Combining *In Vitro* with *In Silico* Social Research

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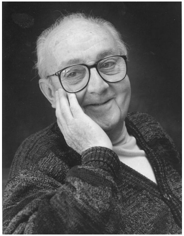
Overview

- What is agent based modeling?
  - Models in social science
  - Characteristics of ABMs
- Combining ABMs with empirical data
  - Segregation
  - Cooperation
  - (Inequality)

Modeling in Social Science

- In the social sciences, a model is a **mathematical abstraction or simplification** of a social process
- Modeling aims to **understand, quantify, or predict** the process
- Types
  - Statistical
  - Analytical
  - Agent based

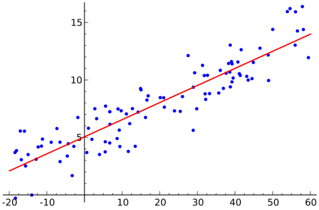


"All models are wrong but some are useful."
– George E. P. Box

Statistical models

- Based on empirical data
- Focus on mean values and average effects
- Estimate using statistical procedures
- May explain data but not necessarily process

$$\widehat{Y} = \alpha + \beta X$$



Analytical models

- Based on theoretical assumptions
- Focus on solving for equilibrium
- Solve using mathematics
- May explain process but not necessarily data

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	5, 5	0, 8
	Defect	8, 0	2, 2

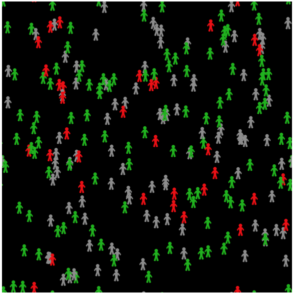
$x^* \in S$ is Nash equilibrium if

$$\forall i, x_i \in S_i: f_i(x_i^*, x_{-i}^*) \geq f_i(x_i, x_{-i}^*)$$

Agent based models

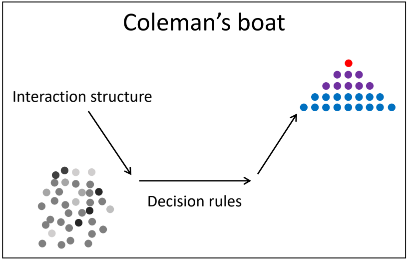
Use a computer program to create a number of "agents" with certain properties and rules of behavior and observe what happens as time passes

- Based on theoretical assumptions and/or empirical data
- Focus on simulating dynamics
- Simulate using computation



Elements of ABMs

- Numerous agents
- Decision rules
- Adaptive processes
  - E.g. learning, reproduction, movement
- Interaction structure
- Environment



- Randomness
  - Monte Carlo methods (Sample randomly → Compute results → Repeat → Aggregate)
  - Noise (errors)

Coleman (1994) *Foundations of Social Theory*. Harvard University Press.

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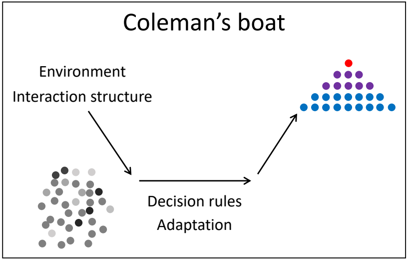

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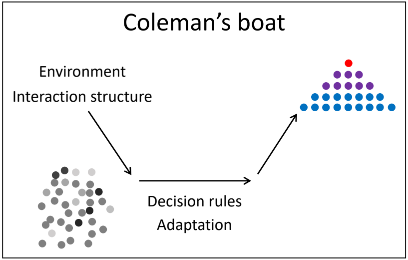

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  - Monte Carlo methods (Sample randomly → Compute results → Repeat → Aggregate)
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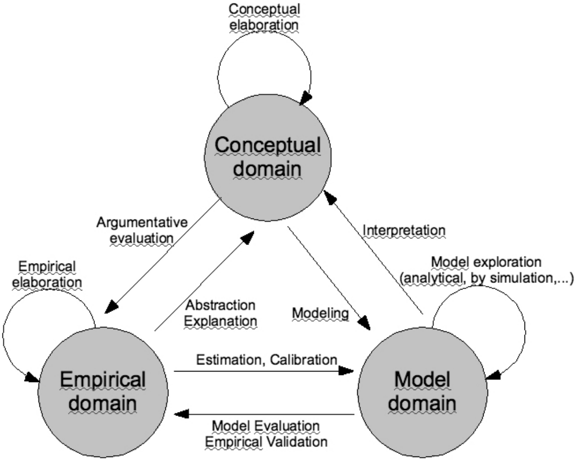
When are ABMs useful?

- To study complex adaptive systems
- To investigate how micro-level behavior leads to macro-level outcomes
  - **Complexity**: Model cannot be solved analytically
  - **Emergence/self-organization**: Macro outcome cannot be explained with the simple aggregation of micro behavior
  - **Chaos**: Similar micro behavior can produce wildly diverging macro outcomes
  - **Oscillation**: There is no equilibrium

Applications of ABMs

- Theory development
  - What are the macro outcomes from a set of empirically grounded behavioral assumptions?
  - What micro assumptions and mechanisms can generate an observed social phenomenon?
    - **Sufficient but not necessary explanations**
- Empirical predictions
  - Spread of epidemics
  - Evacuation of large venues
  - Traffic congestion in case of road closures

Relating ABMs to theory and data



Livet et al. (2010) Ontology, a mediator for agent-based modeling in social science, *JASSS*.

Relating ABMs to data

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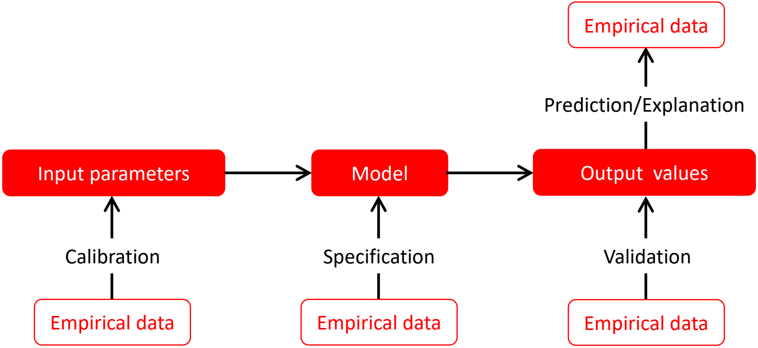

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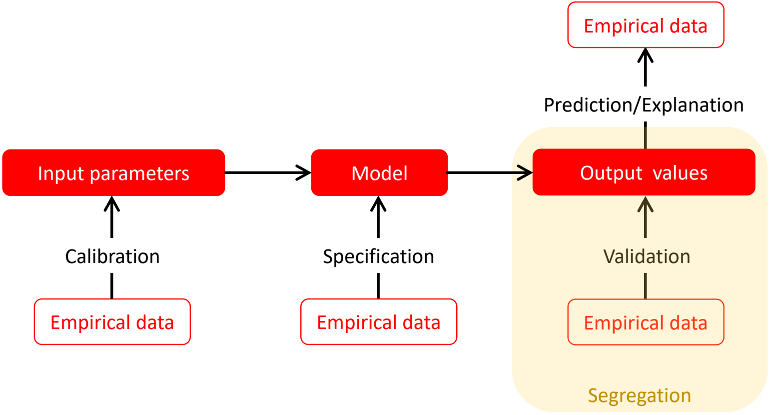

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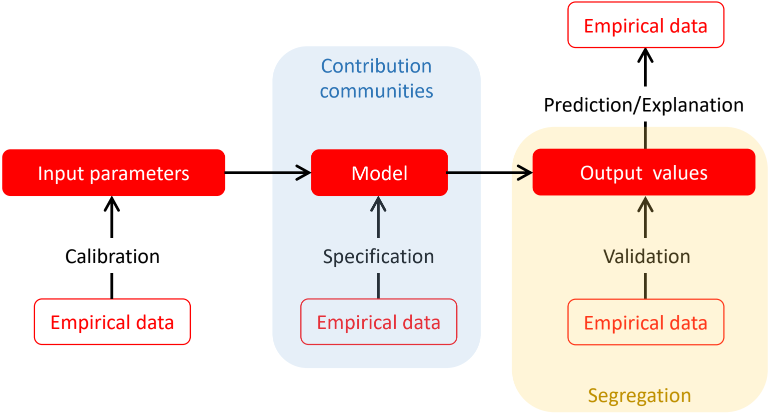

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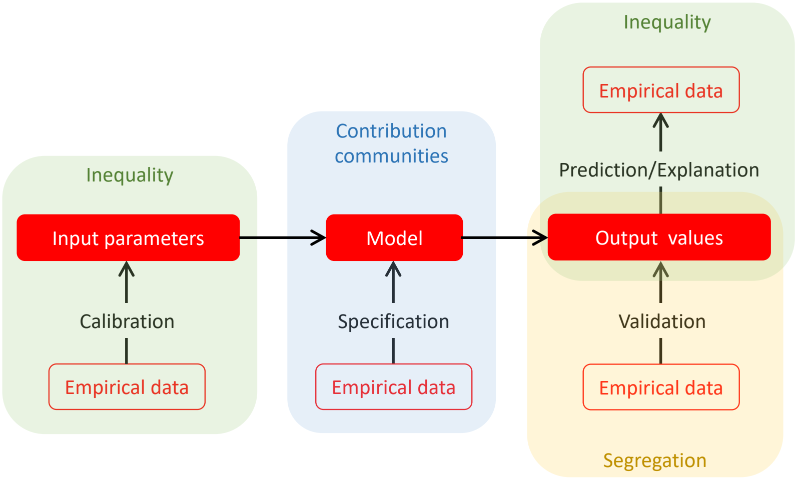
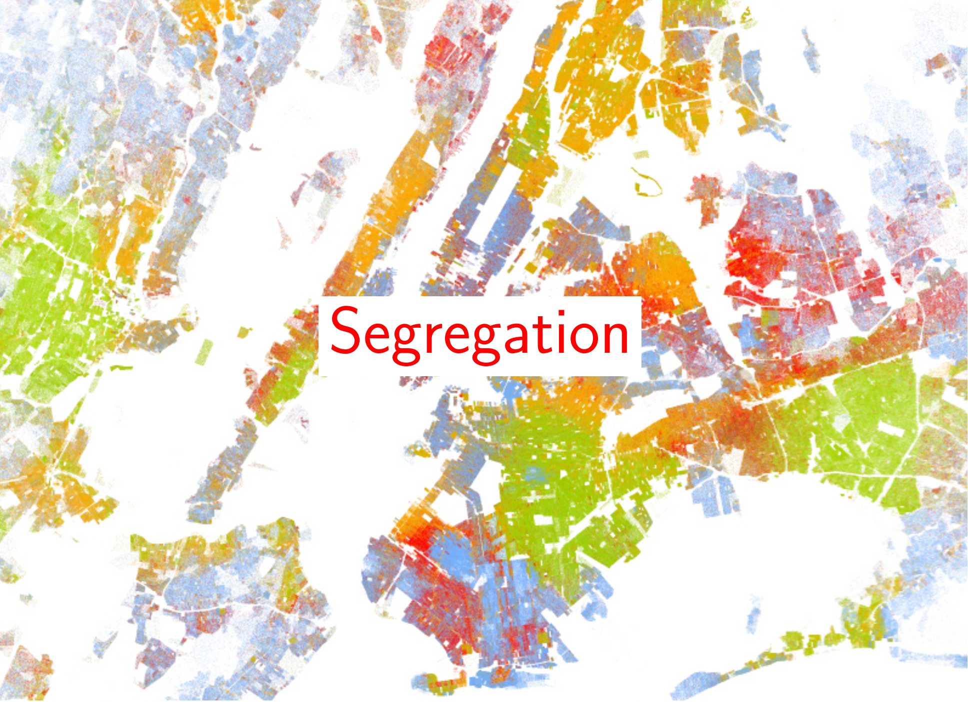


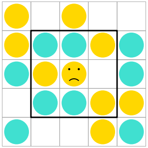
Segregation



https://demographics.coopercenter.org/racial-dot-map

The Schelling model of segregation

- Agents prefer similar neighbors, but only moderately
- If unsatisfied, they move to another location that makes them happy



- Cascades lead to more segregated outcome than what agents prefer

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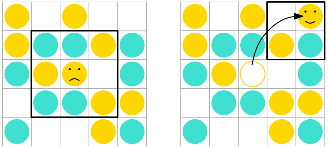

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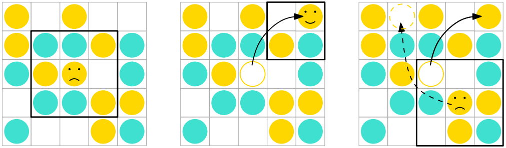

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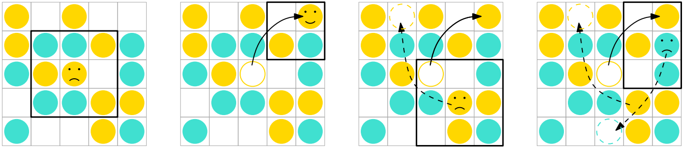

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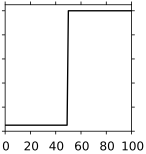
Diversity and segregation



- Even if people are tolerant, they will end up in a segregated world[1]

- Segregation may obtain even when people actively seek diversity. "Hence, public policies that promote tolerance are futile."[2]

1. Schelling (1971) Dynamic models of segregation, *Journal of Mathematical Sociology*.
2. Pancs & Vriend (2007) Schelling's spatial proximity model of segregation revisited, *Journal of Public Economics*.

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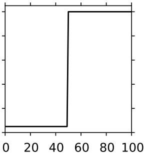

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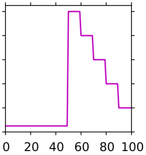

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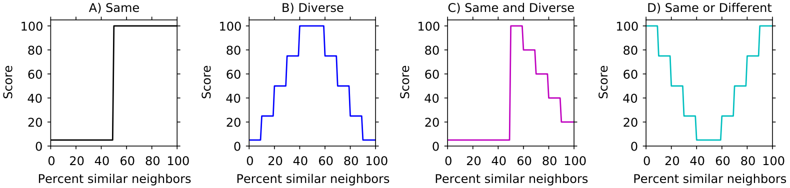
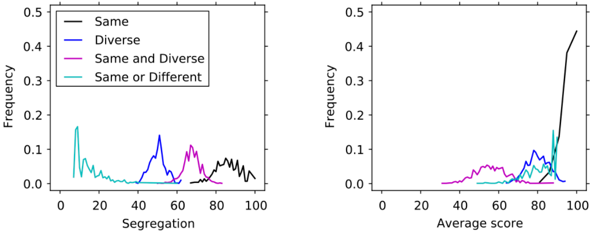
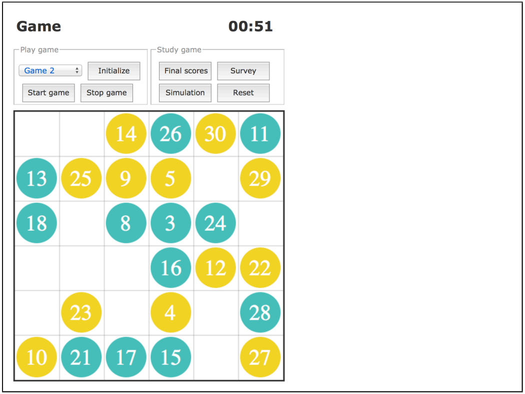
ABM: Segreg. even with pref. for diversity





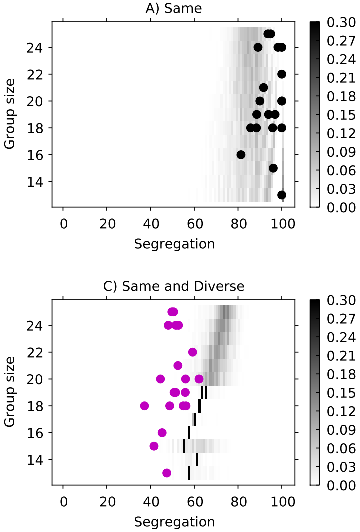
Tsvetkova et al. (2016) An experimental study of segregation mechanisms, *EPJ Data Science*.

Experiment: The segregation game

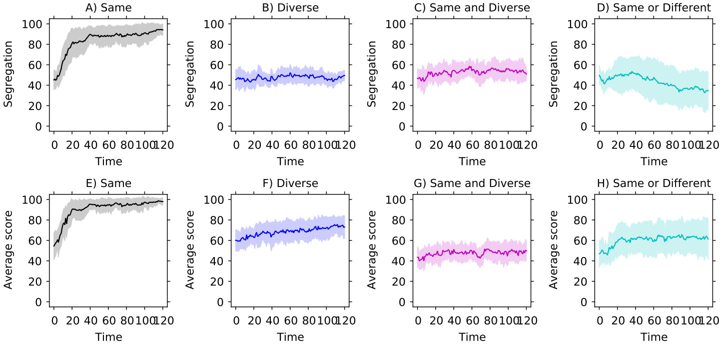



Game
02:00
Play game
Game 1
Initialize
Start game
Stop game
Study game
Final scores
Survey
Simulation
Reset
17 4 24 9 10
23 16 18 29 15 28
30 3 14
27 12 8 22
11 21 5 26
25

Experiment: No segreg. with diversity pref.



Experiment: Validity



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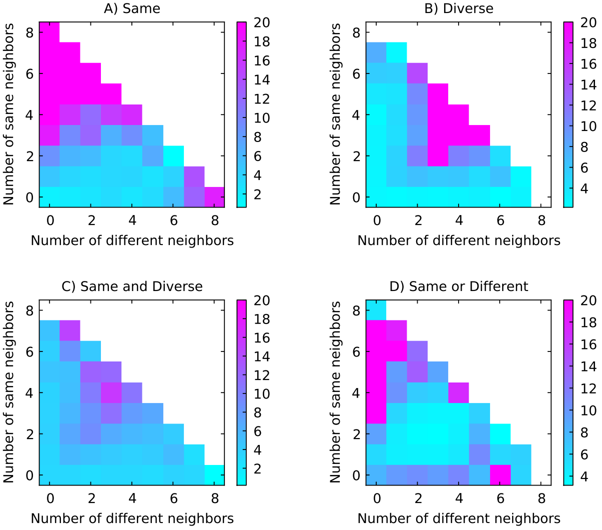

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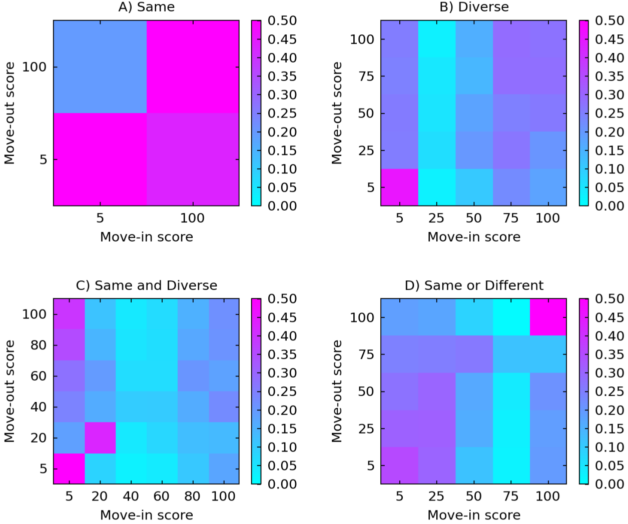
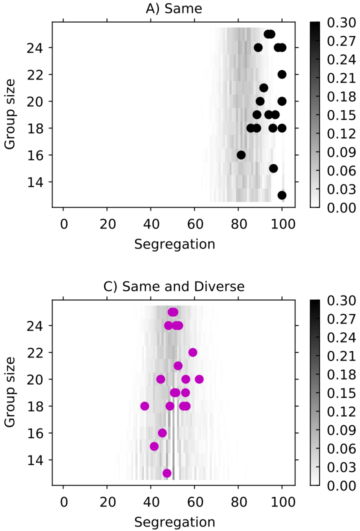


ABM: Modification with random relocation



Summary

- Incentives for homophily produce segregation but incentives for local diversity prevent it
- Rational individuals may produce different macro patterns than simulated agents
- Some model assumptions are not naive
    - e.g. "better response" means one can 1) identify a better location and 2) know when no better location exists

Contribution Communities

Contribution communities

- Why are mutual-help communities far more common online than in traditional offline settings?
- Possible explanation
  - Generosity can be contagious[1]
  - Receiving and observing contributions have different spread effects (online experiment)[2]
  - Non-rival contributions spread more easily (agent-based model)[3]

1. Fowler & Christakis (2010) Cooperative behavior cascades in human social networks, *PNAS*.
2. Tsvetkova & Macy (2014) The social contagion of generosity, *PLoS One*.
3. Tsvetkova & Macy (2015) The contagion of prosocial behavior and the emergence of voluntary-contribution communities, in *Social Phenomena: From Data Analysis to Models*.

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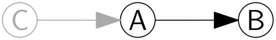
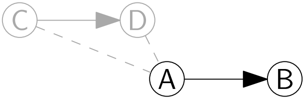
Two contagion mechanisms

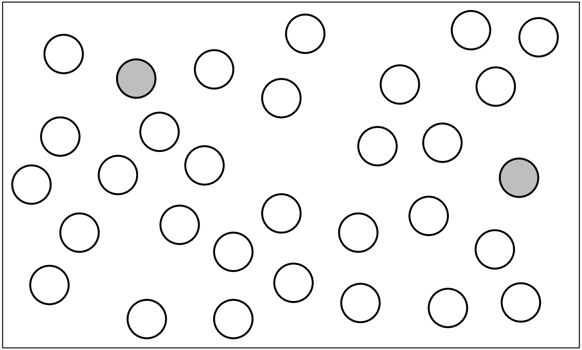
Generalized Reciprocity



Third-Party Influence



Experiment: The invitation game



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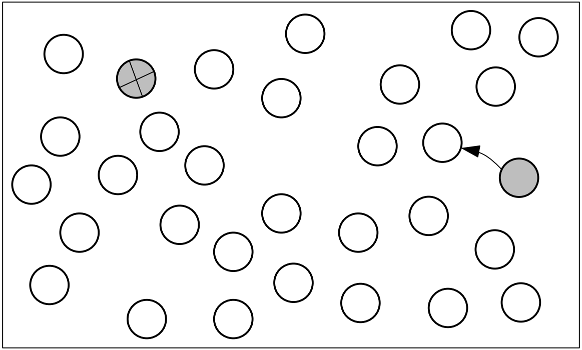

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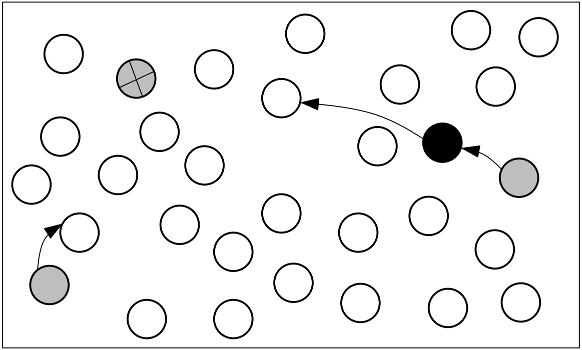

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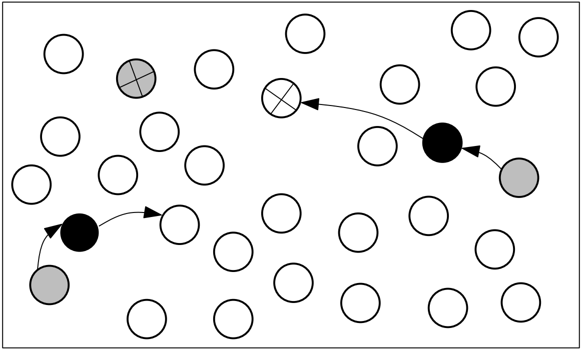

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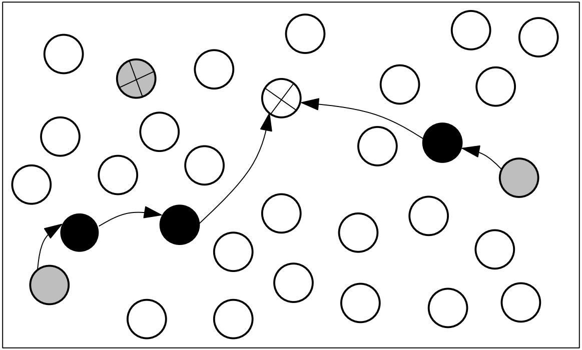

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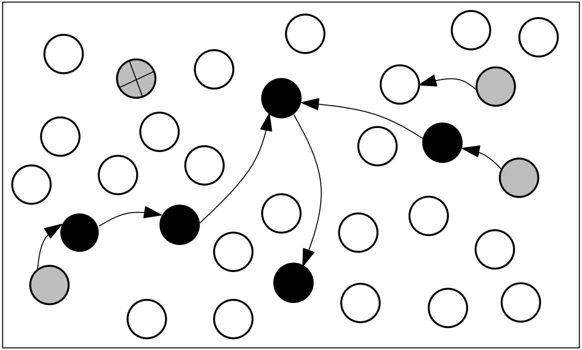

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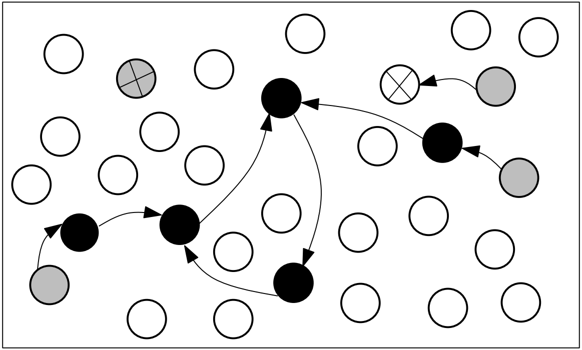

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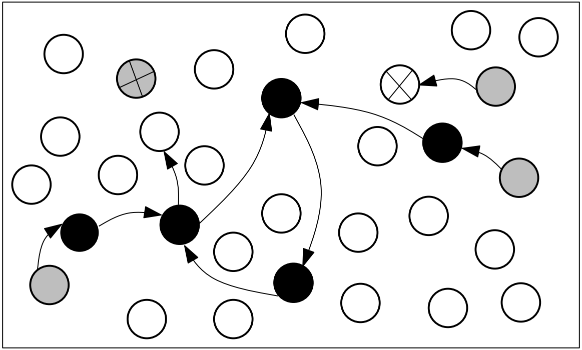
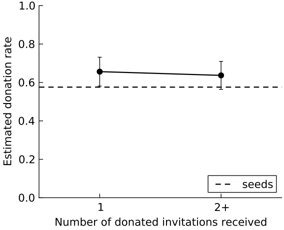
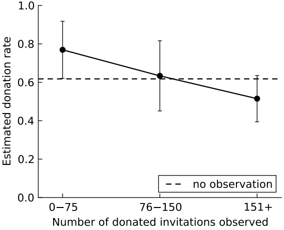
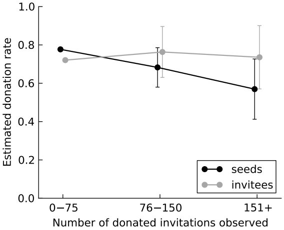


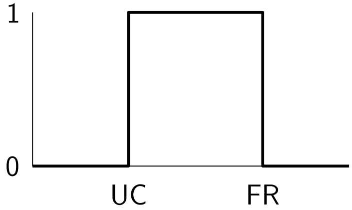
Experiment: Receiving is diff. from observing







ABM: Adaptive contribution threshold



Granovetter (1978) Threshold models of collective behavior. *American Journal of Sociology*.

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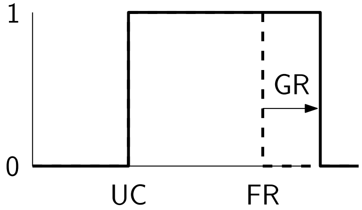

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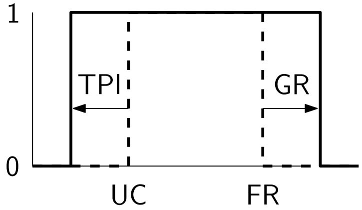

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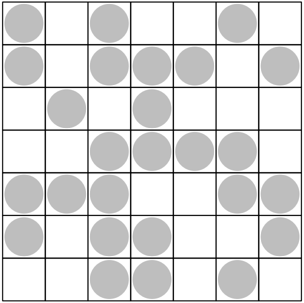
ABM: Spatial interactions



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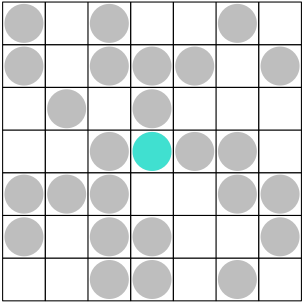

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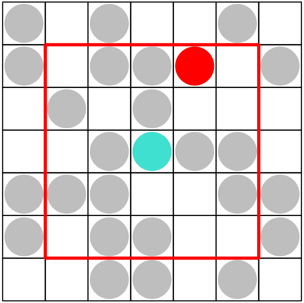

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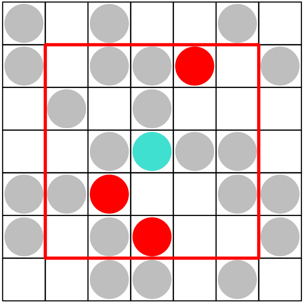

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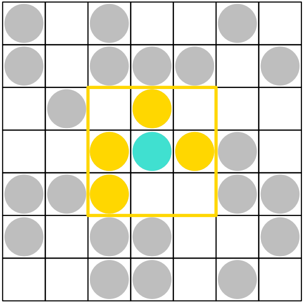

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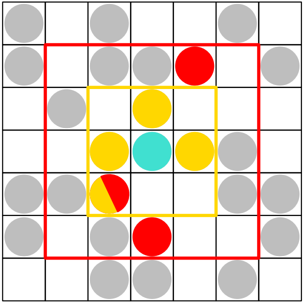
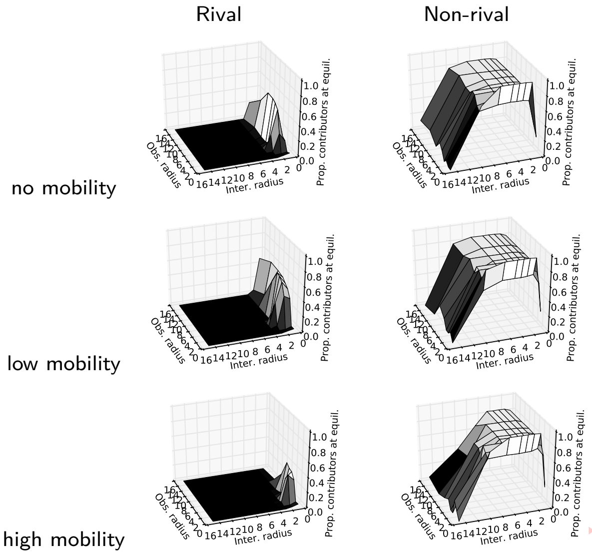
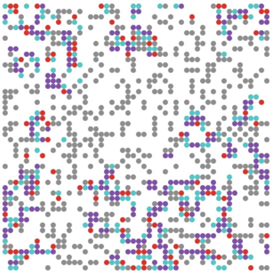


ABM: Conditions for emergence

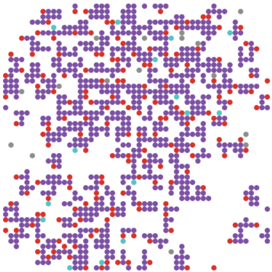


ABM: Two pathways for emergence

Rival



Non-rival

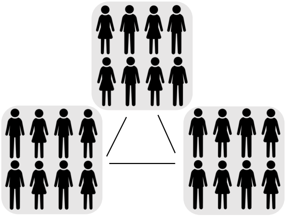


Agents in blue contribute but do not benefit, agents in red benefit but do not contribute, and agents in purple both contribute and benefit.

Inequality in Social Groups

Inequality

Historical analyses



Inequality

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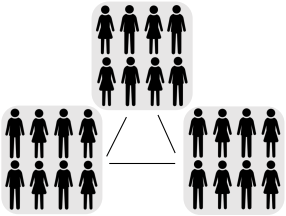
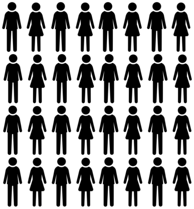
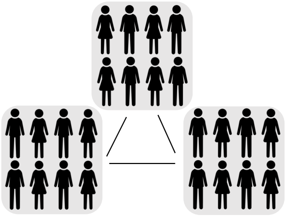


Social stratification

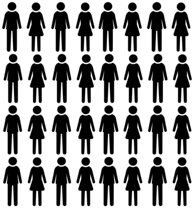


Inequality

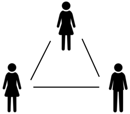
Historical analyses



Social stratification

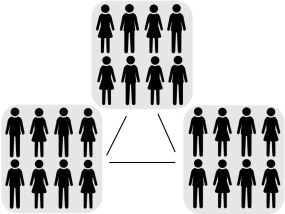


Social psychology

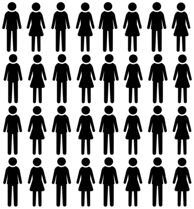


Inequality

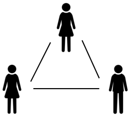
Historical analyses



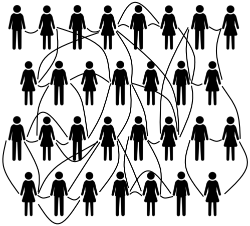
Social stratification



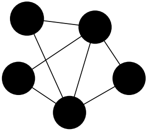
Social psychology



Complex social systems

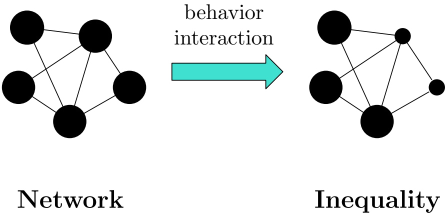


Inequality in social groups

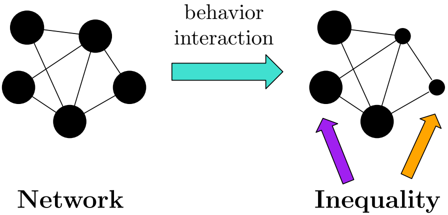


Network

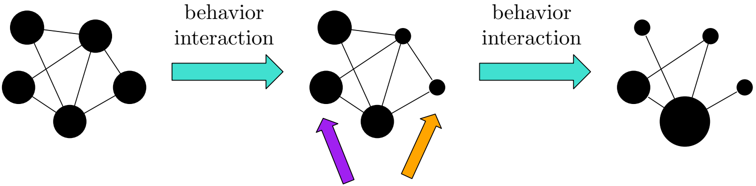
Inequality in social groups



Inequality in social groups



Inequality in social groups



Network **Inequality** **More inequality**

Experiments: Network cooperation games

- Visibility of success[1,2], visibility of wealth[3], reputation systems[4]
- Network cooperation experiments
  - Network structure
  - Network fluidity
  - Visibility of reputation
  - Punishment institutions

1. Salganik, Dodds& Watts (2006) Experimental study of inequality and unpredictability in an artificial cultural market, *Science*.
2. van de Rijt et al. (2014) Field experiments of success-breeds-success dynamics, *PNAS*.
3. Nishi et al. (2015) Inequality and visibility of wealth in experimental social networks, *Nature*.
4. Frey & van de Rijt (2016) Arbitrary inequality in reputation systems, *Scientific Reports*.

Experiments: Network cooperation games

- Visibility of success[1,2], visibility of wealth[3], reputation systems[4]
- Network cooperation experiments
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3. Nishi et al. (2015) Inequality and visibility of wealth in experimental social networks, *Nature*.
4. Frey & van de Rijt (2016) Arbitrary inequality in reputation systems, *Scientific Reports*.

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KIRC07 O. Kirchkamp, R. Nagel. Naive learning and cooperation in network experiments. *Games Econ. Behav.* 58, 269–292 (2007).
NIKI08 N. Nikiforakis. Punishment and counter-punishment in public good games: Can we really govern ourselves? *J. Pub. Econ.* 92, 91–112 (2008).
OGOR09 R. O'Gorman, J. Henrich, M.V. Vugt. Constraining free riding in public goods games: designated solitary punishers can sustain human cooperation. *Proc. Royal Soc. Lon. B: Biol. Sci.* 276, 323–329 (2009).
PAGE05 T. Page, L. Putterman, B. Unel. Voluntary association in public goods experiments: Reciprocity, mimicry and efficiency. *Econ. J.* 115, 1032–1053 (2005).
RAND14 D.G. Rand, M.A. Nowak, J.H. Fowler, N.A. Christakis. Static network structure can stabilize human cooperation. *PNAS* 111, 17093–17098 (2014).
SEIN06 I. Seinen, A. Schram. Social status and group norms: Indirect reciprocity in a repeated helping experiment. *Europ. Econ. Rev.* 50, 581–602 (2006).
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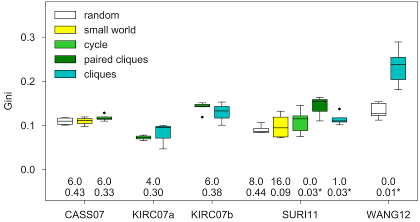
Experiments: Data

Study	Game	N_g	$Size_g$	N_i	k	T	Network	Fluid	Reput	Punish
Network Structure										
CASS07	PD: $4p_C, 0, 5p_C, p_D$	11	18	72	≈ 4	78–84	ran sw cyc	fix	> 1	no
KIRC07a	PD: $5C, 0, 4+5C, 4$	11	8–20	168	4	80	cyc cliq	fix	0	no
KIRC07b	PD: $5C, 0, 4+5C, 4$	11	8–20	190	4	80	cyc cliq	fix	1	no
SURI11	PG: $10 - c_i + 0.4\langle c_j \rangle$	30	24	109	5	10	ran sw cyc pcliq cliq	fix	1	no
WANG12	PD: $4C, aD, 7C, bD$	10	24	108	5	12	ran cliq	fix	5	no
Network Fluidity										
GRAC12a	PD: $7C, 0, 10C, 0$	2/1	625	625	4	51	lat	shuf fix	1	no
GRAC12b	PD: $7C, 0, 10C, 0$	2/1	604	604	2–16	58	sf	shuf fix	1	no
GRUJ10	PD: $7C, 0, 10C, 0$	3/1	169	169	8	47–60	lat	shuf fix	1	no
RAND14a	PD: $40C - 20, -20, 40C, 0$	8	15–34	210	2	15	cyc	shuf fix	1	no
RAND14b	PD: $40C - 20, -20, 40C, 0$	8	15–34	193	2	15	cyc	shuf fix	1	no
RAND14c	PD: $60C - 40, -40, 40C, 0$	8	15–34	210	4	15	cyc	shuf fix	1	no
TRAU10	PD: $0.3C, 0, 0.4C, 0.1D$	25	16	400	4	25	lat	shuf fix	1	no
PAGE05a	PG: $10 - c_i + 0.4\sum c_j$	8	16	128	3	20	cliq	strat fix	avg	no
PAGE05b	PG: $10 - c_i + 0.4\sum c_j$	8	16	128	3	20	cliq	strat fix	avg	yes
WANG12a	PD: $4C, aD, 7C, bD$	43	24	108	(5)	12	(ran)	strat fix	5	no
WANG12b	PD: $4C, aD, 7C, bD$	41	24	108	(5)	12	(cliq)	strat fix	5	no
Reputation Tracking										
BOLT05a	HG: $-0.25, 1.25$	6	16	96	1	14	pair	shuf	$0\ 1\ 1+1$	no
BOLT05b	HG: $-0.75, 1.25$	6	16	96	1	14	pair	shuf	$0\ 1\ 1+1$	no
CUES15	PD: $7C, 0, 10C, 0$	22/11	17–25	243	(4)	25	cyc	strat	0 1 3 5	no
KAME17a	PG: $10 - c_i + 0.65\sum c_j$	12	10	120	1	40	pair	strat	0 50% 100%	no
KAME17b	PG: $10 - c_i + 0.85\sum c_j$	13	10	130	1	40	pair	strat	0 50% 100%	no
KIRC07a	PD: $5C, 0, 4+5C, 4$	9	8–20	158	4	80	cyc	fix	0 1	no
KIRC07b	PD: $5C, 0, 4+5C, 4$	6	8–20	95	4	80	cliq	fix	0 1	no
KIRC07c	PD: $5C, 0, 4+5C, 4$	7	8–20	105	4	80	lcliq	fix	0 1	no
SEIN06	HG: $-150, 250$	8	14	112	1	> 90	pair	shuf	1 6	no
Punishment Institutions										
CASA09	PG: $20 - c_i + 0.4\sum c_j$	12	20	240	4	10	cliq	shuf	0	no yes seq cons
DREB08a	PD: $1, -2, 2, 0$	2	≈ 26	58	1	71	pair	shuf	0	no yes
DREB08b	PD: $1, -2, 4, 0$	2	≈ 26	46	1	87	pair	shuf	0	no yes
FEHR02	PG: $20 - c_i + 0.4\sum c_j$	10	24	236	3	6	cliq	shuf	0	no yes
NIKI08	PG: $20 - c_i + 0.4\sum c_j$	8	12	96	3	10	cliq	shuf	0	no yes
OGOR09	PG: $20 - c_i + 0.5\sum c_j$	6	20–24	136	3	6	cliq	shuf	0	no yes solo
PAGE05a	PG: $10 - c_i + 0.4\sum c_j$	8	16	128	4	20	cliq	fix	avg	no yes
PAGE05b	PG: $10 - c_i + 0.4\sum c_j$	8	16	128	4	20	cliq	strat	avg	no yes

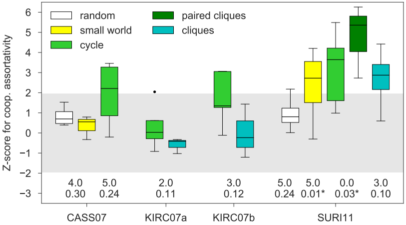
Experiments: Binomial test for effect direction

Experiments: Inequality in clustered networks

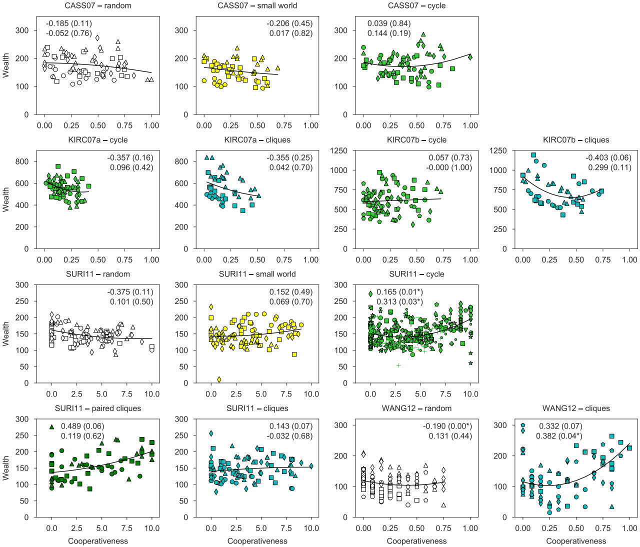


Binomial Test one-tailed $p = 0.020$

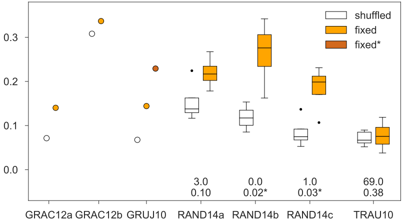
Experiments: Clustering of cooperators



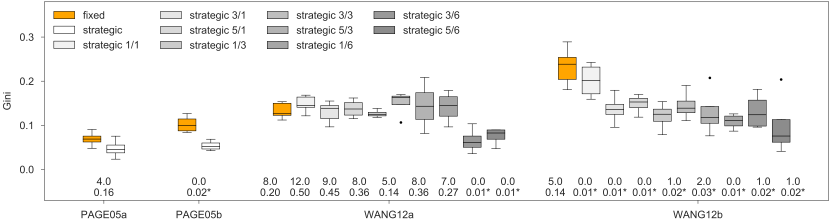
Experiments: Exploitation



Experiments: Inequality in fixed networks

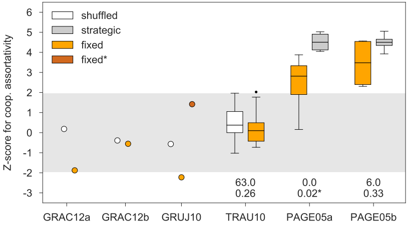


Binomial Test one-tailed $p = 0.008$

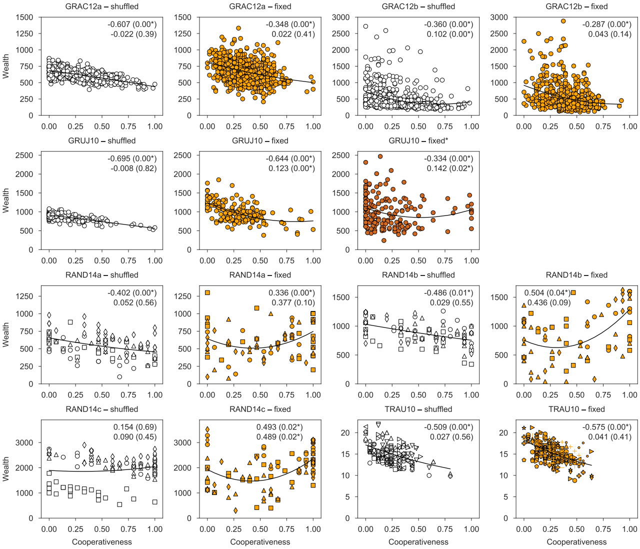


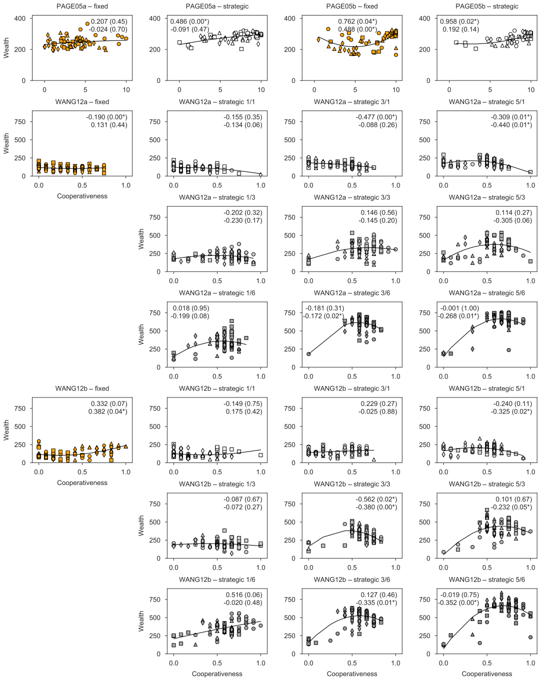
Binomial Test one-tailed $p = 0.058$

Experiments: No clustering of cooperators

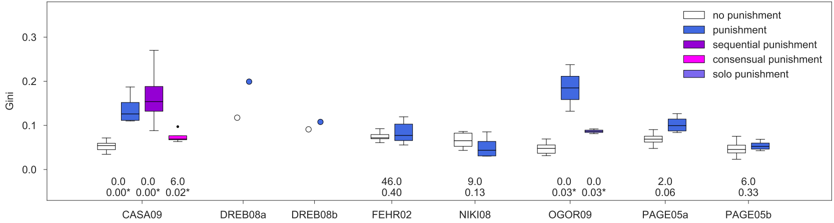


Experiments: Exploitation



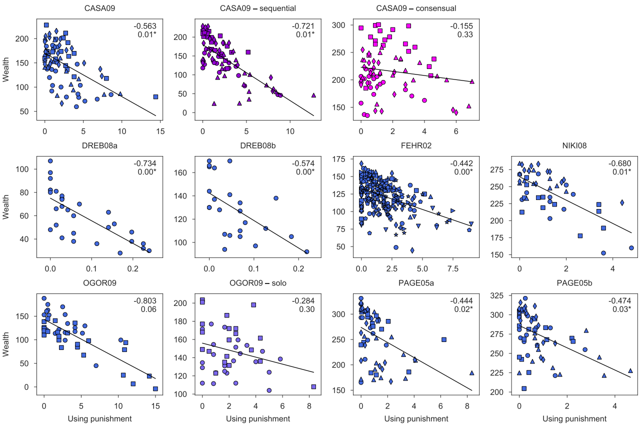

PAGE05a – fixed
0.207 (0.45)
-0.024 (0.70)
PAGE05a – strategic
0.486 (0.00*)
-0.091 (0.47)
PAGE05b – fixed
0.762 (0.04*)
0.488 (0.00*)
PAGE05b – strategic
0.958 (0.02*)
0.192 (0.14)
WANG12a – fixed
-0.190 (0.00*)
0.131 (0.44)
WANG12a – strategic 1/1
-0.155 (0.35)
-0.134 (0.06)
WANG12a – strategic 3/1
-0.477 (0.00*)
-0.088 (0.26)
WANG12a – strategic 5/1
-0.309 (0.01*)
-0.440 (0.01*)
WANG12a – strategic 1/3
-0.202 (0.32)
-0.230 (0.17)
WANG12a – strategic 3/3
0.146 (0.56)
-0.145 (0.20)
WANG12a – strategic 5/3
0.114 (0.27)
-0.305 (0.06)
WANG12a – strategic 1/6
0.018 (0.95)
-0.199 (0.08)
WANG12a – strategic 3/6
-0.181 (0.31)
-0.172 (0.02*)
WANG12a – strategic 5/6
-0.001 (1.00)
-0.268 (0.01*)
WANG12b – fixed
0.332 (0.07)
0.382 (0.04*)
WANG12b – strategic 1/1
-0.149 (0.75)
0.175 (0.42)
WANG12b – strategic 3/1
0.229 (0.27)
-0.025 (0.88)
WANG12b – strategic 5/1
-0.240 (0.11)
-0.325 (0.02*)
WANG12b – strategic 1/3
-0.087 (0.67)
-0.072 (0.27)
WANG12b – strategic 3/3
-0.562 (0.02*)
-0.380 (0.00*)
WANG12b – strategic 5/3
0.101 (0.67)
-0.232 (0.05*)
WANG12b – strategic 1/6
0.516 (0.06)
-0.020 (0.48)
WANG12b – strategic 3/6
0.127 (0.46)
-0.335 (0.01*)
WANG12b – strategic 5/6
-0.019 (0.75)
-0.352 (0.00*)
Wealth
Cooperativeness

Experiments: Inequality with punishment



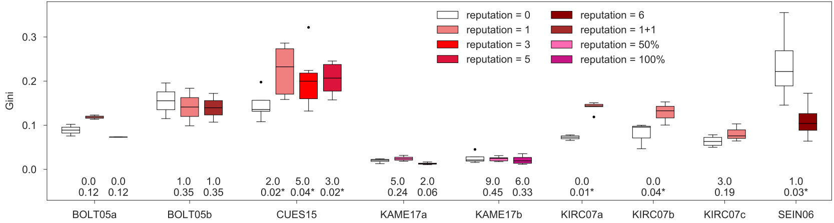
Binomial Test one-tailed $p = 0.006$

Experiments: The rich do not punish



Binomial Test one-tailed $p = 0.000$

Experiments: No effect from reputation



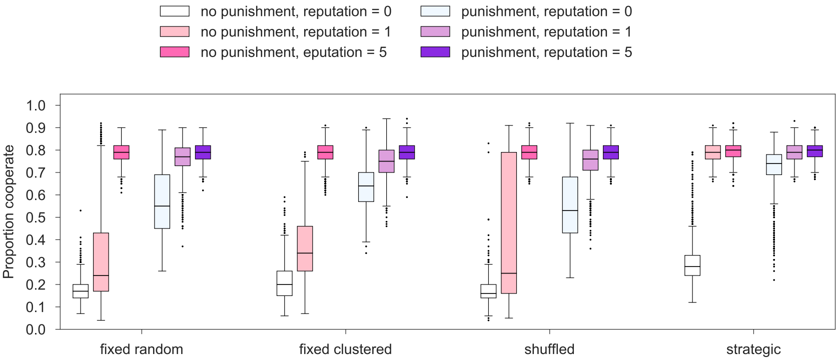
Binomial Test one-tailed $p = 0.304$

ABM: Behavioral types and heuristics

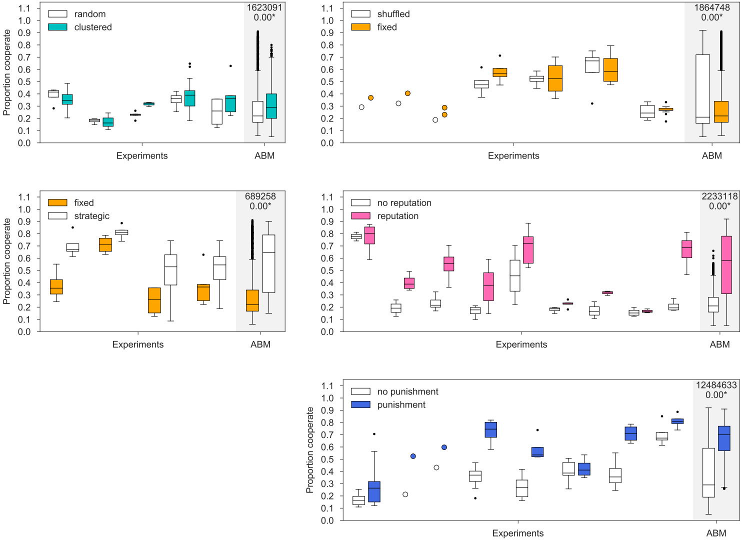
- N-person Prisoner's Dilemma[1]
- 20% defectors, 65% reciprocators, 15% altruists[2]
- Behavioral assumptions
  - Reputation increases initial and conditional probability to cooperate[3]
  - Punish defecting neighbors if low payoff[4]
  - If punished, change to cooperation only if low payoff
  - If updating network, replace defectors

1. Wang et al. (2012) Cooperation and assortativity with dynamic partner updating, *PNAS*.
2. Kurzban & Houser (2005) Experiments investigating cooperative types in humans: A complement to evolutionary theory and simulations, *PNAS*.
3. Melamed et al. (2018) Cooperation, clustering, and assortative mixing in dynamic networks, *PNAS*.
4. Dreber et al. (2008) Winners don't punish, *Nature*.

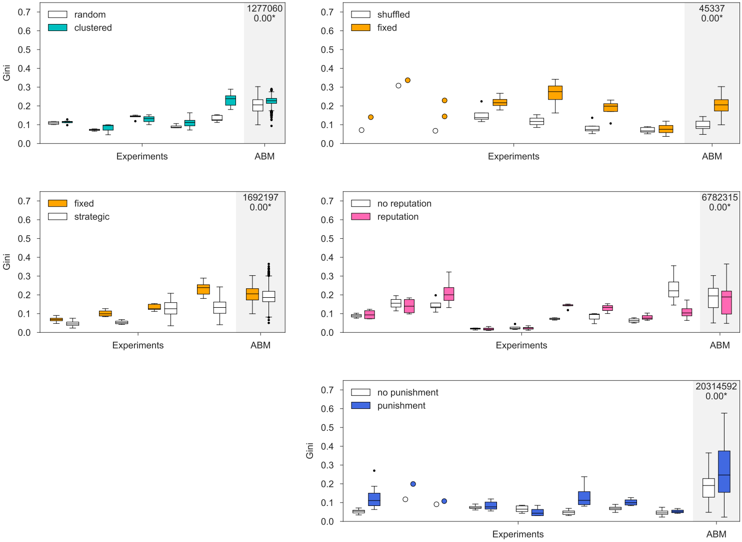
ABM: Calibration



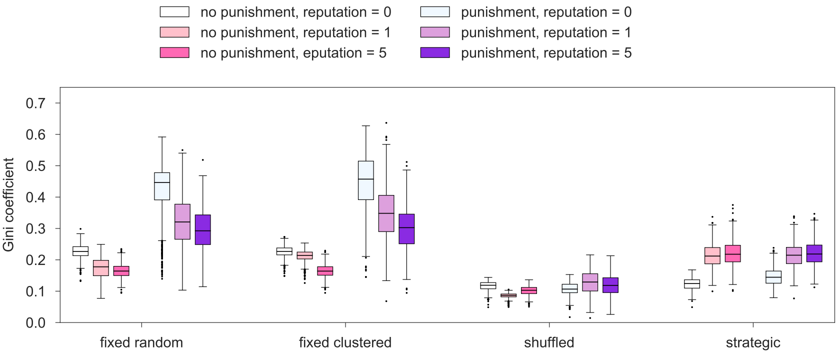
ABM: Calibration



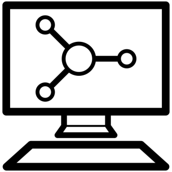
ABM: Calibration

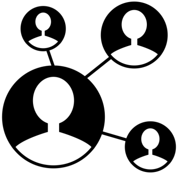


ABM: Complex effects from reputation



Combining *in silico* with *in vitro* research





- Behavioral experiments to specify ABMs
- Behavioral experiments to validate ABMs
- Behavioral experiments to calibrate ABMs
- ABMs to predict and explain behavioral experiments

Thank you!

Collaborators


Michael Macy


Andrew Mao


David Sumpter


Oana Vuculescu


Claudia Wagner

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ScienceAtHome

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