Trade, Conflict and Sentiments: Multi-relational Organisation of Large-scale Social Networks

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with M. Szell and S. Thurner

M. Szell, R. Lambiotte and S. Thurner, arXiv:1003.5137

Imperial College London

Computational social science

Small-scale questionnaire-based approaches

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Fingerprints of individuals in electronic media (mobile phone, email, Facebook, etc.)

Possibility to analyse the dynamics and organisation of large-scale social systems

D. Lazer, A. Pentland, L. Adamic, S. Aral, A.-L. Barabási, D. Brewer, N. Christakis, N. Contractor, J. Fowler, M. Gutmann, T. Jebara, G. King, M. Macy, D. Roy, M. Van Alstyne, Science 323, 721-724 (2009).

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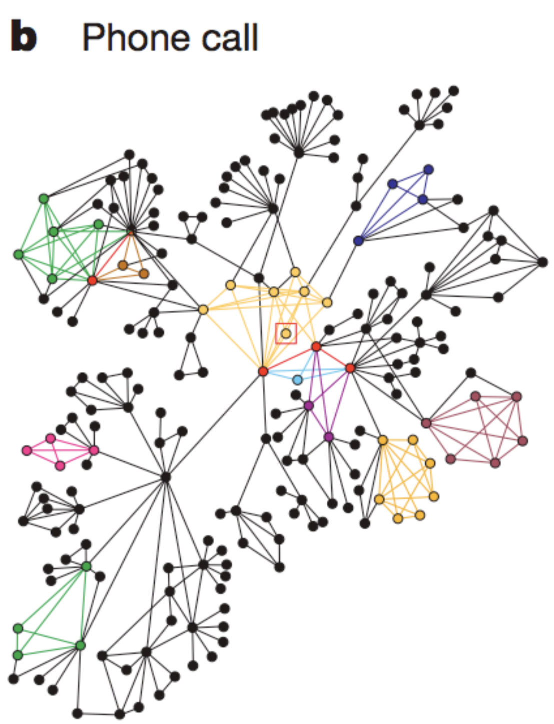
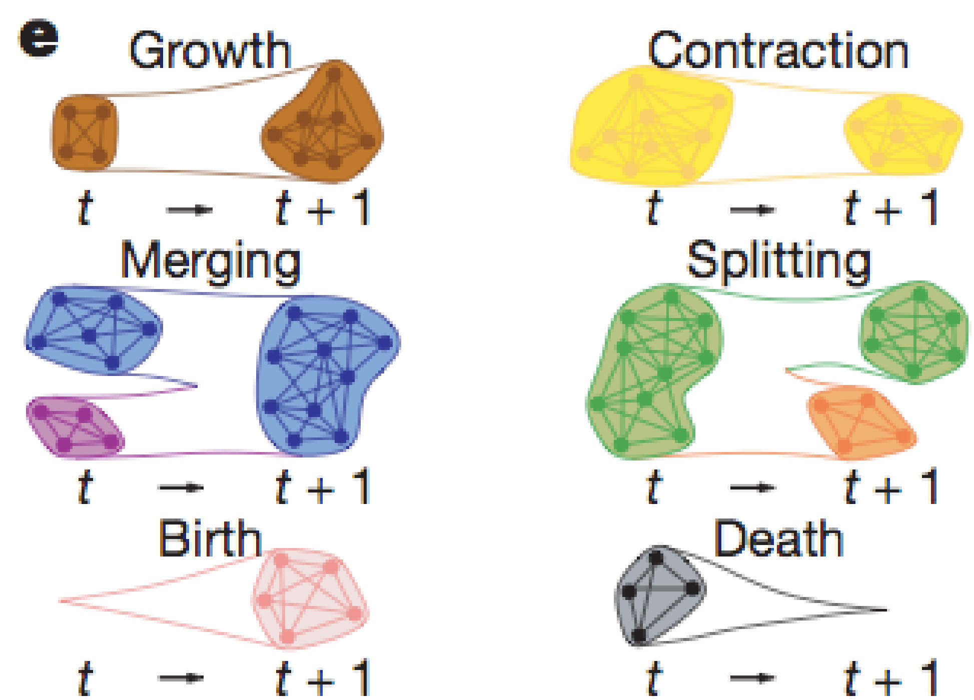
Longitudinal data-sets: quantification of the time evolution of social interactions





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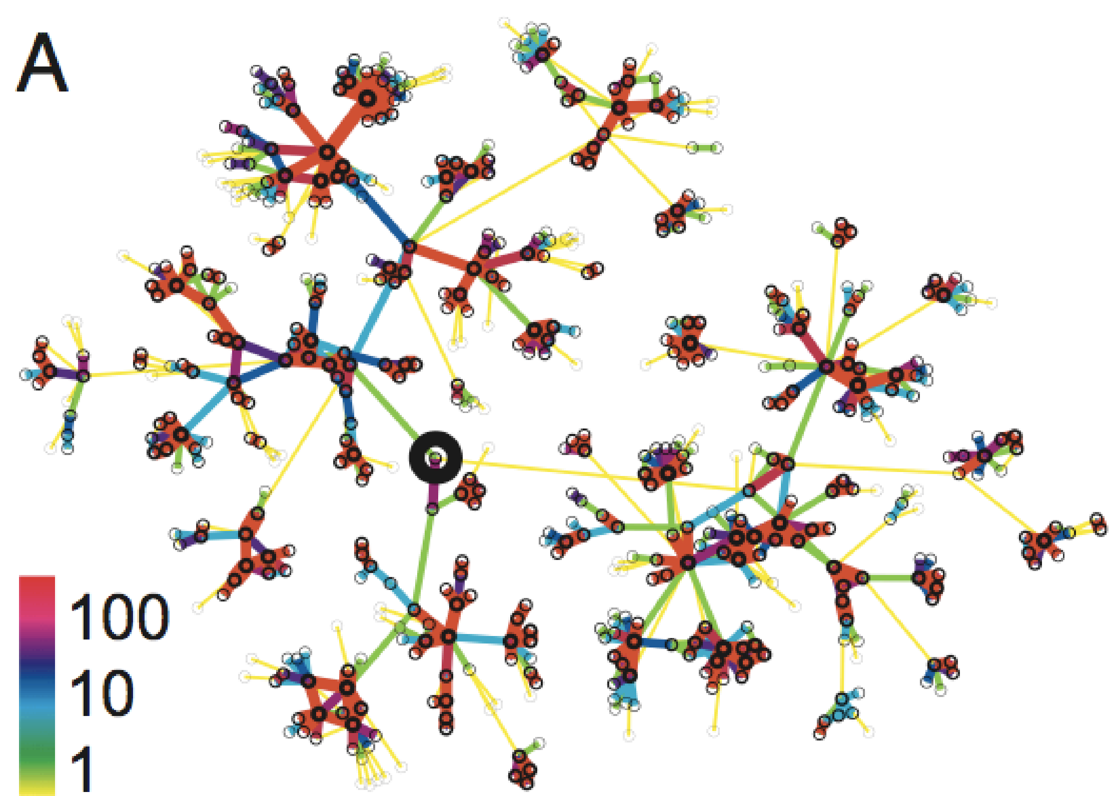
Weighted networks as a measure of the intensity of a tie



J.-P. Onnela, J. Saramaki, J. Hyvonen, G. Szabo, D. Lazer, K. Kaski, J. Kertesz, A.-L. Barabási, PNAS 104 (18), 7332-7336 (2007).

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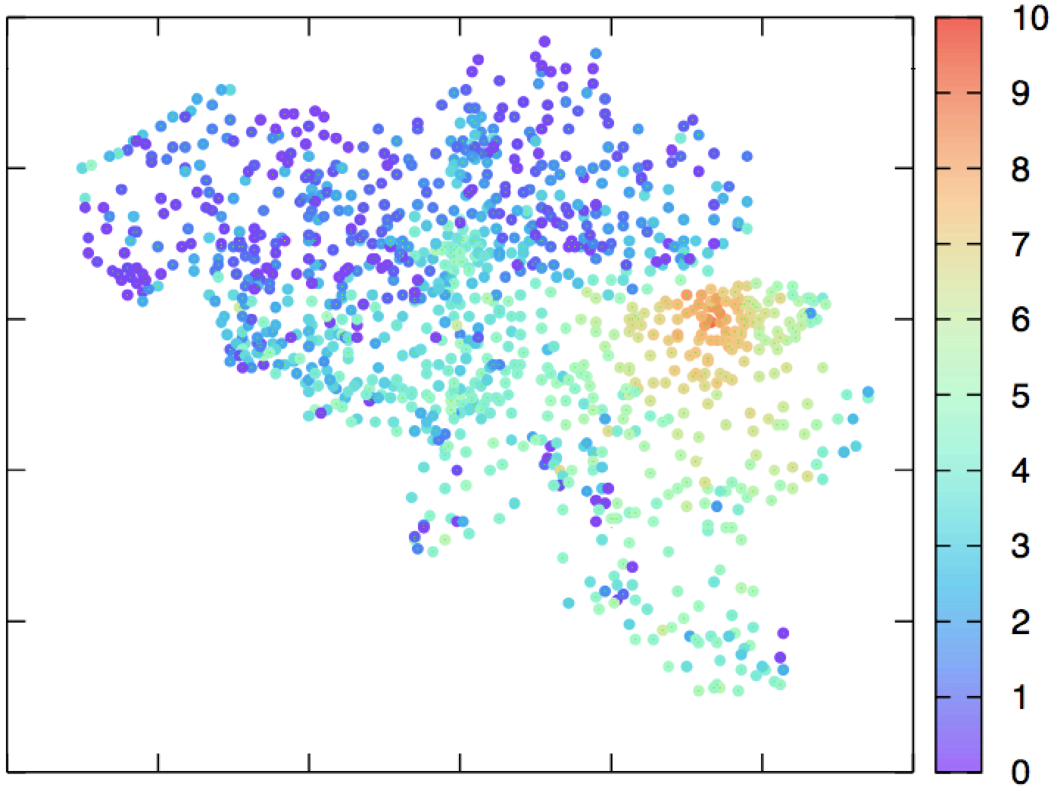
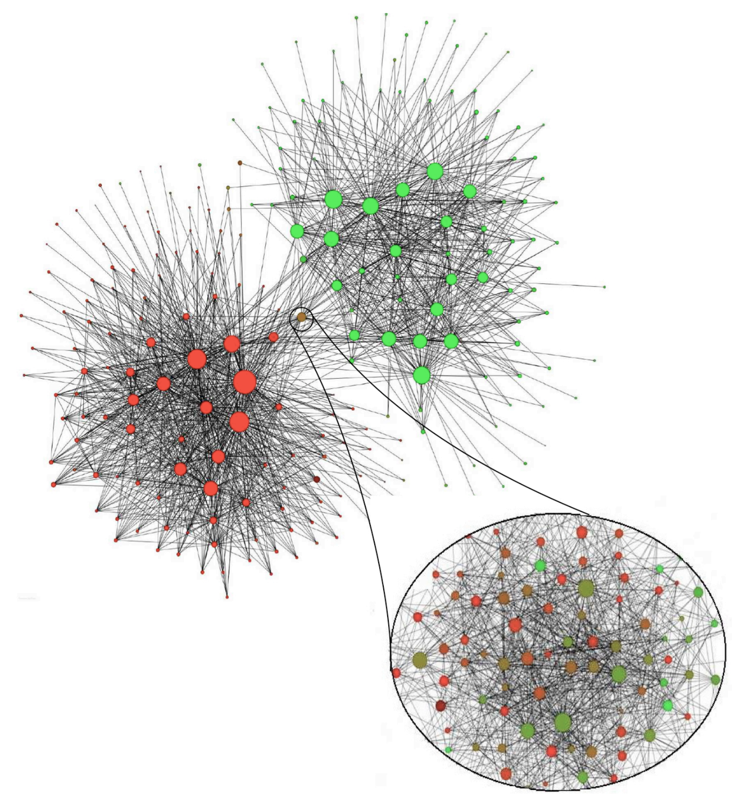
Node attributes: homophily and focus constraint





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V.D. Blondel, J.-L. Guillaume, R. Lambiotte and E. Lefebvre, J. Stat. Mech., (2008) P10008

Computational social science

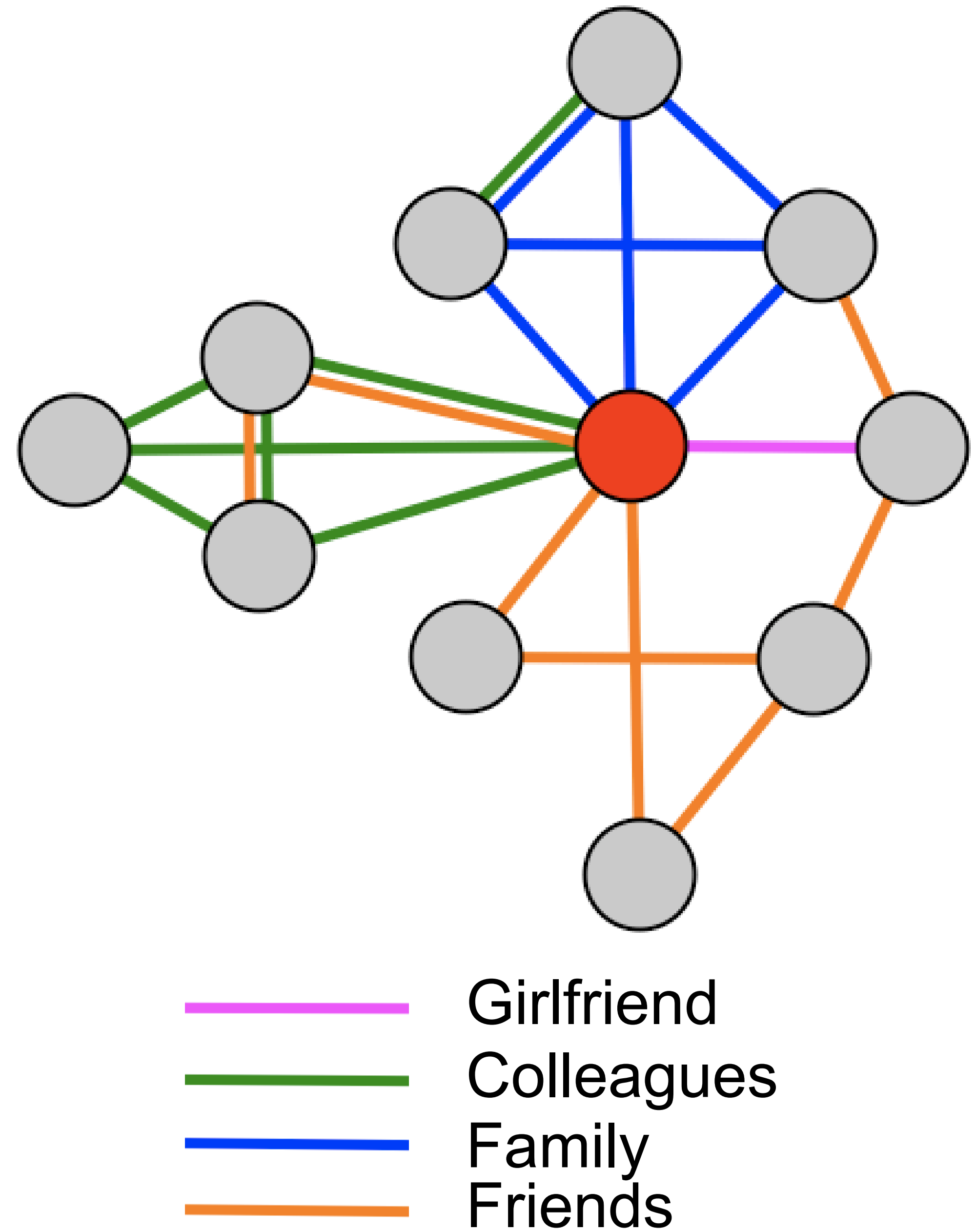
... but is blind to the existence of several types of social interactions between individuals

Relational ties are highly diverse and can represent a feeling, communication, exchange of goods (trade) or behavioural interactions
BUT electronic logs typically capture one channel of communication

Contrary to nodes (characterised by their age, sex, location, etc), the nature of interaction (family or work?) is usually unavailable in electronic data-sets

A society is characterised by the superposition of its constitutive socio-economic networks, all defined on the same set of nodes (multiplex networks)

A systemic understanding of a whole society can only be achieved by understanding these individual networks and how they influence and co-construct each other.



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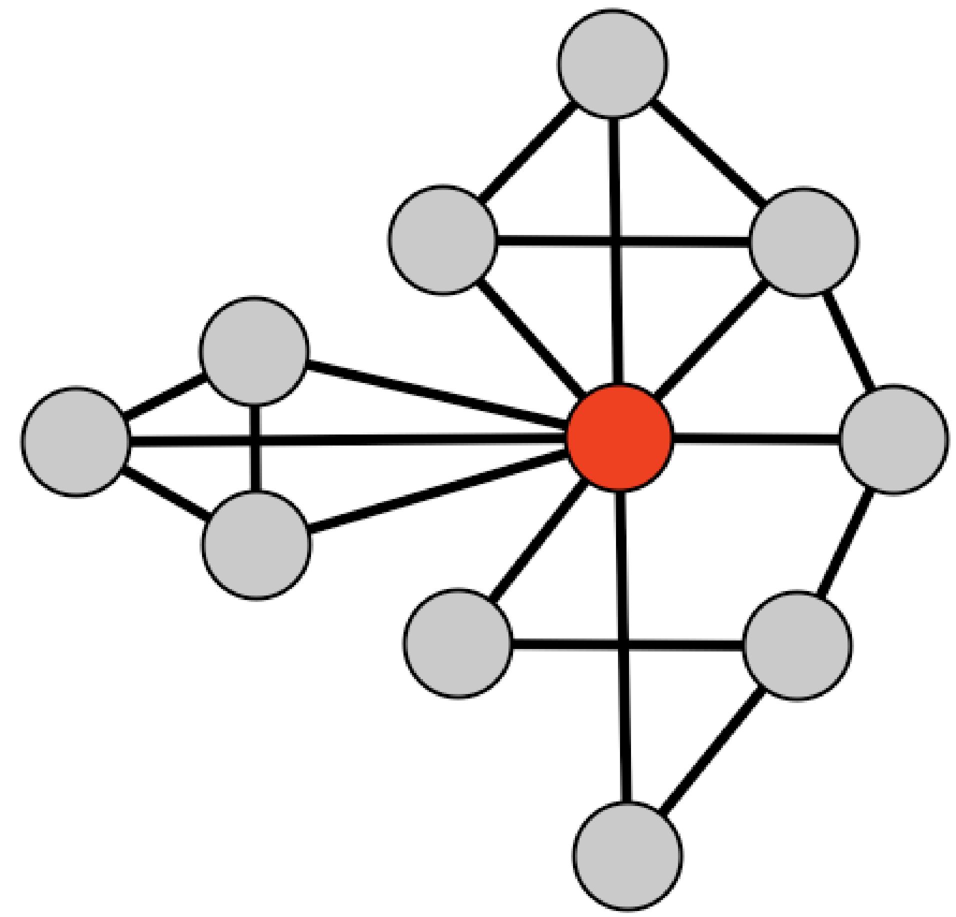

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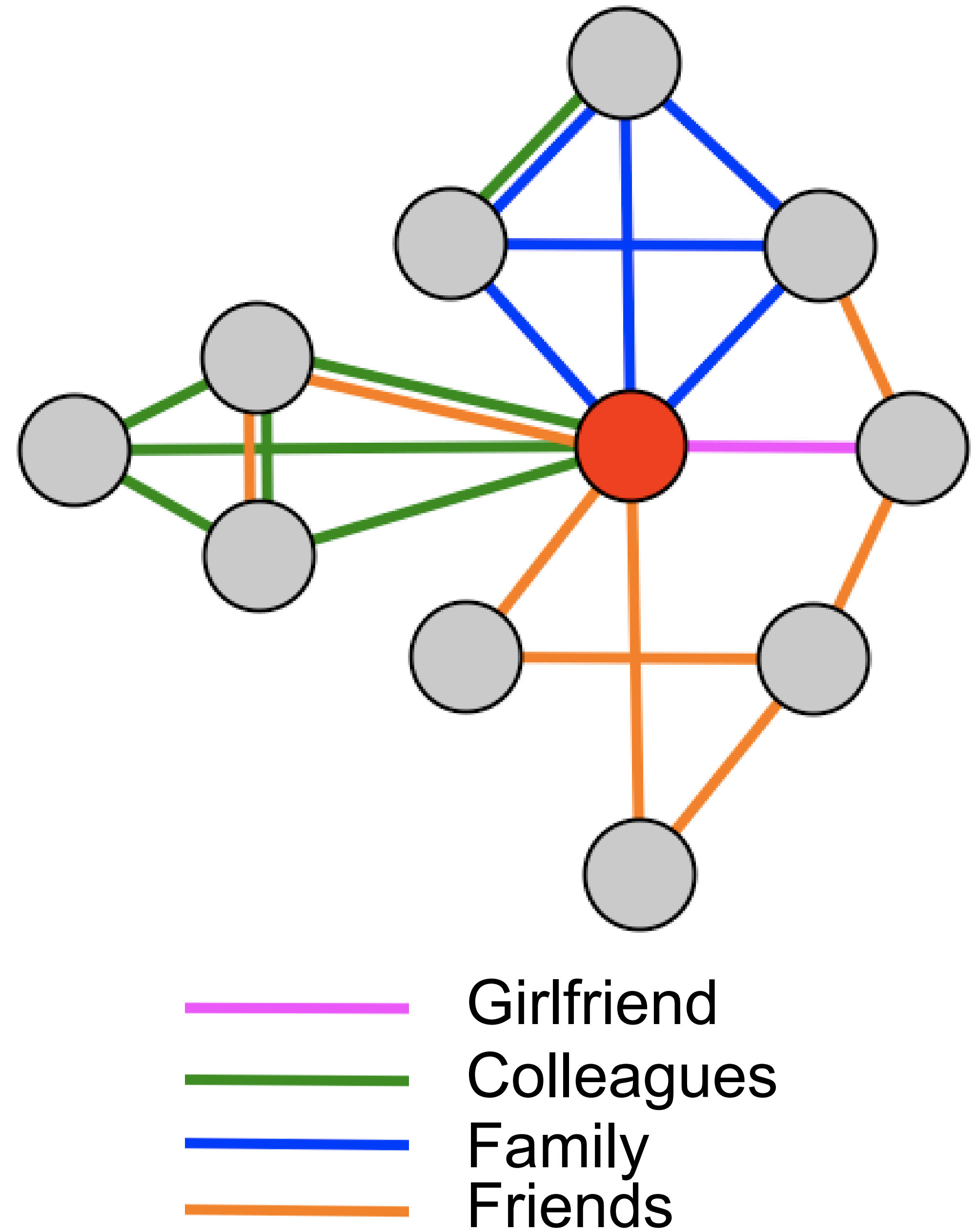

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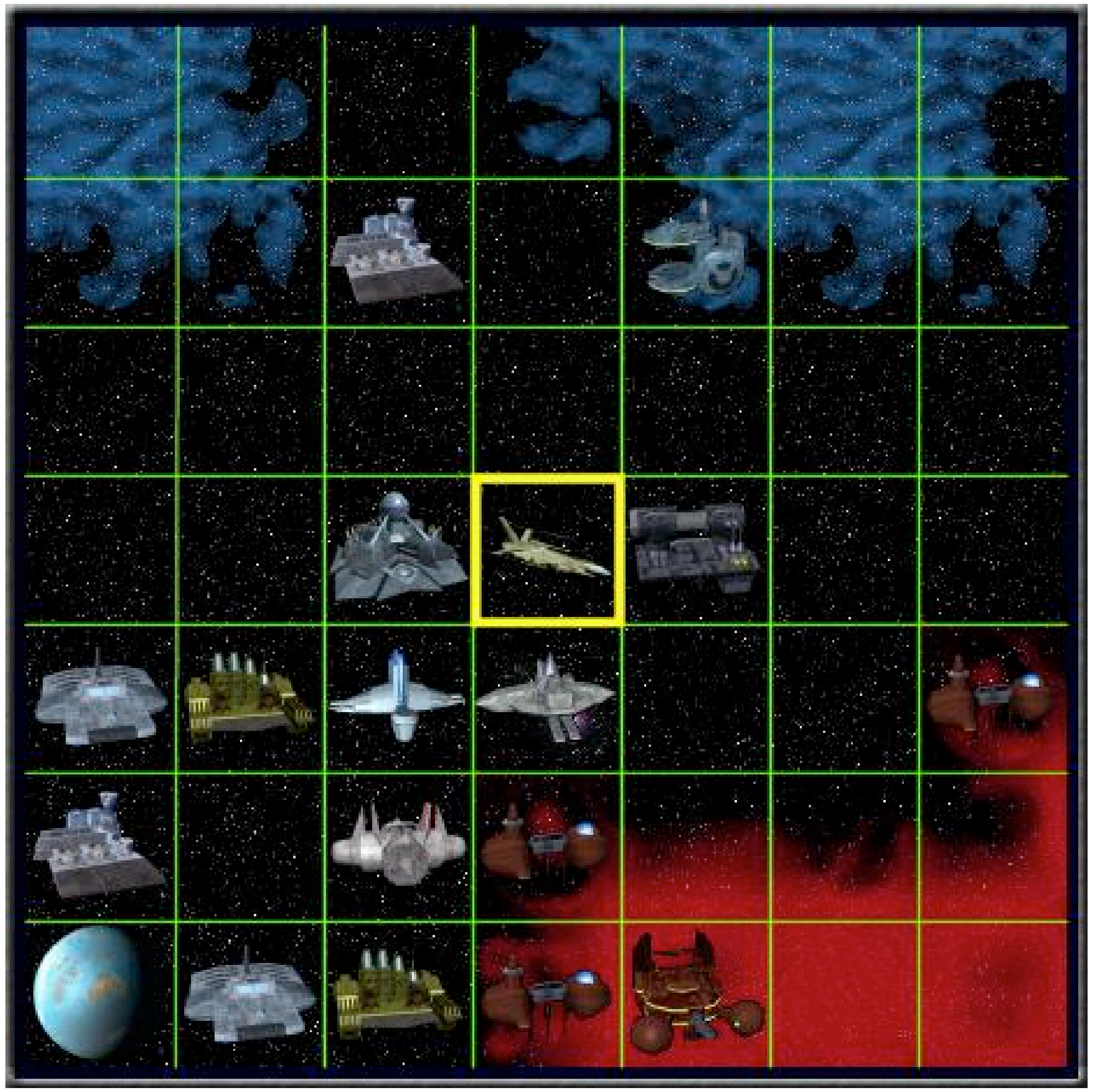
Massive Online Games

Players are immersed in a virtual world where they experience an *alternative* life with a variety of possible social interactions among players.

Motivation: establish friendships, gain respect and status in the virtual community.

All information about all actions taken by all players is stored in log-files



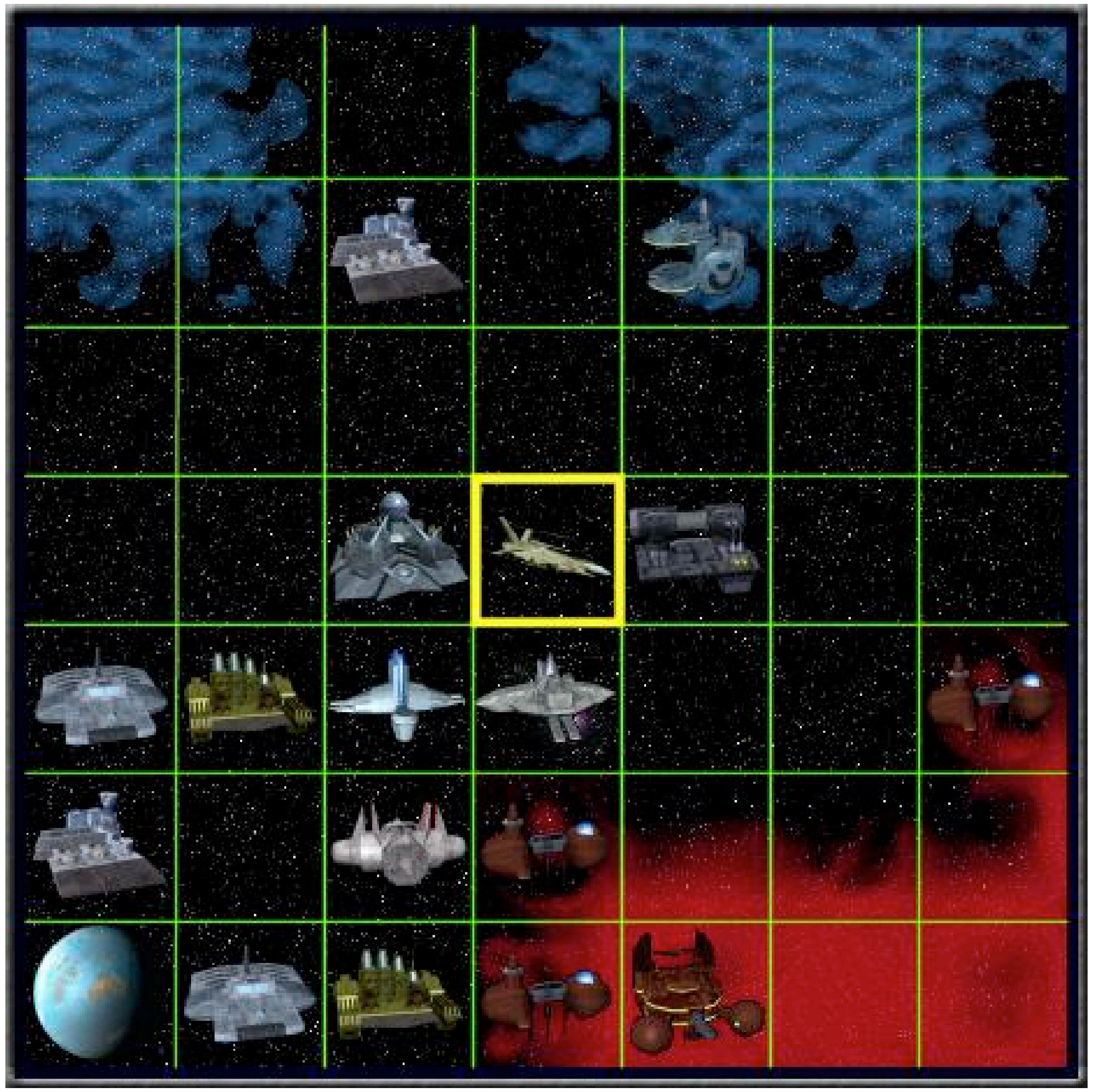
W.S. Bainbridge, The Scientific Research Potential of Virtual Worlds, Science 317 472 (2007);

Massive Online Games

Pardus.at: Massive multiplayer browser game
330,000 registered, 13,000 active players
Played since 2004 (Free, optional 5$/month)

Open-ended game (no winner)
Players self-organise within groups and subgroups, claim territories, decide to go to war, etc., completely on their own account.

Economic life: Trade, production
Social life: Chats, forums, private messages
Exploratory life: explore of an unknown universe



M. Szell and S.Thurner, arXiv:0911.1084.
M. Szell, R. Lambiotte and S. Thurner, arXiv:1003.5137

Massive Online Games

Multiplexity: 6 types of directed, one-to-one interactions

Communication network: personal messages (similar to email)

Trade network: exchange of money for commodity

Friendship network: players can mark others as friends. Only the marker and the marked player know this information

Attack network: attacks performed by one player on the spaceshift of another player

Bounty network: money promised for the destruction of a certain player

Enmity network: players can mark others as friends. Only the marker and the marked player know this information

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positive interactions

Attack network: attacks performed by one player on the spaceshift of another player
Bounty network: money promised for the destruction of a certain player
Enmity network: players can mark others as enemies. Only the marker and the marked player know this information

antagonistic interactions

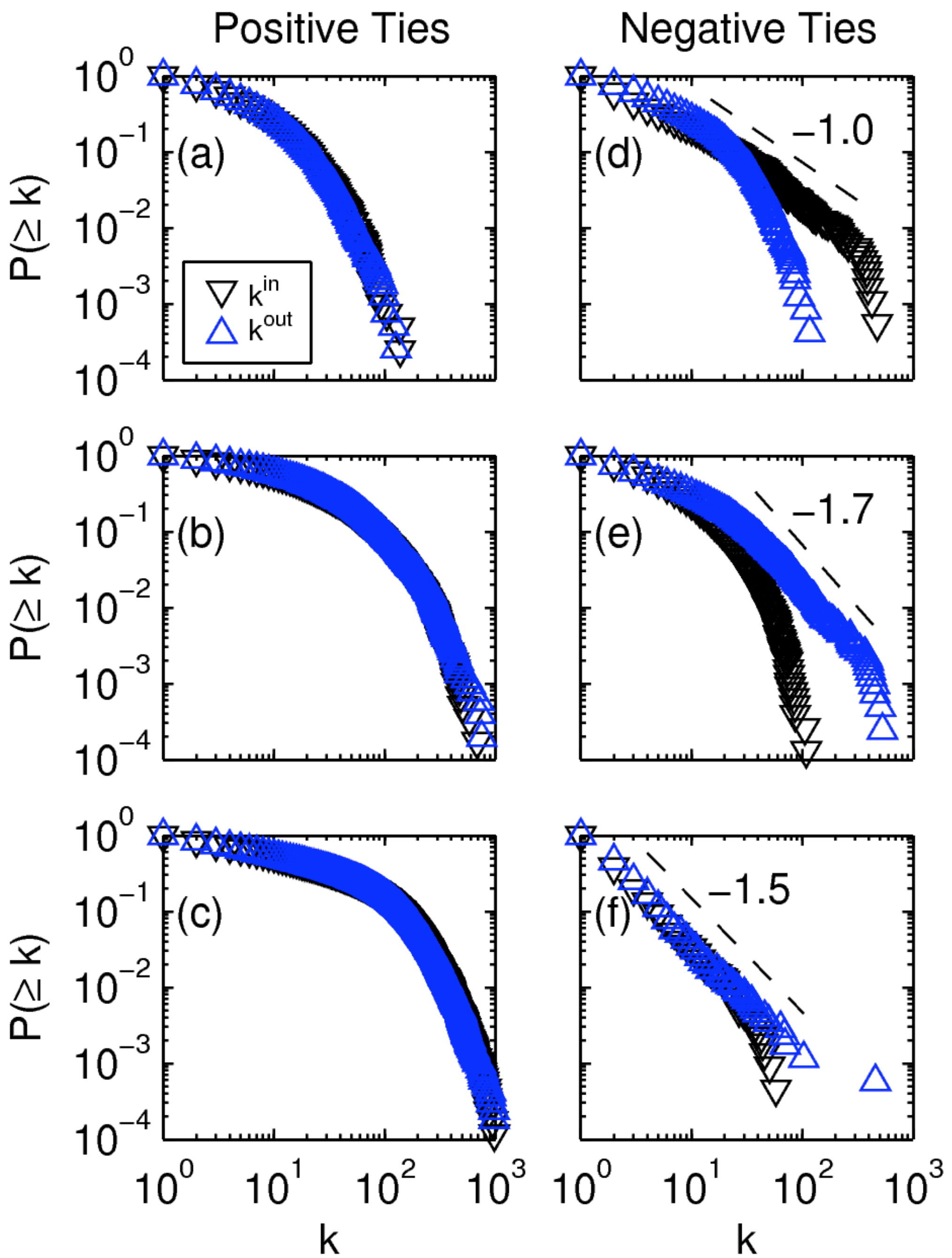
Static networks: Friendship and enmity networks are taken as snapshots at the last available day. All other networks are aggregated over time. For simplicity, we use unweighted, directed networks.
Undirected networks are also constructed: a link exist between i and j if there exists at least one directional edge between those nodes

M. Szell and S.Thurner, arXiv:0911.1084.
M. Szell, R. Lambiotte and S. Thurner, arXiv:1003.5137

1) Structural difference between "positive" and "negative" interactions

	Friends	PMs	Trades	Enemies	Attacks	Bounties
N	4,313	5,877	18,589	2,906	7,992	2,980
$L_{\rm dir}$	31,929	185,908	796,733	21,183	57,479	5,096
ρ	0.68	0.84	0.57	0.11	0.13	0.20
$\rho(k^{\rm in}, k^{\rm out})$	0.88	0.98	0.93	0.64	0.11	0.31
$L_{\rm undir}$	21,118	107,448	568,923	20,008	53,603	4,593
$\bar{k}$	9.79	36.57	61.21	13.77	13.41	3.08
C	0.25	0.28	0.43	0.03	0.06	0.01
$C/C_{\rm r}$	109.52	45.71	131.95	6.13	37.27	13.88

High reciprocity	Low reciprocity
High cohesion	Low cohesion
No power-law	"Power-law"



r reciprocity coefficient: tendency for directed links to be reciprocal

D. Garlaschelli and M.I. Loffredo (2004) Phys. Rev. Lett. 93, 268701

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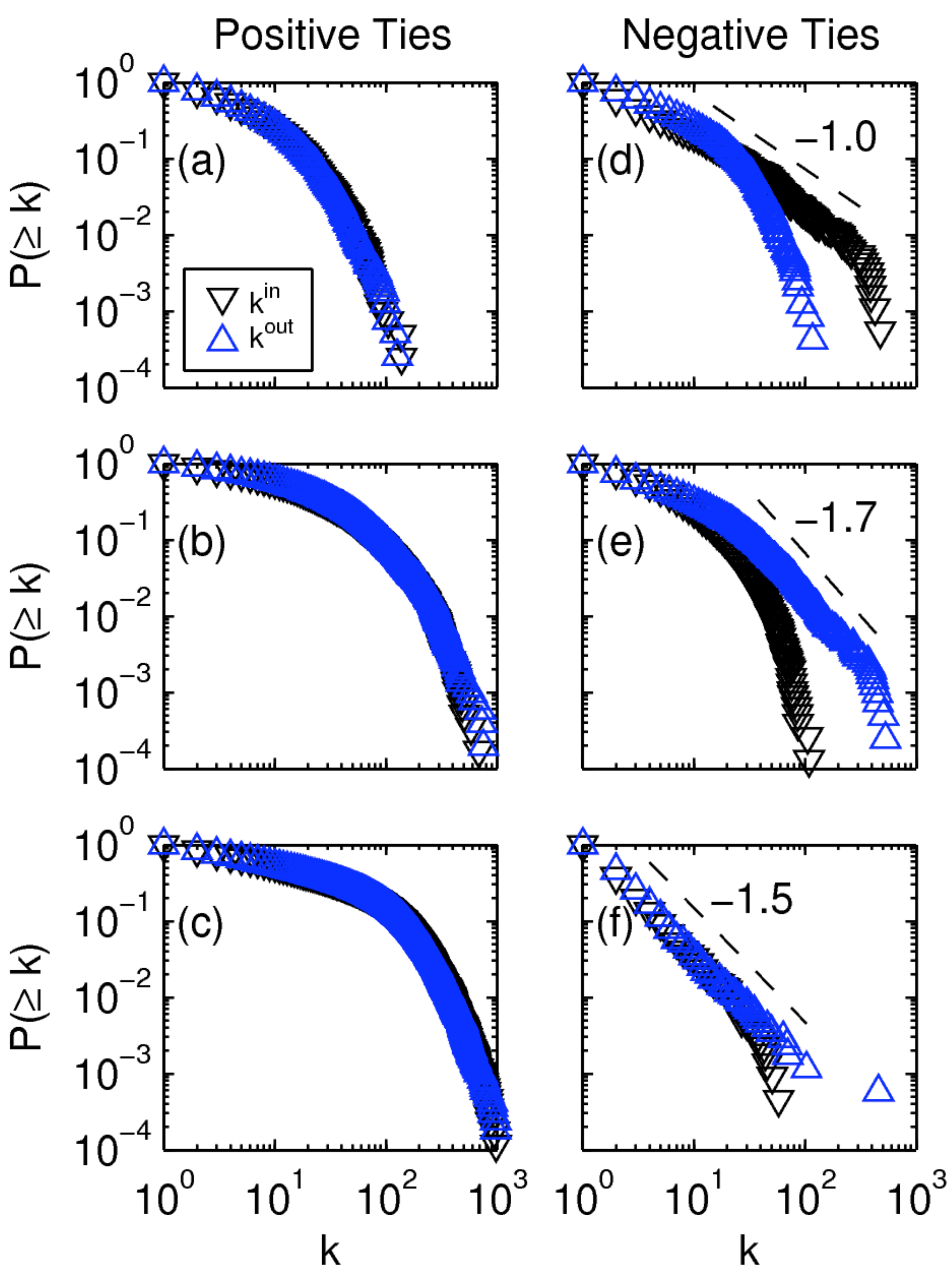

C clustering coefficient

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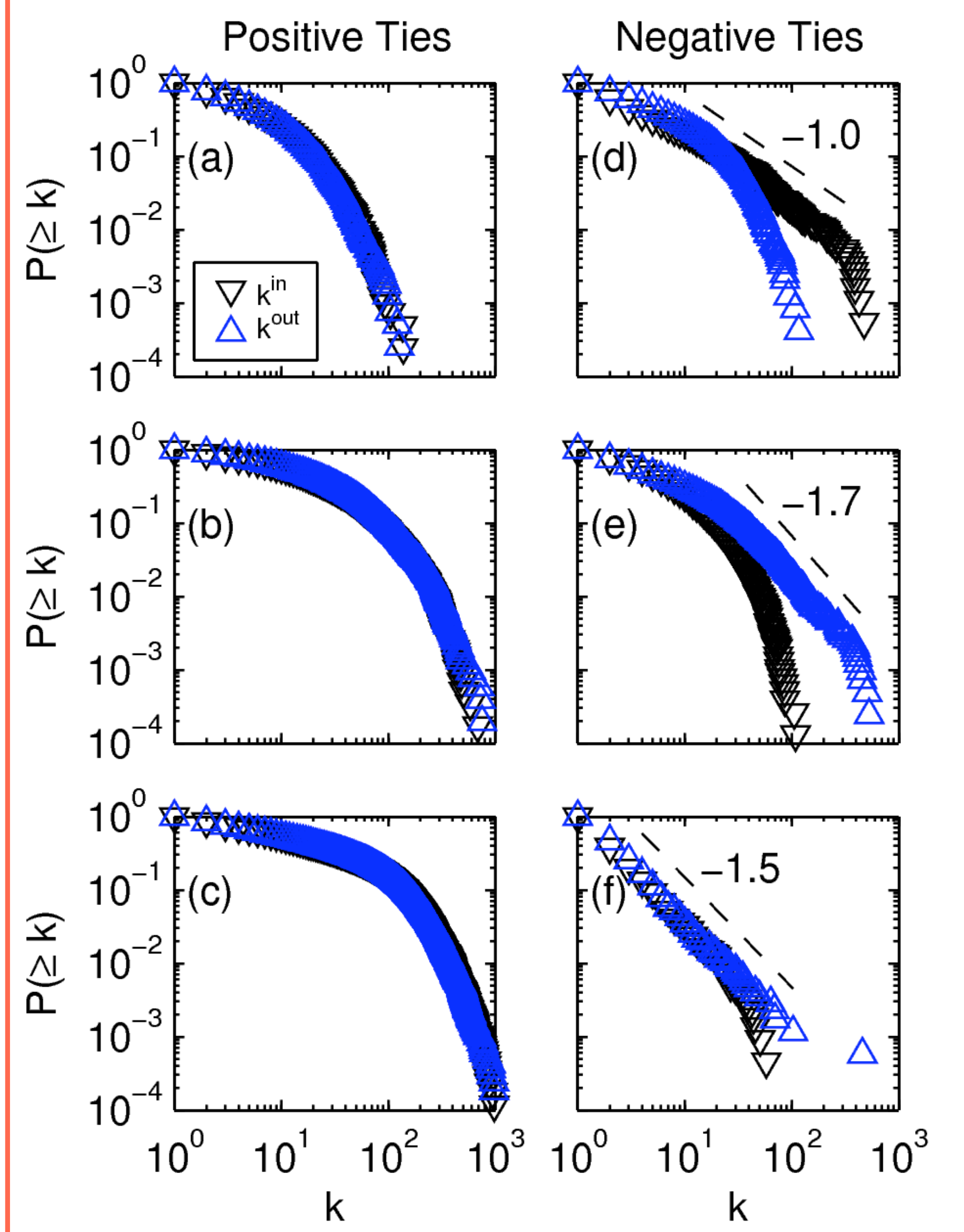

(a) friendship; (b) PM; (c) trade; (d) enmity; (e) attack; (f) bounty

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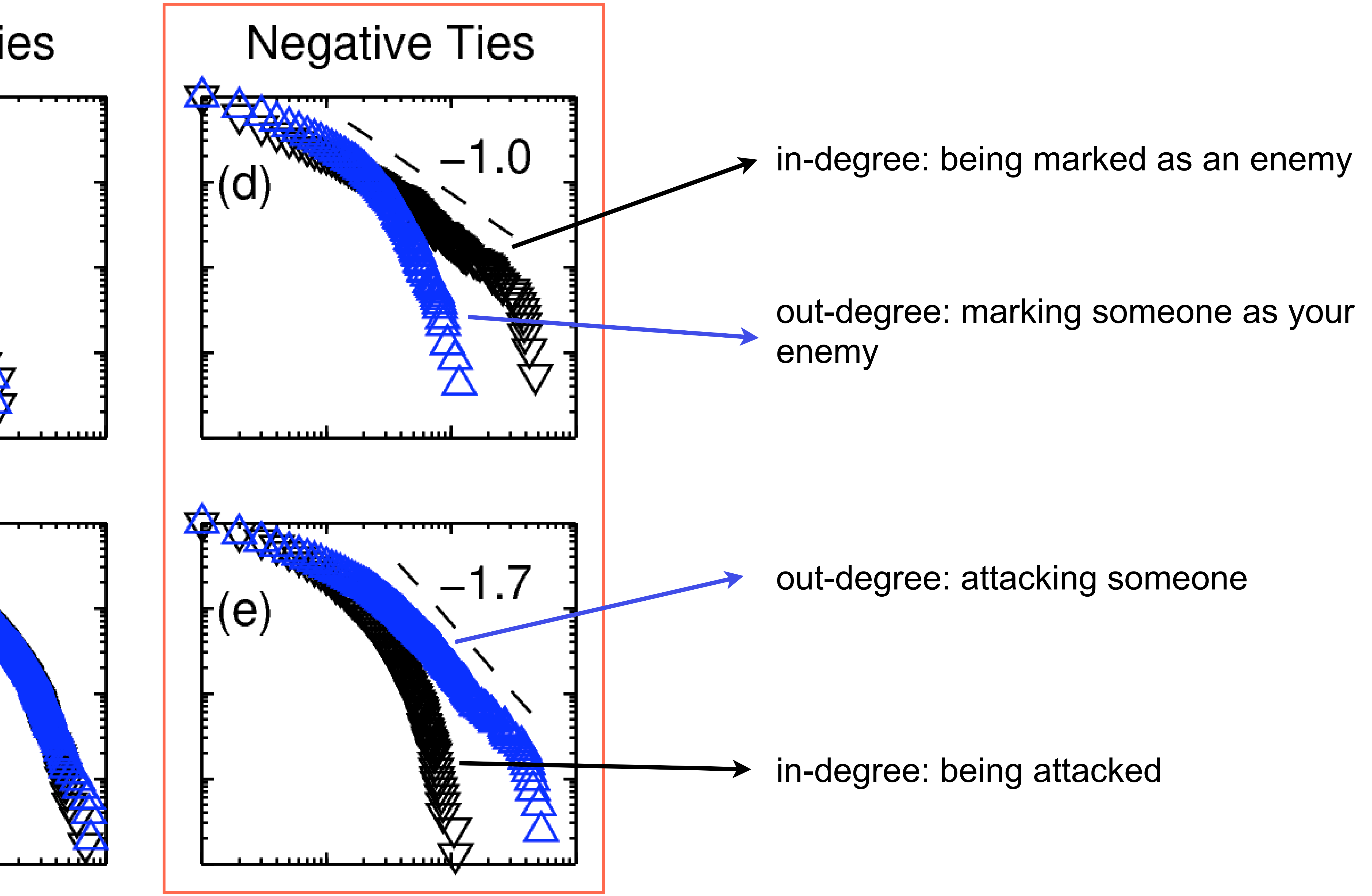

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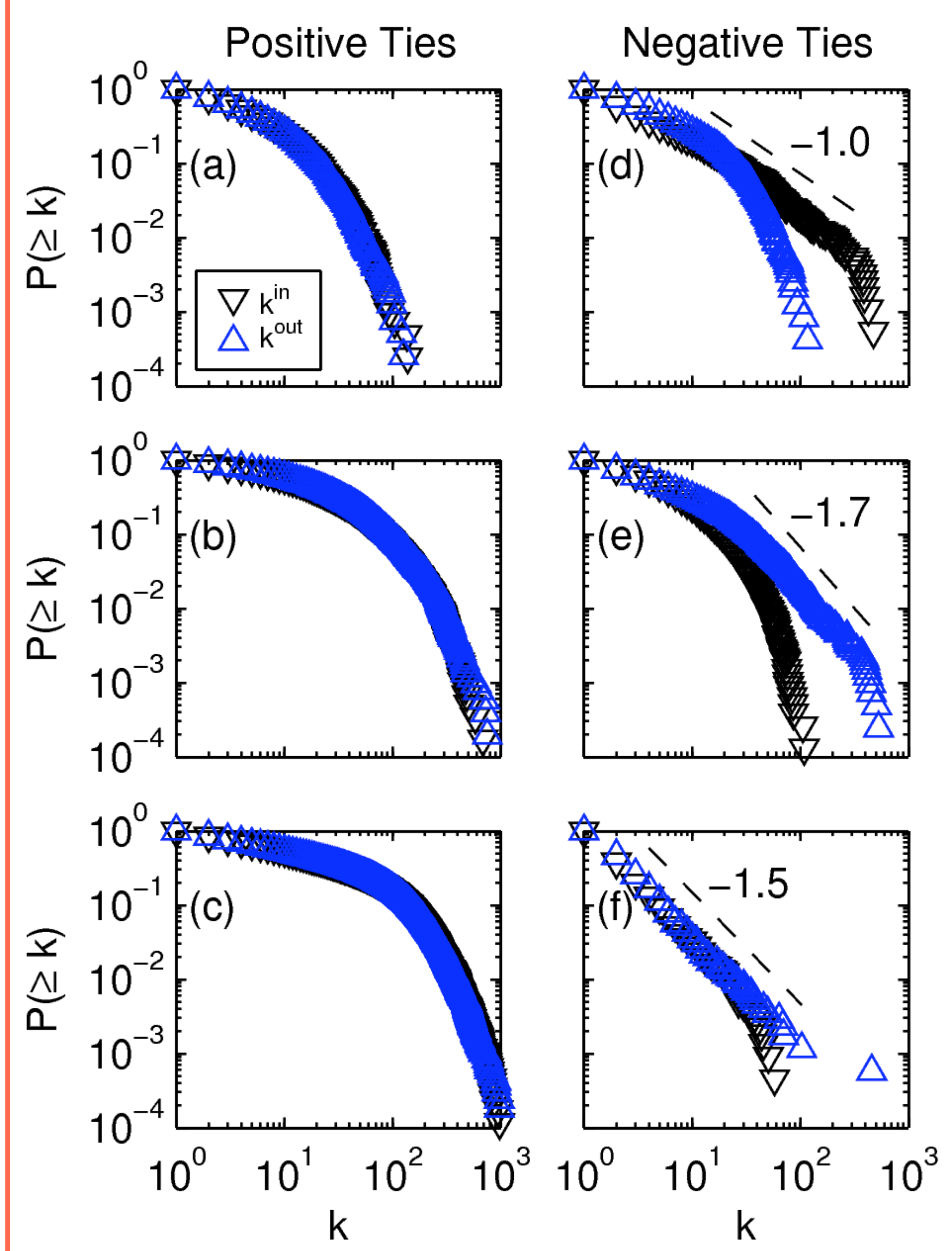


$\rho(k_\alpha^{\mathrm{in}}, k_\alpha^{\mathrm{out}})$ Pearson's correlation of in- vs out-degree

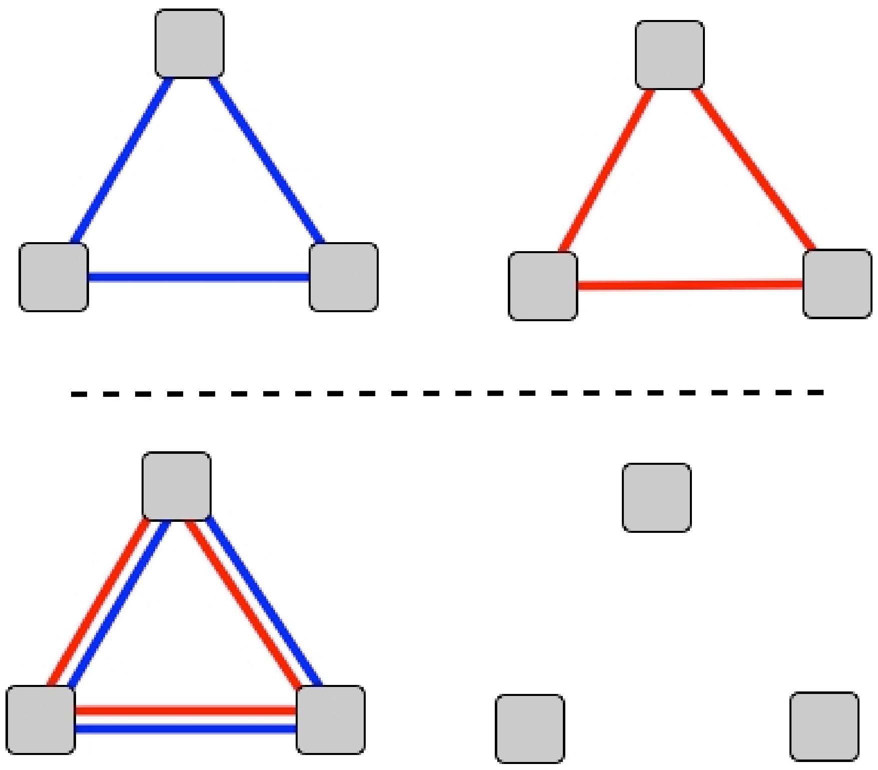
2) Interaction between networks

Interactions between different social relations (positive or negative feed-backs), e.g. network of communications poses constraints on the network of friendships, which itself reinforces communication

Description of the co-existence of different types of links.

To quantify the resulting inter-dependencies between pairs of networks, we follow two approaches:

a) Jaccard coefficient between two different sets of links measures the tendency that links simultaneously are present in both networks => Network overlap



b) Correlations between node degrees in different networks (and between rankings of node degrees). These coefficients measure to which extent degrees of agents in one type of network correlate with degrees of the same agents in another one. Do players who have many (few) links in a network have many (few) links in another network?

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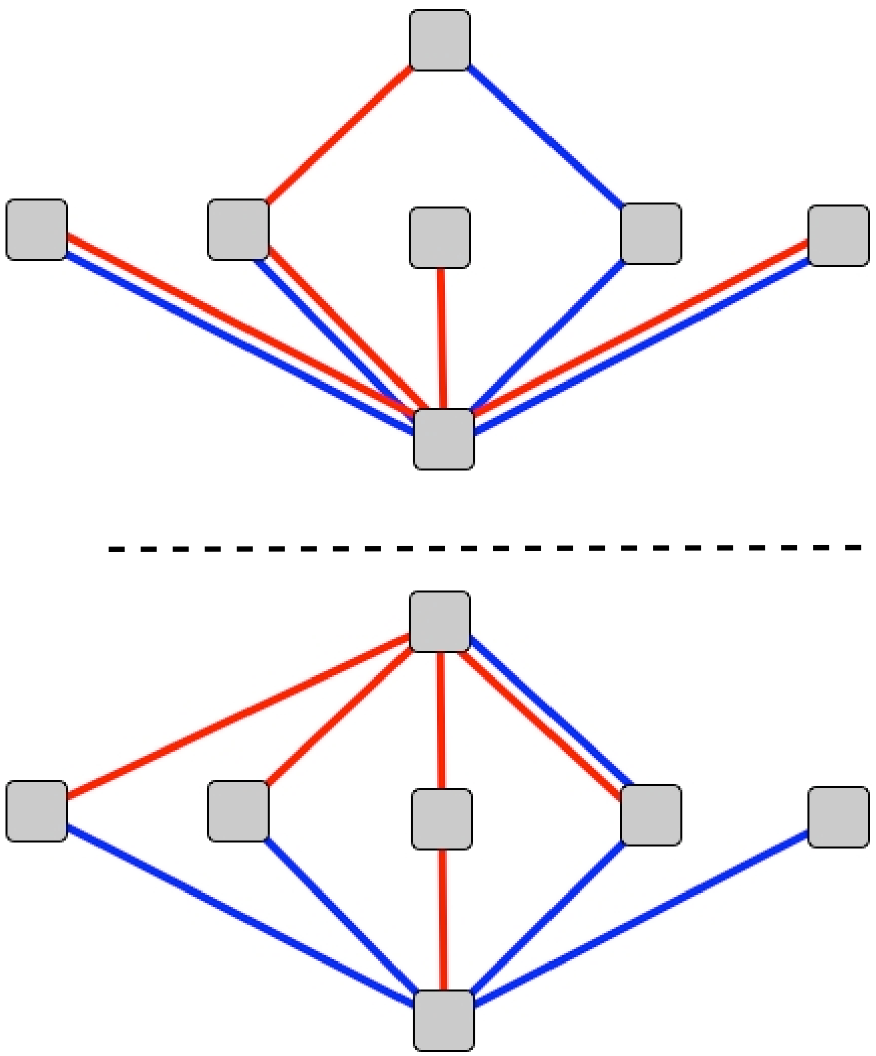

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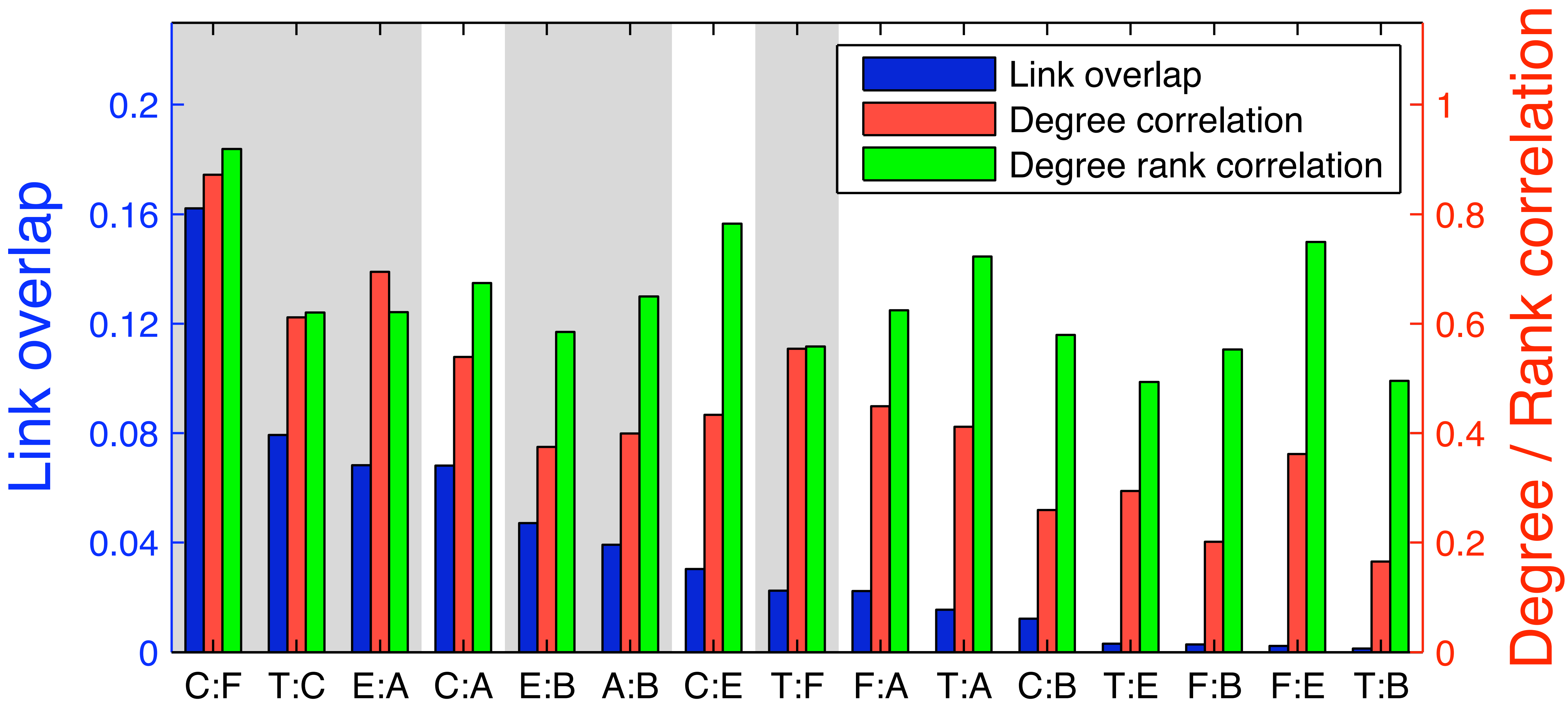
Different roles in different relational networks?

2) Interaction between networks



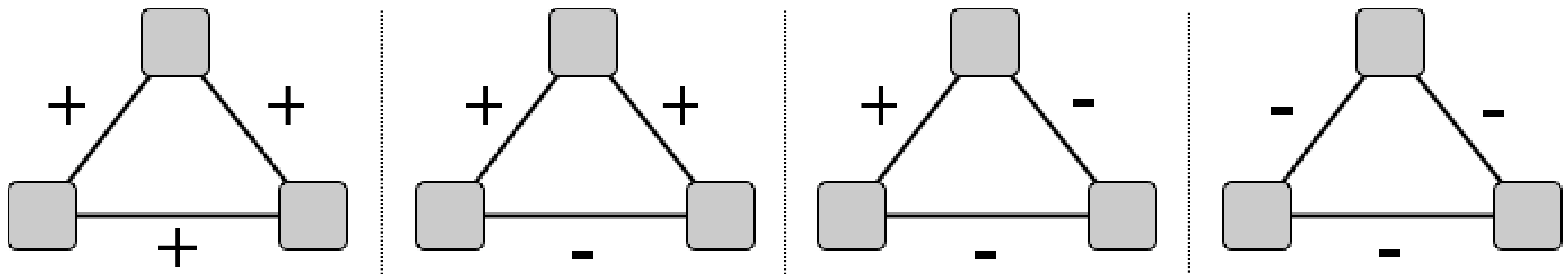
Communication, Friendship, Trade, Attack, Enmity, Bounty

Exclusion of some networks (e.g. F/E, T/E and T/A) vs high overlap for others (e.g. C/F, E/A)

Low degree correlation for some networks: different roles/strategies in different networks (e.g. T/A, T/E and F/E)

3) Empirical verification of structural balance

Some configurations of signed motifs are socially and psychologically more likely than others
Unbalanced triads are sources of stress and therefore tend to be avoided by actors when they adapt their personal relationships

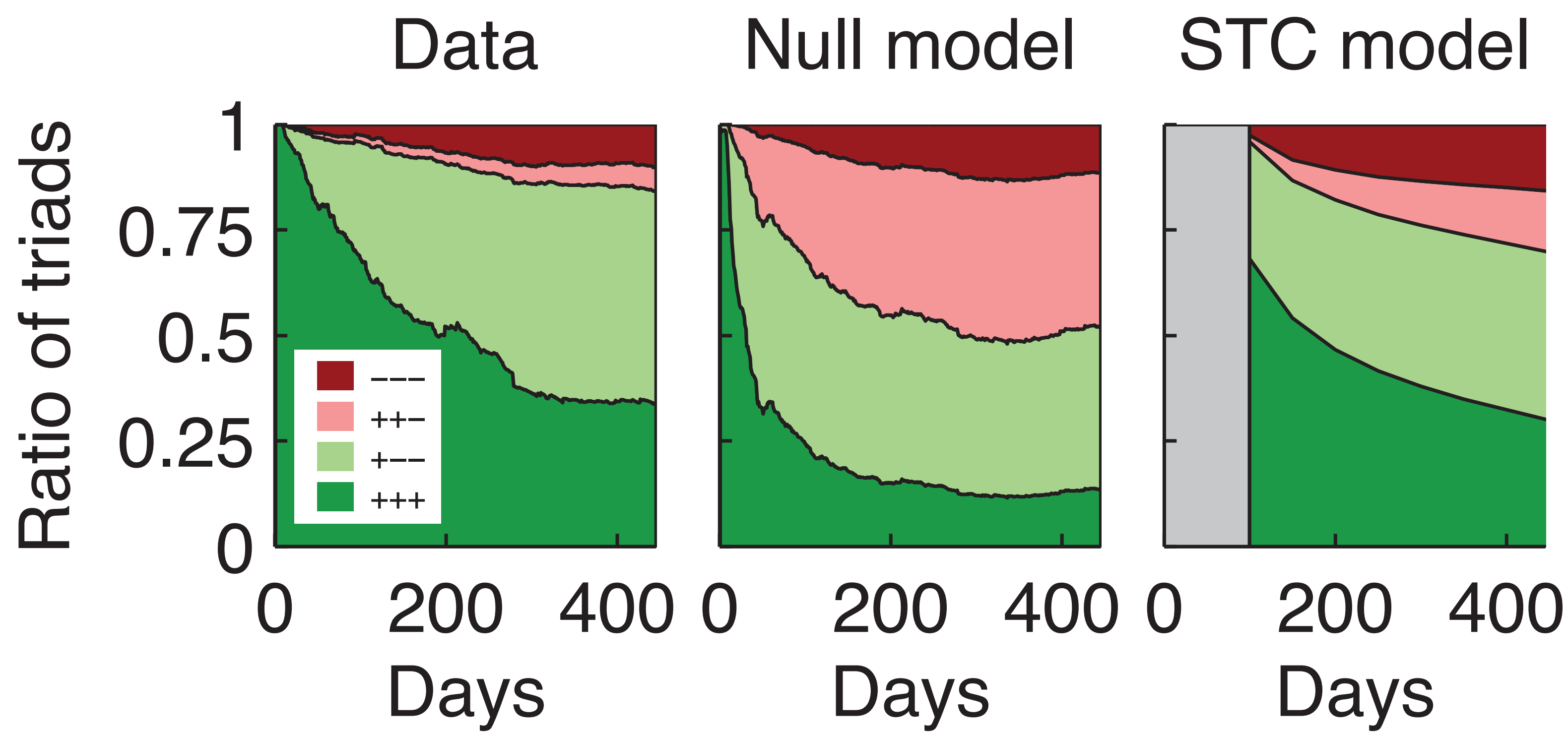


Strong formulation of balance	B	U	B	U	Cartwright (after Heider)
Weak formulation of balance	B	U	B	B	Davis
N_{Δ}	26,329	4,428	39,519	8,032	
$N_{\Delta,r}$	10,608	30,145	28,545	9,009	
z	71	-112	47	-5	

Leskovec J, Huttenlocher D, Kleinberg J (2010) Predicting positive and negative links in online social networks. ACM WWW Int Conf on World Wide Web 2010.

3) Empirical verification of structural balance

Dynamical re-organisation of multiplex networks (dynamics of motifs)



A vast majority of changes in the network are due to the creation of new positive and negative links, and not due to the switching of existing links from plus to minus or vice versa.

This result is in marked contrast with many dynamical models of structural balance which assume that a given social network is fully connected from the start and that only the signs of the relationships are the relevant dynamical parameters, which evolve to reduce stress in the system.

Our observation underpins that network sparsity and growth are fundamental properties and they need to be incorporated in any reasonable model of dynamics of positive and antagonistic forces in social systems.

T. Antal, P. L. Krapivsky, and S. Redner, Phys Rev E 72, 036121 (2005).

Conclusion

- **We usually know the nodes, not the links:** Most electronic data-sets are blind to the wide spectrum of human interactions: nature of the relations between individuals.

- **Opportunity to study multiplexity:** Massive online games provide all information about all actions taken by the players

- **Different relations, different mechanisms:** Different types of organisation exhibit different topological properties, thereby suggesting that they are driven by different driving mechanisms (PA, triadic closure, etc.). An aggregate representation of the different network types, or the representation of one single type will lead to a biased and misleading characterization of the organisation of the system

- **Interaction between different networks:** A network of one type of relation may act as a constraint, an inhibitor, or a catalyst on a network of another type of relation. The inter-dependence of different network types determines the organisation of the social system. Example: structural balance.

M. Szell, R. Lambiotte and S. Thurner, arXiv:1003.5137

Take home message

“IMPLICATIONS FOR FUTURE RESEARCH :
- Need for Studies of Multiplexity .....
- Need for Dynamic Data ....
- Need for Study of Co-evolution ....
”

M. McPherson, L. Smith-Lovin and J.M. Cook (2001) Annu. Rev. Sociol. 27, 415.

Methodological and modelling of multiplex networks

Mucha, Peter J.; Richardson, Thomas; Macon, Kevin; Porter, Mason A.; and Onnela, Jukka-Pekka [2010]. Community Structure in Time-Dependent, Multi-scale, and Multiplex Networks, Science, Vol. 328, No. 5980: 876-878.

Large datasets

K. Lewis, J. Kaufman, M. Gonzalez, A. Wimmer, and N. Christakis (2008) Social Networks 30, pp. 330-342.