Socio-cognitive Networks: Modeling the Effects of Space and Memory on Generative Social Structures

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ABSTRACT: This paper examines the relationships between environmental and cognitive factors as they influenced the formation of social networks through modeling how these factors affect tie formation between pairs of agents in a simulated world. We modeled worlds consisting of 20, 40, and 60 ACT-R agents and examined the influence of population size, run time, map configuration, and navigation strategies, comparing the density and clustering of the resulting networks. We found that all these factors affect tie formation for agents with perfect memories, with population size having the greatest effect. We also examined the effect of these exogenous factors on the ties' strength in the agents' memories by combining and analyzing egonets. We found that changes to each of these exogenous factors affected the network's average memory activation value of each tie, with population size having a negative effect and run time having a positive effect. Map configuration and navigation strategy both influenced network structure. Further, we found that using the agents' activation values as a threshold for network inclusion was a useful way for identifying core groups and subgroups within the network. These findings provide further insights into the cognitive dimensions underlying networks and their structures, as reflected by Dunbar's (1998) number and Simmelian numbers. These results also show that these factors need to be reported when describing network simulations.

1. Introduction

We examine here two socio-cognitive processes that influence the formation of social networks: spatial reasoning and memory retrieval threshold. This work is motivated by a desire to better understand how socio-cognitive processes influence the development of persistent patterns of relations, represented in this paper as network topologies. By socio-cognitive processes, we refer to both those cognitive resources and mechanisms necessary to create and sustain social ties, as well as those group-level factors known to moderate human decision-making (Morgan, Morgan, & Ritter, 2010; Morgan & Carley, 2011). We focus on spatial reasoning and retention in this paper because these two processes seem foundational to understanding the emergence of social networks in a variety of contexts. We hope to deepen our understanding of network formation by modeling the relationship between cognitive and environmental factors, as it pertains to tie formation between agent dyads.

To explore this relationship, we introduce a set of agent-based models and experiments that test the influence of: (a) population size, (b) run time, (c) map configuration, and (d) agent navigation strategies. The outputs of this model are interaction networks (whole networks representing the total number of agent interactions that occurred within a single run) and ego-nets (declarative representations of the agent's friends network). For any one run, there is 1 interaction network and as many ego-nets (networks from the agent's egocentric point of view) as there are agents in the experiment. We compare the number of ties and total degree of 54 interaction networks in 11 different conditions. We also merged the individual ego-nets to examine how the structure of the socio-cognitive network changed as the semantics of the tie were tuned.

Our model is unusual in that we model social processes using a cognitive architecture (ACT-R) that is primarily associated with cognitive science. To our knowledge, Carley (1991, 1992) and Newell (1994) were the first to implement a model based on a cognitive architecture (Plural-Soar) to study organizations. More recently, Gonzalez, Lerch, and Lebiere (2003), Lebiere, Gonzalez, Dutt, and Warwick (2009), Reitter and Lebiere (2010b), and Juvina, Lebiere, Martin, and Gonzalez (2011) have used cognitive architectures to model human decision making in collaborative tasks. Barrett, Eubank, and Marathe (2006) have developed a large simulation with millions of non-cognitive light agents. While our work builds upon these efforts, our interest in network formation poses some unique challenges. We review these challenge in light of the current literature and our solutions to them in the next two sections.

2. Computational Social Models

Researchers have developed agent-based models to explore a variety of questions. We briefly examine two major modeling approaches: cognitive and social modeling. These approaches are not necessarily mutually exclusive; however, combined socio-cognitive models are relatively rare because they are generally expensive to create and run.

Social simulation models frequently, but not always, use bounded rational agents. Bounded agents are bounded both cognitively and socially (Simon, 1991). These agents generally engage in some kind of goal-driven time-constrained decision cycle dependent on local information. In addition, agents are usually adaptive, though options are generally conditioned upon previous action. Often, these simulations demonstrate aggregate behaviors that are emergent. These complex system-level behaviors arise out of the agents' discrete interactions, but cannot be explained entirely in reference to them. Further, at different levels of observation, different kinds of emergent behavior can be seen. It is often these kinds of traits that simulations are uniquely able to capture.

We treat the topology of interaction networks and their associated characteristics as an emergent property of the social system, defined in terms of interaction opportunities and memory constraints. Kraut et al. (2002) found that actor proximity fundamentally influences the evolution of network topologies by determining the interaction frequencies of actors across the network, while Allen (1977) demonstrated that the probability of two people communicating in an environment could be represented with a decreasing hyperbolic function of their distance. After a certain distance, the probability that two people will communicate decreases rapidly, making tie formation unlikely. We, thus, chose to focus on factors that are known to directly affect agent proximity or inter-agent distance: population size, run duration, and map configuration.

Cognitive models have historically focused on modeling human cognition at the symbolic and sub-symbolic level (Newell, 1990; Anderson, 2007). Providing models of perception and memory, we can use cognitive architectures like ACT-R to simulate the formation of social ties in declarative memory. We believe that over time memory constraints fundamentally influence a social network's topology and capabilities by constraining the network's ability to process information, identify important changes in state, and respond to those changes.

Here, we look at the processing of social information by exploring the concept of nodal carrying capacity, the number of agents an agent can retain in memory. To that end, we examine how environmental factors contribute to the consolidation and retention of social ties in memory.

This concept is similar Dunbar's (1998), where limitations associated with the neocortex limit the number bi-directional ties any one person can retain in memory. Dunbar argues that maintaining stable relationships requires repeated memory activations to identify not only one-on-one relationships but also third party relationships (i.e., the knowledge that my friend is also friends with other actors who I monitor). Further, he claims that the cognitive load associated with maintaining this set of relationships in memory rises exponentially as group size increases (Dunbar, 1998, p. 63). Based on retrospective empirical studies, Dunbar (1998, pp. 65-78) argues that this ratio between cognitive load and group size underlies the small-world effect observed by Milgram, Simmel, and others.

Therefore, we expect that larger populations acting over longer time periods in fully connected environments will result in the most connected declarative network structures. We also expect that less connected layouts will result in interaction networks that consist of more fragmented networks, leading to smaller ego-nets. We also expect that map configurations characterized by nexus points will exhibit behaviors similar to the water-cooler effect (DiFonzo, 2008). We, however, are less certain where we might see thresholds in network formation, where for instance population growth no longer has an effect or run time is no longer relevant.

3. Nodal Carrying Capacity: The Effect of Agents' Memory and Space

Having summarized our model's exogenous and cognitive factors, we provide both a definition and a prediction as to how that factor will influence network formation.

3.1 Interaction Frequency

We model three factors that influence interaction frequency: population size, run time, and map configuration.

Population density: We predict population density will have the greatest impact on social interaction frequency. Here, we model such shifts by changing the population size, holding the environment size constant.

Length of simulation (run time): We predict longer run times will lead to more ties and denser networks. Consequently, determining the run time lengths necessary for a network to reach a stable state under a given set of conditions (e.g., memory decay of ties) is important for accurately representing the formation of a group of interest.

Environment configuration: We predict the configuration of the environment will influence the structure of the simulated social network. We measure the relative connectivity of our three map configurations by defining its *grid ratio*. The *grid ratio* is the ratio of the number of edges over the total number of edges possible for a rectangular grid containing the same number of rooms.

We tested three map configurations (Figure 1). The first configuration (1a) is a full 5x5 grid with *grid ratio* 1.0. We expect this environment will result in relatively high connectivity. The second configuration (1b) has a central area with *grid ratio* 0.75. We believe this central meeting point will lead to network densities and clustering that are less pronounced than those associated with the 5x5 map but more than those associated with the hallway map. The third configuration (1c) is a two-hallway configuration with *grid ratio* 0.6. This configuration should lead to low connectivity due to the large distances between agents.

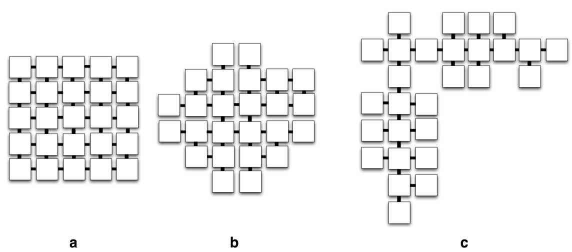


Figure 1. (a) 5x5 grid, (b) Central Area map, (c) and Hallway map

3.2 Cognitive factors

To better simulate the construction of social networks, it is necessary to consider the behavior patterns of agents at the cognitive level. In this paper, we particularly focus on memory decay and navigation strategies.

Memory: We examine memory effects on tie formation by using Anderson's activation theory (2004) to model the construction of social knowledge in declarative memory. In our model, the number of friends depends on the number and size of active long-term memory chunks representing the agent's social relationships. The number of active memory chunks is influenced by several factors, including initial memory activation, retrieval threshold, memory decay rate, time of retrievals, and practice time.

Navigation strategies: In a social network, the agents' movement patterns will influence the social network's topology by influencing any one agent's interaction opportunities. For example, a policeman walking a beat will have more acquaintances than a person who spends most of their time at home, if only because the policeman has more opportunities to meet people.

To replicate human navigation behavior, we implemented two navigation strategies: random-walk and fixed-path.

1) *The Random-walk strategy* replicates navigation patterns without a specific goal. It randomly selects an available direction to move.
2) *The Fixed-path strategy* follows a set path in a small area. This strategy simulates routine navigation behavior, such as going to work or shopping.

4. Experiment Environment

To model multi-agent social behavior using cognitive architectures, we constructed a simulation environment, VIPER. All of our experiments were conducted on a 2GHz eight-core server with 8GB of RAM. The server runs Linux 2.6.31 under Ubuntu 11.04, with SBCL 1.0.52 Lisp, and ACT-R 6 (Anderson et al., 2004).

4.1 The VIPER Server

VIPER models the constraints associated with embodiment on social networks. It supports multi-agent simulations to study network science. It is lightweight in that it is text-based, but is extendable and records agent behaviors. VIPER is designed to be a part of a distributed model that resolves events in either real or accelerated time. The network's speed and frequency of communication are determined by its component agents, with no queue of events being enforced. VIPER is designed so variations in performance originate from the agents participating in the environment, versus being a function of the environment. The VIPER server is based on NakedMUD, an open-source environment. It communicates with client programs using the Telnet Protocol.

Within the environment provided by the server, agents or human subjects are situated on maps of interconnected rooms. The agents can see and communicate within each room. Agents can walk between the rooms, and can interact with objects in the rooms.

To connect ACT-R to VIPER, we implemented the Telnet Agent Wrapper for ACT-R (TAWA) in Common Lisp. It supports logging in, waiting for synchronization, logging, halting, and writing results to CSV files. It also exports a number of functions that provide ways to examine the environment, speak, listen, move, and otherwise control a virtual body in VIPER.

When an ACT-R model is wrapped by TAWA, executions of model code are delayed until a privileged administrator agent signals for synchronization. Error conditions are also caught by TAWA and standard UNIX error codes are returned instead of dropping into the more standard debugger. For example, a successful run returns 0 to the parent process, while any error (e.g., network errors like the server being unreachable) returns a non-0 value. Returning error codes like this allows automated error checking in large-scale experiments.

4.2 Synchronization

Because memory decay and networks are strongly temporal, we paid special attention to time. To synchronize the agents, the administrator agent (which does not take part in the experiment) waits for all of the TAWA wrapped agents to finish loading and logging in. It then signals to TAWA to begin the simulation. Because TAWA delays the evaluation of the model code until synchronization, no agent experiences time before the synchronization signal. Further, all ACT-R models are set to run in real-time and for the same amount of "real time", so they all halt after the same perceived period. Thus, the total time experienced is the same for all agents.

4.3 Scalability

Early benchmarks showed that ACT-R processes took up about 80MB per process. We would only have been able to run about 100 processes on a single 8GB machine before swapping would occur. To reduce the per-process footprint, a number of optimizations were implemented. Basic space reductions were achieved by using the DECLARE Lisp construct, as well as by pre-compiling the components, removing the debugger, and saving the whole system (sans the ACT-R agent model) as a system image. This reduced our per-process memory footprint somewhat, but they were not the biggest contributions towards memory usage reduction.

In SBCL Lisp 1.0.52, the "--merge-core-pages" flag was recently added. This flag enables Kernel SamePage Merging (Arcangeli, 2009) under recent versions of Linux. This optimization flags shared areas of memory as being able to be merged unless modified. Because a significant percentage of our agents were replicated, we found that we could reduce the per-process memory footprint as low as 8MB per process (with one shared copy of the merged pages excepted). Thus, the only activities that increase the size of this footprint are changes within individual agent models. This lets drastically larger number of agents to be run, whether on single processors or HPC.

5. Experiment and Results

We now discuss our experiment's method and results.

5.1 Experiment parameters

We used 54 runs of our simulation to test three environmental factors: population density, running time, and map configuration, which are shown in Table 1.

Table 1. Experiment parameters.

Variable	Values	#
Population	20, 40, 60	3
Run time (s)	125, 250, 500	3
Map	Full-Grid, Central, Hall (100%, 75%, 60%)	3
Navigation strategy	Random, Fixed-Path	2
Total possible combinations		18

We tested the effect of memory retention by analyzing the activation values associated with each agent's friend chunks, represented as an ego-net log file. Each file contains the names and the last meeting locations of that agent's friends. In ACT-R, the activation value represents the memory strength of an object or an event. With the activation value of each relation chunk, we can easily convert the friend weight into a meaningful idea of tie strength.

5.2 Results

Our simulation generates two types of network data: (a) log data extracted from Viper directly, and (b) egocentric data stored in each agent's declarative memory. We examine them and some related network measures.

Log network. Figure 2 shows a sample network. The nodes in the figure are the agents in the simulation (N=20); the ties in the figure are un-weighted and represent the co-occurrence of two agents in the same room at any point in the run. Thus, the log network represents the ground truth of each agent's opportunities to meet with other agents, and the memory of agents with perfect memory.

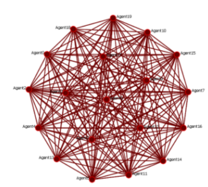


Figure 2. An example ground-truth network from log data (20 agents, 125 s running time, Hallway configuration)

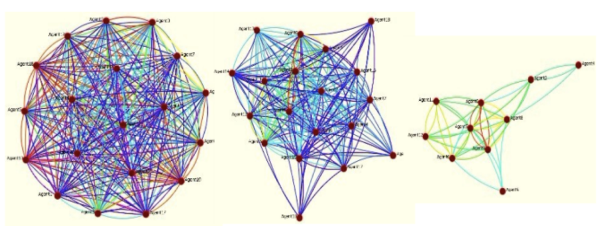
Table 2 compares eight runs on the ground-truth networks. We found that each factor influences the co-occurrence network, reflected in the network's density and tendency towards clustering. Density is the percentage of all possible ties in the network that are found in that network. Population size tends to decrease the network's density and has some effect on clustering. Run time tends to increase the network's density and decreases clustering. The grid ratio increases both density and clustering. Navigation strategy increases density and decreases clustering.

Merged Ego networks. The other type of data collected in the simulation is not ground-truth, but instead the individual ego-networks for each actor stored in that agent's declarative memory. Figure 3 shows an example.

Figure 3. An example ego network.

Each agent represents actors it has met as a working memory element (WME) chunk. The activation of each WME can be used to derive the amount of time a human would require to recall the actor. The semantics of each dyadic tie is important in interpreting a network. Thus, we consider the density of the merged ego-network across various activation levels. An activation value of '-3' indicates that the actor will need as much as 0.2 seconds to recall the chunk, whereas an activation of '3' indicates that the actor will need less than 5 ms to recall the chunk (but perhaps longer to report it).

Figure 4 offers an example of how a single merged ego-network can show how structure changes as the criteria for tie formation increases. Increasing the activation threshold provides a way for identifying core groups and subgroups within the network.



a b c

Figure 4. The same ego network at various memory thresholds, (a) -3.5, (b) 0.0, and (c) 1.0.

We considered two rules for determining whether the tie should exist: bi-directional (where threshold, t, must be met by <u>both</u> A_{ij} and A_{ji}) and directional (where threshold, t, must be met by <u>either</u> A_{ij} or A_{ji}). Figure 5 shows the density of the merged ego-networks as various activation levels are sampled—from this analysis it is clear that map topology influences the creation of the merged ego-network.

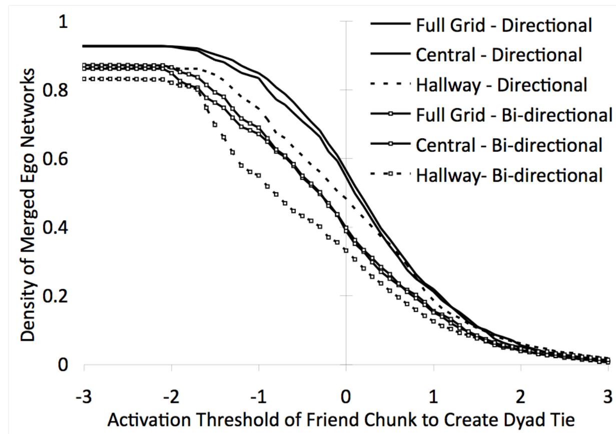


Figure 5. Map configuration and selection criteria affect the generated ego network.

5.3 The Effect of Nodal Capacity

We also examine the relation between influential factors and activation values of each configuration. Table 2 lists the population sizes, run times, navigation strategies, and average activation values for agents across eight runs.

Table 2 shows that these factors influence the activation values between agents. The population size has a negative influence on the average activation because larger populations decrease the average activation value significantly (from 0.304 to -1.117). Running time has a positive influence on the average activation value—it increases from 0.304 to 1.607 as we increase the running time from 125 s to 500 s.

Table 2. Results comparing eight networks to investigate trends in the ground-truth co-occurence networks, the cognitively limited merged ego-centric networks, and the average chunk activations for friends.

				Ground Truth		*Merged Ego-Centric*		Average
Pop	**Run Time**	**Grid Ratio**	**Navigation**	**Density**	**Clustering**	**Density**	**Clustering**	**Activation**
20	125	0.60	Random	0.905	1.000	0.810	0.855	0.304
40	125	0.60	Random	0.880	0.924	0.220	0.467	-0.678
60	125	0.60	Random	0.859	0.961	0.051	0.086	-1.117
20	**125**	0.60	Random	0.905	1.000	0.810	0.855	0.304
20	**250**	0.60	Random	0.947	0.944	0.805	0.852	0.931
20	**500**	0.60	Random	0.947	0.944	0.855	0.897	1.607
20	125	**0.60**	Random	0.905	1.000	0.810	0.855	0.304
20	125	**0.75**	Random	0.947	0.944	0.600	0.696	0.126
20	125	**1.00**	Random	0.950	0.947	0.660	0.724	0.440
20	125	0.60	**Random**	0.905	1.000	0.810	0.855	0.304
20	125	0.60	**Fixed Path**	0.947	0.944	0.855	0.897	1.992

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We also found that the map configuration influences the average activation values, but that this influence does not correspond to the grid ratio. It shows that the "Central" map with a grid ratio of 75%, has the lowest average activation values (0.126); the "Hallway" map with a 60% grid ratio has a higher value (0.304); and the 5-by-5 map with 100% grid ratio has the highest average activation value (0.440). The map configuration's effect on average activation values may be due to some chunks never being formed (and thus never being averaged) in the hall-way map configuration, as indicated in Figure 5.

The results show that the fixed path strategy has a positive influence on the average activation values. Because agents using this strategy walk around a small area, the agents tend to have fewer ties but higher activation values per tie, simulating a neighborhood effect.

5.4 Operationalizing Dunbar's Number

We also preliminarily examine the influence of these factors of Dunbar's number by applying a fixed activation threshold to simulate limits of cognition. For this analysis, we consider networks with an activation threshold of 0.0, ACT-R's RT parameter was set to -3.5, thus the time to recall a chunk is 0.011 seconds based on ACT-R's memory equations.

In Table 2, we use two measures to evaluate the thresh-olded ego-networks, density and clustering. As the net-work's size increases, the network's density decreases and clustering coefficient decreases. As the simulation's length increases, the density and clustering coefficient increases. As the environment becomes more intercon-nected, there is some evidence to suggest that the network density increases and the clustering coefficient increases, although this evidence is mixed. The Fixed Path agent, which traverses the space differently, retains more of its edges and shows more clustering.

In our results we highlight density because it illustrates the effect of nodal carrying capacity (defined in this case by an activation threshold) on a simulated social network. Table 2 suggests that population size has the highest influence on the merged ego-net, which is not surprising, because a network maintaining a constant density as new actors are added would require more and more ties from the marginal actor. Also, the agent's attention is limited, and attending to more agents may require more resources than the agent can bring to bear, which suggests one mechanism for how Dunbar's number may moderate social activities. The other three factors also have some influence on the found density and structuration of the network. In real social contexts, we suspect these three factors with smaller effects would interact, and perhaps magnify the effect of population size.

5.5 Interaction Density on Locations

Additionally, environment configurations can create loci of interaction or activity spaces (Brantingham & Brantingham, 1993). These locations are where the majority of all interactions occur. Brantingham and Brantingham use this concept to study crime densities, but this idea can be expanded to other activities, such as co-occurrence or socialization. When traveling to or between these spaces, people tend to take routine paths. Costanzo et al. (1986) demonstrated that people near one another tend to travel along the same paths to activity hotspots. Therefore, we expect that agents will also tend to take high frequency paths to common locations because they are constrained by the world's geometry.

These high activity spaces for one of our environments are shown in Figures 6a and 6b. Figure 6a shows the connectivity between all agents and the rooms in which they have interacted, while Figure 6b shows a heat map of room activity. Given the concentration and degree of these spaces, we show that agents who traveled between activity spaces tended to travel along the same path. This result is similar to the water-cooler effect, which suggests that interaction happens naturally in shared public locations.

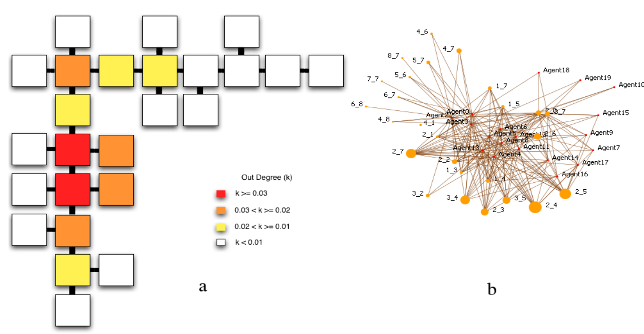

Figure 6. (a) Hallway map's heatmap; (b) Agents-by-location network.

6. Discussions and Future Work

In this study, we created a multi agent social network simulation that provides a flexible platform to examine several influential factors in social networks. Based on the existing literature, we hypothesized two basic types of influential factors, exogenous and cognitive factors. Our exogenous factors included population size, run time, and map configuration, while our cognitive factors included navigation strategies and memory activation parameters.

Our results show how cognitive and environmental factors can influence network growth and shape. From the simulation results, we find that all three factors influenced the ground-truth co-occurrence networks, as well as the merged ego-networks. As expected, the co-occurrence networks are less affected than the cognitively limited merged ego-networks. The effect of running time is not as significant as we expected, and shows plateauing after 250s run for these configurations. The large running time also weakens the effect of map configuration in our ground-truth networks because it provides agents enough time to travel around the whole map. By examining interaction density on locations, we also find that the shared public locations have higher interaction densities, in a manner similar to the water-cooler effect.

Taking advantage of the ACT-R memory mechanism, we are able to create an egocentric view of the social network by looking into the chunks in the declarative memory for individuals and across a whole network. We found the structure and density of the merged egocentric network to depend heavily on the criteria for tie formation, with the most generous criteria producing a network very similar to that suggested by the ground-truth networks.

By examining the activation values between agents, we also found that the four factors examined influence the activation values of ties between agents. The result of agent activation logs show that the population size has a negative influence on the average activation (smaller groups have stronger ties); that running time has a positive influence on the average activation value; and that map configuration has some influence on the average activation but that the change of value does not correspond to changes in grid ratio. This suggests that grid ratio is not a sufficient measure of map configuration at least with these maps, and we need to find a more accurate measure in the future. We also found that navigation strategies do influence activation values, with the Fixed Path strategy resulting in a neighborhood effect (strong localized ties).

From this preliminary study we found that the exogenous influential factors have impact on both measures of the network with a threshold. The population size has the highest influence on the merged ego-network's density, suggestive of the implications of the effect of Dunbar's number on the real social activities.

Finally, we conducted a preliminary study of the effect of these factors on Dunbar's number and of applying a cognitive limit on each agent. We used an activation threshold to implement a cognitive limit on tie strength and to suggest some meaning for the ties. We measured the cognitively limited network's density and inherent structuration.

Thus, reports about simulated networks need to report these factors and similar factors when describing their simulations. Knowing the values of these factors will be necessary for duplicating results because these factors have strong and interacting effects.

Future avenues of work will build upon some of the more interesting issues. First, we would look at analysis of normalized thresholds to see if there are regularities in their effects on network topology. Second, we would run more agents and more runs (Ritter, Schoelles, Quigley, & Klein, 2011), because the system to demonstrate these effects was kept deliberately small. Finally, we would extend our analysis on the effects of cognition on network measures analogous to Dunbar's Number.

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