Exploring network dynamics with agent-based models

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Main points of the lecture

Discussing the central role of agent-based models within the computational social science research programme

Showing examples of ABM research that explored multiple generative paths, which are usually disregarded by statistical models that estimate parameters from data

Using ABM for testing causal explanations or running counter-factual test especially in context of unobservable parameters

Science

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HOME > SCIENCE > VOL. 323, NO. 5915 > COMPUTATIONAL SOCIAL SCIENCE

PERSPECTIVES

Computational Social Science

DAVID LAZER , ALEX PENTLAND, LADA ADAMIC, SINAN ARAL, ALBERT-LÁSZLÓ BARABÁSI, DEVON BREWER, NICHOLAS CHRISTAKIS , NOSHIR CONTRACTOR, JAMES FOWLER, MYRON GUTMANN, TONY JEBARA, GARY KING , MICHAEL MACY, DEB ROY, AND MARSHALL VAN ALSTYNE fewer Authors Info & Affiliations

SCIENCE • 6 Feb 2009 • Vol 323, Issue 5915 • pp. 721-723 • DOI: 10.1126/science.1167742

The predominantly inductive, data-driven, pattern detection-oriented approach of computational social science should be complemented with theoretical, hypothesis-driven, explanatory, generative mechanism-identification models

Renzini, Debernardi, Bianchi, Cremonini & Squazzoni (2023), The new frontiers of social simulation in the data science era, in Squazzoni (Ed.), *Advances in Social Simulation*, Springer Verlag, Berlin.

The New Frontiers of Social Simulation in the Data Science Era: An Introduction to the Proceedings

Francesco Renzini, Carlo Debernardi, Federico Bianchi, Marco Cremonini, and Flaminio Squazzoni

Abstract This chapter introduces the proceedings of the Social Simulation Conference 2022 by providing a brief overview of the impact of social simulation in various research areas. By focusing on the key role of agent-based modeling, we argue that social simulation has a unique position in the wider data science area. This is because it can enrich the predominantly inductive, data-driven, pattern oriented approach of computational social science with deductive, hypothesis-driven, explanatory, mechanism-detection models. Furthermore, social simulation can also work in areas and for contexts where data is not available, experiments cannot be performed or in which scenario exploration is paramount. We would also like to focus on areas and aspects where methodological improvement and cross-methodological integration are required to enhance the potential of social simulation in various communities. In the final section, we introduce the structure and sections of the proceedings.

Keywords Social simulation · Agent-based modeling · Computational modeling · Computational social science · Data science

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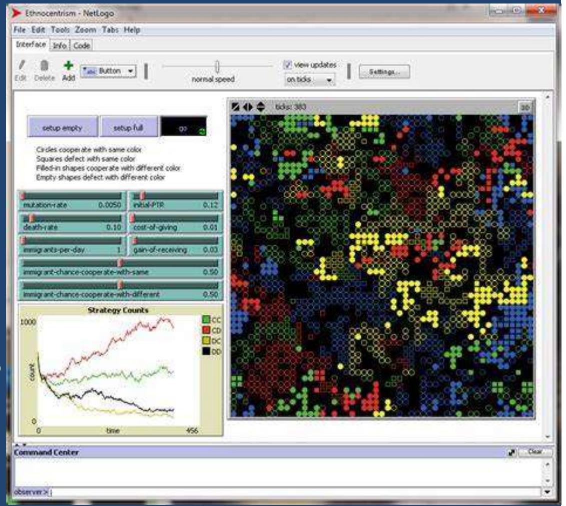
F. Squazzoni (ed.), *Advances in Social Simulation*, Springer Proceedings in Complexity,
https://doi.org/10.1007/978-3-031-34920-1_1

Renzini, Debernardi, Bianchi, Cremonini & Squazzoni (2023), The new frontiers of social simulation in the data science era, in Squazzoni (Ed.), *Advances in Social Simulation*, Springer Verlag, Berlin.

An ABM is a computational model of interaction between heterogeneous agents embedded within given social structures (e.g., social networks, spatial neighbourhoods, markets), n which the dynamic consequences of individual behaviour on macro-level outcomes are studied

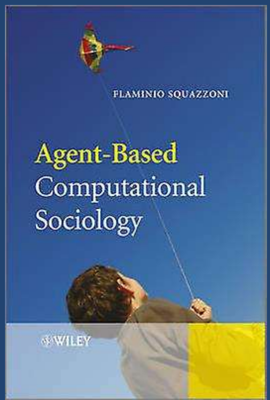


ABM can help us to examine the endogenous effects of initial conditions, stochasticity, and non-linear interactions on the aggregate social system properties and dynamics by performing experimental simulations on complex time-space scales

ABMs explain social dynamics by growing (reconstructing) them computationally via computer simulation

Behaviour

Belief/cognition feedback



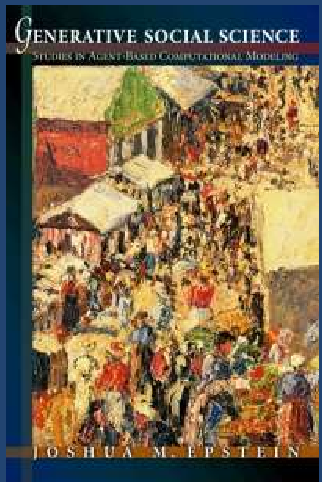
+ ➡ Dynamics

Structure-mediated feedback

Interaction

Squazzoni (2012) Agent-based computational sociology. Wiley, Hoboken, NJ.

The ABM epistemology: if you didn't grow it, you didn't explain it!



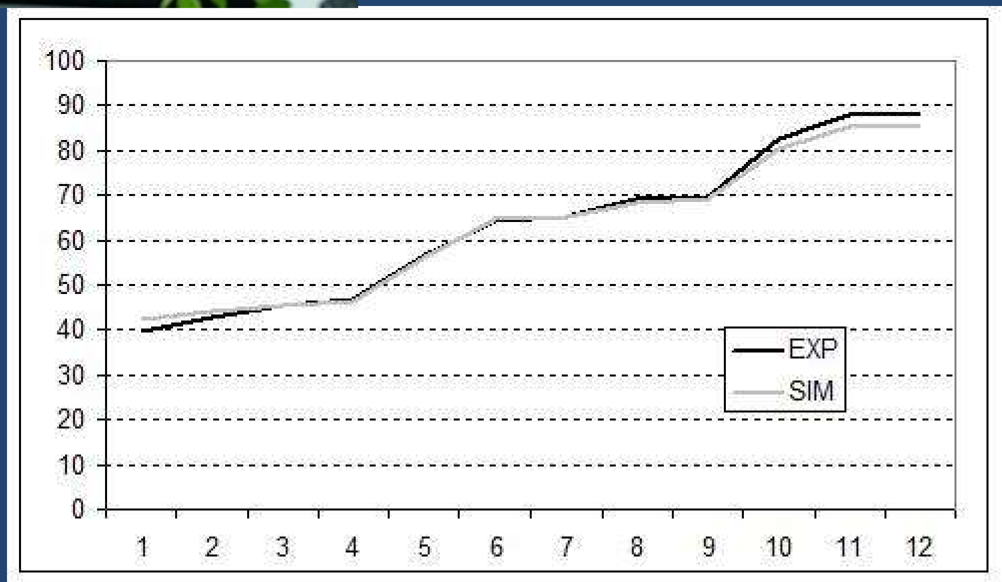


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Table 1. A comparison of four ABM frameworks covering objective categories focusing on ease of use, available functionality and performance. Colours represent implementation quality. Red: poor/none, Yellow: basic, Green: good, Blue: clear class leader. Further details corresponding to the superscript numbers are given in the main text.

	Agents.jl 4.2	Mesa 0.8	NetLogo 6.2	Mason 20.0
	Objective property comparisons.			
Core	Core design decisions and aspects that cannot be changed or implemented by users			
Continuous Space	Yes	Yes	Yes	Yes
Graph Space	Yes, and mutable	Only undirectional	Link Agents (not a Space)	Networks (not a Space)
Grid Space	Yes	Yes (+Hexagonal)	Yes	Yes (+Hexagonal, Triangular)
OpenStreetMap Space	Yes	No	No	No
Dimensionality	Any[1]	2D	2D & 3D (separate applications)	2D & 3D (complicated install for 3D)
License permissiveness	MIT	Apache v2.0	GPL v2	Academic Free License
Mixed-agent models	Yes	Yes	Yes	Yes
Simulation termination	After 'n' steps or user-provided boolean condition of model state	Explicitly written user loop	Manually by pressing a button on the interface, stop command in code	When Schedule is empty, or user provided custom finish function

https://faculty.sites.iastate.edu/tesfatsi/archive/tesfatsi/ace.htm

Counterfactual scenarios with ABM

Social Networks 34 (2012) 481–492

Contents lists available at SciVerse ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Trust and partner selection in social networks: An experimentally grounded model

Giangiacomo Bravo[a,*], Flaminio Squazzoni[b], Riccardo Boero[c]

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[c] Dipartimento di Science Economiche e Finanziarie "G. Prato", Università degli Studi di Torino, and GECS-Research Group in Experimental and Computational Sociology, Italy

Model name	Main characteristics
experimentLike	• Random coupling in each period • One way interaction
twoWays	• Random coupling in each period • Two way interaction
fixedCouples	• Fixed couples • Two way interaction
denseNetwork	• Fixed fully connected network • Two way interaction
smallWorld	• Fixed small-world network • Two way interaction
scaleFree	• Fixed scale-free network • Two way interaction
dynamic1Couples	• Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from random coupling
dynamic1Dense	• Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from dense network
dynamic2Couples	• Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from random coupling
dynamic2k10	• Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from a regular network of degree 10

Experiment replication

Varying initial conditions: matching rules and network topologies

Threshold happiness function tested in different initial network configurations

Compare baseline (the replicated experiment and simulation scenarios)

Bravo, Boero & Squazzoni (2012) Trust and partner selection in social networks: An experimentally grounded model. Social Networks, 34(4), 481-492

Trust and cooperation among subjects interacting in random networks in the lab

Table 1
Average investment and returns by treatment in the first experiment. Standard deviations are in parenthesis.

	A investment (ECU)	*B* return (ECU)
Baseline rounds (all groups)	3.91 (2.67)	3.88 (4.46)

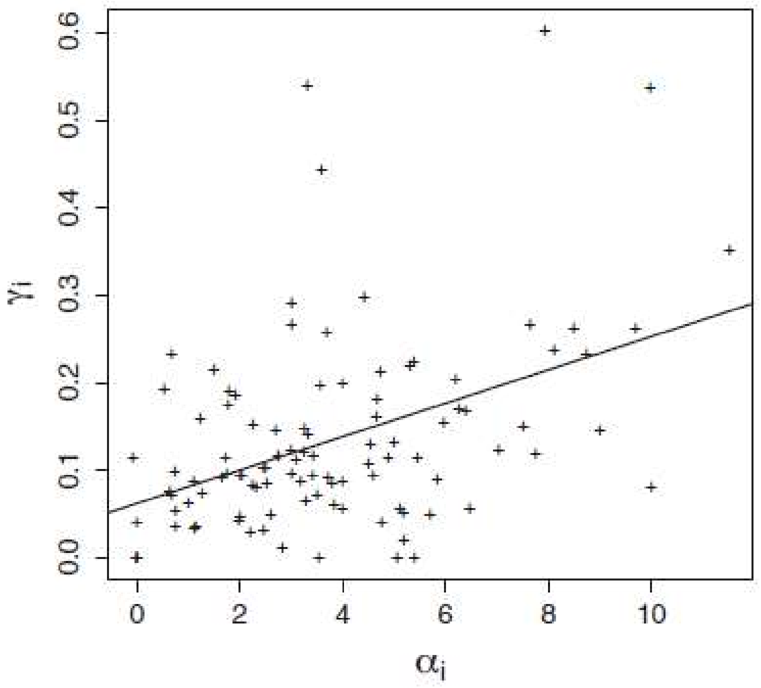


Fig. 3. Distribution of α_i and γ_i with regression line.

Bravo, Boero & Squazzoni (2012) Trust and partner selection in social networks: An experimentally grounded model. Social Networks, 34(4), 481-492

Varying network topologies and adding network dynamics

Model name		Main characteristics
experimentLike	Replication	• Random coupling in each period • One way interaction
twoWays		• Random coupling in each period • Two way interaction
fixedCouples		• Fixed couples • Two way interaction
denseNetwork	Varying initial conditions	• Fixed fully connected network • Two way interaction
smallWorld		• Fixed small-world network • Two way interaction
scaleFree		• Fixed scale-free network • Two way interaction
dynamic1Couples	Ties creation/breaking up	• Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from random coupling
dynamic1Dense	Varying initial conditions	• Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from dense network
dynamic2Couples	Tie replacement	• Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from random coupling
dynamic2k10		• Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from a regular network of degree 10

ABM multi-level validation

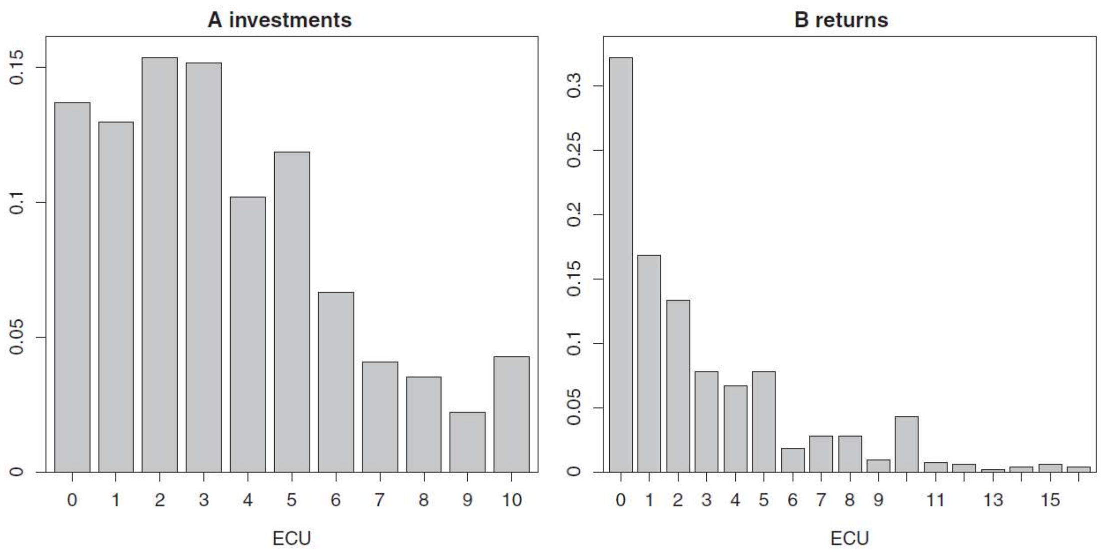


Fig. 2. Distribution of investments and returns in the experiment.

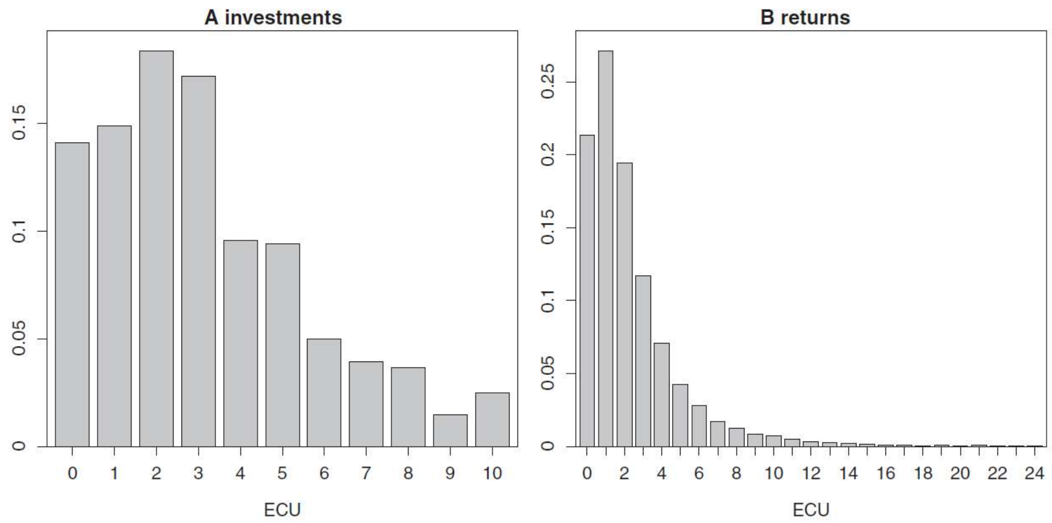


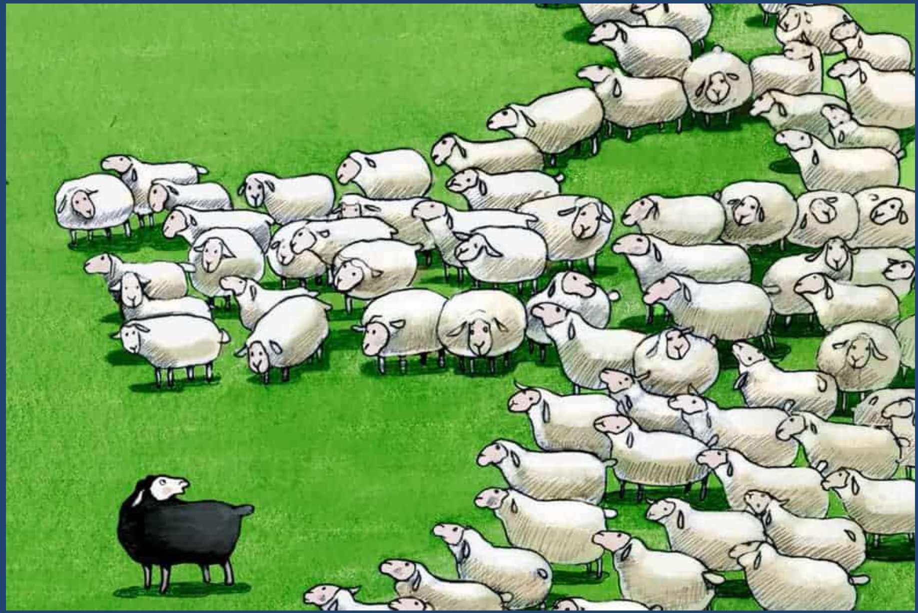
Fig. 4. Distribution of investments and returns in the *experimentLike* model.

We reproduced the same aggregate dynamics of the experiment by varying the initial conditions (i.e. network topologies, the number of rounds and simultaneous two-way decisions).

Table 2
Average investments and returns in the original experiment and in the static network simulation scenarios. Standard deviations are in parenthesis.

Model name	10 period game		30 period game	
	A investments	*B* returns	*A* investments	*B* returns
experimentLike	3.57 (2.50)	2.76 (2.62)	3.56 (2.53)	2.76 (2.63)
twoWays	3.57 (2.52)	2.76 (2.61)	3.57 (2.54)	2.76 (2.61)
fixedCouples	3.65 (2.53)	2.91 (3.13)	3.67 (2.56)	2.92 (3.17)
denseNetwork	3.57 (2.54)	2.76 (2.61)	3.57 (2.54)	2.76 (2.61)
smallWorld	3.58 (2.54)	2.76 (2.62)	3.57 (2.54)	2.76 (2.62)
scaleFree	3.61 (2.54)	2.80 (2.68)	3.61 (2.54)	2.80 (2.69)
Experiment	3.48 (2.69)	2.79 (3.58)	–	–

Cooperation increased when we allowed one of the broken links not to be replaced



	Period 1–10		Period 11–20		Period 21–30	
Model name	*A* invest.	*B* returns	*A* invest.	*B* returns	*A* invest.	*B* returns
dynamic1Couples	3.65 (2.58)	2.92 (2.96)	3.67 (2.60)	2.95 (2.90)	3.68 (2.62)	2.96 (2.93)
dynamic1Dense	3.79 (2.67)	**3.32** (3.20)	3.66 (2.60)	2.96 (2.96)	3.68 (2.62)	2.97 (2.94)
dynamic2Couples	3.82 (2.68)	**3.37** (3.42)	**4.48** (3.01)	**5.02** (4.50)	**4.63** (3.11)	**5.58** (5.12)
dynamic2k10	**4.11** (2.82)	**4.00** (3.59)	**4.43** (3.01)	**4.85** (4.30)	**4.49** (3.04)	**5.02** (4.50)
Experiment	3.48 (2.69)	2.79 (3.58)	–	–	–	–

Table 4: Average investments and returns in the original experiment and in the dynamic network models. Standard deviations are in parenthesis. Averages significantly different (at the 10% level) from the experimental ones are marked in bold.

Network concentration

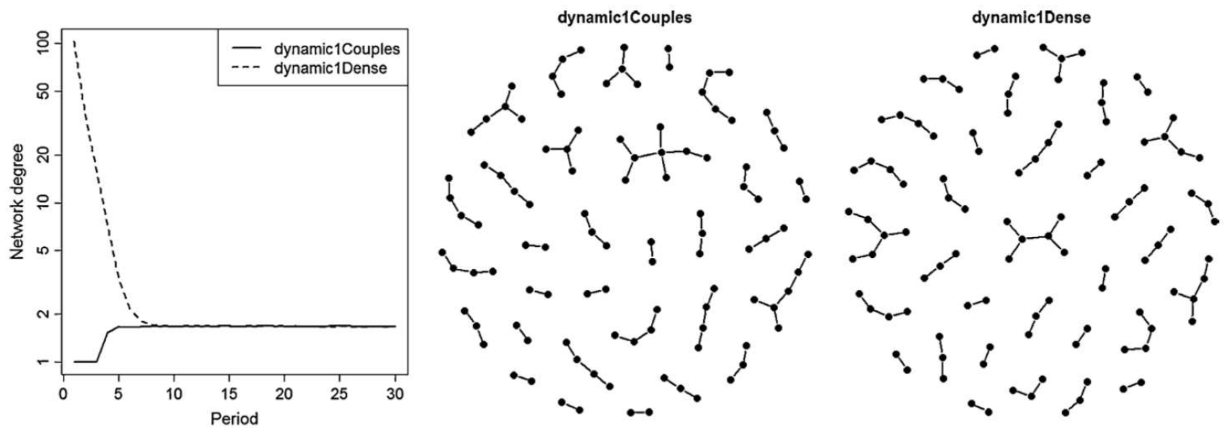
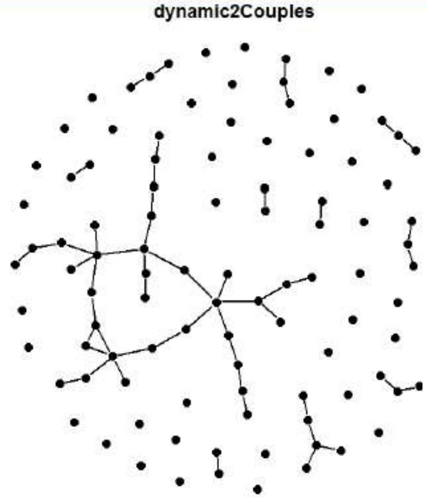


Fig. 5. The system resulting from the *dynamic1* models converged to a fixed equilibrium independently from the starting point. The left panel shows the average degree of the networks in the two models. The center and the right panels show the networks after 30 rounds of a typical run of the *dynamic1Couples* and the *dynamic1Dense* model, respectively.



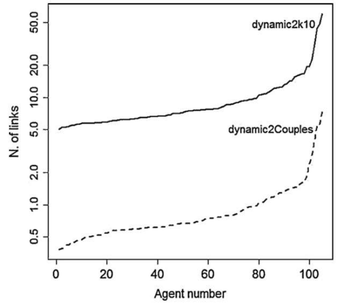


Fig. 7. Average number of links per agent in the *dynamic2Couples* and *dynamic2k10* models.

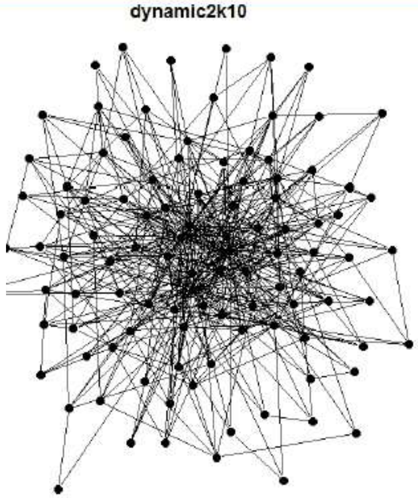


Figure 4: Networks resulting after 30 periods of a typical run of the *dynamic2Couples* model (left) and of the *dynamic2k10* model (right).

What have I learnt?

Using ABMs to perform robustness tests on experimental results by varying parameters that are hardly testable experimentally (e.g. the magnitude and timescale of interactions, initial network configurations, tie selection)

Performing counterfactual analysis on network structures and dynamics

Was the 'new' social structure, which grew endogenously in the simulation, potentially 'present' or 'latent' in the laboratory? Did we 'isolate a signal' in a flux of data?

Exploring the generalisation of experimental findings in an un-excluded 'out of the lab'/'out of real life' setting

The challenge of understanding network formation and dynamics in competitive environments

Article

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Representing Micro–Macro Linkages by Actor-based Dynamic Network Models

Tom A. B. Snijders[1,2] and Christian E. G. Steglich[2]

Abstract

Stochastic actor-based models for network dynamics have the primary aim o statistical inference about processes of network change, but may be regardec as a kind of agent-based models. Similar to many other agent-based models they are based on local rules for actor behavior. Different from many othe agent-based models, by including elements of generalized linear statistica models they aim to be realistic detailed representations of network dynamic in empirical data sets. Statistical parallels to micro–macro considerations car be found in the estimation of parameters determining local actor behavio from empirical data, and the assessment of goodness of fit from the corre spondence with network-level descriptives. This article studies severa network-level consequences of dynamic actor-based models applied to rep resent cross-sectional network data. Two examples illustrate how network level characteristics can be obtained as emergent features implied by micro specifications of actor-based models.

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Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model

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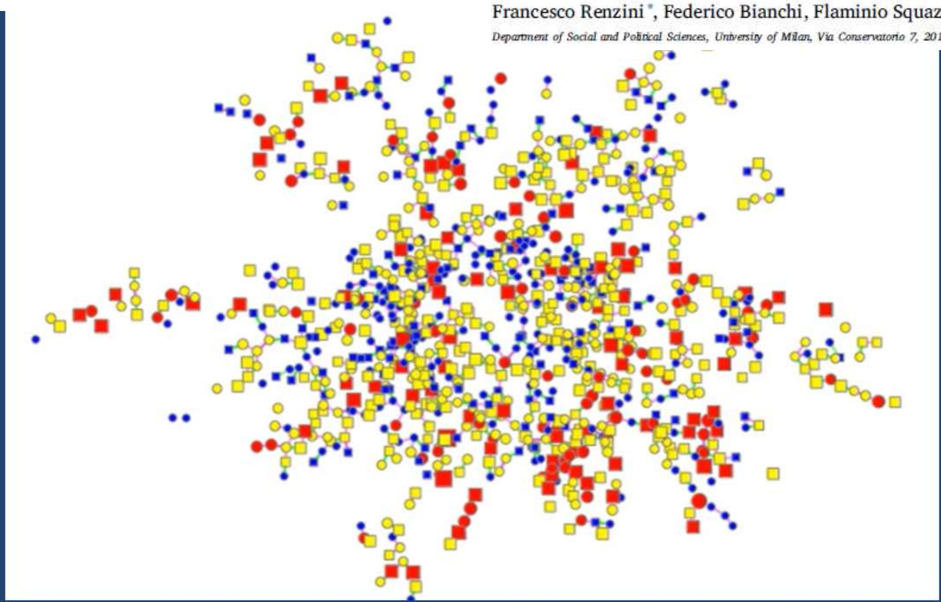
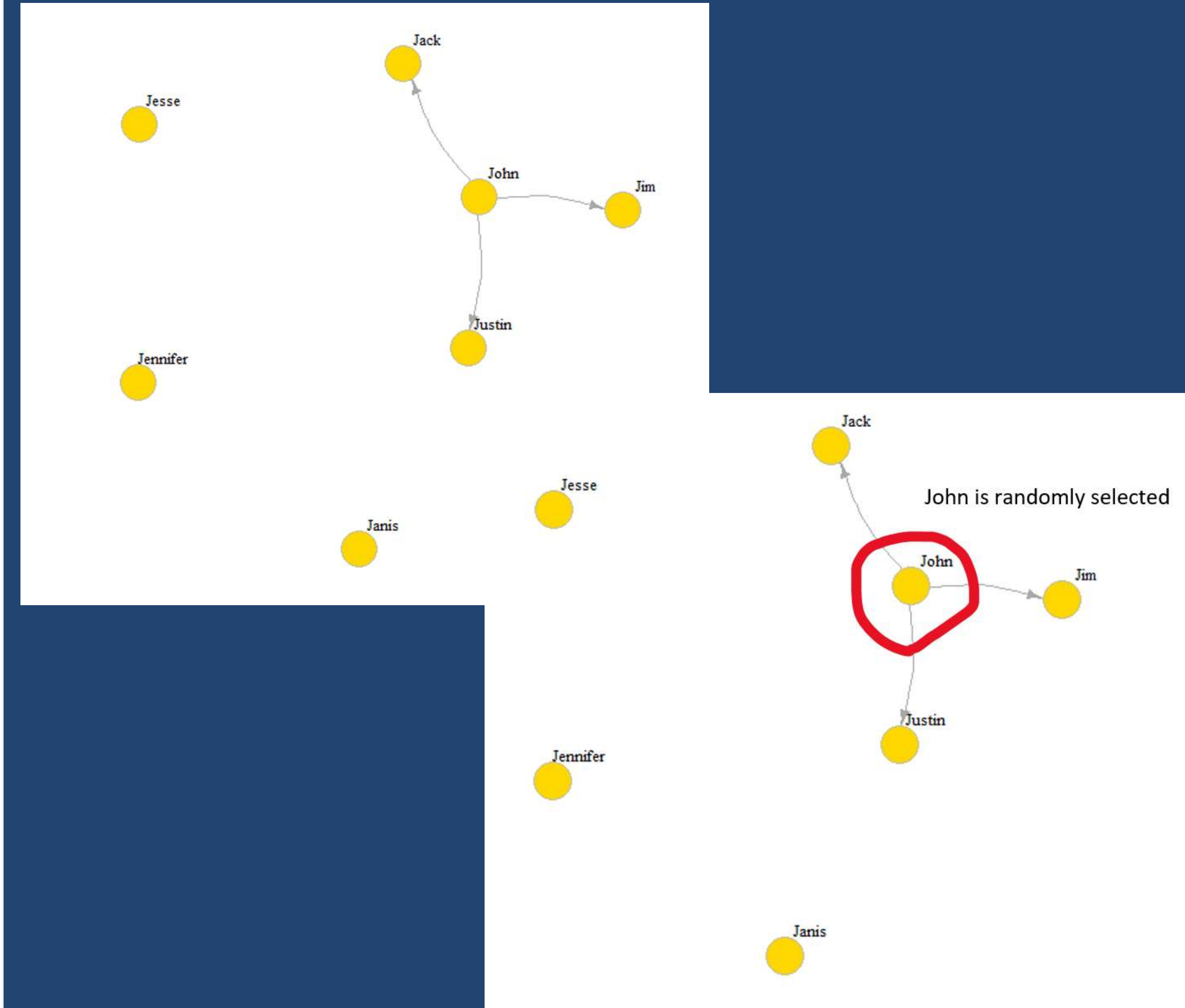
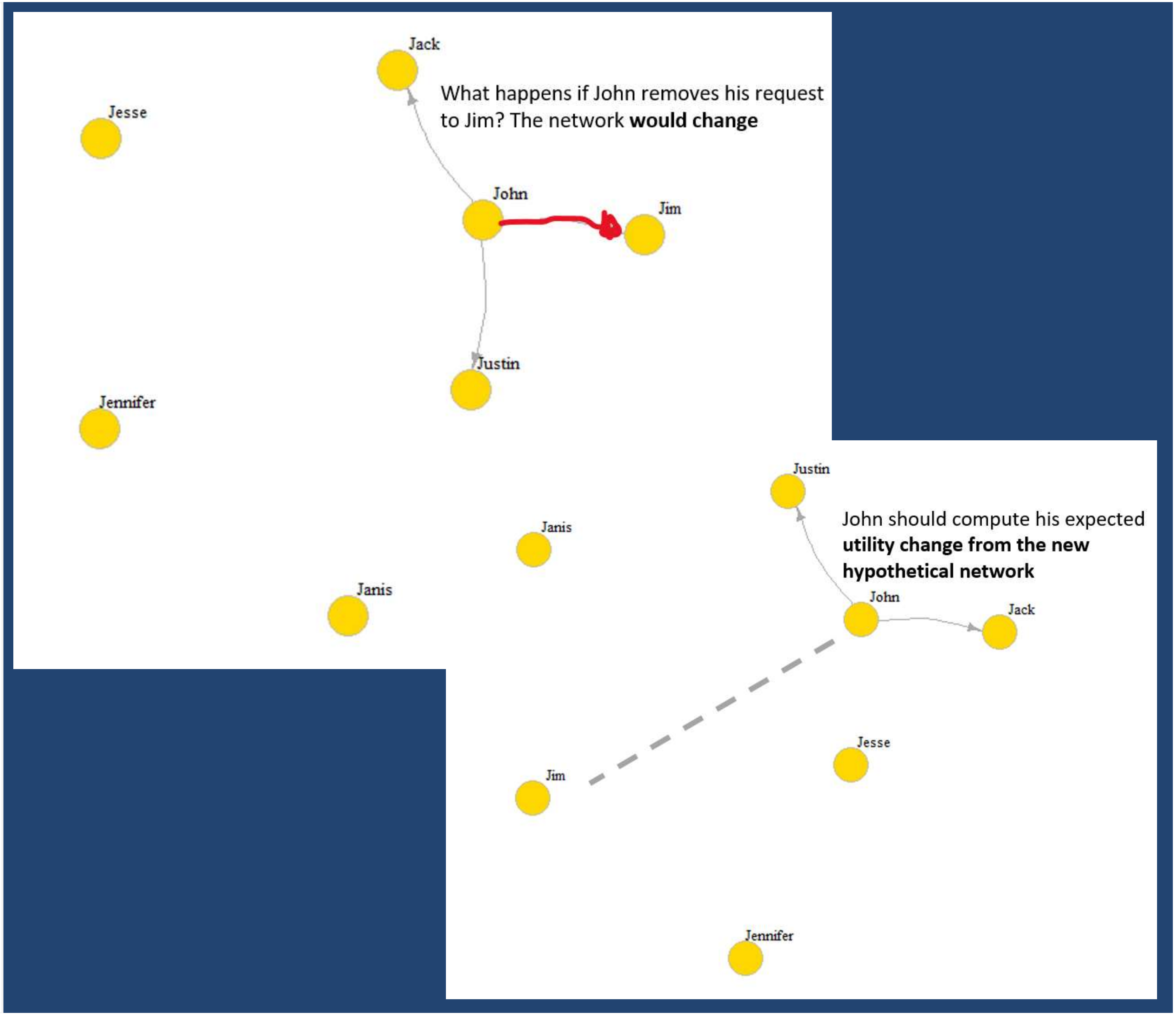
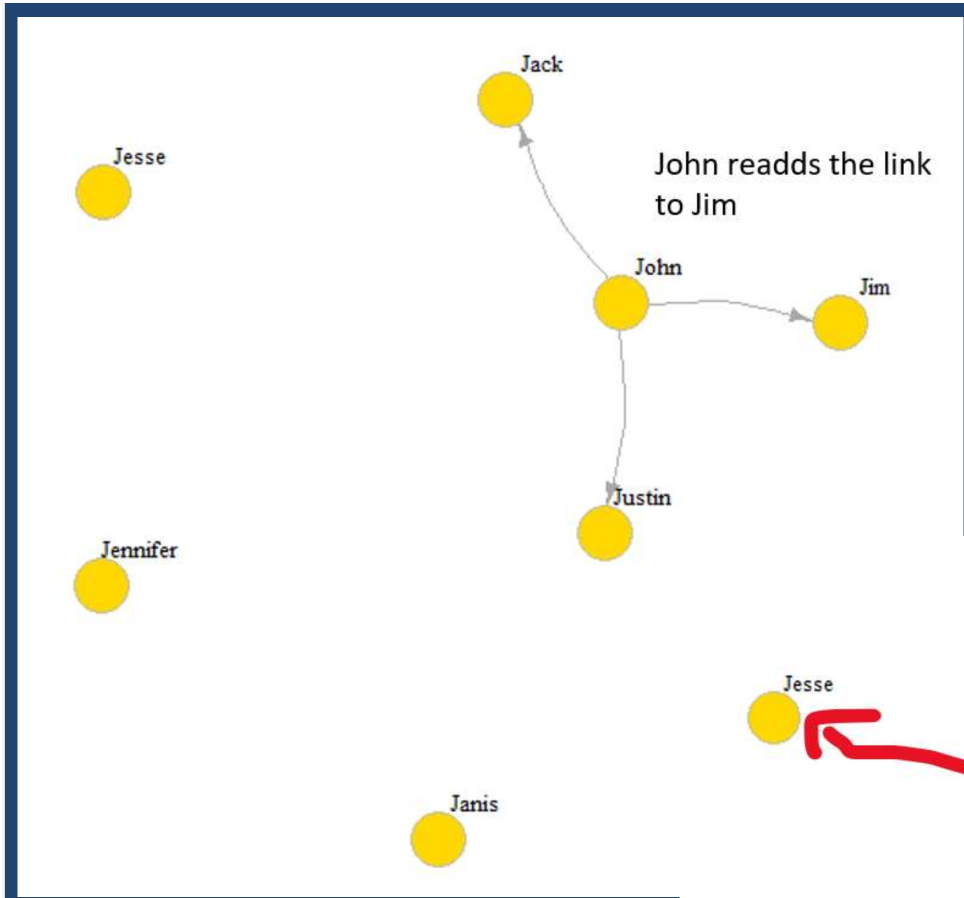
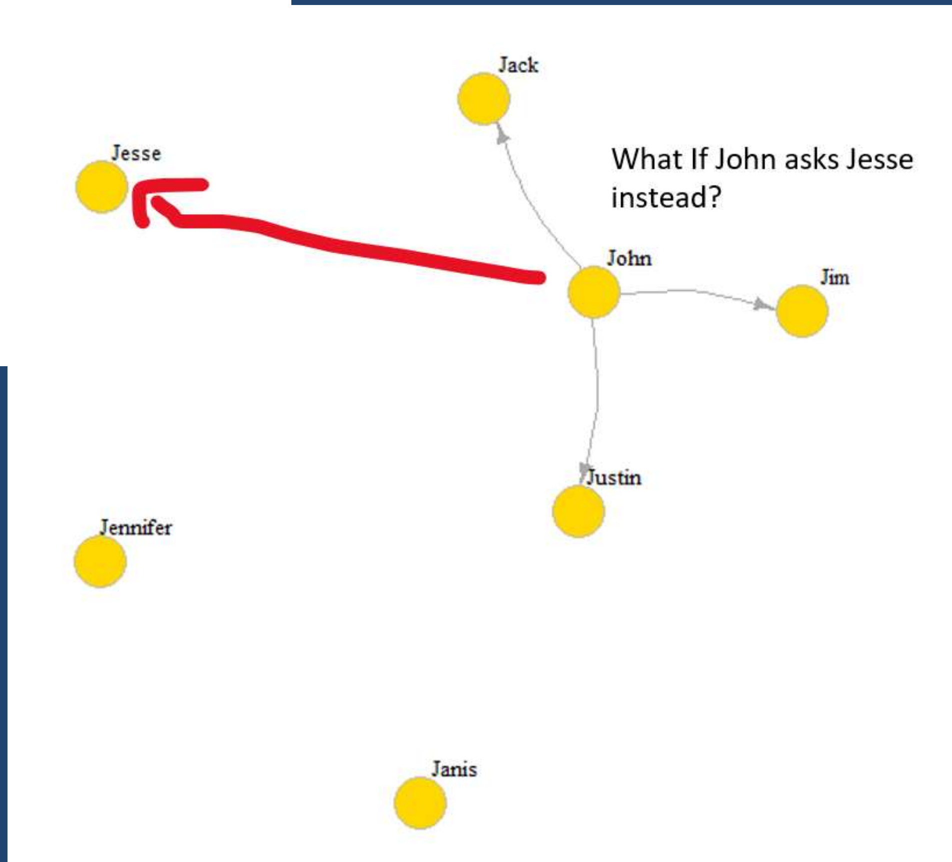


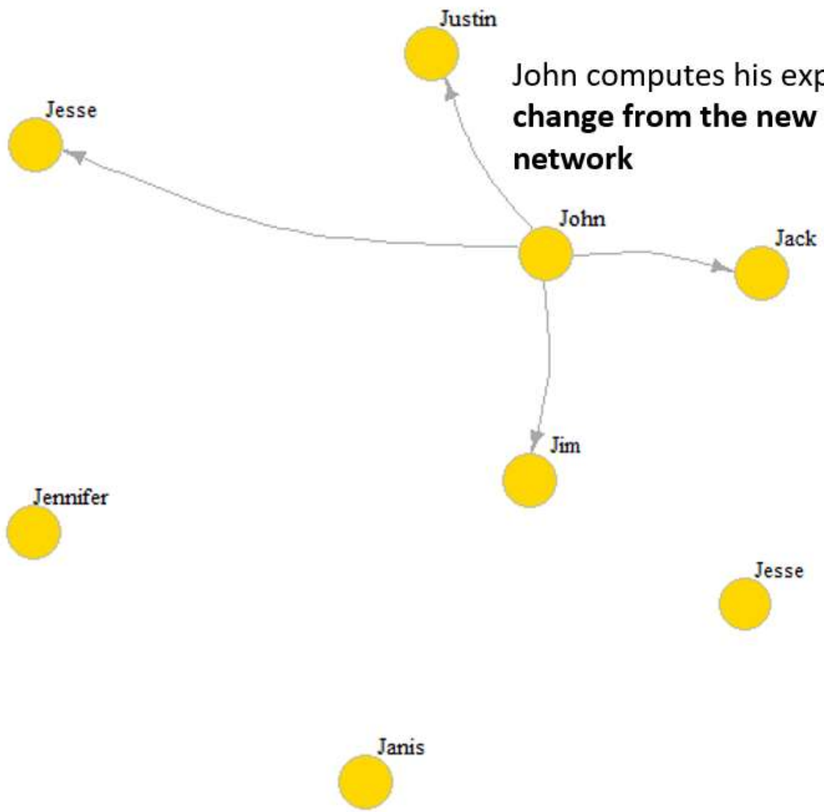

Jack
Jesse
John
Jim
Justin
Jennifer
Janis
Jesse
Jack
John is randomly selected
John
Jim
Justin
Jennifer
Janis



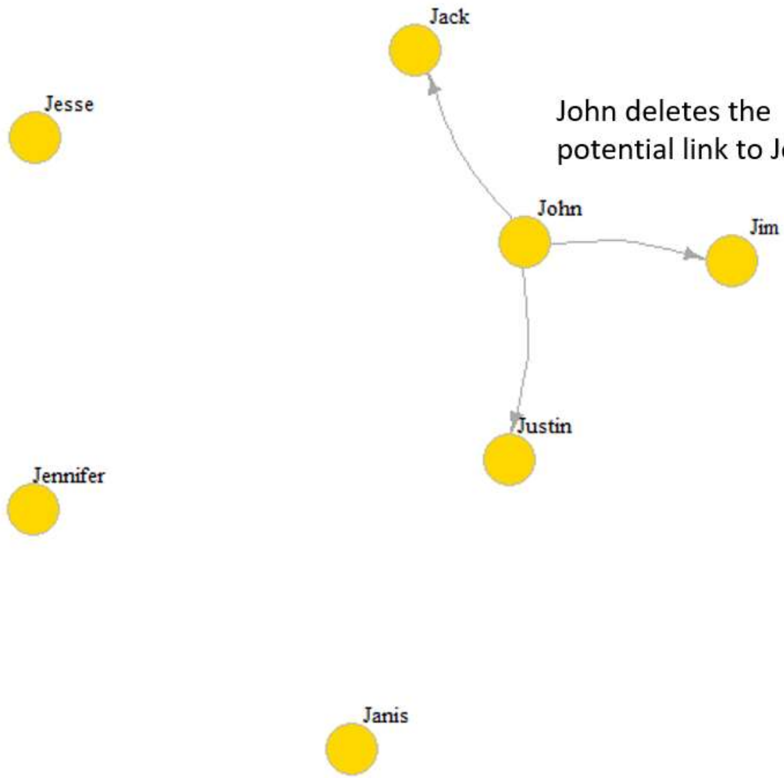
What happens if John removes his request to Jim? The network **would change**
Jack
Jesse
John
Jim
Justin
Jennifer
Janis
Janis
John should compute his expected **utility change from the new hypothetical network**
Justin
John
Jack
Jesse
Jim
Jennifer


Jack
Jesse
John readds the link
to Jim
John
Jim
Justin
Jennifer
Janis

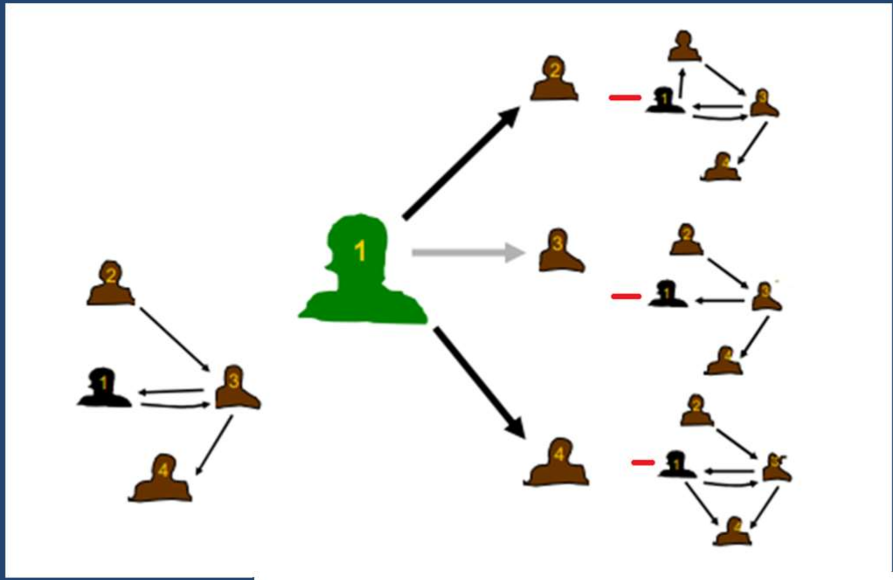

Jack
What If John asks Jesse
instead?
Jesse
John
Jim
Justin
Jennifer
Janis

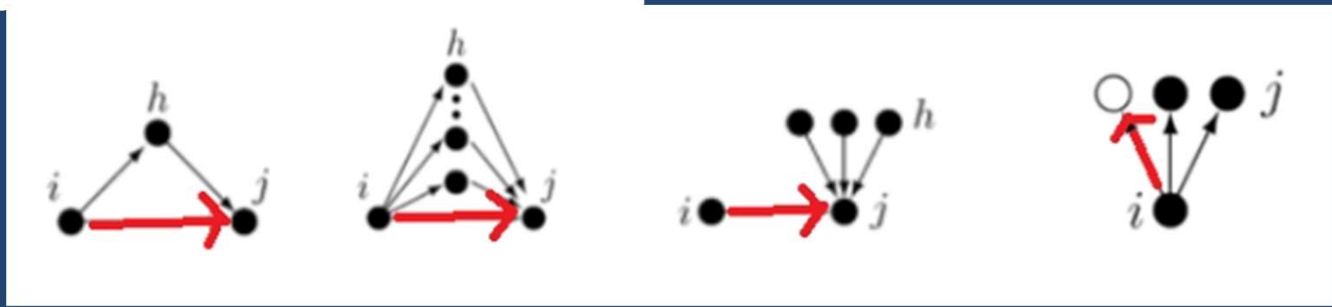


John computes his expected **utility change from the new hypothetical network**



John deletes the potential link to Jesse





A **rate function** determines the probability of each node to change its ties (e.g., uniformly distributed)

Local network configurations reveal micro individual preferences (e.g., homophily attributes, popularity, reciprocity, triadic closure)

These configurations are weighted by an **objective function** that agents maximizes by choosing ties (maintain, breaking, creating new links): **empirically inferred network dynamics are used to estimate agent preferences among *n* potential network configurations with complete network information**

Simultaneous network updates

Table 6. Descriptives for Advice Network Between Lazega' Lawyers.

Number of actors, n	71
Average degree, $\bar{d}$	12.6
Proportion of ties being reciprocated, r	0.39
Largest component size, C_1	71
Number of components, N_C	1
Diameter, D_1	3
Median geodesic distance, $G_{0.5}$	2
Transitivity, T	0.44
Scaled in-degree variance, $\tilde{V}_{in}$	5.62
Scaled out-degree variance, $\tilde{V}_{out}$	4.10
Correlation in- and out-degrees, $r_{in,out}$	0.14
Graph hierarchy, H	0.16
Least upper boundedness, L	1.00

Table 11. Model 5 for Advice Relations: Including also the GWESP Representation of Transitive Closure.

Effect	Parameters	(*SE*)
Out-degree	−1.745	(0.168)
Reciprocity	1.054	(0.128)
Transitive triplets	0.121	(0.016)
Three cycles	−0.055	(0.028)
In-degree—popularity	−0.011	(0.008)
Out-degree—popularity	−0.062	(0.013)
Out-degree—activity	−0.021	(0.005)
GWESP ($\alpha = .69$)	2.045	(0.272)
Seniority receiver	−0.002	(0.003)
Seniority sender	0.009	(0.003)
Seniority similarity	1.110	(0.197)
Seniority of indirect ties	−0.004	(0.002)

Note: GWESP = geometrically weighted edgewise shared partners.

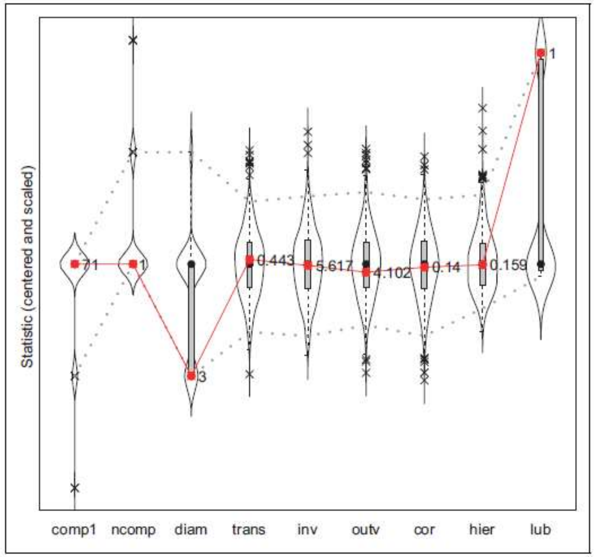


Figure 14. Distribution of macro features for advice network between Lazega's lawyers, model 5.

Agentizing SAOMs

Asking for advice can be costly (e.g., a demotion of status), and mapping the network space can be cognitively so demanding that heuristics are required

This involves adding high- and low-status professionals in an 80/20 distribution (which is poorly captured by Lazega’s seniority measures), group-level heterogeneous preferences and various levels of advice neediness.

High-status professionals should set a tolerability threshold τ for the number of advice requests due to cognitive overload, and tie re-direction should be introduced (exploration vs. exploitation as re-direction preferences)

++ Incomplete network information

++ Removing the constraints of sequential steps for tie selection/formation allows dynamical cascade effects to occur

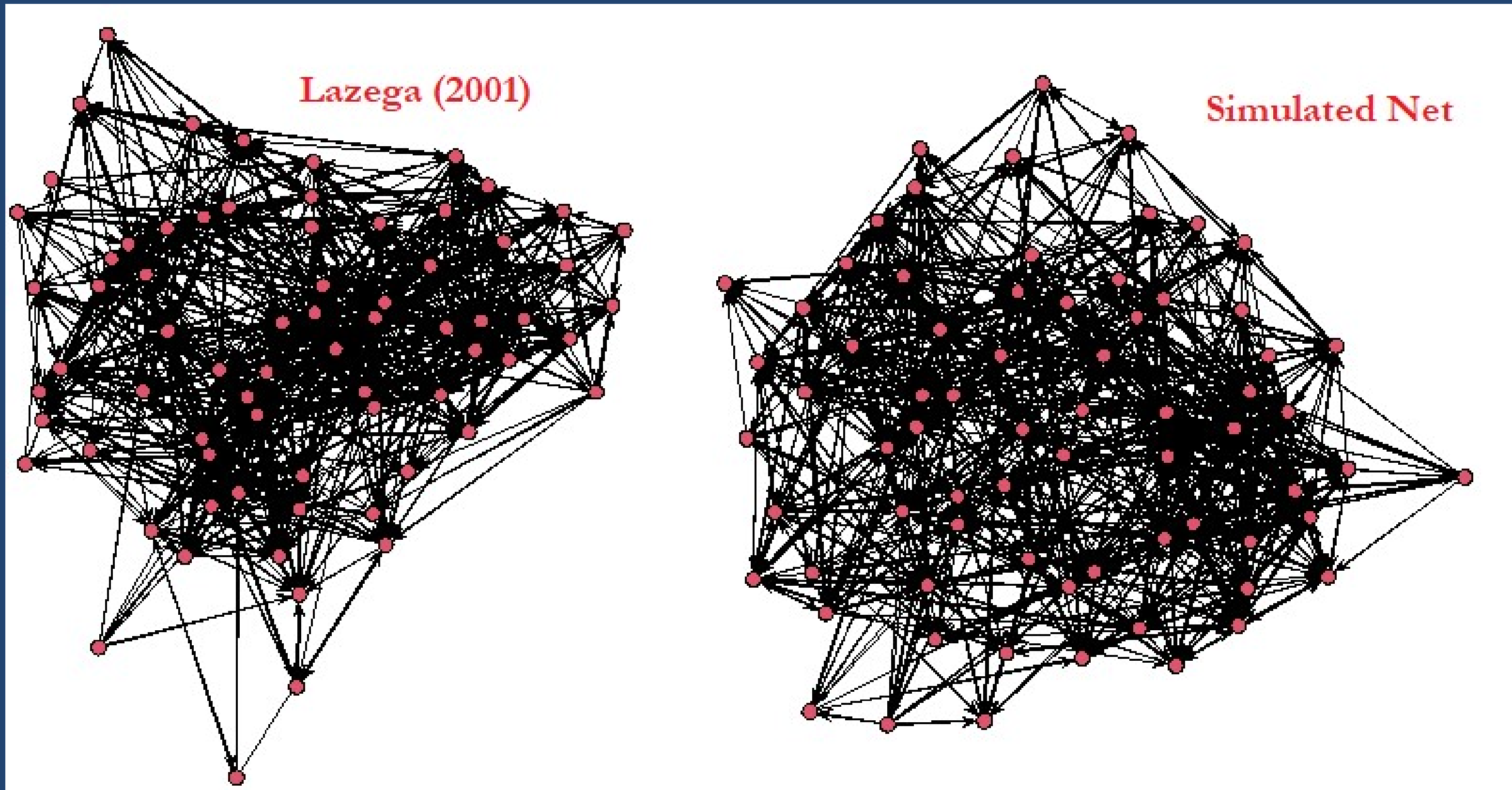
The hypothesis is that these assumptions could explain the two main drivers characterizing advice networks, i.e., centralization (few attractive high-skilled professionals overloaded) and density (many low-skilled who need advice)

Algorithm 2 Network formation from status preferences and cognitive overload

Require: $N > 0$ (number of agents); α (% of high-skilled agents); τ (cognitive overload threshold); $\beta_0^l, \beta_0^h, \beta_{attract}^l, \beta_{attract}^h, \beta_{EL}^l, \beta_{ER}^l, \epsilon$ (preferences and disturbance); T (number of iterations)

  $t \leftarrow 0$
  $G = (N, \emptyset)$ ▷ Initialize an empty network, with N nodes, agents
  Determine who is high-skilled from data (if available) or randomly
  Assign τ to high-skilled agents
  while $t \leq T$ **do**
    $i \leftarrow Rand(1, N)$ ▷ Randomly select an agent
    if i is **low-skilled** (l) **then**
      Evaluate $f_i^l(\boldsymbol{\beta}, X)$ for each $j \neq i$ and for the do-nothing case
      Pick j that maximizes $f_i^l(\boldsymbol{\beta}, X)$, also considering the do-nothing case
      if i asks to j and j is high-skilled and In-Degree $(j) > \tau$ **then**
        Remove and redirect between 1 and τ low-skilled asking to j
        for Every redirecting low-skilled **do**
          Evaluate low-skilled agents via third part of Equation 4
          Pick j that maximizes $f_i^l(\boldsymbol{\beta}, X)$, considering the do-nothing case
          Set x_{ij} to $x_{ij}^{\pm}$ in case best option is to add or remove a link
        end for
      end if
      Set x_{ij} to $x_{ij}^{\pm}$, in case best option is to add or remove a link
    end if
    if i is **high-skilled** (h) **then**
      Evaluate $f_i^h(\boldsymbol{\beta}, X)$ for each $j \neq i$ and for the do-nothing case
      Pick j that maximizes $f_i^h(\boldsymbol{\beta}, X)$, also considering the do-nothing case
      Set x_{ij} to $x_{ij}^{\pm}$, in case best option is to add or remove a link
    end if
    $t \leftarrow t + 1$
  end while

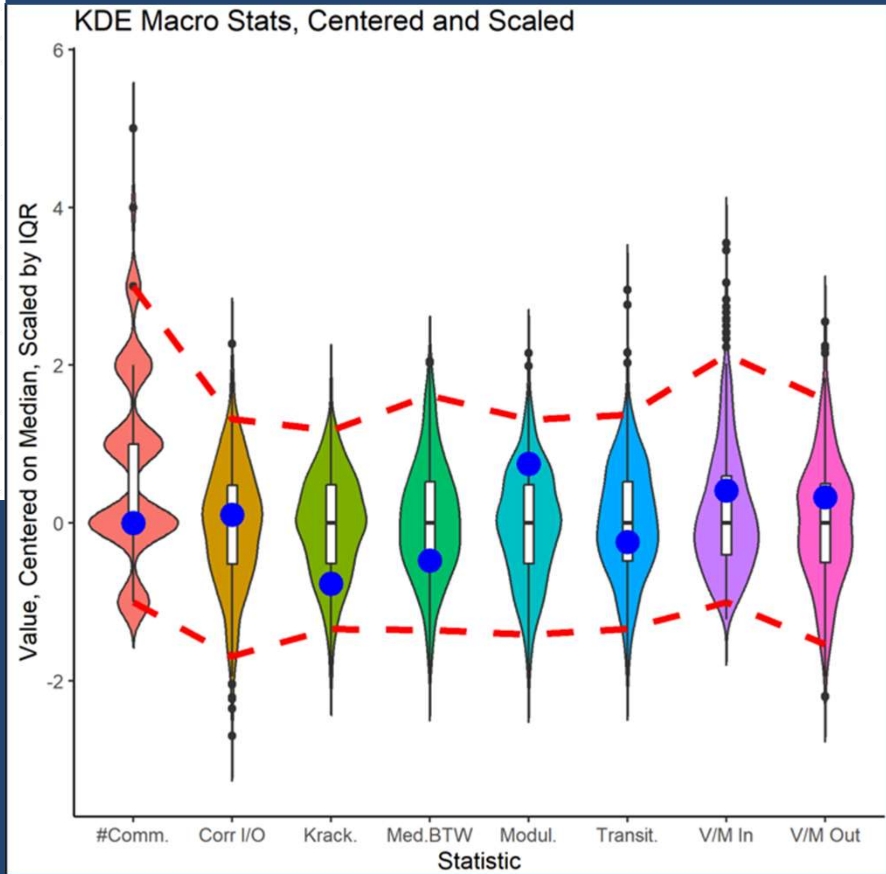
Fitting network outcomes to Lazega's data as in SAOM



Renzini, Bianchi & Squazzoni (2024) Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model. *Social Networks*, 76, 150-159

Reproducing all network metrics estimated by SAOM

Metric	Description
Scaled Variance In-Degree	Variance over the mean of in-degree distribution
Scaled Variance Out-Degree	Variance over the mean of out-degree distribution
Correlation InOut	Pearson correlation between in- and out-degree distributions
Transitivity Index	Number of transitively closed triplets ($i \to j \to k; i \to k$) divided by number of two-paths ($i \to j \to k$).
Diameter	Maximum among all shortest paths between any pair of nodes (i, j)
G50, Median Geodesic Distance	Median among all shortest paths between any pair of nodes (i, j)
Number (No) of Components	Number of fully connected subgraphs that do not belong to any larger connected subgraph
Size Largest Component	Number of agents in the largest connected subgraph
Number (No) of Communities	Number of cohesive sub-groups identified by Pons and Latapy (2005) algorithm
Modularity	Fraction of ties belonging to cohesive sub-groups identified by Pons and Latapy (2005) algorithm minus the expected fraction from the configuration model (Newman 2003)
Median BTW	Median of the distribution of betweenness centrality, normalized
Krackhardt Hierarchy Index	Measures the extent to which directed paths in the network run in one direction only



Renzini, Bianchi & Squazzoni (2024) Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model. *Social Networks*, 76, 150-159

Open model: https://github.com/ceco51/Status-cognitive-overload-and-incomplete-information-ABM

Model Documentation with Code-Snippets

`NetEvolution.py`

To understand the model in its inner workings "pedagogically", we should follow these steps.

First, download `NetEvolution.py` with all the associated libraries versions that are listed in file `requirements.txt`. Place them in the same folder/create an ad-hoc python virtual environment. Import `NetEvolution.py` module and create a `NetEvolution` object by specifying the relevant model parameters. The positional order of parameters is: N, α, τ, β^l_0, β^h_0, $\beta_{attract}$, β^l_{EL}, β^l_{ER}, ϵ (location and scale), ν (location and scale) and $change\ factor\ attract$. The class thus assumes that the first parameter is N, the number of agents, while the last

Languages

Python 67.5% R 32.5%

What have I learnt?

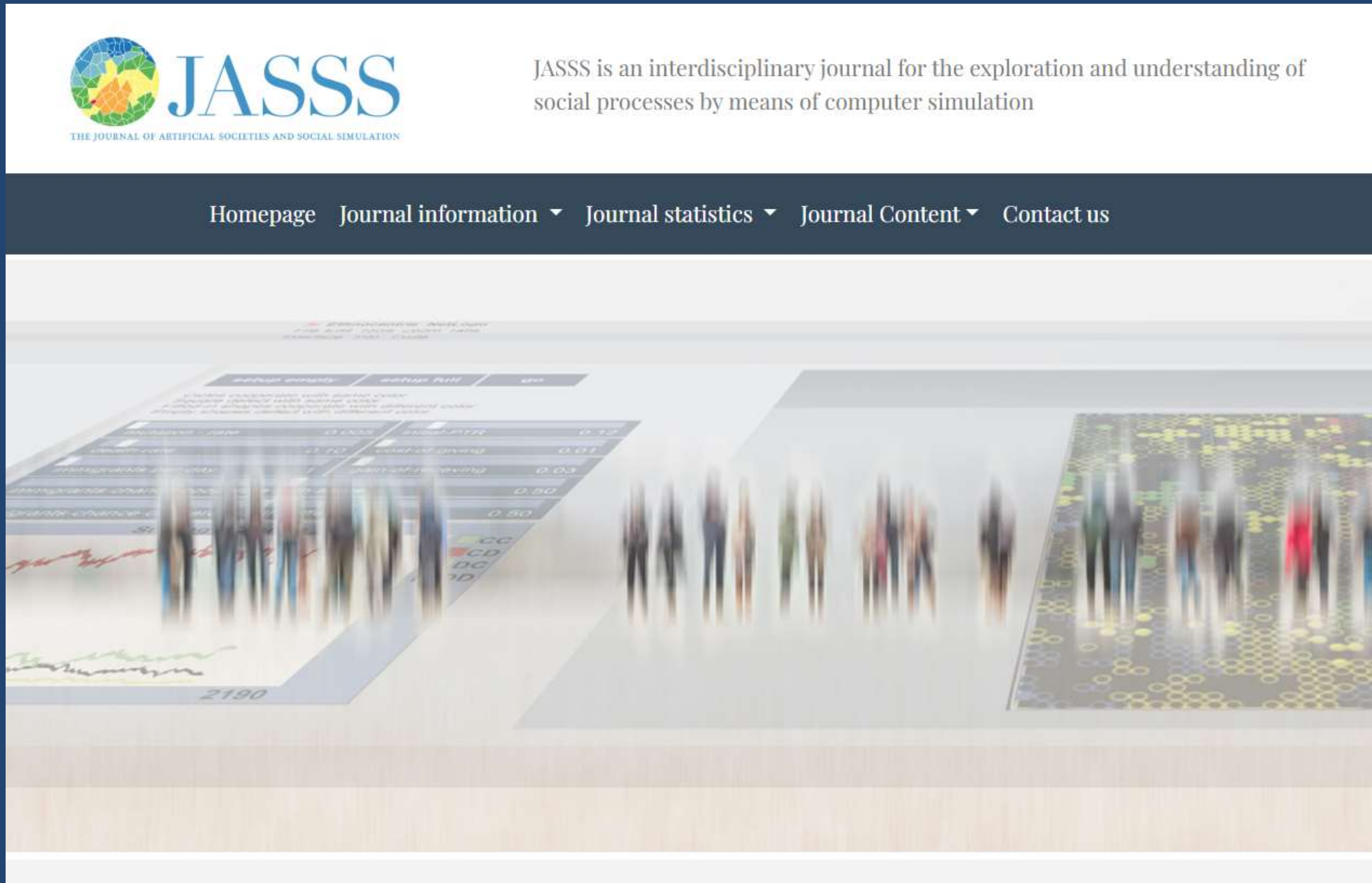
There will always be parameters that cannot be observed (e.g. τ). This is an unavoidable fact!

Providing a more theoretically consistent generative model of advise-seeking networks that explored alternative generative paths (heterogeneous status effects vs. network preferences)

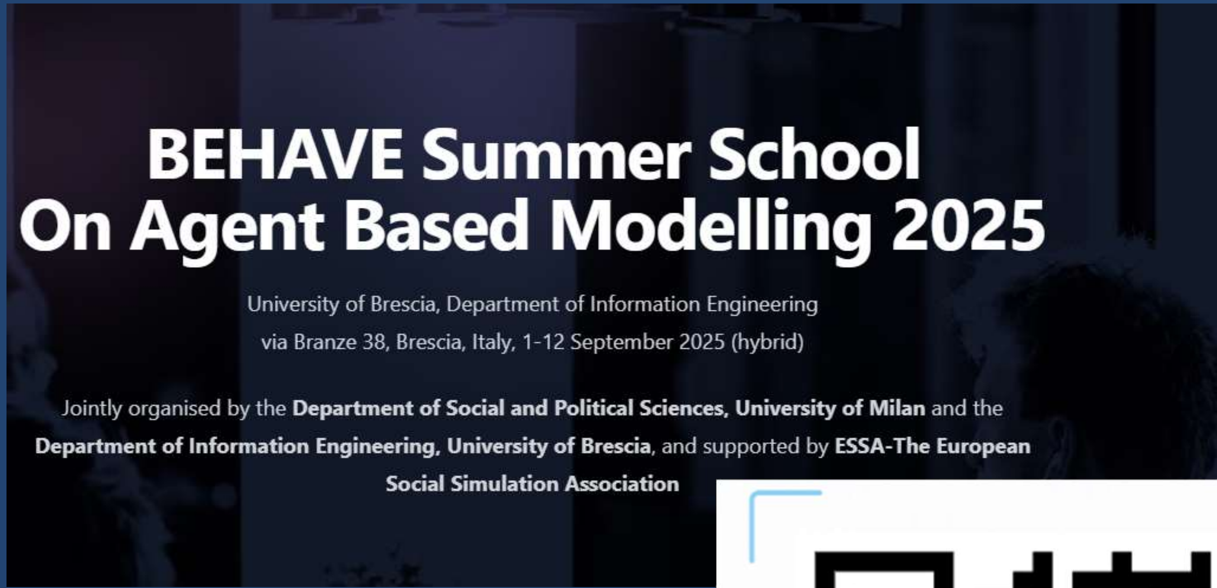
Mapping the behavioural mechanisms behind network formation and dynamics: network as outcomes, not only as “causes”

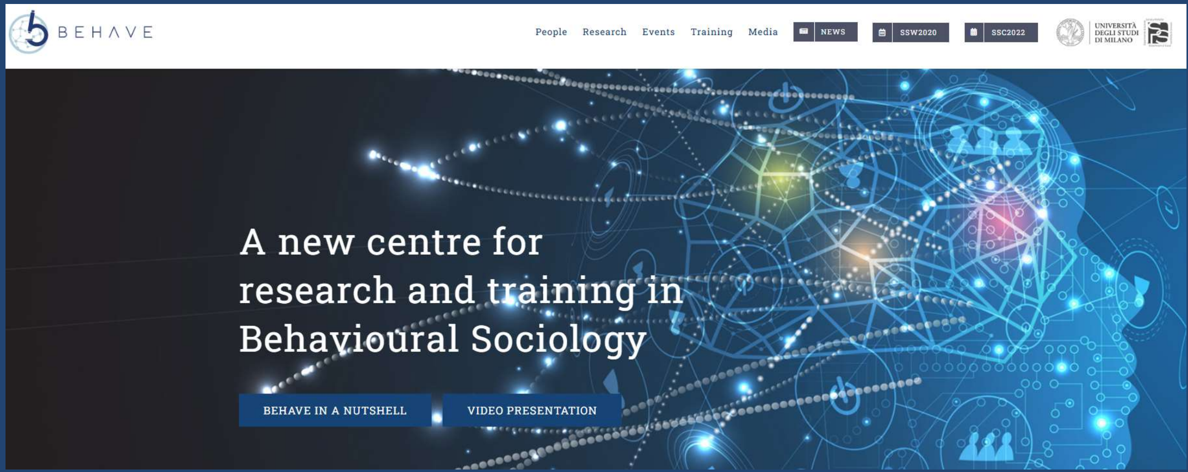
Showcasing a clear case of ‘multiple realizability’, which is often overlooked by inference-based statistical models

https://jasss.soc.surrey.ac.uk/JASSS.html



https://abmschool.behavelab.org





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