Digital Epidemiology

Mobility impact on epidemics spread

Mattia Mazzoli - UniTo

Overview

- Mobility types
- Mobility data
- Human mobility models
- Mobility impact on epidemic spread
- Public health interventions: mobility restrictions
- Population response to interventions

Mobility types

Mobility defined by purpose and distance:

Can you guess what categories we use to define mobility?

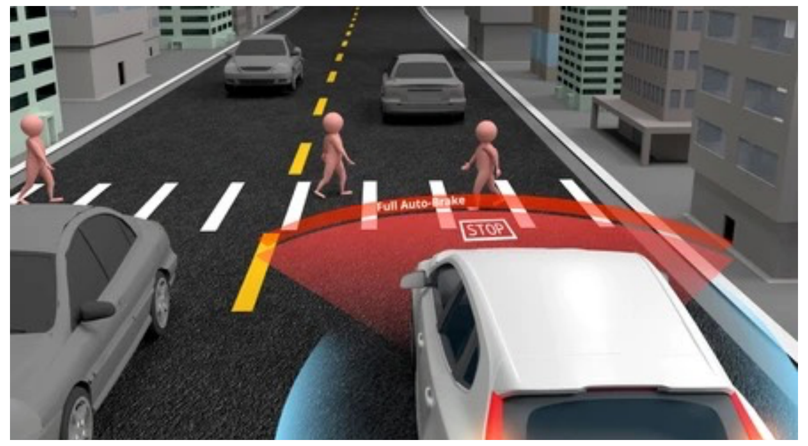
Mobility types

Mobility defined by purpose and distance:

Can you guess what categories we use to define mobility?

Types of mobility:

- Short range: pedestrian (indoor, outdoor, sidewalks)
- Mid-range: commuting (home to work / school), leisure (night time, weekends)
- Long-range: air travel, tourism, migration



Mobility types

Mobility study defined by scale:

Can you guess what spatial scales are used to study mobility?

Mobility types

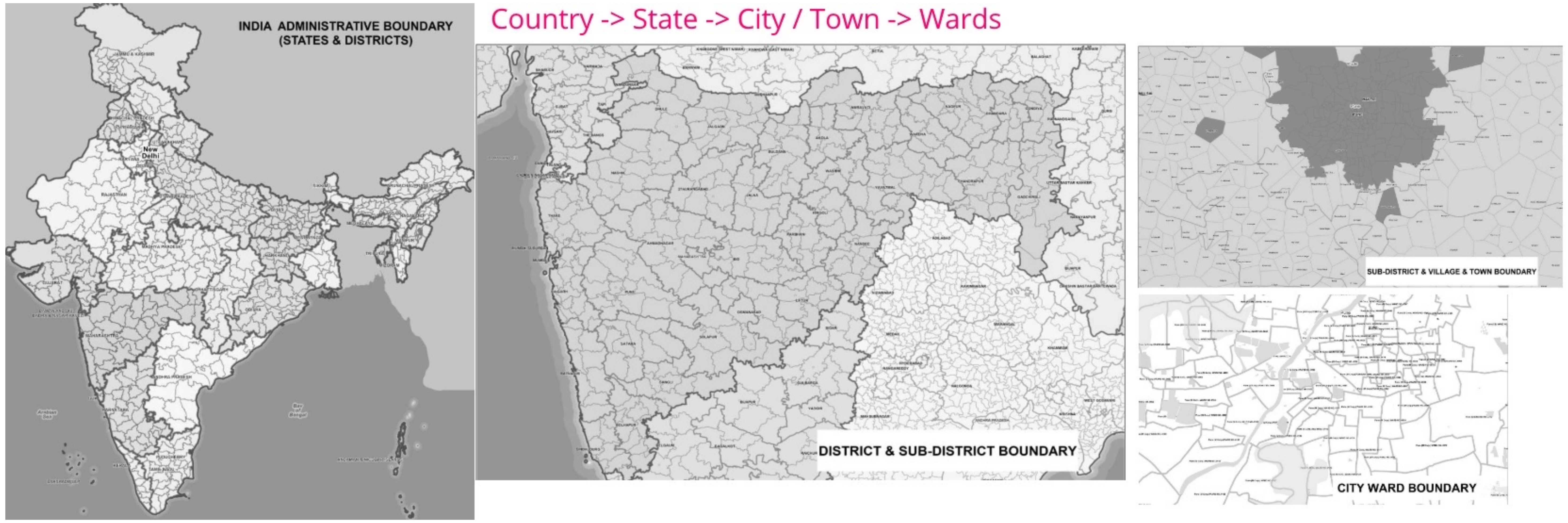
Mobility study defined by scale:

Can you guess what spatial scales are used to study mobility?

Scales of mobility:

- Latitude, longitude
- Spatial grid, ~1x1 sq km.
- Census areas
- Municipalities
- Province
- Regions
- Countries

aggregation



https://community.geodesignhub.com/

Mobility types

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Can you guess what spatial scales are used to study mobility?

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- Short range: pedestrian (indoor, outdoor, sidewalks), cars routes

Mobility types

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Can you guess what spatial scales are used to study mobility?

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- Mid-range: commuting (home to work / school), leisure (night, weekends)

Mobility types

Mobility study defined by scale:

Can you guess what spatial scales are used to study mobility?

Scales of mobility:

- Latitude, longitude
- Spatial grid, ~1x1 sq km.
- Census areas
- Municipalities
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- Countries

- Long-range: air travel, tourism, migration (internal, cross-country)

Why does it matter?

Implications of understanding human mobility:

Can you guess what fields human mobility brings important contributions to?

Why does it matter?

Implications of understanding human mobility:

Can you guess what fields human mobility brings important contributions to?

Fields affected by human mobility:

- <u>Epidemiology</u> (communicable and non-communicable diseases, health accessibility)
- Urban planning (sustainable mobility, smart cities)
- Transportation and infrastructure engineering (travel demand, traffic regulation, logistic and goods)
- Environment and ecology (pollution, car emissions)

Why does it matter?

Some research questions in human mobility:

- What makes people move? [Determinants of mobility, collective models]
- How much do people move, new places or old places? [Individual mobility models]
- Where movements will mostly occur? When? How? [Mobility dynamics analysis]
- How many people usually move from there and where do they go? [Transportation planning]
- Traffic viability design [Traffic regulation]
- How much pollution is generated by traffic [Environmental policies]
- Where and how do migrants move? [Humanitarian response]
- How does traveling affects epidemics? [Epidemiology]

Mobility data

Types of data:

- Mobile phone (CDR, XDR)
- Census (commuting)
- International travel (IATA, Meta Travel patterns)
- GPS traces (Cuebiq, SafeGraph, Meta Co-location, Google location history, Meta Movement range)
- Activity based records (Google mobility reports)
- Surveys

The first study on telephone data and mobility

How were mobile phone data used before the big data revolution?

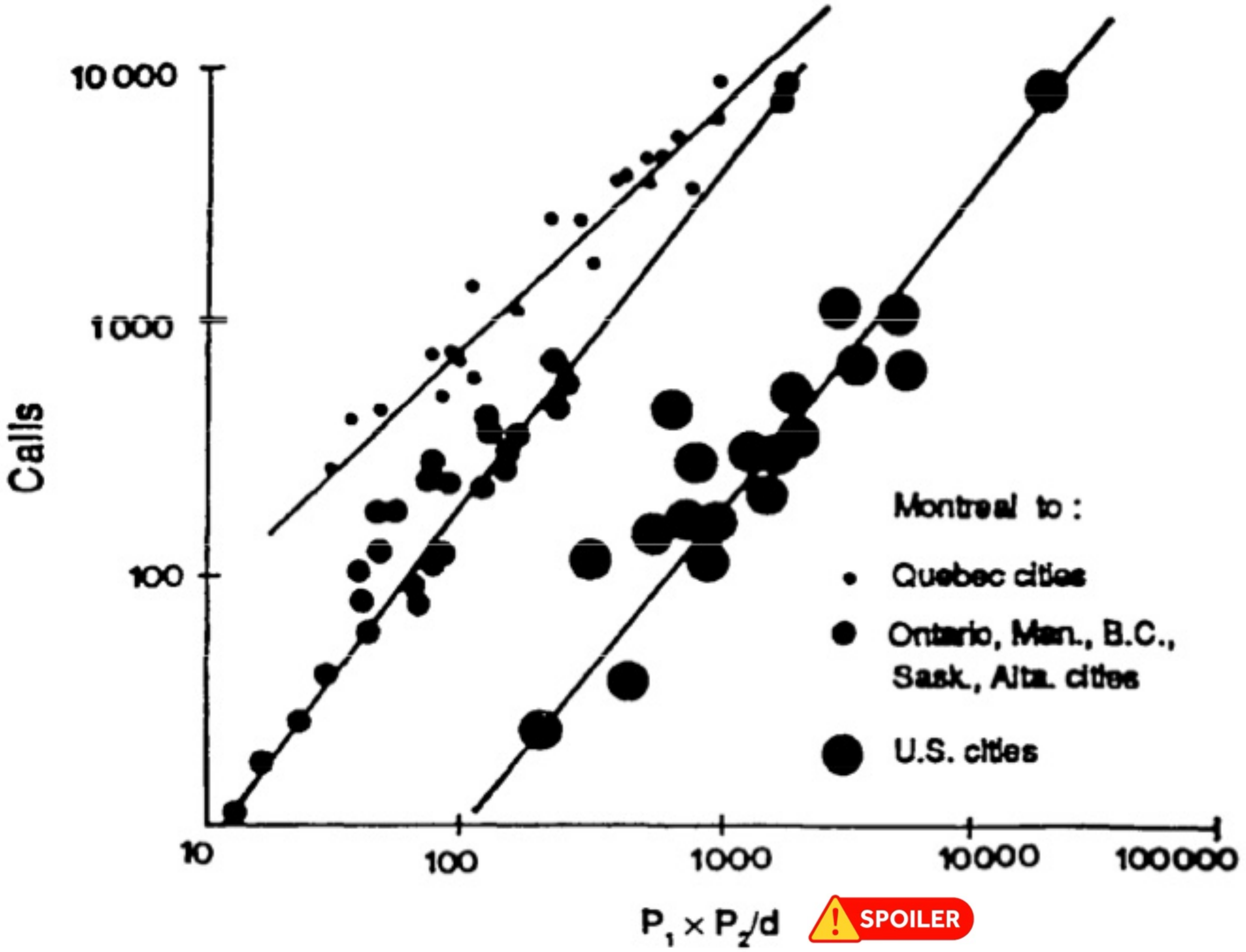
Cesare Marchetti
(Italian Physicist)
Anthropological invariants in travel behaviour (1994)

“Due to parallelism between message exchange by telephone and traveling, we may use the first as a proxy for the second […]”

TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE 47, 75-88 (1994)

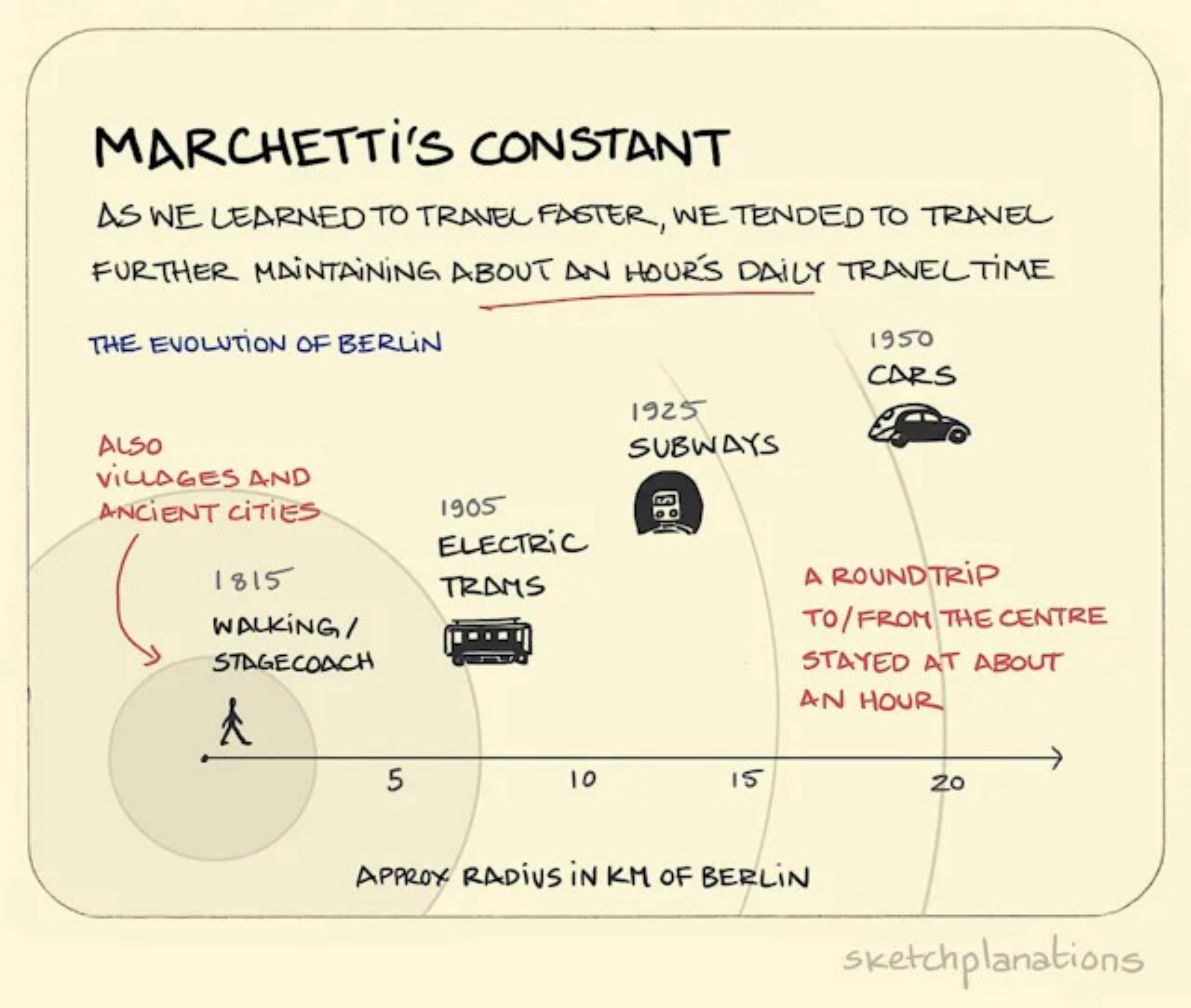
Anthropological Invariants in Travel Behavior

C. MARCHETTI

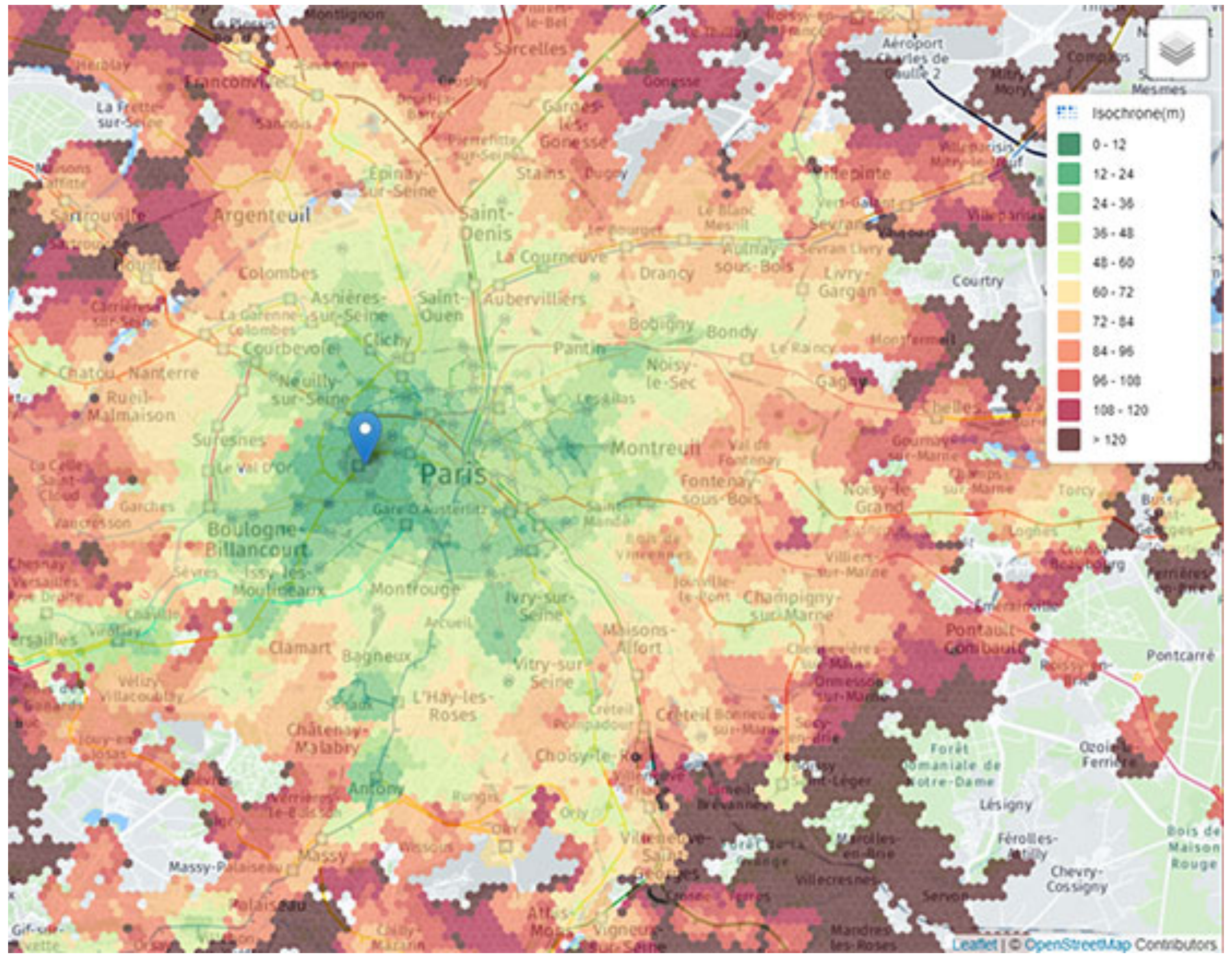


The first study on telephone data and mobility

The original analysis



The big data application



http://whatif.cslparis.com/citychrone.html

The policy

Welcome to the 15-minute city

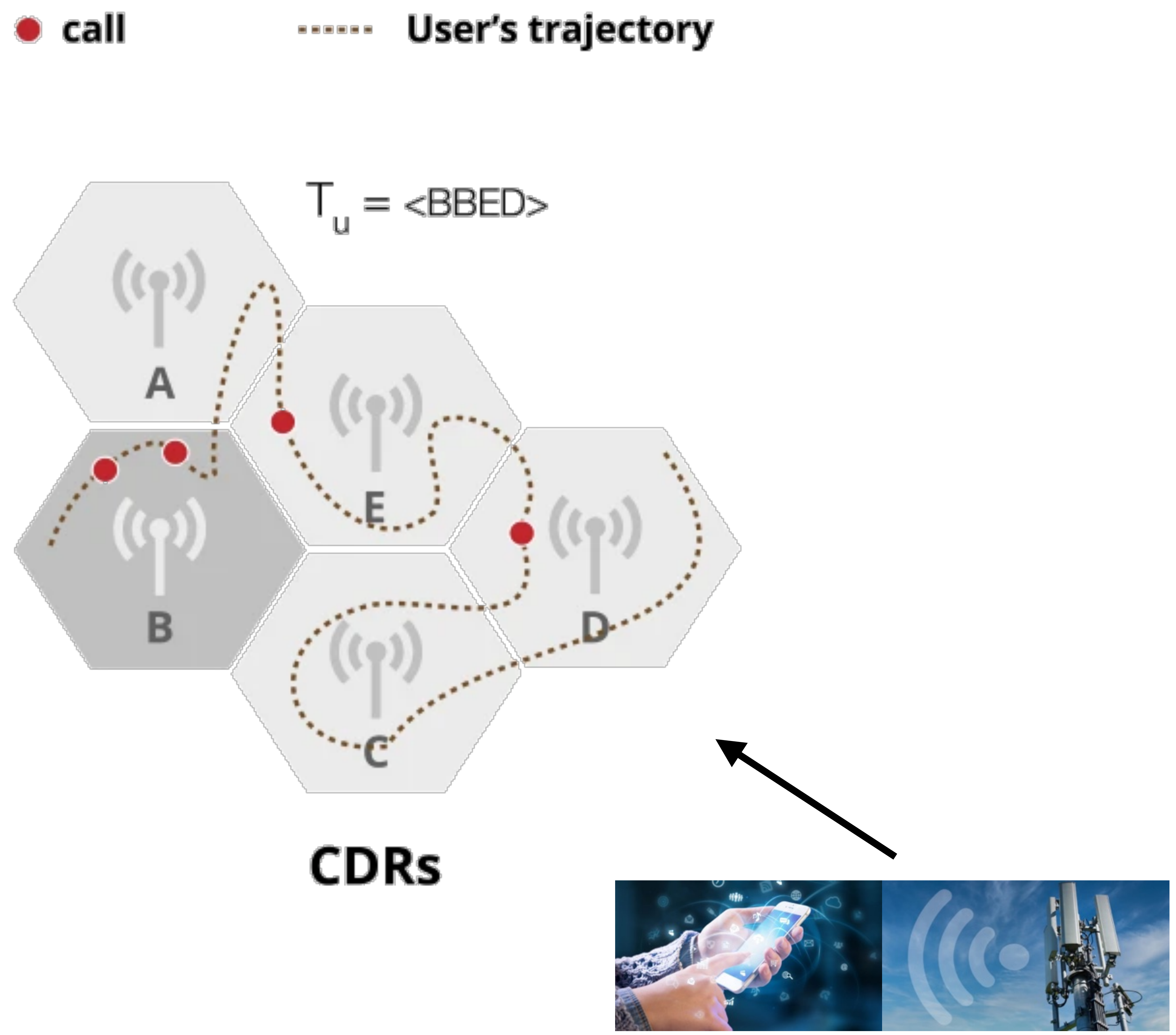
As the switch to home working makes us balk at the back-and-forth of commuting, a new vision of urban living is emerging

https://www.ft.com/content/c1a53744-90d5-4560-9e3f-17ce06aba69a

Marchetti, Cesare. "Anthropological invariants in travel behavior." Technological forecasting and social change 47.1 (1994): 75-88.
Biazzo, Indaco, Bernardo Monechi, and Vittorio Loreto. "General scores for accessibility and inequality measures in urban areas." *Royal Society open science* 6.8 (2019): 190979.
https://csl.sony.it/project/the-15-minutes-city/

Mobile phone data (CDR & XDR)

… and then, the massive adoption of mobile phones occurred ~ 2000s



CDR (Call Detail Records)

- Billing purposes
- Covers most of the population
- Pinged when user calls or sends SMS
- Sparse data
- Low spatial and temporal resolution
- Used since years 2000s

Pappalardo, L., Ferres, L., Sacasa, M. *et al.* Evaluation of home detection algorithms on mobile phone data using individual-level ground truth. *EPJ Data Sci.* **10**, 29 (2021).

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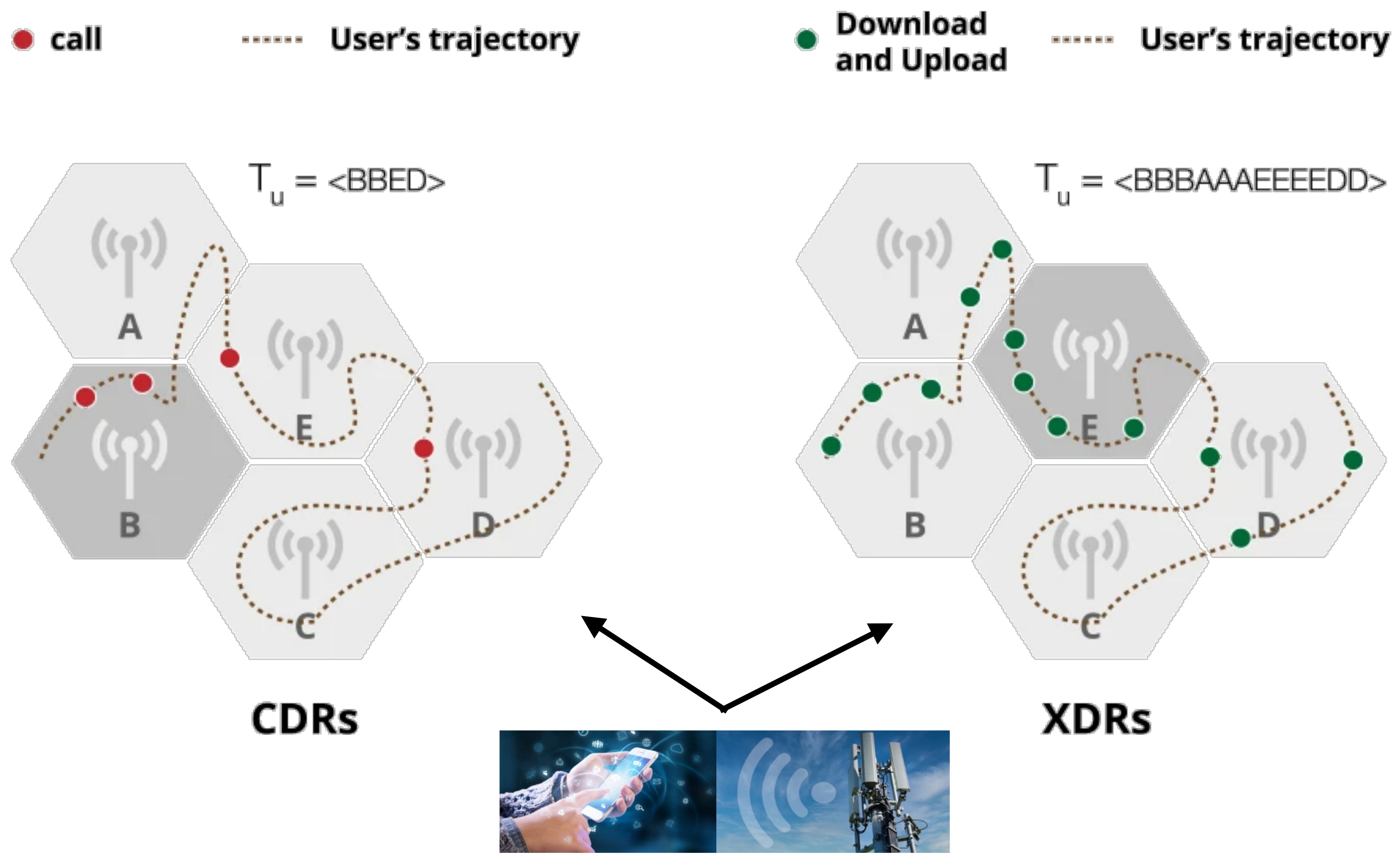

CDR (Call Detail Records)

- Billing purposes
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- Low spatial and temporal resolution
- Used since years 2000s

XDR (eXtended Detail Records)

- Billing purposes
- Covers most of the population
- Pinged also by app behaviour
- Dense data
- High temporal resolution
- Recently deployed

Pappalardo, L., Ferres, L., Sacasa, M. *et al.* Evaluation of home detection algorithms on mobile phone data using individual-level ground truth. *EPJ Data Sci.* **10**, 29 (2021).

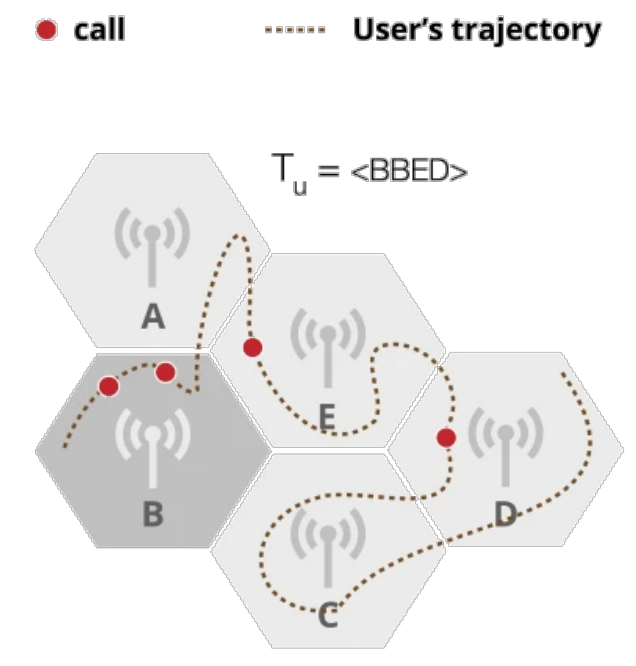
Data structure (CDR & XDR)

CDR

Call / SMS | Origin UUID | Dest Cell Tower ID

`00:00:18,MT,38,B92F1982701DF65DF2FD2CAA,,E14E3DCF280350EBB2C69E6B,41575,38`

Timestamp | Call Length | Dest UUID

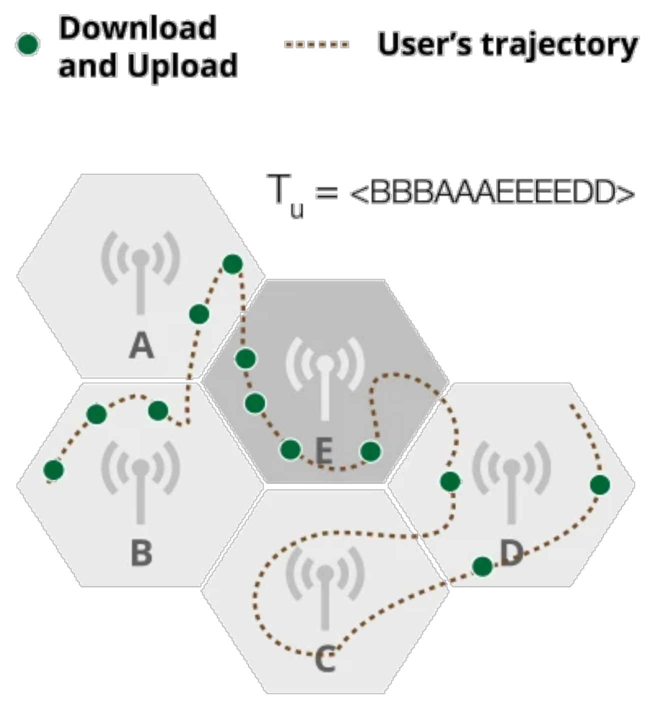


CDRs

XDR

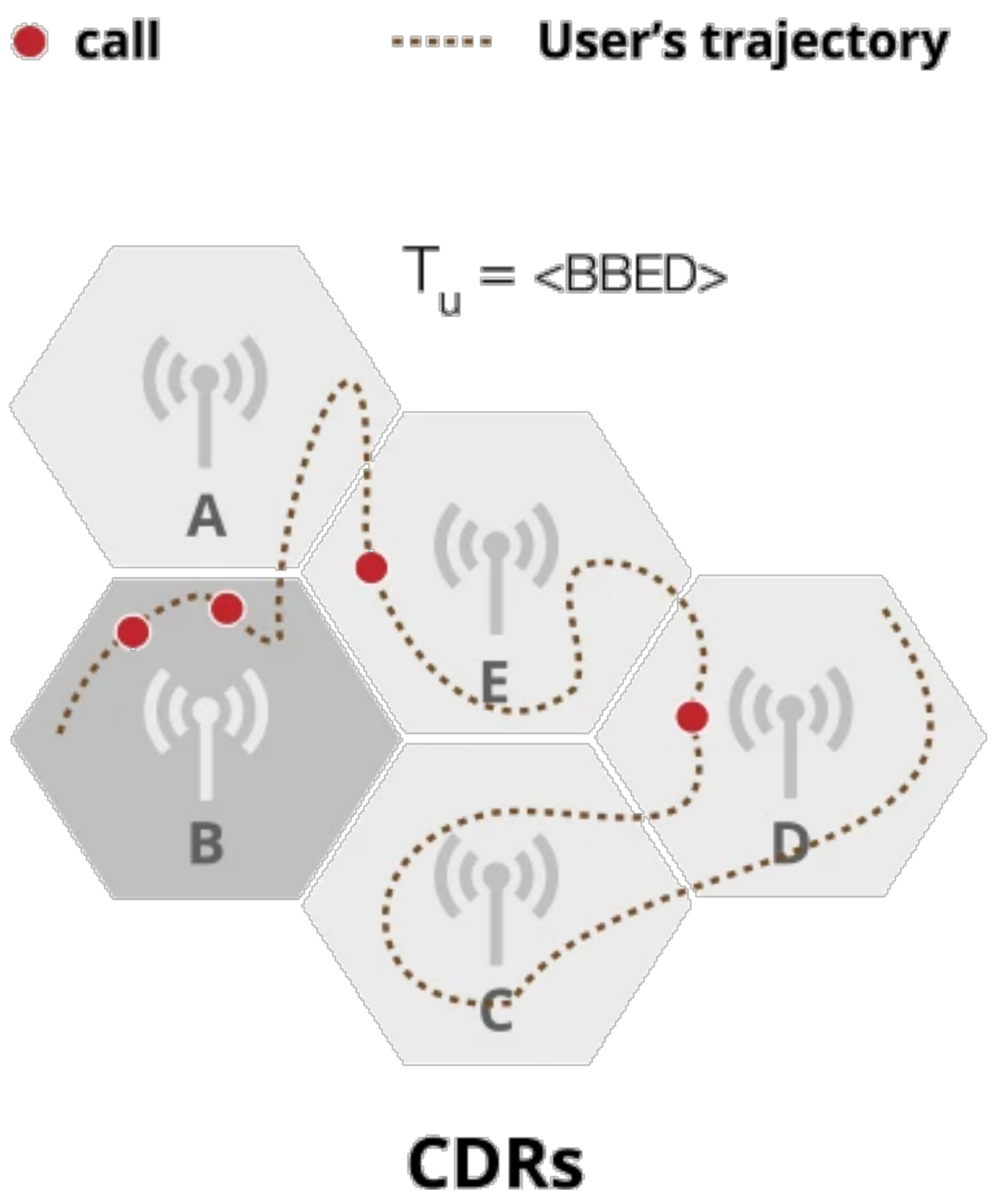
phone_id	cell_id	technology_cell_cd	timestamps	trafico
0000e2806116ad9dab7be18125ce4e8e365c38c4a84b4ef713008ed8fba8e395	1078306	4	2022-03-07 16:05:17	4
0000ee66426b94c621683c5e11ab356c2136ba94134fbf2f1d5a0e0bc05bdee0	159815199	4	2022-03-07 23:47:42	52
0002a5c62fb5f16d3a0100bfea38a17e98fd918212c558ac7d64ffff2a3047d2	44031	3	2022-03-07 03:27:19	1
0002b61943bcb27ce0aca2aa244d588254e237494ee2f055005723dcc5c60712	59685	3	2022-03-07 23:19:38	3
0002f2463d2be1263754374cf78f47c80781c187a7ee7e0153f5cc9ddc8c2660	15509	3	2022-03-07 10:58:16	28

Encrypted device ID | Cell tower ID | Time | Data (KB)

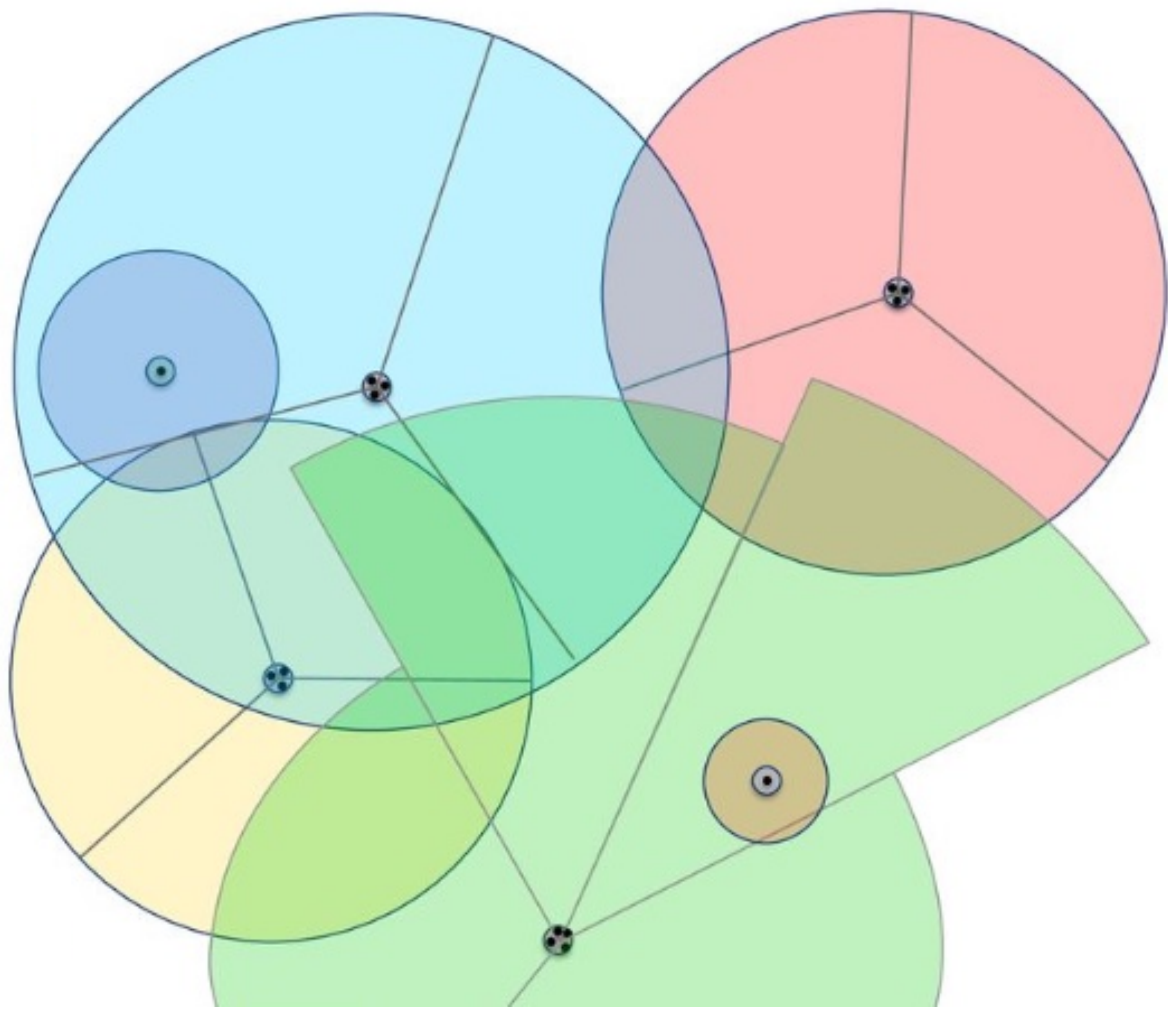


XDRs

Mobile phone data (CDR & XDR)

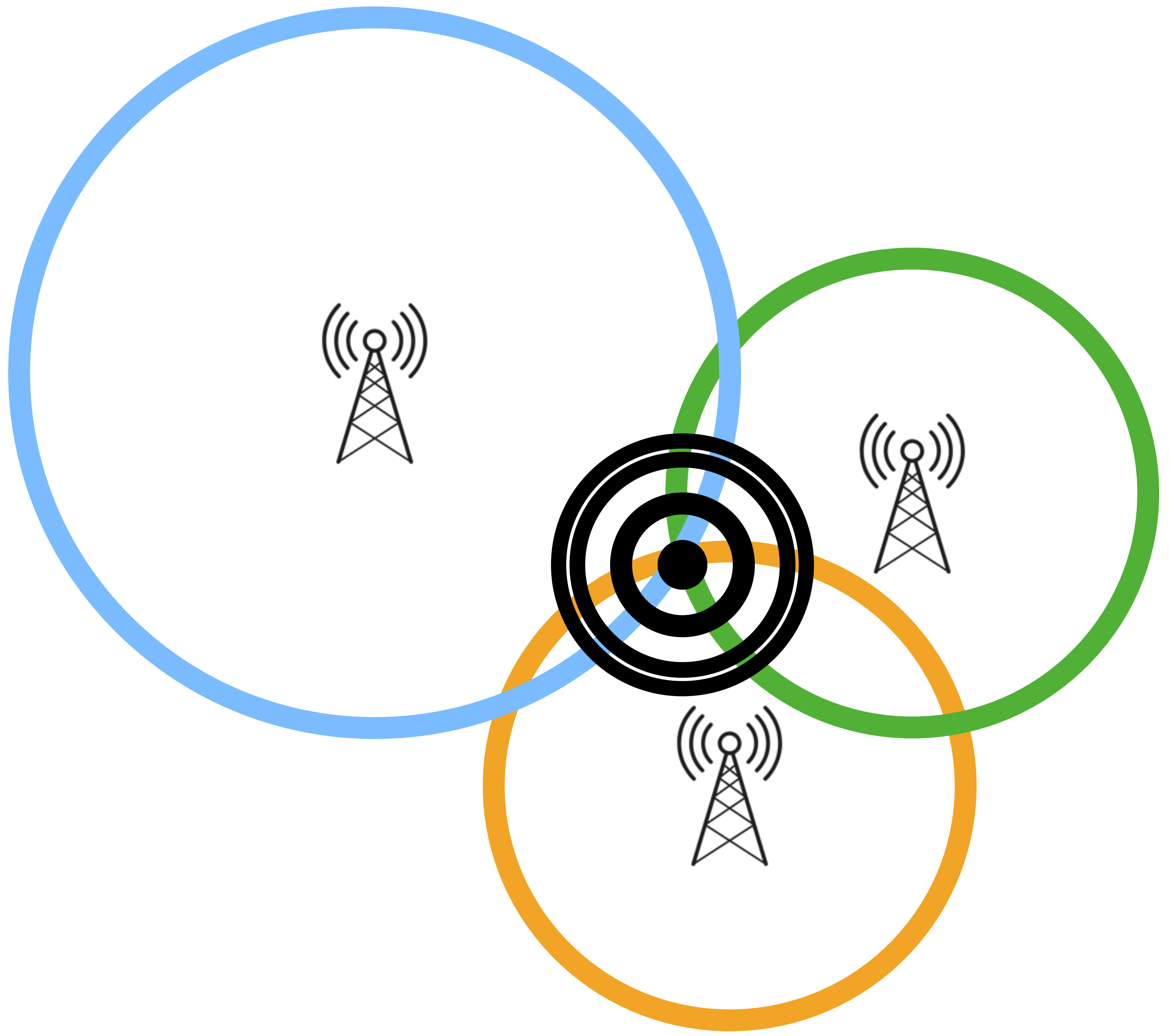


Actual tower cells coverage overlap



Device connects to the tower with the best signal, not always the closest

Towers triangulation



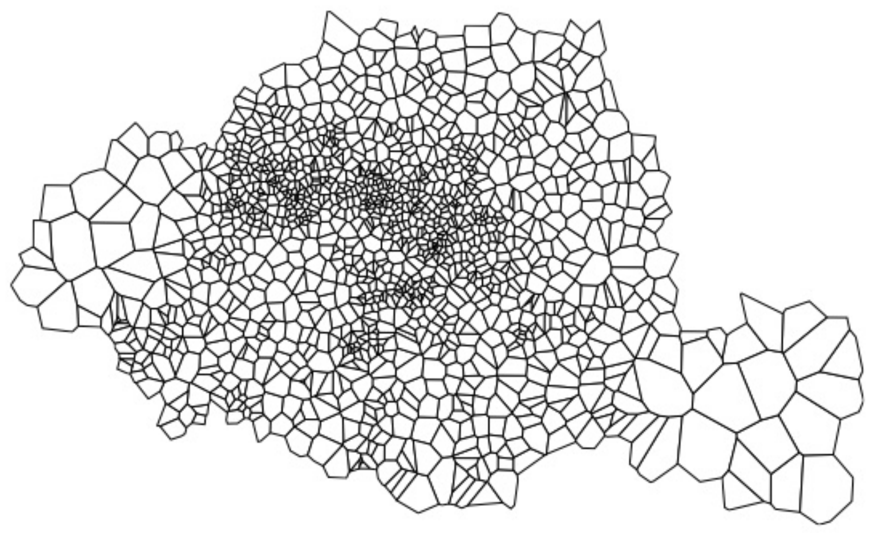
Not performed routinely
For forensic purpose

Pappalardo, L., Ferres, L., Sacasa, M. *et al.* Evaluation of home detection algorithms on mobile phone data using individual-level ground truth. *EPJ Data Sci.* **10**, 29 (2021).
Mobile Phone technology - Maria Sanders https://slideplayer.com/slide/14069191/

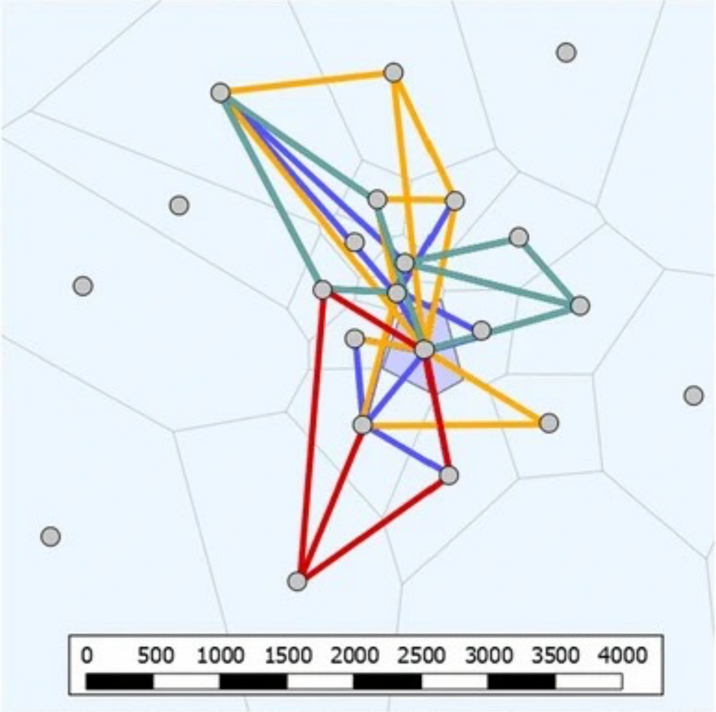
Mobile phone data (CDR & XDR)

Assumption: devices connect to the closest tower (<u>not always true</u>) ~ Voronoi tessellation
CDR and XDR **provide the position of the tower**, not the position of the device!

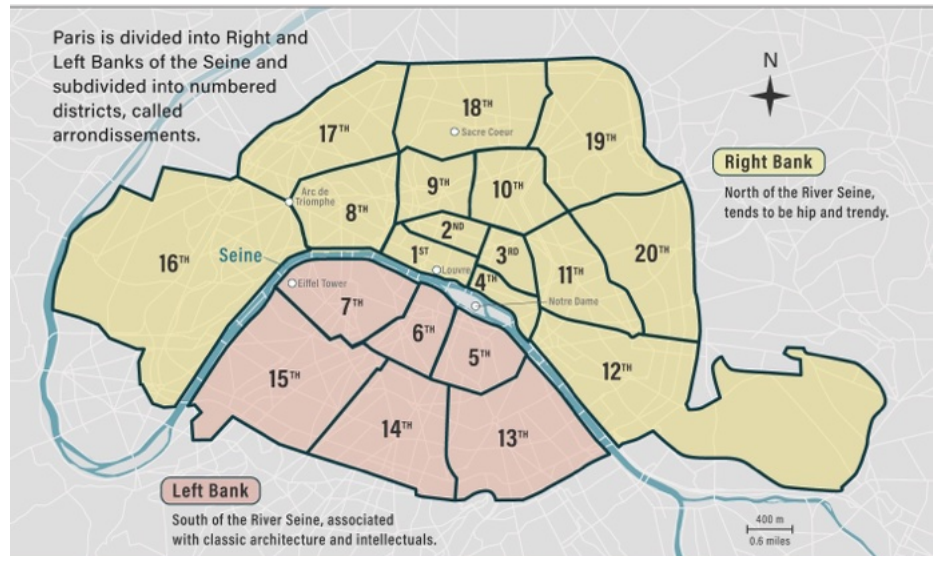
Paris Voronoi cells

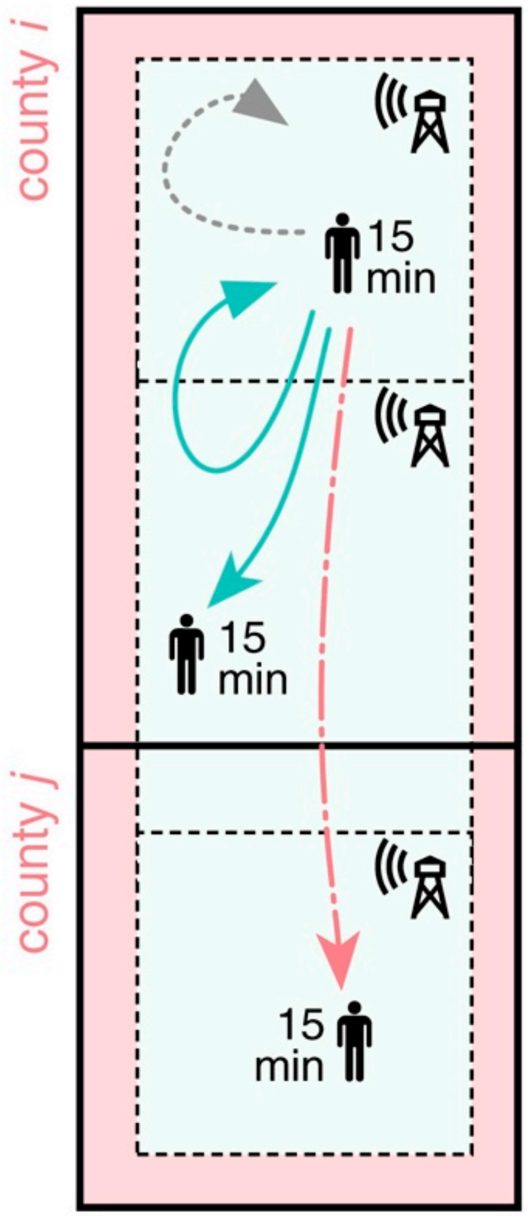


Voronoi cells trips



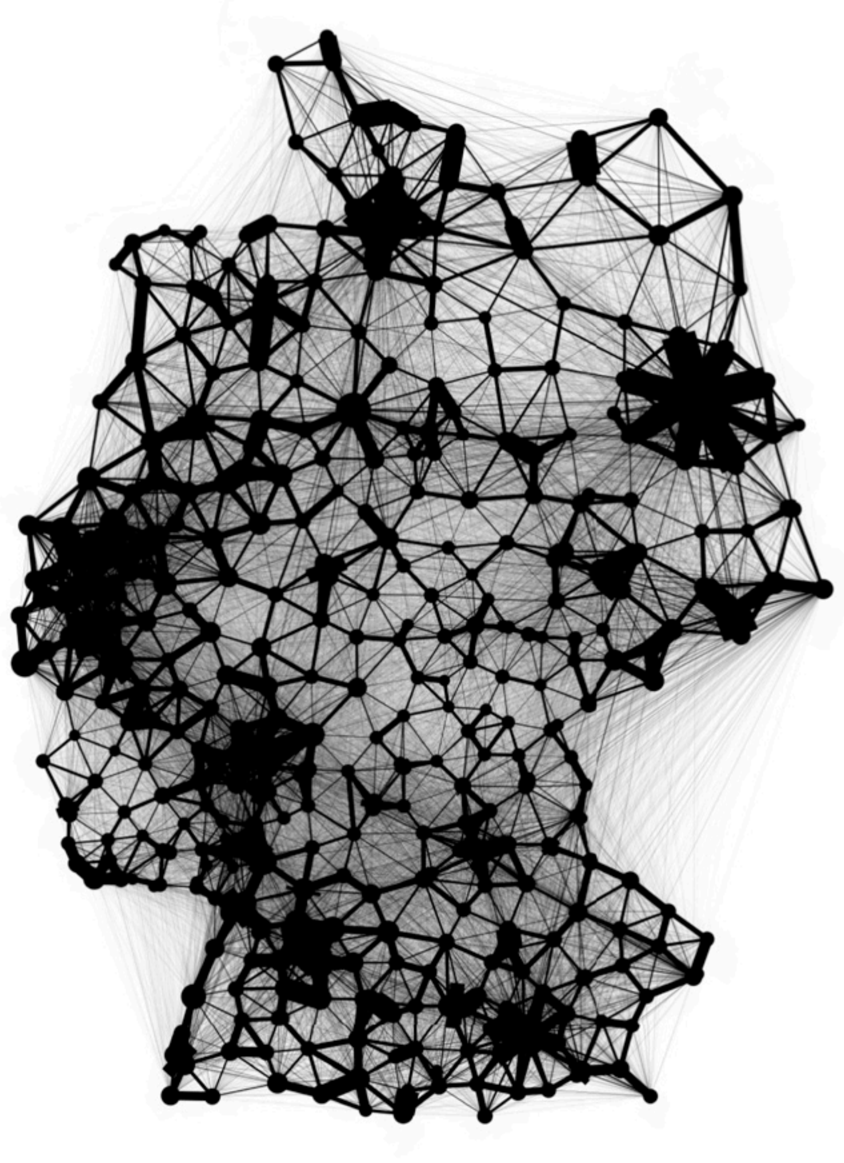
Paris inner admin. boundaries





German provinces

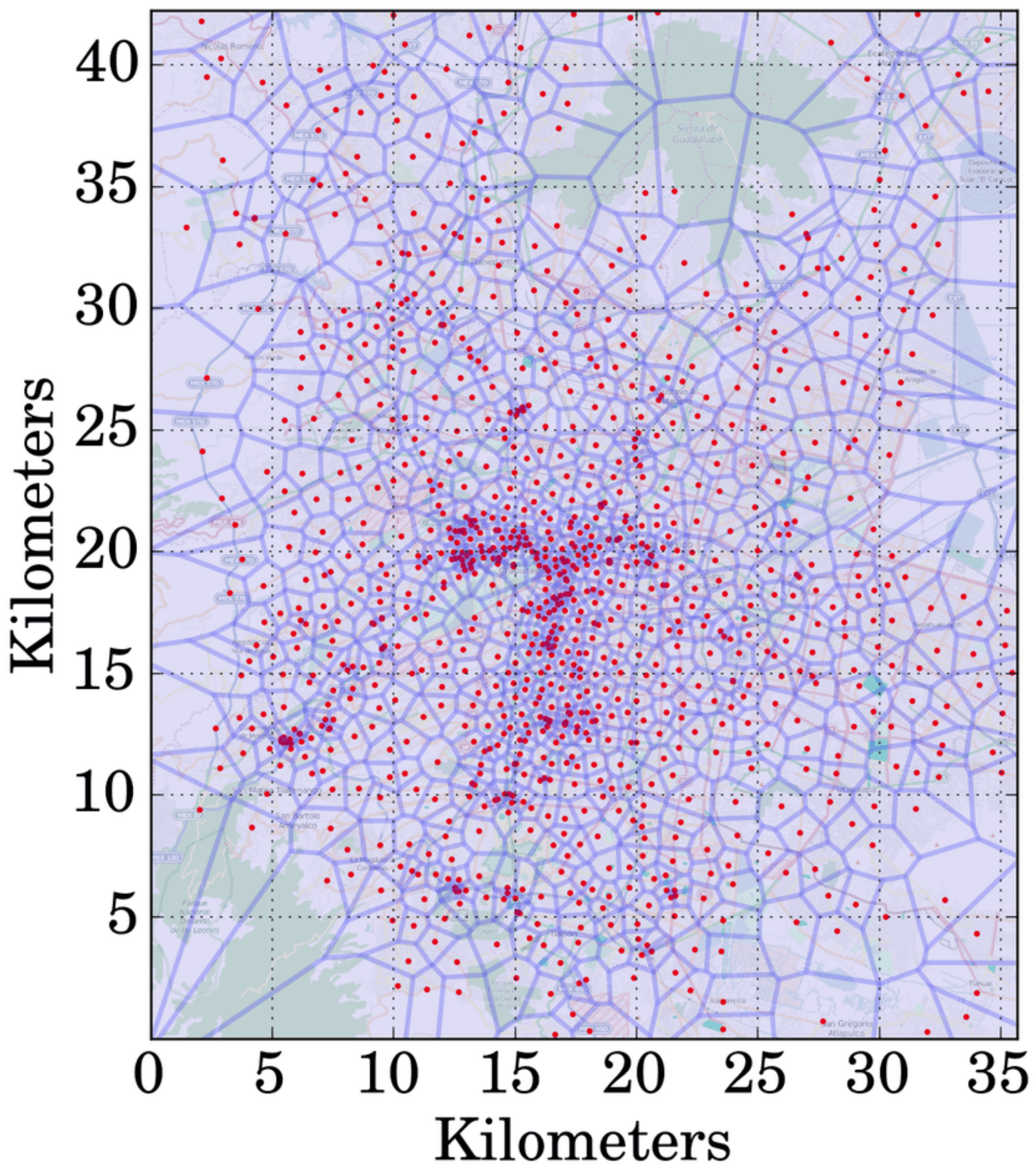
Provinces trips



Louf, Rémi. "Wandering in cities: A statistical physics approach to urban theory." *PhD Thesis* (2015).
Pappalardo, L., Vanhoof, M., Gabrielli, L. *et al.* An analytical framework to nowcast well-being using mobile phone data. *Int J Data Sci Anal* **2**, 75–92 (2016)
Schlosser, Frank, et al. "COVID-19 lockdown induces disease-mitigating structural changes in mobility networks." *PNAS* 117.52 (2020): 32883-32890.

Mobile phone data bias

Urban-rural divide

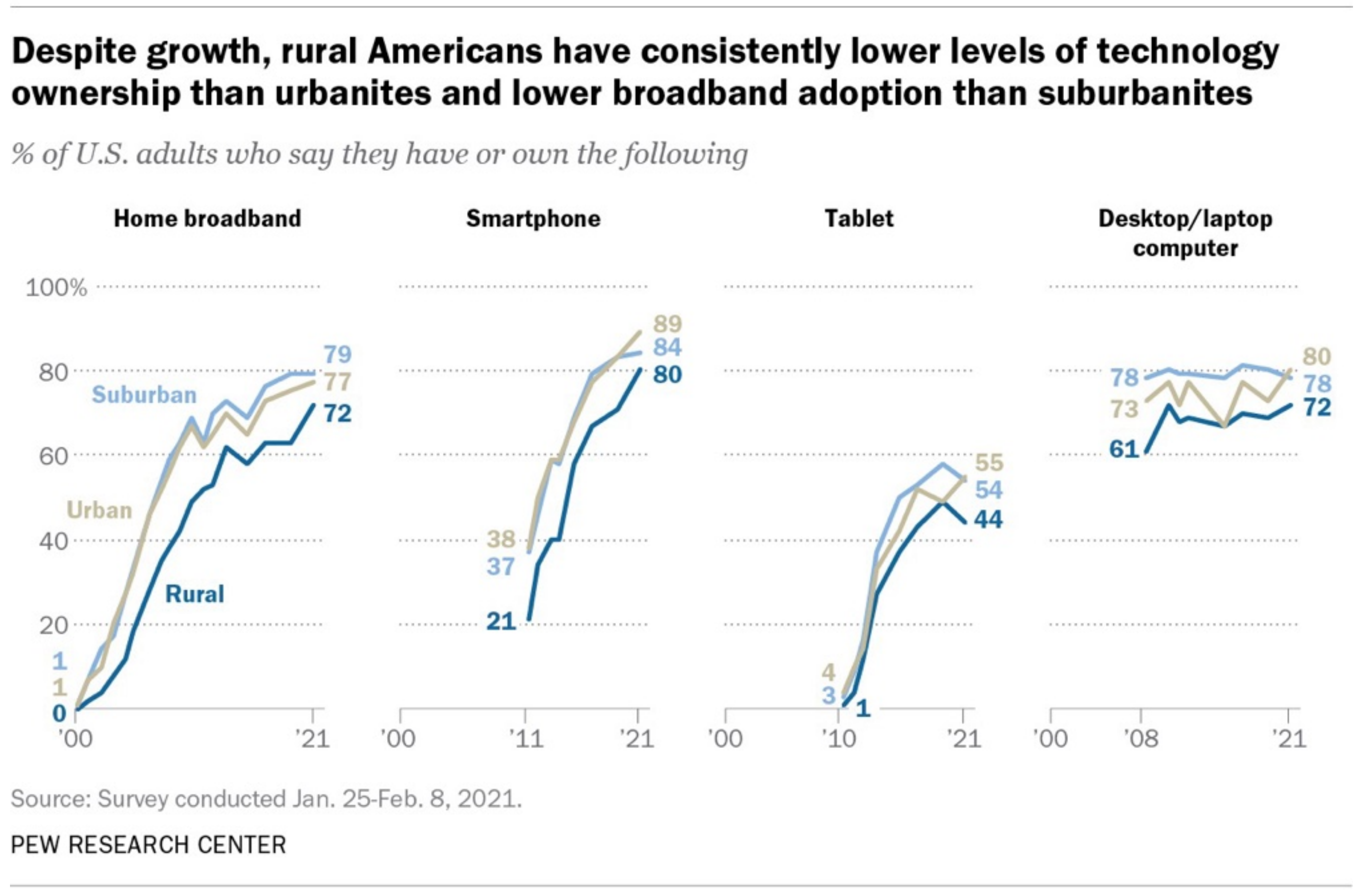


Heterogeneous cell towers spatial distribution (urban vs rural)

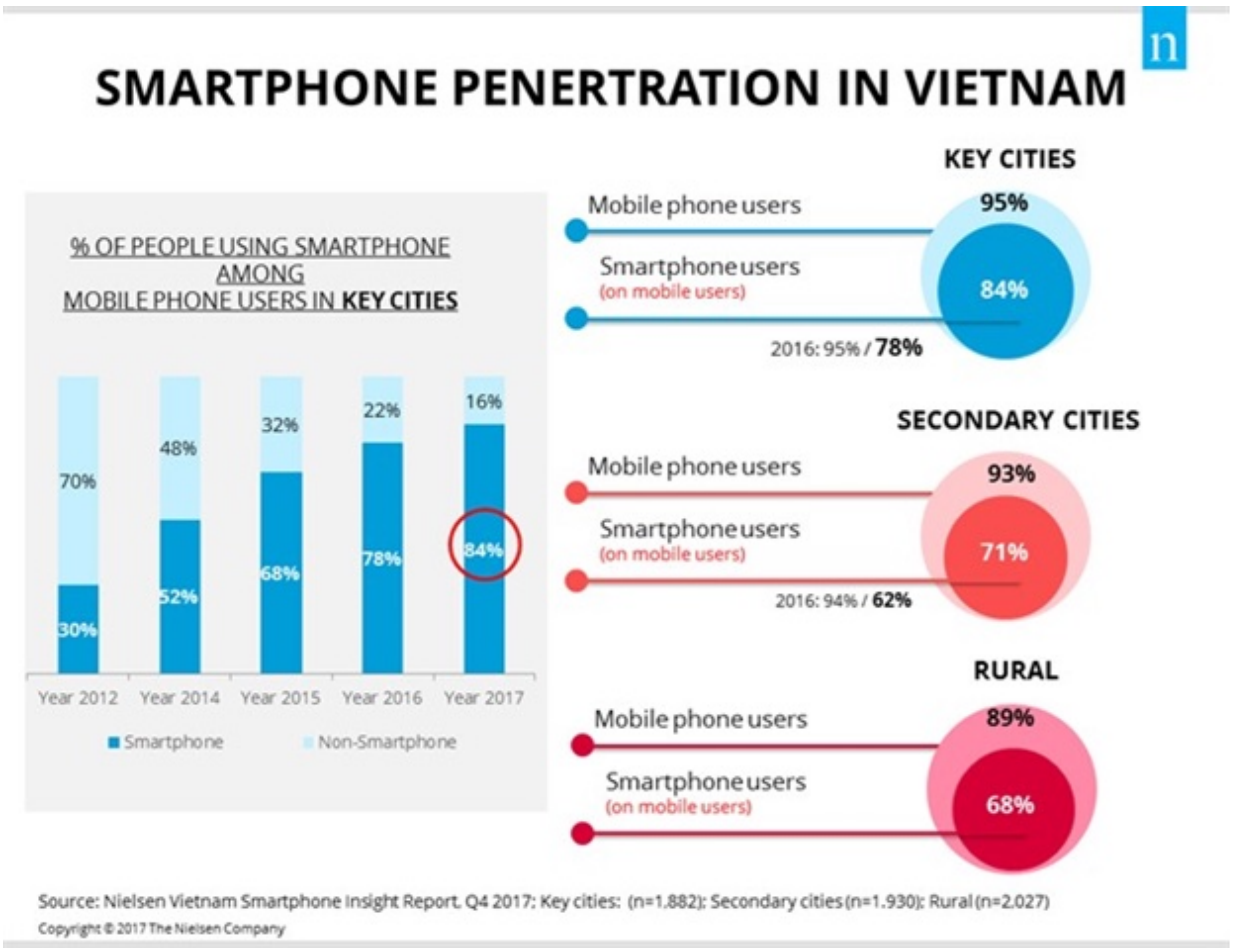
High resolution in densely populated areas
Low spatial resolution in rural areas

Examples of urban-rural divides

US

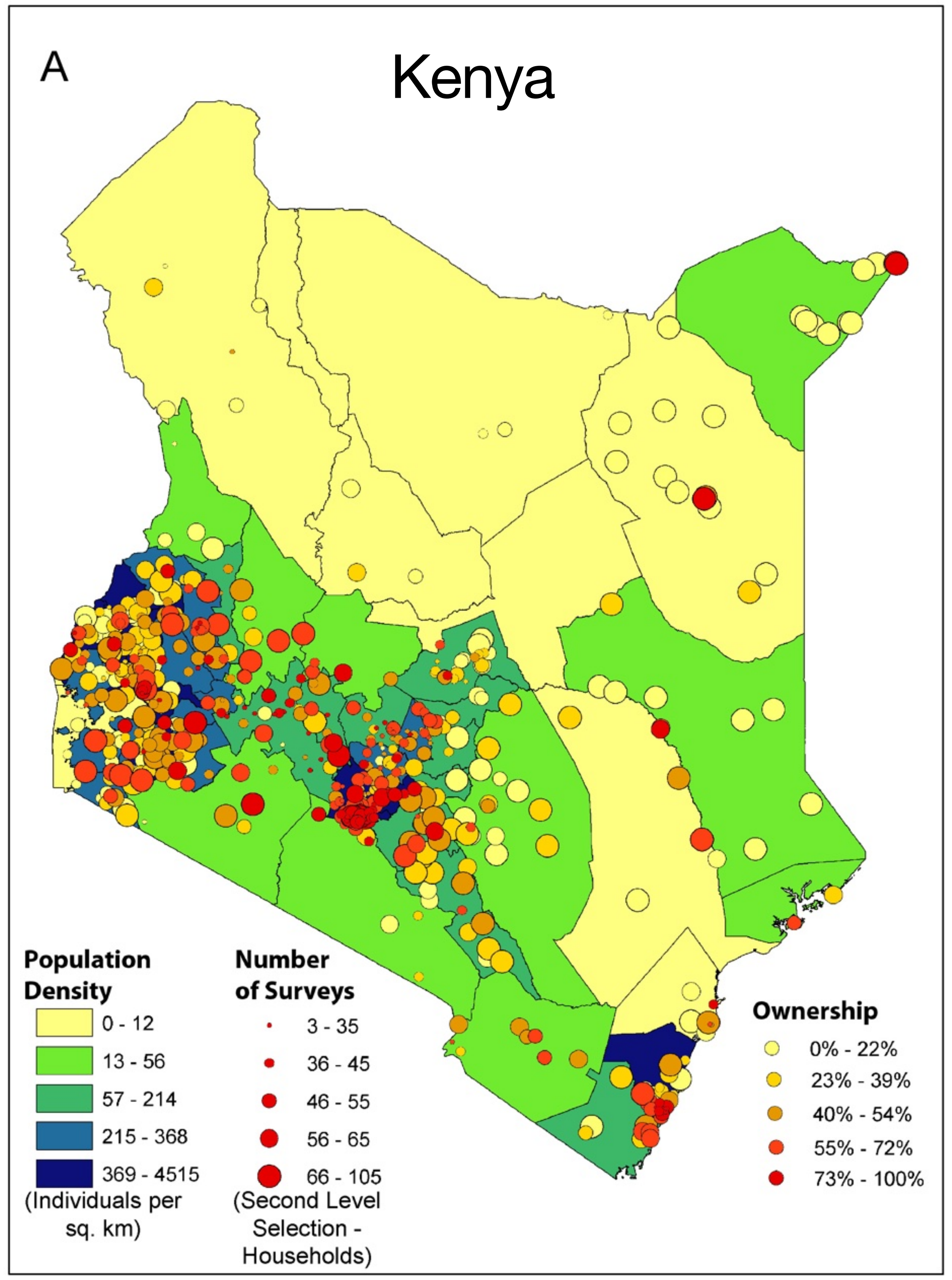


Vietnam



Chen, Guangshuo, et al. "Enriching sparse mobility information in call detail records." *Computer Communications* 122 (2018): 44-58.
https://www.pewresearch.org/short-reads/2021/08/19/some-digital-divides-persist-between-rural-urban-and-suburban-america/

Mobile phone data bias



Different levels of tech adoption translates to **BIAS**

The urban-rural divide in smartphones adoption is one type of bias, let's see more

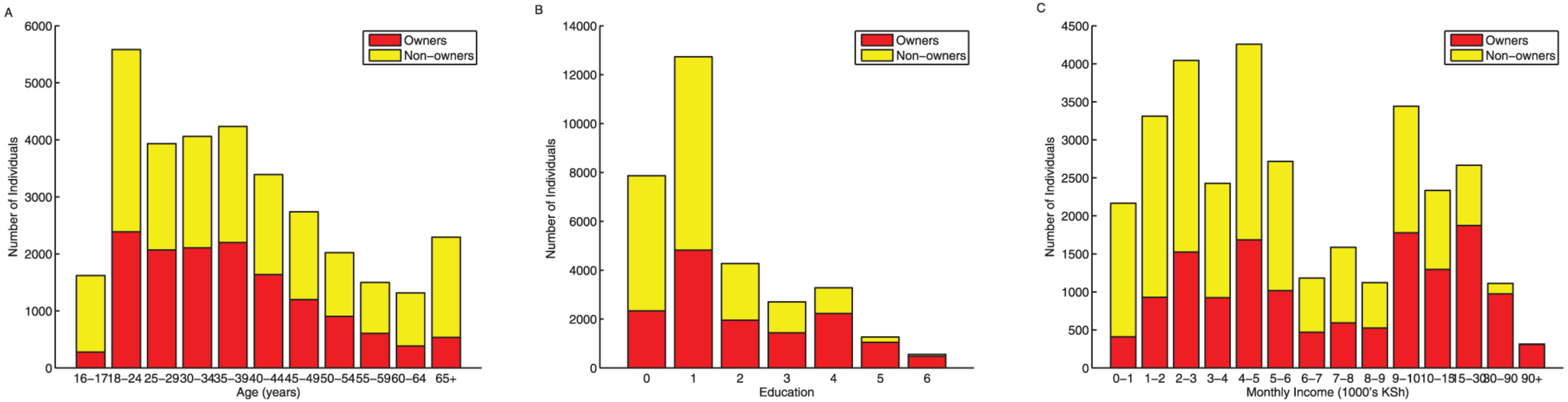
- Socio-economic status
- Gender
- Ethnicity
- Urban vs rural areas

Usually no information on owners' traits
No de-biasing possible without parallel dataset (surveys)
Dataset often shared already aggregated

Wesolowski, Amy, et al. "Heterogeneous mobile phone ownership and usage patterns in Kenya." *PloS one* 7.4 (2012): e35319.

Mobile phone data bias

Mobile phone ownership biases by socio-demographics in Kenya



The impact of biases in mobile phone ownership on estimates of human mobility

Amy Wesolowski[1], Nathan Eagle[2,3], Abdisalan M. Noor[4,5], Robert W. Snow[4,5] and Caroline O. Buckee[3,6]

"[…] Mobility estimates are surprisingly robust to the substantial biases in phone ownership across different geographical and socioeconomic groups."

Wesolowski, Amy, et al. "Heterogeneous mobile phone ownership and usage patterns in Kenya." *PloS one* 7.4 (2012): e35319.
Wesolowski, Amy, et al. "The impact of biases in mobile phone ownership on estimates of human mobility." *Journal of the Royal Society Interface* 10.81 (2013): 20120986.

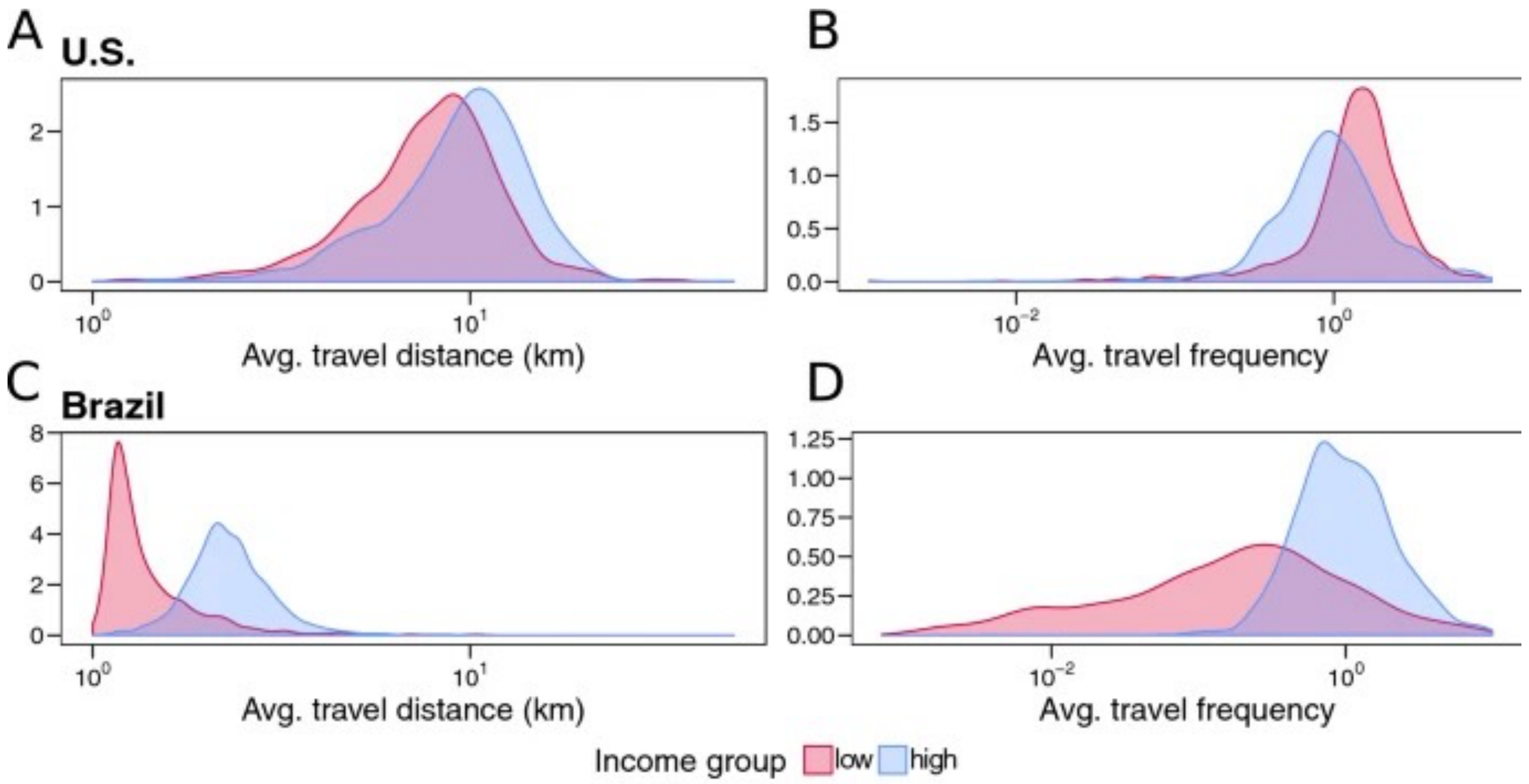
Inequalities in mobility

At the individual level: income, gender and age impact on the traveled distance and frequency of trips.

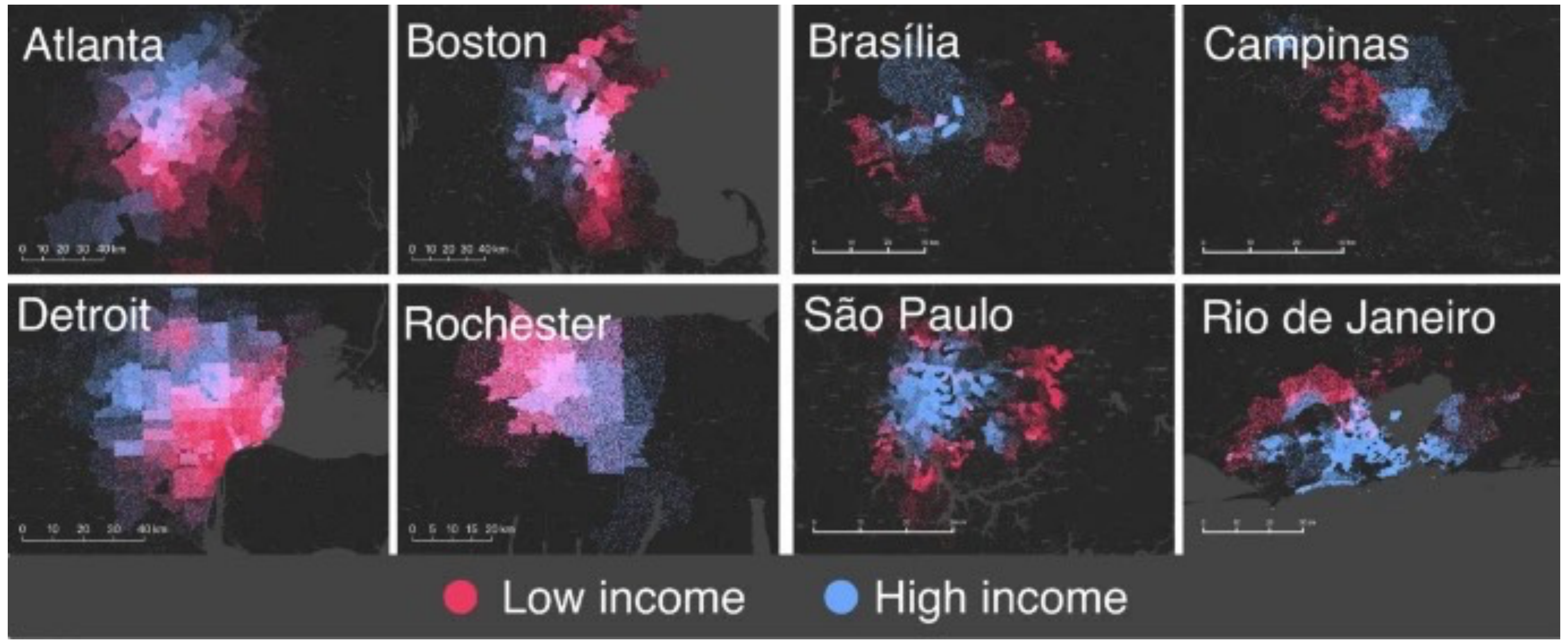
Mobile ownership skewed towards wealthier demographic strata:

- high income individuals, young adults, males are overrepresented in mobile phone data

OK to use the aggregate metrics for epi modeling, caution is required when using individual traces



Another example of inequalities in mobility

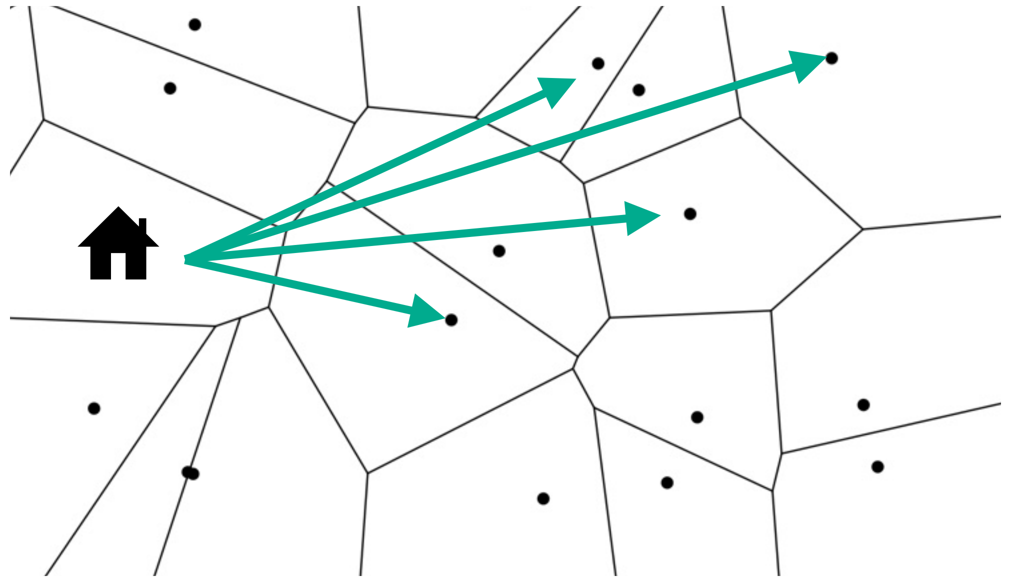


Barbosa, H., Hazarie, S., Dickinson, B. *et al.* Uncovering the socioeconomic facets of human mobility. *Sci Rep* **11**, 8616 (2021).

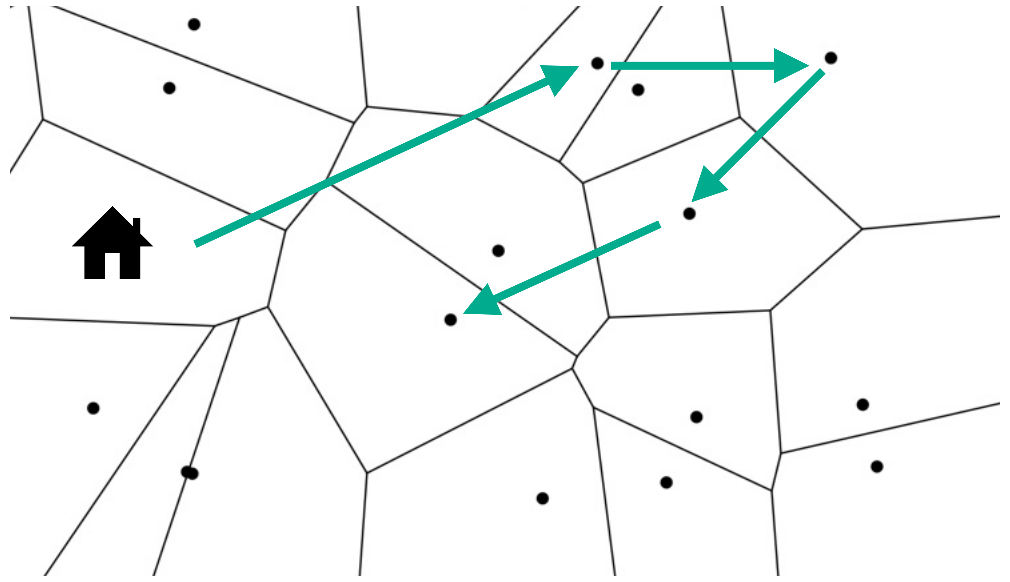
Trips aggregation to OD matrix

Individual data

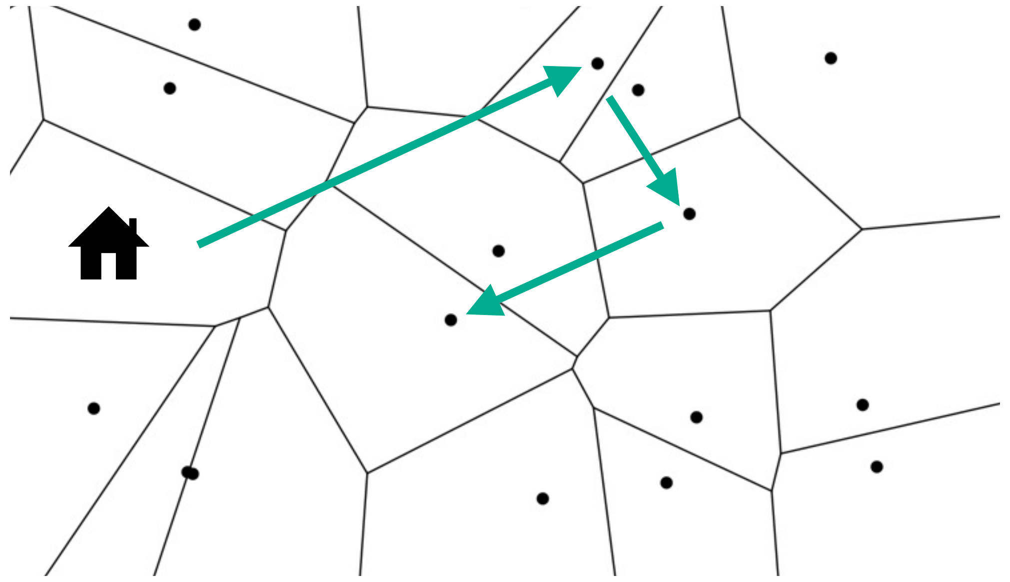
Home to stops



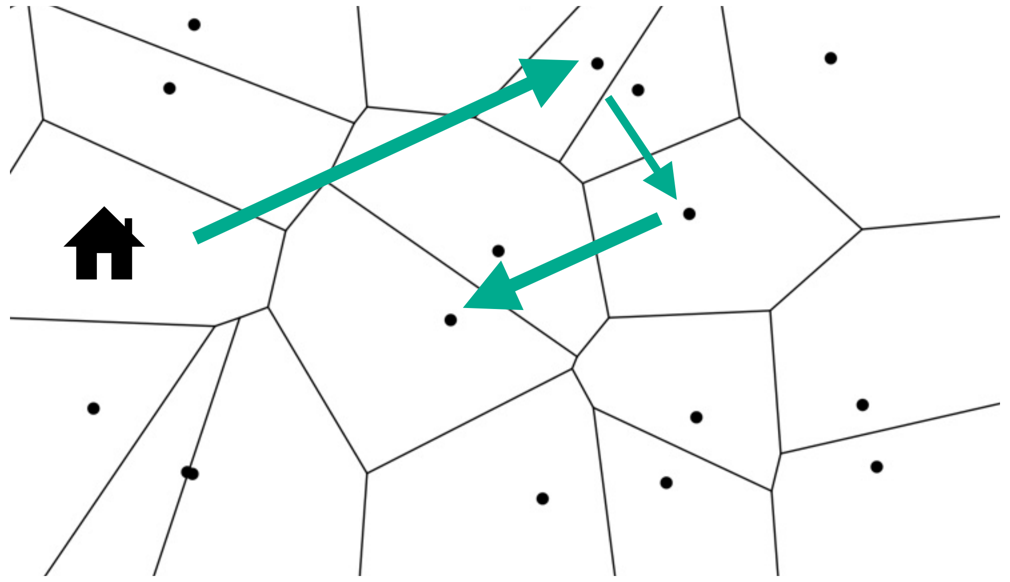
Consecutive trips



Consecutive stays

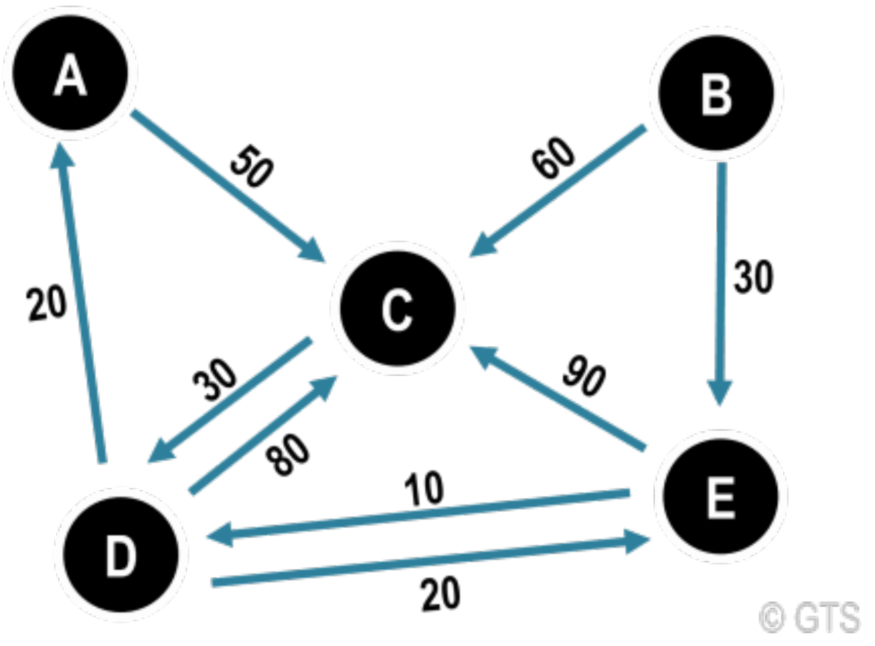


Stay time weighted trips



Population level

SPATIAL INTERACTIONS



O/D MATRIX

	A	B	C	D	E	Ti
A	0	0	50	0	0	50
B	0	0	60	0	30	90
C	0	0	0	30	0	30
D	20	0	80	0	20	120
E	0	0	90	10	0	100
Tj	20	0	280	40	50	**390**

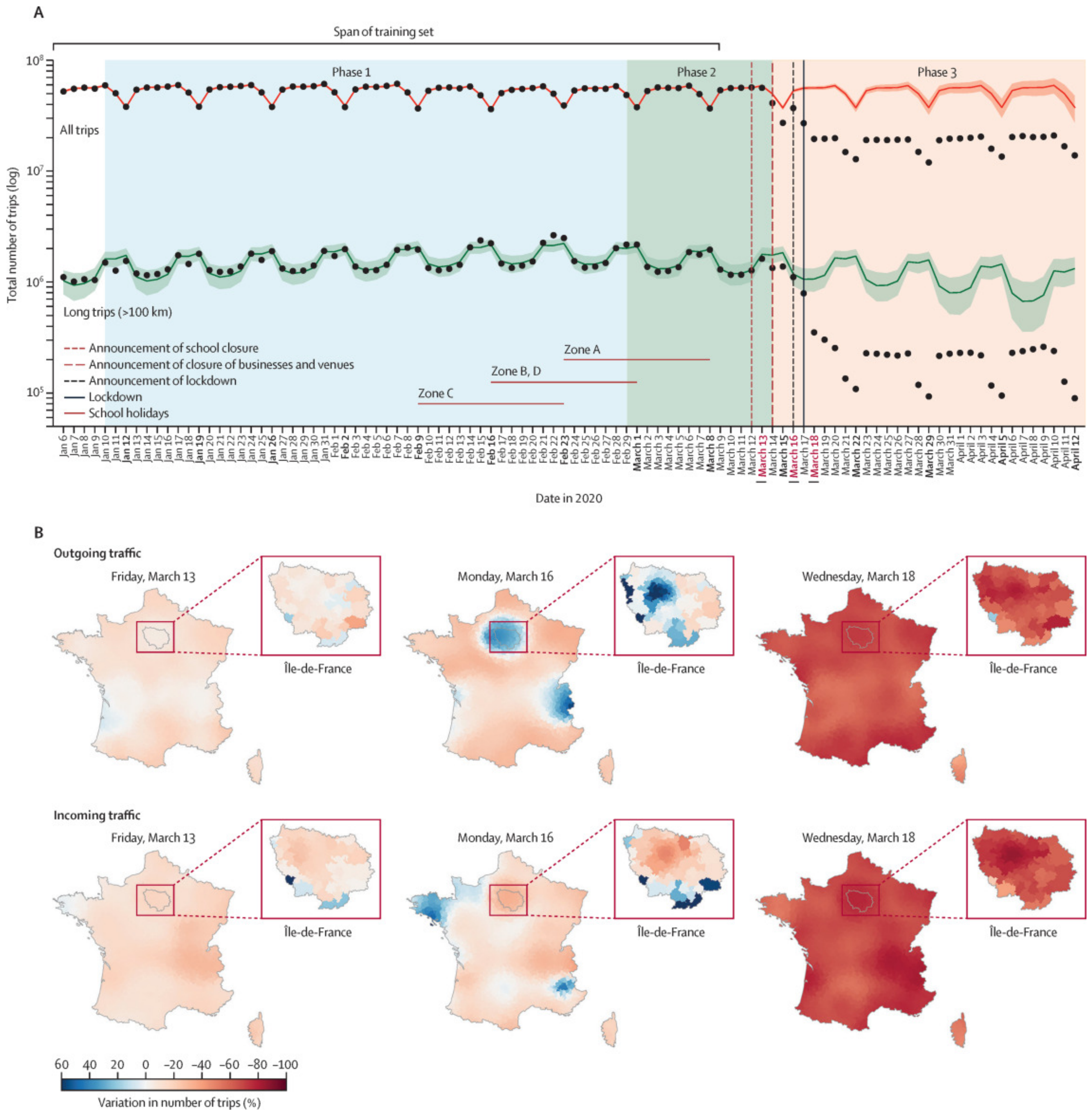
OD matrix depends on type of aggregation

Provided data from Telcos comes already aggregated

Implications for epidemic modeling

Universal standards missing

Mobile phone data usage example



EXAMPLE USAGE

- Quantifying and understanding population response, in terms of mobility reductions, during the 1st lockdown in France

SCALE

- EPCI ~ municipalities

TAKE HOME MESSAGE

- Pullano et al measured a spatially heterogeneous reduction of mobility in the 1st lockdown, with an anticipation effect in the area of Paris. Mobility reductions were associated to local labour structure, active population, hospitalisations and local socio-economic status.

Pullano, Giulia, et al. "Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population-based study." *Lancet Digital Health* 2.12 (2020): e638-e649.

Mobile phone data (CDR & XDR)

PROS

- High representativity of the population wrt other data sources
- High spatial resolution in urban areas
- Aggregated features robust to ownership bias
- Useful at multiple scales, e.g. municipality, provinces, regions
- High temporal resolution for XDR

CONS

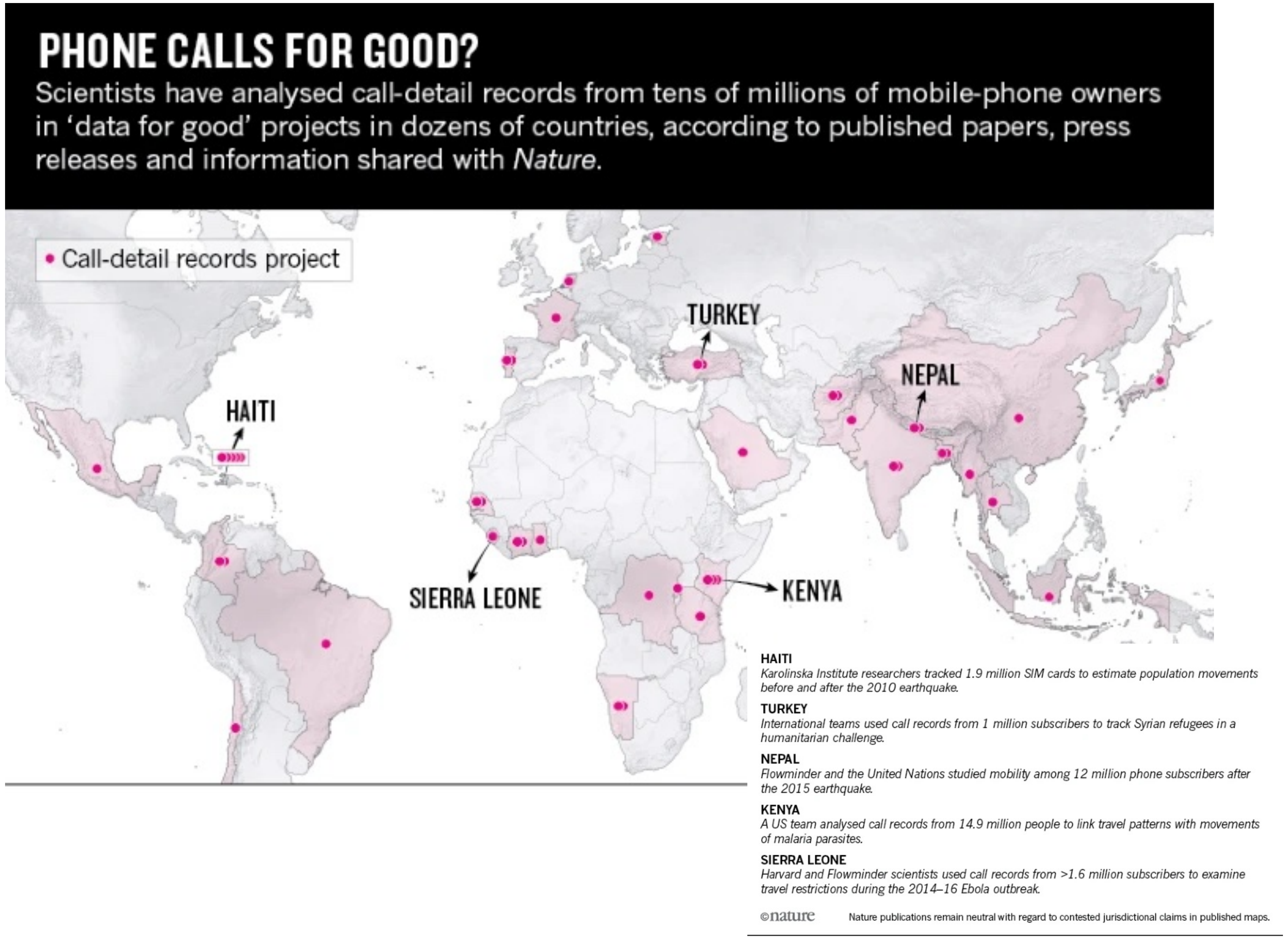
- Low spatial resolution in rural areas
- Low temporal resolution for CDR
- Country segmented market
- Not available in most non-Western countries
- Private, expensive
- Real-time data stream depends on previous collaboration
- Provided already aggregated, no power on type of aggregation
- Device ownership bias, especially in low & middle income countries

USAGE

- Inform sub-national spatial transmission models

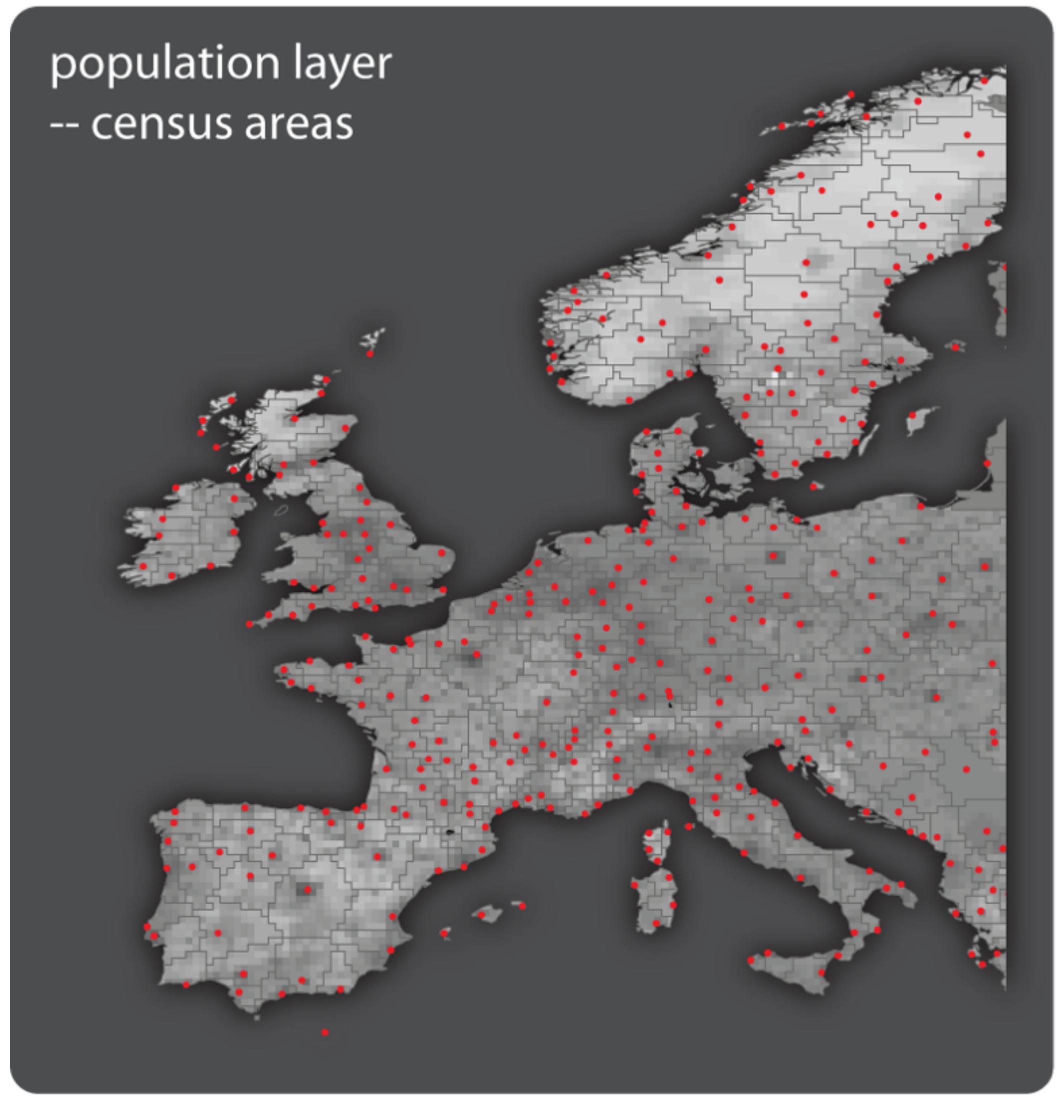
SCALE

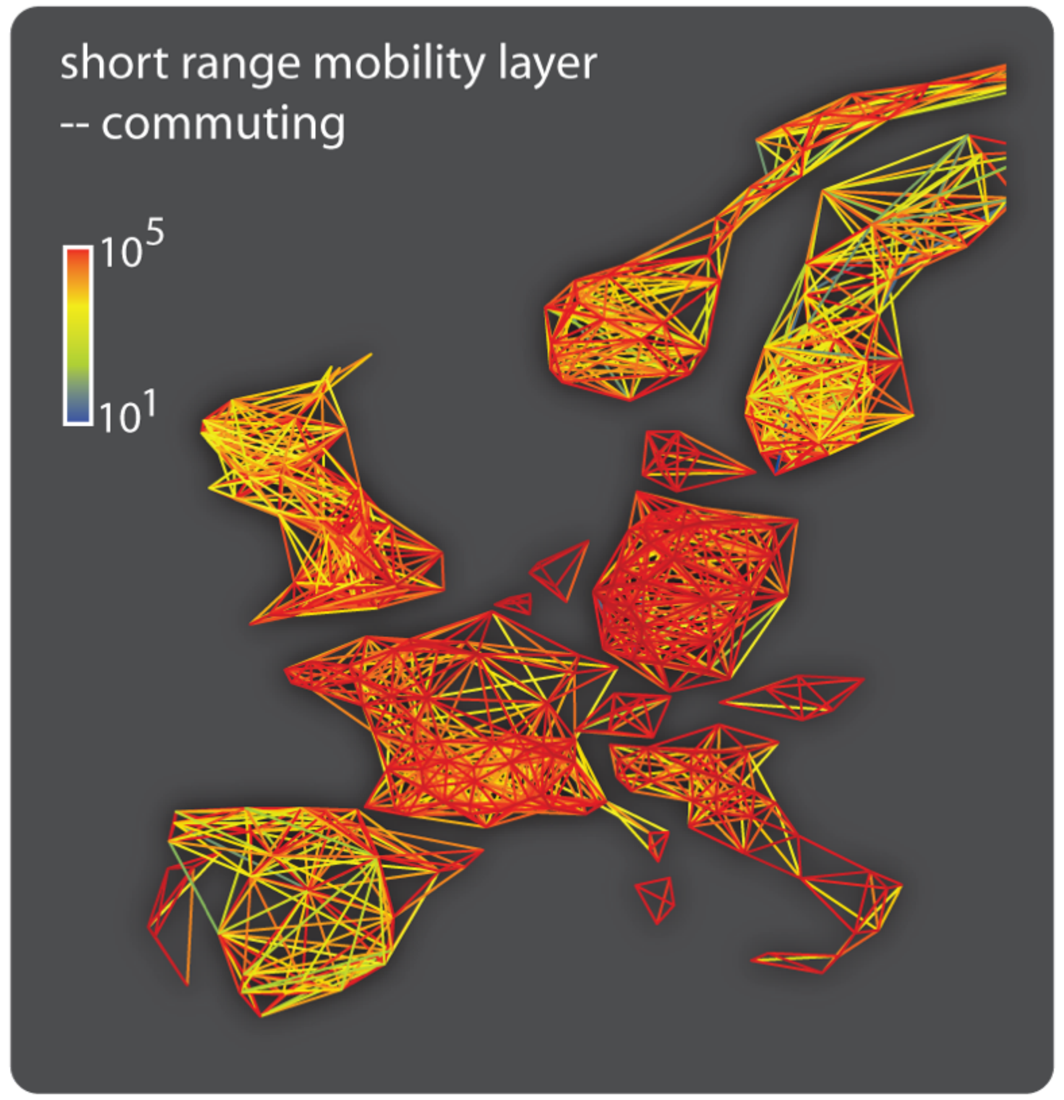
- Cell towers, municipalities, provinces, regions



Maxmen, Amy. "Can tracking people through phone-call data improve lives?." *Nature* 569.7758 (2019): 614-618.

Census (commuting)





PROS

- Highly representative of the population
- Free and public

CONS

- Pre-defined spatial resolution
- Language barriers or not available in some LMICs
- Updated every 5-10 years
- Static dataset
- Only commuting mobility (home - work trips)

USAGE

- Complement dynamic datasets (informs baseline)
- Population estimates otherwise unaccessible
- Validation of other data sources
- Inform sub-national spatial transmission models

SCALE

- Census areas, municipalities, provinces, regions

International travel (IATA air travel data)

IATA: international air travel agency

PROS

- Highly representative of international mobility
- Almost all countries included

CONS

- Pre-defined spatial resolution (airports)
- Private, expensive
- Pre-set temporal scale (usually 1 month)
- Tech access bias (only air traffic)
- Not capturing cross-border mobility in neighbouring countries
- Trips estimated by revenues and sold tickets

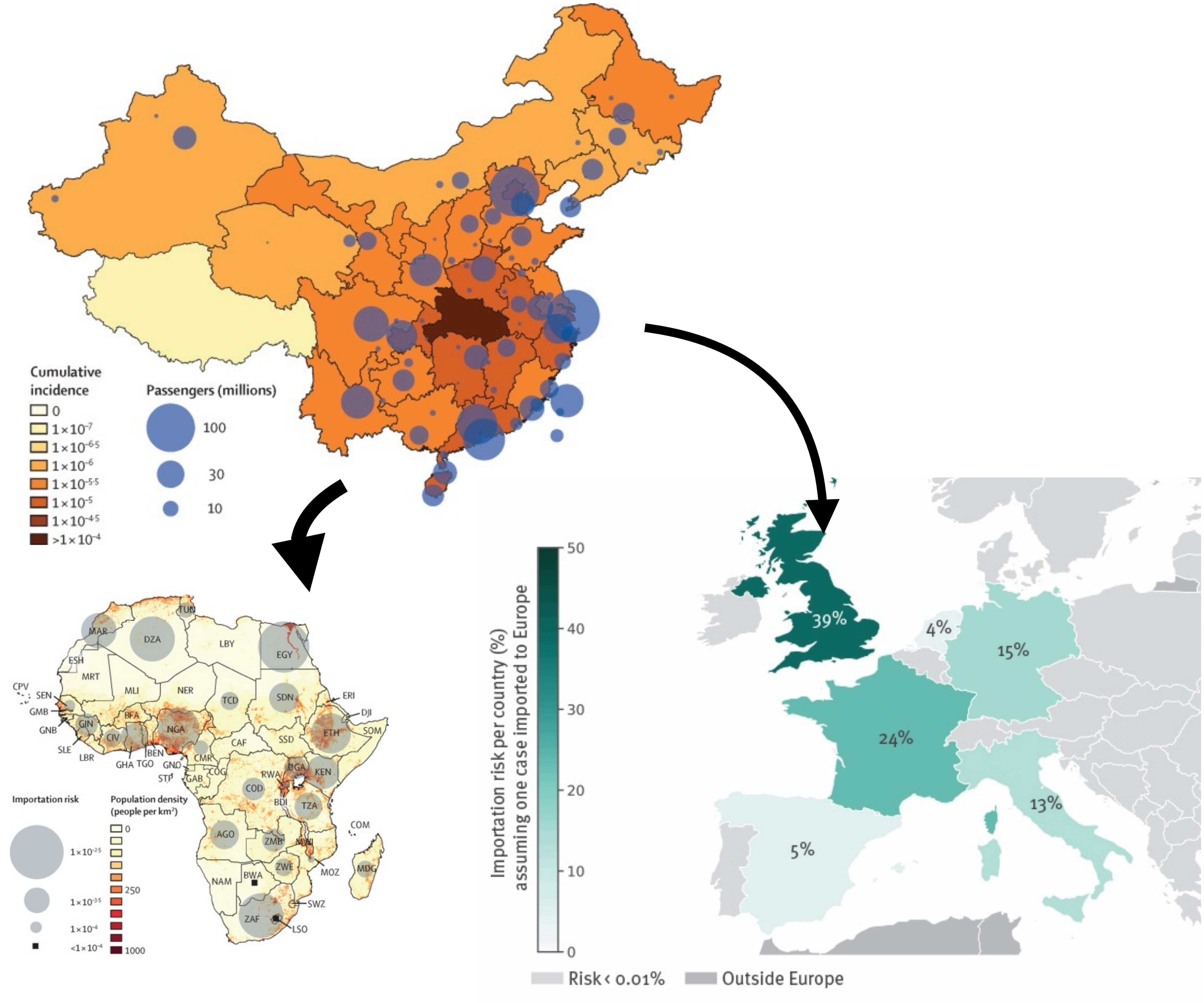
USAGE

- Inform epidemic importation models

SCALE

- Country, airports catchment areas

IATA air travel data usage example



EXAMPLE USAGE

- Compute the importation risk from all cities with Covid-19 cases in China

SCALE

- Countries

TAKE HOME MESSAGE

- Gilbert et al and Pullano et al assessed the risk of importation of SARS-Cov-2 from Chinese cities to European and African countries

Gilbert, Marius, et al. "Preparedness and vulnerability of African countries against importations of COVID-19: a modelling study." The Lancet 395.10227 (2020): 871-877.
Pullano Giulia, Pinotti Francesco, Valdano Eugenio, Boëlle Pierre-Yves, Poletto Chiara, Colizza Vittoria. Novel coronavirus (2019-nCoV) early-stage importation risk to Europe, January 2020. Euro Surveill. 2020

IATA air travel data usage example

Dirk Brockmann, YouTube

EXAMPLE USAGE

- Predict arrival times

SCALE

- Airport catchment areas

TAKE HOME MESSAGE

- Brockmann et al identified the effective distance as a proxy for predicting arrival times of a disease imported from an infected area at destination countries

Dirk Brockmann, Dirk Helbing ,The Hidden Geometry of Complex, Network-Driven Contagion Phenomena.Science342,1337-1342(2013).DOI:10.1126/science.1245200

International travel (Meta Travel Patterns)

PROS

- Representative of highest flows of international travel
- Free and accessible (Meta Data for Good program)
- High temporal resolution (day time scale)
- Include all modes of transportation

CONS

- Pre-defined spatial resolution (country level)
- No info for routes with low number of passengers
- No info on small countries

USAGE

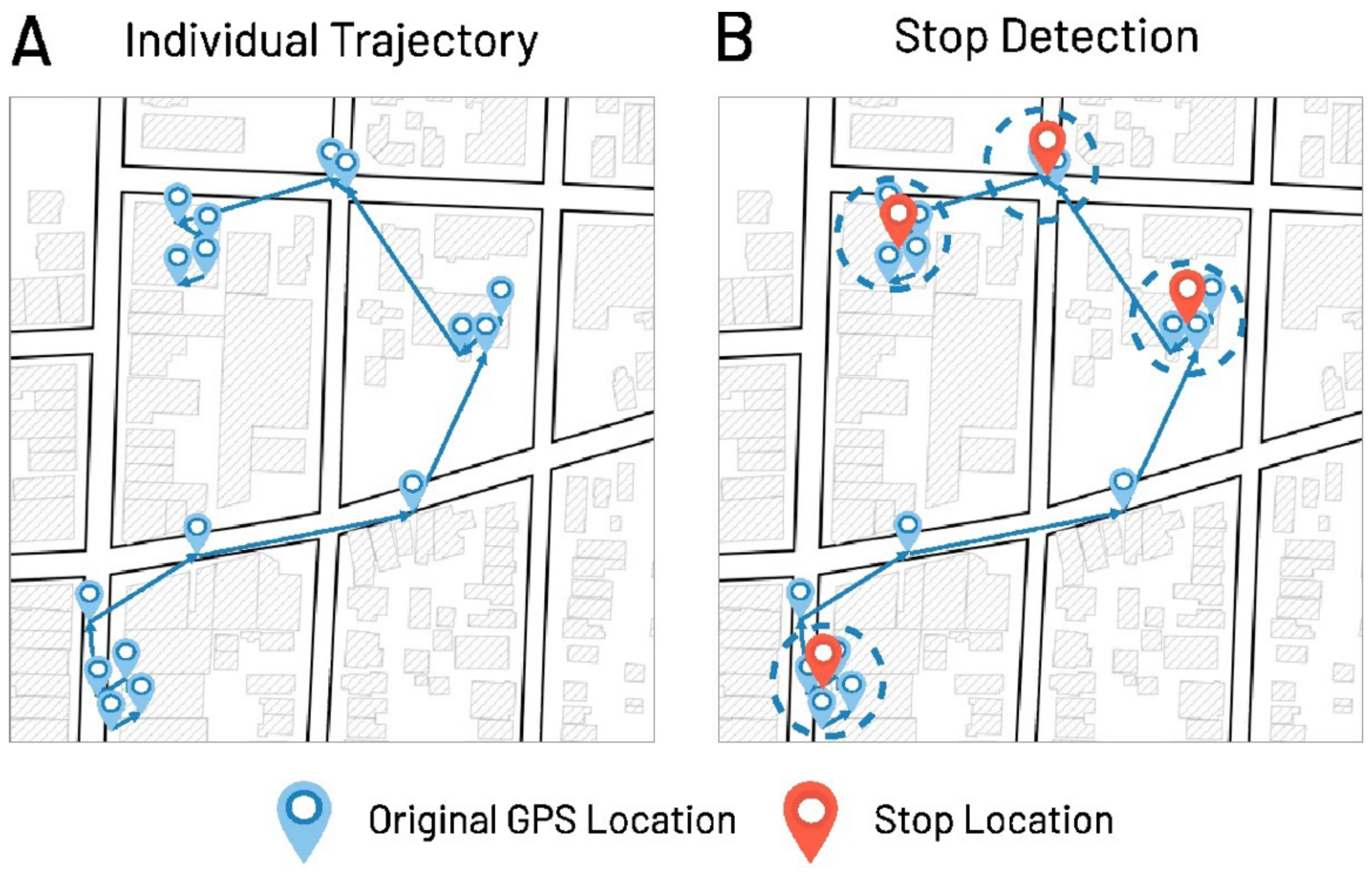
- Inform epidemic importation models

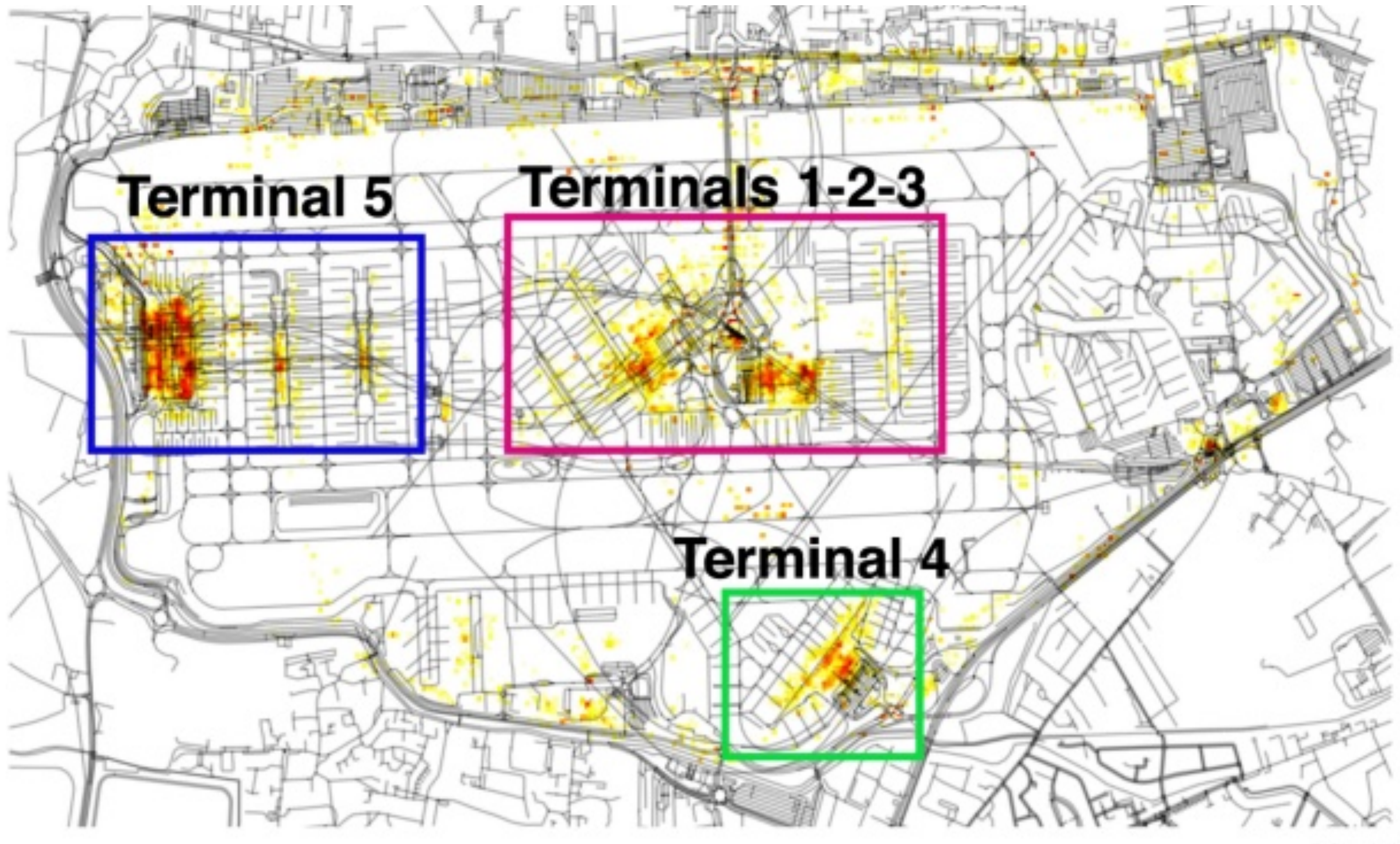
SCALE

- Country

https://www.networkscienceinstitute.org/news/global-vax

GPS traces (Cuebiq / Spectus)





PROS

- Highest spatial and temporal resolution (5m - 5')
- Free and accessible in pandemic period (Cuebiq Data for Good program)
- Include all modes of transportation

CONS

- Very low representativity of the population
- Tech adoption bias
- Available mostly in most Western countries
- Private, expensive (out of pandemic period)

USAGE

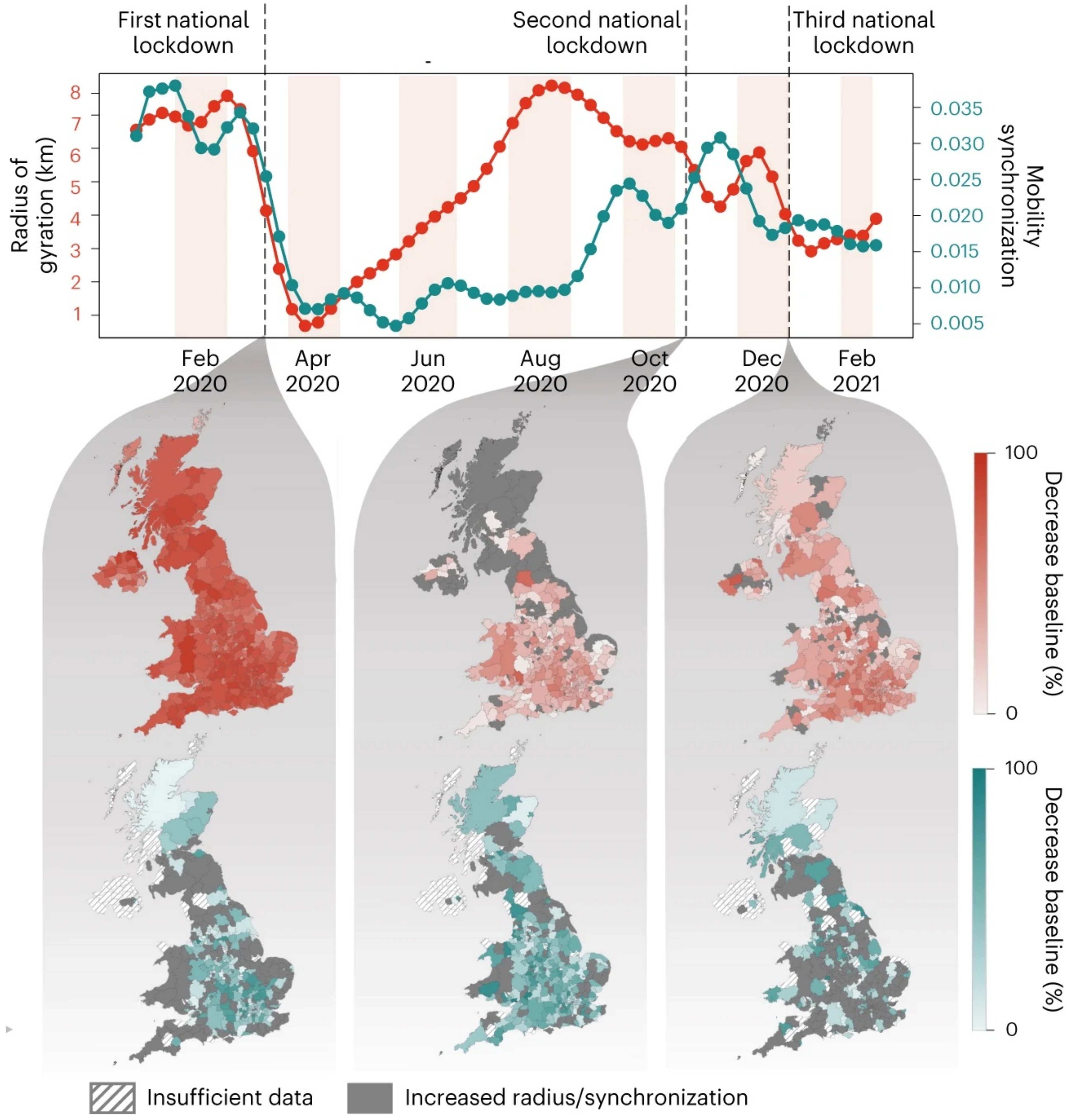
- Inform agent based models in specific settings

SCALE

- Latitude, longitude
- Scalable to lower spatial resolution

Lucchini, L., Centellegher, S., Pappalardo, L. *et al.* Living in a pandemic: changes in mobility routines, social activity and adherence to COVID-19 protective measures. *Sci Rep* **11**, 24452 (2021).
Mazzoli, M., Gallotti, R., Privitera, F. *et al.* Spatial immunization to abate disease spreading in transportation hubs. *Nat Commun* **14**, 1448 (2023).

Cuebiq / Spectus data usage example



EXAMPLE USAGE

- Analyse population response, in terms of mobility metrics, to the 1st lockdown in UK

SCALE

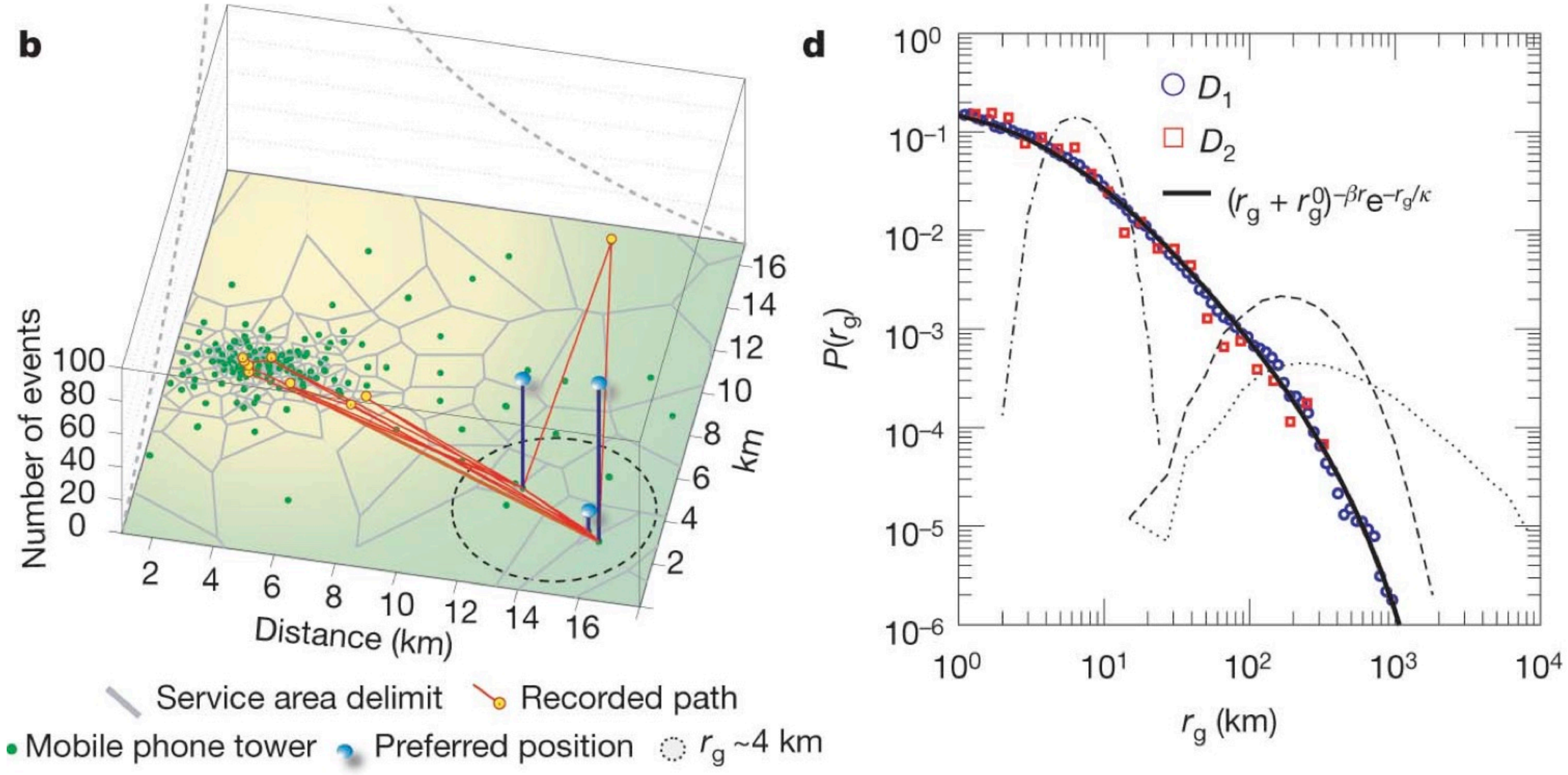
- Latitude, longitude

TAKE HOME MESSAGE

- Santana et al analysed how spatial and temporal dimension of mobility in the UK evolved after the lifting of the 1st lockdown.

Santana, C., Botta, F., Barbosa, H. *et al.* COVID-19 is linked to changes in the time–space dimension of human mobility. *Nat Hum Behav* **7**, 1729–1739 (2023)

Radius of gyration



Radius of gyration ~ Typical distance travelled

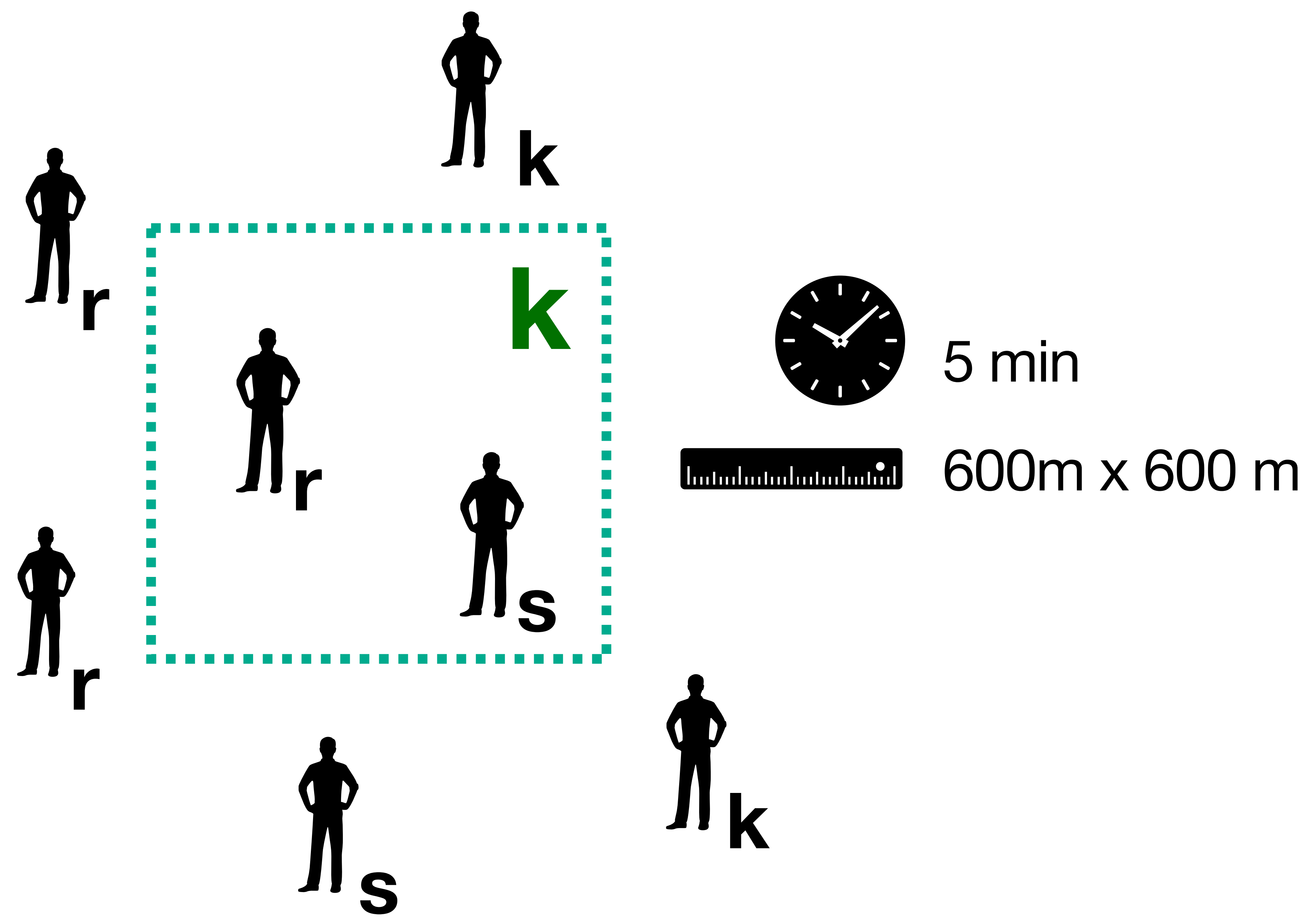
$$r_g = \sqrt{\frac{1}{n}\sum_i^n (r_i - r_{cm})^2}$$

Center of mass

$$r_{cm} = \frac{1}{n}\sum_i r_i$$

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

GPS traces (META Co-location)



Co-location detected at 600x600 sq meters, 5 minutes duration
Provided at province/regional and weekly scale

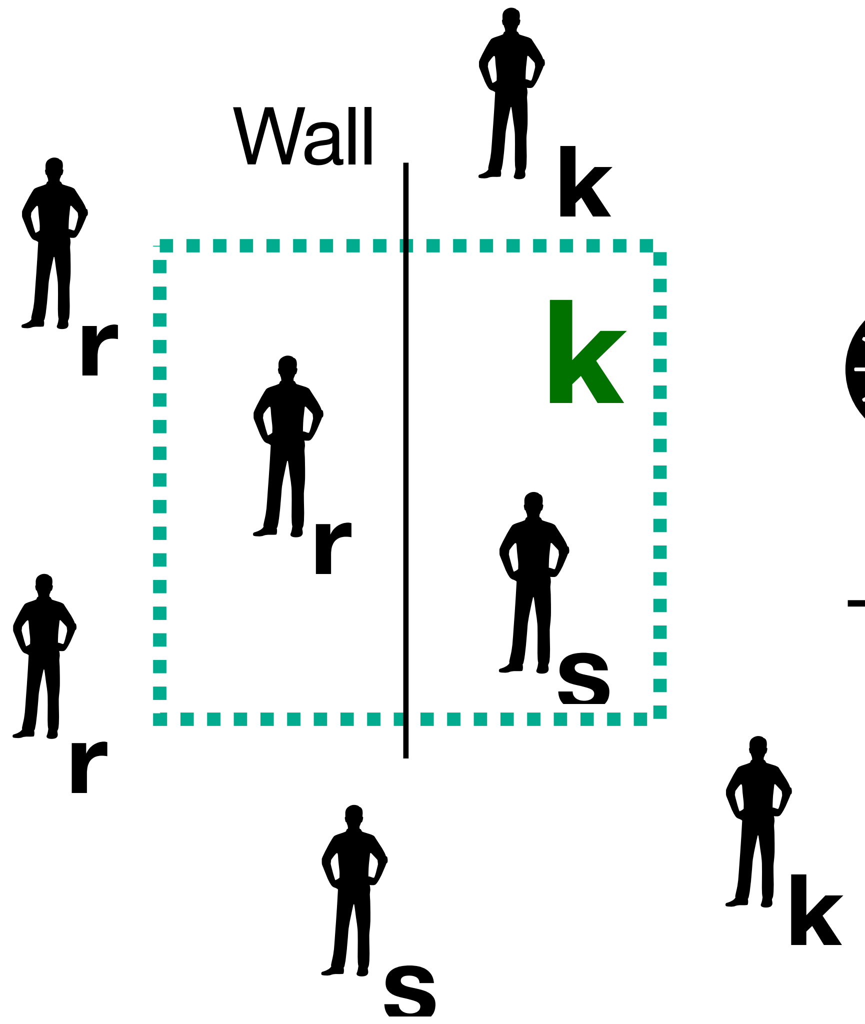
$$m_{rs} = \sum_{ij} X_{ijr} X_{ijs}$$

n of contacts between residents of r and s
occurring in one week, in place i at time slot j

$$p_{rs} = \frac{1}{2016} \frac{m_{rs}}{n_r n_s}$$

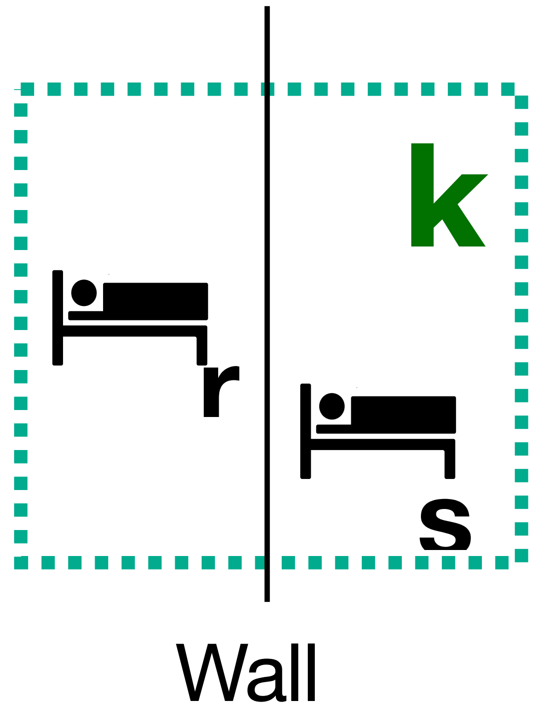
mixing probability of residents of r and s $\in [0,1]$
n_r, n_s = sample of residents in r and in s
2016 = n of 5min time slots in one week

GPS traces (META Co-location)



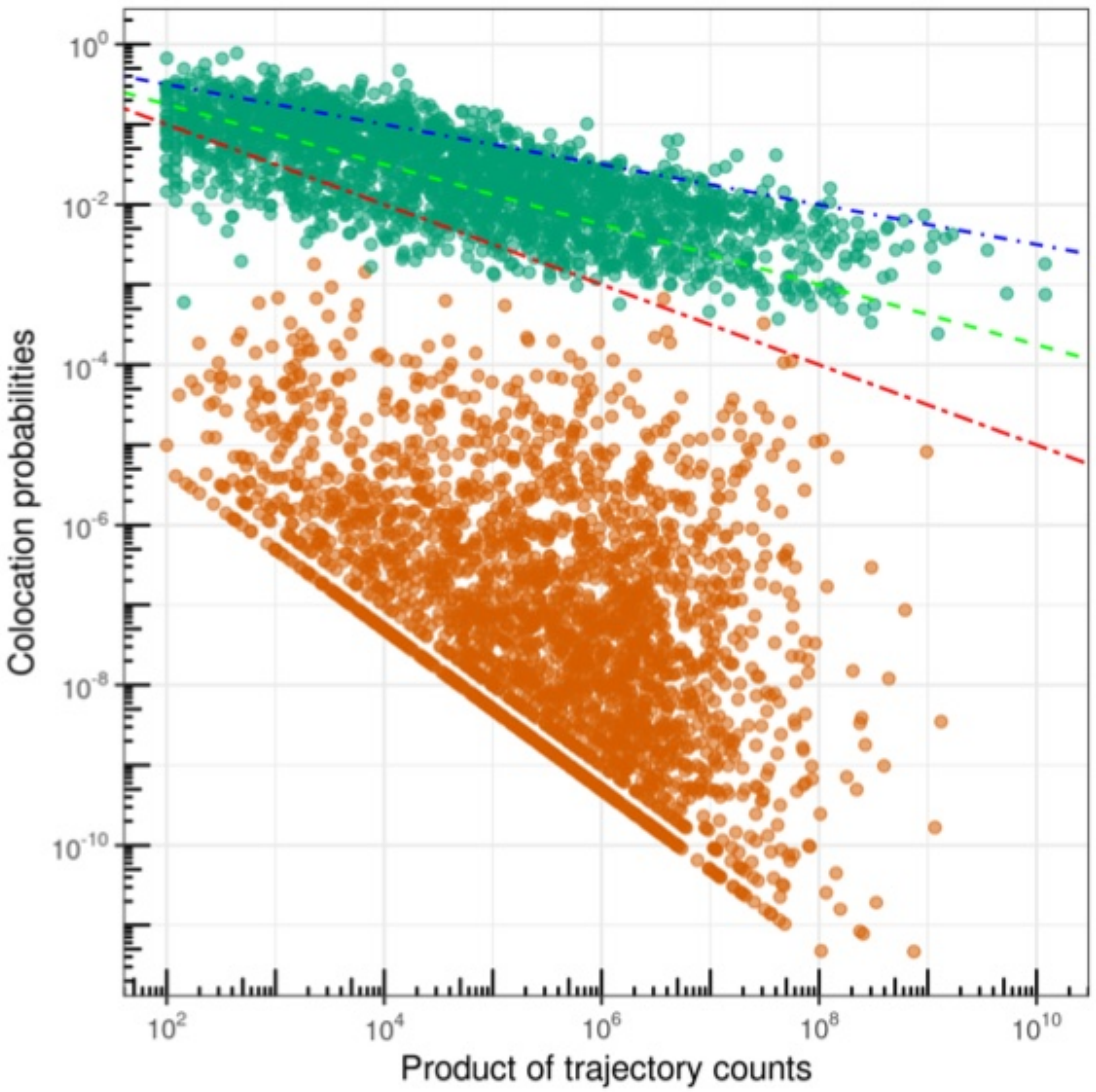
11 AM

This still counts as a co-location



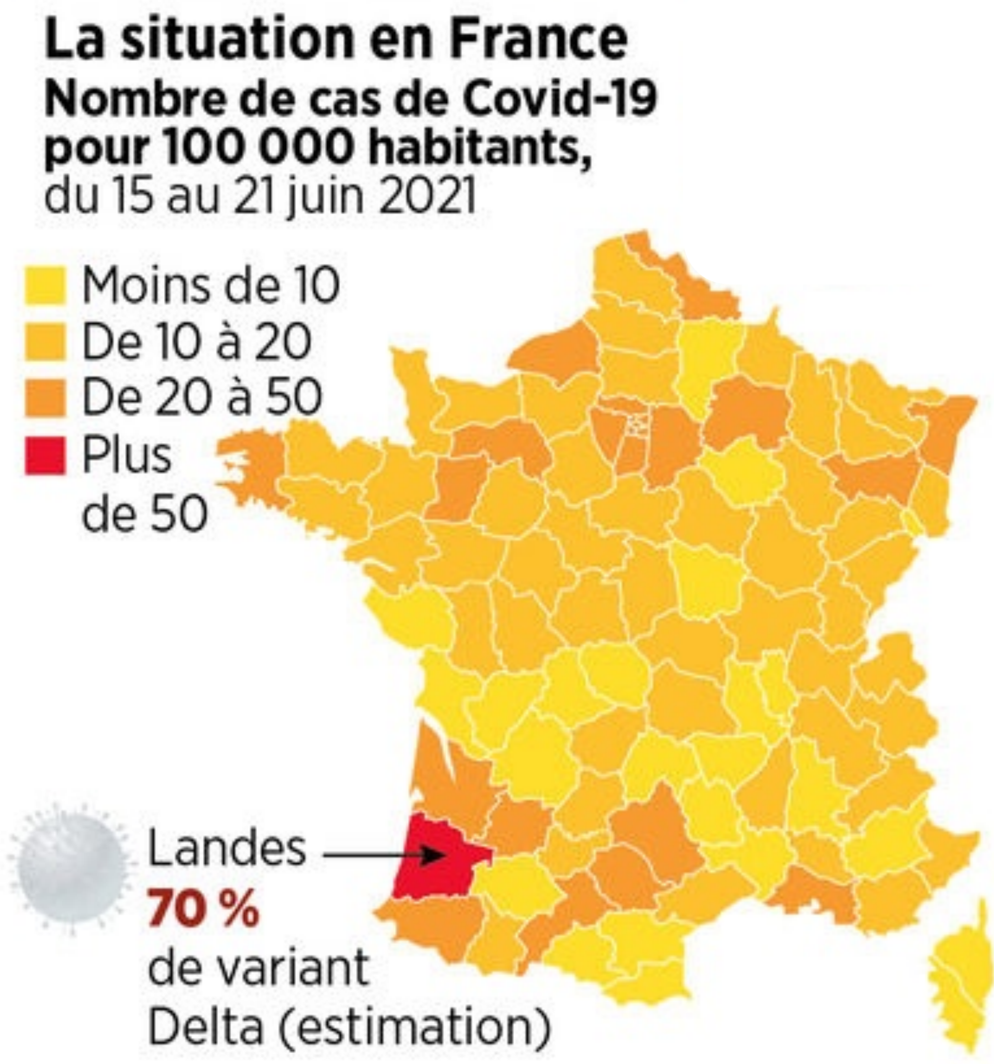
3 AM

This still counts as a co-location



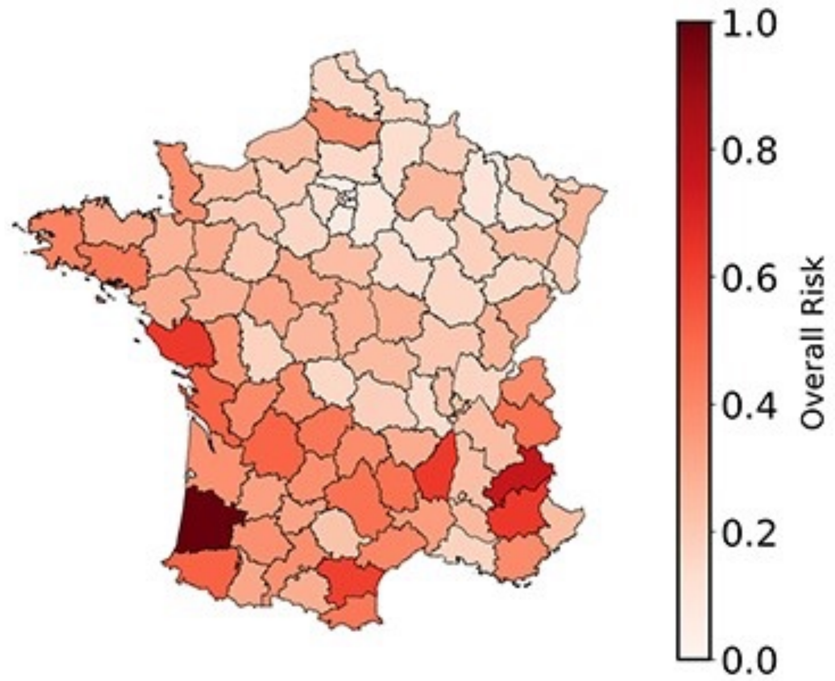
Iyer, Shankar, et al. "Large-scale measurement of aggregate human colocation patterns for epidemiological modeling." *Epidemics* 42 (2023): 100663.

META Co-location data usage example



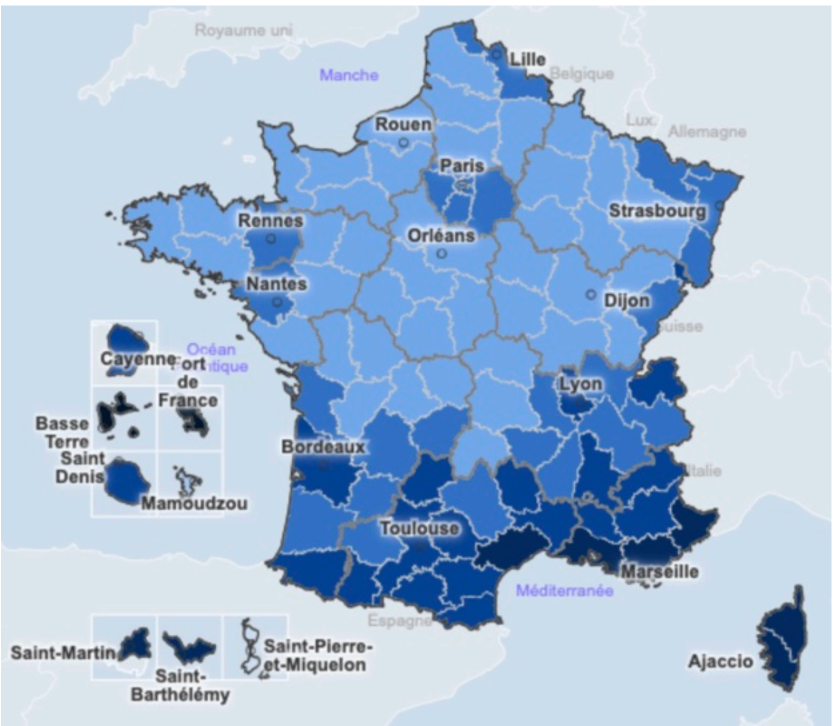
Prediction

With data from early July 2021



Data

Weekly incidence in early August 2021



https://geodes.santepubliquefrance.fr/

EXAMPLE USAGE

- Anticipate Delta variant spatial distribution in summer 2021

SCALE

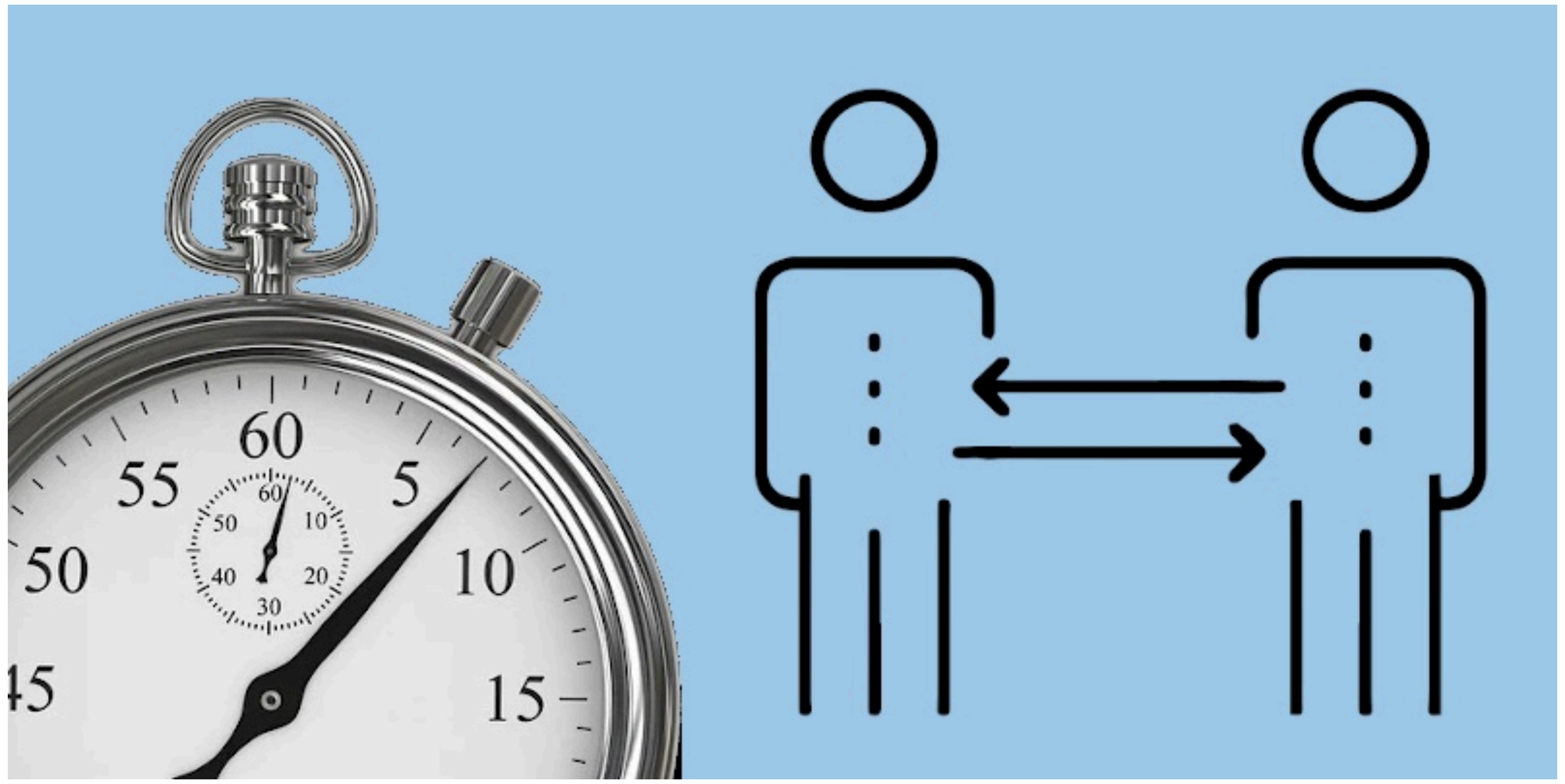
- French departments (provinces)

TAKE HOME MESSAGE

- We used 2020 summer mobility data, leveraging seasonality of mobility, to predict the spread of Delta variant in summer 2021

Mazzoli, Mattia, Eugenio Valdano, and Vittoria Colizza. "Projecting the COVID-19 epidemic risk in France for the summer 2021." *Journal of travel medicine* 28.7 (2021): taab129.

GPS traces (META Co-location)



PROS

- Free and accessible (Meta Data for Good program)
- Include all modes of transportation
- Proxy contacts among resident populations
- Available in many world regions

CONS

- Pre-aggregated data
- Co-location can occur anywhere
- Spatial resolution country dependent
- Pre-set temporal resolution (weekly level)
- Overestimated internal mixing, due to spurious co-locations

USAGE

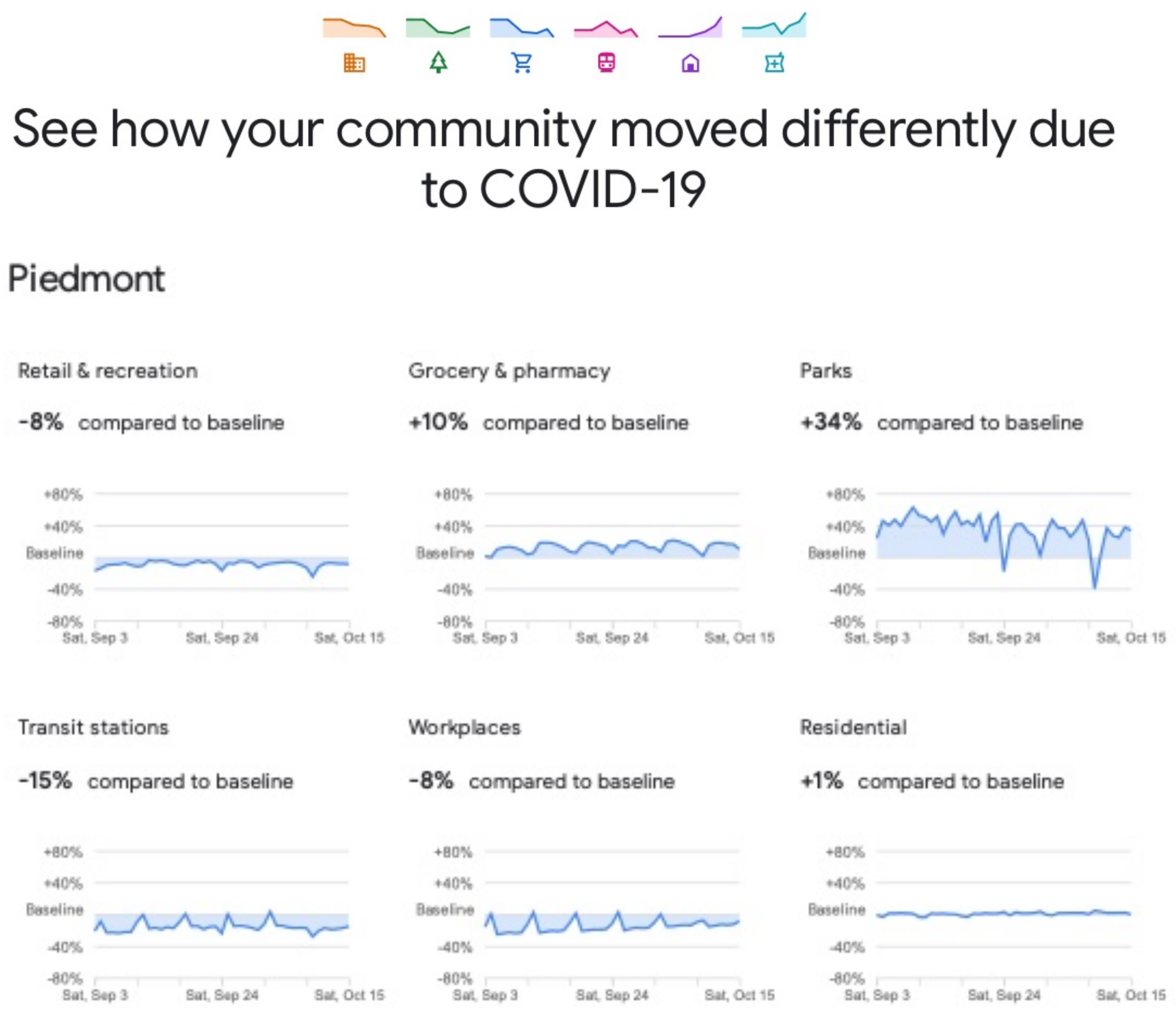
- Inform sub-national spatial transmission models

SCALE

- Provinces or regions, depending on country

Iyer, Shankar, et al. "Large-scale measurement of aggregate human colocation patterns for epidemiological modeling." *Epidemics* 42 (2023): 100663.

Activity based records (Google mobility reports)



PROS

- Free and accessible
- Daily temporal resolution
- Proxy total mobility of local areas
- Available in many world regions

CONS

- Release ended in 2022
- Pre-aggregated data
- Spatial resolution country dependent
- Residential, workplace, parks, grocery
- No mobility coupling information

USAGE

- Inform sub-national spatial transmission models + census

SCALE

- Provinces or regions, depending on country

Surveys

PROS

- Usually free and accessible
- Richness of metadata (age, gender, job, wealth, mode of transport)
- Optimal to target specific communities (medical conditions, migrants, etc)

CONS

- Scarse spatio-temporal resolution
- Non-representative of population

USAGE

- Determinants of mobility, transport mode adoption, sustainable mobility

SCALE

- Municipalities, census areas

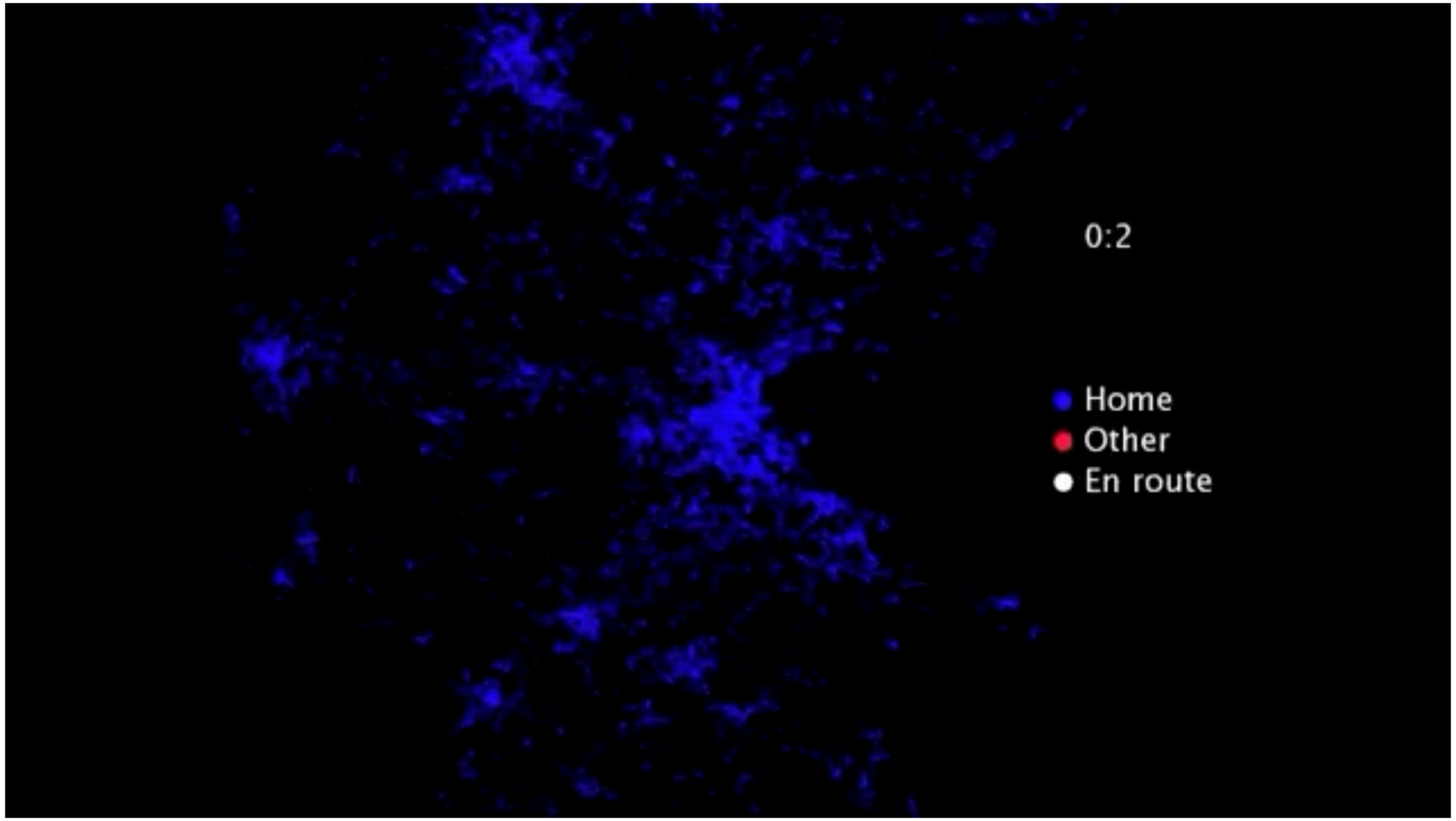
Human mobility modeling

Collective models

- Gravity model
- Radiation model

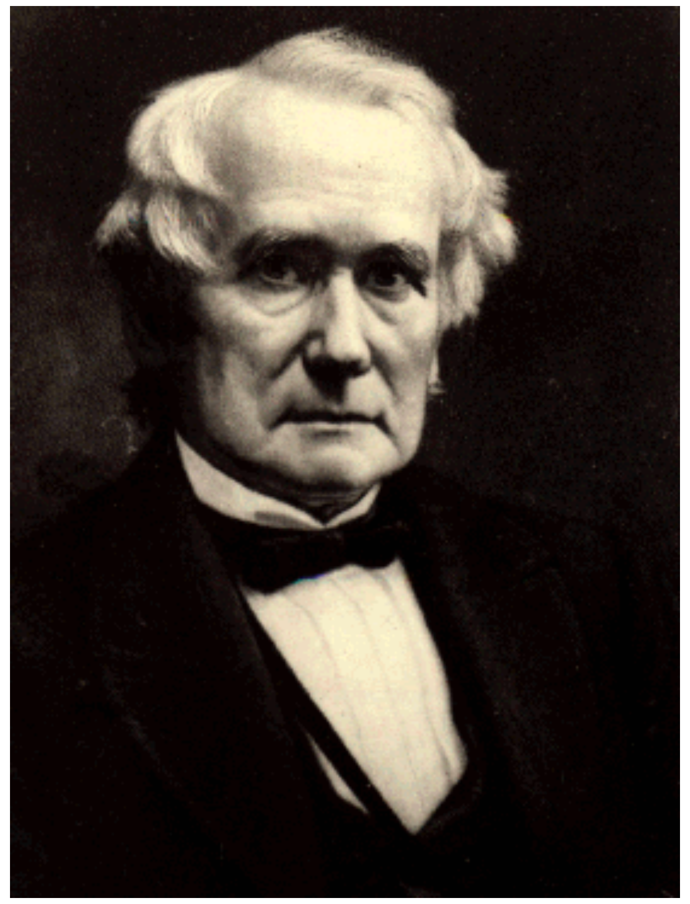
Individual models

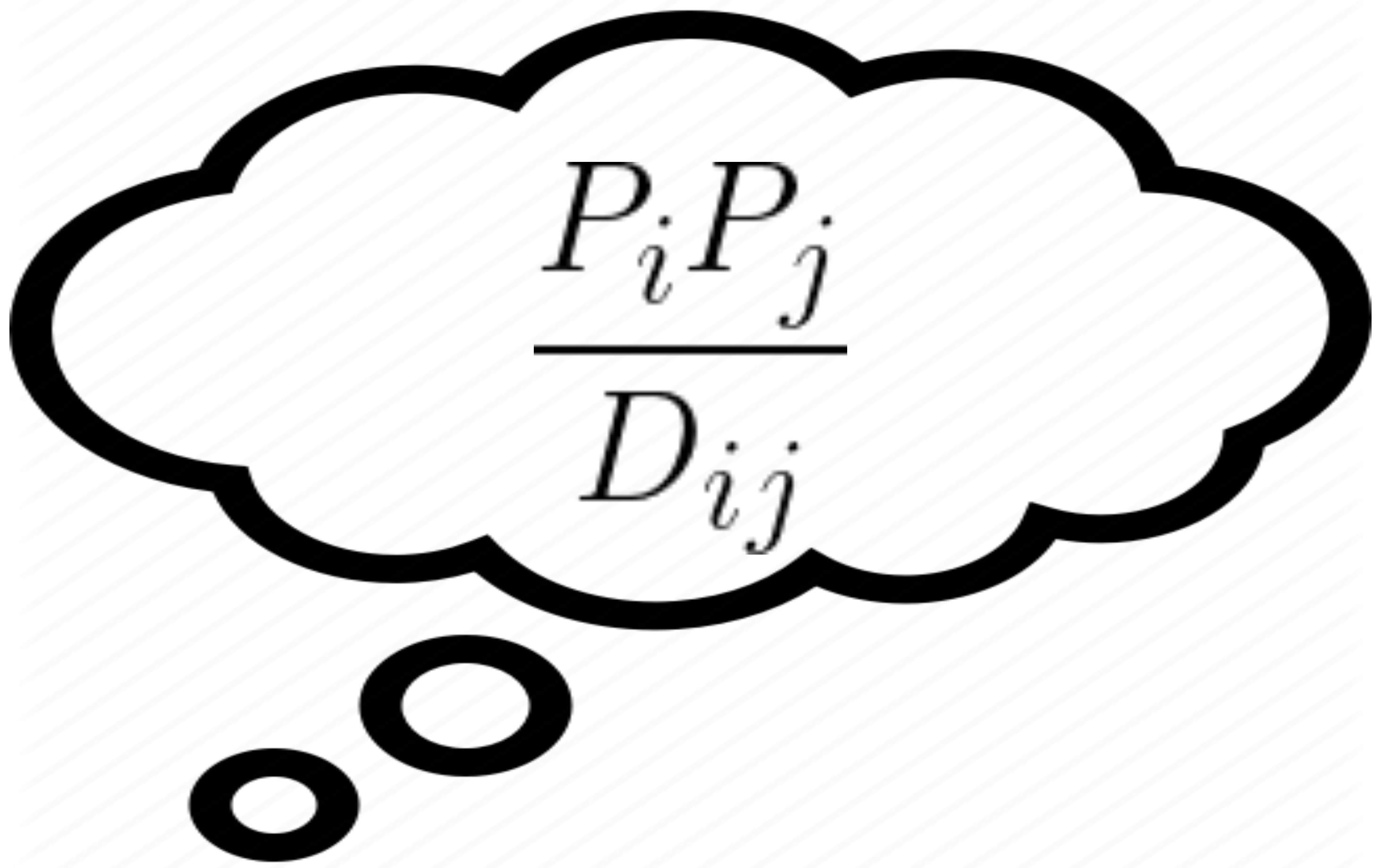
- EPR model
- MATsim
- Containers model



Marta Gonzalez, YouTube

Gravity model

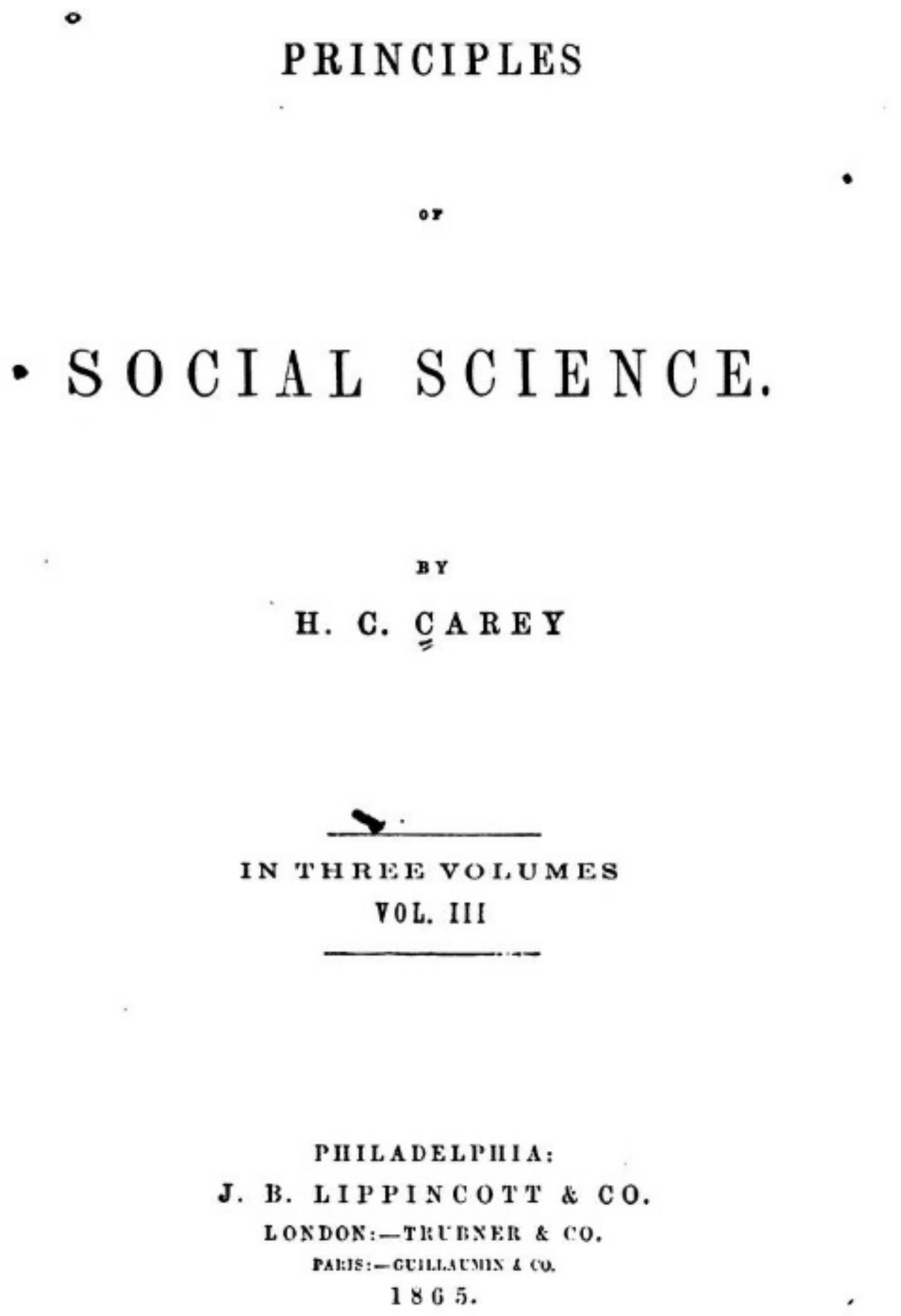




H.C. Carey (1865)
US economist & economic adviser of Abraham Lincoln

"Man tends of necessity to gravitate towards his fellow-man... and the greater the number collected (of man, ndr) in a given space the greater is the attractive force there exerted…"

"Gravitation is here, as everywhere else in the material world, in the direct ratio of the mass, and in the inverse one of the distance"



PRINCIPLES

OF

SOCIAL SCIENCE.

BY

H. C. CAREY

IN THREE VOLUMES

VOL. III

PHILADELPHIA:
J. B. LIPPINCOTT & CO.
LONDON:—TRUBNER & CO.
PARIS:—GUILLAUMIN & CO.
1865.

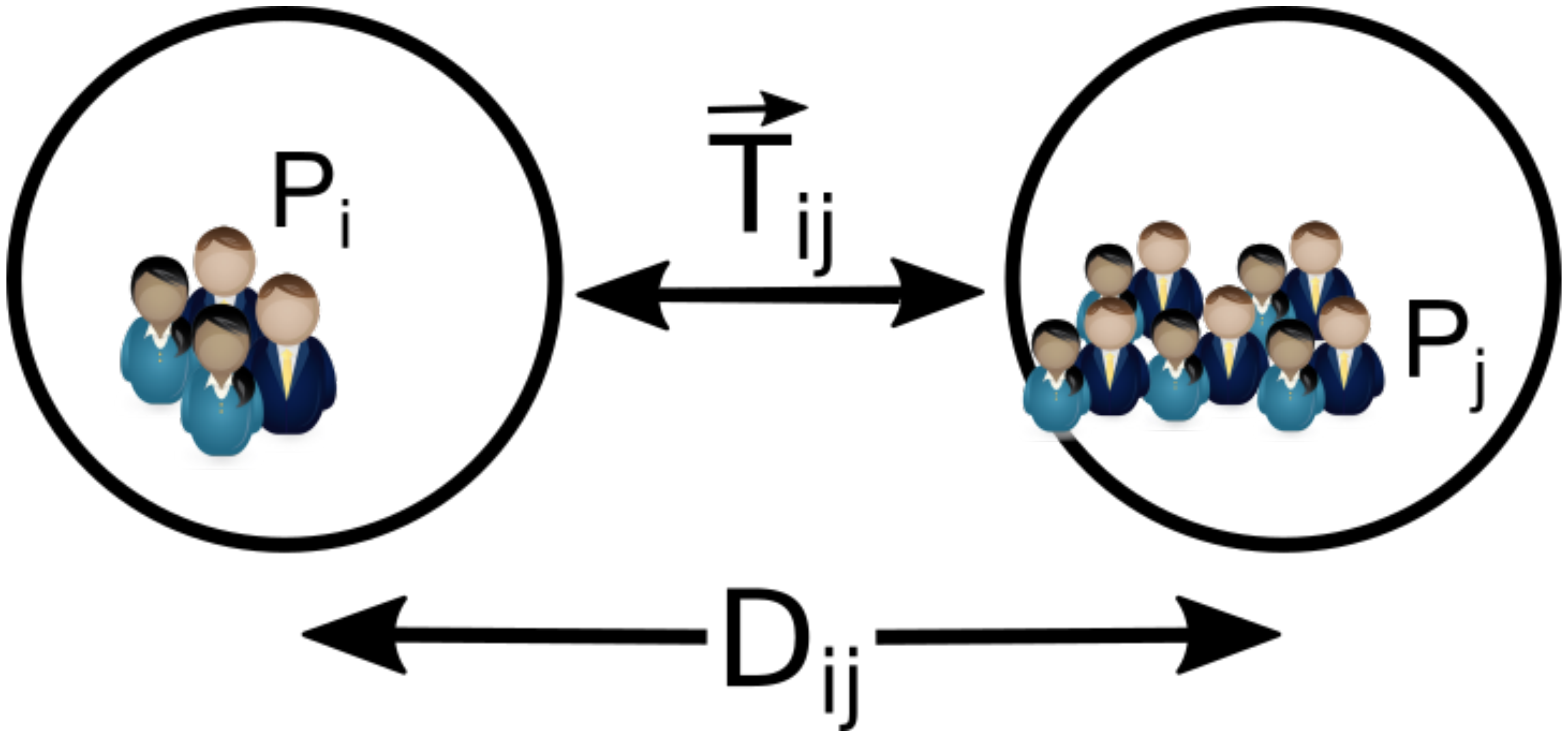
Gravity model

$$T_{ij} \propto \frac{P_i P_j}{D_{ij}}$$

G.K. Zipf (1946)
US linguist and philologist

THE $\frac{P_1 P_2}{D}$ HYPOTHESIS: ON THE INTERCITY MOVEMENT OF PERSONS

GEORGE KINGSLEY ZIPF
Harvard University



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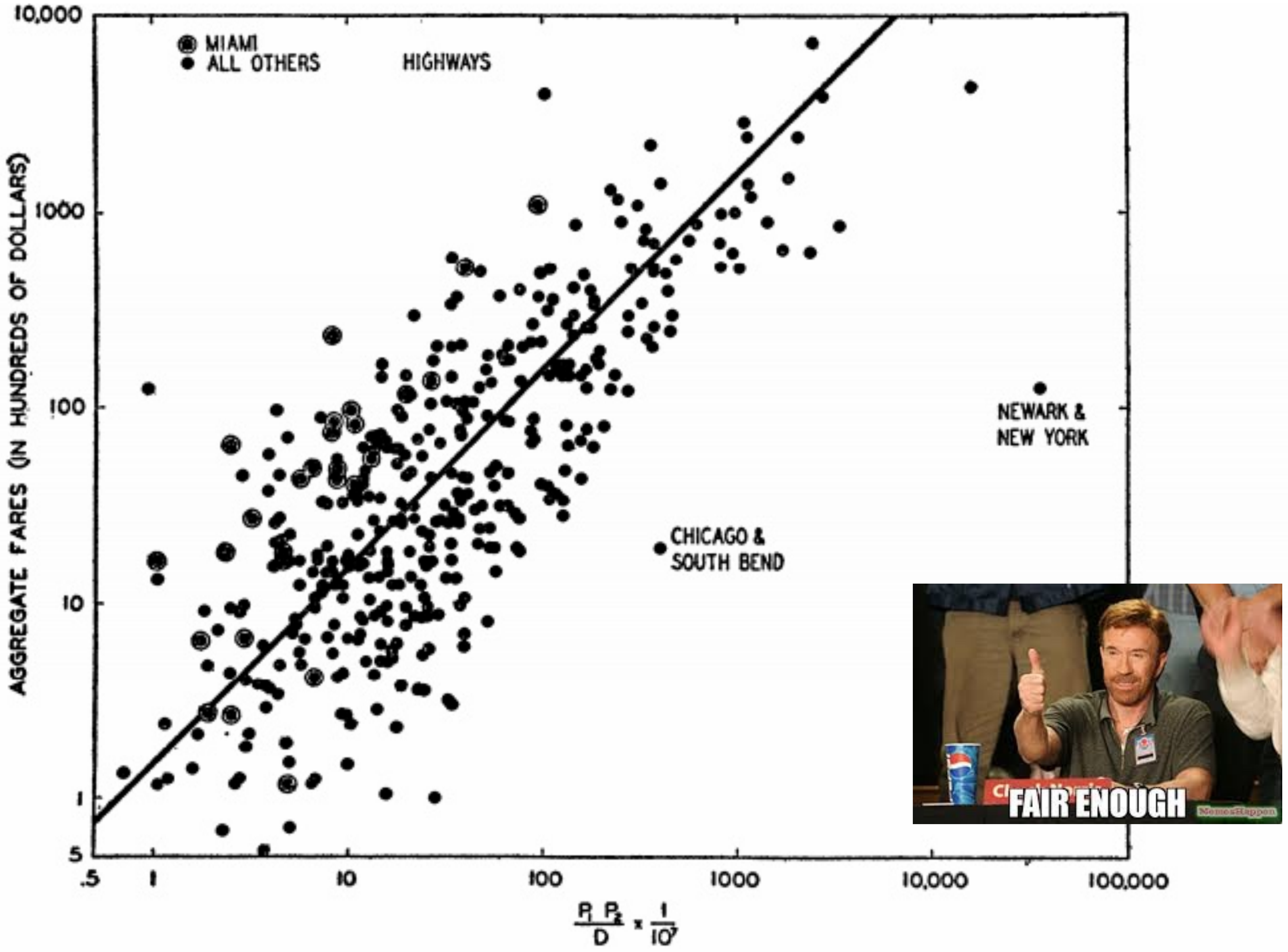

FIGURE 4. The aggregate fares (in hundreds of dollars) paid by the highway passengers reported in Figure 3. The ideal line has a slope of 1.

Gravity model

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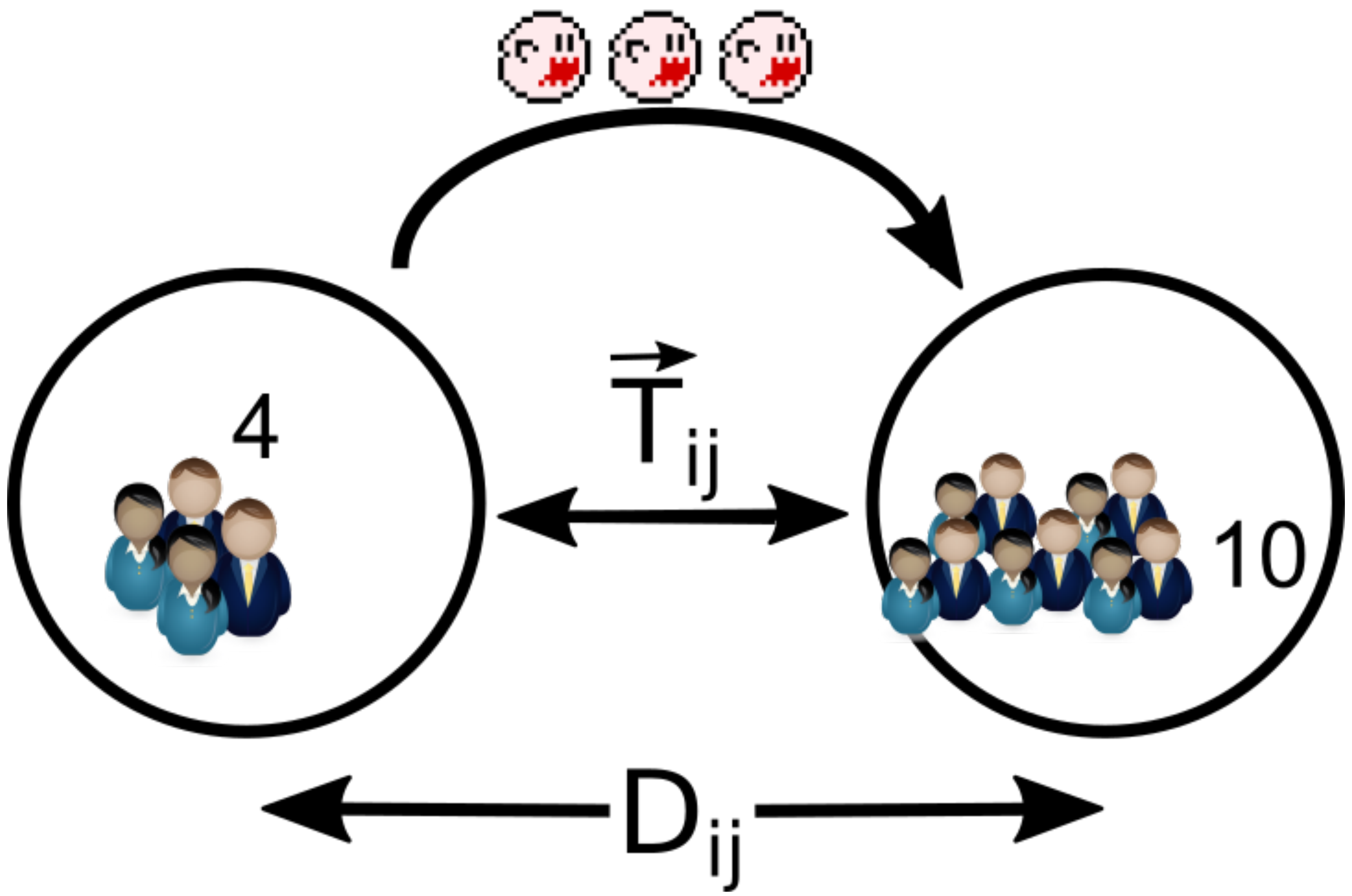


Gravity model

Unconstrained gravity model $T_{ij} = K m_i m_j \underline{f(r_{ij})}$ $\longrightarrow$ deterrence function
$\begin{cases} \text{Power law: } r_{ij}^{-\alpha} \\ \text{Exponential } e^{-r_{ij}/d'} \end{cases}$

Singly constrained gravity model
(Production constrained)

$$T_{ij} = K_i \underline{O_i} m_j f(r_{ij})$$

Doubly constrained gravity model

$$T_{ij} = K_i \underline{O_i} L_j \underline{A_j} f(r_{ij})$$

Needs data on outflows and inflows
Unfeasible without data

$$O_i = \sum_j T_{ij}$$

$$A_j = \sum_i T_{ij}$$

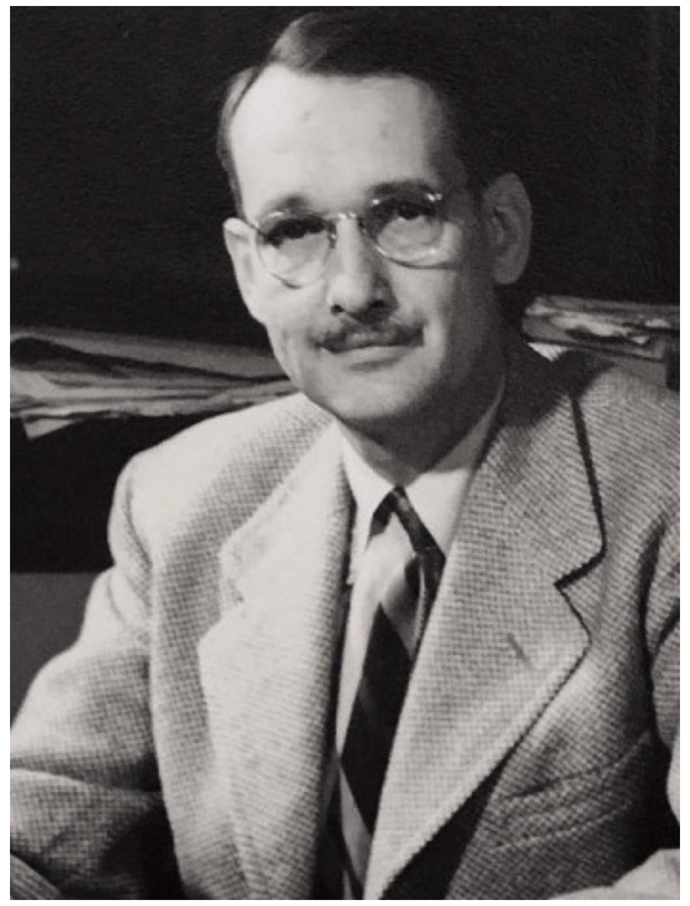
Barbosa, Hugo, et al. "Human mobility: Models and applications." Physics Reports 734 (2018): 1-74.

Radiation model

Meanwhile in Sociology...

Tired of looking at the stars, Professor
Jenkins takes up sociology.

Intervening opportunities model



$$\frac{dy}{ds} = \frac{a}{x}\frac{dx}{ds}$$

S.A. Stouffer (1940)
US Sociologist

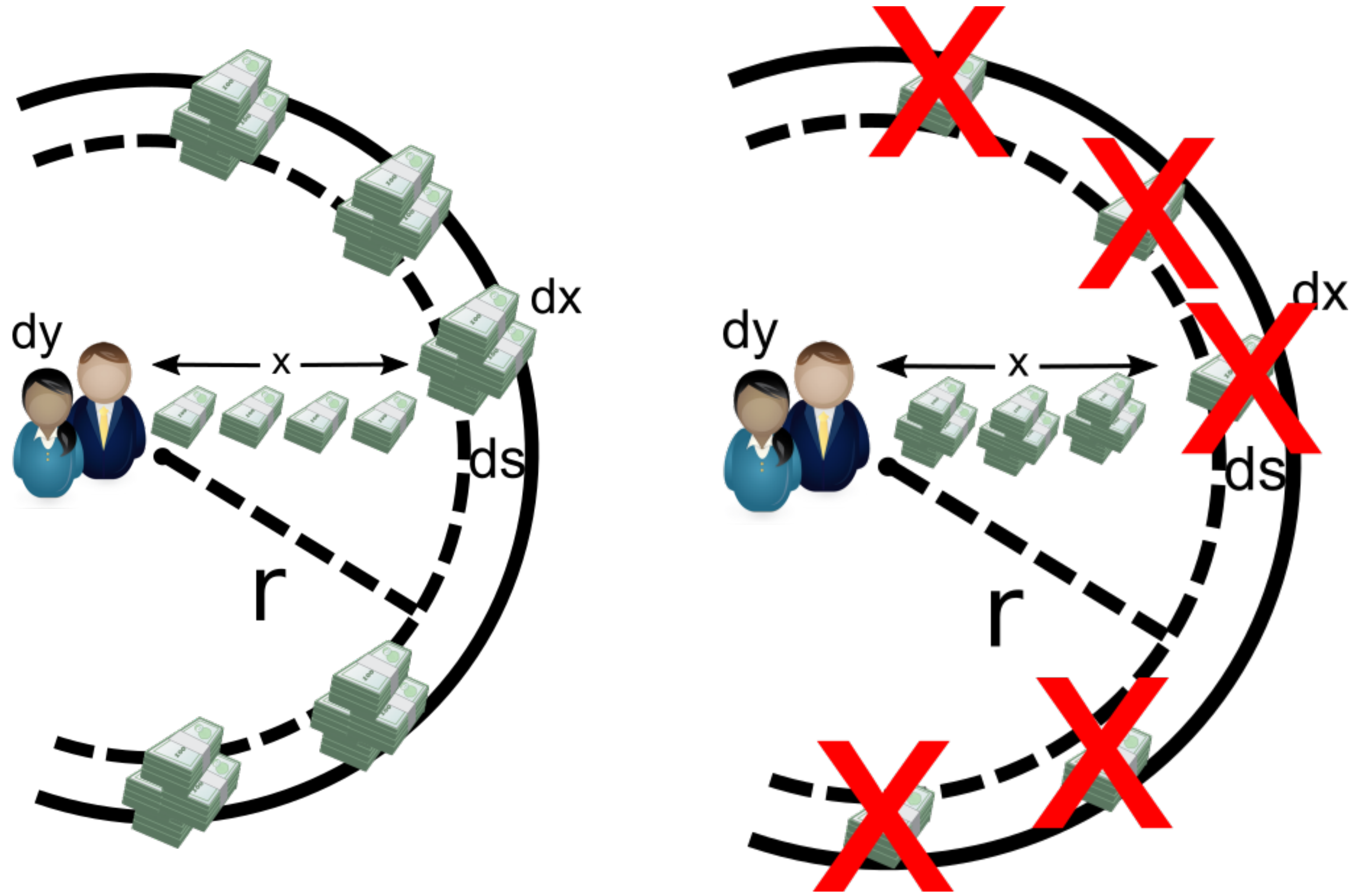
"The number of persons going a given distance is directly proportional to the number of opportunities at that distance and inversely proportional to the number of intervening opportunities."

American
SOCIOLOGICAL REVIEW

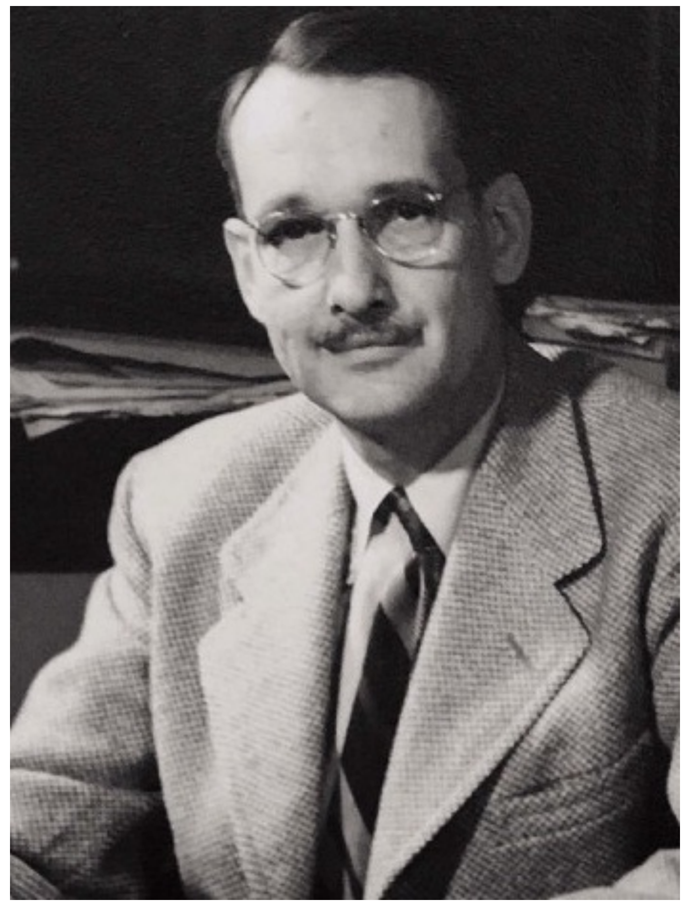
Volume 5 DECEMBER, 1940 Number 6

INTERVENING OPPORTUNITIES: A THEORY RELATING MOBILITY AND DISTANCE*

SAMUEL A. STOUFFER
University of Chicago



Intervening opportunities model



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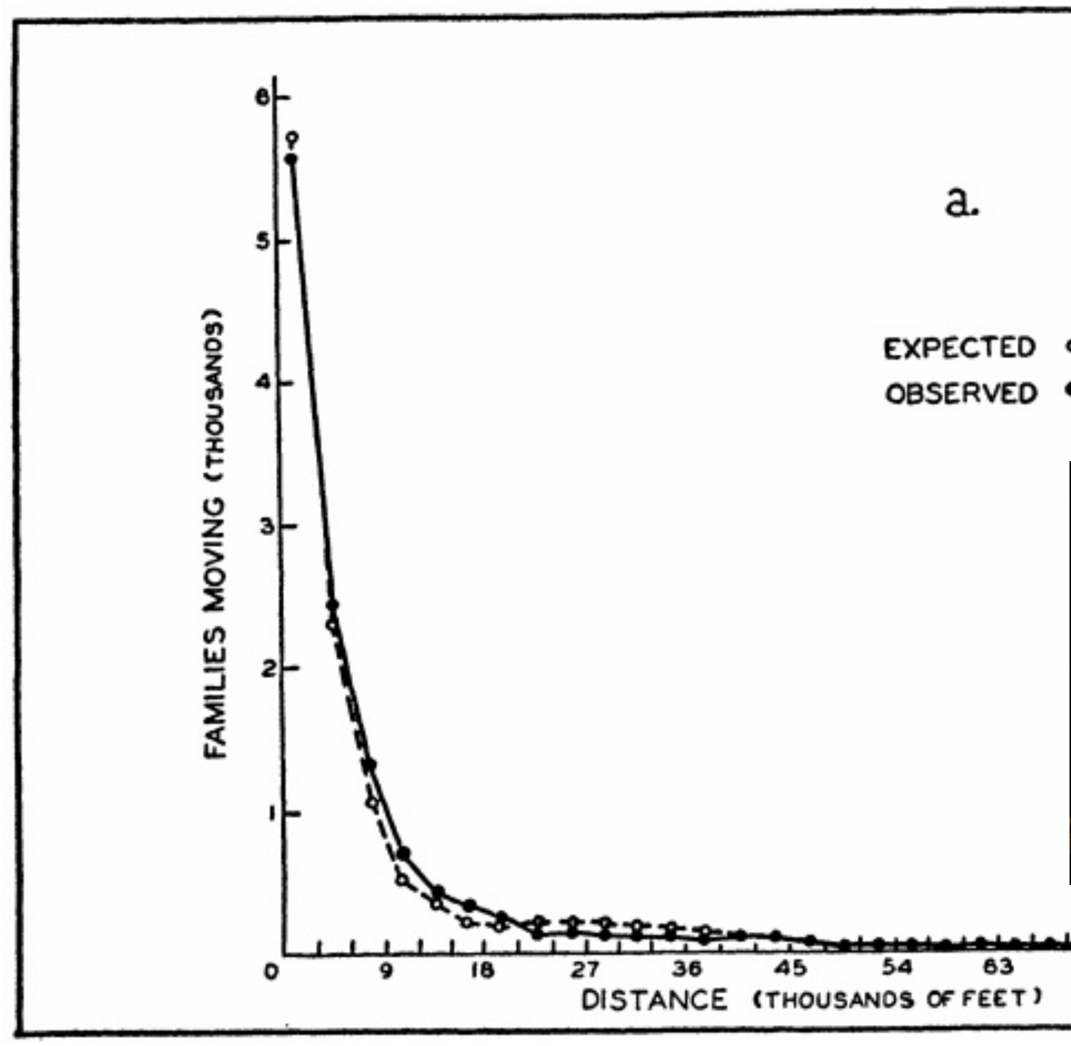
University of Chicago

CHART 1. NUMBER OF FAMILIES MOVING FROM LOCATIONS WITHIN TWELVE WHITE CENSUS TRACTS, BY INTERVALS OF DISTANCE. COMPARISON OF EXPECTATION, FROM EQUATION 1, WITH ACTUAL DISTRIBUTION. CLEVELAND, OHIO, 1933–35.[1]



Radiation model

LETTER

doi:10.1038/nature10856

A universal model for mobility and migration patterns

Filippo Simini[1,2,3], Marta C. González[4], Amos Maritan[2] & Albert-László Barabási[1,5,6] (2012)

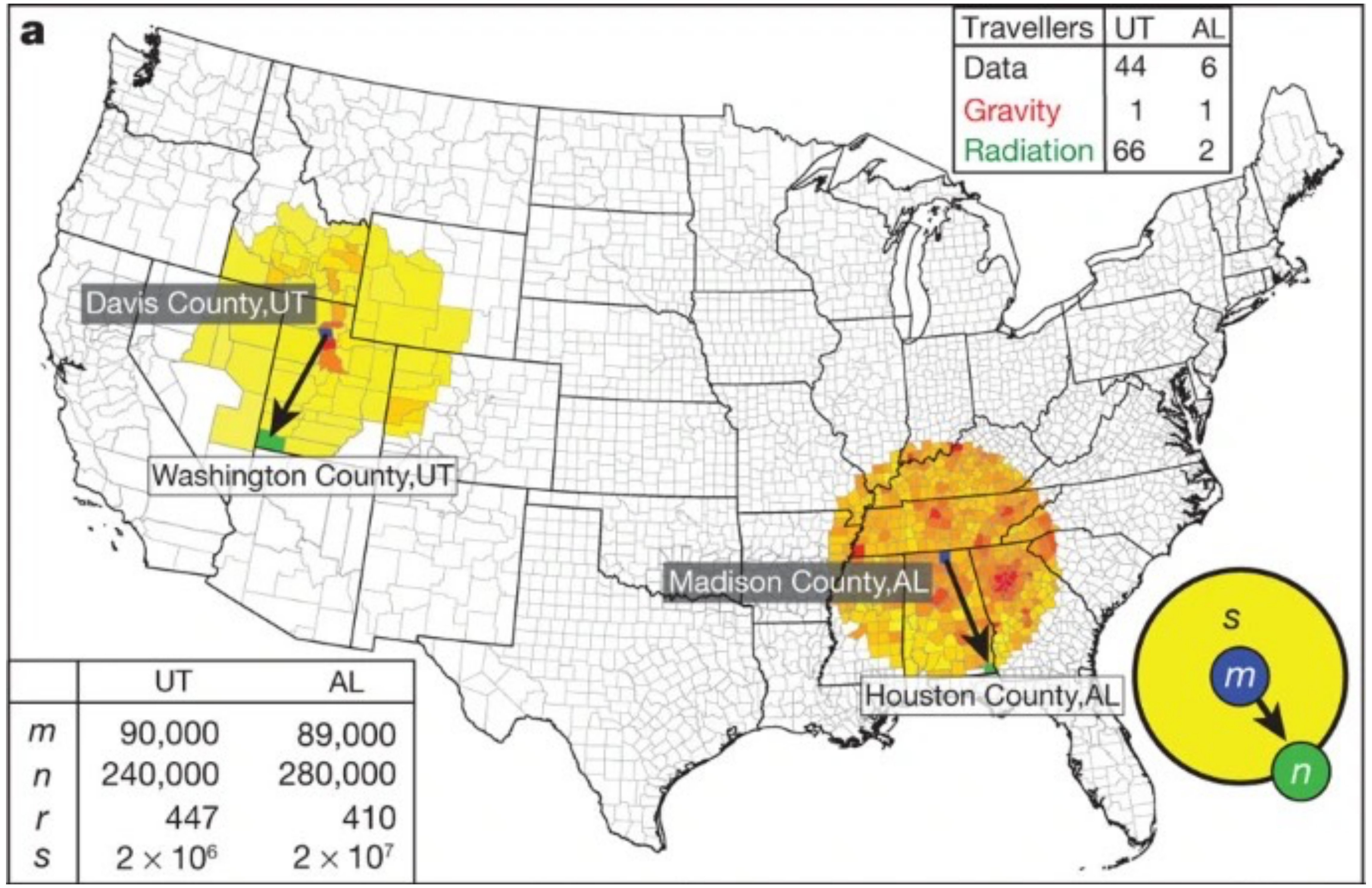
Inspired by the Intervening opportunities model

It mimics the radiation and absorption of particles
Particles emitted and absorbed proportional to local population

Opportunities = individuals

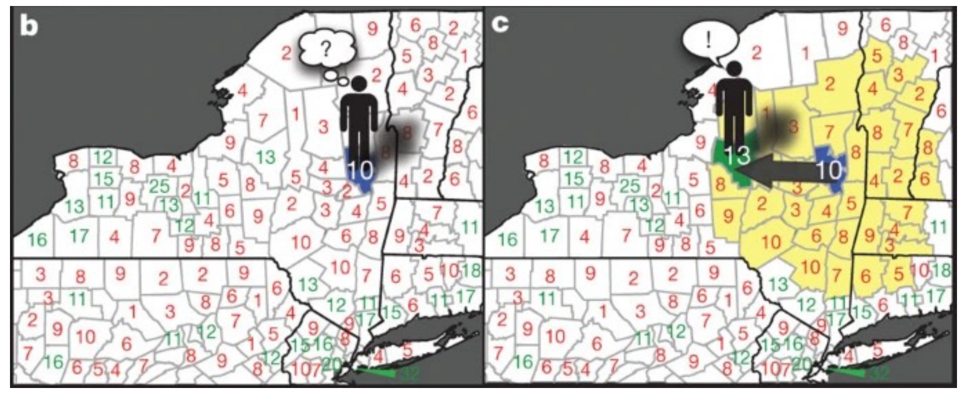
Parameter free

Requires knowledge on the outflows



$$T_{ij} = T_i \frac{P_i\, P_j}{(P_i + s_{ij})\,(Pi + P_j + s_{ij})}$$

$$T_i = \sum_j T_{ij}$$



Simini, Filippo, et al. "A universal model for mobility and migration patterns." *Nature* 484.7392 (2012): 96-100.
Barbosa, Hugo, et al. "Human mobility: Models and applications." Physics Reports 734 (2018): 1-74.

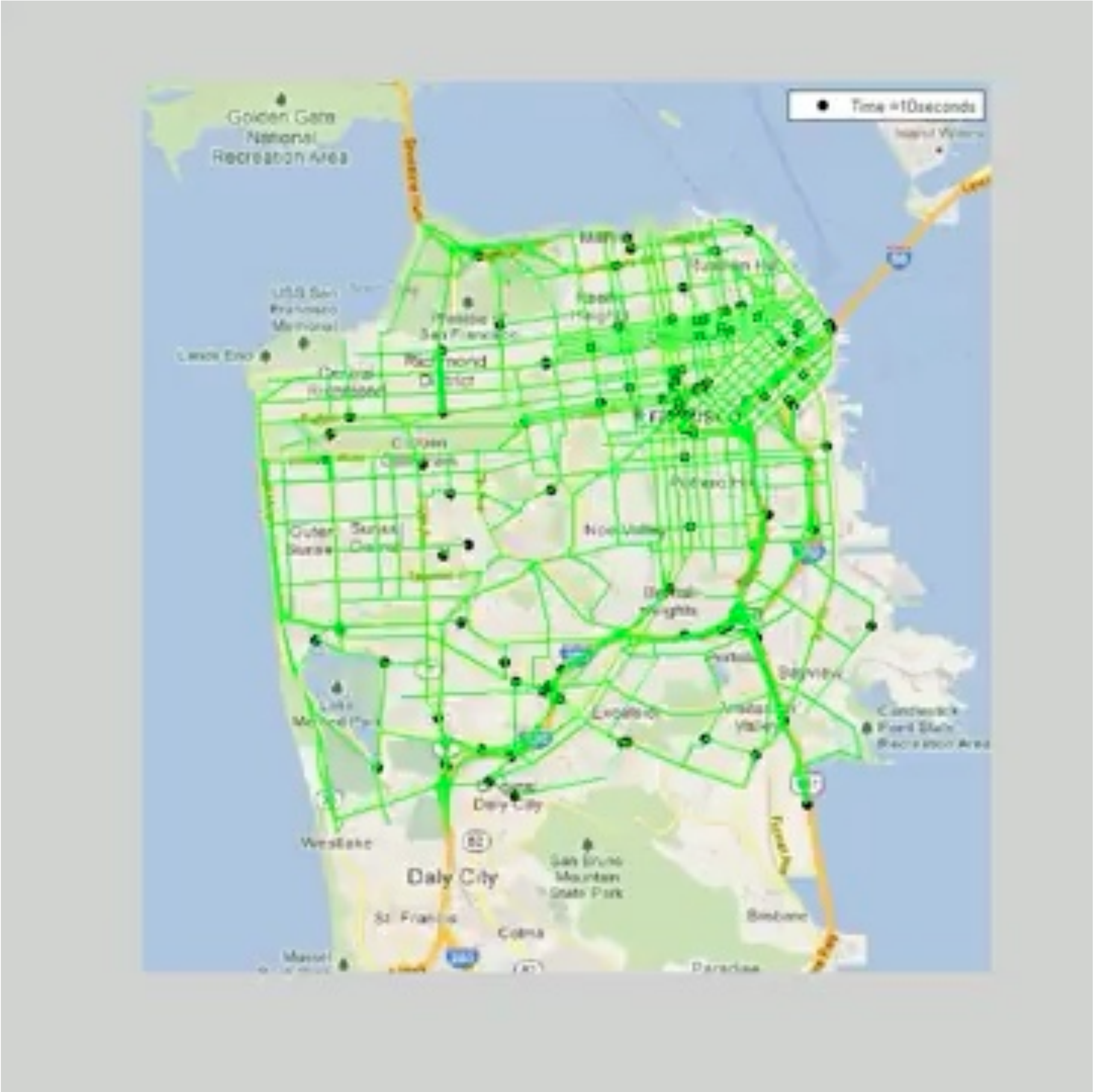
Agent based models (MATsim)

Open-source framework for implementing large-scale agent-based transport simulations.

Needs road and transportation network (OpenStreetMaps)

Useful to:
- Simulate traffic congestions
- Analyse transport demand
- Regulate transport offer
- Estimate car traffic emissions and exposure to pollutants
- propose traffic interventions, e.g. tolls

Make your own simulation!
https://www.matsim.org/about-matsim



Marta Gonzalez, YouTube

Mobility models performance metrics

… among others

Macro-scale metrics:

- CPC: common part of commuters
- Normalised root mean squared error
- Pearson correlation

Micro (individual) scale metrics:

- radius of gyration
- jump length

CPC: common part of commuters

$$CPC\left(T,\tilde{T}\right) = \frac{\sum_{i,j=1}^{n} min\left(T_{ij},\tilde{T}_{ij}\right)}{N} = 1-\frac{1}{2}\frac{\sum_{i,j=1}^{n} |T_{ij}-\tilde{T}_{ij}|}{N}$$

0: no agreement, 1: full agreement

Normalised root mean squared error

$$NRMSE\left(T,\tilde{T}\right) = \frac{\sum_{i,j=1}^{n}\left(T_{ij}-\tilde{T}_{ij}\right)^2}{\sum_{i,j=1}^{n} T_{ij}^{\ 2}}$$

$\tilde{T}_{ij}$: simulated

0: full agreement

Pearson correlation

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y}$$

-1: anti correlated, 1: fully correlated

Lenormand, Maxime, Aleix Bassolas, and José J. Ramasco. "Systematic comparison of trip distribution laws and models." *Journal of Transport Geography* 51 (2016): 158-169.

Hands on mobility models

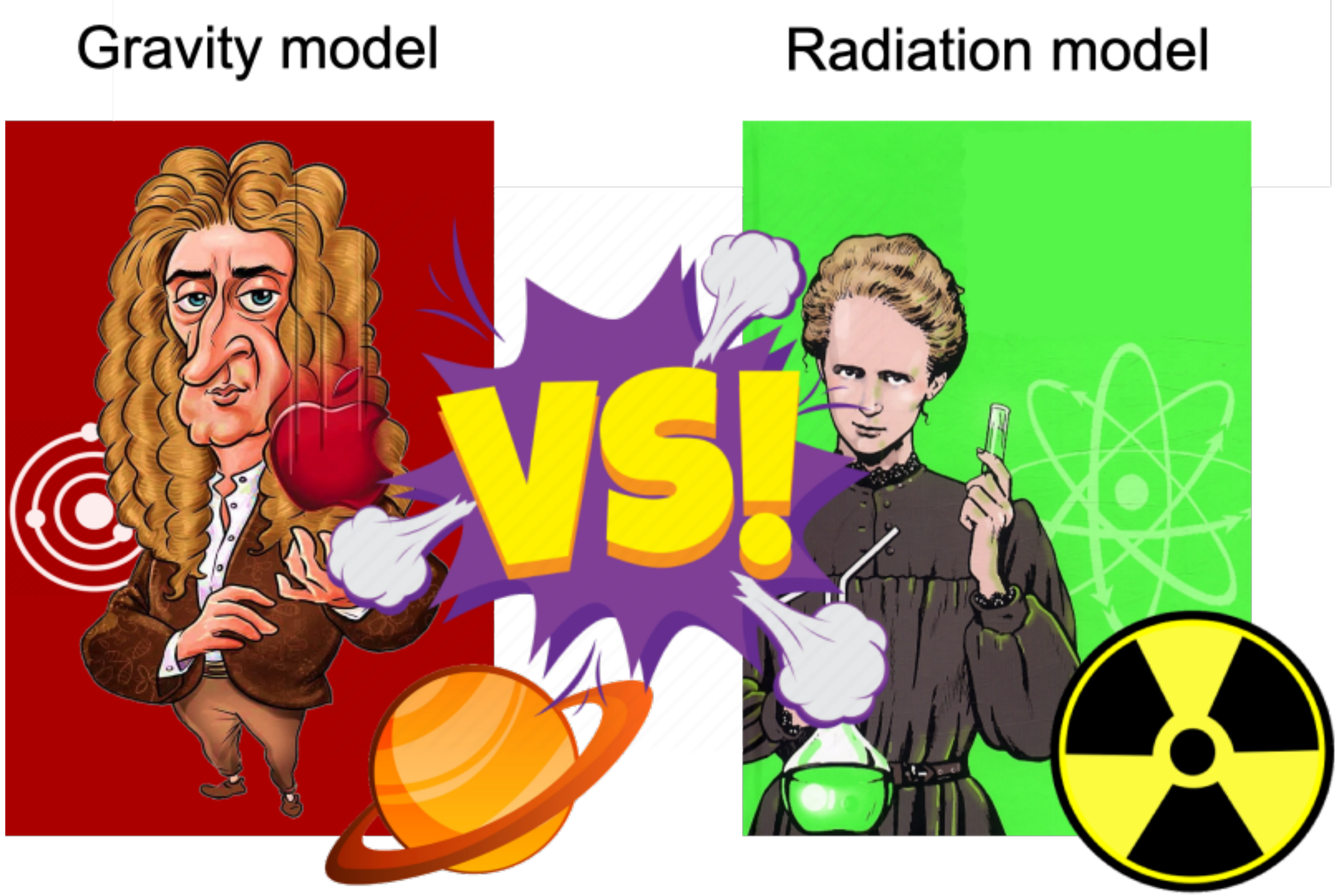
Let's try gravity and radiation models on a real dataset and see which one works best

Data: New York City commuters
Scale: counties

Follow the instructions at
https://scikit-mobility.github.io/scikit-mobility/index.html

```
python3 -m venv skmob
source skmob/bin/activate
pip install scikit-mobility
pip install jupyter
jupyter notebook
pip install scikit-mobility
```

Go to mattiamazzoli.github.com/
Go to Teaching
Download the notebook "mobility models"
Follow the instructions



Some refs on the use of gravity and radiation models in epi modeling

Eggo, Rosalind M., Simon Cauchemez, and Neil M. Ferguson. "Spatial dynamics of the 1918 influenza pandemic in England, Wales and the United States." *Journal of the Royal Society Interface* 8.55 (2011)

Balcan, Duygu, et al. "Multiscale mobility networks and the spatial spreading of infectious diseases." *Proceedings of the national academy sciences* 106.51 (2009)

Tizzoni, Michele, et al. "On the use of human mobility proxies for modeling epidemics." *PLoS computational biology* 10.7 (2014)

Cauchemez, Simon, et al. "Local and regional spread of chikungunya fever in the Americas." *Eurosurveillance* 19.28 (2014)

Perrotta, Daniela, et al. "Comparing sources of mobility for modelling the epidemic spread of Zika virus in Colombia." *PLoS Neglected Tropical Diseases* 16.7 (2022)