Effect of advertising on social networks

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Introduction

The aim of this project is to model the effect of advertising on different social network topologies. The project is based on the idea that the effect of advertising on social networks is not only dependent on the number of people who see the advertisement, but also on the structure of the network. We aim to answer the following questions: Does the effectivness of advertising depend on the network topology? Who should we target in the advertising if we want to reach the best effectiveness for each network topology? We will consider four different network topologies and 5 types of advertising.

The scenario is as follows: there is a referendum coming up, and there are two competing campaigns. Each person has a continuous opinion on the issue, which can be influenced by advertising. The collective opinion in the starting opinion is roughly even. The goal of the project is to model the effect of advertising on the final opinion of the population, and to compare the effect of advertising on different network topologies.

Model

We model the social network as a graph, where each node represents a person, and each edge represents a social connection between two people. The opinion of each person is represented as a continuous value between 0 and 1. The opinion of each person is influenced by the opinions of their neighbors, and by the advertising campaign. The advertising campaign is in the support of opinion 1.

For modeling of the effect of social connections, we use the Voter model. In the Voter model, in each iteration, each person adopts the opinion of one of their neighbors at random. The Voter model is a simple model of opinion dynamics on social networks, and has been used to model the spread of opinions on social networks. We decided to use this model, because it is simple enough that it does not add any additional complexity to the model, which could affect the results. In each iteration, the opinions of nodes are updated in a random order.

The effect of advertising is modeled as a constant increase in the opinion of each person who sees the advertisement (with the exception of the situation, when the person's opinion would exceed 1 - in this case, the opinion is set to 1). The effect of advertising is the same for all people who see the advertisement. The only difference between the types of advertising described lates is the strategy of choosing the targets of advertising - the people who see the ad.

In terms of feedback loops, the model is very simple. There is one positive feedback loop - the higher the opinion is, the more it will grow. This holds both for single nodes and for the network as a whole. The only limit to mean opinion growth is the cap of the opinion at 0 and 1.

Network topologies

We compare the effect of advertising on four different network topologies:

Watts-Strogatz small-world network

In the Watts-Strogatz small-world network, each node is connected to its k nearest neighbors in a ring topology. With probability p, each edge is rewired to a random node in the network. The Watts-Strogatz small-world network has a high clustering coefficient and a low average path length, which means that it has both local and global structure. It lacks the power-law degree distribution of the scale-free network.

Barabasi-Albert scale-free network

In the Barabasi-Albert scale-free network, nodes are added to the network one by one, and each new node is connected to m existing nodes with a probability proportional to the number of connections of the existing nodes. The Barabasi-Albert scale-free network has a power-law degree distribution, which means that there are a few nodes with a very high degree, and many nodes with a low degree. It also has a low average path length, which means that it has a high level of connectivity. However, it has a low clustering coefficient, which means that it has a low level of local structure.

Erdos-Renyi random network

In the Erdos-Renyi random network, each pair of nodes is connected with a fixed probability p. The Erdos-Renyi random network has a low clustering coefficient and a low average path length, however the nodes have a Poisson degree distribution, which means that the network is more homogeneous than the scale-free network.

Grid network

In the grid network, each node is connected to its four nearest neighbors. The grid network has a high clustering coefficient, a high average path length, and nearly all nodes have the same degree.

Types of advertising

We consider multiple types of advertising - all of them target a fixed number n of people in the network. The types of advertising are as follows:

Random advertising

In random advertising, the n people who see the advertisement are chosen at random from the network. This type of advertising does not take into account the structure of the network.

Hubs advertising

In hubs advertising, the n people who see the advertisement are chosen from the nodes with the highest degree in the network. This type of advertising targets the most connected people in the network.

Neighborhood advertising

In neighborhood advertising, the algorithm first chooses a random node in the network and adds it to the list l. Then, while the size of the list is less than n, the algorithm iterates through l, and for each node in l, it adds its neighbors to the list. This type of advertising targets the local structure of the network.

Minimum advertising

In minimum advertising, the p people who see the advertisement are chosen from the nodes with the opinion most different from the advertising campaign. This type of advertising targets the opposition in the network.

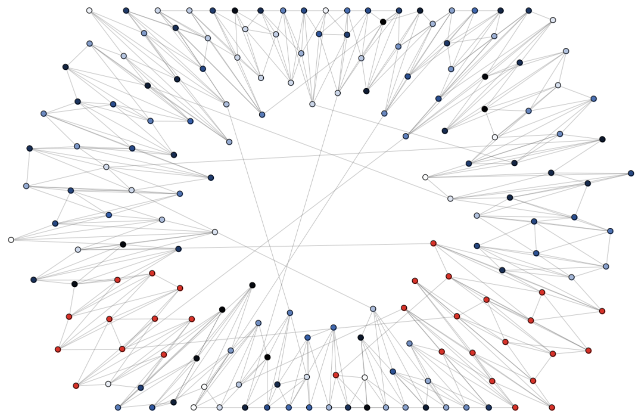

Figure 1: The social network with targeted neighborhood marked red

Maximum advertising

In maximum advertising, the p people who see the advertisement are chosen from the nodes with the opinion most similar to the advertising campaign. This type of advertising targets the supporters in the network.

Implementation in NetLogo

For the simulation, we use NetLogo, a multi-agent programmable modeling environment. We started off from a network science library, from which we primarily used the implementation of the network topologies. We implemented the opinion dynamics and the advertising campaigns ourselves, as well as various statistics reporting the state of the network and their visualization. The initial opinion of each node is set randomly.

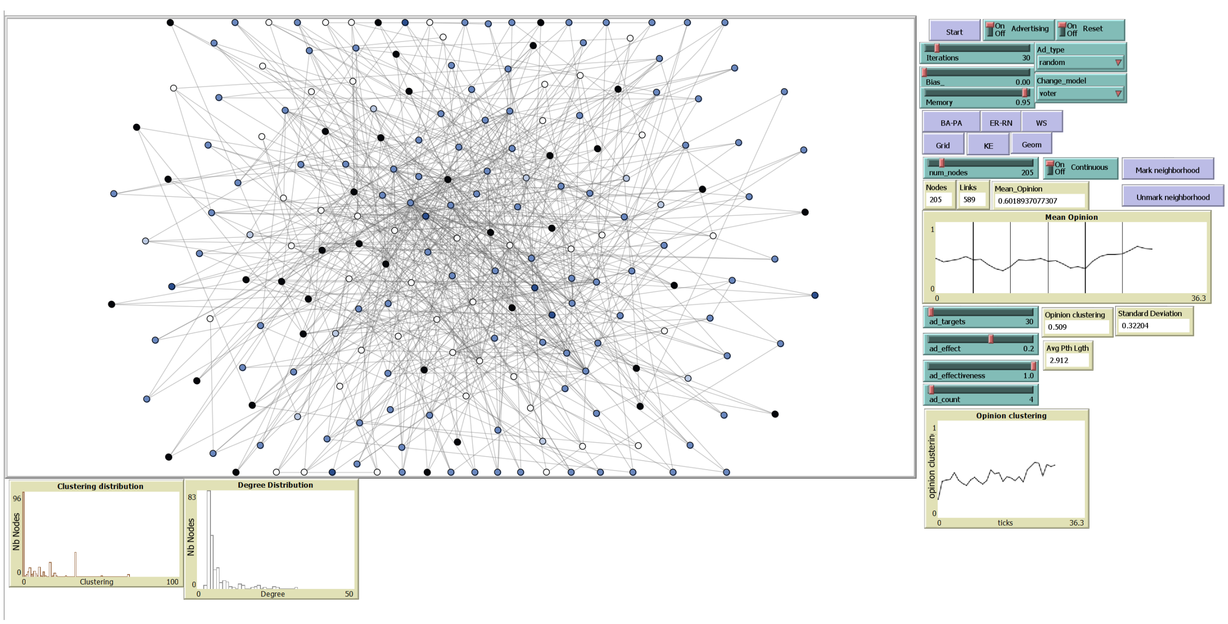

Figure 2: Our project in Netlogo

The nodes are colored according to their opinion - the darker the color of the node, the closer the opinion of the node is to zero. If the advertising is turned on, the Mean Opinion plot contains vertical lines signaling when the advertising occurred. The Opinion Clustering plot shows the percentage of nodes whose neighbors have similar opinions (the difference of their opinions is less than 0.1). The Clustering distribution plot shows the distribution of the clustering coefficient - ratio of connected neighbors to all possible connections between the neighbors.

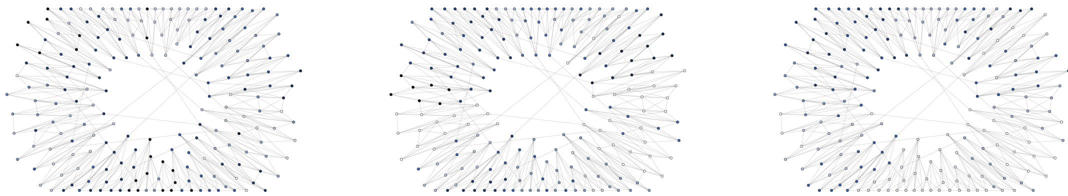

Figure 3: A social network after 10, 20 and 30 iterations

Simulation

We compare the effect of advertising on the final opinion of the population for different network topologies and different types of advertising. We run the simulation on roughly 1000 nodes for 30 iterations. The effect of the ad is an increase by 0.2 of the opinion of the ad target. The ad is run 5 times in regular intervals and targets 100 nodes in the network (the targets of the ad are determined by the advertising strategy). At the end of each run, we measured the mean opinion of all nodes in the network and the percentage of nodes whose opinion is above 0.5. We also decided to measure the sensitivity of the number of targets parameter on the Barabasi-Albert scale-free network with the hubs advertising campaign. We were increasing the number of hubs that see the advertisement and using the same metrics as before. We aggregated the mean opinion of the nodes and the percentage of nodes whose opinion is above 0.5 for each configuration by averaging the results over all runs. The results are presented in the next section.

Analysis

First, we will look at the results of the simulation for different network topologies and different types of advertising. We start by looking at the results for the mean opinion of the nodes in the network. The results are presented in the following table:

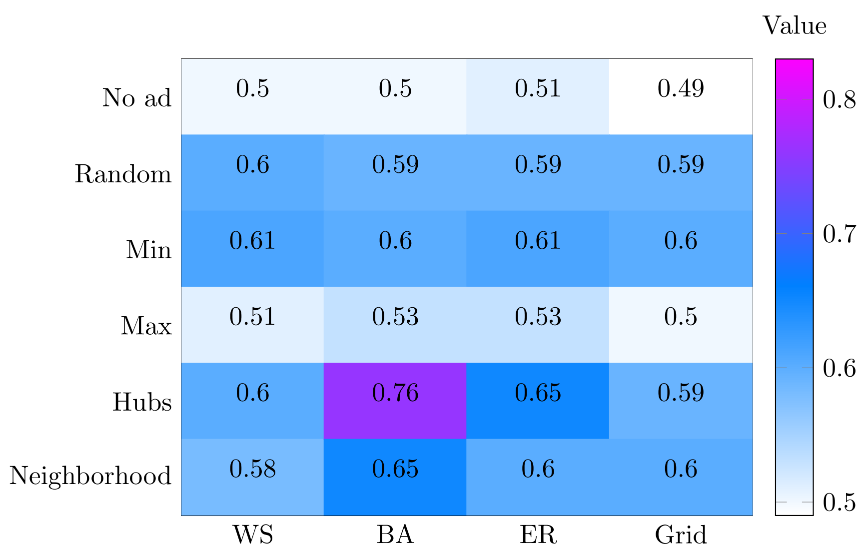

Figure 4: Final mean opinion for different ad strategies and network topologies

Firstly, we can see that the mean opinion of the nodes in the network is always around 0.5 when there is no advertising. This is expected, as the starting opinion of each node is set randomly between 0 and 1.

The Random strategy reaches a mean opinion of around 0.59 in all network topologies. This is expected, as the Random strategy targets a random set of nodes in the network, and does not take into account nor the structure of the network, nor the opinions of the nodes.
The Min strategy reaches a mean opinion of around 0.60 in all network topologies. This is only slightly better than the Random strategy. This type of ad does not "waste" any resources on the nodes, which have opinion higher than 0.8 and would not be influenced as much by the advertising (as the opinion is capped at 1). This is why this strategy is ideal for increasing the mean opinion of the network (if we are ignoring the topology of the network).

The Max strategy reaches a mean opinion of around 0.51 in all network topologies - only a very small increase over no advertising. This is not surprising, as it targets the nodes with the highest opinion, quickly reaching the cap of 1 and then not being influenced by the further advertising directed at them. This strategy is not effective in changing the overall opinion of the network. Notice, that this strategy is only slightly successful in networks with a heterogeneous degree distribution, which points to the fact that highly connected nodes are crucial in the spread of information on social networks.

The Hubs strategy has the most interesting results - it greatly matters in which network topology it is used. The Grid topology had the lowest mean opinion - 0.60. This is not surprising as in this topology all nodes have degree at most 4. The Watts-Strogatz small-world network ended with mean opinion 0.60 - no improvement over random advertising. The Erdos-Renyi random network has a Poisson degree distribution, which means that there are a few nodes with a high degree. This resulted in a mean opinion of 0.65 - significant increase compared to random advertising. The Barabasi-Albert scale-free network has a power-law degree distribution, which means that there are a few nodes with an extremely high degree. This resulted in a mean opinion of 0.76 - the highest increase compared to random advertising. This shows that the Hubs advertising is most effective in networks with a high degree heterogeneity, such as the scale-free networks, despite the fact, that it keeps influencing the same nodes in each ad, as in the Max strategy.

The Neighborhood strategy similar results as the Random strategy except for the Barabasi-Albert network and the Watts-Strogatz network. On the Barabasi-Albert network, the mean opinion was 0.65, which is considerably higher than the Random strategy. This is probably because of the neighborhood building algorithm, in which higher connected nodes are more likely to be added to the list of affected nodes and have a bigger influence on the opinion of the network. On the Watts-Strogatz network, the mean opinion was 0.58, which is lower than the Random strategy. This shows, that on a network with a high clustering coefficient (which is also the case of real world networks), it is not effective to target the local structure of the network.

Note that it is easy to numerically check that in the scenario, where nodes do no interact with each other, any type of advertising, which avoids the nodes with opinion higher than 0.8, will result in the mean opinion of the network being 0.6 ($5 * 100 * 0.2 / 1000 = 0.1$).

Next, we will look at the results for the percentage of nodes whose opinion is above 0.5. The results are presented in the following table:

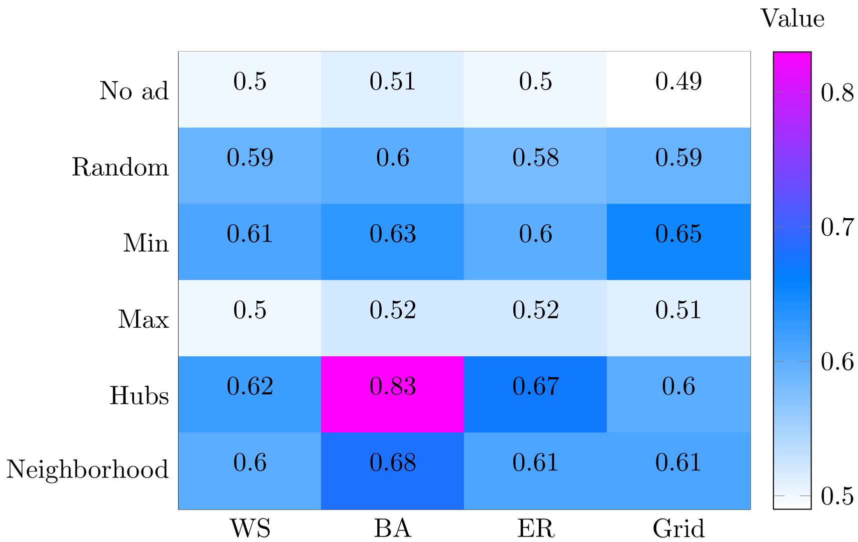

Figure 5: Ratio of nodes with opinion > 0.5 for different ad strategies and network topologies

The results for No advertising and Random advertising are the same as for the mean opinion of the nodes.
In the case of Max advertising, the percentage of nodes whose opinion is above 0.5 is barely over 0.5, an even worse result, than for the mean opinion of the nodes. The reason is the same as for the mean opinion of the nodes.
According to this metric, all other strategies are better than the Random strategy. The percentage of nodes whose opinion is above 0.5 is always higher than the mean opinion of the nodes - the positive effect of the advertising is exemplified in this metric.

Finally, we will look at the results for the Barabasi-Albert scale-free network with the hubs advertising campaign. We have been increasing the number of hubs that see the advertisement and using the same metrics as before. The results are presented in the following table:

Num of targets	**5**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**130**	**140**	**150**
Mean opinion	0.56	0.58	0.63	0.64	0.66	0.69	0.71	0.72	0.75	0.76	0.76	0.78	0.78	0.78	0.79	0.80
>0.5	0.58	0.60	0.65	0.68	0.68	0.72	0.75	0.76	0.80	0.82	0.83	0.83	0.84	0.83	0.85	0.85

From the curve, it is apparent that a even a very small number of targets has a major impact on both the mean opinion and the percentage of nodes whose opinion is above 0.5. Already at 10 targets, the effect of the Hubs advertising is as strong as the Random ad strategy with 100 targets. The positive effect of advertising is still increasing with the number of targets, but the effect is diminishing. This again shows the importance of the highly connected nodes in the spread of information on social networks.

Conclusion

The results of the simulation show that the effect of advertising on the final opinion of the population is dependent on the structure of the network. The Hubs advertising campaign is the most effective in networks with a high degree heterogeneity, such as the scale-free networks. The Max advertising campaign is very ineffective in changing the overall opinion of the network. The results also show that the number of targets in the Hubs advertising campaign has a major impact on the final opinion of the population. Even a small number of targets has a significant effect on the final opinion of the population, and the effect of the advertising is diminishing with the number of targets.

In conclusion, the project was successful in answering the questions we set out to answer. The

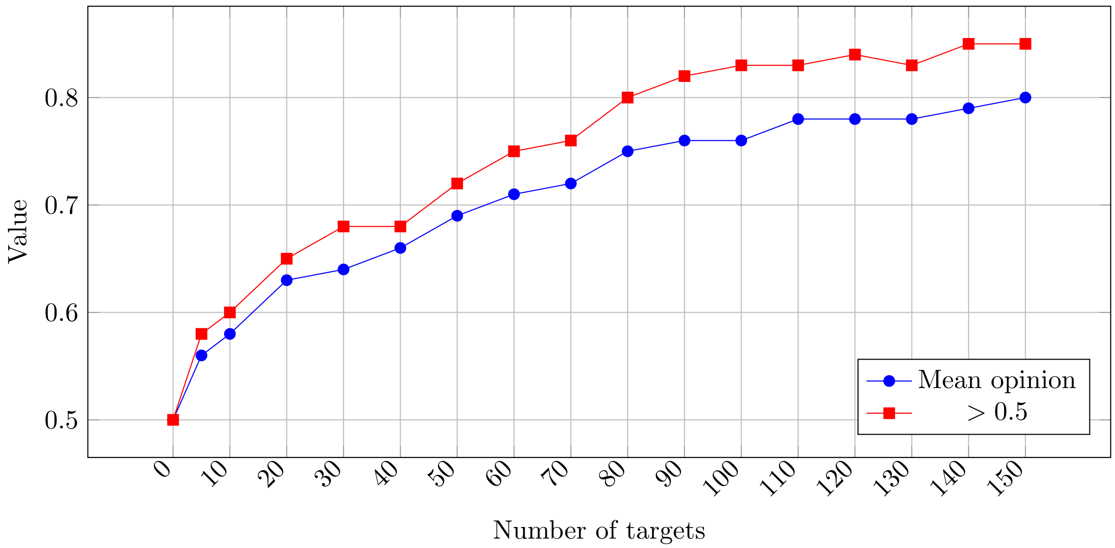

Figure 6: Plot of mean opinion and number of nodes with opinion > 0.5 against number of targets

results of the simulation provide insights into the effect of advertising on social networks, and can be used to inform the design of advertising campaigns in the future.

For further research, it would be interesting to model different frequency of the advertising and different numbers of targets to see which is more effective - a small number of big ads or a bigger number of smaller ads. It is also worth considering other advertising strategies, such as targeting the people whose opinion is near the middle - 0.5. This strategy would certainly be very effective, but how would it compare to Hubs strategy? Another thing to look at is if the results hold even for a network whose initial mean opinion is not 0.5 - the general opinion of the population is skewed towards one side.

References

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