Modeling Social Organizations as Communication Networks

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Abstract

We identify the “organization” of a human social group as the communication network(s) within that group. We then introduce three theoretical approaches to analyzing what determines the structures of human organizations. All three approaches adopt a group-selection perspective, so that the group’s network structure is (approximately) optimal, given the information-processing limitations of agents within the social group, and the exogenous welfare function of the overall group. In the first approach we use a new sub-field of telecommunications theory called network coding, and focus on a welfare function that involves the ability of the organization to convey information among the agents. In the second approach we focus on a scenario where agents within the organization must allocate their future communication resources when the state of the future environment is uncertain. We show how this formulation can be solved with a linear program. In the third approach, we introduce an information synthesis problem in which agents within an organization receive information from various sources and must decide how to transform such information and transmit the results to other agents in the organization. We propose leveraging the computational power of neural networks to solve such problems. These three approaches formalize and synthesize work in fields including anthropology, archaeology, economics and psychology that deal with organization structure, theory of the firm, span of control and cognitive limits on communication.

“Few students of human social dynamics doubt that nations, firms, bands and other groups are subject to selective pressures . . . group competition may explain the success of social arrangements.” — [Bowles and Gintis, 2011]
“Truly, among Man’s innovations, the use of organization to accomplish his ends is among both his greatest and his earliest. But it is perhaps only in our era, and even then haltingly, that the rational design of organization has become an object of inquiry.” — [Arrow, 1964]

1 Introduction

Human social groups are organized in dramatically different ways, ranging from egalitarian horizontal societies to highly unequal vertical hierarchies, from groups of decentralized, modular teams to centralized command and control assemblies. A fundamental problem in social, behavioral, and economic science is explaining why particular social groups exhibit their particular organizational structure. Anthropologists, for instance, are interested in understanding why post-Pleistocene societies typically demonstrate patterns of increasing hierarchy and inequality as they grow in size [18]. Economists, likewise, are interested in why firms demonstrate differing degrees of decentralization and hierarchy, and the conditions under which one form is more advantageous than another [3, 23, 28]. Military theorists seek to understand the relative strengths and weakness of different command structures, and how those may change within and between campaigns.

Here, we consider organizations that have been subjected to a strong group-selection pressure, for example when many separate groups have competed with one another for an extended period. In such scenarios, whatever internal social norms and utility functions lead a social group to adopt a particular organization structure, at the end of the day, those organizations with the best performance best survive. Accordingly, to a first approximation we can ignore such considerations.

There are several advantages to focusing on such scenarios. First, it allows us to presume that the agents in any thriving organization all have goals that all closely align with the overall group welfare function. This allows us to avoid specifying (or inferring from limited data) variation in the utility functions of the agents. Similarly, it allows us to avoid specifying a bounded rationality game theory solution concept for the collection of agents. Modeling can thus focus on the efficiency of the overall organization, and inference from data can concentrate on determining the organization structure and the commonly held welfare function.

There are many factors that have been theorized to drive the form of social organization in group selection scenarios. Many researchers have suggested that a fundamental component of how well any given social organization performs is how well its members can collectively gather and process information [3]. However much of the work that relates an organization’s structure to informational properties of the organization’s agents remains qualitative and case-specific, even though there is reason to believe that general and widely
applicable theories may exist. In particular, in these situations with strong external group pressure, we expect to mostly see organizations whose communication structure is close to optimal. These groups are those that are best able to acquire and then convey information among their members.

To fill such a fundamental gap in the social sciences, we suggest three formal and broadly applicable frameworks that analyze how the informational processing capacities of agents within a group, together with the group’s overall welfare function, determines the group’s optimal organization structure. Since information processing abilities is prevalent in the network and communication sciences, we adopt an “organizations-as-telecommunication-networks” paradigm that explicitly models individuals within an organization as nodes in a telecommunication network. This allows us to leverage tools from those disciplines that have extensive insight into information processing capabilities.

We begin in section 2 by reviewing the various ways that researchers across the social sciences have previously attempted to explain the determinants of social organizations. In section 3, we present three theoretical approaches that can answer various questions relating social organization structure to information processing capabilities of its agents. The first approach leverages a novel sub-field of information theory known as network coding. To our knowledge, we are the first to employ the tools of network coding to answer questions in the social sciences. The details of network coding and its application to social organization structure are presented in section 3.1. Our second approach involves optimizing an organization’s structure when the set of messages it must transmit through the network is subject to uncertainty. A main contribution of our second approach is a linear program that solves for the optimal network structure in such a scenario where the details are given in section 3.2. In our third approach, we seek to model information synthesis among agents. In other words, a social organization’s success is not just related to how well it communicates information but how well agents within the network combine information from various sources and respond optimally to such information. Crucially, the description of each approach is accompanied by a detailed exposition of the approach’s benefits and limitations. We conclude with section 4 that highlights how the three approaches can possibly be synthesized to maximally characterize the properties of social organizations that arise as a result of information processing constraints.

We emphasize that we do not claim that all aspects of social organization can be explained with the kind of analysis considered here, even of social groups that have been subject to strong group-level selective pressure. Rather our goal is to investigate what aspects of social organization can be explained this way, without the need to imputing more factors. Later work would then weaken the group selection focus, to incorporate other kinds of factors that contribute to determining social organization.
2 Background

Understanding the structure of social organizations is of interest to several disciplines including archaeology [20, 22], management science [25], sociology [24], political science [26] and psychology [27]. It is arguably most prominent in the fields of anthropology and economics, since in those domains organizations (ranging from small hunter-gatherer tribes to primary states in archaeology, and from firms to industrial conglomerates in economics) are often the unit of analysis. For this reason, much of the previous work on social organization structure stems from this literature and we summarize such literatures in turn.

2.1 Anthropology and Social Organizations

Early anthropological studies investigating the structure of social organizations emphasized the importance of kinship and exchange in organizing small-scale societies [5, 6]. It is usually accepted that general forms of social organization — whether those are firms, societies, or bureaucracies — are correlated to a great extent with the sizes of the groups. Very large organizations almost always exhibit hierarchical structures, while very small groups, such as temporary task groups of fewer than six or so, typically exhibit “flat” (non-hierarchical) organizations [29]. Small bands of shifting membership common among foragers [15] are likewise relatively flat in their organization.

Larger and more permanent groups of several hundred people, called “local groups” [18] or tribes often include domesticated plants or animals in their diets and their population density is generally considerably higher than for bands. Enormous variability in social structure exists in these societies, but three levels of nested organization beyond the individual are fairly typical, beginning with families, which reside within kin-based corporate groups, which in turn may be nested within inter-group collectivities whose interactions are structured by ceremonial activities and economic exchange.

In the broadest sense, most of the anthropological literature focuses on group size and its relation to organization structure. More elaborate models include problems of resource allocation and cultural norms [9]. However, much of the literature remains case-based and qualitative. More fundamentally, while some models assume (implicitly or explicitly) that information transmission becomes more difficult in larger groups [19], the informational transmission is not directly modeled and the direct causal mechanism that relates information constraints to group size is obfuscated. Our theoretical approaches will contribute to this literature by also explaining how group size partially determines organization structure. However, out theoretical approaches expand beyond the current literature by explicitly modeling the information transmission constraints a group faces as the group size grows. We will then be able to determine what aspects of a social organization are determined by informational constraints and what aspects are a result of other factors that
arise due to an increasing group size.

2.2 Economics and the Theory of the Firm

The economics literature that studies organization structure falls into one of two categories which together comprise what is known as “theory of the firm”. The first category of models analyzes organization structure from the standpoint of the principal-agent problem and incomplete contracts [2, 12, 14, 10]. In such models, agents within an organization—managers and their subordinates within a firm, for example—have conflicting goals. The theoretical predictions then focus on how certain organization structures can arise such that the principal optimizes the welfare of the organization while also taking into account the different incentives that govern the behavior of the other agents. The second category of models is related to what is known as “team theory” in which agents in an organization share a similar goal but face coordination and informational constraints [3, 7, 13, 31]. Our approach falls into the second category and specifically focuses on how informational constraints affect an organization’s optimal structure.

Consideration of information’s role in determining organization structure dates back at least to the 1920’s and 30’s [22, 8]. Those early works suggested that phenomena like informational asymmetries and coordination costs were the key determinants of an organization’s structure. As an extreme version of this approach, some argue that without informational limitations, there would be no need for organizations to act as a coordinating mechanism and each agent could perform in a way that maximizes welfare by acting independently, without regard for communication from the other agents [22]. Considering less extreme scenarios, Arrow succinctly summarized this approach when he wrote “the desirability of creating organizations of a scope more limited than the market as a whole, is partially determined by the characteristics of network information flows” [4]. However such claims by Arrow and others were all informal, with no detailed mathematical model underpinning them; progress in rigorously establishing (or refuting) the validity of such claims remains stagnant. It is our goal to move forward, by building a library of theoretical tools that allow us to quantitatively determine how the characteristics of network information flows influence the performance and behavior of organizations.

3 Theoretical Approaches

This section presents our three theoretical approaches. More of the formal details can be found in the appendix.
Figure 1: The canonical example of the advantages of network coding. The only way that both $R_1$ and $R_2$ can receive both bits $a$ and $b$ is if node $V$ transforms its input via the XOR operation and then forwards the result of the transformation. If $V$ is not allowed to use such network coding, but can only copy and forward its inputs, either $R_1$ or $R_2$ will not get both bits.

3.1 Network Coding and Social Organizations

Network coding is a relatively new branch of information and telecommunications theory that began with the seminal work of [1]. The main question is straightforward: given a telecommunications network, what is the most amount of information (in terms of bits, for example) that can flow from a source to multiple receivers when links in the network have bandwidth constraints. Traditionally, this question was addressed when intermediate nodes in the network were only allowed to “copy and forward” information. The main contribution of network coding is to show that if intermediate nodes are allowed to perform arbitrary transformations on the information they receive, the total amount of information transmission from the sender to the set of receivers can exceed the maximal amount of transmission when the intermediate nodes are only allowed to copy and forward.

The seminal example of network coding is given in figure [1]. Succinctly stated, the question is whether nodes $R_1$ and $R_2$ can obtain the value of bits $a$ and $b$ when each edge in the network can only transfer one bit. If nodes are only allowed to copy and forward, then the answer to the question is negative. For example, if node $V$ forwards the value of bit $b$ to node $W$, then node $W$ would be able to forward that bit to $R_1$. However, it would then be impossible for node $R_2$ to receive the value of bit $a$ since there are no other channels in which $R_2$ can receive such a value. On the other hand, suppose that the intermediate nodes are
Table 1: Typical network coding questions and their possible application to social organization theory.

| Network Coding Question | Social Organization Question |
|-------------------------|-----------------------------|
| Given a **network** and edge capacities, what is the most amount of information (throughput) that can be transmitted from a **source** to a number of **receivers**? | Given an **organization** and **communication constraints**, what is the most amount of information (throughput) that can be transmitted from an **administrator** to a number of **laborers**? |
| How should **intermediate nodes** transform their inputs such that the **network achieves its maximum throughput**? | How should **middle managers** transform the information they receive such that the **workers are maximally informed**? |
| What is the benefit of adding **extra nodes** in the **network**? | What is the benefit of adding **middle managers** to the **organization**? |

Drawing on the insight from [1], network coding has exploded to be a highly active field. Not only does it ask whether a certain amount of throughput is feasible given a network topology and bandwidth constraints but also asks questions about optimal bandwidth allocation, algorithmic approaches to creating network codes and potential benefits of network coding with noisy transmission. The main goal of our theoretical approach is to map the questions in network coding to questions that are relevant in determining the optimal structure of social organizations. Table 1 gives an overview of how some of the tools from network coding can be used to address questions in social organization theory.

We have begun using network coding to determine the benefit of adding middle managers to a firm, using a minimal model. In the model, there is an information source and a set of receivers. The information source can be interpreted either as information from an external environment or commands given by an executive of the firm. We assume that the organization’s welfare is increasing in the amount of information that the receivers get from the source. In other words, the better the organization is at sharing information, the higher the organization’s welfare. However, communication (in terms of edge capacities) among agents in the network is costly. As a crude example, the cost of communication can represent the opportunity cost of employees in the organization having a meeting instead of engaging in other productive activities. Therefore,
the goal of the organization is to maximize the amount of information that the receivers receive from the source minus the cost of the transmission. This is a standard network utility optimization problem with associated optimization algorithm that is found in [34, 33].

Figure 2 depicts a firm without any middle managers. To add concreteness, we can interpret the source node as an external environment and the nodes I0, I1 and I2 as observers of the environment and the links from the I nodes to the R nodes as communication channels. The goal is for the I nodes to transmit as much information about the external environment to the receiver nodes (denoted R) while minimizing the cost of the transmission. At the optimum, the I nodes trade off the benefit of relaying information to the R nodes with the cost of communicating with the R nodes. While an interesting problem in its own right, we can then extend the model to include middle managers whose only purpose is to process information, which is given in figure 3. Now the network optimization problem is repeated and the results show that adding a middle manager can increase throughput and reduce communication costs. More specifically, we can compare the organizations welfare with and without a middle manager to determine the marginal value of such a middle manager. Future work includes extending this scenario to examine how the benefit of a middle manager changes as a result of asymmetries in the network topology and cost parameters.
3.1.1 Benefits

The main benefit of employing network coding to analyze social organization structure is the trove of un-tapped analytical and algorithmic resources that network coding provides. Previously, many models of social organizations were overly simplified due to the difficulty in formulating and solving more complex models. However, network coding and its insights provides a theoretical foundation for modeling complex information transmission problems and gives several scalable algorithms and analytical techniques that can be used to solve such problems. Furthermore, network coding extends beyond questions regarding pure information transmission. For example, network coding can shed light on questions relating to network robustness [35], resilience [17] and security [10], all of which may be relevant concerns for various social organizations.

3.1.2 Limitations

There are limitations to using this network coding approach to analyze social organizations. The main limitation is that network coding is mainly concerned with transferring entire pieces of information from sources to receivers. However, in real-world organizations it may only be necessary to transfer some information from a source to a receiver. For example, a marketing research team does not need to transfer all possible in-
formation it learns to the firm’s CEO. Instead it may only need to inform the CEO of some high-level insight while at the same time, the CEO is receiving high level insight from other departments (finance, accounting, etc.) and must optimally combine such information. Technically speaking, the organization does not need to transfer all information but only transformations of the information. Due to its disciplinary home in telecommunications, this problem is not adequately addressed in network coding. However, we may be able to use “intra-session” coding to establish bounds on communication rates under more complex message sets.

3.2 Contingency Planning

Sometimes an organization is uncertain about which communications need to be made in the future and therefore must allocate communication time for all possible contingencies. For example, imagine a large search and rescue mission in a wildfire scenario. Suppose there is one team that is dedicated to surveillance and extinguishing the fire and another team that is working to locate survivors. The team that is working to put out the fires must give safety commands to the search team (i.e. “don’t go east as the fire is spreading that way”) located in another geographical region. Depending on the information the surveillance team receives from the environment, the surveillance team might have to immediately communicate to the incident base instead of communicating to the search team directly. Therefore, both the search team and the incident base need to be on “standby” so that they can hear what the surveillance team might need to communicate. The search team incurs an opportunity cost because they cannot proceed to areas where radio contact may be compromised and the incident base incurs a cost since it must allocate attention to the radio in the event that the surveillance team needs to communicate. Both the incident base and the search team incur such a cost even if the surveillance team does not communicate with them. In other words, the opportunity cost is incurred as a result of planning to possibly receive communication, not the communication itself.

The above scenario can be modeled as an optimization problem. More specifically, the question can be thought of as “how can agents allocate sufficient future time such that they are available to receive all possible communications in any state of the world but minimize the cost of allocating such time to communication?” With certain parametric assumptions, this problem can be modeled as a linear program. The solution to the linear program indicates how each agent (or team) should allocate future time to communicating with other agents (or teams). The formal details of the optimization problem are given in appendix A.

This problem can easily be extended to include modifications of the original scenario. For example, instead of asking how should agents allocate resources such that they receive all communications, we can ask how agents should allocate resources to optimally trade-off the value of the resources with the benefit of
receiving a communication. This allows for heterogeneity in the importance of the communication. Tying this into the search and rescue scenario, one could imagine that it is more important for the search team to receive the message “don’t go east as the fire as spreading that way” than “the surveillance team is undergoing a shift change.” The linear program framework can easily be extended to include such a scenario.

The model can also be extended to include not just costly communication but constraints on total communication. For example, it might be that an agent can only listen to a limited amount of information in a time period, or can only transmit a limited amount of information in a time period. Similarly, agents may be limited in the number of distinct pieces of information they can convey. Such a constraint can easily be incorporated into the linear program formulation. This is an important constraint because it is well established that individuals face cognitive limits on the number of interpersonal interactions in a fixed time period [11].

3.2.1 Benefits

There are two main benefits to the contingency planning formulation. The first is its tractability and scalability. In preliminary experiments, we have solved for the optimal contingency planning in a linear program with millions of constraints and variables in less than 1 minute on a single core lap top personal computer. This indicates that as we expand the model, computational tractability will be a non-issue. The second main benefit of the linear program and contingency planning formulation is that it allows us to include complicated message requirements. This is in contrast to network coding in which the same message is sent from one source to many receivers. In the contingency planning formulation, it is possible to include messages from multiple sources to multiple destinations, where each message contains different “content.”

3.2.2 Limitations

Like network coding, the contingency planning approach does not immediately allow for transformations of information and is only concerned with full message transmission. Equally as important, the contingency planning approach does not include any coding at intermediate nodes and intermediate nodes are only allowed to “copy and forward.” While this may be considered a limitation, there are indeed a subset of social organizations where agents only copy and forward information (prehistoric signaling networks [30] being one plausible example). Finally, the contingency planning approach is limited as it does not immediately allow messages to be corrupted by noise as the message traverses an edge.
3.3 Information Synthesis

The major shortcoming of the network coding and contingency planning linear program approaches introduced above is that they do not model agents that need to synthesize information. They are only concerned with the best way to transfer information within an organization, not how to (have the agents in the organization) process the information and then use it to take actions back on the environment. Furthermore, the network coding and contingency planning approaches are limited in the ways in which they can include noise in the communication channels.

To surmount these issues, we model each agent \( i \) as a set of \( k + 1 \) separate nodes. Each agent \( i \) has a single “in” node, represented by \( In(i) \), that provides that agent with the ability to receive information from other agents. The remaining \( k \) nodes are “out” nodes, each representing a distinct “message” that the agent can possibly send. These nodes are represented by \( Out(i, j), j = 1...k \). There is one edge from each \( In(i) \) to each of the associated nodes \( Out(i, j), j = 1...k \). To see how this captures synthesis, imagine the following scenario. An agent receives information from two distinct sources. This is represented by two directed edges into \( In(i) \). The agent can then transform the two pieces of information in various ways and send distinct messages along each one of the edges from the agent’s “in” node to \( Out(i, j), j = 1...k \). There are edges from \( Out(i, j), j = 1...k \) to other agent’s “in” nodes which represent communication among agents in a network. Each node has an associated real number “value”, where the value of node \( m \) is a function of the values of all of its parents. (Note the similarity of this model to common neural net architectures.)

This framework allows us to implement many constraints that are plausible in real world organizations. For example, we can constrain the number of edges into \( In(i) \), to represent real psychological limits on how many separate people any given agent can listen to in a given time period. The limit on the number of out nodes represents the similar constraint on how many separate things an agent can say in a given time period [11]. Note though that there is no limit on the total number of other agents that can hear what a given agent has to say. For example, the CEO of a company may only be able to say 5 things during a day, but each of those 5 things can be heard by thousands of others in the organization.

There are several ways to model noise in the transmission of messages. Perhaps the simplest is to add Gaussian noise to each message that traverses a channel. (Note that though for such an approach we should have an upper and lower bound on the possible values of all nodes, as otherwise the set of all agents could collectively remove all noise simply by amplifying their signal relative to the Gaussian standard deviation.)

Some of the agents in the network have inputs from special “environment” nodes, which are root nodes. In addition, the values of some agents are identified as “actions”. So for any given joint value of the environment nodes, there is a resultant set of values of all the agents, and in particular a resultant set of joint actions.
This represents a single “wave”, of information from outside of the organization entering the organization and thereby inducing an action by the organization. Note the analogy of this model to how the inputs to a neural net induce states of the hidden nodes that ultimately result in an output of the neural net. The extension to multiple time-steps, in which the agents get yet more inputs, while continuing to process old inputs, is straightforward. (In particular, we can create a time-extended model of social organizations in much the same way that single-pass neural nets are extended into recurrent neural nets, to allow neural nets to process a sequence of multiple successive inputs.)

The welfare of the organization is a function of the joint state of the environment and the actions. So if there is a distribution over the state of the environment nodes, there is an associated expected value of the welfare function. For any given network structure, varying the functions at the agent nodes will vary that expected welfare. In fact, for any given network structure, there is an associated maximal value of the expected welfare, where we maximize over the space of all possible functions at the agent nodes. Accordingly, by varying the network (subject to the constraints on input and output nodes of the agents that are described above), we vary the maximal expected welfare. Accordingly, for any distribution over environment nodes and welfare function, there is best-possible network structure, which maximizes the expected welfare. The group-selection hypothesis is simply that the network structure of a real human social organization subject to a given welfare function in a given (stochastic) environment can be well-approximated by this optimal network.

Such a formulation is able to capture a wide range of characteristics of real world networks. However actually solving for the optimal network structure (given a welfare function and distribution over environment states) is a large problem that in general requires computational optimization. One possible approach to solve such an optimization problem would be to formalize the analogy mentioned above between the overall social organization net and a neural network. This would allow us to leverage the computational techniques that have been developed for training neural networks. A crucial element of such an approach would be to use regularizers [36] for “training the (social organization) neural net” that capture the cognitive information processing constraints of the agents. In particular, we could start with an all-to-all topology and use an $L_1$ regularizer as a sparsity constraint. Presumably, this would push the solution of the network’s optimal structure to where many of the weights are 0 and therefore can be removed, thereby achieving (a soft version of) the input-output constraints on the agents mentioned above.

3.3.1 Benefits

The main benefit of this “neural network” approach is that it provides a convenient framework for modeling agents that need to synthesize information. For example, suppose that one “message” among a set of
messages is a set of real numbers where one agent needs to know the average of the numbers and another agent only needs to know the minimum of the numbers. An organization modeled in this neural network fashion would be able to achieve this goal, even if the communication channels are noisy.

We can also use this approach to investigate a broad range of social organization phenomena. How does the (optimal) network structure of an organization vary as we change the welfare function confronting the organization? How does it change if we vary the distribution over joint states of the environment? How robust is an optimal network; if we optimize it for one welfare function and distribution over the environment, how much does its performance degrade if the welfare function is changed slightly and/or the distribution over the environment? How robust is a social organization to internal perturbations, e.g., added noise on intra-organization transmission lines, the loss of an entire agent, or the like? If we require that all agents have associated physical locations, and impose constraints on how far a message can travel in going down an edge, how does the optimal organization structure change as we improve the communication technology, so that edges can connect agents who are further apart from one another?

3.3.2 Limitations

A central limitation with this neural network approach is choosing among the large set of parameterizations of the functions at the nodes of the agents. In addition, there may be several computational issues that arise due to the scope of the problem.

4 Conclusion

We have proposed three theoretical approaches aimed at explaining how informational capacities impact the structure of a social organization. Using such a range of approaches has two main advantages. The first advantage is that each approach can address different questions regarding social organizations. For example, the network coding and contingency planning approaches are tractable and parsimonious but do not allow for complex message demands and information synthesis. On the other hand, the synthesis approach allows for such an analysis. In this sense, using all three theoretical approaches does not confine us to the limitations of one approach but allows us to optimally “trade-off” the benefits and limitations of each approach in order to fully canvass the properties of social organization structure. The second advantage of adopting three distinct approaches is that it permits a “robustness check.” These approaches have enough in common that by pursuing all three, we can ensure that results from one theoretical approach do not contradict results from another and therefore we can be more poised to validate the qualitative predictions of the general theory.
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A Details of Contingency Planning and Linear Programming Approach

This section develops a basic problem formulation.

The high level idea is to find the minimum cost network that can successfully communicate a set of “broadcasts”. A “broadcast” is a set of “messages” that must be communicated simultaneously, and each “message” has a single sender and an arbitrary number of receivers.
A.1 The Graph

The network is a directed (possibly cyclic) graph, $\mathcal{G} = (S, T, R, E)$. The nodes in the graph are “sender” nodes $s \in S$, “receiver nodes” $t \in T$, and “relay” nodes, $r \in R$. The edges in the graph, $e \in E$, are as follows

- The pairwise edges from senders to receivers. ($|S||T|$ total edges)
- The pairwise edges from senders to relayers. ($|S||R|$ total edges)
- The pairwise edges from relayers to receivers. ($|R||T|$ total edges)
- The pairwise edges between the relayers ($|R|^2$ total edges).

Each edge has a weight, $w_e$, representing the possible communication strength along that edge. Each edge also has a cost, $c_e$, per unit weight. If $w_e = 0$, the edge cannot be used to communicate, and does not incur any cost. It is as if the edge does not exist. The edges with non-zero weight represent the “existent” communication network, i.e. the optimal topology.

A.2 Messages and Broadcasts

A “message” is an amount of information that must be communicated from exactly one of the sender nodes to one or more receiver nodes. Specifically, a message $m$ is a triple, $m = \{s(m), T(m), \omega_m\}$, where $s(m)$ is the source node $s$ for the message, $T(m)$ is the set of receiver nodes for the message, and $\omega_m$ is the amount of information in the message (in the same units as the edge capacities).

A “broadcast”, $b \in B$, is a set of messages that must be communicated simultaneously. Let $M(b)$ be the set of messages indexed by $b$, and let $m_b$ be an arbitrary message in that set. The network must have sufficient capacity (sufficient edge weights) to transmit all messages in a broadcast simultaneously.

A.3 Objective

The objective is to solve the following optimization problem:

$$\text{minimize } \sum_{e} c_e w_e$$

A.4 Constraints

At a high level, the constraints are that:

- The edge capacities must be sufficiently high to send each broadcast
• Within a broadcast, each message must get from all senders to all receivers.

The constraints will be satisfied using \textit{flow variables}. There are two kinds of flow variables; flow variables per message, and flow variables per sender-receiver pair in a message. The per-message flow variables represent the idea that information can be replicated. A sender can tell a relayer a piece of information, which can then be told to multiple receivers. The sender-receiver flow variables represent the fact that each receiver must receive the entire message.

Let $f_{b,m,e}$ be the flow along edge $e$ for message $m$ in broadcast $b$. Introduce one such flow variable per possibility (a total of $(\sum_{b \in B} |M_b|) |E|$ variables). Similarly, let $\hat{f}_{b,m,e,t}$ to be the flow specifically from $s(m)$ to one of $T(m)$.

In the following sub-sections, let $n$ refer to an arbitrary node, let $p_n$ be the parents to node $n$, and $c_n$ be the children of node $n$. Similarly, let $e_{p_n}$ be the edges from the parents of $n$ to $n$, and let $e_{c_n}$ be the edges from $n$ to the children of $n$.

All variables have the additional constraint that they must be non-negative.

\subsection*{A.4.1 Message constraints}

Each message must leave the sender and arrive at all of the receiver nodes for that message. First, we ensure that the entire message is received by every receiver.

\begin{align}
\sum_{e_{c_n}} \hat{f}_{b,m,e_{c_n},t} &= \omega_m \quad \forall b \in B, m \in M(b), t \in T(m) \\
\sum_{e_{p_n}} \hat{f}_{b,m,e_{p_n},t} &= \omega_m \quad \forall b \in B, m \in M(b), t \in T(m) \\
\sum_{e_{p_n}} \hat{f}_{b,m,e_{p_n},t} &= \sum_{e_{c_n}} \hat{f}_{b,m,e_{c_n},t} \quad \forall b \in B, m \in M(b), t \in T(m) \quad n \in G-\{s,t\}
\end{align}

These are the typical flow constraints of goods. The total message must leave the sender, must get to the receiver, and there must be a “conservation of message” at each intermediate node. This ensures that the entire content of each message reaches every receiver.

Secondly, we consider the “per-message” flows, which incorporate the fact that information can be easily replicated. In particular, once a node receives part (or all) of a message, that same piece of information can be sent out along any or all of the child edges. This is distinct from the flow constraints above, since the conservation constraint becomes an inequality rather than an equality. That is, a node can only repeat as
much of a message as it has heard.

\[ \sum_{e_{cs}} f_{b,m,e_{cs}} = \omega_m \quad \forall b \in B, \ m \in M(b) \]  

\[ \sum_{e_{pt}} f_{b,m,e_{pt}} = \omega_m \quad \forall b \in B, \ m \in M(b), \ t \in T(m) \]  

\[ f_{b,m,e_{cs}} \leq \sum_{p_n} f_{b,m,e_{p_n}} \quad \forall b \in B, \ m \in M(b), \ n \in G_{\{s,T(m)\}} \]  

Finally, there is a consistency constraint between these flows — the sender-receiver flows are upper bounded by the message flows.

\[ \hat{f}_{b,m,e,t} \leq f_{b,m,e} \quad \forall b \in B, \ m \in M(b), \ t \in T(m) \]  

A.4.2 Satisfying a broadcast

A single broadcast may contain multiple messages that must be simultaneously communicated on the network. Each edge must have sufficient capacity to account for the per-message flow across all the messages in a single broadcast.

\[ \sum_{m \in M(b)} f_{b,m,e} \leq w_e \quad \forall b \in B, \ e \in E \]
The full linear program is then given by:

\[
\text{minimize } \sum_e c_e w_e \quad \text{(10)}
\]

subject to

\[
\sum_{m \in M(b)} f_{b,m,e} \leq w_e \quad \forall b \in B, e \in E
\]

\[
\sum_{e_{cs}} f_{b,m,e_{cs}} = \omega_m \quad \forall b \in B, m \in M(b)
\]

\[
\sum_{e_{pt}} f_{b,m,e_{pt}} = \omega_m \quad \forall b \in B, m \in M(b), t \in T(m)
\]

\[
f_{b,m,e_{cn}} \leq \sum_{p_n} f_{b,m,e_{pn}} \quad \forall b \in B, m \in M(b), n \in \mathcal{G}_{\{s,T(m)\}}
\]

\[
\hat{f}_{b,m,e,t} \leq f_{b,m,e} \quad \forall b \in B, m \in M(b), t \in T(m)
\]

\[
\sum_{e_{cs}} \hat{f}_{b,m,e_{cs},t} = \omega_m \quad \forall b \in B, m \in M(b), t \in T(m)
\]

\[
\sum_{e_{pt}} \hat{f}_{b,m,e_{pt},t} = \omega_m \quad \forall b \in B, m \in M(b), t \in T(m)
\]

\[
\sum_{e_{pn}} \hat{f}_{b,m,e_{pn},t} = \sum_{e_{cn}} \hat{f}_{b,m,e_{cn},t} \quad \forall b \in B, m \in M(b), t \in T(m) \; n \in \mathcal{G}_{\{s,t\}}
\]