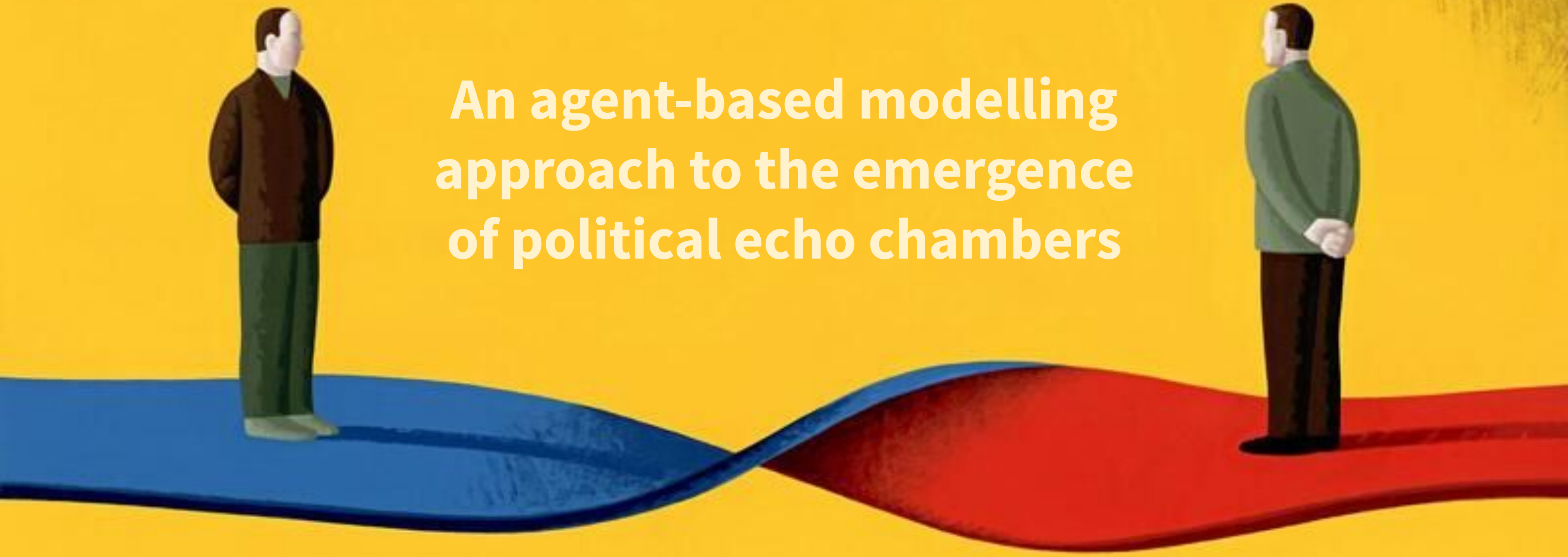
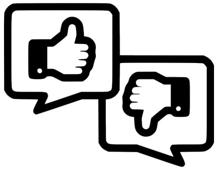
An agent-based modelling approach to the emergence of political echo chambers



Eva Plas, Chang Lin, Anton Andersen
and Seda den Boer

Introduction

Introduction



In a society where people have different beliefs, how they interact and update their beliefs can lead to polarization and the emergence of echo chambers.

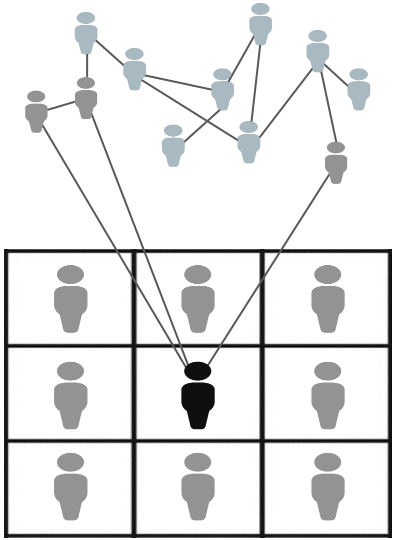
Example: populism in western countries: e.g. US, France, UK

- **online networks**(social media)

  –> the emergence of echo chamber

  (amplify the existing beliefs)

- **offline networks**: roots of the populist



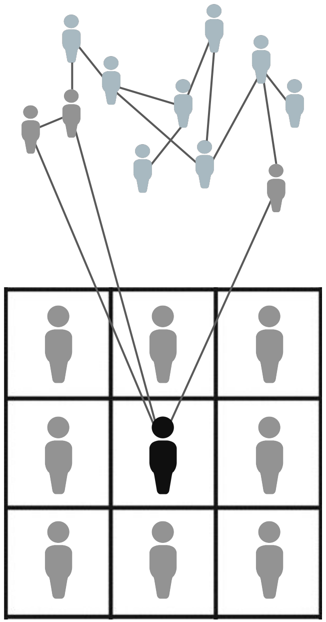
Introduction

It might be interesting to explore:

- Interaction types & the type of echo chambers
    - online interactions (social media)
    - offline interactions (physical)
- Factors affect polarization
    - initial conditions of the system: distribution of agents, density, …
    - parameters: interaction radius, update rate, …

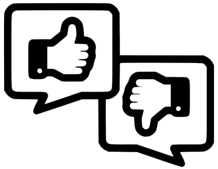
Research questions

- online vs offline interactions
  - which one cause a higher amount of polarisation?
  - which one cause a higher impact on the final belief?



- impact of different types of online networks
  - Scale-free, random, completely connected and idealised networks
  - Does the way in which the network structure of agents impact polarisation?

The model



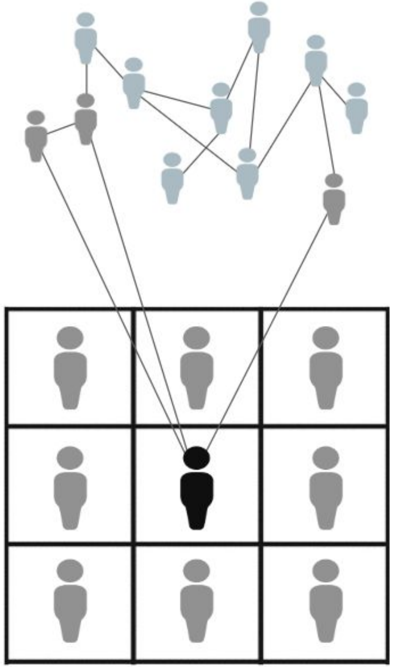
The model

- Why ABM?
  - Model individual interactions
  - Explores how ideas are exchanged and beliefs are updated in real life

- Agents interactions
  - Grid -> physical interactions: friends, family, work
  - Network -> social media

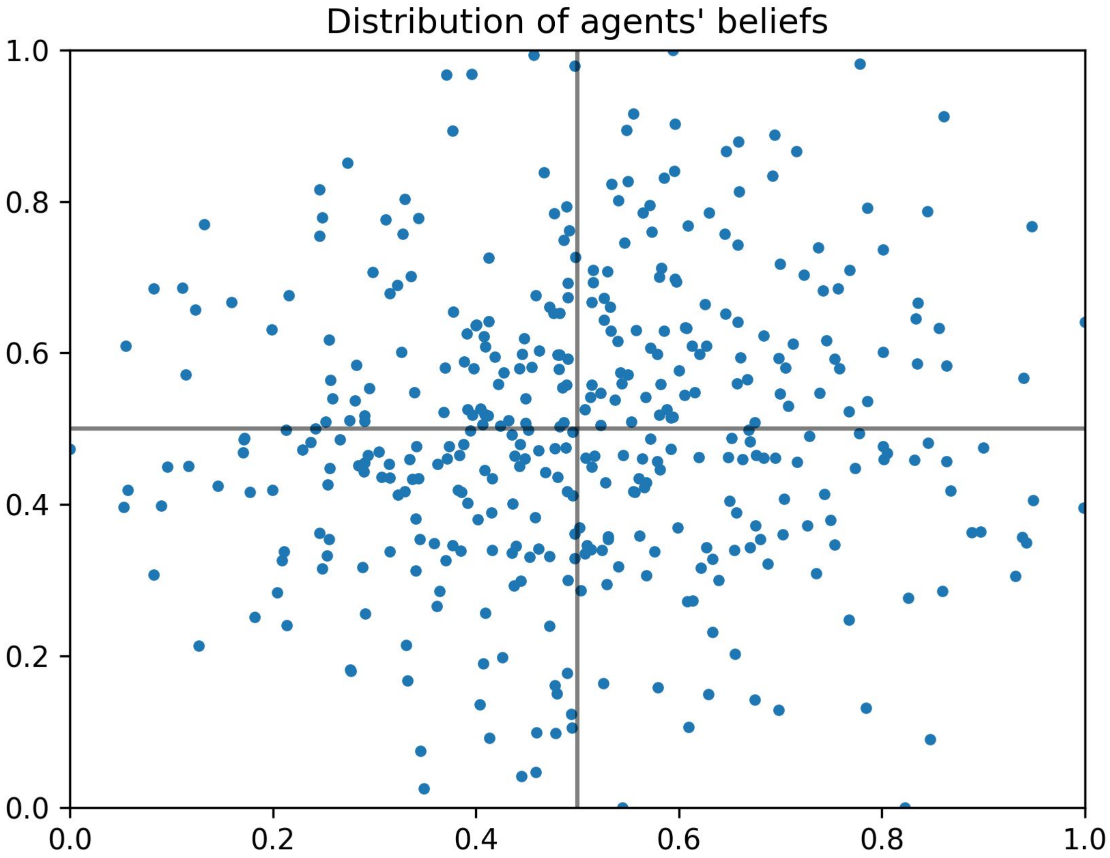
The Model

- Grid and network



Simulatin

- Left - righ
- Normally
- Euclidean



Assimilation effect rule

$$|x_a - x_b| < d_1$$

$$x'_a = x_a + \mu(x_b - x_a)$$
$$x'_b = x_b + \mu(x_a - x_b)$$

i = 1, 2, 3, . . . , n
convergence, $\mu \in (0, 0.5]$
assimilation effect, $d1 \in [0, \sqrt{n}]$

Li & Xiao (2017)

Contrast effect rule

$$|x_a - x_b| > d_2$$

$$x'_a = \xi(x_a - \lambda(x_b - x_a))$$
$$x'_b = \xi(x_b - \lambda(x_a - x_b))$$

divergence, $\lambda > 0$

contrast effect, $d2 \in [0, \sqrt{n}]$, $d2 \geq d1$

normalization function

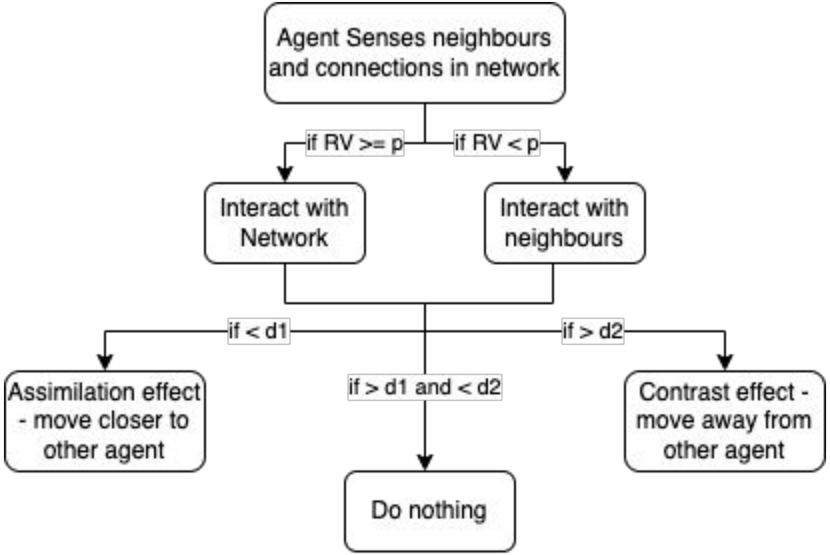
$$\xi(x) = \begin{cases} x, & \text{if } 0 \leq x \leq 1 \\ 0, & \text{if } x < 0 \\ 1, & \text{if } x > 1 \end{cases}$$

Li & Xiao (2017)

Agent behaviour

- Interact with a neighbour
  - Choose neighbour from network or grid
  - Interact based on distance in belief

- Move in the grid (if possible)
  - Movement according to the schelling segregation model
  - Satisfaction based on distance in beliefs



Polarization of the system

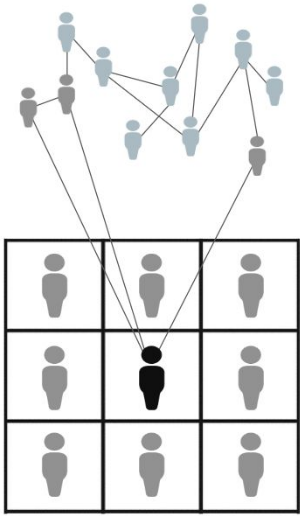
- How is polarization calculated?

$$\text{Polarization} = \frac{1}{N_{connections}} \sum_{i=1}^{N_{agents}} \sum_{j=i+1}^{N_{agents}} \text{dist}(i, j)$$

Experiments

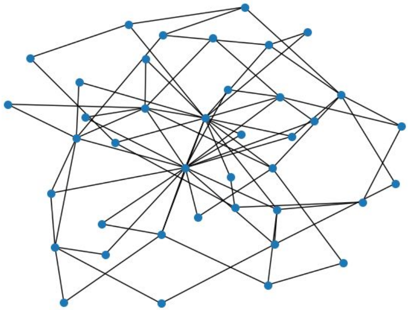
Experiments: default settings

- Population of 400 agents
- Agents are able to move over the grid
- 50/50 chance of interaction between grid or network connection
- Slow belief updating & small difference between assimilation and contrast parameters
- 50 timesteps
- 20 repeats

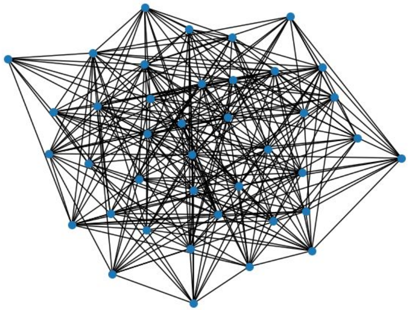


Experiments: polarization over time

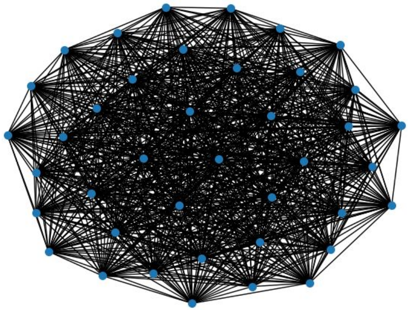
- 200 timesteps
- Network types:



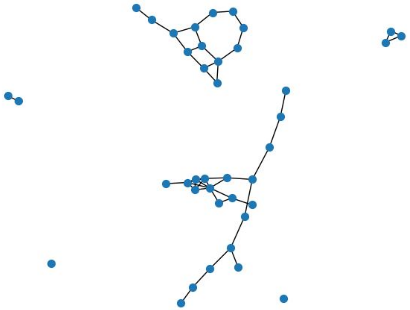
Barabási–Albert
(scale-free)



Erdős–Rényi
(random)



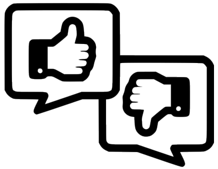
Completely connected



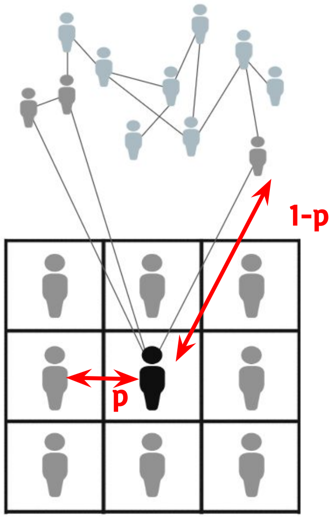
Idealised
(random geometric)

n=40

Experiments: polarization for varying probabilities of grid/network interactions

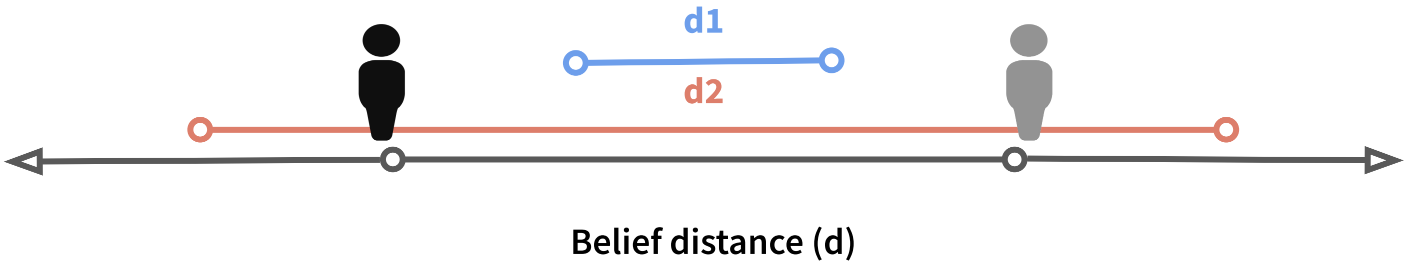


- Measure final polarization state
- Varying probability of interacting with a connection from the network vs. a connection from the grid
    - P(interaction, grid) = p
    - P(interaction, network) = 1 - p
- For all network types



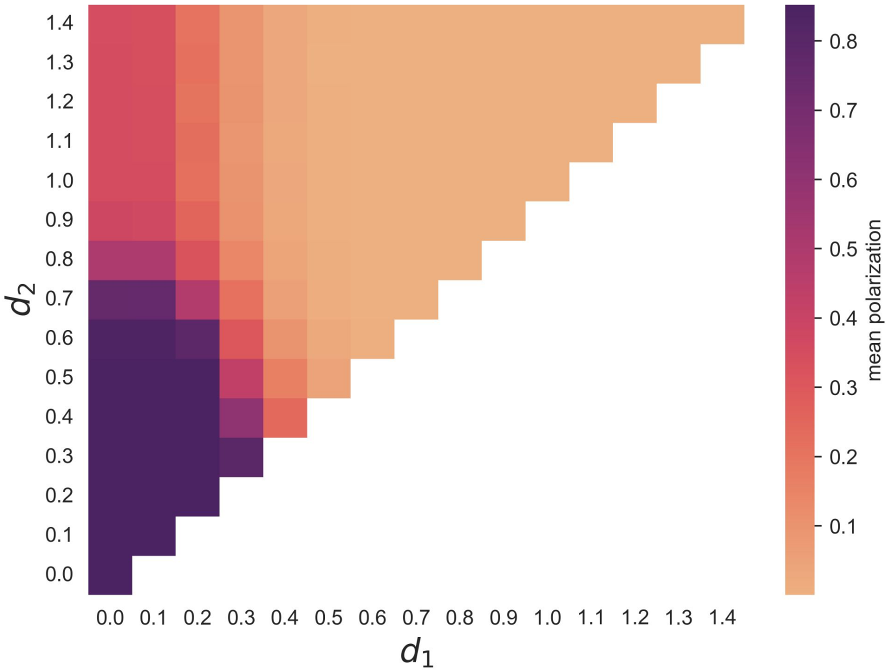
Experiments: polarization for varying d1 and d2

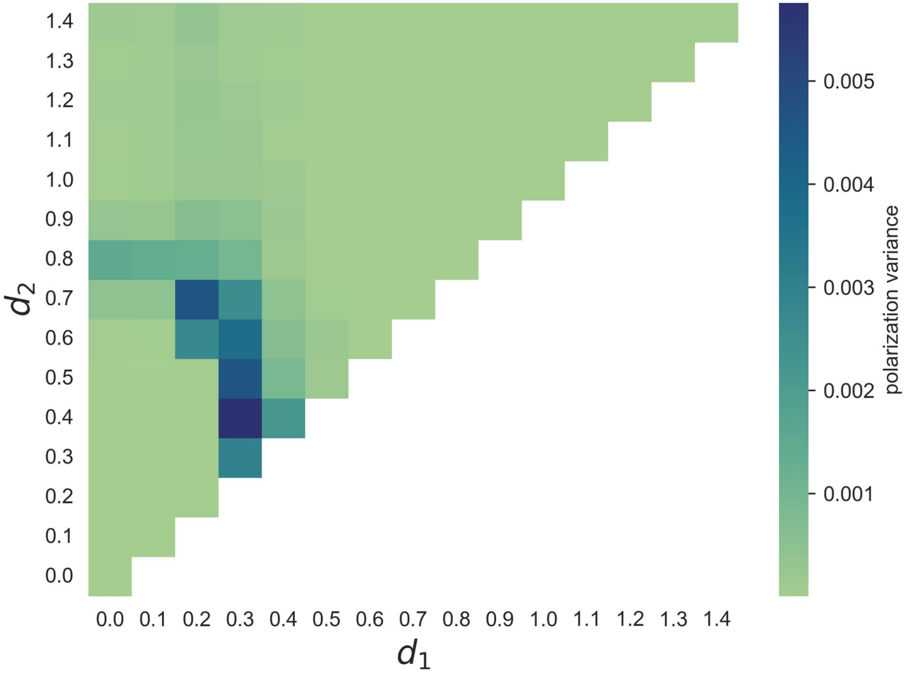
- Measure final polarization state
- Barabási–Albert



Results

Results: polarization for varying d1 and d2





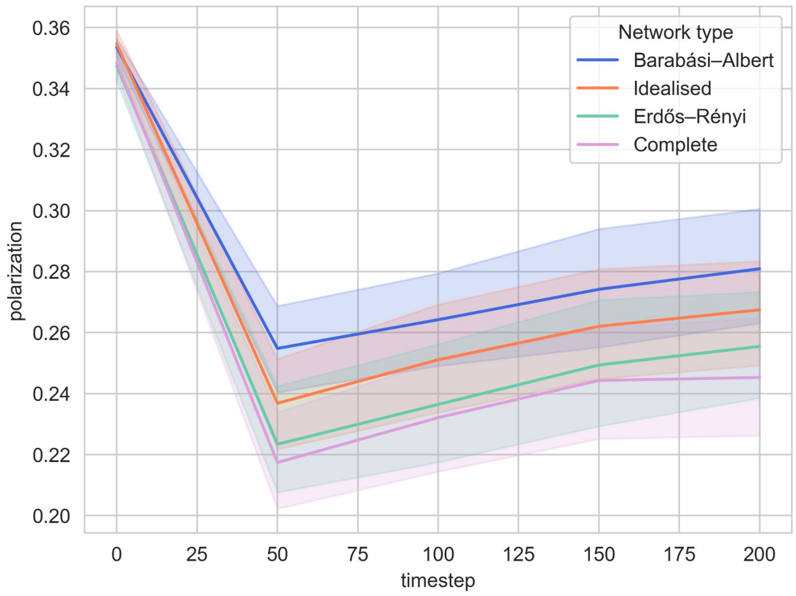
μ=0.2, λ=0.05

Results: polarization over time - network structure effect

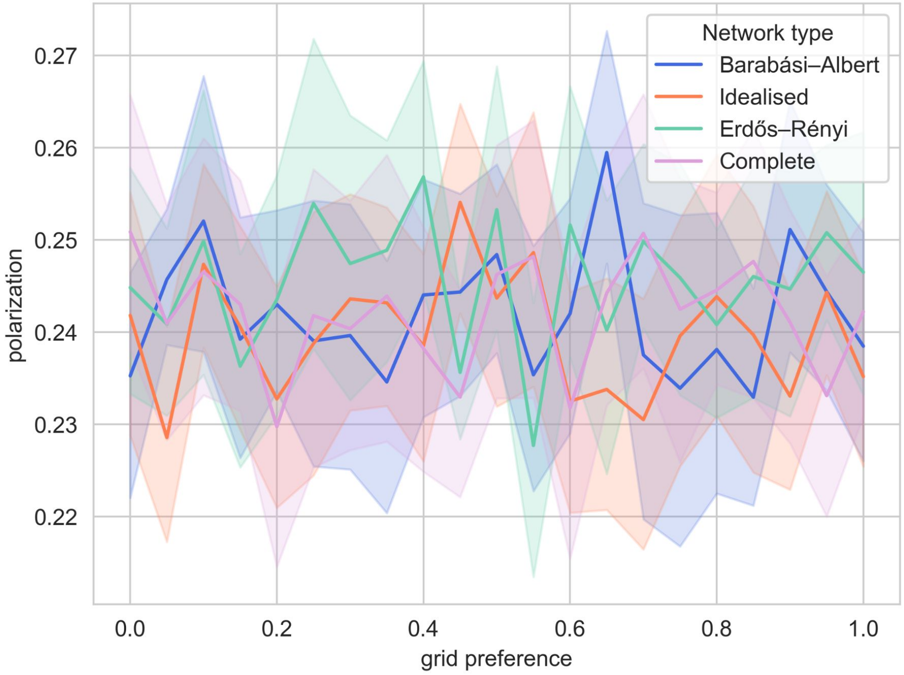
The simulation is run for different network structures, using the d1 and d2 parameters with the highest variance.

- Initial decline in polarization, after which it starts to increase.

- Barabasi-Albert network leads to the highest polarization among the considered networks.



Results: polarization for varying probabilities of grid/network interactions



Varying the preference parameter with which the agent either interacts with the network or the grid.

- Does not seem to have an effect on the polarization.
- Does not seem to differ between the networks.

Sensitivity analysis

...

Conclusion

Conclusion

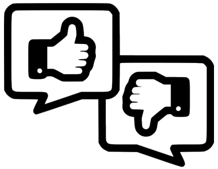
- Our simulations with varying d1 and d2 show region where polarization is stable. Outside of the region the system is either completely polarized or not at all polarized.

- The network structure does not seem to matter all that much for the polarization.

- When varying the network preference over grid, it does not seem to have an effect on the polarization.

Future work

Future work



Validation: find data of a real system and check how precise the model represents this system

Modify the model to make it possible to be applied the model in real world cases to predict the phenomenon

References

Li, J., & Xiao, R. (2017). Agent-based modelling approach for multidimensional opinion polarization in collective behaviour. *Journal of Artificial Societies and Social Simulation, 20* (2).