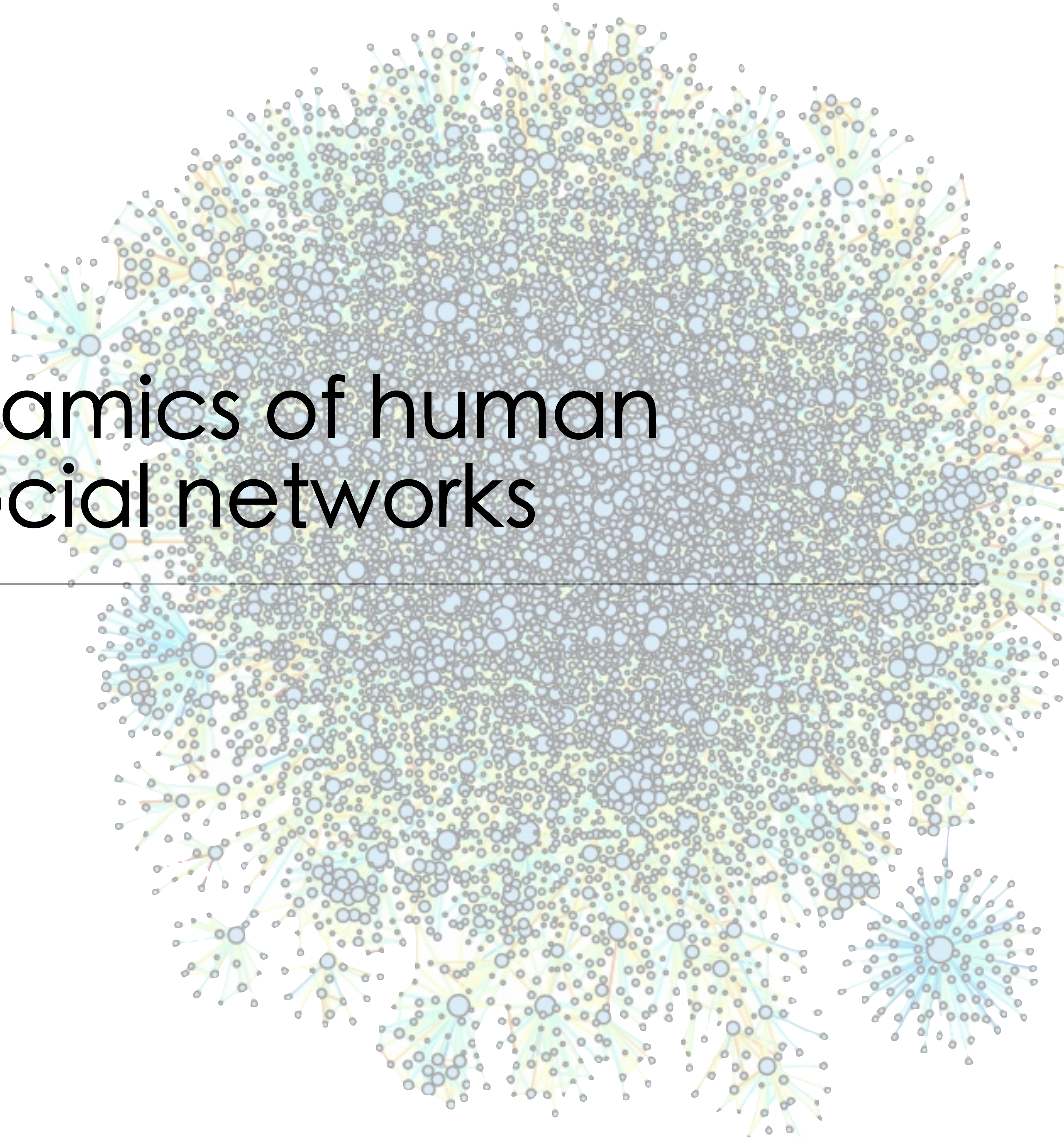
Temporal dynamics of human behavior in social networks



Esteban Moro (UC3M & IIC)

Universidad Carlos III de Madrid

Les Houches '14

Summary

Second Lecture

- Motivation
- Spreading on complex networks
- Effect of tie activity
- Effect of tie dynamics
- Other effects
- Outlook

http://bit.ly/LesHouches

Spreading on complex networks

1

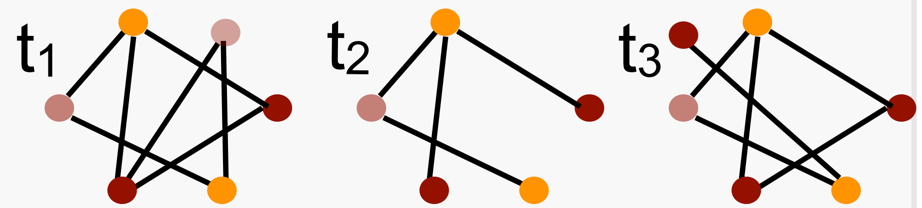
Dynamical processes on real networks

Time scale

Dynamical processes on real networks

Nodes

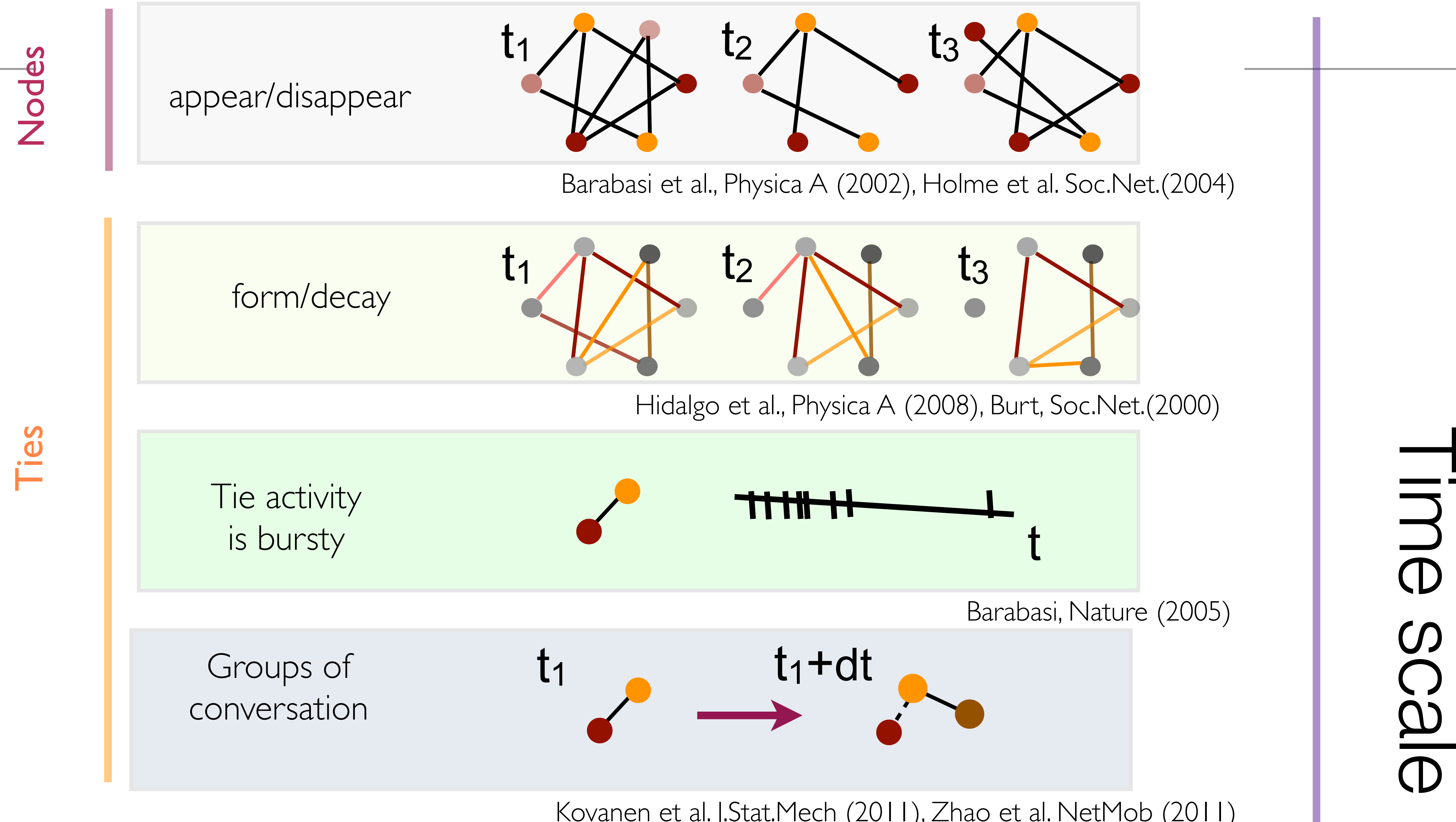
appear/disappear



Barabasi et al., Physica A (2002), Holme et al. Soc.Net.(2004)

Time scale

Dynamical processes on real networks



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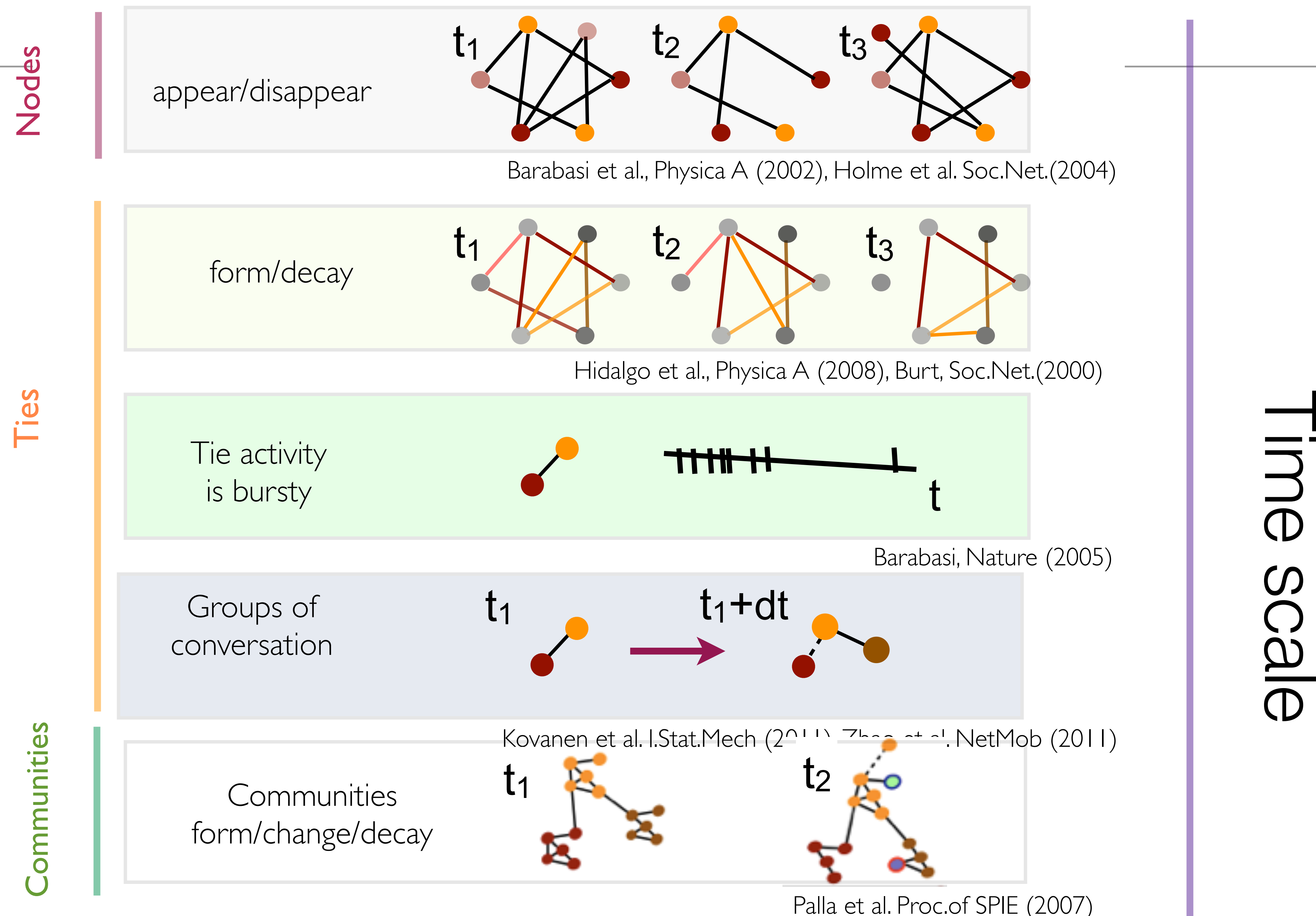
Dynamical processes on real networks



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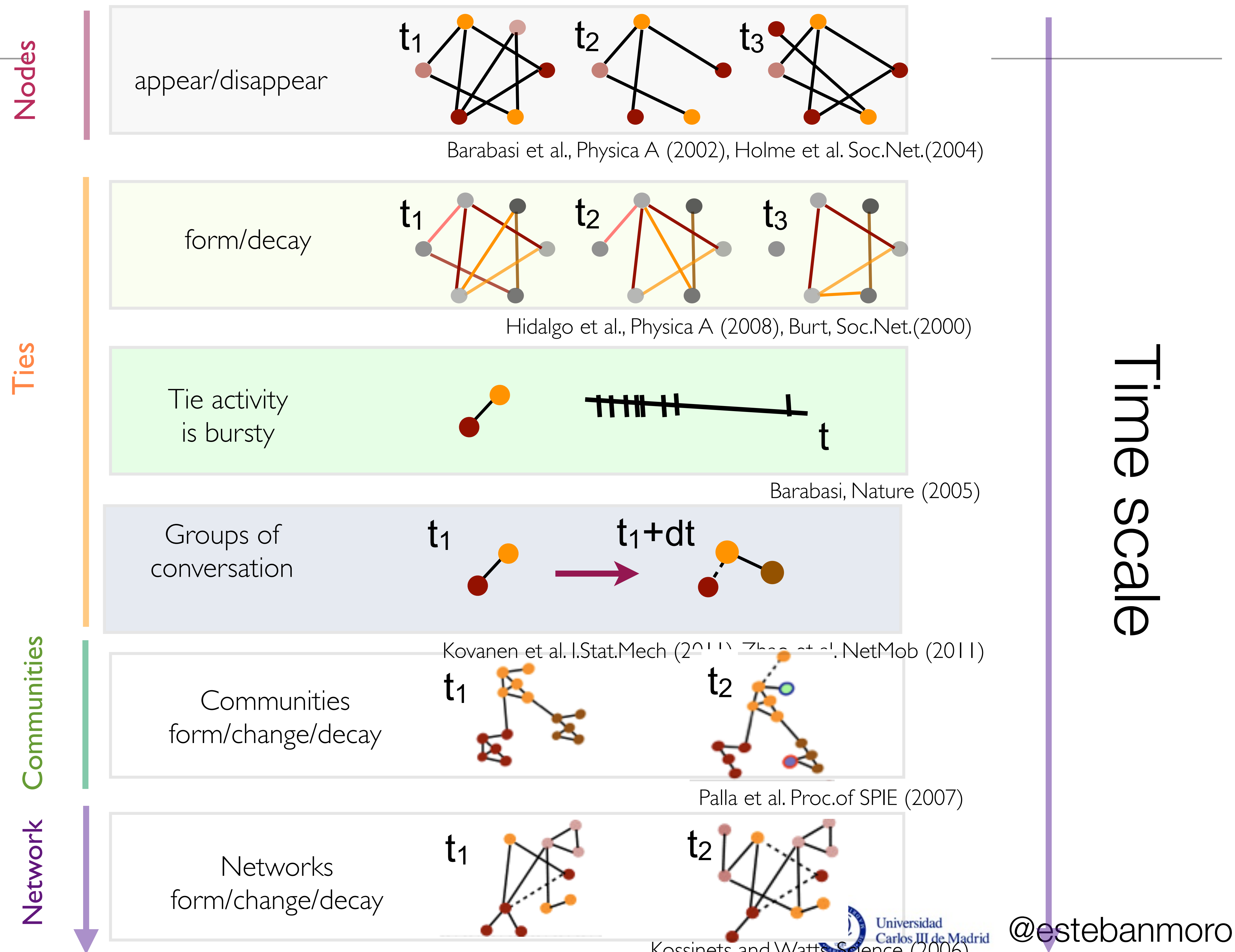
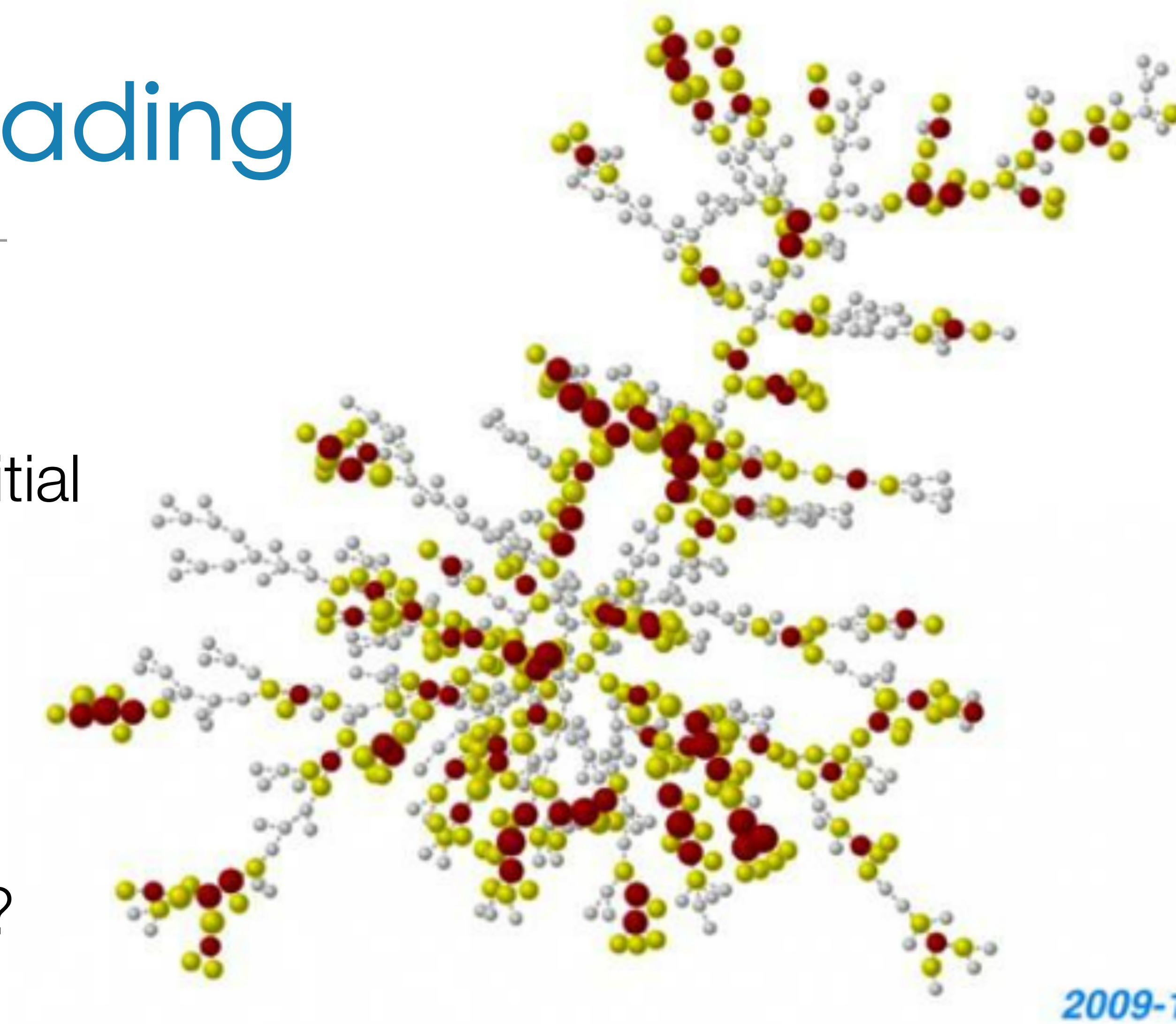
Dynamical processes on real networks



Relevant question in spreading

- **Reach**
  - How many people are infected from a initial spreader?
- **Time**
  - How long does it take to infect them?
  - Early detection of an outbreak, possible?
- **Optimization**
  - How do we choose a given a number N of initial spreaders, so that reach is maximize in a given time? What is the optimal N for a given cost?
  - How do we choose a given number of immune people so that reach of the disease is minimized? (resiliance of networks)
  - How do we choose sensors to detect propagation?



Christakis & Fowler '10

Simple model for spreading

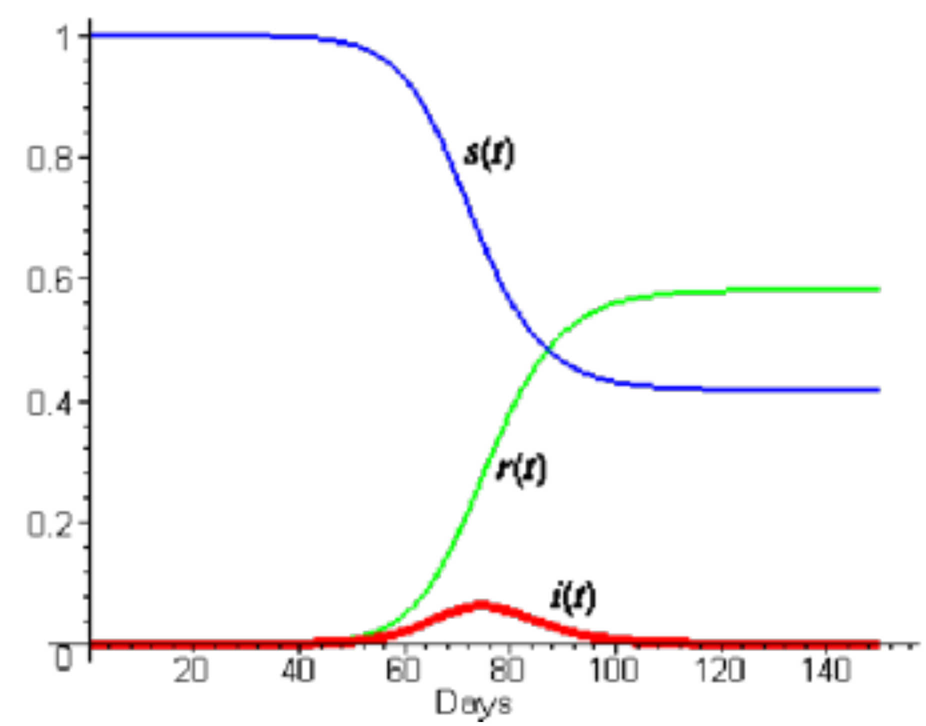
- SI / SIR / SIS models (Kermack & McKendrick '27)
  - S: suceptible (non infected)
  - I: Infected
  - R: resiliant
  - S + I + R = N

$$S \xrightarrow{\lambda} I \xrightarrow{\gamma} R$$

$$\frac{dS}{dt} = -\lambda I S \qquad\qquad R_0 = N\frac{\lambda}{\gamma}$$

$$\frac{dI}{dt} = \lambda I S - \gamma I$$

$$\frac{dR}{dt} = \gamma I \qquad\qquad \frac{dI}{dt} = \gamma(R_0 S/N - 1)I$$



- R_0: basic reproductive number

$$R_0 > N/S(0) \Rightarrow dI/dt > 0$$
$$R_0 < N/S(0) \Rightarrow dI/dt < 0$$

Simple model for spreading

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Simple model for spreading

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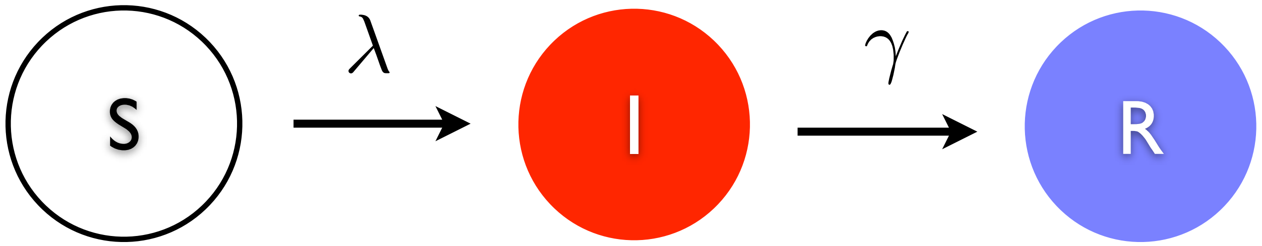

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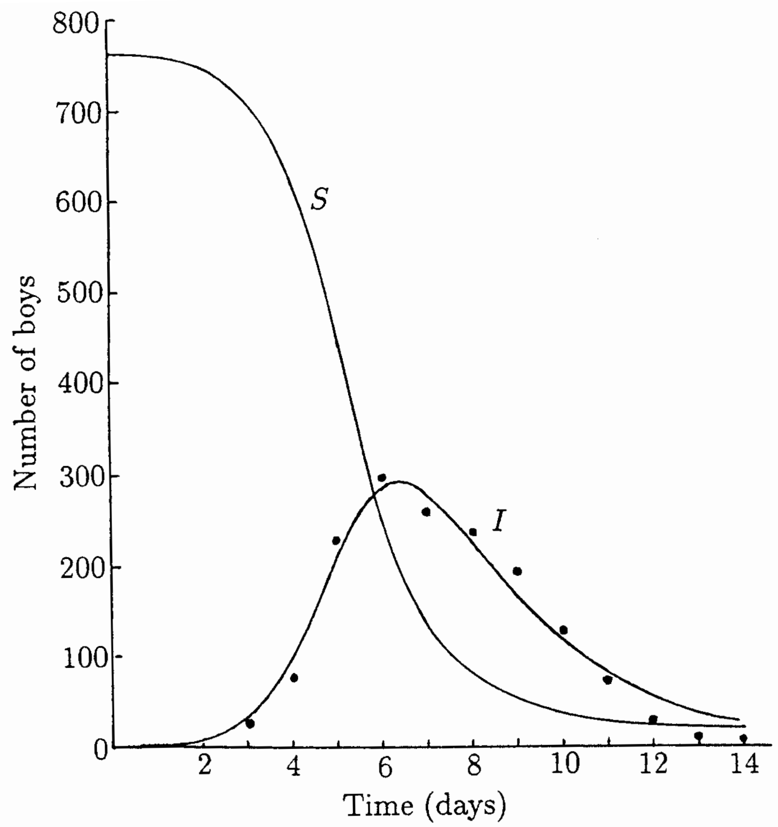
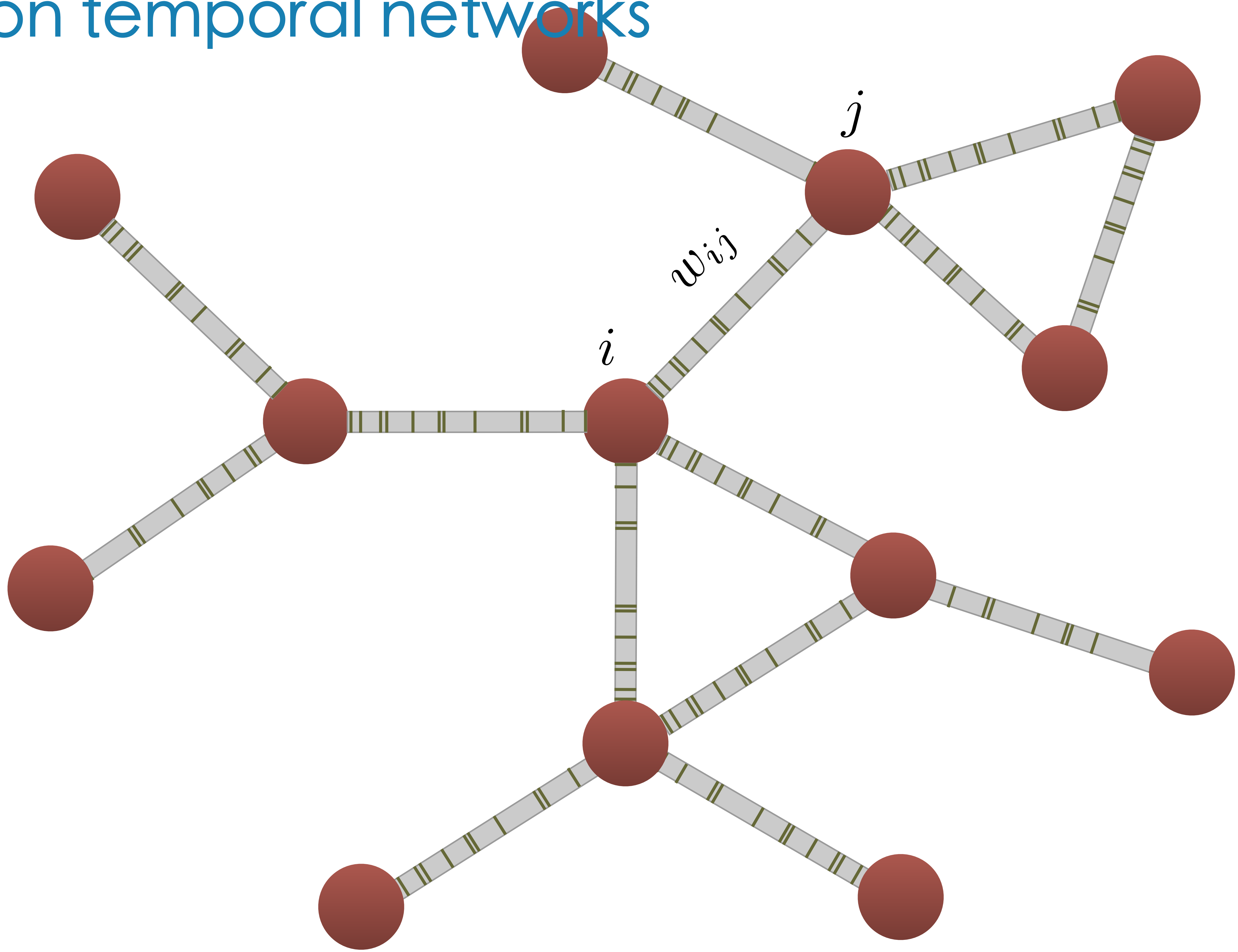
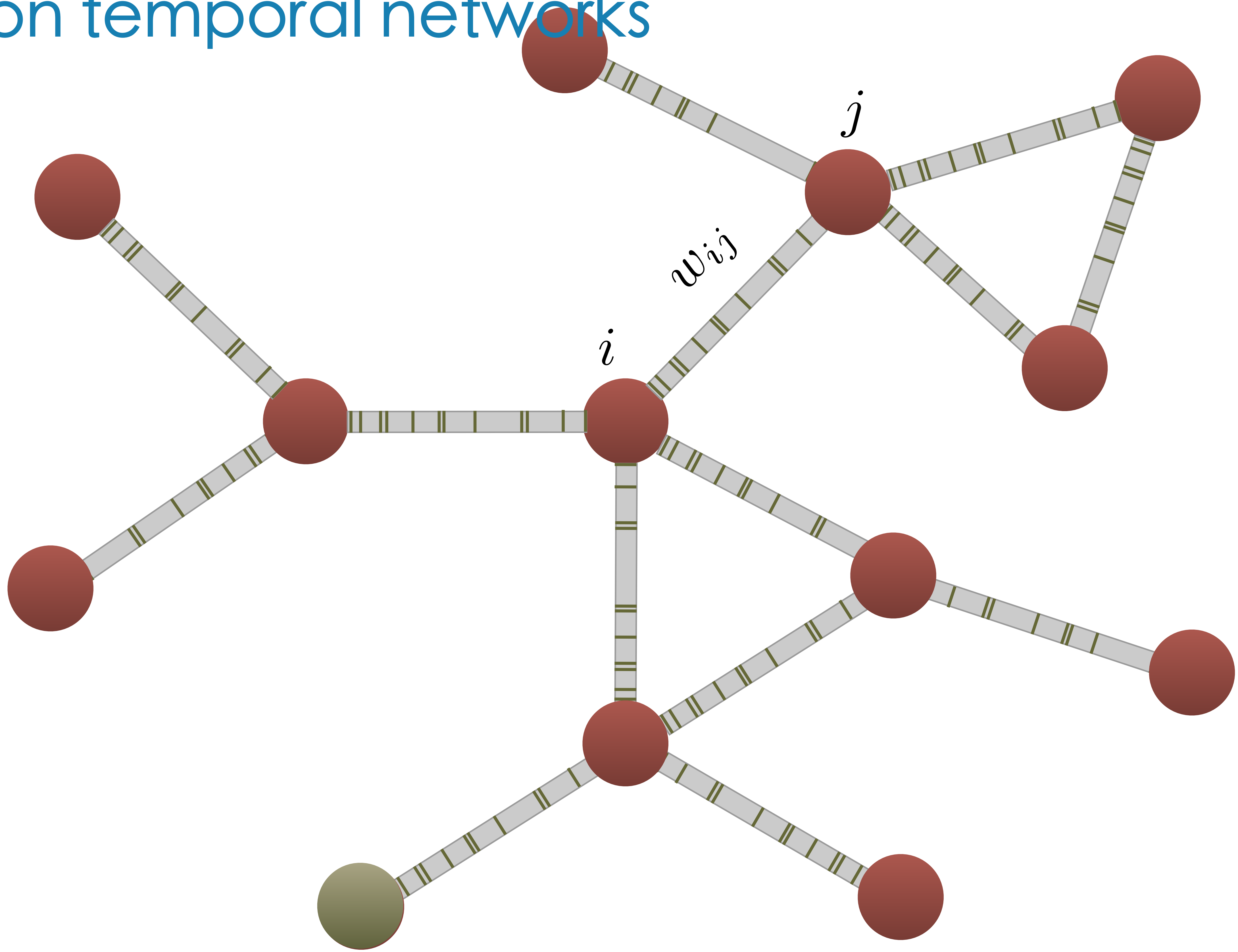


Fig. 19.3. Influenza epidemic data (•) for a boys boarding school as reported in British Me Journal, 4th March 1978. The continuous curves for the infectives (I) and susceptibles (S) obtained from a best fit numerical solution of the *SIR* system (19.1)–(19.3): parameter v $N = 763$, $S_0 = 762$, $I_0 = 1$, $\rho = 202$, $r = 2.18 \times 10^{-3}$/day. The conditions for an epiden occur, namely $S_0 > \rho$ is clearly stisfied and the epidemic is severe since R/ρ is not small

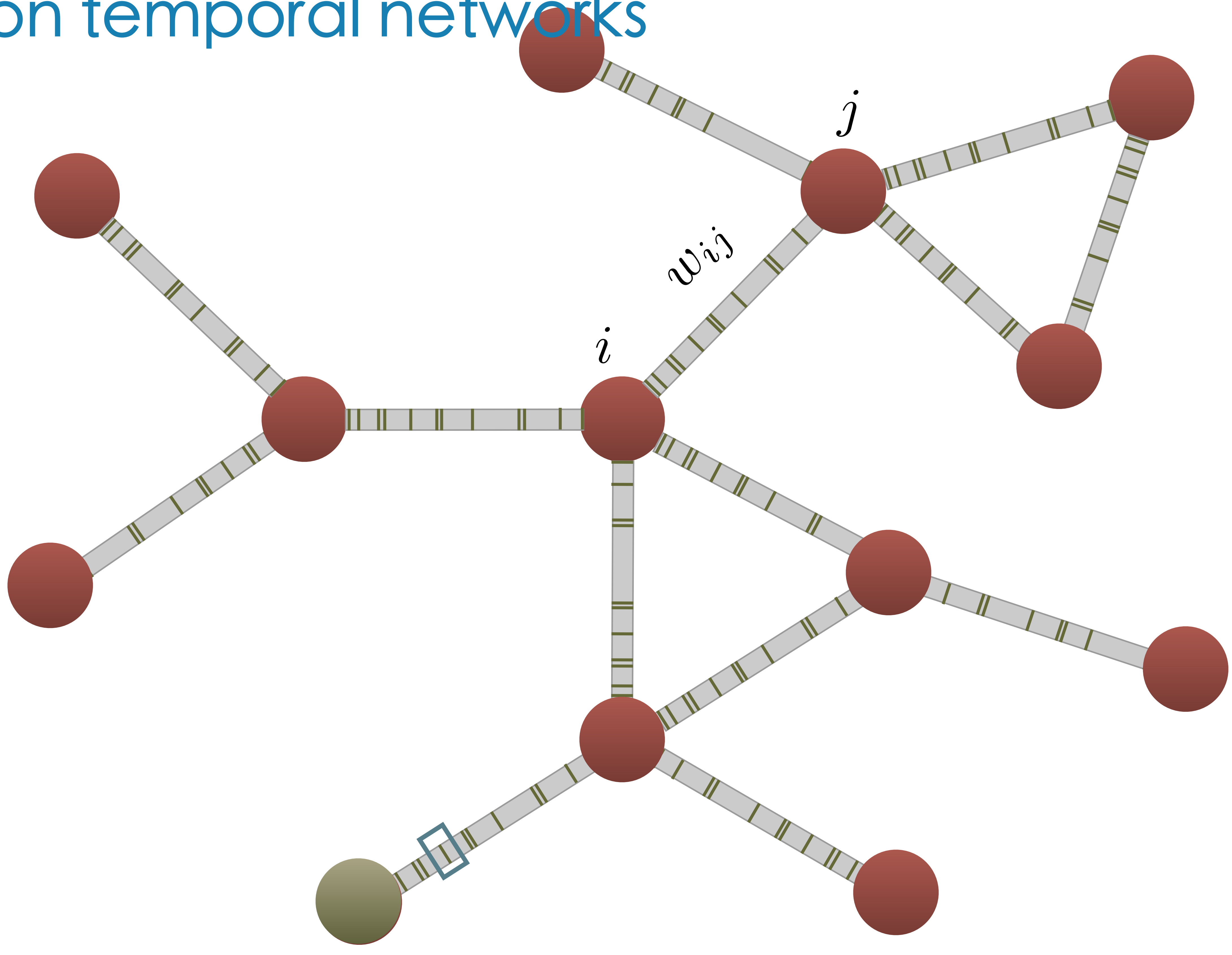
SIR on temporal networks



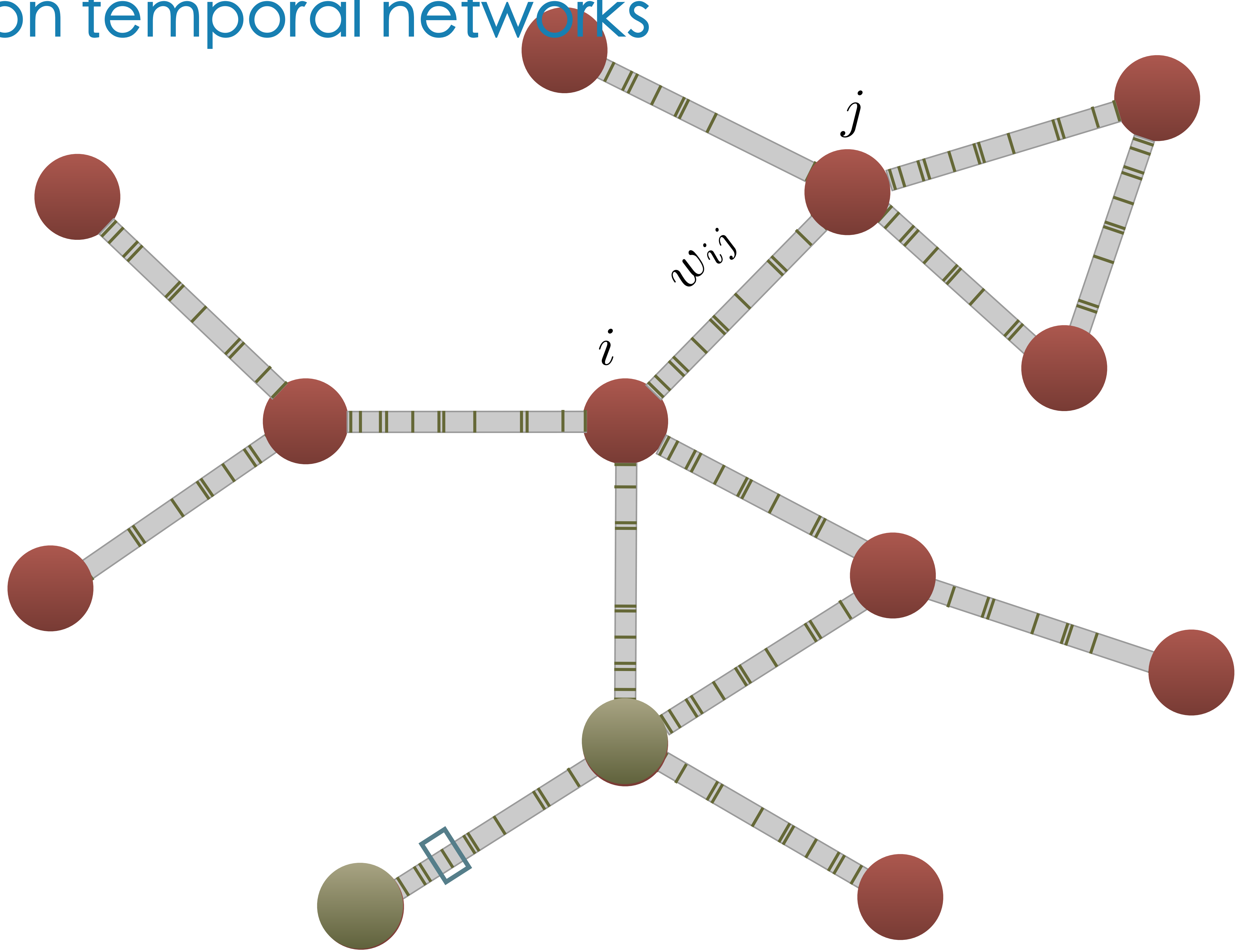
SIR on temporal networks



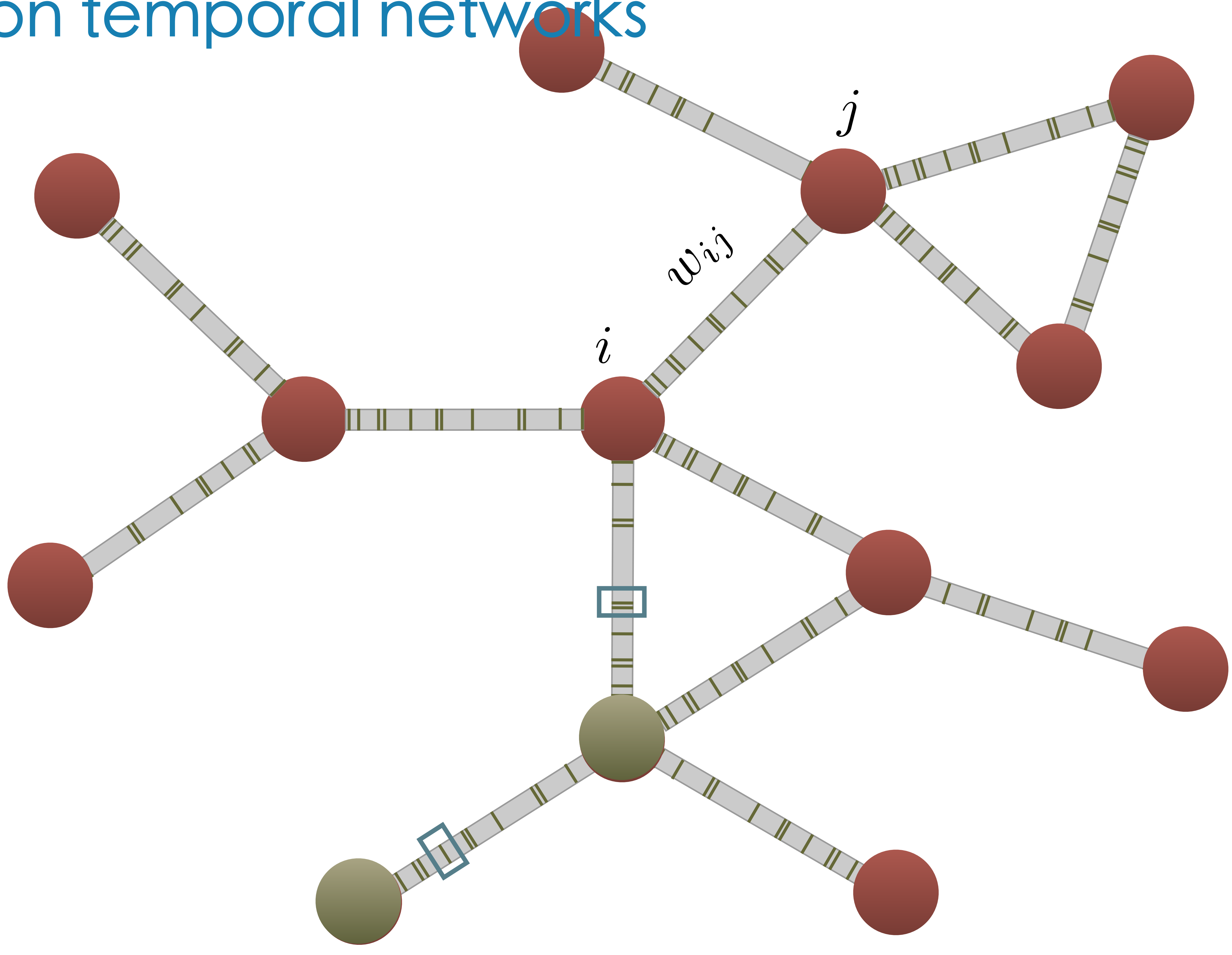
SIR on temporal networks



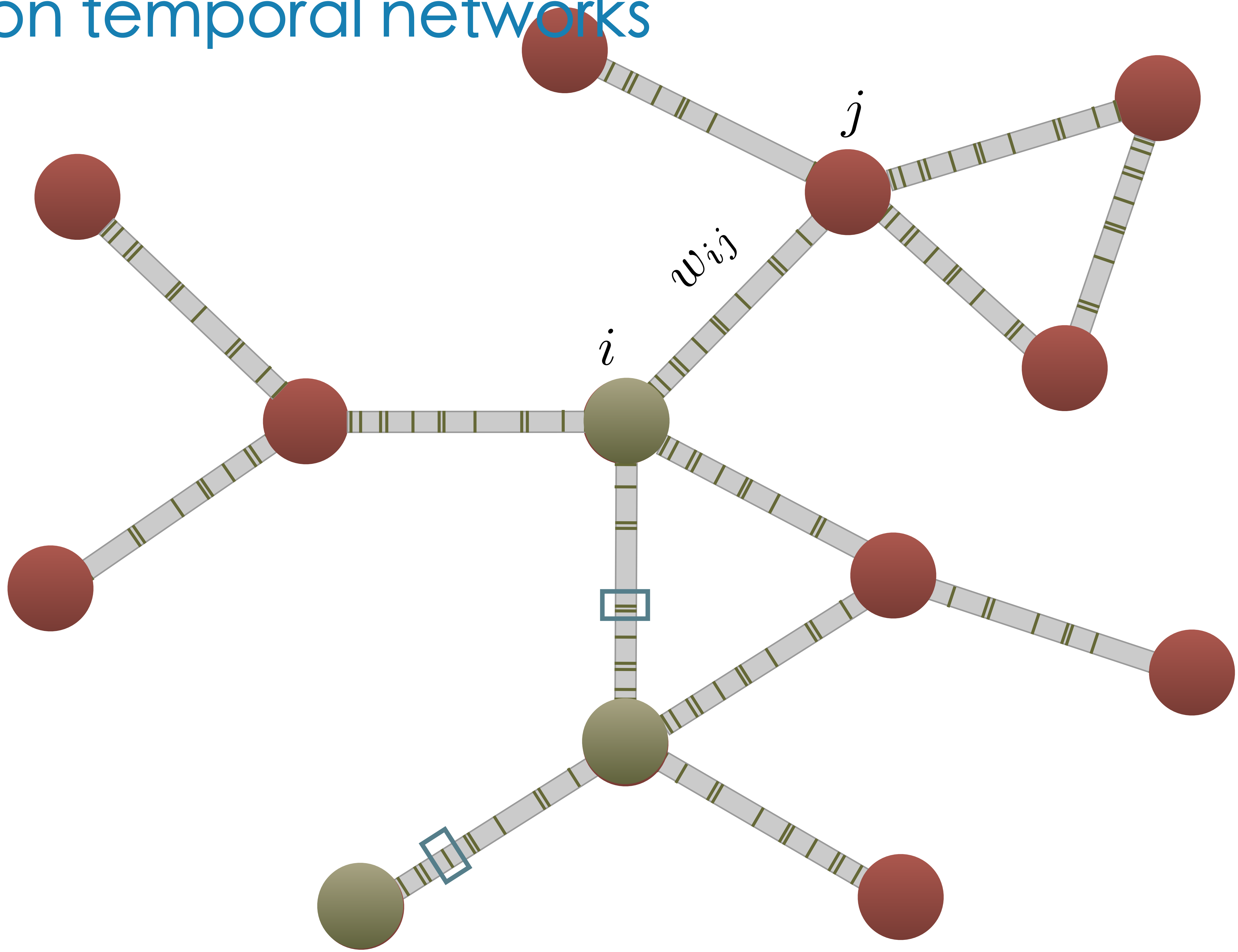
SIR on temporal networks



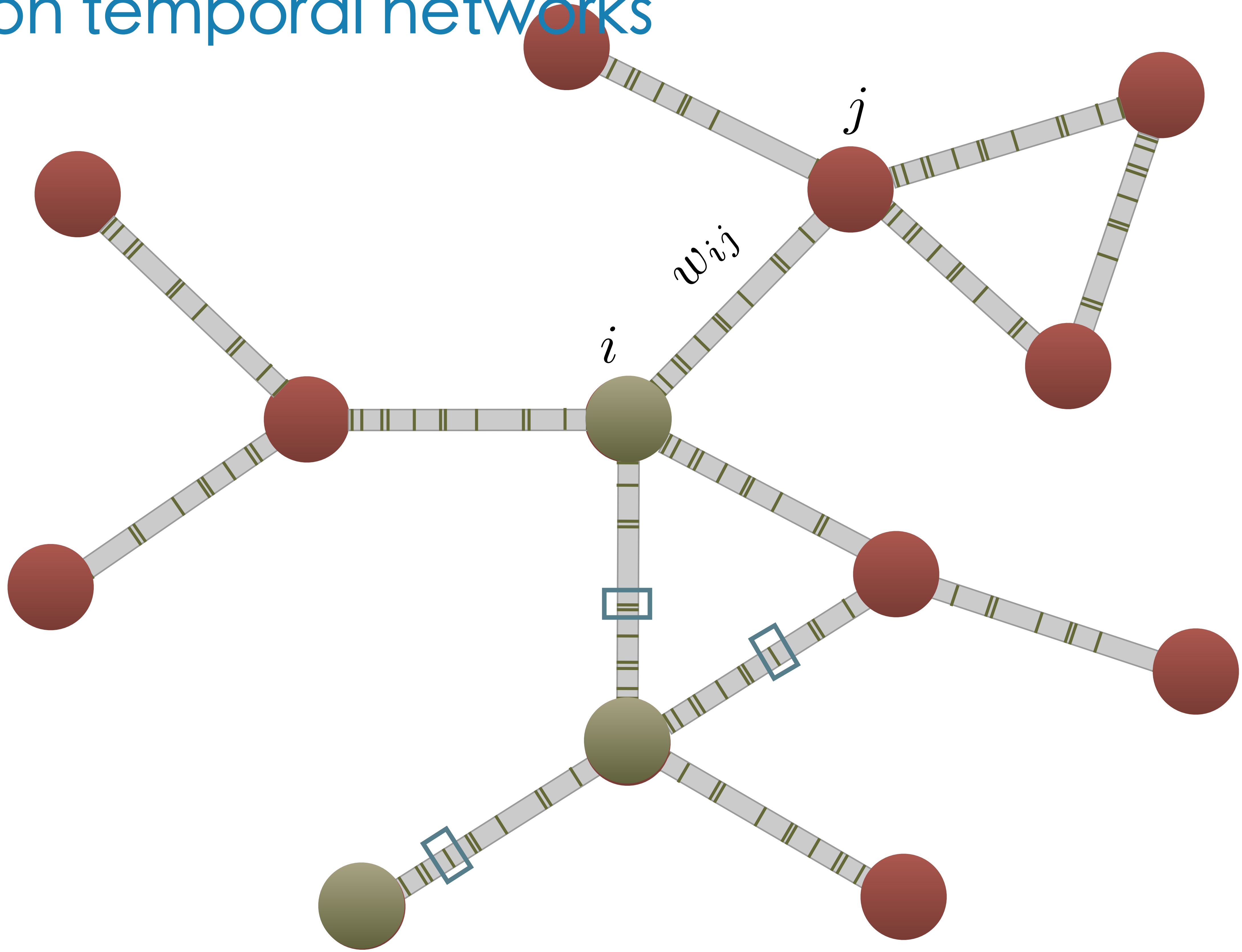
SIR on temporal networks



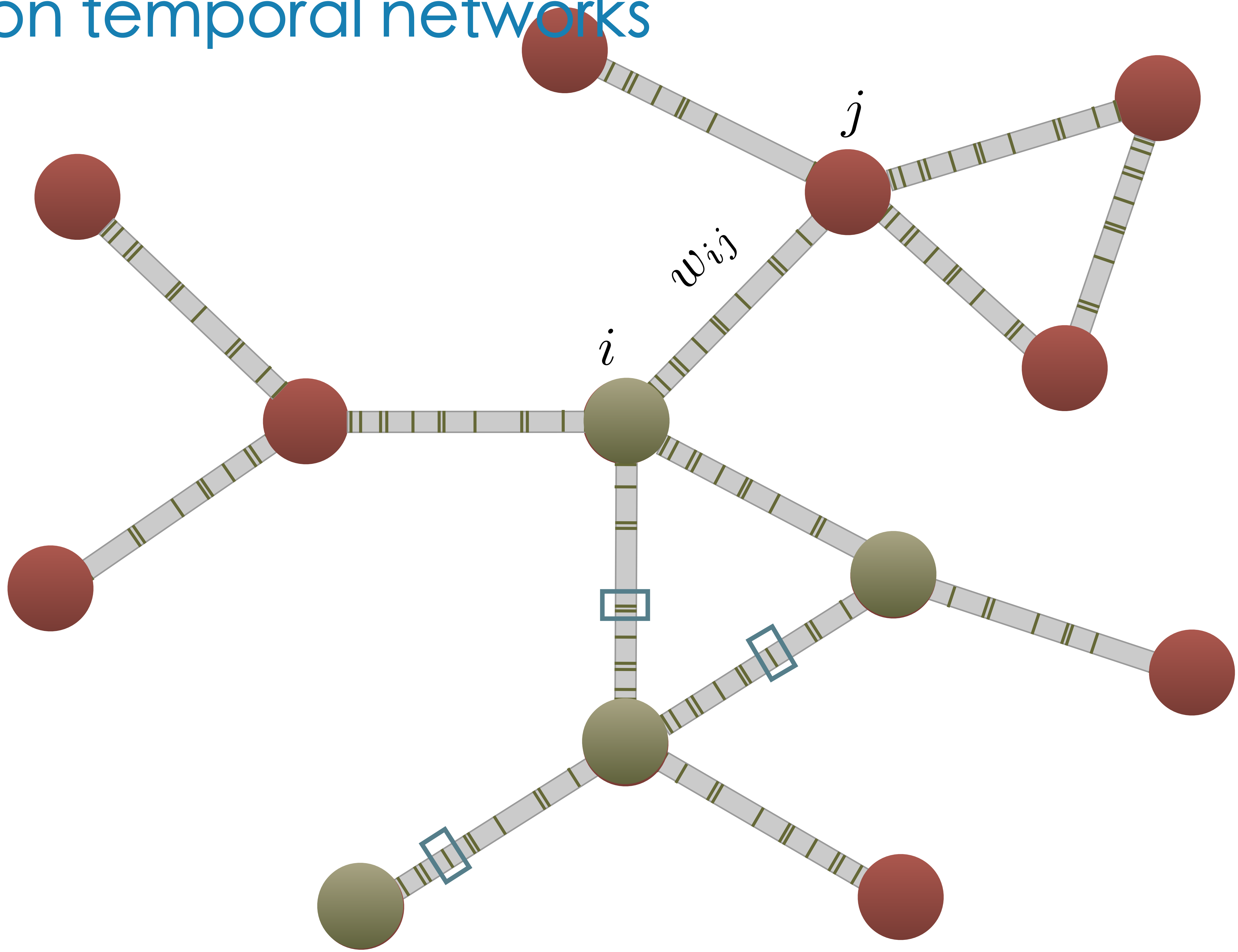
SIR on temporal networks



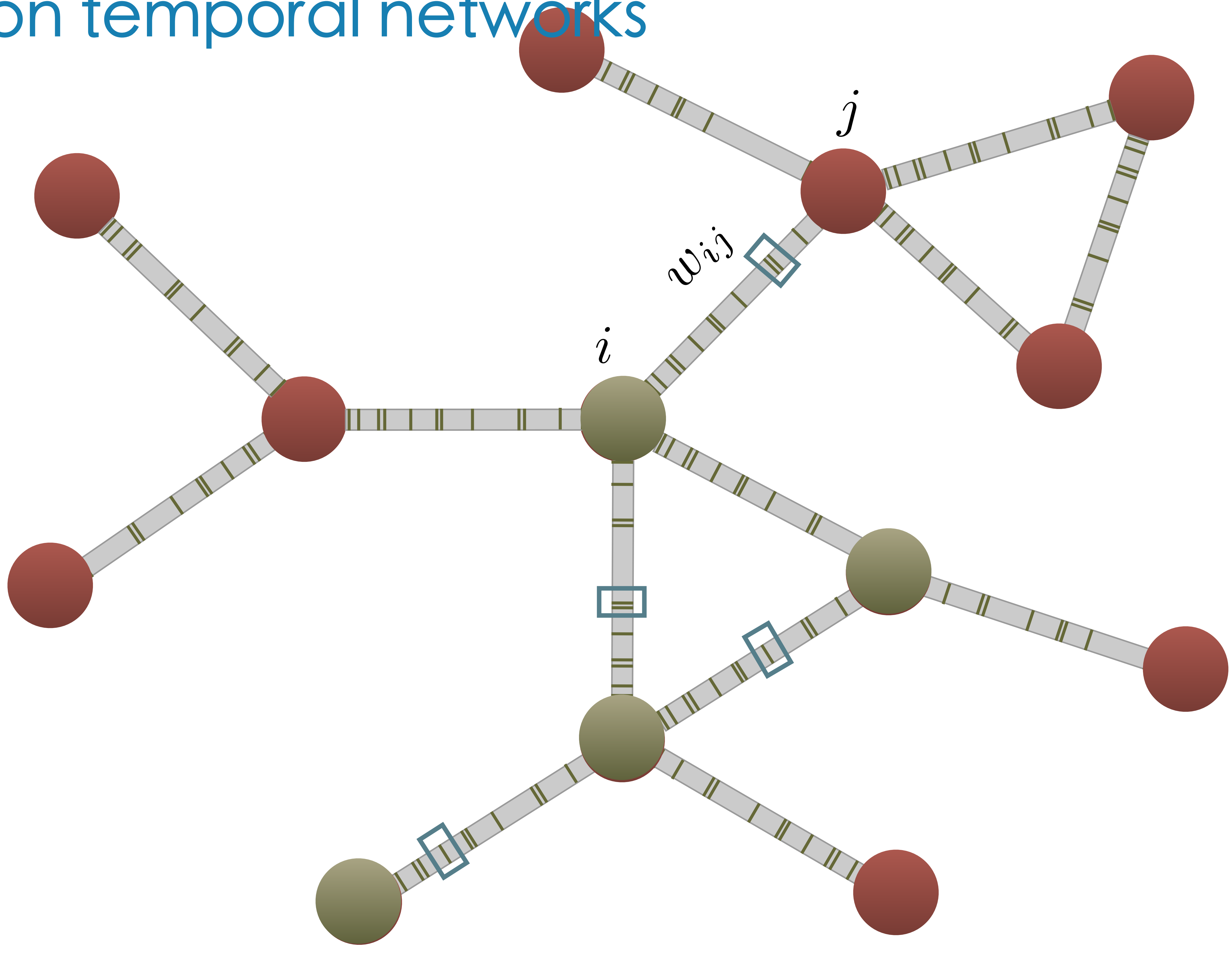
SIR on temporal networks



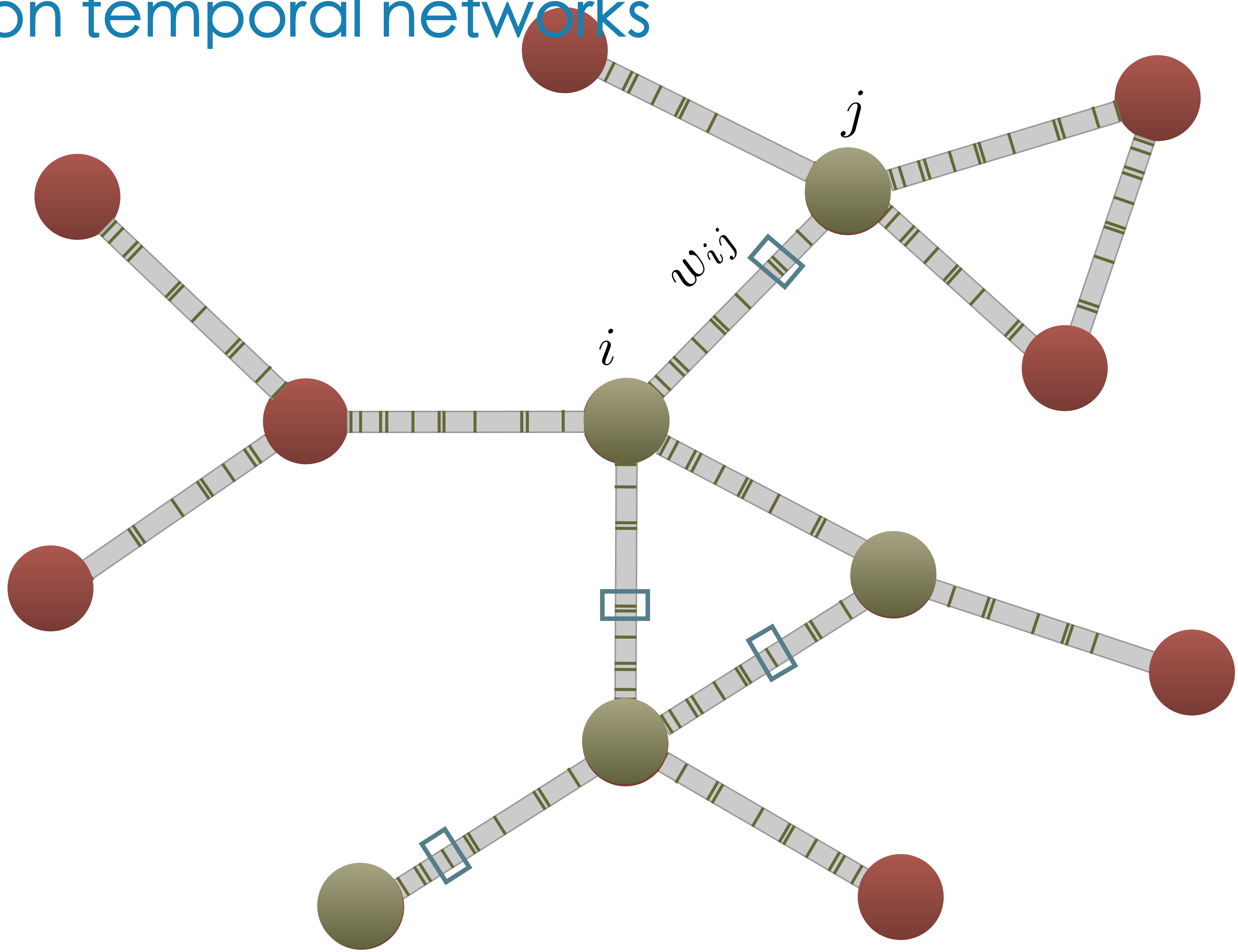
SIR on temporal networks



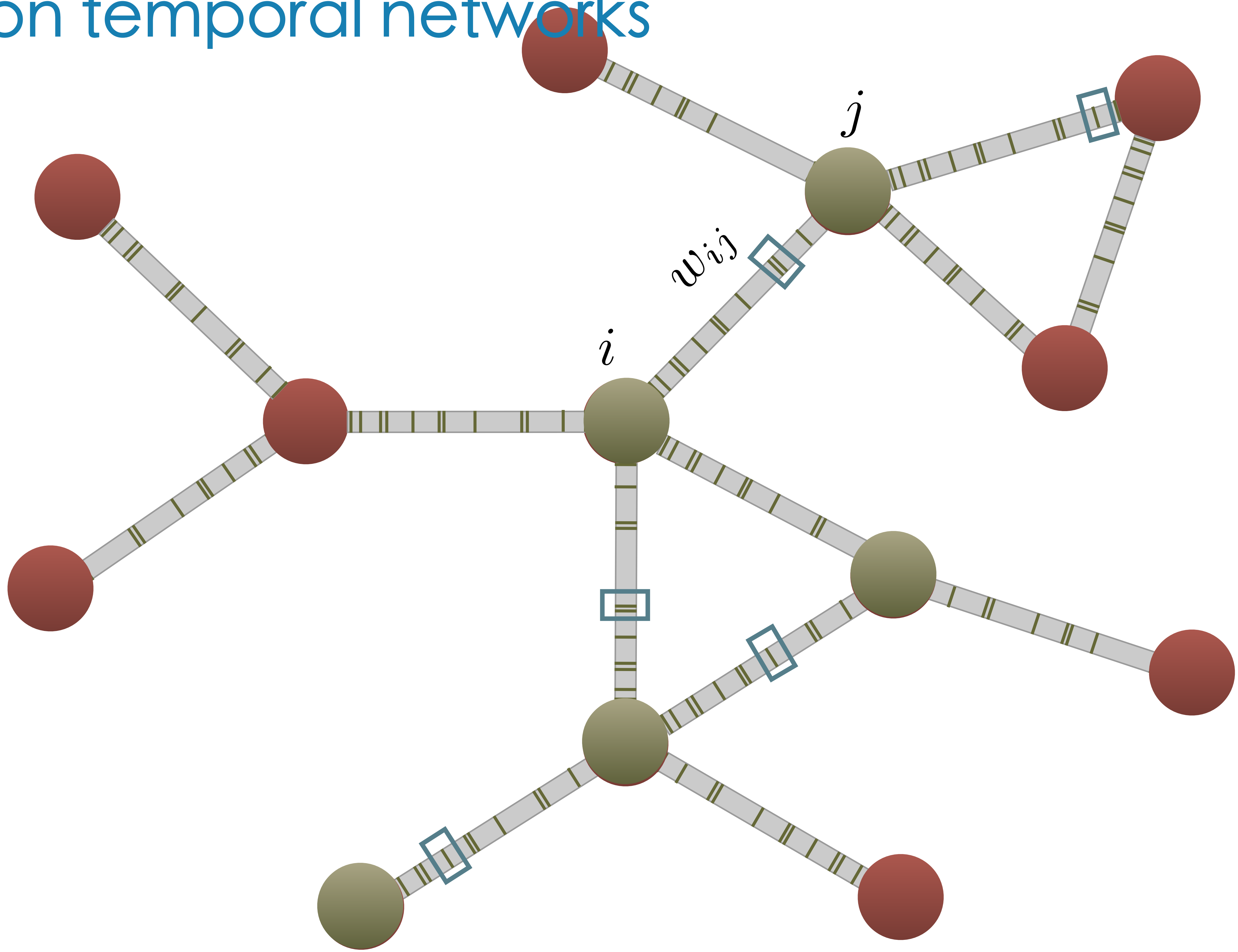
SIR on temporal networks



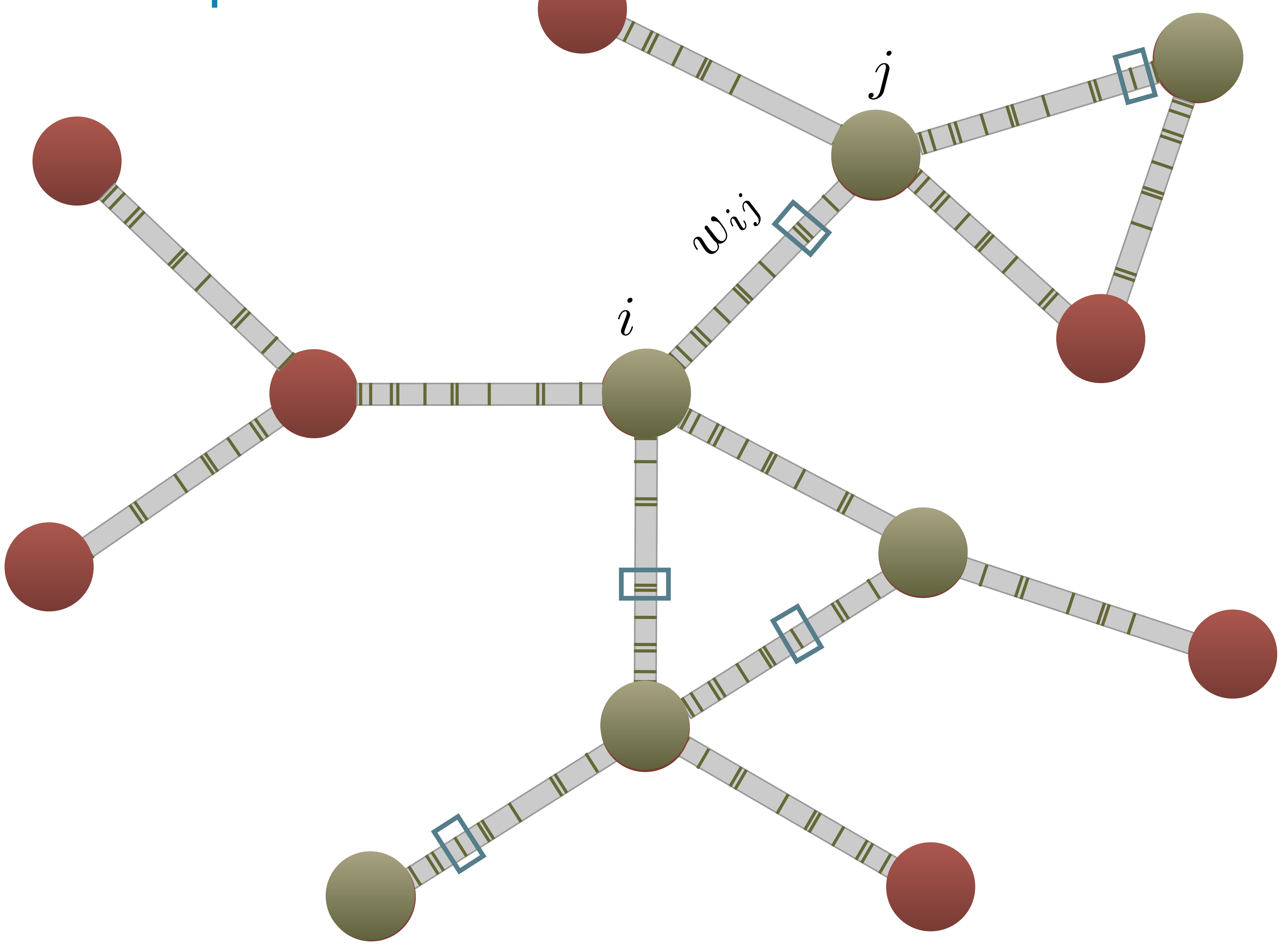
SIR on temporal networks



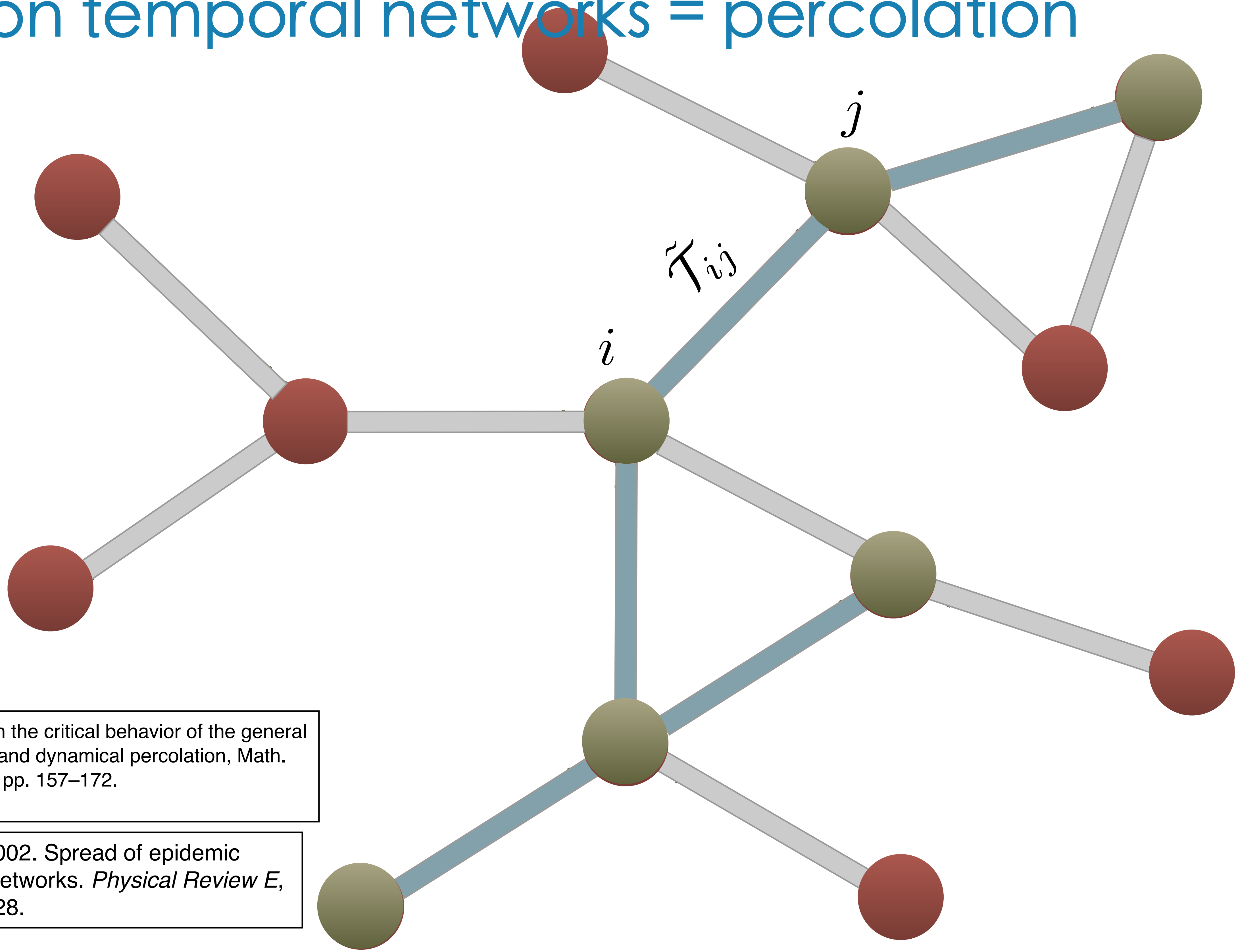
SIR on temporal networks



SIR on temporal networks



SIR on temporal networks = percolation

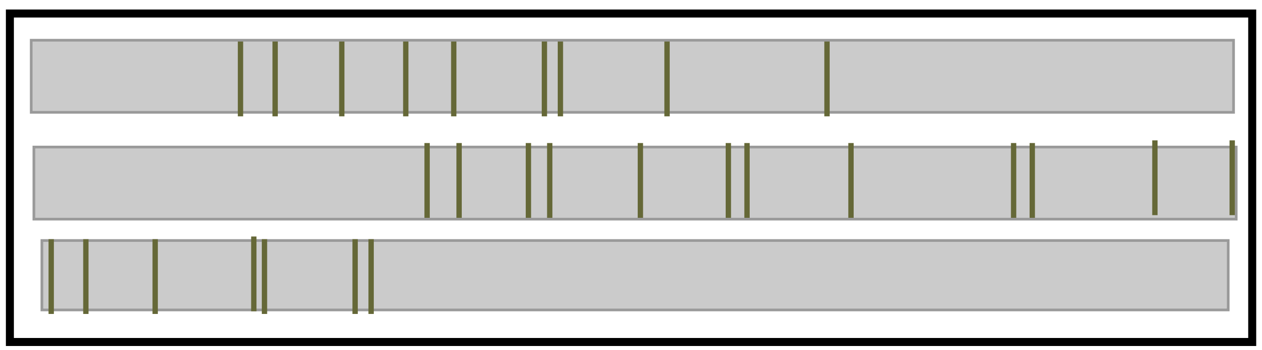


P. Grassberger, On the critical behavior of the general epidemic process and dynamical percolation, Math. Biosci., 63 (1983), pp. 157–172.

Newman, M., 2002. Spread of epidemic disease on networks. *Physical Review E*, 66(1), p.16128.

Comparison with null models

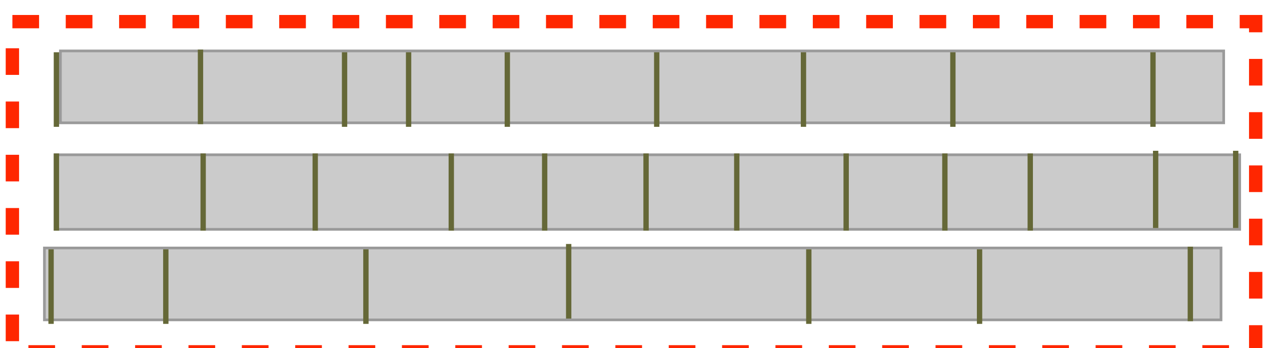
- Real data



Ω

P(dt) heavy tailed
Correlated bursts
Correlated tie activity
Temporal motifs
Tie dynamics

- Time Shuffled data



Ω

P(dt) exponential
Uncorrelated bursts
Uncorrelated tie activity
No temporal motifs
No tie dynamics

Data-driven simulations

- SIR model on real contact data

v_i, v_j, t

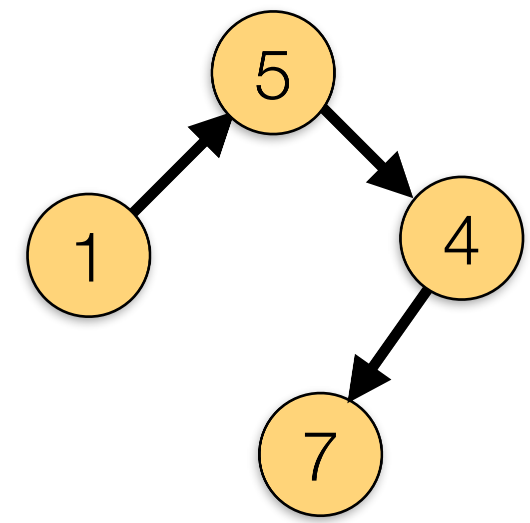
1,5,412
2,3,523
5,4,631
3,7,782
1,2,921
2,7,999

Select seed
+
infect in each contact with probability

v_i, v_j, t

1,5,412
2,3,523
5,4,631
3,7,782
1,2,921
4,7,999

=

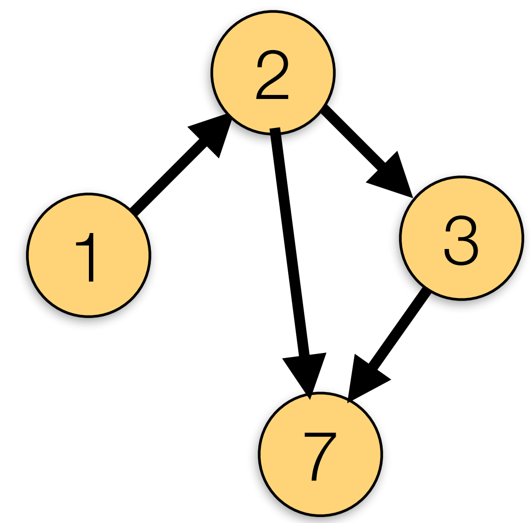


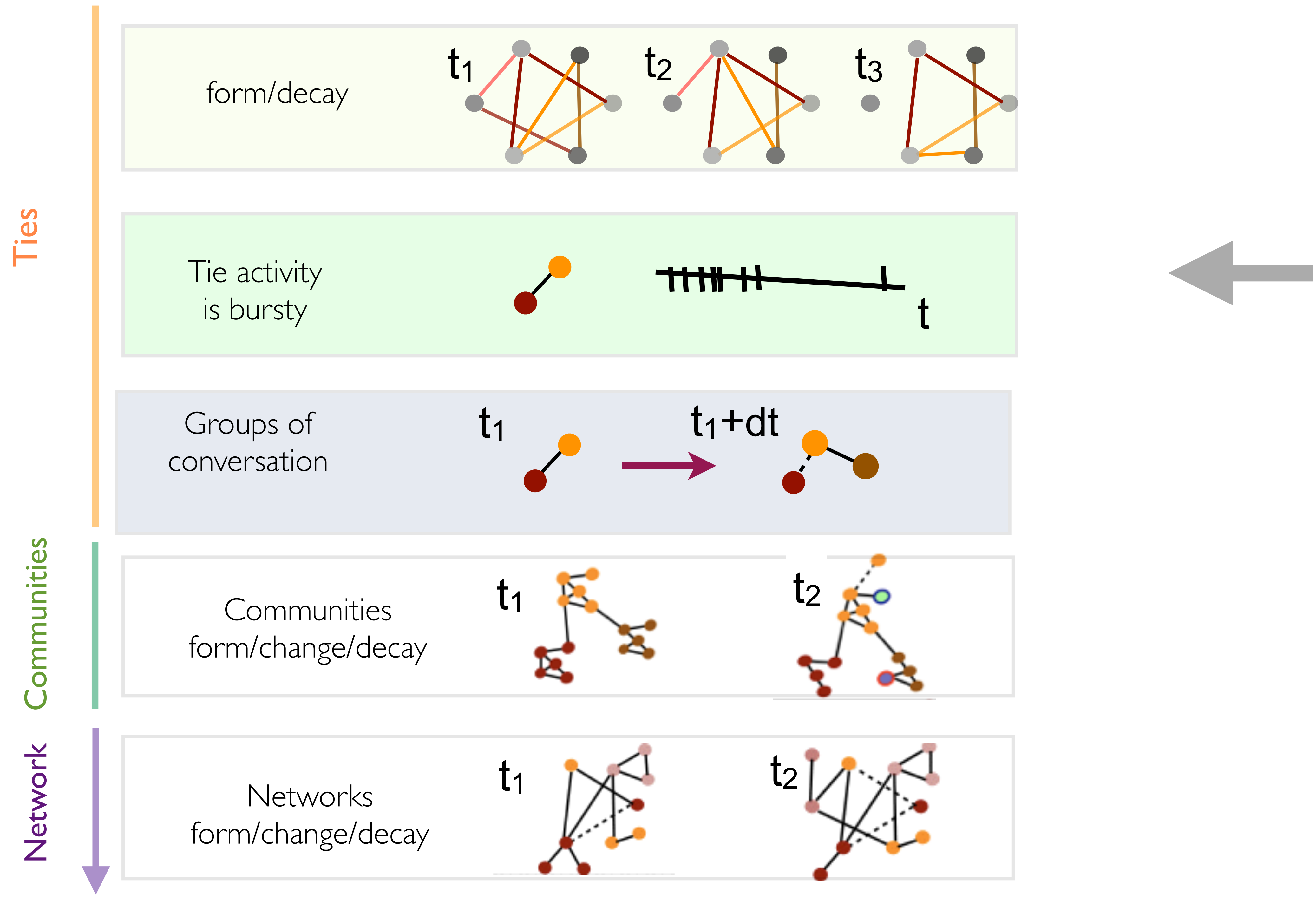
Data-driven simulations

- SIR model on shuffled contact data

v_i, v_j, t		v_i, v_j, t		v_i, v_j, t
1,5,412		1,2,412		**1,2,412**
2,3,523		2,3,523		**2,3,523**
5,4,631	→	1,5,631	Select seed + infect in each contact with probability	1,5,631
3,7,782		2,7,782		**2,7,782**
1,2,921		3,7,921		**3,7,921**
2,7,999		5,4,999		5,4,999
Real data		Shuffled data		

=



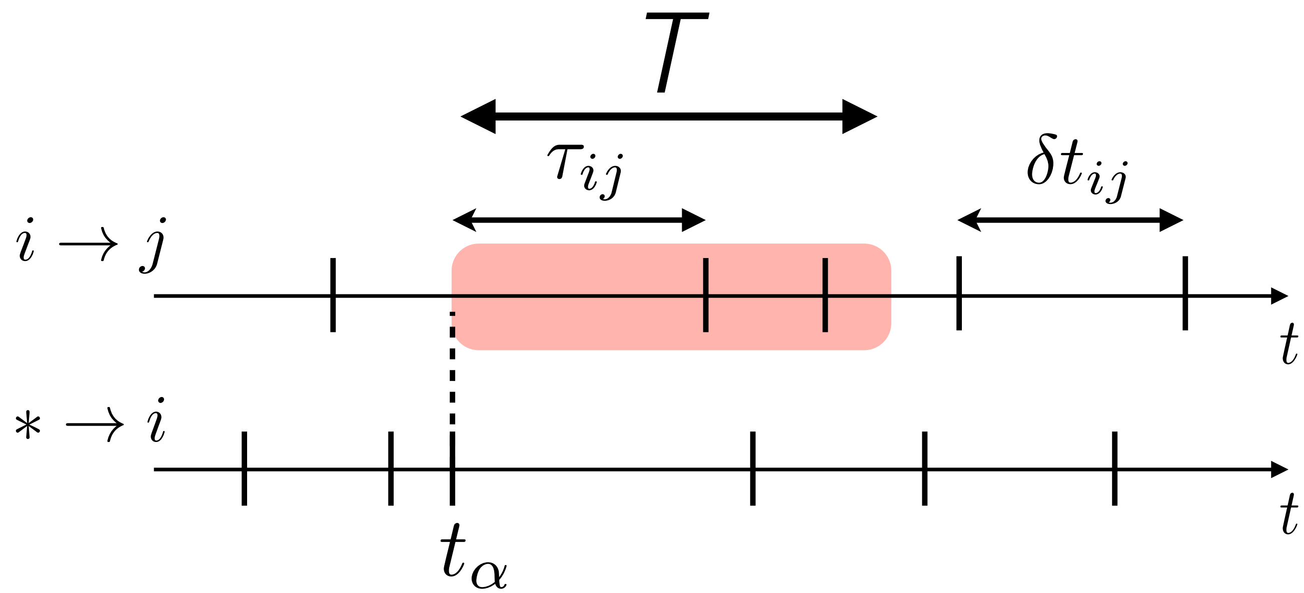


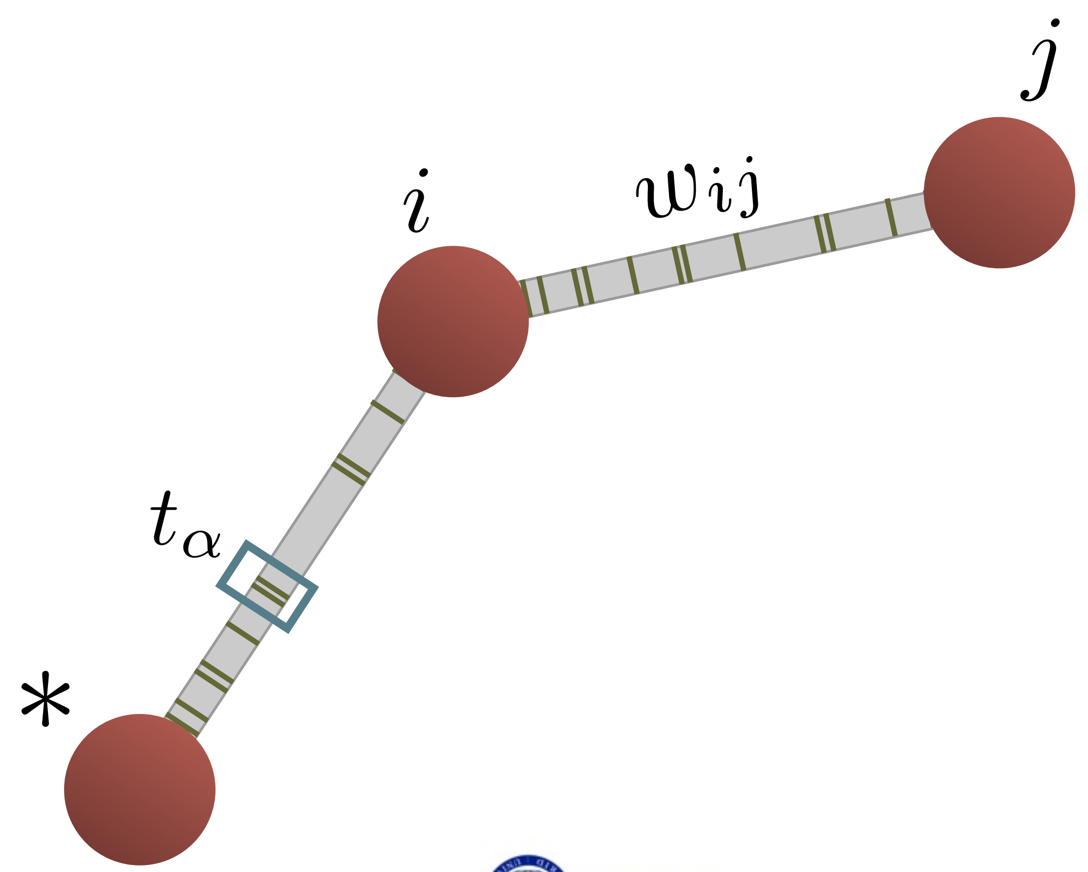
Effect of tie activity

2

Spreading including tie activity

- Spreading (SIR) on contact networks
- Hypothesis:
  - In every contact there is a probability λ to infect
  - Nodes only remain infected for a time “$T \simeq 1/\gamma$“
- **Transmissibility**: probability that *i* infects j after being infected at t_α



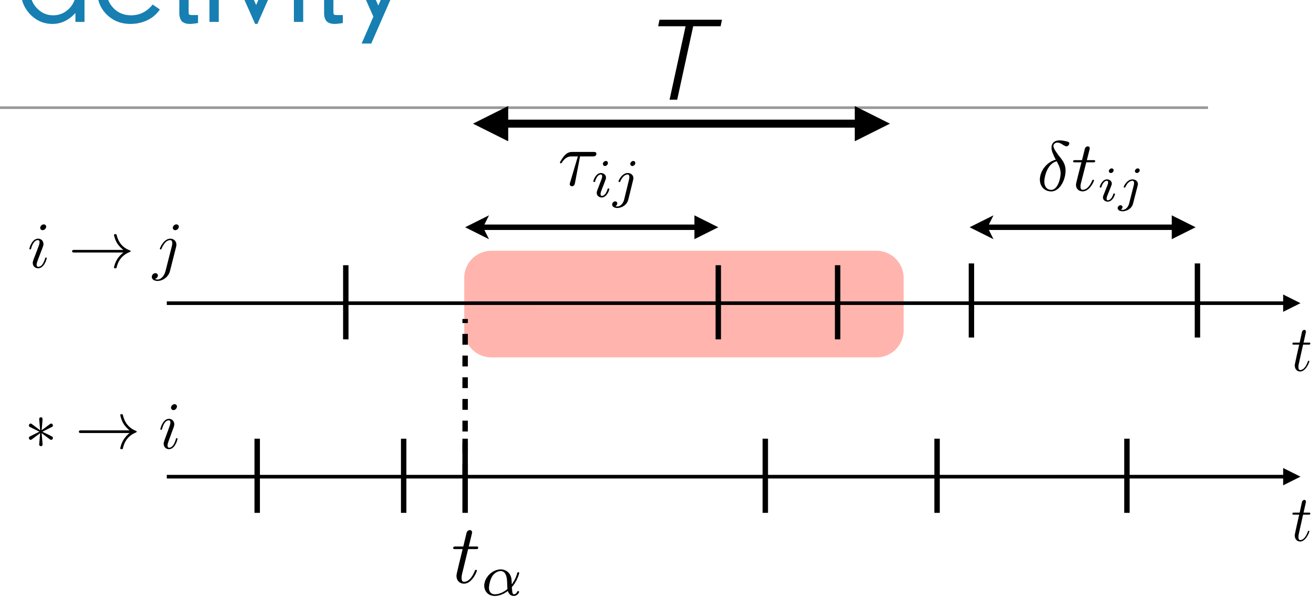


Miritello, G., Moro, E. & Lara, R., 2011. Dynamical strength of social ties in information spreading. *Physical Review E*, 83(4), p.045102.

Spreading including tie activity

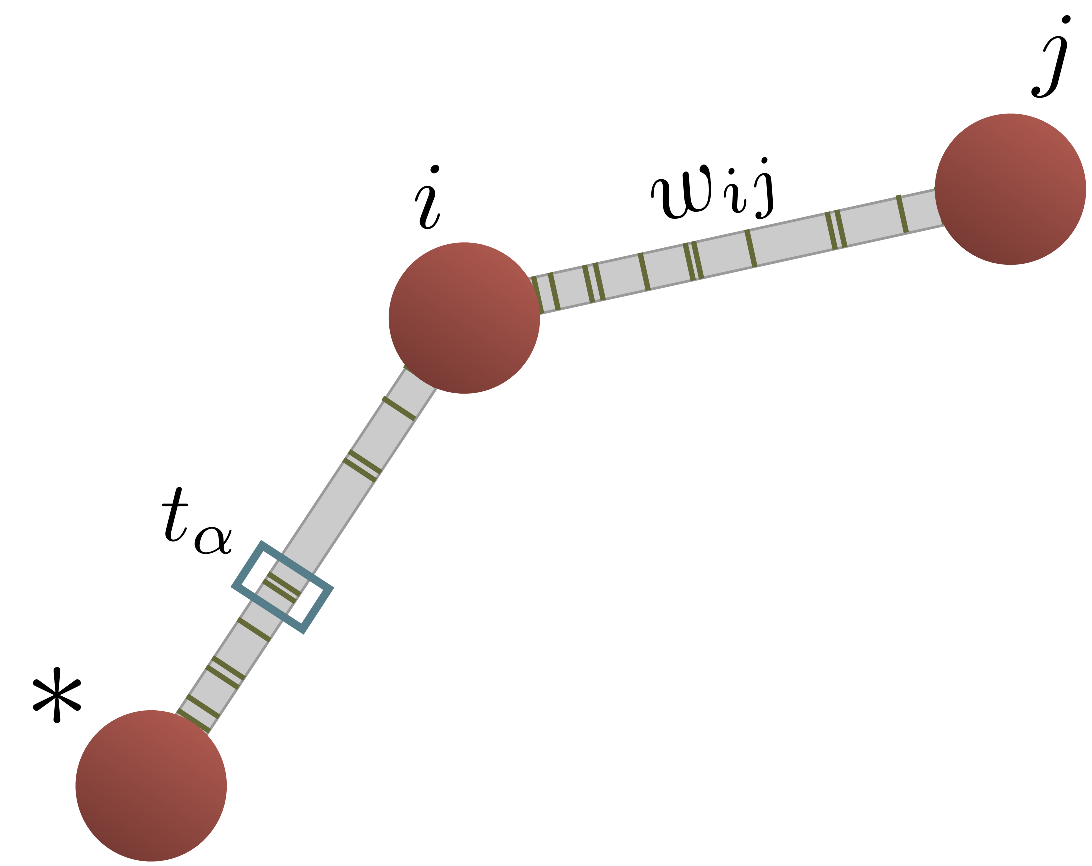
- **Transmissibility**:

$$\mathcal{T}_{ij} = 1 - (1-\lambda)^{n_{ij}(t_\alpha)}$$



- where

$n_{ij}(t_\alpha)$ = number of $i \to j$ events in the time interval $[t_\alpha, t_\alpha + T]$



Spreading including tie activity

- Assuming $* \longrightarrow i$ contacts are independent and equally probable in the observation period

$$\mathcal{T}_{ij}[\lambda, T] = \langle 1 - (1-\lambda)^{n_{ij}(t_\alpha)} \rangle_\alpha.$$

$$\mathcal{T}_{ij}[\lambda, T] = \sum_{n=0}^{\infty} P(n_{ij} = n; T)[1 - (1-\lambda)^n]$$

Probability of having *n* interactions between *i* and *j* in a time interval of length T

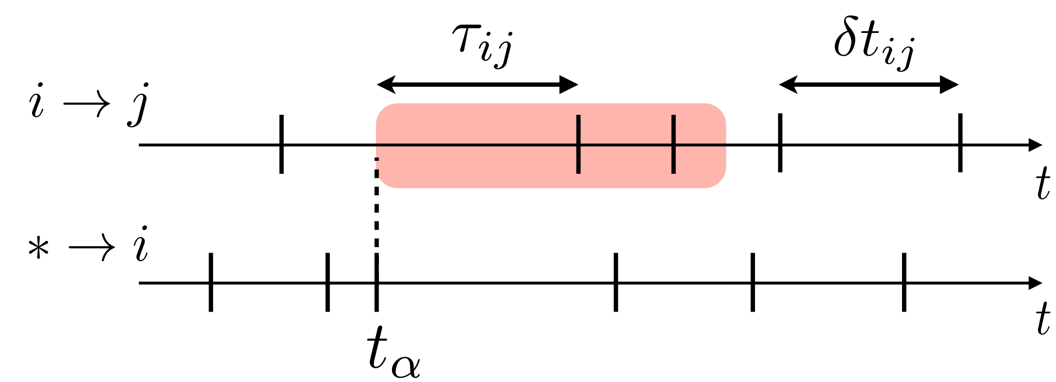
Spreading including tie activity

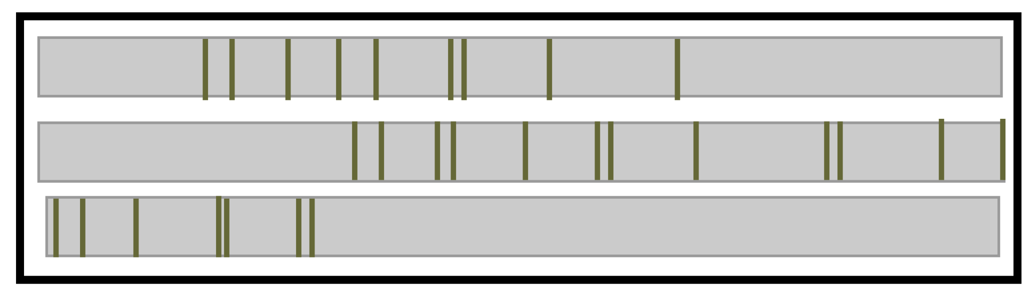
- Example: suppose that the w_{ij} interactions are equally distributed in the observation period.
- Then we have a Poisson process:
  - The interevent time distribution is the exponential pdf

$$P(\delta t_{ij}) = \rho e^{-\rho \delta t_{ij}}$$
$$\rho = w_{ij}/T_0$$

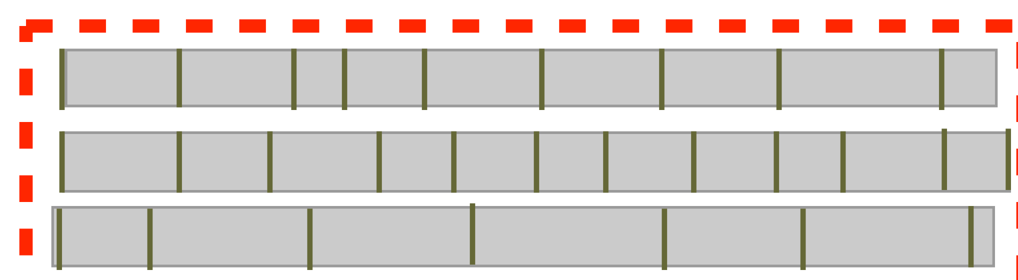
  - The number of events in a window of length T is given by the Poisson distribution.

$$P(n_{ij} = n; T) = \frac{e^{-\rho T}(\rho T)^n}{n!}$$





Ω



Ω

Spreading including tie activity

- Thus in the homogeneous (Poissonian) case:

$$\tilde{\mathcal{T}}_{ij}[\lambda, T] = 1 - e^{-\lambda\rho} = 1 - e^{-\lambda w_{ij} T/T_0}$$

- For small λ

$$\tilde{\mathcal{T}}_{ij}[\lambda, T] \simeq \lambda w_{ij} \frac{T}{T_0}$$

- For general processes? Real data?

Spreading including tie activity

$$\mathcal{T}_{ij}[\lambda, T] = \sum_{n=0}^{\infty} P(n_{ij} = n; T)[1 - (1 - \lambda)^n]$$

- General process. Approximations
  - If $\lambda \ll 1 \Rightarrow 1 - (1 - \lambda)^n \simeq \lambda n$

$$\mathcal{T}_{ij} \simeq \lambda \langle n_{ij} \rangle_{t_\alpha}$$

  - If $\lambda \simeq 1 \Rightarrow 1 - (1 - \lambda)^n \simeq 1 \text{ for } n > 0$

$$\mathcal{T}_{ij} \simeq 1 - P_{ij}^0$$

where $P_{ij}^0 = P(n_{ij} = 0; T) = \int_T^\infty P(\tau_{ij}) d\tau_{ij}$

Spreading including tie activity

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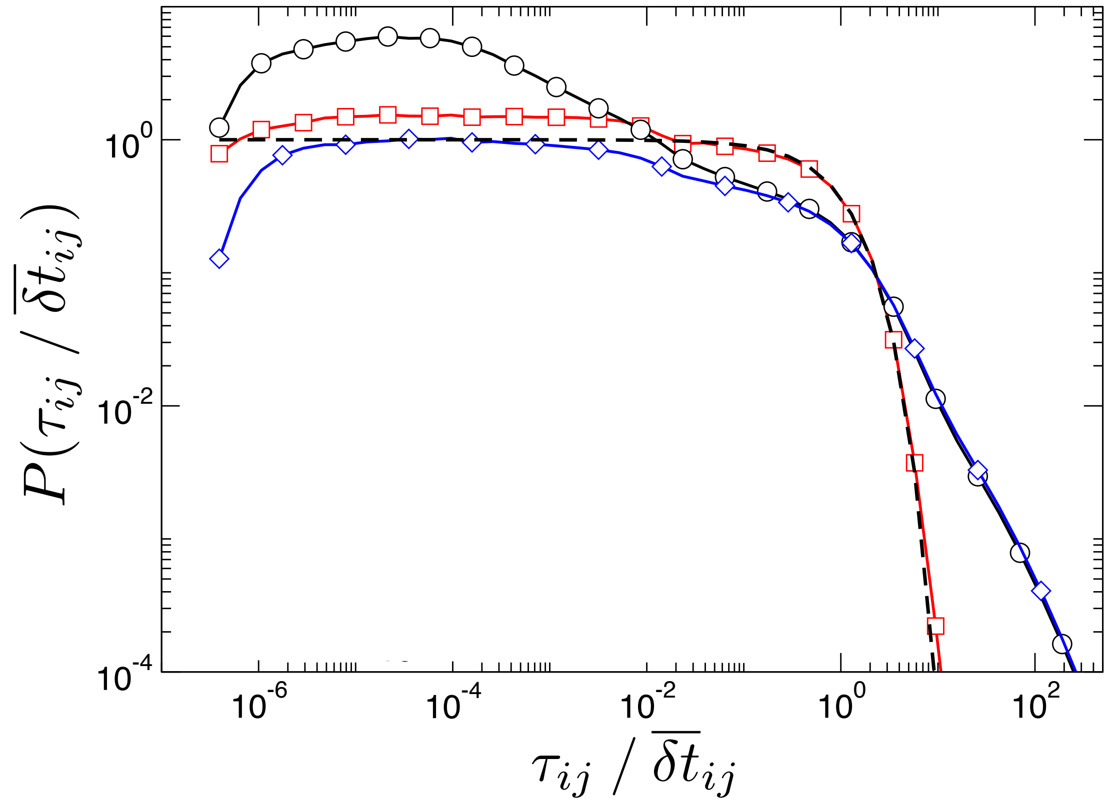
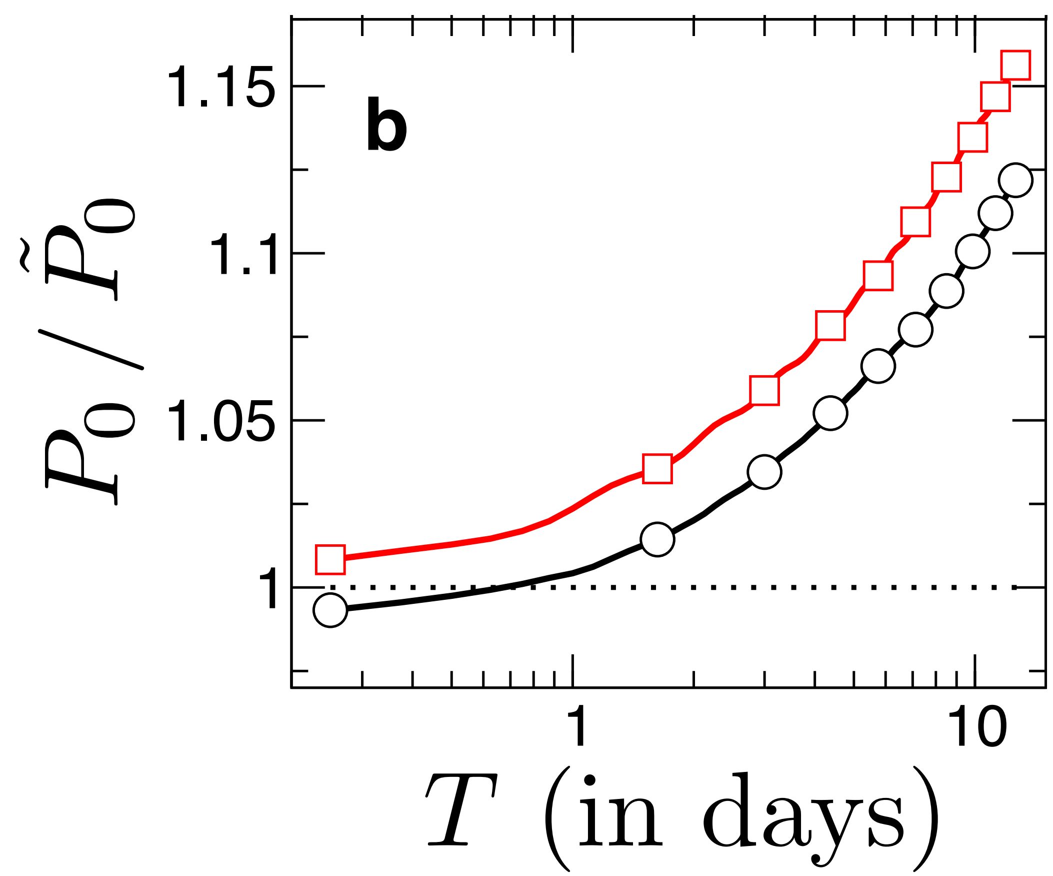
where $P^0_{ij} = P(n_{ij} = 0; T) = \int_T^{\infty} P(\tau_{ij}) d\tau_{ij}$

Spreading including tie activity

- $\lambda \simeq 1$
- Probability of no event P_{ij}^0

$$P_{ij}^0 = P(n_{ij} = 0; T) = \int_T^\infty P(\tau_{ij}) d\tau_{ij}$$





Long waiting times (bursts) make transmissibility smaller

$$\mathcal{T}_{ij} \simeq 1 - P_{ij}^0$$
$$\mathcal{T}_{ij} \leq \tilde{\mathcal{T}}_{ij}$$

Spreading including tie activity

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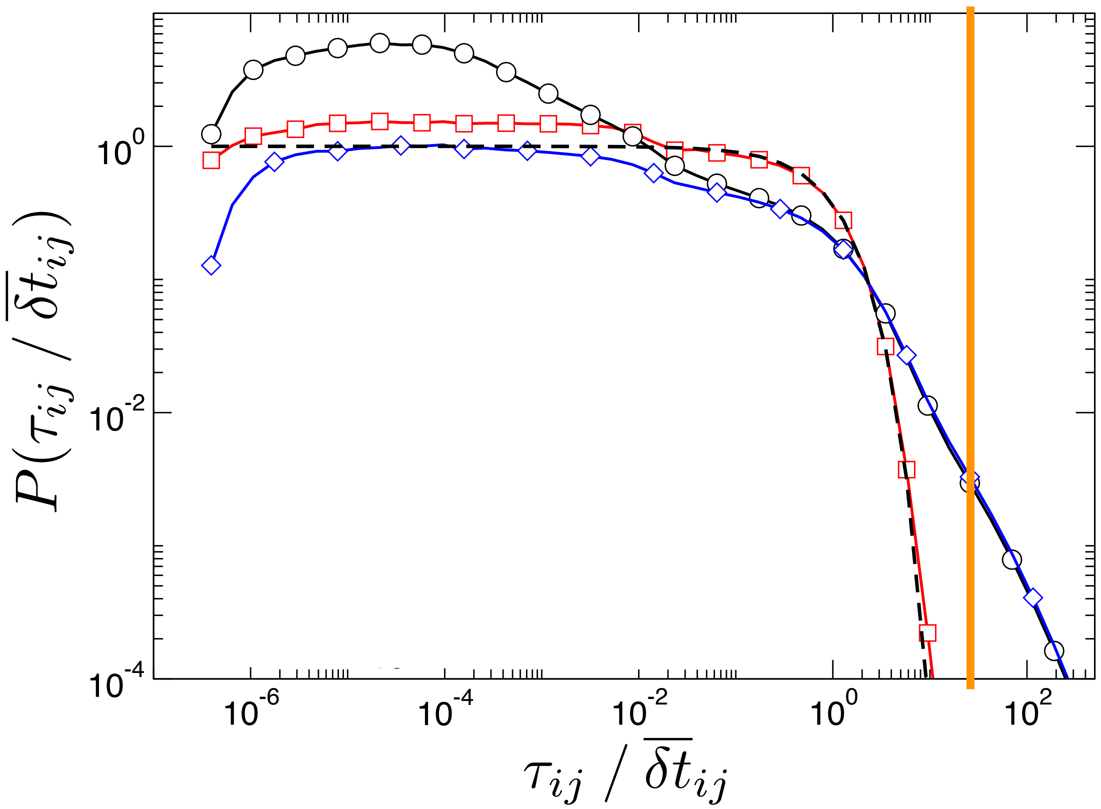

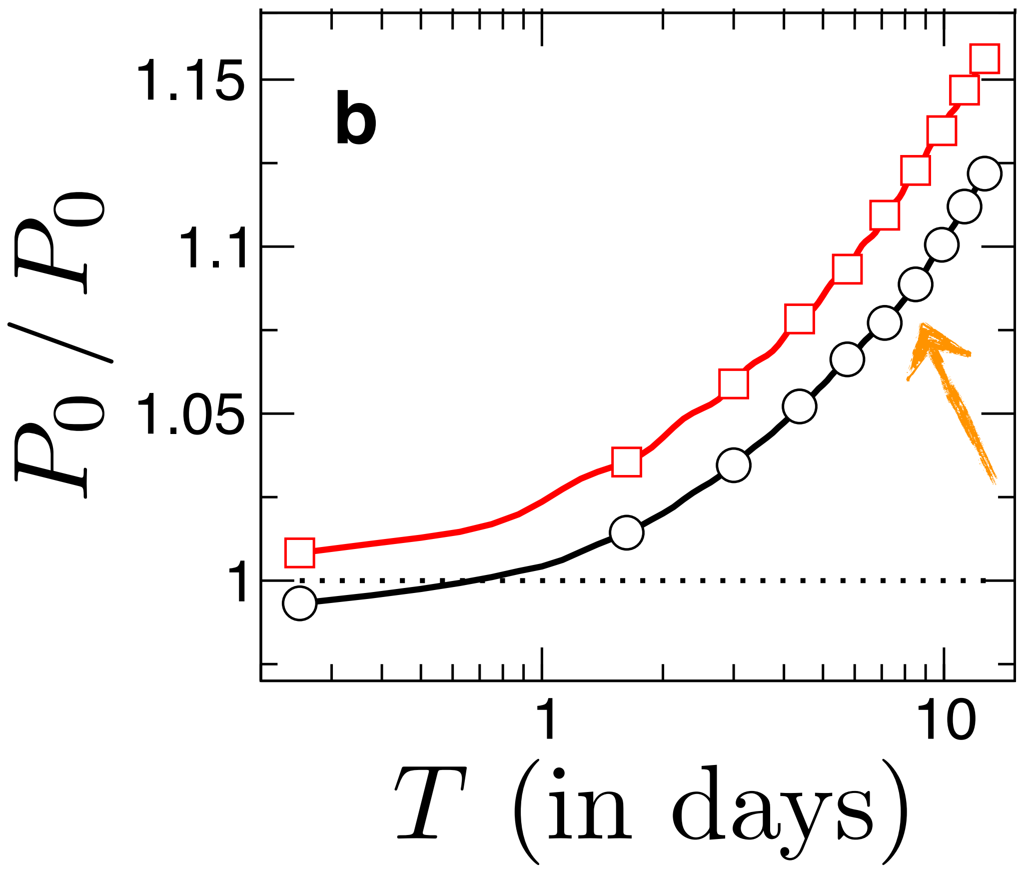

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Spreading including tie activity

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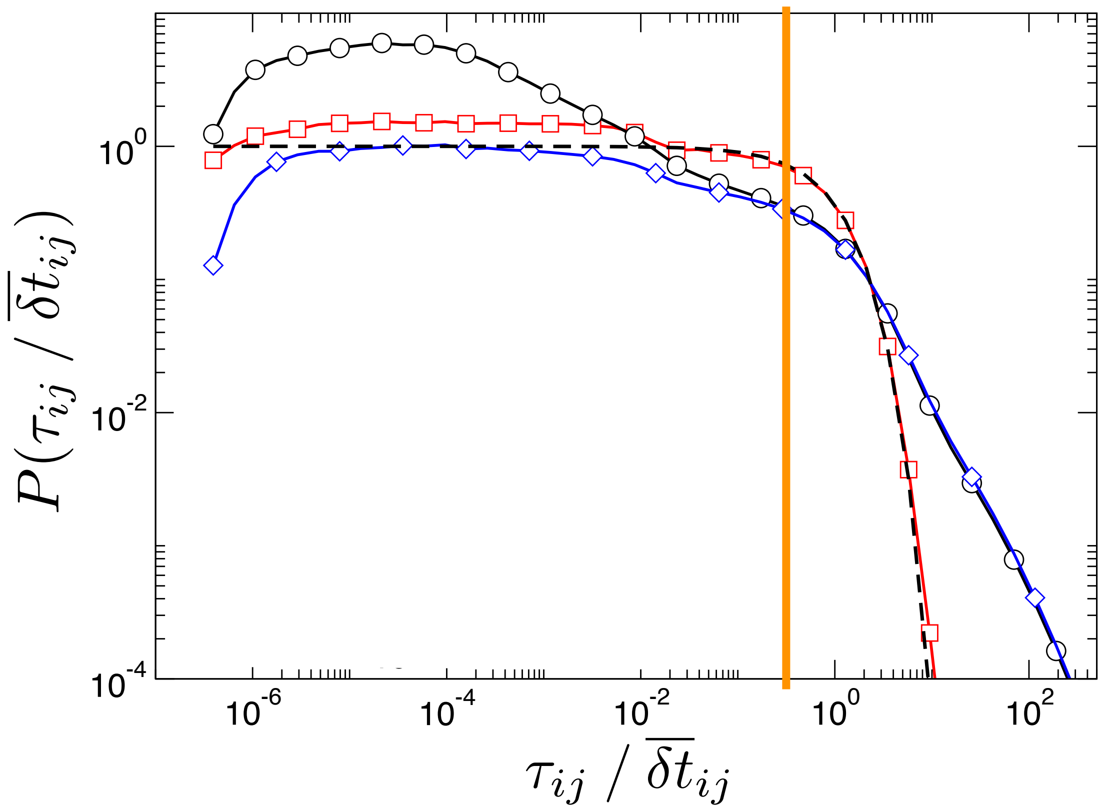

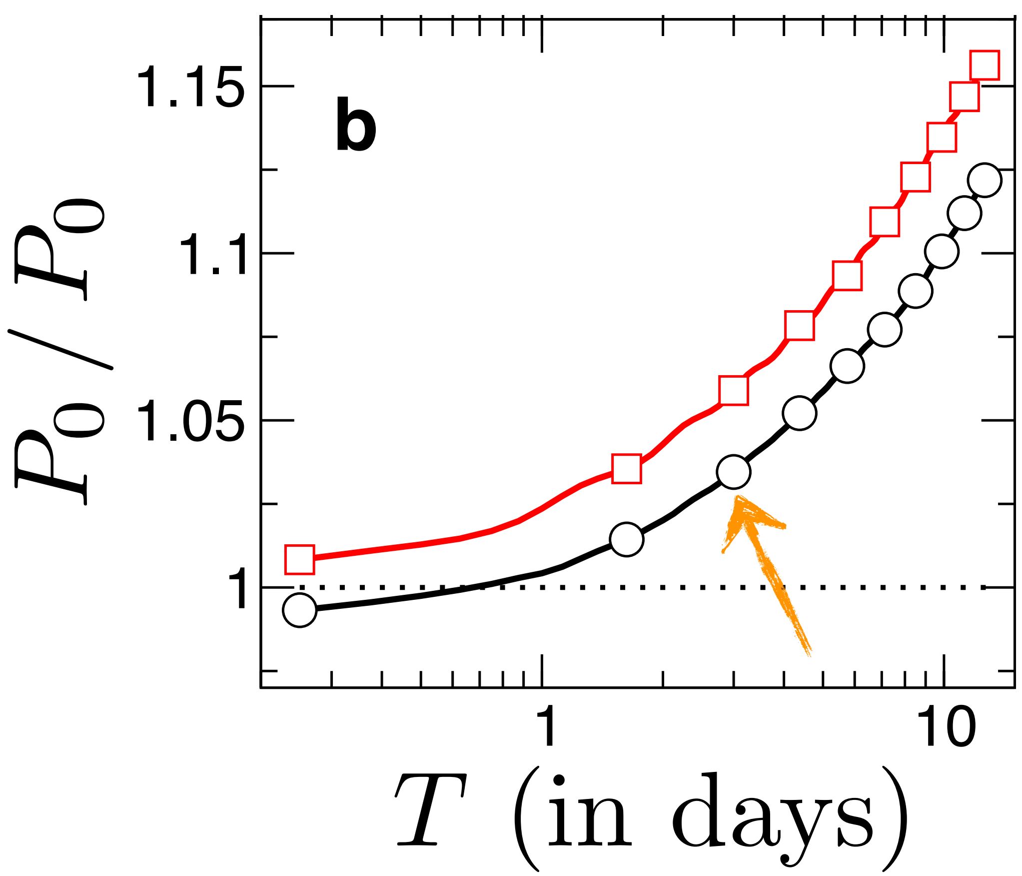

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Spreading including tie activity

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- Probability of no event P^0_{ij}

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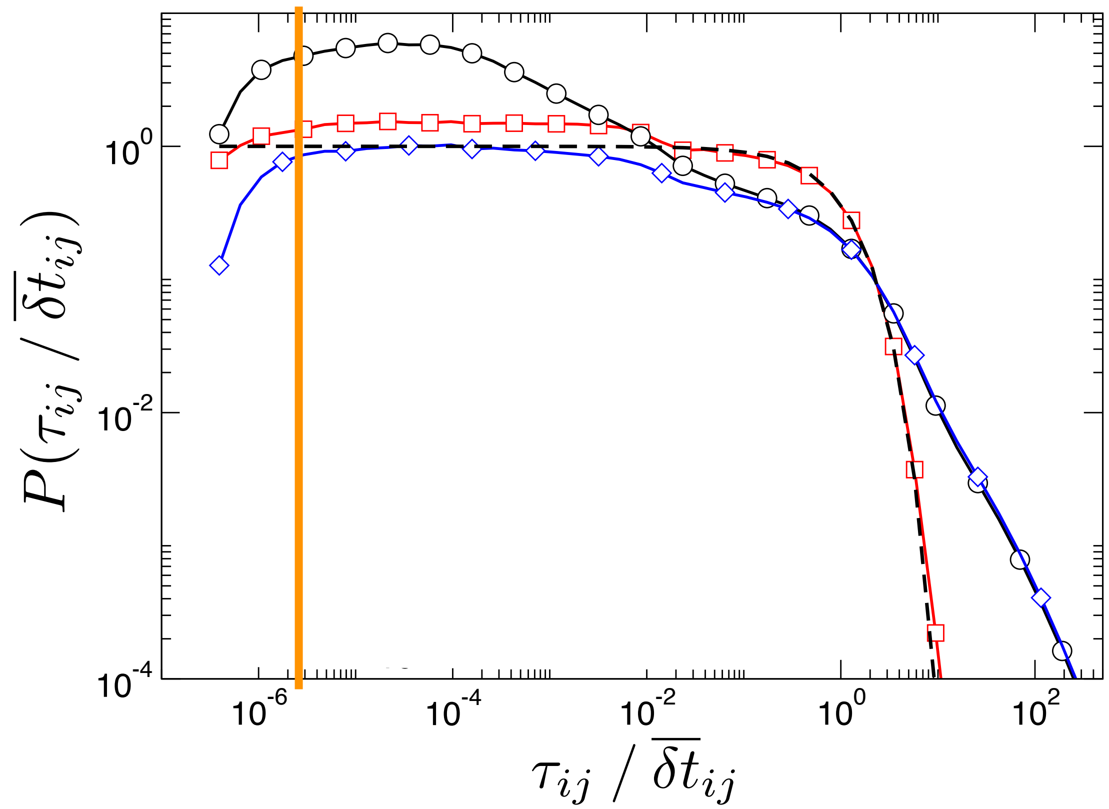
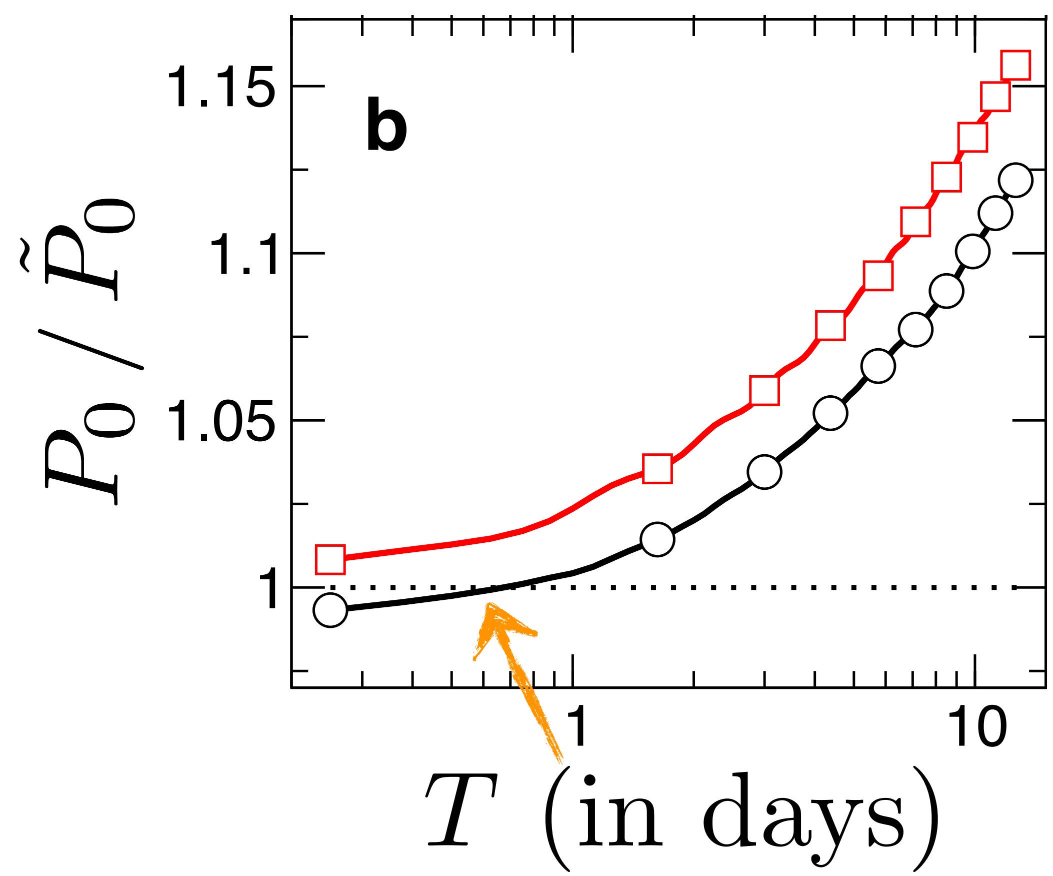




Long waiting times (bursts) make transmissibility smaller

$$\mathcal{T}_{ij} \simeq 1 - P^0_{ij}$$
$$\mathcal{T}_{ij} \leq \tilde{\mathcal{T}}_{ij}$$

Spreading including tie activity

- $\lambda \ll 1$
- Average number of events $\langle n_{ij} \rangle_{t_\alpha}$
  - If there is no correlation between tie activity

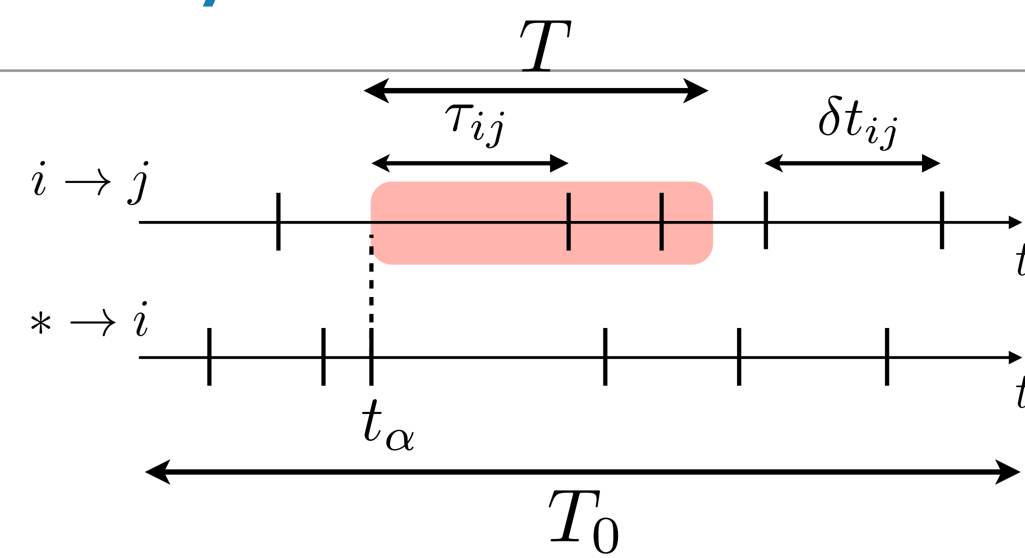
$$\langle \tilde{n}_{ij} \rangle_{t_\alpha} = w_{ij} \frac{T}{T_0}$$

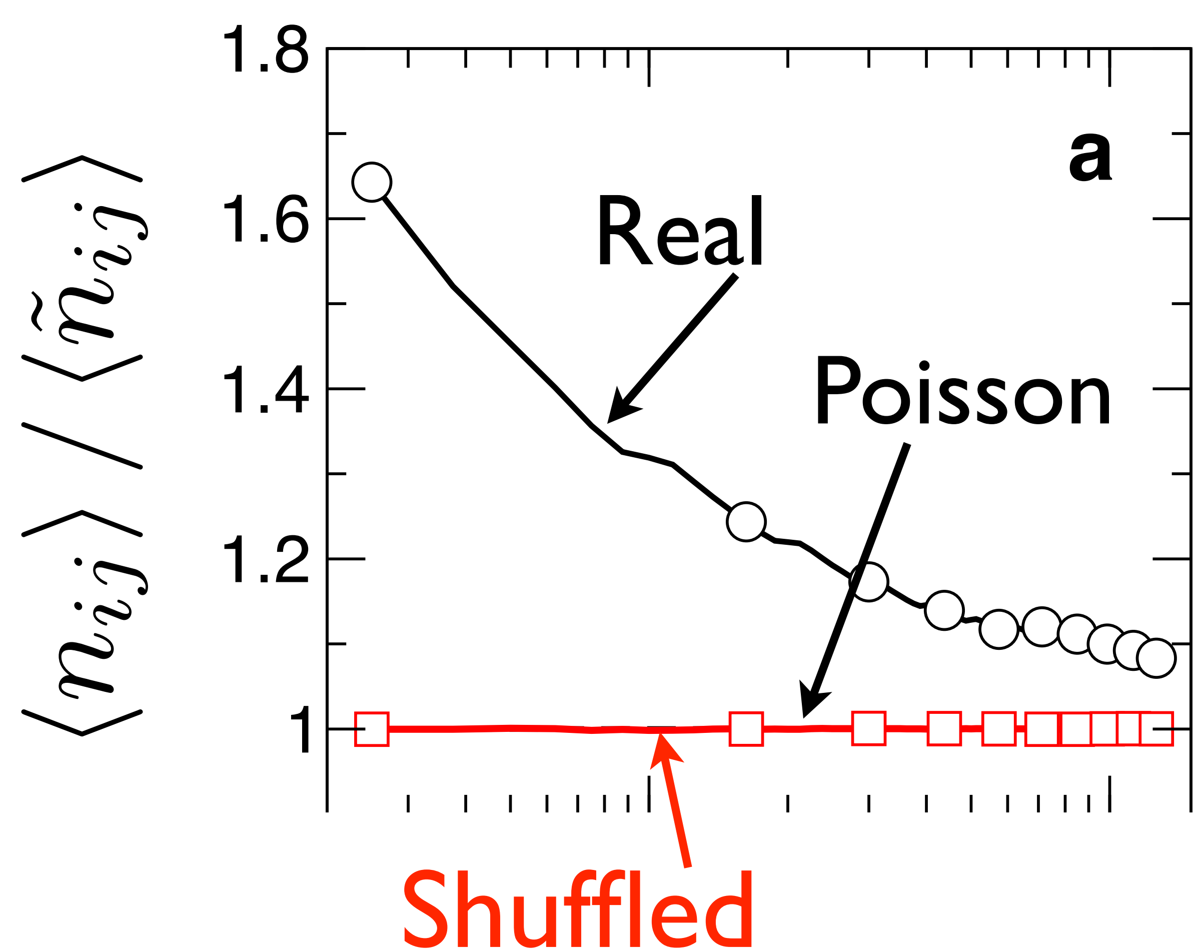
  - Correlation makes

$$\langle n_{ij} \rangle_{t_\alpha} \geq \langle \tilde{n}_{ij} \rangle_{t_\alpha}$$

and thus $(\mathcal{T}_{ij} \simeq \lambda \langle n_{ij} \rangle_{t_\alpha})$

$$\mathcal{T}_{ij} \geq \tilde{\mathcal{T}}_{ij}$$

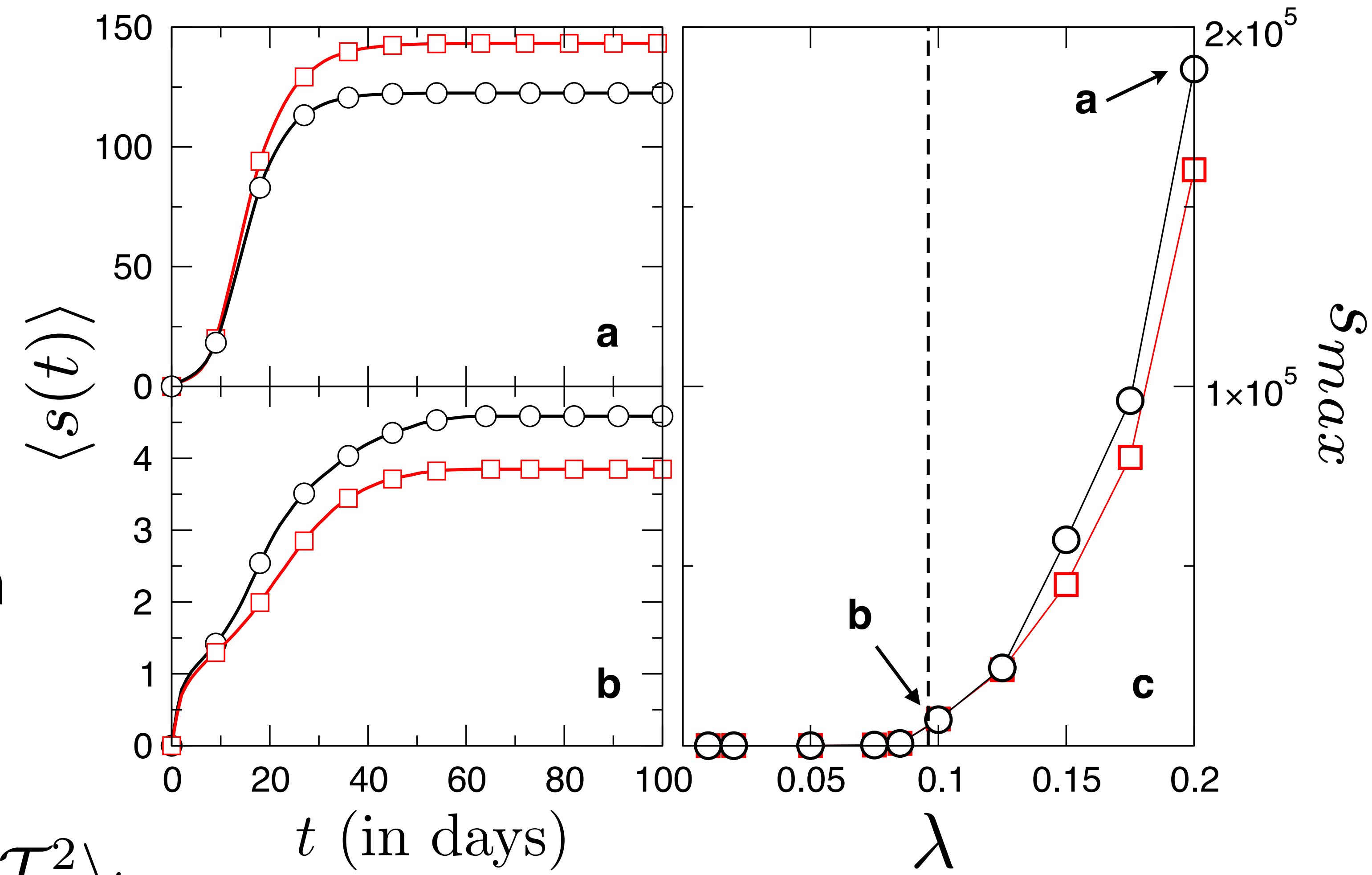




Spreading including tie activity

- Smaller transmissibility =
  - Slower propagation
  - Smaller propagation

- Transmissibility can be used to predict the dynamical percolation transition



$$R_1[\lambda, T] = \frac{\langle (\sum_j \mathcal{T}_{ij})^2 \rangle_i - \langle \sum_j \mathcal{T}_{ij}^2 \rangle_i}{\langle \sum_j \mathcal{T}_{ij} \rangle_i}.$$

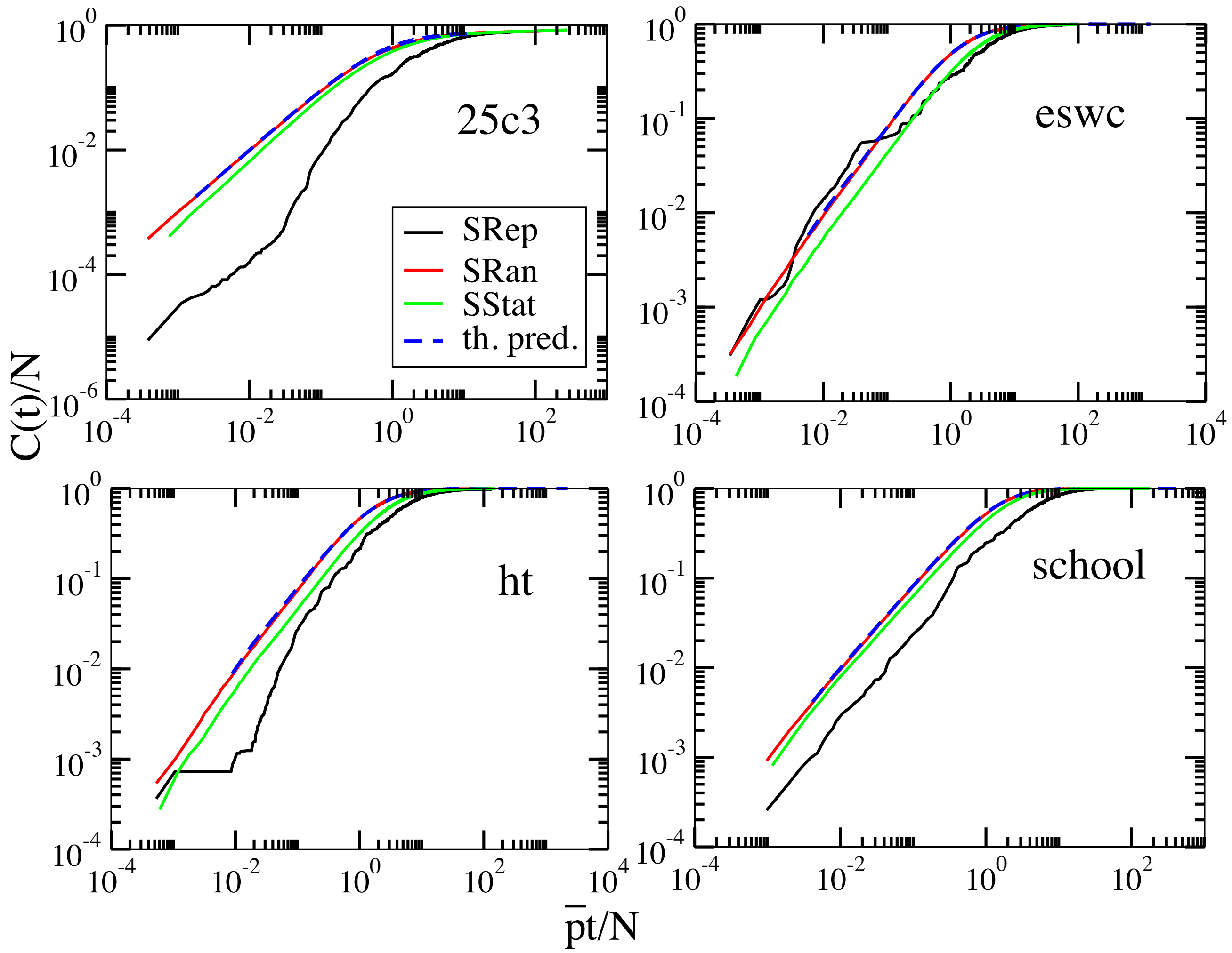
Spreading including tie activity

- Thus, in general

Property	effect on spreading
Bursty tie acitivity	Slows down
Conversations (correlated contact patterns)	Accelerates

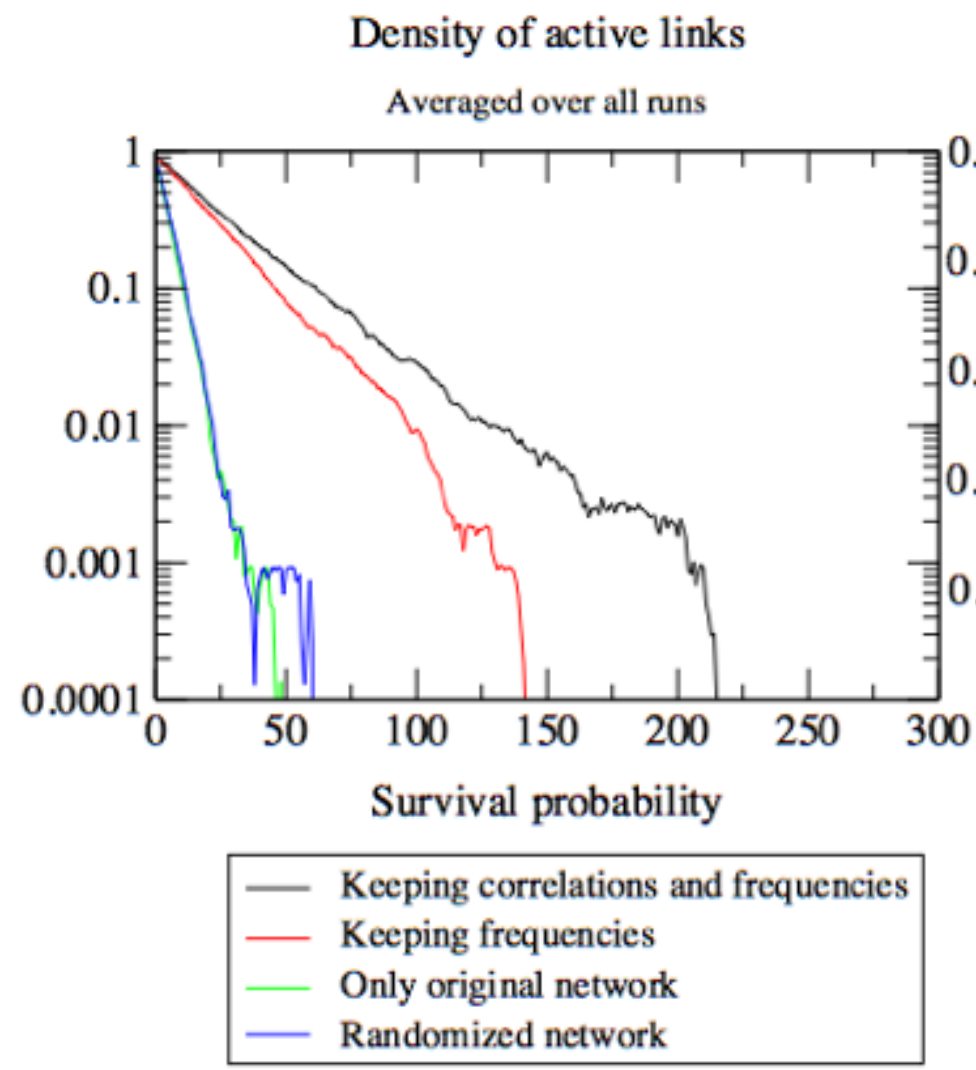
Other models

Random Walks



Starnini, M. et al., 2012. Random walks on temporal networks. *Physical Review E*, 85, pp.056115–056115.

Voter Model

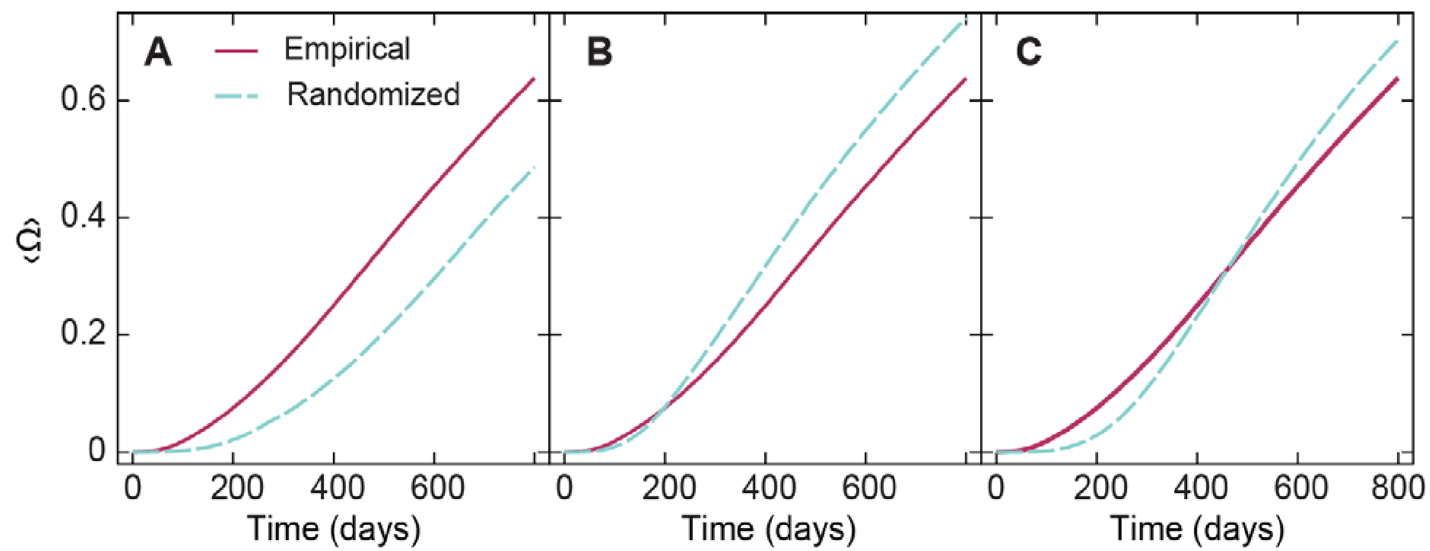


V. Eguiluz & EM, unpublished, 2011

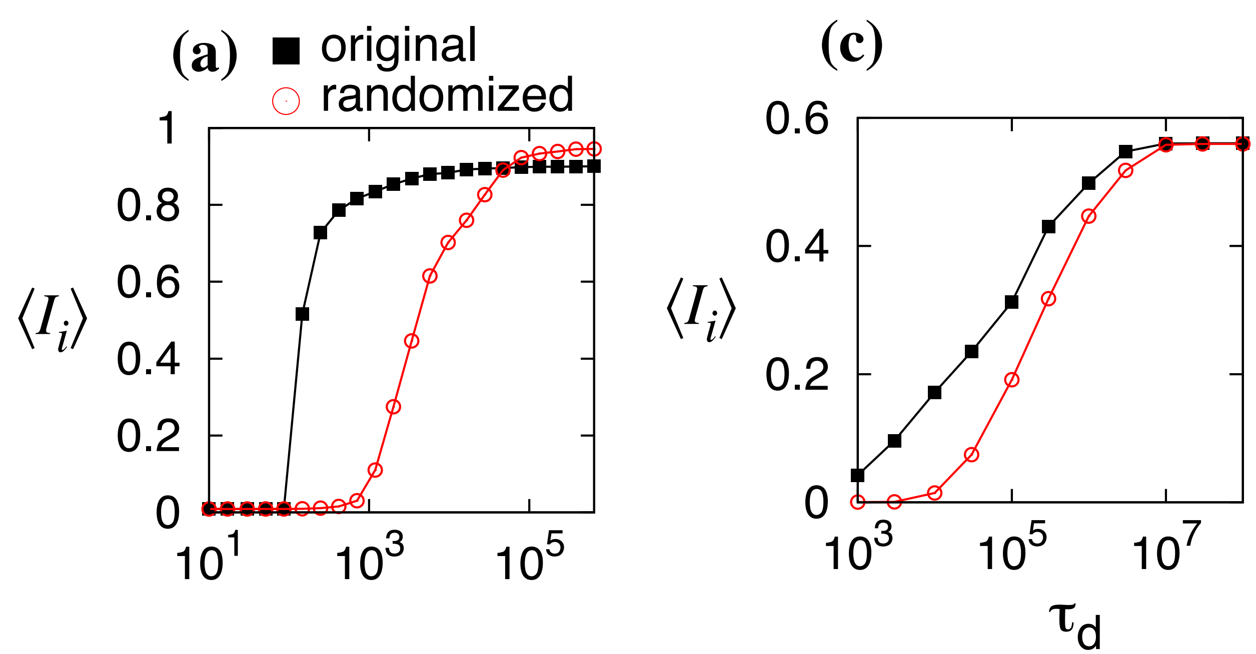
Spreading including tie activity

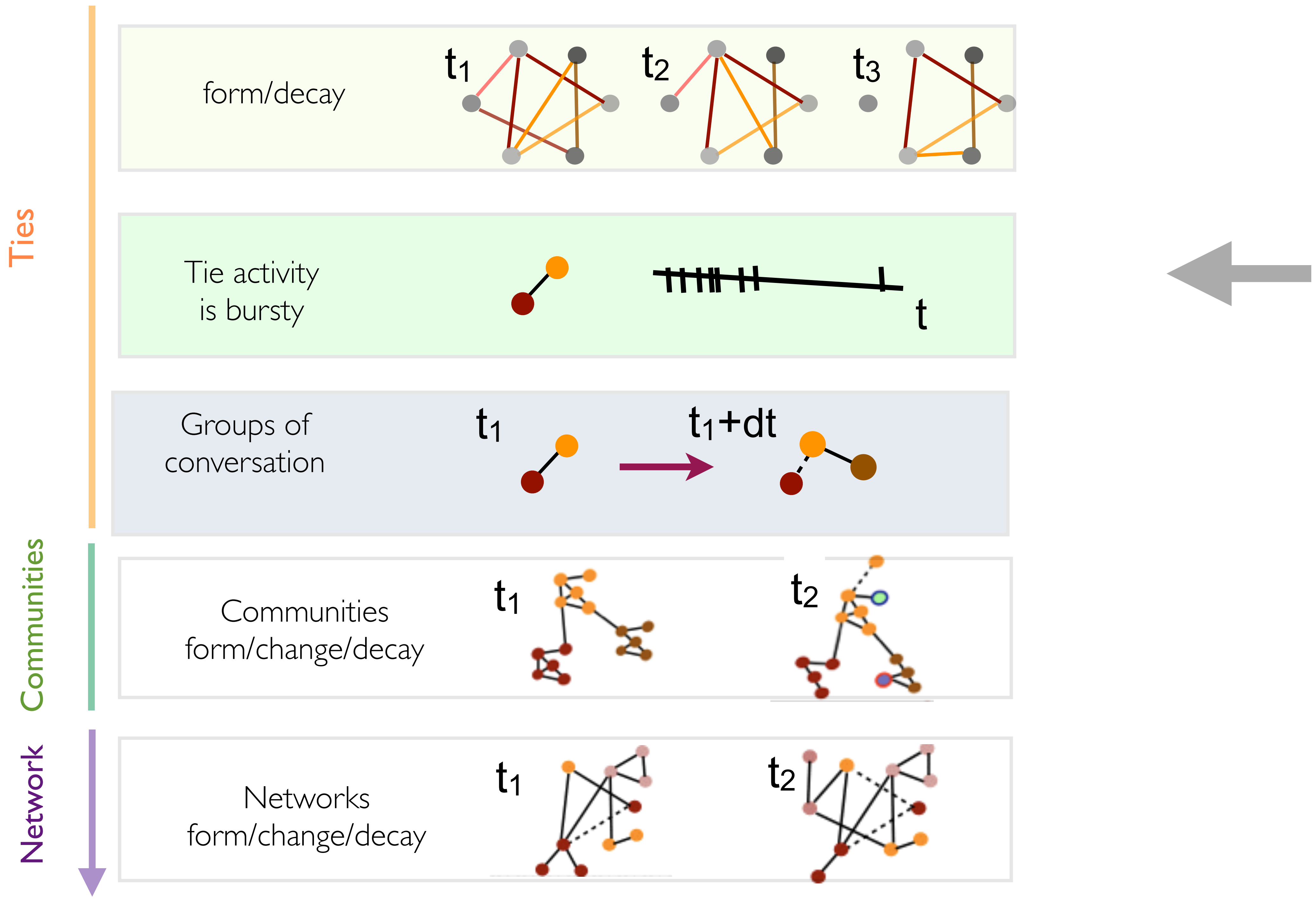
- Some data/models shows that burstiness accelerates contagion

Rocha, L., Liljeros, F. & Holme, P., 2011. Simulated epidemics in an empirical spatiotemporal network of 50,185 sexual contacts. *PLoS Computational Biology*, 7(3), p.e1001109.



Takaguchi, T., Masuda, N. & Holme, P., 2012. Bursty communication patterns facilitate spreading in a threshold-based epidemic dynamics. *PLoS ONE*, 8(7), pp.e68629–e68629.



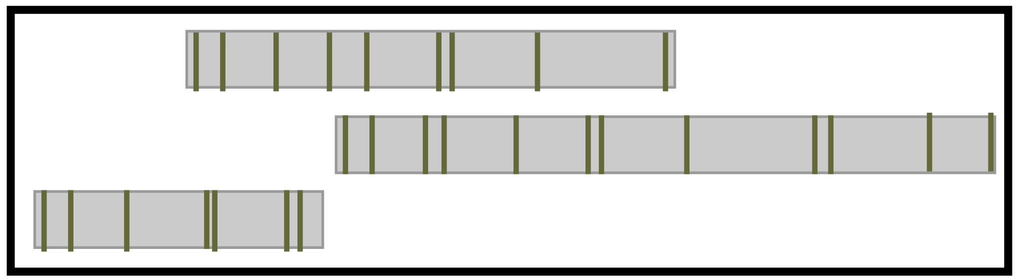


Effect of tie dynamics

2

Comparison with null models

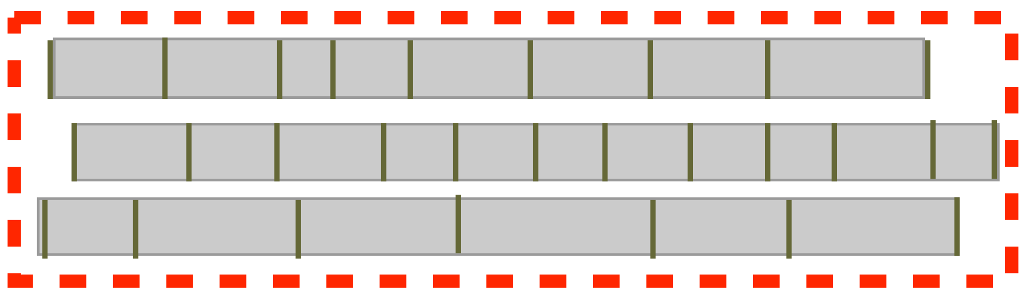
- Real data



Ω

P(dt) heavy tailed
Correlated bursts
Correlated tie activity
Temporal motifs
Tie dynamics

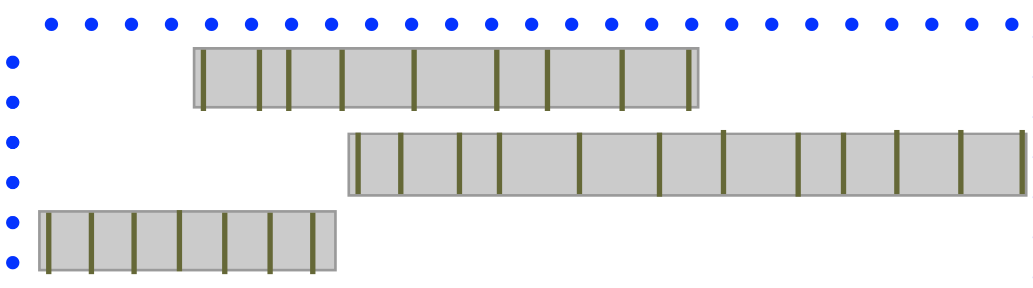
- Shuffled data (1)



Ω

P(dt) exponential
Uncorrelated bursts
Uncorrelated tie activity
No temporal motifs
No tie dynamics

- Shuffled data (2)



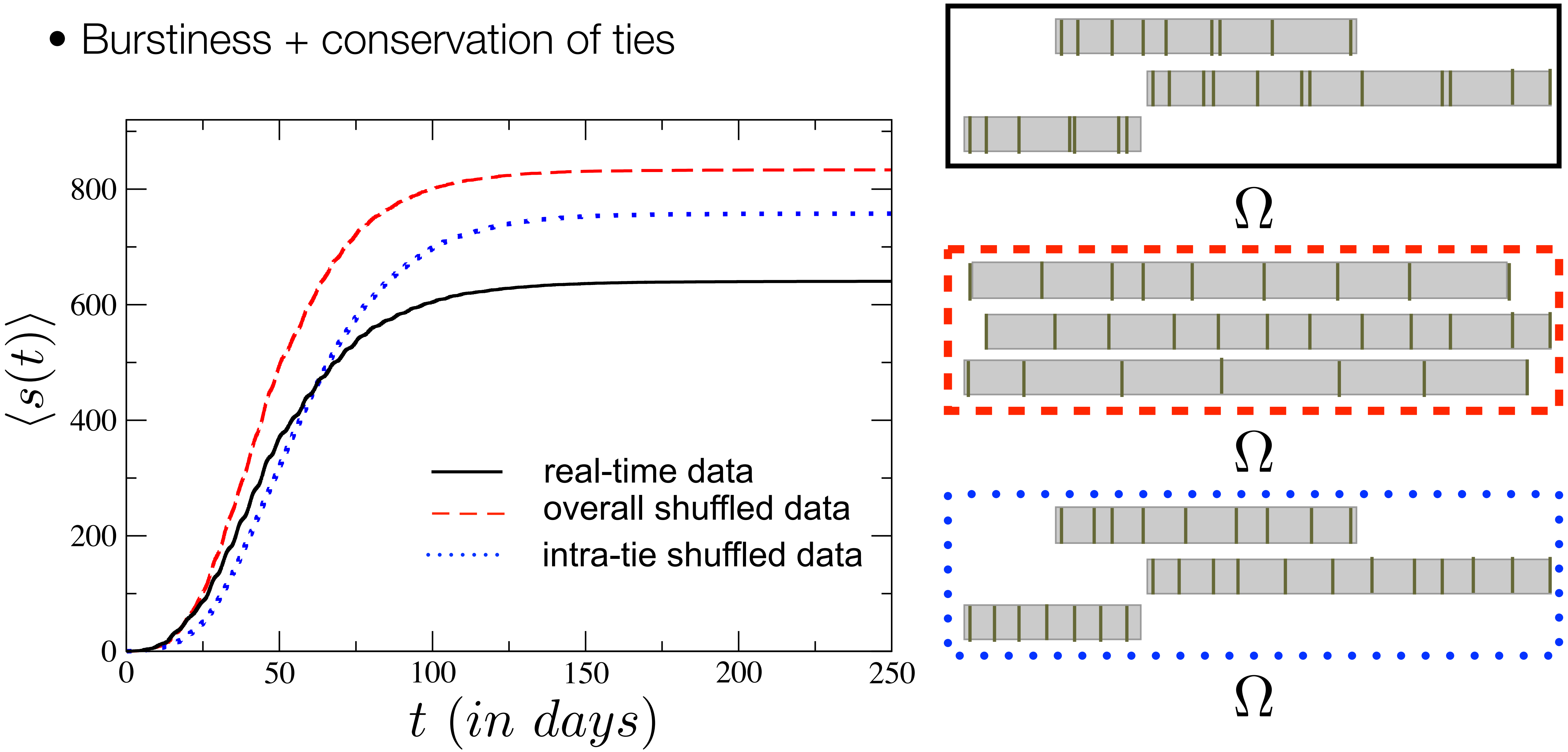
Ω

P(dt) exponential
Uncorrelated bursts
Uncorrelated tie activity
Temporal motifs ?
Tie dynamics

Tie dynamics

Miritello, G. (2013). *Temporal Patterns of Communication in Social Networks*. Springer.

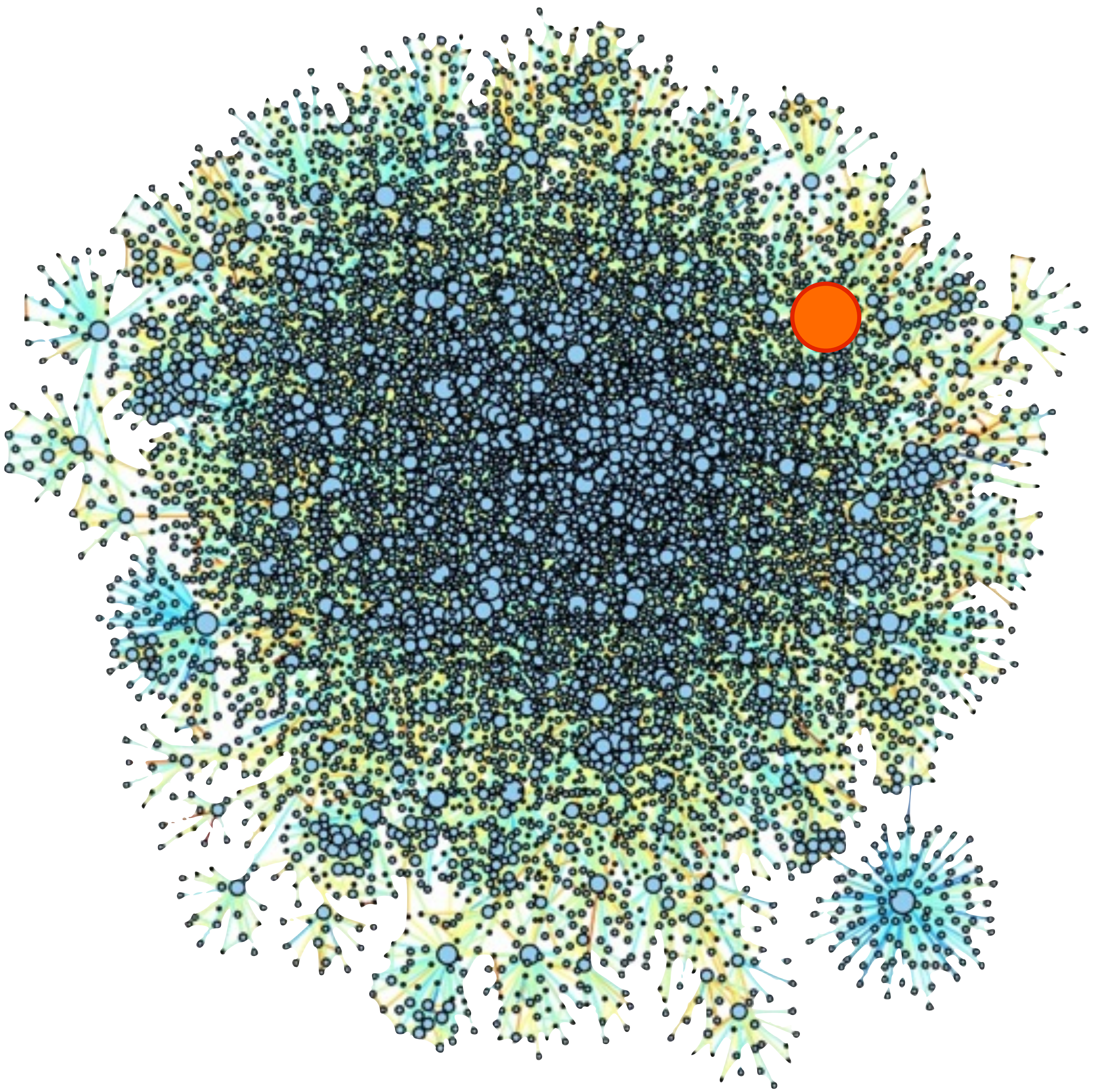
- Burstiness + conservation of ties



- Half of the slowing effect comes from destroying tie dynamics in the **shuffling**

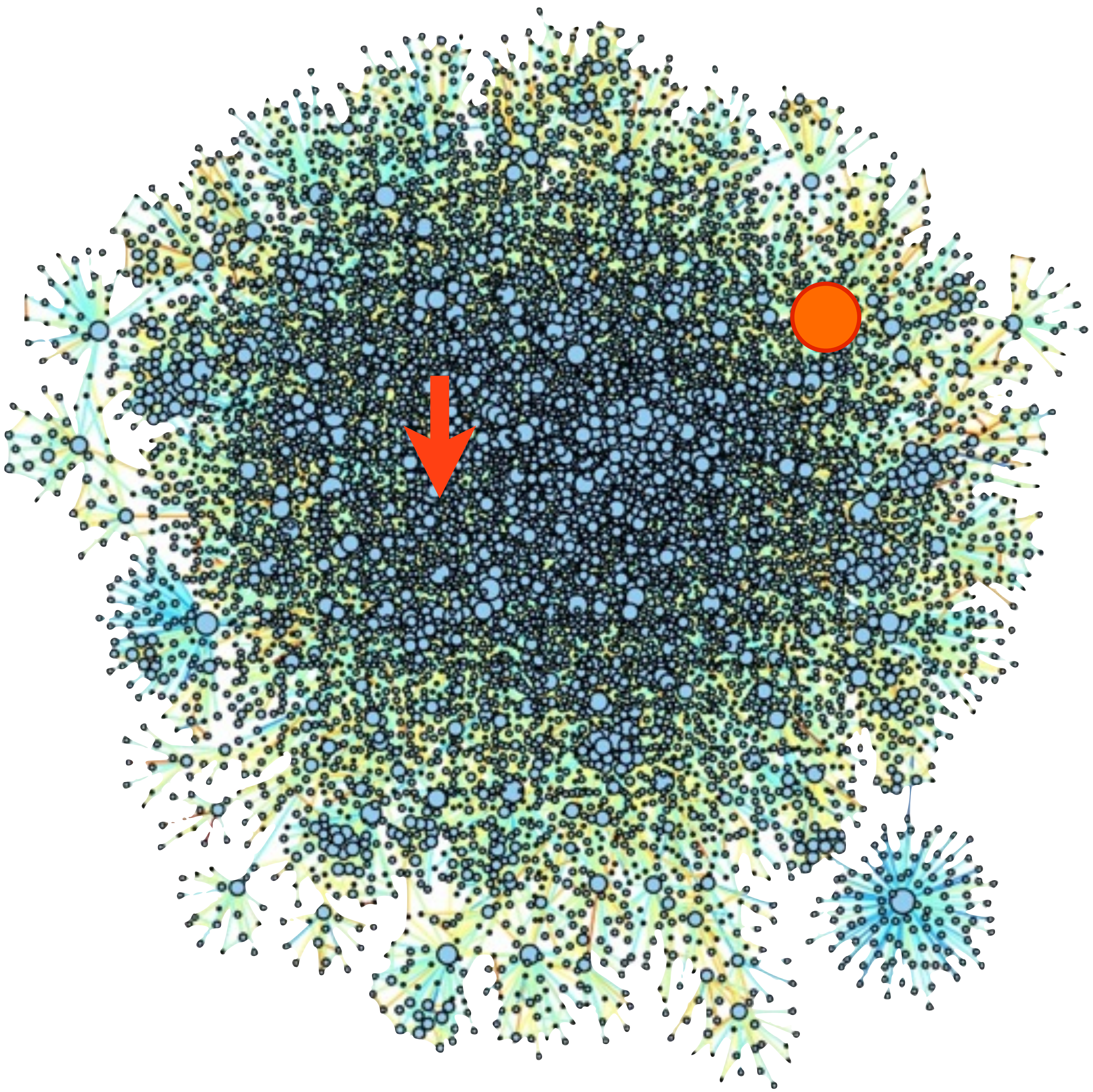
Tie dynamics

- Do strategies give an information awareness advantage?



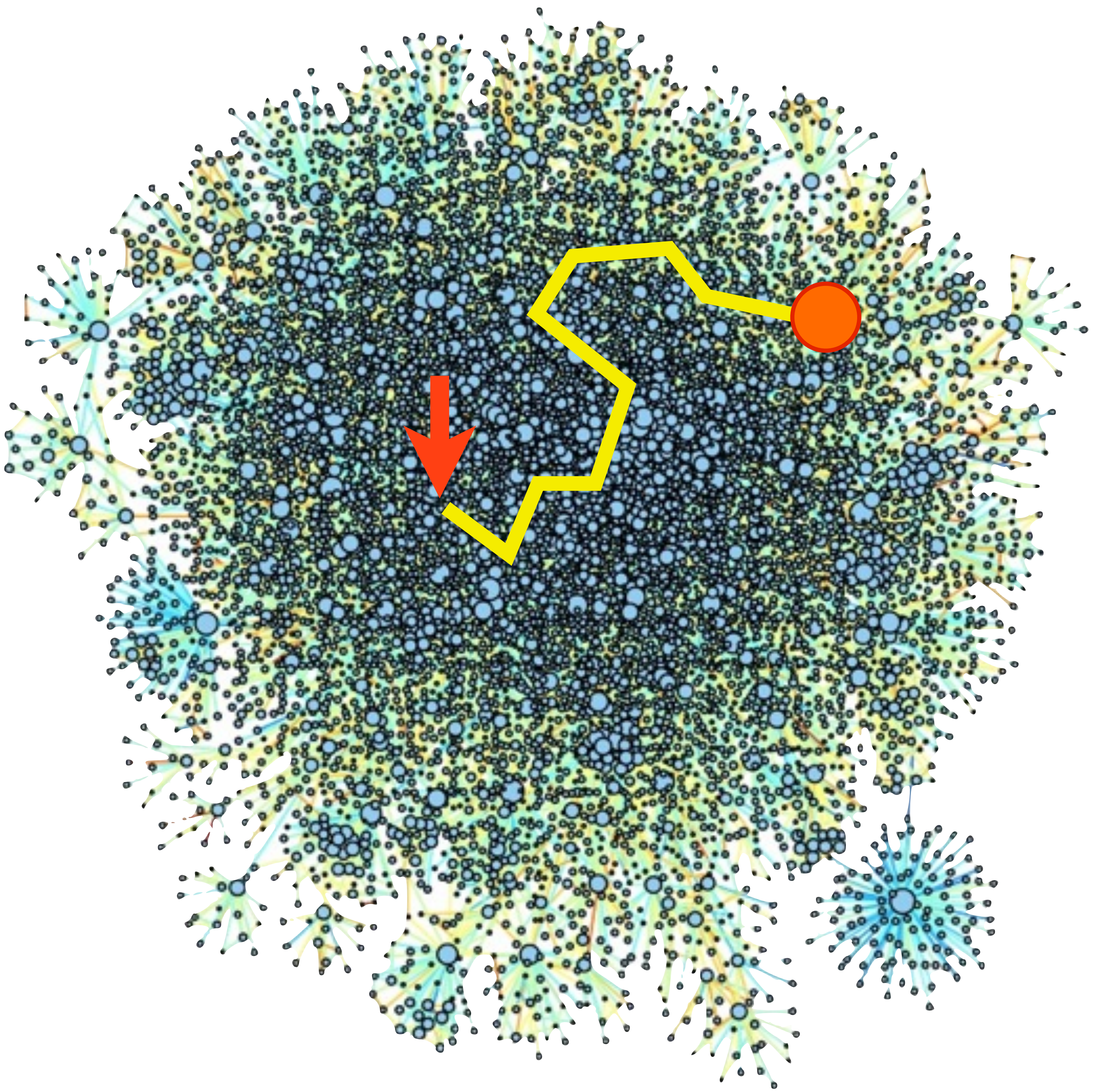
Tie dynamics

- Do strategies give an information awareness advantage?



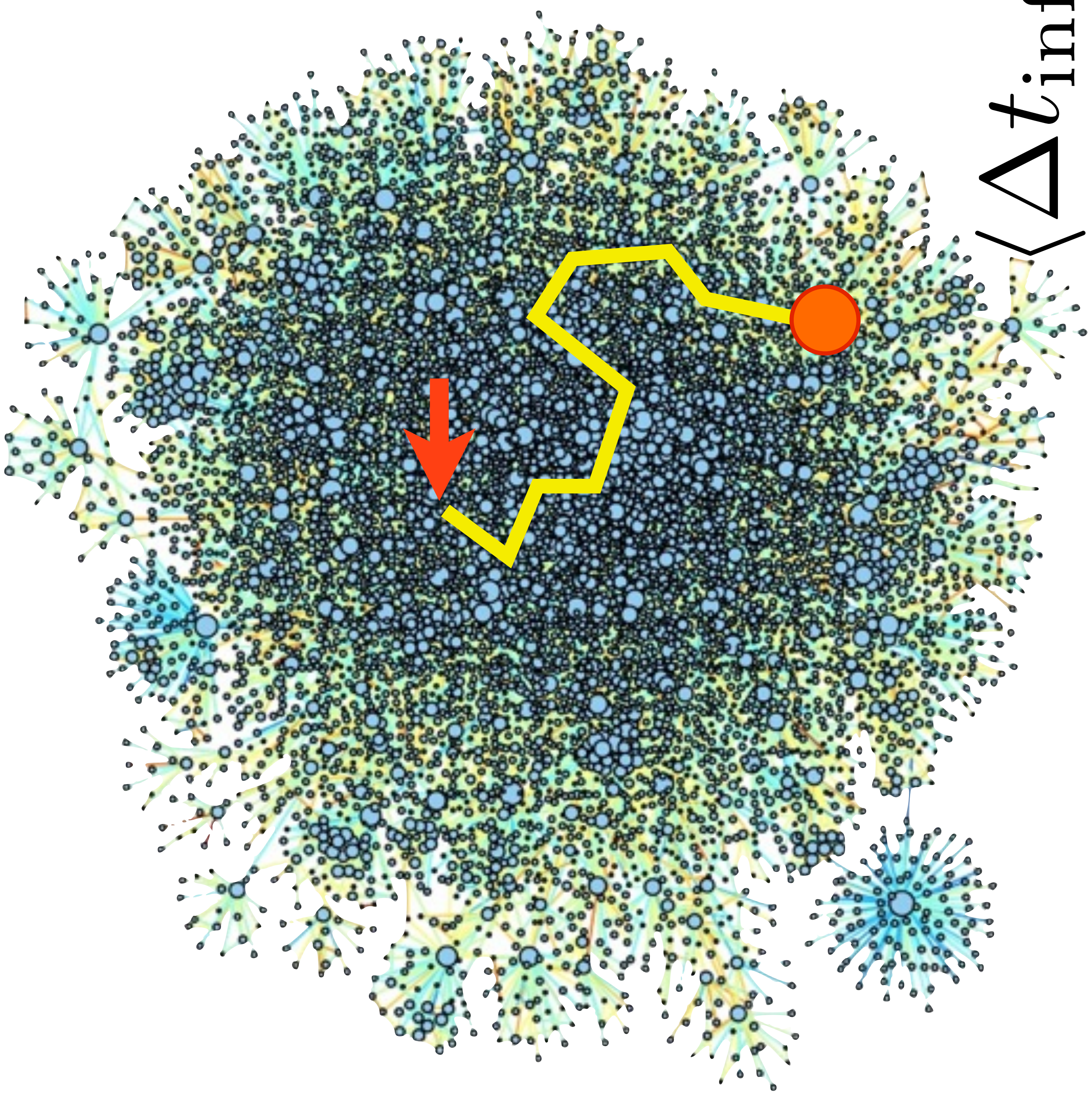
Tie dynamics

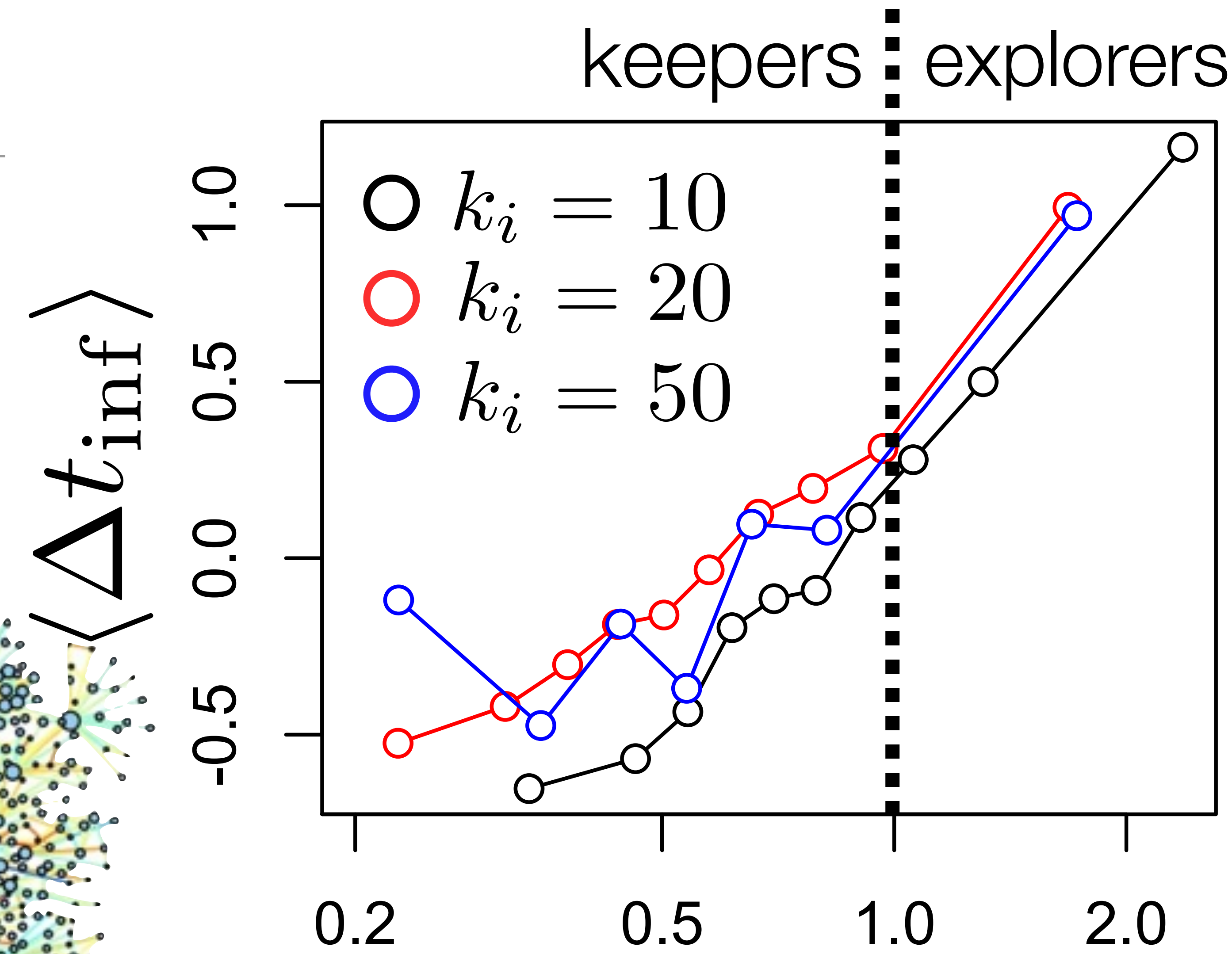
- Do strategies give an information awareness advantage?



Tie dynamics

- Do strategies give an information awareness advantage?





Social keepers received information before

Miritello, G. et al., 2013. Limited communication capacity unveils strategies for human interaction. *Scientific Reports*, 3.

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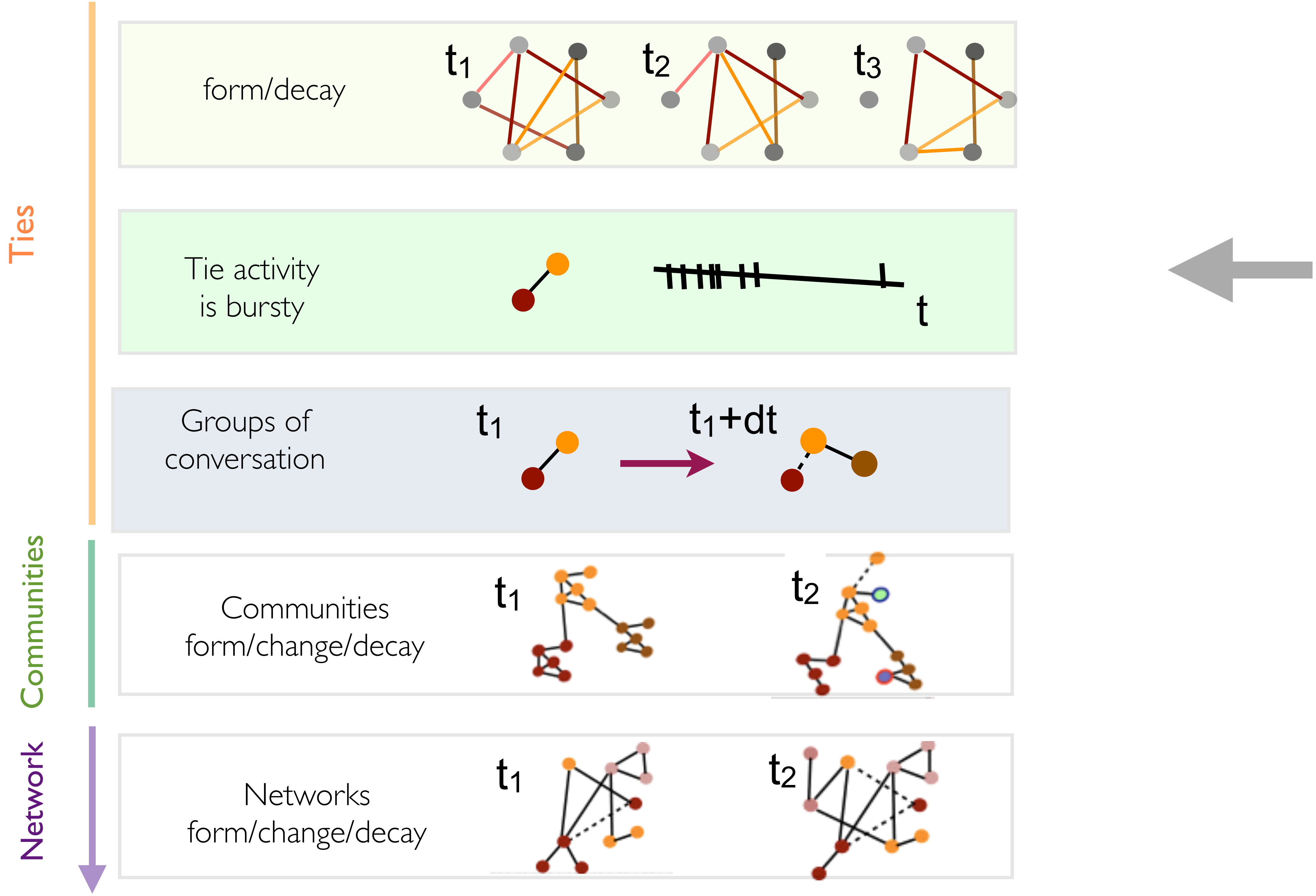
Spreading including tie dynamics

- Thus, in general

Property	*Effect on spreading*
Bursty tie acitivity	Slows down
Conversations (correlated contact patterns)	Accelerates
Tie dynamics	Slows down



Models for temporal/dynamical networks

3

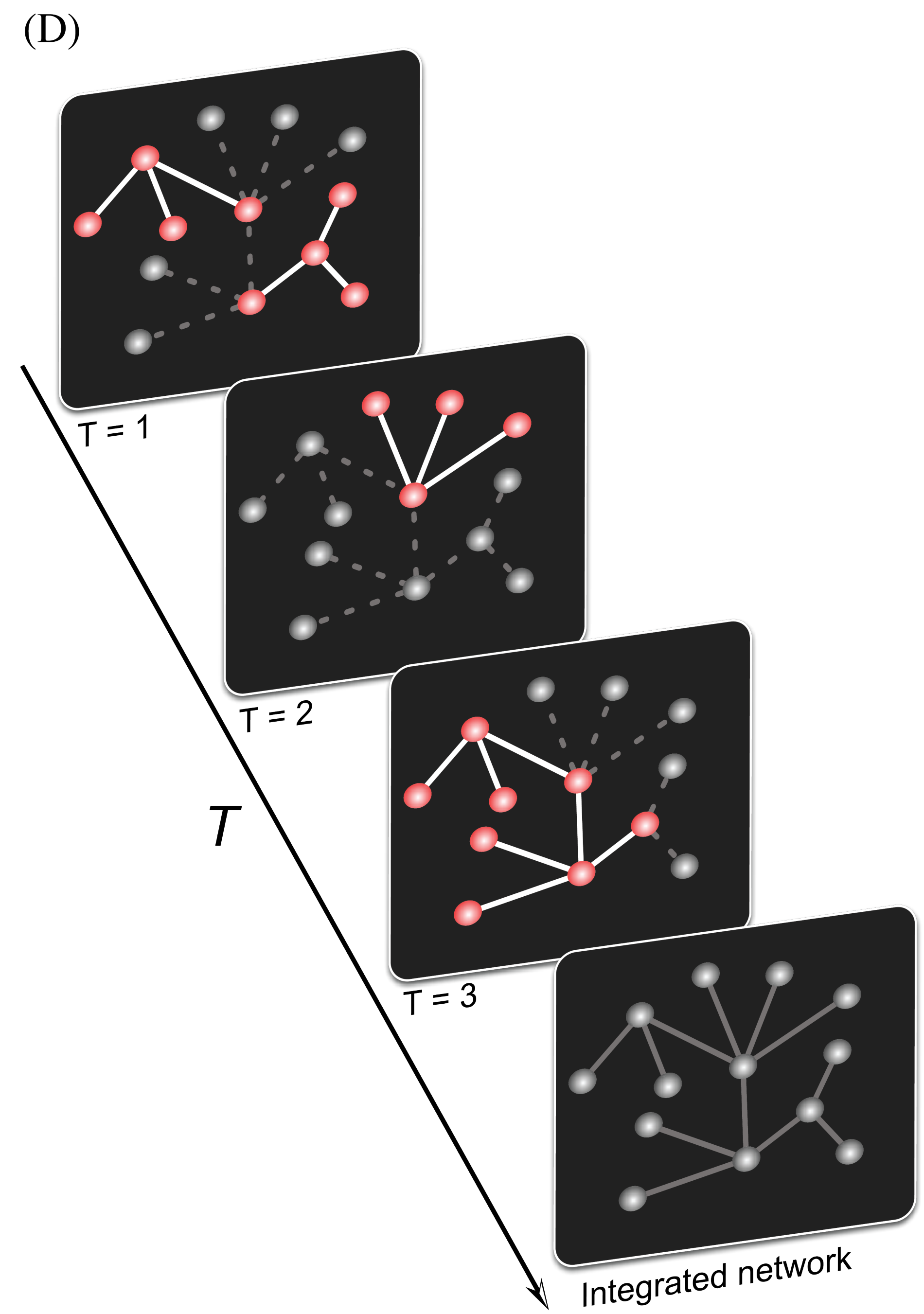
Models for temporal networks

- Activity driven model

Perra, N. et al., 2012. Activity driven modeling of time varying networks. *Scientific Reports*, 2.

  - Each node is assigned an activity a_i from a probability distribution P(a)
  - At each time step t the node is activated and create m links with other nodes
  - At next time step t+Δt all edges are removed
  - With memory:

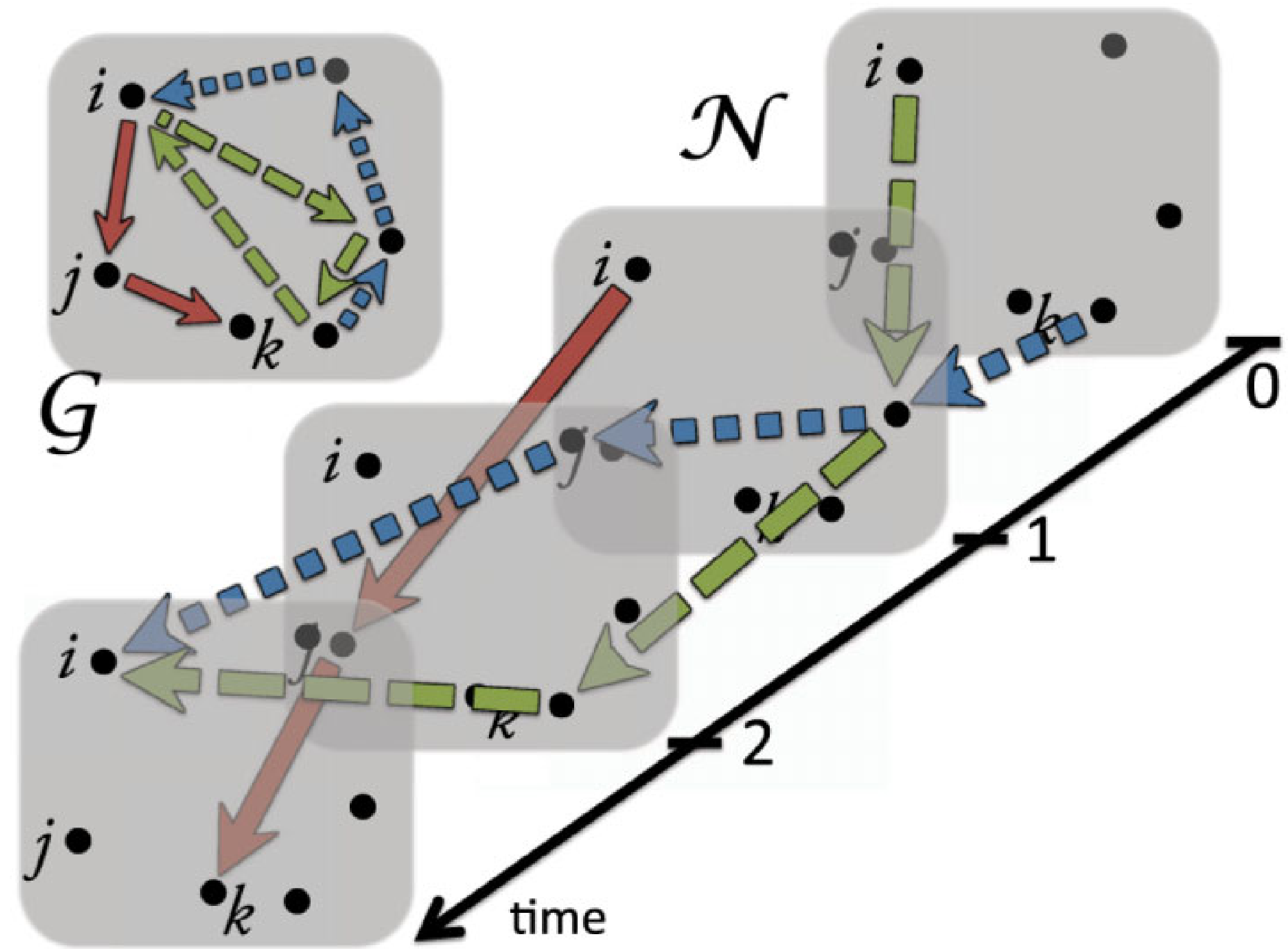
Karsai, M., Perra, N. & Vespignani, A., 2013. Time varying networks and the weakness of strong ties. *Scientific Reports*, 4, pp.4001–4001.



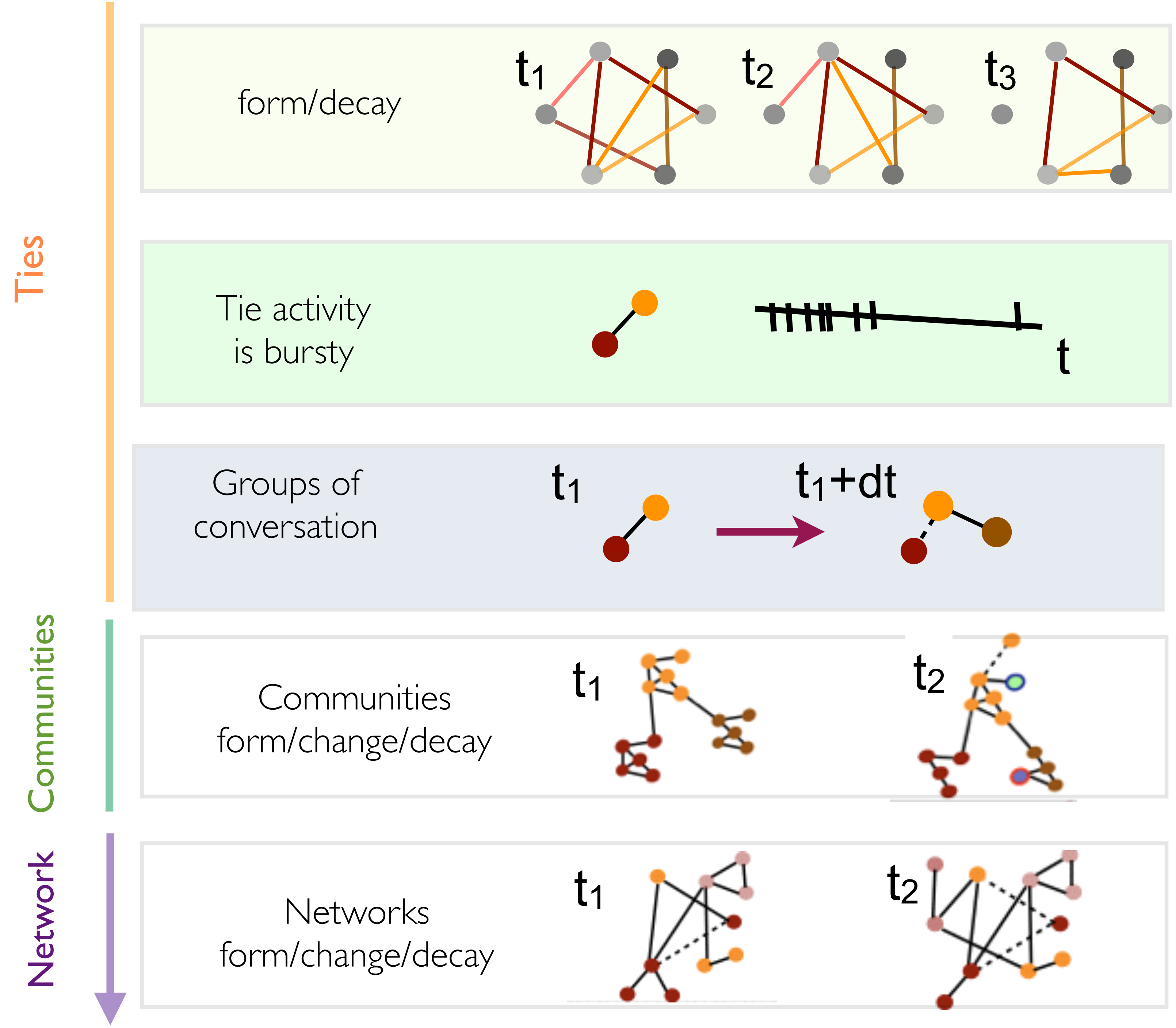
Models for temporal networks

- *Random itinearies*

Barrat, A. et al., 2013. Modeling Temporal Networks Using Random Itineraries. *Physical Review Letters*, 110



  - Given an aggregated graph with egde weights w_{ij}
  - Generate random walk paths through the network
  - Decrease the weights of the path
$$w_{ij} \to w_{ij} - 1$$
  - If $w_{ij} = 0$ edge is discarded
  - Repeat until all edges are discarded



Ties
Communities
Network
form/decay
t1
t2
t3
Tie activity
is bursty
t
Groups of
conversation
t1
t1+dt
Communities
form/change/decay
t1
t2
Networks
form/change/decay
t1
t2

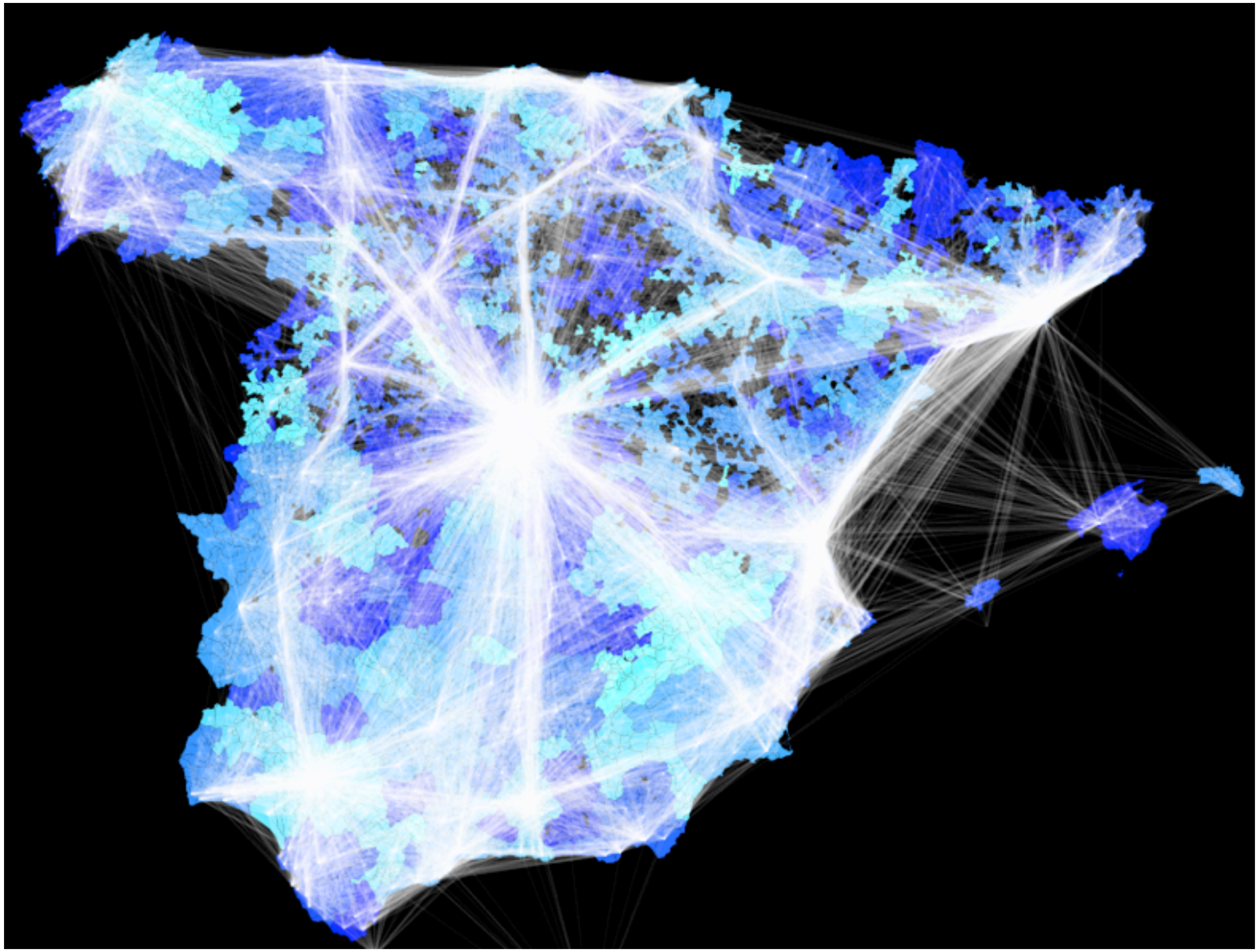
Outlook 3

Outlook

- How universal is temporal/dynamical evolution of the network?
    - **Burstiness**
    - Tie evolution
    - Motifs
    - Community evolution
    - Network birth and death
- How those process impact the way we observe the network?
- What are the Erdos-Renyi / Preferential attachement model in temporal/dynamical networks? We need simple generative models

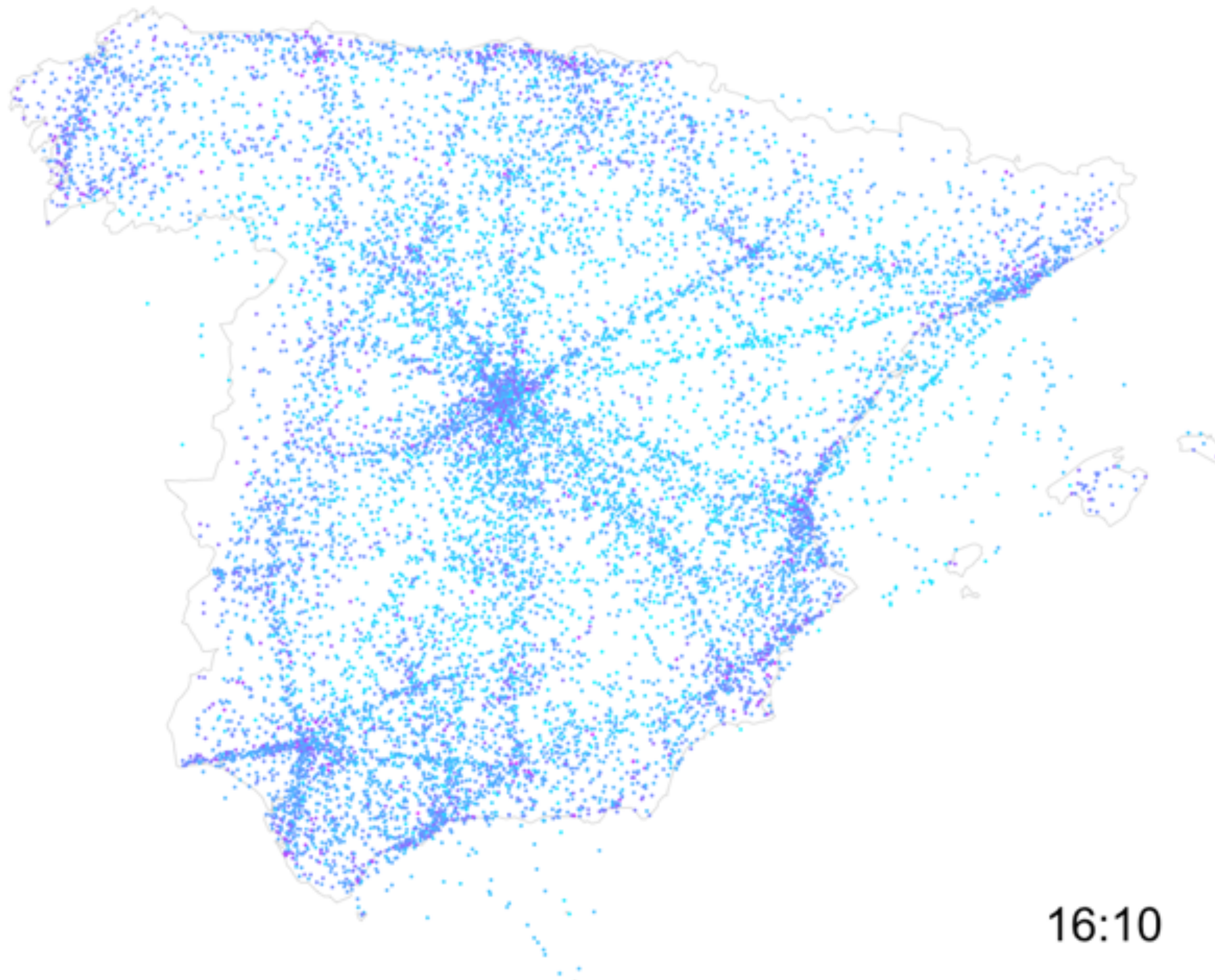
Outlook

- Other human networks: mobility networks



Outlook

- Other human networks: mobility networks



Book

- How two people communicate
  - Detect link decay
- How people allocate their time across their social relationships
  - Find your "best" friends
- How people manage their sociability? Social strategies?
  - Detect social behaviors