Interest-Based Self-Organizing Peer-to-Peer Networks:
A Club Economics Approach

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ABSTRACT

Improving the information retrieval (IR) performance of peer-to-peer networks is an important and challenging problem. Recently, the computer science literature has attempted to address this problem by improving IR search algorithms. However, in peer-to-peer networks, IR performance is determined by both technology and user behavior, and very little attention has been paid in the literature to improving IR performance through incentives to change user behavior.

We address this gap by combining the club goods economics literature and the IR literature to propose a next generation file sharing architecture. Using the popular Gnutella 0.6 architecture as context, we conceptualize a Gnutella ultrapeer and its local network of leaf nodes as a "club" (in economic terms). We specify an information retrieval-based utility model for a peer to determine which clubs to join, for a club to manage its membership, and for a club to determine to which other clubs they should connect.

We simulate the performance of our model using a unique real-world dataset collected from the Gnutella 0.6 network. These simulations show that our club model accomplishes both performance goals. First, peers are self-organized into communities of interest — in our club model peers are 85% more likely to be able to obtain content from their local club than they are in the current Gnutella 0.6 architecture. Second, peers have increased incentives to share content — our model shows that peers who share can increase their recall performance by nearly five times over the performance offered to free-riders. We also show that the benefits provided by our club model outweigh the added protocol overhead imposed on the network for the most valuable peers, that our results are stronger in larger simulated networks, and that our results are robust to dynamic networks with typical levels of user entry and exit.

1. INTRODUCTION

Peer-to-peer (P2P) networks allow a distributed network of users to share computing resources such as processing, storage, or content. A defining characteristic of these networks is that resource availability and consumption patterns on the network are determined by individual user (peer) behavior (Asvanund et al. (2004)). File sharing networks based on decentralized P2P computing architectures have gained popularity in recent years with the emergence of applications such as Napster, and later Gnutella and Kazaa. However, P2P networks are being adopted in a variety of other environments, including widespread use in corporate and government settings for knowledge management and distributed collaboration. For example, Groove Networks' P2P products have been adopted by the U.S. Department of Defense and global consulting firms for distributed knowledge management applications. With the growth of these applications, there is a need to analyze the efficiency of these networks and whether efficiency can be improved by incorporating user incentives into network design (Krishnan, Smith, and Telang 2003).

To this end, in this manuscript we address the efficiency of the current state of the art P2P networks as distributed Information Retrieval (IR) systems, and whether their retrieval performance can be improved by incorporating incentives designed to organize peers into interest-based clubs (communities). Our solution addresses two well-known shortcomings of extant P2P architectures, largely unaddressed in the current literature: the inability of peers to identify other peers in the network with similar content interests, and high levels of free-riding among users.

With respect to the first problem, in extant architectures peers establish connections to a location in the network without regard to their own content interests or the interests of other proximate peers. These connections are used for routing queries for content. Given the constraints on routing[1] that limit the neighborhood of peers that can be queried for content, queries may be routed inefficiently, rather than following a path that would maximize query results. Thus, it is important for peer to identify other peers in the network with similar content interests. However, formulating such a method is nontrivial for at least two reasons. First, content in P2P networks is not uniquely labeled, complicating the identification of peers with matching interests. Second, there are typically no centralized planners in these networks to organize peers based on their content or interests. In this paper, we use techniques from the club goods economics and IR literatures to develop a self-organizing community formation mechanism that improves network performance without requiring centralized planning or uniquely identified content.

With respect to the second problem, free riding has been well documented in P2P file sharing networks (Adar et al. 2000; Asvanund et al. 2002). Free-riding occurs when peers consume scarce network resources (e.g., content, storage, bandwidth) without providing resources back to the network. Free-riding in P2P networks limits network scalability and leads to allocative inefficiencies (Krishnan et al. 2002; Krishnan et al. 2003). Prior work has proposed reducing free-riding in P2P networks through centrally administered systems controlling access to scarce network resources through either pricing or admission control mechanisms (see Krishnan et al. 2003 for a review of this literature). However, such systems are infeasible in most P2P environments with anonymous, geographically dispersed users and no central administration authority. Instead, in this paper we draw on parallels between work in the economics literature on public goods (Olson 1965), club goods (Buchanan 1965), and the provision of information goods in P2P networks to develop a solution that provides peers with incentives to share content based on self-interest

[1] File sharing architectures associate a time-to-live (TTL) parameter with the query packets issued by a peer. TTL is usually set to 7 and limit the number of times a query packet can be forwarded through the network. This effectively limits the set of peers that receive a query packet and thereby limits the quality of the results to a query unless the query originates in the “right” neighborhood. Please see Clip2 (2000) and Krishnan et al. (2003).

alone. The approach has the advantages of being readily implementable in today's distributed P2P networks and of requiring little extension to current P2P protocols.

Thus, we propose a next generation P2P file sharing architecture that employs interest-based self-organization of peers to address these two fundamental shortcomings of extant P2P architectures. We use a model of ultrapeers and leaf nodes from the Gnutella 0.6 architecture (discussed in detail in Section 3) as the context, and conceptualize an ultrapeer and its network of leaf nodes as a "club" (in the economic sense). We define utility as a measure of a peer's ability to satisfy another peer's information needs and conceptualize the network as a collection of interconnected clubs operated by ultrapeers who maximize their club's utility by accepting the right leaf nodes and connecting to the right adjacent clubs. Likewise, leaf nodes seek membership in the right clubs to maximize their private utility. Since all peers wish to connect to the right partners, our model imposes an incentive reinforcing structure on the network: penalizing free riding and enabling the self-organization of peers into clubs that are based on content interests.

To measure the effectiveness of our approach, we simulate our model as a computational game in which leaf nodes and ultrapeers jointly attempt to find optimal club membership. We develop a discrete event simulation platform and parameterize our simulation with real world data collected from Gnutella 0.6 between August 31 and September 29, 2002, which includes information for 10,533 unique hosts. The use of real world data is crucial to our evaluation as we rely on the observed correlation between a peer's information content and queries to motivate our club formation model. In our evaluation, we measure recall, a standard IR performance measure, as the network topology evolves. We compare our protocol's performance to the baseline network (the standard Gnutella 0.6 protocol) and to the best performance achievable by the centralized architectures taking into account added overhead from the revised protocol.

These simulations demonstrate that our club model addresses both major problems with current hybrid P2P architectures. First, in our model peers are 85% more likely to be able to obtain content they are interested in from their local club than in current Gnutella 0.6 networks — suggesting that our club model leads to self-organizing communities of interest. Second, in our club model, peers that share content receive nearly five times greater recall than free-riding peers do — suggesting that our club model places strong incentives on peers to share content. Finally, we show that our performance gains outweigh the small additional overhead our model imposes on the network, that our results are robust to dynamic networks with typical levels of entry and exit by peers, and that our results are strengthened in larger networks.

A major contribution of our work is that we combine elements of the economics and IR literatures to propose an interest-based clustering mechanism that is not only implementable with little protocol extension, but also has the benefit of addressing free riding. Further, we base our model validation on a platform that simulates the operation of a real-world Gnutella network. Finally, our performance results are calibrated with data documenting the content shared and queries issued by actual participants in a Gnutella network. This makes our work an important contrast to most current work in this area that emphasizes only analytical formulations.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents our model. Section 4 discusses the data used in our simulations. Section 5 discusses the simulations and their results. Section 5.4 concludes the paper and presents further discussions.

2. LITERATURE

Our work relates to the economics, online community, and computer science literatures. In the economics literature, recent empirical research suggests that free-riding — consuming network resources without providing resources in return — is extremely common in P2P networks (Adar et al. 2000), and that free-riding worsens in larger networks (Asvanund et al. 2004). High levels of free-riding limit network scalability and lead to inefficiencies from peers who consume scarce network resources without providing benefits in return to the network in the form of content, storage, or bandwidth (Krishnan et al. 2002a; Krishnan et al. 2002b). These high levels of free-riding are consistent with predictions of the public goods economics literature that the private provision of public goods will be socially inefficient in terms of under-provision (a.k.a. free riding) and over-consumption (a.k.a. "the tragedy of the commons") (Hardin 1968) and that users have more incentives to free-ride in larger networks (Olson 1965). In both cases, these inefficiencies arise because individuals only consider their private utility when making consumption and provision decisions, even though these decisions affect the utilities of other network users.

Additionally, P2P networks share parallels with the club goods literature (Buchanan 1965, Samuelson 1954). P2P networks exhibit characteristics of non-excludability in that access is typically made available to all users of the network (Krishnan et al. 2003). In the ideal case, P2P networks also exhibit non-rivalry in demand when a consumer of content becomes a provider of the content, scaling supply to proportionally meet demand (Asvanund et al. 2004). However, in the presence of free riding (when a consumer does not share the files they download), P2P network resources will exhibit rivalry in consumption (i.e., congestion), as in club goods. It is important to note, that P2P networks differ from the traditional club goods model in the economics literature in several respects. First, club members in P2P networks contribute shared resources rather than monetary payments. Second, a consumer of content also becomes its provider. Third, clubs can have inter-club relationships (Sterbetz 1992) through ultrapeer-to-ultrapeer connections

Our work also draws on the online communities literature. This literature analyzes the benefits online groups can provide to each other in the form of ties to a community, social support, and access to community resources (e.g., Kraut and Attewell 1993, Constant et al. 1996). More recently, several papers have analyzed motivations for online group participation, concluding that motivations appear to be driven primarily by altruism and reciprocity (Wasko and Faraj 2000, Gu and Jarvenpaa 2003, Subramani and Peddibhotla 2002). The most related study to P2P networks is performed by Butler (2001) who develops a resource-based model of social interaction in online communities and applies this model to data from listserv communities on the Internet.

There have also been emerging efforts in the computer science literature attempting to solve some of the inefficiencies in P2P networks. For example, researchers have investigated the use of ultrapeers to reduce traffic load on low bandwidth peers (Kirk 2003); caching to improve the efficiency of content retrieval (Bhattacharjee et al. 2003); and intelligent linkage promotion based on similarity of interests (Sripanidkulchai et al. 2001). Most importantly, much attention in this literature has been devoted to Distributed Hash Tables (DHTs) (Ratnasamy et al. 2001; Stoica et al. 2001; Zhao et al. 2001). Nevertheless, DHT design criteria may not be suitable for deployment in many P2P settings because, among other reasons, content in P2P networks are not uniquely identified and the entry and exit of peers imposes considerable overhead on the maintenance of the hash tables (Chawathe et al. 2003). In contrast, these characteristics of P2P networks are specifically addressed with the methods proposed in our work.

Finally, there has been a recent emergence of interdisciplinary efforts addressing free-riding levels in P2P networks. The focus has been on providing participants with incentives to provide content and other resources. These efforts include network pricing (Cole et al. 2003); micropayment systems (Golle et al. 2001); reputation systems (Lai et al. 2003); and admission control systems (Kung and Wu 2003). Most of these approaches, however, rely on centralized administration, which as we noted above are infeasible in many common P2P implementations. Further, each of these approaches relies on purely analytic models as opposed to empirically validated protocol extensions developed in this research.

3. Model

3.1. Hybrid Architecture Background

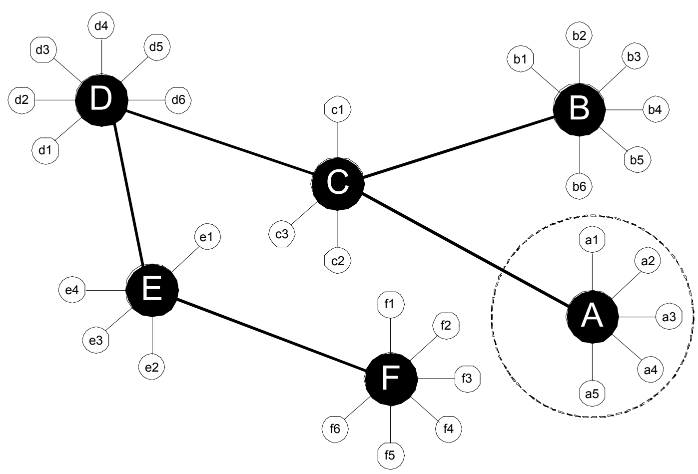
By definition, all P2P networks allow for the bi-lateral sharing of resources distributed among a community of users. P2P architectures vary, however, in regard to how these resources are cataloged within the network (Krishnan et al. 2003). In first generation P2P networks, such as Napster, the network maintained a central catalog of content on the network. When users logged into the network they uploaded a list of the content they were sharing to this central catalog server; and when users wished to locate a file on the network they would search this catalog to determine which peers could provide the content, ultimately accessing the content directly from the identified peer(s). However, while these centralized P2P networks maximize the reach of queries, the central catalog of content also creates a single point-of-failure for the network and potential scalability problems for larger networks (Asvanund et al. 2004).

Second generation P2P networks, such as Gnutella 0.4 (Clip2 2000a), sought to address Napster's weaknesses by distributing the catalog throughout the network. Specifically, in Gnutella 0.4, each user on the network maintained a list of the content they were sharing. In the Gnutella 0.4 network users were interconnected in a web, with each peer typically maintaining connections to 3-4 other peers on the network. To make a query, a peer would forward their information request to the 3-4 other peers they were connected to. These peers would receive this request and reply if they were sharing content matching the query request. They would then forward the query request to each of the 3-4 peers to which they were connected. These peers would perform the same process of responding to and forwarding the query. To prevent the flooding of packets on the network, the protocol only allows query packets to be forwarded a limited number of times (typically 7). This Time-To-Live (TTL) limit also means that each participant on the network can only reach a limited number of other peers on the network. Thus, the design of decentralized networks is robust to the failure of individual peers; however, network reachability is limited and peers incur a higher overhead from processing query requests from their neighbors (Clip2 200b).

Third generation "hybrid" P2P architectures, such as Gnutella 0.6 and Kazaa, attempt to combine the best features of the first and second generation networks with regard to robust design, and network scalability. Because of this, they represent the most popular P2P architecture in use today. Hybrid architectures divide peers on the network into two groups: ultrapeers and leaf nodes. As in centralized P2P networks, leaf nodes connect to ultrapeers and upload a hash of the content (effectively a list of file names) they are sharing. Thus, ultrapeers maintain a catalog of content shared by its locally connected leaf nodes. However, ultrapeers are also interconnected to each other using a similar protocol to that used in Gnutella 0.4, allowing ultrapeers to forward query requests of adjacent ultrapeers, thereby extending the reach of the network. To avoid bottlenecks in updating and querying the catalog, ultrapeers only accept a limited number of connections from leaf nodes. Finally, ultrapeers are required to have both large bandwidth and processing capacity in order to avoid scalability problems in processing queries from neighboring ultrapeers, and are selected by the protocol after demonstrating that they remain on the network for relatively long periods of time.

In effect, ultrapeers shield leaf nodes from receiving unnecessary messages that may overwhelm their connections and cause the problems encountered by Gnutella 0.4. Using the file names listed in the content hash, an ultrapeer will forward queries only to the leaf nodes that are likely to have matching content. The content hash of a given peer is essentially a hash table representing the occurrence of the words in the file names of the peer's content. Figure 1 illustrates a Gnutella 0.6 topology. Ultrapeers are depicted by the dark circles, and leaf nodes by the light circles. Ultrapeer interconnectivity is depicted by the thick lines, while leaf nodes' connections to ultrapeers are depicted by the thin lines. As shown by the figure, leaf nodes operate behind ultrapeers, which access the network on their behalf.

Figure 1: Gnutella 0.6 architecture



Finally, it is important to note that each of these P2P network architectures share three distinguishing characteristics. First, peers in all three networks exhibit high levels of free riding (Adar and Huberman 2000; Asvanund et al. 2004; Krishnan et al. 2003). Second, in each case positive and negative network externalities limit network scalability (Asvanund et al. 2004): at some point, the marginal costs an additional peer imposes on the network in terms of congestion on shared resources will outweigh the value they provide to the network in terms of increased content. This limit on scalability is explicitly incorporated into the design of second and third generation architectures through the TTL limit on query forwarding. Third, in spite of limited reachability, peers establish connections randomly in the network. Each of these three characteristics — low sharing, limited scalability, and lack of content-specific structure — create inefficiencies for the provision of content. The goal of this paper is to use user-level incentives to reduce the impact of these sources of inefficiency.

Because of their popularity and improved scalability, we use the hybrid P2P architectures as the context for this research. Of the hybrid networks, we chose the Gnutella 0.6 protocol as the basis for our research (Kirk 2003) because it is among the most popular P2P networks in use, [2] and has an open protocol. This open protocol allows us to simulate the operations of the network and to obtain representative data on P2P network users. It must be, however, noted that even though our evaluation is performed on the Gnutella architecture and its user data, our models and analyses also apply to any contemporary and future P2P networks that are built on the ultrapeer architecture (e.g., Kazaa, Morpheus). We conceptualize the Gnutella 0.6 network as a collection of clubs, where an ultrapeer manages a club with connected leaf nodes as members. Club utility is the sum of the utility of the ultrapeer and its connected leaf nodes. Clubs are operated by ultrapeers who seek to maximize their club's utility by accepting the right leaf nodes, while leaf nodes seek membership to the right clubs to maximize their private utility. In addition, ultrapeers also choose to connect their club to the right adjacent clubs to further maximize their club utility. This framework imposes an incentive reinforcing structure on the network: encouraging peers to form efficient clubs for content discovery, and improving cooperation through sharing.

[2] See http://www.limewire.com/english/content/netsize.shtml.

3.2. Information Retrieval Methods

We define the utility an individual peer receives from its neighbors as the degree to which the neighbors are able respond to the peer's future information needs. We face two problems in operationalizing this measure. First, future queries typically are not known at the time peers need to evaluate the utility provided by other peers on the network and second content isn't uniquely identified, making it more difficult to determine similarity between two lists of content.[3]

We address the first problem by assuming a peer's content interests are relatively stable over time, meaning that their current content is a reliable proxy for their future information needs.[4] We address the second problem using techniques from the IR literature. These IR methods utilize word frequency statistics for quantifying similarity of interest between catalogs and are designed to function in an unstructured environment such as that found in P2P networks. Specifically, we use the Jensen-Shannon divergence method (Dhillon et al. 2002). Jensen-Shannon divergence produces a scalar value between zero and one, with a lower value signifying higher similarity (see Appendix A for a more detailed presentation of Jensen-Shannon divergence). To ensure that this measure scales consistently with our utility model, by having a higher value signifying higher similarity, in equation (1) we formulate $SIM(I, J)$ for $I, J \in P$, where P is the set of all peers (leaf nodes and ultrapeers). In this equation, JS specifies Jensen-Shannon divergence, and it quantifies the similarity between two word frequency histograms, $p_I(V)$ and $p_J(V)$, which in our case are the word frequency of the names of the files they are sharing.

$$SIM(I,J) = 1 - JS(p_I(V), p_J(V)) \tag{1}$$

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[3] For example, "Phantom Menace," "Episode I," or "Star Wars I" may all identify the same content.

[4] This assumption is tested empirically below, and is borne out through a significant correlation between a peer's content and its future queries.

In our evaluation, we employ *recall*, a standard IR performance measure, as our primary performance measure. Formally, recall is the percentage of all the potential matches on the network that are returned for each query. Our goal is to assess how recall improves as the P2P network topology evolves according to our model. In making the performance assessment, we compare the performance improvement over our Gnutella 0.6 baseline network.

Since our model requires peers to exchange information before making a connection decision (i.e., to create a similarity measure), it imposes a small amount of overhead on the network above what would be required in the baseline protocol. This includes the additional content hash that must be transmitted for the peers to employ our similarity functions. For this reason, our key cost measure is network load: the amount of overhead traffic transmitted within the network.

3.3. Model

3.3.1. Utility Functions and Information Sets

In this paper, we treat network participants as economic actors and develop a set of incentives such that participants will choose actions that are both individually rational and improve the overall social welfare for all other participants. We also design our model to work in a real world decentralized setting where there is no centralized social planner and where peers behave according to their own self-interest. Our model development follows a standard game theoretic specification of each participant's information set, strategy set, and utility function. Following the Gnutella 0.6 architecture, our model participants are leaf nodes and ultrapeers. The aim of our club model is to create self-forming communities of interest where peers with similar content interests are collocated in the same ultrapeer communities and where peers who share content are better able to join ultrapeer communities with content matching their interests.

Utility function: We develop a utility maximizing model for a peer to estimate the benefits of establishing a connection to another peer. In our model we assume that each peer obtains utility U from other peers on the network, where U is a function of the likelihood that the other peer will be able to respond to the peer's information needs. As noted above, we operationalize this measure using a similarity measure (*SIM*) based on Jensen-Shannon divergence such that the utility a peer p receives from another peer p' is given by

$$U(p,p') = F\left(SIM(p,p') * K(p')\right) \tag{2}$$

where *SIM* is defined in equation (1) and $K(p')$ is the number of pieces of content shared by p'.

Information set: Each peer on the network has content that can be shared and this content can be summarized in the form of a content hash. For text documents, the content hash could include a word frequency histogram of all of the words in the document. More commonly, the content hash will include a histogram of the words in the metadata describing the content. In most current P2P networks, this metadata is simply the content's filename.[5] However, metadata can also be more descriptive such as ID3 tags in MP3 filenames.[6] Given a content hash for each peer on the network, we propose a modification (described in more detail below) to the existing Gnutella 0.6 protocol to allow peers to discover the content hash of other peers on the network.

We further assume that each peer's information set includes a subset of the other peers on the network. This is accomplished in the current Gnutella protocol through each peer's host cache, which keeps track of the IP addresses of other peers in the network that a peer has come in contact with or knows about through PONG messages. A peer can also obtain information about

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[5] Filename in current P2P networks typically include the recording artist, track number, song title, and album in the case of music files or the show name, episode title, and season and episode number in the case of television shows.
[6] See www.id3.org

other peers on the network by querying host-cache servers, dedicated servers in the network whose sole purpose is to tell a peer about other peers in the network.

Strategy set: In Gnutella 0.6, a peer's only strategic decision is whether to share their content. Peers also take non-strategic actions to connect to ultrapeers in the network by selecting an ultrapeer at random from their host cache. Similarly, ultrapeers take non-strategic actions by accepting all requested connections up to a predefined maximum number of connections.

In our model, we modify this strategy set to allow leaf nodes and ultrapeers to make utility maximizing strategic decisions about which connections they will initiate and accept. Leaf nodes decide which ultrapeers to request a connection to maximize the leaf node's utility. In doing so the leaf node considers utility it receives from the club managed by the ultrapeer — both content shared by the ultrapeer and content from the ultrapeers' immediately connected leaf nodes. Likewise, ultrapeers attempt to choose which leaf node connections they will accept connections from and which other ultrapeers to connect to in a way that maximizes utility in their club.

Specifically, let *UC*(*l*, *up*) define the utility leaf node *l* receives from the club managed by ultrapeer *up*:

$$UC(l,up) = U(l,up) + \sum_{l' \in LUP(up)} U(l,l') \tag{3}$$

where *LUP*(*up*) defines the set of all leaf nodes connected to *up*. Based on this definition, *l* will solve the following maximization problem

$$\max_{UPL(l)} \sum_{up \in UPL(l)} UC(l,up) \text{ such that } \|UPL(l)\| \leq MUP(l) \tag{4}$$

where *MUP*: $L \rightarrow \{0, 1, \ldots\}$ is the maximum number of ultrapeers a leaf node can be connected to, and *UPL*(*l*) is the set of ultrapeers that *l* is connected to.

Ultrapeers consider to which other ultrapeers to request connections, and from which leaf nodes and other ultrapeers to accept connections. As noted above, an ultrapeer considers its club utility, which includes its own private utility, and the private utility of the leaf nodes immediately connected to it. An ultrapeer's decisions can significantly affect not only its own utility, but also the utility of its leaf nodes. When considering a leaf node to accept a connection from, the ultrapeer considers the utility that the leaf node will provide to the club. Specifically, let *UC*(*up*, *l*) define the utility the club managed by *up* receives from *l*

$$UC(up,l) = U(up,l) + \sum_{l' \in LUP(up)} U(l',l) \tag{5}$$

The ultrapeer will then decide which leaf node connections to accept based on the following maximization equation

$$\max_{LUP(up)} \sum_{l \in LUP(up)} UC(up,l) \text{ such that } \|LUP(up)\| \leq ML(up) \tag{6}$$

where ML: $UP \rightarrow \{0, 1, \ldots\}$ is the maximum number of leaf nodes that an ultrapeer can be connected to.

Similarly, ultrapeers accept and request connections to other ultrapeers based on the utility its club receives from the club managed by the other ultrapeer. Formally, let *UC*(*up*, *up'*) define the club utility ultrapeer *up* receives from the club managed by *up'*:

$$UC(up,up') = \left[U(up,up') + \sum_{l' \in LUP(up')} U(up,l')\right] + \sum_{l \in LUP(up)} \left[U(l,up') + \sum_{l' \in LUP(up')} U(l,l')\right] \tag{7}$$

As before, given this utility function, the ultrapeer will choose *UPUP(up)*, the set of ultrapeers to connect to, according to the following maximization problem:

$$\max_{UPUP(up)} \sum_{up' \in UPUP(up)} UC(up,up') \text{ such that } \|UPUP(up)\| \leq MUP(up) \tag{8}$$

where MUP: $UP \rightarrow \{0, 1, \ldots\}$ is the maximum number of other ultrapeers an ultrapeer can be connected to, which is defined by the protocol or by the processing capacity of the ultrapeer.

3.3.2. Network Evolution Algorithms

Implementing these optimization algorithms within the current Gnutella protocol while minimizing added overhead is complicated by the fact that peers do not have perfect knowledge of all other peers in the network. Both parties to a connection must actively establish a protocol handshake (which transmits the content hash) when initiating a connection, and both parties must determine that it is in their self-interest to complete the connection. In this section, we outline the evolution algorithm necessary to incorporate our model into the existing Gnutella protocol.

Algorithm 1: Existing Gnutella 0.6 Connection Algorithm

Initiating Peer (P) sends **Gnutella Connect** message[7] to Receiving Peer (P^*)	$\Rightarrow$	
	$\Leftarrow$	P^* responds with **Gnutella OK** message[8] if it can accept the connection and any other message if it cannot
P opens connection by sending its Content Hash to P^*	$\Rightarrow$	

In the current Gnutella 0.6 protocol, peers request connections by sending a Gnutella connect message to one of the foreign peers in its host cache (Algorithm 1). If the foreign peer can accept this connection, it responds with a Gnutella OK message and the connection is initiated by having the connecting peer reply with its content hash.

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[7] GNUTELLA CONNECT/<protocol version string>\n\n. See Kirk (2003) for details of the Gnutella 0.6 protocol.
[8] GNUTELLA/<protocol version string> 200 OK\n\n.

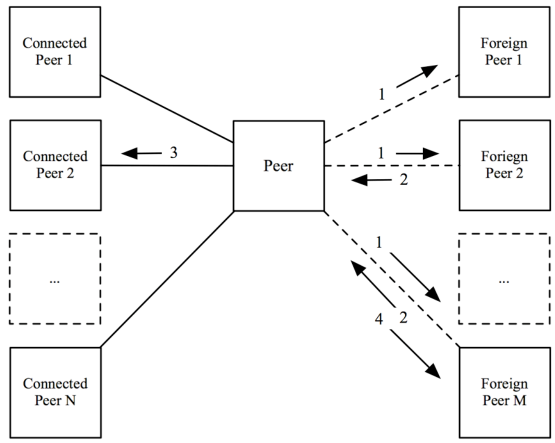
In our modification to this connection algorithm (Algorithm 2), the initiating peer first sends a Gnutella connect message to 10 of the peers in its host cache (selected at random), along with the initiating peer's content hash. The responding peer uses the content hash to determine if the initiating peer offers more utility than at least one of the existing connected peers, and if so replies with a Gnutella OK message including its calculation of the utility its content will provide the initiating peer. The initiating peer then uses this figure to determine if the responding peer offers more utility than at least one of its currently connected peers and if so responds with a Gnutella OK message. This sequence of steps is summarized in Figure 2.

Algorithm 2: Recipient's Algorithm

Initiating Peer (P) sends **Gnutella Connect** message to Receiving Peer (P^*) containing P's content hash	⇒	
	⇐	P^* responds with **Gnutella OK/Connect** message, containing its calculation of $U(P, P^*)$ if P's utility is larger than the lowest utility among P^*'s existing connected peers (and any other message otherwise)
P responds with **Gnutella OK** message if P^*'s utility is larger than the lowest utility among P's existing connected peers (and any other message otherwise)	⇒	
If a connection is established, P and P^* drop the connected peer with the lowest utility in favor of the new peer		

Note that the threat of being dropped and the threat of being refused a connection provide the incentives for peers to behave in a way that is aligned with the network's interests. Further, since all peers wish to connect to partners offering the highest utility, our model imposes an incentive reinforcing structure on the network, which enables self-organization of peers into communities that are based on content interests and aversion against free riders.

Figure 2: Club Formation Sequences



Note: 1) connection requests by (originating) peer; 2) replies to connection request from the foreign peers (recipients); 3) originating peer disconnects "Peer 2" to make room for a new peer; 4) originating peer connects to new peer which provides better utility.

Thus, our club formulation can be implemented with the following minor extensions to the existing Gnutella 0.6 protocol: 1) upgrading content hash information, 2) allowing peers to base their connection decision on the utility they will receive from the connection, and 3) modifying the handshake protocol to allow both peers to evaluate the utility offered by the connection. Currently Gnutella 0.6 only stores binary information for each word in the content hash, which specifies whether a peer's content contains a particular word. To use our club model, the content hash must be upgraded to store word frequencies. Also, peers must now base their connection decision on the content hash offered by the prospective partner. Finally, in Gnutella 0.6, the initiating peer submits its content hash only after the connection request has been accepted. For our club model, the content hash must be submitted as part of the initial connection request to allow the responding peer to calculate the utility this connection would offer to both its club and the initiating peer's club. This change will impose additional overhead on the network, and we discuss the implications of this overhead in more detail below.

3.3.3. Simulation Model

We evaluate the performance of our club formation method using the Javasim discrete-event simulation tool. Our simulation is performed in two parts: a) query simulation, and b) network evolution simulation. For query simulation, we simulate the query relaying and query answering of the peers for all peers in the network to measure IR performance. For network evolution, we simulate club formation as a series of discrete steps, characterized by a peer's execution of its network evolution algorithm. For each step, a peer (a leaf node or an ultrapeer) is randomly chosen to execute its network evolution algorithm. Each peer's algorithm is executed as an atomic event, during which no other peers, except for the peers that receive connection requests, can perform any actions resulting in changes to the network topology. After the peer completes its algorithm the next peer is randomly chosen to execute its algorithm. If the chosen peer is a leaf node, it evolves its connection to the ultrapeers. An ultrapeer, on the other hand, evolves its connection to other ultrapeers.

We interleave our query simulation and our network evolution simulation in the following manner. We initially simulate query performance in a randomly constructed hybrid network topology — representative of the performance of the (baseline) Gnutella 0.6 network. After this we perform our network evolution algorithms for a number of steps — each step represents a peer being chosen to execute its algorithm. Then we repeat our query performance simulation in order to measure any performance improvement that is achieved. Finally, we measure the overhead costs imposed by our club formation method.

4. DATA

As noted above, a key contribution of our work is that we evaluate the performance of our utility framework with data documenting the file shared by real-world users when they log into a P2P network and the queries they issue over time. To obtain this information, we reverse engineered a Gnutella 0.6 client to allow us to become an ultrapeer in the network and to collect information about what files users shared when they logged into the network and what queries they subsequently issued while on the network. We collected this data from between August 31, 2002 and September 29, 2002, during which time we observed 10,533 unique peers including 8,858 leaf nodes and 1,675 ultrapeers (see Table 1 for summary statistics).

Note that 45% (4,726) of the peers on the network do not provide content. This is consistent with the findings of prior studies that P2P networks exhibit high levels of free-riding, albeit slightly lower than Adar and Huberman's (2000) finding that 66% of Gnutella 0.4 users were free-riders in August 2000.

5. RESULTS

5.1. Main Simulation Results

We begin our analysis by simulating a network topology of 2,000 peers, of which 1,800 are leaf nodes and 200 are ultrapeers.[9] Each leaf node can be a member of only one club, while each ultrapeer can be connected to three adjacent ultrapeers. The ratio of ultrapeers to leaf nodes is chosen to approximate the actual ratio observed in the network Gnutella 0.6 network.[10] In our model, each peer has knowledge of 5% of the foreign peers in the network.[11] For each simulation trial, we evaluate the number of evolutions required to achieve maximum performance, and assess the

[9] Note that this represents a fraction of the size of the current Gnutella 0.6 network, which currently numbers nearly 500,000 peers (http://www.limewire.com/english/content/netsize.shtml). Unfortunately, we were unable to simulate the operation of larger network because of the computational demands of our simulation platform.

[10] On September 2, 2004 ultrapeers represented 9% of total peers in the Limewire Gnutella 0.6 network according to http://www.limewire.com/english/content/netsize.shtml (compared to 10% in our simulation). Note the ratio of ultrapeers to total peers is 16% in our data. This is because we parameterized our data collection client to accept more ultrapeer connections than normal to ensure that we were able to obtain a sufficient number of both types of peers.

[11] These percentages are experimentally specified. Higher percentages cause the peers to contact more peers during club formation, which may improve the speed of community formation while increasing overhead. Lower percentages would have an opposite effect.

marginal protocol overhead imposed on the network and the resulting network. In our notation, an evolution is a period in which, on average, each peer has executed its algorithm once (i.e., an evolution equals 2,000 rounds of community formation algorithms). We perform 20 simulation trials and report the means and variances of the achieved recall and overhead results.

Table 1: Descriptive Statistics of Empirical Data

Category	Variables	Value	Mean	Std. Dev.	Min.	Max.
Global Count	Peer Count	10,533				
	Leaf Node Count	8,858				
	Ultrapeer Count	1,675				
	Peers With No Content	4,726				
	Peers With No Queries	6,075				
Individual Peers	Peer Session Length (Secs.)		2,790.73	18,878.57	8.94	990,988.84
	Query Count Per Peer		7.73	129.51	0	8,357
	Query Word Count		4.44	4.08	1	39
	Content Count Per Peer		96.30	454.40	0	21,206
	Content Name Word Count		5.31	3.87	1	45

Values for global count variables are actual values, while values for individual peer variables are means, standard deviations, minimums, and maximums.

In Table 2, we show the resulting network performance when we start from a randomly generated topology and perform our algorithms for a sufficient number of evolutions to achieve stabilization.[12] The average recall for our baseline case (a randomly generated topology) is shown using black bars, while the average recall for the optimized case is shown using white bars. Table 2 further categorizes the results into TTL of 0 (i.e., results from the local club), 1, 2, and 3. Because the level of improvement varies across clubs we separately report performance for all clubs (100%), the top half of all clubs (top 50%), and the top quartile of all clubs (top 25%).

Table 2 shows that, with the exception of the average recall for TTL=3, our algorithm improves the average recall obtained by all peers. Under our algorithm, peers are on average 85% more likely to find the content they are looking for in their local club (TTL=0) than they are under the current Gnutella protocol. This ratio reduces to 45% for TTL=1 and 18% for TTL=2 and is fi-

[12] As will shown in the next section, stabilization typically requires between 1-3 evolutions.

nally statistically the same as Gnutella 0.6 for TTL=3. This decline occurs because as the TTL increases, the reach of any individual peer also increases, reducing the difference between the two networks.

Table 2: Club model performance comparison (2,000 Peer Network)

TTL=0	**Baseline Gnutella**	**Club Model**	**Ratio**
100%	0.0042	0.0078*	1.85
	(0.0013)	(0.0027)	
50%	0.0061	0.0160*	2.62
	(0.0016)	(0.0057)	
25%	0.0083	0.0266*	3.20
	(0.0033)	(0.0015)	

TTL=1	**Baseline Gnutella**	**Club Model**	**Ratio**
100%	0.0192	0.0278*	1.45
	(0.0028)	(0.0089)	
50%	0.0209	0.0546*	2.61
	(0.0031)	(0.0165)	
25%	0.0222	0.0880*	3.96
	(0.0039)	(0.0259)	

TTL=2	**Baseline Gnutella**	**Club Model**	**Ratio**
100%	0.0488	0.0577*	1.18
	(0.0041)	(0.0151)	
50%	0.0494	0.1111*	2.25
	(0.0061)	(0.0230)	
25%	0.0517	0.1720*	3.33
	(0.0067)	(0.0316)	

TTL=3	**Baseline Gnutella**	**Club Model**	**Ratio**
100%	0.1076	0.1070	0.99
	(0.0079)	(0.0287)	
50%	0.1079	0.1988*	1.84
	(0.0101)	(0.0405)	
25%	0.1086	0.2959*	2.72
	(0.0124)	(0.0488)	

Note: Ratio is club recall / Baseline Gnutella recall. Standard deviations are shown in parentheses. * denotes club model recall is statistically significantly different than the baseline Gnutella 0.6 recall.

Our results also show that the top clubs (in terms of recall) see a much stronger increase in recall under our algorithm than under Gnutella 0.6. For example, the top quartile of clubs achieve a 220% higher recall from their local club (TTL=0) than Gnutella 0.6 and a 172% higher recall under TTL=3. In investigating this finding further, we observe that this is because under our algorithm, peers who do not share content are unable to join clubs with higher utility and over time become clustered in clubs with other free-riders. Conversely, peers who share desirable content are able to join clubs with other high utility peers. Thus, under our algorithm, a peer who would not have shared content under Gnutella 0.6, would have added incentive to share content due to the increased recall they would experience.

We quantify this effect in more detail by simulating club formation to compare the value received by a peer (as measured by recall) when the peer provides, and does not provide, content to the network. To do this, we randomly choose a non-free-riding peer and measure the recall it receives in a randomly constructed network.[13] Starting from this random network, we simulate club formation twice: once where the chosen peer provides its content, and once where the chosen peer provides no content. In each case, club formation is performed for until recall stabilizes. We then compare the recall the peer receives when it provides content and when it does not provide content. We repeat this experiment with 100 randomly chosen peers and display the average of the resulting recall measures in Table 3 for the different time-to-live values.

Table 3: Change in Recall Resulting from Decision to Provision Content

	Recall		Ratio: Non-
TTL	Non-provision	Provision	Provision/Provision
0	0.0002	0.0112	73.72
1	0.0031	0.0381	12.16
2	0.0109	0.0868	7.97
3	0.0334	0.1585	4.74

The increase in recall across all TTLs is dramatic. Peers who share content receive 74 times higher recall from their local club than peers who free-ride, and receive nearly 5 times higher recall overall.[14] Thus, we would expect that the dramatically higher recall a peer could gain by sharing would encourage them to make a choice to share. This, in turn, would increase the average recall experienced by all peers in the network. Since our results do not contain this secondary effect, the change in recall of our algorithm versus Gnutella 0.6, shown in Table 2, is a lower bound on the true change after taking into account the impact of reduced free-riding.

[13] We choose non-free-riding peers for this experiment because otherwise we would not know what content they had available to share when we set the peers to provide content.

[14] These recall results are slightly different than our previously reported recall figures because here we are analyzing recall for only non-free-riding peers who, as noted previously, receive higher recall under our algorithm than free-riding peers.

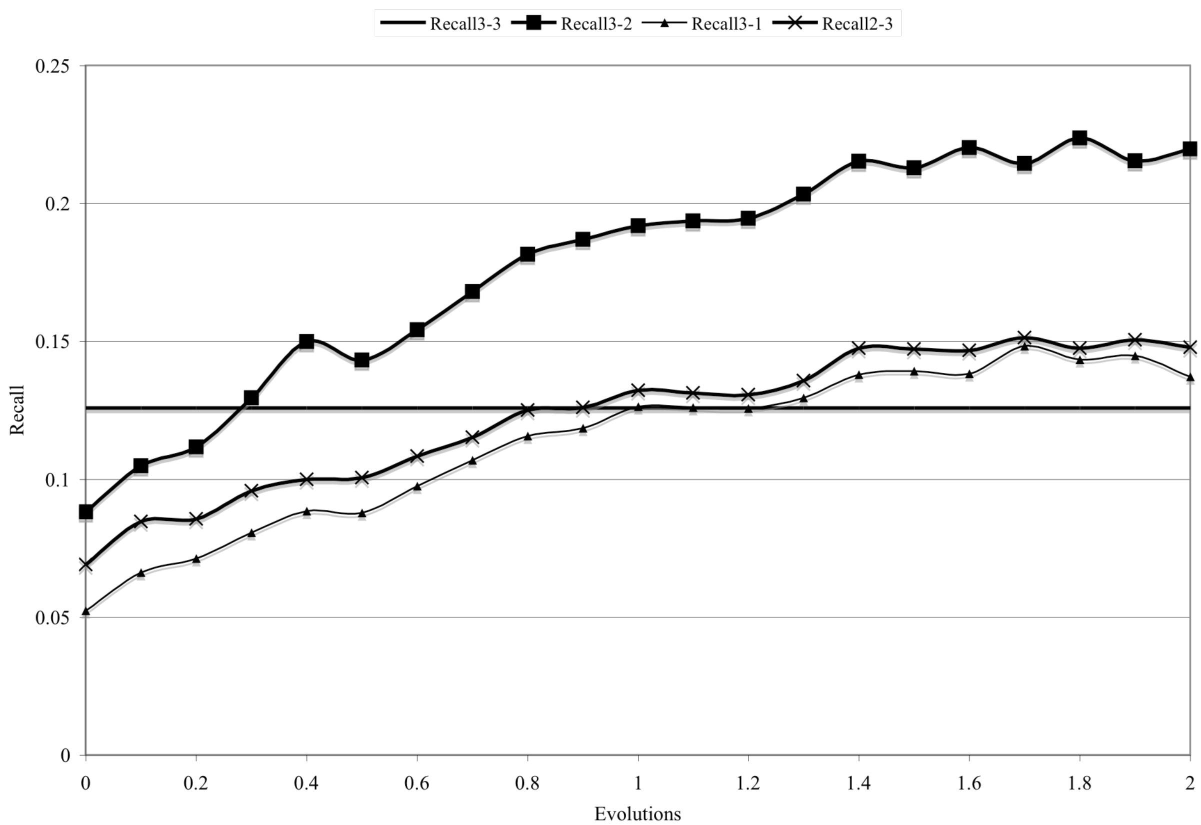
We also make two additional important observations from our data. First, while free-riding peers are generally located in the same clubs as other free-riding peers, they are still able to obtain some content from the network, particularly for larger TTL values. This means that a peer who initially has no content, but is willing to share content, is able to obtain content from the network and over time and build up enough content to join high value clubs. Second, as noted above, as we increase TTL, any individual peer has access to a larger segment of the network, reducing the difference between our algorithm and Gnutella 0.6. However, this reduction is particularly acute in our simulation because we only simulate a 2,000 peer structure. In a larger network, such as the current Gnutella 0.6 network which contains approximately 500,000 peers, even at TTL=3 any individual peer can only reach a small portion of the network. Thus, again we expect our results for larger TTLs represent a lower bound on what would be found in larger networks.

5.2. Cost Overhead

As noted above, while our club formation method improves the recall quite impressively, it imposes additional overhead on the network in terms of transmitting an additional content hash from the receiving to the initiating peer as the network is evolved to an optimized state. Direct comparison of the value gained from increased recall and the cost imposed by increased overhead is complicated by the fact that these two measures have different units. In this section, we provide a consistent way to measure the impact of these "start-up" overhead costs to the longer term benefit peers gain from participating in a network with higher recall.

To do this, we take advantage of the fact that under our algorithm, ultrapeers are aware of the utility offered by each of the other ultrapeers to which they are connected. Because of this, under our algorithm, ultrapeers should be able to selectively forward query requests to other ultrapeers who are most likely to be able to respond. This should reduce the number of queries sent and received in the network and hence the bandwidth requirement. Holding recall constant (i.e., same as in baseline Gnutella 6.0), if the overhead costs (measured in terms of bandwidth) of network optimization in our model are smaller than the savings in number of messages forwarded (measured in terms of bandwidth), then our algorithm becomes even more attractive.

Figure 4: Overhead Requirement for Top 25% Clubs



In Figure 4, we show our results for the top 25% clubs. The horizontal line labeled ("3-3 baseline") is the recall that would be achieved under Gnutella 0.6 using TTL=3. The remaining lines make use of the intelligent forwarding feature of our data. Specifically, in this figure, the notation TTL = *i-j*, means that for the setup we use the time-to-live of *i*, but we use the best *j* (out of 3 total ultrapeer-to-ultrapeer) connections — as determined by interclub utility — from the originating ultrapeers to relay queries. Thus for example, TTL = 3-2 means that we use the time-to-live of 3, but the originating ultrapeer only chooses the best 2 connections out of the 3 connections to broadcast its queries.

The Figure shows that for TTL=2-3, TTL=3-1, and TTL=3-2, we can achieve higher recall using our algorithm and intelligent forwarding than what is achieved by Gnutella 0.6.[15] In particular, note that we can get the same recall as in Gnutella 6.0 (TTL=3), by evolving our intelligent network once but by reducing the TTL by 1 (TTL= 2-3 which is same as TTL = 2). We now evaluate whether the cost savings brought about by reducing the TTL by 1 is worth the cost incurred in creating the clustered network.

The evolution in our simulation requires 1,800 steps of leaf node algorithm and 200 steps of ultrapeer algorithm. The most significant cost of our model is the bandwidth required for the transmission of information sets for the peers to make decisions about which other peers to connect to. In our formulation, we transmit information sets in the form of compressed word frequency list. From our empirical analysis, we find that the word frequency list of a leaf node when compressed with the popular ZLIB compression algorithm (Deutsch 1996) requires 620 bytes on average for the peers in our network. Likewise, for a club of 10 peers, we find that a word frequency list compressed using the same algorithm requires 5,085 bytes on average. Note that we choose a most common compression algorithm, and we do not employ any domain specific techniques for representing a word frequency list (e.g., dictionary, stop words). Using such specialized domain knowledge one could obtain even lower overhead.

[15] Note that, as above, these recall figure do not take into account any additional gains in recall from reduced free-riding due to the added incentives present in our algorithm.

To calculate how frequently these messages will need to be sent to obtain our results, we observe that in a leaf node algorithm, a leaf node sends its information to 10 ultrapeers each time it evolves its position in the network. In the baseline Gnutella 0.6, a leaf node sends its hash only once, hence our algorithm requires the leaf node to send its information 9 more times. Therefore after 1,800 steps, our enhancements have incurred an extra overhead cost of 1,800 * 9 * 620 = 10,044,000 bytes for leaf node evolutions. On the other hand, for the ultrapeer algorithm, an ultrapeer will contact 10 other ultrapeers in each evolution. Thus for 200 ultrapeers, our enhancements will have incurred an overhead cost of 200 * 10 * 5,085 = 10,170,000 bytes, yielding the total overhead cost of 10,044,000 + 10,170,000 = 20,214,000 bytes.

We can then compare this overhead cost to the bandwidth savings from intelligent forwarding of query packets (instead of sending the queries to all connected ultrapeers). Specifically, for TTL=3, each query message is relayed an average of 27 times in our simulation. According to our data, on average, each query message takes up 46 bytes. Thus, each query message imposes 1,242 bytes of overhead the network. For TTL=2, on the other hand, each query message is relayed an average of 9 times, thus each query message imposes 243 bytes of overhead. Let x be the number of query messages that must be sent for the cost overhead of our model to be justified by the reduction in time-to-live. Therefore, x is determined by $20{,}214{,}000 < 1{,}242 * x - 243 * x$. Thus, 20,234 or more queries must be relayed in the network to justify the overhead cost. With a network of 2,000 peers, this translates to each peer having to make slightly more than 10 queries before the cost is justified. Based on our data, each peer issues the average of 10 queries per hour.[16] Therefore, is the overhead cost from optimizing the network using our model can be justified in slightly over one hour.

5.3. Dynamic Networks

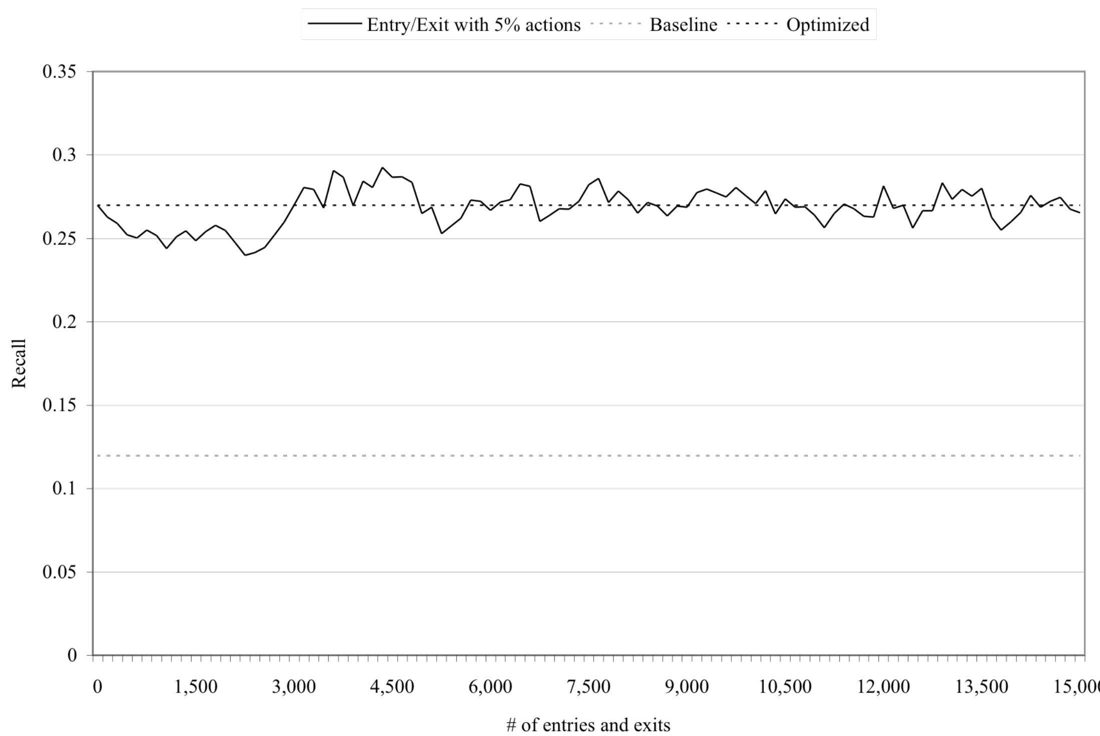
In this section, we analyze how robust our results are to entries to and exits from the network by peers. Under such a dynamic network, the cost in optimizing the network is no longer a one-time fixed cost. Rather, our club model must be periodically executed to keep up with the impact that these entries and exits have on the network — namely in undoing the optimization of our club model. We parameterize our dynamic network simulation using an earlier peer-to-peer study (Asvanund et al. 2002). This study found that a user enters and exits the network approximately 2 times per day, which translates to roughly 0.083 times per hour. To map this factor into our framework, 8.3% of the active (i.e., currently connected) leaf nodes randomly exit the network in a given hour, and are replaced by the same number of new leaf nodes (i.e., leaf nodes in our data sample, but currently not connected to our network), who enter the network.

Using this rate of entry and exit, we find that in order to maintain our network in its optimized state, each of the incoming peers (i.e., 150 peers) must execute our club algorithm, and 5% of the existing peers (i.e., 100 peers) must also execute our club algorithm. Through experimentation, we found 5% to be the smallest percentage that allows the network to maintain operation at the optimized level. Figure 5, we show our recall results in a network setup with 2,000 active peers, with 1,800 leaf nodes and 200 peers are ultra peers. In this setup, 150 randomly chosen active leaf nodes (8.3% of the active leaf nodes) will exit the network, and 150 randomly chosen new leaf nodes join the network each hour after the network has been fully optimized with our club

[16] From Table1, each peer stays on the network for about 0.775 hours and issues about 7.73 queries. This translates to about 10 queries per hour.

model. As shown in the Figure, by having 5% of the existing peers perform our club algorithm (in addition to each of the entering peers) we are able to maintain the level of recall achieved in the optimized network without entry and exit.

Figure 5: Network dynamics when existing peers also perform intelligence



We can characterize the overhead necessary to optimize this dynamic network by noting that, as above, incoming peers consume a total of 1,439,775 bytes per hour to execute the optimization algorithm..[17] The overhead from having 5% of existing peers perform the same optimization requires an additional 1,010,700 bytes per hours, for a total of 2,450,475 bytes per hour. Following section 5.2, the cost savings from using TTL=2 instead of TTL=3 with 10 queries per hour per peer results in 20,214,000 bytes per hours. Thus, in each given hour, the benefit of maintaining

[17] Since 10% of the peers in our setup are Ultrapeers, about 135 leaf nodes and 15 Ultrapeers enter the network. Therefore the cost is 135 new peers per hour * 620 bytes * 9 + 15 Ultrapeers*5,085 bytes per Ultrapeer*10. Because ultrapeers are selected by the current Gnutella protocol based on both their bandwidth and their persistence on the network, our estimation that 10% of exiting peers are Ultrapeers will likely overstate the proportion of exiting ultrapeers, and thus will overstate the overhead these optimizations will impose on the network.

the network in an optimized state is roughly 10 times the cost in maintaining the network at its optimal stage, demonstrating the effectiveness of our model in a dynamic environment.

5.4. Sensitivity Analysis

We perform additional sensitivity analyses on our results in two ways. First, by analyzing how our results change for smaller and larger networks and, second by varying the rate of entries and exits in our dynamic network. To analyze how our results vary for smaller and larger network we reanalyze our results for networks with 1,000 and 4,000 peers. In each case, we maintain the number of leaf-to-ultrapeer and ultrapeer-to-ultrapeer connection used in our initial simulation and the same ratio of ultrapeers to total peers.

Table 4: Club model performance comparison (1,000 Peer Network)

TTL=0	Baseline Gnutella	Club Model	Ratio
100%	0.0074	0.0174*	2.35
	(0.0014)	(0.0031)	
50%	0.0100	0.0318*	3.18
	(0.0025)	(0.0074)	
25%	0.0134	0.0520*	3.88
	(0.0048)	(0.0021)	

TTL=1	Baseline Gnutella	Club Model	Ratio
100%	0.0333	0.0580*	1.74
	(0.0039)	(0.0131)	
50%	0.0339	0.1020*	3.01
	(0.0045)	(0.0193)	
25%	0.0428	0.1582*	3.70
	(0.0041)	(0.0321)	

TTL=2	Baseline Gnutella	Club Model	Ratio
100%	0.0917	0.1021*	1.11
	(0.0062)	(0.0156)	
50%	0.0923	0.1716*	1.86
	(0.0076)	(0.0261)	
25%	0.0996	0.2445*	2.45
	(0.0067)	(0.0414)	

TTL=3	Baseline Gnutella	Club Model	Ratio
100%	0.1979	0.1972	1.00
	(0.0121)	(0.0245)	
50%	0.1983	0.2863*	1.44
	(0.0142)	(0.0452)	
25%	0.2199	0.3631*	1.65
	(0.0162)	(0.0451)	

Note: Ratio is club recall / Baseline Gnutella recall. Standard deviations are shown in parentheses. * denotes club model recall is statistically significantly different than the baseline Gnutella 0.6 recall.

Our results for a 1,000 peer network are similar to our previous results for a 2,000 peer network. As before, peers appear to cluster into groups with similar interests: under our club model, peers in the 1,000 node network are 135% of more likely to find the content they are interested from a member of their local club than in Gnutella 0.6. Likewise, the top clubs provide substantially higher recall than other clubs, providing added incentives for peers to share their content.

Table 5: Club model performance comparison (4,000 Peer Network)

TTL=0	Baseline Gnutella	Club Model	Ratio
100%	0.0018	0.0159*	8.83
	(0.0008)	(0.0011)	
50%	0.0023	0.0239*	10.39
	(0.0014)	(0.0034)	
25%	0.0031	0.0331*	10.68
	(0.0025)	(0.0024)	

TTL=1	Baseline Gnutella	Club Model	Ratio
100%	0.0083	0.0412*	4.96
	(0.0012)	(0.0054)	
50%	0.0085	0.0631*	7.42
	(0.0032)	(0.0152)	
25%	0.0095	0.0892*	9.39
	(0.0024)	(0.0254)	

TTL=2	Baseline Gnutella	Club Model	Ratio
100%	0.0240	0.0841*	3.50
	(0.0035)	(0.0124)	
50%	0.0257	0.1279*	4.98
	(0.0064)	(0.0325)	
25%	0.0259	0.1792*	6.92
	(0.0051)	(0.0351)	

TTL=3	Baseline Gnutella	Club Model	Ratio
100%	0.0527	0.1444*	2.74
	(0.0041)	(0.0352)	
50%	0.0580	0.2134*	3.68
	(0.0030)	(0.0215)	
25%	0.0596	0.2944*	4.94
	(0.0045)	(0.0336)	

Note: Ratio is club recall / Baseline Gnutella recall. Standard deviations are shown in parentheses. * denotes club model recall is statistically significantly different than the baseline Gnutella 0.6 recall.

Our results for the 4,000 are even more dramatic. Peers are nearly 9 times more likely to find the content they are looking for in their local club under our club model than under Gnutella 0.6, and our club model provides statistically significantly higher recall for all clubs and all TTL levels (even TTL=3, unlike in the 2,000 or 1,000 node networks in Tables 2 and 4). Finally, the top quartile clubs provide nearly twice the recall that the average club does.

Finally, we perform a sensitivity analysis on our dynamic network setup by varying the rate of entries and exits of the peers in a network with 2,000 peers. We performed the same experiment with a network in which 300 (15%) and 450 (23%) peers enter and exit the network in each given hour. When 300 peers enter the network per hour we find that to maintain the optimal topology, in addition to the incoming peers performing our club algorithms, 15% of the existing peers are required to perform our club algorithms. Similarity for 450 entries and exits per hour, we find that the incoming peers and 35% of the existing members must perform our club algorithms. Based on the previous analysis, both of these setups are still cost effective when compared to the benefits provided by the optimized network. However, the increase in the number of existing members required to maintain the optimized network at a stable recall level suggests that as entries and exits increase, they will reach a point where our club model can no longer maintain an optimized network. However, from these simulations the rate of entries and exits where this might occur appears to be far above the rate observed in current Gnutella networks.

6. DISCUSSION

P2P networks have gained significant popularity for consumer file sharing and are gaining popularity in corporate and government settings for enterprise knowledge management. However, current P2P networks exhibit two well-known inefficiencies. First, users have weak incentives to share content, resulting in sharing below socially optimal levels (Krishnan et al. 2002a). Second, network reach is limited (Asvanund et al. 2002) and networks are organized without regard to content interest, meaning that in many cases peers are unable to locate their desired content on the network. However, while these two problems are well known there has been little research conducted to address these inefficiencies using the economic characteristics of P2P networks. We use economic models calibrated with real-world data to bridge this gap in the literature.

Our models combine concepts from the club goods economics and the IR computer science literatures. The resulting club models incorporate economic incentives and content-based measures of similarity of interests into the Gnutella 0.6 protocol to create increased incentives for users to share content and to create self-forming communities of interest among users.

A significant contribution of our research is that we evaluate our utility models using real-world data documenting the files initially shared by users when the log into the Gnutella P2P network and the subsequent queries they issue while on the network. These data show that our club model approach results in the formation of communities of interest, and provides users with strong incentives to share content. Our results are robust to entry and exit by peers and the added protocol overhead imposed by our models. Moreover, our results are strengthened in larger networks, which is particularly important given that our simulations are conducted on 1,000 to 4,000 peer networks while the current Gnutella 0.6 network numbers approximately 500,000 peers.

It is important to note that our simulations represent a lower bound on the true gain we expect from incorporating our club models into hybrid P2P networks. First, we do not model the impact of the increased sharing we would expect due to our incentive structures. It would be useful in future work to develop utility models of peers' sharing decisions and incorporate this effect into future simulation studies of these club models. Second, with regard to overhead, there are a variety of techniques that can improve cost overhead (e.g., pruning the content hash, improving the host-cache servers), further reducing the cost requirement for maintaining our network (see Lu and Callan 2003 for examples).

It is also important to note that our results may be further enhanced by recent research suggesting a behavioral explanation for sharing in P2P networks (Gu and Jarvenpaa 2003, Strahilevitz 2002). These papers suggest that cooperation in P2P networks should be easier in networks with tighter social ties. To the extent that this explanation holds, it would further increase sharing in our network as our method of creating communities of interest should result in tighter social ties among these community members. It is also important to note that while our model provides lower recall to peers who do not share content, such peers are still able to access some content from the network. Because of this, peers who come to the network without any content, but with a willingness to share content, should be able to obtain content from the network and eventually gain access to high value clubs.

Our models could be extended in a variety of ways. First, one could allow peers in our model to join multiple ultrapeers, as is the case in current Gnutella 0.6 networks. Incorporating this feature into our model may provide improved service to peers who have multiple distinct content interests, possibly further increasing our recall gains. Our results could also be extended by further refining our utility function to take into account the disutility clubs experience from peers who issue a large number of queries. One could also use different measures of performance, such as a binary measure for whether any results were returned by queries, instead of our (more common) recall measure. It would also be useful to validate this approach in fully distributed (e.g., Gnutella 0.4) or centralized (e.g., OpenNap) settings. Finally, a limitation of our model is that we assume all peers to be telling the truth (i.e., reporting the true content hash or resulting utility). A solution would be an integration of reputation systems (Lai et al. 2003), which is a large area of study in distributed systems. Most of this reputation literature on P2P networks is based on analytical models rather than empirical approaches. Here again, it would be useful for future work to incorporate these analytic models into our simulation framework to further validate our approach.

7. BIBLIOGRAPHY

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APPENDIX A: JENSEN-SHANNON DIVERGENCE

Jensen-Shannon divergence is based on Kullback-Leibler divergence (KL divergence) (Cover 1991). KL divergence quantifies the similarity between two word frequency histograms, $p_A(V)$ and $p_B(V)$ (e.g., the word frequency in a node's queries or shared content). Let V be the set of all words in the vocabulary of all nodes, and let $v \in V$ be a word in the vocabulary. In equation (A.1), $p_A(v)$ is the percentage of the words in $p_A(V)$ that is equal to v, and $p_B(v)$ is the percentage of words in $p_B(V)$ that is equal to v. This measure produces a scalar value between zero and infinity, with a *lower* value signifying *higher* similarity. Note that this measure does not require content to follow a structured naming convention. However, KL divergence, used in its traditional form, requires a workaround to prevent a division by zero. One such workaround requires the global knowledge of the vocabulary in use (Xu et al. 1999). Since Gnutella peers operate in a distributed environment, assuming global knowledge is not realistic in our setting.

$$KL(p_A(V), p_B(V)) = \sum_v p_A(v) \cdot \left(\frac{p_A(v)}{p_B(v)} \right) \in [0, \infty) \qquad \text{(A.1)}$$

Jensen-Shannon (JS) divergence does not require global knowledge of the vocabulary, making it more suitable to our environment (Chechik 2003). As shown in equation (A.2) and (A.3), for any two word frequency histograms, $p_I(V)$ and $p_J(V)$, JS calculates KL divergence against $p\_avg_{I,J}(V)$, the average of the two histograms, preventing division by zero. JS divergence produces a scalar value between zero and one, with a *lower* value signifying *higher* similarity.

$$JS(p_I(V), p_J(V)) = \frac{1}{2}\left[KL(p_I(V), p\_avg_{I,J}(V)) + KL(p_J(V), p\_avg_{I,J}(V)) \right] \in [0,1] \qquad \text{(A.2)}$$

$$p\_avg_{I,J}(v) = \frac{p_I(v) + p_J(v)}{2} \qquad \text{(A.3)}$$