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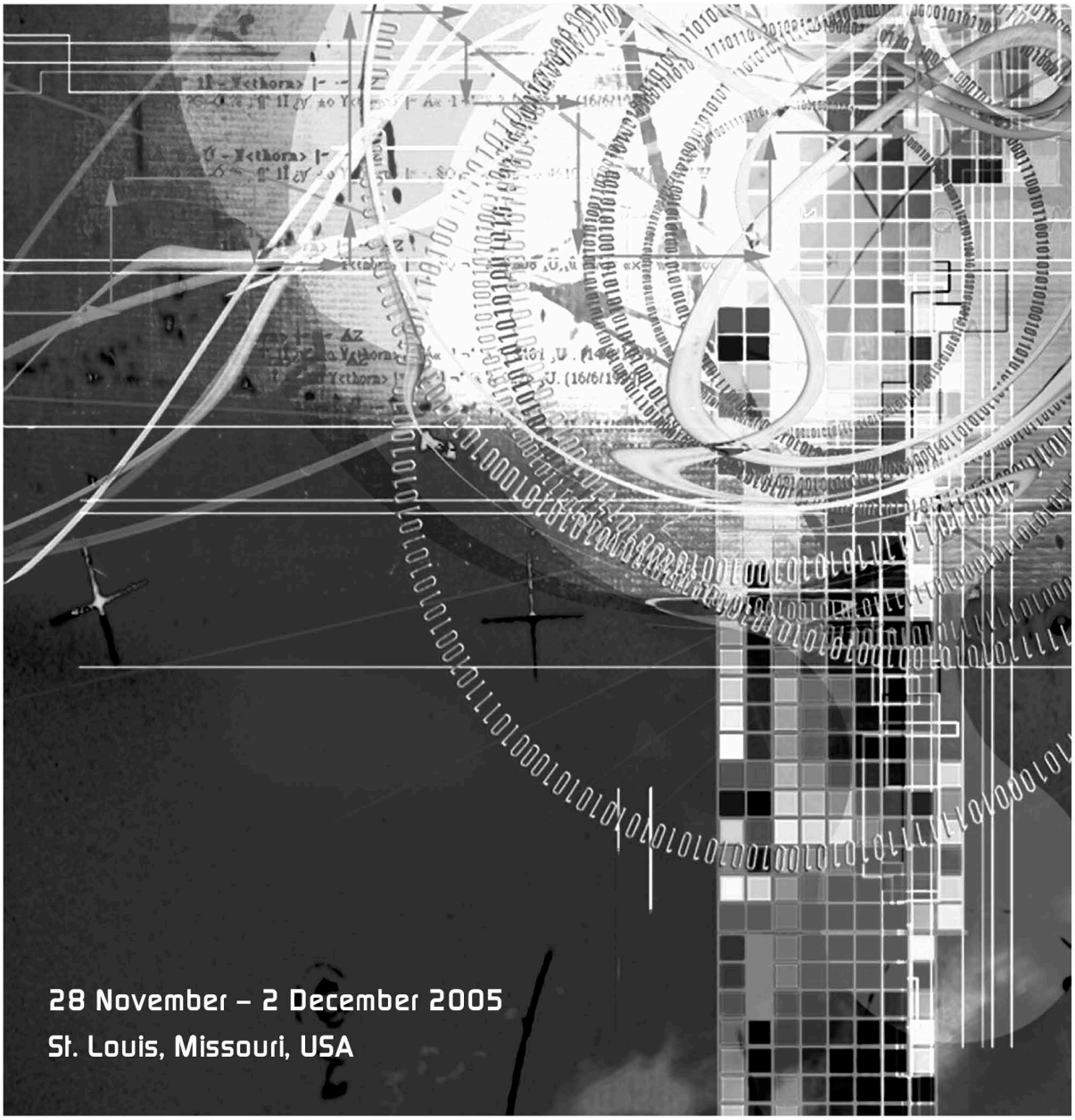


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# Optimizing Neighbors by Objective Functions in Peer-to-Peer Networks

Michael Parker, Amir Nader-Tehrani, Alok Nandan, Giovanni Pau
Computer Science Department
University of California Los Angeles
Los Angeles, CA 90095-1596

***Abstract*— Many Distributed Hash Table topologies, such as Pastry, allow flexible choosing of a peer's neighbors while maintaining routing consistency. Traditionally, such flexibility has been used to only optimize the overlay only for latency. In this paper, we create a set of objective functions that allow a peer to select neighbors for its routing table which minimize ping time, maximize bandwidth, or attempt to do both. In conjunction with a novel algorithm for quickly finding peers that maximize a given objective function without settling to a local maximum in the identifier space, we show through simulation that routing tables optimized in a greedy fashion by each node can have significant impact on end-to-end latency and capacity, such as reducing end-to-end delay by over 50 percent.**

***Index Terms*— Pastry, CapProbe, Vivaldi, PNS, routing table optimization**

## I. Introduction

Distributed Hash Tables, or DHTs, are becoming an increasingly popular tool for decentralized indexing and lookup. Most recently, the official BitTorrent client [2] has integrated the Kademlia [12] protocol, transparently allowing millions of users to find and download files in a decentralized fashion. As the size of these networks inevitably grow, users will become more perceptive of the increasing end-to-end latencies and decreasing bottleneck capacities. To counter this, DHT topologies traditionally concentrate on reducing the order of hops traversed when a message is sent. Most popular topologies today ( [7], [12], [17]) perform routing in $O(logN)$ steps while keeping $O(logN)$ connectivity per node. Recently, efforts have been made to reduce these logarithmic bounds, introducing either $O(1)$ routing ( [1], [16]) or $O(1)$ state ( [5], [14]). These proposals, however, introduce new complexity, have either increased costs of joining, leaving, and maintenance, or place more importance on some peers than others to achieve their ends.

To improve performance while avoiding such compromises, recent research ( [9], [15], [19], [20]) has focused on the incorporation of *proximity neighbor selection*, or PNS, where a peer chooses from a set of potential neighbors the one with the lowest latency. Yet latency is just one metric by which a node could optimize its routing table: Alternatively, a node could optimize its routing table by selecting peers with the highest bandwidth. Until recently, however, measuring the capacity to a remote node has been a slow and expensive process, typically relying on long streams of packet pairs. The recent release of CapProbe, however, has made estimating bandwidth in wired networks on which DHTs typically reside a fast and lightweight process, returning the capacity to another host within seconds and with exceptional accuracy.

In this paper, we explore the design space of extending PNS so that peers can be chosen with respect to maximizing some *objective function* that can incorporate latency, bandwidth, or other quantifiable measures. Customizing the objective function by which a peer judges the quality of its neighbors allows one to tailor a peer-to-peer network for a specific application without changing the underlying routing algorithm: Latency-bound applications such as chat programs or networked games could be optimized to minimize round trip time, while throughput-bound applications such as multicast video streaming or content replication could be optimized to maximize capacity. The driving idea is that if each node on the network greedily chooses for itself neighbors that minimize a network-wide objective function, then end-to-end measurements for the properties associated with the objective function will improve.

This paper makes the following contributions: We demonstrate how, by using the underlying geometry of the Pastry DHT, a node can quickly and efficiently find sets of nodes which could potentially be used as neighbors. Furthermore, we show how by using the Vivaldi distributed coordinate system and the CapProbe capacity estimation tool, we can devise simple objective functions that can select from these nodes new routing table entries that optimize for end-to-end latency, throughput, or a balance of both. Finally, a global tuning algorithm is presented, which prevents a node on a static network from keeping a local maximum as its optimal routing table entry, forcing it to continue searching for the global maximum elsewhere along the ring.

The rest of the paper is organized as follows: Section II describes the Pastry DHT, and the Vivaldi and CapProbe algorithms we employ to optimize it. We then describe in Section III our algorithm for optimizing the network given a objective function, followed by descriptions of all the objective functions we consider in this paper. Section IV details our simulation environment, including parameters used, and the resulting round trip time and capacity characteristics of a 1740 node network when optimized under each objective function. Finally, Section V describes what we will build upon in future papers, while Section VI concludes this paper.

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## II. BACKGROUND

In this section we outline the two key techniques that enable us to select peers intelligently. CapProbe is an accurate, light-weight capacity estimation tool, while Vivaldi allows us to estimate the round-trip time to a remote node without explicit pinging.

### A. CapProbe

CapProbe [6] is an accurate link capacity estimation tool that uses *packet pairs*. Packet pairs, as the name suggests, is a pair of back-to-back packets that are sent over the any network path to estimate the path's characteristics. The basic packet pair relies on the fact that if two packets are sent back-to-back and are queued one after another at the narrow link, they will exit the link with a *dispersion* $T$ given by $T = \frac{L}{B}$, where $L$ is the size of the second packet and $B$ is the bandwidth of the narrow link, i.e., the capacity-limiting link. If the two packets have the same size, their transmission delays are the same. This means that after the narrow link, a dispersion of $T$ will be maintained between the packets even if faster links are traversed downstream of the narrow link. This is shown in Figure 1, where $S$ is the source, $D$ is the destination, and link $A-B$ is the narrow link. The narrow link capacity can then be calculated as $B = \frac{L}{T}$. The packet pair algorithm assumes that the packets will queue next to each other at the narrow link. The presence of cross-traffic can invalidate this assumption.

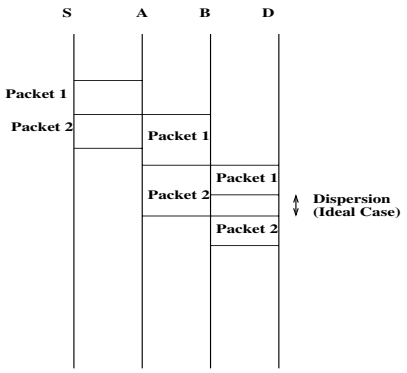


Fig. 1. *Measured dispersion of a packet-pair by CapProbe*

The underlying idea of CapProbe is that at least one of the two probing packets must have queued if the dispersion at the destination has been distorted from that corresponding to the narrow link capacity. This means that for samples that estimate an incorrect value of capacity, the sum of the delays of the packet pair packets, which we call the *delay sum*, includes cross-traffic induced queuing delay. This delay sum will be larger than the minimum delay sum, which is the delay sum of a sample in which none of the packets suffers cross-traffic induced queuing. The dispersion of such a packet pair sample is not distorted by cross-traffic and will reflect the correct capacity. Based on this observation, CapProbe calculates delay sums of all packet pair samples and uses the dispersion of the sample with the minimum delay sum to estimate the narrow link capacity.

### B. Vivaldi

Vivaldi [21] is an algorithm for assigning synthetic coordinates to hosts such that the distance between the coordinates of two hosts accurately predicts the round trip time, or RTT, between them. Unlike previous methods to allow estimation of latency a priori, Vivaldi is distributed among participating hosts and thus scales efficiently as the size of the network grows. Furthermore, coordinates change quickly in reaction to adverse traffic patterns such as congestion.

To briefly describe how Vivaldi works, each host maintains a set of coordinates and an error estimate denoting the accuracy of these coordinates. The error estimate is derived from how well the host's coordinates, when combined with coordinates of remote nodes, estimate the RTT to the remote nodes. If, after a sample, the RTT to another node is not equal to the distance between them, the sampling node moves a fraction toward the coordinates that would have perfectly predicted the RTT for that sample. Thus, if the sample RTT is less than the predicted value, the nodes move closer in the coordinate space; if the sample RTT is more than the predicted value, the nodes separate farther. Nodes with high error estimates are assumed to not yet have found their correct position within the coordinate space. As such, after a sample they are allowed to take larger leaps toward the coordinates that would have perfectly predicted the sample, and thus explore the coordinate space more freely in hopes of finding accurate coordinates.

### C. Pastry

Pastry [17] is a peer-to-peer overlay topology allowing messages to be routed between N participating hosts in $O(logN)$ time while the connectivity of each host scales with only $O(logN)$ complexity. Each host on the network is assigned a randomly chosen Globally Unique Identifier, or *GUID*, in the range $[0, 2^{160})$. Such a value is usually derived by the SHA-1 hash its IP address. The service provided by Pastry, like all other Distributed Hash Tables, is to map messages with the same 160-bit key to a single host on the network regardless of the originating node. In Pastry, messages are mapped to the node whose GUID is numerically closest to the key modulo $2^{160}$. The identifier space is thus circular and commonly referred to as a ring. To enable end-to-end delivery, each node on the network must assume responsibility for forwarding messages not meant for it to nodes that are closer to the destination in some sense. In Pastry, the nodes a host knows are found in either its *leaf set* or its *routing table*.

The leaf set consists of the $\frac{L}{2}$ nodes whose GUIDs immediately precede it in the circular identifier space, and the $\frac{L}{2}$ nodes whose GUIDs immediately succeed it, where $L$ is a fixed value shared by all nodes on the network. The routing table, by contrast, logarithmically increases and decreases in size with the size of the network. In our configuration of Pastry, the routing table is organized as 160 rows, indexed from 0 to 159. Treating GUIDs as a sequence of 160 bits, a remote node on the network belongs in row $i$ of the local host's routing table if its GUID matches the first $i$ bits of the local node's GUID and differs in the bit at position $i + 1$. Such a bit sequence is said to share a *prefix* of length $i$ with

the local node's GUID. Therefore nodes in higher rows of the routing table share successively longer prefixes with the local node's identifier.

The Pastry routing algorithm is as follows: When a Pastry node receives a message, either from a remote host or an application running locally, it first determines whether the message key falls within the range of the identifier space spanned by its leaf set. If this happens, and the local node is the closest node, the message is passed up to the application layer; otherwise, the message is forwarded to the closest remote node in the leaf set, which is necessarily the last hop. If the message key is not spanned by the leaf set, the node finds the length $i$ of the prefix its GUID shares with the key. If some node exists in row $i$ of its routing table, it must share a prefix of at least length $i+1$ with the message key. This node is thus closer to the key than the current node, and so the message is forwarded on to it. If no node exists in row $i$, the message is forwarded to a node whose GUID shares a prefix of length $i$ with the key and is numerically closer. This way the message is still making progress toward the node that is numerically closest to it.

## III. Optimization

### A. Procedure

In Pastry, all nodes that begin their identifiers with a given bit sequence $b$ are found consecutively in the circular identifier space. Therefore, a node whose GUID begins with $b$ can always find in its leaf set another node whose GUID begins if $b$ if one exists; we say their leaf sets *overlap*. Now consider an entry in row $i$ of a given node's routing table; this entry's GUID matches the first $i$ bits of the given node's GUID, and differs in bit $i+1$. We can conclude that if any other nodes exist with a prefix of length $i$, a subset of them must be found in the leaf set of the entry in row $i$. Therefore, by *pulling* the leaf set of the entry in row $i$ of our routing table, we can find a subset of all possible nodes that could go in row $i$. We can then choose one that maximizes a selected objective function, and repeat the process for all rows in the routing table.

Because GUIDs are assigned to nodes by the SHA-1 hash, although a cluster of nodes may share the same subnet or ISP and therefore have similar IP addresses, their positions in the circular identifier space will be diverse. Thus the nodes in a pulled leaf set should have varied geographic locations, exhibiting a wide array of round trip time and capacity characteristics. This increases our chances of finding a node that produces a better value from the objective function than the current node.

Note that simply optimizing each row of our routing table once by the procedure above is not enough, for two reasons: First, if the entry in row $i$ is not optimal, and a node from its pulled leaf set is chosen to replace it, part of this replacement's leaf set does not overlap with the original entry's leaf set. A node that maximizes the objective function even more than the replacement node may exist there, and so it would be beneficial to optimize again later by pulling the replacement node's leaf set and repeating the process. Second, even if pulling a row entry's leaf set yields no nodes of higher quality than that entry, new nodes may later join the network and enter into that entry's leaf set. Alternatively, nodes may later drop from the entry's leaf set, moving entries previously outside its leaf set into it. Either way, we see it would still be beneficial to occasionally pull the leaf set of an optimized entry, hoping to find a new node that has a higher objective function value.

If the *churn rate* of the network is low, however, there is a chance that our algorithm above will stabilize at some entry that is a local maximum. At this point, pulling the leaf set repeatedly of an optimized entry will retrieve the same nodes again and again, all with a lower objective value than the current entry. For a network with size $N$, however, approximately $N/2^{i+1}$ could be used to fill row $i$ of a routing table. Therefore, especially for smaller values of $i$, it is likely that some node exists outside the current entry's leaf set that has a higher objective value. Ideally, we would like to find such a node, and even the global maximum. If an entry in row $i$ of our routing table remains optimal after pulling its leaf set $k$ times, we turn to a technique inspired by *global tuning* in the Bamboo DHT [11], a variant of Pastry.

In our global tuning phase, we first construct a message with a key sharing a prefix of length $i$ with our GUID. Like the current entry in row $i$, the key will first differ from our GUID in the bit at position $i+1$. All bits following position $i+1$ in the key are randomly generated. Because all bits after position $i+1$ are random, there is a high probability that this message will be delivered to a node whose leaf set entries also share a prefix of length $i$, but which is also outside the leaf set of our local minimum. The hope is to sample from a set of nodes outside the optimized entry's leaf set. Once delivered by Pastry, the closest node to the message key returns its leaf set. If a node is found in this leaf set with a higher objective function value than our current entry in row $i$, we choose it as a replacement. Otherwise, row $i$ remains unchanged and we repeat our global tuning if the current entry is still optimal after pulling its leaf set $k$ more times.

### B. Objective Functions

Now that we have devised a technique to quickly find a set of suitable routing table entries, we describe some objective functions to judge which peer in the set is best. Here we describe six functions we seek to maximize; we will evaluate their effectiveness in the next section:

- RTT Only: The estimated latency to each node, provided by Vivaldi, is calculated, and then the reciprocal of each is taken to be its objective value. This method selects the node with the smallest RTT, provided that the Vivaldi coordinates are accurate.
- Capacity Only: CapProbe is run on each node, and the capacity to a node is taken to be its objective value. Because, unlike Vivaldi, CapProbe requires direct communication with each node, this selects the node with the highest capacity without fail.
- RTT First: The $\frac{L}{2}$ nodes whose Vivaldi coordinates are farthest are discarded. CapProbe is then run on the remaining nodes, and the capacity to a node is its objective value.

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- Capacity First: CapProbe is run on each node, and the $\frac{L}{2}$ nodes whose capacities are lowest are discarded. For each of the remaining nodes, the reciprocal of its latency is its objective value.
- RTT-Capacity Joint Ranking: CapProbe is first run on each node. After doing this, nodes are ranked separately by their estimated RTT and their bandwidth. Joint rankings are then computed for each node by adding their respective RTT and bandwidth ranks. The node with the highest joint ranking is chosen, while the node with the higher capacity ranking is chosen in the event of a tie. (This is done because, on average, capacity varies between hosts more than latency.)
- Normalized Deviations: CapProbe is run on each node to find capacities. The average and standard deviation over all RTTs, $\overline{rtt}$ and $\sigma_{rtt}$, are computed. The average and standard deviation over all capacities, $\overline{cap}$ and $\sigma_{cap}$, are also computed. Peer $i$ receives an objective value of:

$$s_i = signum(\overline{rtt} - rtt_i)\left(\frac{\overline{rtt} - rtt_i}{\sigma_{rtt}}\right)^{0.75} + signum(cap_i - \overline{cap})\left(\frac{cap_i - \overline{cap}}{\sigma_{cap}}\right)^{0.75}$$

where:

$$\text{signum}(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}$$

The value of a node is proportional to how many standard deviations it is from an 'average' node, in terms of both RTT and capacity. Note that we damp both components by raising each to a power less than unity (here 0.75); this is so nodes with overwhelmingly low latencies or high capacities do not dominate, promoting well balanced entries. The node $i$ with the highest value $s_i$ is chosen.

## IV. Simulation

### A. Setup

We created a simple, custom, event-driven simulator running Pastry to perform our experiments. The implementation of Pastry in the simulator is based on both the details presented in [17] and the source code of the official FreePastry distribution [10]. To simulate latency between nodes in the simulator, we used the King data set [13] provided by MIT, which consists of a full matrix of pair-wise RTTs between 1740 DNS servers collected using the King method [8]. Our analysis is admittedly hampered by the lack of any capacity matrix of this scale. No surveys into the distribution of end hosts' bandwidth exist, and topology generators such as BRITE [3] cannot infer synthetic bandwidths from a given topology. Instead, a bandwidth distribution must be prescribed to the generator, either of a uniform, exponential, or Pareto type, although no endorsement of any one distribution is made [4].

With no better alternative, for our capacity matrix we use randomly generated real numbers having a uniform distribution between 0 and 50. These numbers represent the capacity that would be found from running CapProbe between peers in a real, networked environment. Because the capacity matrix is synthetic while the RTT matrix is not, we assume no correlation between pair-wise RTTs and capacities. This will stress the effectiveness of our metrics that seek to optimize peers for both RTT and capacity, as finding a peer that scores well with respect to RTT does not imply it will score well with respect to capacity, and vice versa. Finally, unlike the RTT matrix, the capacity matrix is asymmetric, modeling links with different upstream and downstream capacities such as cable and DSL.

Our simulation starts with a single node on the network. Nodes then join the network one by one, each choosing as its bootstrap node a randomly selected node on the network. Between nodes joining, each node selects up to two nodes it knows of (either from its leaf set or routing table) and pings them, allowing it to refine its own Vivaldi coordinates. The 5D Euclidian coordinate space was used for Vivaldi since it yields the lowest absolute error. A node first optimizes its routing table entries once 30 nodes have joined the network after it, and continues to optimize every time 30 more nodes have joined since its last optimization attempt. The leaf set size $L$ is 8, while for the purposes of global tuning we set the parameter $k$ to 3.

This process continues until there are 1740 nodes on the network, at which point we consider the network complete and begin the measurements described below. This leaves some of the last nodes to join the network with inaccurate Vivaldi coordinates and unoptimized routing tables, giving us a snapshot of a network that is still evolving when measurements are performed. Note that such transient conditions are similar to ones encountered in deployed peer-to-peer networks exhibiting churn and no stabilization period. We therefore feel that the results described below are a good approximation to results from a real networked environment.

At this point, two different nodes are selected at random from the network, and a message is routed between them. We sum the RTTs along the links taken get the end-to-end RTT, and find the link taken with the minimum capacity to get the limiting bottleneck capacity. This process is repeated for 2500 iterations.

### B. Results

In Table I and Table II we see average and median end-to-end latencies and capacities over all 2500 source-destination pairs. With the exception of Capacity Only, we can see that all objective functions are effective in reducing latency. The RTT Only objective function, which seeks to optimize only latency by use of Vivaldi coordinates, reduces the median end-to-end latency from 741 ms to 331 ms. As expected, the median capacity remains nearly unchanged, as no correlation between RTT and capacity was introduced. Likewise, these tables show that with the exception of RTT Only, all objective functions are effective in increasing capacity. The Capacity Only objective function increases the median capacity by over 200%, although this number should obviously be approached cautiously: the capacity matrix used in simulation consists of a uniform distribution, when undoubtedly it follows a

different distribution in the real Internet. Still, the bountiful improvements in capacity by the other four metrics that seek to strike a balance between latency and capacity is interesting, as we will discuss later.

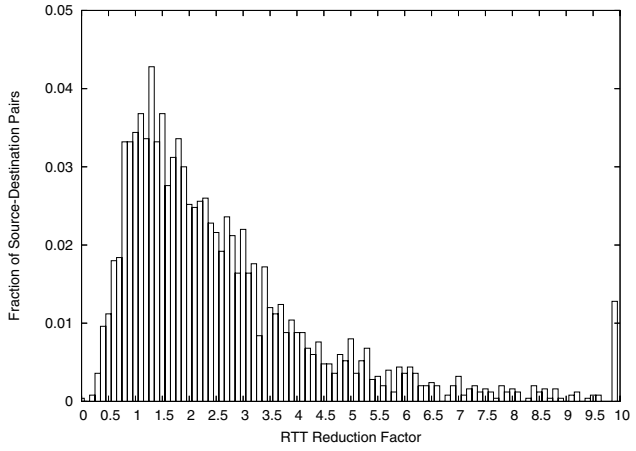


Fig. 2. *RTT reductions for RTT Only objective function, computed as* $RTT_{old}/RTT_{new}$

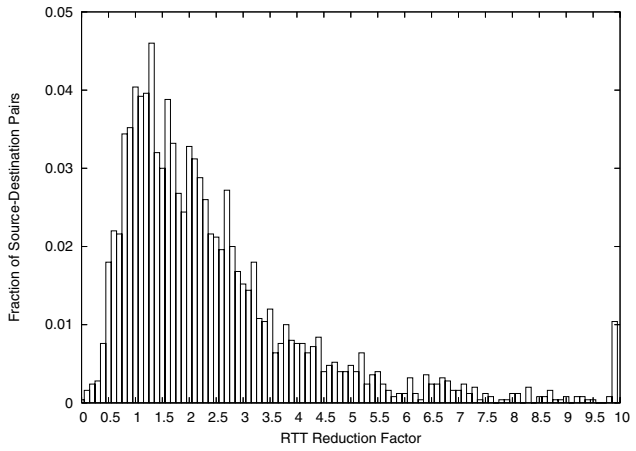


Fig. 3. *RTT reductions for Joint Ranking objective function, computed as* $RTT_{old}/RTT_{new}$

In Figure 2 we show the reduction of the RTT Only objective function over all 2500 pairs of nodes, where reduction is defined as $RTT_{old}/RTT_{new}$. One interesting observation from Figure 2 is that some source-destination pairs have poorer end-to-end performance once optimization is applied. This is due mostly to the greedy approach taken when optimizing nodes are chosen. As an example, say before optimization, node A routes a message to node B by forwarding the message through intermediate hop $X_1$. The end-to-end RTT is thus equal to $rtt(A, X_1)+rtt(X_1, B)$. After optimization, node $X_2$ replaces $X_1$ in node A's routing table, and the end-to-end RTT changes to $rtt(A, X_2) + rtt(X_2, B)$. There is no guarantee, however, that $rtt(X_2, B)$ is less than $rtt(X_1, B)$ because they represent two separate paths through the network. Thus we cannot assert the round-trip-time after optimization is less than the round-trip-time before optimization.

Another reason for this performance degradation is that, as said earlier, some nodes have not yet gone through an optimization round. Consequently, any message forwarded through them goes through an unoptimized node. Still yet other nodes have not found their correct position in the Vivaldi coordinate space. The distance between such a node and another node is thus not a reliable predictor of the RTT between them, which RTT Only relies on for best optimization. However, in the case of Figure 2, only 12.8 percent of end-to-end pairs perform worse after optimization, and one can clearly see the heavy tail toward reduced latency.

The last four objective functions seek to optimize both end-to-end capacity and latency: RTT First, Capacity First, Joint Ranking, and Normalized Deviations. As we can see again in Table I and Table II, each of the four objective functions offers large improvements over an unoptimized network. Note that Joint Ranking and Normalized Deviations maintain a slight advantage over the other two in terms of end-to-end improvement because they are closer to saddle point formed by low RTTs and high capacities in the sample set, while RTT First and Capacity First are only approximations to this point. RTT First, however, has the advantage of using the least amount of overhead. This is because estimating the RTT to a node using Vivaldi coordinates requires no additional traffic and only minor computation, while estimating the capacity to a node requires CapProbe to send packet pairs to it through the network. Since RTT First throws away the $\frac{L}{2}$ leaf entries with the farthest coordinates before CapProbe is invoked, and the size of a leaf set is $L$, we reduce total overhead by approximately 50 percent.

Most interesting is that each of these four objective functions, which attempt to find a careful balance between RTT and capacity, come very close to achieving the end-to-end RTTs

TABLE I
AVERAGES FOR DIFFERENT OBJECTIVE FUNCTIONS

| | Average | |
|---|---|---|
| **Objective Function** | **RTT** | **Capacity** |
| Unoptimized | 802.07 | 9.51 |
| RTT Only | 379.49 | 9.35 |
| Capacity Only | 861.23 | 25.41 |
| RTT First | 388.15 | 21.66 |
| Capacity First | 410.61 | 22.51 |
| Joint Ranking | 398.98 | 23.12 |
| Normalized Deviation | 403.86 | 23.85 |

TABLE II
MEDIANS FOR DIFFERENT OBJECTIVE FUNCTIONS

| | Median | |
|---|---|---|
| **Objective Function** | **RTT** | **Capacity** |
| Unoptimized | 741.00 | 6.97 |
| RTT Only | 331.5 | 7.27 |
| Capacity Only | 786.5 | 27.03 |
| RTT First | 354 | 22.32 |
| Capacity First | 375 | 23.45 |
| Joint Ranking | 367 | 24.32 |
| Normalized Deviation | 371.5 | 25.19 |

and capacities achieved by RTT Only and Capacity Only, respectively. To illustrate this, in Figure 3 we have shown the RTT reduction profile for Joint Ranking, which varies only slightly with respect to the profile in Figure 2 for RTT Only. Even if one wishes to have the end-to-end performance of both RTT Only and Capacity Only without the minor compromises these four objective functions incur, each node can maintain two routing tables: one whose entries are optimized by RTT Only, and another whose entries are optimized by Capacity Only. The consequences of this scheme, however, are the need to classify all data as either RTT-link based or Capacity-link based, and the doubling in state and connectivity at each node (although, asymptotically, both remain a tractable $O(logN)$). We did not include this metric in our paper, as its results are approximately the RTT data from RTT Only and the capacity data from Capacity Only in Table I and Table II.

## V. Future Work

We hope to improve our work by finding and using real-world capacity data between 1740 hosts in our measurements, as opposed to the uniformly distributed synthetic data used in this paper. If this proves to be too ambitious, another approach we are considering is surveying the capacities of a smaller set of hosts, and using the found distribution in our trials between 1740 hosts. Alternatively, we could run all our experiments on a real network, such as PlanetLab [18]. Some drawbacks to Planetlab, however, include its small size, its geographic concentration in North America, and its abundant low-latency, high-capacity links. These are not necessarily properties of peer-to-peer networks in use today.

We would also like to investigate how varying system-wide parameters affect performance. For example, by intuition, if we increase $L$ (the size of each node's leaf set), then when a node pulls a routing table entry's leaf set it should see a larger set of nodes with a wider array of round-trip-time and capacity characteristics. It is therefore more likely that the optimization attempt will find a node that has a lower associated objective value than the current entry, and is closer to the global minimum. Other parameters include the global tuning parameter $k$, how often nodes pull the leaf sets of their routing table entries, and how often node ping one another to update their Vivaldi coordinates.

## VI. Conclusions

In this paper, we have introduced a new technique for optimizing the entries of a Pastry node's routing table. This procedure consists of two steps: First, a given row entry's leaf set is pulled, which as shown must contain another suitable entry for the row if one exists. Second, the quality of these potentially leaf nodes are then evaluated; if the best leaf node exceeds the current routing table entry in quality, it replaces the current entry. To score the quality of peers, we have presented a variety of objective functions that emphasize different metrics, such as RTT or capacity. To avoid stabilizing at a local maximum along the ring under low churn, we have also introduced a global tuning algorithm that aggressively pulls leaf sets from other suitable in the identifier space.

Simulations show that by each node performing greedy selection of its neighbors using objective functions, end-to-end latency and capacity can be drastically improved. Using real RTT data from the Internet, we have shown that our technique can improve end-to-end performance by over 50%. By pairing this data with synthetic capacity data, we see that attempting to optimize for both metrics does not sacrifice much performance in terms of one or the other, and maintains huge gains over unoptimized networks.

We hope that this paper has brought to light how, by using Vivaldi and CapProbe together, nodes in a peer-to-peer network can greedily select their best neighbors while, from an end-to-end perspective, reducing latency and improving throughput. Furthermore, we hope it sparks interest in applying the techniques presented here to other DHTs, and devising new objective functions to evaluate the quality of neighboring peers.

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