Linköping University

Agent-Based Modeling

Positive and negative social influence: testing network topologies on continuous opinion dynamics

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1 Abstract

Early models of opinion dynamics presuppose binary choices, meaning that agents choose between two stances when forming their opinion. However, most aspects of our social and political life are instead driven by opinions that are somewhat on a continuous scale, and that most likely change rather dynamically throughout effects of social influence. In this project, I extend on literature on opinion dynamics by availing of continuous ideologies to assess how the mechanisms of positive and negative social influence as well as different network topologies and their properties, foster macro outcomes such as ideological consensus (convergence) or polarization (divergence). Structurally, I assess how the properties of a small-world network, a scale-free network with preferential attachment and a simple square-lattice lead to differential outcomes in polarization of ideologies or convergence to moderate opinions.

2 Introduction

The question of how and why opinion divergence or general consensus are formed is at the heart of many within the field of sociology. Several scholars have attempted to justify what micro-level mechanisms could be at play that would lead to the real-world phenomena of polarization and consensus. Within the field of modeling opinion dynamics, theories of social influence are proposed to explain how social encounters dictate changes in an agent's attribute. In what is known as the "Bounded Confidence" (BC) model (Hegselmann and Krause 2002), agents influence each other opinion through their exchanges, and the opinion adjustments occur if the opinions differ below a certain threshold (Deffuant et al 2002). The bounded confidence model is an example of a social influence ruled world where agents change their opinions towards each other, as suggested by Abelson (1964). However, it has been argued that social influence can be either positive or negative. The case for negative social influence (or repulsive influence) was advanced by Takács, Flache and Mäs (2014), and addresses the possibility that when two agents interact, depending on the distance between their opinions they might shift their views to become furtherly divergent. The study was deemed inconclusive, as the authors found no evidence for negative social influence in their experiment. Nonetheless, negative social influence makes for an interesting case of study, as it appears a strikingly intuitive mechanisms for the existence of polarized groups in society. Furthermore, as Takács, Flache and Mäs (2016) explain, many popular sociological theories such as cognitive dissonance (Festinger 1957), balance theory (Heider 1958), and social judgement theory (Sherif and Hovland 1961) critically justify the recognition of both positive and negative interpersonal influence. The idea that we disagree with people who are distant from our ideological stance, and that the interaction will perhaps reinforce our ideological position, strengthening and consolidating it, is not at all that bizarre. Yet most existing models of opinion dynamics have left negative influence out, probably due to the challenges it poses within a modeling environment and for the lack of empirical proof of its effect on network's macro structures. Nonetheless, as Macy et al (2003) explain, mechanisms of positive and negative influence are powerful in that they can drive networks to self-organize themselves without its agents purposely following the desire to belong to a particular social group. This is a rather interesting idea to puzzle social identity theorists with, because it denies agents the cognitive conceptualization of a group, yet agents become involved in in-group and out-group dynamics, here thereby conceptualized as potential emergent properties of the network self-organization process resulting from the mechanisms of social influence. Conversely, psychological mechanisms of social identity such as "ego-involvement" can be the drivers of repulsive influence, justifying the need to asses its implications in networks (Flache et al 2017). The aim of this model is therefore to test, to my knowledge in an unprecedented setting, the mechanisms of positive, negative and mixed social influence (the coexistence between the two) in a singular space of opinion dynamics here conceptualized as an ideology, and to observe what macro structures occur given the different preconditions. Beyond that, I introduce several network configurations that will allow me to further address the conditions under which convergence and polarization might occur at a global level.

Even the simplest models are based on assumptions, and these simulations are not short of them. One assumption of the model is that people influence each other opinion positively unless their views are substantially divergent. This is essentially a calculation of the difference between the two opinion values. A second assumption is that people at different levels of the opinion spectrum have a higher or lower likelihood to be affected by another person ideology. In the following model, those who hold more radical views, which therefore have either very low values, close to 0, and really high values, close to 1, will only adjust their opinion positively if interacting with an agent that is either as radical as them, or slightly less. Similarly, people who are in the in-between areas from the central zone and the extremes will change their opinion positively unless the interaction is with an agent who holds a radical opinion in the opposite direction. People in the center of the distribution are fully flexible in changing their opinions. Notably, however, in the present model agents update their threshold whenever their ideology is adjusted in such a manner that they enter a new ideological category. This preserves ideological consistency: if you are radical, or you become one, it will be harder to persuade you to change your ideology towards another one. Ultimately, this formalization of social influence restrained by a calculation of the distant between ideologies can be seen as a reformulation of the Bounded Confidence model.

3 ODD

3.1 Model Purpose

The model has two purposes. The first purpose is to test how the mechanisms of positive and negative social influence at the micro-level impact the ideological landscape at the group level. The justification for such mechanisms is derived from a couple of sociological theories. Negative social influence is based on the idea of Cognitive Dissonance – the fact that we have an inner desire to behave consistently and avoid behavioral dissonance, as a result of which we change circumstance to eliminate the disharmony (e.g. by reinforcing our opinion and distancing ourselves from differing individuals). Cognitive dissonance justifies positive social influence as well, given individuals can seek harmony by becoming more similar to their similar others. I complement cognitive dissonance with Heiders (1958) Balance Theory, arguing that individuals will strive to maintain cognitive balance in their exchanges, and that might come at the cost of changing an opinion, an attitude or a behavior to preserve balance in their relationship. The second purpose is to test the mechanisms under different network topologies, to assess under which world-settings convergence or polarization occur as the macro outcome. Finally, empirical validation is implemented through a comparison of the simulations outputs with empirical data from the European Social Survey capturing the ideological landscape in Sweden, to observe which of the model settings is most resembling the real-world.

Ultimately, the goal of this model is to extend knowledge within the field of opinion dynamics by testing mechanisms of both positive and negative influence under different network configuration. As Flache et al (2017) argue, scientific explanations of polarization and consensus have so far been weak or inconclusive, especially when trying to explain polarization (Abelson 1964). Bonacich and Lu (2012) even deem polarization as one of the most important unsolved theoretical problem in the field. Finally, the justification to use an Agent-Based Model is reliant on the idea that simulation is particularly suitable for the given task to test different mechanisms at the micro level and to test their effect on macro structures. ABMs in fact give emphasis to micro-interactions by making individual behavior explicit (Bianchi and Squazzoni 2015). ABMs are also powerful in that they can explain complex phenomena in a simple, visual, and intuitive manner. In this regard, even counterintuitive outcomes resulting from complex dynamics become finally meaningful in a simulation environment (Schelling 1978).

3.2 State Variables and Scales

Entitities

Nodes The principal entity in this model is a node. Nodes are connected either on a small-world network, a scale-free network and a square lattice. They possess ideologies and during dyadic exchanges they will adjust their ideology to either a more similar one to their neighbor or a further away one.

Attributes

Ideology

What in opinion dynamics is usually conceived as a list of opinions, either binary or continuous, is here conceptualized as a singular continuous value between 0 and 1 representing a nodes ideology. The justification for the continuous nature of the scale is that people fluctuate in their opinions, and that influence can exert changes in ideology to greater or smaller extents, which would not be captured by binary values.

Max-Acceptance

Maximum acceptance represents the threshold value by which nodes change their ideology to one either closer to the linked neighbor or to further away from it. The threshold value is smaller for nodes at the extremes and is larger for individuals with central ideological scores, reflecting the idea the individuals who are further apart are less likely to be affected positively by different individuals, yet they are more likely to be affected negatively by people who are far away from them on the ideological spectrum. The max-acceptance attribute is the crucial determinant of the outcome of the communication exchange for the two nodes' ideologies. It is set at 0.2 for radical individuals, 0.4 for moderates, and 0.6 for people at the centre of the ideological distribution.

World

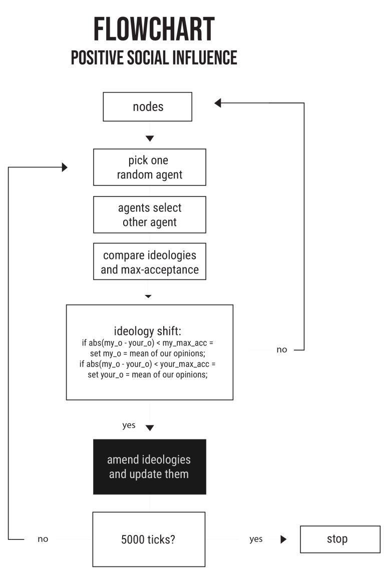
SMALL WORLD – the small-world setup follows the Watts-Strogatz (1998) model, which is structured as a ring lattice characterized by short average path length and high clustering. A network classifies as a small-world whenever most nodes can be connected to everybody in the network within just a few steps. Evidence of small-worlds in the real world have been highly documented, thus I included it in this study as well. Tweakable parameters for the small-world network include the number of nodes the network has (either 100, 200 or 300), and how many nodes is each node connected to on each side, which can be either 1, 2, 3 , 4 or 5, indicating a maximum of 10 connections per node. The small-world is created through a rewiring process, where nodes upon placement on a regular ring lattice are reconnected following a parameter p. In this model, I stick to a rewiring probability of 0.10, that indicates the probability of a node to be reconnected, from its rightmost node, to another node in the network.

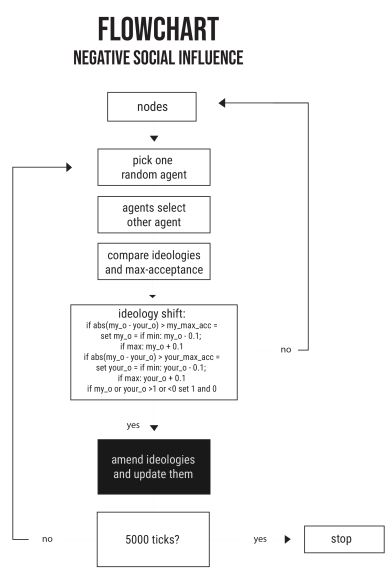
SCALE-FREE – a limitation of the small-world network is that it creates a uniform degree distribution. In many real-world scenarios, some people have more connections and some people are isolates, or less connected. To account for this, I include a scale-free network, ruled by the condition of preferential attachment, that is, a very few nodes will have a very high degree, yet most nodes will have a small one. As in the small-world network, the number of nodes can be set to either 100, 200 or 300. No other parameters can be changed, meaning that the minimum number of connections a node has is set to 1 at all times.

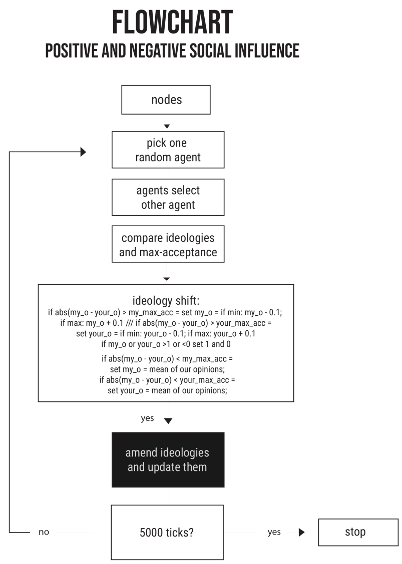
SQUARE-LATTICE – nodes are also located on a spatial lattice, a 33x33 square, where each of them has the possibility to communicate with one randomly selected neighbor located on one of the 8 neighboring patches. The world is thus static, nodes do not move throughout, but can be affected by their neighbors continuously, whose ideologies can also vary overtime.

3.3 Process Overviewing

Generally, the simulation involves a setup procedure and a go procedure. The setup procedure requires the user to make interface choices such as the network-topology and the number of nodes. Additionally, nodes are randomly assigned an ideology, which is a value on a continuous scale between 0 and 1. The outcome is a random distribution of ideologies across the world. Depending on the ideology given, nodes are assigned a threshold value that will affect their likelihood to be impacted by the mechanisms of social influence. The go procedure, depending on the social-influence mode chosen, initiates interaction among randomly selected agents and one of their neighbors at random, and lets them update their ideologies on the basis of the chosen mechanisms of social influence. Therefore, for each tick two connected agents interact and their ideologies are updated whether a condition is met and in line with the specifications of the condition. See in Figure 1, 2, 3 the flowchart of the model under different procedures.







3.4 Design Concepts

The outcome of the model is the distribution of ideologies, which is compared to the distribution of ideologies at t0. At t0, ideologies are distributed randomly across the world, and key outcomes are processes of convergence (consensus), which can happen either towards an extreme or towards mean values of the ideological range [0,1], or polarization, with sharp divides between ideological groups, and which can happen at either one extreme, or two extremes.

The key interaction in the model is the communication exchange between nodes where their ideologies affect one another through the mechanisms of positive and negative social influence. Nodes can interact several times, either as randomly selected agents or as the neighbor or connection of a randomly selected node.

3.5 Initialization

Number of nodes
In the small-world and scale-free networks, the number of nodes can be changed from 100 to 200 or 300. While no large differential outcomes can be expected by such variance in population size, I included those to provide the opportunity to see whether the structural changes occur at a faster or slower rate in larger population sizes.

Numbers of neighbors each side
In the small-world network, the numbers of neighbors each side indicates half of the connections of a node. If the parameter is set at one, a node will have

two connections. Different values are here included to observe whether the number of overall connections in the network affect the opinion dynamics as a whole.

Network topology
The network topology is fundamental at the original stages of the model setup as it determines the network structure in which the nodes will be interacting. As mentioned, nodes can be placed in a small-world or a scale-free network, or a square lattice.

3.6 Input

I initially attempted to calibrate my model with real world data. As noticeable in the .nlogo file, a network-topology named ”empirical” can be loaded in the interface. The network represents friendships in a Glasgow school dataset I have obtained from the RSiena homepage. Unfortunately, I believe the presence of isolates did not allow my procedures to go ahead, therefore I have continued this analysis without it.
I do, later on, empirically validate my model by comparing the ideological distributions observed in the simulations output to real world data from the European Social Survey (ESS). Particularly, I have availed of the latest round of the ESS, round 8, to observe an empirical distribution of a representative sample of Swedish individuals' self-identified ideological stance, on a scale between 0 and 10, with 0 indicating the leftmost ideology and 10 the rightmost one. While in my model I model ideologies to be summarized in 5 groups (2 radical extremes, 2 moderates and 1 central), the distribution curves remain easily comparable. However, I stress here that the overall aim of this model is to test theoretical assumptions of why certain macro structures observed in the real-world arise. The validation would be more meaningful is the model was to be calibrated with a population size and attributes that are somewhat equivalent to the Swedish sample of individuals surveyed through the ESS. The choice to retain a purely theoretical model is pertinent to my research interest of how network configurations and their parametrization combined with micro-processes of positive and negative social influence lead to outcomes observed in the real-world.

3.7 Formulating Positive Influence

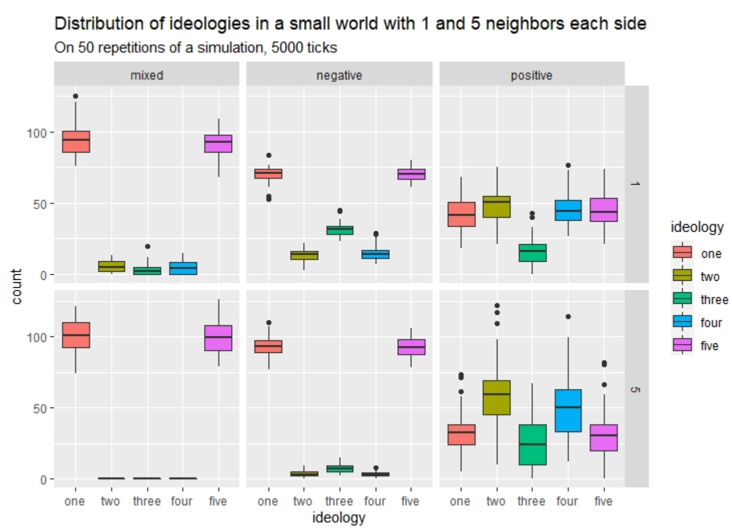
Positive influence in my model operates as follows: whenever two agents interact, for each of them, if the distance between their opinions is lower than their personal threshold (which is ideology dependent), they will adjust their opinion. The opinion adjustment is a change from the original opinion to the mean of the opinion of the two.

3.8 Formulating Negative Influence

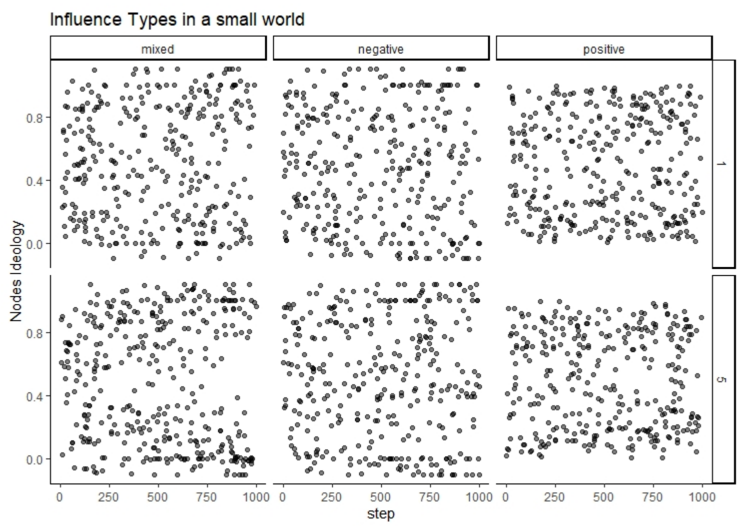
Negative influence in my model operates as follows: whenever two agents interact, for each of them, if the distance between their opinions is greater than their personal threshold (the threshold here is the same as in the positive influence), they will adjust their opinion to +/- 0.1 depending on whether their ideology is the smallest or largest value between the two, the aim of which is to move apart from one another. The value of 0.1 was chosen as a symbolic and reasonable amount for opinion adjustment. While methods out there exist to implement weights or establish non-linear functions to create opinion adjustments that are based on the distance between the opinions or the initial ideological stance of each agent, I here choose one value for all. The choice lies in reasoning that it is hard to say whether initial further ideological distance should apply greater negative influence or not. Also, I wanted to create a simple model of negative influence, thus I preferred choosing a value that is not too large, not too small, basically that makes sense given the opinion space size and the reflection of how much an ideology can change throughout one interaction with a differing individual.

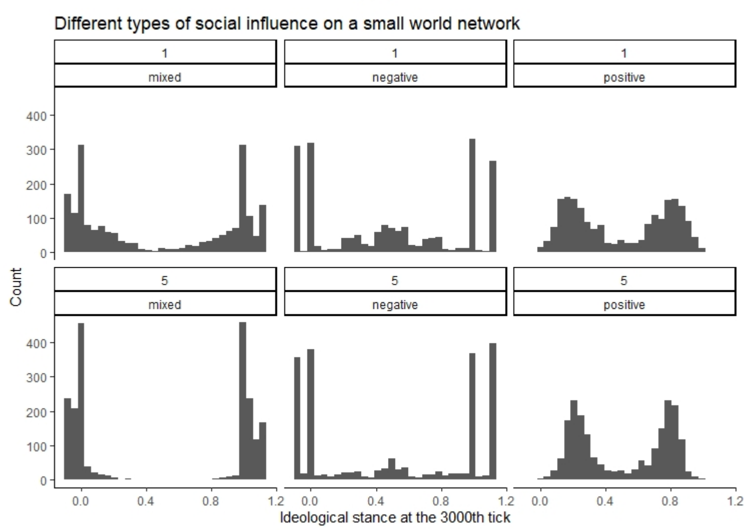
4 Results and Conclusion

I ran three experiments on my model, one per each network topology. In the small-world network, I kept the nodes number to 200, the rewiring probability to 0.1 and the neighbors-each-side parameter to 1 and 5, to test whether different network densities would impact the structural outcomes in any way.

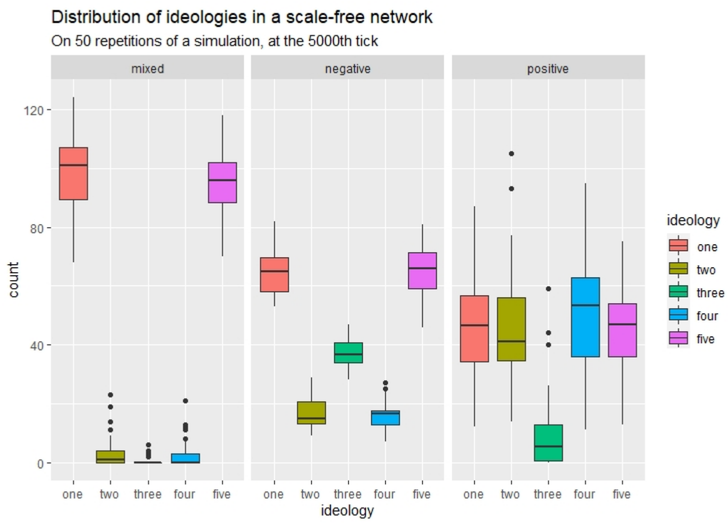


In the image above, we can see that for the mechanism of mixed social influence, the outcomes is of clear bipolarization. Bipolarization occurs in the positive influence model as well, however to a less extreme degree. The negative influence model produces the interesting result of a tri-modal distribution, with a low-peak at the centre and two high peaks on the extremes. A quick glance of the models output suggest that the mechanisms of positive and negative influence somewhat reinforce each other into polarising people from one another, or that the magnitude of the repulsion becomes much stronger when both mechanisms are at play. Here below we can observe the spread of opinions overtime and a histogram of the ideological distributions. A comparison between the density of the networks suggests that denser networks also lead to higher polarization. In the case of positive influence, this also leads to larger confidence intervals, which is not the case for the negative influence particularly.

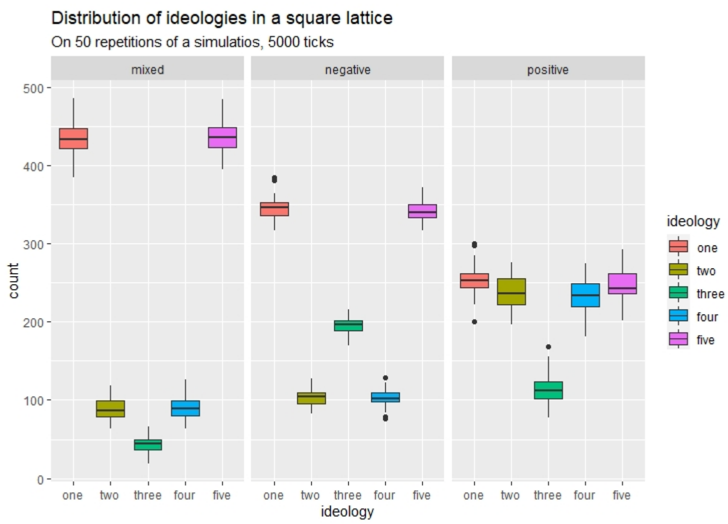




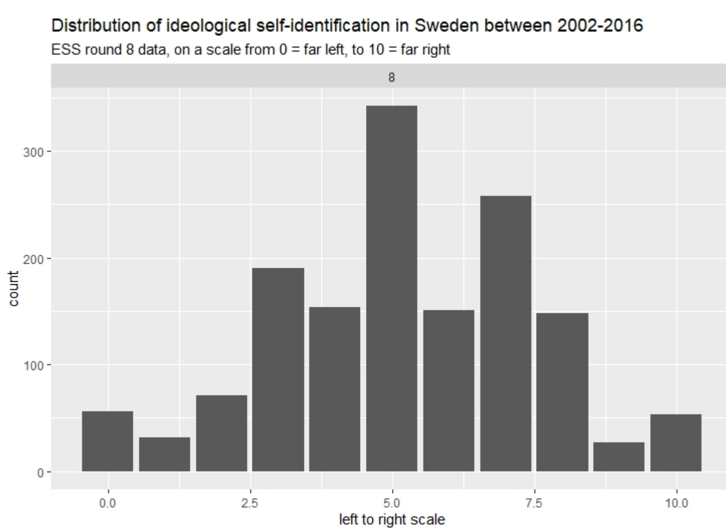
For the scale-free network, I kept the minimum number of connections to 1, and the number of nodes to 200. Compared to the small world network, we can here observe that the confidence intervals appear slightly larger, suggesting perhaps that, depending on the ideology of the most connected nodes, the outcomes can vary to a greater degree than in the small world network. The distribution shapes follow a similar pattern to the small world network ones.



In the square lattice, there were not any parameters to tweak. As displayed below, the confidence intervals are much smaller here, which could be reliant on the presence of a larger population (1089 nodes vs 200 nodes in the networks). The distributions shape is again similar to the models above. This suggests ultimately that, from a theoretical perspective, the network topology is only slightly leading to differential results, and that this mostly occurs in scale-free networks.



The outcomes of these simulations are highly polarized ideological distributions. Here below is the ideological distribution of a sample of Swedish individuals surveyed by the European Social Survey in 2016. The real-world distribution is characterized by convergence to the mean, and two small modes at the extremes. Neither the positive or the mixed influence model have lead to similar results. Interestingly, the model whose output mostly resembled this real world distribution is the negative influence model, which has previously been dismissed in the literature. However, establishing a connection between the two is a stretched proposal as the distribution shapes are substantially differing here as well, although to a less degree than in the other two models.



I believe that this research does not point in any particular direction at the current stage. Modelling opinion dynamics is a highly intricate, complex theoretical challenge, which comes with costly decisions. In this model, I assume a liner type of positive influence, where it is the case that the greatest influence is exercised by people further away on the spectrum, so long they are below the threshold of maximum acceptance. This essentially rules out room in my model for theories of attraction (Byrne 1971), which suggest individuals behave based on an affective bias hold towards similar others. Additionally, for the sake of simplicity I have left out known behavioural trends in social networks such as homophily and the effect of popular individuals in a group (here within the scale-free network). Nonetheless, this research indicates that the mechanisms of positive and negative influence, as well as a combination of the two, lead to far from intuitive macro outcomes. This addresses the need to further investigate real-world problems through the means of agent-based simulations, able to hand the complex and dynamic systems we live and operate in.

5 References

1. Abelson, R.P. 1964. Mathematical Models of the Distribution of Attitudes Under Controversy. Pp. 142-160 in: Frederiksen, N. and Gulliken, H. (eds.): Contributions to mathematical psychology. Holt, Rinehart and Winston, New York.

2. Bianchi F, Squazzoni F. 2015. Agent-based models in sociology. Wiley Interdiscip. Rev. Comput. Stat. 7,284– 306.

3. Bonacich P, Lu P. 2012. Introduction to Mathematical Sociology. Princeton and Oxford: Princeton University Press.

4. Byrne, D. 1971. The Attraction Paradigm. New York, London: Academic Press.

5. Deffuant G, Amblard F, Weisbruch G and Faure T. 2002. How can extremism prevail? a study on the relative agreement interaction model. Journal of Artificial Societies and Social Simulation 5(4).

6. L. 1957. A Theory of Cognitive Dissonance (Stanford University Press)

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

8. Heider, F. 1958. The Psychology of Interpersonal Relations. New York: Wiley.

9. Hegselmann R, and Krause U. 2002. Opinion dynamics and bounded confidence: Models, analysis and simulation. Journal of Artificial Societies and Social Simulation, 5

10. Macy M. W., Kitts J, Flache A, Benard S. 2003. Polarization in dynamic networks: A hopfield model of emergent structure. In R. Breiger, K. Carley, and P. Philippa (Eds.), Dynamic social network modeling and analysis. Workshop summary and papers (pp. 162-73). Washington D.C.: National Academy Press.

11. Schelling TC. 1978. Dynamic models of segregation. J Math Sociol. 1:143–186.

12. Sherif M, Hovland CI. 1961. Social judgement: Assimilation and contrast effects in communication and attitude change. New Haven: Yale University Press.

13. Takács K, Flache A, and Mäs M. 2014. Is there negative social influence? Disentangling effects of dissimilarity and disliking on opinion shifts. arXiv:1406.0900

14. Takács K, Flache A, Mas M (2016) Discrepancy and Disliking Do Not Induce Negative Opinion Shifts. PLoS ONE 11(6): e0157948.

15. Watts D, Strogatz S. 1998. Collective dynamics of 'small-world' networks. Nature. 393 (6684): 440–442.