Modeling collective interactions in social systems

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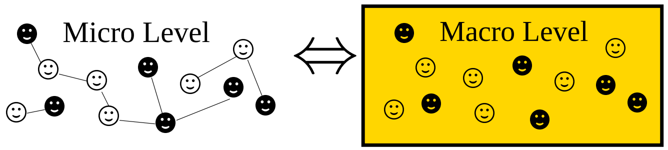
Chair of Systems Design

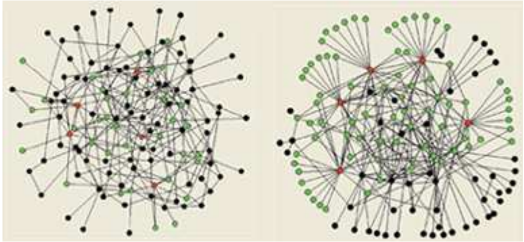
- research on *socio-economic systems* (firms, organizations, ...)
- major focus: *collective effects*: emergence of features
- basis: theory of complex systems



- 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)?

Complex Networks

- agents ⇒ nodes, interactions ⇒ links
- the physics approach: add nodes, draw lines ...



- the real challenges in socio-economic systems:
  - *heterogeneous* agents: firms, banks, individuals, ...
  - *weighted, directed* links: ownership, credit relations, ...
  - *strategic* link formation/deletion
  - *feedback* between agent dynamics and link dynamics

Costs and benefits

- social system: large number of *interacting agents*
- agent i: *utility* from social interaction with agents j:

$$\mathrm{utility}_i(t) = \sum_j \mathrm{benefits}_{ij}(t) - \mathrm{costs}_{ij}(t)$$

  - aim: (i) increase benefits, (ii) reduce costs, (iii) do both
- **benefits:**
  - reach a private goal (purchase the best product)
  - reach a common goal (optimal use of resources)
  - exchange of knowledge (R&D network)
- **costs:**
  - exploration costs (search for partners)
  - transaction costs (costs for interaction)
  - friction from differences in 'behavior', 'opinion', ...
  - costs for *maintenance* of connections

Convergence toward shared behavior

agent i: social behavior $x_i(t) \in [0, ..., 1]$

1. *assumption:* utility increases if everyone shares same behavior
   - 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 *'open-mindedness'* 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
- evidence that in-groups constrain agent behaviour
  - game theory (Fehr & Fischerbacher 2004)
  - group theory (French 1956, Lehrer 1956, Wagner 1978)
  - social impact theory (Latané 1981, Latané & Nowak 1997)
- influence of *emerging in-groups* on agent's i behaviour x_i?
  - *effective behaviour* x_i^{eff} considers *mean in-group behaviour* $\bar{x}_i^I$

$$x_i^{\mathrm{eff}} = (1 - \alpha_i)x_i + \alpha_i \bar{x}_i^I$$

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

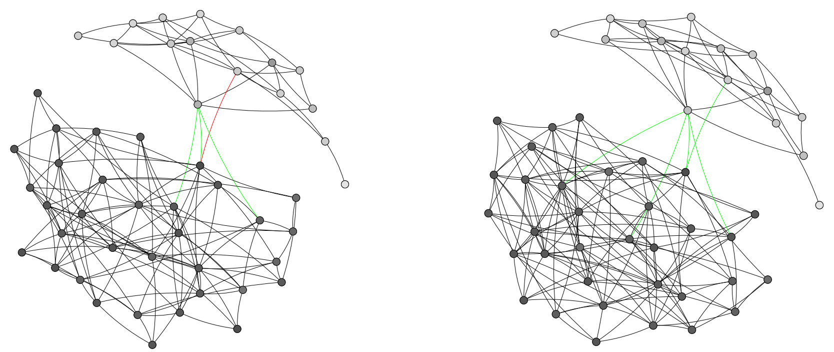
Co-evolution of social network and behavior

- randomly choose agents i, j at time t

1. **link dynamics** (considers existing in-group)
   - $\Delta x^{\mathrm{eff}}(t) < \varepsilon \Rightarrow$ link formation (interaction)
   - $\Delta x^{\mathrm{eff}}(t) > \varepsilon \Rightarrow$ 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: $x_i \rightarrow x_i^{\mathrm{eff}}$, $x_j \rightarrow x_j^{\mathrm{eff}}$
   - in-groups of i and j: x_i^{eff}, x_j^{eff} affected by changed $\bar{x}^{I_i(t)}$, $\bar{x}^{I_j(t)}$

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

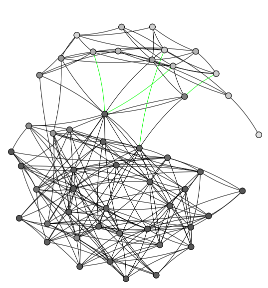
Group Influence: two nearly separated components...

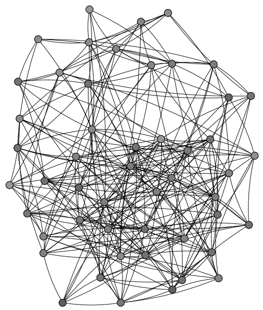


$t = 300$ $t = 350$

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

... finally united

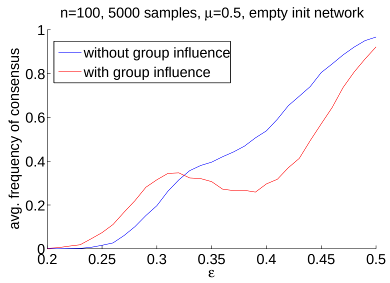


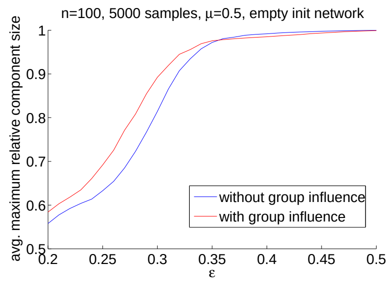


- group influence (on average and a large range of ε)
  - fosters coalescence of components
  - increases maximum component size
  - ⇒ consensus toward a common behavior

Influence of interaction costs on behavioral consensus?

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





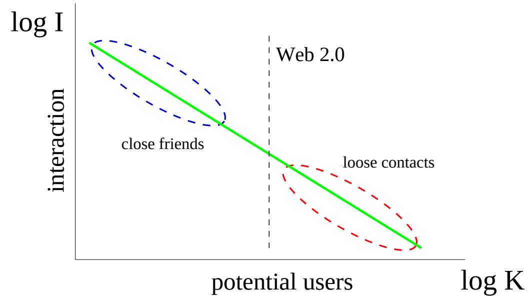
- large costs ($0 < \varepsilon < 1/3$)
  - in-group influence increases probability to reach consensus
  - size of largest component increases
- small costs ($1/3 < \varepsilon < 1/2$)
  - with in-group influence, consensus becomes less probable
  - but size of largest component is not affected by in-group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

Beyond the Social Brain Hypothesis

- Dunbar: social interaction is restricted by our brain capacities
  - reason: human evolution based on interaction in 'small' groups
  - size of the social network for permanent interaction: 150
  - allows person-person emotional relations
- Social networking sites (SNS):
  allow to establish/manage more contacts
  - release the restrictions of the 'social brain'
  - ⇒ 'global village': interaction networks of 1000's of people
  - ⇒ large-scale and real-time self-organization of citizen

"The social brain hypothesis is about the ability to manipulate information, not simply to remember it.", R. Dunbar (1998), The social brain hypothesis. Evol. Anthrop. 6: 178-190:

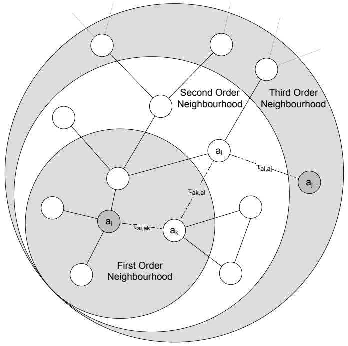
The long tail of human interactions



- Web 2.0 allows to reach more users **instantaneously**
- advantage: *new resources*, disadvantage: *new risks*
  - large number of 'loose contacts': de facto *anonymity*
  - economics of attention: *exaggeration* to raise attention/response
  - subtle amplification mechanisms: impersonal interaction lowers the *threshold for verbal abuses*

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

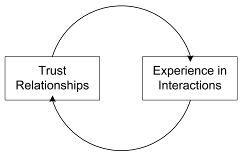
- **utility** increases if recommendation r_k matches preference v_i

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

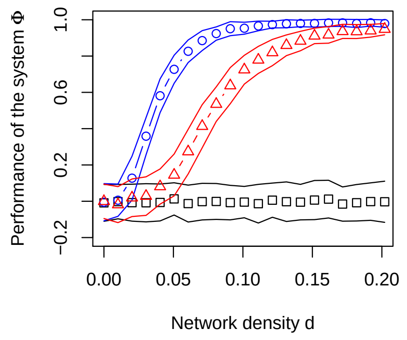
  - r_k: chosen out of different recommendations obtained through *different 'social paths'* with specific weights $\hat{T}_{a_i,\dots,a_k}$
  - decision process

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

- "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): $N_c = 50 \to$ sparseness of knowledge, (black): frequency based recommendation

Social networks evolving based on trust

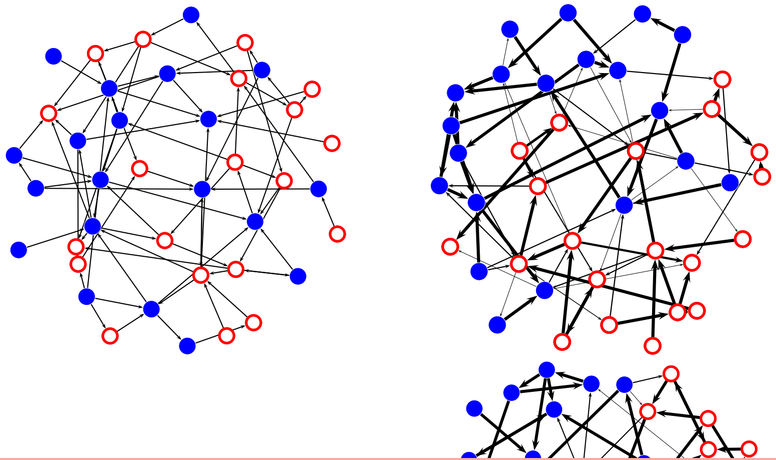
- special case: only two preferences $\{-1, +1\}$
- real networks are *not fixed*, but *evolve*
- assumption: keep *trustworthy* and rewire *untrustworthy* links

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

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

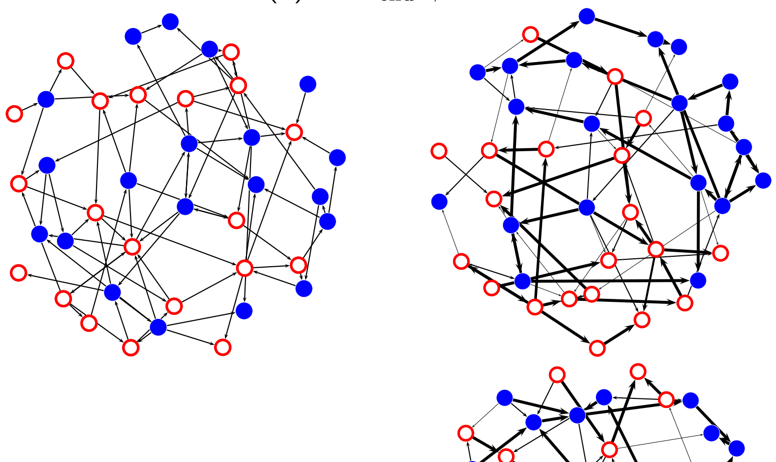
Disconnected Clusters

(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) $t = t_{\text{end}}$, $\beta = 1$



Conclusions

- agents form/keep/change social network to optimize utility
  - increase benefits: reach personal/common goal
  - decrease costs: delete unused links, match preferences
- How do *costs/benefits* shape structure of social network?
  - agent-based modeling, computer simulations, analytical results
- *model 1:* emergence of common behavior ($\sim$ social norm)
  - utility: common behavior reduces costs of interaction (friction)
  - in-group evolves $\rightarrow$ modifies individual behavior $\rightarrow$ feeds back to interaction, social network
  - decreasing c does not increase probability of (full) consensus
  - application: local cultures in economic clusters (in-group model)

- *model 2:* evolving trust relationships
  - utility: good recommendations match preferences
  - 'trust' evolves: weight of reliability of recommendations
  - exploratory behavior results in separated clusters
  - **Application:**
    implementation of the algorithm in electronic devices, "Web 2.0"

Summary:

- costs/benefits/preferences significantly change *dynamics/structure* of social network
- comparison between empirical networks and simulations allow to implicitely deduce agent's utility function