Locating Data in (Small-World?) Peer-to-Peer Scientific Collaborations

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1. Introduction

Locating files based on their names is an essential mechanism for large-scale data sharing collaborations. A peer-to-peer (P2P) approach is preferable in many cases due to its ability to operate robustly in dynamic environments.

Existing P2P location mechanisms focus on specific data sharing environments and, therefore, on specific requirements: in Gnutella[1], the emphasis is on easy sharing and fast file retrieval, with no guarantees that files will always be located. In Freenet [8], the emphasis is on ensuring anonymity. In contrast, systems such as CAN [13] and Chord [14] guarantee that files are always located, while accepting increased overhead for file insertion and removal.

Data usage in scientific communities is different than in, for example, music sharing environments: data usage often leads to creation of new files, inserting a new dimension of dynamism into an already dynamic system. Anonymity is not typically a requirement, being generally undesirable for security and monitoring reasons.

Among the scientific domains that have expressed interest in building data-sharing communities are physics (e.g., GriPhyN project[6]), astronomy (Sloan Digital Sky Survey project[4]) and genomics[3]. The Large Hadron Collider (LHC) experiment at CERN is a proof of the physicists' interest and pressing need for large-scale data-sharing solutions. Starting 2005, the LHC will produce Petabytes of raw data a year that needs to be pre-processed, stored, and analyzed by teams comprising 1000s of physicists around the world. In this process, even more derived data will be produced. 100s of millions of files will need to be managed, and storage at 100s of institutions will be involved.

In this paper we advocate the benefits of exploiting emergent patterns in self-configuring networks specialized for scientific data-sharing collaborations. We speculate that a P2P scientific collaboration network will exhibit small-world

topology, as do a large number of social networks for which the same pattern has been documented.

We sustain our intuition by observing the scientific characteristics data-sharing of collaborations and studying the sharing patterns of a high-energy physics community (Section 2). In Section 3 we propose a solution for locating data decentralized. scientific. data-sharing environments that exploits the small-worlds topology. The research challenge we raise is: what protocols should be used to allow a selfconfiguring P2P network to form small worlds similar to the way in which the humans that use the network do in their social interactions? While we do not have a complete solution, we discuss this problem in Section 5.

2. Small worlds in scientific communities

In many network-based applications, topology determines performance. This observation captivated researchers who started to study large real networks and found fascinating results: recurring patterns emerge in real networks [5]. For example, social networks, in which nodes are people and edges are relationships; the world wide web, in which nodes are pages and edges are hyperlinks; and neural networks, in which nodes are neurons and edges are synapses or gap junctions, are all small-world networks [15]. Two characteristics distinguish small-world networks: first, a small average path length, typical of random graphs (here 'path' means shortest nodeto-node path); second, a large clustering coefficient that is independent of network size. The clustering coefficient captures how many of a node's neighbors are connected to each other. One can picture a small world as a graph constructed by loosely connecting a set of almost complete subgraphs.

The small world example of most interest to us is the scientific collaboration graph, where the nodes are scientists and two scientists are connected if they have written an article together. Multiple studies have shown that such graphs have a small-world character, in scientific collaborations spanning a variety of different domains, including physics, biomedical research, neuroscience, mathematics, and computer science.

Typical uses of shared data in scientific collaborations have particular characteristics:

Group locality. Users tend to work in groups: a group of users, although not always located in geographical proximity, tends to use the same set of resources (files). For example, members of a science group access newly produced data to perform analyses or simulations. This work may result into new data that will be of interest to all scientists in the group, e.g., for comparison. File location mechanisms such as those proposed in CAN, Chord, or Tapestry [16] do not attempt to exploit this behavior: each member of the group will hence pay the cost of locating a file of common interest.

Time locality. The same user may request the same file multiple times within short time intervals. This situation is different, for example, from Gnutella usage patterns, where a user seldom downloads a file again if it downloaded it in the past. (We mention that this characteristic is influenced by the perceived costs of storing vs. downloading, which may change in time.)

It is the intuition provided by the small-world phenomenon in real networks and the typical use of scientific data presented above that lead us to the following questions. Let us consider the following network: a node is formed of data and its provider (the scientist who produced the data), and two nodes are connected if the humans in those nodes are interested in each other's data. The first question is: is this a small-world network? Based on the analysis of data sharing patterns in a physics collaboration (presented in Section 2.1) we speculate that this network will be a small world. Second, how can such small-world topology be exploited for performance in the datasharing environments of interest to us? Finally, how do we translate the dynamics of scientific collaborations into self-configuring network protocols (such as joining the network, finding the right group of interests, adapting to changes in user's interests, etc.)?

We believe this last question is relevant and challenging in the context of self-configuring P2P

networks. We support this idea by answering the second question: in Section 3 we sketch a file location strategy that exploits the small-world topology in the context of scientific data-sharing collaborations. Once we show that a small-world topology can be effectively exploited, designing self-configuring topology protocols to induce specific topology patterns becomes more interesting.

2.1. Data sharing in a physics collaboration

The D0 collaboration [2] involves hundreds of physicists from 18 countries that share large amounts of data. Data is accessed from remote locations through a software layer (SAM [11]) that provides file-based data management. We analyzed data access traces logged by this system during January 2002.

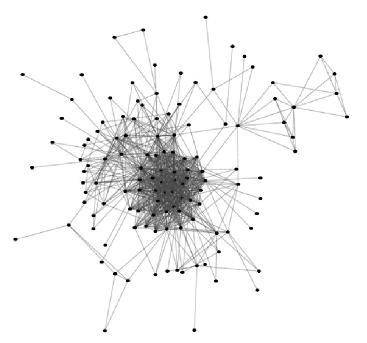


Figure 1: The file-sharing graph of January 2002.

We considered the graph whose nodes are users and whose links connect users that shared at least one file during a specified interval. We found that the graphs generated for various interval lengths exhibit small-world characteristics: short average path lengths and large clustering coefficients. Although these graphs are relatively small compared to our envisioned target (e.g., 155 users accessed files through SAM in January), we expect similar

Time	Whole graph		Largest Connected component				Random Graph	
Interval	# Nodes	# Links	# Nodes #	Links	Clustering	Path length	Clustering	Path length
1 day	20	38	12	34	0.827	1.61	0.236	2.39
2 days	20	77	15	75	0.859	1.29	0.333	1.68
7 days	63	331	58	327	0.816	2.21	0.097	2.35
14 days	87	561	81	546	0.777	2.56	0.083	2.30
30 days	128	1046	126	1045	0.794	2.45	0.067	2.29

Table 1: File-sharing graph characteristics for intervals from 1 hour to 30 days.

Table 1 presents the characteristics of the graphs of users who shared data within various time intervals ranging from 1 day to 30 days. The small-world pattern is evident when comparing the clustering coefficient and average path length with those of a random graph of the same size (same number of nodes and edges): the clustering coefficient of a small-world graph is significantly larger than that of a similar random graph, while the average path length is about the same

3. Locating files in small-world networks

We consider an environment with potentially hundreds of thousands of geographically distributed nodes that provide location information as < logical filename, physical location pairs.

Locating files in this environment is challenging because of scale and dynamism: the number of nodes, logical files, requests, and concurrent users (seen as file location requestors) may all be large. The system has multiple sources of variation over time: files are created and removed frequently; nodes join and leave the system without a predictable pattern. In such a system with a large number of components (nodes and files), even a low variation rate at the individual level may aggregate into frequent group level changes.

We exploit the two environmental characteristics introduced in Section 2—group and time locality—to advance our performance objective of minimizing file location latency. We also build on our assumption that small-world structures eventually emerge in P2P scientific collaborations.

Consider a small world of *C* clusters, each comprising, on average, *G* nodes. A cluster is defined as a community with overlapping data interests, independent of geographical or administrative proximity. Clusters are linked together in a connected network. In this structure, we combine information dissemination techniques with request-forwarding search mechanisms: location information is propagated aggressively within clusters, while inter-cluster search uses request forwarding techniques.

We chose gossip [10] as the information dissemination mechanism: nodes *gossip* location information to other nodes within the cluster. Eventually, with high probability, all nodes will learn about all other nodes in the cluster. They will also know, with high probability, all location information provided by all nodes within the cluster. Hence, a request addressed to any node in the cluster can be satisfied at that node, if the answer exists within the cluster.

A request that cannot be answered by the local node is forwarded to other cluster(s), by unicast, multicast, or flooding. Ideally, clusters can organize themselves dynamically in search-optimized structures, thus allowing a low cost inter-cluster file retrieval. Since any node in a cluster has all information provided in that cluster, the search space reduces from C*G to C.

In this context, nodes need to store the total amount of information provided by the cluster to which they belong. In order to reduce storage costs, we use a compact, probabilistic representation of information based on Bloom Filters (Section 4.2). Nodes can trade off the amount of memory used for the accuracy in representing information.

Each node needs to have sufficient topology knowledge to forward requests outside the cluster. Not every node needs to be connected to nodes from remote clusters, but, probabilistically, every node needs to know a local node that has external connections. The question of how to form and maintain inter-cluster connections pertains to the open question we raise in this paper and discuss in Section 5: what topology protocols can induce the small-world phenomenon?

4. Gossiping Bloom filters for information dissemination

In this section we briefly explain how we use the mechanisms mentioned above: gossip for information dissemination and Bloom filters for reducing the amount of communication. We also provide an intuitive quantitative estimation of the system we consider.

4.1. Gossip mechanism

Gossip protocols have been employed as scalable and reliable information dissemination mechanisms for group communication. Each node in the group knows a partial, possibly inaccurate set of group members. When a node has information to share, it sends it to a number of f nodes (fanout) in its set. A node that receives new information will process it (for example, combine it with or update its own information) and gossip it further to k nodes chosen from its set.

We use gossip protocols for two purposes: (1) to maintain accurate membership information in a potentially dynamic cluster and (2) to disseminate file location information to nodes in the local cluster. We rely on soft-state mechanisms to remove stale information: a node not heard about for some time is considered departed; a logical file not advertised for some time is considered removed.

4.2. Bloom Filters

Bloom filters [7] are compact data structures used for probabilistic representation of a set in order to support membership queries ("Is element x in set X?"). The cost of this compact representation is a small rate of *false positives*: the structure sometimes incorrectly recognizes an element as member of the set.

Bloom filters describe membership of a set A by using a bit vector of length m and k hash

functions, $h_1, h_2,...,h_k$ with $h_i:X \to \{1..m\}$. For a fixed size (n) of the set to be represented, the tradeoff between accuracy and space (m bits) is controlled by the number of hash functions used (k). The probability of a false positive is:

$$p_{err} \approx \left(1 - e^{-kn/m}\right)^k$$
. Here p_{err} is minimized for

$$k = \frac{m}{n} \ln 2$$
 hash functions. In practice, however,

a smaller number of hash functions is used: the computational overhead of each additional hash function is constant while the incremental benefit of adding a new hash function decreases after a certain threshold. Experience shows that Bloom filters can be successfully used to compress a set to 2 bytes per entry with false positive rates of less than 0.1% and lookup time of about 100µs.

A nice feature of Bloom filters is that they can be built incrementally: as new elements are added to a set, the corresponding positions are computed through the hash functions and bits are set in the filter. Moreover, the filter expressing the reunion of multiple sets is simply computed as the bit-wise OR applied over the corresponding filters.

Bloom filters can be compressed when transferred across the network and, in this case, filter parameters can be chosen to maximize compression rate, as shown in [12].

4.3. Advantages of building the system around shared data interests

We model this system built on group and time locality assumptions as follows:

Zipf distribution for request popularity. In Zipf distributions, the number of requests for the k^{th} most popular item is proportional to $k^{-\alpha}$, where α is a constant. Zipf distributions are widely present in the Internet world. For example, the popularity of documents requested from an Internet proxy cache (with $0.65 < \alpha < 0.85$), Web server document popularity ($0.75 < \alpha < 0.85$), and Gnutella query popularity ($0.63 < \alpha < 1.24$) all exhibit Zipf distributions. For our problem, we assume that file popularity in each cluster (group) follows a Zipf distribution.

Locality of interests. As discussed above, clusters are formed based on shared interest. We therefore assume that information on the most popular files is available within the cluster and

only requests for not-so-popular files are forwarded.

With these assumptions, we can estimate the fraction of file requests served by the group as a function of the distribution parameter α and the fraction of files about which the group maintains information. For example, as Figure 1 shows, 68% of all requests are served by the group when information about only top 1% most popular files is available at group level, for α =1. Figure 1 strongly emphasizes the need for efficient, interest based, cluster creation.

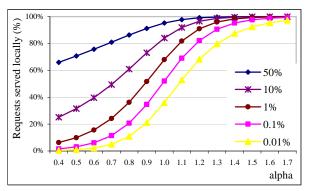


Figure 2: Fraction of requests served locally (by one member of a group) assuming various values for α

We estimate 100s of clusters with 1,000s of nodes in a cluster, sharing information on about 10 million files per cluster. Using Bloom filters, for 0.1% false positives rate, each node needs 2 bytes per file or 20MB of memory to store information about all files available in the cluster. Assuming a 10-day average lifetime for a file at a node, and a self-imposed threshold of 0.1% false positives, then the generated traffic needed to maintain this accuracy level within the cluster can be estimated at about 24 KBps at each node.

False negatives may have two sources: the probabilistic information dissemination mechanism and inaccuracy in the inter-cluster search algorithm. By appropriately tuning the gossip periodicity and fanout, the system can control the rate of false negatives by increasing communication costs.

5. Creating a small world

The question raised and not answered in this paper is: what protocols should be used for allowing a self-configuring network to reflect the

small-world properties that exist at the social level? There are at least two ways to attempt to answer this question. The first approach is to look at existing small worlds and to identify the characteristics that foster the small-world phenomenon. The second approach is to start from theoretical models that generate small worlds [15] and mirror them into protocol design.

The Gnutella network is an interesting case study as it is a P2P self-configuring technological network that exhibits small-world characteristics [9]. How are the small-world characteristics generated? One possible answer is that the social network formed by the Gnutella users reflects its small-world patterns onto the technological network. While this is not impossible, we observe that a user has a very limited contribution to the Gnutella network topology. Hence, we believe the social influence on the Gnutella topology is insignificant.

More significant for the small-world phenomenon may be Gnutella's exploration protocol based on PING and PONG messages: a PING is sent to all neighbors and each neighbor forwards it further to its own neighbors, and so on. The PONG messages return on the same path, allowing a node to learn of its neighbor's neighbors, and hence to improve clustering. However, the influence of this mechanism is limited by the (comparatively) small number of connections per node. This fact explains why, despite an aggressive exploration of the network, the clustering coefficient in Gnutella is not large (e.g., it is an order of magnitude lower than the clustering coefficients in coauthorship networks).

A theoretical model for building small-world graphs [15] starts from a highly clustered graph (e.g., a lattice) and randomly adds or rewires edges to connect different clusters. This methodology would be relevant to us if we had the clusters already formed and connected. Allowing clusters to form dynamically based on shared interests, allowing them to learn about each others, to adapt to users' changing interests (e.g., divide or merge with other clusters) are parts of the problem we formulate and continue investigating. However, if these problems are solved, possible approaches for transforming a

loosely connected graph of clusters into a small world (hence, with small average path length) are:

- The hands-off approach: random graphs have small average path length. It is thus intuitive that "randomly" connected clusters will form a small world.
- The centralized approach at the cluster level: in each cluster, one or multiple nodes are assigned the task of creating external connections.
- The agent-based approach: allow an agent to explore the network and rewire it where necessary. This approach is usually rejected due to associated security issues.

6. Summary

We studied the file location problem in decentralized, self-configuring P2P networks associated with scientific data sharing collaborations. A qualitative analysis of the characteristics of these collaborations, quantitative analysis of file sharing information from one such collaboration, and previous analyses of various social networks lead us to speculate that a P2P scientific collaboration may benefit from a smallworld topology. We sketch a mechanism for lowlatency file retrieval that benefits from the particularities of the scientific collaboration environments and a small-world topology. While we do not provide a solution for building topology protocols flexible enough to resemble the dynamics and patterns of social interactions, we stress the relevance of this problem and we discuss some possible directions for research.

7. Acknowledgements

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