Estimating the near-term changes of an organization with simulations

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Abstract

Estimating the changes of an organization's performance under uncertainty has been one of major topics in management, counter-terrorism, command and control, etc. In this paper, we propose a data-farming framework, 'Near-Term Analysis', to predict the changes over time in network. Near-Term Analysis uses Dynamic Network Analysis metrics (in ORA) for estimating changes in a Multi-Agent Simulation model of social and knowledge network evolution (called Dynet). Specifically, Near-Term Analysis simulates the social dynamics within an organization based on an organization's meta-matrix and expected isolation events of agents, and it generates its estimation about the degree of knowledge diffusion from the simulation over the simulated time period. From this analysis, we found this tool is useful in detecting inefficient entities in organization structures and expecting the impacts of the loss of agents. Furthermore, the simulation result correlated with the social network analysis measures qualitatively. We believe that this framework can be used to detect the vulnerabilities of terrorist groups, military command and control structures, corporate structures, etc.

1. Introduction

In many domains where situations are dynamically changing, 'what-if' analysis is a critical question to prepare for the future. Particularly, some disciplines, such as intelligence, corporate management, military command and control, etc, have some threat scenarios and wonder what will happen if the scenarios become realized. For example, an interesting question for corporate managers is what will happen if some key employees decide to leave their company. These managers want to know the deterioration of the company's performances and the company structure after they leave. Similarly, some military officers have a threat scenario, "What if some officers are killed in action", and a question based on the scenario, "Will our unit be responsive as usual?"

To answer these questions, the ideal method is replicating the target domain and the organization many times in the real world and testing the scenarios in the replicated environments. Such experiments described above are approximated by the organization science community and the social science community where researchers investigate field studies or collect experimental data in labs. However, these techniques are very expensive, unethical or impossible compared to the simulation. Also, there are many real world cases that are complicated to regenerate. Multi-agent simulation (MAS) has a number of benefits. First, the nature of the MAS has a nice analogy to human organizations and actors, so some policy domains, such as civil violence (Epstein, 2001), the transportation of goods (Bergkvist, 2004;Louie and Carley, 2006), used the MAS. Additionally, the growth of computing power allows MAS to run multiple experiments for many times with less cost. For example, Bio-war MAS (Carley, 2006) is a city scale model, and it can be converged in several hours with super computing facilities. Finally, the MAS is now being used for theory building in the organization and strategy literatures (Davis et al, 2006; Cohen et al,1972; March, 1991)

Therefore, in this paper, we performed the 'what-if' analyses of organizations under different possible threat scenarios, and the analyses are done by a MAS system called Dynet. To use Dynet, we integrated it into Near-Term Analysis framework to ask what the impacts to an organization are. The Near-Term Analysis framework puts Dynet in a data-farming environment, so that a large number of simulation runs with different scenarios can be done as a part of a large virtual experiment. Specifically, we collected a structural dataset of a real world military exercise, generated threat scenarios for the organization, simulated the near term impact of each scenario to the organization. All the procedures in the framework are automated, and we minimized the human intervention. After the analyses, we discuss the tendencies and the implications of the results from the simulations.

2. Background and Previous research

Previous research on organizational performance and 'what-if' analyses is done by both methods: experiments with human participants and simulations with multi-agent. Therefore, we introduce the two approaches in the following sections.

2.1. Social experiments with human participants

To observe the differences of organizational performance, many researchers utilized social experiments in the real world. For example, Weber et al (Weber et al 2004) claims that organizational structures and codes influence an organization's performance greatly. Their paper presents experiments that they varied virtual software firm structures from centralized/ hierarchical to decentralized/ egalitarian and measured the performance of the two different kinds of firm structures. According to the paper, centralized/hierarchical firms develop codes more rapidly and decentralized/egalitarian firms assimilate new entrants more easily. Additionally, Bohte and Meier (Bohte and Meier 2001) studied how an organizational structure measure, or span of control, predicts performance in a large set of public organizations. Their research reveals that the span of control variable has the greatest impact on performance under moderately difficult task scenarios. Also, Jin and Levis (Jin and Levis 1990) experimented how two decision makers in different organizational structures, a parallel one and a hierarchical one, perform. The performance was measured in terms of decision makers' response time and accuracy. The experiment confirms that individual difference has more influence on performance in the parallel organization. On the other hand, the interactions in the hierarchical organization restricted the choices of the decision makers and coupled individual decisions with the decisions of other organization members. These research papers utilize real world social experiments, so we can see how researchers examined given organizational structures with possible future scenarios and how they measured the performance of the structures.

The research closely related to the organizational structure and its performance in military C2 is done by Graham. Graham (Graham, 2005) experimented with the Battle Command Group (BCG) C2 structure three times to discover a systematic method to evaluate its efficiency. The experiments used Shared Situation Awareness (SSA) as a performance measure, so the major output was the identification of factors that are the important elements of SSA. First, Graham et al (Graham, 2004) discovered there are evident links between both social network distance and physical distance and SSA. In the paper, he did a regression analysis with physical distance and social network distance against the mental model congruence that is related to the SSA. He could see that the two variables can be predictors for the congruence. After the research, he wrote a dissertation (Graham, 2005) based on measuring SSA of the three experiments. In the dissertation, he derived three explanatory variables, physical distance, social network distance and background similarity, from prior research papers. Then, he proposes a statistical way to calculate the SSA with these three variables. The Unit of Action (UA) experiment information we are using in this paper largely comes from his dissertation, and the SSA measure in this paper follows his definition and calculation formula. These research works show the important aspects, varying and assessing organizational structures, setting the performance measures of experiments, interpreting the results, etc. However, these experiments have not many scenarios that are expected in the real world. Also, the replications of the experiments are limited. Therefore, we will adopt some of their aspects such as, performance measure setting and experiment scenario generation, but we will execute the experiment with simulations, not social experiments.

2.2. Multi-agent simulation

There have been series of research papers with social experiments with human participants. However, there have also been research papers measuring organizational structures in the social network analysis perspective and utilizing computer modeling techniques, not real world experiments. First, MAS has been used to investigate the attributes of organizations and the interactions inside them. For example, the model developed by Snijders et al (Snijder et al, 2005) simulates the co-evolution of an organization and its members' behavior. They used the model for a deeper understanding of the relation between individual behavior and actions and the embeddedness of individuals in social structures. To simulate an organization, they represented the organization as a social network and used measures known in the social network communities such as degree centralities, reciprocity, dyadic covariate, etc. To represent the behavior of members, they utilized tendency, attributed-related similarity, dependence on other behavior, etc. They surveyed the teenage students of a school cohort in Glasgow about their friendship network and self-reported smoke and alcohol consumption. From experiments with the model, they found out the network dynamics and homophily tendencies of the organization. This work is a good example of how the MAS approach is used in social studies. However, it focused only on explaining the social phenomena, neither analyzing 'what-if' scenarios of the given dataset nor estimating measures of the organization in the future.

Among the MAS models for 'what-if' analysis, Virtual Design Team (Kunz, Levitt and Jin, 1998) project aims at developing computational tools to analyze decision making and communication behavior to support organizational reengineering. Their model outputs include the predicted time to complete a project, the total effort to do the project, a measure of process quality, etc. Also, they found out that previously sequential activities of actors are important and should be emphasized to reduce the time to market by using the model. Their usage of the model to tune up the organizational structure and the analysis of the performance of an organization are very insightful. Furthermore, the model using what-if scenarios can predict that the activity and project duration impacts could have managed with the use of additional skilled staffs.

Also, by using MAS, Lin and Carley (Lin and Carley, 1997) identify strong factors of organization's performance, and the organizational structure is one of them. In their paper, they setup a computer modeling of organization's performance based on an information processing and resource dependency. With the model, they compared the performance to various factors, time pressure, training, organizational complexity, environment complexity, which organizational theorists considered as important attributes of the performance. After the comparison they found out that the time pressure, training of agents, organizational complexity and organizational environments are strong factors. Another research paper written by Lin and Carley (Carley and Lin, 1995) shows the importance of organizational structures and their influence on the organization's performance. Specifically, the paper presents the role of organizational design in affecting organizational performance. To show the role of organizational design, they used a computer modeling, CORP, to examine the organizational structure and its performance under certain test conditions, such as operating in optimal conditions, operating under internal/external stress, etc. These examples show how the MAS can be used to determine which factors and 'what-if' scenarios are important in predicting the performance of an organization.

Additionally, the research paper written by Schreiber and Carley (Schreiber and Carley, 2004) is one of the papers motivating this work. The paper clearly shows a framework that collects datasets from a real world organization, calibrates and validates their model, Dynet, and performs 'what-if' analyses with the validated model. It is meaningful that the model is grounded by the empirical data, and the validation with the empirical data enhances the credibility of the results from the 'what-if' analyses of the model. However, it is still questionable whether we can always collect the empirical data from our target domains. For example, it is very difficult to get the grounded data from terrorist networks, and the collected datasets from the domain are often noised and partially hidden compared to the corporate organization where they collected the data and tested the scenarios. Therefore, it is unrealistic for us to perform their rigorous validation procedures, but their 'what-if' analyses with the multi-agent model are very insightful and influential to our work. For instance, they analyze the difference of the performances before and after the use of the database system of the target organizations, and the analysis is quite similar to our research if we substitute the use of the database with the isolation of some nodes in an organization.

3. Method

In this paper, we built a program that utilizes the existing MAS program. The used MAS is Dynet, and our program creates threat scenarios such as isolation strategies of agents and assesses the impacts of the scenarios automatically. Therefore, we introduce 1) Near Term Analysis framework, 2) the agent interaction mechanism of Dynet, 3) the data structure for the representation of organizational structures, 4) the method to generate the threat scenario and 5) the measures to assess the impact of the scenarios.

3.1. Near-Term Analysis

We propose a framework, Near-Term Analysis. Previously, many social simulations are utilized to experiment a limited set of what-if scenarios, and the scenarios are usually created based on an analyst's domain knowledge. However, our proposed framework generates what-if scenarios by processing the input dataset with social network analysis methods. Each automatically generated scenario will be tested by a MAS for a number of times as other researchers replicate the simulation results with different random seeds. We regards data-farming as the generation of what-if scenarios and the replications for each auto-generated scenario together, not mere the replication launch script. Also, the data-farming concepts include the parameter controls and the average statistics calculation across the replicated runs of each scenario.

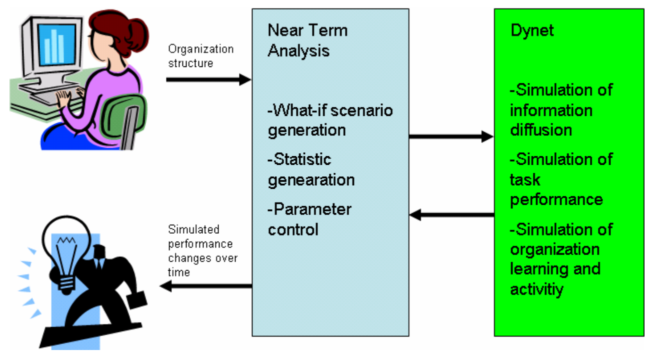

Figure 1 a simple diagram describing Near Term Analysis framework

3.2. Agent interaction mechanism

The goal of the agents of Dynet is getting the pieces of knowledge from other agents. Knowledge pieces are represented in binary strings, and an agent has partial or full bit strings that represent the knowledge pieces they have. To obtain more pieces of knowledge, each agent interacts with other agents based on a probability of interaction. We can represent the probability of interaction between Agent *i* and Agent *j* like the following formula.

$$P_{ij} = w_1 RS_{ij} + w_2 RE_{ij} + w_3 SW_{ij} + w_4 SD_{ij}$$
$$+ w_5 PD_{ij} + w_6 SD_{ij}$$
$$(\sum w_i = 1)$$

The six elements appeared in the above stand for the variables obtained from a meta-matrix that will be introduced in the next section. Among the six elements, *SDemo* for Socio Demographics and *PD* for Physical Distance are ignored because we did not have the

$$RS_{ij} = \frac{\sum_k S_{ik} S_{jk}}{\sum_n \sum_k S_{ik} S_{nk}}, RE_{ij} = \frac{\sum_k X_{jk}}{\sum_n \sum_k X_{nk}}$$
$$(n = \text{num. of agents}, k = \text{num. of target network})$$

information in the tested dataset. The meanings of the used four elements are displayed in table 1, and its specific calculation formula is also introduced in below.

Name	Meaning
Relative Similarity (*RS*)	Relative similarity of two Agents' knowledge networks
Relative Expertise (*RE*)	Relative difference of two Agents' knowledge networks
Shared Work (*SW*)	Relative similarity of two Agents' task networks
Social Distance (*SD*)	Relative closeness of Agent-to-Agent network distance

Table 2 the four factors affecting on the probability of interaction among agents in Dynet

After selecting the target agent to interact with, each agent exchanges a communication containing the binary strings and updates their own knowledge strings. The exchanged binary string includes not only the actual knowledge of the agents, but also their transitive memory such as who knows what information. Therefore, there is a chance to see the emergent behavior such as network healing phenomena from the chains of interactions. Dynet will perform the user-specified number of simulation time-points, and it will also record the degree of the knowledge diffusion over the course of the simulated time period.

3.3. Meta-Matrix

Carley (Carley, 2003) claims that the traditional social network analysis has several limitations. For example, the traditional analysis does not handle multi-modal, multiplex, and dynamically changing social networks. Furthermore, there is no way to represent agent, knowledge, resource and task at the same time with the traditional analysis method even though links and correlations between the different types of nodes are very common in the real world. Thus, she suggests using a meta-matrix representation for such a complex system. As a formal definition, the meta-matrix is nothing but an adjacency matrix of a network. However, the network contains various nodes and inter-nodetype links as described above. Because of included various node types, the network has sub networks such as agent-to-agent networks, agent-to-knowledge and agent-to-task networks. By including additional networks, we try to simulate the interactions among agents, the task performances and the knowledge exchange at the same time. With this assumption, we setup a meta-matrix for an organizational structure as shown in table 2.

3.4. Isolation Strategies

In our analysis, the threat scenarios are isolating a set of agents from an organizational structure. Therefore, the selection of the agents to isolate is the main algorithm for generating the threat scenarios. On the other hand, the social network analysis has been developed metrics to identify the key elements and players in a network. Thus, we used the metrics that detect the key players in an organizational structure, and the detected agents became the agents to isolate. There are seven measures that we used, and the measures are listed in the table 3, and their calculation is done by a dynamic social network analysis tool, Organizational Risk Analyzer (ORA, 2006).

	Agents	Knowledge	Tasks
Agents	Social Network	Knowledge Network	Assignment Network
Knowledge		Information Network	Needs Network
Tasks			Precedence Ordering

Table 2 the used meta-matrix, three types of nodes, agent, knowledge and task, are used. This matrix describes an organizational structure

Measure	Implication
Cognitive demand	Measures the total amount of effort expended by each agent to do its tasks.
Total degree centrality	The Total Degree Centrality of a node is the normalized sum of its row and column degrees.
Clique count	The number of distinct cliques to which each node belongs.
Eigenvector centrality	Calculates the principal eigenvector of the network. A node is central to the extent that its neighbors are central.
Betweenness centrality	The Betweenness Centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v, the percentage that pass through v.
Task/Knowledge exclusivity	Detects agents who exclusively perform tasks or have singular knowledge.

Table 3 the measures used to identify the key agents in an organizational structure. Most of measures only concern the agent-to-agent network of the organization. However, cognitive demand and exclusivity utilize all the networks in the meta-matrix.

3.5. Output measures and evolved organization

Finally, we need a measure to calculate the impact caused by the isolations. In this paper, we use the degree of knowledge diffusion. The knowledge diffusion (*KD*) stands for the degree of how much the agents in an organization exchanged knowledge that was exclusive to certain agents before simulation begins.

$$KD = \frac{\sum_{i=0}^{k}\sum_{j=0}^{n} AK_{ij}}{kn}$$

$n = (\text{num. of agents in a network at the time})$

$k = (\text{num. of knowledge bits})$

$\text{AK} = (\text{Adjacency matrix of Agent - Knowledge})$

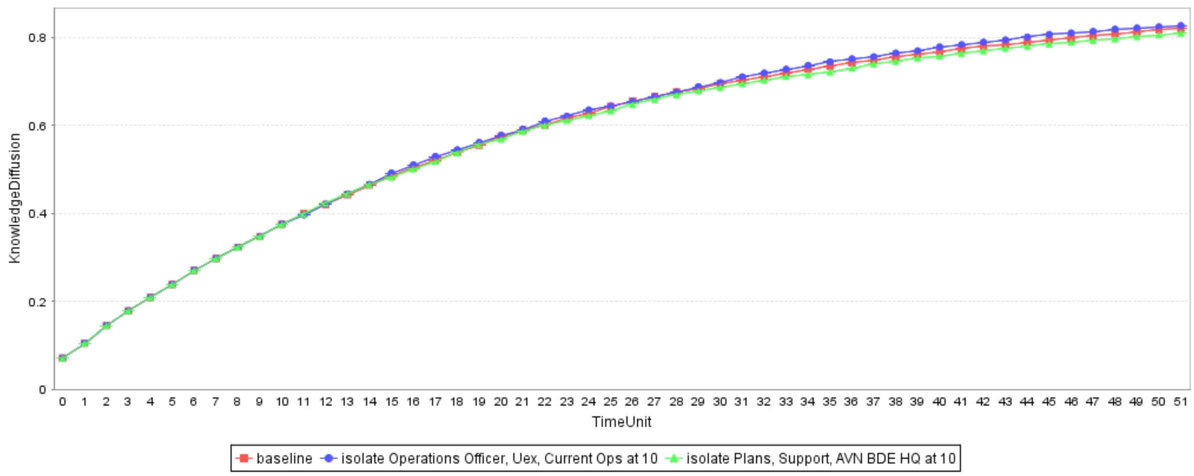

Figure 3 a line chart showing the evolving knowledge diffusion rate over the simulated time

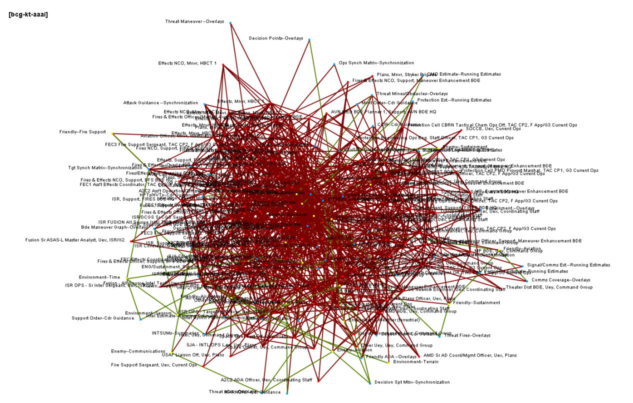

Figure 2 the visualization of a meta-matrix of a battle command group structure

4. Dataset description

For the tests of this simulation framework, we used a dataset: a Battle Command Group (BCG) C2 structure during Unit of Action experiments by the U.S. Army. We used the dataset because we have some contextual knowledge about the dataset for the implication and the validation of the results from the simulation. The BCG is the simulated command and control structures of future brigade/batallions.

The Battle Command Group (BCG) is the unit that will replace the current force battalion in the objective force. The objective force means the future army that the current U.S. Army wants to be in the future. For structure improvements, the C2 system of the BCG is investigated with several UA, the previous terminology for BCG, experiments. During the experiment, numbers of officers were put into several different cells, and each cell functioned like a command post. Though there were no restrictions to the communication within a cell, the inter-cell communication is done by electronic methods like email. During this live simulation, the participants were surveyed periodically, and the network structures were extracted from the survey. We used one of those structures, and the network consisted of 156 agents, 22 knowledge pieces and 51 tasks.

5. Result

This paper has two research purposes: simulating the threat scenarios and evaluating the outcomes of the scenarios. Therefore, we generated the scenarios based on the key agents identified by various social network measures. After the scenarios are generated, the performance measure, knowledge diffusion, is calculated for every simulated time-point, and we analyzed how the performance changed according to the scenarios. Furthermore, we evaluated each scenario based on the deterioration of the performance, and we found the best and the worst scenarios.

We applied the simulation framework to the BCG dataset. The change over time from the simulation of the BCG C2 is described in figure 3 and table 4. As we can expect, the knowledge diffusion grows until it reaches a plateau at a certain level, and the plateaus are located around 0.8, which means the agents are sharing about 80% of knowledge pieces. In figure 3, there are three lines showing the knowledge diffusion evolution results of three isolation cases: baseline that has no isolation, an isolation of ‘Operations Officer, Uex, Current Ops’ (Operation Officer) and an isolation of ‘Plans, Support, AVN BDE HQ’ (Plans AVN). The abbevration in the agents’ names stands for the offcers’ positions in the battle command group. According to the figure, we can see the same degree of diffusion until the isolation, and the diffusion rate starts getting different from the isolation timing, time 10. However, after the isolation, the case of isolating Operation Officer enhanced the knowledge diffusion, while the isolation of Plans AVN damaged the measure.

In the previous section, we regarded the isolation as a threat scenario, and it is interesting to see that the threat can make a positive result. We think that it is possible to see similar result if an agent is positioned in the edge of a network. Dynet simulation is a sequence of an agent interaction for knowledge exchanges. If an agent is not at a focal point of a network, the agent will lose chances to interact with others and cannot gather good enough information to increase the knowledge diffusion rate of the overall network. When we look at the position of the Operation Officer, he has low total degree centrality (ranked at 56 when Plans AVN at 9) and low betweenness centrality (ranked at 83 when Plans AVN at 2). On the contrary, the isolation of Plans AVN located at the center of a network decrease the diffusion rate.

Also, we found out that the exclusive knowledge that agents have affects little on the isolation effect compared to the position on a network. For instance, average rank of task exclusivity of the cases resulted the increase is higher than that of the cases showed the decrease. This means that the isolation of an agent with exclusive knowledge does not always result the decrease in knowledge diffusion.

Table 4 the improvement of the performance measures at the end time-point from battle command group C2 structure.

	Knowledge Diffusion	
	Isolated agent	Improve
Best case 1	Operations Officer, Uex, Current Ops	0.71
Best case 2	SOCCE, Uex, Current Ops	0.21
Best case 3	C4/G6 Cell G6, TAC CP1, G3 Current Ops	0.14
Worst case 3	ISR Assistant G2, TAC CP1, ISR	-0.89
Worst case 2	ACOFS G3, TAC CP1, Command Group	-0.89
Worst case 1	Plans, Support, AVN BDE HQ	-1.28

Table 5 average rank of cases that showed increase or decrease in knowledge diffusion measure, a higher rank (lower in number) means that the cases have higher value for the measure

Average rank	Case with positive effect	Case with negative effect
Cognitive demand	54.00	61.00
Total degree centrality	83.33	45.12
Clique count	65.67	45.88
Eigen vector centrality	56.00	52.24
Betweenness centrality	89.00	47.35
Task exclusivity	56.00	68.53
Knowledge exclusivity	72.33	80.59

Not only the presented analysis of the battle command group, but also there are two more additional analyses with two different datasets: allies and German command and control structures during World War II. We applied the same meta-matrix format dataset to the introduced Near-Term Analysis. The function detected important commanders and sub-organizations, and the removal of detected nodes showed similar effects, both positive and negative effects that we observed in the battle command group analysis. We will publish these two analyses in the following publication related to Near-Term Analysis.

6. Conclusion

In this paper, we used multi-agent simulation and social network analysis to estimate the near-term impact of isolations of agents in a command and control structure, a Battle Command Group. Particularly, we used some dynamic network analysis measures to select the nodes to isolate. Then, we used Dynet, a multi-agent simulation, to evolve the network with and without the selected nodes. We calculate the degree of knowledge diffusion over the simulation time as an output from the simulations.

By applying the simulation framework to the real world command and control structure, we observed some capabilities of the framework. First, the framework can detect personnel causing inefficiency in the structures. For example, the agents, ‘Operations Officer, Uex, Current Ops’, ‘SOCCE, Uex, Current Ops’ and ‘C4/G6 Cell G6, TAC CP1, G3 Current Ops’, are selected as the best isolation scenarios to increase the knowledge diffusion. According to our investigation, these agents do have some degree of exclusive knowledge compared to others. However, they are located at the margin of the structure, which makes them difficult to gather and diffuse knowledge pieces. These insufficient interaction results not-enough knowledge piece. By removing these agents, the knowledge diffusion rate can ironically be increased because the others agents are interacting with each other more tightly and the inefficient agent are removed from the calculation of the measure. On the other hand, (decrease case explanation)

We used Dynet for specific isolation strategies based on elite actors of a structure. The results were informative by utilizing historical and real-world datasets. Future work is needed to validate the used MAS, Dynet, with these isolation strategies. A portion of Dynet was validated by a paper (Schreiber and Carley, 2004). Additionally, it should be validated whether the used dynamic network measures are really capturing the key personnel in the organization. Furthermore, the used performance measures, knowledge diffusion, should be validated with more datasets to confirm whether they reflect the true performance of an organization. Also, additional performance measures need to be developed.

This paper demonstrates how we can use bridge multi-agent simulation and social network analysis. It also shows the value of data-farming environments by successfully generating and testing multiple different what-if scenarios. This framework can be used to predict the impacts of corporate personnel movements, removal of terrorists from their networks, repositioning officers in command and control structures, etc.

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