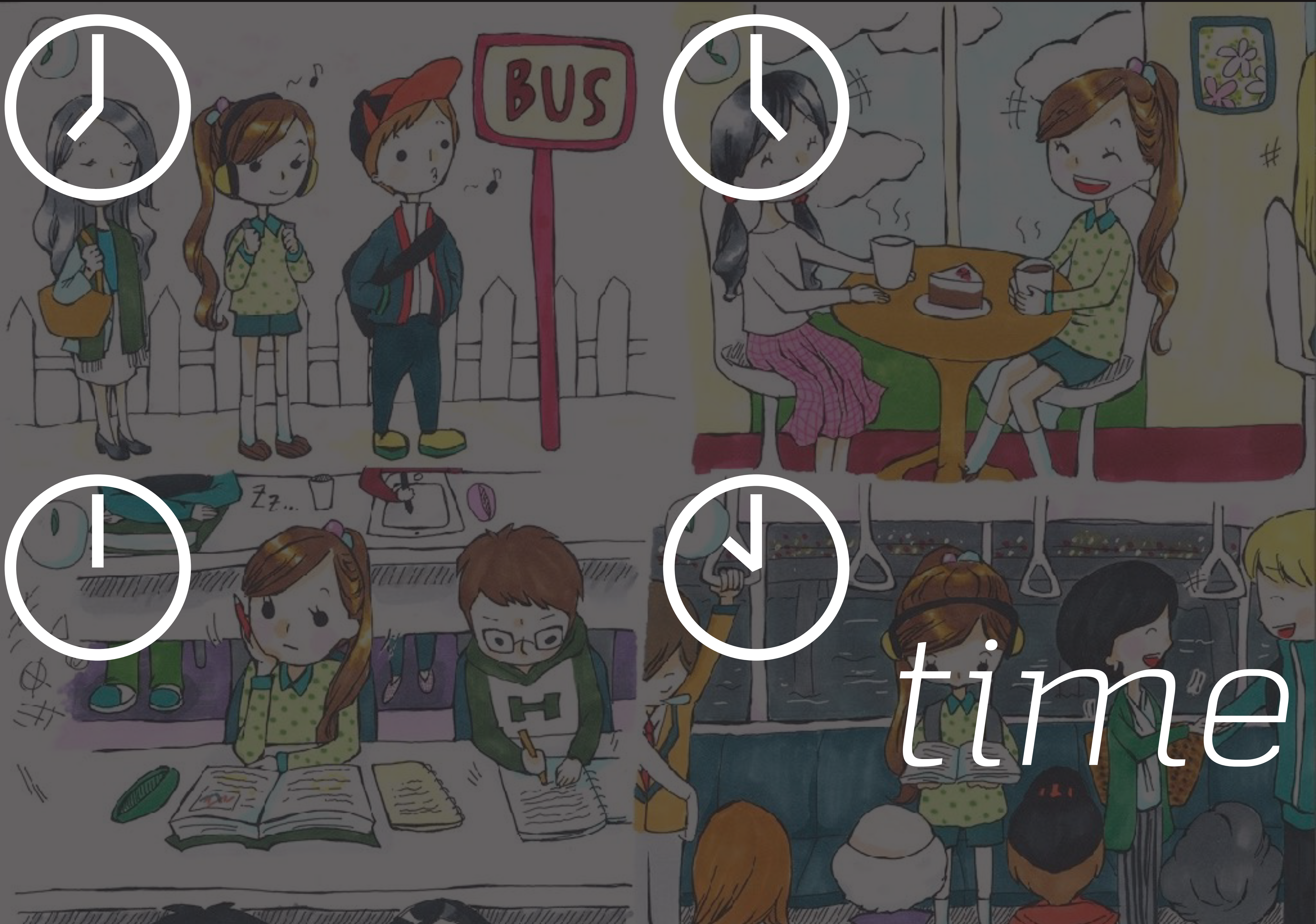
Temporal networks of human interaction

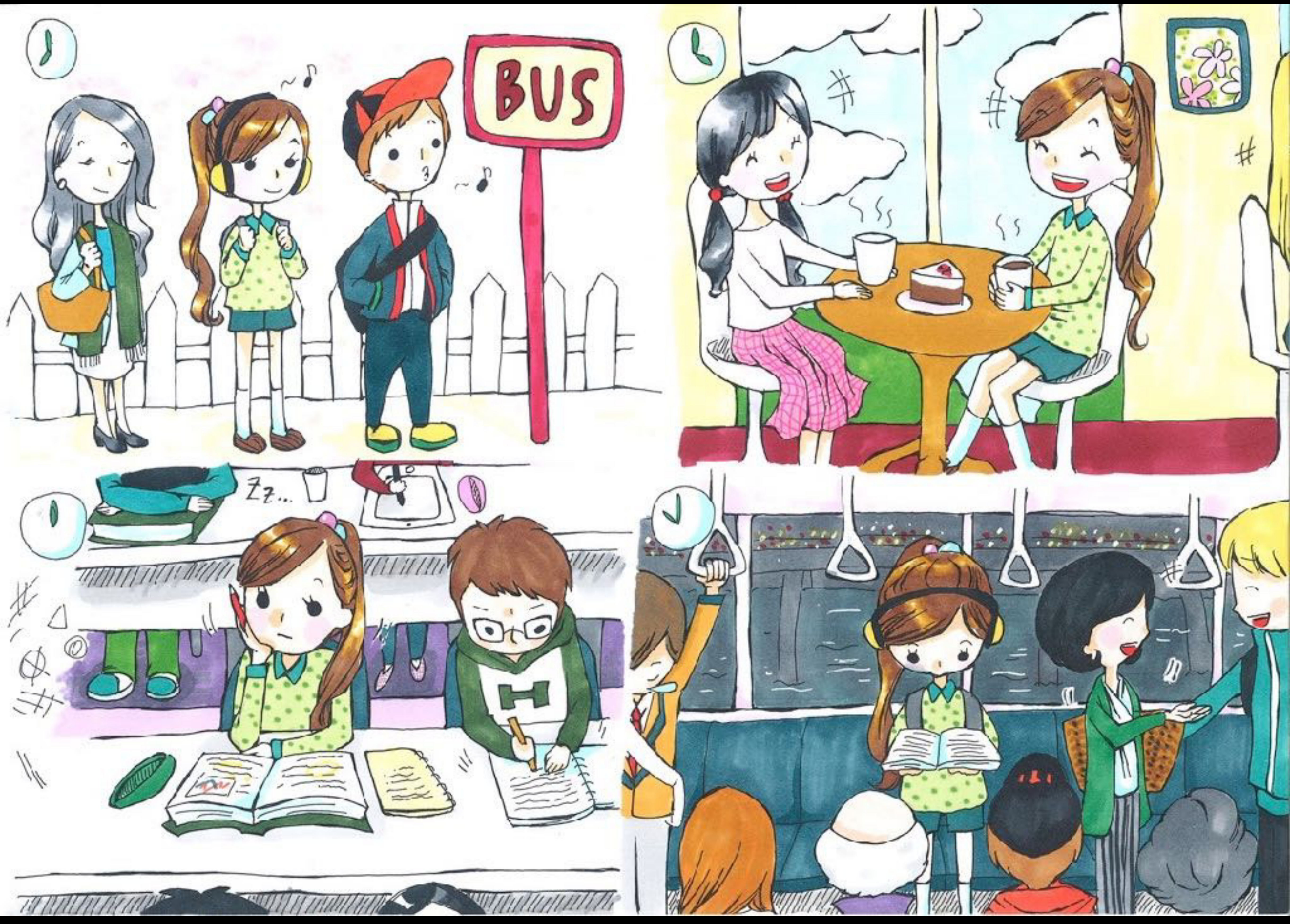
Petter Holme

Temporal networks


BUS
Zz...


BUS
network


BUS
Zz...
time

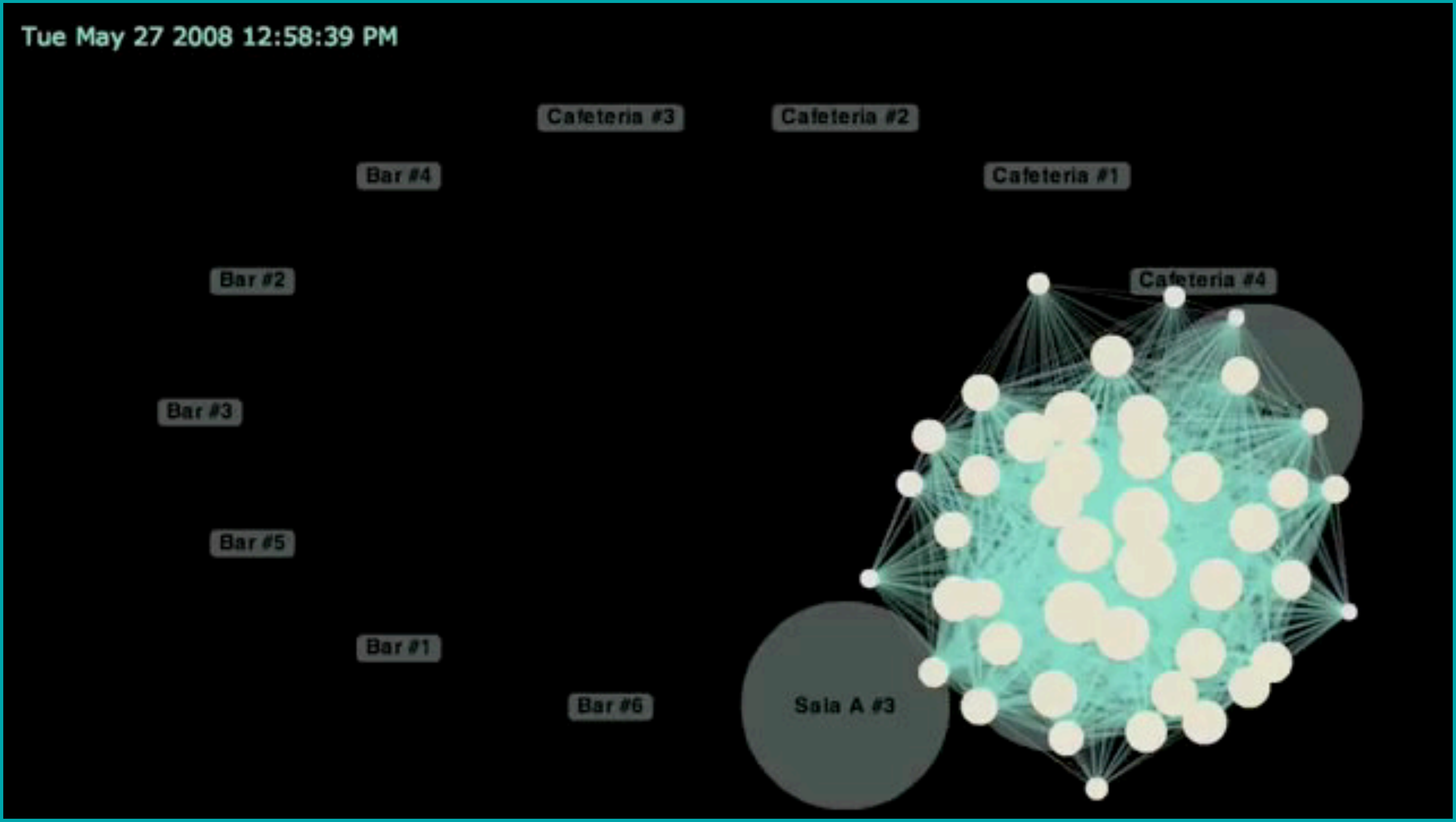

BUS
ZZ...

Temporal (proximity) networks

How can we measure them?

RFID tags
Smartphone Bluetooth
Hospital records
Public transportation
Sensor nodes
Wi-fi routers
Cell phone towers
. . .
Co-tagged in images
Sexual contacts
Internet dating

Temporal (proximity) networks



sociopatterns.org

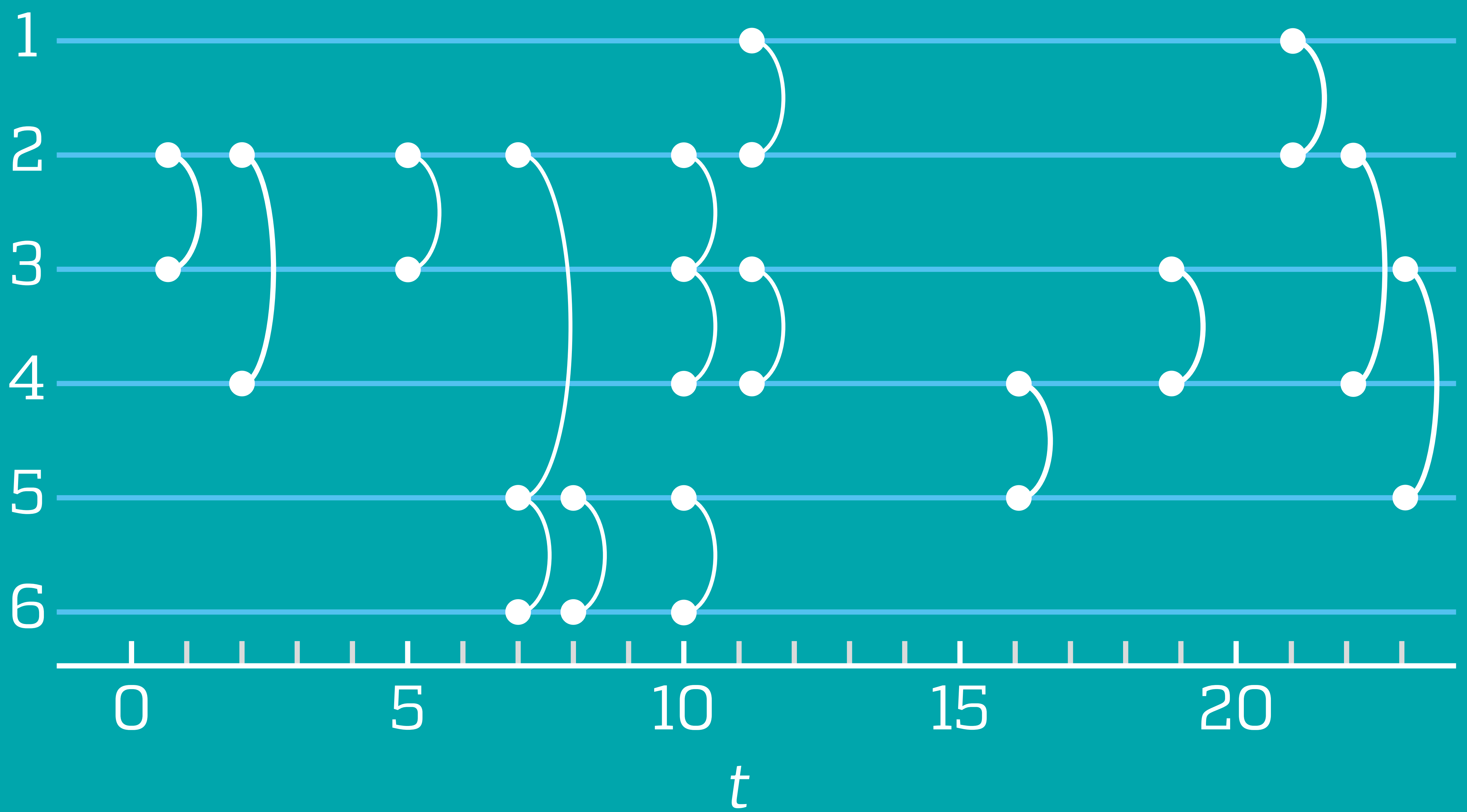
Temporal networks

Contact sequences

i	j	t
2	4	10
6	8	10
2	8	15
10	11	20
7	2	22
3	5	25
5	3	30
2	10	30
7	3	31
10	2	34

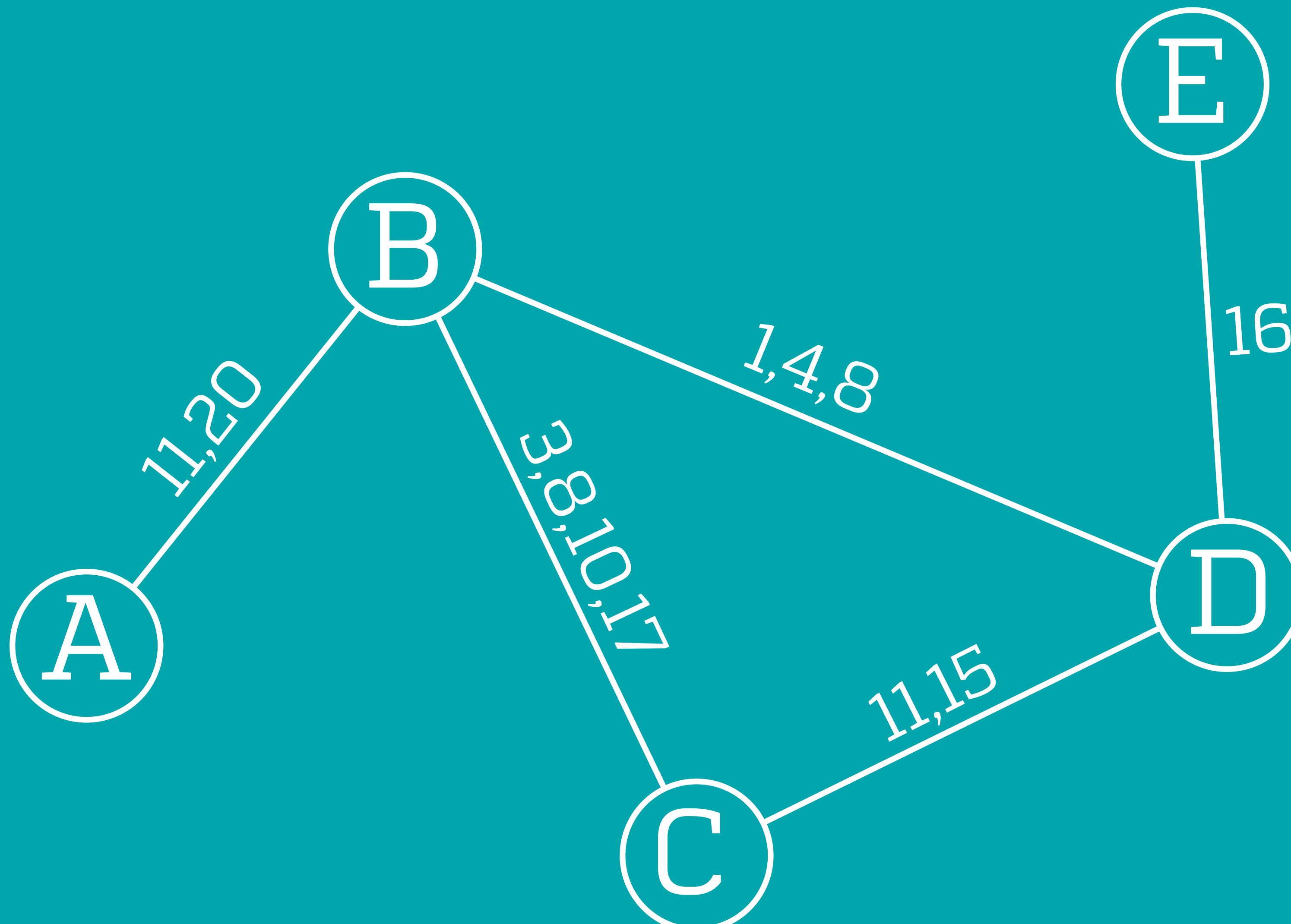
Temporal networks

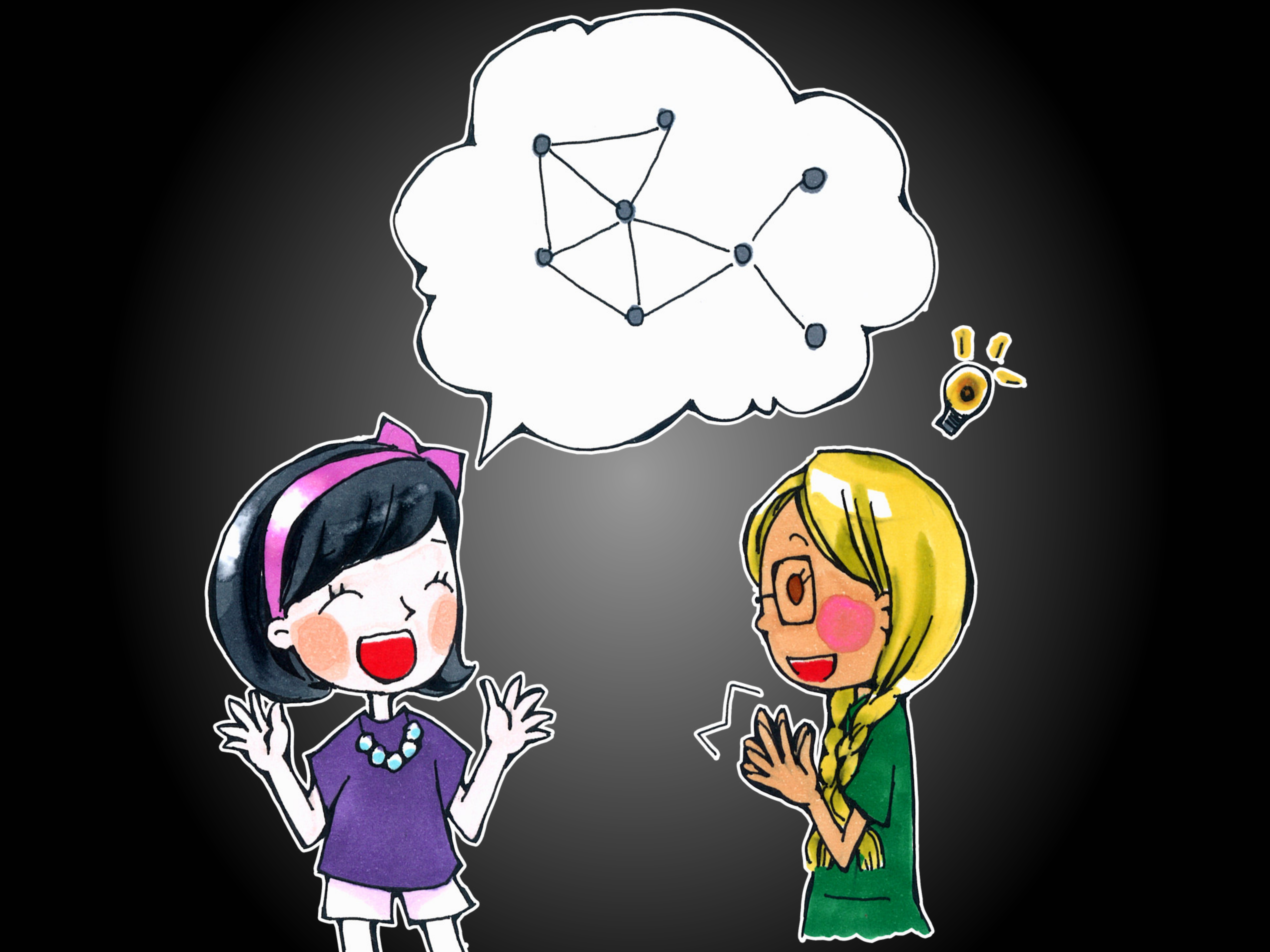
Timelines of nodes

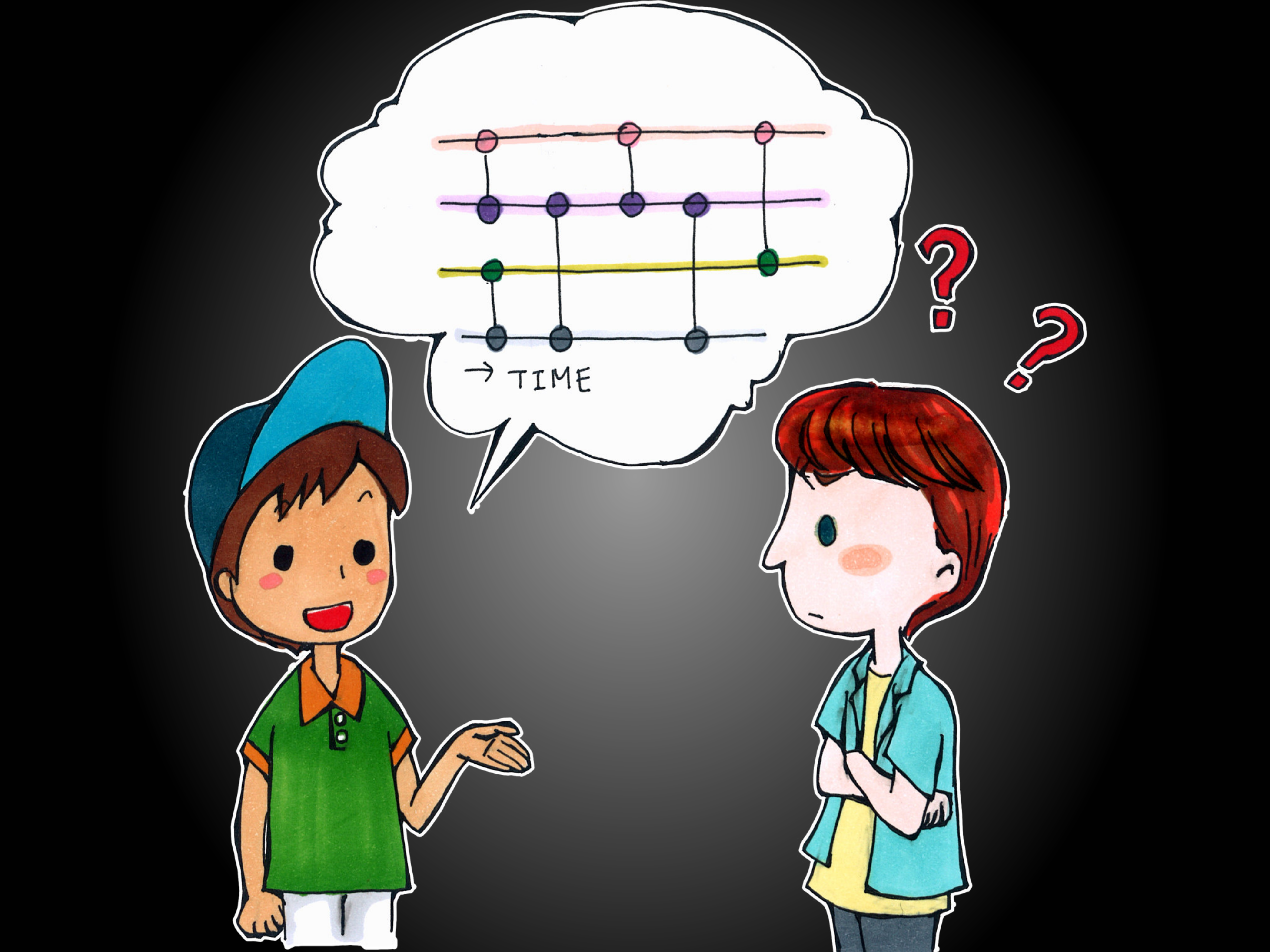


Temporal networks

Annotated graphs






→ TIME

Temporal network epidemiology

Temporal nwk. epidemiology

Step 1: Compartmental models

Temporal nwk. epidemiology

Step 1: Compartmental models

Susceptible
meets
Infectious

Temporal nwk. epidemiology

Step 1: Compartmental models

With some probability or rate

Susceptible
meets
Infectious

→

Infectious

Temporal nwk. epidemiology

Step 1: Compartmental models

With some probability or rate

With some rate or after some time

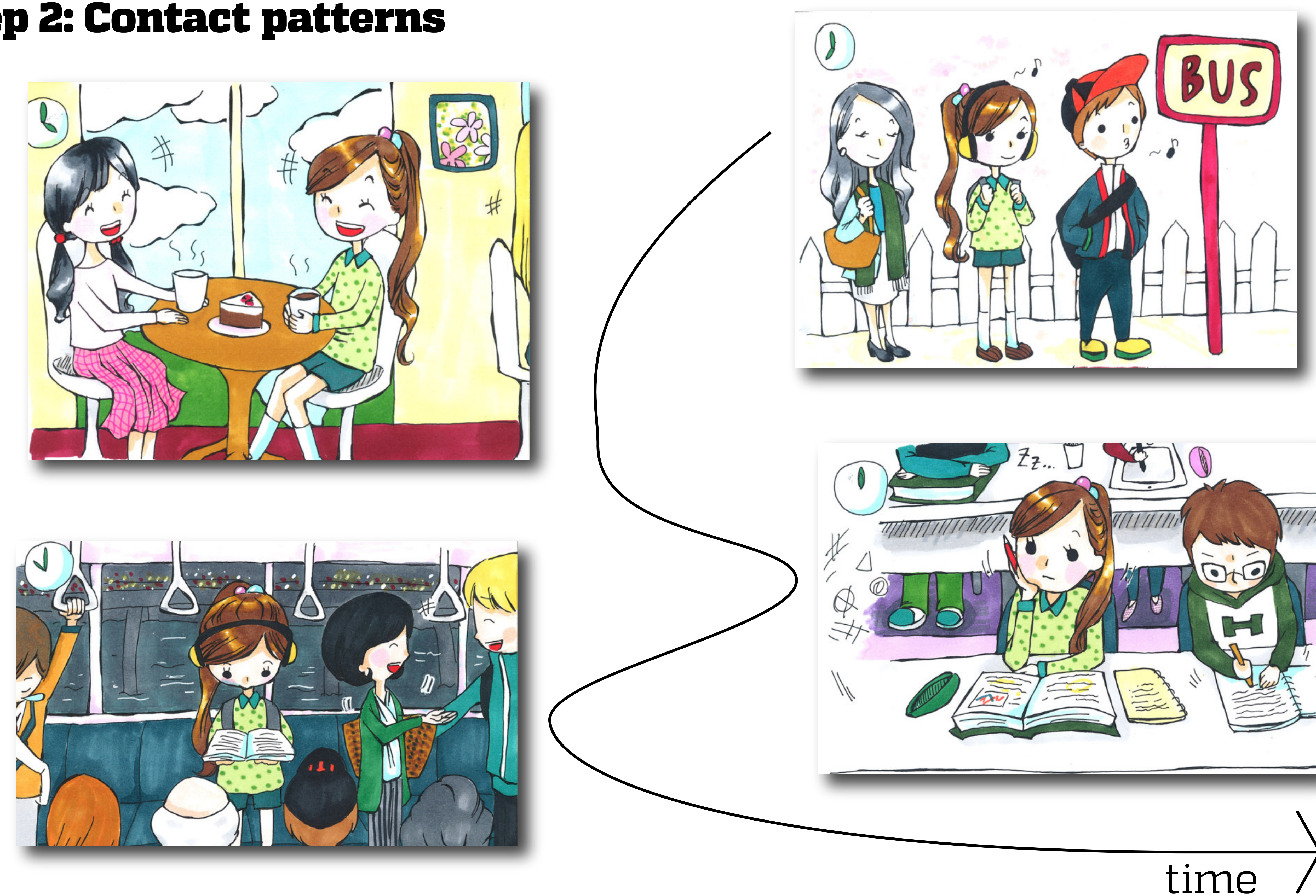
Susceptible meets Infectious

Infectious

Susceptible or Recovered

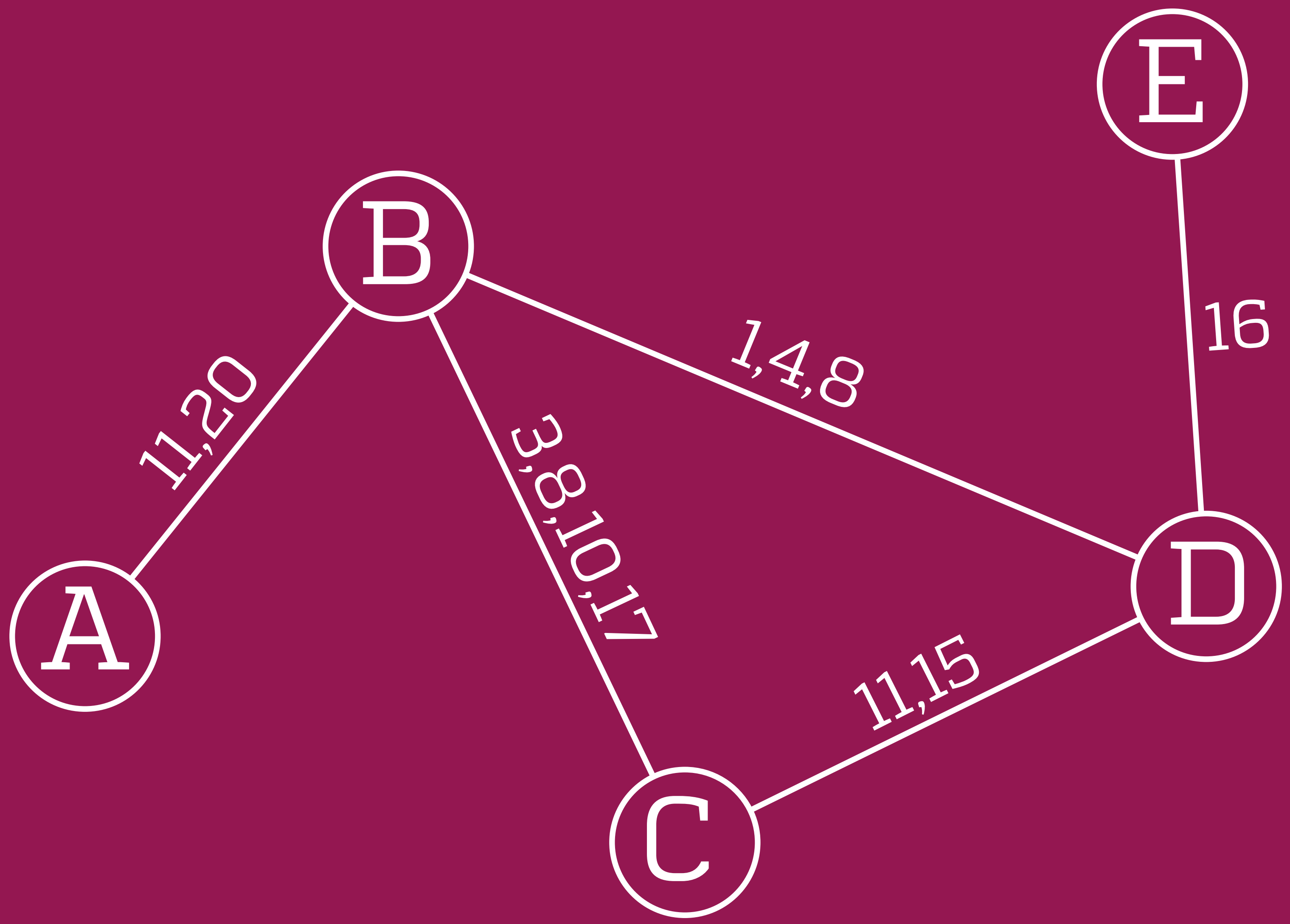
Temporal nwk. epidemiology

Step 2: Contact patterns



Time matters

Time matters



Time matters

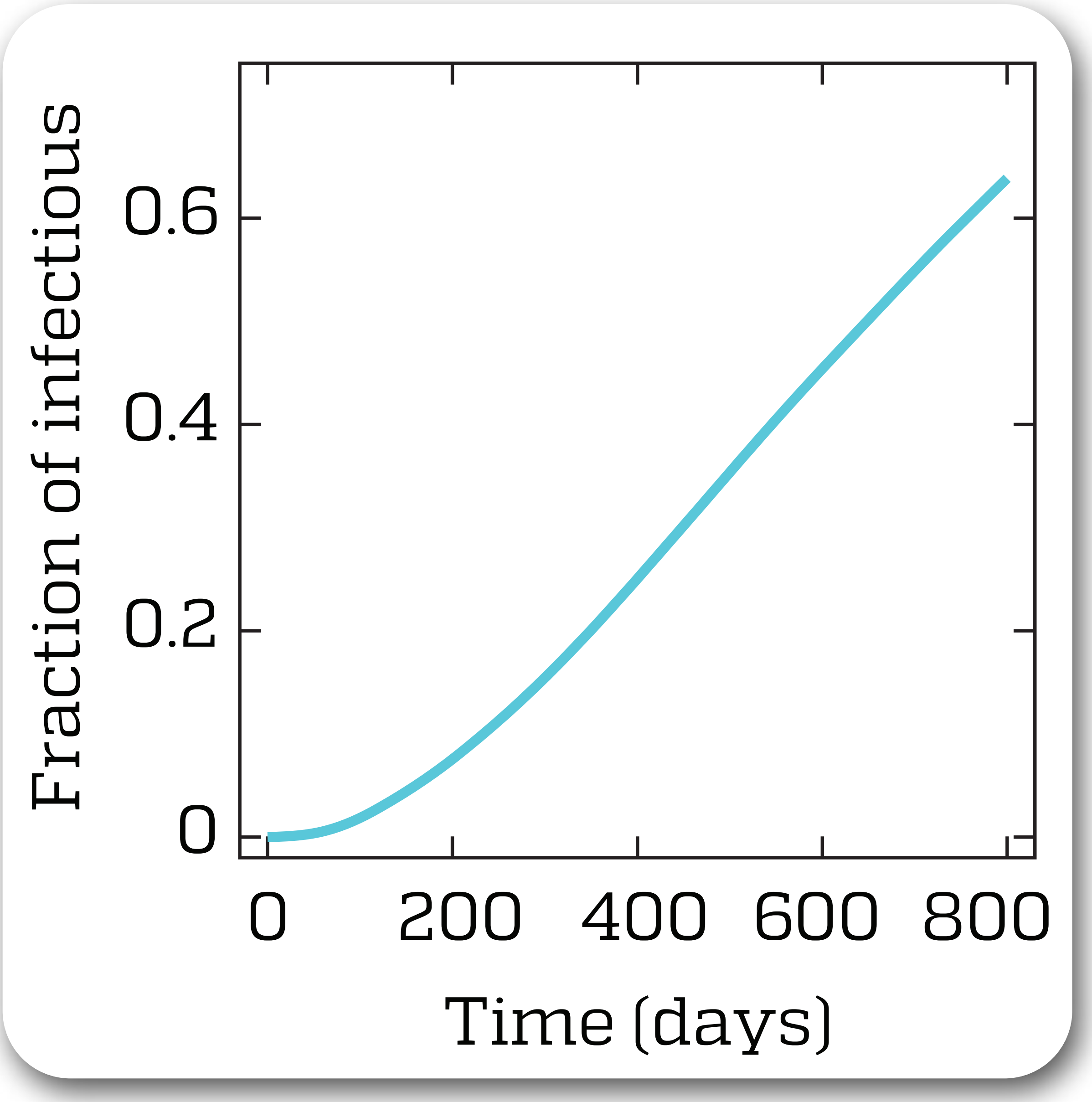
Rocha, Liljeros, Holme, 2010. *PNAS* 107: 5706-5711.

Escort/sex-buyer
contacts:
16,730 individuals
50,632 contacts
2,232 days

Time matters

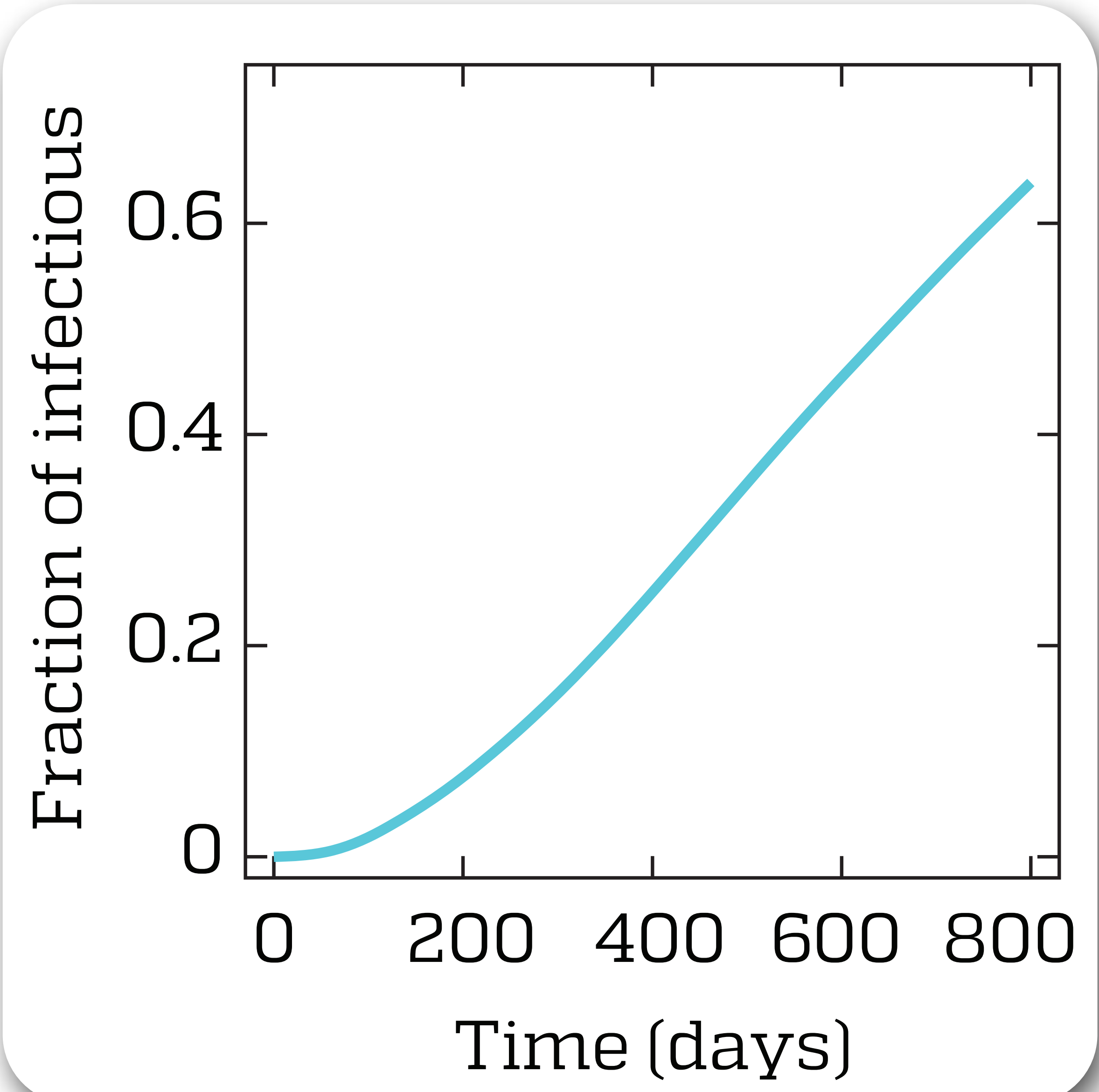
Rocha, Liljeros, Holme, 2010. *PNAS* 107: 5706-5711.

Rocha, Liljeros, Holme, 2011. *PLoS Comp Biol* 7: e1001109.



Time matters

Rocha, Liljeros, Holme, 2010. *PNAS* 107: 5706-5711.
Rocha, Liljeros, Holme, 2011. *PLoS Comp Biol* 7: e1001109.



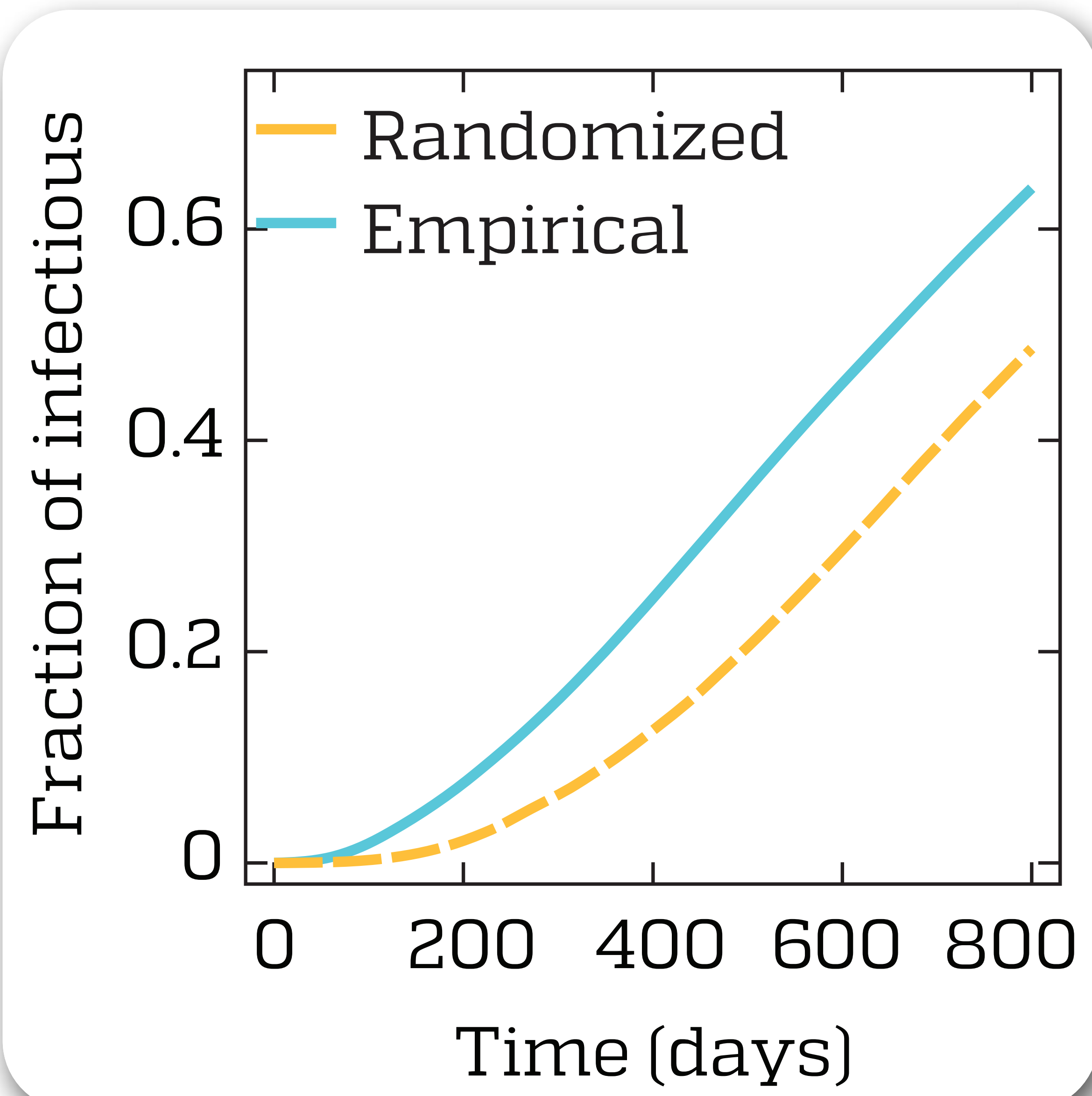
i	j	t
5	7	1021
20	9	1119
4	30	1539
4	20	1555

i	j	t
5	7	1555
20	9	1021
4	30	1119
4	20	1539

Time matters

Rocha, Liljeros, Holme, 2010. *PNAS* 107: 5706-5711.

Rocha, Liljeros, Holme, 2011. *PLoS Comp Biol* 7: e1001109.



i	*j*	*t*
5	7	1021
20	9	1119
4	30	1539
4	20	1555

i	*j*	*t*
5	7	1555
20	9	1021
4	30	1119
4	20	1539

Time matters

arXiv.org > physics > arXiv:1006.2856

Search or

Physics > Physics and Society

Simulated epidemics in an empirical spatiotemporal network of 50,185 sexual contacts

Luis Enrique Correa Rocha, Fredrik Liljeros, Petter Holme

(Submitted on 14 Jun 2010)

arXiv.org > physics > arXiv:1006.2125

Sear

Physics > Physics and Society

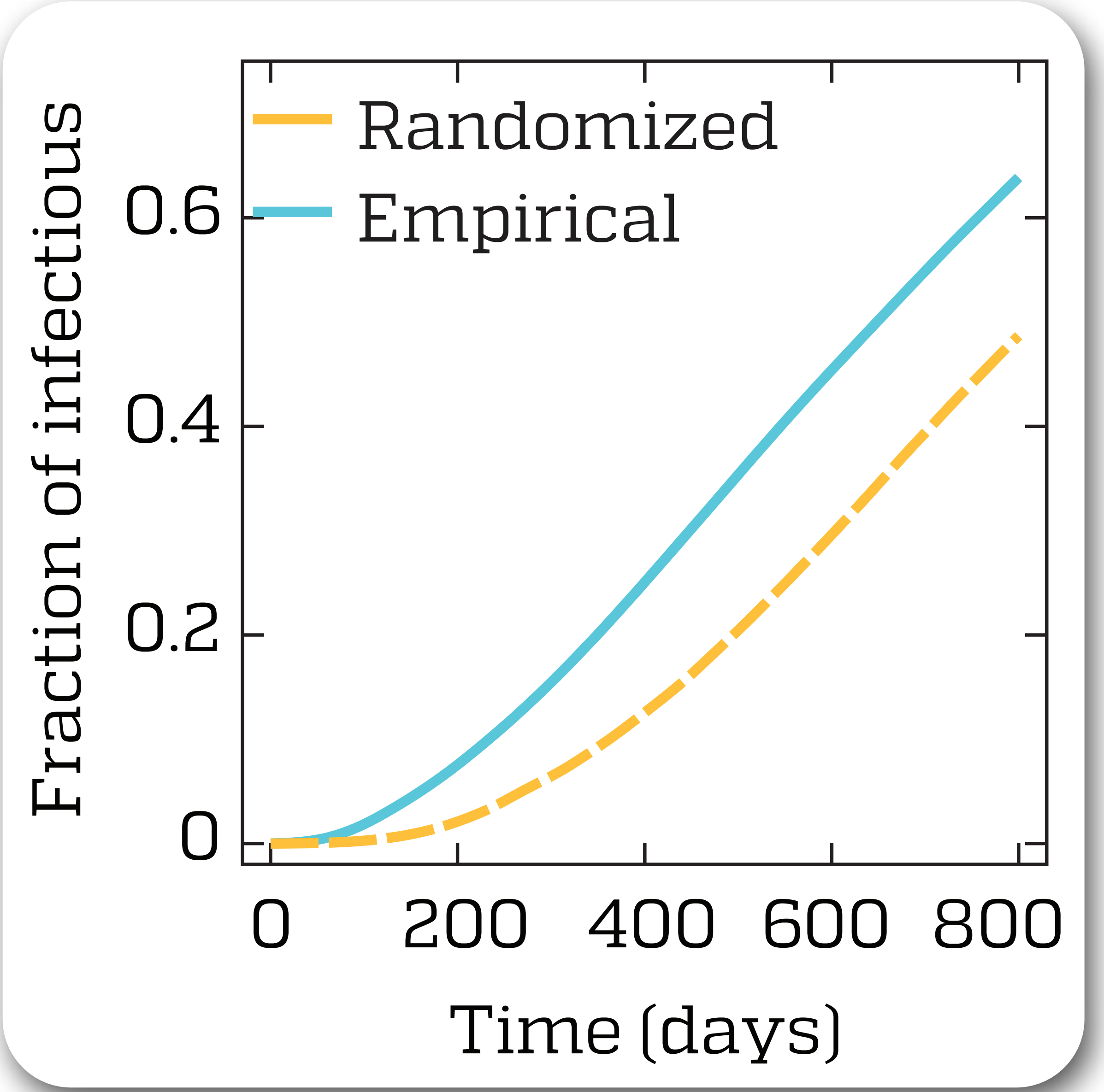
Small But Slow World: How Network Topology and Burstiness Slow Down Spreading

M. Karsai, M. Kivelä, R. K. Pan, K. Kaski, J. Kertész, A.-L. Barabási, J. Saramäki

(Submitted on 10 Jun 2010 (v1), last revised 22 Aug 2010 (this version, v3))

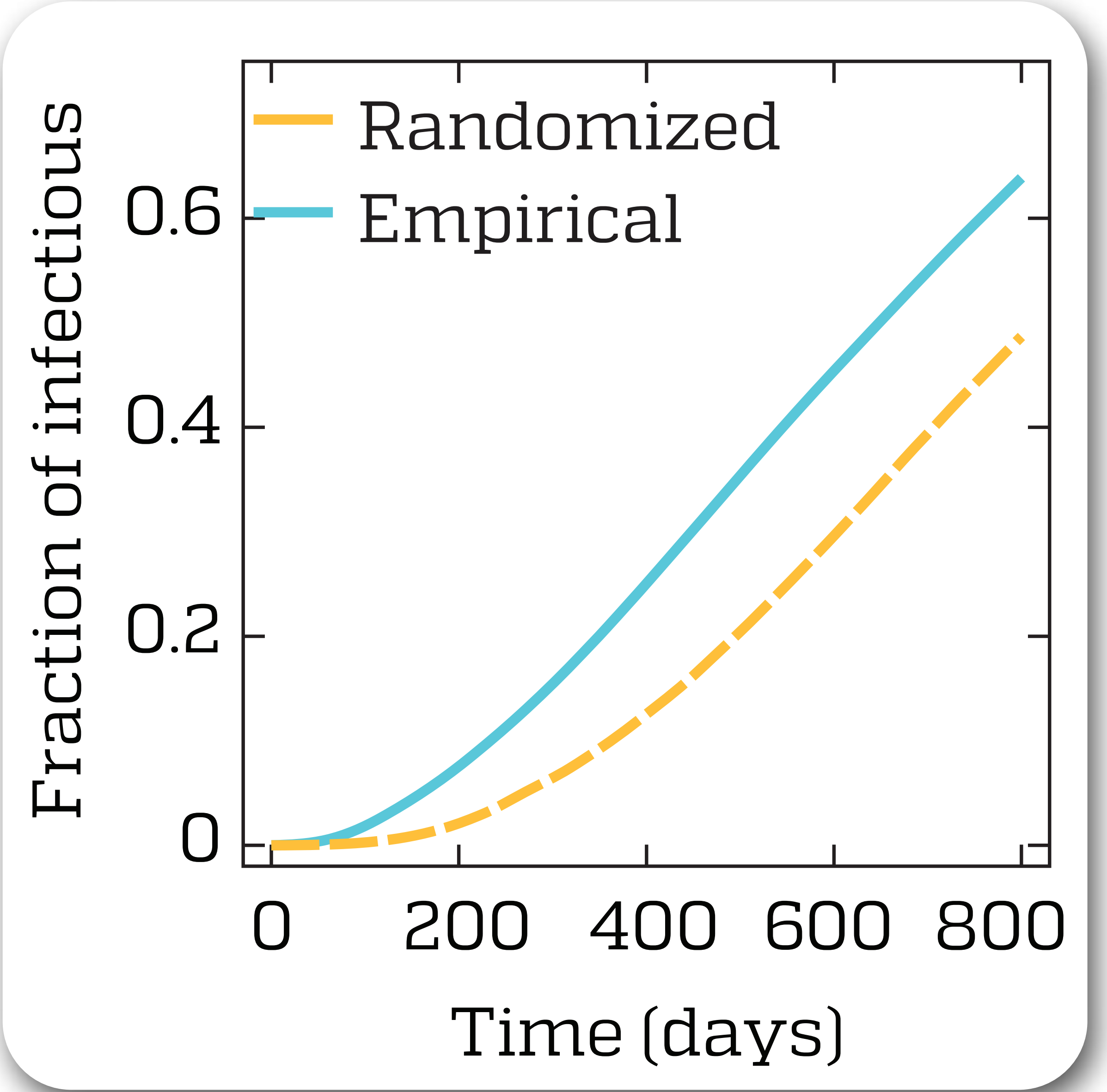
Time matters

Rocha, Liljeros, Holme

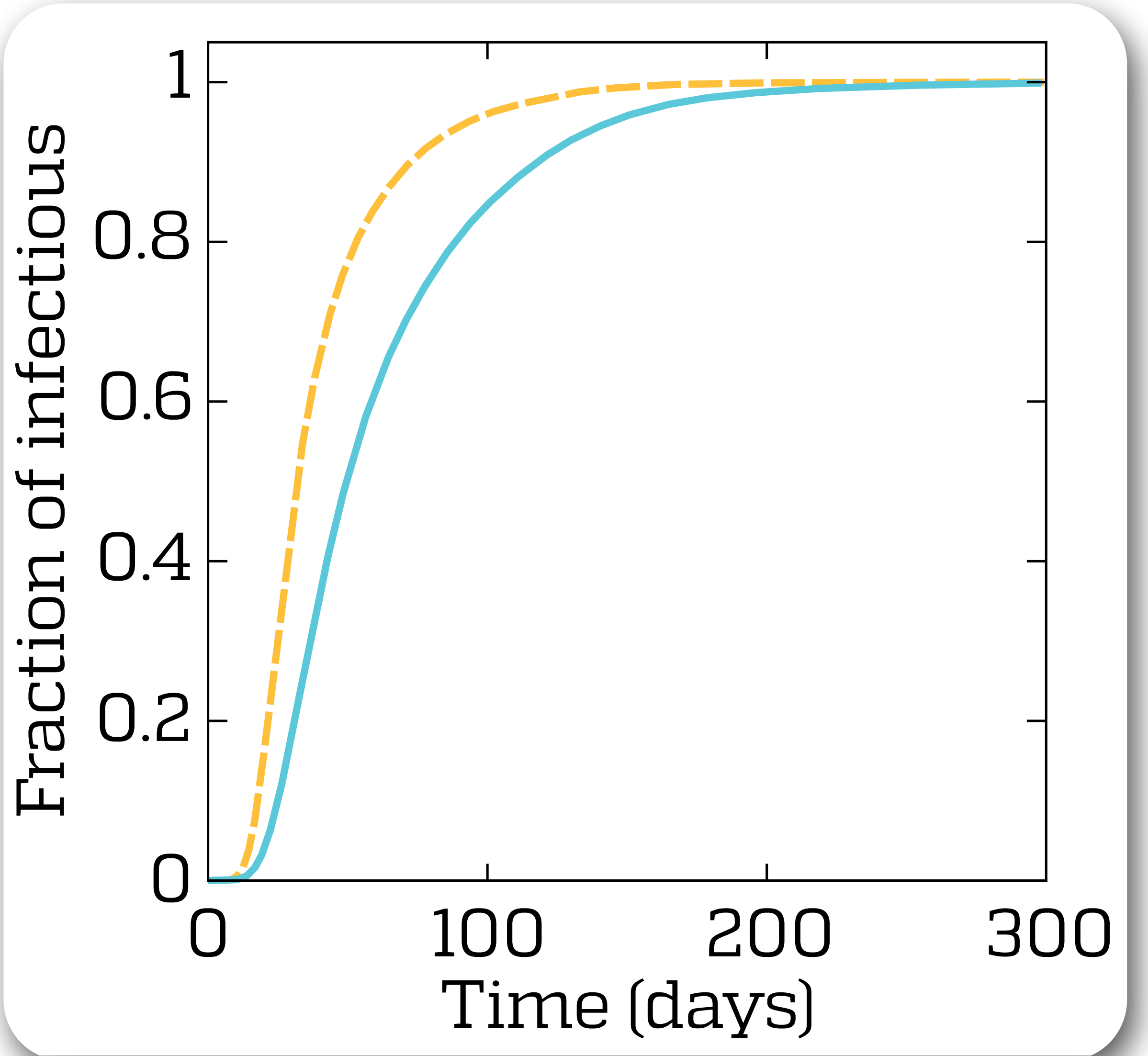


Time matters

Rocha, Liljeros, Holme

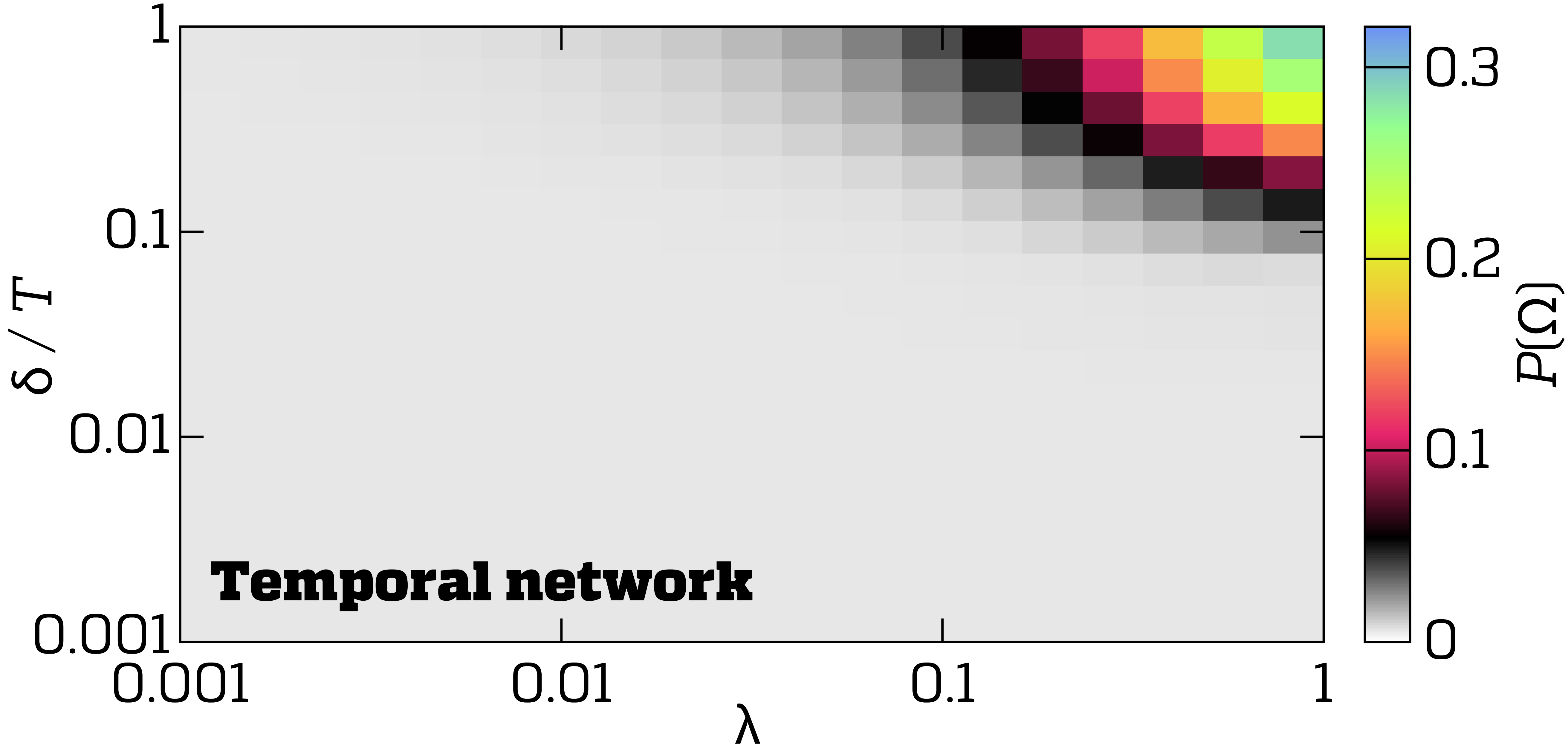


Karsai, & *al.*



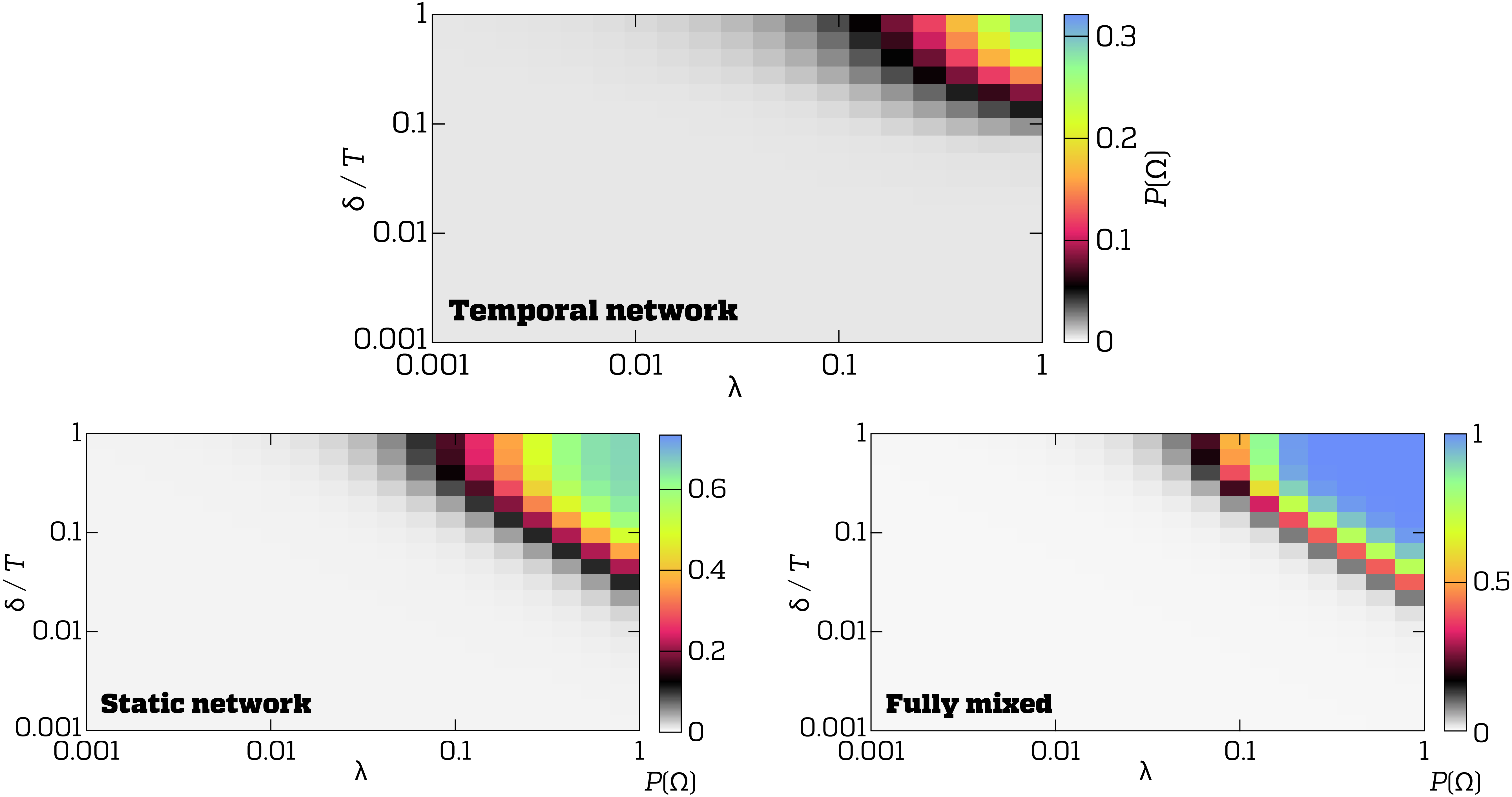
Time matters

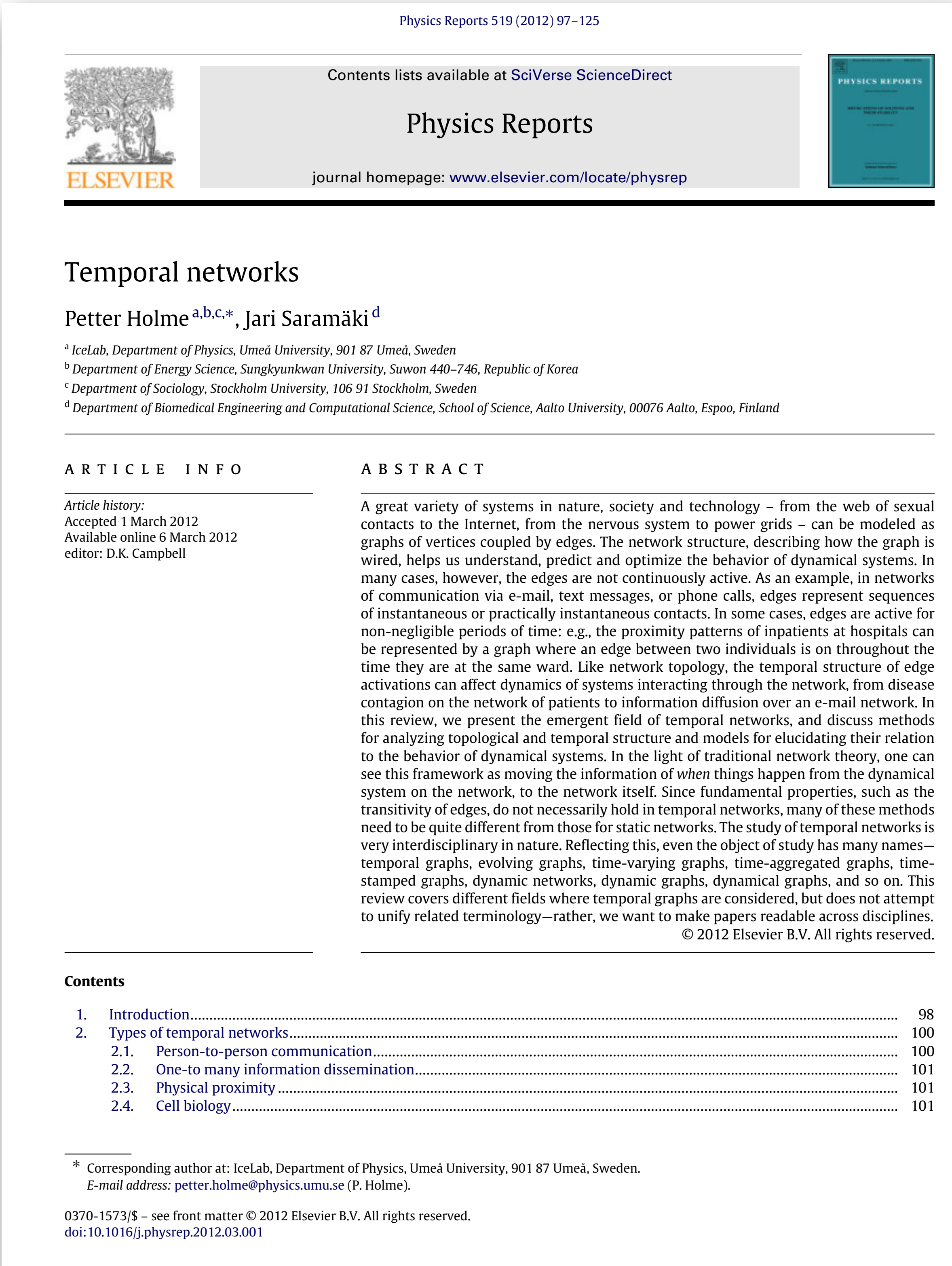
Holme, *Scientific Reports*, 2015.



Time matters

Holme, *Scientific Reports*, 2015.




Physics Reports 519 (2012) 97–125

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Temporal networks

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ABSTRACT

A great variety of systems in nature, society and technology – from the web of sexual contacts to the Internet, from the nervous system to power grids – can be modeled as graphs of vertices coupled by edges. The network structure, describing how the graph is wired, helps us understand, predict and optimize the behavior of dynamical systems. In many cases, however, the edges are not continuously active. As an example, in networks of communication via e-mail, text messages, or phone calls, edges represent sequences of instantaneous or practically instantaneous contacts. In some cases, edges are active for non-negligible periods of time: e.g., the proximity patterns of inpatients at hospitals can be represented by a graph where an edge between two individuals is on throughout the time they are at the same ward. Like network topology, the temporal structure of edge activations can affect dynamics of systems interacting through the network, from disease contagion on the network of patients to information diffusion over an e-mail network. In this review, we present the emergent field of temporal networks, and discuss methods for analyzing topological and temporal structure and models for elucidating their relation to the behavior of dynamical systems. In the light of traditional network theory, one can see this framework as moving the information of *when* things happen from the dynamical system on the network, to the network itself. Since fundamental properties, such as the transitivity of edges, do not necessarily hold in temporal networks, many of these methods need to be quite different from those for static networks. The study of temporal networks is very interdisciplinary in nature. Reflecting this, even the object of study has many names—temporal graphs, evolving graphs, time-varying graphs, time-aggregated graphs, time-stamped graphs, dynamic networks, dynamic graphs, dynamical graphs, and so on. This review covers different fields where temporal graphs are considered, but does not attempt to unify related terminology—rather, we want to make papers readable across disciplines.

Contents

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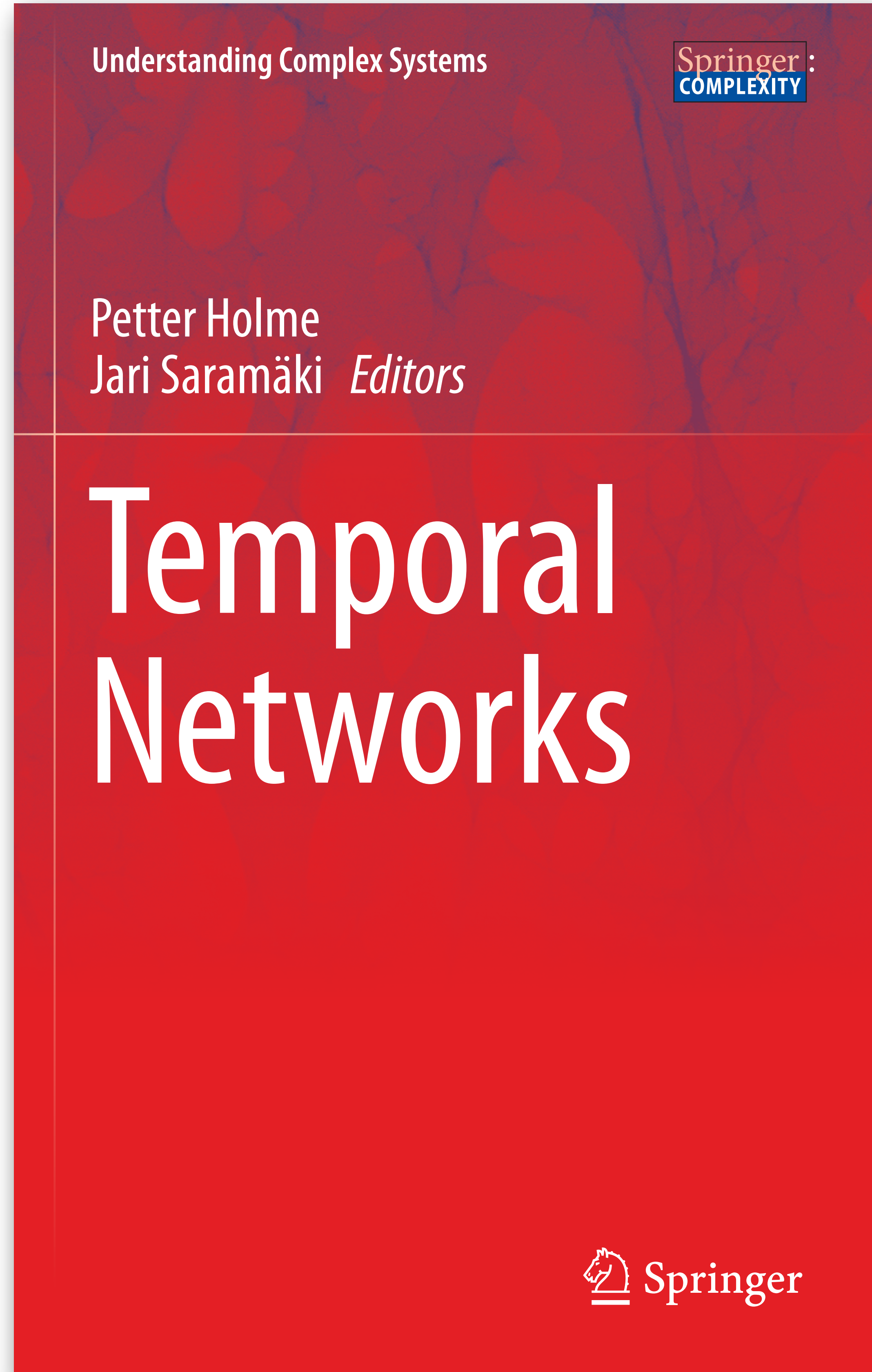
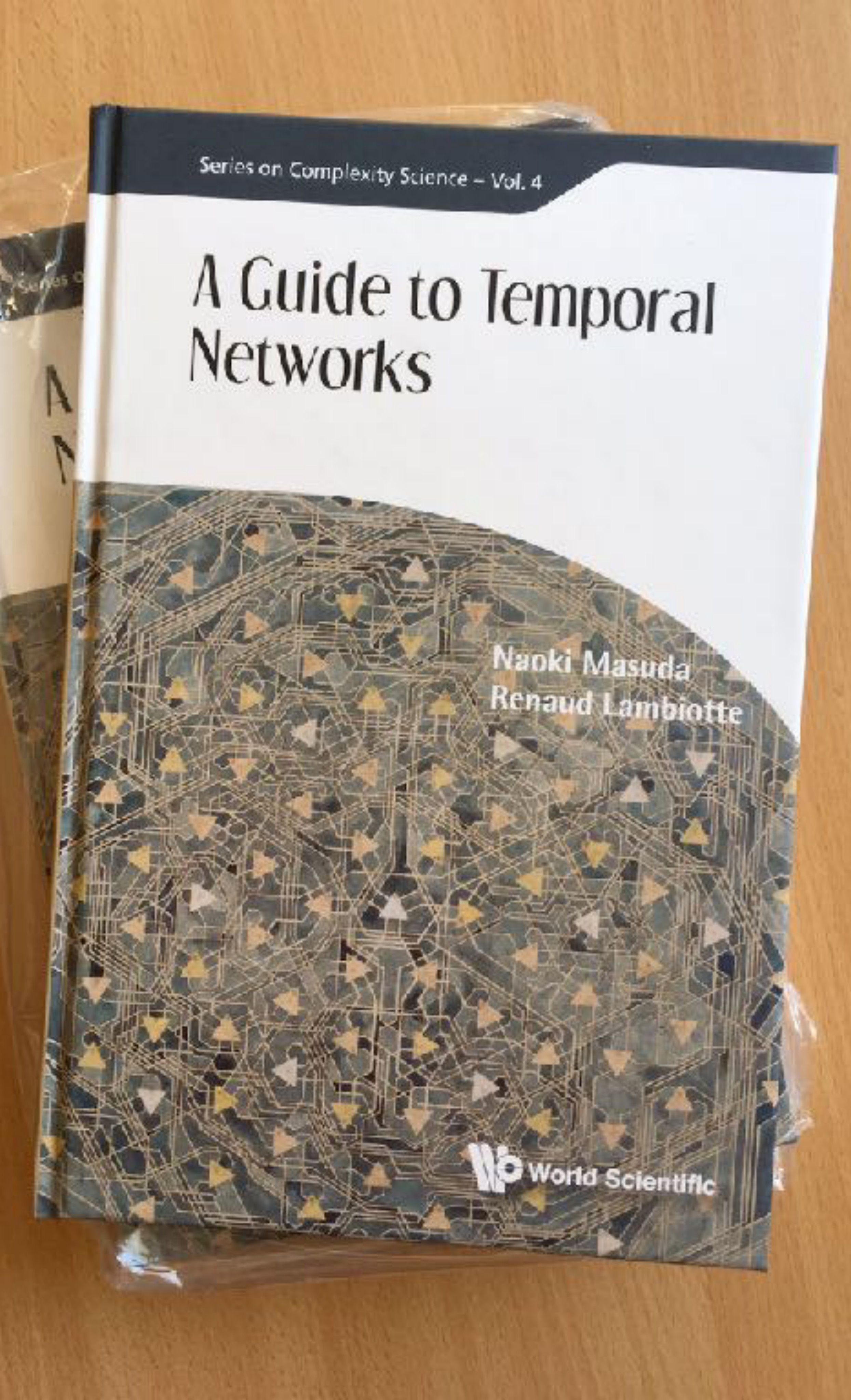
doi:10.1016/j.physrep.2012.03.001





Eur. Phys. J. B (2015) 88: 234
DOI: 10.1140/epjb/e2015-60657-4

THE EUROPEAN
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Colloquium

Modern temporal network theory: a colloquium*

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Abstract. The power of any kind of network approach lies in the ability to simplify a complex system so that one can better understand its function as a whole. Sometimes it is beneficial, however, to include more information than in a simple graph of only nodes and links. Adding information about times of interactions can make predictions and mechanistic understanding more accurate. The drawback, however, is that there are not so many methods available, partly because temporal networks is a relatively young field, partly because it is more difficult to develop such methods compared to for static networks. In this colloquium, we review the methods to analyze and model temporal networks and processes taking place on them, focusing mainly on the last three years. This includes the spreading of infectious disease, opinions, rumors, in social networks; information packets in computer networks; various types of signaling in biology, and more. We also discuss future directions.

1 Introduction

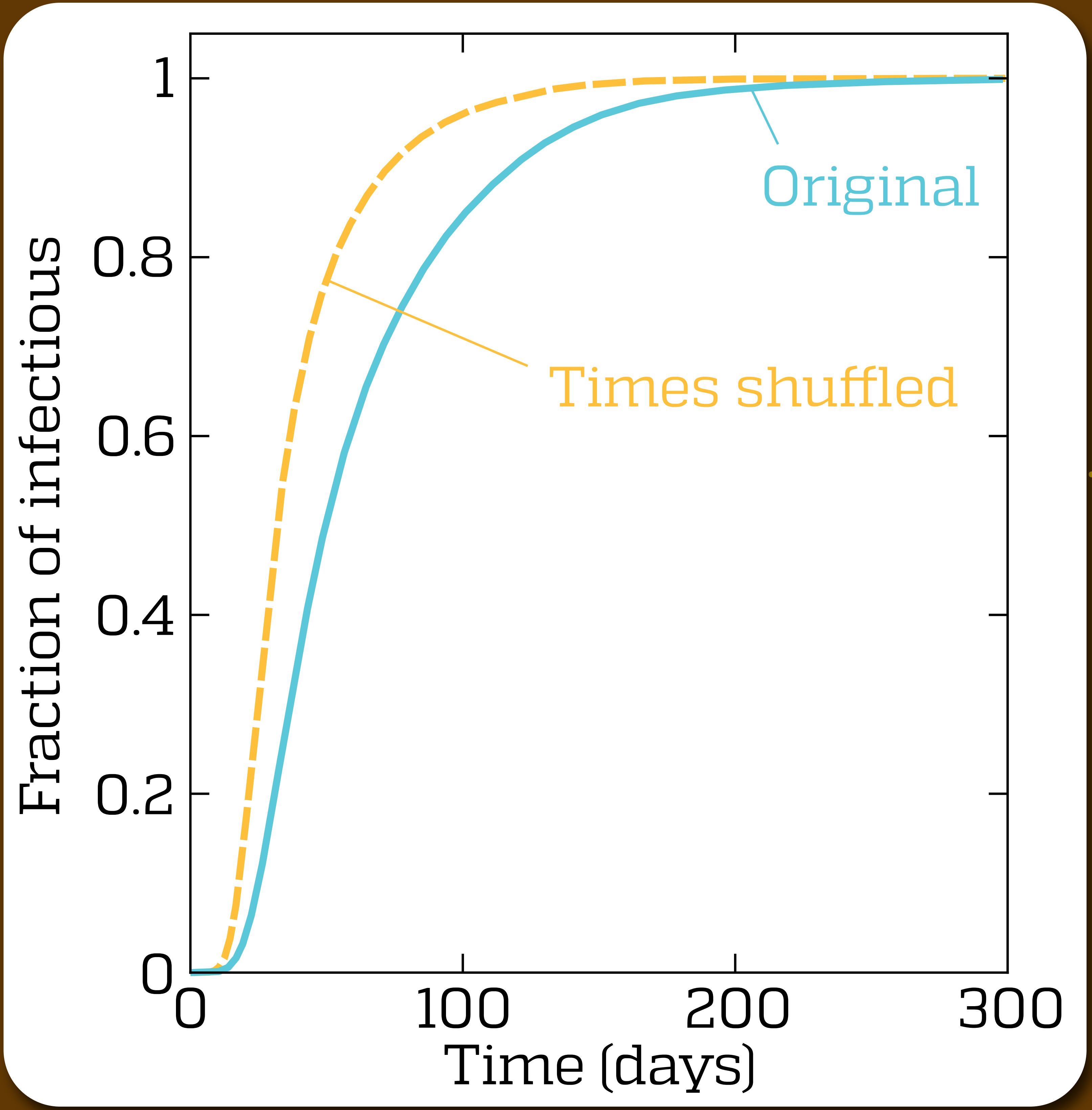
To understand how large connected systems work, one needs to zoom out and view them from a distance. In other words, one needs a principled, consistent way of discarding irrelevant information. A common way of doing this is to represent the system as a network, where nodes are connected if they interact. For many systems one has more information that just about who interacts. Including that information into a *temporal network*, of course, goes against the idea of simplifying the system. Sometimes, however, it could be worth the effort in terms of increased accuracy of predictions, increased mechanistic understanding, etc. The drawback is that many of the methods and models developed for static networks could be inapplicable or could need non-trivial generalizations

oneered temporal network theory. Still today, resear
rediscover the ideas Leslie Lamport and others used i
1970's to build a theory of distributed computing [4]

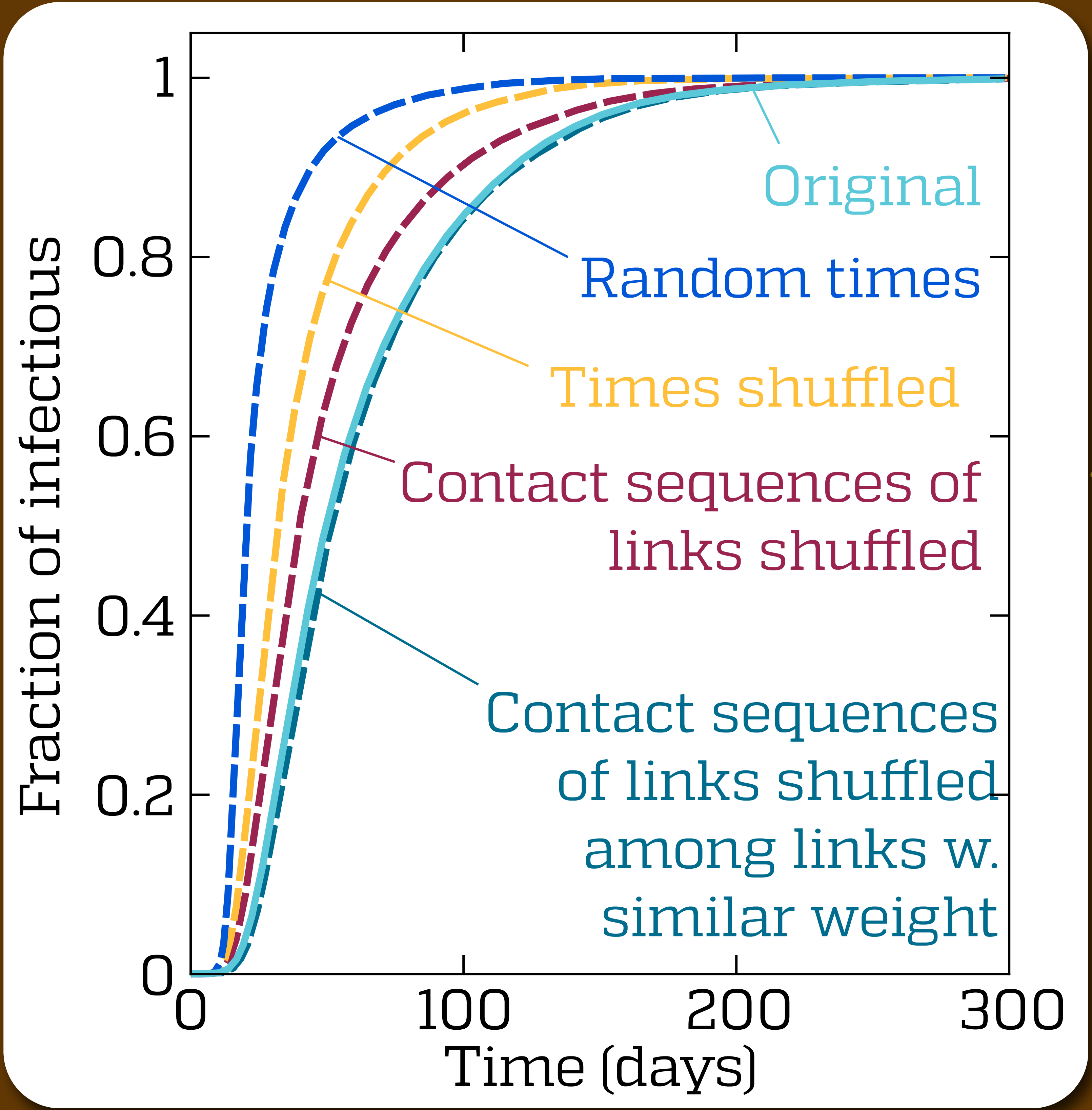
At a very fundamental level, the mathematics of
poral and static networks differ. We will refer to the
unit of interaction in a temporal network as a *con*
It captures information about a pair of nodes intera
and the time of the interaction. A contact is the c
extension of a *link* in static networks (but we will re
link for a static relationship between two nodes – us
that they have one or more contacts). Being connect
a transitive mathematical relation, i.e. if (i, i') and (
are links then i is connected through a path. This is
also for directed static networks, but does not ha
be true for contacts in a temporal network. As a c
lary, there is no way of representing a temporal net

Randomization

Randomization



Randomization



Randomization

Holme, 2005. *Phys Rev E* 71:046119.

Temporal structures

History

Network

1. A power-law distribution is discovered.
2. It makes a difference for spreading dynamics.
3. It helps us to understand real epidemics.

Time

1. A power-law distribution is discovered.
2. It makes a difference for spreading dynamics.
3. ~~It helps us to understand real epidemics.~~

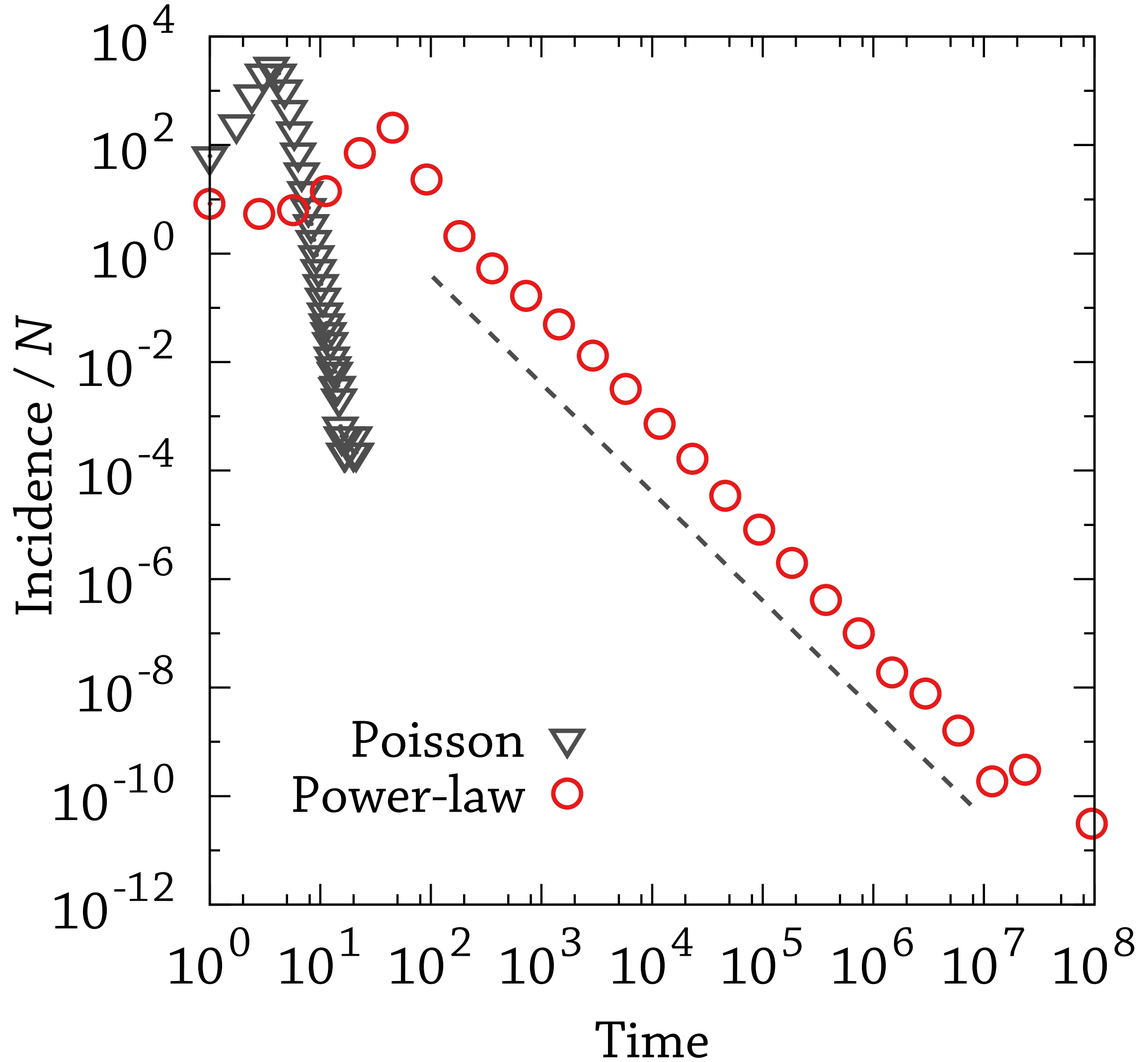
Interevent times

Fat-tailed interevent time distributions

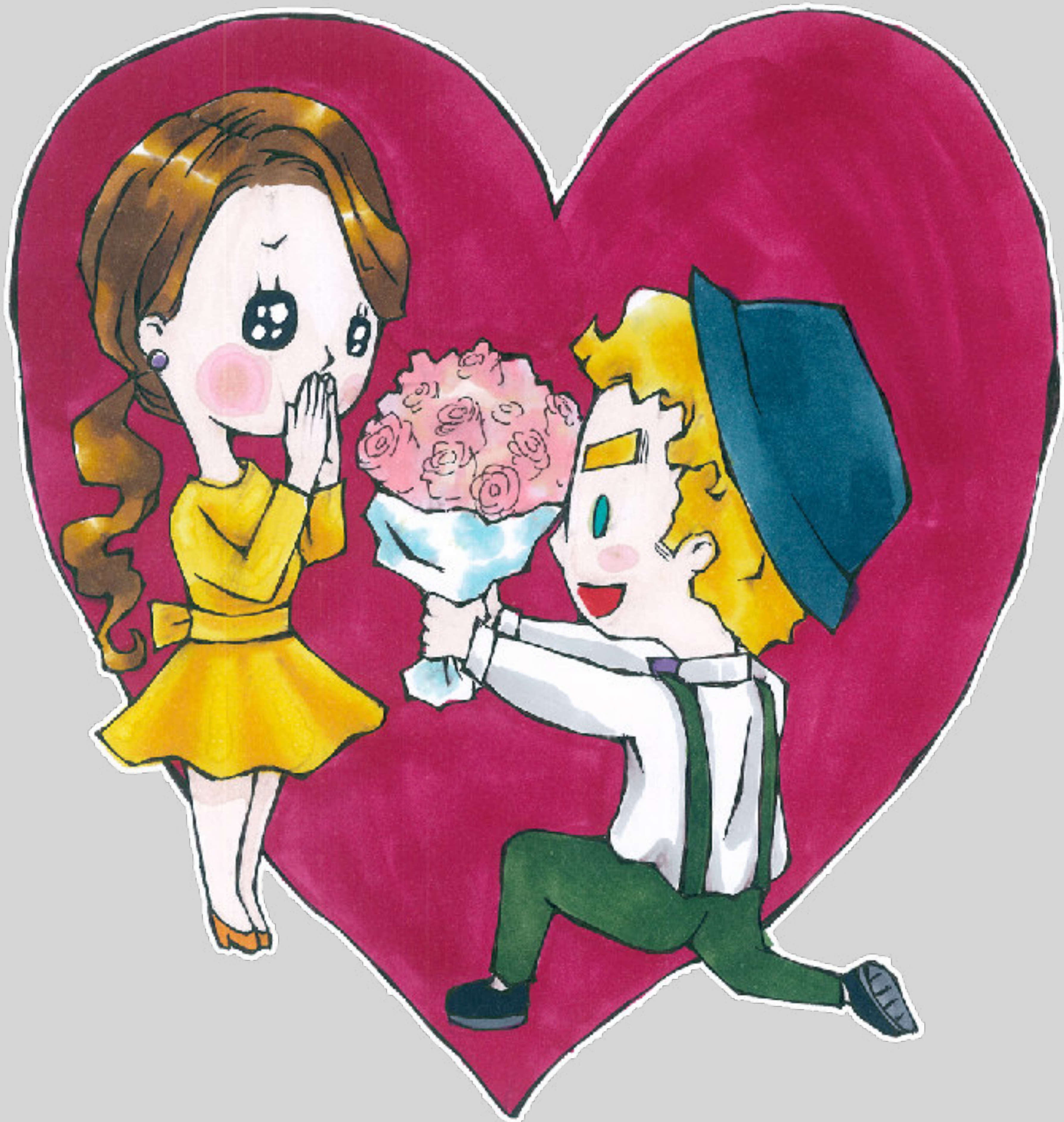
↓

Slowing down of spreading.

But both the cell phone and the prostitution data are bursty. So why are they different w.r.t. spreading?



Min, Goh, Vazquez, 2011. *PRE* 83, 036102.



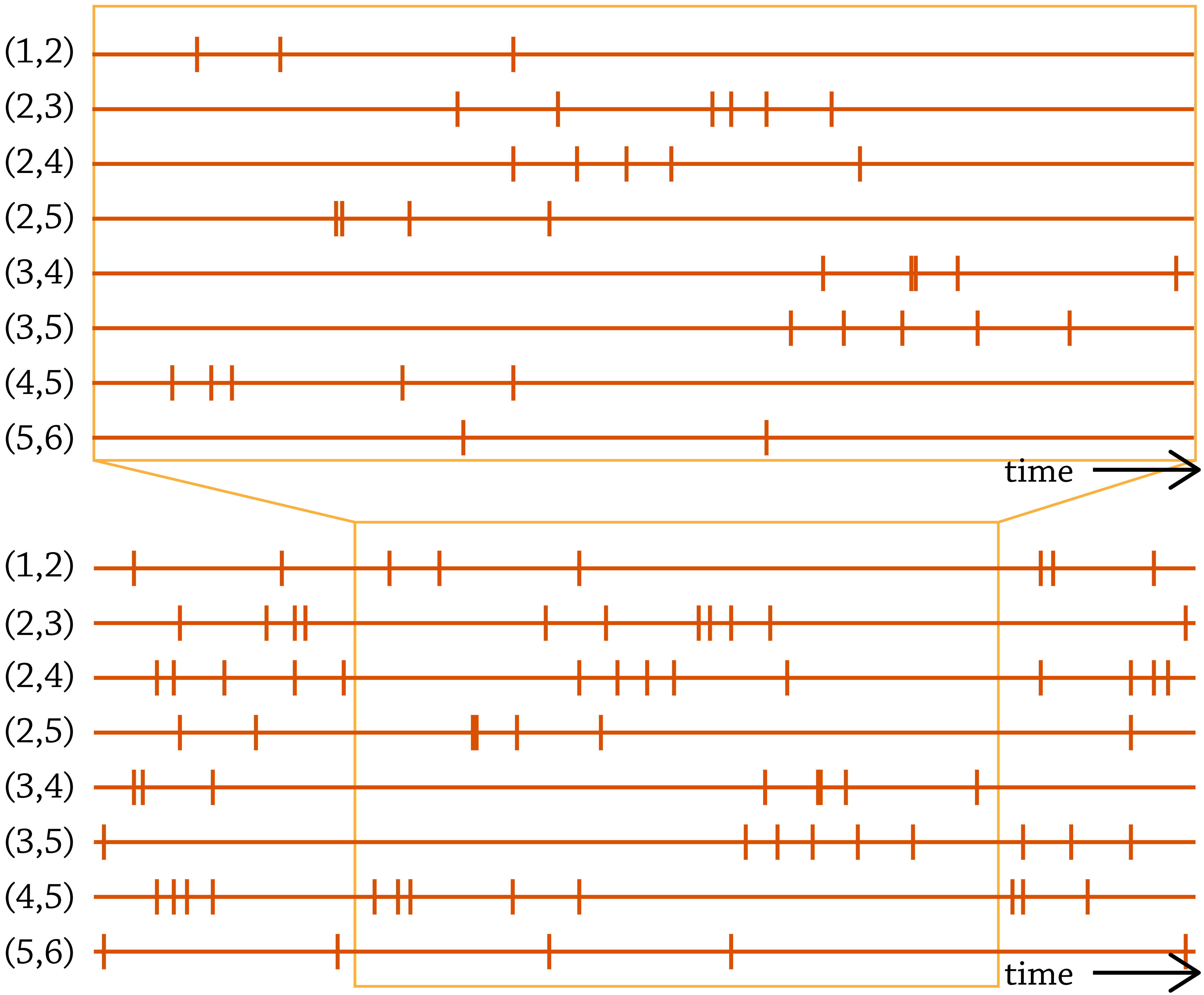

message
MY HONEY
Break up with me...

precursors:

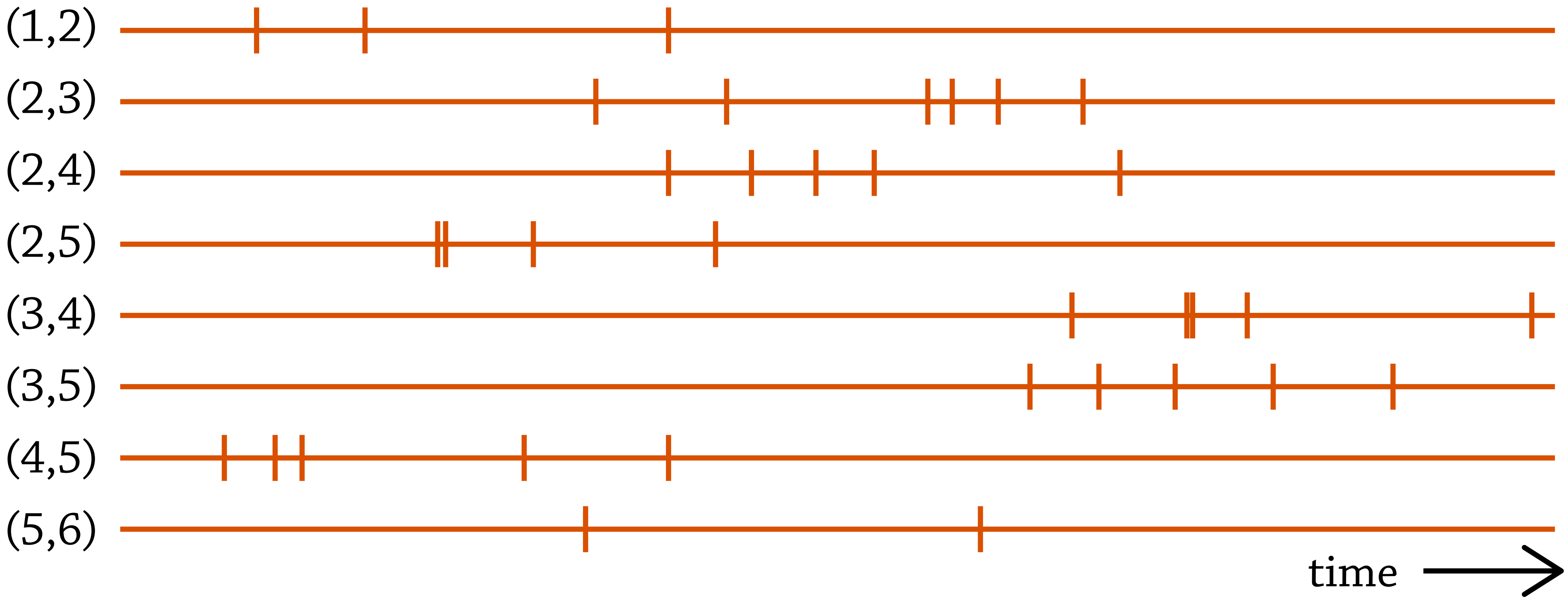
P Holme, 2003. Network dynamics of ongoing social relationships. *Europhys. Lett.* 64:427–433.

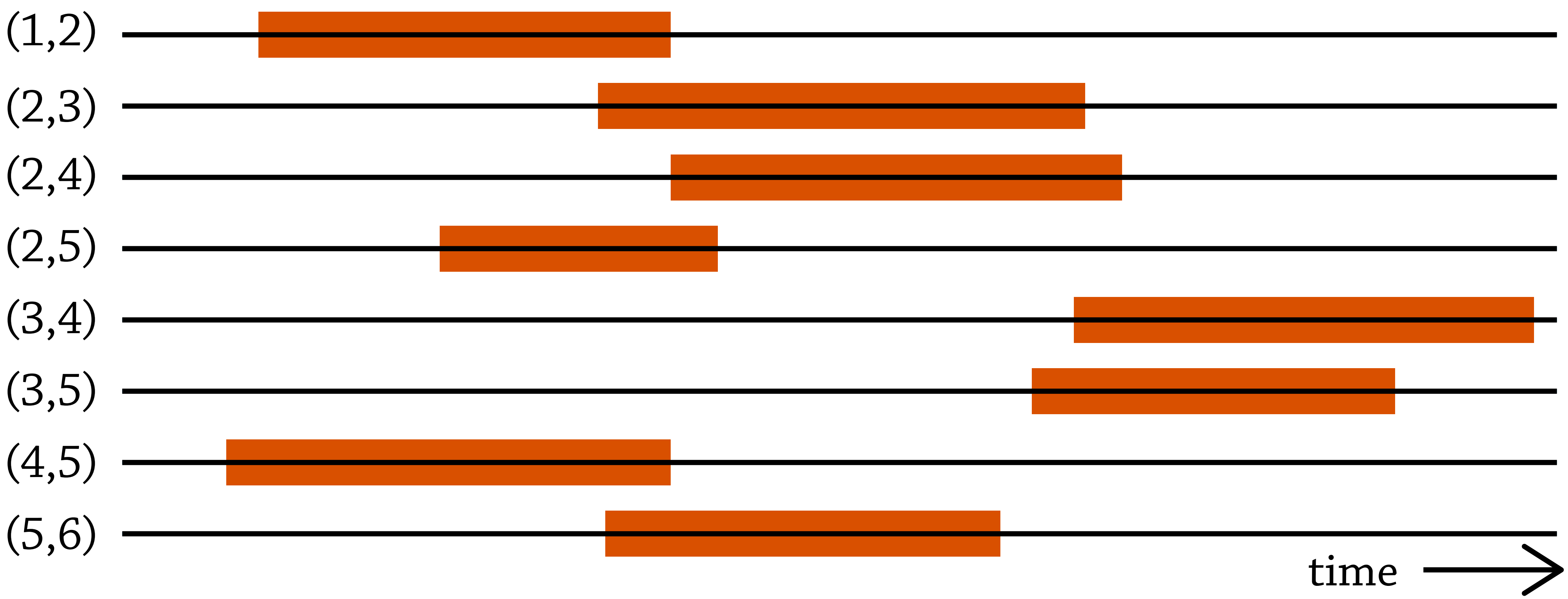
G Miritello, R Lara, M Cebrian, E Moro, 2013. Limited communication capacity unveils strategies for human interaction. *Sci. Rep.* 3:1560.

Ongoing link picture

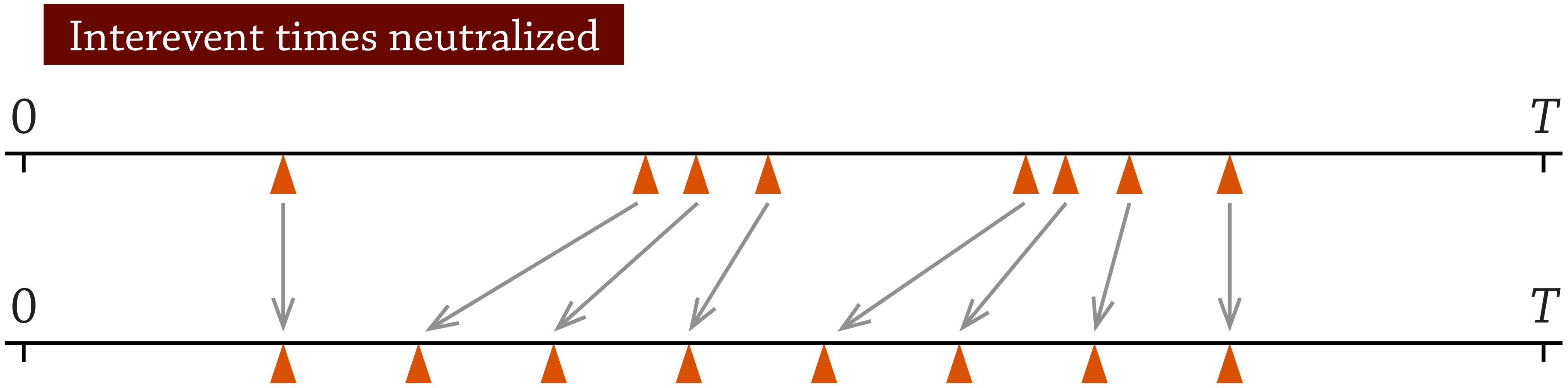


Link turnover picture

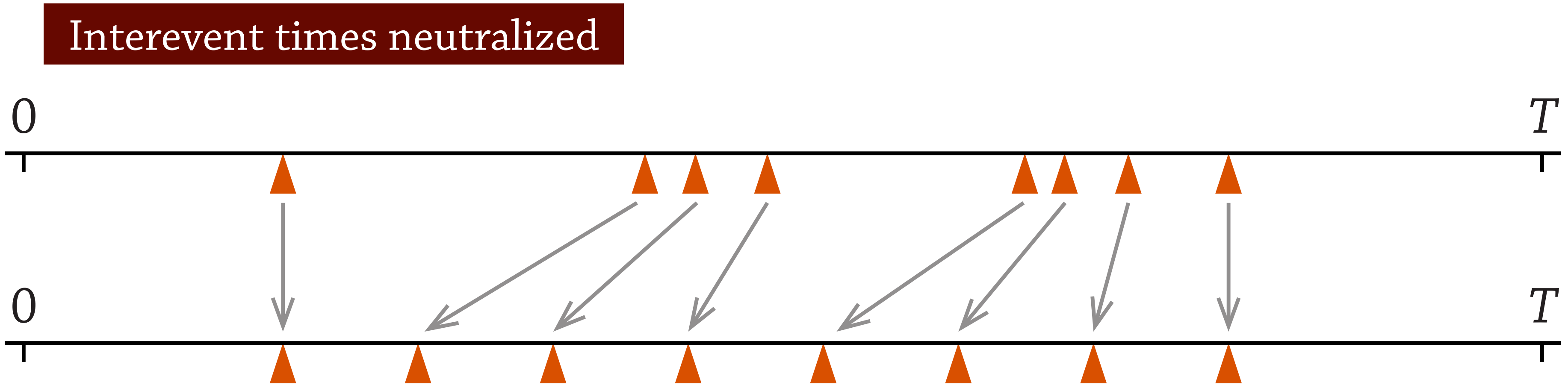


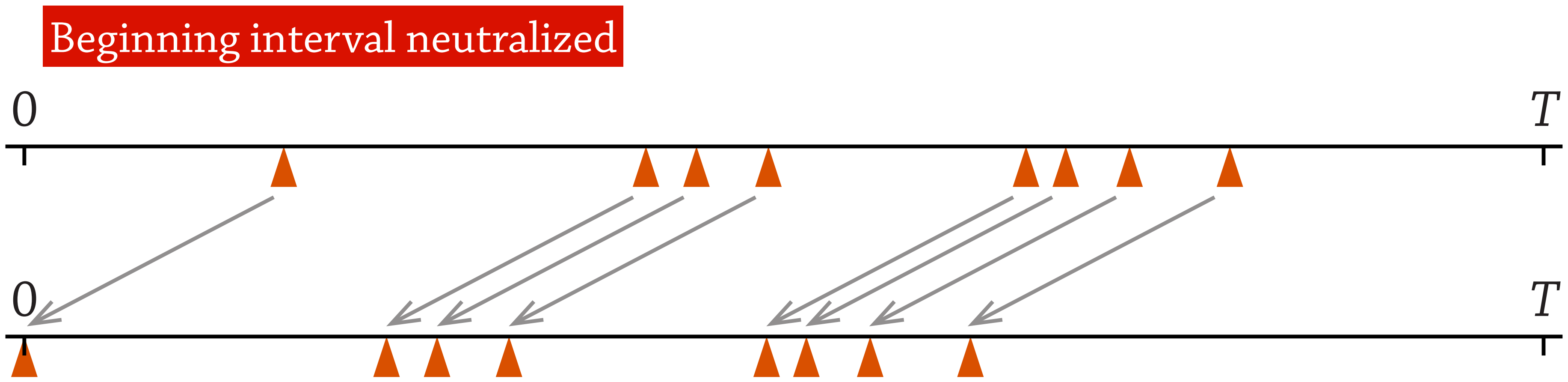


Reference models

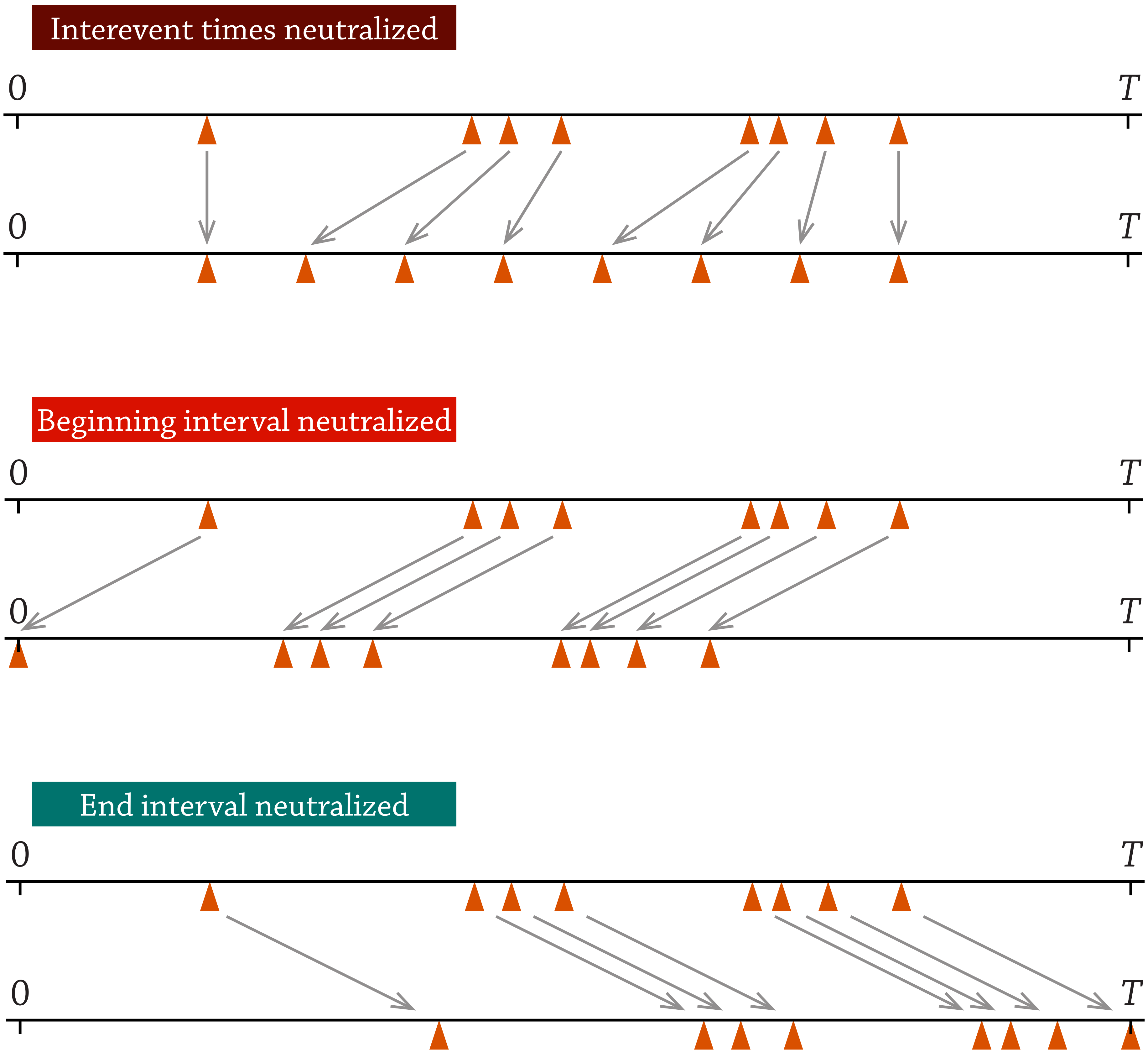


Reference models

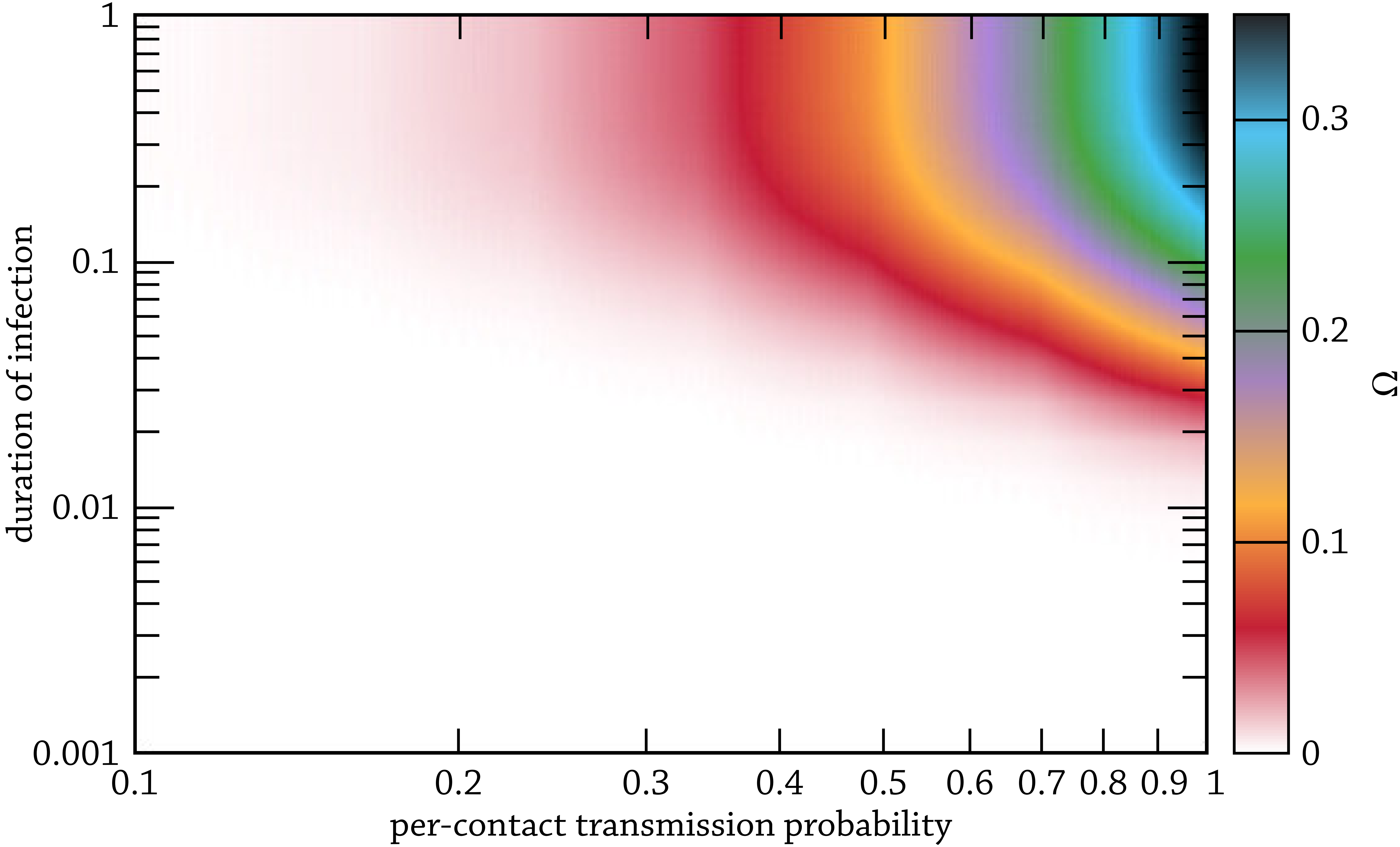




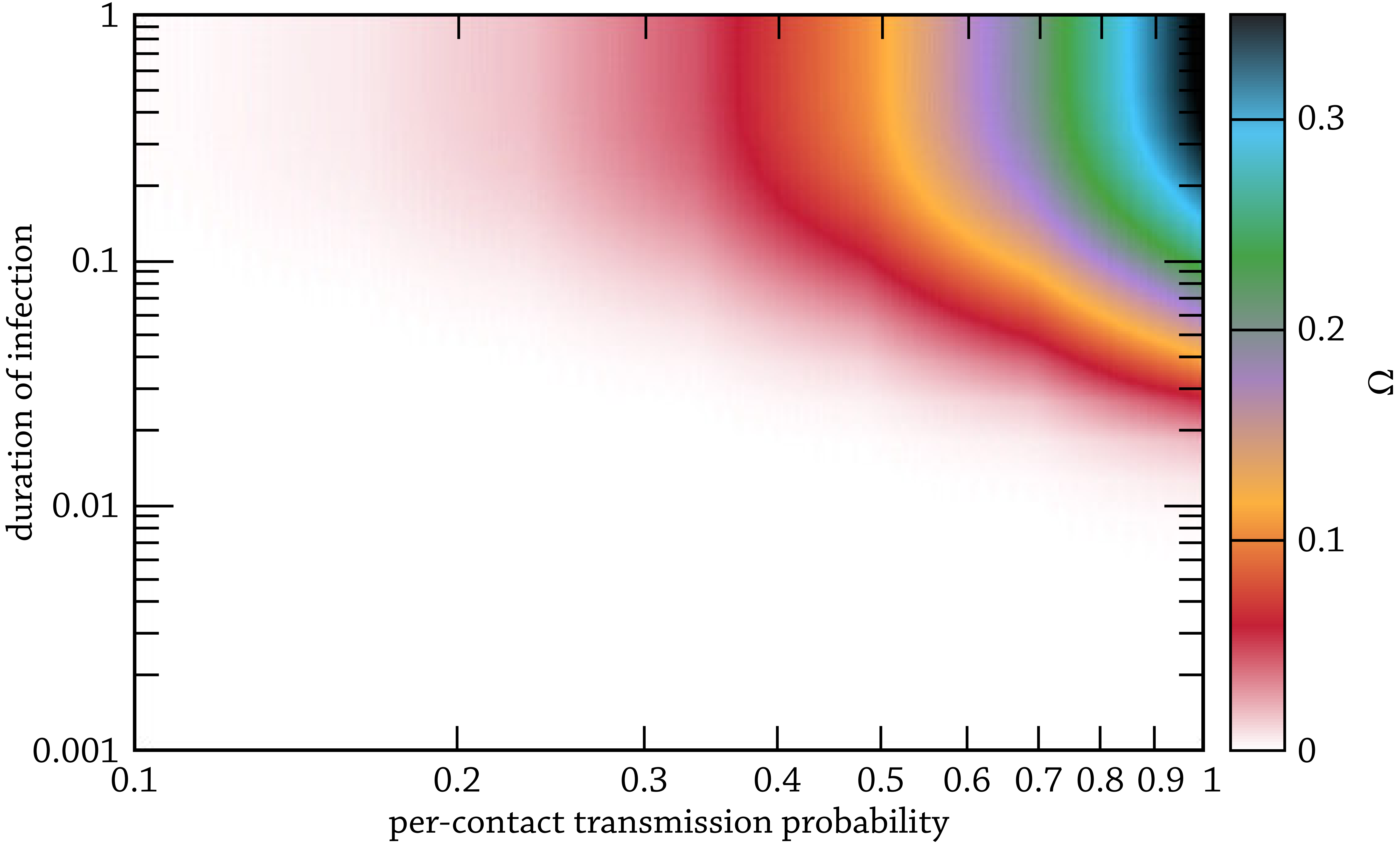
Reference models



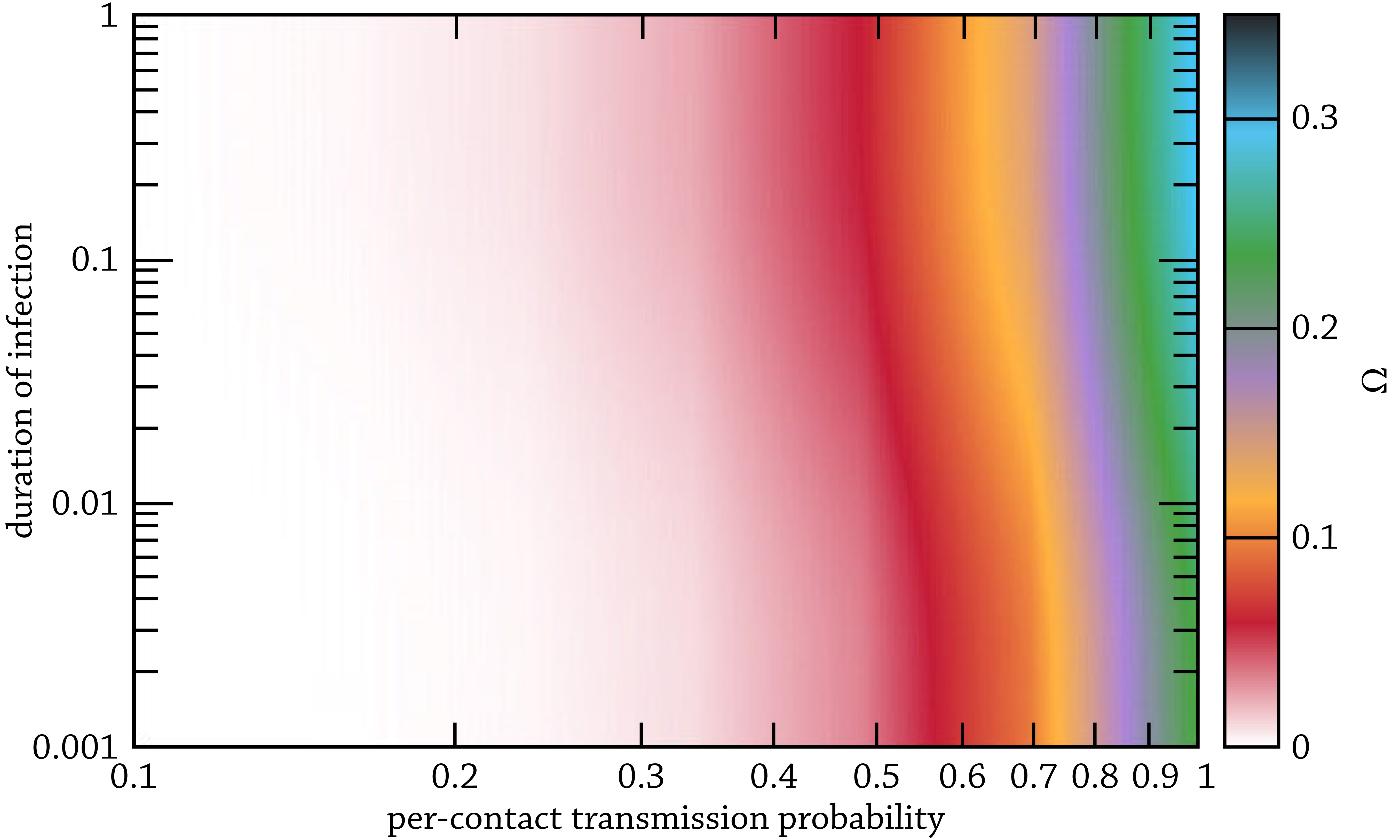
SIR on prostitution data



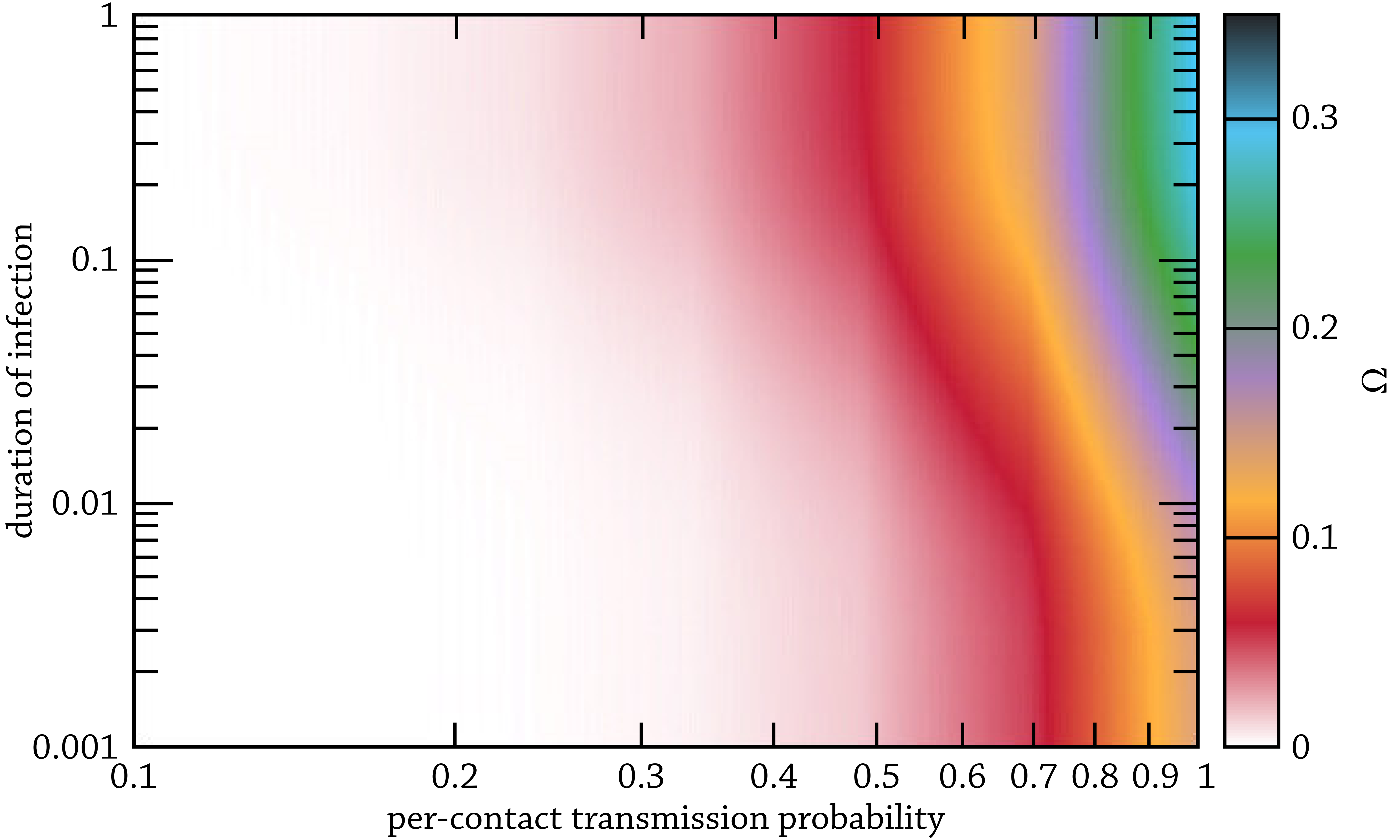
SIR on prostitution data
Interevent times neutralized



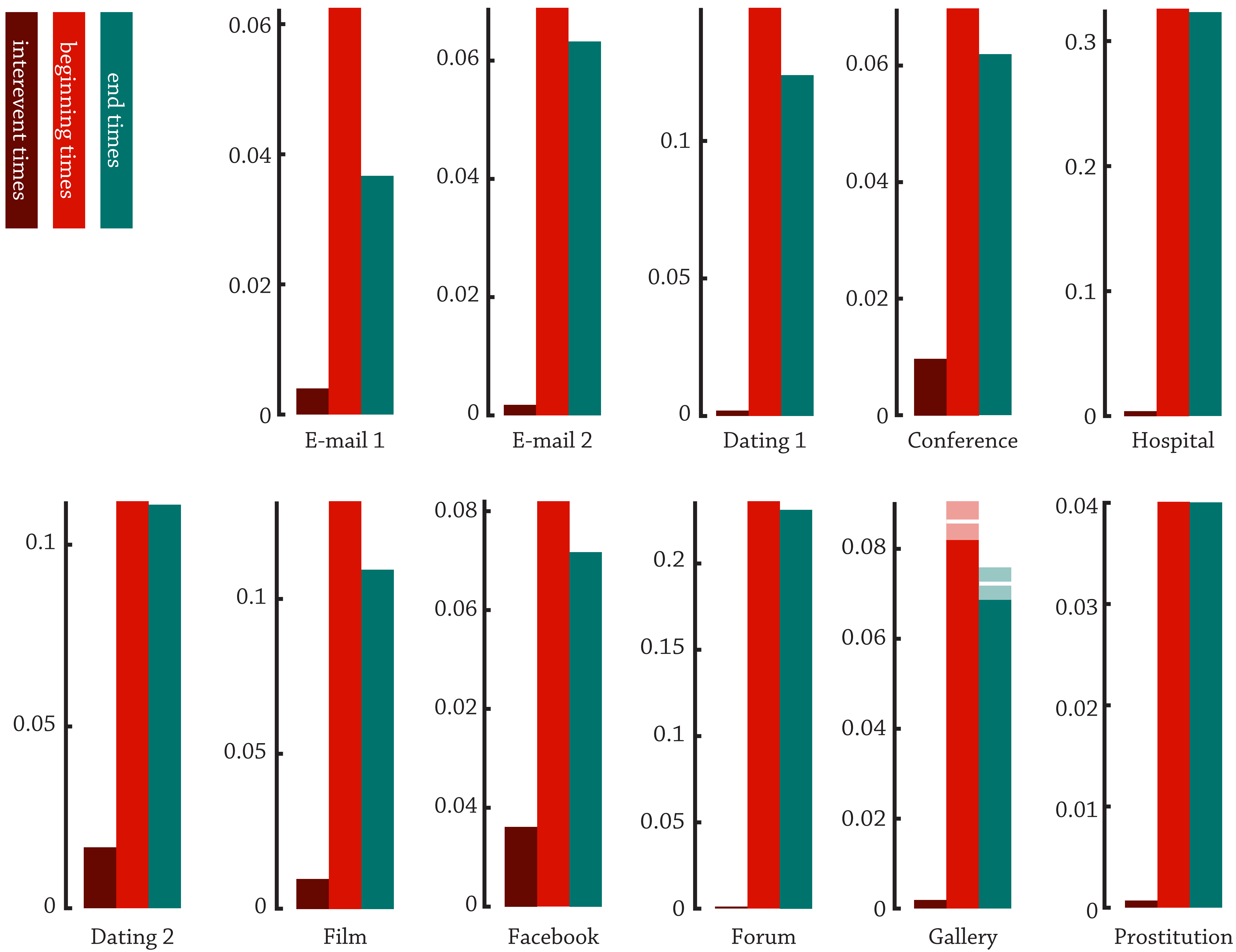
SIR on prostitution data
Beginning times neutralized



SIR on prostitution data
End times neutralized

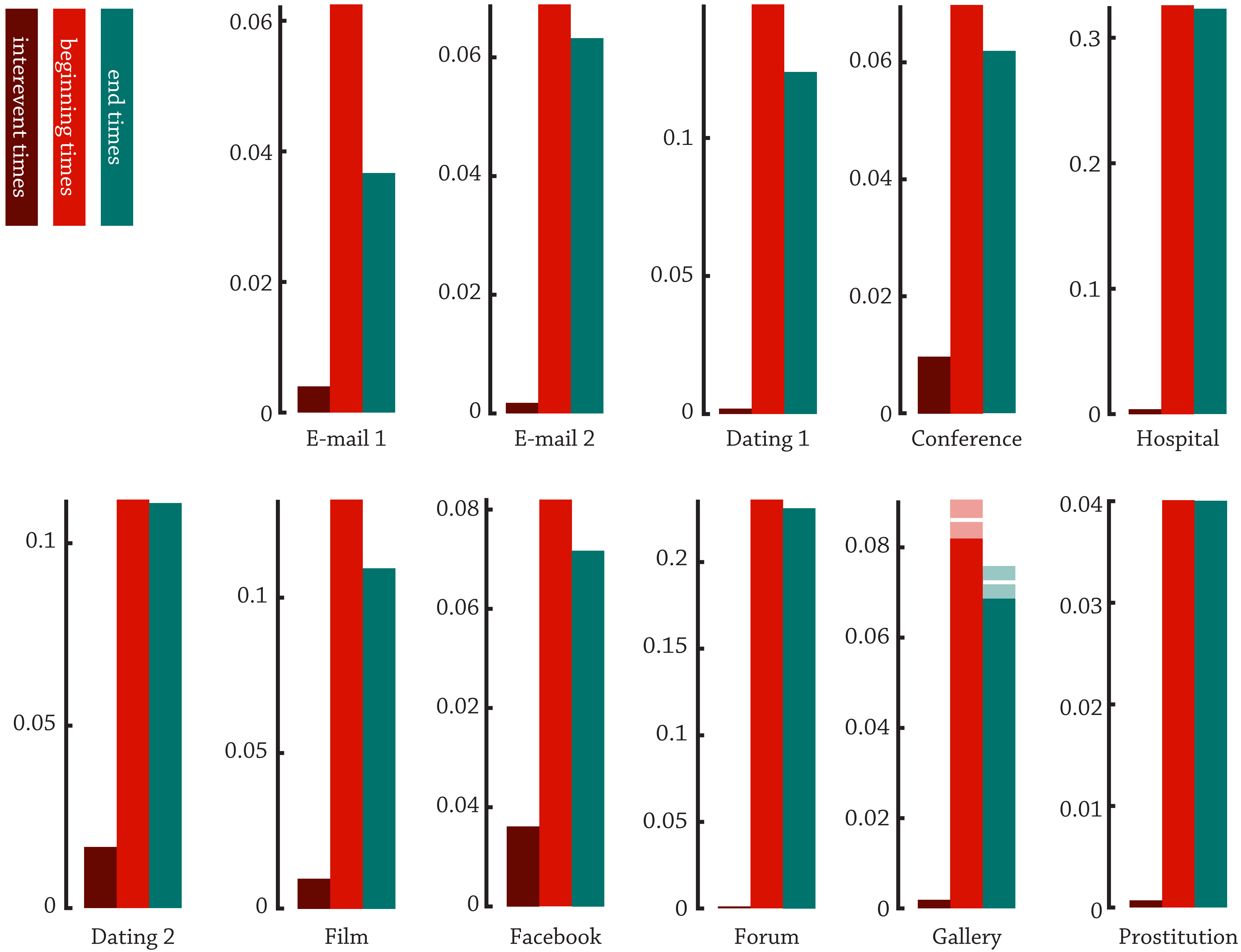


SIR, average deviations



SIR, average deviations

Holme, Liljeros, 2014. *Scientific Reports* 4: 4999.

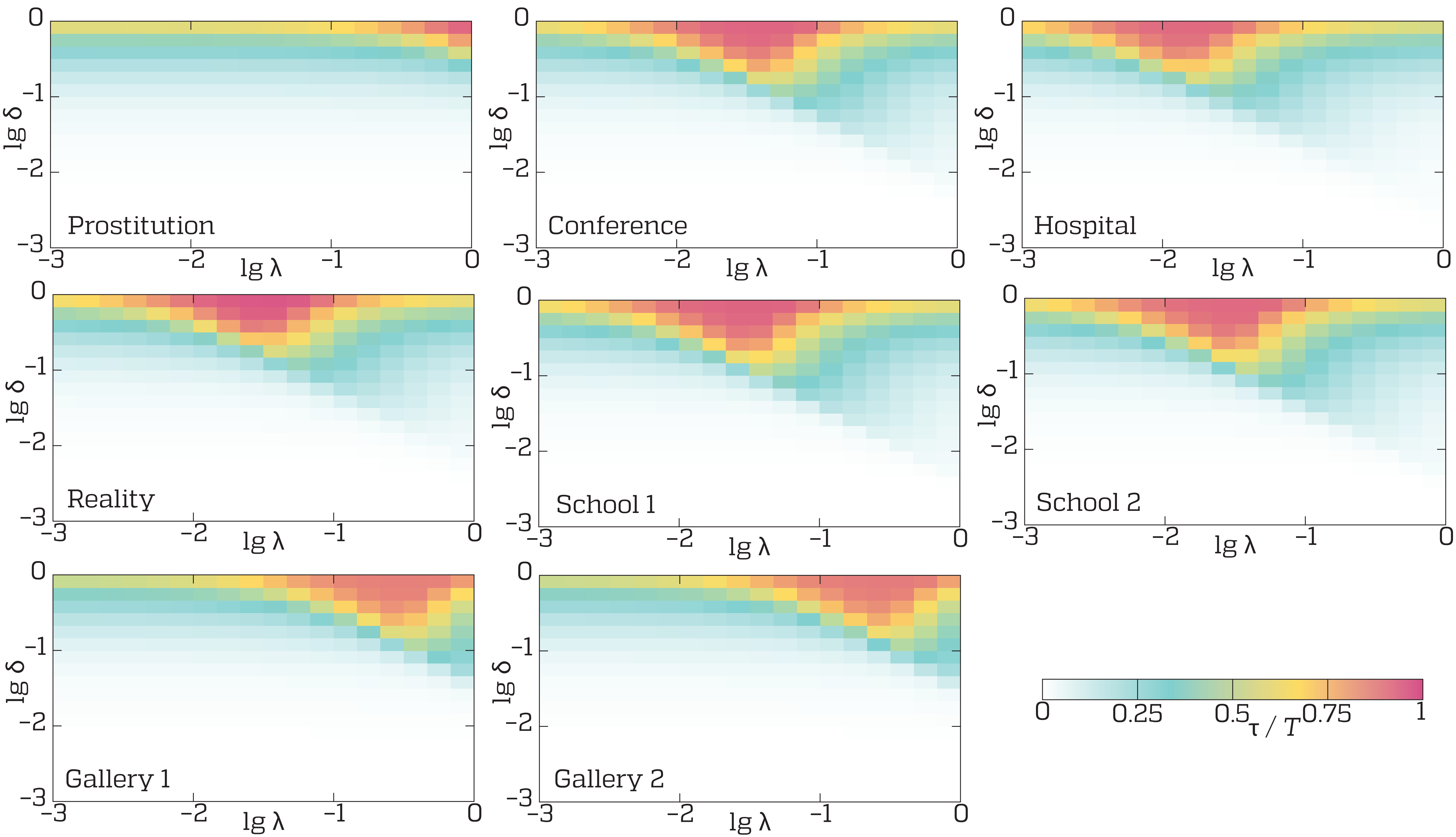


More temporal structures

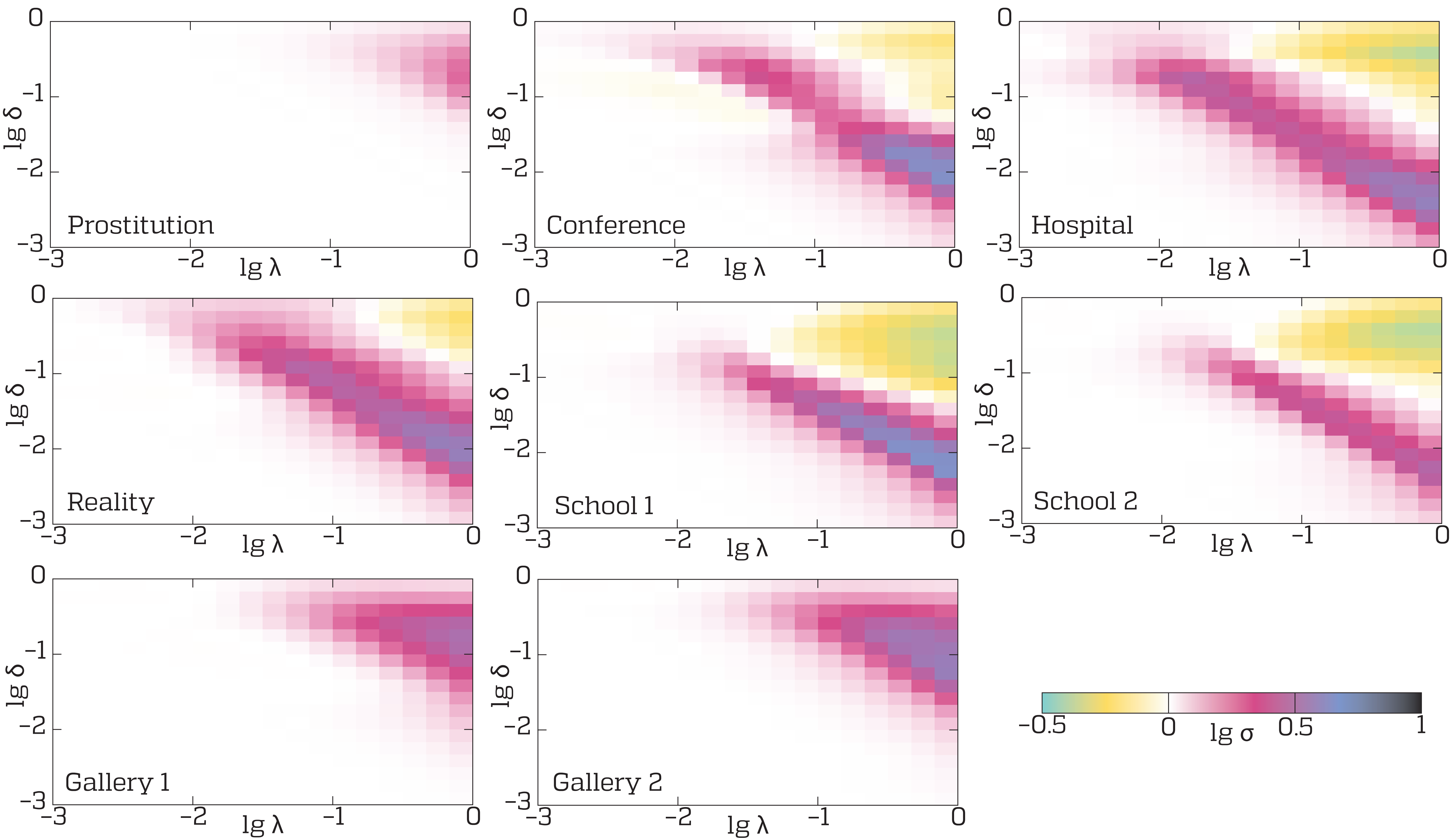
…a no-brain (low-brain?) approach

P. Holme, 2016.
Temporal network structures controlling disease spreading.
Phys. Rev. E 94, 022305.

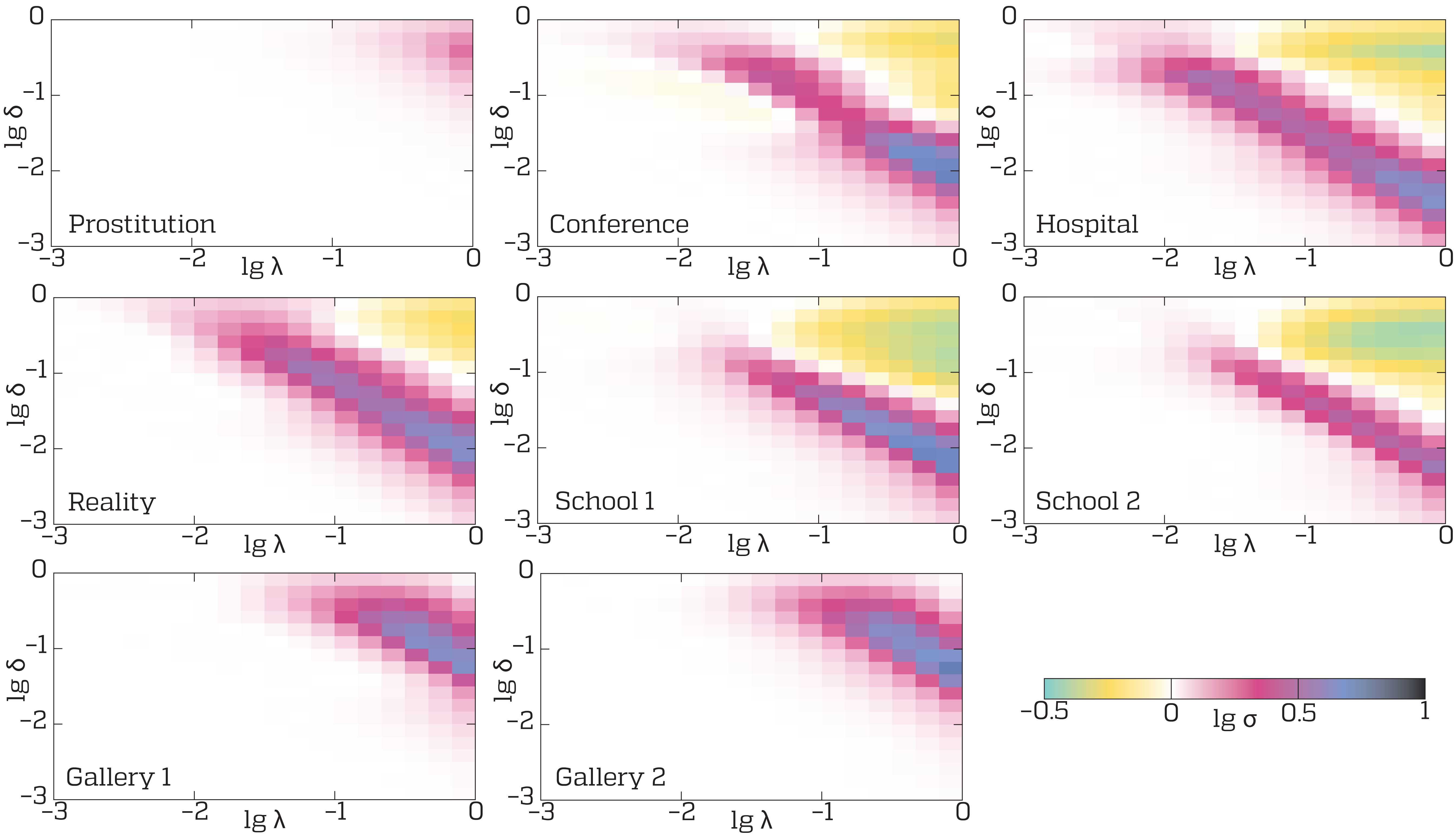
Outbreak duration



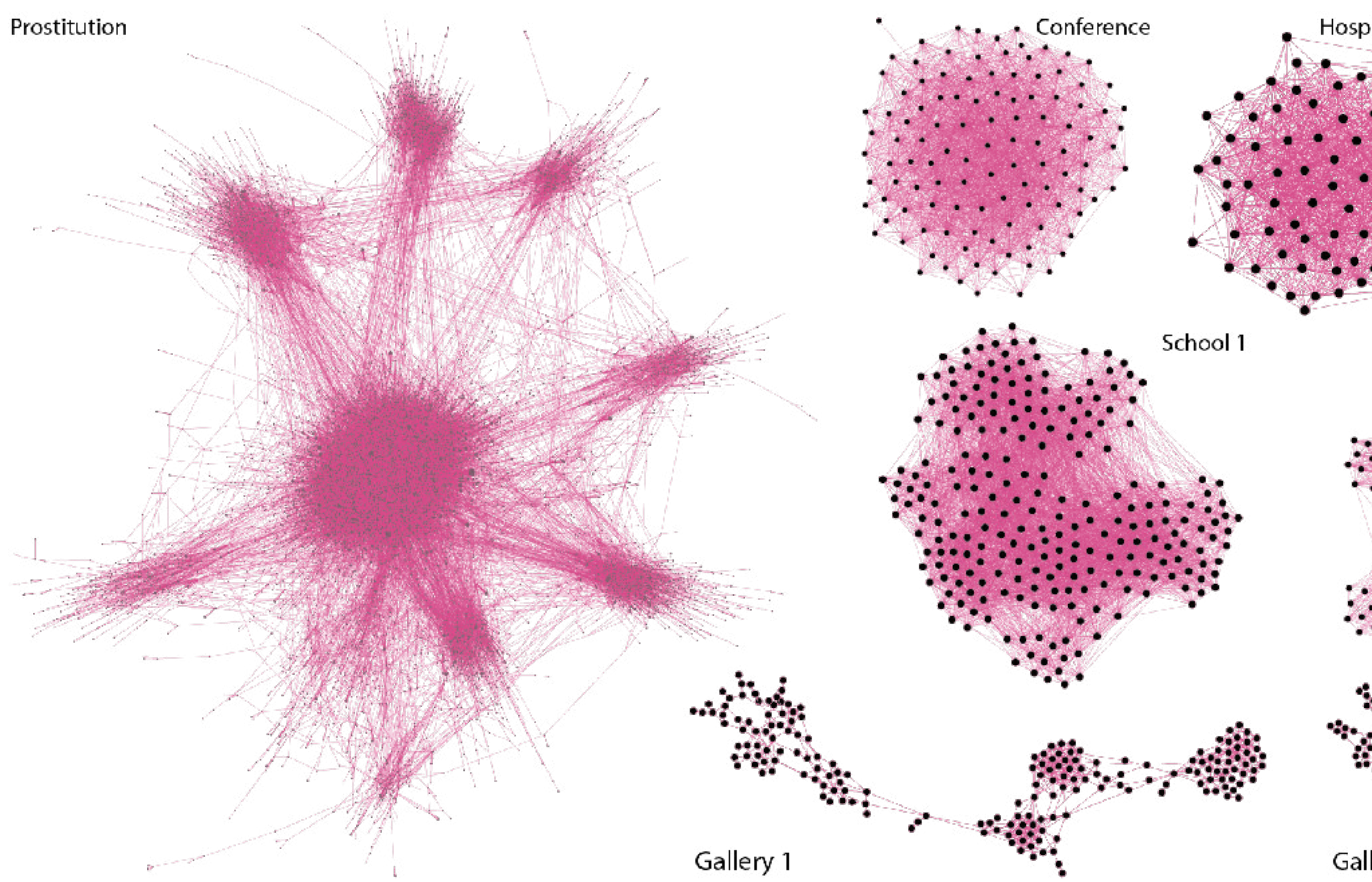
vs static nwks



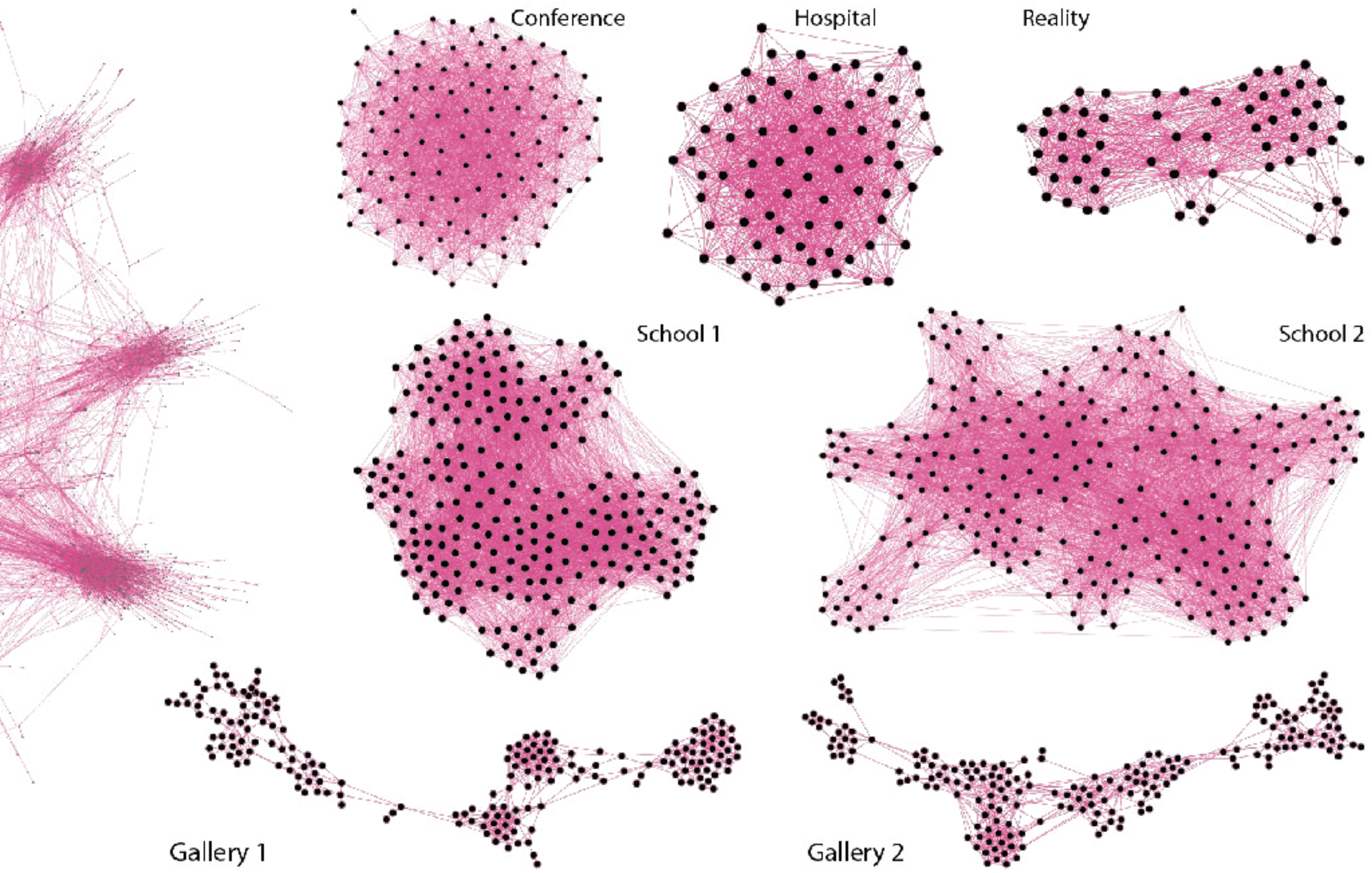
vs fully-connected nwks



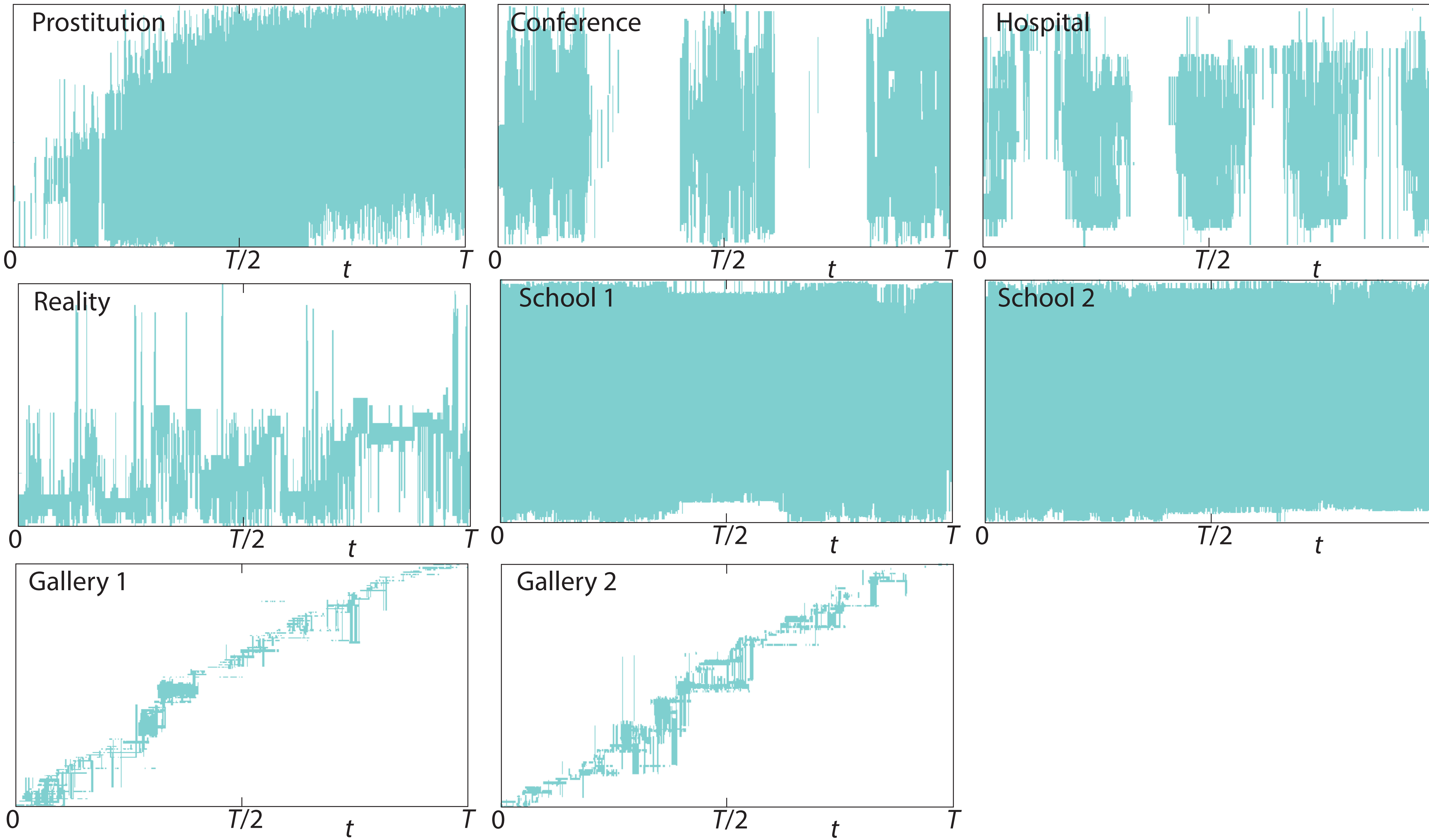
Ridiculograms (network)



Ridiculograms (network)



Ridiculograms (time)



Network structures

Link activity

link duration, mean
link duration, s.d.
link duration, coefficient of variation
link duration, skew
link interevent time, mean
link interevent time, s.d.
link interevent time, coefficient of variation
link interevent time, skew

Time evolution

avg. fraction of nodes present when 50% of contact happened
avg. fraction of links present when 50% of contact happened
avg. fraction of nodes present at 50% of the sampling time
avg. fraction of links present at 50% of the sampling time
frac. of nodes present 1st and last 10% of the contacts
frac. of links present 1st and last 10% of the contacts
frac. of nodes present 1st and last 10% of the sampling time
frac. of links present 1st and last 10% of the sampling time

Node activity

node duration, mean
node duration, s.d.
node duration, coefficient of variation
node duration, skew
node interevent time, mean
node interevent time, s.d.
node interevent time, coefficient of variation
node interevent time, skew

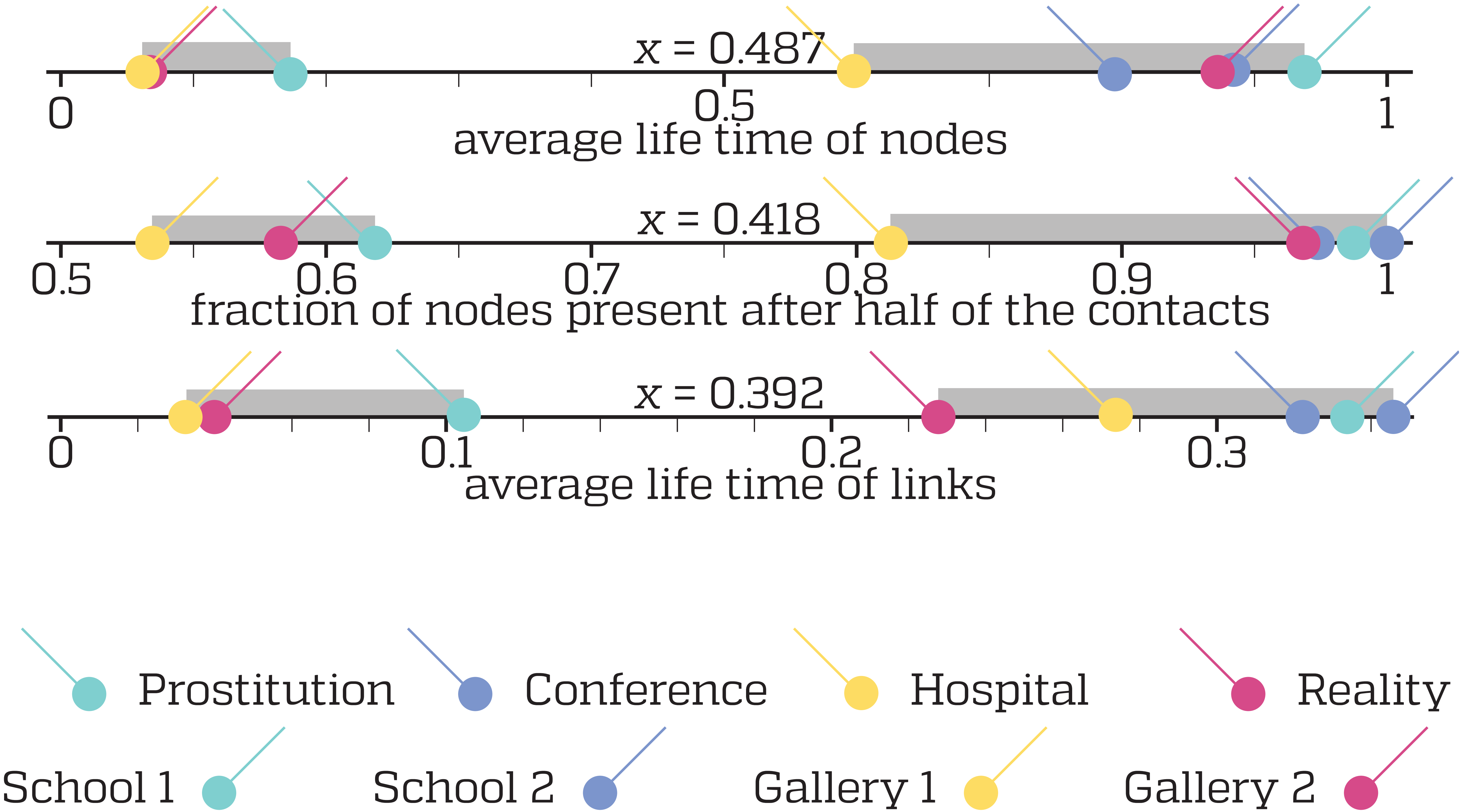
Degree distribution

degree distribution, mean
degree distribution, s.d.
degree distribution, coefficient of variation
degree distribution, skew

Other network structure

number of nodes
clustering coefficient
assortativity

Network structures



Vaccination

Vaccination

Assume we can vaccinate a fraction f, then how can we choose the people to vaccinate? Using only local info?

Vaccination

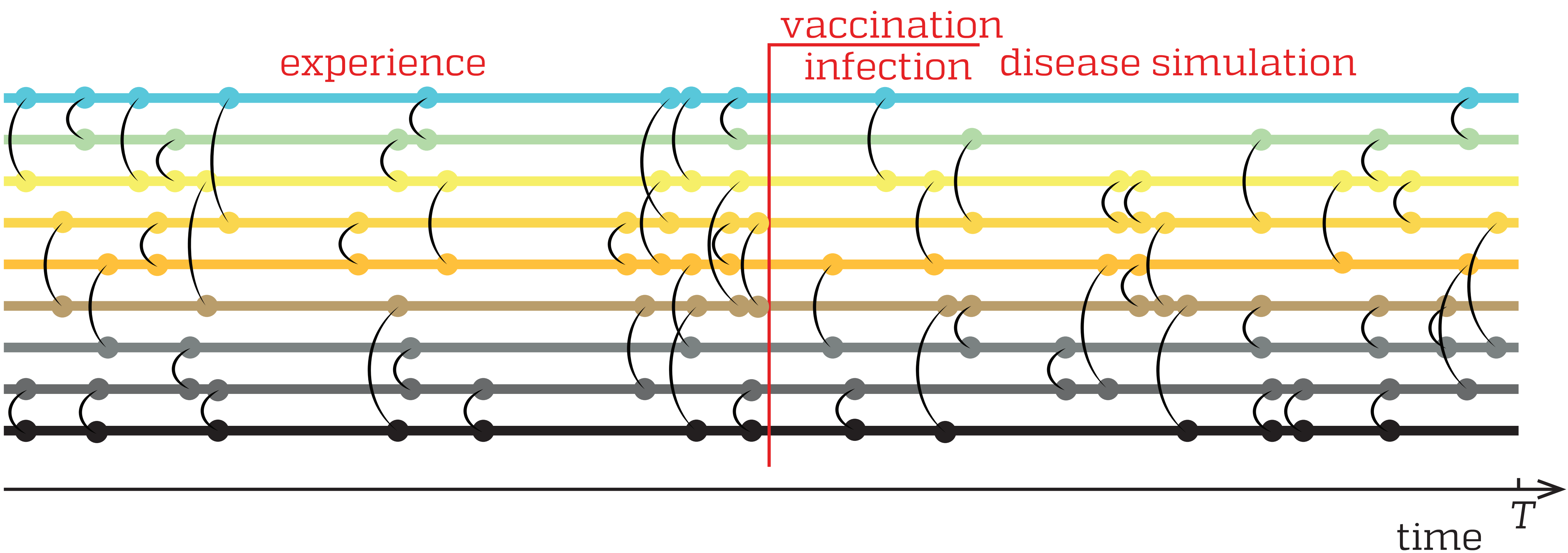
http://vax.herokuapp.com


Chose a person at random.
Neighborhood vaccination
Cohen, Havlin, ben Avraham, 2002.


Ask her to name a friend.
Neighborhood vaccination
Cohen, Havlin, ben Avraham, 2002.

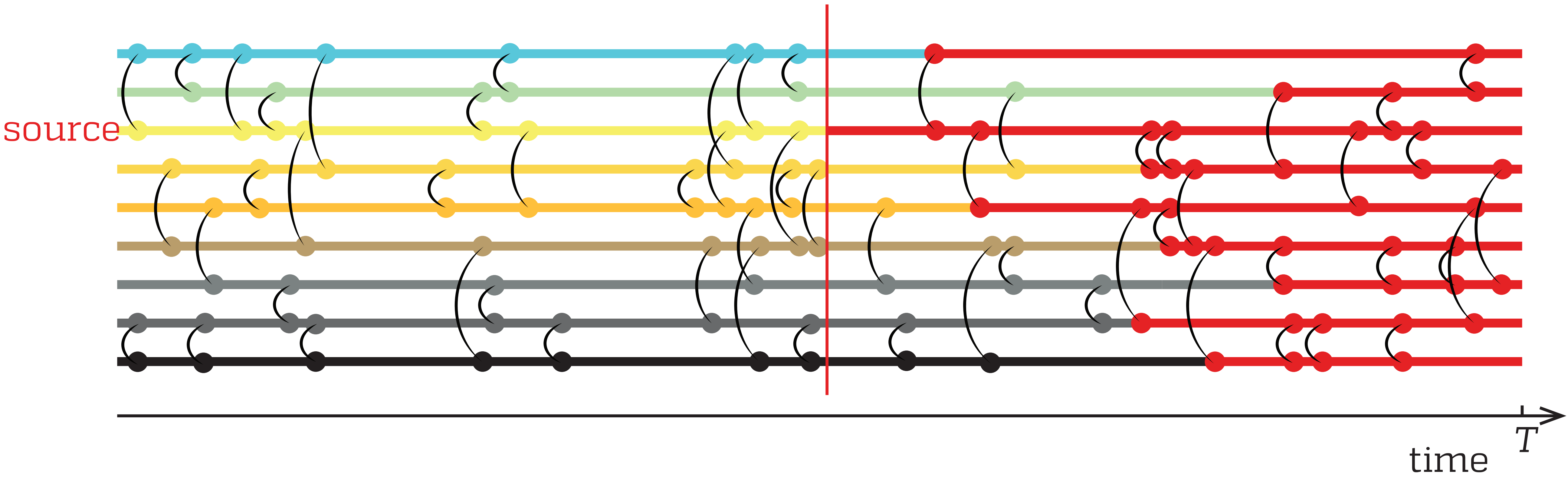

Vaccinate the friend.
Neighborhood vaccination
Cohen, Havlin, ben Avraham, 2002.

Vaccination



Lee, Rocha, Liljeros, Holme, 2012. *PLoS ONE* 7:e36439.

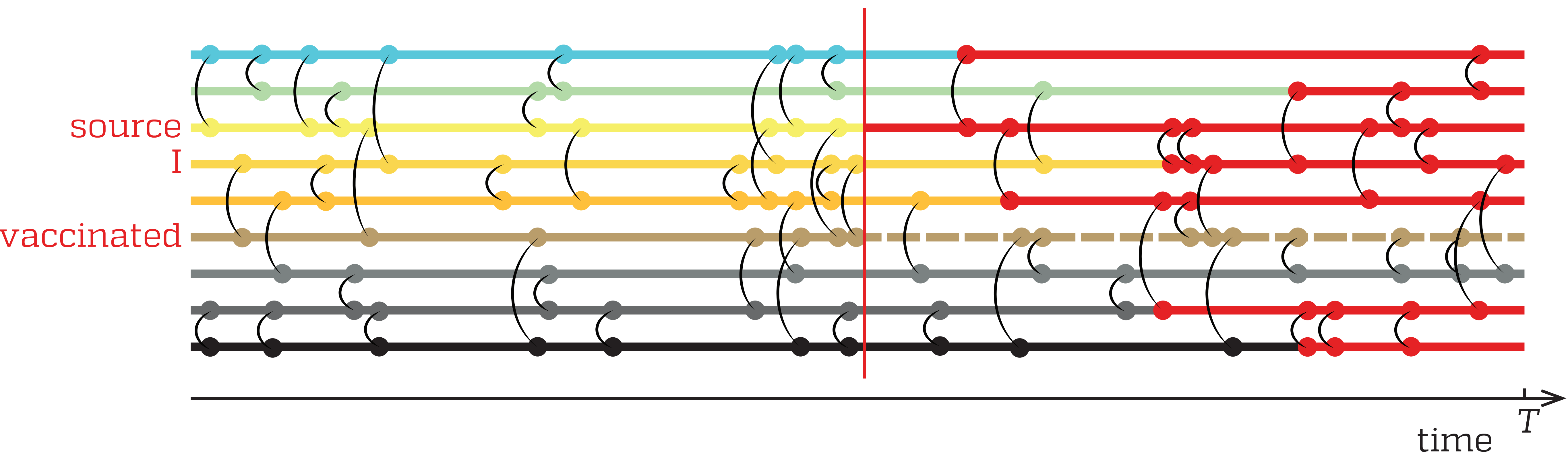
Vaccination



Lee, Rocha, Liljeros, Holme, 2012. *PLoS ONE* 7:e36439.

Vaccination

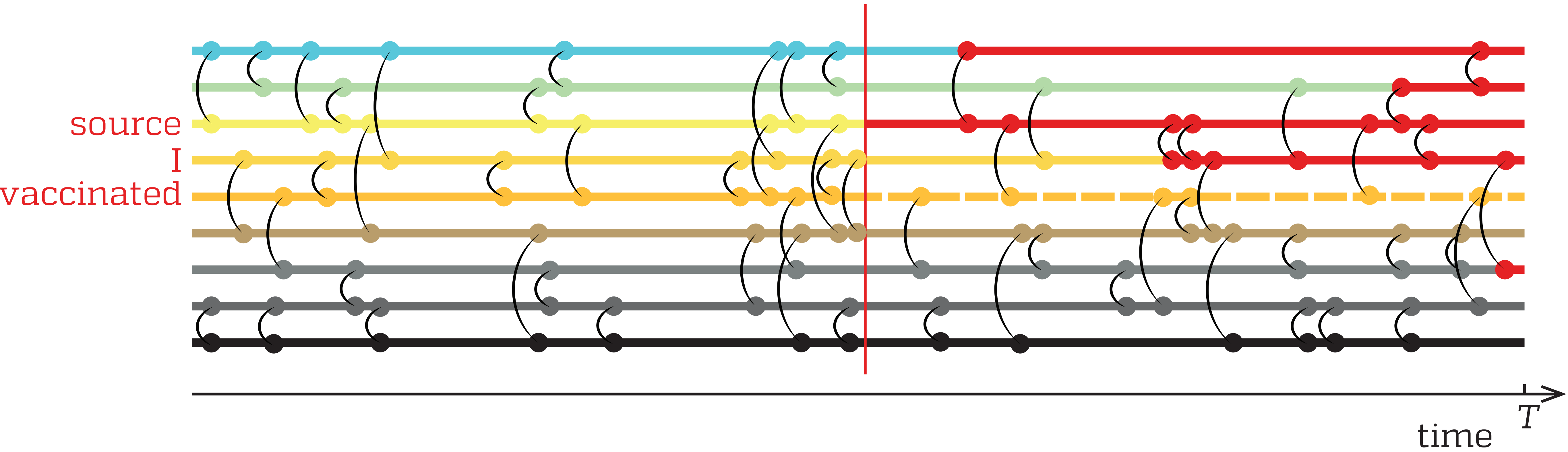
The *recent* version



Lee, Rocha, Liljeros, Holme, 2012. *PLoS ONE* 7:e36439.

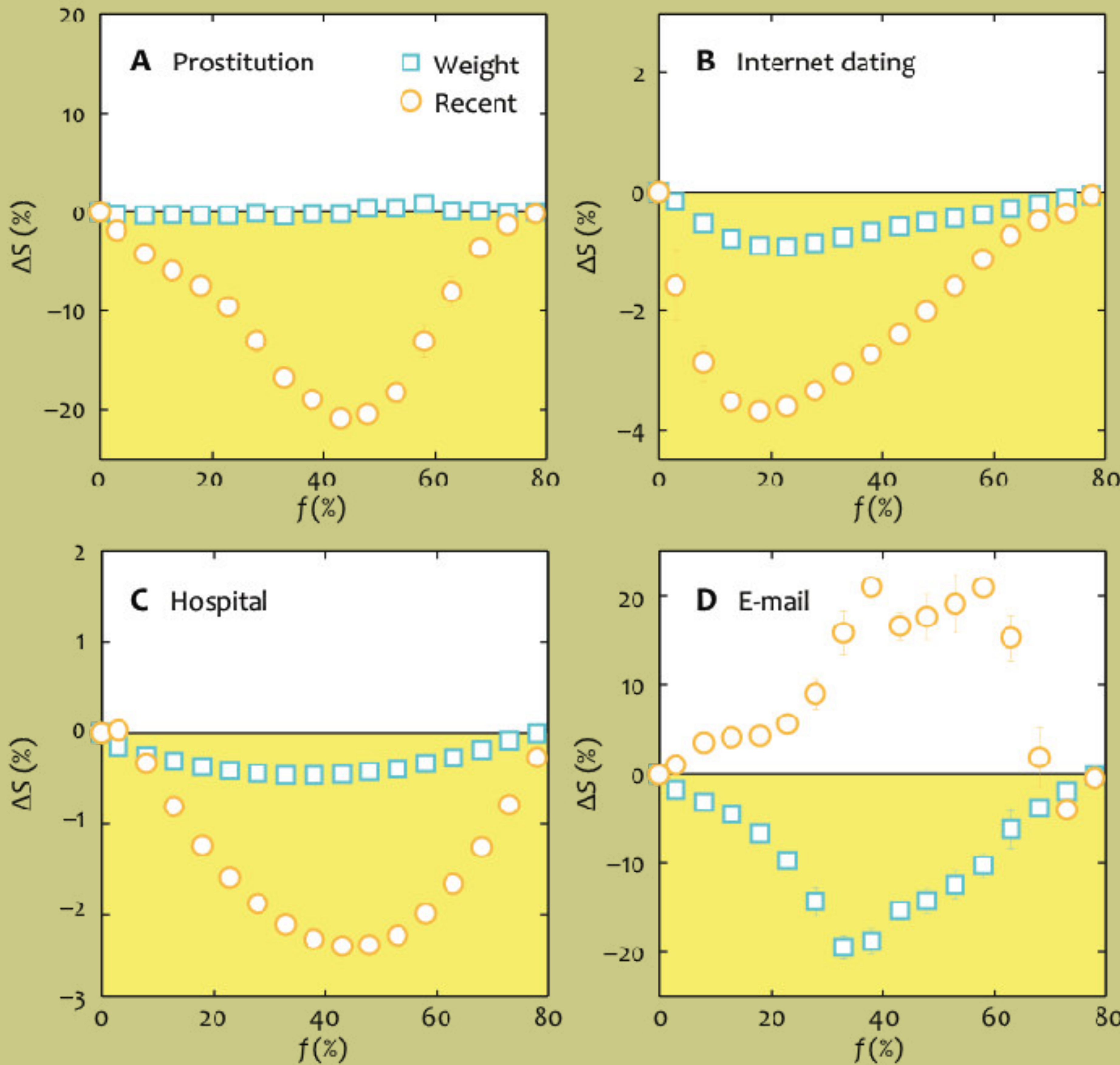
Vaccination

The *weight* version



Lee, Rocha, Liljeros, Holme, 2012. *PLoS ONE* 7:e36439.

Vaccination



Other temporal networks results & future outlook

Other results

Spreading by threshold dynamics

Takaguchi, Masuda, Holme, 2013. Bursty communication patterns facilitate spreading in a threshold-based epidemic dynamics. *PLoS ONE* 8:e68629.

Karimi, Holme, 2013. Threshold model of cascades in empirical temporal networks. *Physica A* 392:3476– 3483.

Random walks

Holme, Saramäki, 2015. Exploring temporal networks with greedy walks. *Eur J Phys B* 88:334.

Review papers

Masuda, Holme, 2013. Predicting and controlling infectious disease epidemics using temporal networks. *F1000Prime Rep*. 5:6.

Holme, 2015. Modern temporal network theory: A colloquium. *Eur J Phys B* 88:234.

Holme, 2014. Analyzing temporal networks in social media, *Proc. IEEE* 102:1922–1933.

Future

Visualization.

Important temporal-network measures.*

Mesoscopic structures.*

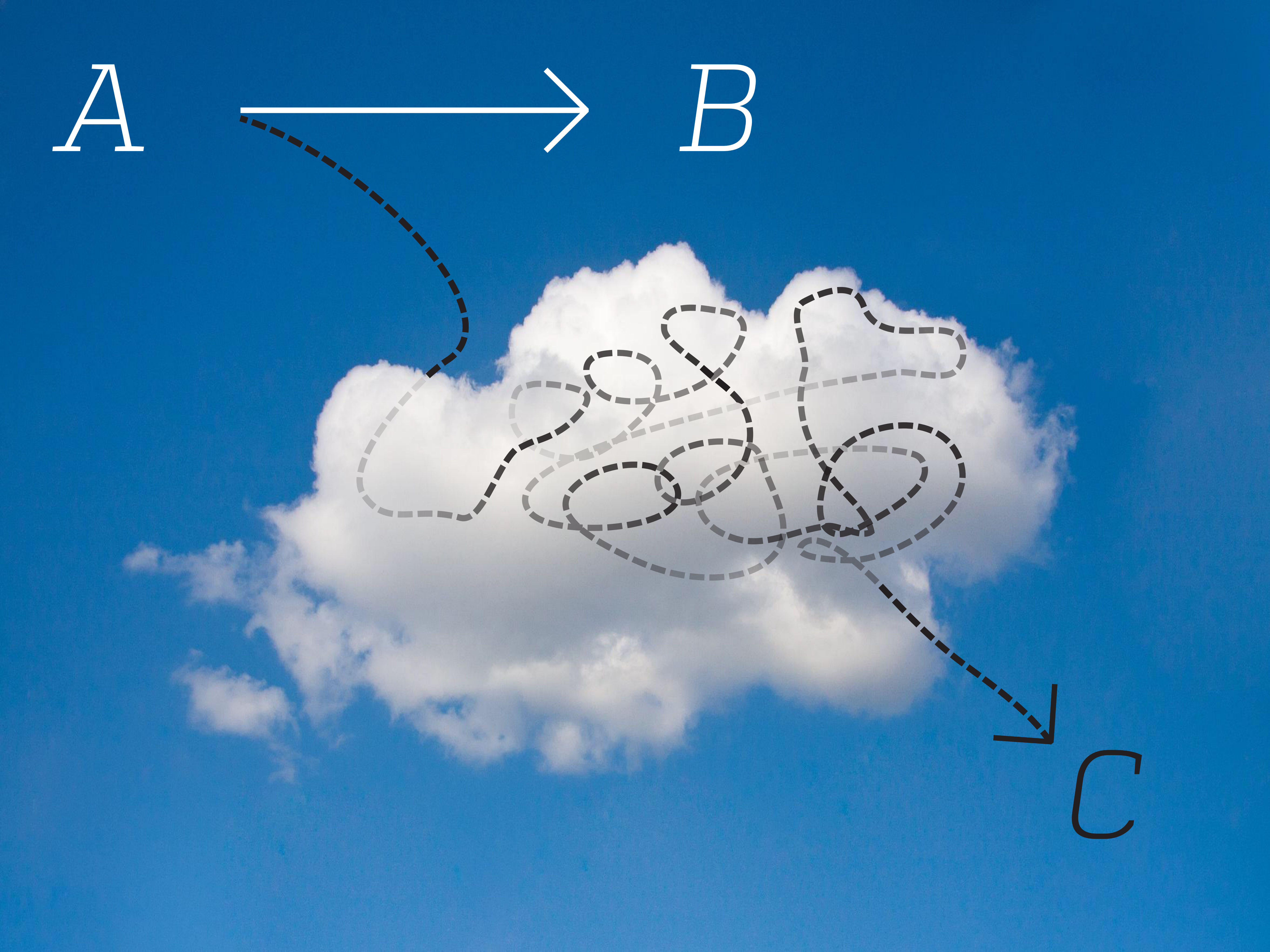
Finite-size scaling (how to scale up results to populations).

Generative models.

New kinds of data.

*beyond generalizations from static networks

$$A \longrightarrow B$$


A
B
C

Thank you!

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Fariba Karimi

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