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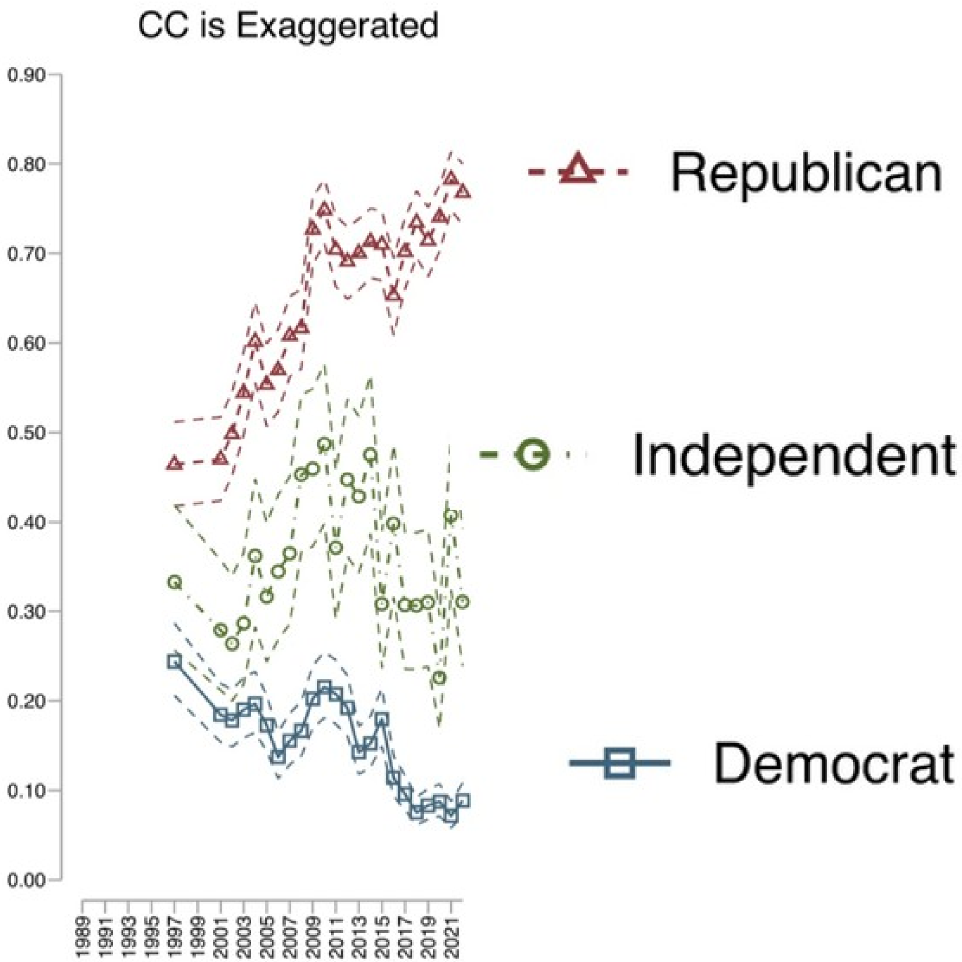
The complexity of social polarization Connecting individual opinions and societal dynamics with agent-based models and experiments

Andreas Flache

Presentation @ SG Final Symposium
The Complexity of Social and Economic Systems:
From Models to Measures
31 October 2024, ETH Zurich

One danger of polarization: loosing common ground on key societal issues



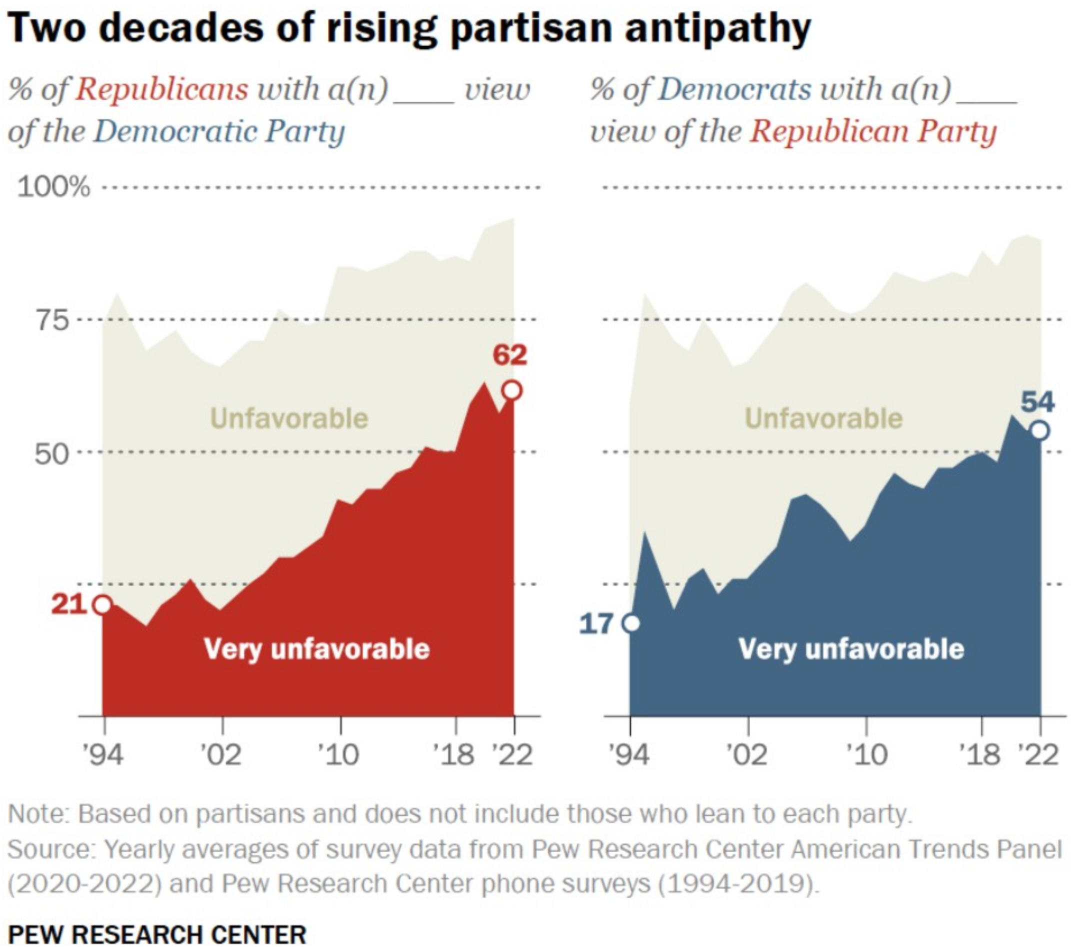
“Climate polarization” in the US

Based on “General Social Survey (GSS), PEW + Gallup Polls (*N* about 100k)

Source:

Smith, E.K., Bognar, M.J. & Mayer, A.P. Polarisation of Climate and Environmental Attitudes in the United States, 1973-2022. *npj Clim. Action* 3, 2 (2024).

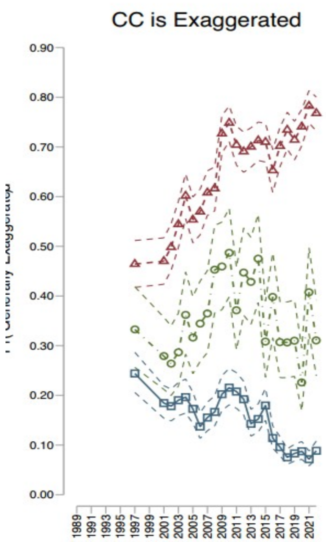
“Affective polarization”
Negative views of (ideological) outgroups



PEW “American Trends Panel”, ca. 10.000 respondents per wave

Source: Pew Research Center, August 2022, “As Partisan Hostility Grows, Signs of Frustration With the TwoParty System”

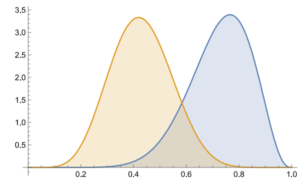
Polarization and social complexity



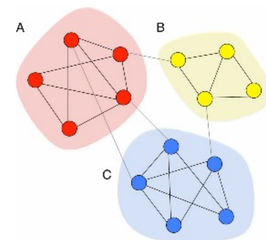
Macro + meso-level societal context

theory + data:

inequality

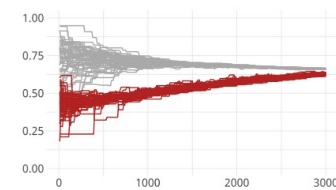


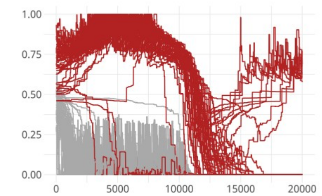
belief distributions

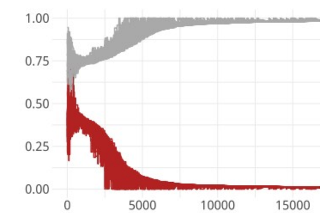


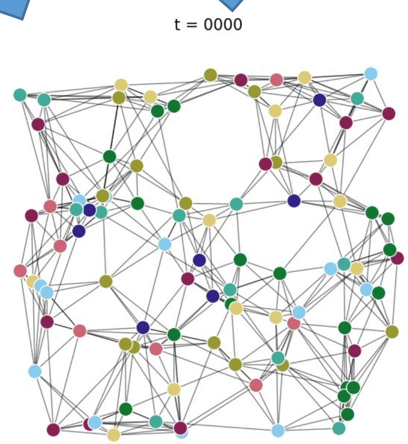
segregation

Macro-level outcomes: polarization?









Micro-level processes:
Changing opinions, emotions, network relations:

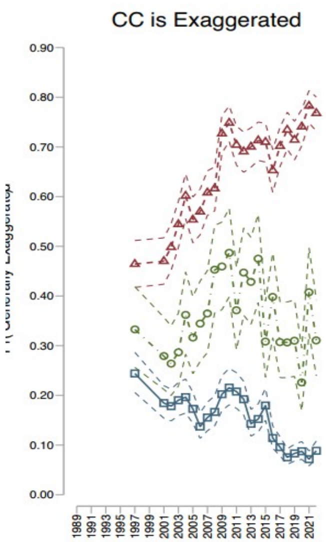
Behavioral theory +
on- offline data + experiments

Empirically grounded ABM of "opinion dynamics"
- energy policies
- migration policies ...

What can we expect?
In which context?
Under which assumptions
And how to influence this?

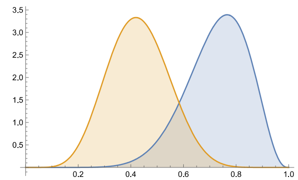
"In silico" experiments +
Empirical validation

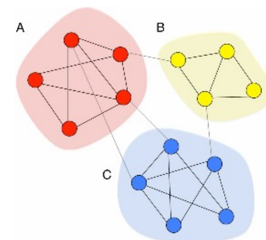
Polarization and social complexity



Macro + meso-level societal context

theory + data:





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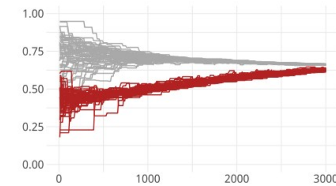
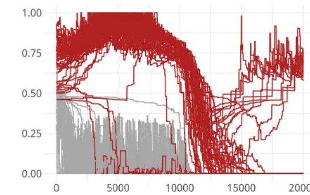
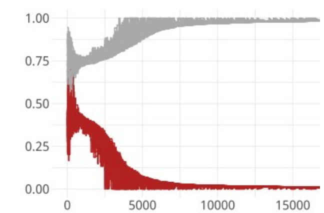
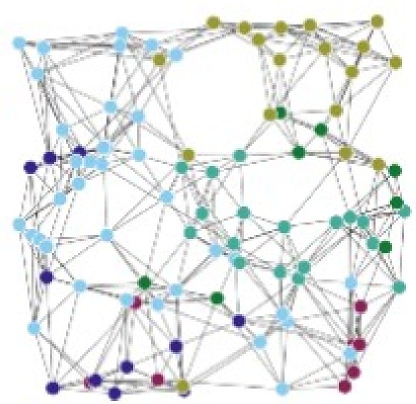
Macro-level outcomes: polarization?









Micro-level processes:
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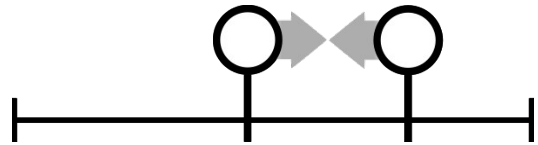
Classical models of social influence in networks
(e.g. French, Abelson, Harary, Lehrer & Wagner,…)

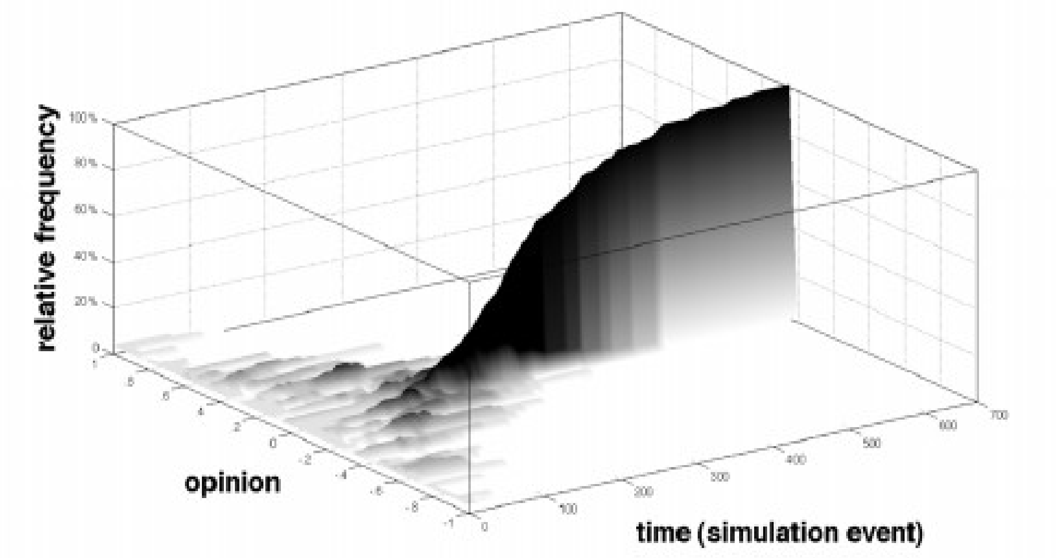
Assimilative Influence:
move towards opinion of network neighbors



$$\Delta o_{i,t} = \frac{\sum_{j=1}^{N} w_{ij,t} \cdot (o_{j,t} - o_{i,t})}{\sum_{j=1}^{N} \left| w_{ij,t} \right|}$$

$0 \le o \le 1$
$0 \le w \le 1$

In connected networks, opinions will always converge to perfect consensus



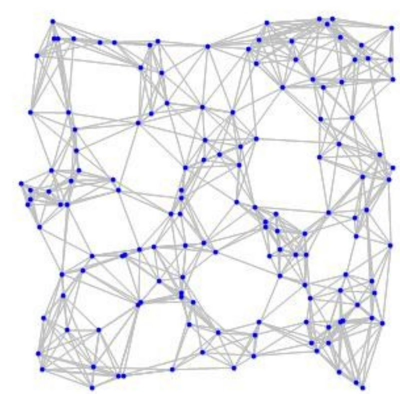


Figure: Mäs & Flache A 2013. PLoS ONE 8(11): e74516.

How reconcile social influence at micro-level with polarization at macro-level?

Axelrod's puzzle (1997)

"If people tend to become more alike in their beliefs, attitudes, and behavior when they interact, why do not all such differences eventually disappear?"

Abelson's puzzle (1964)

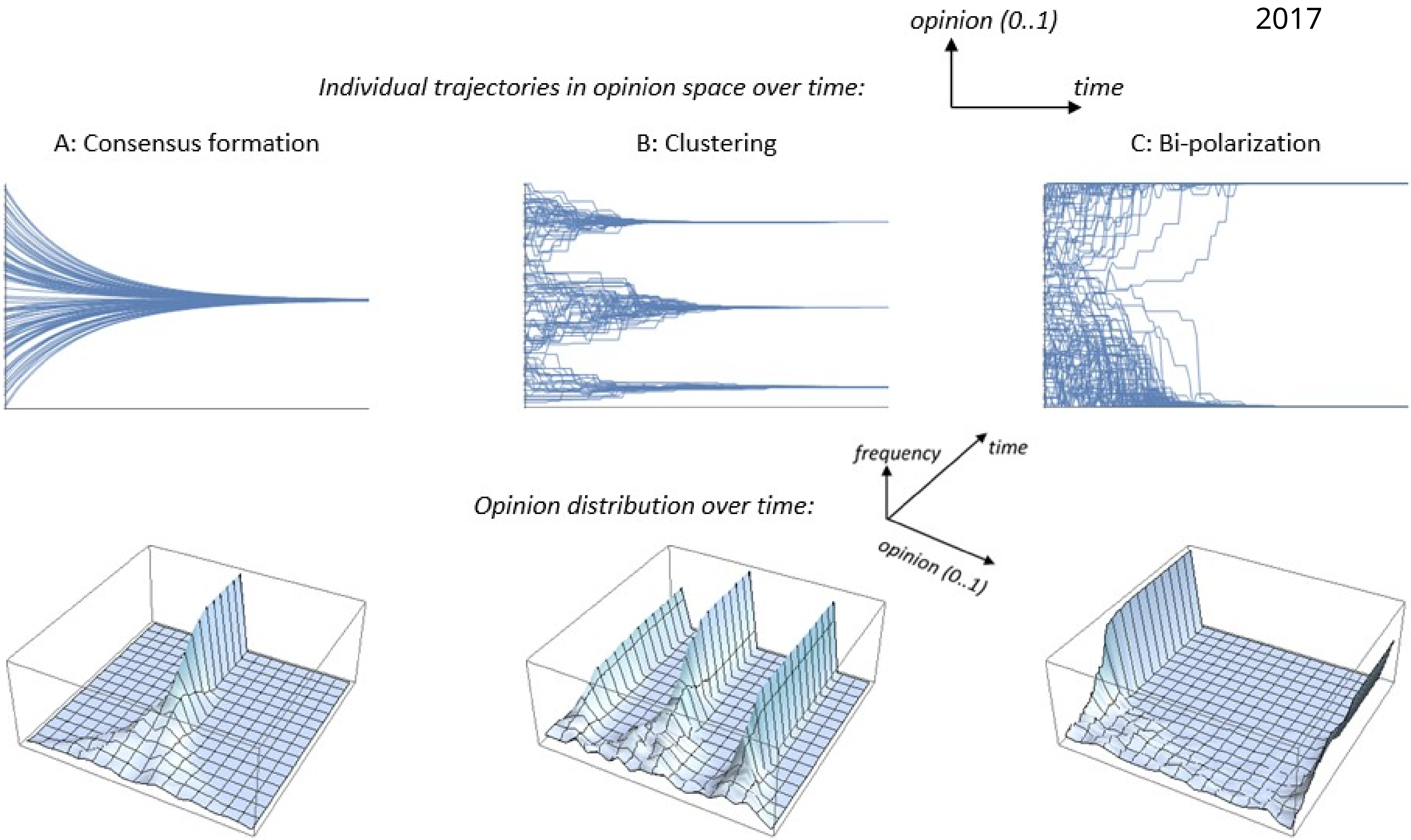
"What on earth one must assume in order to generate the bimodal outcome of community cleavage studies?"

- Axelrod, R. (1997). The dissemination of culture a model with local convergence and global polarization. *Journal of Conflict Resolution*, 41(2), 203–226.
- Abelson, R. P. (1964). Mathematical models of the distribution of attitudes under controversy. In N. Frederiksen & H. Gulliksen (Eds.), *Contributions to mathematical psychology* (pp. 142–160). New York: Holt, Rinehart & Winston.

Models of Social Influence: Towards the Next Frontiers

Andreas Flache[a] , Michael Mäs[a] , Thomas Feliciani[a] , Edmund Chattoe-Brown[b] , Guillaume Deffuant[c] , Sylvie Huet[c] and Jan Lorenz[d]

2017

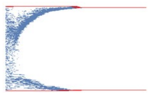


Typical opinion dynamics generated by different agent-based models of social influence

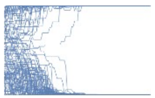
3 classes of models that can generate clustering and polarization

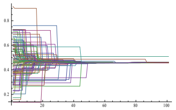
- **Bounded confidence & homophily**
  Accept influence only from similar sources



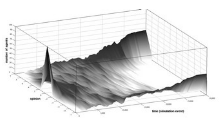
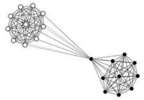
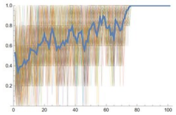


Deffuant et al 2000; Hegselmann & Krause 2002; **Lorenz & Urbig 2007, Urbig ea 2008**





- **Assimilative + repulsive influence**
  Move towards similar sources, distance from dissimilar sources
  Macy ea 2003; Jager & Amblard 2005; **Fent, Groeber, & Schweitzer, 2007;** Flache & Macy 2011;

- **Reinforcing influence**
  Similar sources strengthen opinion, dissimilar sources moderate

2 major challenges for ABM of opinion dynamics

- **Theoretical: comparing and integrating models**
  - For which situations do models make different predictions?
  - Which assumptions cause different model behavior?
  - What are deeper-level behavioral mechanisms of different influence processes, and how do they affect polarization patterns?

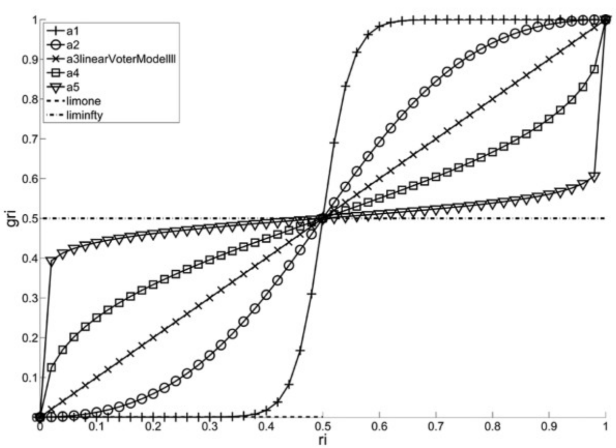
- **Empirical: calibration, measurement and testing**
  - Micro-level foundations: lab experiments, behavioral data
  - Macro-level predictions: e.g. voting outcomes, spatial data

Tackling the challenges:

some (of many) contributions from the Chair of Systems Design at ETH Zürich

Which assumptions cause different model behavior?

What are deeper-level behavioral mechanisms of different influence Processes?



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DISSONANCE MINIMIZATION AS A MICROFOUNDATION OF SOCIAL INFLUENCE IN MODELS OF OPINION FORMATION

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Frank Schweitzer
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Models of opinion formation are used to investigate many collective phenomena. While social influence often constitutes a basic mechanism, its implementation differs between the models. In this article, we provide a general framework of social influence based on dissonance minimization. We only premise that individuals strive to minimize dissonance resulting from different opinions compared to individuals in a given social network. Within a game theoretic context, we show that our concept of dissonance minimization resembles a coordination process when interactions are homogeneous. We further show that different models of opinion formation can be represented as best response dynamics within our framework. Thus, we offer a unifying perspective on these heterogeneous models and link them to rational choice theory.

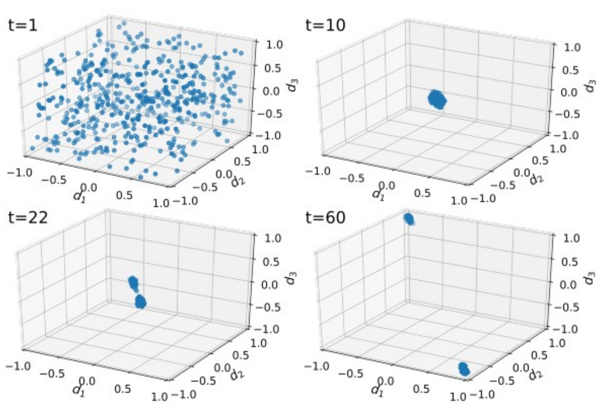
Keywords: conventions, coordination, opinion dynamics, social influence

Tackling the challenges:

some (of many) contributions from the Chair of Systems Design at ETH Zürich

What are deeper-level behavioral mechanisms of different influence processes,

and how do they affect polarization patterns?



A Weighted Balance Model of Opinion Hyper-polarization

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[1]*Complexity Science Hub Vienna, Josefstädter Str. 39, 1080 Vienna, Austria*
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Doi: 10.18564/jasss.4306 Url: http://jasss.soc.surrey.ac.uk/23/3/5.html

Received: 19-12-2019 Accepted: 09-04-2020 Published: 30-06-2020

Abstract: Polarization is threatening the stability of democratic societies. Until now, polarization research has focused on opinion extremeness, overlooking the correlation between different policy issues. In this paper, we explain the emergence of hyperpolarization, i.e., the combination of extremeness and correlation between issues, by developing a new theory of opinion formation called "Weighted Balance Theory (WBT)". WBT extends Heider's cognitive balance theory to encompass multiple weighted attitudes. We validated WBT on empirical data from the 2016 National Election Survey. Furthermore, we developed an opinion dynamics model based on WBT, which, for the first time, is able to generate hyperpolarization and to explain the link between affective and opinion polarization. Finally, our theory encompasses other phenomena of opinion dynamics, including mono-polarization and backfire effects.

Keywords: Polarization, Balance Theory, Opinion Dynamics, Agent-Based Modeling

Tackling the challenges:
some (of many) contributions from the Chair of Systems Design at ETH Zürich

What are deeper-level behavioral mechanisms of different influence Processes

Empirical: calibration, measurement and testing

Micro-level foundations: behavioral experiments testing Assumptions of ABM cyber-emotions modelling framework

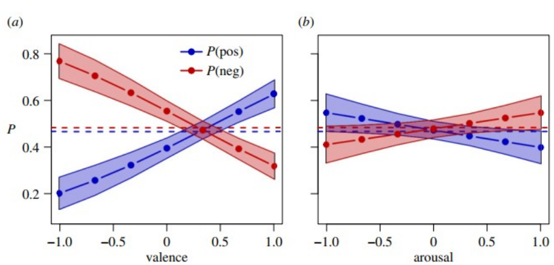

Figure 5. Results of logistic regression of post positive and negative content measured with SentiStrength as a function of (*a*) valence and (*b*) arousal. Error bars show standard errors of the estimate of the probability of being positive or negative.

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Research

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Subject Category:
Psychology and cognitive neuroscience

Subject Areas:
psychology/human–computer interaction

Keywords:
computational social science, emotions, online interaction

Author for correspondence:

The dynamics of emotions in online interaction

David Garcia[1], Arvid Kappas[2], Dennis Küster[2] and Frank Schweitzer[1]

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We study the changes in emotional states induced by reading and participating in online discussions, empirically testing a computational model of online emotional interaction. Using principles of dynamical systems, we quantify changes in valence and arousal through subjective reports, as recorded in three independent studies including 207 participants (110 female). In the context of online discussions, the dynamics of valence and arousal is composed of two forces: an internal relaxation towards baseline values independent of the emotional charge of the discussion and a driving force of emotional states that depends on the content of the discussion. The dynamics of valence show the existence of positive and negative tendencies, while arousal increases when reading emotional content regardless of its polarity. The tendency of participants to take part in the discussion increases with positive arousal. When participating in an online discussion, the content of participants' expression depends on their valence, and their arousal significantly decreases afterwards as a regulation mechanism. We illustrate how these results allow the design of agent-based models to reproduce and analyse emotions in online communities. Our work empirically validates the microdynamics of a model of online collective emotions, bridging online data analysis with research in the laboratory.

Tackling the challenges:
some (of many) contributions from the Chair of Systems Design at ETH Zürich

Empirical:
calibration, measurement and testing

Micro-level foundations + polarization outcomes:

Measuring positive and negative links in social networks from behavioral data

scientific reports **2023**

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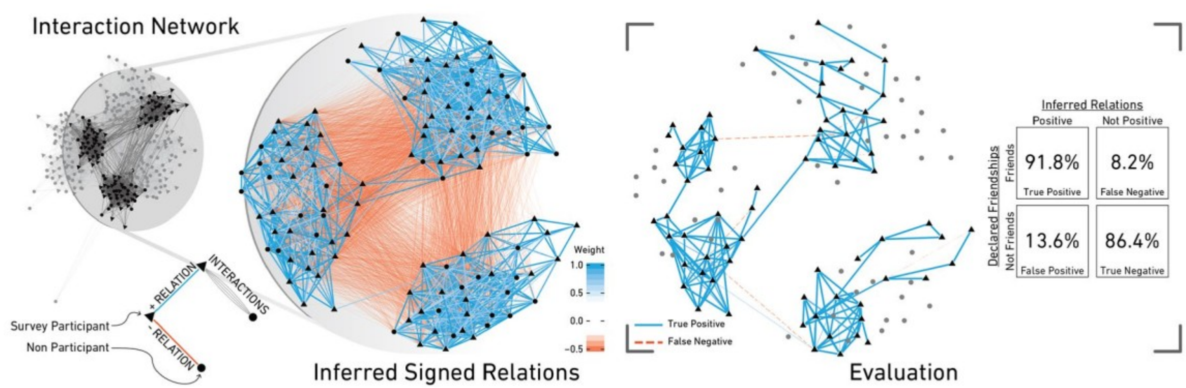
OPEN

Reconstructing signed relations from interaction data

Georges Andres, Giona Casiraghi, Giacomo Vaccario & Frank Schweitzer✉

Positive and negative relations play an essential role in human behavior and shape the communities we live in. Despite their importance, data about signed relations is rare and commonly gathered through surveys. Interaction data is more abundant, for instance, in the form of proximity or communication data. So far, though, it could not be utilized to detect signed relations. In this paper, we show how the underlying signed relations can be extracted with such data. Employing a statistical network approach, we construct networks of signed relations in five communities. We then show that these relations correspond to the ones reported by the individuals themselves. Additionally, using inferred relations, we study the homophily of individuals with respect to gender, religious beliefs, and financial backgrounds. Finally, we study group cohesion in the analyzed communities by evaluating triad statistics in the reconstructed signed network.



Experimental test and model calibration: Should we pop filter bubbles in online social media … or better not?

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Home > 27 (1), 7

Polarization on Social Media: Micro-Level Evidence and Macro-Level Implications

Marijn Keijzer[a], **Michael Mäs**[b] and **Andreas Flache**[c]

[a]Institute for Advanced Study in Toulouse, France; [b]Karlsruhe Institute of Technology, Germany; [c]University of Groningen, Netherlands

Other articles by these authors

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<https://www.jasss.org/27/1/7.html>

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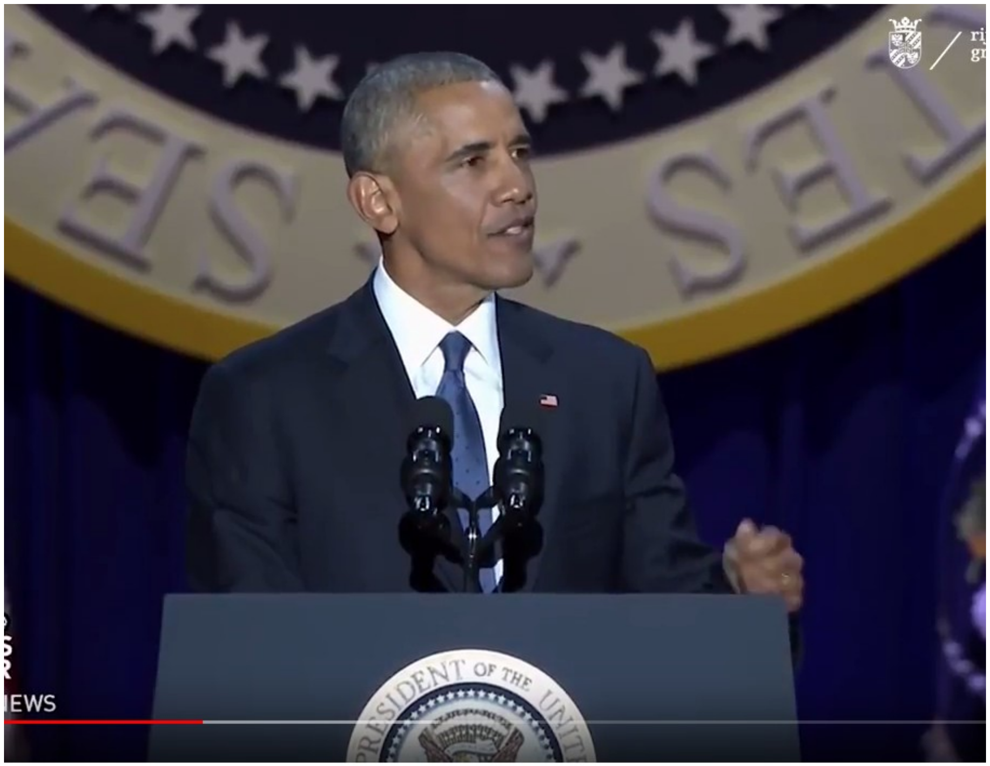
Does "sorting" in social media foster polarization? Obama says "yes"



Retreating in your own bubble fosters polarization

> "For … too many of us it's become safer to **retreat into our own bubbles**, whether in our neighborhoods, … or especially our social media feeds, surrounded by people who look like us and share the same political outlook and never challenge our assumptions."

Farewell address Barack Obama, Chicago, January 10, 2017.

Others (e.g. Mark Zuckerberg) claim that "popping the bubble" could make things even worse

Source: Wikipedia (Anthony Quintano)

Popping the bubble may foster polarization

"some of the most obvious ideas, like showing people an article from the opposite perspective, actually deepen polarization by framing other perspectives as foreign"

Zuckerberg, M. 2017. "Building global community". https://www.facebook.com/notes/3707971095882612/

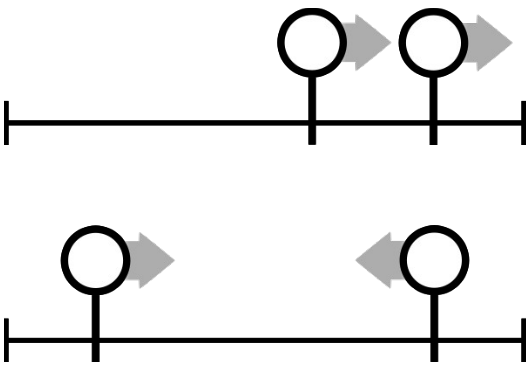
Modelling these intuitions

A model based on **persuasive argument theory**

- Opinion is constituted by **arguments**
  arg_vector ++---- ⇒ *opinion* = -0.33

- **Influence**: if *i* interacts with *j*, then *i* adopts argument from *j*.

- **Homophily**: the more similar *i* and *j*, the more likely they interact
  - Similarity in opinions, ethnicity, gender, …



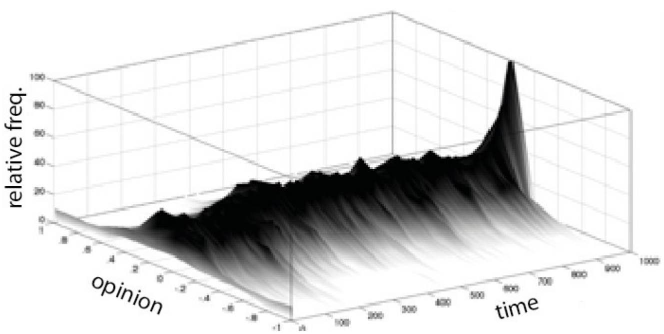
⇒ interaction with similar others

- strengthens "extreme" views, *and*
- is more likely than interaction with dissimilar others

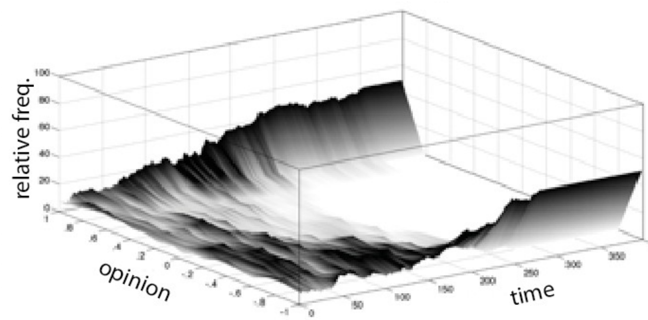
- Mäs, M., Flache, A., Takács, K., & Jehn, K. (2013). *Organization Science* 24. 3: 716–736.
- Mäs, M., & Flache, A. (2013). *PLoS ONE* 8(11): e74516.

Simulation model of collective opinion dynamics assuming as microfoundation “opinion reinforcement” (say, Obama)

No sorting



Strong sorting (filter bubble)



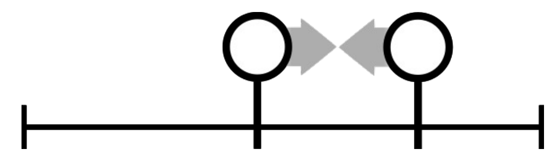
less sorting would decrease polarization

Mäs et al 2013, *Organization Science*
Mäs & Flache 2013, *PLoS One*
Feliciani et al 2021, *CMOT*

Another possible model of polarization: xenophobia and repulsive influence

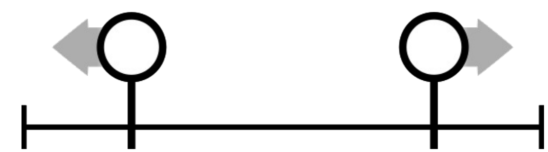
- **Xenophobia**

  differences too large ⇒ relations become negative



- **Repulsive influence**

  relations negative ⇒ people want to become more dissimilar from each other



Theories

social balance, cognitive dissonance, social judgement

Experiments

group categorization, group polarization, negative referents

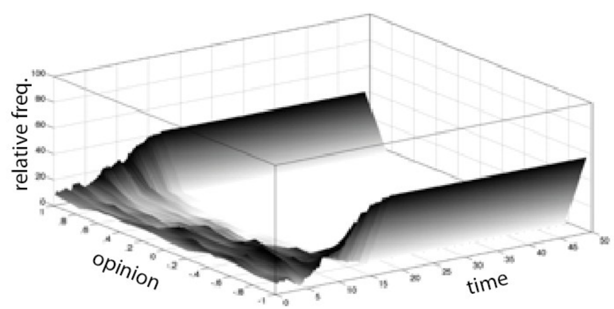
Several computational models →

- Macy, Kitts, Flache, Benard (2003)
- Jager & Amblard (2005)
- Fent, Gröber & Schweitzer, 2007
- Flache & Mäs (2008)
- Flache & Macy (2011, JMS) ...

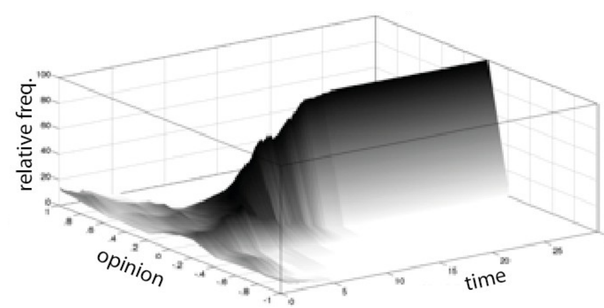
Simulation model of collective opinion dynamics assuming microfoundation

“repulsive influence” (say, Zuckerberg)

No sorting



Strong sorting



less sorting would INCREASE polarization

Flache & Mäs 2008, *CMOT*
Flache & Macy 2011, *JMS*
Feliciani, Flache & Tolsma 2017, *JASSS*
Feliciani, Tolsma & Flache 2023, *JoCSS*

What now?
Experiments to test microfoundation

Online social influence experiments (Keijzer et al 2024).

- Extending earlier experiments

  Takács, Flache & Mäs 2016. *POne* 11(6): e0157948

- Participants received opinion messages with systematically varied characteristics, then opinion change was measured
- **Results:**
  - participants tend to move towards message from source
  - less so if source is “ideologically distant”
  - and there is a tendency towards “repulsive influence” among “right wing” participants if disagreement is strong

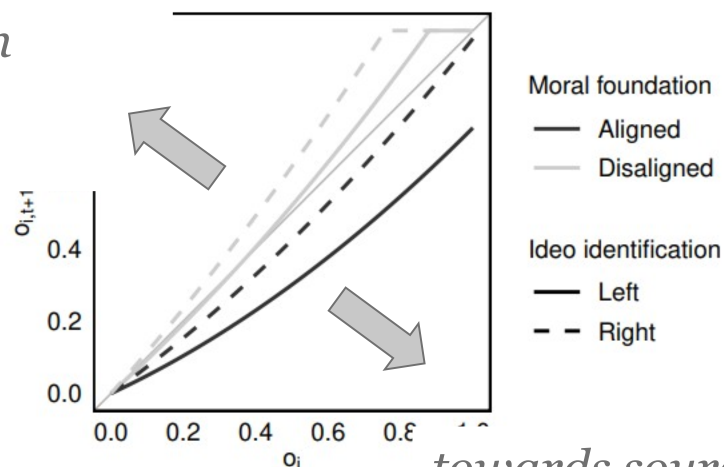
⇒ We estimated parameters influence function from data

⇒ Feeded this into simple simulation model

Table 2: Posterior distribution and model fit for Bayesian weighted linear influence models with stimulus morality and ideological identification

	Model 0		**Model 1**		**Model 2**	
	Estimate	**SD**	**Estimate**	**SD**	**Estimate**	**SD**
persuasiveness (α)	0.041	0.036	0.209	0.103	0.533	0.131
distance (β_0)			0.259	0.152	0.265	0.143
moral (β_1)					-0.437	0.116
right (β_2)					-0.652	0.176
moral $\times$ right (β_3)					0.843	0.238
σ	0.212	0.011	0.216	0.012	-0.203	0.010
elpd_{LOO}	143.402	23.428	143.282	24.266	147.872	23.300
WAIC	-286.835	46.845	-286.623	48.509	-295.809	46.590
N	311		311		311	

away from source of influence



towards source of influence

Shift opinion when exposed to argument oj = 0,

by

- alignment moral foundation
- ideology participant

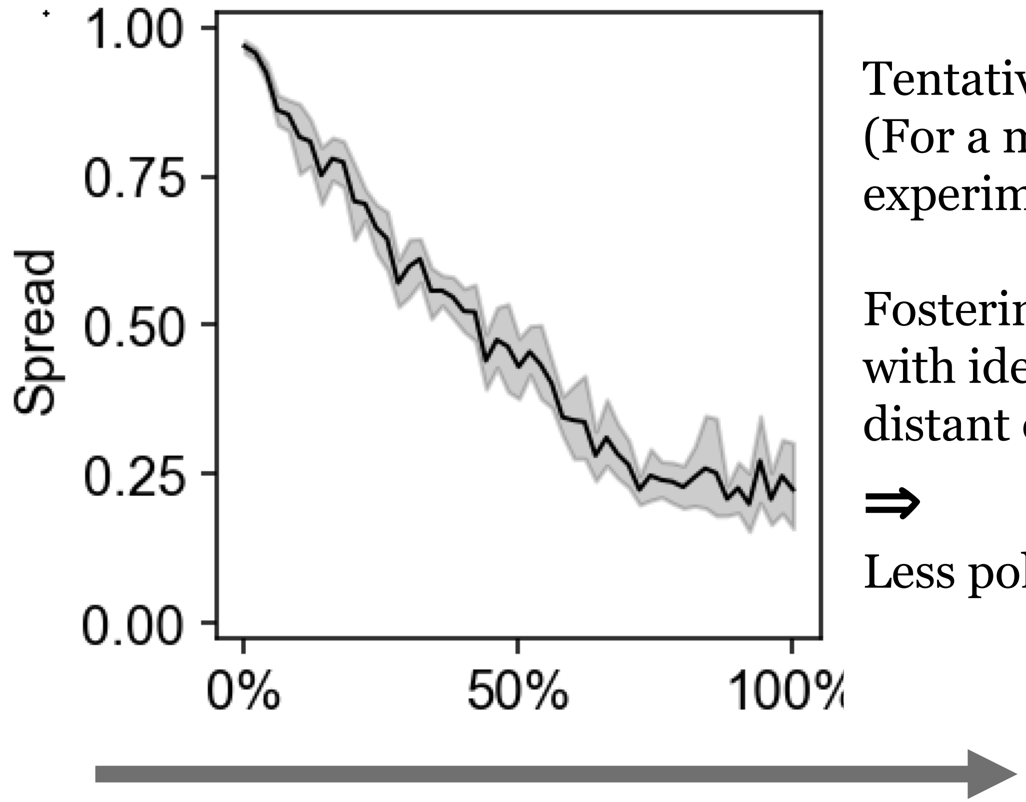
Figure 4: Predicted argument response function by political orientation and alignment of moral foundation. Opinion shifts are predicted relative to an argument $o_j = 0$

Keijzer et al, 2024

"Empirically informed" (calibrated) simulation of "popping the filter bubble"

Keijzer, Mäs & Flache 2024 JASSS

Polarization indicator



Tentative hypothesis (For a macro experiment):

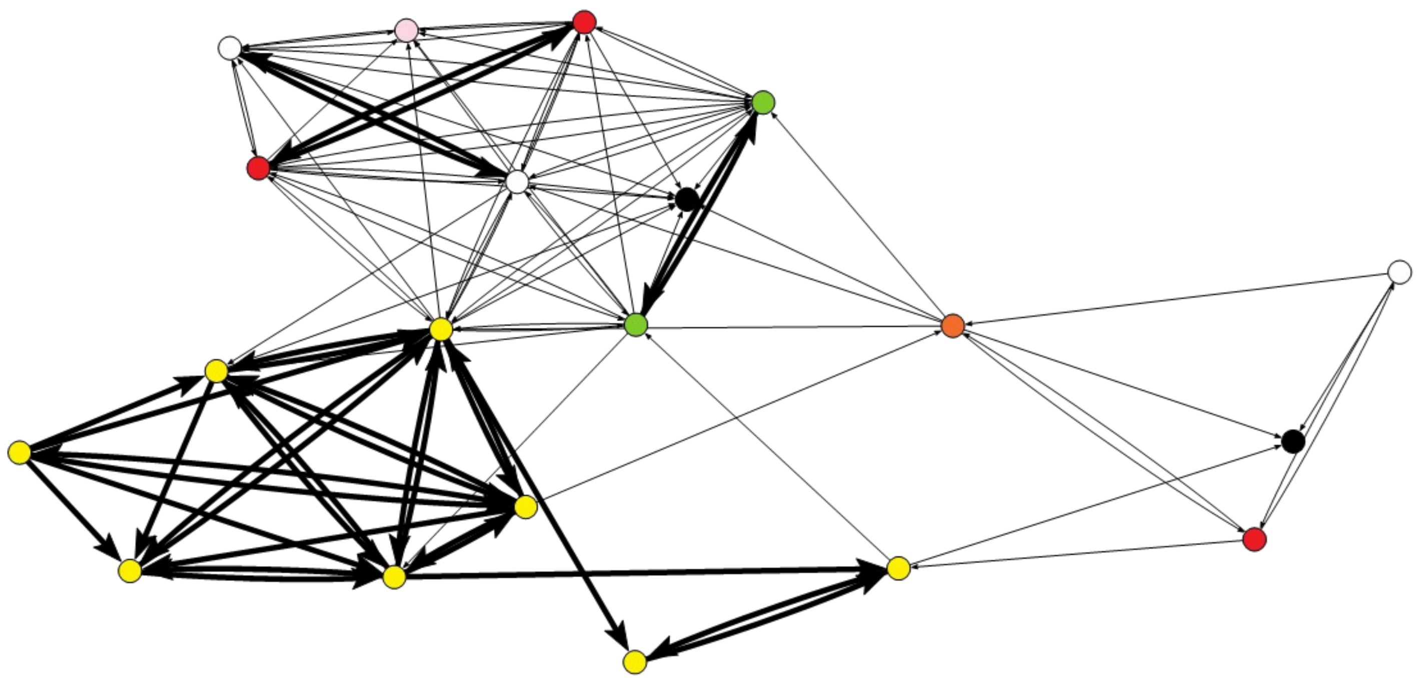
Fostering interaction with ideologically distant others
⇒
Less polarization

"bubble size" (ideological distance still allowing interaction)

From experiments to real evolving networks:

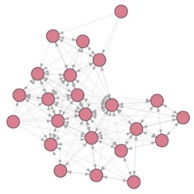
An empirical Investigation of Bounded Confidence and Repulsive Influence in Adolescents' Networks

Thanze Tang, Tom A.B. Snijders & Andreas Flache
(under review)



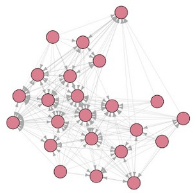
Test critical ABM assumptions in stochastic actor-oriented modelling framework (SAOM)

(Tang, Snijders & Flache, under review)



Wave 5

- **Limitation of experiments:**
  - "in the field" there are multiple interdependent dynamics
  - Limited time span
  - "lack of external validity"



Wave 6

- **In this project:**
  - We use longitudinal co-evolution data opinions + networks (Arnhem school study)
  - **Control for simultaneous interdependent processes of network + attitude changes**

    "SAOM": stochastic actor oriented model (Snijders et al)
  - Develop and estimate SAOM parameters capturing key social influence assumptions
    - Negative (aka repulsive) social influence
    - "bounded confidence" (influence only from similar others)

Effects of main interest in this study:

- *simAllNear*:

If the estimate is positive→
people shift opinions to be closer to others with similar opinions
(Positive influence with bounded confidence is supported)

- *simAllFar*:

If the estimate is negative →
people move their opinions to be different from others with dissimilar opinions
(Negative aka repulsive influence is supported)

Controls:
Network endogenous processes (e.g. reciprocity, transitive closure, homophily)

Trends in opinion changes independent from influence
(e.g. shift in one direction, tendency to move towards extremes or towards center, …)

RESULTS

Based on

46 classrooms
begin secondary school

2 waves
6 months apart

N= 991 adolescents

SAOM with Bayesian method for estimating parameters, random coefficients
Koskinen & Snijders 2023

Effect	Feature	p.m.	p.s.d.	b.s.d.	p
Network Effects					
out-degree (density)	Random	−2.1250	0.0889	0.2916	0.00
reciprocity	Random	2.2937	0.0924	0.3104	1.00
transitive triplets	Fixed	0.3687	0.0167	.	1.00
transitive reciprocated triplets	Fixed	−0.0603	0.0259	.	0.01
in-degree related popularity	Fixed	−0.0894	0.0108	.	0.00
out-degree related activity	Fixed	0.0828	0.0057	.	1.00
reciprocal degree-related activity	Fixed	−0.2567	0.0149	.	0.00
opinion similarity	Fixed	0.2405	0.0836	.	1.00
log class size	Fixed	−0.3550	0.1589	.	0.01
same gender	Random	0.6124	0.0533	0.2051	1.00
Opinion Effects					
linear shape	Random	−0.2903	0.0749	0.3379	0.00
quadratic shape	Random	−0.2598	0.0868	0.1655	0.00
1-near similarity	Random	0.0018	0.0272	0.0937	0.53
3-far similarity	Random	−0.1664	0.0863	0.1796	0.03
average similarity	Fixed	1.0573	0.6339	.	0.95

p.m. = posterior mean; p.s.d. = posterior standard deviation;
b.s.d. = posterior between-groups standard deviation;
p = posterior probability that the parameter is greater than 0.

Main conclusions Tang et al (under review)

The results show

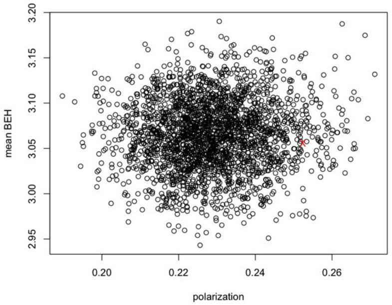
- **evidence of discrepancy-induced negative influence**
- **no evidence of bounded confidence induced positive influence**

However:

Simulation of the aggregate dynamics resulting from the interplay of all network and attitude change processes included in the empirical model of the data shows:

Despite negative influence, the observed microprocesses do NOT induce a clear tendency towards opinion polarization

Posterior predictive check:



Polarization indicator < 0.5: low polarization

Unravelling polarization?

Work in progress

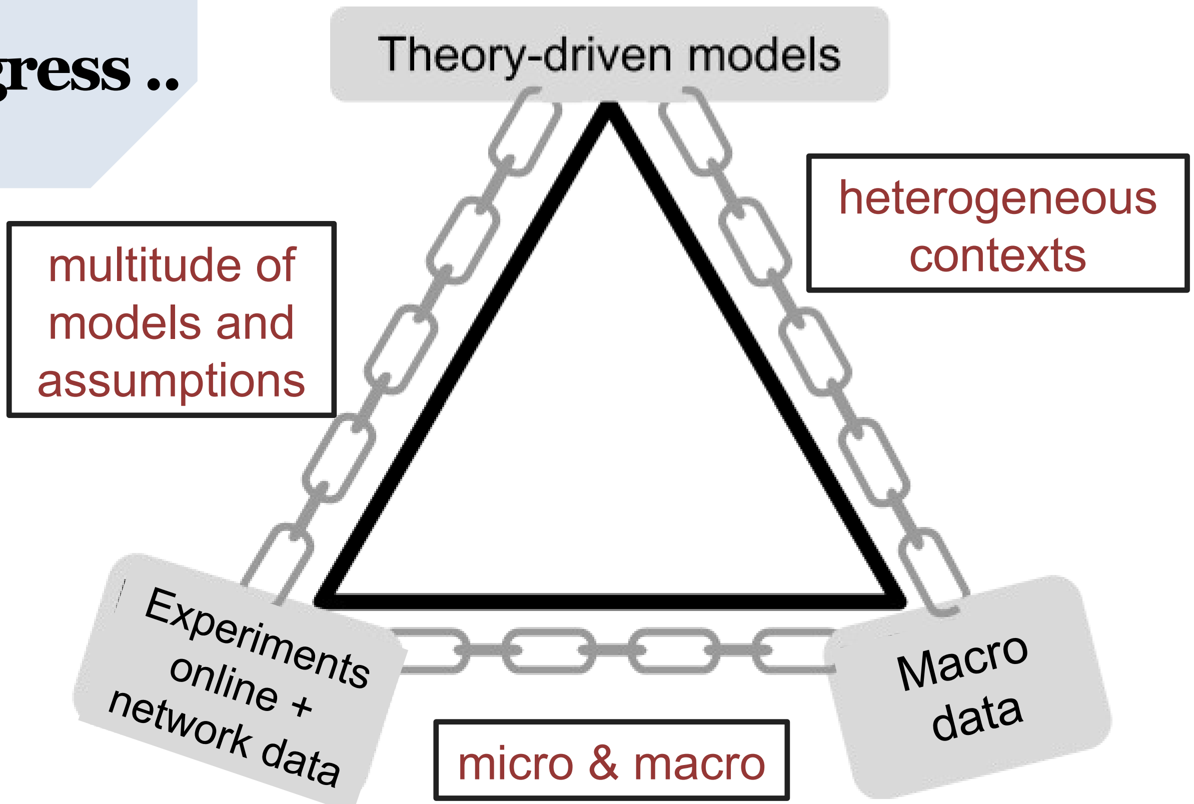
But there also is progress ..

Much of this progress we owe to 2 decades of work at:

Chair of Systems Design

ETH zürich

Challenges



Thank you for your attention

https://flache.gmw.rug.nl/

Looking forward to your comments and questions!

Credits

Tom Snijders
Vincenz Frey
Norms and Networks Group

Marijn Keijzer

Tanzhe Tang

Michael Mäs

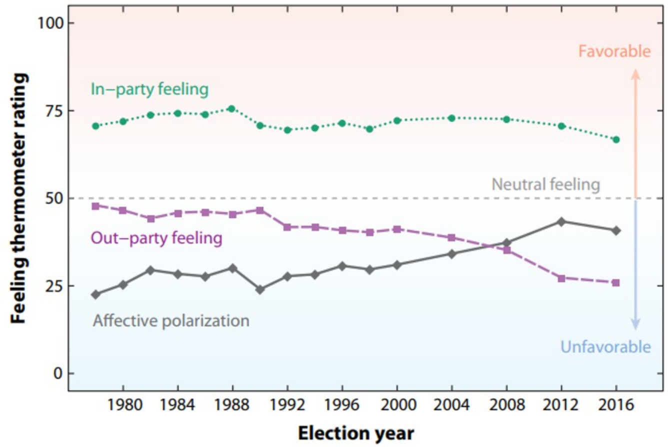
Reserve slides below here

Affective polarization

2008, Fiorina et al. 2008). But regardless of how divided Americans may be on the issues, a new type of division has emerged in the mass public in recent years: Ordinary Americans increasingly dislike and distrust those from the other party.

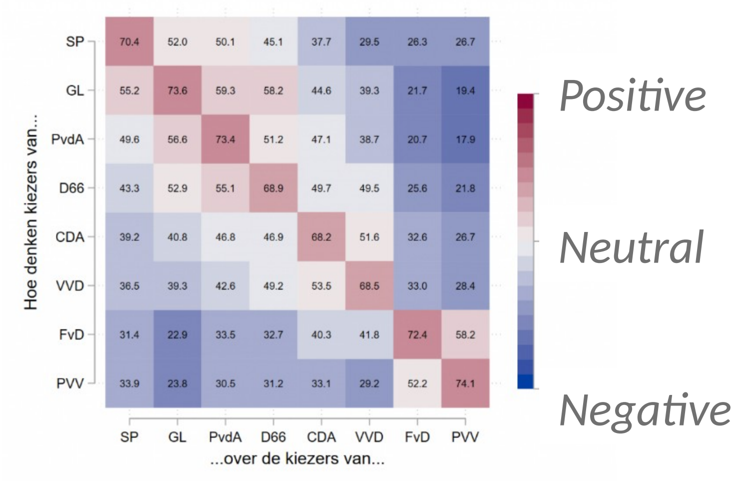
Democrats and Republicans both say that the other party's members are hypocritical, selfish, and closed-minded, and they are unwilling to socialize across party lines, or even to partner with opponents in a variety of other activities. This phenomenon of animosity between the parties is known as affective polarization.

Iyengar et al 2019, Annu. Rev. Political Sci. 2019. 22:129–46



U.S.

Source: Iyengar et al 2019



Netherlands

Source: Harteveld, E. 2020

Stochastic Actor-Oriented Modelling (SAOM) implemented by software **RSIENA** (Stochastic Investigation of Empirical Network Analysis, in R)

- Input:

Longitudinal data on co-evolution network relations + “behavior” individuals in a complete network

A selection of effects (mechanisms) that are (potentially) important for explaining observed network + opinion dynamics

⇒

Agents are modelled as myopically optimizing “objective functions” capturing their preferences about desirable network states and behavioral states (e.g. opinions)

- Output:

The parameter estimates for each effect (can be roughly interpreted as the relative importance of each effect governing the dynamics)

Snijders, T.A.B., Van de Bunt, G.G., Steglich, C.E.G., 2010. Introduction to stochastic actor based models for network dynamics. *Social Networks* 32, 44-60

Two new SAOM effects capturing key assumptions of social influence ABM's

- *simAllNear*:

Captures the influence from those whose opinion difference with the focal agent is **smaller** than p, a pregiven threshold. NOT ONLY FROM NETWORK TIES.

- *simAllFar*:

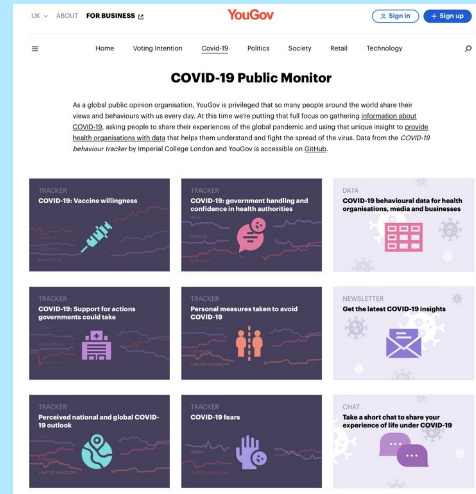
Captures the influence from those whose opinion difference with the focal agent is **larger** than p, a pregiven threshold. NOT ONLY FROM NETWORK TIES.

Effects are estimated controlling for – i.a. – influence from friends (average similarity) and individual tendencies (linear + quadratic shape)

Macro level data on “conditions” and “outcomes”

How warm feelings do you have towards party X?

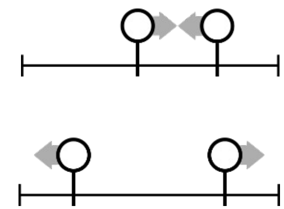
P6	--	--	-	+/-	+/-	++
P5	--	--	-	+/-	++	-
P4	-	+	+/-	++	+	+/-
P3	+/-	+	++	+	-	--
P2	+	+	+/-	+	-	--
P1	++	+/-	+/-	-	--	--
	P1	P2	P3	P4	P5	P6



[r1] To what extent do you agree or disagree that…?

-[r1_1]	Coronavirus (COVID-19) is very dangerous for me
-[r1_2]	It is likely that I will get coronavirus (COVID-19) in the future
-[r1_3 fixed]	Wearing a mask will protect me against coronavirus (COVID-19)
-[r1_4 fixed]	Wearing a mask will protect others against coronavirus (COVID-19)
-[r1_5 fixed]	Wearing a mask to protect me against coronavirus (COVID-19) is not possible for me
-[r1_8 fixed]	Getting a vaccine will protect me against coronavirus (COVID-19)
-[r1_9 fixed]	Getting a vaccine will protect others against coronavirus (COVID-19)
-[r1_10 fixed]	Getting a vaccine to protect me against coronavirus (COVID-19) is not possible for me
-[r1_6]	I feel it is important to carry out activities which will improve my health
-[r1_7]	My life has been greatly affected by coronavirus (COVID-19)
<1>	1 – Disagree
<2>	2
<3>	3
<4>	4
<5>	5
<6>	6
<7>	7 - Agree

Modelling effect of "feeling temperature" on micro-interactions in OD framework



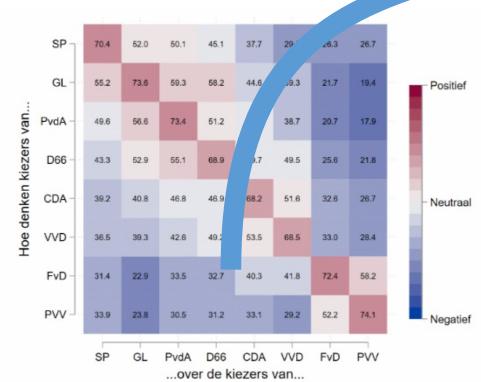
Start from "usual" pairwise interaction.

Then:

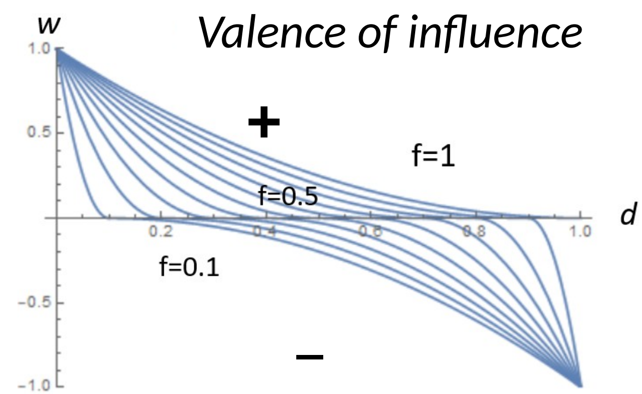
$$o_{i,t+1} = o_{i,t} + w\left(o_{i,t}, o_{j,t}, \varepsilon\right)\left(o_{j,t} - o_{i,t}\right)$$

$0 \leq o \leq 1$
$-1 \leq w \leq +1$
$0 \leq \varepsilon \leq 1$

⇒Incorporate "feeling thermometer" into influence weight.

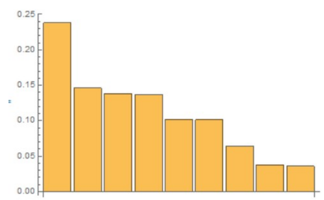


The "colder" the feeling, the less disagreement suffices to induce negative (repulsive) influence



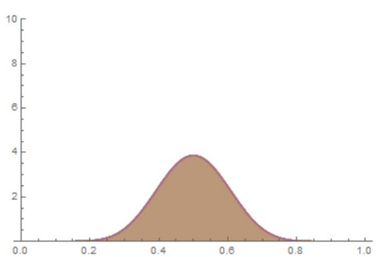
Further country-level characteristics affecting micro-level interactions in model (CSES data)

- Number and voteshare parties (group composition)
  - ⇒likelihood of interaction between members of party i and party j

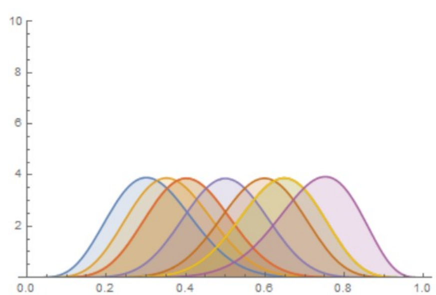


Currently “random mixing”

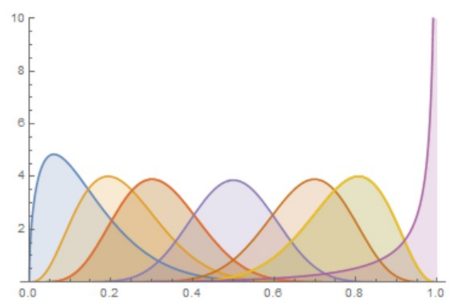
- Ideological dispersion parties (left-right position)
  - ⇒Affects distribution *initial opinions* across different parties
  - ⇒**Model parameter**



igd = 0



igd = 0.5



igd = 1

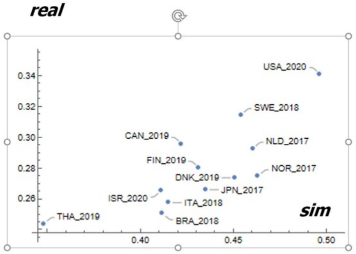
Simulation experiments

Compare different models with different parametrizations, assessing:

How well does a model explain differences between countries in extent of disagreement (s.d. in real data) in final week of observation period?

⇒Correlation sdReal with sdSim where correlations mean across X realizations

(N=12 country cases)



Simulations for 3 different items:

- r1_1 Coronavirus is very dangerous for me
- r1_3 Wearing a mask will protect me against coronavirus
- **r1_4 Wearing a mask will protect others against coronavirus**

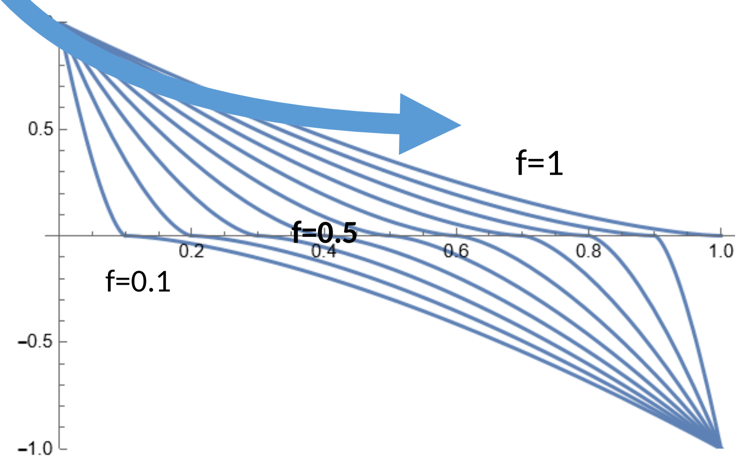
Wolfram Mathematic a

One experiment with 12 countries, 2500 parameter combinations

Parameters varied:

Name	*Note*	*Range of variation*
ε^0	Baseline threshold disagreement for pos / neg switch	0..1, step 0.25
φ	**Sensitivity threshold to feeling value**	**0..1, step 0.25**
s	Steepness weight function in distance	0.5..2, step 0.5
igd	Intergroup distance, alignment initial opinions with lr-position party	0..1, step 0.25
itPerAgent	average # of iterations per agent until simulation stops	0..16, step 4

Main parameter of interest: φ



Further

- N=100
- Party sizes proportional vote share in CSES data
- 100 realizations per parameter vector
- **Target statistic:**

  average correlation simulated variance opinions with real variance opinions in last week observation period

Issue r1_4
“Wearing a mask will protect others against coronavirus”

And the winner is …

Top 10 parameter combinations in terms of correlation:

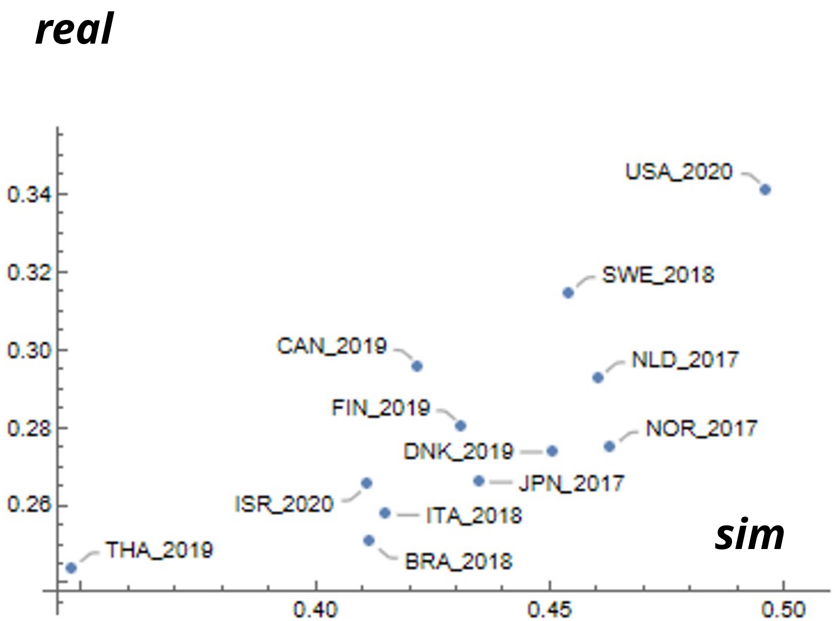
sF	eps0	phi	igd	itPerAgent	meanCorr
2	0.25	1	1	12	0.731549
1.5	0.25	1	1	8	0.716998
2	0.25	1	1	8	0.707923
2	0.25	0.75	1	12	0.707878
1.5	0.25	0.75	1	8	0.701111
2	0	1	1	8	0.700327
1.5	0.25	1	1	12	0.699055
2	0.25	0.75	1	8	0.697642
2	0.25	1	1	16	0.695283
1	0.25	1	1	8	0.694987

Issue r1_4 “Wearing a mask will protect others against coronavirus”

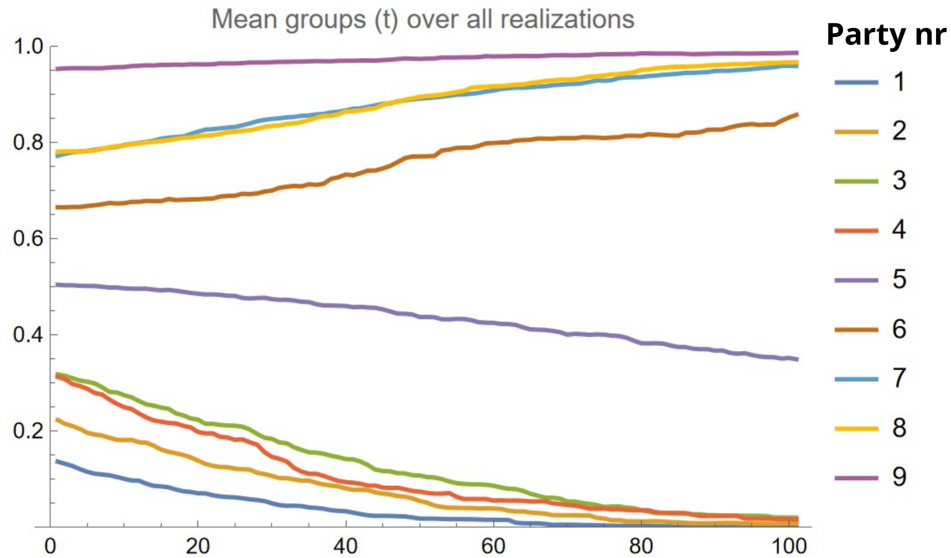
Properties of “winners”:
- Consistently low eps0
- Consistently high igd
- **Consistently high phi**
- Relatively short runtime (8 itPerAgent)

These models tend to generate
- high disagreement between ideologically and affectively distant parties
- Low disagreement (consensus) between ideologically and affectively close parties
- **Can pick up well extent to which a country is “polarization prone”**

Example “best fitting”model:



NL_2017. Average evolution party means (10 realizations)



Many more experiments with more different parameter combinations:

- general profile of “well-explaining models” remained largely the same
- Correlations are somewhat lower for the other issues (r1_1 and r1_3)
- Models tend to (strongly) overestimate real polarization