

Digital health and computational epidemiology

Lesson 12

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Center for
Computational Social Science
and Human Dynamics

Temporal networks

References



Temporal networks

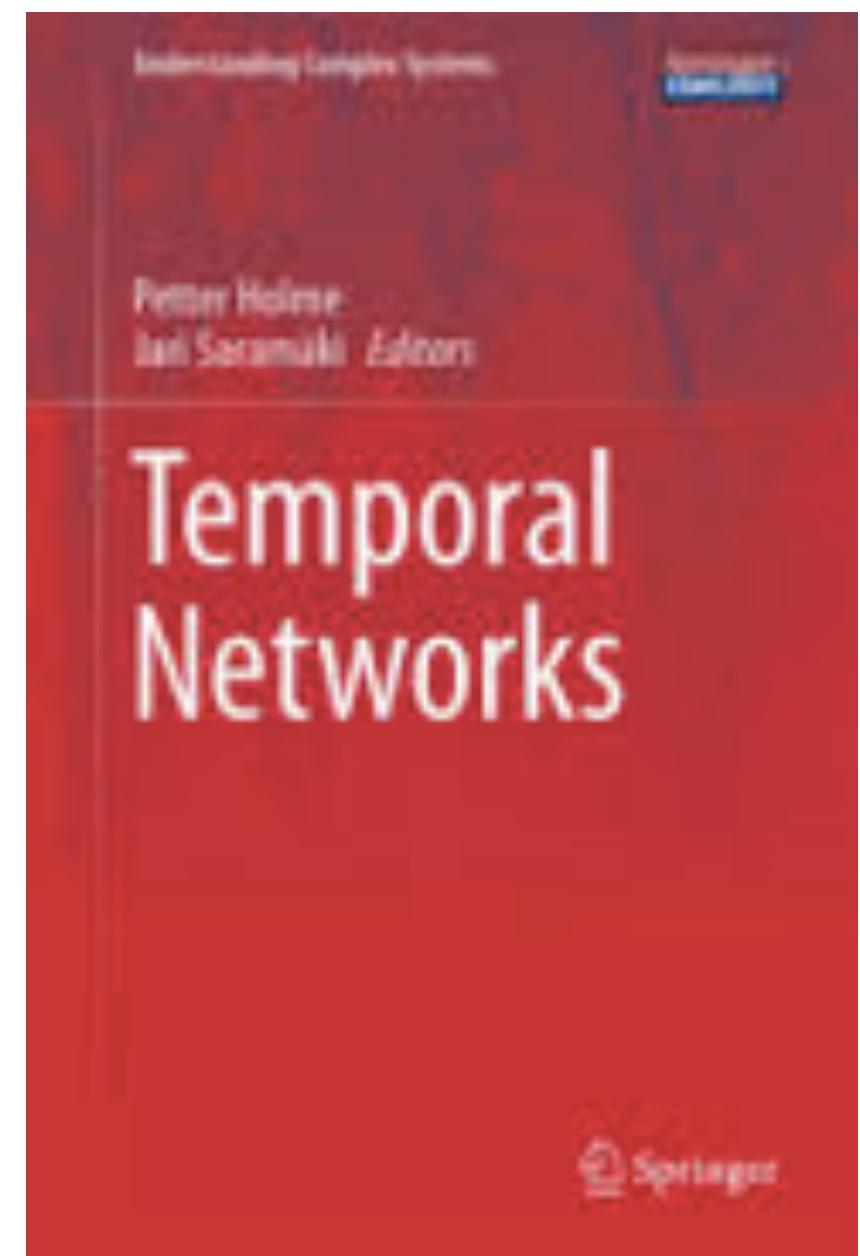
Petter Holme^{a,b,c,*}, Jari Saramäki^d

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Regular Article The Dynamics OF Networks: General Theory

The European Physical Journal Special Topics

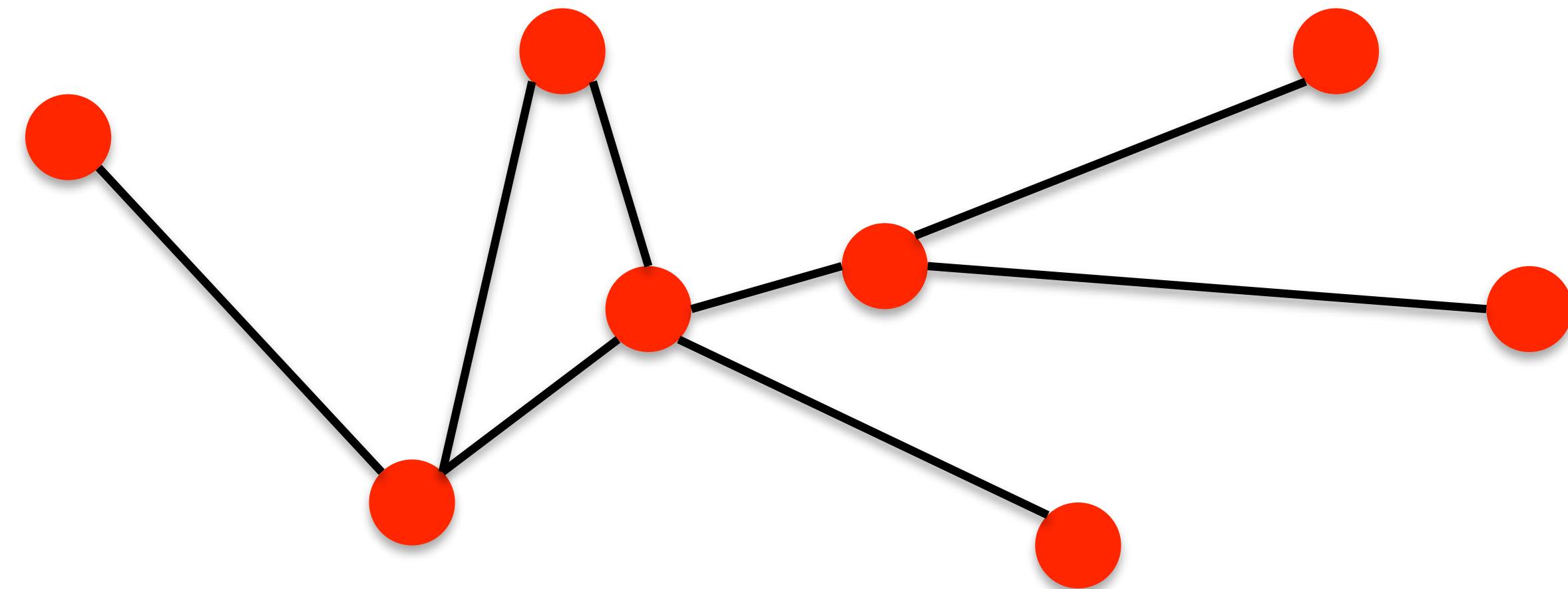
September 2013, Volume 222, Issue 6, pp 1295-1309

First online: 13 September 2013

Empirical temporal networks of face-to-face human interactions

A. Barrat, C. Cattuto, V. Colizza, F. Gesualdo, L. Isella, E. Pandolfi, J. -F. Pinton, L. Ravà, C. Rizzo
and 4 more

Static networks



- **components:** nodes, vertices

N

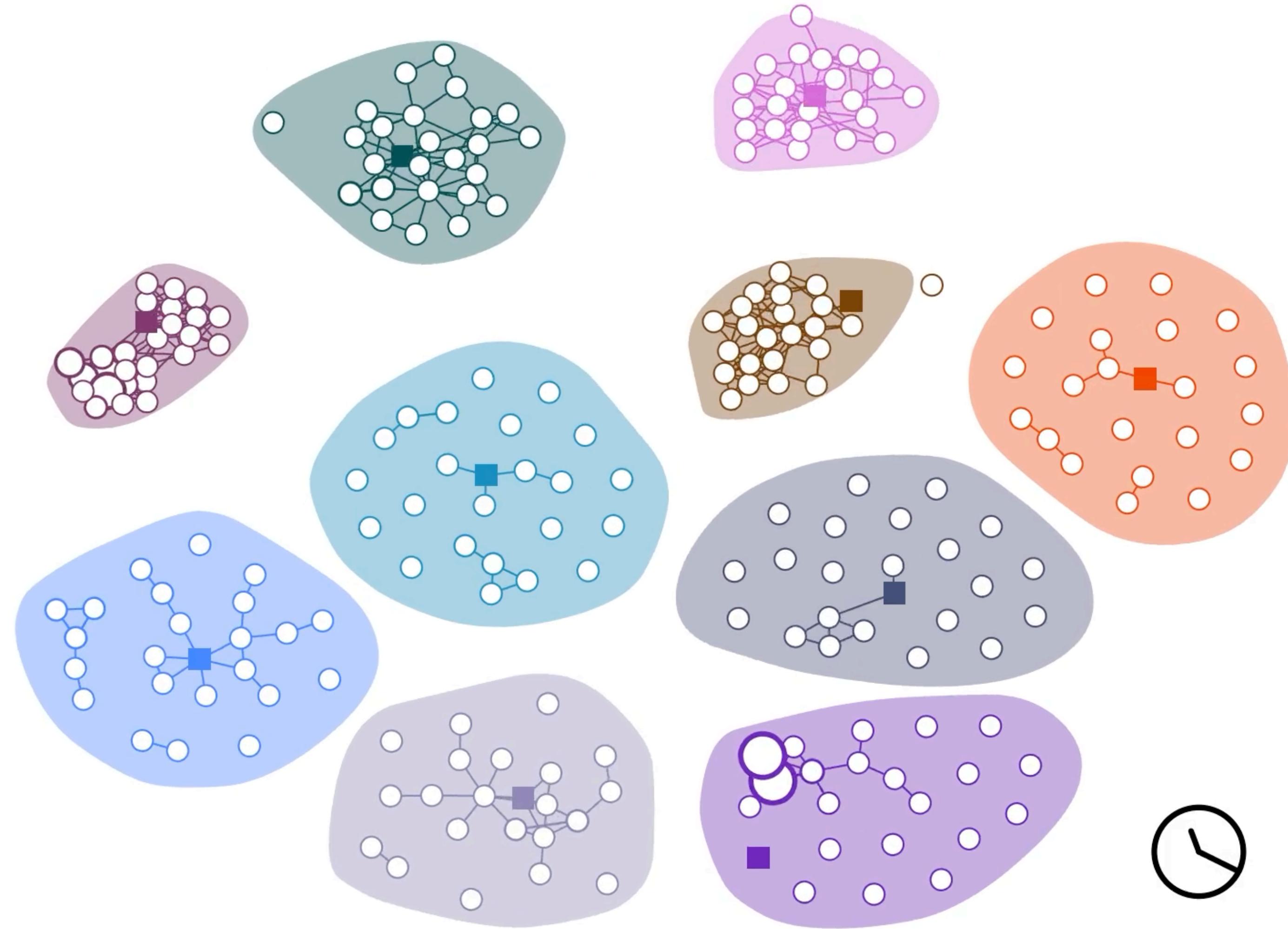
- **interactions:** links, edges

L

- **system:** network, graph

(N,L)

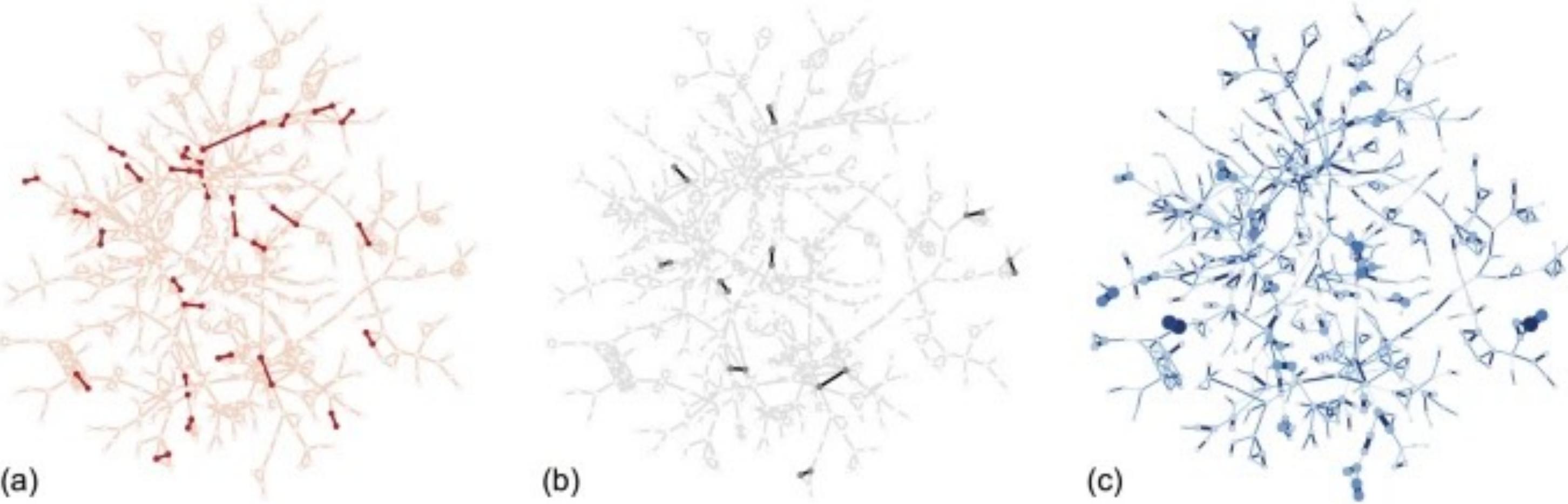
Networks change over time



Data: Stehlé J, et al. PLOS ONE
2011
Author: Petter Holme

Examples

- ▶ **Social networks:**
 - ▶ Friendships
 - ▶ Collaborations
- ▶ **Communication networks:**
 - ▶ Mobile phone data
 - ▶ Online social networks (Twitter, Facebook, etc.)
- ▶ **Mobility networks:**
 - ▶ Flights, movements
 - ▶ Animal movements



Karsai M, et al. *Scientific Reports* 2014

Definitions

Temporal network: $T=(V,S)$

V = set of nodes

S = set of event sequences assigned
to pairs of nodes

$$s_{ij} \in S : s_{ij} = \{(t_{ij}^{s,1}, t_{ij}^{e,1}) \dots (t_{ij}^{s,\ell}, t_{ij}^{e,\ell})\}$$

Alternative definition: a time dependent adjacency matrix

$$A(i,j,t) = 1 \iff i \text{ and } j \text{ connected at time } t$$

Representation

Contact sequences

Time	ID1	ID2
2	2	4
2	1	5
3	2	4
3	1	6
4	2	3
5	2	4
5	1	4
8	4	6

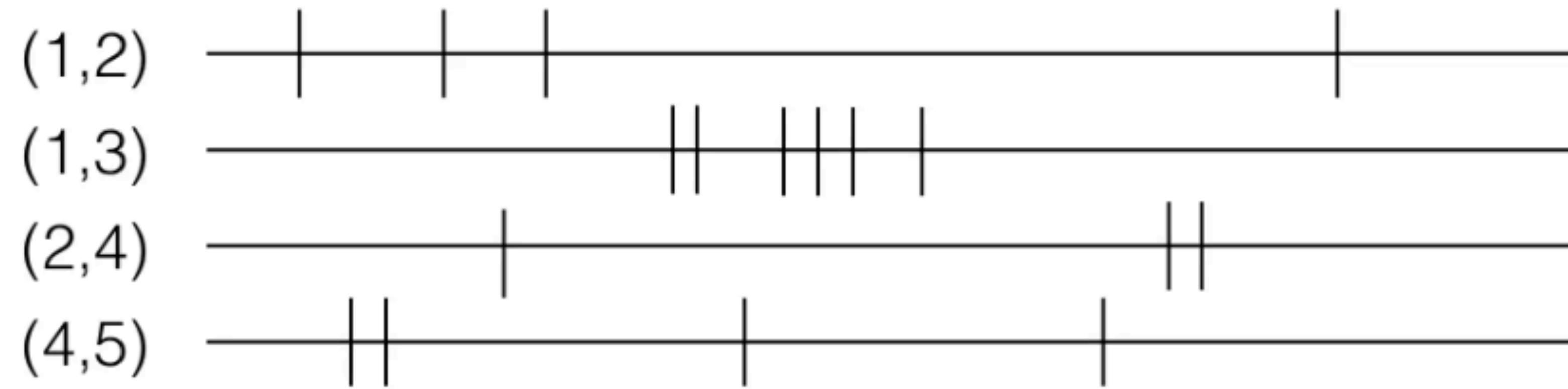
Contact intervals

ID1	ID2	Time interval
2	3	[1,5]
2	1	[2,4]
4	6	[5,9]
1	3	[7,15]
5	3	[7,9]

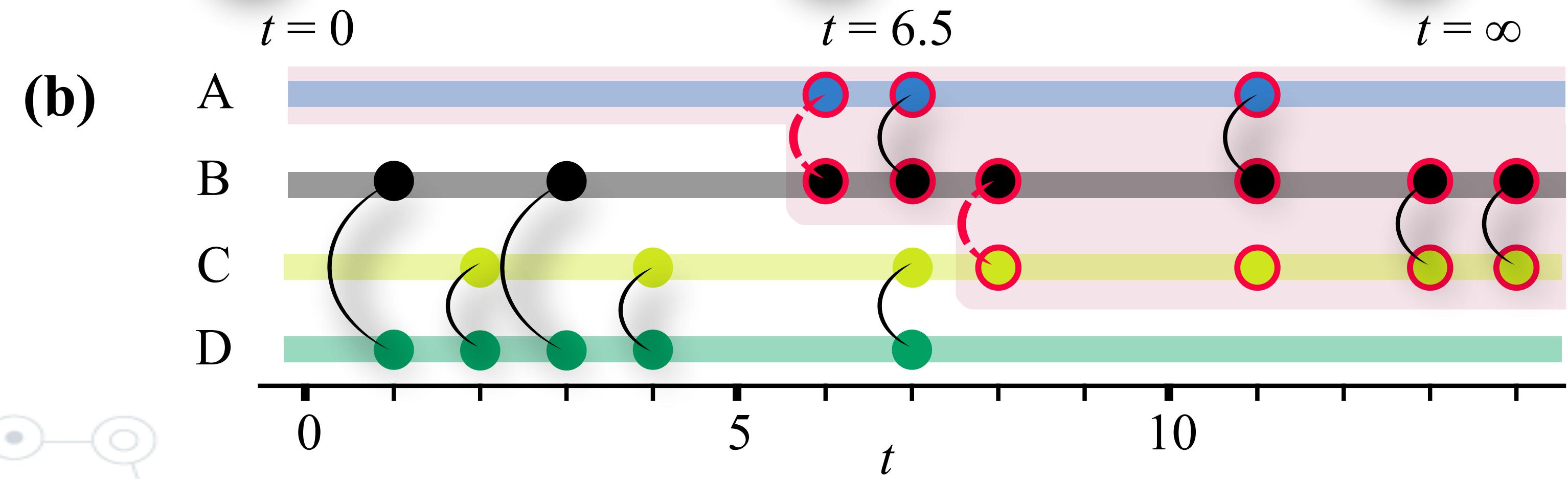
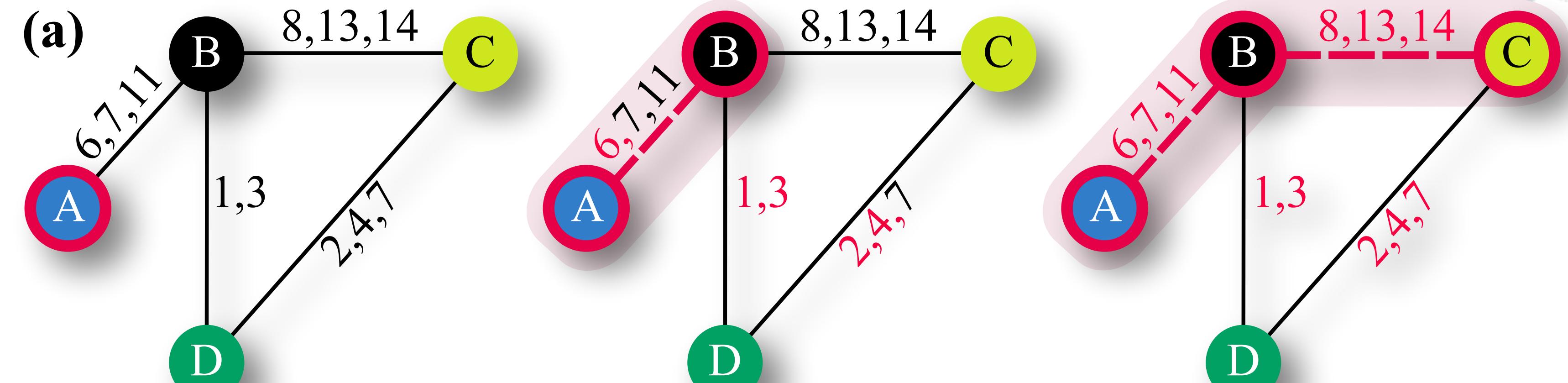
.....

Representation

Timelines of links

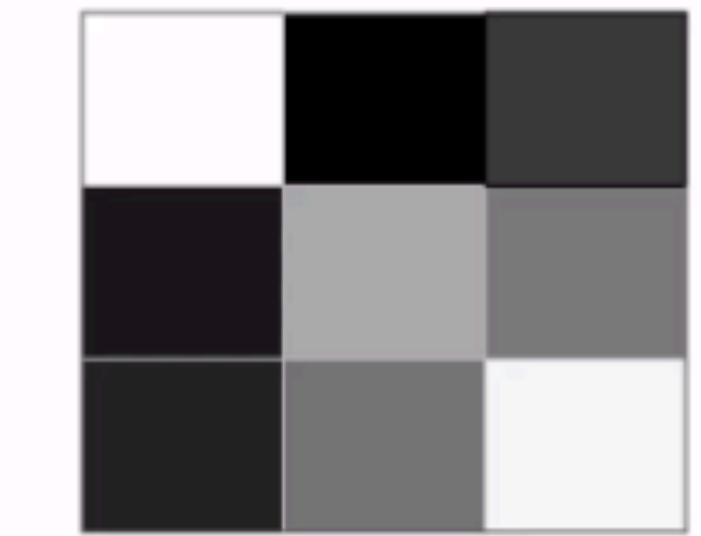
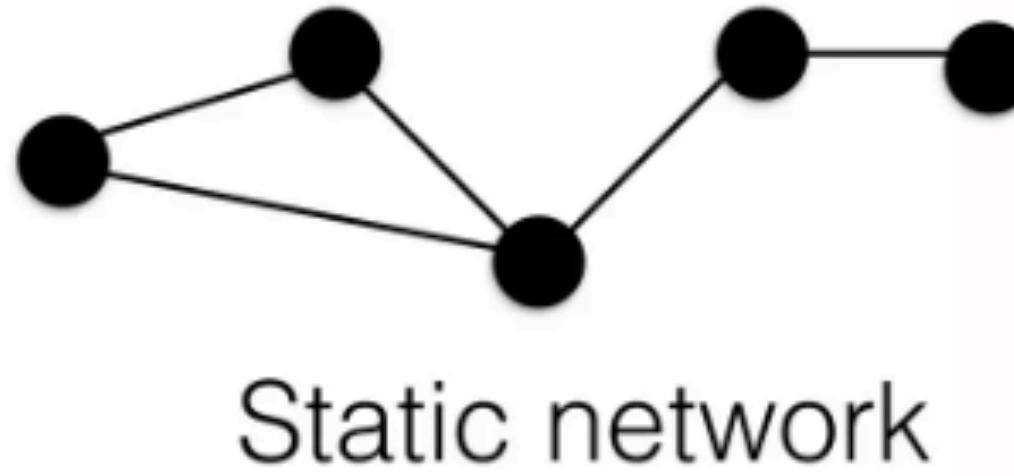
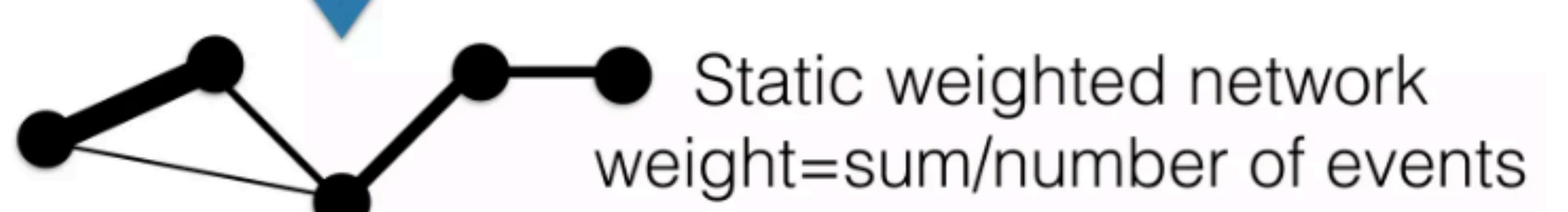


Annotated graph

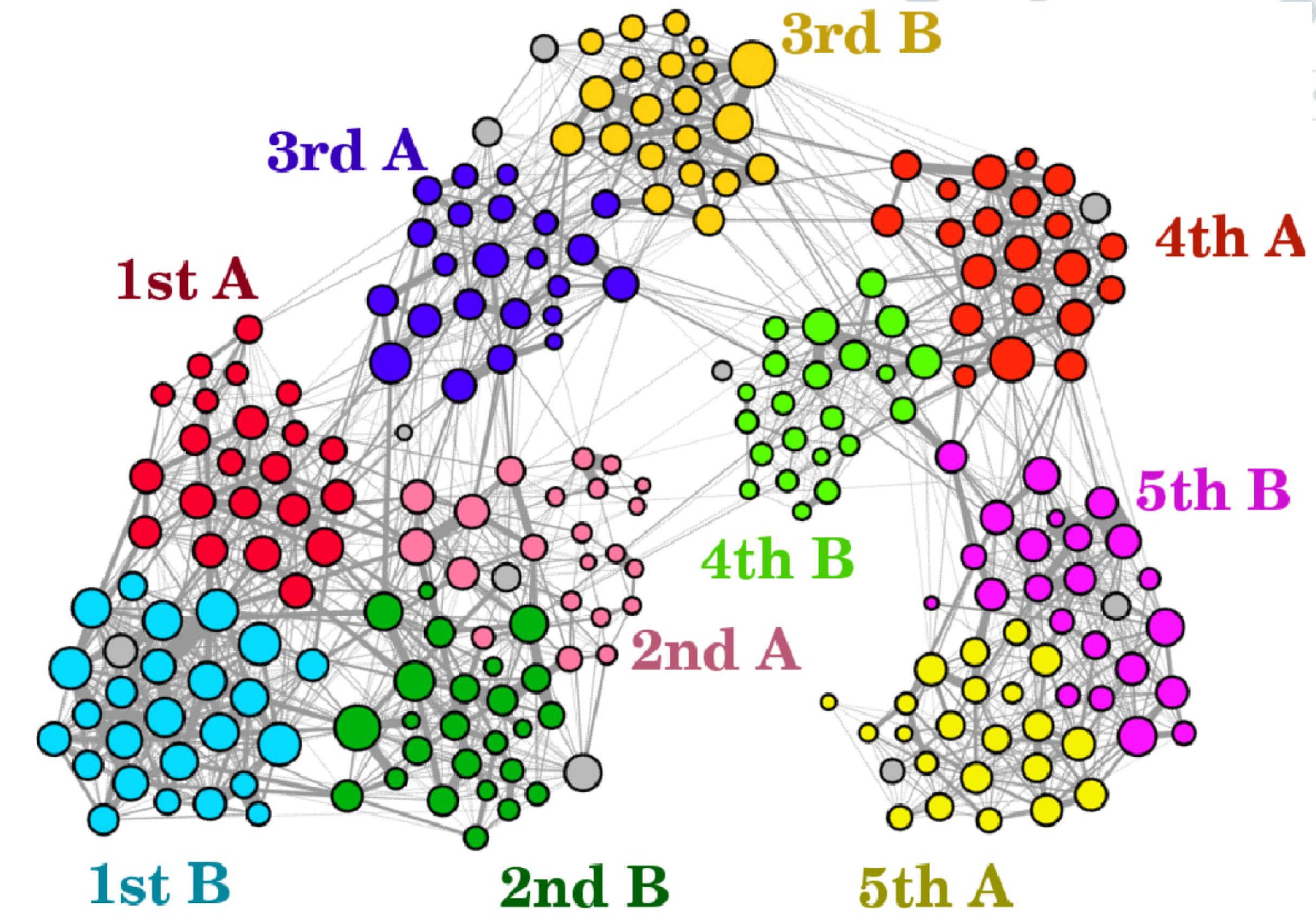
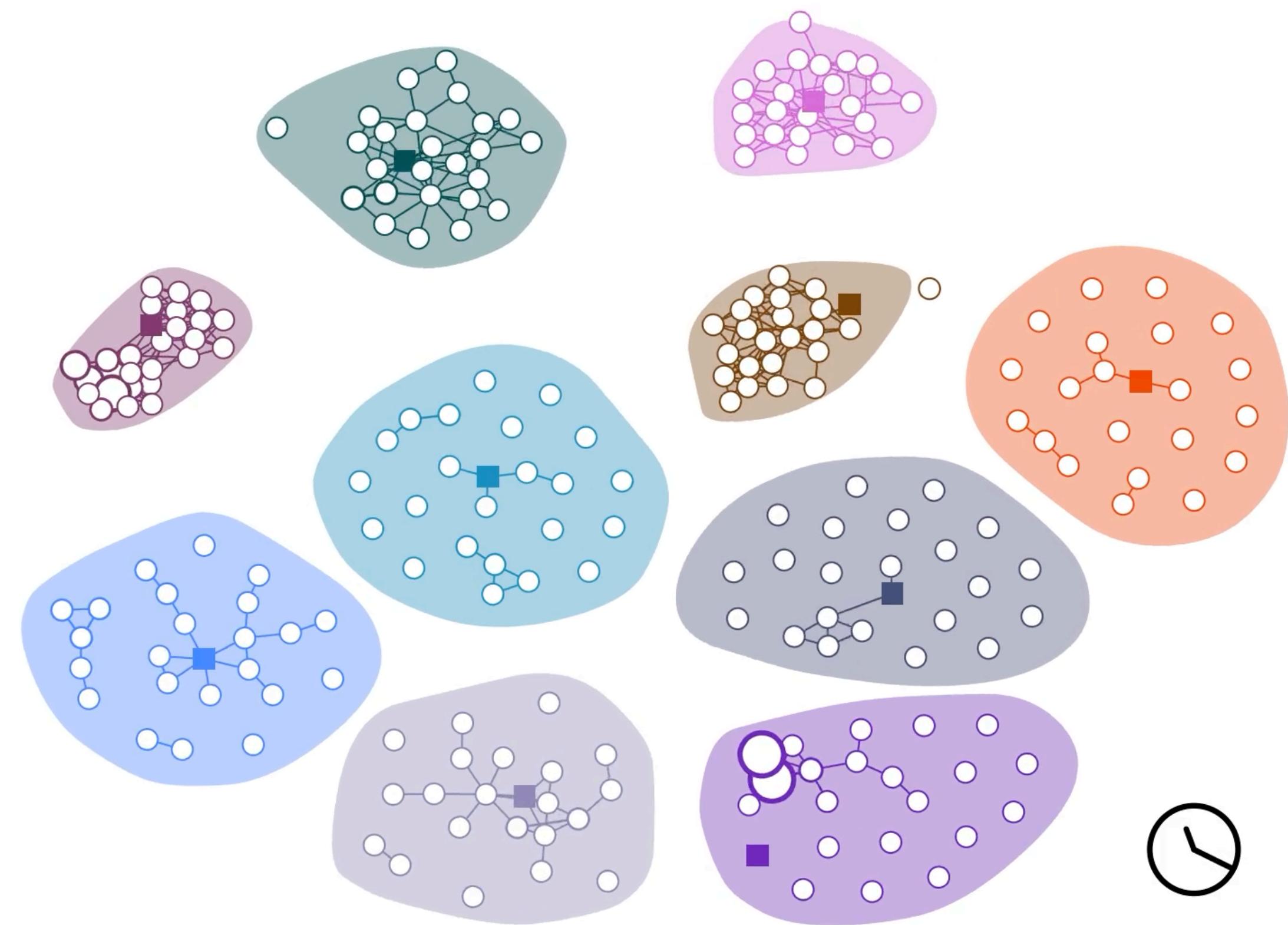


Aggregation

From **temporal** to **static**:



Aggregation

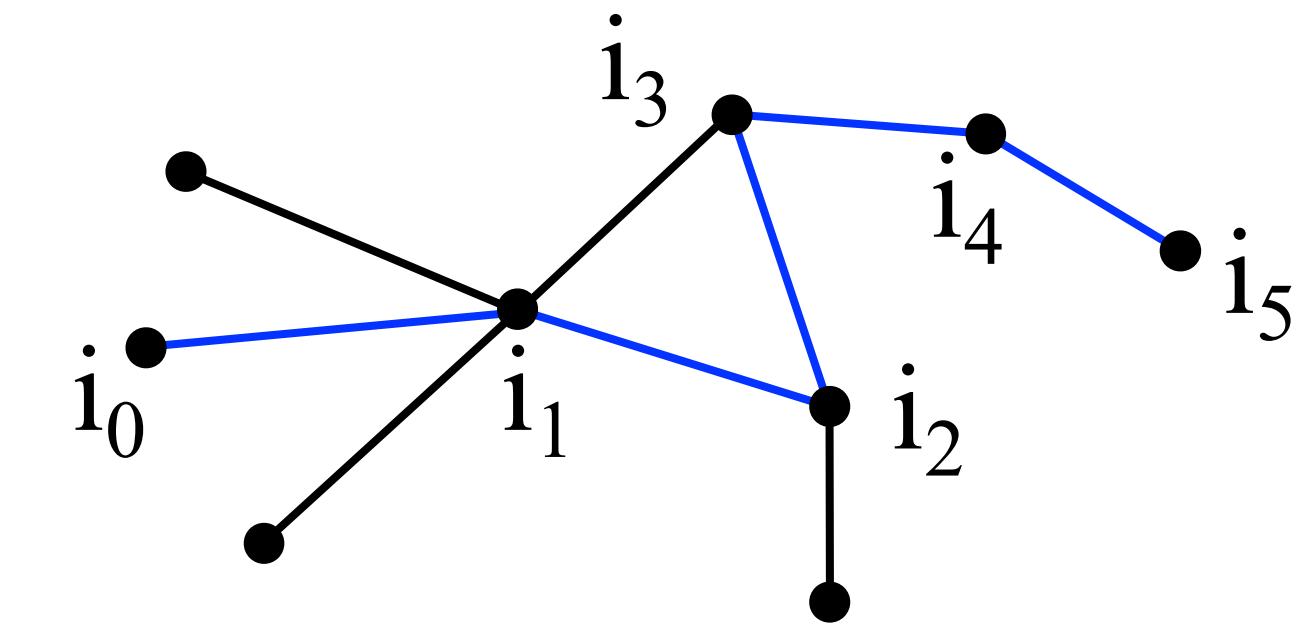


Paths in static networks

$$G=(V,E)$$

Path of length n = ordered collection of

- $n+1$ vertices $i_0, i_1, \dots, i_n \in V$
- n edges $(i_0, i_1), (i_1, i_2), \dots, (i_{n-1}, i_n) \in E$



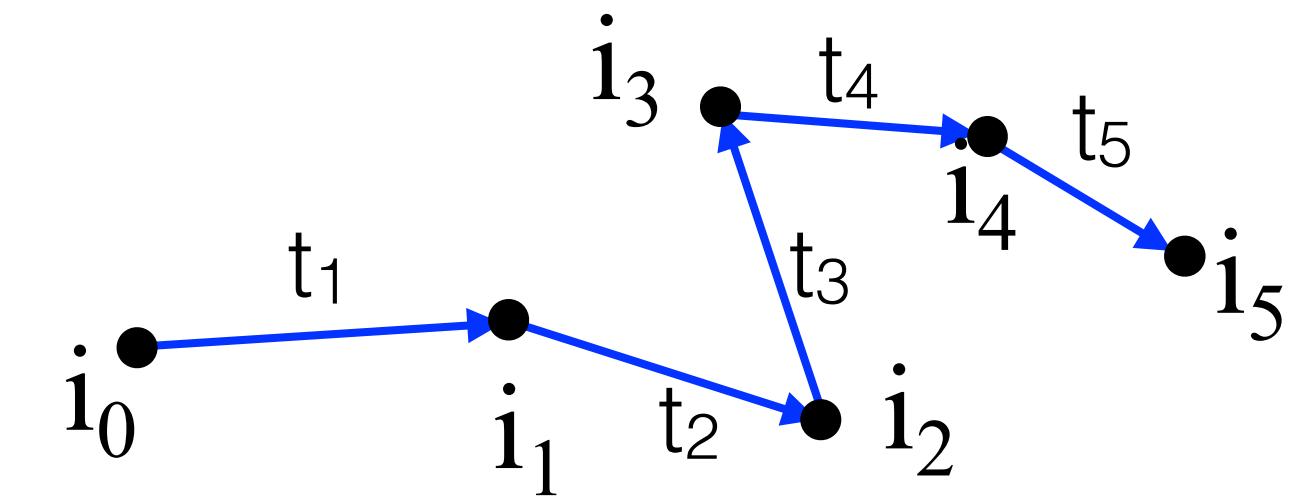
Notions of **shortest** path, of connectedness

Paths in temporal networks

Path = $\{(i_0, i_1, t_1), (i_1, i_2, t_2), \dots, (i_{n-1}, i_n, t_n) \mid t_1 < t_2 < \dots < t_n\}$

Length of path: n

Duration of path: $t_n - t_1$



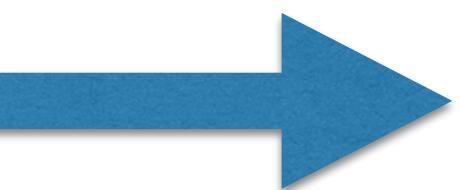
Sequence of **events**



Notions of **shortest** path and of **fastest** path

Reachability

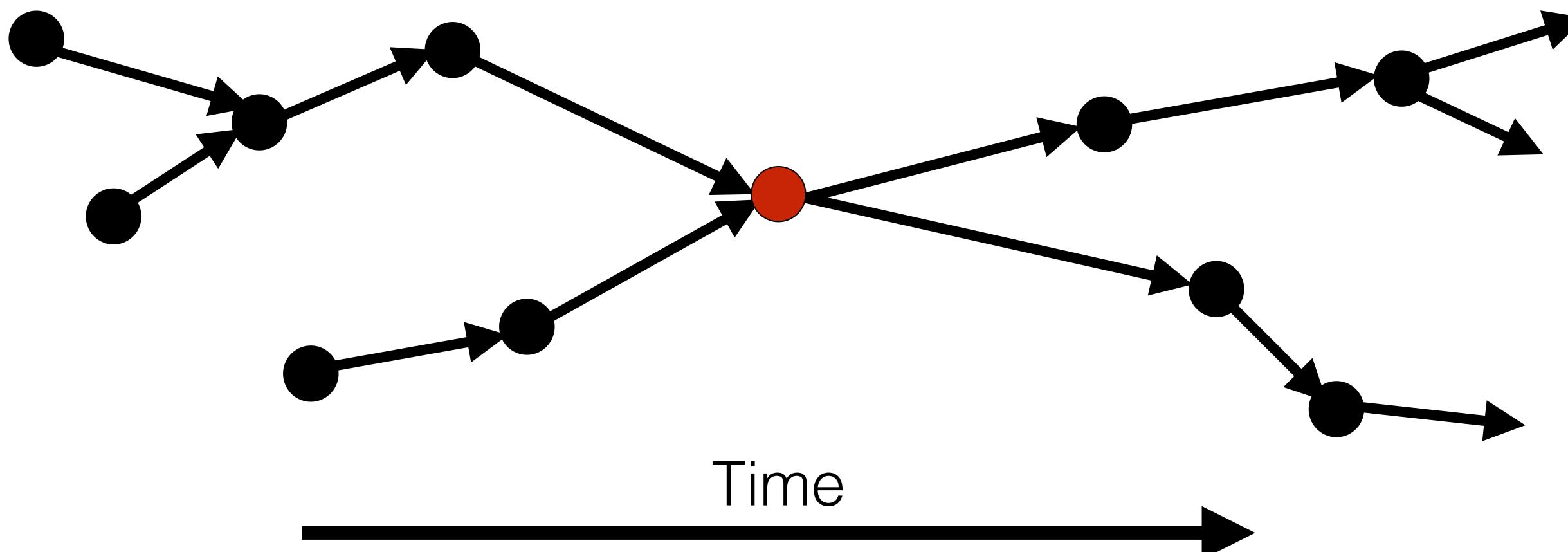
Node i at time t



“Light cone”

Source set:
set of nodes that
can reach i at time t

Reachable set:
set of nodes that
can be reached from i
starting at time t



Paths in temporal networks

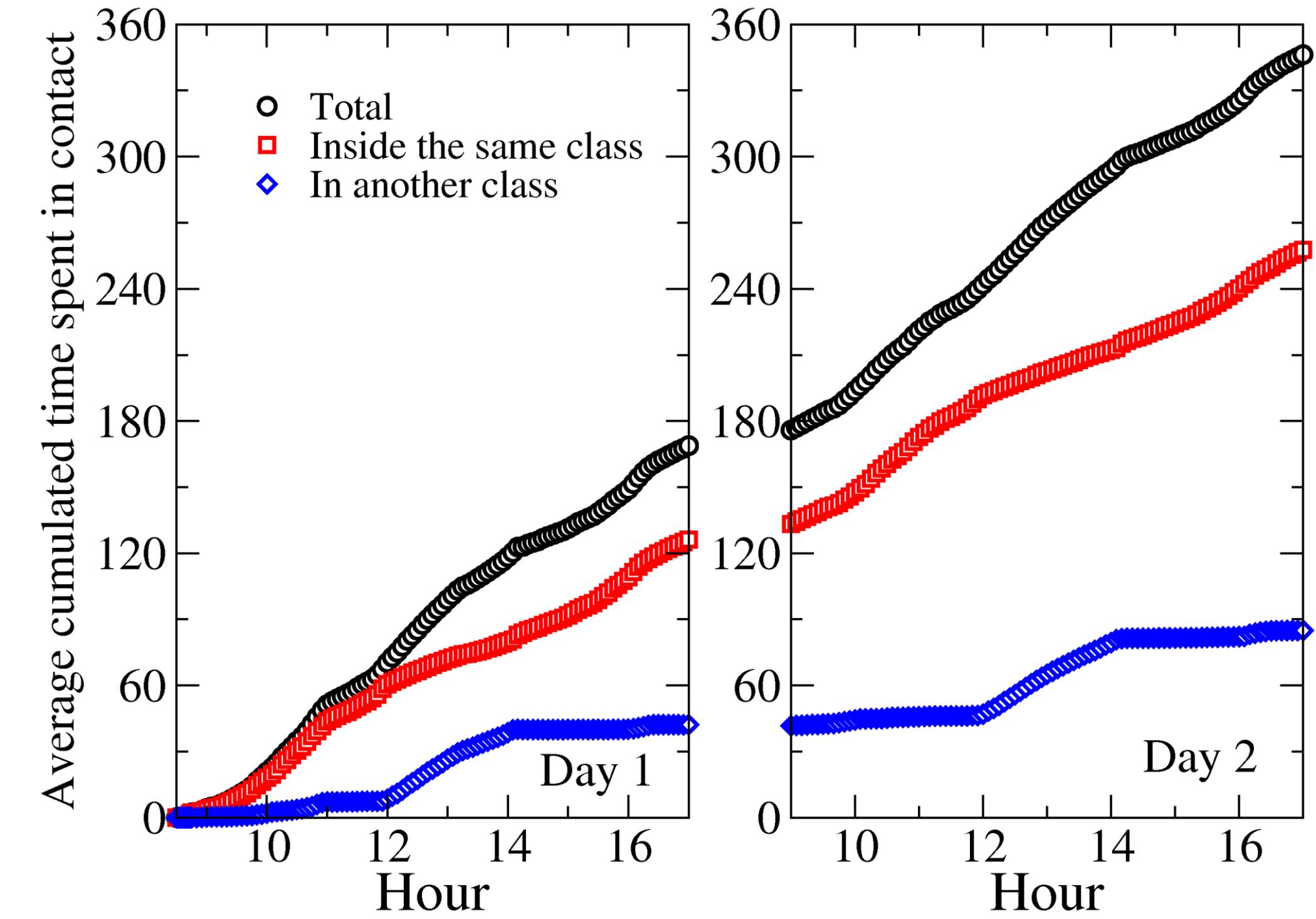
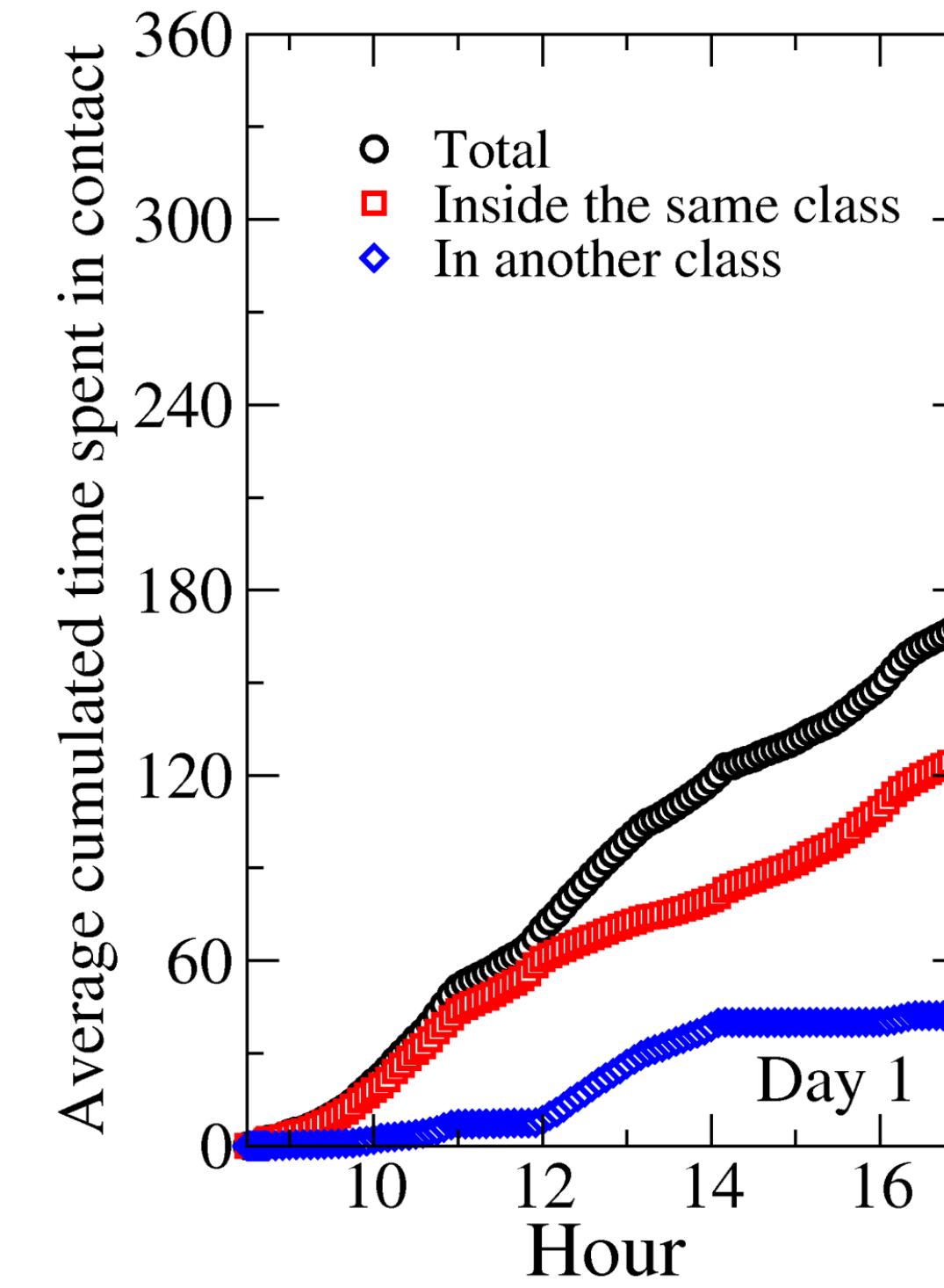
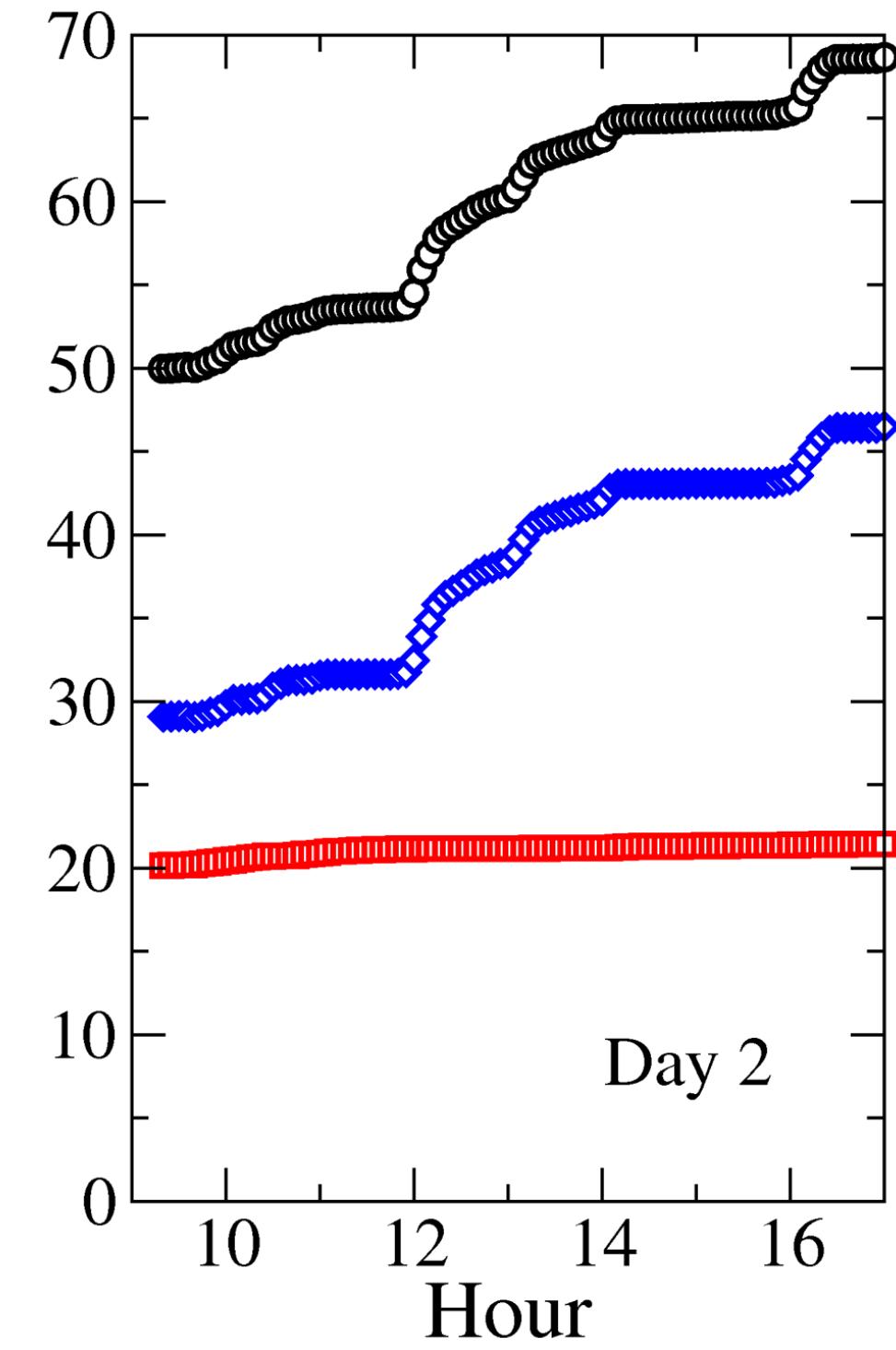
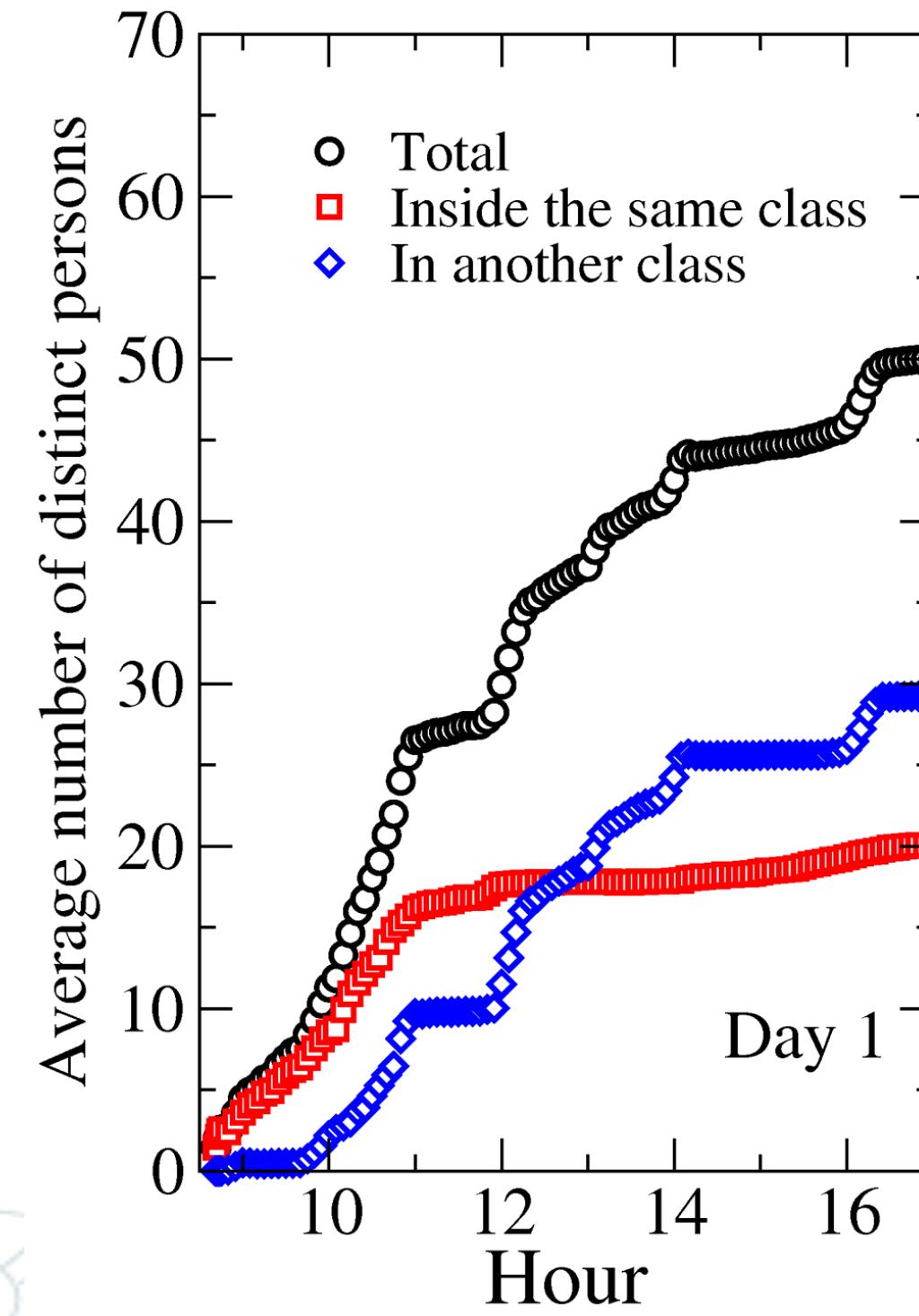
- **Not always reciprocal:** the existence of a path from i to j does not guarantee the existence of a path from j to i
- **Not always transitive:** the existence of paths from i to j and from j to k does not guarantee the existence of a path from i (to j) to k
- **Time-dependence:**
 - there can be a path from i to j starting at t but no path starting at $t' > t$
 - shortest and fastest paths can differ
 - length of shortest path can depend on starting time
 - duration of fastest path can depend on starting time
 - there can be a path starting from i at t_0 , reaching j at t_1 , and another path starting from i at $t'_0 > t_0$ reaching j at $t'_1 > t_1$, with $t'_1 - t'_0 < t_1 - t_0$ (i.e., smaller duration but arriving later), and/or of shorter length (smaller number of hops)

Structure in static networks

- ▶ Degree distribution $P(k)$
- ▶ Clustering coefficient (of nodes of degree k)
- ▶ Average degree of nearest neighbours k_{nn}
- ▶ Communities
- ▶ Distribution of link weights $P(w)$
- ▶ Distribution of node strengths $P(s)$
- ▶

Structure in temporal networks

- Properties of networks aggregated on different time windows: $P(k)$, $P(w)$, $P(s)$, etc...
- Evolution of averaged properties when time window length increases: $\langle k \rangle(t)$, $\langle s \rangle(t)$

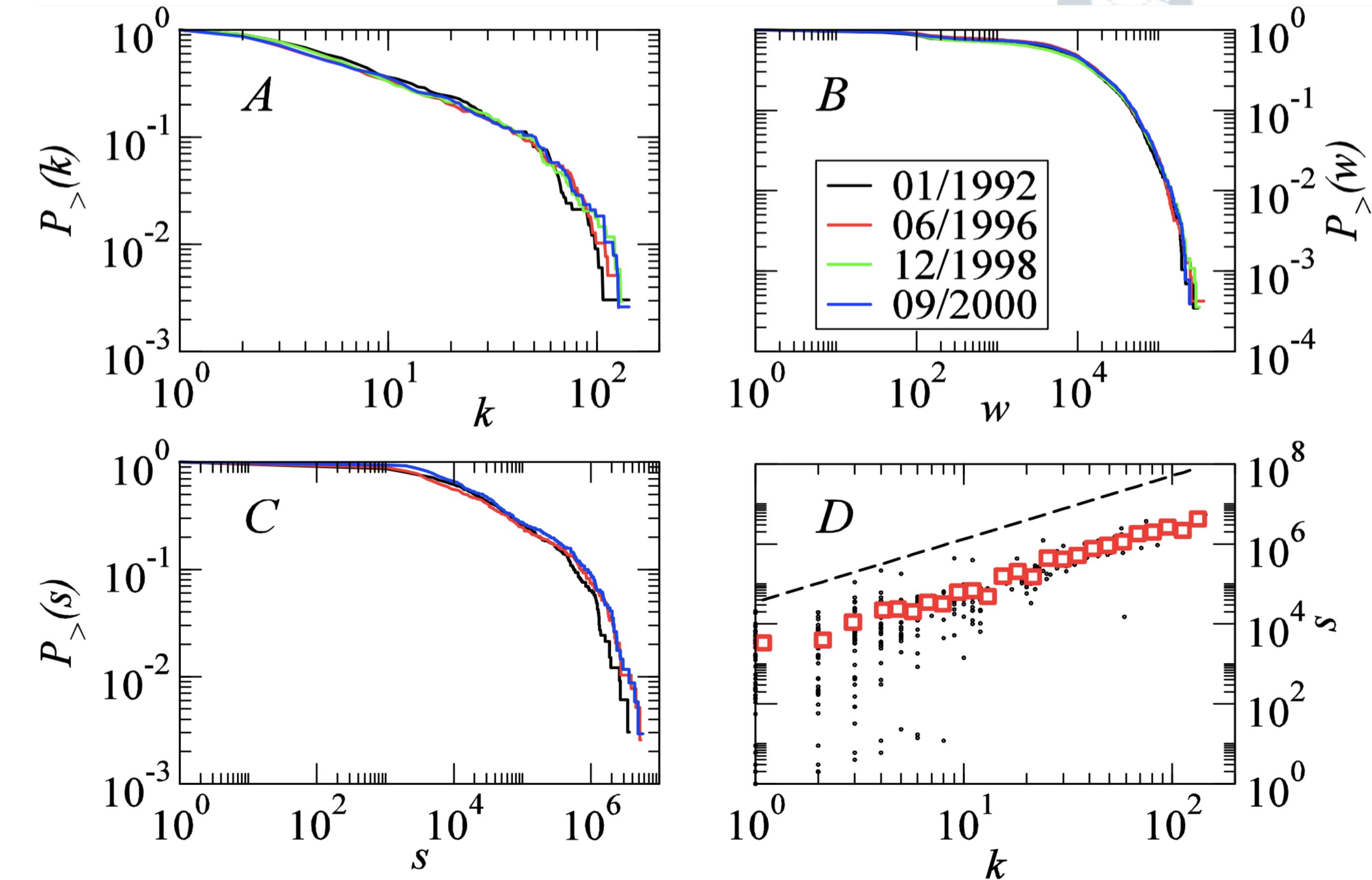


Structure in temporal networks

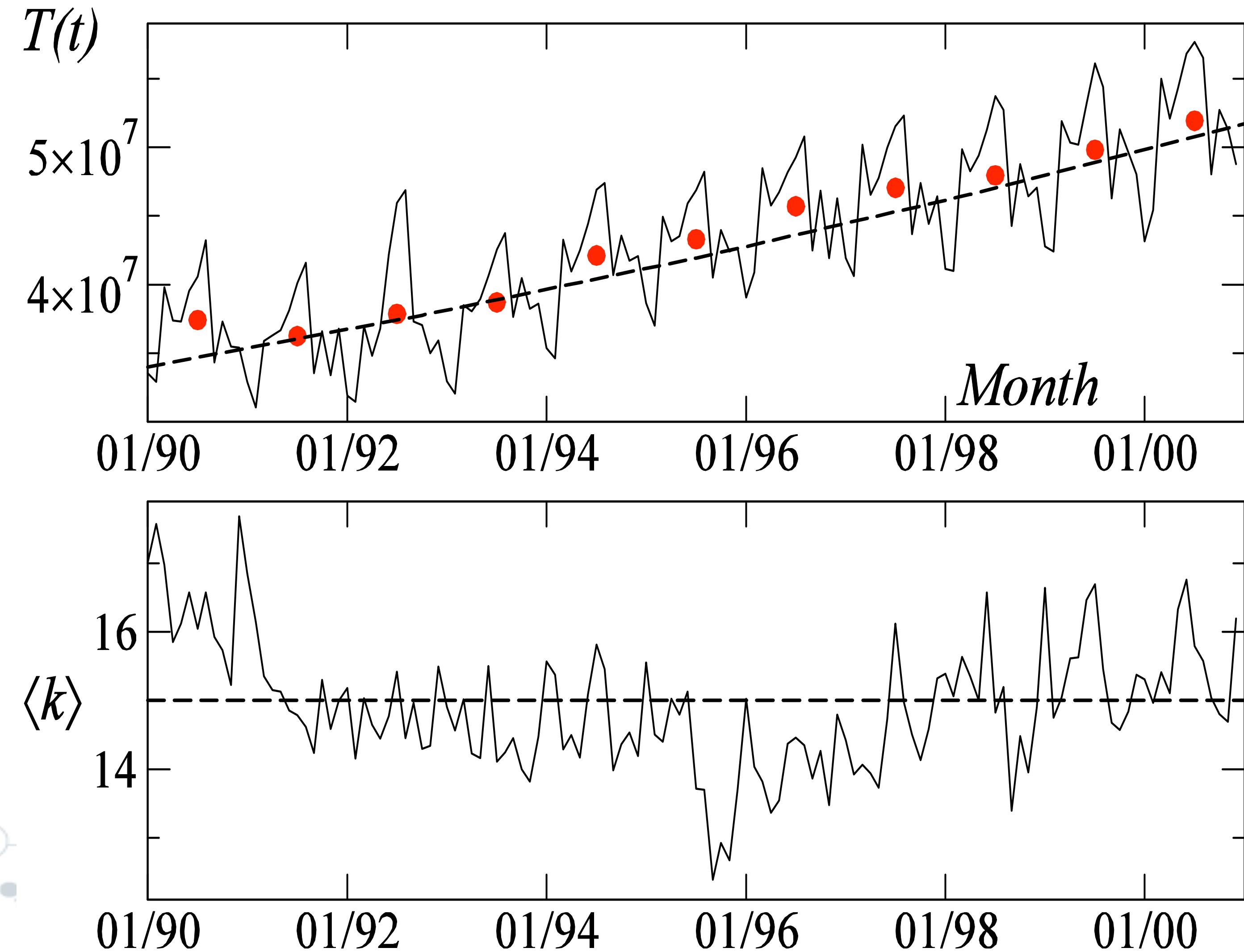
- ▶ Temporal statistical properties:
 - distribution of contact numbers $P(n)$,
 - distribution of contact durations $P(\tau)$,
 - distribution of inter-contact times $P(\Delta t)$ for nodes and links
- ▶ Stationarity of distributions
- ▶ (Non-)stationarity of activity
- ▶ **Burstiness**

Example: US airport network

Stationarity of distributions



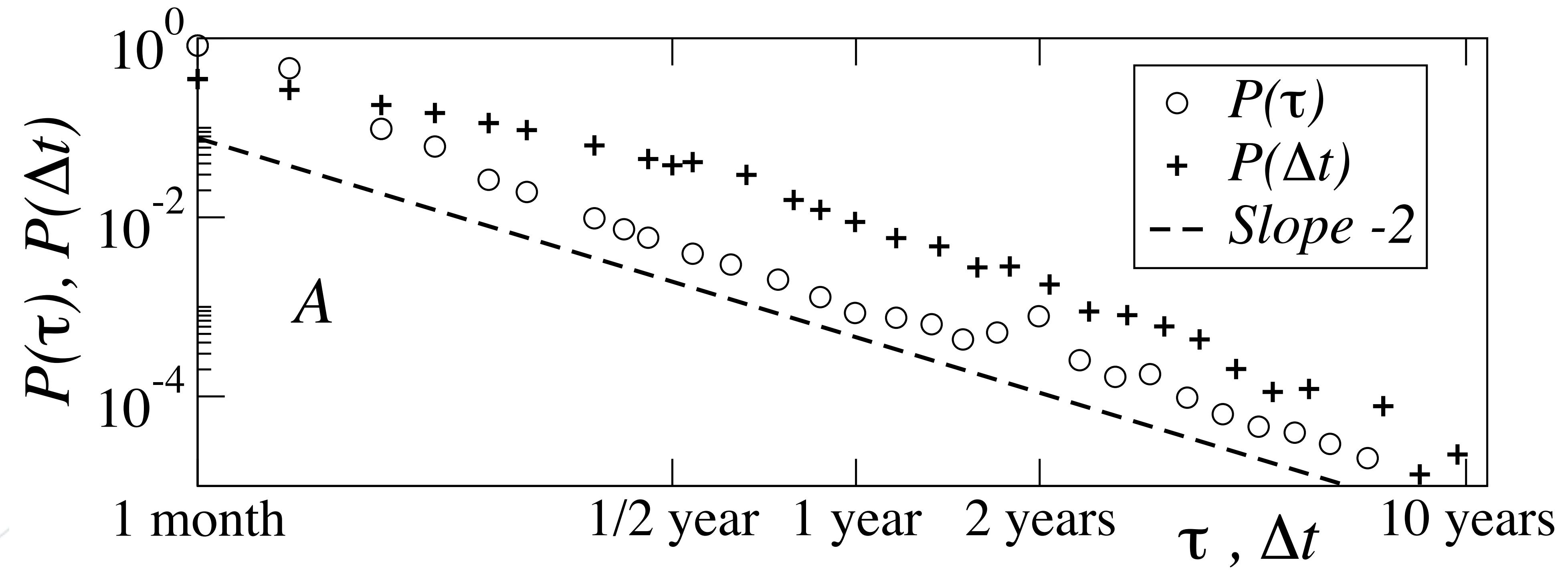
Example: US airport network



Example: US airport network

τ = duration of a link

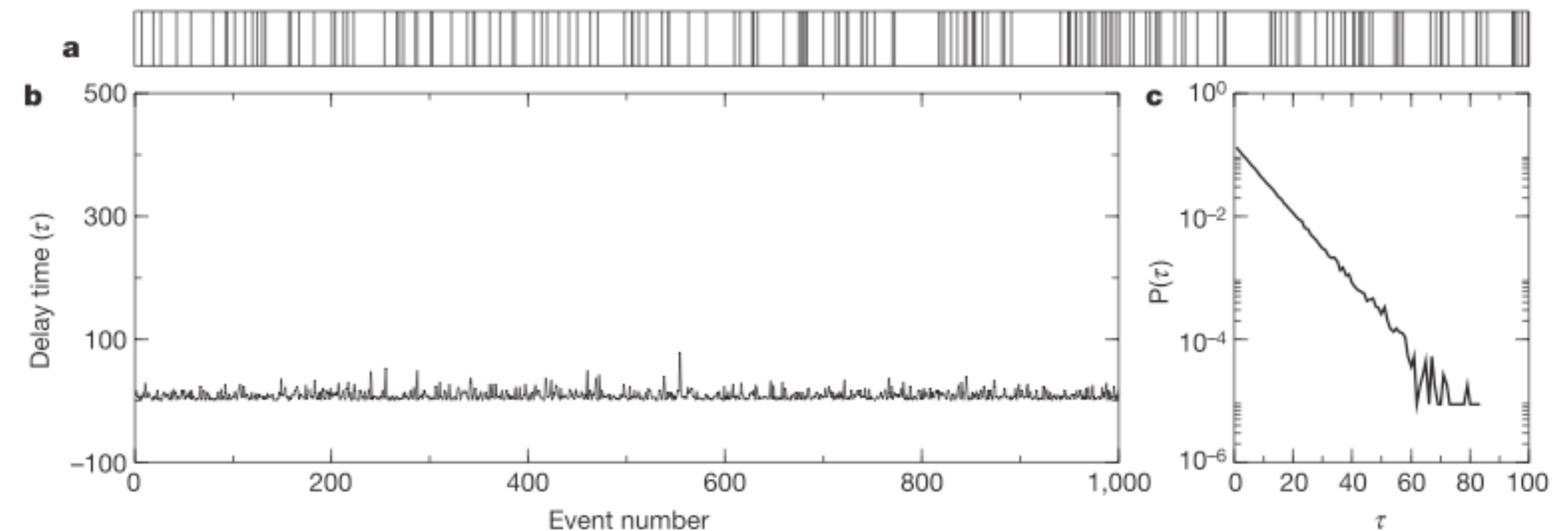
Δt = interval between active periods of a link



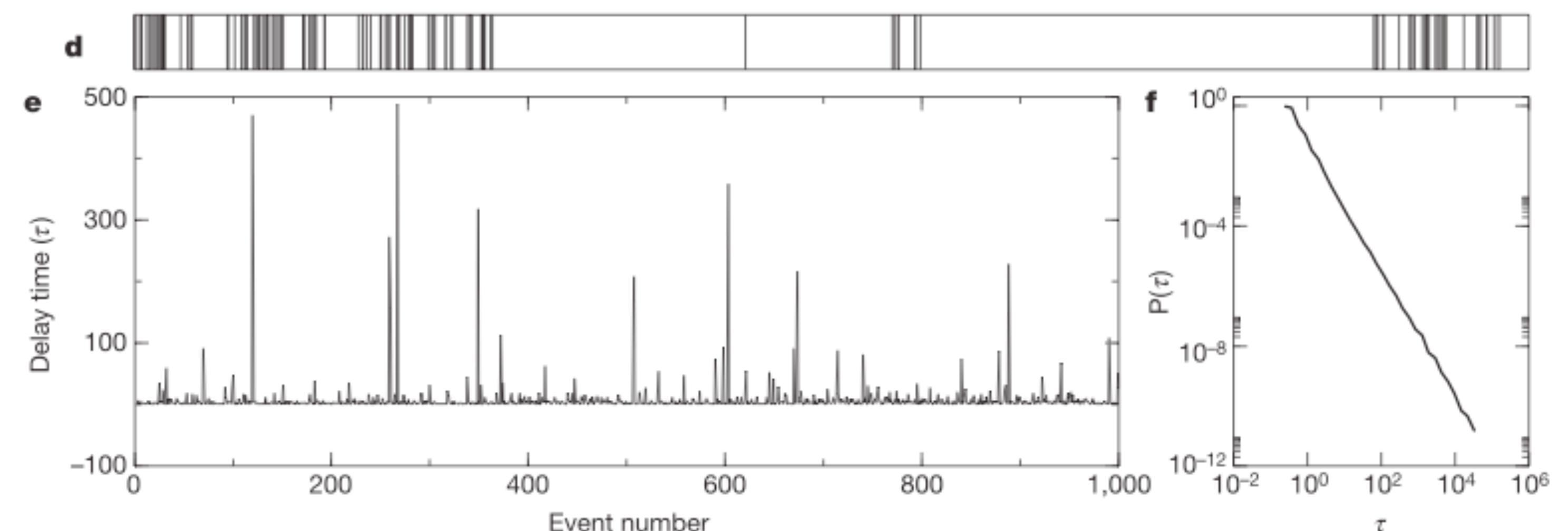
Burstiness

A.-L. Barabási, Nature (2005)

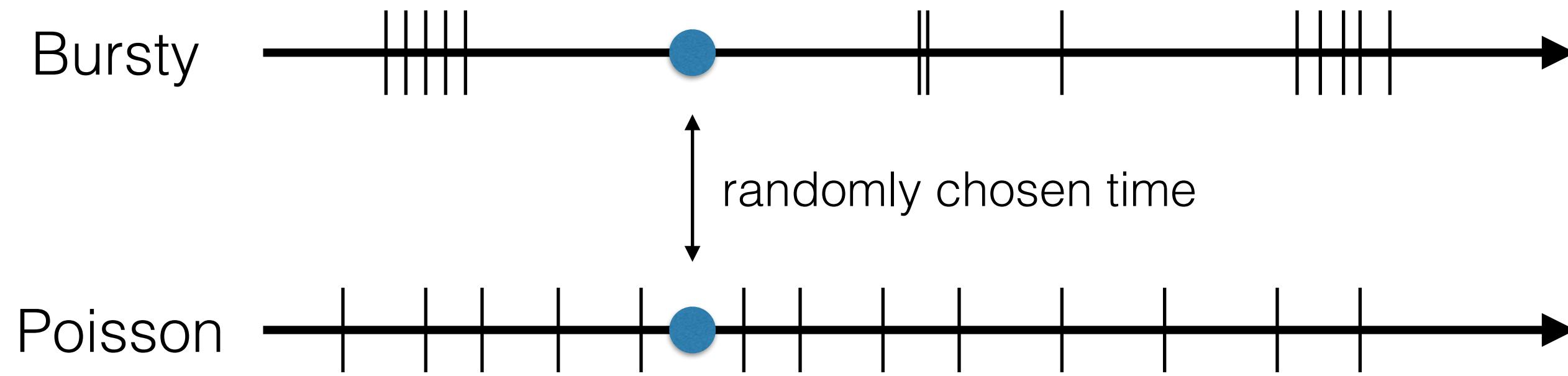
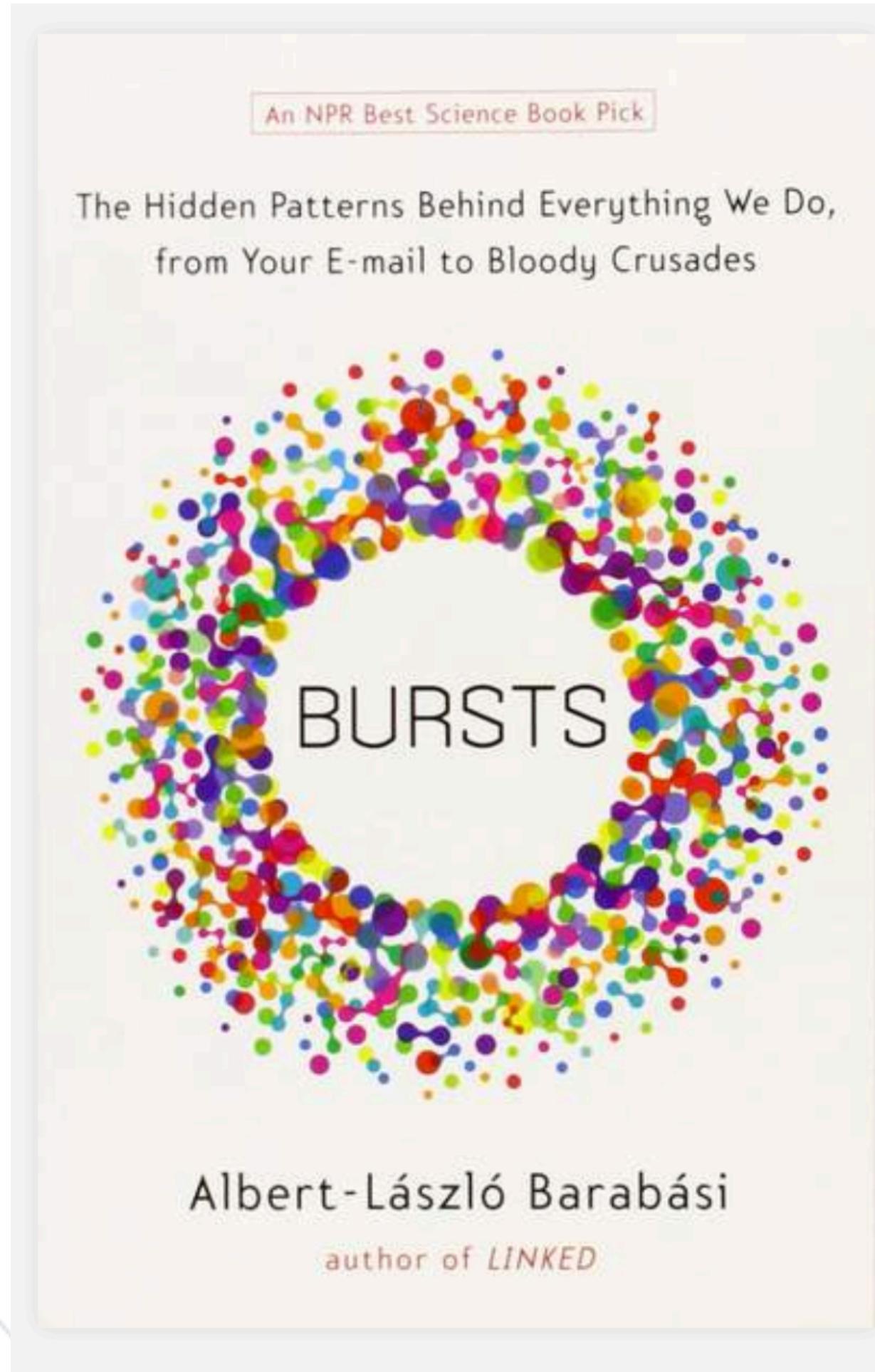
► Poisson process



► Bursty behaviour



Consequences of burstiness



- ▶ Bursty timeline implies larger waiting time with higher probability
- ▶ It typically implies a slower diffusion (if no correlations)

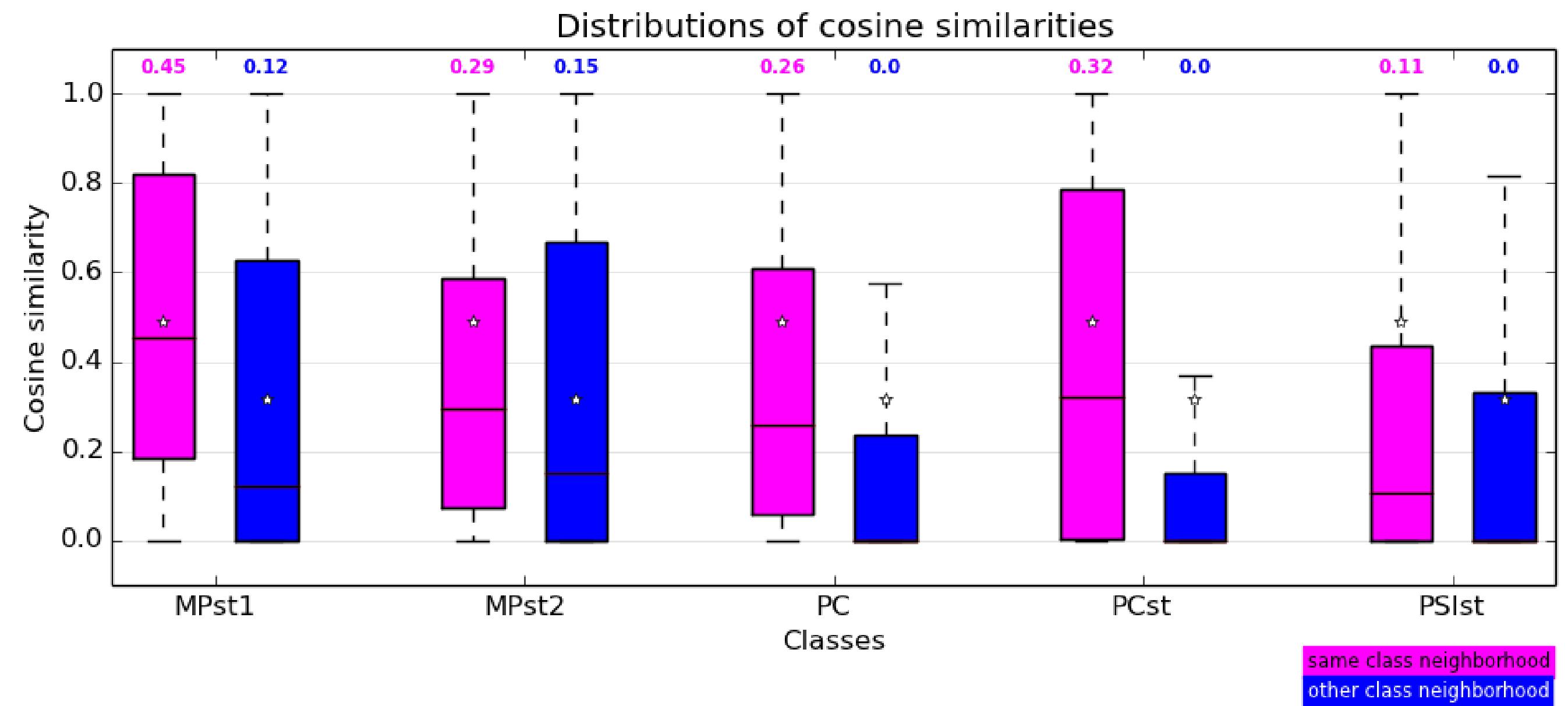
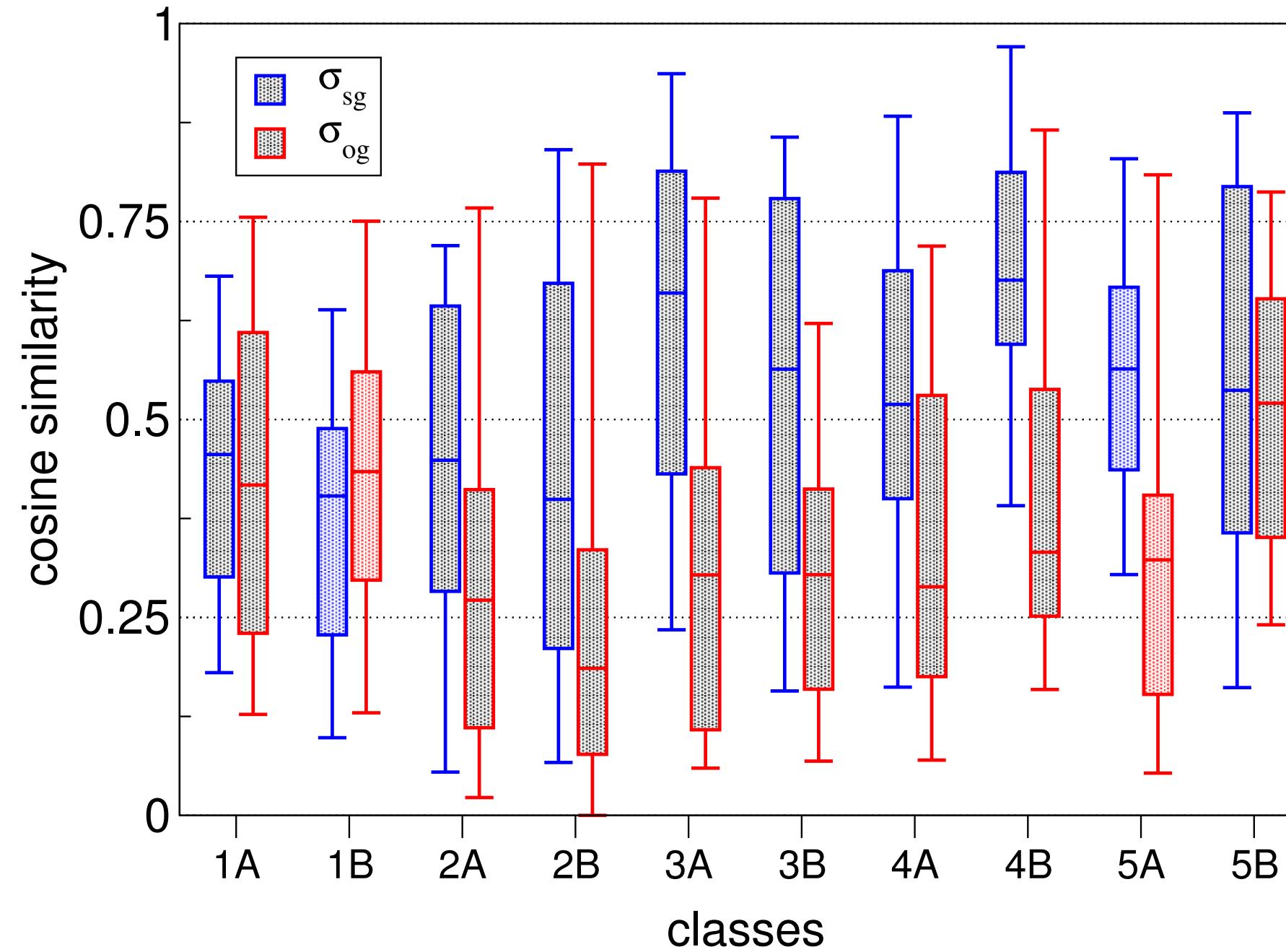
Structure: persisting patterns

Compare successive snapshots or time-aggregated networks:

- correlation between (weighted) adjacency matrices
- correlation between contact matrices
- **local similarity** of neighbourhoods

$$\sigma_i = \frac{\sum_j w_{ij,(1)} w_{ij,(2)}}{\sqrt{\sum_j w_{ij,(1)}^2 \sum_{i,j} w_{ij,(2)}^2}}$$

Persistence of patterns



Example: contacts in a high school, neighbourhood similarities between different days, classes and genders

Are these differences significant? **Need to compare with a null model!**

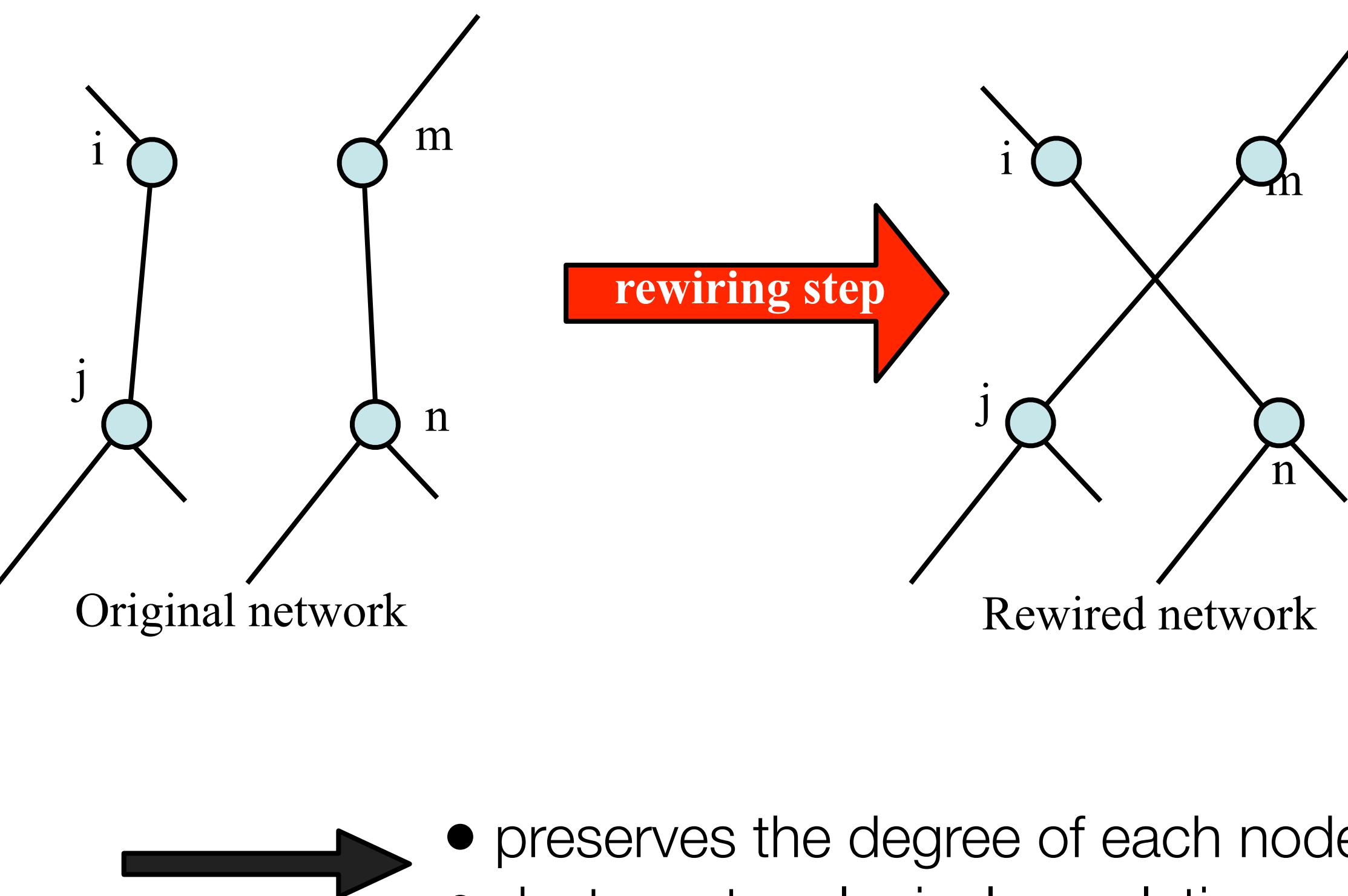
Null models

- ensemble of instances of **randomly built** systems
- that **preserve** some properties of the studied systems

Aim:

- understand which properties of the studied system are simply random, and which ones denote an underlying mechanism or organizational principle
- compare measures with the known values of a random case

In static networks:
Configuration model / rewiring links preserving the degree of each node



Null models in temporal graphs

Random times:

for each link event: pick time at random



keeps:

- link structure
- number of events per link
- corresponding static correlations

destroys:

- global time ordering
- activity timeline
- burstiness
- all temporal correlations

Time shuffling:

shuffle time of events

ID1	ID2	time
1	4	2
2	3	8
1	5	12
3	4	15
.....		



ID1	ID2	time
1	4	8
2	3	15
1	5	2
3	4	12
.....		

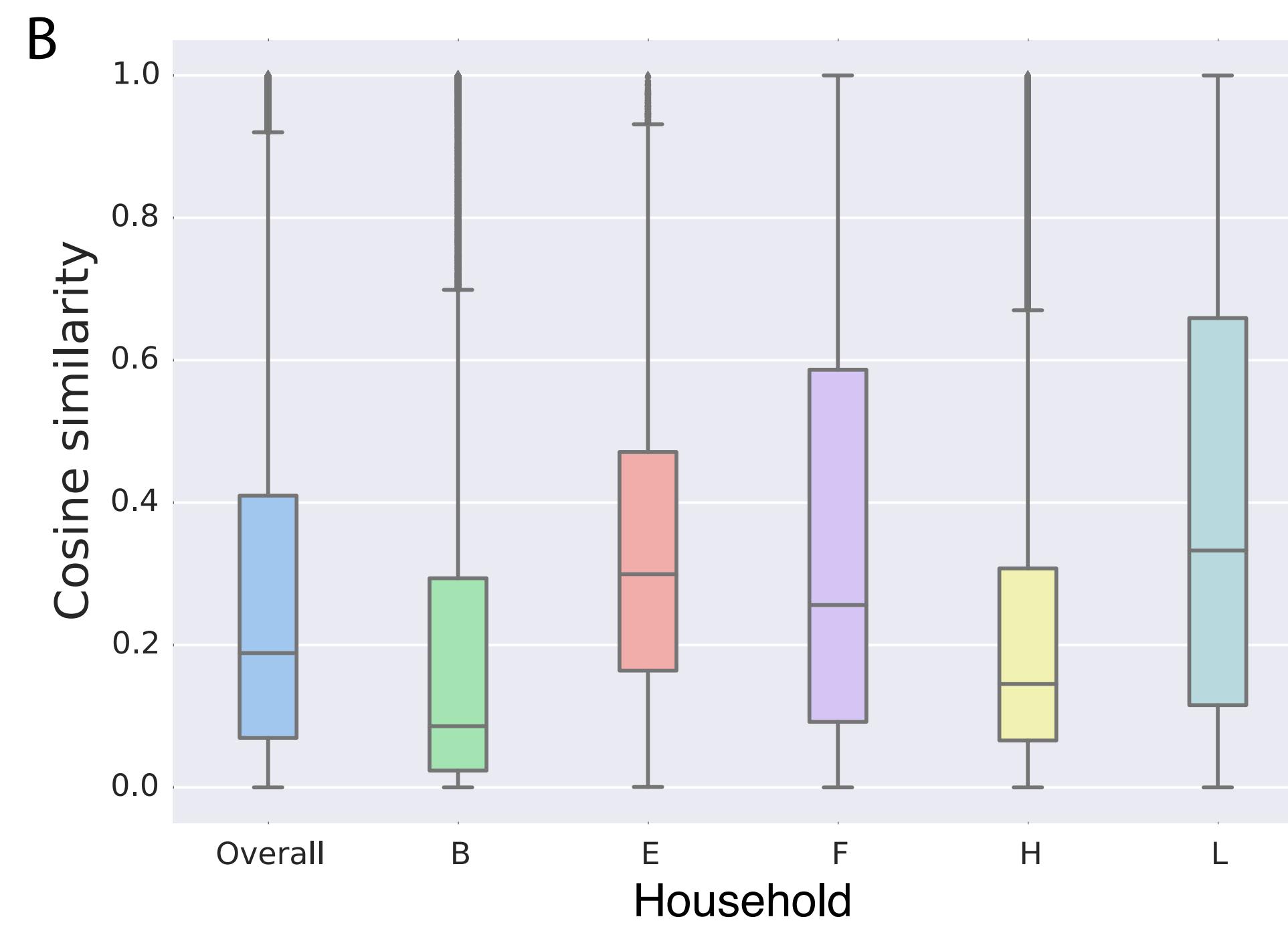
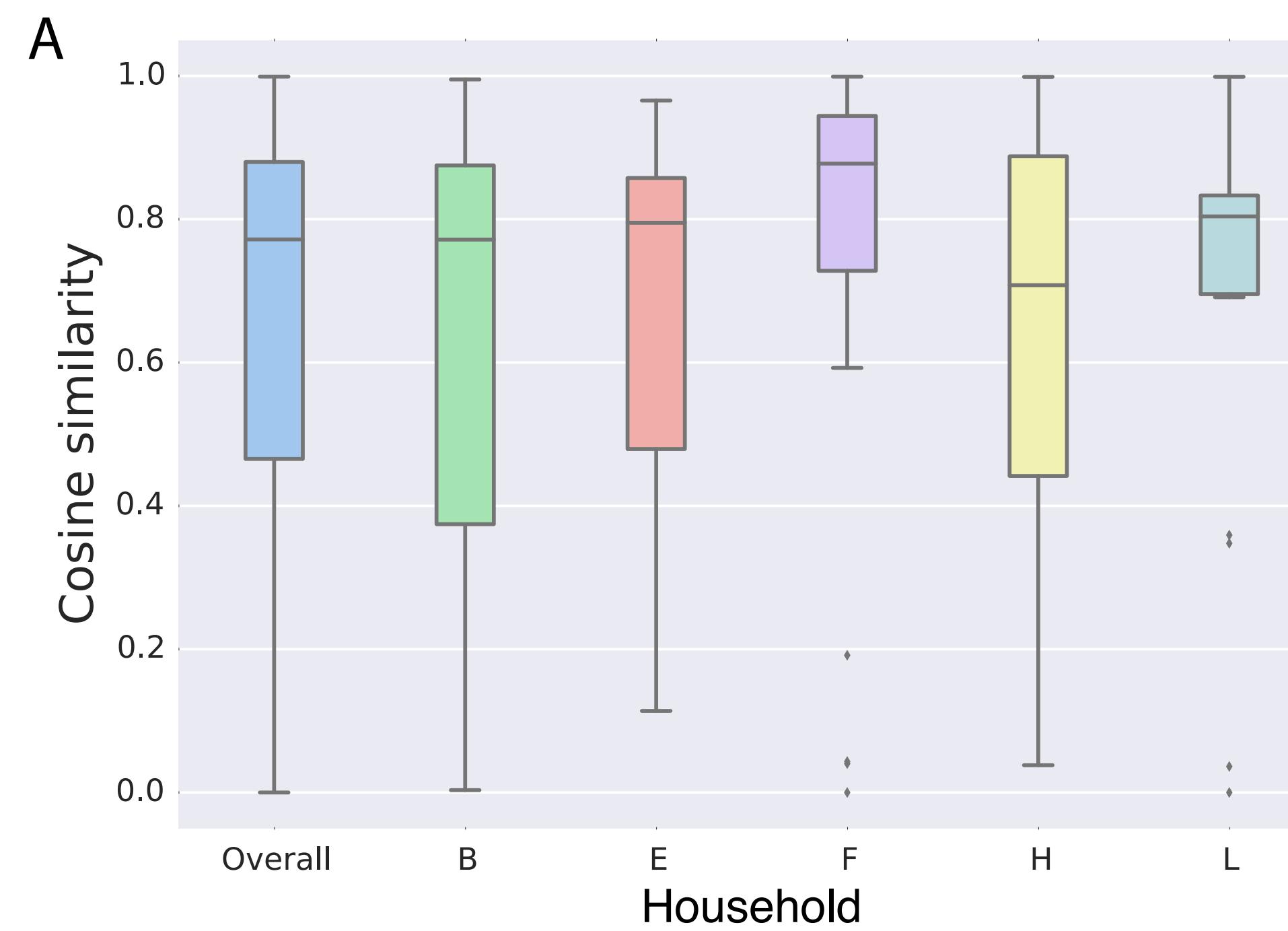
keeps:

- link structure
- number of events per link
- corresponding static correlations
- global activity timeline

destroys:

- interevent times
- all temporal correlations

Example: household contacts



Measured contact network

Null model

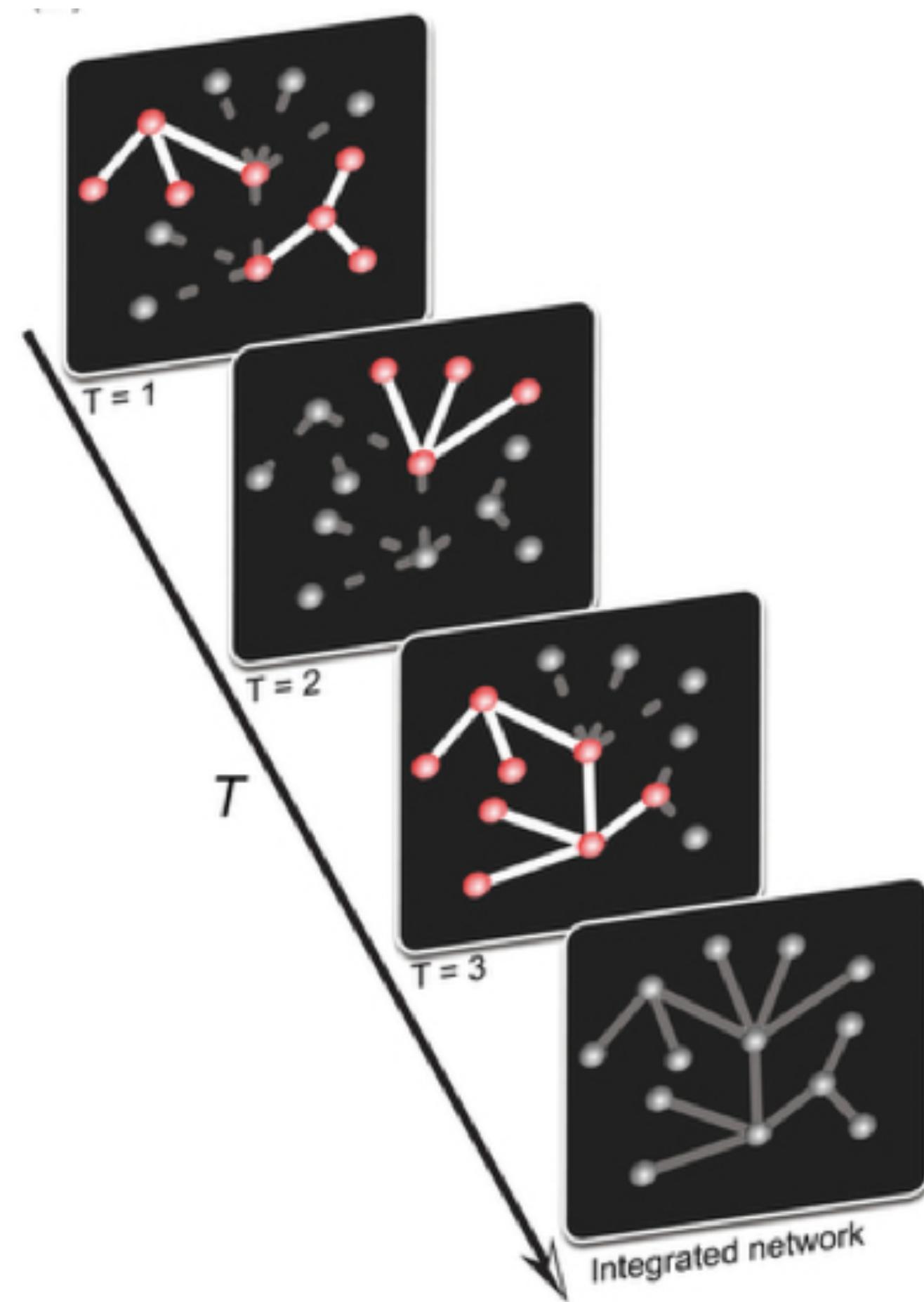
Activity driven model

Model: N nodes, each with an “activity” a , taken from a distribution $F(a)$

At each time step:

- ▶ node i active with probability $a(i)$
- ▶ each active node generate m links to other randomly chosen nodes
- ▶ iterate with no memory

No memory, no correlations...
“Toy” model allowing for analytical computations

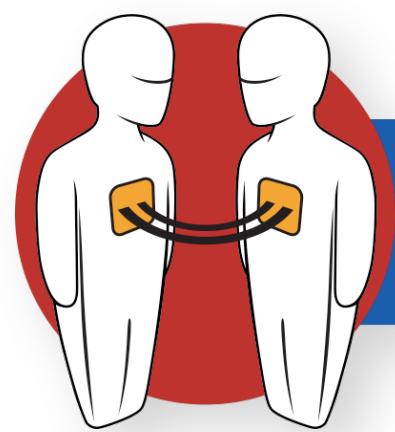


Activity driven modeling of time varying networks

Data and epidemiology

Sociopatterns

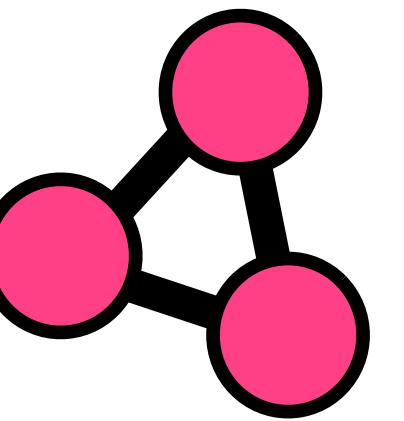
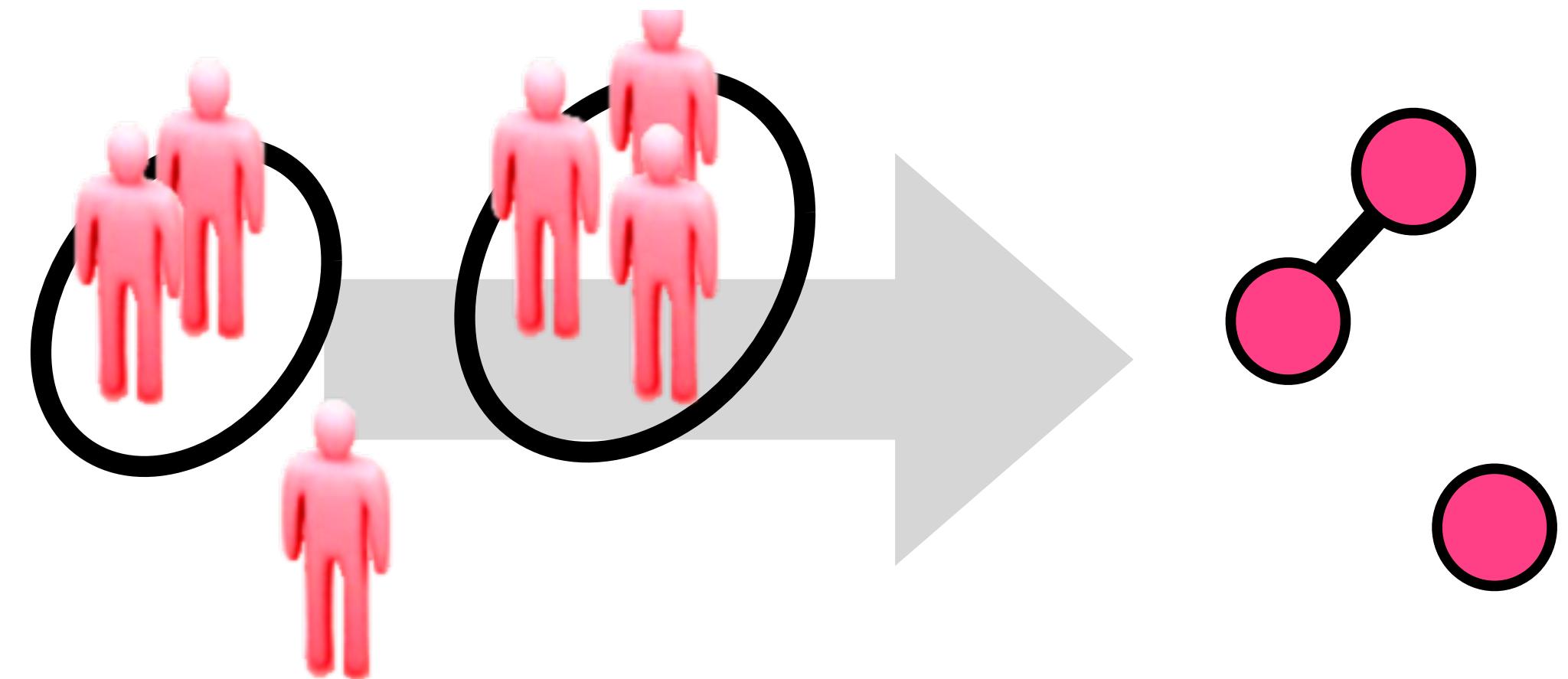
what are the statistical and **dynamical** properties of the networks of contact and co-presence of people in social interaction?
(fine-grained spatial ($\sim m$) and temporal (<min) resolution)



SocioPatterns.org

Motivations

- ★ fundamental knowledge on human contact
- ★ epidemiology
- ★ social sciences
- ★ ad-hoc networks
- ★ integration with on-line information
- ★ ...

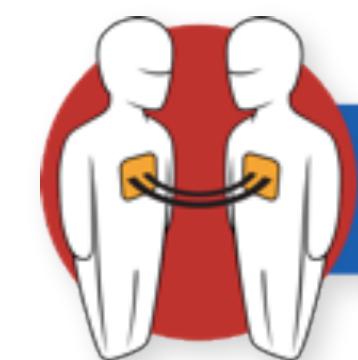


Sociopatterns

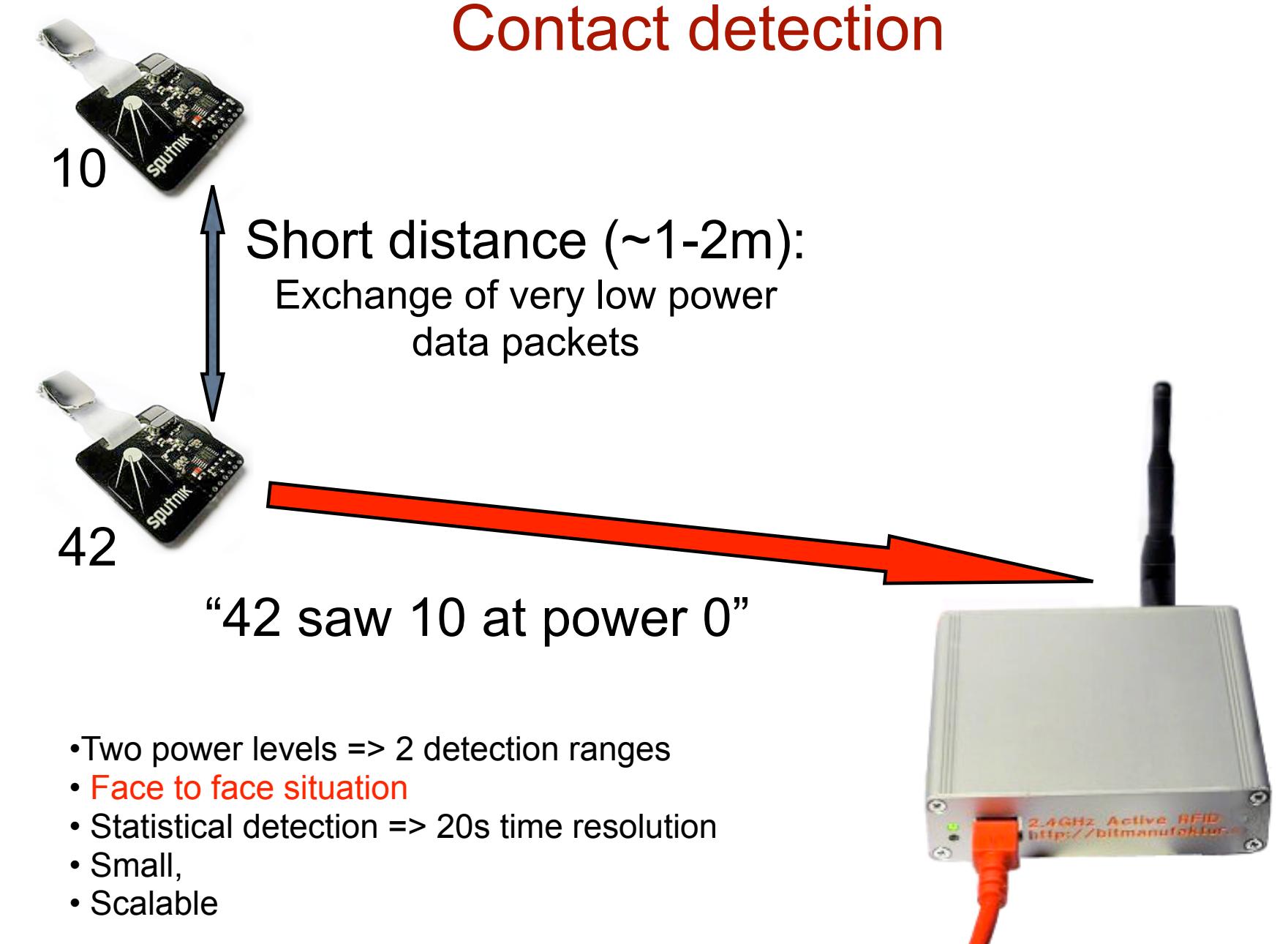
wearable proximity sensors



openbeacon.org



SocioPatterns.org



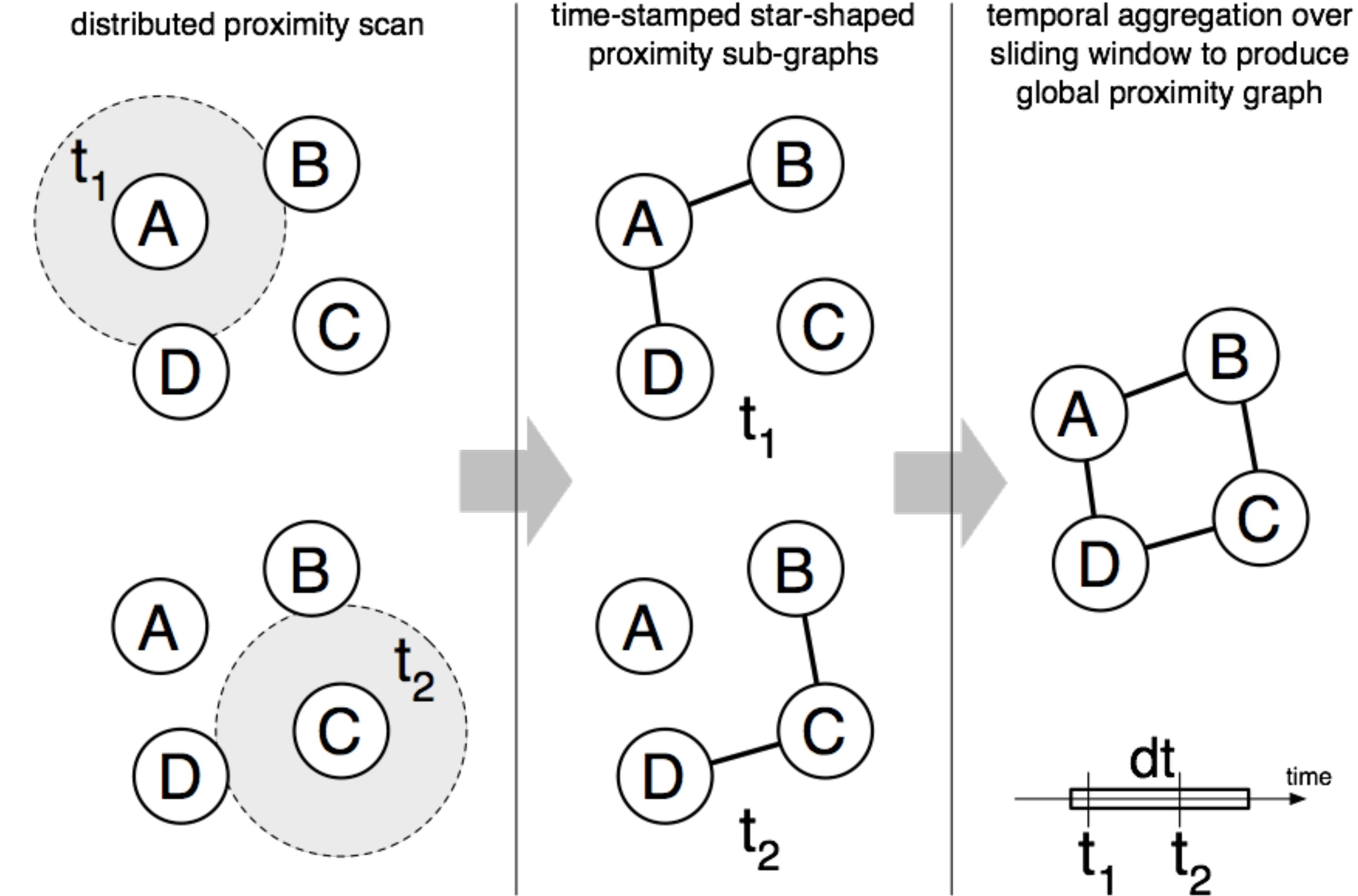
Contact detection

Short distance (~1-2m):
Exchange of very low power
data packets

"42 saw 10 at power 0"

- Two power levels => 2 detection ranges
- Face to face situation
- Statistical detection => 20s time resolution
- Small,
- Scalable

Face-to-face proximity networks



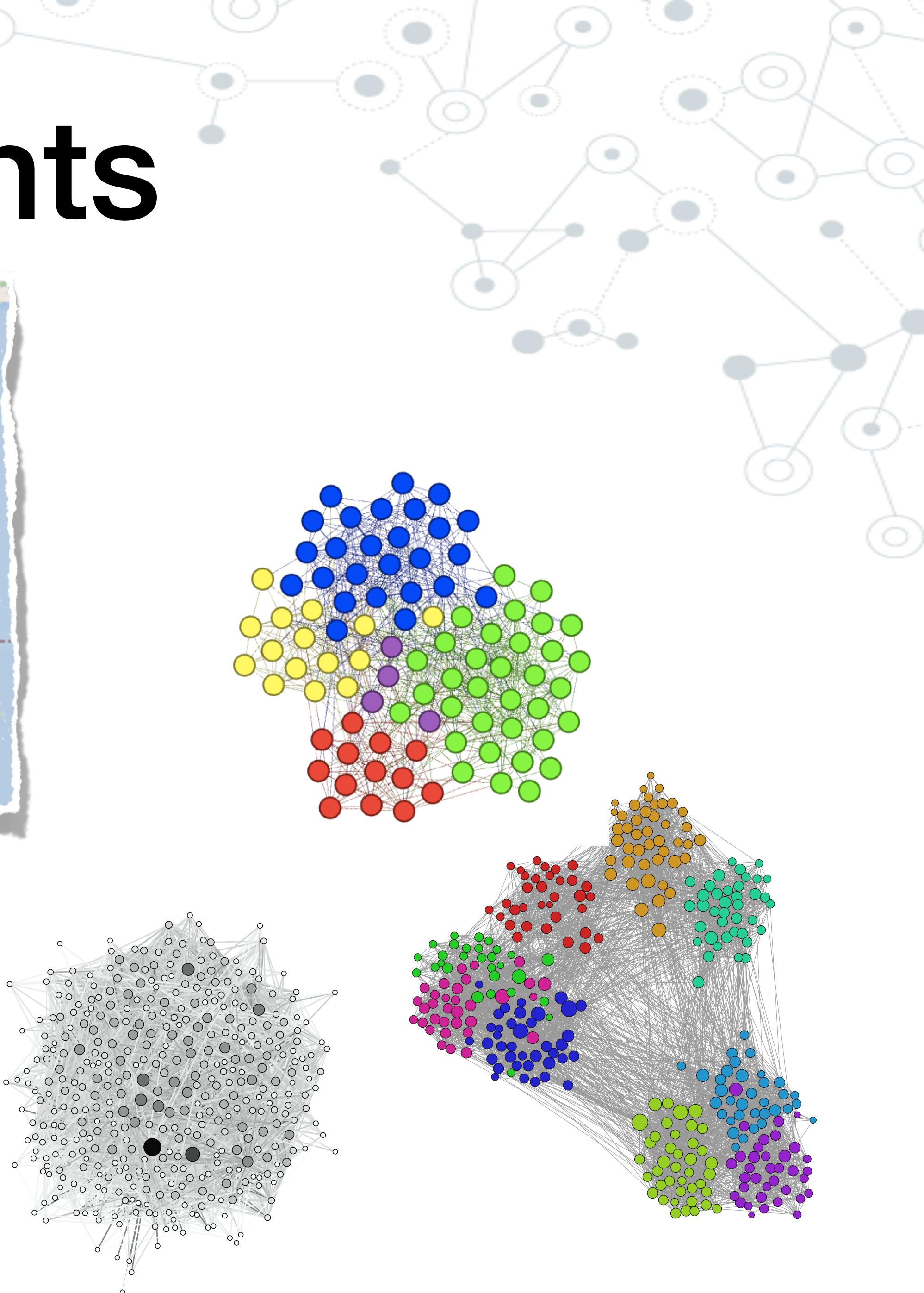
Deployments



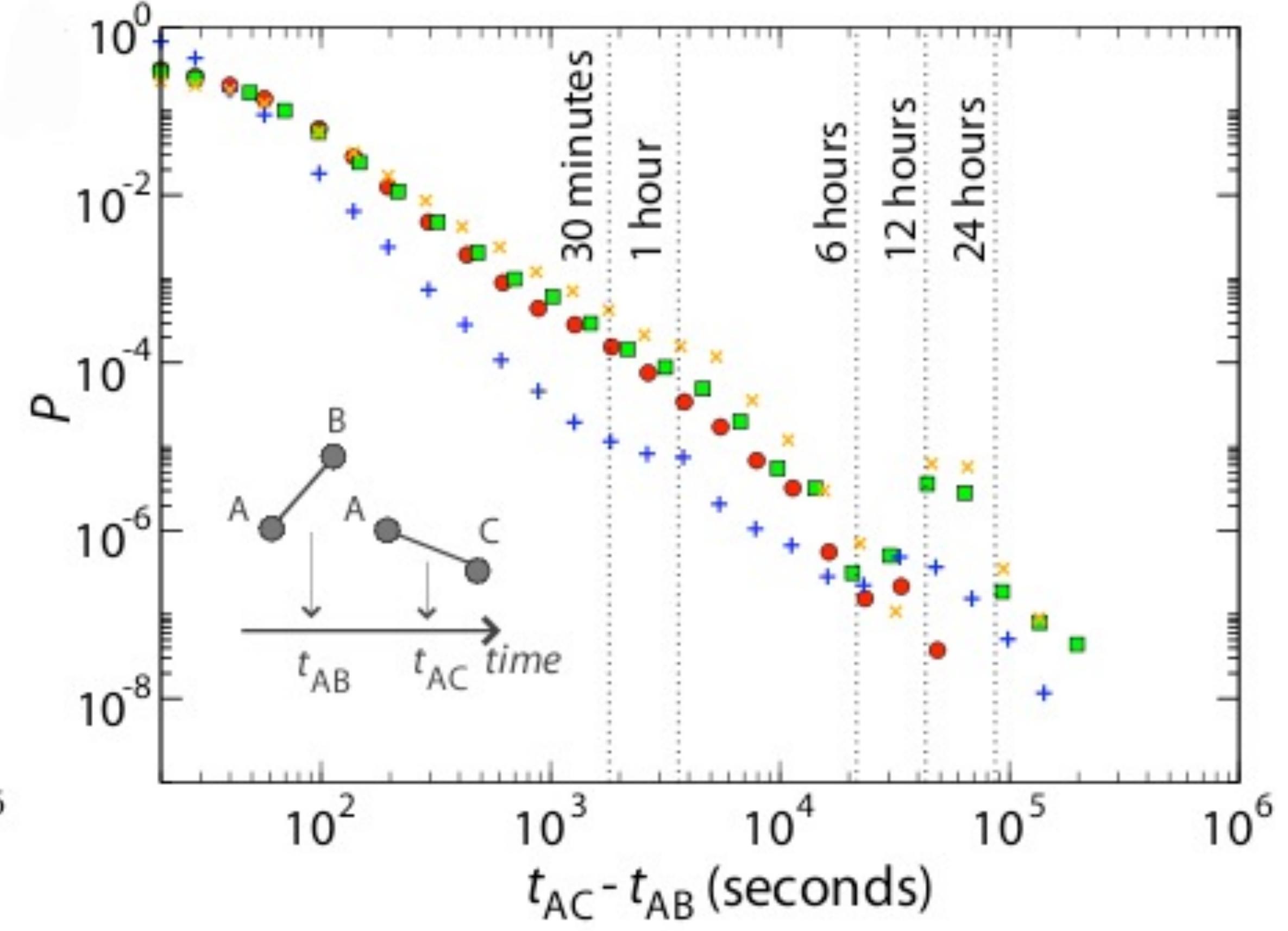
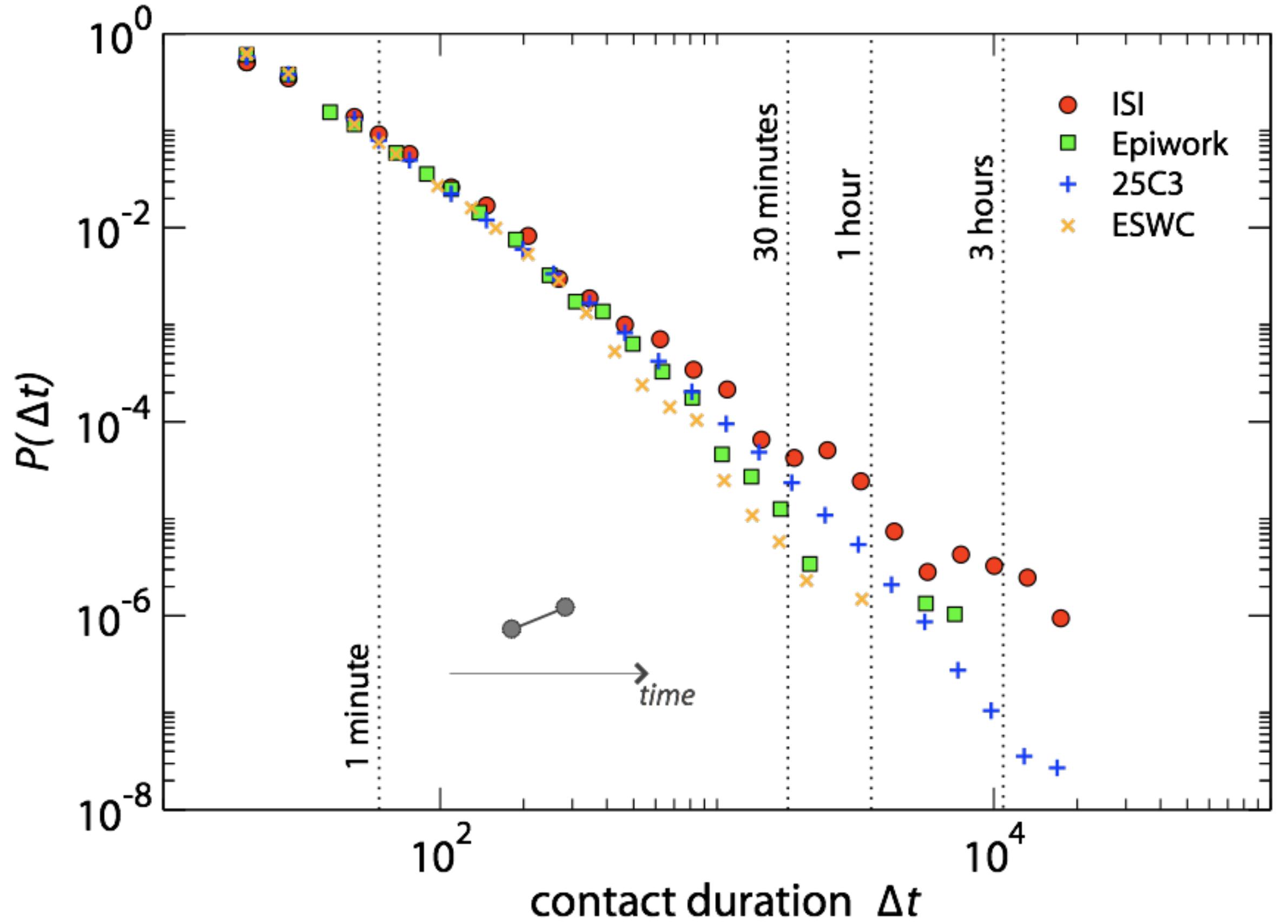
9 years, 30+ deployments, 10+ countries,
50,000+ ppl

schools, hospitals, conferences, households

www.sociopatterns.org/datasets



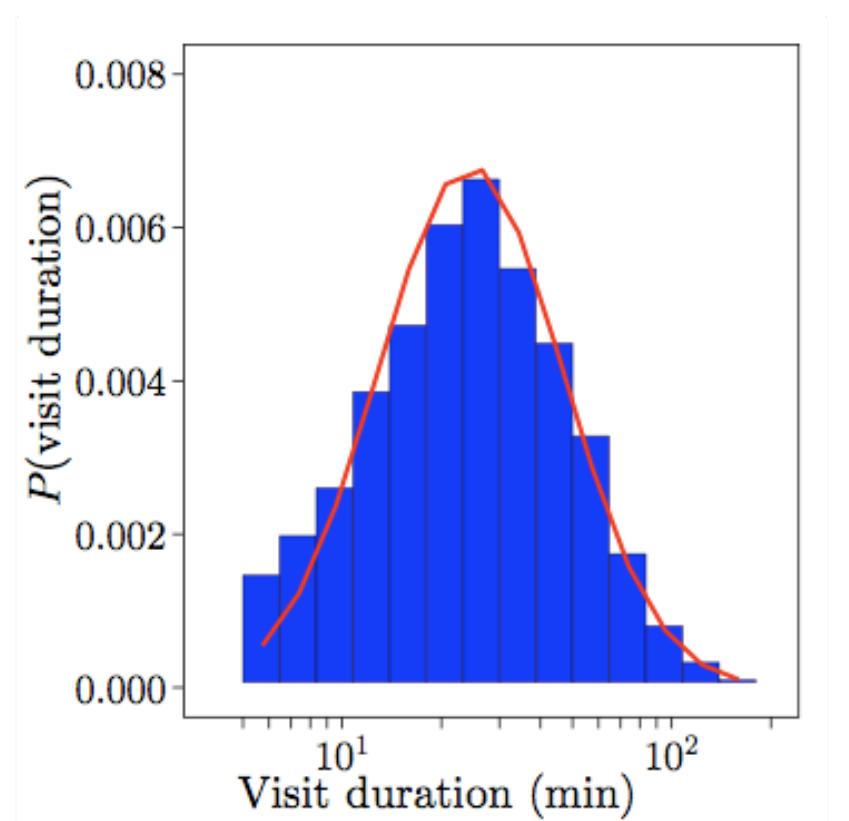
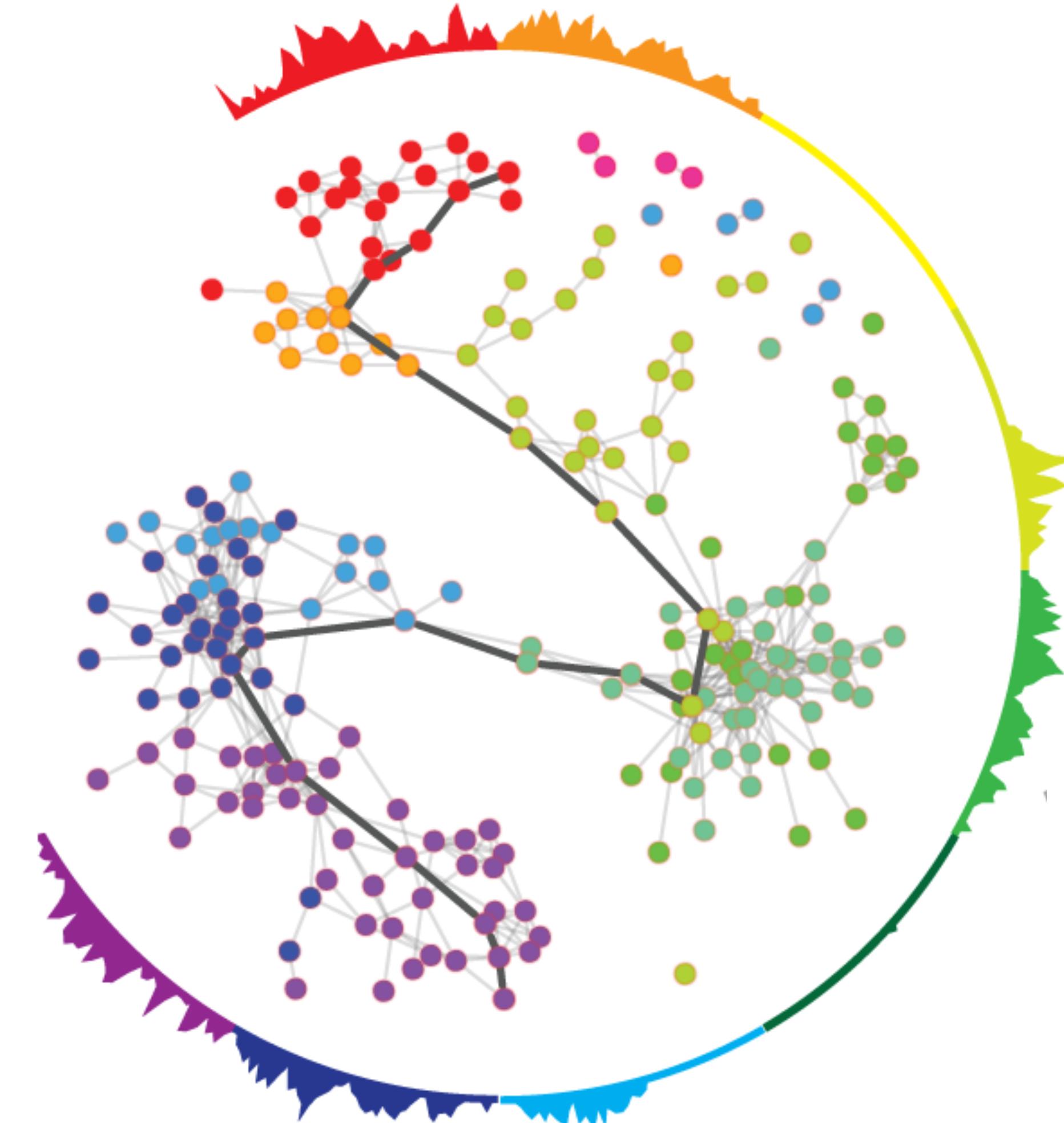
Empirical measures



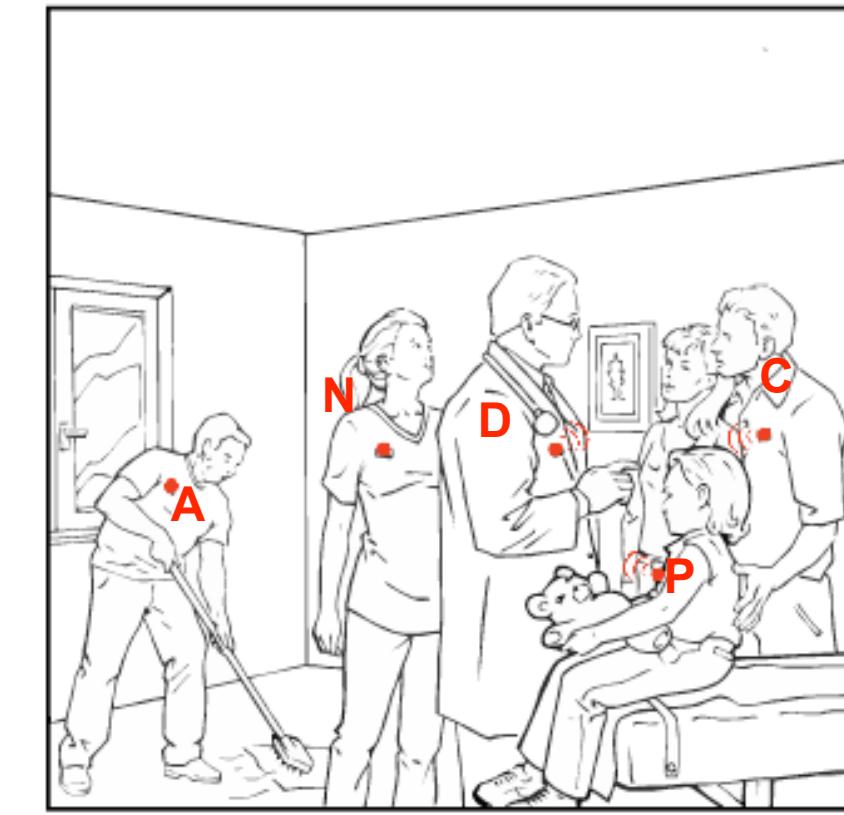
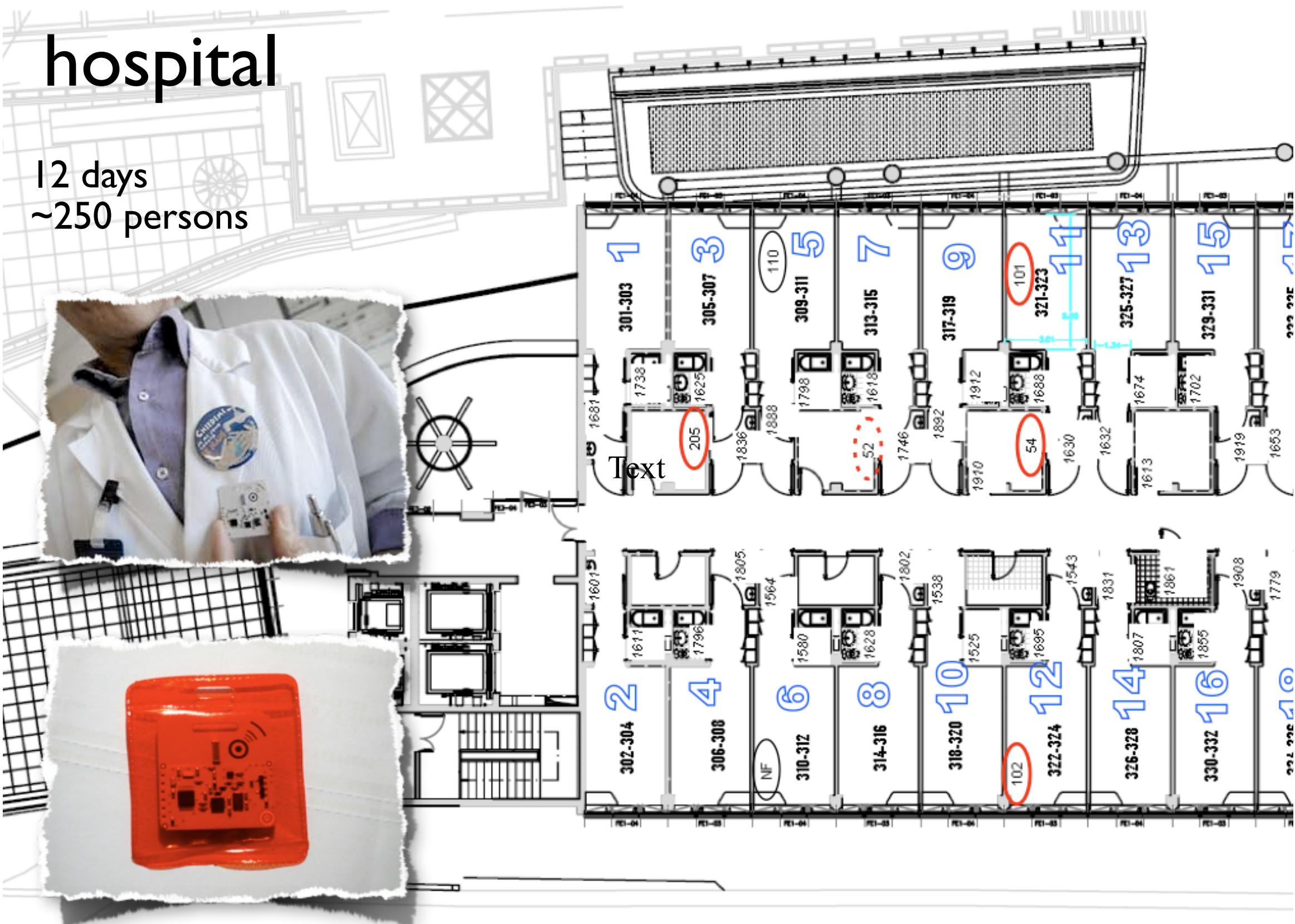
Museum



SocioPatterns.org



Hospital



number of contacts s^n

	A	D	N	P	C
A	63.0	0.5	15.9	1.1	2.3
D	0.3	7.4	2.4	0.9	0.0
N	6.5	2.4	23.0	2.0	0.0
P	0.1	0.4	0.8	0.1	12.8
C	0.4	0.5	0.9	15.0	0.9

number of distinct contacts s^p

	A	D	N	P	C
A	1.1	0.4	1.9	0.8	1.1
D	0.0	0.0	0.0	0.0	0.0
N	0.0	0.0	0.0	0.0	0.0
P	0.1	0.3	0.4	0.1	0.3
C	0.3	0.4	0.5	0.3	0.1

cumulative time in contact s^t (min)

	A	D	N	P	C
A	38.5	0.2	7.8	0.4	1.0
D	0.0	0.8	1.0	0.5	0.2
N	0.0	0.2	12.9	0.9	1.0
P	0.1	0.2	0.4	0.0	11.3
C	0.2	0.3	0.5	15.3	0.3

Inform epidemiological models

L. Isella et al., PLoS ONE 6(2), e17144 (2011)

Households



Household

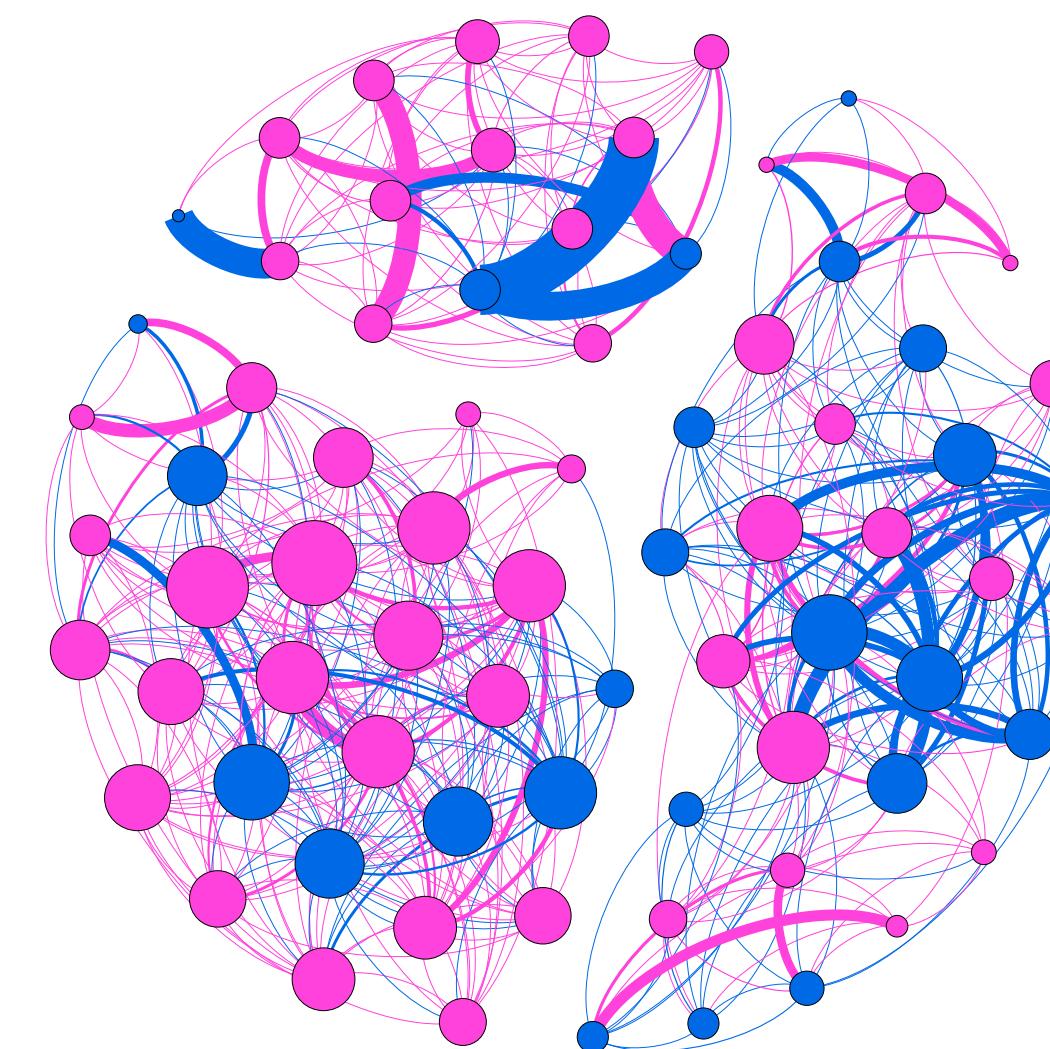
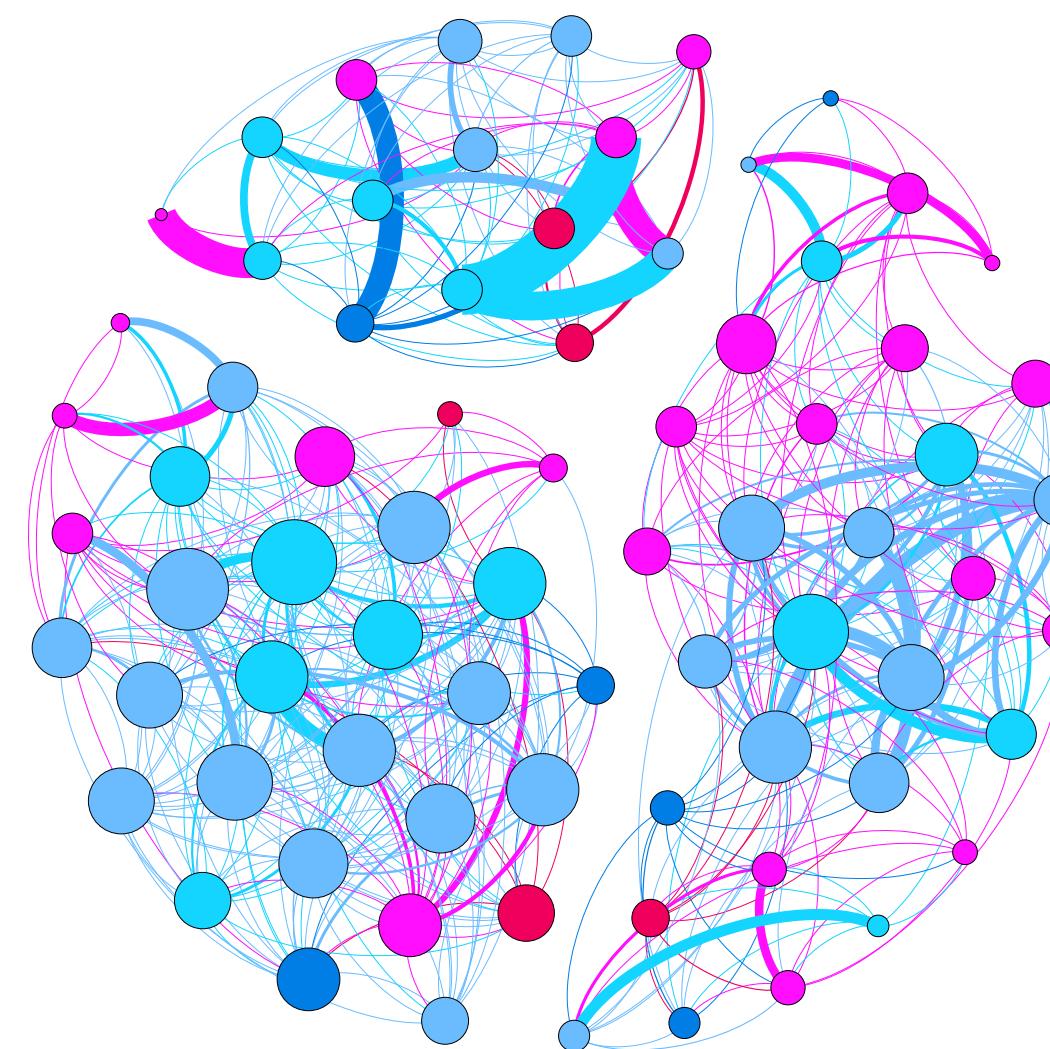
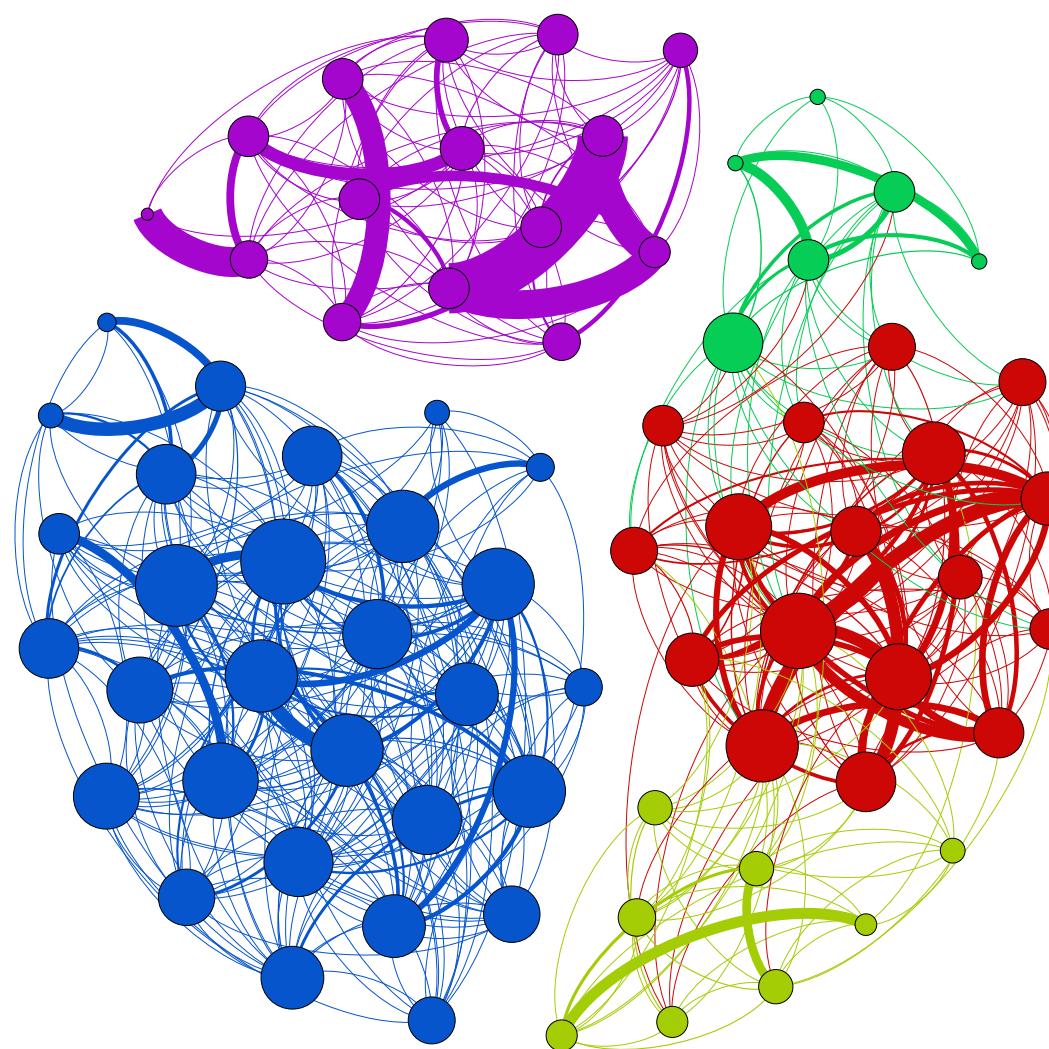
- B
- E
- F
- H
- L

Age

- 0-5
- 6-14
- 15-19
- 20-49
- >50

Gender

- F
- M



Epidemic processes

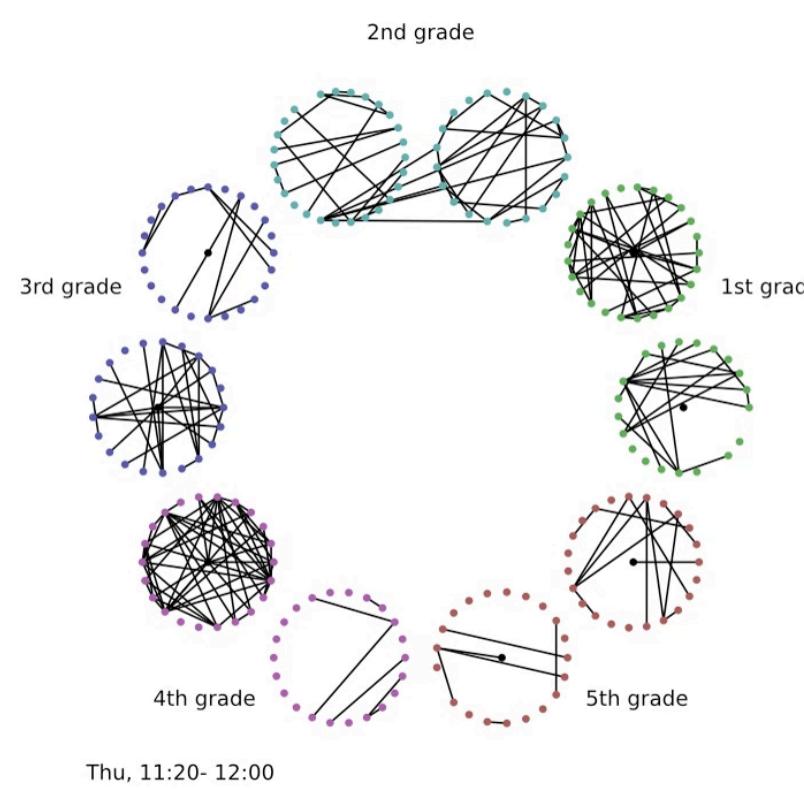
► Analytical results.

- Epidemic threshold for activity-driven networks (Perra et al. 2012)
- Case of activity-driven with memory effects (Sun et al. 2013)
- General formula of epidemic threshold for an empirical temporal network (Valdano et al. 2015)
- etc.

► Data-driven simulations.

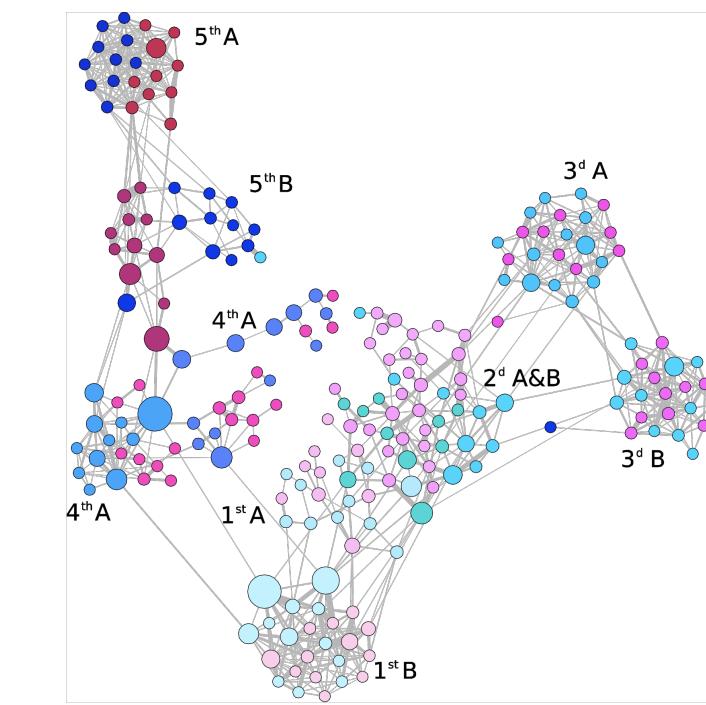
- Several results based on epidemic simulations on empirical temporal networks, including the effects of **vaccinations, link removal, and many possible interventions**

How much detail for a model?



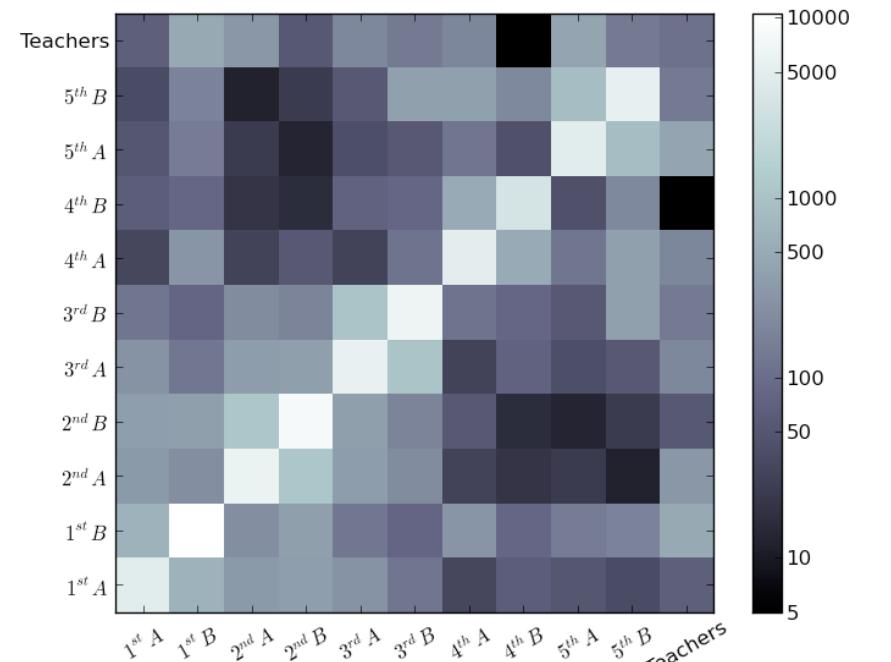
Detailed dynamic network

- very detailed ✓
- very realistic ✓
- takes into account individual heterogeneities of behavior ✓
- very specific (context+period), not easy to generalize ✗



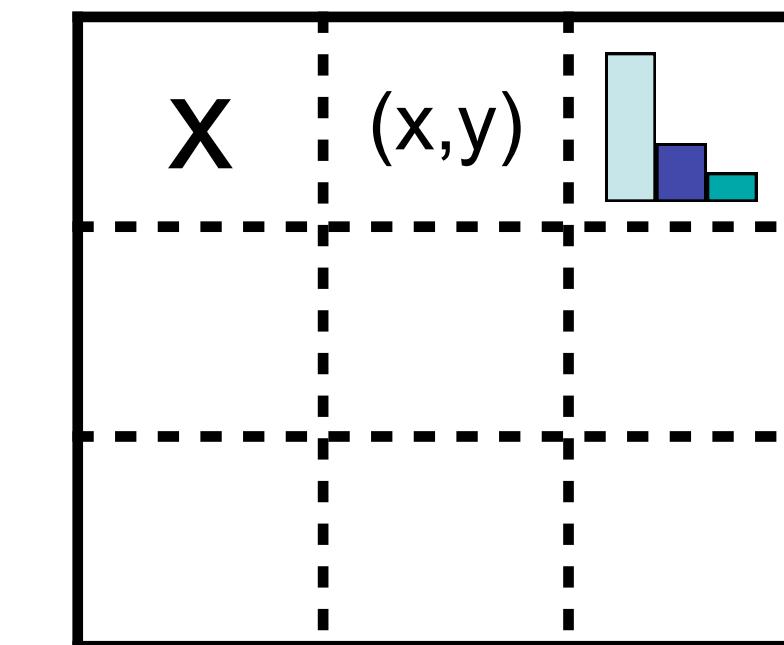
Static network

- Realistic and detailed ✓
- Takes into account heterogeneities ✓
- Very specific ✗
- Lacks variations in behaviour ✗



Contact matrix

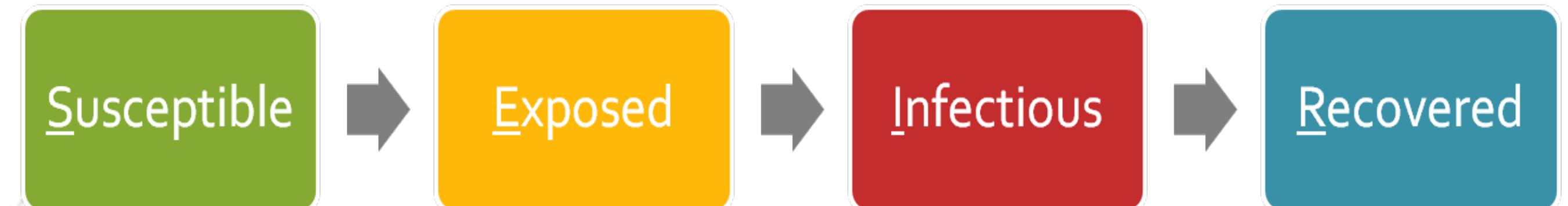
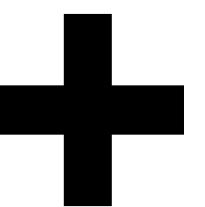
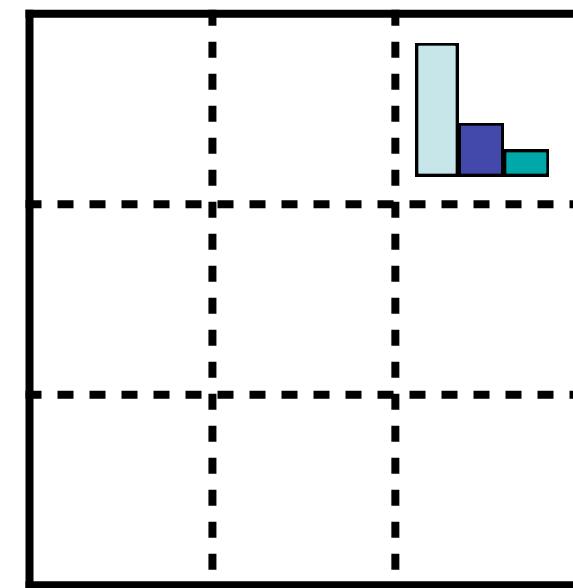
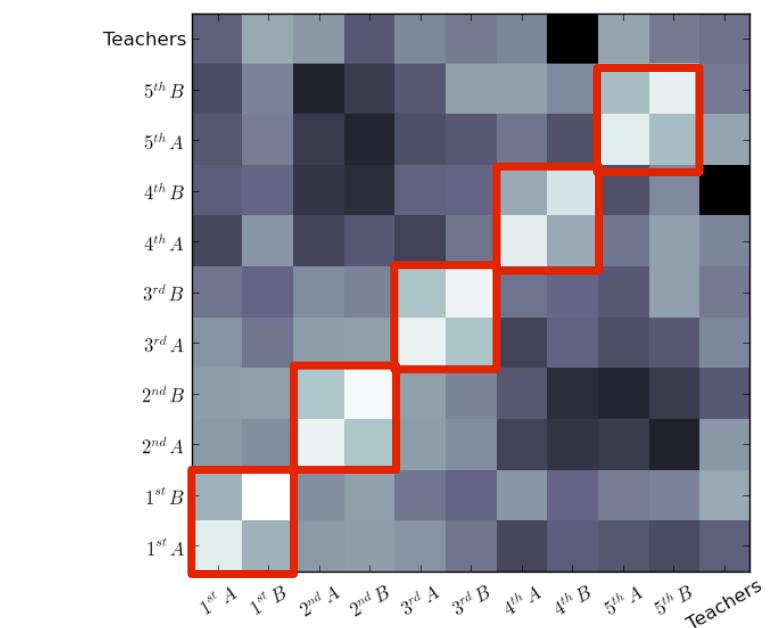
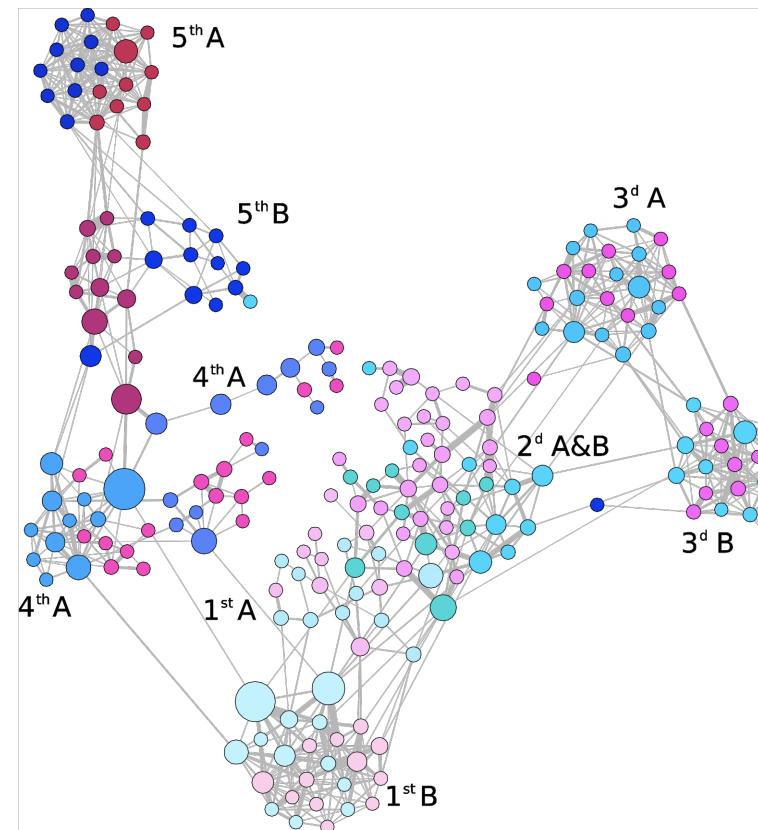
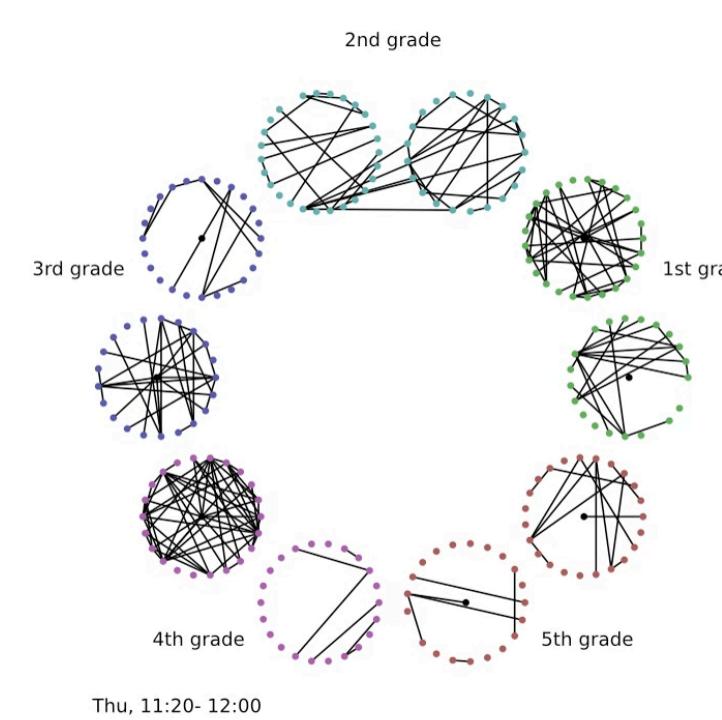
- coarse-grained ✗
- fully connected structure ✗
- only heterogeneities between groups ✗
- very easy to generalize ✓



Contact matrix of distributions

- Role based ✓
- Takes into account heterogeneities ✓

Evaluating representations

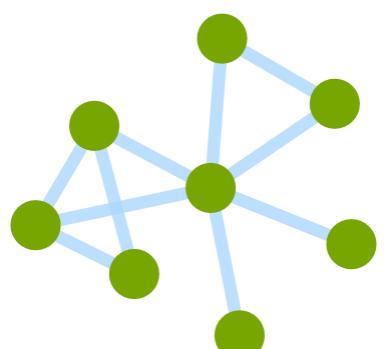
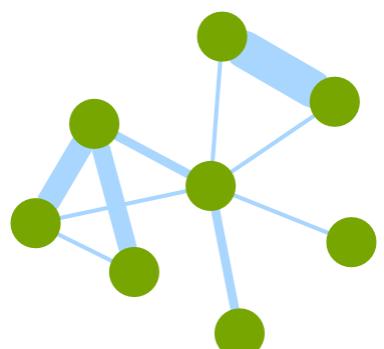
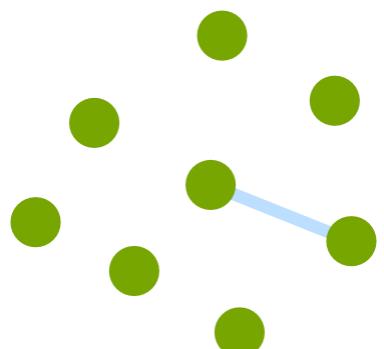


J. Stehlé et al., BMC Medicine (2011); A. Machens et al, BMC Inf Dis (2013)

Evaluating representations

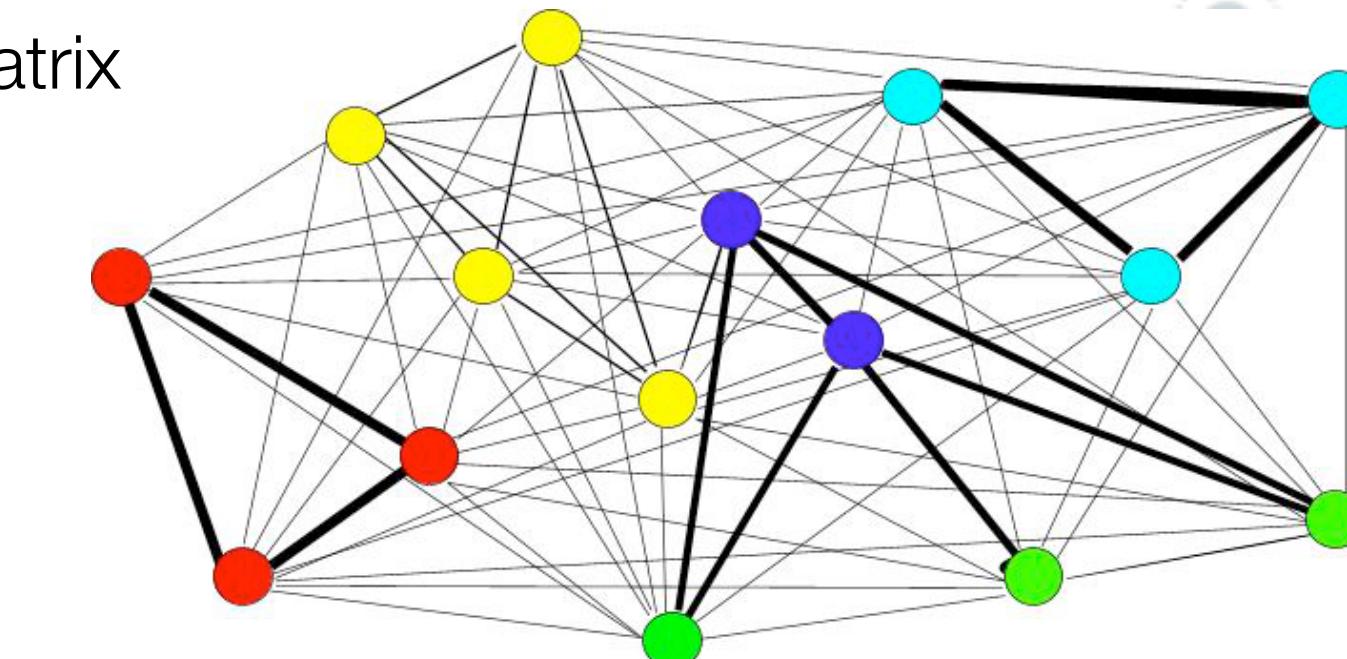
Construction of 3 networks:

1. Dynamic network (DYN):
Real sequence of successive contacts



2. Heterogeneous network (HET):
1-day aggregated network
A–B if A and B have been in contact
 W_{AB} = cumulative duration of the contacts A–B

4. Contact matrix



$$w_{ij} = w_{AB} / 86400s$$

w_{AB}	Average contact time in seconds per day				
	Assistants	Doctors	Nurses	Patients	Caregivers
Assistants	298	1.16	24.7	0.95	1.92
Doctors	1.16	20.8	3.99	0.95	1.20
Nurses	24.7	3.99	47.3	2.32	2.57
Patients	0.95	0.95	2.32	1.27	46.9
Caregivers	1.92	1.20	2.57	46.9	1.80

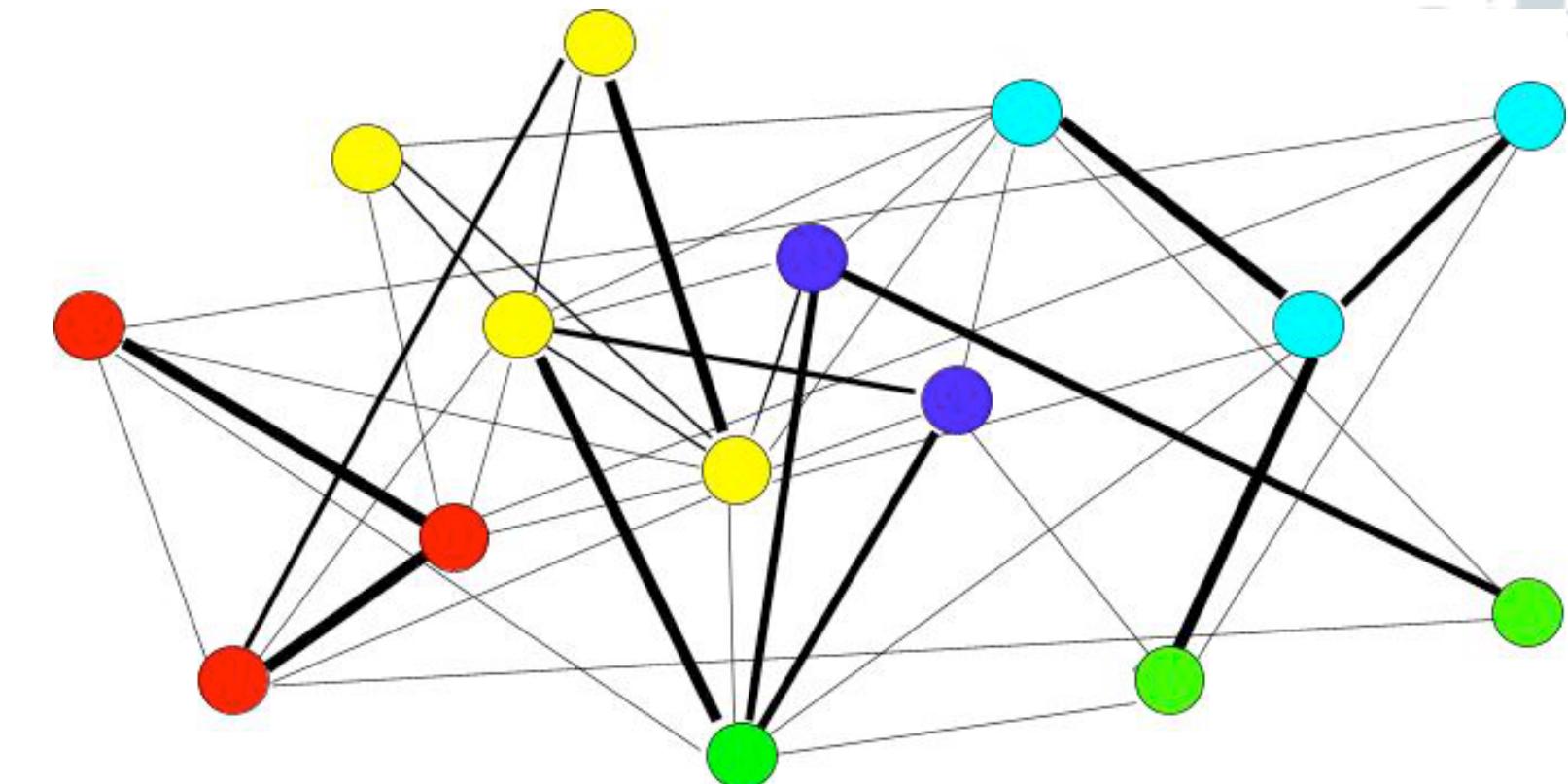
3. Homogeneous network (HOM):
1-day aggregated network
A–B if A and B have been in contact
 W_{AB} = average cumulative duration

Evaluating representations

5. Novel representation: Contact matrix of distributions

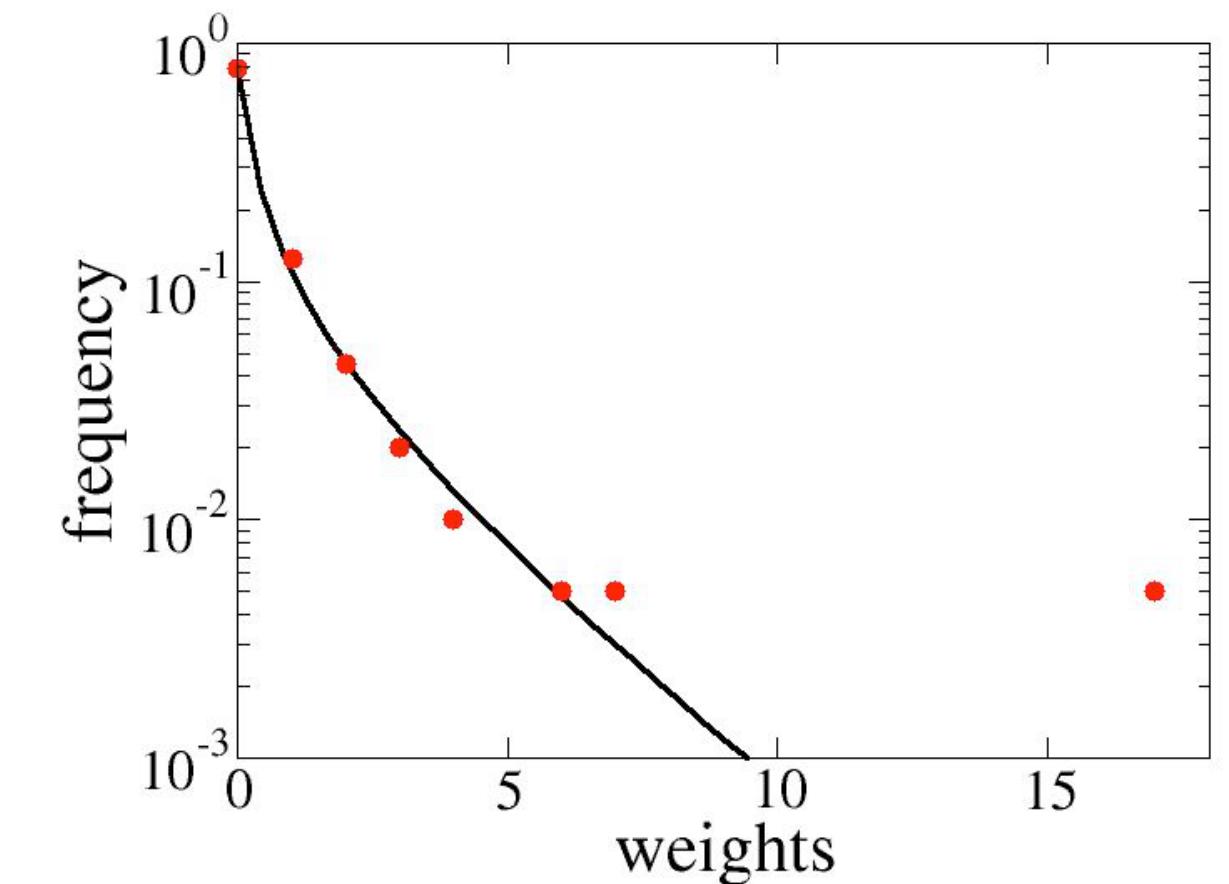
a. Fit each role-pair distribution of weights
(using negative binomials)

b. Create a network in which weights are drawn
from the fitted distribution (NB: including zero weights)



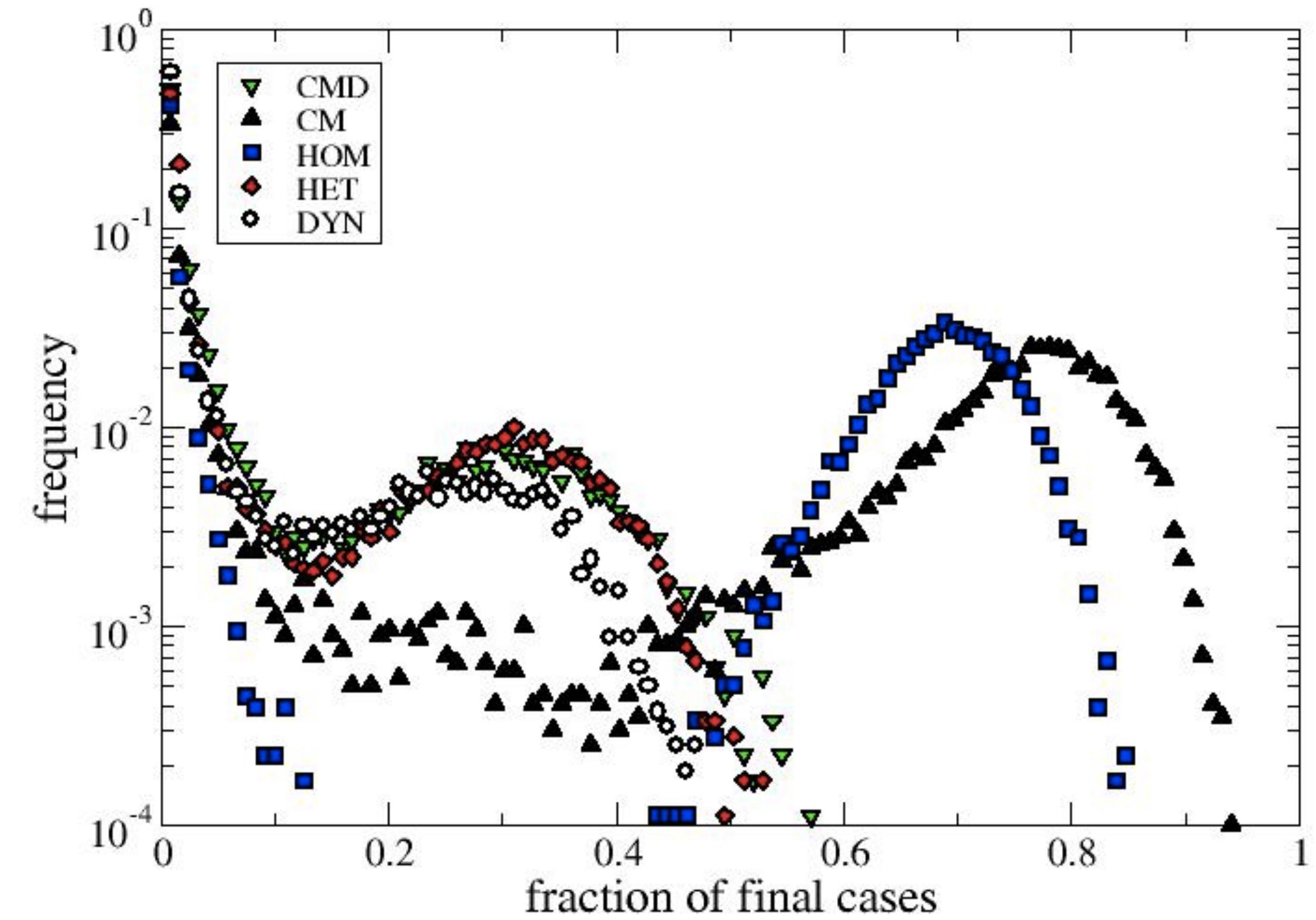
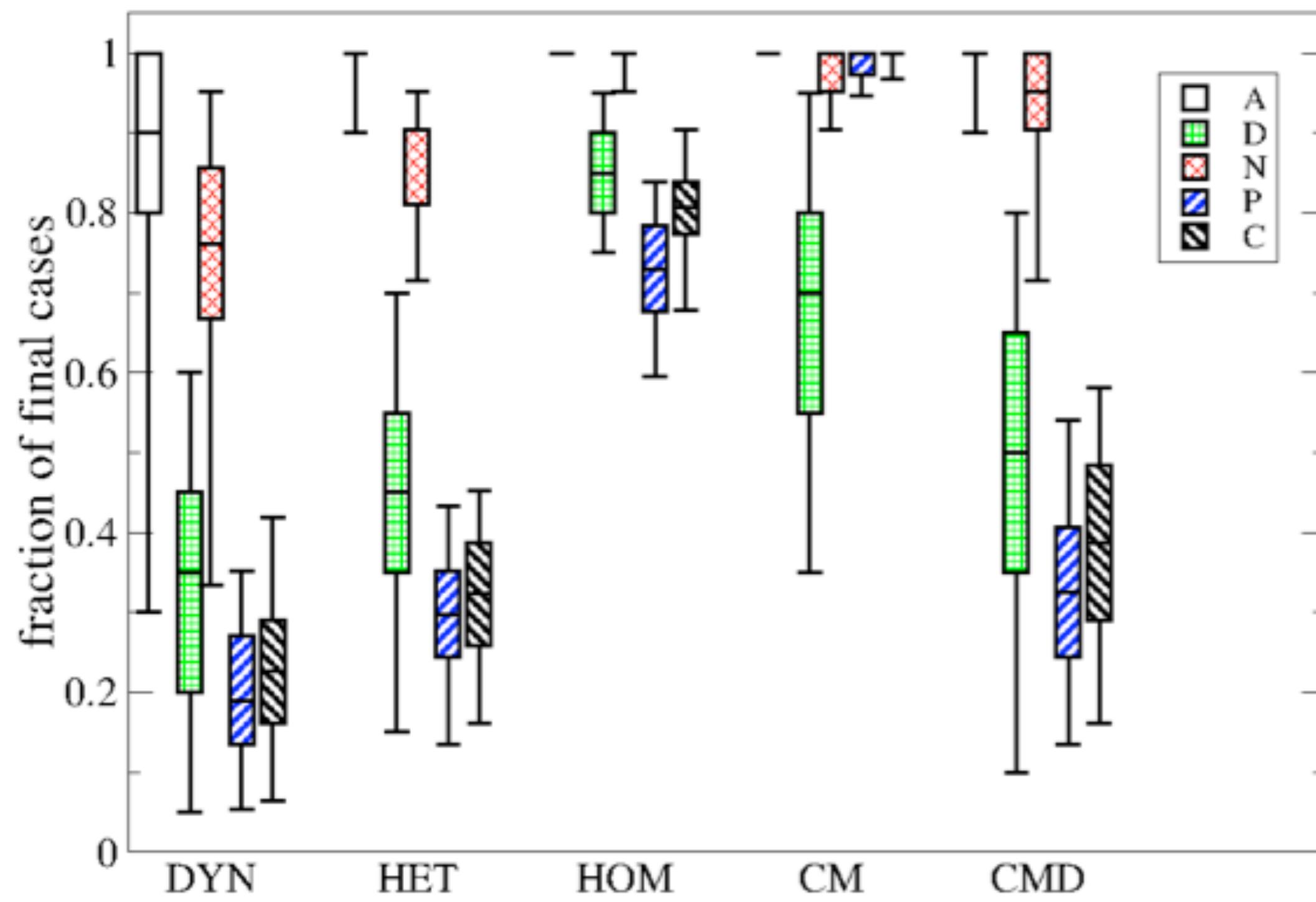
- Underlying realistic network structure
- Takes into account role structure
- Takes into account heterogeneities within each role
- Easy to generalize

Example: Assistant-Doctor



SEIR simulation results

Attack rate by groups (for AR > 10%)



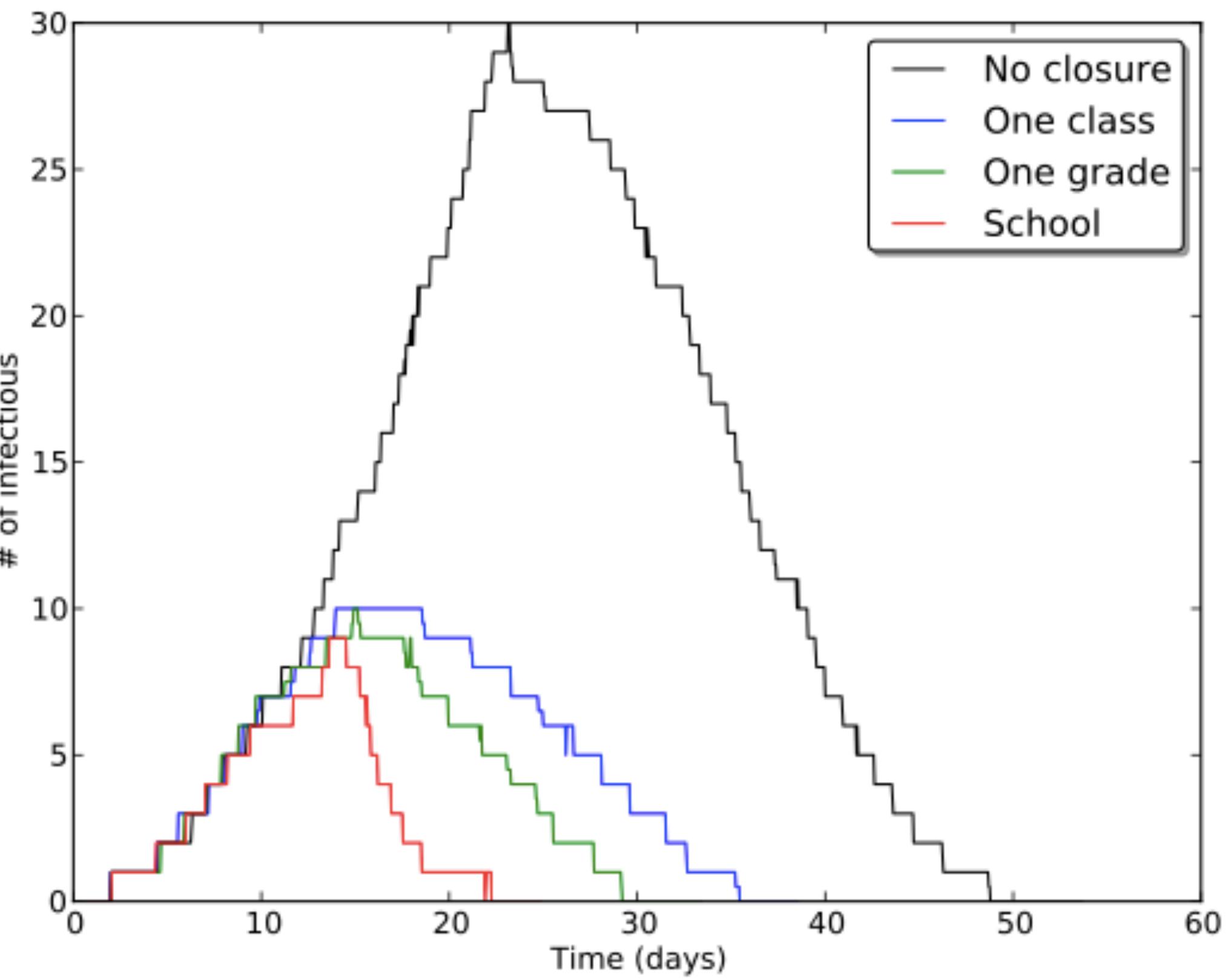
Interventions

Model:

- ▶ SEIR with asymptomatics
- ▶ contact data as proxy for possibility of transmission inside school
- ▶ when children are out of school: residual homogeneous risk of contamination by contact with population

Containment strategies (suggested by the data):

- ▶ detection and subsequent isolation of symptomatic individuals
- ▶ whenever symptomatic individuals are detected (more than a given threshold), closure of:
 - (i) class
 - (ii) class + most connected other class (same grade)
 - (iii) whole school



Interventions

Closure strategy (Threshold, duration)	Targeted class	Targeted grade	Whole school
3, 24h	6.2	6.6	10.0
3, 48h	7.6	8.0	14.3
3, 72h	8.2	9.7	16.1
3, 96h	11.3	13.7	22.4
3, 120h	12.2	13.5	26.5
3, 144h	13.3	13.9	27.9
2, 24h	5.8	5.8	10.0
2, 48h	6.5	7.6	13.5
2, 72h	6.4	8.1	16.1
2, 96h	8.5	9.4	21.5
2, 120h	8.5	10.6	24.3
2, 144h	8.3	9.8	25.3

Cost in number of
lost class-days

Immunization

Lee et al., PLOS ONE (2012)

Inspired by “acquaintance protocol” in static networks

- “Recent”: choose a node at random, immunize its most recent contact
- “Weight”: choose a node at random, immunize its most frequent contact in a previous time-window

Starnini et al., Journal Theoretical Biology (2012)

- aggregate network in time window $[0, T]$
- compare strategies:
 - immunize nodes with highest k or BC in $[0, T]$
 - immunize random acquaintance on $[0, T]$
 - recent, weight strategies
- vary T
- find saturation of efficiency as T increases

COVID-19

Interventions

Screening and vaccination against COVID-19 to minimise school closure: a modelling study

Elisabetta Colosi, Giulia Bassignana, Diego Andrés Contreras, Canelle Poirier, Pierre-Yves Boëlle, Simon Cauchemez, Yazdan Yazdanpanah, Bruno Lina, Arnaud Fontanet, Alain Barrat, Vittoria Colizza

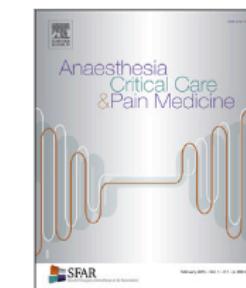


Anaesthetist Critical Care Pain Med 41 (2022) 101047



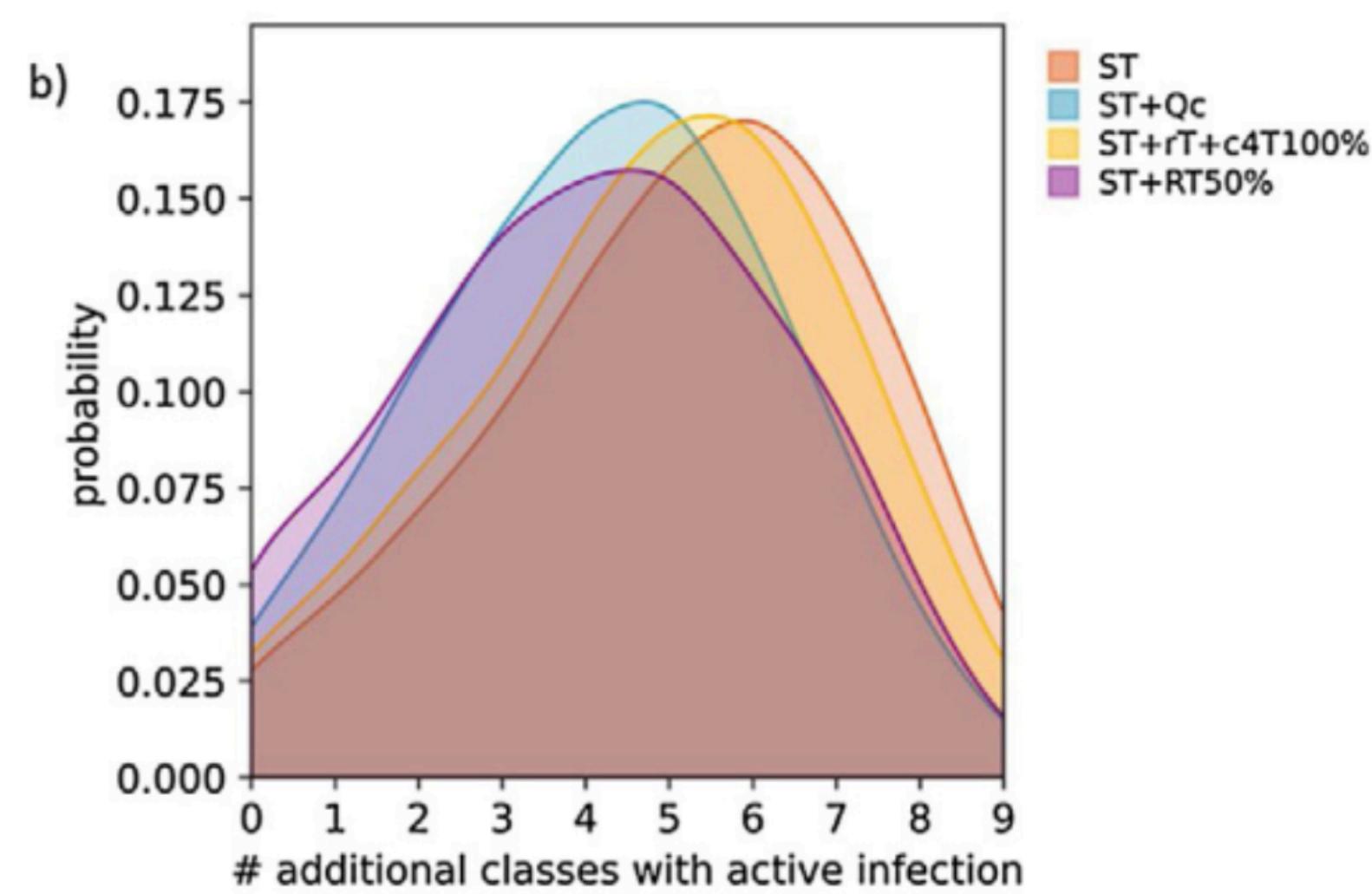
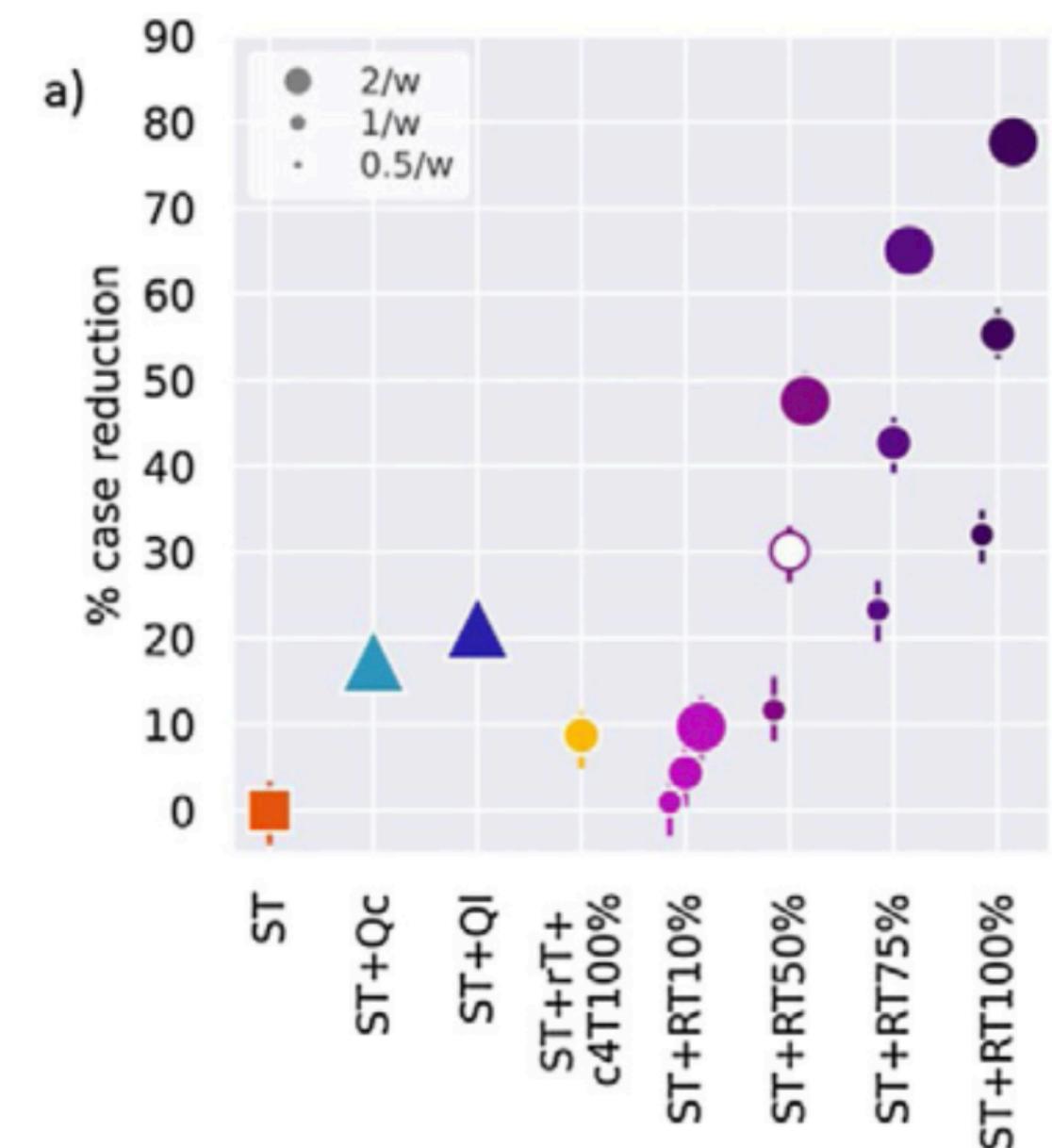
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Editorial

Modelling COVID-19 in school settings to evaluate prevention and control protocols



Digital contact tracing

ARTICLE

<https://doi.org/10.1038/s41467-021-21809-w>

OPEN

Digital proximity tracing on empirical contact networks for pandemic control

G. Cencetti^{1,10}, G. Santin  ^{1,10}, A. Longa  ^{1,2}, E. Pigani  ^{1,3}, A. Barrat  ^{4,5}, C. Cattuto^{6,7}, S. Lehmann  ⁸, M. Salathé⁹ & B. Lepri  ¹✉

 Check for updates

Effect of manual and digital contact tracing on COVID-19 outbreaks: a study on empirical contact data

A. Barrat^{1,2}, C. Cattuto^{3,4}, M. Kivelä⁵, S. Lehmann⁶ and J. Saramäki⁵

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SCIENCE ADVANCES | RESEARCH ARTICLE

CORONAVIRUS

Anatomy of digital contact tracing: Role of age, transmission setting, adoption, and case detection

Jesús A. Moreno López^{1,2}, Beatriz Arregui García^{1,2}, Piotr Bentkowski¹, Livio Bioglio³, Francesco Pinotti¹, Pierre-Yves Boëlle¹, Alain Barrat^{4,5}, Vittoria Colizza¹, Chiara Poletto^{1*}

The efficacy of digital contact tracing against coronavirus disease 2019 (COVID-19) epidemic is debated: Smartphone penetration is limited in many countries, with low coverage among the elderly, the most vulnerable to COVID-19. We developed an agent-based model to precise the impact of digital contact tracing and household isolation on COVID-19 transmission. The model, calibrated on French population, integrates demographic, contact and epidemiological information to describe exposure and transmission of COVID-19. We explored realistic levels of case detection, app adoption, population immunity, and transmissibility. Assuming a reproductive ratio $R = 2.6$ and 50% detection of clinical cases, a ~20% app adoption reduces peak incidence by ~35%. With $R = 1.7$, >30% app adoption lowers the epidemic to manageable levels. Higher coverage among adults, playing a central role in COVID-19 transmission, yields an indirect benefit for the elderly. These results may inform the inclusion of digital contact tracing within a COVID-19 response plan.

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Non-pharmaceutical interventions are crucial to mitigate the COVID-19 pandemic and contain re-emergence phenomena. Targeted measures such as case isolation and contact tracing can alleviate the societal cost of lockdowns by containing the spread where and when it occurs. To assess the relative and combined impact of manual contact tracing (MCT) and digital (app-based) contact tracing, we feed a compartmental model for COVID-19 with high-resolution datasets describing contacts between individuals in several contexts. We show that the benefit (epidemic size reduction) is generically linear in the fraction of contacts recalled during MCT and quadratic in the app adoption, with no threshold effect. The cost (number of quarantines) versus benefit curve has a characteristic parabolic shape, independent of the type of tracing, with a potentially high benefit and low cost if app adoption and MCT efficiency are high enough. Benefits are higher and the cost lower if the epidemic reproductive number is lower, showing the importance of combining tracing with additional mitigation measures. The observed phenomenology is qualitatively robust across datasets and parameters. We moreover obtain analytically similar results on simplified models.

Next... digital contact tracing