Network Deliberation: The role of network structure in large-scale, internet-enabled, participatory decision-making

by

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DEDICATION

TODO

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TABLE OF CONTENTS

LIST OF FIGURES

FIGURE

LIST OF TABLES

LIST OF APPENDICES

ABSTRACT

As groups grow in size, they gain access to additional resources, creating opportunities for collective intelligence and collective action. However, at very large scales, group decision-making becomes prohibitively slow and difficult to coordinate. Traditional solutions include representative decision-making and/or a shift from deliberation to voting. Both approaches sacrifice desirable properties. Representative decision-making loses the potential benefits of collective intelligence and introduces hierarchies that may place the interests of specific individuals ahead of the interests of the group. Voting sacrifices generativity: allowing a choice between predefined options, without allowing for improvement to those options. Arrow's impossibility theorem also fundamentally limits the fairness of voting. This project proposes Networked Deliberation as a potential means of large-scale decision-making. In Networked Deliberation, members of a large group are repeatedly partitioned into small deliberative pods. Overlap between pods at different stages enables group-wide diffusion of information and preferences. Different methods for assigning members to pods result in different network topologies. In partnership with large community groups, this project will use a web-based platform to evaluate Network Deliberation. For a variety of network topologies, the speed and quality of preference convergence will be evaluated using quantitative information from ranked-choice polls throughout the process. Deliberator satisfaction and experience will also be evaluated using qualitative analysis of deliberative text and surveys. This work seeks to improve the ability of very large groups to quickly develop a consensus, enabling a more effective use of shared resources to achieve common goals.

CHAPTER 1

Introduction

The ability of large groups to reach mutually agreeable decisions is key to democratic governance, social movements, and peer production (e.g., Wikipedia). Faced with the intractability of large-scale decision-making, traditional systems have sacrificed one or more desirable properties, such as participation (as in representative democracy), deliberation (as in voting), equality (as in command hierarchies), and speed (as in formal consensus). This dissertation examines the emerging role of internet-enabled collaborative networks in overcoming these historical limitations.

In recent years, examples of large-scale collaborations have emerged that seem to achieve the previously unachievable. Millions of volunteer Wikipedia editors have created a high-quality encyclopedia without centralized leadership [49, 33]. The Free Software movement has produced the Linux kernel and GNU operating system, which power much of the modern internet [18, 8, 65]. Social movements such as the Arab Spring, Occupy, Black Lives Matter, and Podemos have reshaped national governments and brought attention to deeply entrenched social issues [75, 37]. The emergence of these large-scale decentralized collaborations has been attributed to the fast, bidirectional, and global communication enabled by the internet [75, 8]. A better understanding of how specifically such communication sidesteps historical barriers to large-scale collaboration will contribute to more effective policy as well as best practices for organizational design and intervention. This dissertation focuses on one particularly challenging aspect of such collaborations: decision-making I specificaly examine how, when groups are too large for all members to participate in all discussions, the course and outcome of the decision-making process is influenced by the communication network structure: the shape of who talks to whom.

1.1 Theoretical Framework

This dissertation draws on ideas from network science, economics, and complex systems. While a topic as broad as decision-making can be studied from many perspectives, these fields provide a minimal framework for studying how individual preferences and behaviors interact with interpersonal communication networks to influence group decisions.

The fundamental challenge of large-scale collective decision-making is how to reconcile the conflicting preferences of individual group members. This challenge has been studied formally in social choice theory, a sub-field of economics. Prior work in social choice theory has found, somewhat discouragingly, that even when all individual preferences are known perfectly, making a fair collective decision isn't always possible. In some cases, the method of aggregating individual preferences (i.e. the voting system) can influence the outcome. Social choice theory focuses on understanding of these limitations, such as the Condorcet Paradox [19] and Arrow's Impossibility Theorem [4]. This dissertation finds hope in the transformative potential of the deliberative process. Social choice theory typically assumes fixed individual preferences. Deliberation allows individuals to influence and change each other's preferences, which creates the potential to sidestep the historical limitations of social choice theory. When individual preferences are allowed to vary, it becomes possible for an irreconcilable set of preferences to evolve into one with a clear winner. So far, this possibility has received relatively little attention, most likely due to the historical intractability of large-scale deliberative decision-making. This dissertation explores the potential of the internet to enable effective deliberation in large collectives. Such large-scale deliberation creates the potential for members to resolve conflicting preferences and reach mutually acceptable decisions without relying on coercive or hierarchical processes that might introduce power imbalances or informational biases.

Network science provides the tools for analyzing the structure of interpersonal networks. Interpersonal interactions in large collaborations are necessarily structured: when a group is too large for each individual to interact with all other individuals, the question of "who talks to whom?" creates a network structure. By modelling collaborative groups as a collection of abstract "nodes" connected by interpersonal communication links, a group's communication structure can be studied in isolation. Findings from network science suggest that social processes on networks can be influenced by structural properties such as the *degree*: the number of links a node has, *geodesic distance* the number of links separating two nodes, and *clustering*: how common it is for two linked nodes to share links with a third [10]. While network structure is certainly not the only factor to influence collective decision-making, studying network structure in isolation provides a baseline for the further study of social dynamics and other non-structural factors. Network structure is also significant as a potential point of intervention in cases where social dynamics may be difficult to influence.

This dissertation also incorporates theoretical and computational models from social learning theory. Social learning theory acknowledges that individuals rarely learn or make decisions in isolation, but rather learn from and imitate others in their social network [35]. Social learning theory formalizes both the types of tasks collectives perform [42] and the behavioral strategies individuals might employ [53, 7]. These strategies range from pure imitation to critical evaluation, depending on the circumstances being modeled. Social learning models provide a baseline to compare empirical observations against, as well as a language and framework for contextualizing findings.

Throughout this dissertation, I motivate and develop a novel theoretical framework, which I call *network deliberation*. My review of the literature identifies a common theme among successful large-scale internet-enabled collaborations: large collectives composed of interlocking smaller groups. These groups have various names, including: committees, working groups, teams, circles, cores, syndicates, affinity groups, zones, and nodes. As an abstraction of these small interlocking group, I will use the term ”pods.” Network deliberation describes large-scale collective deliberation achieved through interlocking pods. As in the theories of interlocking directorates [54], interlocking publics [40], and network rotation [68], pods allow for beneficial small group dynamics, while the overlap between pods enables diffusion of information and opinions through the greater collective. In network deliberation, the method of assigning individuals to pods (whether deliberate or self-organized) can produce interpersonal networks with varying structures. The central question of this dissertation is how the structure of these interlocking-pod networks influences the process and outcome of deliberation in large collaborations.

1.2 Methodology

Studying collective behavior on the scale of hundreds, thousands, and millions presents significant methodological challenges. To address these challenges, this dissertation combines multiple methodologies, including: observational study, agent-based modelling, and field experiment. I use observational studies to reconstruct real-world collaborative networks from the English-language Wikipedia and analyze the collaborative output of those networks (Chapter 2). Observational study has the benefits of scaling to millions of individuals in a real-world environment. However, observational studies typically cannot establish causal relationships, only correlation.

To begin to address the causal relationship between network structure and deliberative outcome, I use agent-based models (Chatpers 2 and 3). Agent-based models are computational models of large systems composed of many agents following simple behavioral rules. In this case, agents represent individual collaborators, and their behavior is determined by their preferences and their strategy for incorporating information learned from their neighbors. Agent-based models can establish causality, and do so in group sizes limited only by available computing power. As simplified models, however, their results cannot necessarily be generalized to real-world scenarios.

To bridge the limitations of the above methods, this dissertation will include a controlled field experiment evaluating the effect of network deliberation in real-world collective decision-making (Chapter 4).

1.3 Contributions

This dissertation describes the contributions of three projects. Chapter 2 describes an observational and computational study of WikiProjects on the English-language Wikipedia, and reports the following contributions:

- Despite an overall productivity/performance trade-off, WikiProjects with low-degree coeditor networks tend to have both higher productivity and higher performance;
- Short geodesic lengths are associated with higher performance, consistent with a conformity-based learning strategy;
- Structural inequality, as measured by degree skewness, is associated with lower performance;
- The agent-based model shows that the productivity and performance of collaborations can depend on network degree, and that the direction of that dependence can depend on social learning strategy.

Chapter 3 describes an agent-based model of network deliberation, comparing performance across several network topologies and social learning strategies. The primary contributions are:

- When agents conform to social influence, Network deliberation identifies solutions of higher quality than conventional deliberation, while requiring less time to converge.
- Within network deliberation conditions, the structurally-efficient random pod network outperforms the structurally-inefficient long-path network when agents conform to social influence. However, when agents prefer their own judgement to social influence, the inefficient network yields higher performance, consistent with findings for conventional networks. [7].
- A novel social learning strategy, confident-neighbor, which outperforms or matches the conventional best-neighbor strategy across all networks considered, despite using strictly less information about solution quality.

Chapter 4 proposes and describes current progress on a field experiment to study network deliberation in large-scale human collaborations. The study design uses periodic ranked-choice polls to track individual preferences throughout the course of a large-scale online deliberation. By varying communication network structure and tracking the evolution of individual preferences, this experiment evaluate the ability of network deliberation to resolve conflict and build consensus, relative to conventional single-group deliberation.

1.4 Dissertation Progress and Timeline

At the time of this proposal, the analysis of English-language WikiProjects described in Chapter 2 has been completed and resulted in a published paper [64]. The agent-based modelling project described in Chapter 3 has been completed and resulted in a finished manuscript. I have completed custom software, obtained IRB exemption, and conducted several pilot studies for the field experiment described in Chapter 4. I expect to have data collected from at least one full-scale experiment by the end of 2021, and to have the data analyzed by mid-February, 2022. I plan to have my dissertation completed by mid-May, 2022.

CHAPTER 2

Network structure, productivity, and performance in WikiProjects

> The problem with Wikipedia is that it only works in practice. In theory, it's a total disaster.
>
> —Gareth Owen [27]

The internet has enabled collaborations at a global scale. Wikipedia, a free encyclopedia that invites anyone to edit articles, is one of the most successful and visible examples of such a collaboration. Organizing groups without top-down control is notoriously difficult [30], and yet Wikipedia, with millions of self-organized editors, has produced a high-quality encyclopedia [33, 49]. A better theoretical understanding of projects like Wikipedia is highly desirable as it could help inform the design of new collaborative projects. We focus on one aspect of a large-scale decentralized collaboration: its network structure [61]. How does Wikipedia's non-hierarchical structure relate to its success?

We look at WikiProjects on the English-language Wikipedia. WikiProjects are collections of thematically related articles, each with their own standards and norms. When measuring the quality of collaborative projects, there are at least two distinct measures to consider. The first measure is short-term: how effective a unit of work is at improving the collaboration's output, which we call *productivity*. The other measure is long-term: the highest quality typically reached by an output, which we call *performance*. These two terms are often used interchangeably, but we find it fruitful to distinguish between the two. We find that Wikipedia exhibits an overall trade-off between performance and productivity. However, some WikiProjects surpass others in both productivity and performance, suggesting the existence of factors that correlate positively with both.

Our study focuses on the coeditor networks of each WikiProject: which editors have edited at least one article in common? These relationships represent the possible flow of information. We focus specifically on mean degree, degree skewness, and path length. High-degree editors have more collaborators, which can increase diversity and access to information at the possible expense of higher coordination costs [43, 35]. Highly skewed degree distributions can amplify the biases of high-degree editors while reducing the need for explicit coordination [47]. Networks with shorter path lengths allow information to travel more quickly at the possible expense of less local diversity [57, 7].

In addition to our empirical study, we use agent-based modeling to examine the consequences of specific assumptions on networked collaboration. We model individual behavior using a *social learning strategy* that assumes agents 1. can only access a fraction of the model's state, 2. interact with others who share their concerns, and 3. integrate their preferences into a single state. Our model is the first we are aware of to incorporate these assumptions, which are present across many real-world collaborations, including Wikipedia.

Our main findings are:

- Despite an overall performance/productivity trade-off, WikiProjects with low-degree coeditor networks tend to have both higher performance and higher productivity;
- Short paths are associated with higher performance, consistent with a conformity-based learning strategy;
- Structural inequality, as measured by degree skewness, is associated with lower performance;
- Our agent-based model shows that the productivity and performance of collaborations can depend on network degree, and that the direction of that dependence varies with social learning strategy.

Our findings shed light on the importance of network structure for successful collaboration. These findings might be informative for future interventions that recommend tasks based on how they will influence network structure, or for interventions that seek to encourage behaviors complementary to existing network structure.

2.1 Background and Related Work

The present paper investigates the relationship between social networks and collaboration outcomes. This connection has been explored by a number of theoretical, numerical, and small-scale lab studies in the field of *social learning*. We contribute to this literature with a large-scale, empirical field study. In much of the existing literature, degree distribution correlates with outcome measures. But aside from the naive Bayes case, it is unknown whether the correlation is explained best by degree or by another structural property, such as characteristic path length. In the empirical networks we study, unlike artificial networks, the structural properties vary independently, making it easier to isolate individual network properties that correlate with outcome variables.

Social Learning. In *networked social learning*, agents are represented by nodes on a network and can interact only with their neighbors. Social learning tasks can be divided into cases where agents have *generated signals* (independently noisy estimates of a true value) and those where agents have *interpreted signals* (solutions based on different selections of available data) [42]. The behavior of individual agents is described by their *social learning strategy*. For generated signals, a naive Bayesian approach converges to the truth when all agents have the same degree, while the speed of convergence depends on the *spectral gap* between the two largest eigenvalues of the network's interaction matrix [22, 35]. Complex social learning tasks can also be modeled as the problem of maximizing an objective function with many local maxima, referred to as a *rugged landscape* [53, 57, 56, 39, 7]. Numerical simulations have shown that efficient networks (those with short paths between nodes) can result in faster convergence at the cost of a less optimal solution, due to less time for exploration [57, 39]. However, when conformity-based social learning strategies are used, efficient networks can sometimes find more optimal solutions than inefficient ones [7]. Using an agent-based model, Hong and Page [43] found that diverse groups can outperform groups composed of the best individual problem-solvers.

Lab experiments. Lab-based experiments on networked collaboration suggest a complex interaction between network topology and other factors. While groups of networked human subjects perform very well on difficult graph-coloring tasks, the best performing network architectures (e.g., fully-connected vs. small-world) vary from task to task [47]. The same studies found that while human subjects tend to perform well on many networks, they perform worst on self-organized networks, possibly due to higher structural inequality (degree skewness). Similarly, some network topologies are able to reach faster decisions in the presence of more information, while others show the opposite effect [48]. Based on lab experiments, Fowler and Christakis [29] suggest that individual decisions towards altruism are conditional on their neighbor's behavior and "contagious" up to three degrees away. Later experiments by Suri and Watts [74] confirmed the existence of conditional altruism, but concluded that altruism influences only first-degree neighbors.

Digital Communities. Research on digital communities has also examined the role of diversity and inequality in collaborative work and decision-making. In sociology, research has focused on the relationship between network structure and social capital. Powerful individuals are often "brokers" who act as exclusive intermediaries between disconnected portions of the social network [72]. Similarly, successful innovation in organizations often occurs in "structural holes" between groups [38].

For Wikipedia specifically, Robert and Romero [67] found that larger group sizes yield higher article ratings when the groups are diverse and experienced. Kittur and Kraut found that different types of coordination have a complex effect on the quality of Wikipedia articles [51]. Both explicit and implicit coordination result in higher quality articles, with explicit coordination being especially central in the early life of an article. Shaw and Hill [70] found that behavior in online wiki communities is consistent with the "iron law of oligarchy," which states that earlier members of a group will, over time, gain disproportionate decision-making power and act increasingly out of self-interest rather than the good of the group [58]. Similarly, Halfaker et al. [41] attributed decreasing participation on Wikipedia to poor retention of new users. Looking specifically at Wikipedia policies determined by editor consensus, Keegan and Fiesler [49] found a trend from flexible rule-making towards less flexible maintenance and deliberation. Using content analysis, Morgan et al. [60] found WikiProjects to be more loosely organized than traditional teams.

Across the broad range of work discussed above, a few key themes emerge. Both the productivity and the performance of a collaboration are important considerations and vary depending on both network structure and type of task [47]. While generated signal models of social learning predict no relationship between the two [35], contagion-style innovation models predict a trade-off [56, 7]. Such a trade-off has been observed in simulations and lab experiments on collaboration [47, 39].

2.2 WikiProjects

Many articles on Wikipedia belong to one or more WikiProjects. WikiProjects are groups of thematically-related articles (e.g., articles related to Philosophy). Information about an article's associated WikiProjects can be viewed on that article's talk page (Figure 2.1). Each WikiProject has its own page and talk page, containing information about conventions within the project as well as discussions about individual articles. WikiProjects are thus distinct communities, with distinct norms and processes. These communities are the fundamental units of analysis in this paper.

One of the main roles of a WikiProject is to evaluate the quality of its articles. Quality assessments are made through consensus-based deliberation on the WikiProject talk page. Within a WikiProject, assessments are typically made using the following *assessment classes* (in order of increasing quality): Stub, Start, C, B, A. Different WikiProjects can assign different quality assessments to the same article. Differences between quality assessments could reflect different quality standards, different grading systems, different responsiveness to changes in an article, etc.

In addition to the above assessment classes, articles on Wikipedia can be tagged as "good article" (GA) or "featured article" (FA) quality. FA and GA determinations are made using a Wikipedia-wide consensus, independently of WikiProject-based evaluations. FA articles are "the best articles Wikipedia has to offer" [21]. GA articles meet "a core set of editorial standards" but are "not featured article quality" [20]. When an article is assigned GA or FA status, WikiProject quality assessments are often updated to reflect that status. For example, the article *Mewtwo* was assessed as GA status on October 5, 2009 and shortly afterwards its quality assessment was changed

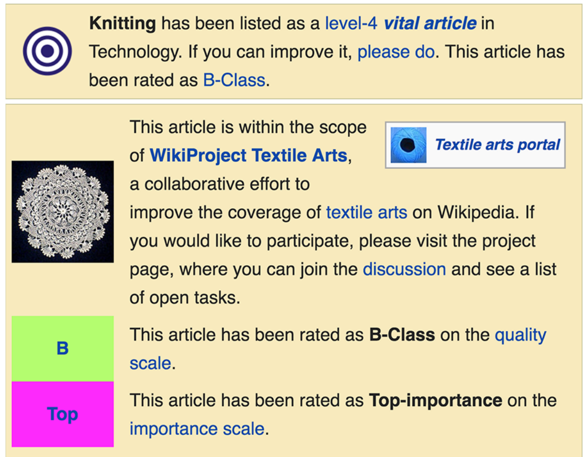

Figure 2.1: From Wikipedia *Knitting* talk page. Two WikiProjects have assessed the article as B-class quality.

from B to GA within both *WikiProject Pokémon* and *WikiProject Video Games*. This example also illustrates a quirk of conventions on Wikipedia: very often, articles pass to GA or FA directly from B, skipping A. The majority of WikiProjects rarely use the A class quality assessment.

2.2.1 Data

Our analysis combines multiple data sets from the English-language Wikipedia [63]. For information about edit history, we used a publicly-available data set containing metadata (time, article id, user) about all edits from July 12, 2006 to December 2, 2015. We used a custom script to scrape article quality assessments from logs produced by WP 1.0 Bot for 2279 unique WikiProjects between May 4, 2006 and December 2, 2015. Finally, we used a publicly-available database dump of page events (including rename events) to reconstruct the article id for each title mentioned in the assessment logs.

2.2.2 Productivity and Performance

When individuals collaborate to solve a problem, there are many ways to gauge their success. One possibility is *productivity*: how quickly they find a solution. Another is *performance*: how good their solution is. Evidence from numerical simulations [53, 57, 56, 39, 7], lab studies [47], and field observations [32] all suggest a trade-off between productivity and performance. While common, this trade-off is not absolute, suggesting it is sometimes possible to simultaneously increase performance and productivity. The identification of factors associated with both higher productivity and higher performance has obvious practical importance. In this paper, we focus on how network structure relates to productivity and performance within WikiProjects.

For a WikiProject, productivity quantifies how much participants can raise the assessed quality of an article for a fixed amount of work. We measure work by the number of revisions made. Quality assessments are made through consensus of the project participants themselves. Different projects can have different standards and practices for assessing article quality, so the productivity is not a measure of how quickly some objective measure of quality improves, but rather of how quickly the project participants can reach consensus on the improvements that need to be made and make those improvements. Because our definition relies on assessment transitions, we must define productivity variables for each of the project-level quality assessments: A, B, and C. For a particular grade G, we desire our definition of productivity to meet the following conditions:

- Strictly increasing in the number of articles reaching grade G (with revision count fixed);
- Strictly decreasing in the number of revisions (with transition count fixed);
- Independent of WikiProject size: not affected by adding an article having the same productivity.

We now define an productivity measure which meets the above criteria. Let $T(W, G)$ be the set of article assessment transitions from below grade G to grade G or higher in project W. Let $N(W, G)$ be the number of articles in project W which ever transition from below grade G to grade G (or higher). Given a transition t, let $r(t)$ be the number of revisions to the article since its previous grade transition, and let $g(t)$ be the number of grade levels crossed bt t. We quantify the productivity $E(W, G)$ as the inverse of the mean number of revisions per transition:

$$E(W, G) = \left[\frac{1}{N(W, G)} \sum_{t \in T(W,G)} \frac{r(t)}{g(t)} \right]^{-1}, \tag{2.1}$$

where the $g(t)$ term accounts for assessments that raise article quality by several grades by dividing the revisions evenly between all grade levels achieved.

For performance, we wish to quantify how good articles tend to be when they reach a stable state. Measuring performance is difficult for two reasons: there is no objective measure of article quality available, and articles are always changing, making it difficult to know which articles should be considered complete or stable. We use an extremely simple performance measure that gives surprisingly consistent results. In addition to per-project quality assessment, articles can be given “featured article” or “good article” status. The criteria for these statuses are consistent across all of Wikipedia, and any editor can participate in the discussion and decision to award good or featured status. In other words, the good and featured statuses are less subjective than per-project assessments.

Our performance measure $P(W)$ is defined simply as the percentage of articles in project W which have reached good or featured status:

$$P(W) \;=\; \frac{f(W)+g(W)}{n(W)}, \tag{2.2}$$

where $f(W)$ and $g(W)$ are the numbered of featured and good articles respectively, and $n(W)$ is the total number of articles.

2.2.3 Coeditor Networks

We would like to determine how the social network structure of Wikipedia—the pattern of who interacts with whom—relates to productivity and performance. There are several types of interactions we could focus on, including: coediting, user talk messages, and talk page replies. We choose to focus on coediting: when two editors have made changes to the same article or talk page. While editors can communicate directly through user talk messages, the number of such messages is small compared to the number of edits to article and talk pages. We also could have considered direct replies between editors on article talk pages, but these replies are typically seen (and intended to be seen) by everyone reading the talk page, and are part of larger conversations. When an editor views a page, they are potentially viewing content from and interactions between all editors who came before them, motivating our choice to focus on the social network structure of coeditors.

The *coeditor network* of a WikiProject consists of nodes representing editors and edges connecting pairs of editors who have edited the same article. The edges are directed, with the direction representing *plausible information flow*; an edge from Alice to Bob exists if Alice edited an article and then Bob edited the same article at a later time. Note that edges can exist in both directions. We make the simplifying assumption of unit weight for all edges. We focus on three structural properties: degree, characteristic path length, and min-cut. Degree and characteristic path length have been shown to correlate with performance and productivity in some social learning settings [35, 57, 39], while min-cut can be interpreted as a measure of decentralization, common feature of peer-produced communities such as Wikipedia [9].

The degree distribution is the simplest network property we analyze. The in-degree (out-degree) of a node is the number of edges to (from) that node. Taking the average of either in-degree or out-degree gives the same value: the *mean degree* of the network. In our context, the mean degree represents, on average, how many other editors each editor has collaborated with. We also consider the *skewness* of the in-degree and out-degree distributions. A large positive degree skewness for a WikiProject coeditor network implies that a small number of editors have a very large number of collaborators, while a small positive value implies that the editors having the most collaborators don't have many more than a typical editor.

We also calculate the characteristic path length for each WikiProject coeditor network. The *distance* from node s to node t is the distance of the shortest path from s to t. The *characteristic path length* (or just *path length*) is the mean distance between all editor pairs, excluding unconnected pairs. To account for unconnected nodes, we also measure the *connected fraction*: the fraction of ordered node pairs with a directed path from source to sink. The path length represents how quickly information can move through the network. Networks with longer paths require more interactions for information to propagate, which has been shown to reduce productivity in some settings [57, 7].

Our final network measure quantifies the connectivity of a project's coeditor network using min-cut size. The minimum st-cut between nodes s and t is the set of edges that must beremoved for no path exists from s to t. The minimum cut (min-cut) of a graph is the smallest minimum st-cut over all node pairs st. The size of the graph min-cut quantifies the connectivity of a graph, but only incorporates information about edges lying on paths crossing the min-cut. Instead, we use the mean size of all minimum st-cuts, which we refer to as the *mean min-cut*. This measure quantifies the number of redundant paths information can take through the network. Networks with higher redundancy are more resilient to errors on one path [2] and allow innovations to propagate through complex contagion, in which innovations are only adopted after multiple exposures [17].

The mean path and min-cut are computationally intensive, requiring distance and minimum st-cut calculations for all node pairs. For larger projects, these calculations are impractical and we thus employed sampling to determine mean path length and mean min-cut. For mean path length, source nodes were sampled, and path length was calculated to all destination nodes from each of these. For min-cut, node pairs were sampled. In both cases, stratification was used to ensure the same number of nodes were were sampled from each of 12 node degree quantiles. We estimated the error due to sampling by determining true values for a medium-sized project, and calculating error as a function of sample-size. Sample sizes were chosen such that relative error was below 10%. Even with sampling, however, it was impractical to calculate these properties for the largest projects, so we exclude the 183 largest projects from the analysis.

2.2.4 Empirical Results

We find that both productivity and performance are highly right-skewed, with a small number of projects having values much higher than the average. After log-transforming the values, both the productivity and the performance have a unimodal distribution with low skew (see Figure 2.2). Our findings confirm the trade-off between performance and productivity observed in many

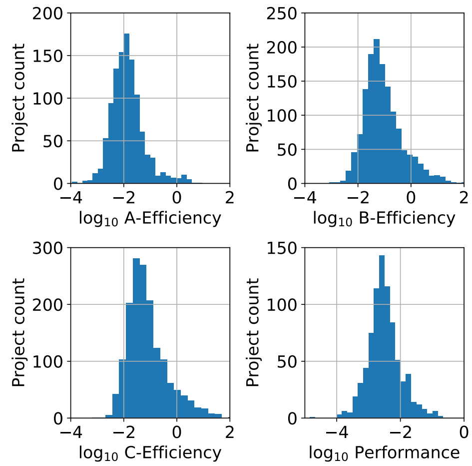

Figure 2.2: Histograms of WikiProject productivity and performance. Both measures are highly right-skewed, but form unimodal distributions with low skewness after log transformation.

other settings (Figure 2.3). However, when looking at specific projects, some are higher in both performance and productivity, suggesting the existence of factors which correlate positively with both.

We also find that mean min-cut is highly correlated with degree ($r = 0.980$, $p < 0.001$), so we exclude min-cut from regression models to prevent collinearity. The high correlation between mean degree and min-cut implies that, in most cases, the minimum st-cut is simply the set of edges from s or the set of edges to t. The rarity of non-trivial min-cuts suggests that WikiProject coeditor networks have very few central bottlenecks and are thus highly decentralized.

To study the relationship between network structure, productivity, and performance, we model the performance and productivity of WikiProjects using ordinary least-squares linear regression. Each WikiProject is a single observation. The models include each project's coeditor network properties as independent variables. We also include the following project-level variables to control for confounding factors.

C-productivity (performance only). Quantifies how quickly a WikiProject improves articles. Efficiencies for different grades are highly correlated, so we include only one.

Connected fraction. Fraction of coeditor pairs connected by a path.

Talk fraction. Fraction of total revisions made to talk pages.

Mean similarity. Mean Jaccard similarity (by article) with other WikiProjects; a measure of topical complexity.

Mean editors/article. Mean number of editors collaborating on each article in a WikiProject.

Article count. Total number of articles in the WikiProject.

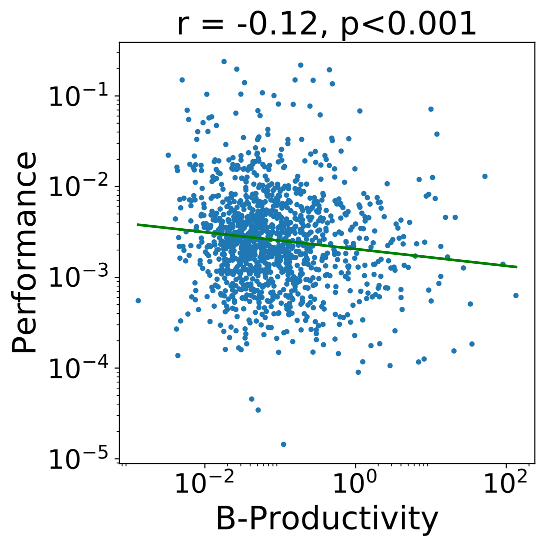

Figure 2.3: WikiProject performance is anticorrelated with B-level productivity, with Pearson r of -0.12. Results are similar for other grade levels. On average, highly productive WikiProjects are under-performing, but when looking at specific WikiProjects, some are higher than others in both performance and productivity.

Editor count. Total number of editors working on articles within a WikiProject.

Revision count. Total number of revisions to articles in a WikiProject.

First assessment. Timestamp of first assessment; a measure of how long a WikiProject has been active.

Mean article age. Mean age of articles within a WikiProject.

Our models are summarized in Table 2.1. Min-cut is excluded from all models to avoid collinearity, as it is highly correlated with degree. In-degree and out-degree skewness were also highly correlated, so we only include out-degree skewness (results are similar for in-degree skewness). Heavy-tailed variables are log-transformed. To test the robustness of our results, we also computed models using cube root instead of logarithmic transformations, and using only top- and high-importance articles. The results were qualitatively similar results for all variables, except for degree-skewness, which had an inconsistent sign across models.

We see that B-productivity and C-productivity have very similar models, but that A-productivity behaves differently in its dependence on degree skewness and connectivity. The different behavior of A-productivity is likely explained by the observation that the A-Class quality is infrequently used in practice. The A-Class quality level is usually passed when an article reaches good or featured article status, which follow deifferent a consensus process from other ratings.

	Perf†	A-Eff†	B-Eff†	C-Eff†
Mean degree†	-0.7***	-0.8***	-0.6***	-0.3*
Out degree skew†	-0.4***	-0.5**	-0.3*	-0.06
Mean path length†	-0.33***	-0.09	-0.05	-0.09
C-productivity†	-0.08*	—	—	—
Connected frac.	0.01	0.09*	0.15***	0.06
Talk fraction†	0	-0.02	-0.03	0.01
Mean similarity†	0.06**	-0.03	0.01	0.02
Mean editors/art.†	0.3**	0.3	0.2*	0.09
Article count†	-0.4	0.7*	0.8**	0.7**
Editor count†	0.4	0.9**	0.8**	0.5*
Revision count†	0.6*	-1**	-1.1***	-1***
First assessment	0.05	0.11**	0.31***	0.43***
Mean article age	-0.03	-0.04	-0.01	-0.05*
N	1179	966	1260	1415
R^2_{adj}	0.37	0.17	0.30	0.43

† Log-transformed. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 2.1: Standardized coefficients for OLS models.

The negative dependence of performance on C-productivity suggests there is generally a trade-off between performance and productivity. However, low degree is correlated with both higher productivity and higher performance, suggesting that it is possible to improve both simultaneously. Much of the existing numerical work on networked social learning focuses on path length rather than degree, so we explore this result further using simulations in the next section.

For path length, we find that longer lengths correspond to lower performance, contrary to the conjecture that longer path lengths allow more exploration [57] but consistent with a conformity-based social learning strategy [7].

We also observe that high degree skewness is correlated with lower performance and lower A-productivity, suggesting that projects with decentralized coeditor networks produce featured or good status articles more quickly, and reach higher quality ratings in general.

2.3 Agent-Based Model

In addition to our empirical study, we use a simple agent-based model of collaboration to better understand the relationship between node degree, productivity, and performance. Numerical models allow us to determine the effect of changing a single variable (e.g., network structure, learning strategy), which is impractical in the empirical setting. It is important to note that the goal of our model is not to simulate all the intricacies of Wikipedia or any other specific platform. Rather, our goal is to determine whether the correlations we observe between degree and outcome variables

Name	Social stage	Individual stage	Limited concern	Unknown objective	Single truth
Best+I	Best neighbor	Global			
Conf+I	Conformity	Global		✓	
Best+LI	Best neighbor	Local	✓		
Conf+LI	Conformity	Local	✓	✓	
LMaj+LI	Local majority	Local	✓	✓	✓

Table 2.2: Definitions and properties of social learning strategies. Each consists of a social stage and an individual stage. Individual stages use hill-climbing based on either the global state, or the agent's local concern.

on Wikipedia can be reproduced in a more general setting.

Past work in the field of social learning typically models collaboration as an optimization problem: finding a state of the world which maximizes some objective function [53, 57, 56, 7]. Wikipedia itself can be regarded as an optimization problem. On Wikipedia, editors are generally seeking to improve the quality of articles and have some personal preference over possible states of an article. When editors do not agree on the optimal state of an article, the conflict is resolved through a consensus-based deliberation. This consensus process can be regarded as a *social choice function* [4, 14] which maps individual preferences to community preferences. Wikipedia can thus be thought of as a group of editors with individual preferences for article states, collaborating to optimize articles according to community preferences. Note that these community preferences do not assume the existence of any ground truth, other than the preferences themselves.

To simulate collaboration, we need a model problem for collaborators to solve. Following existing literature on social learning, we use the NK model [46] to create NP-hard, nonlinear optimization problems. The NK model produces an objective function with a *rugged landscape*, i.e., many local optima. The ruggedness of the model can be tuned through the parameters N (the dimensionality of the solution space) and K (the level of inderdependence between dimensions). Formally, the NK model produces an objective function F mapping a binary string S of length N to a real value in $[0, 1]$. Model state is divided into N *loci*, with locus i having a binary state S_i and a value $f_i(S)$ dependent on its own state and on the state of K random other loci. The functions $f_i(S)$ are created by selecting a random value in $[0, 1]$ for each possible state of locus i and its K neighbors. The value of the model $F(S)$ is the mean of all locus values $f_i(S)$. In our simulations, agents iteratively search for a bit string S that maximizes $F(S)$.

In a typical social learning model, a set of agents each maintain an estimate of the optimal state and iteratively update that estimate based on information available from other agents, according to some *learning strategy*. In networked social learning, agents are associated with the nodes of a network and share information only with their neighbors. We define productivity and performance in terms of the solution values for each time step (averaged over many trials). We define the performance to be the mean solution value after the process has converged, while the productivity is the reciprocal of the number of steps required to converge. We measure the time to convergence as the number of steps required to reach 99% of the maximum mean solution value.

Without additional constraints, the above model is missing several key properties of real-world collaborations. In designing our agent-based model, we paid attention to the following properties.

Limited concern. Agents are concerned only with a subset of the entire state when making decisions and determining preferences. (On Wikipedia, editors typically interact with a small subset of the articles.)

Concern-based network. Agents interact with other agents who share a common concern over some subset of the state. (On Wikipedia, editors interact with others who share interests in the same articles.)

Unknown objective. Agents rank states in order of preference, but do not have access to the objective function. (On Wikipedia, there is no ground truth measure of quality.)

Single source of truth. At any given time, the system is in a single state and agent preferences are based on local modifications to that state. (At any point in time, there is only one current version of Wikipedia.)

2.3.1 Concern-Based Networks

On Wikipedia, editors interact by editing articles and talk pages. Thus, the editors who interact with each other are exactly those who care about the same content. Rather than using arbitrary networks, we devise a network structure inspired by the above observation. We do so by associating agents with particular loci in the NK model. We also wish to study the effect of varying network degree, which we achieve through a rewiring process described below.

Our concern-based networks are generated directly from the structure of the NK model. The value of each NK locus depends on its own state and the state of K other loci. For each locus, we define an agent and assign these $K + 1$ loci as its concern. Next, an agent-agent co-affiliation network is created by connecting two agents if they share at least one locus in their concerns. This process is analogous to our construction of WikiProject coeditor networks.

To create a tunable degree, we duplicate each agent and its concern, then randomly rewire a fraction of agent concerns before creating the agent-agent network. With no rewiring, the duplication process creates a high overlap between agent concerns. This overlap results in redundant links to a small number of agents, rather than unique links to a large number of agents, and therefore to an agent-agent network with small average degree. By randomly rewiring the agent concerns, the redundancy is reduced and the average degree of the agent-agent network is increased.

2.3.2 Networked Learning Strategies

Learning strategies determine how agents update their preferences based on available information [7]. Agents can engage in individual learning by applying a hill-climbing algorithm to their current solution. In each iteration, one bit of the NK solution string is flipped to maximize the solution value. If no change improves the value, the original solution is kept. The above strategy relies only on rankings of states, satisfying the unknown objective assumption. However, it relies on information about the entire state, violating the limited concern assumption. In order to satisfy this assumption, we also define a local variant in which only a subset of bits in the NK solution string are considered. This variant reflects a more realistic style of collaboration, in which individual agents focus on sub-problems.

In social learning, agents can also incorporate information from other agents they are connected to by an edge. While individual learning always converges to the local maximum relative to the starting point, social learning strategies allow agents to "jump" to drastically different solutions with higher local maxima. In our model, we use both the conformity and best-neighbor strategies from [7]. In the *best-neighbor* strategy, each agent compares its solution to a sample of neighbors, and chooses the solution with the highest value. In order to compare solutions between neighbors, the exact value of the objective function must be known for each solution, so this strategy does not satisfy the unknown objective assumption or the limited concern assumption. In the *conformity* strategy, agents simply choose the most common solution among their neighbors (ties are broken uniformly at random). This strategy does not rely on solution value at all, so clearly satisfies the unknown objective and limited concern assumptions. In both cases, a single iteration of individual learning is performed after each social learning iteration. Because each agent maintains a separate estimate of the solution, neither strategy satisfies the single source of truth assumption.

2.3.3 Local Majority Strategy

To satisfy the single source of truth assumption, we introduce a new strategy: *local majority*. In local majority, agents all begin with the same starting state and apply individual learning to their concern to generate possible improvements to the solution. Next, a new solution is constructed by considering each locus of the NK solution individually. Every agent concerned with a locus votes for its state based on their preferred new solution and the majority state is chosen. The result of this process is that all agents integrate their solutions into a single state, which forms the basis for the next iteration. This strategy more realistically reflects collaborations like Wikipedia: at any given time, a Wikipedia article has a single state, determined by consensus, but editors may have differing opinions on how to improve that article.

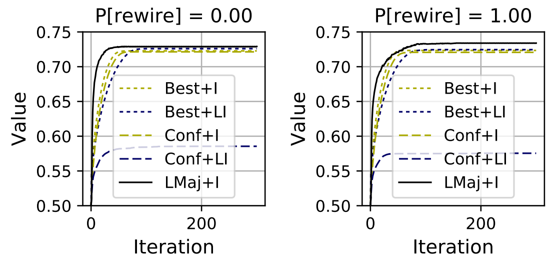

Figure 2.4: Mean agent solution value over time, averaged over 100 trials. Strategies are defined in Table 2.2.

Strategy	Performance	productivity
Best+I	0.722 $\pm$ 0.001	0.0221 $\pm$ 0.0003
Conf+I	0.721 $\pm$ 0.001	0.0174 $\pm$ 0.0002
Best+LI	0.726 $\pm$ 0.001	0.0131 $\pm$ 0.0002
Conf+LI	0.586 $\pm$ 0.001	0.030 $\pm$ 0.001
LMaj+LI	0.729 $\pm$ 0.001	0.046 $\pm$ 0.002

Table 2.3: Simulated Performance and productivity. Results shown for 100 trials with P[rewire] = 0. Strategies are defined in Table 2.2. Local strategies are less productive than their non-local counterparts. Local best-neighbor out-performs global, while local conformity is the worst performer in all cases. The local majority strategy is both most productive and most performant.

2.3.4 Simulation results

We simulated 100 trials for rewiring values of 0.0, 0.167, 0.333, 0.5, 0.667, 0.833, and 1.0. For each trial we generated an NK model with $N = 250$ and $K = 7$, generated a concern-based network, and ran each social learning strategy (Table 2.2) for 300 iterations. For conformity and best-neighbor strategy, we used a sample size of 3, following [7]. We confirmed that all trials converged to their maximum value before reaching the last iteration. Networks had mean degree 116.6 with 1.3 standard deviation, and mean path length of 1.766 with 0.0027 standard deviation. The coefficient of variation for degree is approximately 10%, while only 1% for mean path length, confirming that the rewiring process has a stronger influence on degree than on path length.

Figure 2.4 shows how agents' solutions improve after repeated applications of different learning strategies and rewiring values. Each curve represents an average over 100 trials, each with 250 agents. The mean performance and productivity are reported in Table 2.3. For all rewiring values, local strategies are less productive and more performant than their non-local counterparts. For the best-neighbor strategy, local outperforms global. Local conformity performs notably worse than all others. Local majority is both more productive and more performant than others, with its performance increasing with higher rewiring. This implies that, at least in a simple collaboration

Strategy	Perf. Std. Coeff.	Eff. Std. Coeff.
Best+I	-4.2×10^{-5}	4.1×10^{-5}
Conf+I	2.7×10^{-5}	9.4×10^{-5}
Best+LI	-9.6×10^{-4} **	7.7×10^{-5}
Conf+LI	-1.5×10^{-3} ***	8.7×10^{-5} *
LMaj+LI	1.2×10^{-4} **	-0.038***

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 2.4: Degree regression coefficients for simulations.

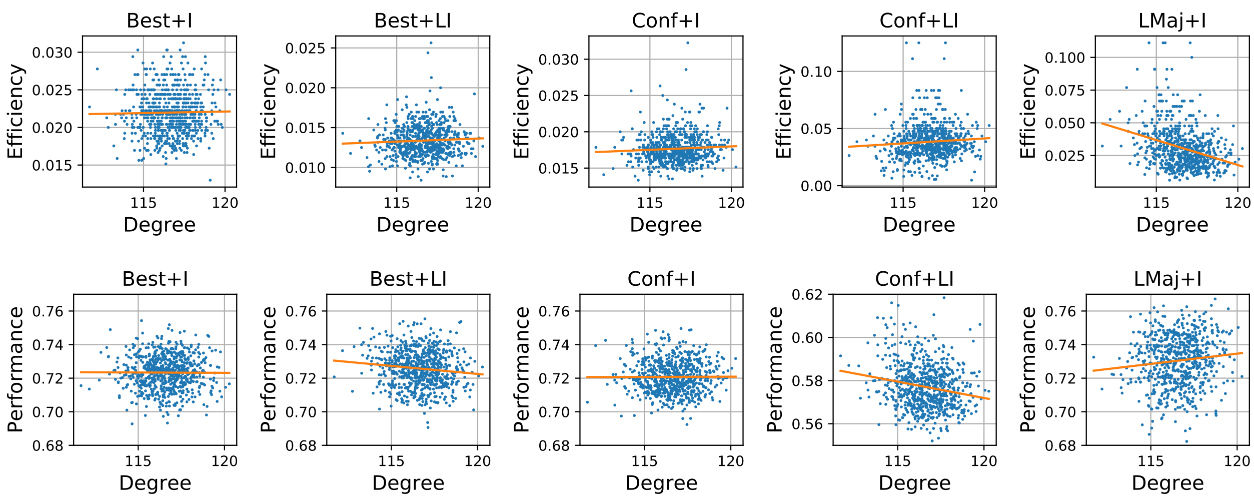

Figure 2.5: productivity and Performance of social learning strategies vs. mean network degree. Each point represents a single trial of 300 iterations. Strategies are defined in Table 2.2. The local best-neighbor strategy shows decreased performance at high degree, with no significant change in productivity. Local conformity shows decreased performance and increased productivity at high degree. Local majority shows the opposite behavior: increased performance and decreased productivity at high degree, with the productivity showing the largest effect size of all strategies.

model, performance and productivity can be simultaneously increased. Furthermore, performance and productivity are potentially affected by both the choice of learning strategy and the average degree of the agents' social network.

The effects of degree on performance and productivity are shown in Figure 2.5 and Table 2.4. For non-local versions of both conformity and best-neighbor strategy, there is no significant effect of degree on performance or productivity. The local best-neighbor strategy shows reduced performance with increasing degree, but no change in productivity. Local conformity and local majority show opposite behavior as degree increases: with local conformity gaining productivity at the expense of performance, while local majority increases in performance and decreases in productivity. The largest effect size is achieved for productivity in the local majority simulation, which is consistent with the productivity behavior observed in WikiProjects. However, the performance behavior for local majority is opposite that observed on Wikipedia. These agent-based models confirm that network degree has the potential to influence the performance and productivity of collaborations. Furthermore, this influence can be drastically different depending on the strategies used by collaborators.

2.4 Discussion

While existing research into the role of network structure in collaboration has focused on numerical simulations and lab experiments, analysis of large real-world systems is an important next step. Our empirical analysis contributes several findings towards a better understanding of large, decentralized, real-world collaboration. We observe several results consistent with previous work: a trade-off between performance and productivity [57, 39], higher performance for shorter path lengths in a conformity setting [7], and a reduction in performance with increased structural inequality [47]. By using real-world networks, we were also able to analyze network properties independently. While most existing work has focused on the importance of path length, our findings suggest degree distribution may be just as, or more, important. The association of low degree with both high performance and high productivity is compelling, as it sidesteps the usual trade-off between performance and productivity. In low-degree networks, agents have more repeated interactions with smaller groups of collaborators, suggesting that small team sizes could be beneficial for large collaborations. Similarly, the observation that performance is higher in projects with less structural inequality suggests that, if the challenges of egalitarian organizing are overcome, decentralized collaborations may produce better outcomes than those with centralized, top-down structures.

Our agent-based models offer a several insights. We observe degree-dependent performance and productivity for both local conformity and local majority strategies. However, these two strategies have opposite degree dependence, suggesting that different strategies may be preferable for high-degree and low-degree networks. Our local majority strategy, designed to satisfy several properties found in real-world collaborations, shows the strongest effects on performance and productivity as network degree changes. For the local majority strategy, the relationship between degree and productivity is consistent with our empirical observations on Wikipedia, suggesting one possible mechanism underlying that productivity dependence. However, the performance dependence of this strategy is opposite that observed on Wikipedia, suggesting that either the local majority strategy is incompatible with actual behavior on Wikipedia or that other factors outweigh the contribution of mean degree.

Our work has several limitations. Our empirical analysis is purely correlative and cannot be used to draw conclusions about the causal influence of network structure on collaboration. However, the consistency of our results with other lab-based and numerical studies suggests that the causal link is worthy of further study. Similarly, our study focuses entirely on a single online community, and while the results are suggestive, they do not necessarily generalize. We have focused on structure, ignoring content-related variables. For simplicity, we have assumed unweighted edges and measured work by revision counts rather than bytes changed.

Our work suggests several directions for future work. Is the correlation between network structure, performance, and productivity causal? A time-dependent analysis of our data could offer insight. Are similar relationships observed in other large-scale collaborations? Does varying degree independently of path length influence performance and productivity in a controlled lab setting?

A better understanding of the relationship between network structure and collaboration outcomes has practical applications. Online communities using recommender systems could make recommendations guided by desirable network properties. Similarly, network structure could be used to identify under-performing groups in need of an intervention. The relationship between network structure and learning strategy suggests that behaviors interact with network structure, which could be used to encourage behaviors complementary to existing network structure.

2.5 Conclusion

In this paper, we have described the relationship between the structural properties of WikiProject coeditor networks, their performance, and their productivity. As in other studies, we see a trade-off between performance and productivity. However, some properties, such as low degree, are associated with both higher performance and higher productivity. We also find that the correlations between path length and performance are consistent with a conformity-based social learning strategy, but not a greedy best-neighbor strategy. We observe improved performance in more decentralized projects, as has been seen in small-scale lab experiments. We have also proposed a novel local majority learning strategy that is more realistic, more productive, and higher performance than existing strategies. While most previous social learning simulations focus on path length, we observe degree-dependent performance and productivity in both the local majority strategy and a localized version of the conformity strategy. We find that the direction of that dependence varies with the specific strategy being used. While additional work is needed to determine causal relationships and the generalizability of our results, we have shown evidence that several phenomena predicted by numerical and small-scale lab experiments are present in a large, real-world collaboration. Our results suggest that the success of large-scale collaborations may be aided by greater decentralization, consensus or conformity-based decision-making, and more tightly-knit collaborations between smaller teams.

CHAPTER 3

Small interlocking groups improve mass deliberation in the presence of strong social influence

3.1 Introduction

Deliberation enables the generation, aggregation, and synthesis of diverse knowledge [24, 3, 1, 62], as well as the early identification and resolution of conflict [32]. As a participatory process, deliberation builds trust among participants, increases the perception of fairness, and incentivises cooperation with group decisions [62, 12]. As a dynamic process, deliberation alters private preferences through discourse [40], sidestepping fundamental limitations of voting, e.g., the Condorcet paradox [19, 14] and Arrow's impossibility theorem [4, 14]. Despite these benefits, deliberation becomes prohibitively difficult in larger groups, due to the increased time and effort needed to reach decisions [28, 32] and to the emergence of power inequalities [30, 11]. Yet examples of successful mass deliberation do exist, including Wikipedia [33, 49], free and open source software projects [8], grassroots protest and crisis-response networks [37, 15] and self-managed organizations [52]. The commonalities between such projects provide insight into overcoming the challenges of mass deliberation. Specifically, we evaluate a model of mass deliberation inspired by common network features observed in successful projects.

Communication in large collaborations is necessarily restricted when group size exceeds individual members' capacity for communication. The structure of the resulting communication network is an important factor in the success of collaborative tasks [47, 56, 57], such as deliberation. Among successful mass deliberative projects, communication networks often exhibits a common structure: small interlocking groups [8, 37, 15, 52]. A similar structure has been observed in the interlocking directorates of corporate boards [45] and the interlocking publics of the public sphere [40], as well as utilized for collective design in network rotation [68]. These interlocking groups have been given various names: committees, working groups, projects, modules, affinity groups, circles, teams, cores, nodes, zones, cells, or syndicates. We shall use the term *pods* to encompass all groups exhibiting two key characteristics: small enough to enable deliberation, and interlocking to enable information diffusion. We shall use the term *network deliberation* to refer to mass deliberation using an interlocking pod structure. Communication network structure also influences the success of collaborations by controlling the speed of information diffusion [53, 57, 56, 7, 36, 23, 47]. Structurally efficient networks enable fast diffusion and favor exploitation of known information over exploration of the unknown [53, 7]. In the context of network deliberation, structural efficiency is determined by how individuals are assigned to pods. We will focus on two such methods: one efficient, one inefficient.

Collective tasks such as deliberation are influenced not only by communication structure, but also by individual behavior. Individuals weigh social influence against their personal knowledge and expertise [13]. Even in a collective setting, individuals sometimes work independently to search for new and innovative ideas [53, 7], to utilize their unique information and perspectives [42], and to critically evaluate the ideas of others [66]. Alternatively, individuals can defer to others in order to exploit and propagate good ideas [7, 13], to conserve their own resources through free-riding and social loafing [45], or due to a high level of trust [68] or social influence [5, 73]. Individual behavior interacts with network structure to vary the level of exploration of new ideas versus the exploitation of known information [7]. While the focus of network deliberation is structural, the effect of network structure must be understood in the context of individual behavior and social dynamics.

We model network deliberation using a social learning framework to address two questions. How effective is network deliberation compared to conventional single-group deliberation? And how do network efficiency and individual behavior influence the outcome of network deliberation? We present the following three contributions. First, network deliberation out-performs conventional deliberation in both solution speed and quality when agents rely heavily on social learning. This suggests that network deliberation is a promising deliberation design for groups with a high degree of social influence. Second, network deliberation performs best on structurally efficient networks when agents exhibit conformist behavior, while it performs best on structurally inefficient networks when agents greedily maximize solution quality, consistent with findings for conventional networks [7]. Third, the naive greedy strategy can be modified to improve performance on conventional networks despite using strictly less information. In the case of network deliberation, the naive and modified greedy strategies are equivalent.

3.2 Methods

Deliberation can be modeled as a form of collective problem-solving and social learning in which agents hold private beliefs, share information with their neighbors, and update their beliefs based on a combination of individual analysis and social influence. Following existing models of collective problem-solving [53, 7, 36], our model comprises: 1. a collective task, 2. a network, and 3. a learning strategy. Agents maintain a candidate solution to the task and iteratively apply their learning strategy to the available information, yielding an updated candidate.

3.2.1 Overview

As their collective task, agents seek an optimal point on a rugged fitness landscape. This landscape is generated using the NK model [46, 77] (see Appendix 5). The NK model is a "tuanbly rugged" objective function parameterized by two variables: the number of bits in the input string (N), and the number bits used to compute each contribution to the objective function ($K + 1$). These parameters can be used to tune problem size and complexity, respectively. The resulting objective function maps N-bit strings to real numbers in $[0, 1]$.

To model network deliberation, we construct interlocking networks in stages. At each stage, agents are partitioned into small *pods* and connected to all other agents in the same pod. Our choice of pod size is informed by real-world The upper limit of effective small group size has been estimated variously as five [30], five–eight[55], and eight [59]. We choose a pod size of 5. Different methods for assigning agents to pods produce networks with different properties. Interlocking structure is created when agents are placed with others they have not yet interacted with. We thus require that pod assignment methods satisfy the following mixing property:

Property 1. *For any agent v, and any two assignment stages t, t', the probability that at least one neighbor of v at stage t is also a neighbor at stage t' approaches 0 as $|V|$ grows.*

We study two such methods: a random assignment method that produces structurally efficient networks, and a long-path method that produces inefficient networks. For comparison, we also simulate conventional deliberation. While the potential communication links in conventional deliberation form a fully connected network, actual communication is better modeled by preferential attachment [6] or small-world [76] networks (see Methods).

An agent's learning strategy models both informational constraints and behavioral dynamics [53, 7] such as social influence and social loafing [45]. We consider three social learning strategies. The *best-neighbor* strategy is the naive greedy strategy: agents simply adopt the neighboring solution with the highest value. This strategy requires that agents have the ability to compare the quality of two arbitrary solutions, a strong assumption representing either skilled agents, or a simple task. The *conform* strategy is pure social influence. Agents adopt the most common solution among their neighbors. This strategy requires no knowledge of solution quality, modeling contexts where agents are unable to compare solution quality, or where agents choose not to, as in social loafing [45]. We also introduce the *confident-neighbor* strategy, a variant of best-neighbor in which agents announce when they have the best solution in their neighborhood. This variant makes weaker assumptions about agent ability but is equivalent to best-neighbor when network deliberation is used. This strategy allows us to compare low-social influence and high-social influence strategies under equivalent assumptions of agent ability.

Between each stage of social learning, agents may perform individual learning. Following existing literature [53, 7], we model individual learning by mutating a single bit of an agent's solution, and keeping it if the mutation improves solution quality. A complete learning strategy must also specify how social and individual learning are integrated. Existing literature [53, 7] applies individual learning only when social learning fails to produce an improved solution. We refer to this method as *fallback* individual learning. Fallback can be also be interpreted as a model of social loafing [45]. For completeness, we include analysis for a second method in which agents first perform social and individual learning in *parallel* and then choose the better of the two learning outputs.

3.2.2 Agent-Based Model

We use an agent-based simualation to model deliberation between individuals. We model communication between agents using a time-dependent network (V, E_t). The vertices V correspond to the agents (individuals). The edges E_t allow agents to exchange information with their immediate neighbors at time t. Over the course of the simulation, agents seek to maximize some objective function $Q(s)$. We use binary strings of length d as our solution space: $s \in \mathbb{Z}^d$. We generate the objective function $Q(s)$ using the NK model [46, 77] (see Appendix 5).

The simulation begins at time $t = 0$ by generating a set of initial solutions $s_{v,0}$ for the agents. These are generated randomly, with each possible solution having equal probability. The simulation proceeds iteratively. At time t each agent applies one of several *learning strategies*, to determine its preferred solution at time $t+1$. Learning strategies can rely on the agent's own solution, the solutions of its neighbors, and potentially additional information shared by its neighbors. Learning strategies may also incorporate information about the objective function, modeling an agents' ability to evaluate the quality of solutions. To allow for ties, learning strategies produce a set of solutions rather than a single solution. In our simulations, we choose winners at random in the case of a tie. We present results for 1000 randomly generated NK model objectives. with each network/strategy combination simulated once per objective function. In keeping with other authors [7, 53] we use $N = 15$ and $K = 6$. We allow each simulation to proceed for 300 iterations, which we have found sufficient to guarantee convergence with our chosen parameters.

3.2.3 Networks

We carry out simulations for four different network topologies. In addition to the well-known preferential-attachment [6] and small-world [76] networks, we construct two types of networks to model network deliberation. Both types exhibit interlocking structure and satisfy Property 1. These two network deliberation conditions differ in how agents are assigned to pods and in the structural efficiency of the resulting network. At each iteration, existing edges are replaced with cliques corresponding to the pods. An edge is created between two agents if and only if they share a pod. In *random-pod* assignment, agents are assigned to pods at random. This assignment method produces short geodesic paths and efficient network structure. In *long-path* assignment, agents are assigned using an algorithm which guarantees interlocking structure while preventing the creation of long-distance "shortcut" edges, producing a structurally inefficient network. All networks are constructed with 100 vertices/agents and a mean degree of 4 (pod size of 5).

3.2.4 Conventional Deliberation

We model the communication network structure of conventional deliberation using two static networks: small-world networks [76], and preferential attachment networks [6]. In typical deliberative settings, from deliberative assemblies to online forum threads, the contributions of any member are potentially visible to all other members. The network of *potential* communication can be modelled by a complete graph. However, a complete graph may not be the best model for the *actual* communication that takes place in such a network. In a real-world deliberation, some participants are more influential than others [34, 70], and many communications can be missed or ignored by any particular participant.

Human social networks often exhibit large clustering, and short path lengths. To model such dynamics, we use Watts-Strogatz small-world networks [76]. These networks model, for example, when participants interact mostly with their strong ties, but occasionally with a weak tie. Social networks have also been found to exhibit skewed degree distributions with long tails [6]. We model these networks using the Barabási-Albert preferential attachment model. These networks model settings where a small number of individuals produce a disproportionate share of the communication due to factors such as social capital, expertise, or confidence.

3.2.5 Network Deliberation: Interlock Networks

Both of our network deliberation conditions use networks built from interlocking pods. These pods are small complete graphs of roughly equal size. At any given time, each agent can communicate with all other agents in exactly one pod. Periodically, all agents are simultaneously reassigned to new pods. These reassignments create an interlocking structure, allowing information to flow through the entire group. This structure can be represented as a time-dependent or directed network. The properties of an interlock network depend on the particular method for assigning agents to pods. Crucially, interlocking structure is created when agents are placed with others they have not yet interacted with. We thus require that pod assignment schemes satisfy the mixing property (Property 1).

3.2.5.1 Random-Pod Assignment

The *random-pod* assignment method (Algorithm 1) simply assigns agents to groups at random. Pseudocode for this method is shown in Algorithm 1.

Algorithm 1: Random-Pod Assignment

```
Data: A vertex list V, the pod size M ∈ ℤ.
Result: A partition of the vertices.
N ⟵ ⌈|V|/M⌉
P ⟵ List of N empty sets
for i ∈ 1, ..., M do
    foreach s ∈ P do
        if not V.empty() then
            v ⟵ V.removeRandom()
            s.insert(v)
        end
    end
end
return P
```

Claim 1. *Random-pod assignment satisfies Property 1.*

Proof. Let v be a vertex of graph $G = (V, E_t)$ with a set of M neighbors at stage t denoted $N_t(v)$. The probability that the kth neighbor chosen at time $t' \neq t$ belongs to $N_t(v)$, given that the first $k-1$ did not, is:

$$\begin{aligned} p_{\text{repeat}}(k) &= \frac{M-1}{|V|-k} \\ &\leq \frac{M-1}{|V|-M}. \end{aligned}$$

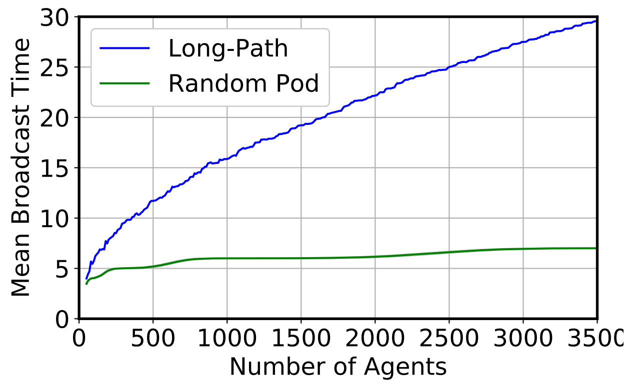

Figure 3.1: Mean time necessary for a signal broadcast from one node to reach the entire network. We use mean broadcast time as a measure of geodesic length for time-varying networks.

The probability that none of the $M-1$ neighbors chosen at time t' belong to $N(v)$ thus satisfies:

$$p_{\text{mixed}} \geq \left(1 - \frac{M-1}{|V|-M}\right)^{M-1}$$
$$\lim_{|V|\to\infty} p_{\text{mixed}} = 1 \qquad \square$$

Random pod assignment also creates structurally efficient networks with short geodesic distances, as shown in Figure 3.1. There has been evidence both for [53, 23, 57, 7] and against [56, 7] the effectiveness of structurally efficient networks in social learning.

3.2.5.2 Long-Path Pod Assignment

To study the effects of path length, we require an alternative pod assignment method that produces long paths. However, we must still retain Property 1 such that it is rare for two agents to repeatedly share the same pod. This property ensures the creation of many new edges at each stage, which is difficult–but not impossible–to reconcile with long average path length. We now present a *long-path* pod assignment method, which meets both of the above goals.

We begin with a high-level overview. Agents are assigned an integer position on a 1-dimensional circular lattice. By preferring short-distance links on this lattice, we maintain long path lengths. We also partition agents according to the remainder of their position, modulo some prime, i.e., their residue class. By limiting links to agents in the same residue class, and using a unique prime at each stage, we ensure that it is rare for multiple agents to share a pod twice in a row. Specifically, for stages using primes p and q, two agents will share a pod for both stages when their positions are equal modulo pq. Pseudocode for long-path assignment is shown in Algorithm

2.

Algorithm 2: Long-Path Assignment

Data: A vertex list V, the pod size $M \in \mathbb{Z}$, the stage $t \geq 0 \in \mathbb{Z}$, a list of co-prime integers `moduli`.

Result: A partition of the vertices.

$N \longleftarrow \lceil \frac{|V|}{M} \rceil$
$P \longleftarrow$ List of N empty sets
if $t = 0$ **then**
    // Place all vertices in same residue class
    $p \longleftarrow 1$
else
    // Choose integer to define residue class
    $p \longleftarrow \texttt{moduli}[t]$
end
// Assign vertices to residue classes
$R \longleftarrow$ List of p empty queues
for $z \in 0, \ldots, |V| - 1$ **do**
    $R[z \bmod p].\texttt{enqueue}(V[z])$
end
// Divide each residue class into pods
$P \longleftarrow$ Empty list of lists.
for $r \in R$ **do**
    $N_r \longleftarrow \lceil \frac{|r|}{M} \rceil$
    $P_r \longleftarrow$ List of N_r empty lists
    for $i \in 1, \ldots, M$ **do**
        for $j \in 0, \ldots, N_r - 1$ **do**
            if **not** $r.\texttt{empty}()$ **then**
                $v \leftarrow r.\texttt{dequeue}()$
                $P_r[j].\texttt{append}(v)$
            end
        end
    end
    $P.\texttt{concatenate}(P_r)$
end
return P

Claim 2. *When the pod size M is less than the modulus p_t for all stages t, long-path pod assignment satisfies Property 1.*

Proof. Let p and q be co-prime integers used as moduli for stages t and t' respectively. Let $z(x)$ denote the integer position of vertex x. Let v be a vertex, and let us assume vertex w belongs to the same pod as v at both time t and t'. This assumption implies:

$$\begin{aligned}
z(v) &\equiv z(w) \pmod{p} \\
z(v) &\equiv z(w) \pmod{q} \\
\implies z(v) - z(w) &\equiv 0 \pmod{p} \\
&\equiv 0 \pmod{q} \\
&= npq && \text{for some integer n.}
\end{aligned}$$

By the definition of the long-path algorithm:

$$\begin{aligned}
|z(v) - z(w)| &\leq (M-1)p \\
\implies |n|pq &\leq (M-1)p \\
|n|q &\leq (M-1).
\end{aligned}$$

By assumption, $q \geq M$, so the above can only be satisfied by $n = 0$, which in turn implies $v = w$. □

To see that the long-path procedure produces long geodesics, note that the pods of size M connect nodes at most $(M-1)p_i$ apart in position, preventing the creation of any shortcut edges, as long as p_i is small compared to $|V|$. Numerical simulations confirm that the long-path algorithm produces geodesics larger than random pod assignment (Figure 3.1). The number of agents may not be an exact multiple of M, so the final pods may be truncated. However, the network will be a sub-graph of a network that does have a multiple of M nodes, so the structure will not be fundamentally changed, and these edge effects should become negligible as the number of agents increases.

3.2.6 Learning Strategies

The choice of network structure defines which agents can exchange information, but not how those agents act on the information received. An agent's actions based on available information are determined by that agent's *learning strategy*. Learning strategies can be divided into *individual learning strategies* which use only information directly observable by the agent, and *social learning strategies* which use information communicated by neighboring agents. Generally, a learning strategy may incorporate both social and individual components. In this paper, we consider three separate strategies: *best-neighbor*, *confident-neighbor*, and *conform*. Each is combined with the same mutation-based individual learning strategy.

To understand why real-world deliberators might choose different strategies, it is necessary to realize that the social learning strategies available to an individual depend on that individual's ability to evaluate the quality of candidate solutions. Individuals with less information about solution quality, must rely more heavily on the recommendations and influence of their peers. We formalize an agent's ability to evaluate the quality of a candidate solution as its *capabilities*, which we now explore in further detail.

3.2.6.1 Agent Capabilities

In human social learning, the ability of individuals to evaluate the quality of a solution can vary with factors such as expertise and task type. When comparing learning strategies, it will be helpful to classify them according to the capabilities they require of agents. We formalize these capabilities as oracle functions, which accept one or more task solutions as input and reveal whether the supplied state(s) satisfy some particular property.

One of the strongest capabilities an agent might posses, is to compare two arbitrary solutions to determine which yields a higher value of the objective function. We represent this capability using the *arbitrary comparison* oracle.

Definition 1. *The arbitrary comparison oracle $\mathcal{O}^{>}(s_1, s_2)$ is given by:*

$$\mathcal{O}^{>}(s_1, s_2) \equiv Q(s_1) > Q(s_2) \tag{3.1}$$

Under a weaker assumption, agents might be "experts" on their current solution and able to compare that particular solution to any other. This ability is represented by a *single-solution comparison* oracle.

Definition 2. *The single-solution comparison oracle for solution s is given by:*

$$\mathcal{O}_s^{>}(\tilde{s}) \equiv Q(\tilde{s}) > Q(s) \tag{3.2}$$

In many contexts, it is reasonable to assume that agents can explore the effects of small changes to their current solution. When the solutions are binary strings, such variations can be modeled by flipping a single bit of the solution string. We formalize this capability through the *mutation comparison* oracle.

Definition 3. *The mutation comparison oracle for solution s is given by:*

$$\mathcal{O}_s^{\oplus}(i) \equiv Q(s \oplus e_i) > Q(s), \tag{3.3}$$

where $\oplus$ represents addition mod 2 and e_i represents the binary string with a single 1 at index i.

3.2.6.2 Mutation-Based Individual Learning

In real-world collaborations, individuals sometimes work independently, even when communication is available. Independent work might be motivated by practical concerns (such as distributing labor) or by social dynamics. We model individual learning using single-bit mutations, following the examples of [53] and [7]. Agents constructs a candidate solution by flipping a single bit of their solution at an index selected uniformly at random. If the candidate solution yields a higher value of the objective function, the agent adopts it as the new solution. As this strategy requires comparing solutions that differ by at most one bit, an oracle at least as powerful as the mutation comparison oracle is required.

Definition 4. *The mutation individual learning strategy $\mathcal{L}_I(v)$ is defined as:*

$$\begin{aligned} i &\sim \mathrm{unif}(1, d) \\ \mathcal{L}_I(v) &\equiv \begin{cases} \{s(v) \oplus e_i\} & \textit{if } \mathcal{O}^{\oplus}_{s(v)}(i) \\ \{s(v)\} & \textit{otherwise}. \end{cases} \end{aligned} \tag{3.4}$$

3.2.6.3 Best-Neighbor

Among social strategies, the straightforward greedy approach results in the *best-neighbor* strategy, which has been widely used in prior work [53, 57, 7]. In this strategy, an agent simply compares the solutions of all agents in its neighborhood and adopts the best. While straightforward, this strategy makes a strong assumption about agent capabilities: access to the arbitrary comparisons.

Definition 5. *The Best-Neighbor strategy $\mathcal{L}_{BN}(v)$ is defined as:*

$$\mathcal{L}_{BN}(v) \equiv \{\, s \in S(v) \mid \forall \tilde{s} \in S(v) \ \neg\, \mathcal{O}^{>}(\tilde{s}, s), \tag{3.5}$$

where $S(v)$ is the multiset of solutions of v's neighbors.

3.2.6.4 Confident-Neighbor

This paper introduces *confident-neighbor*, an alternative to the best-neighbor strategy which relies only on the single comparison oracle and which reduces to best-neighbor for interlocking pod networks. The confident neighbor strategy also represents a moderate level of social loafing [45], in which agents do not actively seek to improve their solution, but passively adopt better solutions if they are presented.

Confident neighbor proceeds in two stages. In the first stage, agents determine if their current solution is at least as good as all others in their neighborhood. If so, we call the agent *confident*. In the second stage, confident agents broadcast their solution to all of their neighbors. Non-confident agents choose randomly between any broadcast solutions they receive, or keep their original solution if they receive none.

Definition 6. *The confident-neighbor strategy $\mathcal{L}_{CN}$ is defined as:*

$$\begin{aligned} C(v) &\equiv \{\, s(w) \\ &\qquad \mid \forall w \in N(v)\, \forall u \in N(w) \neg\, \mathcal{O}^{>}_{s(w)}(s(u)) \,\} \end{aligned} \tag{3.6}$$

$$\mathcal{L}_{CN}(v) \equiv \begin{cases} C(v) & \text{if } C(v) \neq \varnothing \\ \{\, s(v) \,\} & \text{otherwise,} \end{cases} \tag{3.7}$$

where $N(v)$ is the set of vertices neighboring v and $s(v)$ is the current candidate solution for agent v.

Confident-neighbor differs from best-neighbor because of two subtle but important considerations. First, an agent's neighbors need not be adjacent to each other. Second, an agent's neighbors can be adjacent to others outside that agent's neighborhood. As a result, an agent might receive zero, one, or many broadcasts. The exception is when agents belong to a clique (e.g., in network deliberation), in which case agents receive exactly one broadcast for each maximal solution in the clique, thus yielding the same results as best-neighbor. Confident-neighbor is thus more appropriate than best-neighbor for comparing network deliberation to single group deliberation, as the same information is utilized in both cases.

3.2.6.5 Conform

In some contexts, agents might rely on information other than solution quality in their learning strategies. Agents might do so out of necessity if they are not able to compare arbitrary solutions. Alternatively, agents might ignore solution quality due to social dynamics, e.g. social loafing [45]. In these contexts, agents might instead evaluate solutions based on popularity, which produces the *conform* learning strategy. When using the conform strategy, agents count the number of times each solution appears among their neighbors, and adopt the most popular.

Definition 7. *The conform strategy $\mathcal{L}_C(v)$ is defined as:*

$$\mathcal{L}_C(v) = \mathrm{mode}(S(v)), \tag{3.8}$$

where $S(v)$ is the multiset of candidate solutions for all vertices neighboring v, and $\mathrm{mode}()$ *returns a set containing the mode or modes of a multiset.*

Note that the conform strategy does not depend on the objective function or any oracles, meaning it incorporates no new information about the quality of the solutions.

3.2.6.6 Combining Learning Strategies

Models of social learning often combine truly social strategies with individual learning [53, 7, 36]. We find that the method used to combine social and individual strategies can result in a notable difference in outcome.

Parallel Agents apply both social and individual learning strategies to their initial solution to produce two competing intermediate solutions, then adopt the better of the two. This method relies on the arbitrary comparison oracle.

Fallback Agents first apply social learning to the current solution, but "fall back" to individual learning if the result is not an improvement on the original solution [53, 7, 36]. Fallback relies on the single comparison oracle and could be motivated by limited agent capability or social loafing.

Serial Agents first perform individual learning to produce an intermediate solution, and then apply social learning to the intermediate solutions. This method does not rely on any of the solution comparison oracles.

We follow existing literature by focusing on the fallback method. As a robustness check, we also consider the parallel method, which uses the same agent capabilities but is arguably more powerful.

Combined social learning strategies may also differ in their *criticality* [7, 66]. After combining individual and social learning according to one of the above methods, non-critical agents immediately adopt the result. Critical agents, on the other hand, compare the quality of the new solution to their previous solution, only adopting the new one if it provides an improvement. Note that critical behavior relies on information about solution quality and requires single-solution comparison capability, or stronger.

3.2.7 Statistical Methods

All comparisons are made using two-tailed paired t-tests. Pairs of observations correspond to the same instance of the NK-model objective function. Significance values have been corrected for multiple comparisons using the Bonferroni correction.

3.3 Results

Here we present the results of 1000 runs of an agent-based model of deliberation. In each run, an NK model is generated (N=15, K=6) and the model is simulated for 300 iterations for each network/strategy combination. The results of these simulations are shown in Figure 3.2. Figures 3.3 and 3.4 show pairwise comparisons of solution quality between strategy/network settings. Figures 3.3–3.10 show the complete solution quality distributions for all settings. Tables 3.1–3.4 show the t-values and Bonferroni-corrected p-values for comparisons across networks and strategies.

We find that network deliberation identifies higher quality solutions than conventional deliberation when agents use the conform strategy, while requiring less time to converge. Within network deliberation, we find that the structurally efficient random pod network outperforms the structurally inefficient long-path network when agents use the conform strategy. However, when either best-neighbor or confident-neighbor is used, the inefficient network is preferable, consistent with findings for conventional networks [7]. We also find that the confident-neighbor strategy matches or outperforms best-neighbor across all networks, despite using strictly less information about solution quality.

3.3.1 Network vs. Conventional Deliberation

We are particularly interested in comparing the performance of network deliberation to that of conventional single-group deliberation. When the conform strategy is used, we find that both of the network deliberation conditions yield better performance than conventional networks (Figure 3.11). Analysis of the solution quality distributions (Figure 3.12) shows two distinct effects. First, network deliberation frequently finds maximal solutions while conventional deliberation does not. Second, even when non-maximal solutions are found, network deliberation finds higher-quality solutions. This benefit is robust across both parallel and fallback individual learning. The effect size is dramatic. Conventional networks combined with the conform strategy show the lowest performance of all conditions, while random pod network deliberation combined with the conform strategy shows higher performance than nearly all other conditions. The exception being small world network combined with the best/confident-neighbor strategy, which shows equal performance within our statistical resolution. Often, increased performance comes at the expense of speed as more time is devoted to exploring novel solutions. However, we find that network deliberation improves both performance and speed when the conform strategy is used, suggesting that interlocking network structure can enable more efficient exploration.

The conform strategy models contexts in which individuals rely heavily on social influence. Such contexts can arise from pro-conformity social norms, high levels of trust, social loafing, and limited information. As a form of rational ignorance, conformist behavior can conserve individual

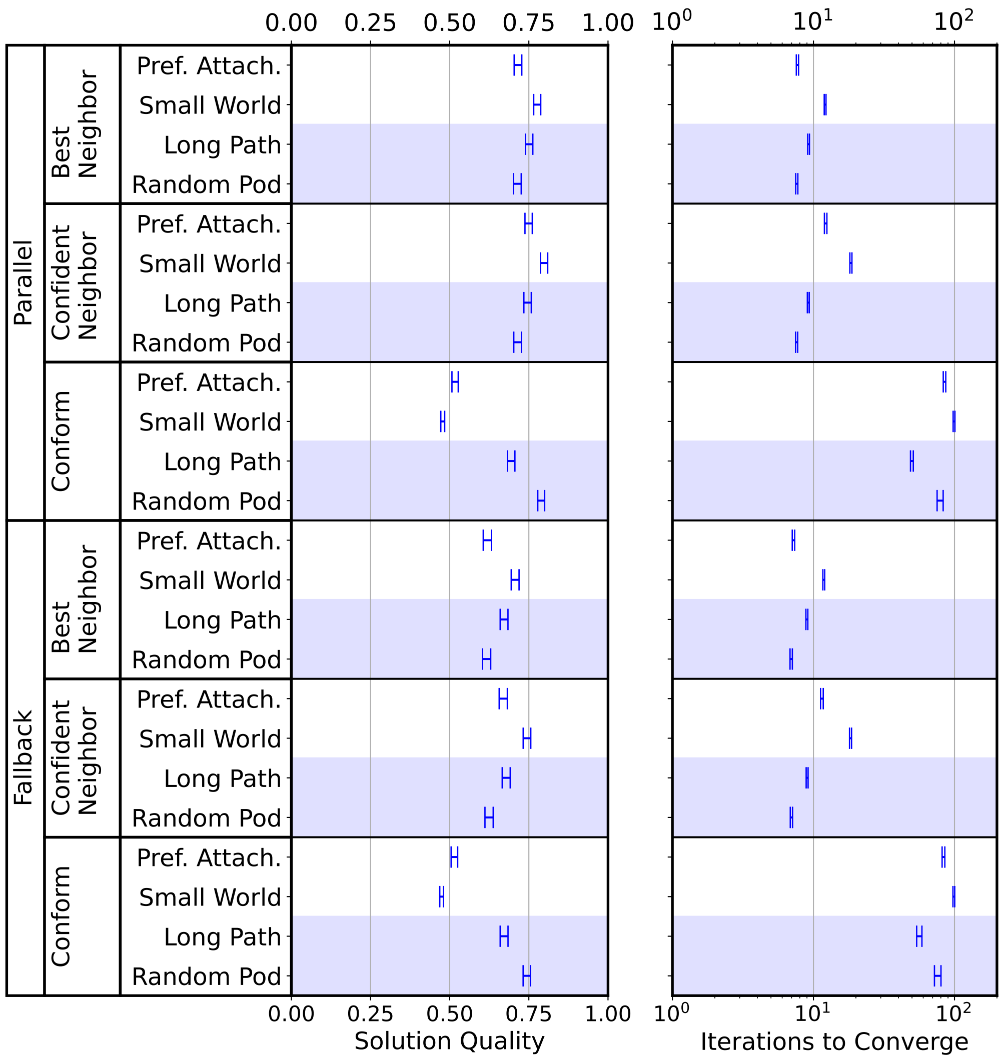

Figure 3.2: Solution quality and convergence time for agent-based simulations of different learning strategies. Error bars represent 95% confidence interval. Results for network deliberation are shown shaded.

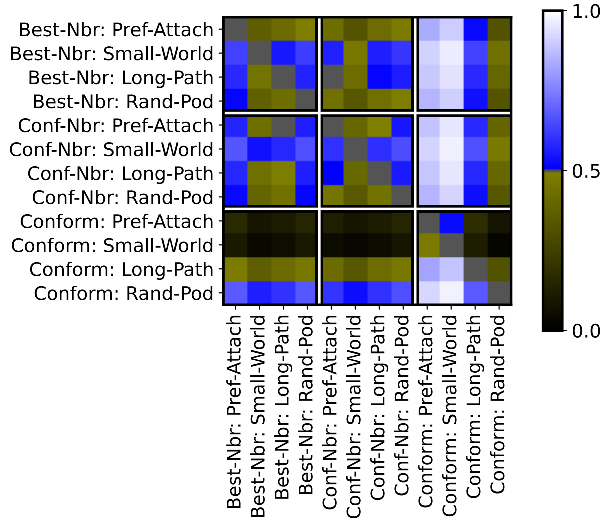

Figure 3.3: Fraction of simulations in which the row condition outperforms the column condition. Results are shown for parallel individual learning. In the case of a tie, weight is divided evenly.

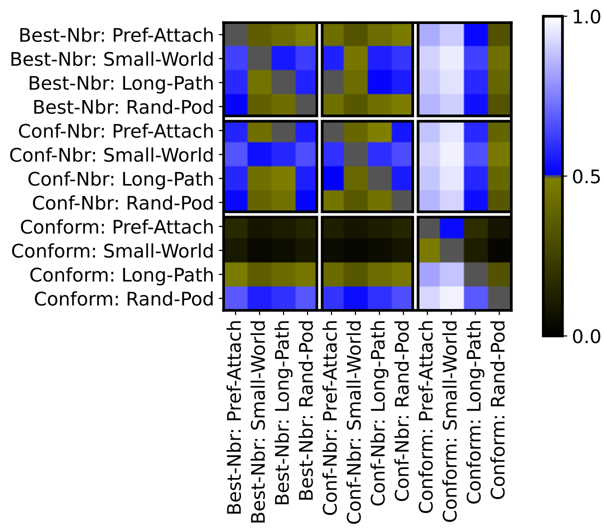

Figure 3.4: Fraction of simulations in which the row condition outperforms the column condition. Results are shown for fallback individual learning. In the case of a tie, weight is divided evenly.

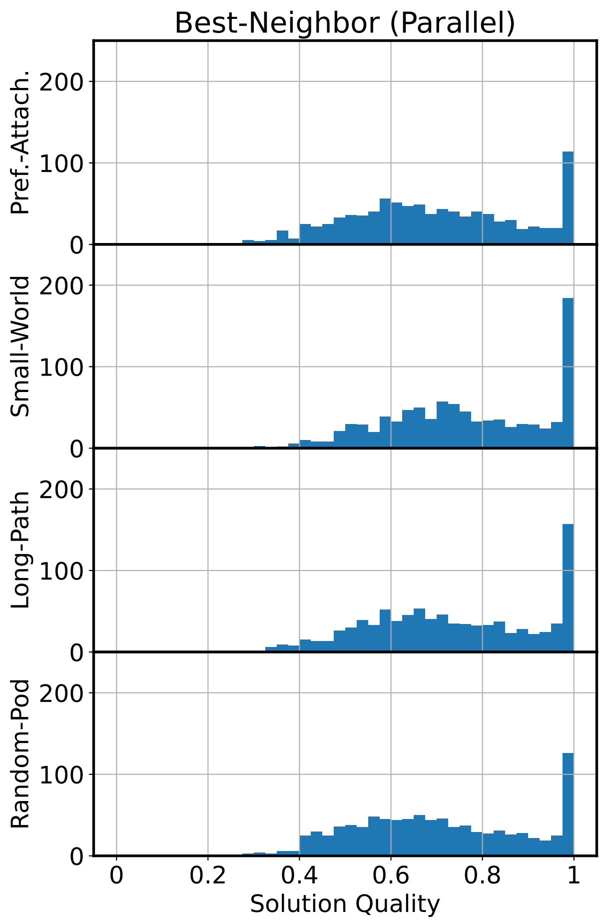

Figure 3.5: Solution quality distribution for best-neighbor strategy with parallel individual learning.

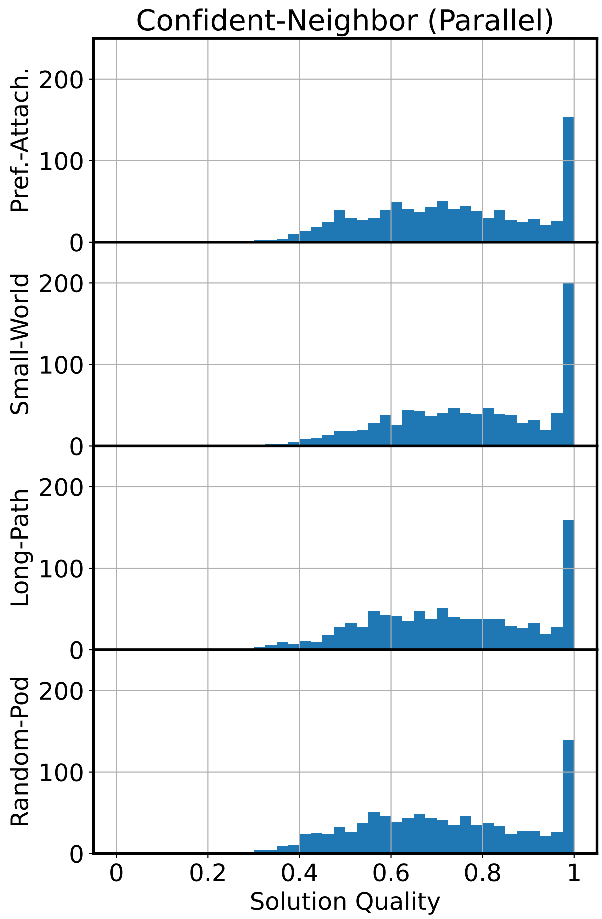

Figure 3.6: Solution quality distribution for confident-neighbor strategy with parallel individual learning.

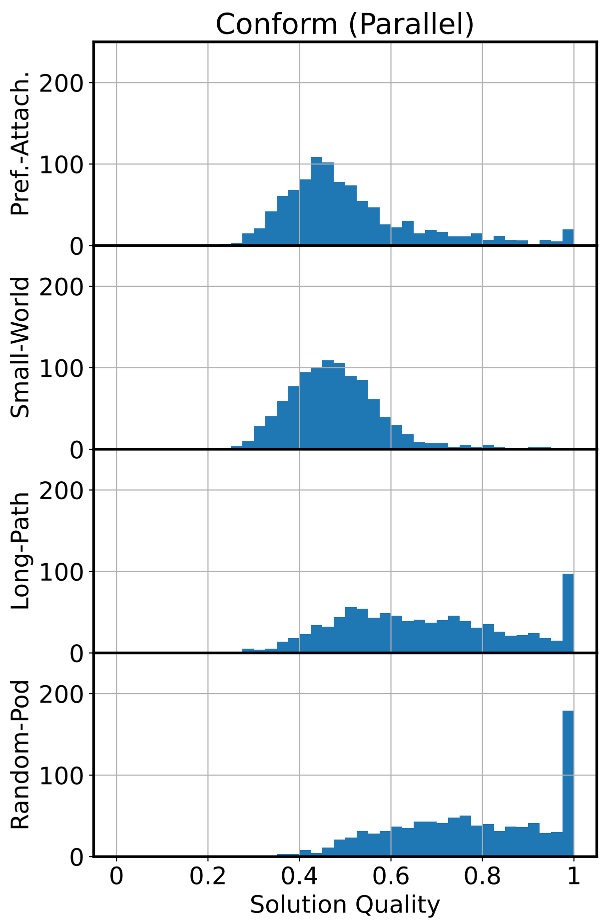

Figure 3.7: Solution quality distribution for the conform strategy with parallel individual learning.

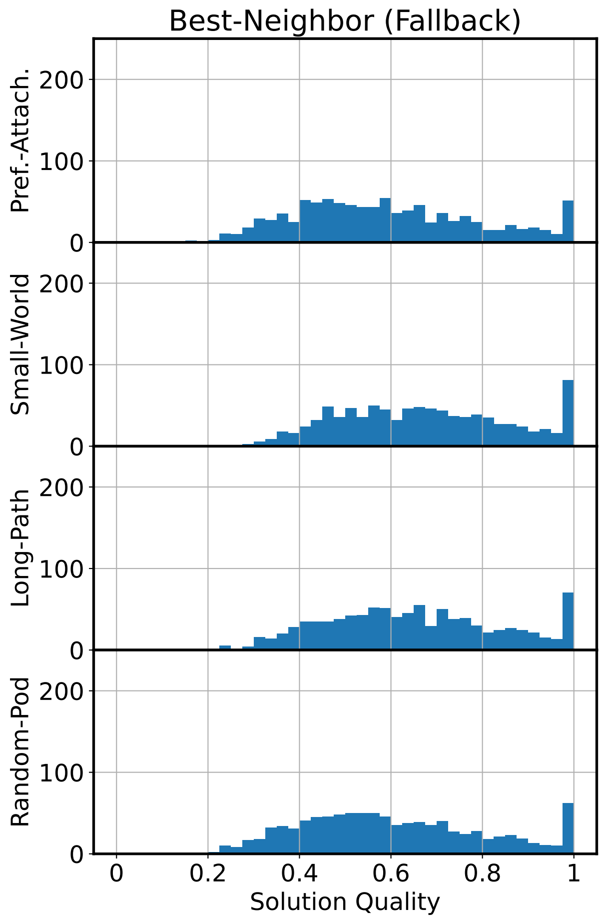

Figure 3.8: Solution quality distribution for best-neighbor strategy with fallback individual learning.

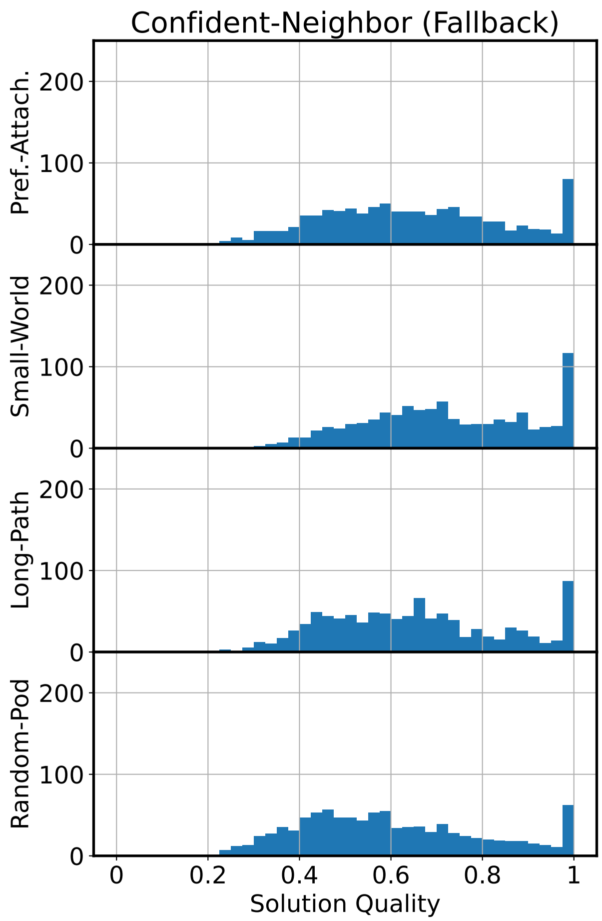

Figure 3.9: Solution quality distribution for confident-neighbor strategy with fallback individual learning.

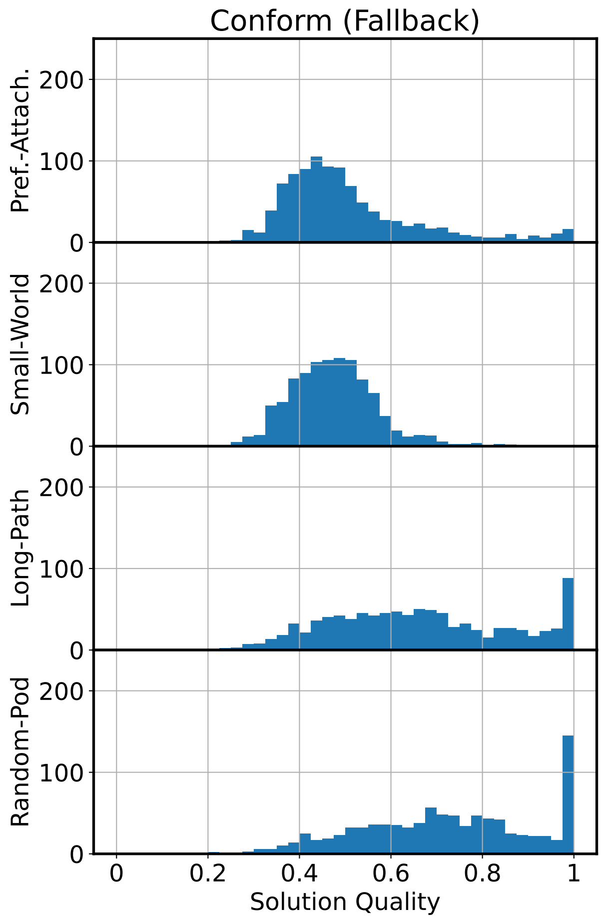

Figure 3.10: Solution quality distribution for the conform strategy with fallback individual learning.

Strategy	Net A	Net B	$\overline{B-A}$	t	p*
Best Neighbor	Pref. Attach.	Small World	-8.70e-02	-1.33e+01	1.27e-35
Best Neighbor	Pref. Attach.	Long Path	-5.98e-02	-8.62e+00	1.51e-15
Best Neighbor	Pref. Attach.	Random Pod	-1.15e-02	-1.83e+00	4.01e+00
Best Neighbor	Small World	Pref. Attach.	8.70e-02	1.33e+01	1.27e-35
Best Neighbor	Small World	Long Path	2.72e-02	4.53e+00	3.88e-04
Best Neighbor	Small World	Random Pod	7.55e-02	1.18e+01	1.66e-28
Best Neighbor	Long Path	Pref. Attach.	5.98e-02	8.62e+00	1.51e-15
Best Neighbor	Long Path	Small World	-2.72e-02	-4.53e+00	3.88e-04
Best Neighbor	Long Path	Random Pod	4.83e-02	7.34e+00	2.69e-11
Best Neighbor	Random Pod	Pref. Attach.	1.15e-02	1.83e+00	4.01e+00
Best Neighbor	Random Pod	Small World	-7.55e-02	-1.18e+01	1.66e-28
Best Neighbor	Random Pod	Long Path	-4.83e-02	-7.34e+00	2.69e-11
Confident Neighbor	Pref. Attach.	Small World	-7.52e-02	-1.13e+01	2.94e-26
Confident Neighbor	Pref. Attach.	Long Path	2.39e-03	3.64e-01	4.30e+01
Confident Neighbor	Pref. Attach.	Random Pod	5.80e-02	8.88e+00	1.86e-16
Confident Neighbor	Small World	Pref. Attach.	7.52e-02	1.13e+01	2.94e-26
Confident Neighbor	Small World	Long Path	7.76e-02	1.21e+01	1.08e-29
Confident Neighbor	Small World	Random Pod	1.33e-01	1.92e+01	1.36e-68
Confident Neighbor	Long Path	Pref. Attach.	-2.39e-03	-3.64e-01	4.30e+01
Confident Neighbor	Long Path	Small World	-7.76e-02	-1.21e+01	1.08e-29
Confident Neighbor	Long Path	Random Pod	5.56e-02	8.50e+00	4.00e-15
Confident Neighbor	Random Pod	Pref. Attach.	-5.80e-02	-8.88e+00	1.86e-16
Confident Neighbor	Random Pod	Small World	-1.33e-01	-1.92e+01	1.36e-68
Confident Neighbor	Random Pod	Long Path	-5.56e-02	-8.50e+00	4.00e-15
Conform	Pref. Attach.	Small World	3.60e-02	6.78e+00	1.24e-09
Conform	Pref. Attach.	Long Path	-1.63e-01	-2.22e+01	2.25e-87
Conform	Pref. Attach.	Random Pod	-2.28e-01	-3.19e+01	9.08e-153
Conform	Small World	Pref. Attach.	-3.60e-02	-6.78e+00	1.24e-09
Conform	Small World	Long Path	-1.99e-01	-3.17e+01	1.59e-151
Conform	Small World	Random Pod	-2.64e-01	-4.43e+01	2.20e-236
Conform	Long Path	Pref. Attach.	1.63e-01	2.22e+01	2.25e-87
Conform	Long Path	Small World	1.99e-01	3.17e+01	1.59e-151
Conform	Long Path	Random Pod	-6.48e-02	-8.31e+00	1.79e-14
Conform	Random Pod	Pref. Attach.	2.28e-01	3.19e+01	9.08e-153
Conform	Random Pod	Small World	2.64e-01	4.43e+01	2.20e-236
Conform	Random Pod	Long Path	6.48e-02	8.31e+00	1.79e-14

Table 3.1: Two-tailed paired t-values across networks, within strategies. Results are for fallback individual learning. For all rows, dof=999 and p^* is the Bonferroni-corrected p-value with m=60.

Network	Strategy A	Strategy B	$\overline{B-A}$	t	p*
Pref. Attach.	Best Neighbor	Confident Neighbor	-6.43e-02	-9.39e+00	2.33e-18
Pref. Attach.	Best Neighbor	Conform	8.96e-02	1.19e+01	6.83e-29
Pref. Attach.	Confident Neighbor	Best Neighbor	6.43e-02	9.39e+00	2.33e-18
Pref. Attach.	Confident Neighbor	Conform	1.54e-01	2.06e+01	7.57e-77
Pref. Attach.	Conform	Best Neighbor	-8.96e-02	-1.19e+01	6.83e-29
Pref. Attach.	Conform	Confident Neighbor	-1.54e-01	-2.06e+01	7.57e-77
Small World	Best Neighbor	Confident Neighbor	-5.26e-02	-8.39e+00	9.70e-15
Small World	Best Neighbor	Conform	2.13e-01	3.52e+01	4.46e-175
Small World	Confident Neighbor	Best Neighbor	5.26e-02	8.39e+00	9.70e-15
Small World	Confident Neighbor	Conform	2.65e-01	4.45e+01	1.24e-237
Small World	Conform	Best Neighbor	-2.13e-01	-3.52e+01	4.46e-175
Small World	Conform	Confident Neighbor	-2.65e-01	-4.45e+01	1.24e-237
Long Path	Best Neighbor	Confident Neighbor	-2.12e-03	-3.42e-01	4.39e+01
Long Path	Best Neighbor	Conform	-1.37e-02	-1.71e+00	5.20e+00
Long Path	Confident Neighbor	Best Neighbor	2.12e-03	3.42e-01	4.39e+01
Long Path	Confident Neighbor	Conform	-1.16e-02	-1.44e+00	8.96e+00
Long Path	Conform	Best Neighbor	1.37e-02	1.71e+00	5.20e+00
Long Path	Conform	Confident Neighbor	1.16e-02	1.44e+00	8.96e+00
Random Pod	Best Neighbor	Confident Neighbor	5.18e-03	8.40e-01	2.41e+01
Random Pod	Best Neighbor	Conform	-1.27e-01	-1.64e+01	1.07e-51
Random Pod	Confident Neighbor	Best Neighbor	-5.18e-03	-8.40e-01	2.41e+01
Random Pod	Confident Neighbor	Conform	-1.32e-01	-1.67e+01	1.39e-53
Random Pod	Conform	Best Neighbor	1.27e-01	1.64e+01	1.07e-51
Random Pod	Conform	Confident Neighbor	1.32e-01	1.67e+01	1.39e-53

Table 3.2: Two-tailed paired t-values across strategies, within networks. Results are for fallback individual learning. For all rows, dof=999 and p^* is the Bonferroni-corrected p-value with m=60.

Strategy	Net A	Net B	$\overline{B-A}$	t	p*
Best Neighbor	Pref. Attach.	Small World	-6.75e-02	-1.13e+01	2.48e-26
Best Neighbor	Pref. Attach.	Long Path	-4.24e-02	-6.78e+00	1.25e-09
Best Neighbor	Pref. Attach.	Random Pod	-8.14e-03	-1.32e+00	1.12e+01
Best Neighbor	Small World	Pref. Attach.	6.75e-02	1.13e+01	2.48e-26
Best Neighbor	Small World	Long Path	2.50e-02	4.25e+00	1.42e-03
Best Neighbor	Small World	Random Pod	5.93e-02	9.38e+00	2.54e-18
Best Neighbor	Long Path	Pref. Attach.	4.24e-02	6.78e+00	1.25e-09
Best Neighbor	Long Path	Small World	-2.50e-02	-4.25e+00	1.42e-03
Best Neighbor	Long Path	Random Pod	3.43e-02	5.36e+00	6.14e-06
Best Neighbor	Random Pod	Pref. Attach.	8.14e-03	1.32e+00	1.12e+01
Best Neighbor	Random Pod	Small World	-5.93e-02	-9.38e+00	2.54e-18
Best Neighbor	Random Pod	Long Path	-3.43e-02	-5.36e+00	6.14e-06
Confident Neighbor	Pref. Attach.	Small World	-4.49e-02	-7.20e+00	7.03e-11
Confident Neighbor	Pref. Attach.	Long Path	-5.03e-03	-7.65e-01	2.67e+01
Confident Neighbor	Pref. Attach.	Random Pod	2.61e-02	4.02e+00	3.74e-03
Confident Neighbor	Small World	Pref. Attach.	4.49e-02	7.20e+00	7.03e-11
Confident Neighbor	Small World	Long Path	3.99e-02	6.96e+00	3.80e-10
Confident Neighbor	Small World	Random Pod	7.10e-02	1.18e+01	1.98e-28
Confident Neighbor	Long Path	Pref. Attach.	5.03e-03	7.65e-01	2.67e+01
Confident Neighbor	Long Path	Small World	-3.99e-02	-6.96e+00	3.80e-10
Confident Neighbor	Long Path	Random Pod	3.11e-02	4.89e+00	7.03e-05
Confident Neighbor	Random Pod	Pref. Attach.	-2.61e-02	-4.02e+00	3.74e-03
Confident Neighbor	Random Pod	Small World	-7.10e-02	-1.18e+01	1.98e-28
Confident Neighbor	Random Pod	Long Path	-3.11e-02	-4.89e+00	7.03e-05
Conform	Pref. Attach.	Small World	3.67e-02	6.85e+00	7.73e-10
Conform	Pref. Attach.	Long Path	-1.73e-01	-2.40e+01	7.10e-99
Conform	Pref. Attach.	Random Pod	-2.77e-01	-4.08e+01	6.29e-213
Conform	Small World	Pref. Attach.	-3.67e-02	-6.85e+00	7.73e-10
Conform	Small World	Long Path	-2.09e-01	-3.46e+01	3.46e-171
Conform	Small World	Random Pod	-3.14e-01	-5.68e+01	1.63e-313
Conform	Long Path	Pref. Attach.	1.73e-01	2.40e+01	7.10e-99
Conform	Long Path	Small World	2.09e-01	3.46e+01	3.46e-171
Conform	Long Path	Random Pod	-1.04e-01	-1.43e+01	8.55e-41
Conform	Random Pod	Pref. Attach.	2.77e-01	4.08e+01	6.29e-213
Conform	Random Pod	Small World	3.14e-01	5.68e+01	1.63e-313
Conform	Random Pod	Long Path	1.04e-01	1.43e+01	8.55e-41

Table 3.3: Two-tailed paired t-values across networks, within strategies. Results are for parallel individual learning. For all rows, dof=999 and p^* is the Bonferroni-corrected p-value with m=60.

Network	Strategy A	Strategy B	$\overline{B-A}$	t	p*
Pref. Attach.	Best Neighbor	Confident Neighbor	-3.78e-02	-5.94e+00	2.39e-07
Pref. Attach.	Best Neighbor	Conform	2.00e-01	2.77e+01	3.28e-124
Pref. Attach.	Confident Neighbor	Best Neighbor	3.78e-02	5.94e+00	2.39e-07
Pref. Attach.	Confident Neighbor	Conform	2.38e-01	3.40e+01	1.67e-167
Pref. Attach.	Conform	Best Neighbor	-2.00e-01	-2.77e+01	3.28e-124
Pref. Attach.	Conform	Confident Neighbor	-2.38e-01	-3.40e+01	1.67e-167
Small World	Best Neighbor	Confident Neighbor	-1.52e-02	-2.74e+00	3.80e-01
Small World	Best Neighbor	Conform	3.05e-01	5.30e+01	1.25e-290
Small World	Confident Neighbor	Best Neighbor	1.52e-02	2.74e+00	3.80e-01
Small World	Confident Neighbor	Conform	3.20e-01	5.89e+01	0.00e+00
Small World	Conform	Best Neighbor	-3.05e-01	-5.30e+01	1.25e-290
Small World	Conform	Confident Neighbor	-3.20e-01	-5.89e+01	0.00e+00
Long Path	Best Neighbor	Confident Neighbor	-3.88e-04	-6.64e-02	5.68e+01
Long Path	Best Neighbor	Conform	7.02e-02	9.34e+00	3.64e-18
Long Path	Confident Neighbor	Best Neighbor	3.88e-04	6.64e-02	5.68e+01
Long Path	Confident Neighbor	Conform	7.06e-02	9.15e+00	1.83e-17
Long Path	Conform	Best Neighbor	-7.02e-02	-9.34e+00	3.64e-18
Long Path	Conform	Confident Neighbor	-7.06e-02	-9.15e+00	1.83e-17
Random Pod	Best Neighbor	Confident Neighbor	-3.59e-03	-5.46e-01	3.51e+01
Random Pod	Best Neighbor	Conform	-6.84e-02	-9.54e+00	6.11e-19
Random Pod	Confident Neighbor	Best Neighbor	3.59e-03	5.46e-01	3.51e+01
Random Pod	Confident Neighbor	Conform	-6.48e-02	-8.96e+00	9.43e-17
Random Pod	Conform	Best Neighbor	6.84e-02	9.54e+00	6.11e-19
Random Pod	Conform	Confident Neighbor	6.48e-02	8.96e+00	9.43e-17

Table 3.4: Two-tailed paired t-values across strategies, within networks. Results are for parallel individual learning. For all rows, dof=999 and p^* is the Bonferroni-corrected p-value with m=60.

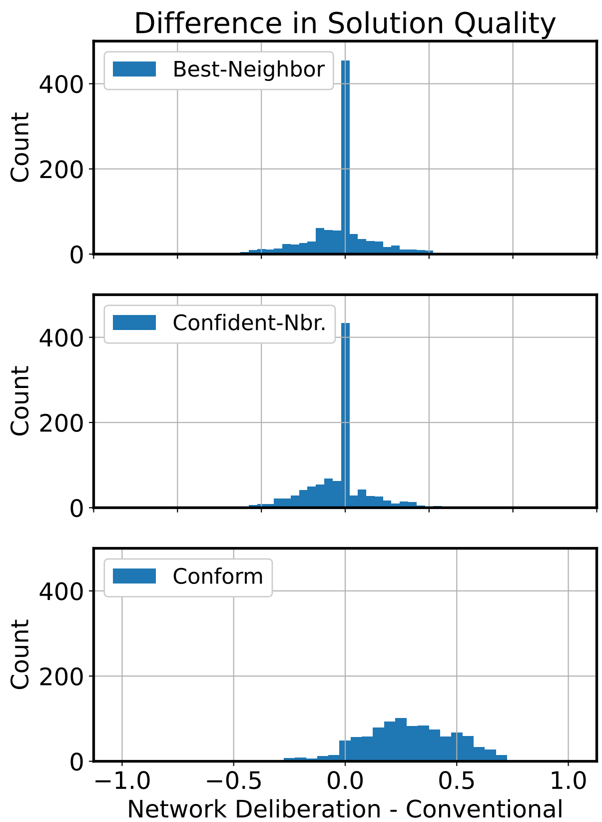

Figure 3.11: Difference in solution quality between network deliberation and conventional deliberation. Plots for Best/Confident-Neighbor show results for long-path and small-world networks, while the plot for conform shows results for random-pod and preferential-attachment networks. Results are shown for parallel individual learning.

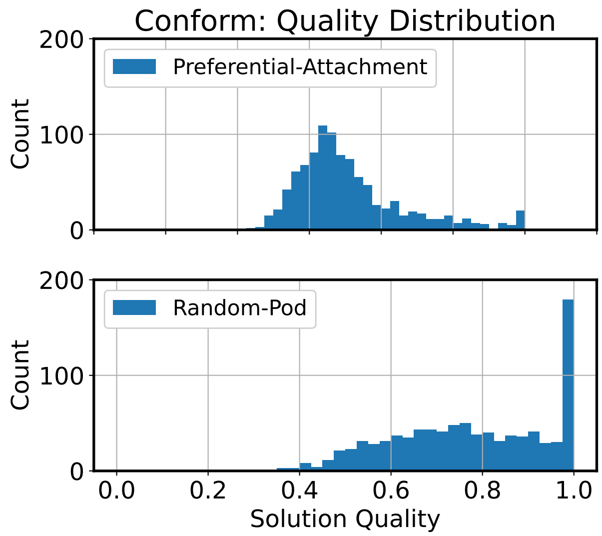

Figure 3.12: Distributions of solution quality for social learning on a preferential-attachment network and random-pod network deliberation. Results are shown for parallel individual learning.

resources, but poses the risk of forming information cascades and propagating misinformation and inferior or harmful innovations [5]. Our simulations show that network deliberation can greatly improve the outcome of deliberation in the presence of strong social influence. This insight suggests one possible mechanism behind the success of mass deliberative projects, as well as the potential for network-based interventions in mass deliberation.

3.3.2 Structural Efficiency

The speed at which information can move through a communication network, i.e., it's structural efficiency, has been found to influence the success of collective problem-solving. We might expect the same to be true in network deliberation. In network deliberation, network structure is created through group membership. We compare the results of two group assignment methods: a random pod assignment yielding an efficient network, and a long-path method yielding a less efficient network (Figure 3.13). We find that for greedy strategies (best-neighbor and confident-neighbor), the inefficient network yields the better results. The results are opposite for the conform strategy, with the efficient network yielding better results. These results are consistent with those observed for conventional single-group networks [7], but to the best of our knowledge, they had not been explored for interlocking network like the ones we use to model network deliberation.

The role of structural efficiency in collective tasks can be partially attributed to diversity [53, 43]. Greedy strategies such as best/confident-neighbor result in agents adopting the highest quality solution they have seen so far and discarding all others. Such strategies quickly reduce

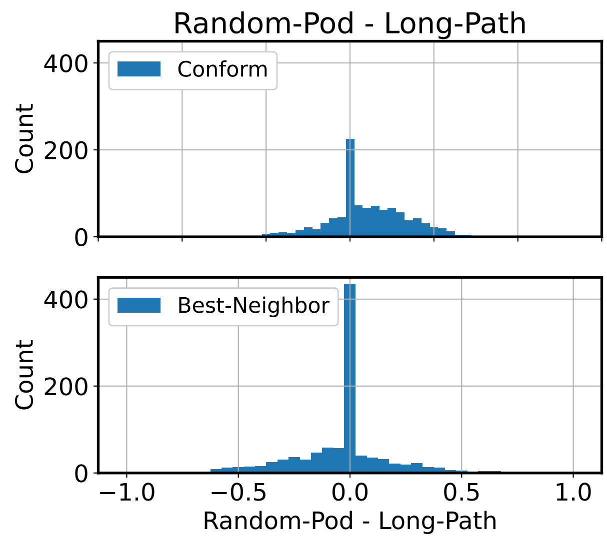

Figure 3.13: Difference in solution quality between random-pod (efficient) and long-path (inefficient) network. Results are shown for parallel individual learning.

the number of solutions present in the population, quickly identifying a local maximum at the cost of diversity. As a result, agents duplicate efforts during individual learning, exploring mutations of the same solution. Inefficient networks can mitigate this effect by slowing the spread of high-quality solutions and allowing time for the exploration of new and potentially better solutions. Our results show exactly this, with long-path pod assignment improving the performance of greedy algorithms. The improved performance of the conform strategy in random pod assignment can be attributed to the converse of the above. When social influence is strong, efficient networks can interrupt information cascades by introducing new information from far across the network. Our results are thus generally consistent with existing theory on structural efficiency and collective problem-solving. However, we note an interesting deviation: under the conform strategy, long-path network deliberation out-performs the two conventional networks, both of which are more efficient.

3.3.3 Confident-Neighbor Strategy

In general, the best-neighbor strategy requires strong assumptions about agents' ability to evaluate solutions. In the special case of network deliberation, the assumptions can be weakened by applying a variant of the strategy, which has not been previously studied. The variant, which we call *confident-neighbor*, is equivalent to best-neighbor for network deliberation, but not in general. Confident-neighbor thus provides a comparison between network deliberation and conventional single-group deliberation under weaker informational assumptions than best-neighbor. Surpris-

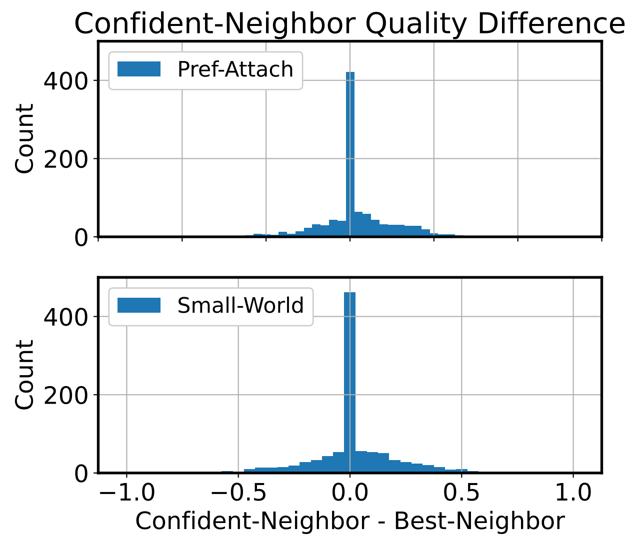

Figure 3.14: Histograms of the difference in solution quality between confident-neighbor and best-neighbor for both conventional networks. Results are shown for parallel individual learning.

ingly, the weaker assumptions of confident-neighbor lead to higher performance on the preferential attachment network, and similar performance on the-small world network (within our statistical resolution). Figure 3.14 shows histograms of the quality difference between confident-neighbor and best-neighbor for both conventional networks. In the majority of cases, both strategies find comparable solutions. However, we find that when these strategies do find different solutions, those found by confident-neighbor are more often better, at least for the preferential-attachment network.

As with conform, the confident-neighbor strategy can be used when available information is insufficient to use best-neighbor. Unlike conform, confident-neighbor models weak social influence. The improved performance of confident-neighbor over best-neighbor, despite using less information, can be attributed at least in part to diversity and exploration. Confident neighbor takes significantly longer to converge, suggesting it maintains a diversity of solutions and allows more time to explore new solutions. Our results suggest several interventions with the potential to improve conventional single-group deliberation. In the presence of weak social influence, reducing the amount of information available can counter-intuitively increase performance. Conversely, when information is already limited, performance might be increased by weakening social influence. However, while confident-neighbor can increase the success of conventional deliberation, it performs comparably to network deliberation using the conform strategy, suggesting that when social influence is strong, network deliberation remains preferable.

3.4 Discussion

We have proposed and evaluated a model of mass deliberation based on the observed interlocking network structure of successful mass-deliberative projects. Our central finding suggests that network deliberation can improve deliberative output in the presence of strong social influence (i.e., the conform strategy). Individuals rely on social influence for a number of reasons. Strong social influence can stem from social factors such as trust or social loafing. Alternatively, social influence can be used to supplement individual skill when it is insufficient for a given task. We see that a variety of contexts can lead to reliance on social influence. Empirical evidence suggests the presence of strong social influence in real-world collaborations such as Wikipedia [64] and in lab studies of human collaboration [56, 7]. In the case of weak social influence (i.e., the best-neighbor and confident-neighbor strategies), we do not observe a significant difference in output quality between network deliberation and conventional single-group deliberation. In all cases, network deliberation performs better than single-group deliberation or comparatively well. Our results suggest that network deliberation is both a contributing mechanism to the success of mass-deliberative projects as well as a useful tool for the design of large-scale sociotechnical systems and interventions for existing systems.

How does network deliberation improve collaborative output? In part, the high performance of random-pod network deliberation can be attributed to the high structural efficiency of the resulting network. However, structural efficiency cannot be the complete mechanism. Long-path network deliberation is extremely inefficient, but still outperforms conventional networks in the presence of strong social influence. The additional mechanisms at play remain an open question.

In order to distinguish between the effects of social influence and individual ability, we have introduced the confident-neighbor strategy, which (unlike best-neighbor) assumes the same agent capabilities as the conform strategy (in a critical learning setting). While not central to our study of network deliberation, our findings regarding the confident-neighbor strategy have important implications for the study of social learning in general. Our findings show that just as reducing network efficiency can improve solution quality by raising diversity, reducing the available information can improve the performance of greedy learning strategies. Our investigation of confident-neighbor stems from a careful formal analysis of the information required by each strategy. The surprisingly high performance of confident-neighbor shows the importance of isolating social influence from agent ability.

Our work is limited by a number of assumptions, which require further investigation to achieve greater generalizability. We assume a static objective function, while real-world objectives can change with changing external conditions as well as changing individual preferences. We also assume a homogeneous strategy across all agents, which raises questions of how different strategies interact within the same collaboration. We have also assumed that agents are truthful and do not form coalitions outside of the existing network, both assumptions which can be violated in real-world settings. We have also assumed that agents have access to the full solution string, and that agents incorporate all bits of the string into their quality estimates. Extremely complex real-world tasks might be better-modeled by a collection of sub-tasks, with agents having access to only a subset of the solution string. Finally, we have limited our study to learning strategies that explore new solutions solely through small mutations of existing solutions. Other potential strategies might generate entirely new solutions, for example, by combining parts of multiple previous solutions. Such generative strategies would add the ability to explore a wider range of solutions. While our work extends the understanding of social learning and collaboration, many questions still remain open for exploration.

Effective mass deliberation is key to realizing the democratizing power of the internet. Our findings suggest that the presence of small and interlocking pods can contribute to the success of mass deliberation, particularly when the topic is complex and social influence is strong. These findings have implications for a range of deliberative contexts: participatory government and budgeting, worker-owned cooperatives, grassroots social movements, and the governance of decentralized systems (e.g., cryptocurrency). By enabling better deliberation at larger scales, we hope this work will contribute to democratizing the governance of large sociotechnical systems, and empowering the individuals impacted by those systems.

CHAPTER 4

Experimental evaluation of Network Deliberaiton

4.1 Introduction

Networks of small interlocking pods appear as a common thread throughout successful large-scale collaborations. However, it remains unclear whether that network structure plays a causal role in the success of those collaborations, and whether the specific structural properties of that interlocking network matter. Observational study suggests a correlation between properties such as degree, structural efficiency, and structural inequality and the performance/productivity of collaborations [64]. Numerical simulation suggests a causal relationship in a simplified theoretical setting (Chapter 3). To bridge these two findings, this chapter presents the results of an online experiment studying the role of network deliberation in the evolution of group preferences.

Collaboration and collective action allow groups of individuals to manage shared resources and combine efforts towards common goals, but also introduce the problem of governance and collective decision-making. While collective governance of common resources is a historically hard problem, Ostrom described principles seen in successful systems [62]. More recently, the proliferation of inexpensive point-to-point global communication via the internet has enabled a number of successful large-scale collaborations and movements, including free/open-source software [8, 18, 65], Wikipedia [49, 8, 33], and social movements [75, 37].

Scholars of democracy commonly describe governance systems in terms of two axes: representation and argumentation [1, 37]. Here, *representation* refers to how many people participate in decision-making, while *argumentation* refers to the amount of discourse between the decision-makers. While both can improve governance, they are difficult to achieve simultaneously [32, 30] and tradeoffs can be made to favor one over the other, as in voting (high representation, low argumentation) and representative democracy (low representation, high argumentation).

We focus on deliberation due to fundamental limitations of voting. Results from social choice theory showt that any ranked-choice voting system is subject to limitations such as the Condorcet Paradox [19] and Arrow's Impossibility Theorem [4]. Deliberation offers one way to avoid these limitations by changing individual preferences [1]. The success of deliberation at generating consensus has been attributed to its ability to identify and resolve conflict [32]. However, deliberation also carries risks, such as the posibility of pushing individuals towards extreme and polarized preferences [69].

In any sufficiently large group, it becomes unfeasible for all members to interact with each other. Understanding collaboration in large groups thus requires attention to the network structure of who interacts with whom. The field of social learning has studied both simple estimation tasks [22, 35] and more complex rugged-landscape optimization tasks [53, 7]. Observational studies have been used to analyze the network structures of online collaborations [37, 64]. Lab and field studies have also been used to study real-world collaborations on a small scale [68, 47]. As discussed in Chapter 3, the successful large-scale collaborations enabled by the internet often exhibit network sructures characterized by small, interlocking groups, reminiscent of interlocking directorates [54] and interlocking publics [40]. In Chapter 3, we describe agent-based simulations showing that such network deliberation can improve performance on complex tasks when individuals exhibit strong social influence.dsd Here, we expand on existing research by performing a controlled online experimental evaluation of network deliberation. We use periodic polling to track preference evolution, allowing causal inference in a real-world setting.

While many studies have examined the role of network structure in collaboration, there has so far been little attention to the interlocking pod structure of network deliberation. The closest we are aware of is the study of network rotation by Salehi & Bernstein [68]. The present experiment goes beyond existing work primarily by tracking preferences throughout the experiment and by the use of a conventional single-group control condition. We also describe multiple network deliberation topologies for achieving efficient or inefficient networks. For the present study, we focus on an efficient topology.

The experiment described here focuses on several issues. Based on observational and numerical findings that successful large-scale collaborations often exhibit network deliberation struture, we test the following hypothesis:

H1: Network deliberation results in higher agreement among participants than single large-group deliberation.

We are also concerned with the dynamics of preference evolution under network deliberation, which may provide insight into possible mechanisms. One such mechanism proposed in consensus decision-making literature is the ability to identify and resolve conflict. We thus also seek to address two research questions:

RQ1: How do preferences evolve throughout network deliberation?

RQ2: How effective is network deliberation at identifying and resolving conflict?

We find difference in preference evolution between network deliberation and conventional deliberation. Our primary contributions are:

- We find experimental support for the hypothesis that network deliberation is better at facilitating agreement than conventional deliberation.
- We find evidence suggesting network deliberation can provide protection against information cascades.
- We find no evidence that network deliberation facilitates substantial conflict-resolution, but that it may provide protection against polarization.

We present relevant theory in Section 4.2. We describe the experiment in Section 4.3 and present the results in Section 4.4. We discuss the results in Section 4.5 and conclude in Section 4.6.

4.2 Theory

4.2.1 Social Choice Theory

Our analysis of preferences is foudned in the formalism of social choice theory [4, 31]. In social choice theory, individual's *preferences* are represented by a ranked ordering of *alternatives* (e.g., proposals, candidates). The set of preferences for all individuals in a group is called the *preference profile*. A *social welfare function* can be applied to the profile to generate a *social preference*: an ordering of alternatives representing the preference of the group as a whole. A *social choice function* represents a voting system: it selects a subset of winners from the available alternatives.

4.2.2 Quantifying Agreement

Social choice theory typically focuses on identifying and describing the limitations of specific voting systems. Instead, we build on social choice theory to quantify the level of agreement in a group, based in individual profiles.

We use ranked-choice polls to construct preference profiles which are used to quantify agreement and conflict over the course of deliberation. Within social choice theory, agreement can be defined by a *consensus class*, a set of preference profiles meeting one of several consensus criteria [26]. Examples include strong unanimity (of rank orders), unanimity (of winners), majority (existence of majority), Condorcet (existence of Condorcet winner), and transitivity (of social preference). On the most restrictive end, in strong unanimity and unanimity, all decision-makers prefer the same alternative. In contrast, transitivity only requires that the social preferences induced by individual preferences are transitive. Distance-rationalizable voting systems are defined by projecting the preference profile onto the nearest consensus profile according to a suitable distance. For example, Dodgson's method [25, 14] defines a distance based on swapping adjacent entries in individual preference profiles. However, for most voting systems, finding the consensus profile that minimizes distance is NP-Hard [26]. Social choice theory also provides measures of distances between two individual preference rankings. These measures can be extended to create measures of agreement for entire preference profiles that can be calculated efficiently.

One possibility is to measure the distance from strong unanimity. Any distance metric δ with a range of $[0, 1]$ can be converted to a measure of correlation with range $[-1, 1]$ by taking $1-2\delta$. One such measure is based on the Kendall tau metric, and the corresponding Kendall tau correlation [50]. The Kendall tau metric is the fraction of pairwise contests that have different results between two profiles. By averaging the corresponding correlation over all pairs of members, an overall measure of agreement can be calculated for the group. While commonly used in social choice theory, the Kendall tau weights all contests equally, regardless of the ranks of the alteratives. In practical settings with a small number of winners, the contests between highly-ranked alternatives are more consequential than those of low-ranked alternatives; participants don't care if they disagree on the ordering of losing alternatives as long as they agree on which ones win and lose. Various weighted extensions of the Kendall metric have been proposed [71, 16], each with benefits and drawbacks. We propose our own based on metric structure, uniqueness, and efficiency of calculation, which we describe below.

4.2.2.1 Weighted Crossing Distance

We propose the following weighted distance metric for preference rankings. Given a set of M alternatives, there are $M-1$ ways to divide an ordering into two nonempty sets of adjacent alternatives, i.e., a high set and a low set. For a pair of preferences p, q, we define a length $M-1$ *crossing vector* $v_m(p, q)$ to be equal to the number of alternatives in the highest m positions of p and not in the highest m positions of q (it is easily shown that this measure is symmetric in p and q). Informally, v_m is the number of alternatives that cross place m. Each element of v_m is an integer in the range $[0, v_m^{\max}]$ dependent on the index:

$$v_m^{\max} = \begin{cases} m & m \leq (M-1)/2 \\ M-m & (M-1)/2 < m \leq M-1. \end{cases} \tag{4.1}$$

We construct the weighted crossing distance by taking a weighted sum over this vector. There are many potential choices for weights. We choose the weight of place m to be equal to the highest total of all lower ranked places plus one. Thus the weight at index $i = M - m$ (noting that low rank corresponds to high m) is given by:

$$w_i = 1 + \sum_{k=1}^{i-1} w_k v_k^{\max}. \tag{4.2}$$

4.2.3 Quantifying Social Influence

We are particularly interested in the role of social influence in preference evolution and require a formalism to quantify and analzye social influence. If two individuals preferences become closer, can we say whether one influenced the other? And if so, can we say which influence which? We cannot answer either question with certainty from preferences alone, but we can construct a reasonable proxy based on some simplifying assumptions. Namely, we will construct measures of social influence based on the assumptions that:

- The magnitude of an individual's change in preference increases with their susceptibility with social influence;
- The magnitude of an individual's change in preference increases with the magnitude of the distance between their preference and the influencing preference.

Thus, if the distance between the preferences of individuals A and B decreases, and the preference of B changed more than the preference of A, we assume that individual A influenced individual B. We now describe two formal measures that use these assumptions to quantify how susceptible to influence and how potential influential an individual is.

4.2.3.1 Conformity and Hipness

Let X be a set of alternatives (e.g., proposals or candidates) and let $\mathcal{L}$ be the set of strict total orders over X. We represent the preference of an individual p at time t by a strict total order $R_p(t) \in \mathcal{L}$. Given n individuals, we call the n-tuple of their preferences at time t the profile $R(t)$.

Let $d : \mathcal{L} \times \mathcal{L} \to \mathbb{R}$ be a dissimilarity function on preferences. We define the mean dissimilarity of the profile R at time t as:

$$\frac{1}{n(n-1)} \sum_{p} \sum_{q \neq p} d\left(p_t, q_t\right), \tag{4.3}$$

where p_t is shorthand for $R_p(t)$. The above quantity can be interpreted as a measure of disagreement among a group of individuals.

Let t_i be an initial time, and t_f be some later time. The negative change in mean dissimilarity is given by:

$$\Delta = \frac{-1}{n(n-1)} \sum_{p} \sum_{q \neq p} \left[d\left(p_f, q_f\right)\right) - d\left(p_i, q_i\right)\right]. \tag{4.4}$$

This quantity can be interpreted as the increase in agreement within the group between times t_i and t_f, with negative values signifying a decrease in agreement.

We wish to quantify whether a change in agreement/disagreement is due to individuals converging towards initially popular alternatives, or to the the group being persuaded towards initially unpopular alternatives. In the former case, we would expect the majority of individuals to change their preferences by a small amount, while a smaller number of individuals holding unpopular opinions make larger shifts towards popular preferences. In the latter case, we would expect the opposite: some individuals with unpopular preferences hold closely to those opinions, while a large number of individuals move away from the previous popular preferences. So we are interested not just in the total change in agreement/disagreement, but also in how that change is distributed across the individuals in the group.

To apportion the change in agreement between individuals p and q, we make the assumption that an individual's contribution to the change in agreement is proportional to the change in their own preference. Specifically, we define the conformity $c(p, q)$ of individual p toward individual q as:

$$\begin{aligned} d_i &= d(p_i, q_i) && (4.5) \\ d_f &= d(p_f, q_f) && (4.6) \\ |p| &= d(p_i, p_f) && (4.7) \\ c(p, q) &= -(d_f - d_i)\frac{|p|}{|p| + |q|}. && (4.8) \end{aligned}$$

Note that the change in agreement between two individuals can be written in terms of the conformity:

$$-(d_f - d_i) = c(p, q) + c(q, p). \qquad (4.9)$$

Similarly, the total change in agreement (4.4) can be rewritten as a sum of conformity over all pairs of individuals:

$$\Delta = \sum_p \sum_{q \neq p} c(p, q). \qquad (4.10)$$

By performing only one of the sums above, the change in agreement Δ can be written as a sum of terms, each corresponding to one individual. The sum can be performed over either the first or second argument of c. If the sum is performed over the second argument of c, the result is the mean conformity of a particular individual p toward all others:

$$C(p) = \sum_q c(p, q). \qquad (4.11)$$

Alternatively, if the sum is performed over the first argument of c, the result is the mean conformity of all others toward p, which we call the hipness $H(p)$:

$$H(p) = \sum_q c(q, p). \tag{4.12}$$

Both $C(p)$ and $H(p)$ are equal to Δ when summed over all individuals, but they describe conceptually different attributes of an individual. The conformity quantifies how much an individual has increased agreement by changing their preferences to match others. The hipness quantifies how much an individual has increased agreement due to holding an unchanging preference near to others' final preferences.

4.2.4 Network Topologies

In Chapter 3, we describe two models of network deliberation structure: random-pod and long-path. In order to expect a measurable difference from the control condition and between each other, a minimum network size is required. We decribe these considerations below. For the present experiment, we opt for only a control and random-pod condition based on the avaialble number of participants.

4.2.4.1 Network Size

The minimum number of participants required is determined by a number of factors. First, the long-path assignment method results in a minimum number of pods, determined by the chosen parameters. Specifically, the pod assignments for each round beyond the first are determined by a unique prime number, and the number of pods is a multiple of that prime. For $T = 3$ rounds, two primes are necessary and choosing the lowest two (2, 3) yields the lowest minimum number of pods: 3. For all pods to have at least 4 members, the minimum number of participants in the long-path treatment is 12.

The two network deliberation treatments must also have meaningfully different structural properties, which also necessitates a minimum number of participants. Structural differences between these two networks become more pronounced with a greater number of participants. While properties such as the broadcast time (see Chapter 3) and average geodesic length can be used to compare the structural efficiency of two networks, they encounter a problem for these particular networks when there is a small number of rounds: for many pairs of individuals, no path will exist. In practical terms, an idea proposed by one participant may not have a plausible path to reach some of the other participants by the end of the deliberation, even if that idea is repeatedly shared by all who encounter it. As an alternative, a form of k-connectivty can be used to measure structural

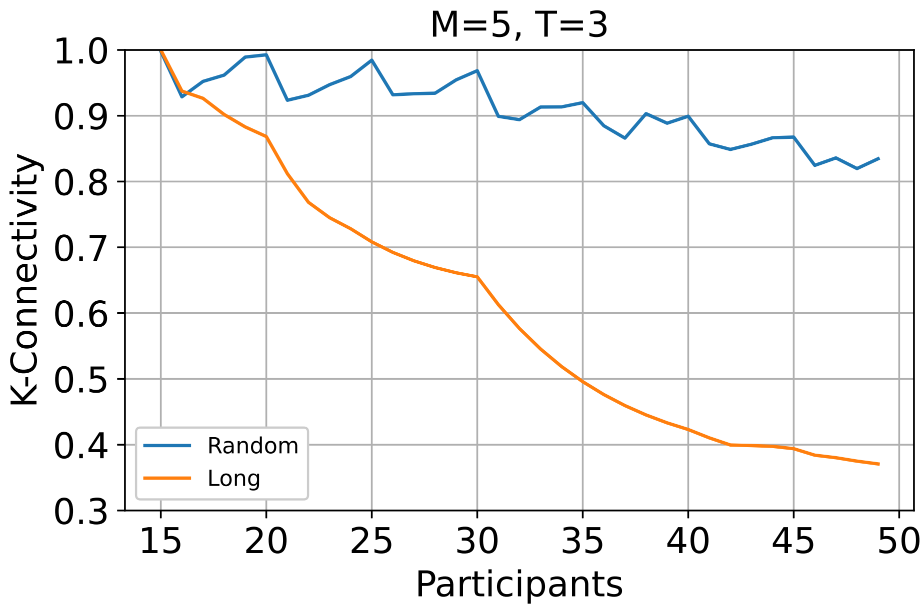

Figure 4.1: The k-connectivity of long-path and random-pod network deliberation networks for $T = 3$ stages and a pod size of $M = 5$.

efficiency. The k-connectivity is simply the fraction of possible paths that exist. In other words, if each participant broadcasts a message, and that message is repeated by all who encounter it, what is the average fraction of participants a broadcast will reach? Figure **??** shows the k-connectivity as a function of number of participants for both the long-path and random-pod deliberation networks. While there is no clear threshold for the necessary number of participants, choosing a k-connectivity of 0.5 (half of possible paths exist) seems a reasonable heuristic. For the chosen parameters, 35 or more participants are necessary to produce a random-pod network with > 0.5 k-connectivity and a long-path network with < 0.5 k-connectivity.

Combining the above considerations, an absolute minimum of 12 participants per treatment is necessary to conduct a wave of the experiment, and a minimum of about 35 participants per treatment group is necessary to observe differences between the random-pod and long-path conditions.

4.3 Experimental Study

4.3.1 Experimental Design

Participants used a pseudonymous online platform (described in Section 4.3.3) to deliberate on a policy issue.

The deliberation took place asynchronously over a period of 7 days, from Monday, November

Stage	Prompt
1	Which proposals do you prefer, and why? If there are disagreements, try asking questions to understand the perspective of others and to understand the causes of the disagreement.
2	In the previous round of discussion, what opinions and reasoning did you observe in your group? How much agreement was there? Were there any disagreements or conflicts? If so, what were the sources of conflict, and how might they be resolved?
3	What seem to be the most popular opinions? Do you agree with them? Has your opinion changed over the course of the discussion?

Table 4.1: Prompts shown to participants during each round of deliberation.

15, 2021 through Sunday, November 21, 2021. The deliberation was divided into 3 rounds of 2–3 days each. During each round, participants were shown a discussion prompt and were able to post a response to that prompt (Table **??**). Participants were able to view and comment on the posts of other participants assigned to the same pod. Participants were also able to view posts and comments that were visible to them in previous rounds, but could only interact or reply to posts and comments in the current round. Before and after each round, participants completed a ranked-choice poll regarding the deliberation topic, allowing the evolution of their preferences to be tracked over the course of the experiment.

Participants were recruited from students in an undergraduate university course and received extra credit for participating. 65 participants enrolled and completed at least one round of deliberation. Basic demographic information was collected and is shown in Table 4.2.

Participants were assigned to one of two conditions at the time of enrollment. Assignments were uniformly at random. Stratified sampling would be preferable in order to ensure even demographic distributions, but was not feasible due to software and time constraints. However, we manually confirmed that each condition had comparable demographics. The two conditions were:

Control Participants in the control condition engaged in conventional deliberation in a single large group. Posts and comments by participants in the control condition were visible to all others in the control condition for the duration of the deliberation.

Random-Pod (Network Deliberation) Participants in this condition were divided into small pods (≤ 5 participants). Posts and comments made by participants in this condition were only visible to others in their current pod. Participants in this condition were assigned to a new pod at the beginning of each round of deliberation using the random-pod assignment method, producing a structurally efficient communication network.

Demographic		Control	Random-Pod
Age	18–24	30	31
	25–29	1	0
	30–34	0	1
	Non-disclosed	2	0
Gender	Man	18	14
	Non-binary	0	1
	Woman	13	17
	Non-disclosed	2	0
Race	Asian	14	16
	Black or African American	1	1
	Hispanic	1	0
	White	13	11
	White, Asian	1	4
	Non-disclosed	3	0

Table 4.2: Demographic statistics for experiment participants.

4.3.2 Deliberation Topic

The policy issue chosen as the topic of deliberation is a crucial component of the experiment. The topic was chosen carefully according to several criteria:

- Relevant to the experimental population;
- Amenable to participants changing their preferences based on new information or reasoning;
- Amenable to a predefined list of proposed solutions;
- Sufficiently complex to have three or more proposed solutions;
- Timely, but unlikely to be influenced by current events during the deliberation.

Participants were students in a university undergraduate course and deliberated on the topic and format of one section of their final exam. As the outcome of the final poll determined the content of a real portion of their final exam, participants had an intrinsic incentive to advocate for their true preferences. The question and alternatives presented to participants were:

> The 2021 [redacted] final exam will include a section worth up to 10% based on the content covered during the first part of the semester. Which of the following options should be chosen for the topic and format of that section of the exam?

Prop. 1 Open-ended with partial credit (2 questions, 5 points each) - Ch. 1-2: Intro to networks.

Prop. 2 Open-ended with partial credit (2 questions, 5 points each) - Ch. 3: Bridges, clustering, triadic closure, strong and weak ties, and the Strong Triadic Closure Property.

Prop. 3 Multiple choice with no partial credit (5 questions, 2 points each) - Ch. 4: Homophily, selection, social influence, and social-affiliation networks.

Prop. 4 Multiple choice with no partial credit (5 questions, 2 points each) - Ch. 5: Signed networks and balance theory.

Prop. 5 True/false with no partial credit (10 questions, 1 point each) - Ch. 6: Game theory, best responses, and Dominant Strategies, Nash equilibrium.

Prop. 6 True/false with no partial credit (10 questions, 1 point each) - Ch. 9: Auctions.

4.3.3 Experimental Platform

We have modified the free and open-source Loomio platform [44] to implement network deliberation. Loomio is a widely-used online deliberation platform which provides both forum functionality (Figure **??**) and various forms of voting, including ranked-choice (Figure **??**). Loomio is popular among worker-owned cooperatives and grassroots organizations (Loomio itself is a worker-owned cooperative). Loomio was chosen for its combination of built-in functionality, existing user base, and open-source extensibility.

The modified platform implements both random-pod and long-path assignment methods and automatically reassigns participants when the stage is advanced. In addition to network deliberation features, we have made several modifications used by the experiment. Upon signing in for the first time, participants are randomly assigned to a treatment condition. Participants are also assigned an alias which they will use throughout the deliberation (Figure **??**).

4.4 Results

4.4.1 Preferences and Outcome

We report the outcomes of several voting methods over the course of the deliberation in Table 4.3 and show the evolution of first-choice vote distributions in Figure 4.5. The pre-deliberation poll shows similar initial preferences across the control and random-pod groups. A Condorcet winner exists in both groups, and in both cases that winner is Prop. 2. Prop 2. also claims a plurality of first-choice votes in both groups. The only notable difference is that in the control group, Prop. 1

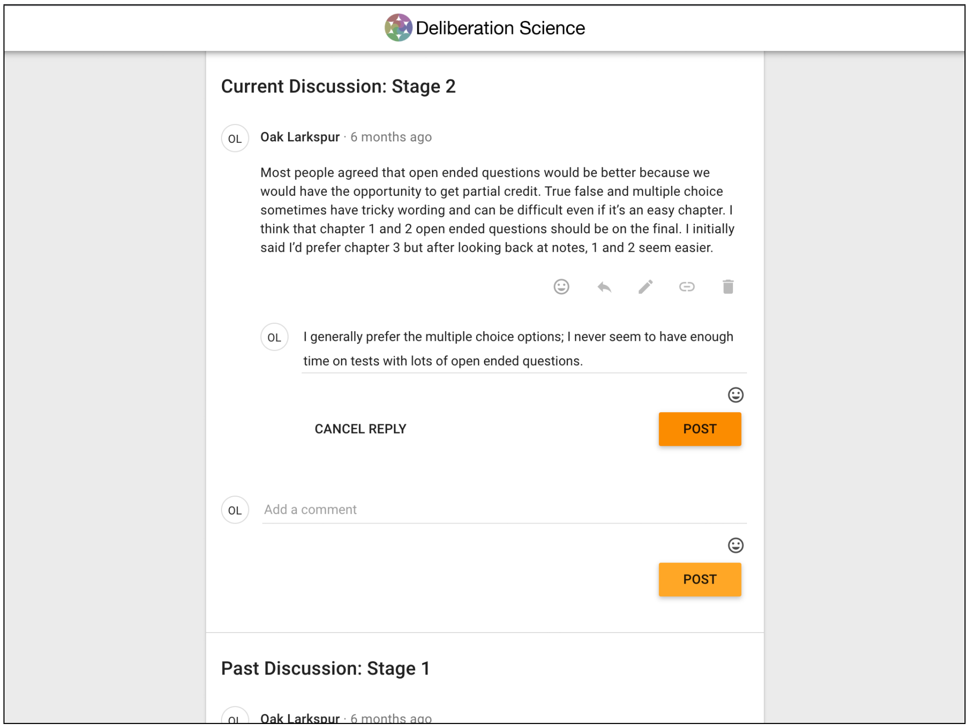

Figure 4.2: Participants can perform standard forum actions, such as posting and commenting.

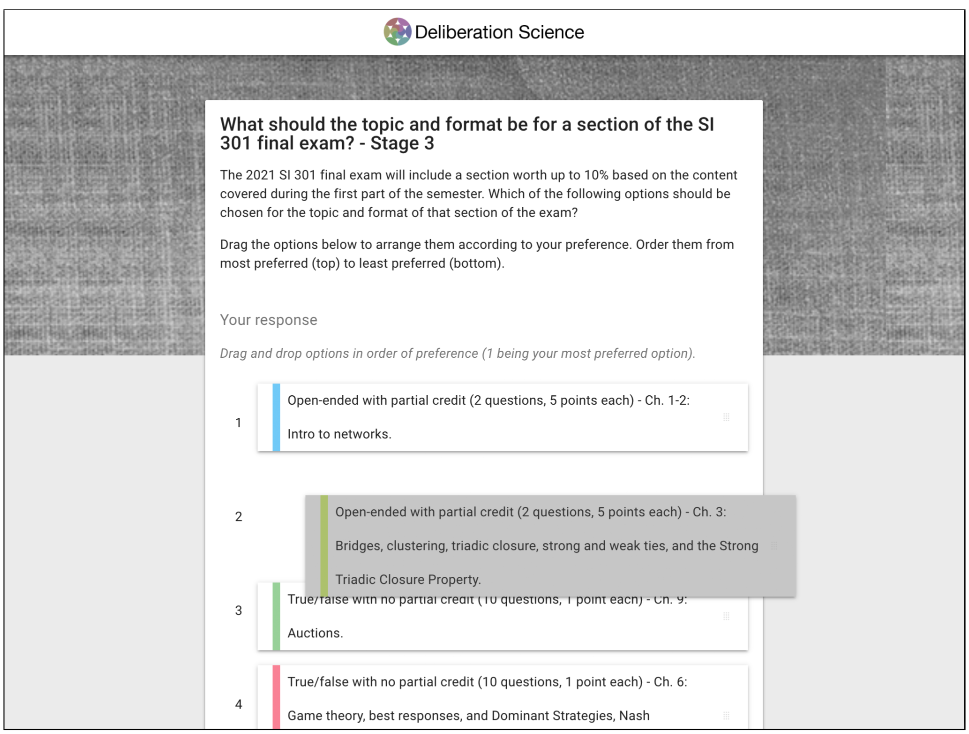

Figure 4.3: Participants are presented with a ranked-choice voting screen between rounds of deliberation.

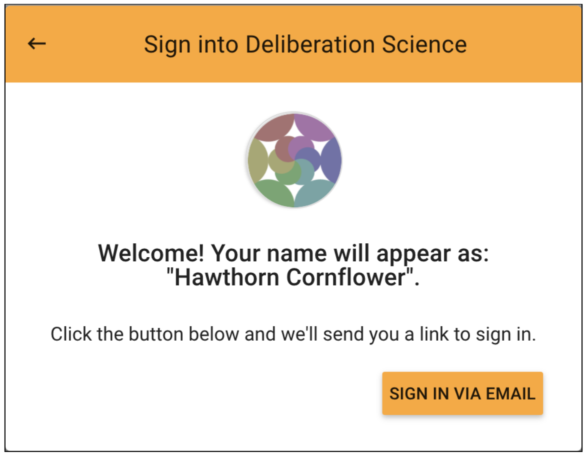

Figure 4.4: Participants are assigned an alias for the duration of the experiment.

	Control			Random-Pod		
Round	Condorcet	Plurality	Borda	Condorcet	Plurality	Borda
0	prop2	prop2	prop1	prop2	prop2	prop2
1	prop1	prop1	prop1	prop2	prop2	prop2
2	prop1	prop1/prop2	prop1	prop2	prop2	prop2
3	prop1	prop1	prop1	prop2	prop2	prop2

Table 4.3: Referendum outcome after each round of deliberation (initial=0).

wins under the Borda Count method, suggesting that the contest between Props. 1 and 2 are very close and that participants who did not list Prop. 1 in first place still ranked it highly.

Over the course of the deliberation, the preference profiles of the control and random-pod groups show notable differences. In the control group, Prop. 1 becomes the Condorcet winner after round 1 and wins across all other voting methods. Prop 1. remains the winner in the control group throughout the rest of the deliberation, with one exception: Prop. 1 and Prop. 2 tie for plurality voting in round 2. In the random-pod group, Prop. 2 remains the winner across all voting methods throughout the entire deliberation. We compare participants' preferences before and after the deliberation in Figure 4.6. The most striking feature is that a number of participants (4) in the control group who initially ranked Prop. 2 highest then went on to rank Prop 1. the highest in the final poll. These participants are a significant driver of the switch from Prop 2. to Prop 1. in the control group. While the random-pod group does show some participants switching away from Prop. 2, those participants shift to the less popular Props. 3 and 4 rather than Prop 1. In the sections that follow, we will further analyze the evolution of participant prefernces and the potential mechanisms driving them.

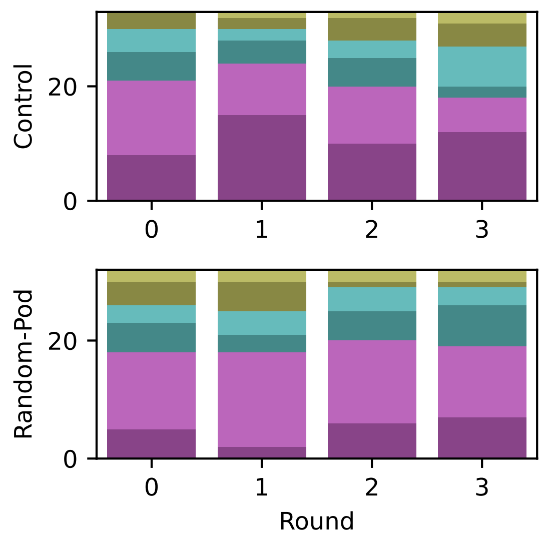

Figure 4.5: Number of first-choice votes for each alternative over the course of the deliberation.

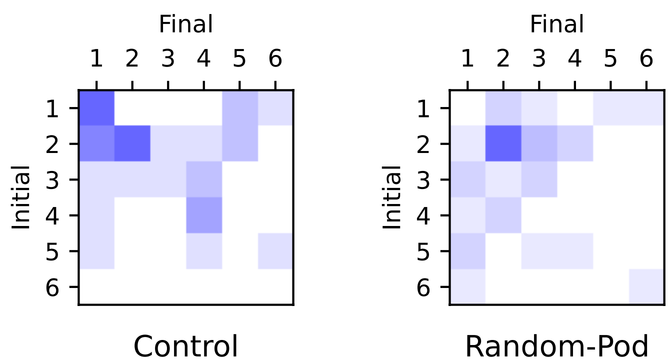

Figure 4.6: Histogram of participants' initial (row) and final (column) first-choice votes.

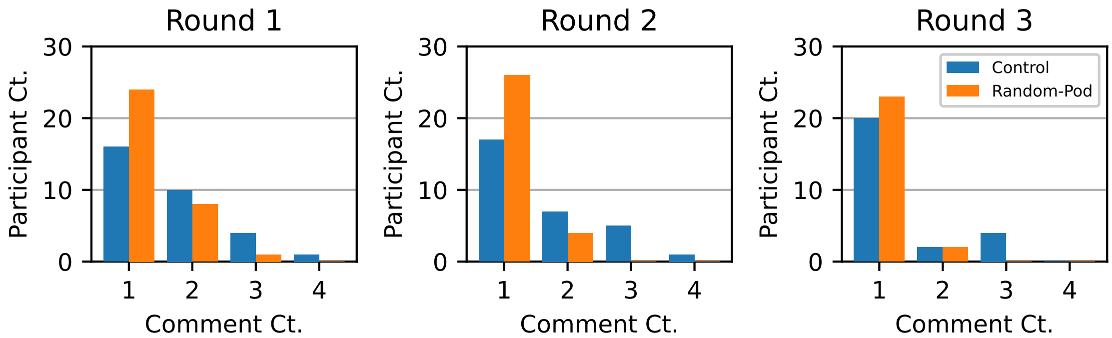

Figure 4.7: Histogram of the number of posts made by participants during each round of deliberation.

4.4.2 Activity

Here we describe the trends we observe in participants' deliberation activity and the potential impact on participant preferences. Overall, the nubmer of comments per participant shows a heavy-tailed distribution (Figure 4.7) with a mode of one comment per participant. The random-pod group shows less of a heavy-tail, with more participants posting a single comment per round and a smaller maximum count (2–3 comments vs. 3–4 for control). The random-pod group thus shows a more equal division of activity across participants.

Figure 4.8 shows the comment counts for each round as well as the Shannon entropy of participant comment counts. The random-pod group shows a lower total number of comments and a higher entropy, again showing a more equal division of activity across participants.

The more equal distribution of comments in the random-pod group is consistent with our expectation that network deliberation promotes equal participation. The reduction in overall participation is also notable and suggests low participation as a potential consideration in network deliberation settings.

4.4.3 Deliberation Content

The content of participant comments gives additional insight into how preferences were infuenced by deliberation. We pay special attention to comments pertaining to the two most popular alternatives: Props. 1 and 2. Preferences for these alternatives evolved differently between the control and random-pod groups.

Comments across both groups frequently advocated for Props. 1 and 2 without specifying a preference between the two:

> P09: Opened ended questions allow for partial credit while multiple choice and true

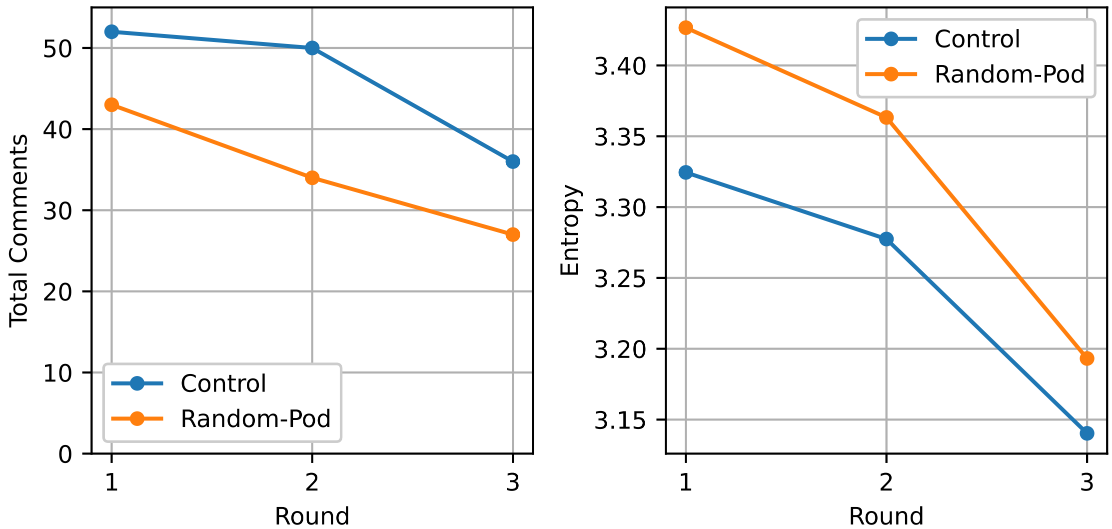

Figure 4.8: The total number of comments in each round (left) and the Shannon entropy of participant comment counts (right).

> false has no partial credit. I feel comfortable with chapters 1, 2, and 3 [Props. 1 & 2] as they are the easiest. I am least comfortable with auctions [Prop. 6].

However, some participants advocated for one or the other:

> P64: I think Intro to Networks [Prop. 1] should be chosen. I like the open ended question format of this, as it allows for partial credit. In addition to this, since these were the topics that were taught in the beginning they provide a base of everything we have learned in the class and as a result I think this material would be very helpful for it to be covered on our final exam.

> P10: I prefer the open-ended questions on chapter 3 [Prop. 2] because I feel like many of these types of questions would have several requirements, so it is very possible to receive partial credit if you partially understand. The main reason I choose chapter 3 [Prop. 2] over chapters 1/2 [Prop. 1] is because I don't know what questions from chapters 1/2 [Prop. 1] would look like, and I know how to prepare for chapter 3 [Prop. 2].

While in the minority, some participants advocated for other proposals:

> P43: I think the topics covered in chapter 6 [Prop. 5] should definitely be on the final. I'm personally indifferent between true/false.

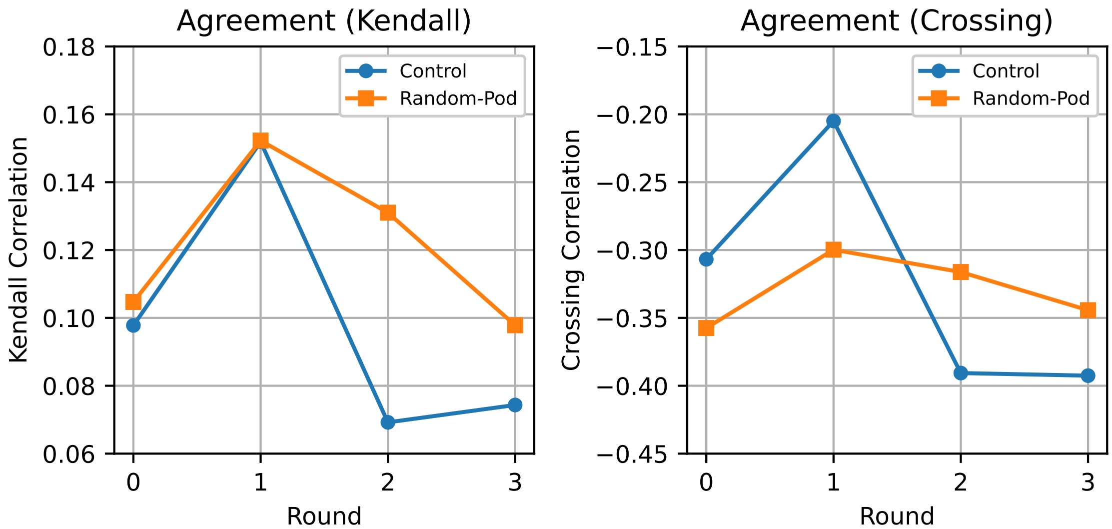

Figure 4.9: Treatment-level agreement over the course of the deliberation. Agreement is calculated as the mean pairwise correlation between participants using either Kendall corellation (left) or weighted crossing correlation (right).

4.4.4 Preference Evolution

As shown in Table 4.3 and Figure 4.5, both groups initially preferred Prop. 1, with the control group switching to Prop. 2 after round 1 while the random-pod group maintained its initial preference. We now analyze participant preferences and their evolution in more detail.

4.4.4.1 Agreement

We report the intra-group agreement throughout the course of the deliberation in Figure 4.9. We calculate agreement using both the Kendall correlation and the weighted crossing correlation. The Kendall correlation is commonly used in social choice and weights contributions from each rank equally. The weighted crossing correlation places a higher weight on higher-ranked preferences. In both cases, the avarage pairwise agreement follows similar a similar pattern. Both the control and random-pod groups show an increase in agreement after the first round of deliberation, followed by a decrease. In the control group, the decrase is more rapid and more extreme than in the random-pod group. Using weighted crossing agreement, the difference-in-differences between control and random-pod groups is 0.68, noting that weighted crossing ranges from -1 to +1.

Our results show that in our experiment, the random-pod group experienced a small but robust increase in agreement, wile the control group experienced a sharp increase followed by an even sharper decrease. These results support the hypothesis H1 that network deliberation contributes to increased agreement relative to conventional single-group deliberation. However, this effect is

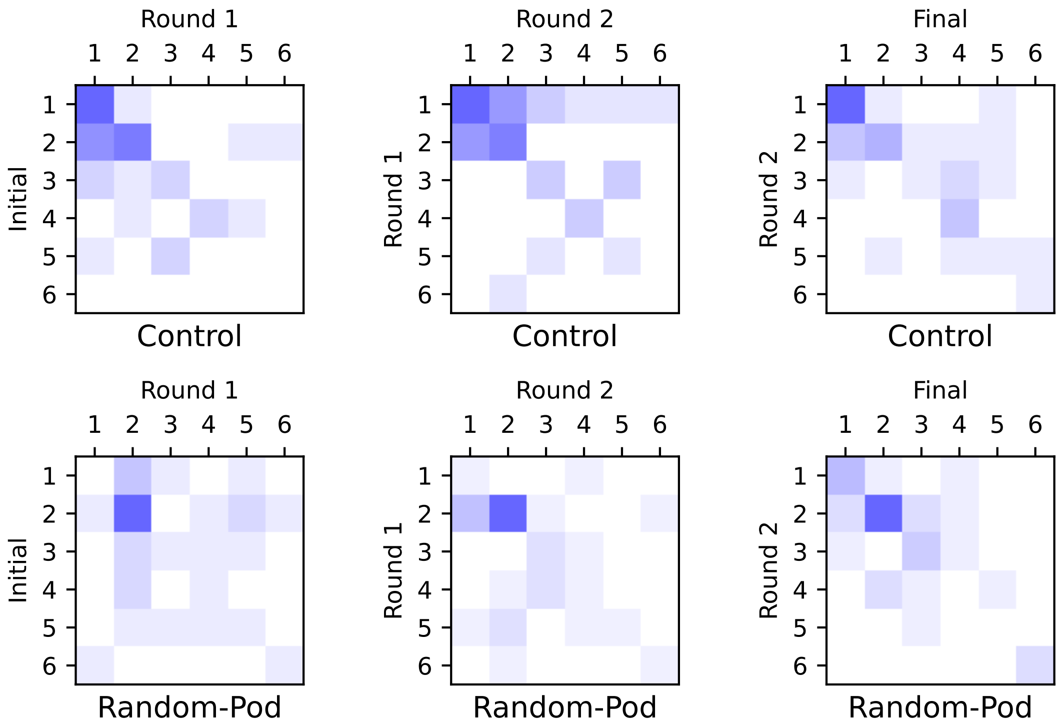

Figure 4.10: Histograms of participants' first-choice votes before and after each round.

due more to a decrease in agreement within the control group than an increase in the random-pod group. After an initial increase in agreement, both groups showed an unexpected "rebound" effect. In the control group, this rebound resulted in a net reduction in agreement, suggesting the presence of negative social influence.

4.4.4.2 First-Choice Votes

By focusing on first-choice votes and on the most popular alternatives (Props. 1 & 2), we can offer some insight into the differences in preference evolution we observe between the control and random-pod groups. Figure 4.10 shows the evolution of first-choice preferences over the course of each round of deliberation. Initially, the control and random-pod groups had similar distributions of first-chioce votes for Props. 1 & 2, with both clearly favoring Prop. 2 (13:8 for control and 13:5 for random-pod). However, first-round comments regarding these two proposals differed substantially between the two groups. In the control group, a majority of comments (7:2) favored Prop. 1 while in the random-pod group, a majority favored Prop. 2 (9:2). Remarkably, the support expressed for Prop. 1 by the control group during round 1 was counter to the group's initial preference for Prop. 2. After that round however, a majority of control group participants reported a first-choice preference for Prop. 1 over Prop. 2 (15:9). In the random-pod group, Prop. 2 remained the most popular and received an even higher share of first-choice votes (16:2) after round 1.

In both the control and random-pod groups, we see round 1 deliberation clearly favoring one alternative, which then gains a number of first-choice votes, suggesting social influence. This social influence is further evidenced by the increase in agreement observed for both groups over the course round 1 (Figure 4.9).

The control group varies from the random-pod group in that the round 1 advocacy and subsequent preference shifts are opposite to the original preferences. In other words, there is evidence of an information cascade flipping the control group's preference from Prop. 2 to Prop. 1 over the course of round 1. While many factors contribute to the formation of an information cascade, we suggest that network deliberation structure of the random-pod group may have reduced the liklihood of such a cascade in that group. The pod structure limits how many participants can be exposed to influence from any particular individual during a single round. Furthermore, the more even distribution of participation observed in the random-pod group provides participants with more accurate information on the preference distribution of ther peers. The discussion is less skewed towards highly-vocal participants.

In rounds 2 and 3, the preferences for Props. 1 & 2 continued to evolve differently for the control and random-pod groups (Figure 4.10). In both cases, participants partially reverted towards their initial preferences. In the control group, particularly during round 2, Prop 1. lost many of its round 1 gains to Props. 3–6, although it still remained the most popular first-choice vote, and Prop 2. retained a sizeable minority of first-choice votes. As a result, the control group exhibited a divergence of preferences after round 2, contributing to the drop in agreement seen in Figure 4.9. In the random-pod group, many of the participants who had switched from Prop. 1 to Prop 2. after round 1 switched back, partially reverting the winning margin of Prop 2. towards its original value and contributing to a reduction in agreement. However, the observed drop in agreement values can't be explained by first-choice votes alone. The two groups show similar distributions of first-choice vote counts (although assigned to different alterantives) but a notably different level of overall agreement.

4.4.5 Social Influence

To better understand the role of social influence in the evolution of preferences, we report the conformity and hipness distributions in Figure 4.11. Summing either of these quantities over all participants yields the overall change in mean agreement: -0.597 for control and +0.049 for random-pod.

In the control group, the participants with negative conformity outnumber those with positive conformity: more participants moved away from others' preferences than toward them, resulting

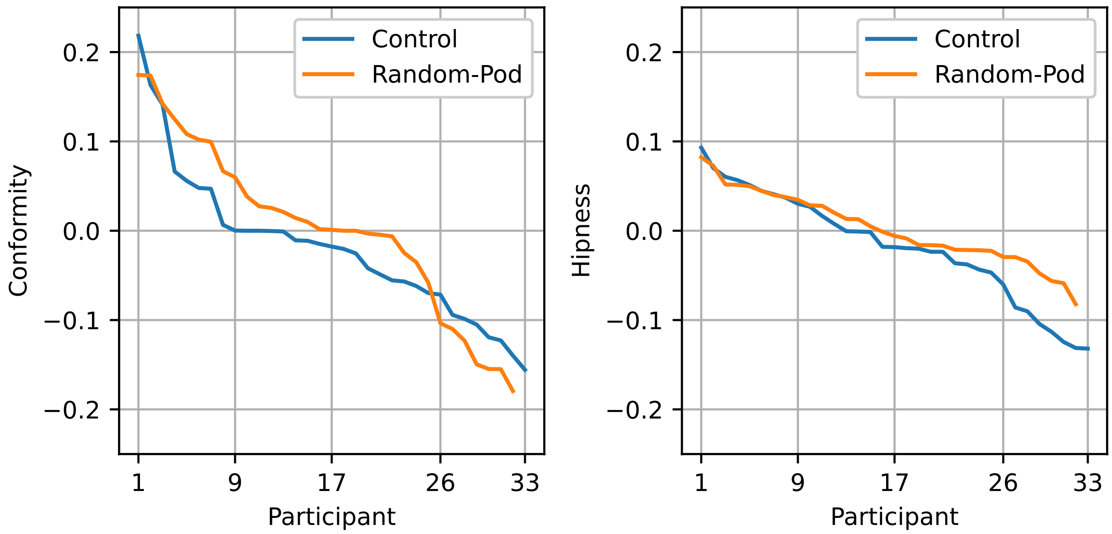

Figure 4.11: Conformity and hipness by participant, calculated using initial and final preferences. Values are sorted in descending order for ease of comparison.

in a negative shift in agreement. In the random-pod network deliberation group, the number of participants with positive conformity is slightly larger than the number with negative conformity, leading to a slightly positive change in agreement. The difference between the two groups is most pronounced among small magnitude conformity participants: those who did not change their preferences much over the deliberation.

Alternatively, we can analyze the change in agreement in terms of hipness. The negative change in agreement in the control group can be attributed primarily to a small number of participants with highly-negative hipness. These participants did not change their preferences much over the course of the deliberation, but other participants' preferences moved away from theirs considerably. Among participants in the random-pod network deliberation group, those with negative hipness have a notably smaller magnitude, resulting in more agreement.

4.4.5.1 Dynamics of Social Influence

Figure 4.12 shows the conformity and hipness contributions of individual participants after each round (relative to initial preferences). The sum of positive and negative contributions (equivalent to the mean difference in agreement) is overlaid. In the control group, conformity begins mostly positive and high-magnitude after the first round, but switches to mostly negative in subsequent rounds. In contrast, the random-pod group shows a combination of positive and negative conformity throughout the experiment, with positive conformity maintaining a small majority. These observations suggest that participants in the control group first conformed towards initially pop-

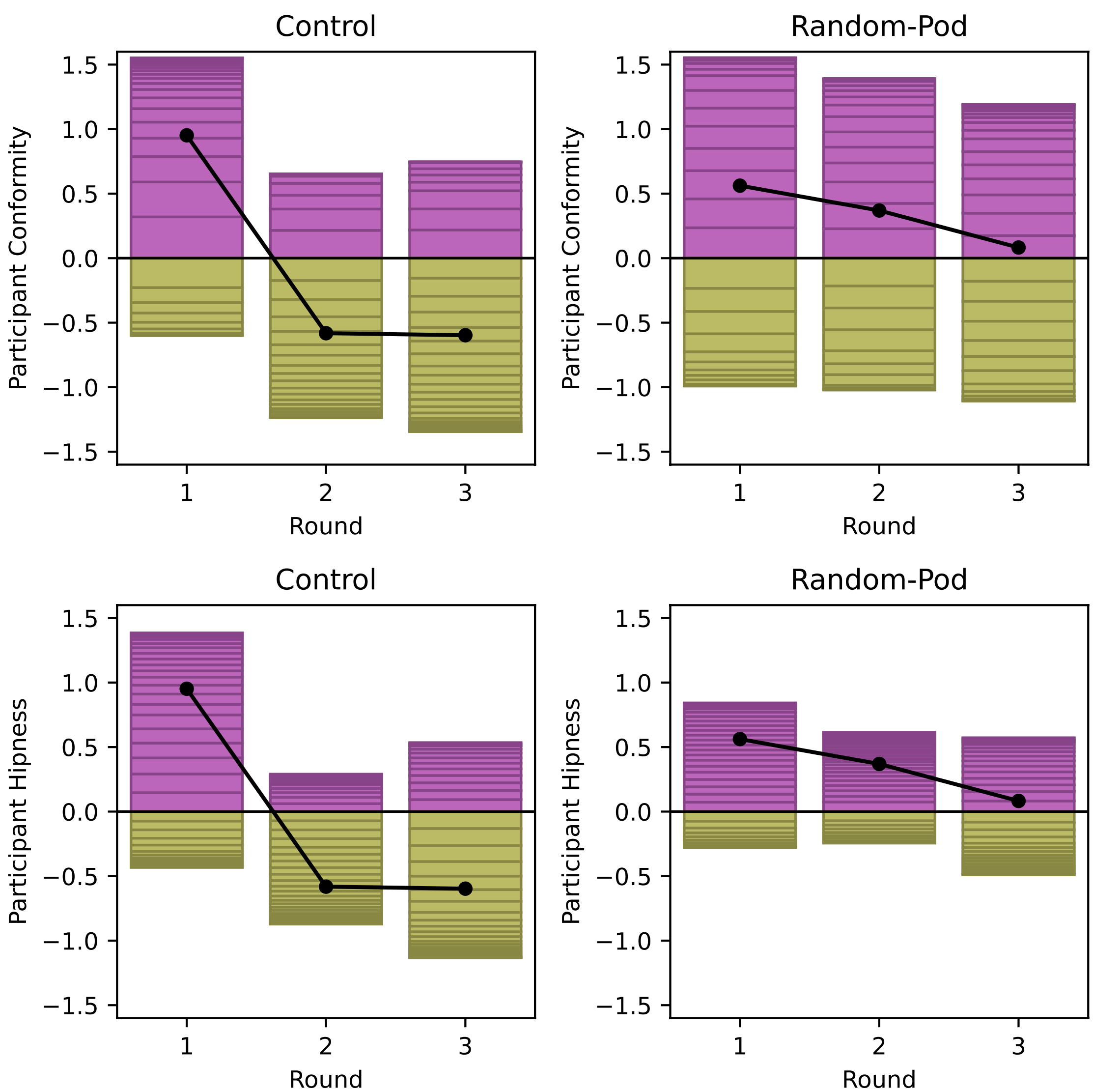

Figure 4.12: Participant contributions to conformity and hipness at each round.

ular preferences, but shifted away from them after the second round of deliberation. While in the random-pod group, participants showed diverse changes in perference with some convergence towards initially-popular preferences.

Analyzing hipness suggests a similar picture. The control group shows overwhelmingly positive hipness after round 1, with a switch to primarily negative hipness in subsequent stages. The random-pod group shows primarily positive hipness throughout most of the experiment, although both positive and negative values are small in magnitude. So in the control group, changes in preference are divided unevenly between participants. At first, these changes conform towards the more fixed participants, but after round 2 diverge away from them. In constrast, within the random-pod group, changes in preference are distributed more evenly and consistently converge towards the more fixed participants.

4.4.5.2 Interpretation of Social Influence

Combining the above insights from conformity and hipness measures suggests the following. The negative shift in agreement in the control group is due to a majority of participants shifting their preferences away (negative conformity) from a samll number of stubborn participants (highly-negative hipness) without converging on an alternative (lack of positive conformity). Furthermore, this shift occurs after round 2, following an initial stage of high-conformity. The random-pod participants also exhibit stubborn participants, but fewer and with smaller magnitude, and the the majority of participants converge toward each other's preferences (positive conformity).

Our findings show that the random-pod network deliberation group experienced a positive change in agreement relative to the conventional deliberation control group. The above analysis of individual preference shifts suggests that the decreased agreement in the control group is due to social influence leading a number of participants to shift from more popular preferences to a divergent set of less popular preferences.

4.4.6 Survey

The results of the post-experiment survey are shown in Table 4.4 and Figure 4.13. After correcting for multiple comparisons using the Šidák correction, the Mann-Whitney test finds no significant difference between the control and random-pod groups. However the observed differences (and lack of differences) in median suggest a starting point for future work. We expected the random-pod group to be better at identifying and resolving disagreements, which would result in a lower score for Q1 and a higher score for Q2. Instead, we observe a higher median score for both. Given that initial preference profiles were similar for the two groups, the lower perception of agreement in the control group could be driven by a number of mechanisms, such as higher visibility of

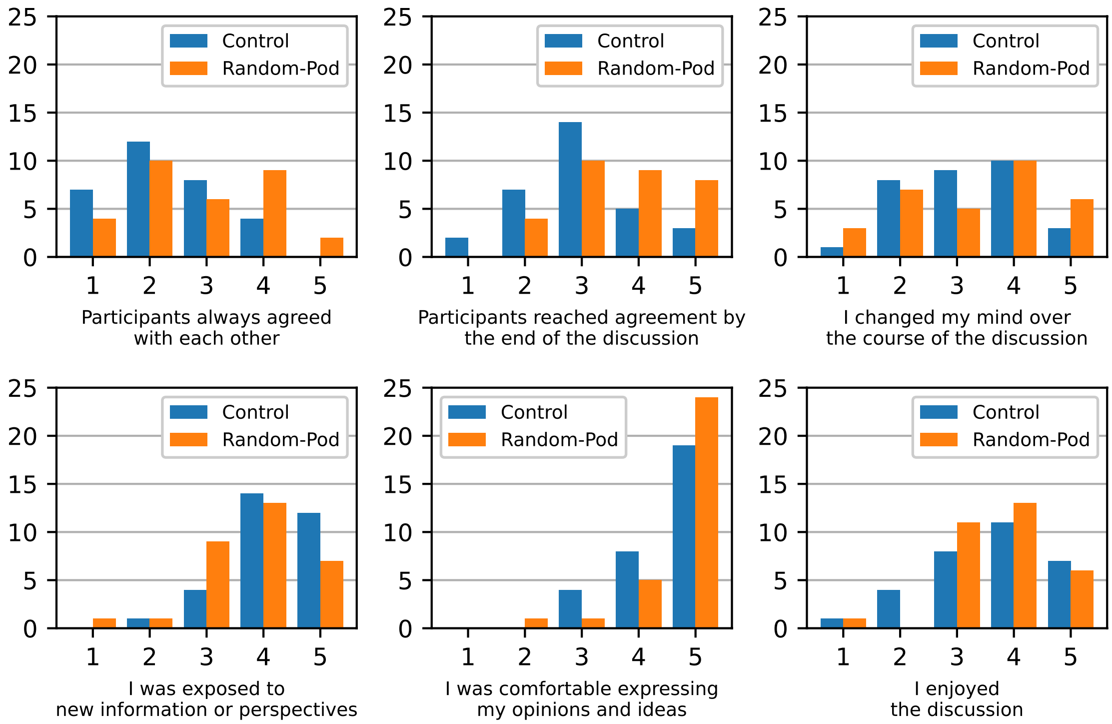

Figure 4.13: Participant post-experiment survey responses on a 5-point Likert scale.

Question	Median		p
	Control	Random-Pod	
Q1: Participants always agreed with each other	2	3	0.070
Q2: Participants reached agreement by the end of the discussion	3	4	0.015
Q3: I changed my mind over the course of the discussion	3	4	0.663
Q4: I was exposed to new information or perspectives	4	4	0.068
Q5: I was comfortable expressing my opinions and ideas	5	5	0.181
Q6: I enjoyed the discussion	4	4	0.722

Table 4.4: Median responses for post-experiment survey (5-point Likert scale). Reported p values are for a two-sided Mann-Whitney test. The Šidák correction places the threshold at $p < 0.0085$ for a FWER of less than $\alpha = 0.05$.

disagreements or polarization over the course of the deliberation. The difference in perceptions of agreement across conventional and network deliberation could be a fruitful area for future research.

4.5 Discussion

We hypothesized (H1) that network deliberation tends to reach a higher level of agreement than conventional single-group deliberation. The observed agreement calculated from polls throughout the experiment experiment supports this hypothesis (Section 4.4.4.1). However, our hypothesis was based on the assumption that network deliberation would more effectively identify and resolve disagreements, leading us to expect a large increase increase in agreement in the random-pod group. Instead, we observe a small increase of agreement within the random-pod group and a large decrease within the control group. So while we do see more of an improvement in agreement under network deliberation, our observations are more consistent with a protective effect against a disagreement-producing mechanism, than with the originally hypothesized agreement-producing mechanism.

We also sought to understand how preferences evolve during network deliberation vs. conventional deliberation (RQ1). We focused our analysis on first-choice votes in particular (Section 4.4.4.2). We also quantified the observed social influence throughout the experiment (Section 4.4.5.1). In both the control and random-pod group, we observed preferences shifting in favor of alternatives that received overwhelming support in round 1 deliberation comments. These comments were consistent with initial preferences in the random-pod group, but counter to initial preferences in the control group. An information cascade, in which participants conformed to a less popular opinion believing it to be more popular, is one likely mechanism. The skewed distribution of activity in the control group (Section 4.4.2), as well as the large number of negative-conformity participants (Section 4.4.5) are both consistent with an information cascade in the control group. In network deliberation, participants are limited to interacting with others in the same pod, creating a barrier to the spread of information cascades. Thus, the network deliberation structure may explain why round 1 comments in the random-pod group were consistent with initial preferences, i.e., did not show evidence of an information cascade.

It is interesting to note that while the control group showed considerable positive conformity in round 1, most participants switched to negative conformity in later rounds, while in the random-pod group, positive conformity was relatively consistent. In other words, the preferences of the control group converged in round 1, but diverged in later rounds, resulting in the observed sharp drop in agreement (Figure 4.12). As nothing changed in the control group between the first and subsequent rounds, it is interesting to consider why the conformity switched from mostly positive to mostly negative, e.g., why preferences diverged during round 2 after converging in round 1.

Possible explanations include a "rebound" effect from an information cascade or a time-dependent effect only emerging in later rounds.

Motivated by prior literature identifying conflict discovery and resolution as a benefit of participatory decision-making, we also considered the effect of network deliberation on conflict resolution (RQ2). Unexpectedly, we found that the random-pod group provided only a small increase in agreement, but that the control group actually produced disagreement by the end of the deliberation. Interestingly, the first-choice votes show a similar level of agreement in the two groups, so the control group disagreement is largely due to second-choice votes and below. One possible explanation is that participants disagreeing on first-place votes became more polarized against each other, lowering each other's top-choice in their own preferences, but additional research is necessary to test this hypothesis.

We note that in this experiment, the skewed distribution of participation in the control group acted to amplify proponents of a minority preference, which later became the majority preference in a possible information cascade. However, a skewed distribution of participation could potentially have the opposite effect of further amplifying an already majority preferences and overshadowing minority preferences. A better understanding of the factors determining which preferences are amplified would contribute to an understanding of when network deliberation is preferable to conventional.

We also note that the overall level of participation was lower in the random-pod group, very likely due to the smaller group size. The low level of activity could be one factor contributing to the lack of conflict identification in the random-pod group. It is thus desirable to better understand how factors including group size contribute to activity level.

4.6 Conclusion

We have reported the results of a controlled experiment comparing an efficient network deliberation network to conventional single-group deliberation. We found that network deliberation produced a more positive change in agreement consistent with our hypothesis. However, we found that this change was due primarily to a decrease in agreement in the conventional group, suggesting a mechanism that protects against disagreement rather than facilitating agreement. We find evidence of an information cascade in the conventional group strong enough to alter the Condorcet winner. Our findings suggest that protection against information cascades may be one mechanism underlying the success of network deliberation in large-scale collaborations.

CHAPTER 5

Discussion

The assumption that coordination requires coercive hierarchy is so pervasive that it is common to see the words "hierarchy" and "organization" used interchangeably, as in the conventional "org chart." Hierarchy is certainly a well-demonstrated tool for achieving coordination, but that coordination comes with costs. In terms of principles, hierarchical organizations rely on coercion and power imbalances, sacrificing egalitarianism. More practically, when information is distributed but decision-making is centralized, that decision-making necessarily excludes potentially useful information. The emergence of successful large-scale, internet-enabled, non-hierarchical collaborations suggests that perhaps, at leaast in some cases, neither the principle of egalitarianism nor the practical wisdom of the crowd needs to be sacrificed to achieve effective coordination and collaboration. The key question is: how do such large-scale participatory projects achieve success?

The work described and proposed here is motivated by and founded on empirical observations, but it is also speculative in nature. By employing agent-based models and experiment, it is possible to understand not just how things are, but how things could be. Rather than seeking to identify principles that apply broadly to existing collaborations, this work starts from empirical observations of collaborations that have done something unusual and attempts to identify robust principles that might be applied to transform existing collaborations or create new ones. The repeated appearance of small interlocking groups in successful large-scale participatory collaborations suggests that this type of network structure might be such a principle. It may seem counterintuitive or even impossible that collaborations and organizations might deliberately alter their interpersonal network structure. But in fact, countless practices such as job interviews, letters of recommendation, performance reviews, internships, mentorships, etc. all serve exactly this purpose; to deliberately shape the social network within a collaboration. By analogy, the task of deliberately designing a neighborhood might seem impossible, but urban planners have made a science of it.

Between the completed chapters of this dissertation, a few commonalities emerge. While it is conventional to describe the "quality" of a collaborive output, both Chapter 2 and Chapterchap:abm demonstrate that quality can be multidimensional. Specifically, Chapter 2 shows that productivity and performance can be anti-correlated in some contexts and not in others. Similarly, Chapter

3 identifies contexts where altering network structure and social learning strategies can improve just performance, just productivity, or both. Another common theme is that subtle differences in task or behavior can have dramatic influences on output quality. With regards to network deliberation in particular, Chapter 3 suggests that it is most effective in collaborations with a tendancy towards conformity. Such conformity might occur because of social norms, or to compensate for sparse information. Interestingly, the correlations between network properties and performance on Wikipedia were consistent with a conformity-based social learning strategy. Why network deliberation seems to improve conformity-based collaboration remains an open question for future work. And whether network deliberation has a similar effect in a controlled experimental setting is yet to be seen.

While this work only scratches the surface of factors contributing to successful collaboration, especially in the messiness of the real world, it identifies previously overlooked distinctions that may help refine the study of participatory collaboration. Furthermore, starting from empirical observation of large-scale participatory collaborations, this work has identified, refined, and formalized network deliberation, and shown that, at least in agent based models, exhibits a distinct influence on collaborative outcomes, independent of other network properties. The ongoing work described in Chatper 4 will shed light on whether network deliberation plays a causal role in enabling large-scale participatory collaborations.

The NK Model [46] is an optimization problem particularly well-suited for modelling complex tasks. The model is used to create a fitness function $Q(s)$ over some discrete space $\mathcal{S}$, typically binary strings of a fixed length. The model is parameterized by two variables. The first, N, is the dimension of the solution space, i.e., the length of each binary string. The second parameter, K, determines the "ruggedness" of the fitness function, i.e., the number of local maxima. In effect, the K parameter allows the complexity of the optimization problem to be tuned. The ability to tune task complexity makes the NK model well-suited for studying the role of complexity in various settings. The construction of an NK fitness function from a set of parameters is a stochastic process. So particular values of N and K define a class of fitness functions, which can be sampled to produce a specific fitness function.

We now show the construction of the NK model fitness function. A class of NK model fitness functions can be defined by a tuple of integer parameters (N, K) such that $N > 0$ and $0 \leq K < N$. We begin by defining N fitness contributions functions:

$$q_i \quad : \quad \mathbb{Z}^{K+1} \rightarrow [0,1]. \tag{1}$$

The value of each $q_i(x)$ is chosen uniformly at random in the range $[0,1]$ at the time the function is defined. We also define N projection operators P_i which select $K+1$ bits from a length-N bit string. Each P_i selects the bit at index i and K other indices, chosen uniformly at random at the time P_i is constructed. For a solution s, the ith fitness contribution is evaluated on the $K+1$ bits selected by the ith projection: $q_i(P_i(s))$. The value of the fitness function is the mean of all fitness contributions:

$$Q(s) \quad = \quad \frac{1}{N}\sum_{i=1}^{N} q_i(P_i(s)). \tag{2}$$

The parameter K alters the ruggedness of the fitness function by controlling the interdependence between the q_i. When $K = 0$, each q_i depends on a single unique index of s, allowing the q_i to be optimized independently. In this case, $Q(s)$ has a single maximum: the global maximum. However, for $K > 0$, two things happen: it becomes possible for each q_i to have multiple local maxima, and some of the q_i become coupled due to dependence on the same indices of s. The result is that as K increases, both the number of local maxima of $Q(s)$ [77] and the difficulty of simultaneously optimizing the q_i increase. In other words, Q becomes more rugged, and more complex.

The distribution of local maximum values is asymptotically normal for large K [77]. When a skewed distribution is preferred, it is common to exponentiate the value of $Q(s)$ as a final step [53, 7, 36].

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