New data for old questions

R. Lambiotte
Department of Mathematics
University of Namur, Belgium

Multi-relational Organization of Large-scale Social Networks in an Online World, M. Szell, R. Lambiotte and S. Thurner, PNAS, 107 13636-13641 (2010)

A tale of many cities: universal patterns in human urban mobility, A. Noulas, S. Scellato, R. Lambiotte, M. Pontil and C. Mascolo. Plos One 2012

The Personality of Popular Facebook Users, D. Quercia, R. Lambiotte, M. Kosinski, D. Stillwell and J. Crowcroft, ACM CSCW (2012)

naxys
Namur Center for Complex Systems

Plethora of new services - new opportunities

Interweaving the social and the physical world
Offering more and more refined data about individuals and their interactions

Computational social science

Small-scale questionnaire-based approaches

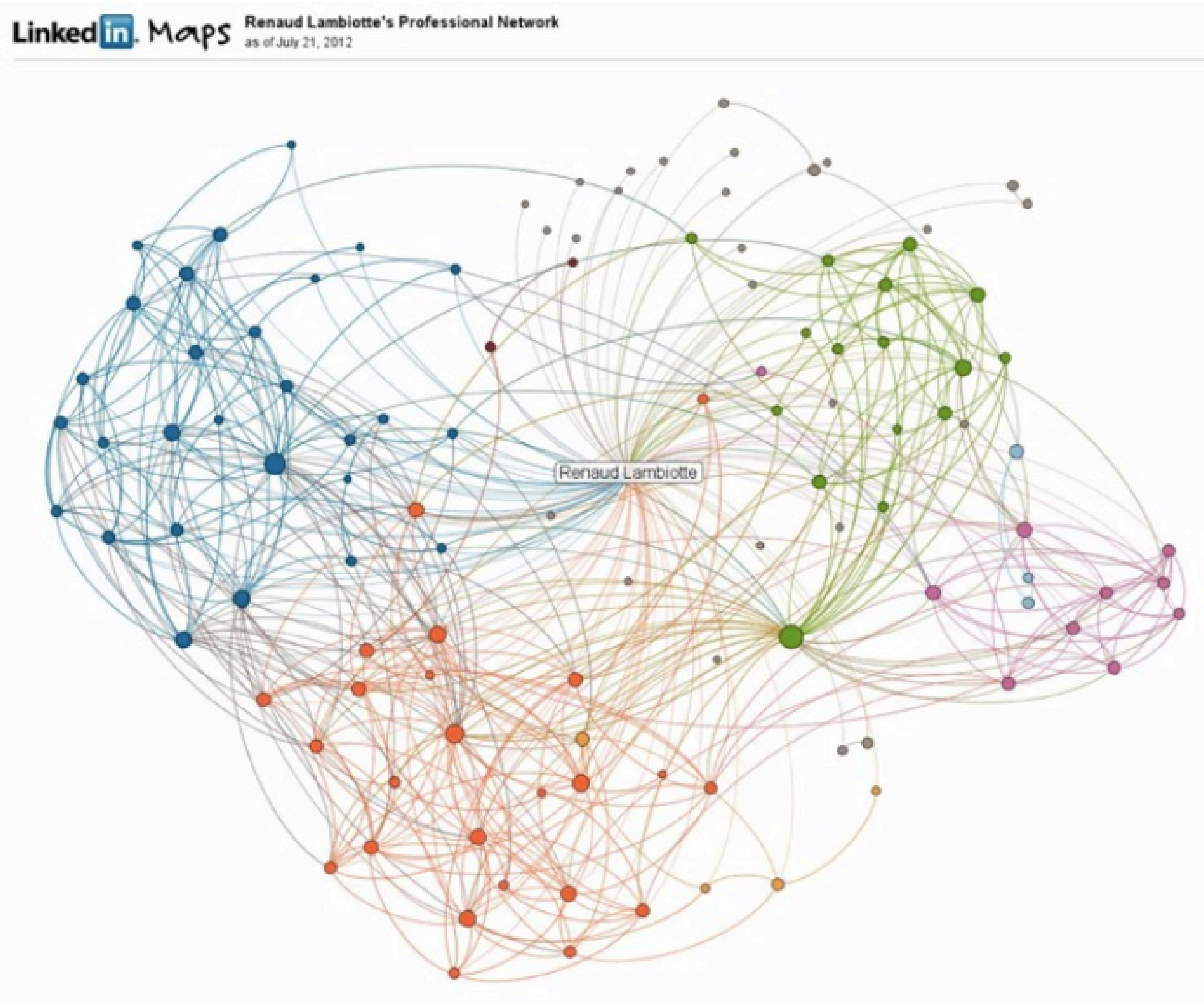
Fingerprints of individuals in electronic media (offline: mobile phone, or online: email, Facebook, etc.)
+ Large-scale experiments in online media

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).

Computational challenges: big and relational but incomplete, biased, noisy...
How to visualize and understand

Analytic and visualisation tools



Computational challenges: big but incomplete, biased, noisy...
How to visualize and understand

Theoretical challenges: models that reproduce observed patterns
and predict future ones

Computational challenges: big but incomplete, biased, noisy...
How to visualize and understand

Data inspire models

Models improve the algorithms

Theoretical challenges: models that reproduce observed patterns
and predict future ones

Social scientists
(their interactions)

Psychologist
(people)

Urban planners
(where they live)

Social scientists
(their interactions)

Psychologist
(people)

Urban planners
(where they live)

Physicists
(models)

Computer scientist
(data)

Applied mathematician
(algorithms)

Social scientists
(their interactions)

Psychologist
(people)

Urban planners
(where they live)

M. Szell (MIT) and S. Thurner (Vienna) => Online games

E. Fleury (ENS Lyon), A. Friggeri (Facebook), and D. Quercia and M. Kosinski (Cambridge) => Personality

Mason Porter and Till Hoffman (Oxford) => Modeling of temporal networks

Tim Evans (Imperial College) and Pietro Panzarasa (Queen Mary) => Communities

Michael Gastner (Bristol) => Mobility

Vsevolod Salnikov (UNamur) => App development

Lionel Tabourier (UNamur) and JC Delvenne (Louvain) => Algorithms for temporal nets

Martin Rosvall (Umea) => Communities and ranking

C. Mascolo, A. Noulas (Cambridge) and S. Scellato (Google) => Mobility

Physicists
(models)

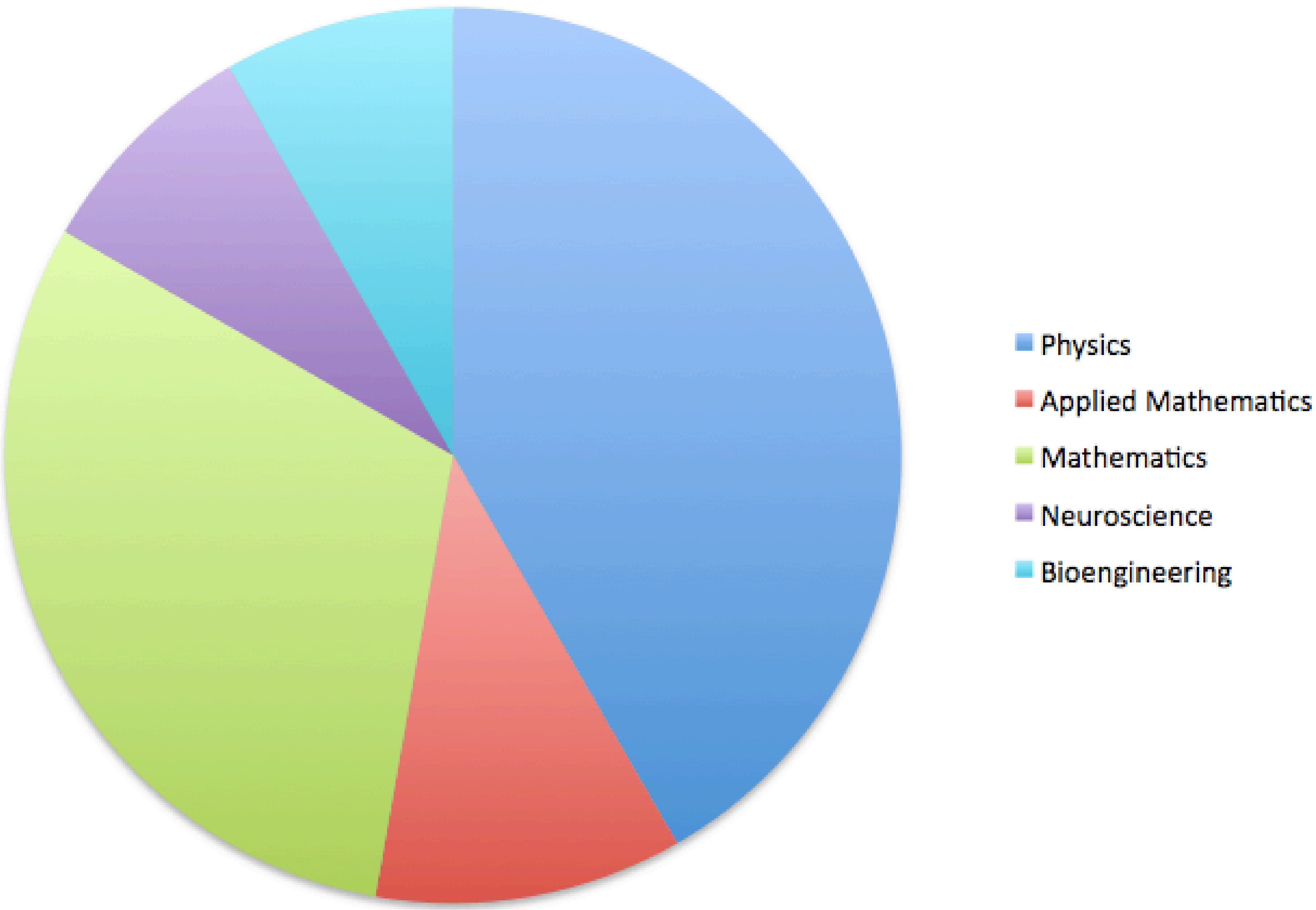
Computer scientist
(data)

Applied mathematician
(algorithms)

Social scientists
(their interactions)

Psychologist
(people)

Urban planners
(where they live)



Physicists
(models)

Computer scientist
(data)

Applied mathematician
(algorithms)

Social scientists
(their interactions)

10^2

Psychologist
(people)

10^0

Urban planners
(where they live)

10^4-10^6

Physicists
(models)

∞

Computer scientist
(data)

10^6-10^9

10^6-10^9

Applied mathematician
(algorithms)

Social scientists
(their interactions)

10^2

Psychologist
(people)

10^0

Urban planners
(where they live)

10^4-10^6

Different scales
Different methodologies
Different interests

Yet the same problem

Bridge the gap
Enhance the dialogue between the fields

Physicists
(models)

∞

Computer scientist
(data)

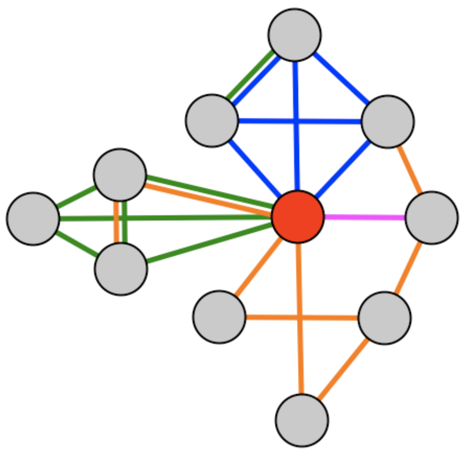
10^6-10^9

10^6-10^9

Applied mathematician
(algorithms)

New data for old questions

... what a physicists can learn from (and hopefully help) a social scientist



Dynamics of conflict

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

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

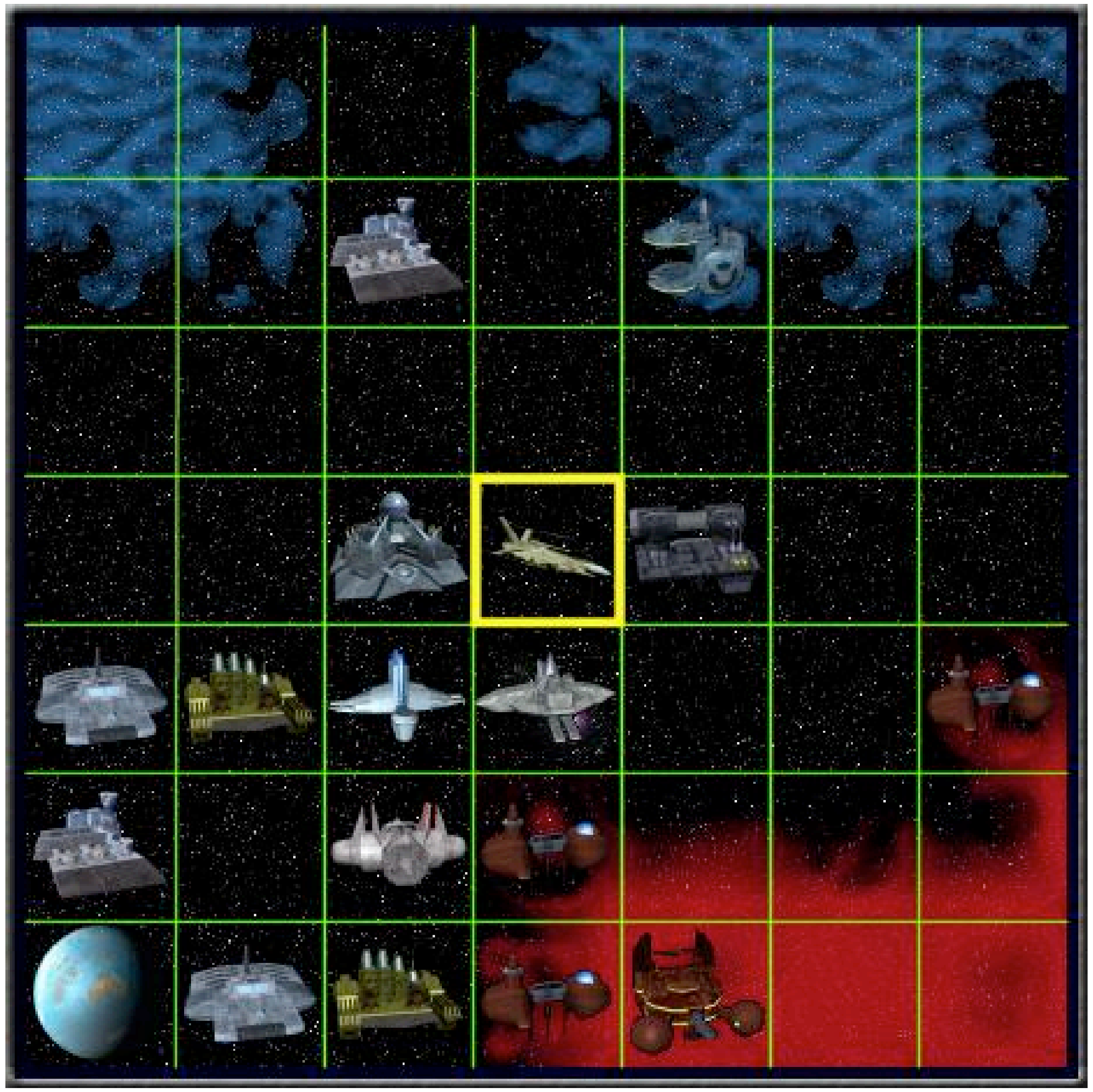
Online games

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.

Self organisation

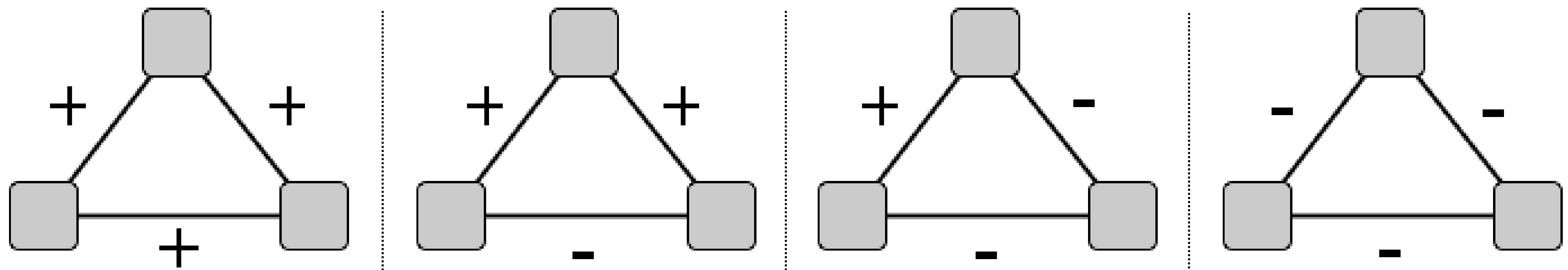
All information about all actions taken by all players is stored in log-files



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



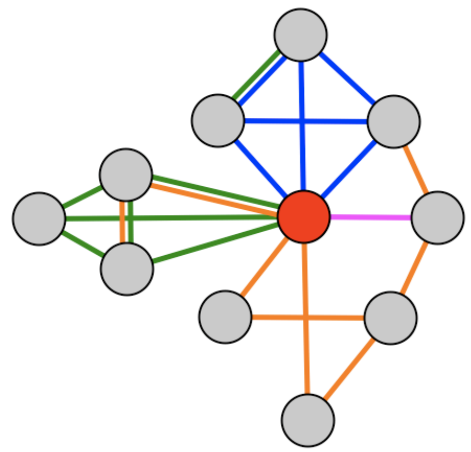
Strong formulation of balance	B	U	B	U	Cartwright (after Heider)
Weak formulation of balance	B	U	B	B	Davis
N_Δ	26,329	4,428	39,519	8,032	
$N_{\Delta,r}$	10,608	30,145	28,545	9,009	
z	71	-112	47	-5	

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

Multi-relational Organization of Large-scale Social Networks in an Online World, M. Szell, R. Lambiotte and S. Thurner, PNAS, 107 13636-13641 (2010)

New data for old questions

... what a physicists can learn from (and hopefully help) a social scientist



Dynamics of conflict

Human mobility

Effect of personnality on behaviour

Quantitive laws of human mobility

"Gravity laws"

Mobility is deterred by the costs in time and energy associated to physical distance.
The flow of individuals is predicted to decrease with physical distance, typically as a power-law
P(jump) ~ 1/d^{alpha}

Intervening Opportunities

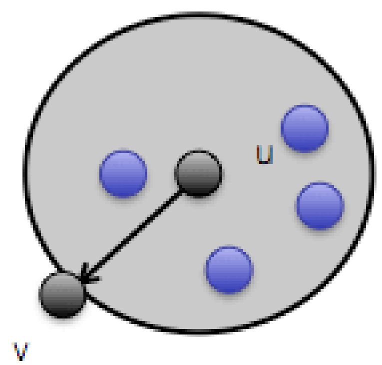
No direct relation between mobility and distance.
Distance is a surrogate for the effect of "intervening opportunities".
Migration from origin to destination depends on the number of opportunities closer than this destination.
Absolute value of distance does not matter.
Ranking matters.
P(jump) ~ 1/rank^{alpha}

Which camp in agreement with universal laws of mobility?

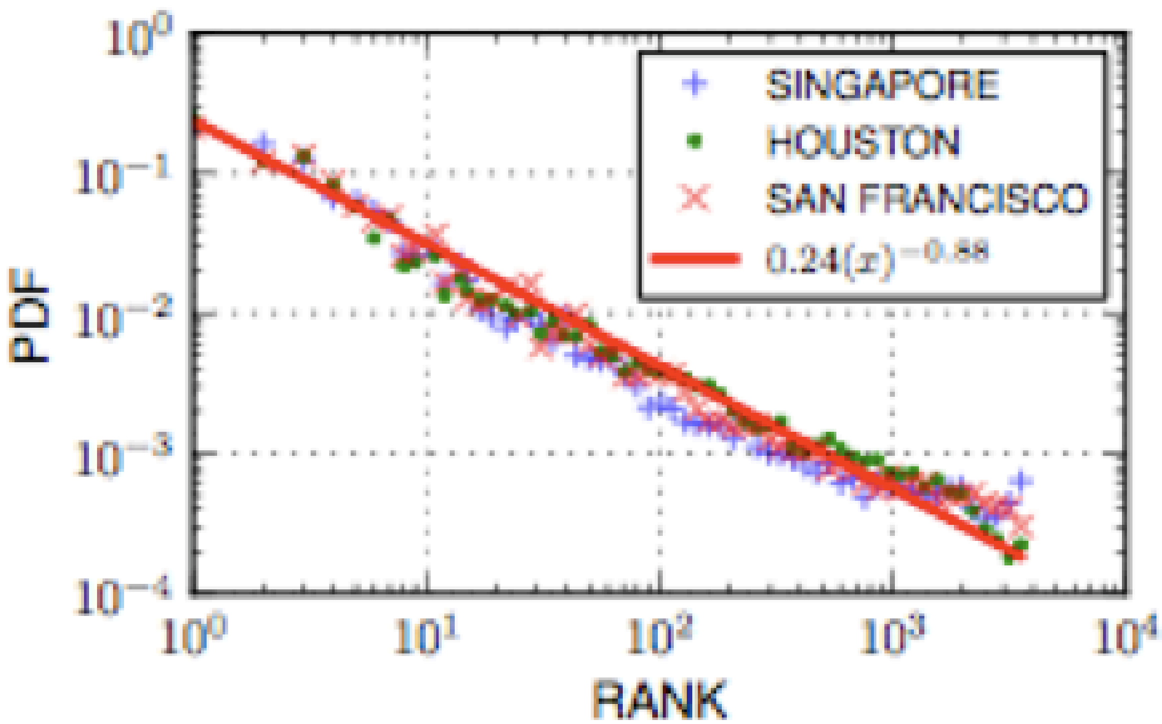
A tale of many cities: universal patterns in human urban mobility, A. Noulas, S. Scellato, R. Lambiotte, M. Pontil and C. Mascolo. Plos One 2012

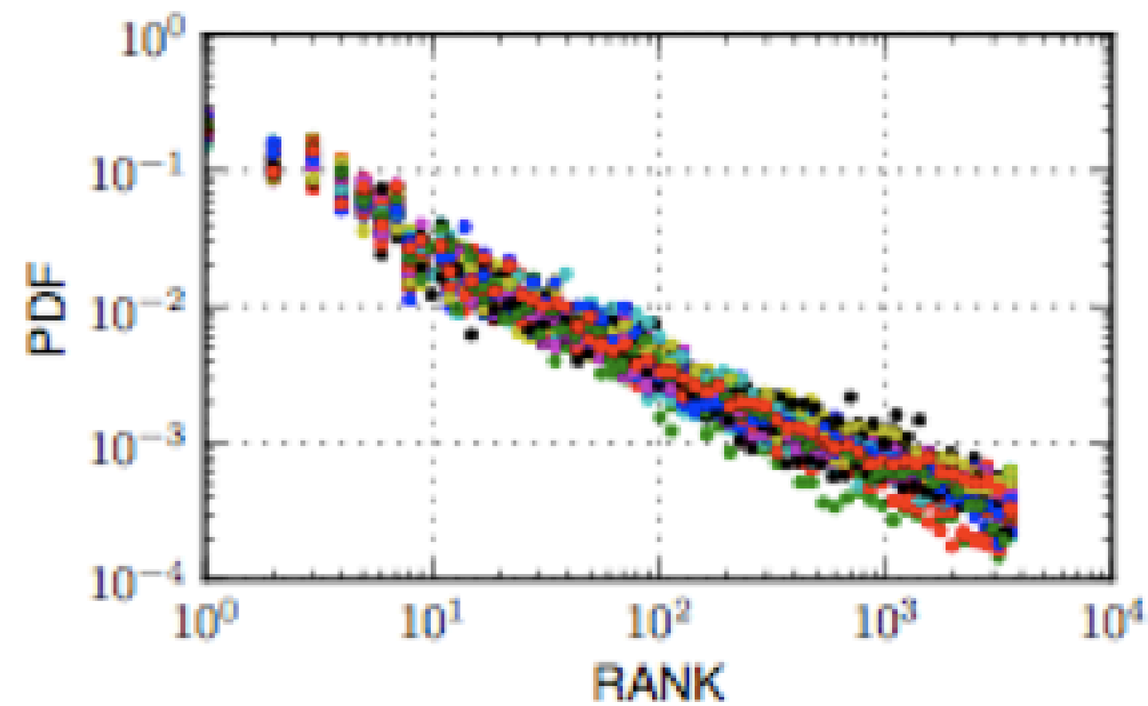
Quantitive laws of human mobility

Universal laws of mobility: no dependence on the properties of the city, e.g. its size, its density, etc.



$$rank_u(v) = |\{w : d(u,w) < d(u,v)\}|.$$

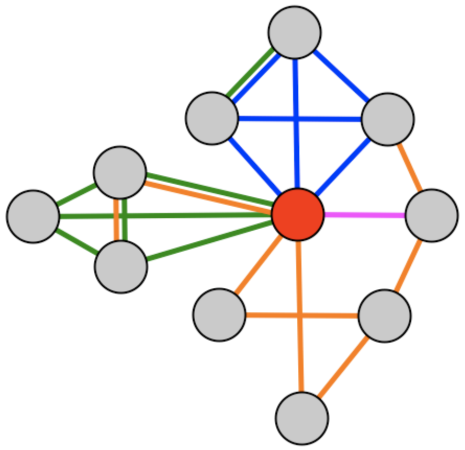




A tale of many cities: universal patterns in human urban mobility, A. Noulas, S. Scellato, R. Lambiotte, M. Pontil and C. Mascolo. Plos One 2012

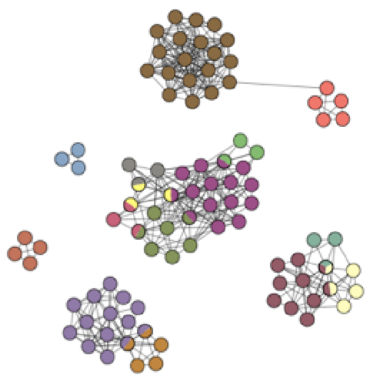
New data for old questions

... what a physicists can learn from (and hopefully help) a social scientist



Dynamics of conflict

Human mobility



Effect of personnality on behaviour

Relation between personality and ego-network

Dimension	High scorers	Low scorers
Openness	Imaginative	Conventional
Conscientiousness	Organized	Spontaneous
Extraversion	Outgoing	Solitary
Agreeableness	Trusting	Competitive
Neuroticism	Prone to stress and worry	Emotionally stable

Table 1: The big five personality dimensions.

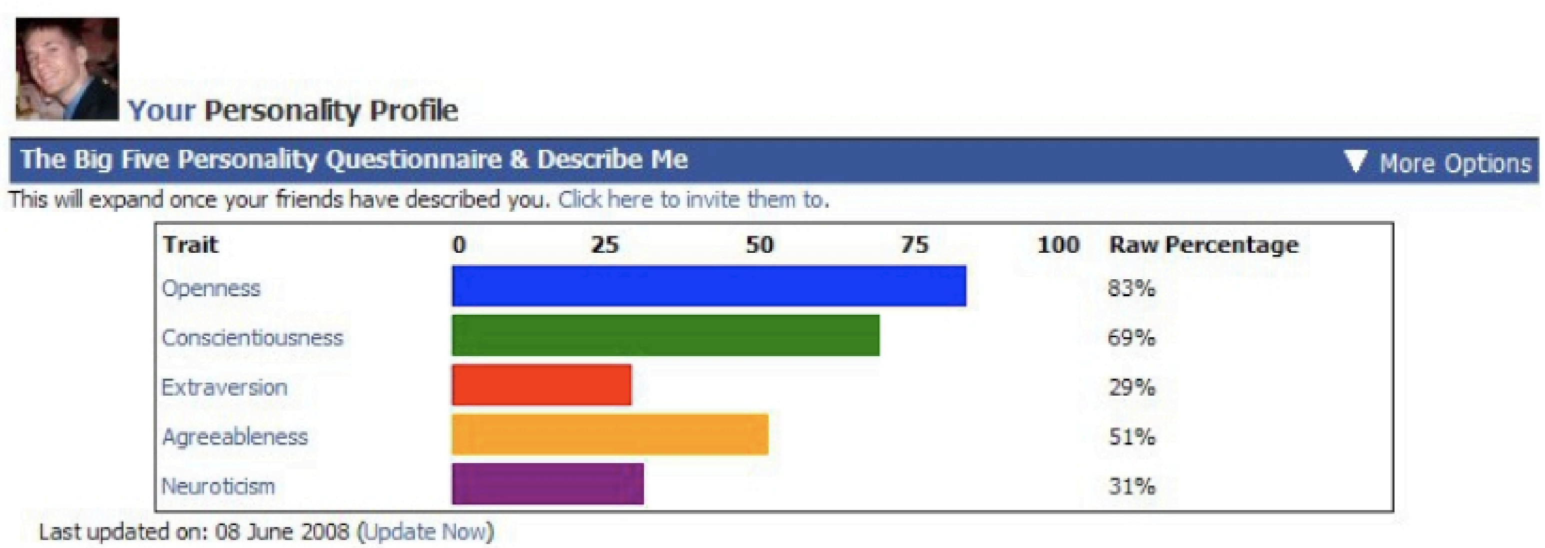
Numerous studies:
- The trait of Extraversion is the strongest predictor for the number of real-world friends. Extraversion has been shown to be consistently associated with structural measures of social support, including network size and contact with network members.
- Neuroticism has been associated with negative social interactions.
- Findings for the traits of Agreeableness, Conscientiousness and Openness are inconsistent.

But usual limitations of questionnaire-based studies: very small (poor statistics), biased samples (WEIRD, White, Educated, Industrialized, Rich, and Democratic)

The Revised NEO Personality Inventory, P. Costa and R. Mccrae, SAGE Publications (2005)

Relation between personality and ego-network

- Facebook application: 5.5 million users
- Users can opt in and give their consent to share their profile information (40%)
- Right incentives: subjects are not paid nor receive college credits. myPersonality users are solely motivated by the prospect of receiving reliable feedback and test results that accurately describe their personalities.
- Unreliable results are removed. Numerous validity tests



- myPersonality is able to obtain test results that are more reliable than those in pen-and-paper studies.
- myPersonality users are far less biased than those studies' subjects for gender, age, and geography.
- VERY large scale data

Relation between personality and ego-network

200k users with between 30 and 1000 Facebook friends and between 18 and 54.

Significant factors for predicting *log(k)*: Extraversion and Age

$$\log(k_i) = \alpha + \sum_{l=1}^{5} \beta_l R_{l;i} + \beta_S S_i + \beta_A A_i + \epsilon_i$$

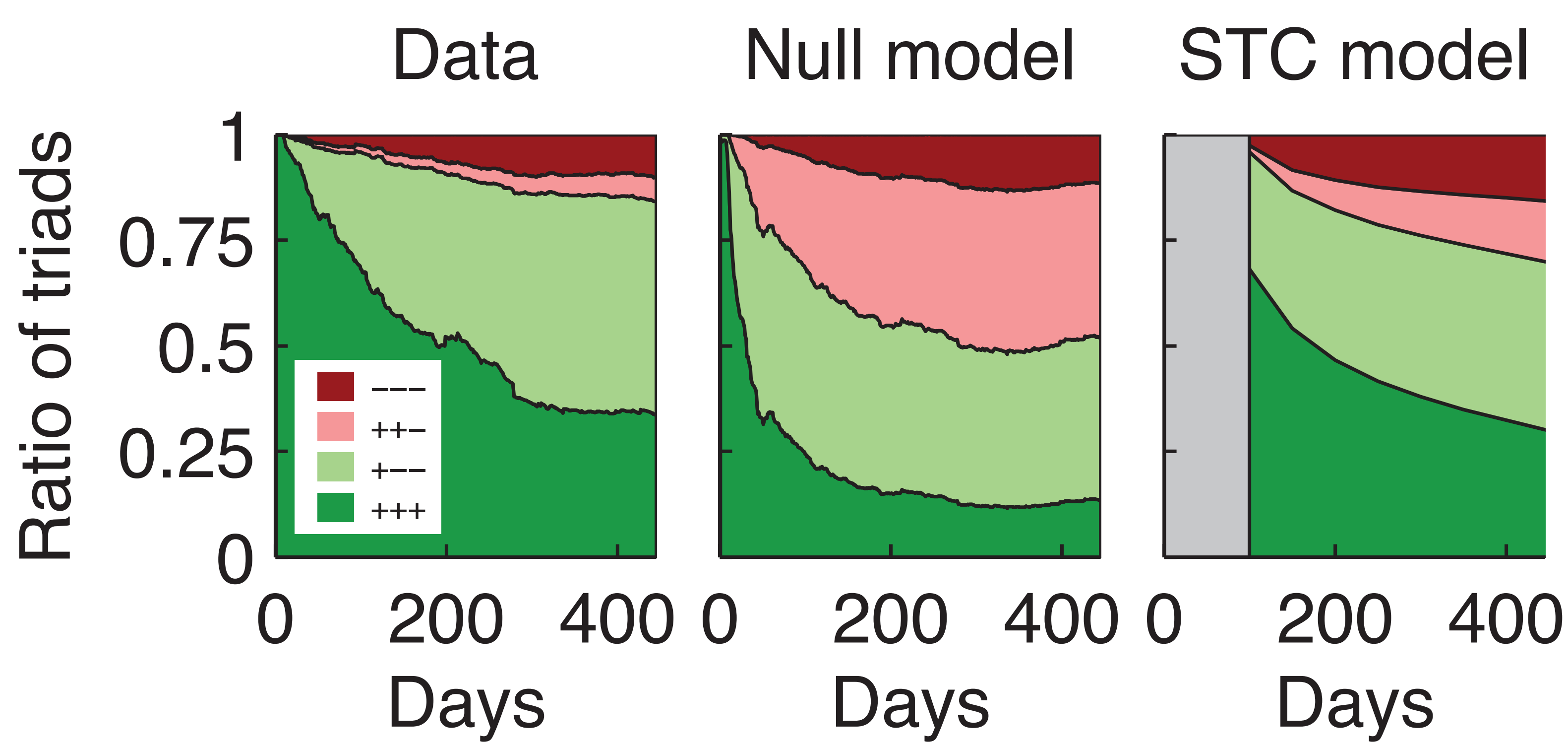
Variables	β	**t-test**	β	**t-test**
Openness	-0.031	-12.6	-	-
Conscientiousness	0.004	1.5	-	-
Extraversion	0.174	**79.7**	0.171	79.8
Agreeableness	0.013	5.1	-	-
Neuroticism	0.005	2	0	0
Sex	0.005	1.4	-	-
Age	-0.015	**-64.5**	-0.014	-64.7

The Personality of Popular Facebook Users, D. Quercia, R. Lambiotte, M. Kosinski, D. Stillwell and J. Crowcroft, ACM CSCW (2012)

New data for old questions
... lead to new questions and models

New data for old questions
... lead to new questions and models

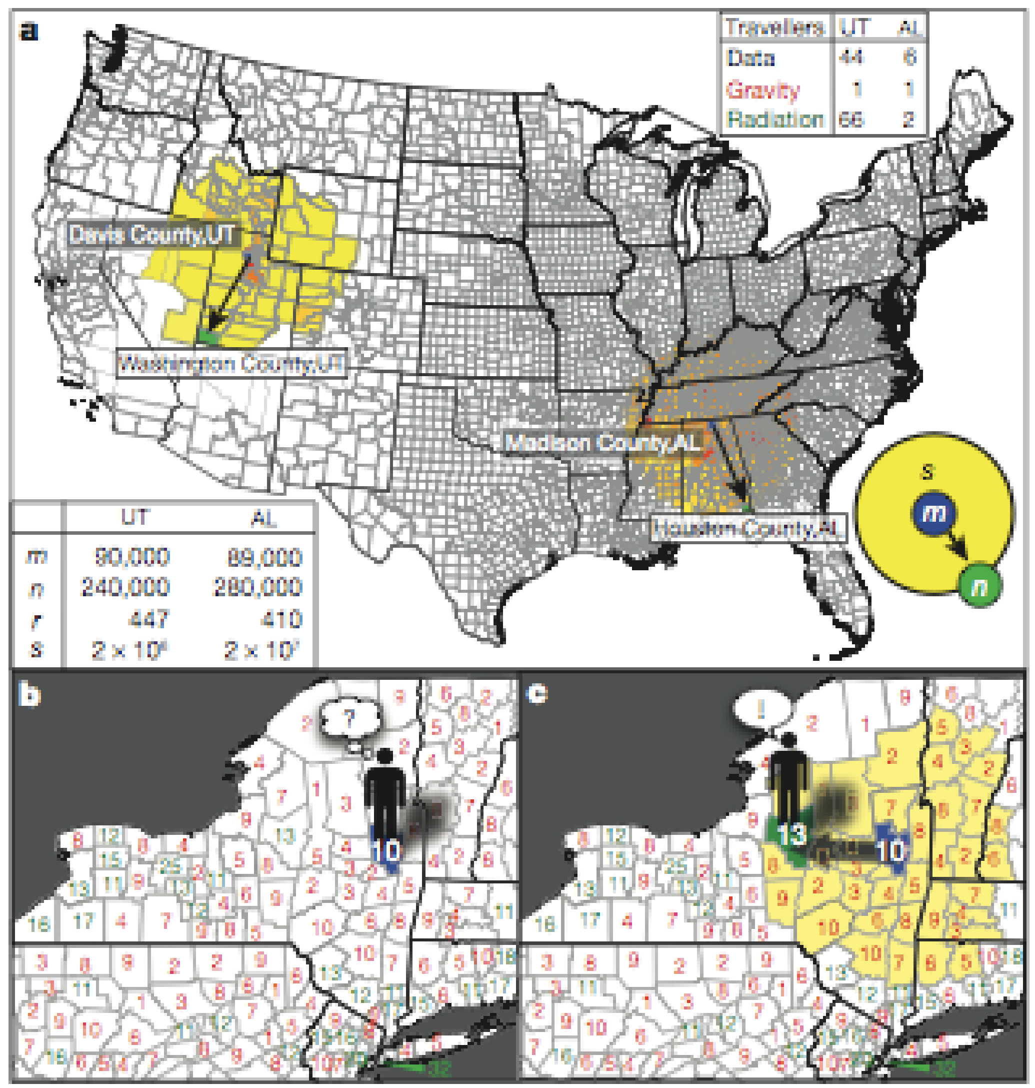
Static predictions of structural balance are correct but the dynamics is very different because of the sparsity of the networks



Multi-relational Organization of Large-scale Social Networks in an Online World, M. Szell, R. Lambiotte and S. Thurner, PNAS, 107 13636-13641 (2010)

New data for old questions
... lead to new questions and models

New models for human mobility based on the idea of IO

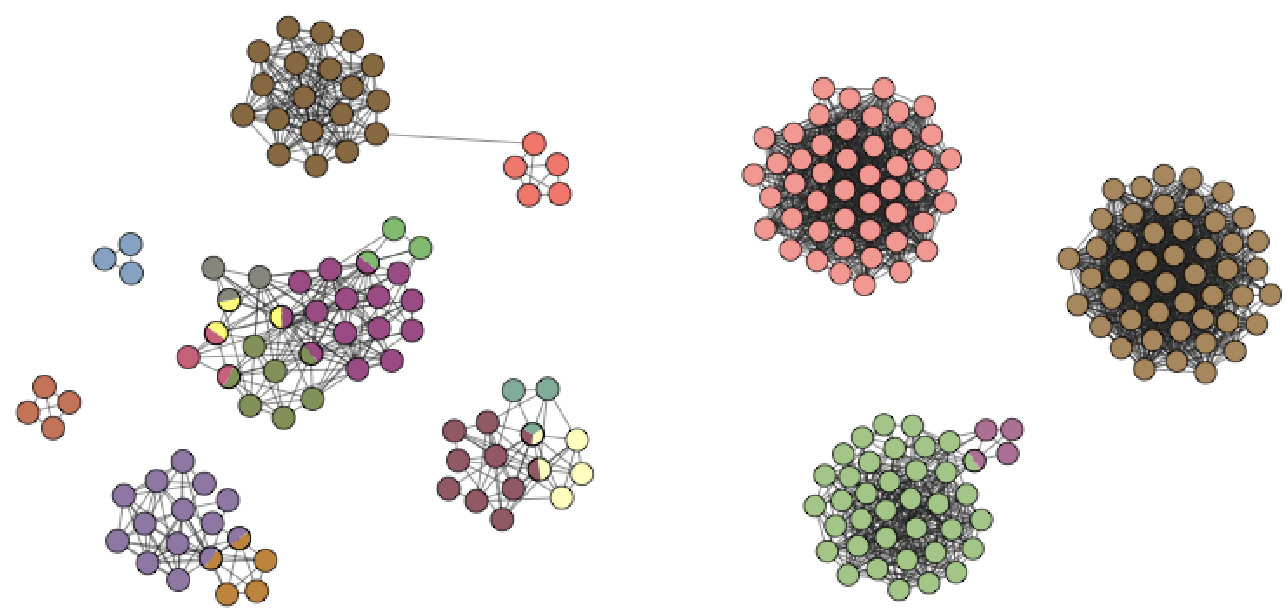


A universal model for mobility and migration patterns, F. Simini et al. Nature 2012

New data for old questions ... lead to new questions and models

The size **and** structure of social networks is affected by personality

Introverts tend to have less, larger communities: they *hide* into large communities.
Extroverts exhibit a higher overlap of the communities: they act as *bridges* between communities



(a) User A, 26 years old: high extraversion (ext = 1.33), 101 friends of which 91 are split across 15 communities of size varying between 3 and 19, and average cohesion $\bar{C} = 0.46$.

(b) User B, 19 years old: low extraversion (ext = -1.21), 145 friends of which 136 are split across 4 communities of size 4, 37, 48 and 48, and average cohesion $\bar{C} = 0.31$.

Fig. 8. Examples of two ego-networks of subjects with different psychological traits and structural features.

Psychological Aspects of Social Communities, A. Friggeri, R. Lambiotte, M. Kosinski and E. Fleury, SocialCom (2012)