Testing Higher-Order Network Structures in an Online Experiment

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Abstract
Currently, the de facto representational choice for networks is graphs which capture pairwise relationships between entities. This dyadic approach fails to adequate capture the array of group relationships that are more than the sum of their parts and prevalent in real-world situations. For example, collaborative teams, wireless broadcast, and political coalitions all contain unique group dynamics that need to be captured. In this paper, we use simplicial complexes to model these supra-dyadic relationships in networks. We argue that a number of problems within social and communications networks such as network-wide broadcast and collaborative teams can be elegantly captured using simplicial complexes in a way that is not possible with graphs. In this study, we operationalize several types of simplicial complexes in an online-based experiment using the Wildcat Wells paradigm. We then run subjects in these experiments to investigate measures of team strength and hub behavior using simplicial complex models.

Author Keywords
Networks, Groups, Online Experimentation, Computer Science, Problem Solving

ACM Classification Keywords
Design, Experimentation, Measurement, Performance

Introduction

Research on networks is largely driven by graph-based models of network structure. These models define networks as the set of dyadic connections between a collection of nodes. The inability of this dyadic approach to operationalize higher order structures like groups, communities, and collaborations has long been noted [1,2]. However, alternative approaches to network analysis have remained largely within algebraic topology [3,4]. Our research attempts to apply these models to empirical phenomena. In this presentation, we focus on laboratory experiments using simplicial complexes in both the design and analysis of the study. We show how simplicial complexes can be operationalized in a laboratory setting and how network effectiveness and structure can be observed within the simplicial framework.

An Alternative Approach of Networks

Network science is based on graphical models which theorize networks as a set of dyadic relations among nodes. Simplicial models add to this a grouping concept called faces (or simplex). Faces are collections of dyads which interact concurrently. Faces aggregate further to form Facets which are faces that are not subsets of other faces. Figure 1 shows an example of a graphical model of networks and a simplicial complex model of a similar network.

In the graphical model, all nodes are related dyadically via edges. In the simplicial model, nodes may be related dyadically and by a face. For example, Face 1 connects nodes A, C, D, and E while Face 2, a subset of Face 1, connects A, C, and D. In Face 2, E can communicate with A only when E communicates with A,

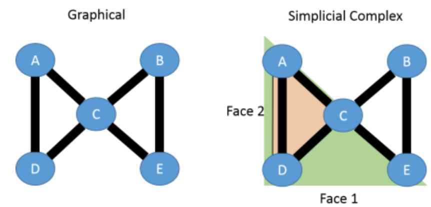

Figure 1: Comparison of Graph and Simplicial Representations of Networks.

C, and D as well. Note, because Face 2 is a subset of Face 1, it is not a facet. However, Face 1 is a facet because it is not a subset of a larger face.

The primary alternative to simplicial complexes is hypergraphs [5]. The difference between hypergraphs and simplicial complexes is that simplicial complexes do not assume that subsets of a face can interact independently. For example, in Figure 1, nodes D and E can interact only when Face 1 is activated. That is, D and E can interact only when A and C are involved simultaneously. If we were using a hypergraph model, then D and E would be able to interact. This property that members of the group must be dyadically connected is called "closure" and hypergraphs assume closure while simplicial complexes do not. In this study, we limit ourselves to simplicial model. Elsewhere we investigate hypergraphs.

Empirical Application of Simplicial Complexes

Models based on simplicial complexes are needed to handle the kinds of real-world networks which involve collective synchronous behavior such as broadcasting, collaboration, friend groups, and committee decision-making [6,7,8]. In this research, we operationalize one

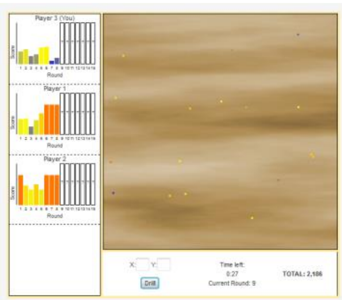

Figure 2: Wildcat Wells Interface

Wildcat Wells

Participants: Participants will be recruited from Mechanical Turk using the Volunteer Science platform.

Methods: Experiments 1 and 2 (Figure 3) will be run as separate experiments and Turkers will be able to participate multiple times.

Procedure: Within each experiment, Turkers will be matched randomly into the skeletal and simplicial conditions. They will be told to find as much oil as possible in 10 rounds but they will not be informed of their network condition.

such situation using the Wildcat Wells experimental framework [11].

In the Wildcat Wells experiment, users are tasked with finding oil on a map over a series of rounds. Users do not know the distribution of oil on the map and must drill wells to find the most oil. Users are connected to others in networks such that neighbors can see the well locations and amount of oil found by their neighbors each round. Thus, if neighbors find high-value wells, subjects can drill in the same location in the next round and receive the same amount of oil. The reason for using this framework is that it operationalizes the effect of communication patterns on success. That is, individuals and networks succeed when they share information and learn from one another.

In our version of the experiment we implement two graph-based network structures, which we call "skeletal" networks and two simplicial networks. In this study, we test the performance of teams in simplicial networks against teams in the skeletal networks (Figure 3). The goal is to see whether these different approaches produced different patterns of success.

In Experiment 1, we test behavioral differences between skeletal and synchronous simplicial networks. In the skeletal version, users are able to see wells drilled by their neighbors. In the synchronous model, individuals see the wells drilled by other members of their face. For example, in Experiment 1, if the face containing (A,B,D) is selected, then A sees the wells of B and D. If not, A only sees his or her own wells. Our hypothesis based on preliminary analysis is that more oil will be found in the simplicial networks.

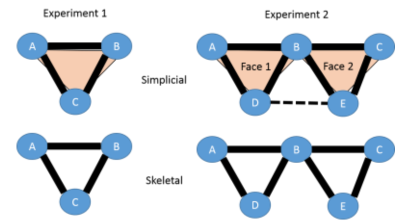

Figure 3: Experimental Network Structures

In Experiment 2, we test the same skeletal and simplicial networks but examine brokerage behavior. In the skeletal model, individuals see the wells drilled by their neighbors randomly each round. In the simplicial model, individuals see the wells of members of their face. However, faces are exclusive. For example, because Face 1 and Face 2 share node B, Face 1 and Face 2 cannot "convene" simultaneously. Node B cannot be in two places at once as the saying goes. Given our preliminary results described below, we expect simplicial networks to produce more oil on average than skeletal networks.

Finally, in a third variant of Experiment 2, we retain the simplicial structure, but add dyadic connection between nodes D and E. This enables us to examine how brokerage influences performance in simplicial complexes.

Preliminary Results

We are currently implementing these experiments on the Volunteer Science research platform. However, we have performed preliminary experiments with human subjects. The goal was to build a simple model of individual behavior in order to create an agent based model for simulating behavior in this experiment.

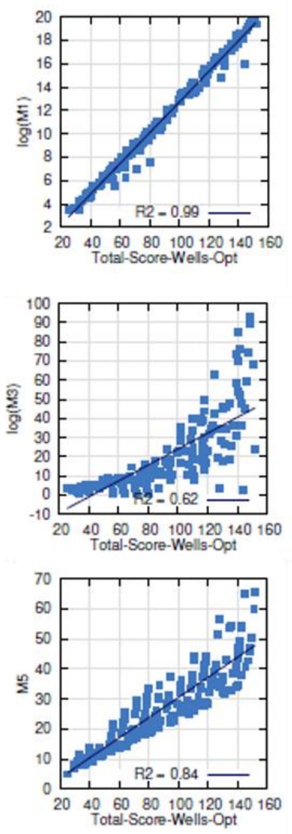

Figure 2: Measures of Monotonicity. Each graph shows the correlation in the amount of oil found (x-axis) and different measurements of network structures (y-axis)

Similar to [9] we found that individuals tend to ignore their neighbors' wells until later rounds unless a neighbor finds a particularly high-value well in which case they immediately start drilling in that location.

Based on these behaviors, we created a series of agent-based models to simulate human behavior in an array of networks to determine what features of networks would maximize the amount of oil found. We found that monotonicity held in all but the fewest cases (Figure 2). That is, the more connections between nodes and the more faces in a network, the more oil tended to be discovered.

Following monotonicity, for Experiment 1 and 2, we expect that subjects in the simplicial condition will find more oil on average than subjects in the skeletal condition. In the brokerage test in Experiment 2, we expect subjects in the condition with the extra tie to find more oil on average.

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References

1. Ram. Ramanathan, A. Bar-Noy, P. Basu, M. Johnson, W. Ren, A. Swami, and Q. Zhao. 2011 Beyond graphs: Capturing groups in networks. In *International Workshop on Network Science for Communication Networks, Proceedings of the IEEE*. 870–875.
2. T. Moore, R. Drost, P. Basu, Ram. Ramanathan, and A. Swami. 2012. Analyzing collaboration networks using simplicial complexes: A case study. In *International Workshop on Network Science for Communication Networks, Proceedings of the IEEE*. NetSciComm. 238–243.
3. James. R. Munkres, Elements of Algebraic Topology. Addison-Wesley, 1984.
4. Edwin H. Spanier, Algebraic Topology. Springer, 1994.
5. Claude Berge, Hypergraphs. North-Holland, 1989.
6. Wojciech Matusik, Matthias Zwicker, and Fredo Durand. 2005. Texture design using a simplicial complex of morphable textures, ACM Transactions on Graphics, 24, 3, 787–794.
7. Alireza Tahbaz-Salehi and Ali Jadbabaie. 2010. Distributed coverage verification in sensor networks without location information. In *IEEE Transactions on Automatic Control*, 55, 1837 –1849.
8. Minh X. Hoang, Ram Ramanathan, and Ambuj K. Singh. 2014. Structure and evolution of missed collaborations in large networks. In *Computer Communications Workshops (INFOCOM WKSHPS), 2014 IEEE Conference*.
9. Winter Mason and Duncan J. Watts. 2012 Collaborative learning in networks. In *Proceedings of the National Academy of Sciences*, 109, 3, 764–769.