

Dynamics in complex networks. Analysing real-world (mobile) data

Esteban Moro

Universidad Carlos III de Madrid



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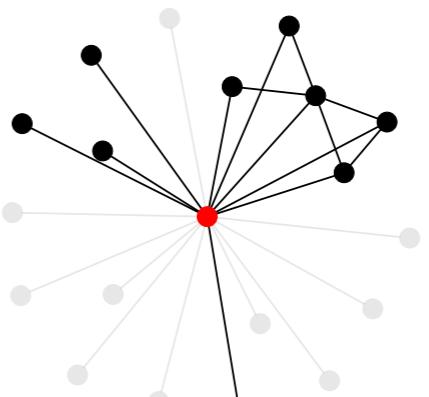
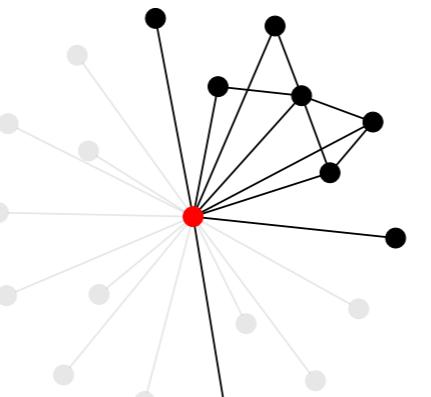
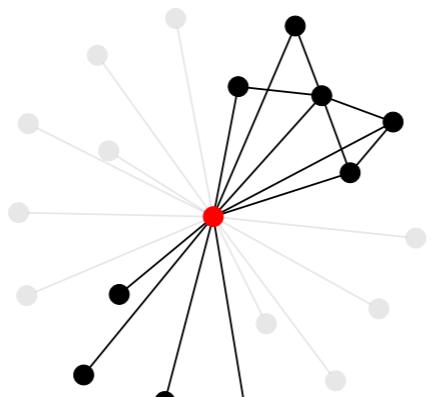
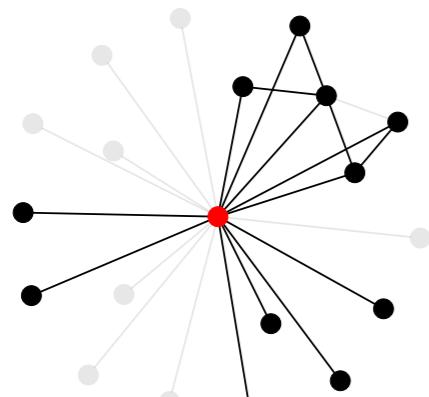
DPCN 2016, Wrocław

Summary

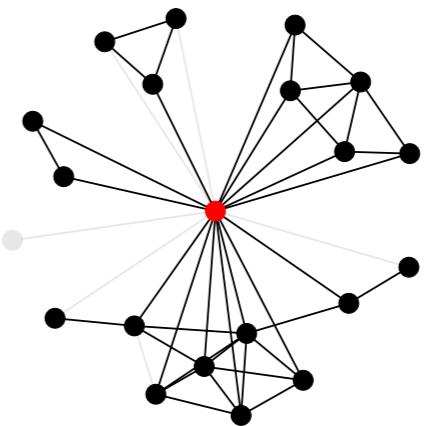
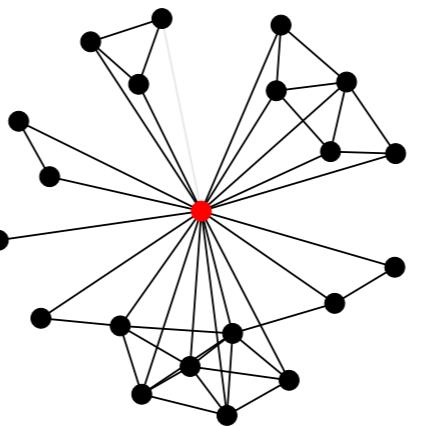
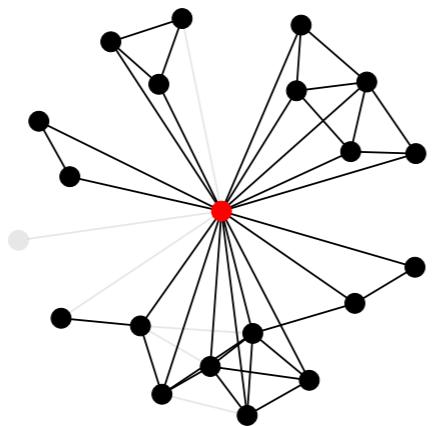
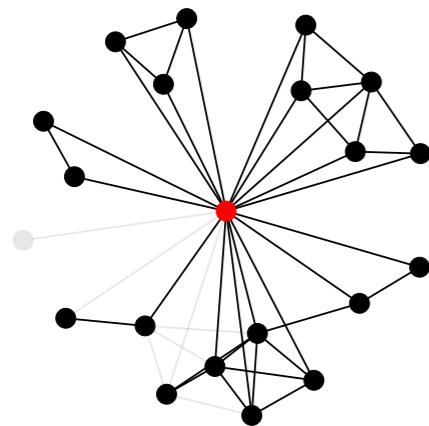
1. Motivation
2. Social dynamical processes
 - 2.1. Individual dynamics
 - 2.2. Tie dynamics
 - 2.2.1. Tie interaction activity
 - 2.2.2. Tie formation/decay dynamics
 - 2.3. Geographical dynamics
3. Impact on information diffusion
4. Applications to real-world problems



A



B



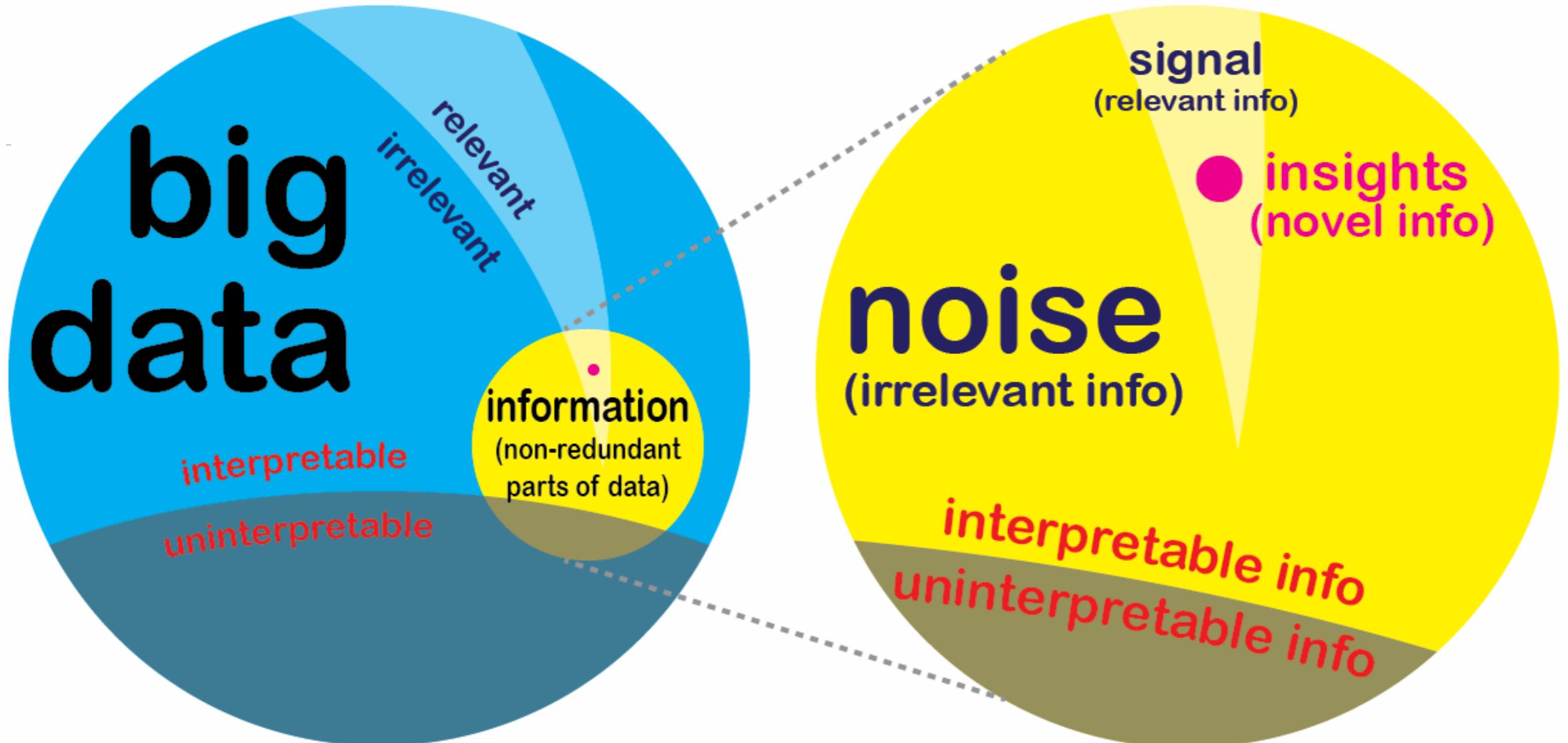
Motivation

1

Motivation



Motivation



Motivation

You are what you *repeatedly do* [Aristóteles]

Using BigData to infer behavior or society situation

Situation

Demographics
Health
Economy
Unemployment
Transportation
Geography
Politics

Behavior

Social
Mobility
Activity
Content

Observation

Surveys
Credit card
Mobile phone
Social media
Searches
....

Individual - Group - City

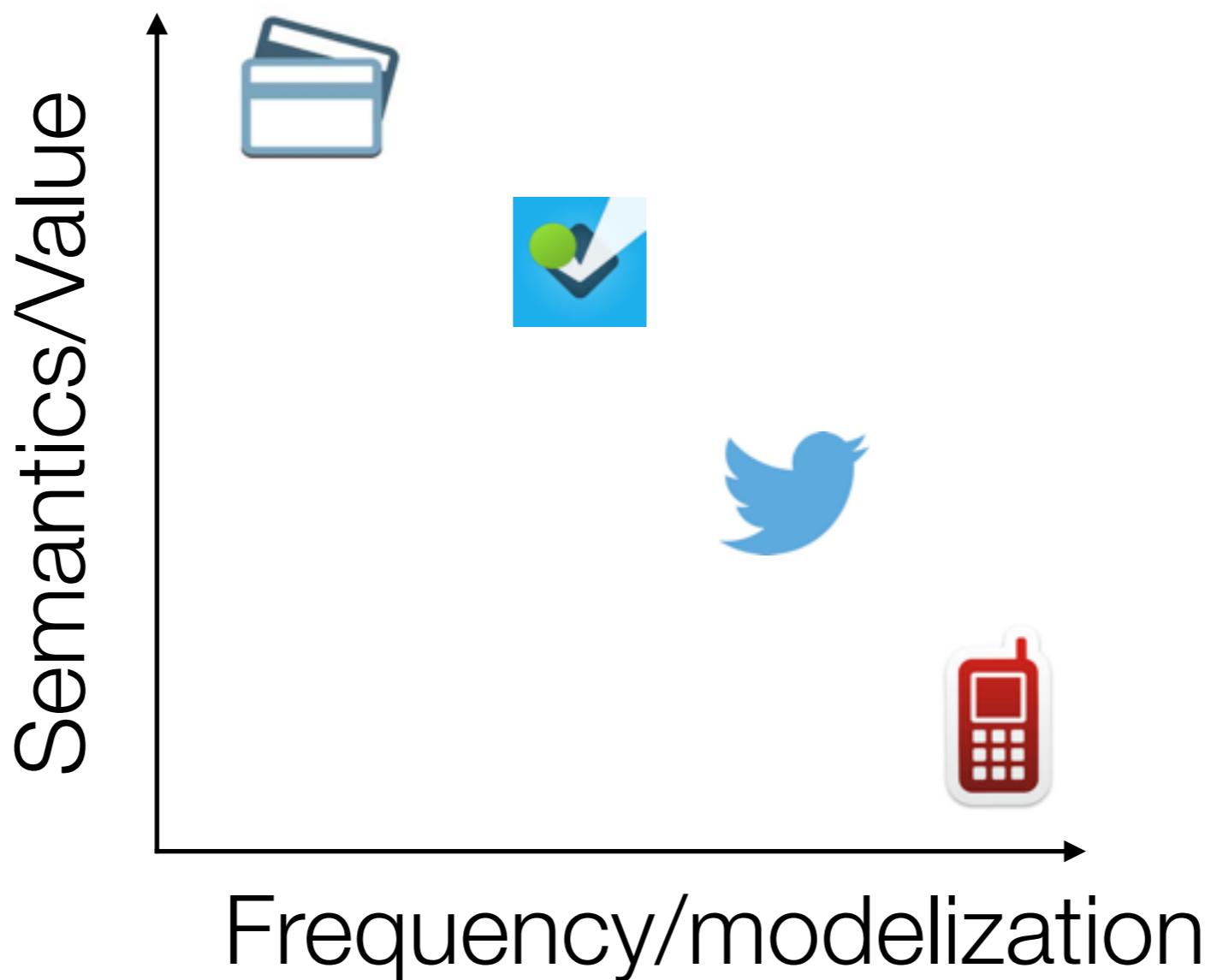


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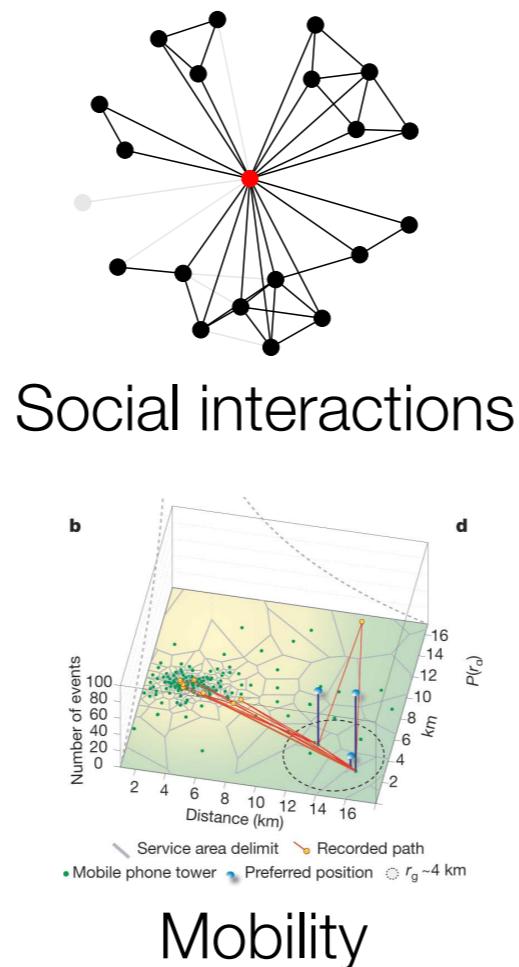
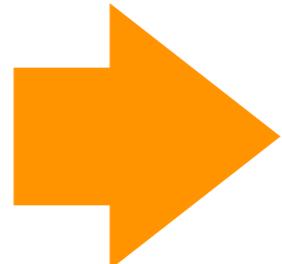
Motivation

Sources of BigData



Motivation

Sources of BigData



Mobility

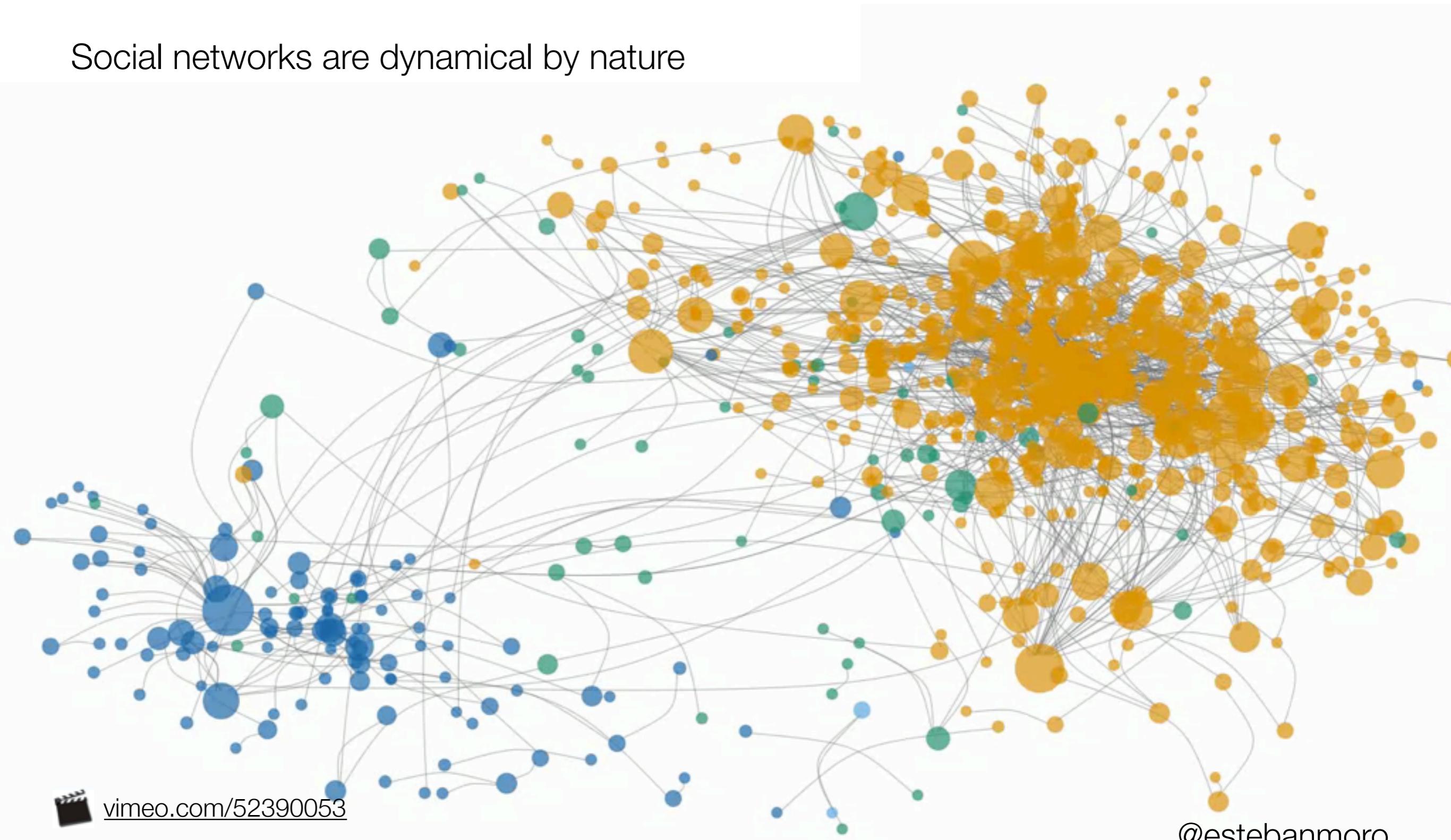
Transport Marketing
Development
Food Consumption
Economy Energy
Retail Analytics
Unemployment
Smart Cities Geography

netmob.org

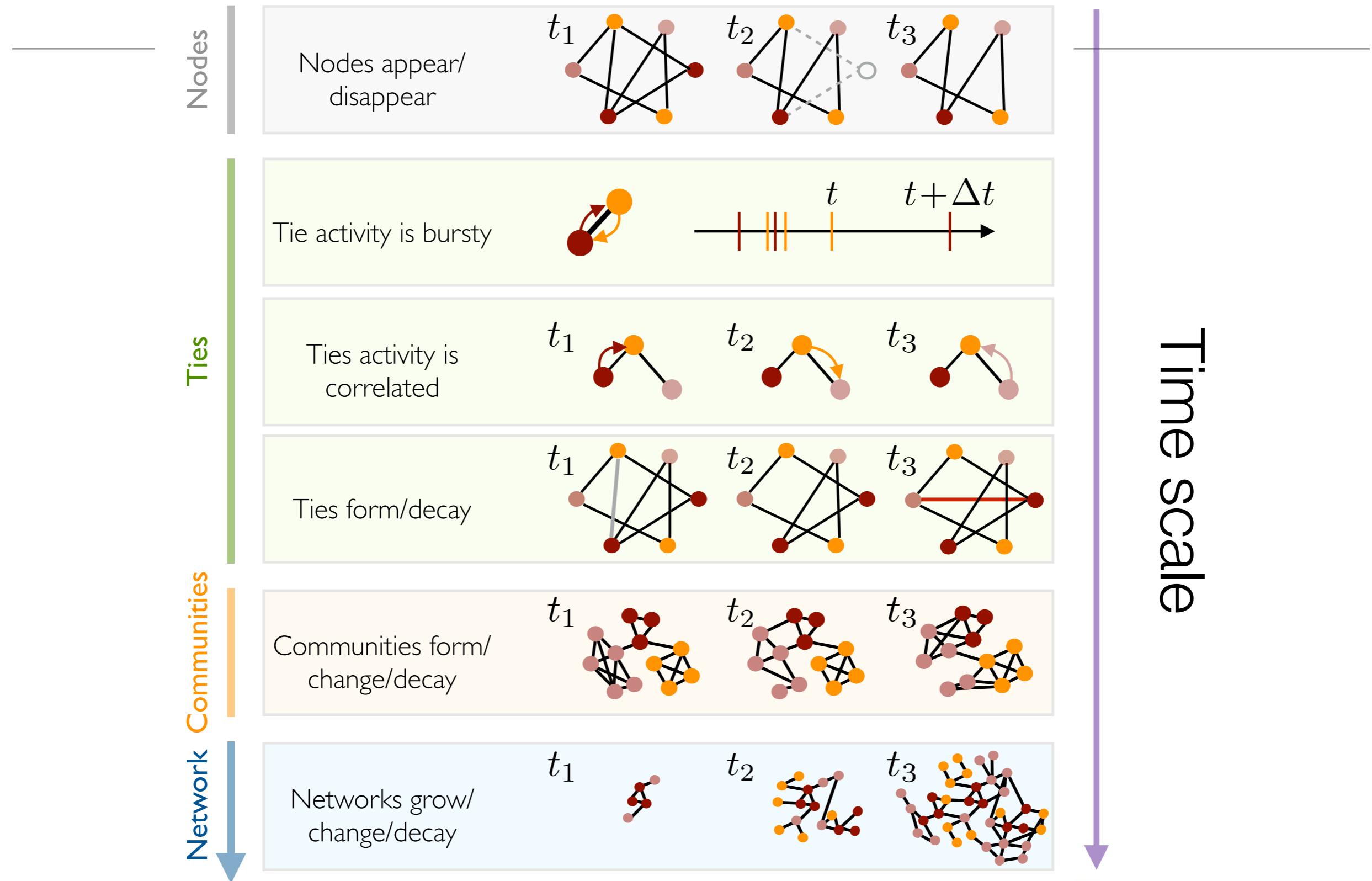
- Blondel, V. D., Decuyper, A., & Krings, G. (2015). A survey of results on mobile phone datasets analysis. *EPJ Data Science*, 4(1), 10. <http://doi.org/10.1140/epjds/s13688-015-0046-0>
- MOBILE PHONE NETWORK DATA FOR DEVELOPMENT. (2013). UN Global Pulse
- Saramaki, J., & Moro, E. (2015). From seconds to months: an overview of multi-scale dynamics of mobile telephone calls. *The European Physical Journal B*, 88(6). <http://doi.org/10.1140/epjb/e2015-60106-6>
- Naboulsi, D., Fiore, M., Ribot, S., & Stanica, R. (n.d.). Large-scale Mobile Traffic Analysis: a Survey. *IEEE Communications Surveys & Tutorials*, 1–1. <http://doi.org/10.1109/COMST.2015.2491361>

Motivation

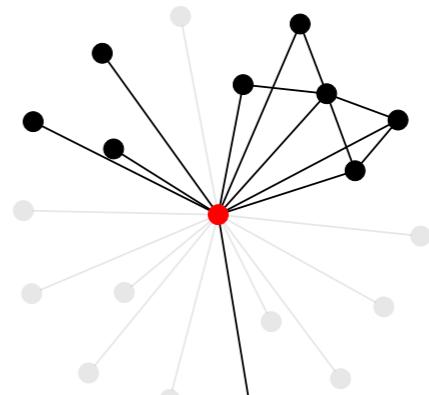
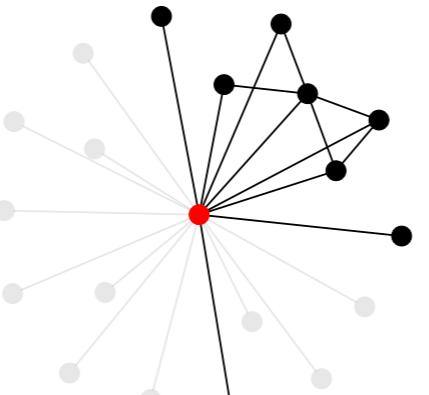
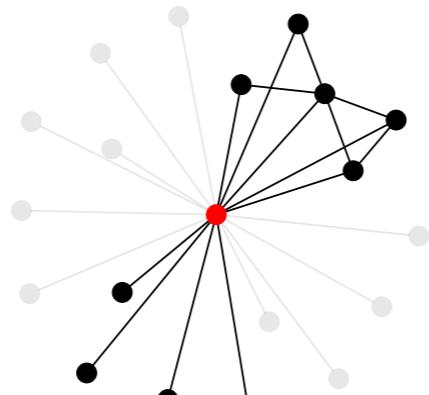
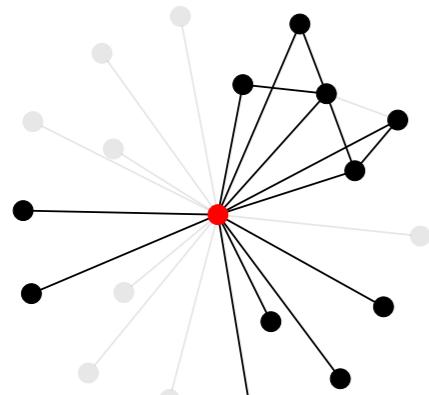
Social networks are dynamical by nature



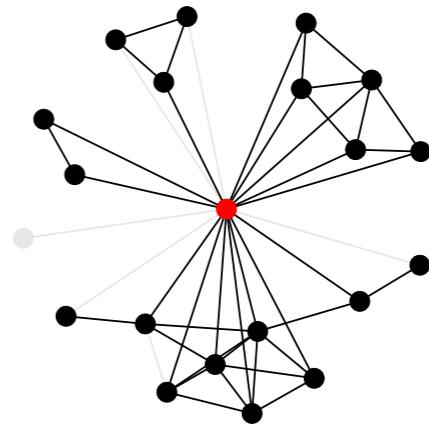
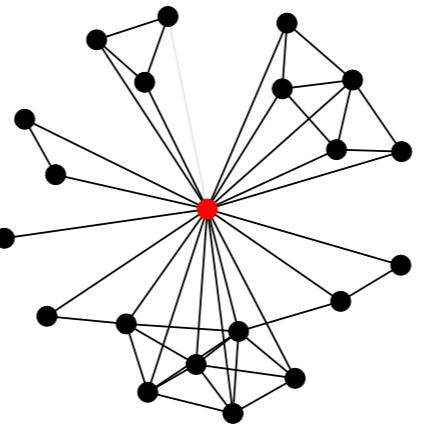
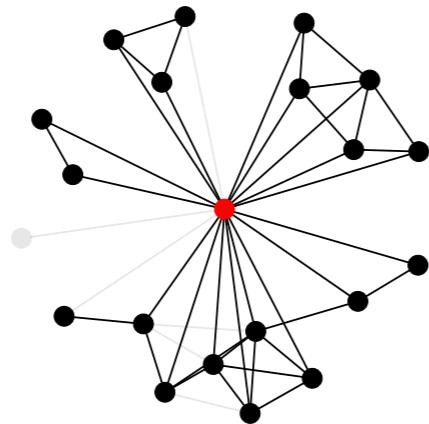
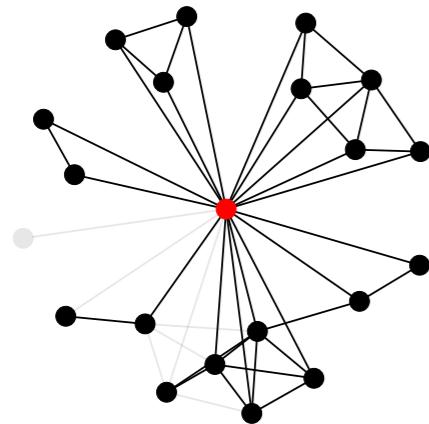
Complex dynamics of real networks



A



B



Social dynamical process

2

Social dynamical process

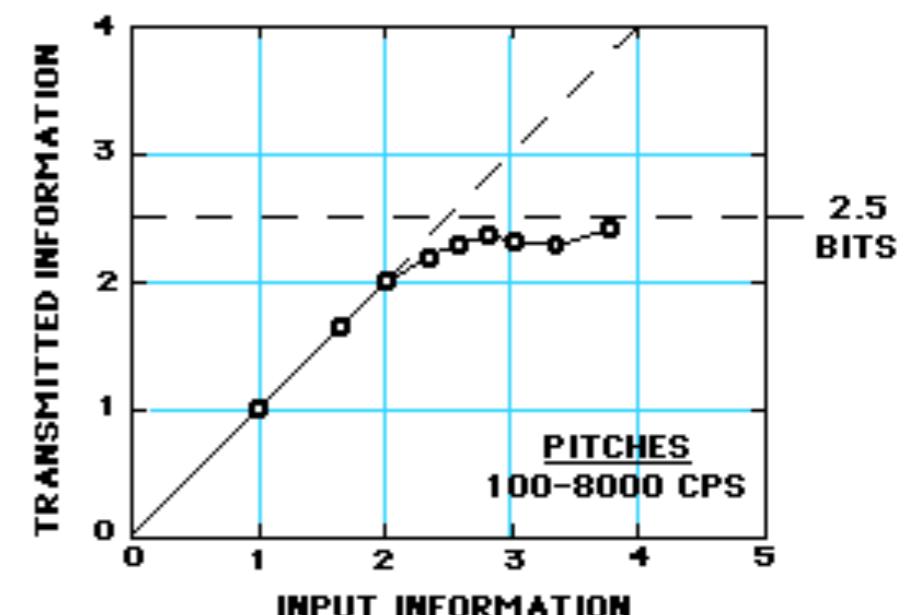
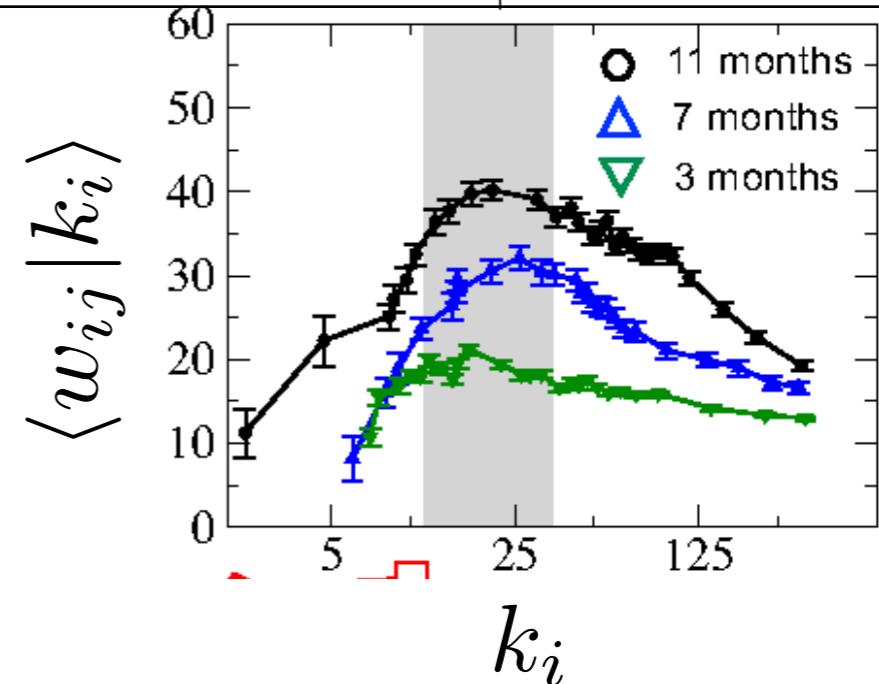
- **Cognitive limits**

- Dunbar's number

- There is a cognitive limit to the number of people with whom one can maintain stable social relationships. (Dunbar 1992)

- The magical number Seven Plus Minus Two
 - The number of objects an average human can hold in working memory is 7 ± 2 (Miller '56)

Miritello, G. et al., 2013. Time as a limited resource: Communication strategy in mobile phone networks. *Social Networks*.



Social dynamical processes

- **Embeddedness / clustering / triadic closure / weak ties**

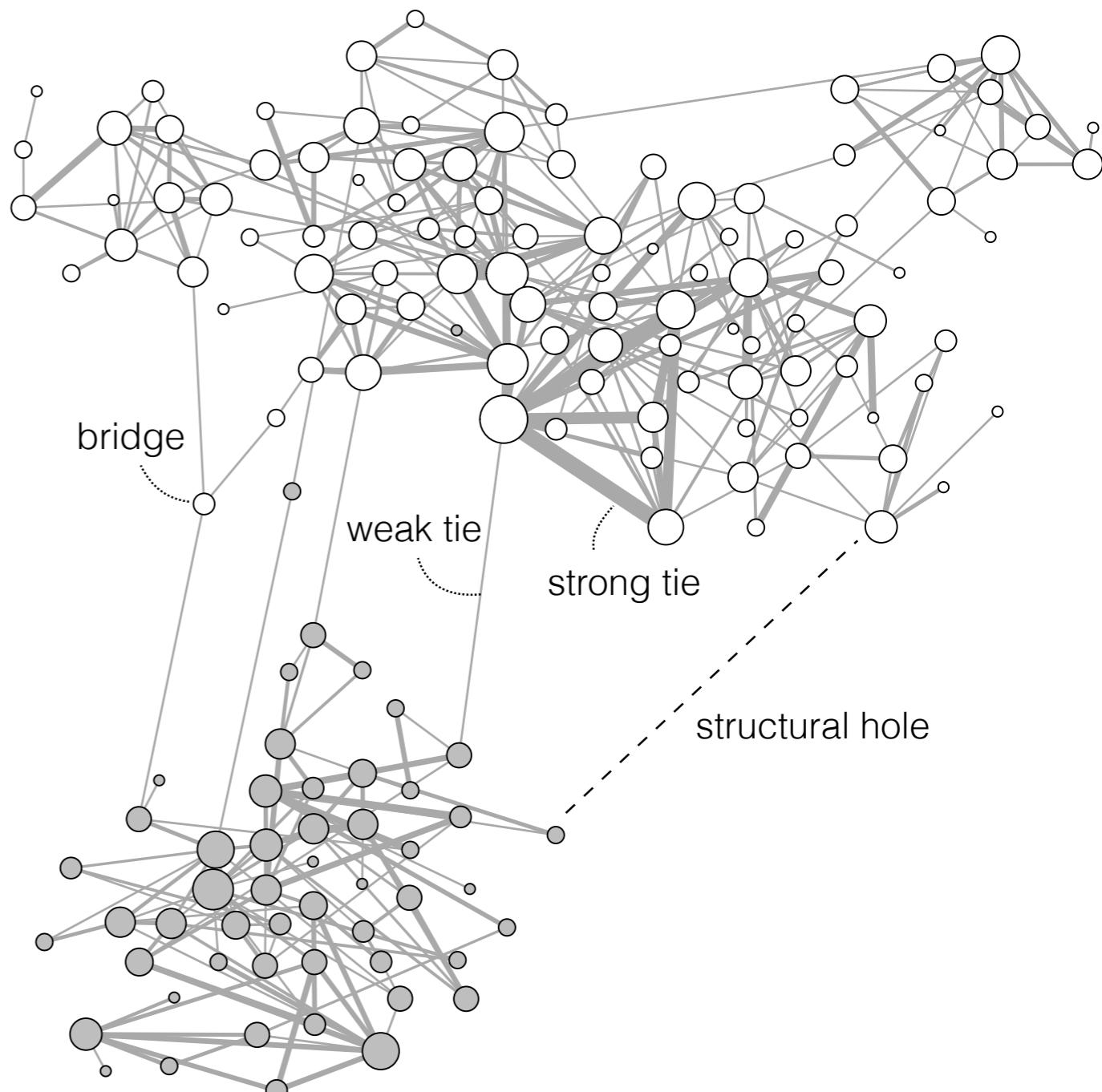
- *Embeddedness, clustering:*

People who spend time with a third are likely to encounter each other (triadic closure). Minimizes conflict, maximizes trusts,...

- *Bridges, structural holes (Burt):*

Bridges have structural advantages since they have access to non-redundant information

- *Weak ties (Granovetter):* weak ties tend to connect different areas of the network (they are more likely to be sources of novel information)



Rivera, M.T., Soderstrom, S.B. & Uzzi, B., 2010. Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms. *Annual Review of Sociology*, 36(1), pp.91–115.

Social dynamical processes

- **Contagion**

- Human behaviors spread on the network
- Dynamics too

- **Homophily**

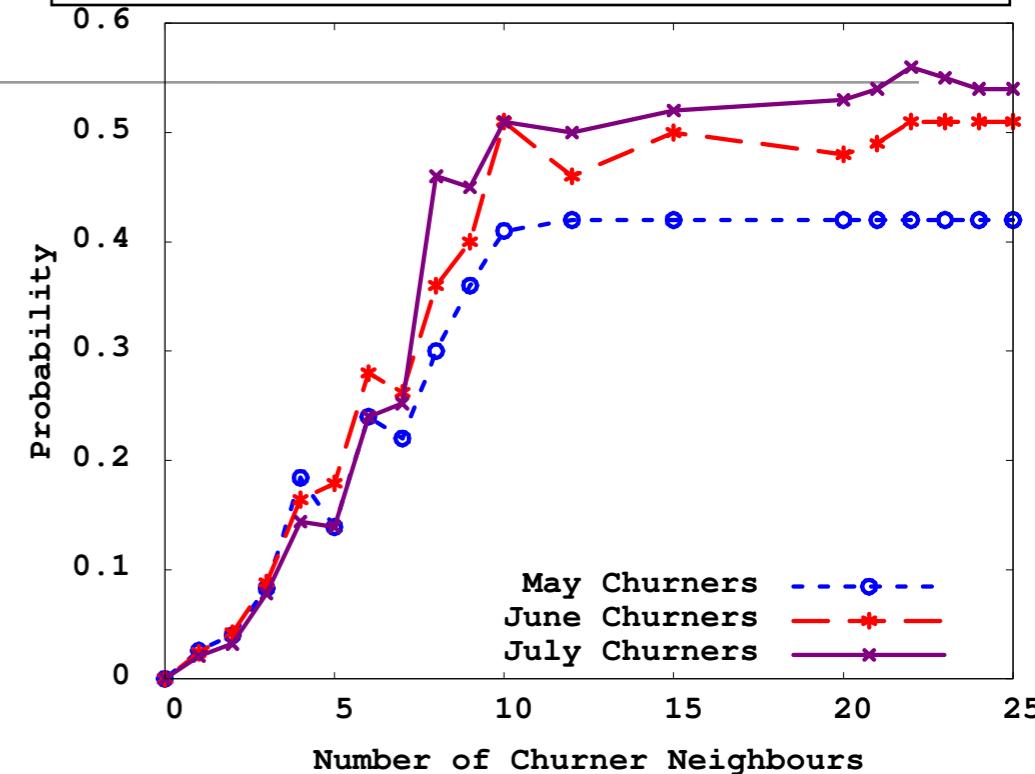
- The greater the similarity between individuals the more likely they are to establish a connection

Attribute	Random	Communicate
Age	-0.0001	0.297
Gender	0.0001	-0.032
ZIP	-0.0003	0.557
County	0.0005	0.704
Language	-0.0001	0.694

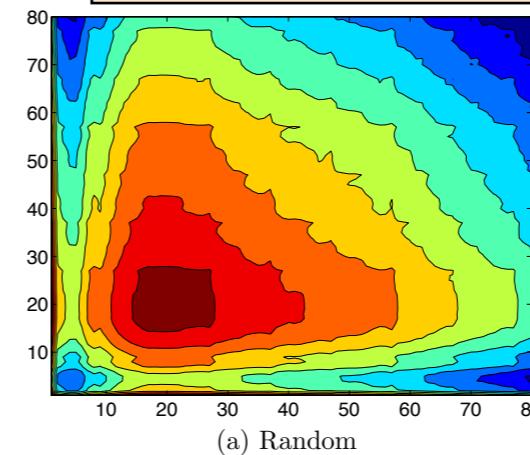
Correlation coefficient

Leskovec, J. & Horvitz, E., 2008. Planetary-scale views on a large instant-messaging network. pp.915–924.

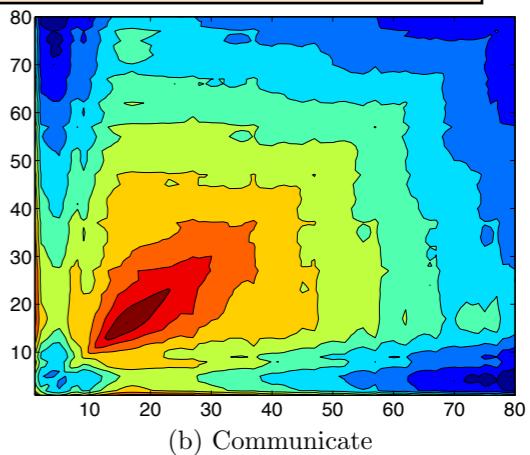
Dasgupta, K. et al., 2008. Social ties and their relevance to churn in mobile telecom networks.



Number of pairs of people at different ages



(a) Random



(b) Communicate



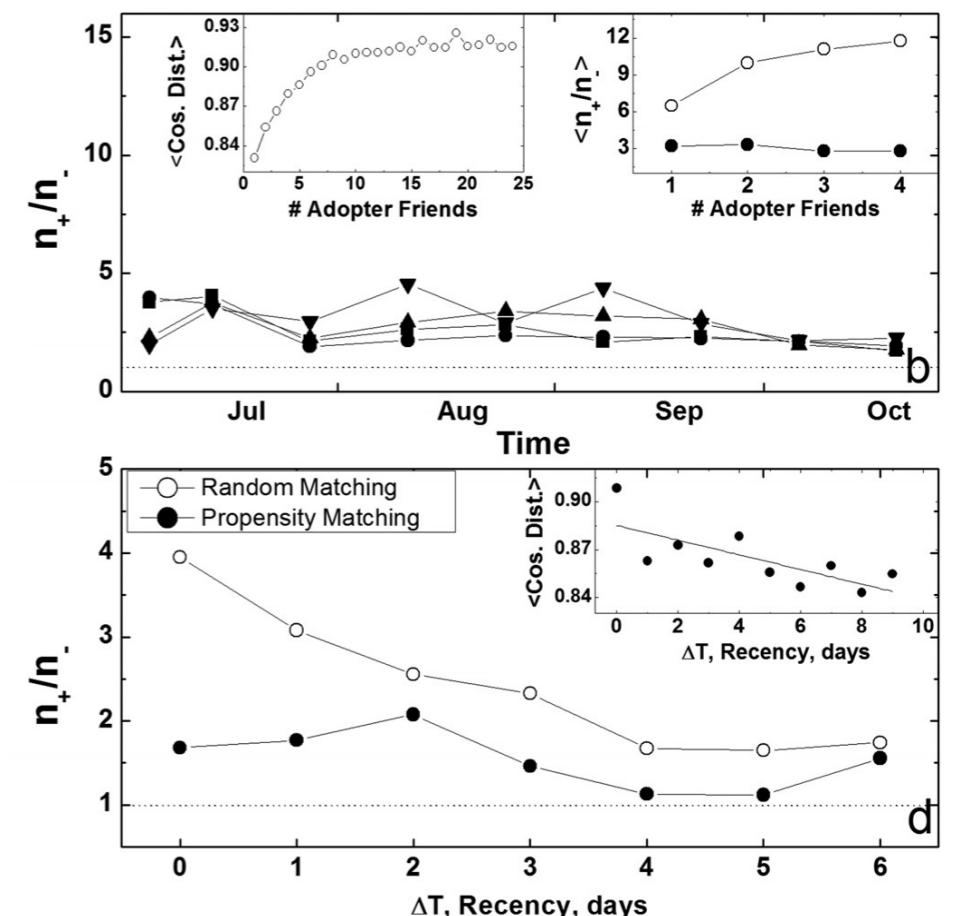
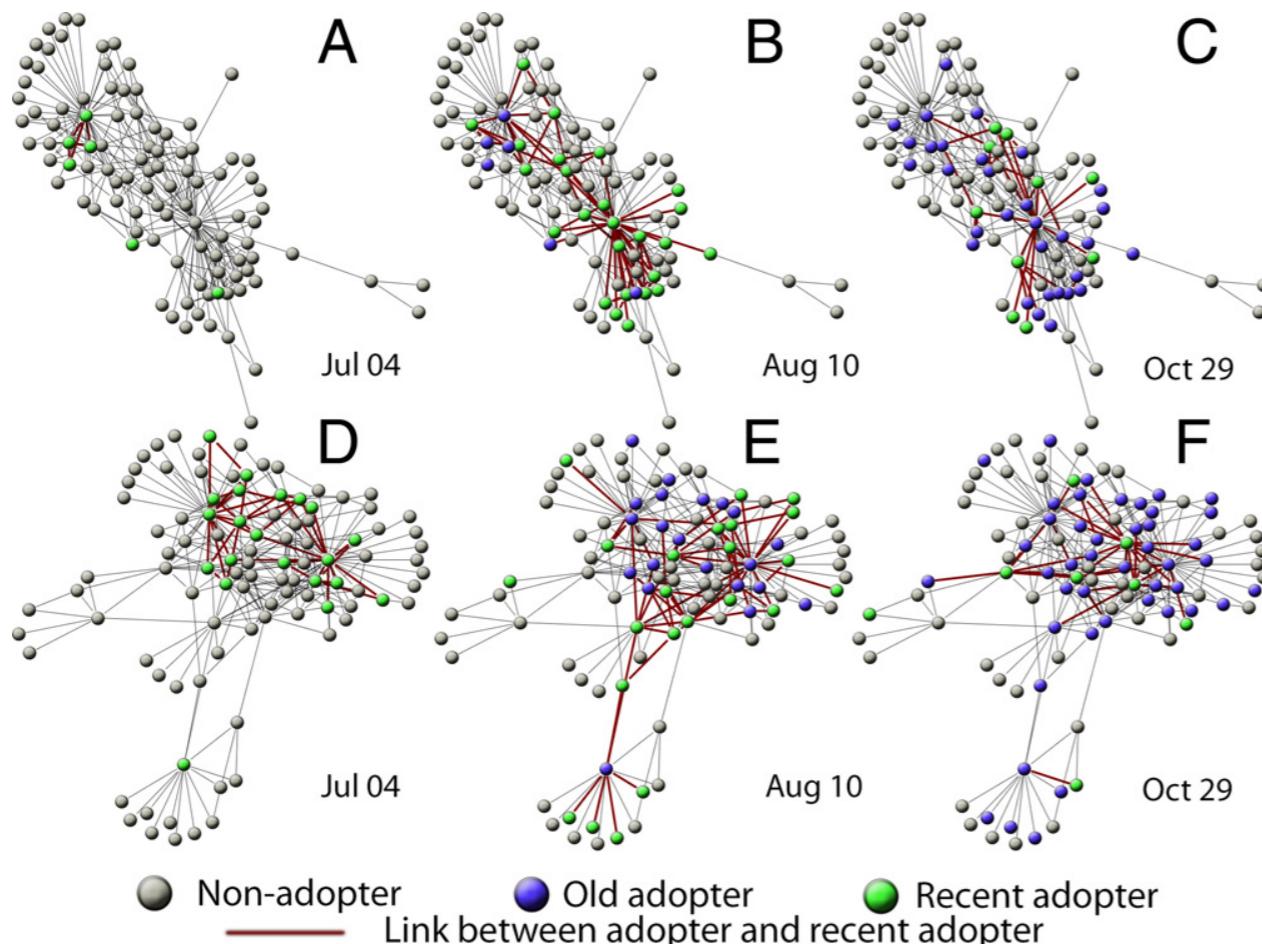
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Social dynamical processes

- **Contagion = Homophily?**

- Influence and homophily are usually confounded in observational social network studies

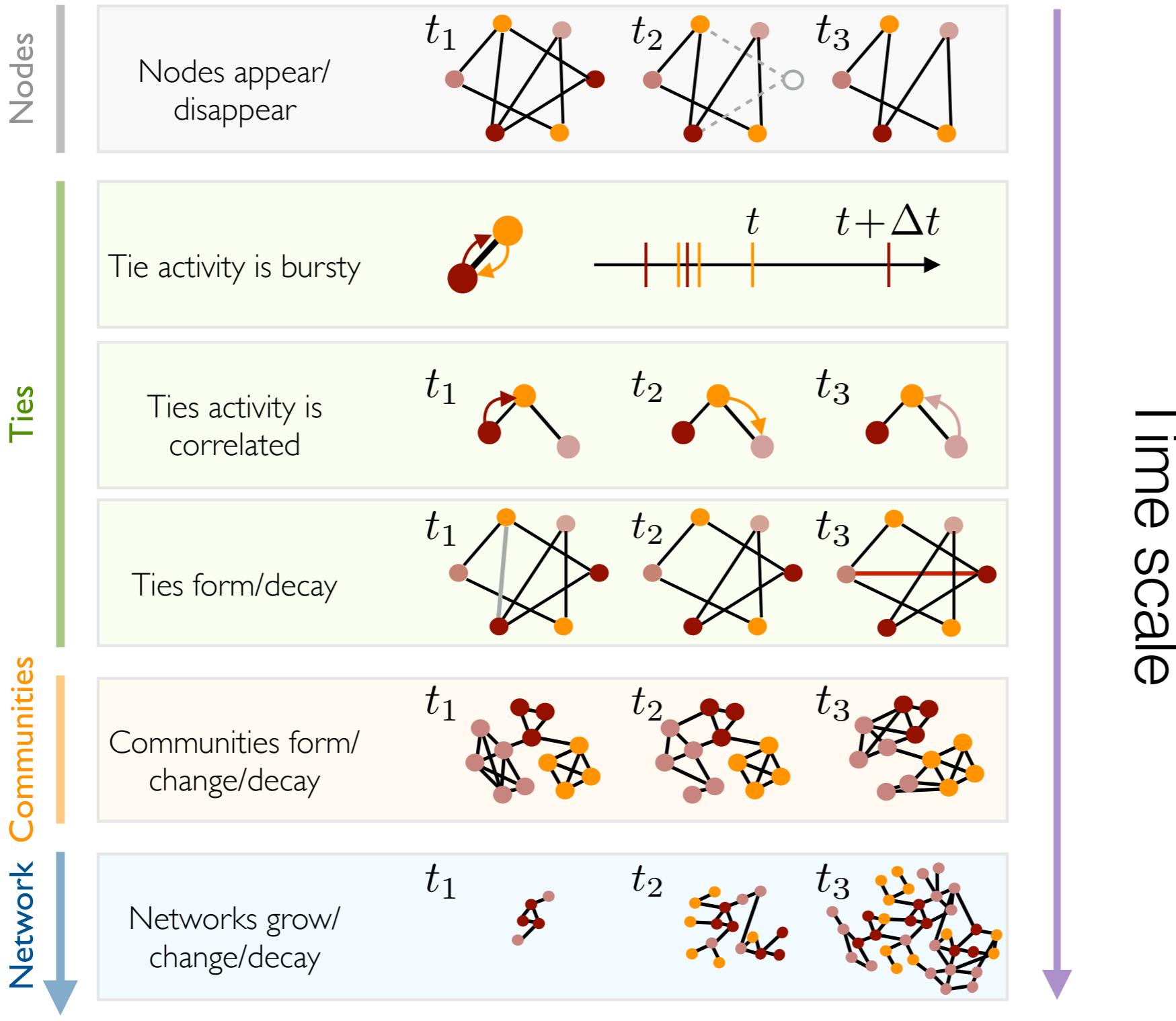


Aral, S., et al. 2009. Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51), p.21544.



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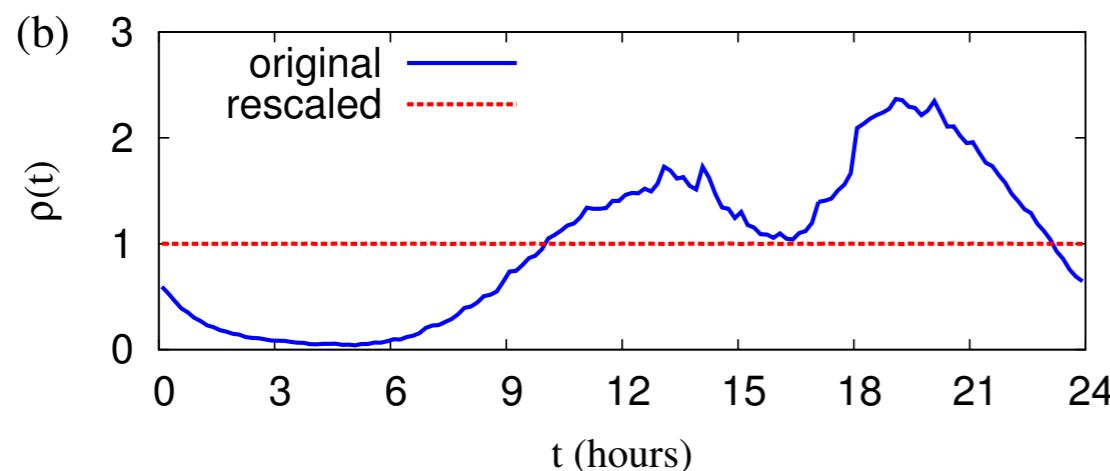
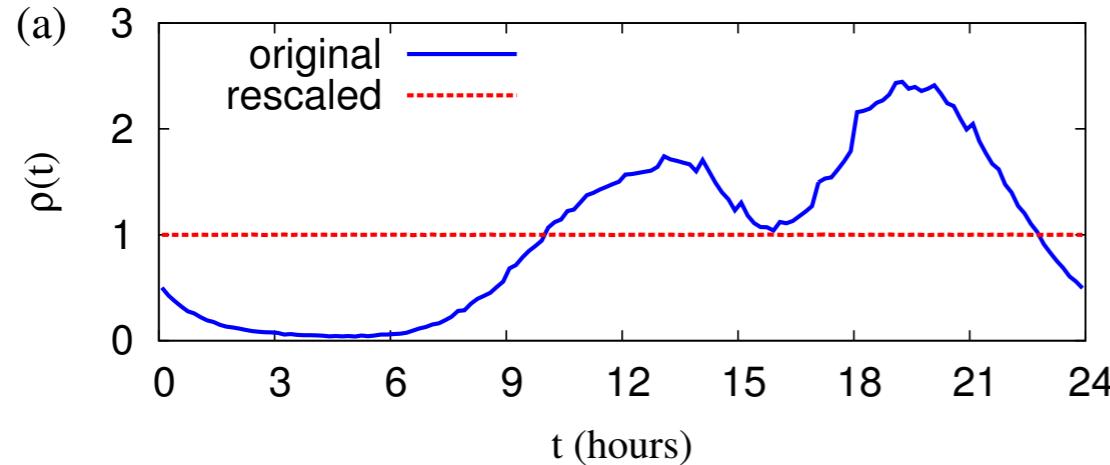


Individual dynamics

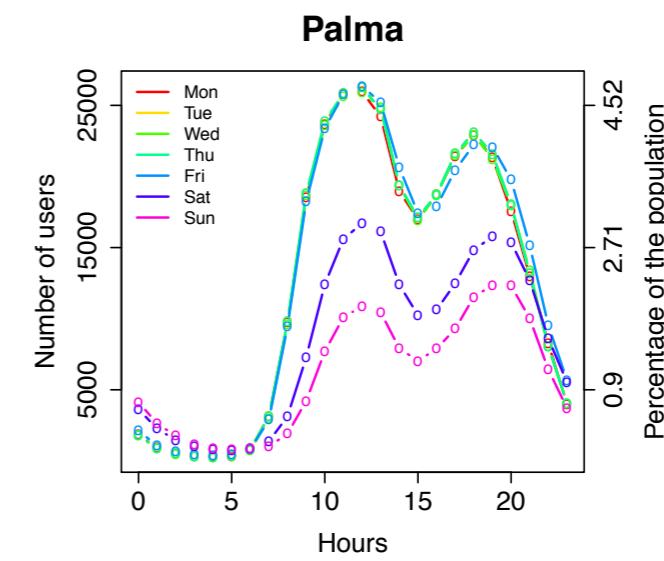
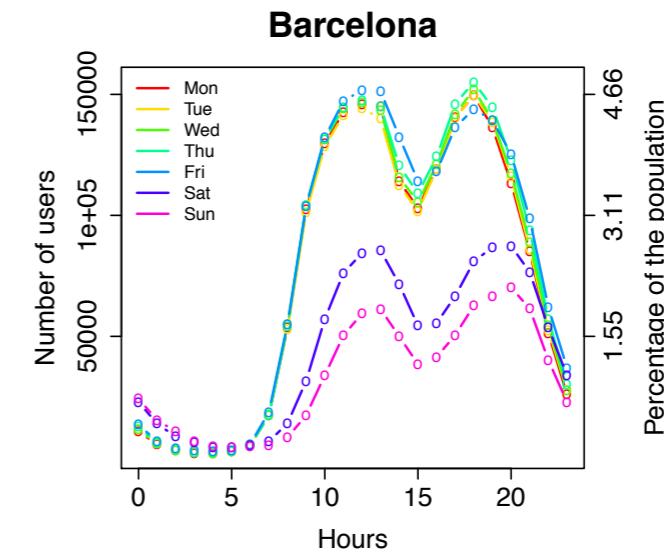
2.1

Individual dynamics

- Humans distribute their time differently along the day (circadian rhythms)



Jo, H.-H., Karsai, M., Kertesz, J., & Kaski, K. (2012). Circadian pattern and burstiness in mobile phone communication. *New Journal of Physics*, 14(1), 013055. <http://doi.org/10.1088/1367-2630/14/1/013055>

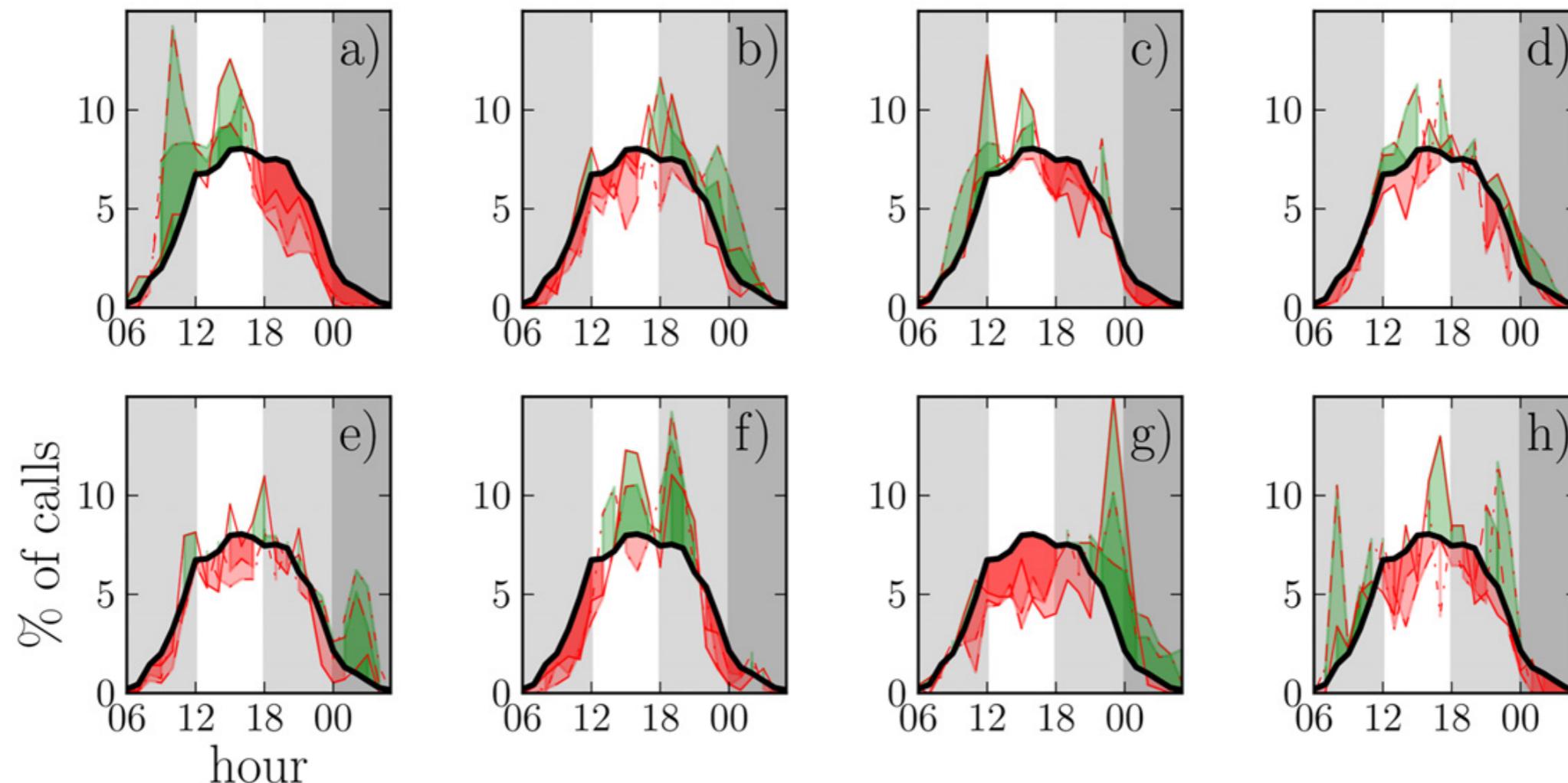


Louail, T., Lenormand, M., Cantú, O. G., Picornell, M., Herranz, R., Frias-Martinez, E., et al. (2014). From mobile phone data to the spatial structure of cities. *Scientific Reports*, 4. [@estebanmoro](http://doi.org/10.1038/srep05276)



Individual dynamics

- Individual heterogeneity is significant and persistent.



Aledavood, T., López, E., Roberts, S. G. B., Reed-Tsochas, F., Moro, E., Dunbar, R. I. M., & Saramaki, J. (2015). Daily Rhythms in Mobile Telephone Communication. *PLoS ONE*, 10(9), e0138098. <http://doi.org/10.1371/journal.pone.0138098>

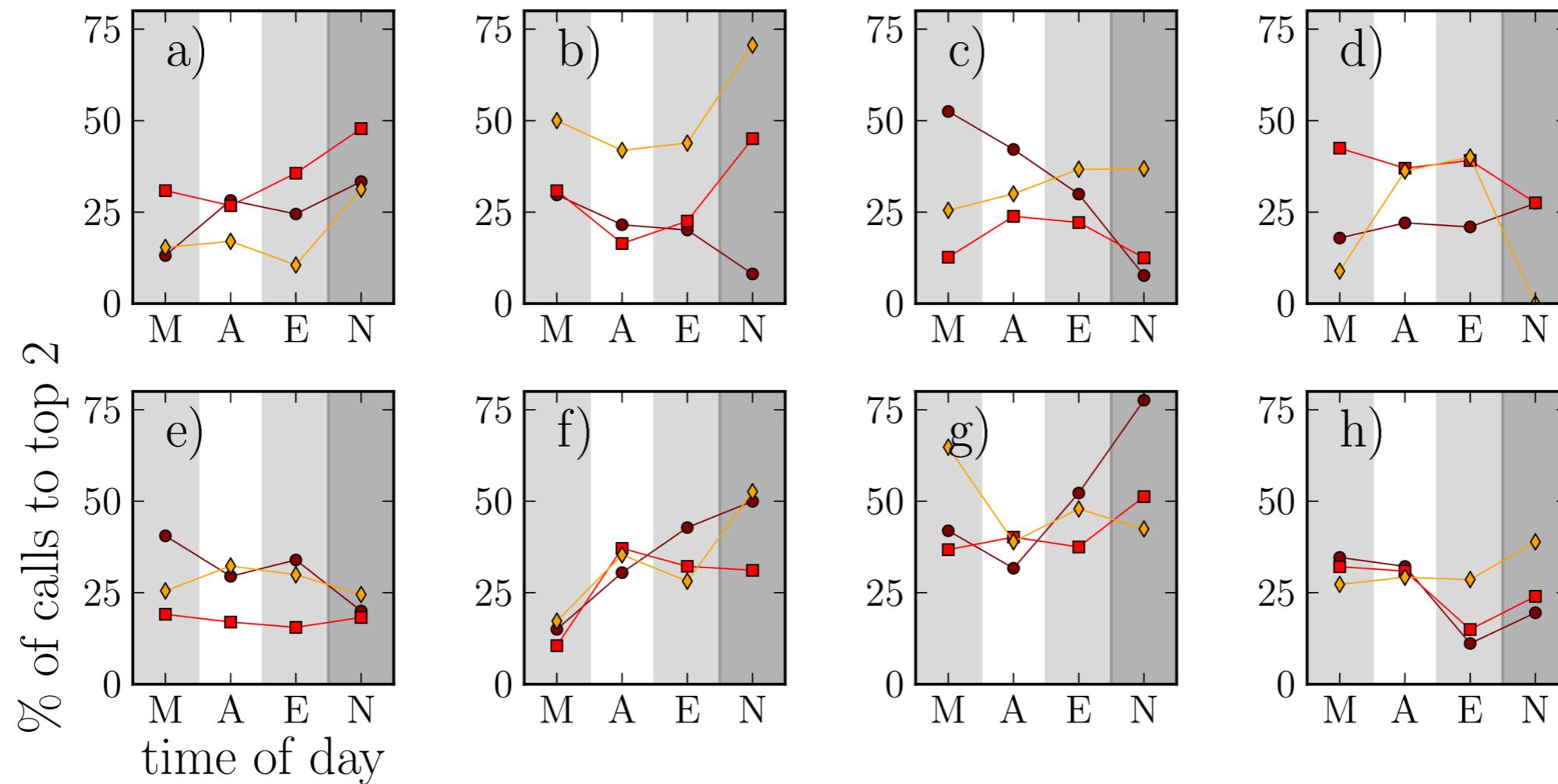


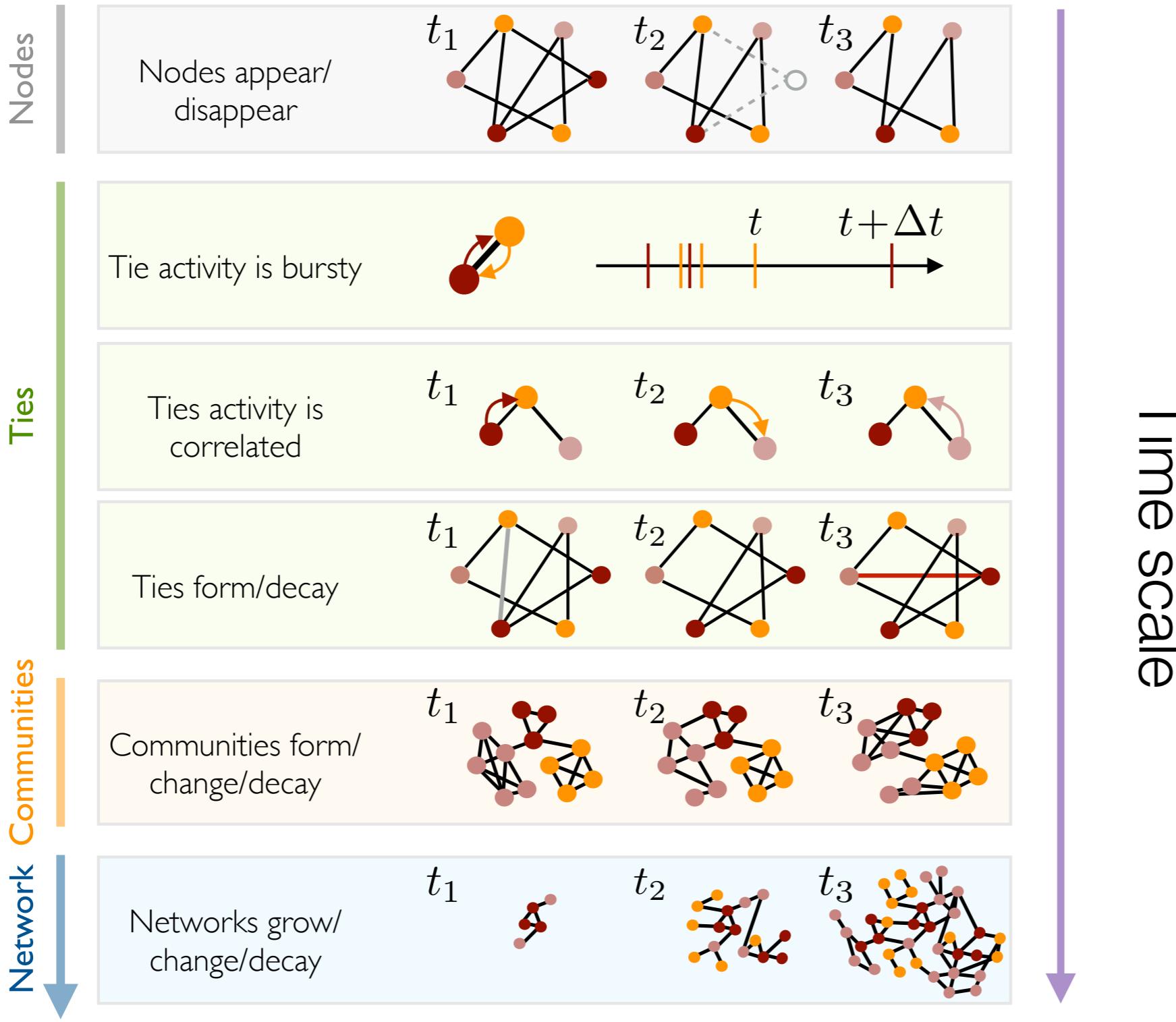
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Individual dynamics

- Calling patterns are different at different times of the day
 - At mornings we call a lot of new people
 - At nights we call less people and those are the more significant ones



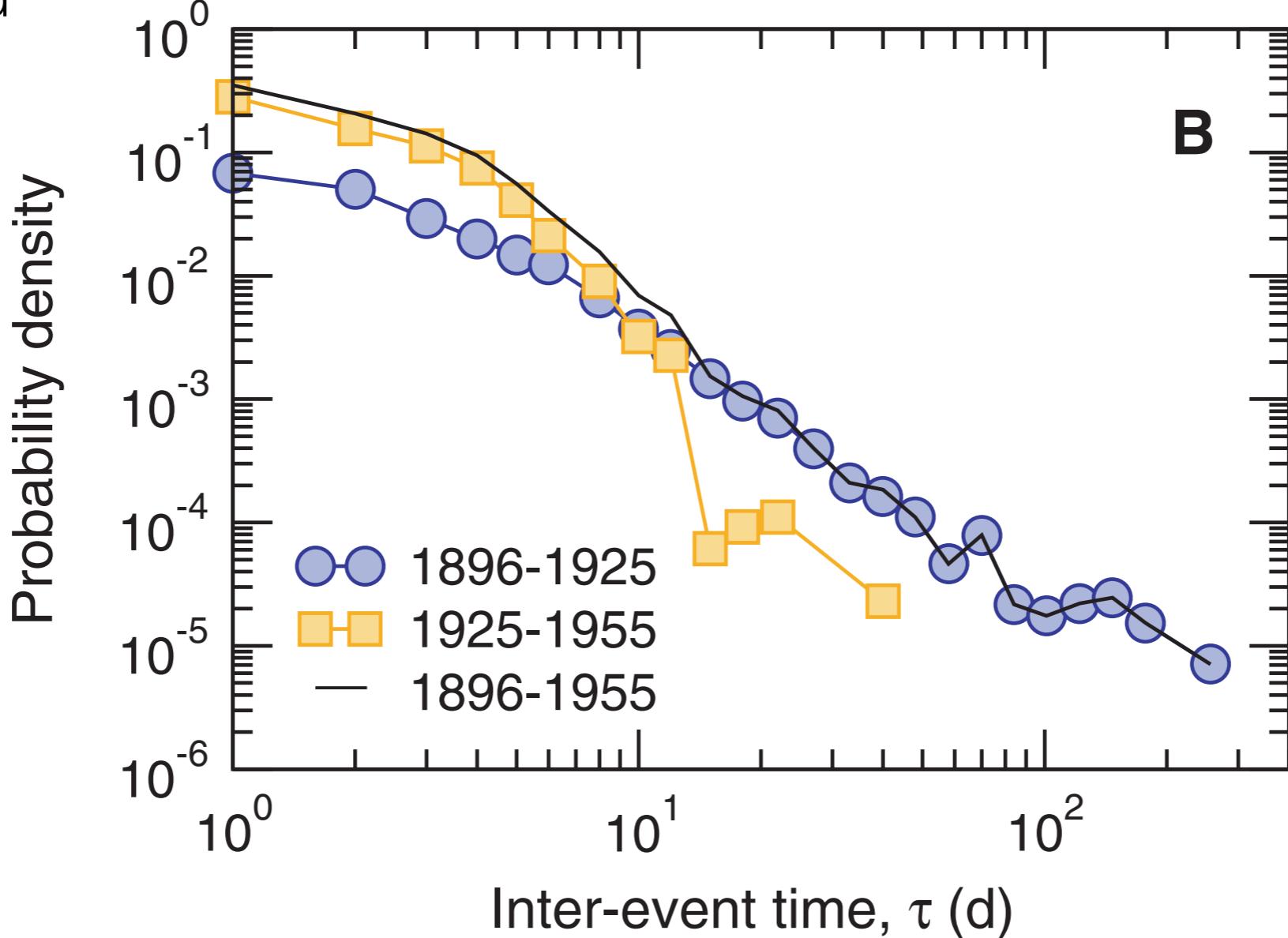


Tie dynamics

2.2

Contact dynamics

- Bursty human dynamics: inter-event time between activities is heavy-tailed distributed



Malmgren, R. et al., 2009. On universality in human correspondence activity. *Science*, 325(5948), p.1696.

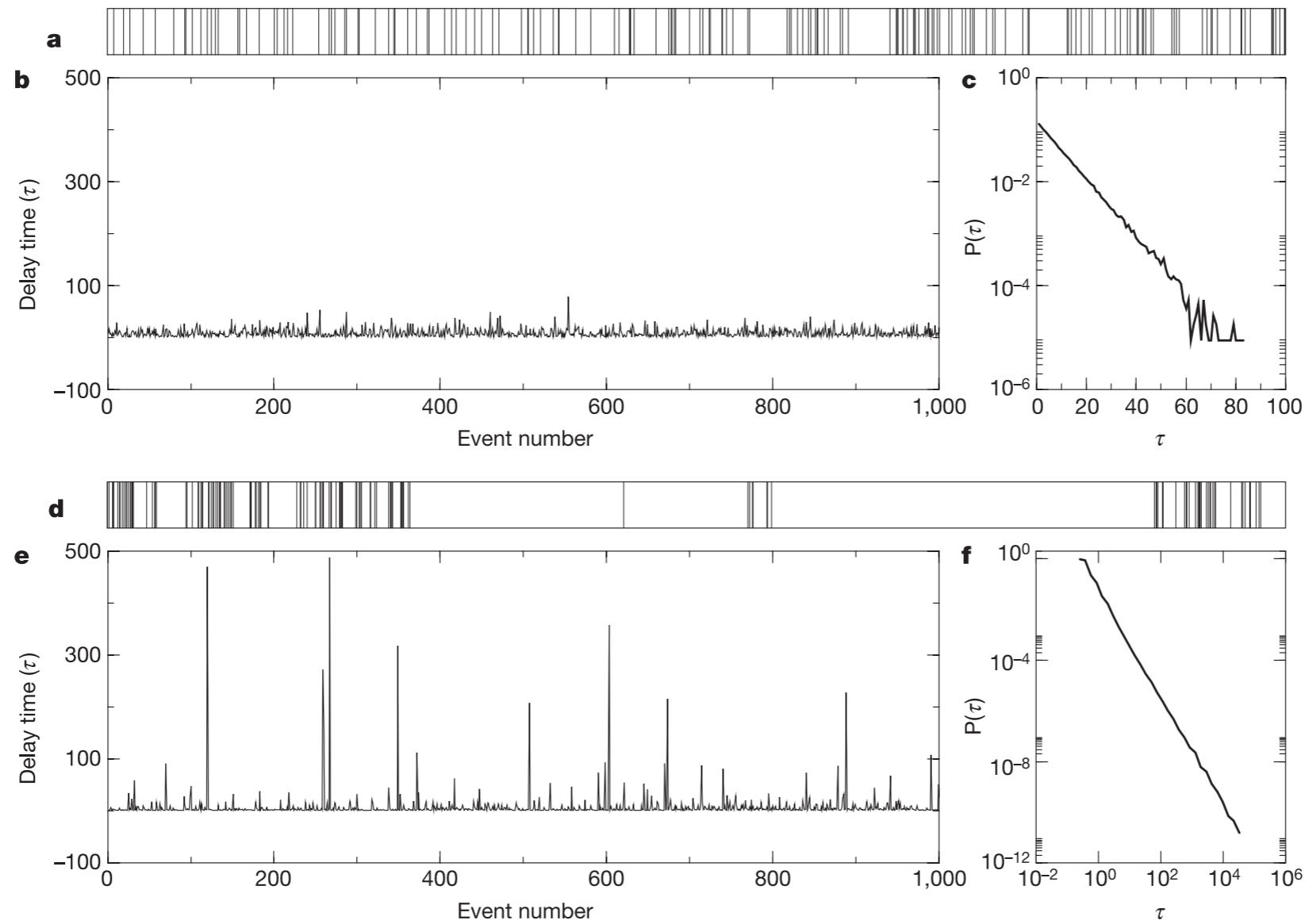


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Contact dynamics

- Bursty human dynamics: inter-event time between activities is heavy-tailed distributed



Barabasi, A.-L., 2005. The origin of bursts and heavy tails in human dynamics. *Nature*, 435(7039), pp.207–211.

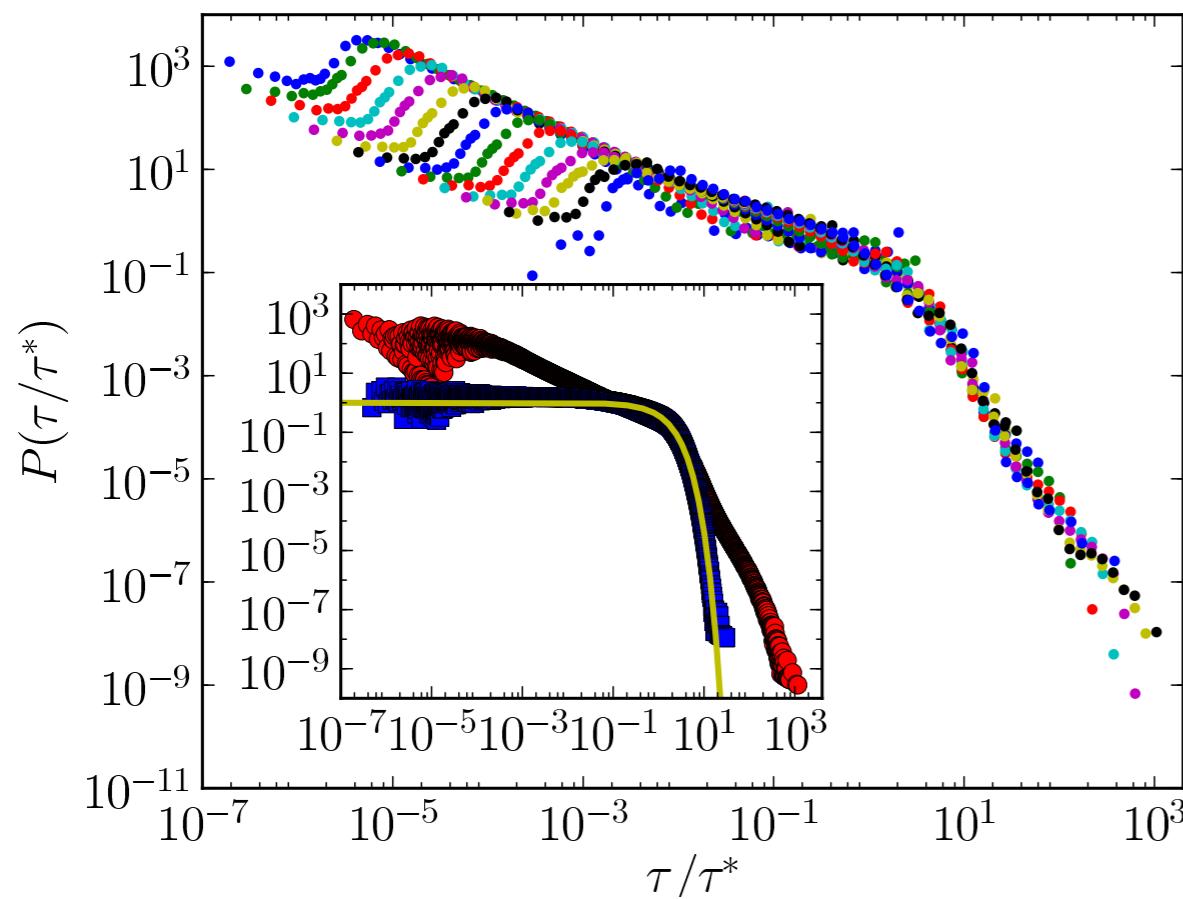


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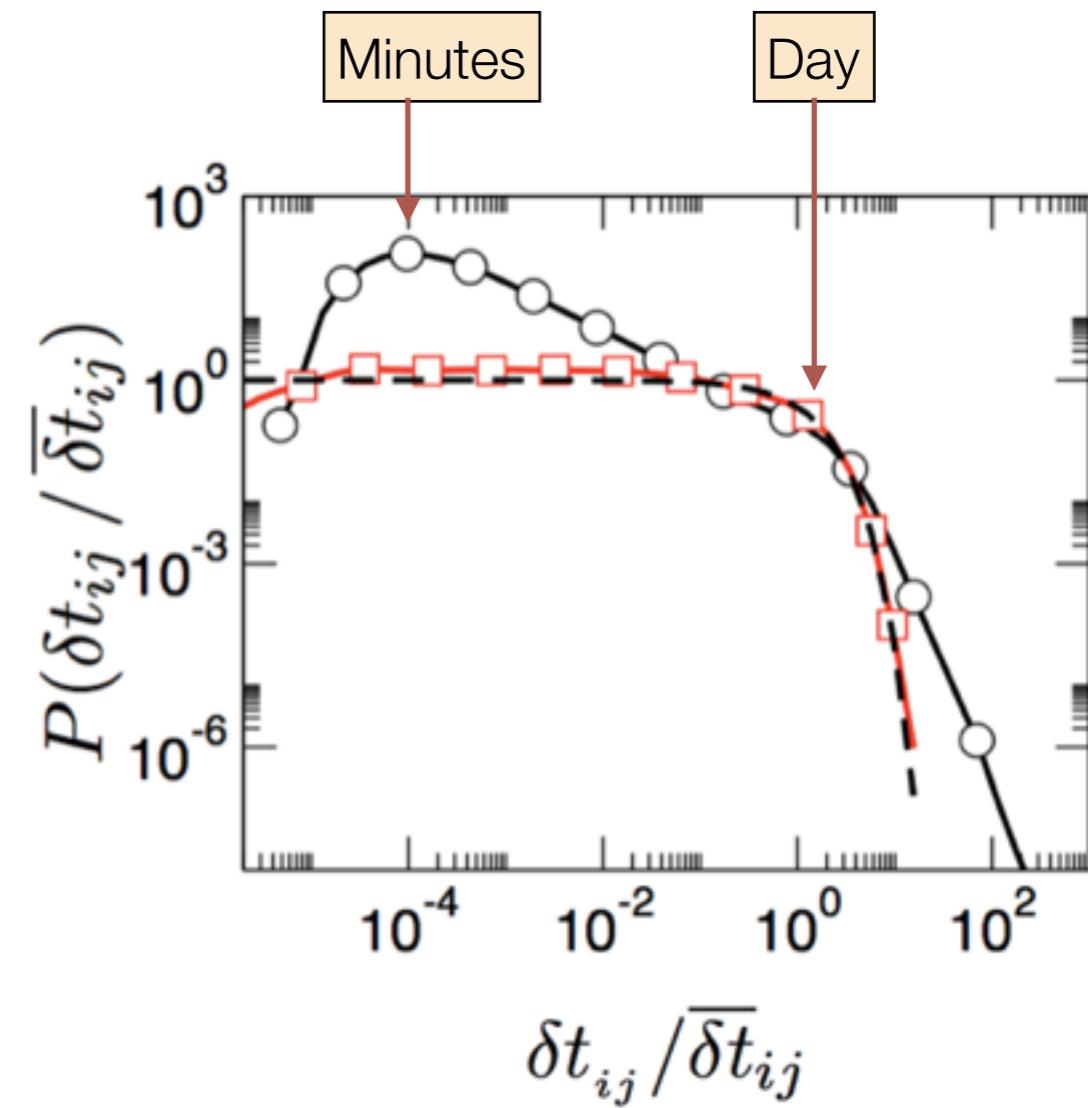
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Tie activity

- Bursty contacts: inter-event times on ties are also heavy-tailed distributed



Karsai, M. et al., 2011. Small But Slow World: How Network Topology and Burstiness Slow Down Spreading. *Physical Review E*, 83(2), p.025102.



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



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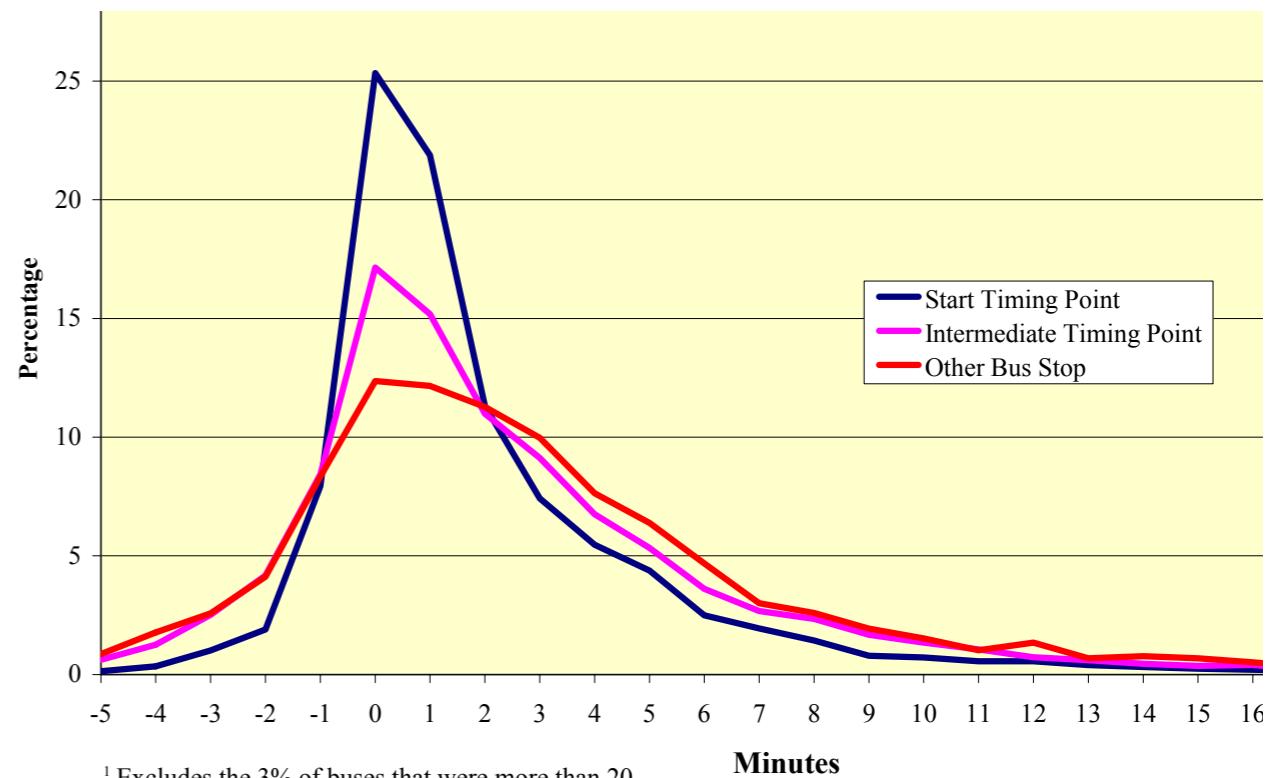
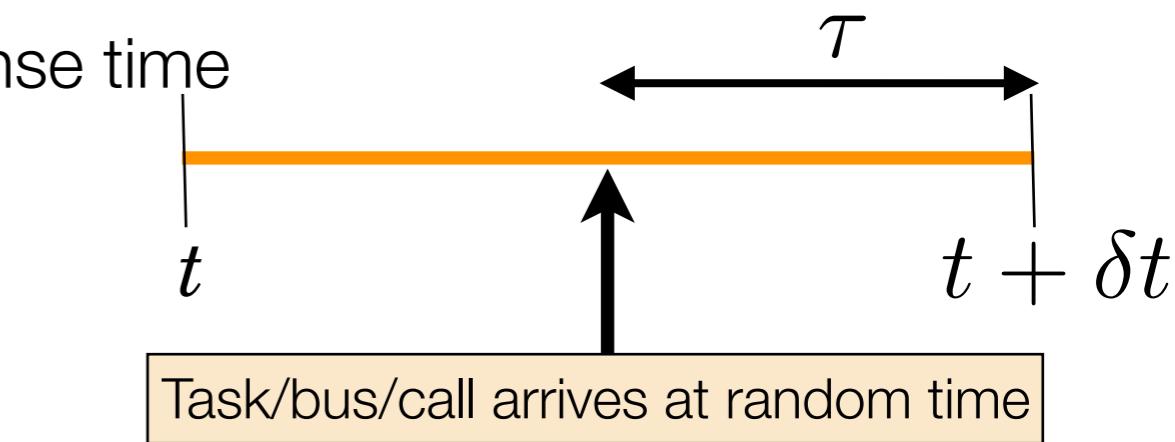
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Tie activity

- Bursty contacts: impact on the waiting/response time
- When should I wait next call from a friend?
- When is the next bus coming?
 - Given $P(\delta t)$, calculate $P(\tau)$

$$P(\tau) = \int_{\tau}^{\infty} d\delta t \frac{\delta t P(\delta t)}{\overline{\delta t}} \frac{1}{\delta t}$$

$$\bar{\tau} = \frac{\overline{\delta t}}{2} \left(1 + \frac{\sigma_{\delta t}^2}{\overline{\delta t}^2} \right)$$



Bus Punctuality Statistics GB
2007. Dept. of Transport



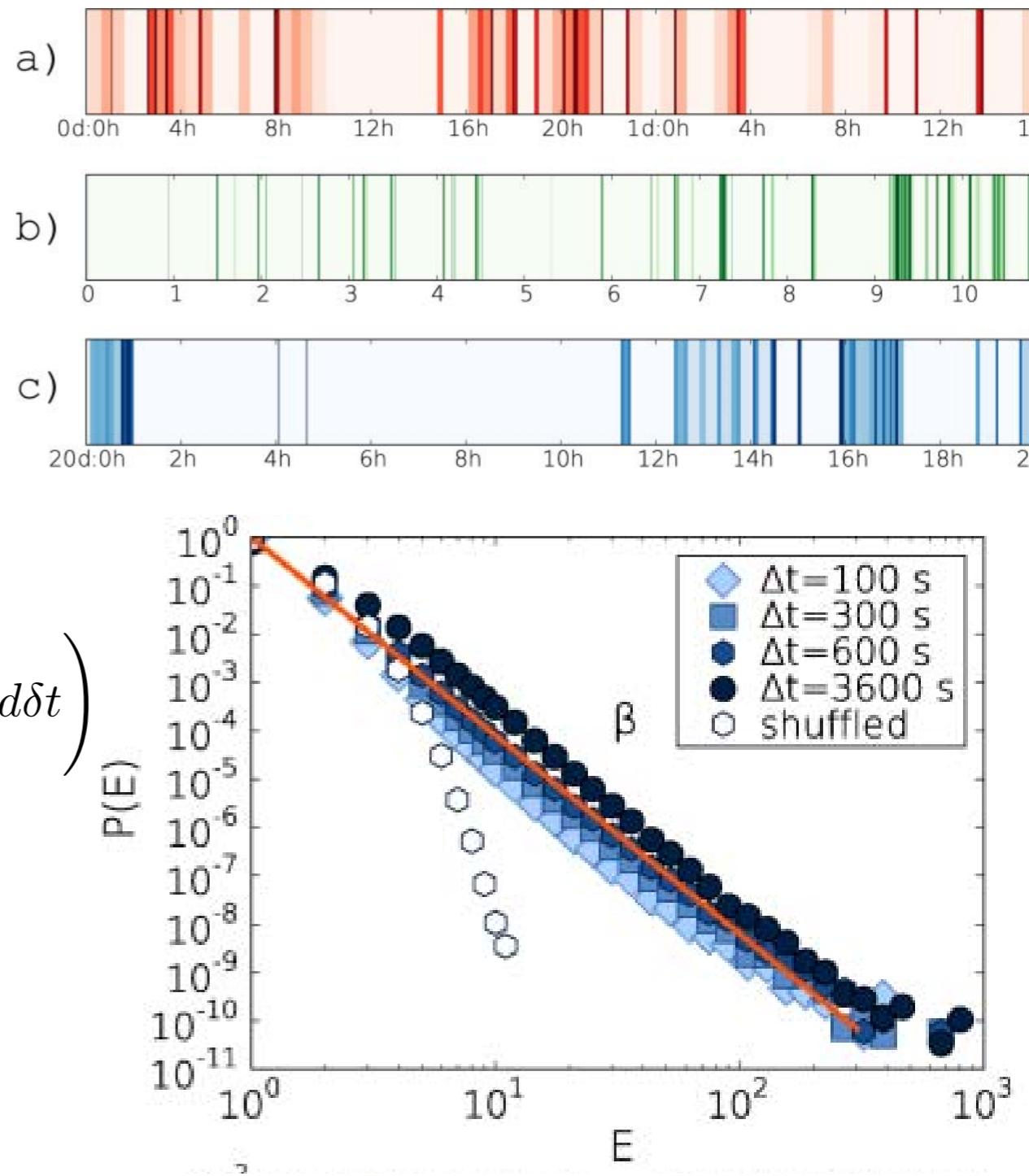
Tie activity

Karsai, M. et al., 2012. Universal features of correlated bursty behaviour. *Scientific Reports*, 2.

- Is that all? Nope: bursts are correlated in time
- To find correlation, detect sequence of events with $\delta t < \Delta t$
- If activity is a renewal process, the probability that we find n of such events in a row is

$$P(E = n) = \left(\int_0^{\Delta t} P(\delta t) d\delta t \right)^{n-1} \left(1 - \int_0^{\Delta t} P(\delta t) d\delta t \right)$$

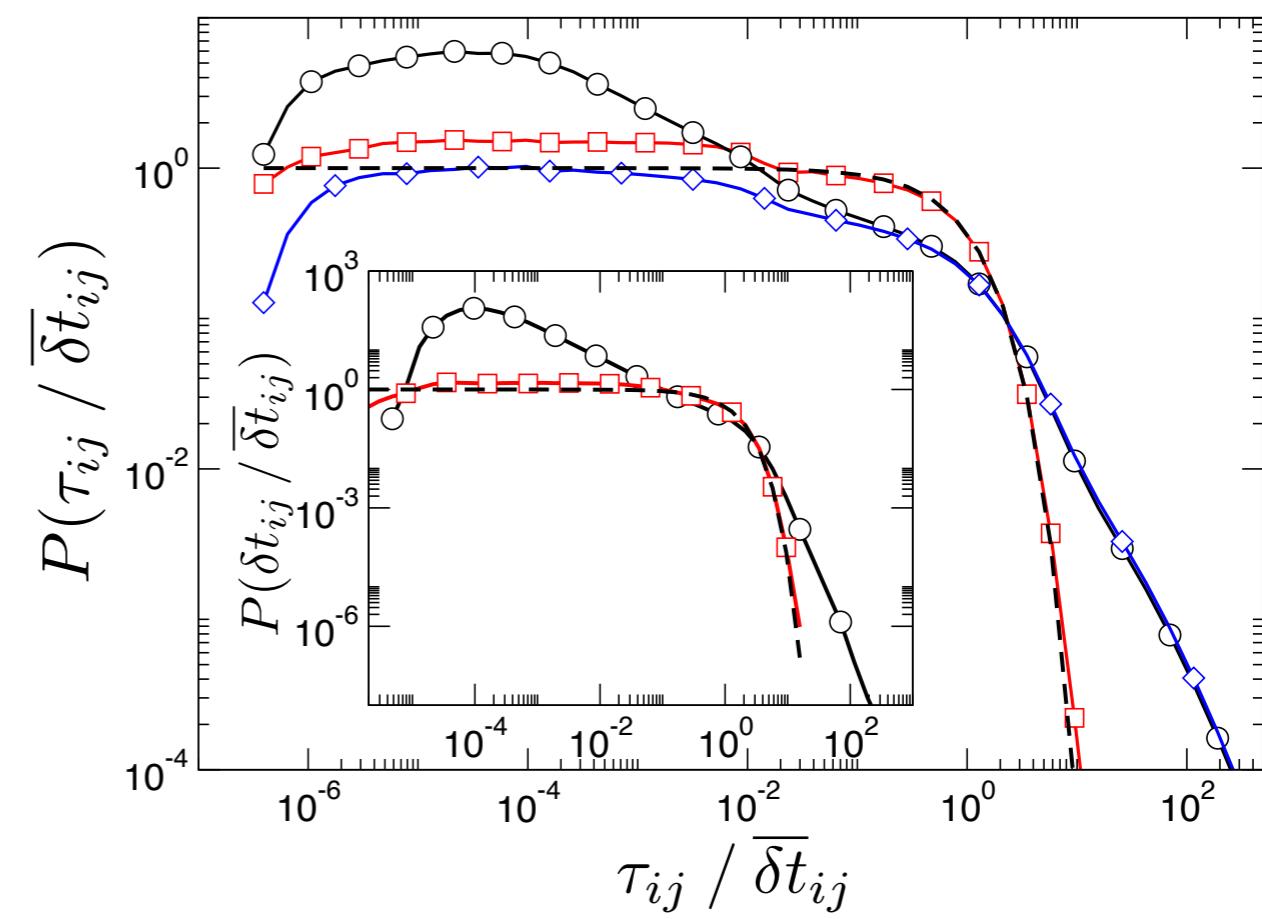
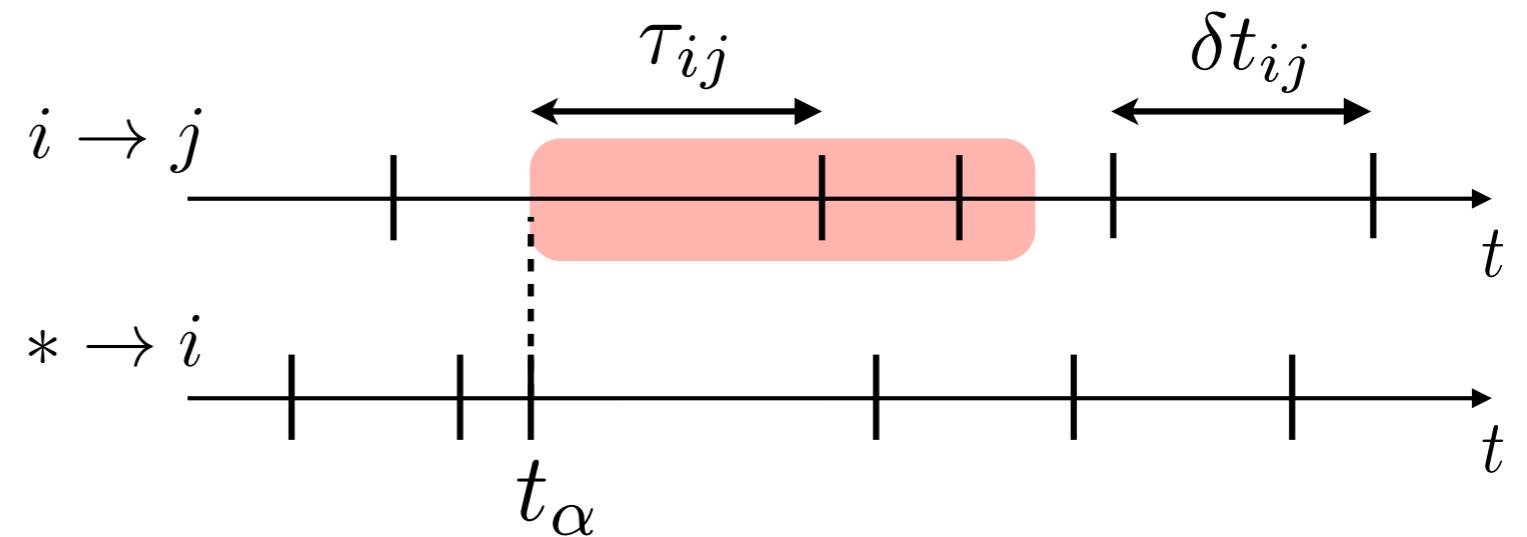
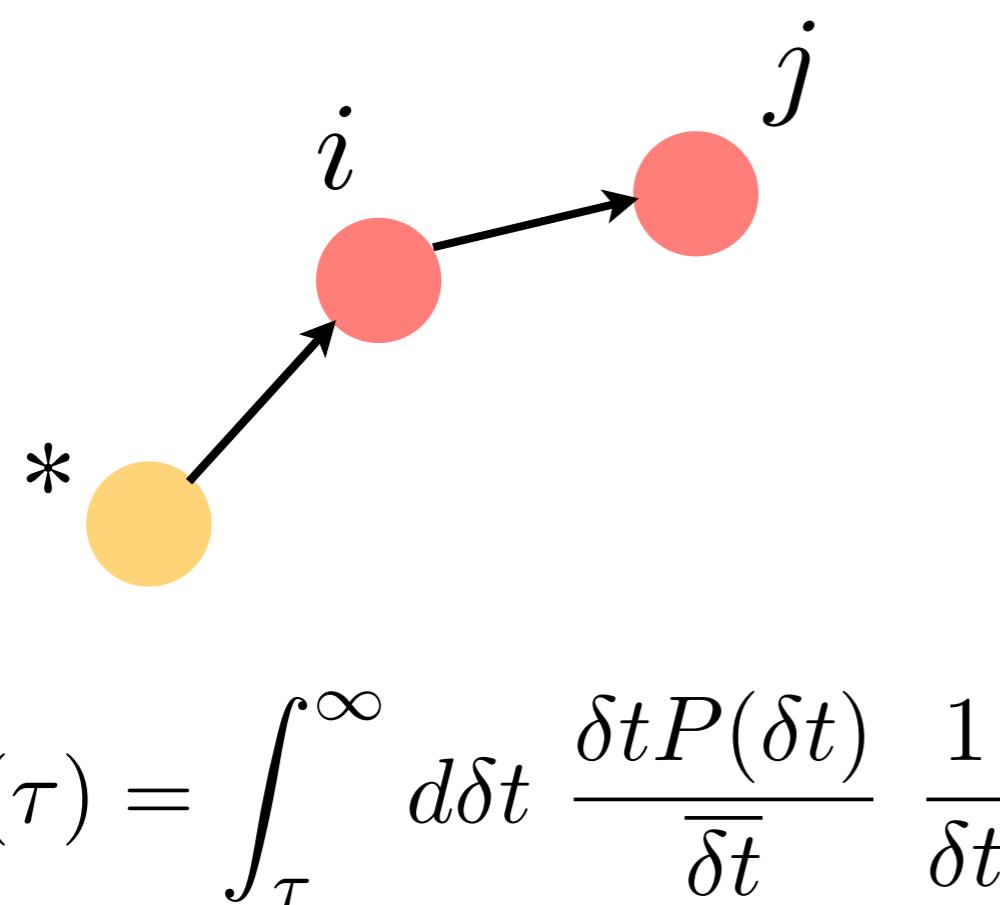
- $P(E)$ decays exponentially
- However, in real data it decays like a power-law



Tie activity

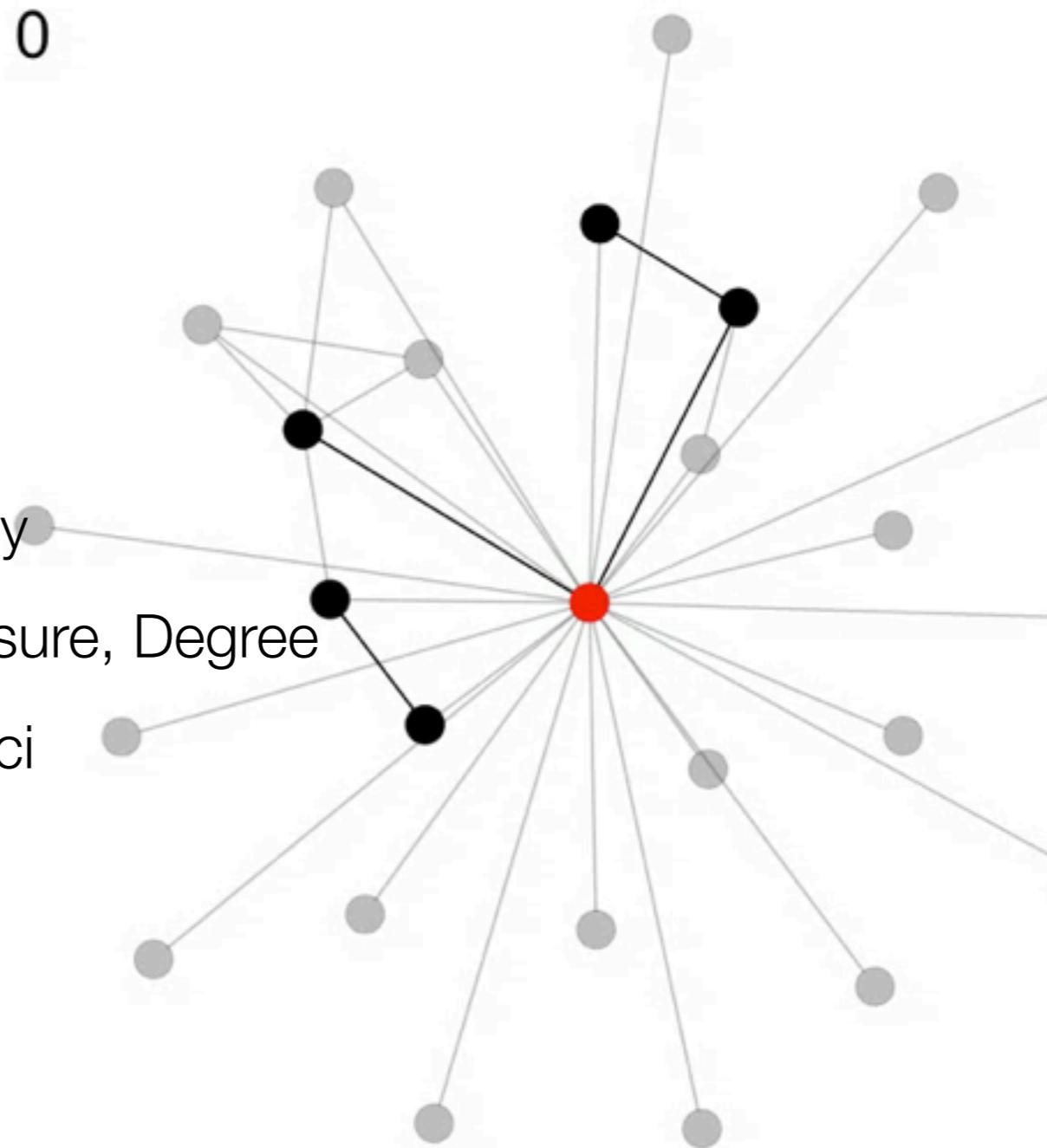
Miritello, G., Moro, E. & Lara, R., 2011. Dynamical strength of social ties in information spreading. *Physical Review E*, 83(4), p.045102.

- Is that all? Nope
 - Adjacent tie contacts are correlated in time



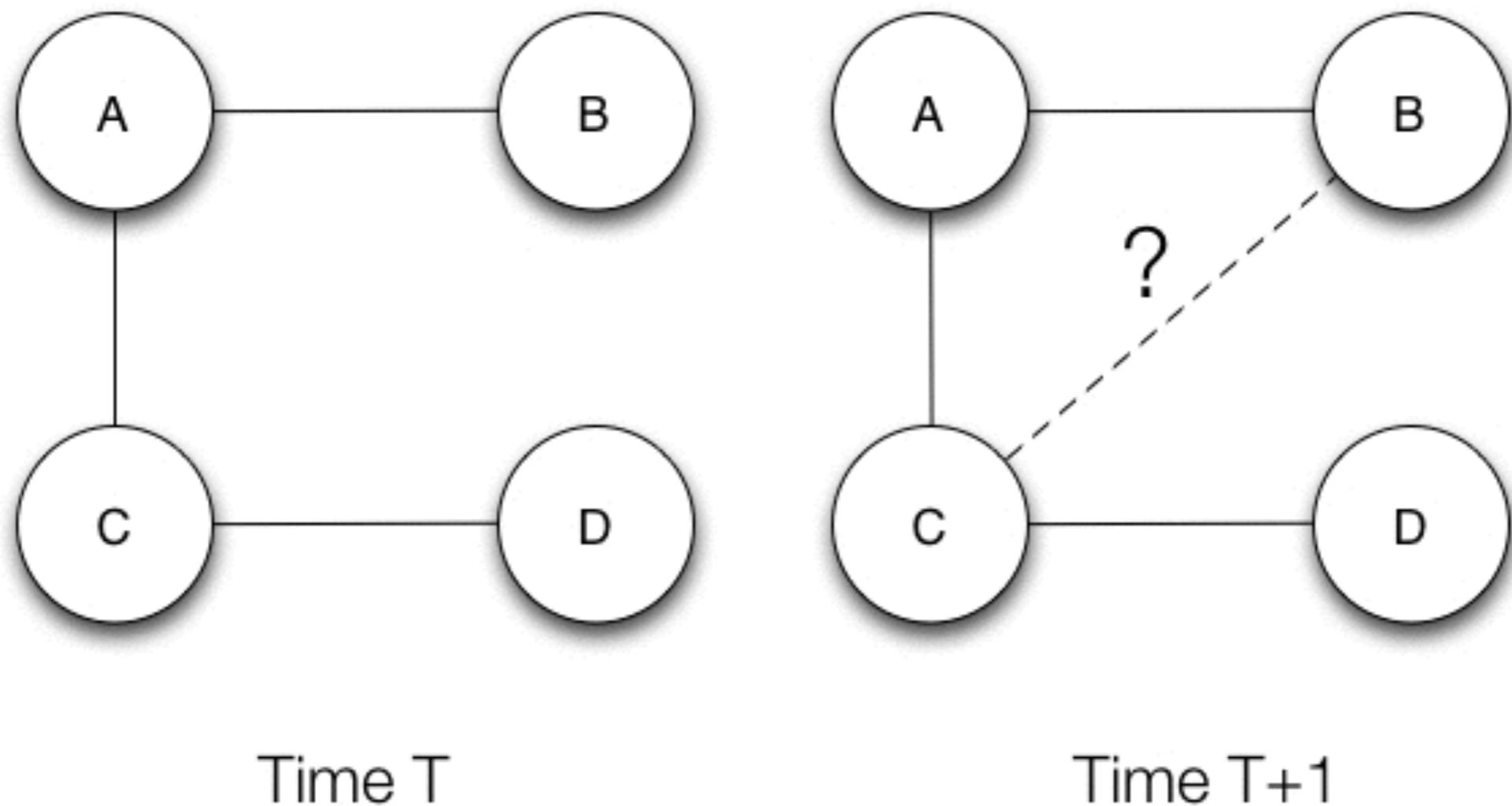
Tie dynamics

- Ties are formed and decay
 - **Why?**
 - *Creation*
 - Node creation/decay
 - **Assortative:** Homophily/Heterophily
 - **Relational:** Reciprocity, Triadic Closure, Degree
 - **Proximity:** Proximity and Social Foci
 - *Decay*
 - **Idem**
 - **How?**
 - Social limitations / strategies



Tie dynamics

- Tie formation: Relational predictors



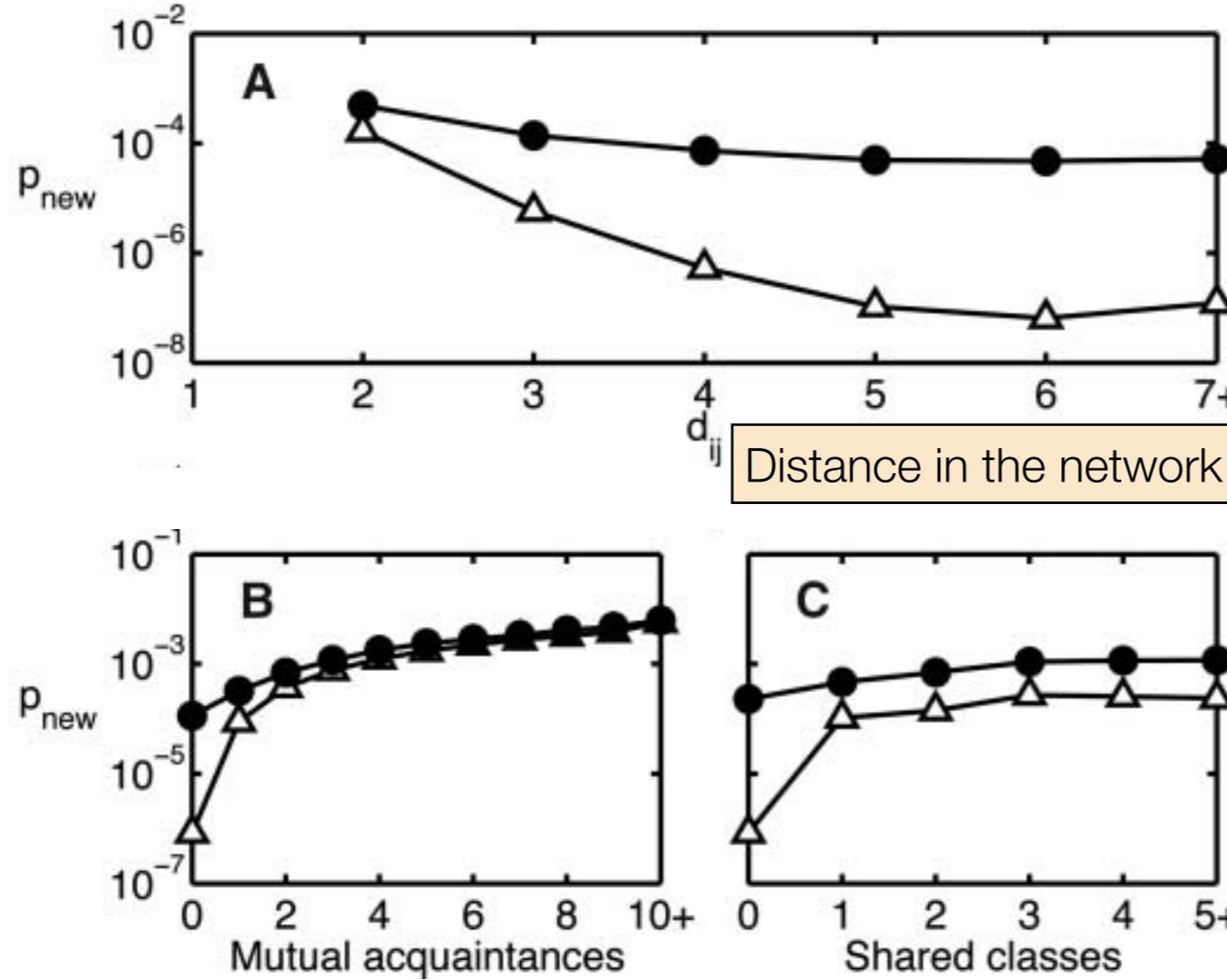
- Triadic closure
- Mutual acquaintances / embeddedness

Tie dynamics

Liben Nowell, D. & Kleinberg, J., 2007. The link-prediction problem for social networks. *Journal of the American Society for Information Science and Technology*, 58(7), pp.1019–1031.

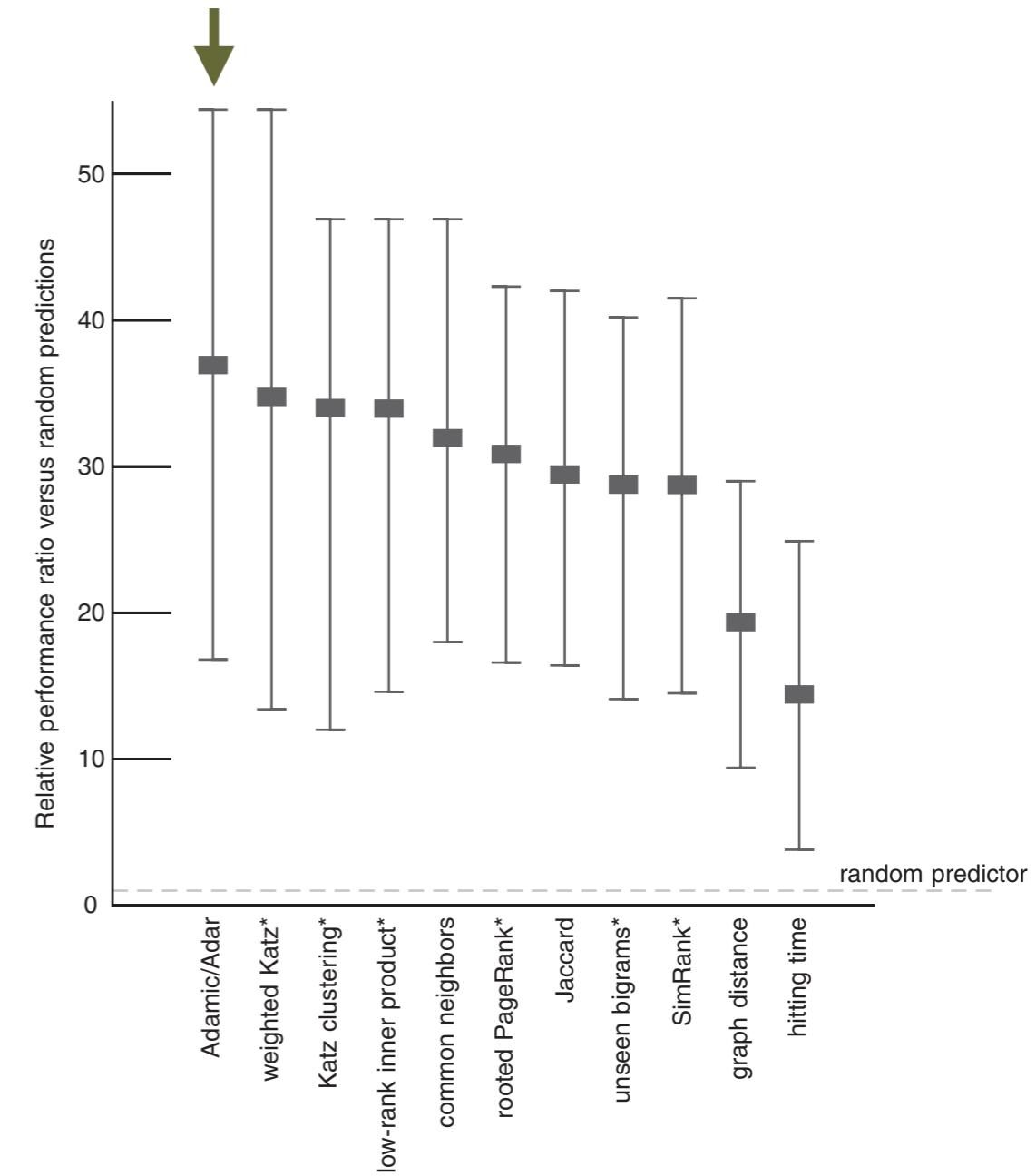
- Tie formation: predictors

Probability of a new tie



Kossinets, G. & Watts, D.J., 2006. Empirical analysis of an evolving social network. *Science*, 311(5757), pp.88–90.

$$\sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log|\Gamma(z)|}$$



Tie dynamics

- Tie decay: predictors

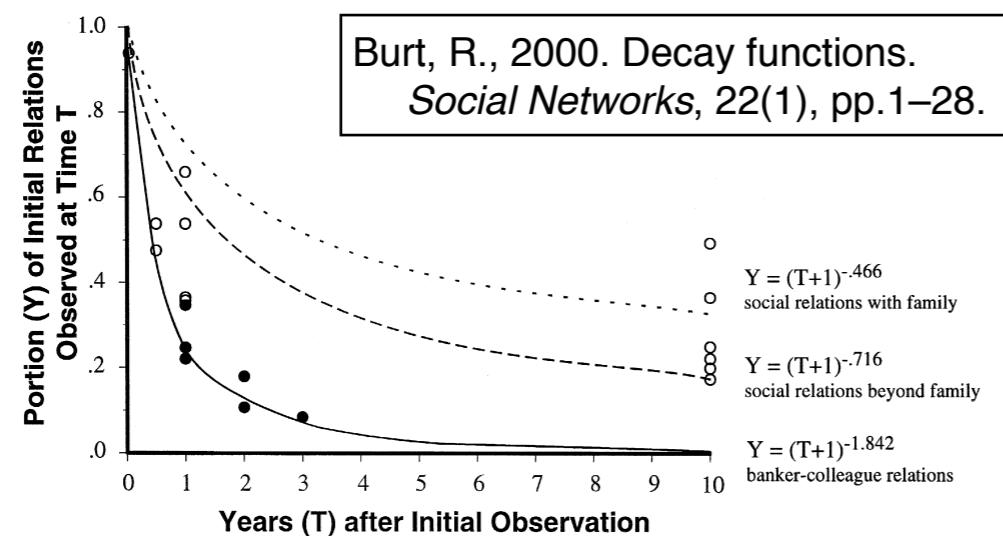
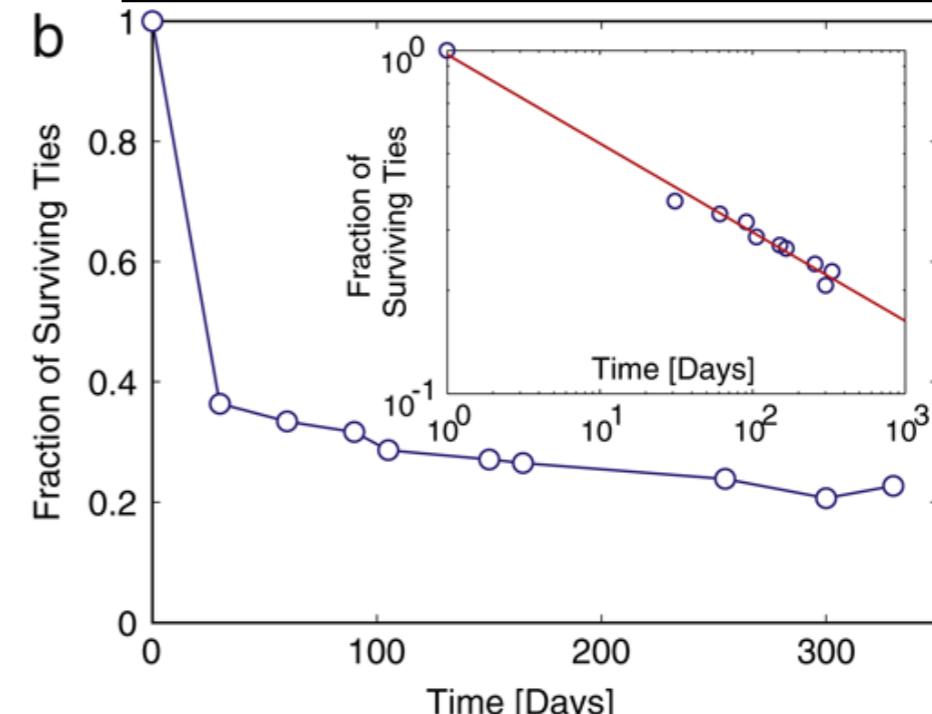


Table 1
Persistence of ties and link attributes

Pearson's correlation	ΔC	Δk	Δr	R	TO	Persistence
ΔC	1	0.023	0.15	0.11	0.23	0.15
Δk		1	0.02	-0.13	-0.19	-0.16
Δr			1	-0.68	-0.073	0.033
R				1	0.2964	0.5886
TO					1	0.3537
Regression coefficients	0.09	0.002	0.15	0.35	0.56	
Partial correlations	0.0027	0.0032	0.007	0.26	0.034	

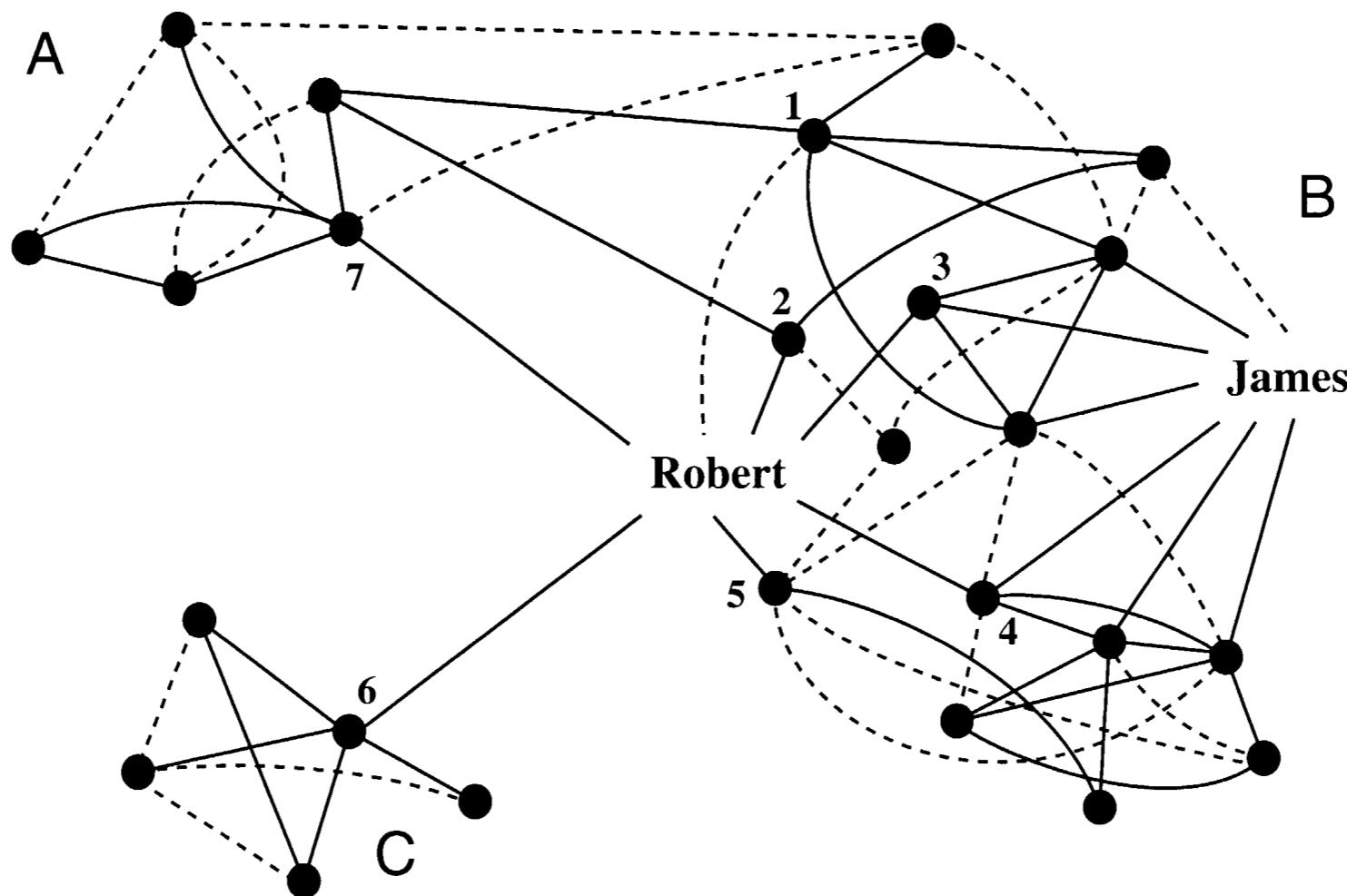
- Links with large embeddedness and reciprocity are more likely to persist

Hidalgo, C. & Rodriguez-Sickert, C., 2008. The dynamics of a mobile phone network. *Physica A*, 387(12), pp.3017–3024.



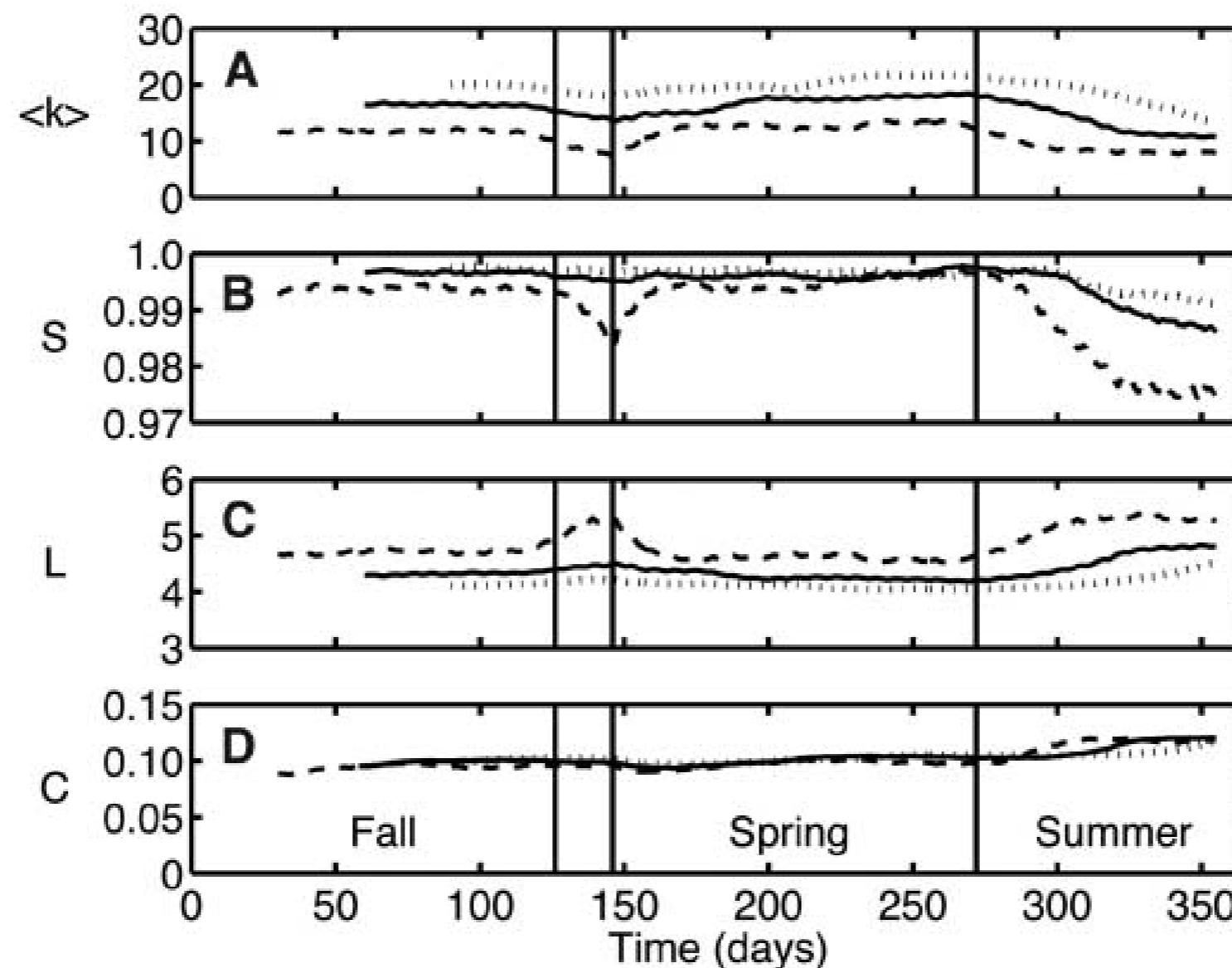
Tie dynamics

- Two paradoxes
 - Ties bridging distant parts of the network (the ones important for information diffusion, achievement) are not only the least likely to be created, but also the most likely to decay



Tie dynamics

- Two paradoxes
 - Tie formation tends to close triangles. But ties embedded in triangles are less likely to decay. Thus, network should become more clustered



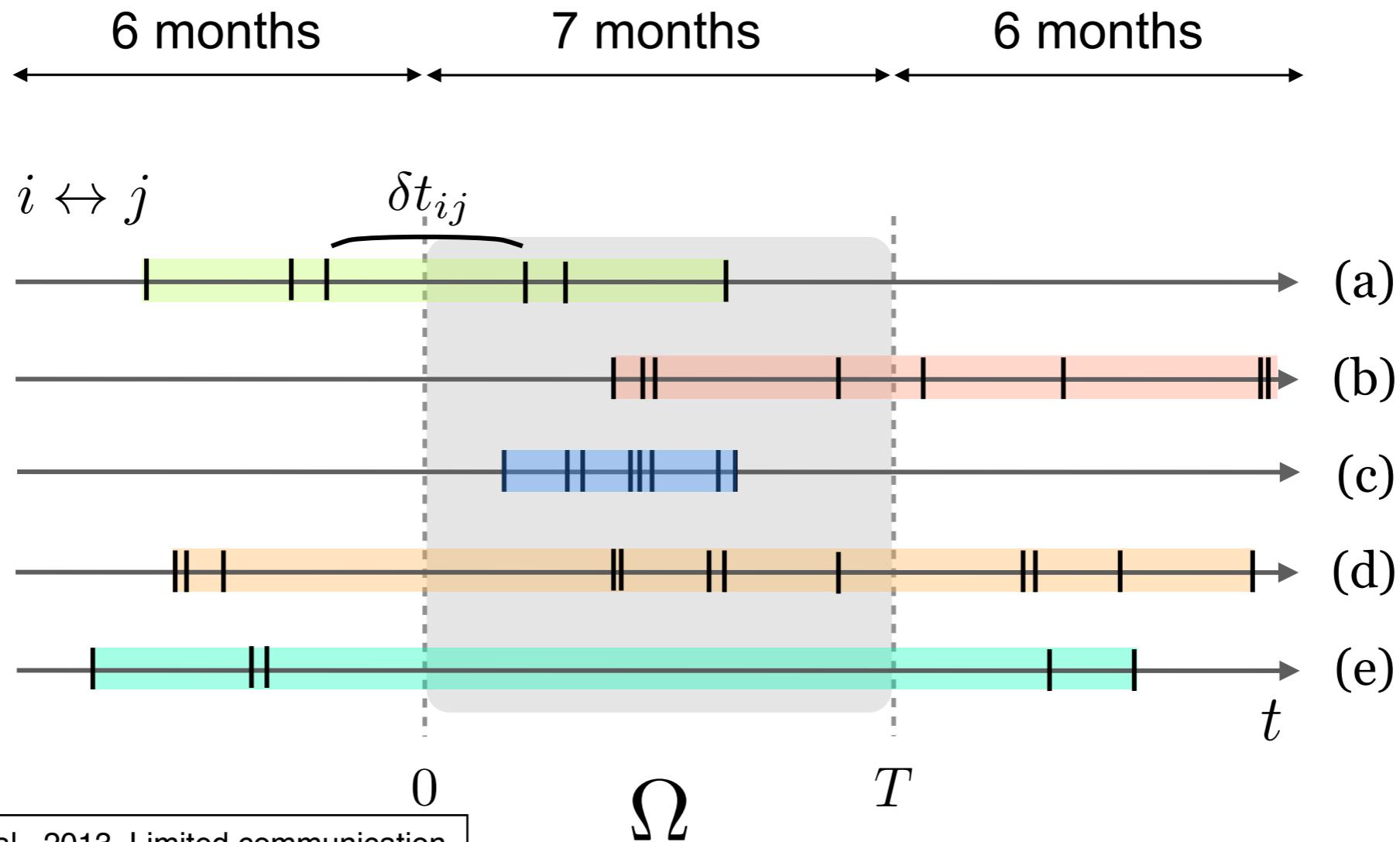
Tie dynamics

- How are ties formed and destroyed?
Is there any strategy?
- Cognitive limitations, time limitations
 - Dunbar number: there is a limit to the number of people with whom one can maintain stable social relationships.
 - Time/attention is limited: how do we manage relationships if our time is limited?



Tie dynamics

- How are ties formed and destroyed?
- Disentangling tie burstiness and formation/decay



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

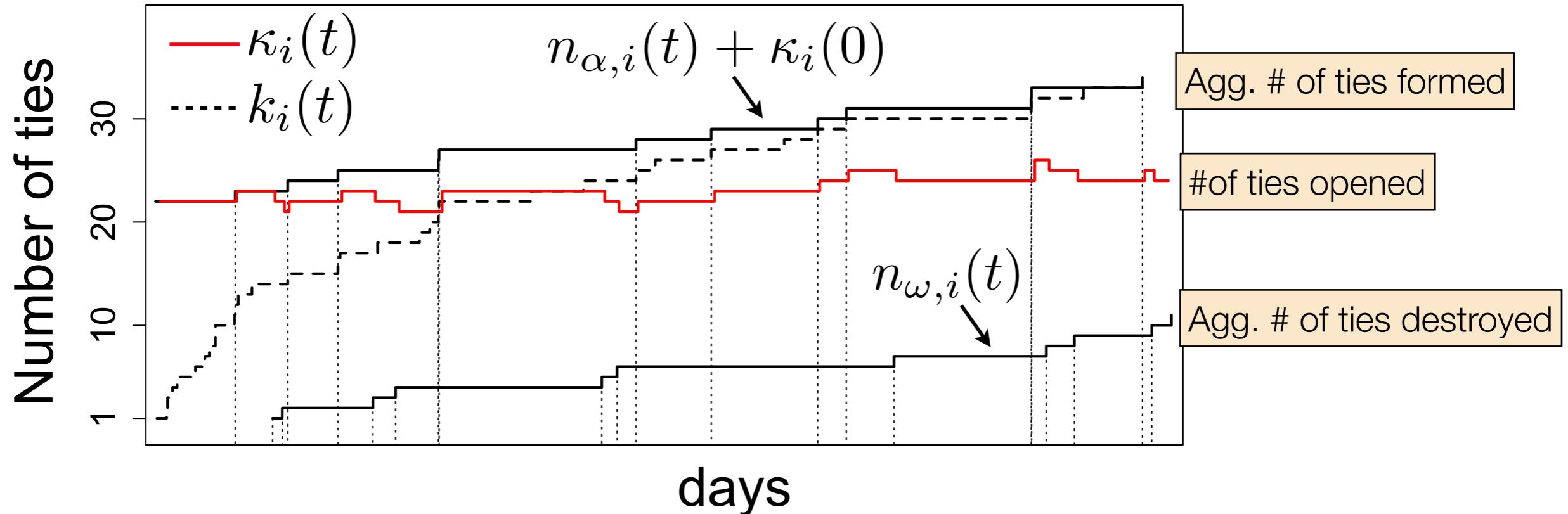


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Tie dynamics

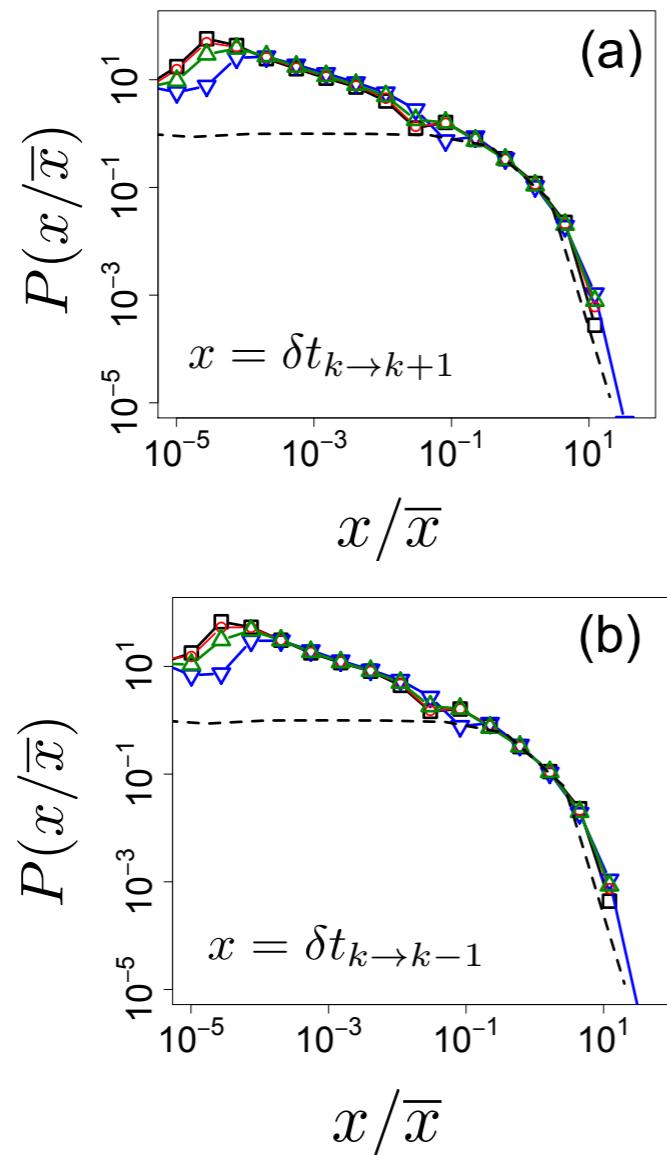
- How are ties formed and destroyed?
- Very heterogeneous tie evolution



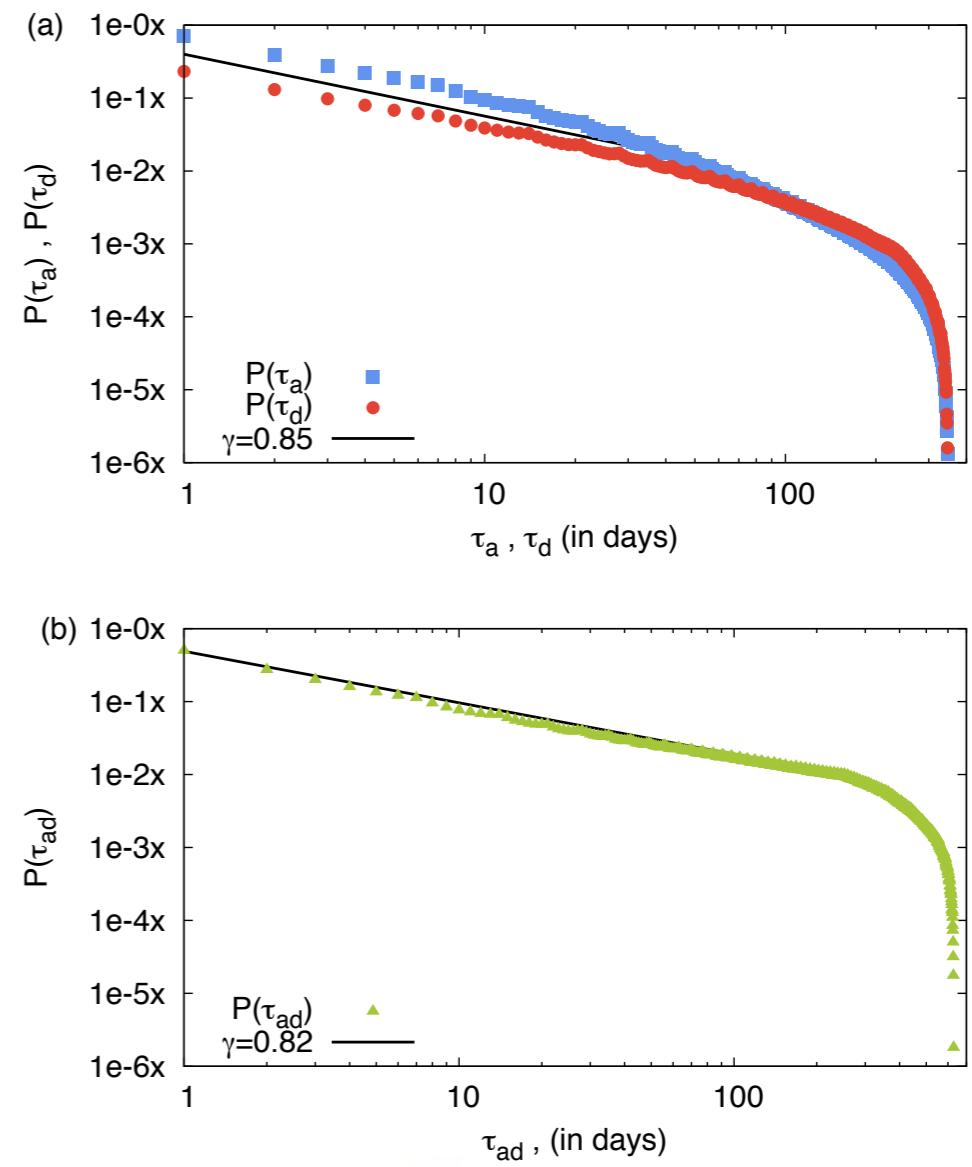
- Mean $\langle n_{\alpha,i} \rangle \simeq \langle n_{\omega,i} \rangle \simeq 8$ $\langle k_i \rangle \simeq 16$
- But $n_{\alpha,i} > 15$ for 20% of nodes

Tie dynamics

- How are ties formed and destroyed?
- Tie formation/decay is bursty

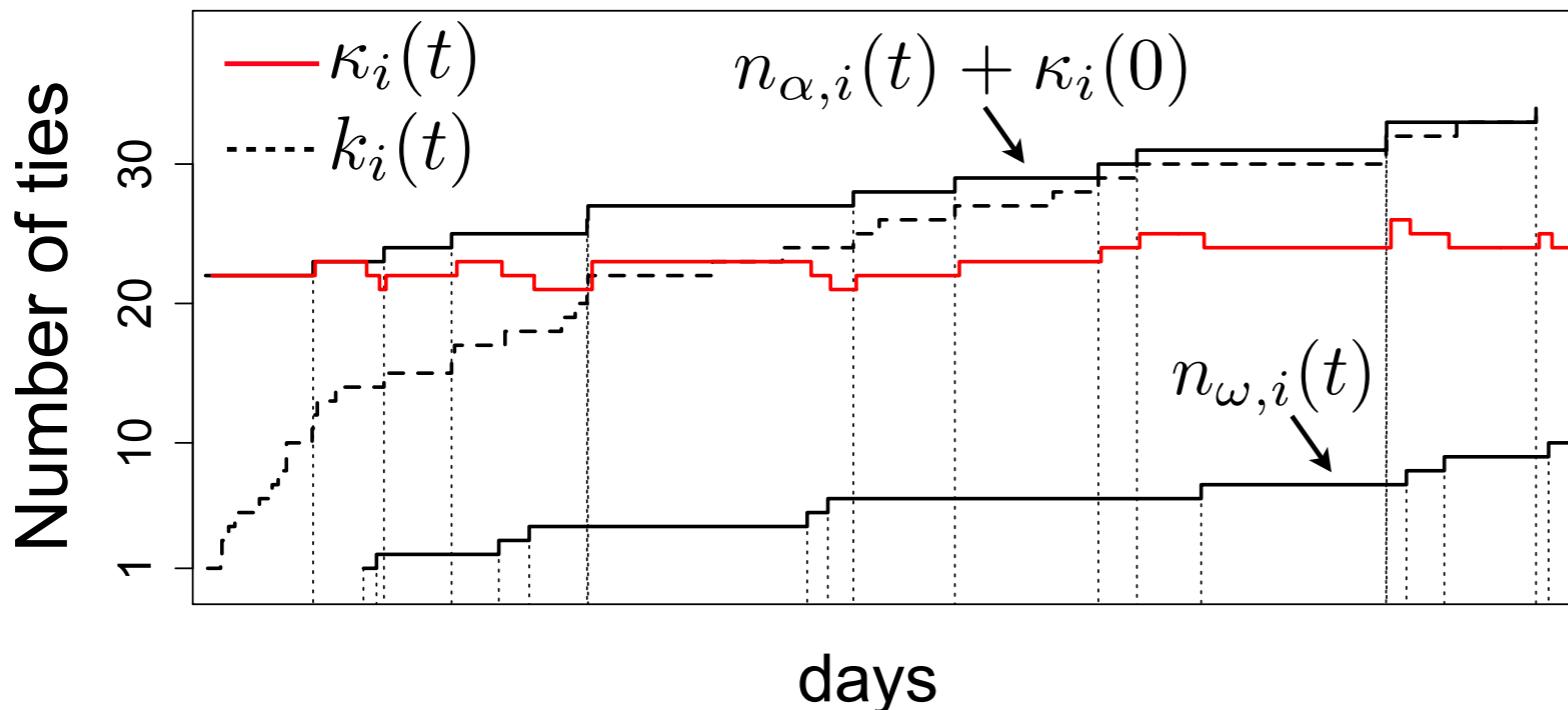


Kikas, R., Dumas, M. & Karsai, M., 2012. Bursty egocentric network evolution in Skype. *arXiv.org*, physics.soc-ph.



Tie dynamics

- How are ties formed and destroyed?
- Linear tie formation/decay and conserved capacity

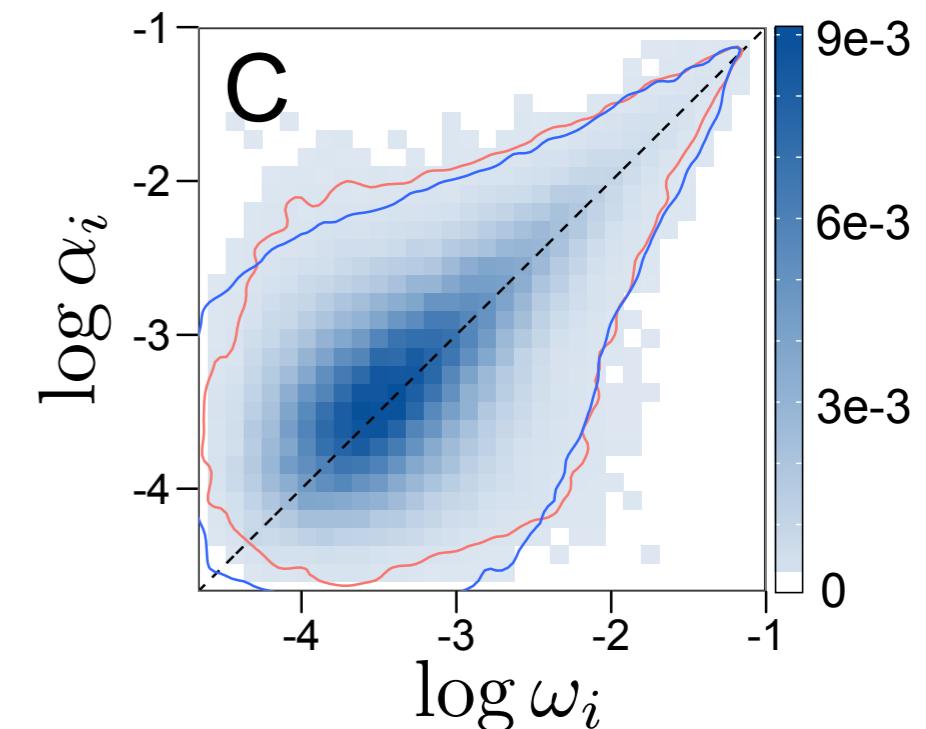


$$n_{\alpha,i}(t) \simeq \alpha_i t$$

$$n_{\omega,i}(t) \simeq \omega_i t$$

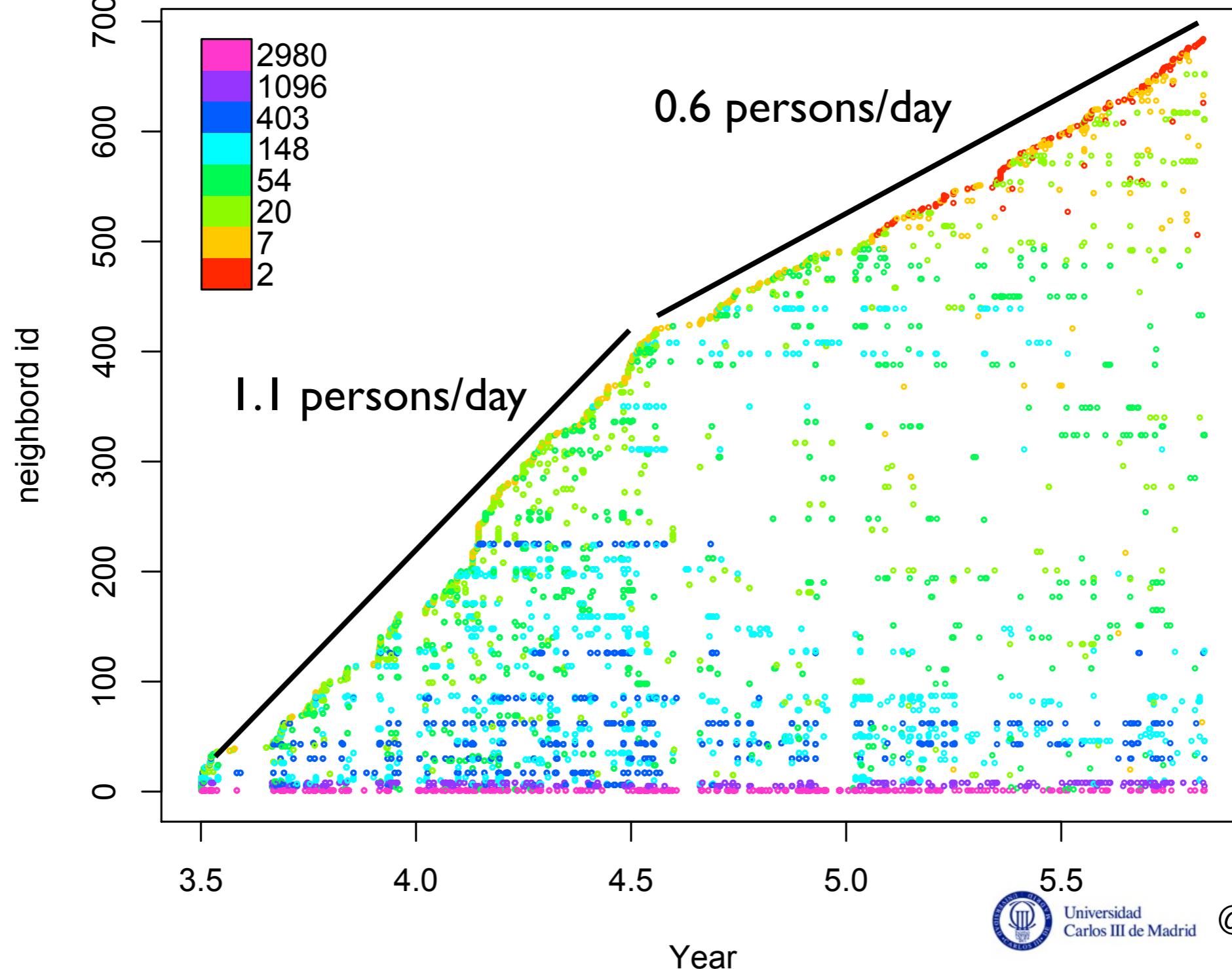
$$\alpha_i \simeq \omega_i$$

$$\kappa_i(t) \simeq \kappa_i(0)$$



Tie dynamics

- How are ties formed and destroyed? Linear tie formation/decay



Tie dynamics

- How are ties formed and destroyed?
- Social capacity and activity are not independent

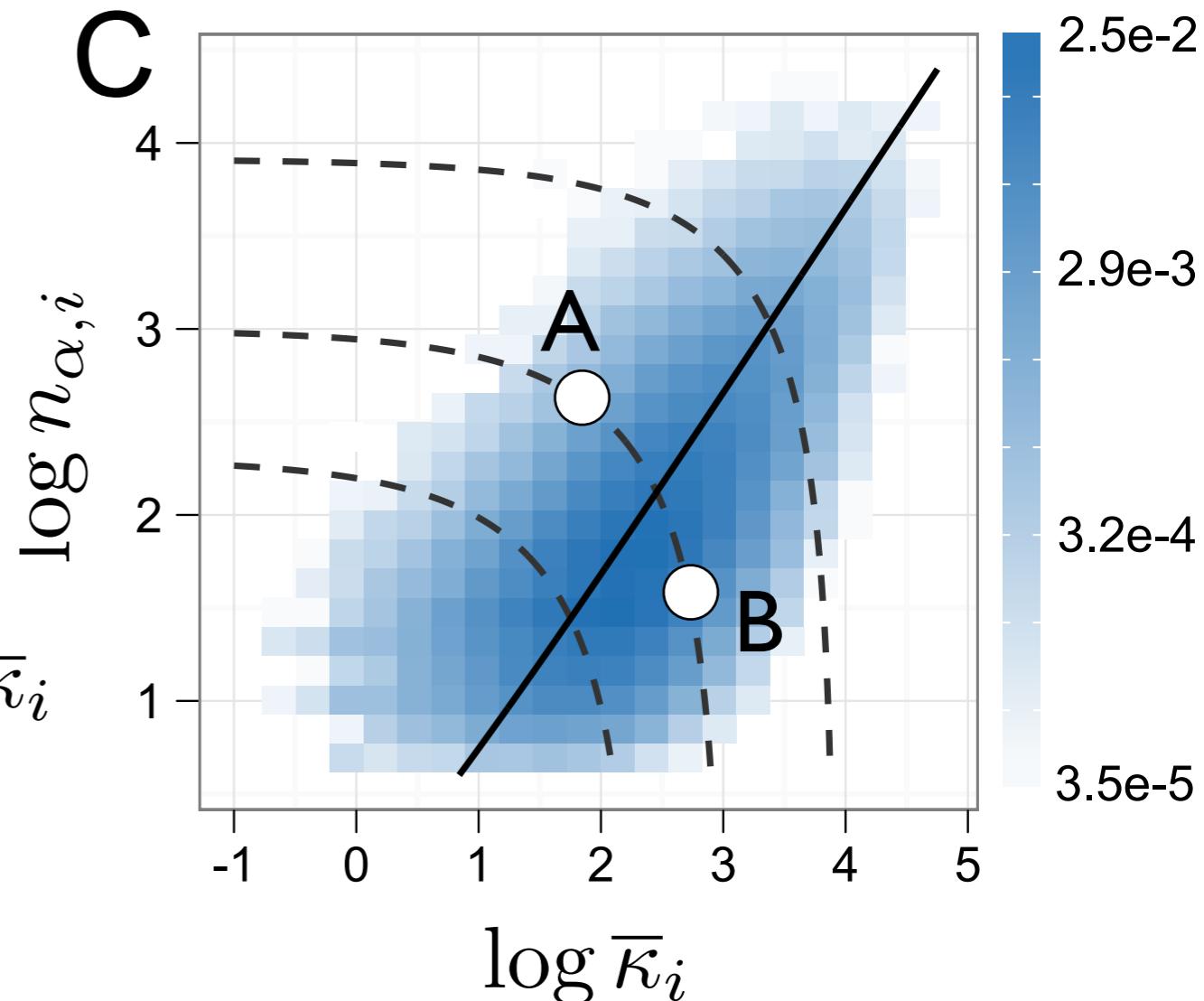
$$n_{\alpha,i} \propto \bar{\kappa}_i$$

- For a given k_i we have

- Social explorers (**A**) $n_{\alpha,i} \gg \bar{\kappa}_i$

- Balanced (-) $n_{\alpha,i} \simeq \bar{\kappa}_i$

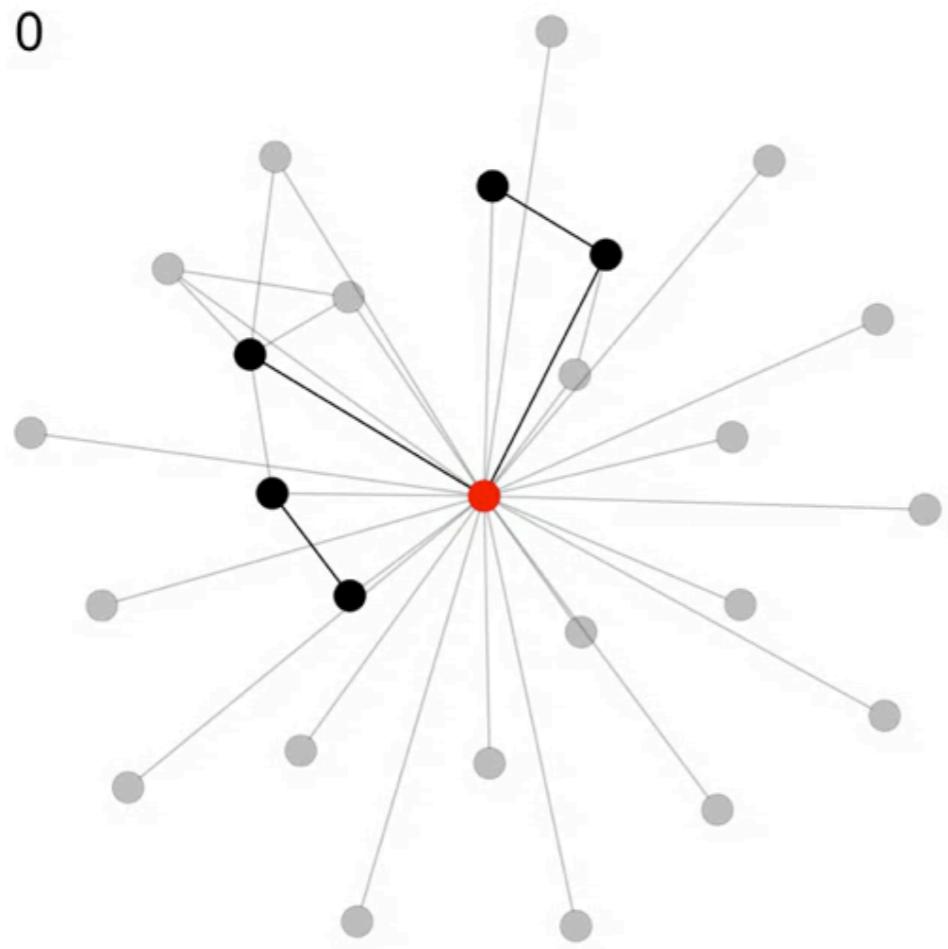
- Social keepers (**B**) $n_{\alpha,i} \ll \bar{\kappa}_i$



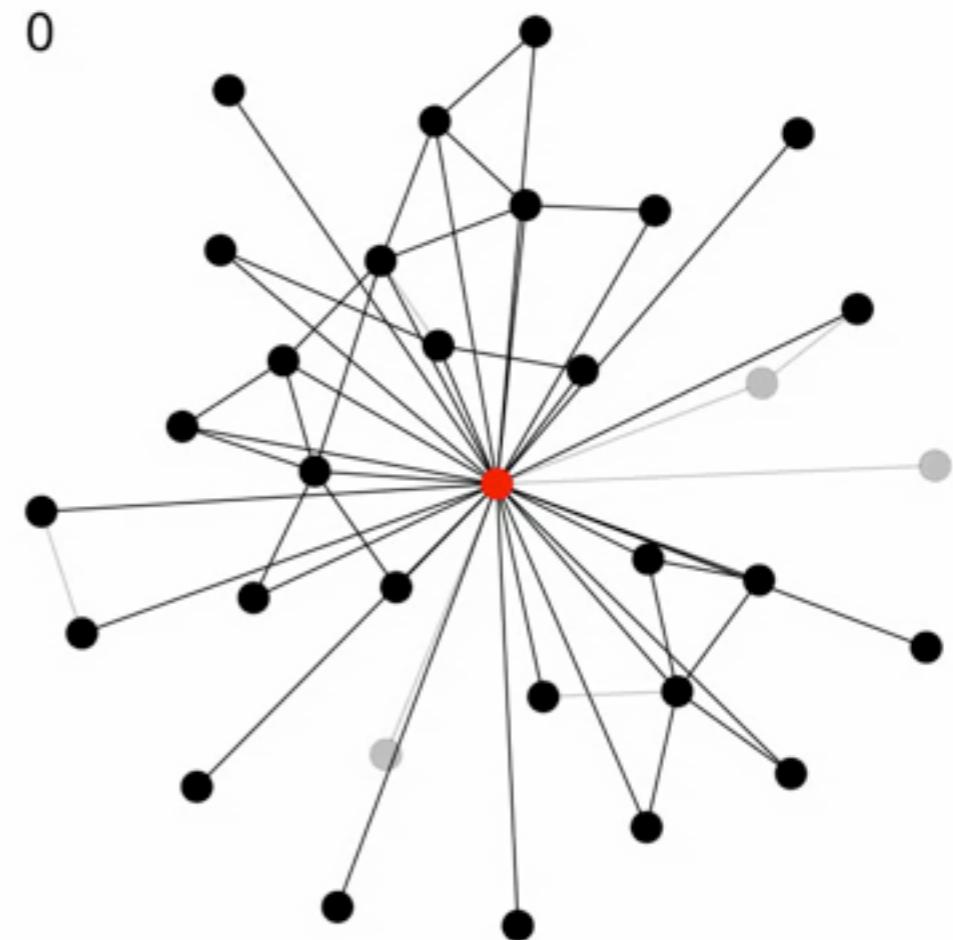
Miritello, Lara, Cebrián and EM
Scientific Reports 3, 1950 (2013)

Tie dynamics

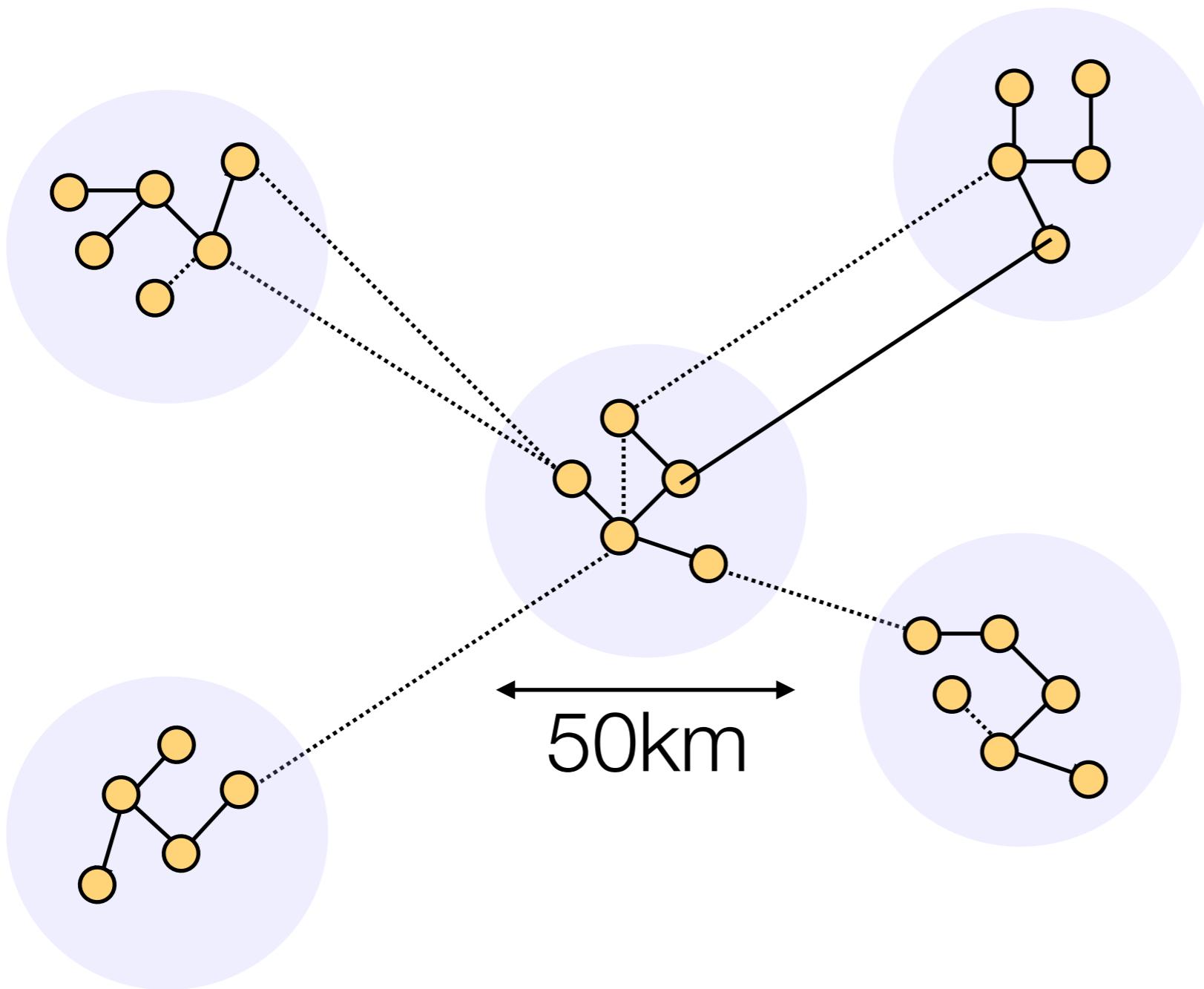
- H



$n_{\alpha,i} = 23, \bar{\kappa}_i = 4$
Social explorer



$n_{\alpha,i} = 3, \bar{\kappa}_i = 24$
Social keeper

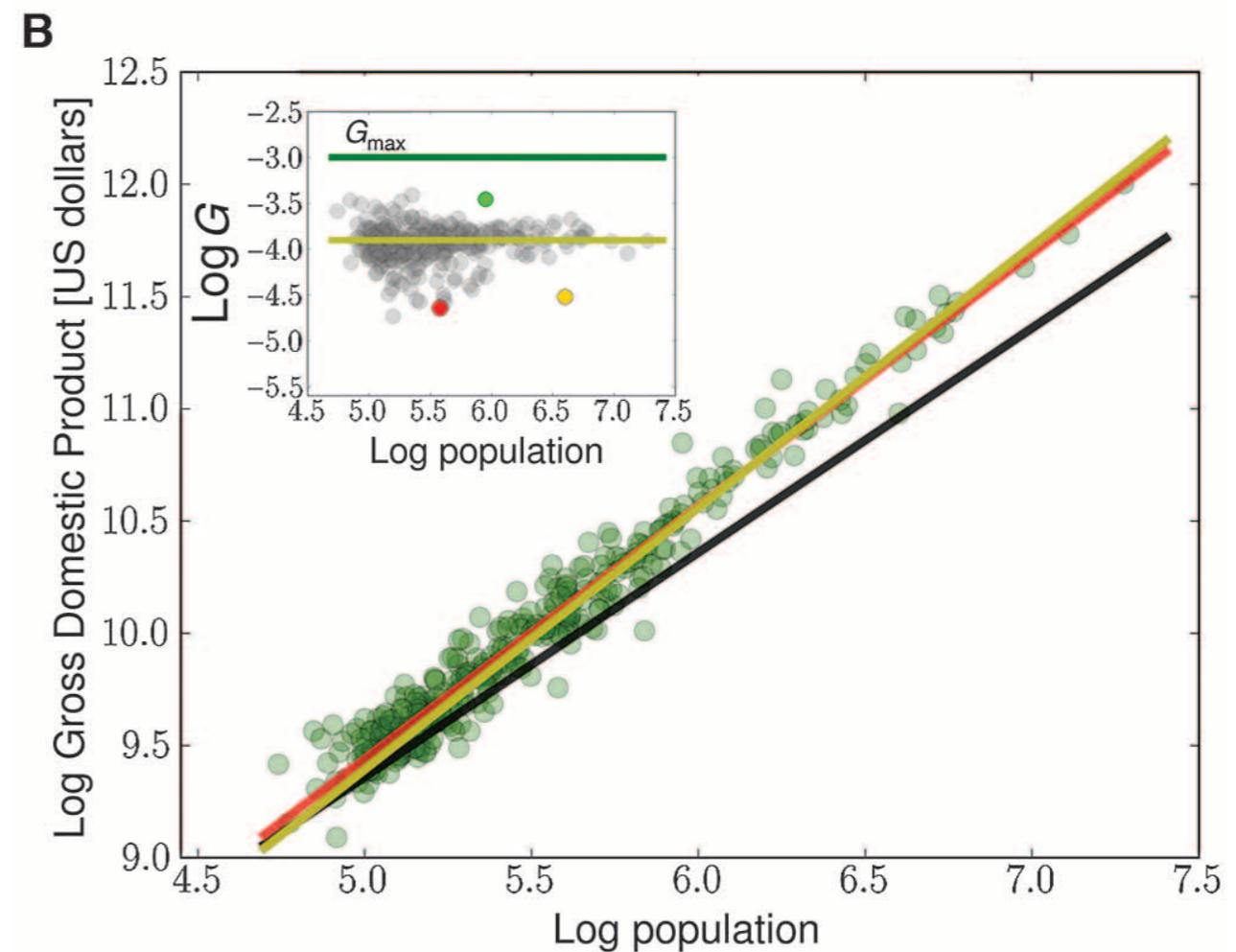
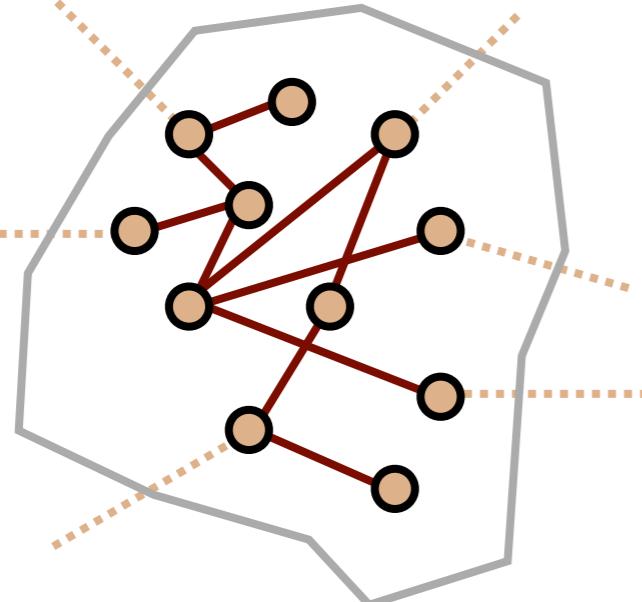


Geographical dynamics

2.3

Geography and network dynamics

- Does geography play a role in the dynamics of human communication?
- Known results:
 - City properties scale super-linearly with population
 - Including #links within the city!!

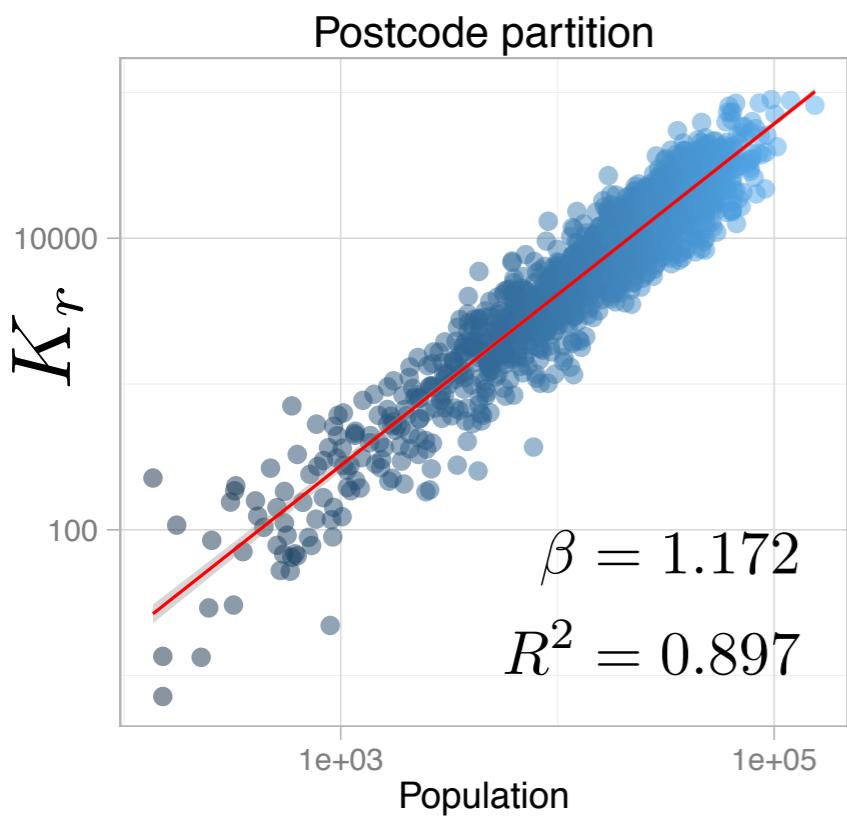


Bettencourt, L.M.A., 2013. The Origins of Scaling in Cities. *Science*, 340(6139), pp.1438–1441.

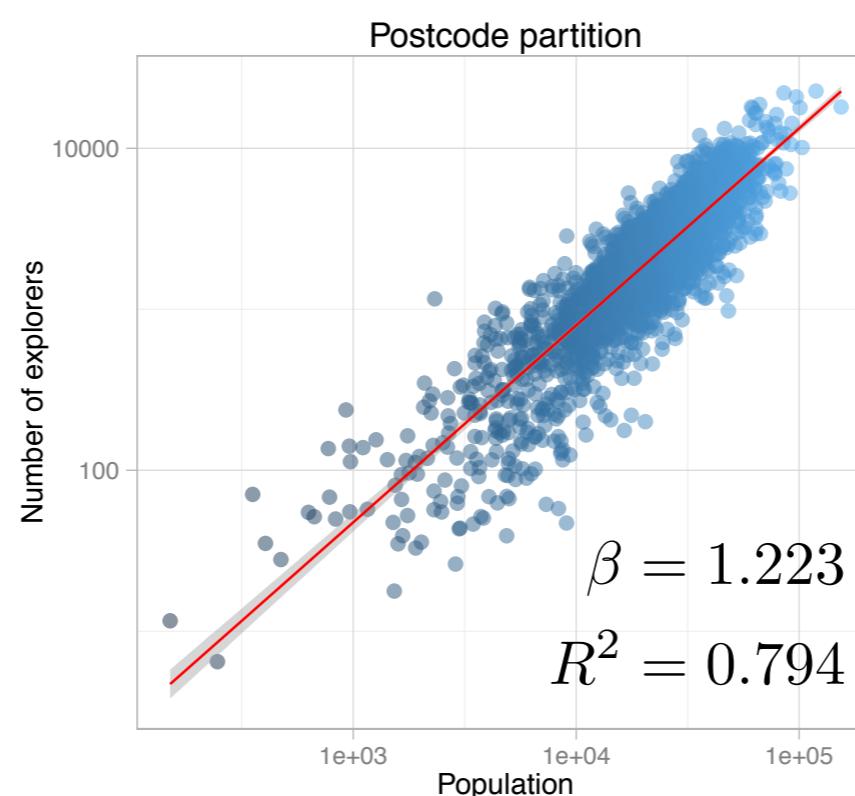
Geography and network dynamics

- Dynamics also scale super-linearly with the size of the city
 - Bigger cities have more dynamical networks

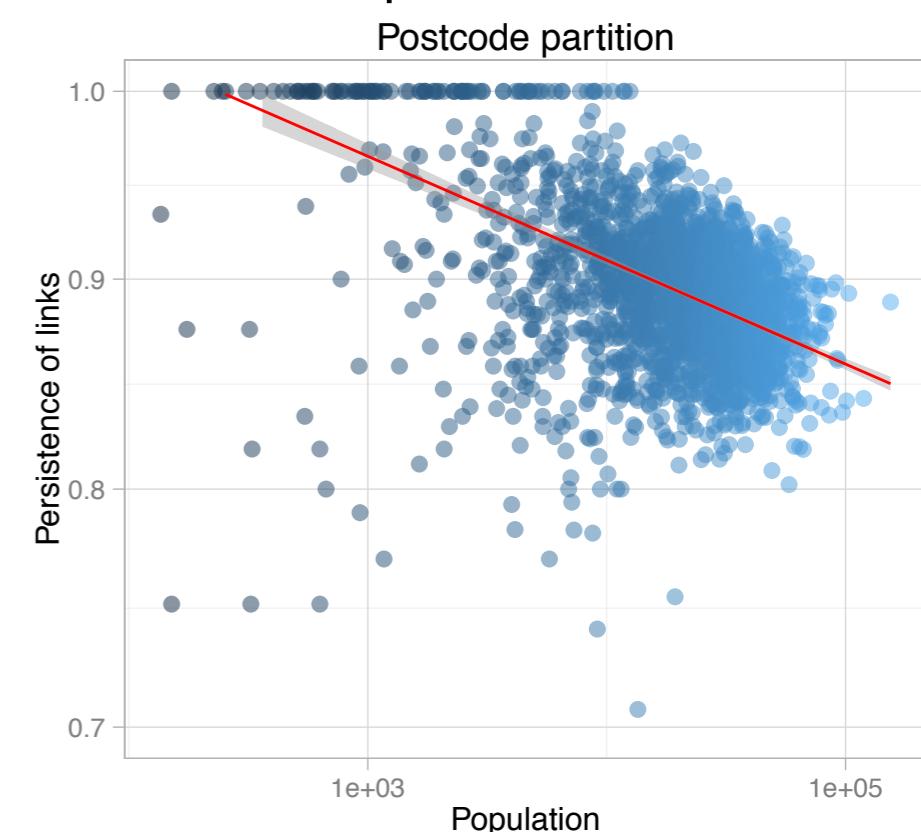
Number of links



Number of explorers



Tie persistence

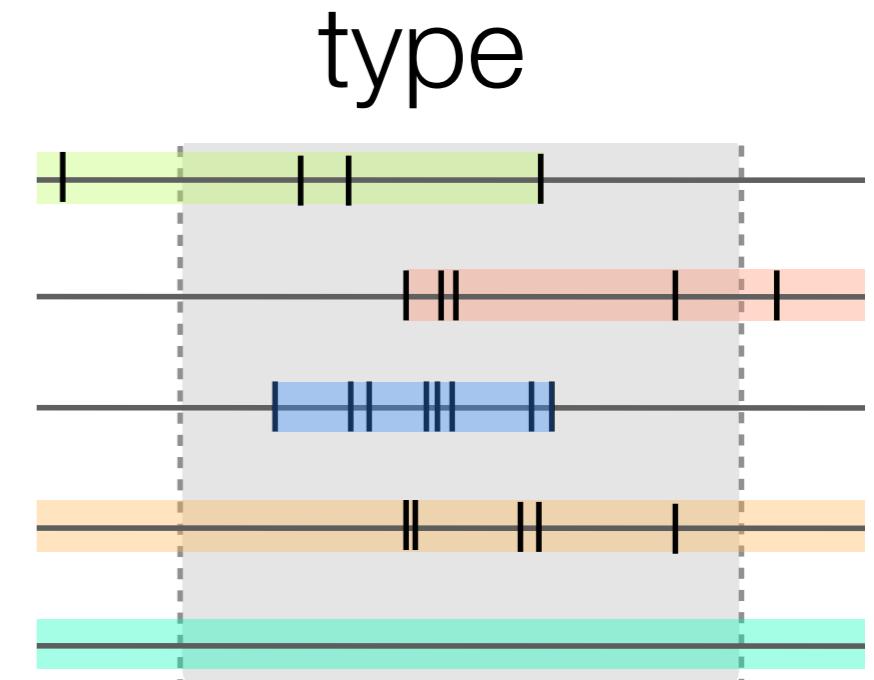
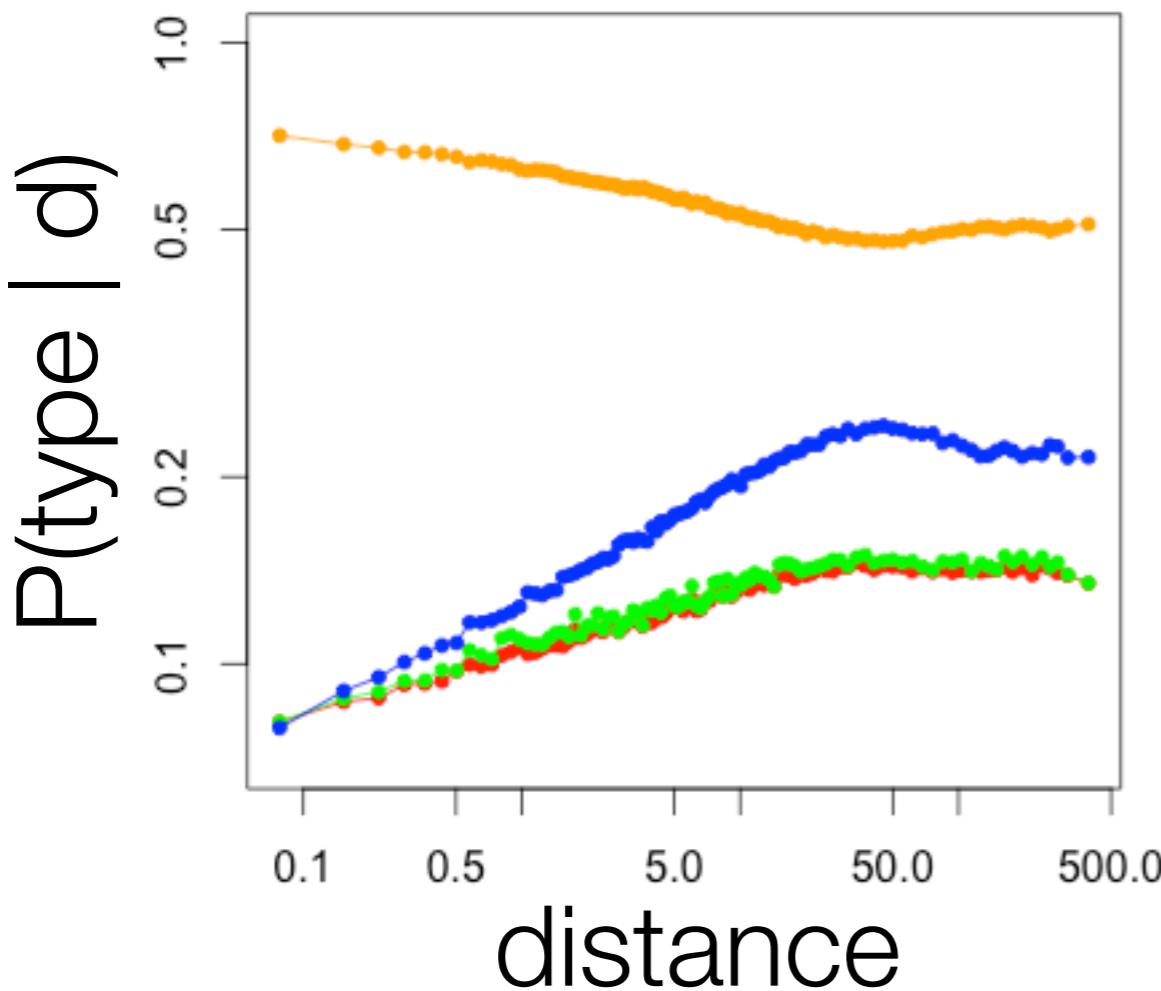


$$Persistence = \frac{|E(t+T) \cap E(t)|}{|E(t)|}$$



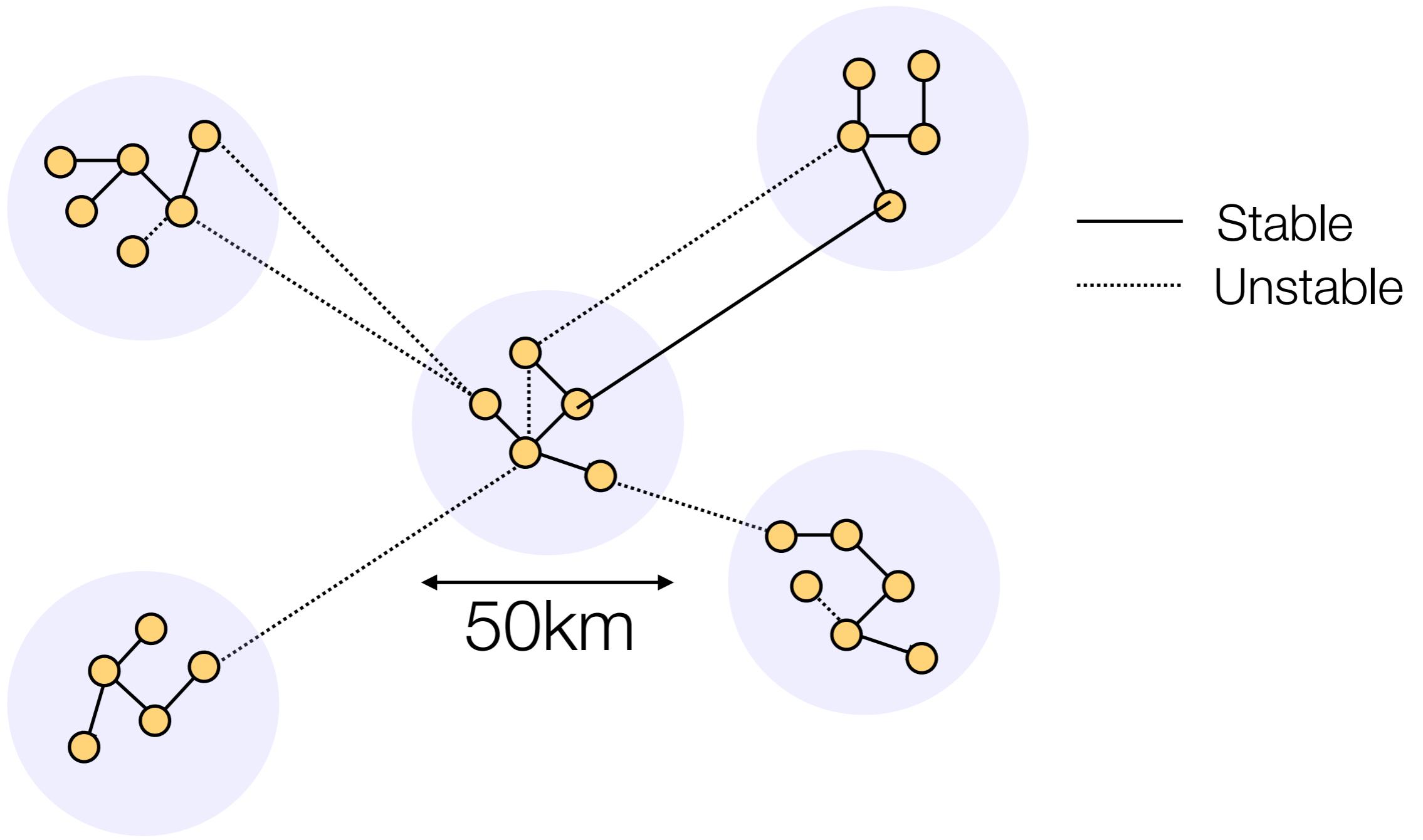
Geography and network dynamics

- Tie Dynamics also depend on the distance between people:
 - At small distances ties are very stable
 - At large distances ties are very unstable



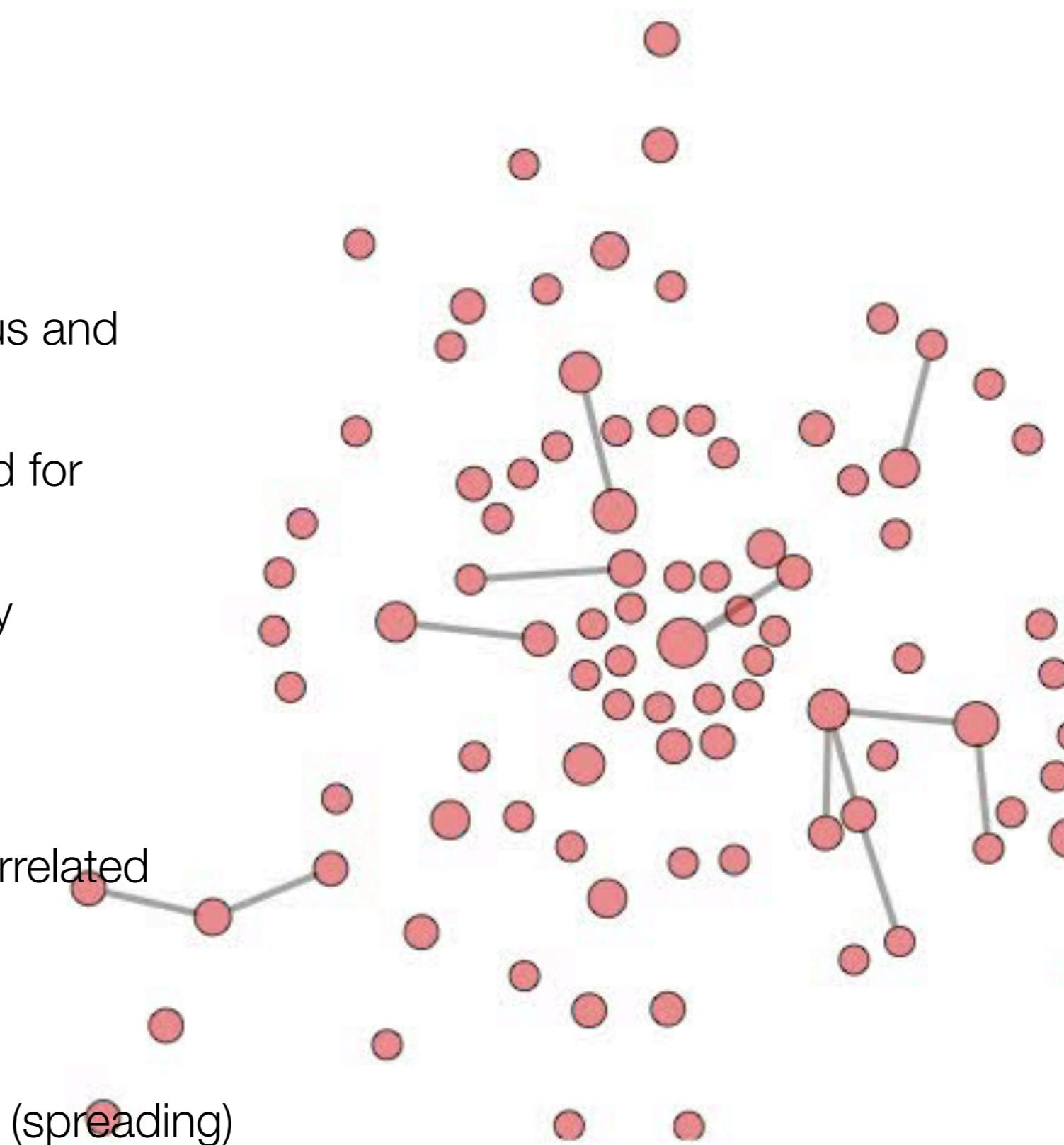
There is a geographical
scale for dynamics
 $d \sim 50\text{km}$

The geographical picture of temporal networks



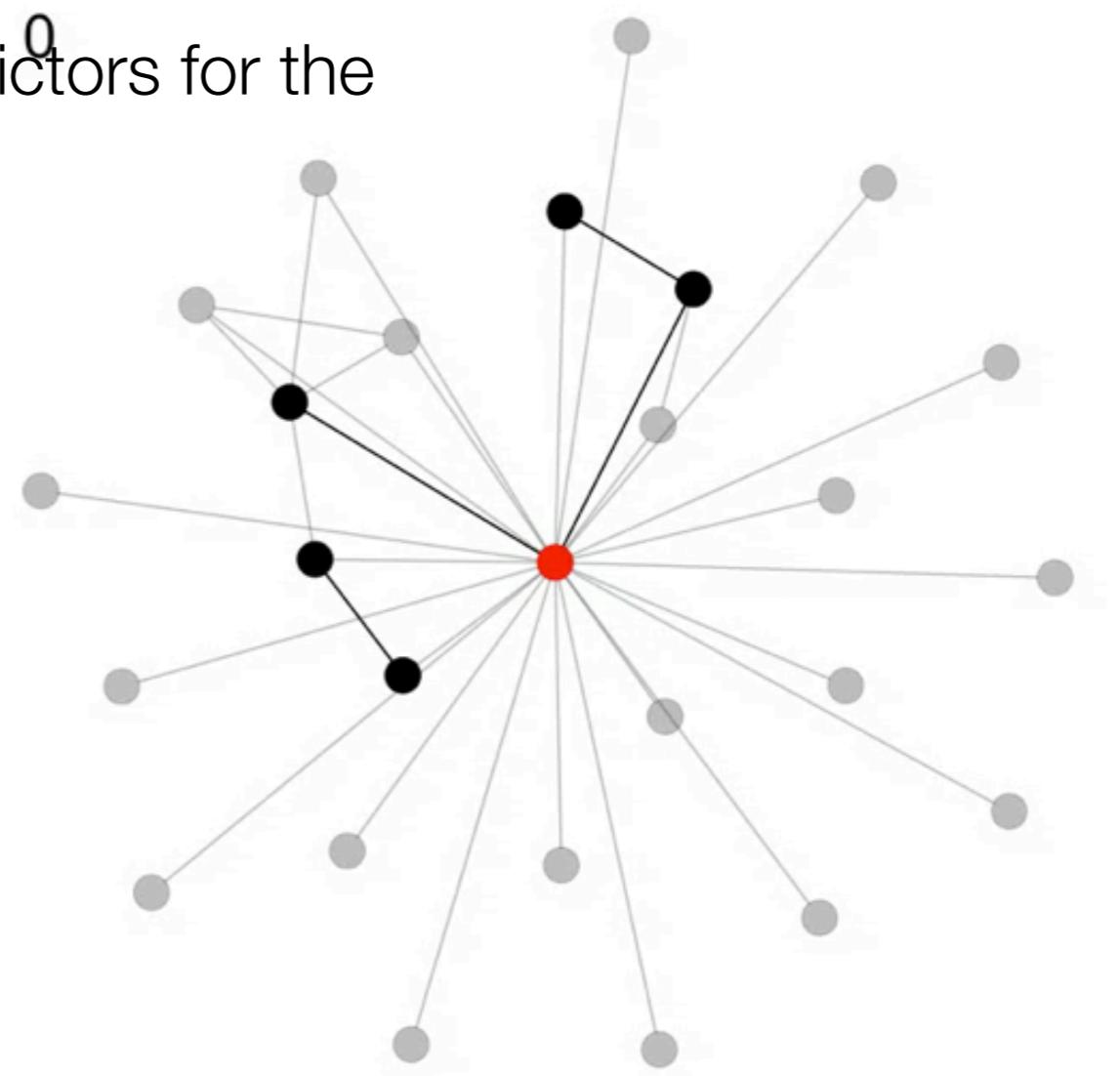
Tie dynamics

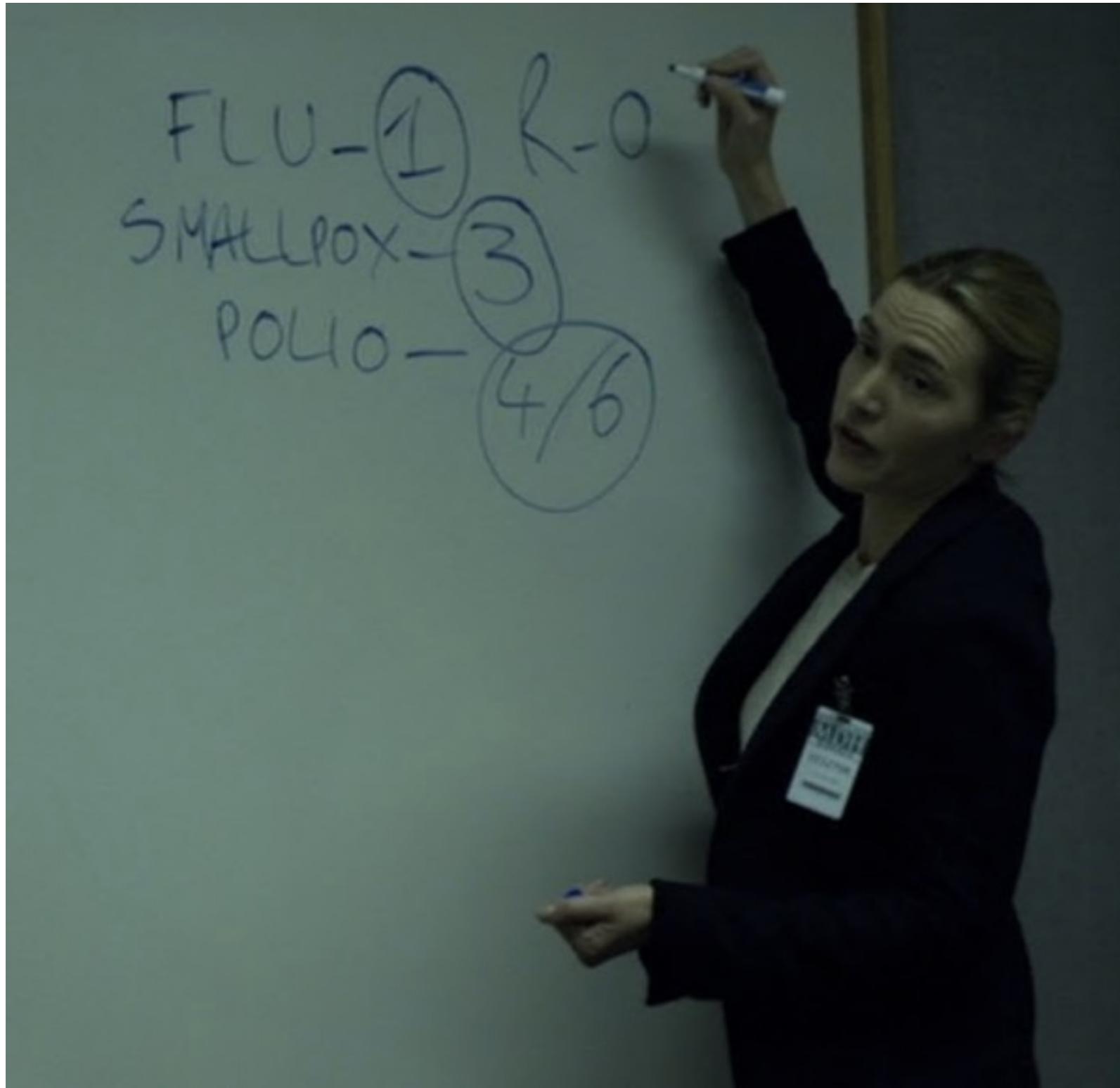
- Wrap-up
 - Individual activity is heterogeneous and persistent
 - Different parts of the day are used for different social tasks
 - Activity within a single tie is bursty
 - $P(dt)$ is a heavy tailed
 - Bursts are correlated
 - Activity across adjacent ties is correlated
 - Two adjacent ties
 - Group conversations
 - Impact on the waiting time (spreading)



Tie dynamics

- *Triadic closure, reciprocity* are predictors for the formation of a link
 - *Embeddedness, reciprocity* are predictors for the persistence of a link
- Tie formation/decay is *bursty*
- Tie formation/decay strategy:
 - Heterogeneous
 - Linear in time
 - Social explorers / social keepers
- Geography:
 - Larger cities are more dynamical
 - At larger distances links are more unstable





Impact on diffusion processes

3

Relevant question in spreading

- **Reach**

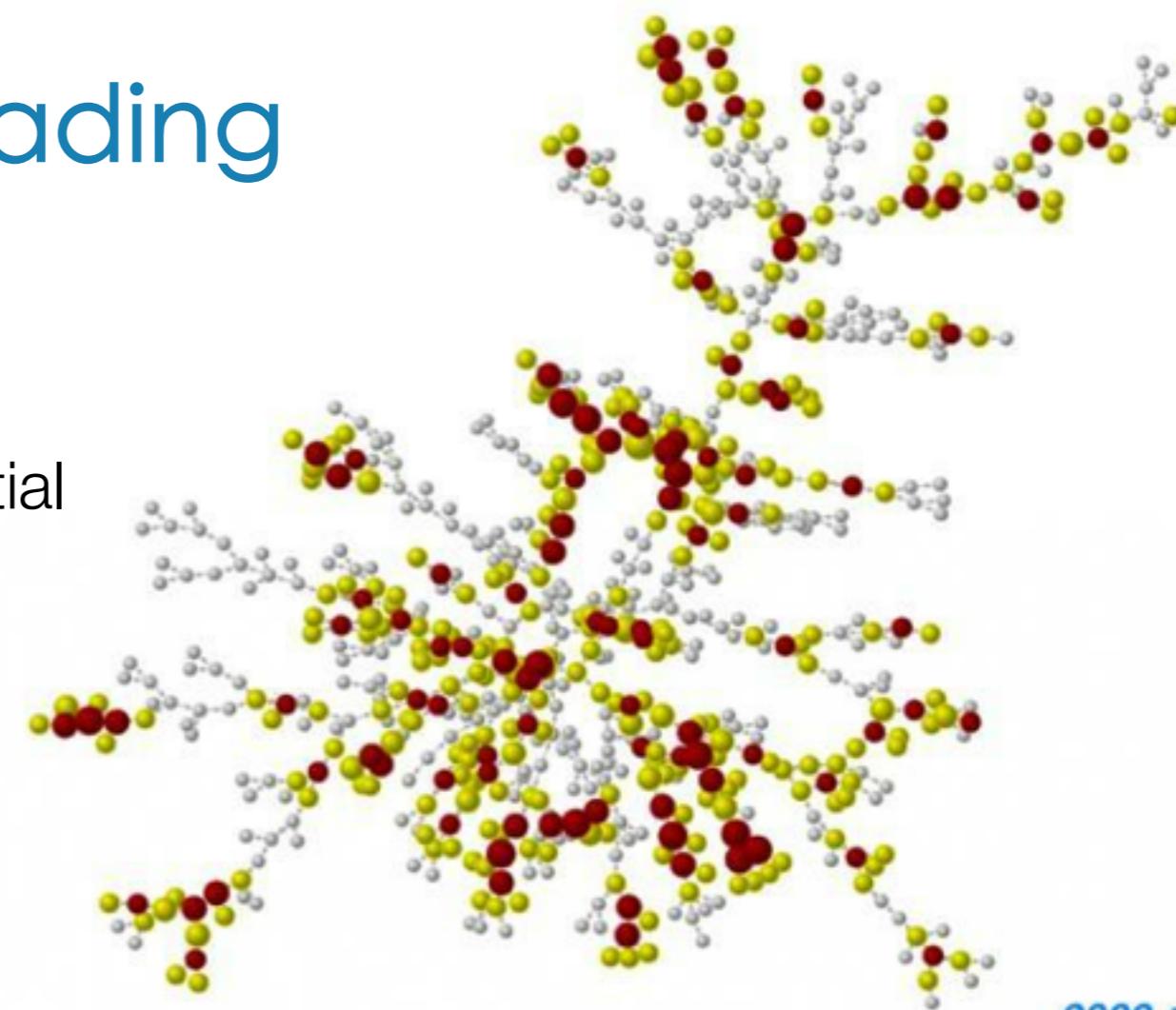
- How many people are infected from a initial spreader?

- **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

2009-



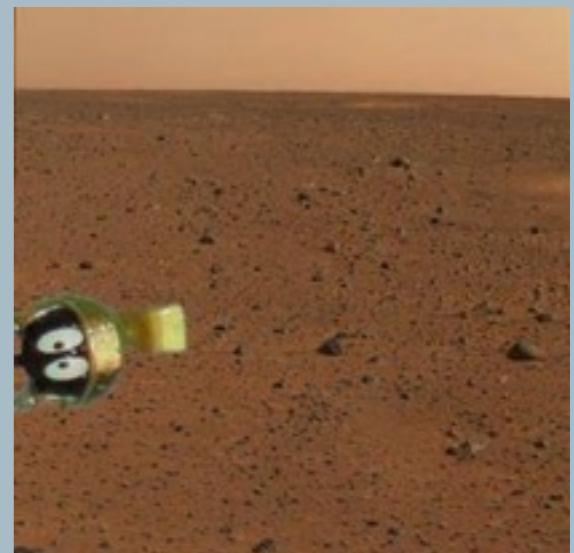
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Information spreading as cascades

<http://www.facebookstories.com/stories/2200/data-visualization-photo-sharing-explosions>

2012.08.05 23:05



Simple model for spreading

- SI / SIR / SIS models (Kermack & McKendrick '27)

- S: susceptible (non infected)
- I: Infected
- R: resiliant
- $S + I + R = N$

$$\begin{aligned}\frac{dS}{dt} &= -\lambda IS \\ \frac{dI}{dt} &= \lambda IS - \gamma I \\ \frac{dR}{dt} &= \gamma I\end{aligned}$$

$$R_0 = N \frac{\lambda}{\gamma}$$

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

- R_0 : basic reproductive number

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

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

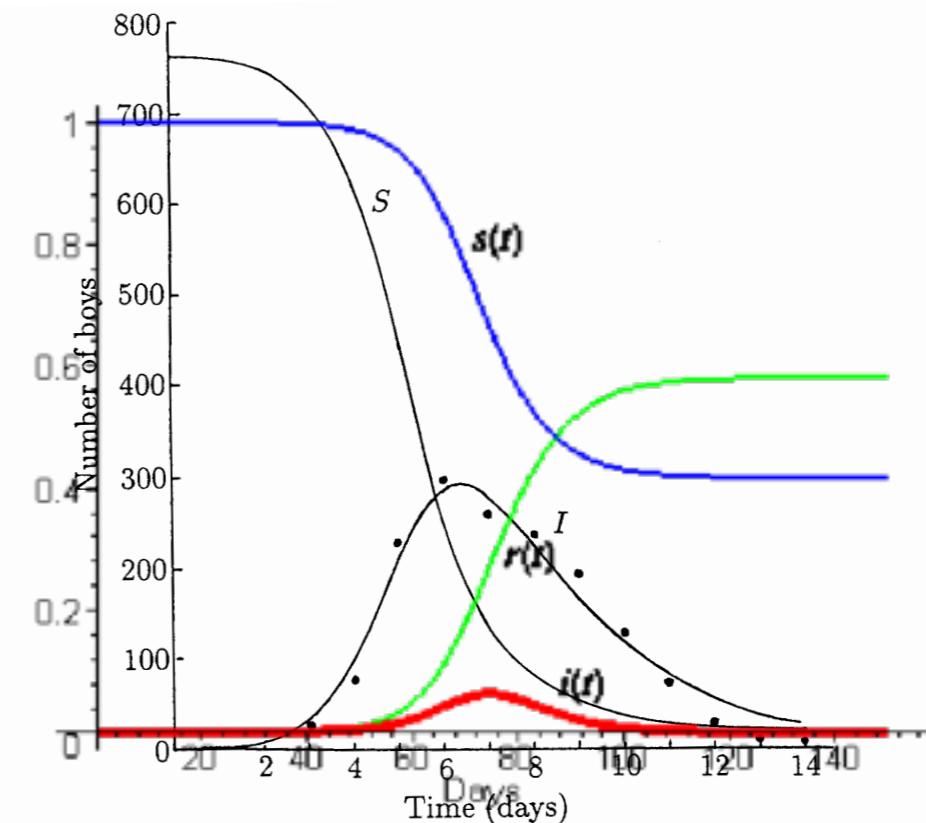
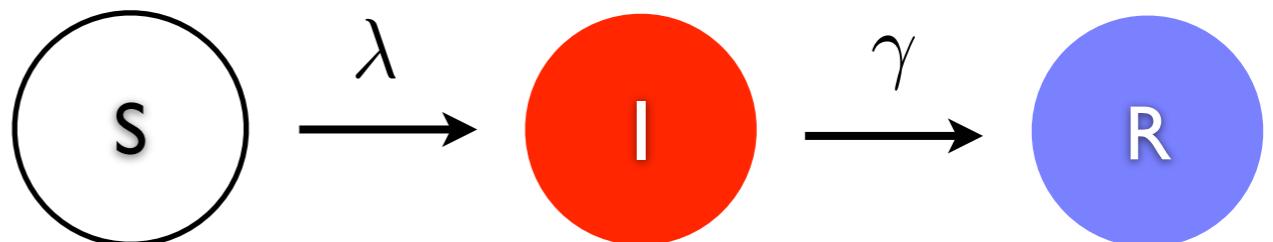
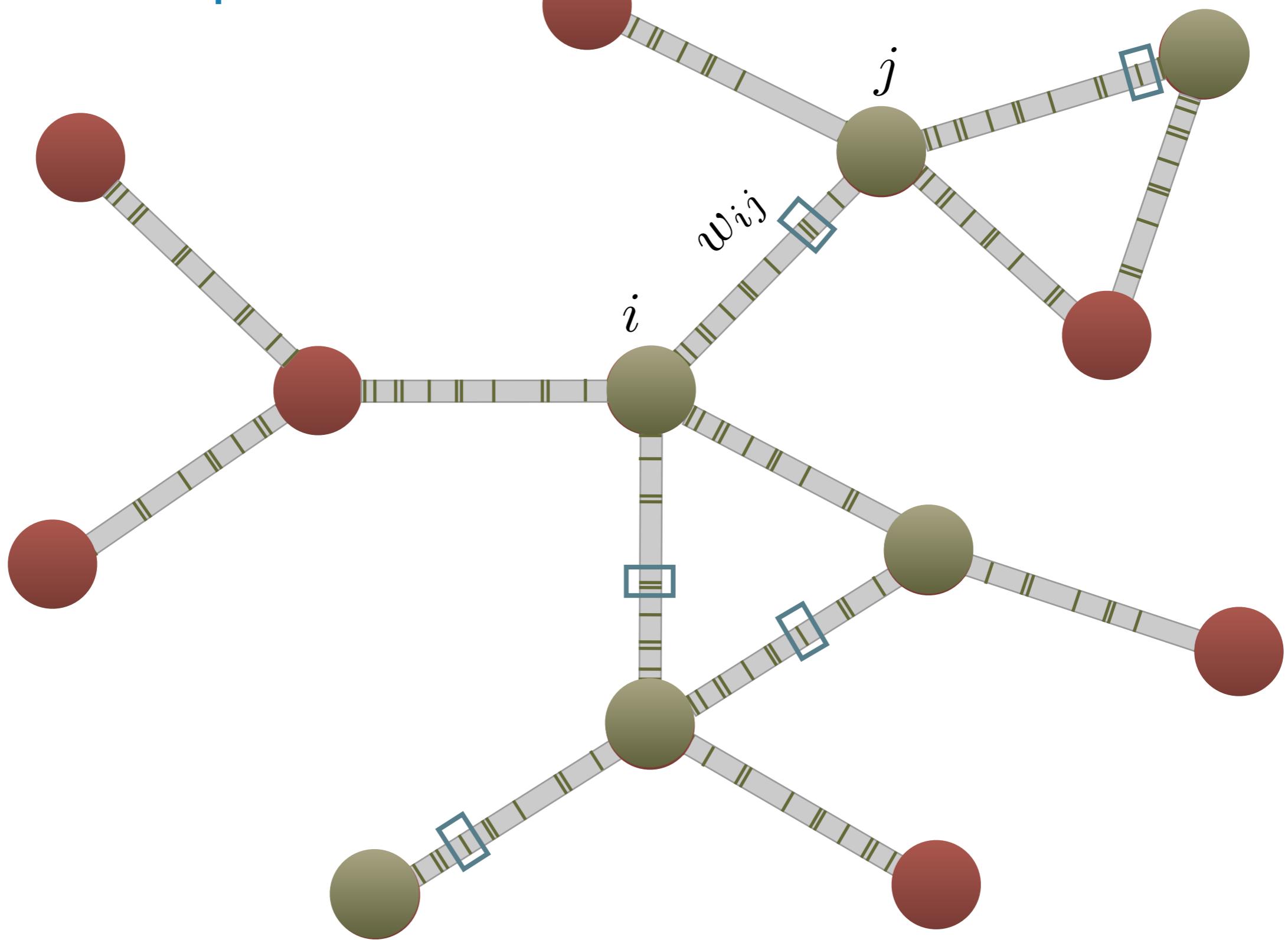
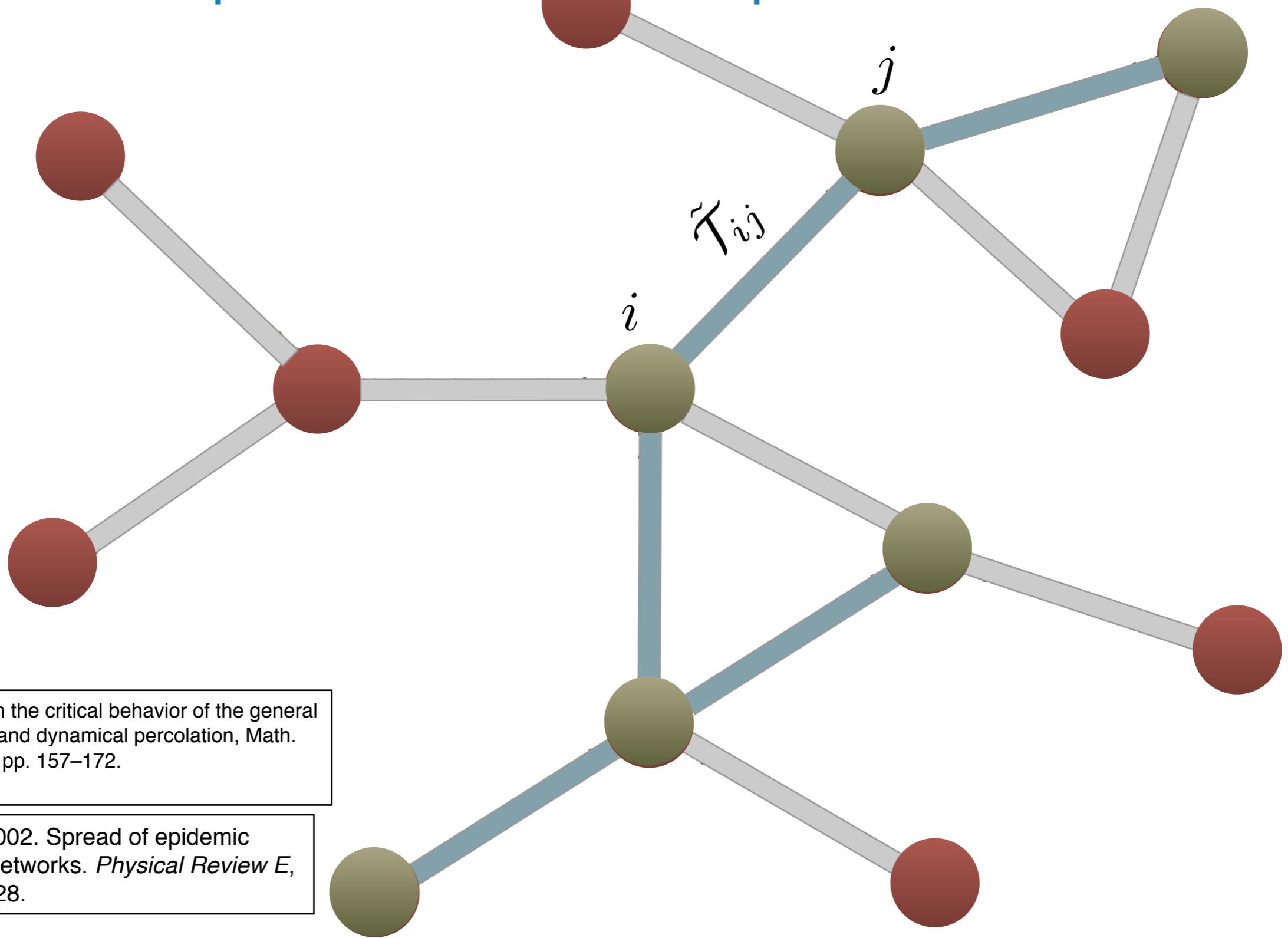


Fig. 19.3. Influenza epidemic data (●) for a boys boarding school as reported in British Medical Journal, 4th March 1978. The continuous curves for the infectives (I) and susceptibles (S) obtained from a best fit numerical solution of the SIR system (19.1)–(19.3): parameter values $N = 763$, $S_0 = 762$,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

SIR on temporal networks



SIR on temporal networks = percolation

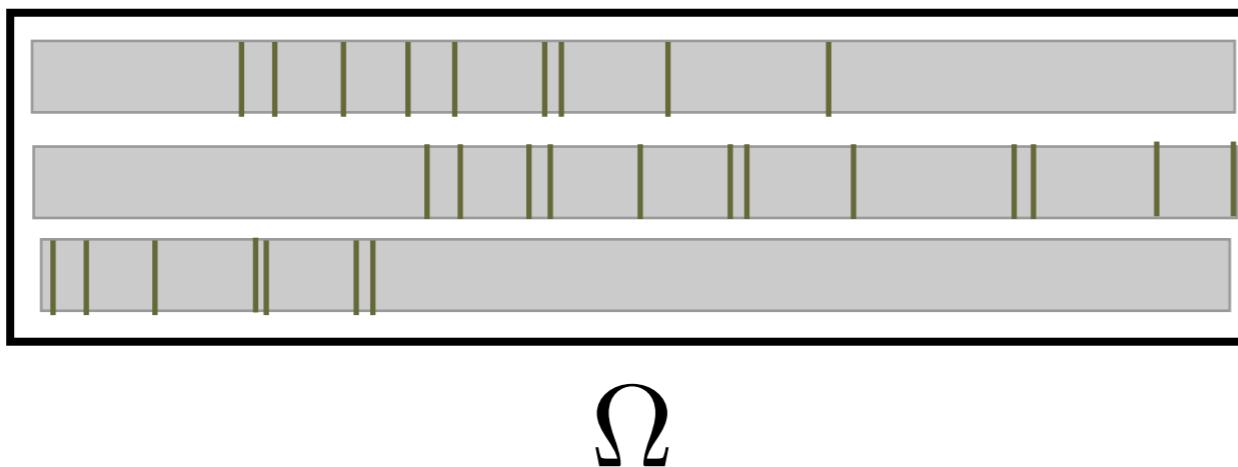


P. Grassberger, On the critical behavior of the general epidemic process and dynamical percolation, Math. Biosci., 63 (1983), pp. 157–172.

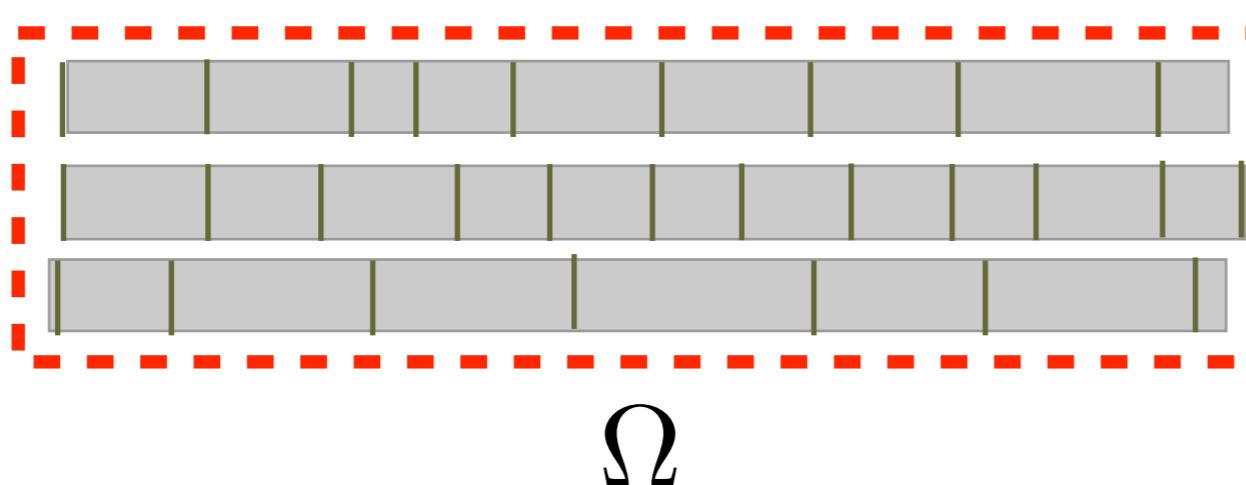
Newman, M., 2002. Spread of epidemic disease on networks. *Physical Review E*, 66(1), p.16128.

Comparison with null models

- Real data



- Time Shuffled data



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

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



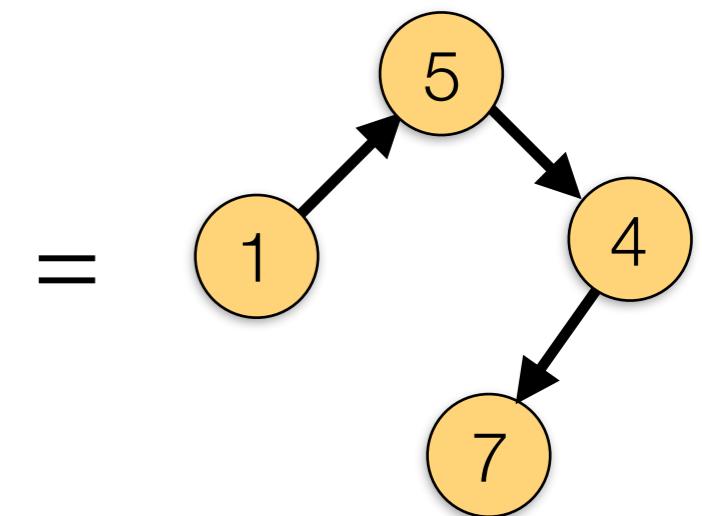
Data-driven simulations

- 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

1,5,412

2,3,523

5,4,631

3,7,782

1,2,921

2,7,999

Real data

v_i, v_j, t

1,2,412

2,3,523

1,5,631

2,7,782

3,7,921

5,4,999

Shuffled data

Select seed
+

infect in each
contact with
probability

v_i, v_j, t

1,2,412

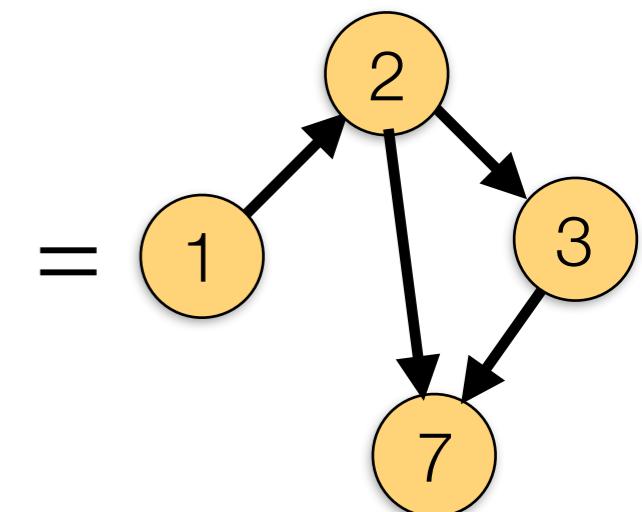
2,3,523

1,5,631

2,7,782

3,7,921

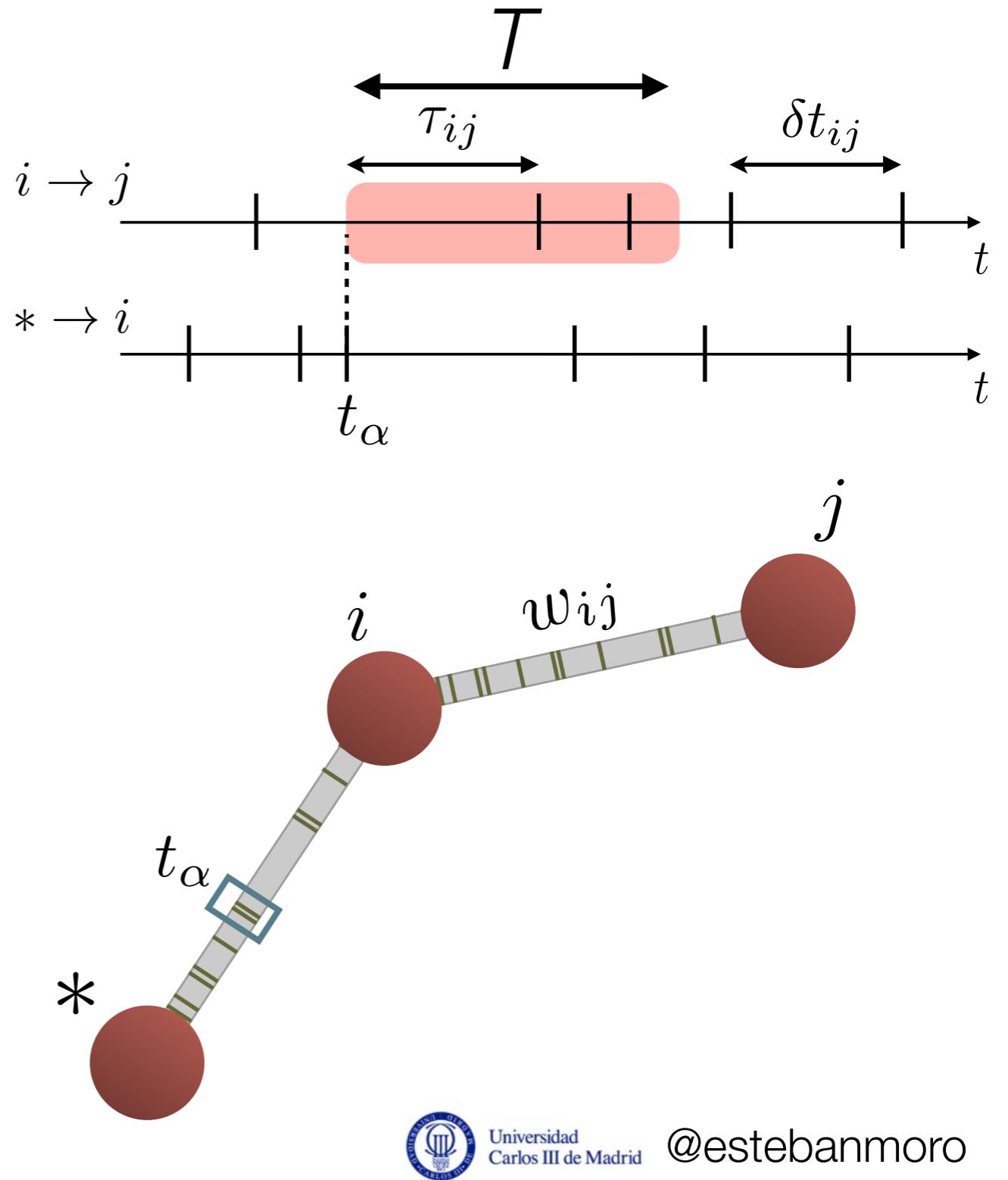
5,4,999



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.



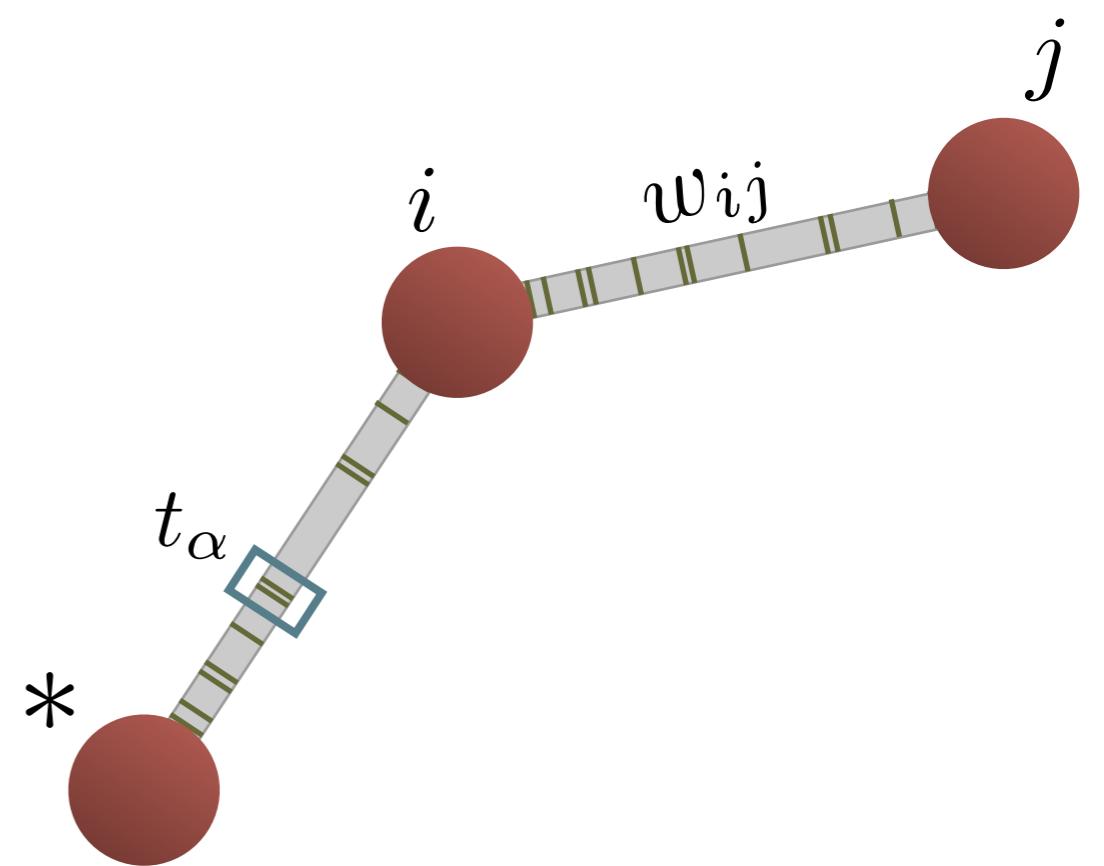
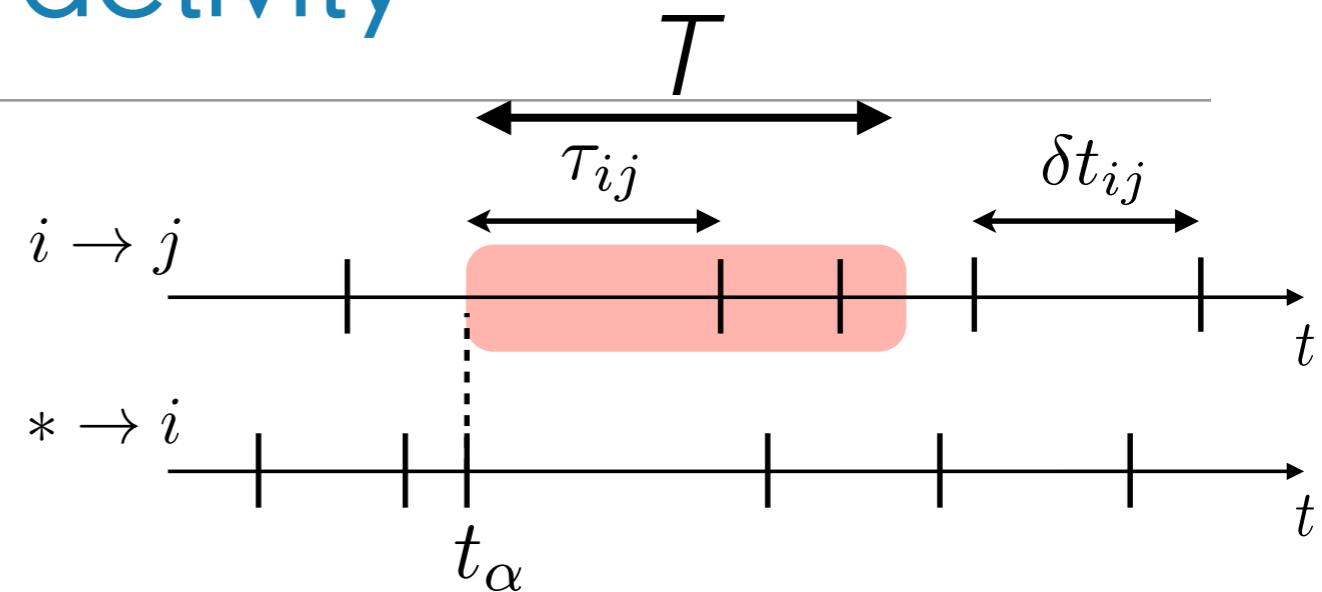
Spreading including tie activity

- **Transmissibility:**

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

- where

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



Spreading including tie activity

- Assuming $* \rightarrow i$ 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

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

- General process. Approximations

- If $\lambda \ll 1 \Rightarrow 1 - (1 - \lambda)^n \simeq \lambda n$

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

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

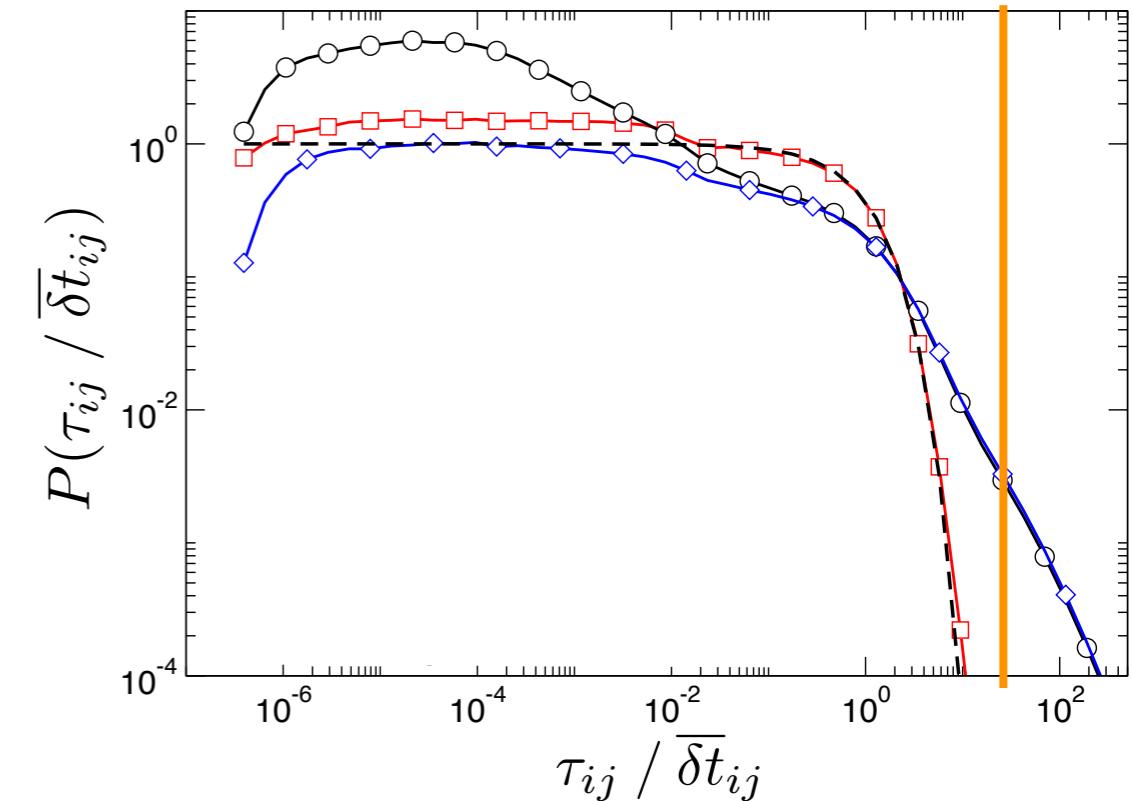
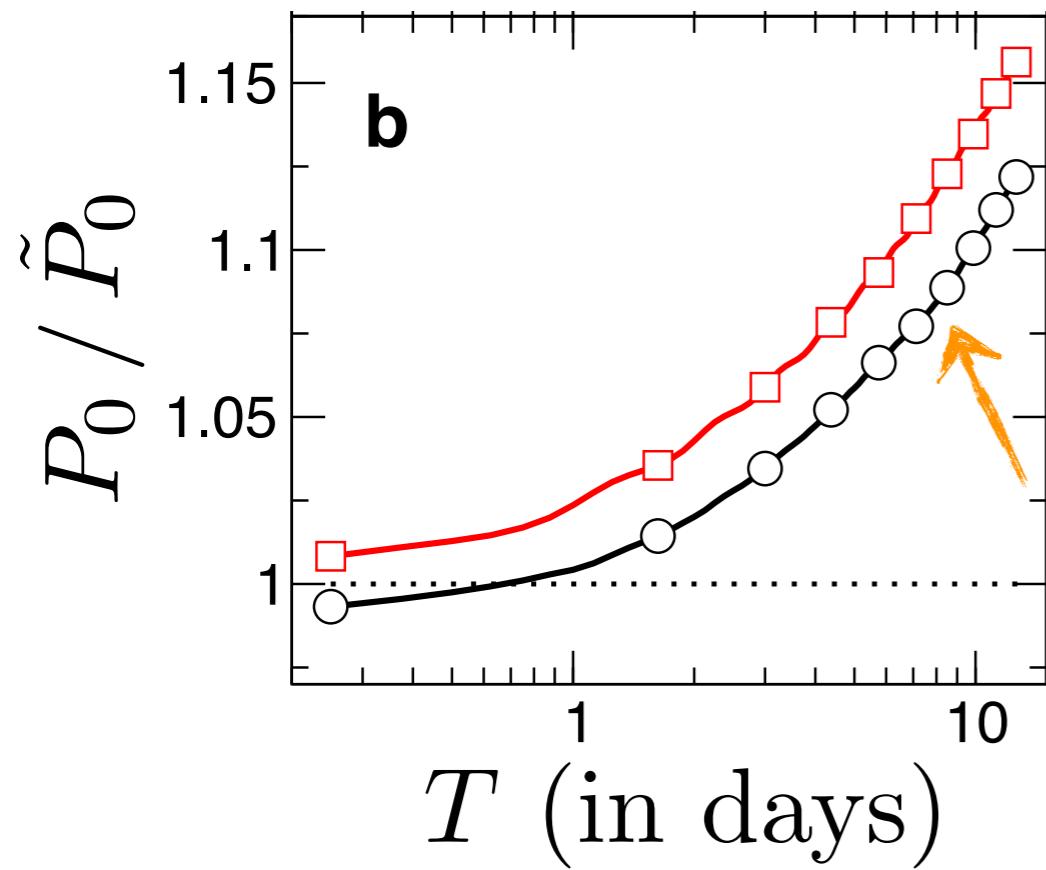
$$\mathcal{T}_{ij} \simeq 1 - P_{ij}^0$$

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

Spreading including tie activity

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

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



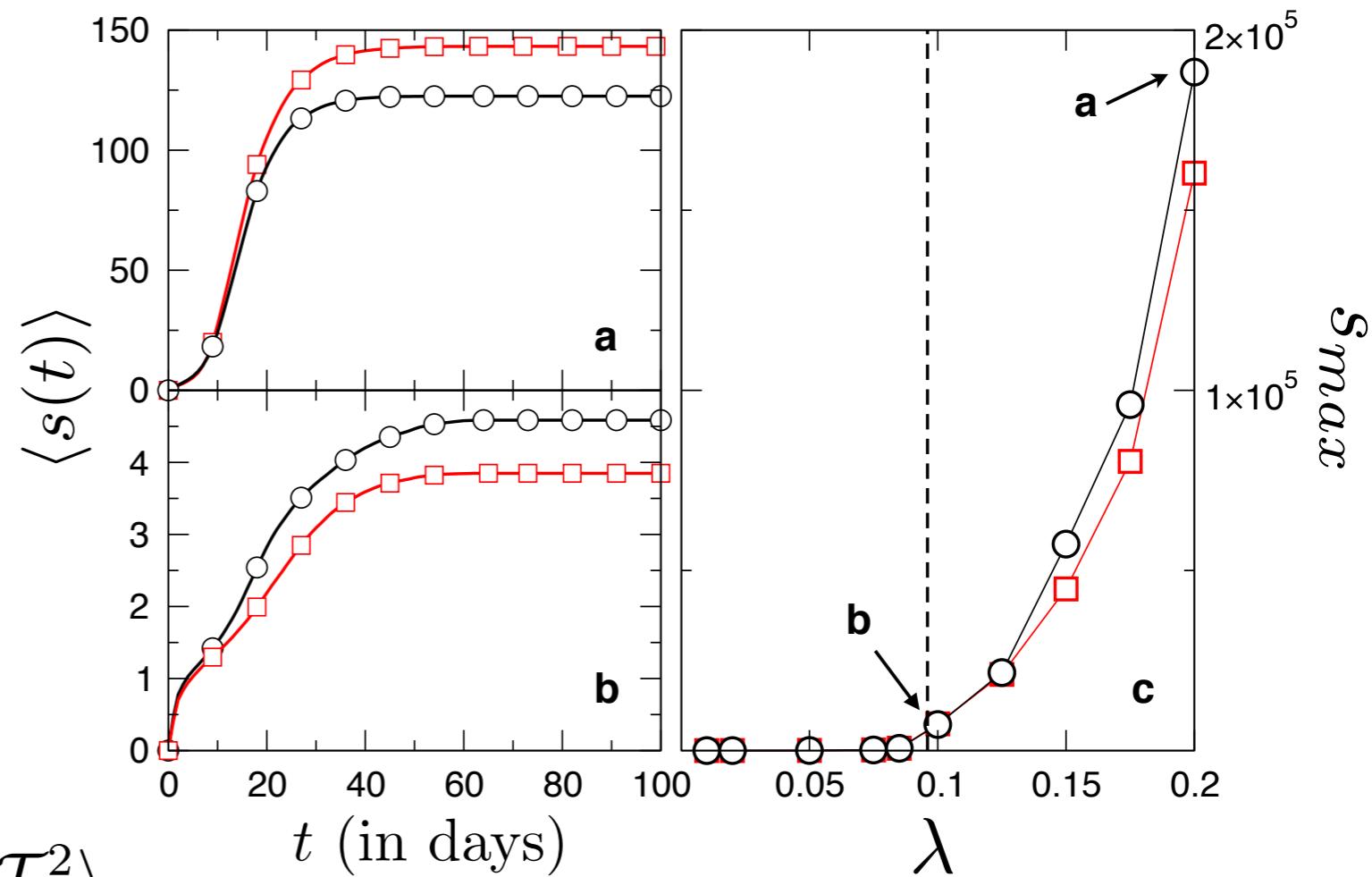
Long waiting times (bursts)
make transmissibility smaller

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

Spreading including tie activity

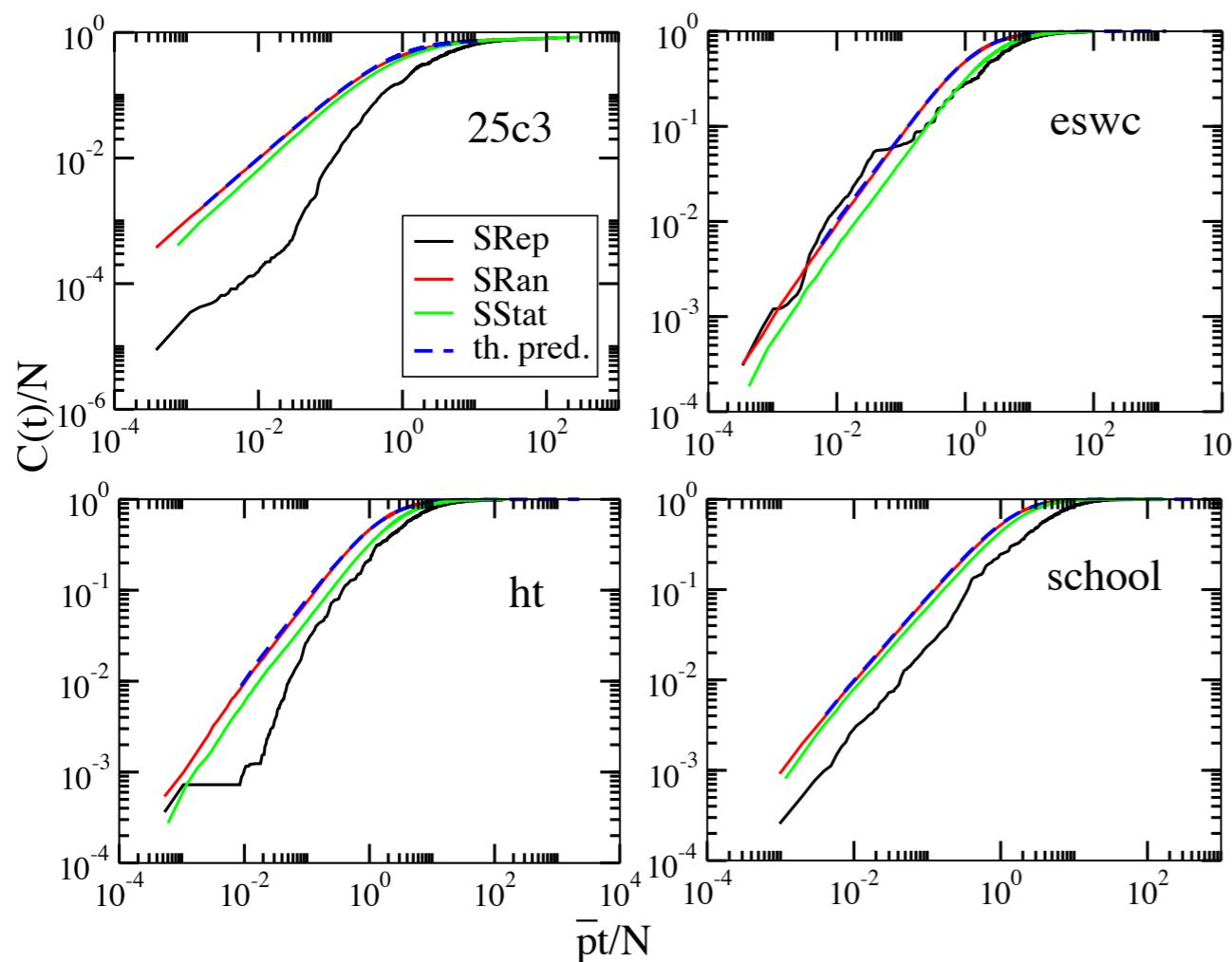
- Smaller transmissibility =
 - Slower propagation
 - Smaller propagation
- Transmissibility can be used to predict the dynamical percolation transition

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



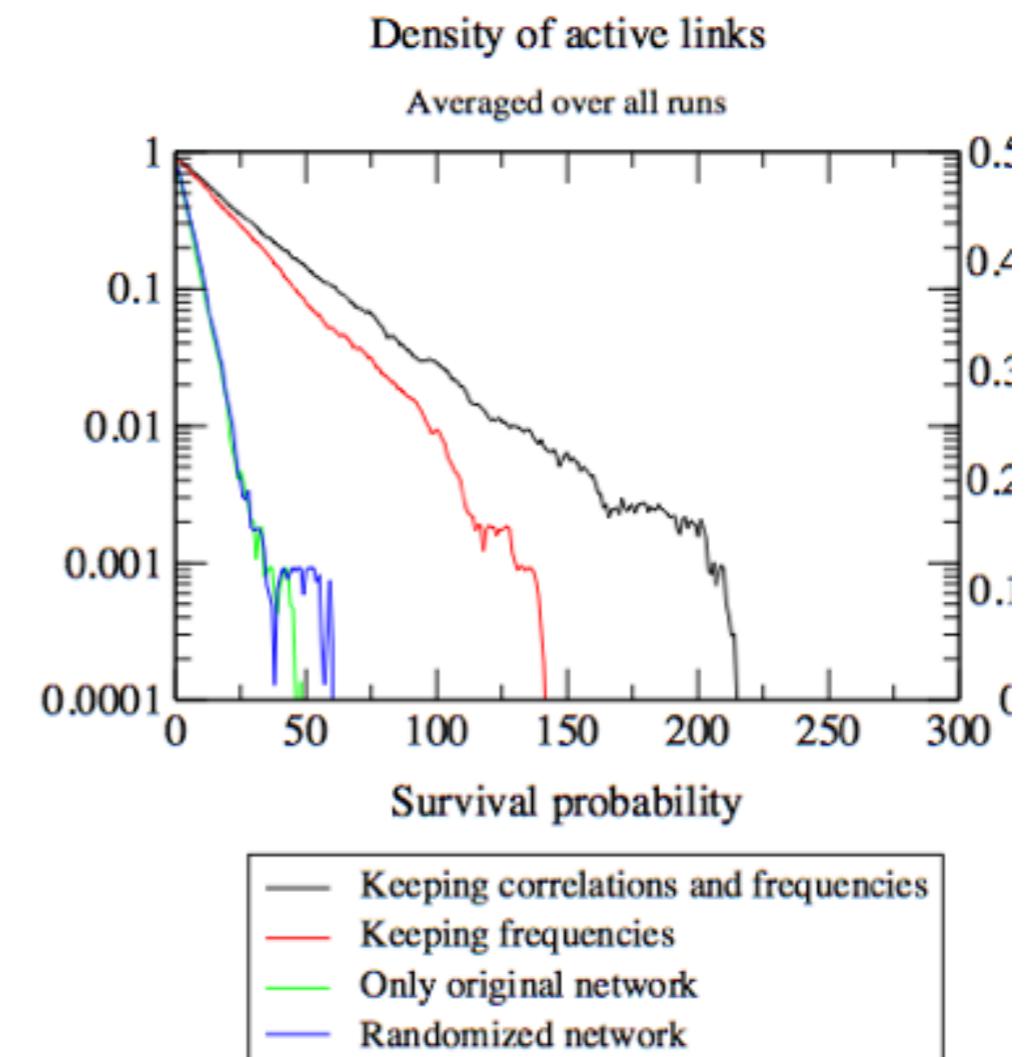
Other models

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



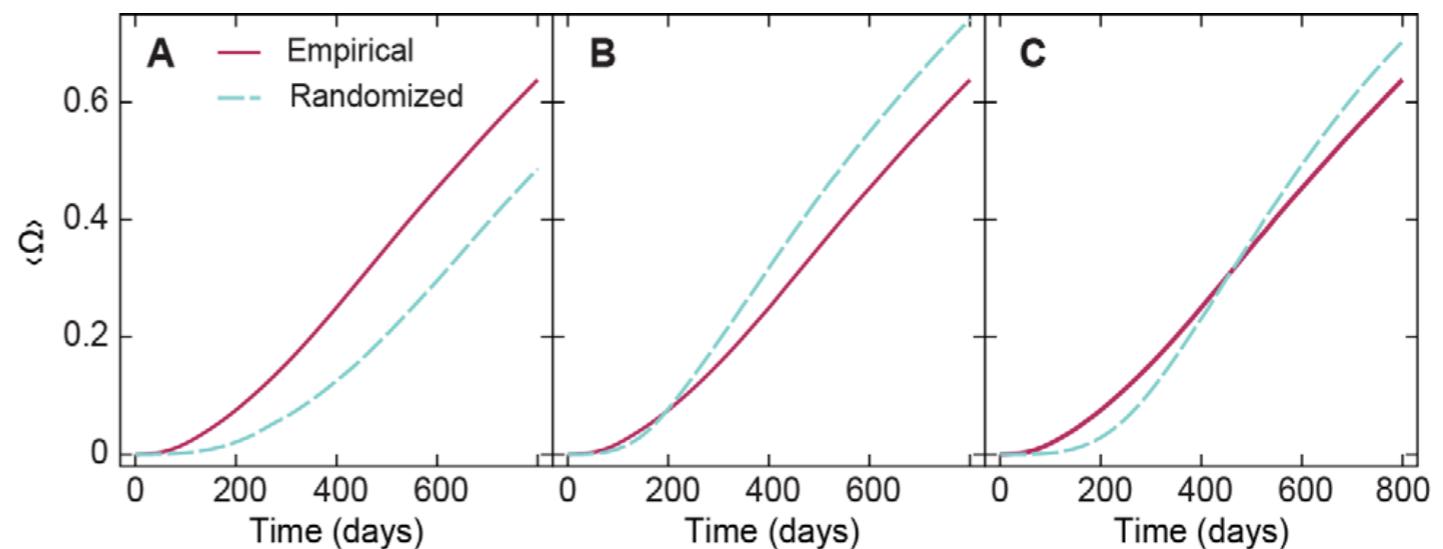
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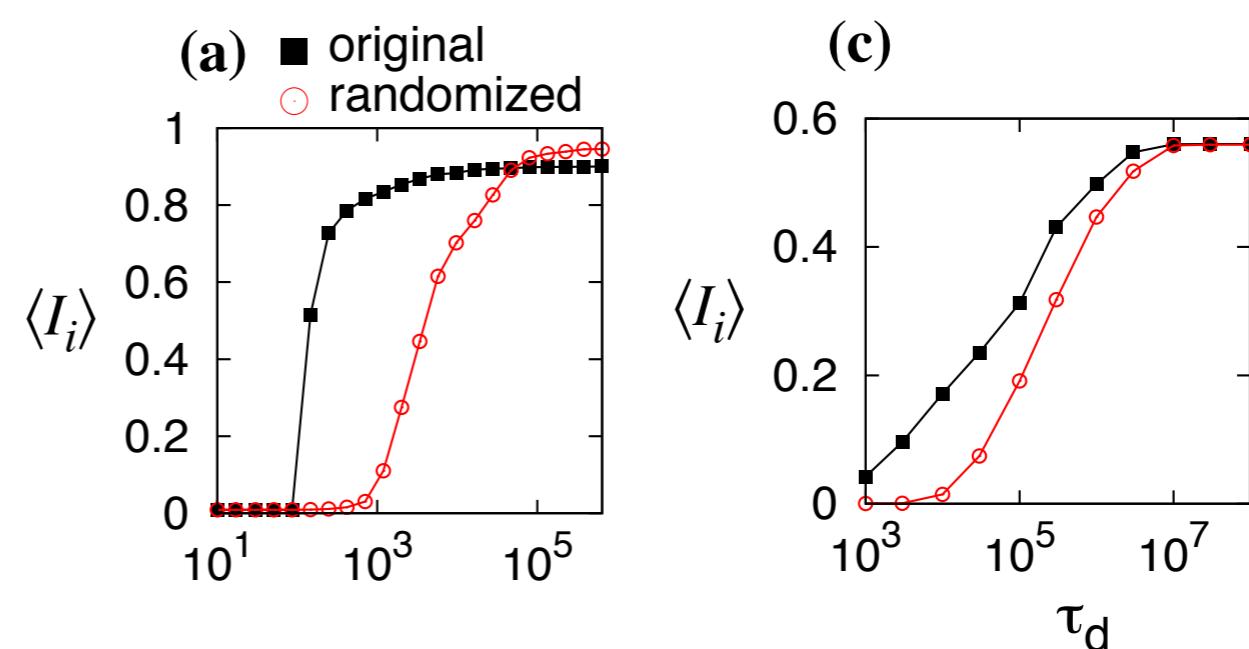
Spreading including tie activity

- 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.

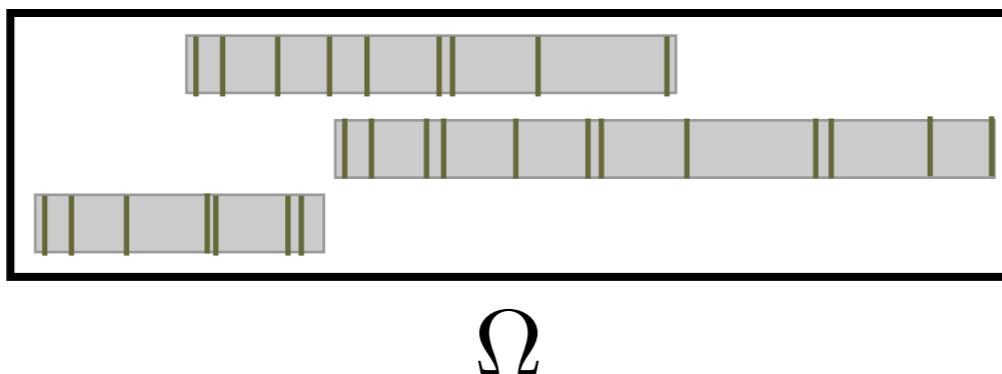


Takaguchi, T., Masuda, N. & Holme, P., 2012.
Bursty communication patterns facilitate
spreading in a threshold-based epidemic
dynamics. *PLoS ONE*, 8(7), pp.e68629–
e68629.



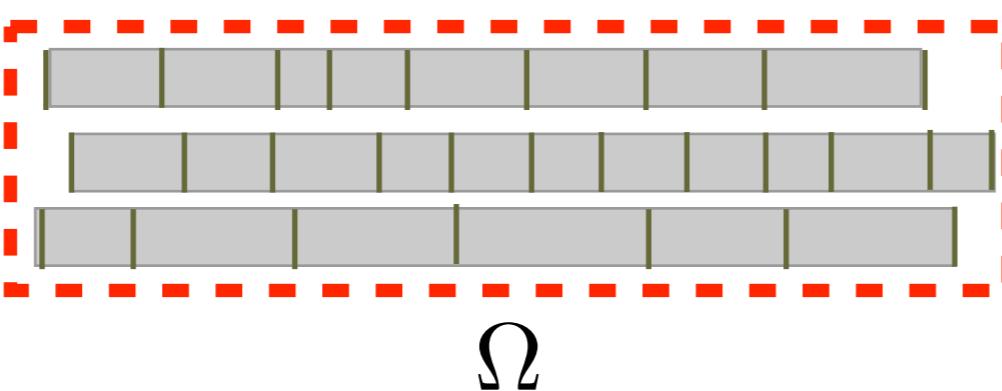
Spreading including tie dynamics

- Real data



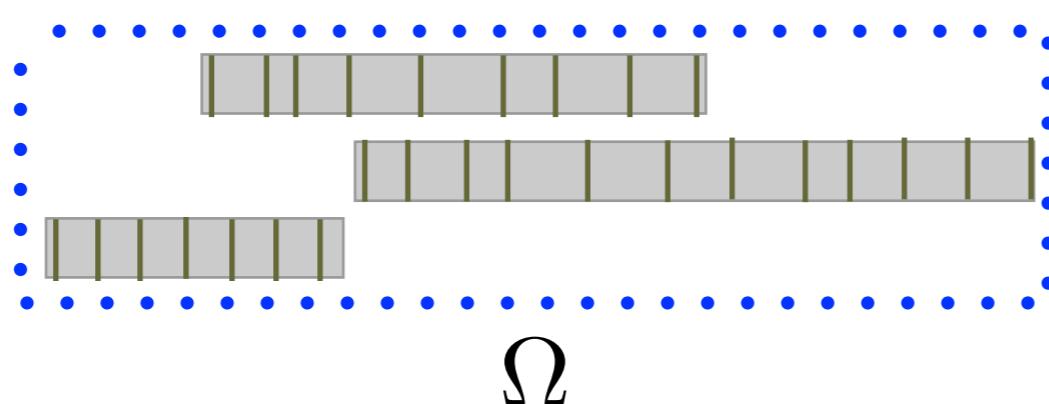
P(dt) heavy tailed
Correlated bursts
Correlated tie activity
Temporal motifs
Tie dynamics

- Shuffled data (1)



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

- Shuffled data (2)

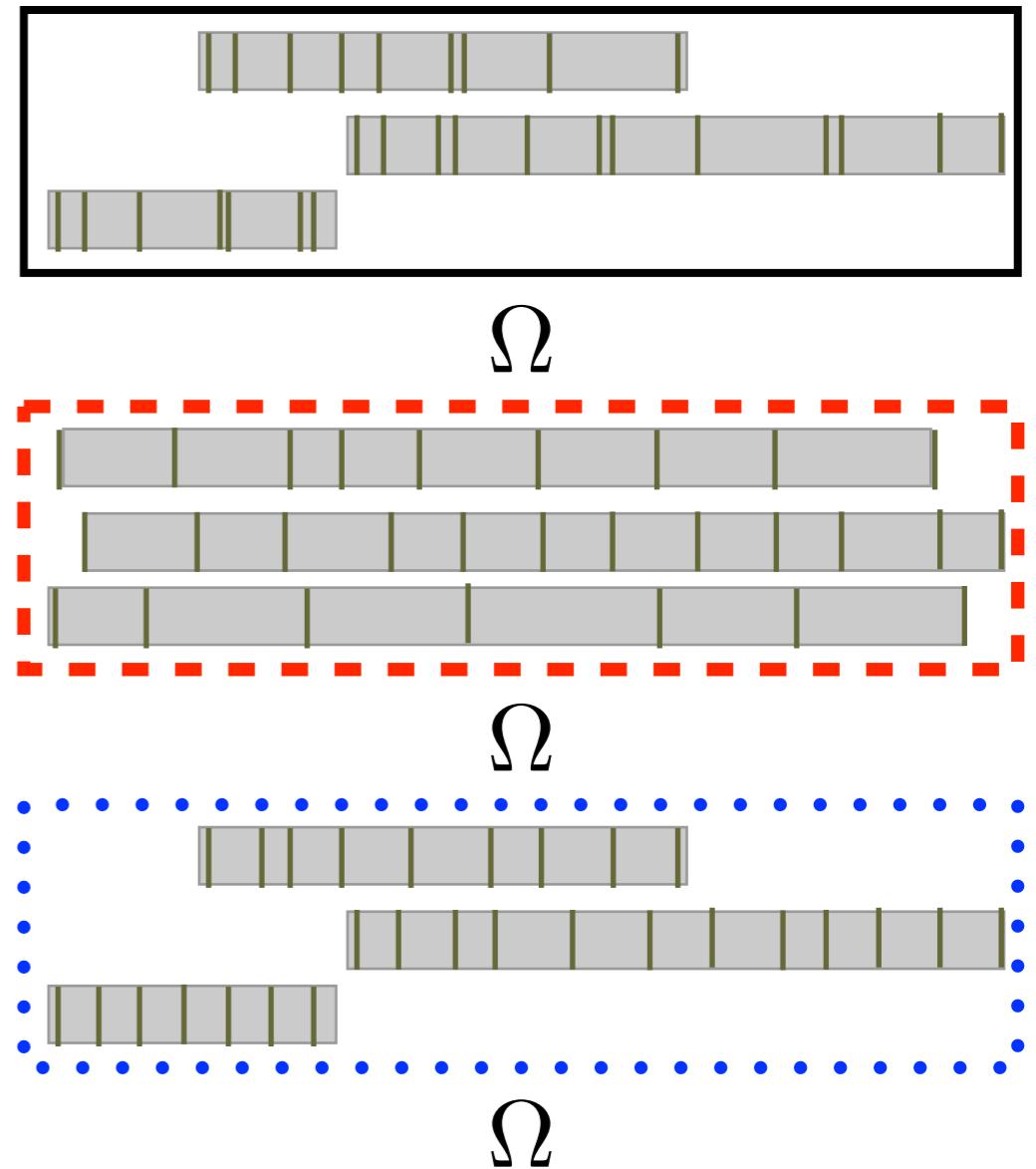
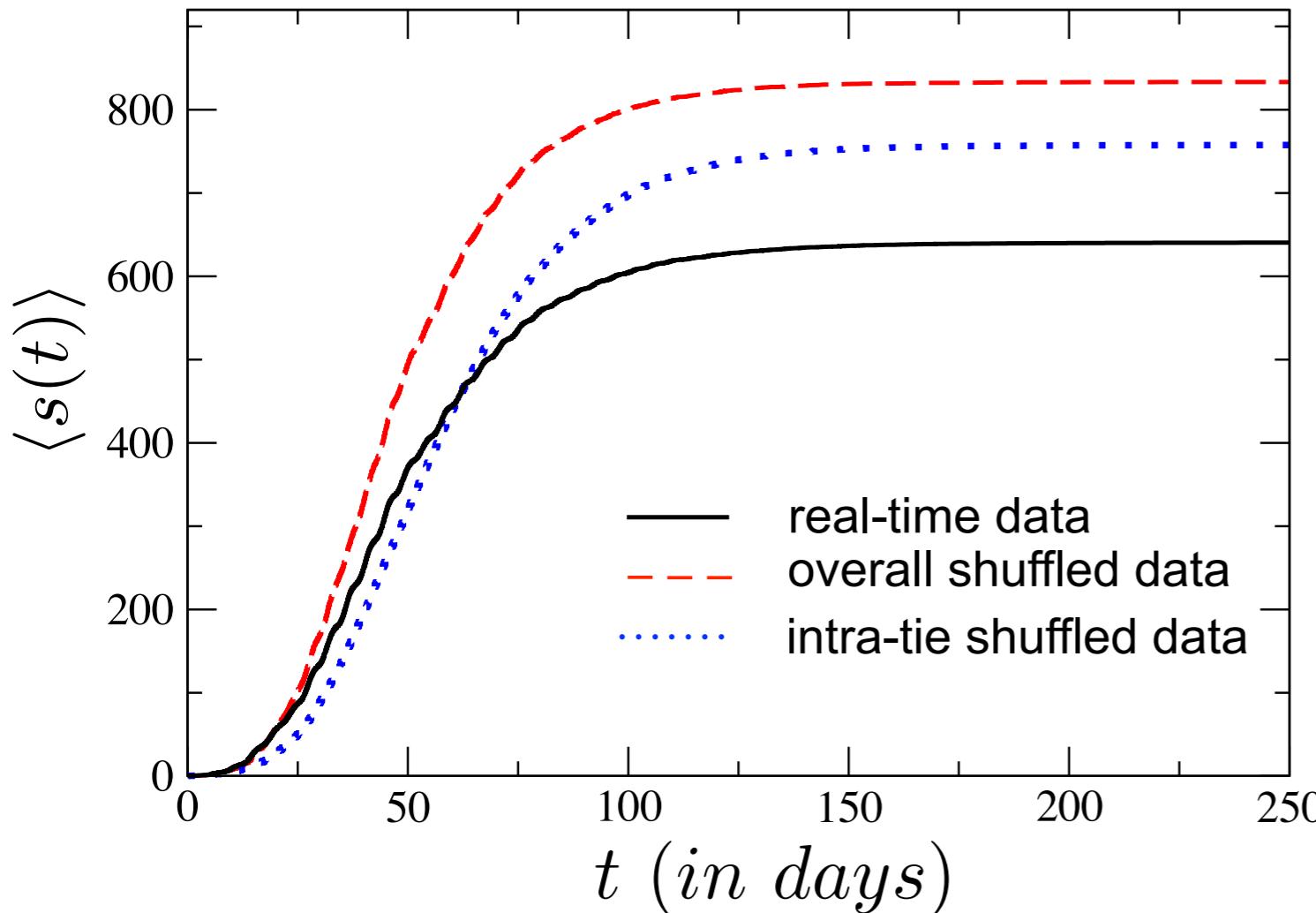


P(dt) exponential
Uncorrelated bursts
Uncorrelated tie activity
Temporal motifs ?
Tie dynamics



Spreading including time dynamics

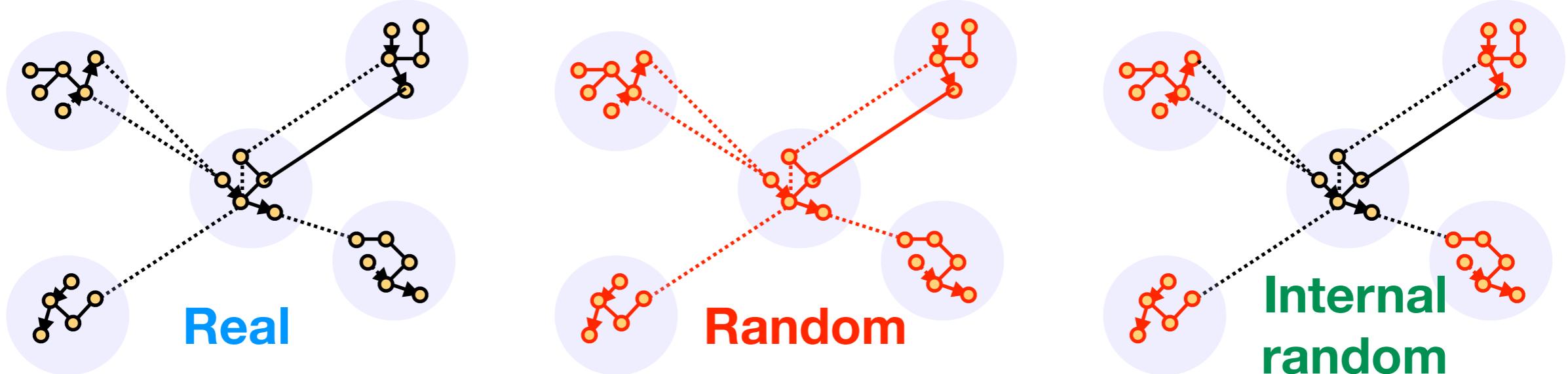
- Burstiness + conservation of ties



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

Spreading including geography

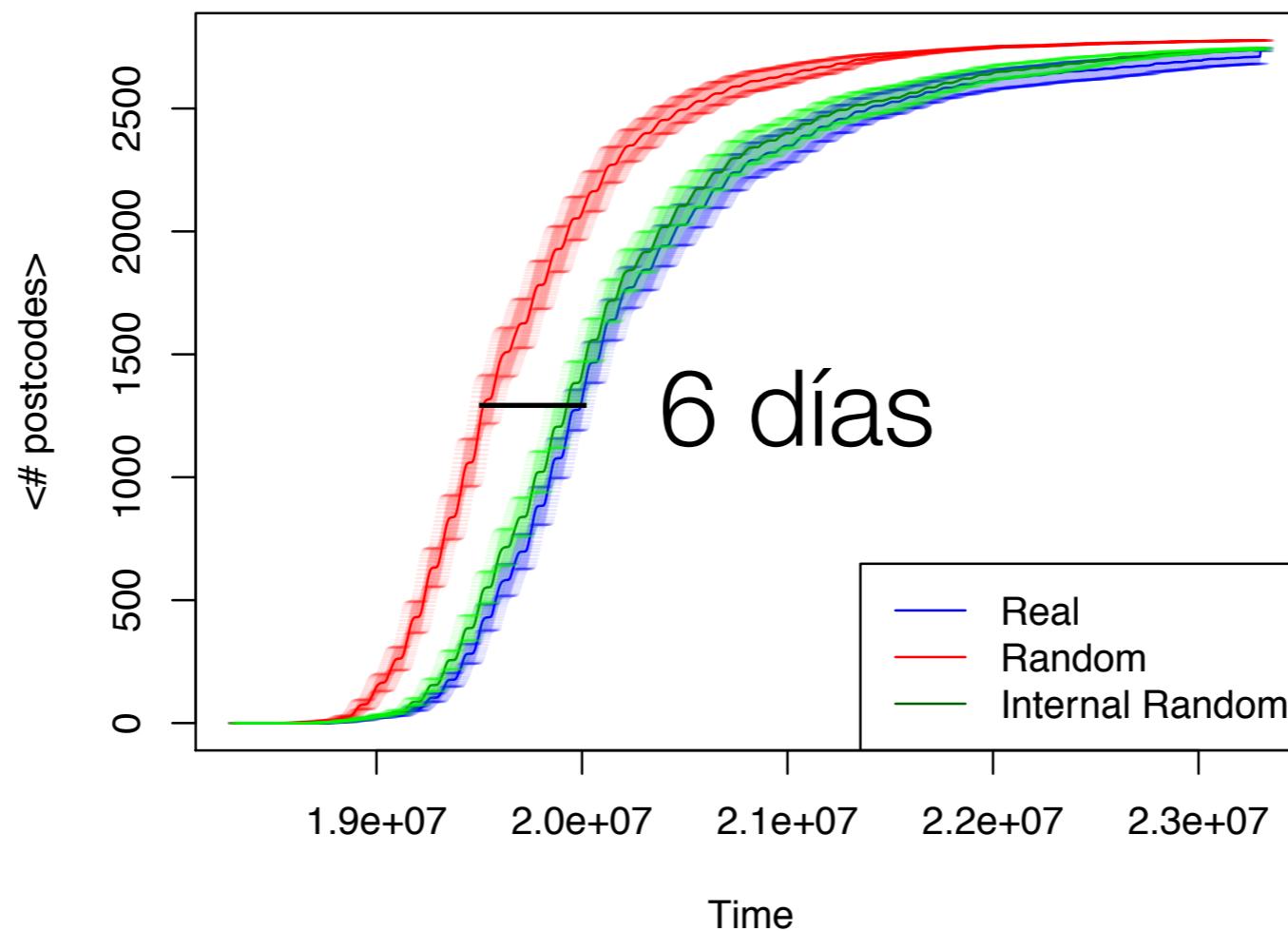
- Reminder: the fraction of unstable links is high at larger distance
- We consider another shuffling: we only shuffle ties within geographical areas

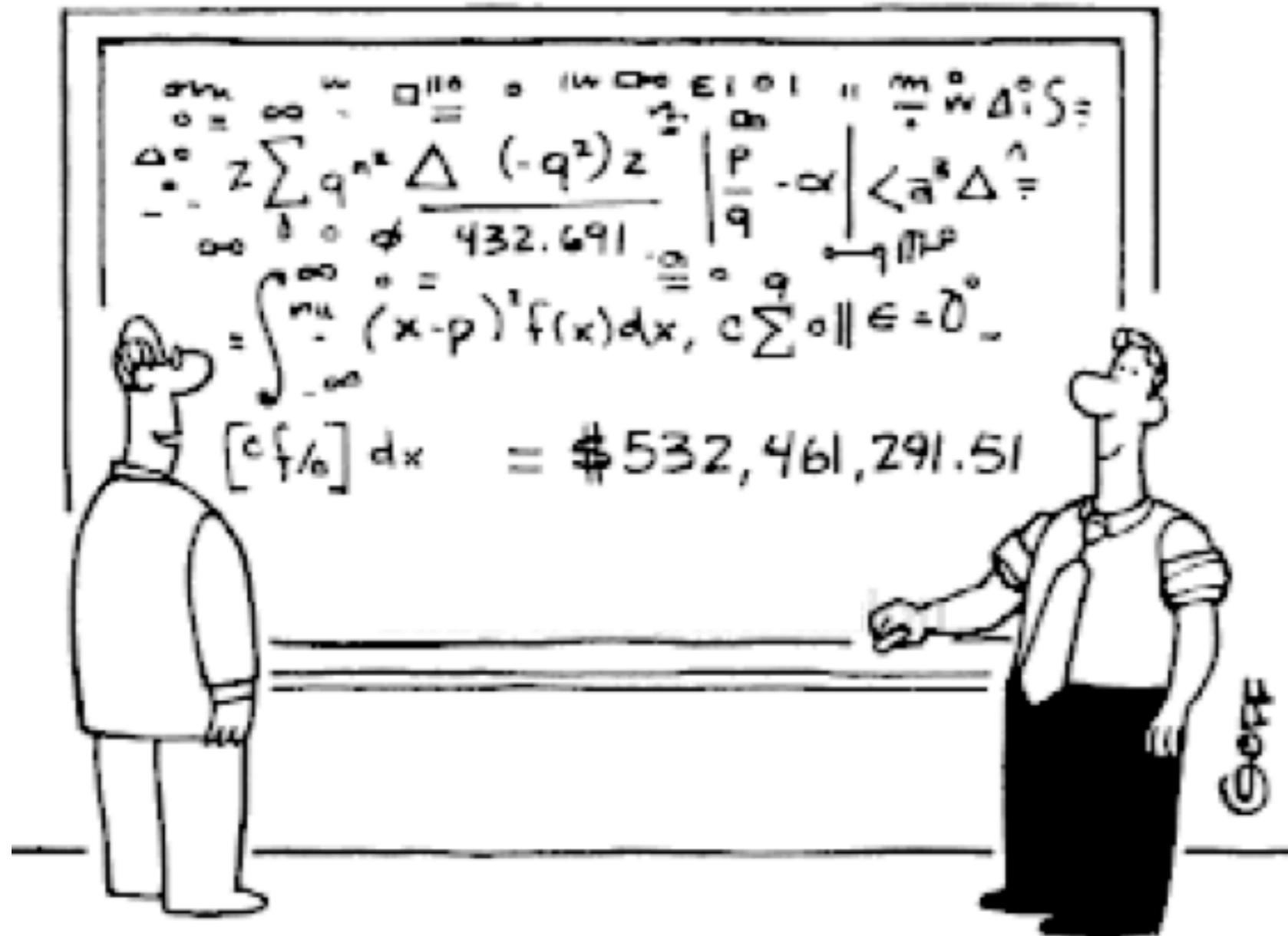


- We study propagation of information across geographical areas with the SI model
 - A geographical area is “infected” if at least a fraction of the nodes in the area is infected.

Spreading including geography

- Information spreads geographical much slower than in the shuffled case
- Most of the slowing down of information diffusion comes from inter-city links. Those links are the most unstable



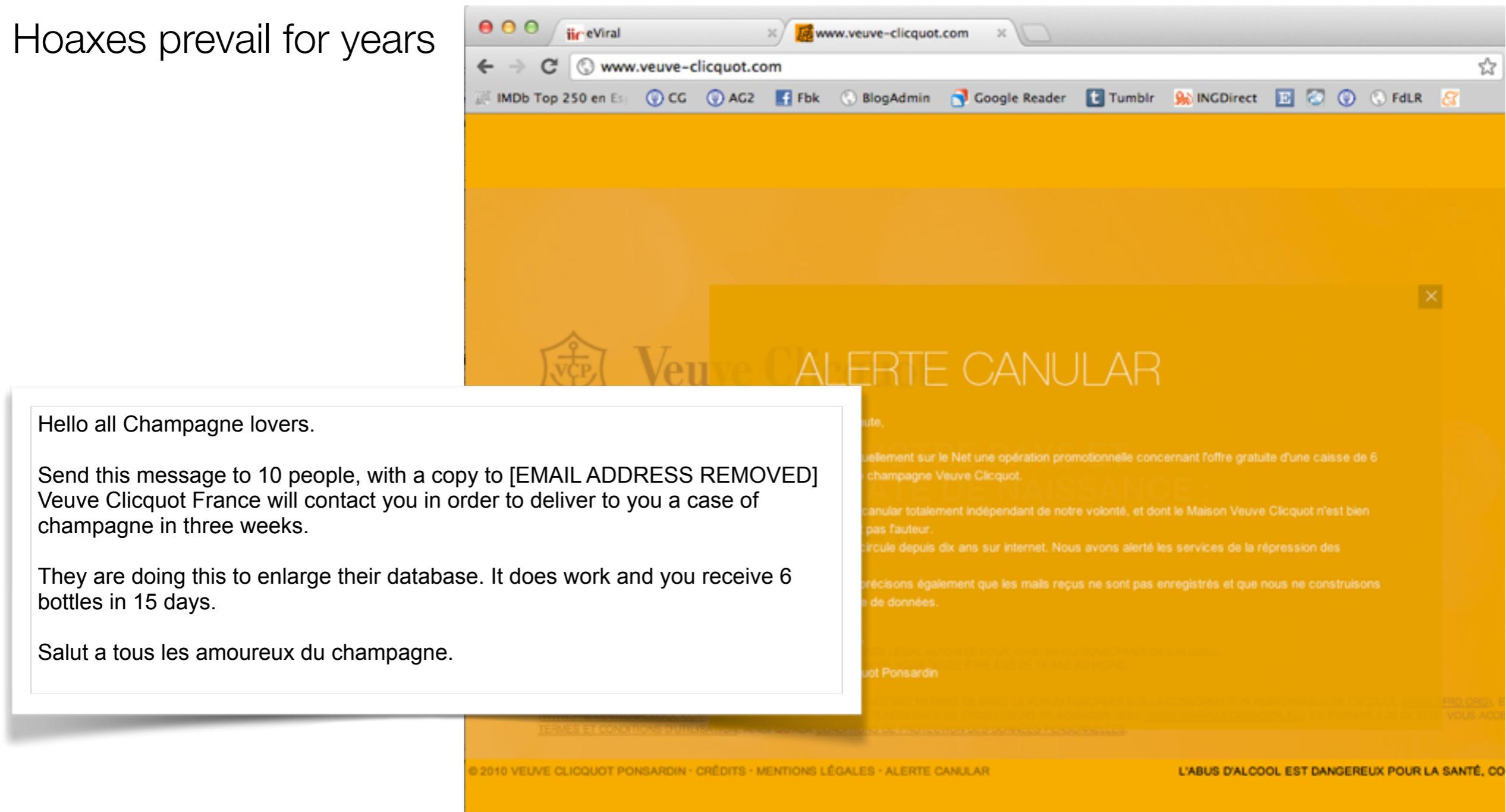


"Now that's what I call a breakthrough!"

Applications to real world

Information

- Hoaxes prevail for years

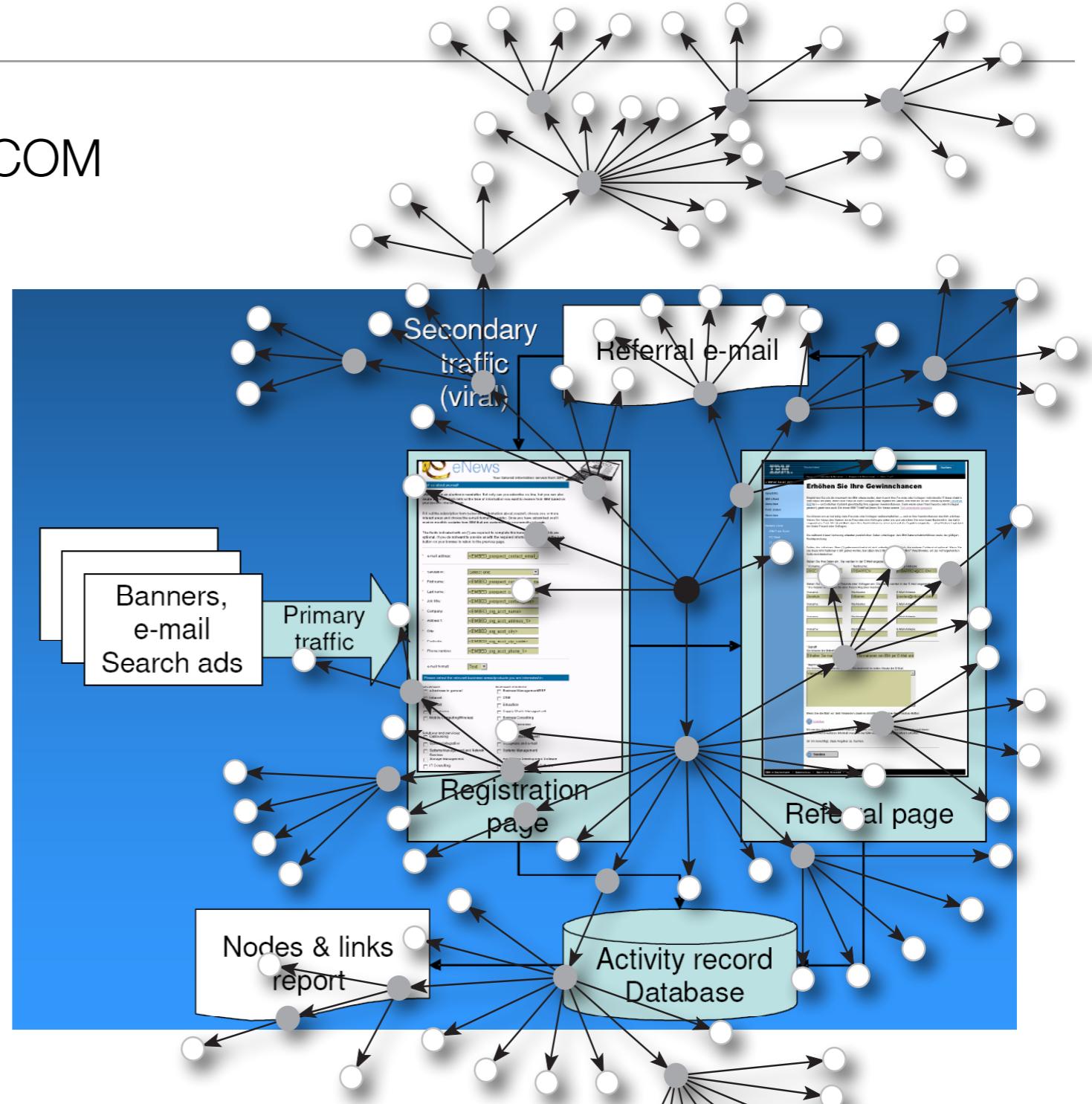
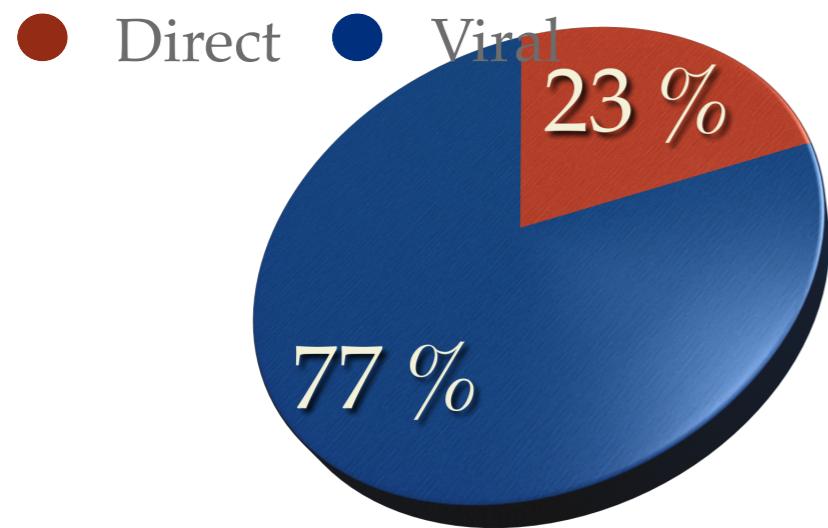


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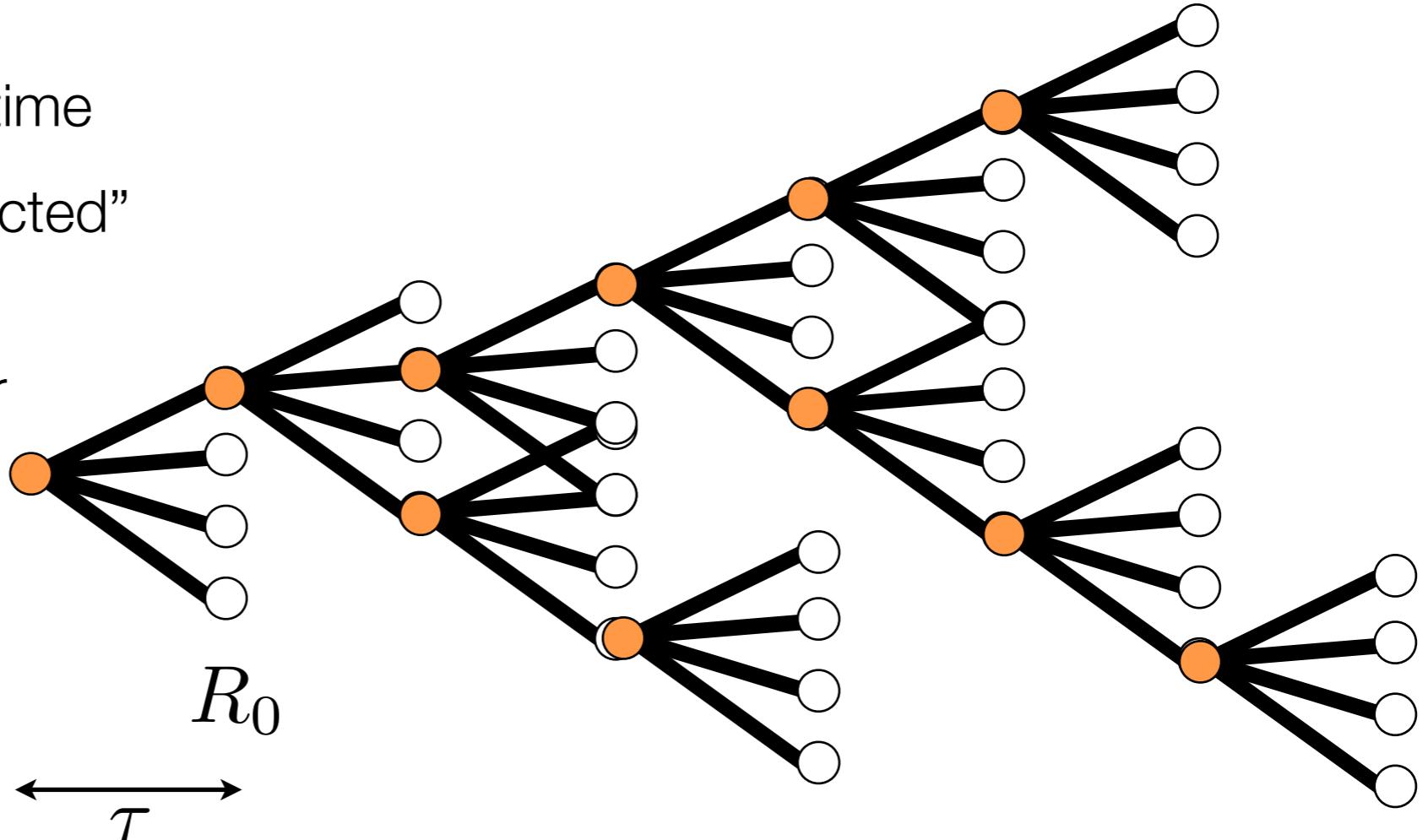
Viral marketing experiments

- Viral marketing campaigns IBM.COM
 - 2003-2005 IBM.COM
 - 30000 B2B clients
 - 11 european countries
 - 2 months of campaign



Back-of-the-envelope calculation

- Assuming
 - constant response time
 - and number of “infected” friends
- What is $i(t)$, the number of infected people at time t ?

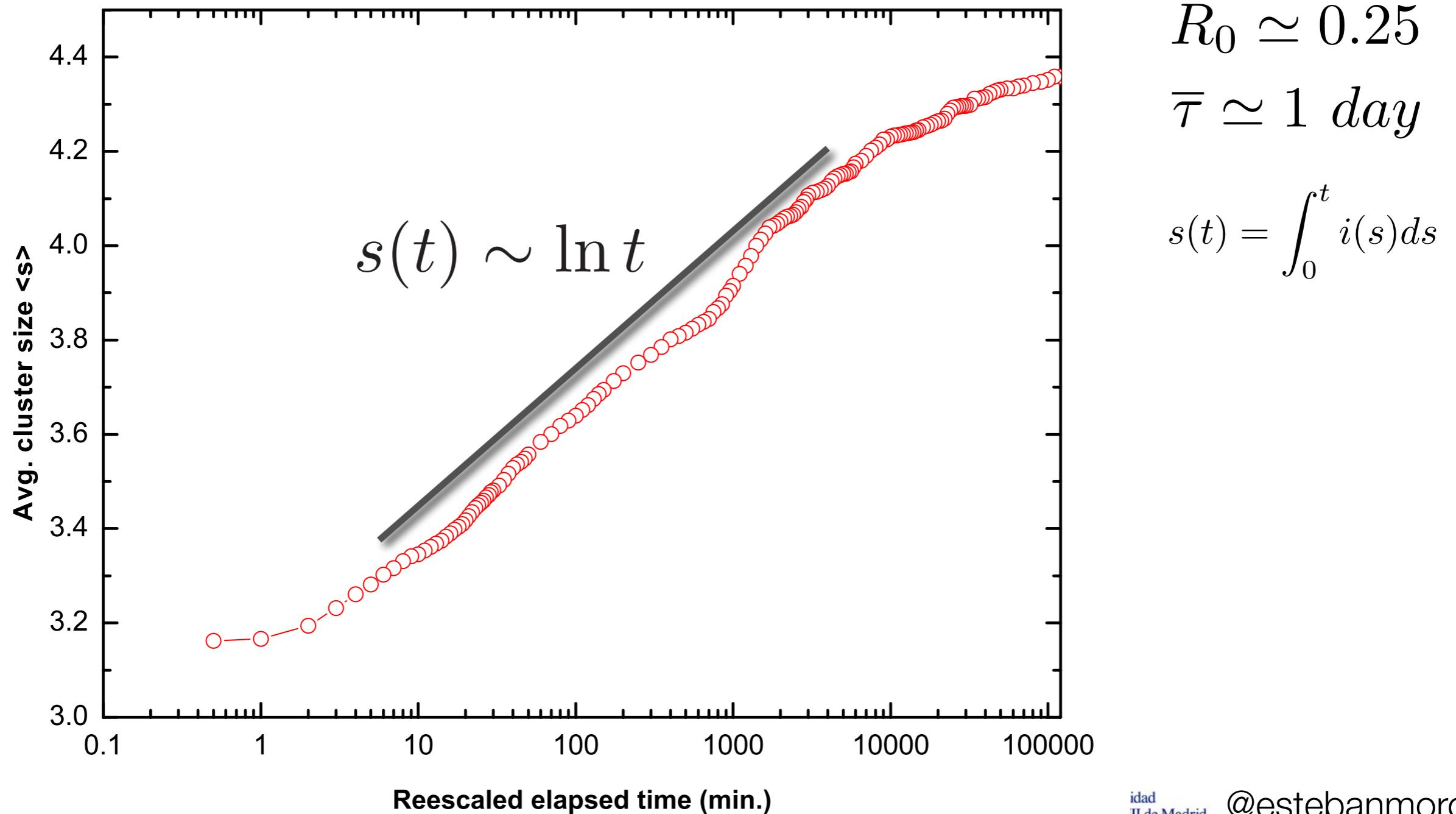


$$1 + R_0 + R_0^2 + R_0^3 + R_0^4 + R_0^5 + \dots$$

$$\frac{di}{dt} = \frac{R_0 - 1}{\tau} i \quad i(t) = i(0)e^{\alpha t}$$

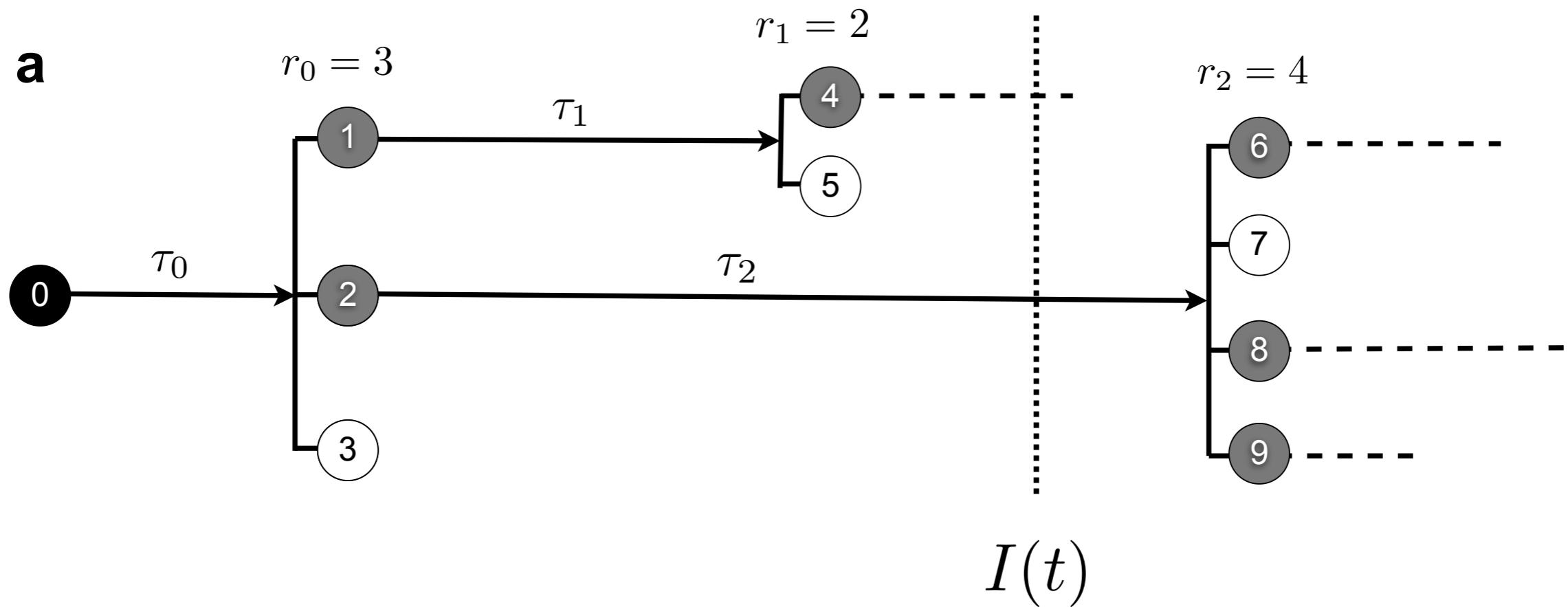
Viral marketing experiments

- Viral marketing campaigns prevailed for weeks/months



Bellman-Harris process

- The process is characterised by the distribution of number of recommendations and response time $P(k)$ [$P(r)$] $G(\tau)$



Bellman-Harris Process

- It is the well-known Bellman-Harris Process

$$i(t) = 1 - G(t) + R_0 \int_0^t dG(\tau) i(\tau)$$

- where R_0 is the secondary reproductive number and $i(t) = \langle I(t) \rangle$
- The dynamics is determined by the tail of the distribution

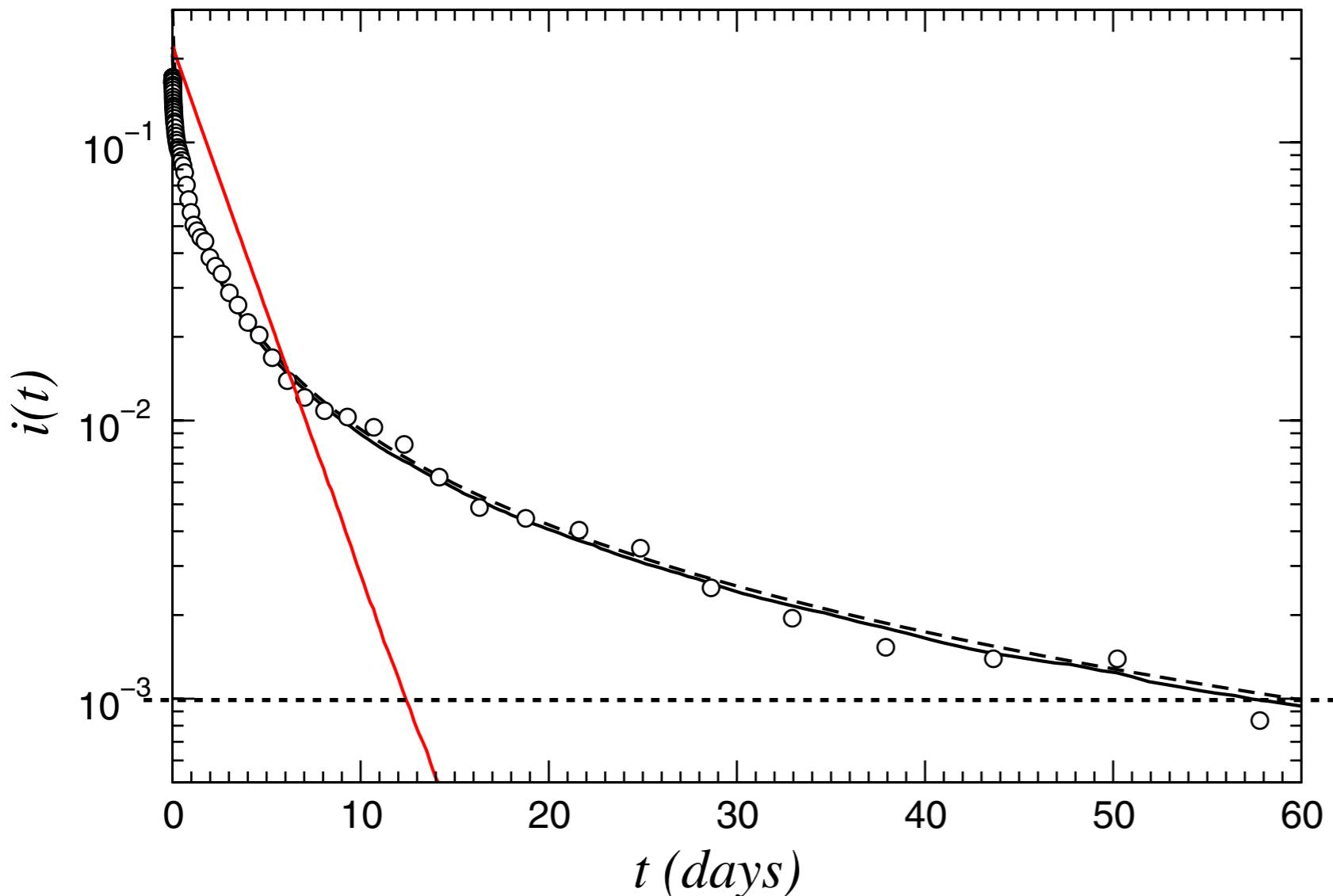
Theorem. (Athreya & Ney '70s) If $R_0 < 1$ and G is in the sub-exponential class \mathcal{S} , then

$$i(t) \sim \frac{1 - G(t)}{1 - R_0}$$



Information travels in logarithmic time

- Prevalence



$$i(t_f) \simeq 10^{-3}$$

$$t_f \simeq 12 \text{ days}$$

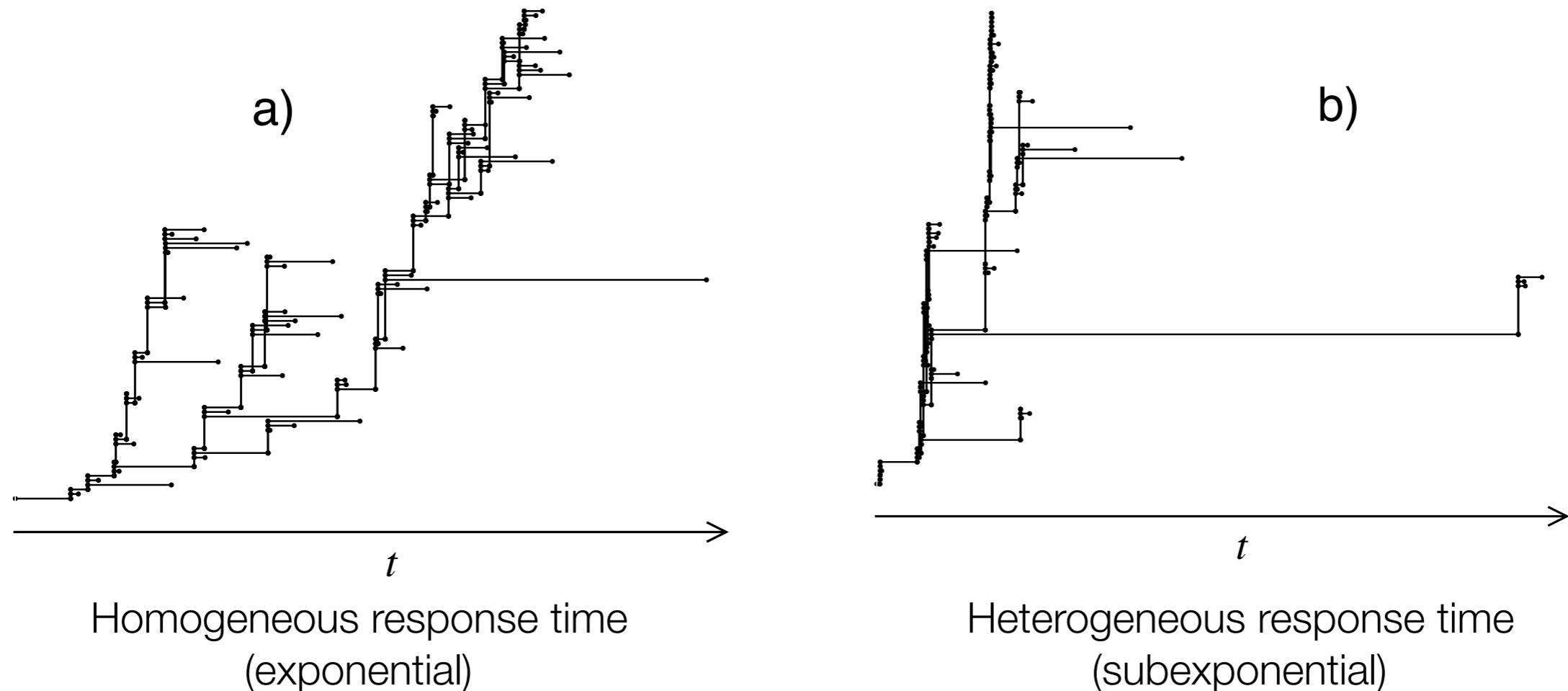
$$t_f \simeq 2 \text{ months}$$

$$i(t_f) = 10^{-4}$$

$$t_f \simeq 17 \text{ days}$$

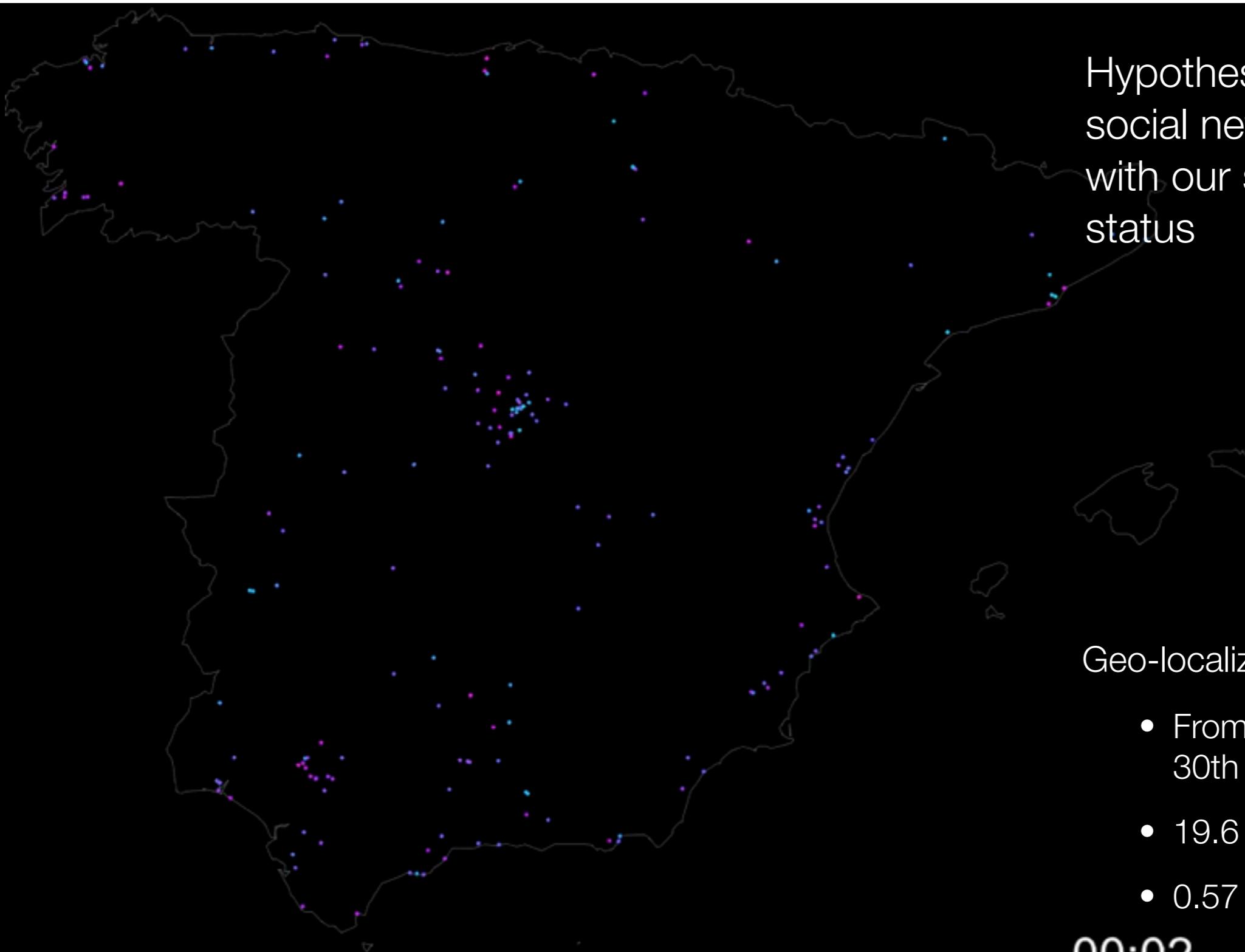
$$t_f \simeq 1 \text{ year}$$

Information spreading is dominated by the tail of the distribution



1. Iribarren, J. E. L., & Moro, E. (2009). Impact of human activity patterns on the dynamics of information diffusion, 103(3), 038702–038702. <http://doi.org/10.1103/PhysRevLett.103.038702>
2. Iribarren, J. L., & Moro, E. (2011). Branching dynamics of viral information spreading, 84(4), 46116. <http://doi.org/10.1103/PhysRevE.84.046116>

Individual activity and socio-economical situation



Hypothesis: our activity in social networks is correlated with our socio-economical status

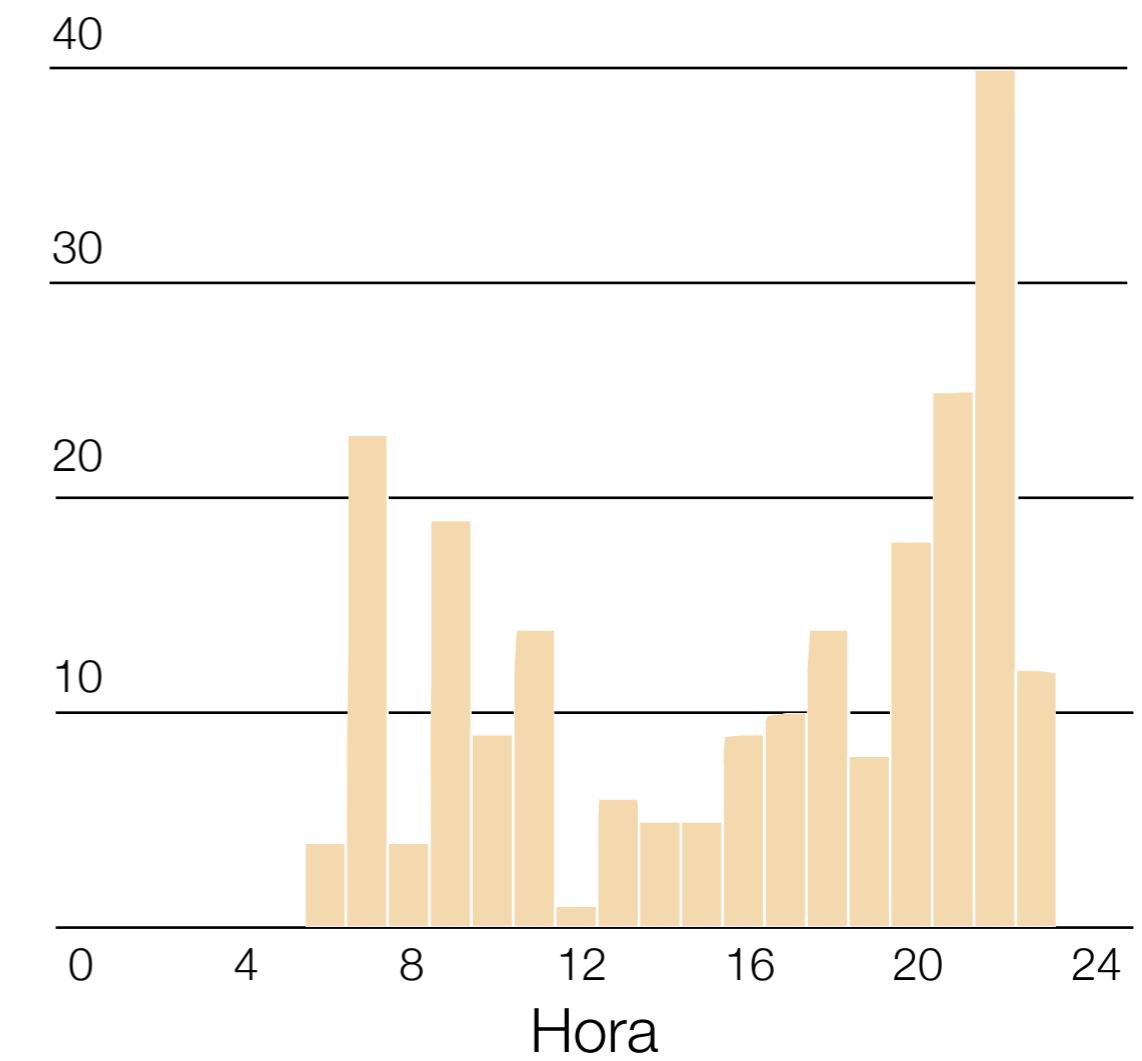
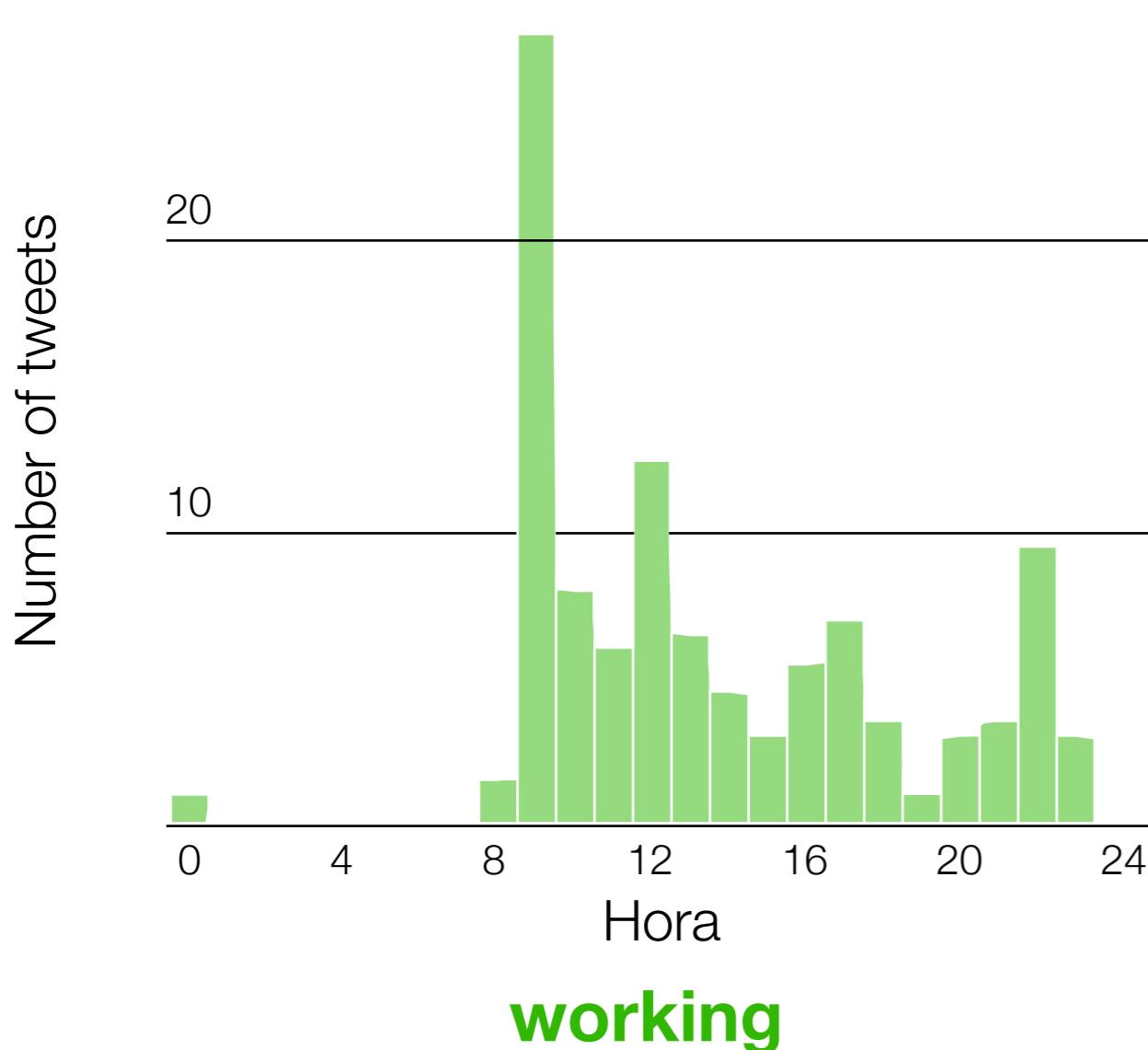
Geo-localized tweets in Spain

- From 29th Nov 2012 to 30th June 2013
- 19.6 million tweets
- 0.57 million unique users

00:02

Individual activity and socio-economical situation

- Our daily activity is impacted by our socio-economical situation
 - At the individual level



Unemployed

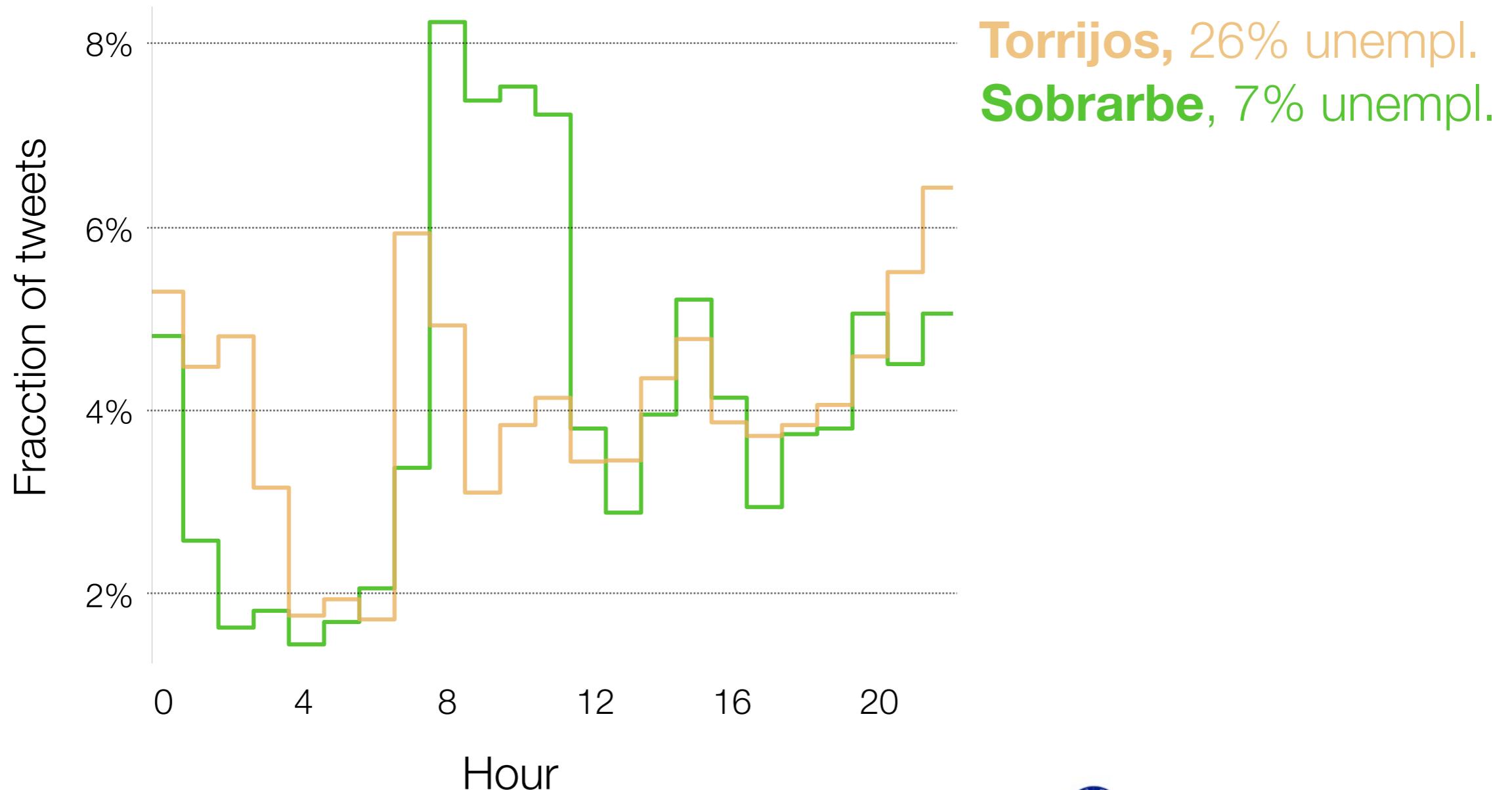


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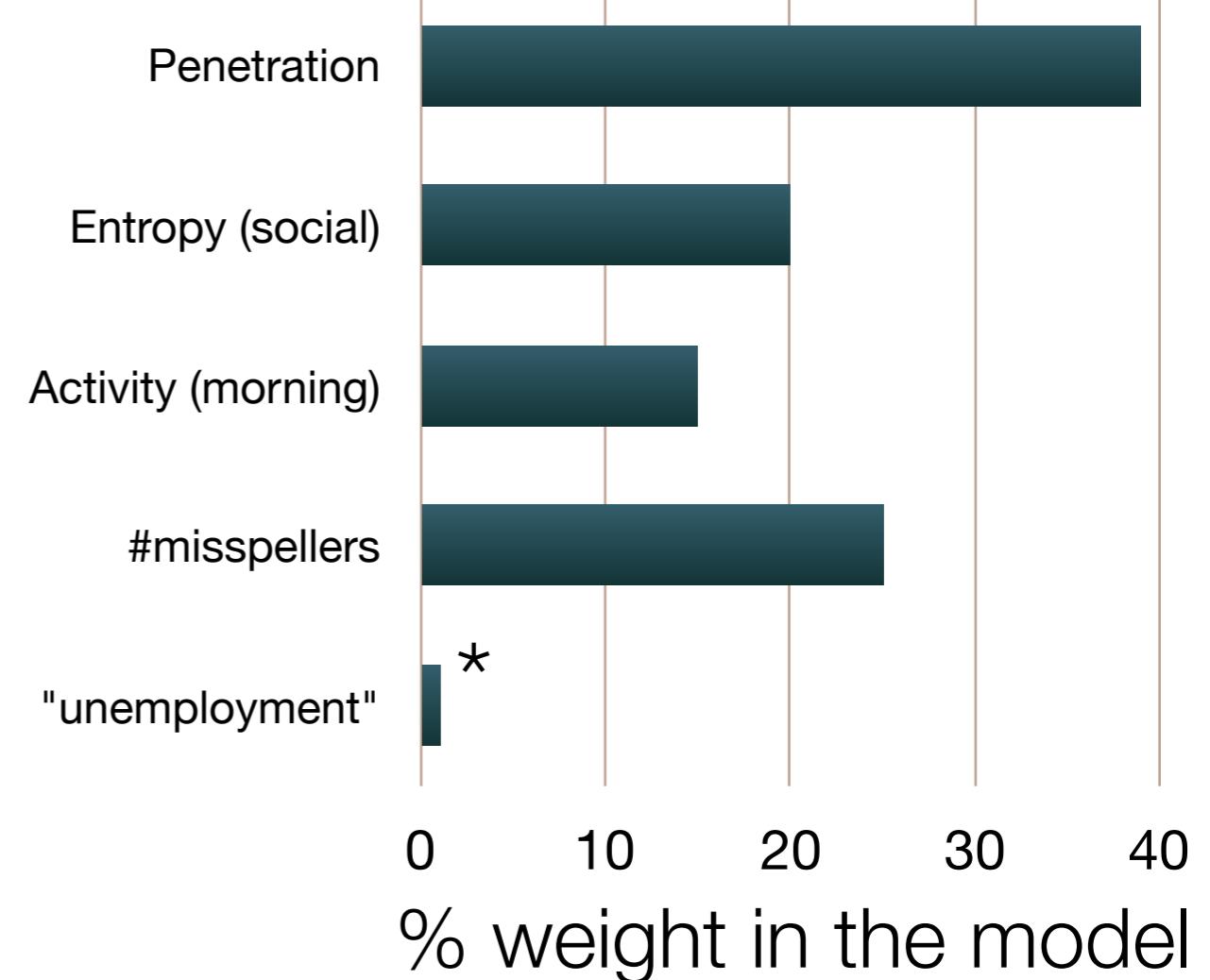
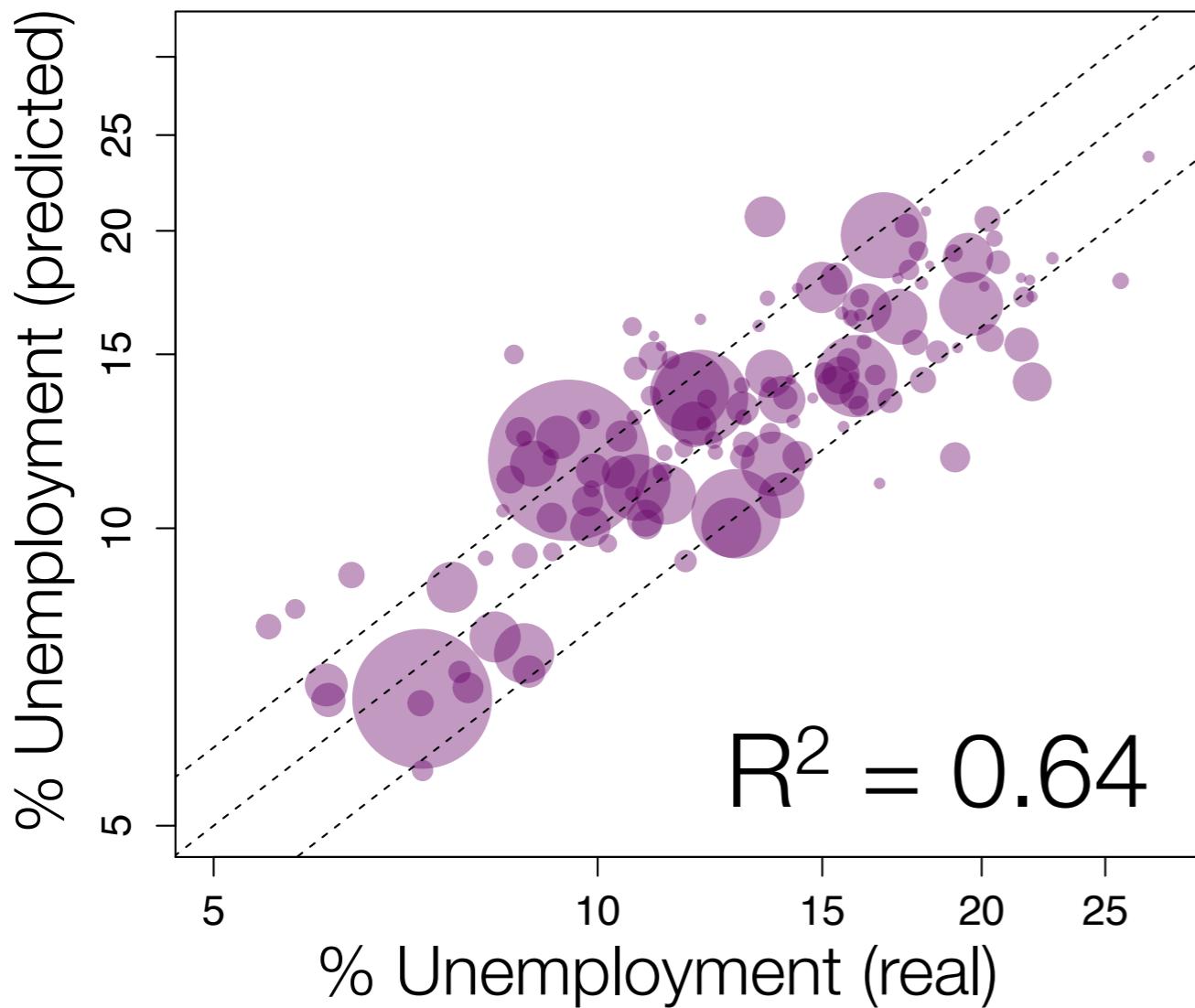
Individual activity and socio-economical situation

- Our daily activity is impacted by our socio-economical situation
 - At group/city level



Explanatory power of Twitter variables

- Simple linear regression

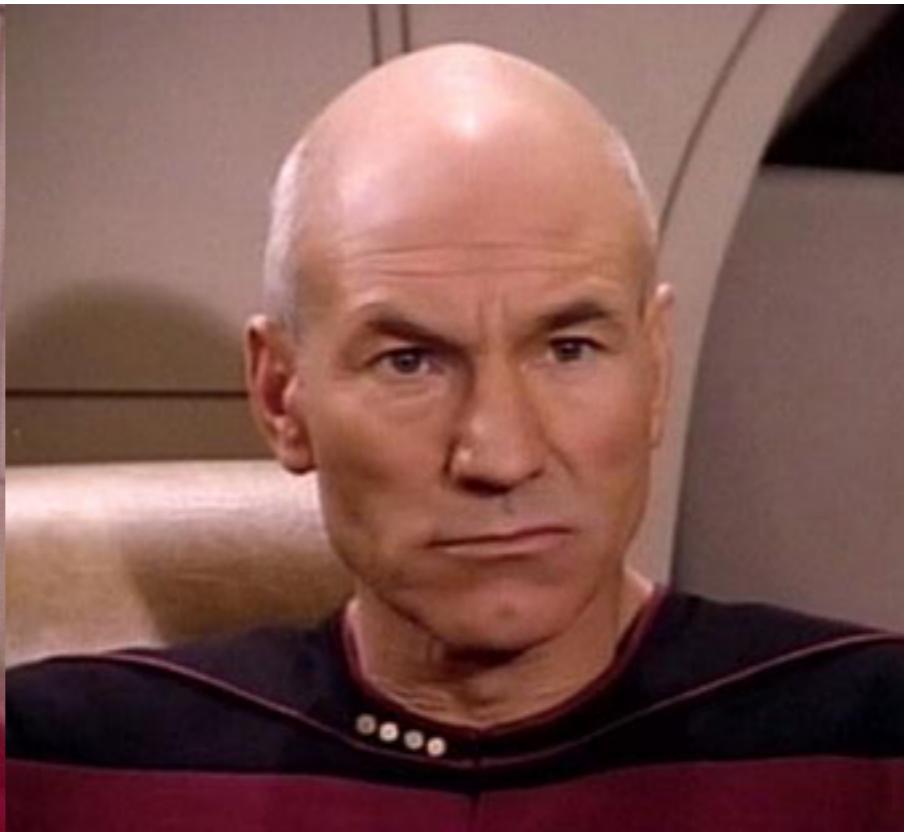


Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment. PLoS ONE, 10(5), e0128692. <http://doi.org/10.1371/journal.pone.0128692>

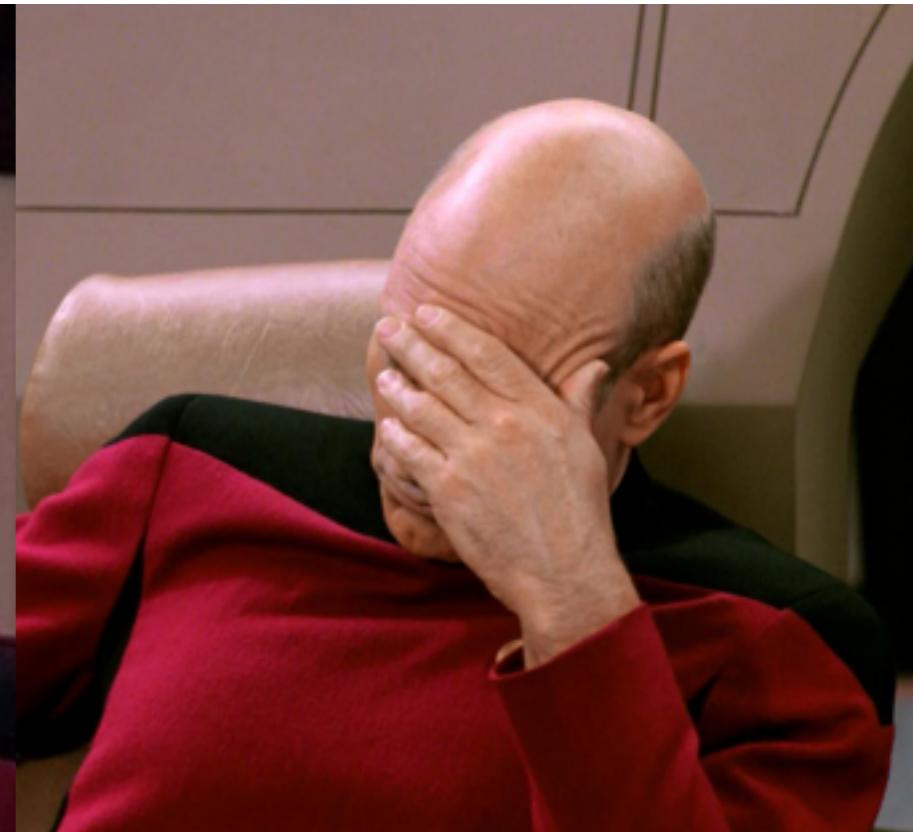
Researcher



Data scientist



Policy maker



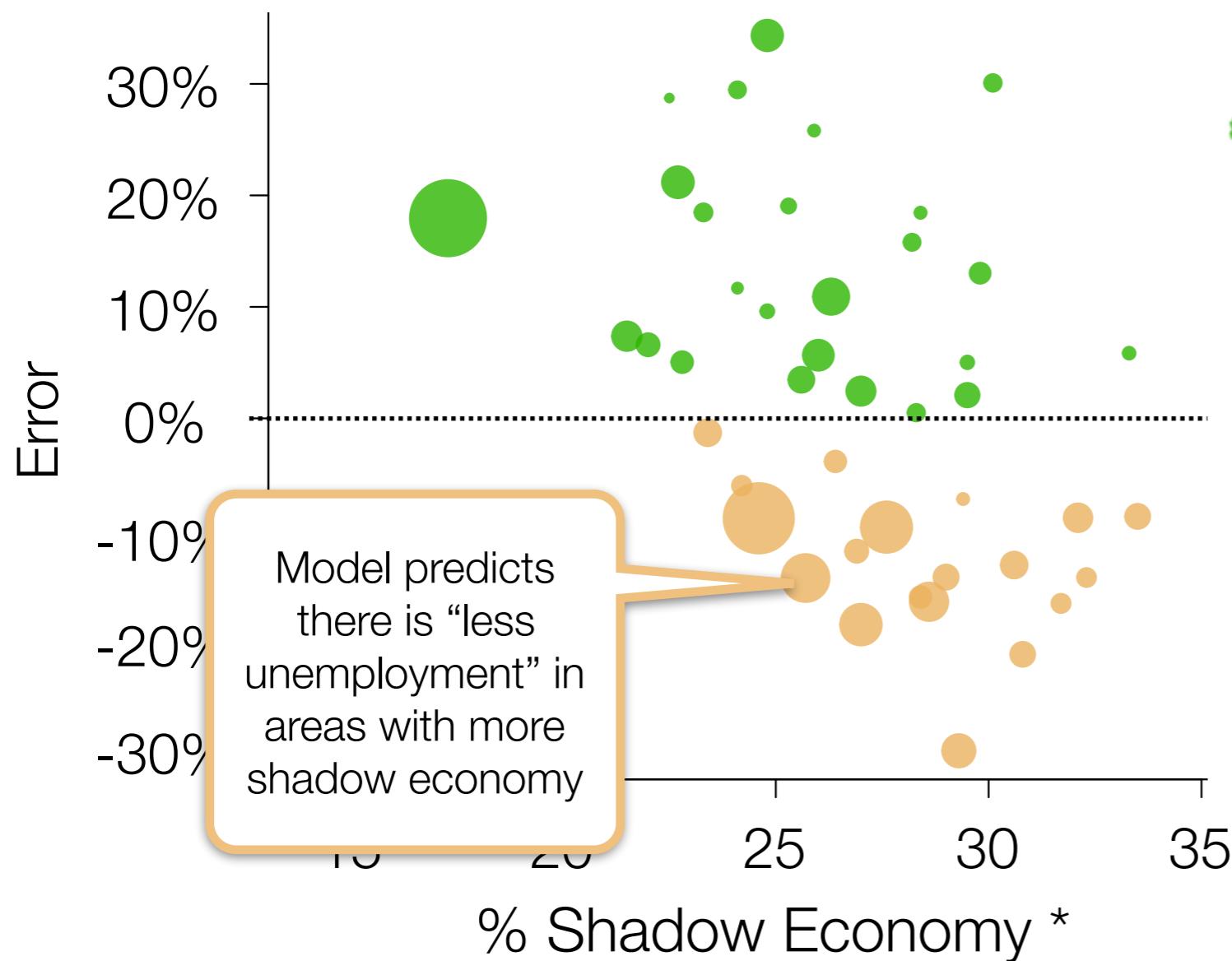
Researcher

Editor

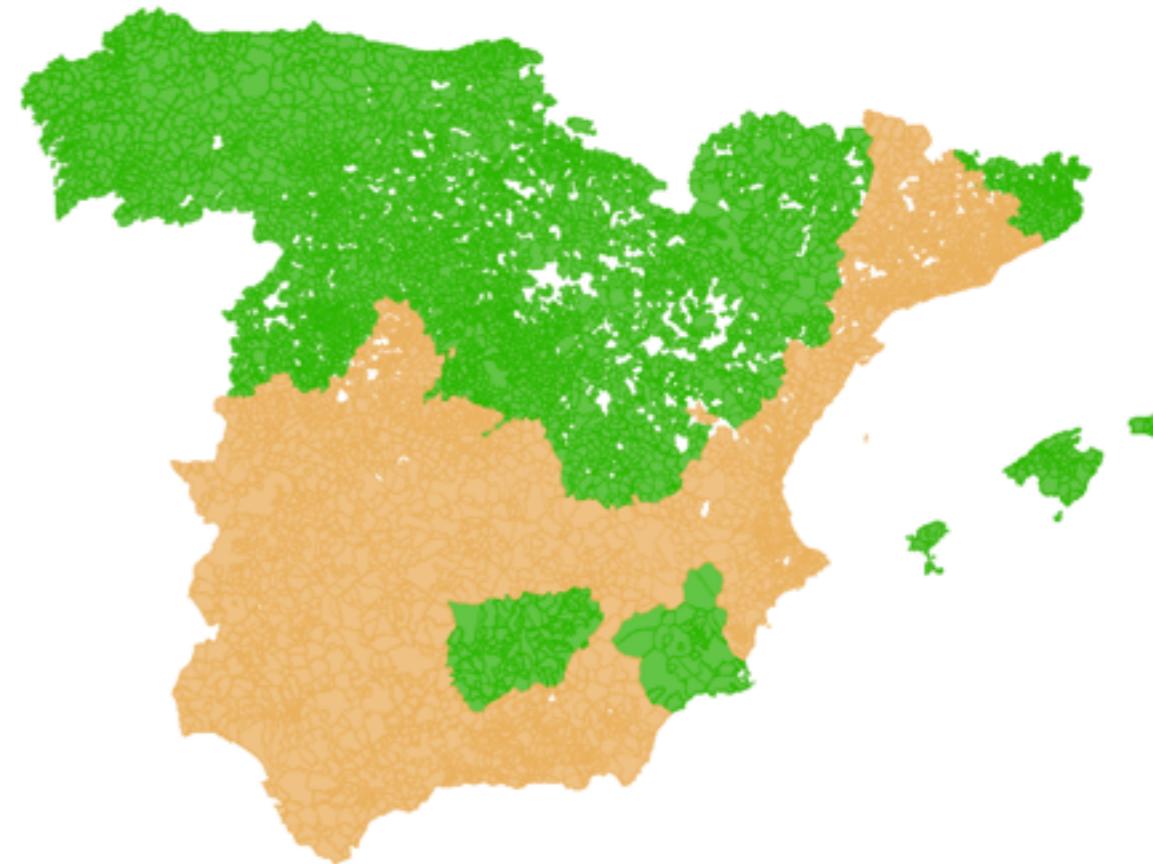
Referee

Are we really wrong?

Model Error = Model[variables] - Official unemployment



(* GESTHA report 2012)



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References

- Reviews
 - Blondel, V. D., Decuyper, A., & Krings, G. (2015). A survey of results on mobile phone datasets analysis. *EPJ Data Science*, 4(1), 10. <http://doi.org/10.1140/epjds/s13688-015-0046-0>
 - MOBILE PHONE NETWORK DATA FOR DEVELOPMENT. (2013). UN Global Pulse
 - Saramaki, J., & Moro, E. (2015). From seconds to months: an overview of multi-scale dynamics of mobile telephone calls. *The European Physical Journal B*, 88(6). <http://doi.org/10.1140/epjb/e2015-60106-6>
 - Naboulsi, D., Fiore, M., Ribot, S., & Stanica, R. (n.d.). Large-scale Mobile Traffic Analysis: a Survey. *IEEE Communications Surveys & Tutorials*, 1–1. <http://doi.org/10.1109/COMST.2015.2491361>
- Conferences
 - NetMob <http://netmob.org>
 - NetSci <http://netsci2016.net>
- Libraries
 - <http://bandicoot.mit.edu> an open-source python toolbox to analyze mobile phone metadata
 - igraph <http://igraph.org> (python, R, C)
 - NetworkX <https://networkx.github.io> (python)



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