On Communicative Mechanisms Producing Filter Bubbles

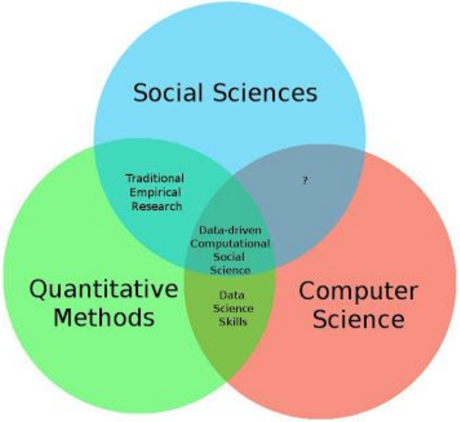
DISMA, Nov 6, 2019, Torino, Italy

Jan Lorenz
Computational Social Science, Jacobs University Bremen

Joint work with Daniel Geschke and Peter Holtz

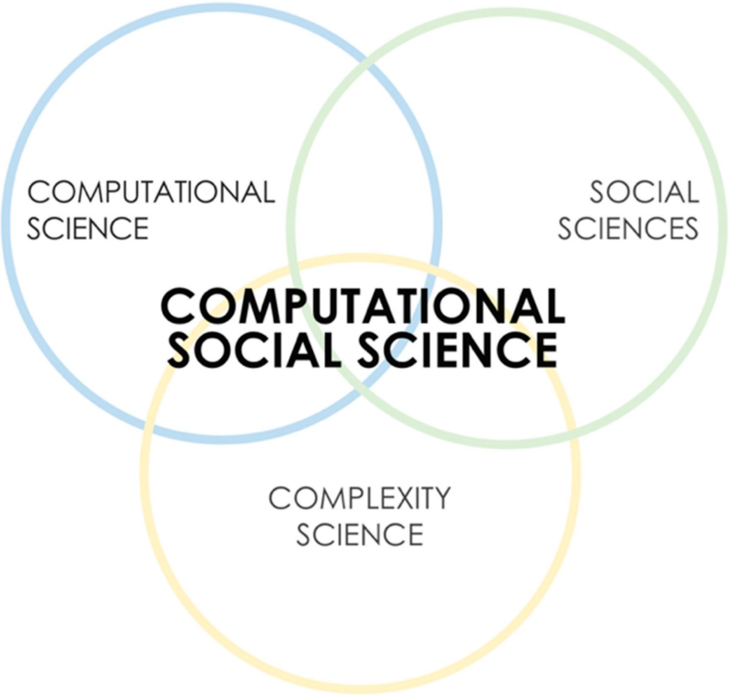
Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Computational Social Science

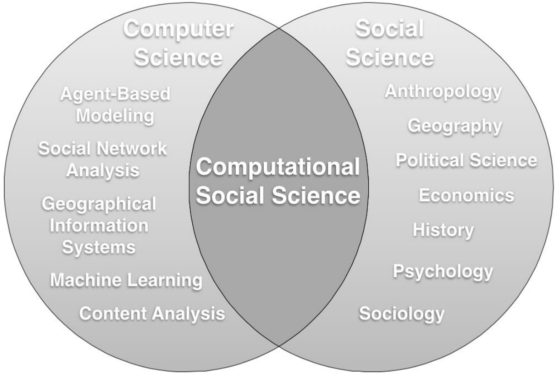


https://www.r-bloggers.com/data-science-in-businesscomputational-social-science-in-academia/

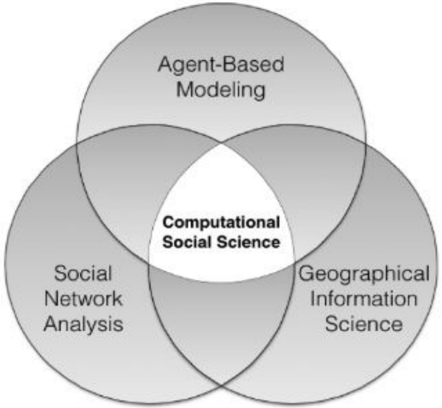
Lettieri, N. (2016). Computational Social Science, the Evolution of Policy Design and Rule Making in Smart Societies. *Future Internet*, *8*(2), 19.



What is CSS?



https://cos.gmu.edu/cds/computational-social-science/



https://www.slideshare.net/kimlyman/sdal-pires-bianica-riots-in-an-urban-slum-140813

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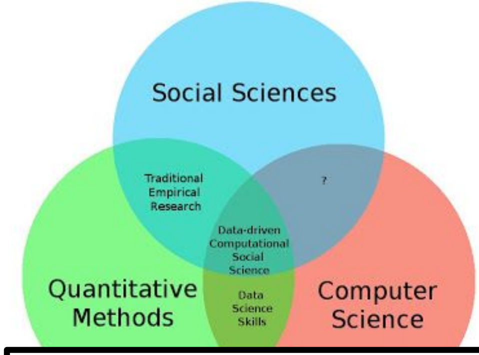
Computational Social Science

What is CSS?



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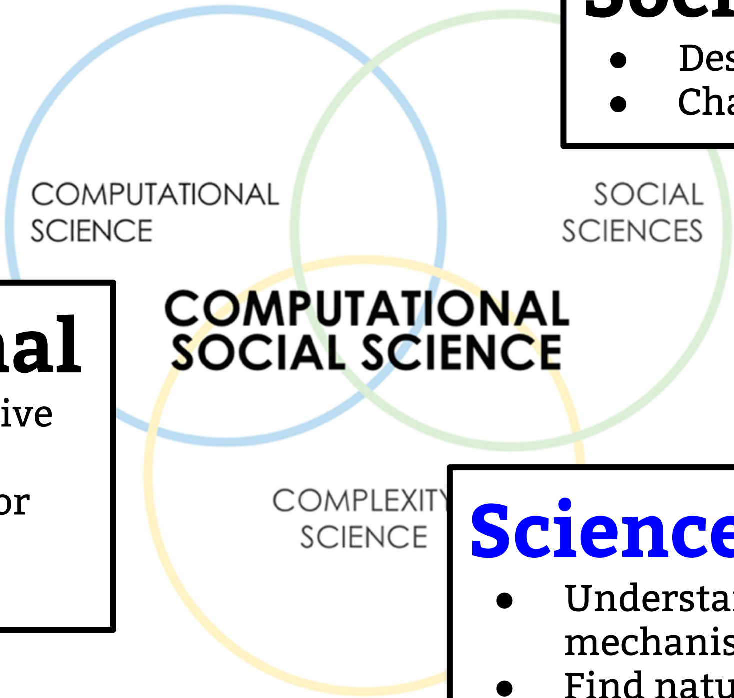
Design and Rule Making in Smart Societies. *Future Intern*



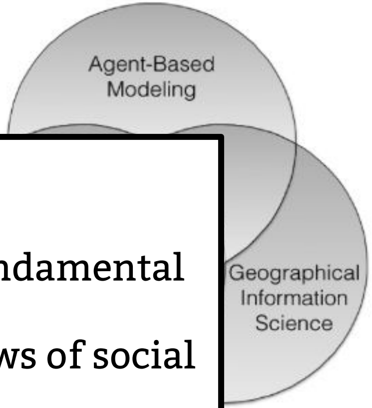
https://cos.gmu.edu/cds/computational-social-science/

Social

- Describe the social world
- Changes through digitalization

Computational

- Engineering perspective
- How to measure / implement / decide for practical purposes



Science

- Understand fundamental mechanisms
- Find natural laws of social systems

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CSS Summer School / Research Incubators

Computational Social Science **research incubator** on **social cohesion**. July 06-17, 2020 in Groningen

https://css.bigsss-bremen.de

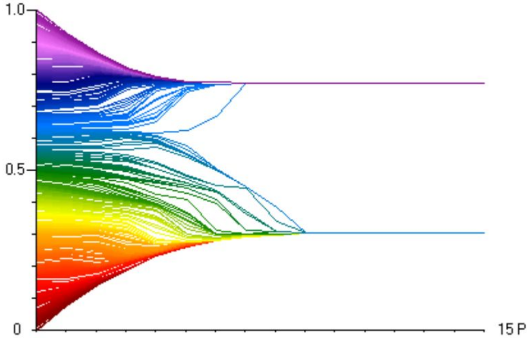
Deadline for **Projects**:

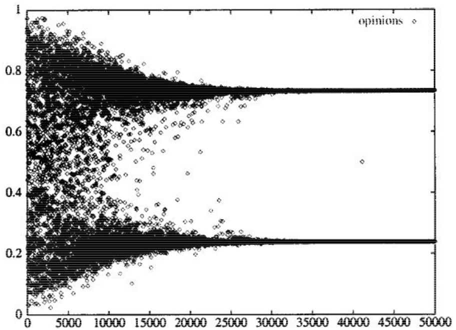
Nov 3 🙁

Please talk to me if interested to join!

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Opinion Dynamics under Bounded Confidence





Hegselmann, R., & Krause, U. (2002). Opinion Dynamics and Bounded Confidence, Models, Analysis and Simulation. JASSS, 5(3), 2.
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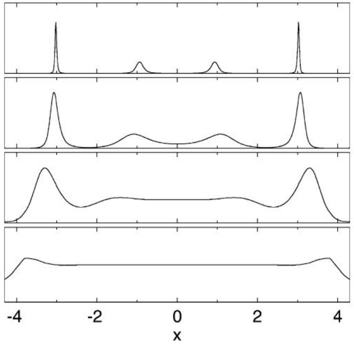

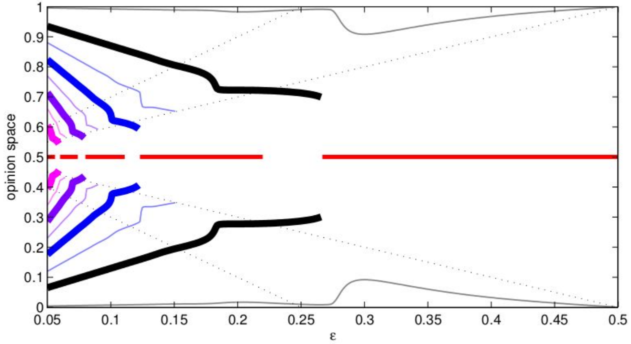

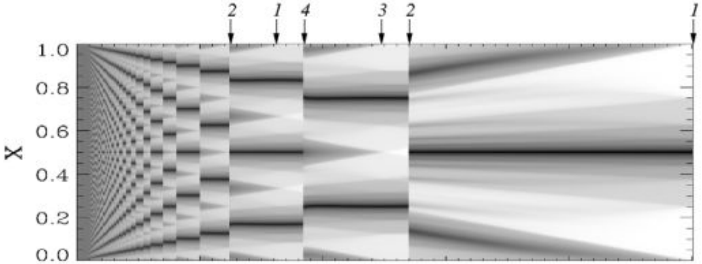

Ben-Naim, E., Krapivsky, P. L., & Redner, S. (2003). Bifurcation and Patterns in Compromise Processes. Physica D, 183, 190–204.
Lorenz, J. (2007). Continuous Opinion Dynamics under bounded confidence: A Survey. Int. Journal of Modern Physics C, 18(12), 1819–1838.
Pineda, M., Toral, R., & Hernandez-Garcia, E. (2009). Noisy continuous-opinion dynamics. J. of Stat. Mech.: Theory and Experiment, 2009(8)

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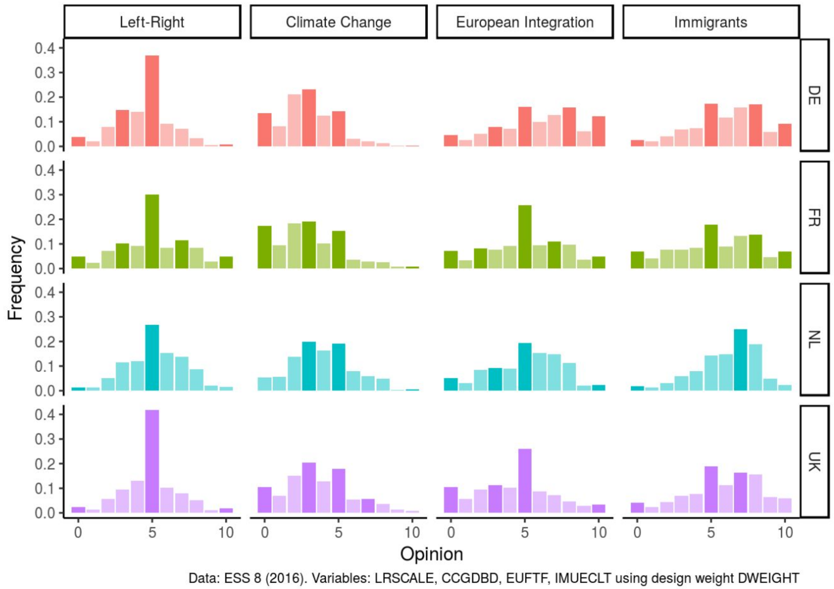
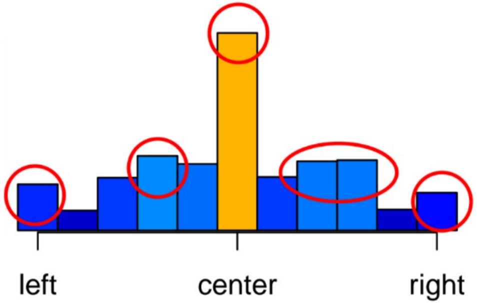
Opinion Dynamics under Bounded Confidence

- Fascinating clustering dynamics
- Complicated to validate …
- My current project "ToRealSim" with survey data. Model this →





Based on:

Flache, A., Mäs, M., Feliciani, T., Chattoe-Brown, E., Deffuant, G., Huet, S., & Lorenz, J. (2017). Models of Social Influence: Towards the Next Frontiers. Journal of Artificial Societies and Social Simulation, 20(4), 2.

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Different Model Idea

- Measuring opinions with surveys is costly
- Opinions manifest in attitudinally loaded information which people have in memory
- This information constructs their viewpoint
- Attitudinal information may be quantified in shared content on social media

Today: A model with people and bits of information. (No data yet.)

The triple-filter bubble

Geschke, D., Lorenz, J., & Holtz, P. (2019).
The triple-filter bubble: Using agent-based modelling to test a meta-theoretical framework for the emergence of filter bubbles and echo chambers. *British Journal of Social Psychology*, *58*, 129–149.
http://doi.org/10.1111/bjso.12286
OPEN ACCESS

Download NetLogo model from github:
https://github.com/janlorenz/TripleFilterBubble

Or try in NetLogoWeb:
http://netlogoweb.org/web?https://raw.githubusercontent.com/janlorenz/TripleFilterBubble/master/TripleFilterBubble_Web.nlogo

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Special section paper

The triple-filter bubble: Using agent-based modelling to test a meta-theoretical framework for the emergence of filter bubbles and echo chambers

Daniel Geschke[1]*, Jan Lorenz[2,3] and Peter Holtz[4]

[1] Institut für Demokratie und Zivilgesellschaft (Institute for Democracy and Civil Society, IDZ), Jena, Germany
[2] BIGSSS Bremen International Graduate School of Social Sciences, Jacobs University, Bremen, Germany
[3] Department of Computational Social Science, GESIS Leibniz Institute for the Social Sciences, Cologne, Germany
[4] Leibniz-Institut für Wissensmedien IWM (Knowledge Media Research Center), Tübingen, Germany

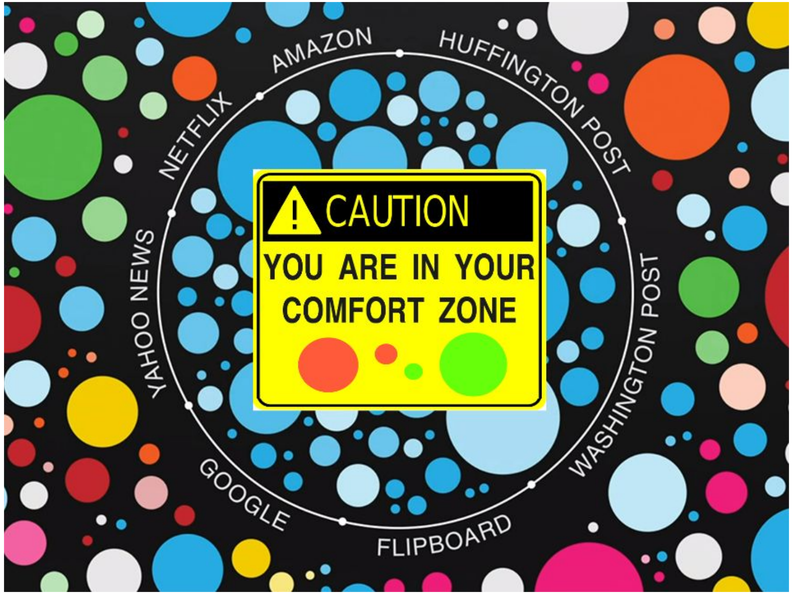
Filter bubbles and echo chambers have both been linked recently by commentators to rapid societal changes such as Brexit and the polarization of the US American society in the course of Donald Trump's election campaign. We hypothesize that information filtering processes take place on the individual, the social, and the technological levels (triple-filter-bubble framework). We constructed an agent-based modelling (ABM) and analysed twelve different information filtering scenarios to answer the question under which circumstances social media and recommender algorithms contribute to fragmentation of modern society into distinct echo chambers. Simulations show that, even without any social or technological filters, echo chambers emerge as a consequence of cognitive mechanisms, such as confirmation bias, under conditions of central information propagation through channels reaching a large part of the population. When social and technological filtering mechanisms are added to the model, polarization of society into even more distinct and less interconnected echo chambers is observed. Merits and limits of the theoretical framework, and more generally of studying complex social phenomena using ABM, are discussed. Directions for future research such as ways of comparing our simulations with actual empirical data and possible measures against societal fragmentation on the three different levels are suggested.

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Filter Bubbles

Attitude polarization and fragmentation in societies are increasingly linked to **Filter Bubbles**

State of an individual in which it receives mostly likable information through technological filters, such as the recommender algorithms of personalized search engines and social media.



Source: https://medium.com/@flewterry/should-we-be-worried-about-filter-bubbles-8fc2dcf01ad

Filter Bubble goes back to:
Pariser, E. (2011). The filter bubble: What the Internet is hiding from you. Penguin UK.

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Cognitive Filters and Echo Chambers

- Individuals like information which fits pre-existing attitudes. Such a confirmation bias is a **cognitive filter**.
- Cognitive filters don't prevent individuals from receiving unlikable information but from integrating it into their viewpoint
- Such cognitive filters are the basis for the effectiveness of **algorithmic filters**
- Further on, social media is blamed to foster echo chambers
- **Echo chamber:** Individuals receive information from friends who are mostly like-minded constituting a **social filter**

Triple Filter Bubble Model

Basic idea:

Individuals build their viewpoint on the information they have.

With new information, humans encounter 3 types of filters

1. **Cognitive**
2. **Social**
3. **Technological (Algorithmic)**

Research Question:

How do these filters contribute to the emergence of filter bubbles?

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Triple Filter Bubble Model

Research Questions (Social Science):

- How do we quantify bubbles?
- In what way does posting of information on social media matter?
- Do clustered friendship networks in social media matter?
- Do recommendation algorithms in media consumption matter?

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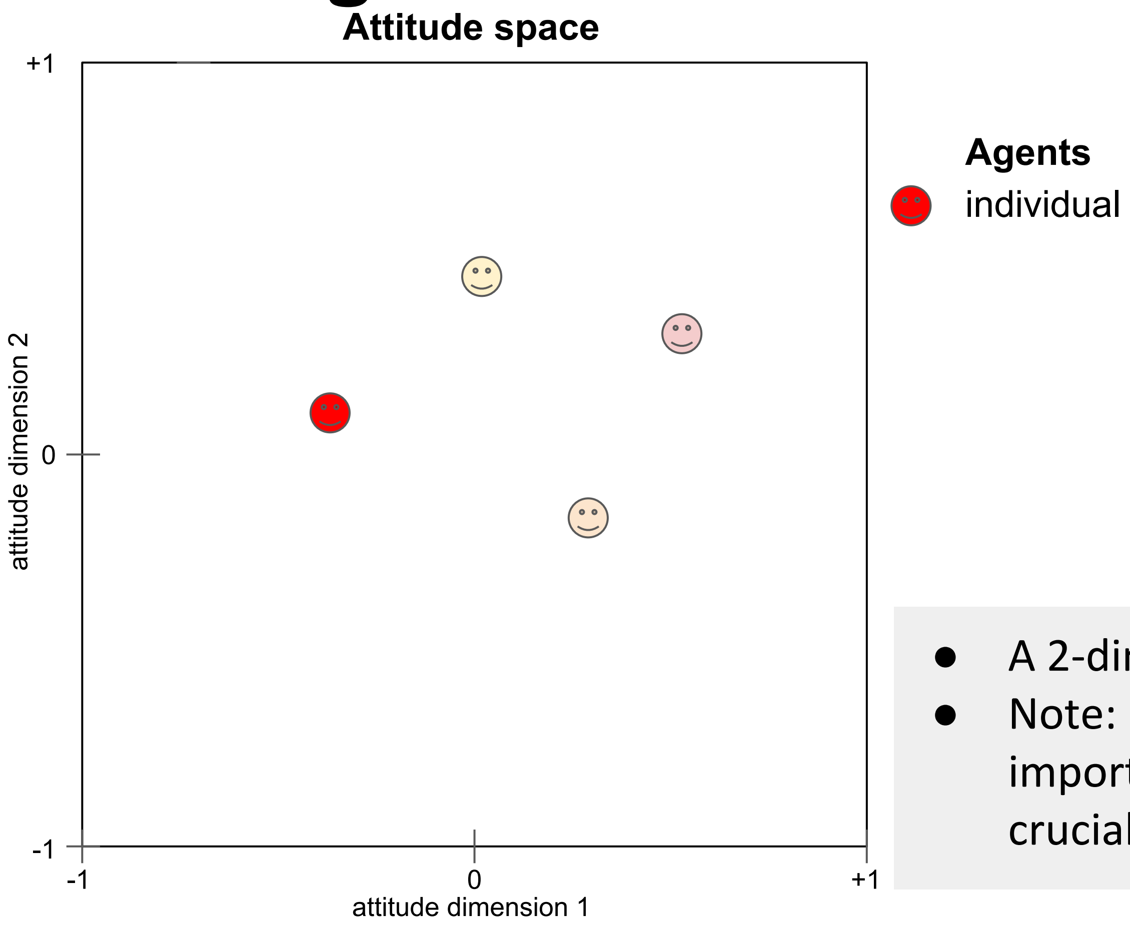
Modeling: Basic entities



- A 2-dimensional attitude space
- Note: Number of dimensions is an important, but not a fundamentally crucial parameter

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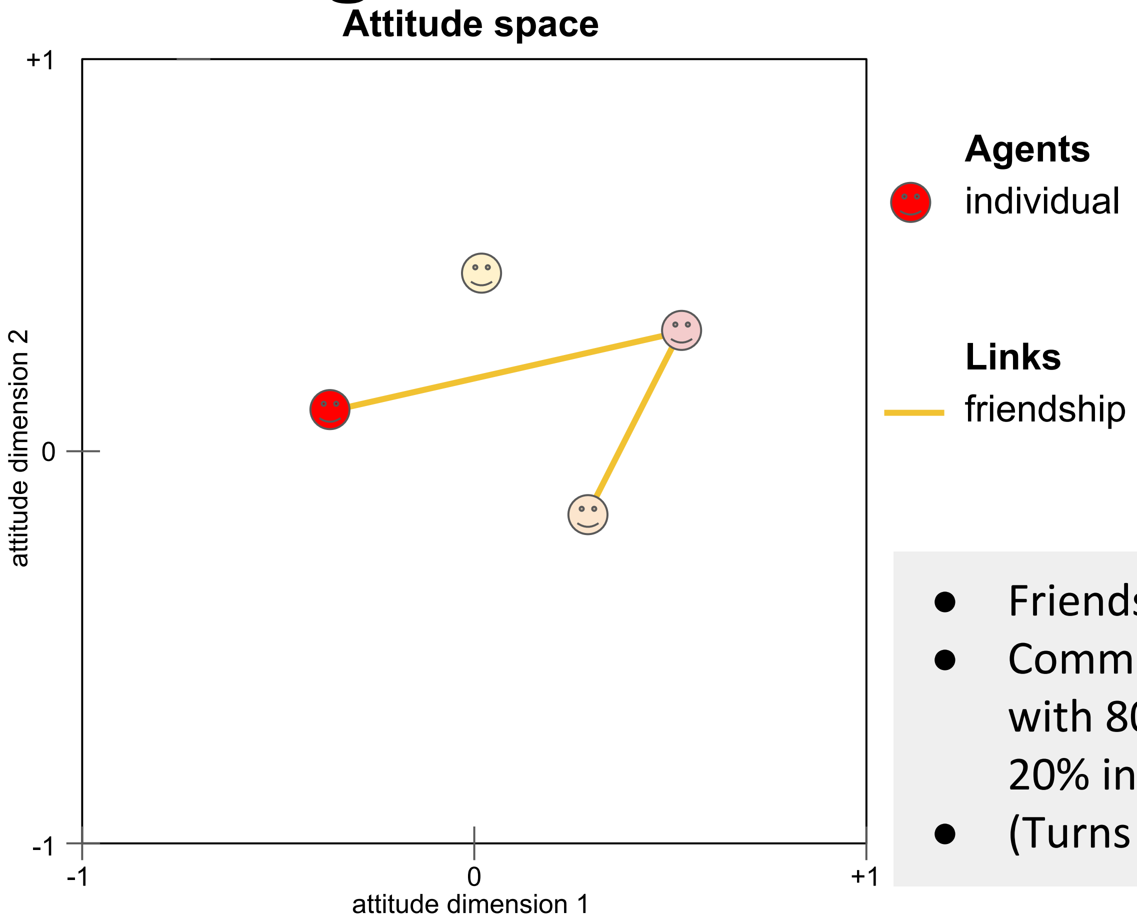
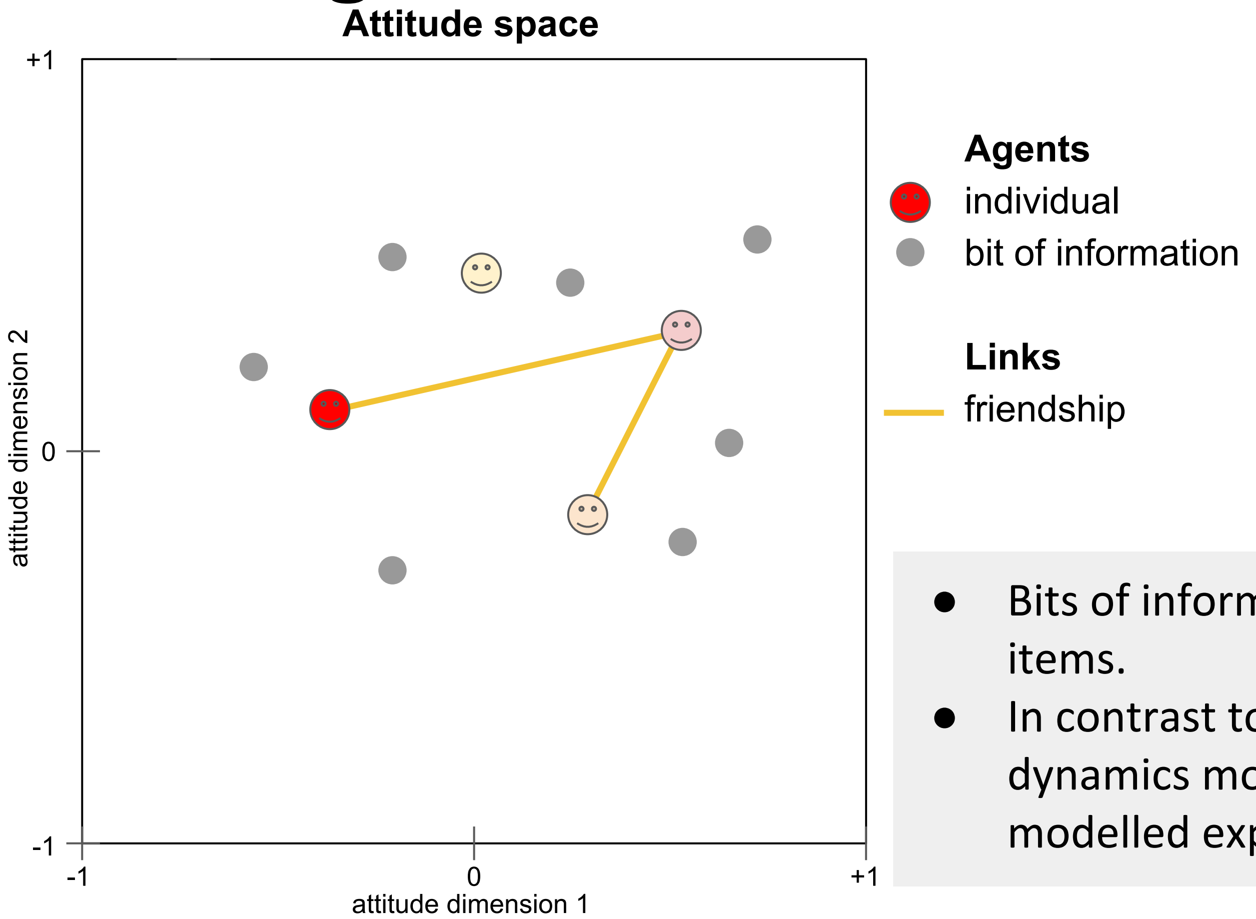
Modeling: Basic entities



- Friendship network
- Community structure with 4 groups with 80% intra-community links and 20% inter-community links
- (Turns out to be not essential)

Modeling: Basic entities



- Bits of information represent media items.
- In contrast to many other opinion dynamics models, media items are modelled explicitly

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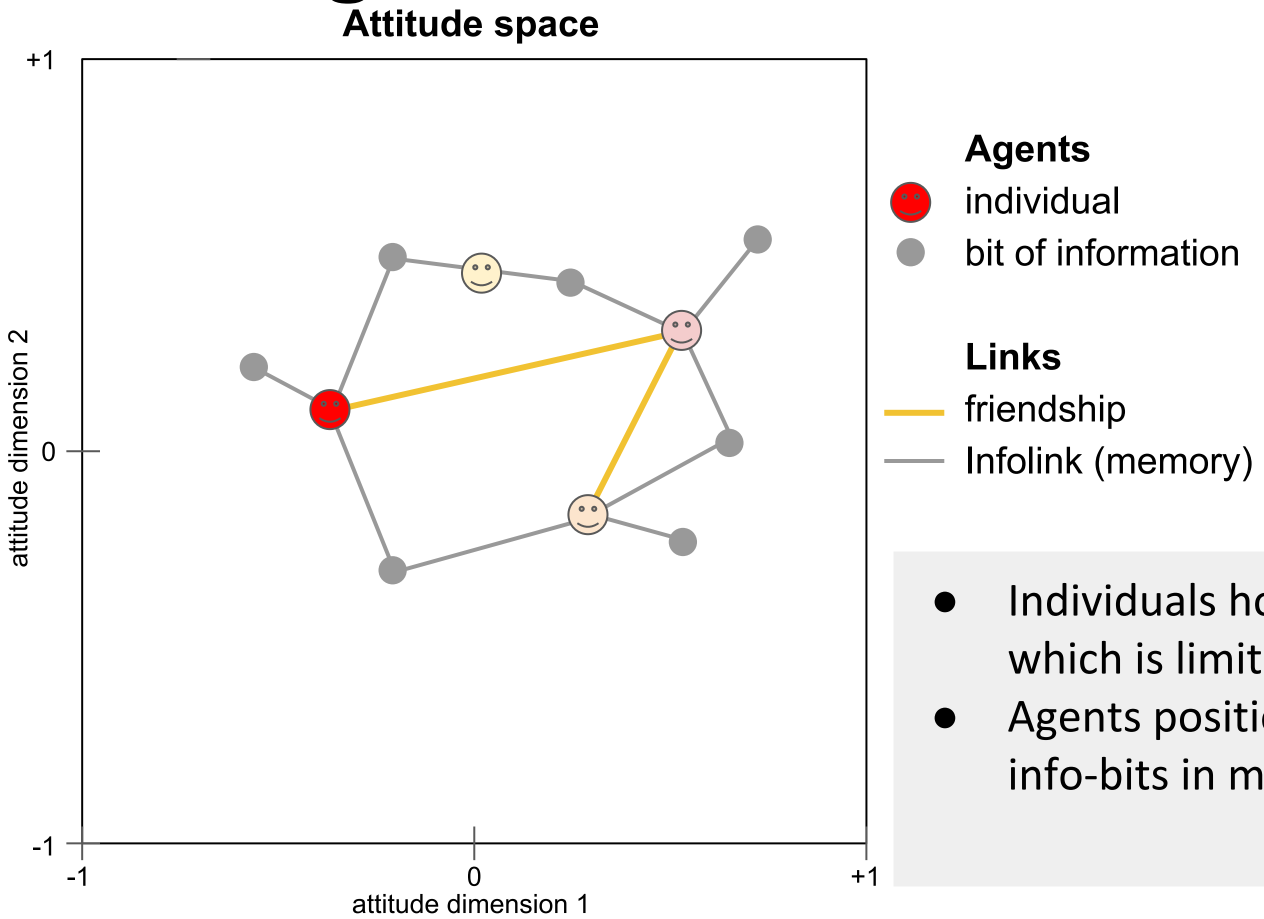
Modeling: Basic entities



- Individuals hold info bits in memory which is limited, e.g., max. 20 info-links
- Agents position at average value of all info-bits in memory

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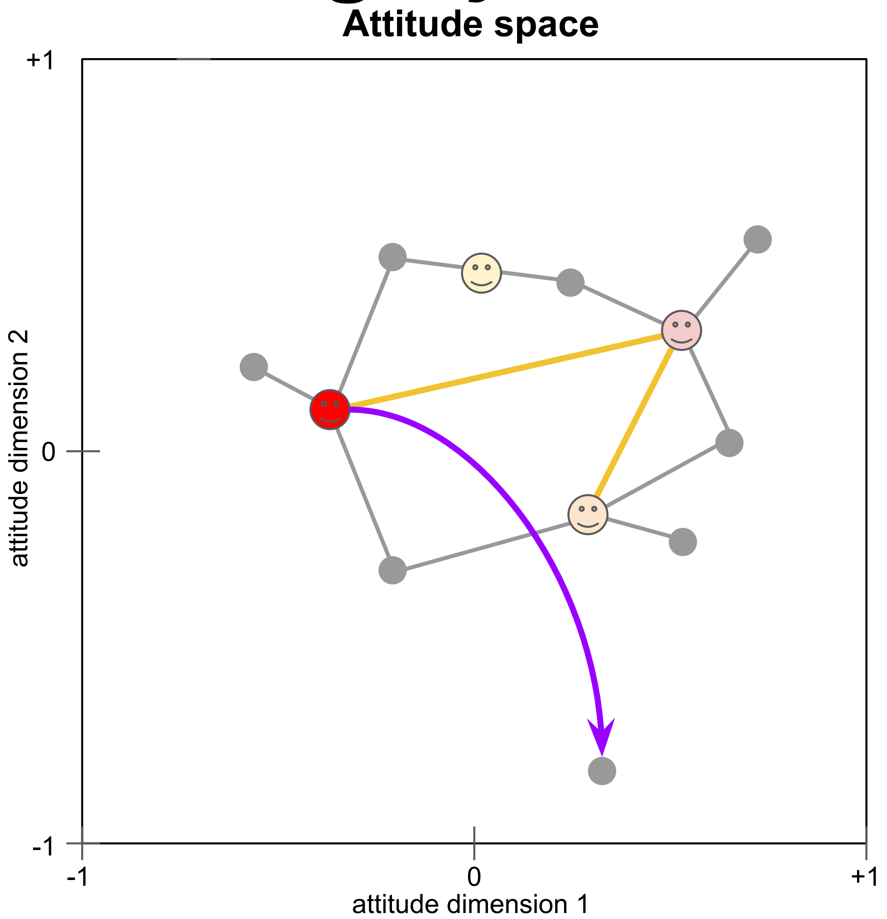
Modeling: Dynamics for New Info-Bits



New Info-bits appear through

1. **Individual discovery** (one agent exposed to a new bit with random position)

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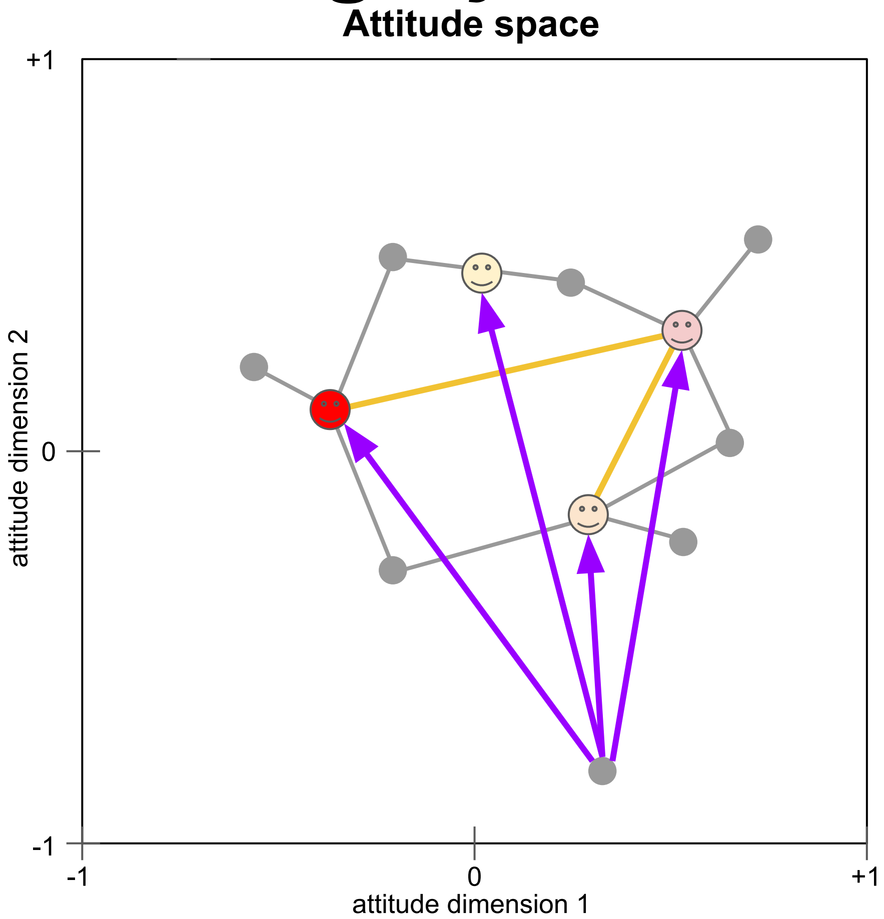
Modeling: Dynamics for New Info-Bits



New Info-bits appear through

1. **Individual discovery** (one agent exposed to a new bit with random position)
2. **Mass media** (all agents are exposed to one new random info-bit)

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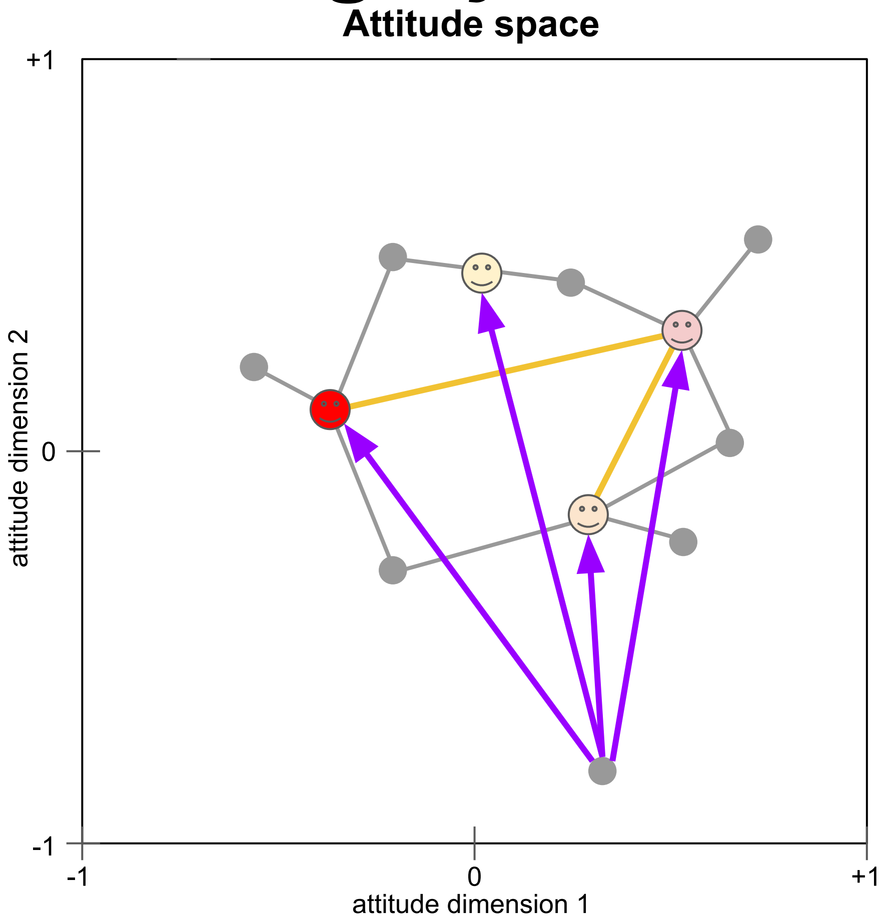
Modeling: Dynamics for New Info-Bits



Motivated Cognition:
Agents are more likely to integrate info-bits when its attitudinal position is close to their viewpoint.

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Integration Probability

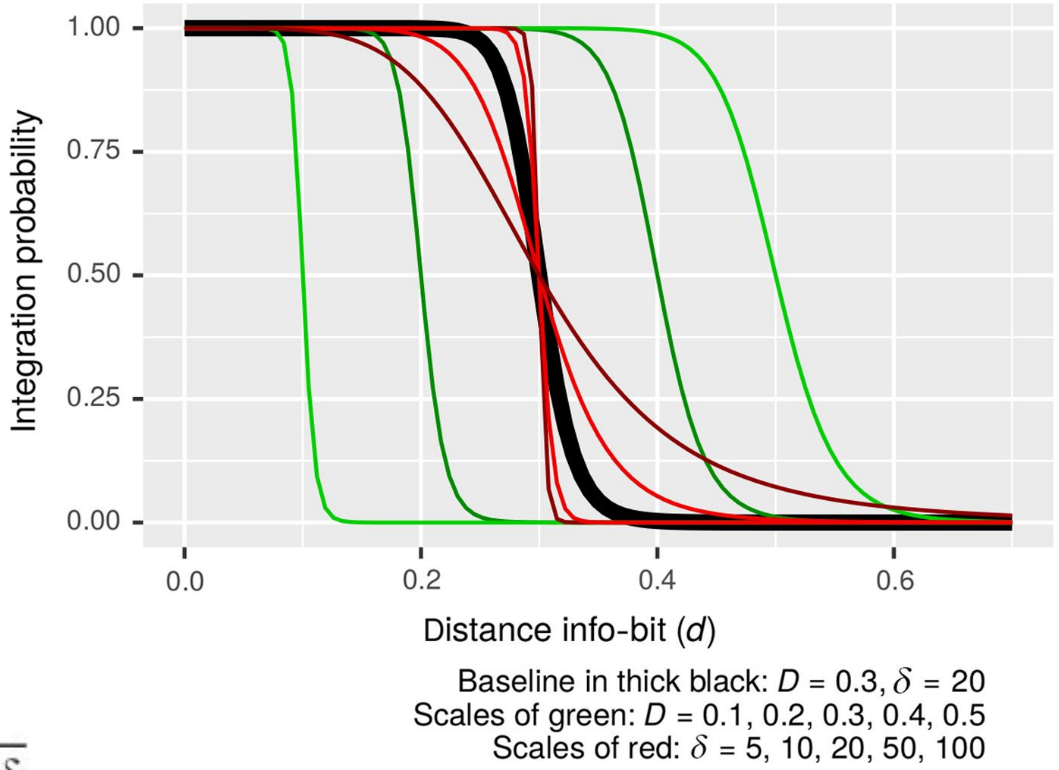
Probability to create an Info-link, based on

D latitude of acceptance

δ acceptance sharpness

d distance to info-bit

$$P(d; D, \delta) = \frac{D^\delta}{d^\delta + D^\delta}$$



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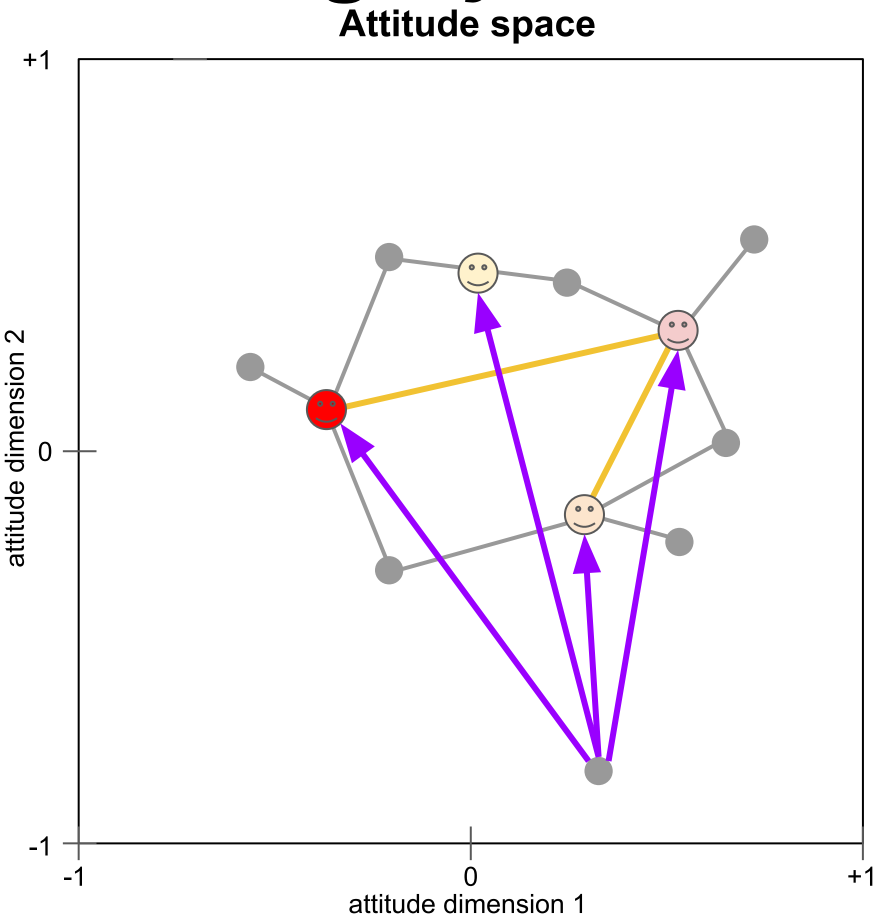
Modeling: Dynamics for New Info-Bits



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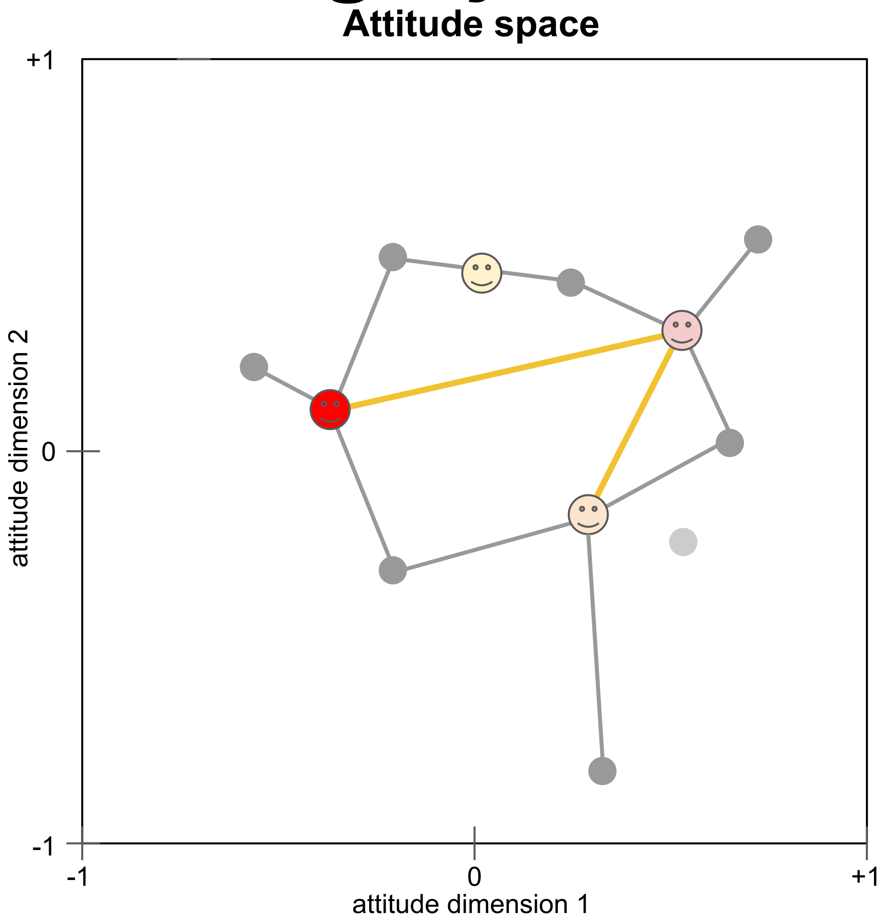
Modeling: Dynamics for New Info-Bits



Motivated Cognition:

- New info-links may be created
- If memory is full a random old link is deleted

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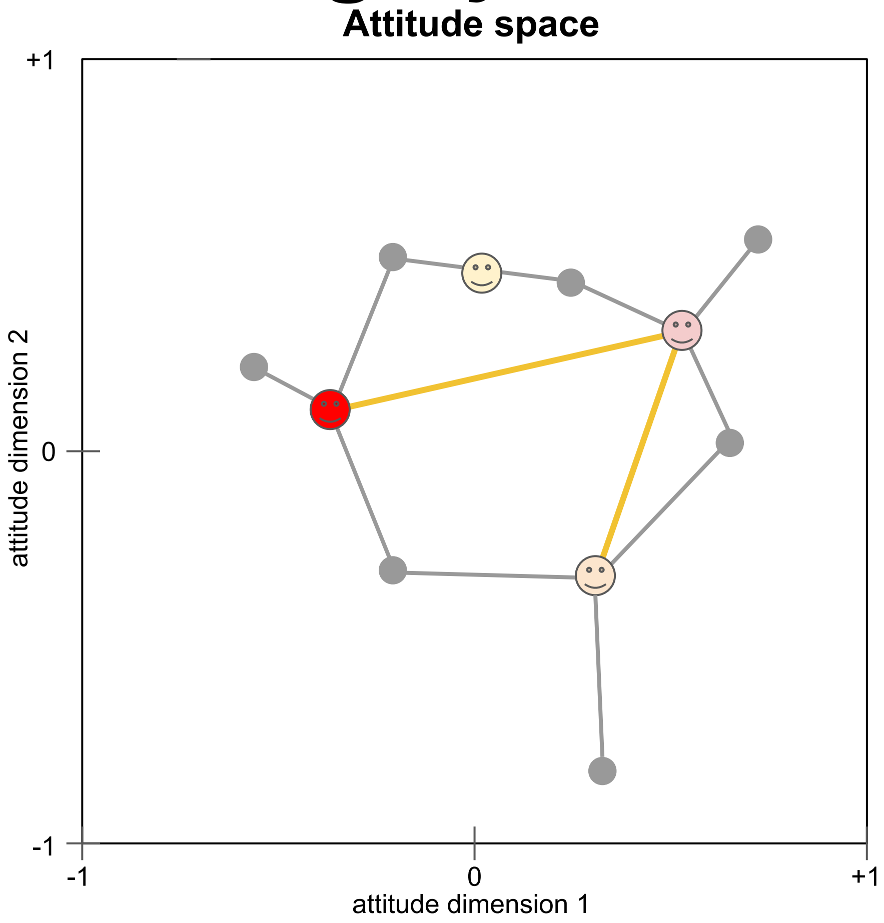
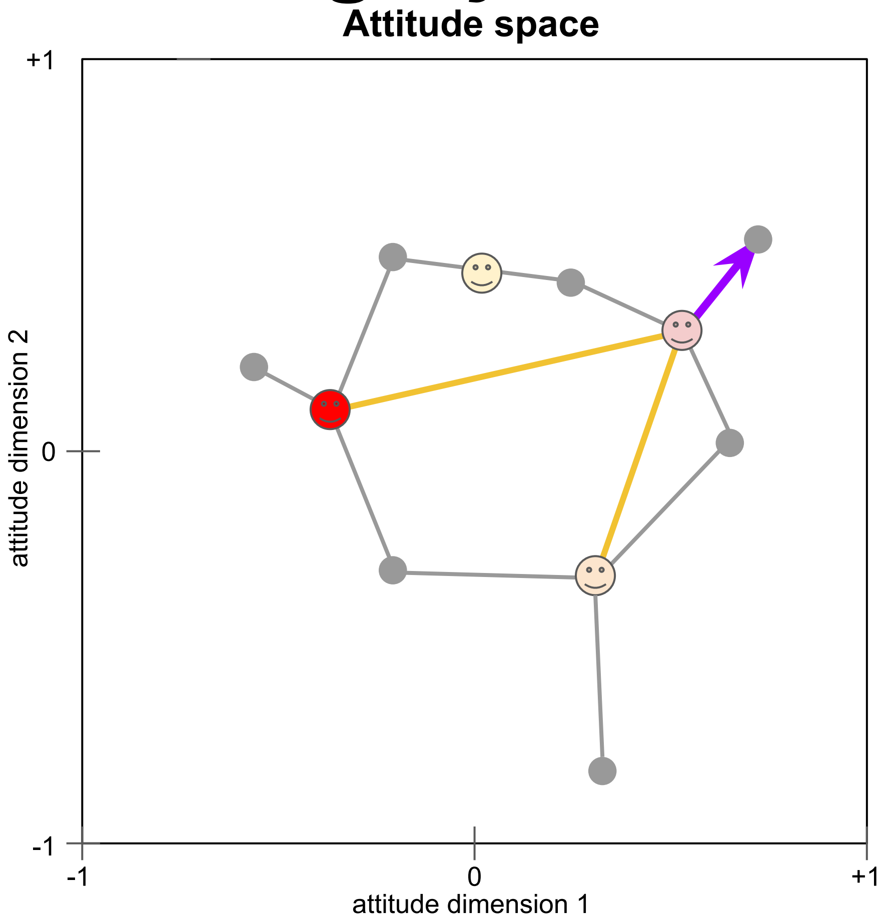
Modeling: Dynamics for New Info-Bits



Motivated Cognition:

- The individual re-positions
- Info-bits with no links to vanish

Modeling: Dynamics of Social Posting



Social Posting:

1. Individual selects a random info-bit in memory

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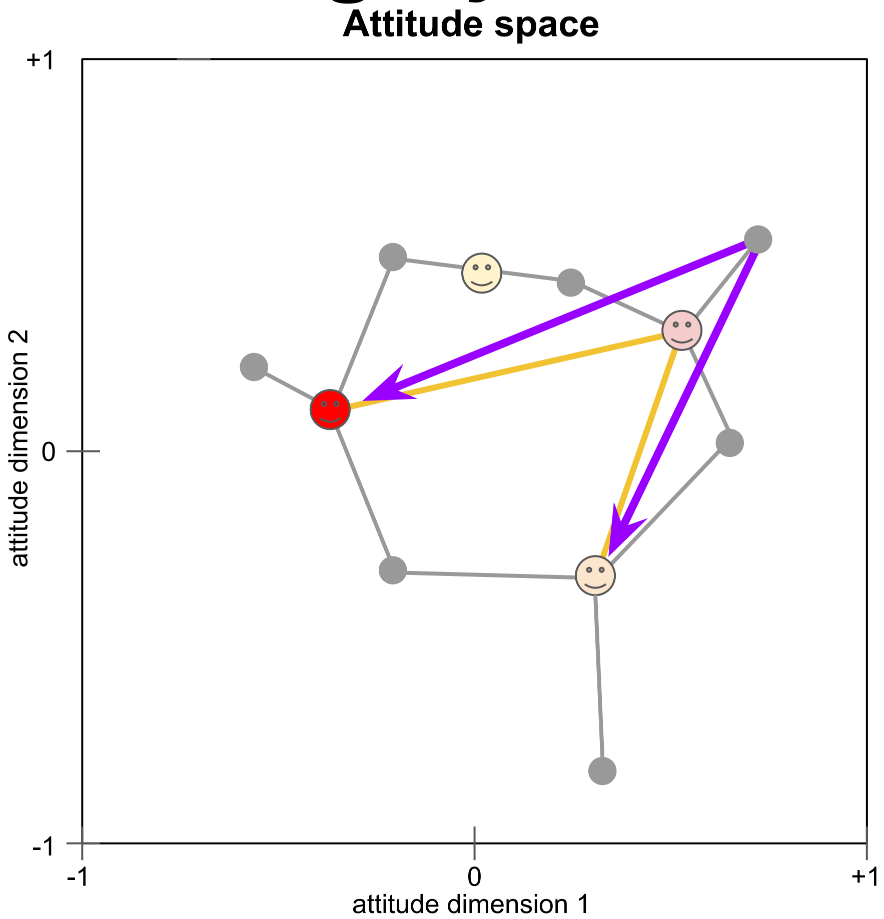
Modeling: Dynamics of Social Posting



Social Posting:

1. Individual selects a random info-bit in memory, and
2. Broadcasts it to all friends
3. Probabilistic integration of information as before

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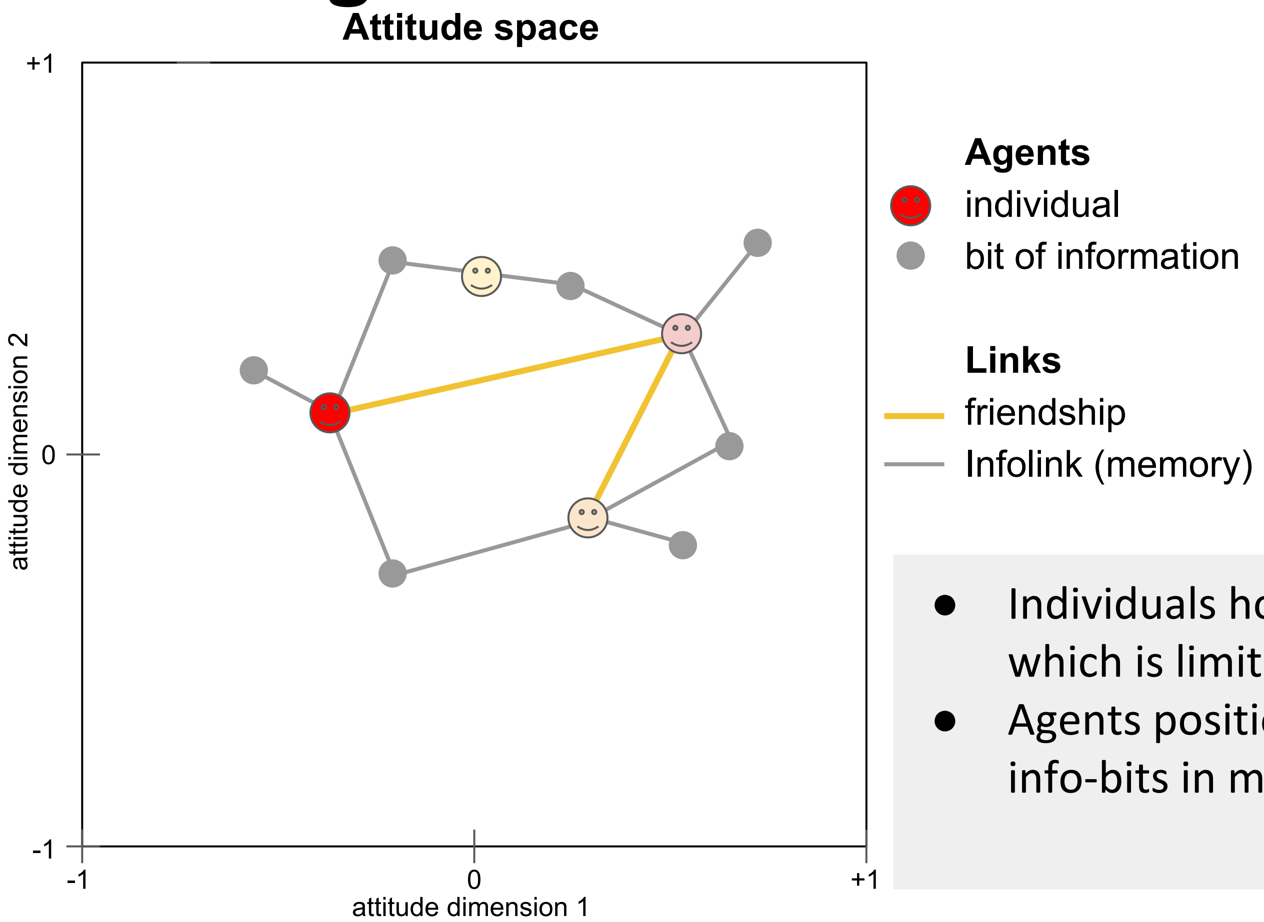
Modeling: Basic entities



- Individuals hold info bits in memory which is limited, e.g., max. 20 info-links
- Agents position at average value of all info-bits in memory

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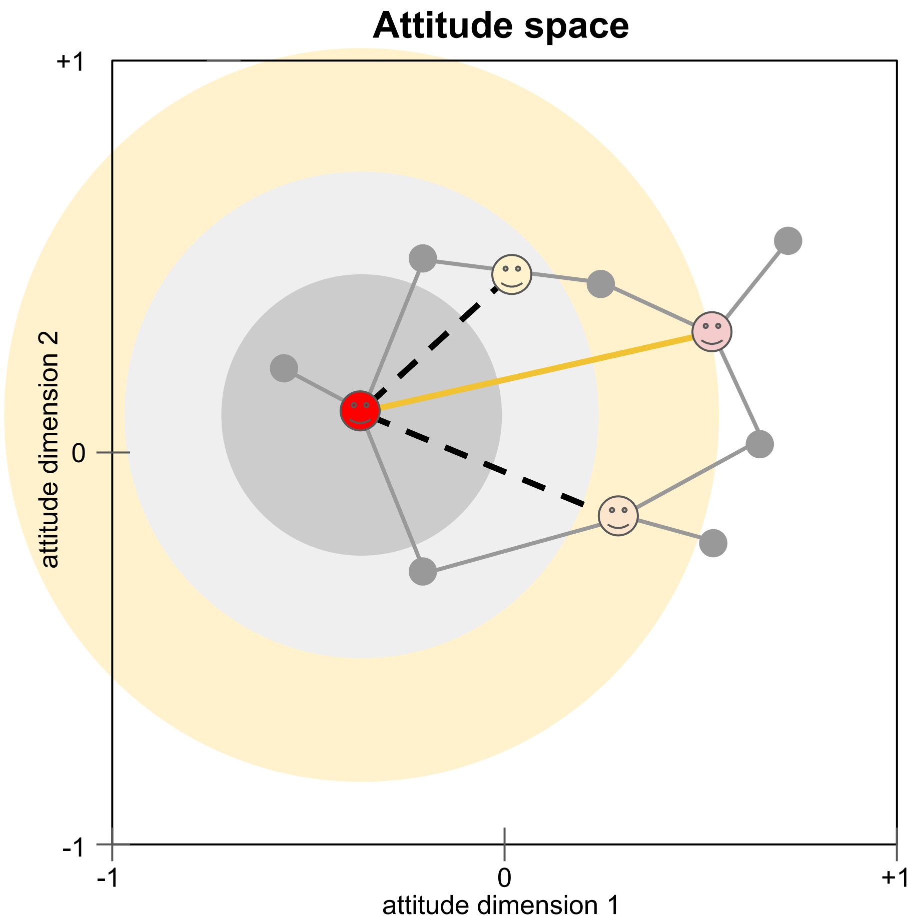
Outcome measures



Agents

individual

bit of information

Links

friendship

Infolink (memory)

sharer of information

Outcome variables

mean distance info. bits = **cognitive bubble**

mean distance info. sharers = **info-sharer bubble**

mean distance friends = **social bubble**

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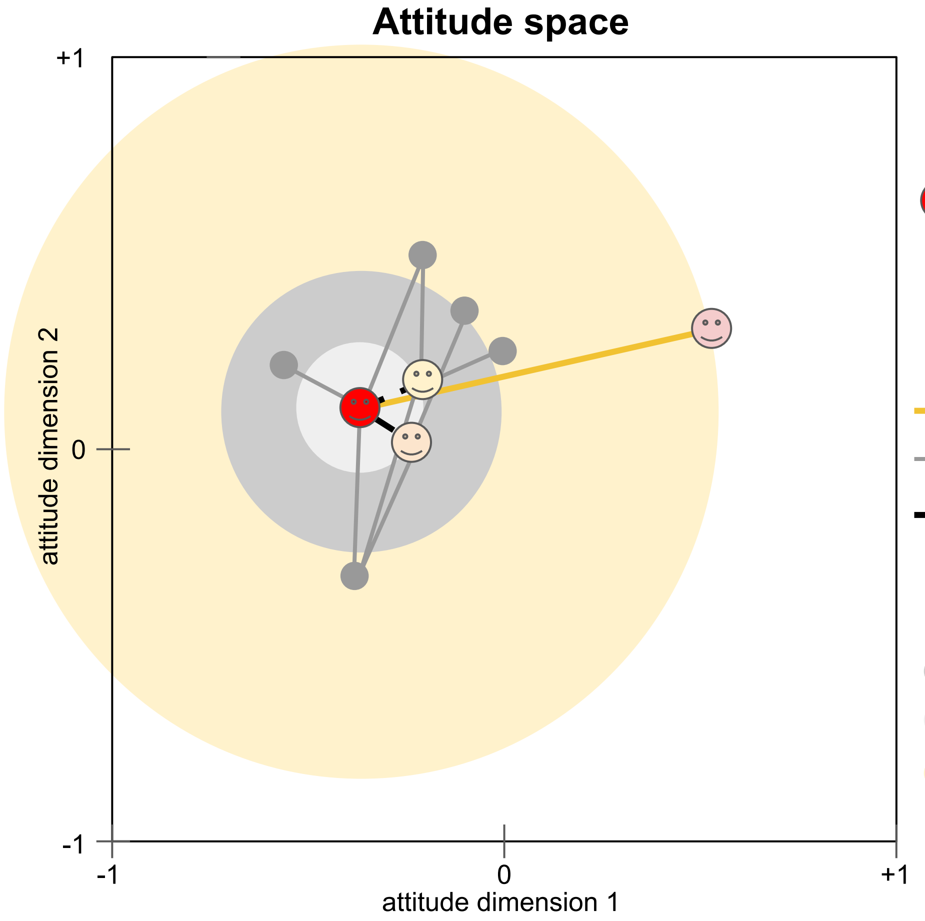
Example: Smaller Info-Sharer Bubble



Agents

individual

bit of information

Links

friendship

Infolink (memory)

sharer of information

Outcome variables

mean distance info. bits = **cognitive bubble**

mean distance info. sharers = **info-sharer bubble**

mean distance friends = **social bubble**

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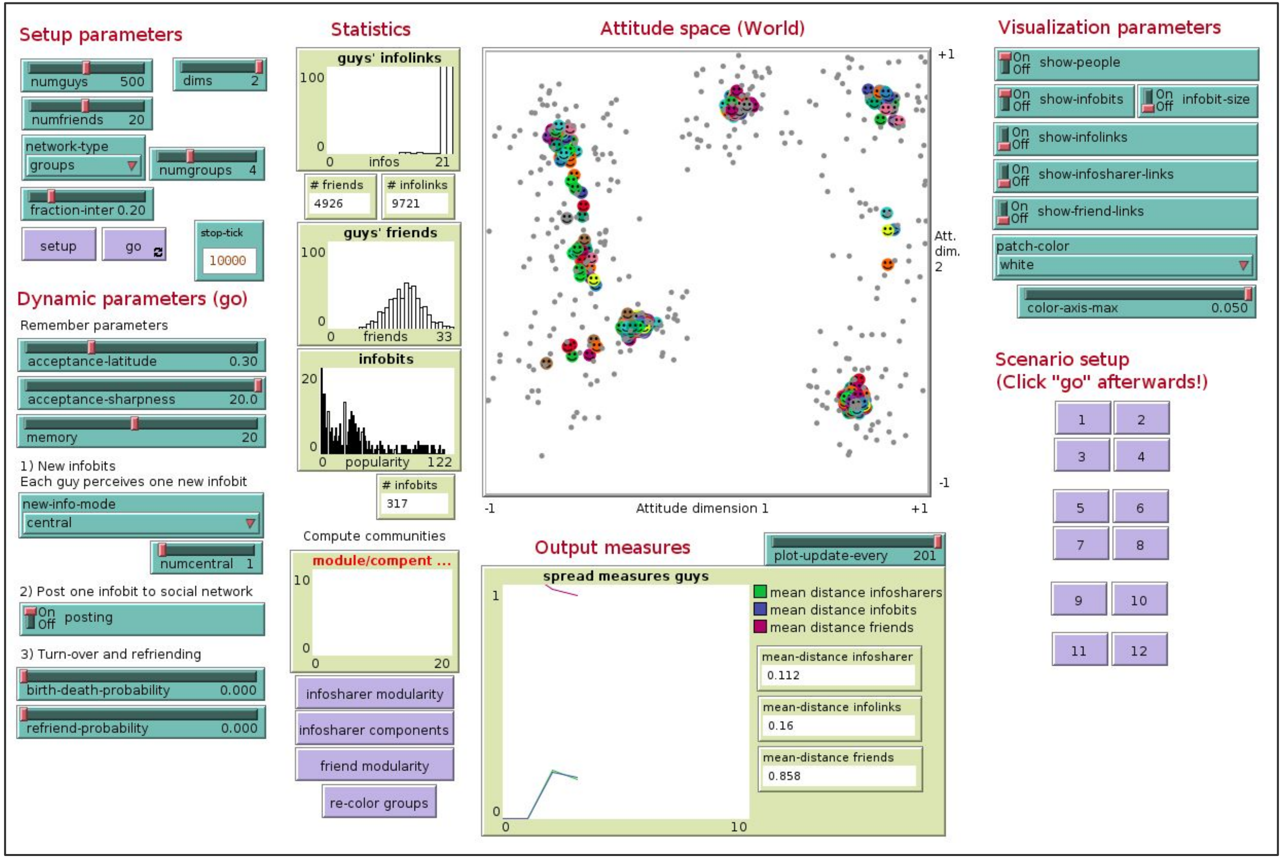
Simulation in NetLogo



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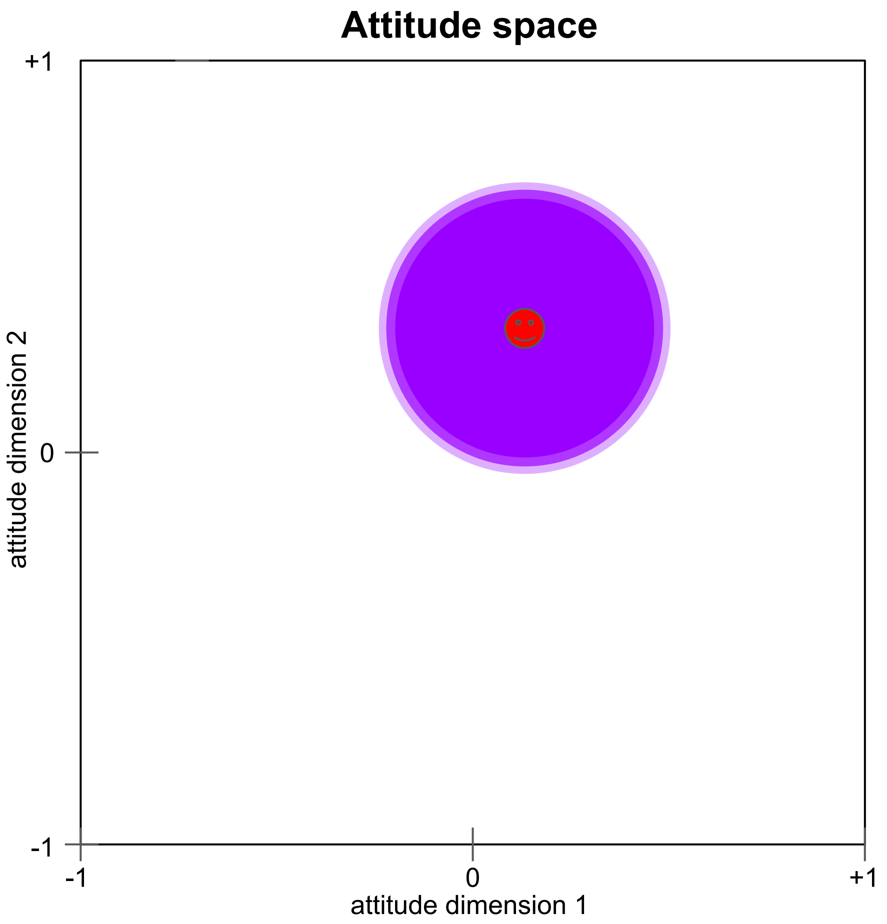
Baseline parameter

- latitude of acceptance ***D* = 0.3**
- acceptance sharpness ***δ* = 20** (sharp "bound of confidence")
- **memory = 20** (info-links per ind.)
- friends network with avg. degree 20, **4 groups, fraction-inter = 0.2**
- no birth/death of agents
- no refriending



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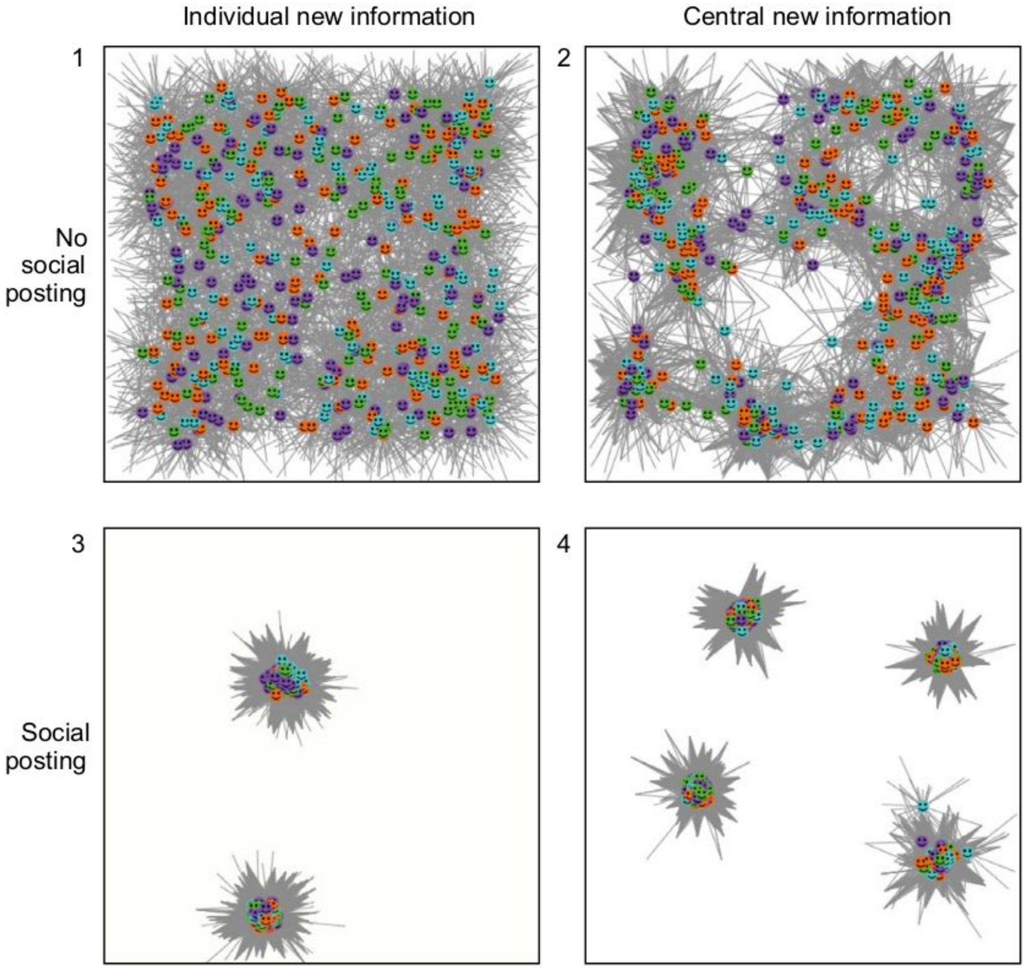
Outcomes

1. Motivated cognition alone → No bubbles
2. With Mass Media → Some clustering
3. (and 4.) With social posting → Bubbles!

Communities and friend links play no role!

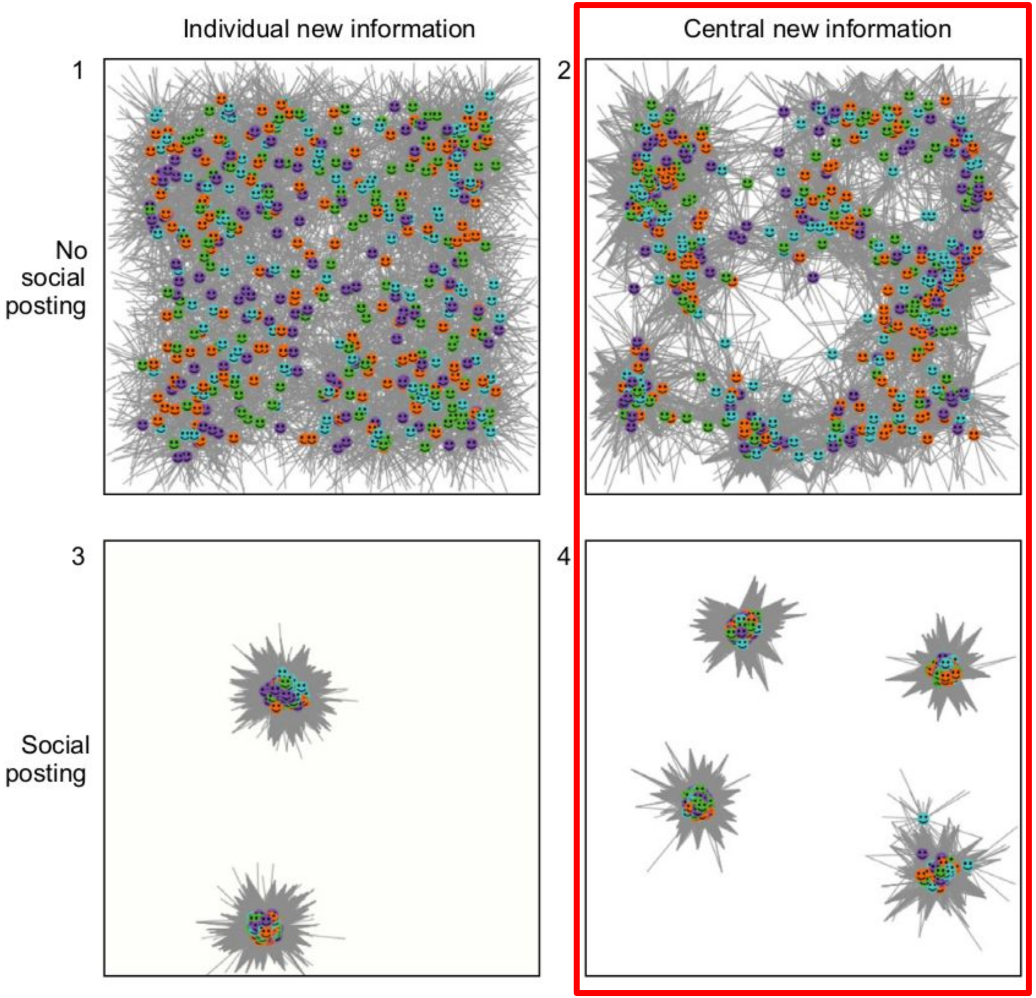


Outcomes

Focus on central information

with and **without**

social posting.



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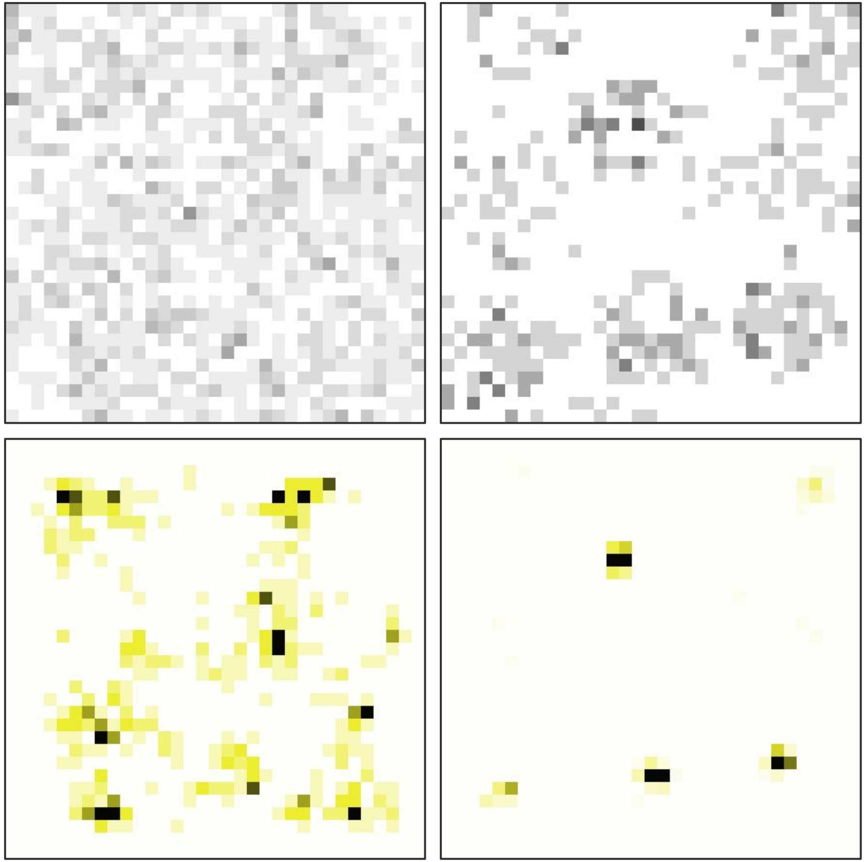
Outcomes Central Info: Agent / Info densities

Without social posting

- Agents clustered
- Info-bits not



With social posting

- Agents clustered
- Info-bits, too:

  Empty space exists

What drives the clustering in social posting?

- **Cognitive filter of confirmation bias** together with repeated attention on already existing information through **re-posting.**
- Crucial: **Information went through cognitive filters of others.**
- Note: Enough sharpness δ is crucial!

- Not, distancing from others!
- Not, reinforcement of certain trends in one direction!
- Not, sorting by communities!
- Not, that individuals receive most information fitting pre-existing attitudes!

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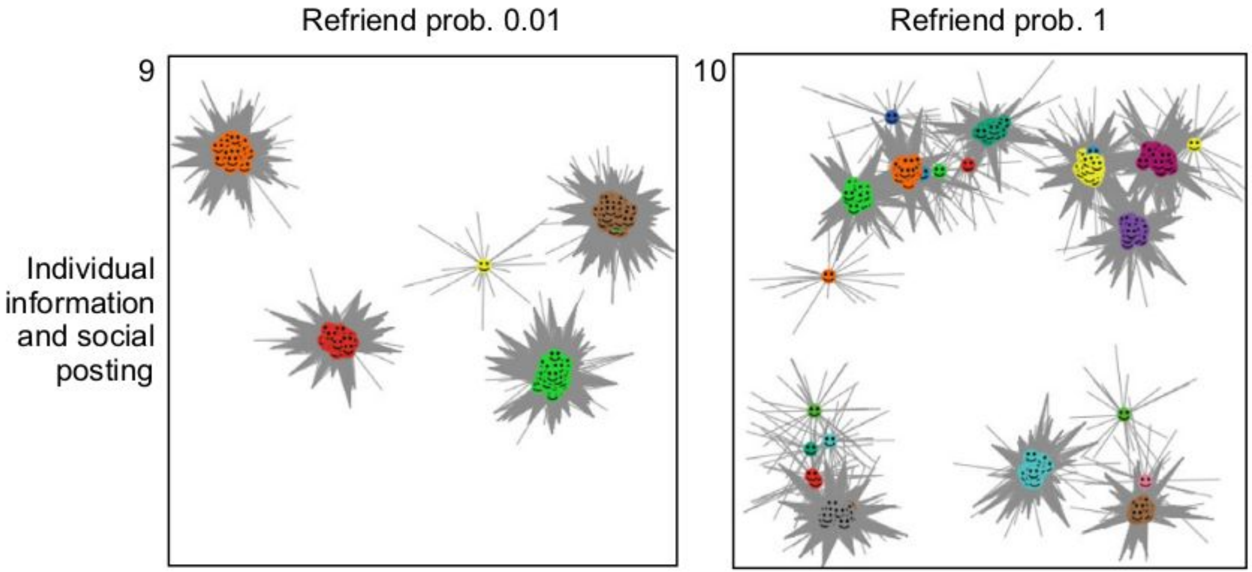
Extension: Re-friending

- With a small probability friendship links die and individuals select a new friend of a friend



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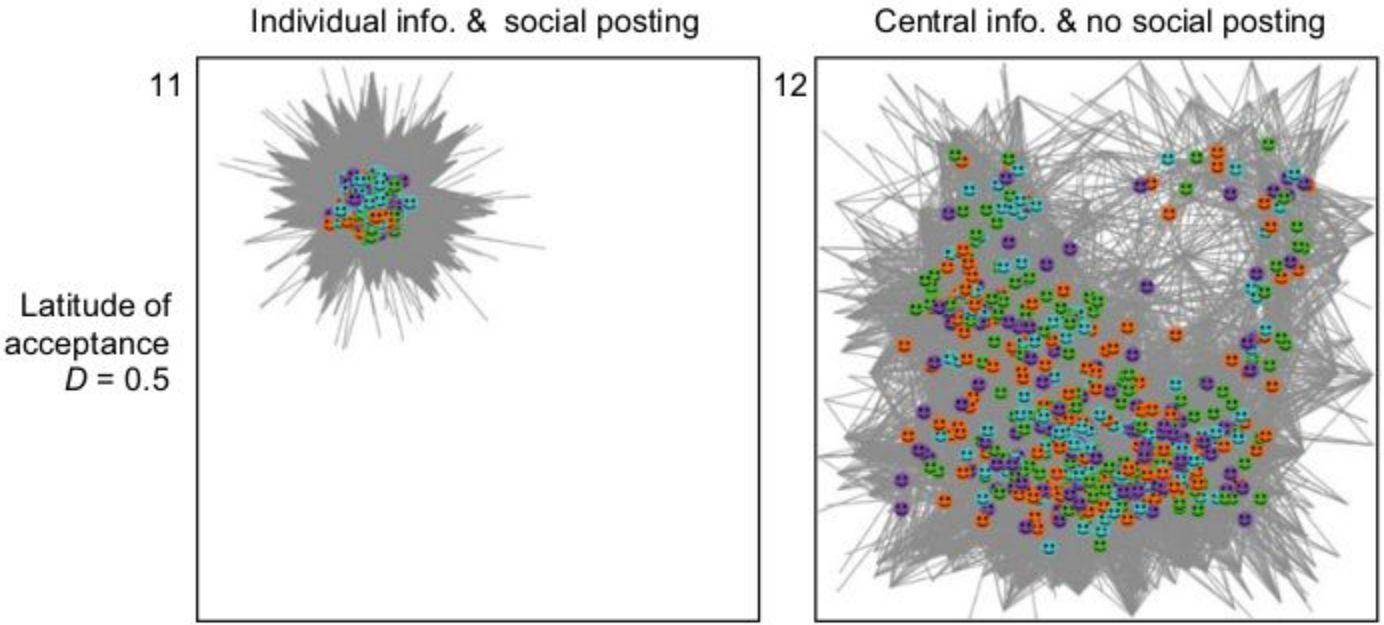
Higher latitude of acceptance: 0.5 (not 0.3)

- With social posting: **Consensus Bubble**
- Without social posting: No consensus

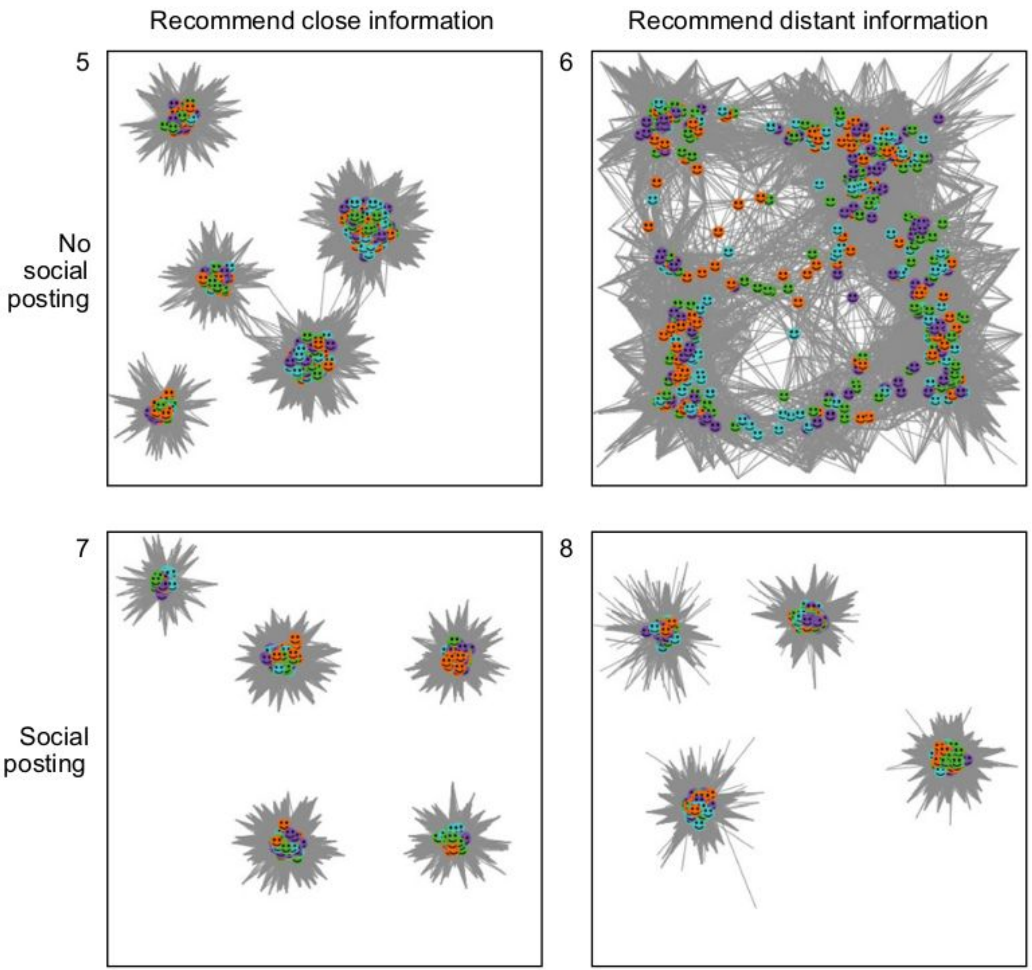


Technological Filters for New Info-Bits

- Initially as individual discovery.
- Once 500 info-bits exist, an algorithm picks for each individual an existing info-bit and brings it to their attention.
- Two version:
  a. The algorithm selects **close info-bits** the agent will like with more than 50% probability
  b. … **distant info-bits** ... with less than 50% probability (challenging information)

Outcomes

- Recommending close info-bits can **trigger bubbles** without social posting
- Recommending distant info-bits without social posting **prevents bubbles**



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Triple Filter Bubble Model

Research Questions, Answers:

- How do we quantify bubbles?
  Compare mean individual info-bit and info-sharer distance
- In what way does posting of information on social media matter for their emergence?
  It keeps attention on already cognitively filtered information!
- Do clustered friendship networks in social media matter? **No.**
- Do recommendation algorithms in media consumption matter?
  They can replace social posting.

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Conclusion, Problems, and Questions

Data for validation and refinement:

How to quantify attitudinal positions of social media postings?

Model Analysis: Not done yet

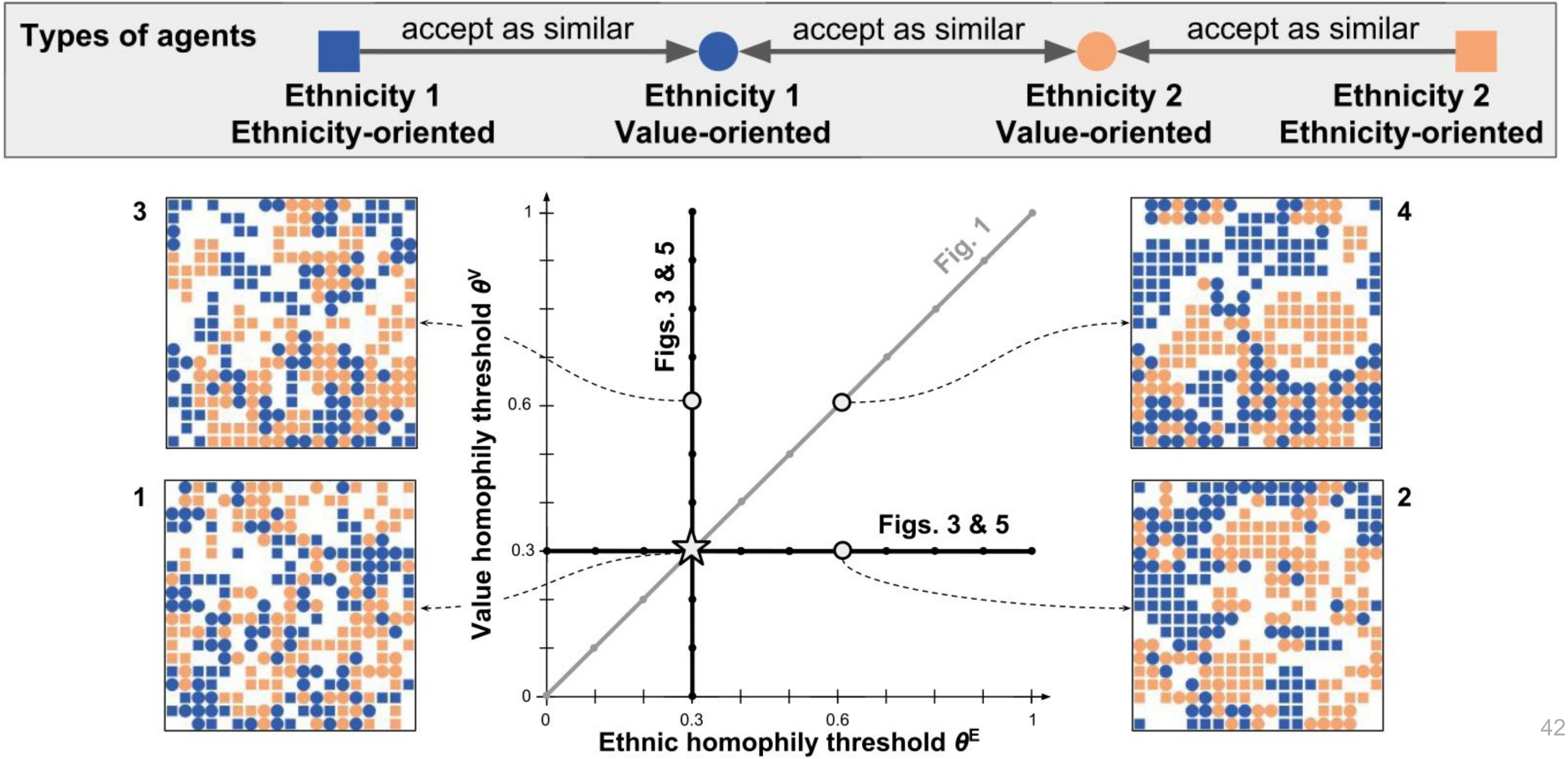
- systematic parameter exploration
- mathematical analysis

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Add-on: Ethnic and Value Segregation

Jan Lorenz post@janlo.de www.janlo.de @jalorenz

Schelling’s Model with Value-orientation



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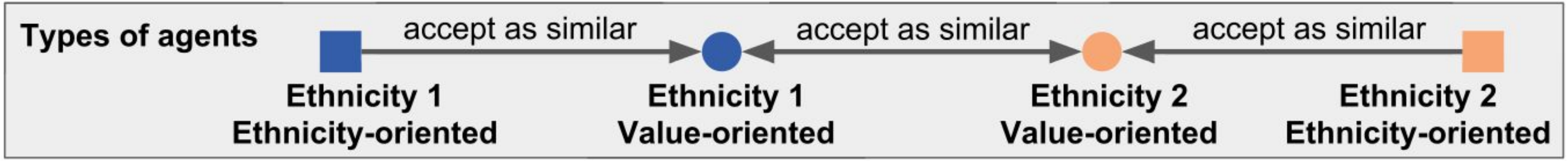

3 Low ethnic, high value homophily

$\theta^E = 0.3$, $\theta^V = 0.6$	Total	Ethnicity-oriented	Value-oriented
Ethnic Segreg. Θ^E	0.67	0.81	0.52
Value Segreg. Θ^V	0.78	0.76	0.80
Neighbor density d	0.72	0.60	0.85

1 Low ethnic, low value homophily

$\theta^E = 0.3$, $\theta^V = 0.3$	Total	Ethnicity-oriented	Value-oriented
Ethnic Segreg. Θ^E	0.62	0.69	0.54
Value Segreg. Θ^V	0.61	0.59	0.62
Neighbor density d	0.72	0.66	0.78

Measures in a initial distribution (baseline)	
Ethnic Segreg. Θ^E	0.5
Value Segreg. Θ^V	0.5
Neighbor density d	0.7

Cell color: Emergent segregation / density

baseline [-0.15, -0.05]
baseline [-0.05, +0.05]
baseline [+0.05, +0.15]
baseline [+0.15, +0.25]
baseline [+0.25, +0.35]
baseline [+0.35, +0.45]

4 High ethnic, high value homophily

$\theta^E = 0.6$, $\theta^V = 0.6$	Total	Ethnicity-oriented	Value-oriented
Ethnic Segreg. Θ^E	0.73	0.95	0.51
Value Segreg. Θ^V	0.88	0.88	0.89
Neighbor density d	0.75	0.67	0.83

2 High ethnic, low value homophily

$\theta^E = 0.6$, $\theta^V = 0.3$	Total	Ethnicity-oriented	Value-oriented
Ethnic Segreg. Θ^E	0.73	0.90	0.56
Value Segreg. Θ^V	0.69	0.68	0.70
Neighbor density d	0.74	0.70	0.77