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## Information Exchange and Robustness of Organizational Networks

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## Abstract

The dynamics of information exchange is an important but understudied aspect of collective communication, coordination, and problem solving in a wide range of distributed systems, both physical (e.g., the Internet) and social (e.g., business firms). In this paper, we introduce a model of *organizational networks* according to which links are added incrementally to a hierarchical backbone and we test the resulting networks under variable conditions of information exchange. Our main result is the identification of a class of *multiscale networks* that reduce, over a wide range of environments, the likelihood both that individual nodes will suffer congestion related failure and also that the network as a whole will disintegrate when failures do occur. We call this dual robustness property of multiscale networks *ultrarobustness*. Furthermore, we find that multiscale networks attain most of their robustness with surprisingly few link additions, suggesting that ultra-robust organizational networks can be generated in an efficient and scalable manner. Our results are directly relevant to the relief of congestion in communication networks and also more broadly to activities, like distributed problem solving, that require individuals to exchange information in an unpredictable manner.

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## I. INTRODUCTION

Information exchange is central to the performance of a wide range of networked systems, including infrastructures such as the Internet [1], airline, postal, and transportation networks, as well as peer-to-peer file sharing systems [2], communication networks, and organizations such as public bureaucracies [3, 4] and business firms [5, 6]. Despite considerable recent exploration of the structure of real world networks [7–9], the dynamics of information exchange in networks has attracted limited attention [10, 11]. In this paper, we introduce a model of what we call *organizational networks*—networks whose purpose is to organize and coordinate the decentralized exchange of information. In focusing on information exchange, our general aim is to construct a framework for exploring organizational robustness with respect to a range of environmental stresses.

The topic of optimal organizational architecture has long been of concern to economists [5, 12–15], but their emphasis has been on efficiency rather than robustness. As a result, the economics literature on organizations has focused almost exclusively on multilevel hierarchies: acyclic, undirected branching networks that originate at a single root node and descend through a series of levels or ranks to their terminal leaf nodes. By connecting  $N$  nodes together with the minimum required number of  $N - 1$  links and creating a chain of command that is only  $L \propto \log N$  links in depth, hierarchies are almost as efficient as possible. Unlike *hub-and-spoke networks* (a special case of a hierarchy with a single subordinate level), multilevel hierarchies require each node to interact directly with, on average,  $b$  other nodes where  $b \ll N$  and is generally called the “span of control”. Thus hierarchies are attractive, scalable architectures whenever individual capacity is bounded (e.g., managers in business firms) or else not easily augmented (e.g., terminals in airline networks). Numerous variations on this basic argument have been invoked to justify the optimality of hierarchical organizational networks for exerting control [3, 12, 16], performing decentralized computations [5], distributing processing load [14], making decisions [13], and accumulating knowledge [15].

However, a critical, and often unstated, assumption of this line of investigation is that the organization’s task is decomposable into simpler subtasks, such that each subtask can be completed independently and therefore in parallel with others. Radner [5], for example, analyzes the case of summing a set of integers, a linearly associative task that is trivially

decomposable. In contrast, most modern business firms and public bureaucracies face problems that are not only large and multifaceted but also *ambiguous*: objectives are specified approximately and typically change on the same time scale as production itself, often in light of knowledge gained through the very process of implementing a solution. As a result, problem solving is almost always a collective activity [17], embodied in strategies such as mutual monitoring [18, 19] and simultaneous design [20] in which initial designs or solutions are regularly adjusted on the basis of information-rich collaboration between individuals, teams, departments, and even different organizations.

Under these circumstances, the chief problem facing an organization is not efficiency, understood roughly as being maximized by minimizing the number of costly links needed to support a defined burden. Rather, the challenge is robustness: on the one hand, protecting individual nodes from being overtaxed by the direct and indirect effects of changing and unpredictable patterns of collaboration; and on the other hand, protecting the organization as a whole from disintegration in cases where failures occur regardless. When task definition is ambiguous, individual collaborators will often exchange information with other problem solvers indirectly (e.g., via a superior), if only to ask after and obtain information about potential partners, or to keep abreast of design changes relevant to their immediate task. In such cases, the relevant intermediaries incur an information processing burden. The burden imposed by any single coordinating message may be small, but high rates of message passing in combination with concentration of traffic will tend to overload key nodes. An analogous problem arises in other kinds of organizational networks, such as the Internet, airline networks, or the postal system, which must redistribute information, personnel, or materials while simultaneously minimizing the likelihood of overload. Organizational networks that minimize the probabilities of such failures exhibit what we call *congestion robustness*.

In addition to resisting failure at the level of individual nodes, contemporary organizational networks must continue to function even when individual elements do fail. The Internet suffers little performance loss in the event that individual routers fail. Business firms can display remarkable resilience with respect to (seemingly) catastrophic breakdowns in their supply chains [17], involving loss of key component producers, equipment, personnel, and office space [21, 22]. Under conditions of environmental uncertainty and catastrophe recovery, hierarchies, in contrast, are extremely prone to cascading breakdowns because the failure of nodes near the top of the hierarchy effectively severs large subnetworks from the

main organization, thereby impairing global coordination. Organizations that reduce the adverse consequences of externally driven failures exhibit what we call *connectivity robustness*. Finally, we call organizational networks that exhibit both congestion and connectivity robustness *ultrarobust*.

## II. MODELING ORGANIZATIONAL NETWORKS

Our model requires four components: (1) an algorithm for constructing organizational networks; (2) a specification of the *task environment* from which the requirement for information exchange is derived; (3) a precise description of information exchange in terms of an algorithm for passing messages; and (4) a well defined way of establishing ultrarobustness.

(1) *Network construction algorithm*: Our algorithm takes as its point of departure the simplest version of an organizational network: a pure hierarchy with branching ratio  $b$  and  $L$  levels. The number of nodes is therefore  $N = (b^L - 1)/(b - 1)$ , where the  $l$ th level possesses  $b^l$  nodes and  $l = 0, \dots, L - 1$ . As illustrated schematically in Figure 1, the algorithm proceeds by adding links stochastically between pairs of nodes. The probability  $P(i, j)$  that two nodes  $i$  and  $j$  will be connected depends on the depth  $D$  of their lowest common ancestor  $a_{ij}$  in the backbone and also their own depths  $d_i$  and  $d_j$  respectively beneath  $a_{ij}$  (in Figure 1, for example,  $D = 2$ ,  $d_i = 2$ , and  $d_j = 3$ ). We treat links that are added in this manner differently from links that are part of the hierarchical backbone: backbone links define a node's coordinates in the network and also transmit information; added links only transmit information. Thus the hierarchical backbone may be thought of as the formal organization (chain of command) while added links correspond to the informal organization—a common distinction in the sociological literature of organizations [23].

We thus map the theoretical problem of how organizational networks should be structured into the question of what is the corresponding functional form of  $P$ . Furthermore, whatever form of  $P$  appropriate for a particular kind of organization in a given environment (e.g., an early 20th automobile manufacturing firm) may well be inappropriate elsewhere (e.g., an early 21st century software manufacturer). We therefore seek a class of functions that is sufficiently general to explore a wide range of alternative topologies yet not so general that the resulting space of networks cannot be explored systematically.

In order to restrict the possible form of  $P$  we make the following assumptions that we

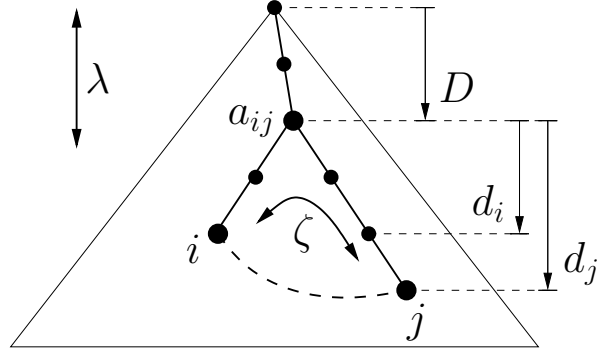


FIG. 1: Schematic of the network construction algorithm. Links to be added are chosen stochastically according to Equation 1 (without replacement) to a hierarchical backbone with  $L$  levels and branching ratio  $b$ . Equation 1 takes as its arguments the organizational distance  $x_{ij}$  between two nodes  $i$  and  $j$ , as well as the depth  $D$  of their lowest common ancestor  $a_{ij}$ . Organizational distance is defined as  $x_{ij} = (d_i^2 + d_j^2 - 2)^{1/2}$ , where  $d_i$  and  $d_j$  are measured relative to  $a_{ij}$  (see text for details). The two parameters  $\lambda$  and  $\zeta$  set characteristic lengths in  $D$  and  $x_{ij}$  respectively beyond which links are unlikely to form, thus embodying the influence of rank and homophily on link formation within an organizational network.

claim are plausible for the case of organizational networks: (1) Because it is a probability, we require that  $P$  is non-negative for all values of  $D$ ,  $d_i$ , and  $d_j$ . (2) Because immediate subordinates and superiors in the underlying hierarchy ( $d_i + d_j = 1$ ) are connected by default,  $P$  is effectively constrained to be non-zero for values of  $d_i + d_j \geq 2$  (we disallow self-connections and duplicate links). (3) We assume that individuals are identical aside from their relative position in the hierarchy; hence  $P$  is symmetric with respect to  $d_i$  and  $d_j$ . (4) All else being equal, we assume that individuals of the same rank are “closer” than individuals of different ranks: for fixed  $d_i + d_j$ , distance is minimized when  $d_i = d_j$ . Incorporating assumptions 1–3, we choose as a definition of *organizational distance*  $x_{ij}$  between two nodes  $i$  and  $j$  to be  $x_{ij} = (d_i^2 + d_j^2 - 2)^{1/2}$ . (5) We assume that  $P$  decreases monotonically with increasing  $x_{ij}$ —a familiar property of social networks known generically as *homophily* [24], or the “tendency of like to associate with like” (we note that together, assumptions 4 and 5 effectively incorporate two kinds of homophily that can be roughly attributed to similarity in class and profession respectively) (6)  $P$  is also assumed to decrease monotonically with respect to increasing  $D$ ; that is, all other things being equal, nodes of higher rank are more

likely to interact. (7) Because both homophily and rank effects will apply to varying extents across different organizations we introduce two tunable parameters,  $\zeta$  and  $\lambda$  that can be interpreted as characteristic lengths in  $D$  and  $x_{ij}$  respectively, beyond which connections become unlikely.

Incorporating assumptions (1)–(7), we propose the following stochastic rule governing the formation of new interactions:

$$P(y, x_1, x_2) \propto e^{-D/\lambda} e^{-x_{ij}/\zeta}. \quad (1)$$

We use Equation 1 to choose (without replacement) the sequence of links to be added to an initial hierarchical backbone, where different choices of  $\lambda$  and  $\zeta$  will result in different network topologies for the same choice of  $b$ ,  $L$ , and  $m$  (i.e., the same number of links added to the same backbone).

We immediately observe four stylized classes of organizational networks that arise for limiting values of  $(\lambda, \zeta)$ , as depicted in Figure 2. *Random*: for  $(\lambda, \zeta) \rightarrow (\infty, \infty)$ , links are allocated uniformly at random; that is, neither rank nor homophily has any influence on partner selection. *Team-based*: for  $(\lambda, \zeta) \rightarrow (\infty, 0)$ , links are allocated exclusively between pairs of nodes that share the same immediate superior, regardless of rank. Hence homophily is important to partner selection, but rank is not. The result is that “teams” form at all levels of the hierarchy. *Random interdivisional*: for  $(\lambda, \zeta) \rightarrow (0, \infty)$ , links are allocated exclusively between nodes whose lowest common ancestor is the single node at the top of the hierarchy. Links only form between nodes in different “divisions” (the largest subunits) of the organization, but otherwise they are allocated randomly meaning rank is important but homophily is not. *Core-periphery*: for  $(\lambda, \zeta) \rightarrow (0, 0)$ , links are added exclusively between subordinates of the top node alone. The resulting networks are characterized by a fully connected central core from which pure branching hierarchies extend. For non-zero, but small, values of  $\lambda$  and  $\zeta$  (i.e., in the vicinity of the origin in Figure 2), the core-periphery dichotomy continues to pertain, but the core extends beyond the top layer.

Finally, we identify a fifth, qualitatively distinct class of networks that arise in the central region of Figure 2 [i.e., intermediate values of  $(\lambda, \zeta)$ ]. We call this class multiscale networks because, unlike the four classes of networks defined above, whose connectivity is dominated by a single *scale* [either *local* (team-based) or *global* (random) ties], these networks display connectivity at all scales simultaneously. Multiscale networks, however, do not display

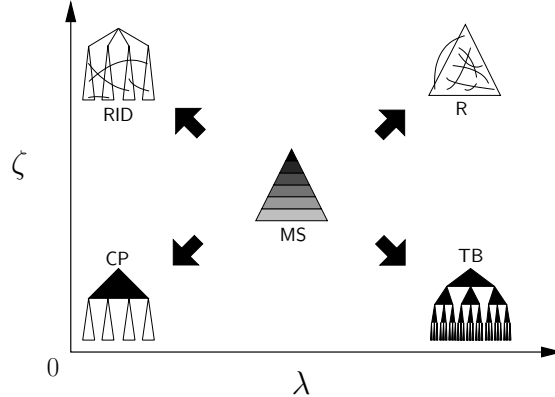


FIG. 2: Classes of networks realized in different regions of  $(\lambda, \zeta)$ -space. multiscale networks occupy a broad interior region of space, while random (R), random interdivisional (RID), team-based (TB), and core-periphery (CP) networks arise when both parameters approach their limiting values (see text for details).

*uniform* density of links at all scales—link density decreases monotonically with depth, such that the top rank (the core) exhibits the highest density—thus distinguishing multiscale networks from earlier ‘small-world’ network models [25] in which random links are distributed uniformly. This difference is critical for the problem at hand because, in a wide variety of environments, the hierarchical nature of organizational networks tends to place the burden of information exchange disproportionately on higher ranks. Thus multiscale networks and core-periphery networks have much in common. But by exhibiting significant connectivity across all other ranks as well, multiscale networks also embody the salient features of team-based and random networks—a combination that, as we show in Section III, yields desirable robustness properties.

(2) *Task Environment:* We specify the organization’s task environment in terms of the *rate* and *distribution* of messages to be exchanged between individual problem solvers in the course of completing some global task. Stable environments correspond to a low rate of information exchange  $\mu$  (defined as the average number of messages initiated by each individual at each time step), whereas volatile environments are equivalent to high  $\mu$ . In addition to volatility, the environment may also allow for varying task decomposability: tasks that are nearly decomposable correspond to a pattern of message passing that requires



only individuals within the same team (i.e., nodes with the same immediate superior) to communicate; tasks that cannot be decomposed even approximately require constant communication between remote, as well as nearby, individuals. In practice, for each message initiated at a node  $s$  at rate  $\mu$ , a corresponding target node  $t$  is selected by weighting all nodes a distance  $d$  from  $s$  with a factor  $\exp\{-d/\xi\}$ , normalizing appropriately, and then choosing  $t$  at random according to the resulting distribution. Thus, for  $\xi = 0$  (local dependencies only) all messages are to be delivered to local targets, while for  $\xi = \infty$  (global dependencies)  $t$  is chosen uniformly at random.

(3) *Information Exchange*: Once initiated, a message is passed from source to target through a chain of intermediaries. Each node in the chain must process each message that it initiates or receives in the same time step by forwarding it to an immediate neighbor who shares the lowest common ancestor (in the hierarchy) with the target node (in case of equally distant neighbors, one such neighbor is chosen at random). Thus each node  $i$  is assumed to have complete information regarding its own location in the hierarchy, as well as the locations of its neighbors. Each node also has general information about targets beyond its immediate neighborhood—an assumption we call *pseudo-global knowledge*. If node  $i$  is an indirect superior of  $t$  in the hierarchy, then pseudo-global knowledge implies that  $i$  “knows” in which of the subunits  $t$  belongs but not specifically where (or else  $i$  could send the message directly); if  $t$  is not beneath  $i$ , then the message must be passed up or across the hierarchy until it locates the correct subunit. Pseudo-global knowledge therefore embodies an inherent tradeoff between quantity and quality of information: high ranking nodes tend to possess general information about more subordinates than nodes in lower ranks but have less specific information about any one subordinate.

Pseudo-global knowledge can also be interpreted in terms of distributed problem solving, where the target’s address, rather than being the location of an individual in an organization, can be thought of instead as a complete description of the solution required by a particular problem (by analogy, the call number of a book in a library characterizes the knowledge contained therein). Neither the knowledge itself nor its address, however, is initially available to the problem solver (the sender) who must therefore poll his or her acquaintances in the organization for a relevant recommendation. The closer an acquaintance is to the eventual target, the more accurately he or she can direct the problem solver, and the fewer intermediaries are required to conclude the search (we do not consider the case where the

relevant knowledge does not exist in the organization). The progress of a message therefore corresponds to a problem solver acquiring increasingly specific knowledge about the problem to be solved; a process that can only succeed with the cooperation of increasingly knowledgeable intermediaries.

(4) *Measures of Robustness:* As defined in Section I, the property of ultrarobustness requires an organizational network to exhibit both *congestion robustness*, the capacity to protect individual nodes from congestion, and *connectivity robustness*, the capacity to remain connected even when individual failures do occur. To measure congestion robustness precisely, we initiate an average of  $\mu$  messages per node each time step over a total of  $T$  time steps, where messages are removed from the system upon reaching their designated target. Assuming that each node  $i$  can process a maximum of  $R_i$  messages per time step without failure, then an organizational network will, on average, remain free of failures only if  $R_i > r_i = \mu N \rho_i$  for all  $i$ , where  $r_i$  is the rate of messages to be processed by node  $i$  and *congestion centrality*  $\rho_i$  is the probability that any given message will be processed by  $i$ . While congestion centrality is similar to other centrality measures in graph theory [26] and social network analysis [27], it is more appropriate to the problem of information exchange in that it depends on task decomposability ( $\xi$ ) and the message passing algorithm as well as a node's position in the network. (For example, when message passing is sufficiently global ( $\xi$  is large), high-ranking nodes will be more central than low-ranking nodes, as would be the case for betweenness centrality [27]. When message passing is purely local ( $\xi \rightarrow 0$ ), nodes at all ranks (other than the bottom rank) will be equally central.) Assuming that environmental volatility ( $\mu$ ) and individual capacities ( $R_i$ ) are beyond the control of the organization, a robust architecture is one that reduces the congestion centrality—hence the likelihood of failure—of its constituent nodes. We therefore associate congestion robustness with the reduction of maximum congestion centrality  $\rho_{\max}$  over the entire network (we have also considered  $\langle \rho \rangle$ , obtaining qualitatively similar results).

Even a network that is highly robust with respect to congestion related failures can suffer failures that, like sickness, accidents, sabotage, attack, and natural disasters, are imposed upon it from the outside [17, 21, 22]. In accordance with previous work [28–30], we therefore define connectivity robustness in terms of the fractional size  $C = S/(N - N_r)$  of the largest connected component  $S$  remaining after the removal of  $N_r$  nodes. Because different removal strategies have previously been shown to yield dramatically different conclusions regarding

the connectivity robustness of other classes of networks [28] we have examined a number of such strategies: preferential elimination of nodes by rank (*top-down*); elimination of nodes radiating out from a random start point (*cascade*); preferential elimination of highly connected nodes (*hubs*); and uniformly random elimination (*random*).

### III. RESULTS AND DISCUSSION

We now investigate congestion and connectivity robustness of organizational networks as measured by  $\rho_{\max}$  and  $C$  respectively, as a function of both environmental conditions  $(\mu, \xi)$  and network topology  $(m, \lambda, \zeta)$ . Before commencing, we note that when  $\mu = 0$  (i.e. a static environment) and in the absence of exogenous failures, all networks perform identically. Efficiency arguments similar to those outlined in Section I therefore dictate that pure hierarchies ( $m = 0$ ) will be superior to all other network topologies. Thus in the trivial limit of an unchanging environment, our model is consistent with the standard economics literature on organizations (e.g. [5, 12]).

*Congestion robustness* We first consider message congestion associated with an intermediate level of task interdependency,  $\xi = 1$ . Figure 3A shows  $\rho_{\max}$  for a fixed network density  $m = N$  as a function of the network topology parameters  $\lambda$  and  $\zeta$ . Equating the axes of Figures 2 and 3A, we can infer that multiscale networks minimize congestion at least as well, and generally much better than, the other four generic network classes. Furthermore, the congestion minimizing property of multiscale networks persists over a broad region of the parameter space, ensuring that the congestion robustness property is stable with respect to small changes in parameters. Core-periphery networks (bottom left) can also exhibit desirable congestion properties. But because their performance depends so heavily on the relatively small population of nodes in the core, they suffer from extreme sensitivity to parameter selection with the best and worst performing networks arising for almost identical choices of parameters.

Figure 3B generalizes the above result by comparing  $\rho_{\max}$  for the different network classes over the full range of network density  $m$  (where particular choices of parameters have been used as proxies for each class). We note that  $\rho_{\max}$  eventually decreases as a function of increasing network density  $m$ , regardless of the procedure used to add links, and that when  $m$  is sufficiently large, all networks perform similarly. However, Figure 3B also points to

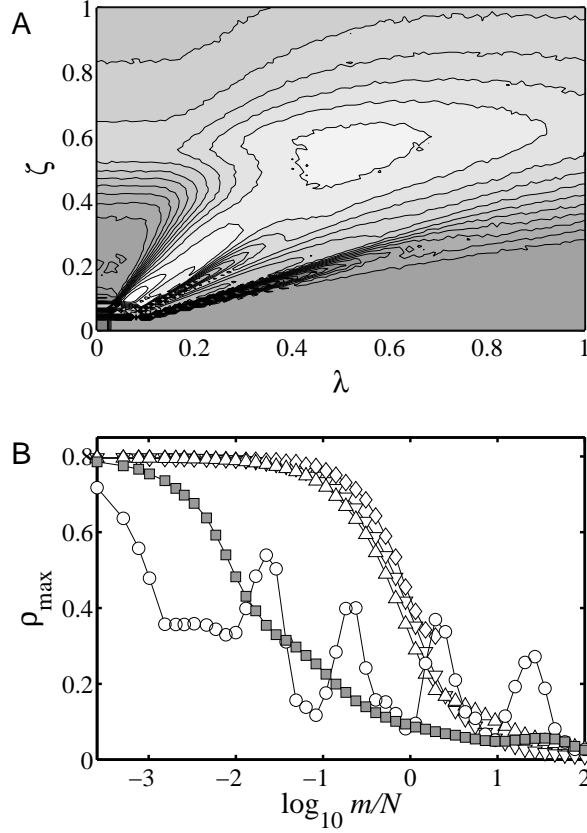


FIG. 3: Congestion centrality  $\rho_{\max}$  as a function of the network parameters  $(m, \lambda, \zeta)$ . For both plots, the underlying hierarchy of the networks examined here has  $N = 3905$  nodes with branching ratio  $b = 5$  and depth  $L = 6$ . A: Contour plot of  $\rho_{\max}(\lambda, \zeta)$  for  $\xi = 1$  averaged over an ensemble of 100 networks. Lighter regions correspond to lower values of  $\rho_{\max}(\lambda, \zeta)$ . For each parameter pair  $(\lambda, \zeta)$ ,  $m = N$  links are added and the resulting network is tested by initiating messages at each node with probability  $\mu = 2.561 \times 10^{-3}$  for  $T = 10^3$  time steps (i.e. an average of 10 messages are generated per time step). The broad local minimum centered around  $(\lambda, \zeta) = (0.5, 0.5)$  corresponds to multiscale networks. B: Change in  $\rho_{\max}$  with the addition of links. The networks tested here are random ( $\lambda = \infty, \zeta = \infty, \nabla$ ), team-based ( $\lambda = \infty, \zeta = 0, \diamond$ ), random interdivisional ( $\lambda = 0, \zeta = \infty, \Delta$ ), core-periphery ( $\lambda = 0.1, \zeta = 0.15, \circ$ ), and multiscale ( $\lambda = 0.5, \zeta = 0.5, \square$ ). Each data point is the average of 100 realizations. In the case of multiscale networks, most of the reduction of  $\rho_{\max}$  is obtained by the addition of only  $m = N$  links (the same holds for  $\langle \rho \rangle$ ).

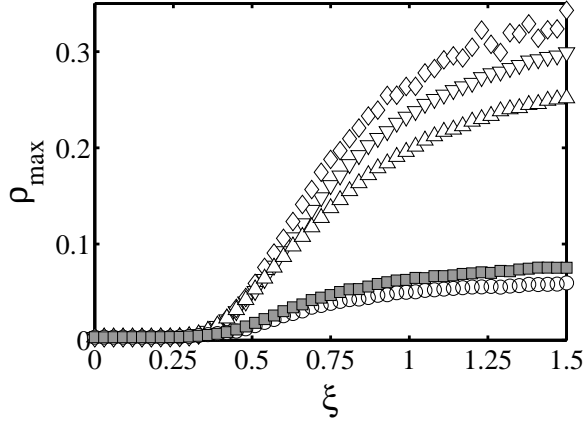


FIG. 4: Variation of congestion centrality  $\rho_{\max}$  as a function of  $\xi$ , where increasing  $\xi$  corresponds to decreasing task decomposability. Symbols correspond to the same parameter choices of  $(\lambda, \zeta)$  as in Figure 3B, with 100 samples per data point. Multiscale networks perform almost as well as core-periphery networks over the entire range of  $\xi$ , and significantly better than all other classes (random, random interdivisional, and team-based) for any but completely decomposable ( $\xi \rightarrow 0$ ) tasks.

some less obvious conclusions: 1)  $\rho_{\max}$  does not necessarily decrease monotonically with  $m$ . In particular, the congestion experienced by the most congested node in a core-periphery network can increase significantly as more edges are added, before falling again, giving rise to oscillations periodic in  $\log(m/N)$  (a consequence of the sensitivity to parameters noted above). 2) The drop in  $\rho_{\max}$  occurs an order of magnitude earlier for multiscale networks than for random, random interdivisional, and team-based networks. In fact, almost all of the drop in  $\rho_{\max}$  for multiscale networks occurs for  $m \approx N$ , which for large  $N$  is negligible compared with  $m_{\max} = O(N^2)$ .

Figure 4 continues the comparison between multiscale and other classes of organizational networks, extending it across the entire range of environmental complexity  $\xi$ , for fixed  $m = N$  and for the same canonical choices of  $(\lambda, \zeta)$  as in Figure 3B. In the limit of full task decomposability  $\xi \rightarrow 0$ , at which messages are passed exclusively between closely separated individuals, all types of organizational networks perform equally well. As decomposability decreases, however, large differences in congestion robustness manifest themselves, with multiscale networks always performing almost as well as any other class, and much better than most. Furthermore, while core-periphery networks can also perform well, outperforming

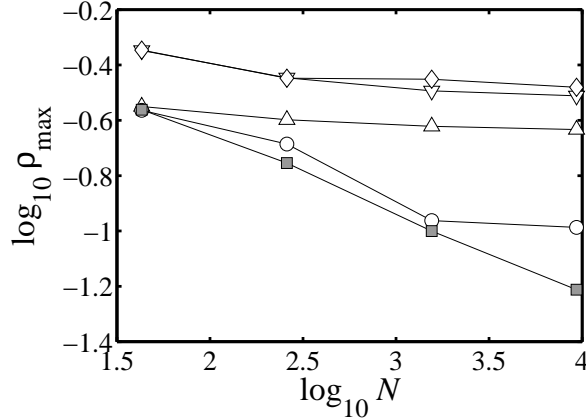


FIG. 5: Scaling of  $\rho_{\max}$  with increasing network size  $N$  (symbols represent the same choices of  $(\lambda, \zeta)$  as in Figure 3B). The task environment is given by  $\xi = \infty$  and constant  $\mu$  (i.e., individual nodes send the same number of messages independent of network size), and  $N$  is increased by fixing the branching ratio  $b = 6$  and increasing the number of levels  $L = 3, 4, 5,$  and  $6$  (i.e.,  $N = 43, 259, 1555,$  and  $9331$ ). Congestion centrality  $\rho_{\max}$  rapidly approaches a constant for team-based, random, and random interdivisional networks, and also appears to approach a constant at large  $N$  for core-periphery networks, while for the multiscale example given,  $\rho_{\max}$  decreases roughly as  $N^{-0.28}$ .

multiscale networks for some parameter choices, they continue to exhibit the same sensitivity to parameter choices mentioned above (i.e., a slightly different choice of parameters would generate much worse core-periphery results (circles) in Figure 4). multiscale networks display no such sensitivity; hence they represent a more reliable solution to congestion robustness.

Finally, for fixed  $\mu$  (volatility), congestion increases, regardless of topology, as a function of organizational size; that is, an organization can break simply under the burden of its own coordination requirements [31]. However, the manner in which congestion increases with  $N$  can vary across different network topologies, leading to large differences in the maximum size that an organization can attain in any particular environment. In particular, for large  $N$  the maximum congestion  $r_{\max} = \mu N \rho_{\max}$  at any one node scales linearly with  $N$  for random, random-interdivisional, team-based, and core-periphery networks but scales slower than linearly for multiscale networks. Thus multiscale networks display the surprising property that congestion centrality  $\rho_{\max}$  actually decreases with the size of the system (while approaching a constant for the other network classes)—a result we confirm in Figure 5. Another way to

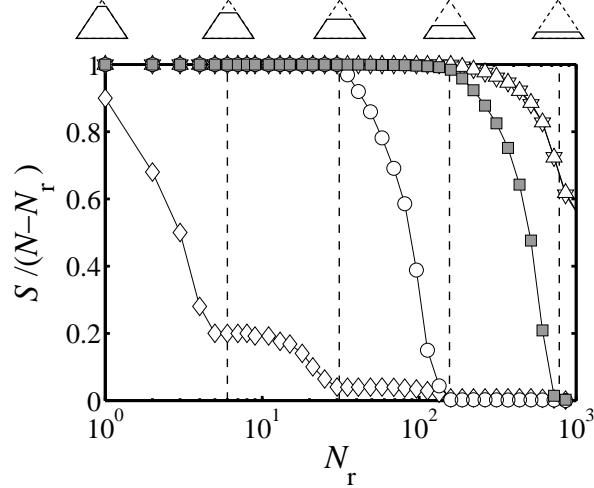


FIG. 6: Connectivity robustness of multiscale networks as measured by the largest cluster size  $S$  after targeted removal of  $N_r$  nodes. Cluster size is normalized by the size of the remaining network  $N - N_r$ . The networks are same as those described in Figure 3B with 10 samples per data point. Nodes are removed according to a top-down targeting strategy (see text) where  $N_r$  is increased until the top five levels of a possible six have been eliminated. The hierarchies depicted and dashed vertical lines correspond to complete removal of nodes down to a depth of 1, 2,  $\dots$ , 5. Random and random interdivisional networks are the most resilient to this form of network degradation while team-based networks perform poorly. multiscale networks, however, are almost as robust as random networks. In the case of  $(\lambda, \zeta) = (0.5, 0.5)$ , disintegration of the remnant components begins only after four of the six levels of the hierarchy are removed.

interpret the scaling of  $r_{\max}$  is in terms of the maximum size  $N_{\max}$  attainable by an organization, given some constraint  $R_{\max}$  above which failures become inevitable. In Figure 5, for example, setting  $R_{\max} = 570$  yields estimates of  $N_{\max} \approx 1600$  for random networks,  $N_{\max} \approx 1800$  for team-based networks,  $N_{\max} \approx 2400$  for random interdivisional networks,  $N_{\max} \approx 5500$  for core-periphery networks, and  $N_{\max} \approx 9300$  for multiscale networks. In other words, given the same individual-level capacities and the same environmental conditions, multiscale networks can grow to nearly twice the size of the next best class without incurring failures.

*Connectivity Robustness* As discussed in Section II, the second aspect of robustness that is of interest to organizational networks is their capacity to remain connected and thereby

functional in the event of failures, whether induced endogenously (as with congestion) or exogenously. To quantify connectivity robustness we measure  $C = S/(N - N_r)$  after the targeted removal of  $N_r$  nodes, where we have studied a number of different targeting strategies, specified in Section II. In Figure 6, we present the results for the *top-down* elimination strategy, as it results in the most damaging choice of targets, and also is the most likely result of congestion related failures (even in multiscale networks, congestion is concentrated in the top ranks). Team-based networks are by far the least robust of the five classes, followed by core-periphery networks, while random and random interdivisional are the most robust. multiscale networks, however, are almost as robust as random networks, performing measurably worse only after all of the organization but the bottom rank has been eliminated. The other targeting strategies yield similar results, except that all classes of networks perform better than in the top-down case, and that core-periphery networks replace team-based networks as the worst performing class when the hubs strategy is employed.

Taken together, the above results suggest that multiscale networks display a remarkable combination of properties. 1) Over a wide range of environmental conditions, multiscale networks minimize the likelihood of congestion related failure. 2) Even in the event that failures occur anyway, multiscale networks remain extremely resilient to disconnection. 3) No other class of organizational networks studied exhibits both congestion and connectivity robustness: core-periphery networks handle congestion well but are easily disconnected; random and random-interdivisional networks are difficult to disconnect, but easy to congest; and team-based networks are bad in both senses (where this last observation suggests that commonly held assumptions about the efficacy of teams [32] may be overly broad). Hence multiscale networks are not only ultrarobust but appear to be uniquely so. 4) multiscale networks achieve ultrarobustness efficiently in the sense that most of the attendant benefits are generated by a relatively small number  $O(N)$  of additional links. 5) The superior robustness of multiscale networks also conveys better scaling properties than other classes of networks in that for a given level of environmental volatility  $\mu$ , multiscale networks can grow to larger sizes before suffering failure. 6) The properties of multiscale networks are themselves robust in the sense that they are insensitive to small (or even quite large) changes in the network parameters  $\lambda$ ,  $\zeta$ , and  $m$ . Networks resembling multiscale networks may therefore be expected to arise in real world business firms and bureaucracies, at least some of which do appear to display properties that resemble our notion of ultrarobustness [17, 21, 22].



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