ABSTRACT
A growing literature on human networks suggests that the way we are connected influences both individual and group outcomes. Recent experimental studies in the social and computer sciences have claimed that higher network connectivity helps individuals solve coordination problems. However, this is not always the case, especially when we consider complex coordination tasks; we demonstrate that networks can have both constraining edges that inhibit collective action and redundant edges that encourage it. We show that the constraints imposed by additional edges can impede coordination even though these edges also increase communication. By contrast, edges that do not impose additional constraints facilitate coordination, as described in previous work. We explain why the negative effect of constraint trumps the positive effect of communication by analyzing coordination games as a special case of widely-studied constraint satisfaction problems. The results help us to understand the importance of problem complexity and network connections, and how different types of connections can influence real-world coordination.

Categories and Subject Descriptors
J.4 [Social and Behavioral Sciences]: Economics; E.1 [Data Structures]: Graphs and Networks; F.1.3 [Computation by Abstract Devices] Complexity Measures and Classes—machine-independent complexity

General Terms

Keywords
human-subject experiments, graph coloring, coordination, game theory, social network

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1. INTRODUCTION
Networks are a key element of social, economic, and political interaction. Social scientists have argued that connections in a network affect health outcomes [12], social behavior [27], and economic exchange [16, 8]. In medicine and computer science, network structure has been identified as a key determinant of the spread of human and computer viruses [23, 30]. Despite the prevalence of networks in social situations and the vast amount of knowledge that has been accumulated about network structures across a broad spectrum of human endeavors, we still know relatively little about the effects of networks on strategic interaction and group outcomes.

In this paper we study how networks facilitate groups solving coordination problems. We show that network connectivity structure (as given by the adjacency matrix of the underlying graph) affects outcomes when groups are incentivized to solve common tasks. We show that there is an interaction between the connectivity of the network and the complexity of the task under consideration.

How do we build networks that maximize the efficiency with which distributed agents can achieve coordination? Watts [31] noted the problem but could not find a satisfactory answer, considering it “a hard question to answer, requiring as it does a balance between local capacity constraints and global (system-wide) performance.” Previous work in this vein concluded that greater network connectivity improves coordination. Kearns et al. [18] explain that adding chords to a cycle “apparently makes the collective problem easier by reducing the number of links coloring conflicts must travel to be resolved.” McCubbins et al. [20] conclude that “increasing the density of the network, ceteris paribus, can improve coordination.”

Our results show that the coordination-enhancing effect of additional edges is only true under certain narrow conditions. Higher connectivity can impede coordination because the network not only defines the amount of communication; it also constrains the number of solutions to the coordination problem. In particular, we show that adding “constraining edges” that eliminate solutions causes groups to be less successful in solving the coordination game (even though these edges also increase communication), whereas adding “redundant edges” that facilitate communication without affecting the number of solutions causes groups to be more successful. In the Conclusion, we provide a complexity-
theoretic explanation for this finding. We hope this work will help unify the disparate game-theoretic and complexity-theoretic network literatures identified by Schweitzer et al. [26].

Our distinction between constraining and redundant edges may help to resolve a conflict in the literature on networked coordination. Observational studies have come to differing conclusions about the effect of network structure on coordination and cooperation: while some argue that network connections help foster coordination [24], others argue that more connections hinder efforts at coordination [1, 13]. We show that some edges constrain the number of solutions to the coordination problem, while others merely increase communication without affecting the number of solutions. Further, we show that the former hinders coordination while the latter helps it.

2. GRAPH COLORING, CONNECTIVITY, AND COMPLEXITY

To study experimentally how network structure affects coordination, we use a distributed version of the Graph Coloring Problem (GCP), first adapted for experiments by Kearns et al. [18]. In our experiments, each of 16 human subjects controls the color of one node in a network, and the subjects are asked to choose a color from a choice of three or four, so that no two directly connected nodes share the same color. (A coloring that satisfies this condition is called a proper coloring of the graph.) Each subject can change the color of his node costlessly at any time and can only observe the color of their network neighbors, though they also have two pieces of weak global information: the elapsed time and the percentage of edges whose end nodes have different colors. If all the subjects together achieve a proper coloring of the graph within three minutes, they are each paid a dollar. Each experimental session included about 35 trials.

The GCP is a workhorse problem in computer science, operations research, and applied mathematics, with applications to complex allocation problems like air traffic management [5] and radio channel assignment [19]. The GCP is a constraint satisfaction problem that is known to be equivalent (under polynomial-time reductions) to other important combinatorial optimization problems. It is used to model complex phenomena because it is simple to describe but can be difficult to solve, and these qualities make it an ideal experimental task. The distributed GCP is a natural analog to many social settings in which decisions are not centrally coordinated, but rather arise as a byproduct of the interaction of decentralized decision makers. From a game-theoretic perspective, because there are multiple proper colorings, and each proper coloring constitutes a pure-strategy Nash equilibrium, the distributed GCP is a coordination game [22].

Even with pure common incentives and plenty of information, this coordination game is a difficult one. Computer scientists have shown that coordination problems such as the graph coloring problem can be extremely difficult even for a centralized decision-maker. In particular, it is shown that the decision problem whether a graph is k-colorable for $k \geq 3$ is NP-complete [14]. Even if the graph is known to be k-colorable, finding a proper $k$-coloring is shown to be NP-hard for $k \geq 3$ [17]. There are highly efficient algorithms for checking if a graph is 2-colorable and finding a proper coloring if it is. But until recently, even for 2-colorable graphs it was not clear that distributed human agents could find proper colorings. Pioneering experiments of Kearns et al. [18] and their subsequent elaboration by McCubbins et al. [20] have clearly demonstrated that without conflicting incentives, small groups of subjects (up to 38) can solve the distributed 2-coloring problem. Both studies conclude that increased network connectivity leads to faster solution times.

This paper is motivated by the hypothesis that the effect of connectivity on solvability is not always positive. This hypothesis, that some connections impede coordination, can be deduced from computational complexity theory.

A key to understanding the complexity of individual instances of an NP-complete problem is the number of solutions (proper colorings in the case of graph coloring problem). It is well known in the literature on computational complexity that detecting whether a NP-complete problem instance has a unique solution is as hard as detecting whether it has any solution [29, 9]. Furthermore, for the important subclass of NP-complete problems called constraint satisfaction problems—of which graph coloring is a member—there are several centralized algorithms for finding a solution whose speed improves with an increase in the number of solutions [25, 21, 9]. Theoretical evidence shows that the complexity of 3-coloring a 3-colorable graph increases nonlinearly as the number of proper colorings decreases and is highest when the number of proper colorings is small or unique [29].

To understand the effect of adding edges on the solvability and solution time for the graph-coloring problem, one must consider the effect of adding edges on the number of solutions or proper colorings. Starting with an existing graph, we call any additional edge constraining if it decreases the number of proper $k$-colorings. On the other hand, any additional edge whose constraint is implied by the existing edges, we call redundant. Redundant edges do not decrease the number of proper colorings.

Guided by complexity considerations, we propose two hypotheses about the effect of increased connectivity on the solvability of the distributed GCP.

H1: Increasing the number of constraining edges, ceteris paribus, will decrease the probability of human subjects successfully solving the graph-coloring problem.

H2: Increasing the number redundant edges, ceteris paribus, will increase the probability of human subjects successfully solving the graph-coloring problem.

Instance complexity also explains why previous work concluded that higher connectivity is good for collective action. This work focused on 2-colorable graphs, and all such graphs are maximally constrained. Since a minimally connected bipartite graph (a tree) has a unique (up to isomorphism) 2-coloring, every additional edge which maintains 2-colorability is redundant. Our experiments use 3- and 4-colorable graphs, so that we have the opportunity to add constraining edges, edges that actually decrease the number of solutions to the coloring problem.

2.1 An Illustration of Constraining and Redundant Edges in 3-Colorable Graphs

We illustrate the effect of adding edges on the number of proper colorings by considering the simple network in Figure 1A. Figure 1A presents a line with a single added edge—a minimally constrained connected 3-colorable graph. If subjects select colors in order from left to right, and each subject is given three colors from which to choose, then the leftmost node can select any one of the three colors, the next can select either of the two remaining
colors, and the third node must pick the one color unused by the first two. The rest of the 13 nodes can choose either one of the two colors not chosen by the preceding node. The number of solutions to the GCP on this network is $3 \times 2 \times 1 \times 2^{13}$, or 49,152.

If we add a constraining edge between the second and fourth nodes of the graph in Figure 1A, the number of choices available to the fourth node decreases from 2 to 1, reducing the number of solutions from 49,152 to 24,576. We can continue adding constraining edges between all pairs of nodes $v_i$ and $v_{i+2}$, reducing the number of solutions by half with each new edge, until we arrive at the graph in Figure 1B, a line of tessellated triangles, for which there are only six solutions. This is a maximally constrained 3-colorable graph; a 3-colorable network can have no fewer than six solutions because there are six permutations of three colors.

Finally, starting with a maximally constrained network as in Figure 1B we can add redundant edges between any two nodes that must have different colors as implied by the existing constraints, until we create the graph in Figure 1C (in which the original line is curved for the sake of clarity). These edges are redundant, because they do not affect the number of solutions to the graph-coloring problem. These additional edges do, however, provide subjects more information about each other’s actions.

**3. EXPERIMENTAL RESULTS**

Our experiments systematically vary the number of constraining and redundant edges in the graphs our subjects attempt to solve. For $k = 3$ or 4, we generate a series of $k$-colorable graphs from minimal constraint to maximal constraint to considerable redundancy: we start with a $k$-colorable graph with minimal number of edges and then add a series of constraining edges while maintaining $k$-colorability until the number of such edges is maximized. We then add a series of redundant edges while maintaining $k$-colorability. The order in which we presented these graphs to our subjects was randomized. The networks are all “small-world” networks [32] that are designed to limit leadership or hierarchy, unlike “scale-free” networks in which the degree distribution follows a power law [4]. Because the election of a leader helps autonomous agents to solve coordination problems, and because variance in degree (which is locally observable in our experiments) would facilitate leadership election, we hold the variance in degree close to zero. Examples of 3-colorable graphs used in our experiments are shown in Figure 1.

We conducted experiments with five different groups of 16 subjects (all undergraduates at the University of California, San Diego). We collected data from 179 different trials to solve instances of the GCP. Of those 179 attempts, 75 trials involved 3-colorable graphs and 104 involved 4-colorable graphs. The payment for coordination was $1 per subject and groups had three minutes to achieve coordination. Each experimental trial ends either when the time limit is reached or the group achieves coordination successfully, and all subjects in the experiment know this. Each experimental group completed a large subset of the 3- and 4-colorable graphs to allow us to make within- and between-group comparisons.

The computer interface that subjects use provides them with a view of the other nodes to which they are connected and the degree of each of these nodes. The interface also provides subjects with a bar showing the portion of the network already solved, and a time bar showing the amount of time remaining. Subjects are only paid if the group successfully achieves coordination. All these aspects of the experiment (but not the full structure of the networks) were common knowledge among the subjects.

The experimental results indicate that network structure has enormous effects on a group’s ability to solve the coordination problem. In particular, constraining edges clearly hinder coordination, and redundant edges clearly help it, as shown in Figure 2. In fact, successful coordination depends crucially on the number of constraining and redundant edges in the network connecting players. The charts in Figure 2 show that the proportion of trials solved decreases with the number of constraining edges until the graph is fully constrained, at which point the proportion solved increases with the number of redundant edges. At the minimum number of constraining edges, both 3- and 4-colorable graphs were solved in every trial. With the addition of more constraining edges, success rates dropped precipitously, and without redundant edges, subjects were completely unable to solve maximally-constrained graphs of either three or four colors.

Figure 2 clearly shows that adding edges can impede coordination. However, the addition of redundant edges can make an otherwise unsolvable problem tractable. Adding these edges does not change the actions, outcomes, incentives, or solutions to

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**Figure 1. Examples of three-colorable graphs with varying degrees of constraint and redundancy. Bold edges in (C) belong to the subgraph in (B), and bold edges in (B) belong to the subgraph in (A).**

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the game; it simply increases the amount of information available to actors. Nonetheless, the frequency with which subjects solved maximally-constrained graphs rose sharply with the addition of redundant edges. This results show that redundant edges facilitate coordination even when we start with the most difficult coordination problem possible for a given chromatic number.

While constraining edges inhibit coordination, each constraining edge has both a positive and a negative effect, that is, it allows two nodes to communicate and it reduces the number of solutions. We use a statistical model to estimate the relative strength of the effects of communication and constraint. Specifically, we employ a random-effects logistic regression using the combined data from 3- and 4-colorable graphs. The results are presented in Table 1.

To estimate directly the effect of constraint in our statistical model, we introduce a new measure, Random Solution Likelihood (RSL). RSL is the probability of reaching a proper coloring by chance if every subject simultaneously chooses a color at random, that is, the number of proper colorings divided by the number of possible colorings. RSL is the inverse of constraint, and a negative exponential function of the number of constraining edges. Since we are interested in the effect of the constraint introduced by a single constraining edge, we take the logarithm of RSL in our statistical analysis, as log(RSL) is a linear function of the number of constraining edges.

Measuring constraint directly (rather than by the number of constraining edges) allows us to pool the 3- and 4-color data. In charting the relationship between constraining edges and success rates, graphs of different chromatic number must be analyzed separately, since each constraining edge in a 3-color graph eliminates only one of three available colors, whereas each constraining edge in a 4-color graph eliminates only one of four possible actions. By contrast, when we use log(RSL) we can estimate the effect of additional constraint on success rates independent of chromatic number. Since RSL accounts for the constraint introduced by a constraining edge, any remaining effect of a constraining edge is the effect of communication. We therefore use the total number of edges (rather than the number of redundant edges) as a measure of the amount of communication between subjects, since both constraining and redundant edges enable communication.

Finally, we attempt to control for two unwelcome sources of variation: trial order and group effects. To control for order we simply add a variable for trial number, in case subjects do better or worse later in the session (due to learning or fatigue). To account for potential variation between subject groups, we allow

### Table 1: Logistic regression showing the effect of constraint and communication on likelihood of success. Constraint is measured by the inverse of (logged) random solution likelihood, and communication is measured by the number of edges. Trial number and a subject group parameter are included to control for any learning or group differences.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Random Solution Likelihood)</td>
<td>0.48** (0.074)</td>
</tr>
<tr>
<td>Number of edges</td>
<td>0.084** (0.016)</td>
</tr>
<tr>
<td>Trial number</td>
<td>0.017 (0.021)</td>
</tr>
<tr>
<td>Random effects parameter: subject group</td>
<td>0.44 (0.31)</td>
</tr>
<tr>
<td>Number of trials</td>
<td>179</td>
</tr>
<tr>
<td>Number of subject groups</td>
<td>5</td>
</tr>
</tbody>
</table>

Entries are logit coefficients, with standard errors in parentheses. Positive coefficients indicate a higher likelihood of solution. *p < 0.05 and **p < 0.001

Figure 2: Adding edges first decreases, and then increases a group’s ability to solve coordination problems. Starting with the minimally connected graph, increasing connectivity decreases the proportion of trials subjects are able to solve, until the least-connected fully-constrained graph is reached. Once maximum constraint is reached, further increasing connectivity increases the proportion of trials solved.
for random effects associated with each group. Our estimated logit model is shown in Table 1.

Table 1 shows that increasing constraint impedes coordination and increasing communication facilitates coordination. Table 1 also shows that trial ordering and subject-group effects are statistically insignificant. The lack of correlation between trial number and success rate suggests that subject performance is not affected by learning or fatigue. The fact that the random effects were statistically insignificant indicates that the subject groups did not vary in their ability to perform the experimental task.

4. CONCLUSIONS
In this paper we argue theoretically and show experimentally that network edges affect coordination through two mechanisms: by spreading information in the network and defining the constraints that determine successful coordination. The ambiguous effect of additional edges mirrors the model of Siegal [27], and comport with the claim of Borgatti et al. [7]: “Perhaps the most fundamental axiom in social network research is that a node’s position in a network determines in part the opportunities and constraints that it encounters, and in this way plays an important role in a node’s outcomes.”

Our experiments show that increased connectivity can impede the ability of groups to solve collective problems, when complex coordination games in the form of k-colorability for k ≥ 3 are considered. As we add edges to a 3- or 4-colorable graph (while maintaining its 3- or 4-colorability), solvability of the problem by human subjects decreases to zero. The further addition of redundant edges improves the solvability. This is in contrast to the situation in two-colorable graphs where human subjects have always been to solve the problem and moreover they have been able to solve the problem faster with increased connectivity (because the edges that provide this increase are redundant) as reported in Kearns et al. [18] and McCubbins et al [20].

We can provide a complexity-theoretic explanation for this phenomenon: when we consider centralized algorithms, theoretical evidence shows that the complexity of coloring a 3-colorable graph increases nonlinearly as the number of proper colorings decreases and is highest when the number of proper colorings is small or unique [29, 9, 2]. On the other hand, it is well known that the centralized complexity of coloring a 2-colorable graph is linear in the number of edges. It turns out that we can add edges to constrain the solutions of a 3-colorable graph until it has a unique (up to symmetry) 3-coloring. Once the network has a unique 3-coloring, we can add edges (maintaining 3-colorability) to increase the local information available to the human subjects without constraining solutions thereby leading to improved solvability. Our motivation is to explore how this aspect of complexity plays out in the case of distributed decision-making over a network (a restricted case of centralized algorithms). Our work provides the first evidence that complexity as well as connectivity is an important factor in determining outcomes in networked context and the interaction between the two factors can be subtle.

This paper shows that the computational complexity of a coordination game has a significant bearing on the ability of humans to find solutions. Before we ran our experiments with 3-colorable graphs, based on our general understanding of the complexity of NP-complete problems, we guessed that additional edges would increase the difficulty to a point, after which adding more edges would make the coloring problem easier (assuming that we maintain 3-colorability all the while). However, we do not know of any results that state how the complexity of finding a 3-coloring behaves as a function of density. For a related and well-studied problem of k-SAT, there are algorithms which show that a satisfying assignment can be found quickly for random formulas of high density with a planted solution [3]. Even if similar results were to hold for the 3-coloring problem, it is not clear whether humans would be able to solve the problem with similar ease in the presence of a large number of redundant edges in a distributed set-up with only local information. Indeed, there was some reason to wonder wonder whether human performance would mirror that of a well-designed distributed algorithm. For example, Kearns [18] compared their subjects’ behavior to that of a simple algorithm they developed, and found the differences “striking, with the order of difficulty within the cycle family exactly reversed...and the preferential attachment networks being relatively easy for the heuristic.”

Given that more connections don’t always help groups to solve coordination problems, under what circumstances might more connections be a good thing? Our taxonomy of constraining and redundant edges suggests a solution to this outstanding problem. When a particular subgraph is already maximally constrained (that is, when there exists a unique solution to the coordination problem, forcing every member of the subgraph to align with that one solution), then any additional edges are redundant. For example, if there are units within a firm that necessarily require high connectivity (for example, in an assembly line where the success of each individual’s task is contingent upon the successful completion of all his predecessors’ tasks), then it may be that the addition of redundant edges would help spread information efficiently enough to overcome the complexity of the coordination problem.

We have identified two ways in which network structure affects collective outcomes: by defining the level of constraint and communication. However, our experimental method has two major limitations: the size of our networks is relatively small and the subjects do not create their own networks. It may be that in situations where agents create networks endogenously, they build them to minimize constraining edges and maximize redundant edges by only building connections to agents like themselves, giving rise to the well documented feature of homophily in social networks. If this is true, we may not see many constraining edges in real-world networks. More fundamentally, our analysis deals only with collective outcomes. We have data and simulations designed to shed light on individual strategies, and this work is still in progress. (Chaudhuri et al. [11] have developed a distributed algorithm that converges to solution when agents have at least two more colors than the maximum degree.)

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1 We only added redundant edges to the fully-constrained graph, so our results do not directly speak to the effects of redundant edges on networks that are not fully constrained. However, since redundant edges do not reduce the number of solutions but do add information we expect they should improve coordination even if network is not fully constrained.
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Foreword

The papers in these proceedings were presented at the 12th ACM Conference on Electronic Commerce — EC’11, held June 5–9, 2011, in San Jose, California, USA. Since its inception in 1999, ACM EC has served as the leading scientific conference on advances in theory, systems, and applications for electronic commerce. The conference is interdisciplinary and addresses a number of facets of electronic commerce, including (1) theory and foundations; (2) architectures and languages; (3) automation, personalization, and targeting; (4) security, privacy, encryption, and digital rights; (5) applications, experimental and empirical studies; and (6) social factors. In addition to the main technical program, EC’11 featured five workshops and six tutorials. EC’11 was also co-located this year with fifteen other computer science conferences as part of the 2011 ACM Federated Computing Research Conference.

The call for papers attracted 189 submissions from authors in academia and industry from all around the world. Each paper was reviewed by at least three program committee members and one senior program committee member on the basis of scientific novelty, technical quality, and importance to the field. After discussion and deliberation among the program committee, senior program committee and program chairs, 49 papers were selected for presentation at the conference. Thirty-eight of these are published in these proceedings. For the remaining eleven, at the authors’ request, only abstracts are included along with pointers to full working papers. This option accommodates the practices of fields outside of computer science in which conference publishing can preclude journal publishing. It is expected that many of the papers in these proceedings will appear in a more polished and complete form in scientific journals in the future.

After the review process, an Outstanding Papers committee of Shuchi Chawla, David Reiley and Rahul Sami was established. The committee singled out the following two papers as co-winners of the EC’11 Best Student Paper Award:

- Polynomial-time Computation of Exact Correlated Equilibrium in Compact Games, by Albert Xin Jiang and Kevin Leyton-Brown, University of British Columbia;
- A Truthful Randomized Mechanism for Combinatorial Public Projects via Convex Optimization, by Shaddin Dughmi, Stanford University.

Putting together EC’11 was a team effort. We first thank the authors for providing the content of the program. We are grateful to the program committee and the senior program committee, who worked very hard in reviewing papers and providing feedback to authors. We also thank Workshops Chair Sanmay Das, Tutorials Chair Vahab Mirrokni, Webmaster Ann Marie King, and Lisa Tolles of Sheridan Printing Company. Finally, we thank our sponsor, ACM SIGecom, and our generous corporate supporters, Facebook, Google Research, Microsoft Research, Yahoo! Labs and eBay.

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