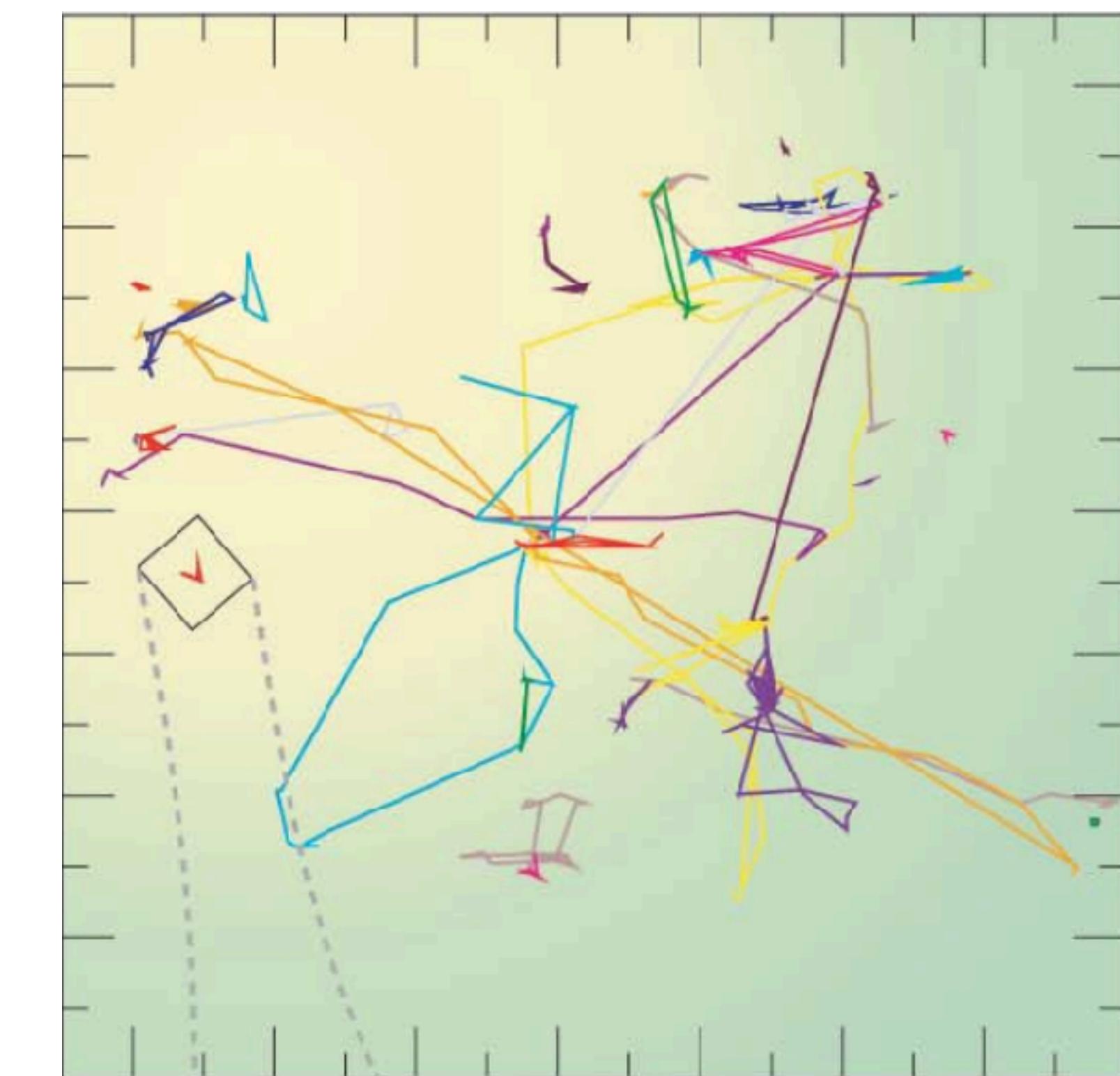


## Lecture 11: Individual mobility

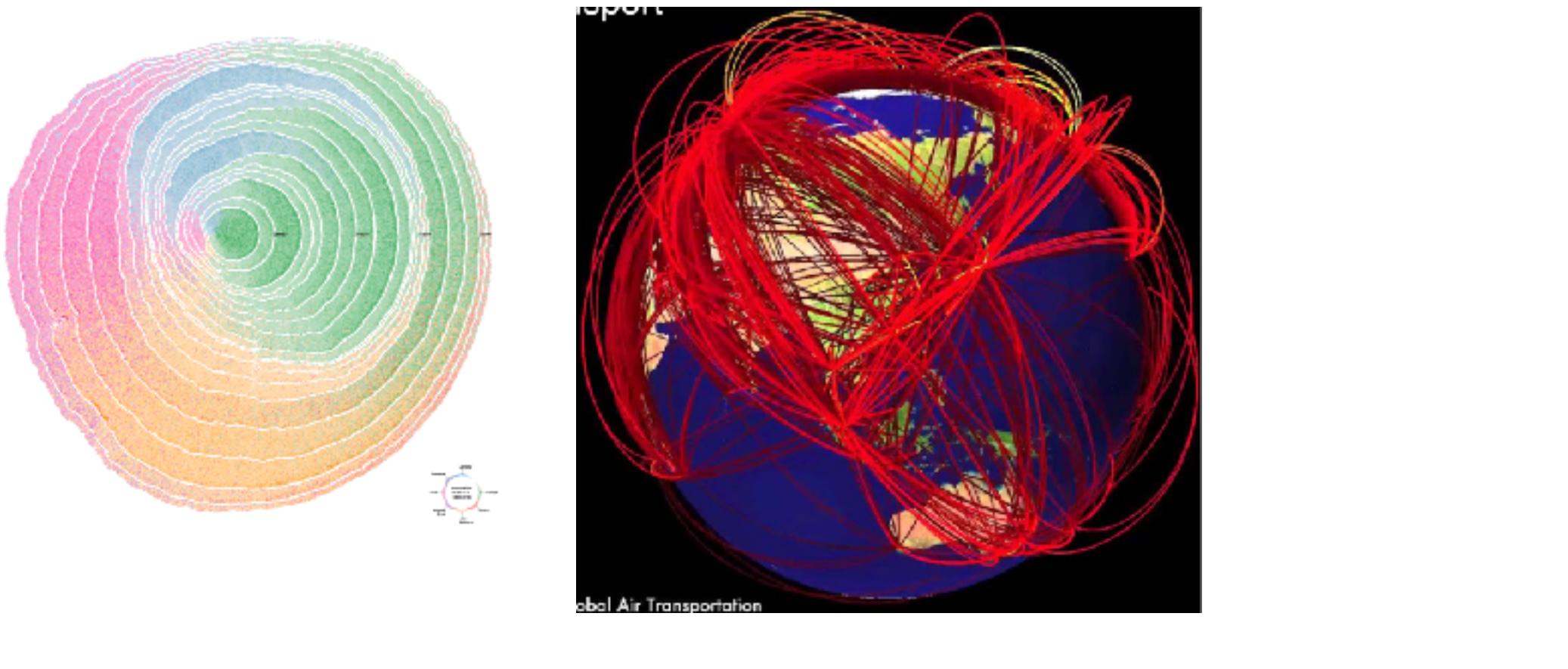
Instructor: Michael Szell

Mar 31, 2022



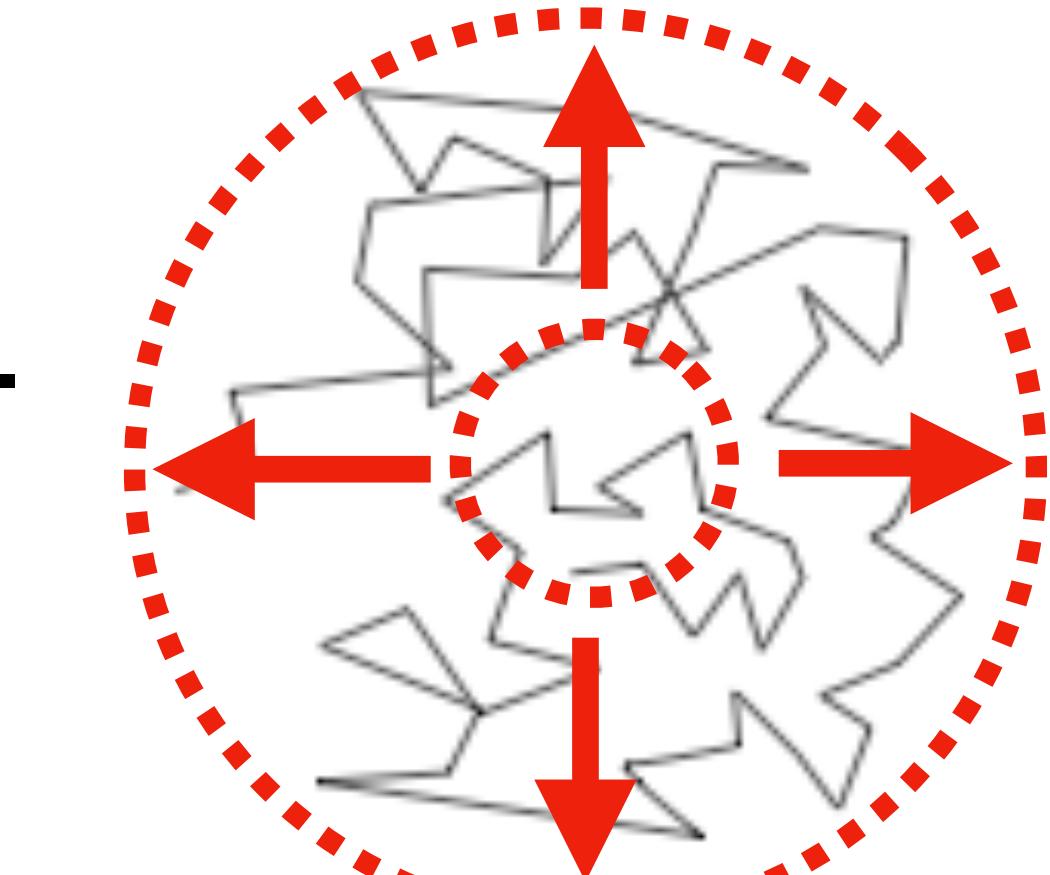
# Today you will learn about individual mobility

## Overview of mobility approaches

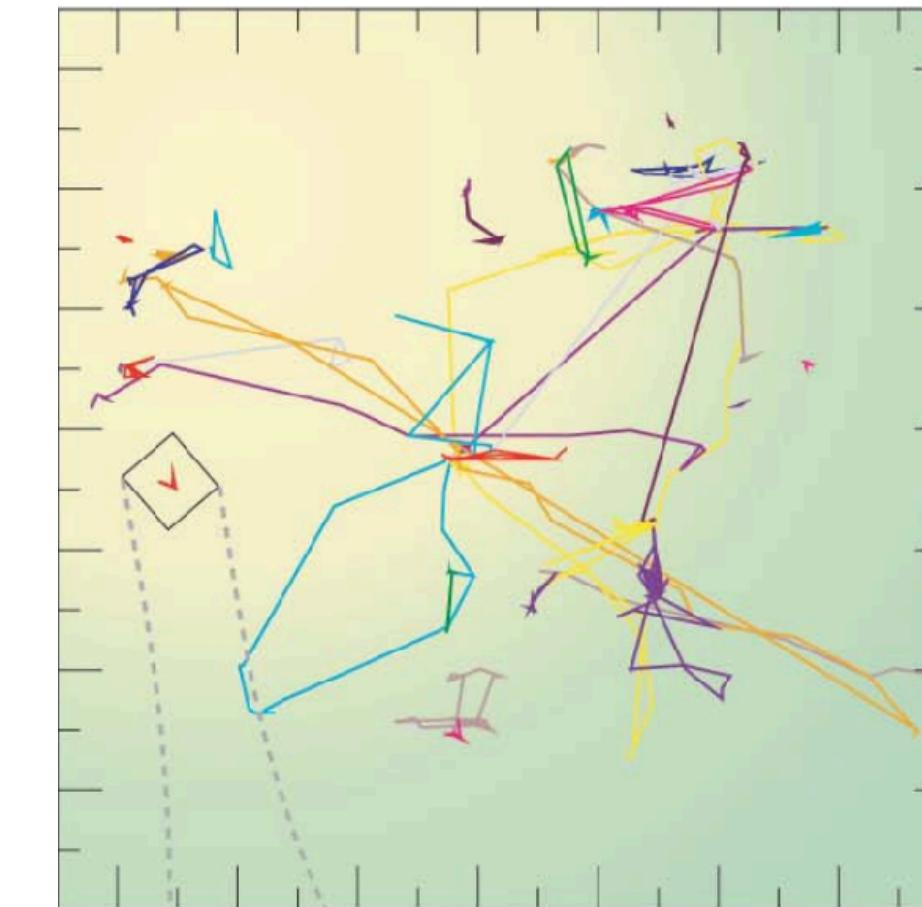


Physics-inspired metrics

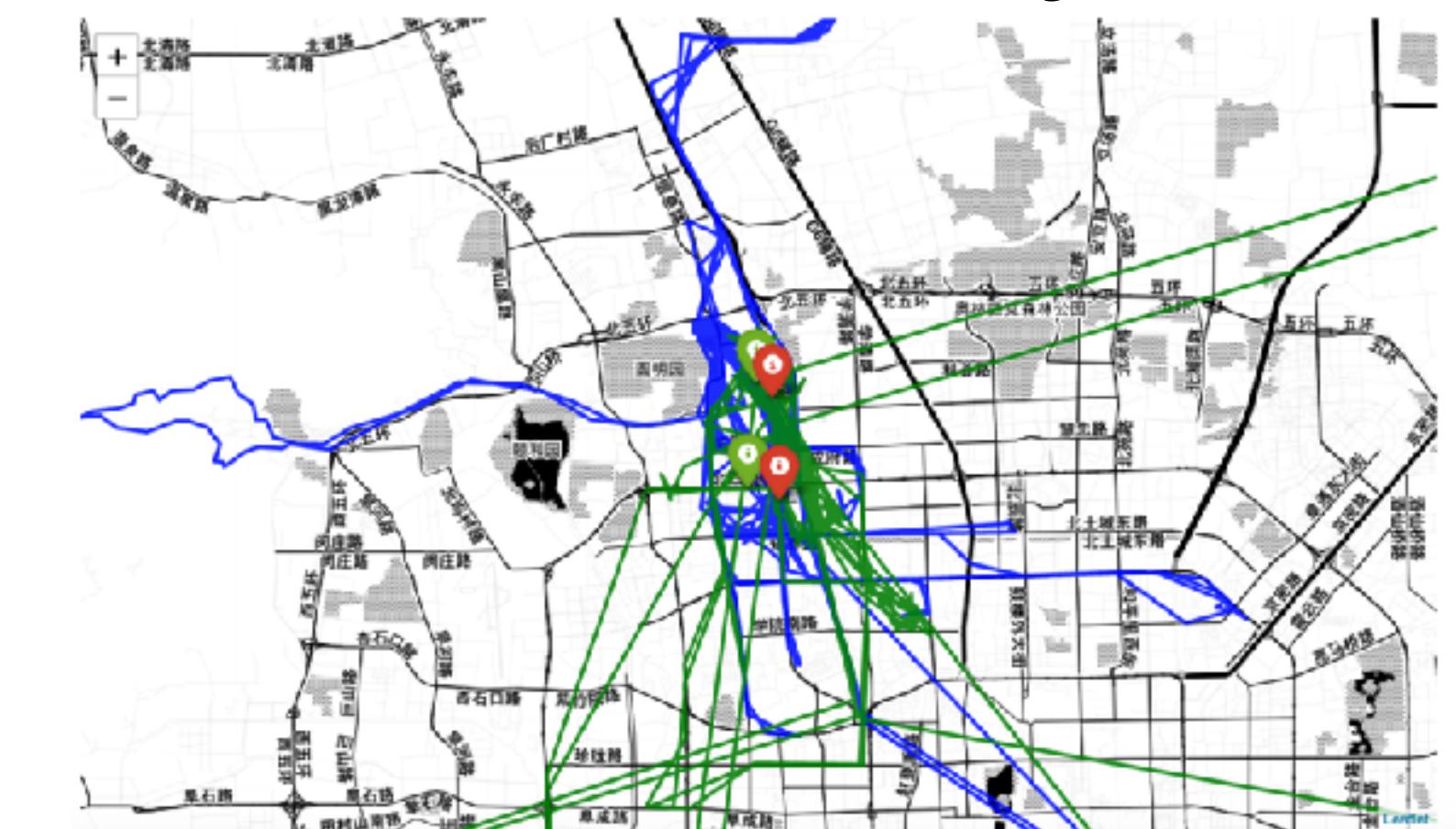
$$MSD = \langle r^2(\tau) \rangle = \frac{1}{N} \sum_{n=1}^N (x_n(\tau) - x_n(0))^2$$



## Research on individual trajectories



scikit-mobility



You can study mobility=human movements at different scales

## Individual

Single-scale

Pedestrian movements

Air transport

Sea networks

## Population / Aggregate

Migration

Spatial Interaction

## Multi-scale

Intra/Inter-urban mobility

Epidemic spreading

## Virtual scale

You can study mobility=human movements at different scales

## Individual

Single-scale

Pedestrian movements

Air transport

Sea networks

## Population / Aggregate

Migration

Spatial Interaction

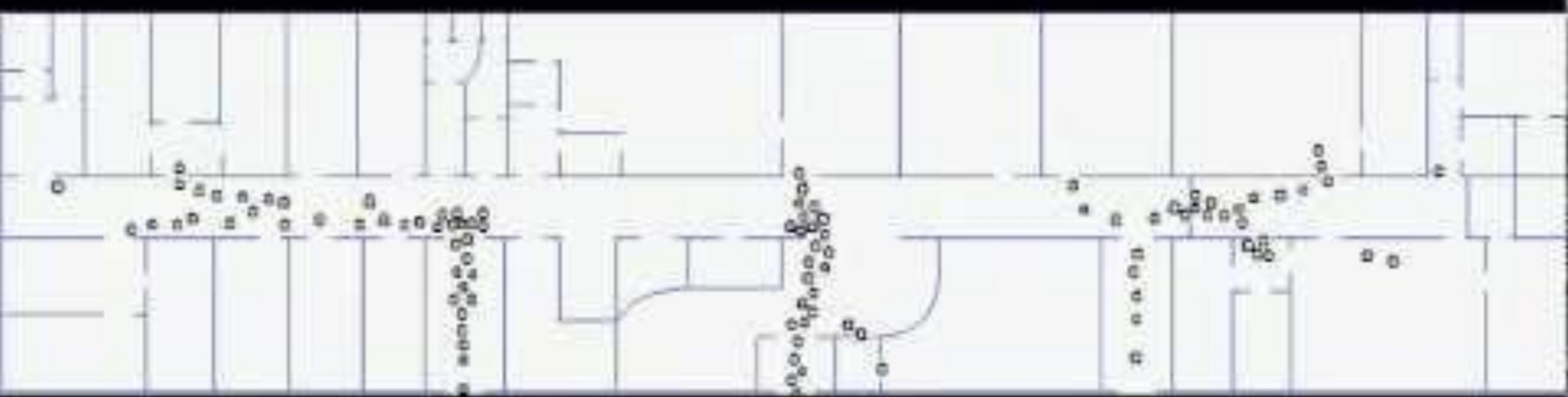
## Multi-scale

Intra/Inter-urban mobility

Epidemic spreading

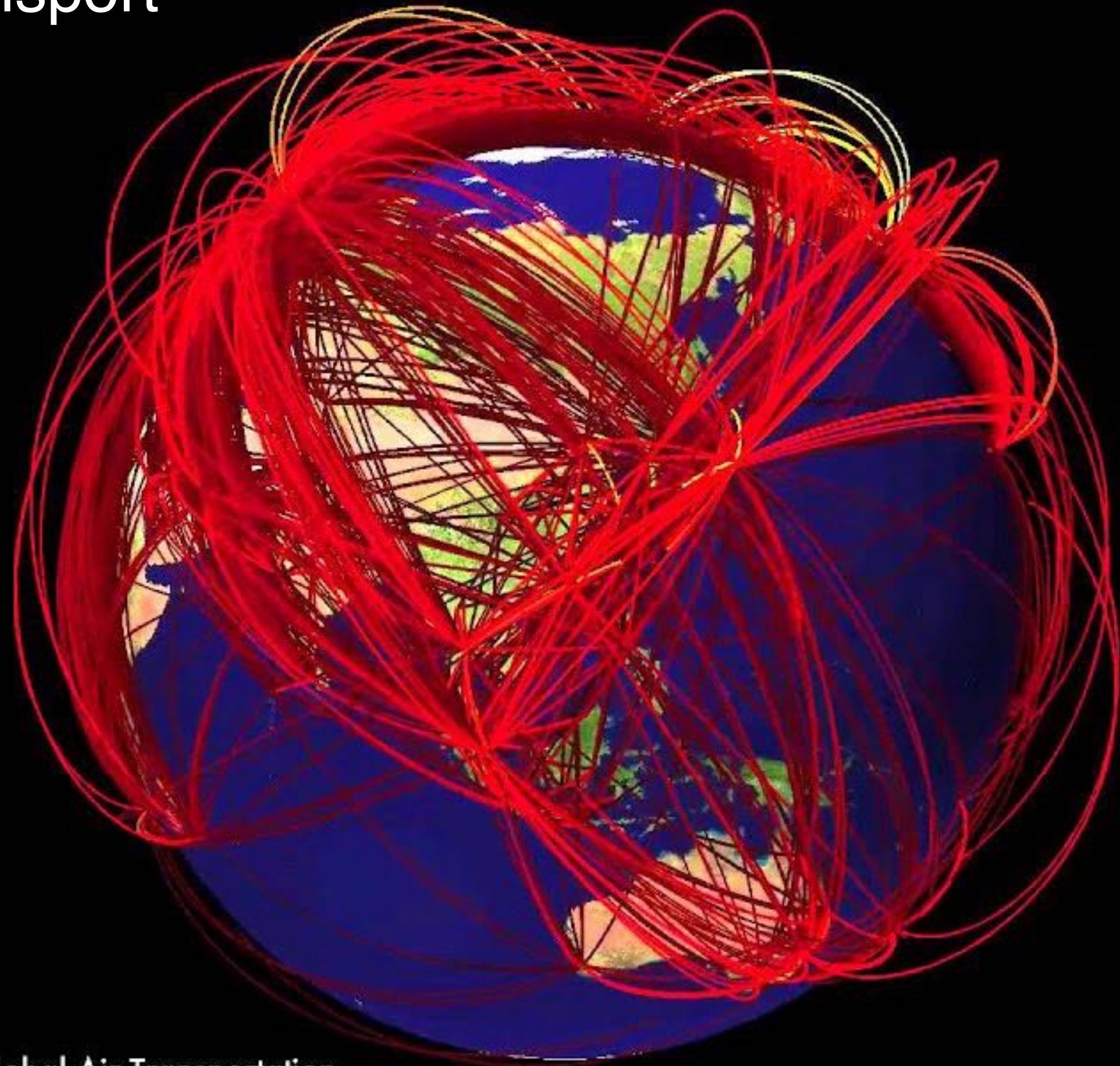
Virtual scale

# Single scale: Pedestrian movements



Agent-based simulations with the social force model

# Single scale: Air transport

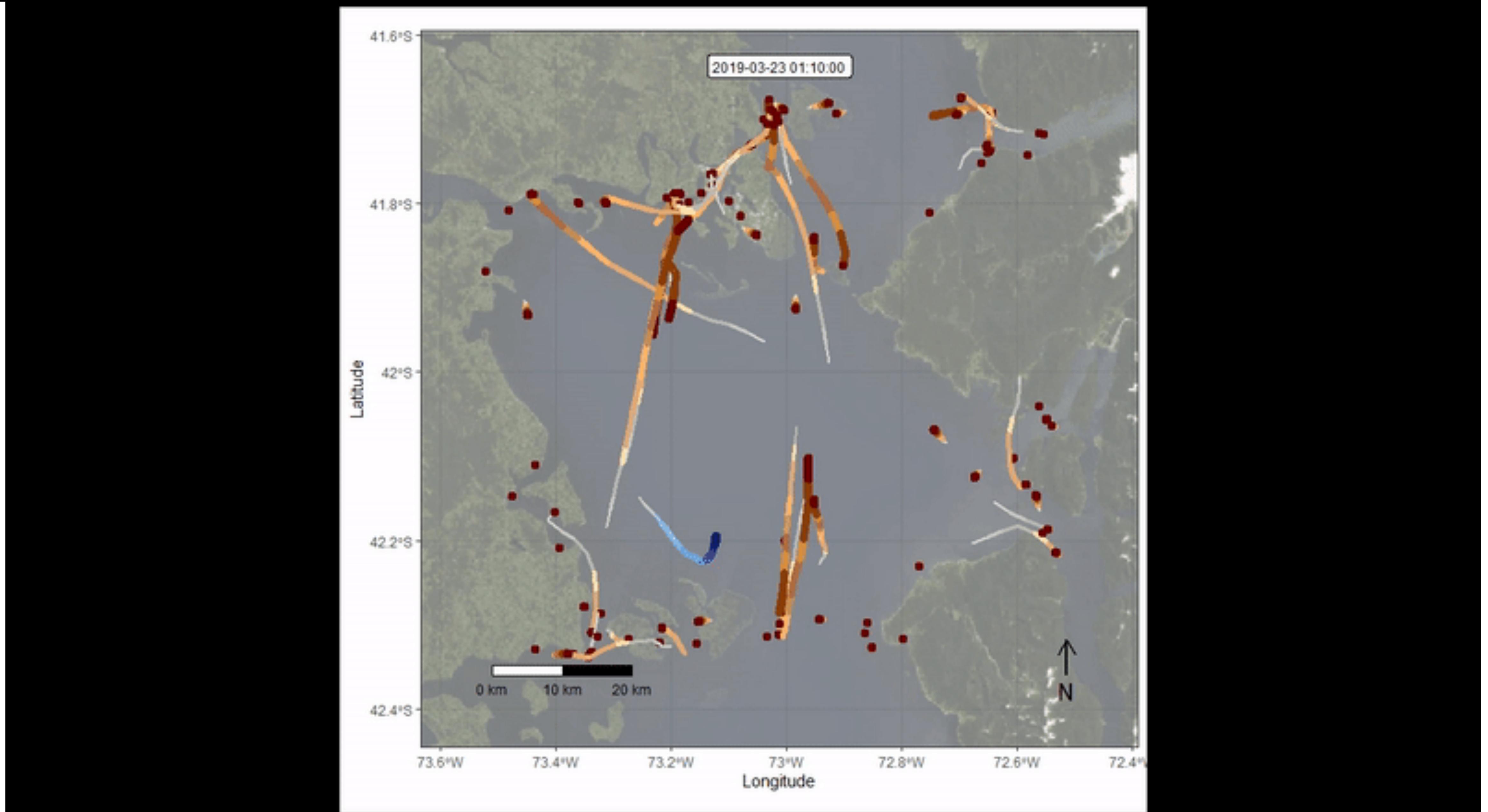


Global Air Transportation

Daniel Grady & Dirk Brockmann  
Northwestern University  
Evanston, IL

<https://youtube.com/watch?v=a6Wh6-6toiQ>

# Single scale: Sea transport



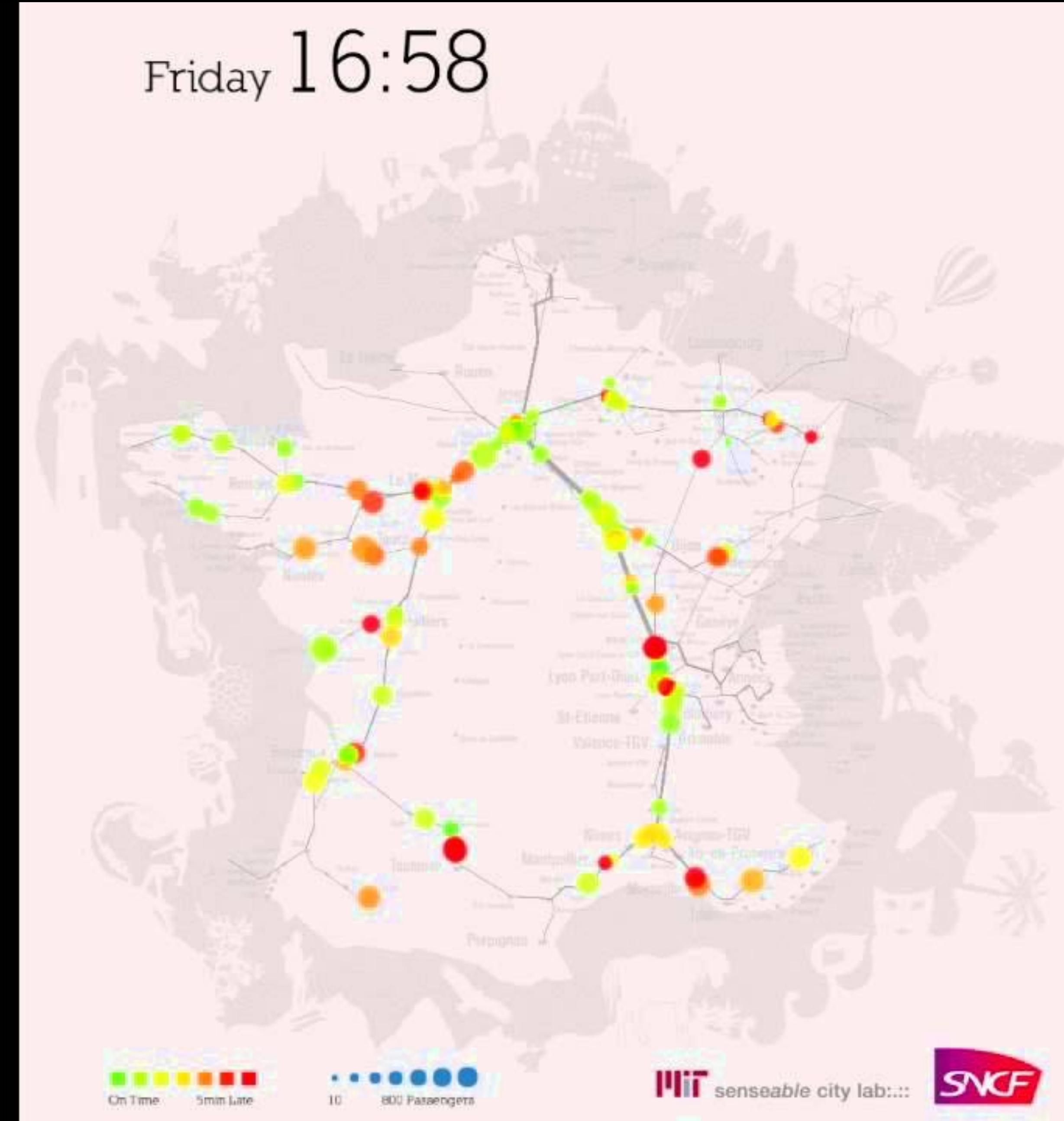
# Multi-scale: Intra-urban mobility



# Multi-scale: Intra-urban mobility

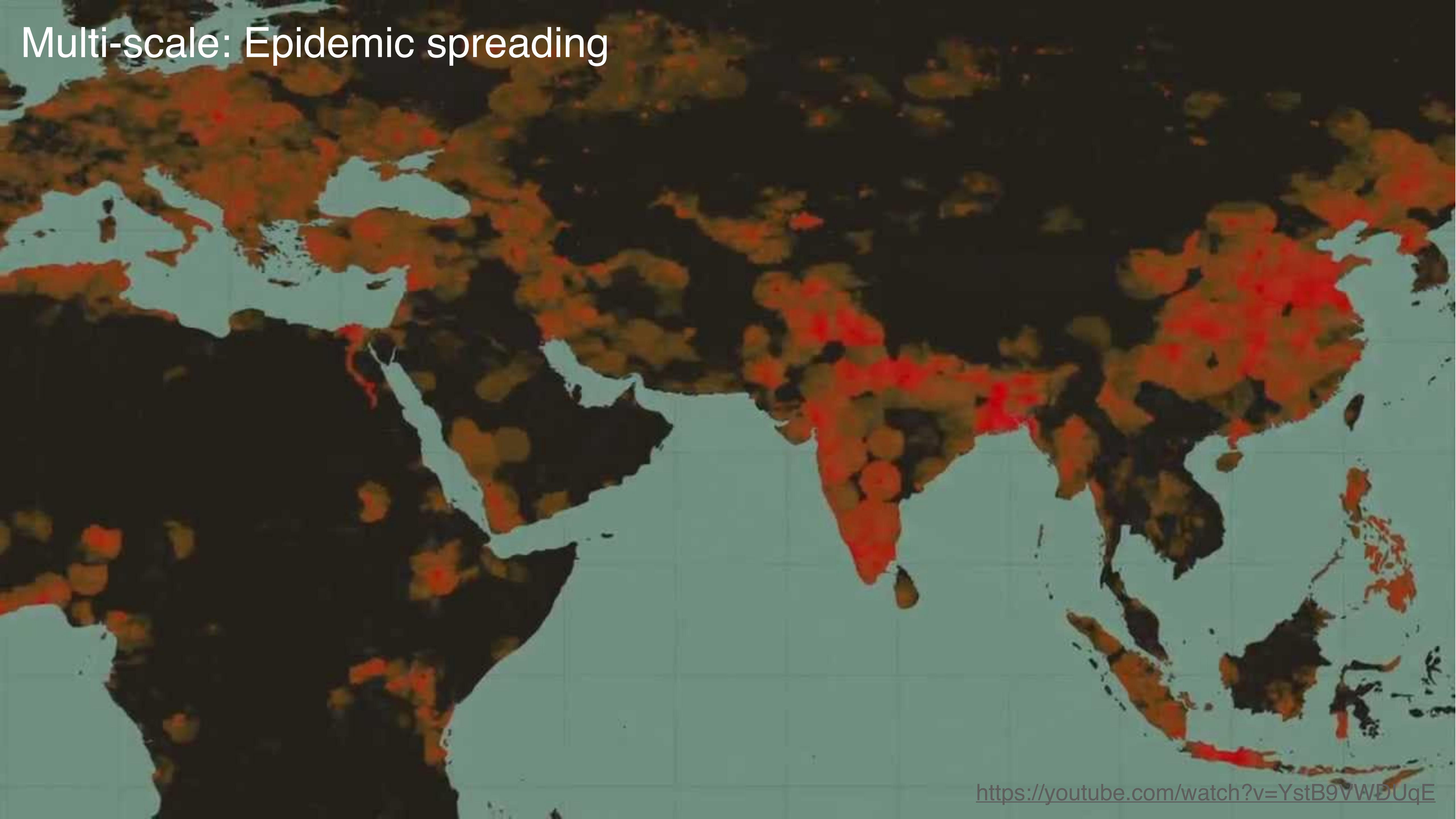


# Multi-scale: Inter-urban mobility



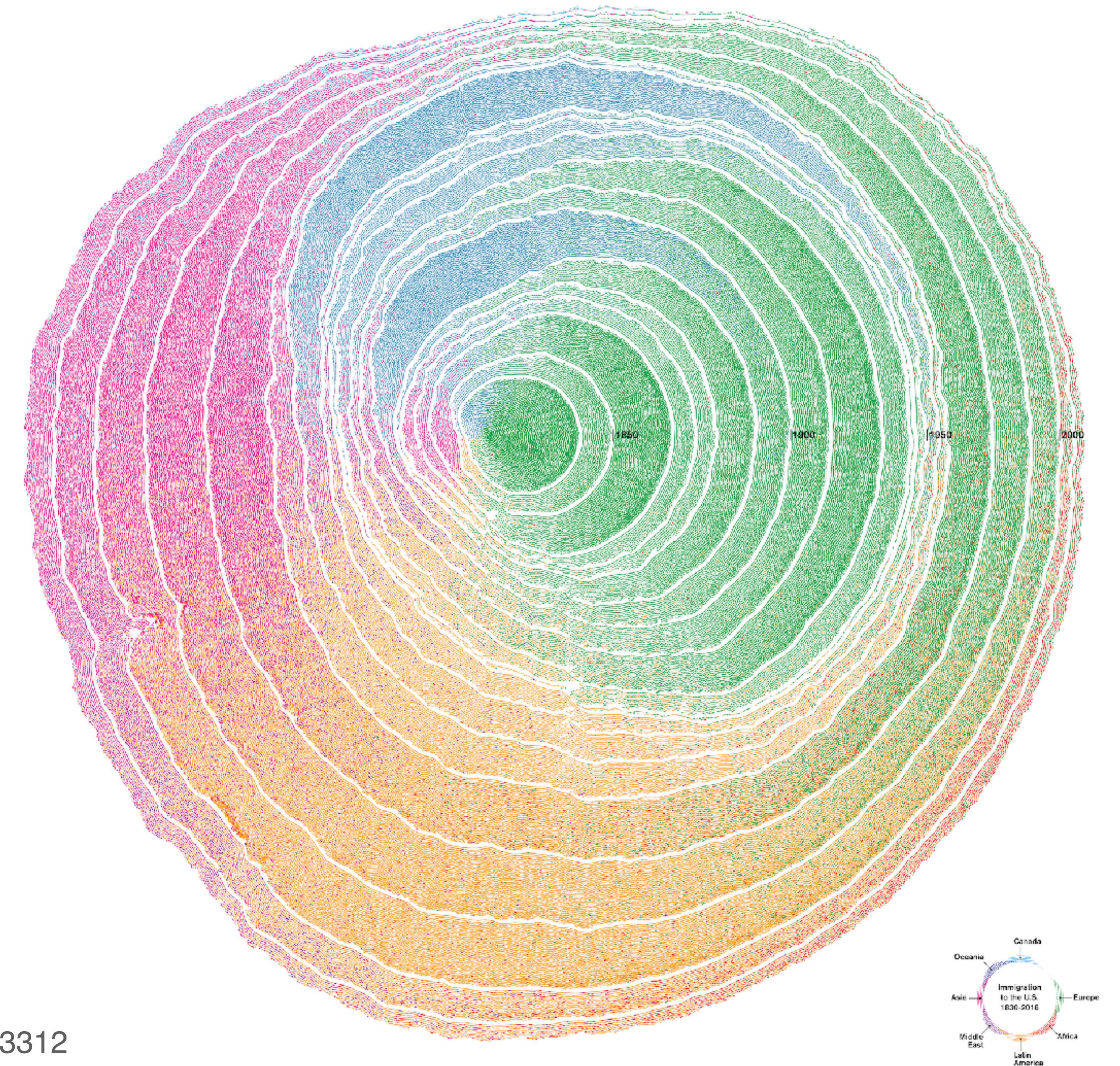
[https://youtube.com/watch?v=l17\\_nuPiJI4](https://youtube.com/watch?v=l17_nuPiJI4)

# Multi-scale: Epidemic spreading



<https://youtube.com/watch?v=YstB9VWDUqE>

# Population scale: Migration



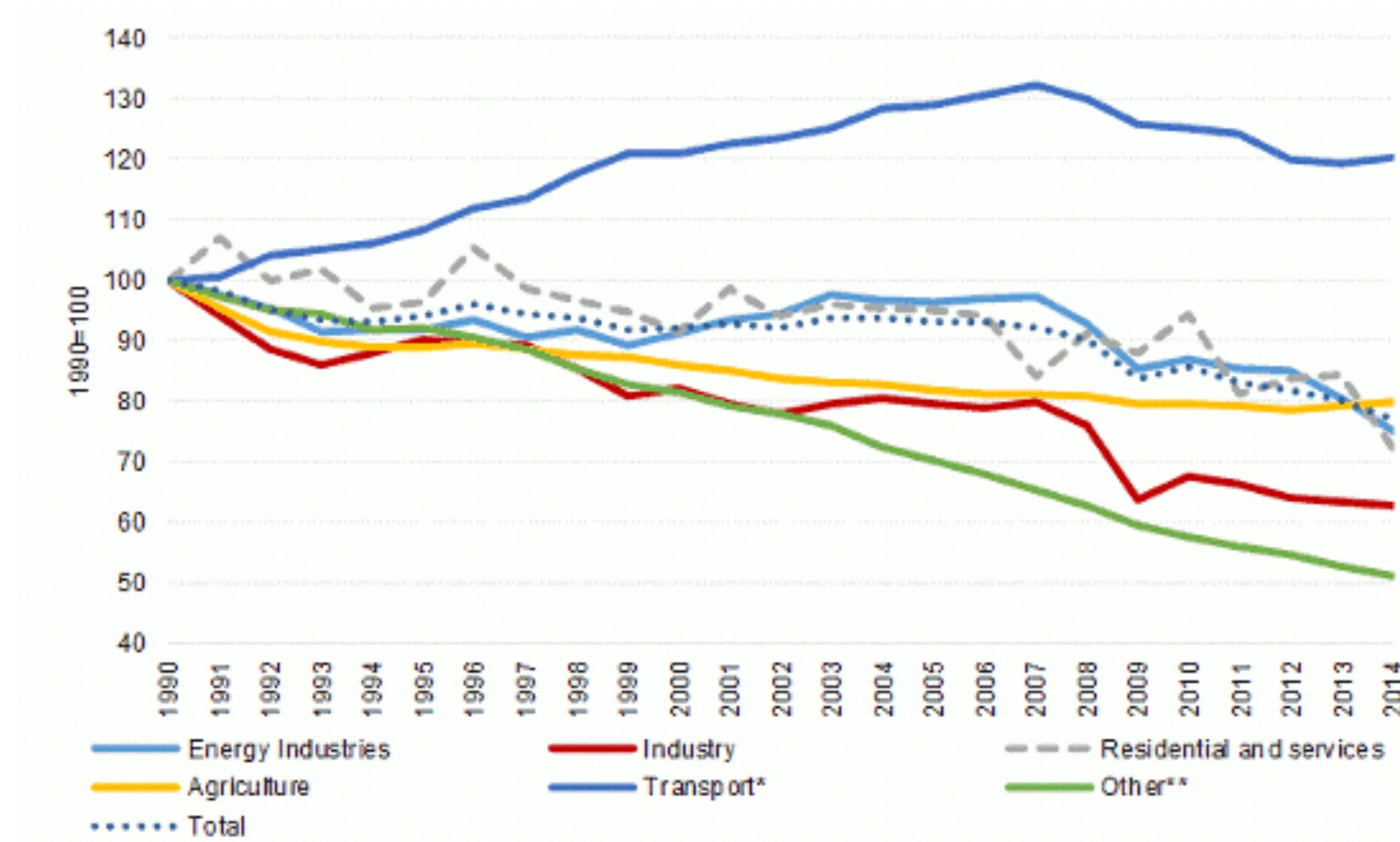
# Urban mobility

# Mobility takes many resources

Average household spending: ~20%

# Mobility takes many resources

Average household spending: ~20%



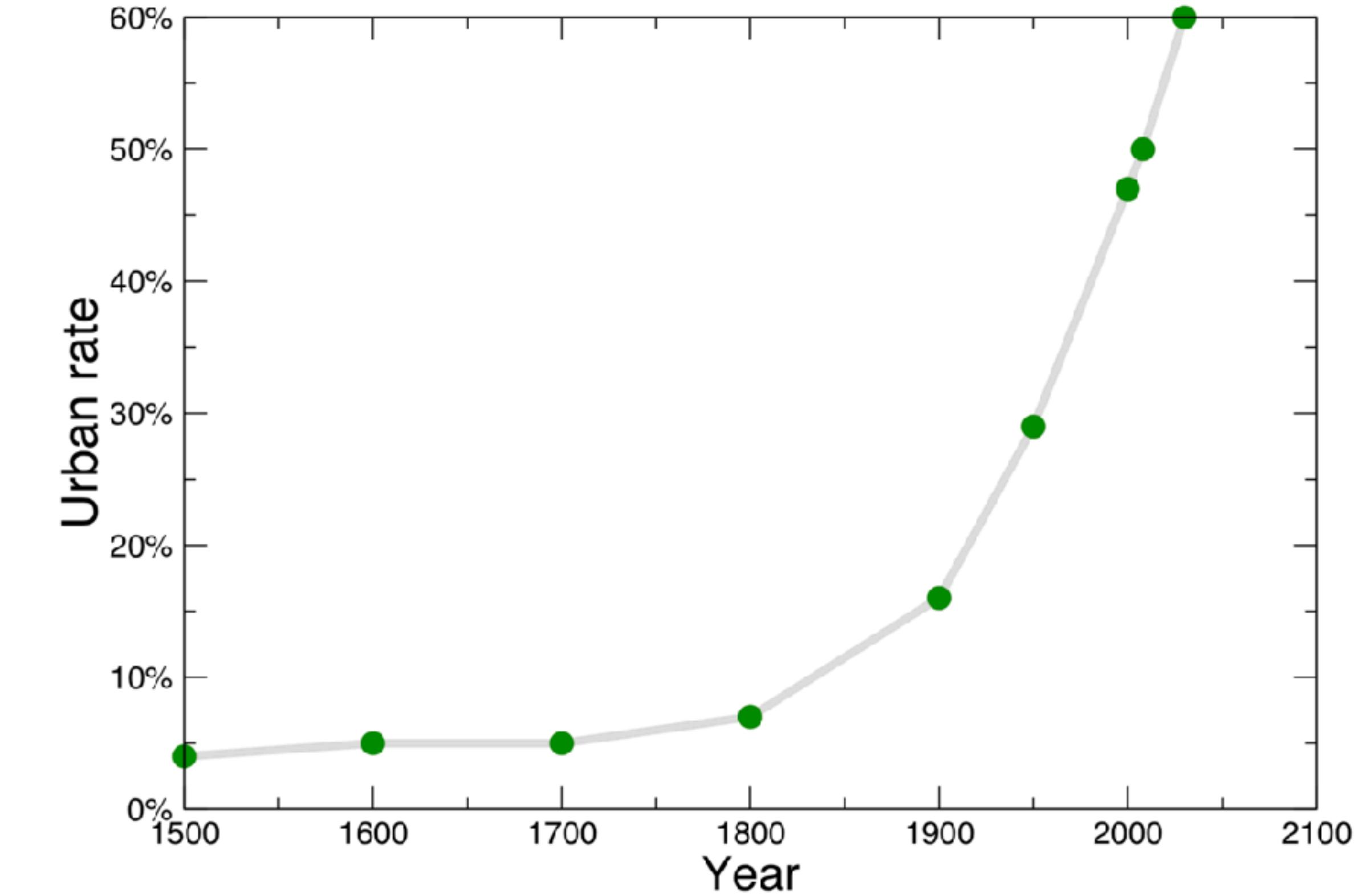
*Transport represents almost a quarter of Europe's greenhouse gas emissions and is the main cause of air pollution in cities.*

# Mobility is an ever bigger issue in cities

55% of the world's population lives in cities

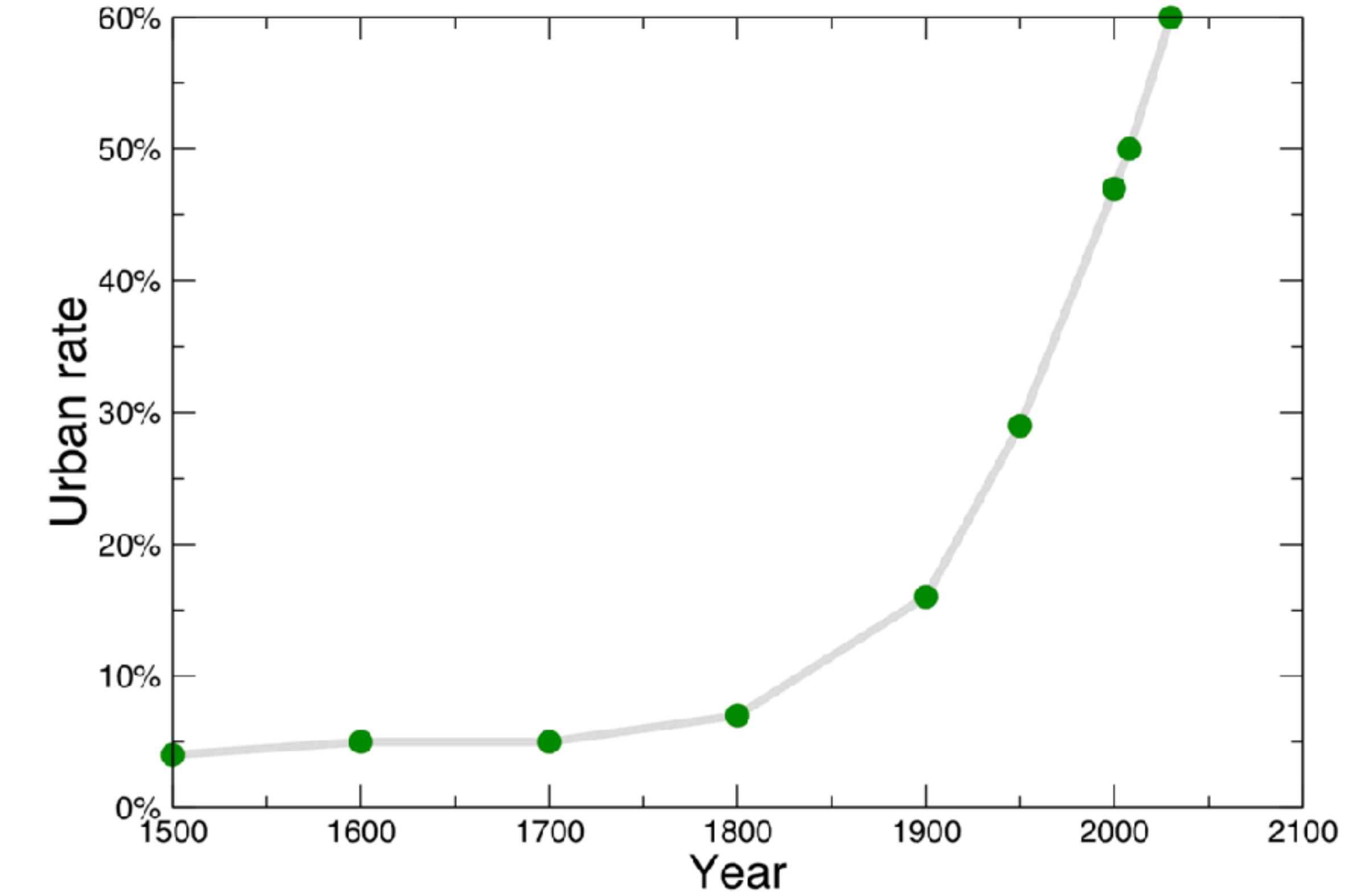
By 2050, it will be 70%

In north america, it is already 82%



# Mobility is an ever bigger issue in cities

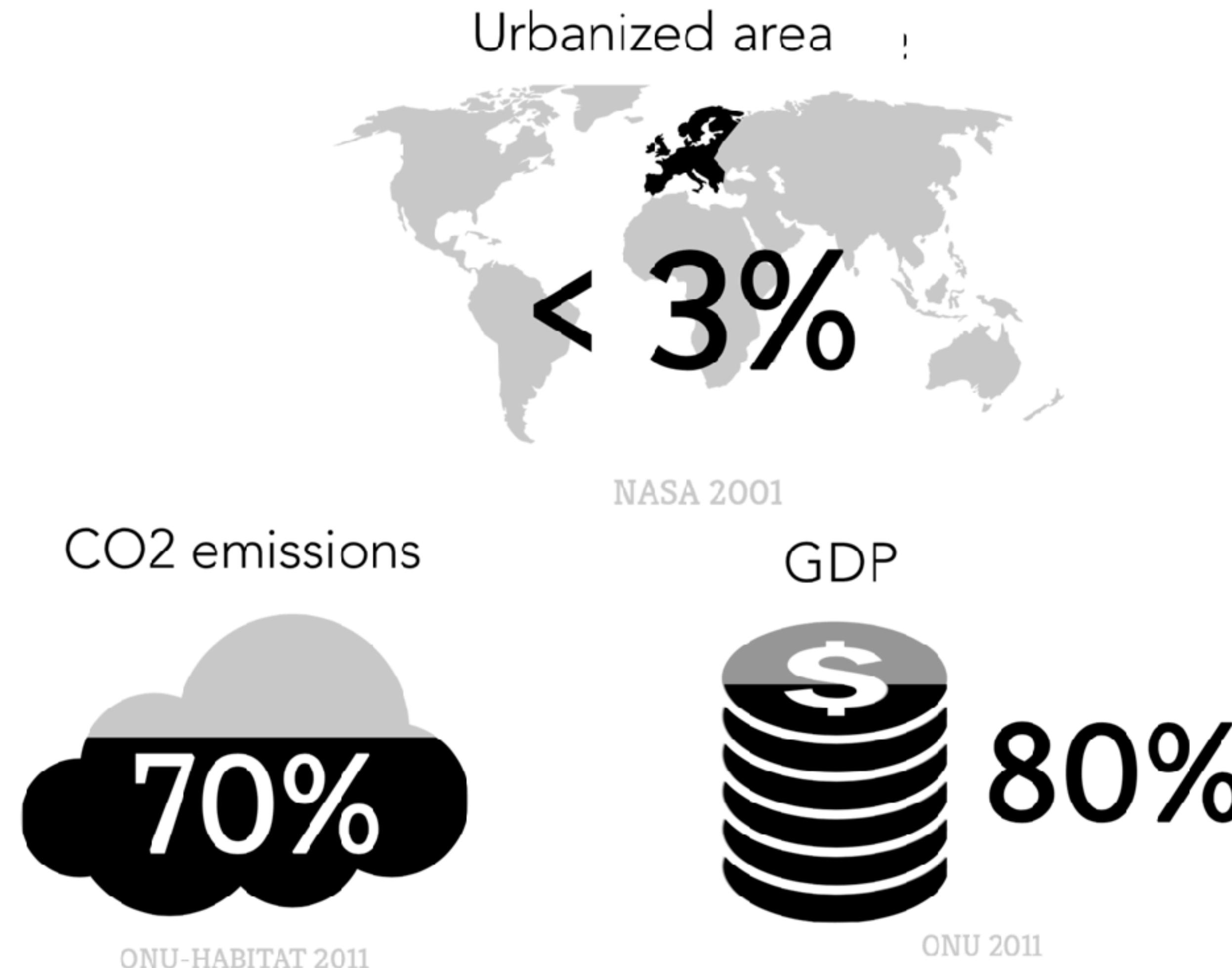
Based on satellite images, already **84%** of the world's population lives in cities



<https://www.reuters.com/article/us-global-cities/everything-weve-heard-about-global-urbanization-turns-out-to-be-wrong-researchers-idUSKBN1K21UU>

<https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html>

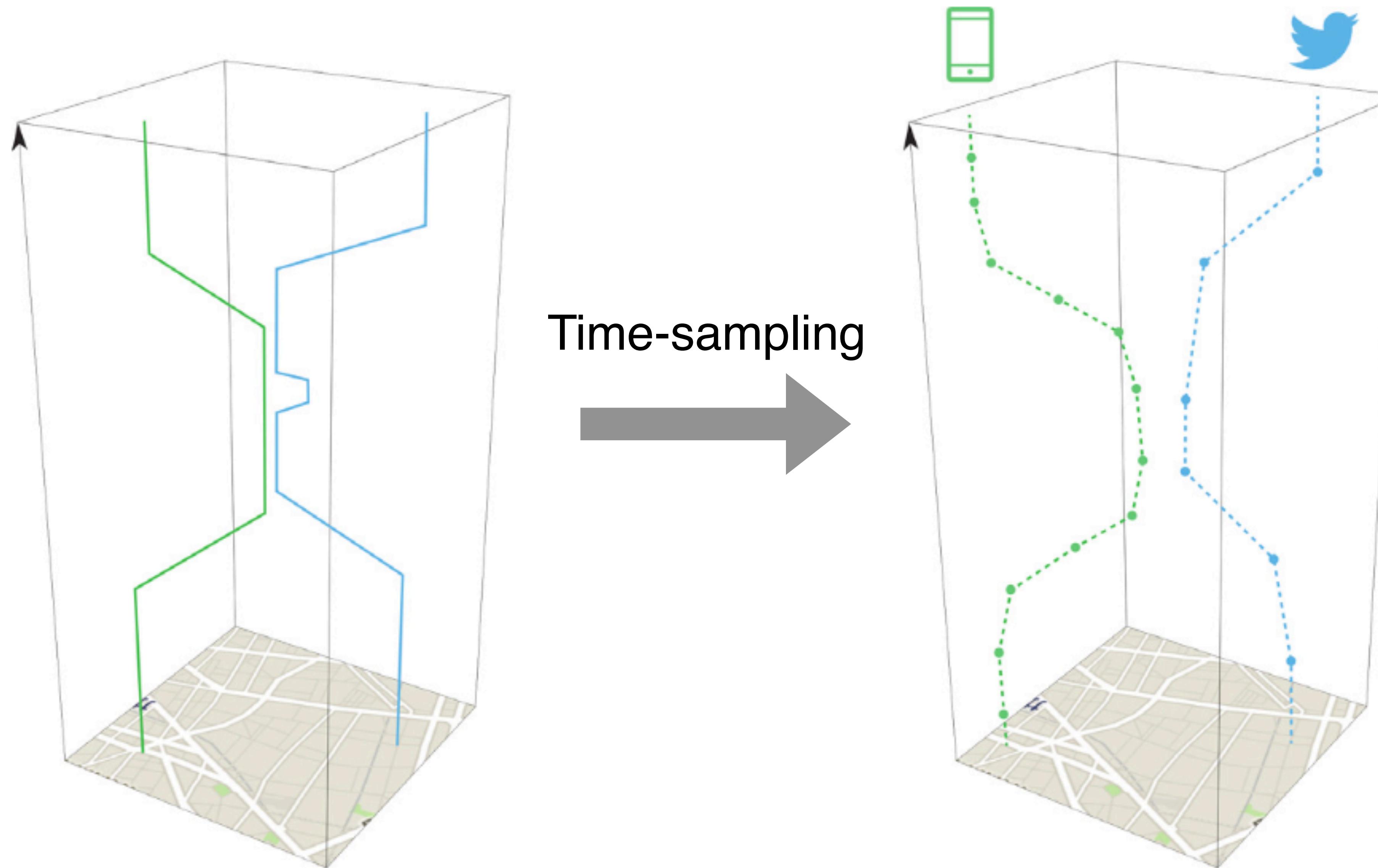
# Mobility is an ever bigger issue in cities



Solving problems in cities means solving problems for most of humanity

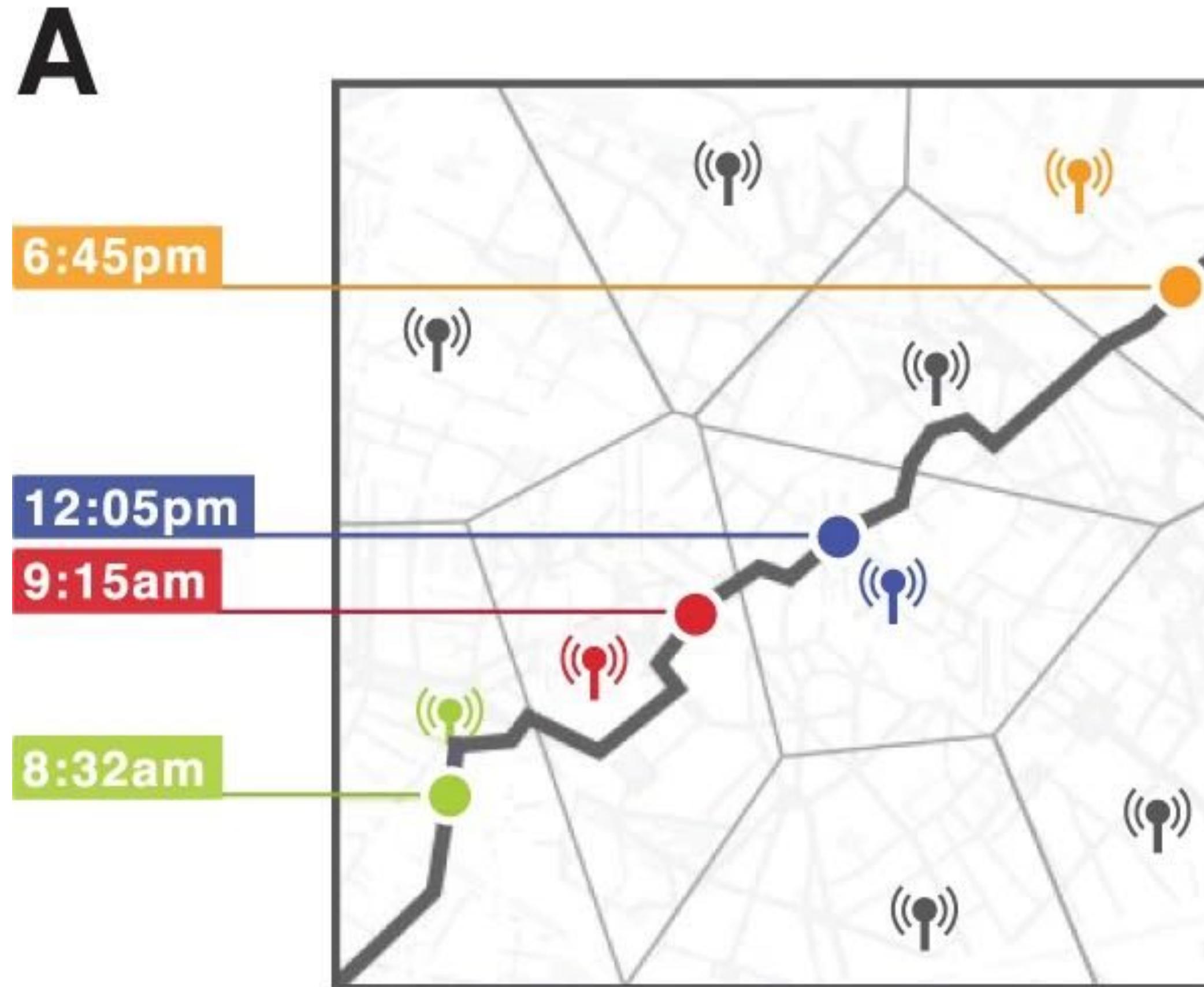
# Measuring individual trajectories

# The cube of time geography shows mobility in space-time

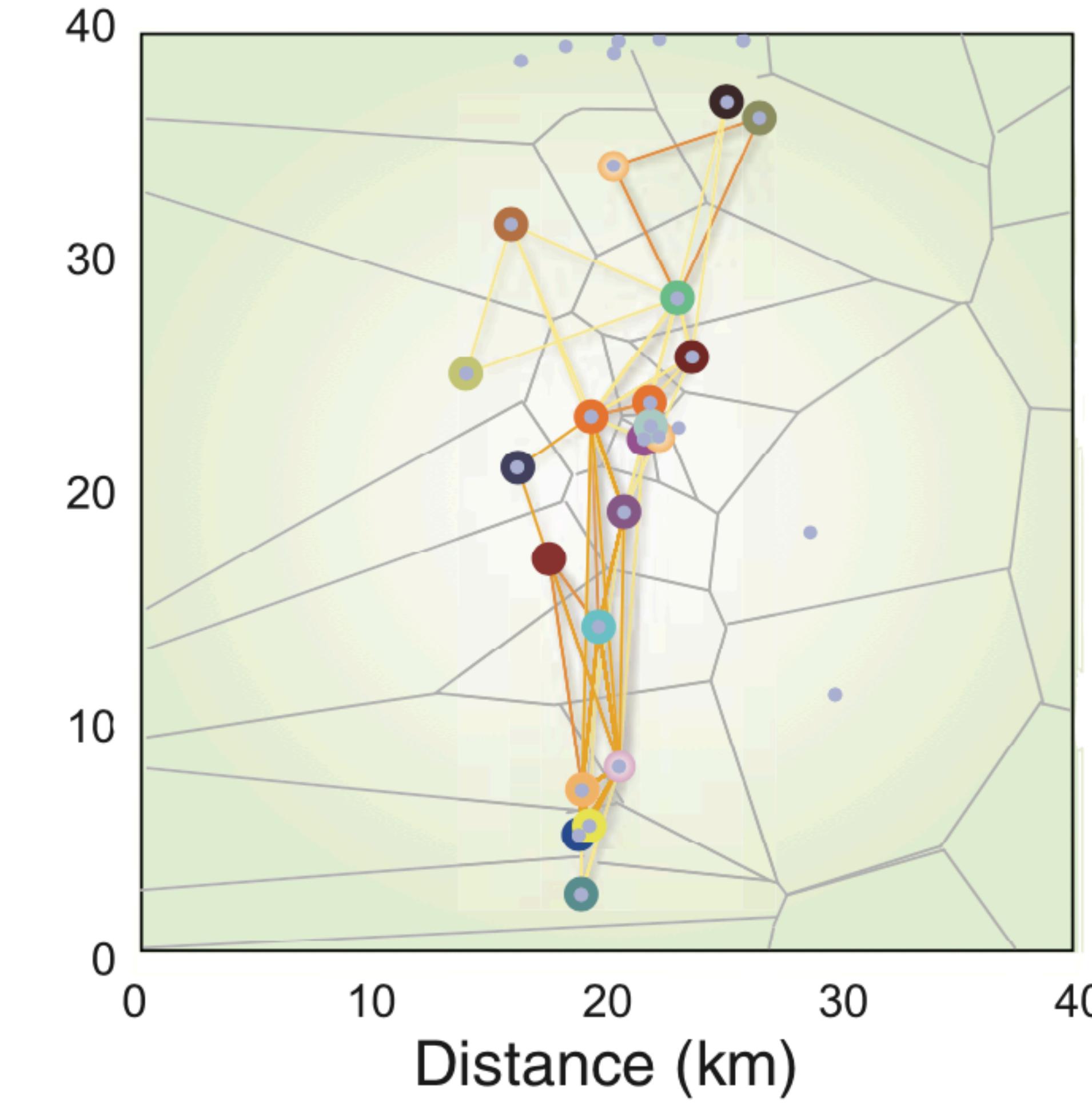
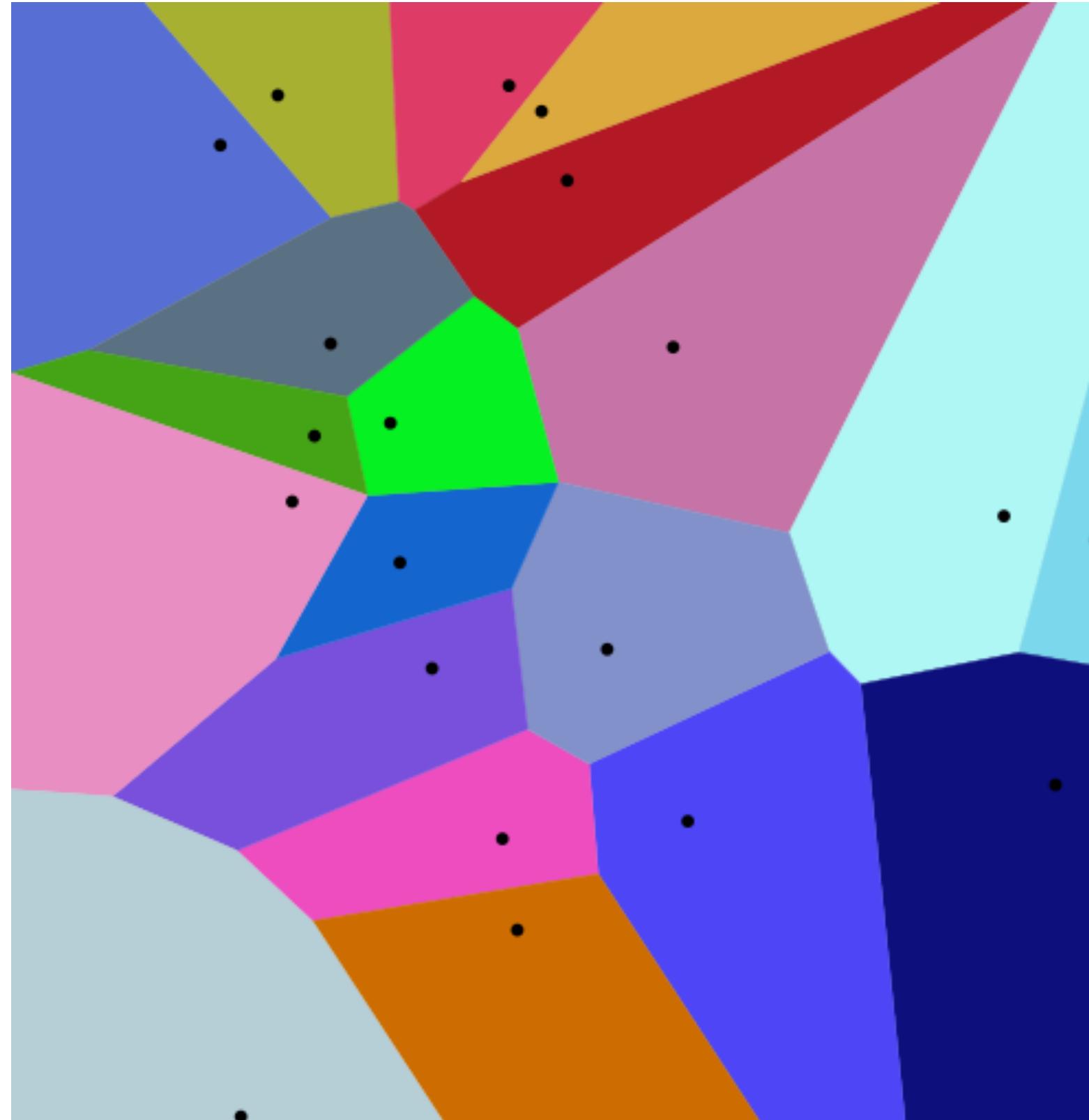


Hägerstrand (1970)

# Call Detail Records (CDR) match location to the nearest tower

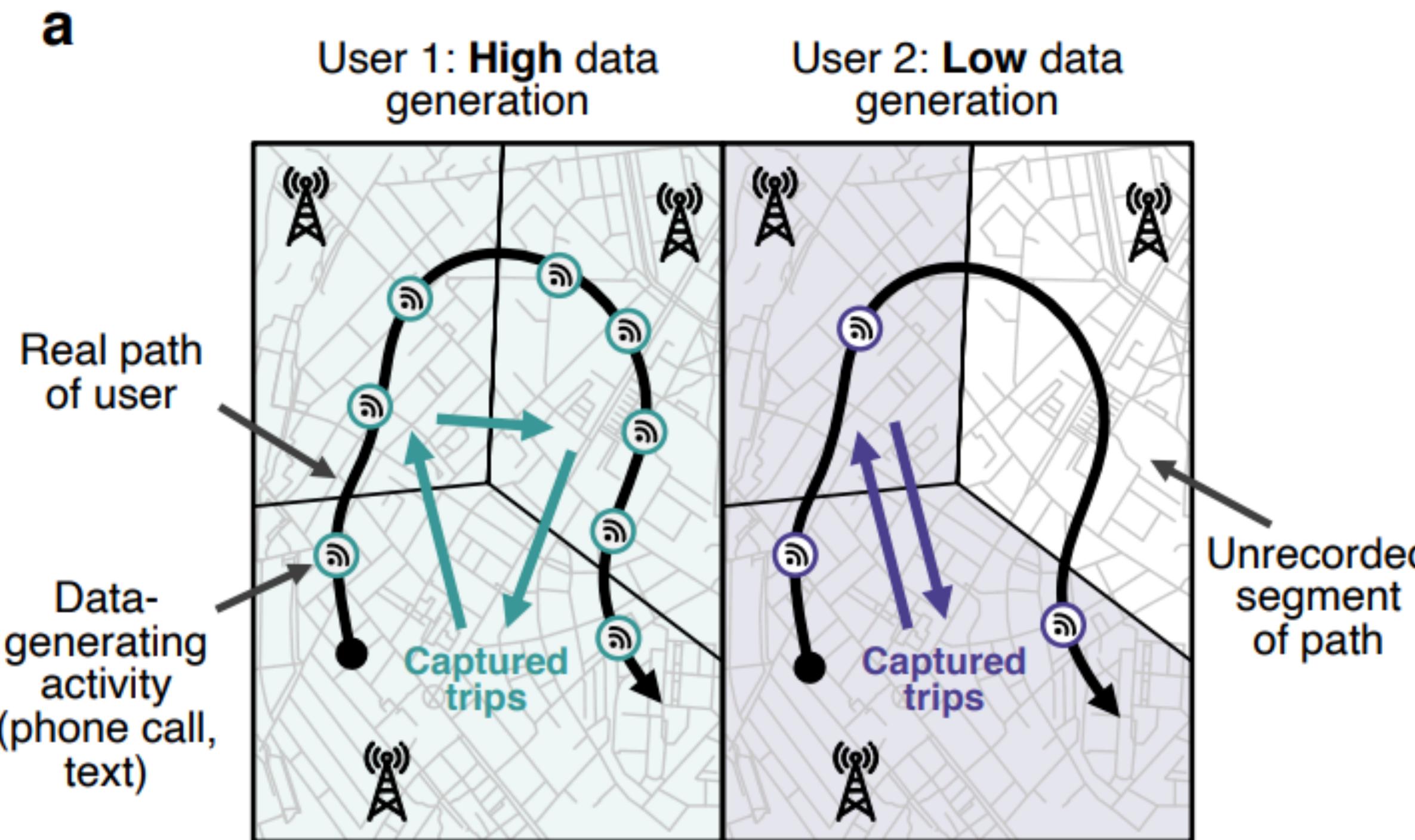


# Call Detail Records (CDR) match location to the nearest tower



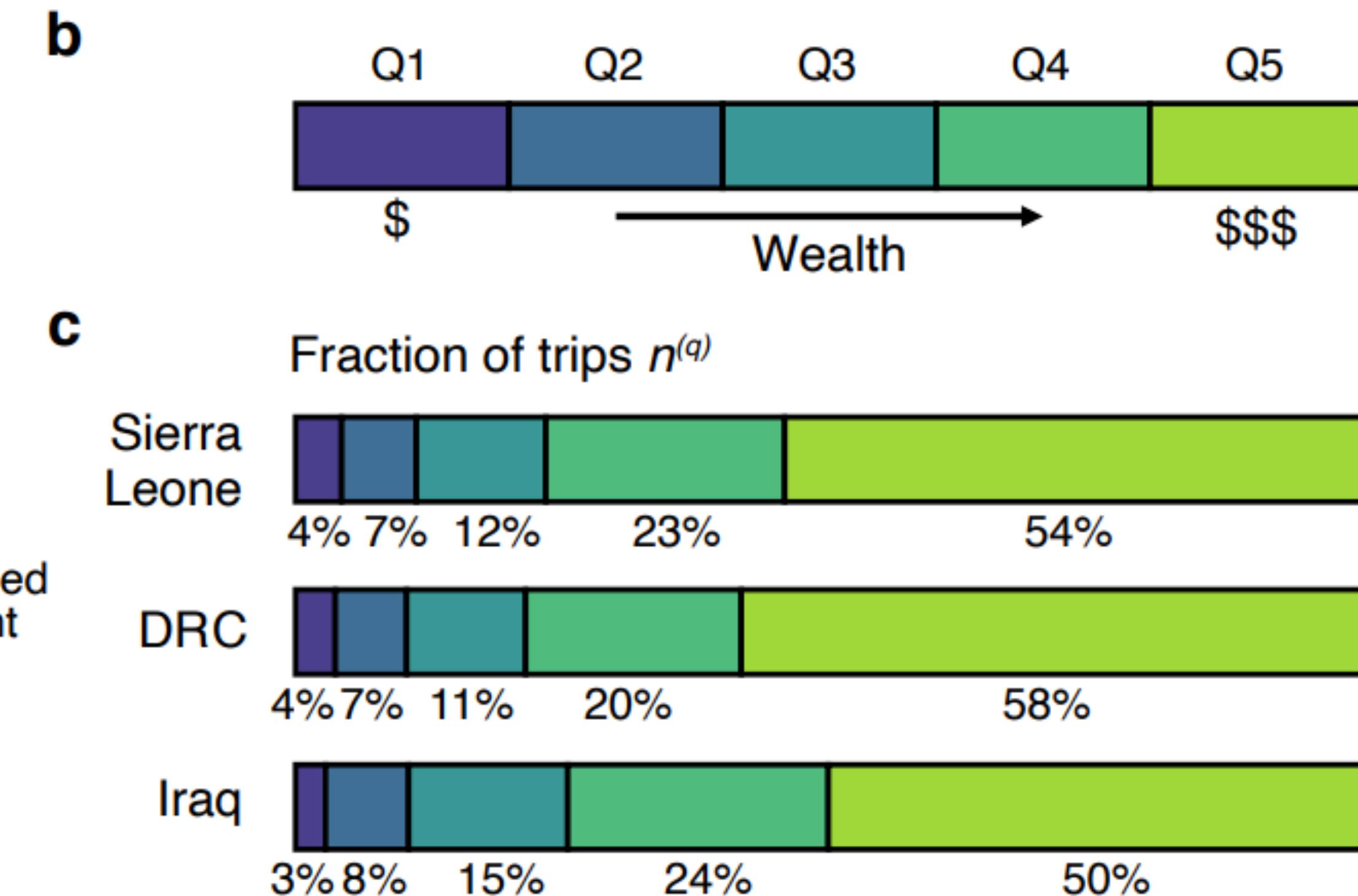
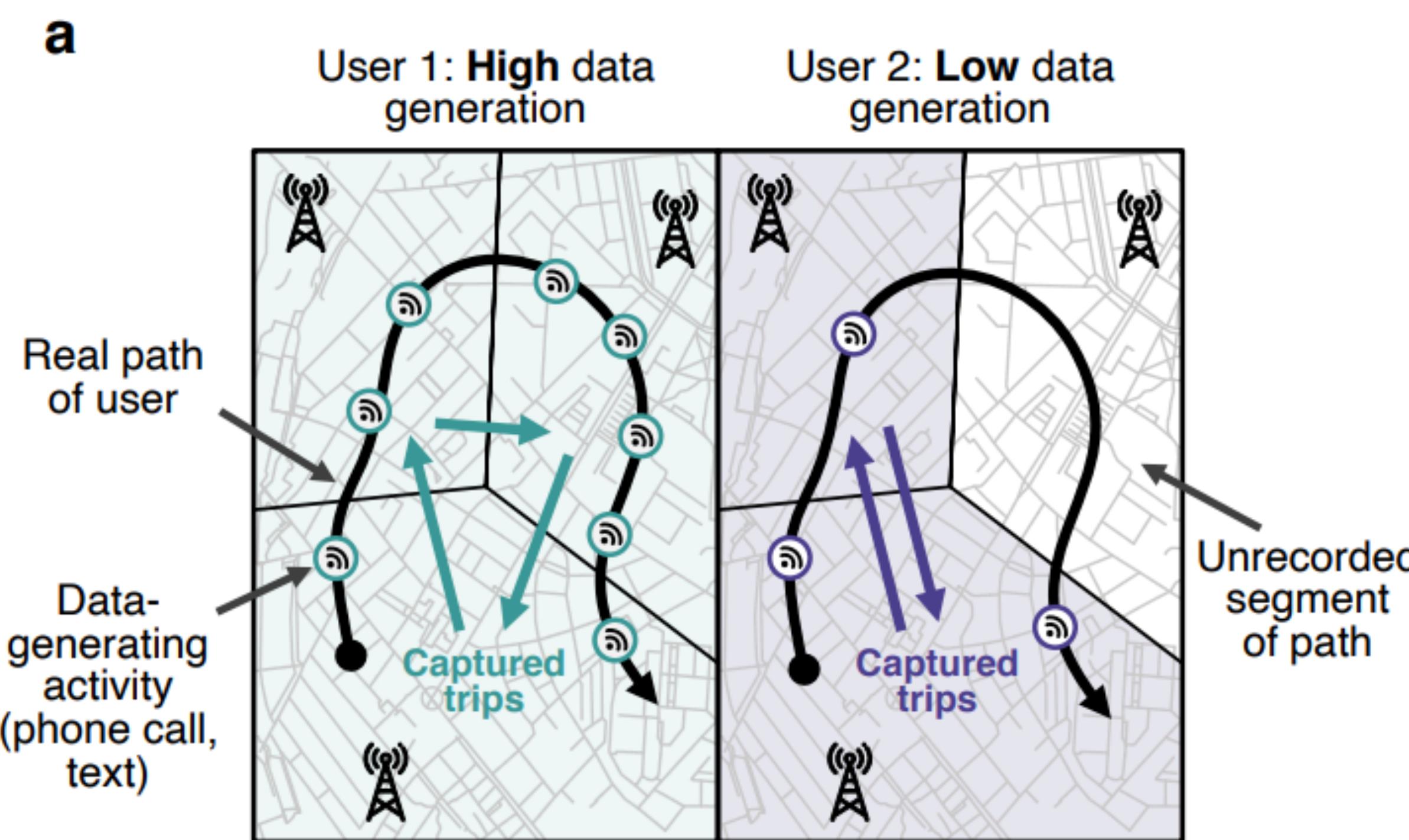
# Call Detail Records (CDR) have a lot of biases

Sampling bias: record only when making a call or being called



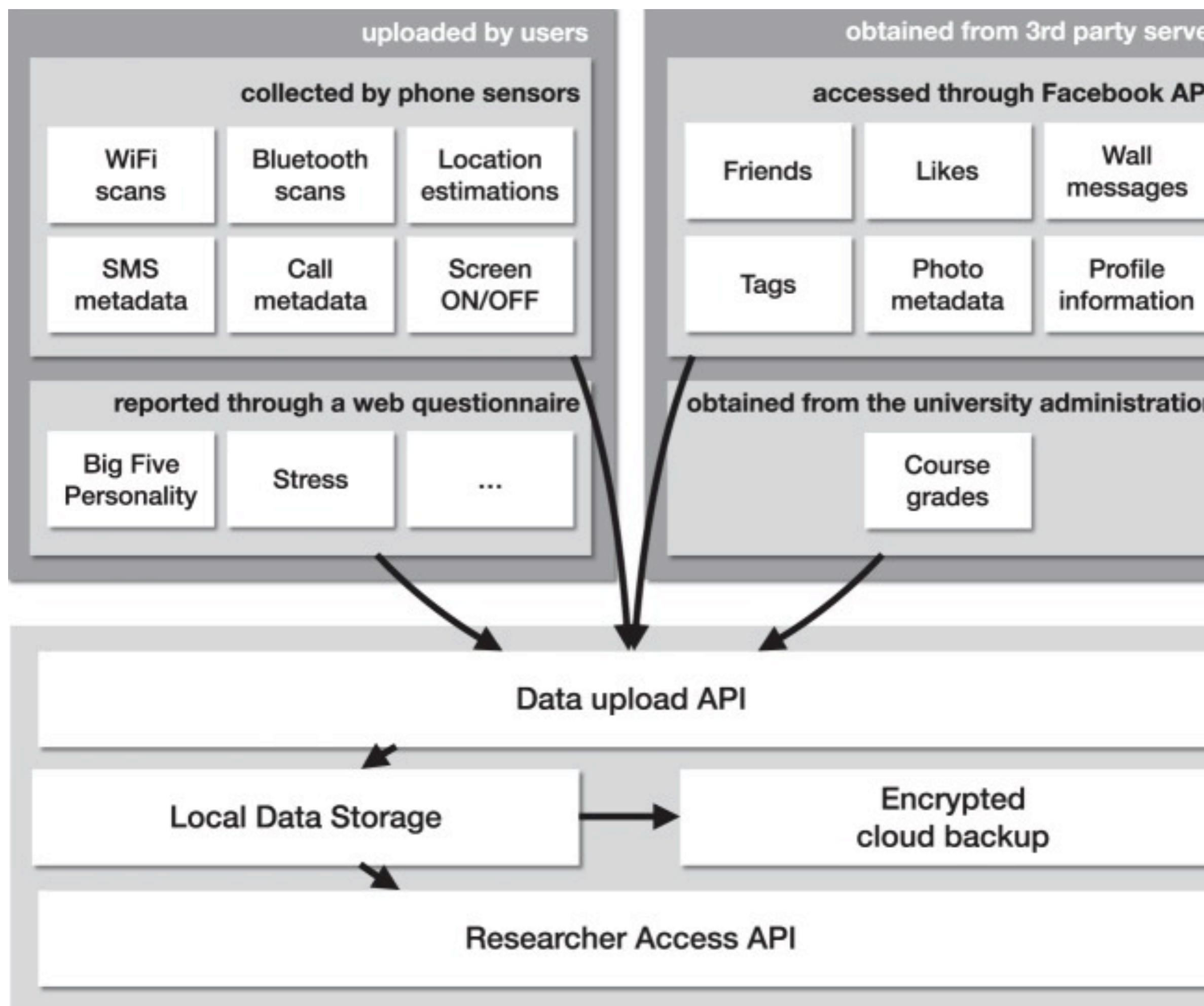
# Call Detail Records (CDR) have a lot of biases

# Sampling bias: record only when making a call or being called

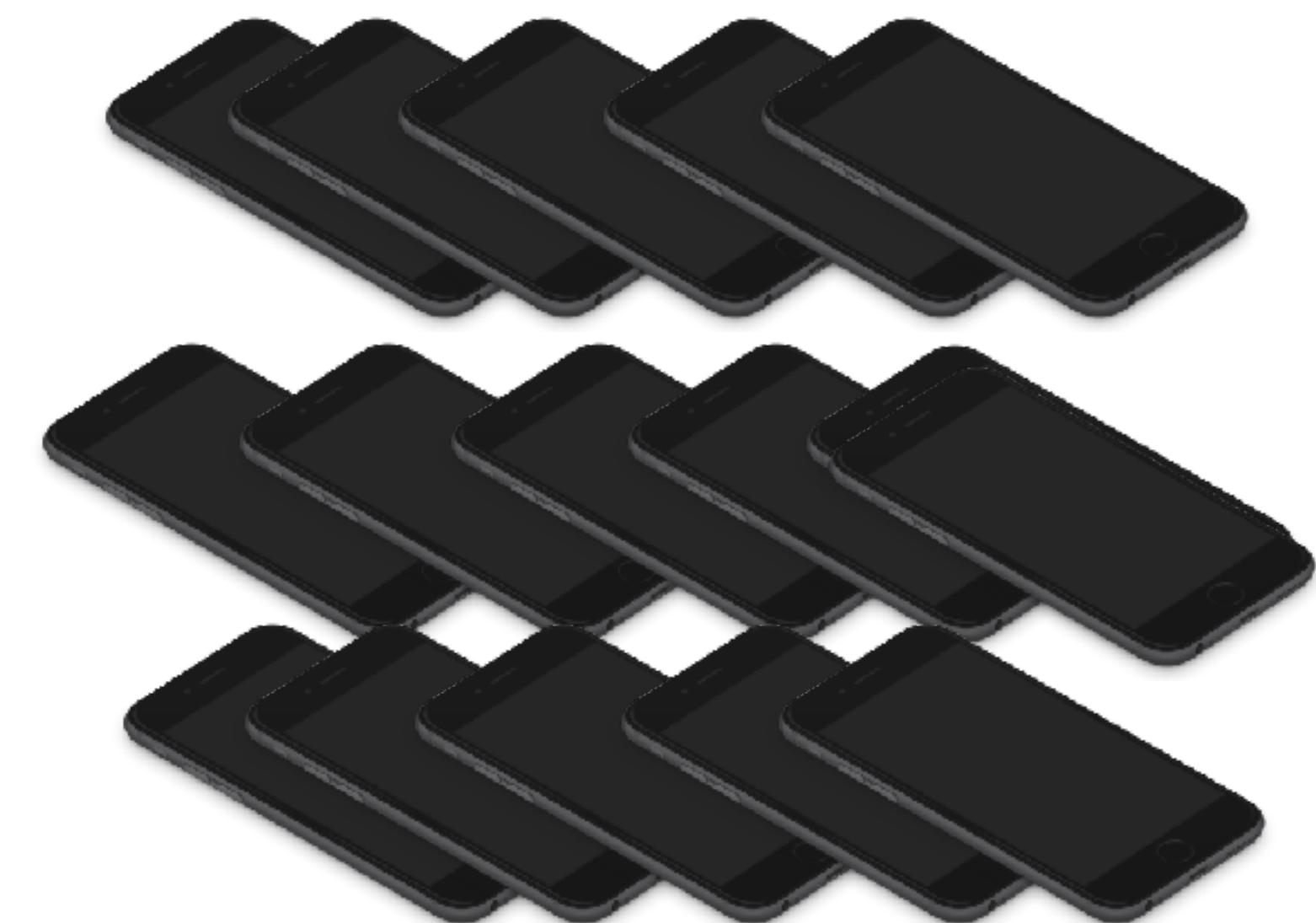


# You could track more than just CDR

Activity Data Records (XDR) or deliberate tracking can give more data:  
Copenhagen Network Study



1000 x

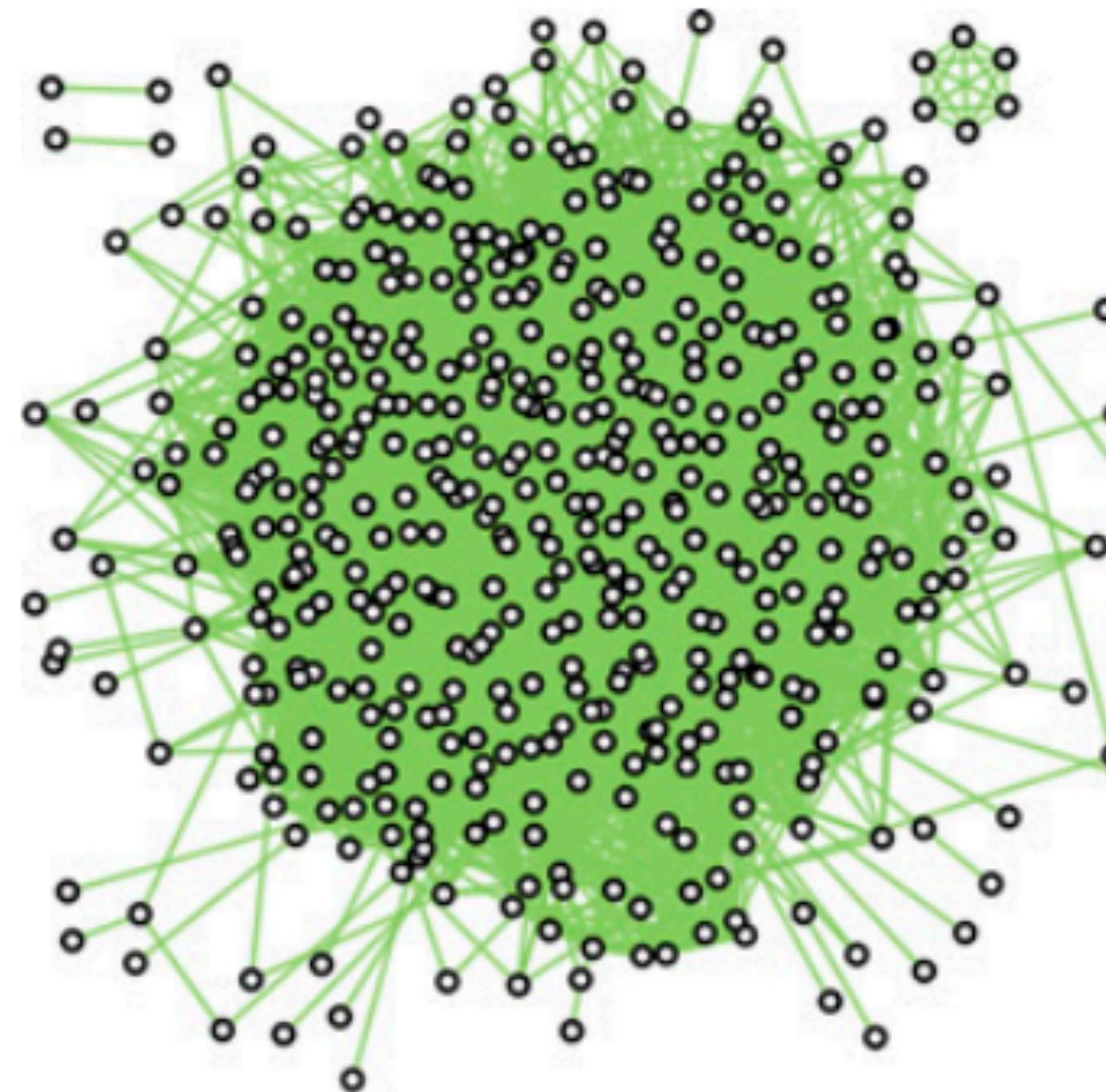


# You could track more than just CDR

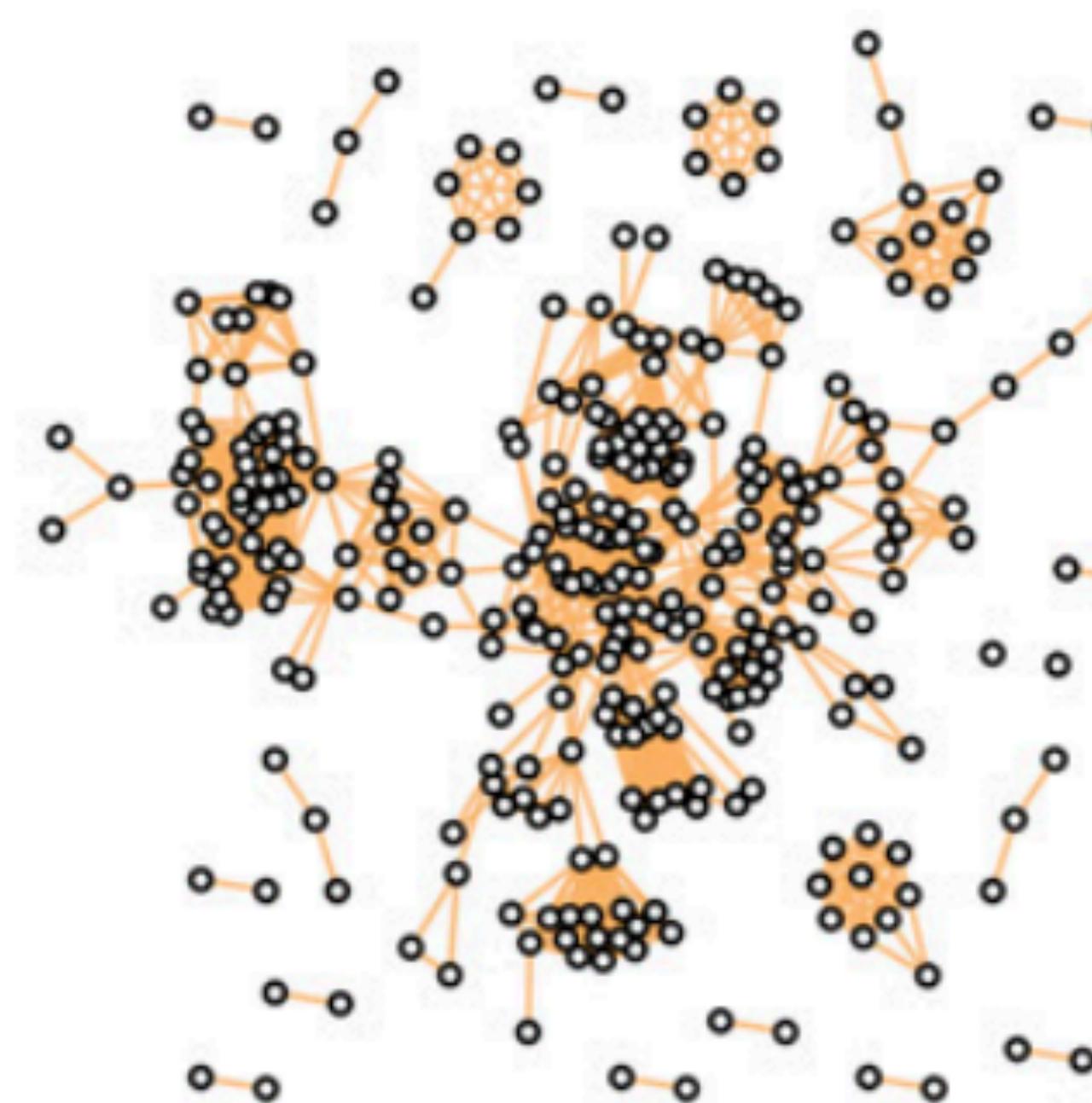
Activity Data Records (XDR) or deliberate tracking can give more data:  
Copenhagen Network Study

A

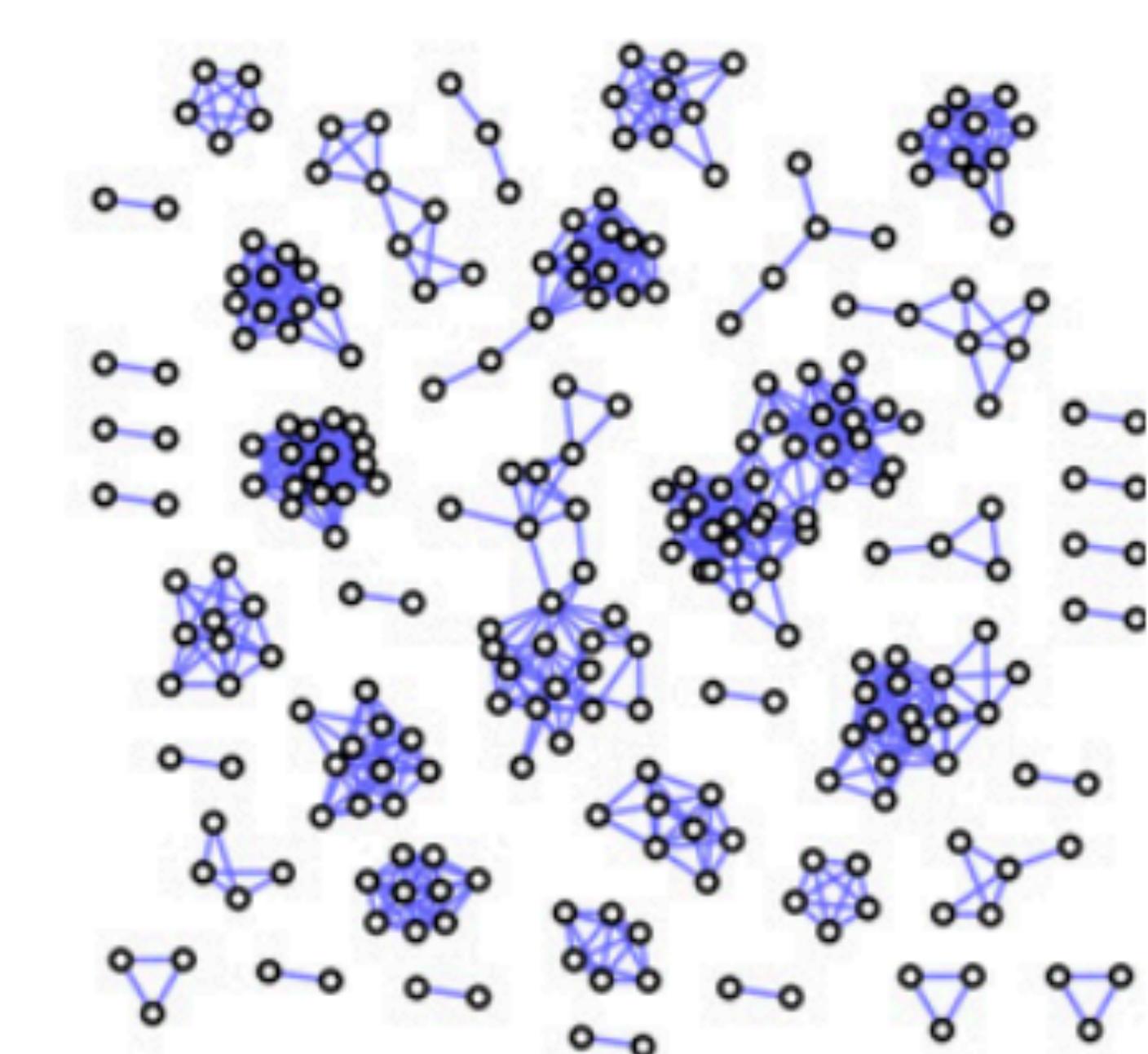
Daily



Hourly



Micro (5min)



# Many other sources or proxies for mobility data exist

## Transport

TomTom

Oyster cards

Taxi

Bike sharing

## Social media

Foursquare / Facebook check-ins

Geolocated social media posts (Twitter)

## Other

Credit card spending

Where's George?

# Analyzing tracked dollar bills as proxy for travel



[wheresgeorge.com](http://wheresgeorge.com)



1. Original entry - Dayton, OH
2. Received as a tip at Sonic in Louisville
3. Change at Denny's in Tampa
4. Change at a country store in Unionville, TN
5. Won it at the racetrack in Grapevine, TX
6. Found on the floor of a restroom at Mt. Rushmore
7. Change at Target in Phoenix

Humans carry banknotes, so they are a proxy for travel

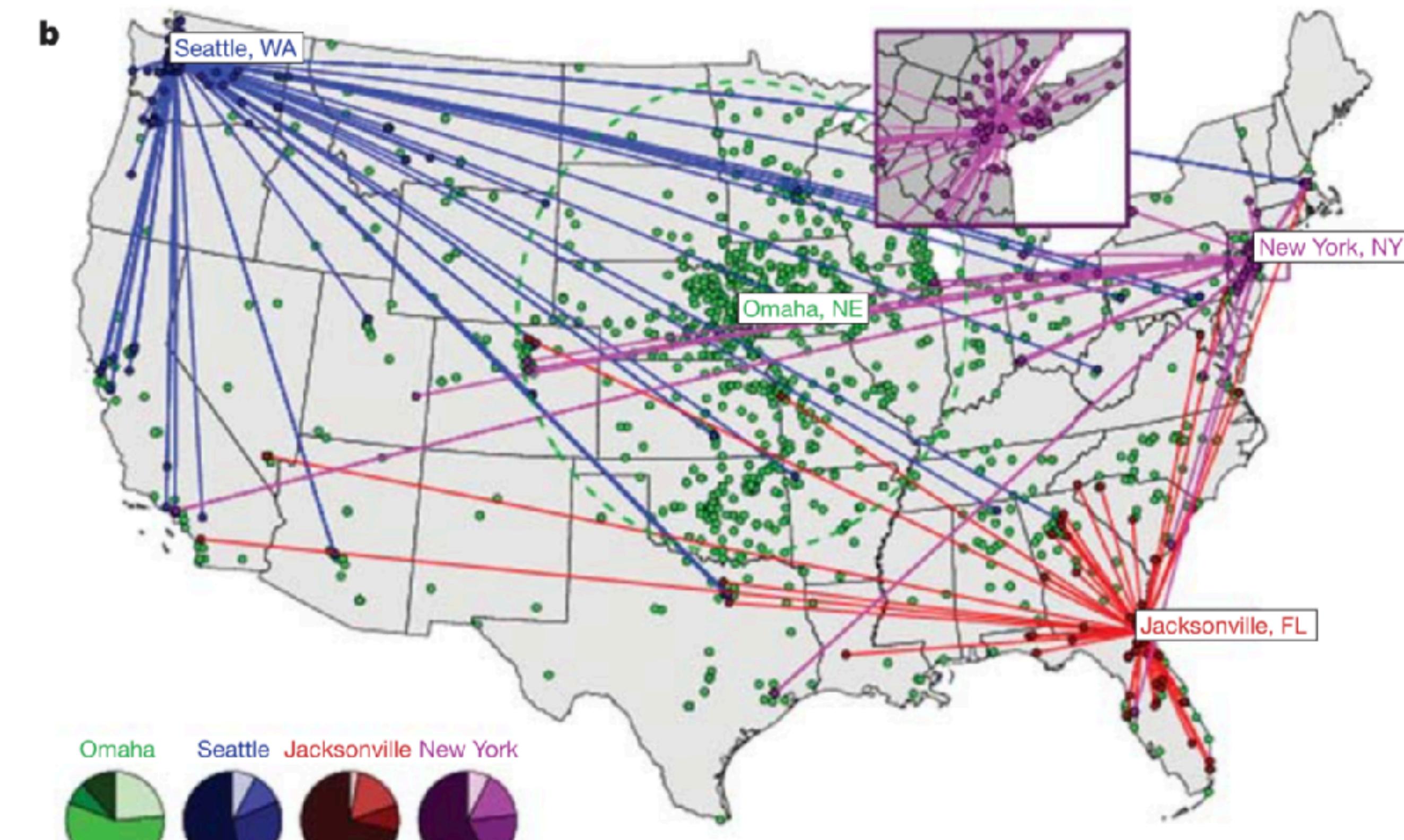
# Analyzing tracked dollar bills as proxy for travel

nature

LETTERS

## The scaling laws of human travel

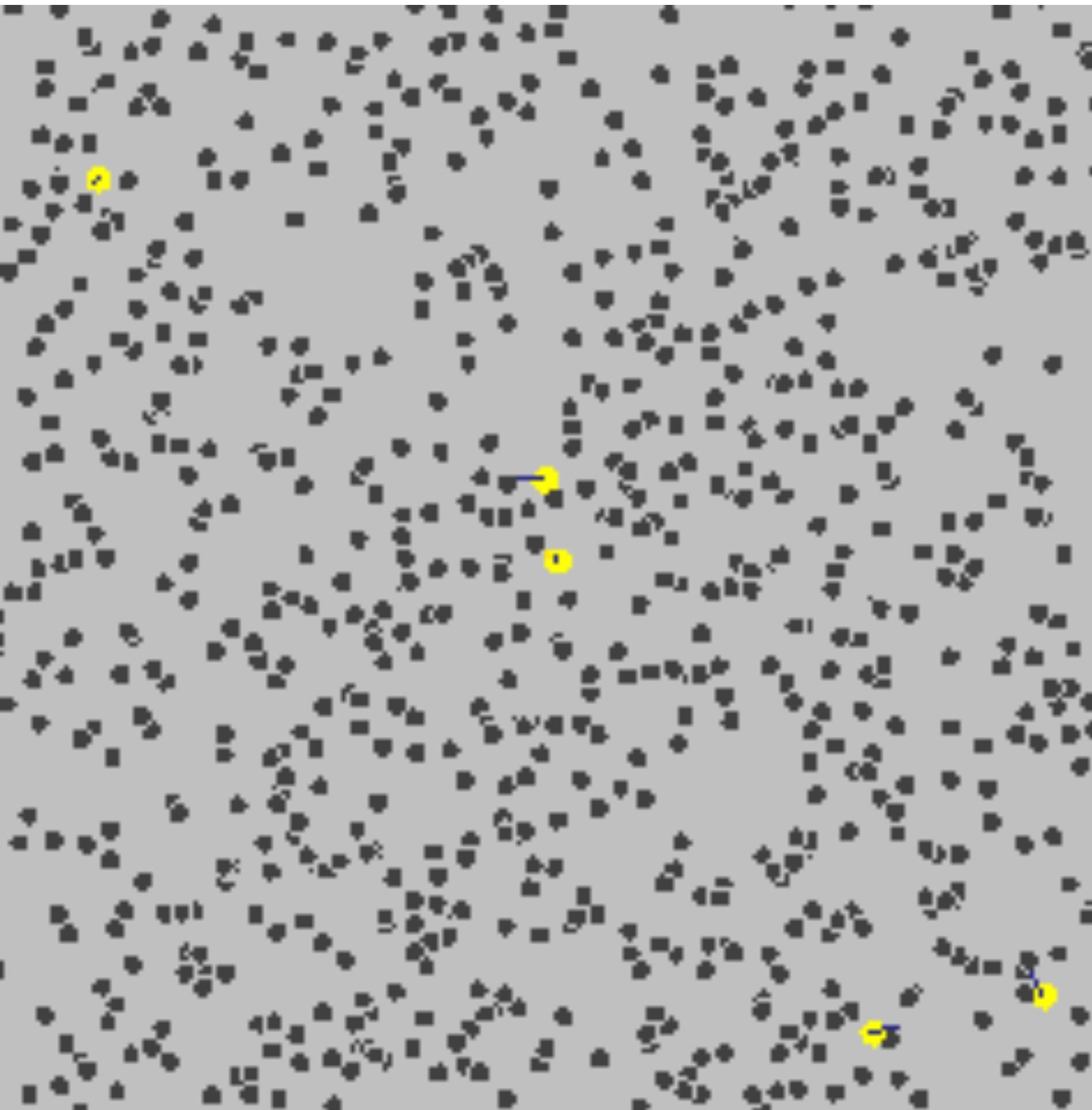
D. Brockmann<sup>1,2</sup>, L. Hufnagel<sup>3</sup> & T. Geisel<sup>1,2,4</sup>



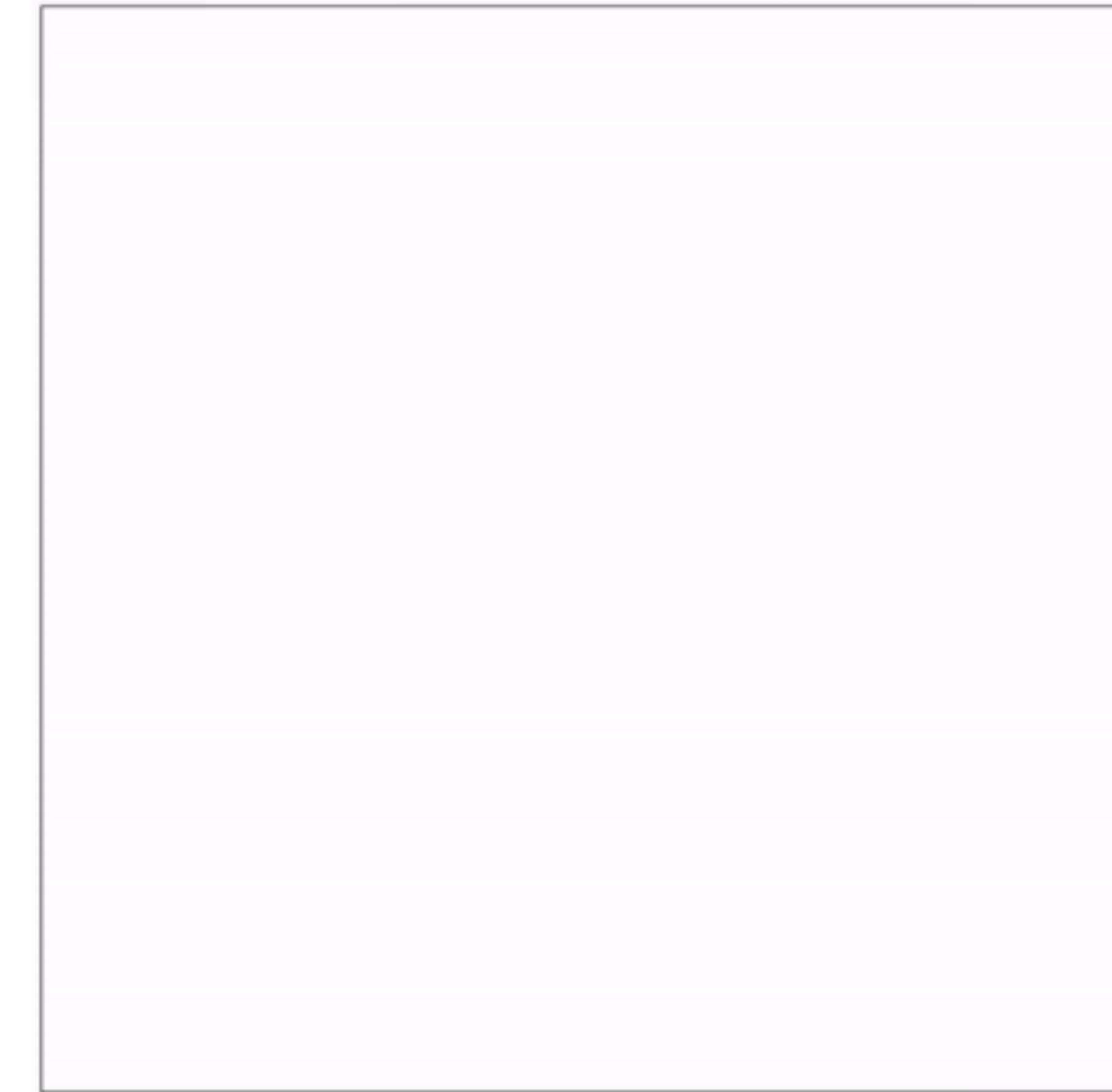
Brockmann, 2006: Are there statistical laws? Is it a random walk?

# A physics approach to human mobility

In the simplest mobility model, a random walker moves a fixed distance every fixed time step into a random direction (**random walk**)



[https://en.wikipedia.org/wiki/Brownian\\_motion](https://en.wikipedia.org/wiki/Brownian_motion)



[https://en.wikipedia.org/wiki/Random\\_walk](https://en.wikipedia.org/wiki/Random_walk)

# A physics approach to human mobility

This is a **jump process**: Discrete movements (jumps) rather than continuous movement

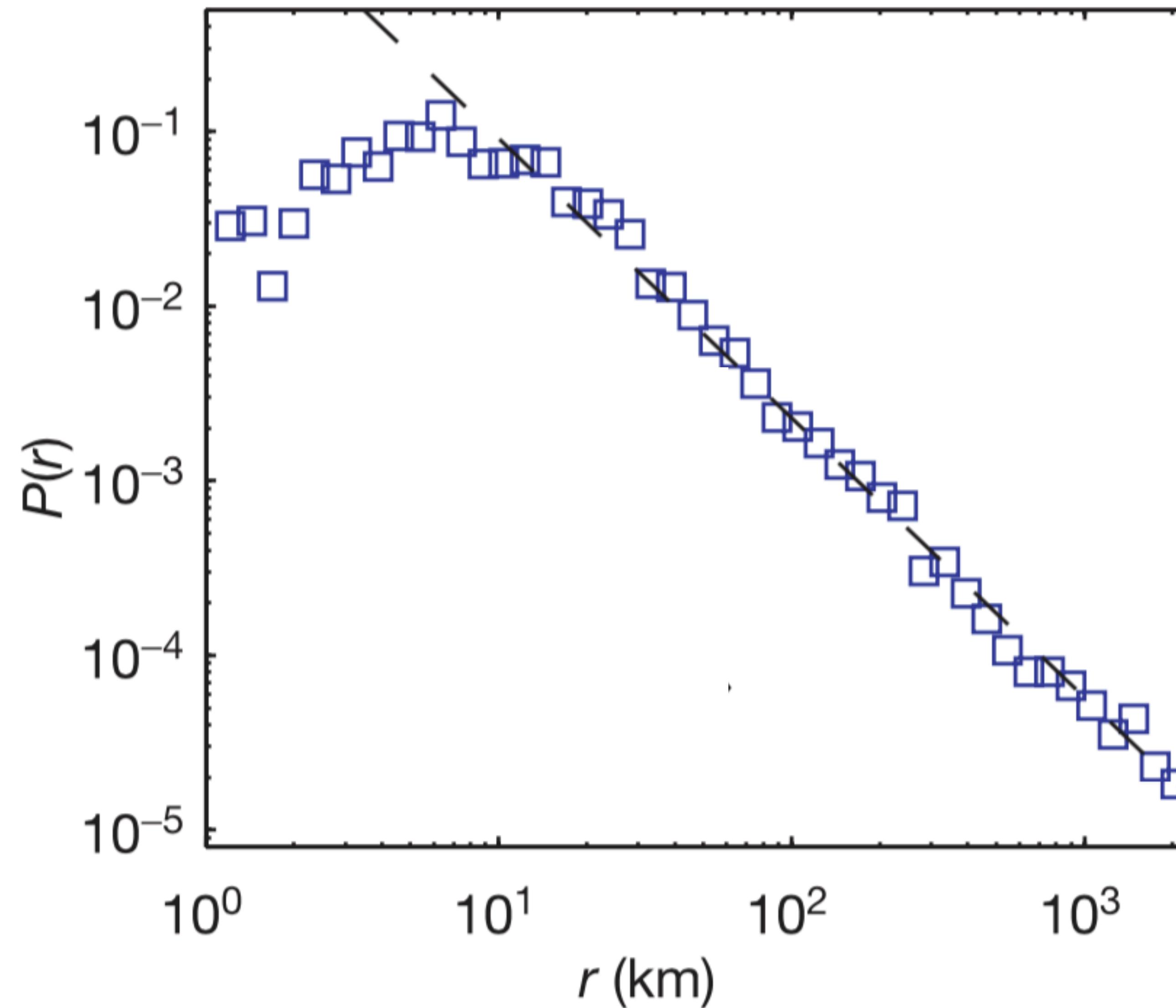
Here the displacement  $\Delta r$  is constant

Here the waiting time  $\Delta t$  is constant

How is it for Where's George?

# Displacement distribution of banknotes is heavy-tailed

Probability that a banknote travels distance  $r$  in less than 4 days

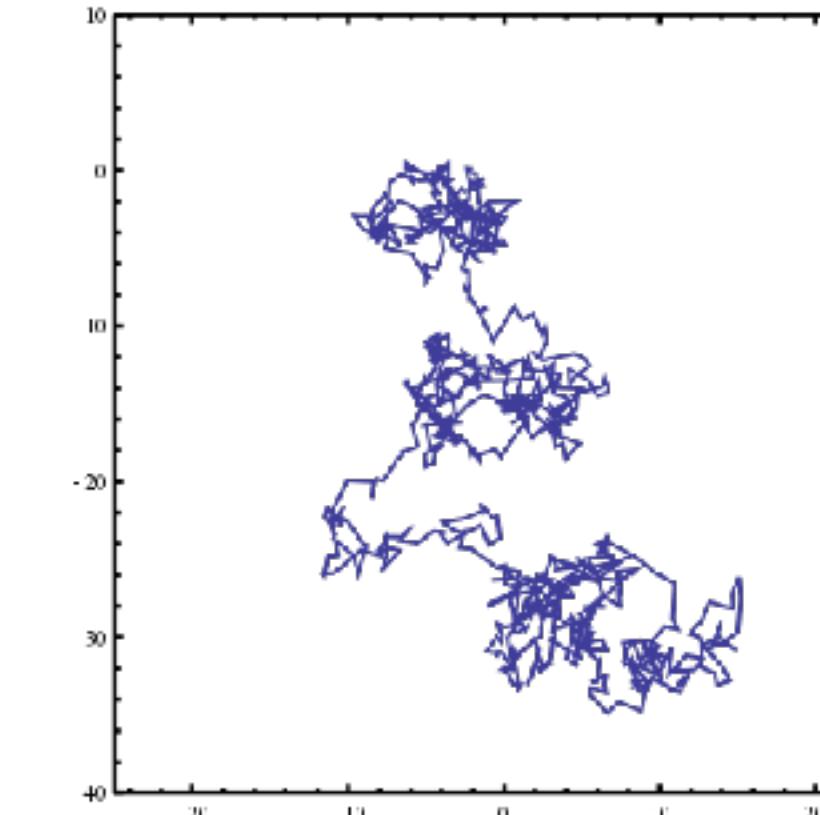
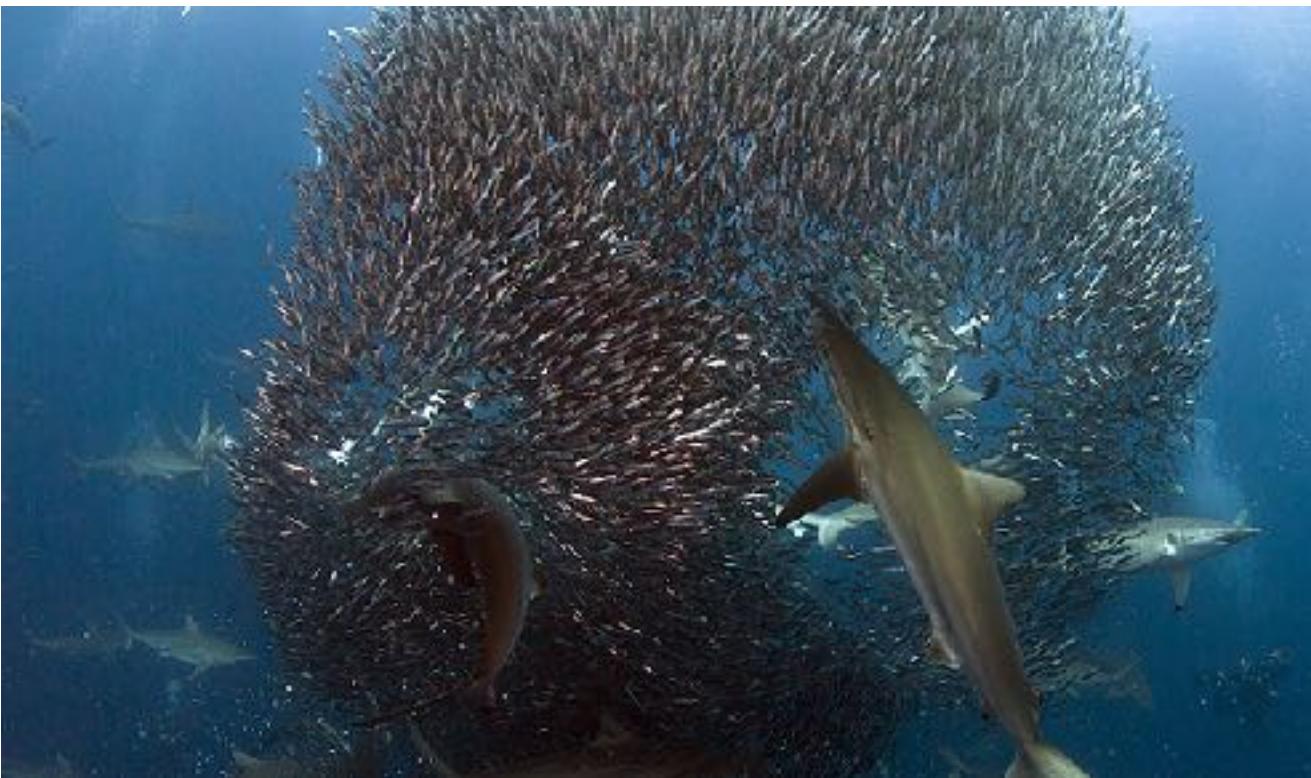


This is called a  
Lévy-flight

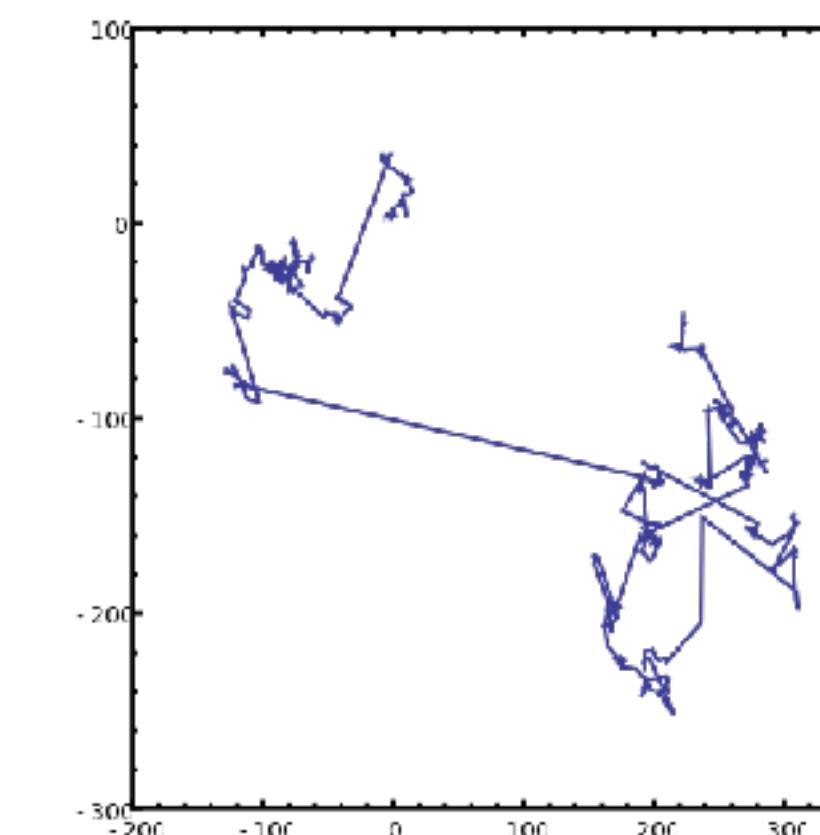
# A Lévy flight has huge jumps sometimes

Biology: Levy flight foraging hypothesis

If there is enough food around, use brownian motion (small steps)



If there is not enough food around, use Levy flight (add big jumps)



# A Lévy flight has huge jumps sometimes

Finance: Black Swans and big jumps in stock market movements

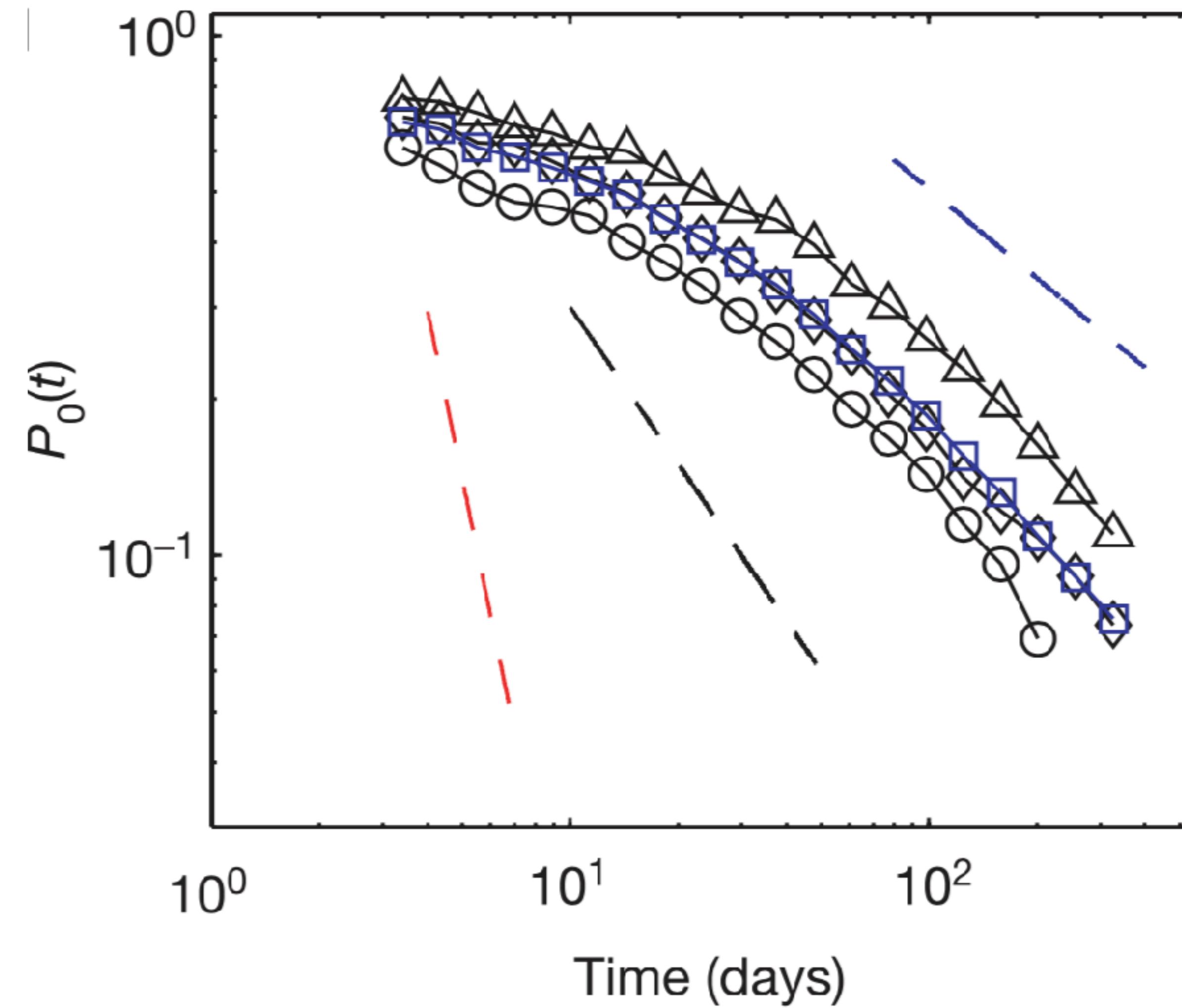


# A physics approach to human mobility

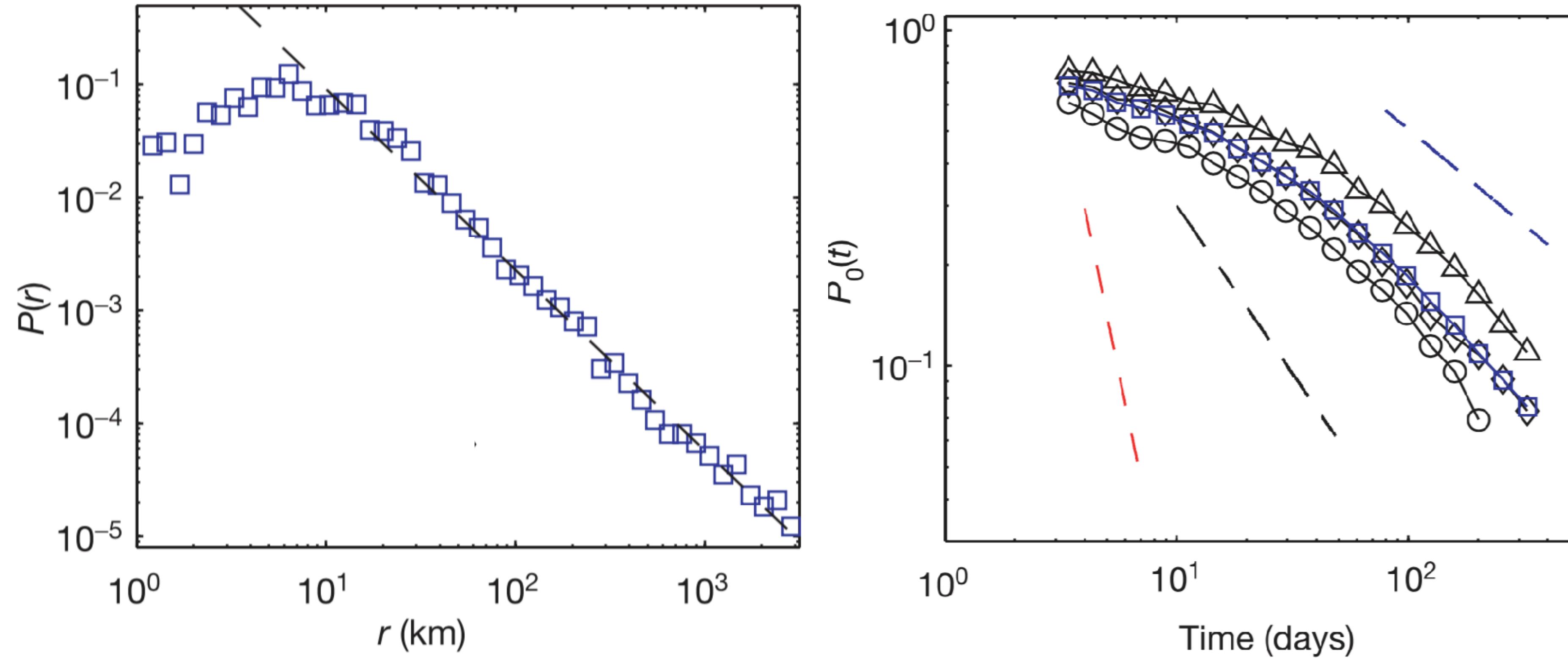
A **continuous-time random walk** (CTRW) is a generalized random walk with random waiting times between jumps

# Waiting time distribution of banknotes is also heavy-tailed

Probability that a banknote does not travel for  $t$  days  
(waiting time distribution) is also heavy-tailed

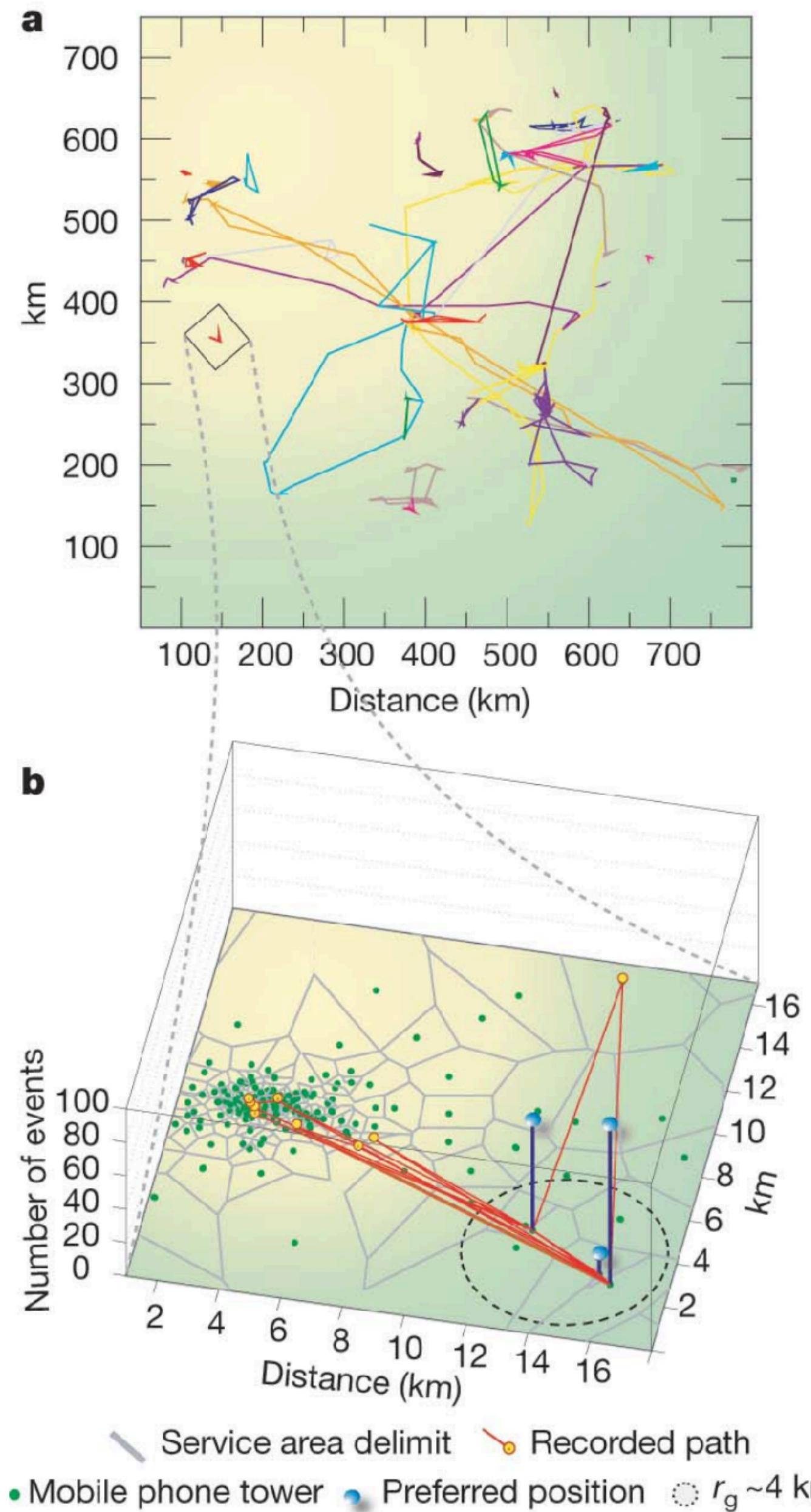


These two properties suggest "superdiffusive" mobility



Important for modeling spread of diseases!

# With mobile phone data researchers revisited WheresGeorge



Vol 453 | 5 June 2008 | doi:10.1038/nature06958

nature

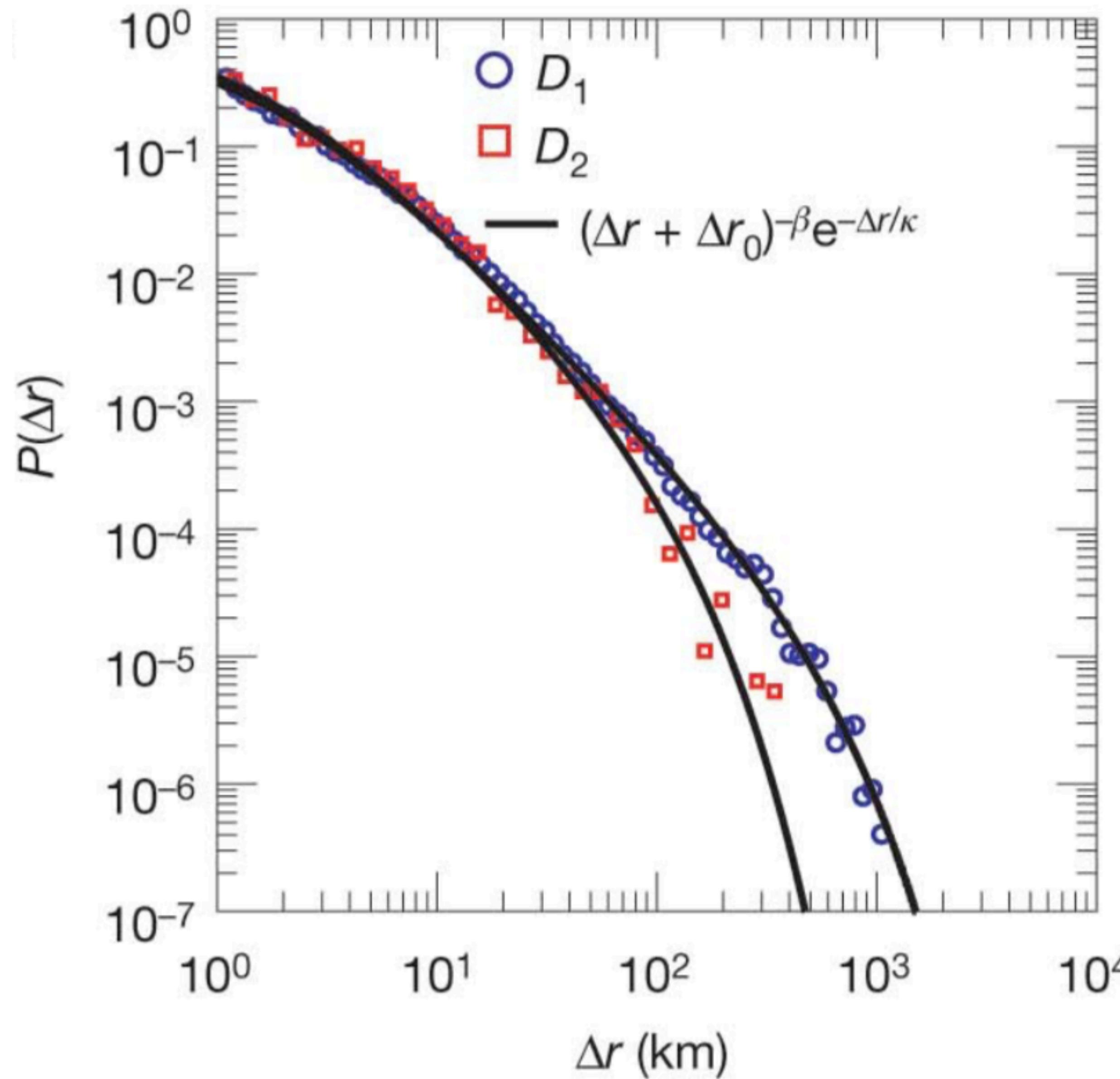
LETTERS

## Understanding individual human mobility patterns

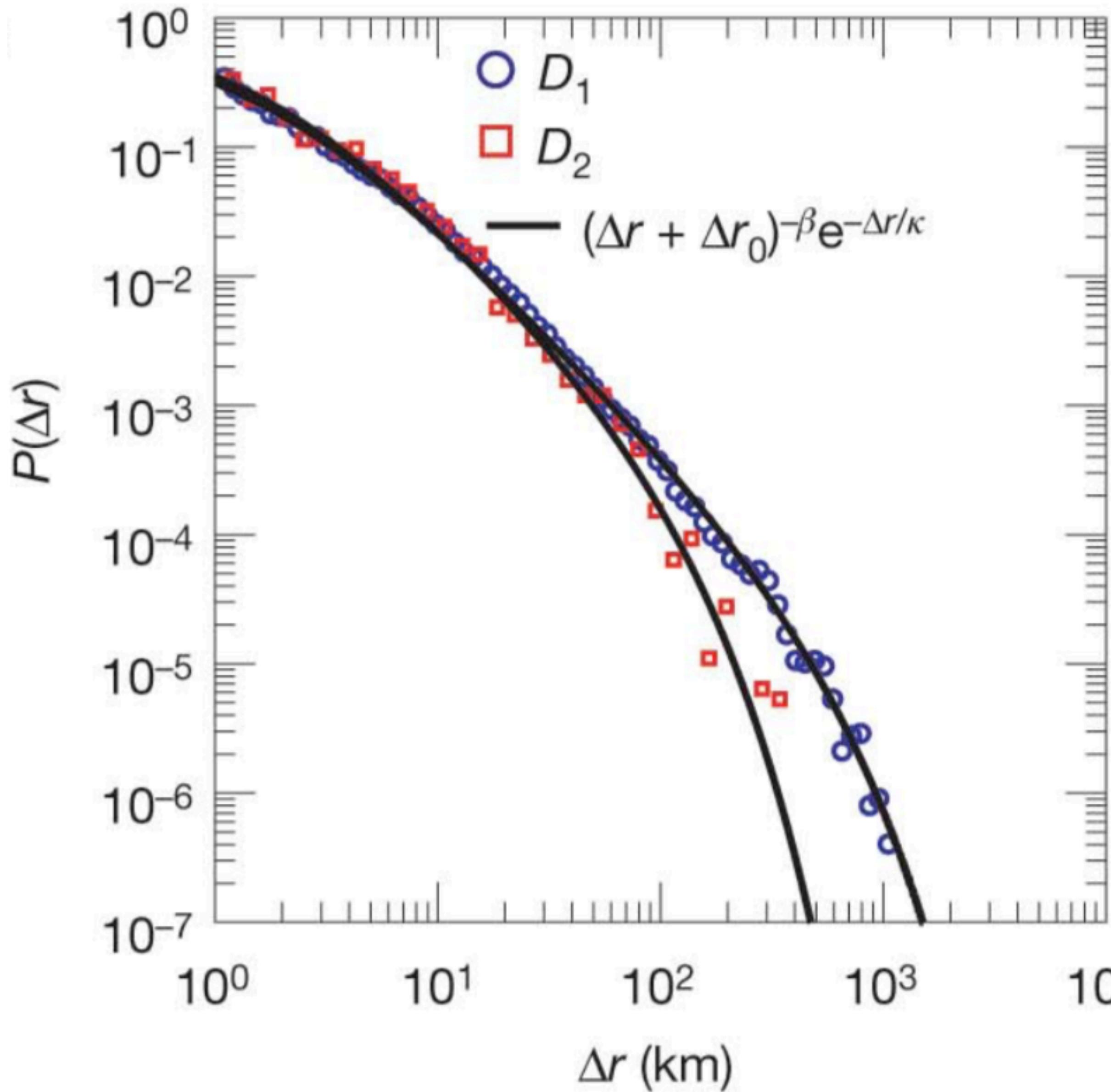
Marta C. González<sup>1</sup>, César A. Hidalgo<sup>1,2</sup> & Albert-László Barabási<sup>1,2,3</sup>

Now the data is better: We can follow individuals!

Again the displacement distribution is heavy-tailed



# With individual trajectories, we can test 3 hypotheses



## A) All same Levy flight:

Each individual follows the same Levy flight process

## B) Different mobility, but no Levy flights:

The distribution results from individuals moving differently

## C) Different Levy flights:

Individuals follows different Levy flight processes

# With individual trajectories, we can test 3 hypotheses

## A) All same Levy flight?

Each individual follows the same Levy flight process

# With individual trajectories, we can test 3 hypotheses

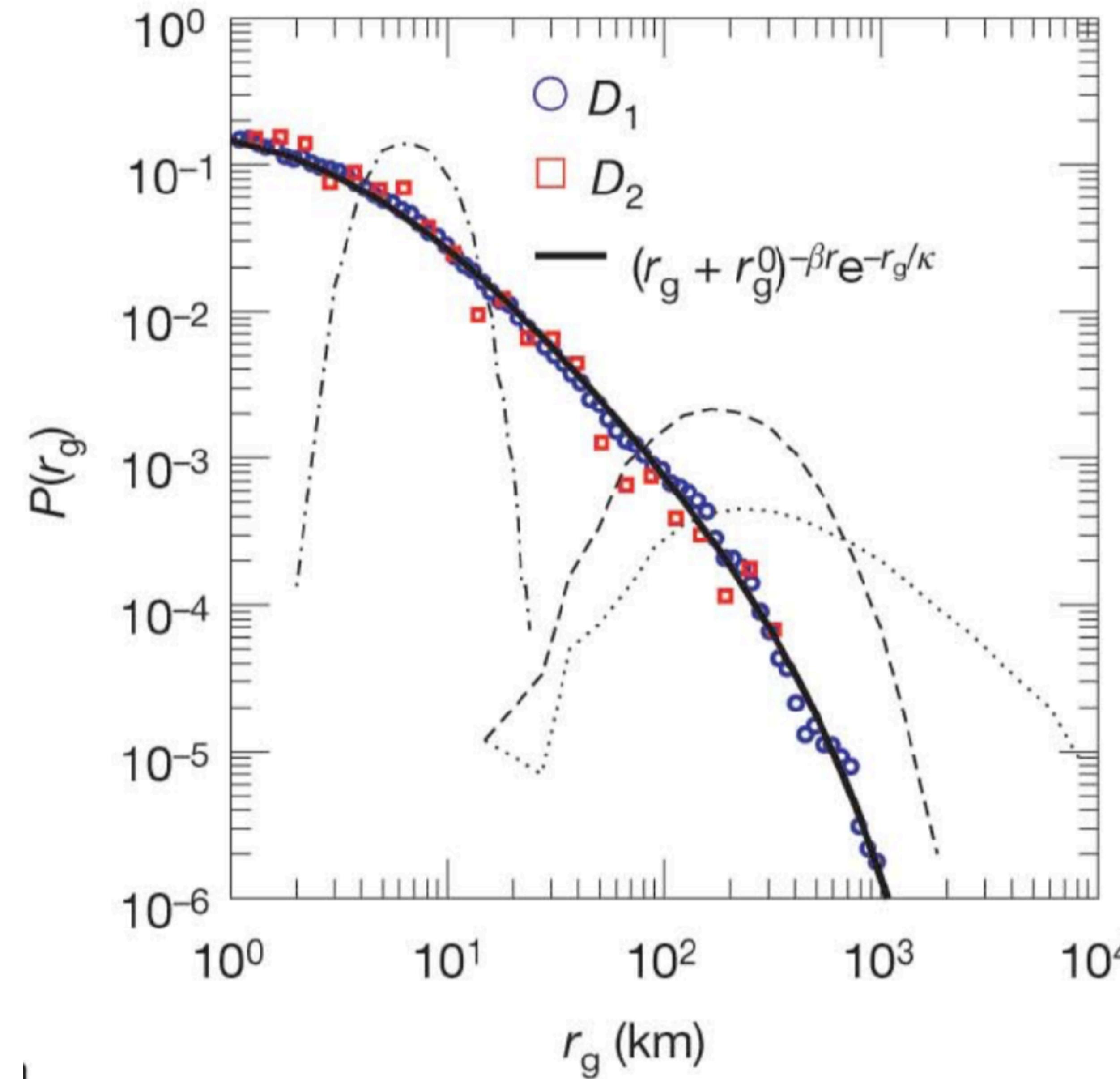
## A) All same Levy flight?

Each individual follows the same Levy flight process

The **radius of gyration**  $r_g$  is the typical distance travelled by an individual over a fixed timespan

$$r_g = \sqrt{\frac{1}{n} \sum_{i=1}^n |r_i - r_{\text{cm}}|^2}$$

# With individual trajectories, we can test 3 hypotheses



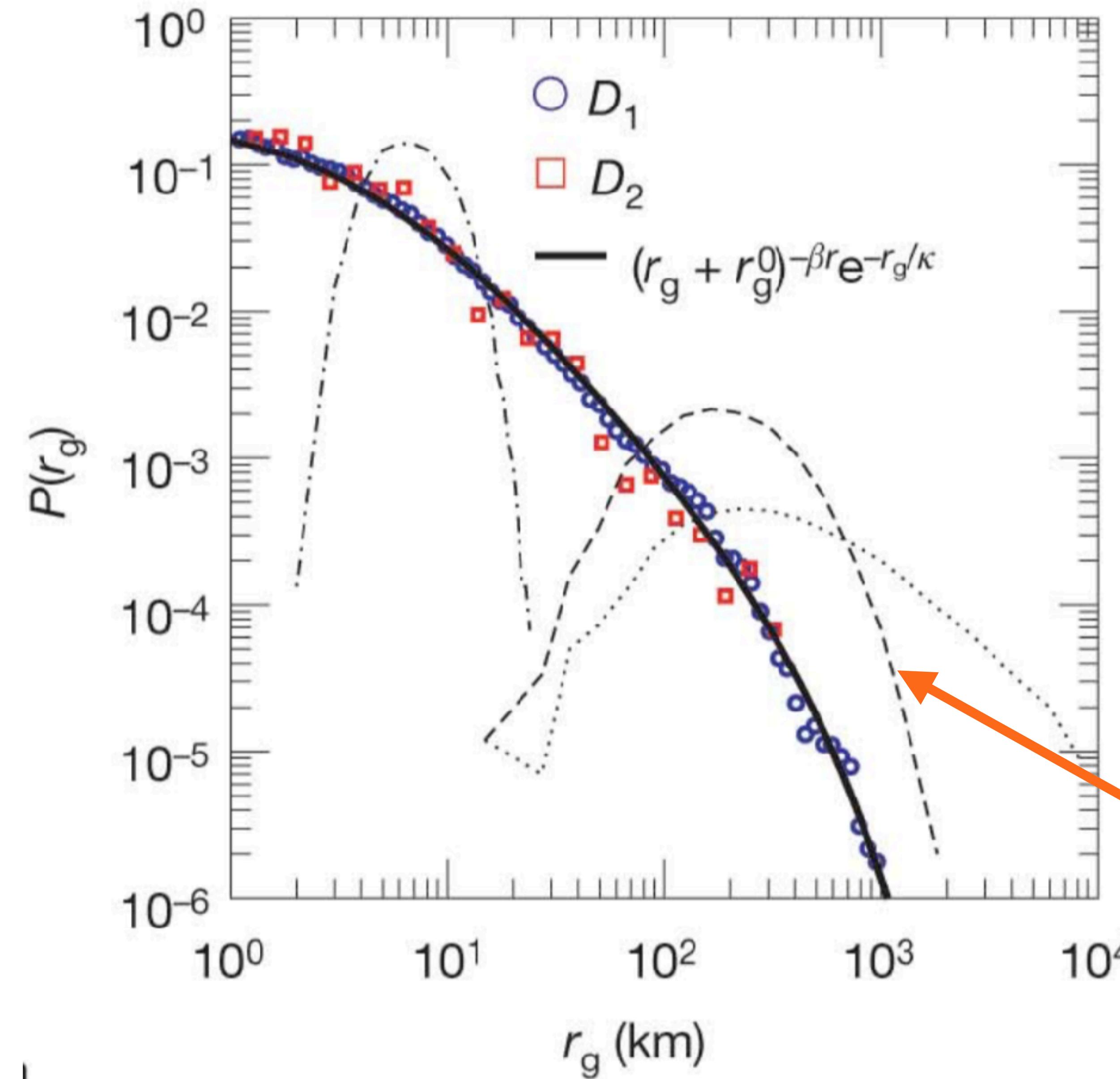
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# With individual trajectories, we can test 3 hypotheses



**A) All same Levy flight?**

~~Each individual follows the same Levy flight process~~

The **radius of gyration**  $r_g$  is the typical distance travelled by an individual over a fixed timespan

$$r_g = \sqrt{\frac{1}{n} \sum_{i=1}^n |r_i - r_{cm}|^2}$$

People have different mobility behaviors.  
If hypothesis A were true, we would see this.  
We can now rule out hypothesis A.

# With individual trajectories, we can test 3 hypotheses

**A) All same Levy flight?**

— Each individual follows the same Levy flight process

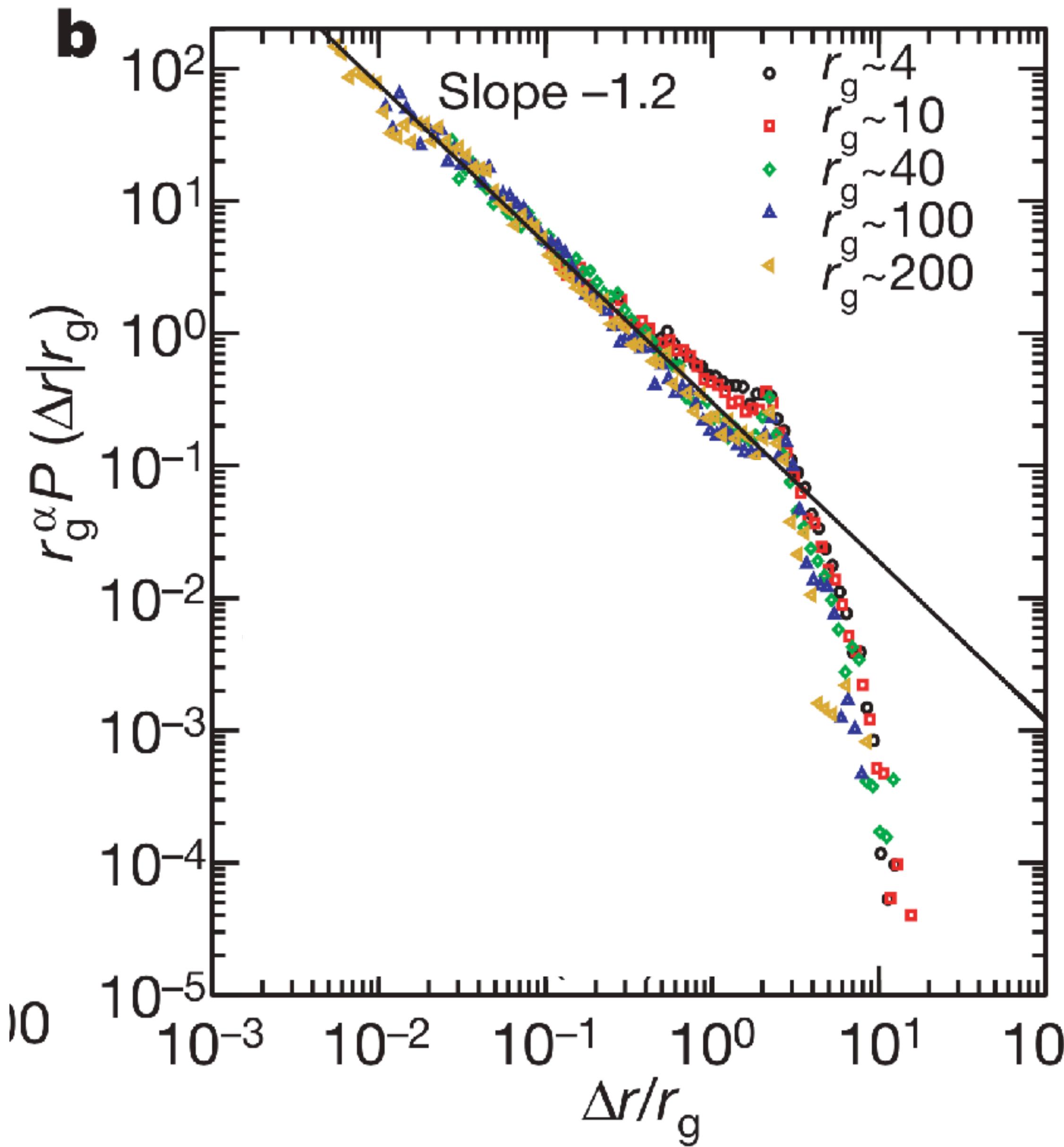
**B) Different mobility, but no Levy flights?**

The distribution results from individuals moving differently

**C) Different Levy flights?**

Individuals follows different Levy flight processes

# With individual trajectories, we can test 3 hypotheses



**A) All same Levy flight?**

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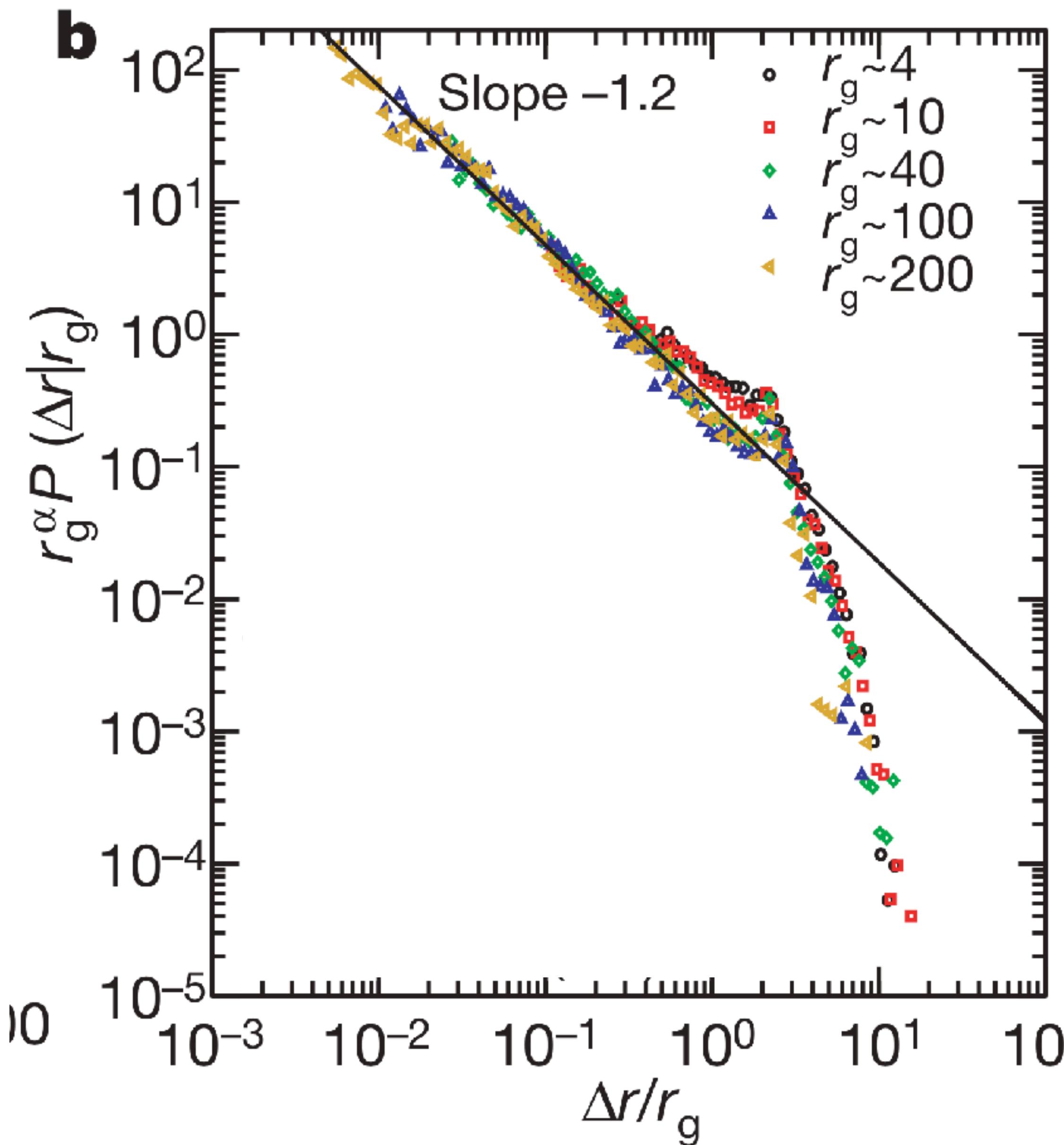
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The distribution results from individuals moving differently

**C) Different Levy flights?**

Individuals follows different Levy flight processes

# With individual trajectories, we can test 3 hypotheses



**A) All same Levy flight?**

~~Each individual follows the same Levy flight process~~

**B) Different mobility, but no Levy flights:**

The distribution results from individuals moving differently

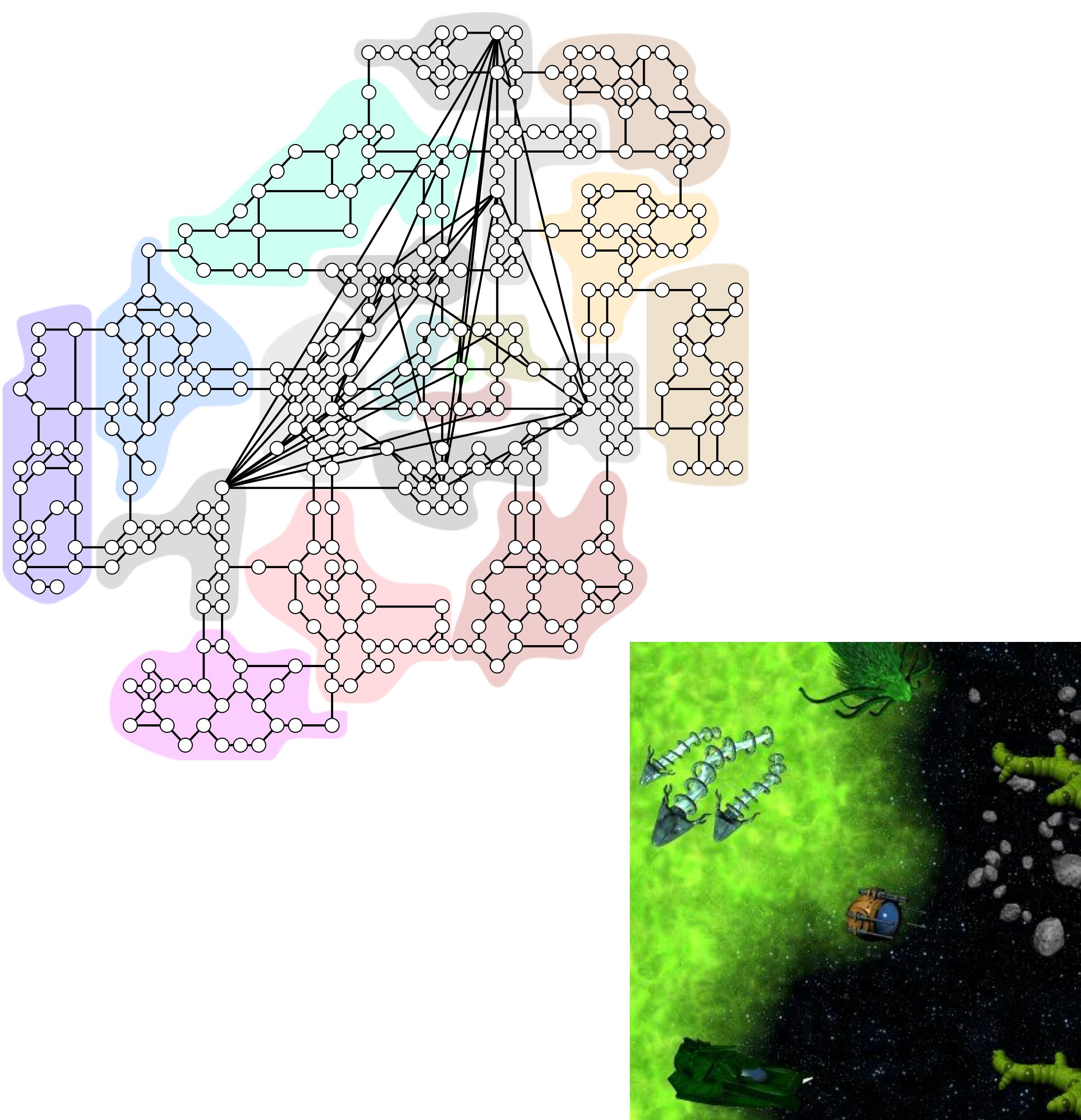
**C) Different Levy flights:**

Individuals follows different Levy flight processes

People with different  $r_g$  have different mobility behavior, **but they can be rescaled on one curve**

Consistent with hypothesis C.

# Mobility in a virtual world



**SCIENTIFIC REPORTS**



**OPEN**

## Understanding mobility in a social petri dish

Michael Szell<sup>1</sup>, Roberta Sinatra<sup>2,8</sup>, Giovanni Petri<sup>3,9,10</sup>, Stefan Thurner<sup>1,6,7</sup> & Vito Latora<sup>4,5,8</sup>

<sup>1</sup>Section for Science of Complex Systems, Medical University of Vienna, Spitalgasse 23, 1090 Vienna, Austria, <sup>2</sup>Center for Complex Network Research and Department of Physics, Northeastern University, Boston, Massachusetts 02115, USA, <sup>3</sup>Institute for Scientific Interchange (ISI), Via Alassio 11/c, 10126 Torino, Italy, <sup>4</sup>School of Mathematical Sciences, Queen Mary, University of London, London E1 4NS, United Kingdom, <sup>5</sup>Dipartimento di Fisica e Astronomia, Università di Catania and INFN, Via S. Sofia, 64, 95123 Catania, Italy, <sup>6</sup>Santa Fe Institute, Santa Fe, NM 87501, USA, <sup>7</sup>IASA, Schlossplatz 1, 2361 Laxenburg, Austria, <sup>8</sup>Laboratorio sui Sistemi Complessi, Scuola Superiore di Catania, Via San Nullo 5/i, 95123 Catania, Italy, <sup>9</sup>Centre for Transport Studies, Department of Civil and Environmental Engineering, Imperial College London, London SW7 2AZ, UK, <sup>10</sup>Complexity and Networks group, Imperial College London, London SW7 2AZ, UK.

Received  
9 March 2012

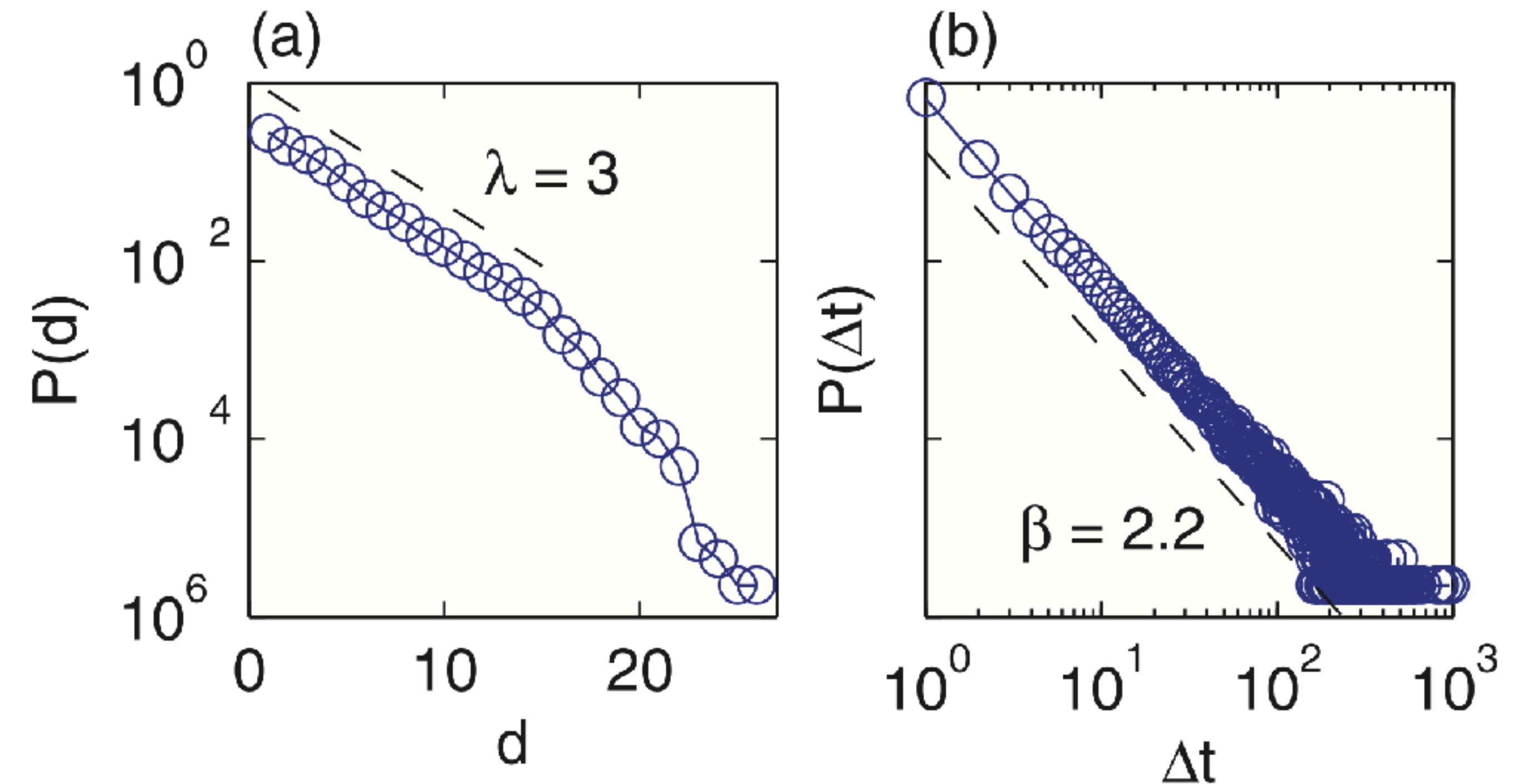
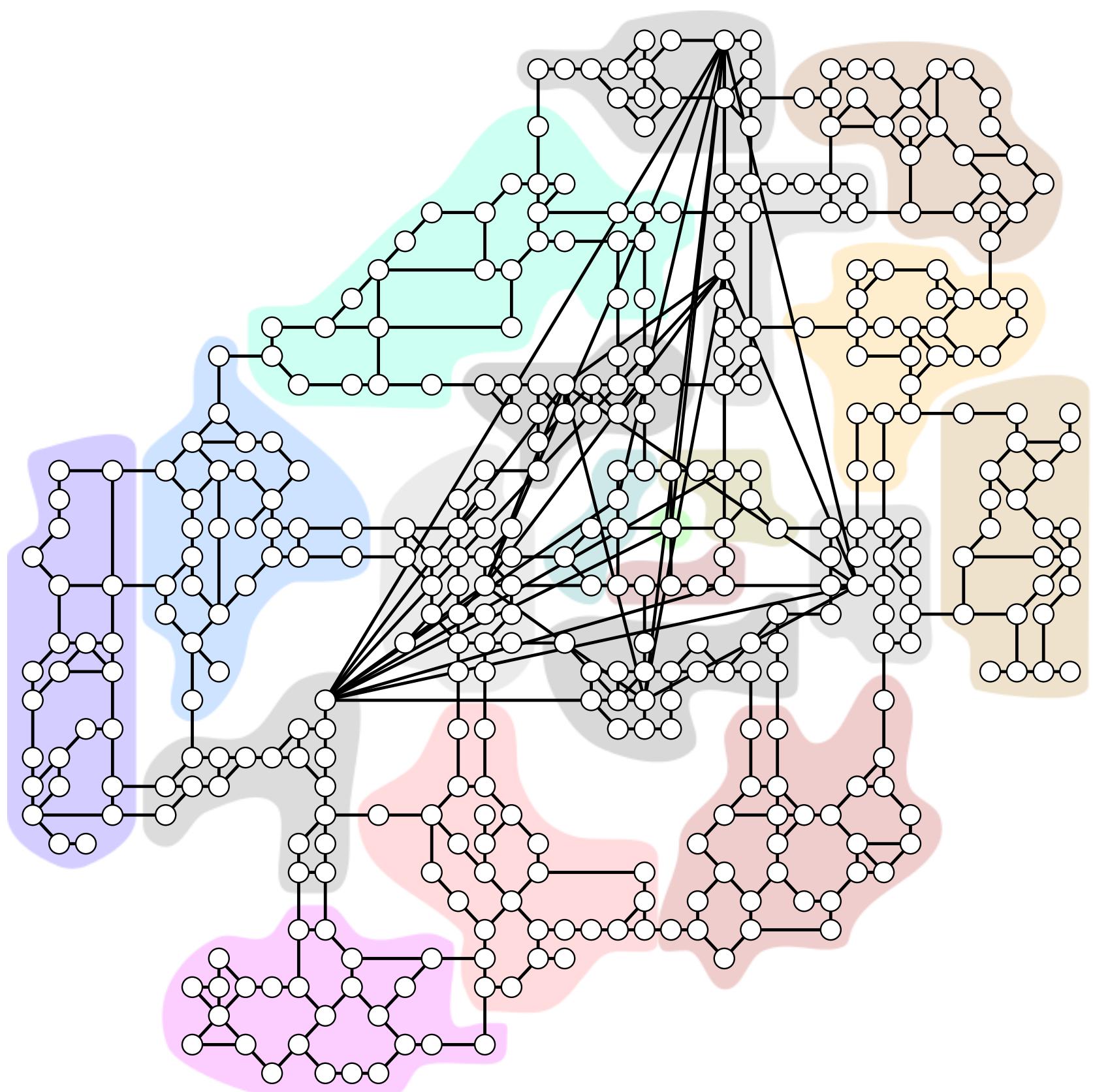
Accepted  
21 May 2012

Published  
14 June 2012

Correspondence and requests for materials should be addressed to

Despite the recent availability of large data sets on human movements, a full understanding of the rules governing motion within social systems is still missing, due to incomplete information on the socio-economic factors and to often limited spatio-temporal resolutions. Here we study an entire society of individuals, the players of an online-game, with complete information on their movements in a network-shaped universe and on their social and economic interactions. Such a “socio-economic laboratory” allows to unveil the intricate interplay of spatial constraints, social and economic factors, and patterns of mobility. We find that the motion of individuals is not only constrained by physical distances, but also strongly shaped by the presence of socio-economic areas. These regions can be recovered perfectly by community detection methods solely based on the measured human dynamics. Moreover, we uncover that long-term memory in the time-order of visited locations is the essential ingredient for modeling the trajectories.

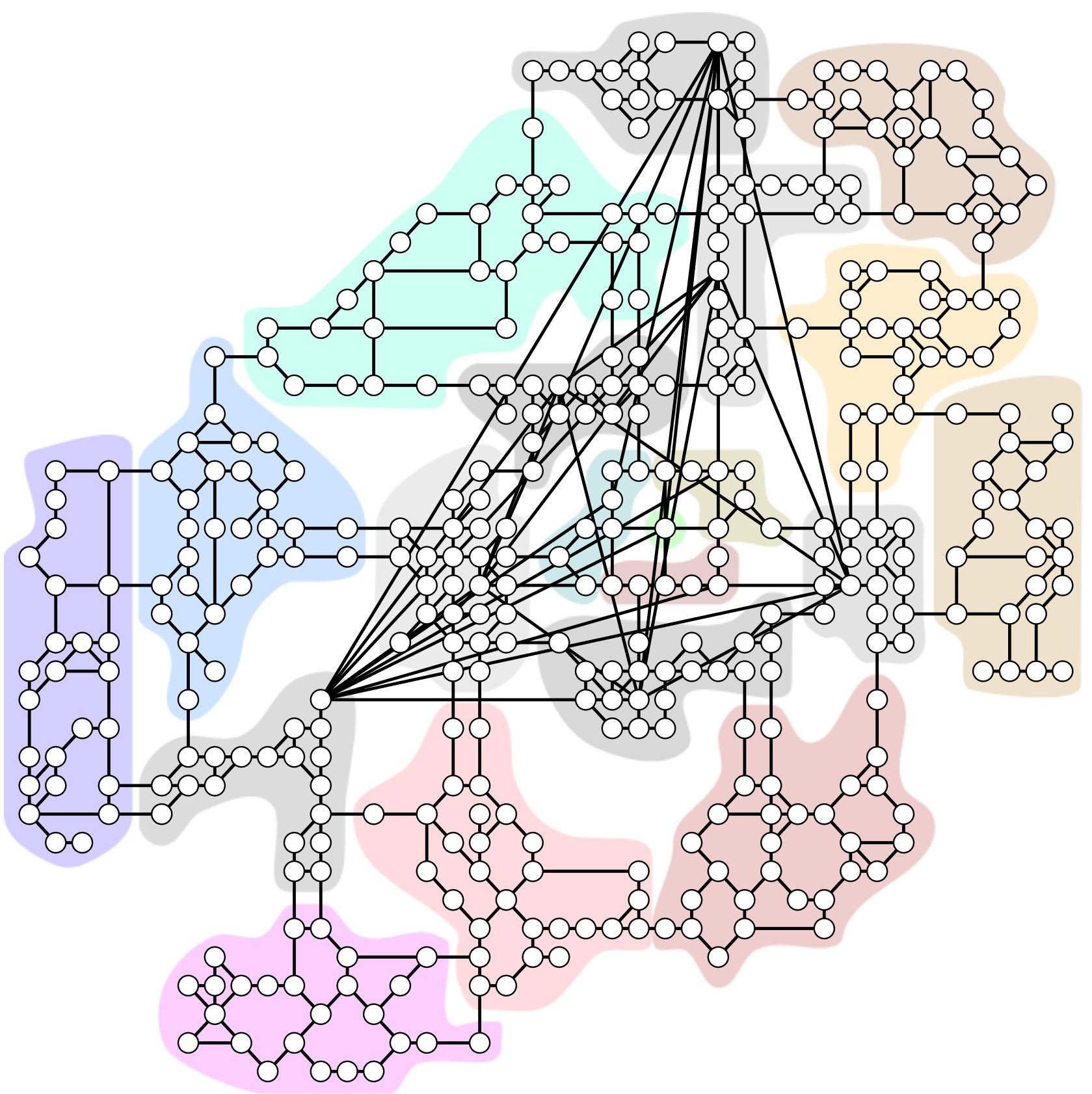
# Mobility in a virtual world



Jump distances  
are exponential

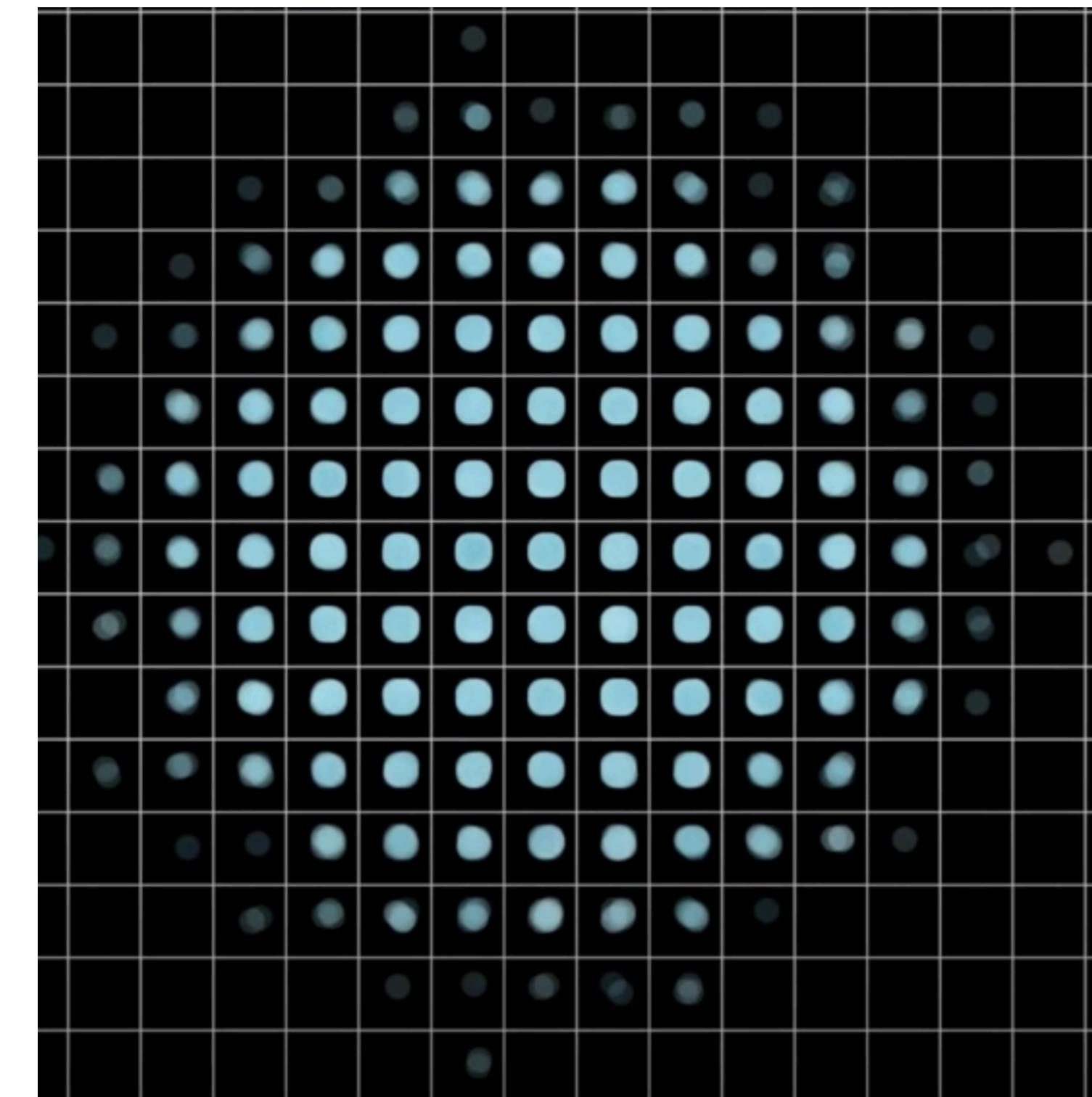
Waiting times  
are heavy-tailed

# The MSD measures deviation from an initial position

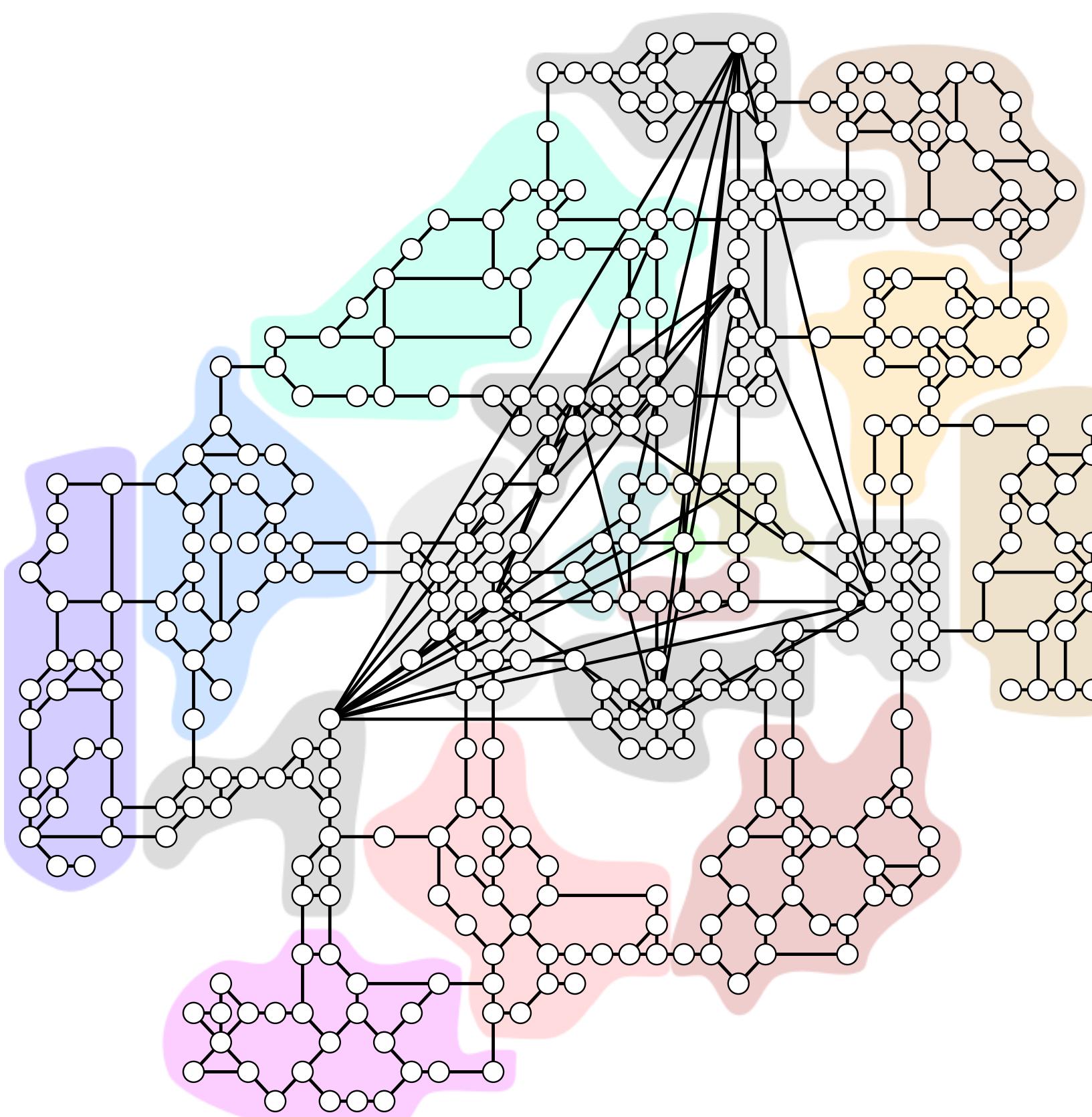


The mean squared displacement characterizes diffusion

$$MSD = \langle r^2(\tau) \rangle = \frac{1}{N} \sum_{n=1}^N (x_n(\tau) - x_n(0))^2$$

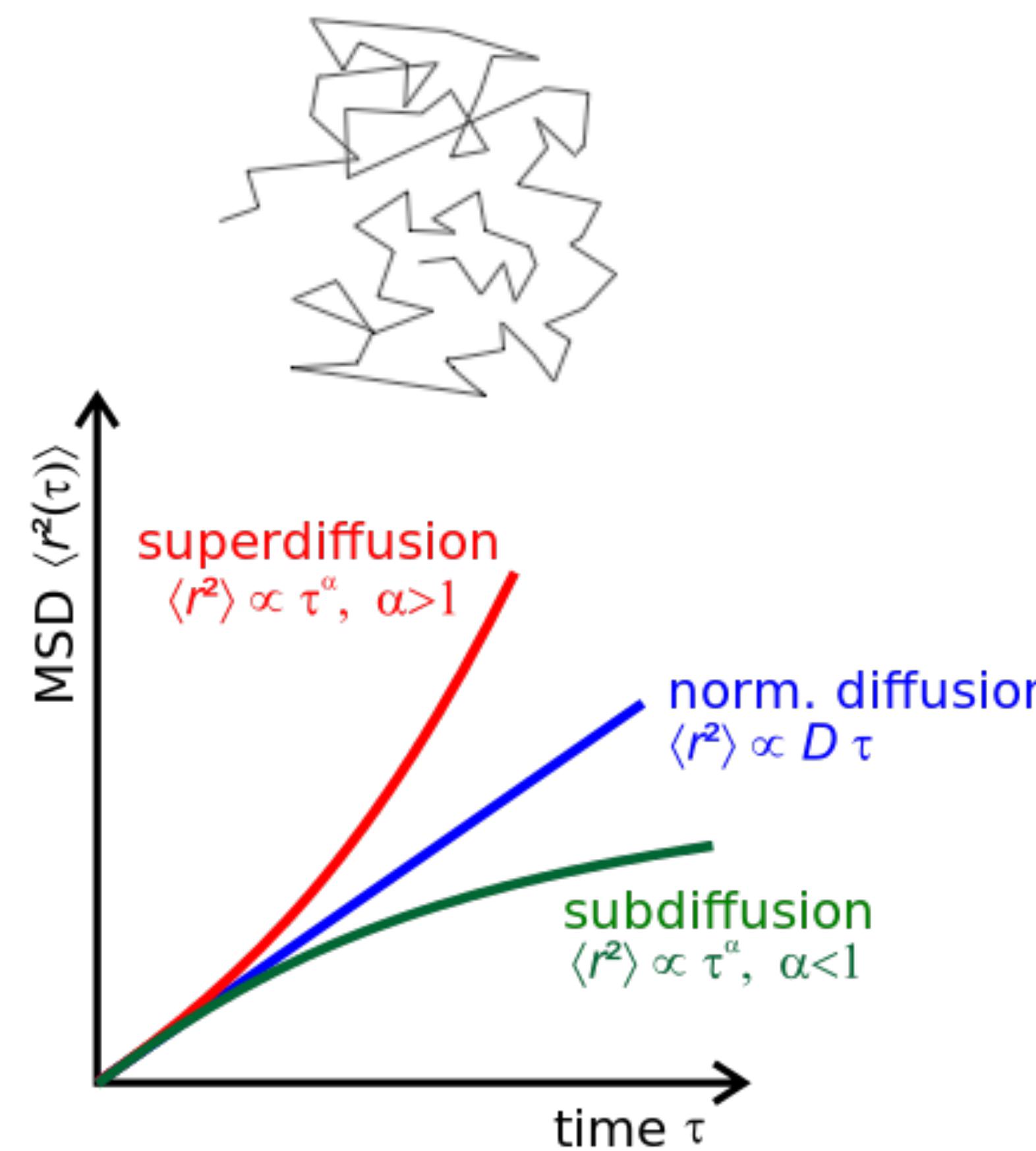


# The MSD measures deviation from an initial position

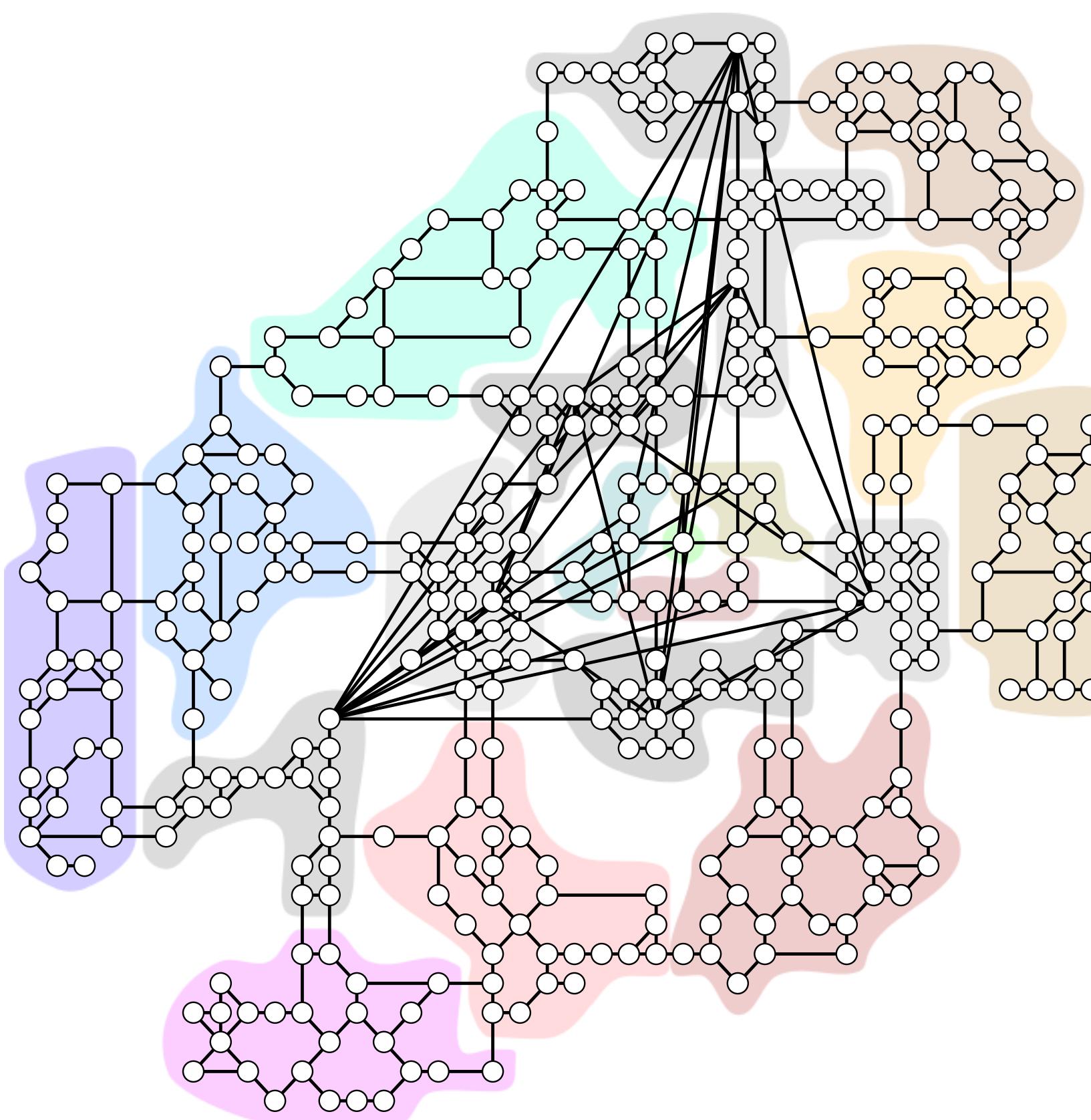


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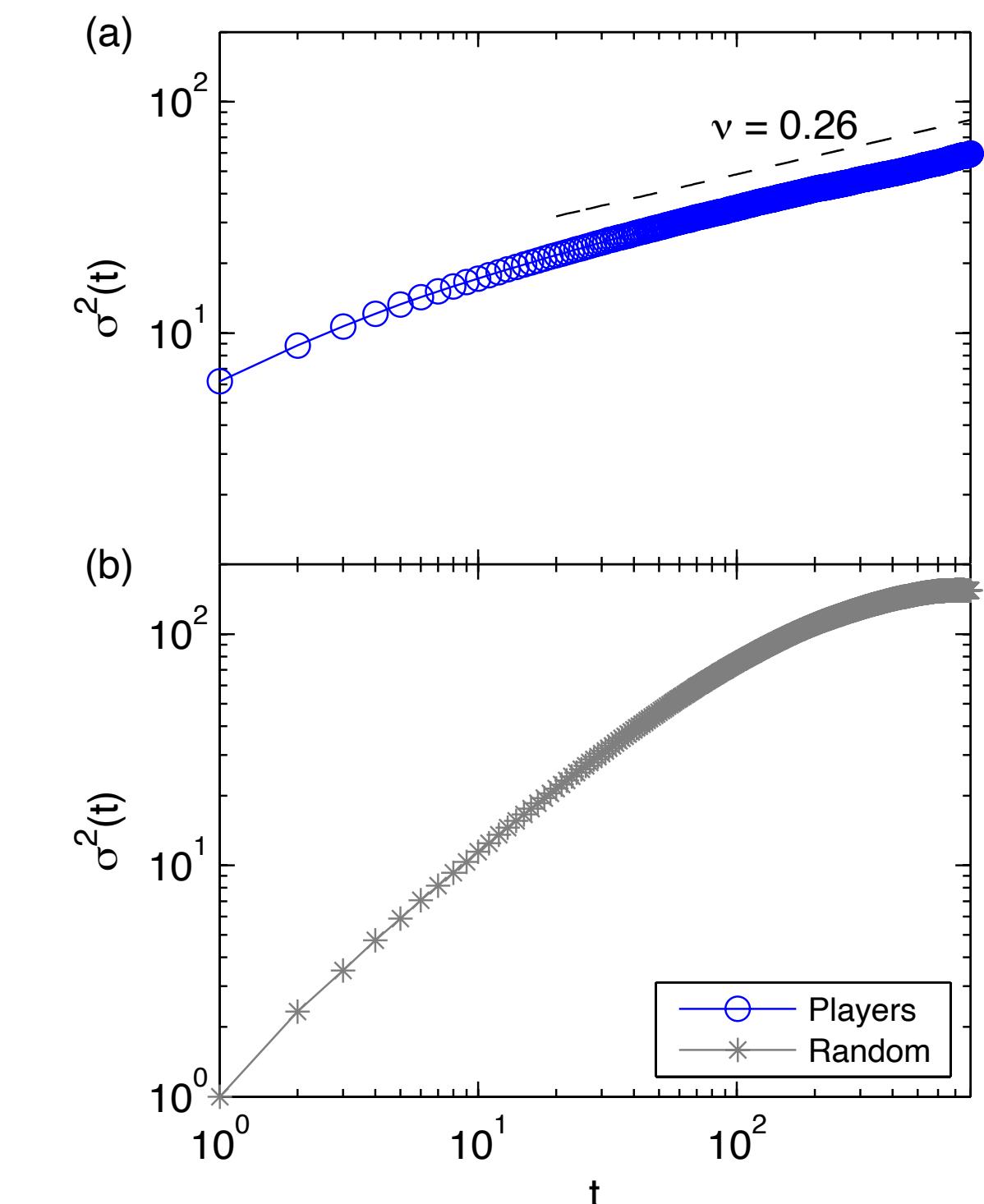
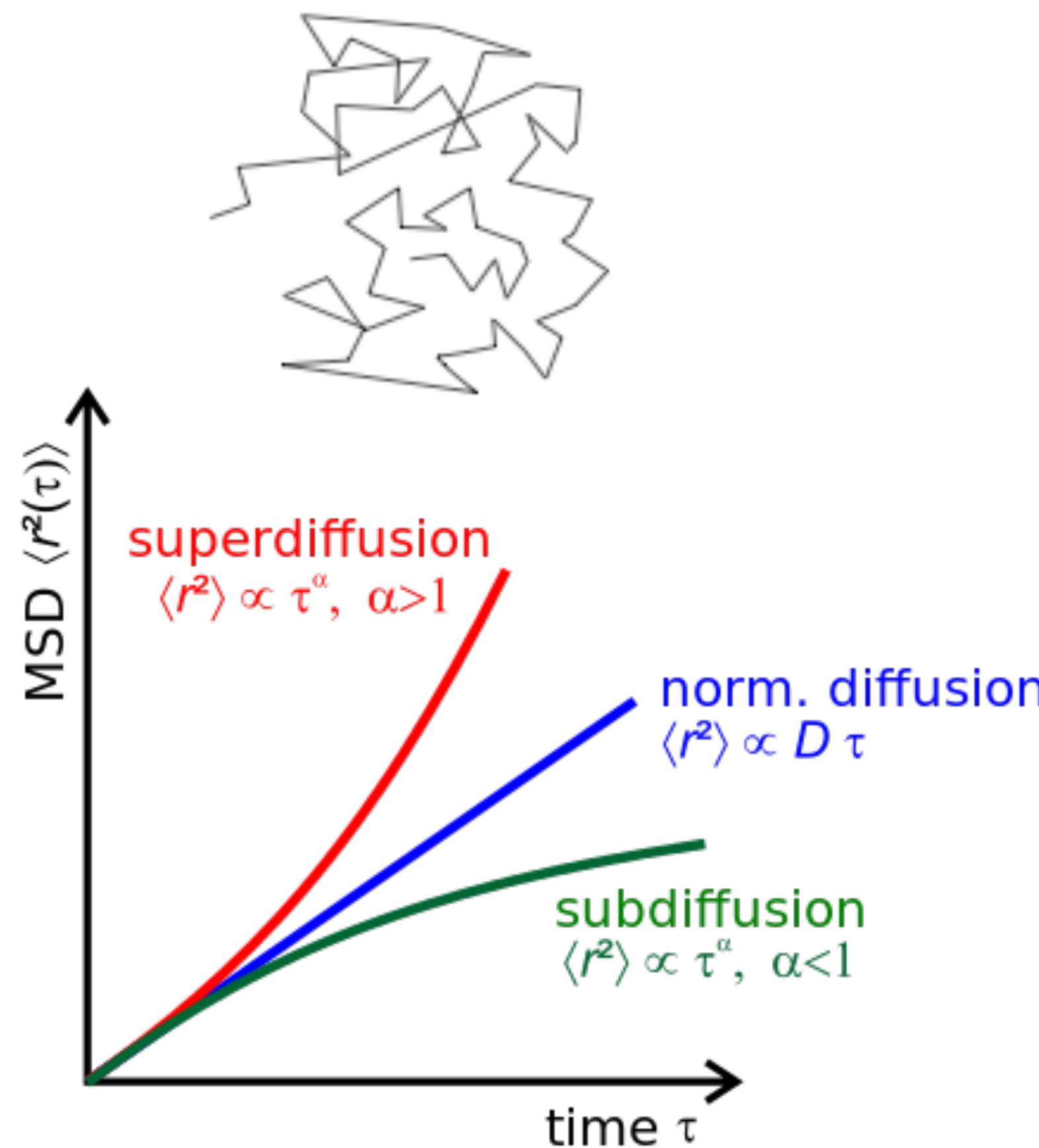
# The MSD measures deviation from an initial position



We found  $\alpha = 0.26$ :  
Players explore \*much\* less  
than a random walker

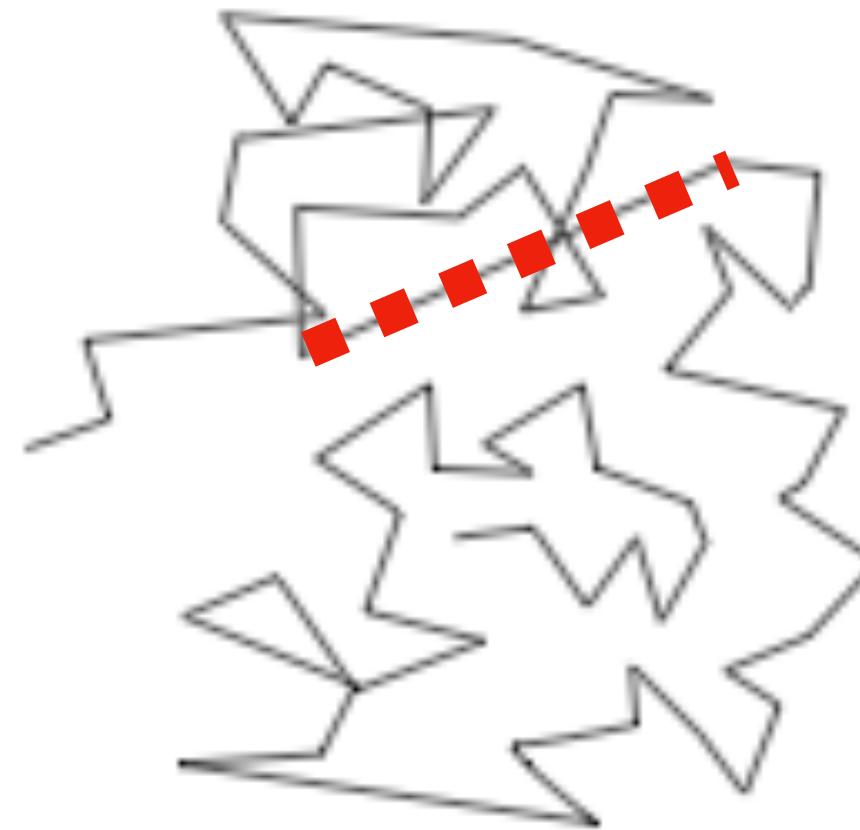
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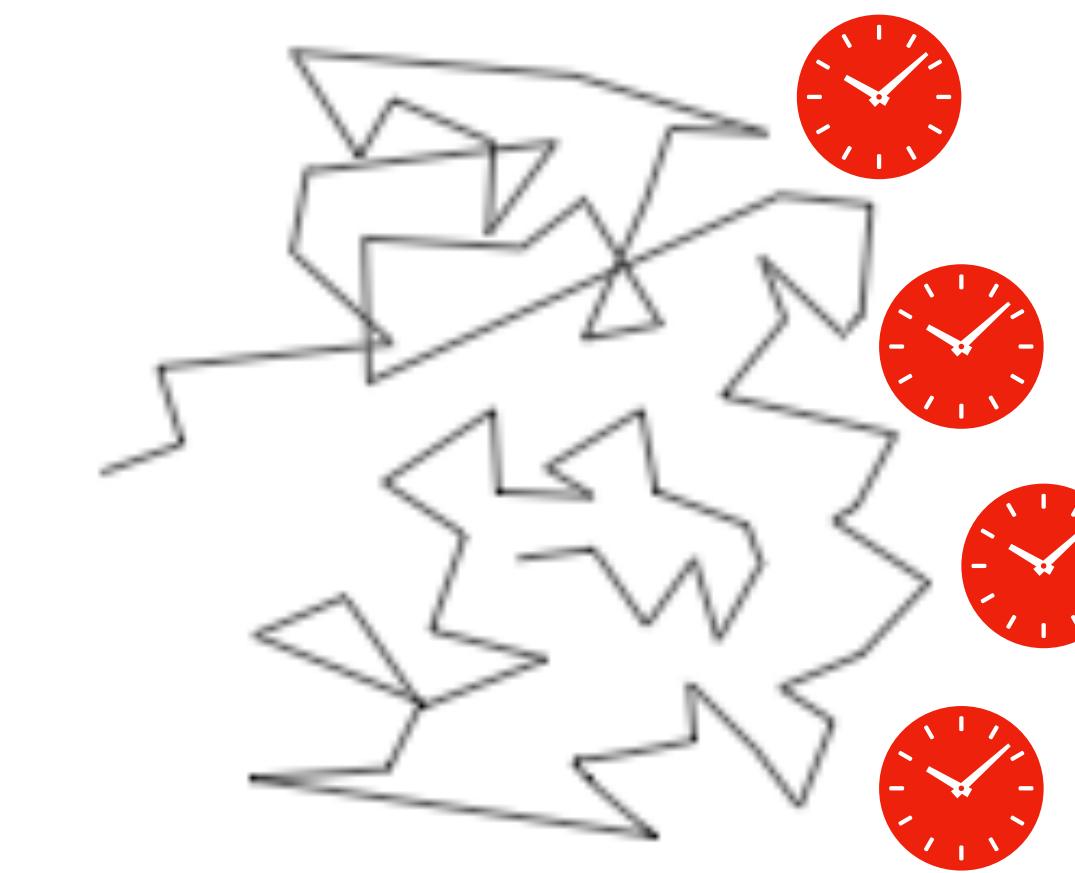


# Summary of physics-inspired mobility measures

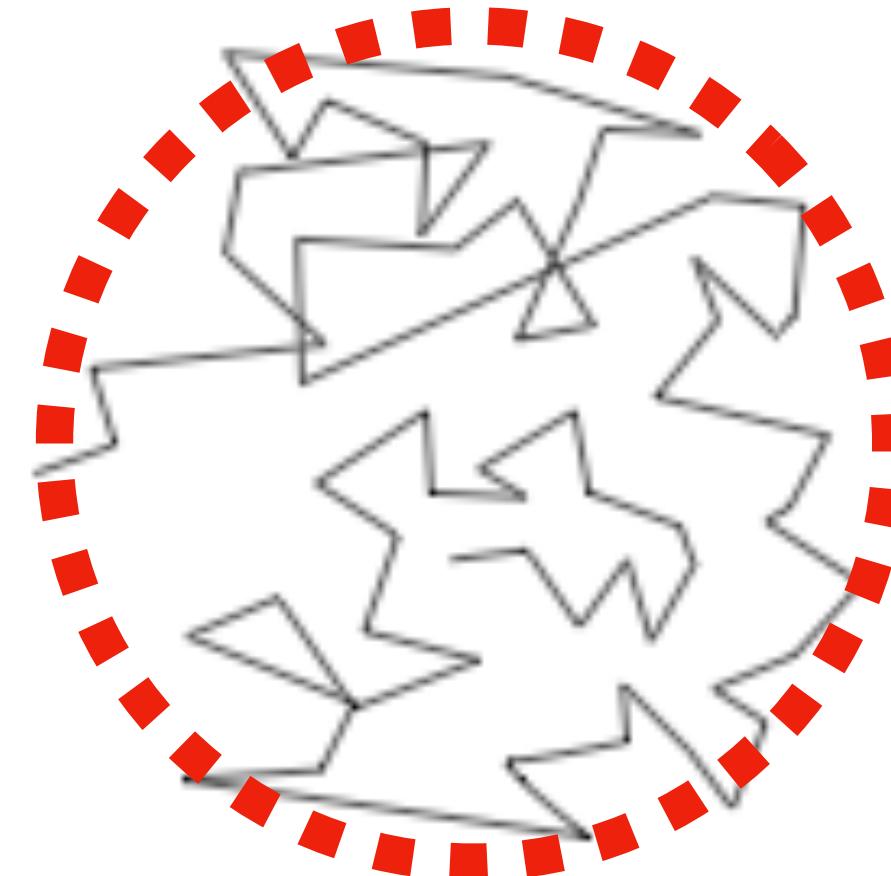
Jump distribution



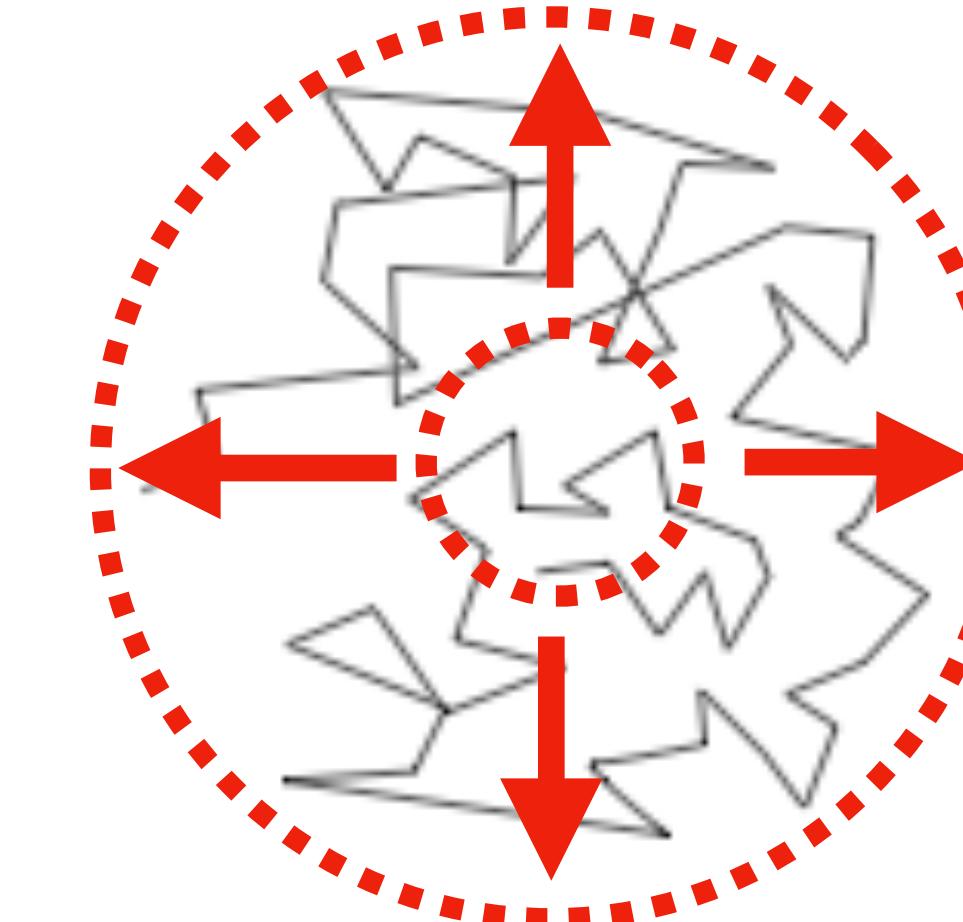
Waiting time distribution



Radius of gyration

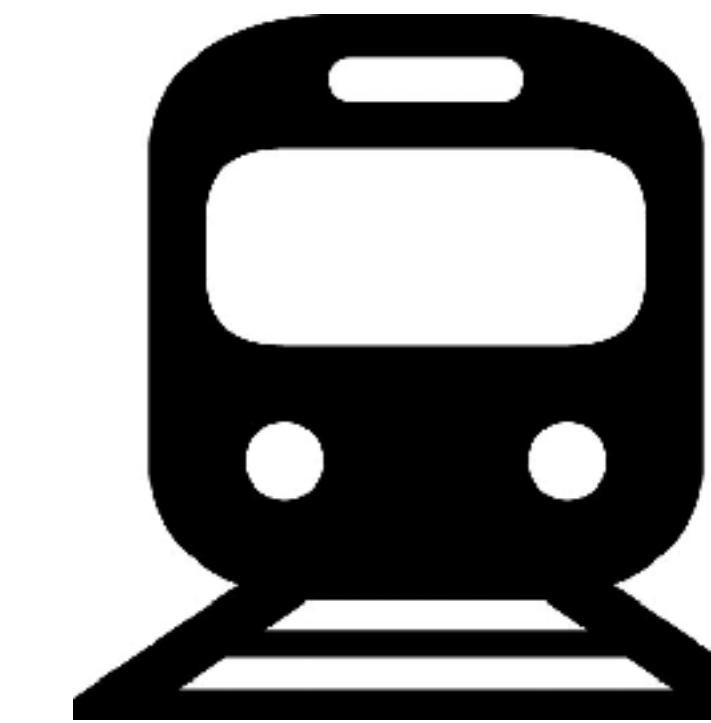


Mean squared displacement



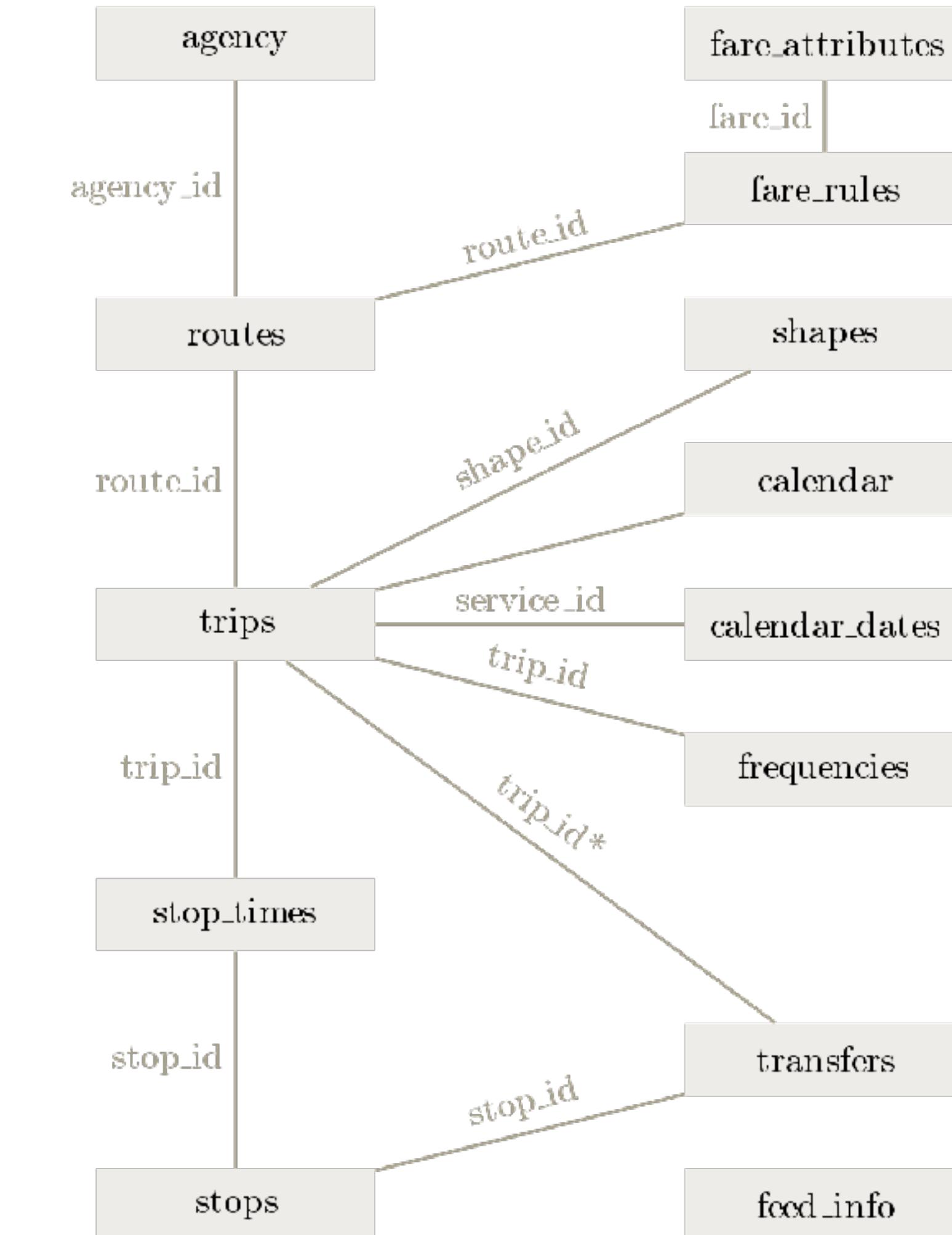
# GTFS defines a format for public transportation schedules

## General Transit Feed Specification



Denmark data:

<https://transitfeeds.com/p/rejseplanen/705>

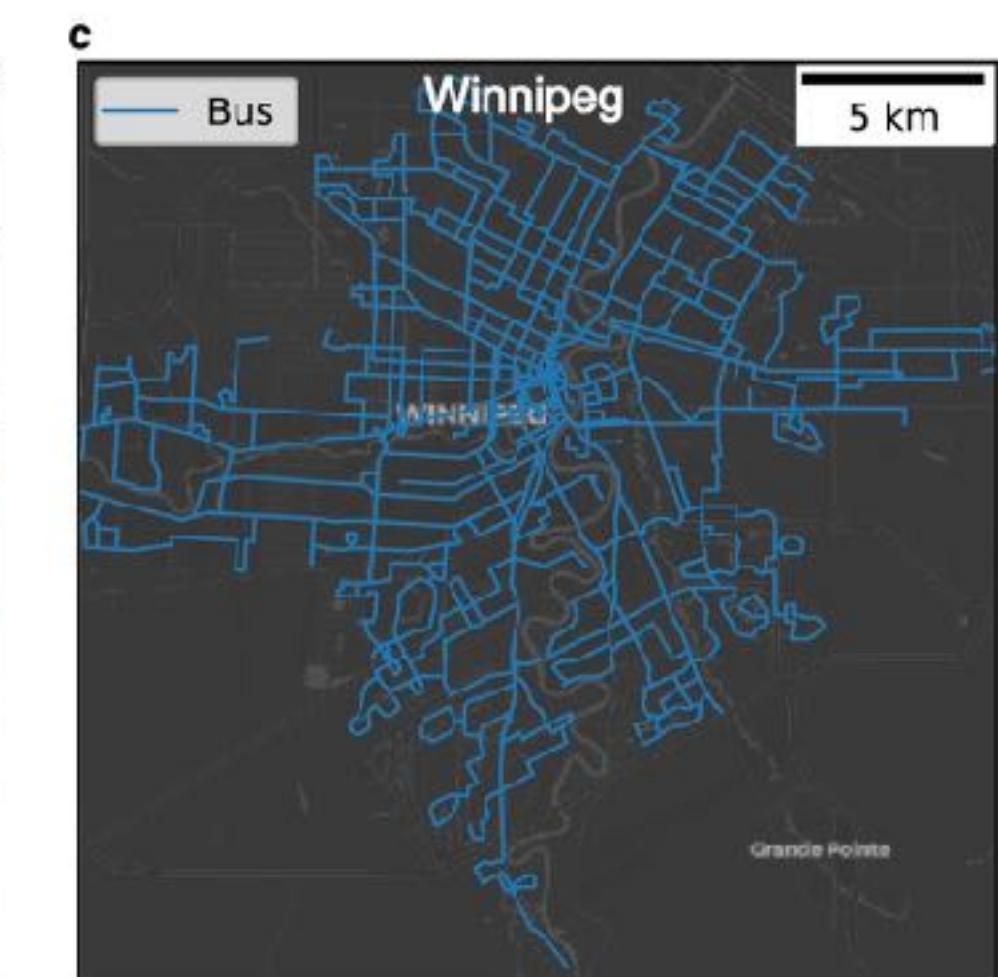
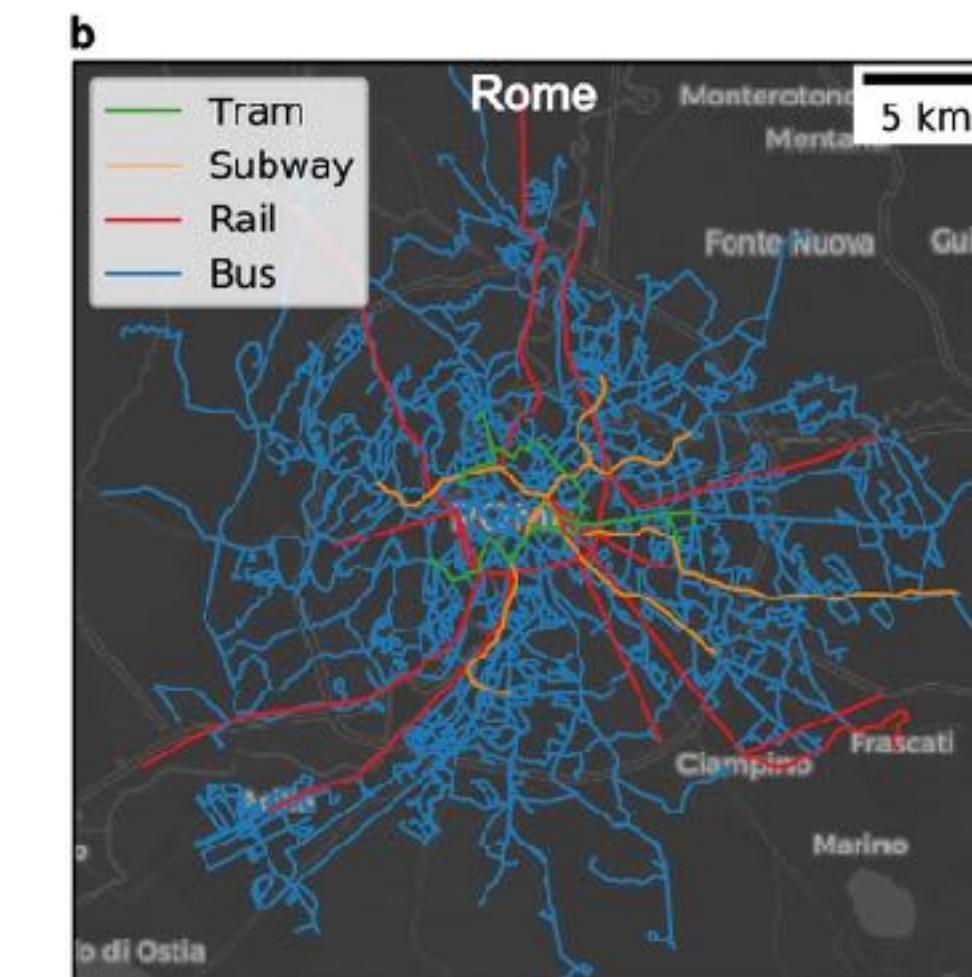
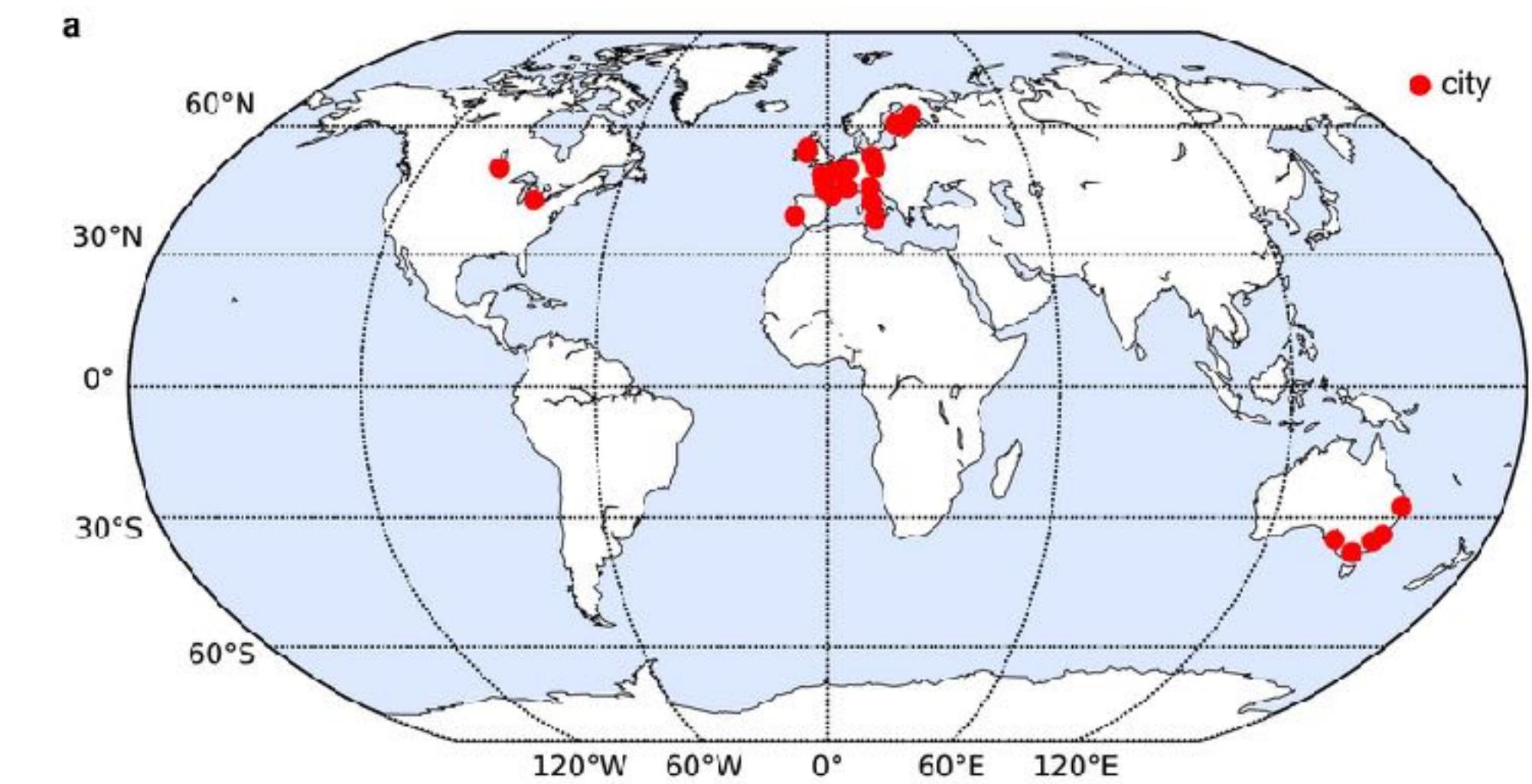


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## General Transit Feed Specification



Open, curated data set of 25 cities:



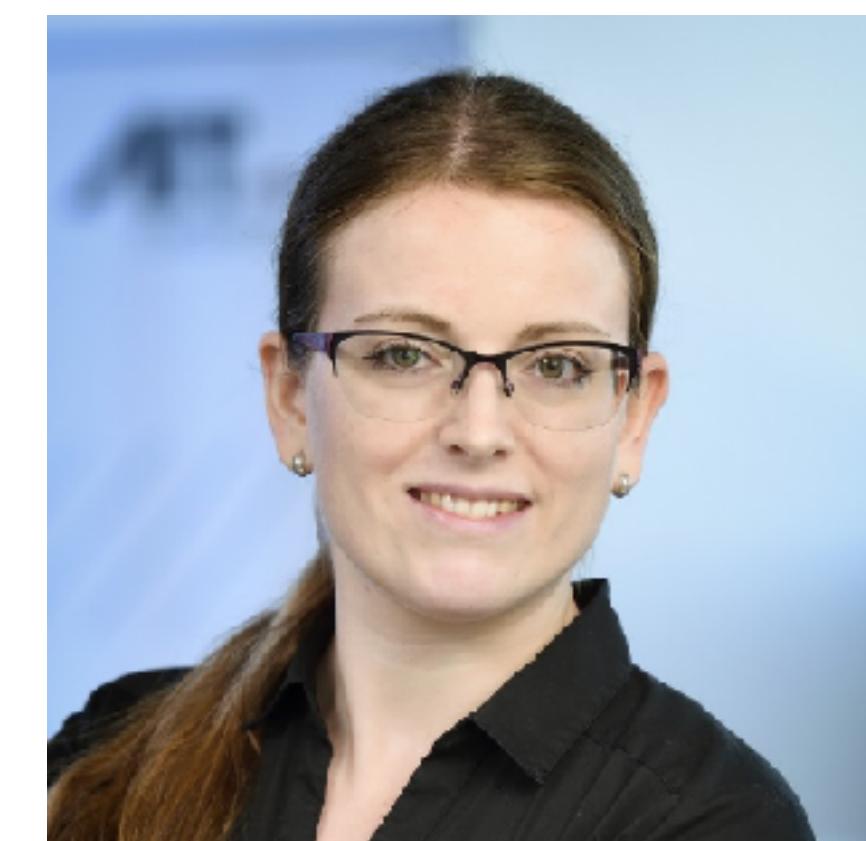
# Python packages to study human mobility



Physics-based metrics and models



GIS exploration and visualization



# From individual trajectories to OD matrices and flow maps

Individual trajectories are aggregated spatially in a **tesselation** = tiling of the plane without gaps. These tiles are called origins and destinations.

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Origin \ Destination	1	2	3	z
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2	$T_{21}$			
3	$T_{31}$			
z	$T_{z1}$			$T_{zz}$

The **OD-Matrix** (Origin-Destination), or trip table, trip matrix, gives the number of trips going from each origin to each destination.

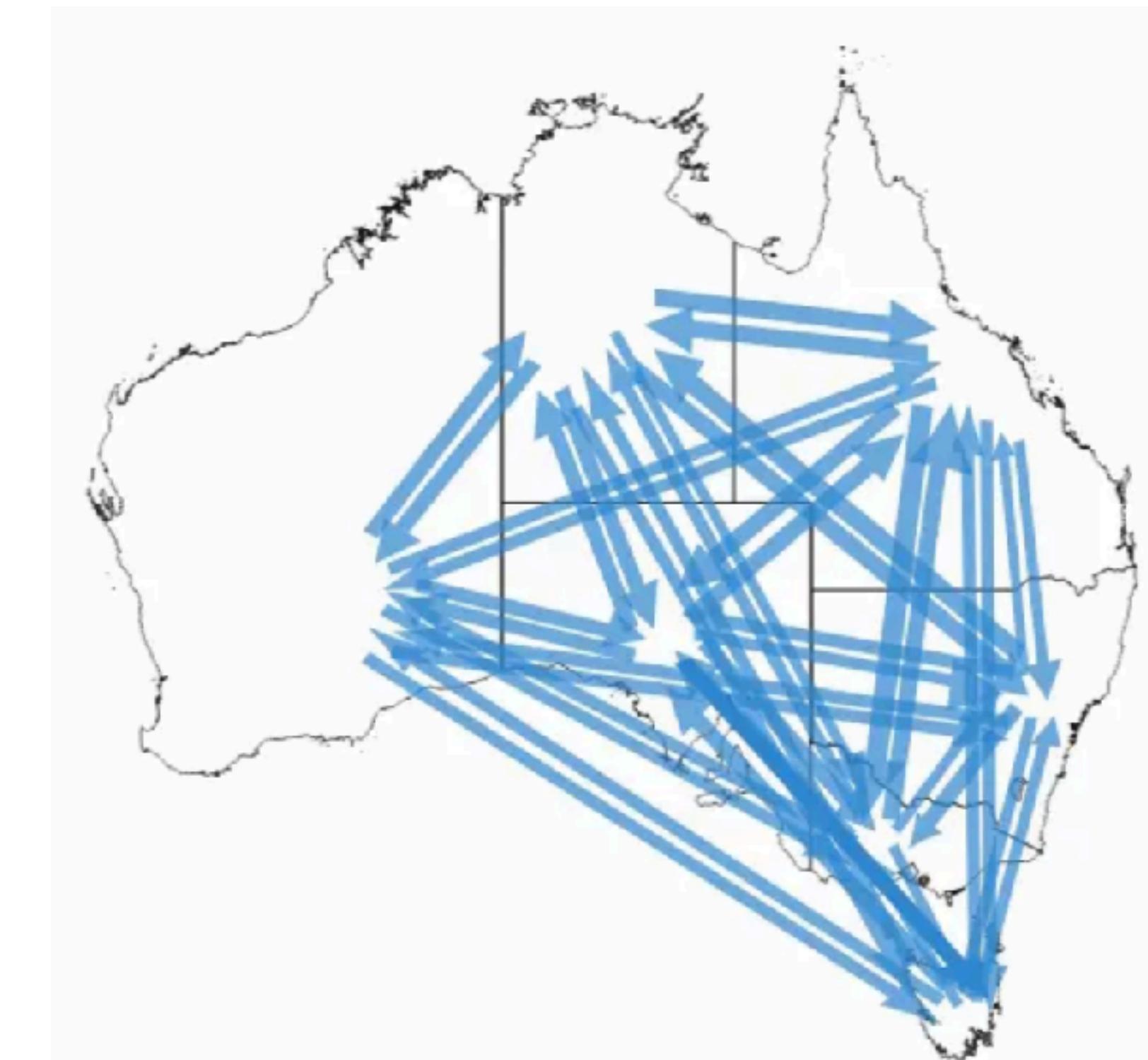
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This is visualized in the **flow map**:



# Jupyter