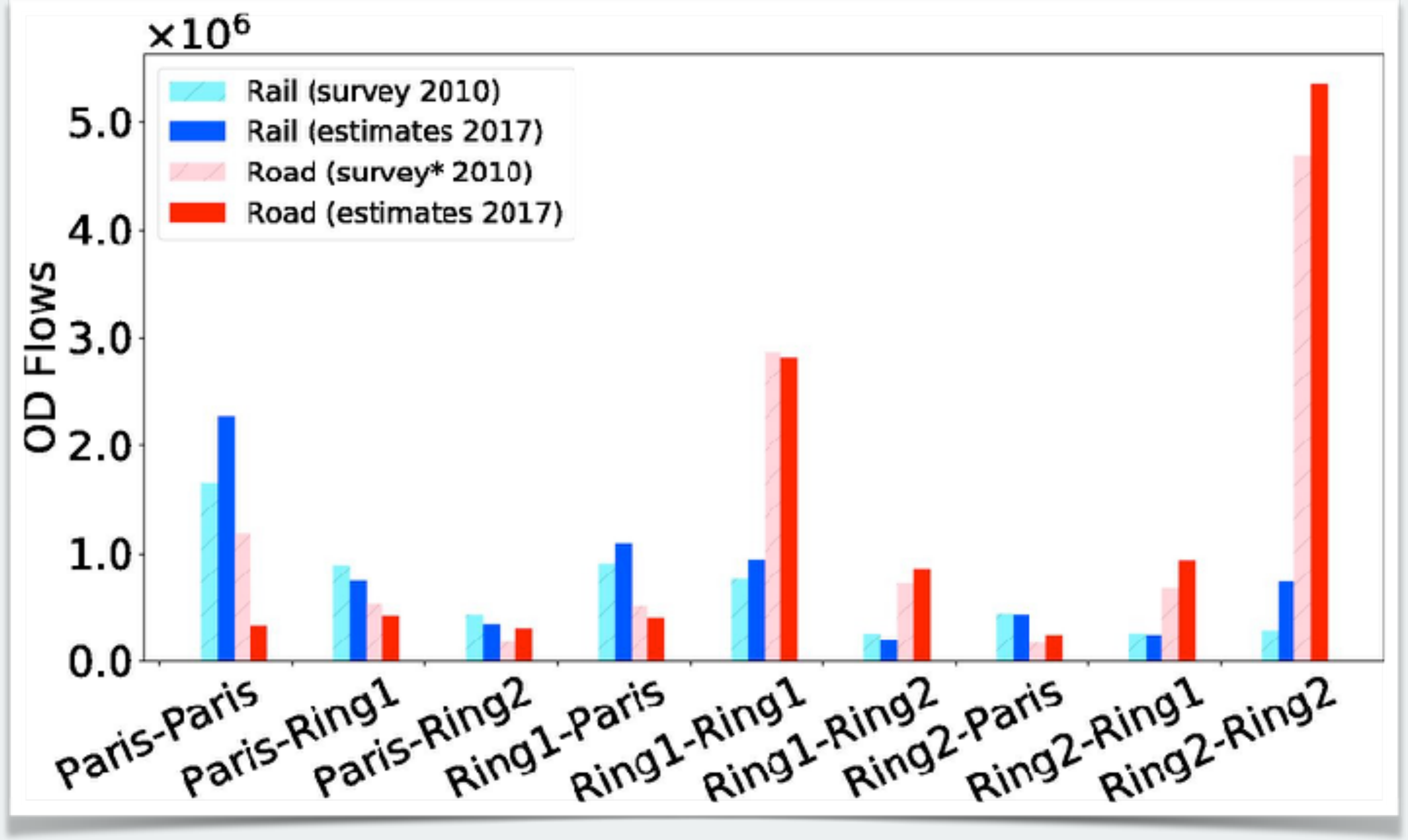
$$\underbrace{P(m_i|T_j)}_{\text{Probability of transport mode i given a trajectory sequence Tj}} \sim \prod_{k \in T_j} \underbrace{P(S_k|m_i)}_{\text{prob of being in cell k (of the trajectory Tj) gi-ven the transport mode i}} P(m_i)$$

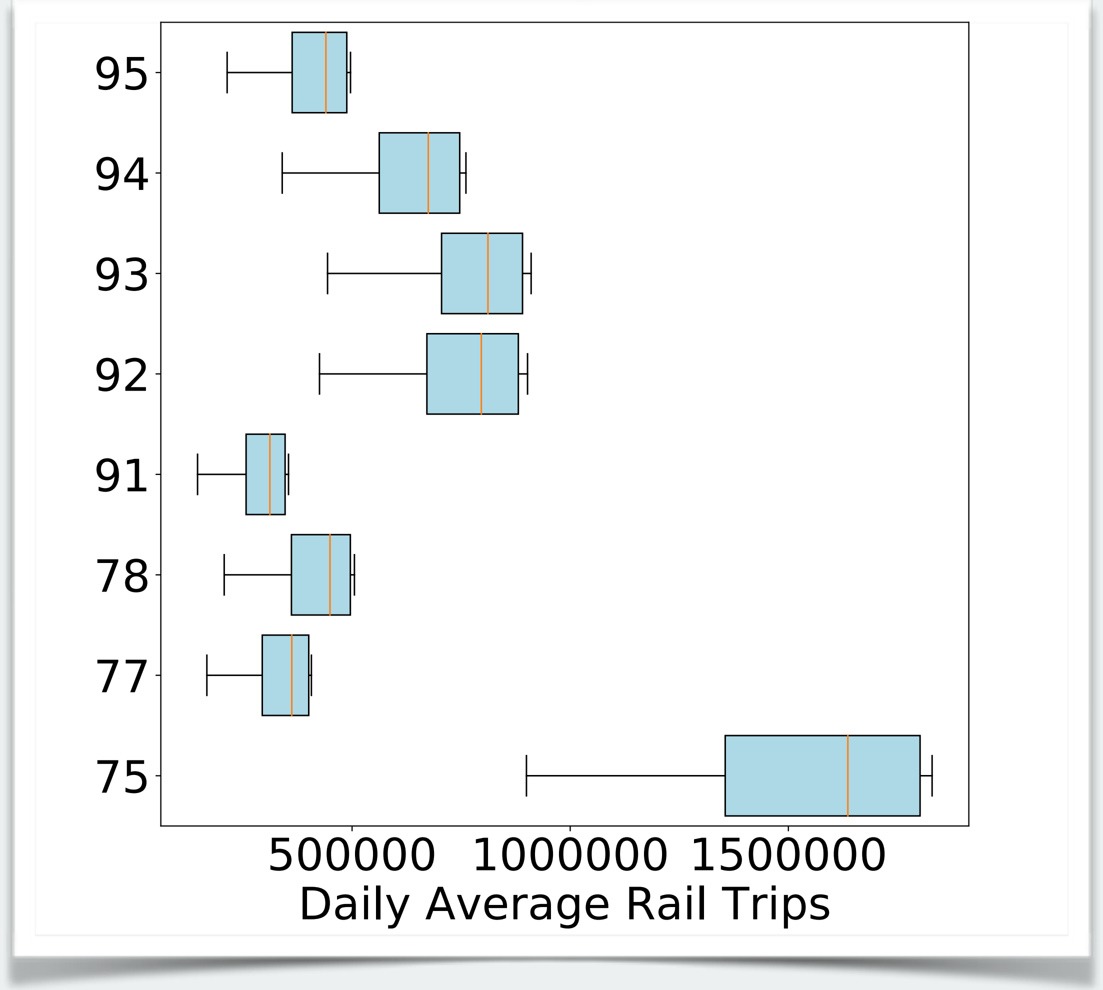
Our main data are mobile network records representing billions of rows each day (Terabytes). The mobile operator providing the data has a market share of 11.7 % in France, at the time of the study. Records are collected for the Greater Paris region over a two months period during spring 2017. Records are produced at the start and end of voice calls, and every time a message is sent or received. Data records are generated at the start and end of 3G and 4G data sessions (i.e., IMSI attach/detach).

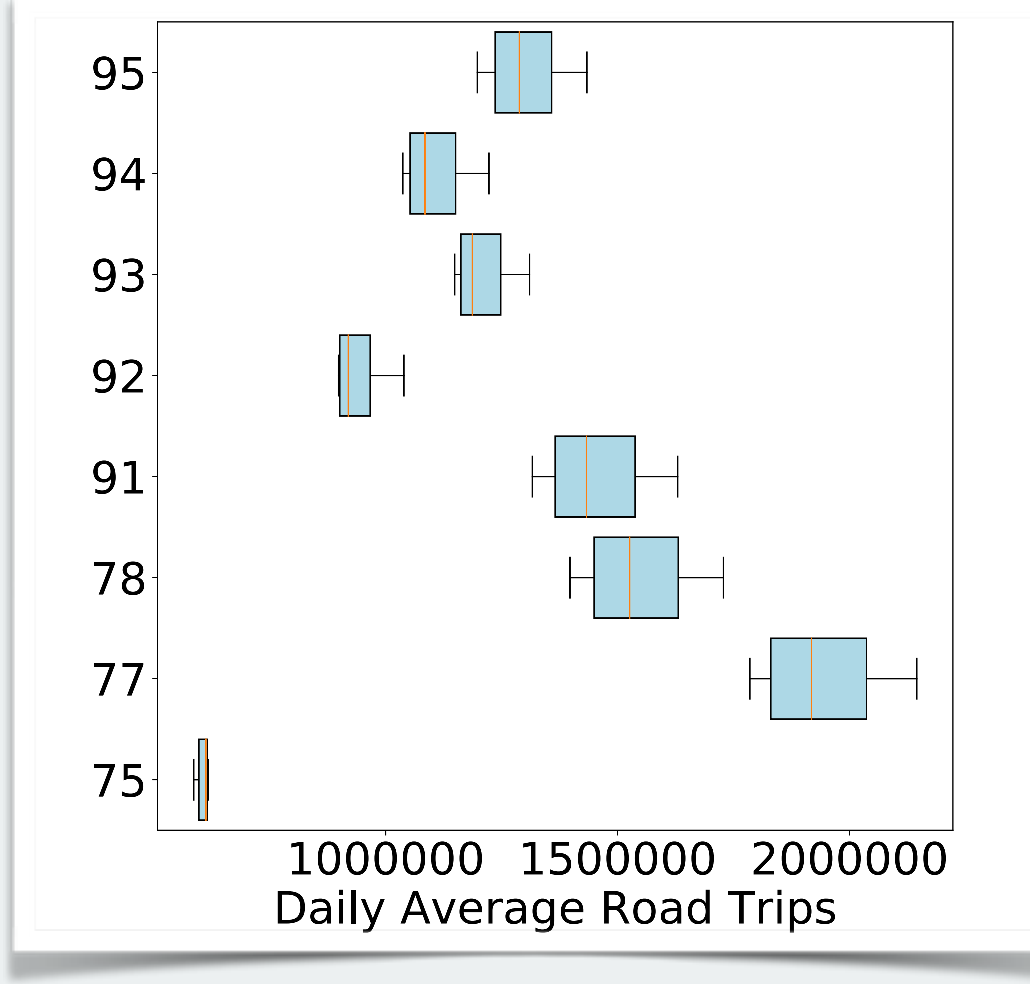
Survey : source: EGT 2010-Île de France Mobilités-OMNIL-DRIEA)

Table 4
Total flows per transport mode in the Greater Paris for a typical business day. Flows are calculated with mobile phones (MP) before and after rescaling. In the column 'Survey' all road and rail trips from the 2010 survey are considered. In the column 'Survey∗', we filter short-distance trips i.e., shorter than 1.5 km in suburb ring 1 and shorter than 2.5 km in suburb ring 2 to cope with the heterogeneous density and coarseness of the mobile network.

Mode	MP (raw)	MP (rescaled)	Survey	Survey∗ (filtered)
Rail flows	12,27,284	63,83,103	59,99,183	58,43,650
Road flows	21,28,750	1,10,34,581	1,82,15,180	1,13,68,597
$\frac{\text{Rail flows}}{\text{Road flows}}$	0.55	0.58	0.33	0.51

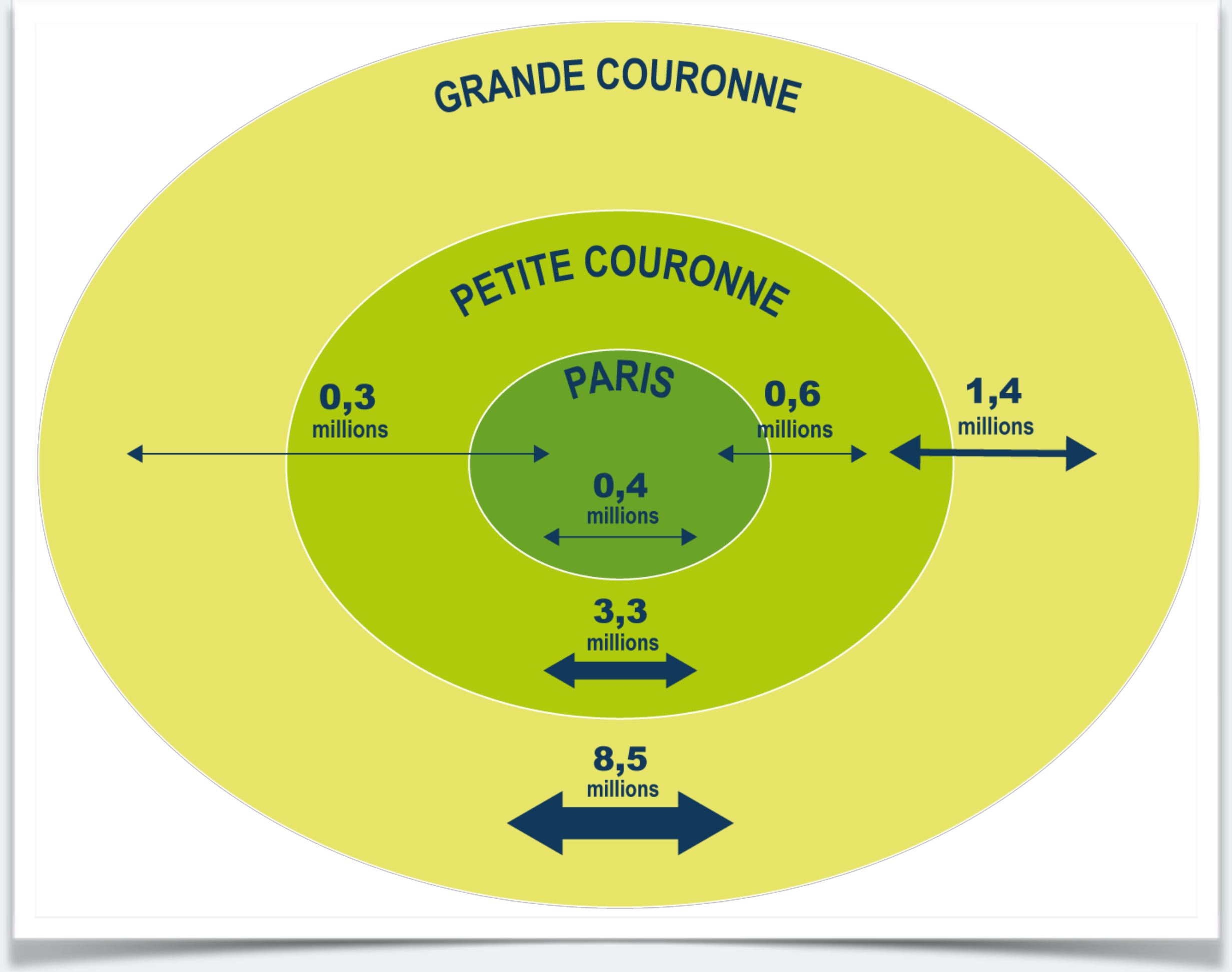




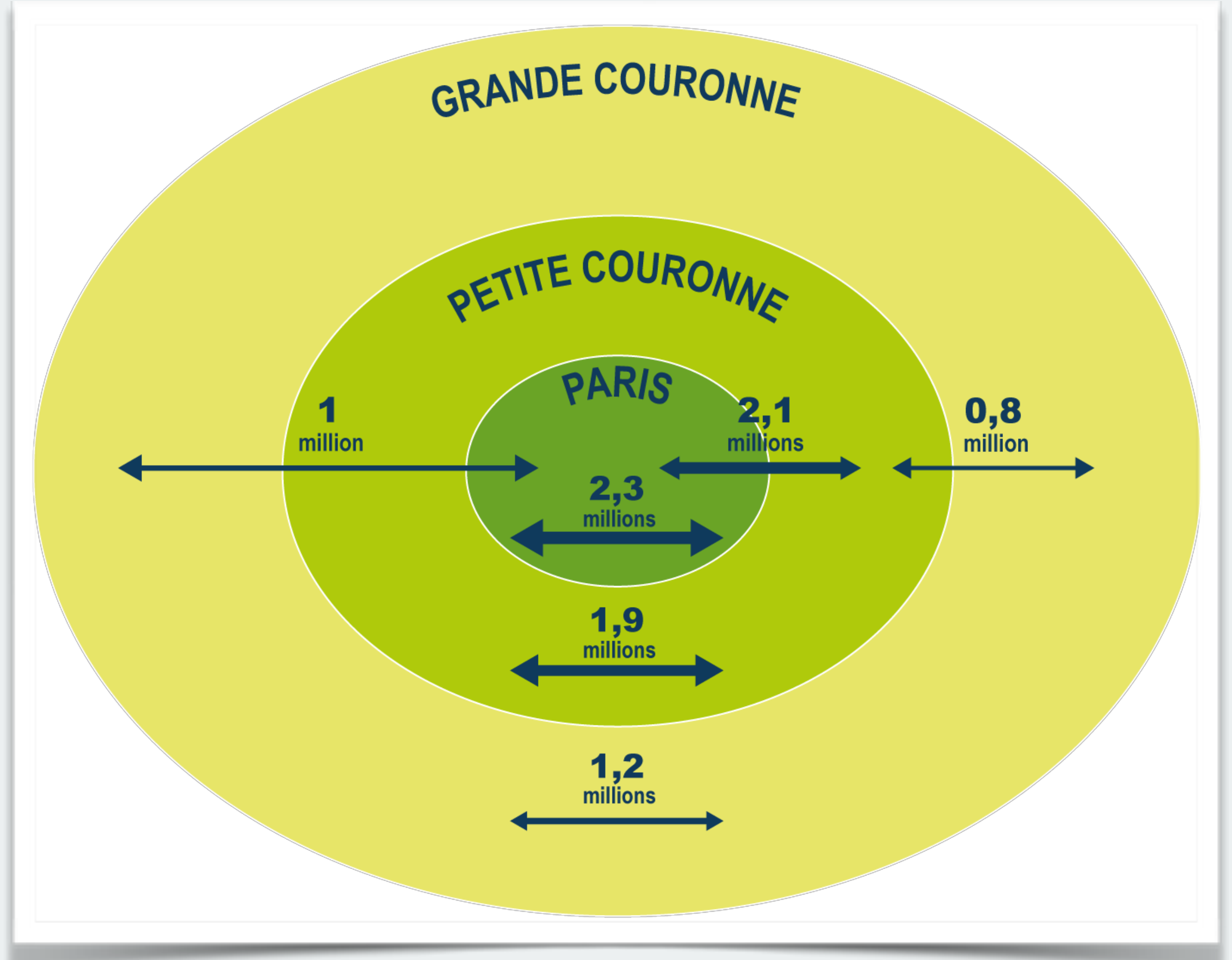


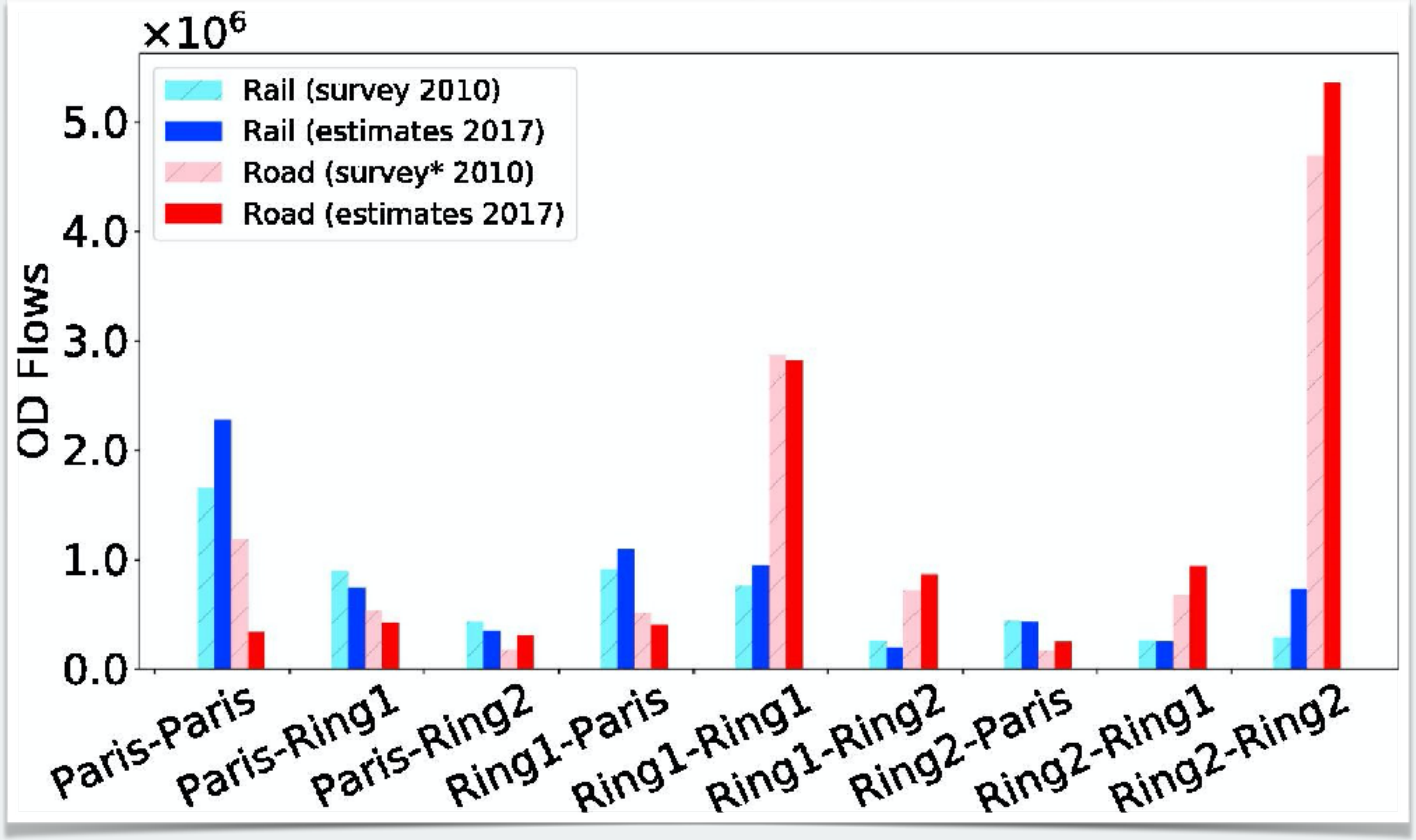
Mobile phone survey vs EGT-H2020

EGT – H2020 – Cars



EGT – H2020 – Public transport





Mains finding

① **Huge amount of mobility flow happen between suburbs.**

- The public transport infrastructure poorly supply the mobility between suburbs, the ”Grand Paris” infrastructure is suppose to change the statu quo.
- As consequence the majority of suburb to suburb trips are ride by car.

② **At the time of the study, we didn’t have access to the EGT 2020, but our result seems in line with it.**

- Change of behavior ≠ number of trips observed

③ **During the public transport strike of Mai 2018**

- No modal shift were observed
- Reduction of the number of trip perceptible some days but not for all

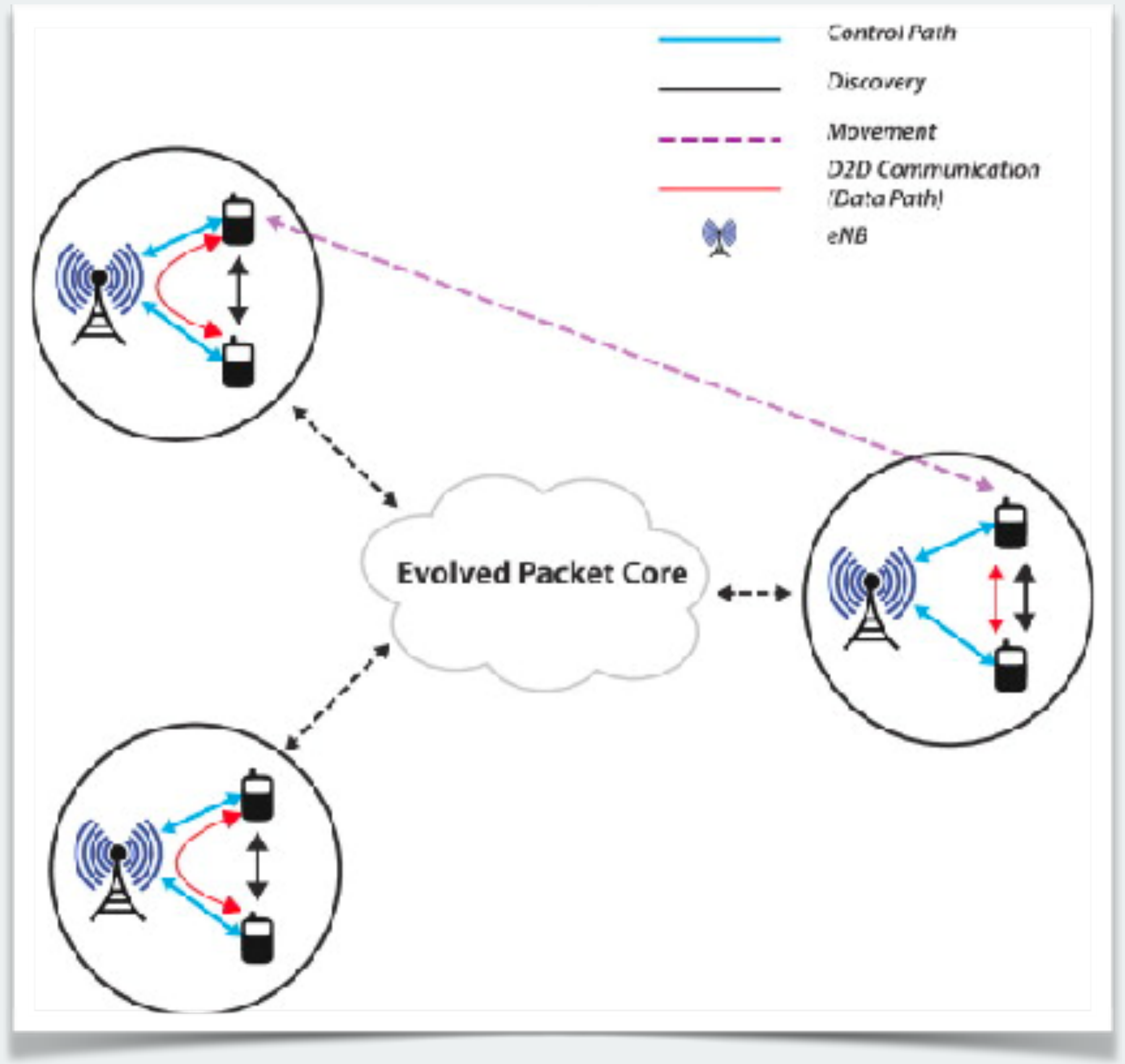
Epidemic modeling using cellphone metadata

Telecom application of the mobility

Can we diffuse public safety message through peer to peer mobile communication scale to country size ?

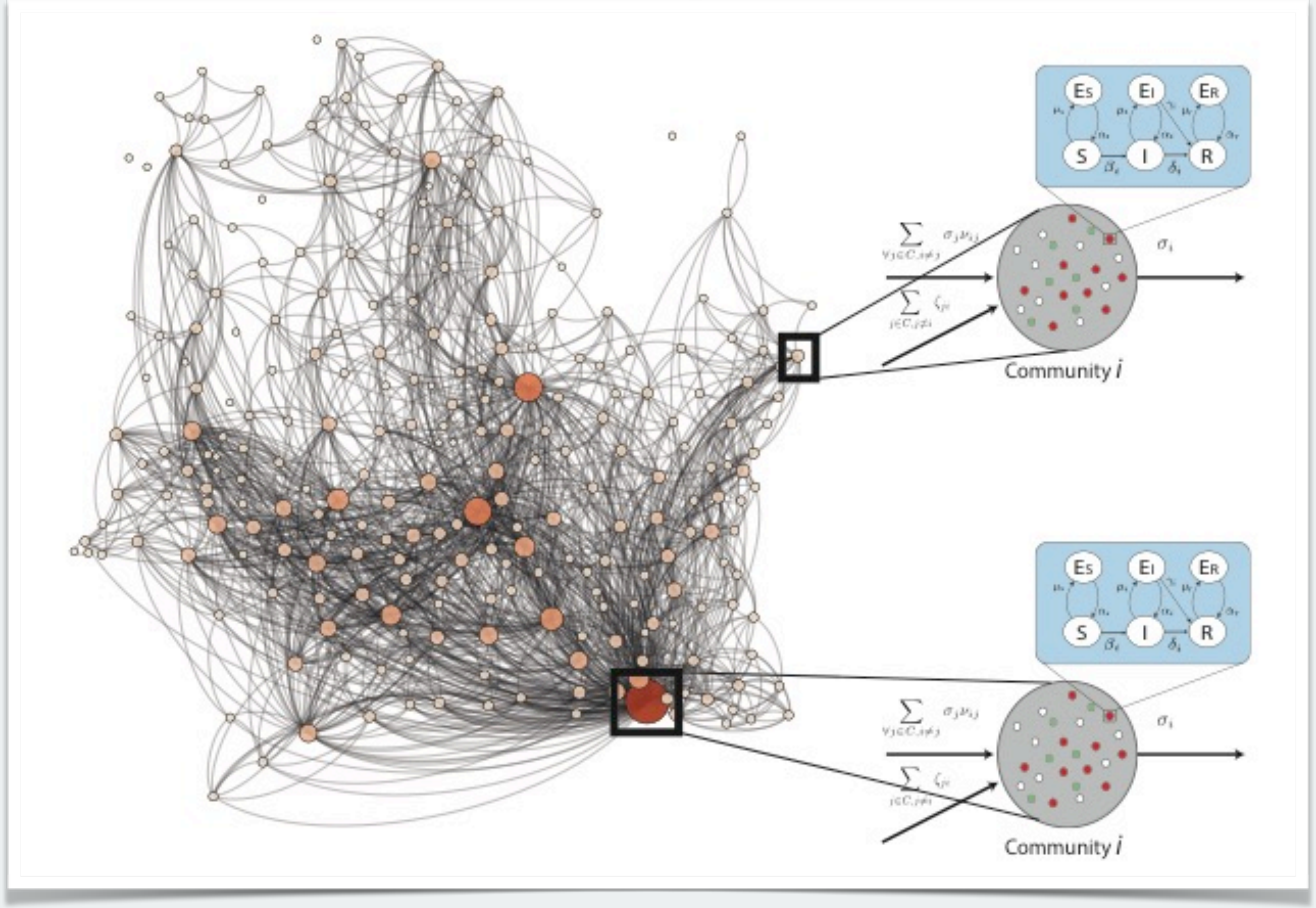
We use only mobile handset with D2D communications (device to device communication) (5G devices).

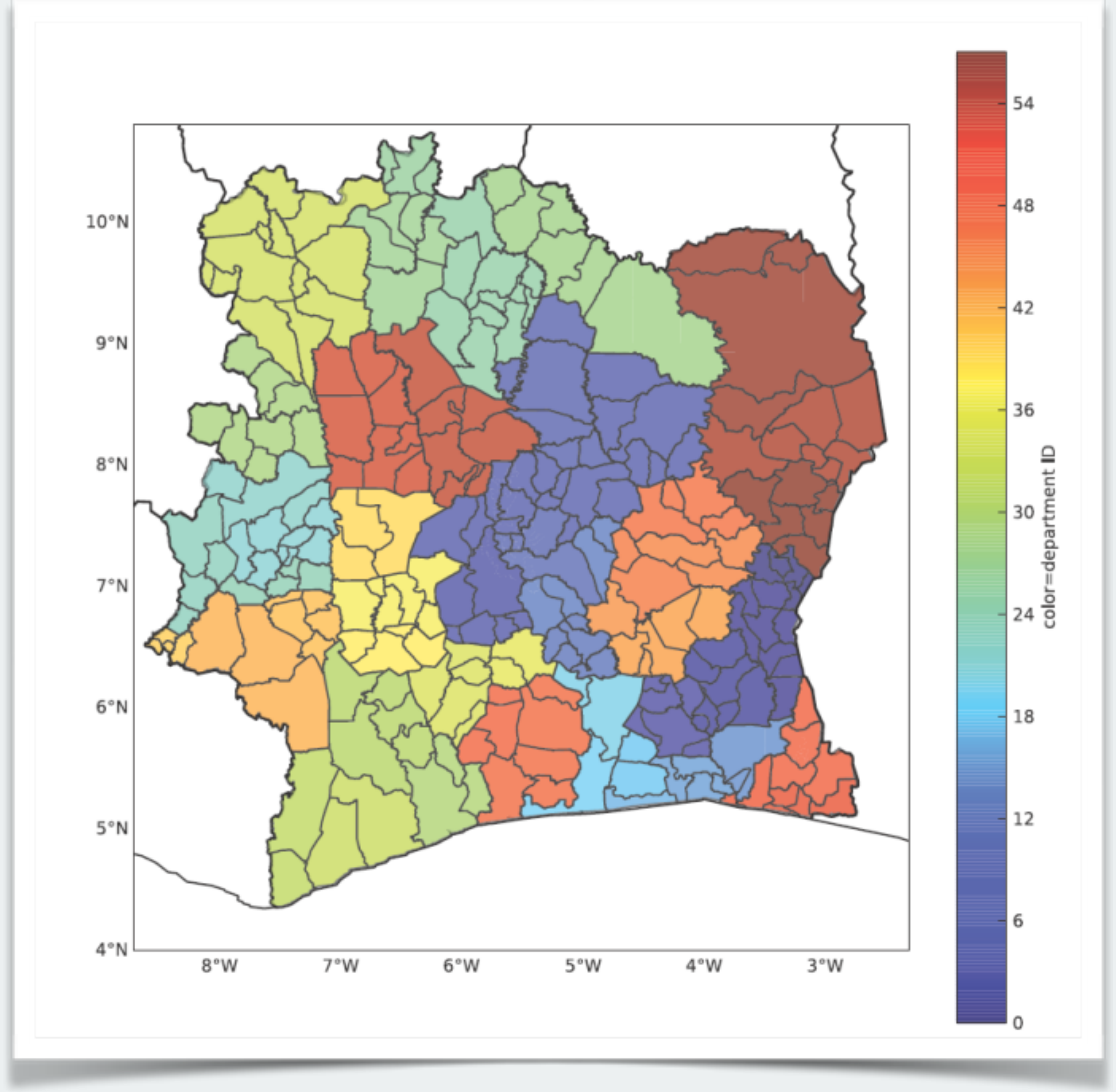
People carry the message in their mobile device throughout their daily trips.



Emergency Alert and Warning Systems: Current Knowledge and Future Research Directions
National Academies of Sciences, Engineering, and Medicine. 2018. https://doi.org/10.17226/24935.

Mobility with meta population





Mobility extracted from the D4D orange dataset

Dataset

Ivory Coast

- 19 Regions
- 81 Departments
- 255 Sub prefectures
- 1201 Antennas

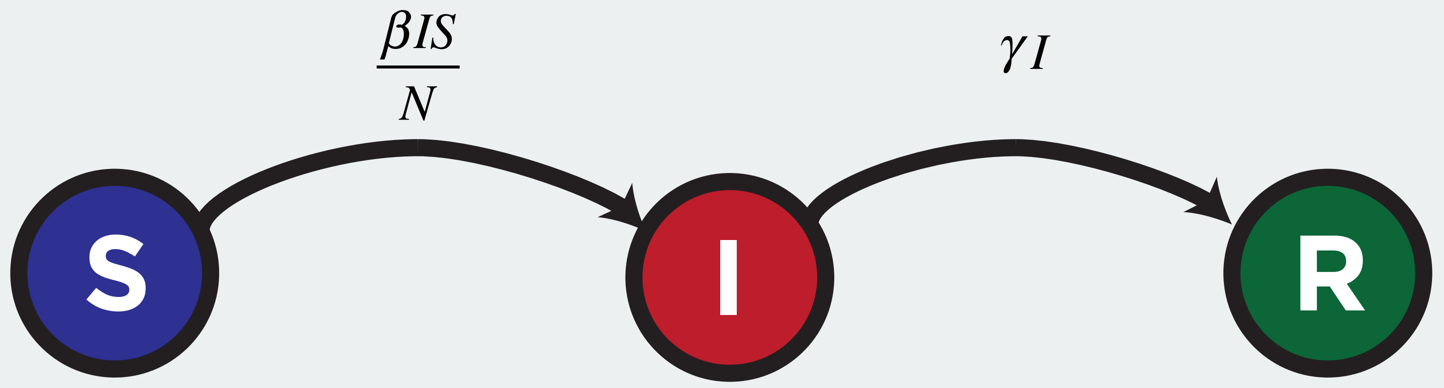
Orange Subscribers

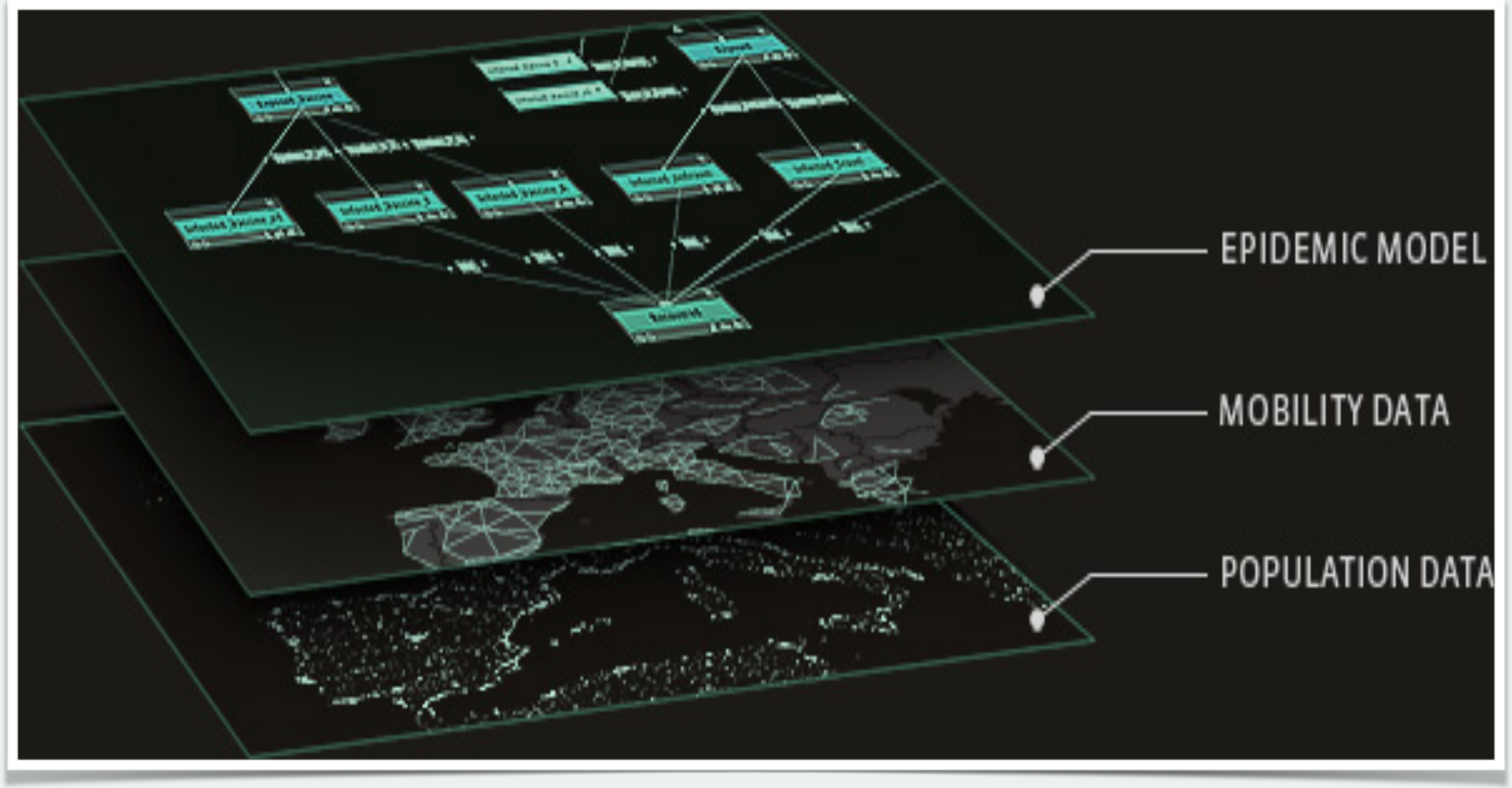
CDR (Call Data Record)

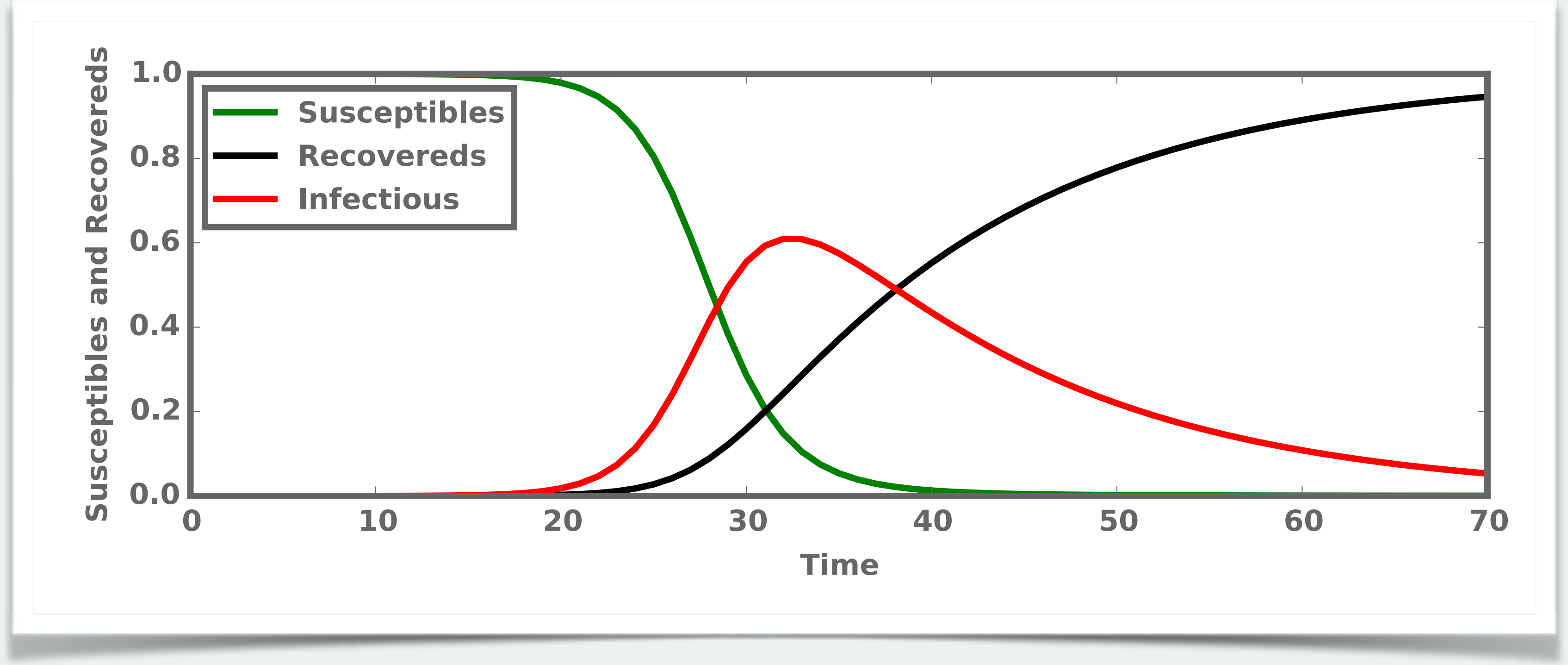
- coarse grain
- fine grain

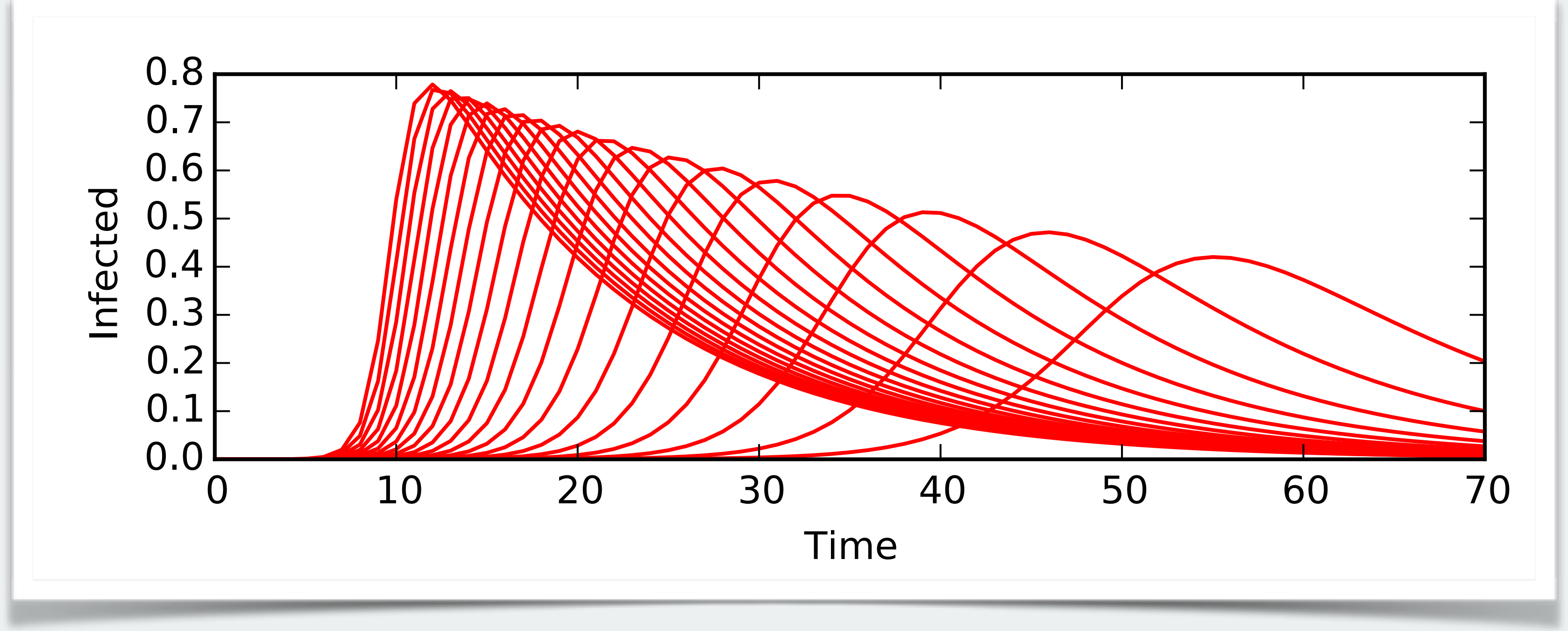
Data for Development: The D4D Challenge on Mobile Phone Data
V. Blondel, et al, 2013.

General overview of the model





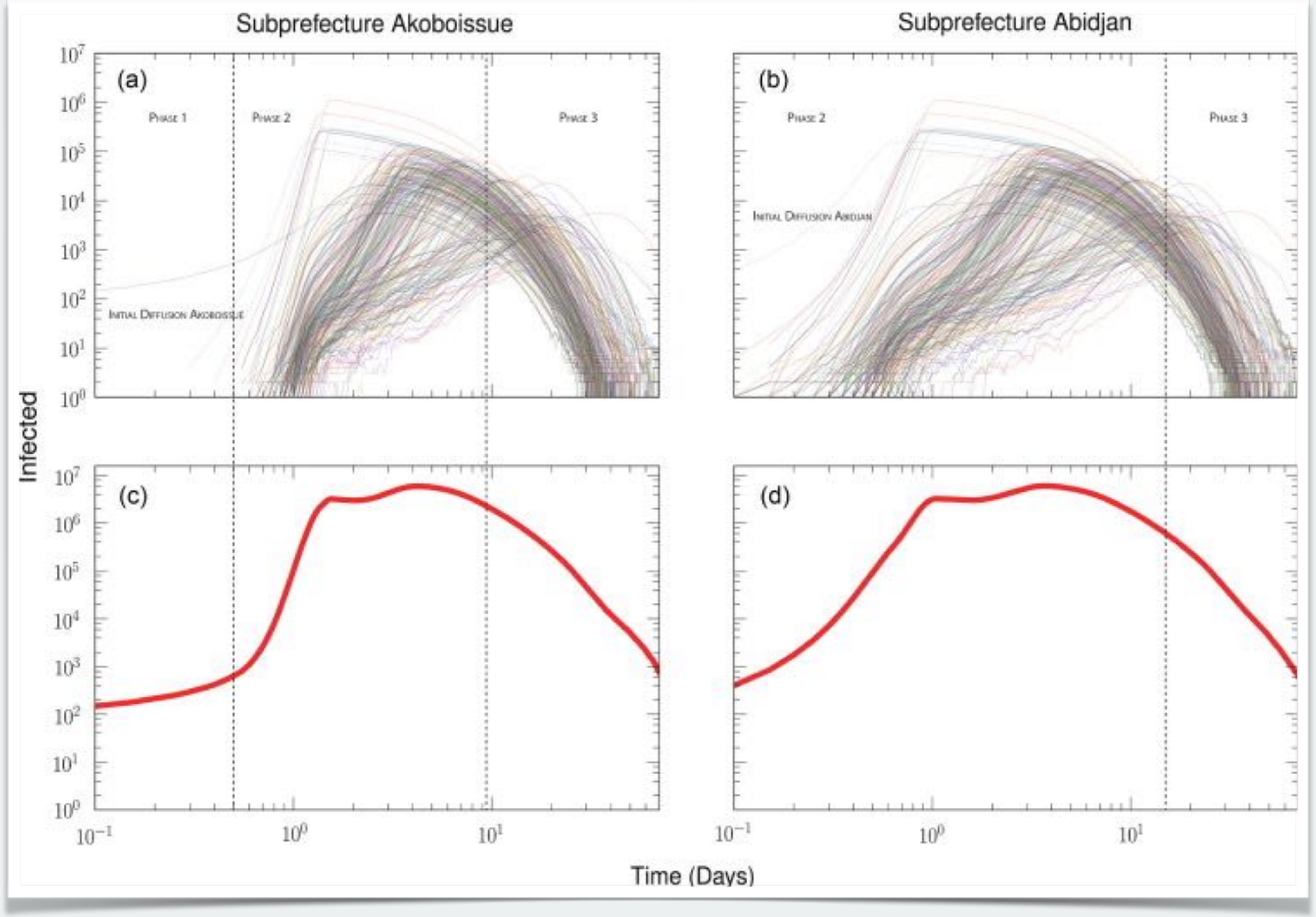




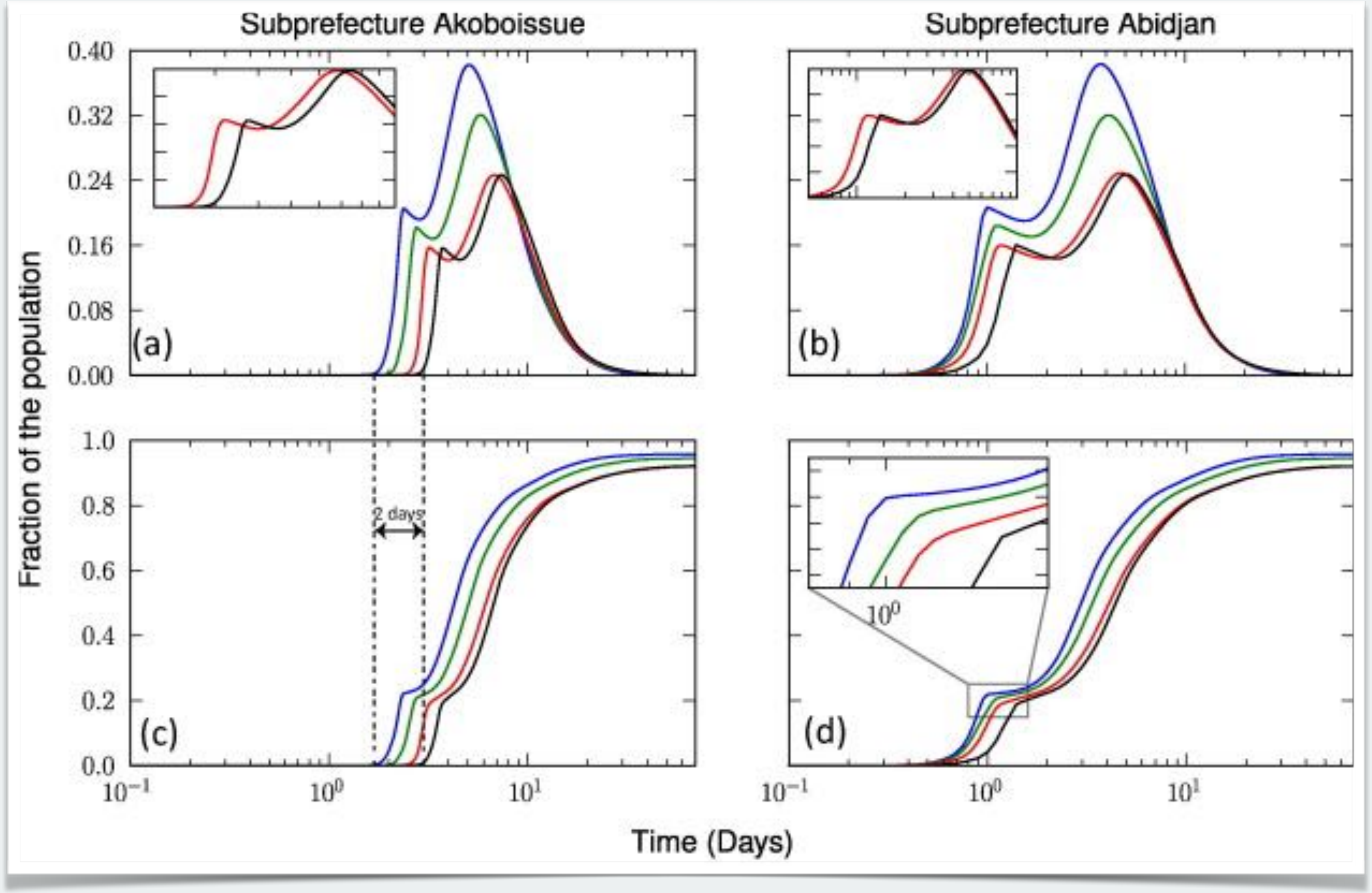
- Modelization of the population with mean field assumption:
  - Homogeneous mixing
- One relevant information:
  - Epidemic threshold
- Wildly used systems of equations to compute efficiently spreading behaviors

Balcan, D. et al.
Multiscale mobility networks and the spatial spreading of infectious diseases.
Proc. Natl. Acad. Sci. U.S.A. 106, 21484–9 (2009).

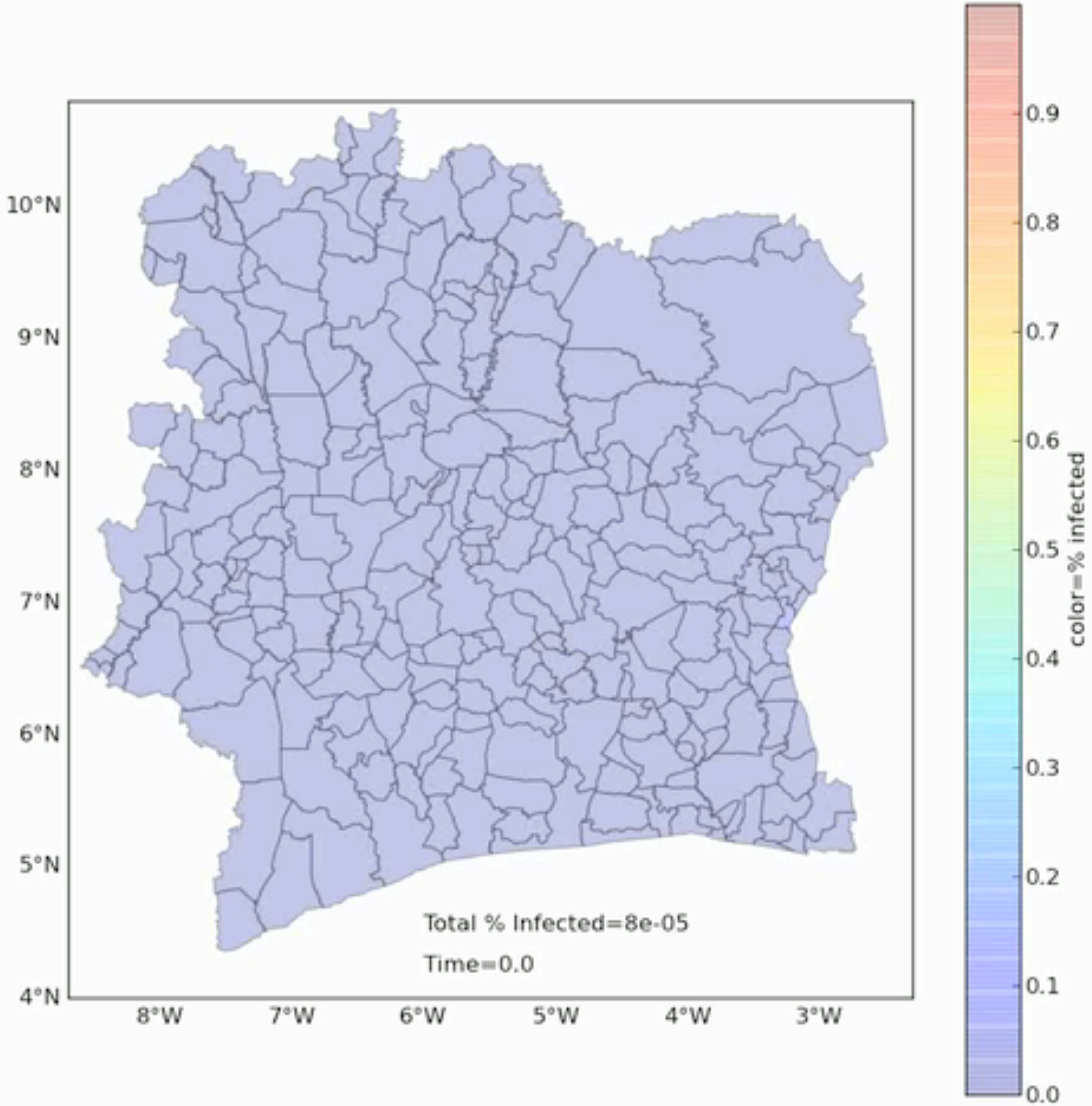
Results



Subprefecture Akoboissue
Subprefecture Abidjan
(a)
(b)
(c)
(d)
Phase 1
Phase 2
Phase 3
Initial Diffusion Akoboissue
Initial Diffusion Abidjan
Infected
Time (Days)



Subprefecture Akoboissue
Subprefecture Abidjan
(a)
(b)
(c)
(d)
2 days
Fraction of the population
Time (Days)


10°N
9°N
8°N
7°N
6°N
5°N
4°N
8°W
7°W
6°W
5°W
4°W
3°W
Total % Infected=8e-05
Time=0.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
color=% infected

Evolution of the cellular network

4G networks:

- The voice channel is not used anymore
- All the mean of communication are using the data channel
- Geolocalization by triangulation possible but for a restricted set of mobiles?

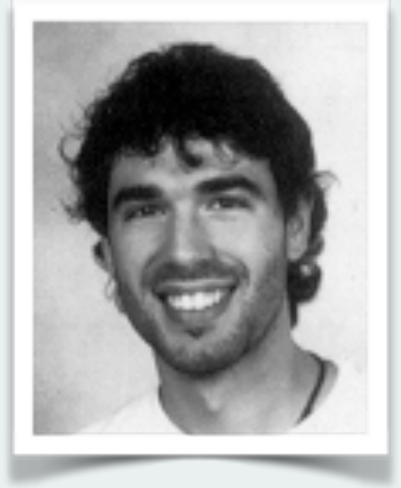
5G networks

- Geolocalization by triangulation will be available at large scale (measurement of the Signal Strength more robust to the fading)
- Low level metadata will be more easy to collect

Main Investigator

Vincent Gauthier Mounim El-Yacoubi

Main Collaborators



Marco Fiore Jakob Puchinger

Collaborators at TSP

- Hossam Afifi
- Monique Becker

Collaborators outside TSP

- Farid Benbadis (Thales)

PhD and Post-Doc

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- Danya Bachir (IRT)
- Alexis Sultan (SFR)
- Fereshteh ASGARI
- Haoyi Xiong
- Rachit Agrawal

Patent Filed in 2015/19

inpi

Scientific collaborations

Politecnico di Torino
Consiglio Nazionale delle Ricerche
Nanyang Technological University
Future Cities Laboratory

Sponsors & Industrial partners

bpifrance
Systematic Paris Region Digital Ecosystem
SFR
THALES
intersec
SystemX
eit Digital
bouygues telecom

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G. Khodabandelou, V. Gauthier, M. Fiore, M. A. E. Yacoubi
IEEE Transactions on Mobile Computing, 2019. (In Press)

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R. Agarwal, V. Gauthier, M. Becker, T. Toukabrigunes, H. Afifi
Computer Communications , vol. 59 , pp. 1 - 11, 2015.

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G. Khodabandelou, V. Gauthier, M. El-Yacoubi, M. Fiore
17th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM) , pp. 1 - 9, 2016.

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