SocioAware Agents – Better Agents?

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Distinguished Lecture at 1st International Workshop on Socio-Aware Networked Computing Systems

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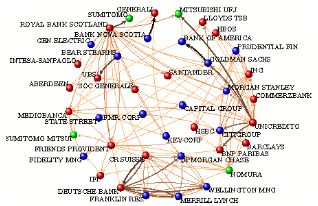
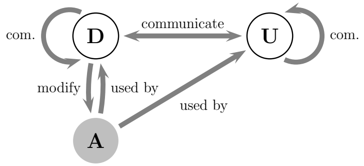
- **Main Research Areas**
  - **Economic Networks** & **Social Organizations**
    - e.g. ownership networks, R&D networks, financial networks, ...
    - e.g. online communities, OSS projects, animal societies, ...

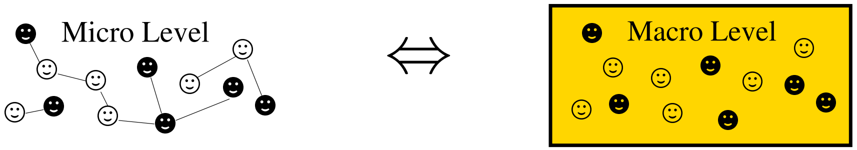




- **Methodological Approach: Data Driven Modeling**
  - **economic databases**: ORBIS, Bloomberg, patent databases
  - **online data**: user interaction, communication records, blogs

Theory of Complex Systems

- system comprised of a *large* number of *strongly* interacting (similar) subsystems (entities, processes, or '*agents*')
  - examples: brain, insect societies, *sensor networks*, *P2P networks* ...
- challenge: The micro-macro link
  - How are the properties of the elements and their interactions ("microscopic" level) related to the dynamics and the properties of the whole system ("macroscopic" level)?



Collective Interaction

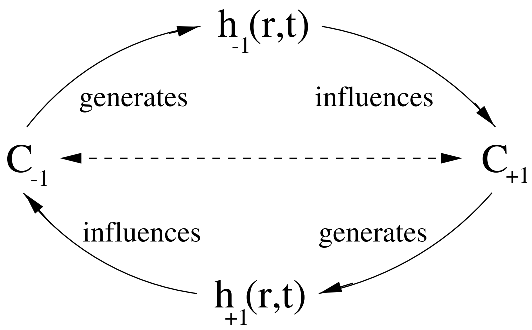
What happens if we connect a large number of simple units?

- *systems dynamics:* cannot be simply inferred from the behavior of the components
- collective phenomena ⇒ *emergence of new systems qualities*
  - spontaneous creation, development and differentiation of new structures
  - examples: traffic jams, panics, swarm intelligence

"Self-Organization is the process by which individual subunits achieve, through their cooperative interactions, states characterized by new, emergent properties transcending the properties of their constitutive parts."

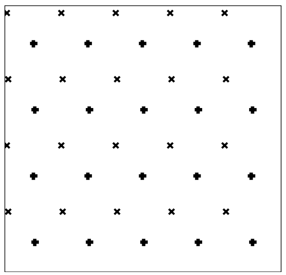
Interaction as communication

- **direct communication**
  - interaction as directed information transfer between two agents
  - uni- or bidirectional, time bound, different weights
- **indirect communication**
  - interaction via medium ("blackboard", mean field)
  - medium with restricted access, finite lifetime



Example: Self-wiring of networks

- **agent-based model**: indirect communication
  - two different kind of information, local access, limited 'lifetime'
  - combine *exploration* and *exploitation* strategies
- *task:* connect a set of "unknown" nodes **without** external guidance
- self-organized networks: adaptivity, self-repairing
- Simulation 1 Simulation 2



Selforganization works!

- solution is "created" (distributed problem solving)
- *agents generate* relevant information
  - new kind of information: **success** $\Rightarrow$ gets amplified
  - different links compete for agent's maintainence
    $\Rightarrow$ ensures *adaptivity* and *optimality*

What is the problem?

1. **control**
   - limited ways of designing/influencing structures
2. **reliability**
   - final structure hard to predict, high failure rate, slow
3. **path dependence**
   - system develops a memory, not irreversible, gets 'trapped'

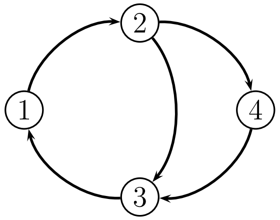
Getting social? – More problems ahead ...

Social context: layer that adds new conditions and feedback loops to self-organization

4. **Costs vs benefits of communication**
   - interaction is costly, has to pay off
   - strategic decision: cooperation vs defection (free riding)
5. **Social herding**
   - agents compensate incomplete information by imitation
   - consensus finding (e.g. share tasks, labor division) takes long
6. **Homophily**
   - interacting agents become more similar $\Rightarrow$ 'in-group', peer pressure
   - restricts options for future communication

Example: Access to other's knowledge

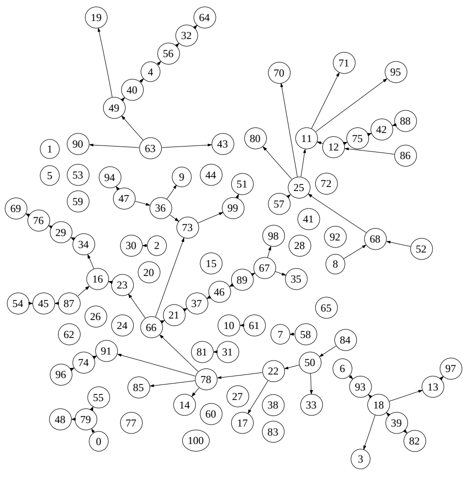
- agent's (device) information value x_i depends on others
  - sharing of information: *act of cooperation*, indirect *reciprocity*



$$\frac{dx_i}{dt} = \sum_{j=1}^{N} A_{ij} x_j$$

- agents have an average number of connections at no costs
- *two time scales:*
  agents adjust (fast), network dynamics (slow)
- *assumption:* extremal dynamics ⇒ minimum performance threshold
  - agents with bad performance dissappear from the system
  - a new agent with random connections is added to the system

Results of computer simulations – no costs for links



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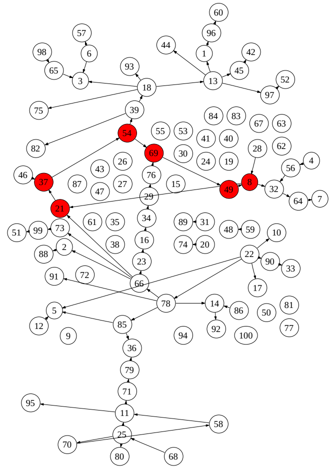
A. Seufert, F.S., Int. J. Modern Physics C, vol. 18, no. 10 (2007)



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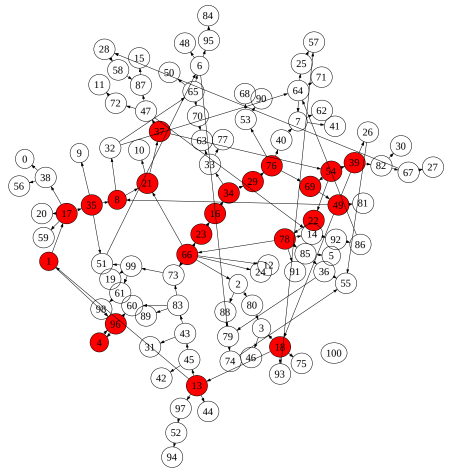
A. Seufert, F.S., Int. J. Modern Physics C, vol. 18, no. 10 (2007)

- emergence of cycles of cooperating agents ⇒ *indirect reciprocity*
  - core of *cooperative* agents, and a *parasitic* pheriphery



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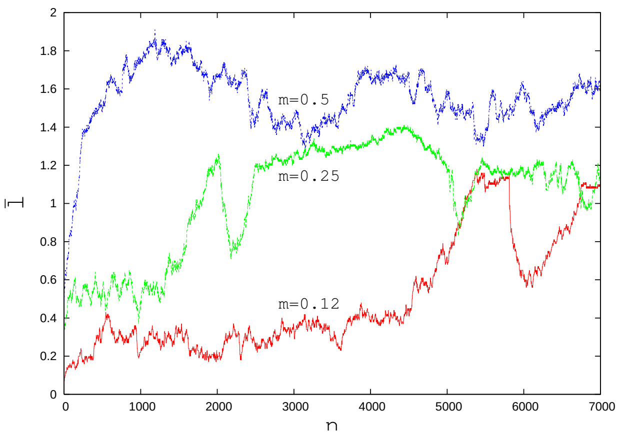
A. Seufert, F.S., Int. J. Modern Physics C, vol. 18, no. 10 (2007)

Average connection as performance measure



- robustness of network against shocks: *crashes and recovery*

A. Seufert, F.S., Int. J. Modern Physics C, vol. 18, no. 10 (2007)

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The message: No costs – High vulnerability

- **links are created at** **no cost**
  - *agents* (!) do not optimize
- **role of core:** **boosts knowledge production**
  - indirect reciprocity
- **role of periphery:** **"spare for selection"**
  - agents are sustained because it is not costly
- **optimization on the systems level**
  - removing less performing agents **makes the system vulnerable**

Next step: Costly interaction ⇒ Stategic decision

- costs for **maintenance** of connections
- **exploration costs** (search for partners)
- **transaction costs** (costs for interaction): share information
- **friction** from differences in 'protocols', 'standards' ...

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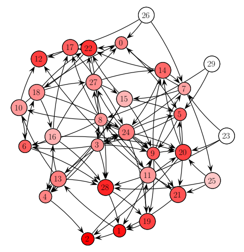
Case 1: indirect Reciprocity, linear benefit, squared costs

- agent i with time horizon T:
  - random unilateral link creation, optimal unilateral link deletion
  - accepted, if knowledge stock x_i increased

t=0



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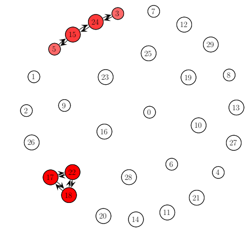

- initial links break down in favour of few bilateral cooperations
- free-riders get isolated

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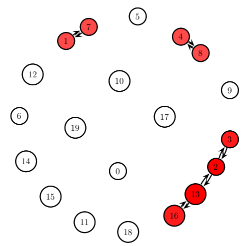
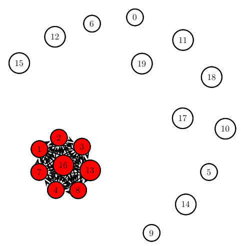
Case 2: direct reciprocity, linear benefit, squared costs

- agents i and j with time horizon T:
  - random bilateral link creation, optimal bilateral link deletion
  - accepted, if both knowledge stocks x_i and x_j increased

t=0



t=1.000



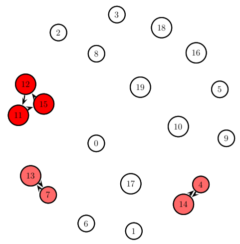
- initially connected agents evolve towards fully connected network
- initially isolated agents have nothing to contribute

Case 3: ind. reciprocity, weighted linear benefit, squared costs

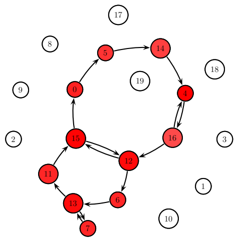
$$\frac{dx_i}{dt} = -dx_i + b\sum_{i=1}^{n} a_{ji}x_j + b_{\text{ext}}\sum_{i=1}^{n} w_{ji}x_j - c\sum_{i=1}^{n} a_{ij}x_i^2$$

- *externalities:* higher weights to
  - links providing shorter paths (Jackson, Watts 2002)
  - links contributing to cycles $\Rightarrow$ feedback on knowledge production

t=500



t=500



- cyclic externalities support emergence of indirect reciprocity

The costs for breaking up

0 agent's utility: $u_i = \lambda_{PF} - cd_i$, initialization: empty graph

1 **quasi-equilibrium**: fast knowledge growth with fixed $\mathbf{A}$

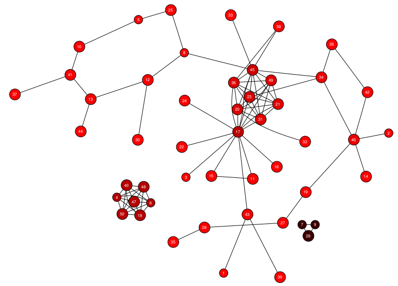
2 **perturbation** of network: pair of agents (i, j) is selected at random

- link $ij \notin E(G)$ is *created* if
  - either u_i or u_j is increased and none of u_i and u_j is decreased (*incremental improvement*)
- link $ij \in E(G)$ is *deleted* if
  - at least one agent gains from the change (asymmetry!)
    link deletion involves severance cost: $v(\alpha, c) = (1-\alpha)c$ with $\alpha = c'/c$
    $\alpha \in [0, 1]$: $\alpha = 0$: full loss of investment, $\alpha = 1$: no loss

3 **stop** if network is pairwise stable, otherwise go to **1**

Example: Equilibrium network for $\alpha = 0.0$

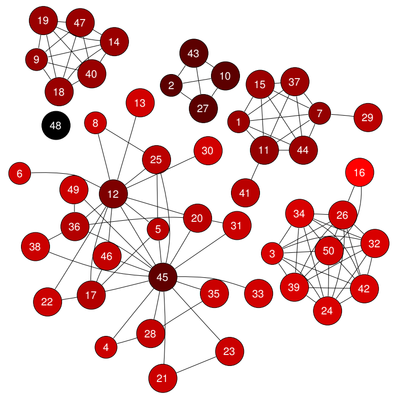
- heterogeneous degree distribution (hubs), giant component
- high severance cost prevent agents from further deleting links
- pairwise stability $\neq$ efficiency (suboptimal solution)



$n = 50$, $c = 0.15$, darker colours $\rightarrow$ higher profits

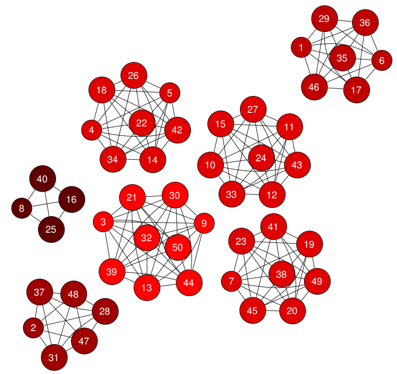
Example: Equilibrium network for $\alpha = 0.2$

- stronger clustering, disconnected components



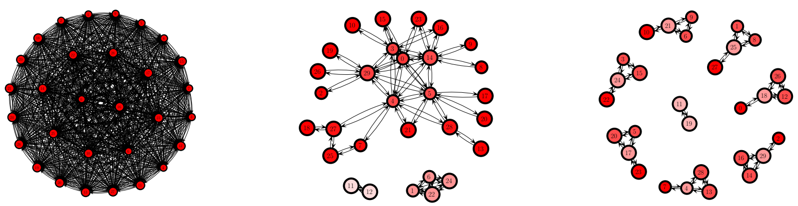
Example: Equilibrium network for $\alpha = 1.0$

- the smaller severence costs (loss after reconfiguration), the larger the tendency to form disconnected cliques (fully connected groups)



Simulations: Growing Networks with $\alpha = 1$

- intial setting: empty graph $\Rightarrow$ final setting: equilibrium network
- $0 < c < 0.5$: fully connected graph is efficient network



$c = 0.01$ $c = 0.2$ $c = 0.5$

- equilibrium networks more sparse and clustered with increasing c
- inefficient equilibrium networks are reached
  - for given cost, *multiple equilibria* exist
  - equilibrium network is *path dependent* (stochastic influences)

The message: High costs – Less optimality

- linear/nonlinear cost functions $\Rightarrow$ **limits** for connected networks
- multiple equilibria: many stable, but **inefficient** equilibrium networks
- **breakdown** of indirect reciprocity: only direct interactions

Next step: Include group effects

- information sharing not beneficial for single agent, but for the group
- social relationships: **trust**, **similarity** $\Rightarrow$ enhance cooperation

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Compare to: No costs – High vulnerability

Convergence toward shared characteristics

agent i: 'device' with certain characteristics $x_i(t) \in [0, ..., 1]$

1. *assumption:* interaction is easier with same characteristics
   - benefit: $b = \mathrm{const.}$, costs: $\sim \Delta x$

$$u_i(t) = \sum_j b - c\,|x_i - x_j|$$

2. *assumption:* interaction ij occurs only iff $u_{ij}(t) > u_{\mathrm{thr}}$

$$|x_i - x_j| < \varepsilon = (b - u_{\mathrm{thr}})/c$$

   - possibility of interaction depends on *'flexibility'* ε
   - bounded confidence model (Deffuant *et al.*, 2000)

3. *assumption:* interaction leads to more similar behavior

$$x_i(t+1) = x_i(t) + \mu\,[x_j(t) - x_i(t)]$$
$$x_j(t+1) = x_j(t) + \mu\,[x_i(t) - x_j(t)]$$

   - $\mu = 0.5$: both agents adopt the 'mean' behavior

Influence of emerging in-groups

- interacting agents added to each other's in-group I_i and I_j
  - partnership relations from past interactions
- influence of *emerging in-groups* on agent's i behaviour x_i?
  - *effective behaviour* x_i^{eff} considers *mean in-group behaviour* x_i^I

$$x_i^{\text{eff}} = (1 - \alpha_i)x_i + \alpha_i x_i^I$$

  - group influence α_i increases with group size
- permanent influence of in-group on interaction: $\left|x_i^{\text{eff}} - x_j^{\text{eff}}\right| < \varepsilon$
  - search for new partners is costly $\rightarrow$ keep past partners
  - keep behavior close to past partners to allow further interaction

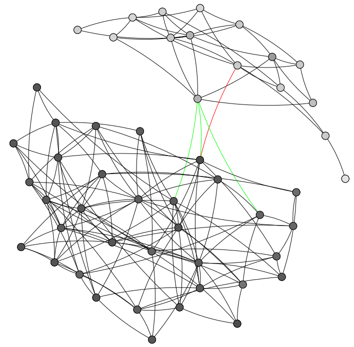
Co-evolution of interaction network and characteristics

- randomly choose agents i, j at time t

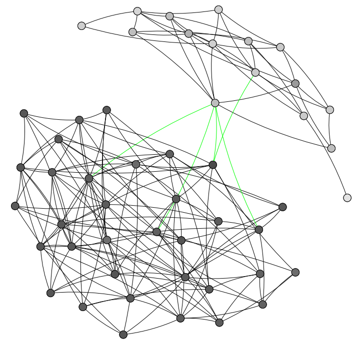
1. **link dynamics** (considers existing in-group)
   - $\Delta x^{\text{eff}}(t) < \varepsilon \Rightarrow$ link formation (interaction)
   - $\Delta x^{\text{eff}}(t) > \varepsilon \Rightarrow$ no link created or *existing link is removed*
2. **dynamics in individual behavior** (considers $x_i(t)$, $x_j(t)$)
   - interacting agents become more similar
3. **adjustment of effective behavior**
   - agent i, j: $x_i \rightarrow x_i^{\text{eff}}$, $x_j \rightarrow x_j^{\text{eff}}$
   - in-groups of i and j: x_i^{eff}, x_j^{eff} affected by changed $x^{I_i(t)}$, $x^{I_j(t)}$

Result: *feedback between agents' behavior and their in-group structure* $\Rightarrow$ $\boxed{\text{Computer simulation}}$

Group Influence: two nearly separated components...



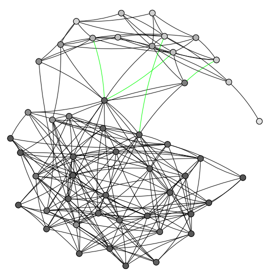
$t = 300$



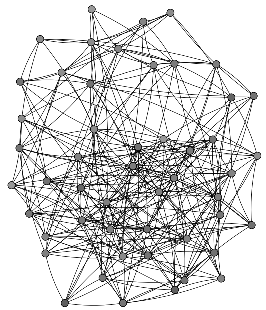
$t = 350$

- 50 agents, $\varepsilon = 0.3$
  - green link: agents would not interact without group influence
  - red link: agents would not interact anymore

... finally united



$t = 400$



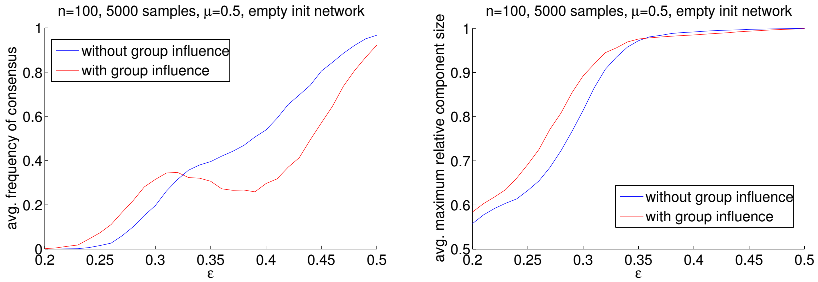
$t = 500$

- group influence (on average and a large range of ε)
  - fosters coalescence of components
  - increases maximum component size

$\Rightarrow$ consensus toward a common characteristics

Influence of interaction costs on consensus?

large costs $\Leftrightarrow$ small 'open-mindedness' $\varepsilon = (b - u^{\mathrm{thr}})/c)$

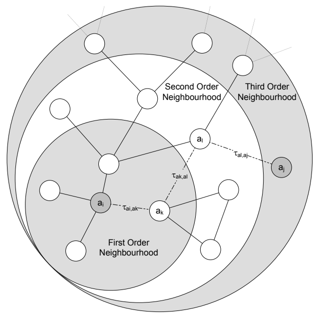


- large costs $(0 < \varepsilon < 1/3)$
  - in-group influence increases probability to reach consensus
  - size of largest component increases
- small costs $(1/3 < \varepsilon < 1/2)$
  - with in-group influence, consensus becomes less probable
  - but size of largest component is not affected by in-group influence

The message: Costs from being different

- **ambigious effect** of group influence
  - can enhance, but also reduce performance
- general problem of **systemic risk**: heterogeneity
  - faster failure spreading for homogeneous agents

Next step: Trustful relationships



- use *existing social network* of agents to inquire recommendations for objects
- design *artificial algorithm* to update weights of links between neighboring agents dependent on success ($\rightarrow$ 'trust')
- *reach* distributed knowledge, *filter* incoming information

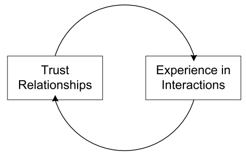
- **utility** increases if recommendation r_k matches preference v_i

$$u_i(t) = b - c\,|v_i - r_k|$$

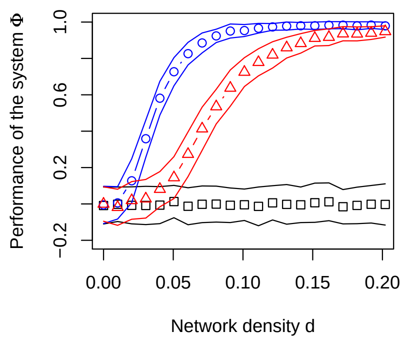
  - r_k: chosen out of different recommendations obtained through *different 'social paths'* with specific weights $\hat{T}_{a_i,\ldots,a_k}$
  - decision process

$$P \sim \frac{\exp(\beta\,\hat{T}_{a_i,\ldots,a_k})}{\sum_R \exp(\beta\,\hat{T}_{a_i,\ldots,a_l})}$$

- "trust": weights reliability of former recommendations
  - trust relationships *evolve through feedback* from experiences



- **Critical Network Density**
  - special case: only two preferences $\{-1, +1\}$
  - social network: directed random graph with density p
  - complete search: return responses more than once
  - performance measure: aggregated utility of agents



(blue): $N_c = 10$, (red): $N_c = 50$ $\rightarrow$ sparseness of knowledge, (black): frequency based recommendation

Social networks evolving based on trust

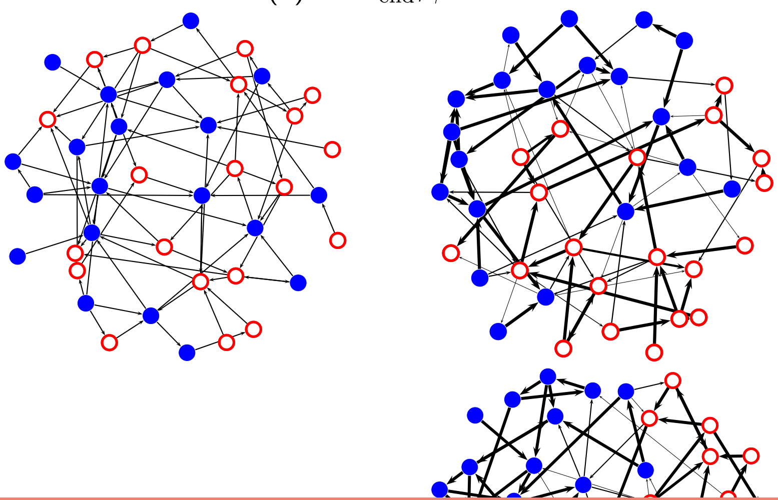
- special case: only two preferences $\{-1, +1\}$
- real networks are *not fixed*, but *evolve*
- assumption: keep *trustworthy* and rewire *untrustworthy* links

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

- *random rewiring mechanism*:
  - role of β: exploratory behavior of agents

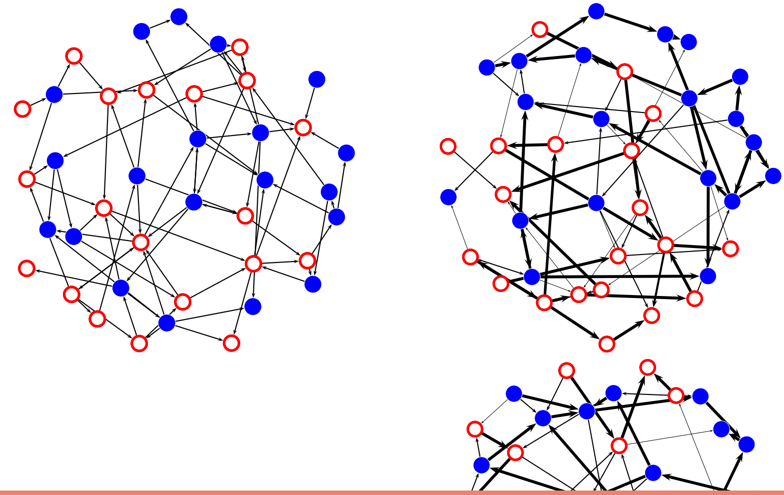
Disconnected Clusters

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



Interconnected Clusters

(a) $t = t_{start}$, $\beta = 1$ (b) $t = ...$, $\beta = 1$
(b) $t = t_{\text{end}}$, $\beta = 1$



The message: Build trustful links

- **What is the difference?**
  - *consensus example*: agents change characteristics (agents adapt)
  - *trust based network*: agents weight links (network adapts)
- **What is the advantage?**
  - *cost-benefit analysis*: agents do not 'learn', rational decisions
  - *trust-based network*: agents keep links, but weight them
- **What is the problem?**
  - no guarentee that *suboptimal solutions* are improved
  - mutations introduce new configurations, but also *risk to fail*

Conclusions

1. **Self-organisation works** ⇒ adaptive structures
   - *problems:* control, reliability, path dependence
2. **Socio-aware agents**
   - *strategic decisions* based on costs and benefits
   - *local optimization*: trapped in suboptimal configurations
   - *agent adaptation* to 'in-group' (previous interactions)
   - *link adaptation*: weights assigned based on experience ("trust")
3. **Social mechanisms**: new possibilities for designing interactions
   - "there is no free lunch": social means not "better"

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SocioAware Agents – Better Agents? - Conclusions

This research overview is based on the publications:

- F. Schweitzer: *Brownian Agents and Active Particles. On the Emergence of Complex Behavior in the Natural and Social Sciences*, Berlin: Springer 2003
- F. Schweitzer, B. Tilch: Self-Assembling of Networks in an Agent-Based Model, *Physical Review E* 66 (2002) 026113 (1-9)
- F. Schweitzer, K. Lao, F. Family: Active Random Walkers Simulate Trunk Trail Formation by Ants, BioSystems 41 (1997) 153-166
- A. Seufert, F. Schweitzer: Aggregate Dynamics in an Evolutionary Network Model, *International Journal of Modern Physics C,* vol. 18, no. 10 (2007) pp. 1659-1674
- P. Groeber, F. Schweitzer, K. Press: How groups can foster consensus: The case of local cultures, *J. Artificial Societies and Social Simulations* vol. 12, no. 2/ 4 (2009)
- M. D. König, S. Battiston, M. Napoletano, F. Schweitzer: Recombinant Knowledge and the Evolution of Innovation Networks, *Journal of Economic Behavior and Organization*, vol. 79, no. 3 (2011) pp. 145-164
- M. D. König, S. Battiston, M. Napoletano, F. Schweitzer: On Algebraic Graph Theory and the Dynamics of Innovation Networks, *Networks and Heterogeneous Media* vol. 3, no. 2 (2008) pp. 201-219
- M. D. König, S. Battiston, F. Schweitzer: Modeling Evolving Innovation Networks, in: *Innovation Networks - New Approaches in Modeling and Analyzing* (Eds. A. Pyka, A. Scharnhorst), Heidelberg: Springer (2009) pp. 187-267
- F. E. Walter, S. Battiston, F. Schweitzer: A Model of a Trust-Based Recommendation System on a Social Network, *Journal of Autonomous Agents and Multi-Agent Systems*, vol. 16, no. 1 (2008) pp. 57-74
- **further publications/downloads:** `http://www.sg.ethz.ch/publications/` and `http://arxiv.org/a/schweitzer_f_1`