










# Investigating Key Factors for Social Network Evolution and Opinion Dynamics in an Agent-Based Simulation

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**Abstract.** In recent years social media platforms have experienced increasing attention of researchers due to their capabilities of providing information and spreading opinions of individuals, thus establishing a new environment for opinion formation on a societal level. To gain a better understanding of the occurring opinion dynamics, the interactions between the users and the content that has been shared in those environments has to be investigated. With our work, we want to shed light on the part played by the underlying network structure as information spread relies directly on it and every user of social media is affected by it. Therefore, we analyzed the role of network properties and dealing with friendships in such networks using an agent-based model. Our results reveal the capability of such models for investigating the influence of these factors on opinion dynamics and encourage further investigation in this field of research.

**Keywords:** Opinion dynamics · Social networks analysis · Agent-based modelling · Network evolution

## 1 Introduction

In the past decade, the evolution of the internet and social media platforms raised new forms of social networks that changed our interpersonal communication and the methods of information procurement considerably [14]. It has become very easy to connect to existing friends online, making new friends and exchange information with them, for example, using platforms like Facebook or Twitter. Looking at the formation of political opinions in our digital society it becomes evident that such social media platforms do also play an important role in that process as those social networks facilitate information and opinion sharing tremendously. Through Facebook, for example, it is now very easy to voice the own opinion, even with just liking or sharing posts of others [25].

One problem that arises through social media platforms is that certain behaviors and heuristics of humans like selective exposure and spirals of silence can interfere with an independent opinion formation process as individuals tend to surround themselves with like-minded others [37] and opinion minorities are harder to perceive in such environments. As a consequence, echo chambers in social networks may lead to reducing the tolerance of other opinions and reinforcing the own political stance, thus hampering important democratic processes like consensus formation and acceptance of other opinions [19].

On the other side, social media can also provide an opportunity to enhance political information and participation among citizens as those platforms can encourage discussions and opinion exchange among individuals who would not meet in the real world. Besides providing a public discourse and revealing more diverse political opinions that would not have been voiced offline, social networks like Facebook or Twitter can also help with promoting offline political events and actual political participation. However, current research shows that the potential for this has not been exhausted yet [5].

Through analyzing online social networks and their users' interactions it is possible to understand how certain political campaigns may influence the public discourse and the opinion formation of social media users [21]. But besides passively analyzing the influence of social networks, it is also important to actively develop approaches for facilitating an independent political opinion exchange online which can be done through adjusting the mechanisms of information spread, friendship maintenance and providing further clues for credibility evaluation of particular posts.

For gathering better knowledge about the effects that occur in such social networks, it is necessary to develop simulation models that allow for replicating the reality and also testing imaginable assumptions about the effect of individual behaviors on the overall system.

Online social networks consist of human beings who are very different from each other in terms of behavior, information reception, networking and lots of other factors due to their particular personality. Thus, it seems rather impossible to create an equation-based model that would aggregate all individuals' behavior into one singular kind of acting. Agent-based modeling (ABM), in contrast, provides a toolbox for modeling the desired behavior bottom-up, starting at an individual's or rather agent's called behavior space. A particular agent can hold its own beliefs and will act in the simulation according to them, while she is still interdependent with other agents. Through their adaptivity and the dependency on the past, agents' behaviors in sum lead to so-called emergent behavior. This means that the overall system behavior evoked by bottom-up modeling is harder to describe by a formula that summarizes all individual behavior [20].

Therefore, we decided to implement an agent-based model that consists of an environment and behavior space comparable to realistic social media platforms. Our study contributes to the existing research on opinion dynamics in social networks by combining existing theories about opinion dynamics in agent-based systems with topologies and mechanisms of real-world social media platforms. It

serves as a first insight into modeling such systems and reveals the interplay of particular mechanisms and behaviors of the network members with the actual network structure.

## 2 Related Work

Our work implements the state of the art knowledge about how opinion formation happens and how friendship networks evolve in online environments. This section supplies the prerequisites for creating such a simulation model by looking into the dynamics that occur, indicating how they can be modeled and investigating how the surrounding network can be replicated appropriately.

### 2.1 Opinion Dynamics in Social Media

In their initial purpose, social media services as Facebook and Twitter were created to open up an online space for interacting with current friends and finding new ones. Nowadays, those services provide far more features as news media entered these environments and people started to not only share their everyday activities and cat photos, but also are voicing their opinions and perceiving the reactions of others.

It has been shown that social media platforms expose their users to a larger range of diverging opinions and information that may or may not fit their initial beliefs than other media could do [1]. While this increased exposure could be suspected as a positive influence on the opinion formation, this type of media also shows more vulnerability for misleading the public discourse on certain topics like it got evident for events as the Brexit [12] or most recently the spread of wrong information about the coronavirus [23].

Furthermore, it is crucial to consider the imbalance of activity of social media users. As Romero et al. found, the majority of users passively consume content on social media platforms and rarely take part in interactions, while only a little part of the users utilize those platforms to actively contribute new content and spread their opinions which transforms them into secondary gatekeepers of information spread [29, 32]. Those individuals are also referred to as opinion leaders [6]. Besides a higher intention to share news and other information via social media [31], opinion leaders also get apparent through their prominent position in social networks as they show more ties to other users and a higher influence on information spread [15].

This serves as motivation to take a closer look at the underlying network structure of social media platforms as the structure impacts both active and passive users equally. Looking at the influence of network dynamics, Szymanski et al. revealed an effect on the formation of political opinions among multicultural societies. They found that both sociocultural factors and network dynamics steer the opinion formation of an individual as the initial ties a certain individual holds keep influencing her opinion formation permanently. These initial ties evolve due to cultural factors, ethnicity, and gender [33].

Azzimonti et al. showed that the vulnerability of a social network to the propagation of misinformation and polarization depends on its structure and the features that are provided to the users. They investigated multiple factors that could lead to opinion polarization and spread of misinformation in an agent-based network and showed that particular network characteristics and the behavior of the central agent can foster those two effects. Higher clustering, for example, increases polarization while it does not affect the spread of misinformation. Regarding centrality it is the other way round: if potential spreaders of misinformation occupy positions in the network with high follower count, the dissemination of misinformation is facilitated whereas the polarization is not significantly promoted [2].

In addition to the deception that is initiated through particular users, the algorithms that are used by social media platforms for presenting relevant content can also lead to misguided perceptions of the opinion climate [26]. To reveal the true effect of such algorithms it is inevitable to precisely analyze their interaction with the users [8].

## 2.2 Modelling Opinion Dynamics

After shedding light on the role of social media platforms on providing social ties and their importance for information and opinion spread it is also central for our research approach to understand, how opinion dynamics can be modeled. Therefore, we take a closer look at research that deals with the operationalization of opinion on the one hand, and the modeling of social networks in simulation environments on the other hand.

It is necessary to transform the opinion of a social network member into a value that allows for comparing it to others based on mathematical operations. Only in this way we can implement mechanisms for the interaction and mutual influence of opinions inside the simulated network community.

The initial idea for turning opinion into a concrete value derives from the objective to measure promoting factors in the process of consensus finding. For this Degroot [11] replicated the beliefs into subjective probability distributions which allowed to perform the required calculations that are modeling the opinion formation.

Another approach for modeling opinion dynamics is to build an agent-based model that directly allows for manipulating various factors in the process of opinion formation.

Deffuant et al. developed such a model and implemented a bounded confidence approach. Their work shows how a fixed threshold in which opinion change occurs alters the overall opinion distribution in a simulation. They chose to opinion is modeled on a one-dimensional, continuous scale from 0 to 1. Besides the condition that the agents talk to each other randomly and each conversation is considered for a possible opinion change, they also applied a network model for regulating communication partners within the agents. Using square lattices as underlying topology, the agents were restricted to only talking to four others directly adjacent to them. In comparison with a model that uses complete

mixing of agents, the network version shows that consensus is no longer found for a major group of agents but rather depends on the connectedness of agent clusters, especially for low opinion thresholds [10].

The research of Weisbuch et al. continues the evaluation of network influence on a bounded confidence model by comparing the original fully mixed mode of Deffuant et al. with a model that incorporates scale-free networks as limiting environments for the agent communication. They also found that a scale-free network structure does not have a radical influence on opinion dynamics. Most prominent, the use of scale-free networks leads to far more isolated agents and the role of the most-connected node provides useful information. It could be shown that such supernodes were most influential compared to all other nodes and processed themselves also a significant opinion change during the clustering process. With decreasing density, differences to the standard mixed variant get more visible. Further motivation for investigating the effect of Barabási-Albert networks is given by the research of Stauffer et al. who also differentiated between directed and undirected networks. They discovered that especially for small  $\epsilon < 0.4$  for the bounded confidence intervals the opinions of the simulated agents show stronger deviations from each other. For  $\epsilon > 0.4$  their agents always end up finding a consensus. Studies of Fortunato et al. show equal indications that for  $\epsilon < 0.5$ , an opinion dynamics model based on the approach of Deffuant et al. always leads to the formation of a consensus, independent of the underlying network structure [34].

Later on, Hegselmann and Krause extended the complexity of the bounded confidence approach by implementing dependencies on symmetry and individual agent properties for the confidence value. Looking at the continuous scale of opinions, the threshold for bounded confidence therewith can adapt to the actual position of an agent on this scale and the direction of potential consensus finding. Besides, agents can also hold now individual confidence which allows for implementing different types of agent personalities [17].

### 2.3 Modelling Structures of Online Social Networks

Several approaches were made to incorporate network structures that are close to real social networks. The previously mentioned study of Deffuant et al. showed a comparison of fully connected agents and a square-lattice topology [10]. Further research shows the importance of an accurate model of the network topology as all examined interactions in such simulations are influenced by the underlying structure [28]. The review of Mastroeni shows three prominent approaches for dealing with the interaction of individuals in an agent-based simulation model: Pairwise interaction (Every agent only talks to one other agent in a certain time step), any-to-any interaction (Every agent talks to every other agent within a time step), and closest neighbors approach (An agent talks only to other agents that are in her neighborhood) [22]. We decided on the last approach as it allows for implementing a network and certain dynamics that are similar to those in existing social media platforms.

In the following, we will describe how we implemented the desired opinion and network dynamics and show how we analyzed the results of our simulation models.

### 3 Method

We chose the programming language Julia to conduct our research. With the LightGraphs package, this language provides performant network simulation and the required network generators for our agent-based model. We also implemented random seeds so that the performed batch runs can be repeated with reaching the same results as in our analysis.

In our research, we focused on the variation of limited parameters for answering our research questions:

- Size of the network: How do network and opinion dynamics interplay with the size of a social network?
- Adding friends: What is the difference between randomly making friends in the network and choosing only from the friends of existing friends?
- Removing friends: How does the threshold for accepting opinion differences interfere with the overall opinion and network dynamics? The distribution of opinions throughout the agents was not varied but uniformly distributed, because their variation would have blurred the effect of the examined parameters on the network evolution.

To analyze the effect of our parameters, we chose different approaches of social network analysis and evaluated the resulting networks and their nodes regarding their degree distribution, centrality, community structure, and the opinion dynamics.

#### 3.1 The Network Model

We designed a network in which agents interact with each other through publishing posts to their followers and receiving content through their followees. Currently, most of the popular social networks allow for unidirectional relationships therefore we chose a directed network for our simulation. The different edges represent the direction of information spread: outgoing edges from agent  $x$  show to which agents the posts of agent  $x$  will be sent while incoming edges show from which agents the agent  $x$  receives posts.

The initial network is created by using the Barabási Albert Network generator of the LightGraphs package in Julia. We decided on the Barabási Albert topology as it provides an artificial network structure that is similar to real-world social networks [38]. This generator allows defining the size of the network and an initial average edge count per agent that follows a power-law distribution. Through following a preferential attachment algorithm, the degree distribution of the nodes sticks to the power law, including very few nodes with high degrees and a long tail of nodes with rather low degrees [3].

After creating the network, the agents are generated with the following attributes:

- Opinion  $[-1, 1]$ : The Main attribute to change their network of incoming edges (followers). Initially, the opinion is uniformly distributed over all agents.
- Perceived Public Opinion  $[-1, 1]$ : The mean opinion a particular agent perceives in its neighborhood through seeing the posts of in-neighbors. If the absolute distance between the public and its own opinion is within a defined threshold, the agent’s opinion converges towards the public opinion. If not, the agent’s position will move into the opposite direction of the perceived opinion (therewith increasing the distance). If an agent ends up having no neighbors, the perceived public opinion mirrors its own opinion.
- The inclination to Interact  $[0, \text{Inf}]$ : The willingness of agents to share posts. A distribution function sets 80% of the agents to passive receivers who rarely share a post. Very few agents have a higher inclination to interact than 1 and share multiple posts per simulation step. After its initial generation, this attribute is fixed.
- Feed (Array of max. 15 posts): Storage of received posts. The feed of agent  $x$  contains all shared posts from agents who are in-neighbors of agent  $x$ .

The perceived public opinion is the only factor that has an influence on an agent’s opinion and is driven by the posts that are visible to this agent. The most important attributes of a post are:

- Opinion  $[-1, 1]$ : A post’s opinion is generated from the opinion of the agent who publishes it. Its opinion is randomly varied by applying a random addition between  $[-0.1, 0.1]$ .
- Weight: The weight of a post represents the influence of an agent as it is equal to the count of outgoing edges of the posting agent. Posts with high weights are perceived as more important and influential through the receiving agents compared to posts that have been published from agents with low outdegree.

### 3.2 The Simulation Architecture

A simulation consists of an initiating phase that creates the required initial network and agents with their properties, the main simulation phase where the agents interact and time steps are performed and a data saving phase. Every simulation timestep follows the same order of actions. First, the agent list is shuffled to ensure that the order in which the agents perform their interactions don’t have an impact on the simulation outcomes. Following, the actions of a certain agent in a simulation step are described:

1. *Update the feed*: The posts that were received in the previous step get sorted by their weight and the weight of all posts in the feed is reduced by the factor 0.5 to provide higher visibility to newer posts. The feed is limited to the 15 highest-weighted posts, all other posts are dropped and not further considered for calculation of the perceived public opinion.

2. *Update perceived public opinion:* The updated feed is used to calculate the perceived public opinion. The opinion of posts with higher weights have a higher influence on the calculation. If the feed of the agent is empty, the perceived public opinion mirrors the opinion of the agent.
3. *Update the opinion:* With the perceived public opinion an agent now updates its own opinion. If the absolute distance between public opinion and own opinion is inside a defined threshold, the agent approaches the public opinion by a factor of 0.05. If the absolute distance lies outside the range, the agent moves into the opposing direction and therewith increases the distance what we call the “backfire effect”.
4. *Drop ingoing edges:* Regarding its updated opinion, an agent checks if the current posts in his feed are in an accepted absolute distance to the own opinion. If not, the agent also checks the real opinion of the source agent and if this opinion is also outside the accepted range, the agent drops the incoming edge so that it won’t receive further posts of the former followee. In one step, an agent can only drop a tenth of his current number (rounded up) of ingoing edges so that a realistic behavior is maintained.
5. *Add ingoing edges:* After disconnecting from agents that are outside of the accepted opinion range, an agent adds new ingoing edges if his in-neighbors count is below the desired value. All agents try to maintain an indegree that equals a tenth of the network size. Adding edges is based on the configuration either done by selecting candidates from the neighbors of the agent’s in-neighbors without regarding the opinion or selecting candidates randomly from the whole network that lie inside a defined absolute distance from the own opinion. In the third configuration, both approaches are combined. From the selected candidates, an agent always chooses the one with the highest outdegree first and creates a new directed edge towards itself. This process is continued until the number of new in-neighbors is reached or the list of candidates is empty.
6. *Publish posts:* When the network maintenance is finished, an agent starts to publish posts concerning its inclination to interact. A post is generated through multiplying the own opinion with a randomly chosen factor in  $[-0.1, 0.1]$  and setting the post-weight equals to the own current outdegree. After generating the post it is shared with all feeds of the current agent’s out-neighbors.

The actions described above are performed by every agent during a simulation step. After all agents are finished, their current states and network measures are logged for analysis. After all steps are done, the simulation object is saved containing the initial and final state, intermediate states at each 10% of the simulation, agent and post logs and the configuration of the certain run.

### 3.3 Implementation of Opinion Dynamics

As shown in the previous section there are several ways to model the dynamics in opinion formation. We decided to implement a variant of the bounded confidence model proposed by Hegselmann et al. that relies on an initially randomly



generated social network. When in a certain threshold, agents approach towards the perceived public opinion regarding the outdegree of the other agents who influence them. Outside this threshold, a backfire effect is triggered that leads the agent to reinforce her own opinion by increasing the distance between her own and the perceived public opinion. As a result, the agent will tend to disconnect from others who are too far apart in their opinion and thus again reducing the distance between the public and their own opinion.

### 3.4 Network Analysis

For an appropriate analysis of the resulting social networks, we investigated various measures to evaluate effects on the distribution of degrees, centrality and community structure. Our chosen measures comprise the following:

- The density of the networks, the standard deviation of degrees for ingoing and outgoing edges, the ratio of outdegree to indegree for the analysis of degree distribution
- Closeness betweenness, and eigenvector centrality for the understanding of centrality features
- Clustering coefficient and community detection through label propagation for gaining insights on the community structure

We looked on multiple measures to detect the effect of network structure and the investigated factors on opinion dynamics in the network:

- Standard deviations of opinions
- Opinion Change Delta Mean (Opinion Change from initial to the final opinion of an agent)
- Difference between an individual’s opinion and its perceived public opinion

Besides calculating the means of all aforementioned measures we also investigated them for the most important node in the networks in particular.

The measures were all calculated from the final state of the simulation runs and averaged over all repetitions of the same run so that we can calculate confidence intervals for the outcomes of the simulation runs.

## 4 Results

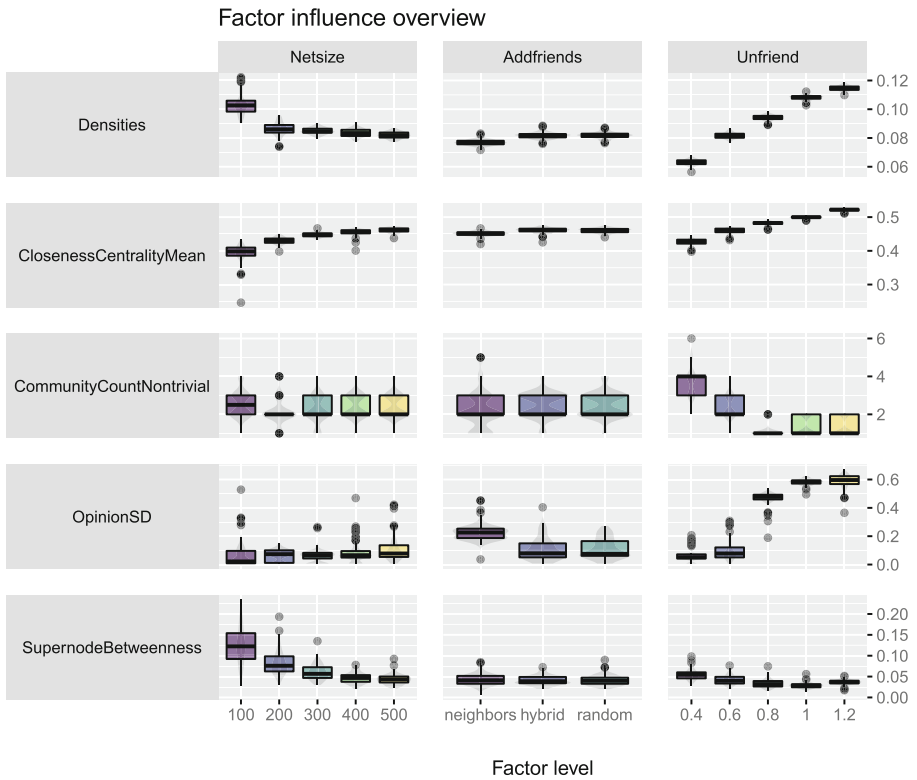
We performed a total of 13 different simulation runs that cover the following variations of factor configuration:

- Network Size in 100, 200, 300, 400, 500 Agents
- Add friends Method as Neighbors, hybrid and random
- Unfriend Threshold of 0.4, 0.6, 0.8, 1.0, 1.2

This allows us to examine subsequently the influence of the factor levels separately. Each distinct simulation configuration was repeated 100 times to eliminate effects that are due to the usage of random number generators in the simulations. The results that are reported in the following are always averaged over the repetitions of a particular configuration run.

The influence of the factors was evaluated with various measures that can be classified into the following facets:

- 1) Degree Distribution
- 2) Centrality Measures
- 3) Community Measures
- 4) Opinion Dynamics
- 5) Supernode properties



**Fig. 1.** Overview of the factor influences on exemplary measures of the analyzed facets.

Figure 1 shows the influence of each factor on one representative measure of those facets. As can be seen, the network size did not affect the community structure and opinion dynamics significantly. In comparison, the add friends method

had additional on the opinion dynamics and only the unfriend threshold showed an influence on all facets. Subsequently, the particular effects are examined more detailed and separately per factor.

#### 4.1 Impact of Network Size

In our simulation, the size of a social network is especially influential for the deviation of network parameters and opinions throughout the members of a network (see Table 1). While the density of a network decreases significantly from 10.3% in a network of 100 agents to 8.6% for  $n = 200$  and further on to 8.2% for  $n = 500$ , the standard deviations of outdegree and indegree increase (outdegree from 5.48 for  $n = 100$  up to 28.09 for  $n = 500$ , indegree from 5.18 for  $n = 100$  up to 23.13 for  $n = 500$ ) which shows that the preferential attachment algorithm overruns the pursuit of each agent to connect to one-tenth of the network members. In terms of network centrality, only the closeness centrality increases through more agents while betweenness and eigenvector centrality decrease. This shows that while the agents' connectivity to each other agent in the network rises, the agents have on average less influence on their neighbors.

The influence and the outreach of the supernode in a network depend on the overall network size. While in a network of 100 agents every third follows the supernode directly, this value increases continuously for networks with more agents. In a network with 500 agents already every second agent is a follower of the supernode. Regarding the other centrality measures, the supernode shows higher closeness centrality for larger networks (from 0.55 for  $n = 100$  to 0.63 for  $n = 500$ ), but lower betweenness (from 0.12 for  $n = 100$  to 0.04 for  $n = 500$ ) and eigenvector centrality (from 0.28 for  $n = 100$  to 0.16 for  $n = 500$ ) with higher network size. This shows that while the supernode is more central in terms of connectedness to all other nodes, its importance as a connector between all other agents is decreasing. The network size did not affect the opinion difference between the two agents with the highest outdegrees as their opinions were always rather conforming with each other.

The network size did not influence the cluster and community structure within a network consistently. The opinion dynamics did not differ significantly regarding network size either. The opinion diversity in the network had a slight upgoing trend for larger networks. The mean difference between an agent's own opinion and its perceived public opinion in the final state increased slightly with network size as well.

#### 4.2 Impact of the Add Friends Mechanism

The mechanism for adding new friends shows an influence on the network and the opinion distribution in it (see Table 2). When picking new friends only from friends of current friends, the density of a network stays with 7.7% lower than for picking randomly from all agents in the network concerning the opinion difference (8.2%) and for a hybrid approach of both methods (8.2%). While the standard deviations of outdegree and indegree for each agent to not differ

**Table 1.** Influence of the network size.

Network size	100	200	300	400	500
Densities	0.103	0.086	0.085	0.084	0.082
OutdegreeSD	5.483701	11.163	16.946	22.654	28.092
IndegreeSD	5.182528	9.722809	14.309	18.885	23.130
OutdegreeIndegreeRatioMean	0.503	0.495	0.493	0.491	0.491
ClosenessCentralityMean	0.396	0.430	0.448	0.455	0.461
BetweennessCentralityMean	0.016	0.007	0.004	0.003	0.002
EigenCentralityMean	0.082	0.055	0.045	0.038	0.034
ClustCoeff	0.069	0.056	0.056	0.056	0.055
CommunityCount	3.010	3.020	3.090	3.420	2.960
OpinionSD	0.062	0.065	0.063	0.082	0.105
OpChangeDeltaMean	0.484	0.498	0.498	0.493	0.487
PublOwnOpinionDiff	0.020	0.021	0.021	0.023	0.026
SupernodeOutdegree	32.83	75.74	121.670	161.250	210.860
SupernodeCloseness	0.551	0.609	0.625	0.625	0.633
SupernodeBetweenness	0.126	0.082	0.060	0.047	0.043
SupernodeEigen	0.283	0.238	0.205	0.178	0.164
Supernode1st2ndOpdiff	0.023	0.007	0.009	0.009	0.032

significantly between the different approaches, the mean ratio between outdegree and indegree per agent is less balanced when agents only choose from neighbors of neighbors (0.48) compared to random and hybrid approaches (both 0.49).

The least influence of the add friends mechanism can be perceived in terms of network centrality of each agent. Only the closeness centrality is slightly higher for the random and hybrid approach (0.45 for neighborhood and 0.46 for random and hybrid approach), while betweenness and eigenvector centrality do not show significant changes. Concerning clustering and community structure, the clustering coefficient increases slightly by using the random approach (0.055 compared to 0.052 for the neighborhood approach) while the number of communities is higher for networks where agents only pick neighbors of neighbors (6.41 compared to 3.47 for the random approach).

The node with the highest influence and outreach in the network is not affected by the add friends mechanism. The opinion difference between the two nodes with the highest outdegree shows more extreme outliers for the random add friends method but no significant difference to the other approaches. The opinion distribution, on the opposite, is significantly higher if the agents only connect to others that are already in their indirect neighborhood. The sum of opinion changes per agent is slightly higher when agents pick their new friends randomly and according to the opinion difference (0.49 for random and 0.44 for neighborhood approaches). Looking at the distance between perceived public

and own opinion in the final state, those two values are significantly closer to each other when the random or hybrid approach for choosing new friends is used (0.03 for random and hybrid approach and 0.04 for neighborhood approach).

**Table 2.** Influence of the addfriends method.

Addfriends method	Neighbors	Hybrid	Random
Densities	0.077	0.082	0.082
OutdegreeSD	29.148	28.074	28.230
IndegreeSD	24.148	23.102	23.263
OutdegreeIndegreeRatioMean	0.483	0.491	0.491
ClosenessCentralityMean	0.451	0.461	0.460
BetweennessCentralityMean	0.002	0.002	0.002
EigenCentralityMean	0.034	0.034	0.034
ClustCoeff	0.052	0.055	0.055
CommunityCount	6.410	3.820	3.470
OpinionSD	0.226	0.106	0.110
OpChangeDeltaMean	0.442	0.488	0.489
PublOwnOpinionDiff	0.041	0.026	0.026
SupernodeOutdegree	206.700	209.100	207.850
SupernodeCloseness	0.626	0.631	0.630
SupernodeBetweenness	0.043	0.042	0.041
SupernodeEigen	0.165	0.165	0.163
SupernodeOpinion	-0.019	-0.007	0.000
Supernode1st2ndOpdiff	0.090	0.028	0.047

### 4.3 Impact of Unfriend Threshold

The threshold of an agent to accept diverging opinions (in the following abbreviated as  $ut$ ) was influential for both the network structure and the opinion distribution in a network. If the agents in a network are more tolerant in keeping friendships, the density of the network increases significantly from 6.3% for  $ut = 0.4$  to 11.5% for  $ut = 1.2$  and with it also the variety of outdegrees and indegrees within the network members. The ratio between outdegree and indegree gets more balanced for networks of agents with higher opinion tolerance (0.48 for  $ut = 0.4$ , 0.50 for  $ut = 1.2$ ).

The centrality of each agent in the network changes with the unfriend threshold as closeness and eigenvector centrality increase with higher tolerance of friends with diverging opinions. The betweenness, in contrast, decreases with a rising threshold. The clustering and community measures show that while

clustering increases through higher unfriend thresholds, the number of separate communities detected through label propagation decreases.

The role of the agent with the highest follower count also depends on the unfriend threshold (see Table 3). While outdegree and closeness centrality stay rather equal for a threshold from 0.4 to 1.0, in a network with an unfriend threshold of 1.2, both values increase significantly. So the supernode profits only in terms of post reach when every agent is very tolerant with keeping fellowships that bear a high opinion difference. The betweenness and eigenvector centrality decrease continuously with rising unfriend threshold, but this trend seems to turn around at least for the eigenvector centrality with an unfriend threshold of 1.2. Comparing the opinion of the most important and second most important agent we observe a significantly higher difference for unfriend thresholds of 0.8 and 1.2 whereas for the lower and higher thresholds the opinions of them are close to each other.

With changing the unfriend threshold it is possible to subsequently influence the opinion distribution within the network. While in networks with low thresholds the standard deviation of opinions is below 0.1 on average, this measure rises notably up to 0.5 for a network with an unfriend threshold of 0.6 and even continues with higher thresholds to 0.6 for a threshold of 1.2. Meanwhile, the mean delta between the initial and the final opinion of all agents in the networks shows the opposite trend. While the opinion change is with 0.5 rather large for thresholds below or equal to 0.6, it falls below 0.3 for networks with a larger threshold. The least opinion change occurs for a threshold of 1.0 while with 1.2 the opinion change starts to increase again. With rising unfriend threshold also the distance between perceived public and own opinion increases significantly.

## 5 Discussion

Our work revealed several results that call for further investigation. Subsequently, we will discuss the results concerning other research and look into the lessons learned from our initial approach and possible further steps.

As we could show, the overall model configuration was capable of simulating the opinion dynamics in a social network and suitable to perform experiments regarding specific factors of the network size and behavior. The programming language Julia proved robust as a simulation environment and provided all necessary flexibility to implement our approach as well as enough performance to run several configurations and repetitions in a reasonable time.

With changing the overall agent count in the network, we wanted to observe how a higher availability of possible friends in a network and the strengthening of supernodes through the preferential attachment mechanism will change the structure and dynamics in the network. The obtained results indicate that through increasing the network size, the agents grow closer together although the overall network density decreases significantly. This counterintuitive result can be explained with the significant influence growth of the supernode in the network. We interpret the absent influence of network size on all measures of

**Table 3.** Influence of the unfriend threshold.

Unfriend threshold	0.4	0.6	0.8	1.0	1.2
Densities	0.063	0.082	0.094	0.108	0.115
OutdegreeSD	26.693	27.921	29.209	31.545	36.109
IndegreeSD	19.050	23.133	26.923	30.335	35.134
OutdegreeIndegreeRatioMean	0.479	0.491	0.496	0.498	0.498
ClosenessCentralityMean	0.426	0.460	0.482	0.499	0.521
BetweennessCentralityMean	0.003	0.002	0.002	0.002	0.002
EigenCentralityMean	0.031	0.034	0.036	0.038	0.038
ClustCoeff	0.051	0.055	0.055	0.058	0.060
CommunityCount	6.700	3.200	1.170	1.350	1.290
OpinionSD	0.070	0.096	0.470	0.582	0.589
OpChangeDeltaMean	0.496	0.487	0.256	0.215	0.274
PublOwnOpinionDiff	0.021	0.025	0.120	0.170	0.184
SupernodeOutdegree	208.030	205.920	201.590	206.360	244.780
SupernodeCloseness	0.629	0.628	0.624	0.631	0.663
SupernodeBetweenness	0.054	0.041	0.033	0.029	0.037
SupernodeEigen	0.183	0.164	0.152	0.139	0.148
Supernode1st2ndOpdiff	0.005	0.027	0.252	0.362	0.085

opinion dynamics except for the higher deviation of opinions in larger networks as confirmation for the robustness of our implementation.

Looking at the other two factors we were able to establish significant influences on both network and opinion dynamics. While the unfriend threshold depicts the effects of direct individual behavior of the agents, the add friends mechanism can be seen as indirect individual behavior as a certain platform could provide recommendations for new friends in various ways and therewith lead the user to establish new connections more locally (through looking into neighbors of neighbors) or more globally (through looking randomly in the whole network). Being limited to the local environment naturally leads to lower network densities as the number of agents who hold similar opinions decreases. As a consequence, the opinion deviation increases and so does the difference between the own opinion and the perceived public opinion. The higher delta of opinion change in networks with random or hybrid add friends mechanisms compared to the other mechanism can be reasoned with the effect of bounded confidence: if agents act in an environment that is closer to their own opinion, they will more likely approach to the opinions of the others and the higher density of networks with randomly chosen friends allows for more opinion fluctuation. The restriction to local neighbors, on the other hand, leads more often to local environments where the public perceived opinion is too distant from their own opinion and alternatively the backfire effect is triggered.

The unfriend threshold showed the most diverse influence on the measured network and opinion dynamics. Inherently, the density of a network increases when its members are less rigorous with cutting unsuitable friendship ties. Also, the effects on centrality and clustering of the network seem rather obvious and the decrease of opinion change delta orthogonal to the rise of the distance between public and own opinion shows again the incidence of the bounded confidence dynamics. More interesting, however, is the sharp change of measures for unfriend thresholds of 0.6 and 0.8. Previous research suggests that members of online social networks tend to unfriend other individuals due to offensive or counter-attitudinal posts but it shows simultaneously that a large share of users is rather lazy in cutting their weak ties [18]. John et al. also found that cutting ties because of political posts happens more often around individuals who hold stronger political inclinations and with the reason to increase homogeneity in their Facebook Newsfeeds. For less politically interested individuals the primary motivation in cutting those ties lay in reducing the number of political posts in their feed.

With our initial approach, we were able to target proof of concept for an agent-based model that provides more closeness to reality through implementing certain dynamics of real-world social media platforms like Facebook and Twitter. Concurrently, our results motivate for further investigation of the examined factors and inclusion of further dynamics into the network model. Like other research showed it is difficult to set a limit on fitting the model to real-world dynamics as almost every effect that occurs can be implemented with more or less complexity into a certain simulation environment. Han et al. for example considered more precisely the personality of agents and focused specifically on the effect of adding “stubborn” agents to a simulation. For simulations with a higher share of agents who stick stubbornly to their opinion, they found that the number of opinion clusters decreased [16].

As Dunbar et al. found, people tend to interact on social media platforms within certain communicational layers [13]. That means that our connections to other individuals hold similar connotations to those in the offline world and that we would differentiate between our interactions with friends, colleagues and more distant acquaintances. For introducing such dynamics into simulation models Salehi et al. showed an approach through varying additional trust levels for the friendship connections of the agents [30]. Along with the implementation of more complex friendships connections, we will also strive to incorporate more features of social networks like the function to share a post from the individual’s news feed into her friendship network.

Another important question while simulating opinion dynamics is how one assumes a simulation state to be final or converged. While in cases with consensus formation the answer seems trivial, other cases with unstable opinion distributions in the network might hardly get into a stable final state. Meng et al. found that the convergence time of models operating under the bounded confidence approach of Deffuant et al. strongly depends on the underlying network structure. Also, they stated that there is a critical border for the bounded



confidence of  $\epsilon = 0.5$  for certain network topologies. When this border is crossed, the convergence time of simulation runs increases significantly [24]. Hence, for advancing our approach in the future it will be also inevitable to investigate the convergence behavior of our simulation.

The last consideration has to be given to the modeling of the network structure. As we aim to simulate the opinion dynamics in real social networks it is also crucial to run our models on suitable network structures that are capable of replicating the real-world conditions. An extensive analysis of the friendship relations in Facebook of Wilson et al. shows that the actual structure of the social graph shows similarities and a power-law distribution of degrees like in Barabási-Albert networks. Nevertheless, fitting of the model parameters is required to facilitate the generation of a realistic artificial network and additional factors as network growth have to be taken into account [38].

In conclusion, there is still a lot to do for simulating the opinion dynamics on social media platforms as realistic as possible. Nevertheless, this process is worth tackling all the obstacles as it will facilitate the understanding of opinion formation in online social networks and help with designing social media platforms in a way so that they actually will support an independent and democratic opinion formation in online environments. As shown by De et al., the prediction of opinion dynamics in social media platforms is a solvable problem and will be of high value for reaching this goal ultimately [9].

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