Paper Title: Using Social Network Analysis to Model the Spread of Misinformation in Simulated Environments

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ABSTRACT

A central question for social interaction is to recognize the circumstances under which exchange of information will lead to the spread of misinformation (incorrect information) and how misinformation spread can be stopped. What is unclear is the importance of variables within networks in curtailing the spread of misinformation. Specifically, if we were trying to stop the spread of misinformation within certain network types (i.e. clustered, small world, scale-free) what network elements should we consider most important, given that we may not know where the misinformation is arising from? We pose this research question: what are the relationships between network types and misinformation spread inventions types? Using simulated models we find that only in the small world network setting do we see a statistical difference in the misinformation spread rate among the four intervention types (random placement, and targeting based on degree centrality, betweenness centrality and closeness centrality). We also find that the misinformation spread rate for the three network settings is different only in the case of the closeness centrality targeted intervention type and not in the others types. Next, we apply this model to a virtual world training scenario under which basic social network principles are taught to help soldiers recognize how to infiltrate networks that may cause misinformation spread.

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INTRODUCTION

Human culture depends strongly on the dissemination, sharing, and acceptance of information. While believability has been identified as a factor determining which information is propagated, people seem to mainly pass on information that will evoke an emotional response in the recipient, irrespective of its truth value (Cotter, 2008). When first considering the spread of information, it is important to understand how new information – or misinformation – becomes accepted as truth. Several studies in the social influence and persuasion literature have shown that information is more likely to be accepted when it is consistent with other information the person assumes to be true (McGuire, 1972; Wyer, 1974). Misinformation often starts from nodes that are less influential (in our model those of weak ties) and its propagation speed is thus constrained by the trust relationships inherent in the diffusion process from these origins (Ibid). It is equally important to know how to stop the spread of misinformation once it has gained a foothold within the network. Budak et al. designed a model where "good" information was used to fight against misinformation propagation in social networks (Budak, 2011). Nguyen's work in restricting misinformation within a social network described the importance of an effective strategy to contain or limit the viral effect of such misinformation. Nguyen's aim was to make sure that most of the network users are aware of the good information by the time the bad one reaches them (Nguyen, 2012). Leskovec et al. studied the influence propagation mechanism in the context detecting outbreak situations. In particular, they aimed to find the set of nodes in networks to detect the outbreak, e.g., the spread of virus, as soon as possible. Centola (2007) described how social networks are the pathways along which "social contagions" propagate, and similar to the model we propose, the willingness to participate may require affirmation or reinforcement from multiple sources (Centola, 2007).

In the paper, we design an approach to inhibit the spread of misinformation by placing inhibitor nodes at critical locations within a network. We use a complex contagions[1] approach to sharing information where information will be accepted only if it is reinforced through neighboring connections (Centola, 2007). The model will also consider a variety of network types (random clustered, scale-free, and small-world) and where inhibitor nodes should be placed within those network types. For the purposes of this paper, we will compare random placement of inhibitor nodes with nodes of high centrality measurements to determine if in addition to randomly targeting nodes see which strategy is most effecting at inhibiting the spread of misinformation. This latter strategy is done to ascertain whether a random strategy works just as well as a centrality measurement to inhibit the spread of information.

Data and Method

Model Design: A model was developed within the Netlogo programming language to mimic the spread of misinformation from some outside source. The approach is as follows: nodes exist within a sub community society where each node is represented as either a either a relationally strong or weak tie. Three network types were created to evaluate models developed for Trials 1 and 2.

[1] Multiple sources of exposure to an innovation are required before an individual adopts the change of behavior

- *Scale Free*: A network type where a few "hubs" have lots of connections, all others have a few. This model generates these networks by a process of "preferential attachment" in which new network members prefer to make a connection to the more popular existing members.
- *Spatially clustered*: The network that is created is based on proximity (Euclidean distance) between nodes. A node is randomly chosen and connected to the nearest node that it is not already connected to. This process is repeated until the network has the correct number of links to give the specified average node degree.
- *Small World (Watts and Strogatz):* A small-world network is a type of mathematical graph in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of hops or steps. Specifically, a small-world network is defined to be a network where the typical distance L between two randomly chosen nodes (the number of steps required) grows proportionally to the logarithm of the number of nodes *N* in the network. A small-world network is one that is highly clustered (friends of friends tend to talk to each other) but still characterized by short path distances between any two actors.

Building Networks: An *N* number of nodes were added to one of three network where nodes would be given a status of either strongly or weakly connected based on a parameter setting within the Neglogo model. Each node exist in the environment of set $N = \{1, . . . n\}$ which represent a strong or weak tie source. A source example may be a website, Twitter feed, blog, or other media venues. The represented network connections are modeled as a bi-directional graph $G = (N, E)$ consisting of nodes N and edges E. In the context of influence spread, N can be viewed as the users of the social network. In addition, our model assumes edges are continuous, i.e. connections may not be broken at any time during the simulation.

Each node contains a homogeneous misinformation threshold Mi where, if the threshold is reached, the node is marked as 'misinformed' and turns blue on the Netlogo interface. At the onset of the simulation, an injection of misinformation is added to the weak tie network based on the variable *initial-misinformation-nodes*, and with a probability that this information crosses over to strong tie nodes, variable called *misinformed-spread-chance*. Each node develops a belief Bn about whether the information is valid by calculating mean belief Bi from its neighbors, and combining that with its initial belief Bi.

$$Bi = \frac{1}{n}\sum_{i=0}^{n} a_i = \ 1/n(a_1 + a_2 + .. + a_n)$$

$$Bn = Bi * \mathrm{Nv}\ + B0 * (1 - \mathrm{Nv}\,)$$

A global *node-vulnerability* Nv parameter is included in the equation to calculate the strength of influence of the connected nodes. In other words, if $Nv = 1$, the node would be fully influenced by its connected nodes, where a value of $Nv = 0$ would mean it would not be influenced by connected nodes. So we would expect no change in the network when the global parameter Nv is set to 0.

Research Topic 1: Evaluating small world long distance connections in the spread of misinformation

We began by evaluating the small-world network configuration and the gradual inclusion of long distance ties. The structural strength of a tie refers to the ability of a tie to facilitate diffusion, cohesion, and integration of a social network by linking otherwise distant nodes. Granovetter's concept is that ties that are weak in the relational sense—that the relations are less prominent or recurrent—are frequently structural where they provide shortcuts across the social topology (1973). The estimate is based on the "complex contagion" model (Centol, Macy 2007) is that, although information may spread through a small number of 'hops' or steps (and presumably more often as the nodes are rewired to contain more 'hops'), it does not guarantee that misinformation will spread 100% throughout the network. This is because rewiring methods may introduce new pathways to share information, but information will only become accepted if neighbors also agree with what is being shared.

Parameter Sensitivity Analysis in Netlogo

In order to evaluate the developed model as a predictive tool, statistical analyses can be performed to reveal the influence that a parameter has on simulation behavior. The Netlogo application contains a tool called *BehaviorSpace* that runs a model many times, systematically varying parameters within a prescribed model and records the results of each model run. This process, called "parameter sweeping" helps to evaluate which combinations of settings cause the behaviors of interest. When a parameter sweep is done to evaluate the model, it will be marked in the table as *(Parameter Sweep)*.

Method

The Netlogo model is set to variables described in the table below, where an initial small-world network is composed of local (strong) and long-distance ties. During each trial, a percentage of new node connections are introduced into the network model. As new rewiring takes place, we evaluate an average amount of misinformation that is spread in the network. 800 runs of the network are recorded, where for each 'rewire' setting between 0 and 100 (increments of .5), four repetitions are completed (200 iterations x 4 repetitions). It is noted that an upper time bound of 1000 seconds is used to assuming that above this value a full 100% spread of misinformation is never reached.

Table 1 Research Topic 1: Netlogo Parameters

Variable	Discussion	Value	Controlled/Measured
number-of-nodes	Number of total nodes in the network	425	Controlled
initial-weaktie-size	Initial number of long-distance nodes	18%	Controlled
initial-misinformation-nodes	Initial number of nodes containing misinformation in the network	20% (.2) 60% (.6)	Measured
rewiring-probability	Percentage of nodes that are 'rewired' within small world model	0-100	Measured *(Parameter Sweep)*

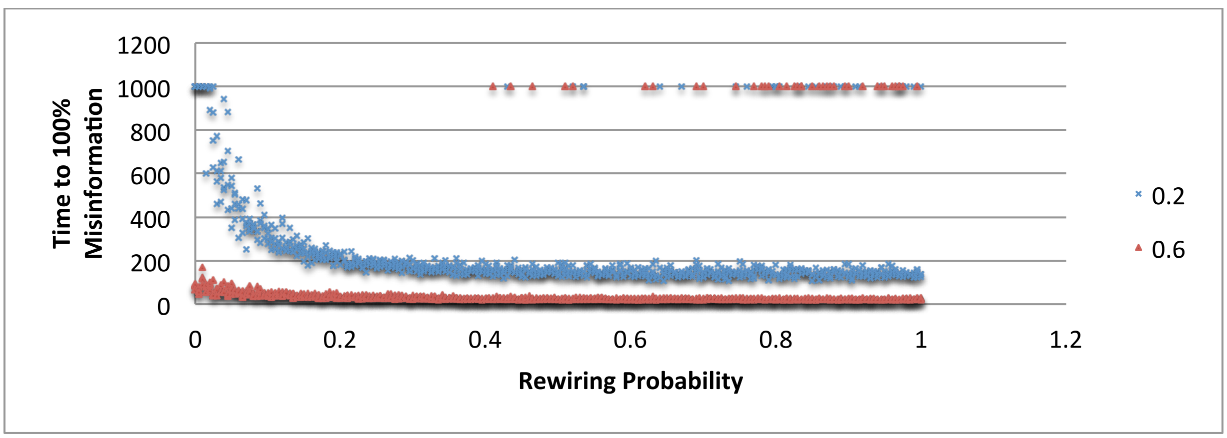

Figure 1: Small World Network Rewiring

Results

Figure 1 describes the amount of time (ordinate) it takes for misinformation to spread within the network based on varying the probability of small-world rewiring (abscissa) with two variations (20% and 60% of network contains misinformation). In the first set of trials (MI = 20%), misinformation reached a stable 100% acceptance at close to 40% rewiring. Once this threshold is reached there the model shows a consistent time frame of information spread at roughly 200 seconds. With the addition of more misinformation nodes, there is significantly less variation in the amount of time it takes to populate 100% misinformation spread within the network, and the time to 100% misinformation was closer to 10-20 seconds.

Research Topic 1 Discussion

This initial work is designed to model inclusion of new information through weak tie connections within a small-world network, and also how the network topology and a contagion model may produce a spread and then stabilization of the amount of new information in the network. As the number of hops is increased by rewiring the network, the chances of new information spreading throughout network does increase, but there is an opposing force, namely the existing nodes that are connected to neighbors who do not accept the misinformation. We therefore refer to the strength and value of strong ties, namely those nodes that you are directly connected to and are influencing the decision to accept misinformation. Weak (long-distance) ties can provide a network with new information but there reflects an underlying influence from what Centola (2007) refers to as non-adopters. Centola also describes *fractional threshold contagions* in which both adopters and non-adopters exert influence, but in opposite directions. We can see this effect in our Netlogo graph where network neighbors are competing for a consensus. A stable state is reached but with some competing between adopters and non-adopters.

Cascading Effects: Within the trials, particularly within the $n < 20\%$ rewiring phase, there is a threshold that must be achieved before new information is spread through the network and maintains a stable state in the network. We observe in the data that a stable state is reached if one of two situations occurs:

a) Nodes contain neighboring nodes that also contain the new information
b) Both of the nodes that are newly connected contain some of the new information

The reason for one or both of these criteria is simple; there must be some reinforcement of the information before it becomes accepted. If the node's local neighbors are influencing its belief, then its own belief in misinformation is stronger. This strong influencing value can then be passed on to its new tie, and there is a larger likelihood that it will accept that information. The cascading effect may continue towards 100% new information if the criteria mentioned above continue to be met. This continuous process of receiving new information, and being reinforced through connected nodes is an important aspect of how information can spread but can also be curtailed. This topic will be discussed in the next section.

Research Topic 2: Evaluating centrality measurements and node placement on spread of misinformation

In Topic 2, we wish to evaluate the importance of number and placement of nodes that can stop the spread of misinformation. Akin to Nguyen (2012), the goal of our problem is to choose the set of least nodes and optimal placement that can inhibit the spread of misinformation. We begin by choosing a network type with a specified topology (number of nodes, node degree) and number of misinformation nodes. We then introduce varying numbers of misinformation nodes at random locations within each network type, and introduce *intervention nodes* to stop the spread of misinformation. Intervention nodes are fundamentally nodes with 0 misinformation and 0 *node-vulnerability* and are not affected by spreading misinformation; In other words they can only reduce misinformation when it is shared in a socially contagious environment. Importantly, intervention nodes are introduced using one of four centrality measurements, random (control), betweenness, closeness, and eigenvector, and at varying numbers during running of the model.

Calculating Centrality Measurements within Netlogo: Betweenness and closeness centrality measurements were calculated based on an algorithm developed by Ulrik Brandes (Brandes, 2001). Degree centrality measurements were devised through determining the largest number of connections within a network. Degree centrality shows the connectivity of each node to other nodes in the network; betweenness centrality shows a node's relative position through being an interconnected node of at least one pair of nodes; closeness centrality shows the inverse of the sum of distances from a node to the rest of the nodes in the network; and eigenvector centrality shows a node's important in the network accounting for the connectedness of its' neighboring nodes. (Wasserman, Faust, 1994) A graph was created for each network type to illustrate the percentage of misinformation in the environment for each of the four network intervention types. The abscissa represents the percentage of network intervention nodes added to the network and the ordinate presents the overall amount of misinformation within the network.
For each centrality measurement, a graph was created where with a trend line based on polynomial line of degree 6 (appearing to be the closest to each of the trend lines).

Table 2 shows the controlled parameters within the study and the variations including sensitivity based measured parameters within the study.

Table 2:Research Topic 2: Netlogo Parameters

Variable	Discussion	Value	Controlled/Measured
number-of-nodes	Number of nodes in the network	425	Controlled
average-node-degree	Average node degree of strong tied nodes	10	Controlled
initial-weaktie-size	Initial number of weak tied nodes	15%	Controlled
initial-misinformation-nodes	Initial misinformation nodes (weak tied)	10%	Controlled
type-of-network	Network Type	• spatially-clustered-network Network • Scale-Free • Small-World	Measured
intervention-node-placement	Placement of intervention nodes based on centrality and random measures	• Random placement • Degree centrality • Betweenness centrality • Closeness centrality • Eigenvector centrality	Measured
Percent-intervention-nodes	Number of intervention nodes added to the network	0-100%	Measured (Parameter Sweep)

Trial 1: Spatially clustered Network

The spatially clustered network illustrates that Eigenvector and Degree centrality appears to be the most appropriate method to restrict the spread of misinformation in this network type, although all methods did better than closeness centrality measurements. Cucuringu considered two spatially distributed networks: a population migration flow network within the US, and a network of mobile phone calls between cities in Belgium and observed that some eigenvectors localize very well and seem to reveal small cohesive regions. (Cucuringu, 2011). In reference to degree centrality, by some simple logic we can deduce that more connections are more likely to produce optimal locations to place intervention nodes and will expect to see degree as an important infiltration method. Interestingly though, degree centrality can be deceiving, because it is purely a local measure. In other words, if we had devised a spatially clustered network with a significant portion of degree central nodes clustered in a corner, it is unlikely that the algorithm would have worked effectively. In a real world example, if we consider a group of corporate insiders that are well connected to one another but are not well connected to the rest of their employees, those high degree central nodes would not effectively inhibit misinformation spread. Although technically this description is not an accurate representation of a spatial proximate (Euclidean distance) based network where a node is randomly chosen and connected to the nearest node that it is not already connected to.

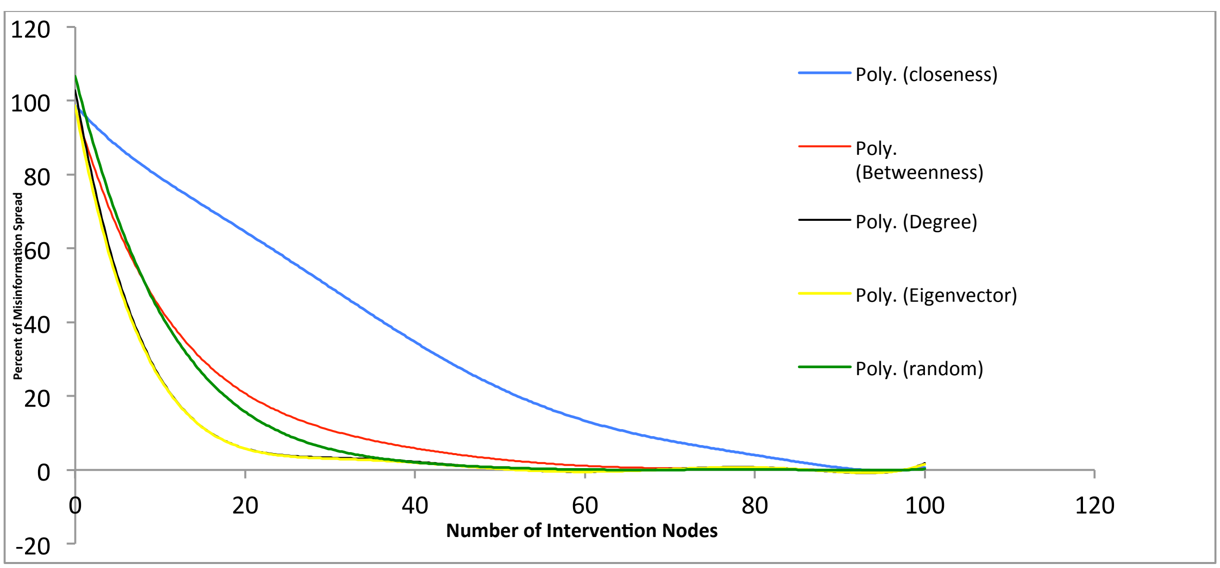

Figure 2: Spatially clustered Network

Trial 2: Scale-Free Network

The scale-free network represents a power law distributed network with several key central nodes (Figure 6 below). It is observed that of the intervention types, once again eigenvector and degree centrality contains the most optimal ability to decrease the spread of misinformation compared to the other methods of intervention in this kind of a network. Beginning with degree centrality where a network structure that is power law distributed, namely that there are a very few central nodes with many connections and many others with fewer connections, high degree central nodes in a scale-free network are extremely important when considering how information is being shared. So, given that degree centrality $di = \sum_{j=}^{n} Aij$ measures the sum of all network connections for a node, it is very likely that identifying that node will aid greatly in stopping the spread of misinformation. Figure 3 provides an eigenvector example illustration where its connections have many connections, and their connections have many connections, etc. We can then see how, within a scale-free network a properly selected eigenvalue node could be an important way to stall the spread of misinformation. Although, it is important to consider the eigenvalue node (i.e. V in Figure 3), if the misinformation began at some sub node within a network, it is likely to spread through the entire hub before it is stopped from spreading to another. So in Figure 3 (C) node e may be fully misinformed before V was able to stop the spread of misinformation.

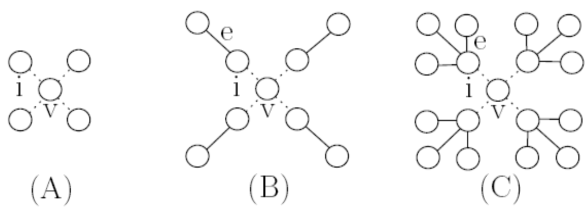

Figure 3: V=High Eigenvector Value

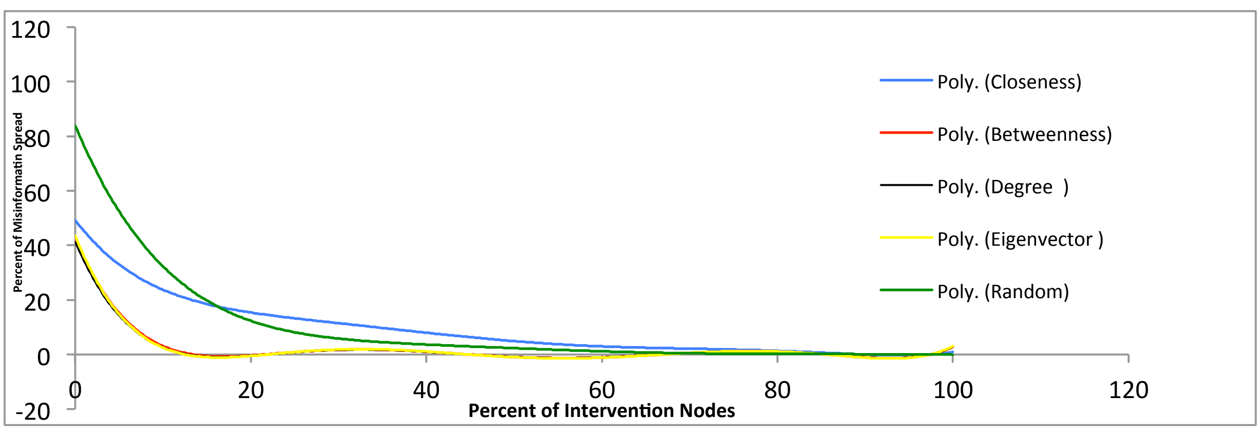

Figure 4: Scale-free Network results

Trial 3: Small-World Network

The third trial was based on the small-world model discussed in Research Topic 1. Once again, the values were based on the initial conditions discussed in Table 2:. The values used for the small-world network were somewhat different relative to the network configurations above: here, average node degree was replaced by the parameter *rewiring-probability*, based on an how the model creates connection 'hops' within a small-world network. Given that it was our intention to keep the model consistent with earlier trials (not modifying node degree), we set the rewiring-probability parameter at .1 (10%).

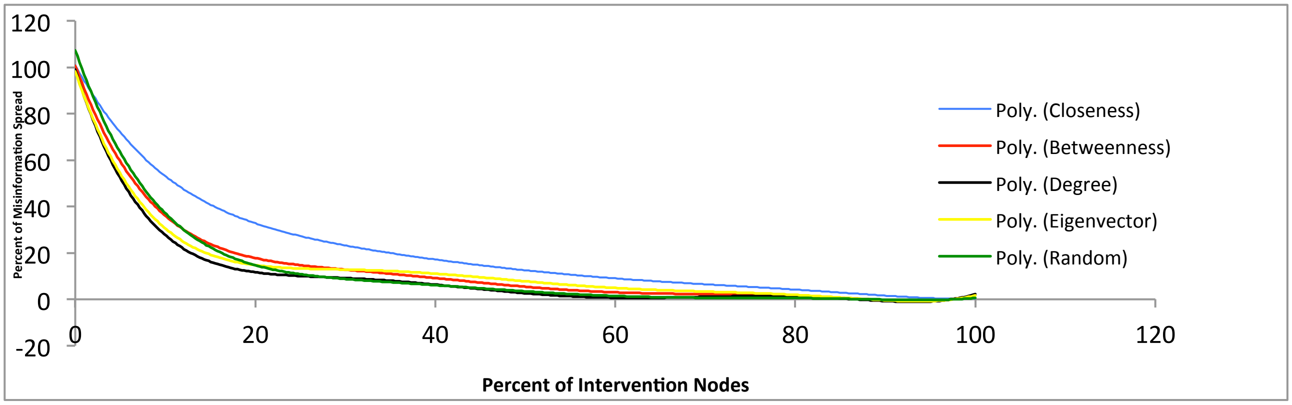

Figure 5: Small World Network Results

Statistical Analysis

The above analysis clearly showed that for each of the three network setting types that we considered (random clustered, scale free, and small world), the five intervention methods (targeting nodes randomly, or based on closeness centrality, betweenness centrality, degree centrality, and eigenvector centrality) produced values of the percent of misinformation spread that varied very differently as the percent of targeted intervention nodes (inhibitor nodes) changed from 0% to 100%. We wanted to test of these differences were statistically significant. We conducted Friedman's Fr-tests to see if the five intervention types have the same effect on the percentage of misinformation spread in the environment, for each network type. For the test design we blocked on the level of countering misinformation spread (from 0% to 100% in increments of 0.5%, with 4 replications for each value), so that variation within the levels of countering misinformation spread will be coming from the intervention type and not the levels. Since this is a 1 factor 5 level design, with "random assignment," measurements ranked within blocks, and the 5 probability distributions from which the samples within each block are drawn are continuous, the Friedman's Fr-test will yield valid results. We avoided parametric tests due to not knowing the normality of the underlying distributions.

The Friedman *F*r-statistic**,** which is based on the rank sums of the "treatments," in this case the intervention types, measures the extent to which the *k* samples differ with respect to their relative ranks within the blocks. The Friedman's Fr-statistic is:

$$Fr = 12b/k(k + 1)^* \Sigma(Rj - R)^\wedge 2$$

where *b* is the number of blocks, *k* is the number of treatments, *Rj* is the mean rank corresponding to treatment *j,* and *R* is the mean of all the ranks. The Friedman *F*r-statistic is approximately distributed as a Chi-square distribution with (k-1, in this case 4) degrees of freedom. The relevant null and alternate hypotheses pair for the test is as follows:

*H*0: The populations of percentages of misinformation spread in the environment are identically distributed for all five intervention types.
*H*a: At least two of the intervention types have probability distributions that differ in location

We conducted Friedman's Fr-tests separately for each of the three networks. Under the null given above, the results for the Friedman's Fr-tests for the three networks are given below in Table 1.

Table 1: Friedman's Fr-tests for Intervention Type

	Clustered Network	Scale Free Network	Small World Network
*F*r-statistic	1.4 e+0.3 *** (0.0000)	1.6 e+0.3 *** (0.0000)	1.5 e+0.3 *** (0.0000)
Kendall's W	0.4488	0.5049	0.4688
The p-values for the *F*r-statistic are given below in parentheses. *** denotes significance at α=0.01. Sample size is 804.			

According to Table 1 it is clear that in all three network types we see a statistically significant difference between the five intervention types after blocking for levels of intervention. In every case the Friedman's Fr-statistics were well over 1400 with p-values less than 0.0000, while the Kendall W statistics were larger than 0.44 in every case. So there was statistically significant evidence to reject our null that the population distributions of the five intervention types are identical in favor of the alternate for all of three network types. These findings confirmed the graphical analysis discussed above.

We also conducted Friedman's Fr-tests to see if the three network types (clustered, scale free and small world) have the same effect on the percentage of misinformation spread in the environment, for a given intervention type. Once again for the test design we blocked on the level of countering misinformation spread (from 0% to 100% in increments of 0.5%, with 4 replications for each value) so that variation within the levels of countering misinformation spread will be coming from the network and not the levels (as before we had 804 total observations). We examined the results for each intervention type separately although we did not block based on intervention type. Since this was a 1 factor 3 level design, with "random assignment," measurements ranked within blocks, and the 3 probability distributions from which the samples within each block are drawn are continuous, the Friedman's Fr-test will yield valid results. The relevant null and alternate hypotheses pair for the tests is as follows:

*H*0: The populations of percentages of misinformation spread in the environment are identically distributed for all three network types
*H*a: At least two of the network types have probability distributions that differ in location

We conducted Friedman's Fr-tests separately for each of the five intervention types. Under the null given above the results for the Friedman's Fr-test are given below in Table 1.

Table 2: Friedman's Fr-tests for Network Type

	Intervention Type				
	Random Intervention	Degree Centrality Intervention	Betweenness Centrality Intervention	Closeness Centrality Intervention	Eigenvector Centrality Intervention
*F*r-statistic	230.1947 *** (0.0000)	802.7861 *** (0.0000)	821.5746 *** (0.0000)	888.1953 *** (0.0000)	918.1119 *** (0.0000)
Kendall's W	0.1432	0.4992	0.5109	0.5524	0.5710

The p-values for the *F*r-statistic are given below in parentheses. *** denotes significance at α=0.01. Sample size is 804.

According to Table 2 it is clear that once again for each intervention type we see a statistically significant difference between the three networks after blocking for levels of intervention. The Friedman's Fr-statistic was larger than 230 in every case (with p-values less than 0.0000), and larger than 800 for the four centrality intervention types considered. All Kendall W statistics are significantly larger than 0.0, and are above 0.49 for the centrality intervention types. So there was statistically significant evidence to reject our null that the population distributions of the three network types are identical for all of the five intervention types, in favor of the alternate hypothesis.

Research Topic 2 Discussion

Understanding the importance of placement and number of intervention nodes is an important aspect to the study. In a large, complex social network (from socio-cultural to a cyber security based network), one cannot assume that there is an infinite supply of intervention resources. Interventions could be cost prohibitive, or simply not viable for any number of reasons. The study aims to determine if there is a minimum threshold of intervention that can squelch the spread of misinformation.

As discussed earlier, we observed certain patterns in the data as we examined the values of the response variable when we changed intervention type for different network settings, and then when we changed network setting for different intervention types. These patterns were compelling and calls for further research even though statistically we was able to generate significant results only for two cases considered. There was some promising data on optimal use of intervention approaches (number and location) based on network types. For example, if we observe the spatially clustered network there are two ways to view conduits to the spread of information. One is that we simply locate the most central nodes and hope that the misinformation spreading nodes will be closer to those central nodes. What the data tentatively shows is that if we were to randomly choose nodes within the network, that approach works as good (if not better) than using centrality measurements. And although we chose an arbitrary threshold value for squelching misinformation, random intervention in the spatially clustered network appeared not only the best option, but also did reasonably well at low numbers of intervention nodes, although statistically this result was not borne out given our dataset. We also observed that scale-free networks appeared to respond well to degree centrality and closeness centrality measurements. This would certainly make sense given scale free networks have a few nodes with very high degree centrality. Identifying these nodes as intervention nodes would likely minimize path length to any infected (misinformed) nodes. We would expect this result as well using closeness centrality measurements given closeness measures how long it will take to spread information from *Node S* to all other nodes sequentially[2].

Applications to Virtual World Training

The next stage of our ongoing work is to apply our misinformation-model to a realistic virtual world training scenario where learners must accurately evaluate a social network structure within an environment, then use that knowledge to minimize the spread of misinformation. A protocol was then developed to address the learning need as a combination didactic learning, assessment, and capstone exercise approach.

Didactic Learning: Learners are first introduced to the basic concepts of social network analysis, network types (random clustered, small world, scale-free), and centrality measurements. Based on our research results, learners are then familiarized with how information can spread within a social network and where to optimally place intervention nodes given network types. Learners are provided simple interactive scenarios describing how variables may impact the spread of misinformation. Within the Netlogo model, the learner is asked to select network types, modify parameters, and view how variation in the model influences the spread of information. Learners are assessed on their ability to understand and apply these topics (See Figure 6).

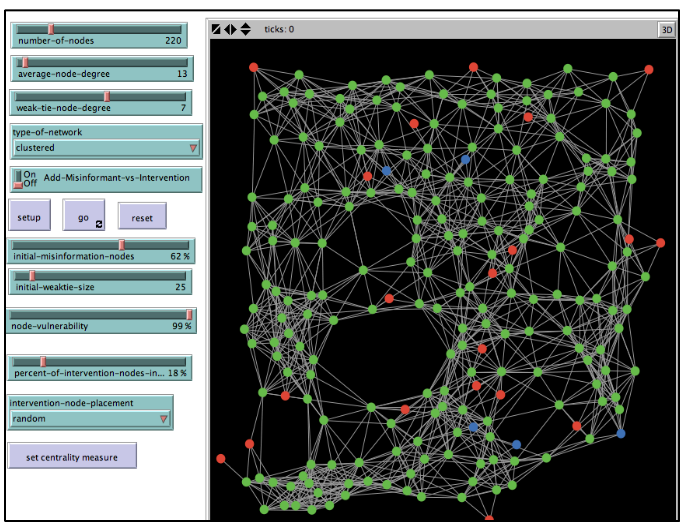

Figure 6: Netlogo Simulation Model

Capstone Exercise: Trainees are asked to gather information about a local terrorist cell within a fictitious North African city of Mubasi, developed for the Center for Army Leadership[3] (See Figure 7) A random number of misinforming agents are placed within the virtual environment and are clustered into a random network type. The player is then given a social network map describing the family relationships, asked to assess the network type and assign a number of infiltrators that would minimize the spread of misinformation. The results of these infiltrators placements impact the dynamics within the simulation. For example, inaccurate placement of infiltrators may impact villager relationships to the US troops assigned to the region. It may also cause undo stress on security forces that may be responsible for keeping the peace. Additional events may be triggered due to the spread of inaccurate information about peacekeeper actions within the region.

[2] Small-world networks have a small diameter and a spike-shaped shortest distance distribution

[3] *Mission at Mubasi* Decision Making Simulation, US Center for Army Leadership

Figure 7: Mubasi Virtual Environment

Discussion

This proposed model investigates how misinformation may spread based on a variety of social network variables and topologies. This skill is not easy to hone as it is often unclear what truly does matter when trying to stop the spread of misinformation. It is also important to recognize that there may not be unlimited resources when trying to control the spread of information, and understanding key locations within social networks can be a powerful tool. Proper social network mastery can be applied to the development of cross-cultural competence, situational awareness, crowd behavior analysis, and the formulation of options to keep the peace in unstable regions. The paper presents a research based case for how information travels based on a network topology; but it also provides a key insight into how to manipulate the network structure to achieve a desired flow of information. A highly variable clustered network may be controlled through key placements in highly clustered areas; in the case, number of connections may not matter, but location does. A network structure with key central nodes (scale-free) resembling a familial hierarchical structure may be handled best from the most central figure (i.e. patriarch, elder); networks with minimal connections but key 'hops' across groups may benefit from controlling only those adjacent nodes. We hope to continue our research towards creating true value to the warfighter where knowledge of how to handle the spread of misinformation can be applied to a variety of contexts with measurable results.

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