Enhancing Social Interaction: Preferences, Similarities, and Trust

Frank Schweitzer
fschweitzer@ethz.ch

in collaboration with:

Frank E. Walter, Stefano Battiston

Physics of Socio-Economic Systems

- Adolphe Quetelet (1796-1874) ("body mass index")
  - introduced the term "**social physics**" (1835)
- **AKSOE**: focus section on 'Physics of Socio-Economic Systems' (DPG – German Physical Society)
  - annual AKSOE Conferences (part of DPG March meeting) 120 contributions (2007)
  - International **Young-Scientist Award** for Socio- and Econophysics (about 35 nominations/year)
- International Conference "SocioPhysics" (ZIF Bielefeld, 2002)
  http://intern.sg.ethz.ch/fschweitzer/until2005/sociophysics/
- DPG Summer School: "Dynamics Of Socio-Economic Systems: A Physics Perspective" http://intern.sg.ethz.ch/events/Summerschool05/

Social Physics – The Challenge

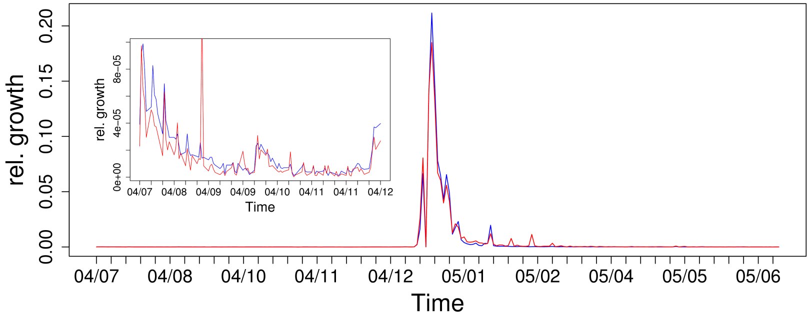
1. **Empirics**
   - data mining (internet databases, "social networking sites")
   - find statistical regularities ("power laws") → stylized facts
2. **Modeling**
   - KISS ("keep it simple and stupid") type agent models
   - reproduce the stylized facts
3. **Application**
   - making use of it all → what have we achieved?
     - ★ is there a meaning compatible with social sciences?
   - design interaction to improve system behavior?
     - ★ improved vaccination strategies
     - ★ optimized pedestrian facilities /traffic schedules
     - ★ trustworthy recommendations

Social Physics

- **complex systems theory**
  - interaction of many ($10^3 - 10^{10}$) agents leads to the emergence of new collective properties
  - examples: public opinion, social norms, fashion, ...
  - can the outcome be predicted? ... influenced? ... exploited?
- **social interaction in the age of mass media**
  - broadcasting → mean-field coupling, short time scale of interaction
  - critical amplification of small initial fluctuations
  - bias → early symmetry break

1. Empirics – Example: Donations

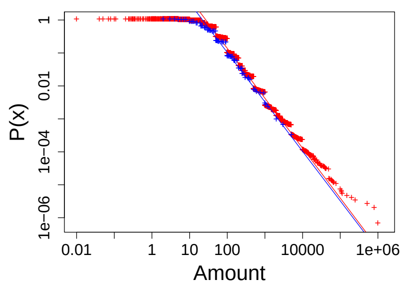
Wave of donations after tsunami desaster (inset: before tsunami)



01-06/2005: $N_{\rm tot} = 1,556,626$, $A_{\rm tot} = 126,879,803$

F.S., R. Mach, PLoS ONE, Jan (2008)

Cumulative probability distribution: $P(x) \sim x^{-\alpha}$



- clear power law over several orders of magnitude
  - scale free nature of donations
- exponent α similar before ($\alpha = 1.501 \pm 0.023$) and after ($\alpha = 1.515 \pm 0.002$) the desaster
  - similarities to other German and Swiss donor organizations

F.S., R. Mach, PLoS ONE, Jan (2008)

2. Modeling – Example: Donations

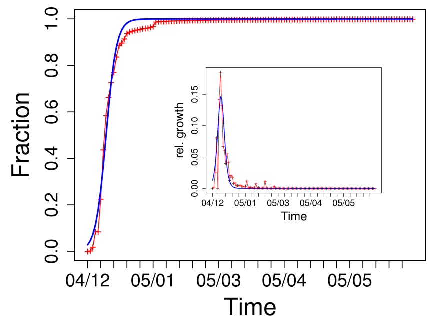
- epidemic (SI) model of donations

$$P \xrightarrow{k} A\,; \quad k = \gamma\kappa N_{\rm a}(t)/N_{\rm p}$$

  - non-local interaction via a mean field representing the *media*
  - γ: number of interactions per time interval between P and A
  - $0 \le \kappa \le 1$: prob. that interaction leads to donation
- with $f(t) = N_{\rm a}(t)/(yN)$ and time scale $\tau^{-1} = \gamma\kappa$

$$\frac{df(t)}{dt} = \frac{1}{\tau} f(t)\,[1 - f(t)]\;; \qquad f(t) = \frac{1}{1 + e^{-\frac{(t-\mu)}{\tau}}}$$

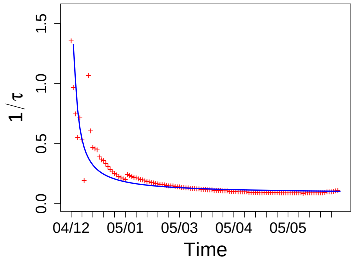
  - μ: time where $f(t)$ has reached maximum



- Fraction of the total number of donations (inset: relative growth of amount of donations)
  - Fit: $\mu = 8.05 \pm 0.07$, $\tau = 1.98 \pm 0.06$

F.S., R. Mach, PLoS ONE, Jan (2008)

Influence of the media



F.S., R. Mach, PLoS ONE, Jan (2008)

- slowing-down of mean-field interaction

$$1/\tau = \left[a + (b/t) + (c/t)^2\right]$$

- $(\gamma\kappa)$: number of successful interactions per time interval
  - early stage: people were more enthusiastic to donate money
  - later stage: became more indifferent
- decrease of τ in time $\Rightarrow$ lack of public interest

Example: Donations – Conclusions

First glimpse: Sociophysics works!

- statistical regularities (power laws), universality
- KISS model with a number of crude, but appropriate assumptions:
  - mean-field coupling $\longrightarrow$ provided by mass media
  - simple amplifying feedback: social herding
  - simple stabilizing feedback: limited resource (P)
  - simple slowing down dynamics: lack of interest

Second glimpse: what do we learn from all this?

- generalization?
- open problems on the horizon:
  - heterogeneity of agents $\longrightarrow$ individual preferences
  - individuality of agent interaction $\longrightarrow$ social network
  - social herding $\Leftrightarrow$ malicious groups, trustworthiness

“Exploiting” social herding behavior

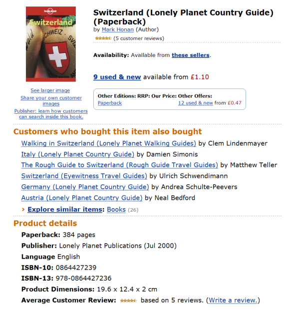
- **social herding as recommendation**
  - donation example: A “recommends” donation to P
  - P follows this recommendation with probability $\sim k$
- multiple choice problem $\longrightarrow$ which recommendation to follow?
  - **frequency-based** recommendations (majority rule)
  - **similarity-based** recommendations (CF)
  - what matches agent’s preferences?
  - trustworthiness of recommendations?
- sparse information $\Leftrightarrow$ likelyhood of amplification
  - communication structure: broadcast vs social network
  - role of Web 2.0 technologies (blogs, Social Networking Services)

Recommendation Systems in Reality

Recommendations are used to *rank particular items*

e.g. books that claim to be travel guides to Switzerland

Recommendations are used to *make choices based on ratings*

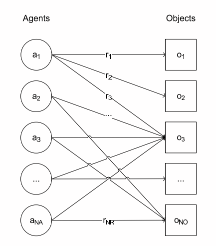


e.g. whether to buy/not to buy a particular book

(Screenshots taken from Amazon.co.uk)

Agents rating Objects → Preference Profiles

- N_a agents $a_1, a_2, a_3, \ldots \in S_A$, N_o objects $o_1, o_2, o_3, \ldots \in S_O$
  - each object classified into one of N_c categories $c_1, c_2, c_3, \ldots \in S_C$
    example: object → book, category → travel guide
- agent a_i:
  - preference profile $\{p_1, p_2, \ldots, p_{N_o}\}$ $(p_i \in [-1, 1])$
  - knowledge about particular objects → *ratings* $r_k = p_k$



Bipartite graphs on agents (left) and objects (right); the set of all possible ratings of an agent constitutes its preference profile

How to generate recommendations?

- frequency-based recommendation → preference of 'majority'
- **collaborative filtering** → 3-step computational approach

1. *neighbourhood* $\hat{N}_i$ of agent a_i:
   agents a_j which rated items that agent a_i also rated
2. **similarity** between profiles of a_i and a_j (Pearson correlation)
3. *one* recommendation based on weighted average (wrt similiarity) of agents a_j's preferences

major pitfalls

- bad performance for cold start users
- no feeback from users about recommendation success

Alternative: Trust-based Recommendations

*New approach:** combines (1) a social network, (2) weighted recommendations and (3) a feedback mechanism

1. neighbourhood of agent a_i ⇒ *social network* $\hat{S}_i$ of *reachable* agents
2. compute level of trust between agents a_i and a_j
   - trust relationships updated *only between direct neighbours* (local)
   - indirect connections through *paths in the network*: trust value

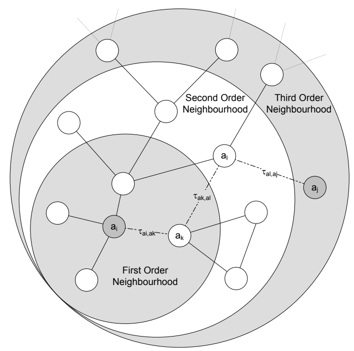
   $$T_{a_i,\ldots,a_j} = \prod_{(a_k,a_l)\in \mathrm{path}(a_i,a_j)} T_{a_k,a_l} \in [0,1]$$

   - *different* recommendations from a_j weighted by T_{a_i,a_j}
     stochastic selection rule with β (exploratory behaviour)
3. trust update based on utility of agent a_i

* F. E. Walter, S. Battiston, F. Schweitzer: A Model of a Trust-Based Recommendation System on a Social Network, J. Autonomous Agents and Multi-Agent Systems (2008), http://arxiv.org/abs/nlin/0611054

Idea: Design of Social Network Interaction

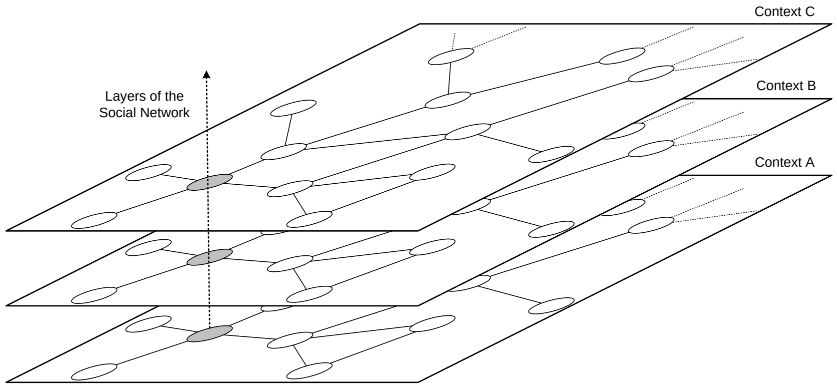
1. **use** existing (real/virtual) social network structure of agents to inquire recommendations for objects
2. **design** artificial algorithm to update weights of links between neighboring agents dependent on success



- **reach** distributed knowledge
- **filter** incoming information

Context-dependent trust relations within a social network

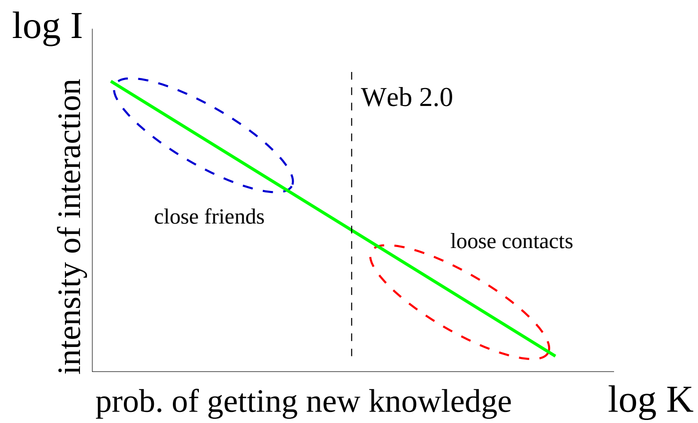
- agents trust recommendations from different neighbors dependent on the context ('food' ≠ 'computer hardware')
- result: different trust layers within the same social network



Social Interaction and the Internet

- **allow to establish/manage more contacts**
  ⇒ 'global village': interaction networks of 1000's of people
  - Web 2.0 (Youtube, Delicious, Facebook, dating sites, ...)
- **virtualization of human relationships**
  - two networks: real (NN) and virtual ('loose contacts')
- **advantage: find/use the friends of your friends**
  - hypothesis: everyone knows something
  - your friends act as door opener/reference to contact other people

The long tail of human interactions



- Web 2.0 allows to reach (the knowledge of) more users
- large number of 'loose contacts' in different fields

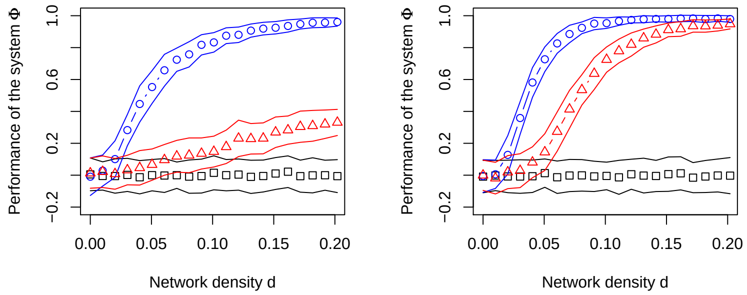
Simulating Trust-based Recommendations

- $N_a = 100$ agents, $N_c = \in \{10, ..., 50\}$ categories (with equal number of items), $N_o \geq 2N_c$ different objects
- special case: two discrete preferences $\{-1, +1\}$
  - 2^{N_o} possible profiles $\{-1, -1, +1, -1, +1, ...\}$
  - fraction of agents with inverse profiles p_1, p_2: $n_1 = N_{p_1}/N$, $n_2 = 1 - n_1$ ($2^{N_o - 1}$ different possibilities)
- social network: directed random graph with density d
- performance measure: aggregated utility of agents
  - utility $u(a_i, t) = p_k$ for consuming object o_k

$$\Phi(t) = \frac{1}{N_A} \sum_{a_i \in S_A} u(a_i, t)$$

- results averaged over 100 runs
- analytical treatment: mean-field approximation

Network Density



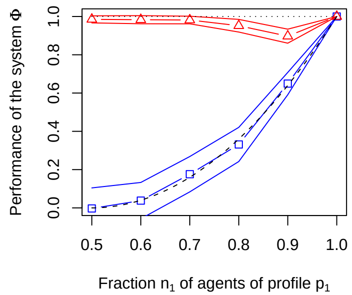
incomplete search: process one random path

complete search: process all possible paths

(blue): $N_c = 10$, (red): $N_c = 50$ $\longrightarrow$ sparseness of knowledge

- critical network density for performance
- search type is crucial when knowledge is sparse
- frequency-based approach (black): performance is 0 on average

Preference Heterogeneity, Knowledge Sparseness



(red): with trust, (blue): without trust, (black): analytical result

- very homogeneous agent populations $\longrightarrow$ good performance
- very heterogeneous agent populations $\longrightarrow$ performance drops
- minority can be satisfied if remains connected

Evolving Social Network

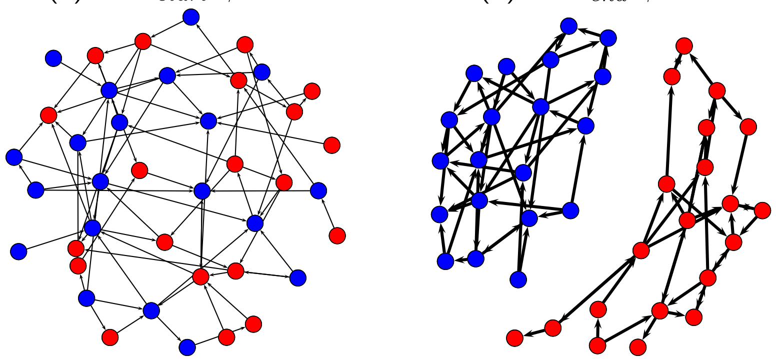
- real networks are *not fixed*, but *evolve*
- assumption: keep *trustworthy* and rewire *untrustworthy* links

$$P_{\mathrm{rewire}} = 1 - T_{a_i,a_j} \; ; \quad P_{\mathrm{keep}} = T_{a_i,a_j}$$

- role of β: exploratory behavior of agents for picking recommendations
  - $\beta = 0$: agents choose randomly $\longrightarrow$ broader experience $\longrightarrow$ well-informed decision
  - $\beta = 1$: agents choose wrt trust $\longrightarrow$ restricted exploration $\longrightarrow$ limited decision

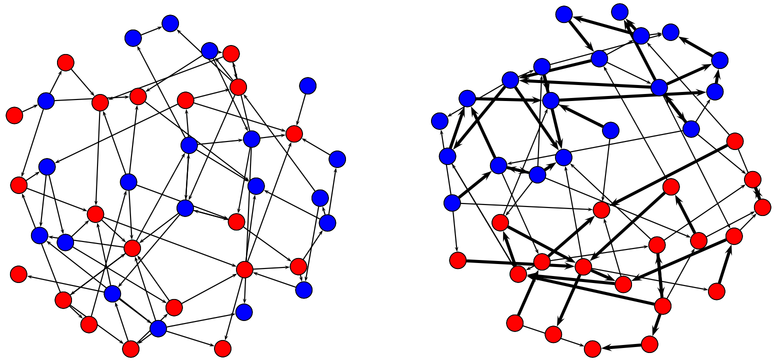
Disconnected Clusters

(a) $t = t_{start}$, $\beta = 0$ (b) $t = t_{end}$, $\beta = 0$



Interconnected Clusters

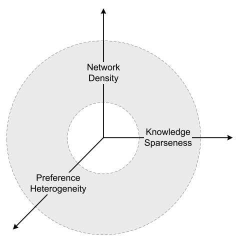
(c) $t = t_{start}$, $\beta = 1$ (d) $t = t_{end}$, $\beta = 1$



Result: links between agents of different profiles become weaker (but still exist), links between agents with the same profile become stronger

Conclusions

- social herding behavior and epidemic spreading
  - mean-field interaction (broadcasting), "small" threshold, abundant information
- trust-based recommendations: individualized, instead of herding
  - builds on *existing social network structures* to receive recommendations
  - *artificial algorithm* to update weights of links between neigboring agents dependent on success



outperforms majority-based recommendations in a certain range of parameters

Specific features:

- adaptivity (specific "learning" approach)
- can cope with heterogeneous preferences
  $\longrightarrow$ *multi-layered* context dependent network
- maximum system performance *emerges*
  utility maximization of *all* agents) based on *local interaction* only
  - satisfies even the minority (if remains connected)
  - works for sparse knowledge (given sufficient network density)

Applications?

- implementation of the algorithm in electronic devices, "Web 2.0"
- creation of new "virtual" communities