The Role of Local Effects in Collective Decision Processes

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Collective Decisions

- aggregated outcome of many individual decisions
 - most individual implications are averaged out
 - interaction among agents play crucial role
 - system utility (social welfare) $\neq \sum_i U_i^{\text{indep}}$
- our focus:
 - prediction of global/system quantities, not of individual decisions
 - role of local/neighborhood effects in collective decisions
 - influence of social elements (herding behavior)



Consensus versus Coexistence

Public polls \Rightarrow collective decision processes

- examples from Europe (2005):
 - ▶ May 29: French vote for/against Europ. constitution (45/55)
 - ▶ June 5: Swiss vote for/against Schengen (54.6/45.4)
- characteristic features
 - two alternatives: YES/NO (binary decision)
 - no simple utility maximization
 - hard to predict ($\sim 50/50$)
- find minimalistic agent models to explain generic dynamics



Voter Models

- simple model of opinion formation with consensus
- population of agents: i = 1, ..., N
- each agent *i*: spatial position *i*, "opinion" $\theta_i(t) \Rightarrow \{0, 1\}$
- "decision": to keep or change opinion $\theta_i(t)$

 $heta_i(t+1) = \left\{egin{array}{cc} heta_i(t) & {
m keep} \ 1- heta_i(t) & {
m change} \end{array}
ight.$

• rate to change opinion depends on other agents

 $w(1- heta_i| heta_i) = \kappa(f) f_i^{1- heta_i}$

- 0 ≤ f_i^{1−θ_i} ≤ 1: frequency of agents with *opposite* opinions in "neighborhood" of agent i
- $\kappa(f)$: nonlinear response to frequency of other opinions



 neighborhoods are defined by an adjacency matrix C_{ij} ⇒ network structure



 simplified geometry: regular grid







Nonlinear response $\kappa(f)$





Results of computer simulations

1. Linear voter model

- stochastic simulation, $w(1 \theta|\theta) = f^{1-\theta}$
- initially x = 0.5, random distribution

• results:

- coordination of decisions on medium time scales
- asymptotically: "no opposition" (\rightarrow equilibrium)









Online Simulation



 $t = 10^1$, 10^2 , 10^3 , 10^4

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Time to reach consensus au







Coexistence? \Rightarrow 2. Non-linear voter model

- Online simulation 1 :
 - coexistence, but no spatial coordination
- Online simulation 2 :
 - small pertubation for $f^{1- heta} = 1 \ (
 ightarrow arepsilon = 10^{-4})$
 - coordination of decisions on long time scales
 - asymptotically: coexistence, but non-equilibrium



 $arepsilon = 10^{-4}$ $t = 10^1$, 10^2 , 10^3 , 10^4





Simulations of VM





(a)
$$\varepsilon = 10^{-4}$$
, $\alpha_1 = 0.2$,
 $\alpha_2 = 0.4$ (linear VM)

(b)
$$\varepsilon = 10^{-4}$$
, $\alpha_1 = 0.25$, $\alpha_2 = 0.25$

Phase diagram for coexistence

Chair of Systems Design http://www.sg.ethz.ch/

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1d CA:



- long-term nonstationarity
- only temporal domination of one opinion

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Results:

- collective decisions \Rightarrow nonlinearity in the voter model
- consensus:
 - time scale?, symmetry of outcomes?
- coexistence:
 - non/stationarity? spatial correlations?, different attractors?¹
- missing
 - memory effects, various opinions
 - influence of social structure, agent's utility

¹Schweitzer, F.; Zimmermann, J.; Mühlenbein, H.: Coordination of Decisions in a Spatial Agent Model, Physica A 303/1-2 (2002) 189-216

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Including memory effects

- $\nu_i(\tau_i)$: reluctance of agent *i* to change opinion θ_i
 - ▶ persistence time τ_i (opinion was *not* changed) \Rightarrow "history"
 - reflects local experience with agents in neighborhood

$$rac{d
u}{d au} = \mu \,
u (1-
u) \quad \Rightarrow \quad v_i = rac{1}{1+e^{-\mu au_i}}$$

• decision dynamics:

 $w(\theta_i'|\theta_i) = [1 - \nu_i(\tau_i)] f_i^{\theta_i'}$

- $\mu > 0$: slowing down of opinion dynamics
- consensus vs. coexistence of opinions ??
 - decision between 3 opinions: $\{-1, 0, +1\}$

Simulation Video



└─VM with memory effects

Time to reach consensus



• *heterogeneity* of agents important:

 local groups of "confident" agents convince an indifferent neighborhood

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Do not change the Status Quo

- conservative society: if you are in doubt, stay to the established opinion (Galam 2000, 2002)
- *N* agents with $\theta_i \in \{-1, +1\}$; ruling opinion $\theta_G = +1$
- government proposal \Rightarrow N_+ supporters, N_- objectors
 - ? how much support needed to accept the proposal?
 - ! depends on mechanism of collective opinion formation!

example: local interaction between 4 agents

- majority rule: $\{4+, 0-\} \rightarrow 4+$, $\{3+, 1-\} \rightarrow 4+$, $\{1+, 3-\} \rightarrow 4-$, but: $\{2+, 2-\} \rightarrow 4+$
- n consecutive random interactions

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Propagation of opinions

Spearding of minority opinions



initial condition: 24% supporters (black), 76% objectors result: after 7 iterations or voting levels \Rightarrow 100% support \Rightarrow minority wins (Cube 2000, 2002)

(Galam 2000, 2002)

Decisions in hierarchical organizations

Problem: propagation of new ideas through organization

- initialization on lowest level ⇔ conviction at the top level??
- depends on acceptance threshold f_c and social structure
 - asymmetry of C_{ij}
 - reporting/authority links

 $heta_i(t+1) = \Theta\left[f_i^{(1)}(t) - f_c
ight]$



Online simulation



Local versus global trends

- agents exploit two different information
 - Iocal: "do what your neighbors do"
 - global: "do not follow the trend"

• dynamics: *N* agents on a lattice, two opinions $\theta_i \in \{-1, +1\}$

$$\theta_i(t+1) = \begin{cases} +1 & \text{with } p = \frac{1}{1 + \exp\{-2\beta h_i(t)\}} \\ -1 & \text{with } 1 - p \end{cases}$$
$$h_i(t) = \sum_{j \in NN} J_{ij} \theta_j - \alpha \theta_i \left| \frac{1}{N} \sum_j \theta_j \right|$$

Online Simulation²

²(Bornholdt 2001, cond-mat/0105224)

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Using Social Networks for Decisions

- decision based on recommendations
 - cope with information overload through filtering
- advantages: get *personalized* information
 - majority rules: based on frequency of recommendations
 - similarity-based: low effort, but passive and no active tuning
- *social network*: reduced effort *and* tuning of the recommendation at the same time!
 - use an agent's social network to reach distributed knowledge
 - incorporate trust to filter reachable knowledge
- "Trust": appropriateness and reliability of former recommendations
 - \blacktriangleright \rightarrow *trust-based*: high effort, not passive but active tuning



Sketch of Model Outline

• agents with *preference profiles* select products with *feature profiles* based on recommendations (from distant agents)







Decision Making

- querying agent a_q chooses from k responses obtained from the network: {f_{ar,p}, \(\tau_{a_q,a_r}\)}, r = 1, ..., k
 - ▶ $f_{a_r,p}$: preference of recommender, τ_{a_q,a_r} : trust along the path

$$au_{a_q,a_r} = \prod_{(a_k,a_l) \in \text{ path}(a_q,a_r)} au_{a_k,a_l}$$

• probability of selecting recommendation r:

$$P_{a_q,p_r} = \frac{\exp(\beta \tau_{a_q,a_r} f_{a_r,p_r})}{\sum_r \exp(\beta \tau_{a_q,a_r} f_{a_r,p_r})}$$

• β : measure of the *risk aversion* of agents

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Update of Trust

- only towards neighbours a_j of agent a_i and only if
 - **(**) a_i has chosen an item directly recommended by a_j
 - a_i chooses a recommendation which came through a_j
- *local information:* agents only know the identity of a_n, (neighbour that the recommendation came through)





Results on Trust-Based Networks

Recommendation systems in trust-based networks outperform majority-based recommendation systems within a range of:

- network density:
 - if the network is not dense enough, agents receive replies with recommendations on only a fraction of the items they query about
- preference heterogeneity:
 - if agents are very homogeneous, there is no need for filtering, almost any recommendation will be appropriate
 - if agents are too heterogenous, they cannot find other agents that act as suitable filters



Results of Computer Simulations

special case: only two preferences {-1, +1}
 social network: directed random graph with density p



• Trust causes a performance gain above a critical density

• Performance gain decreases with increasing homogeneity

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Decisions based on trust

Evolving Social Network

• rewiring based on trust: $P_{\text{rewire}} = 1 - T_{a_i,a_i}$, $P_{\text{keep}} = T_{a_i,a_i}$













Result: links between agents of different profiles become weaker, between agents of the same profiles stronger



Conclusions

- collective decisions ⇔ aggregated individual decisions??
- 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)?



$$\Leftrightarrow$$



- approach: multi-agent models
 - ▶ agent: "intermediate" internal complexity $\rightarrow \theta_i$
 - simple update dynamics: non-linear VM, utility maximization, ...
 - ▶ interaction: local neighborhood $\rightarrow C_{ij}$: topology, trust dynamics



• minimalistic agent models:

- cover generic features of collective decisions
 e.g. influence of hierarchies, memories, lobbies,
- fitting with data within reach
- but: will not predict your next "Volksabstimmung"
- KISS (Keep It Simple, Stupid) principle
 - details: not as much as possible, only as much as necessary
 - systematic understanding: role of parameters, feedbacks ...
 - abstract modeling level: elucidates dynamic key features