THE INFLUENCE OF NEWS ON POLARISING SOCIETIES

A PREPRINT

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ABSTRACT

Societies seem to become increasingly more polarised. In this work the potential influence of news on this process of polarisation is explored. News dynamics are added to an existing opinion dynamics model. In the existing model a population with a neutral opinion is initialised. Afterwards, a small portion of agents are initialised with a radical opinion. While agents interact with one another they exchange information that can cause a shift in their opinion. This paper investigated the influence of several news distributions to the polarisation and radicalisation of a social network. News causes faster radicalisation of the population, however extreme news causes radicalisation to one side of the opinion spectrum, thus a lower polarisation degree.

Keywords Agent based modeling · Computational science · social networks · Opinion dynamics

Contents

1 Introduction

In recent years, our society has experienced different heavily polarised and radicalised debates. For example, the Brexit discussion in the UK or the Black Pete debate in the Netherlands. As noted by Van der Maas [1], these debates have developed rather quickly from a seemingly neutral population to a population filled with strong opinions. From a scientific perspective, it is interesting to try to understand the key dynamics at play that drive such a quick transformation in a social network.

Van der Maas [1] has made a first step in researching this phenomena. His study models opinion dynamics based on 3 parameters: attention, information and opinion. With this model, he finds that a few slightly radicalised agents can drive the rest of the population towards a polarised and radicalised state. However, in modern debates, interactions and discussions between people is not the only development. In the media-integrated society we live in, we constantly are in contact with news and articles. This study builds on the model introduced by Van der Maas [1] in order to to investigate the new dynamics that arise due to news. It tries to answer the question: What is the influence of different types of news on the opinion dynamics of a social network?

This research makes use of Agent Based modelling, for which a solid argument can be made. Social networks often contain a heterogeneous mix of people, which all make different choice. Due to the many local interactions, social networks often show complex and emergent behaviour. These are all indicators that call strongly for an agent based model.

First of all, this paper will shortly discuss background theory on social networks. Subsequently, the new model and its implementation will be discussed, followed by a short explanation of how it was validated. Then, the sensitivity analysis on the model and the results will be presented. Lastly, these results are interpreted and discussed to understand the priorities for future work.

2 Theory

2.1 Social networks

Social networks describe a population and the personal relations within that population. It is commonly visualised as a graph of nodes and edges as in figure 1. The nodes represent persons (or agents) that operate individually within the social network. The edges between nodes represent the social connection between agents. This might represent the amount of social interactions or physical encounters. These edges can be weighted, but it is not a requirement. Social networks are typically characterised by three parameters [2]:

- Size - the total size of the network;
- Path length - the average distance (of edges) between pairs of agents;
- Whole network density - the ratio of actual edges in the network compared to the total amount of possible edges.

Most of the form of a social network is described by these three parameters. For this research is important to note that the dynamics of a social network depends on the form and may vary for different networks. Therefore, the results found by studying a social network should always be associated with the characteristics of the subjective network.

3 Model implementation

3.1 Network implementation

As stated before, this study is based largely on the model produced by Han Van der Maas. The opinion dynamics in our model are based on that model. However there are some key differences between the two models. Firstly the proposed model does not place the agents on a grid, like Van der Maas does, but instead uses a network structure. This network is a representation of a social network. Agents are placed on the nodes and can only interact with their neighbours. This study opted to model the society this way in order to better capture the structure of social circles (families and friends) in the opinion dynamics. In a real social network some people have many social connections and some have few. This could lead to interesting dynamics with regards to opinion spread. To model this type of dynamics, networks are best suited. In order to create a representation that is as close as possible to a real social network, the networks parameters where calibrated using parameters from a real social network data set (see section 4.5 for details).

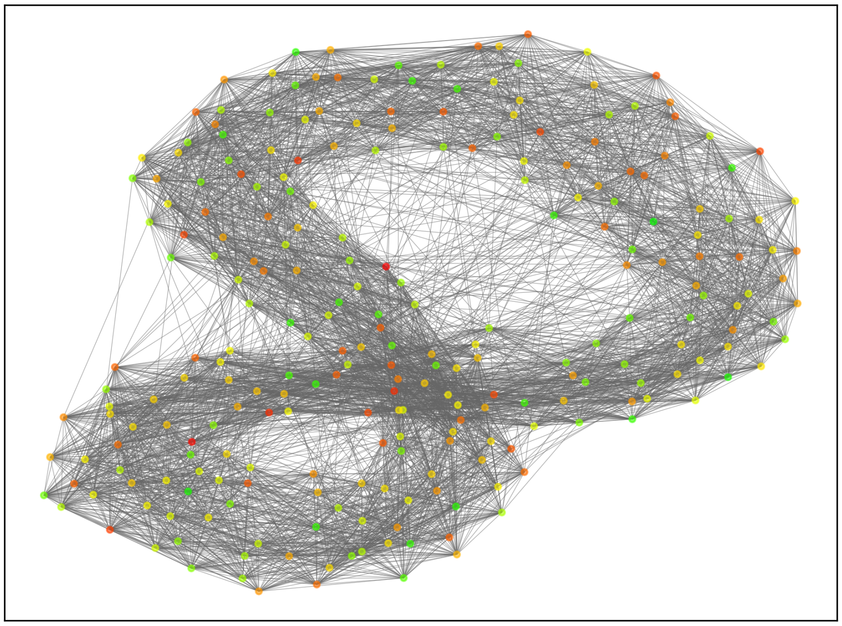


Figure 1: Social network visualised as graph.

3.2 News interaction

This study proposes a novel addition to the model introduced by Van der Maas [1] in the form of news. We hypothesise that the type of news that is spread in a society can be of substantial influence on the radicalisation and polarisation that occurs on the topics that the news covers. The implementation of news dynamics in the Van der Maas model is discussed in section 4.6. In the conducted experiments two types of news are spread throughout the model: moderate news and extreme news. These news types are modelled to be loosely representative of two Dutch broadcasting associations: the NOS and PowNews, where the former is the moderate and the latter the extreme.

4 Model description

The model description follows the ODD (Overview, Design concepts, Details) protocol ([3], [4])

4.1 Purpose

The purpose of the proposed model is to investigate the influence of news on polarization in societies. Differing news outlets are represented by different news value distributions, will produce news with different core opinions, for instance more left leaning on the political spectrum. The model is designed to answer the question of what effect these different new outlets have on the polarization of the modelled society.

4.2 Entities, state variables, and scales

The entities in the proposed model are agents representing humans. These agents exist on the nodes of a network, which is initialised in such a way that it represents a social network. Edges between nodes represent connections between agents. The current state of agents is defined by the following three variables: opinion, attention and information. Following Maas [1], these variables are represented as numbers on the intervals $[-1, 1]$, $[0, 1.5]$ and $[-0.5, 0.5]$, respectively. Since the network the agents operate on represents a social network the model, it does not have an explicit scale. The model is event driven, where an event is defined as an interaction between two agents. The simulations where run for 4000 timesteps. An overview all the parameters used in the model can be found in table 1.

Name	Symbol	Nominal Value	Range	Description
News probability	p_η	0,3	0 - 1	Probability that news is distributed
News proportion	p_{prop}	0,4	0 - 1	Percentage of agents that receives news when there is a newsflash
Trust threshold	t_d	0,2	0 - 1	Maximum difference in opinion for interaction to occur
News shift	η_{shift}	0,3	0 - 1	Shift towards news
Initial information	I_{init}	0.05	0 - 0.25	Information value with which agents are initialized
Opinion noise	s_O	0.01	0.0 - 0.05	Variance of the normal distribution from which the noise that is added to an agent's opinion when it is updated
Information noise	s_I	0.0	0.0 - 0.05	Variance of the normal distribution from which the noise that is added to an agent's information when it is updated
Attention increase news	δA	0.05	0 - 0.25	Attention increase when hearing news
News information moderate news	η_{dm}	0 - 0.25		Distribution from which the information value of moderate news is sampled
News information extreme news	η_{de}	0.3 - 0.5		Distribution from which the information value of extreme news is sampled
News threshold	η_t	0.3	0 - 0.5	The minimum distance between the information value of the news and the information value of the agent
Attention increase interaction	ΔA	0.15	0.0 - 0.3	Attention increase when interacting with other agents
Attention decay	A_{decay}	1	0 - 25	Magnitude of the attention decrease for each agent at each timestep
Initial radicals	p_{rad}	0.1	0 - 0.5	Percentage of agents that's initialized radical
Agents	N	250		Number of agents
Initial opinion	O_{init}	0		Initial opinion value of each agent
Initial attention	A_{init}	$1.0e-6$		Initial attention agent of each non-radical agent
Persuasion	P	10		causes more attentive agents to persuade others with their information
Initial information radicals	I_{rad}	-0.1		Initial information value of radicals
Initial attention radicals	A_{rad}	0.4		Initial attention value of radicals

Table 1: Overview of all the relevant parameters that were used in the model. Note that for parameters that were included in the sensitivity analysis (section 6), the range from which samples were taken is also given.

4.3 Process overview and scheduling

In this section a brief overview of the schedule of the model is given. After the initialisation step, the model performs a set number of steps. The procedure of such a step is given in the pseudo-code of algorithm 1. At the start of a step there is a probability that news is distributed. Afterwards, agents can be picked to interact with some other agent. This is a stochastic process which depends on the attention of an agent. Agents that have higher attention are assumed to be more likely to try and spread their opinion, this more likely to interact. This has been modelled by selecting agents with a chance proportional to their attention. Specifically Gillepsies Algorithm [5] has been used to implement this. The selected agent randomly picks one of its neighbours for interaction. If their opinion distance lies within a certain threshold, the agents interact with one another and their information and attention is updated. At last, the opinion of all agents is updated. The above described actions such as distributing news are submodels which will be discussed more in detail in section 4.6.

General procedure of the opinion model:
initialization;
while *current step < total number of steps* **do**
    if *News chance* **then**
        distribute news;
    end
    stochastically pick agent *i*;
    from neighbours of *i* randomly pick agent *j*;
    if *Bounded confidence* **then**
        update information agents *i* and *j*;
        update attention agents *i* and *j*;
    else
        update attention agents *i* and *j*;
    end
    forall *agents* **do**
        update opinion
    end
end

Algorithm 1: General overview of a step of the used opinion model.

4.4 Design concepts

4.4.1 Basic principles

The proposed model builds upon the model introduced by Van der Maas [1], using the same strategy to model opinion dynamics. The proposed model expands on the model introduced by Van der Maas by adding news dynamics to it, and placing the agents on a network. The network resembles a social network, where the edges mean that two agents are socially connected, i.e. they know each other and can interact. The combination of the Van der Maas model with a social network and news dynamics will be used to answer the question of how news influences opinion dynamics.

4.4.2 Emergence

From the experiments we find that speed of the spread of opinion, measured by the total absolute opinion and the Deffuant distance (introduced in section 4.4.7), vary when the interaction dynamics change. This is also the case for changes in the news spread parameters. It is important to note that this is true for the speed of opinion change, not opinion change in itself. By default, the model proposed by Van der Maas results in polarisation to some degree, depending on the specific parameter setting. To summarise: the speed of the polarisation and radicalisation present in the model are properties emerging from the rules of interaction between the agents.

4.4.3 Sensing

Agents perceive other agents opinion. Based on the distance between their opinions interaction occurs. An agent however can only sense the opinion of its neighbors, which are defined by the structure of the social network that is made upon initialisation of the model. This network structure is imposed and rigid, it does not change and agents can not influence it.

4.4.4 Interaction

The interactions among the agents are governed by the network structure of the model. The agents can only interact with their direct neighbors, so only agents connected by an edge of the network will interact. The interaction happens only if the bounded confidence threshold is met, that is when the difference in opinion is smaller than some predetermined threshold. These interactions form the basis for the spread and change of opinions throughout the model. If the opinions are too far apart one another, no interaction occurs.

4.4.5 Stochasticity

There are multiple stochastic components present in the proposed model. To start the selection of the agents and their neighbors happens in a stochastic manner, as mentioned in section 4.2. Furthermore the updating of the opinion after interaction is subject to some noise. This also applies to the update of the information parameter in agents after interaction. The added noise is normally distributed, for the parameters used in the experiments and sensitivity analysis refer to table 1.

4.4.6 Collectives

The model contains collectives in the sense that after running clusters of agents with the same opinion can be observed. These clusters are an emergent property of the way the opinion dynamics are defined, there is no explicit parameter responsible for this model behaviour.

4.4.7 Observation

There are two model outputs that are the most important to our research. The first output, following Deffuant [6], is the average paired opinion distance between all agents. This metric is calculated by taking the average of the difference in opinion (recall that opinion is a scalar) between all possible pairs off agents, regardless of whether they are connected by an edge. This metric, which from now on will be referred to as Deffuant distance, is an indicator of the degree of polarisation in the population. When the average Deffuant distance is high, the degree of polarisation is high as well.

The second output is the average of the absolute opinion of each agent. Recall that opinion can range from -1 to 1, so simply taking the average over all opinions may lead to a misleading result (e.g. a population where 50% of the agents has an opinion value of 1, and 50% has an opinion value of -1, will have an average opinion on 0). Average absolute opinion is an indicator of radicalisation. Intuitively, a high value corresponds to a high degree of radicalisation.

4.5 Initialization

As mentioned before, the form of social networks varies immensely, which can have significant impact on the observed dynamics. For this research, a Watts-Stogartz social network was studied. Due to computational and time limits, the size of this network was set to 250 nodes, correpsonding to 250 agents. The other network characteristics (path length & density) were matched to a dataset of a Facebook social network, published by Stanford. [7]. Using these characteristics and the python package networkx (version 2.4) the networks where the agents operate on is created. Every agent is initialised with a opinion of 0 and an information of 0.05, as is done in the model introduced by Van der Maas [1].

4.6 Submodels

As mentioned in section 4.3 a step of the model consists of several substeps, i.e. submodels. The first submodel in algorithm 1 is the distribution of news. This action is executed during each step of the model with some probability called *news chance*. If executed a set randomly chosen proportion of the population receives the news. The news is modelled as a information parameter that influences the information of an agent. If the information of an agent lies within certain threshold of the news information value, the agent's information shifts towards the news. The update to the information is conducted using formula 1.

$$I_{agent} = (1 - \eta_{\text{shift}})I_{agent} + \eta_{\text{shift}} \times I_{news} \tag{1}$$

Furthermore, if an agent receives news the attention of the agent will increment at all times. This increment is done according to formula 2. The parameters used in the experiments and sensitivity analysis for these formulas can be found in table 1

$$A_{agent} = A_{agent} + \delta A \tag{2}$$

The second submodel in a step of the algorithm is the interaction model between agents. This interaction model is based on the hierarchical ising opinion model [1]. In this interaction model agents interact with one another if their opinion lies within a certain threshold, also known as the bounded confidence. During this interaction agents exchange information between each other. This update in information happens according to equation (3). This equation shows that the information of agents *i* is the sum of the information of agent *i* and *j*, weighted by their attention. Therefore, the relatively higher the attention of agent *j* the more agent *i* shifts towards *j*'s information and vise versa. Besides the attention also persuasion (p) is of influence on the update of an agent's information. As p gets higher, the more attentive agent has a stronger weight on their informational status. Thus, one shifts more towards the informational status of the agent with a higher attention as p increases. The right hand side of the equation consists of the normal distribution, which could be visualised as noise. If $s_I > 0$, some noise is added to the agent's information. Subsequently, the attention is updated for the two agents that had interaction. The attention for both agents is increased with a fixed step: ΔA. If two agents don't share a bounded confidence no information is exchanged, since they disagree to much. In this case only their attention increases with ΔA.

$$I_i = \left(I_i A_i^p + I_j A_j^p\right) / \left(A_i^p + A_j^p\right) + \mathcal{N}\left(0, s_I\right) \tag{3}$$

The last part of the opinion model, algorithm 1, is to update the opinion of all the agents. This deviation is given by the differential equation in (4).

First, the deviation in opinion depends on the three variables of an agent, opinion, information and attention. At all times O_i will deviate if attention and information are not zero. Furthermore, the higher an agent's attention the more an opinion shifts towards the extreme opinion values $(-1.0 \vee 1.0)$. The agent's information determines to which direction the opinion will change. If $s_O > 0$ some noise is added to the opinion.

$$dO_i = -\left(O_i^3 - \left(A_i + A^{min}\right) O_i - I_i\right) dt + \mathcal{N}\left(0, s_O\right) \tag{4}$$

5 Validation

Having established a run-able model, the next goal was to determine whether the model showed the expected dynamical behaviour. It was necessary to check whether the model is a valid representation of opinions in a social network. For this research, this was done by facial validation and using the idea of a "transitive relation" to validate the model without news. [8] As the model was strongly based on the model of Van der Maas, the model without news was compared to that of the behaviour described by Van der Maas. [1] After some parameter calibration, the same characteristic behaviour was found: an almost neutral population (agent have a slightly positive bias) with a small fraction being radical (slightly opposite opinion and higher attention) transforms into a polarised and radicalised population over time.

The advantage of an Agent-Based Model, which is that subtle dynamics are easily implemented, is also a disadvantage for the validation of the model. The eventual, complex behaviour is a result of many local dynamics, which makes it hard to determine which process on local level drives a certain behaviour [8].

6 Sensitivity Analysis

Since it is relatively easy to add an extra dynamic to the model, one can easily end up with many parameter. This makes it hard to understand how each of these dynamics contributes to the outcome of the simulation. The problem of understanding how the model outcome depends on the many macro- and micro processes, is one of the reasons to perform a sensitivity analysis. By doing this, a further understanding is gained in how the model responds to different sets of input parameters. Another motive to perform a sensitivity analysis is to understand how the interaction of parameters affects the model outcome.[9]

The sensitivity analysis is performed in two ways in this paper, which is the local (OFAT) and global (Sobol) way. In the local analysis we will see how the change of one parameter value changes the model's outcome. For the global analysis, interaction effects between parameters are analyzed, by not only changing one parameter at a time, but taking different samples from the parameter space. The variance in the model outcome of these different parameter samples is decomposed, such that it can be calculated which portion of the variance is caused by a parameter.[9]

6.1 OFAT

To perform an OFAT analysis, we first need define a nominal set of parameter values. The model is then run multiple times with these values, such that we can compare it to model outcomes when shifting one of the parameters. The 'baseline'-model is run with and without the influence of news.

As figure 2 and figure 3 show, the sum of absolute opinions is not that much affected by distribution of news in the network. The Deffuant distance on the other is influenced when agents receive news messages. When news is spread, it leads, most of the time, to a highly polarized population.

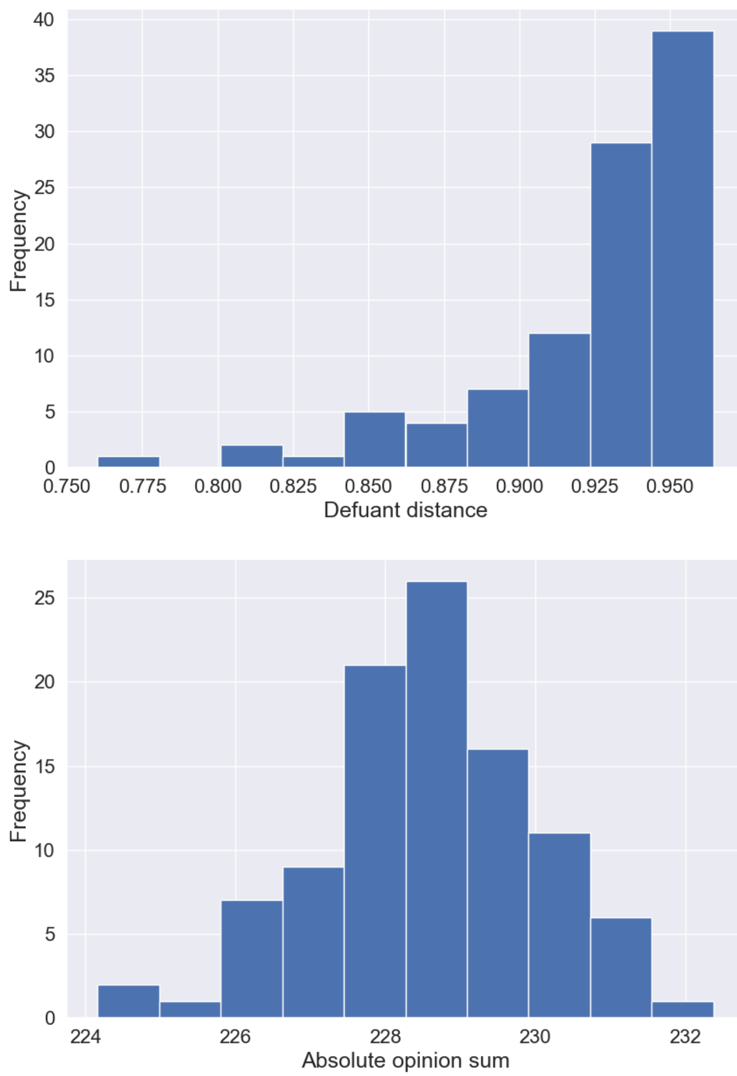


Figure 2: Histogram of 100 runs with nominal values, with news.

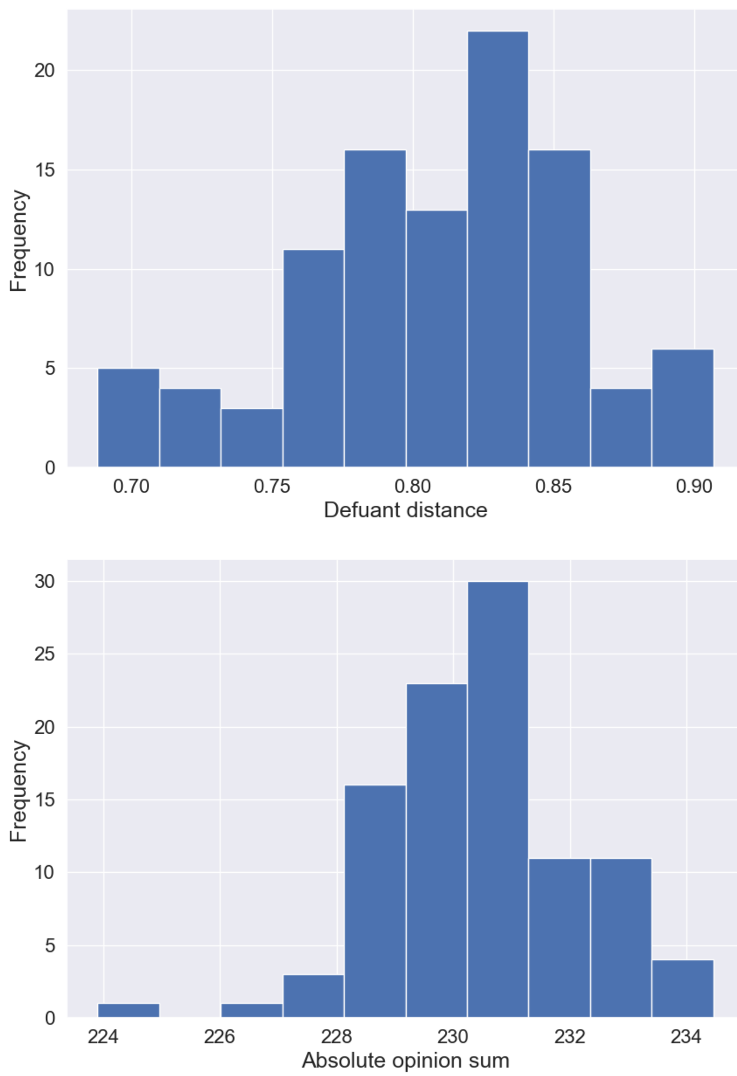


Figure 3: Histogram of 100 runs with nominal values, without news. This means that the proportion is set to 0.

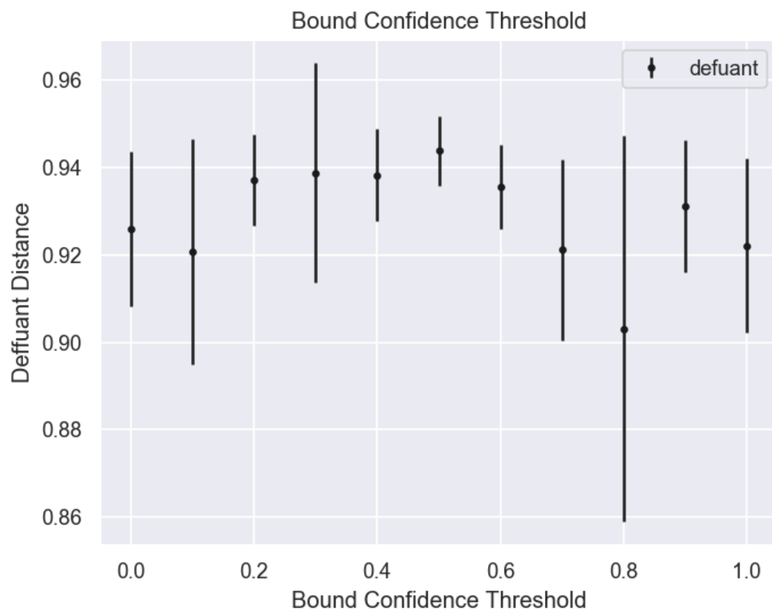


Figure 4: Plot with errorbars. Each errorbar is run with 10 replicates. The parameter determines what the accepted difference between two agents is, before they talk.

The OFAT analysis is executed with the spreading of news and computing the Deffuant distance each run, because we are interested in how the model's parameters influence the outcome. We will discuss some of the interesting results. For all results we refer to the appendix.

As can be seen from figure 4, the threshold is not that determining for the Deffuant distance. Regardless the value, the Deffuant distance stays around the mean of figure 2 (upper figure). The initial information of each agent in figure 5 on the other hand, is an important factor to the Deffuant distance output. The model outcome is sensitive to it. Another two interesting parameters are "News Chance" and "News Distribution". The model outcome is sensitive to the first one until it reaches a value of about 0.3, after which is stabilizes. A explanation can be that once the population is highly polarized, it is harder to make it even more polarized. The latter, "News Distribution", is interesting because the model outcome varies when the value increases (which means that more 'extreme' news is spread), until it reaches a tipping point and the extreme news tends to depolarize the population.

6.2 Sobol

The sensitivity of the model to a parameter is measured by how much the variance of the outcome is caused by that parameter. This method is possible because of the total law of variance. The decomposition of the total variance is done with the Sobol method. After decomposition, the final result is measuring how much the variance of the total outcome can be explained by the parameter. We will discuss two indexes that measure sensitivity, namely the first-order and total-order sensitivity indexes. The Sobol Analysis is performed on 5 parameters due to computational limitations.

The first-order sensitivity index explains what the variance reduction would be if the parameter we were interested in, would be known. This means that the model is run with that parameter value fixed and analyzing how that would effect the model outcome.

Instead of keeping the parameter of interest fixed, the total-order sensitivity index indicates how much variance there is left when all other parameters values are known[9].

Figure 8 shows that for each of the chosen parameters, the variance of the model more or less stays the same. The reduction in variance when fixing each parameter, has a large spreading itself. So there are not any conclusions to make about one particular parameter. In figure 9 we see that the most variance remains when all but the initial information is not fixed. The influence of this parameter can also be seen in figure 5. The additional information that figure 9 gives, is that this remaining variance, like all parameters, varies.

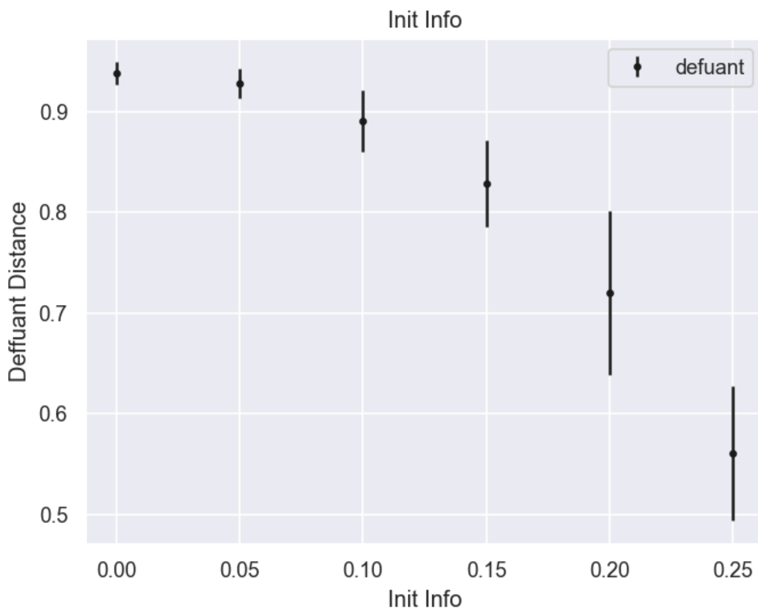


Figure 5: Histogram of 100 runs with nominal values, without news. This means that the proportion is set to 0.

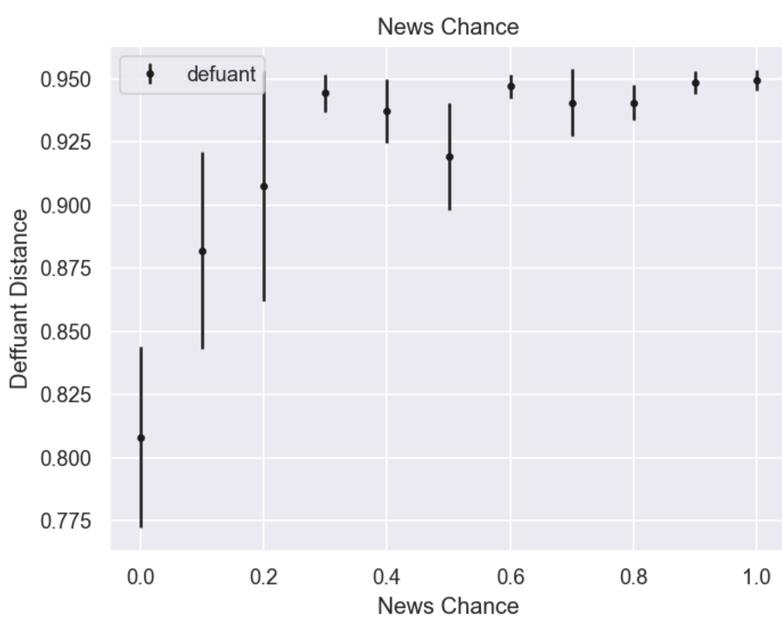


Figure 6: Histogram of 100 runs with nominal values, without news. This means that the proportion is set to 0.

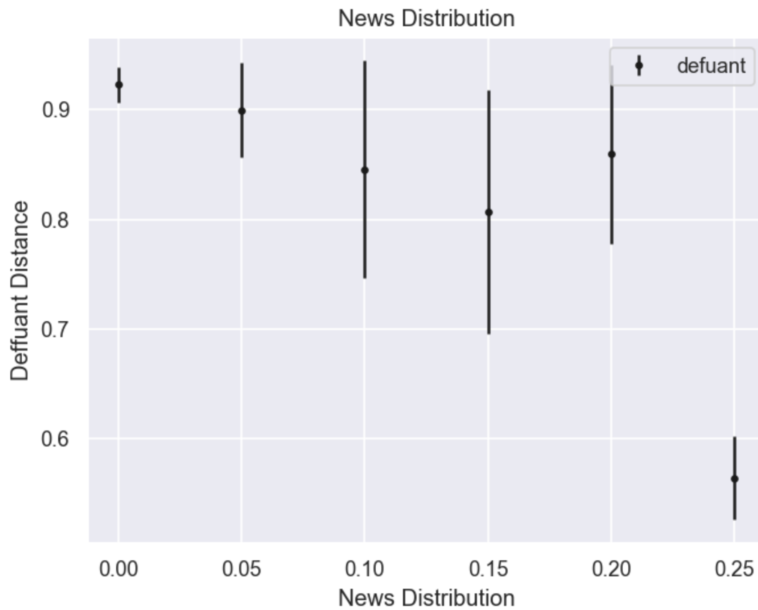


Figure 7: Histogram of 100 runs with nominal values, without news. This means that the proportion is set to 0.

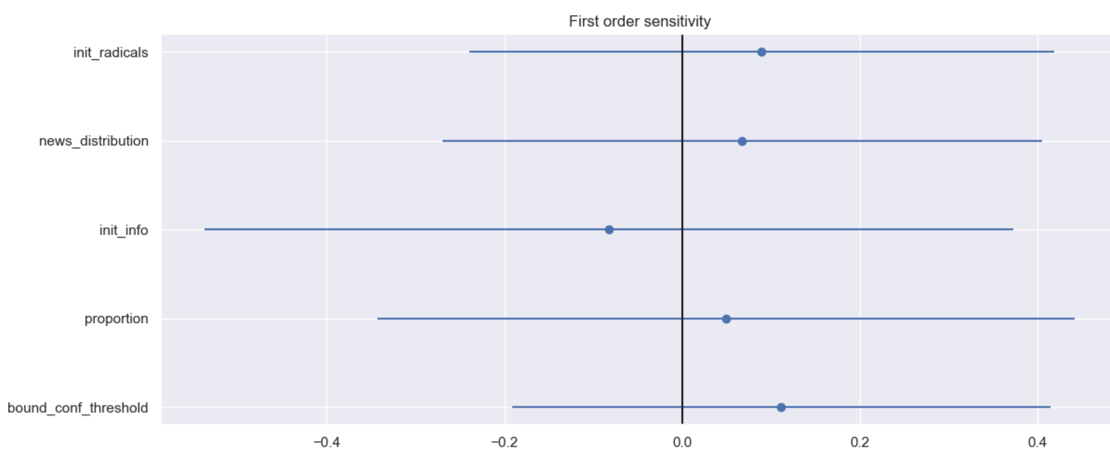


Figure 8: First-order sensitivity index.

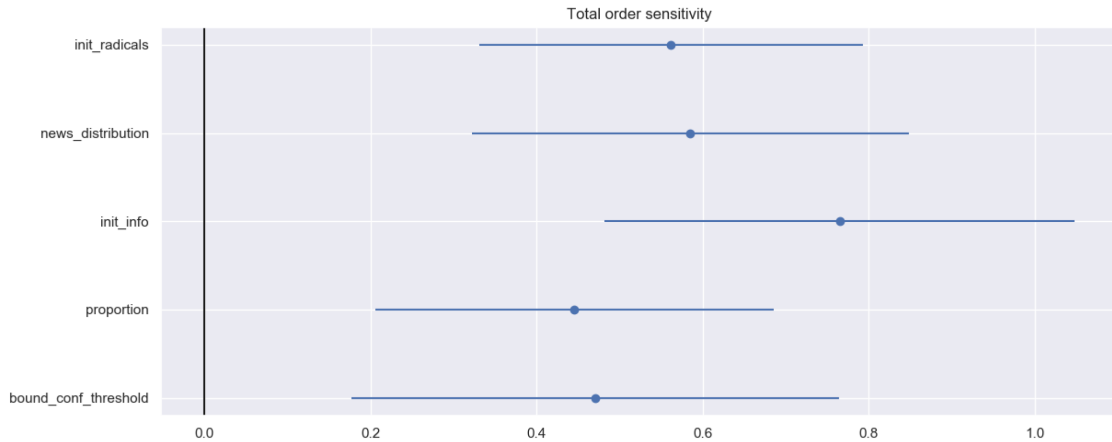


Figure 9: Total-order sensitivity index.

7 Results

For this research, two types of populations were tested for two types of news. The first population is one that represents the real world as parameterised by Van der Maas. The thrust-threshold is set at 0.2, which leads to interactions being dependent on the closeness of opinions of two agents. The second population is very trustful, were the threshold is set at 1.0.

As a benchmark, simulations were ran for a population that does not experience news at all. Subsequently, a population with moderate news (opinion of news centered at 0.0) and a population with extreme news (opinion of news centered at 0.25 which is equally likely to be negative or positive each step).

7.1 The effect of news on polarisation

In figure 10a, the Deffuant distance is plotted for each run. As mentioned before, this is a metric that provides insight on the polarisation of the social network. Remarkable is both the effect of extreme news as well as moderate news on the population.

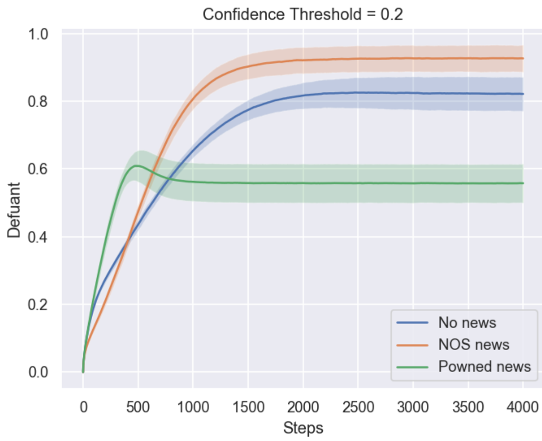
Moderate news seems to drive the social network to a more polarised state. This interesting emergent behaviour can be understood locally. As the moderate news is sometimes neutral and sometimes positive/negative, it sometimes drives agents to a more extreme opinion. Consequently, it might result in an agent that is too extreme for neutral agents and therefore stops interacting with neutral agents or news. This local dynamic drives the population further into polarisation.

In addition, extreme news appears to have a negative effect on the polarisation. This can be explained by the initialisation of the model. Most of the population is initialised at a slightly positive opinion. Therefore, the major part of population is only influenced by the extreme positive news. This results in a less polarised social network as most agents are driven to the same extreme opinion. It is important to note the difference between polarisation and radicalisation here: a high polarisation means that many agents have differing opinion, whereas a high radicalisation means that many agents have extreme opinions, either positive or negative. In the case of PowNews an explanation for the low polarisation is that all agents are radicalised to one side.

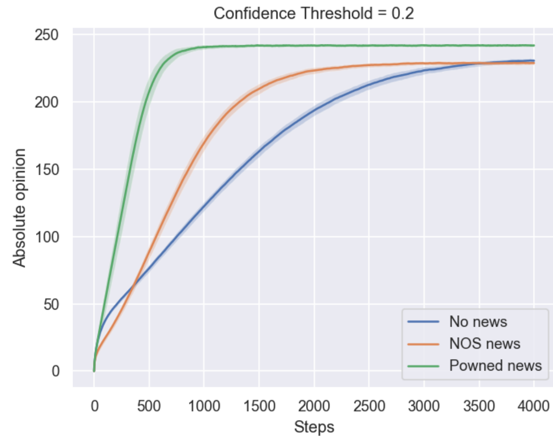
7.2 The effect of news on radicalisation

The result on the effect of the different types of news on radicalisation was already hinted at just above. In figure 10b, the total sum of absolute opinions is plotted for each type of news. These results seem to confirm the explanation given above. First of all, although extreme news reduced the polarisation 10a, it significantly speeds up the process of radicalisation while also increasing the total level.

The moderate type of news appears to have a smaller driving force on the speed of radicalisation, however it is significantly visible. The degree of radicalisation does not appear to be influenced by the presence of moderate news.



(a) The polarisation degree of the network over time.
The mean and standard deviation over 100 runs is plotted.
Clearly lower polarisation degree when PowNews news is distributed throughout the network.
Furhtermore, NOS news seems to cause more polarisation populations, than no news.



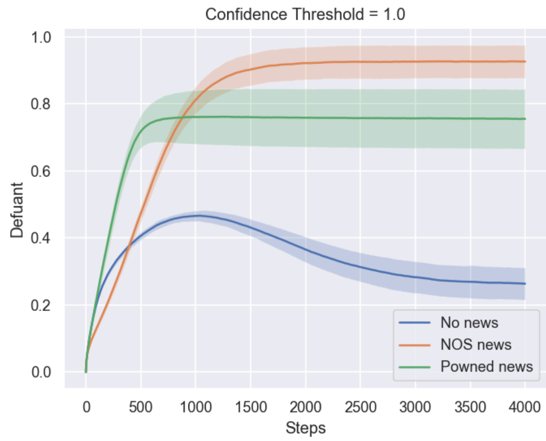
(b) The sum of absolute opinion of all agents.
PowNews news does cause faster and more radicalised agents, when compared to the other two news distributions.

Figure 10: Plots of the polarisation and the radicalisation degree of the population with a bounded confidence threshold of 0.2.

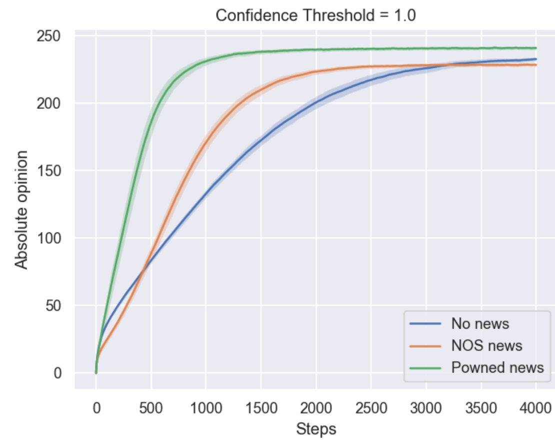
This is perfectly explainable, as the news is able to drive agents towards a negative of positive opinion. However, as it is non-extreme news, it does not have influence on the almost-extreme agents. Thus, it is logical that radicalisation is not further enhanced in the end.

7.3 The effect when everybody talks with everybody

One last and interesting finding was done when the confidence threshold of the agents was set to 1.0. This means everybody exchanges information with one another. Figure 11, show the results if this is the case in a social network. What is remarkable is that in case of no news the population demonstrates a very low polarisation degree. An explanation for this phenomena could be that everybody is convinced by the initial radicals, since they have a higher probability of persuading their interaction partner. Therefore, everybody shift towards the opinion of the few persuading radicals, despite their large opinion distance.
As figure 11 demonstrates, the confidence threshold has no influence on the radicalisation degree of the network. Since, in the end almost all agents have an radicalised opinion. Which is just like the networks run with nominal values, figure 2.



(a) The polarisation degree of the network over time.
The mean and standard deviation over 100 runs is plotted.
Clearly lower polarisation degree when PowNews news is distributed throughout the network.
Furthermore, NOS news seems to cause more polarisation populations, than no news.



(b) The sum of absolute opinion of all agents.
PowNews news does cause faster and more radicalised agents, when compared to the other two news distributions.

Figure 11: Plots of the polarisation and the radicalisation degree of the population with a bounded confidence threshold of 1.0.

8 Conclusion

The main goal of this paper was to find the influence of news on the opinion dynamics in social networks. In order to investigate this, we used an extension of the model introduced by van der maas, where we introduced a social network structure. The parameters of this network where calibrated using a real life social network. In this paper, we introduced the distribution of news trough the network. News was modeled as an external force to the model, influencing the agent's information value. By using this approach, the opinion of the agents gets influenced indirectly, rather than directly. We described our model using the ODD format, giving a detailed overview of the modelling decisions we have made. We defined deffuant distance (i.e. paired opinion distance) and average absolute opinion as our output parameters, respectively quantifying the degree of polarisation and the degree radicalisation. We validated our model using facial-validation by comparing it to the Van der Maas model. Next, a sensitivity analysis was conducted, using both a local (OFAT) and a global (Sobol') approach. We concluded that input parameters "Trust Threshold", "News Chance" and "News Distribution" where highly influential to our output parameters.

From the results (section 7) we can conclude that in the proposed model the addition of moderate news leads to a more polarised society than one in which no news is present. The introduction of extreme news leads to a less polarised society, which seems counteractive at first. When we take the radicalisation of the society under extreme news into account however we find that there is a consensus where the agents are all strongly opinionated towards one side, explaining the low level of polarisation. From this we con conclude that, in societies where people tend not to take differing opinions into account too much, the addition of news leads to a less polarised society.

We also see that the time it takes for the model to radicalise get smaller when news is introduced, where extreme news leads to an even quicker polarisation than moderate news. From this we can conclude that news, and particularly heavily opinionated news, leads to radicalisation around the topic.

Finally we find that when the confidence threshold is removed, i.e. all agents always interact with each other no matter how different their opinion, the society always polarises with the introduction of news. Without news we find that the society does not polarise or at least not to a significant degree. Furthermore, the model always radicalises with these confidence settings, no matter the news. The news however does influence the speed of radicalisation. From this we can draw the conclusion that news does increase the polarisation of societies where people are likely to listen to opinions very different from theirs.

9 Discussion

First of all, it is important to note that the results obtained rely partially on the initialisation of the model. It was argued that a major part of the population has a slight bias towards a positive opinion. Only a small minority of the population was initialised with an opposite opinion and a raised attention towards the subject. This initialisation is based on the development of discussions like the Brexit or the Black Pete debate. However, this initialisation could be very different for other debates, which in turn might influence the dynamics observed.

Secondly, the results of this research were obtained from one specific social network type (i.e. Watts-Stogartz). Although this social network was fitted to real life data of a Facebook network as published by Stanford [7], the results of this paper can only be assumed for this type of network. As stated in the theory section, the characteristics of a real-word social networks can vary greatly. The effects of news should be investigated along a greater set of social networks to be able to universalise these conclusions.

As a final remark, the model was not verified against real life data. In order to be able to use this model for real life cases, it must first be tested against data observed. Therefore, the results presented in this paper must be interpreted purely theoretically.

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