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The effect of transmission modality on information spread: A network simulation approach

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Abstract:	An important hallmark of our globalized, modern society is the rapid information flow through densely connected networks composed of people and personal technologies. People could obtain knowledge, communicate over distances, and perform activities previously unfeasible. However, false information can also proliferate in the global network and induce real harm. Thus, it is essential to understand how data flows through human networks in order to harness the benefits and reduce the potential harms. We created two models, the social network model and the broadcast model, to investigate how information flow is affected by parameters such as persuasiveness, selection method, and network structure. In the social network model, information is spread through interactions between individuals in the given network, initiated by a selected individual. In the broadcast model, information is spread to everyone simultaneously through a broadcasting system. Using the models to simulate different scenarios, we sought to answer two questions: 1) how does the selection method of the source affect information spread? and 2) how does the persuasiveness parameter change information spread? Our experiments showed that higher persuasiveness effectively improved the spread of information. We found that the persuasiveness of the initial node, rather than the number of its connections, had more impact on information spread. Moreover, the highest persuasiveness selection method in both the social network and broadcast models consistently influenced the opinions of the entire network. Our findings, if utilized alongside social psychology research, may help the society facilitate more effective communication and counter the prevalence of misinformation.
Additional Information:	
Question	Response
In what setting was the research conducted?	At home
What year in school are the student authors?	Year 11
Author Comments:	(By student author) I first became interested in this project because I always found simulations to be intriguing, as you can magically create accurate real-life assumptions on certain topics. The biggest obstacle that I had encountered while conducting this project was learning a new programming language, Python, as I have no experience beforehand. However, I managed to learn Python through online courses and used

	that knowledge to code the program for this project. In the end, it was a successful project.

JOURNAL OF EMERGING INVESTIGATORS

The effect of transmission modality on information spread: A network simulation approach

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SUMMARY

An important hallmark of our globalized, modern society is the rapid information flow through densely connected networks composed of people and personal technologies. People could obtain knowledge, communicate over distances, and perform activities previously unfeasible. However, false information can also proliferate in the global network and induce real harm. Thus, it is essential to understand how data flows through human networks in order to harness the benefits and reduce the potential harms. We created two models, the social network model and the broadcast model, to investigate how information flow is affected by parameters such as persuasiveness, selection method, and network structure. In the social network model, information is spread through interactions between individuals in the given network, initiated by a selected individual. In the broadcast model, information is spread to everyone simultaneously through a broadcasting system. Using the models to simulate different scenarios, we sought to answer two questions: 1) how does the selection method of the source affect information spread? and 2) how does the persuasiveness parameter change information spread? Our experiments showed that higher persuasiveness effectively improved the spread of information. We found that the persuasiveness of the initial node, rather than the number of its connections, had more impact on information spread. Moreover, the highest persuasiveness selection method in both the social network and broadcast models consistently influenced the opinions of the entire network. Our findings, if utilized alongside social psychology research, may help the society facilitate more effective communication and counter the prevalence of misinformation.

INTRODUCTION

With the rapid proliferation of information technologies and the globalization of communication systems, the flow of data and information has become increasingly important as internet service usage rises between 40% and 100% in comparison to pre-lockdown levels before the Covid-19 pandemic (1). For example, as people engage in social media, large amounts of data and information are transferred from one location to another. This information can then be utilized to forecast behavioral or social changes, such as daily sales of a company, with a higher accuracy of “relative improvements ranging from 12.85% to 23.23%” (2). By receiving a particular information faster, you can gain many advantages over others, such as predicting the sales correctly to increase profits in this case. To do so, it is necessary to determine the most effective way at transmitting information to people in a wide variety of regions. Then, it can be implemented in many aspects of our life to ensure better connectivity with global news. This could strengthen the effectiveness of the global network organization, improving the mass data flow and integrated customer support (3). For instance, hospitals and governments can effectively provide the most recent COVID updates, promote preventative measures to the public, and even track down infectious individuals through information transmission and surveillance, such as using the Covid-19 tracker app in China (1). With this fast, effective statistical data and information transmission and distribution, people could maximize the speed and spread at which the information is distributed. This study aims to investigate how to better spread information in a network.

Before starting the study, we need to first understand several concepts about how information spreads within a network. First, a network must be constructed to simulate the social interactions of the people in the network. In a network, a node represents one individual while an edge connects nodes, denoting social interactions between connected individuals (4). The Watts-Strogatz model has many properties that closely resemble a social network consisting of humans. The model “start with a d-dimensional lattice network and add a small number of long-range links out of each node, to destinations chosen uniformly at random”, it would result in a “network created by this superposition” that would have “local clustering and short paths”, which is similar to “many of the networks found in the real world” (4). Using this model, we can accurately portray the changes in each individual within the network to analyze the information spread similar to that of a real-world network. Furthermore, the precise number of simulations is needed to be conducted to yield statistically significant results. As one might know, smaller sample sizes cause an increase in confounding variables as the conditions between each sample is not evenly maintained, leading to a higher probability of producing false results (5). However, sample sizes that are too large would also cause problems. For instance, a large sample size requires more network simulations, increasing the time, effort, money, and other resources placed into those simulations (5). We decided to conduct 100 simulations for each experimental setting, which is sufficiently large yet computationally feasible.

The overarching goal of the model and the simulation is to determine the best way to spread information to a mass audience with varying opinions on a particular subject. To address this goal, two models were created: the social network model and the broadcast model. In the two models, different values of opinions are assigned to each node, representing how different people have unique opinions on a particular subject. In the social network model, information would be spread from person to person while information would be spread to everyone in the network in the broadcast network model. By comparing the results of the two models, the most effective way of spreading information could be determined, answering the two experimental questions “how does the procedure of selecting the nodes to be the source of information change the effectiveness at which the information is spread in the social network model?” and “how does persuasiveness change the models?”. We hypothesize that using the highest persuasiveness selection method in experiment 1 and using the highest persuasiveness value in experiment 2 would produce the most significant results in terms of information spreading speed within the network. To test this out, we conducted 2 separate experiments.

RESULTS

To perform the experiment, a simulation of a network was conducted. With the network, we can modify its settings so that it encompasses different parameter values that can be experimented with to test the hypothesis. Two different network models would be used for this purpose to analyze the results: social network model and broadcast model. Both models have a total of 50 nodes, each with different persuasiveness values and opinion values. Nodes can be connected to other nodes via edges, representing interactions between the nodes. Both models share parameters, opinion update functions, and network initialization.

However, the two models have different information distributing methods. In the social network model, information is spread through the interaction between person to person only if the two individuals have established edges and connections (meaning that they are familiar with each other, like how one friend would tell secrets to another friend but not to strangers). Meanwhile, information is spread through a broadcast system, such as the radio or television, simultaneously to everyone in the network regardless of their connections, but it has low persuasiveness and influence on the opinions of the individuals in the network as online information may be perceived as less convincing.

Using the two models, the network was simulated to determine which of the node selection methods is the best and how persuasiveness affects the effectiveness of information spread. To make an accurate generalization of the results, 100 simulations were conducted, each with a number of simulated steps of 1000 times, meaning that the opinion values of the individuals in the network are updated 1000 times in a single simulation. These repeated simulations yield the mean and confidence intervals of how opinion values change over time, which is more reliable for comparison. ‘

Experiment 1

To answer the first question "how does the procedure of selecting the nodes to be the source of information change the effectiveness at which the information is spread in the social network model?", three methods of selecting the initial transmitter node that has a vastly different opinion value of 1 were devised and incorporated in the social network model to simulate different outcomes: selecting the node with the highest persuasiveness, selecting the node with the highest connections with other nodes, and selecting multiple different nodes in the network. By selecting the highest persuasiveness, we mean that the program would select the node which has the most influence on the other node's opinion, changing their opinion values the most through their interaction, which is similar to how your best friends can easily have an impact on your ideas. Next, the node with the highest number of connections means that it has multiple connections or familiarity with people in this network, indicating that it can interact with multiple nodes similar to how a popular kid has many friends that he can talk to in school. Finally, the random node selection method is to just incorporate chances and probability into the experimental design by randomly converting a node to be the transmitter node.

For the comparison of the three methods, we decided to use the one random node selection method out of the three deviations random node selection methods tested. This is because by looking at **Figure 2** we can clearly notice the fact that the three and five random node selection methods resulted in a significantly higher opinion value(approximately 1.0) than the one random node selection method(approximately 0.9). Since the resulting opinion values are drastically higher, using one of those two methods would produce biased results. This is caused by the fact that the three and five random node selection methods select more than one node to be the transmitter while all other methods select only one node, meaning that the information can be spread significantly faster within the network. With those two methods disrupting the results of the experiment, we decided to only use the one random node selection method for Experiment 1. This allows us to accurately compare the three methods without confounding variables such as the number of nodes selected as information transmitters.

In experiment 1, the selection methods where the node with the highest persuasiveness were selected as the main information distributor clearly is the most effective way at spreading ideas and opinions as it has an average opinion value of approximately 0.92 at the end of the simulation shown in **Figure 3**. This means that this method is a more effective network than the method that selects the node with the highest connections with other nodes or the method that selects a random node as they both have a lower average opinion value of about 0.88 according to **Figure 3**. Furthermore, by looking at the plotted lines for all three methods, the highest persuasiveness line, indicated by the red line in **Figure 3**, always has the greatest slope at each hundredth step as it is always above the other two lines. This means that using this method would not only effectively transmit information more believably, but it would also spread the information faster than using the other two methods. Although the highest persuasiveness method resulted in a greater slope, the general shape of the curve of the three lines of the three methods is about the same, with greater slope at the beginning of the simulation and decreasing slope over time, shown in **Figure 3**. This could be explained by the fact that there are more people that do not have the information in the beginning. As time goes on, however, more and more individuals would start to obtain this information, thus changing their opinion values. With more people agreeing to the information, it would be more difficult to further amplify their opinion values to make them strongly agree with the information, thus decreasing the change in slope at the end of the simulation. Since the simulation is simulated for 100 times and the mean drawn on the graph in **Figure 3** for the highest persuasiveness is clearly higher than those of the highest connections and random node simulation, the variations between individual simulations are accounted for, making the results accurate and credible.

Experiment 2

To address the second question "how does persuasiveness change the models?", the persuasiveness parameter is altered in both the social network and broadcast models to simulate the impacts of the change. In the social network model, the persuasiveness values of a normal distribution with a standard deviation of 0.2 and a mean of 0.8, 1, and 1.2 are tested. In the broadcast model, the persuasiveness values of 0.001, 0.005, 0.01, 0.05, and 0.1. Obviously, a value of 0.001 means that there's low persuasiveness while a value of 0.1 means that there's high persuasiveness. These five persuasiveness values represent how influential the broadcast system's information is on the opinions of the individuals in the network, with higher values implying the use of effective promotional advertisement and lower values implying the lack of reliable facts and appealing designs. Using these five persuasiveness values, we can effectively simulate how a broadcast system can persuade people with certain information, spreading them through the network faster.

For the social network model, we tested three persuasiveness values for Experiment 2. The results show that the network with the normally distributed persuasiveness value with a mean of

1.2 and a standard deviation of 0.2 clearly shows the strongest effectiveness in spreading information and opinions as it ends up with the highest average opinion value of approximately 0.9 (shown in **Figure 4**). As speculated, the network with the highest mean persuasiveness value distribution was the most effective at spreading ideas as the higher probability of persuading someone in a particular topic can spread the opinions faster while the network with the medium mean persuasiveness value distribution is the second most effective with a value of about 0.86 and the network with the lowest mean persuasiveness value distribution is the least effective with a value of about 0.8. Moreover, the value of the persuasiveness also determines the slopes of the plotted lines, with the green line representing the highest mean persuasiveness value distribution having greater slope than the other two lines. Similarly to Experiment 1, all three lines tend to follow the same curve with a higher degree of curvature (greater slope) at first then decreases gradually.

For the broadcast model, we tested five persuasiveness values for Experiment 2. The results show that the network with the persuasiveness value of 0.1 portrays the strongest effectiveness in spreading information and opinions as it ends up with the highest average opinion value of approximately 1.0, shown in **Figure 5**. Although the network with the persuasiveness value of 0.05, which is the second-highest value, also ends up with an average opinion of approximately 1.0, the network with the persuasiveness value of 0.1 has the greatest exponential increase in its slope, indicated by the black line in **Figure 5**. This greater slope means that its effect on information spreading is the strongest as information can spread faster to influence the opinions of the individuals in the network beter. This result also correlates with the one in the social network model in Experiment 1 and Experiment 2, as higher persuasiveness values increase the rate of information distribution. However, the shape of curvature of the plotted lines does not seem to match the ones drawn before. Previously, all lines had a similar shape, as shown in **Figure 3**, but this does not apply for the broadcast model. For the network with the two lowest persuasiveness values of 0.005 and 0.001, the shape of the line is a straight line but the higher persuasiveness value of 0.005 does have a greater slope, as indicated by the yellow and blue lines in **Figure 5**. Although the medium persuasiveness value of 0.01 also has a similar straight line feature, its line has a little bit of curvature. This does not correlate with any of the shapes seen in Experiment 1 or Experiment 2 for the social network model as too little curvature is present in the lines. However, we started to see a huge increase in slope in the network with the two highest persuasiveness values of 0.05 and 0.1. In both networks, huge degrees of curvatures are present, which does not seem to correlate the slow, steady increase of the straight lines in the three other persuasiveness values. This curvature is even significantly greater with the one seen in the previous data, with a proliferating rate of increase in opinion value, especially in the first 300 steps, followed by a steady decrease in the slope of the line as the average opinion value of the network reaches a maximum of 1. This shows that the higher two persuasiveness values could affect the process of information transmission significantly.

DISCUSSION

The results in experiment 1, as shown in **Figure 3**, clearly show that selecting a node to be the main transmitter and distributor of a certain idea and opinion using the highest persuasiveness method was the most effective in terms of the speed at which the information was spread. This implies that the best way to spread information effectively with speed is to ensure that the individual performing this task has the most impact and influence or that the individual chosen at random simply has more peers that listens and shares his opinions with others frequently. With more persuasiveness, people are more willing to believe in what you say. Therefore, your words and opinions would have a much greater influence on them, influencing them to share the same ideas with other people at a faster pace. Although the random method has about the same average opinion values as the highest connection method, this result may be due to luck and may not always be true (although the simulation has been repeated multiple times, there's still a possibility that randomly choosing an individual may result in a less effective information transmission), which means that the highest connection method is probably still a better second choice(over random nodes but under highest persuasiveness method) legit and accurate as it does not depend on chance. This method has already been used on multiple aspects of life. For instance, companies would try to find celebrities to promote their products since celebrities have more influence over people as they have more followers and fans, leading to more customers wanting to buy the products of the company. With the use of this method, information could be spread at a much faster pace.

The results in experiment 2 for the social network model, as shown in **Figure 4**, also clearly show that using a persuasiveness distribution with a mean of 1.2 and a standard deviation of 0.2 for the network would be the most effective way of spreading the information. Although the differences between each simulated network is small, it still has strong implications as the simulation is simulated 100 times. It implies that the best way to spread information is for the individual performing this task to be more persuasive in spreading the idea. This corresponds and supports the results of experiment 1, where the highest persuasiveness selection method is the most effective one. It also demonstrates that although the increase in persuasiveness mean is the same (0.2 difference each time), the increase in the resulting opinion values are different as each method has a difference in their opinion value difference. This means that as persuasiveness increases linearly, opinion values are changed exponentially, indicating that persuasiveness is a strong tool used to enhance the effectiveness of the information spreading network. Similar to experiment 1, the results of this experiment can be utilized in areas such as the schools, where inviting famous speakers to campus can increase the students productivity, allow them to engage more actively, and allow them to learn more from the speaker.

The results in experiment 2 for the broadcast model, as shown in **Figure 5**, clearly shows that using a persuasiveness distribution with a mean of 0.1 would be the most effective way of spreading the information. Although the line graph of the 0.1 persuasiveness value ends up with only a slightly higher average opinion value than that of the line graph of 0.05 persuasiveness value, it still has larger differences in the first few steps of the simulation, meaning that the network with the 0.1 persuasiveness value would spread information a lot faster than all other persuasiveness values from beginning to end. This also correlates the results of experiment 1 and experiment 2 for the social network model as it also shows that higher persuasiveness values lead to higher increase in network effectiveness. Overall, it implies that the broadcast model, although functions differently than the social network model, is defined by the same parameter value: persuasiveness of the individuals in the network. In this case, however, it means that the broadcasting node, such as TV programs or radios, have to present people with more compelling and attractive products in order to convince them to believe the present information.

The experiments, run under distinct, reasonable assumptions, demonstrated the differential impacts on the rate at which information is spread. In the social network model where three methods were tested, highest persuasiveness, highest connection, and random nodes, highest persuasiveness recorded the highest overall average opinion value of the network. Similarly, in the broadcast model, where different persuasiveness values of the broadcasting program are tested, the value of 0.1, which is the highest test value, also resulted in the highest overall average opinion value of the network. These two experiments conducted and the two models tested have shown that the higher the persuasiveness value is the more effective the information is spread throughout the network. With this result, it is reasonable to incorporate this method in our daily life, which is shown in many instances already. For instance, large companies have been hiring celebrities or models to assist them in selling their products, which is done so to better persuade the audiences and customers to believe in the products with familiar, recognizable, and popular faces. Another way that this could be implemented is to help contain the spread of misinformation. With this fast-paced information network with reliable, persuasive sources, any misinformation or false contents could be eradicated through the rapid spread of factual information. Given the double-edged nature of communication technology, more research on this topic should be pursued to help the society understand and leverage its potential.

METHODS

Shared Rules

In both models, there would be two main things working together to show the flow of information and changes in opinions: nodes and edges. Each node represents a person, and each edge represents the connections the person has with another individual. At first, the model will be initialized to assign a random value of opinion to each node, with 0 being against and 1 being for the topic, and create random edges for the nodes. There would also be a random value of persuasiveness for each node, indicating the degree of impact and influence a person has on another's opinion during an interaction. After the initialization, there would be 50 nodes in the network.

We chose to use the Watts-Strogatz graph as our network structure, for its small world properties. It would allow us to accurately simulate the conditions of a human social network. Since all nodes are connected randomly, it simulates the realistic conditions that people's interactions with one another are random. It also precisely simulates the various interactions a person could have with others by connecting multiple edges to several nodes. All these help us determine how information is spreading from person to person through interactions, and thus how their opinion values are affected by this spread.

We assumed that each individual node has a particular opinion and persuasiveness value that's normally distributed, which is similar to that of a real society where each person has different opinions and different degrees of persuasiveness with some with more persuasiveness and some with less persuasiveness.

Another assumption is that all nodes are updated at the same time, which means that all individuals in the network interact with its connected individuals each time the network is updated. This is done so as we want the information to spread as fast as possible, which is plausible in reality especially when social media and communication technologies proliferate the rate and frequency of information spreading.

The change in each node's opinion will be calculated by the following formula:

$$_{oi}=(oi-oj),$$

where oi equals the change of the opinion value of individual i after an interaction, equals the rate at which nodes adjust their opinions during interactions, equals the edge weight of the interaction, oi and oj equals the opinion value of individuals i and j respectively.

After multiple experimental trials testing out these values, we discovered that a network size of 50 and an alpha value of 0.03 best demonstrate a real world network simulation where information is spread rapidly. That's why we changed the default values of network size and alpha(the rate at which nodes adjust their opinions to match neighboring nodes' opinions during interactions) by setting them to 50 and 0.03, respectively.

Both models will run for 1000 steps in a single simulation to better demonstrate the significant changes in the opinions of each individual in the network. To make the results of the model even more accurate, the simulation will be repeated for 100 times. In each step, the network will update itself by looking into every single edge and its connected nodes, allowing interaction between the nodes. As two nodes interact with each other, their opinions on the subject are shared. If two nodes have similar opinion values(both close to 1 or 0), then their opinion values wouldn't be altered too much, meaning people with similar opinions would keep in contact while those with different opinions would grow apart from each other.

Social Network Model

In this model, several assumptions on how the network functions were made. First of all we assumed that the node that's chosen to be the main distributor of the information with an opinion value changed to 1 would not be influenced by the opinions of other nodes. This assumption is made to ensure that the node's opinion stays the same throughout the simulation so that it can continue to spread the same idea, which is justified as people who strongly agrees with their own opinion, in this case the person who shares this opinion to everyone in the network, would not be easily influenced by others' opinions and ideas. However, if the individuals are not the main distributor of this piece of information, then their opinions values would change when they interact with one another, decreasing or increasing the values toward the other individual's opinion value. This is evident in real life as the opinions of two interacting people become more alike as they share and discuss ideas. We also made the assumption that the connections between each node would not get weakened over time, which is reasonable as those who interact frequently would not have weakened their relationship and interaction. The program would also have a one percent chance of forming a random connection between two nodes, as it is assumed that there's a one percent probability that two people might become associates and start interacting and sharing information with each other, which is justified as people make new friends, even with strangers, sometimes.

Broadcast Network Model

In this model, the fundamental functions and procedures are exactly the same as the social network model. However, one crucial change is that instead of having each individual node, which each represents a person with a unique opinion, interact with one another, there will be a broadcast system that spreads the information to everyone, or every node in this case, simultaneously. This would be similar to how a TV or a radio operates, spreading similar information of the same idea and opinions to all those watching or listening on a worldwide scale.

In this model, several assumptions were also made when coding for its program. First, we assumed that the broadcasting node is not present in the network, meaning that all nodes are not interacting with each other but are instead interacting with an outside node and updating their opinion values with each interaction. This means that there will be no opinion value reductions as the nodes are not interacting with one another, which is how broadcasts, such as TV commercials, work, influencing your opinions while not decreasing the influential contents of the advertisements. However, we also assumed that the broadcast model would have a significantly lower persuasiveness value as the information that each node gets is not from the interaction of reliable close friends, but from unfamiliar, untrustworthy broadcast sources. For example, you would be more willing to trust the information from your best friend than that from a 10 seconds TV advertisement.

Similarly, the opinions of the nodes will be updated simultaneously using the same formula as the one shown in the social network model by a broadcast system that spreads the same information and idea to all nodes but with a lower persuasiveness than that of the social network model. This broadcast system is not shown on the graphs depicted in **Figure 1** as it is merely a tool within each of the nodes, not a separate entity that can be represented by another node. For example, every node represents an individual, and every individual may have a TV themselves. All TVs in the network would project the same commercial, for instance, that would alter the opinion values of the individuals. However, there's not a single TV that broadcasts this information to all individuals, so there isn't an extra node representing the broadcast system. Furthermore, since the broadcast system is a source of information not interacting with other nodes, the opinion value of the broadcast system will not be altered when spreading information, unlike the nodes in the social network model.

Implementation

For the code of all the analysis in Experiment 1, refer to this gist. For the code of all the analysis in Experiment 2, refer to this gist for the social network model and this gist for the broadcast model. In each gist, the code is separated into three main parts: Library Implementation, Class Construction, and Experimental Conduct.

In the first code segment, Library Implementation, the program would call in many different libraries that contain the codes and functions that would be needed during the Experimental Conduct section.

Next, the Class Construction section sets up the class for its use in the Experimental Conduct section. This class would contain an initialization method that creates the wanted network and initializes all the parameter values within that network, an observe method that helps draw the out the network with varying colors to represent the different opinion values, and an update method that updates the opinion values of the nodes in the created network using the specified method, which depends on the type of network that's initialized. This would provide the necessary functions that would be used later when running the experiment to perform simulations of the network and the model.

Lastly, the Experimental Conduct section would use the class constructed in the Class Construction section to initialize a network. With the network, it would run and simulate 1000 steps each time by using the observe method and the update method included in the class to draw the network graphs and to update the nodes' opinion values. After each 1000 steps, the network would be refreshed, meaning that all of its parameters would be set back to the initial values, and the simulation would run again until 100 simulations each of 1000 steps are simulated. Therefore, the program would have enough data from all the simulations to create line graphs by plotting the means and confidence intervals of the opinion values of all the simulated networks. By varying the functions included in the Class Construction section, the Experimental Conduct section would simulate different outcomes and produce different graphs, which could be utilized for Experiment 1 and 2.

These functions change the way the program selects a node to be the information transmitter node by changing its opinion value to 1 in Experiment 1, and they also slightly alter the persuasiveness values of each network in Experiment 2. In the highest persuasiveness selection method, the functions created in the Class Construction section would iterate through each node's persuasiveness value, comparing them to find the maximum value. Similarly, in the highest connections method, each node is looped through to see how many connections it had with other nodes, and the node with the highest number of connections would be selected. Lastly, the function would use the random function supplied by the *random* library to randomly select one, three, or five nodes in the random node method. In Experiment 2, the program would change the initialization of the persuasiveness value distribution of the nodes for the social network model and change the persuasiveness of the broadcast system for the broadcast node.

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Figures and Figure Captions

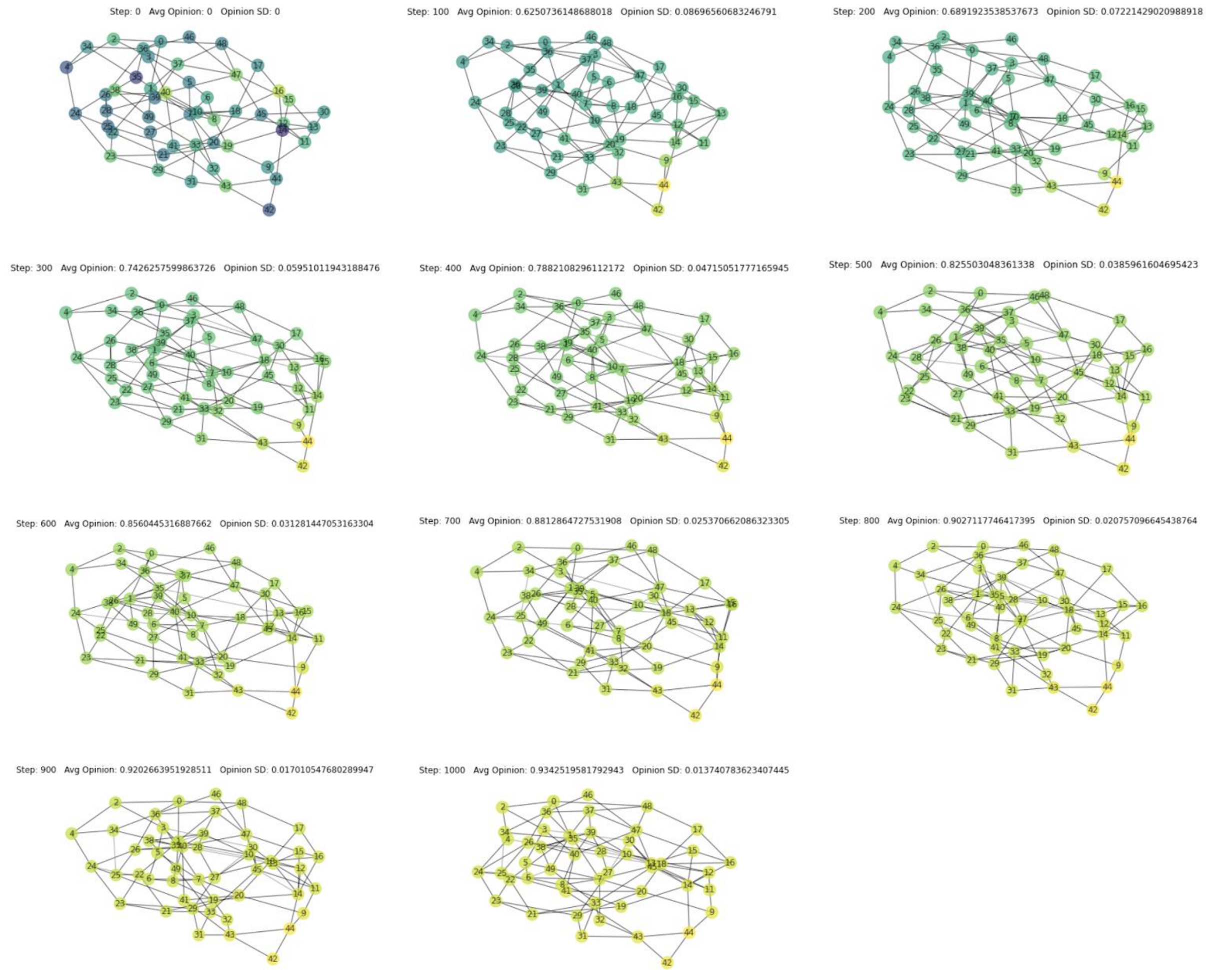


Figure 1. An example simulation of the changes in each node's opinion over 1000 steps where the node with the highest persuasiveness is selected as the main transmitter and distributor of information and opinions with the color purple representing an opinion value of 0 and the color yellow representing an opinion value of 1.

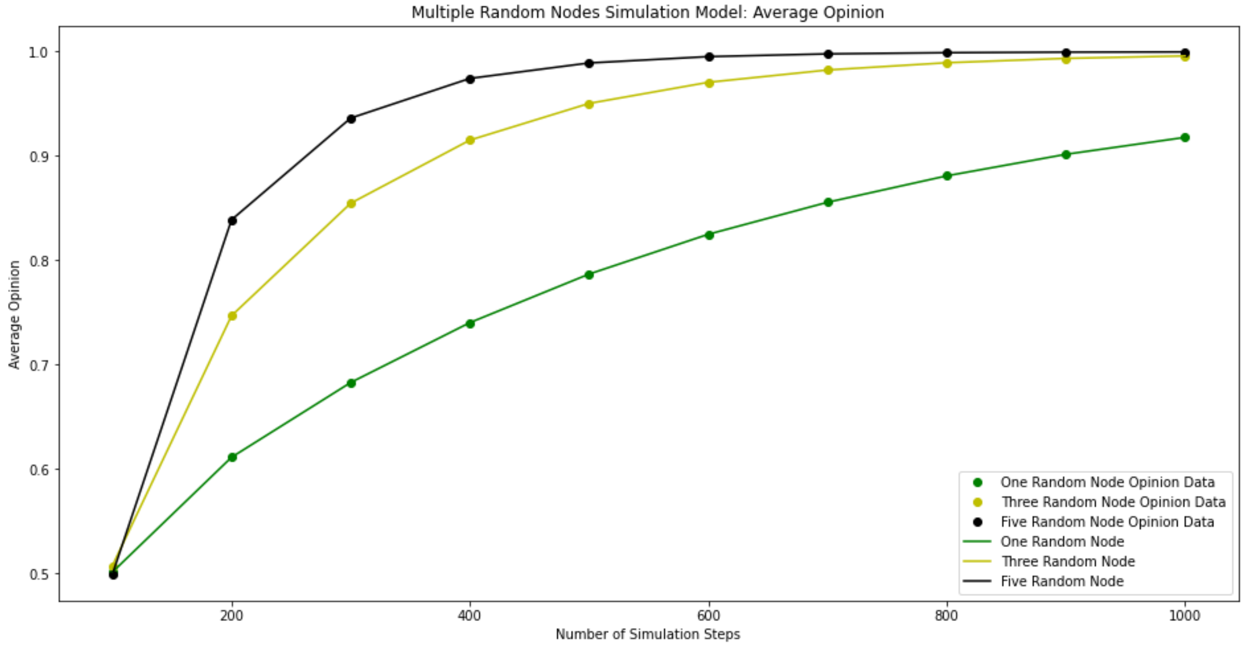


Figure 2. The average opinions of the random node selection method where 1,3, and 5 nodes selected in each network are plotted on this line graph.

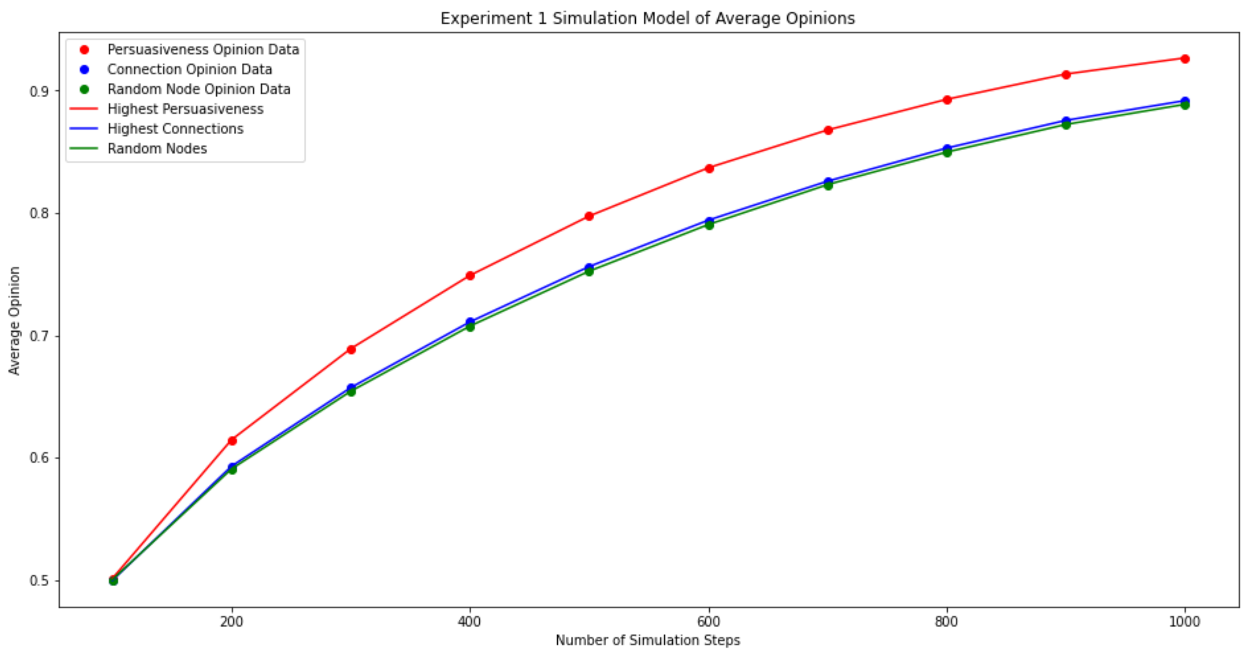


Figure 3. This graph shows the overall average opinions of all three selection methods over a span of 100 similar simulations of 1000 steps of opinion updates and interactions.

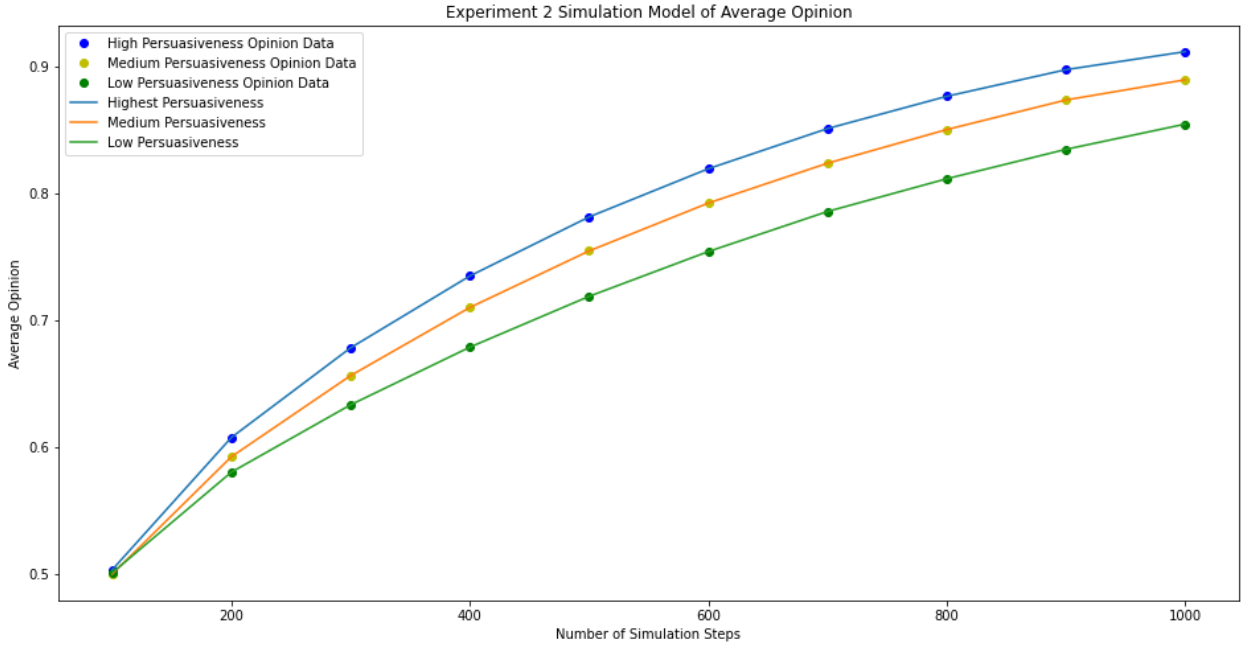


Figure 4. This graph shows the overall average opinions of all three persuasiveness values of the social network model over a span of 100 similar simulations of 1000 steps of opinion updates and interactions.

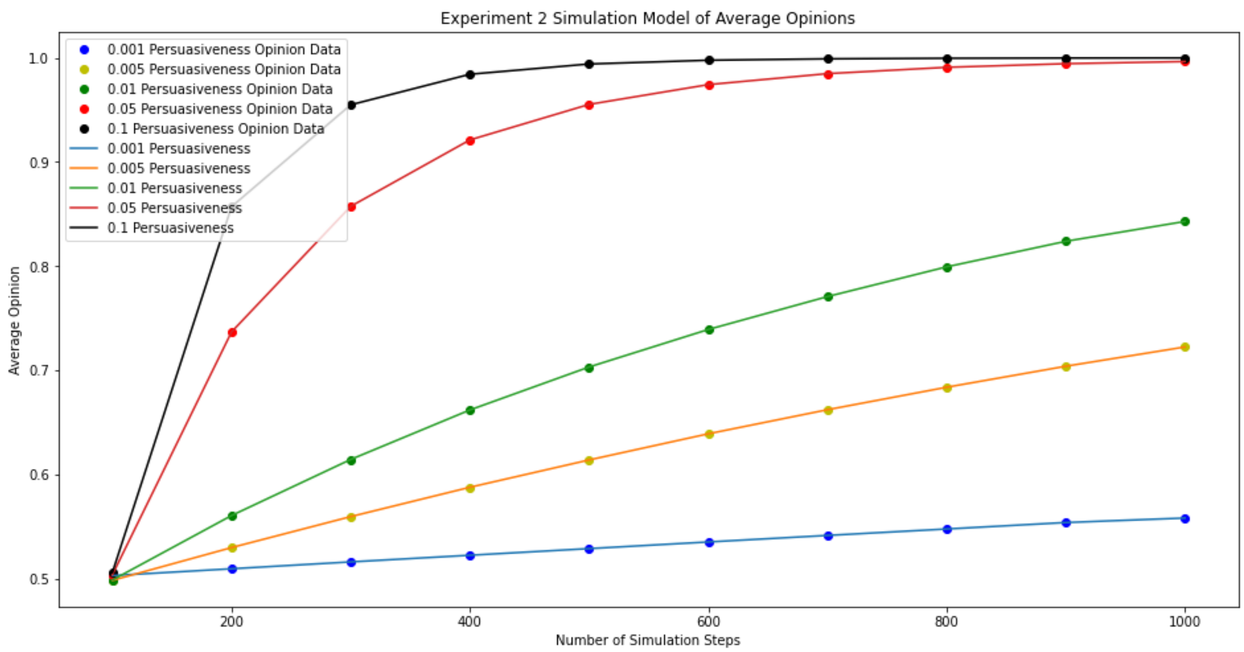


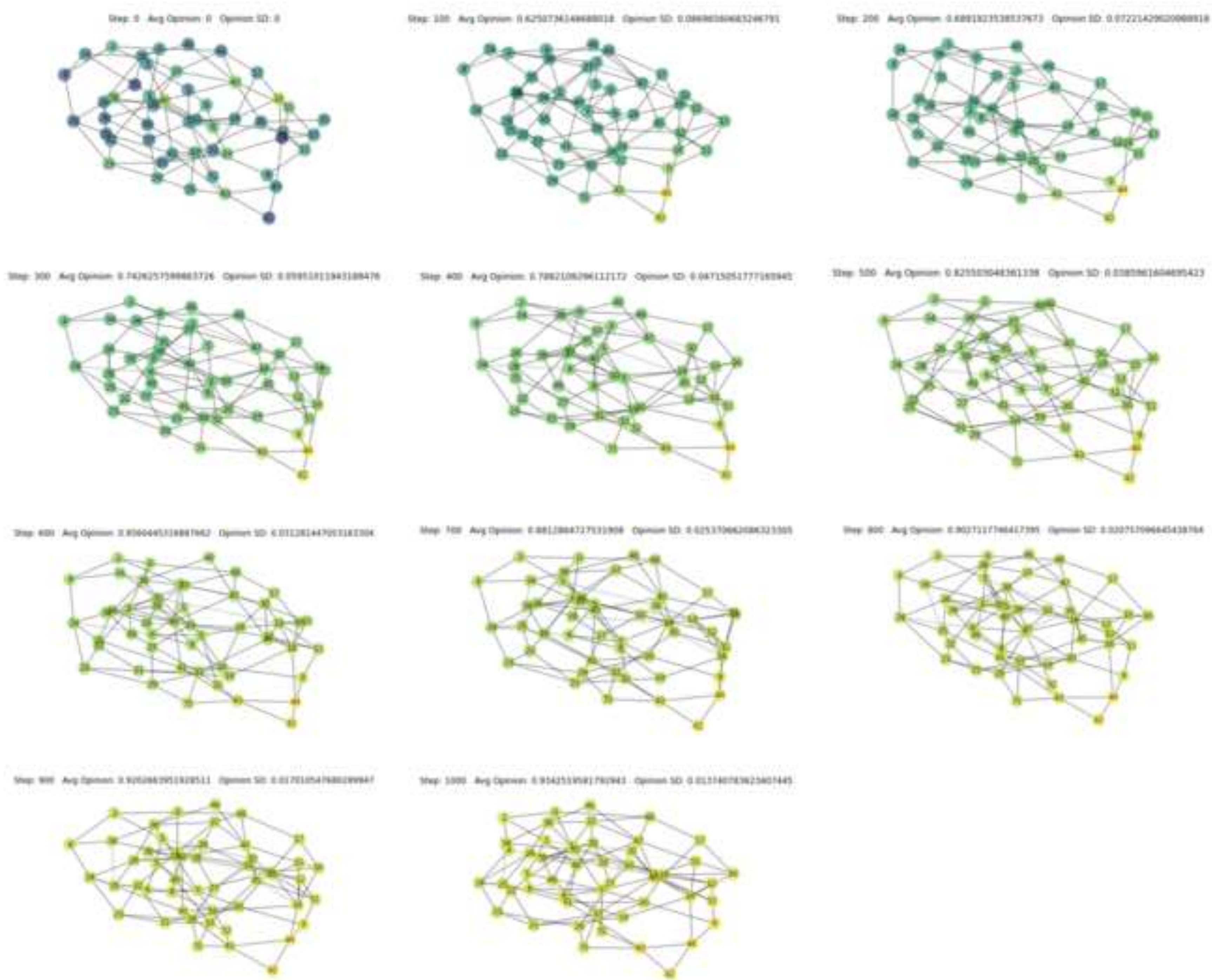
Figure 5. This graph shows the overall average opinions of all five persuasiveness values of the broadcast model over a span of 100 similar simulations of 1000 steps of opinion updates and interactions.

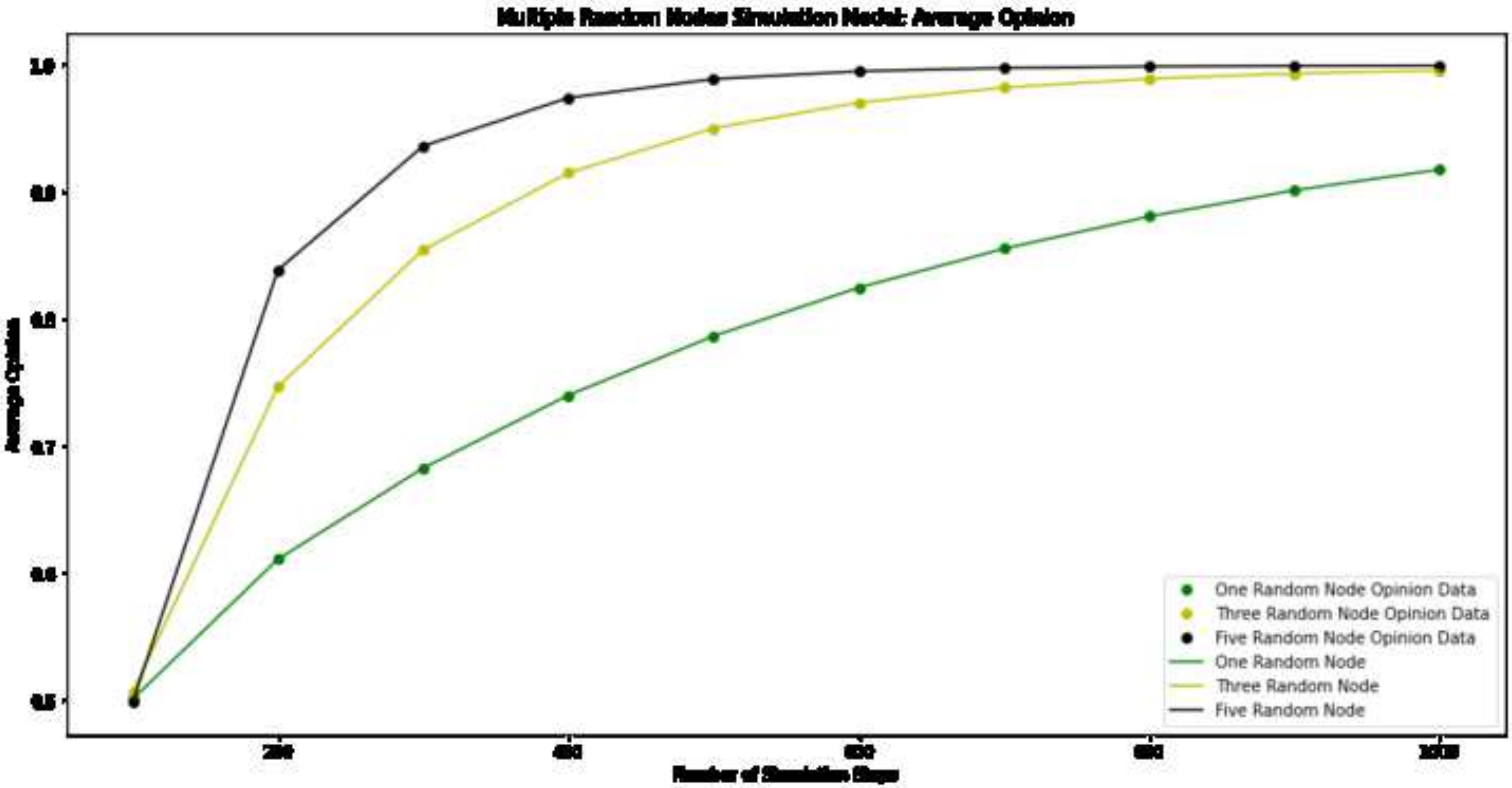
Appendix A: Code

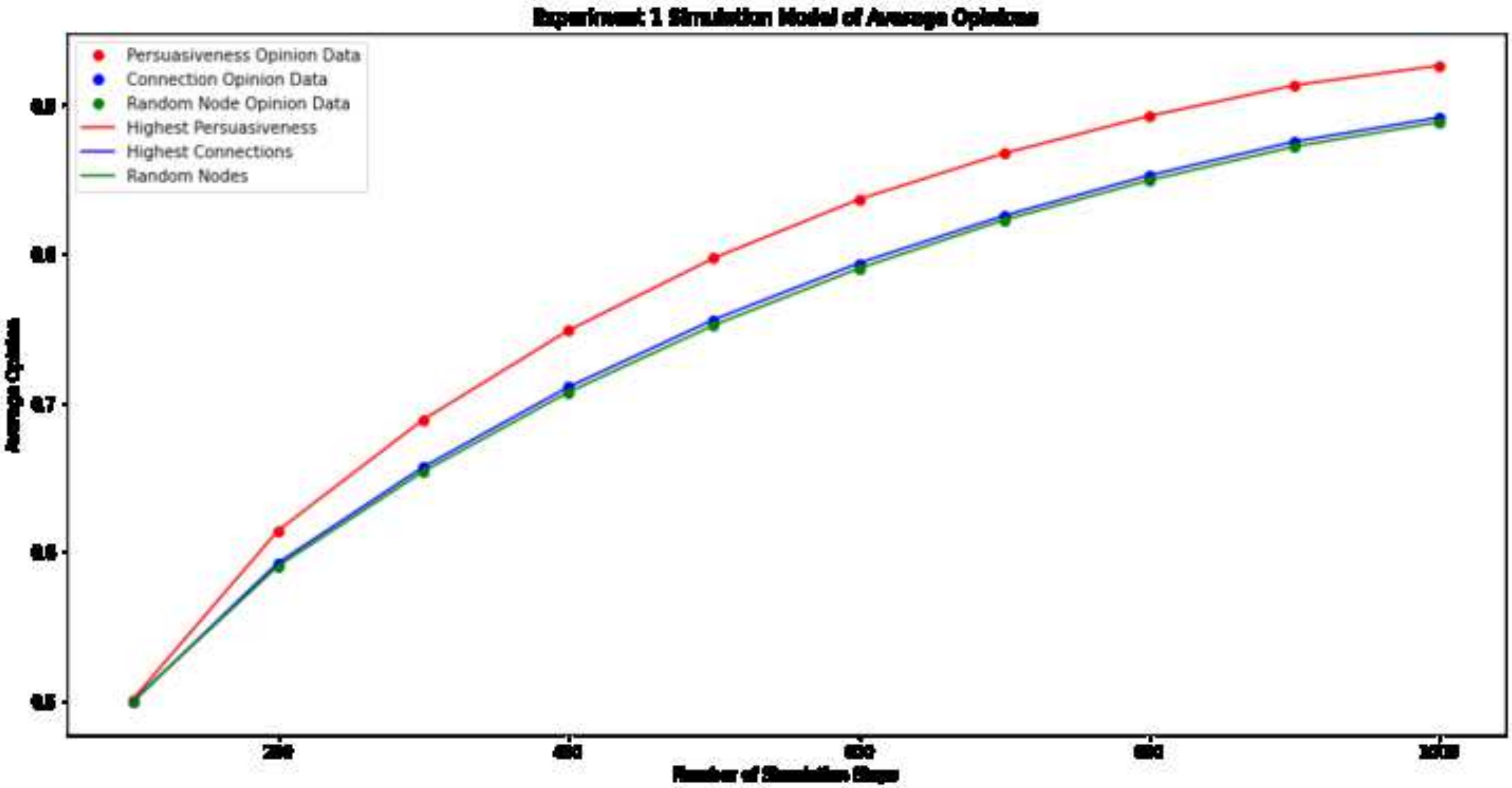
Experiment 1: https://gist.github.com/Cheng-I-Lin/4e334af2c7a81ba100956c8d8562171f

Experiment 2 (1/2): https://gist.github.com/Cheng-I-Lin/77598447e75d902ea063ce9d19681ed0

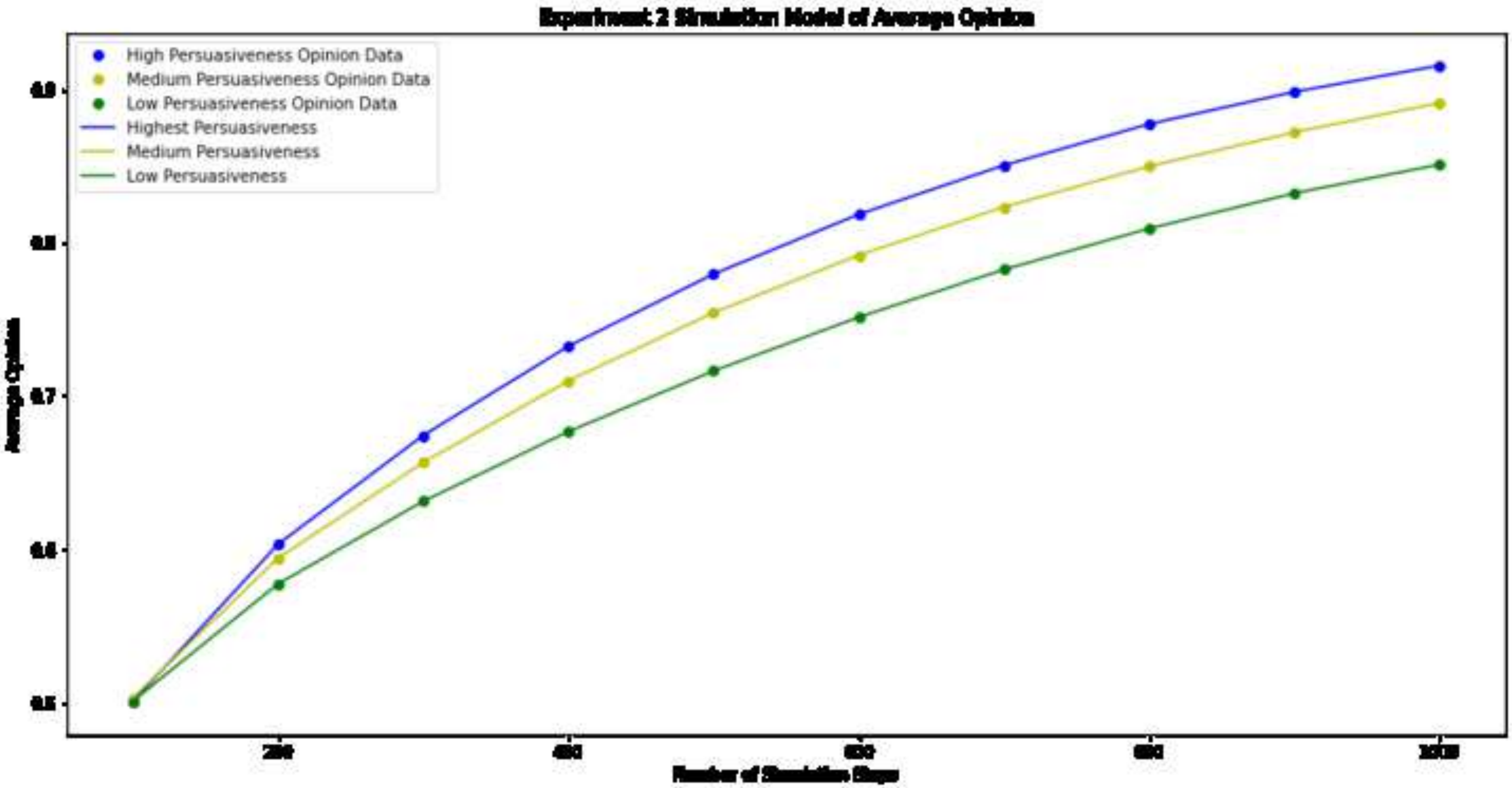
Experiment 2 (2/2): https://gist.github.com/Cheng-I-Lin/c1c38d041aaa5c30866f493cd7cf96a9

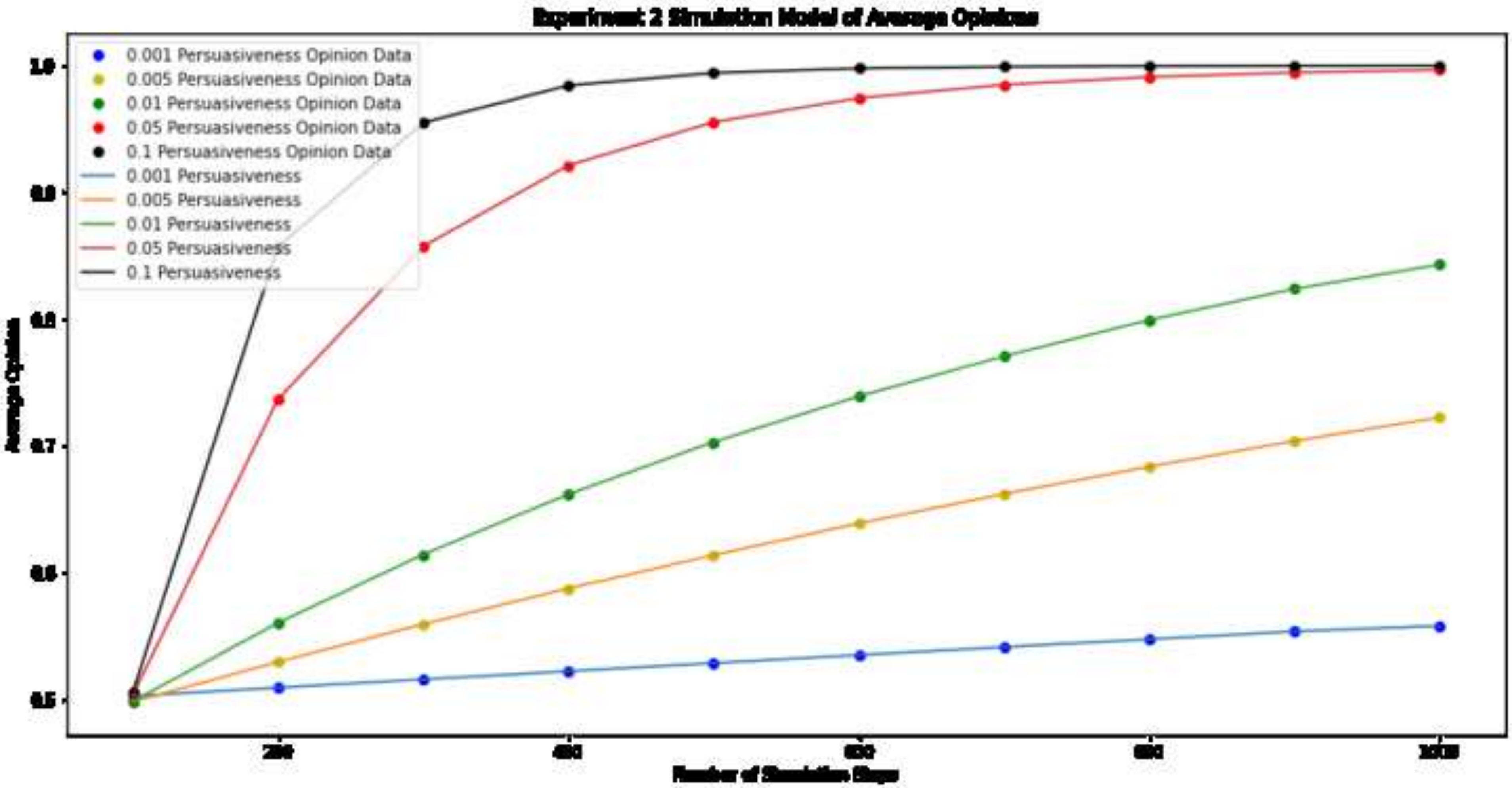

Step: 0 Avg Opinion: 0 Opinion SD: 0


Multiple Random Nodes Simulation Model: Average Opinion
One Random Node Opinion Data
Three Random Node Opinion Data
Five Random Node Opinion Data
One Random Node
Three Random Node
Five Random Node



Experiment 1 Simulation Model of Average Opinions
Persuasiveness Opinion Data
Connection Opinion Data
Random Node Opinion Data
Highest Persuasiveness
Highest Connections
Random Nodes
Average Opinion
Number of Simulation Steps


Experiment 2 Simulation Model of Average Opinion
High Persuasiveness Opinion Data
Medium Persuasiveness Opinion Data
Low Persuasiveness Opinion Data
Highest Persuasiveness
Medium Persuasiveness
Low Persuasiveness


Experiment 2 Simulation Model of Average Opinions
0.001 Persuasiveness Opinion Data
0.005 Persuasiveness Opinion Data
0.01 Persuasiveness Opinion Data
0.05 Persuasiveness Opinion Data
0.1 Persuasiveness Opinion Data
0.001 Persuasiveness
0.005 Persuasiveness
0.01 Persuasiveness
0.05 Persuasiveness
0.1 Persuasiveness