A Comparison of Structured and Unstructured P2P Approaches to Heterogeneous Random Peer Selection *

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Abstract

Random peer selection is used by numerous P2P applications; examples include application-level multicast, unstructured file sharing, and network location mapping. In most of these applications, support for a heterogeneous capacity distribution among nodes is desirable: in other words, nodes with higher capacity should be selected proportionally more often.

Random peer selection can be performed over both structured and unstructured graphs. This paper compares these two basic approaches using a candidate example from each approach. For unstructured heterogeneous random peer selection, we use Swaplinks, from our previous work. For the structured approach, we use the Bamboo DHT adapted to heterogeneous selection using our extensions to the item-balancing technique by Karger and Ruhl. Testing the two approaches over graphs of 1000 nodes and a range of network churn levels and heterogeneity distributions, we show that Swaplinks is the superior random selection approach: (i) Swaplinks enables more accurate random selection than does the structured approach in the presence of churn, and (ii) The structured approach is sensitive to a number of hard-to-set tuning knobs that affect performance, whereas Swaplinks is essentially free of such knobs.

1 Introduction

A number of P2P or overlay applications need to select random peers from the P2P network as part of their operation. A simple but poorly scaling way to do random peer selection is to disseminate a list of all nodes to all nodes. To randomly select another node, each node simply selects randomly from its list. Early gossip protocols that needed uniform random peer selection typically assumed this approach. A scalable alternative approach is to build a sparse graph among the peers, and then use some kind of walk through the graph to do random node selection.

An early example of this approach was an overlay multicast protocol called Yoid [1]. Yoid constructed a random graph over which random walks would be used to discover nodes that might be included in a multicast tree. More recent overlay multicast protocols that utilize random node selection include Bullet [2] and Chainsaw [3].

Gnutella-style unstructured file sharing networks utilize a random selection component when searching for nodes having desired files. To improve the scalability of this file search, GIA [4] proposes using random walks rather than flooding.

Random node selection also plays an important role in proximity addressing schemes like Vivaldi [5] and PALM [6]: these schemes need to select random peers in the network to measure their latencies from the peers and compute their coordinates.

In many of these examples, it is important that random selection follow a given non-uniform probability distribution. In other words, some nodes are to be selected with higher probability than others. The primary reason for this is to accommodate nodes with differing capacities. We refer to this problem of selecting each node with probability proportional to its specified capacity as *heterogeneous random selection*. The need to accommodate heterogeneity is especially acute for file searching in Gnutella-like file sharing networks, as the use of supernodes attests. The primary focus of GIA is this heterogeneity in unstructured networks. Accommodating node heterogeneity is also important in overlay multicast algorithms [7, 8, 9, 10].

Given the number and variety of P2P and overlay applications that use random node selection, in previous work [11], the authors designed Swaplinks, a general-purpose unstructured P2P algorithm to provide a heterogeneous random node selection *primitive* that could be used by a wide range of P2P and overlay applications. Swaplinks builds a random graph in which each node's degree is proportional to its desired degree of heterogene-

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ity, and then uses random walks over that graph to do node selection. The previous work showed, using simulations, that Swaplinks was the most attractive unstructured random selection technique: It gives fine-grained control over both the probability that a node is selected and the overhead seen at each node. It is efficient, scalable, robust (to churn, and to wide variations in node capacities), and simple. In this paper, we implement Swaplinks, and provide a comprehensive evaluation of the Swaplinks implementation, thus validating the previous simulation results.

Heterogeneous random selection in the example applications cited earlier can also be potentially realized by structured approaches. Our previous work, however, examined only unstructured approaches to random selection, because of our intuition that they would be simpler than structured approaches, and that this simplicity would ultimately lead to a more scalable and robust system. A primary goal of this paper is to test our intuition about the relative simplicity of structured and unstructured approaches to heterogeneous random selection through a performance comparison between the two approaches. We choose the "item-balancing" algorithm by Karger and Ruhl for load balancing in structured P2P networks [12] as the basis for the structured random selection approach, and we use Swaplinks as the unstructured approach. The basic idea in using the item-balancing algorithm in our setting is to assign identifiers in the DHT number space such that a larger portion of the number space maps proportionally into high-capacity nodes, and a smaller portion maps into low-capacity nodes. High capacity nodes, by virtue of "owning" a larger portion of the number space, will be selected proportionally more often by queries issued to uniformly random identifiers. We implement the Karger/Ruhl approach over the Bamboo DHT [13], and call this approach KRB. We chose Bamboo because it is a stable well-maintained open software for DHTs, and because it is a second generation DHT, designed using the best principles from the earlier, first generation DHTs (like Chord [14] and Pastry [15]). This minimizes the chances that the results are an artifact of a poor DHT implementation.

The performance comparison between KRB and Swaplinks shows that KRB performs less well in the face of churn, and has a number of hard-to-set tuning knobs that affect performance. While we need more comparisons (with other structured approaches) to be certain of this, the performance comparison goes a long way toward validating our intuitive concern about the relative complexity of using DHTs for heterogeneous peer selection.

Overall, this paper makes two contributions:

- We implement an open source library [16] that provides heterogeneous unstructured random graph construction and random node selection primitives based on Swaplinks. We also measure the performance of the Swaplinks implementation for both random graph construction and random selection, and in so doing validate earlier simulation results.
- We modify the Karger/Ruhl load balancing algorithm for heterogeneous random peer selection, and compare its performance as a random selection mechanism with that of Swaplinks.

We next describe related work in Section 2. We describe the Swaplinks algorithm and its implementation in Sections 3 and 4, and the KRB method in Section 5. In Section 6 we give a performance evaluation and comparison of both algorithms. Finally, we discuss issues and future work in Section 7.

2 Related Work

2.1 Structured P2P Networks

All structured P2P systems modeled as DHTs (e.g. [17, 14, 15], etc.) assign identifiers to nodes, typically at random. Random selection in DHTs can be done by randomly choosing a value from the DHT number space, and routing to that value. The problem of random node selection in DHTs, then, boils down to the problem of assigning identifiers appropriately.

Even where uniform random selection is desired, assigning a single random identifier to each node is inadequate, because any non-uniformities in the random assignments persist over time. Consistent hashing schemes deal with this by assigning multiple random identifiers[18], and DHTs have proposed something similar, namely creating multiple virtual replicas of each node in the DHT. To achieve heterogeneity, each node is replicated a number of times proportional to its capacity ([19, 20]). This approach however entails a blowup in network and computational overheads, and so is not an attractive approach.

A modified multiple virtual node approach is used in Y_0 [21]. Here, virtual node identifiers for each node are selected from a small range of identifiers; the authors utilize the proximity of the node's identifiers to avoid having to maintain separate routing entries for each virtual node. While this scheme is interesting, and a potential candidate for comparison, it has not been analyzed or tested for robustness to high churn. Y_0 also needs all nodes to know (at least roughly) the number of nodes in the system, which might be an issue under high churn.

Ledlie and Seltzer [22] present the *k-choices* algorithm for load balancing in settings with skewed query distributions and heterogeneous capacities. *k-choices* is similar to KRB, in that both place nodes at IDs that minimize

load imbalance. The difference is that *k-choices* assumes that each node knows its absolute desired load, whereas in KRB, nodes only have a notion of relative desired load.

Accordion [23] and HeteroPastry [24] give schemes that tailor nodes' degrees and their message loads according to capacity and network activity. These schemes however do not provide capacity dependent namespace partitioning, and so cannot support heterogeneous random selection by routing to uniformly randomly selected IDs. An alternative approach might have been to use unbiased random walks over these networks for random selection, but the control over degrees in these schemes is not fine-grained enough (i.e., average node degrees are not proportional to capacities) for this to result in the desired selection distribution[1].

Karger and Ruhl propose two schemes in their papers for load balancing in DHTs [12, 25]. The first results in a constant factor bound on ID spaces between successive nodes, but cannot handle the case where the ID spaces are to be split according to capacities. The second scheme looks at item load balancing, where the number of items that are stored at any node should be within bounds and dependent on node capacity. With minor variations, we could modify this scheme to split ID space according to node capacities and run over Bamboo – we call this KRB. We use KRB as the candidate structured approach for our performance comparisons.

2.2 Unstructured P2P Networks

In previous work [11], we found Swaplinks to be the best algorithm for constructing unstructured P2P graphs suitable for heterogeneous random selection. Here is a brief overview of other unstructured approaches.

GIA extends Gnutella by making both graph-construction and query-resolution sensitive to node capacities [4]. High-capacity nodes here have higher degrees, and are more likely to be traversed by random walks. While Swaplinks shares these two features with GIA, Swaplinks exhibits more accurate control over degree and probability of selection. Other examples of unstructured graph construction schemes include Araneola [26], an approach by Law and Siu [27], and SCAMP [28]. None of these take node heterogeneity into account.

The Ransub [29] mechanism can be used as a random node selection primitive, but as was the case with the previously mentioned schemes, does not take into account node heterogeneity. The Metropolis-Hastings algorithm [30] and the Iterative-Scaling algorithm [31] can be used to achieve desired probabilities of selection over any underlying graph. But when the underlying graph has node degrees close to the desired probabilities, like Swaplinks does, random selection primitives achieve the desired distribution much more efficiently (e.g., random walks need to take far fewer hops).

3 The Swaplinks Algorithm

Our random selection API consists of the following core procedures:

- $join(numLinks)$
- $node = select()$
- $listOfNodes = listNeighbors(callBack)$

The $join()$ procedure causes the joining node to establish random links with other, already joined nodes. The parameter $numLinks$ indicates how many neighbors the joining node should try to obtain. On average a node will end up with twice as many neighbors as the value $numLinks$. This is because other nodes will in turn select a given node as their neighbor.

The value of $numLinks$ is set to be proportional to the probability with which the node should be selected. For instance, if a node A should be selected with twice the probability of node B, then node A will set $numLinks$ to be twice that of node B. It is up to the application to know what values to choose for $numLinks$. Typically an application would choose a value of $numLinks = 3$ for its lowest capacity nodes, and select values proportionally higher for higher capacity nodes. The value 3 is chosen as the minimum to insure that even the lowest capacity node has a low probability of partition from the rest of the network. Higher values reduce the probability even more.

When a node wishes to randomly select another node, it calls $select()$. This causes a random walk to be taken through the random graph. The number of hops in the walk is a fixed value, 10 by default. The node at which the walk ends is the selected node. The value $numLinks$ plays two important roles here. First and foremost, the Swaplinks design ensures that the walk will end at nodes with higher $numLinks$ values with proportionally higher probability. Second, nodes with a higher $numLinks$ value will serve as intermediate hops in walks with higher probability. This second effect results in the load required to participate in the algorithm by any given node to also be proportional to its capacity. There are a number of possible variations on the $select()$ call: for instance the length of the walk may be specified, or the identity of all nodes traversed during the walk may be returned.

Some P2P applications may simply wish to use the underlying graph directly. For instance, a BitTorrent might use the neighbors selected by the $join()$ procedure as the nodes with which it exchanges file blocks. The $listNeighbors(callBack)$ procedure allows this. In

addition to providing the current set of neighbors, a callback routine allows Swaplinks to inform the application whenever the neighbor set has changed.

In building and maintaining a random graph, each node labels each of its links to a neighbor node as either an outlink or an inlink. These labels have nothing to do with the direction messages may pass over them: messages may pass in both directions. Rather, the label is chosen based on which node initiated creation of the link. The node that initiated the link labels it an outlink, and other node labels it an inlink. Correspondingly, neighbor nodes are labeled as out-neighbors or in-neighbors. The outdegree is the number of outlinks, and the indegree is the number of inlinks. Every link is an outlink in one direction and an inlink in the other.

Likewise, there are two types of fixed-length random walks:

OnlyInLinks: The walk is forwarded to a randomly chosen in-neighbor.

OnlyOutLinks: The walk is forwarded to a randomly chosen out-neighbor.

Every node always maintains an outdegree of $numLinks$, by finding $numLinks$ out-neighbors when it first joins, and by replacing any out-neighbor it loses with another one. This is done in such a way that nodes tend to have the same number of inlinks as outlinks, though they may have slightly greater or fewer than $numLinks$ inlinks.

There are three cases the algorithm must cover:

1. A joining node is adding selected out-neighbors
2. A node is replacing a lost out-neighbor
3. A node is replacing a lost in-neighbor

To find a new out-neighbor for the first case, a joining node (say A) initiates a fixed length OnlyInLinks walk from one of its entry nodes. The node (say B) where the walk ends is chosen as an out-neighbor for the new node. Node B then randomly selects one of its in-neighbors C, and "gives" that in-neighbor to A. In other words, C loses B as an out-neighbor, and gains A as an out-neighbor.

The result of this transaction is that A gains both an out-neighbor (B) and an in-neighbor (C). After A is done finding all of its $numLinks$ out-neighbors, it will also have an equivalent number of in-neighbors. Node B will have gained one in-neighbor (A) and lost another (C), so it comes out even. Node C will have lost one out-neighbor (B) and gained another (A), so it also comes out even.

If a node (say A) loses an existing out-neighbor (the second case above), it likewise takes an OnlyInLinks walk, and creates an outlink with the discovered node (say B). However, in this case, B does not give one of its in-neighbors to A. Rather, B ends up with an extra in-neighbor. Had B given A an in-neighbor, then A would have ended up with an extra in-neighbor instead.

Finally, if a node (A) loses an existing in-neighbor (the third case above), it sees if its number of in-links is less than its $numLinks$. If so, it takes an OnlyOutLinks walk. The node (B) discovered by the walk then donates one of its in-neighbors to A if B's number of inlinks is greater than half its $numLinks$.

The above modes of link-formation could lead to the creation of multiple links between the same pair of neighbors; Swaplinks makes no effort to eliminate these multiple links. This makes dealing with very small networks straightforward.

The rationale behind using the OnlyInLinks and OnlyOutLinks walks in Swaplinks is as follows: The OnlyInLinks walk selects each node with a probability roughly proportional to its outdegree. The OnlyOutLinks walk, on the other hand, selects each node with probability roughly proportional to its indegree. Thus Swaplinks, by using the OnlyInLinks walk, ensures that the load placed on each node is proportional to its outdegree. And by employing OnlyOutLinks to deliberately look for inlinks in the presence of churn, it tends to find nodes with disproportionately large indegrees, thus stealing the surplus inlinks from such nodes and ensuring that nodes' indegrees stay close to their outdegrees.

In this paper, application-requested node selection ($select()$) uses OnlyInLinks walks, as opposed to the other random walks tested in [11]. While both OnlyInLinks and the random selection walks in [11] result in selection proportional to nodes' outdegrees, OnlyInLinks is simpler and thus the more attractive method to use.

Simulations in [11] show that Swaplinks builds graphs where the degree distribution closely resembles the desired distribution. The graphs scale well to large sizes, and lend themselves well to random peer selection. The resultant message load on nodes and the frequency of selection vary linearly with the degree. Swaplinks implementation results presented later in this paper corroborate these findings.

A feature of Swaplinks that makes it attractive from a practical viewpoint is that it is free of "tuning knobs": It has no parameters to set, apart from the neighbor heartbeat frequency parameter (present in most distributed systems). We avoid having to tune the hop-length for different random walks by making all walks 10 hops in length, which is a conservatively large value.

4 Swaplinks Implementation

Our system is implemented in C++ on Linux. We use TCP sockets for neighbor connections. Each node sends heart-beat messages to each of its neighbors every 2 sec-

onds, and assumes that a neighbor is dead if it does not receive a heart-beat from it for 10 seconds. [2]

A newly entering node initiates the required number of neighbor discovery walks, restricting the number of outstanding neighbor walks to 10 at any time. A neighbor discovery walk is re-attempted if it fails to return an appropriate neighbor within a period of 2 seconds.

We currently have an implementation of a *rendezvous server* that helps new nodes join the system. The rendezvous server remembers a small number (currently 10) of the most recently joined nodes, and newly joining nodes use these nodes to start their neighbor discovery walks. This rendezvous mechanism is light-weight, and makes sure no single node is overloaded with the responsibility of helping new nodes join the network. The rendezvous mechanism could be made more robust by also having the rendezvous server remember a small number of random other nodes in the network, by periodically taking random walks, or by having newly joined nodes report one or two of their neighbors.

The application using Swaplinks communicates with the Swaplinks module via a TCP socket. Swaplinks exports the API described in section 3 to the application over the socket by using appropriate serialization.

One application has currently been implemented over Swaplinks, namely a heterogeneous overlay multicast protocol called ChunkySpread [7] that uses Swaplinks to both construct a heterogeneous random graph and do random peer selection. Each Chunkyspread node is involved in multicast data transmission (and reception) with multiple other nodes; this set of peers is a subset of the set of the neighbors in the Swaplinks graph. A small set of ChunkySpread nodes (the nodes that originate the multicast stream) need to discover an additional set of peers. This is done using Swaplinks peer selection. In addition to ChunkySpread, the Swaplinks algorithm is being used in other applications under current development, like the NUTSS toolkit for NAT traversal in P2P systems [32], and a P2P file backup system.

We are also currently experimenting with an alternate heart-beat mechanism, called *smart-pinging*, that reduces heart-beat load at nodes with very high degrees. We describe smart-pinging and give a preliminary evaluation of the technique in Section 6.4.

5 Adapting Bamboo to Heterogeneity

Performing random selection on a DHT, with no regards to heterogeneity, and assuming the ID space is apportioned uniformly among all nodes, is simple: pick a uniformly random ID in the ID space, issue a random selection query to that ID, and select the node where the query ends. For this simple querying mechanism to still be applicable when there are differences in node capacities, we need to split nodes' ID spaces in proportion to their capacities (where a "node's ID-space" denotes the extent of ID-space that the node owns). For a simpler design of the heterogeneous random selection scheme, we choose to compute a node's ID space as the space between its successor in the ring and itself. We discuss how we simulate this feature in Bamboo later in this section.

To achieve capacity-dependent ID space allocation, we develop a scheme based on the item-balancing algorithm (henceforth referred to as *K-R*) presented in [12, 25]. Nodes in K-R periodically send messages to one another, and share loads when a load imbalance is perceived. The item-balancing algorithm in [12] performs load sharing through movement of nodes to new IDs, but does not address the issue of heterogeneity, whereas the one in [25] takes heterogeneity into account, but does load sharing by transferring *items* from heavily loaded nodes to lightly loaded ones. Our scenario is slightly different from either of the above two, since we need nodes to move to new IDs so as to do ID space partitioning, and we need this partitioning to be capacity sensitive.

We now outline KRB, our adaptation of the K-R algorithm. The basic aim of KRB is to even out the *relative* loads of all nodes, where a node's relative load is its ID space load divided by its capacity. As in K-R, each node periodically sends out a message to a randomly chosen ID, embedding its load information – we call such messages "KRB load messages". Noting that a node's moving to a new ID can affect the ID spaces of (up to) 3 nodes (the moving node, the moving node's old predecessor, and the moving node's new predecessor), in KRB, we examine the change in load at *all* nodes whose loads are affected by the move. This is an extension of K-R, where the loads at only the moving node and the moving node's new predecessor are examined. If we examined the loads at only these two nodes, it would be possible for a huge load to be inadvertently dumped on the unconsidered third node (the moving node's old predecessor) as a result of the move; by considering all the three nodes, we avoid this possibility.

Looking at a single KRB load message, let us denote by S the node that sent out the message, by R the node that receives the message, and by P the predecessor of R. Now R decides if it should move to share S's ID-space, based on the value of the *objective function*, computed as follows:

$$r = \frac{L_R + L_S + L_P}{C_R + C_S + C_P}$$

$$ObjFn(R,S,P) = \Sigma_{N \in \{R,S,P\}} \left| \frac{L_N}{C_N} - r \right| \qquad (1)$$

where L_N is node N's ID-space load, which is equal to the space between N and its successor, and C_N is node N's capacity.

If R were to move, it would move to ID R' such that

$$L_{R'} = \frac{L_S \cdot C_R}{C_R + C_S} \quad (2)$$

That is, the new ID is the one that splits the space between S and its successor in direct proportion to their capacities. If R were to move to R', the objective function would take on a new value, computed similarly to above. Finally, R does make the move if the objective function value reduces by more than a threshold ratio (called the *KRB-threshold*, set to 0.2).

The computation of the objective function above can be seen as a greedy step taken towards minimizing the system-wide objective function, given below.

$$r_{all} = \frac{\Sigma_{N\ in\ system}(L_N)}{\Sigma_{N\ in\ system}(C_N)}$$

$$ObjFn(overall) = \Sigma_{N\ in\ system} \left| \frac{L_N}{C_N} - r_{all} \right| \quad (3)$$

Since individual nodes do not know the value of r_{all}, they use local knowledge to compute r as shown above as an estimate.

The above description assumes that the node that sent the initial message S is not already the predecessor of the node that receives the message R. If R does happen to be the successor of S, there is no other third node whose load will be affected if R were to move to any point in between S and its successor. So now R moves if the following condition holds:

$$\frac{L_S}{C_S} < \epsilon \frac{L_R}{C_R} \quad OR \quad \frac{L_R}{C_R} < \epsilon \frac{L_S}{C_S}$$

where we set ϵ to 0.8. This criterion is identical to the one used in K-R.

Simulating a node's ID-space in Bamboo:
To make this scheme work in Bamboo, we need to make sure that the probability that a node is selected is proportional to the ID space for which it is the closest predecessor. However, in Bamboo, a query is routed to the node numerically closest to the destination, rather than to the closest predecessor. So when a node receives a random selection query, it examines the intended destination ID and forwards it to the immediate predecessor of that ID.

Our primary goal in adapting the Karger/Ruhl scheme to Bamboo was capacity-sensitive random peer selection. Admittedly, this scheme does not balance message load according to capacities (during the construction of the KRB network or during random selection), as we only tailor nodes' ID spaces, and not their routing tables. Accordingly, in this paper, we evaluate KRB as a heterogeneous selection mechanism alone, and do not place emphasis on the message load distribution that occurs while constructing the KRB P2P network. Schemes that reactively tailor the neighborhood size based on capacity, such as those proposed in Accordion [23] and HeteroPastry [24] could be used with KRB to achieve both capacity-sensitive probability of selection and capacity-sensitive message load distribution during graph construction.

6 Performance Evaluation

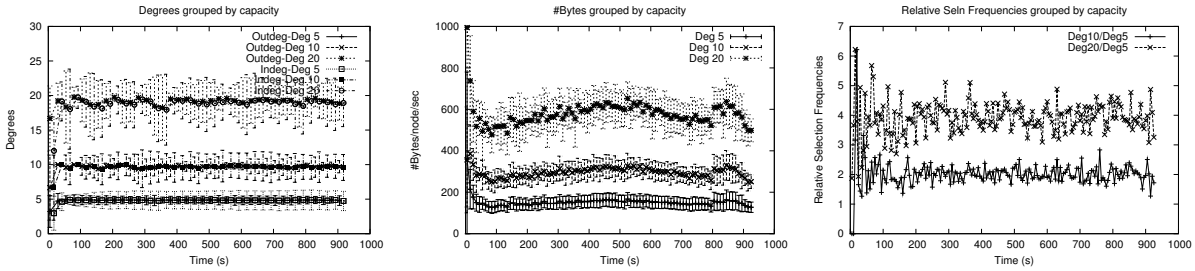
We test Swaplinks through an emulation of a 1000 node network on either a local (Cornell) cluster of 5 machines with 4 CPU's each, or a 20 CPU cluster on Emulab. We achieve this size by launching a number of processes that in turn launch the required number of individual instances of our system. We preserve the semantics of communication here: all communication still takes place through sockets. The CPU loads here were mostly small enough to be negligible as a factor in the results. We also test the same implementation on PlanetLab.

For the emulation, we use a Transit-stub [33] topology consisting of 100 routers to mimic latencies between peers. Each peer picks a stub router uniformly at random. All messages to be sent are buffered at the sender for the appropriate amount of time (computed as a function of the stub routers of the source and destination). We also add jitter as a random value that ranges between 0 and 25% of the end-to-end latency.

Launching KRB networks of a similar size (500-1000 nodes) by multiplexing several instances on single hosts on local clusters proved infeasible because of high CPU load factors due to the Bamboo implementation. We instead evaluate KRB using the simulator available with Bamboo's standard code distribution. We use the same Transit-Stub topology as earlier to calculate message delays in the KRB network. We had to restrict our comparisons to 1000 node networks as the Bamboo simulator, with our modifications, consumes too much memory for larger sizes.

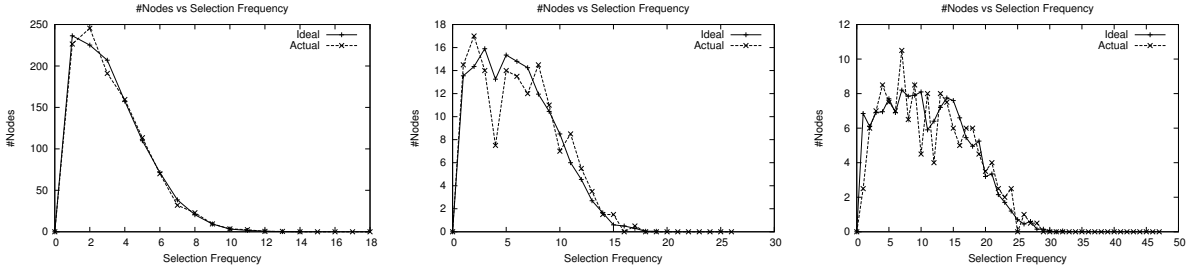
All KRB nodes use a single entry node (called a $gateway$ node by Bamboo) when they first enter the system. A node that leaves its present spot and rejoins the system as part of the KRB ID space readjustment scheme uses the set of neighbors it had before it left the system as its gateway nodes.

We now give a road map of the experimental results that we will be presenting in the subsequent portions of the paper. We first test 1000 node networks of both Swaplinks and KRB under two different representative



(a) Degree Distribution (b) Message Loads (c) Relative Selection Frequencies

Figure 1: Swaplinks under high churn and moderate capacity distribution



(a) Outdegree 5 (b) Outdegree 10 (c) Outdegree 20

Figure 2: Swaplinks #Nodes vs Selection Frequency for each degree: high churn and moderate capacity distribution

values of churn, and, similarly under two different distributions of node capacities (Section 6.1). Next, we subject both to more demanding churn scenarios: one where network size doubles in the space of 10 seconds, and one where network size halves instantaneously (Section 6.2). We give results of a 250-node experiment over planetlab in Section 6.3. Finally, in Section 6.4 we describe how we can use "smart-pinging" to reduce the heart-beat load incurred by high degree nodes.

In all of these experiments, we evaluate Swaplinks as both a heterogeneous graph construction mechanism (e.g., how well node degrees match desired degrees) and as a heterogeneous peer selection mechanism (e.g. how close the selection probabilities are to the desired values). We evaluate KRB on the other hand as solely a heterogeneous peer selection mechanism.

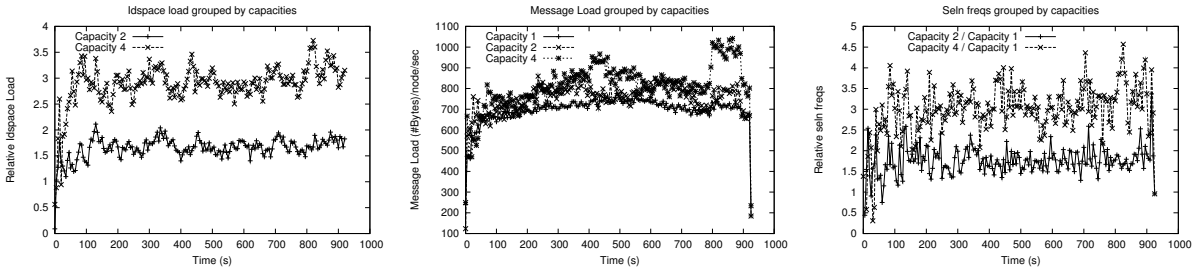
6.1 Evaluation under representative churn scenarios

We use two separate churn scenarios: a "high-churn" scenario in which the median session time is 2 minutes , and a "low-churn" scenario in which the median session time is 30 minutes. These session time values have been taken from previous studies [34, 35, 36]. We similarly use two capacity distributions: (i) The first capacity distribution is a 'moderate' 5:10:20 distribution, with 80% of Swaplinks nodes having outdegree 5, 10% having outdegree 10, and 10% with outdegree 20. We realize the same (relative) capacity split in KRB by having 80% of the nodes have a capacity of 1, 10% have a capacity of 2, and 10% of the nodes have a capacity of 4. (ii) The second capacity distribution is an 'extreme' 3:60:150 distribution, with 98% of the nodes with outdegree 3, 1% of the nodes with outdegree 60, and 1% of the nodes with outdegree 150. Again, we similarly realize the same relative capacity distribution in KRB as well. We restrict the number of high-capacity nodes in the extreme capacity distribution to the relatively small proportion of 1% for the following reason: We run most of our experiments on networks of size 1000. With an increase in the number of high-capacity nodes, it gets more likely that there is a completely connected 'core' made of the high-capacity nodes, and all other nodes directly connected to the core nodes. The fact that this behavior is not retained when the network grows to a larger size (where the network maintains the same capacity distribution) makes such networks not representative of general P2P settings.

We use node session times that are independent of capacities, and follow the Pareto distribution. Networks start from scratch (zero nodes), and total experiment times are typically set to more than 5 times the median

	High Churn						Low Churn					
Target Outdeg	5	10	20	3	60	150	5	10	20	3	60	150
Avg Load(B/s)	150.26	297.87	581.49	98.16	1621.23	3449.41	124.33	247.34	491.49	79.62	1275.89	2903.17
Relative Load	1	1.98	3.86	1	16.43	35.05	1	1.98	3.95	1	15.92	36.20
Avg Totaldeg	9.68	19.41	38.23	5.80	111.77	255.25	9.98	19.93	39.95	5.98	119.98	298.18
Relative Selns	1	2.01	3.95	1	19.78	44.43	1	2.00	3.99	1	20.10	50.16
Seln p-values	0.815	0.862	0.977	0.757	0.579	0.819	0.292	0.784	0.583	0.224	0.957	NaN

Table 1: Swaplinks results for moderate and extreme capacity distributions under high and low churn.



(a) Relative Id Space Distribution

(b) Message Loads

(c) Relative Selection Frequencies

Figure 3: KRB under high churn and moderate capacity distribution

node session times. We ran tests where node session times were dependent on capacities (i.e., where high capacity nodes are likely to stay in the system longer) and where session times were Poisson distributed, and we found the results to be similar to those we present here.

Unless otherwise mentioned, we run ongoing background peer selections, where the 80 longest living nodes perform a random selection every 250 ms for the duration of their lifetime. We call such selections 'periodic' selections. We use the periodic selections to evaluate whether, for instance, the degree 20 nodes receive, in aggregate, twice as many selections as do degree 10 nodes, over the course of the experiment. We also have two other nodes perform a 'burst' of 10,000 selections with a gap of 10 ms between successive selections. We use the short-term burst to obtain a set of selection measurements with relatively little churn. This allows us to more accurately compare the measured distribution of selections among a group of same-capacity nodes with the ideal distribution. This is because each node present in the network during the burst receives a statistically large number of (measured or ideal) selections. The burst selections are performed just before the end of each experiment.

We measure message loads in both Swaplinks and KRB by counting only the bytes in the message payloads; we do not consider TCP/IP or UDP header overheads.

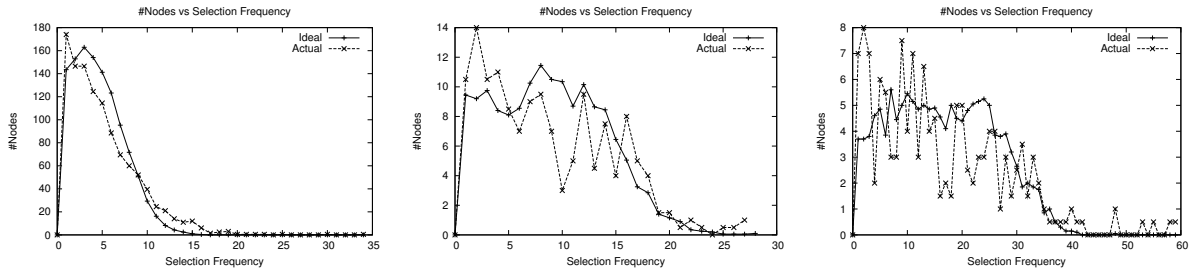
6.1.1 Swaplinks Results

Figures 1 and 2 show the results of the high-churn, moderate capacity distribution experiment for Swaplinks. The node degrees closely track the desired values (Figure 1(a)), while the selections and message loads are split among the different nodes in proportion to their capacities: for example, nodes with outdegree 10 receive twice as many selections, on an average, as the nodes with outdegree 5. Both periodic and burst selections are counted to compute the curves in Figure 1(c).

Figure 2 shows the selection frequencies that result from the burst selections. The figure has one plot for each of the three different capacity classes, where a capacity class is just a set of nodes with the same capacity. The "actual" curve represents the Swaplinks selections. The "ideal" curve represents the ideal distribution of the particular class' 'fair share' of the total number of successful selections; the intersection of each node's lifetime with the time-span of the burst selections is taken into account in computing this distribution. These values don't include failed selections, which occur with churn because nodes take about 10 seconds to detect that a neighbor is down. Thus, the higher the churn-rate is, the greater the probability is that a selection walk fails by being forwarded to a now-dead neighbor at some hop. High churn has about 40%-45% failed selection walks, while low churn has about 2% failed walks.

As can be seen from the plots in figure 2, Swaplinks' actual selection frequency distribution closely tracks the ideal curve for each of the different capacities. This, coupled with the fact that Swaplinks also realizes capacity-wise selection distribution (Figure 1(c)), demonstrates that the selection mechanism realizes the desired distribution.

Table 1 gives a summary of results from all of the Swaplinks experiments in this section by averaging each value over the second half of the experiment time. The duration of high-churn experiments here is around 930



(a) Capacity 1 (b) Capacity 2 (c) Capacity 4

Figure 4: KRB #Nodes vs Selection Frequency for burst selections: high churn and moderate capacity distribution

	High Churn						Low Churn					
Target Split	1	2	4	1	20	50	1	2	4	1	20	50
Idspace Split:	1	1.68	2.99	1	6.14	5.89	1	1.95	3.98	1	23.59	37.41
Msg Load(B/s)	711.30	765.04	853.78	736.63	922.48	923.40	261.73	290.59	318.45	297.01	474.06	413.49
Relative Selns	1	1.78	3.13	1	5.74	5.29	1	1.98	4.02	1	23.23	34.44
Seln p-values	0.000	0.231	0.054	0.000	0.000	0.002	0.000	0.645	0.774	0.000	NaN	0.001

Table 2: KRB results for moderate and extreme capacity distributions under high and low churn.

seconds, whereas the duration of the low-churn experiments is around 14,000 seconds. Each row in the table corresponding to a 'relative' value shows the corresponding value for the capacity class as a ratio over the equivalent value in the lowest capacity class in the experiment. Both periodic selections and burst selections are taken into account in computing the 'Relative-Selns' row. The last row plots the χ^2- test p-values of the selection frequency distribution (for burst selections): this is an indicator of how well the actual selection frequencies of nodes within each capacity class match the ideal selection frequencies. Larger values indicate a closer match; p-values greater than 0.05 are generally believed to indicate a good match of the observed distribution with the expected distribution.

As can be seen from the table, with the one exception of the high-churn extreme-capacity case, node degrees and selection frequencies closely track the desired values. The valid p-values are all comfortably greater than 0.05, indicating good selection distribution.[3]

In the high-churn extreme capacity case, high degree nodes have an average total degree that is less than the respective ideal values: High degree nodes need some time to reach their full degrees upon entering the system, because they have at most 10 neighbor discovery walks outstanding at any time. This effect is more prominent during high-churn, where new nodes enter more frequently. The values for the relative selection frequencies suffer because of the imperfect degree distribution, but they nevertheless are still reasonably close to the target ratios.

The message load ratios in the extreme capacity distribution deviates from the ideal 3:60:150; this is because some of the high-degree neighbors have duplicate links between them, resulting in a reduction of the heart-beat load incurred. This is an artifact of the fact that the total degree of the highest capacity nodes here is non-negligible in comparison to the total number of links in the system, and we expect the number of duplicate links to decrease and the load-ratios to get closer to the 3:60:150 proportion in larger networks.

Looking at the message loads from an alternate perspective, the absolute values of the message loads for the outdegree 60 and outdegree 150 nodes seem relatively high. The bulk of this load is caused by neighbor heart-beats. In Section 6.4 we describe how we can reduce this load by doing heart-beats in a more sophisticated fashion.

We ran similar experiments for 5000 nodes Swaplinks graphs over a 20 CPU cluster on the Emulab testbed, and found the results to be broadly similar, demonstrating that Swaplinks retains its properties in larger networks as well.

6.1.2 KRB Results

We make a few changes to the parameters used by the default Bamboo source distribution to get KRB to approach the desired relative capacity-wise ID space distributions. For the high-churn results shown in this section, we set ping and leaf-set-alarm periods in Bamboo to 1 second. We set the near and far routing table alarm periods to 2.5 and 5 times the leaf-set-alarm respectively (these ratios are based on the values in Bamboo's code distribution). We use a period of 5 seconds between successive KRB load messages sent to random locations in the network (we denote this period the *KRB period*). For the low-churn results, we set the ping period to 2 seconds, the leaf-set alarm period to 3 seconds and the KRB period to

	Flash Crowd				
Target Out-deg	Avg Load(B/s)	Relative Load	Avg Total deg	Relative Selns	Seln p values
5	146.88	1	9.82	1	0.936
10	291.94	1.98	19.73	2.06	0.935
20	578.49	3.93	39.18	4.02	0.722
3	91.29	1	5.9	1	0.751
60	1553.79	17.01	114.61	19.66	0.873
150	3320.49	36.34	269.54	46.94	0.567
	Mass Departures				
5	179.52	1	9.54	1	0.457
10	351.01	1.95	19.11	2.04	0.912
20	681.62	3.79	37.59	3.96	0.988
3	121.57	1	5.73	1	0.338
60	1886.01	15.5	102.19	17.87	0.418
150	4343.61	35.66	251.1	45.84	NaN

Table 3: Swaplinks performance with flash-crowds and mass departures under high churn.

10 seconds. Bamboo has a time-out value between when a node suspects a neighbor to be down (as a result of failure of message delivery) to when it actually decides it's down (as a result of lack of response to pings sent to the neighbor). We reduce this timeout value to 1 second from the earlier value of 60 seconds. We use a leaf-set size of 4 and a KRB-threshold value (see Section 5) of 0.2 in all KRB simulations. We restricted KRB low-churn simulations to a shorter duration of 1800 seconds; longer simulations took unreasonably longer (wall-clock) times to complete.

Figures 3 and 4, and Table 2 show the results for KRB. The results show that KRB is not successful in maintaining the relative ID-spaces at the desired levels under high churns – it is only able to achieve around a 1:1.65:3 relative division in the ID spaces in the moderate capacity distribution, while its response to the extreme capacity distribution under high churn is worse. KRB is able to achieve the desired relative ID-space distribution in the low-churn moderate-capacity case, but again fails to fully achieve the desired ID-space distribution in the extreme-capacity low-churn scenario. KRB also fails to consistently achieve the desired selection distribution within each capacity class, as seen by the burst selection p-values computed for the selection frequencies. The p-values for the lowest capacity class in the moderate capacity distribution is 0 in both the high and low churn scenarios. This is mainly because the actual selection distributions here have quite a few outliers – nodes with an actual selection frequency close to or greater than the maximum selection frequency (for any node) predicted by the ideal curve. KRB's selection frequency curves within capacity classes 2 and 4 do match the ideal curve closely enough that they succeed the p-value test, but during high-churn, nodes in the higher capacity classes are still less likely to get selected than they should ideally be.

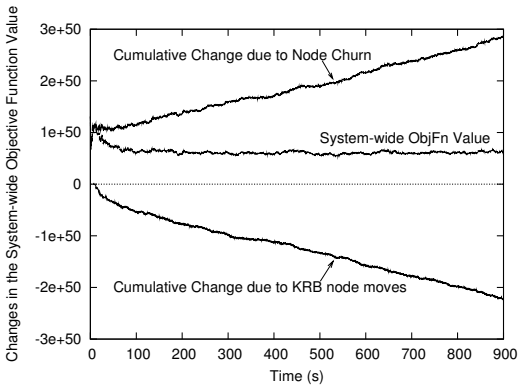
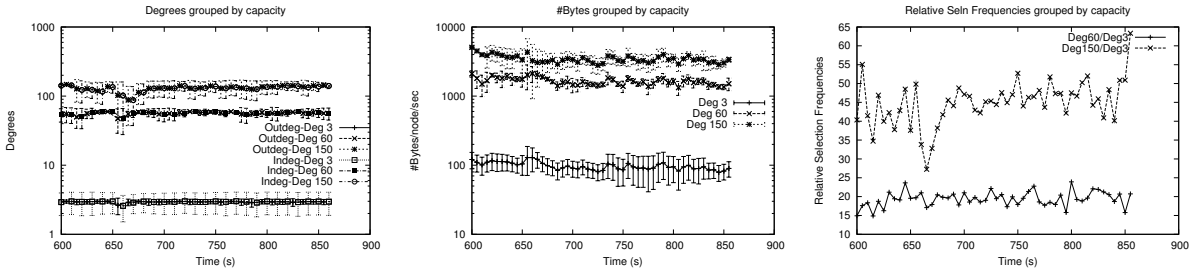


Figure 5: Change in the universal objective function as a result of KRB node moves and node churn in a high-churn, moderate-capacity simulation.

Figure 5 shows why KRB underperforms under high churn: The system-wide objective function (Equation 3, Section 5) settles to a more or less stable positive value in the presence of the steady churn. KRB's attempts to improve the objective function value below this stable value using node movements are exactly counterbalanced by the effects of node churn, indicating that this is the best KRB can do under this high churn. Increasing the frequency of KRB node movements here does not lead to an improvement in performance, as becomes clear next.

We evaluated the relative ID-space distribution realized by KRB under high churn and moderate capacities for various values of the KRB parameters (ping, alarm, KRB periods, KRB-threshold), and we found that the combination of the parameters we present here results in the best ID-space distribution. In general, we found that more frequent pings and alarm messages of Bamboo resulted in better results (as can be expected), while there generally was an 'optimal' KRB message frequency and an optimal value for the KRB threshold given the frequencies used for the other messages. Setting the KRB message frequency to higher values resulted in an increase of the number of incorrect KRB moves, where nodes switched positions based on an incorrectly perceived local state, thereby worsening the ID-space distribution. Among the combinations of parameters we tested, the worst performing set yielded about 50% less accurate selection than the setting we use. This experience indicates that it is harder with KRB to decide on the exact set of various parameters to use in a general setting.[4]

KRB achieves a higher average message load (across all nodes) than does Swaplinks: this is mainly a result of the increased message rates we used to improve KRB's capacity-based ID space distribution. We however do not think that the message load values are high enough to be a concern here.



(a) Degree Distribution (b) Message Loads (c) Relative Selection Frequencies

Figure 6: Swaplinks: Flash-crowd with high churn and extreme capacity distribution

	Flash-crowd			Mass Departures		
Target Split	1	2	4	1	2	4
Idspace Loads	1	1.52	2.41	1	1.19	1.68
Relative Selns	1	1.55	2.47	1	1.14	1.75
Seln p-values	0.00	0.00	0.01	0.00	0.48	0.00

Table 4: KRB Results for flash-crowds and mass departures for moderate capacity distributions and high churn

6.2 Extreme churn

We now look at the reaction of Swaplinks and KRB to more extreme churn events, the first where a flash-crowd leads to the network size doubling from 1000 nodes to 2000 nodes in the span of 10 seconds, and the second where a half of the network dies instantaneously.

Figure 6 shows the results of the Swaplinks flash-crowd scenario under a 3:60:150 degree distribution under high-churn (a median node session time of 2 minutes). The flash-crowd appears in the period 650-660 seconds after the system is started, and two sets of burst-selections are performed starting at 723 seconds and spanning 100 seconds. Table 3 summarizes the flash-crowd results over the last 175 seconds of the experiment for both the moderate and extreme capacity distributions.

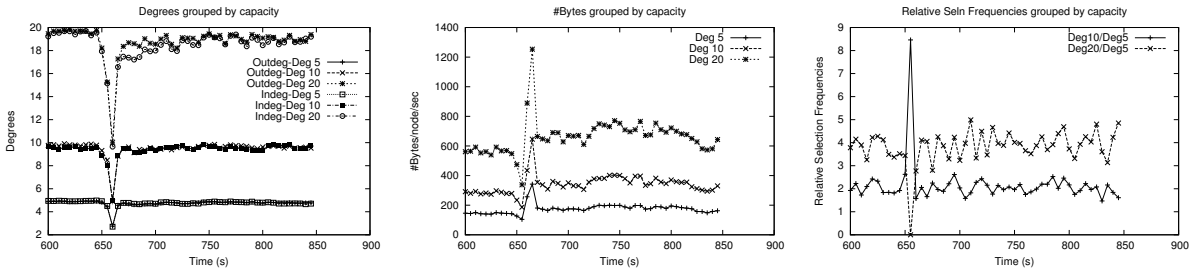
Figure 6 shows that while there is a temporary deterioration in all the metrics of interest for a short duration of time immediately after the entry of the flash-crowd, the system quickly recovers to re-establish desired behavior. The Swaplinks graph in fact generally benefits from nodes entering the system, since this pushes the average degree distribution across the graph towards the ideal value; a comparison of Table 3 with Table 1 shows that the average values for the degree and relative selection frequencies in fact improve as a result of the arrival of the flash-crowd!

Figure 7 and Table 3 show results of the Swaplinks mass departure experiments. The mass departures occur at 649 seconds after system start, and burst selections are performed at 719 seconds after system start. From figure 7 (for high churn and moderate capacity distributions), we observe that the network suffers for a short duration of time immediately after the huge perturbation, but things start to improve thereafter. The message loads and the selection frequencies recover to re-approach the desired 1:2:4 split of message loads and selection frequencies. The extreme capacity results from Table 3 also look encouraging: the degrees and the relative selection frequencies are similar to the high (stable) churn, extreme-capacity results shown earlier in Table 1. Overall, these experiments demonstrate that Swaplinks is robust to various kinds of network churn under widely different capacity distributions, and that it manages to retain its fine-grained sensitivity to the desired heterogeneity under these conditions.

Table 4 summarizes KRB results from the last 175 seconds of the flash-crowd and the mass departure simulations for only the moderate capacity distribution under high churn. The flash-crowds and mass departures occur at the same times as those reported in the Swaplinks experiments. The results indicate that the KRB performance suffers significantly as a result of the extreme churn induced. The relative ID-spaces and selection frequencies differ markedly from the target values, resulting in a failure to realize the desired selection distribution. We noticed that while KRB had started to recover from the flash-crowd to approach its stable ID-space distribution towards the end of the simulation, in the mass departure simulation its stable ID-space distribution deteriorated after the mass departures, leading to worse relative selection values at the end of the simulation. [5] Since we have already seen that KRB fails to adapt to the extreme-capacity setting under high churn, we do not subject it to the more demanding circumstances of both extreme churn (mass departures and flash crowds) and extreme heterogeneity.

6.3 Evaluation over PlanetLab

We evaluated Swaplinks over PlanetLab by deploying a 250-node network over 50 PlanetLab hosts distributed across the world. We scaled down the number of selec-



(a) Degree Distribution (b) Message Loads (c) Relative Selection Frequencies

Figure 7: Swaplinks: Mass departures with high churn and moderate capacity distribution

	High Churn			Low Churn		
Target Outdeg	5	10	20	5	10	20
Avg Load(B/s)	210.88	418.36	794.16	196.81	384.10	745.75
Load split	1	1.97	3.76	1	1.95	3.76
TotalDeg	9.54	19.15	37.46	10.04	19.79	39.48
Relative Selns	1	2.07	3.99	1	2.01	3.94
Seln p-values	0.000	0.000	0.001	0.000	0.023	0.002

Table 5: PlanetLab results with moderate capacity distribution

tions performed in the burst mode here to about 2500.

Figure 8 shows the variation of average node degrees, message loads and the relative selection frequencies with time in a high-churn moderate capacity experiment , and Table 5 summarizes both the high-churn and low-churn experiments. While the node-degree curve in the high churn case is not completely stable, due to the high churn, all the values nevertheless adhere reasonably closely to the desired 5:10:20 ratio. But there is a gap between the ideal distribution of #Nodes vs Selection Frequencies and the actual distribution here, leading to poor p-values for the selection distribution. We observed that a few of the planetlab nodes hosting our experiments appeared to freeze occasionally, causing the Swaplinks instances hosted on these nodes to be eventually excluded from the neighbor-sets of other Swaplinks instances. This also means that such nodes would not be selected by any subsequently launched random selection walk, thus causing the discrepancy between the actual and observed selection distributions.

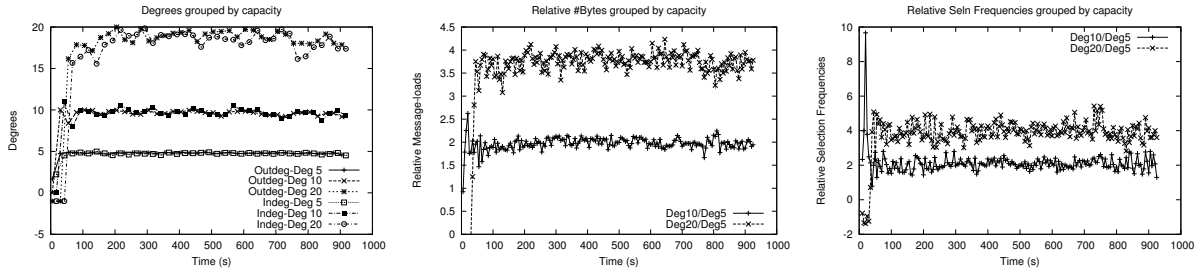
We do not show results for the extreme capacity distribution here: the fact that each high capacity class constitutes just 1% of the total node population means that there would be too few high capacity nodes in a 250-node experiment to draw reliable conclusions.

6.4 Smart-Pinging

The bulk of the message load seen by Swaplinks nodes is from the heart-beat messages used to determine when a neighbor is down. We would like to minimize this load, in part because in extreme heterogeneity situations some nodes have many neighbors, but in part because a given application might result in a computer belonging to many P2P networks, and therefore have many neighbors. Our basic approach to minimizing heart-beats is as follows: Rather than have every neighbor determine for itself whether a node *A* is down, one neighbor (at a time) determines if a node *A* is down. If a neighbor determines that node *A* is down, it informs the other neighbors of node *A*, using a flood, that node *A* is down.

Specifically, the *smart-pinging* scheme we designed works as follows: Node *A* tells each of its neighbors about some random set of its other neighbors, such that each neighbor is known by at least some small number of other neighbors. Node *A* sends each neighbor in turn a small series of (say five) heart-beat messages, each spread two seconds apart. For example, node *A* sends neighbor 1 five heartbeats, neighbor 2 five heartbeats, and so on. Each neighbor knows when to expect its series of heartbeats, based on timing information conveyed during the previous series of heartbeats. If a neighbor misses all of its heartbeats, it informs all the neighbors of *A* it knows of that node *A* is down. These neighbors in turn inform the neighbors they know, and the ensuing flood of packets quickly informs all neighbors that node *A* is down.[6]

Smart-pinging reduces the amount of bandwidth consumed under no churn, at the cost of a burst of messages that occurs when there is churn, and the possibility of incorrect notifications of node departure. While we need to explore these trade-offs in greater detail, we have currently implemented a preliminary version of smart-



(a) Degree Distribution

(b) Message Loads

(c) Relative Selection Frequencies

Figure 8: PlanetLab 250 nodes with high churn and moderate capacity distribution

Target Outdeg	5	10	20
Avg Load (B/s)	38.23	57.97	89.21
Relative Load	1	1.50	2.30
Avg Totaldeg	9.99	19.90	40.01
Relative Selns	1	2.06	4.08
Seln p-values	0.831	0.904	0.877

Table 6: Smart Pinging: moderate capacity, low churn

pinging, and observe that it does indeed result in a saving on message load under low-churn scenarios. In the current implementation, if node *A* has d out-neighbors, *A* has each of its neighbors know of 2 $log_2(d)$ of its (*A*'s) neighbors. Table 6 summarizes the results over the second half of the duration of the experiment. This experiment was run with just 8 periodic selectors (instead of 80 as in the previous cases), to isolate the heart-beat load.

7 Conclusions

Node heterogeneity, where different nodes have different capacities, is an important issue in current peer-to-peer systems. In this paper, we provide the implementation and performance evaluation of the Swaplinks heterogeneous graph construction and peer selection mechanism. We also compare its heterogeneous selection properties with that of *KRB*, a structured P2P approach derived by adapting the Karger-Ruhl load-balancing scheme to node ID spaces in the Bamboo DHT.

We find that while Swaplinks generally gives good performance along all metrics of interest, KRB finds it hard, under relatively high churn rates, to maintain the desired selection probabilities even for moderate distributions in desired selection probabilities. Also, with KRB, it is non-trivial to zero in on a good set of tuning parameters to use in a general setting. Overall, we find that Swaplinks outperforms KRB in performing heterogeneity-sensitive random peer selection.

In terms of enhancements to Swaplinks, we need to experiment further with smart-pinging, for instance to insure that it doesn't suffer from false negatives. In addition, we note that Swaplinks discovers truly random neighbors. Some P2P applications, however, would like to also discover neighbors that are nearby in terms of latency. While a P2P application is free to do that on its own (i.e. by using Swaplinks to discover random peers, and then measuring latency to them), we believe that it would beneficial to explore efficient ways to do this, and add the capability to the Swaplinks toolkit.

A limitation of Swaplinks is that it has no defense against misbehaving nodes. For instance, if a node wished to obtain a huge number of neighbors (for instance to DoS a file-sharing application), Swaplinks has no mechanism to prevent this. While we are interested in exploring such mechanisms, Swaplinks is currently only appropriate for use with trusted P2P software.

We are currently exercising Swaplinks by using it as a basis for a number of P2P applications: The Swaplinks toolkit is being used as the basis for the Chunkyspread P2P multicast system [7]. In addition, the Swaplinks algorithm is being used in building a toolkit for NAT traversal in P2P applications, and a P2P file backup system. We invite researchers to use our Swaplinks toolkit in their unstructured P2P applications [16].

8 Acknowledgments

We would like to thank Grant Goodale and Victoria Krafft for help in adapting the Bamboo simulator to KRB.

Notes

[1]To be fair, neither of these schemes expressly aim to maintain node degrees perfectly proportional to capacities.

[2]For the results shown in this paper, we do not utilize the TCP socket close signal as an indicator of neighbor departure, so as to have a fair comparison with KRB, since Bamboo uses UDP

[3]The single "NaN" entry indicates that there were too few (<5) nodes of the particular capacity during the time when the burst selections were performed for a meaningful p-value to be computed

[4]In the search for the best combination of KRB parameters, we did not try out sub-second values for the different parameters: We could conceivably use sub-second values, and achieve better results, but we did not consider this option due to the enormous amount of load it places on the network.

[5]The single positive p-value result here seems to be a lucky one for the nodes in the second capacity class – the smallest capacity nodes get more of the selections than their fair share while the largest get fewer, leaving the capacity 2 nodes with the number of selections closest to its fair share (while still less than it)

[6] Structella [37] uses a similar mechanism to reduce heart-beat loads in maintaining leaf-sets, but their mechanism is not applicable in maintaining any arbitrary set of neighbors.

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