DYNAMICS OF KNOWLEDGE-SEEKING INTERACTIONS IN ORGANIZATIONAL NETWORKS

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ABSTRACT

Organizational communication structures (OCS) enable and constrain information flow and are, therefore, influential in the organization's efficiency and productivity. Companies have often reorganized their structure to improve efficiency. However, OCS is a function of the informal network as well as the formal hierarchical structure within the organization. Any analysis of OCS must include informal networks to be valid. Individual interactions are what define the OCS and aids knowledge transfer. Using Agent-based Modeling, we create OCS with agents that have the same knowledge-seeking goals but different knowledge environments. Agents develop an informal communication network through which they obtain knowledge elements to complete tasks. Their network expands through references provided by peers when the knowledge sought cannot be found within their group. We compare the networks to determine if the knowledge-seeking theory alone is sufficient to determine the OCS. Network differences indicate that theory alone is insufficient to explain the formation of informal OCS.

Keywords: organization, communication structures, agent-based modeling, simulation.

1 INTRODUCTION

Organizations are a collection of two or more individuals operating in a cooperative manner to achieve a common goal. The strength of organizations is often in the formalization of the division of labor or its organizational structure. The formal structure of an organization is typically a hierarchy in which individuals maintain different roles and levels of authority based on their position within the structure. However, coincident to this hierarchy is a social or informal structure that is comprised of relationships not defined by the formal hierarchy. The combination of these structures provides a network through which communication occurs. Organizational Communication Network (OCN) is defined as "the pattern of open channels of communication or information exchange between members of a particular group (Mullen, Johnson et al. 1991)."

Communication networks are an essential part of an organization. Organizations can be viewed as information-processing entities (Galbraith 1974). That is, the function of an organization is to process information to complete specific tasks. The implication is that the better an organization is at processing the information, the more it will be efficient. The organizational communication structure enables and constrains the flow of the information (Carley and Hill 2001) and, therefore, determines to some extent an organization's efficiency. Organizations use the formal structure to control the flow of messages vertically and horizontally (Johnson 1992); however, the informal network provides significantly more flexibility by changing the information flow. In organizations, "… the informal can cut through formal reporting

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procedures to jumpstart stalled initiatives … [or] sabotage companies' best laid plans by blocking communication … (Krackhardt and Hanson 1993)." Thus, it is important to examine the communication structure and network connections that enable or constrain communication flows.

There are several different theories regarding the formation of the informal network. Krackhardt and Stern (Krackhardt and Stern 1988) theorize that friendship links create the strongest informal network that allows an organization to perform efficiently even during a crisis. Carley and Hill (2001) suggest that the knowledge network, in addition to the people (who you know) structure, affects organizational performance. Monge and Contractor (2001) enumerate several other prevailing families of theories on the possible basis for the formation of these informal, communication networks such as theories of self-interest, cognitive theories and theories of homophily to name a few. Self-interest theories, for example, "…postulate that people make what they believe to be rational choices in order to acquire personal benefits (Harrison, Lin et al. 2007)." This implies that the reason for creating a link with another person is to acquire some benefit. Thus, a communication network formed via self-interest theories consists of connections created for personal gain. Communication networks based on homophily theories, alternately, consist of connections between individuals based on commonalities. For example, historically smokers would know other smokers within an organization. Cognitive theory researchers look to semantic networks, knowledge networks, cognitive social structures and cognitive consistency to understand how and why communication networks are formed.

The purpose of these theories is to enable researchers to study how informal communication structures in organizations effects organizational learning (Carley and Hill 2001), the impact on the opinion dynamics of an organization (Song, Shi et al. 2015), or the effect on an organization's culture (Krackhardt and Hanson 1993). The approach to these studies varies dramatically between researchers. Carley and Hill (2001) examine the effect of communication structure on organizational learning. They develop a model in which agents decide to create connections with others based on homophily and expertise. (Kleinbaum, Stuart et al. 2013) study homophilous dyadic communications within the formal structure of an organization. Krackhardt and Hanson (1993) study the advice and trust networks' drive of the informal communication structure. Song et al. (2015) model the informal networks using traditional social network structures (i.e. small-world, scale-free, tree, and fully connected networks) constrained with a degree of tolerance of the formal network to compare the time to consensus of the different informal network structures. Krackhardt and Stern (1988) attempt to identify the optimal informal network structure.

The research has been advanced from the study of different informal structures or the structures that are formed from different theories of networking. However, none of the research examines the sufficiency of one theory of networking to explain the differences, if any exist, in the networks that occur. We attempt to determine if significantly different networks are formed when the choice theory is the same but the environment is different. We use a framework that consist of creating peer-links to obtain knowledge through references from existing peer-links or links from the formal hierarchy. We utilize network analysis to compare the structures.

In this paper, we examine the minimum the sufficiency of knowledge-seeking as the basis for producing an efficient informal communication network. We examine the different communication network structures that occur from the same basic rule set and we explore the differences in efficiency created by these differing structures. We use Agent-based modeling and simulation (ABMS) to generate a communication structure. The model contains the formal structure and peer-to-peer links between managers and directors. Network links are created as workers attempt to obtain knowledge to complete the assigned tasks. The efficiency of the network is determined by the overall number of tasks completed and the total communication costs accumulated during the simulation. The communication cost is calculated as the number of requests made, including requests to self, for information to complete the task. Agents expand their peer network through references received when a peer does not have the knowledge item but knows someone that does. Several different communication network structures occur in this scenario. We use network analysis techniques to examine the differences in these networks and evaluate the efficiency of each structure.

The paper is organized in five sections. Section two describes the model used to create and explore the communication networks as well as providing the design of experiment. Section three provides the results and analysis of the networks. Section four discusses the implication of this work and the potential for future work. Section five concludes the paper.

2 MODEL

2.1 Design

Our model is designed to portray an organization that has all the knowledge required to complete its tasks. In this study, we do not attempt to analyze how new knowledge is acquired. We use a four-level hierarchy represented by a directed graph to represent the formal organizational hierarchy and peer-links to represent the informal network. Example of this hierarchy is given in Figure 1a. Peer-links are undirected connections that are the initial source of knowledge seeking. Agents at the lowest level of the hierarchy are charged with completing tasks. A task, K, is a vector of n knowledge elements [k_1, k_2, …, k_n]. Knowledge element, k, is an integer from 0 to 999. Each agent possesses a 1000-bit knowledge array, A, representing all the knowledge elements required by the organization. Agents with a zero value in the array element, A_i, do not possess the knowledge element k_i; agents with a 1 have the knowledge element.

Agents seeking knowledge that they do not possess choose an agent in their peer-link network at random. If the agent chosen possesses the required knowledge, the knowledge is transferred to the seeking agent. Otherwise, the peer agent will poll its peer network to determine if anyone has the knowledge element. If the peer finds a connection to the knowledge element, it returns a reference to the agent. The knowledge seeking agent will then establish a peer-link with the reference agent. If the agent seeking knowledge is unsuccessful in obtaining the knowledge through its peer-link network, it requests the knowledge from its supervisor designated by the formal organizational hierarchy. Supervisors without the requested knowledge will seek a reference from their subordinates first, then from their peer-link network in the same manner as an agent seeking knowledge. Supervisors can only handle a request from one agent at a time. Therefore, if a supervisor is seeking information, all other requests must wait.

The referencing process produces different configurations of the peer-link network. We measure the efficiency of each of these networks through communication costs. The communication cost is calculated as the number of requests made to gain all the knowledge elements required to complete each task and the number of tasks completed. The requests include: (1) request to self; (2) request to peer; (3) request of peer for reference; (4) request to supervisor; and (5) wait time for supervisor. From this framework, we create a simulation system in NetLogo (Wilensky 1999) to generate and examine possible configurations.

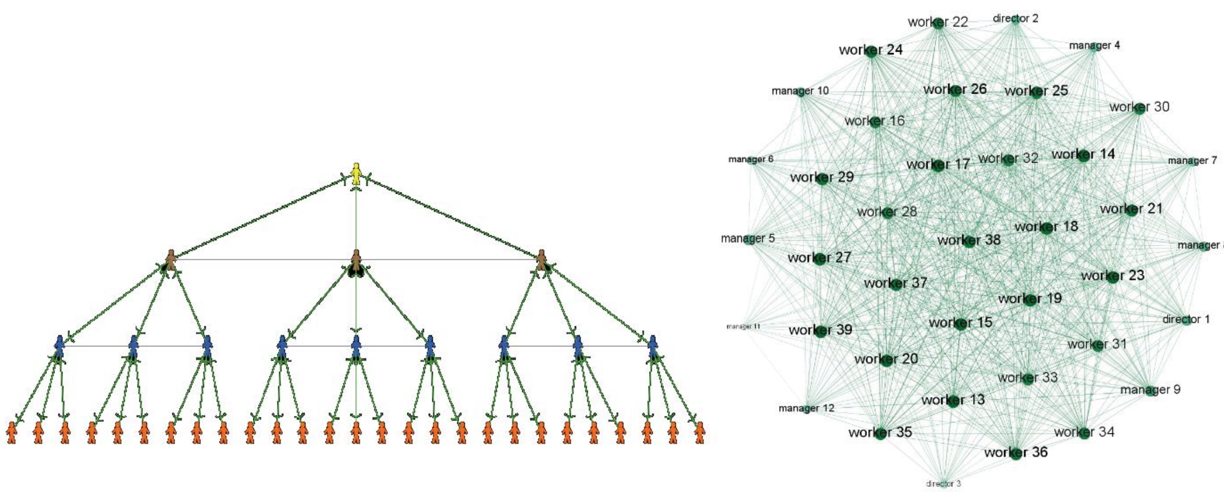
2.2 Simulation Model

The system consists of 40 agents – no agents are added or removed during the simulation. The system boundaries are as follows:

- The hierarchy has four levels – CEO, director, manager, and worker.
- Each managerial level has three subordinate agents reporting to them.
- Workers have no direct reports.
- There is a total of 40 agents in the system – 27 workers and 13 managerial agents.
- Only the 27 workers complete tasks.
- Knowledge is represented as a 1000-bit array.
    - Each agent possesses a unique knowledge array.

- A value of one in the array signifies the agent has that particular knowledge element; zero means it does not have the knowledge element.
- CEO has complete knowledge – all bits of the knowledge array are one. This is done to represent a closed system in which all knowledge is known. New knowledge is neither needed nor available.
- Directors' knowledge and managers' knowledge will vary according to the different experiments.
- Workers begin with no knowledge – all bits of the knowledge array are zero.

Three networks are established in the initial setup: (1) the supervisor (or boss) network which is a directed graph that represents the organization's top-down reporting structure; (2) a subordinate network which is the same network but with the graph direction reversed; (3) and the initial peer-link network which connects directors to other directors and managers to other managers. Tasks are randomly assigned to works and the task length is the same for all tasks throughout the simulation. The elements are chosen from a uniform random distribution of integers from 0 to 999; duplicate items are permitted. The formal hierarchy including peer-links at the managerial level is shown in Figure 1a. A sample of the resulting communication network structure generated by the simulation is shown in Figure 1b.



(a) (b)

Figure 1: (a) Formal hierarchical organization structure of the model; (b) Informal network organizational structure resulting from interactions.

2.3 Design of Experiment

The goal of the experiment is to compare networks that use the same set of rules, for connection, in different environments. In the first case, called random, the data is uniformly random throughout the system with the probabilities described in the section above. Directors have a 50% chance of having any knowledge element; managers have a 30% chance of having any knowledge element. The second case, called structured, divides the knowledge array into three distinct regions corresponding to the director groups. The first director group has extensive knowledge in knowledge region one and limited knowledge in the other two regions. That is, the director has an 80% probability of having knowledge of an element in region one but only a 35% probability of knowledge elements in regions two and three. Likewise, the managers reporting to director one have an 80% and 5% probability of having knowledge elements in region one and outside of region one respectively. These probabilities are selected to ensure that the overall knowledge probabilities in each case are the same. Workers in both cases begin the simulation with no knowledge.

In a closed system such as this, eventually all participants will acquire full knowledge (Carley and Hill 2001). However, it will occur at different times based on the informal network that evolves. Thus, this research is interested in non-steady-state behavior.

The informal network of an organization is akin to other social networks (Tichy, Tushman et al. 1979, Balkundi and Kilduff 2006). The core focus is the relationships between individuals rather than the attributes of the individual. A systematic way of studying the overall configuration of organization communication structures is, therefore, network analysis (Johnson 1992). Network analysis, in particular social network analysis, provides better insight into organization behavior than formal structure (Krackhardt and Hanson 1993). Social network analysis (SNA) focuses on the actors and relationships. It provides a structure within which we can examine the links between individuals that arise based on different theories and the structure that results from these links. SNA provides a means of evaluating empirical evidence of the communication network (Johnson 1992) to gain insight into the relationships. In previous research, empirical evidence has allowed researchers to draw conclusions about existing networks. However, this approach is only applicable to existing organizational structures. Simulation, including agent-based simulation, has developed a range of applications in social science, business, and operations management (Cheng, Macal et al. 2016) as an alternative to these field studies because it allows for researcher to study a wide variety of structure not naturally present. Agent-based modeling and simulation (ABMS) in particular is a popular method for social science (Gilbert 2008). It is a method that allows for the direct representation of individuals and relationships or interactions (Gore, Lynch et al. 2016). Hence our analysis is drawn completely from our simulation output.

The task size is set to 100 for each of the simulation runs. The base case and the structured knowledge case are each executed 30 times. The data generated for analysis includes a file of all undirected peer-links, average knowledge of the workforce, and the total communication costs between agents to gather data. The simulation executes until all workers have full knowledge. The network data is captured and transferred to Gephi for network analysis and comparison. (Gephi is an open graph visualization platform for graphs and networks. https://gephi.org/).

The research goal is to determine whether knowledge-seeking theory is sufficient for explaining OCN structure. If the comparison of the networks for the two cases show no appreciable difference, we conclude that the knowledge-seeking theory is sufficient for determining the communication network structure as the environment of the knowledge will have yielded no effect. If they are different then we conclude the must be something in addition to knowledge-seeking theory for explaining OCN structure.

3 RESULTS

The key factors compared are the time to full knowledge, the average communication costs, and the network structure elements of density, degree, betweenness, and closeness. "The density is an indicator for the general level of connectedness of the graph (Otte and Rousseau 2002)." That is, density allows us to examine the organizational communication structure in terms of the number of links to nodes. Degree centrality provides insight into the most connected nodes or the largest peer-link network. Degree centrality is the number of ties (links) attached to a node (Otte and Rousseau 2002). Betweenness allows us to explore nodes that lie on the shortest path between two other nodes (Freeman 1977). Nodes with high betweenness can facilitate or constrain information sharing in a network. (Formulas for network measurements can be found in (Otte and Rousseau 2002) and (Diallo, Lynch et al. 2016).) Based on these factors, we conclude that the networks are substantively different.

Figure 2 shows the rise of worker knowledge at selected times during the simulation. The acquisition of full knowledge is nearly identical in both cases. However, it does not examine the communication costs expended to achieve that knowledge. The communication cost is the number of requests that an agent makes to acquire knowledge elements.

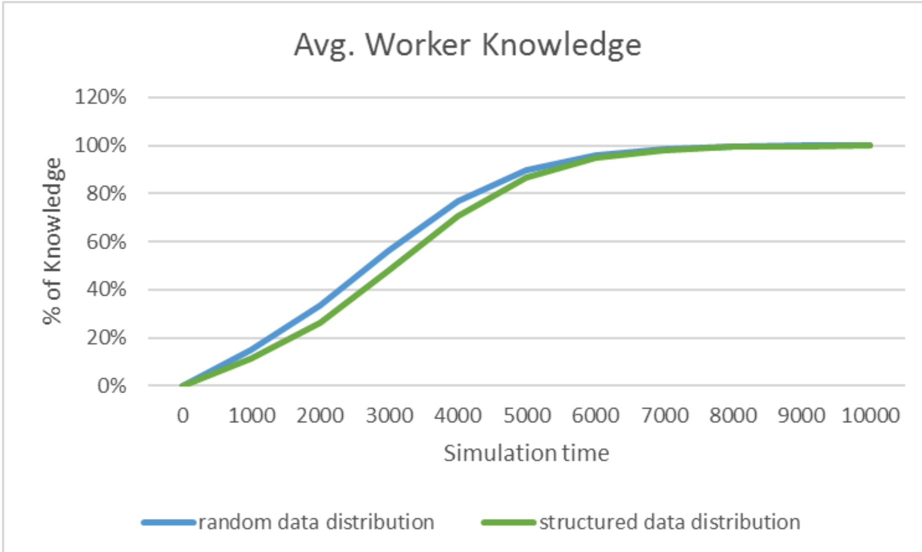


Figure 2: Average worker knowledge levels during the simulation.

Figure 3 compares the average number of requests required to complete a task. We consider this to be the communication costs. The communication cost examines the level of involvement of the peer network in the information exchange. When information is localized or specific to a group, the initial overall communication costs of the organization acquiring information is lower. As knowledge increases, the communication costs decrease. The initial gap in the graph is due to no tasks being completed in first 200 time-steps.

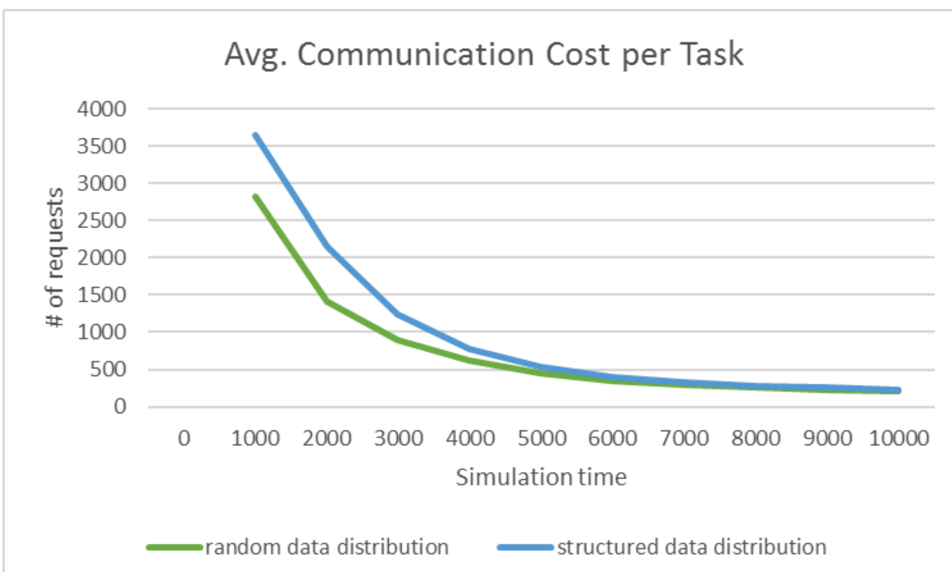
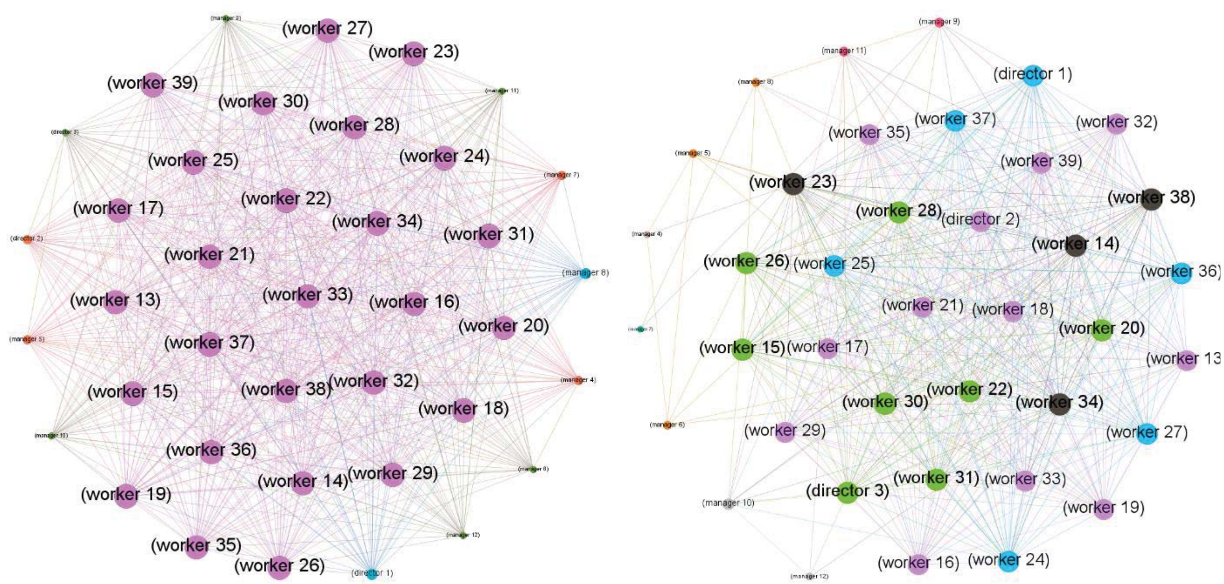


Figure 3: Average communication costs per task completed measured as the number of requests required to complete the task.

We examine the growth of the communication networks, in an environment where knowledge is randomly placed and an environment where it is structured, prior to full knowledge to determine if the networks indistinguishable. Table 1 provides a comparison of the average network measures when worker knowledge is at 25%, 50% and 100% respectively. All categories were statistically different at the 99% level. Visually, Figure 4 shows a clear distinction in the degree of the network nodes when the data is random vs. structured. The node size and color is used to reflect the degree. For example, the deeper purple in Figure 4a denotes nodes with 38 degrees (19 peer-link connections); while the lighter purple in Figure 4b denotes nores with 30 degrees (15 peer-link connections). Other colors reflect smaller degree connectedness.

Table 1: Comparison of the average network structures of the two environments at discrete knowledge levels.

	25% knowledge		**50% knowledge**		**100% knowledge**	
	Random	**Structured**	**Random**	**Structured**	**Random**	**Structured**
Simulation time	1592.80	1850.60	2729.05	2938.70	10655.25	11858.55
Communication cost	1839.13	2340.29	1022.19	1190.23	197.29	204.63
Average degree	35.56	24.25	35.56	24.59	35.56	24.87
Avg. betweenness centrality	0.49	4.69	0.43	4.62	0.49	4.64
Average closeness centrality	0.96	0.85	0.96	0.85	0.96	0.86



(a) (b)

Figure 4: (a) Network node degree connection with randomly distributed knowledge (b) Network node degree connection with structured knowledge.

The simulation time and communication costs to reach knowledge milestones is consistently greater in the structured environment than the random environment. This implies that when the knowledge is held in smaller, more specialized groups but the tasks are randomly assigned, knowledge is more difficult and costly to acquire. The network measurements provide insight into the higher costs. Network connections, as indicated by the degree centrality, are higher in the random environment. That is, more connections are being generated early on creating a more fully connected network prior to even the first task being completed. The betweenness measure provides insight into the potential for delays. Individuals that are on the shortest path to other individuals, when busy, create delays in information exchange. The structured environment has a significantly higher level of betweenness. The average density of the communication network in the random environment shows that the network is almost fully connected early on in the process while the structured network takes significantly longer to achieve the necessary level of connectedness.

The significant differences in the networks shows that knowledge-seeking alone is insufficient for determining the communication network that will form.

4 DISCUSSION

Organizational study has long used simulation in its efforts (Cohen and Cyert 1965). However, there is opportunity for simulation to have a more prominent role. ABMS is a powerful tool for generating data to test sufficiency of organizational theories. This experiment shows why most researchers have used multiple theories to explore organizational communication networks. These networks are complex interweaving the ideas of knowledge-seeking, friendship, and trust to name a few. Before we can understand the combined effect, we examine the individual effects. However, this must include an exploration of the environment. In this example, a simple change in the environment changed the network.

Theory sufficiency testing is a field that holds significant possibilities in advancing the use of modeling and simulation in organizational theory. It provides the opportunity to clarify assumptions and conditions under which one theory might be superior to another. Future work in this area will include the creation of a framework to provide a structured means of testing theory sufficiency.

5 CONCLUSION

In this paper, we study the sufficiency of knowledge-seeking interactions as the sole basis for creating an organizational communication structure. Using ABMS we created OCS in an environment where knowledge is randomly distributed and one in which agents of similar knowledge are structured into specific groups. The networks with randomly distributed knowledge completed tasks in less time with lower communication costs. There was a higher degree of centrality and density indicating that the network was more fully connected early on in the process. It also contained a lower betweenness centrality demonstrating fewer potential delays due to a given agent residing on the shortest path between two other agents. This distinct difference in the networks demonstrates that knowledge-seeking alone is insufficient to determine what network structure will be produced.

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