Finding structures in temporal graphs

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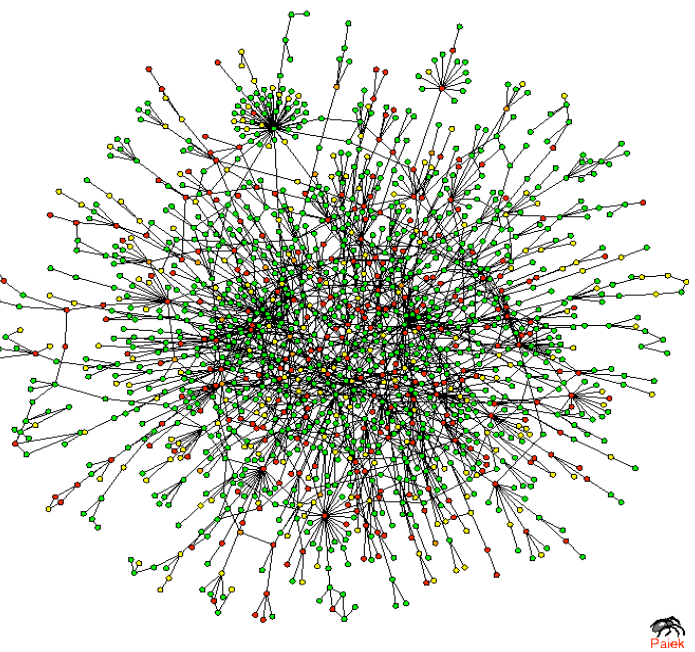
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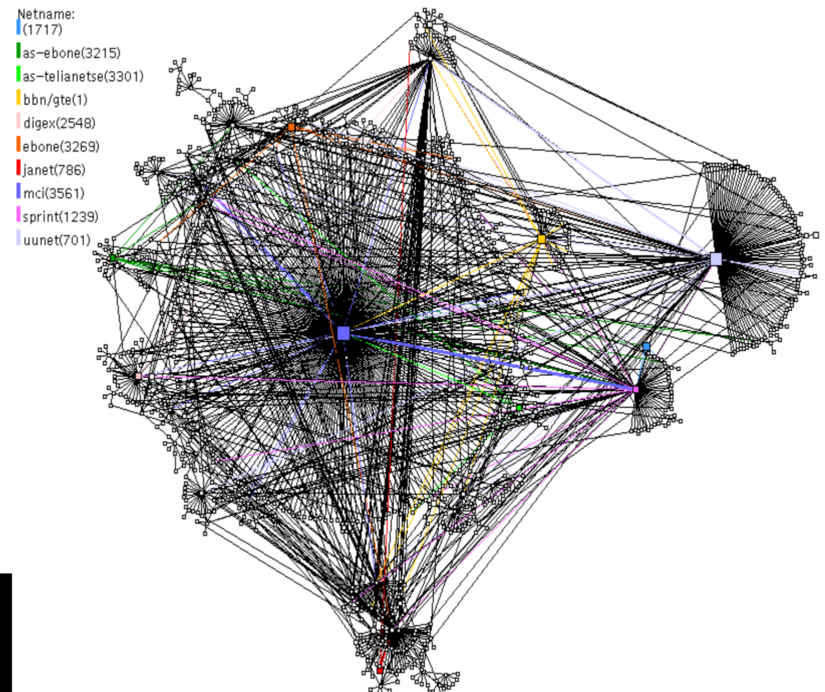
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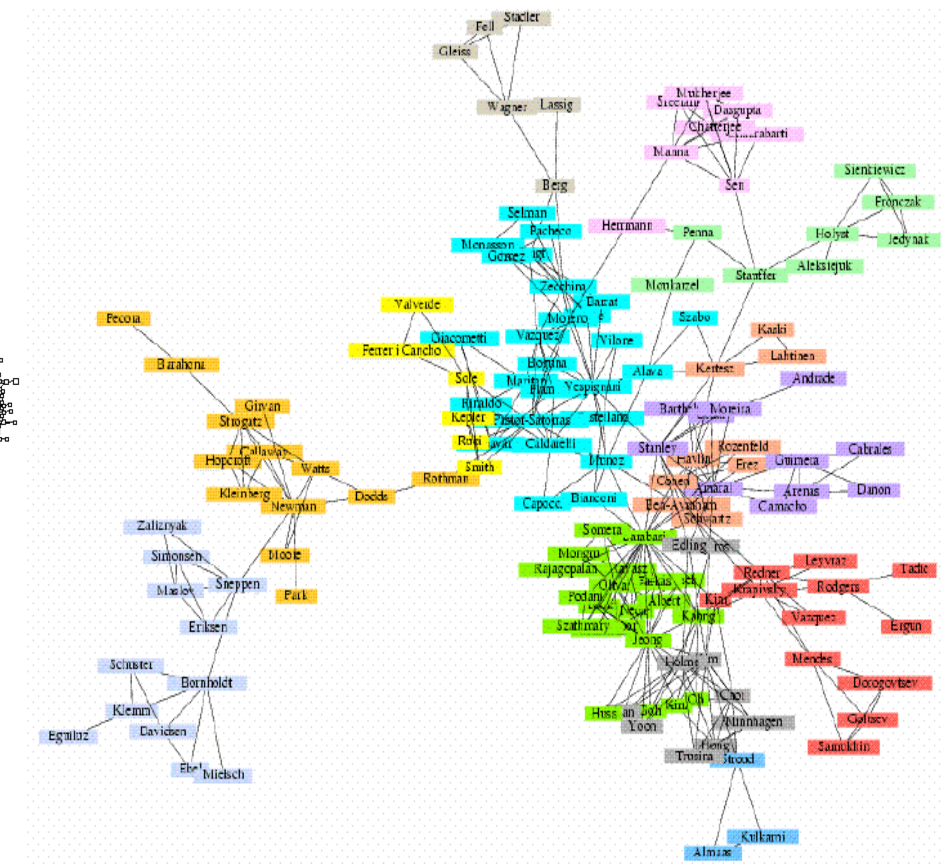
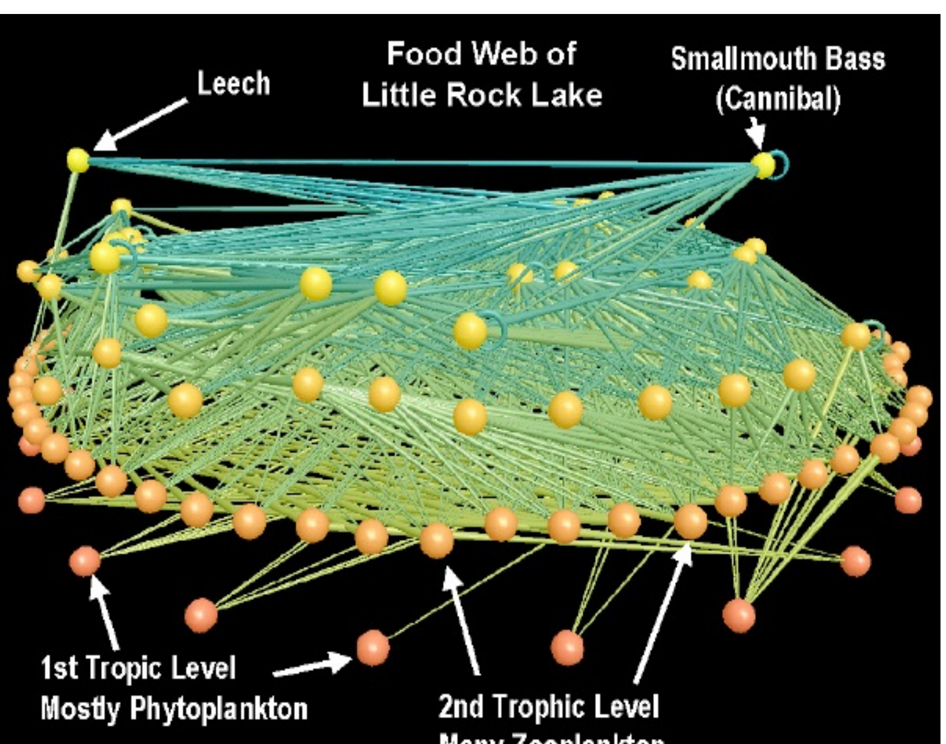
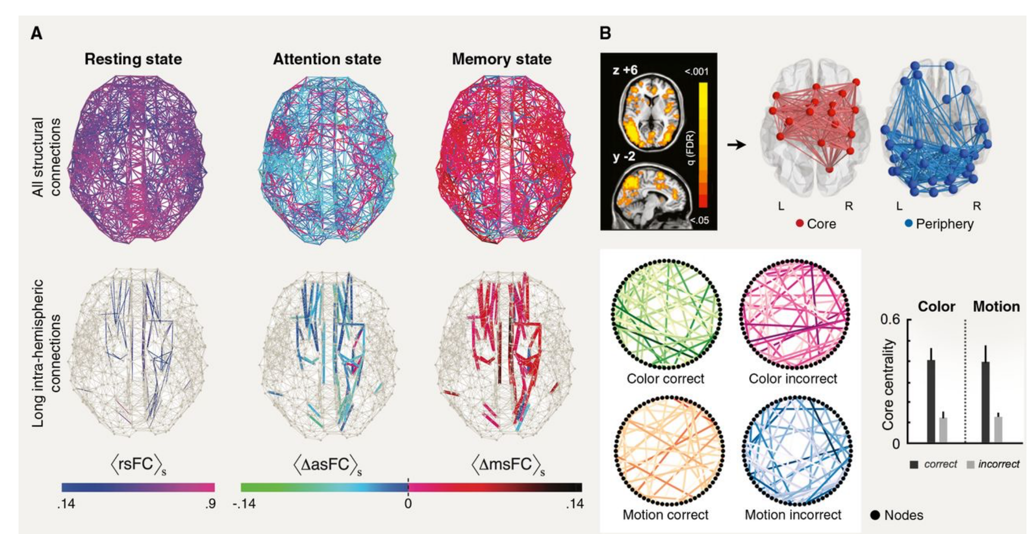



Food Web of Little Rock Lake
Leech
Smallmouth Bass (Cannibal)
1st Tropic Level Mostly Phytoplankton
2nd Trophic Level Many Zooplankton


A
Resting state
Attention state
Memory state
All structural connections
Long intra-hemispheric connections
⟨rsFC⟩s
⟨ΔasFC⟩s
⟨ΔmsFC⟩s
.14
.9
-.14
0
.14
B
Core
Periphery
Color correct
Color incorrect
Motion correct
Motion incorrect
Color
Motion
Core centrality
correct
incorrect
Nodes

Infrastructure networks
Biological networks
Communication networks
Social networks
Virtual networks
…

many **datasets**
+
common network representation framework/language

Emergence of **data-driven, interdisciplinary** "network science"

NetSci

- Empirical study and characterization
- Modeling: understand formation mechanisms
- Consequences of the empirically found properties on dynamical phenomena taking place on the networks (epidemic spreading, resilience, synchronization,…)

Static networks

Structures in static graphs

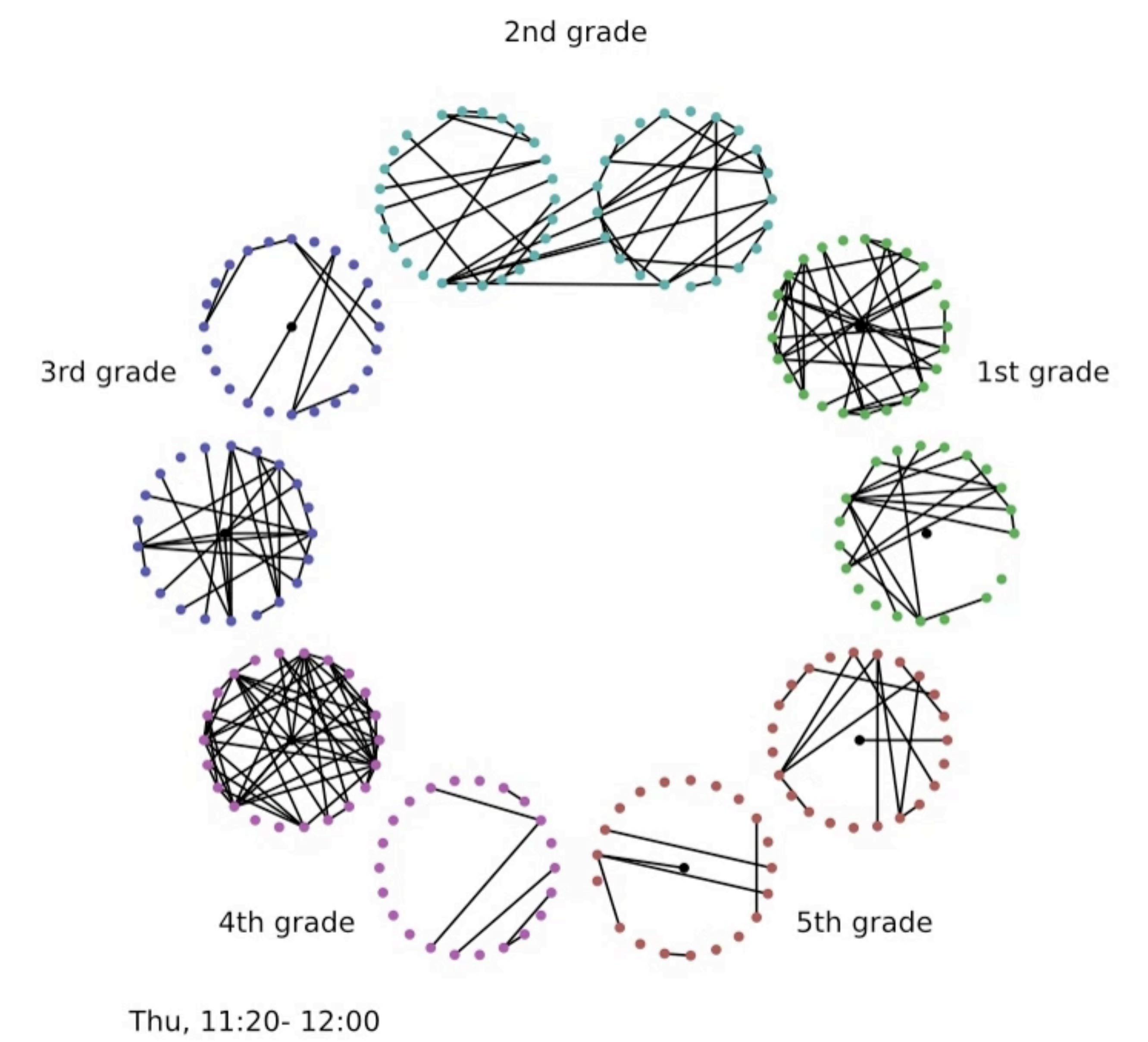
Various scales

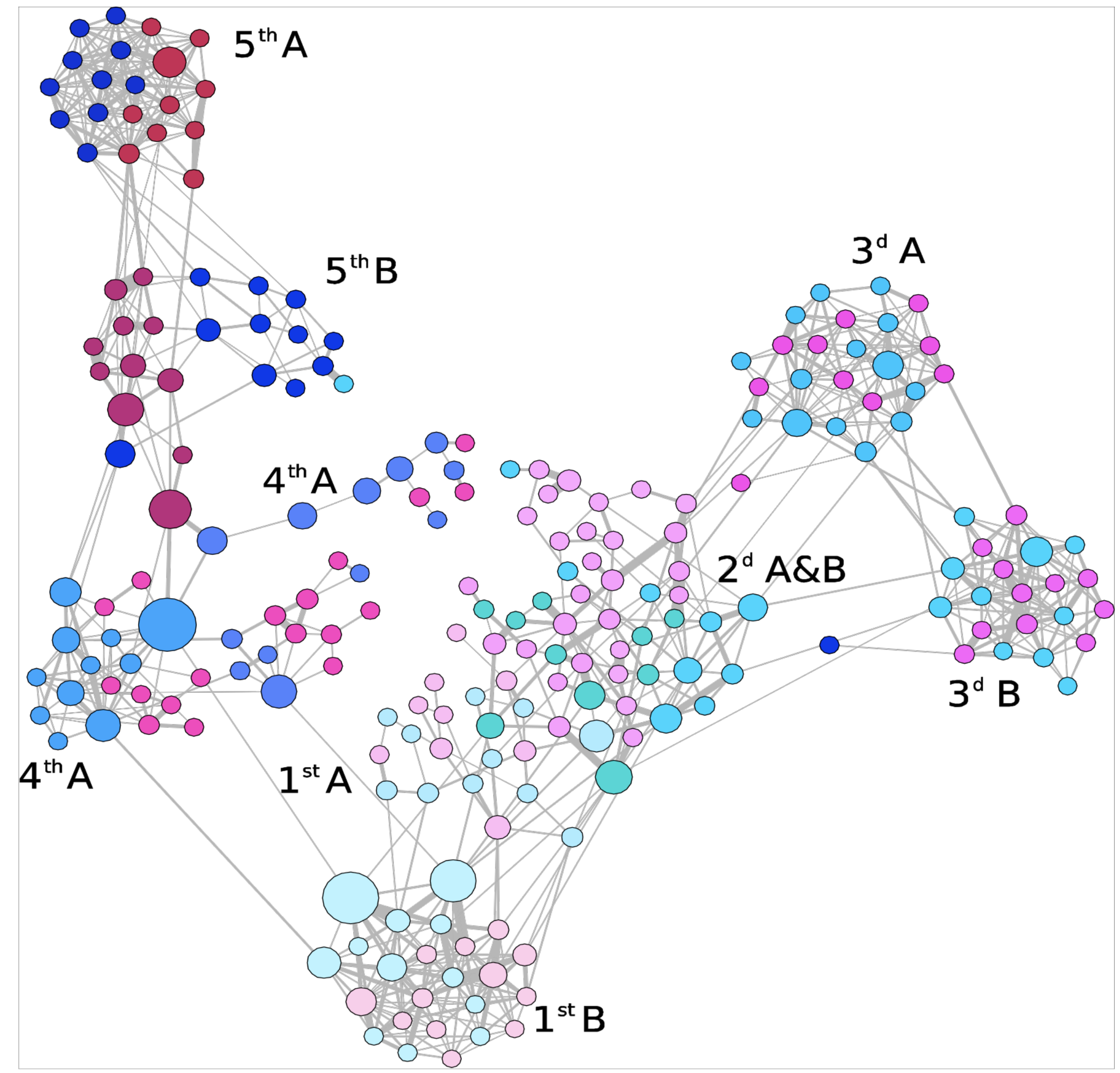
- Clustering coefficient, local cohesiveness, small-world
- Heterogeneities (degree distribution, hubs…)

- Motifs (small subgraphs more frequent than expected)
- Communities
- Backbones (most “relevant” parts of a network)
- Hierarchies (e.g., k-core decomposition)
- …

>Networks change over time

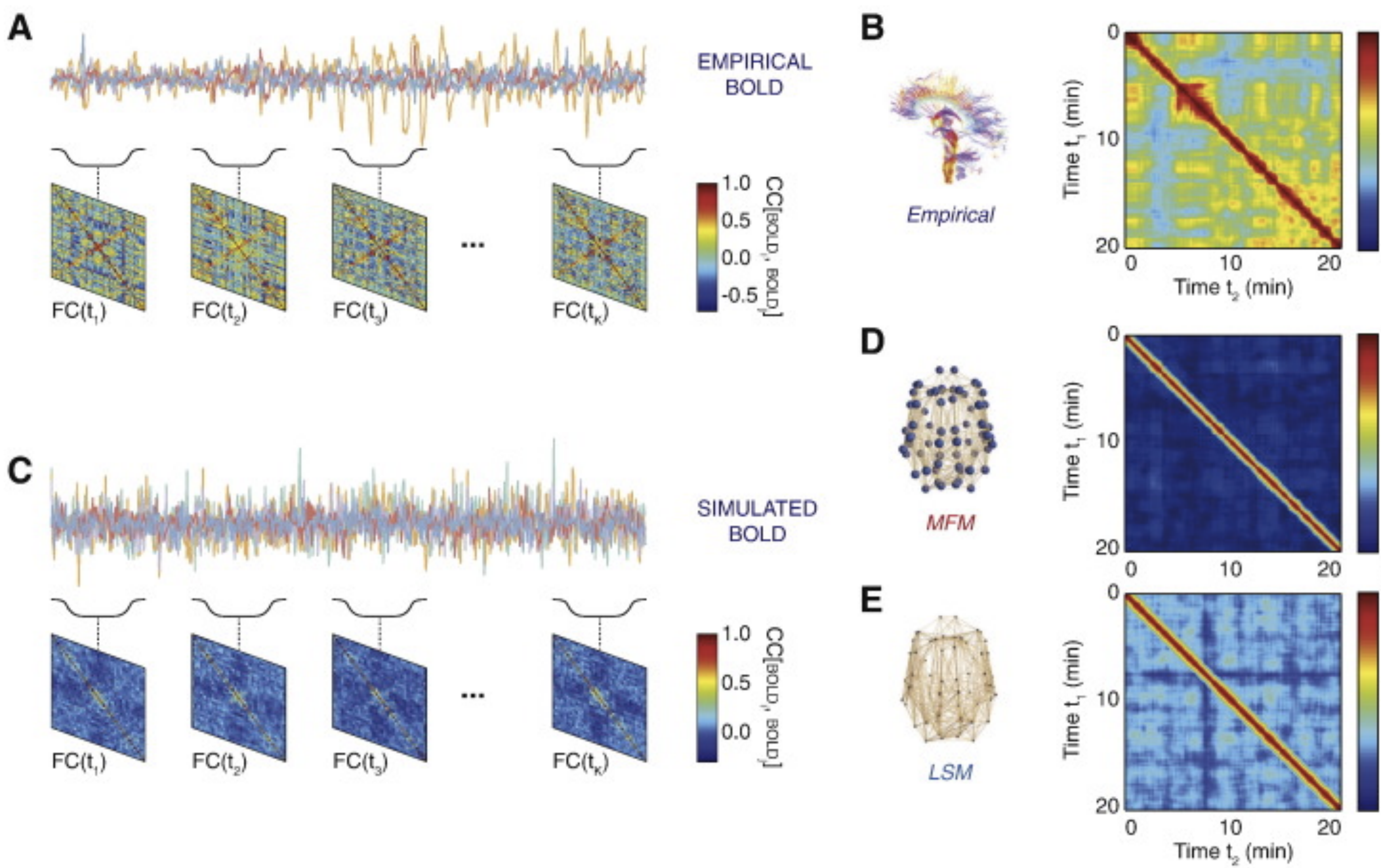
Example: contacts in a primary school,





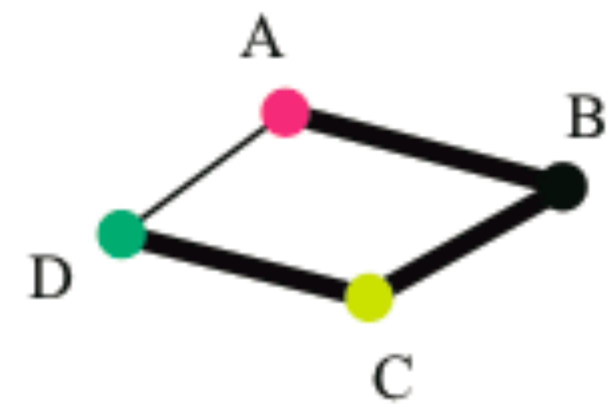
J. Stehlé et al. PLoS ONE 6(8):e23176 (2011)

Example: brain functional connectivity



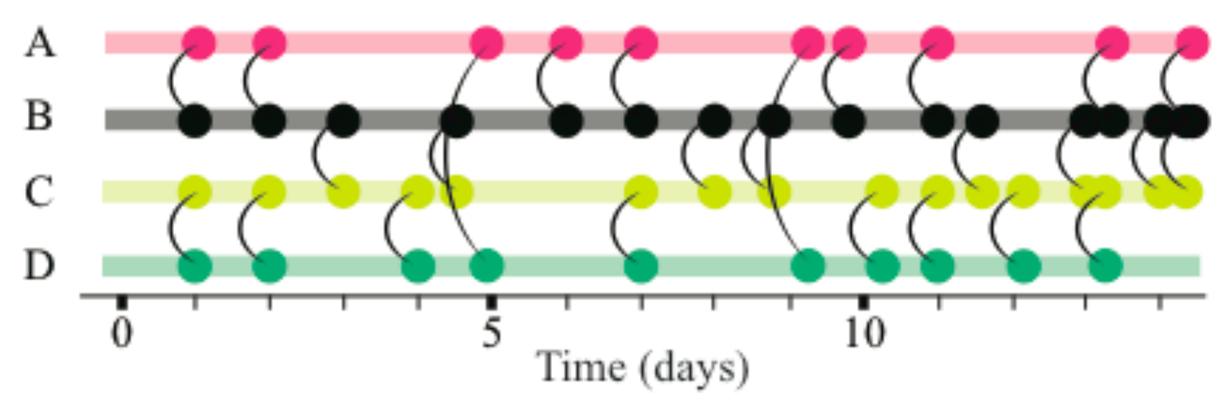
Hansen et al., Neuroimage 2015

Beyond static networks



Infrastructure networks
Biological networks
Communication networks
Social networks
Virtual networks
...

static representation of

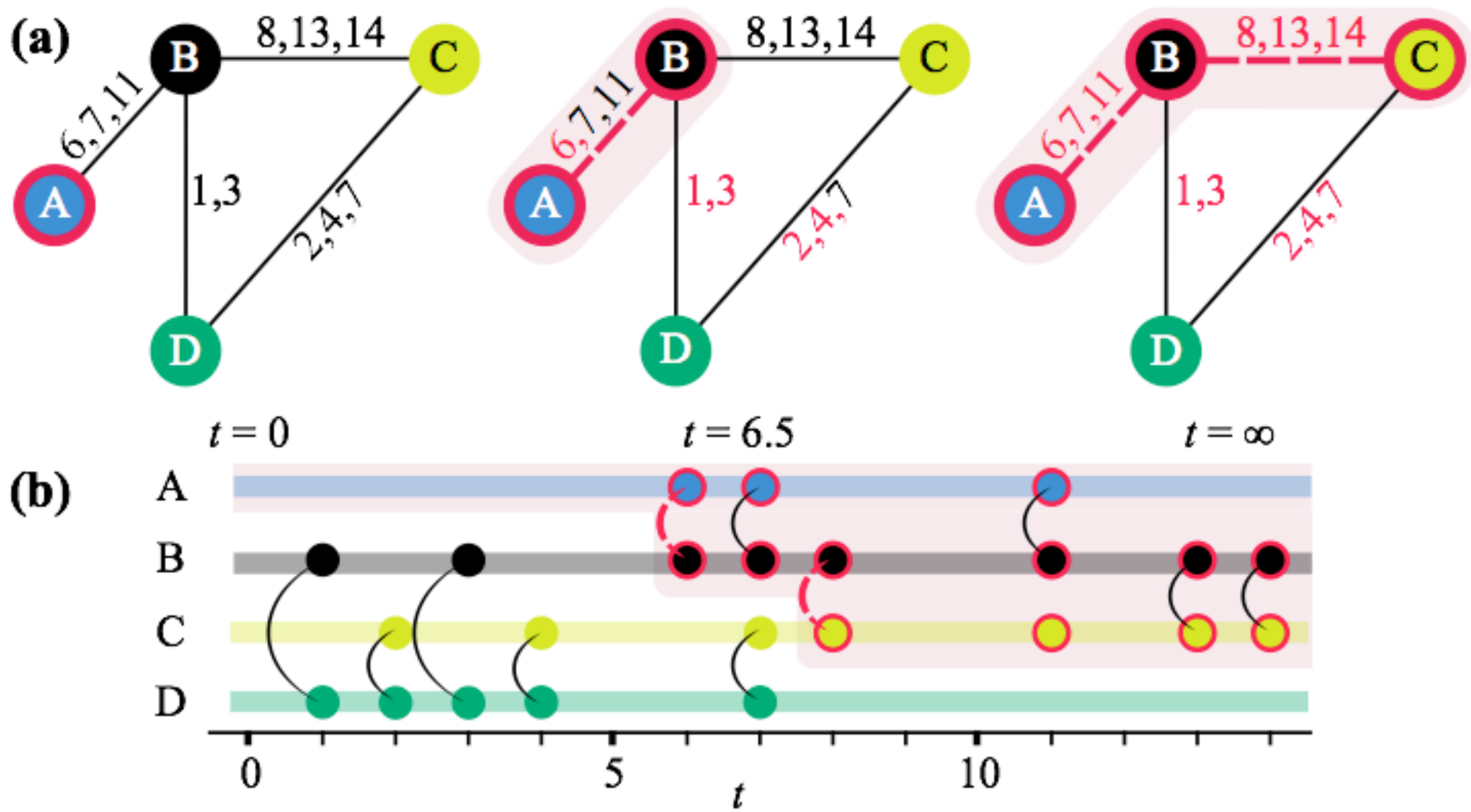


many datasets:

static network representation framework

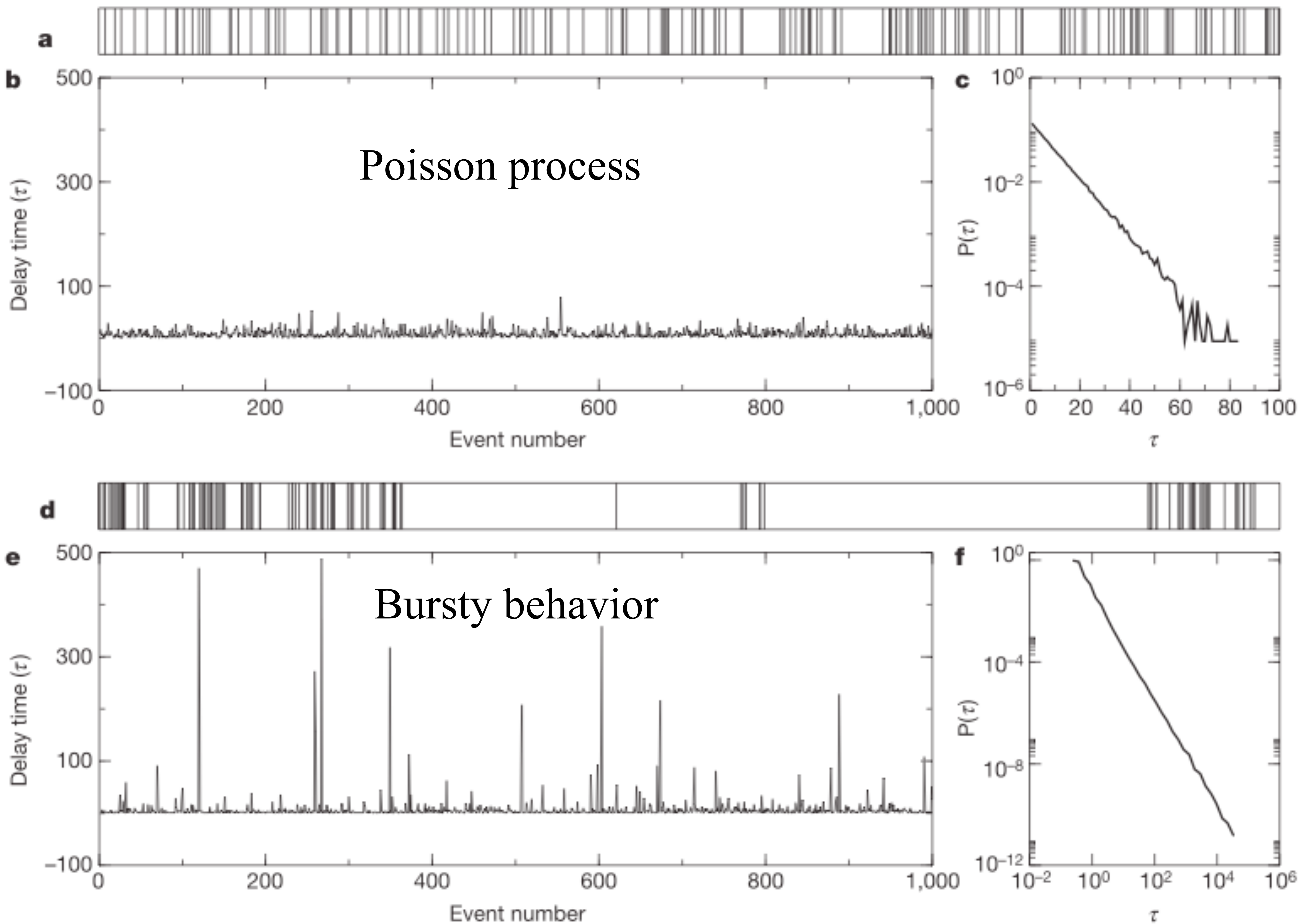
- As first approach
- If timescale of process << timescale of network reconfiguration

Impact of temporality: Reachability issue



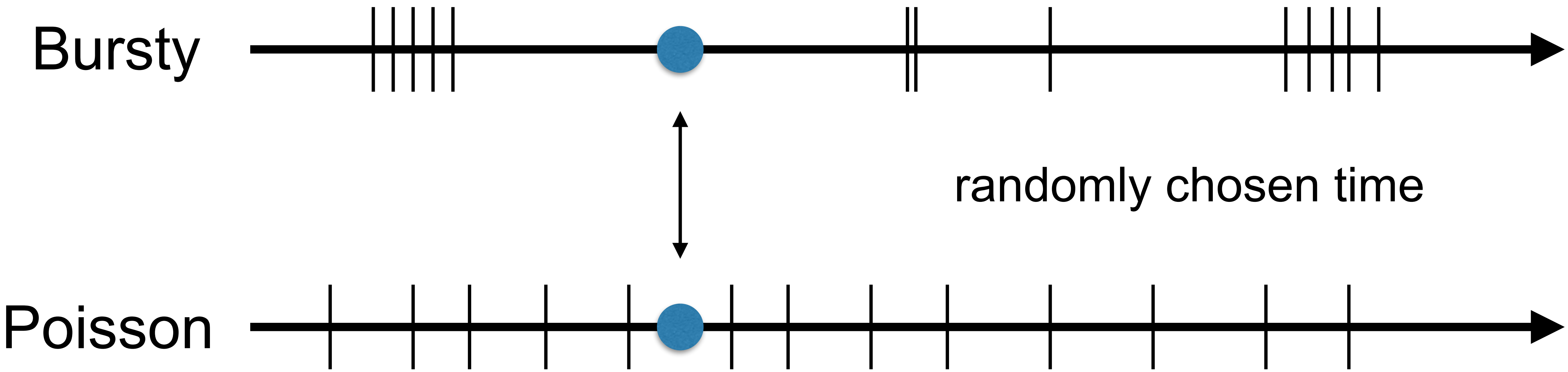
Holme-Saramaki, Phys. Rep. (2012), arXiv:1108.1780

Burstiness



A.-L. Barabási, Nature (2006)

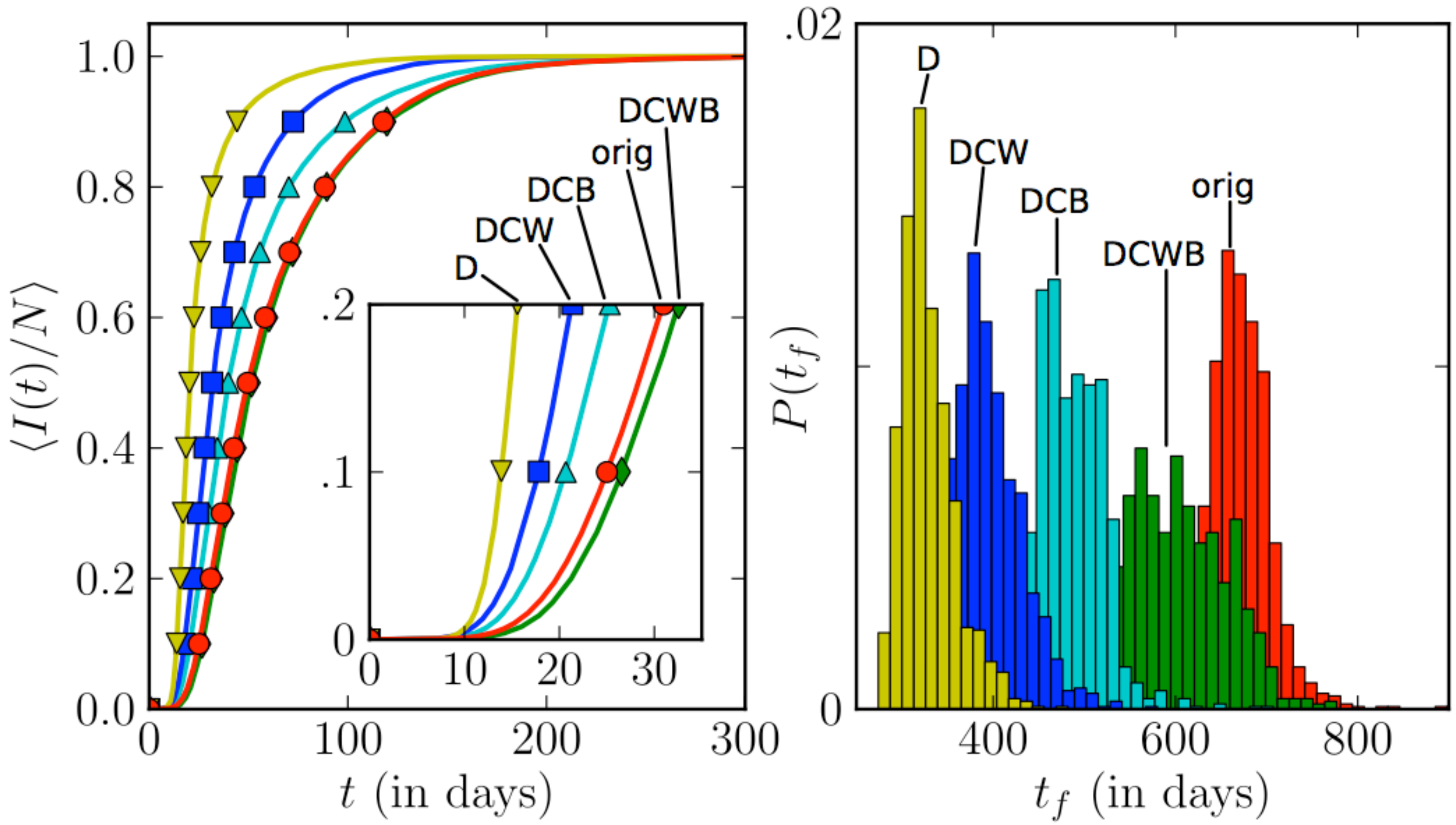
Consequence of burstiness



Bursty timeline implies larger waiting time with higher probability
=> typically slows down diffusion (if no correlations)

Impact on processes on networks

Mobile phone data



- community structure (C)
- weight-topology correlations (W)
- burstiness on single links (B)
- daily patterns (D)
- event-event correlations between links (E)

Burstiness slows down spread
Correlations slightly favour spread

M. Karsai et al., Small But Slow World: How Network Topology and Burstiness Slow Down Spreading, Phys. Rev. E (2011).
Kivelä et al, Multiscale Analysis of Spreading in a Large Communication Network, J Stat Mech (2012)

Physics Reports
Volume 519, Issue 3, October 2012, Pages 97–125

Temporal networks

Petter Holme[a, b, c], Jari Saramäki[d]
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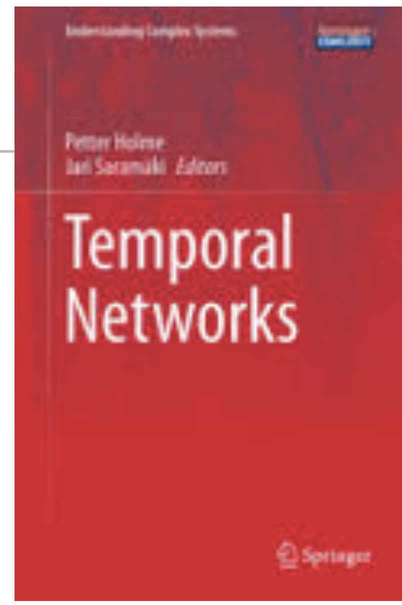
http://dx.doi.org/10.1016/j.physrep.2012.03.001



The European Physical Journal B
September 2015, 88:234

Modern temporal network theory: a colloquium

Authors   Authors and affiliations

Petter Holme

Colloquium

First Online: 21 September 2015

DOI: 10.1140/epjb/e2015-60657-4

Cite this article as:
Holme, P. Eur. Phys. J. B (2015) 88: 234. doi:10.1140/epjb/e2015-60657-4

Part of the following topical collections:
- Topical issue: Temporal Network Theory and Applications

Many challenges:

- Definitions and **representations** at various levels of temporal information
- **Characterization**/measures/signatures of temporality/temporal features
- **Modeling**
- Consequences on **dynamical phenomena** (e.g. epidemics, information propagation…)
- Link temporal+topological structure and function
- **Structures**
- …

>What kind of structures in temporal networks?

- Small scale: motifs (small temporal subgraphs more frequent than expected)
- Decomposing a temporal network into “components”: non-negative tensor factorisation
- Most “relevant” part: Backbones
- Well connected structures: temporal cores
- Finding relevant timescales, “states” of a temporal network
- …

- knowledge on structure/evolution of system
- filtering out noise
- relevance for dynamical processes on temporal networks

Definition: temporal network

Temporal network: T=(V,S)

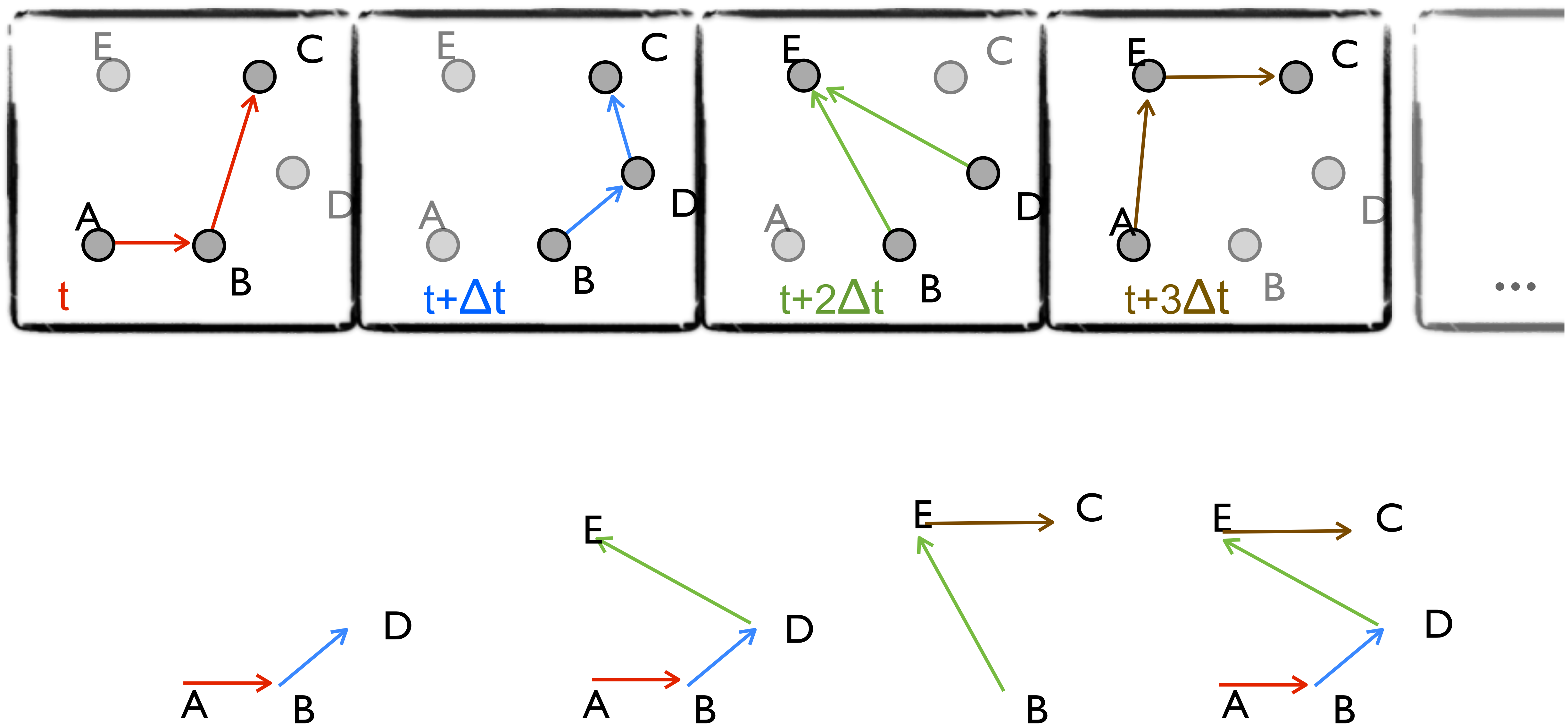
- V=set of nodes
- S=set of event sequences assigned to pairs of nodes

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

Other representation:
time-dependent adjacency matrix:
a(i,j,t)= 1 <=> i and j connected at time t

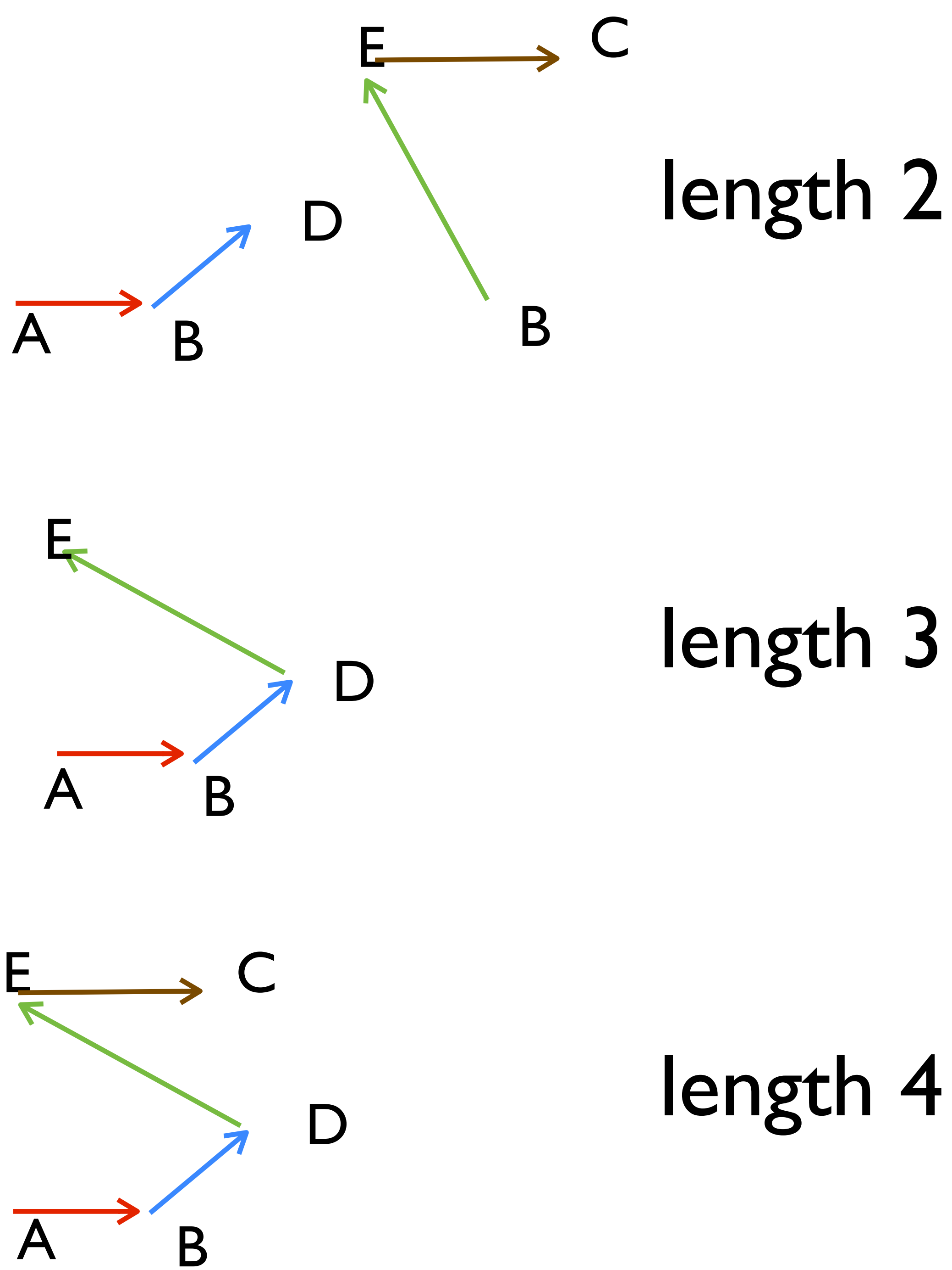
>Finding structures: Temporal motifs

Dynamical motifs



Bajardi et al, PLoS ONE (2011)

Dynamical motifs



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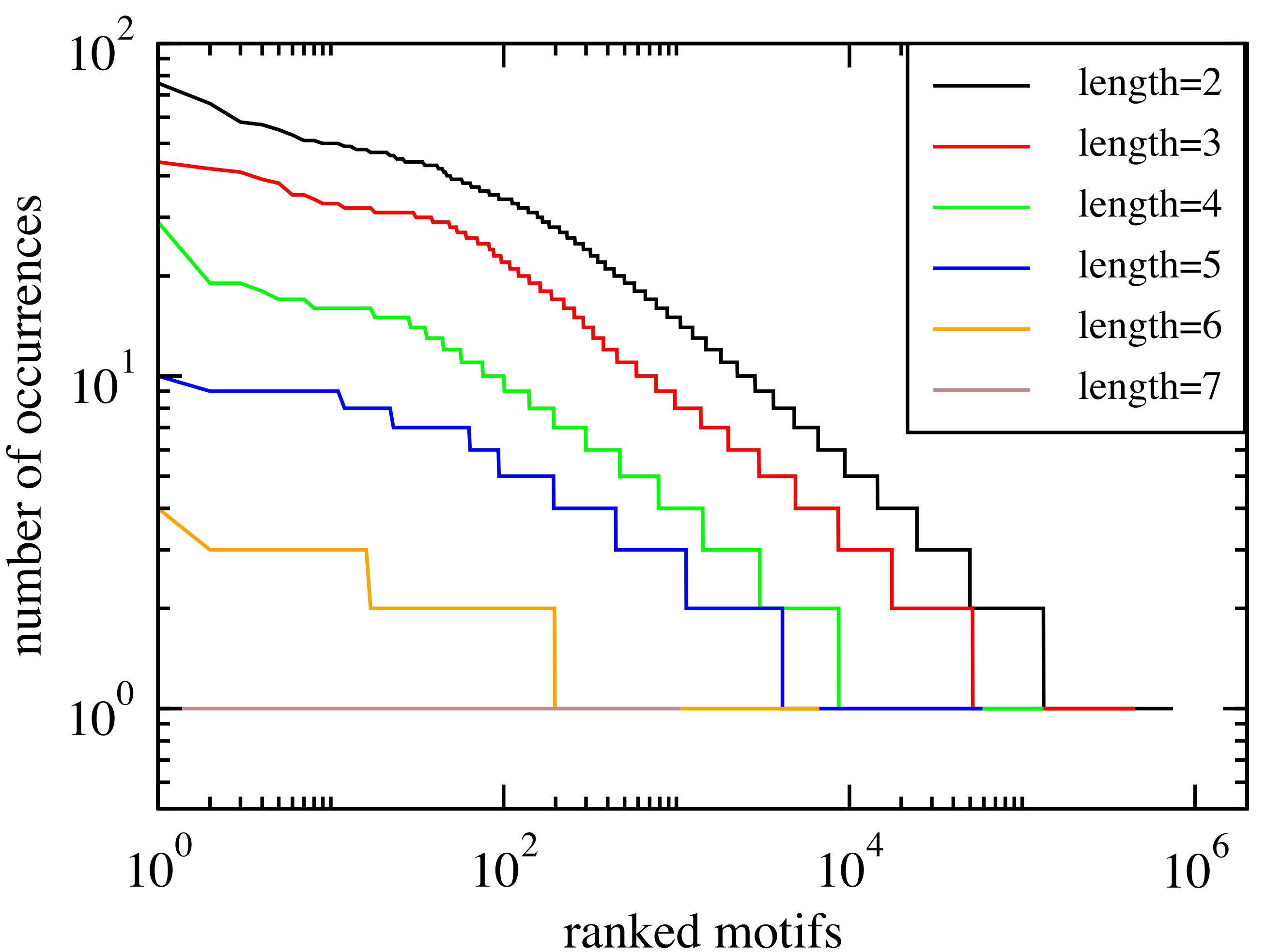
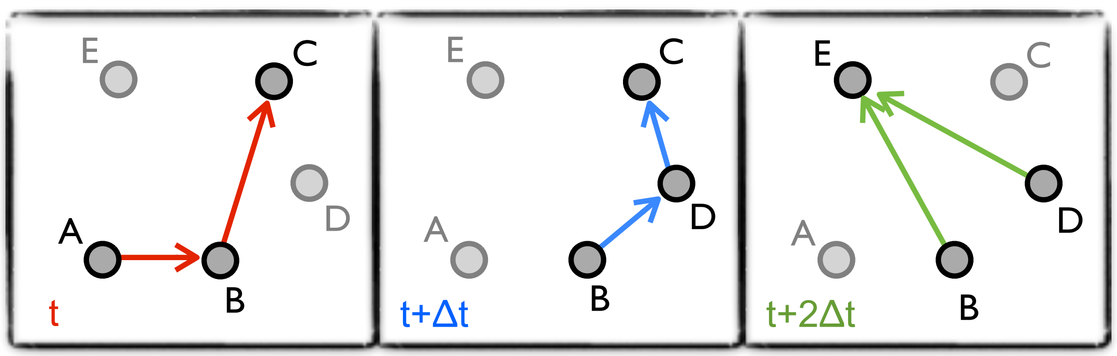
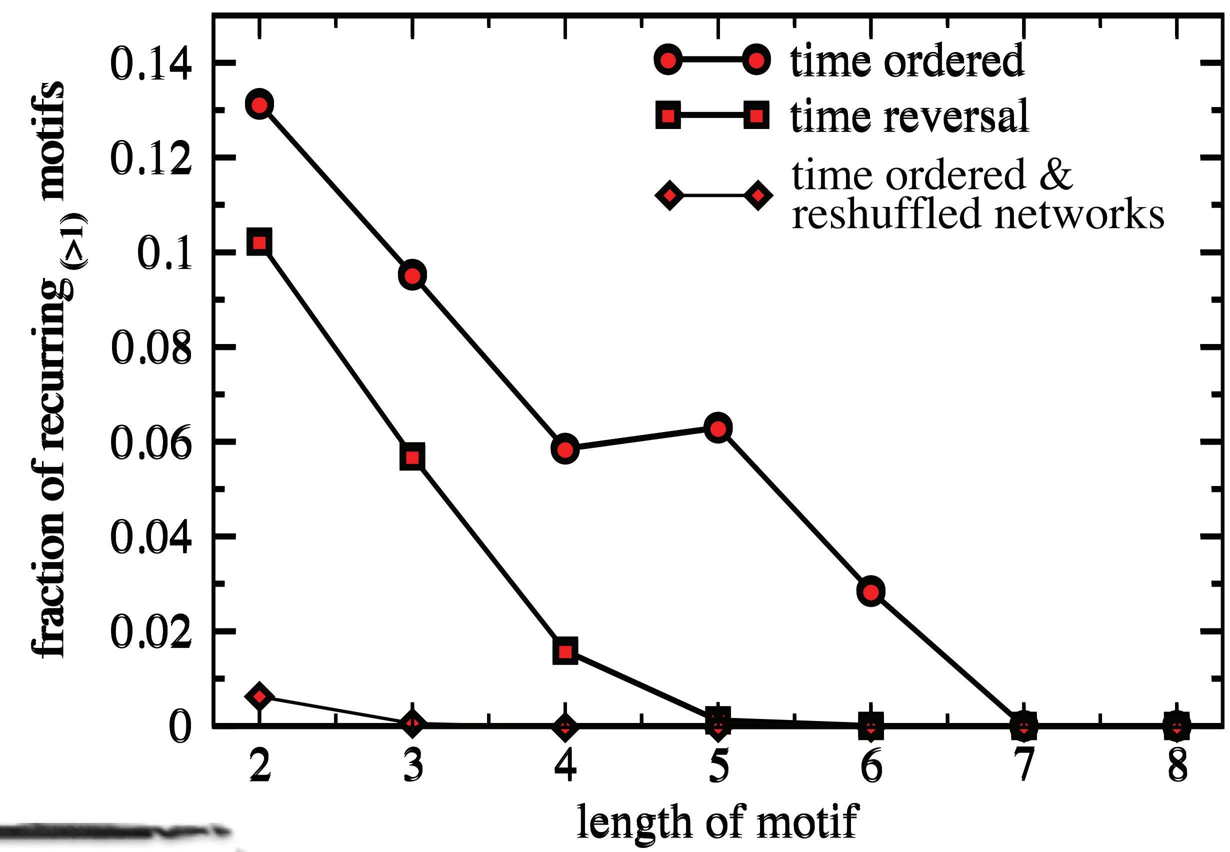
Bajardi et al, PLoS ONE (2011)



Dynamical motifs

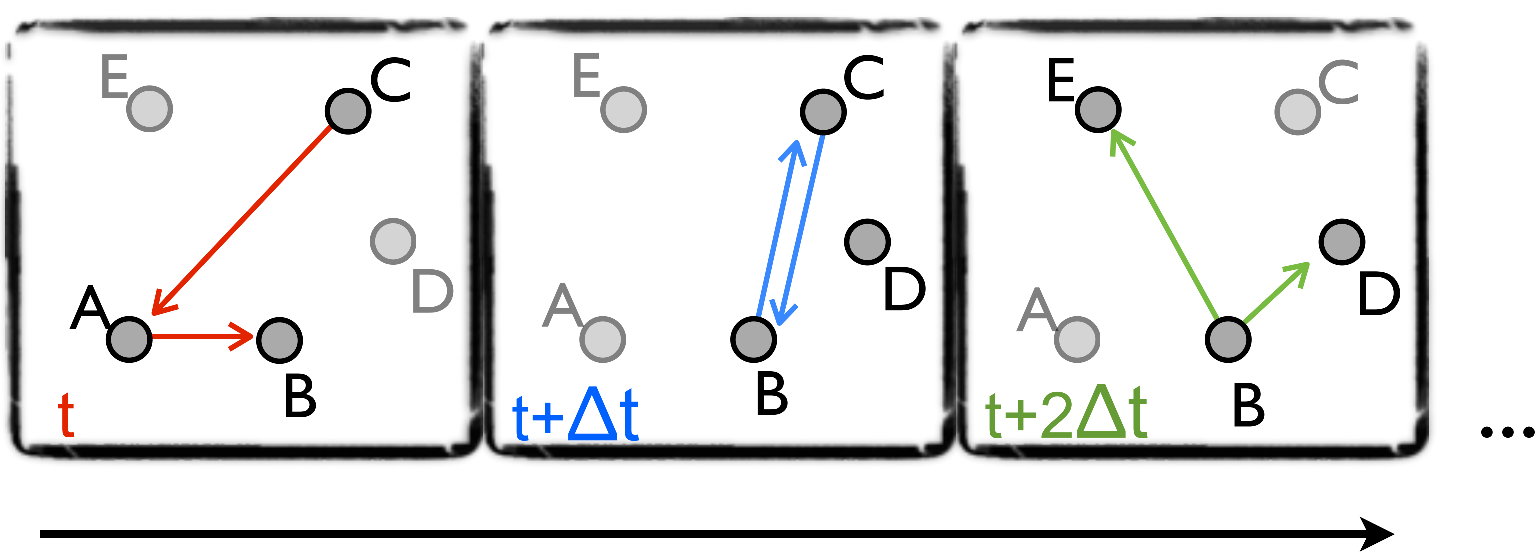
Original network:





Null model:

reshuffled networks

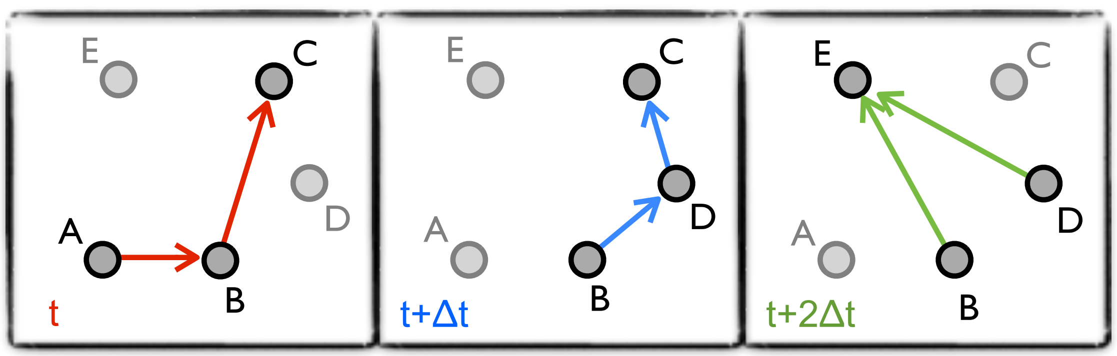


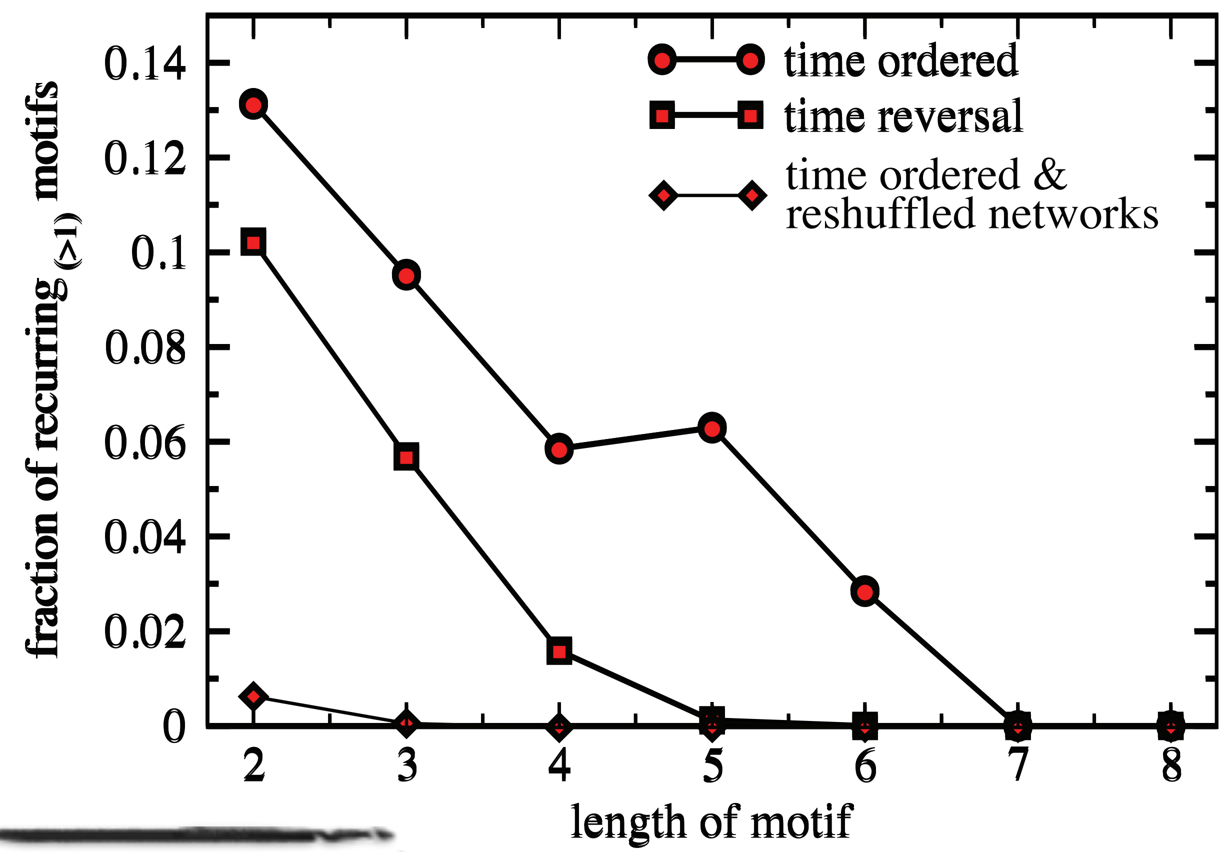
time

Bajardi et al, PLoS ONE (2011)

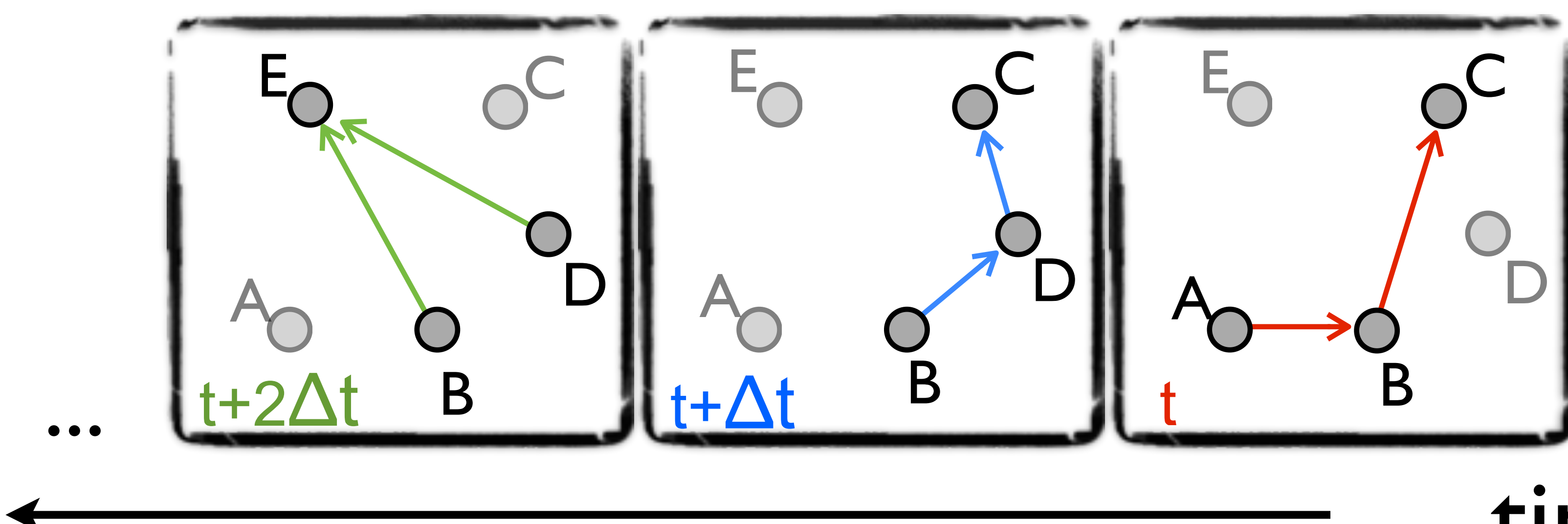
Dynamical motifs

Original network:





Null model:
time reversal

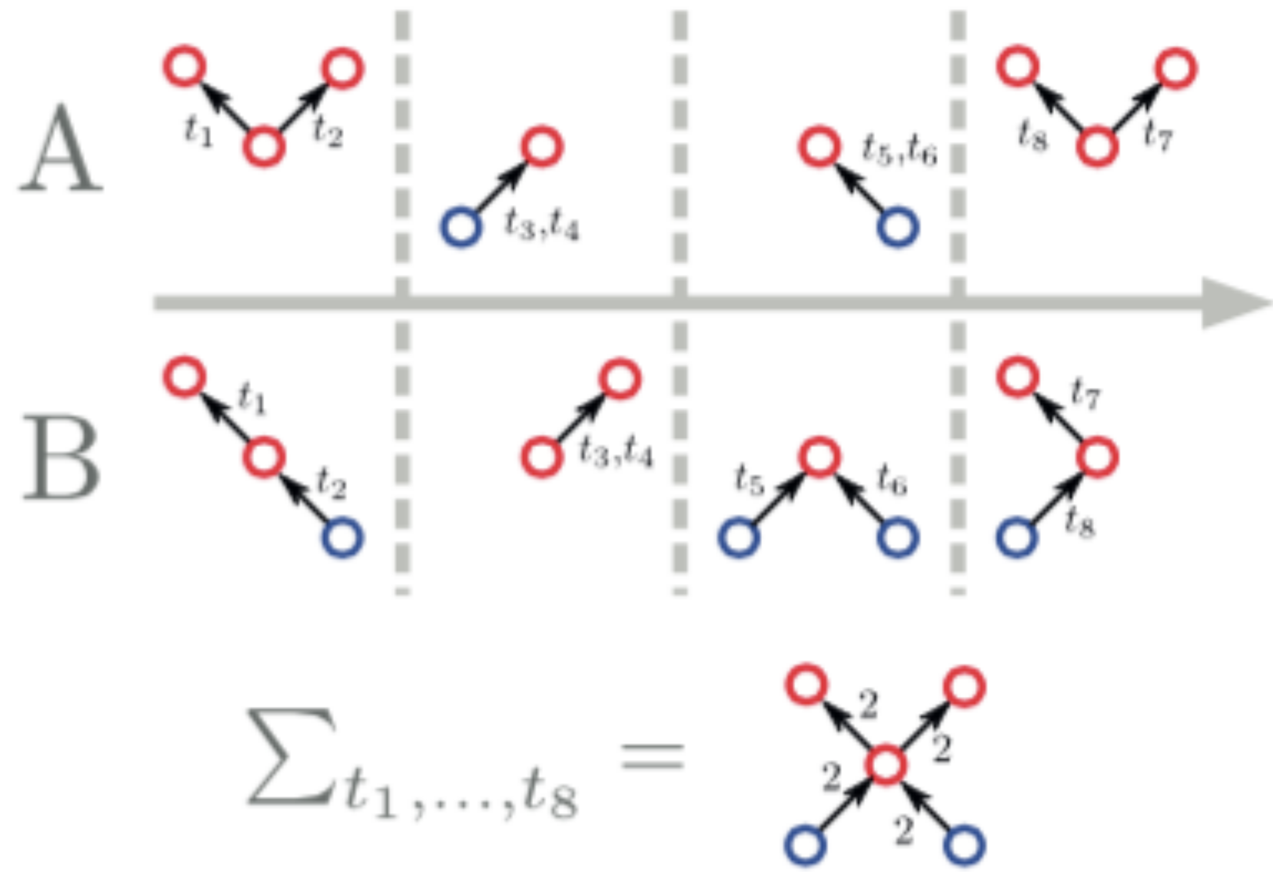


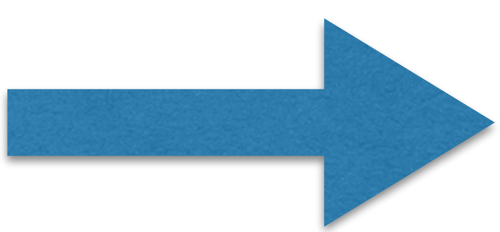
time

Bajardi et al, PLoS ONE (2011)

Temporal motifs

Same aggregated network, different temporal sequences



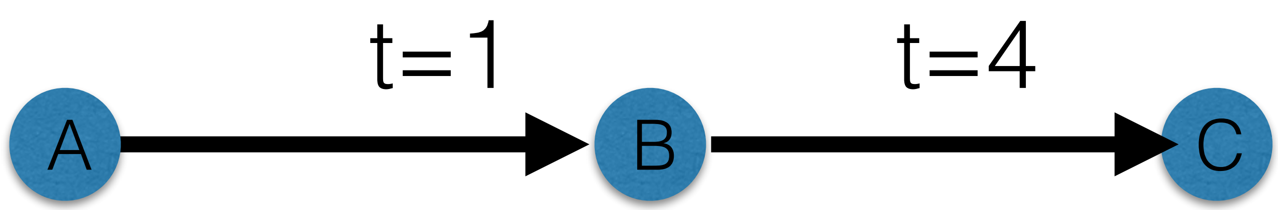


detection of temporal patterns?

L. Kovanen et al., J. Stat. Mech. (2011) P11005

L. Kovanen et al., PNAS (2013)

Δt-adjacent events



events Δt-adjacents for Δt=4

events Δt-adjacent:

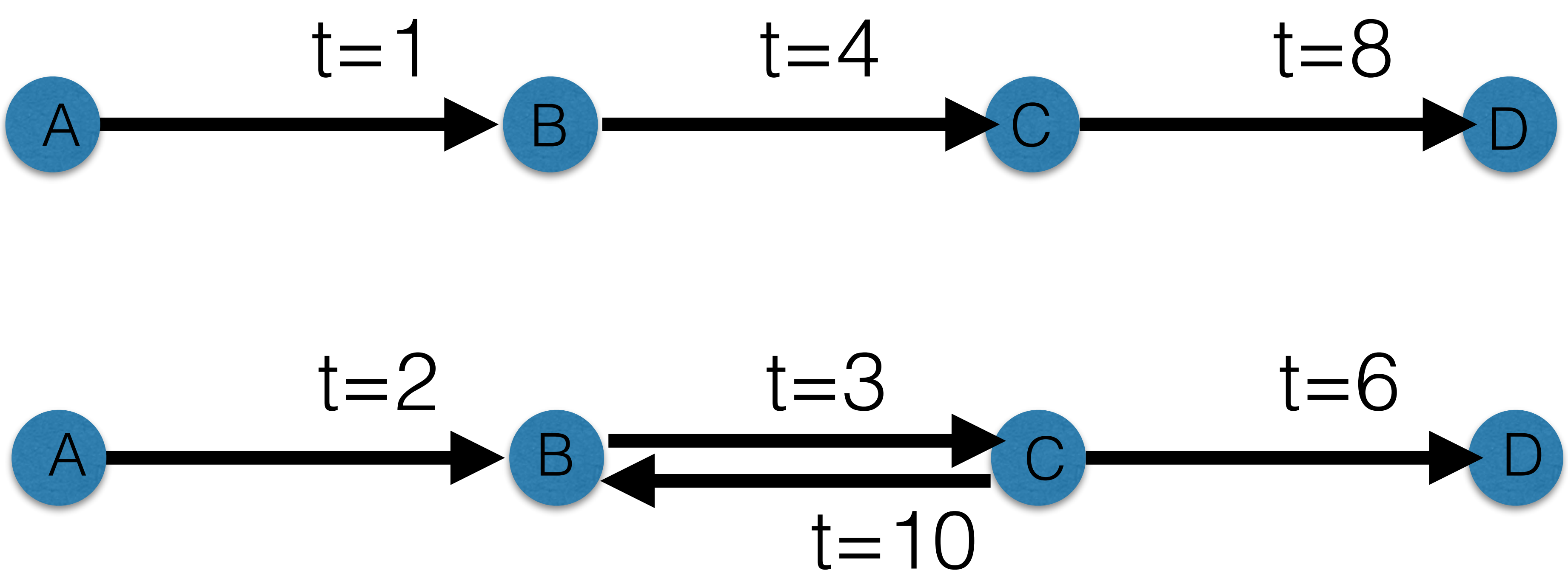
- at least one node in common
- at most Δt between end of 1st event and start of 2nd event

L. Kovanen et al., J. Stat. Mech. (2011) P11005

Δt-connected events

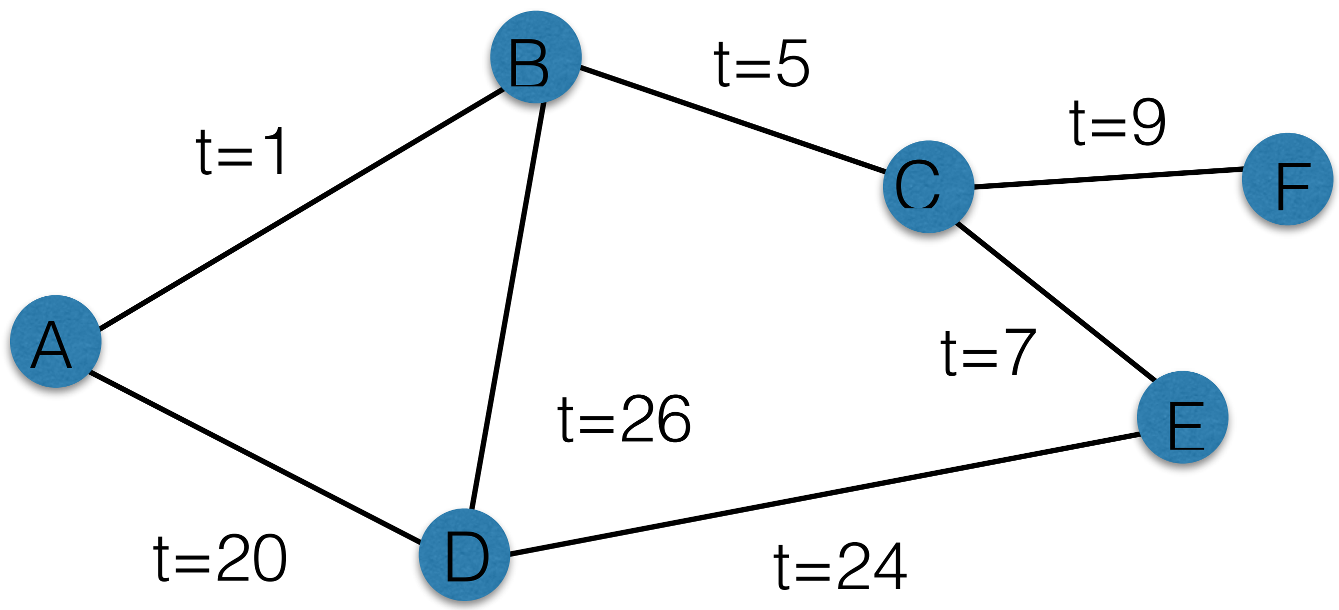
=events connected by a chain of Δt-adjacent events

Examples (Δt=5):

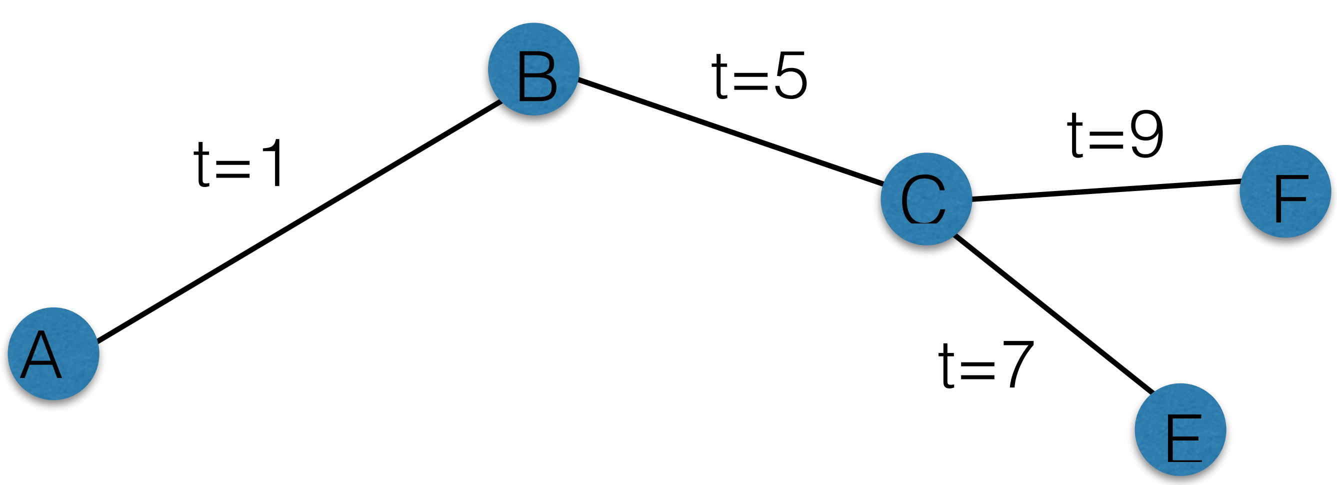


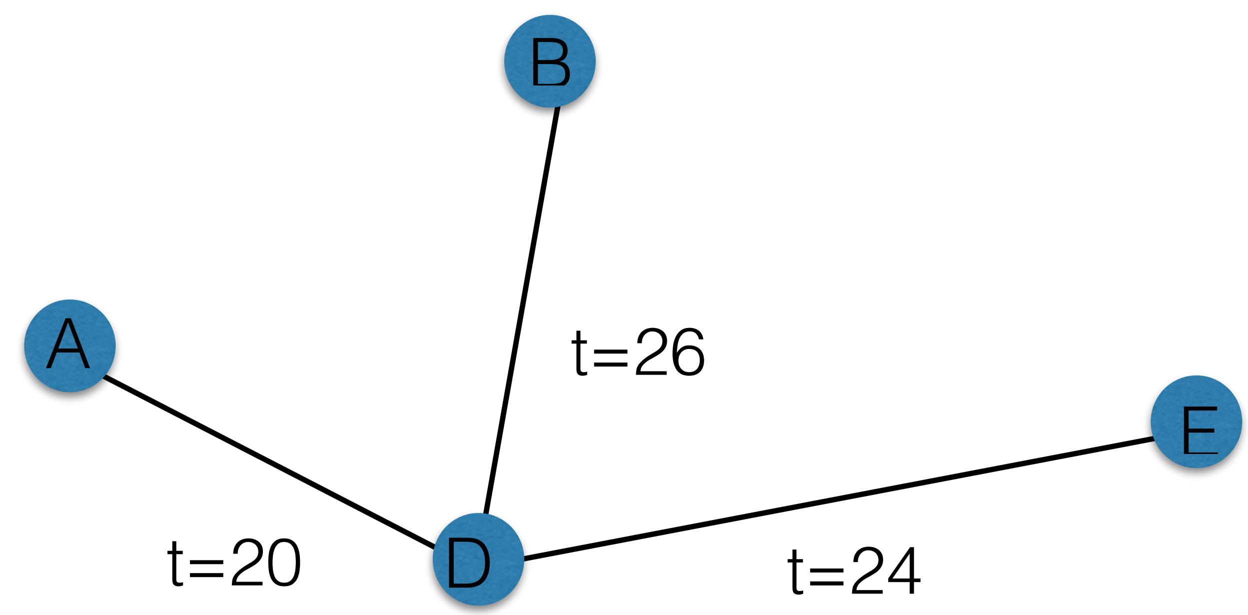
L. Kovanen et al., J. Stat. Mech. (2011) P11005

Temporal subgraph = set of Δt-connected events



Maximal temporal subgraphs (Δt=5):





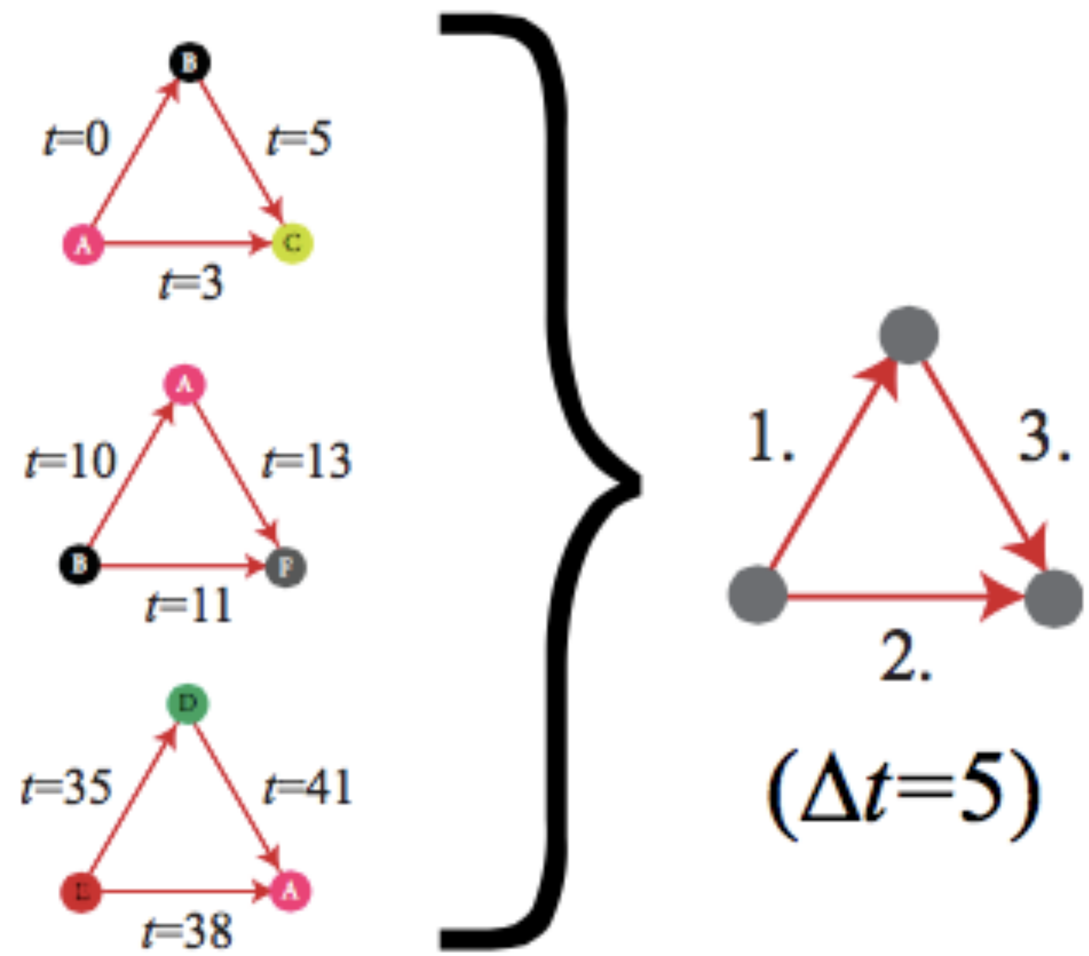
L. Kovanen et al., J. Stat. Mech. (2011) P11005

Temporal motifs

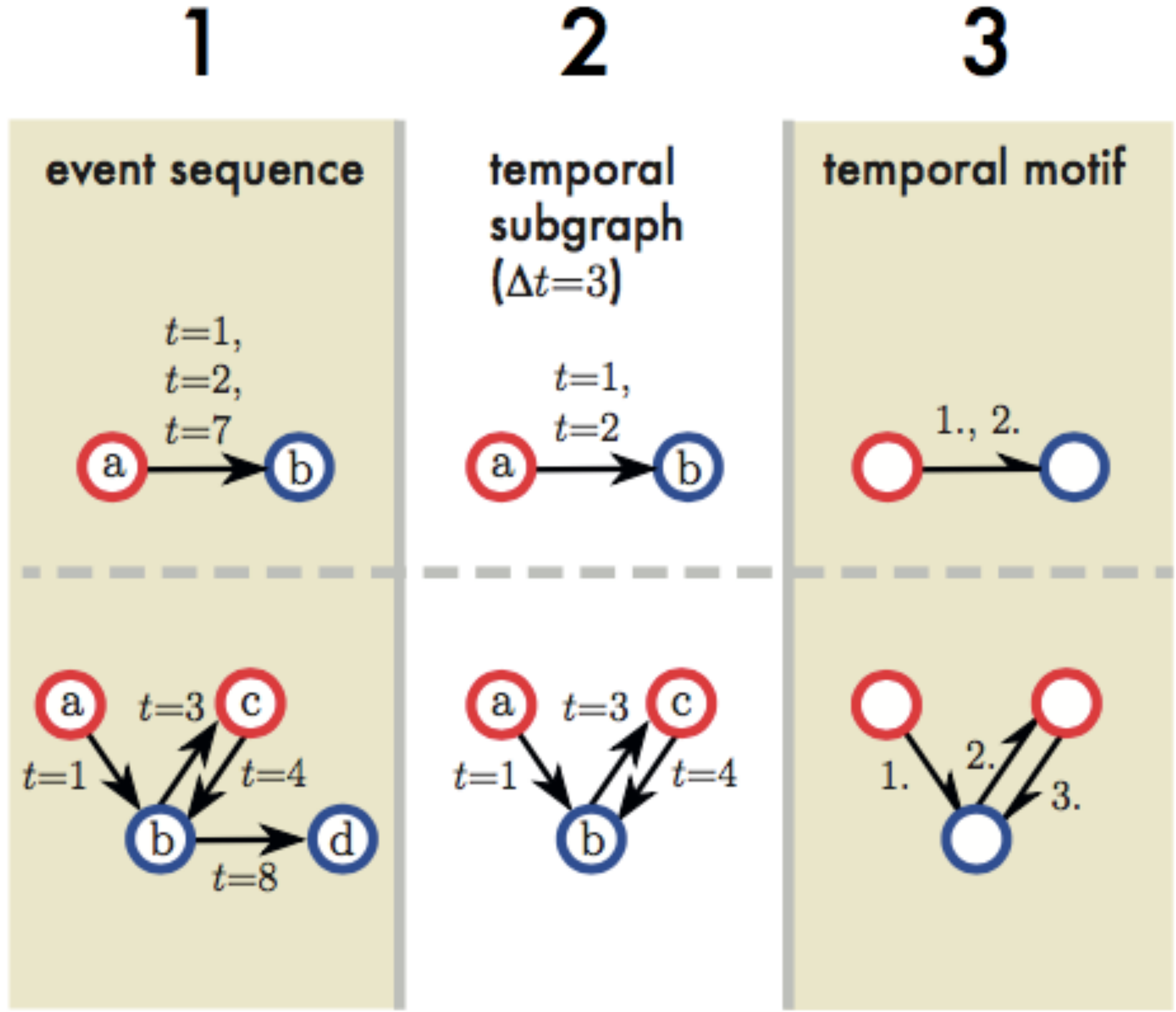
= Equivalence classes of valid temporal subgraphs

Valid: no events are skipped at each node

Equivalence classes: forget identities of nodes and exact timing



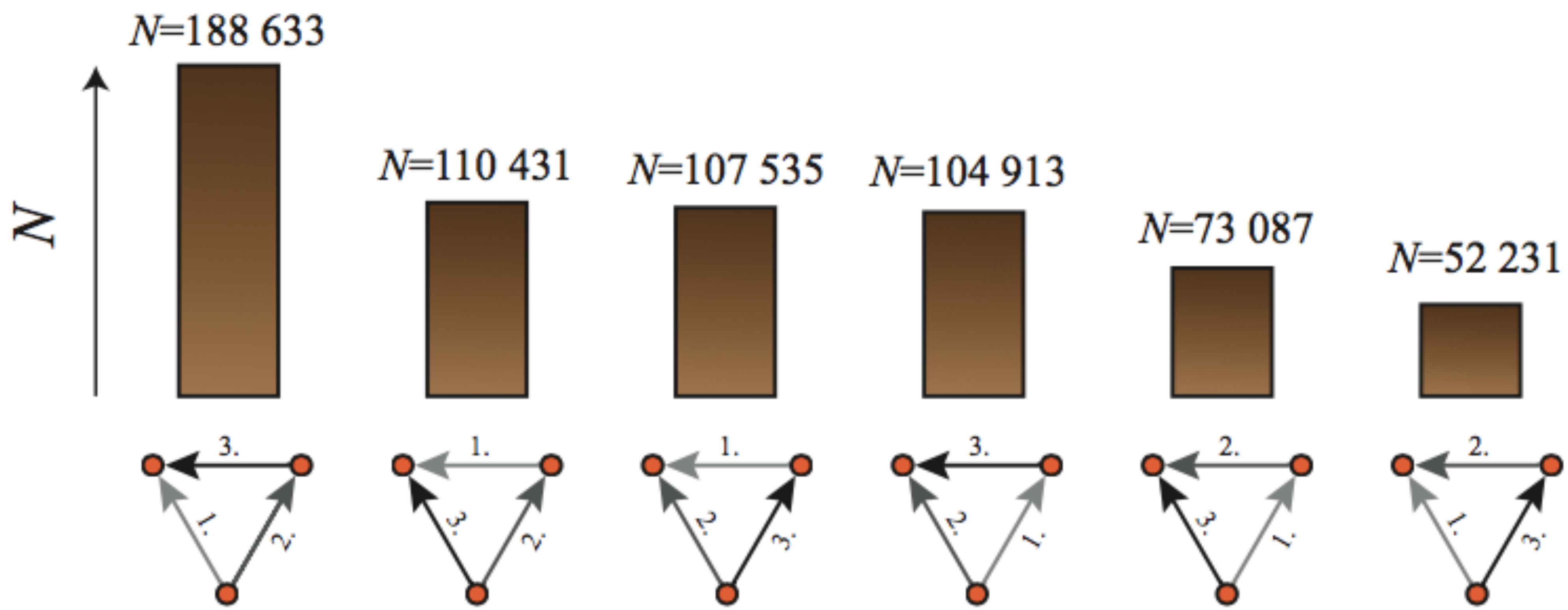
Sketch by J. Saramäki



which motifs are most frequent?
metadata on nodes, compare with null models, …

Temporal motifs reveal homophily, gender-specific patterns, and group talk in call sequences
L. Kovanen et al., PNAS (2013)

Structure: temporal motifs



Motifs in mobile phone call networks

Kovanen et al. (2012)

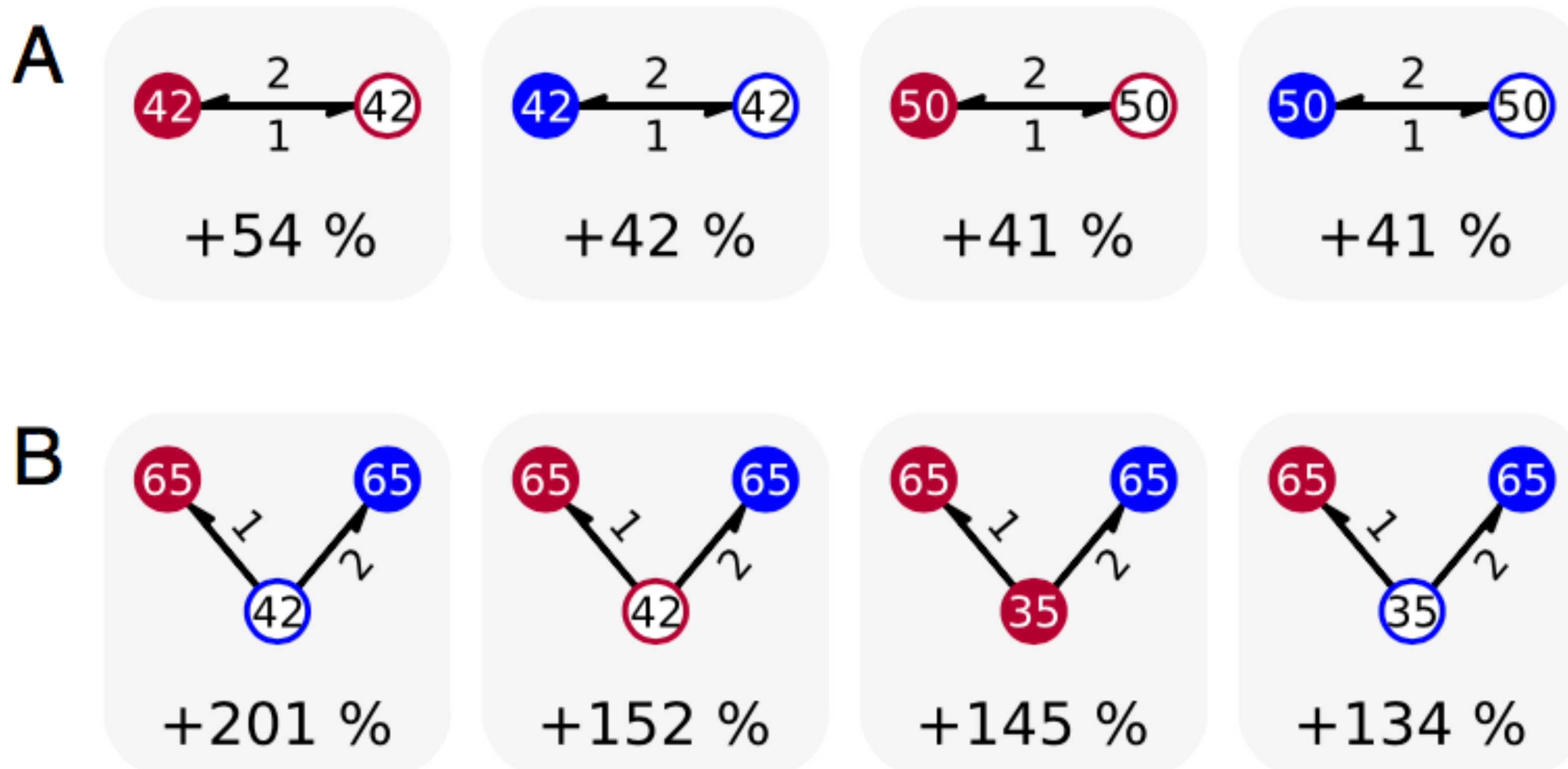


Fig. 4. The most common temporal motifs exhibit shared properties. (*A*) The four most common returned-call motifs. The numbers inside the nodes denote the age group (18–26, 27–32, 33–38, 39–45, 46–55, or 56–80; the value shown is the weighted average rounded to closest integer). The open nodes denote postpaid and filled prepaid customers; red denotes female, and blue, male. The arrows denote events, and the numbers next to them show their temporal order. In all four cases, the first call takes place from the prepaid (filled node) to the postpaid (open node) customer. The number below each motif shows the relative occurrence compared with the null model. (*B*) The four most common out-star motifs. In all four cases, the two receivers have the same age, a pattern that is typical for the most common out-stars.

Temporal motifs reveal homophily, gender-specific patterns, and group talk in call sequences
L. Kovanen et al., PNAS (2013)

> Finding Structures: decomposing a temporal network

Detection of structures: decomposition of temporal network

Data: temporal network with discrete time intervals

$$\Updownarrow$$

Time-dependent adjacency matrix A(i,j,t)

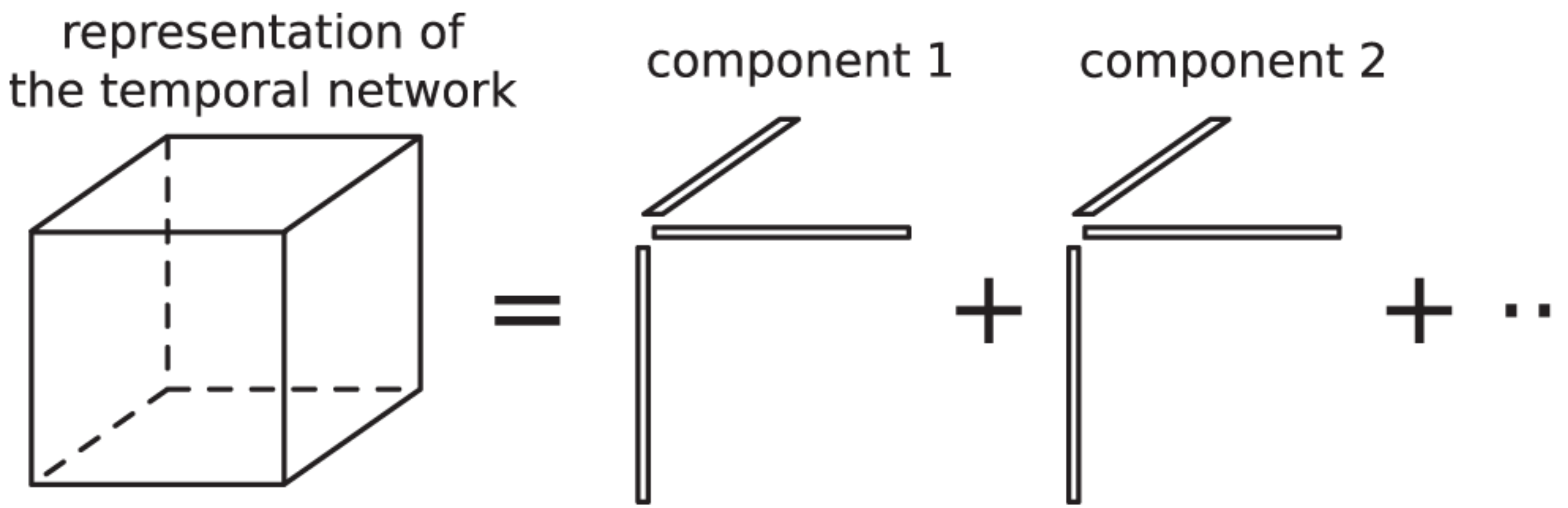
$$\Updownarrow$$

Three-way tensor T

L. Gauvin et al., PLoS ONE (2014)

Detection of structures: decomposition of temporal network

Kruskal decomposition



$$T \approx \tilde{\mathcal{T}} = \sum_{r=1}^{R} \mathcal{S}_r = \sum_{r=1}^{R} \mathbf{a_r} \circ \mathbf{b_r} \circ \mathbf{c_r}$$

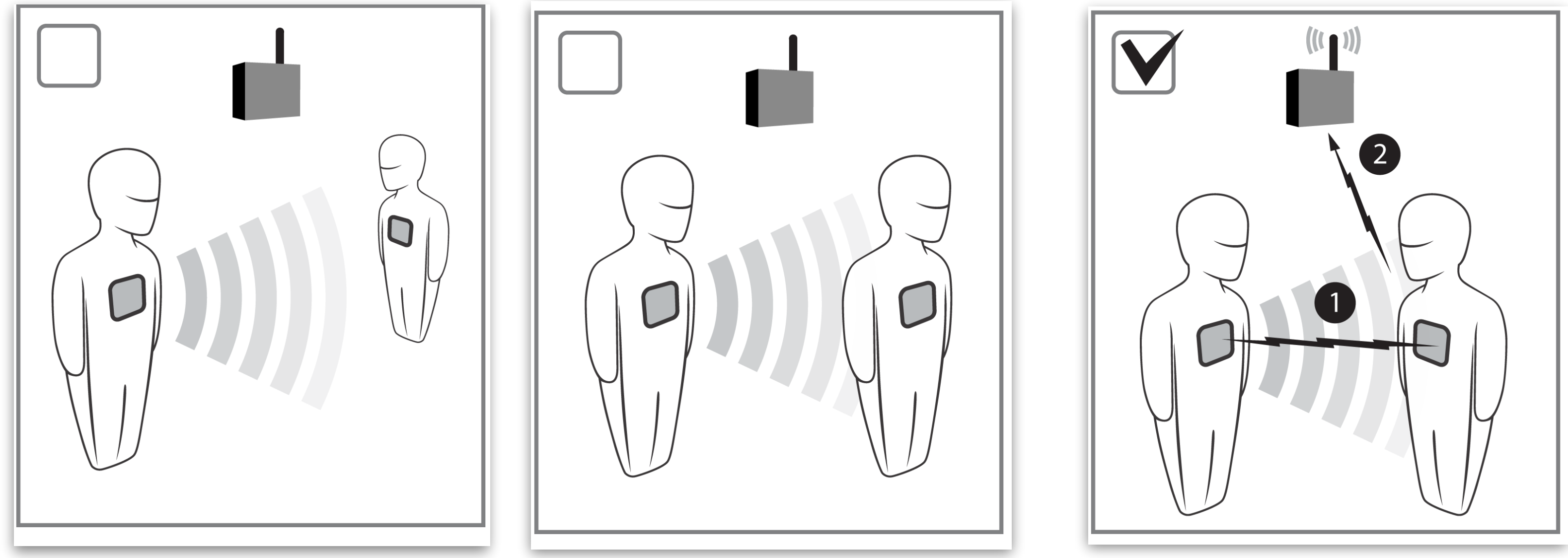
$$t_{ijk} \approx \sum_{r=1}^{R} a_{ir} b_{jr} c_{kr}$$

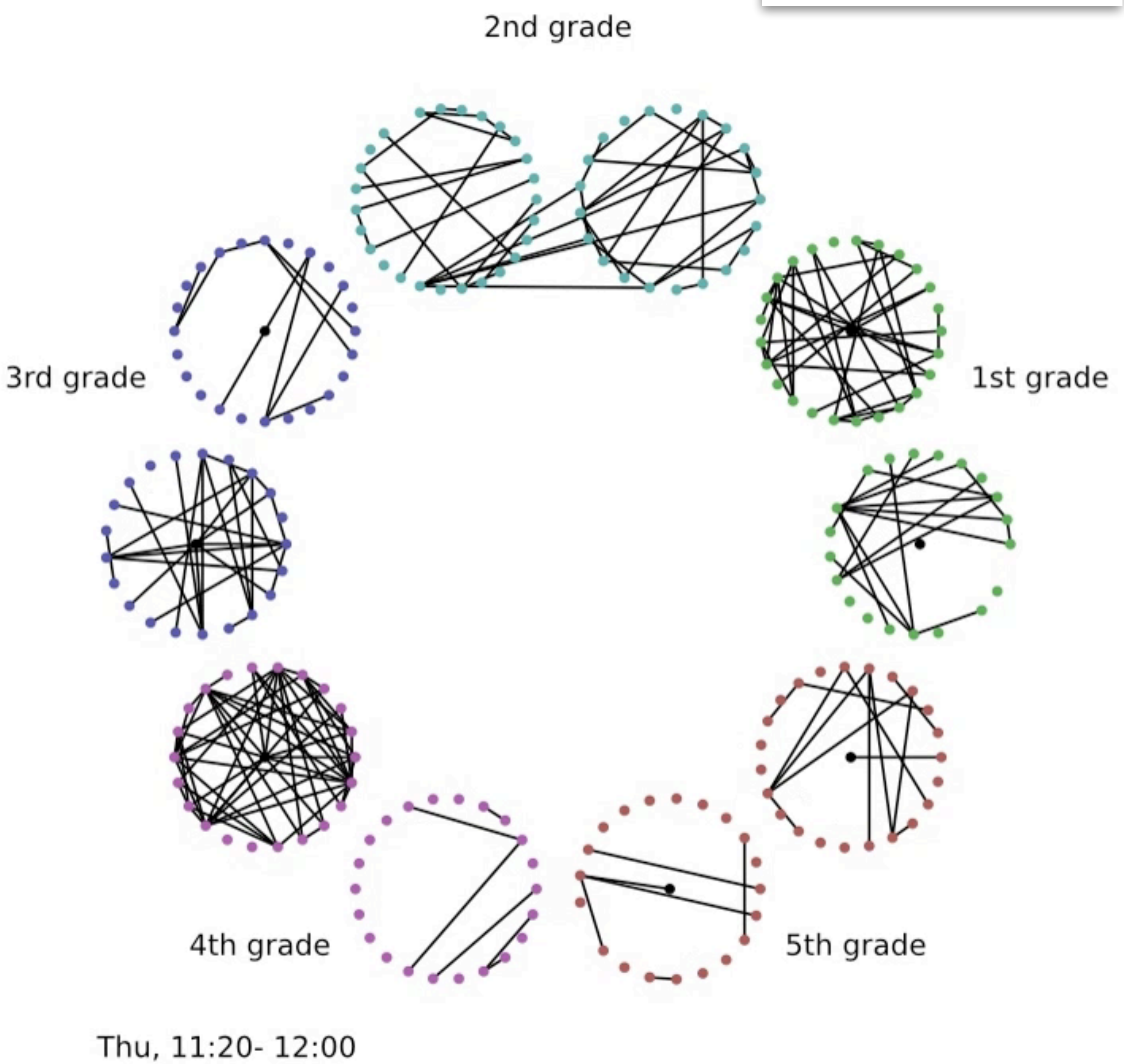
undirected network: a=b

a_{ir}= membership of node i to component r
c_{kr}=timeline of component r

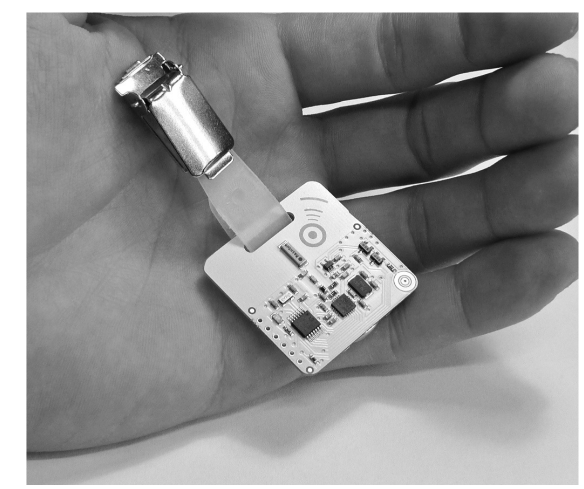
L. Gauvin et al., PLoS ONE (2014)

Example: contacts in a primary school





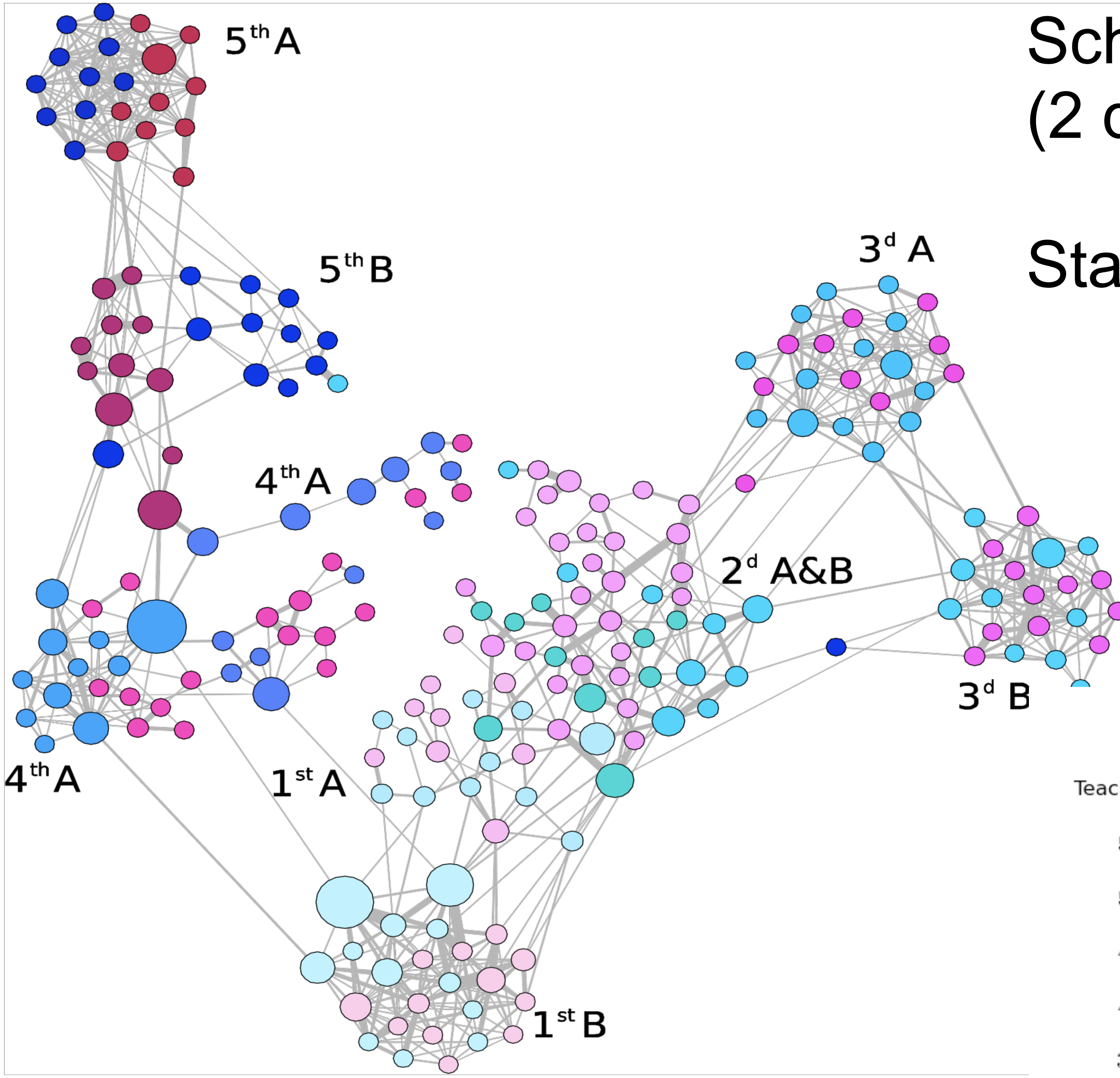
SocioPatterns.org

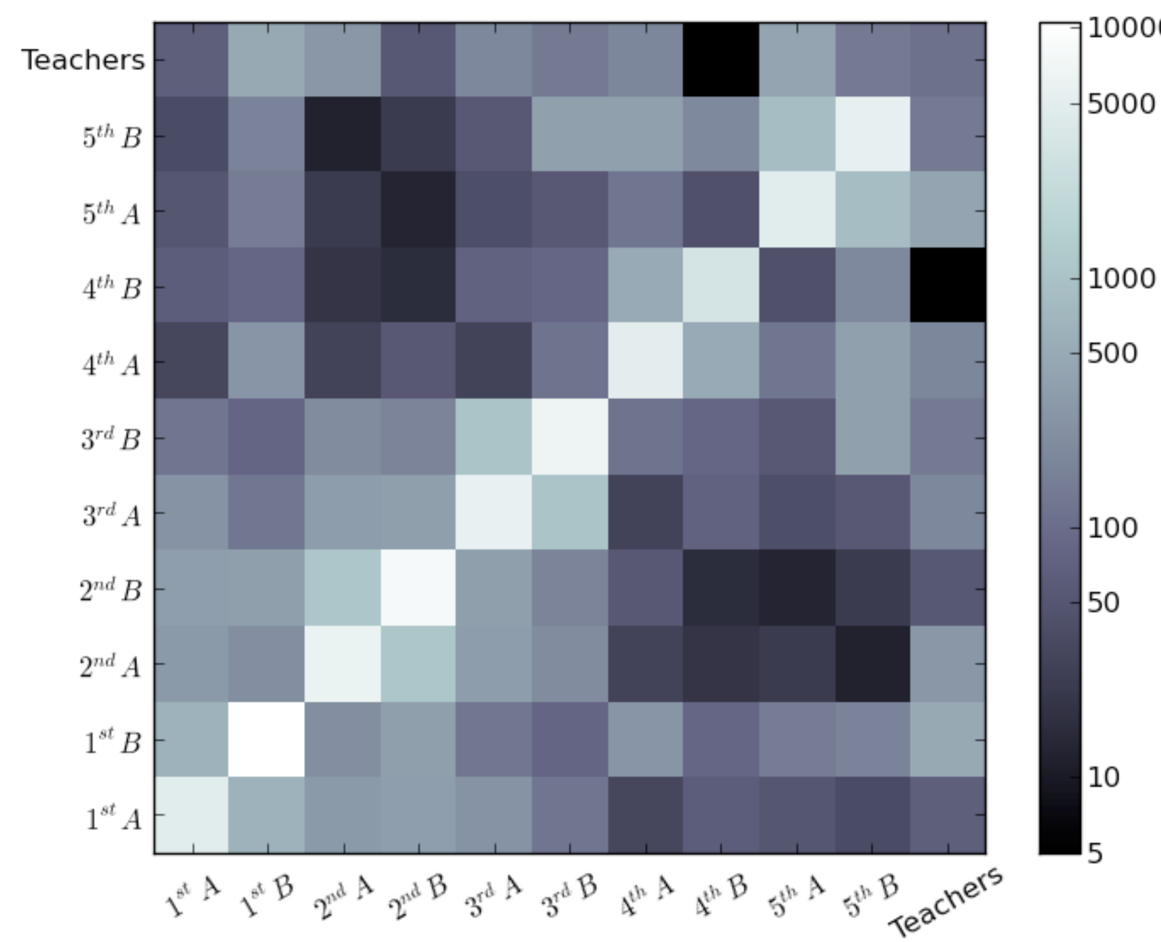


J. Stehlé et al. PLoS ONE 6(8):e23176 (2011)

School cumulative f2f network
(2 days, 2 min threshold)

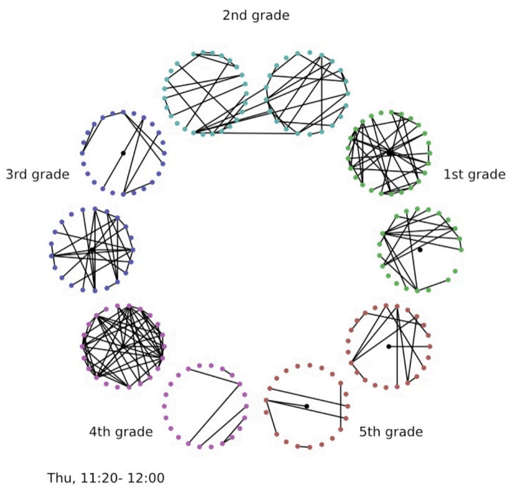
Statically: 10 classes

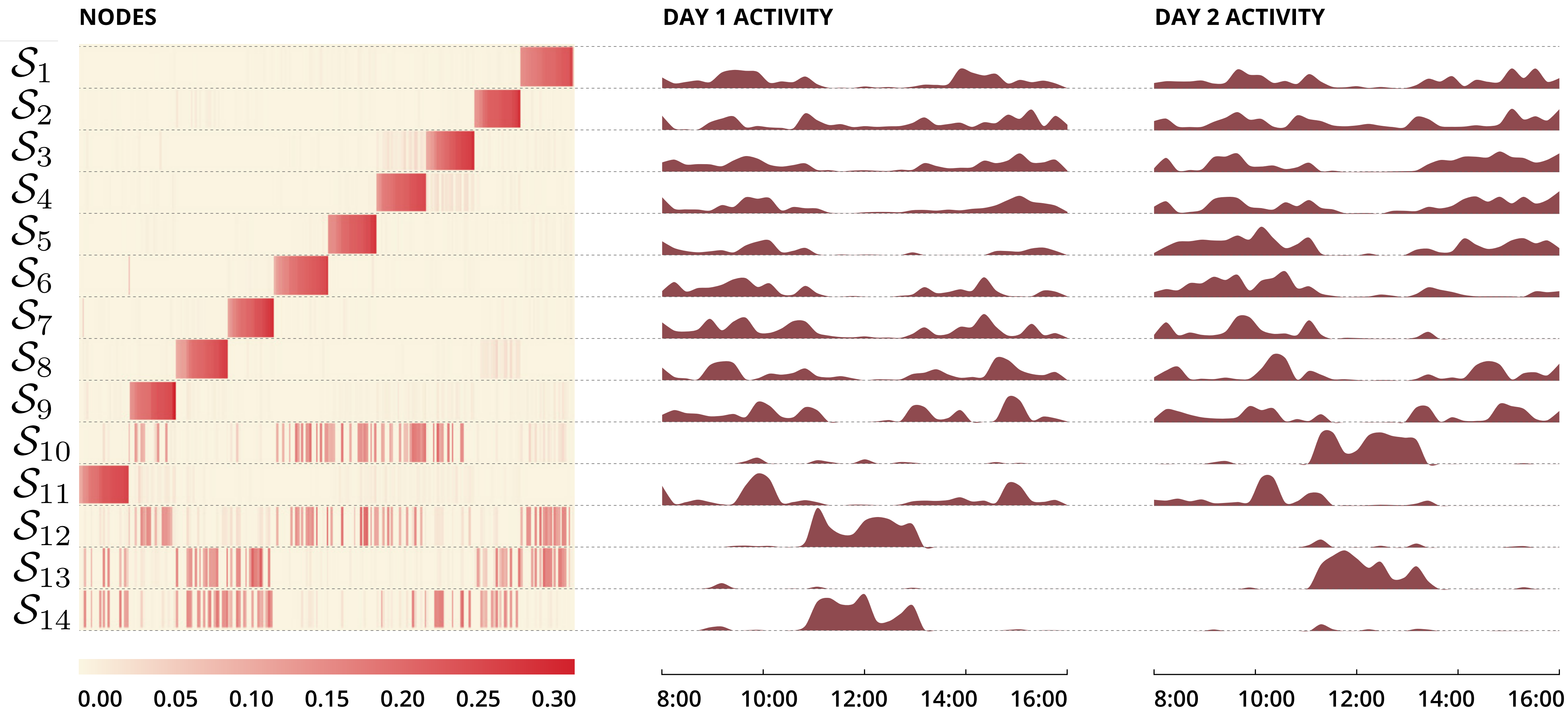




J. Stehlé et al. PLoS ONE
6(8):e23176 (2011)

Primary school case study





10 classes (also revealed by static analysis)
4 mixed-membership components (links with synchronised activities) = breaks

L. Gauvin et al., PLoS ONE (2014)

Relevance for spreading processes

arXiv.org > physics > arXiv:1501.02758

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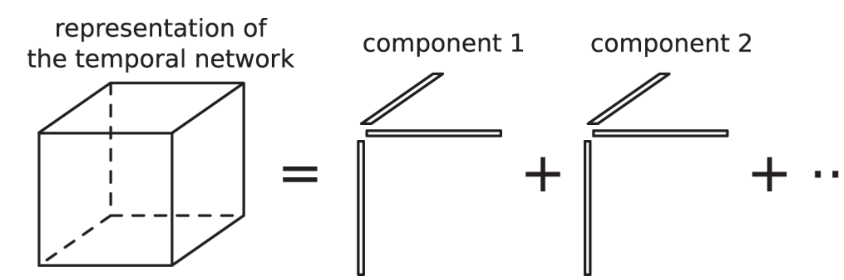
Physics > Physics and Society

[Submitted on 12 Jan 2015]

Revealing latent factors of temporal networks for mesoscale intervention in epidemic spread

Laetitia Gauvin, André Panisson, Alain Barrat, Ciro Cattuto

The customary perspective to reason about epidemic mitigation in temporal networks hinges on the identification of nodes with specific features or network roles. The ensuing individual-based control strategies, however, are difficult to carry out in practice and ignore important correlations between topological and temporal patterns. Here we adopt a mesoscopic perspective and present a principled framework to identify collective features at multiple scales and rank their importance for epidemic spread. We use tensor decomposition techniques to build an additive representation of a temporal network in terms of mesostructures, such as cohesive clusters and temporally-localized mixing patterns. This representation allows to determine the impact of individual mesostructures on epidemic spread and to assess the effect of targeted interventions that remove chosen structures. We illustrate this approach using high-resolution social network data on face-to-face interactions in a school and show that our method affords the design of effective mesoscale interventions.



$$T \approx \tilde{\mathcal{T}} = \sum_{r=1}^{R} \mathcal{S}_r = \sum_{r=1}^{R} \mathbf{a_r} \circ \mathbf{b_r} \circ \mathbf{c_r}$$

Effect of removing a component:

NB:
- components 12, 14 correspond to less total weight than "class"-components
- actionable interventions

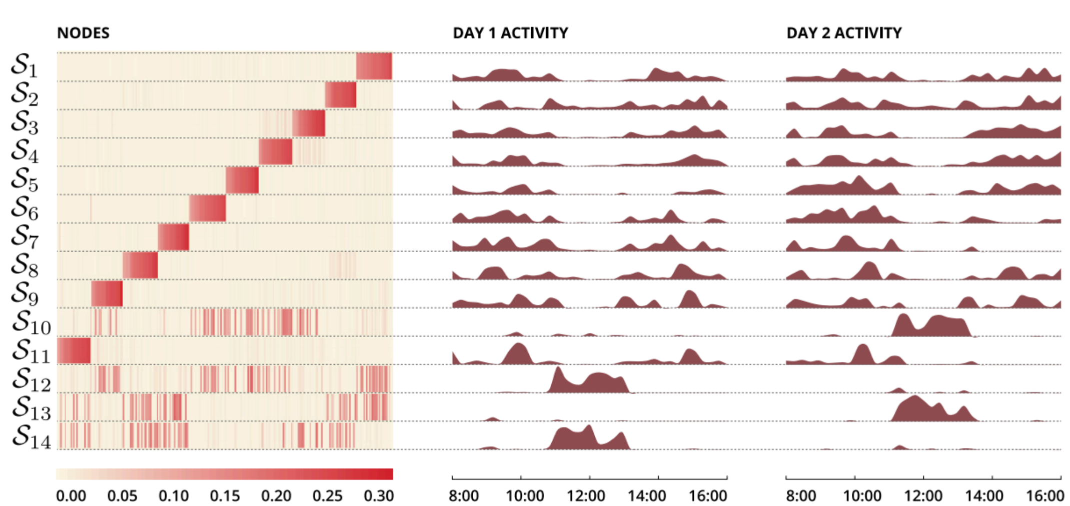


Figure 1: **Components obtained by tensor factorization of the school temporal network.**

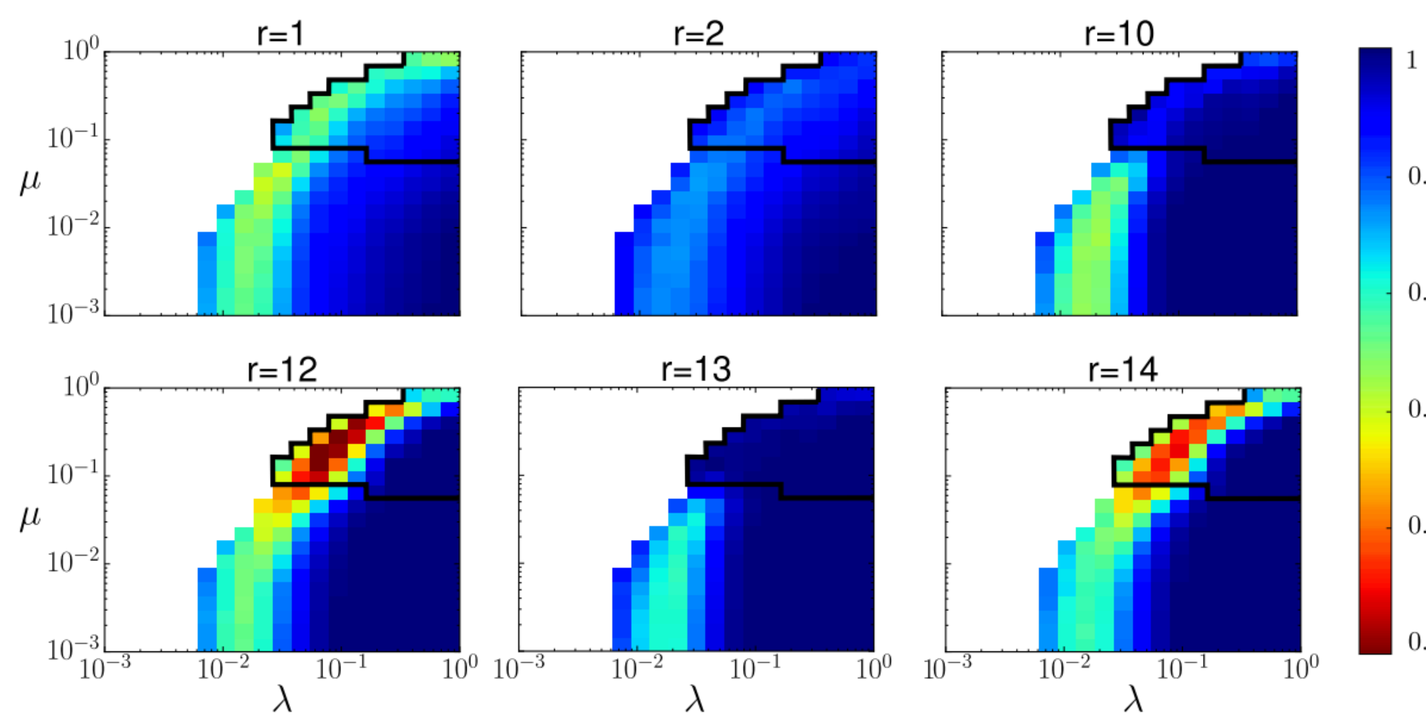


Figure 3: **Epidemic size ratio as a function of SIR model parameters.** Each heat map corresponds to a targeted intervention that selectively removes one component. For each removed component

>Finding structures: Backbones - significant ties

nature COMMUNICATIONS

Article | OPEN | Published: 15 January 2019

The structured backbone of temporal social ties

Teruyoshi Kobayashi, Taro Takaguchi & Alain Barrat

Nature Communications **10**, Article number: 220 (2019) | Download Citation

Filtering methods - static networks

Large scale data: mix of “important” and “random/noisy” links

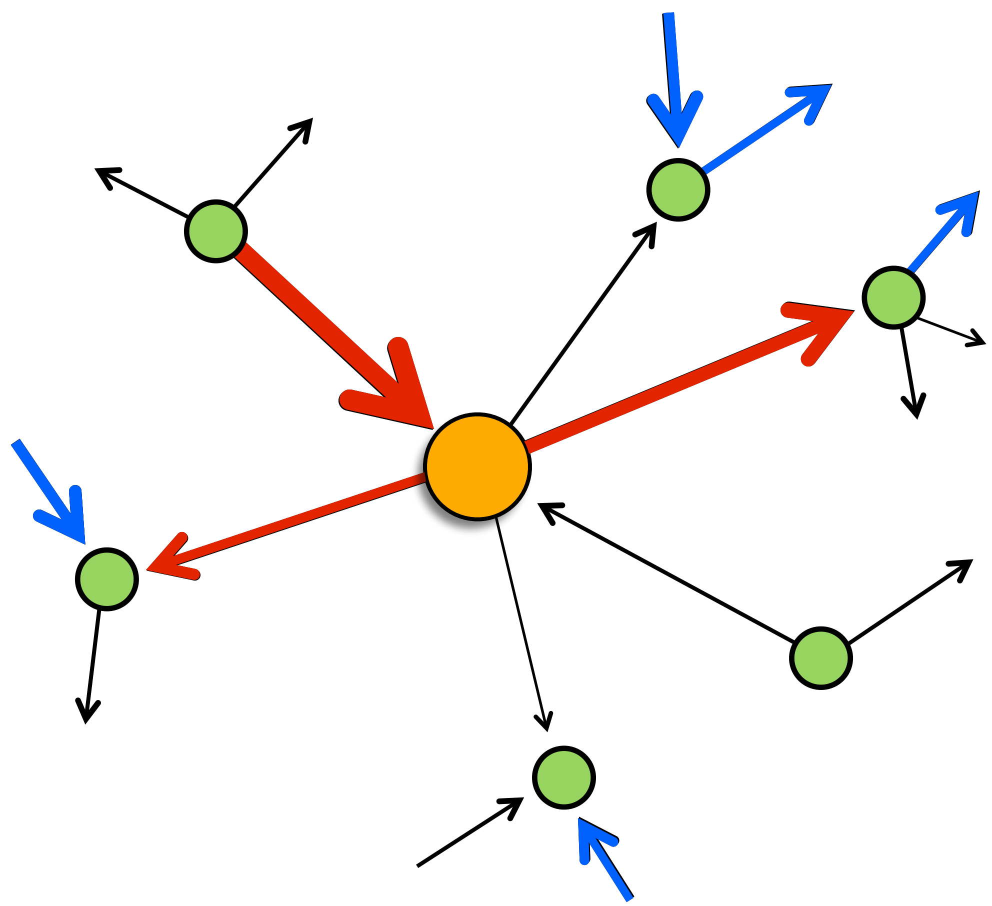
How to extract the most relevant ties?

Filtering methods - static networks

- Retaining only large weights: links with weights larger than a (tunable) threshold => **global filter**

- Filters **based on a null model**: retain only weights larger than expected in a null model
  - **Disparity filter**: multiscale backbone (Serrano et al., PNAS 2009): for each node, retain edges that are "important for that node" => local filter

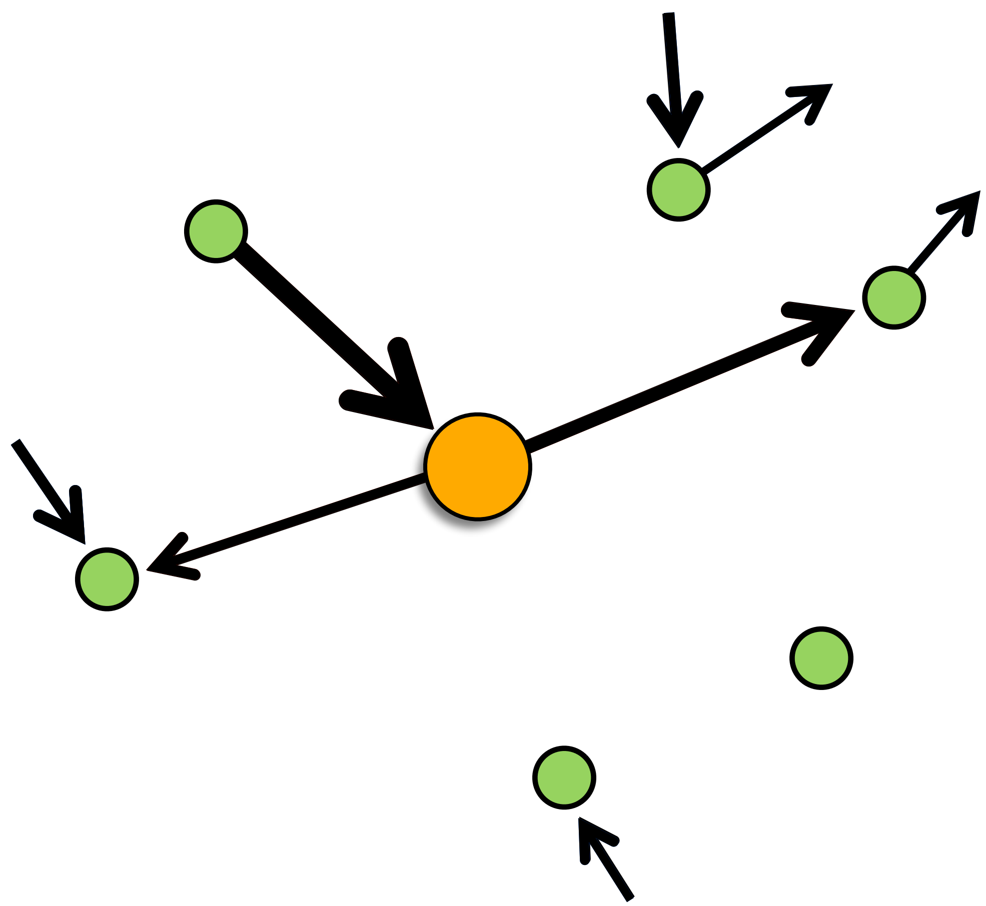
Disparity filter



The <u>disparity filter</u> selects the statistically significant links when the weights are heterogeneously distributed.

Serrano, Boguna, Vespignani - PNAS 2009

Disparity filter



The disparity filter selects the statistically significant links when the weights are heterogeneously distributed.

Serrano, Boguna, Vespignani - PNAS 2009

Filtering methods - static networks

- Retaining only large weights: links with weights larger than a (tunable) threshold => **global filter**

- Filters **based on a null model**: retain only weights larger than expected in a null model
    - **Disparity filter**: multiscale backbone (Serrano et al., PNAS 2009): for each node, retain edges that are “important for that node” => local filter

    - **Enhanced configuration model** (Gemmetto et al., arXiv: 1706.00230) = max entropy ensemble of networks with fixed degree and strength sequences (null model) => **p-value of observing a weight w_{ij} between i and j larger than or equal to the real weight** => retain only links with small p-value

Filtering method - temporal network

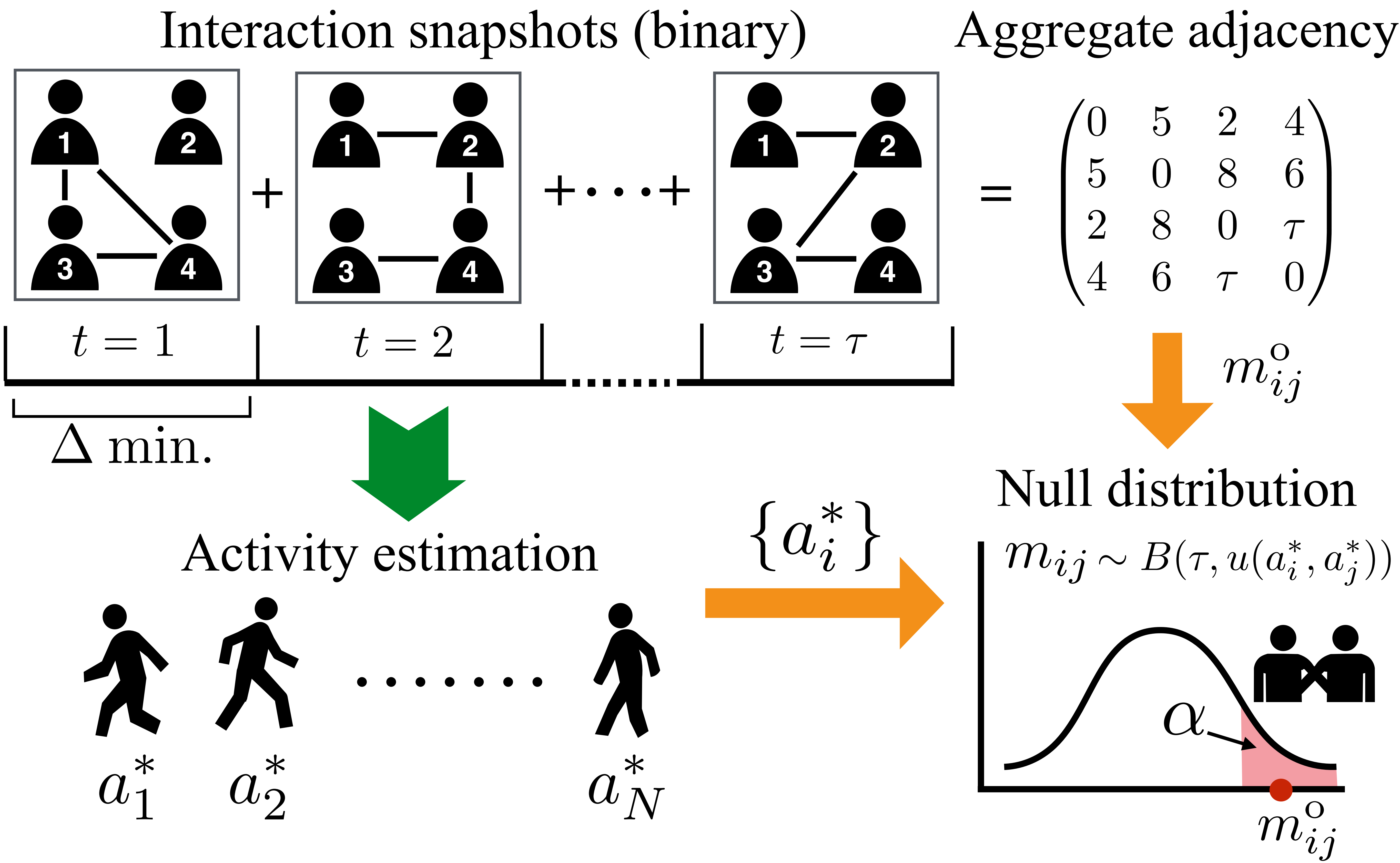
Use a **temporal null model**:

- define the temporal fitness model
  - node i, activity a_i
  - probability of interaction at any time: $u(a_i, a_j) = a_i a_j$
- evaluate activities a_i^* of nodes (max likelihood)
- compute the probability distribution of the number of interactions

$$g(m_{ij} \,|\, a_i^*, a_j^*) = \binom{\tau}{m_{ij}} u(a_i^*, a_j^*)^{m_{ij}} (1 - u(a_i^*, a_j^*))^{\tau - m_{ij}} \,.$$

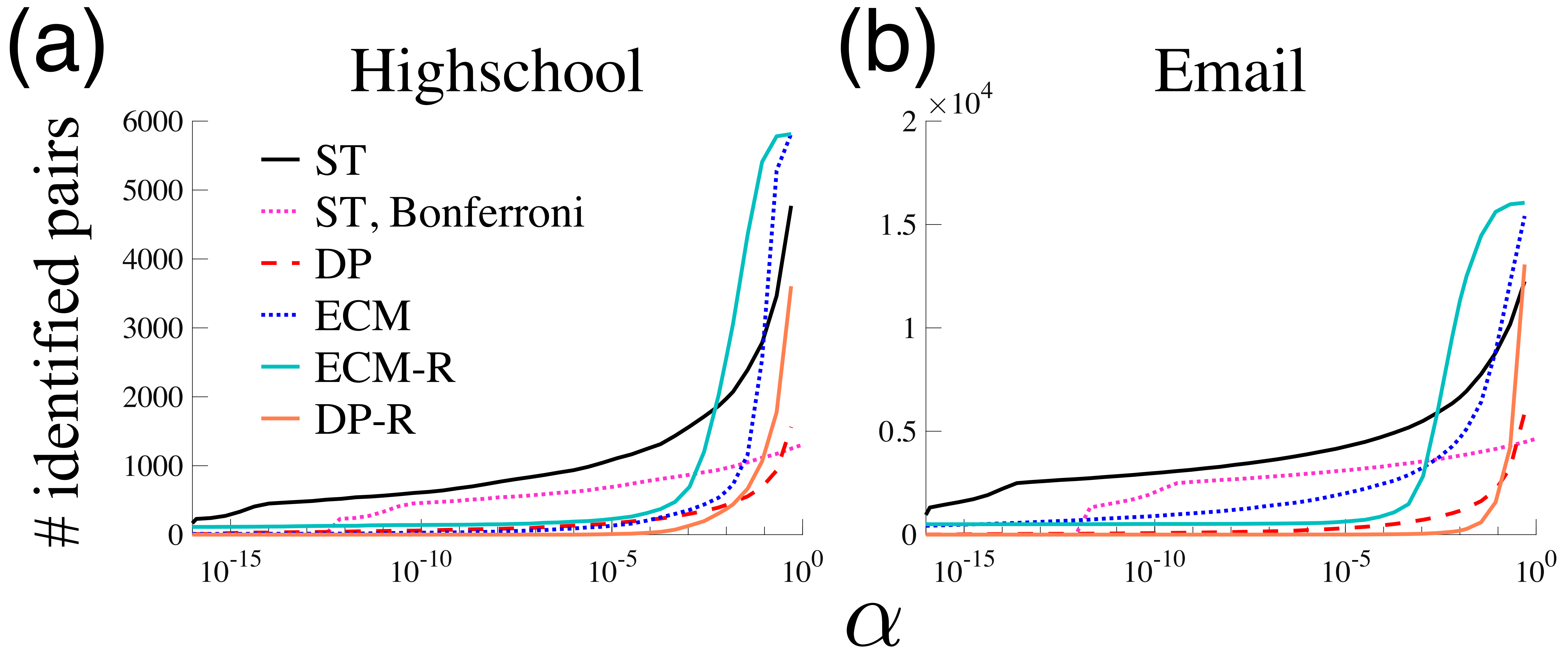
- ij is a significant tie if the observed number has a small p-value w.r.t. g

T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019



T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019

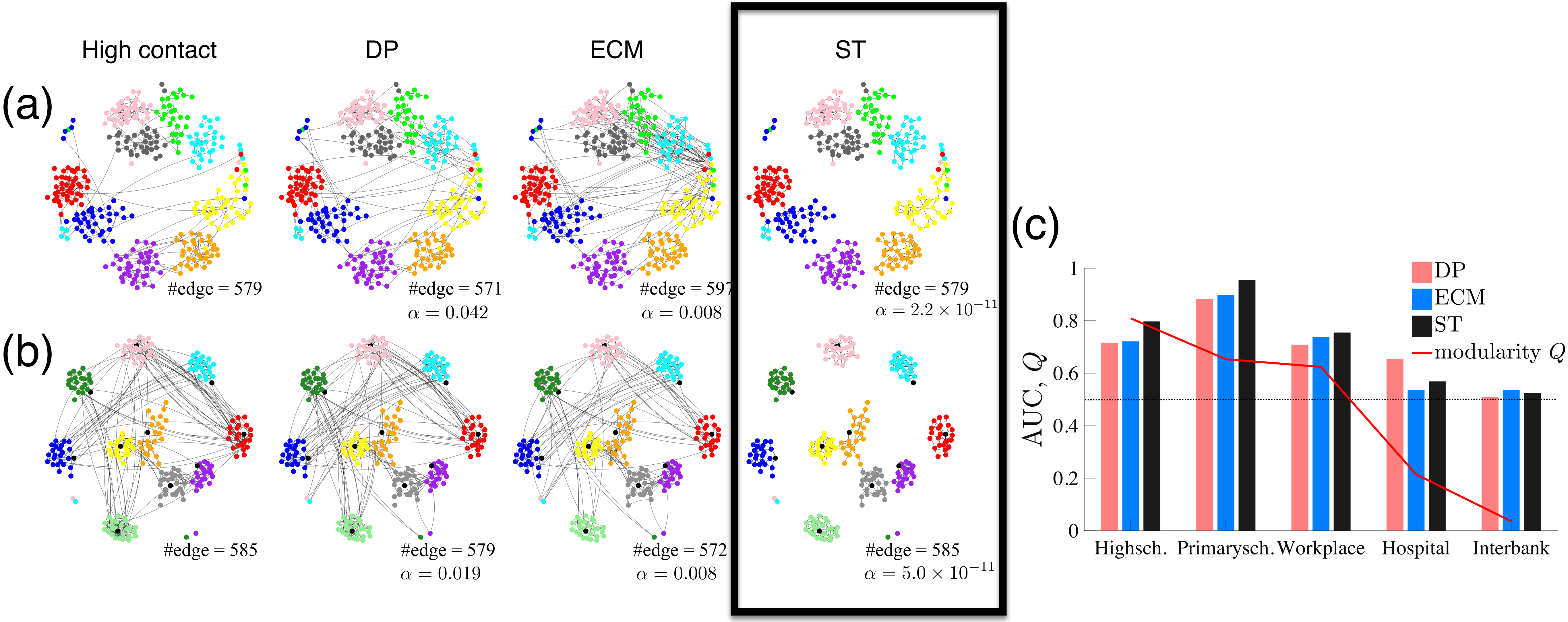
Examples



- More ties detected than with other methods
- Range of significance values with ***stable*** backbone
-

T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019

Example: SocioPatterns datasets



- More ties detected than with other methods
- Range of significance values with stable backbone
- Significant ties seem to be mostly within groups, when a community structure is present

T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019

Beyond significant ties: significant structures

Probability that i,j,k form a triangle of **simultaneous** interactions at a given time

$$v(i,j,k) = u(a_i^*, a_j^*) \cdot u(a_j^*, a_k^*) \cdot u(a_k^*, a_i^*)\,,$$

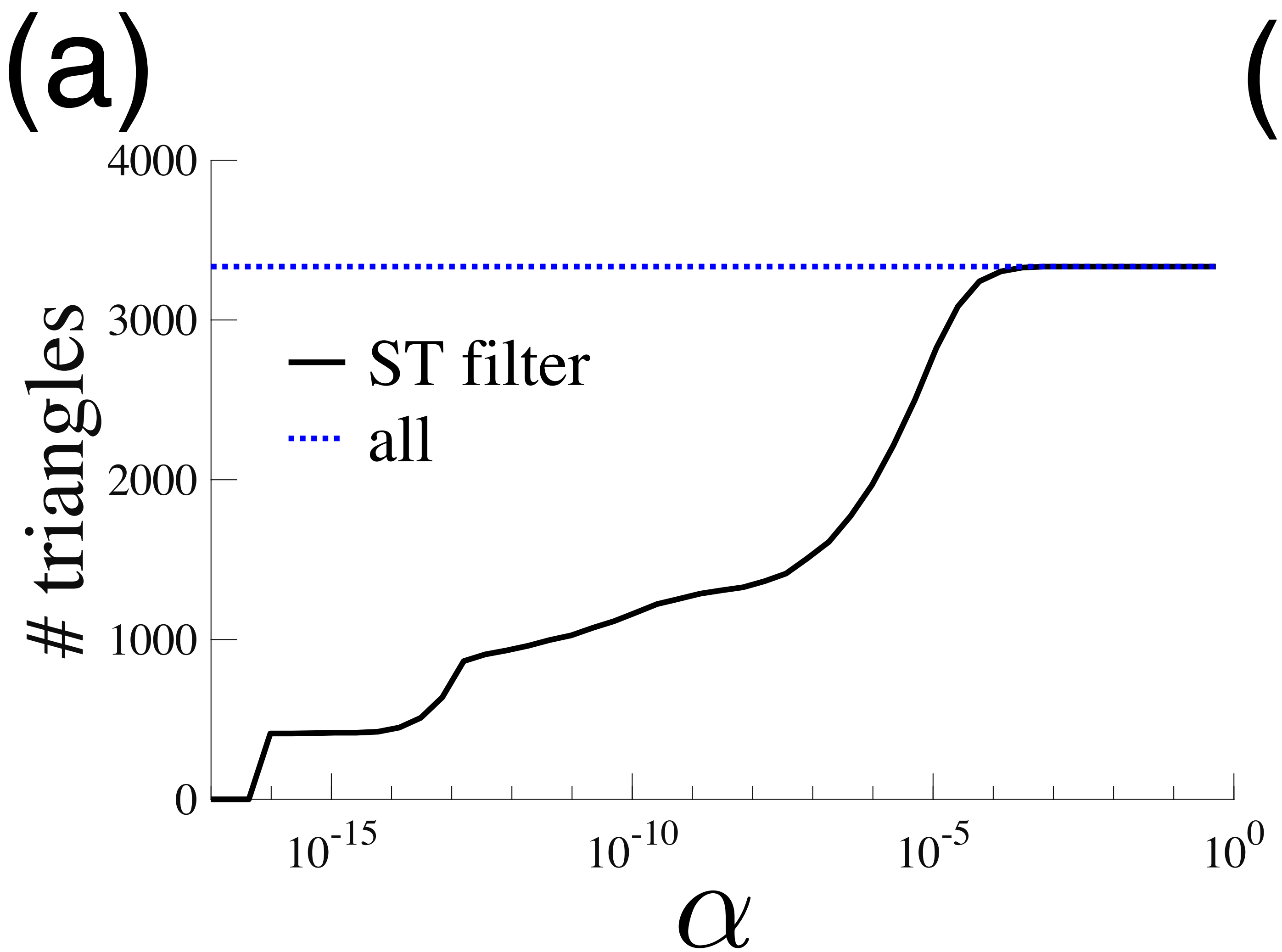
Probability that the triangle i,j,k is observed r_{ijk} times in the null model:

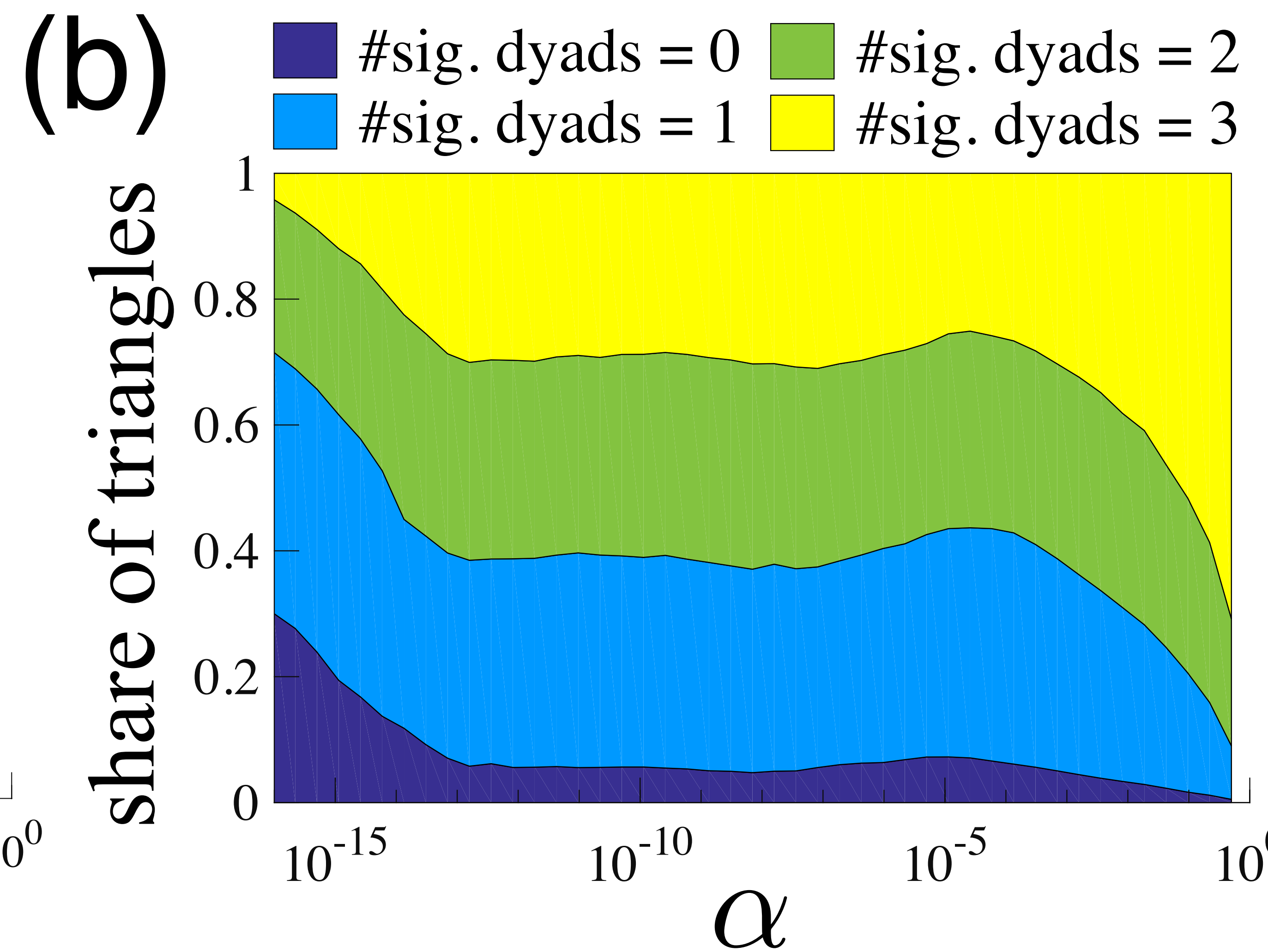
$$h(r_{ijk} \,|\, a_i^*, a_j^*, a_k^*) = \binom{\tau}{r_{ijk}} v(i,j,k)^{r_{ijk}} (1 - v(i,j,k))^{\tau - r_{ijk}}$$

=> possibility to **assign a significance to a triad of simultaneous interactions** or to other temporal motifs/structures
(not possible with static filters)

T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019

Beyond significant ties: significant structures

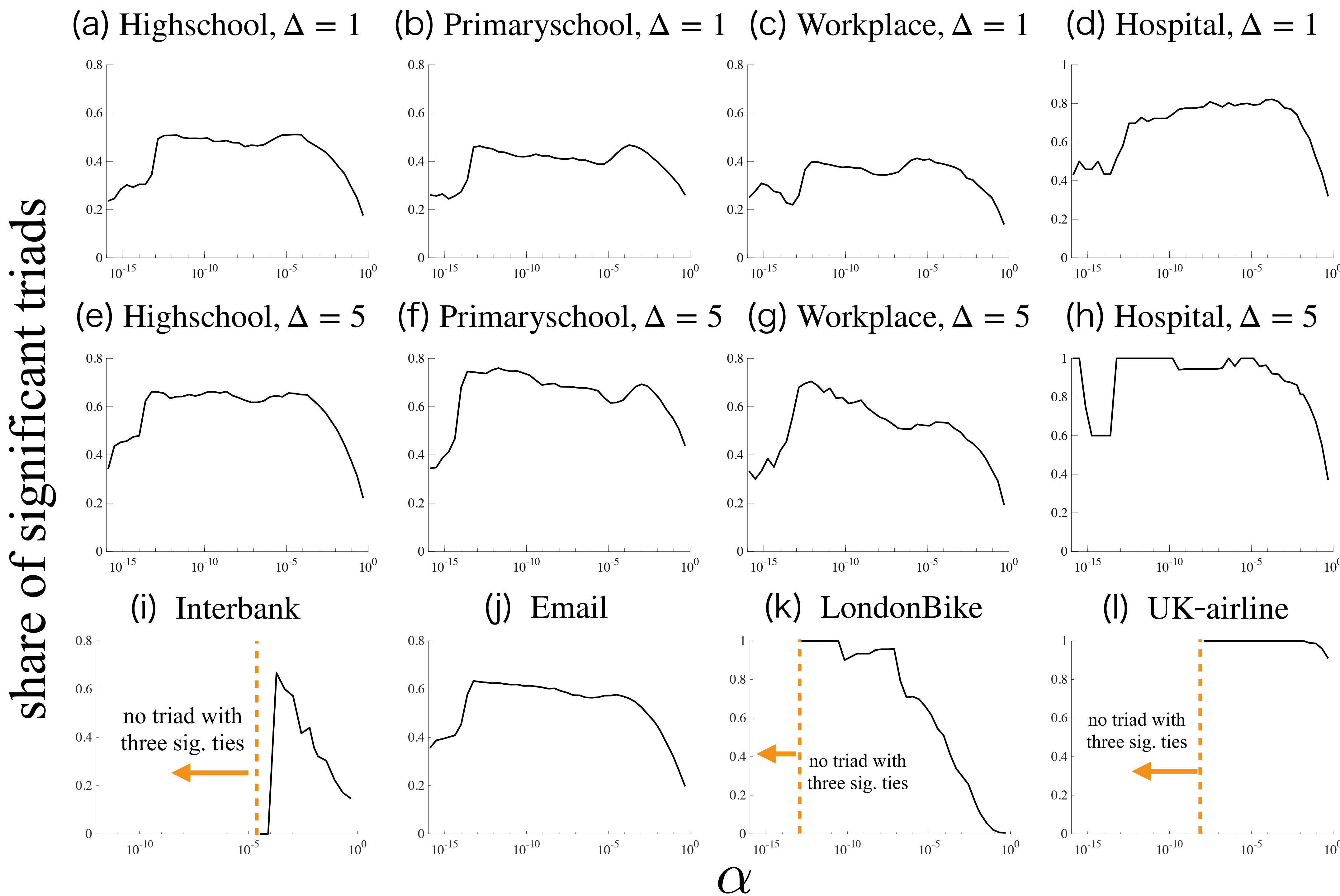




Significant structures are not only sets of significant ties

T. Kobayashi, T. Takaguchi, A. Barrat, Nat Comms 2019

Not all triangles of 3 significant dyads are significant triads



Share of significant triads among the triangles composed by three significant ties vs. the filtering level α, for various data sets and temporal resolutions.

Extension: taking into account groups

Modified **temporal null model**:

- node i, activity a_i, group c_i
- probability of interaction at any (discrete) time:

$$u(a_i, a_j) \equiv a_i a_j \times (\delta_{c_i,c_j} + p(1 - \delta_{c_i,c_j}))$$

evaluate activities a_i^* of nodes and parameter p^* (max likelihood)

compute the probability distribution of the number of interactions m_{ij} during τ in the null model

$$g(m_{ij} \,|\, a_i^*, a_j^*) = \binom{\tau}{m_{ij}} u(a_i^*, a_j^*)^{m_{ij}} (1 - u(a_i^*, a_j^*))^{\tau - m_{ij}} .$$

ij is a Significant Tie if the observed number of interactions m_{ij}^0 has a small p-value w.r.t. g

with C. Présigny, P. Holme

Using the backbone

Q1: does the backbone contain *enough* information?
if not, what additional information should we keep?

Q2: to do what?

A2: to use in data-driven numerical simulations of dynamical processes

A1: Main idea: original network ≈ backbone + noise

➡ create surrogate data by adding “noise” (null model) to the backbone

➡ use the surrogate data in numerical simulations

nature communications

Open Access | Published: 13 November 2015

Compensating for population sampling in simulations of epidemic spread on temporal contact networks

Mathieu Génois, Christian L. Vestergaard, Ciro Cattuto & Alain Barrat

with C. Présigny, P. Holme

Creating surrogate data

- Input:
  - backbone $\mathscr{B}_f$ (fraction f of original data)
  - number W of temporal edges in original data
  - (fitted) statistics of (inter-)contact times

- Procedure:
  - compute activities a_i of nodes in backbone
  - $\forall i, j$ not in $\mathscr{B}_f$ extract m_{ij} from binomial distribution $g(m_{ij} \mid a_i, a_j)$
  - if $\sum m_{ij} = W^* < W$, use $u(a_i, a_j) = a_i a_j W / W^*$
  - create timelines on each link i, j , using statistics of (inter-)contact times

NB: case of groups
additional input: group membership, W_{inter}, W_{intra}

nature communications

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Compensating for population sampling in simulations of epidemic spread on temporal contact networks

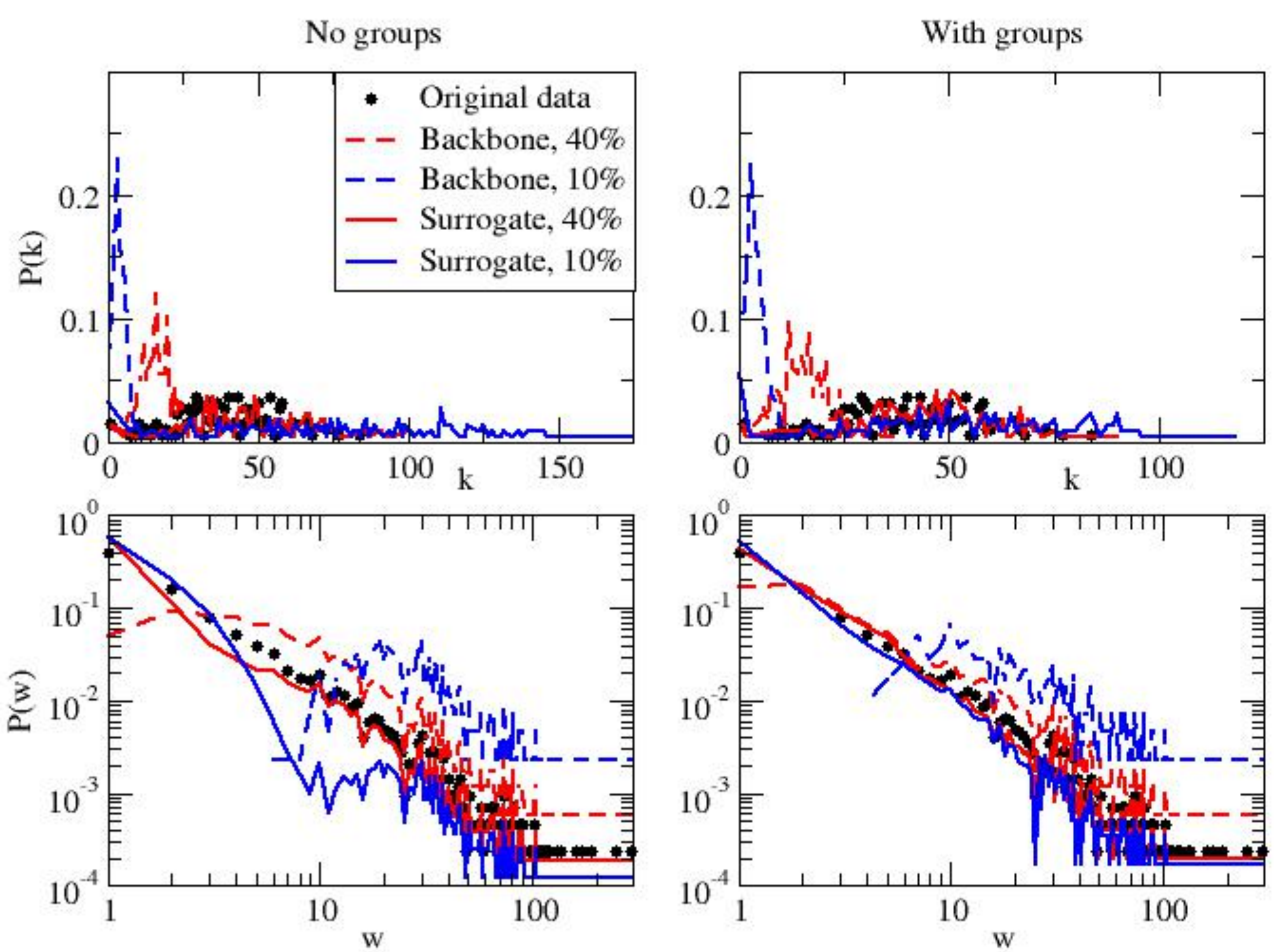
Mathieu Génois, Christian L. Vestergaard, Ciro Cattuto & Alain Barrat

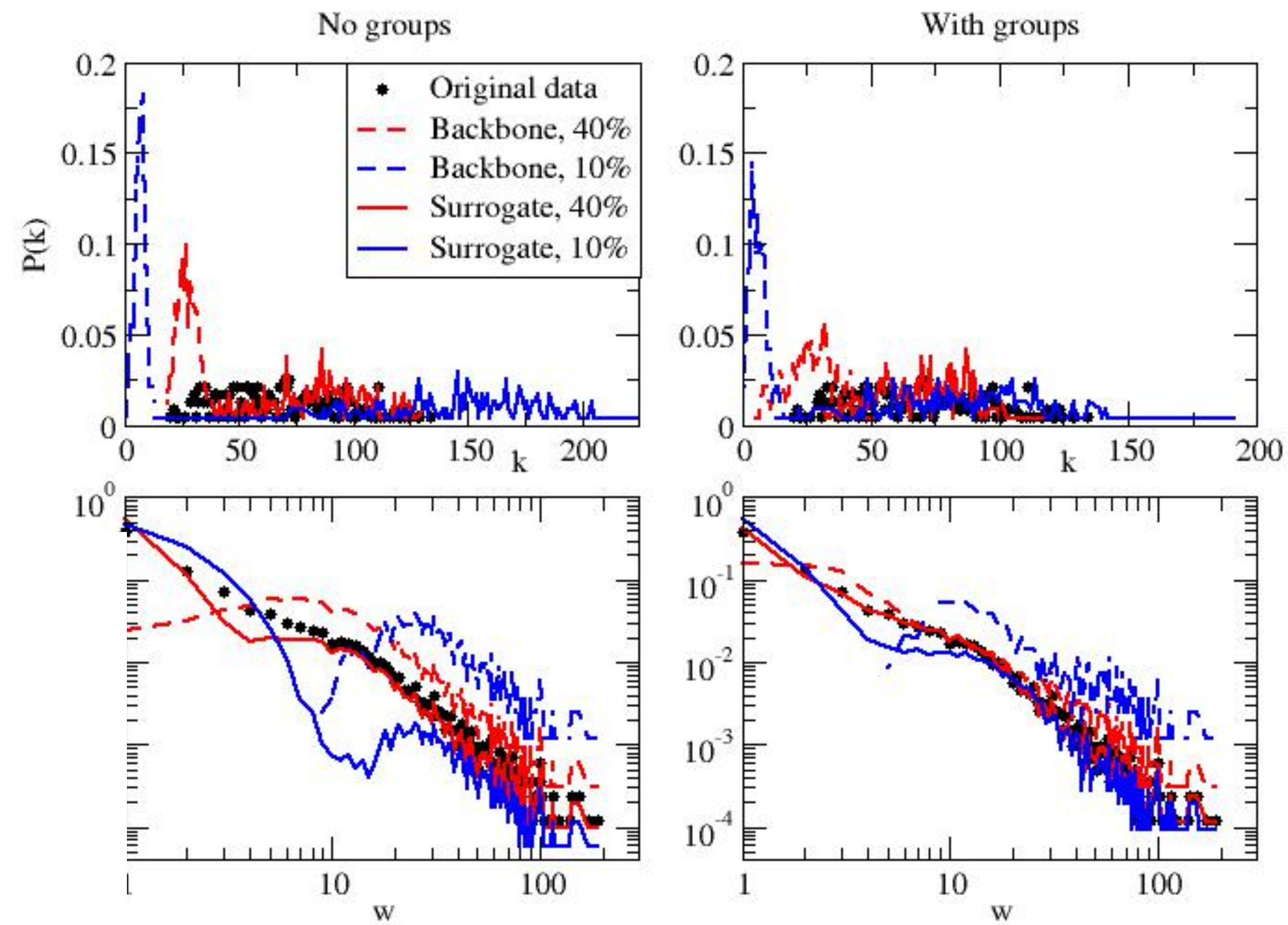
Preliminary results

Degrees and weights statistics

- original data
- backbone
- surrogate data

Offices



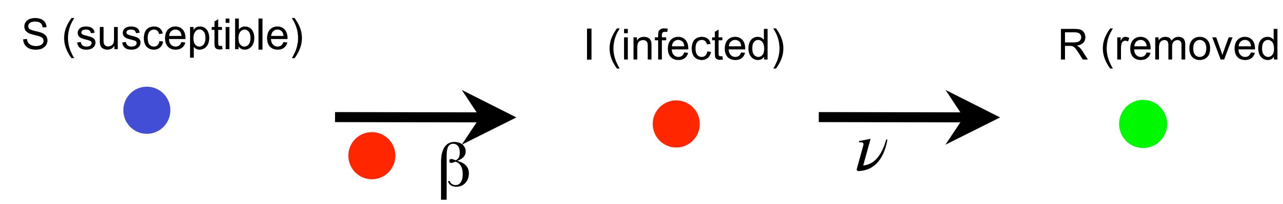


School

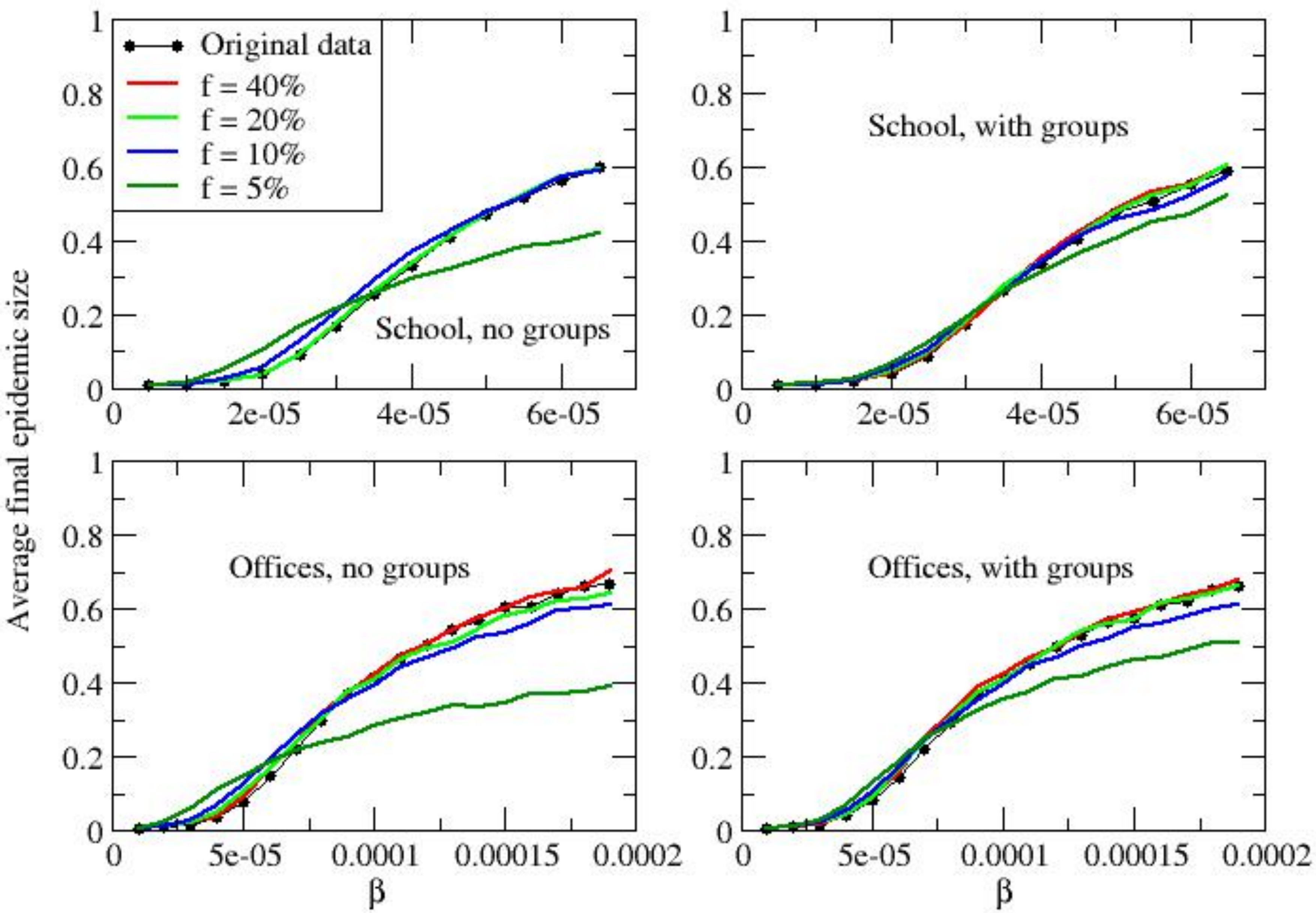
Also:
strong correlation between strength in surrogate and strength in data
weaker correlation between degree in surrogate and degree in data

Preliminary results

(static) SIR process on (i) original data (ii) surrogate data



f = size of backbone



School:
groups (classes) of same size
strong community structure

Offices:
groups of different sizes
weak community structure

Future work:

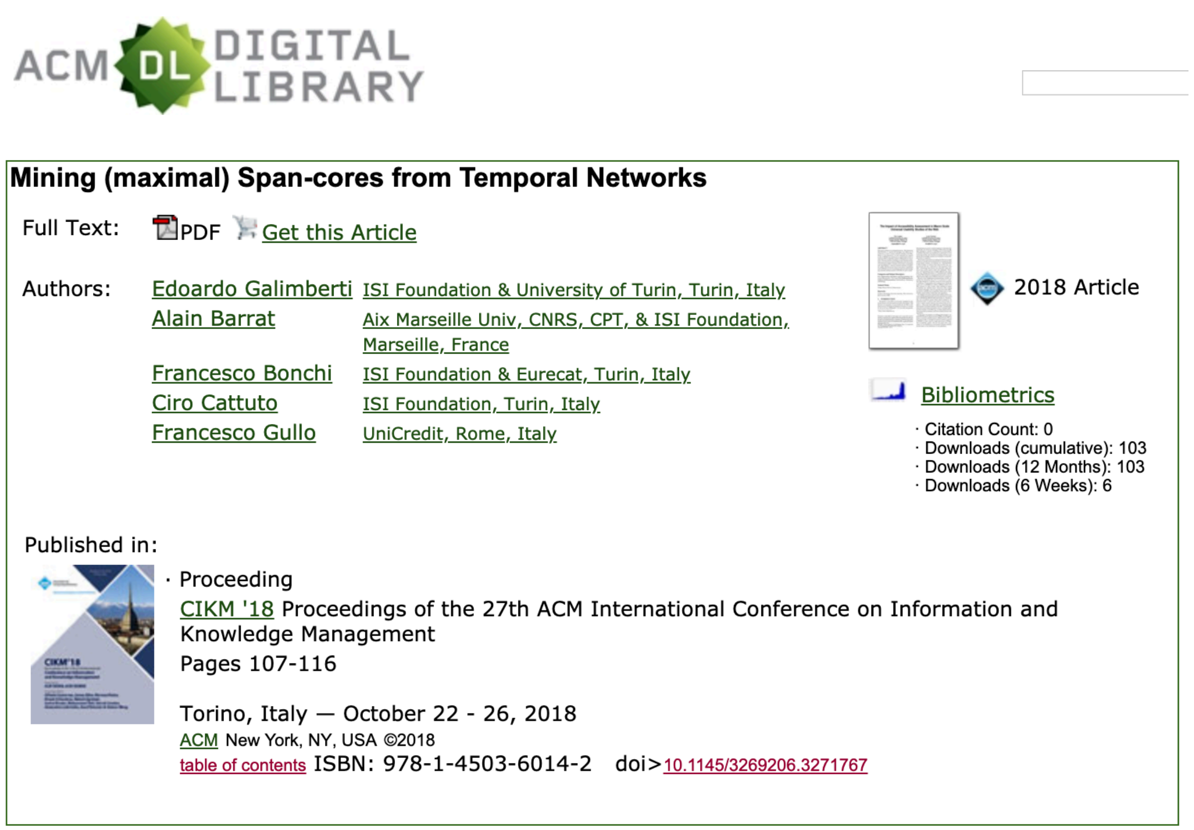
Other reconstruction methods

SIR on temporal surrogate (in progress, with C. Présigny, P. Holme)

Other dynamical processes

Backbone of events (in progress, with M. Karsai)

>Finding structures: Span cores



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Mining (maximal) Span-cores from Temporal Networks

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2018 Article

Authors: Edoardo Galimberti ISI Foundation & University of Turin, Turin, Italy
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ACM New York, NY, USA ©2018
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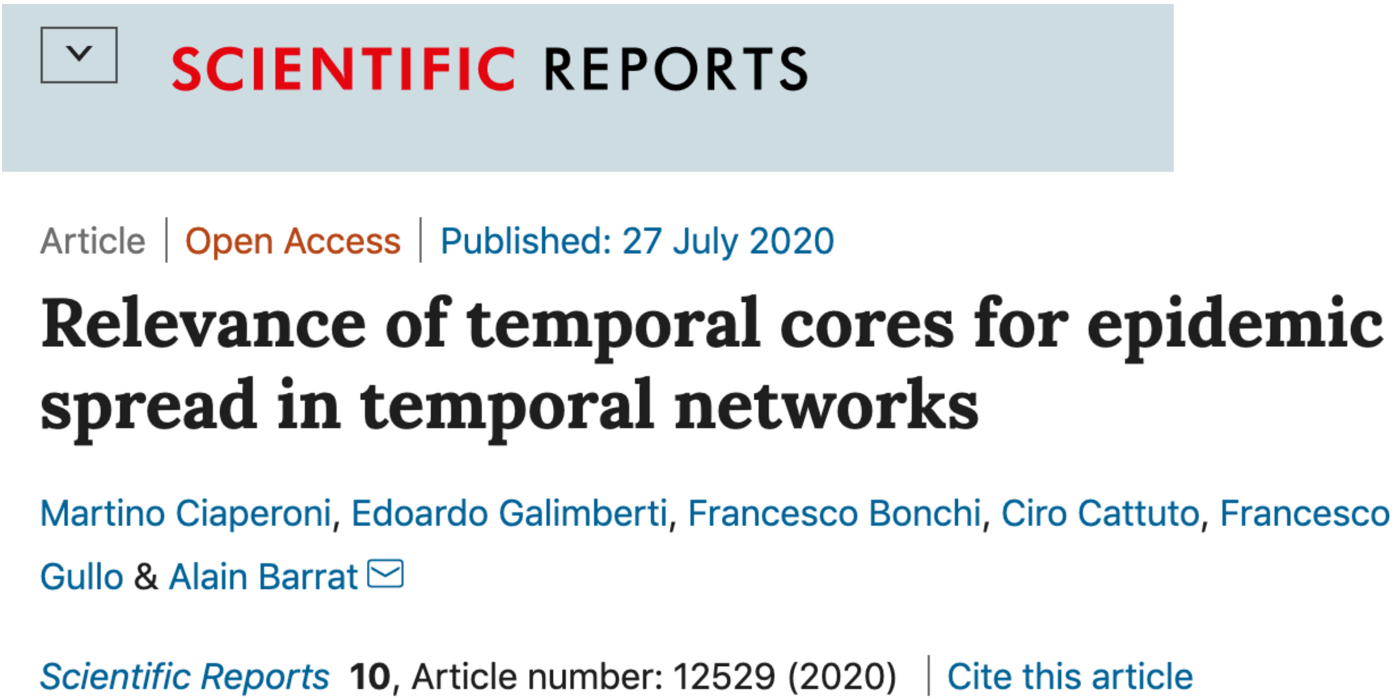


SCIENTIFIC REPORTS

Article | Open Access | Published: 27 July 2020

Relevance of temporal cores for epidemic spread in temporal networks

Martino Ciaperoni, Edoardo Galimberti, Francesco Bonchi, Ciro Cattuto, Francesco Gullo & Alain Barrat

Scientific Reports **10**, Article number: 12529 (2020) | Cite this article

Reminder:
k-core decomposition for static networks

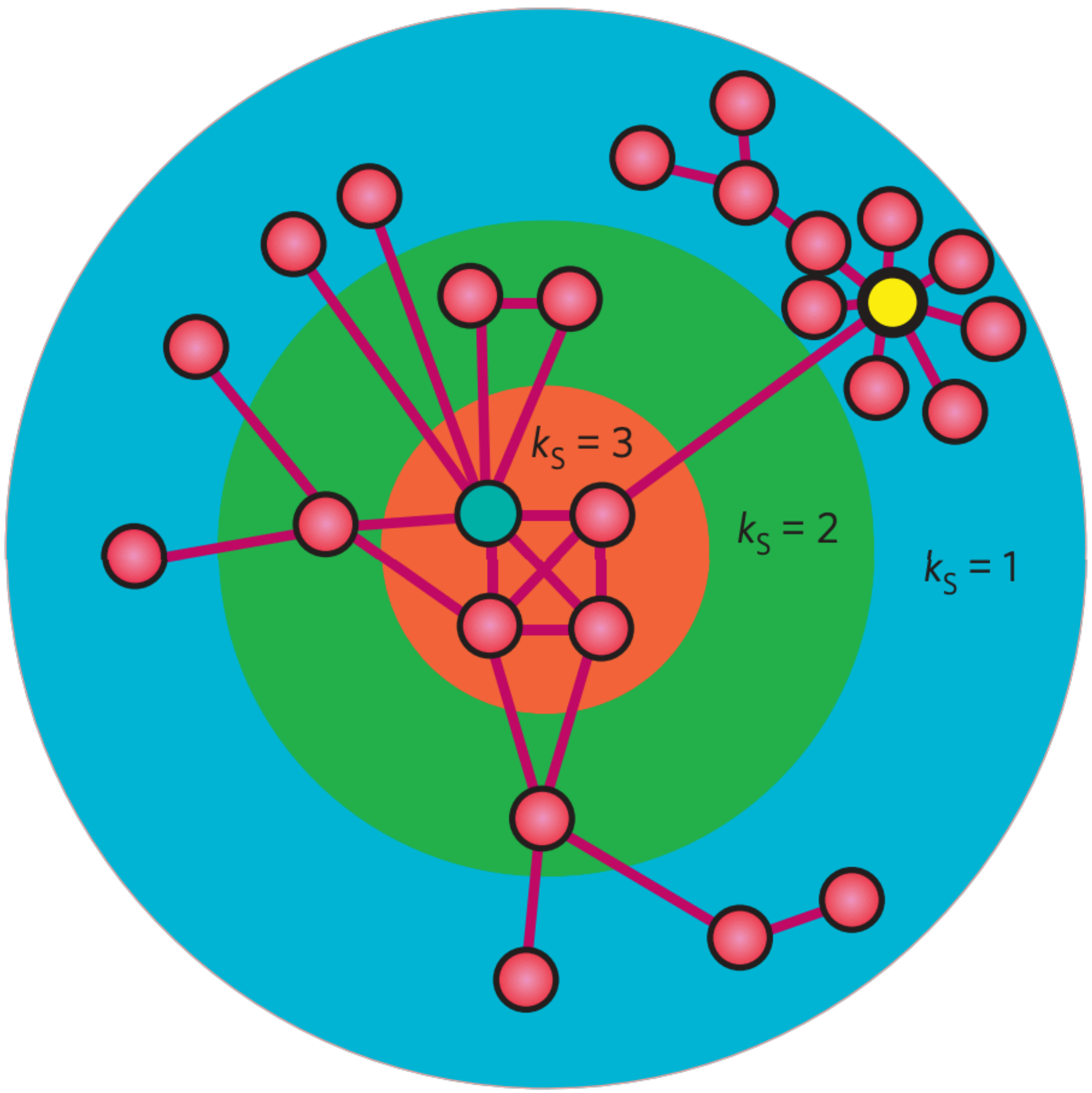
graph G=(V,E)

–k-core of graph G: maximal subgraph such that for all vertices in this subgraph have degree at least k

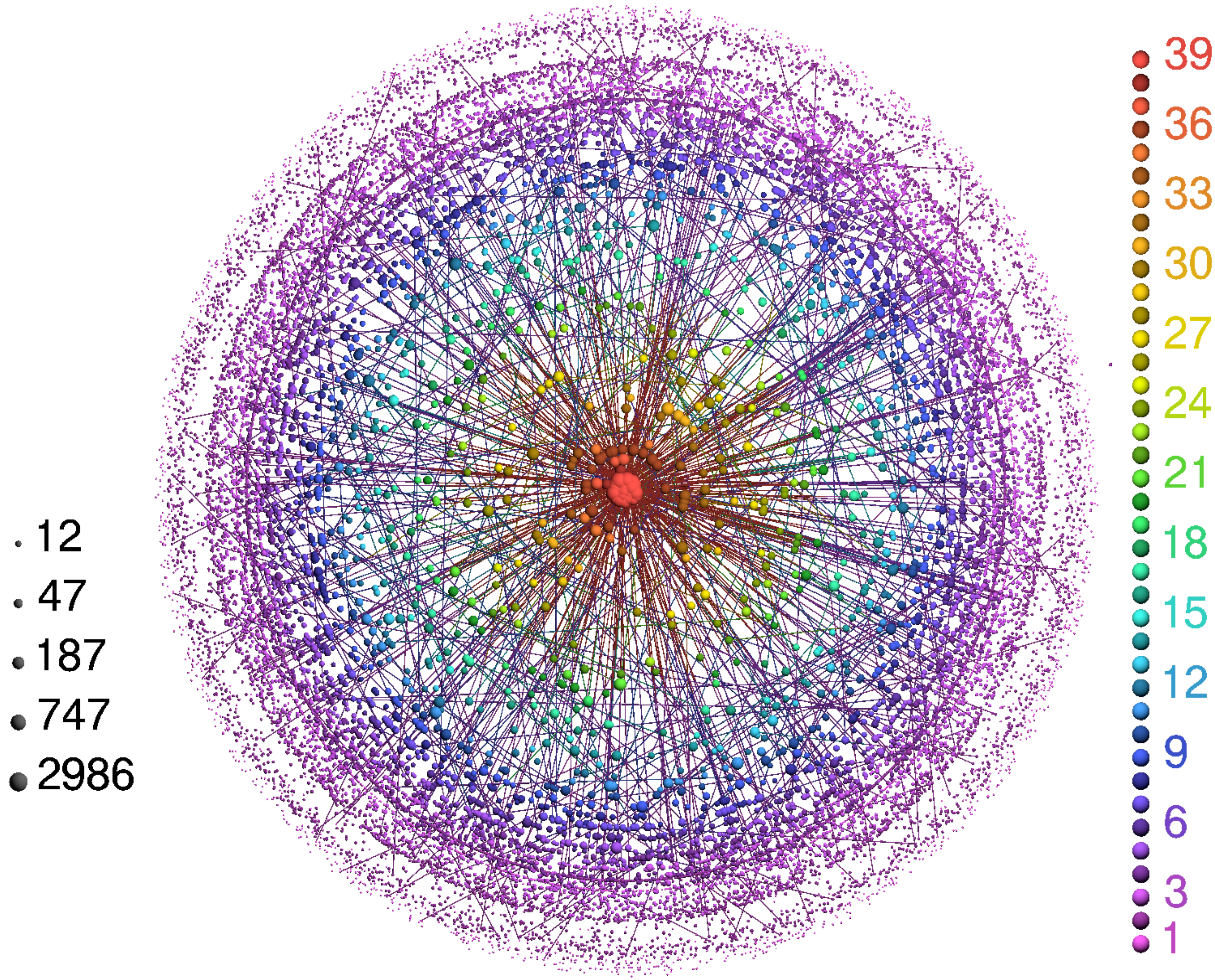
–vertex i has shell index k iff it belongs to the k-core but not to the (k+1)-core

–k-shell: ensemble of all nodes of shell index k

Reminder:
k-core decomposition for static networks



(picture from Kitsak et al., Nat Phys 2010) http://lanet-vi.fi.uba.ar/



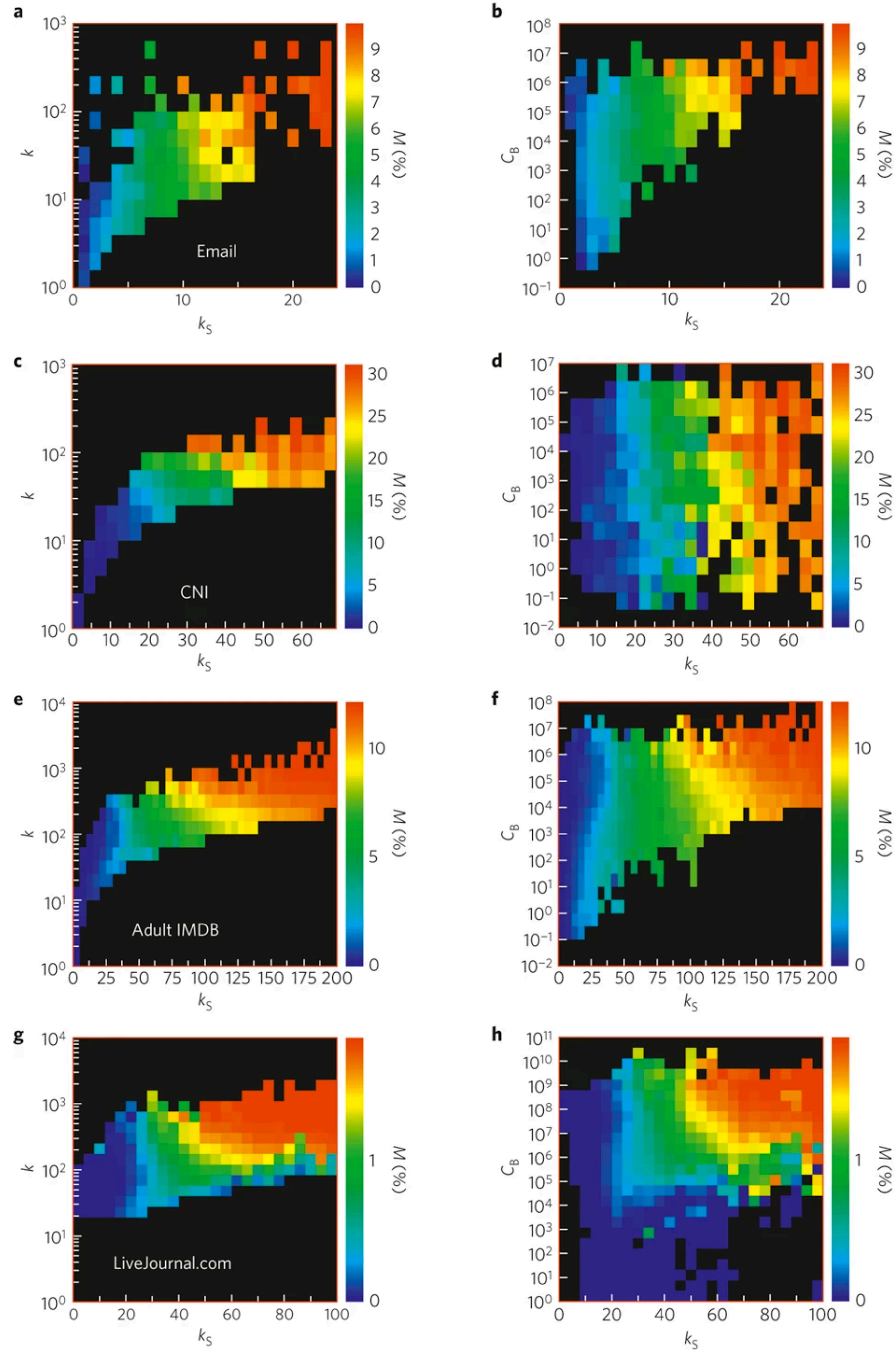
nature physics

Published: 29 August 2010

Identification of influential spreaders in complex networks

Maksim Kitsak, Lazaros K. Gallos, Shlomo Havlin, Fredrik Liljeros, Lev Muchnik, H. Eugene Stanley & Hernán A. Makse

Nature Physics **6**, 888–893(2010) | Cite this article



Size of an outbreak as a function of the seed's properties

Span-core: definition

Temporal network G, set of vertices V,
temporal interval $T = [0,1,\ldots,t_{max}]$

Set of edges at time t: E_t

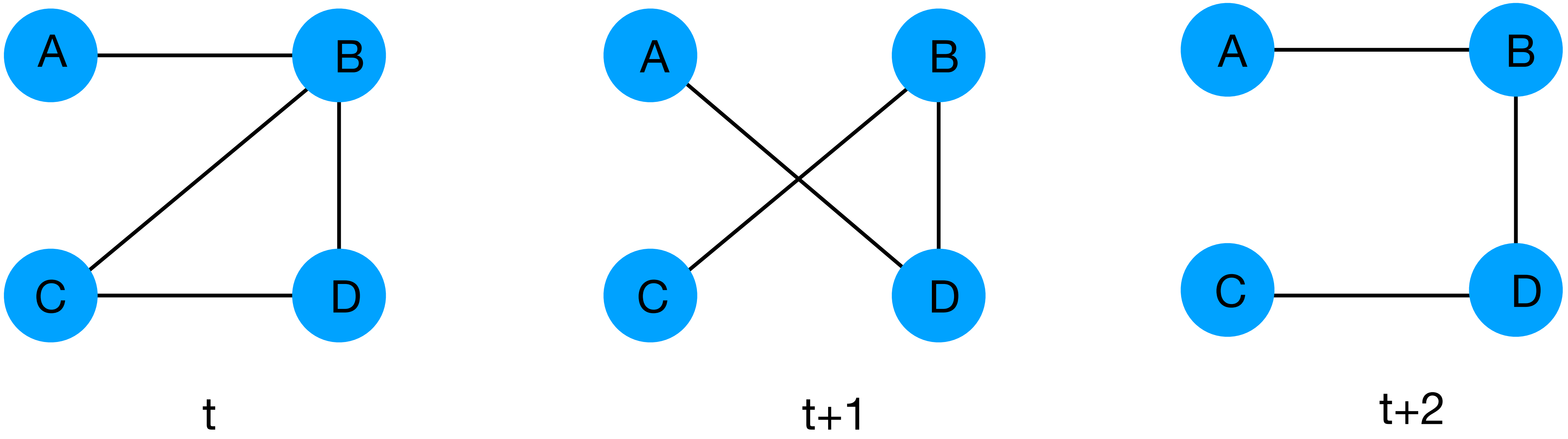
Set of edges active **at all times** t of an interval $\Delta : E_\Delta = \bigcap_{t \in \Delta} E_t$

Temporal degree of a node within a subgraph S during Δ :

$$d_\Delta(S, u) = |\{v \in S \mid (u, v) \in E_\Delta[S]\}|$$

=number of nodes **in S** to which u is linked **at all times** during Δ

Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376



Temporal degrees on [t,t+1]:

d(A,[t,t+2]) = 0
d(B,[t,t+2]) = 1
d(C,[t,t+2]) = 0
d(D,[t,t+2]) = 1

Span-core: definition

Definition 2 ((k,Δ)-core). *The* (k,Δ)-core *of a temporal graph* $G = (V, T, \tau)$ *is (when it exists) a maximal and non-empty set of vertices* $\emptyset \neq C_{k,\Delta} \subseteq V$*, such that* $\forall u \in C_{k,\Delta} : d_\Delta(C_{k,\Delta}, u) \geq k$*, where* $\Delta \sqsubseteq T$ *is a temporal interval and* $k \in \mathbb{N}^+$.

i.e., all nodes of the core have **degree at least k within the core** during the temporal interval,
and have **at least k "constant" neighbors in the core** during that interval

Definition 3 (Maximal Span-core). *A span-core* $C_{k,\Delta}$ *of a temporal graph G is said* maximal *if there does not exist any other span-core* $C_{k',\Delta'}$ *of G such that* $k \leq k'$ *and* $\Delta \sqsubseteq \Delta'$.

Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Extracting the span-cores

https://github.com/egalimberti/span_cores

Naive algorithms

- All span cores:
  - generate all temporal intervals,
  - construct graphs of permanent links for each interval
  - build the k-core decomposition for each graph
- Maximal span cores:
  - for each interval, consider the cores of highest order
  - keep only the maximal ones

Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Extracting the span-cores

More efficient algorithms

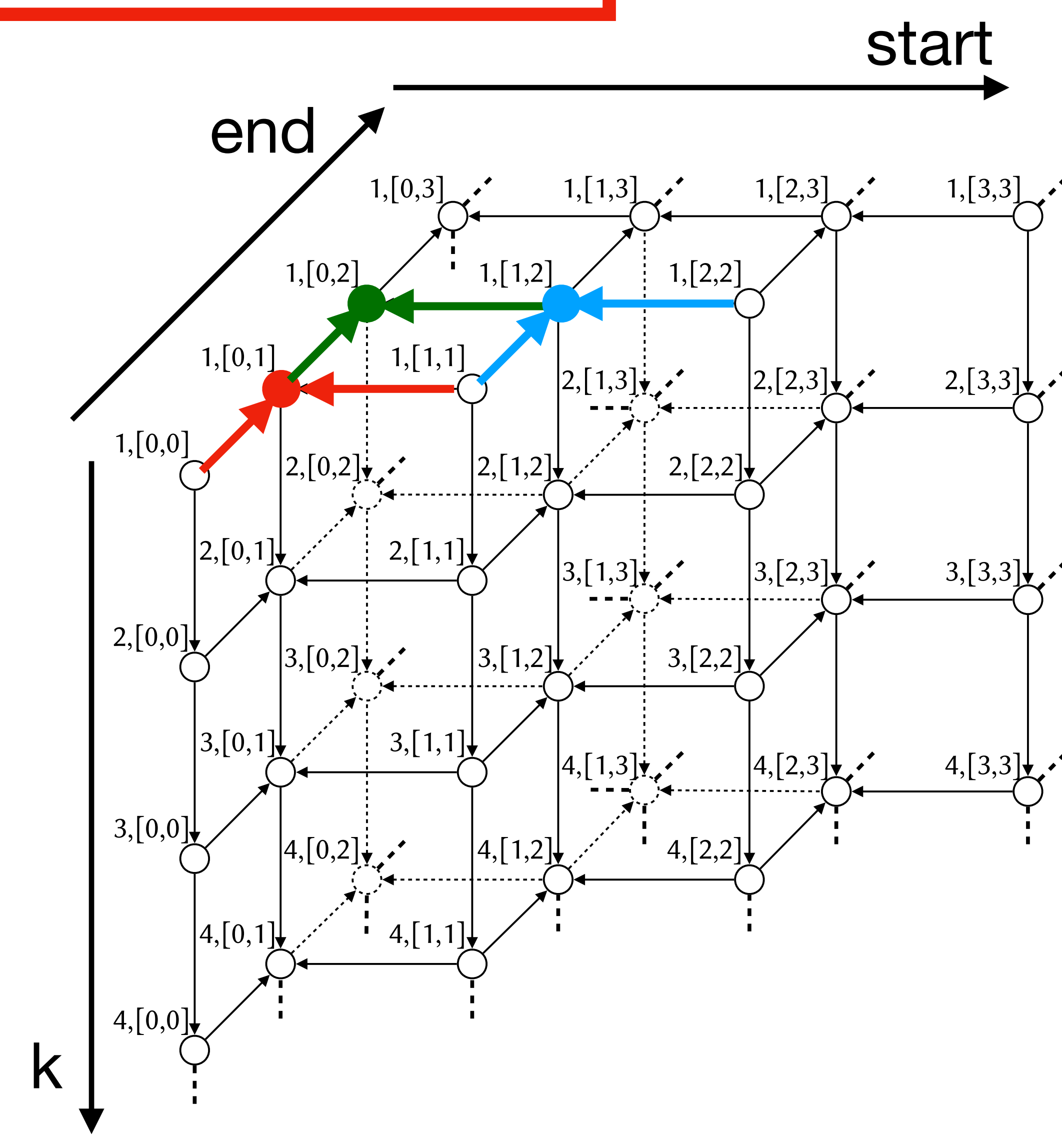
https://github.com/egalimberti/span_cores

- Exploit the containment property:

Proposition 1 (Span-core containment). *For any two span-cores $C_{k,\Delta}$, $C_{k',\Delta'}$ of a temporal graph G it holds that*

$$k' \leq k \wedge \Delta' \sqsubseteq \Delta \;\Rightarrow\; C_{k,\Delta} \subseteq C_{k',\Delta'}.$$

- generate temporal intervals of increasing size
- start the decomposition from intersection of previously found cores



Examples:

core k=1 on interval [0,1] is obtained by starting from the intersection of **core 1 on interval [0,0] and core 1 on interval [1,1]**

core k=1 on interval [0,2] is obtained by starting from the intersection of **core 1 on interval [0,1] and core 1 on interval [1,2]**

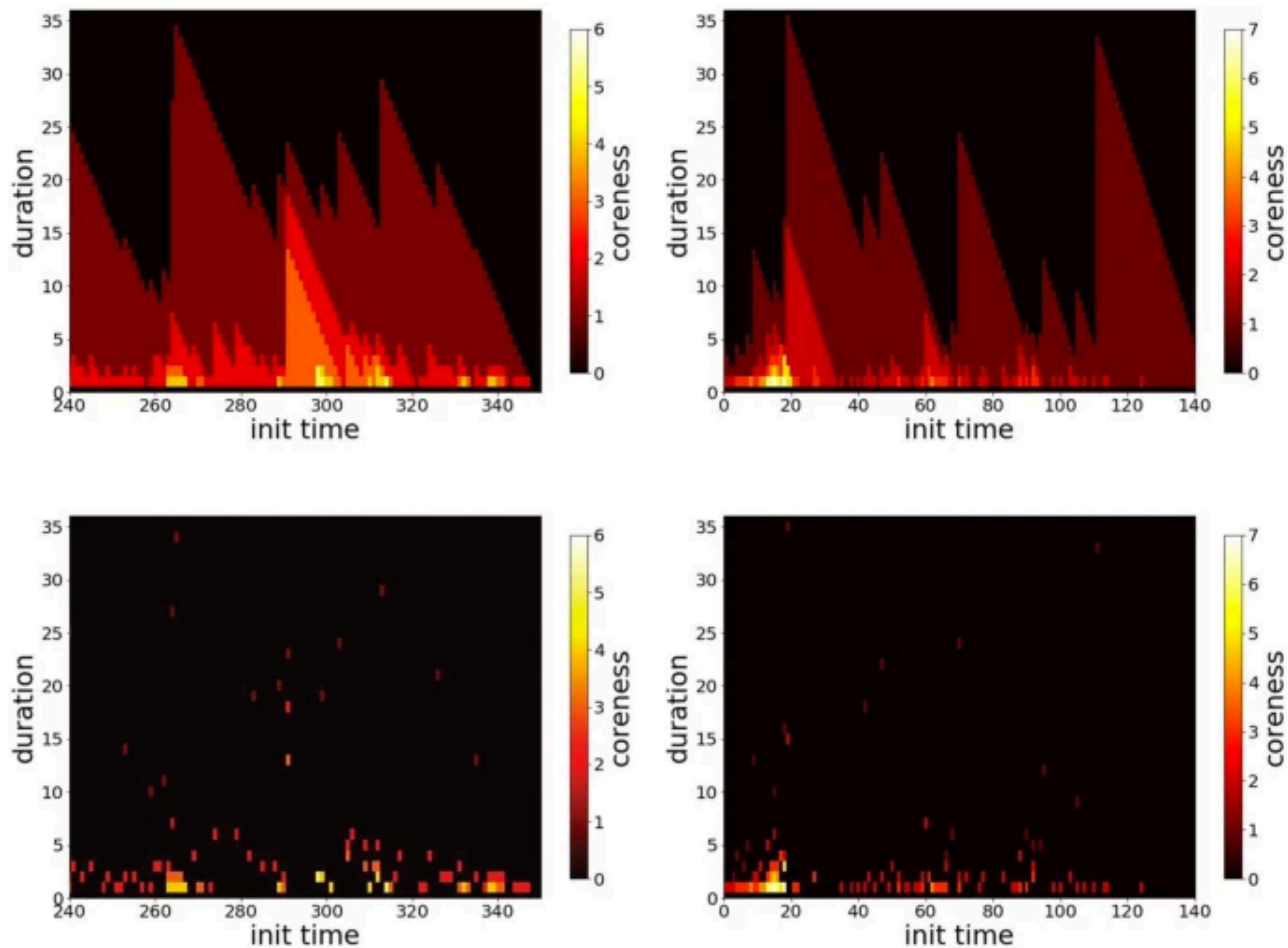
Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Span-core: examples

Face-to-face contact networks
Highschool (left) and Workplace (right) data:
Order of the span-cores as a function of their starting time and of the temporal span length

All span cores

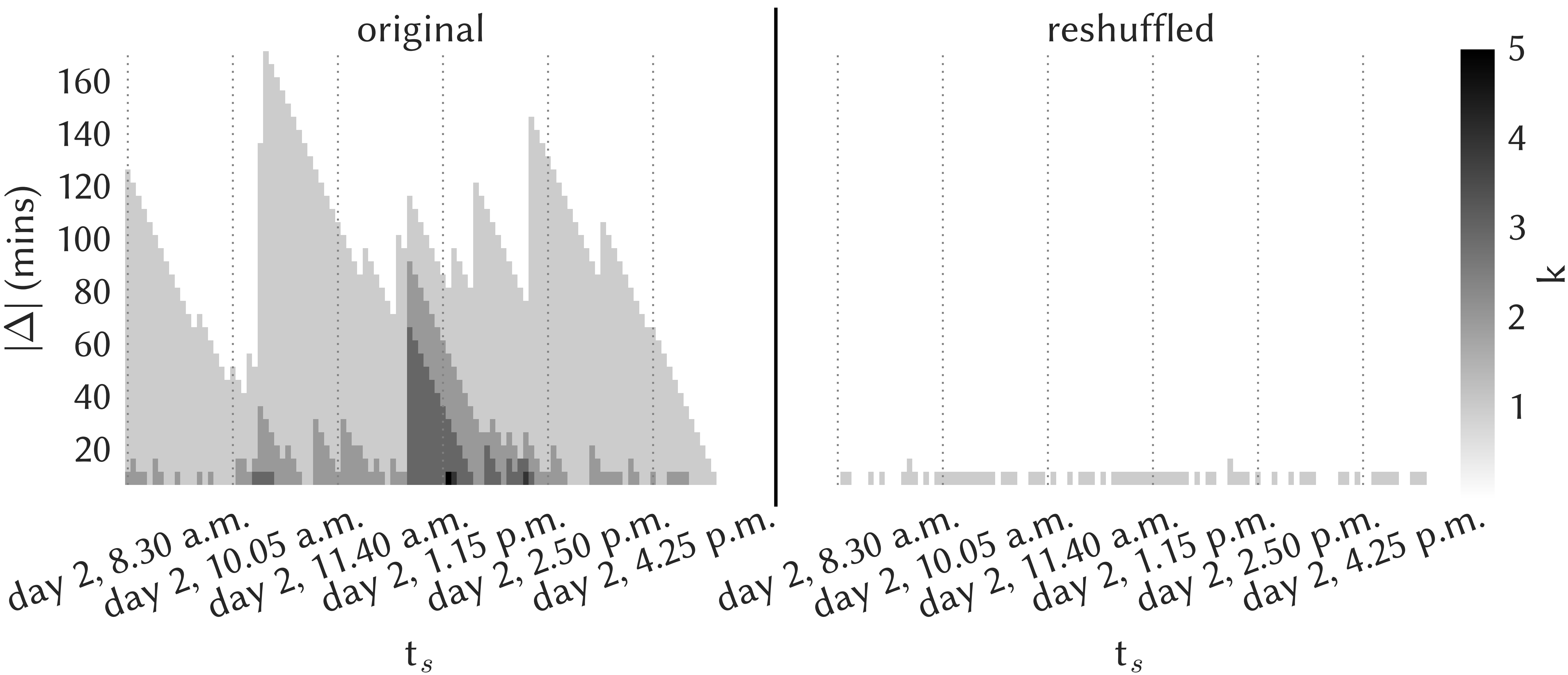
Maximal span cores



Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376
Ciaperoni, Galimberti, Bonchi, Cattuto, Gullo, Barrat, Sci Rep 2020

Span-core: examples

Primary school data:
Order of the span-cores as a function of their starting time and of the temporal span length



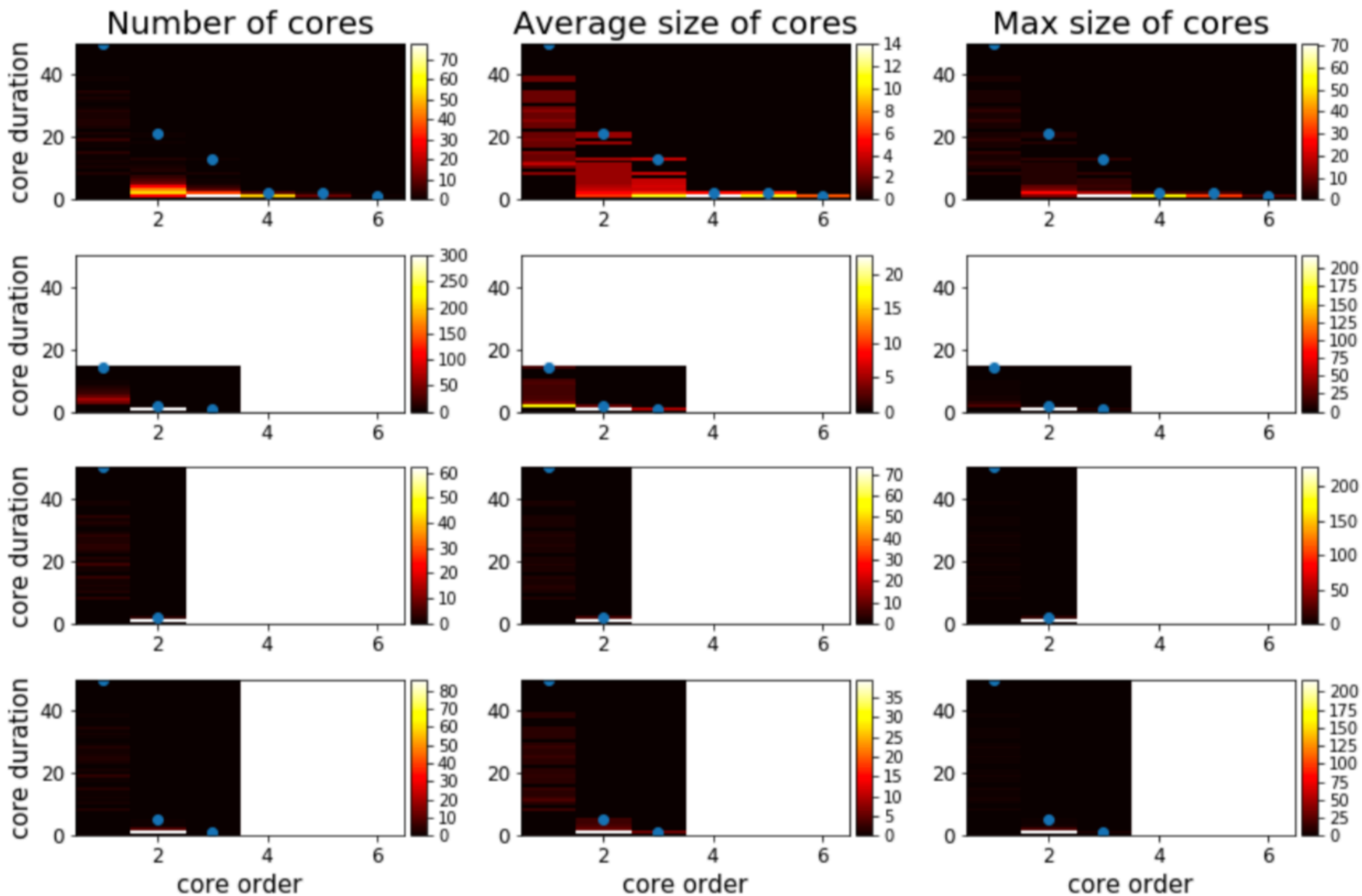
Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Span-core: examples

Face-to-face contact networks
Highschool data, maximal span cores

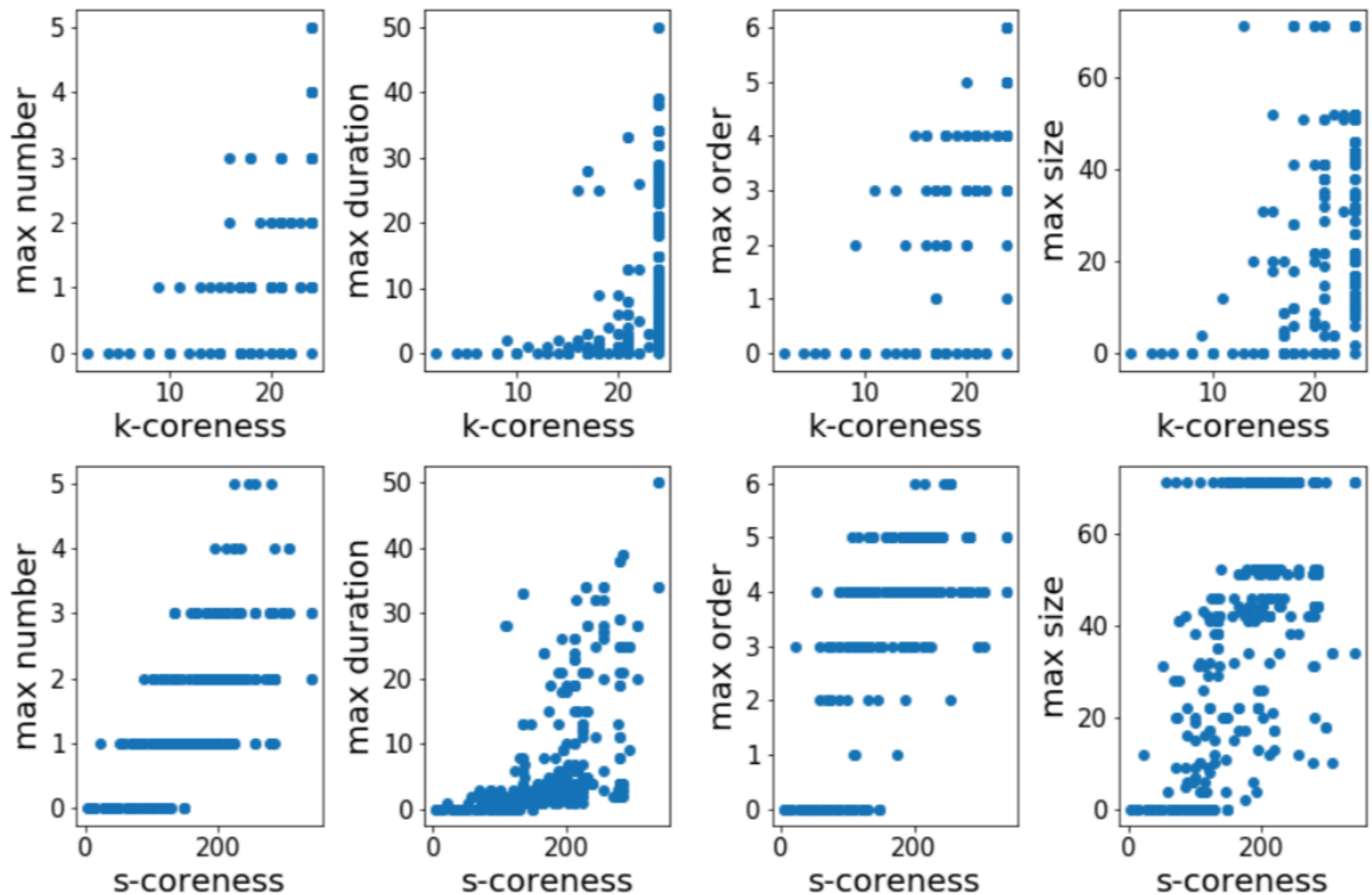
Original data

Reshuffled data

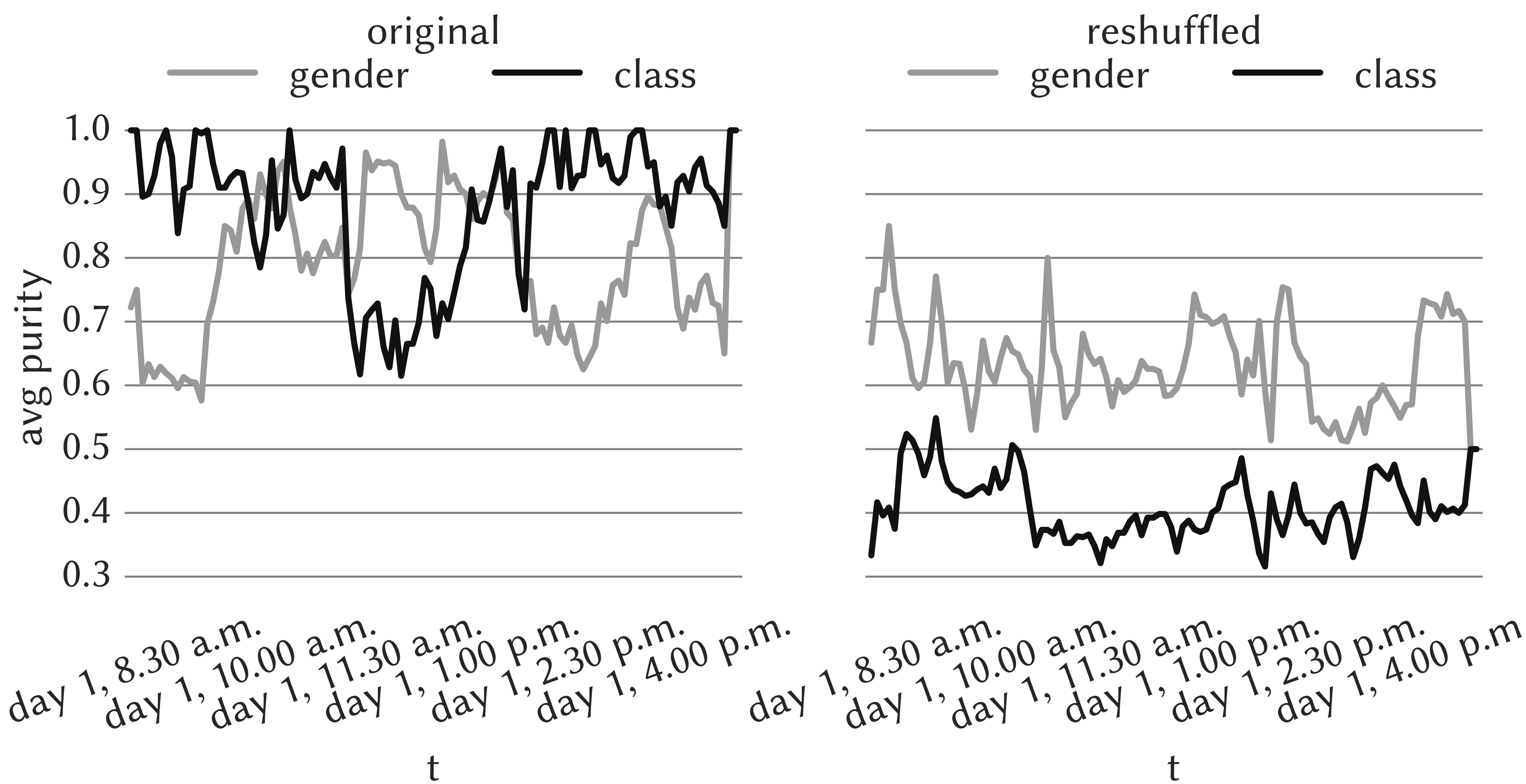


Span-core: examples

Face-to-face contact networks
Highschool data, maximal span cores properties vs static (aggregated) coreness measures



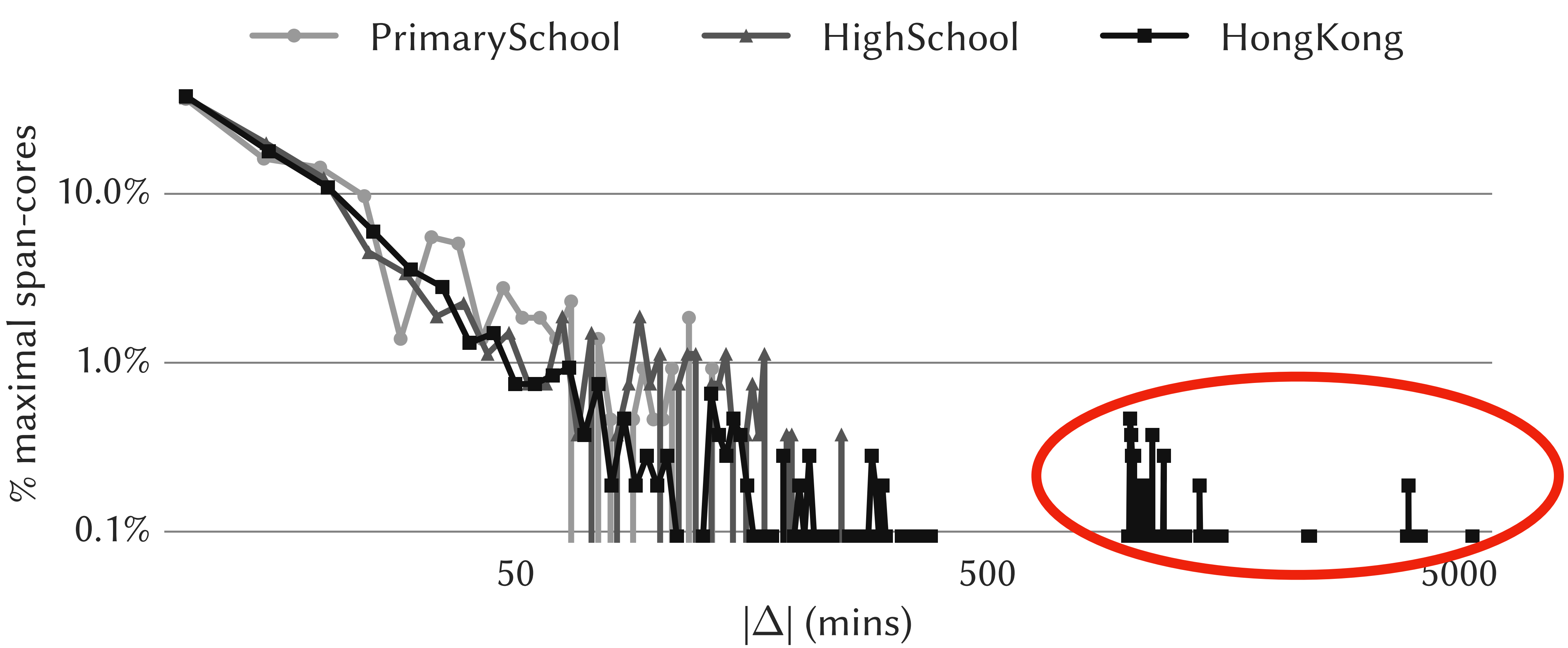
Span-core: examples



Primary school:
Average gender and class purity of the maximal span-cores

Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Span-core: examples

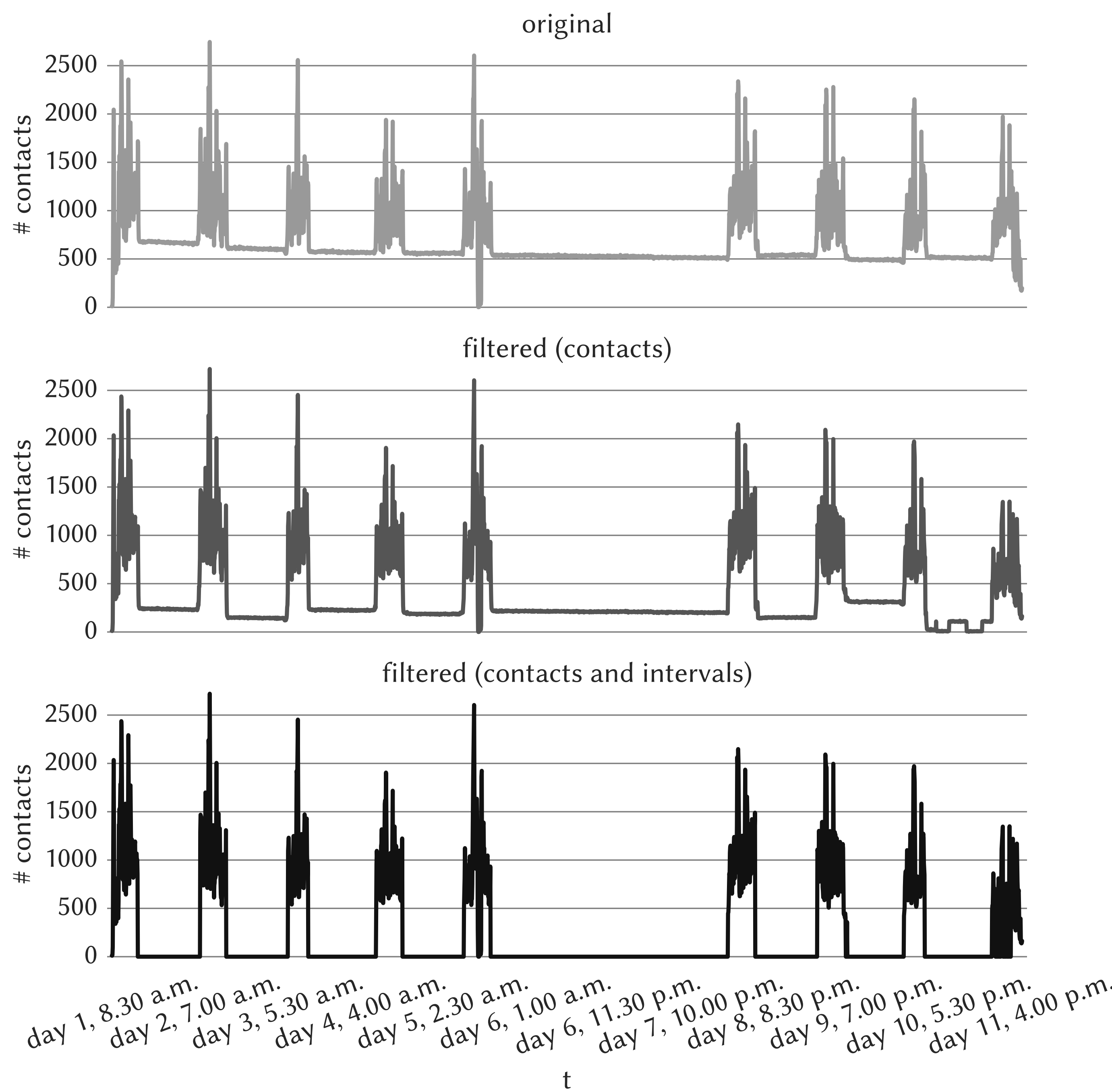


Distributions of maximal span-cores lengths

Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Span-core: anomaly detection

Hong-Kong primary school: filtering anomalous contacts

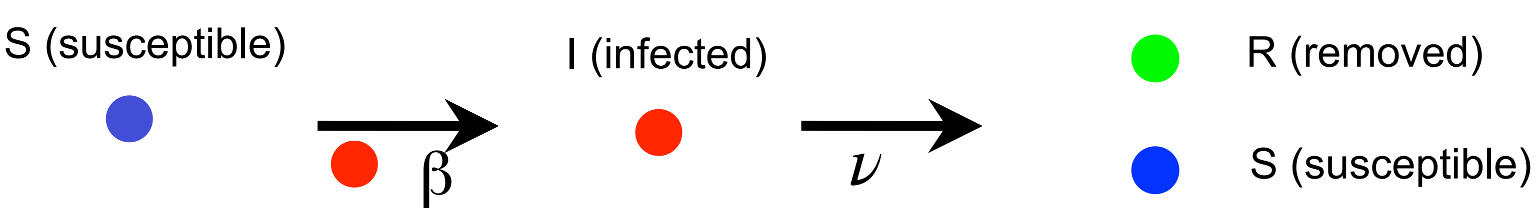


Galimberti, Barrat, Bonchi, Cattuto, Gullo, CIKM 2018, arXiv:1808.09376

Span cores and spreading processes

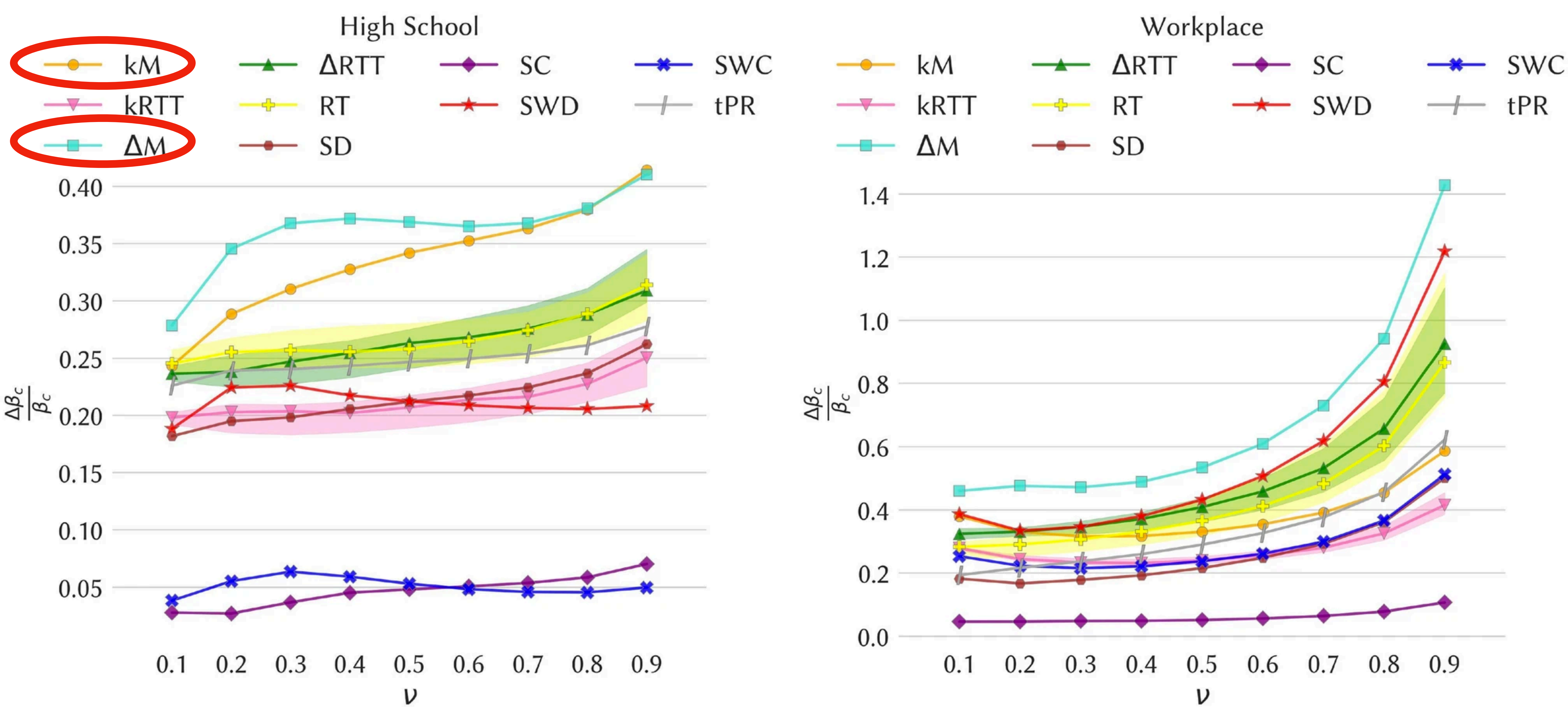
Procedure

1. remove temporal edges from maximal span-cores with large order/duration
2. observe impact on outcome of spreading processes, e.g. SIS, SIR
3. compare with removal of same number of temporal edges according to other strategies



Span cores and spreading processes

Relative change in SIS epidemic threshold when removing temporal edges with targeted strategies based either on span-cores or on aggregated measures or on temporal PageRank



Span cores and spreading processes

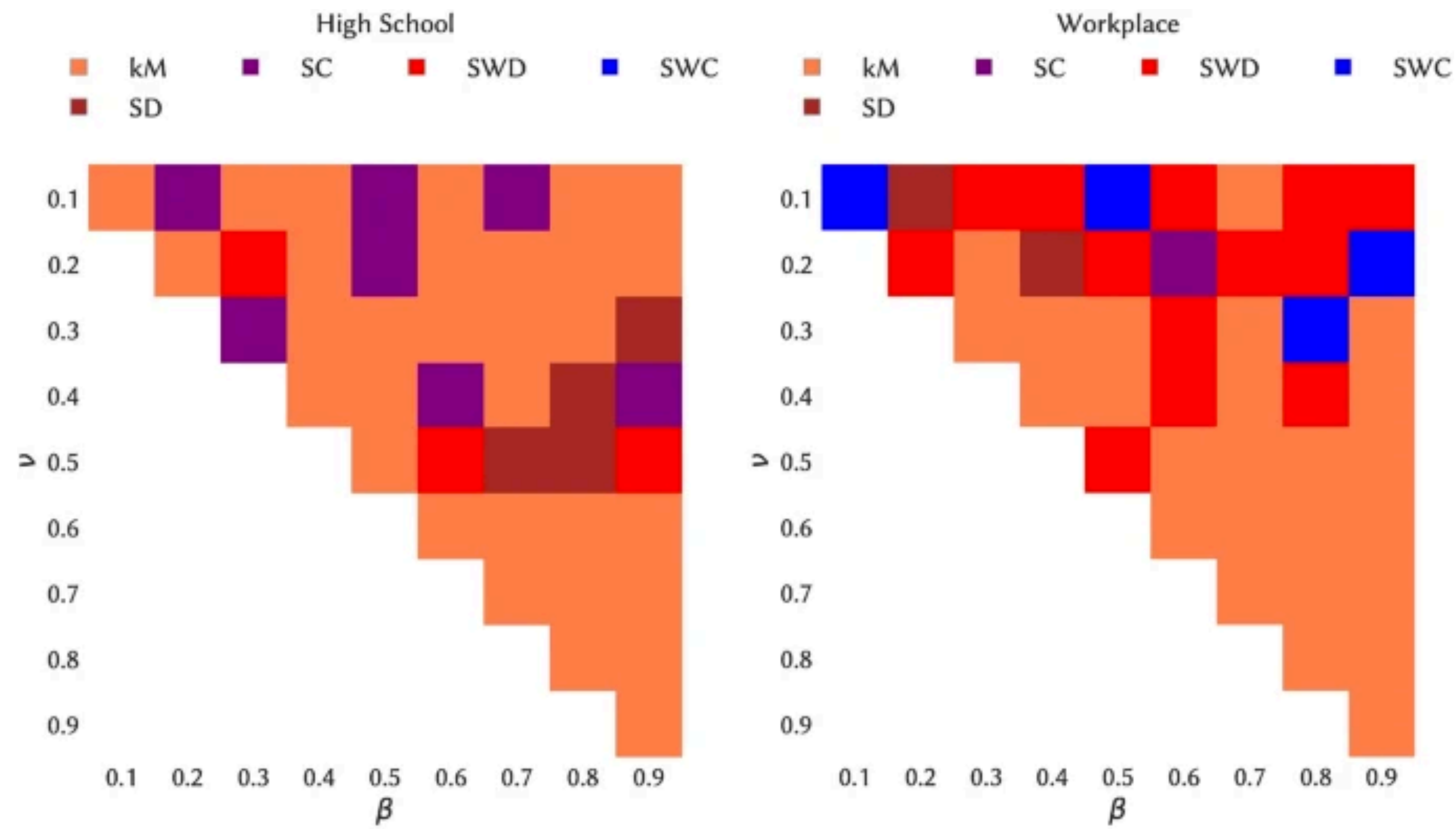
Procedure

1. consider an SIR process with seed in maximal span cores
2. compare outbreak size with random seed
3. compare with other seeding strategies

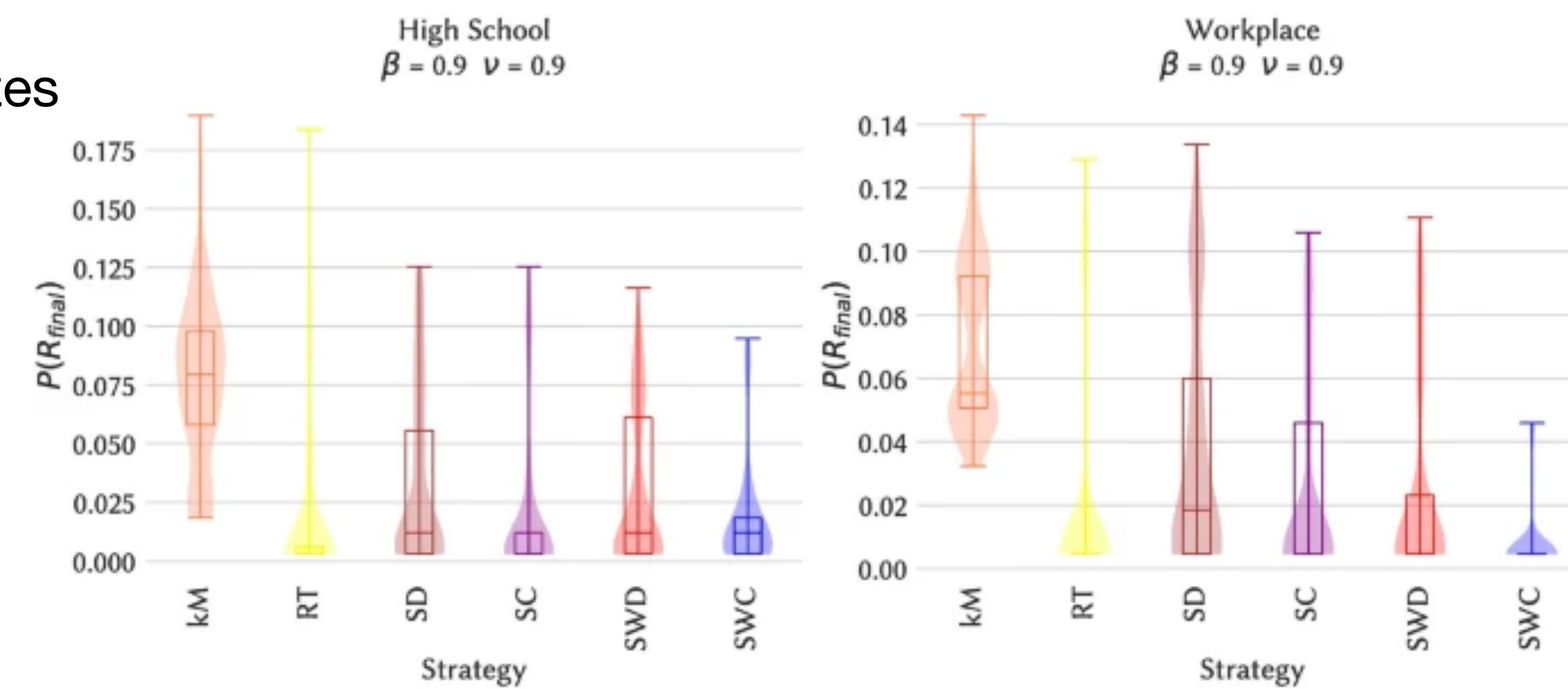
Span cores and spreading processes

Best seeding strategy

kM: cores with largest order

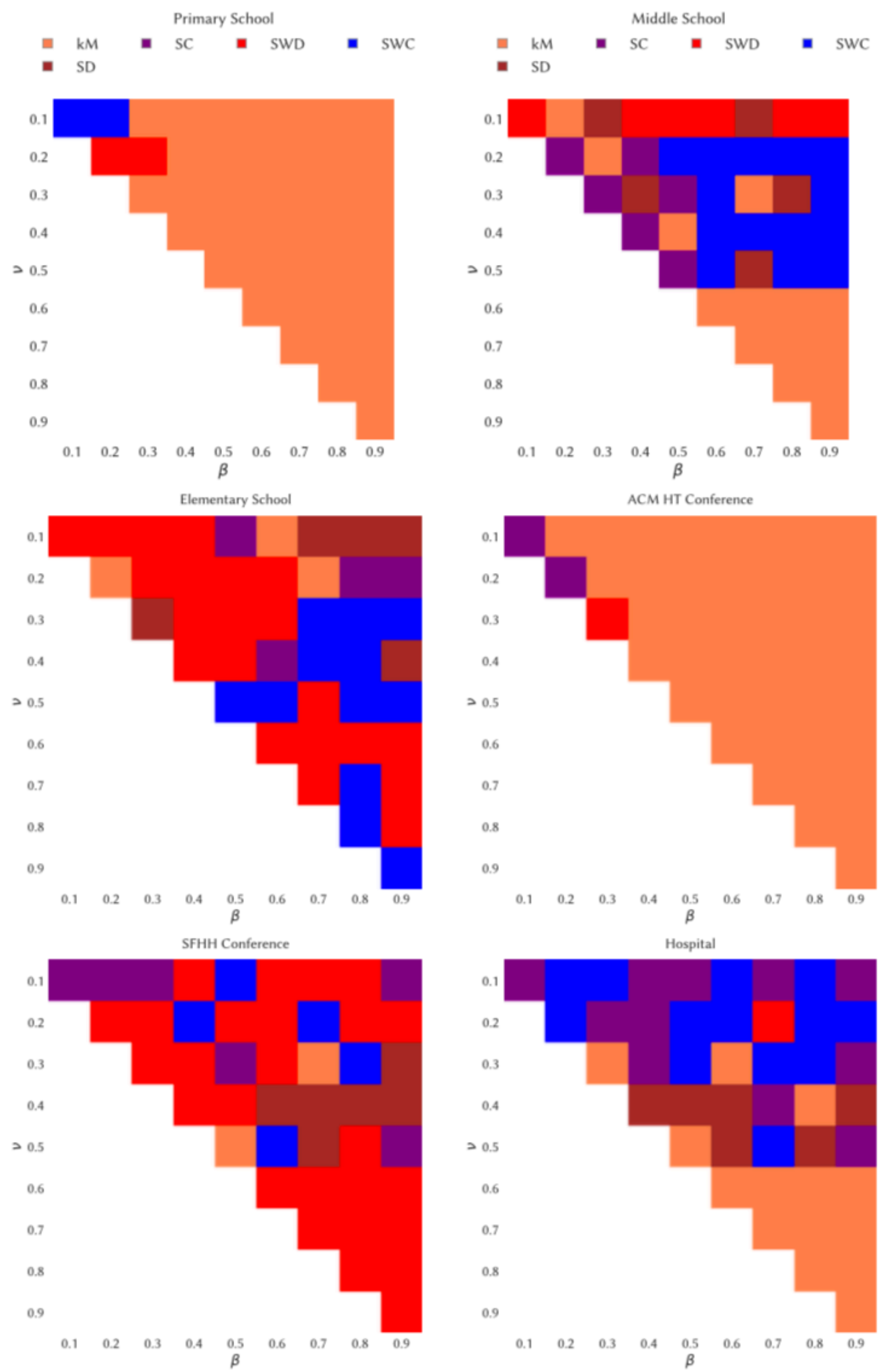


Distributions of outbreak sizes

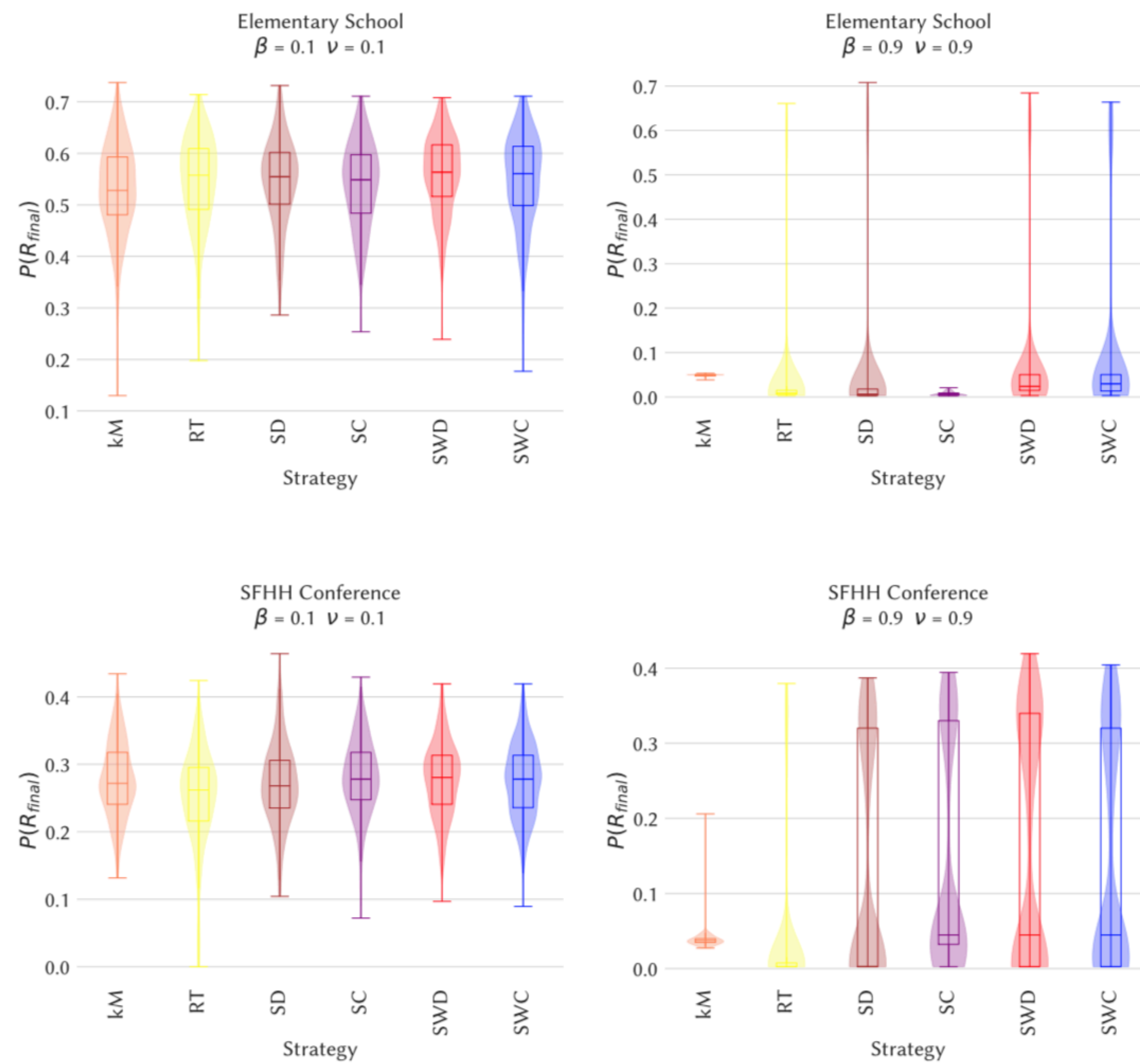


Span cores and spreading processes

Best seeding strategy

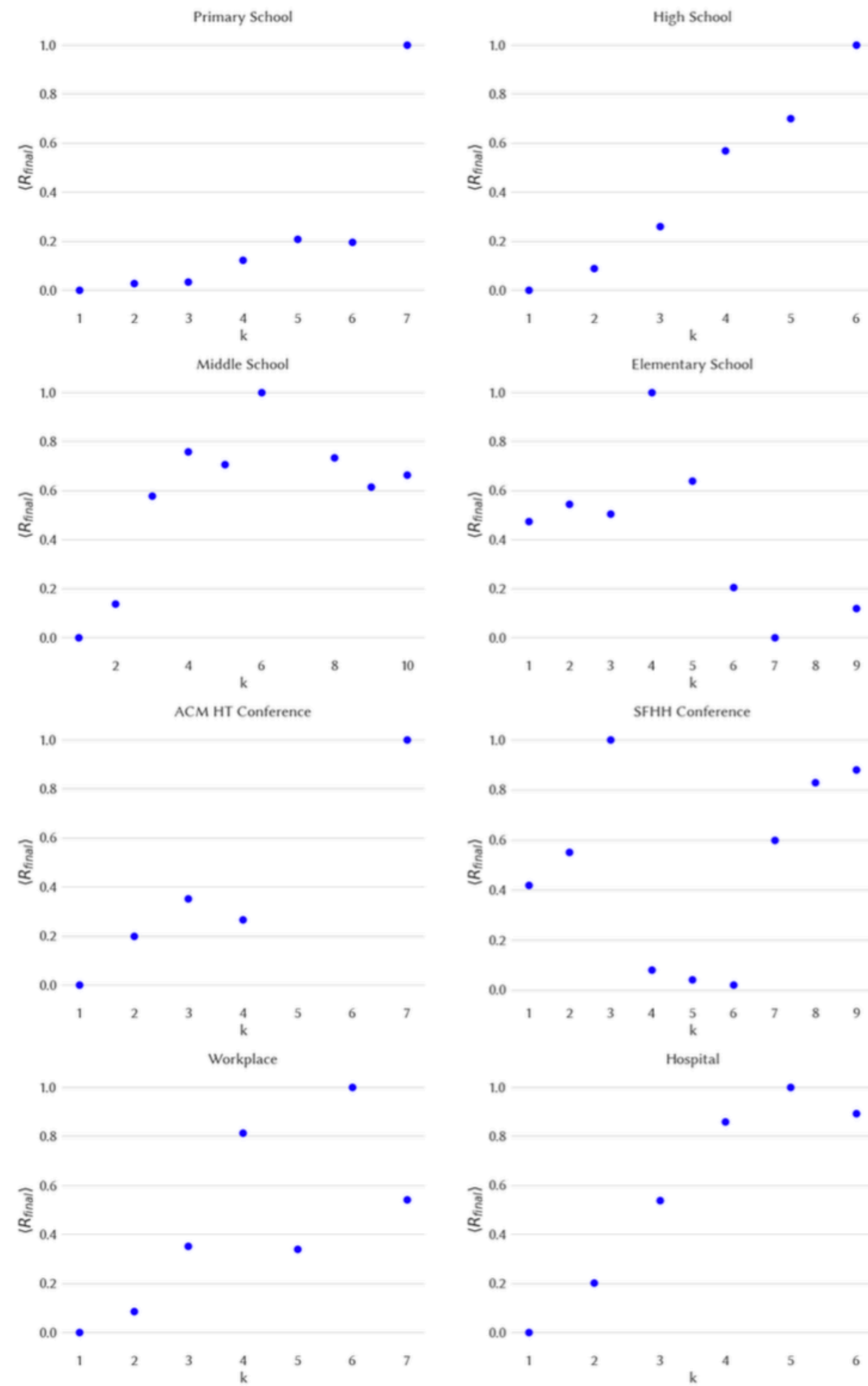


Distributions of outbreak sizes



Span cores and spreading processes

Effect of the order of the core to which the seed belongs



Span-cores

- Generalization of static core decomposition
- Effective algorithms to find (maximal) span-cores
- Uncovers strongly connected structures together with their duration/span
- Uncovers structures not trivially related to activity
- Broad distributions of durations
- Detection of anomalies in data
- Relevance in spreading processes

➡Need to take span-core structures into account in temporal network modelling

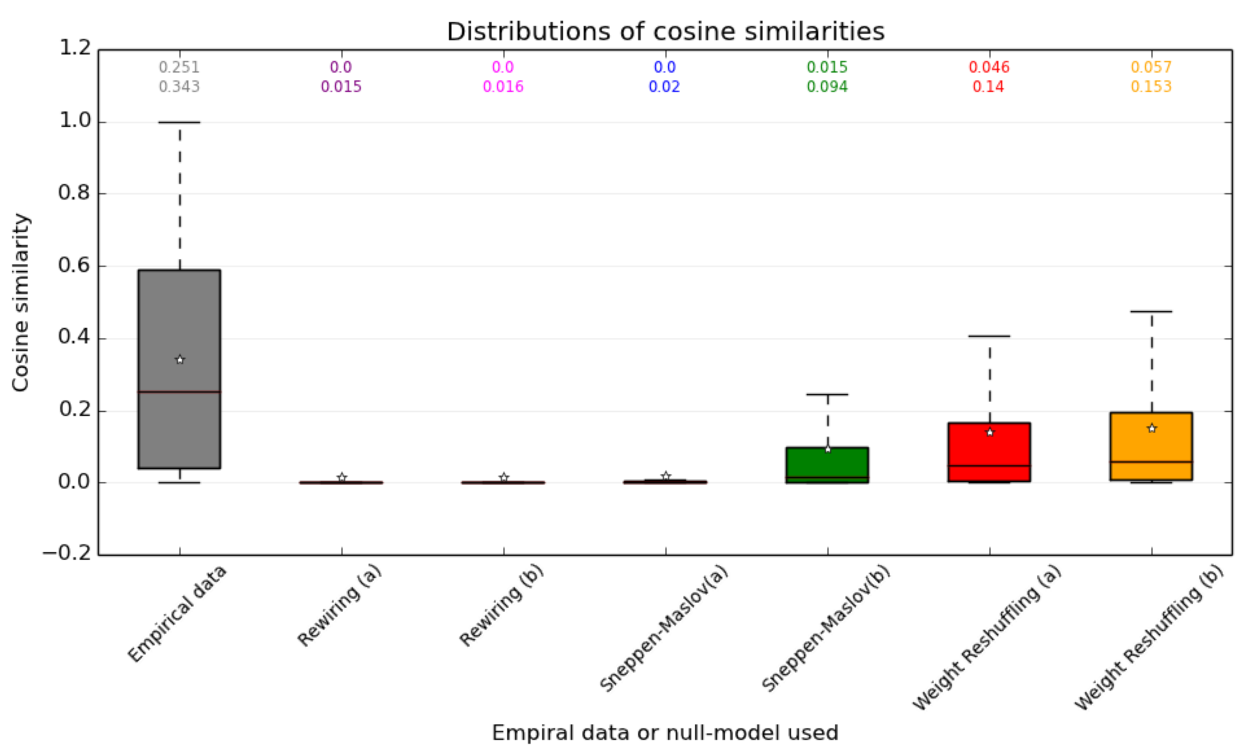
>Timescales and states

Persistence of patterns

Compare **successive snapshots** or time-aggregated networks:

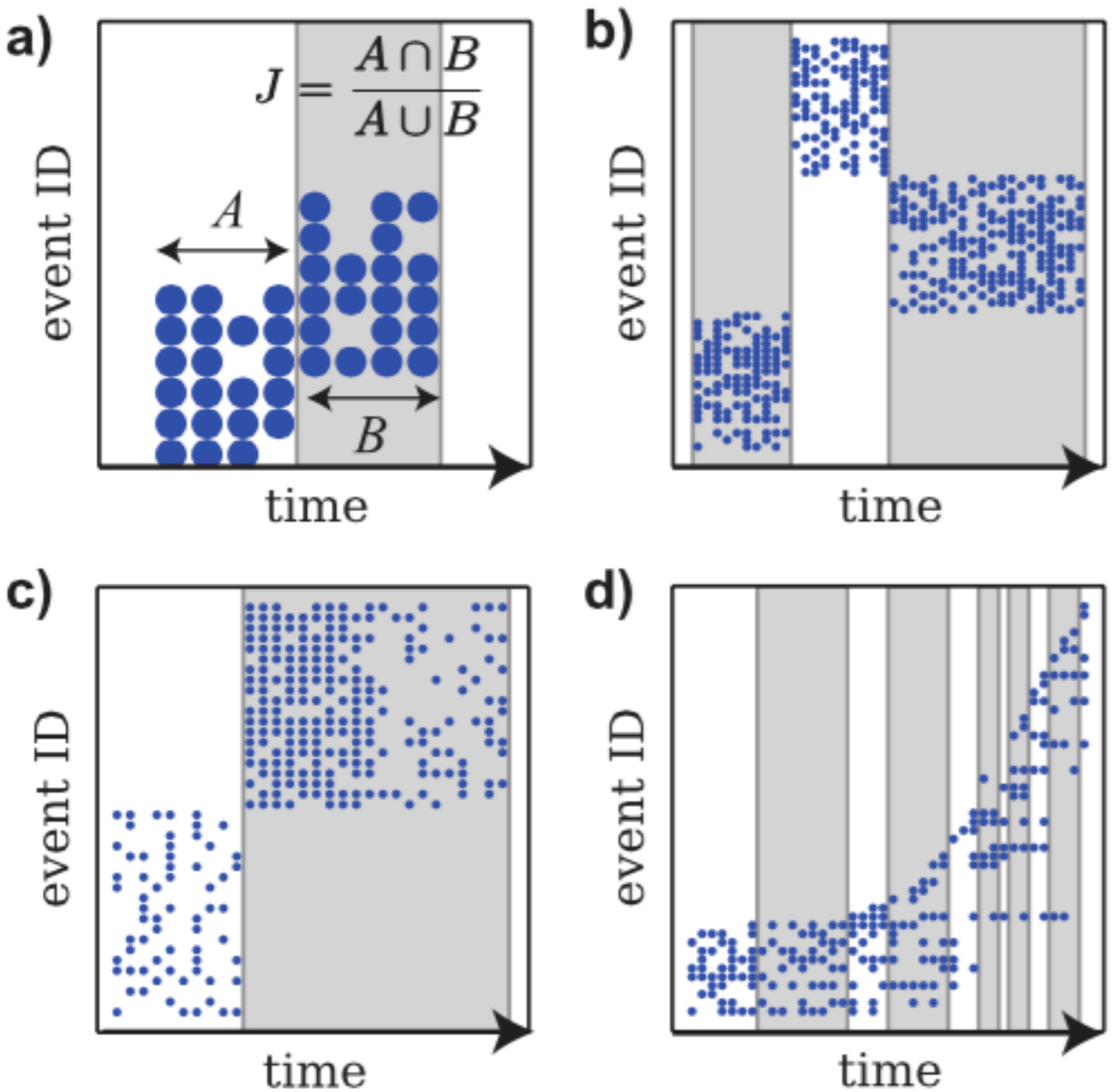
- correlation between (weighted) adjacency matrices
- correlation between contact matrices
- local similarity of neighbourhoods

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



Example: contacts in a high school, neighbourhood similarities between different days, vs different null models (Fournet & Barrat, PLoS ONE 2014)

Detection of time-scales



Comparison of successive time-windows of growing length
Maximisation of overlap

Darst et al., Sci Rep (2016)

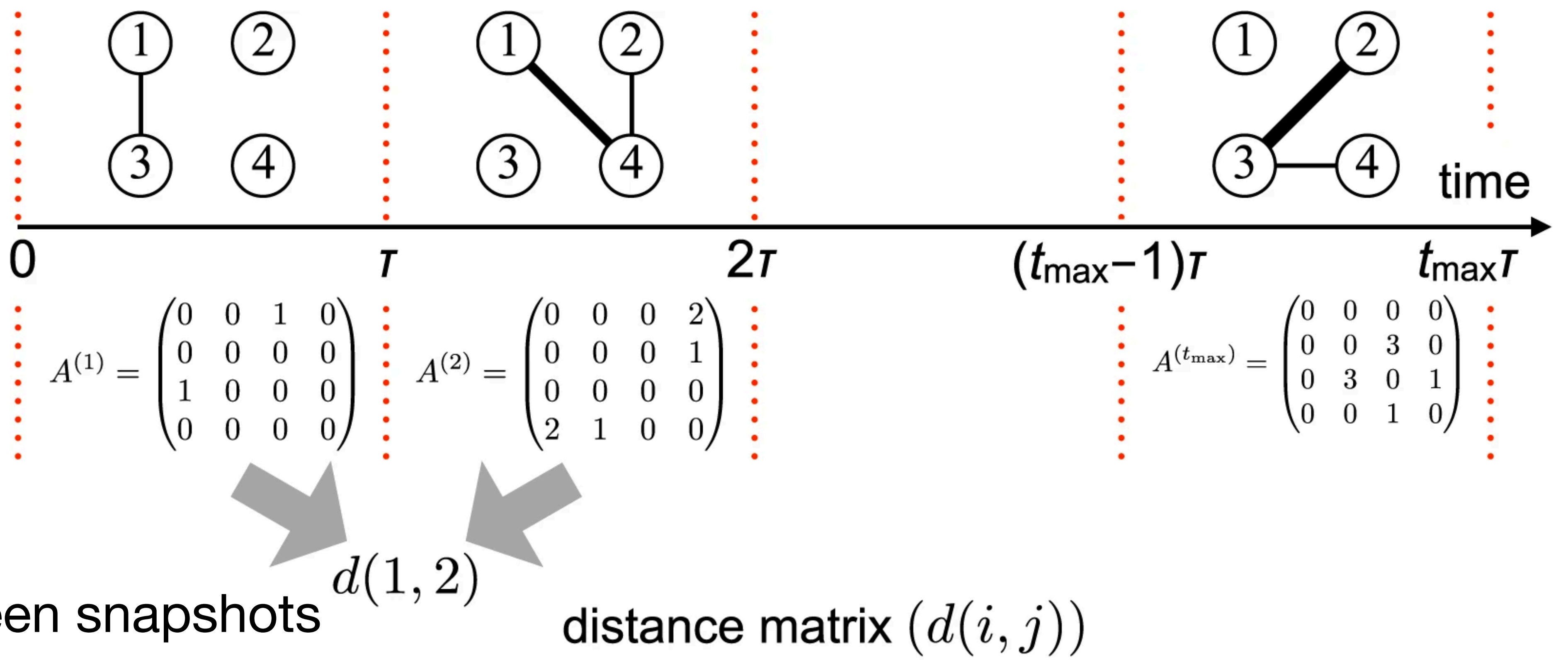
SCIENTIFIC REPORTS

Article | Open Access | Published: 28 January 2019

Detecting sequences of system states in temporal networks

Naoki Masuda & Petter Holme

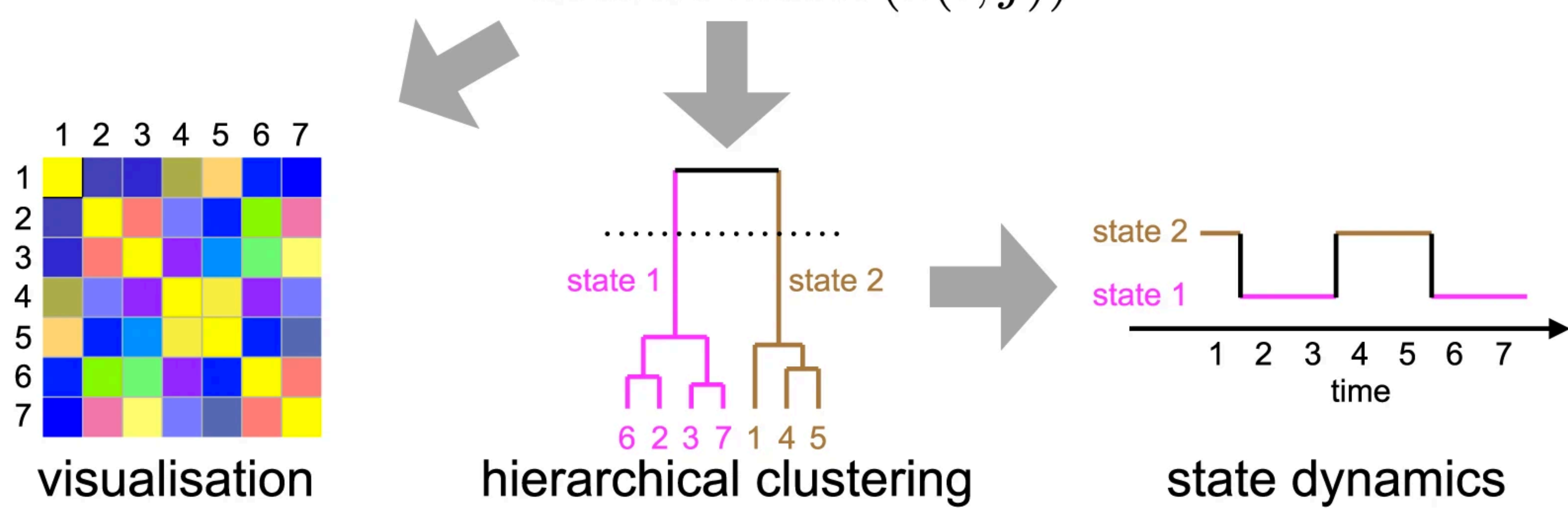
Scientific Reports **9**, Article number: 795 (2019)



$$A^{(1)} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \quad A^{(2)} = \begin{pmatrix} 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 \end{pmatrix} \quad A^{(t_{\max})} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 3 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

1. matrix of distance between snapshots
2. hierarchical clustering

➡ states



NB:
various possible distances
various clustering algorithms

nature > scientific reports > articles > article

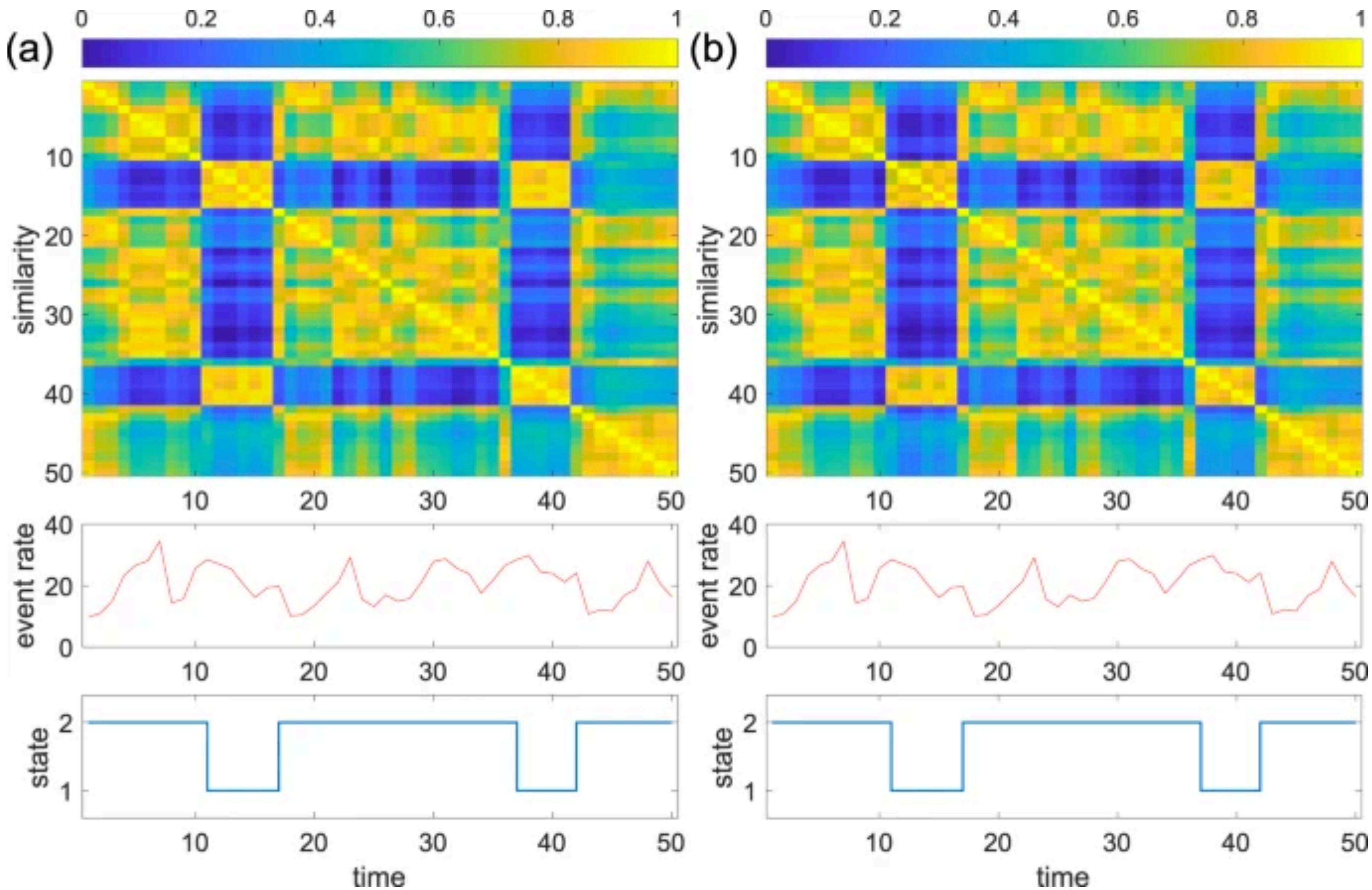
SCIENTIFIC REPORTS

Article | Open Access | Published: 28 January 2019

Detecting sequences of system states in temporal networks

Naoki Masuda & Petter Holme

Scientific Reports **9**, Article number: 795 (2019) | Cite this article

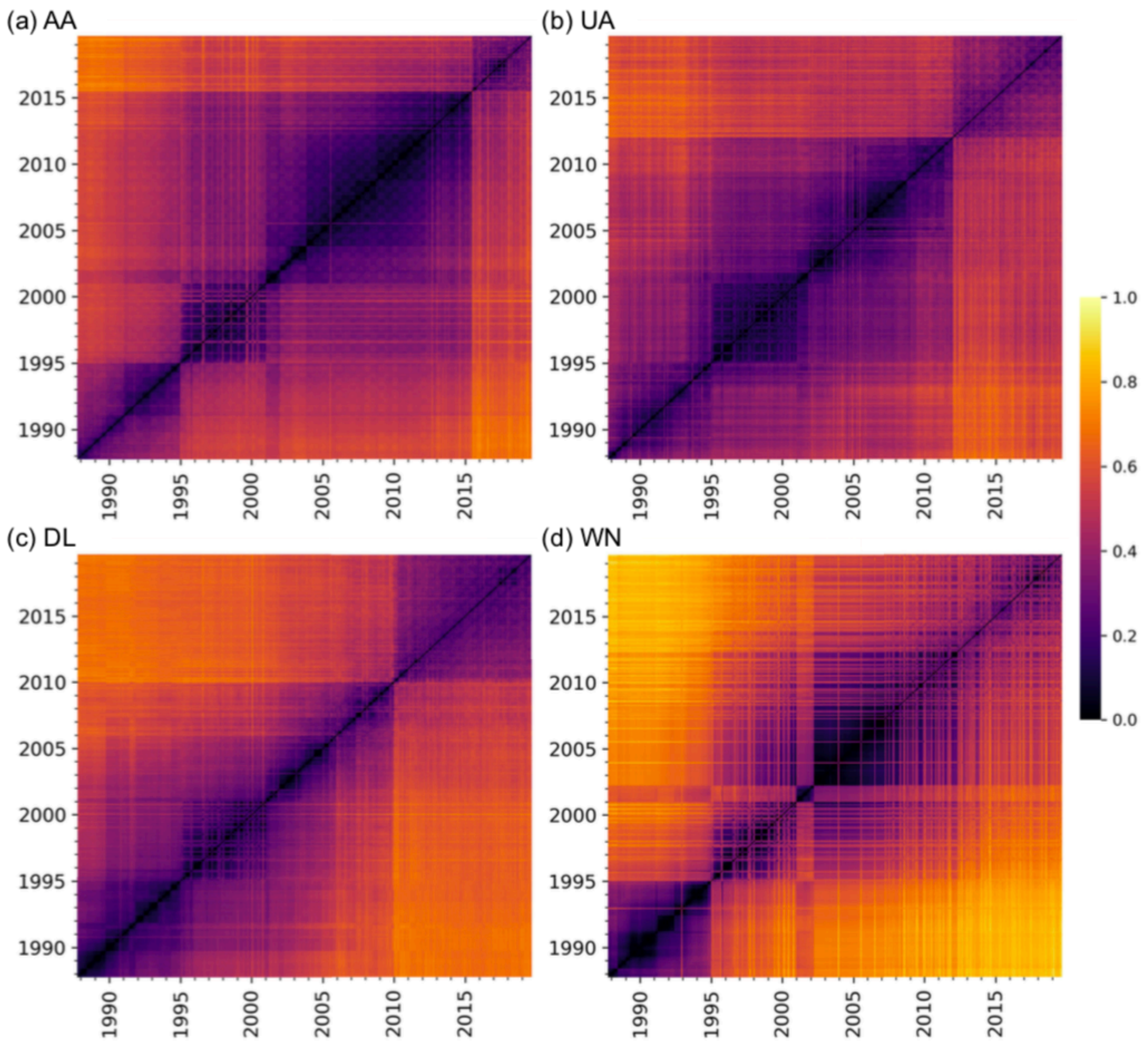


Face-to-face contacts in a primary school

[Submitted on 29 May 2020]

Recurrence in the evolution of air transport networks

Kashin Sugishita, Naoki Masuda

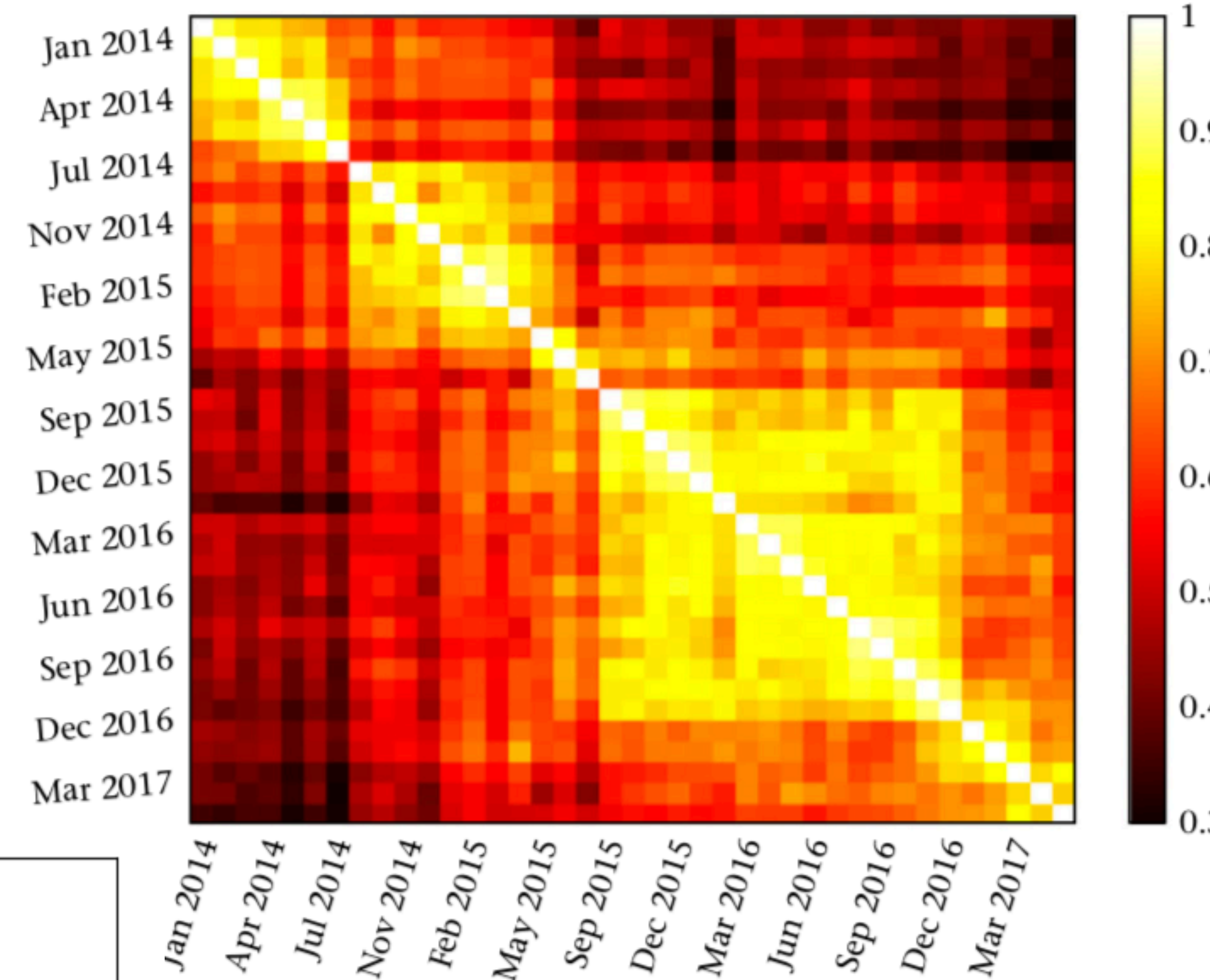


ELSEVIER
Animal Behaviour
Volume 157, November 2019, Pages 239-254

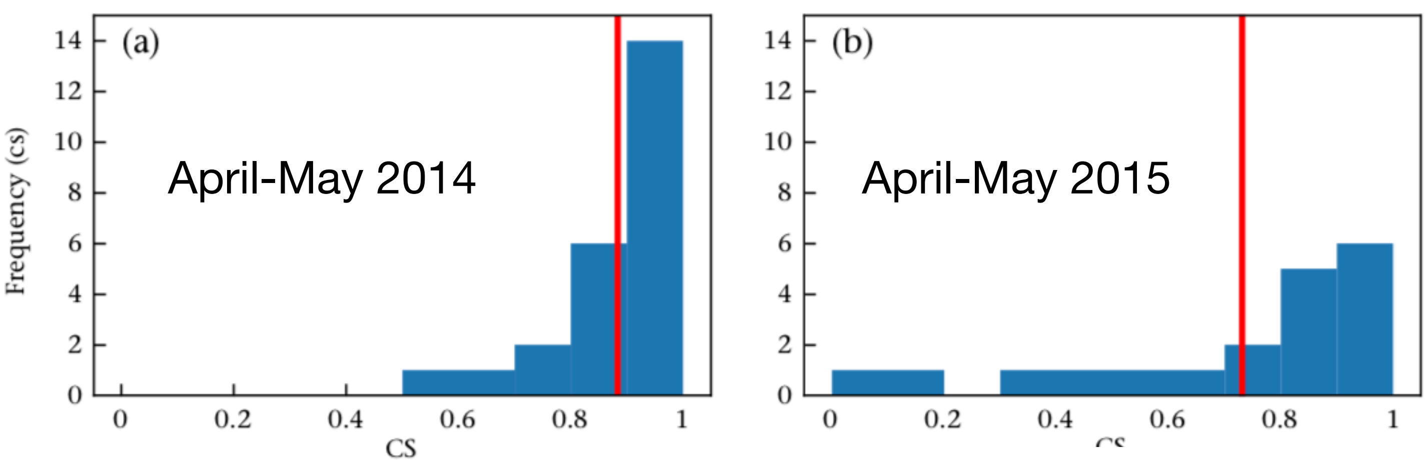
Detecting social (in)stability in primates from their temporal co-presence network

Valeria Gelardi [a], Joël Fagot [b], Alain Barrat [a, c], Nicolas Claidière [b]

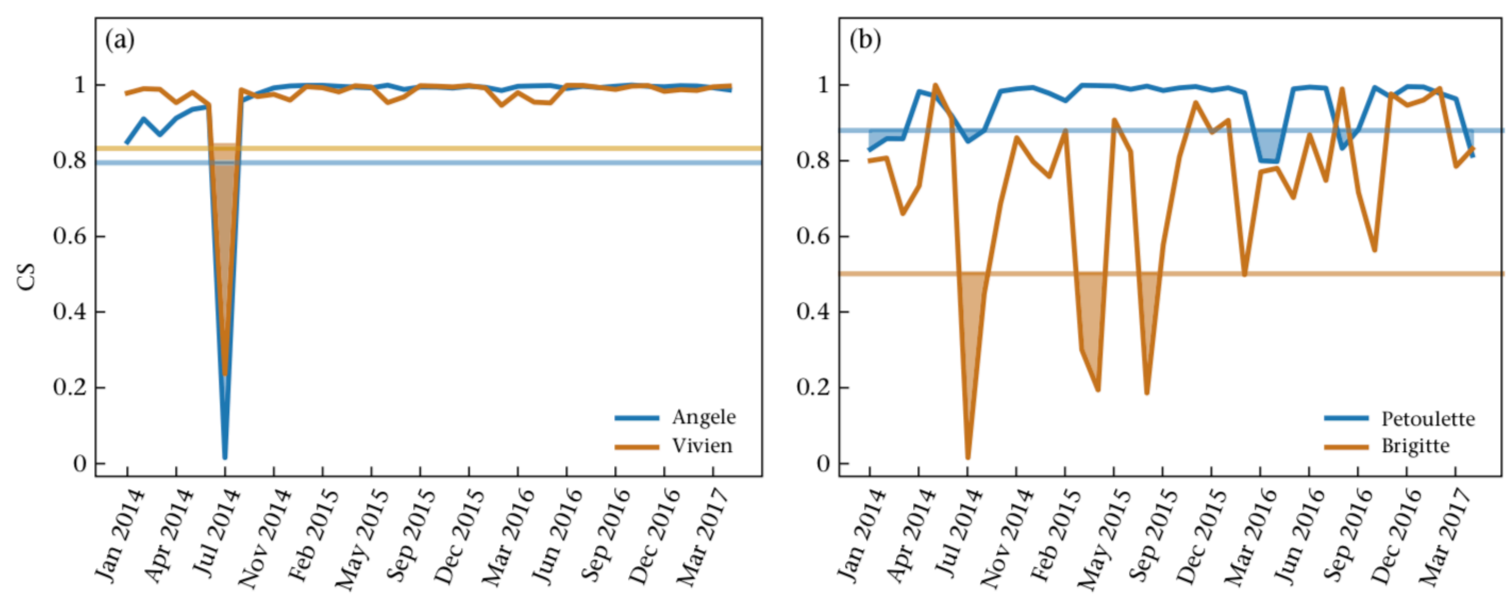
Cosine similarities:



Distributions of similarities
(analysis beyond the average):



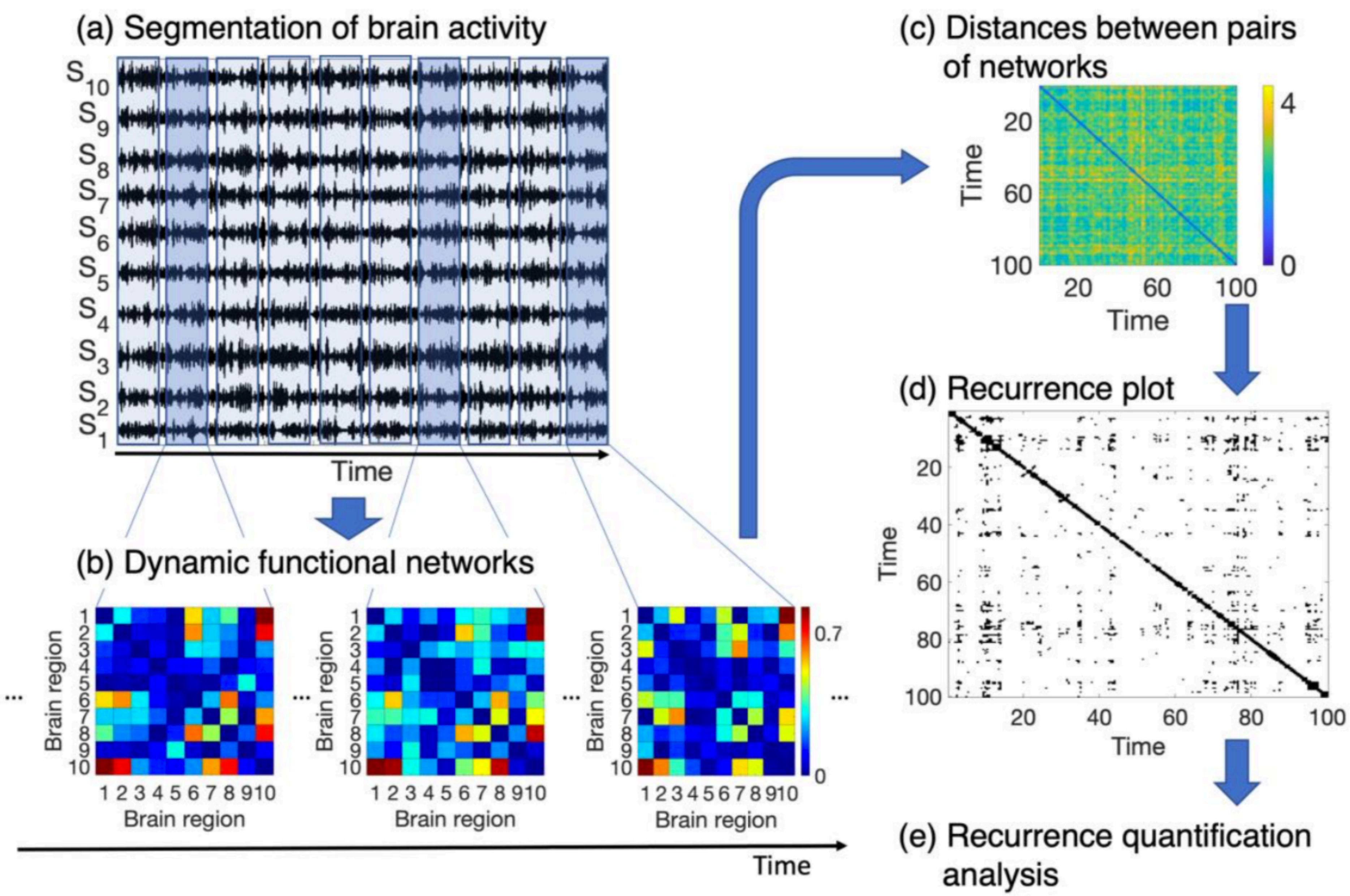
Ego networks
CS(t,t+1):



[Submitted on 11 Jan 2020]

Recurrence Quantification Analysis of Dynamic Brain Networks

Marinho A. Lopes, Jiaxiang Zhang, Dominik Krzemiński, Khalid Hamandi, Qi Chen, Lorenzo Livi, Naoki Masuda



[Submitted on 24 Jul 2020 (v1), last revised 19 Aug 2020 (this version, v3)]

Detecting Dynamic States of Temporal Networks Using Connection Series Tensors

Shun Cao, Hiroki Sayama

Many temporal networks exhibit multiple system states, such as weekday and weekend patterns in social contact networks. The detection of such distinct states in temporal network data has recently been explored as it helps reveal underlying dynamical processes. A commonly used method is network aggregation over a time window, which aggregates a subsequence of multiple network snapshots into one static network. This method, however, necessarily discards temporal dynamics within the time window. Here we develop a new method for detecting dynamic states in temporal networks using information regarding the timeline of contacts between each pair of nodes. We apply a similarity measure informed by the techniques of processing time series and community detection to sequentially discompose a given temporal network into multiple dynamic states (including repeated ones). Experiments with empirical temporal network data demonstrated that our method outperformed the conventional approach using simple network aggregation in revealing interpretable system states. In addition, our method allows users to analyze hierarchical temporal structures and to uncover dynamic state at different spatial/temporal resolutions.

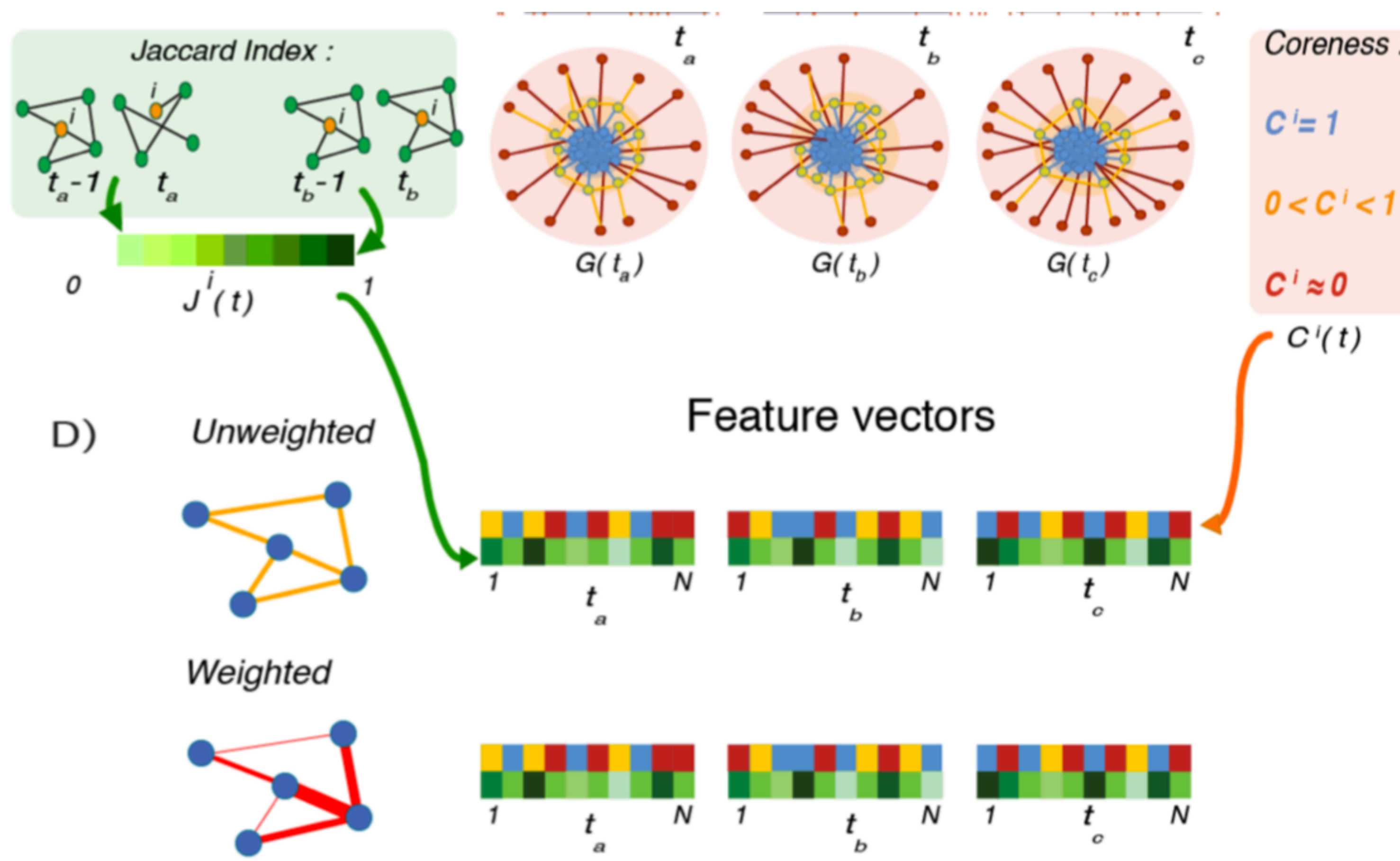
Dynamic core-periphery structure of information sharing networks in entorhinal cortex and hippocampus

NETWORK NEUROSCIENCE
Quarterly (winter, spring, summer, fall)

Nicola Pedreschi, Christophe Bernard, Wesley Clawson, Pascale Quilichini, Alain Barrat and Demian Battaglia

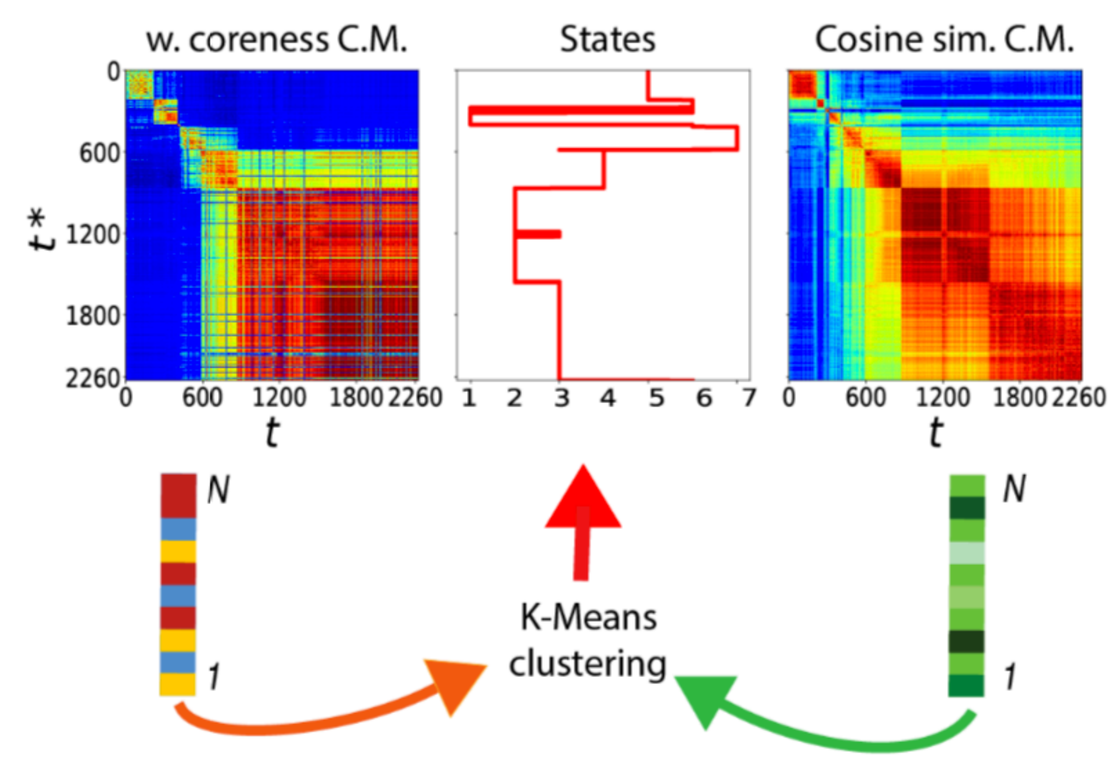
Posted Online April 28, 2020
https://doi.org/10.1162/netn_a_00142

Network Neuroscience
Early Access
p1-30



1. Vector of features (here coreness+liquidity) at each time
2. K-means clustering of times

➡ states



Dynamic core-periphery structure of information sharing networks in entorhinal cortex and hippocampus

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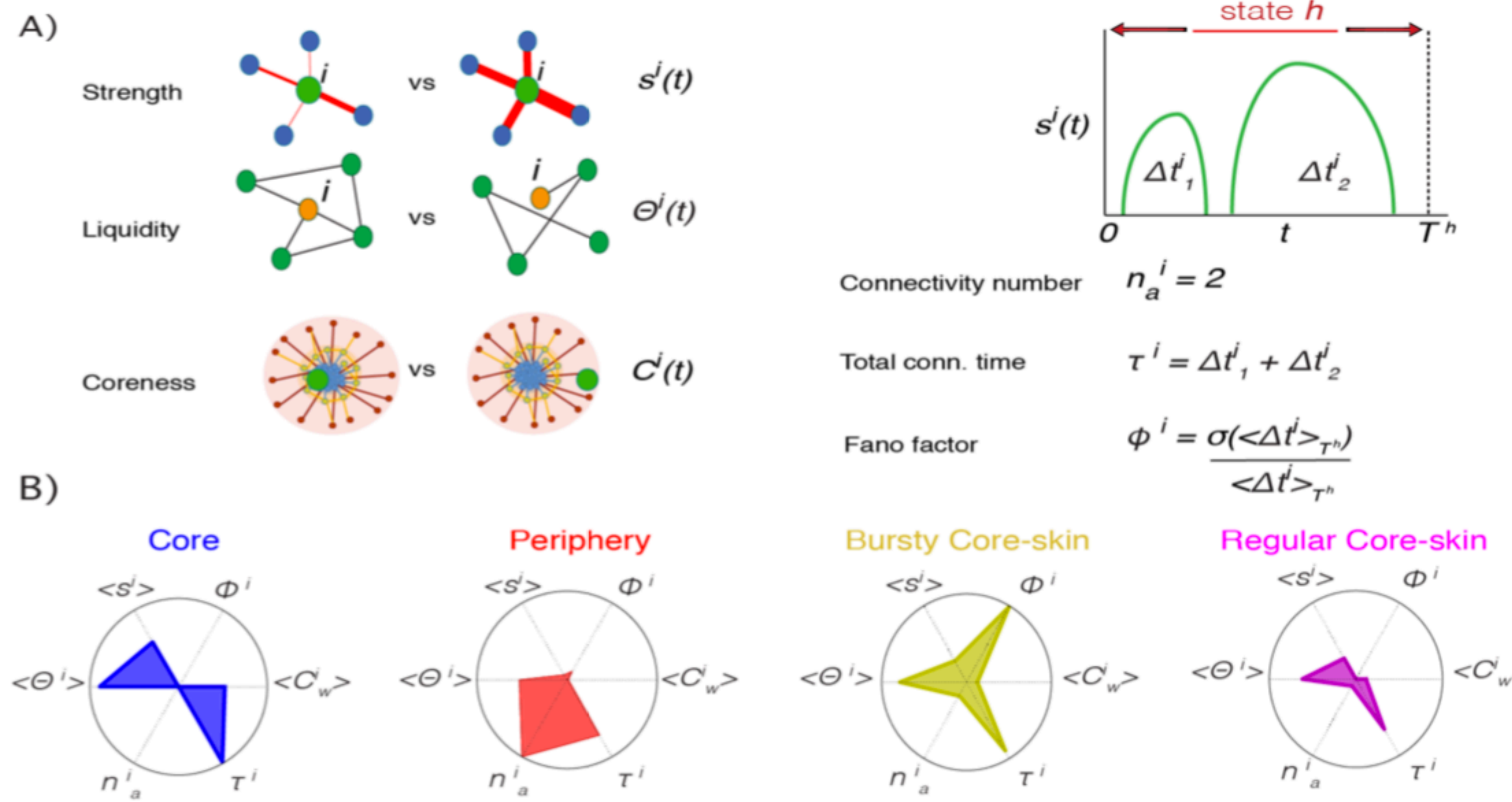
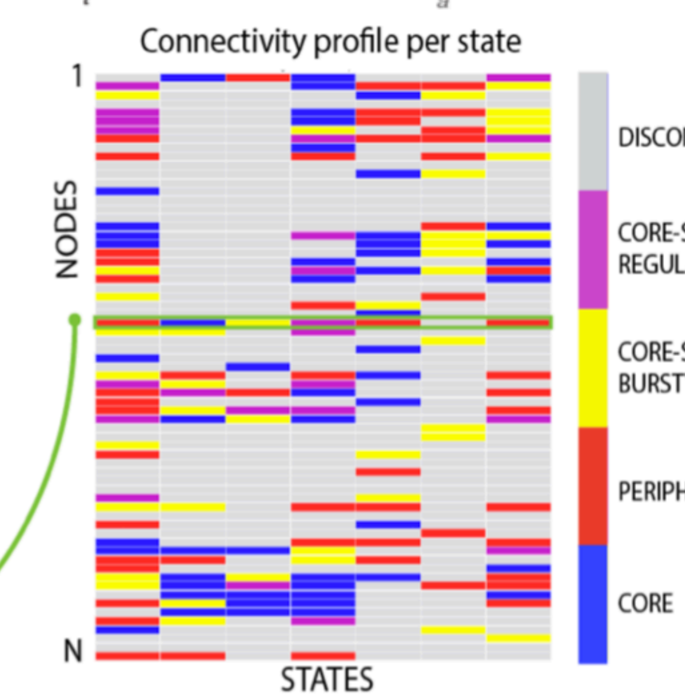
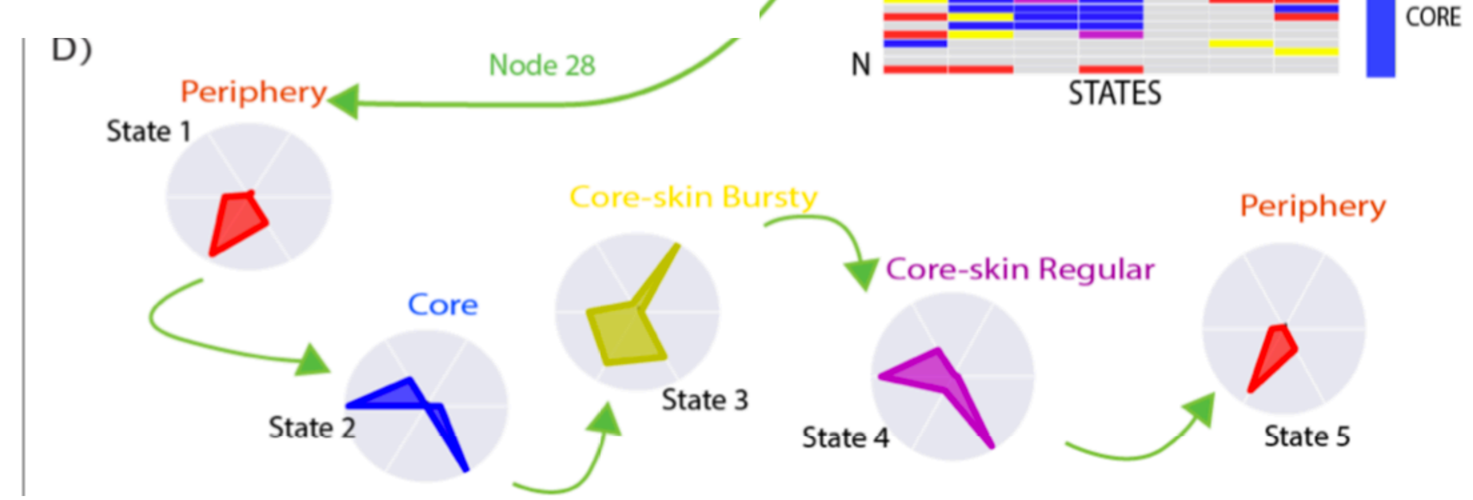


NB:
dynamics *within each state*
different types of dynamics for different nodes

➡different connectivity profiles





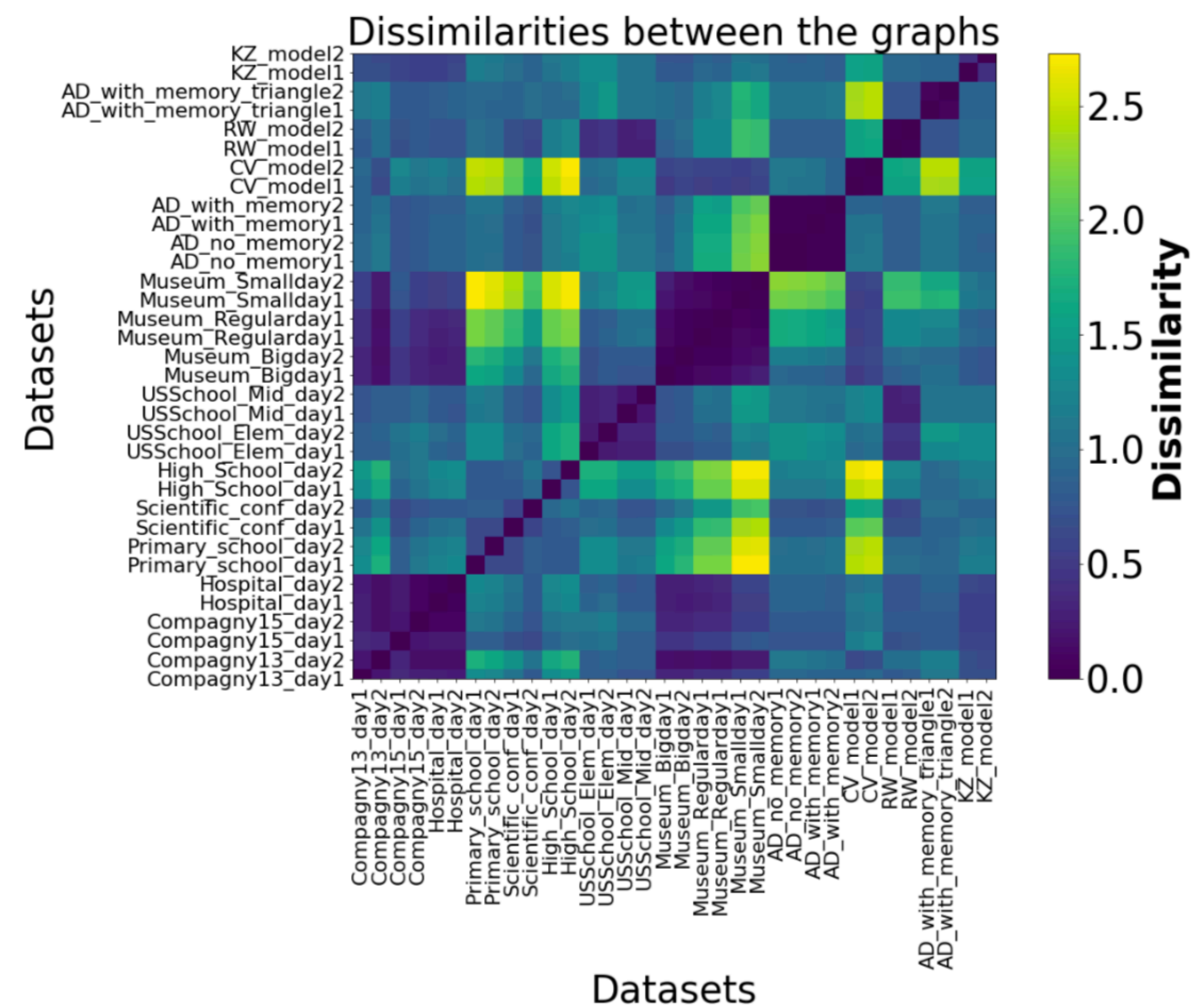
Current work

Backbone of events (with T. Bassanetti, M. Karsai)

Beyond spreading processes

Comparison of temporal networks (with E. Andres, M. Karsai)

Temporal simplicial complexes



Temporal networks: Still very open field!

Data
Structures in data
Incompleteness of data
Models
Processes on temporal networks
…

Datasets: www.sociopatterns.org/datasets