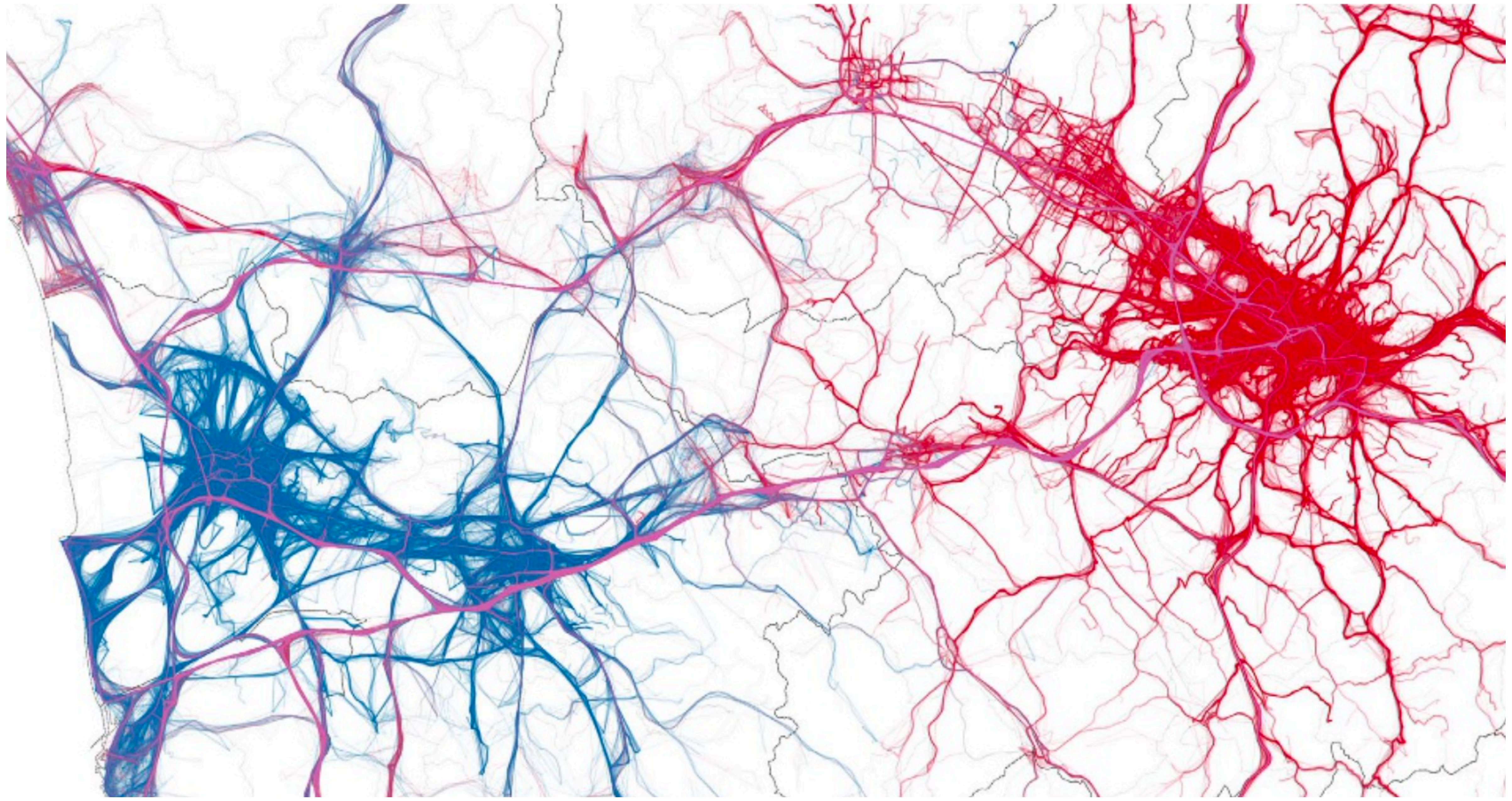
Lecture 12: Human mobility

Instructor: Ane Rahbek Vierø

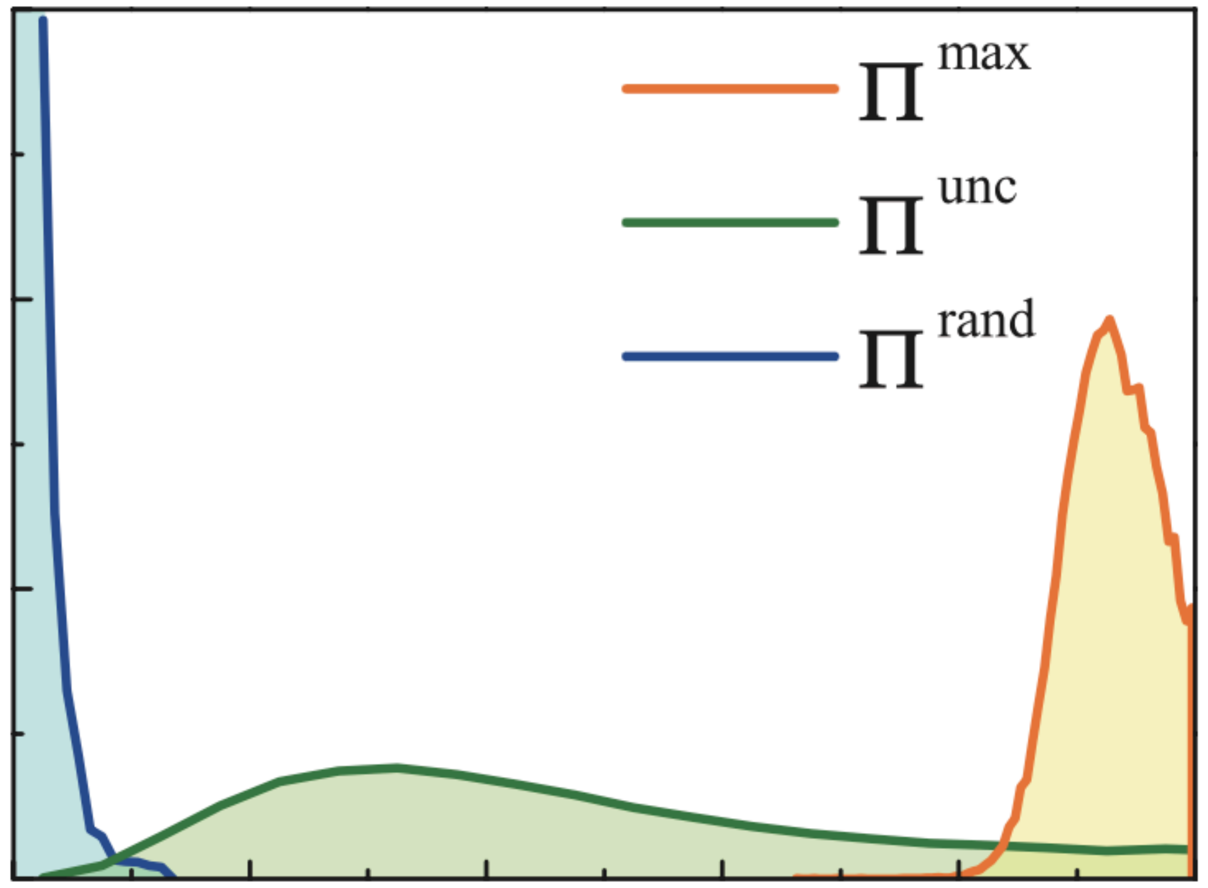
Apr 24, 2023



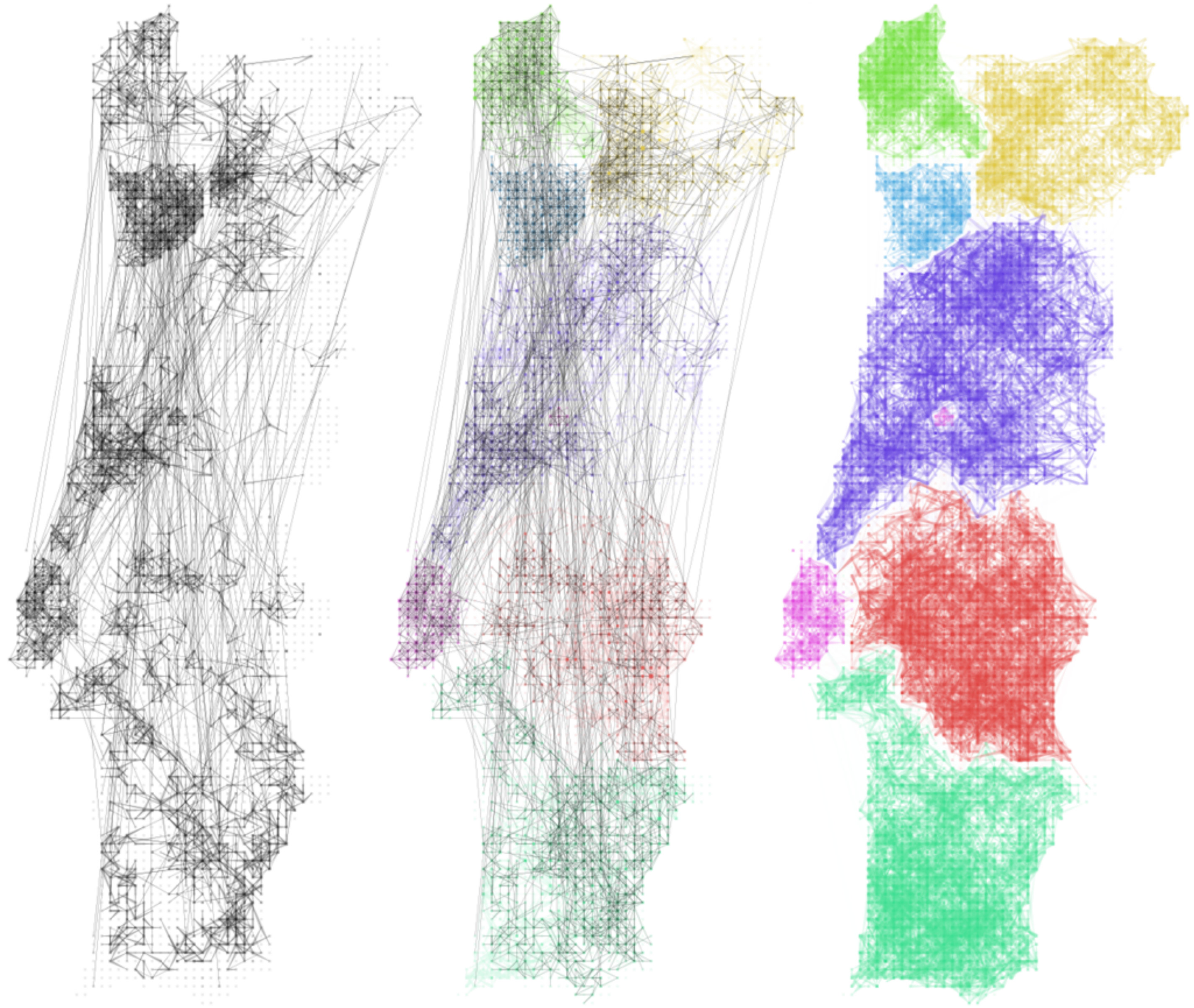
IT UNIVERSITY OF COPENHAGEN

Today you will learn about mobility patterns

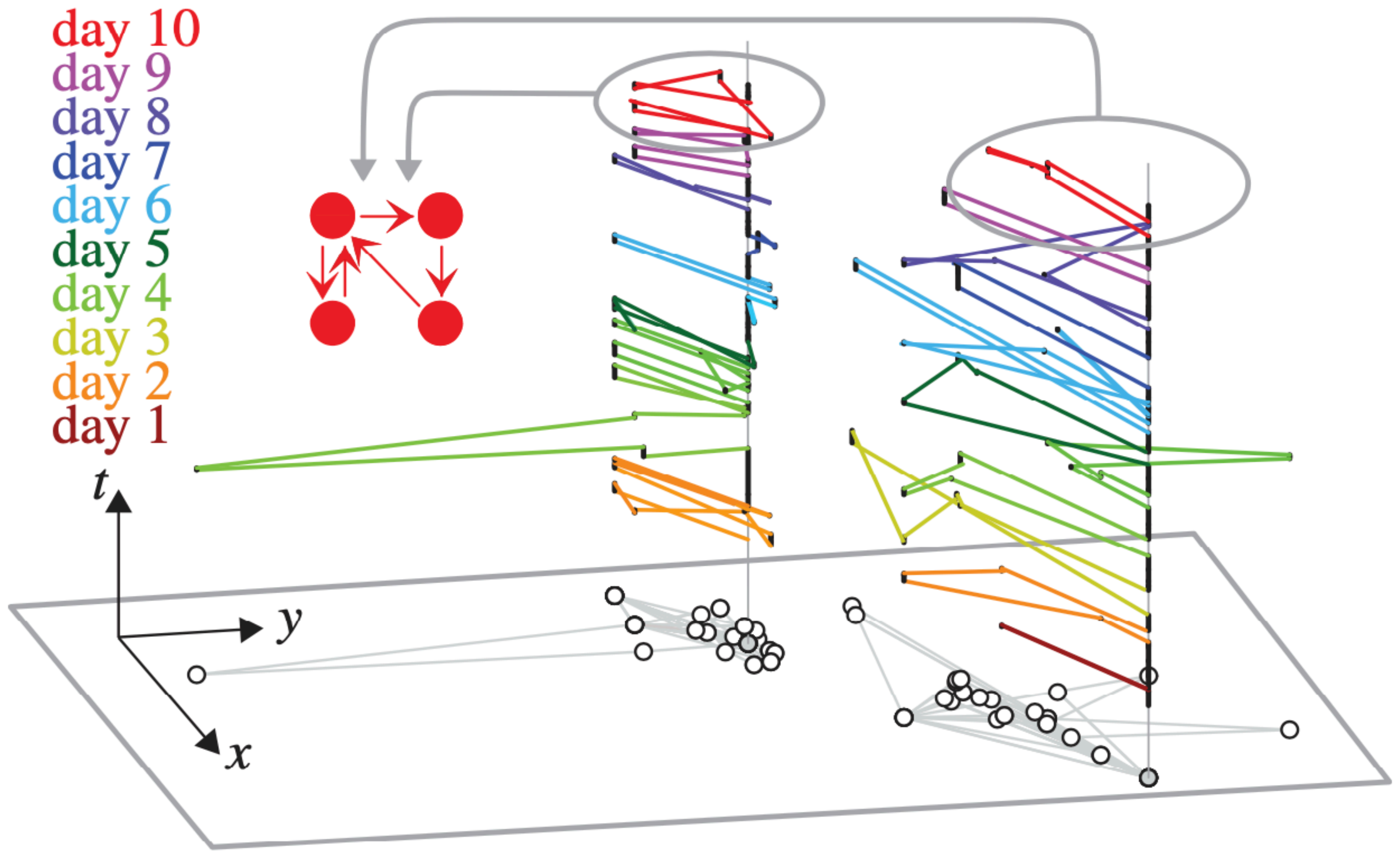
Predictability and privacy



Aggregate mobility



Mobility motifs

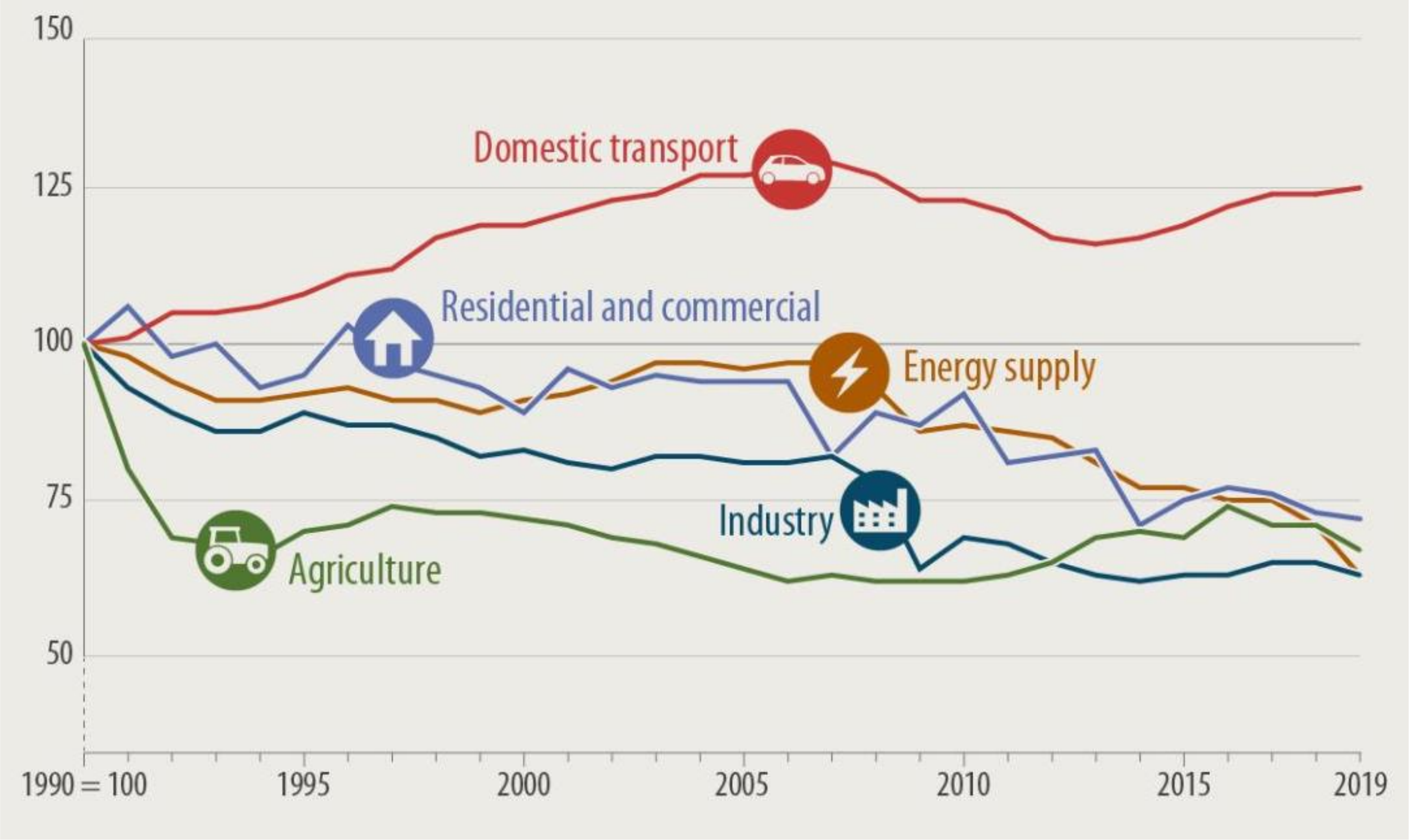


Why care about mobility?

Why care about mobility?

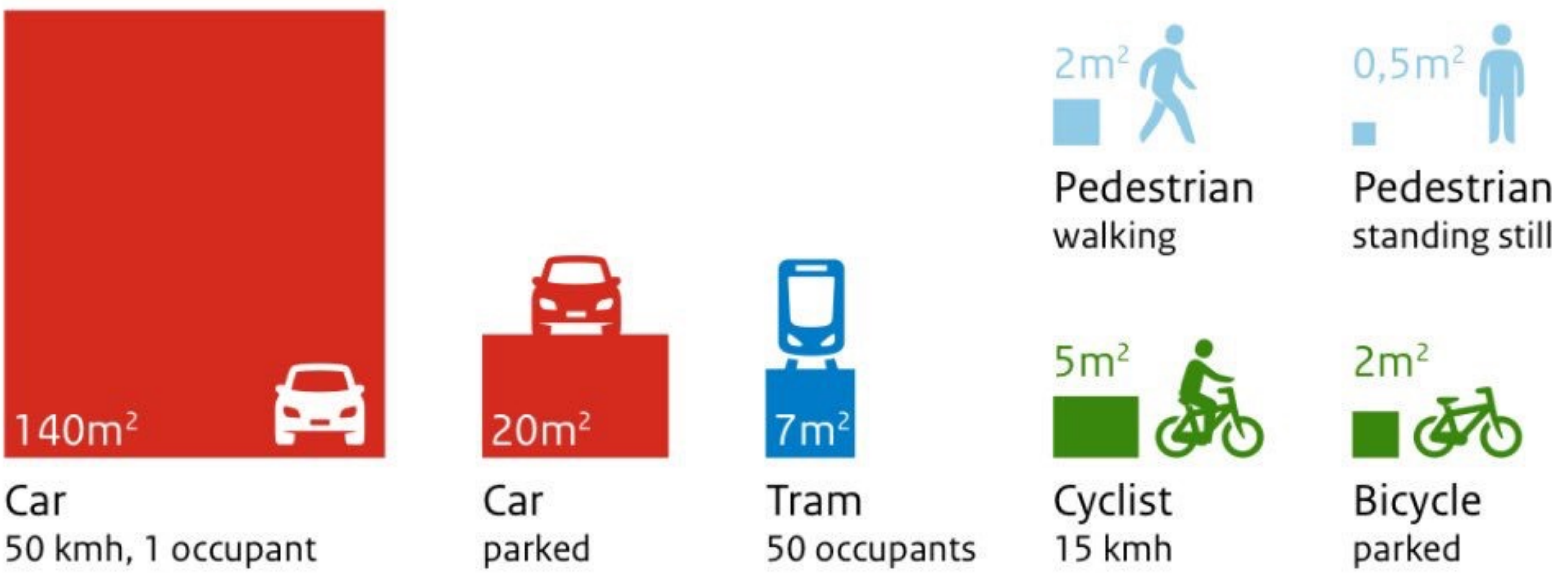
Mobility = human movement

Transport plays a key role in the climate crisis



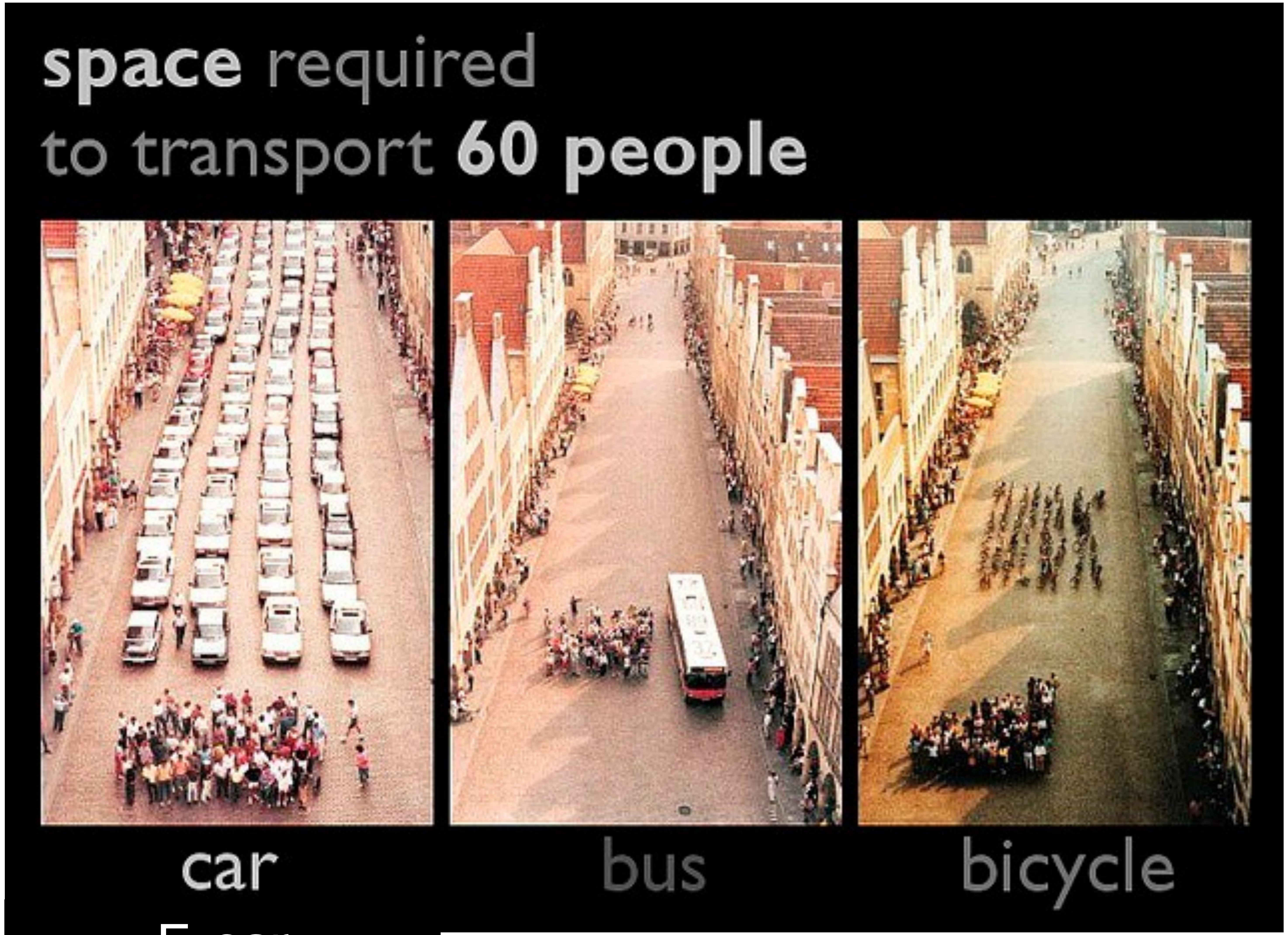
https://www.eureporter.co/environment/co2-emissions/2022/06/06/co2-emissions-from-cars-facts-and-figures-infographics/

Space is one of the most sparse resources in cities



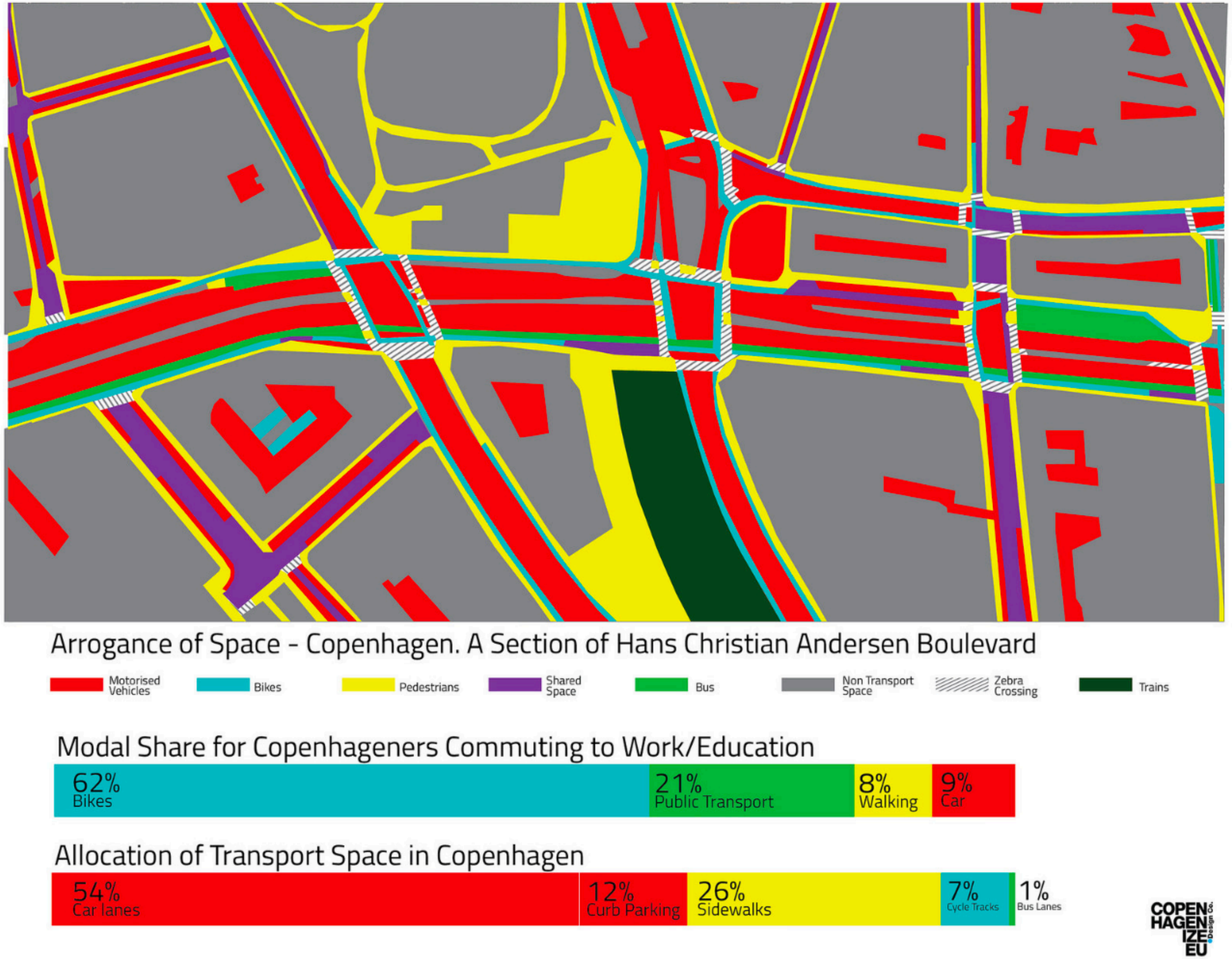
Harms and Kansen, Netherlands Institute for Transport Policy Analysis (2017)

Spatial efficiency shows us what works and what doesn't



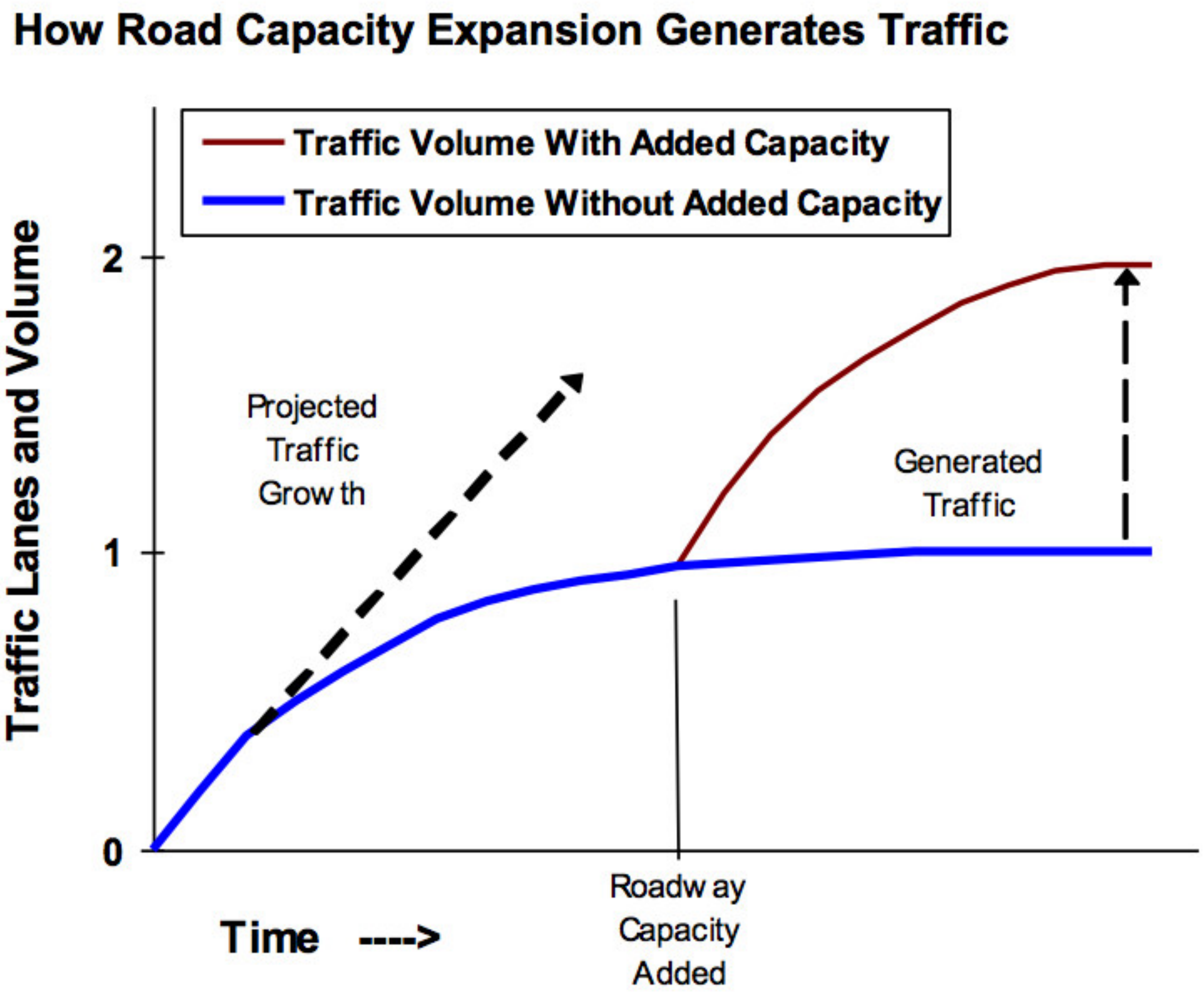
E-car

Most space is for cars, but most people use bikes



Copenhagenize

Induced demand: Building roads causes more traffic



https://www.governing.com/now/why-the-concept-of-induced-demand-is-a-hard-sell

https://www.bloomberg.com/news/features/2021-09-28/why-widening-highways-doesn-t-bring-traffic-relief

Traffic hazards are highly asymmetrical

https://epjdatascience.springeropen.com/articles/10.1140/epjds/s13688-022-00339-5

You can study mobility at different levels & scales

Individual vs. **Population / Aggregate**

Pedestrian movements

Commuter flows

Migration

You can study mobility at different levels & scales

Individual vs. **Population / Aggregate**

Pedestrian movements

Commuter flows

Migration

Single-scale

International migration

Neighborhood interaction

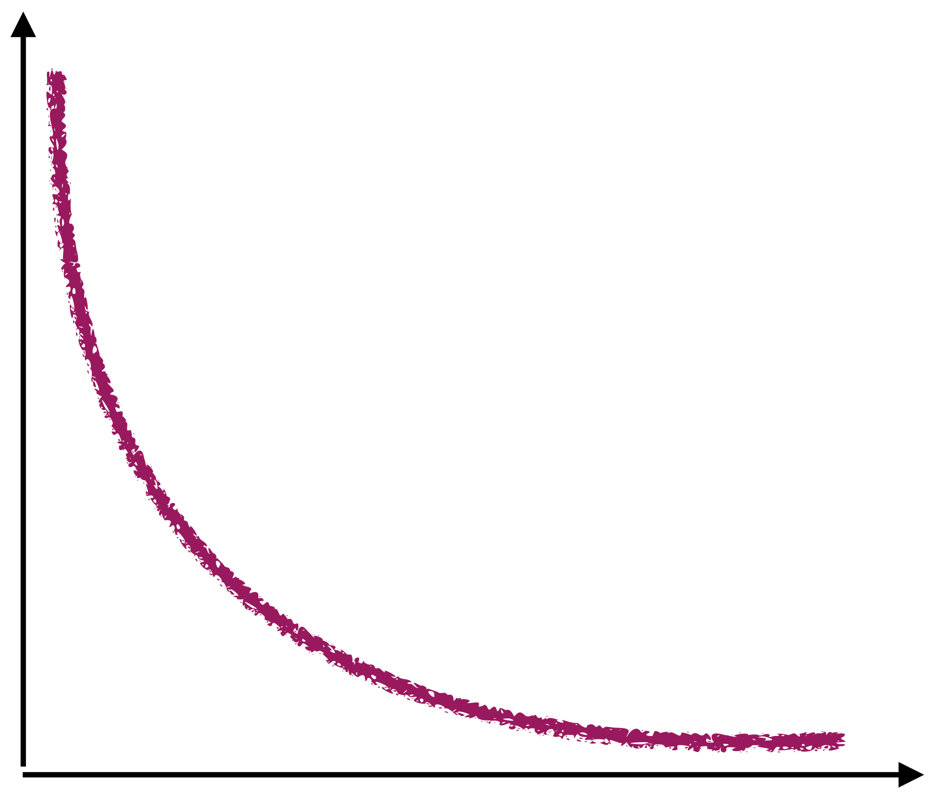
Multi-scale

Intra/Inter-urban mobility

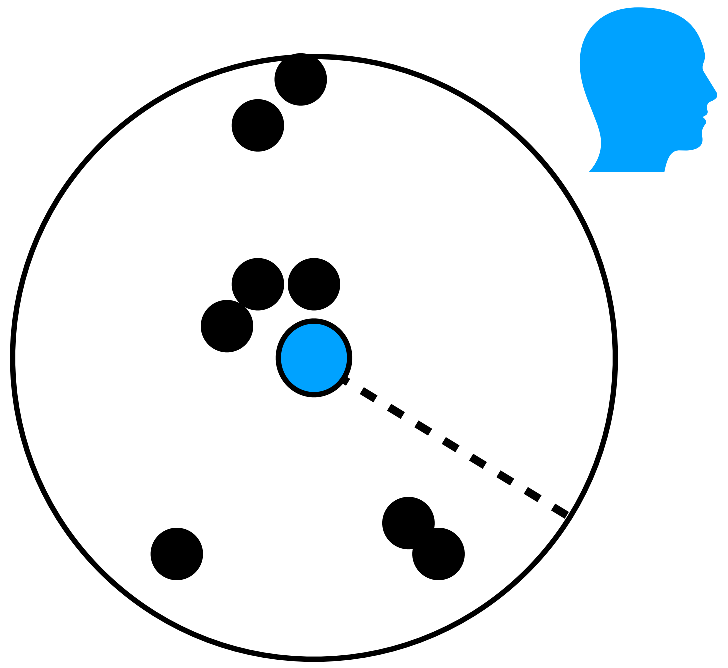
Epidemic spreading

Mobility patterns can be described by 3 indicators

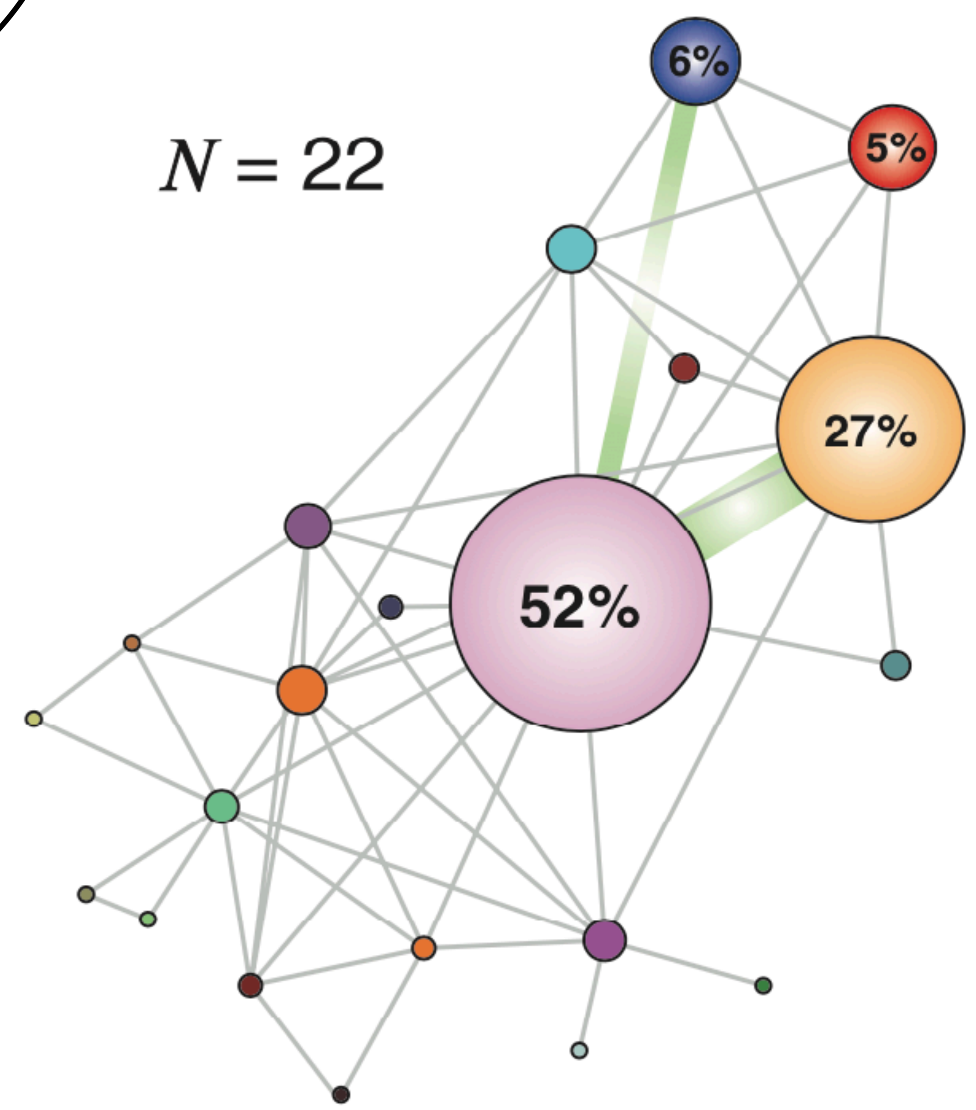
Trip distance distribution



Radius of gyration



Number of visited locations

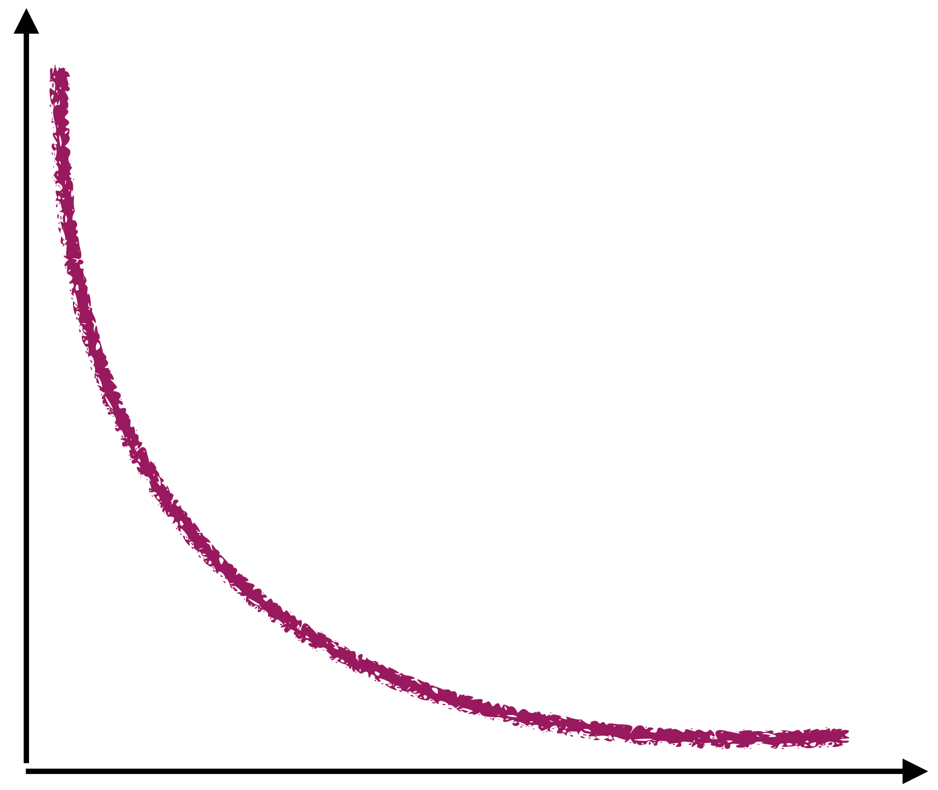


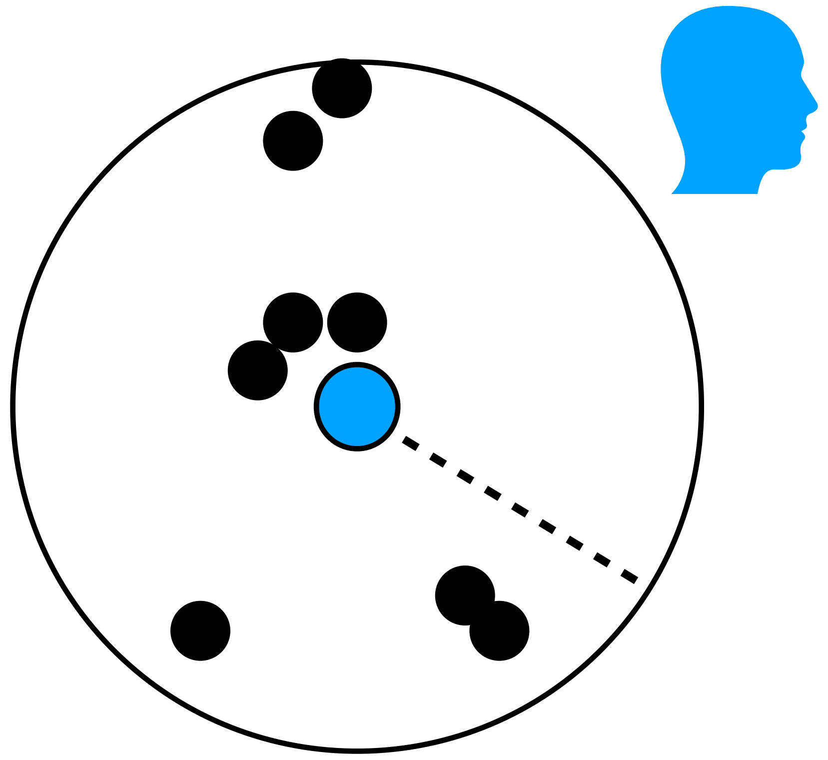
What is the value of your 3 indicators?

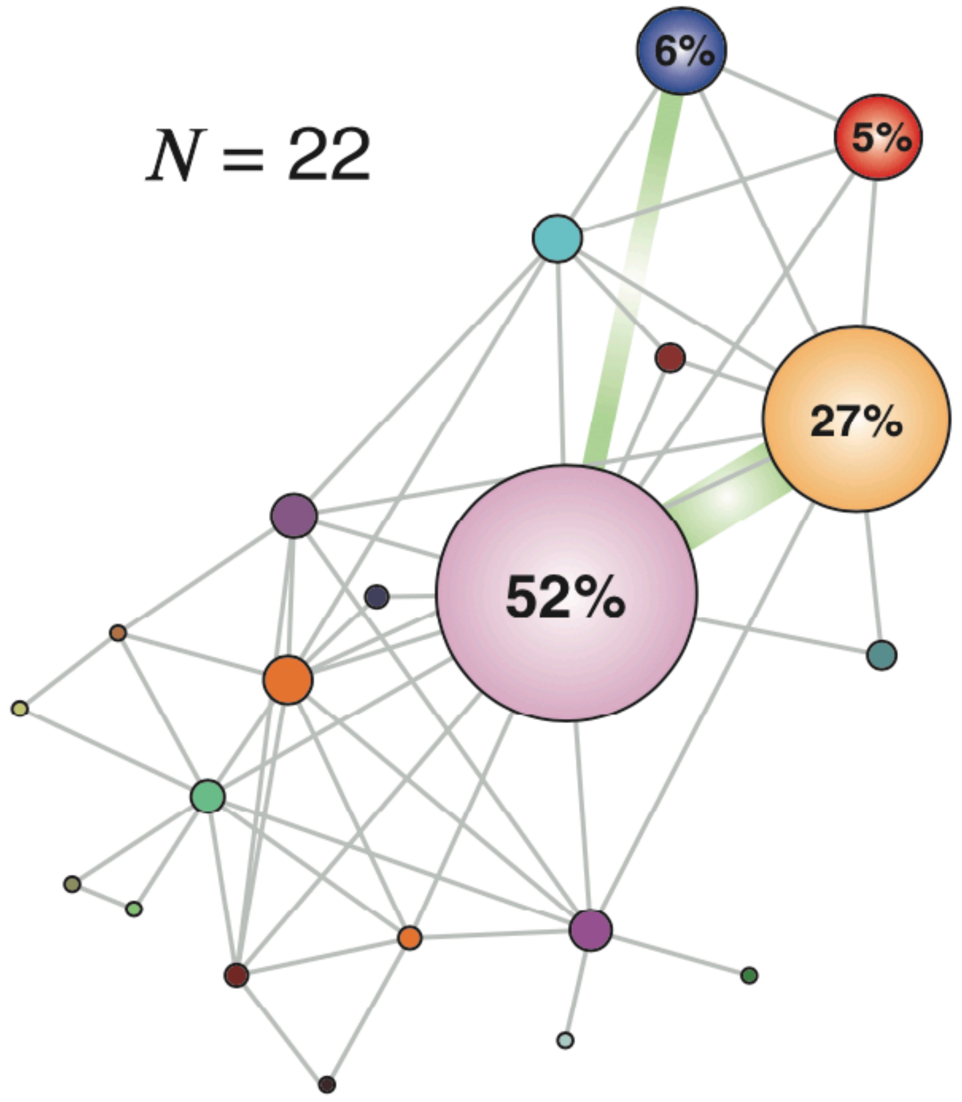
Discuss in groups:

- What do you estimate your **trip distribution, radius of gyration**, and **number of visited locations** to be?
  It can be for last week or your average week.

(5 mins.)





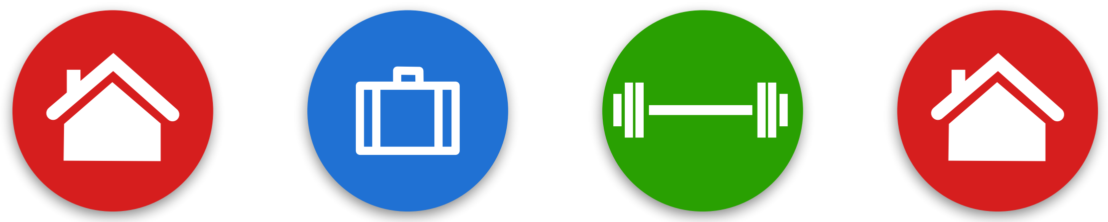


Individual mobility

Predictability of individual trajectories

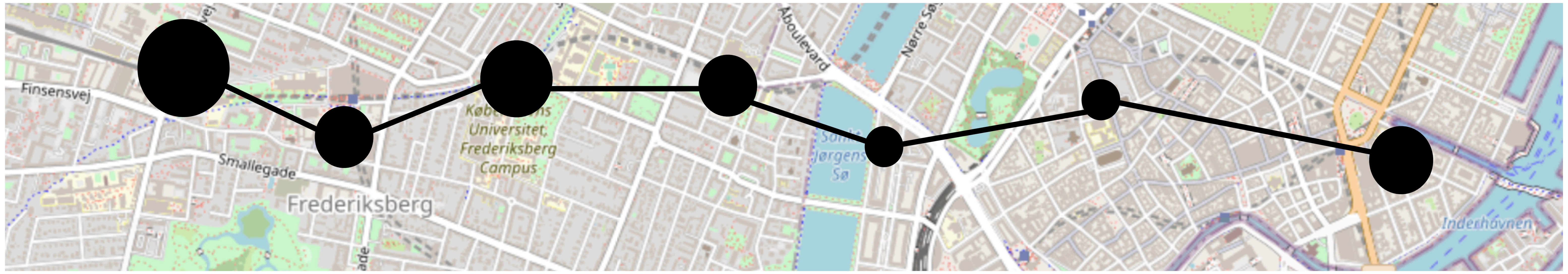
Trajectories

Sequence of locations

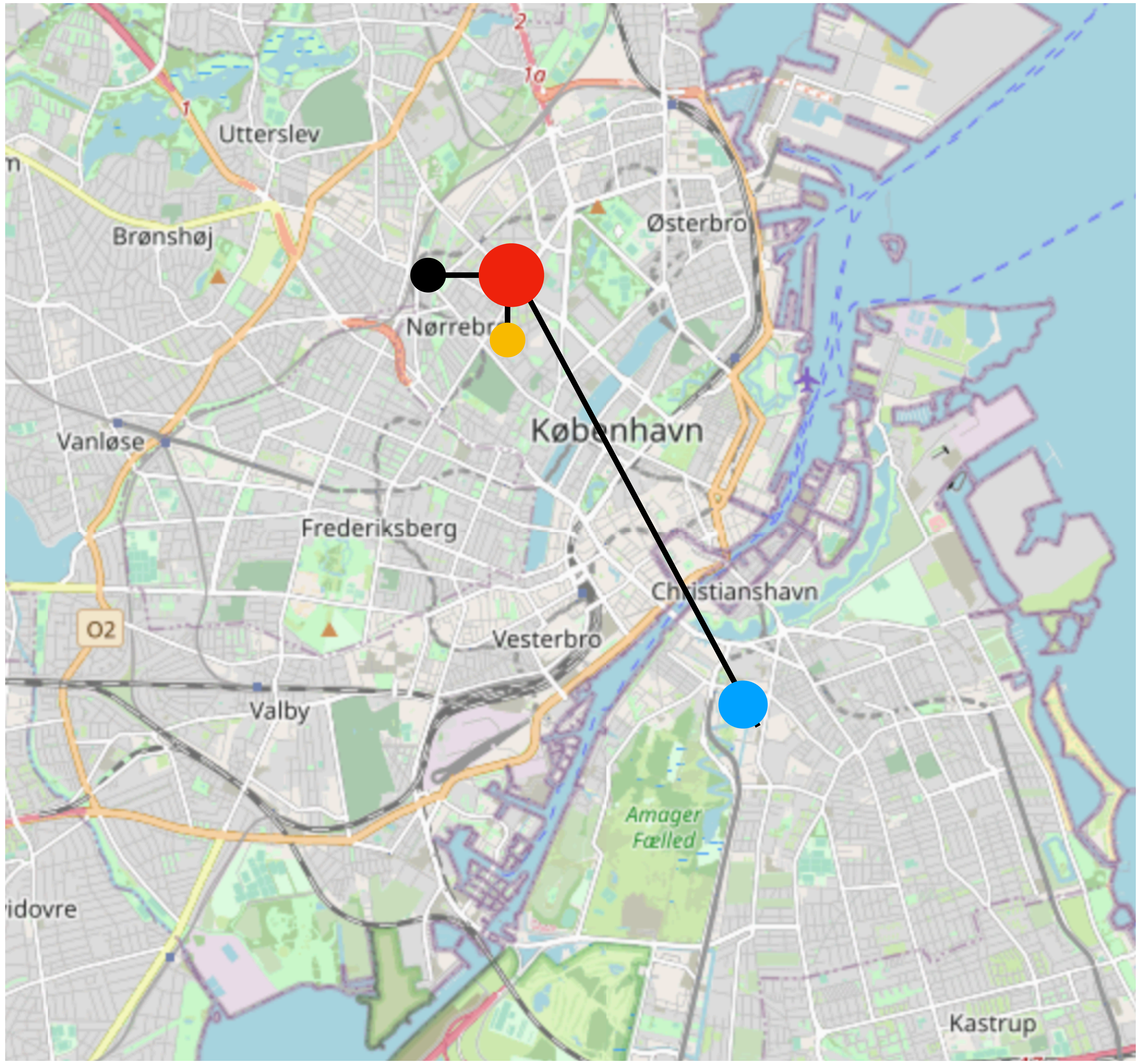


Sequence of locations embedded in space and time

High-frequency trajectories

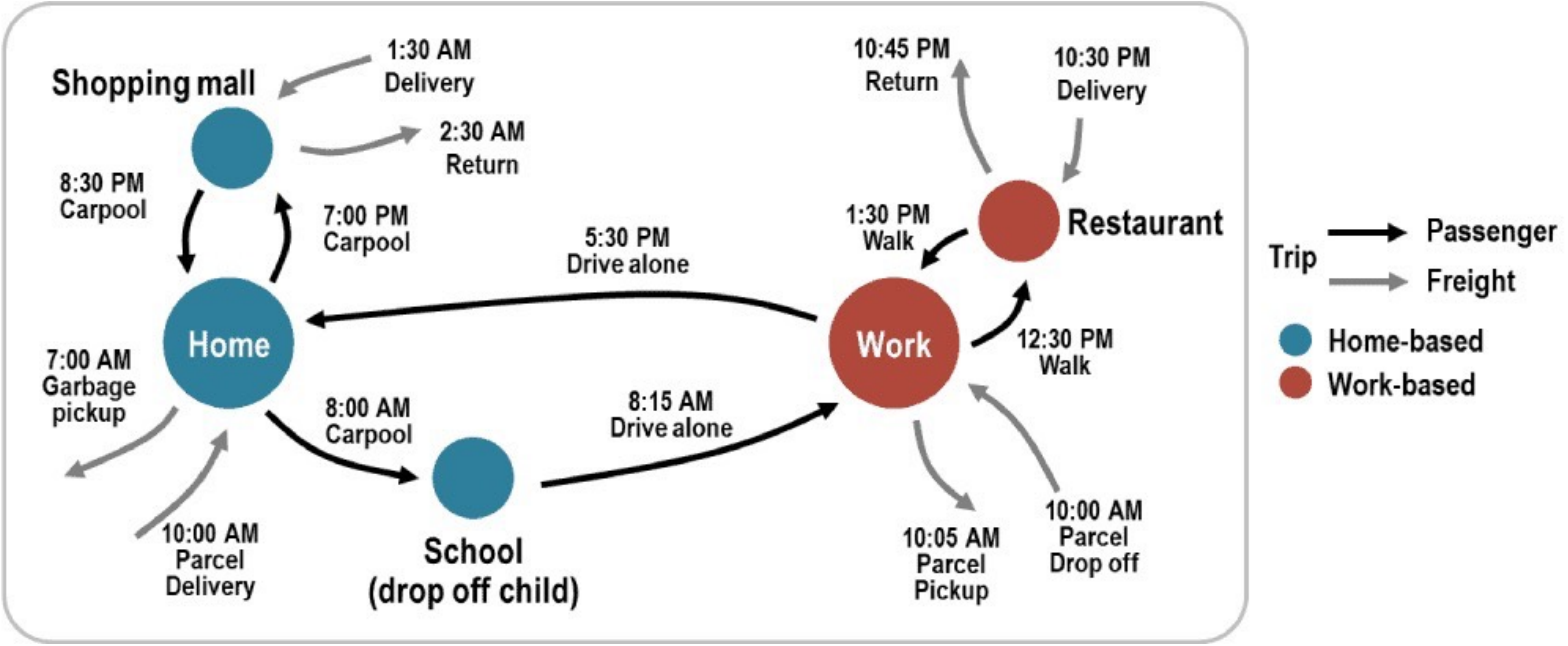


We have the option to visit many places in our lives…



…but are we actually doing it?

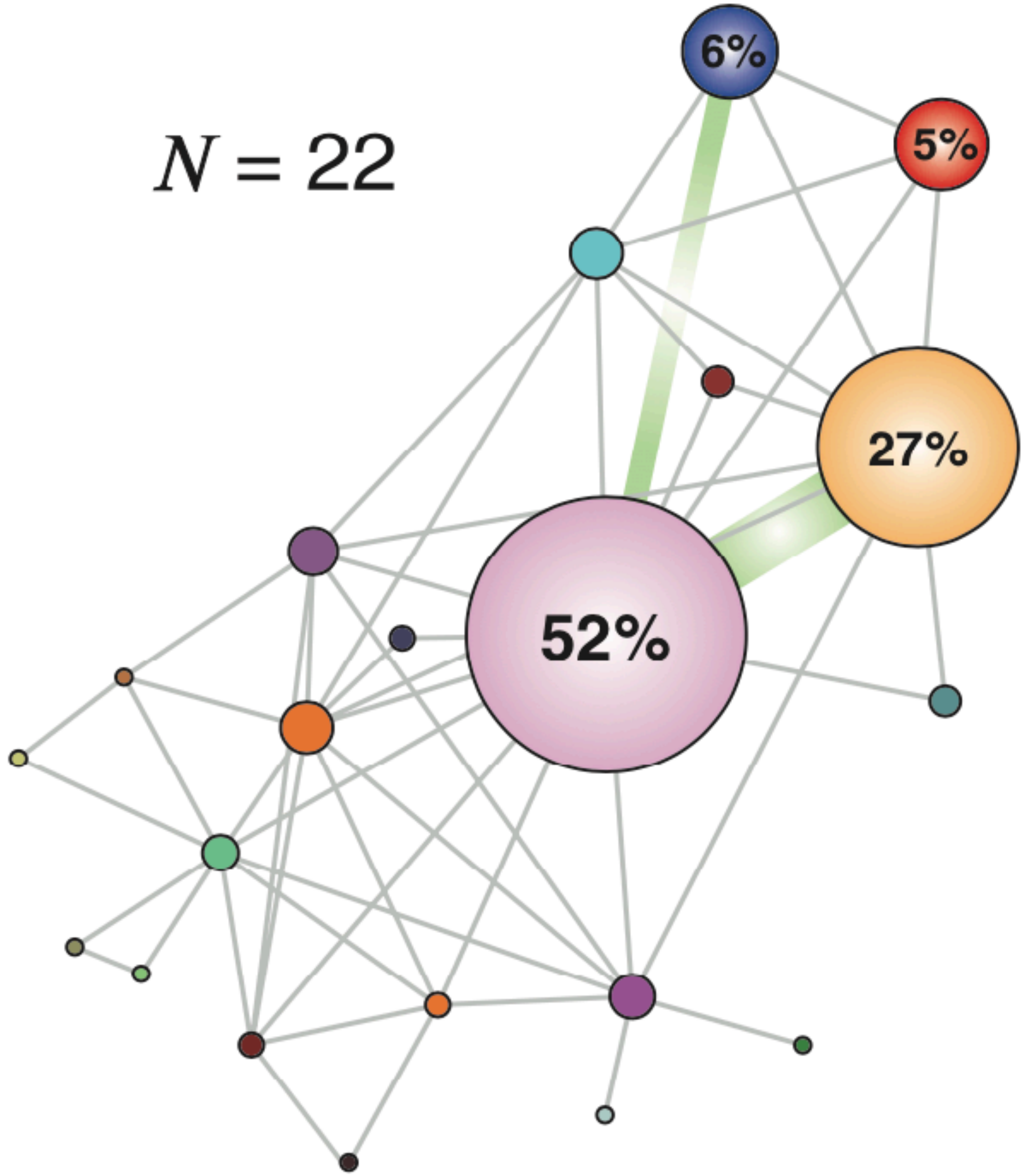
Anecdotally, we have very regular lives



How boring is our life, and what does that mean for predicting it?

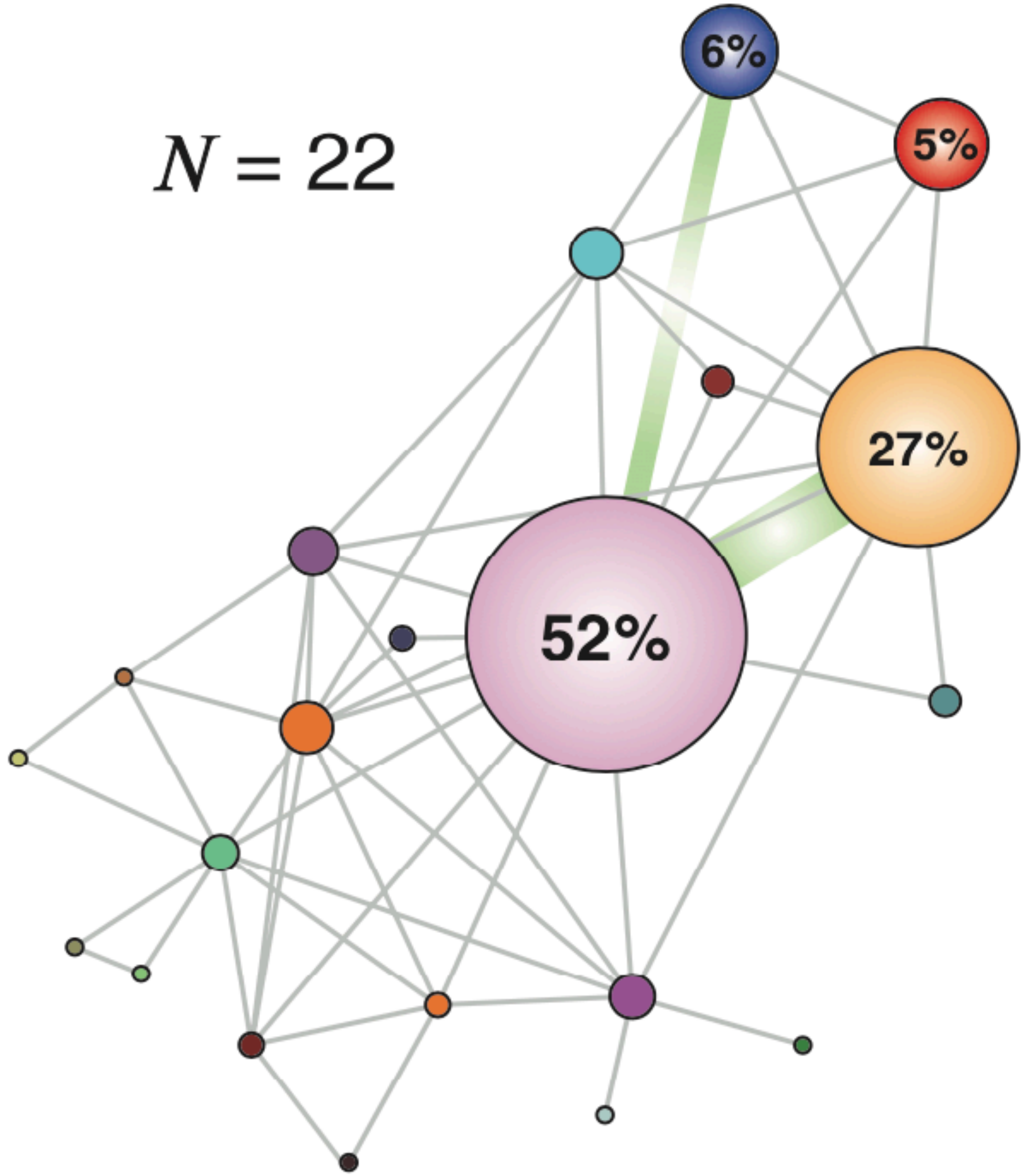
https://transportgeography.org/contents/chapter8/urban-mobility/activity-space-adult/

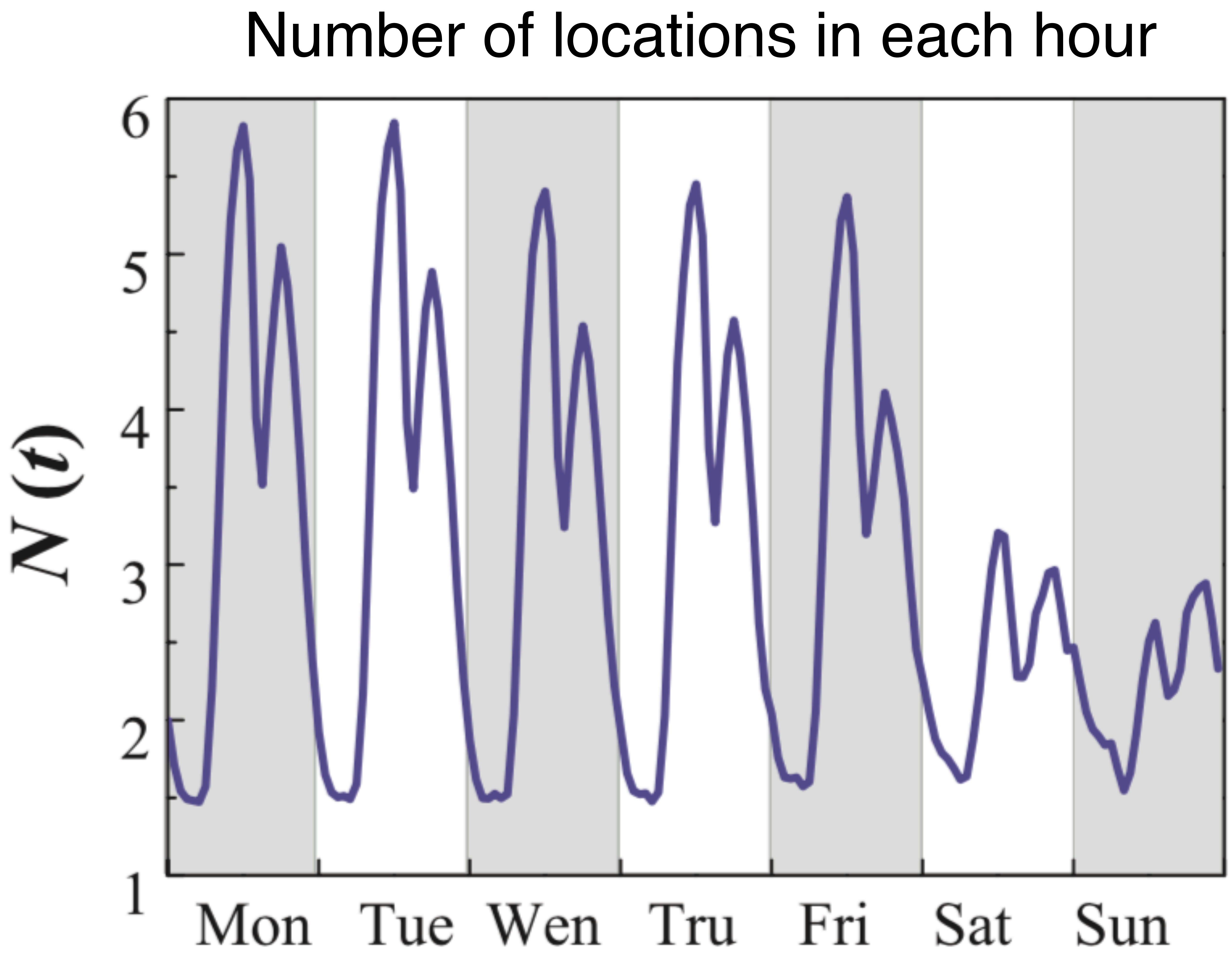
For most people, most visits are only to a few places



Limits of Predictability in Human Mobility https://www.science.org/doi/abs/10.1126/science.1177170

For most people, most visits are very regular





How can we quantify how easy it is to predict a next location?

Entropy

A measure for uncertainty, or randomness

Random entropy S^{rand}: How many unique places were visited?

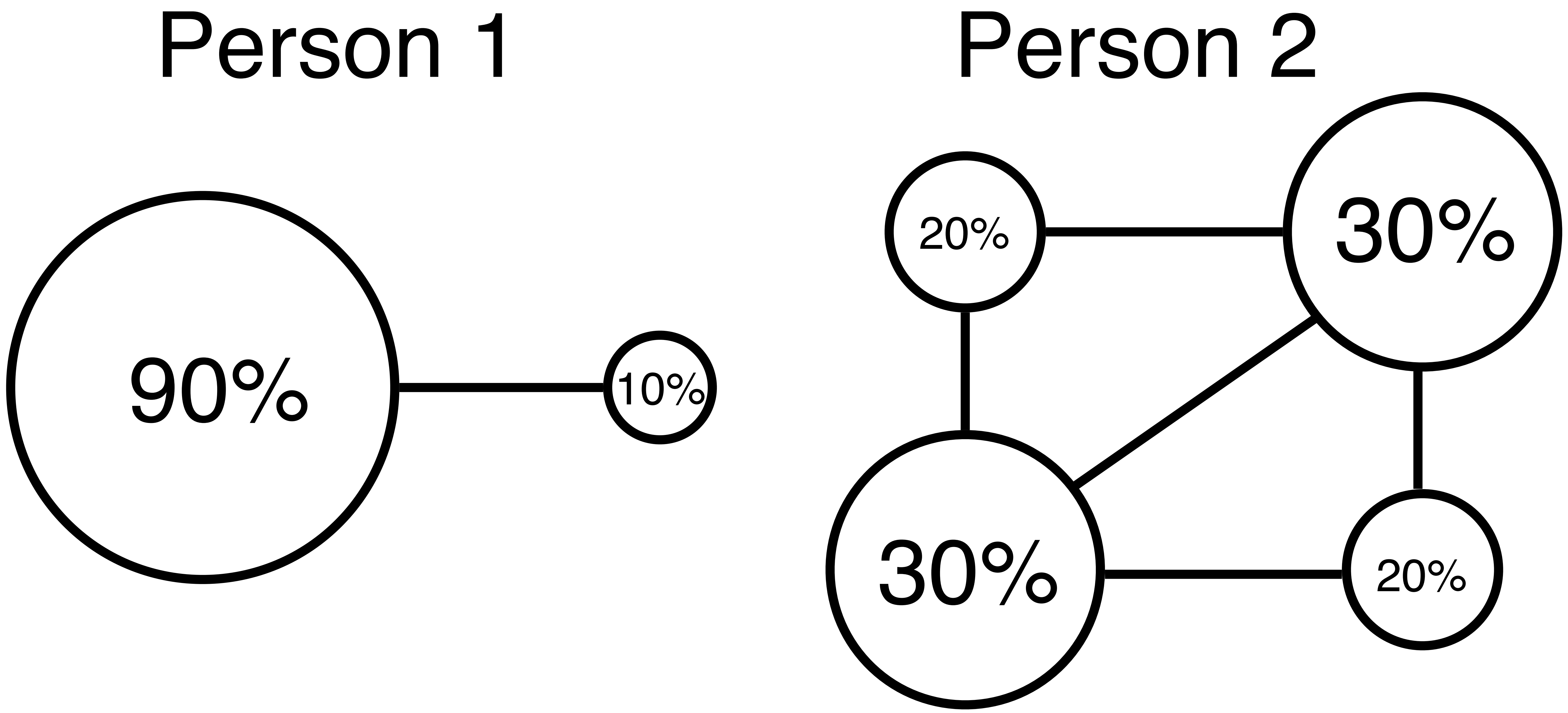
$$S_i^{\mathrm{rand}} = \log_2 N_i$$

Number of places visited

"S^{rand} captures the degree of predictability of the user's whereabouts if each location is visited with equal probability"

Random entropy S^{rand}: How many unique places were visited?

$$S_i^{\text{rand}} = \log_2 N_i$$



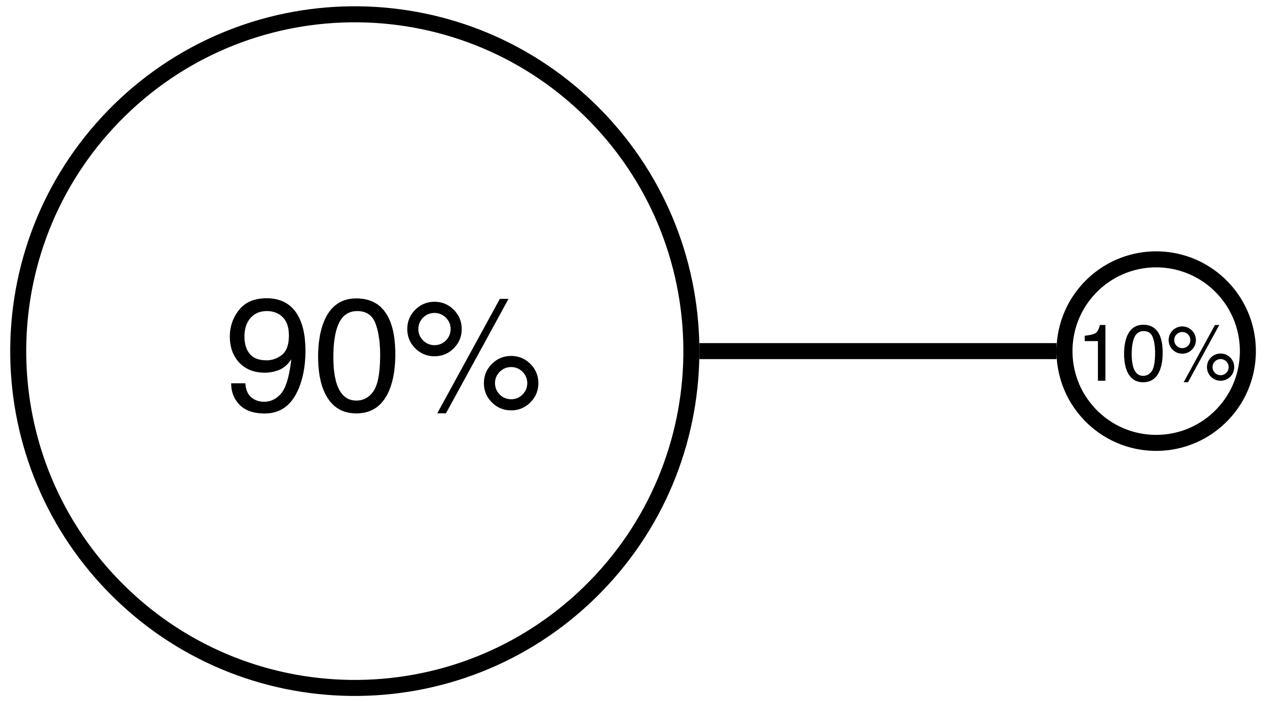
	Person 1	Person 2
S_i^{rand}	1	2

Temporal-uncorrelated entropy S^{unc}

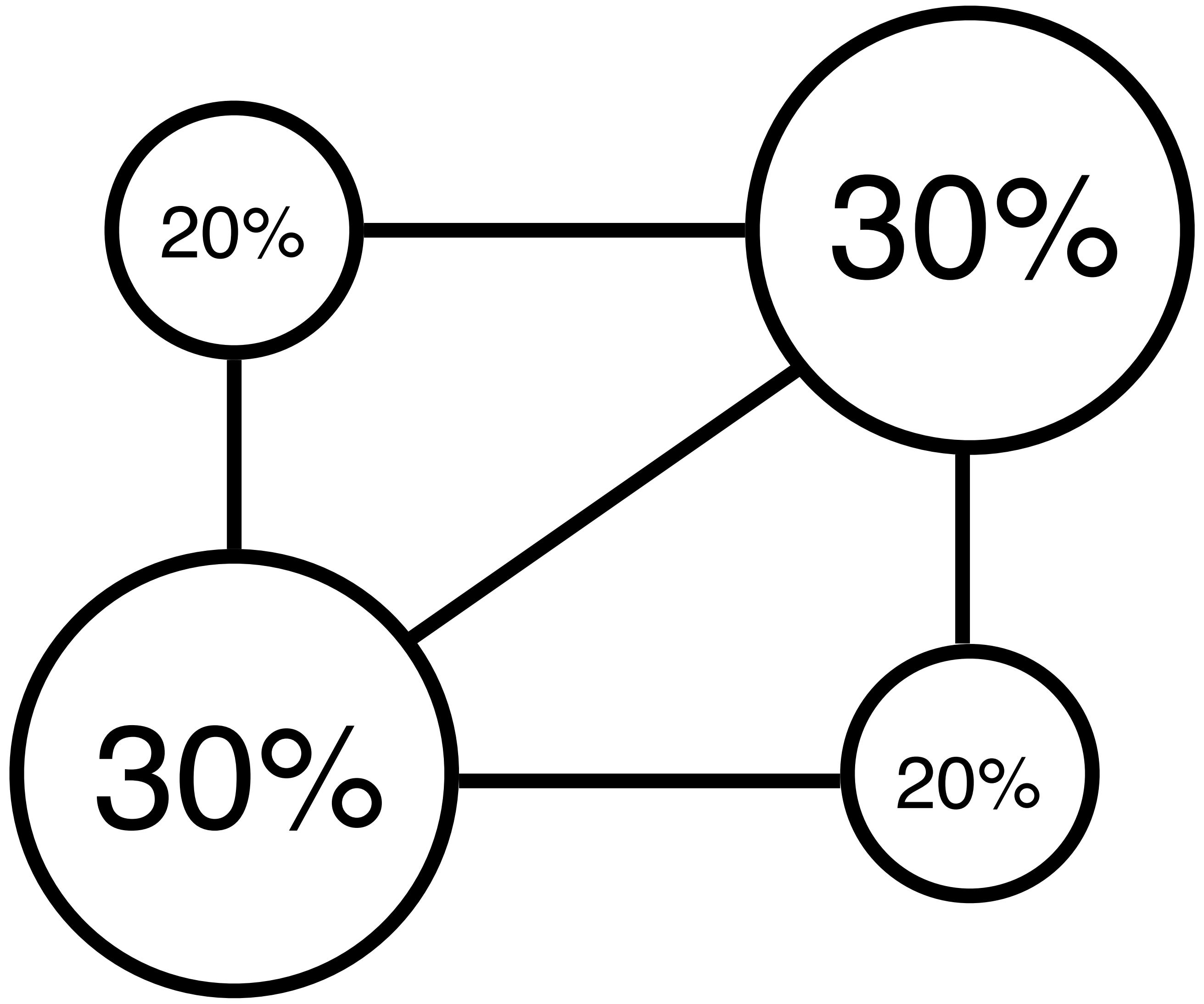
$$S_i^{\mathrm{unc}} = -\sum_{j=1}^{N_i} p_i(j)\log_2 p_i(j)$$

Historical probability of visiting location j

Person 1



Person 2

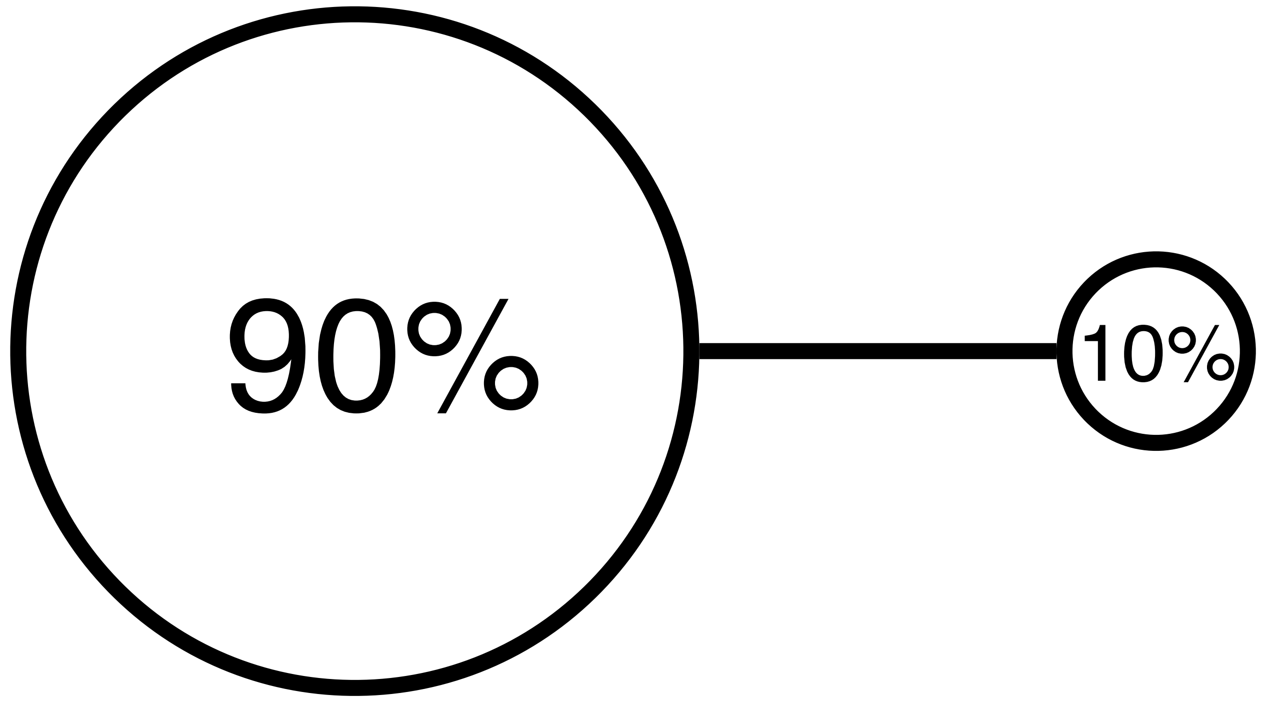


	Person 1	Person 2
S_i^{rand}	1	2

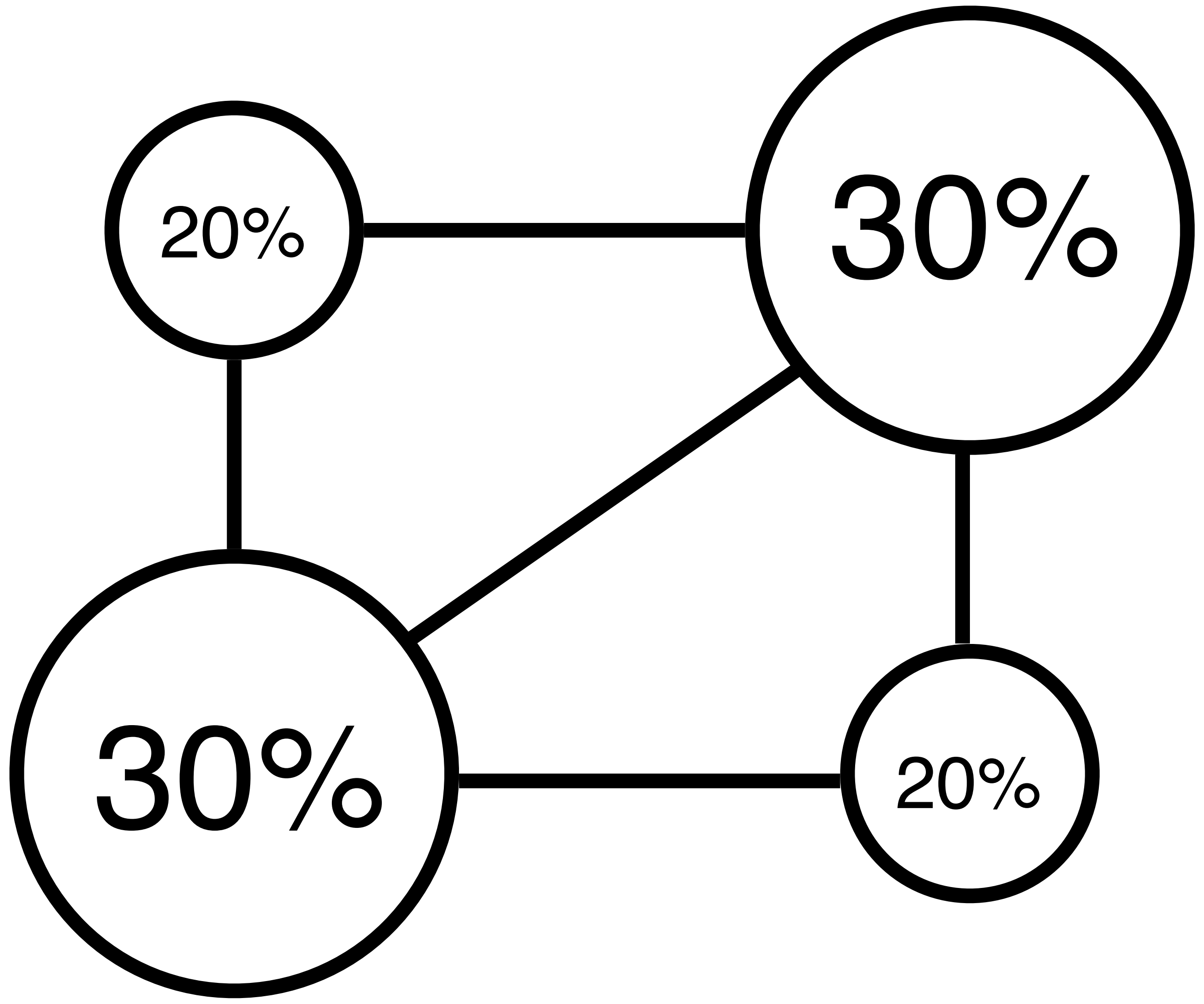
Temporal-uncorrelated entropy S^{unc}

$$S_i^{\mathrm{unc}} = -\sum_{j=1}^{N_i} p_i(j)\log_2 p_i(j)$$

Person 1



Person 2

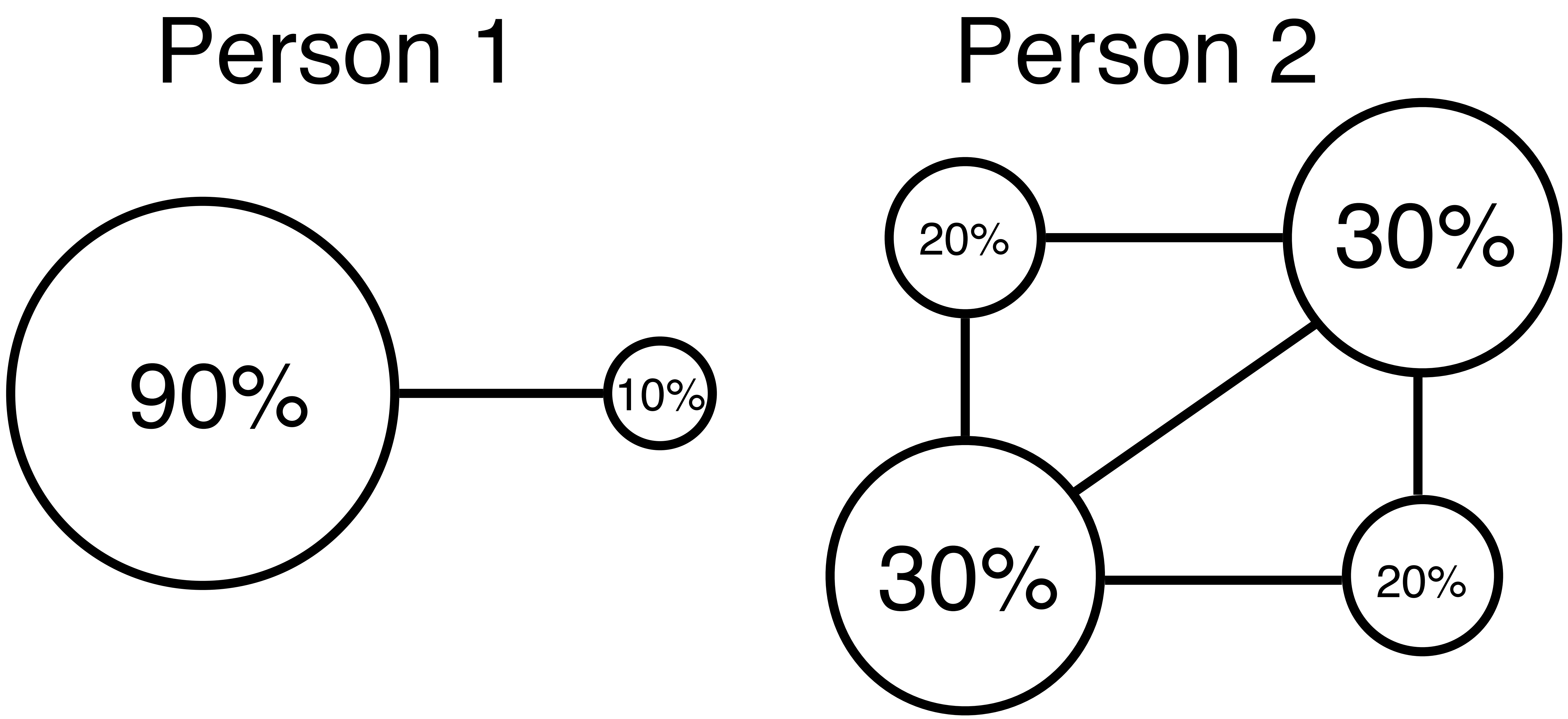


	Person 1	Person 2
S_i^{rand}	1	2
S_i^{unc}	0.469	1.971

Interpretation: Heterogeneity of visitation patterns

Temporal-uncorrelated entropy S^{unc}

$$S_i^{\mathrm{unc}} = -\sum_{j=1}^{N_i} p_i(j)\log_2 p_i(j)$$



	Person 1	Person 2
S_i^{rand}	1	2
S_i^{unc}	0.469	1.971

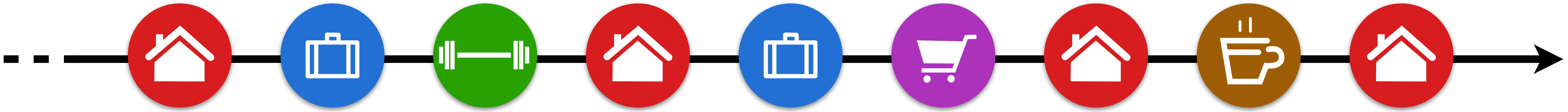
We get the maximum value $S^{\mathrm{unc}} = S^{\mathrm{rand}}$ when all locations are visited with equal probability

Entropy S: How heterogeneous were the visitations in space & time?

$$S_i = -\sum_{T_i' \subset T_i} P(T_i') \log_2 P(T_i')$$

probability of finding a particular time-ordered subsequence Ti′ in the trajectory

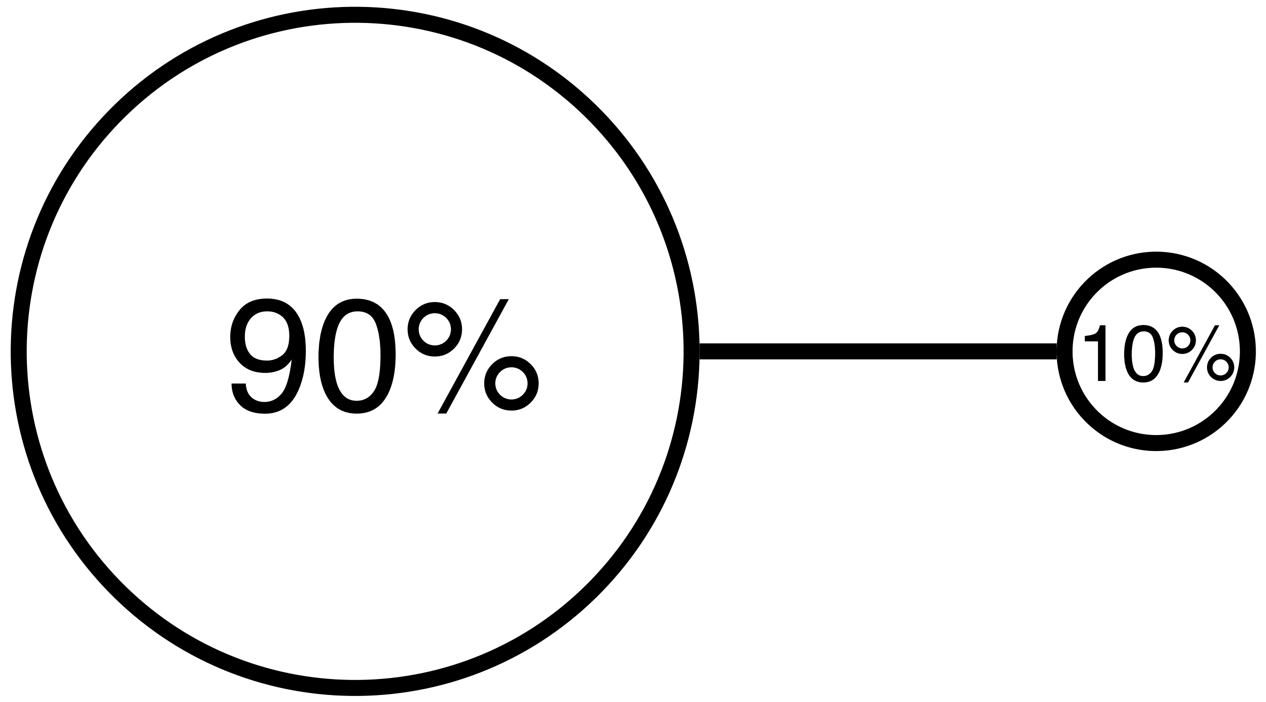
T_i



Entropy S: How heterogeneous were the visitations in space & time?

Person 1

$$S_i = -\sum_{T_i' \subset T_i} P(T_i') \log_2 P(T_i')$$

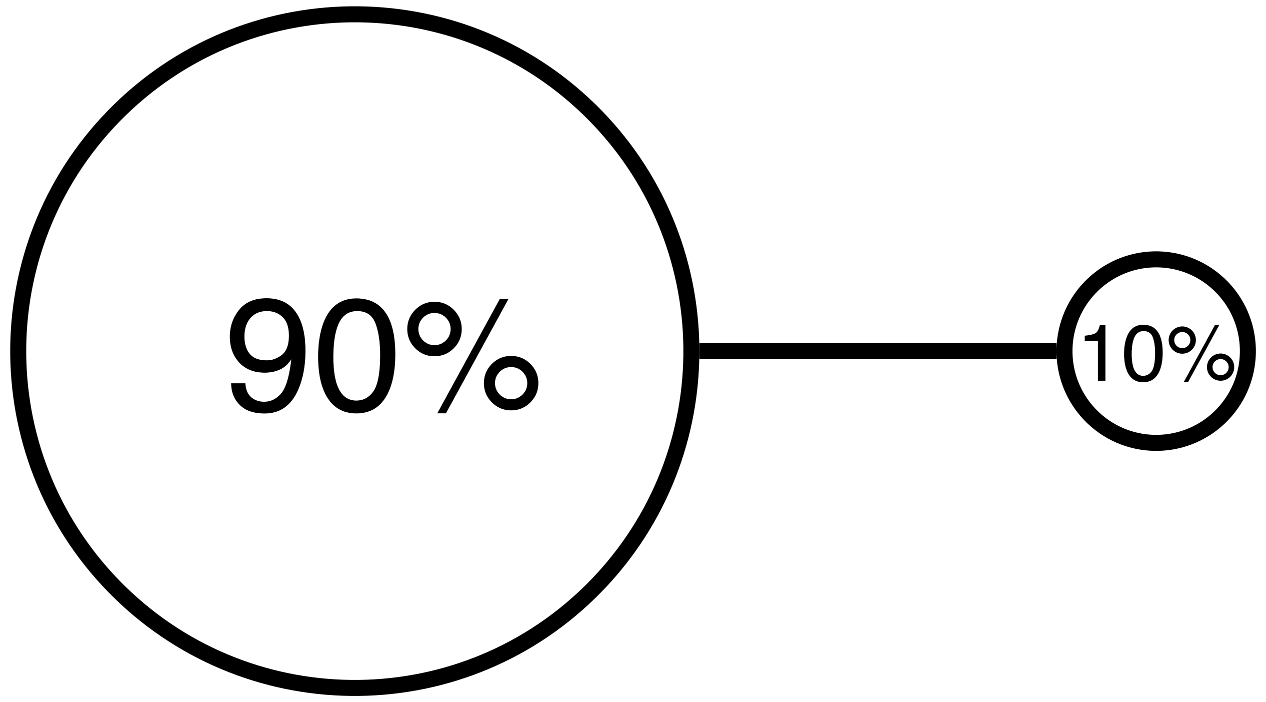


S_i^{rand}	1
S_i^{unc}	0.469
S_i	$\ll$ 0.469

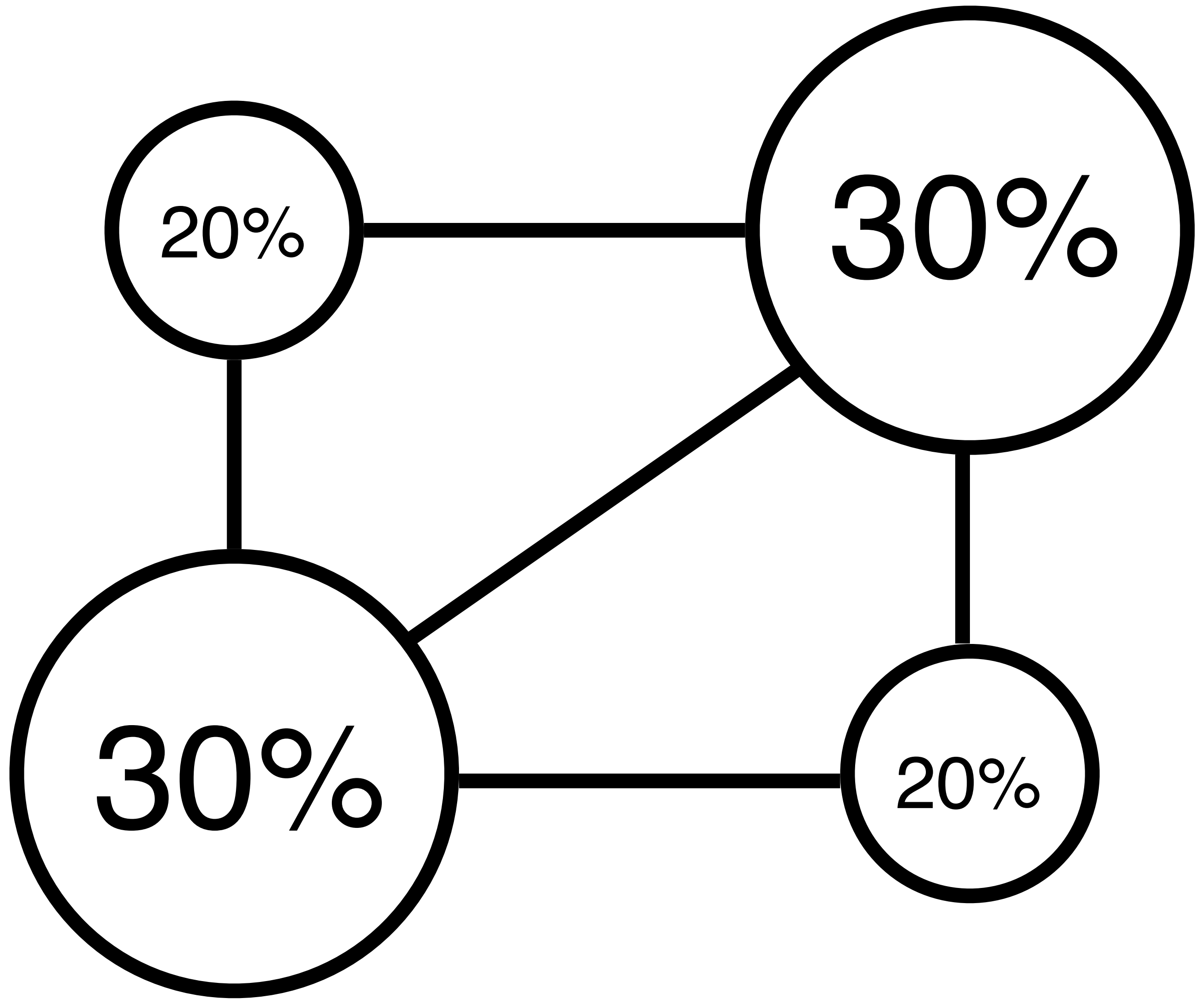
Entropy S: How heterogeneous were the visitations in space & time?

$$S_i = -\sum_{T_i' \subset T_i} P(T_i')\log_2 P(T_i')$$

Person 1



Person 2

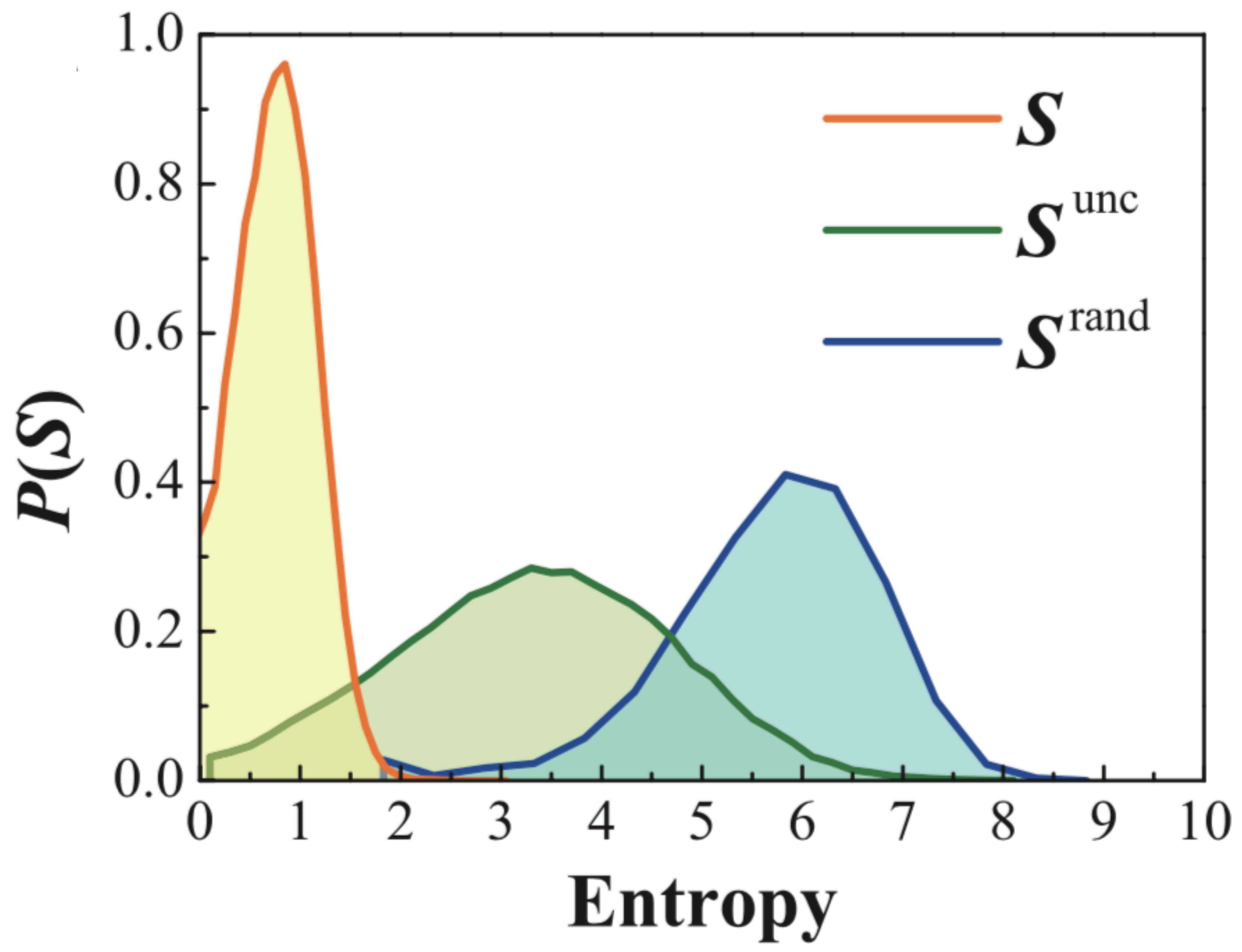


	Person 1	Person 2
S_i^{rand}	1	2
S_i^{unc}	0.469	1.971
S_i	$\leq$ 0.469	$\leq$ 1.971

We get the maximum value $S = S^{\mathrm{unc}}$ when the probability of the next location is independent of the current one

Accounting for more information reduces the entropy

$$S \leq S^{\mathrm{unc}} \leq S^{\mathrm{rand}}$$



https://www.science.org/doi/10.1126/science.1177170

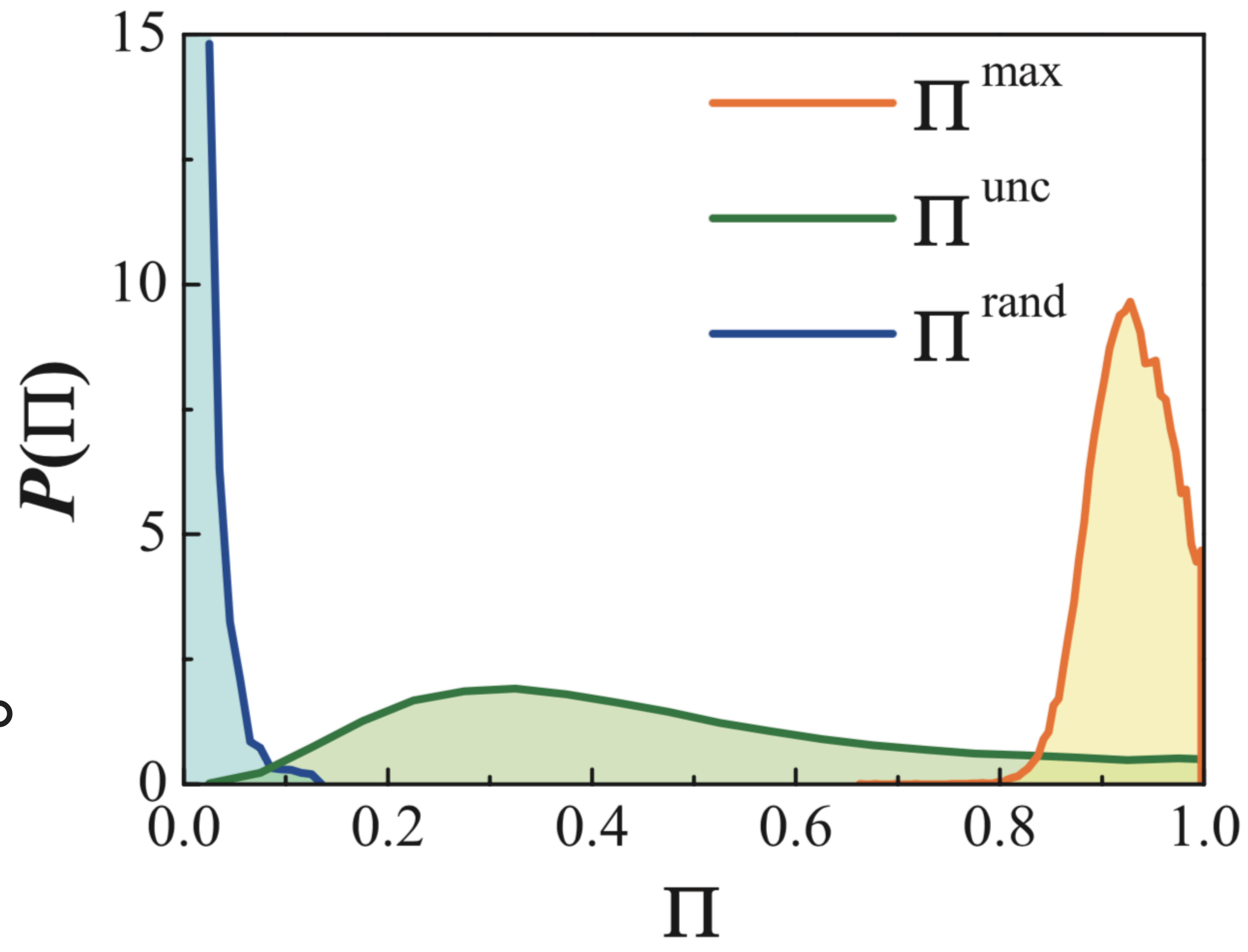
Accounting for more information increases predictability drastically

$$\Pi^{\mathrm{rand}} \leq \Pi^{\mathrm{unc}} \leq \Pi$$

A significant share of predictability is encoded in the temporal order of locations

93% of trips could be predicted

There is nobody with predictability below 80%

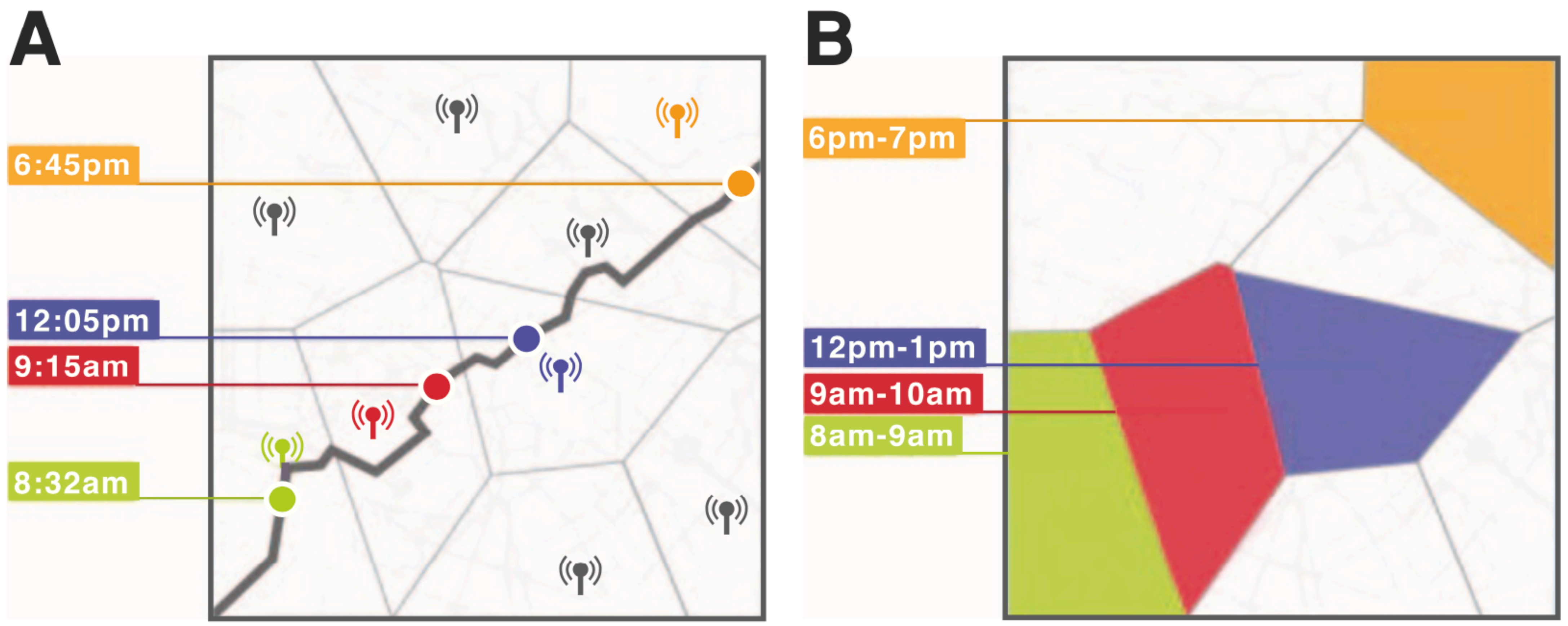


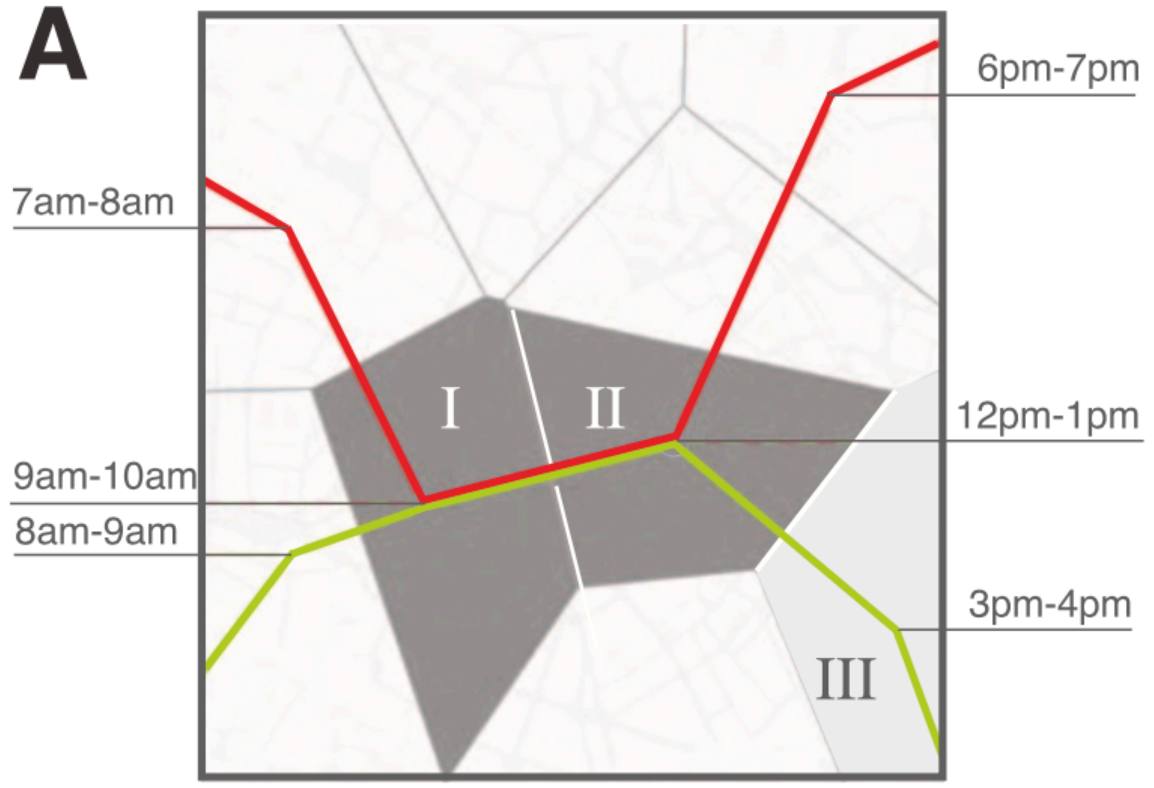
High predictability means low privacy

2013

15 months, 1.5 million people

6500 towers, 114 calls per month/user





With hourly aggregation,

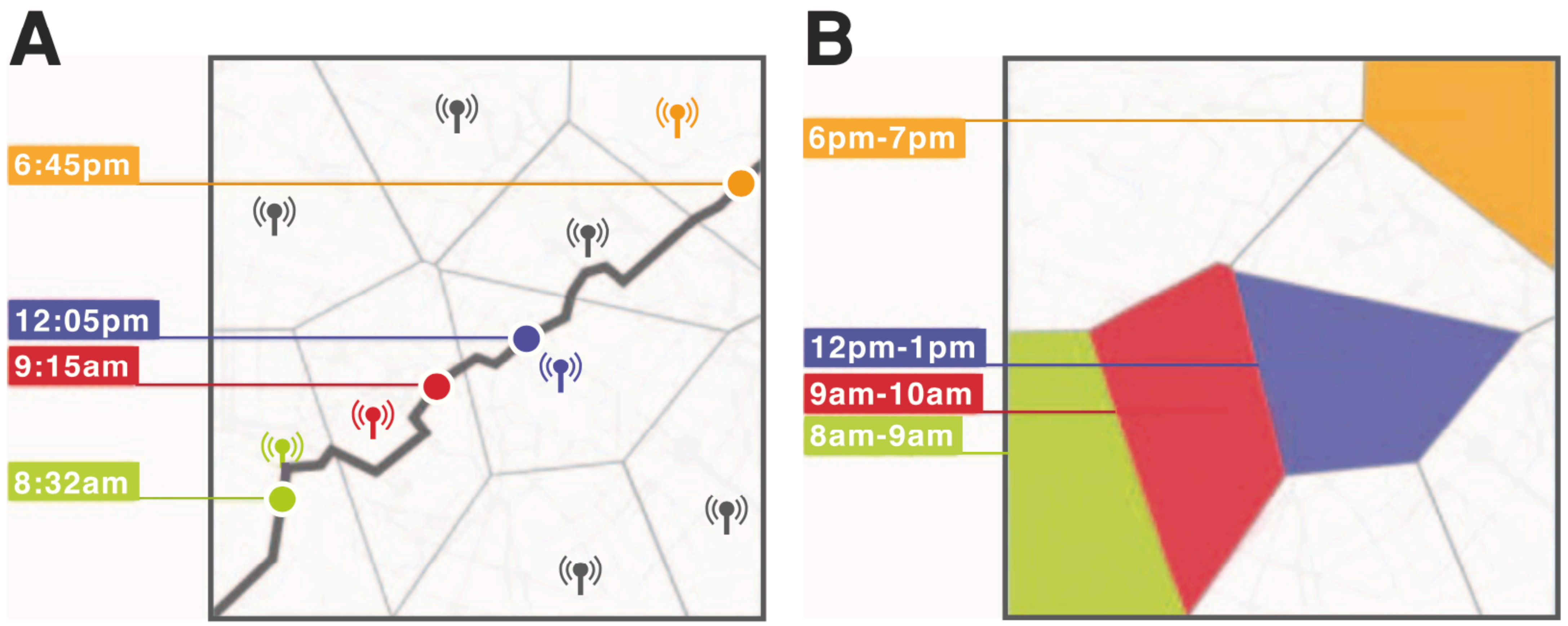
How many random spatiotemporal points are needed to identify 95% of users?

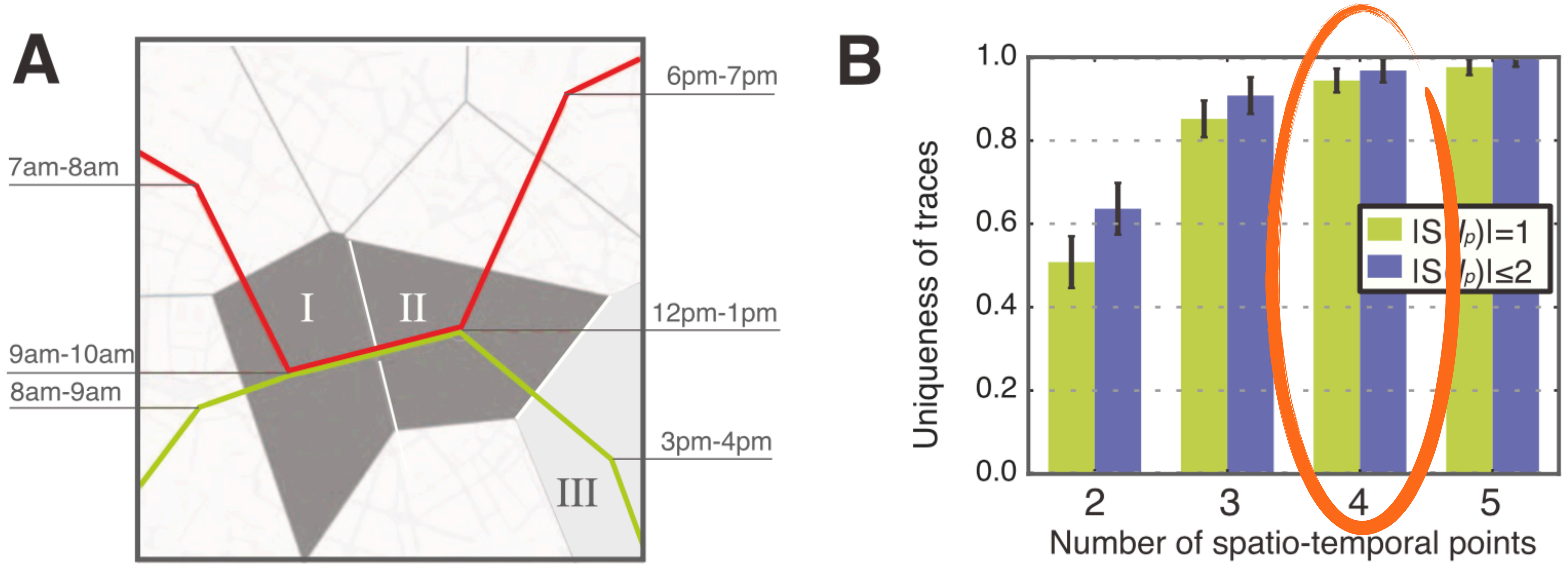
https://www.nature.com/articles/srep01376

High predictability means low privacy

15 months, 1.5 million people

6500 towers, 114 calls per month/user





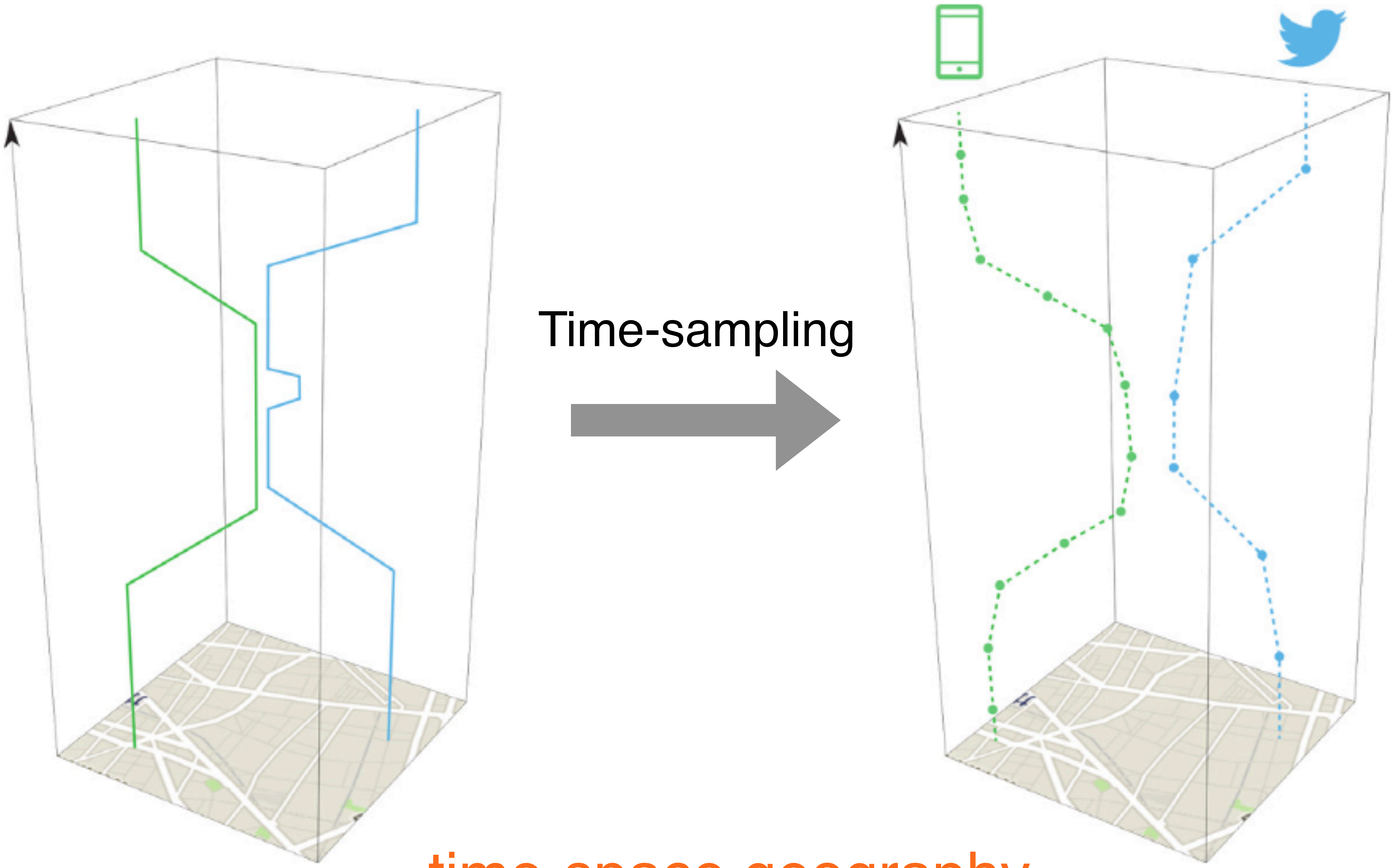
With hourly aggregation,

only **4** random spatiotemporal points are needed to identify 95% of users!

https://www.nature.com/articles/srep01376

Motifs & time-geography

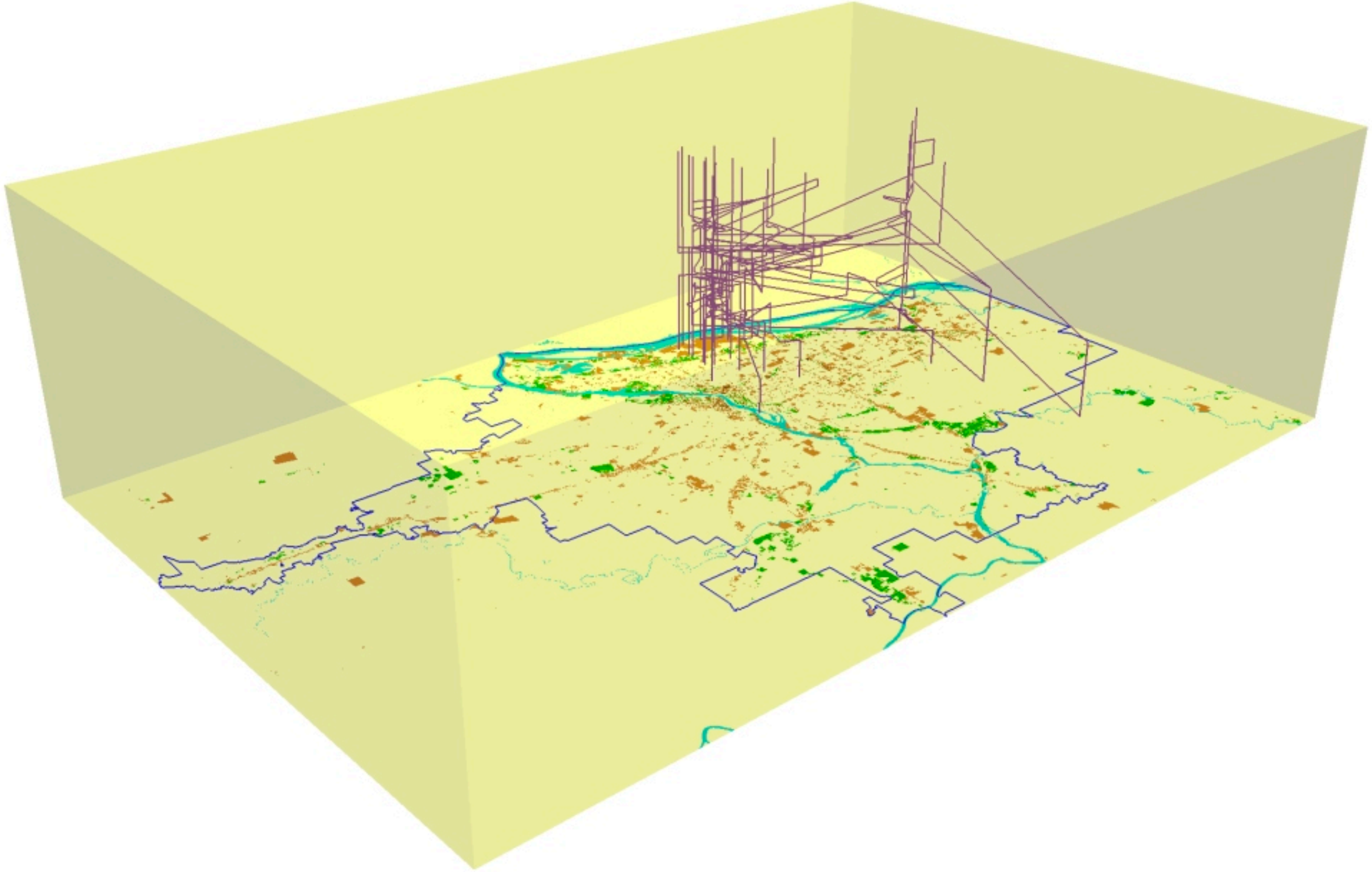
The cube of time geography shows mobility in space-time



time-space geography

Hägerstrand (1970)

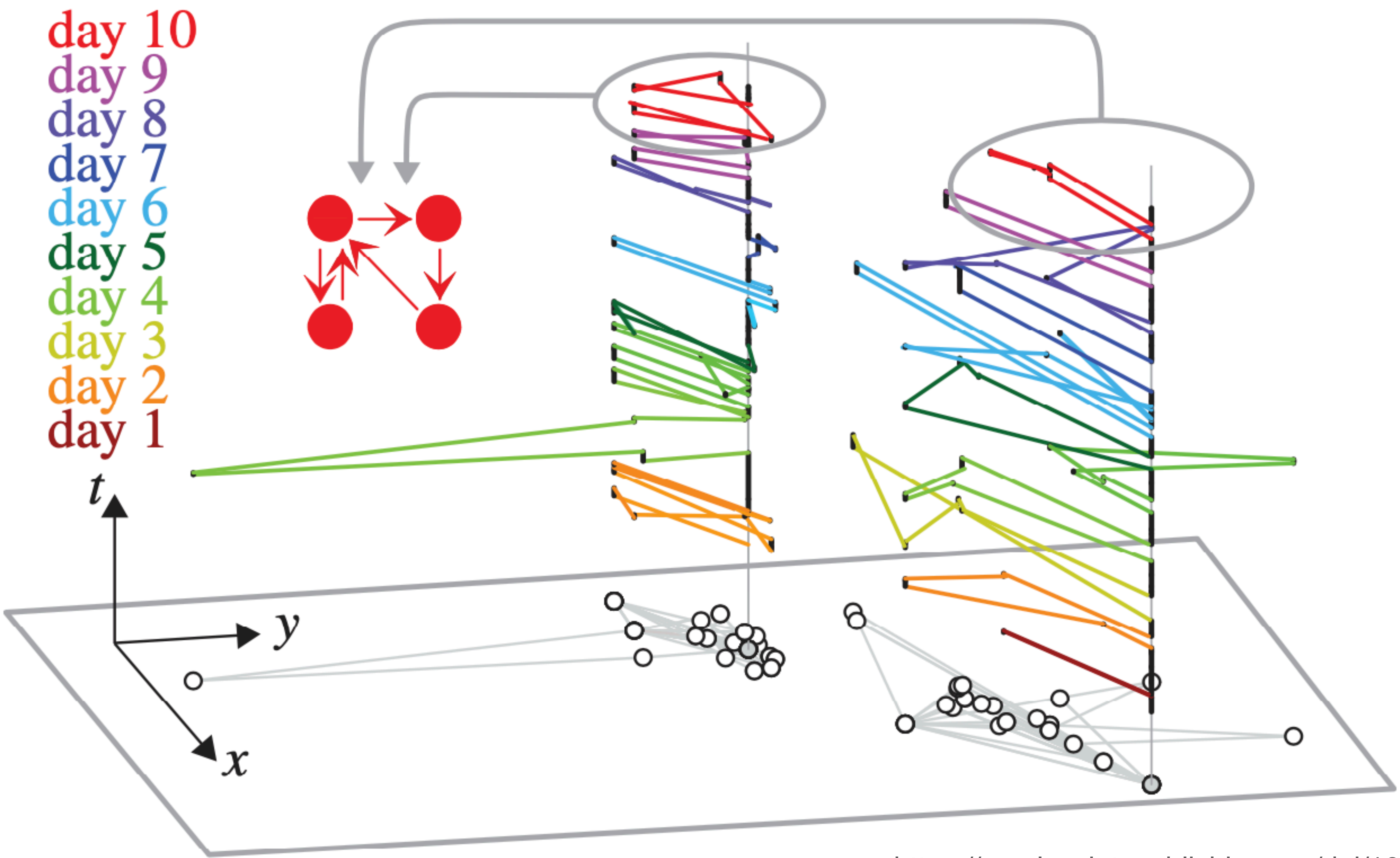
Time-space geographies can help us understand people's lives



Kwan 2002

We can now measure daily patterns: motifs

2013

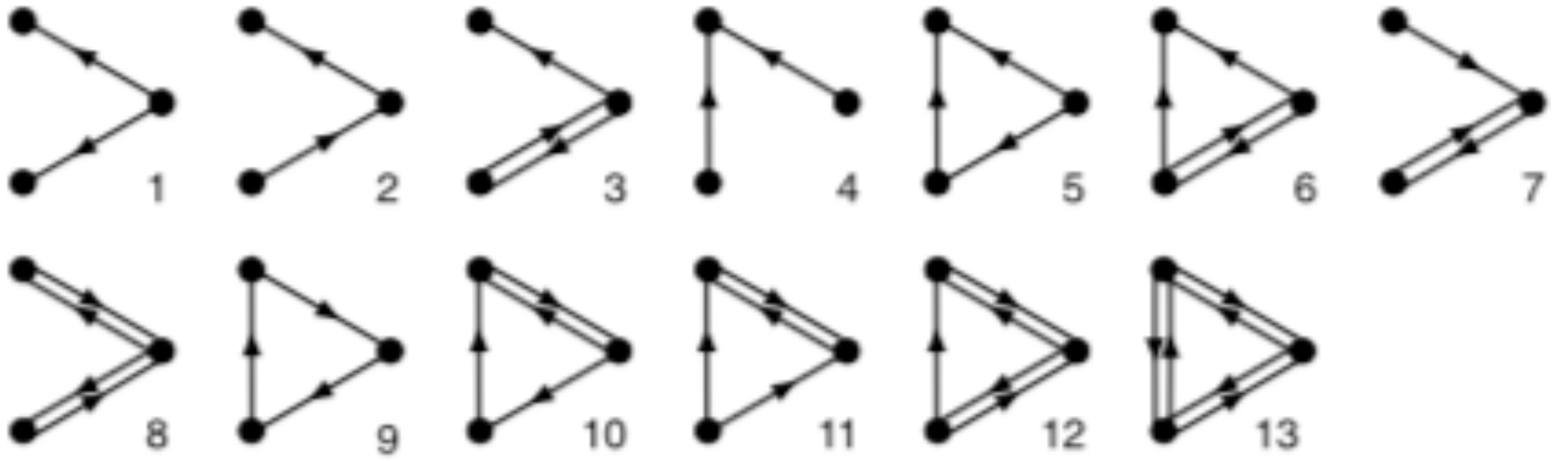


https://royalsocietypublishing.org/doi/10.1098/rsif.2013.0246

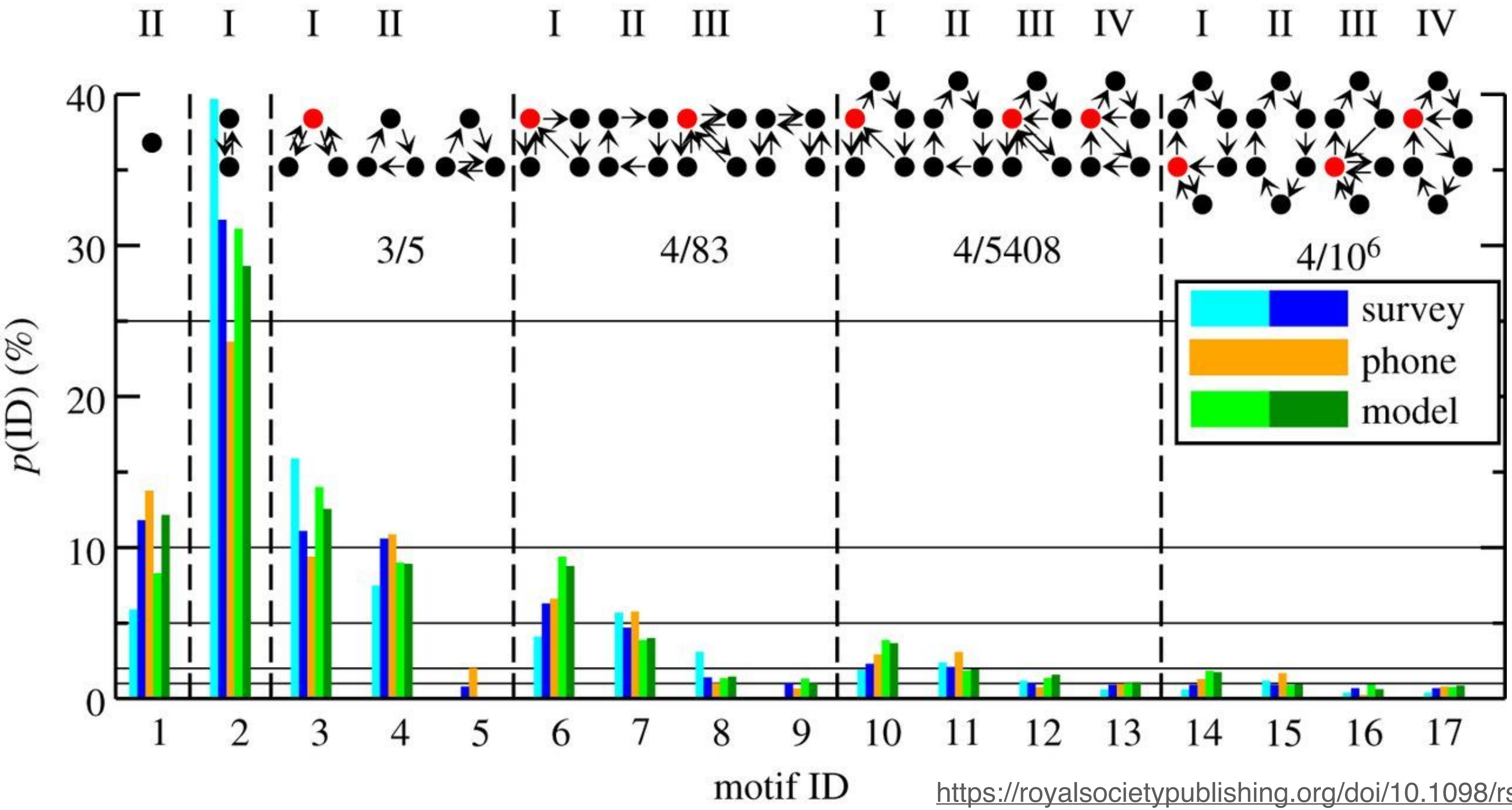
We can now measure daily patterns: motifs

A network motif is a recurrent and statistically significant sub-graph.

Motifs are usually small: 3-5 nodes

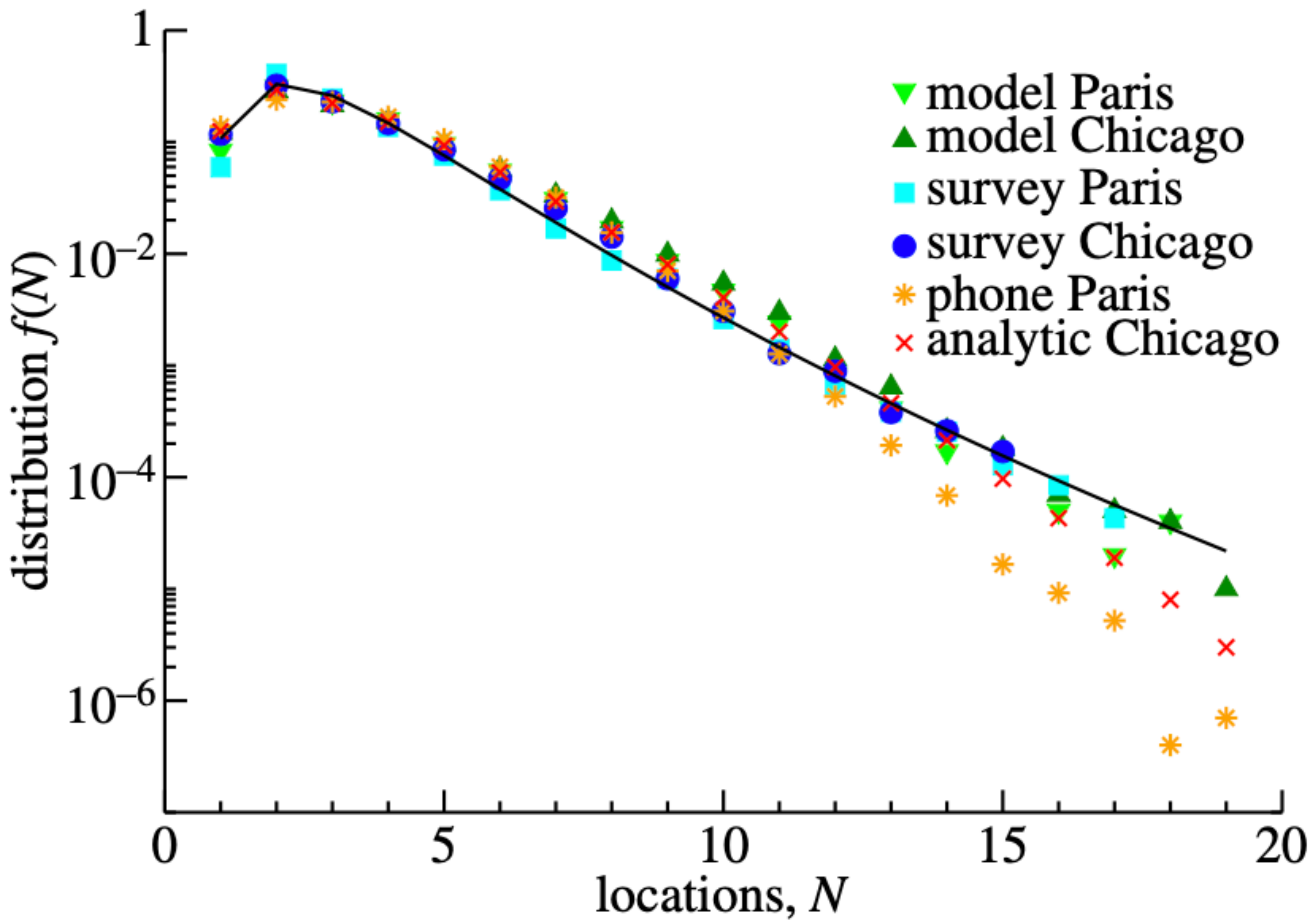


90% of movement can be described by only these 17 patterns



https://royalsocietypublishing.org/doi/10.1098/rsif.2013.0246

Most people do not visit more than 5 places per day



But some visit a lot

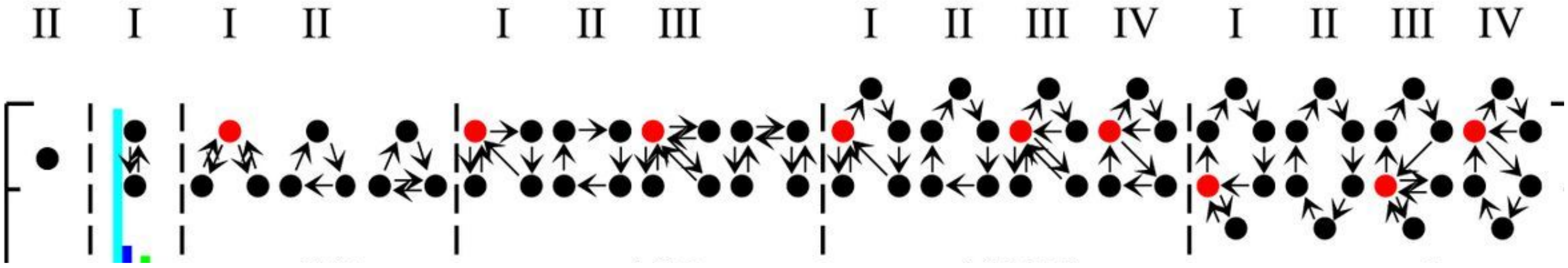
https://royalsocietypublishing.org/doi/10.1098/rsif.2013.0246

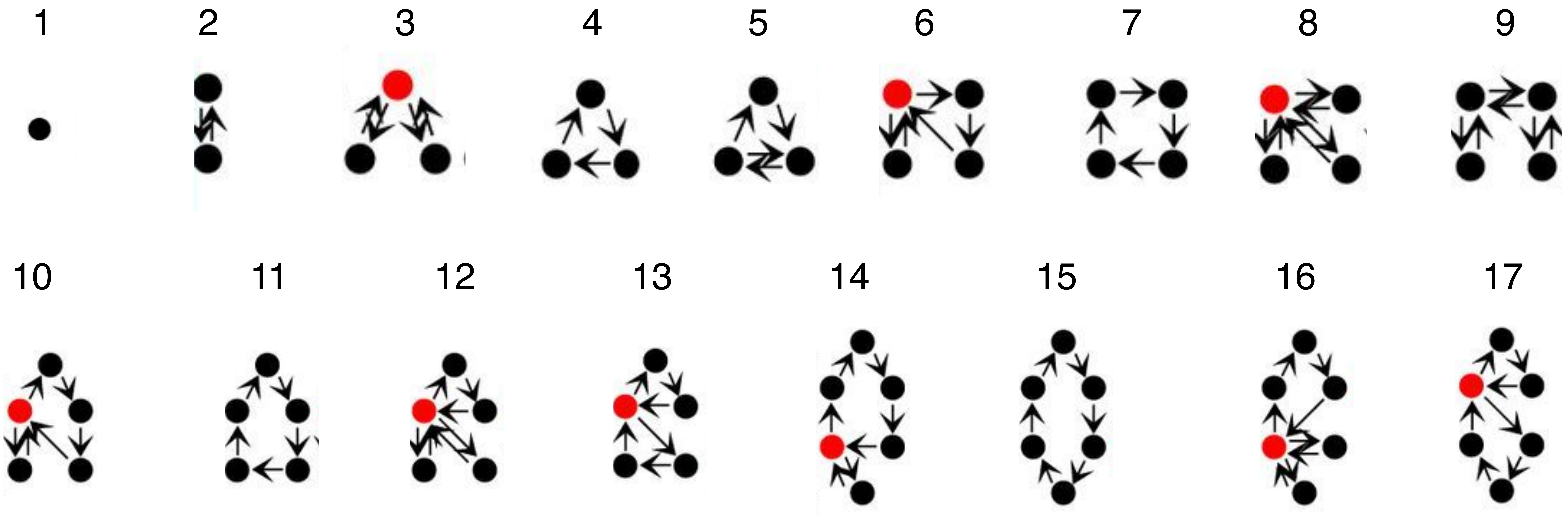
Which motif(s) describe your daily pattern?

Discuss in groups:

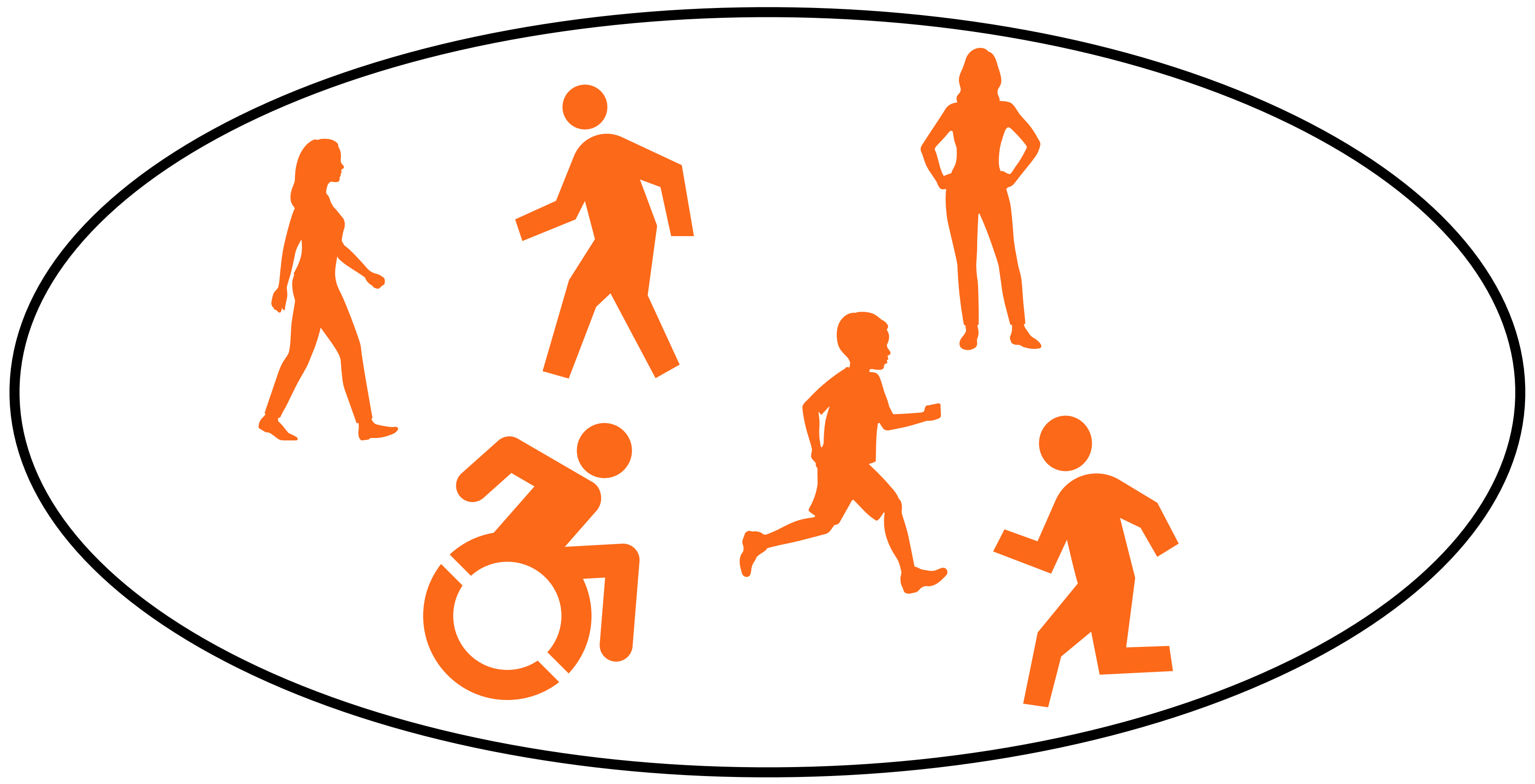
- Which motifs describe your typical mobility pattern?

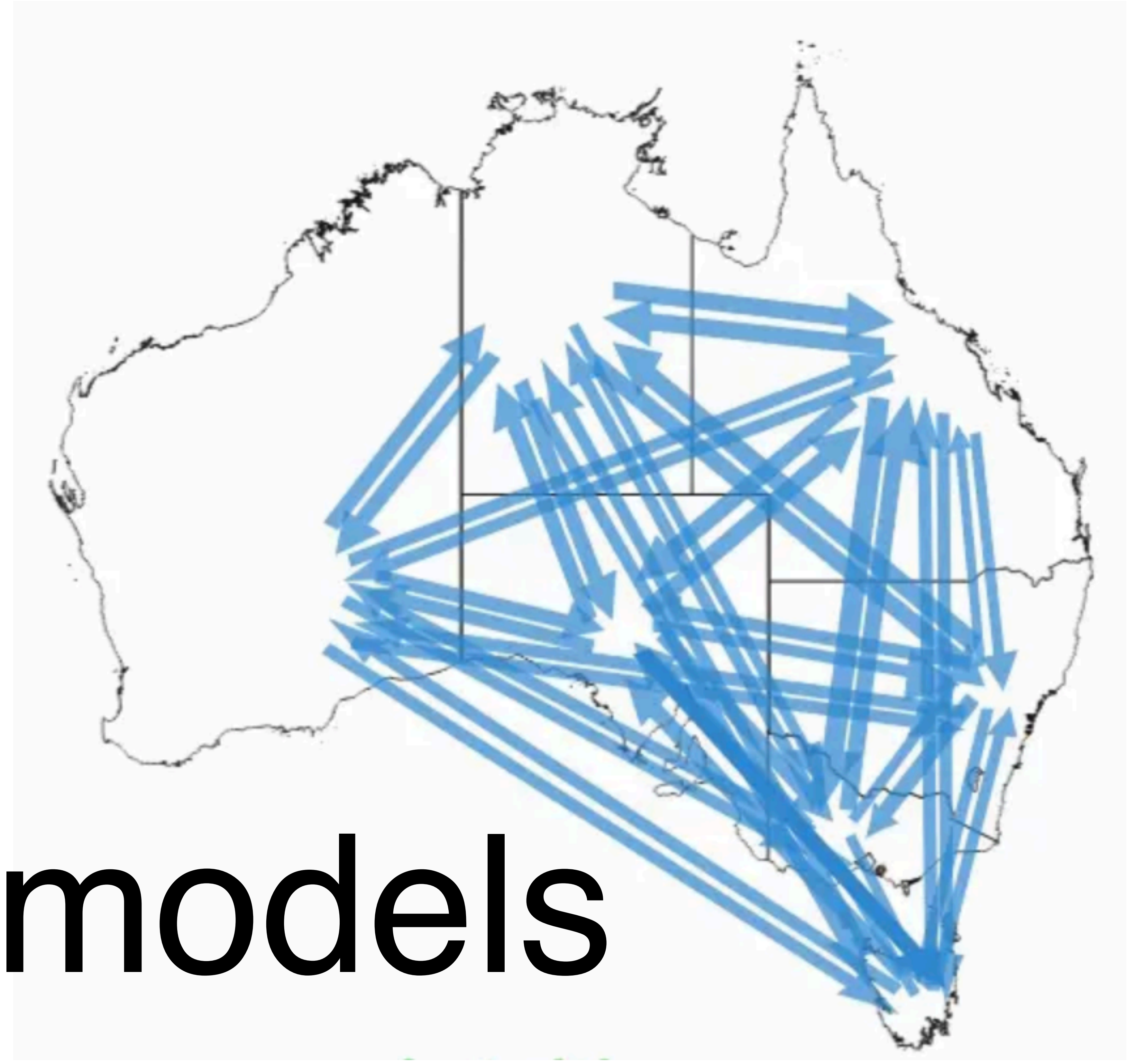
(5 mins. - pdf with motifs on LearnIT)




1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17

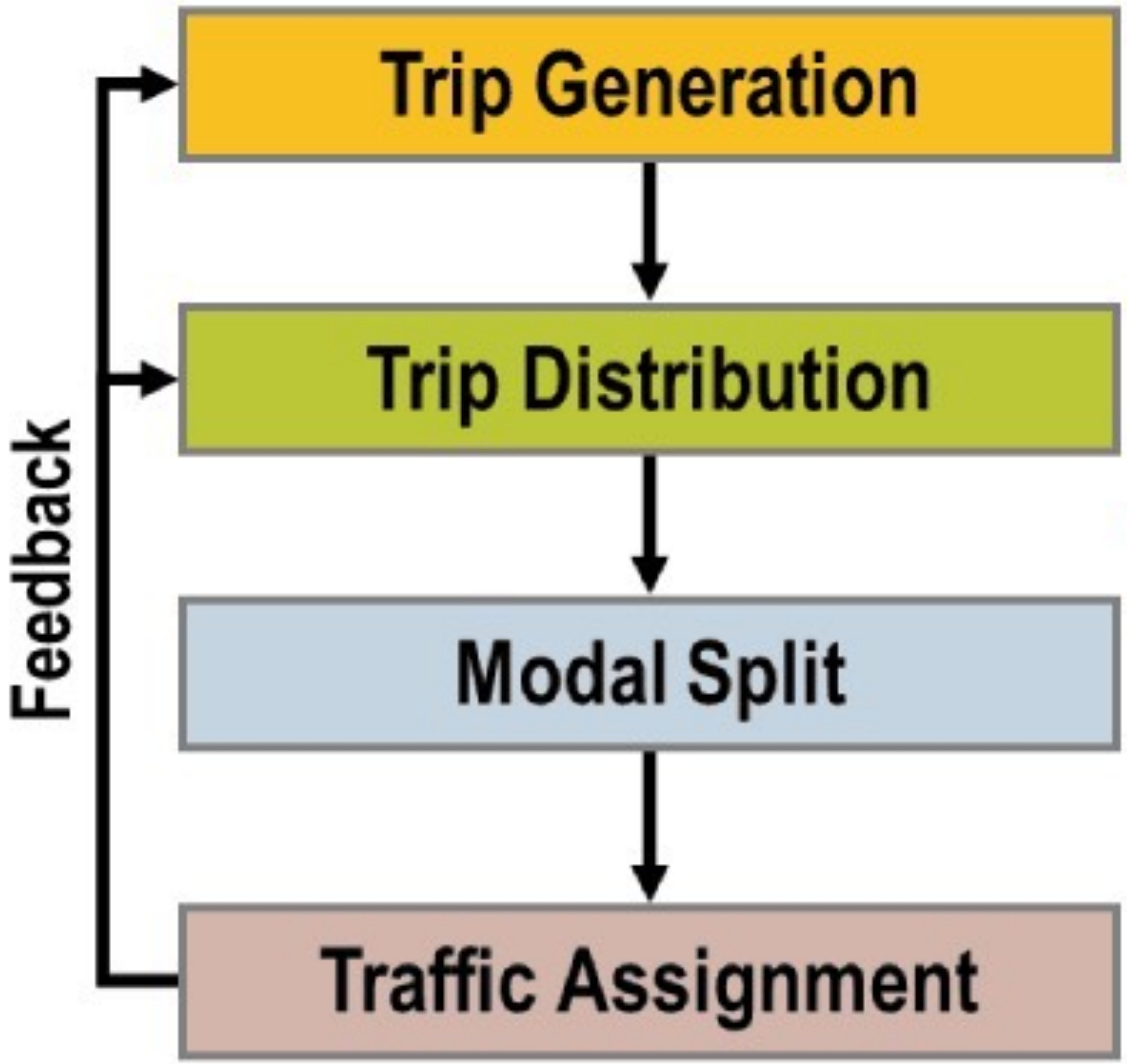
Aggregate mobility





Spatial interaction models

The four-stage model of transport estimates flows between spatial units

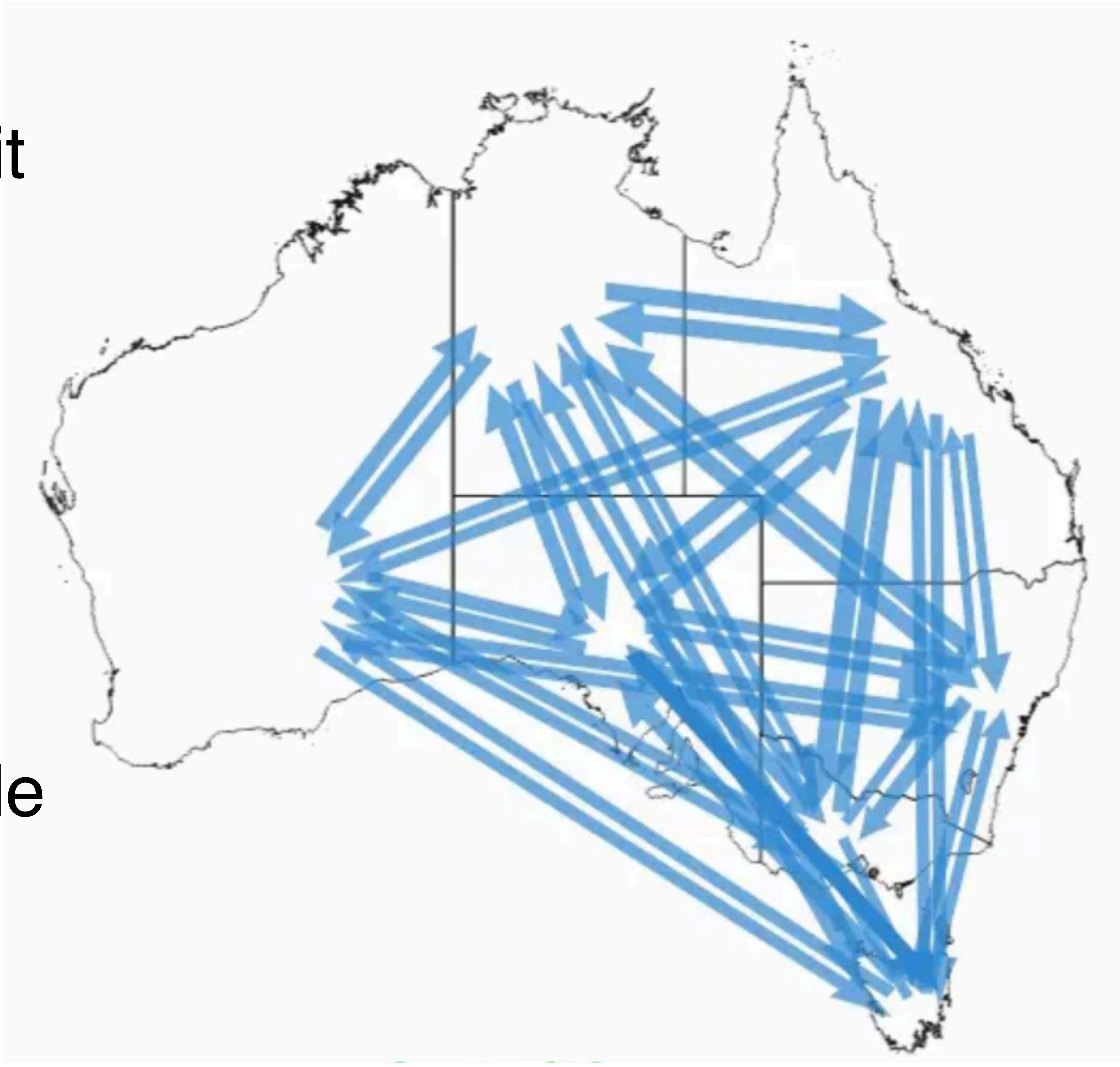


Demand from/to each unit

OD-matrix

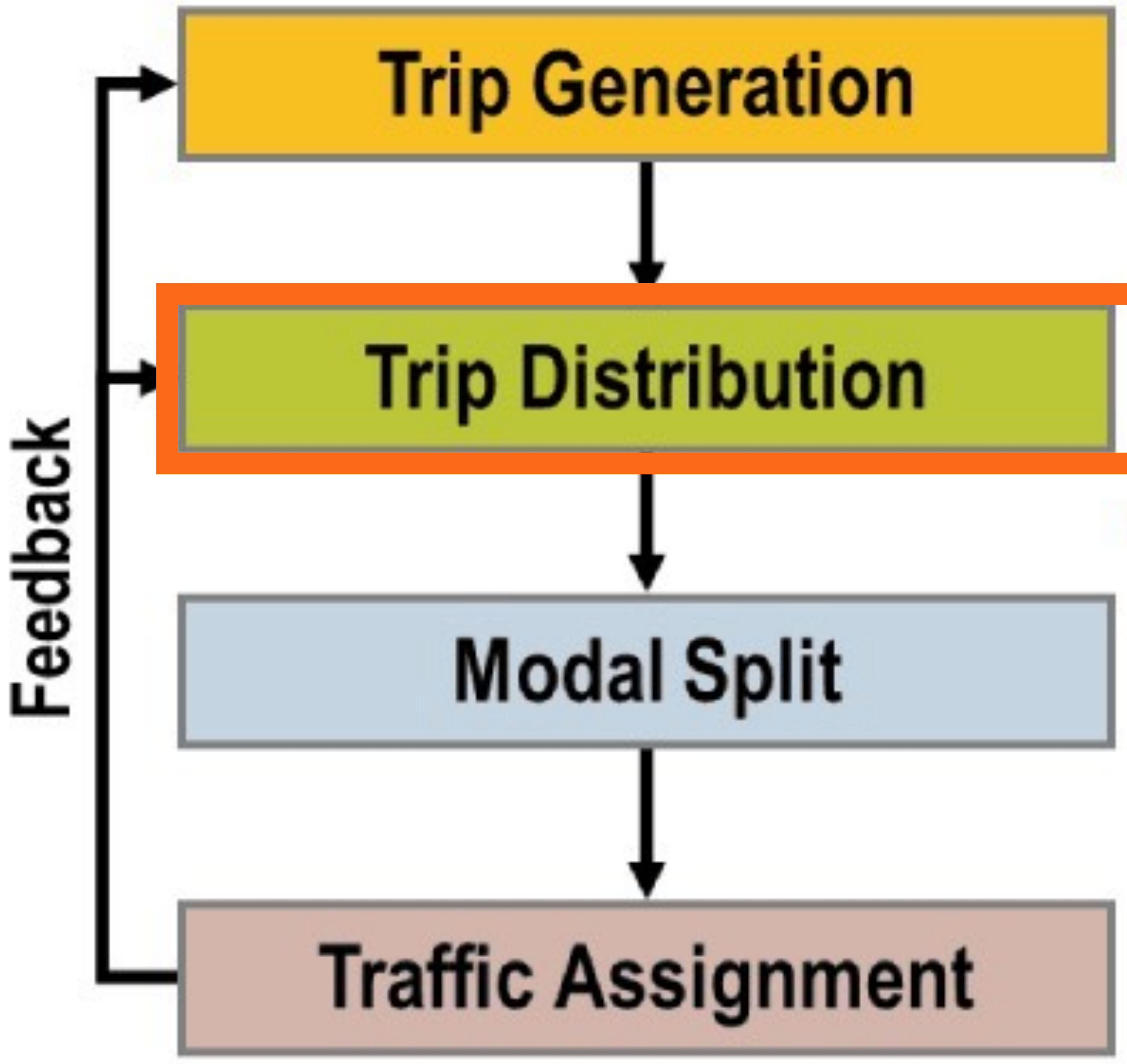
OD-matrix per travel mode

Route flows



https://transportgeography.org/contents/methods/spatial-interactions-gravity-model/transportation-land-use-four-stages-model/

Spatial interaction models aim to predict the OD-matrix

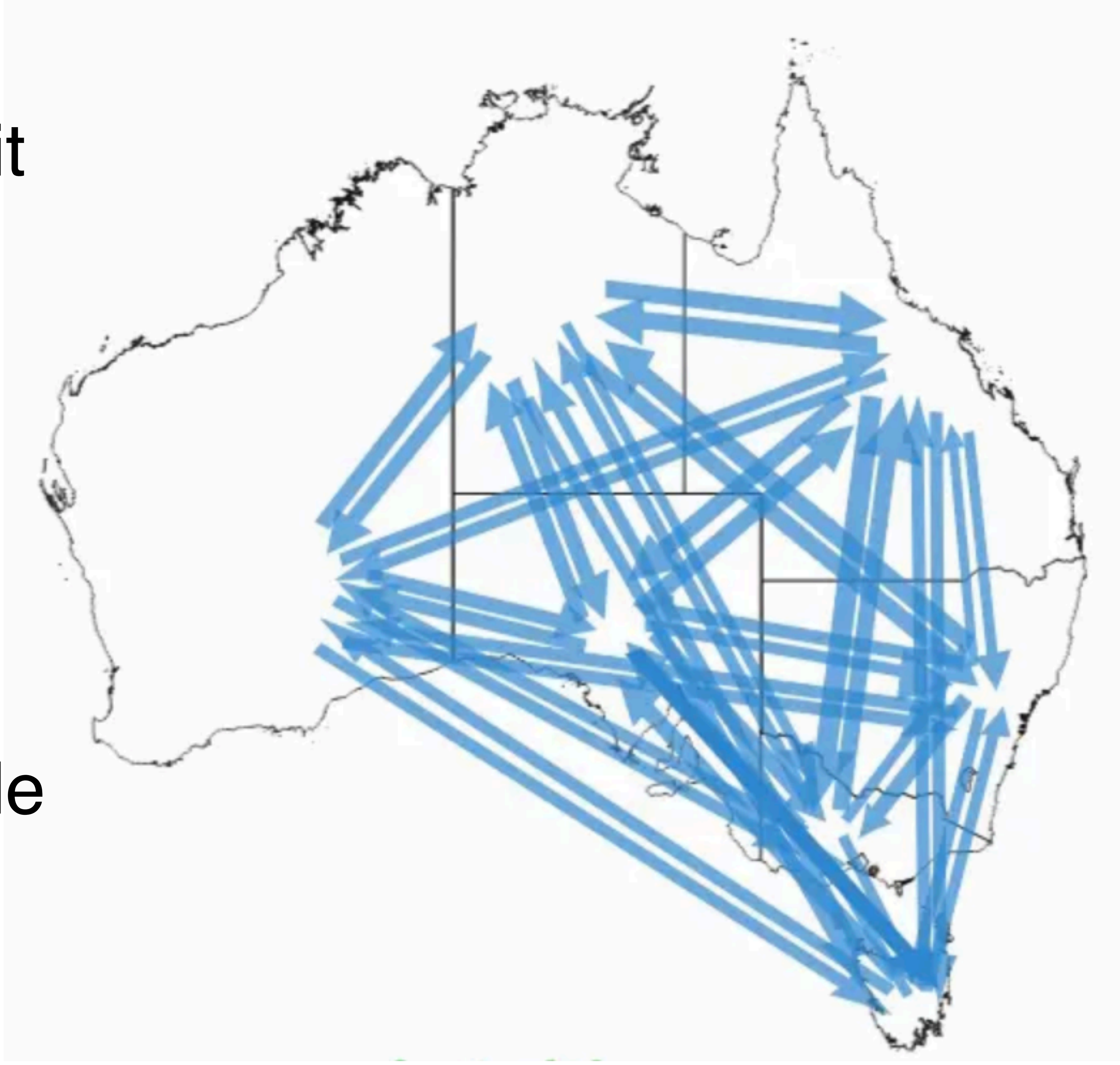


Demand from/to each unit

OD-matrix

OD-matrix per travel mode

Route flows



https://transportgeography.org/contents/methods/spatial-interactions-gravity-model/transportation-land-use-four-stages-model/

Spatial interaction models aim to predict the OD-matrix

Gravity model	**1858, 1885**
Intervening opportunities model	**1940**
Radiation model	**2012**
Hierarchy model	**2017**
Accounting for frequencies	**2021**

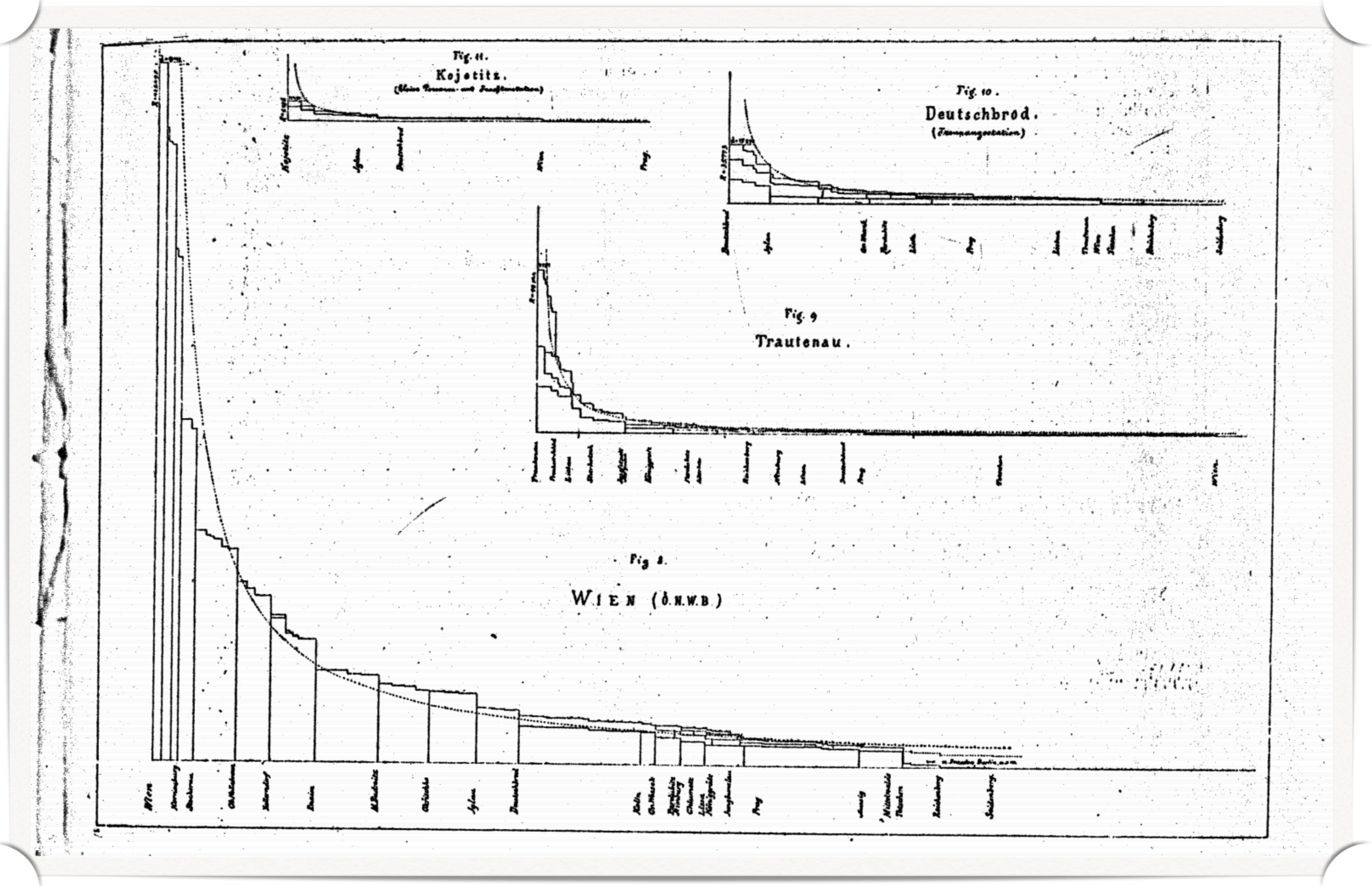
Mathematical travel laws have been noted since the 19th century

ZEITSCHRIFT
für
Eisenbahnen und Dampfschiffahrt
der
ÖSTERREICHISCH-UNGARISCHEN MONARCHIE.

HERAUSGEBER: PROF. DR. LORENZ v. STEIN.
REDACTEUR: SIGMUND SONNENSCHEIN.
A. Hartleben's Verlag in Wien.

35. HEFT. | 25. AUGUST 1889. | II. JAHRGANG.

Die Grundgesetze des Personenverkehrs.
Eine Studie.
Von
Eduard Lill,
Oberinspector der k. k. priv. österreichischen Nordwestbahn.



Lill, 1889: The number of people traveling from a place decreases with distance

Gravity model

Based on Newton's law of gravitation:

$$F = G\frac{m_1 m_2}{r^2}$$

The number of individuals T_{ij} that move between locations i and j is proportional to the populations m of the source and destination:

$$T_{ij} = G\frac{m_i m_j}{r_{ij}^2}$$

Gravity model

Based on Newton's law of gravitation:

$$F = G\frac{m_1 m_2}{r^2}$$

The number of individuals T_{ij} that move between locations i and j is proportional to the populations m of the source and destination:

$$T_{ij} = G\frac{m_i m_j}{r_{ij}^2}$$

$$T_{ij} = G\frac{m_i^\alpha m_j^\beta}{r_{ij}^\gamma} \qquad T_{ij} = G\frac{m_i^\alpha m_j^\beta}{e^{dr}} \qquad T_{ij} = \frac{m_i^\alpha m_j^\beta}{f(r_{ij})}$$

Variations due to disagreeing measurements

Gravity model

The Gravity model has been used to model:

- *Population flows*
- *Access to health services*
- *International trade*
- *Traffic in transport networks*
- *Phone communications*
- *Etc…*

The gravity model needs many parameters to calibrate

$$T_{ij} = G\frac{m_i^{\alpha} m_j^{\beta}}{r_{ij}^{\gamma}}$$

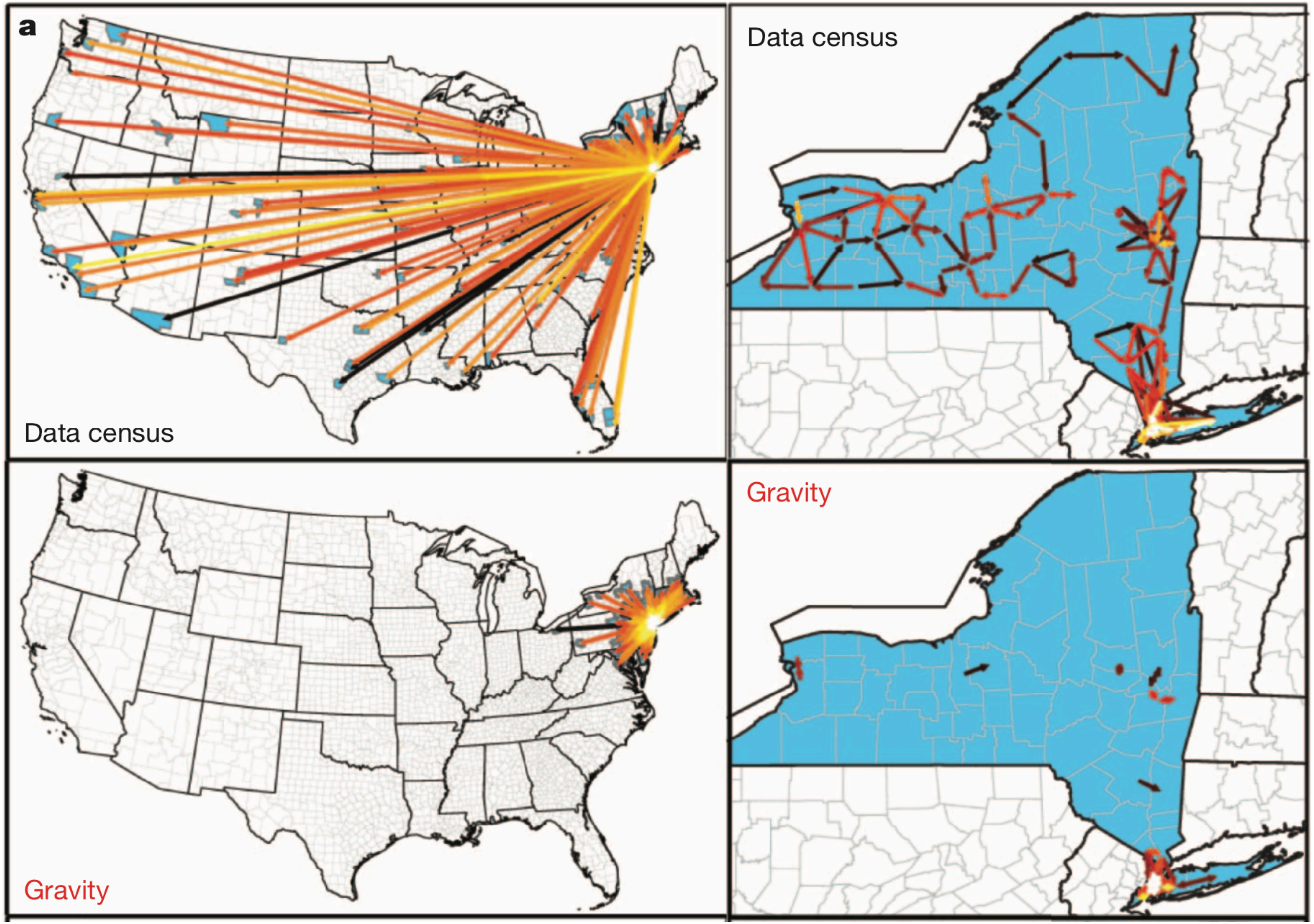
varies between 1.5 and 4.5

Systematic comparison of trip distribution laws and models

Maxime Lenormand,[1] Aleix Bassolas,[1] and José J. Ramasco[1]

[1] *Instituto de Física Interdisciplinar y Sistemas Complejos IFISC (CSIC-UIB), Campus UIB, 07122 Palma de Mallorca, Spain*

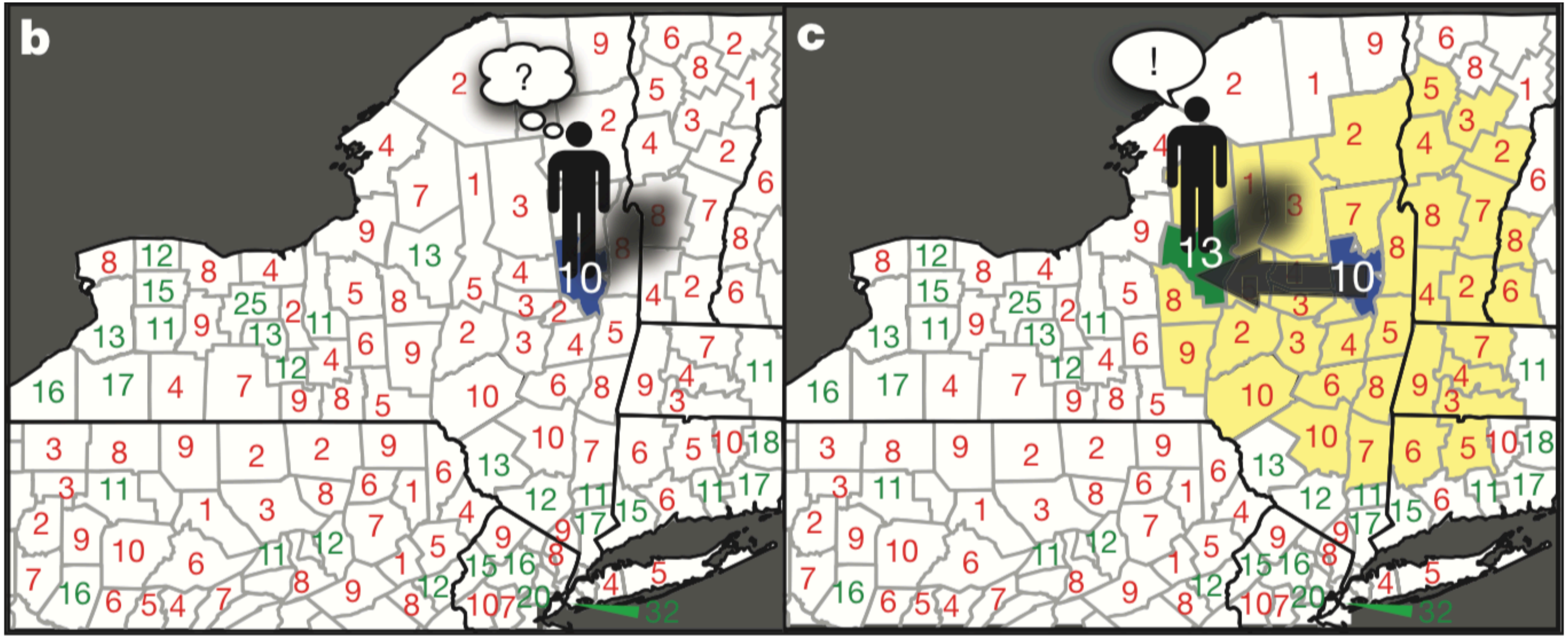
The gravity model underestimates long trips



Simini et al. *Nature* 484.7392 (2012)

Intervening opportunities model

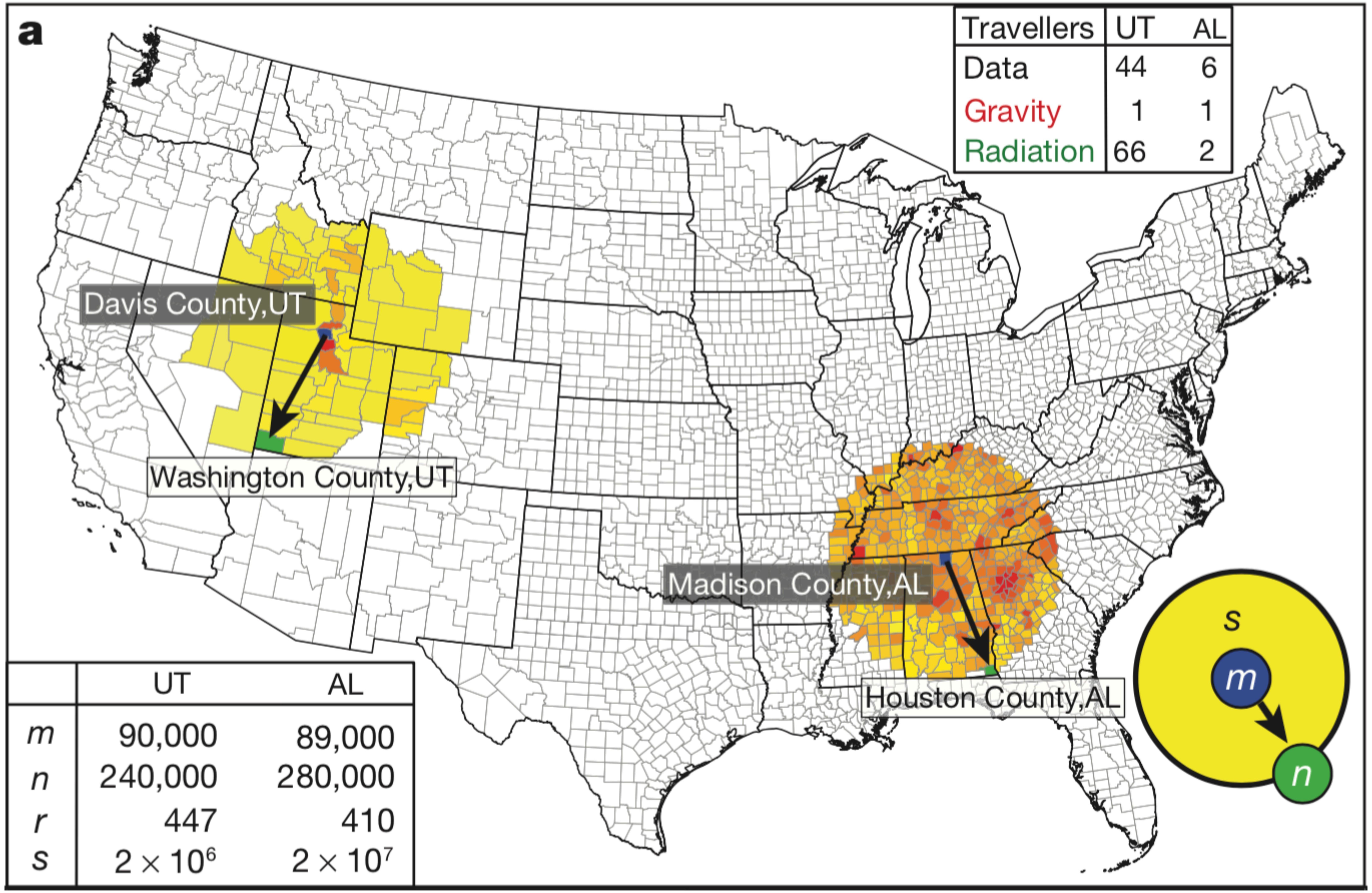
Stouffer (1940): The number of people going a given distance is directly proportional to the number of opportunities at that distance and inversely proportional to the number of intervening opportunities.



Simini et al. *Nature* 484.7392 (2012)

The radiation model aims to fix problems with gravity

based on intervening opportunities



Simini et al. *Nature* 484.7392 (2012)

The radiation model aims to fix problems with gravity

The average flows from i to j are predicted as:

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}$$

Population in location i

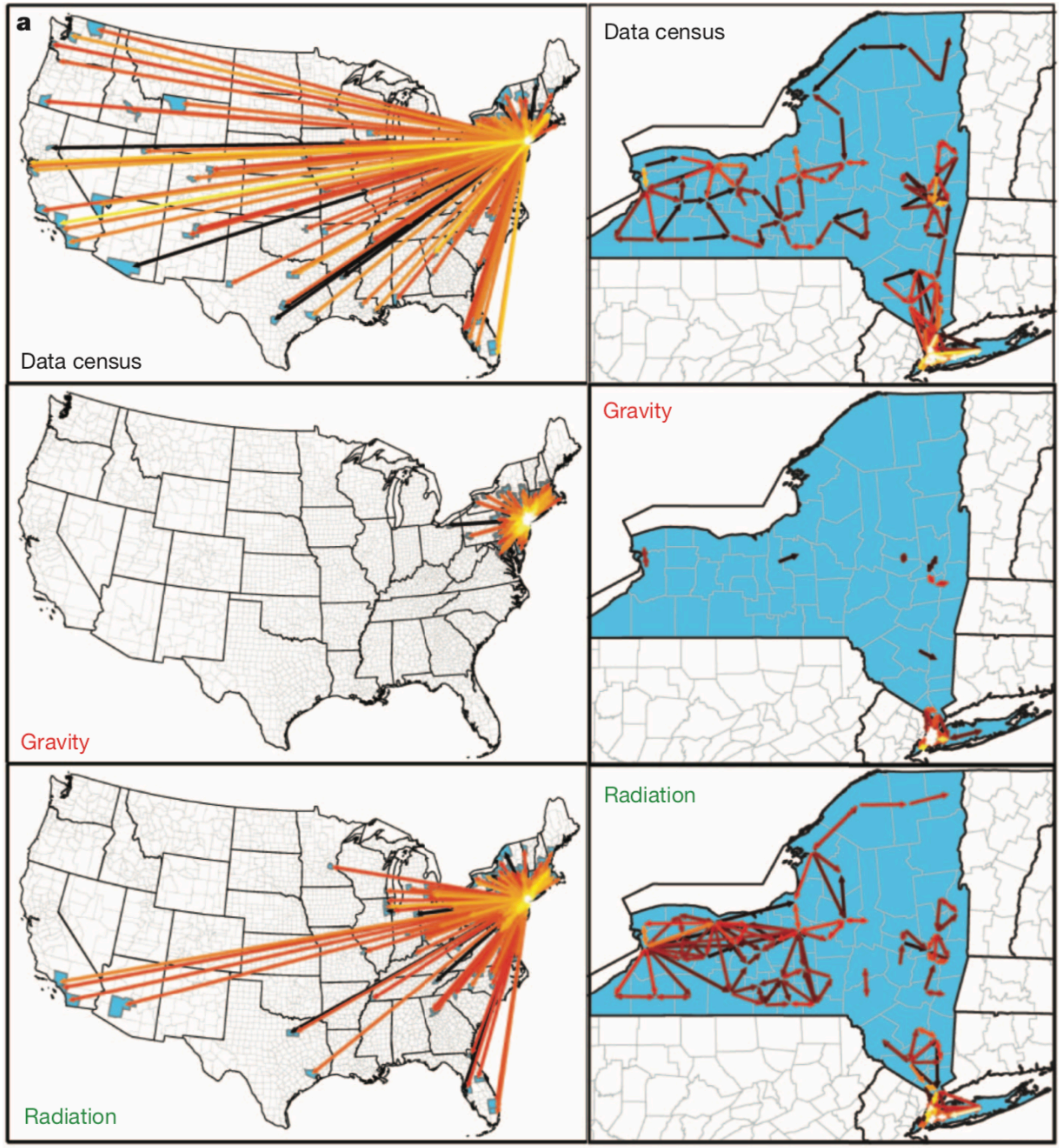
Population in location j

Number of commuters starting at i (proportional to population at i)

Total population in circle with radius r_{ij} centered in i

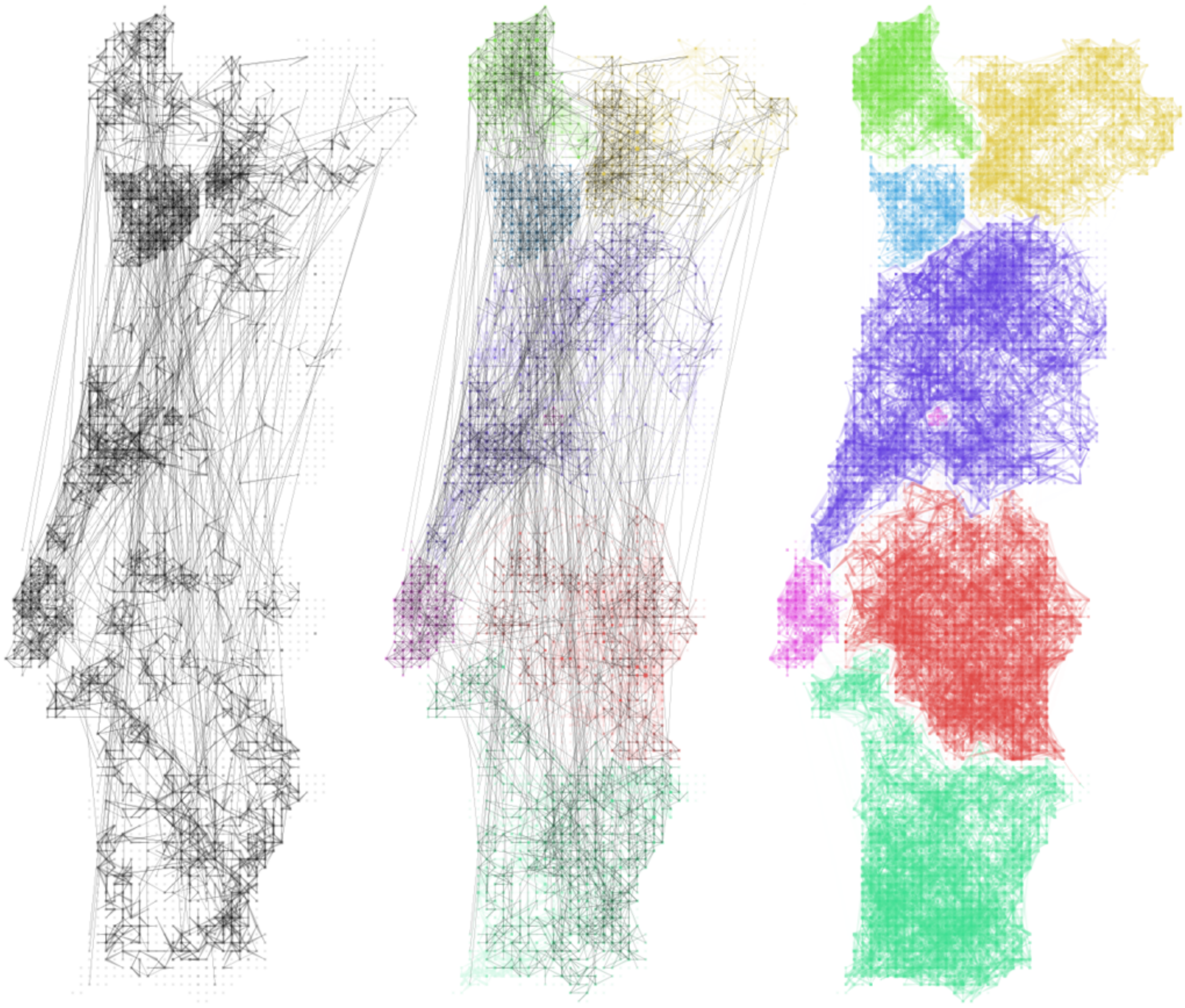
Simini et al. *Nature* 484.7392 (2012)

The radiation model aims to fix problems with gravity



Simini et al. *Nature* 484.7392 (2012)

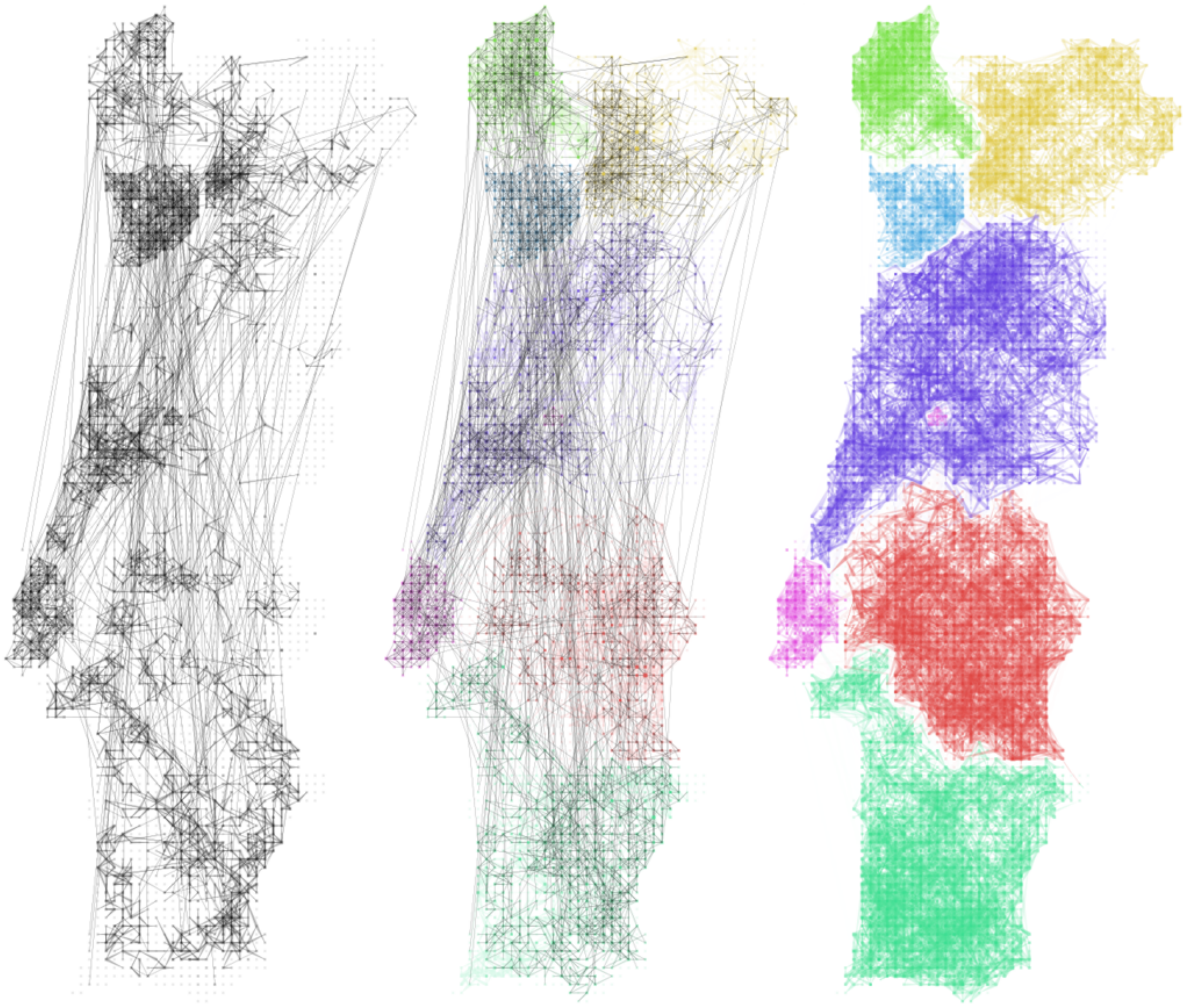
There are structural discontinuities in spatial organization of society



Community detection of human interaction networks

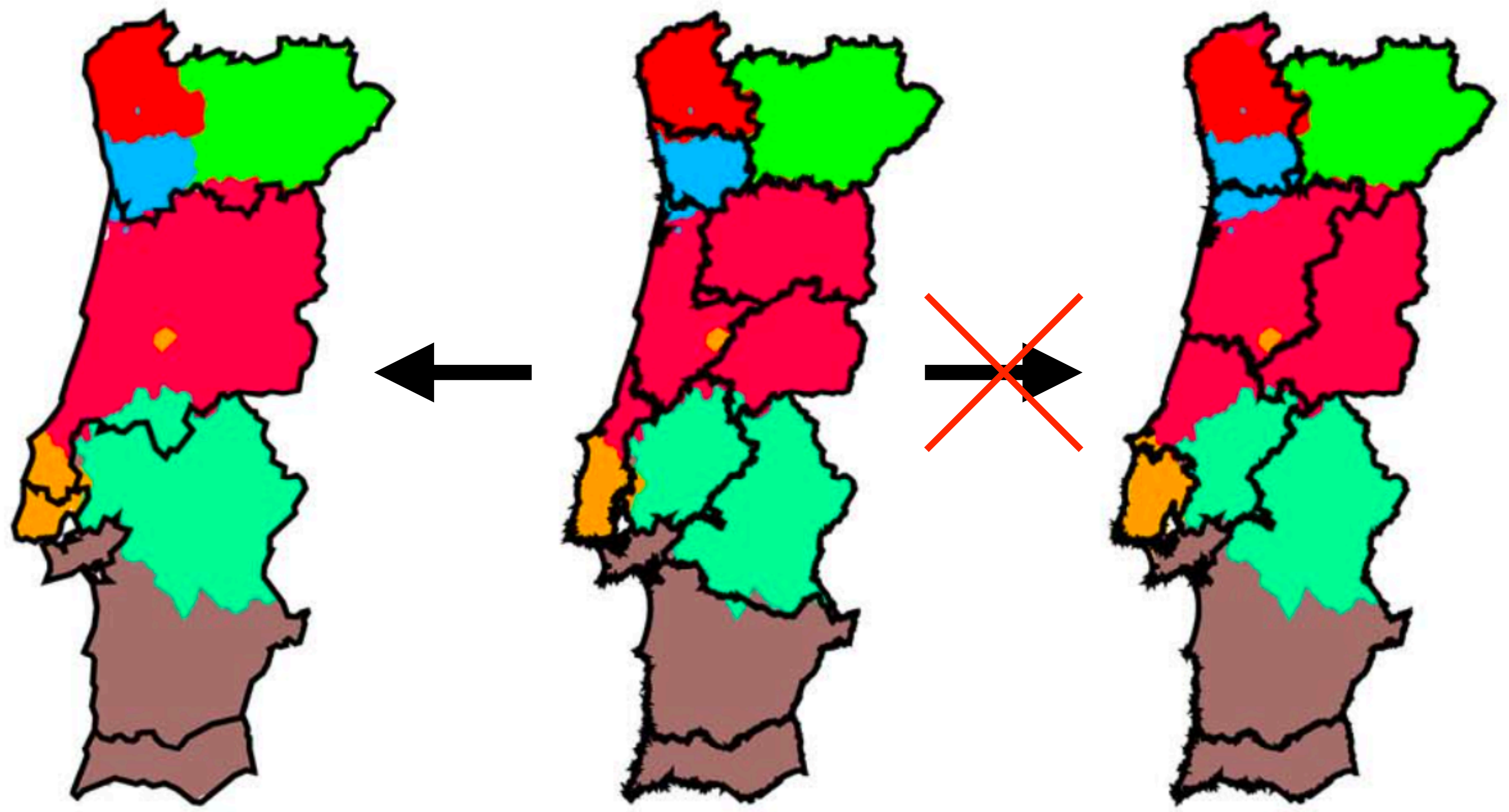
Sobolevsky et al, PLOS ONE 8, e81707 (2013)
Ratti et al, PLOS ONE 5, e14248 (2010)

There are structural discontinuities in spatial organization of society



Community detection of human interaction networks

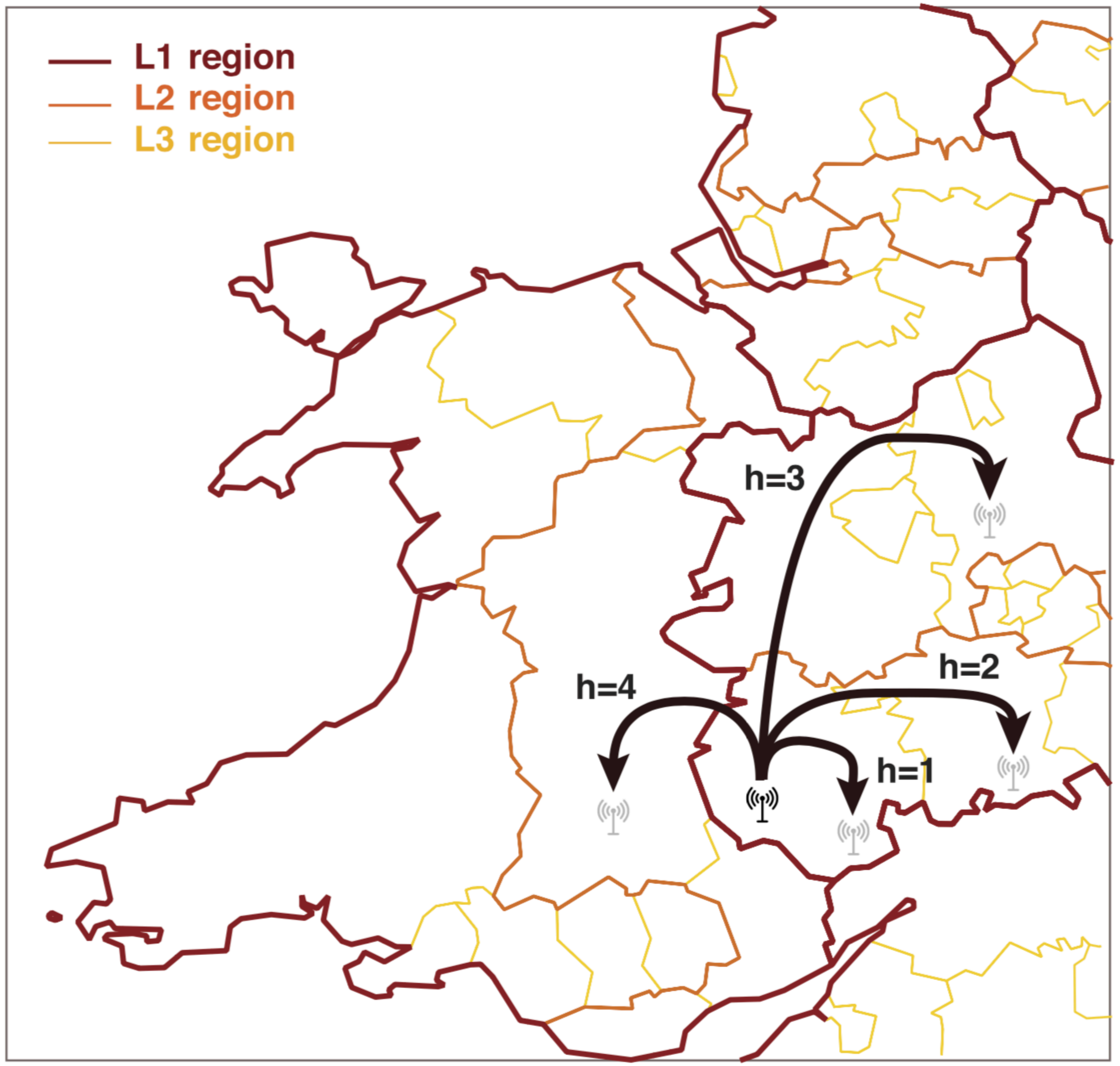
matches closely administrative borders!

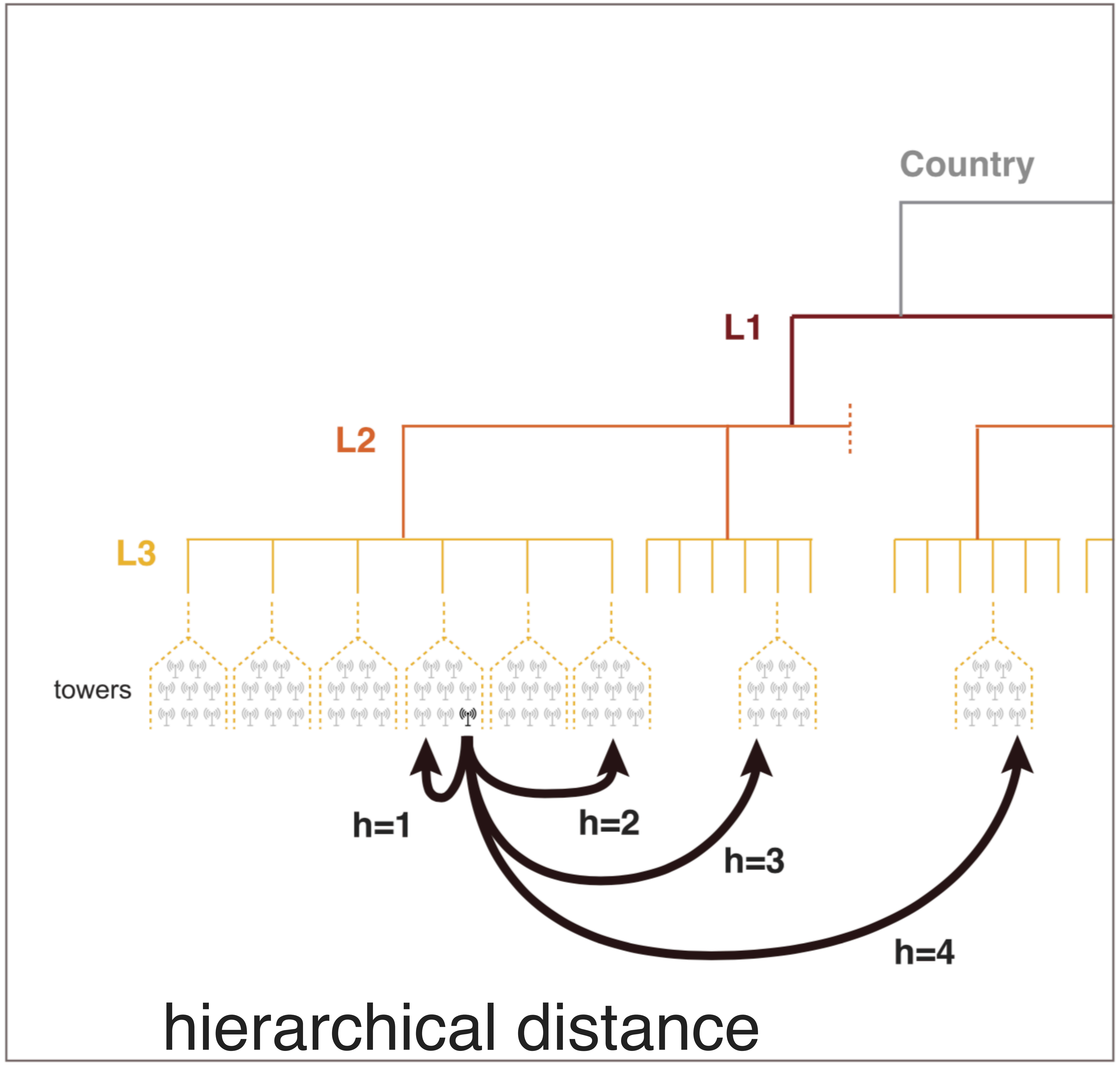


Sobolevsky et al, PLOS ONE 8, e81707 (2013)
Ratti et al, PLOS ONE 5, e14248 (2010)

There are structural discontinuities in spatial organization of society

Idea for new model: Society is organized hierarchically in space





Grauwin et al, Sci Rep 7:46677 (2017)

Working with mobility analysis

scikit mobility has functions for calculating entropy

scikit mobility

`random_entropy` (traj[, show_progress])	Random entropy.
`uncorrelated_entropy` (traj[, normalize, ...])	Uncorrelated entropy.
`real_entropy` (traj[, show_progress])	Real entropy.

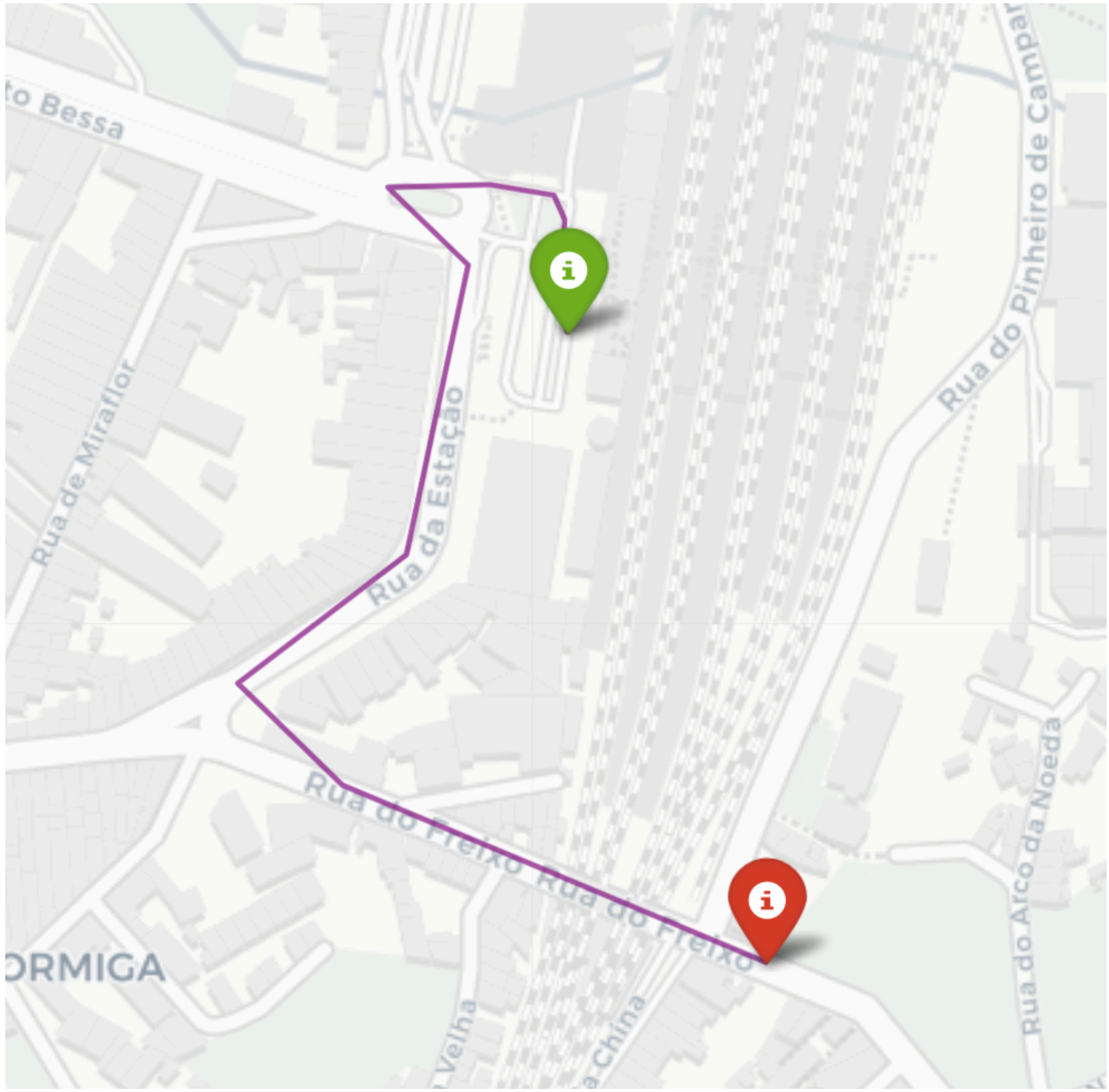
scikit mobility has implementations of mobility models

`gravity.Gravity` ([deterrence_func_type, ...])	Gravity model.
`radiation.Radiation` ([name])	Radiation model.
`geosim.GeoSim` ([name, rho, gamma, alpha, ...])	GeoSim model.
`sts_epr.STS_epr` ([name, rho, gamma, alpha])	STS-EPR model.

https://scikit-mobility.github.io/scikit-mobility/reference/models.html

Today, you'll learn how to work with:

Trajectories

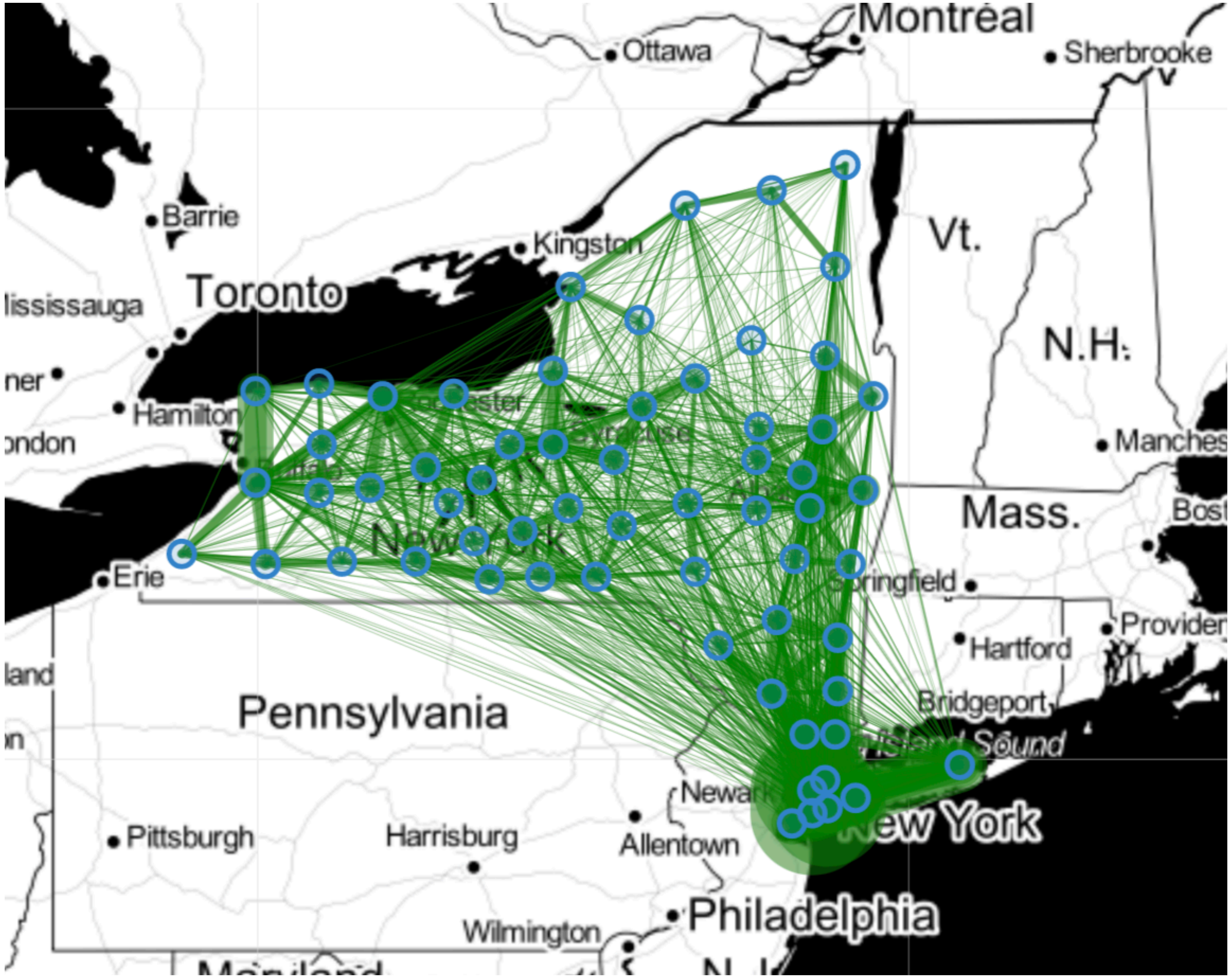


T_i

Today, you'll learn how to work with:

Trajectories

Flows

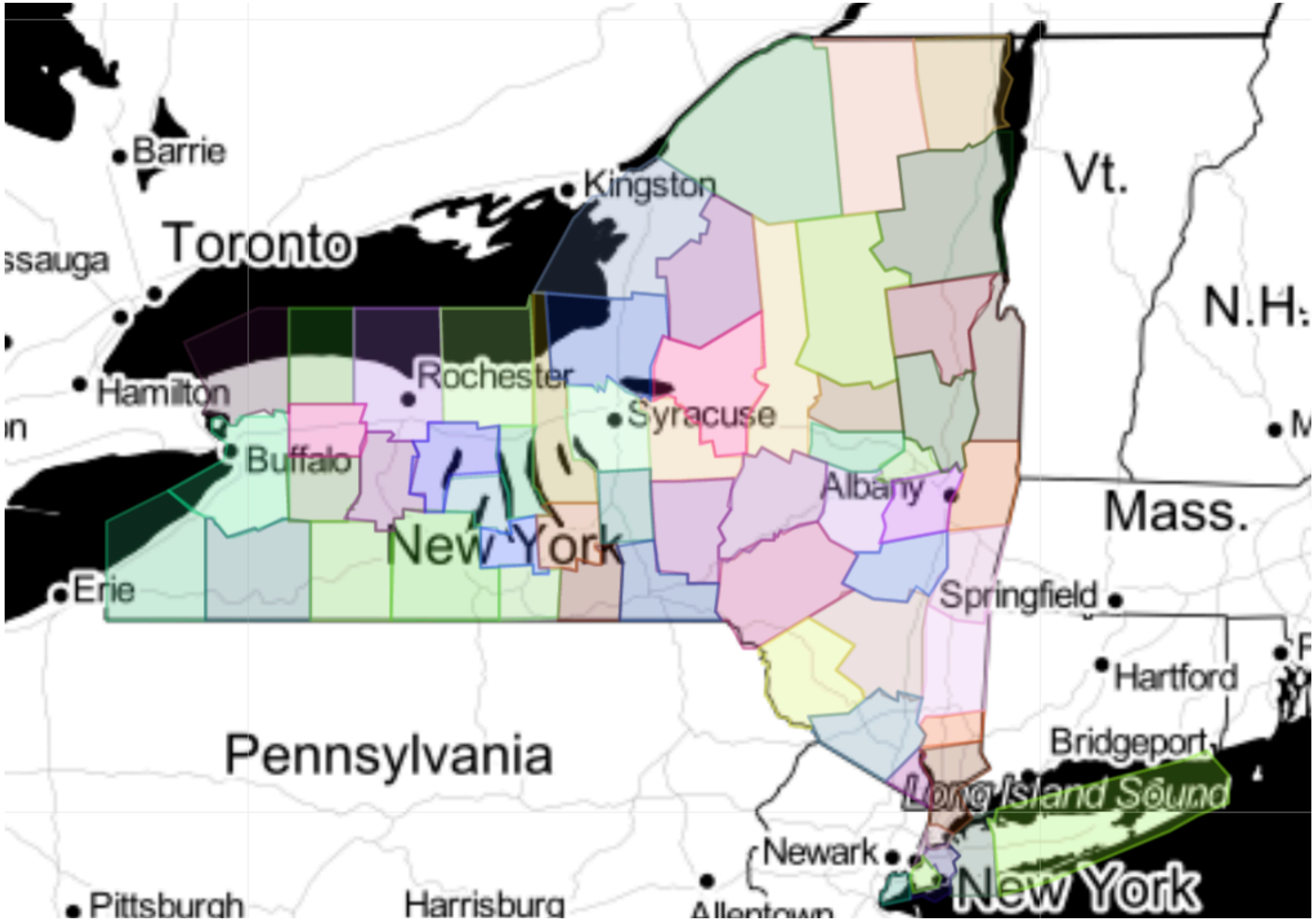


Today, you'll learn how to work with:

Trajectories

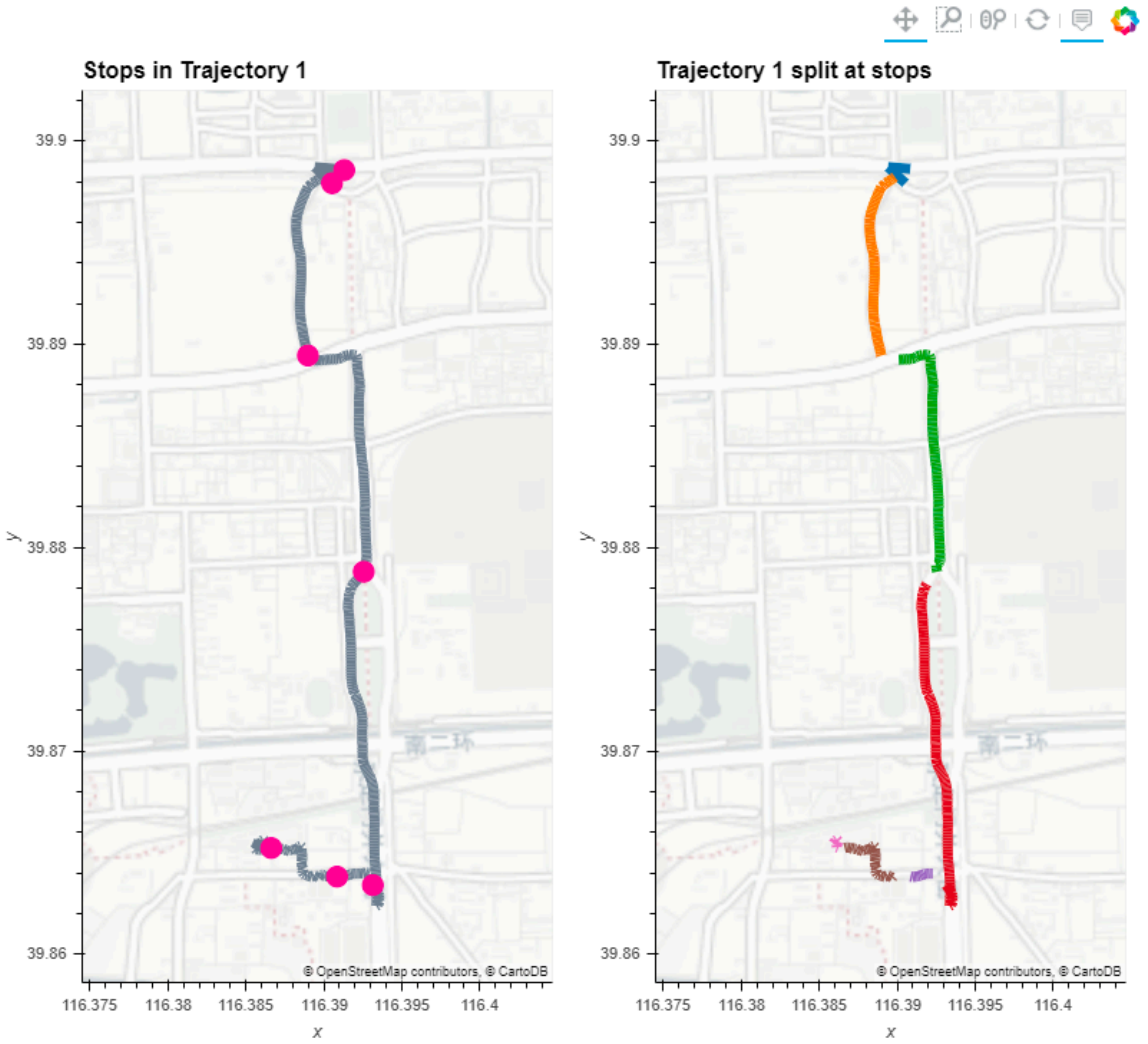
Flows

OD-tessellations



MovingPandas

For trajectory/GPS-data



movingpandas

Tutorial on the exercise repo!

https://github.com/movingpandas/movingpandas

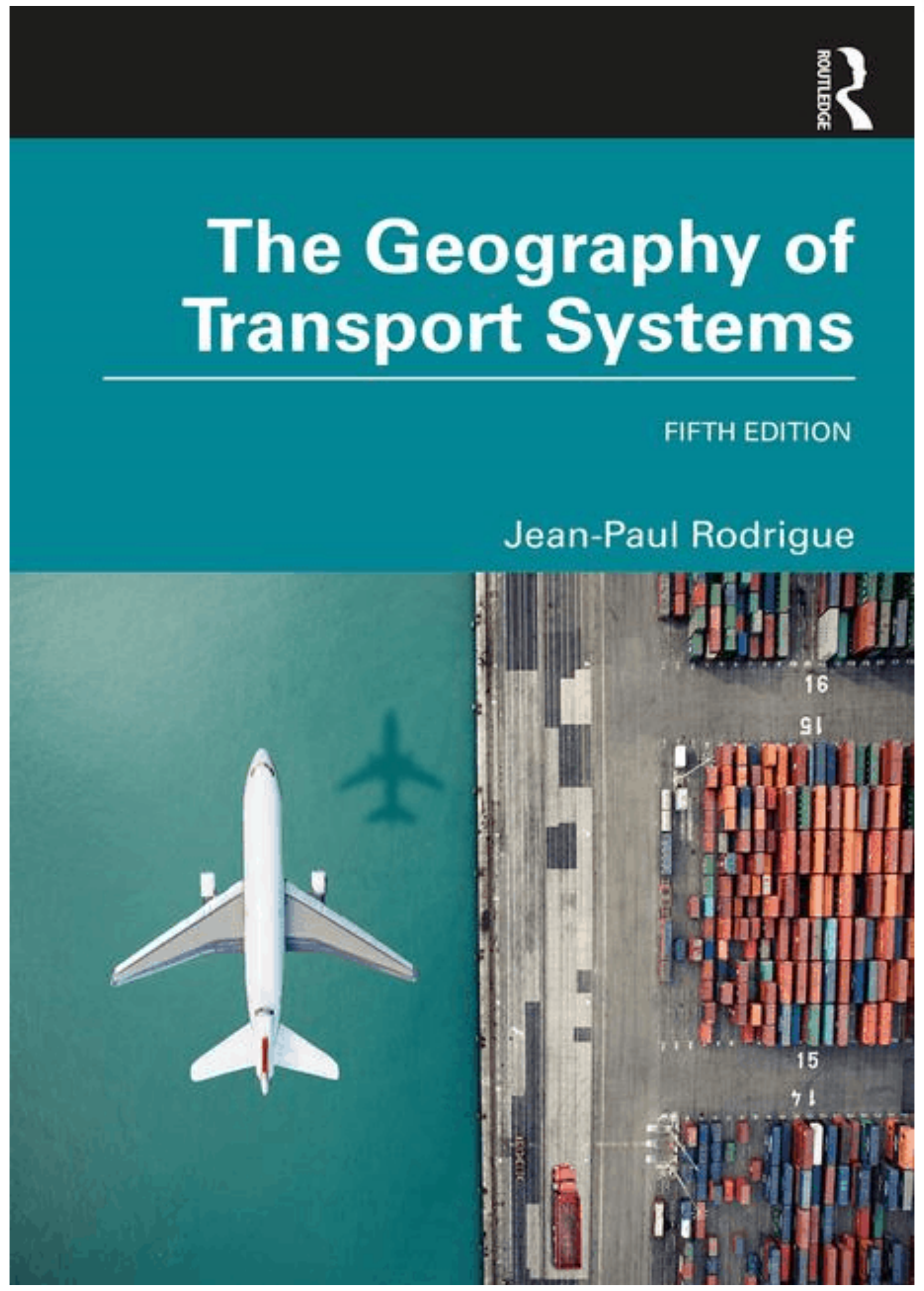
Sci-kit mobility

```
# create a TrajDataFrame
tdf = skmob.TrajDataFrame(data_df, latitude='latitude',
datetime=‘hour', user_id='user')

# create a tessellation
tessellation = gpd.GeoDataFrame.from_file("files/
NY_counties_2011.geojson")

# create a FlowDataFrame from a file and a tessellation
fdf = skmob.FlowDataFrame.from_file(
       “files/NY_commuting_flows_2011.csv”,
        tessellation=tessellation,
        tile_id='tile_id',
        sep=",")
```

Sources and further materials for today's class



Limits of Predictability in Human Mobility

Chaoming Song,[1,2] Zehui Qu,[1,2,3] Nicholas Blumm,[1,2] Albert-László Barabási[1,2]*

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]

Unravelling daily human mobility motifs

Christian M. Schneider[1], Vitaly Belik[1,2], Thomas Couronné[3], Zbigniew Smoreda[3] and Marta C. González[1,4]

Identifying and modeling the structural discontinuities of human interactions

Sebastian Grauwin[1], Michael Szell[1,2,3], Stanislav Sobolevsky[1,4], Philipp Hövel[2,5,6], Filippo Simini[2,7,8], Maarten Vanhoof[9], Zbigniew Smoreda[9], Albert-László Barabási[2,10,11] & Carlo Ratti[1]

Unique in the Crowd: The privacy bounds of human mobility

Yves-Alexandre de Montjoye[1,2], César A. Hidalgo[1,3,4], Michel Verleysen[2] & Vincent D. Blondel[2,5]

Chapter 3
Urban Mobility

Laura Alessandretti and Michael Szell

Delineating Geographical Regions with Networks of Human Interactions in an Extensive Set of Countries

Stanislav Sobolevsky[1]*, Michael Szell[1], Riccardo Campari[1], Thomas Couronné[2], Zbigniew Smoreda[2], Carlo Ratti[1]

For tools for transport/mobility research, see Lovelace 2021

Next week: Big Geospatial Data