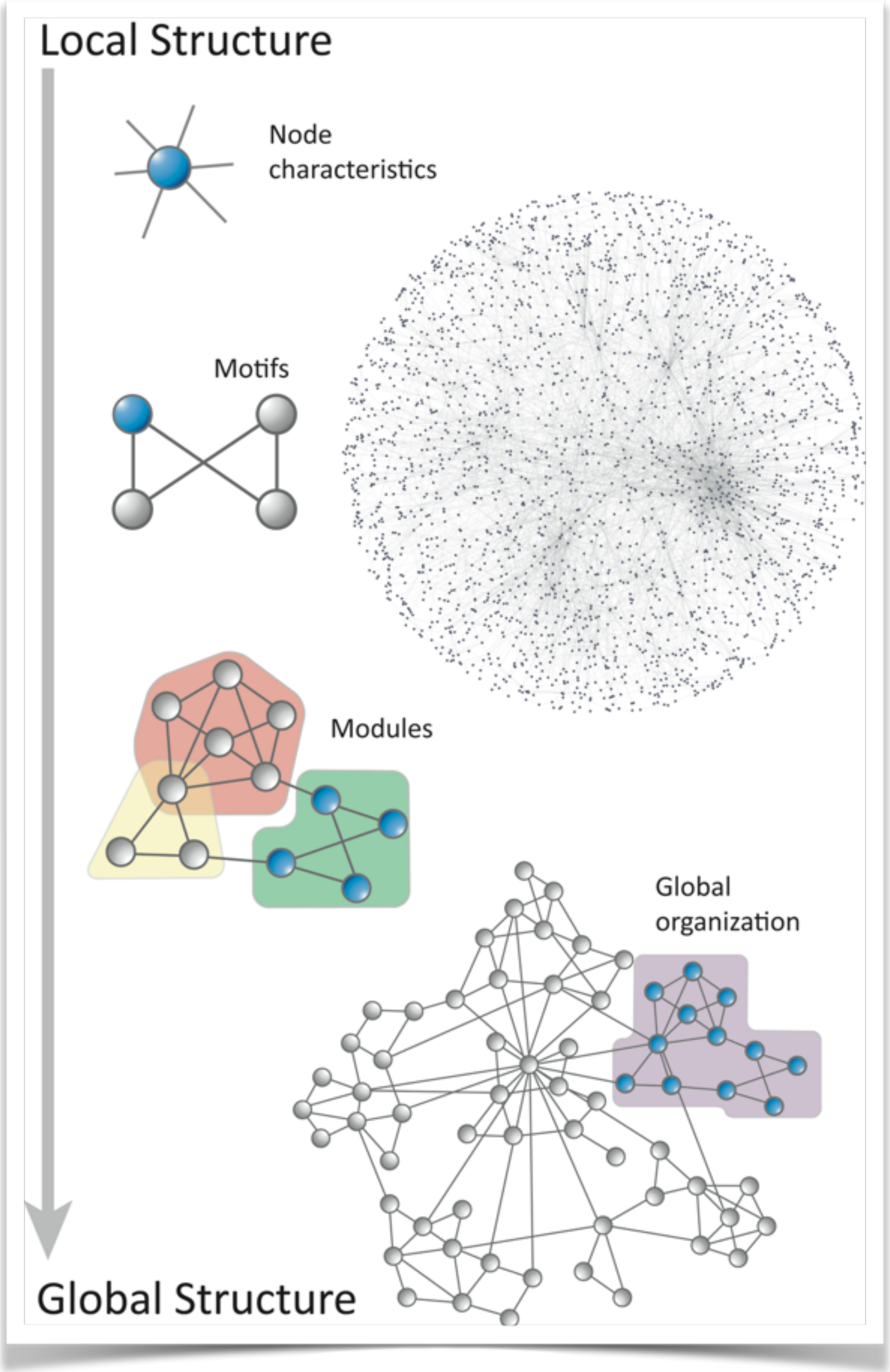
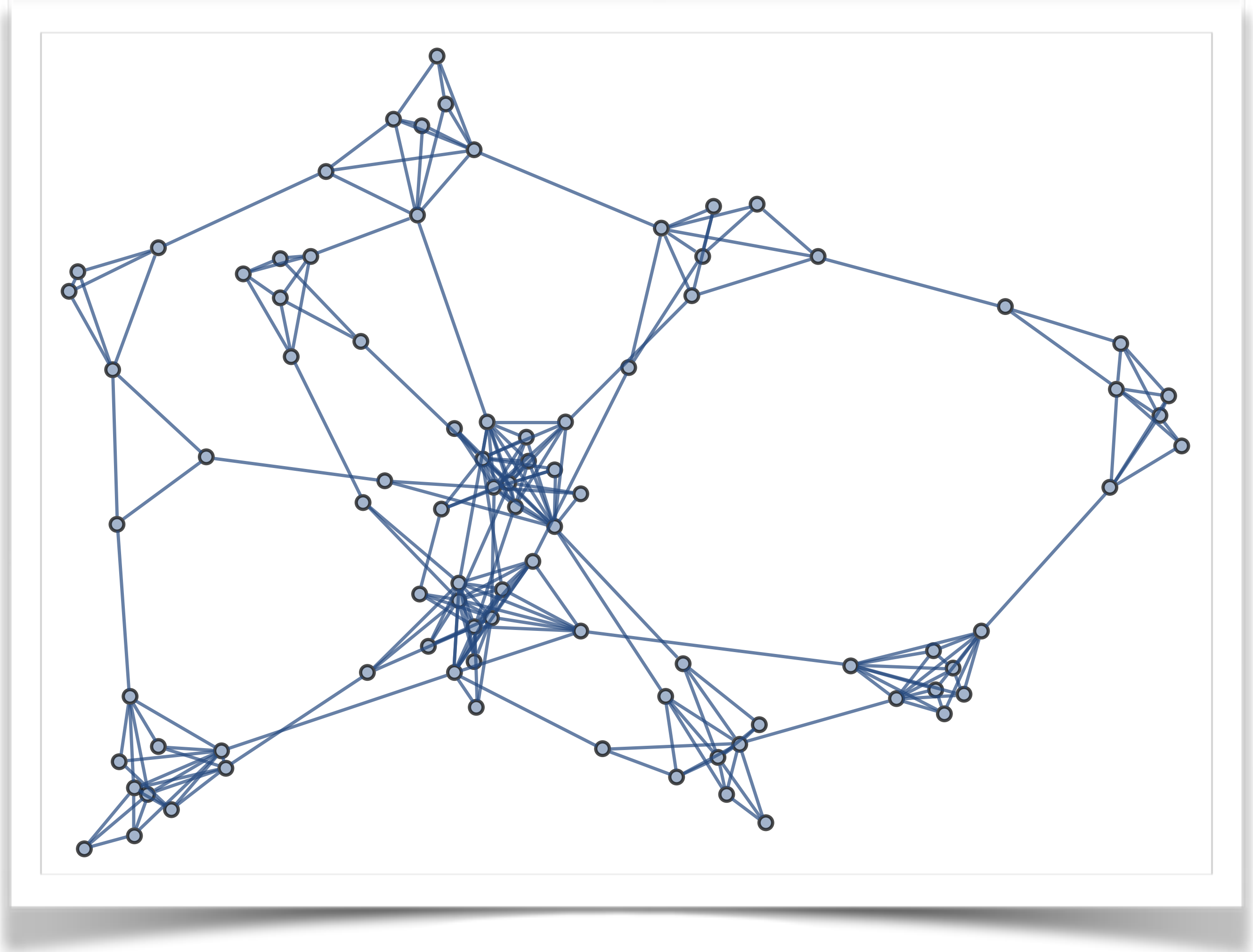
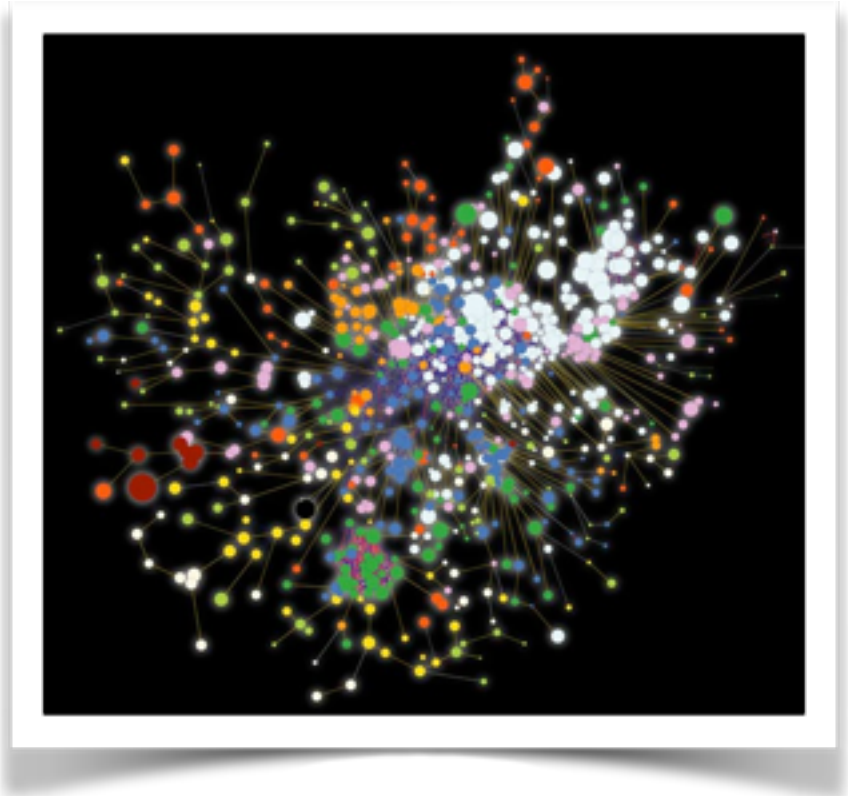
The Copenhagen Networks Study

Sune Lehmann
- Associate Professor, DTU Compute.
- Technical University of Denmark.
- @suneman

complex networks







human mobility

Limits of Predictability in Human Mobility

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

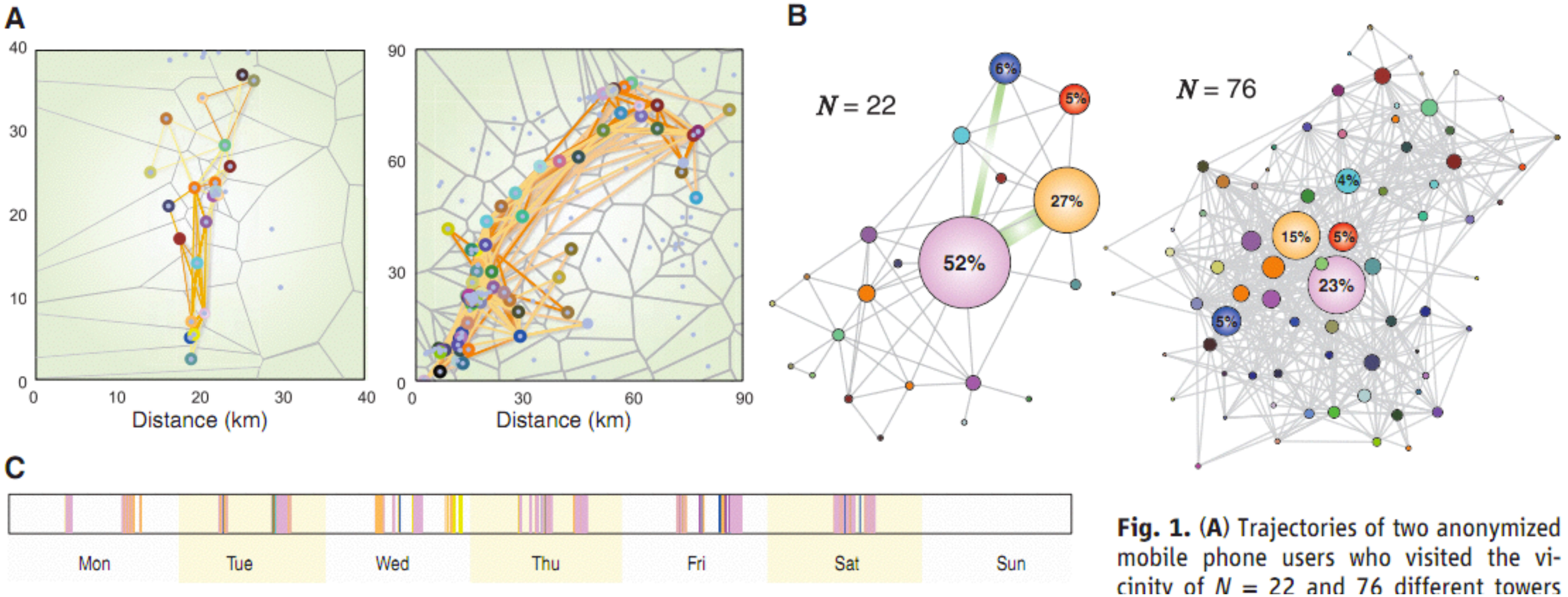
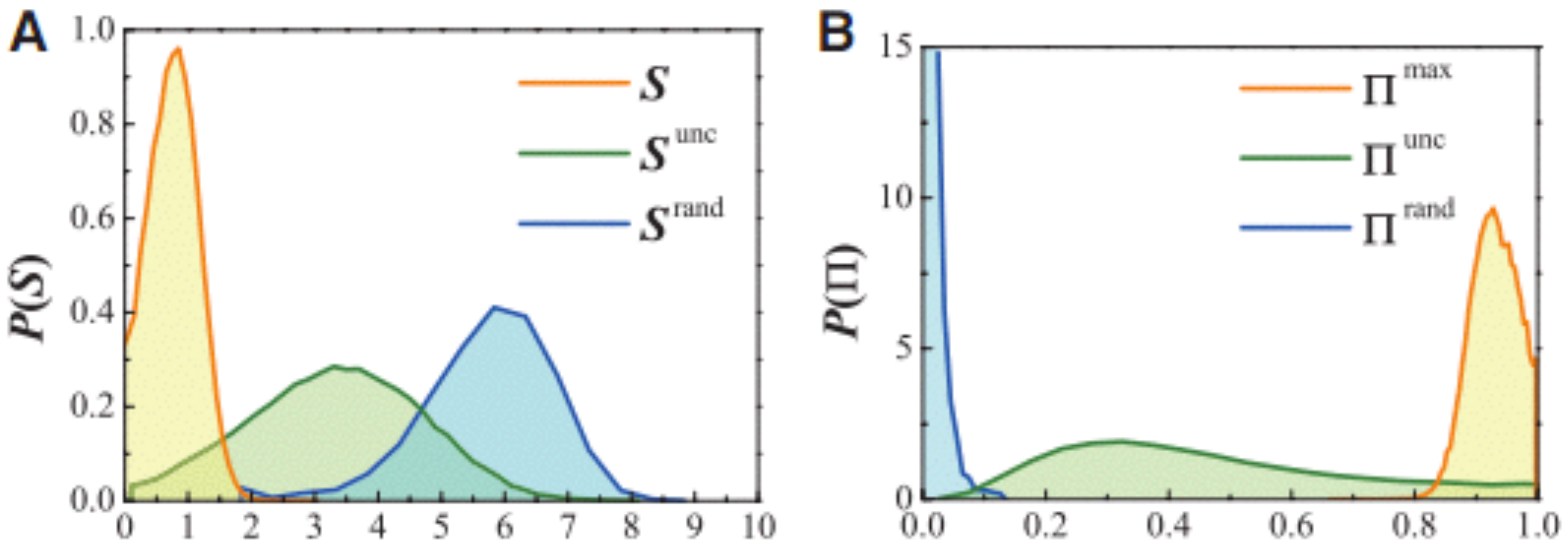


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of N = 22 and 76 different towers



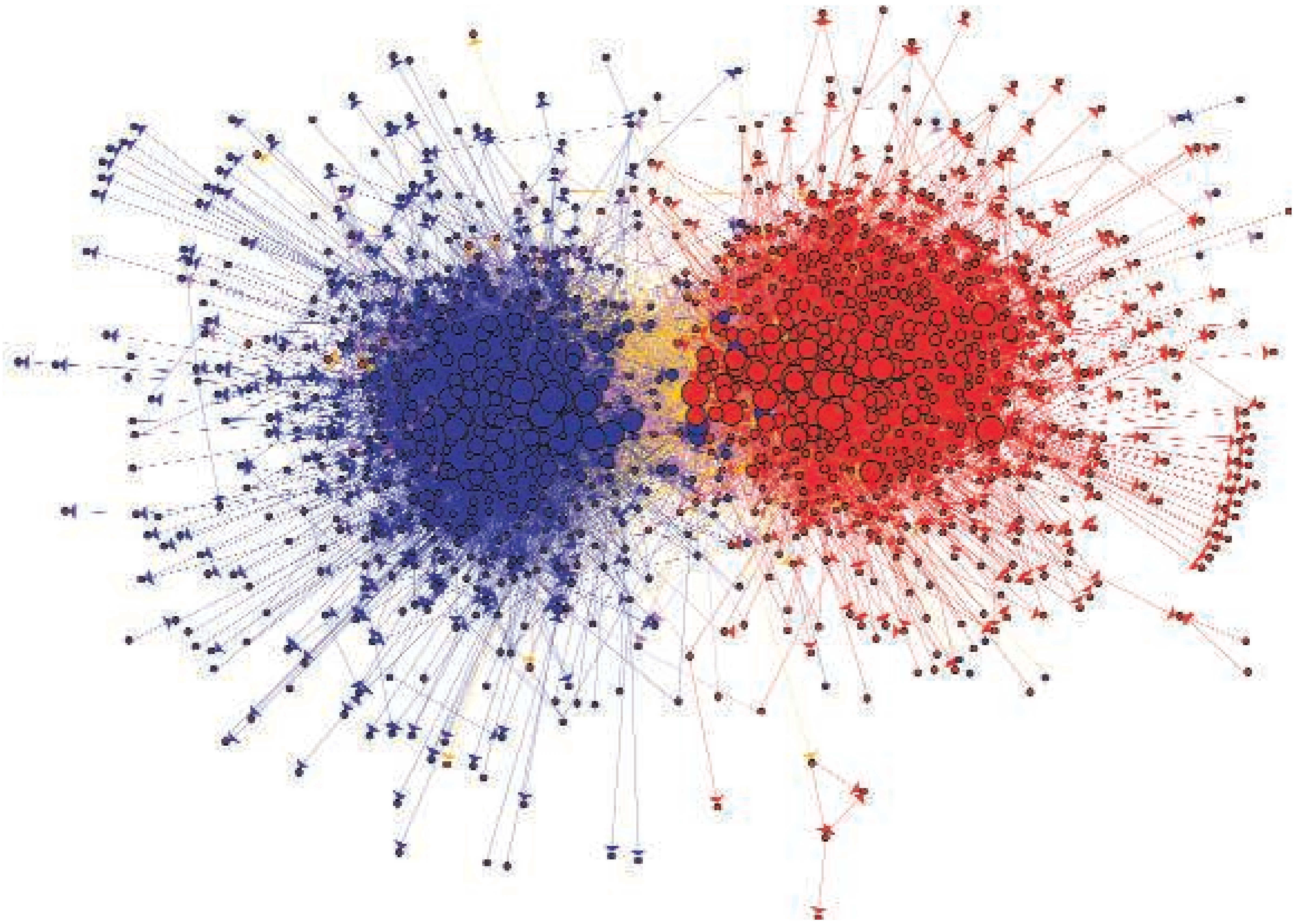
Limits of Predictability in Human Mobility
Chaoming Song, *et al.*
Science **327**, 1018 (2010);
DOI: 10.1126/science.1177170

SOCIAL SCIENCE

Computational Social Science

David Lazer,[1] Alex Pentland,[2] Lada Adamic,[3] Sinan Aral,[2,4] Albert-László Barabási,[5] Devon Brewer,[6] Nicholas Christakis,[1] Noshir Contractor,[7] James Fowler,[8] Myron Gutmann,[3] Tony Jebara,[9] Gary King,[1] Michael Macy,[10] Deb Roy,[2] Marshall Van Alstyne[2,11]

A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviors.



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4:20
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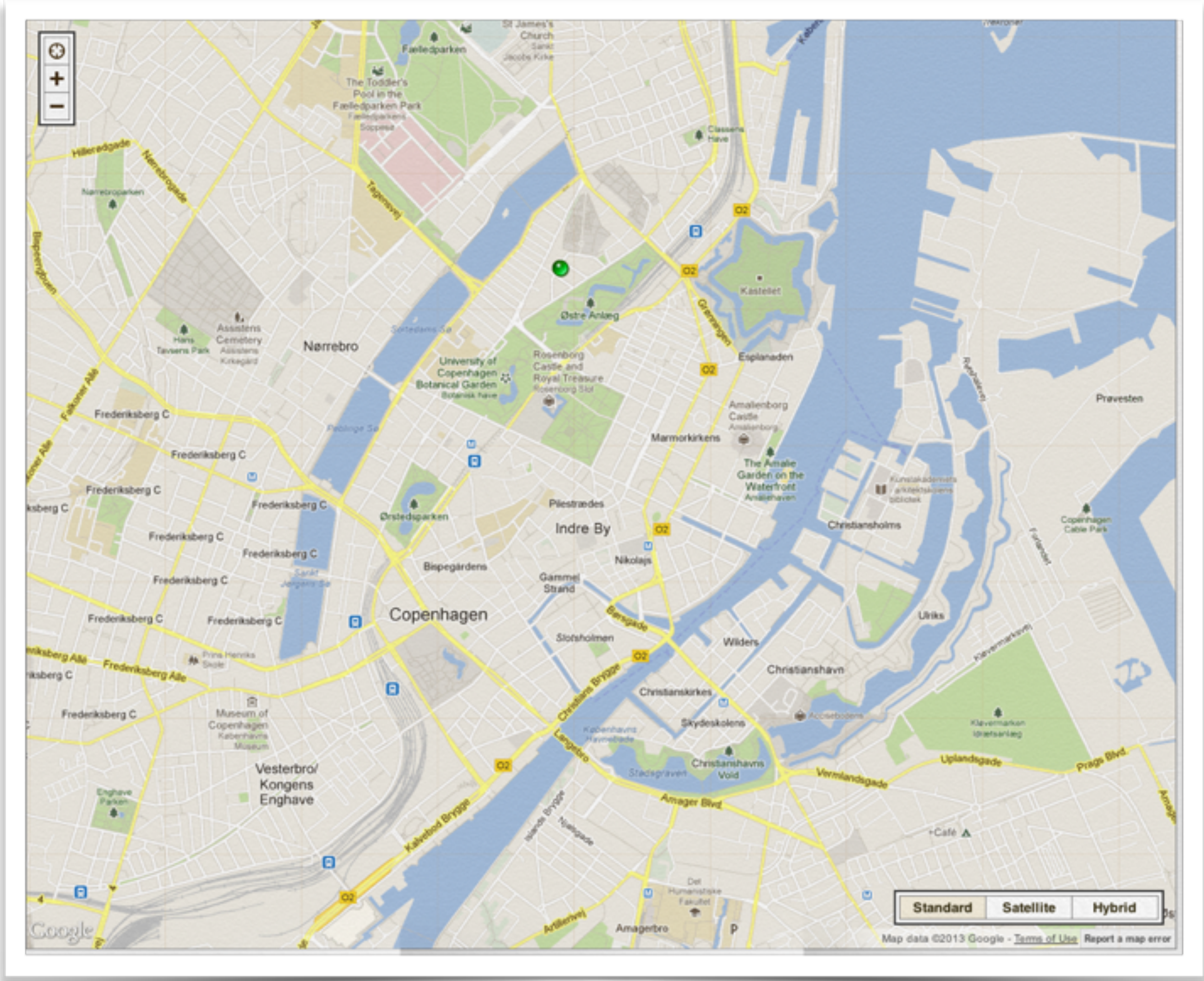
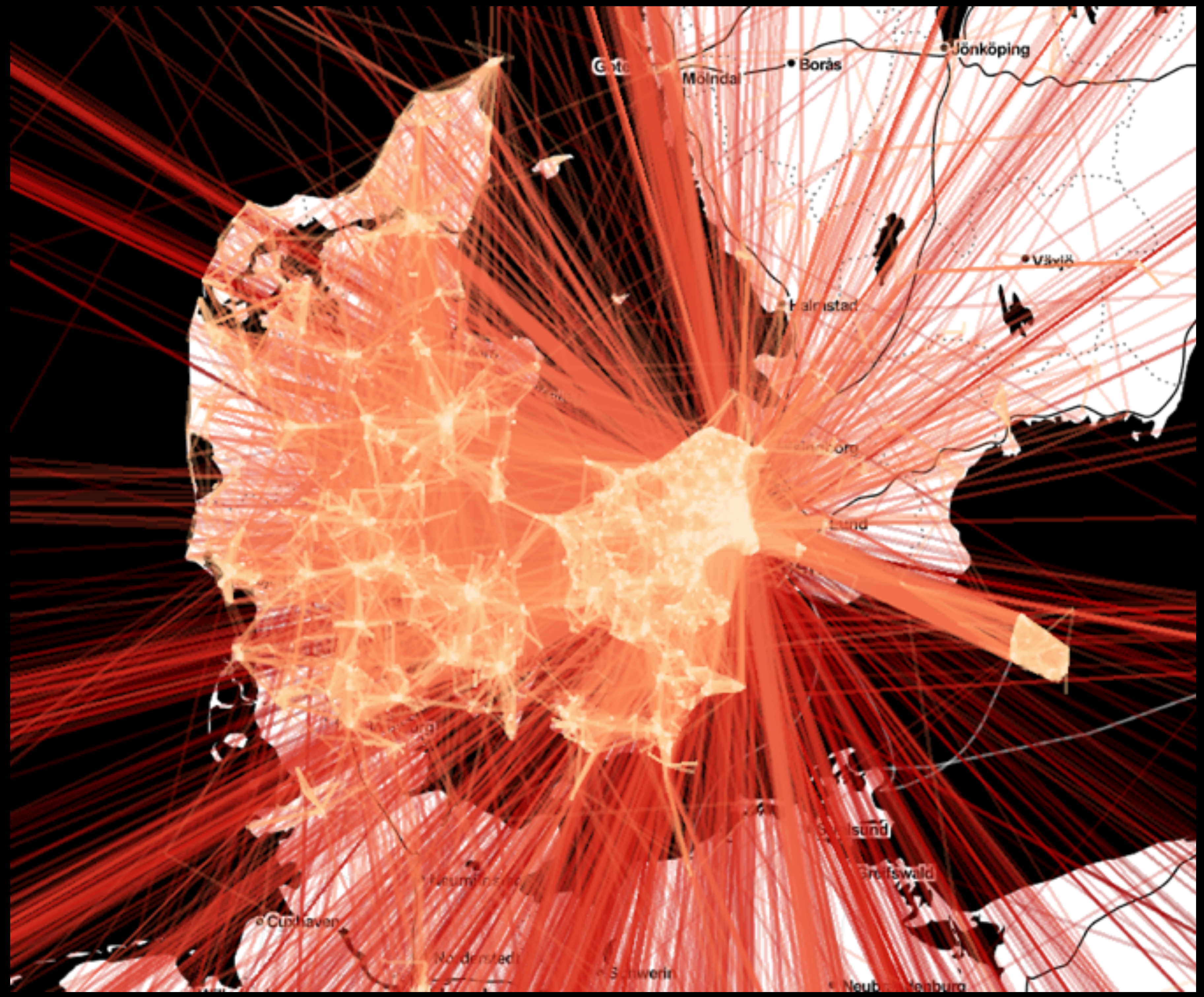
Maps
Play Store
YouTube
Google


Nørrebro
Indre By
Copenhagen
Christianshavn
Vesterbro/
Kongens
Enghave
Standard
Satellite
Hybrid


Pizza Pizza Pizza


ARCTIC OCEAN
North America
NORTH ATLANTIC OCEAN
NORTH PACIFIC OCEAN
NORTH PACIFIC OCEAN
Asia
Africa
South America
SOUTH PACIFIC OCEAN
SOUTH ATLANTIC OCEAN
INDIAN OCEAN
Australia
SOUTH PACIFIC OCEAN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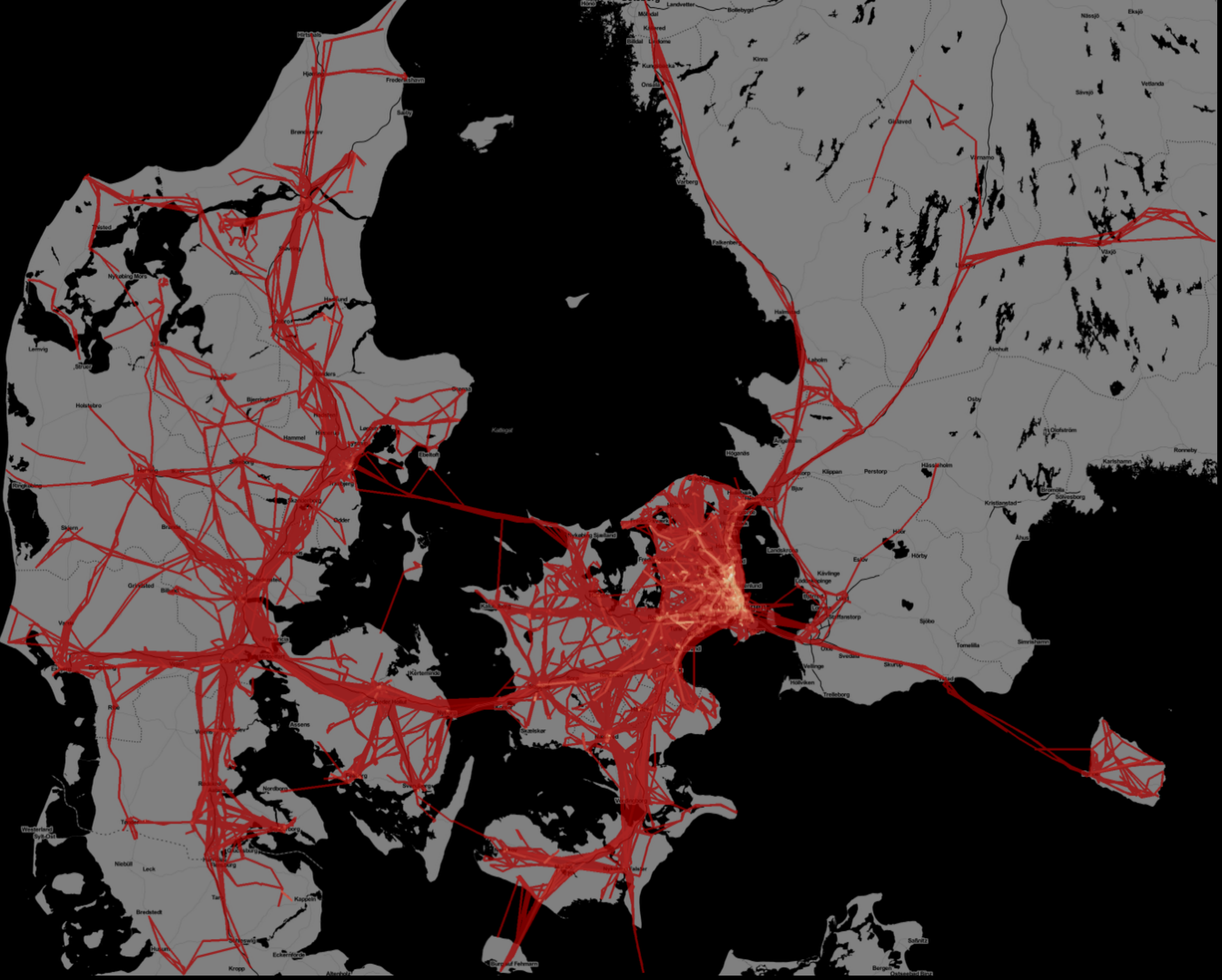
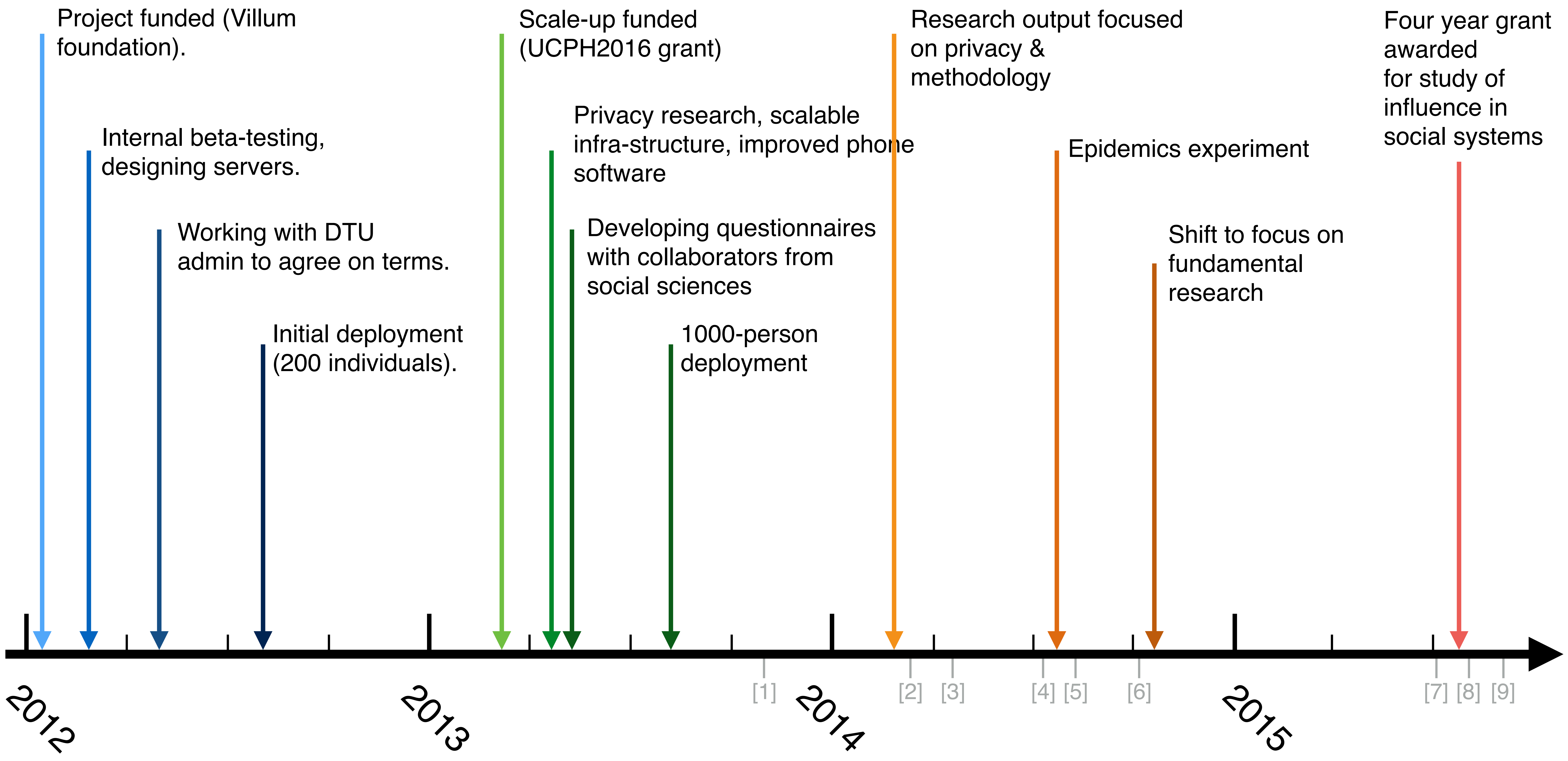
Jönköping
Halmstad
Växjö
Cuxhaven



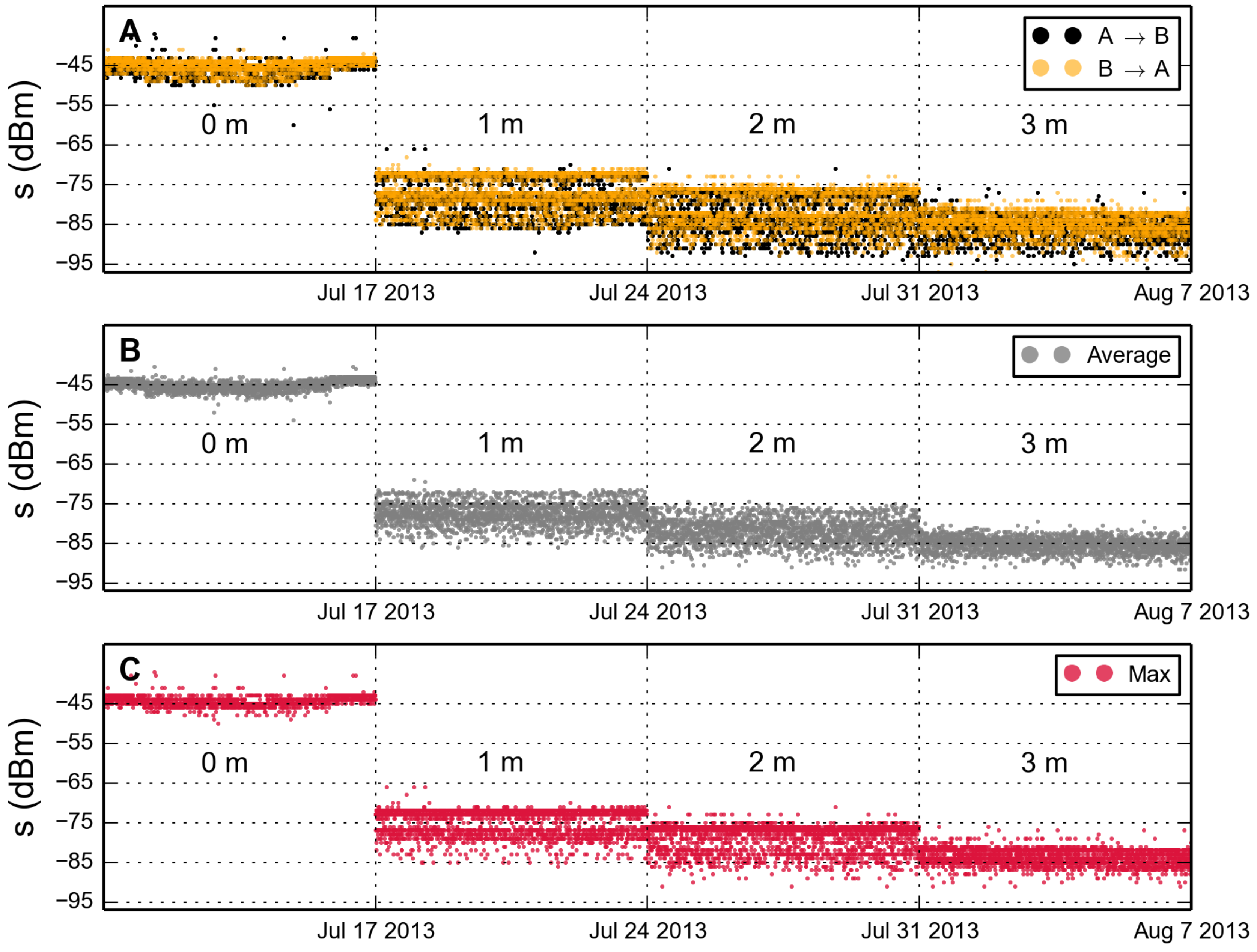
Frederikshavn
Holstebro
Hammel
Ebeltoft
Assens
Nordborg
Niebüll
Leck
Bredstedt
Kappeln
Varberg
Falkenberg
Halmstad
Laholm
Klippan
Perstorp
Hässleholm
Kristianstad
Karlshamn
Ronneby
Höör
Hörby
Eslöv
Kävlinge
Sjöbo
Tomelilla
Simrishamn
Trelleborg

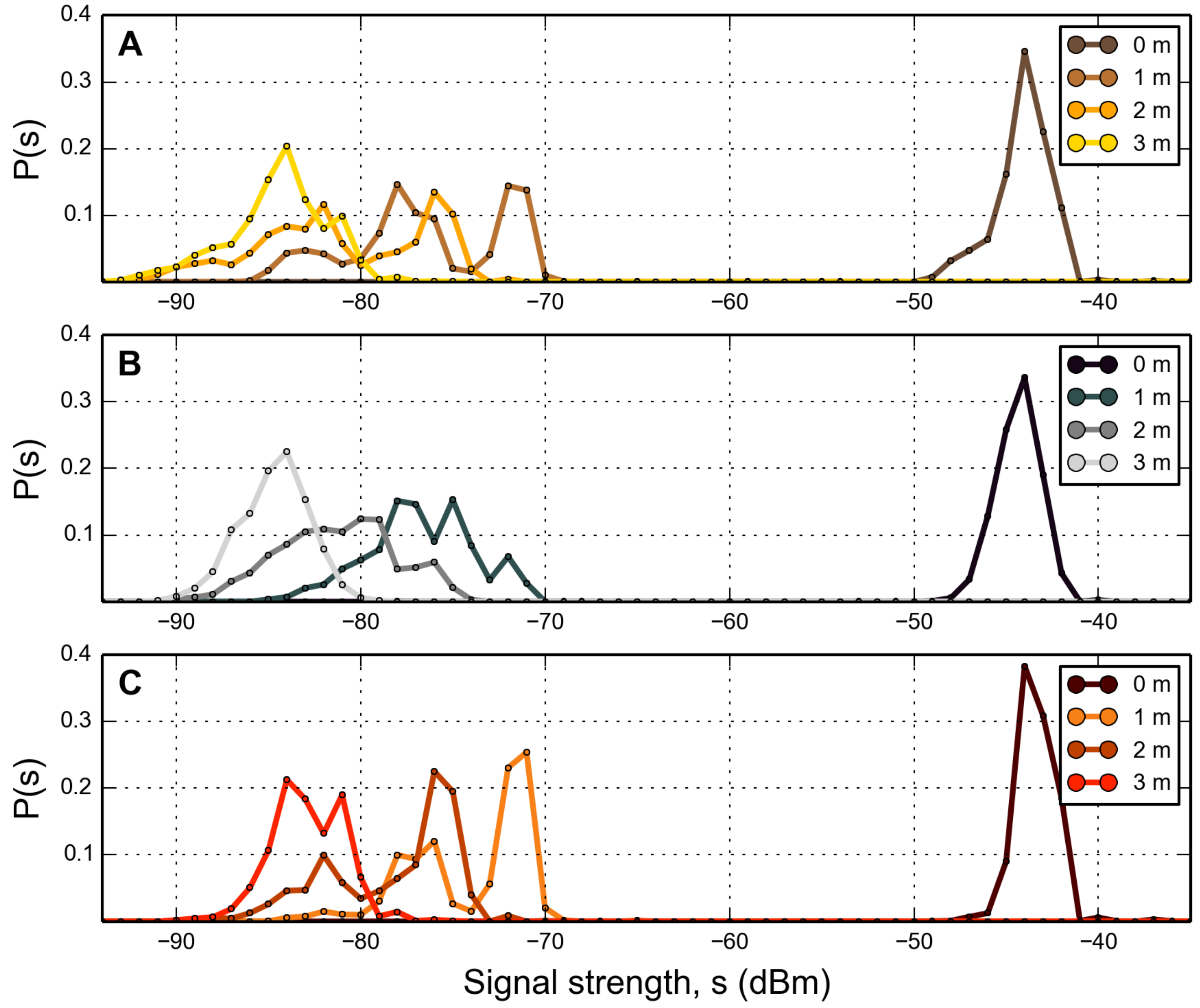


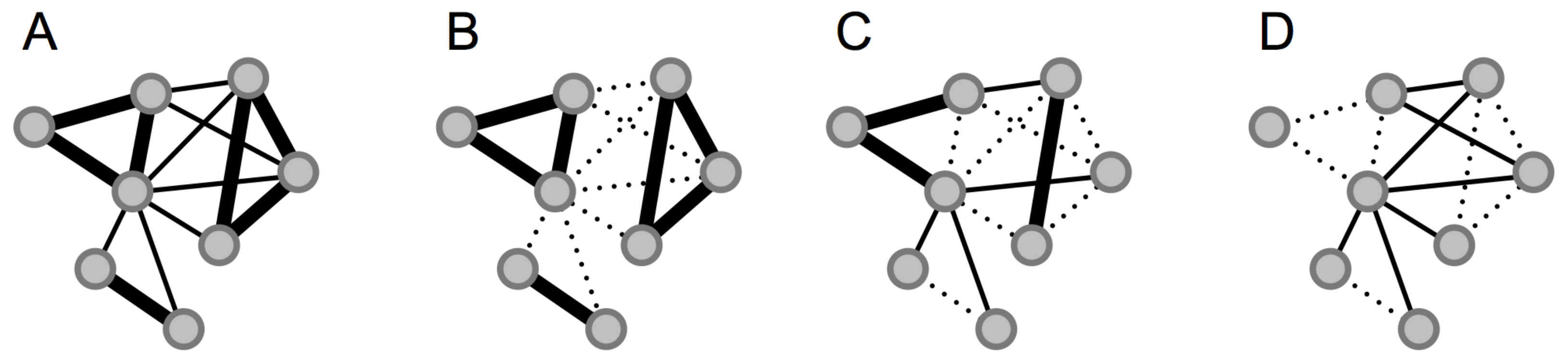
[1]. Cuttone, A., Lehmann, S., & Larsen, J. E. (2013, October). A mobile personal informatics system with interactive visualizations of mobility and social interactions. In Proceedings of the 1st ACM international workshop on Personal data meets distributed multimedia (pp. 27-30). ACM.
[2]. Stopczynski, A., Pietri, R., Pentland, A., Lazer, D., & Lehmann, S. (2014). Privacy in sensor-driven human data collection: A guide for practitioners. arXiv preprint arXiv:1403.5299.
[3]. Stopczynski, Sekara, Sapiezynski, Cuttone, Madsen, Larsen, Lehmann. *Measuring Large-Scale Social Networks with High Resolution*. PLoS ONE 9(4): e95978 (2014).
[4]. de Montjoye, Y. A., Stopczynski, A., Shmueli, E., Pentland, A., & Lehmann, S. (2014). The strength of the strongest ties in collaborative problem solving. Scientific reports, 4.
[5]. Sekara, V., & Lehmann, S. (2014). The strength of friendship ties in proximity sensor data. PL o S One, 9(7).
[6]. Cuttone, A., Lehmann, S., & Larsen, J. E. (2014, September). Inferring human mobility from sparse low accuracy mobile sensing data. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication (pp. 995-1004). ACM.
[7]. Sekara, V., Stopczynski, A., & Lehmann, S. (2015). The fundamental structures of dynamic social networks. arXiv preprint arXiv:1506.04704.
[8]. Stopczynski, A., Sapiezynski, P., Pentland, A. S., & Lehmann, S. (2015). Temporal Fidelity in Dynamic Social Networks. arXiv preprint arXiv:1507.01484.
[9]. Sapiezynski P, Stopczynski A, Gatej R, Lehmann S (2015) Tracking Human Mobility Using WiFi Signals. PLoS ONE 10(7): e0130824. doi:10.1371/journal.pone.0130824.

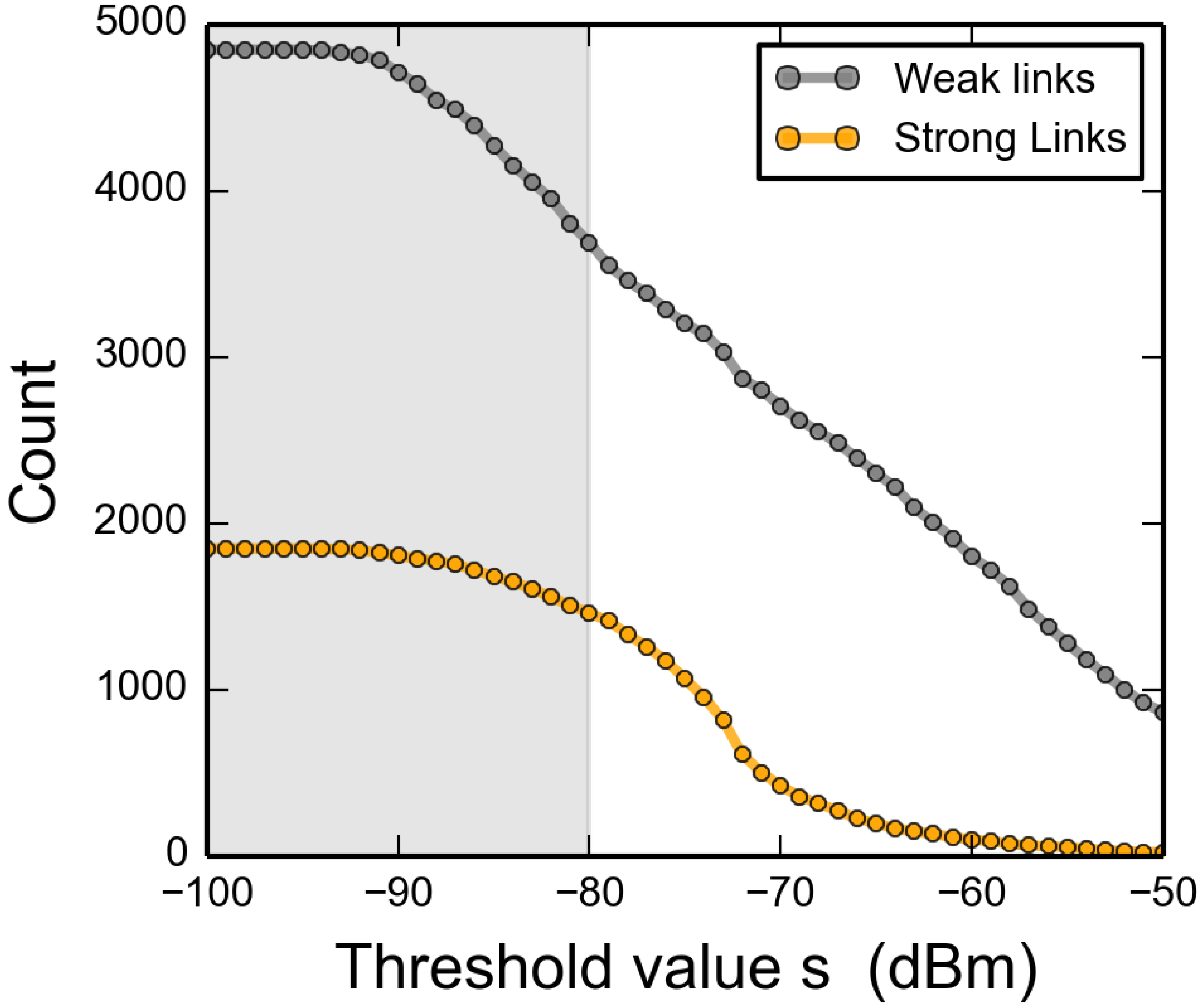

VENEZIA

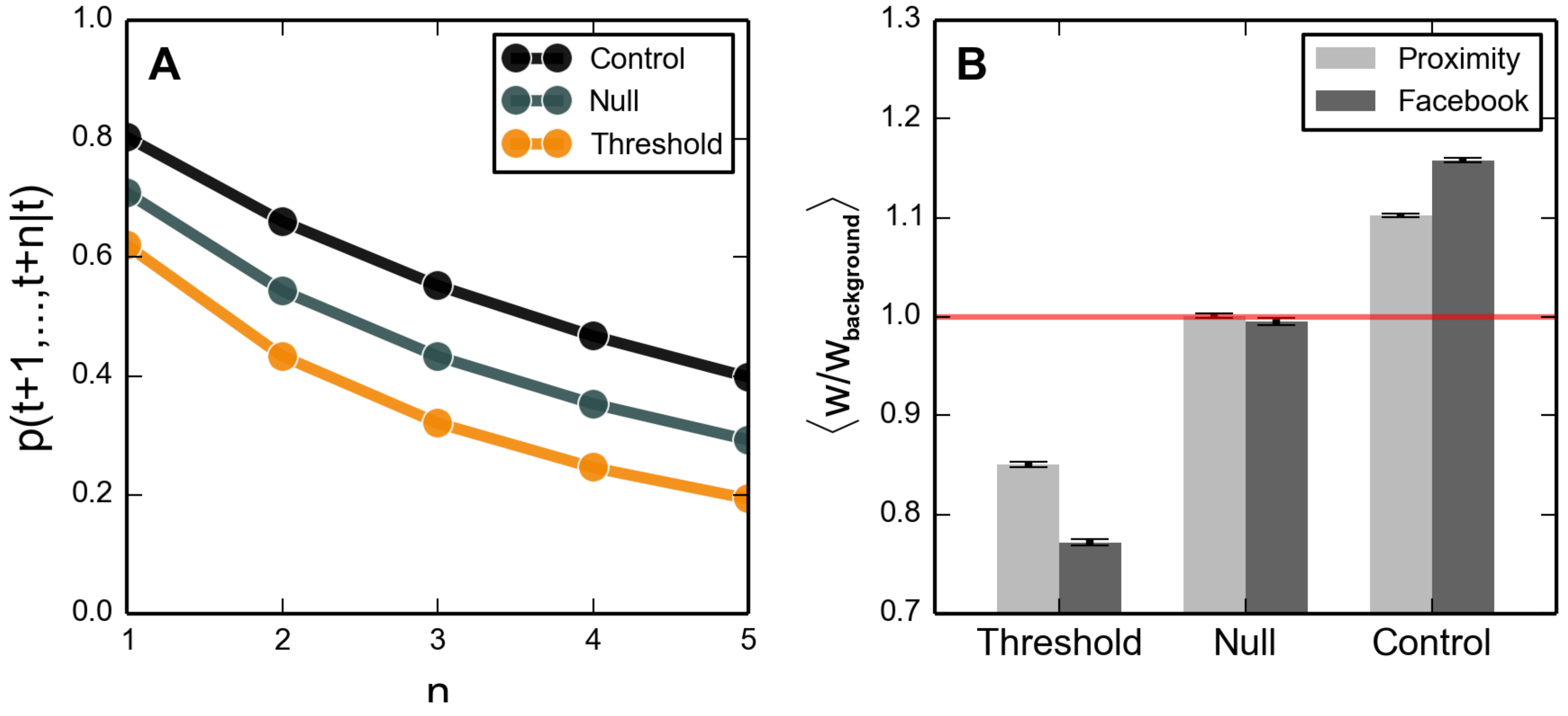
part 1: technology/methodology

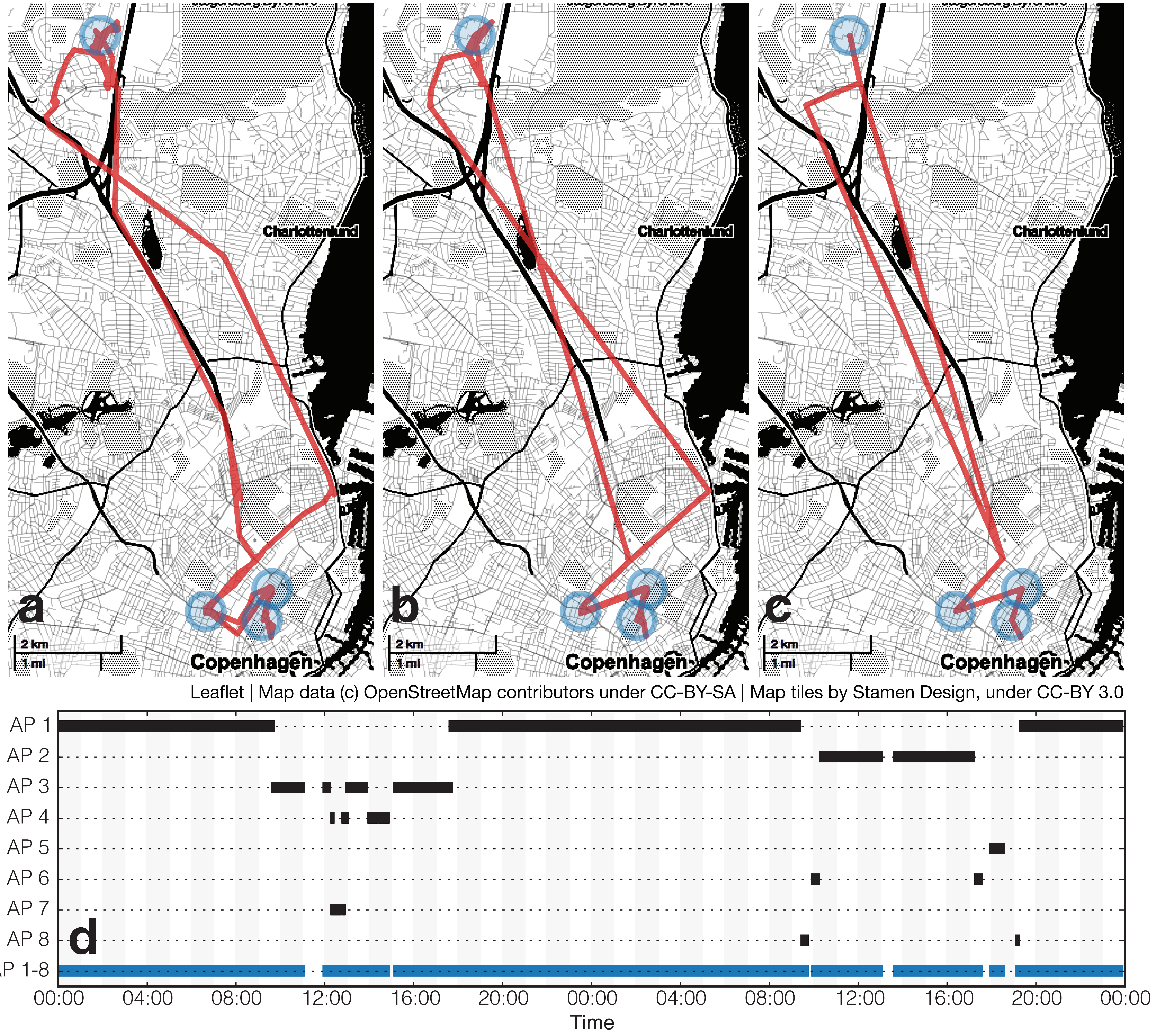

A
B
C
A → B
B → A
Average
Max
0 m
1 m
2 m
3 m
s (dBm)
-45
-55
-65
-75
-85
-95
Jul 17 2013
Jul 24 2013
Jul 31 2013
Aug 7 2013


A
B
C
0 m
1 m
2 m
3 m
P(s)
0.1
0.2
0.3
0.4
−90
−80
−70
−60
−50
−40
Signal strength, s (dBm)


A
B
C
D


Weak links
Strong Links
Count
0
1000
2000
3000
4000
5000
−100
−90
−80
−70
−60
−50
Threshold value s (dBm)


A
Control
Null
Threshold
p(t+1,...,t+n|t)
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
n
B
Proximity
Facebook
0.7
0.8
0.9
1.0
1.1
1.2
1.3
Threshold
Null
Control


Charlottenlund
Copenhagen
2 km
1 mi
a
b
c
Leaflet | Map data (c) OpenStreetMap contributors under CC-BY-SA | Map tiles by Stamen Design, under CC-BY 3.0
AP 1
AP 2
AP 3
AP 4
AP 5
AP 6
AP 7
AP 8
AP 1-8
d
00:00
04:00
08:00
12:00
16:00
20:00
00:00
04:00
08:00
12:00
16:00
20:00
00:00
Time

part 2: fundamental research

Vaccination of real social communities

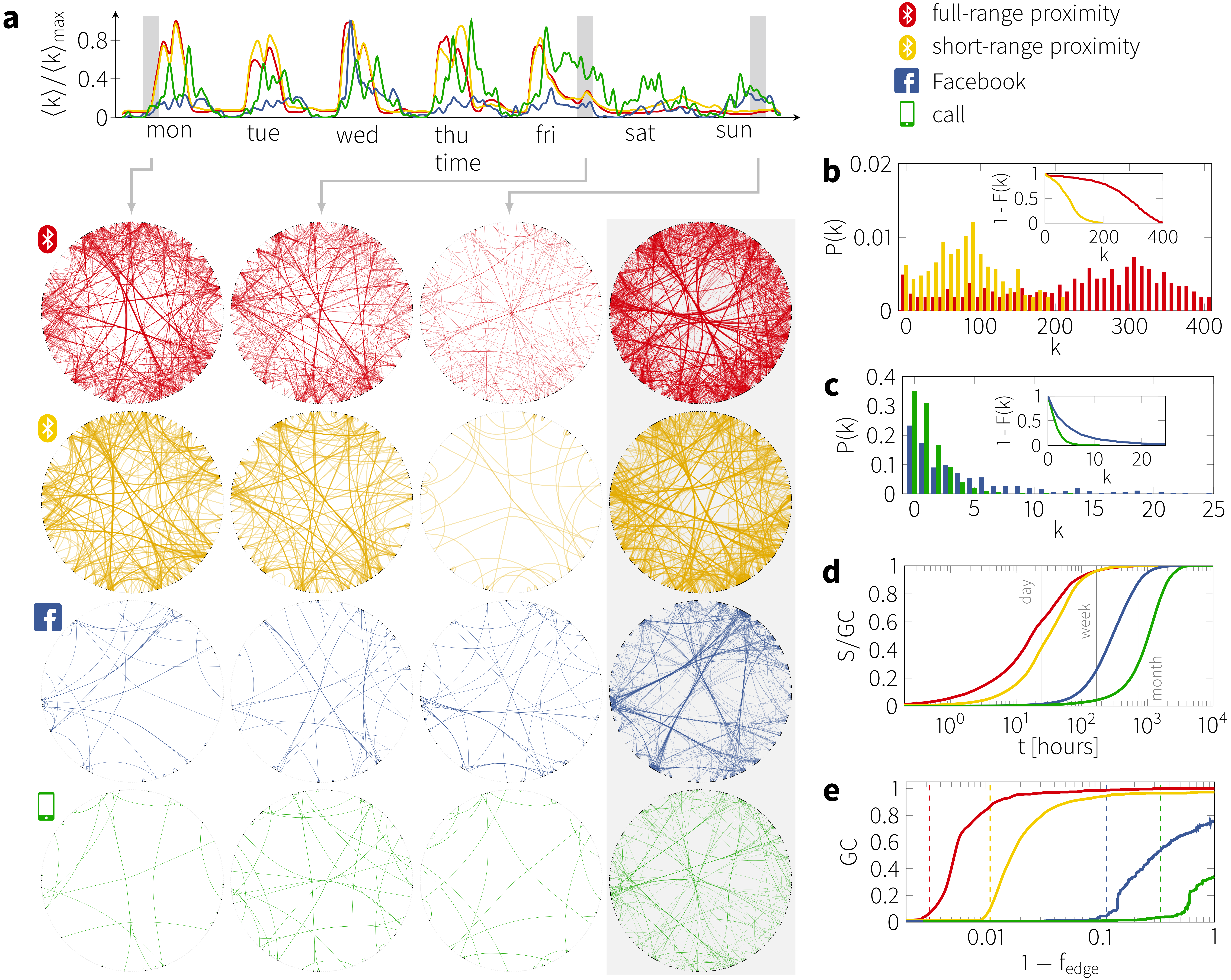
Enys Mones[1], Arkadiusz Stopczynski[1,2], Alex 'Sandy' Pentland[2] & Sune Lehmann[1,3]

[1]*Department of Applied Mathematics and Computer Science, Technical University of Denmark, Kgs. Lyngby, Denmark*

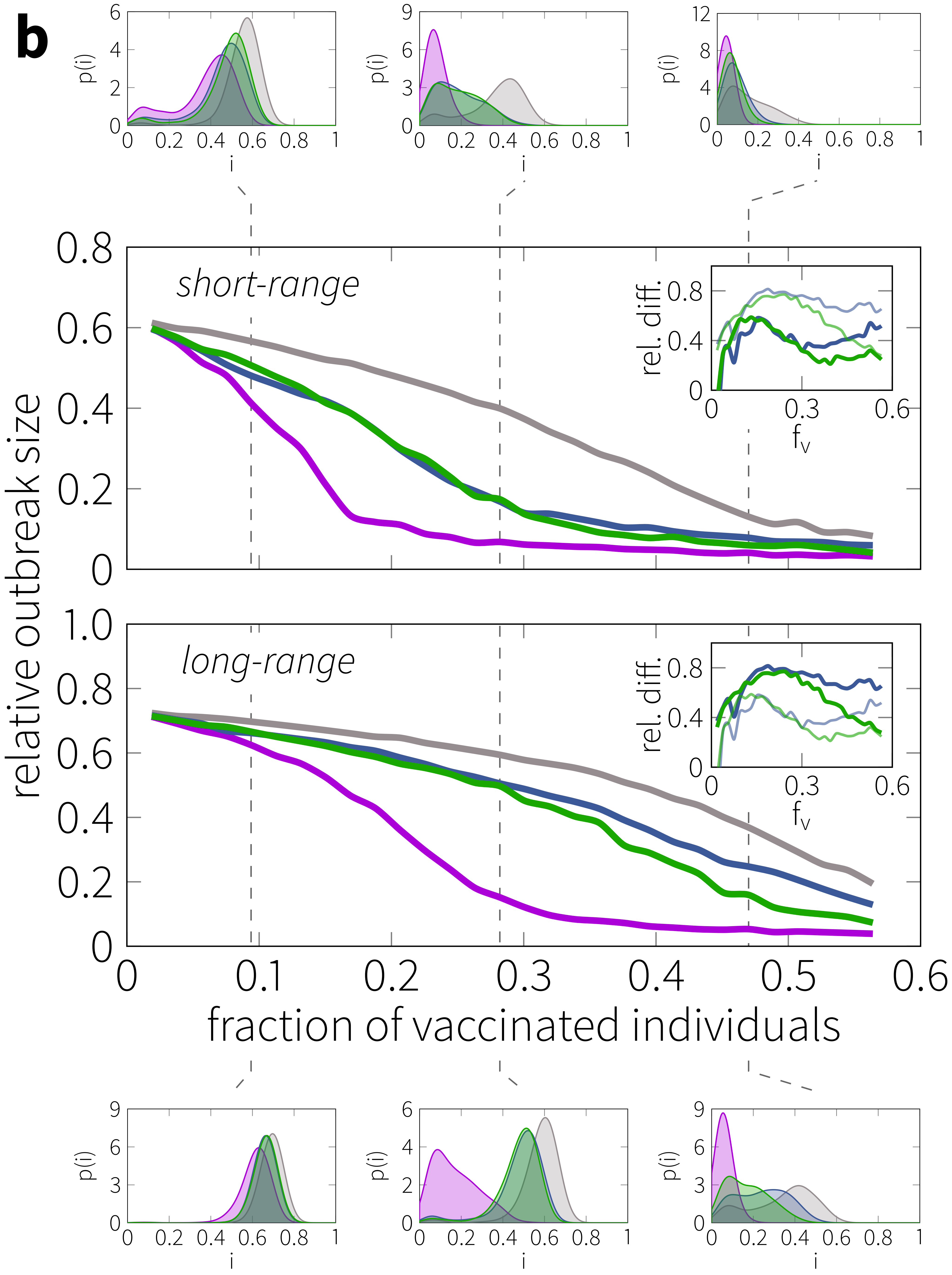
[2]*Media Lab, Massachusetts Institute of Technology, Cambridge, MA, USA*

[3]*The Niels Bohr Institute, University of Copenhagen, Copenhagen, Denmark*

Vaccination is a primary counter-measure against infectious diseases. In this context, knowledge of the social ties between members of a community allows for sophisticated immunization strategies that exploit the inherent characteristics of social networks. State-of-the-art methods designed to identify optimal vaccination target groups in social networks implicitly assume that social networks, as defined by Facebook friends or telecommunication contacts, are similar to the networks of physical contacts that enable actual disease spreading. The nature of the relationship between the network of social ties and the corresponding network of physical contacts, however, has yet to be explored fully for a large population of human actors. Based on epidemic simulations running on networks of real-world physical proximity,



a
⟨k⟩/⟨k⟩max
0.8
0.4
0
mon
tue
wed
thu
fri
sat
sun
time
full-range proximity
short-range proximity
Facebook
call
b
P(k)
0.02
0.01
0
100
200
300
400
k
1 - F(k)
1
0.5
0
c
P(k)
0.4
0.3
0.2
0.1
5
10
15
20
25
d
S/GC
1
0.8
0.6
0.4
0.2
day
week
month
10^0
10^1
10^2
10^3
10^4
t [hours]
e
GC
0.01
0.1
1
$1 - f_{edge}$


b
p(i)
i
short-range
long-range
rel. diff.
f_v
relative outbreak size
fraction of vaccinated individuals

The fundamental structures of dynamic social networks

Vedran Sekara [*], **Arkadiusz Stopczynski** [*] [†], **and Sune Lehmann** [*] [‡]

[*]Department of Applied Mathematics and Computer Science, Technical University of Denmark, Kgs. Lyngby, Denmark,[†]Media Lab, Massachusetts Institute of Technology, Cambridge, MA, USA, and [‡]The Niels Bohr Institute, University of Copenhagen, Copenhagen, Denmark

Submitted to Proceedings of the National Academy of Sciences of the United States of America

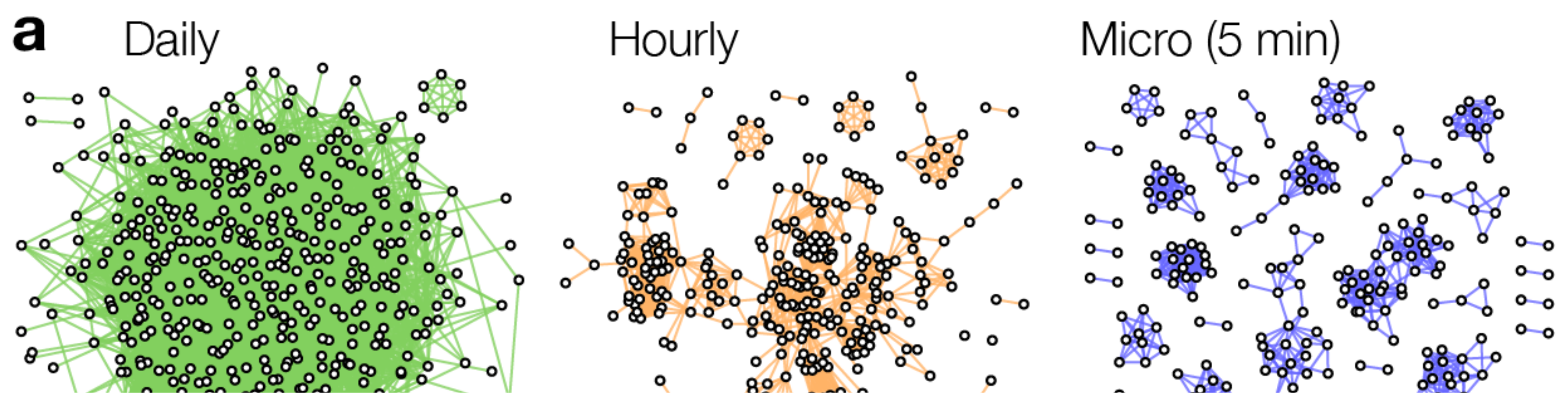
Social systems are in a constant state of flux with dynamics spanning from minute-by-minute changes to patterns present on the timescale of years. Accurate models of social dynamics are important for understanding spreading of influence or diseases, formation of friendships, or the productivity of teams. While there has been much progress on understanding complex networks over the past decade, little is known about the regularities governing the micro-dynamics of social networks. Here we explore the dynamic social network of a densely-connected population at high temporal resolution, uncovering dynamic social structures expressed on multiple timescales. We show that high-resolution data allow us to observe social gatherings directly, rendering community detection unnecessary. On the hourly timescale, we find that gatherings are fluid, with members coming and going, but organized via a stable core of individuals. Each core represents a social context. Cores exhibit a pattern of recurring meetings across weeks and months, each with varying degrees of regularity. Taken together, these findings provide a powerful simplification of the social network as a whole, resulting in a compact description for quantifying the complexity of dynamic social networks. Using this framework, we are able to explore the complex interplay between social and geospatial behavior, and we demonstrate that in analogy to human mobility, social behavior can be predicted with high precision.

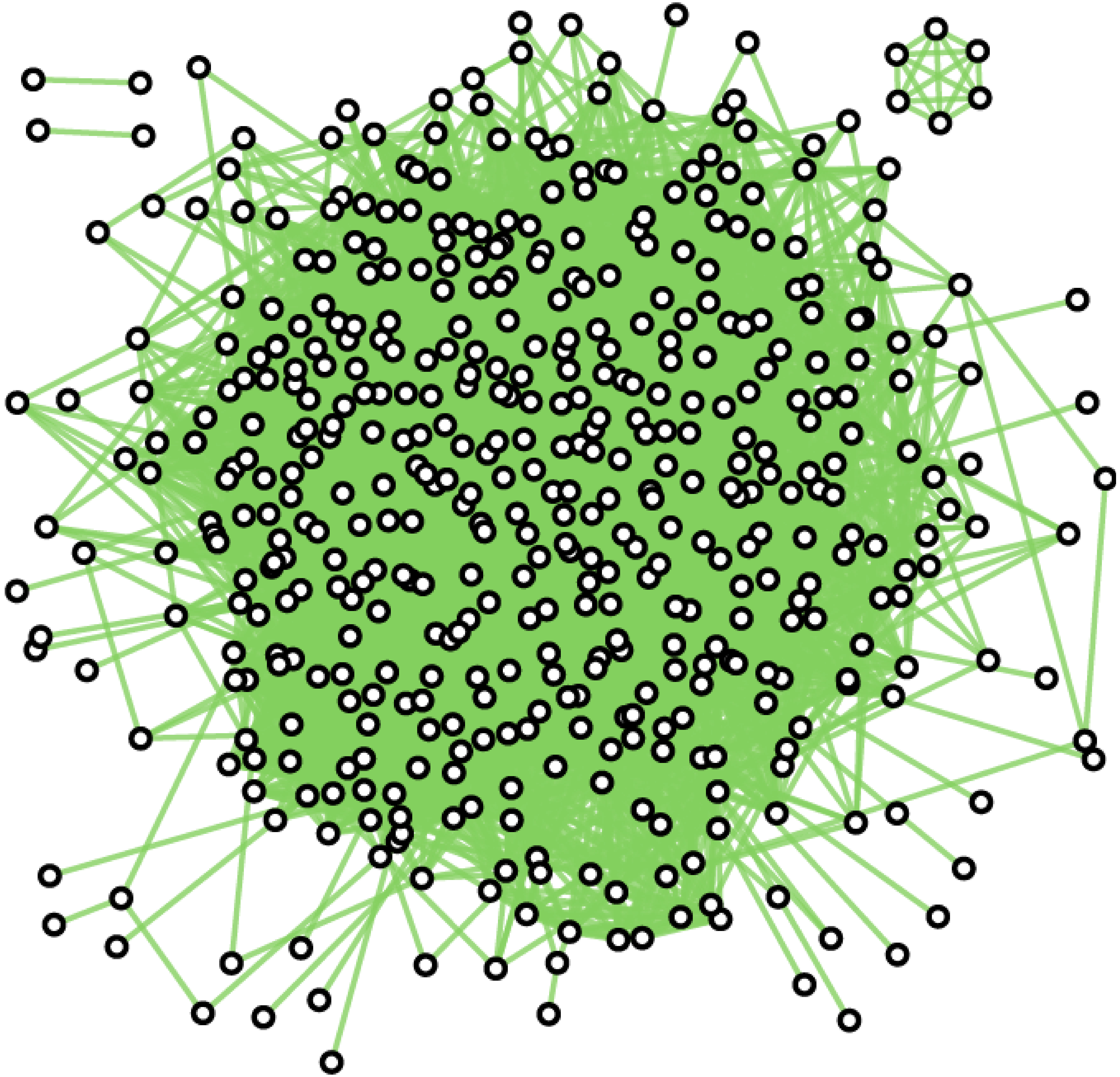
complex networks | social systems | human dynamics | computational social science

Human societies, their organizations, and communities give rise to complex social dynamics that are challenging to understand, describe, and predict. Recently, network sci-

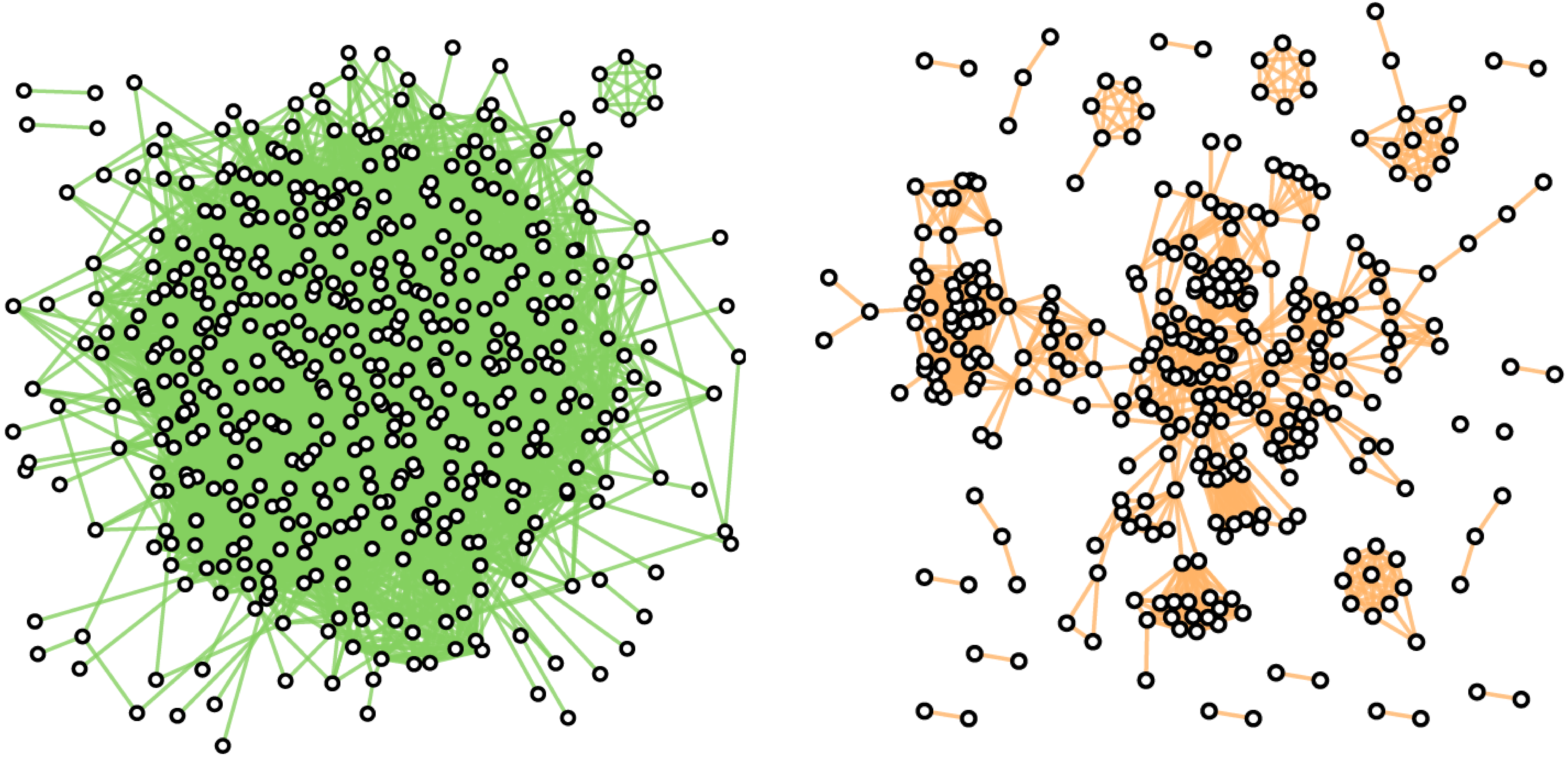
plemented with information from telecommunication networks (phone calls and text messages), online social media (Facebook messages), as well as geo-location and demographic data. This dataset allows us to analyze social dynamics expressed through multiple channels and at a highly granular level [17, 18, 19, 20], rather than focusing only on a particular channel such as call records [7, 21], emails [22], or social media networks [23, 24].

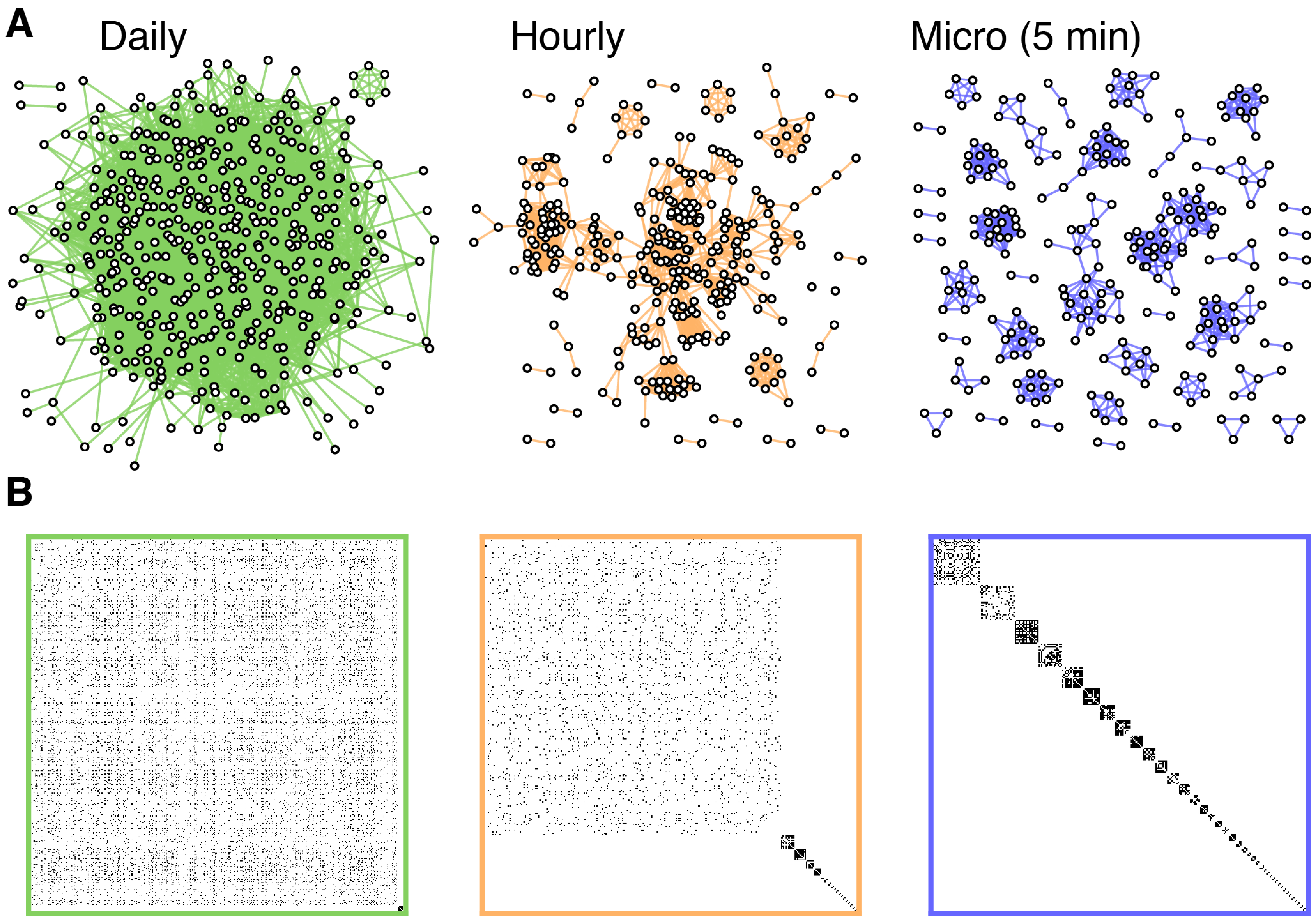
Until this point, community detection in dynamic networks has required complex mathematical heuristics [7, 25, 26]. Here we show that with high-resolution data describing social interactions, community detection is unnecessary. When single time slices are shorter than the rate at which social gatherings change, communities of individuals can be observed directly and with little ambiguity (Fig. 1). Using a simple matching between time slices we can infer temporal communities. These dynamic communities offer a powerful simplification of the complex system of social interactions as it develops over time. Based on these fundamental structures, we are able to show

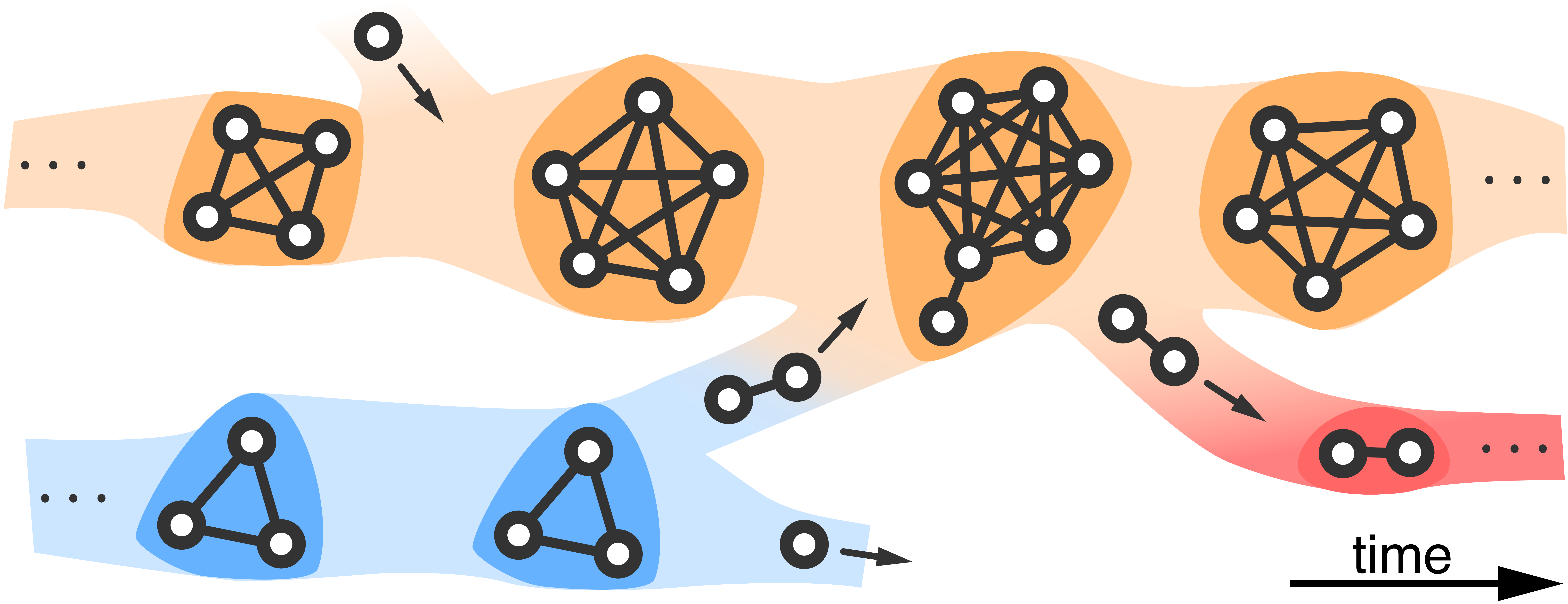


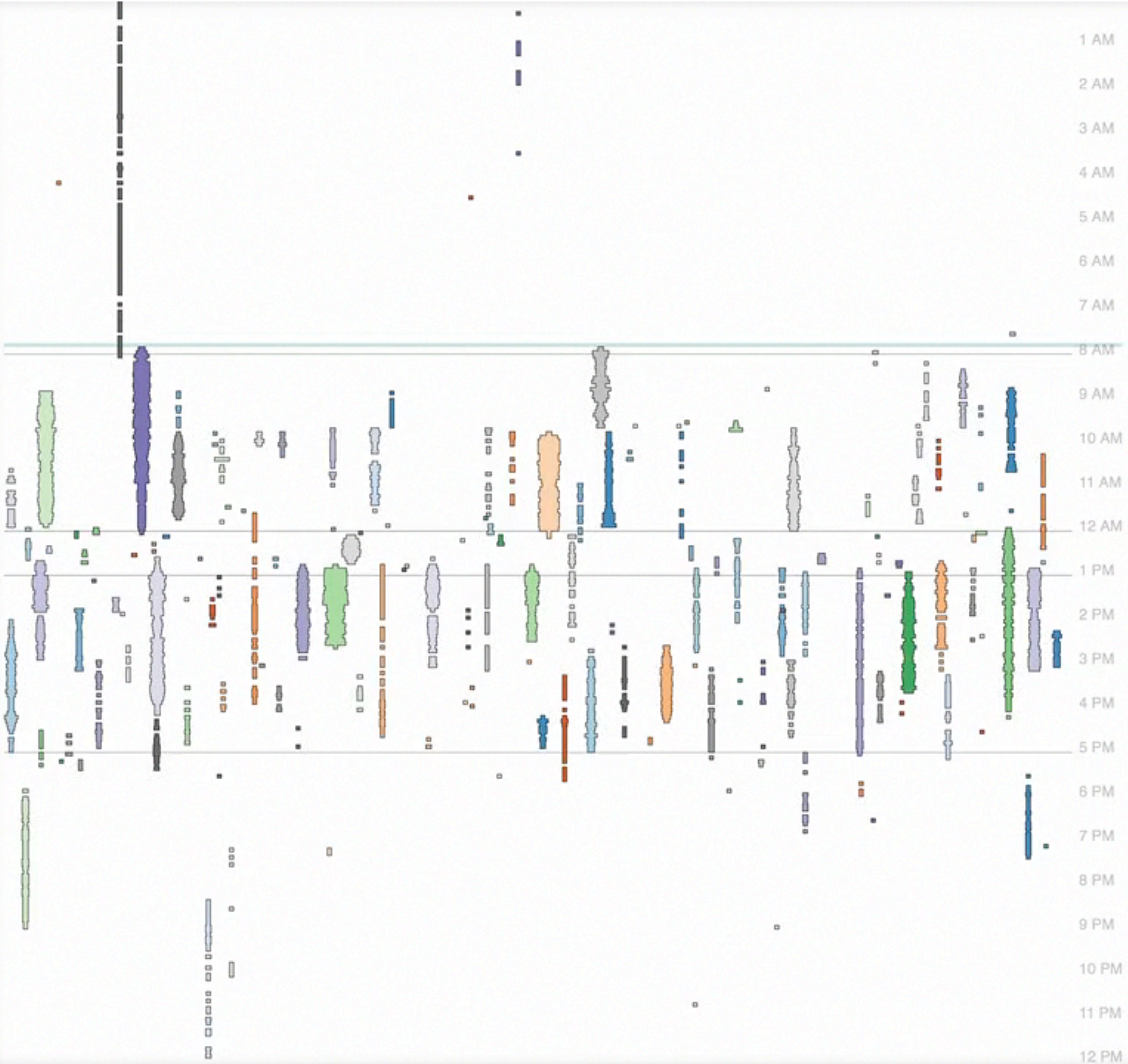


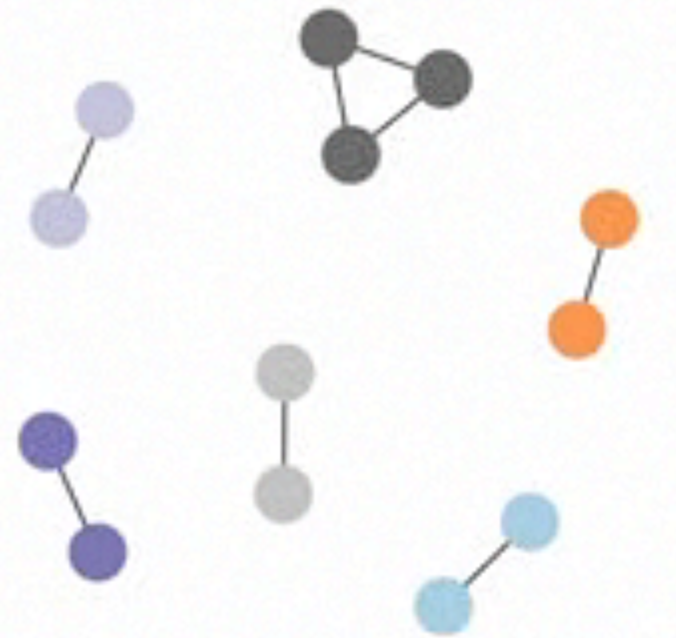
an interesting discovery




A
Daily
Hourly
Micro (5 min)
B


time



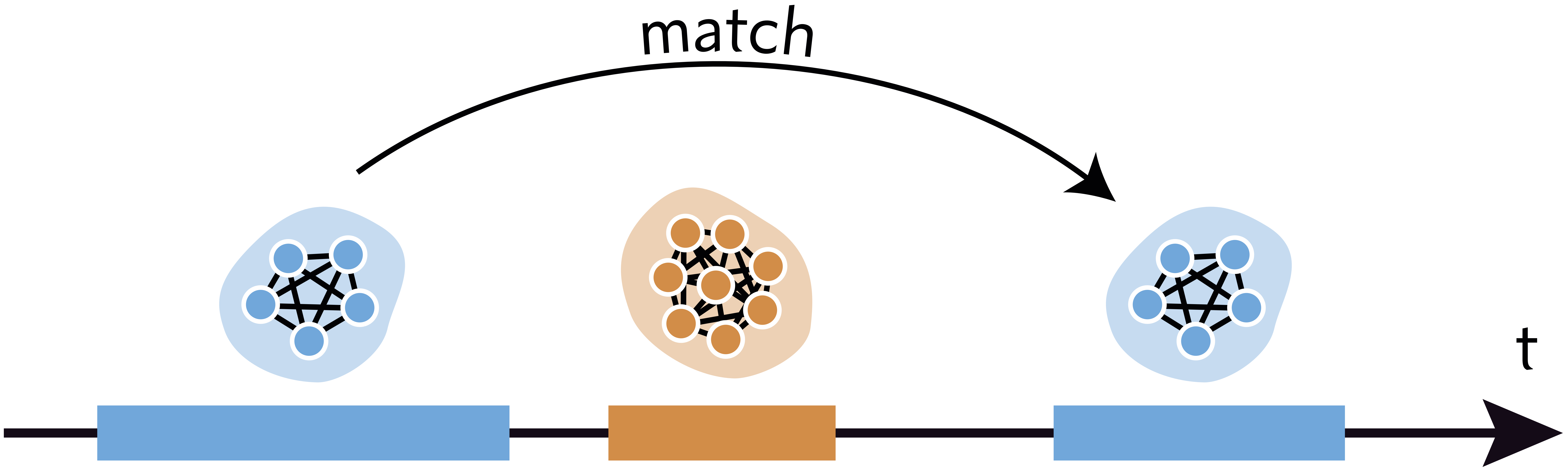


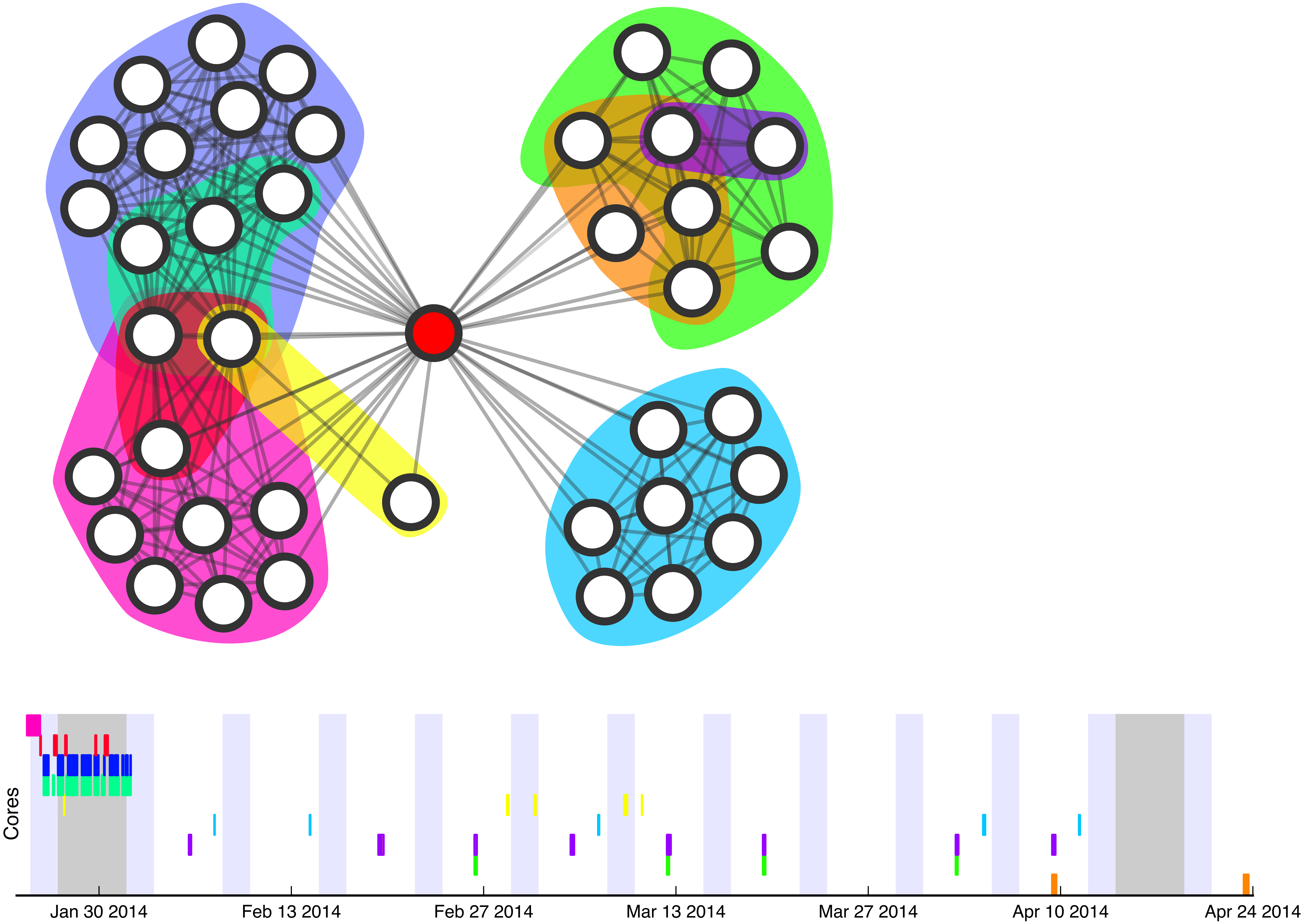
About | Guidebook

This is an attempt to visualise how people flow through social communities throughout a day. On the left you see how social gatherings stretch out over a day and above is a network showing social connections in the narrow time span, which is illustrated as a blue band, initiated around 9 AM.

The data used in this visualisation consists of physical meetings throughout a day, recorded by bluetooth connections between phones carried by the little 500+ participants. Each meeting is represented as a link in the network above, and each circle represents a person. The social communities are inferred using the Map Equation.

produced by Ulf Aslak, ©2015


match
t



Cores
Jan 30 2014
Feb 13 2014
Feb 27 2014
Mar 13 2014
Mar 27 2014
Apr 10 2014
Apr 24 2014

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

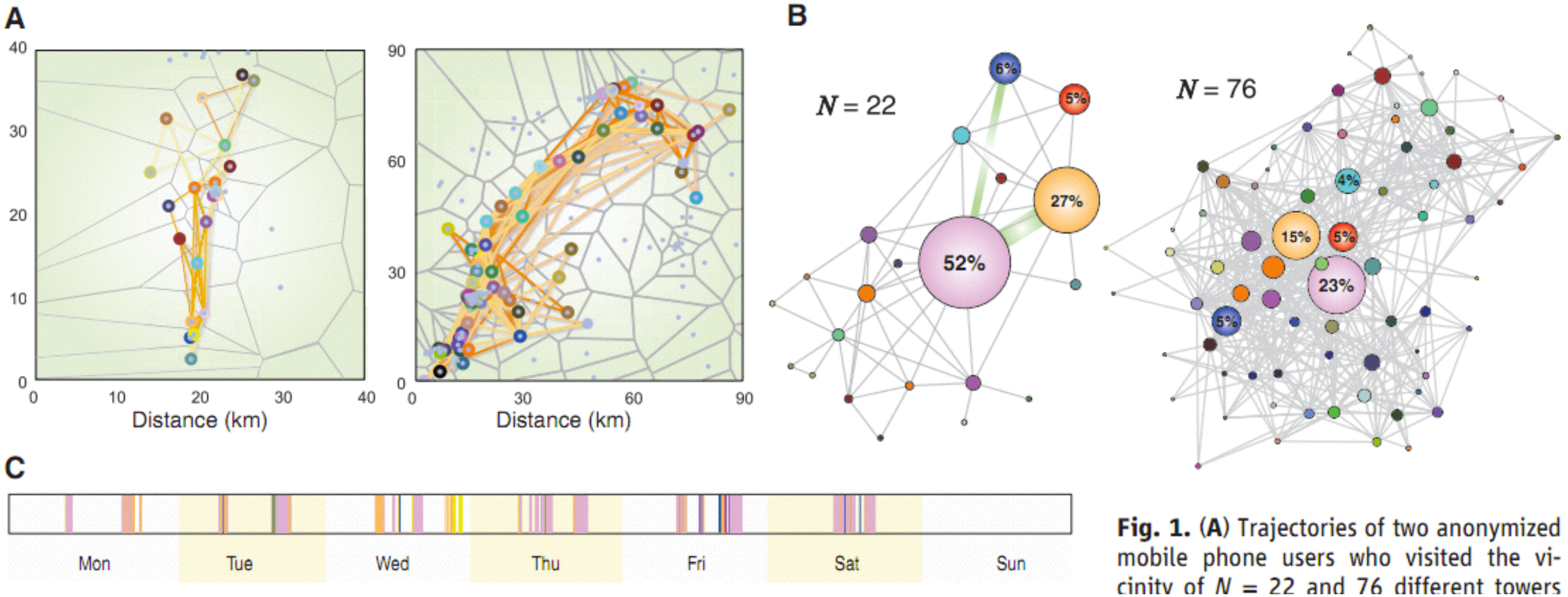
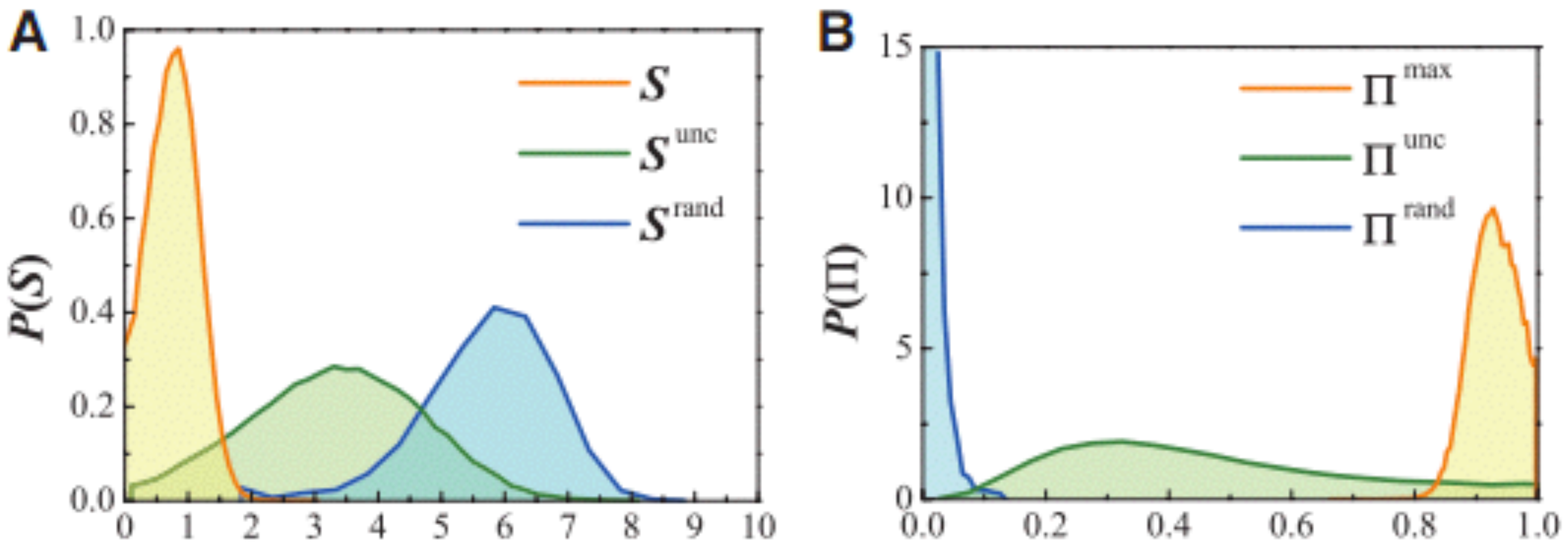


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of N = 22 and 76 different towers



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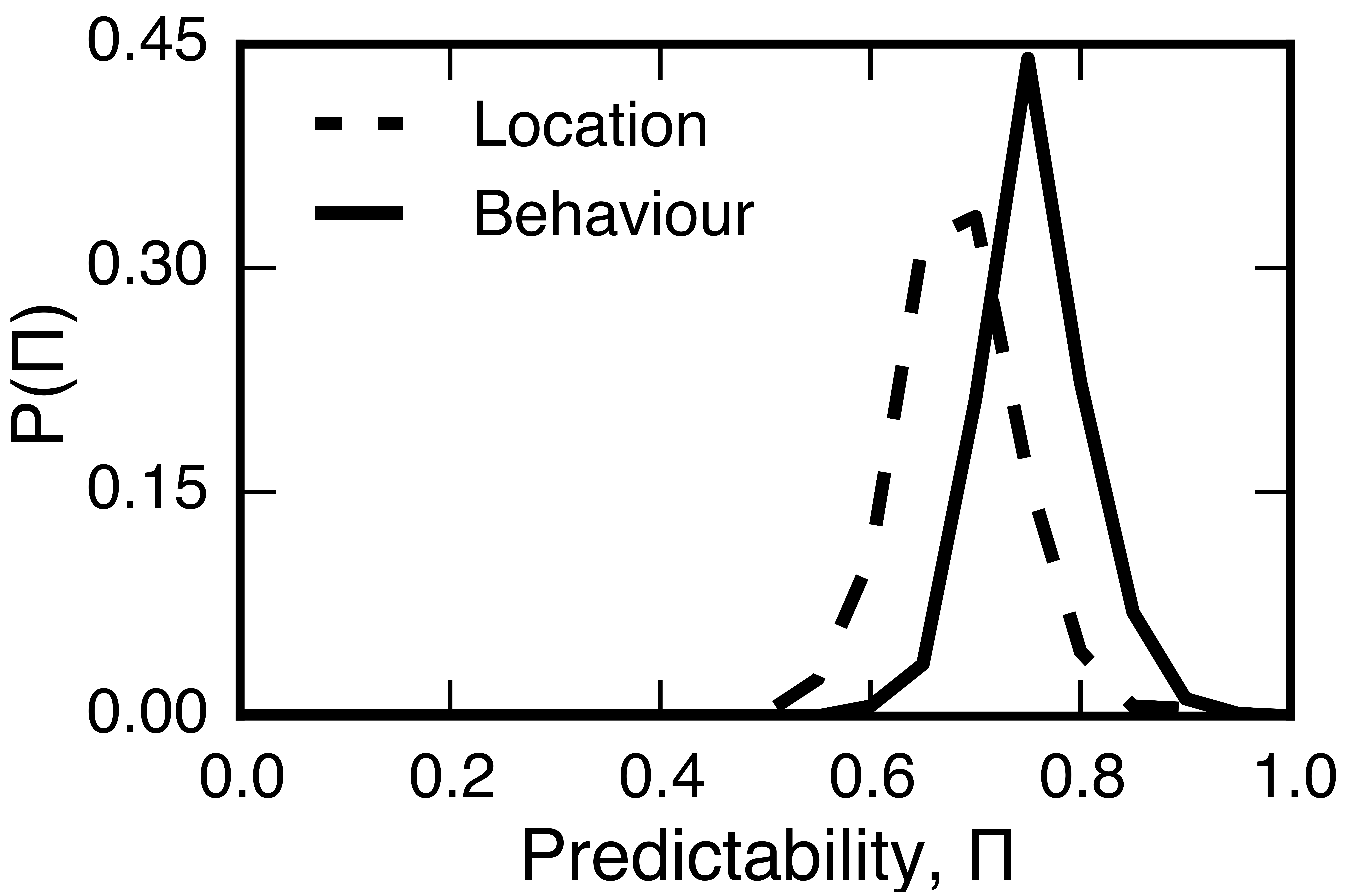
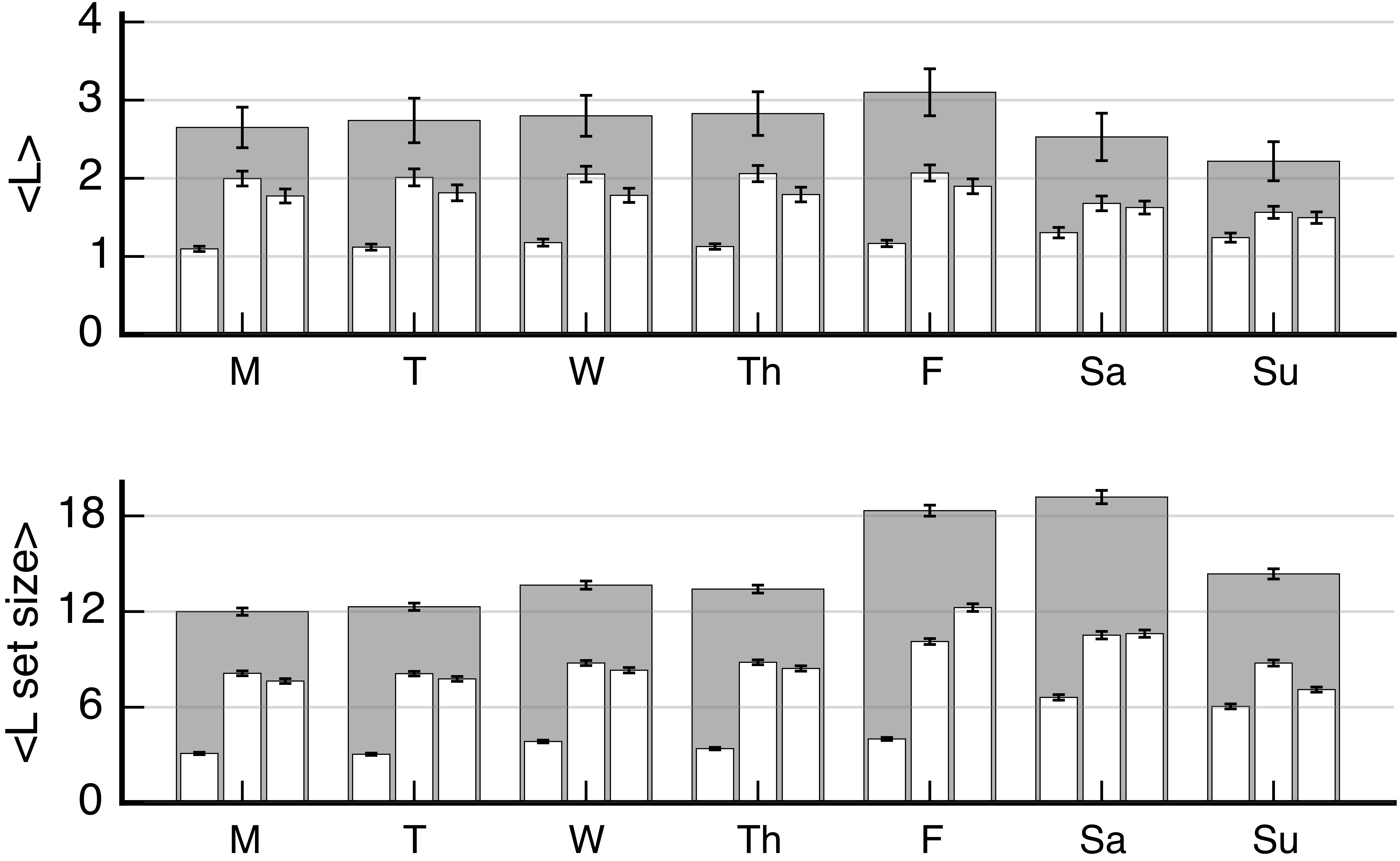
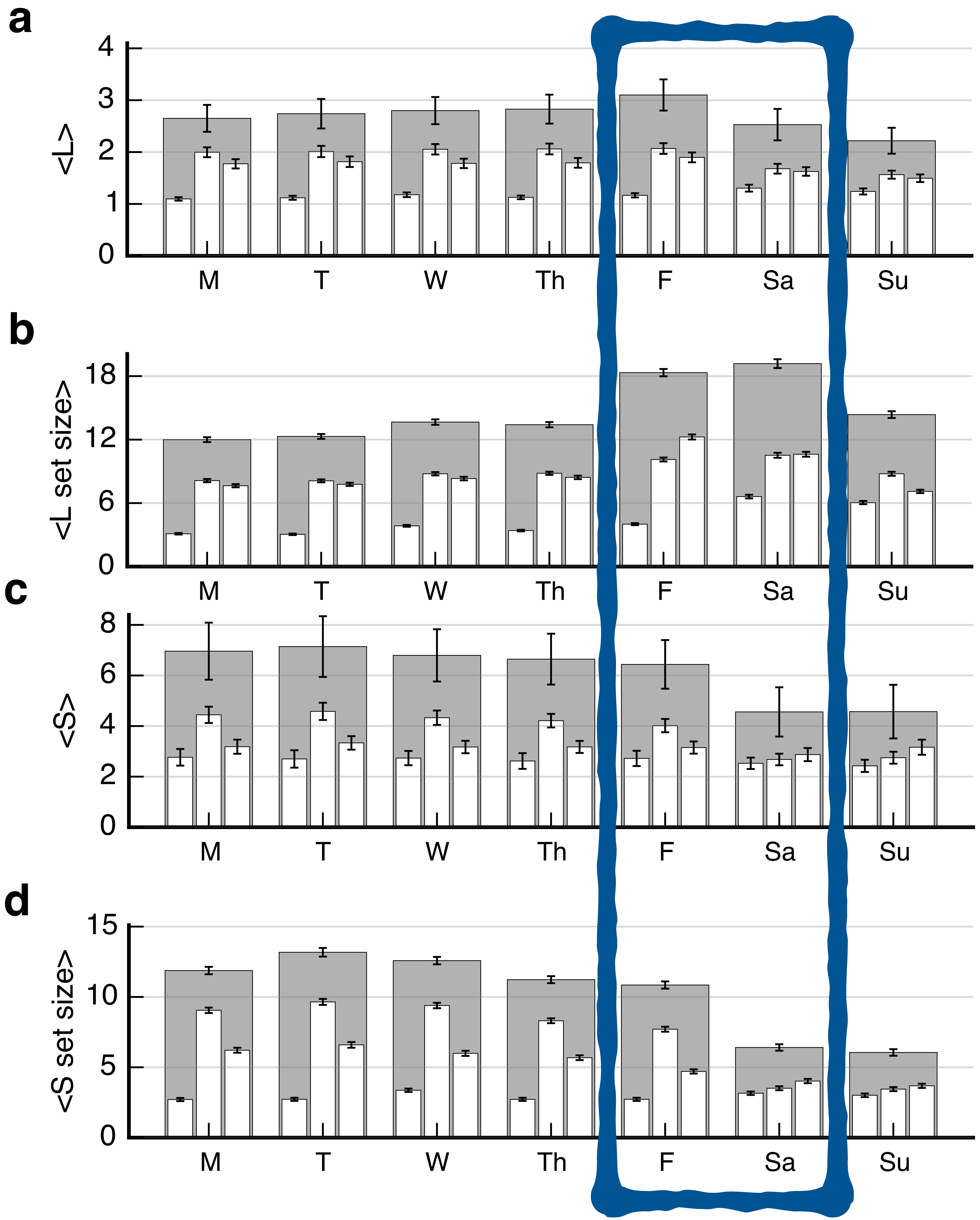


Location
Behaviour
0.45
0.30
0.15
0.00
0.0
0.2
0.4
0.6
0.8
1.0
P(Π)
Predictability, Π

a

b





a
<L>
0
1
2
3
4
M
T
W
Th
F
Sa
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b
<L set size>
0
6
12
18
M
T
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c
<S>
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8
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T
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Sa
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5
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15
M
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