Digital epidemiology

Lesson 12

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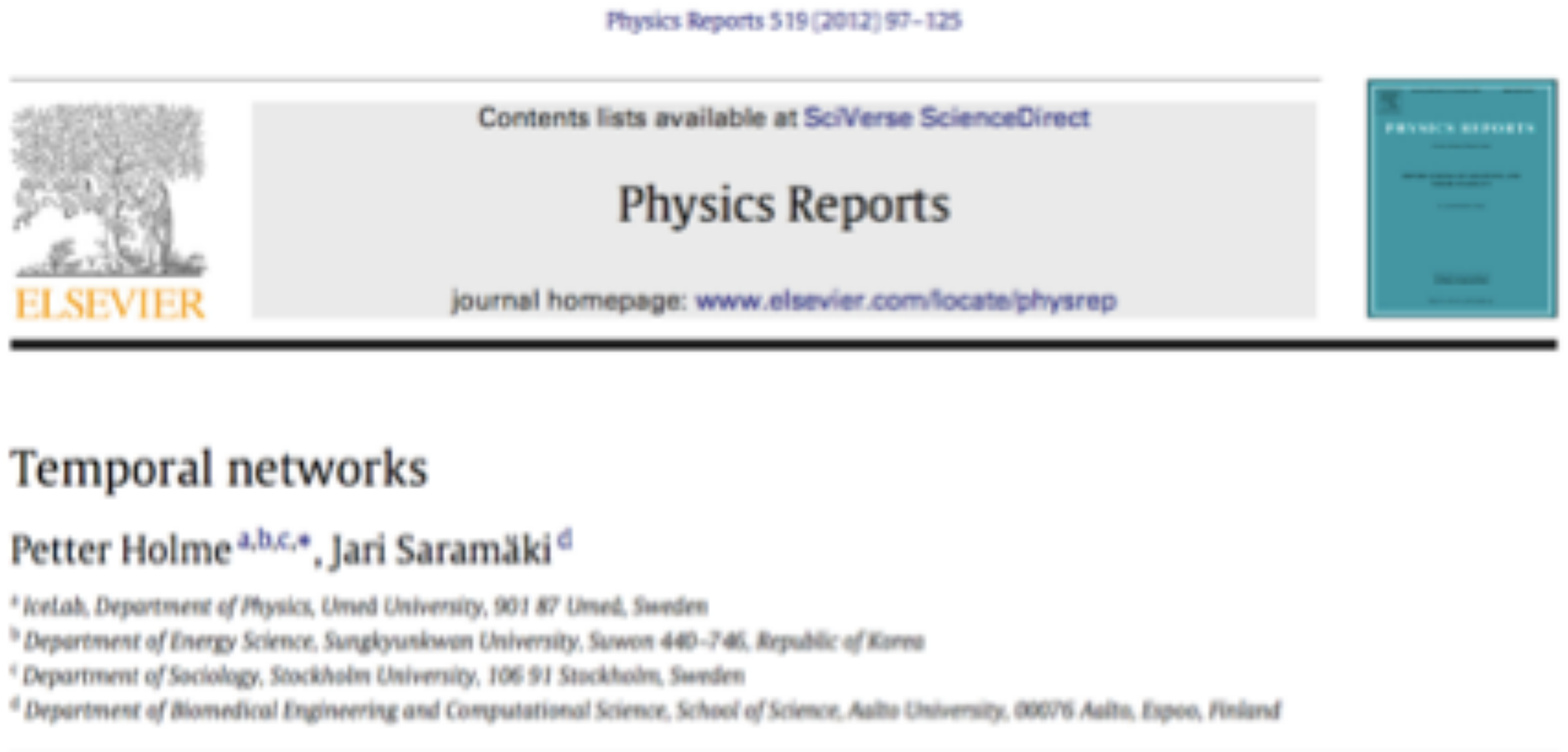
Temporal networks

References



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Temporal networks

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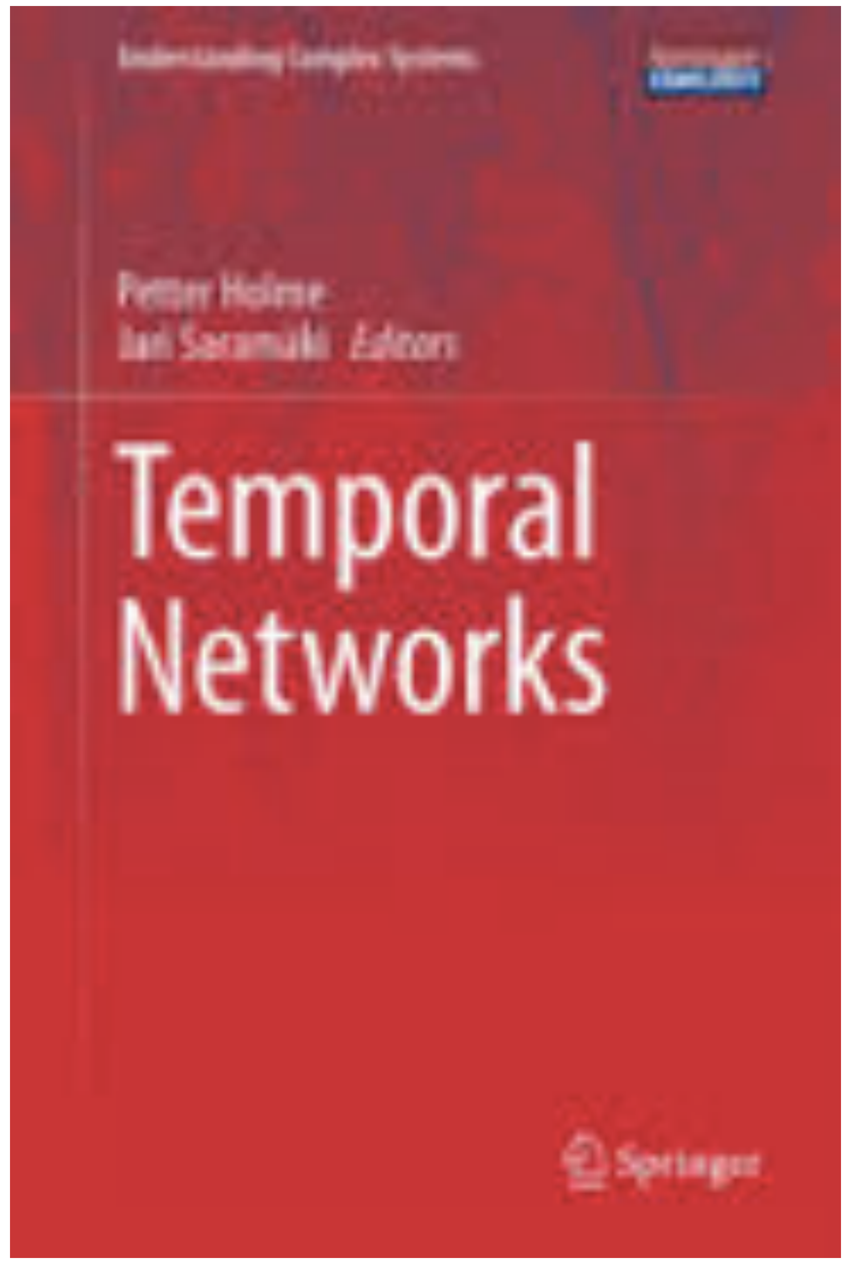

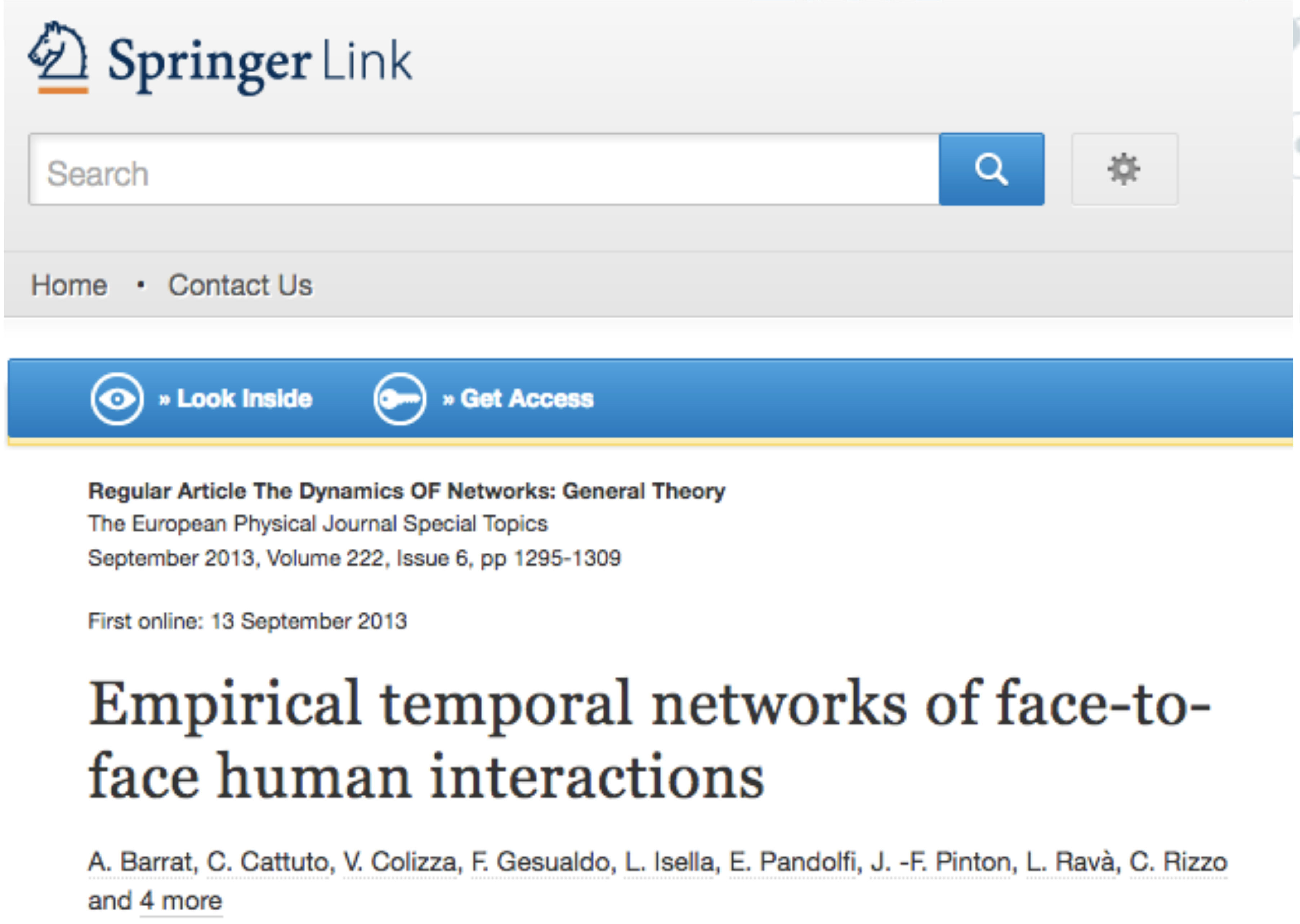

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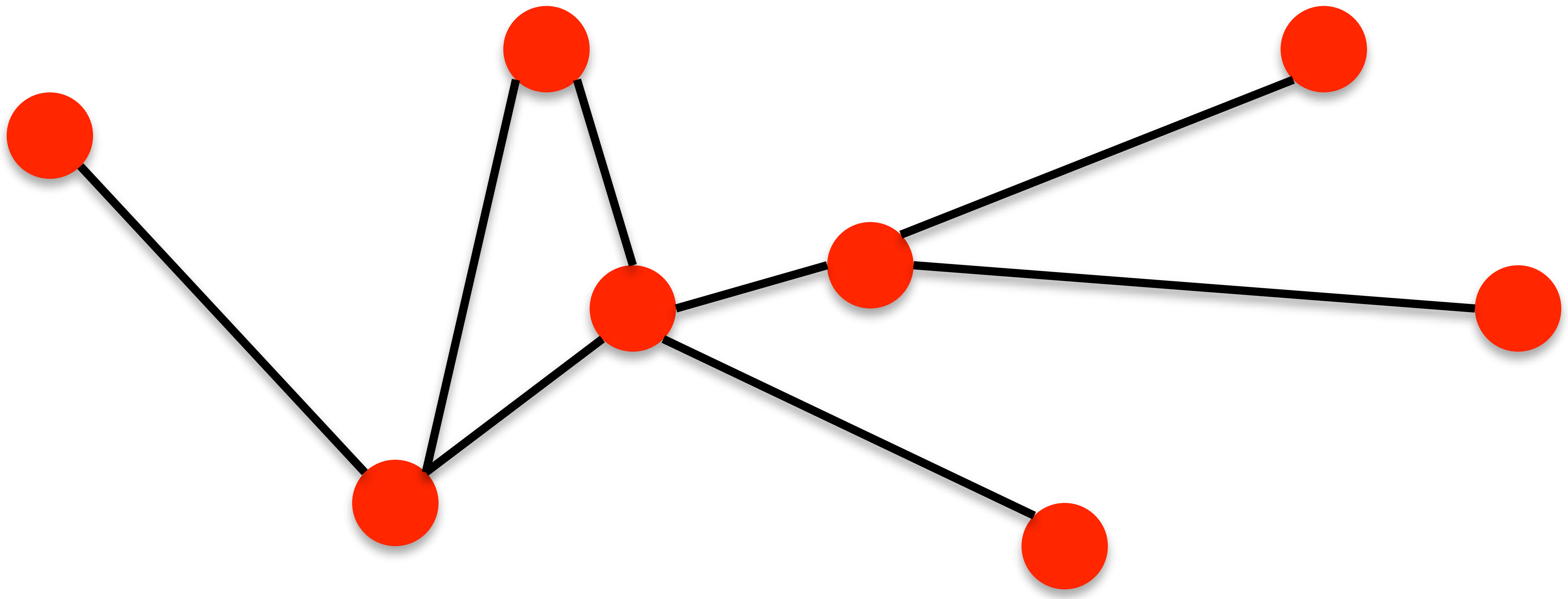
Regular Article The Dynamics OF Networks: General Theory
The European Physical Journal Special Topics
September 2013, Volume 222, Issue 6, pp 1295-1309

First online: 13 September 2013

Empirical temporal networks of face-to-face human interactions

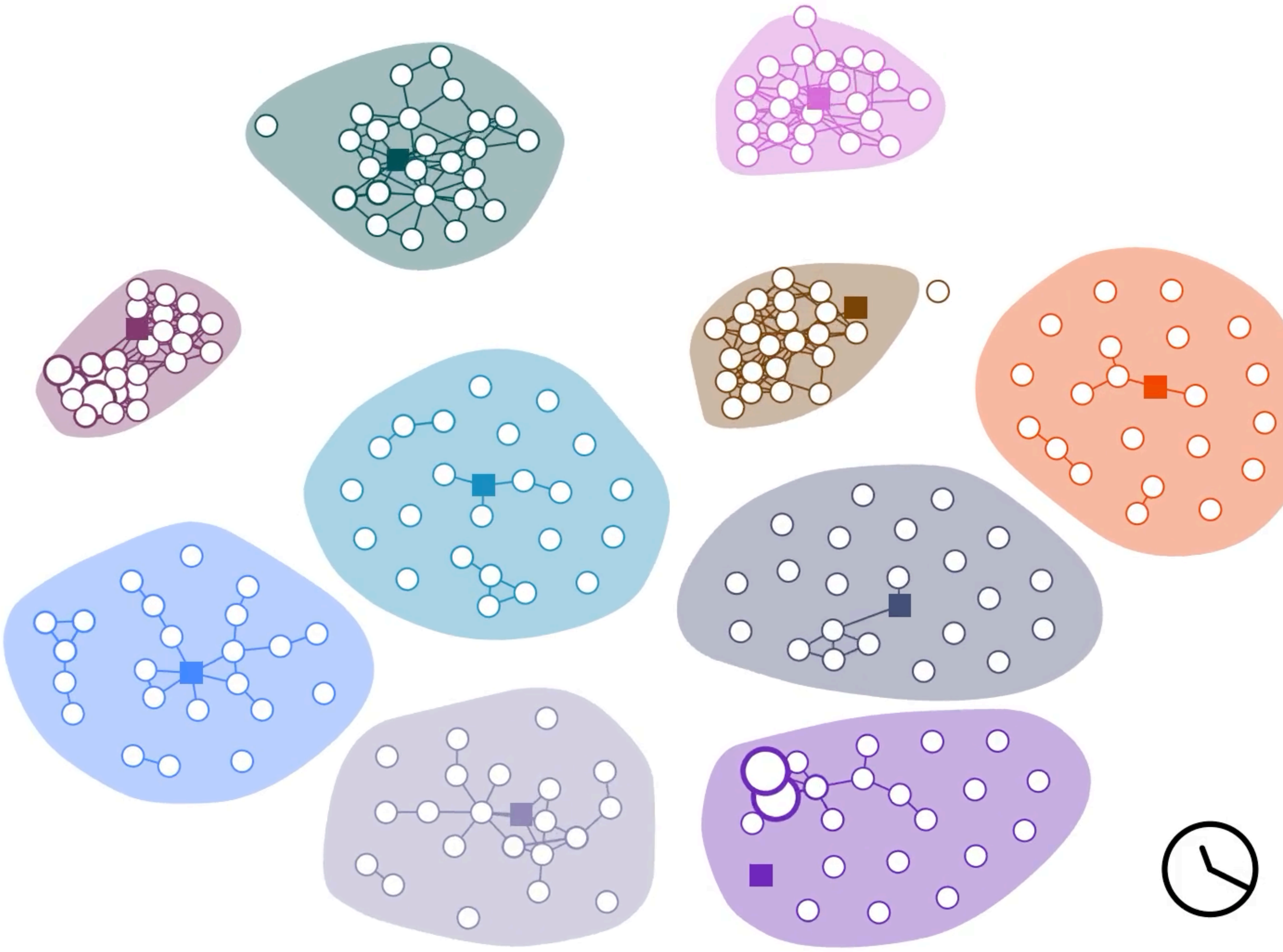
A. Barrat, C. Cattuto, V. Colizza, F. Gesualdo, L. Isella, E. Pandolfi, J. -F. Pinton, L. Ravà, C. Rizzo and 4 more

Static networks



- **components**: nodes, vertices N
- **interactions**: links, edges L
- **system**: network, graph (N,L)

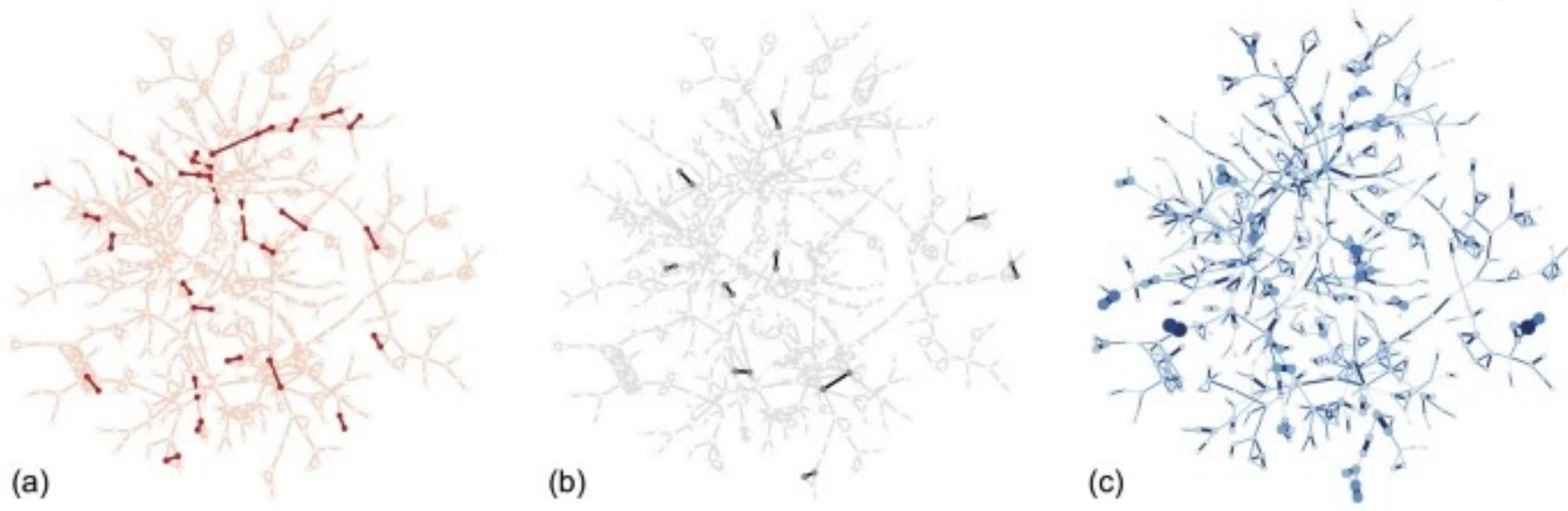
Networks change over time



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

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

Alternative definition: a time dependent adjacency matrix

$$A(i,j,t) = 1 \iff$$ **i and j 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

…….

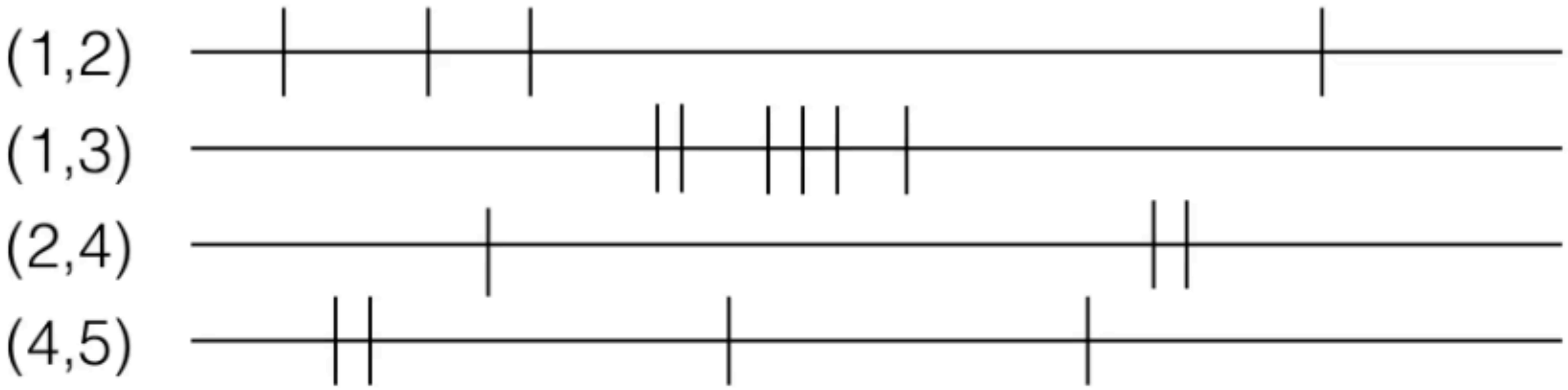
Contact intervals

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

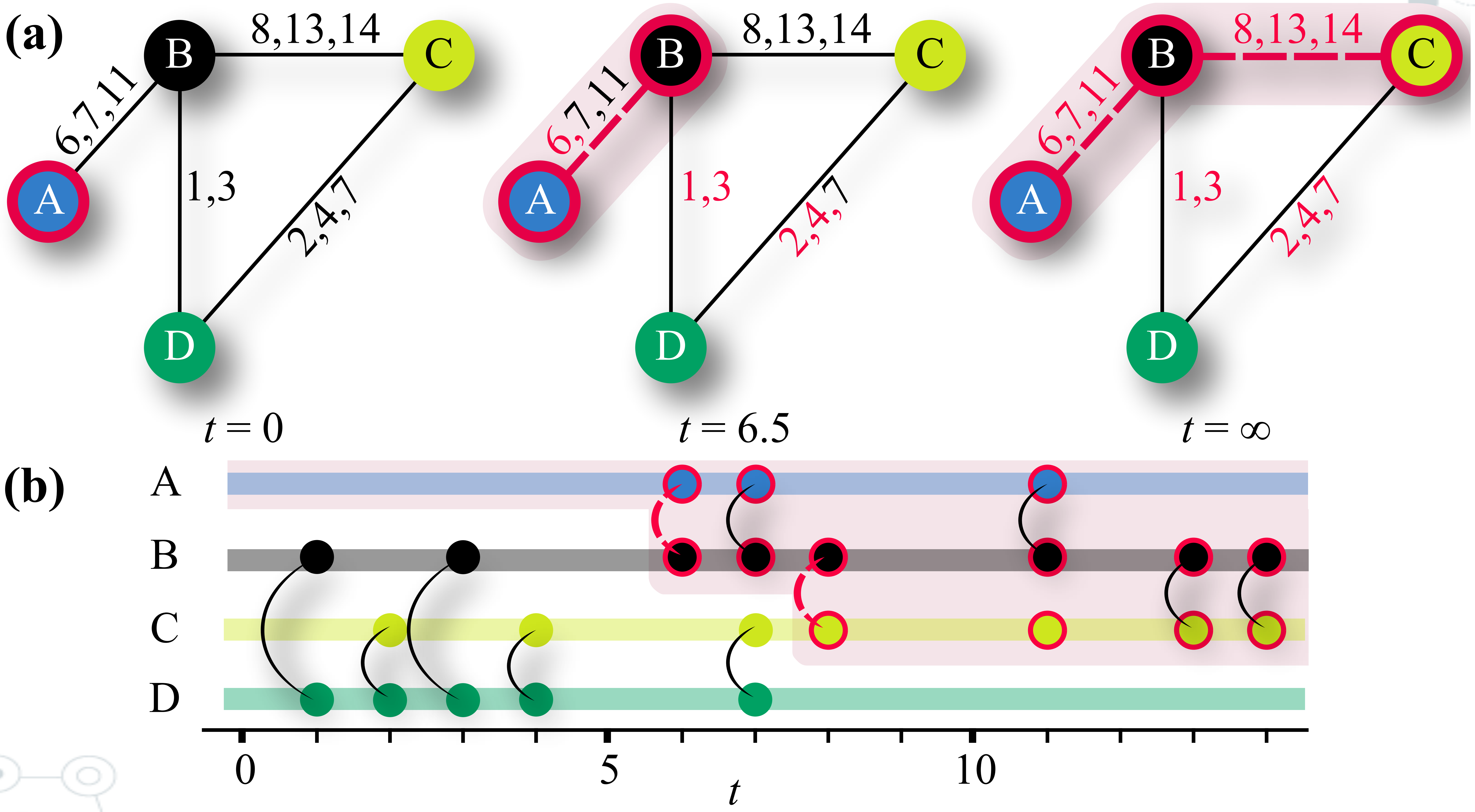
…….

Representation

Timelines of links

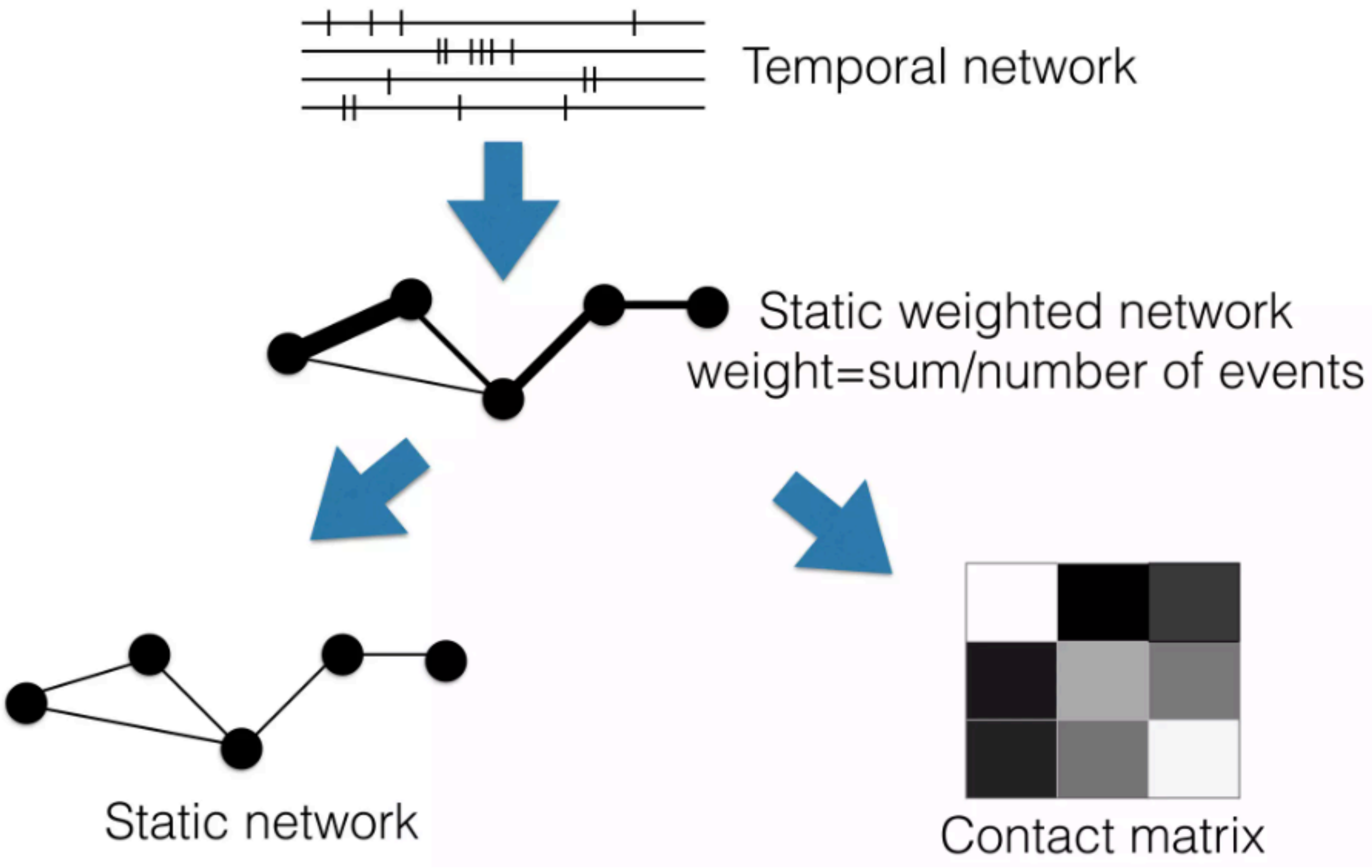


Annotated graph

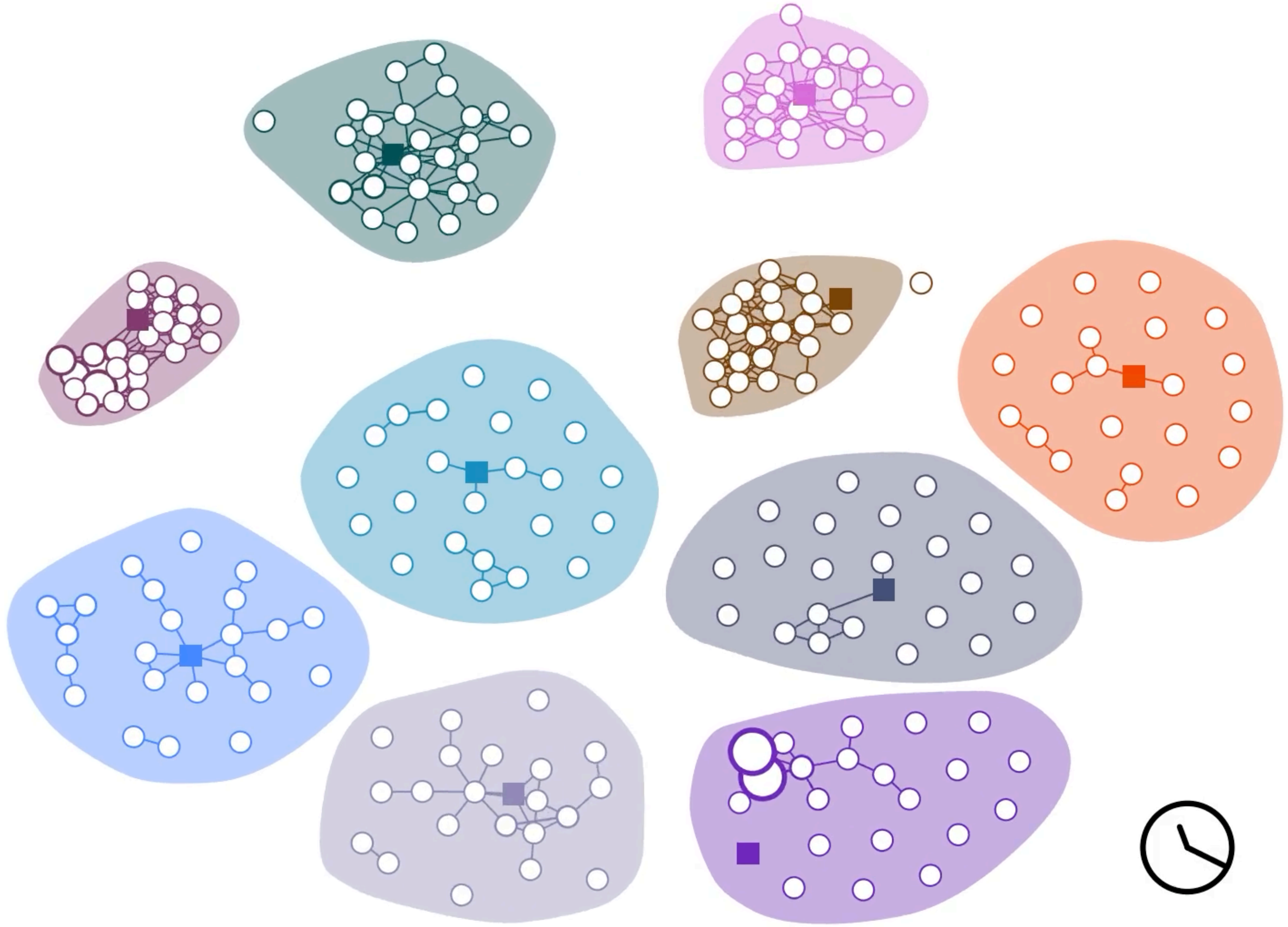


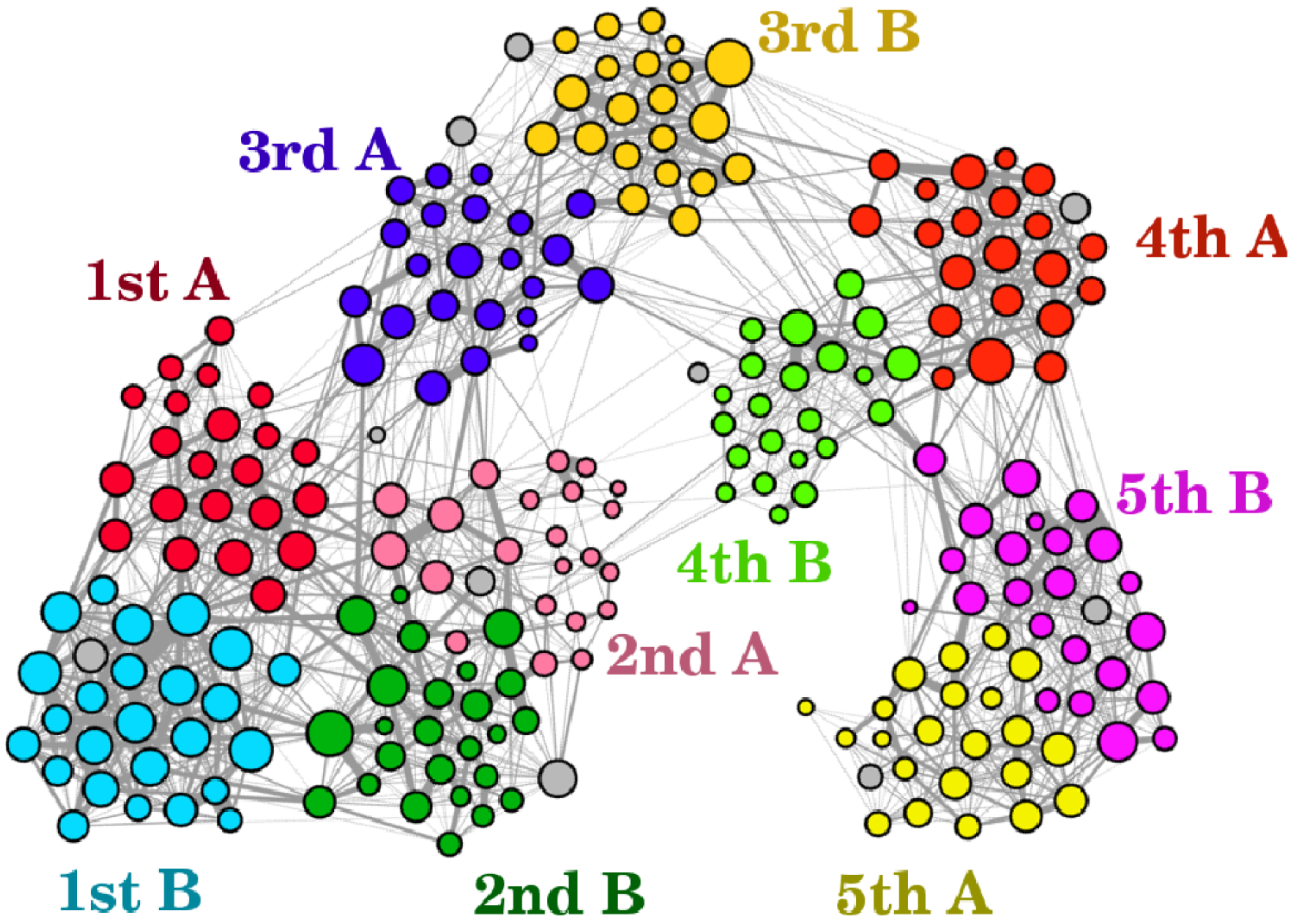
Aggregation

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



Aggregation



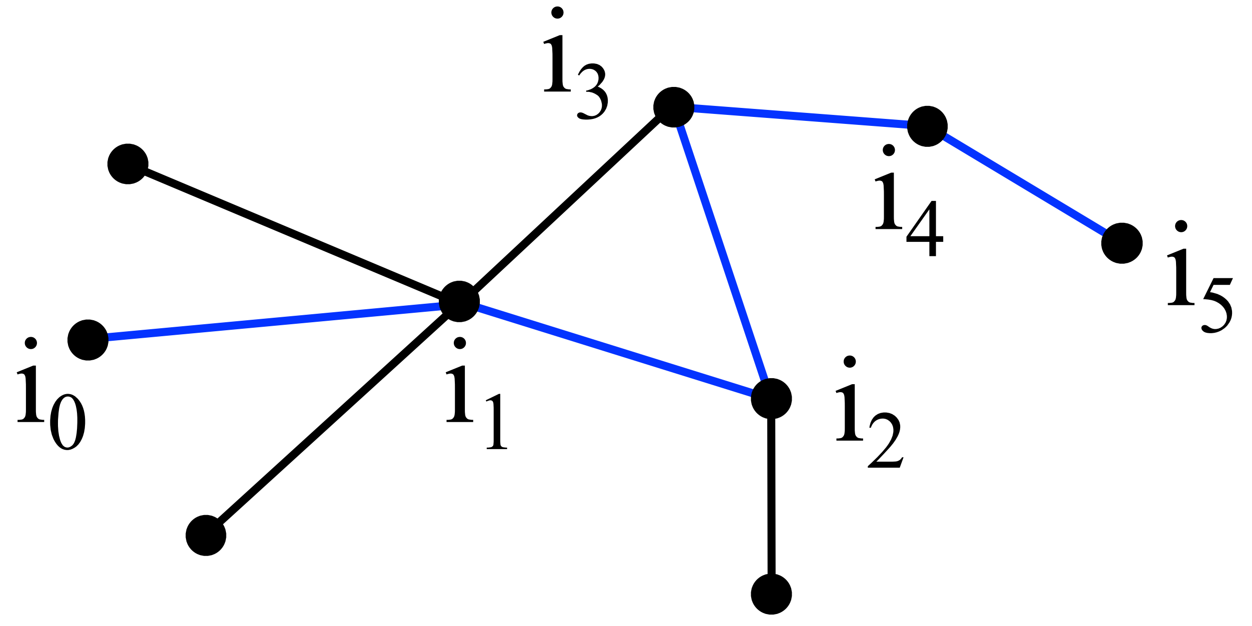


Paths in static networks

$G=(V,E)$

Path of length n = ordered collection of

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



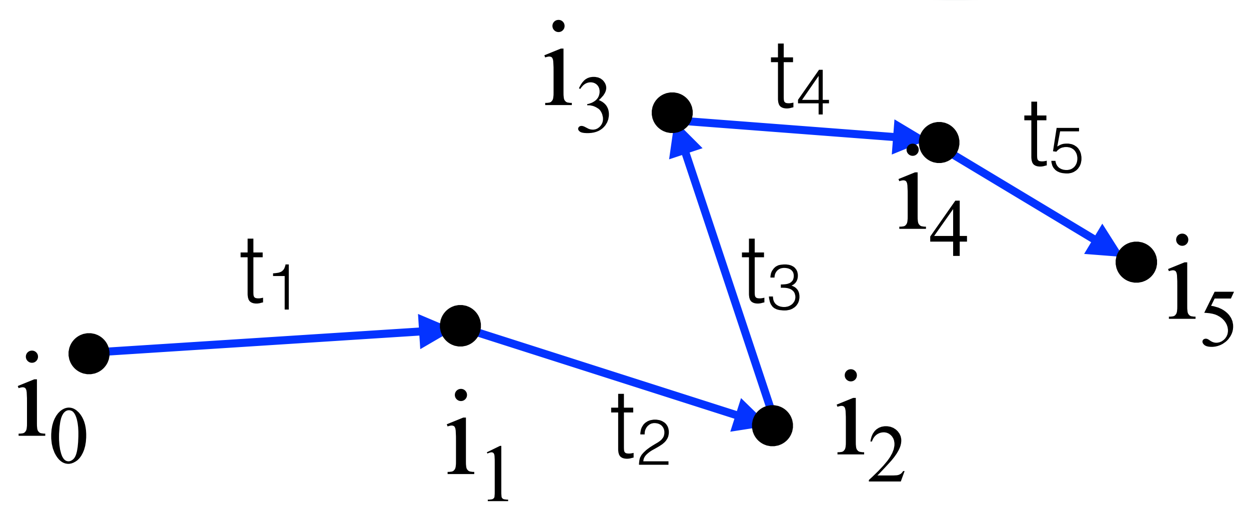
→ Notions of **shortest** path, of connectedness

Paths in temporal networks

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

Length of path: n

Duration of path: t_n - t_1



Sequence of ***events***

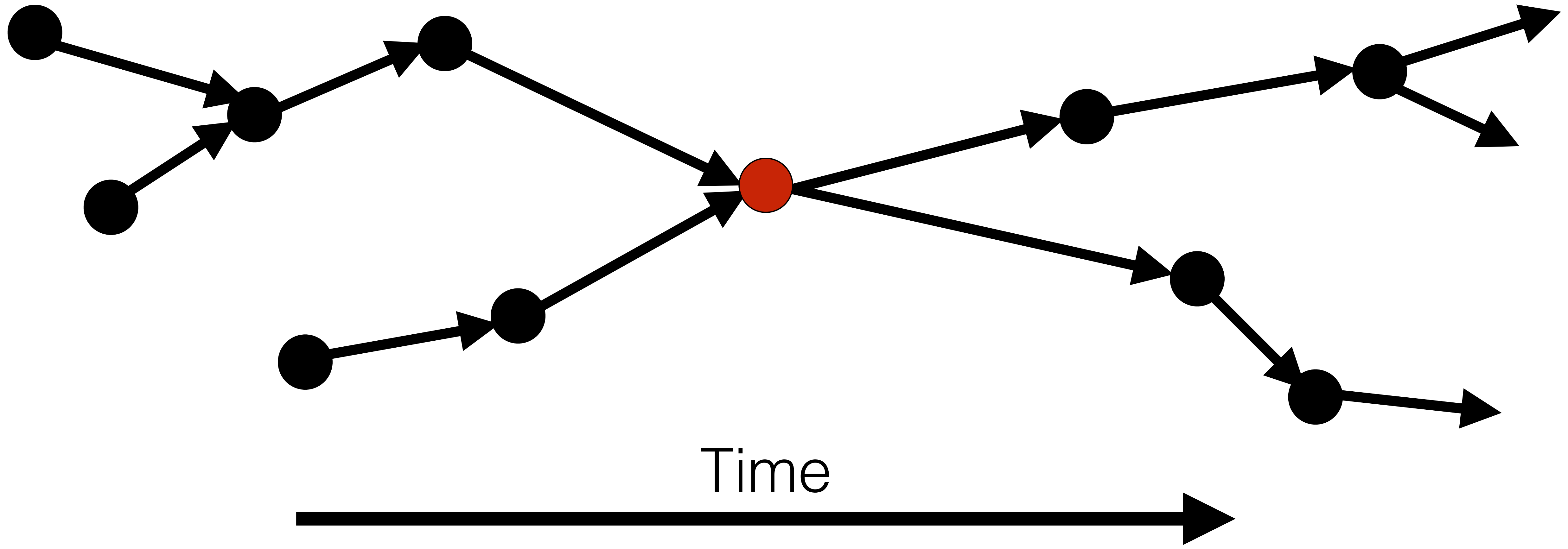
Notions of **shortest** path and of **fastest** path

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

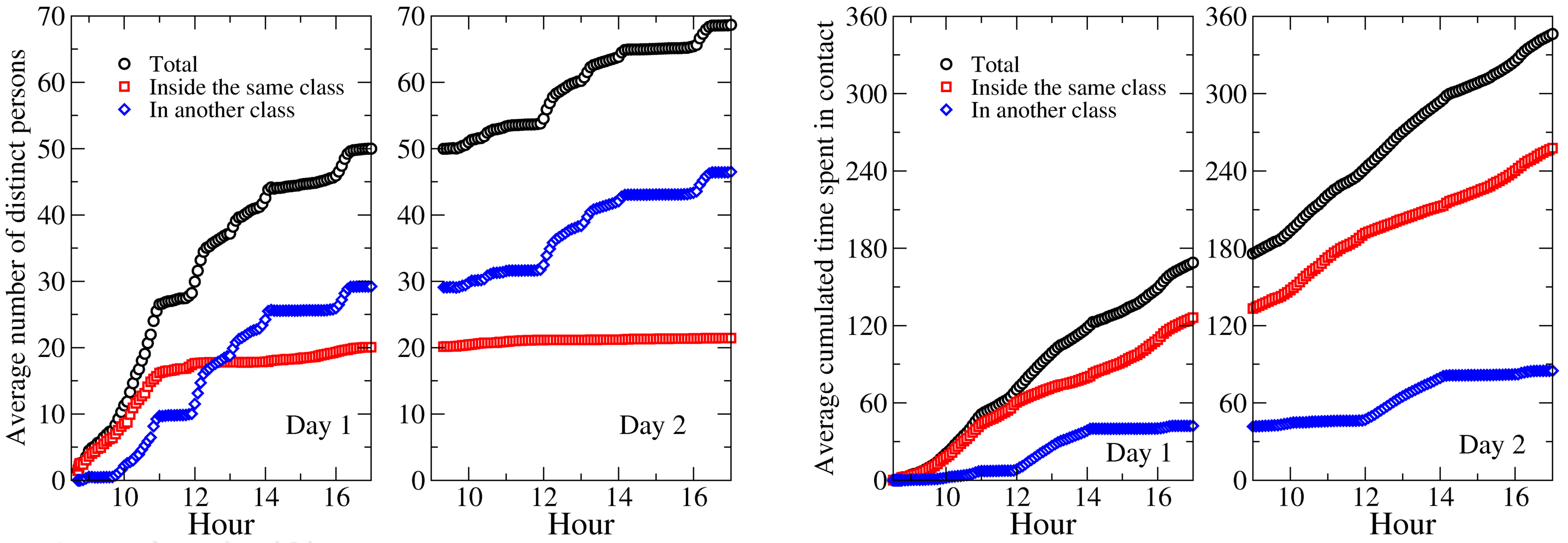
- **Time-dependence**:
  - there can be a path from i to j starting at t but no path starting at $t' > t$
  - shortest and fastest paths can differ
  - length of shortest path can depend on starting time
  - duration of fastest path can depend on starting time
  - there can be a path starting from i at t_0, reaching j at t_1, and another path starting form 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: $\langle k \rangle(t), \langle s \rangle(t)$



J. Stehlé et al. PLoS ONE 6(8):e23176 (2011)

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

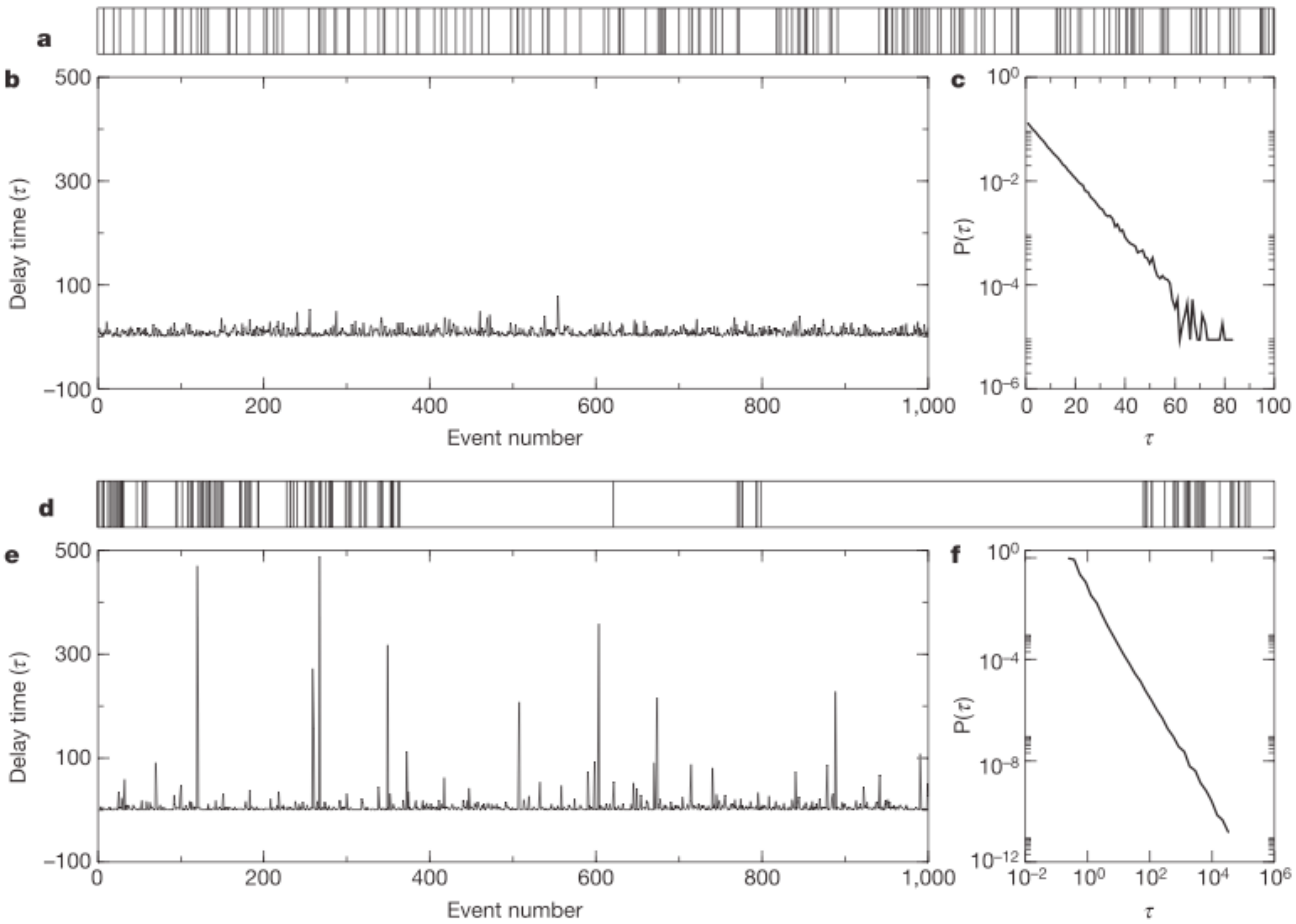
- **Burstiness**

Burstiness

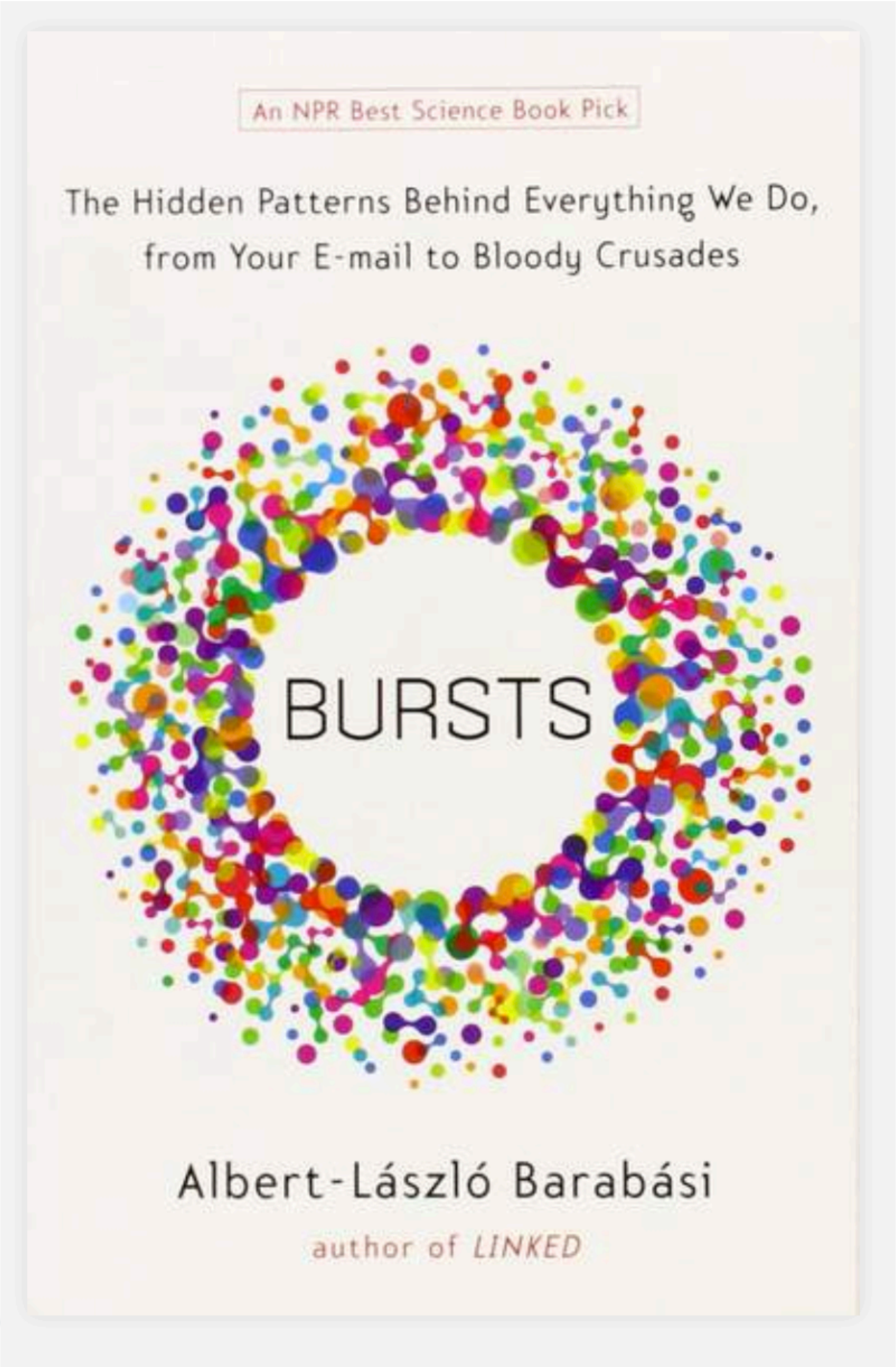
A.-L. Barabási, Nature (2005)

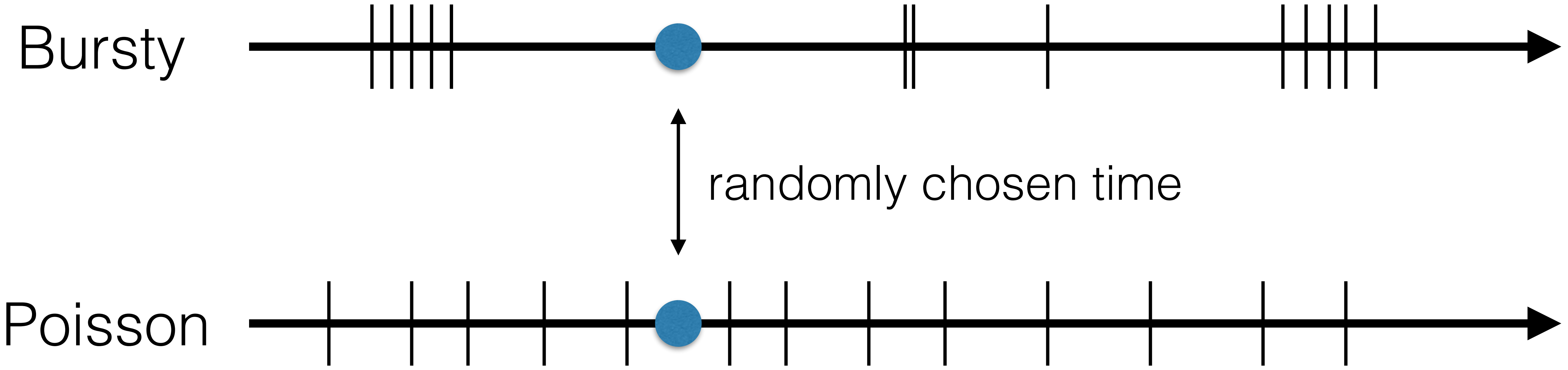
- Poisson process

- Bursty behaviour



Consequences of burstiness





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

Data and epidemiology

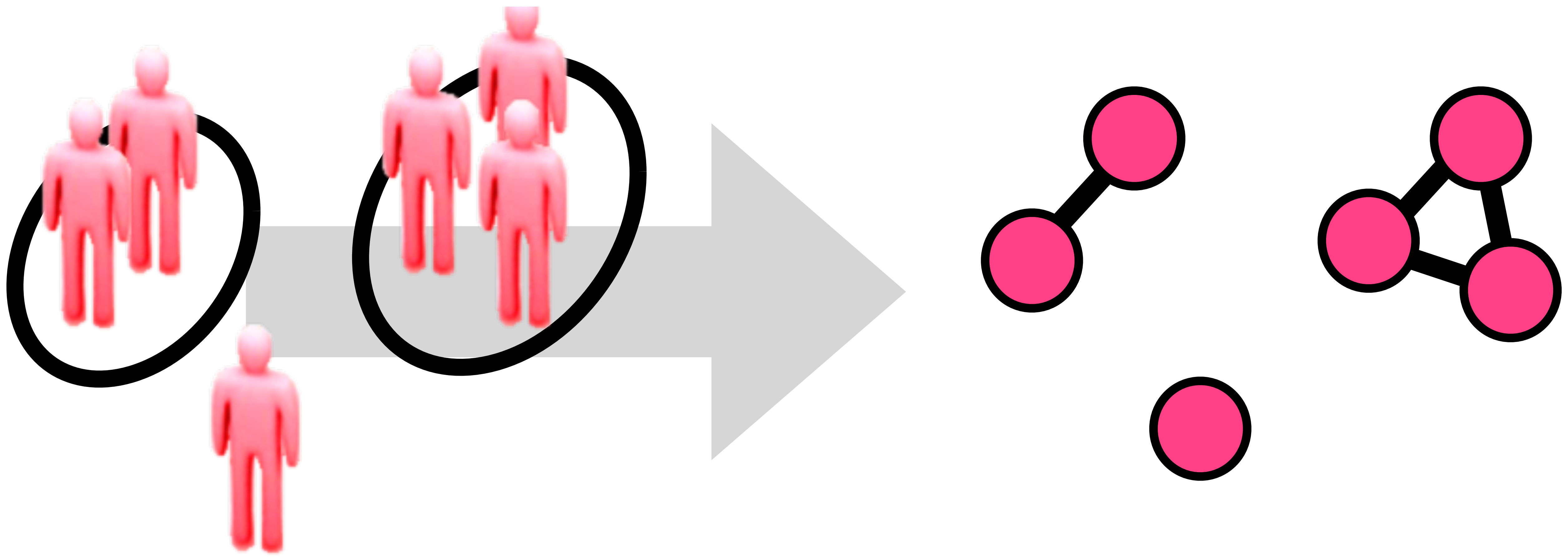
Sociopatterns

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

SocioPatterns.org

Motivations

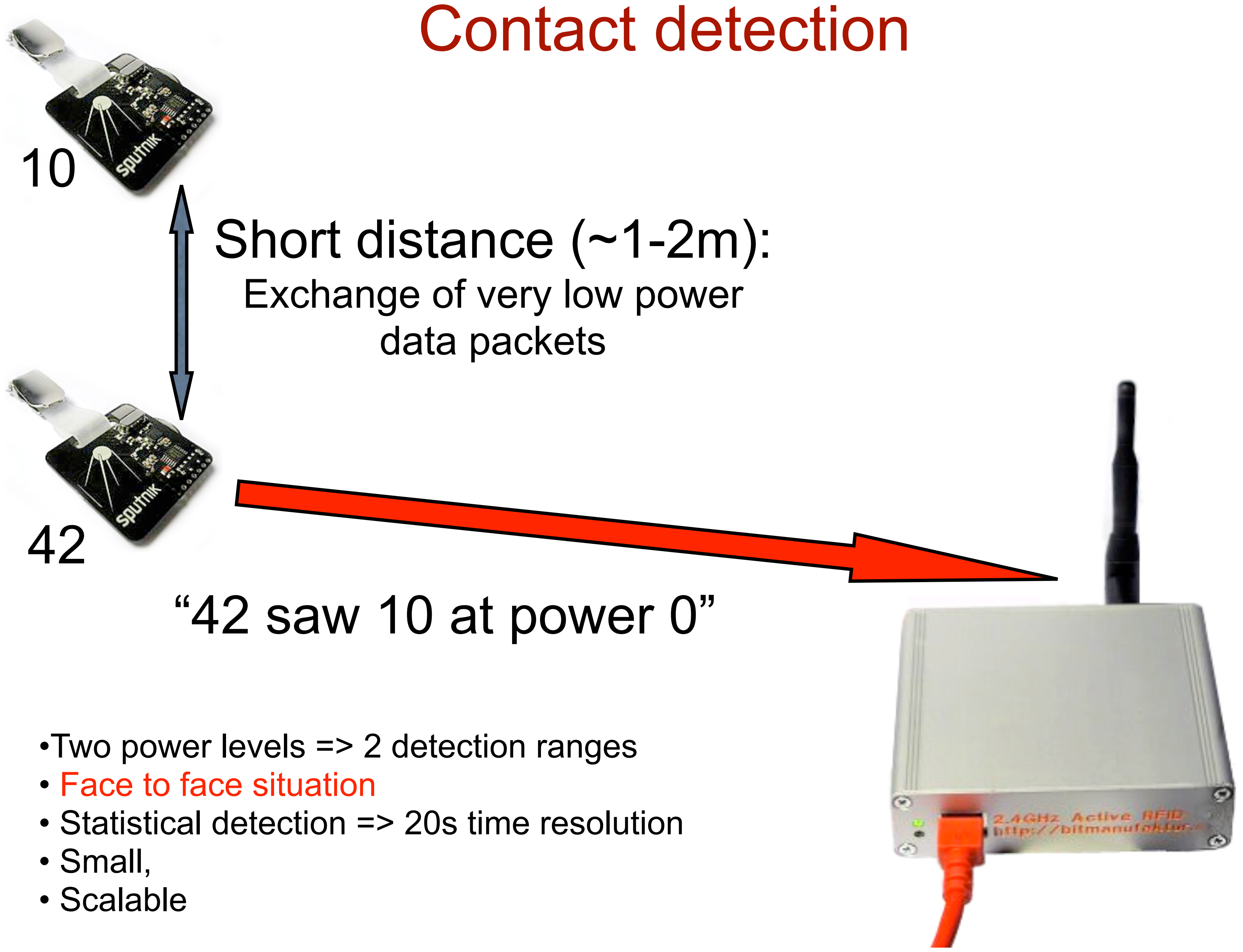
★ fundamental knowledge on human contact
★ epidemiology
★ social sciences
★ ad-hoc networks
★ integration with on-line information
★...



Sociopatterns

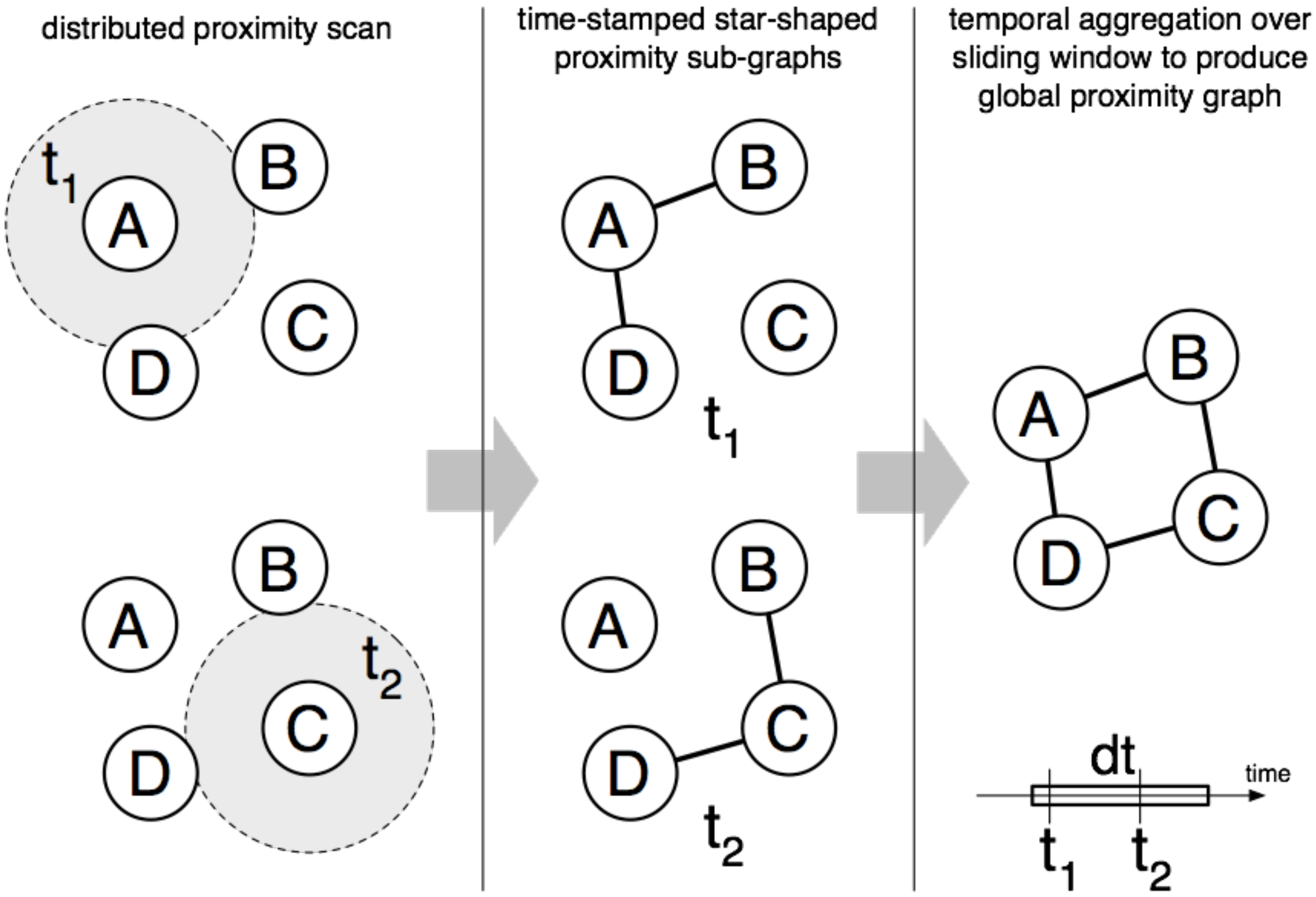
SocioPatterns.org

Contact detection



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

Face-to-face proximity networks

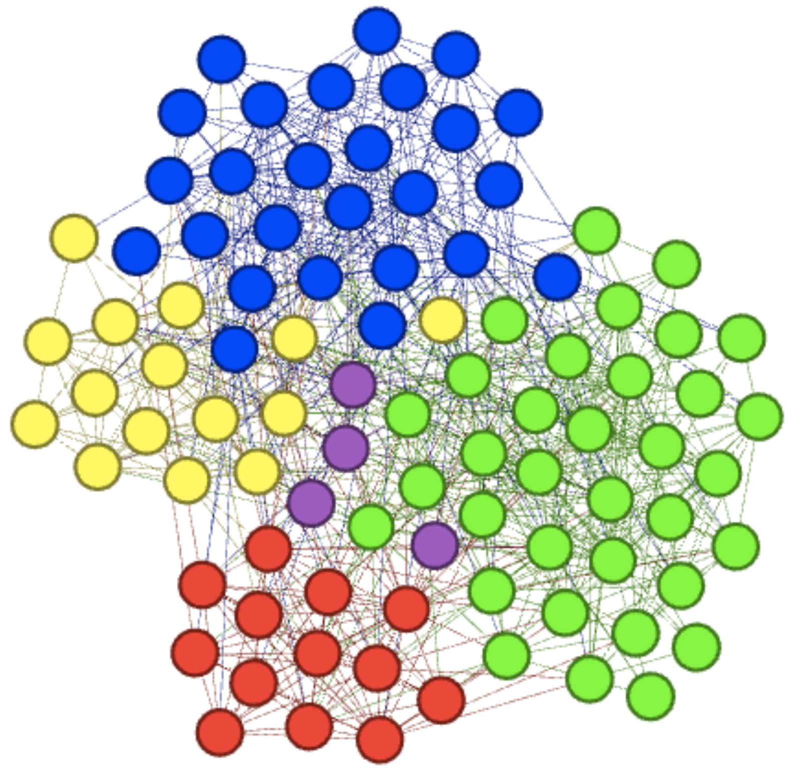


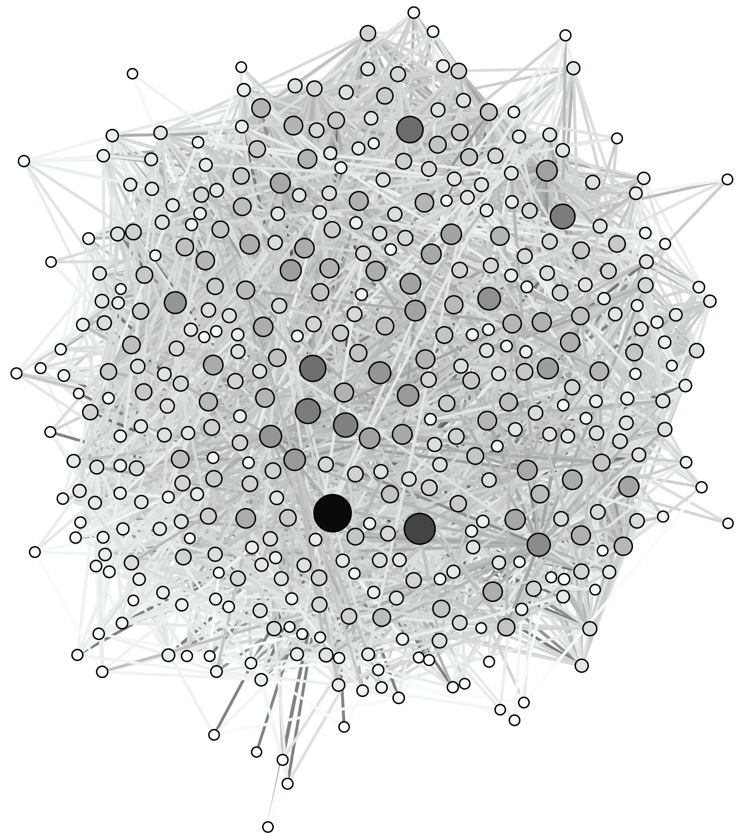
Deployments

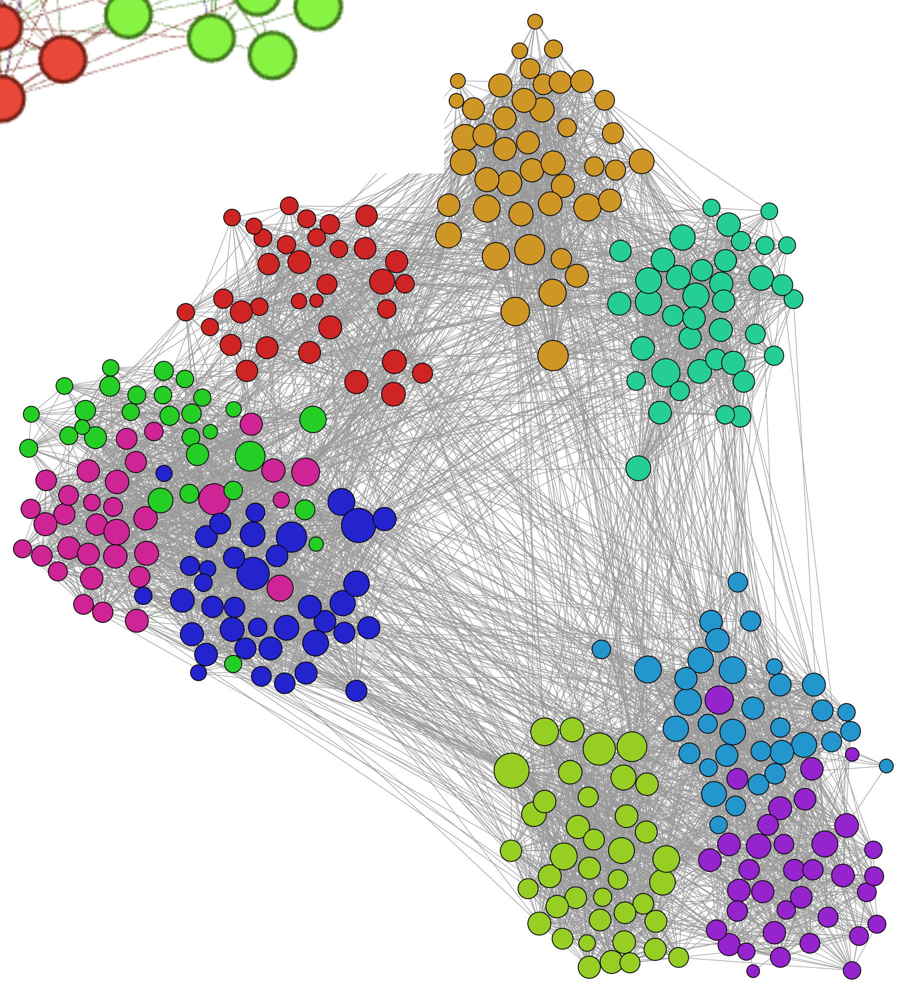
9 years, 30+ deployments, 10+ countries,
50,000+ ppl

schools, hospitals, conferences, households

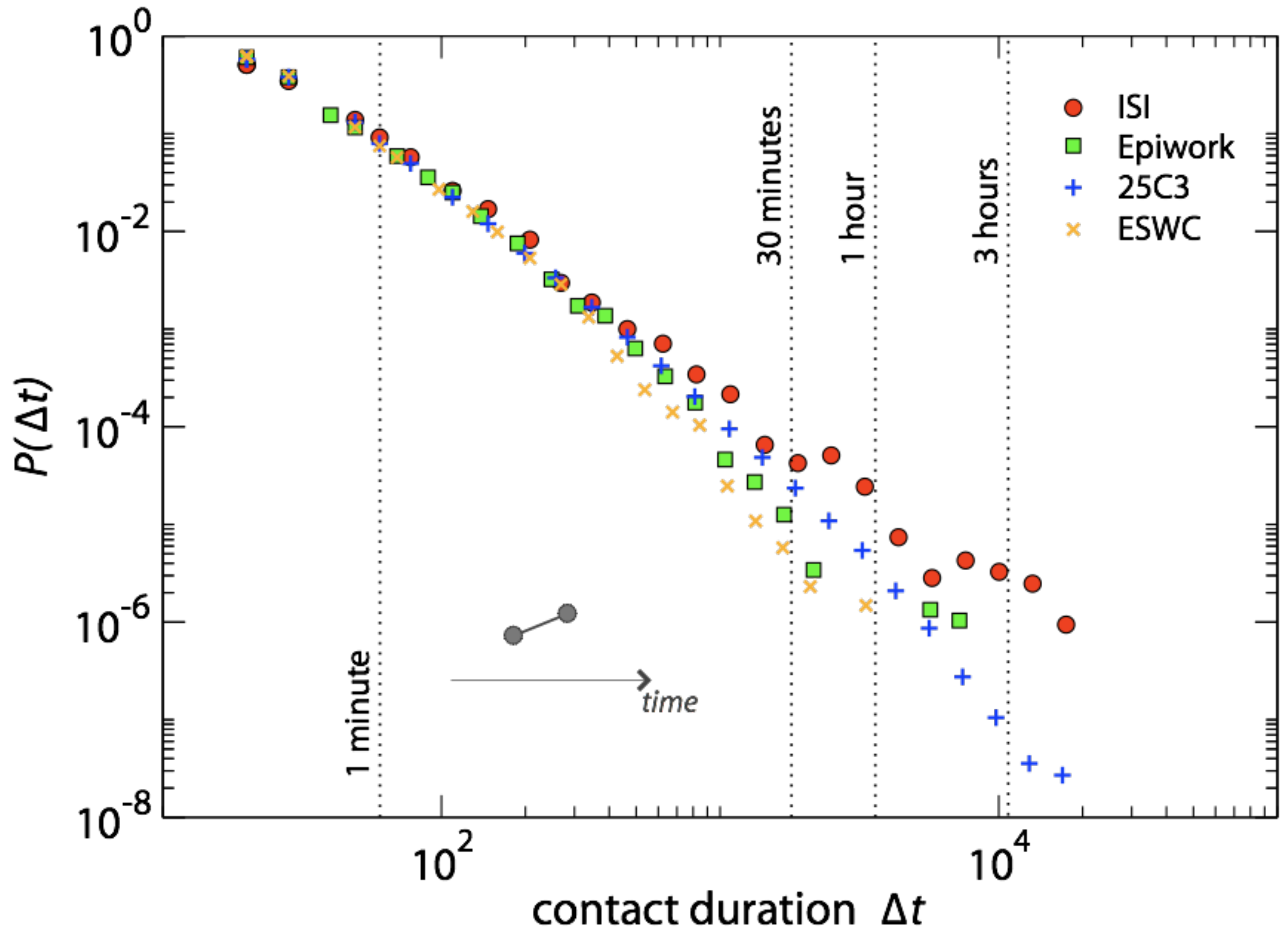
www.sociopatterns.org/datasets

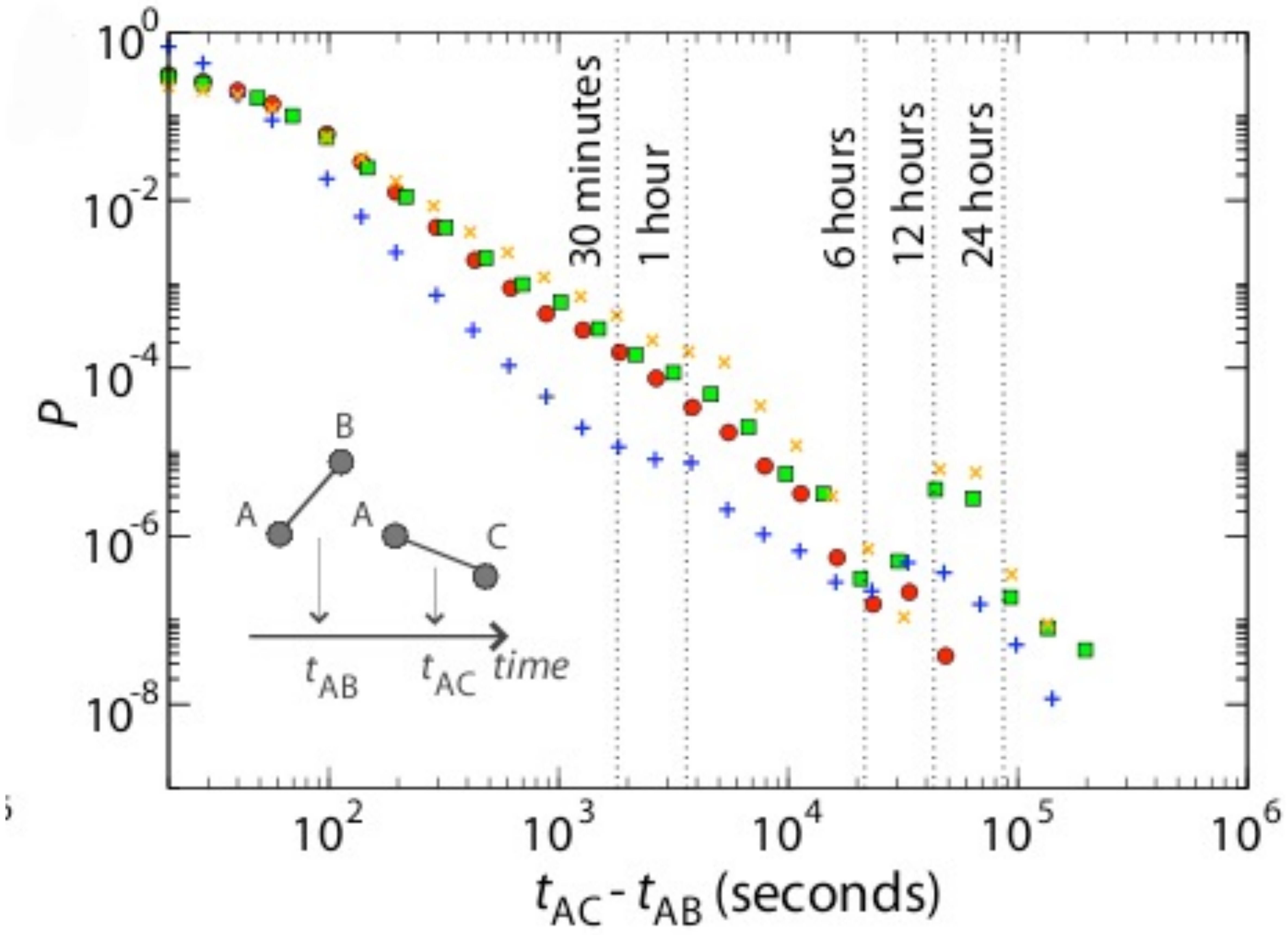






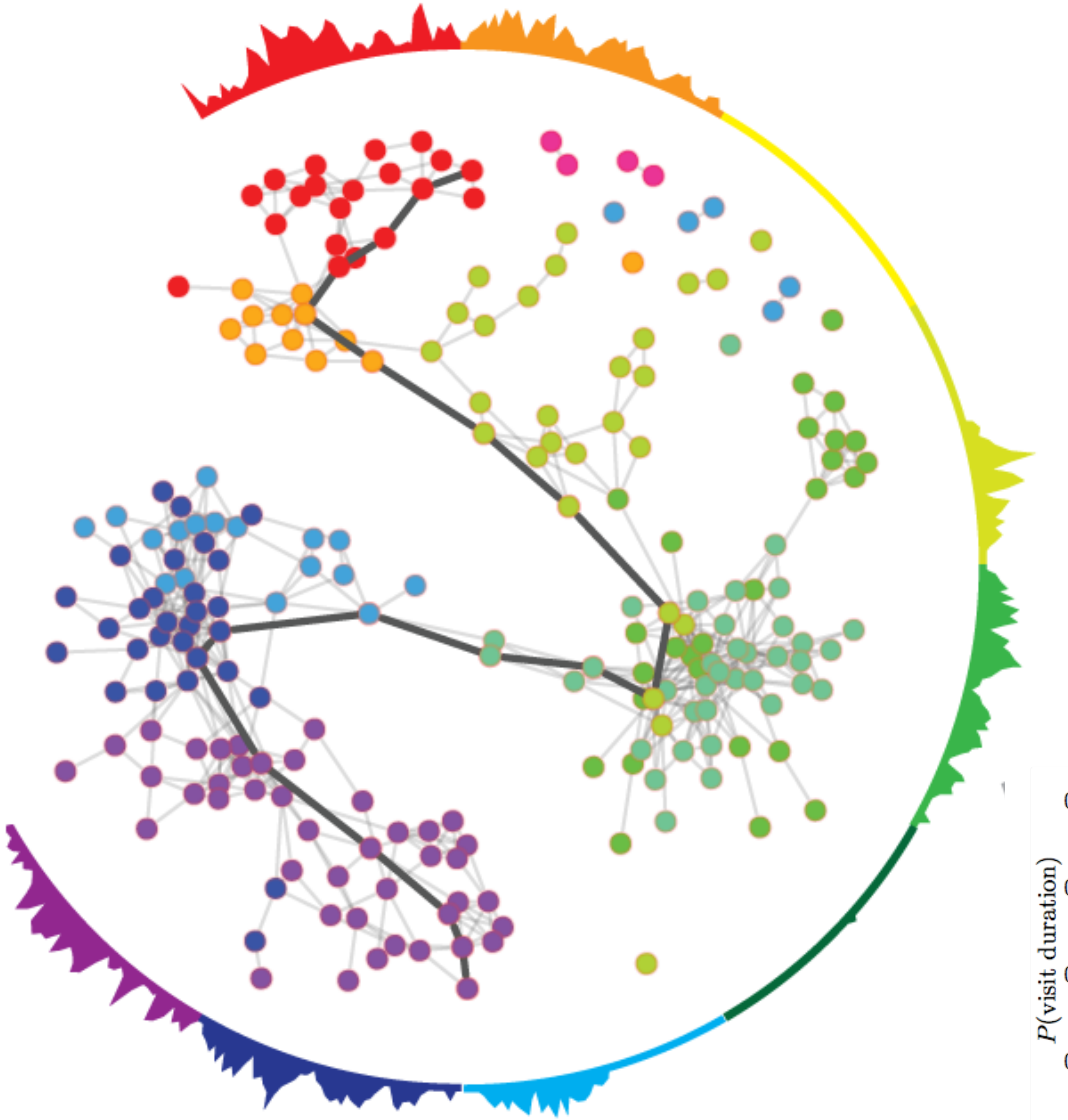
Empirical measures

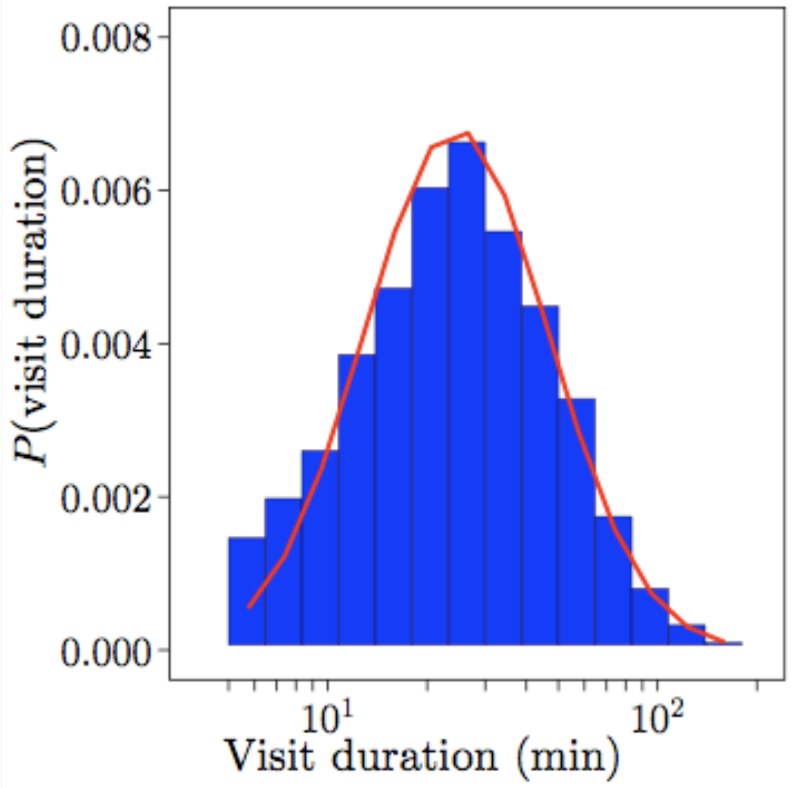




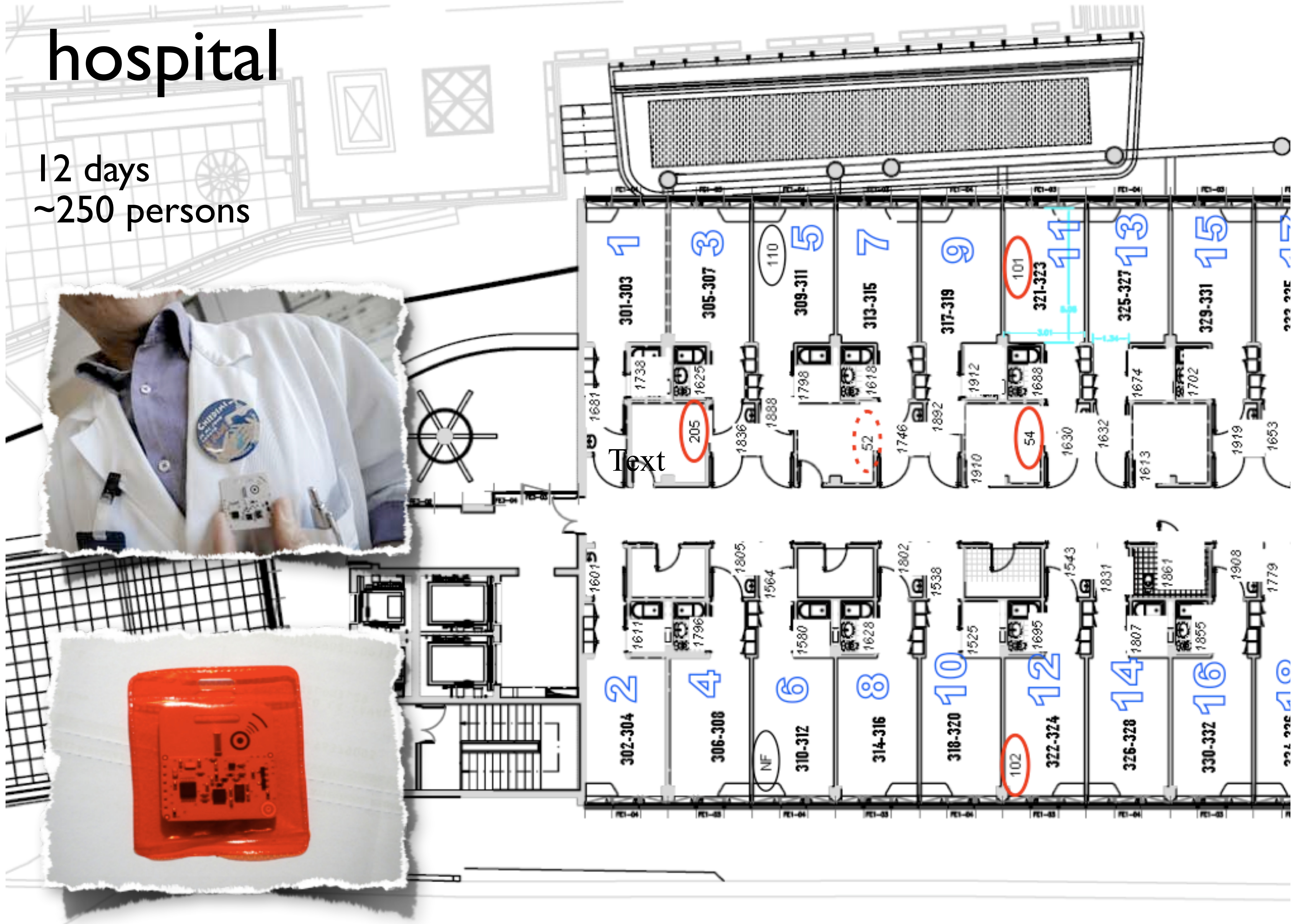
Museum

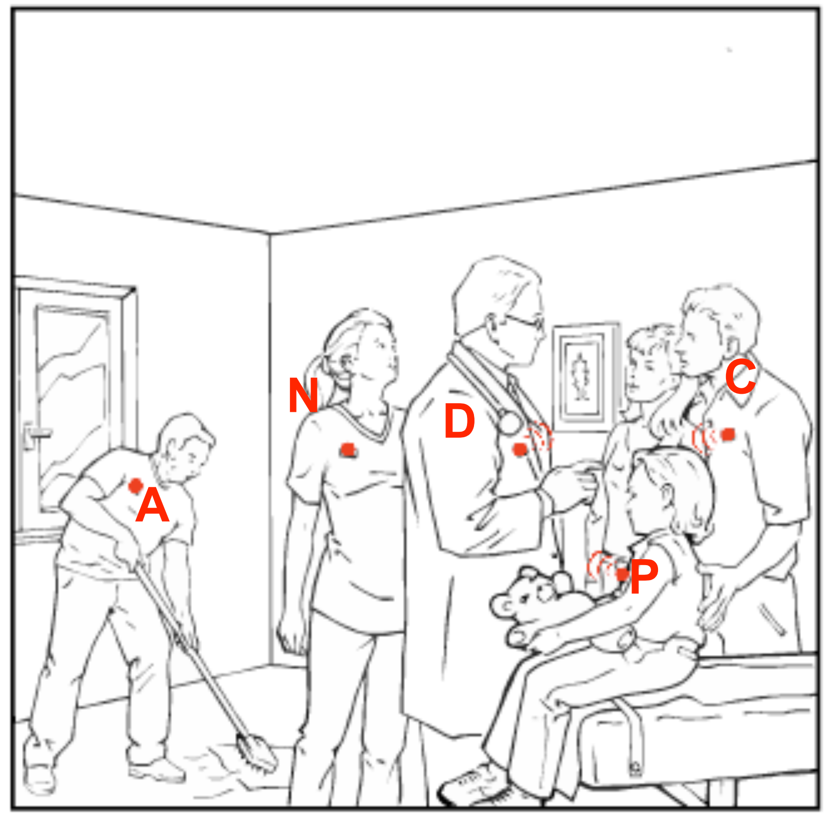
SocioPatterns.org

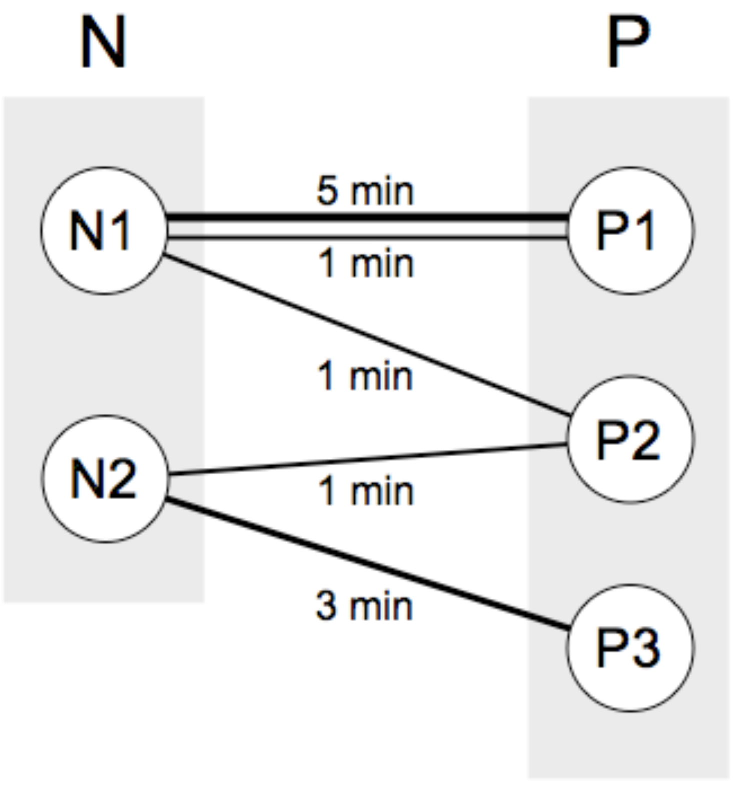


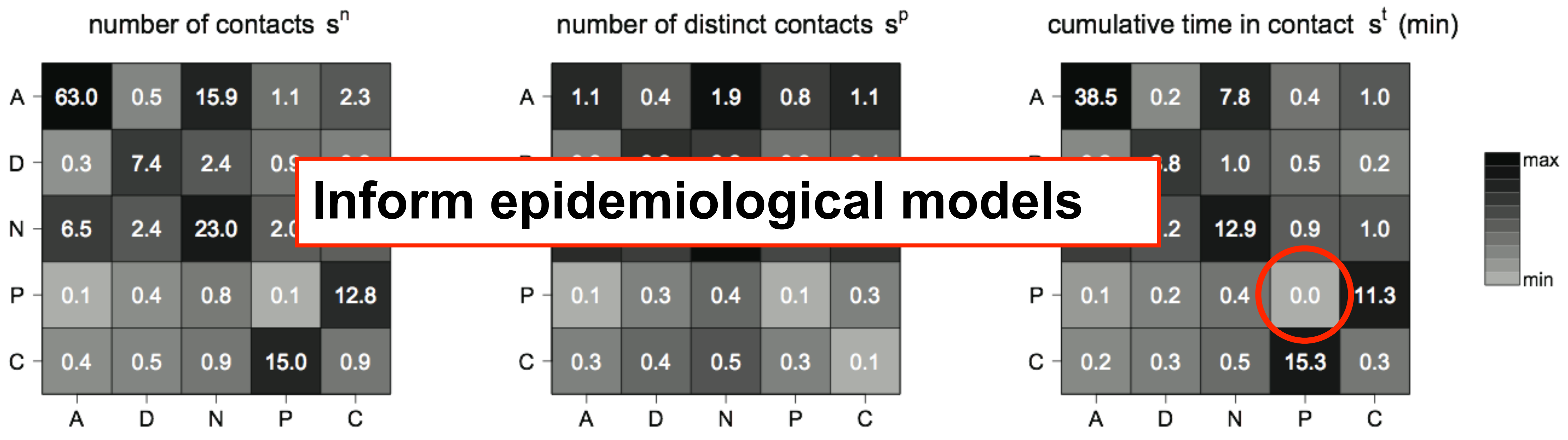


Hospital



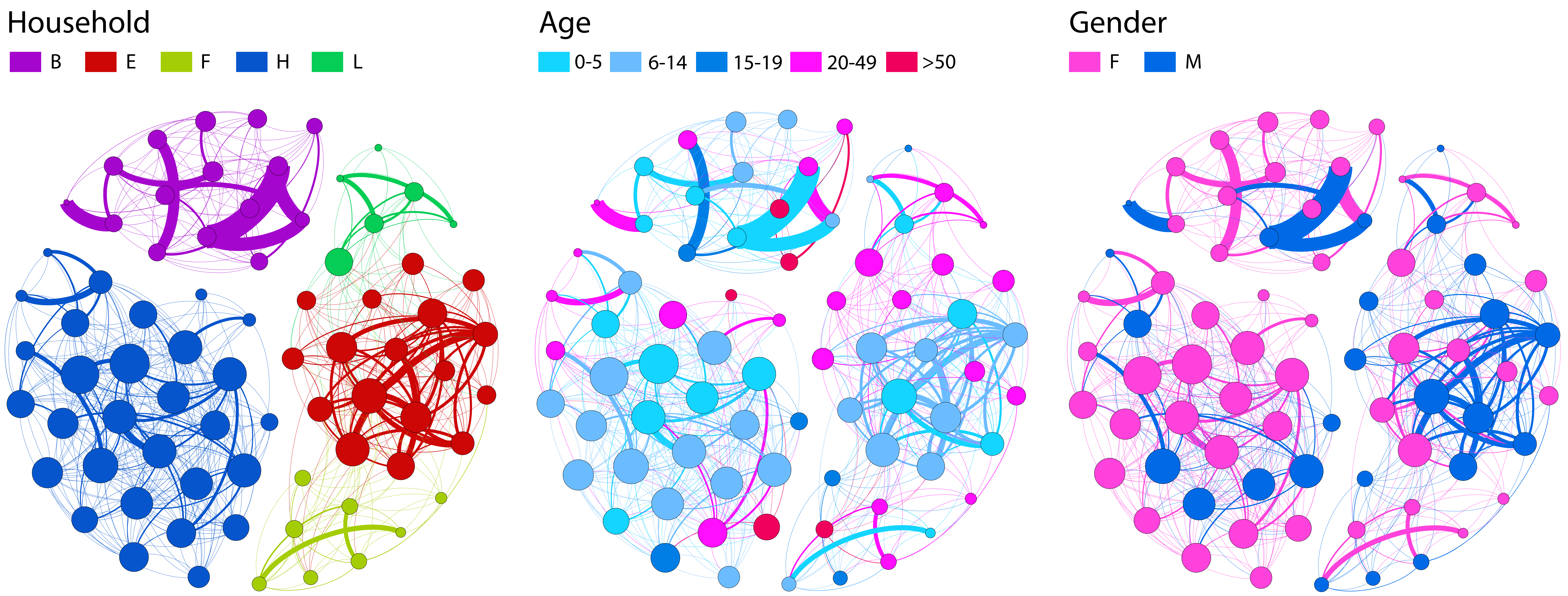






L. Isella *et al.*, PLoS ONE 6(2), e17144 (2011)

Households

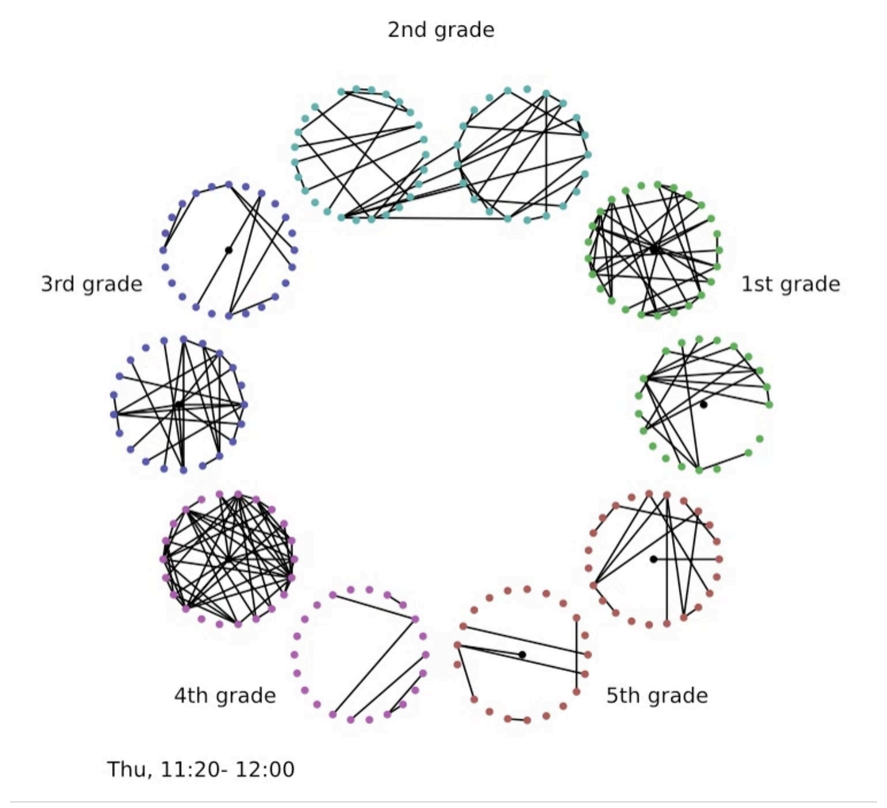


Epidemic processes

- **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.

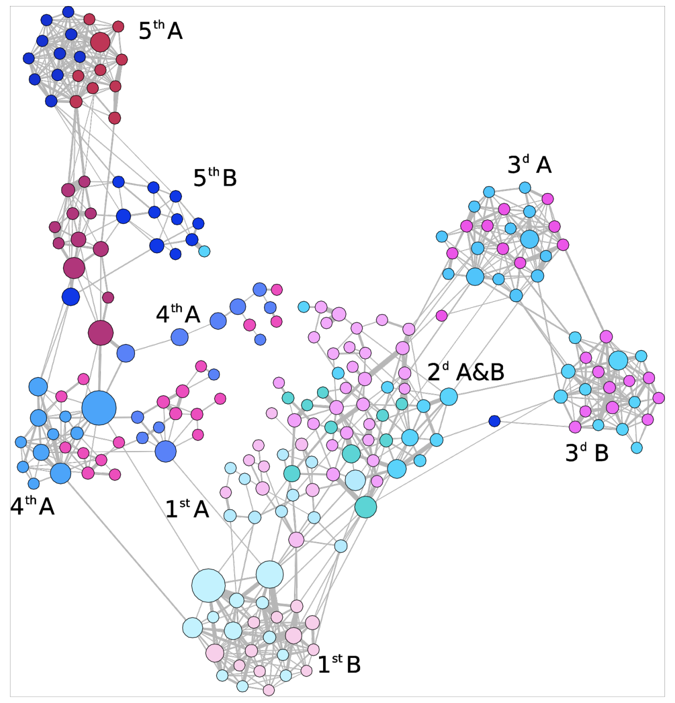
- **Data-driven simulations.**
  - Several results based on epidemic simulations on empirical temporal networks, including the effects of **vaccinations, link removal, and many possible interventions**

How much detail for a model?



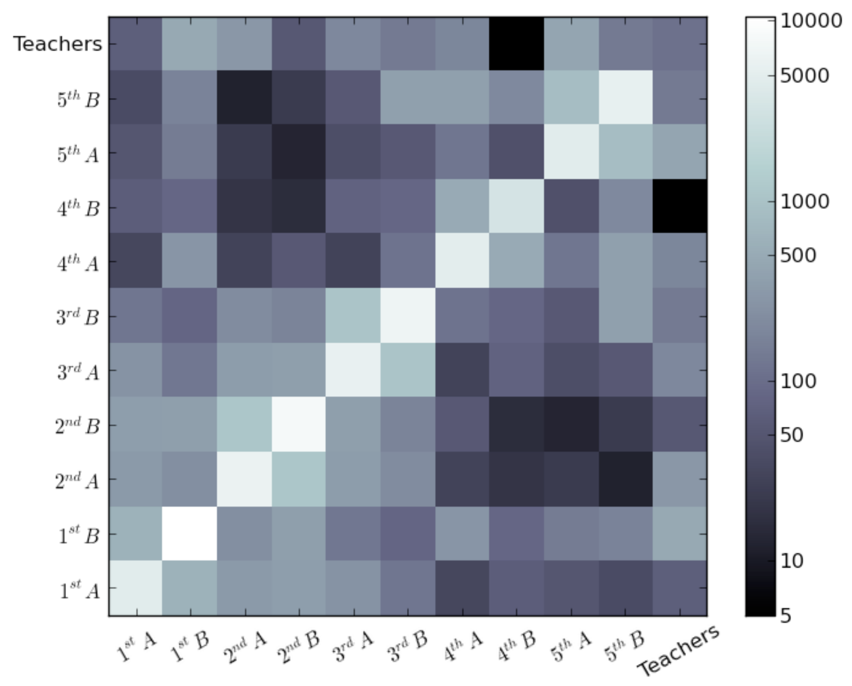
Detailed dynamic network

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



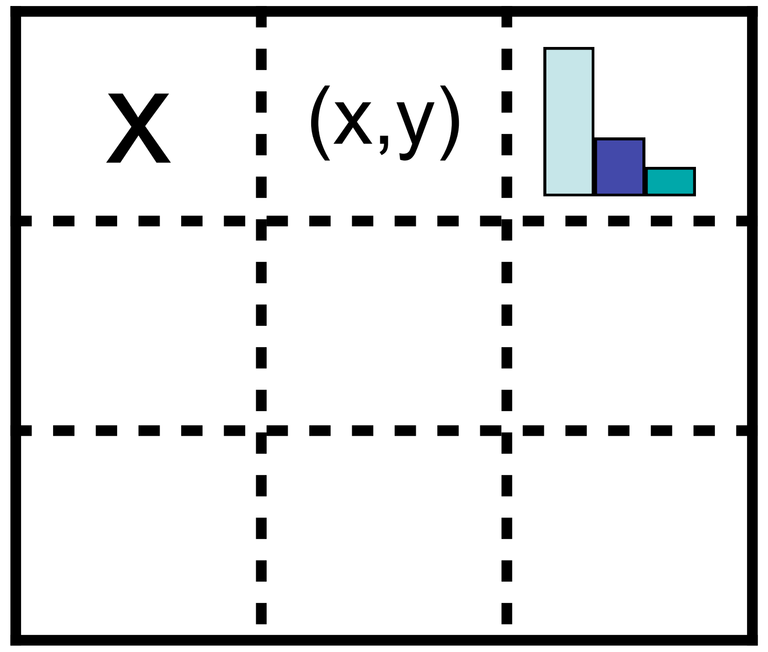
Static network

- 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 ✔

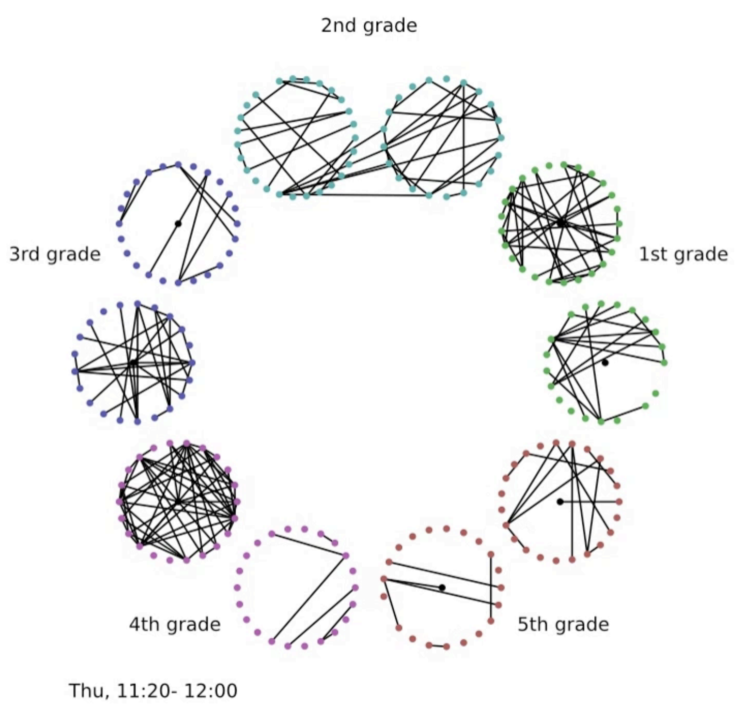


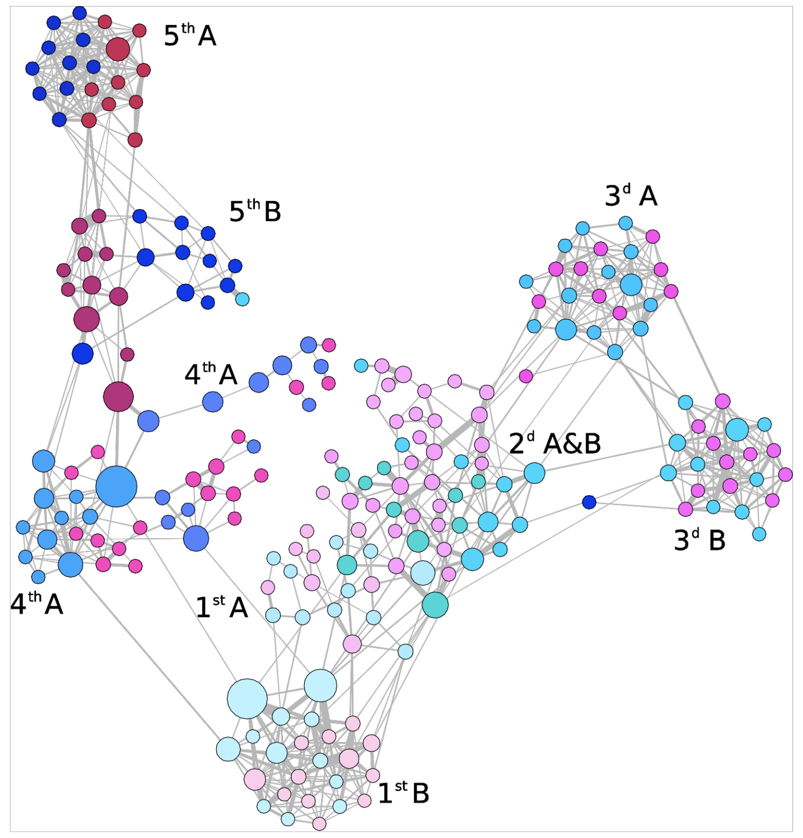
Contact matrix of distributions

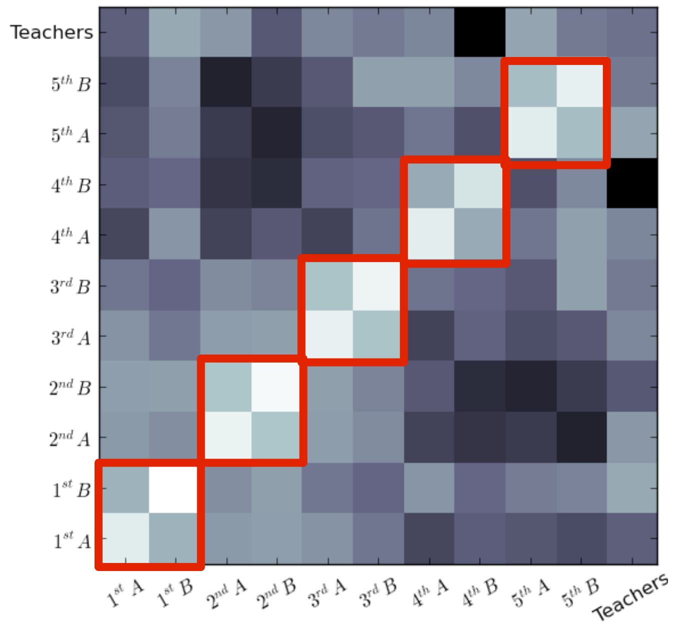
- Role based ✔
- Takes into account heterogeneities ✔

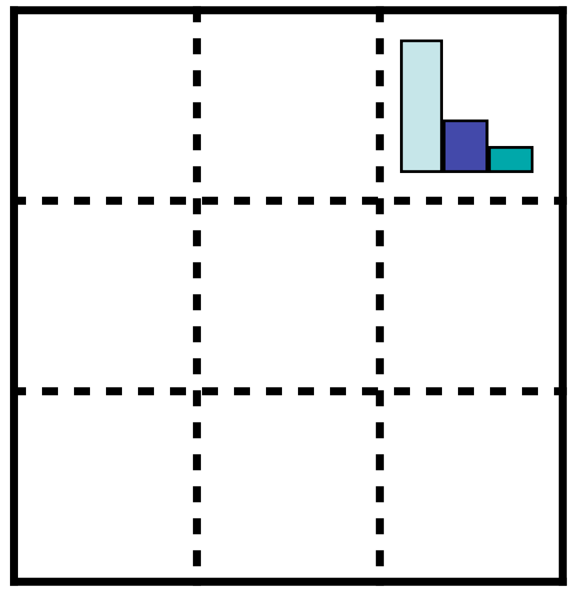
Machens et al, BMC Infect. Dis.(2013)

Evaluating representations









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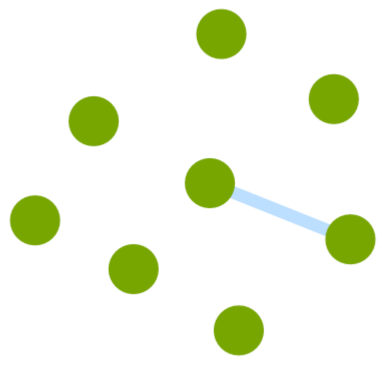
Susceptible → Exposed → Infectious → Recovered

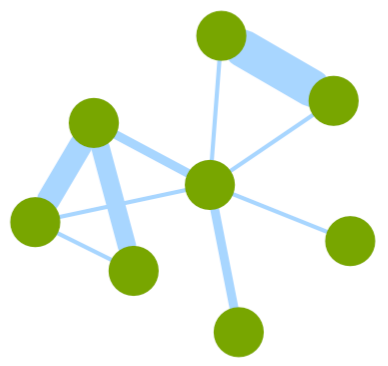
J. Stehlé et al., BMC Medicine (2011); A. Machens et al, BMC Inf Dis (2013)

Evaluating representations

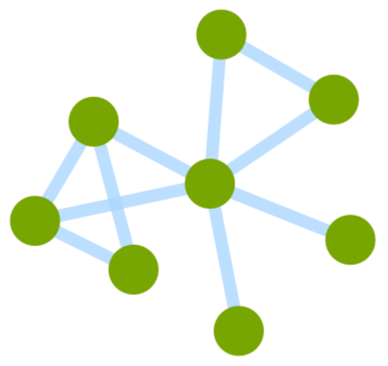
Construction of 3 **networks**:



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

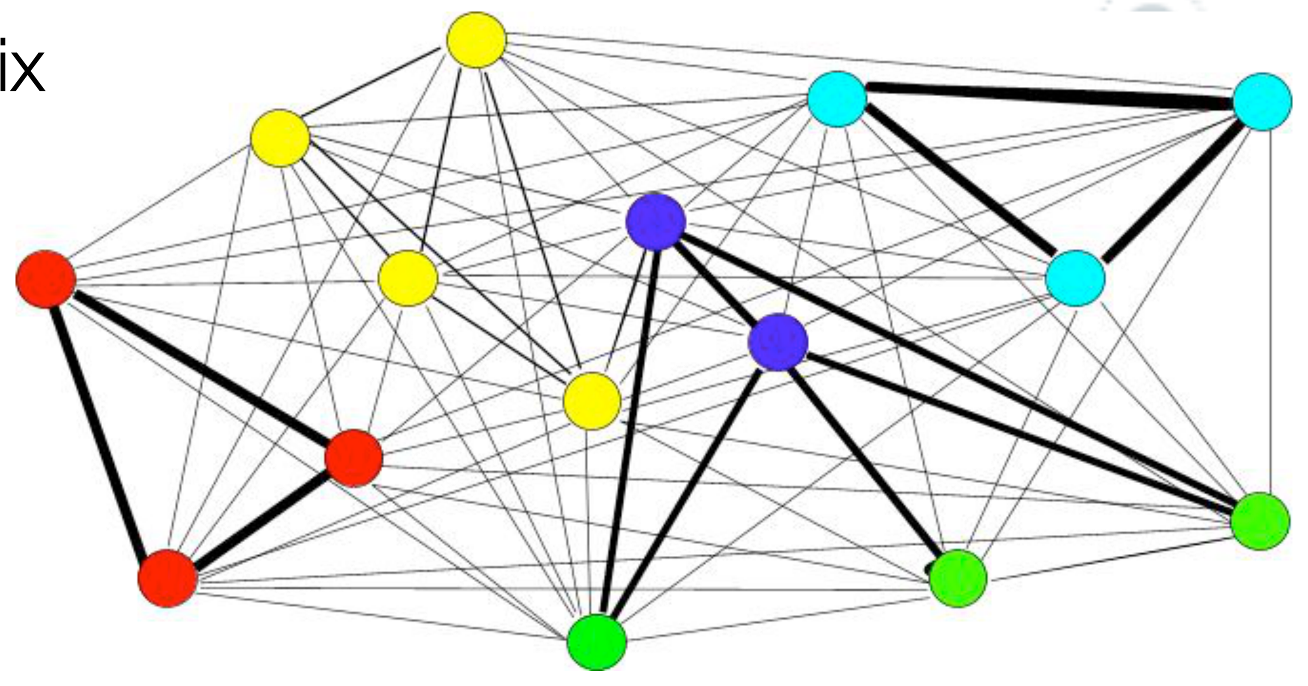


2. Heterogeneous network (HET):
   1-day aggregated network
   A—B if A and B have been in contact
   W_{AB} = cumulative duration of the contacts A-B



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

4. Contact matrix



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

Average contact time in seconds per day

w_{AB}	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

A. Machens et al, BMC Inf Dis (2013)

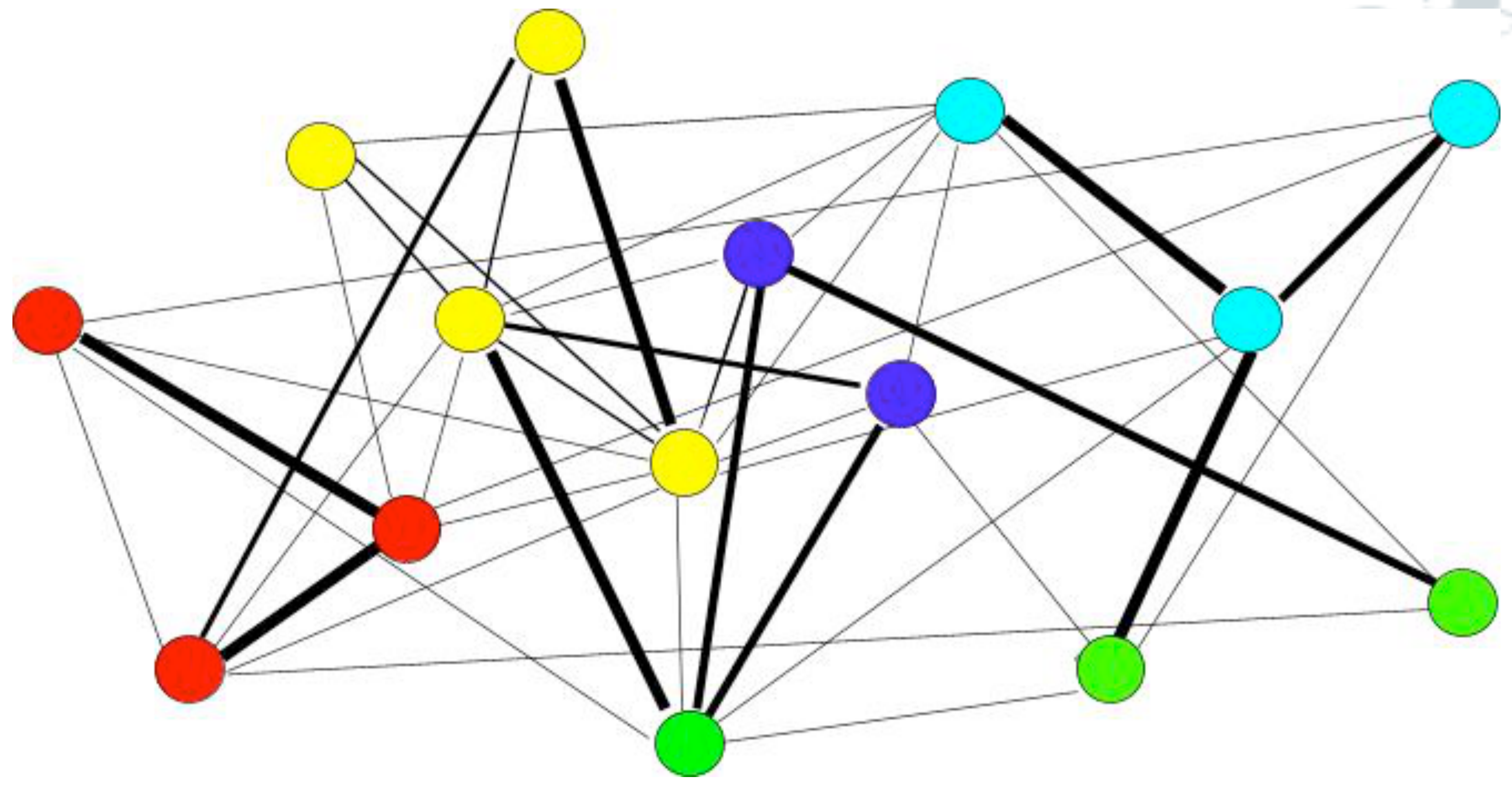
Evaluating representations

5. Novel representation: Contact matrix of distributions

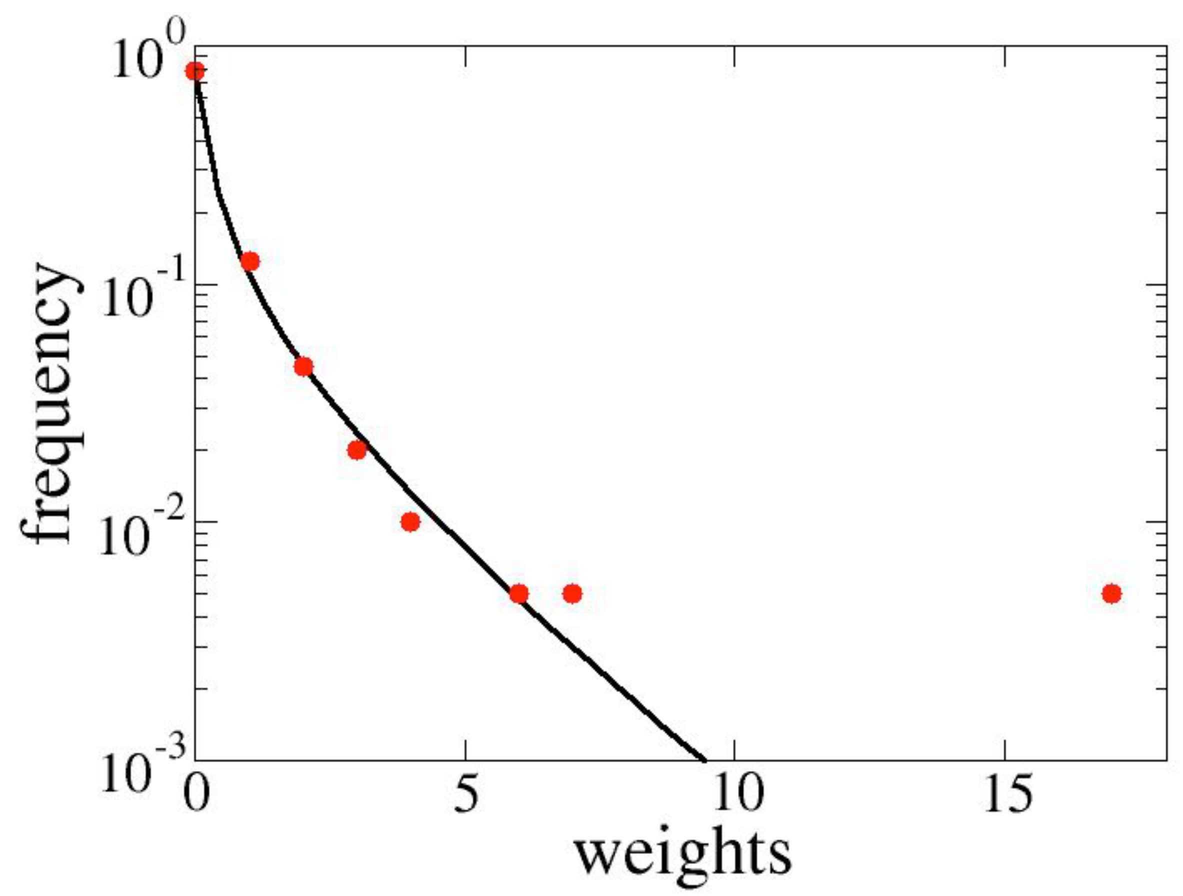
a. Fit each role-pair distribution of weights
(using negative binomials)

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



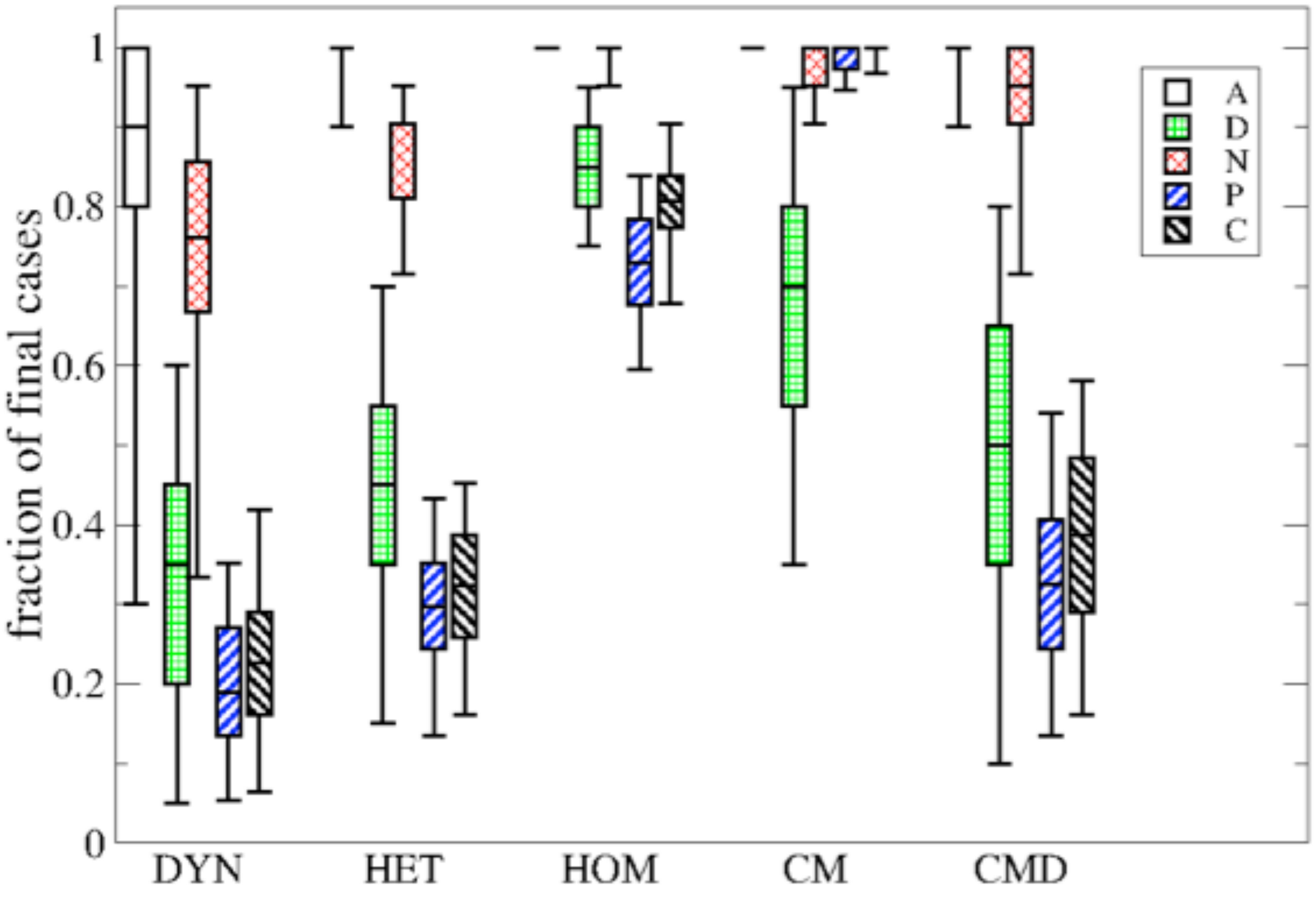
Example: Assistant-Doctor

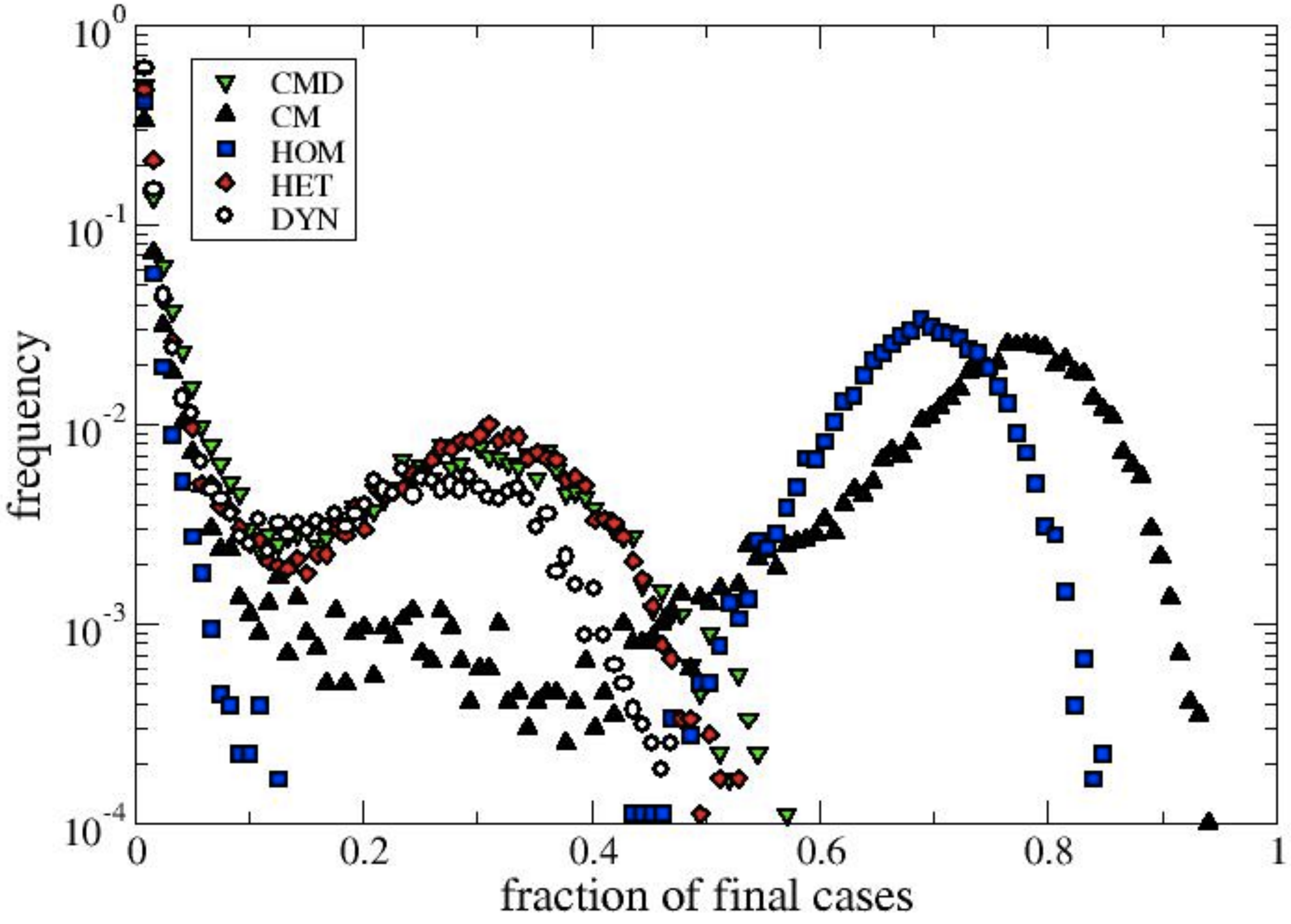


A. Machens et al, BMC Inf Dis (2013)

SEIR simulation results

Attack rate by groups (for AR > 10%)





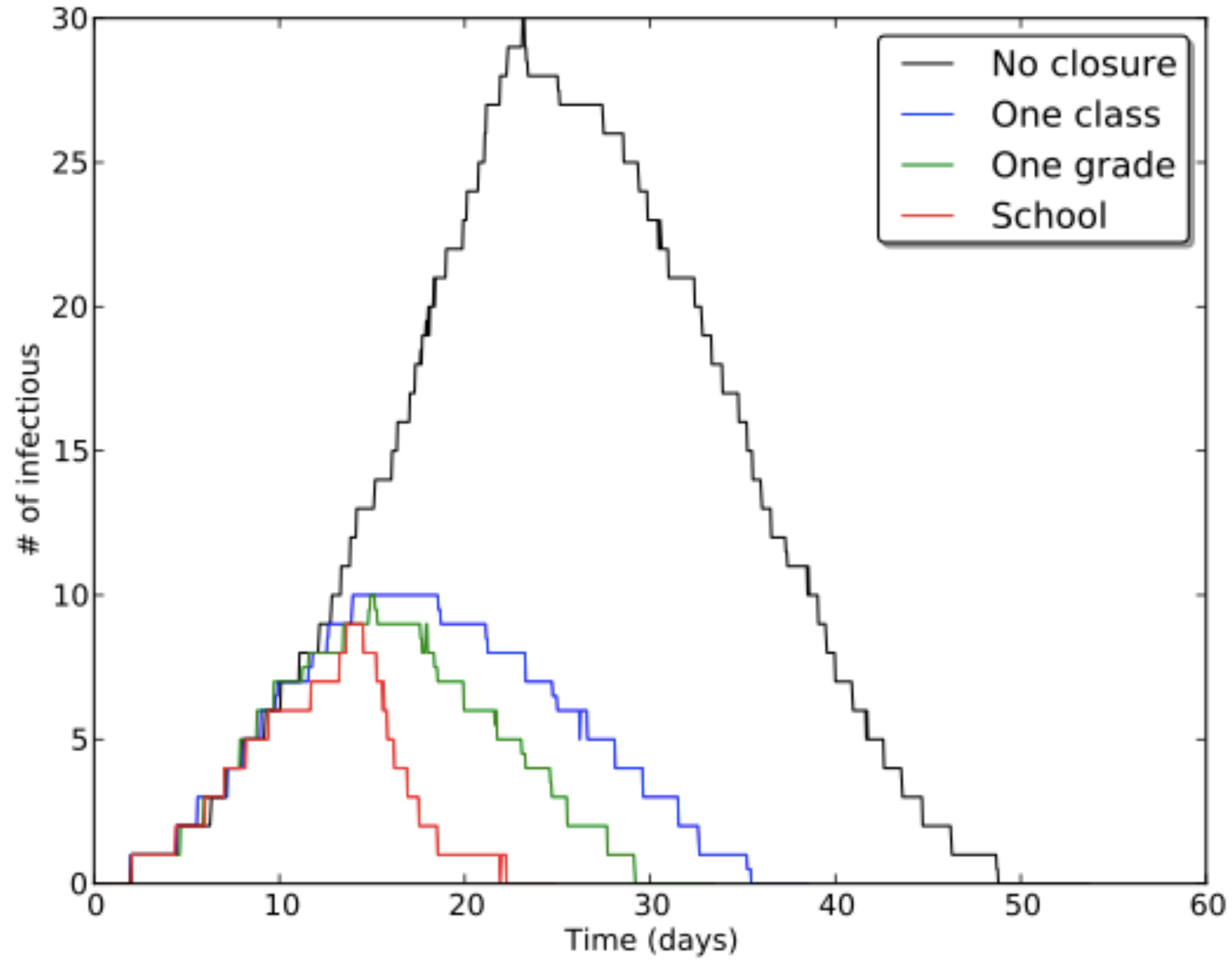
Interventions

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



Gemmetto, Barrat, Cattuto, BMC Inf Dis (2014)

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

Gemmetto, Barrat, Cattuto, BMC Inf Dis (2014)

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

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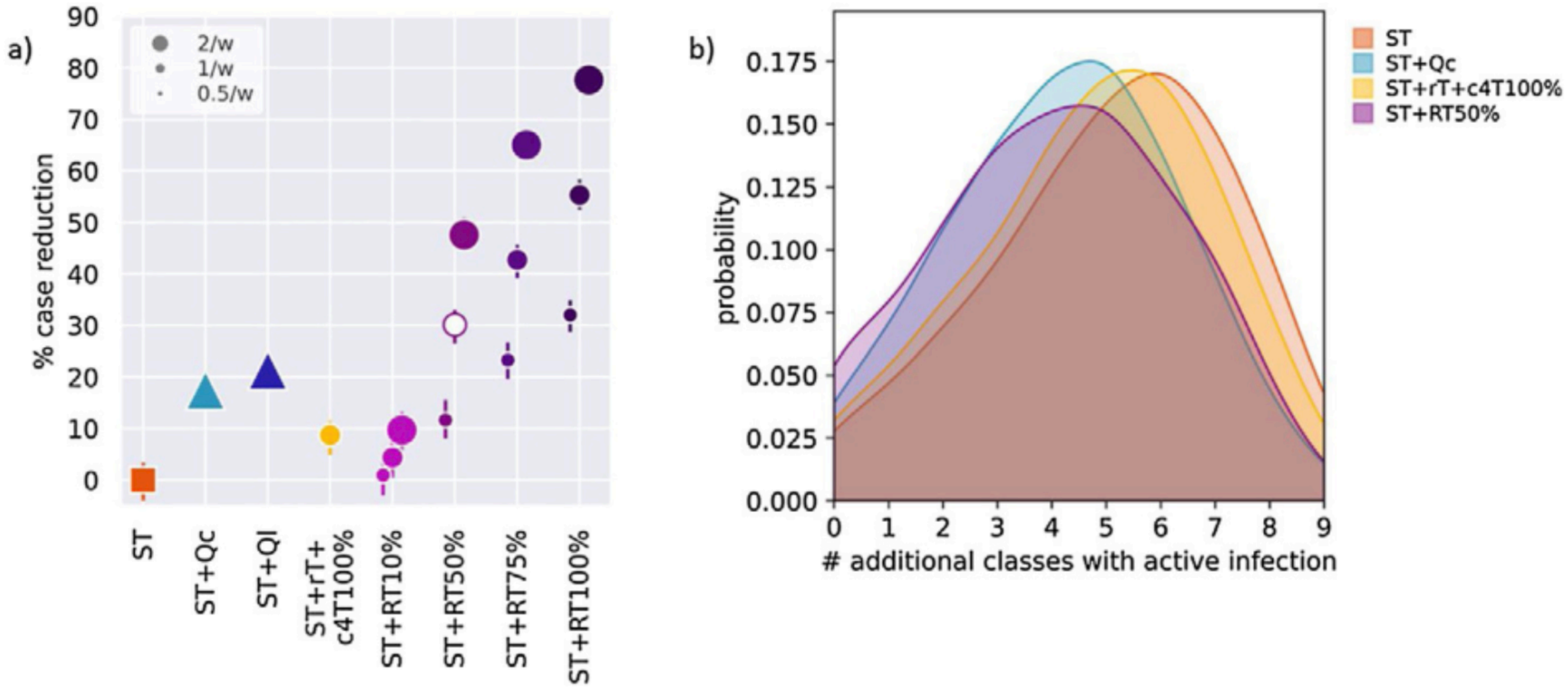
Editorial

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

Check for updates

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. Salathé[9] & B. Lepri[1]✉

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 Bentkowski[1], Livio Bioglio[3], Francesco Pinotti[1], Pierre-Yves Boëlle[1], Alain Barrat[4,5], Vittoria Colizza[1], 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.

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. Kivelä[5], S. Lehmann[6] and J. Saramäki[5]

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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