Estimating Network Proximity and Latency[*]

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ABSTRACT

Network proximity and latency estimation is an important component in discovering and locating services and applications. With the growing number of services and service providers in the large-scale Internet, accurately estimating network proximity/latency with minimal probing overhead becomes essential for scalable deployment. Although there exist a number of network distance estimation schemes, they either rely on extensive infrastructure support, require the IP address of the potential targets, falsely cluster distant nodes, or perform poorly with even few measurement errors. We propose *Netvigator*, a scalable network proximity and latency estimation tool that uses information obtained from probing a small number of landmark nodes and intermediate routers (termed milestones) that are discovered en route to the landmarks, to identify the closest nodes. With very little additional probing overhead, Netvigator uses distance information to the milestones to accurately locate the closest nodes. We developed a Netvigator prototype and report our performance evaluation on PlanetLab and in the intranet of a large enterprise. Netvigator is a running service on PlanetLab as a part of HP Labs' S^3 (Scalable Sensing Service).

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Distributed networks; C.2.3 [**Network Operations**]: Network monitoring; C.2.5 [**Local and Wide-Area Networks**]: Internet

General Terms

Measurement, Management, Algorithms

Keywords

Network measurement, Network distance estimation

1. INTRODUCTION

Proliferation of Internet access has not only whetted consumers' appetite for context-sensitive personalized delivery of services, but has also put the tools for service creation in their own hands. We believe that the distinction between service consumer and provider will blur further. Our vision differs from current hosting of services by large providers because we believe there will be a vast number of small providers in the new Internet economy. Such an environment will cause tremendous growth in service composition and distribution on the Internet. Building a scalable and adaptive Internet service infrastructure is a key enabler for our vision. An important challenge facing future network infrastructure is to balance the tradeoffs between providing individualized service to each client and making efficient use of the networked resources. Efficient resource utilization enables the same infrastructure to accommodate more services and clients and respond better to flash crowds.

A key issue in effectively utilizing network resources and services is efficiently and quickly locating the desired resources or services in specific network locations. These kinds of location services allow a service provider to construct efficient service overlay networks, which for example could be used to distribute rich media content, enable a client to identify the closest cache/proxy that has the desired data or service, enable a client to quickly locate a well provisioned nearby server for participating in a massive multiple-user online game, or to quickly construct a proximity-aware peer-to-peer (P2P) overlay for applications such as content sharing. Hence, techniques that accurately and efficiently estimate locality of resources/services and compute network distances have become important.

Currently proximity estimation is based on pairwise distance estimate between any two given nodes. Such schemes find the node closest to a client from a given set of potential targets by estimating the distance to each candidate and picking the minimum. This process requires a priori knowledge about the set of all the candidates. Furthermore in some systems, such as P2P systems, the set of service providing nodes changes dynamically, necessitating fast recomputation of proximity. In practice, when finding a service/resource, knowledge about the distance to the complete set of potential servers is usually not of interest, and ideally, the proximity estimation tool should be able to answer client queries such as *"Which is the closest node that can provide a media transcoding service?"* without requiring information about all potential nodes. Most of the distance estimation techniques build a globally consistent network model designed to optimize the estimation error averaged globally. For proximity estimation it is more important to lower the distance estimation error between closeby nodes. The global optimization schemes perform poorly for proximity estimation. Their proximity accuracy can be greatly improved by relaxing the global consistency requirement.

Landmark clustering [11, 15] is a popular scheme used for network distance estimation that uses a node's distances to a set of landmark nodes to estimate the node position in a Cartesian space. However, current landmark clustering techniques are prone to false clustering where distant nodes are positioned near each other. Further, the estimation quality of current landmark clustering schemes depends on the quality of measurement data and can be significantly inferior to the optimal when there is bad measurement data.

In this paper, we describe *Netvigator* (Network Navigator), a new network proximity and latency estimation tool that is more efficient and accurate than the existing schemes.[1] Netvigator pri-

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[1] In this paper we use the terms latency and distance interchangeably.

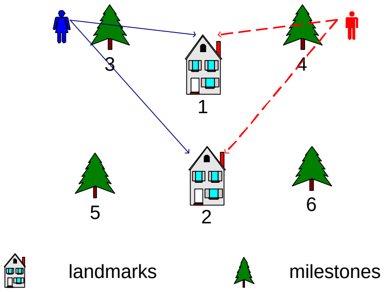


Figure 1: Example of the enhanced landmark scheme.

marily focuses on proximity estimation (i.e. to rank nodes according to proximity to any given node) as well as distance estimation. In Netvigator, each node measures distances to a given set of landmarks, similar to other landmark clustering techniques. Netvigator additionally leverages topology information by recording the distances to the *milestones* that are encountered while probing the landmarks. It must be noted that our scheme does not require deployment of milestones, instead they are discovered during the probing process, e.g., the intermediate routers encountered during a traceroute. The milestones have the capability to intercept measurement packets and respond to the client nodes. Instead of attempting to embed all the nodes in a global Cartesian-space based on measurements, Netvigator performs local clustering for proximity estimation. This paper makes the following contributions:

- We propose three clustering algorithms that utilize the distance information from the landmarks as well as the milestones to obtain higher accuracy in finding the closest node, with relatively small additional measurement overhead. Utilizing distance information from both the landmarks and milestones not only improves the accuracy but also makes our technique robust to bad measurements. In addition to proximity, our scheme also produces a highly accurate distance estimate.
- We developed a prototype of our scheme and evaluated it on PlanetLab [14] and the intranet of a large enterprise (Hewlett-Packard). Our experiments show that with 90% confidence, the real closest node falls in the top two nodes our algorithm identifies. Further, Netvigator's distance estimation outperforms that of GNP and Vivaldi.

Netvigator is a running service on PlanetLab as a part of HP Labs' S^3 (Scalable Sensing Service) [16]. S^3 has been up and running from January 23, 2006, and it provides latency, bandwidth capacity, and available bandwidth estimates between all node-pairs on PlanetLab.

The remainder of the paper is organized as follows. Section 2 describes the details of Netvigator, followed by experimental results in Section 3. We discuss deployment experiences and efficiency issues in Section 4. Section 5 surveys the related work. Concluding remarks are presented in Section 6.

2. NETVIGATOR

Before describing Netvigator techniques we look at how network proximity estimation methods can be used in general. One of the primary use is to find the closest node providing a particular service such as caching, transcoding, etc. Proximity estimation can also be used to narrow down choices in a multi-attribute constraint scenario. In this case, k closest nodes are first computed using proximity estimation and then the constraint matching is performed on the smaller set of k nodes.

In Netvigator, each node measures distances to a given set of landmarks, similar to other landmark clustering techniques. Netvigator additionally records the distances to the milestones that are encountered while probing the landmarks. The idea behind this approach is illustrated in Figure 1 using a simple analogy. Two people estimate their physical location by measuring their distances to the two houses (i.e., the landmarks). Each of them also records their distances to the trees (i.e., milestones) that are on the way to the two houses. Without using the distances to the trees 3 and 4, a naïve landmark clustering approach would conclude that the two people are close to each other because they have similar distances to the two landmarks. By accounting for the distances to the milestones, false clustering can be avoided, thus increasing the accuracy of the proximity estimation.

In Netvigator, a small number of landmarks are used for bootstrapping and a large number of milestones are used for refinement. The milestones are discovered during the probing process, e.g., the intermediate routers encountered during a `traceroute`. The milestones have the capability to intercept measurement packets and respond to the client nodes. It must be noted that our scheme does not require deploying milestones as part of the infrastructure. In Netvigator, given N client nodes and L global landmark nodes, each client conducts a traceroute to each landmark node. Thus a total of N*L traceroutes are conducted asynchronously in each measurement period. The details of our proximity estimation scheme are described below.

(1) Each node sends probe packets to the landmarks for round-trip time measurement.[2] These packets may encounter milestones en route to the landmarks. When a milestone node receives a probe packet, it sends an acknowledgment packet back to the node that originated the probe packet.

(2) After a node receives all acknowledgment packets from the landmarks and milestones (if any), it constructs a landmark vector that includes the distances to all the landmarks as well as the milestones the measurement packets have encountered.

(3) Each node submits its landmark vector to a repository called global information table.

(4) Upon receiving a query from a node to find the k closest nodes, the infrastructure carries out the following steps:

(4.1) With the landmark vectors of all the candidate nodes stored in the global information table and the landmark vector of the querying node, apply the clustering algorithm to reduce the size of the candidate set to identify k top candidates.[3]

(4.2) Send the information of these identified candidates to the client node.

(5) The client node performs RTT measurements to the identified top k candidates.

The better performance of Netvigator as opposed to other landmark based techniques can be attributed to two reasons. First, our use of milestones improves the information about the local network characteristics. This reduces false clustering without increasing the number of landmarks. Second, Netvigator leverages local clustering techniques instead of globally mapping all the nodes to a Cartesian space. Due to increased accuracy, each client needs to probe only a small number of landmark nodes. After performing clustering, a client needs to perform RTT measurements to only a small number of top candidate nodes the clustering algorithm identifies. Note the only additional overhead of our scheme is the ACK packet transmissions from the milestones. A node does not send additional messages to locate the milestones, as they are encountered by probe packets on their way to at least one landmark.

[2] We assume the nodes have landmark information through some announcement and discovery mechanisms.

[3] Section 2.1 describes the clustering algorithms.

Table 1: Notations.

Notation	Description
n	a node that wants to find the nearest service node.
C	the set of candidate nodes the global information table identifies by examining only the distances to the landmarks.
$L(n, c)$ and $c \in C$	the common set of nodes (landmark and milestone) that c and n have measured to.
$dist(a, b)$	the distance(latency) between nodes a and b.

2.1 Clustering Algorithms

Before we describe the clustering algorithms, we first define notations in Table 1. The three clustering algorithms we present are: min_sum, max_diff, and $inner\_product$. The clustering algorithms min_sum and max_diff are based on the *triangle inequality*, while $inner\_product$ is motivated by information retrieval literature.[4] For each node, the k candidates having the smallest clustering metric values are picked as the k closest candidates. While all three clustering algorithms have been designed with the goal of providing proximity information, the min_sum clustering metric can also be used for distance estimation.

2.1.1 min_sum

The intuition behind min_sum is that if there are sufficient number of landmark nodes that two nodes n and c measure against, it is very likely one of the landmark nodes is located on the shortest path between the two nodes. Suppose this landmark node is l. The sum of $dist(n, l)$ and $dist(c, l)$ should be minimal if the triangle inequality holds. For a given node n and its candidate node set C, nodes are ranked in the increasing order of the min_sum clustering metric as follows. For each node $c \in C$,

$$min\_sum(n, c) = min_{\forall l \in L(n,c)}\{dist(n, l) + dist(c, l)\}.$$

Note from the above definition, $min\_sum(n, c)$ is the shortest distance among all overlay paths between nodes n and c constructed using each milestone/landmark common to nodes n and c. Thus $min\_sum(n, c)$ provides an upper bound on latency between nodes n and c and can be used as an estimate of the latency between them. In other words, $\widehat{dist}(n, c) = min\_sum(n, c)$, where the estimate of $dist(n, c)$ is denoted by $\widehat{dist}(n, c)$.

For a given node n, when all nodes $c \in C$ have been ranked using the above metric, the k closest nodes to node n are identified as the first k nodes in this ranked list, i.e., the k nodes that have the smallest values of the min_sum metric. Thus the closest node (say node x) to node n is the one that satisfies the following:

$$min\_sum(n, x) = min_{\forall c \in C: l \in L(n,c)}(dist(n, l) + dist(c, l)).$$

2.1.2 max_diff

Similar to min_sum, the idea behind max_diff is that if there are sufficient number of landmark nodes that both n and c measure against, then there is a large likelihood that there exists a landmark node l such that c is on the shortest path from n to l, or n is on the shortest path between c and l. In that case, $ABS(dist(n, l) - dist(c, l))$ is the maximum when the triangle inequality holds.[5] The formula $max\_diff(n, C)$ is defined as

$$max_{\forall c \in C: l \in L(n,c)} ABS(dist(n, l) - dist(c, l)).$$

2.1.3 $inner\_product$

The algorithm $inner\_product$ is motivated by document ranking algorithm used in information retrieval [21]. The semantic information of a document is represented as a term vector. The weight of each term is set to be proportional to the frequency of the term in the document and inversely proportional to the total number of documents that contain this term in the entire corpus. The intuition is that the more frequent a term in a document, the more likely the term uniquely identifies the document. However, if the term also appears in a lot of other documents, the importance of the term should be diminished. The similarity between a document and a query is determined using the inner product of the vector representation of the two. Applying this concept, $inner\_product$ expects that if a landmark node is close to node n, then it can give a better indication of the physical network position of n. $inner\_product(n, C)$ is defined as

$$max_{\forall c \in C} \Sigma_{l \in L(n,c)}((1.0/(dist(n, l)^2)) \times (1.0/(dist(c, l)^2))).$$

Our experimental results in the following section will show that the algorithms min_sum and max_diff perform better than the $inner\_product$ algorithm. In addition, only min_sum provides a reasonable distance estimate between any two nodes and thus holds the most promise for deployment. For $inner\_product$, the choice of square in $1.0/dist(n, l)$ is somewhat arbitrary with a goal to favor a close landmark node than a far away one. In the future, we will explore possible improvements to $inner\_product$.

2.2 Prototype Implementation

Netvigator comprises the following three modules:

- **Path Probing Module**: The path probing module resides on all participating nodes. It sends probes towards the landmarks to collect the path information. Our system uses the *traceroute* tool. Each client periodically collects the path information and sends landmark vectors to the information data module.
- **Information Data Module**: The information data module collects the path information from the participating nodes. The data is filtered to remove any specious information. If available, it also consults a *router-alias* database to further enhance the data. The router-alias database contains a list of interface IP addresses assigned to the same physical router. This enables the identification of multiple interface IP addresses to a single router, rather than identifying each interface IP address as a separate router.
- **Clustering Module**: From the partial topology information, the clustering module performs the proximity computation for different nodes.

In the current Netvigator implementation, the information data module and the clustering module are centralized and reside on a single node.

3. PERFORMANCE EVALUATION

We experimented with Netvigator prototype on two different *real* networks: a geographically distributed HP enterprise network and a set of *PlanetLab* nodes connected via open Internet [14]. To give the readers a flavor of how our tool performs before diving into a detailed evaluation, Figure 2 visualizes the partial topology information our tool collects and uses to derive the results. Netvigator computes the k closest nodes for each participating node. We also compute the latency estimate for all client node pairs and evaluate its accuracy. We compare our results with two distance estimation techniques - GNP [11] and Vivaldi [5]. While Meridian [26] computes node proximity leveraging an overlay network, it is based on direct measurements rather than estimation, which is our focus.

[4] Violation of triangular inequality in the Internet has been reported in [1, 28]. However, such violations are less likely in this context as they do not include the intermediate routers as points of the triangle.

[5] The function $ABS(x)$ returns the absolute value of x.

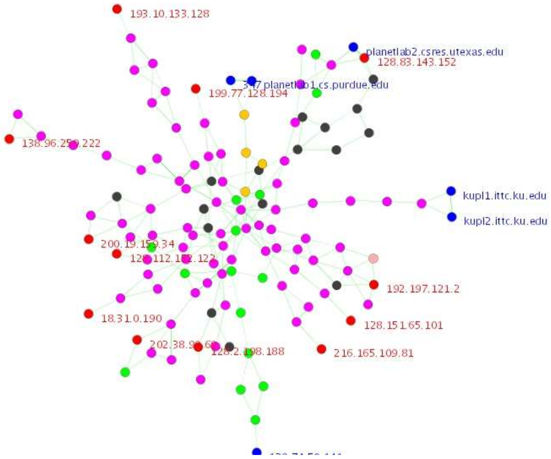


Figure 2: Visualization of the partial topology used in clustering.

Hence we do not compare with Meridian at this time. As described in [26], distance estimation can be coupled with a geographic query routing layer. A similar approach was proposed in [6] and it is more appropriate to compare this distributed approach with that of Meridian. Further, accurate distance estimation rather than direct measurements could be used in conjunction with the Meridian approach and this is an item of our future research.

GNP and Vivaldi do not directly output the k closest nodes and for comparison purposes, we use the output of the distance estimator indirectly. For both GNP and Vivaldi, the k closest nodes for each participating node were computed based on the Euclidean distance calculation from the network coordinates GNP or Vivaldi respectively generates. For the dimension parameter of the coordinate space in the GNP, we use values between 5 and 7, which were shown by its authors to give good performances. For Vivaldi, we use [9], which embeds the client nodes in a 3-dimensional Euclidean space to obtain the end-to-end latency estimate. The same set of $N \times L$ measurements (ping for GNP and Vivaldi and traceroute for Netvigator) are provided as input to the three schemes. To stabilize the Vivaldi coordinates, same set of measurements are fed to the Vivaldi system 100 times. The end-nodes are expected to perform direct ping measurements to these k nodes to find the closest target or use the distance estimates generated.

3.1 Evaluation Metrics

We define three metrics for comparing the performance of Netvigator with other proximity estimation schemes. For each node i of the N participating nodes, let $S^i_{e,k}$ denote the set of k closest nodes *estimated* by the scheme. We also collected the N^2 ping measurements to find the actual closest nodes. These ping measurements are for verification purposes only to comparatively evaluate the performance of the algorithms. Let $S^i_{a,k}$ denote the corresponding set of k *actual* closest nodes. Let c_i denote the actual closest node to node i.

- **Accuracy**: It measures whether the actual closest node was returned in the proximity set $S^i_{e,k}$.

$$a(i) = \begin{cases} 1 & if \;\; c_i \in S^i_{e,k} \\ 0 & o.w. \end{cases}$$

  Mean accuracy is represented as:

$$acc_k = \sum_{i=1}^{N} a(i)/N.$$

- **Precision**: It measures the overlap between the k actual closest nodes and the k closest nodes computed by the proximity scheme. Mean precision averaged over all N nodes for a given k is defined as:

$$prec_k = \frac{\sum_{i=1}^{N} \frac{|(S^i_{a,k} \cap S^i_{e,k})|}{k}}{N}.$$

- **Penalty**: It evaluates the potential cost due to inaccurate estimation. Relative penalty for node i can be represented as:

$$penalty_{k,i} = \frac{(min_{\forall s \in S^i_{e,k}} dist(s,i)) - dist(c_i,i)}{dist(c_i,i)}.$$

  The numerator in the above equations is the absolute penalty. The average penalty is computed over all N nodes. The penalty metric depends on the topology as well as the location of the client nodes.

  As we mentioned earlier, min_sum can also be used for estimating latency between different nodes. For min_sum, we also provide distance estimation results and compare with those obtained from GNP and Vivaldi. The quality of the latency estimation is evaluated using the two metrics given below.

- **Directional Relative Error**: This is the same metric that was used in [11]. The directional relative error for the distance between nodes n and c, $DRE(n,c)$ is given by

$$DRE(n,c) = \frac{\widehat{dist}(n,c) - dist(n,c)}{min(\widehat{dist}(n,c), dist(n,c))}.$$

  The ideal value of $DRE(n,c)$ is 0, which indicates that the estimation is perfect with no estimation error. A DRE value of $(-)1$ indicates that the estimated latency is (smaller) bigger by a factor of 2. Also, we use the metric Relative Error, $RE(n,c)$, which is just the absolute value of the $DRE(n,c)$.

- **Mean Absolute Distance Estimation Error**: This metric computes the mean absolute distance estimation error over all N*(N-1) node pairs. The estimation error for the distance between nodes n and c is given by

$$err(n,c) = \widehat{dist}(n,c) - dist(n,c).$$

  The mean absolute distance estimation error:

$$\overline{E} = \frac{\sum_{\forall n,c \in C, n \neq c} |err(n,c)|}{N(N-1)}.$$

  We also compute the standard deviation of E.

With N end nodes, the brute force method to obtain 100% accuracy and precision would be to conduct $N \times (N-1)$ direct ping measurements. Each node conducts a ping measurement to every other $(N-1)$ nodes. In Netvigator, each node conducts traceroute measurements to L landmarks plus k ping measurements (where k is the number of candidate nodes estimated by the scheme), with a total of $N(L+k)$ measurements. Note however, that the message overhead for a traceroute probe is proportional to length of path from probing node to the landmark. If H is the average number of hops between end nodes and landmark nodes, the total number of probe messages sent from all end nodes is $N(L \cdot H + k)$. It is still $N(N - L \cdot H - k - 1)$ less than $N(N-1)$ ping measurements. In GNP, each node conducts $(L+k)$ ping measurements, with a net savings of $N(N-L-k-1)$ measurements. One way to fairly compare the performance of GNP and Netvigator under the same approximate measurement overhead is to use GNP with H times more number of landmark nodes than Netvigator. In a simulation

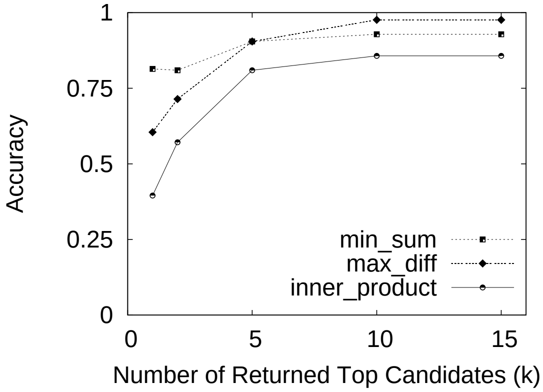


Figure 3: Accuracy of Netvigator algorithms in HP intranet.

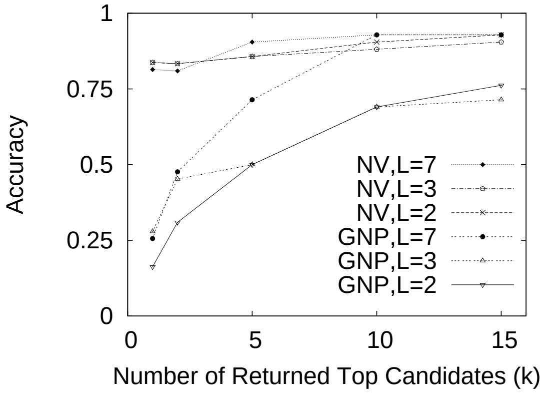


Figure 4: Accuracy of Netvigator and GNP in HP intranet.

study in [27], we found that Netvigator with five landmark nodes significantly outperformed GNP with 40 landmark nodes. Due to space limitations, we omit the simulation results here.

In the next two sections, we present our proximity estimation results on an enterprise network and PlanetLab respectively. For the sake of brevity, the results of our distance estimation are condensed and presented in Section 3.4.

3.2 Enterprise Network

We ran our experiments on a well managed and provisioned enterprise intranet at Hewlett-Packard. We selected 43 globally distributed end-hosts for the experiments. $NetIQ^{TM}$ Chariot [2] performance endpoints were installed on these hosts running Linux or Microsoft windows operating systems. The traceroute capability of the endpoint was used to collect path information when remotely triggered via the Chariot console. Complete router-aliasing information about the enterprise network was available from the management servers. The endpoints were also used for conducting 43^2(=1849) ping measurements required for algorithm verification.

We assigned up to 7 landmark nodes among 43 end hosts in this set of experiments. The landmark nodes were selected manually with some coarse geographical input.[6] We varied the number of landmark nodes (1, 2, 3, and 7 nodes) and computed the metrics for the 43 end nodes as a function of k, the number of top closest candidates returned by the proximity estimation algorithm.

We use our three clustering algorithms— min_sum, max_diff and $inner\_product$ for Netvigator. We denote these as $m0$, $m1$, and $m2$ in the plots. The router aliasing information greatly improves the performance and hence we show results with those information incorporated.

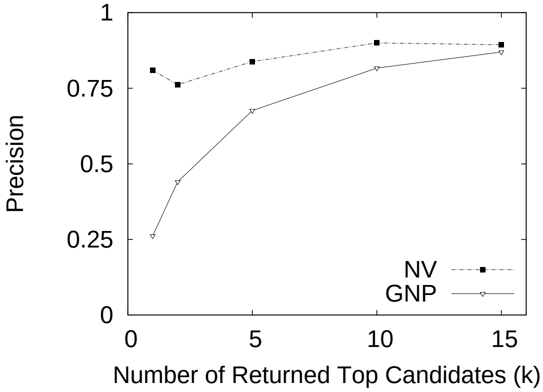


Figure 5: Precision of Netvigator and GNP in HP intranet.

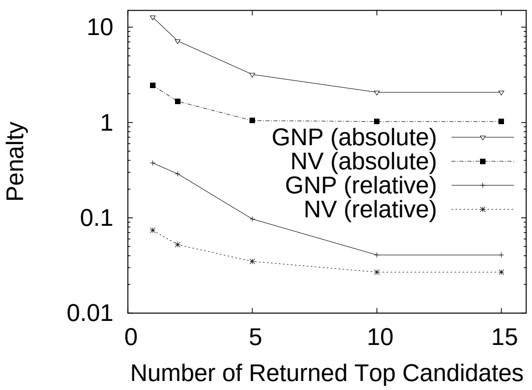


Figure 6: Penalty of Netvigator and GNP in HP intranet.

In Figure 3, we compare the three different clustering algorithms for the Netvigator, with 7 landmarks and the value of k varied. We find that the $inner\_product$ algorithm performs the worst, while the performance of min_sum and max_diff are similar. Although the accuracy of max_diff is the highest when k is large, min_sum has the advantage of providing a higher accuracy at low values of k (which reduces the total overhead). Thus in the remainder of the paper, we only show the results for the min_sum algorithm for Netvigator.

Figure 4 plots the mean accuracy for the Netvigator and GNP as L and k are varied. A key observation from the result is that for GNP, having more landmark nodes shows clear advantage and the accuracy is very poor when k is small. These results indicate that for GNP to have the same accuracy as Netvigator, the overhead has to be significantly higher than Netvigator. When $k = 5$, Netvigator has an accuracy of 90.7% (L=7) and 86.05% (L=2,3), while GNP has an accuracy of only 72.09% (L=7).

In Figures 5 and 6, the mean precision and mean penalty incurred for Netvigator and GNP (with dimension 5) are compared for the 7 landmarks case. The absolute penalty numbers are in milliseconds. As expected, the precision values increase with k, while the penalty numbers decrease with k. We find that Netvigator outperforms GNP in both metrics.

In summary, although the accuracy and precision of Netvigator are not 100%, with L=7, it incurs a significantly less measure-

[6] They are located in Palo Alto, CA, Roseville, CA, Corvallis, OR, Fort Collins, CO, Boise, ID, Atlanta, GA, and Bristol, England.

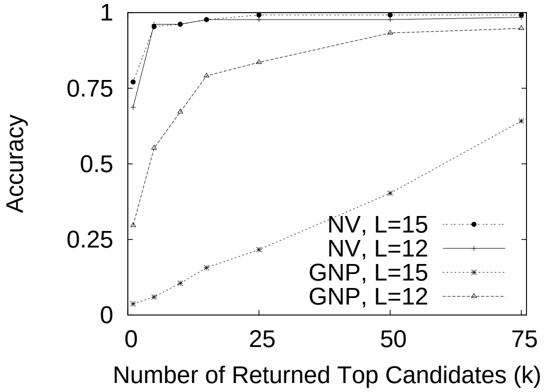


Figure 7: Accuracy of Netvigator and GNP in PlanetLab.

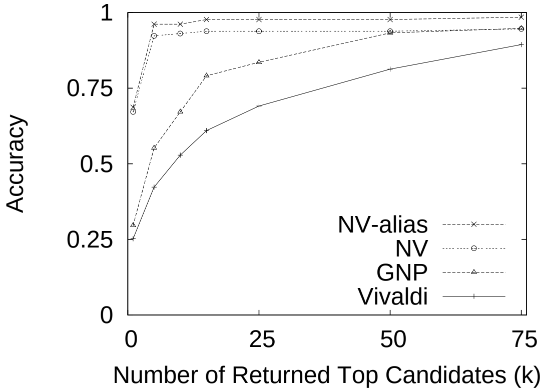


Figure 8: Accuracy of Netvigator, GNP, and Vivaldi in PlanetLab.

ment overhead of about 15% (of what the brute force 100% accurate method would take), and provides over 90% accuracy, with a low penalty. The reason for the superior performance of the Netvigator over existing schemes stems from the fact that it uses a lot of additional information that is easily available without incurring high extra overhead. Utilizing the additional topology information provides robustness to incomplete measurements or measurement errors and also provides high accuracy, high precision, and low penalty. These features of Netvigator become even more apparent in the next section when we discuss an environment that is less predictable than the enterprise intranet.

3.3 PlanetLab

We also conducted experiments on unmanaged, poorly instrumented open Internet using PlanetLab [14]. A set of 131 Linux nodes with 15 landmark nodes was selected for the PlanetLab experiments. The 15 landmark nodes were selected with approximate global geographical representation to the extent possible.[7]

In Figure 7, the mean accuracy is plotted against the number of candidates returned for Netvigator ($m0 - R$) and GNP (dimension 7). With L=15 landmark nodes, Netvigator performs very well, achieving over 90% accuracy with just 5 candidates. However, GNP performs very poorly with L=15. We found that of

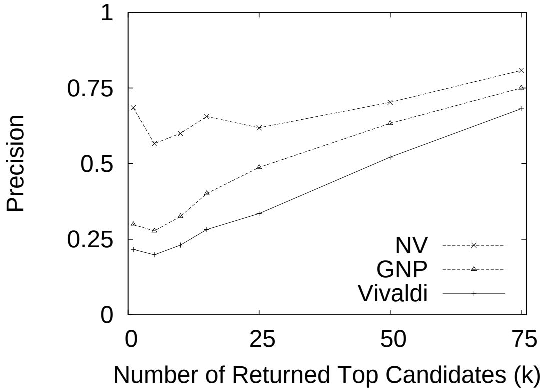


Figure 9: Precision of Netvigator, GNP, and Vivaldi in PlanetLab.

the 15 landmark nodes, 3 landmarks had partially missing measurement data and this affected the GNP results adversely while Netvigator was not affected. When we re-ran the experiment with only L=12 landmarks which had more complete measurement data, the performance of GNP improved dramatically, although it was still comparatively poor to Netvigator especially when k is small. Our experiments show that a small number of bad measurement data can cause the estimation quality of GNP to degrade more than 300%. It is interesting to note that the performance of Netvigator with either number of landmarks was approximately the same. This demonstrates the strong robustness of Netvigator to bad measurements. Realistically on the Internet, it is difficult to get a good and consistent set of measurement data at all times and hence proximity estimation algorithm needs to work well in spite of these measurement issues.

We expect Vivaldi and GNP to perform approximately the same with respect to the proximity estimation metrics. Figure 8 compares the proximity estimation accuracy of Netvigator with GNP (with 7 dimensions) and Vivaldi. GNP and Vivaldi perform approximately the same, with GNP performing a little better than Vivaldi.

As reported in the results from the enterprise network, the router aliasing information improves clustering accuracy. However, unlike the HP enterprise network where we were able to get access to a complete router aliasing database, on the open Internet, this information is hard to obtain. Using the *scriptroute sr-ally* [17], we attempted to get as much information as possible. Due to the large number of router interfaces encountered, the process was very slow and because of non-responsive routers, the resulting aliasing information was incomplete. Nevertheless, we used what aliasing information we had to run the Netvigator (denoted as 'NV-alias'). Figure 8 shows that with the L=12 landmarks, using the router aliasing information does give a boost to the mean accuracy, having over 90% accuracy with just 2 candidates.

Figures 9 and 10 show the precision and relative penalty for Netvigator ($m0\_R$), GNP (dimension 7), and Vivaldi. Netvigator outperforms GNP and Vivaldi in both metrics. It is interesting to compare Figure 10 with Figure 6. The penalty for Netvigator is very similar in both experiments. GNP however, shows much higher penalty in PlanetLab experiments.

Due to traceroute problems described above, we encountered cases where no milestone was found on the paths to the landmarks. This problem can be addressed by active probing from the milestones, though this can cause a higher overhead. Each of the milestones also measures its distances to the landmarks to obtain its own landmark vector. The milestones can use the landmark vector

[7] They are node-1.mcgillplanetlab.org, pl2.6test.edu.cn, planet1.berkeley.intel-research.net, planet1.cs.rochester.edu, planet1.scs.cs.nyu.edu, planet2.cs.huji.ac.il, planet.cc.gt.atl.ga.us, planetlab-1.cmcl.cs.cmu.edu, planetlab-1.cs.princeton.edu, planetlab1.cs.purdue.edu, planetlab1.csres.utexas.edu, planetlab1.inria.fr, planetlab-1.it.uu.se, planetlab1.lcs.mit.edu, and planetlab1.pop-mg.rnp.br.

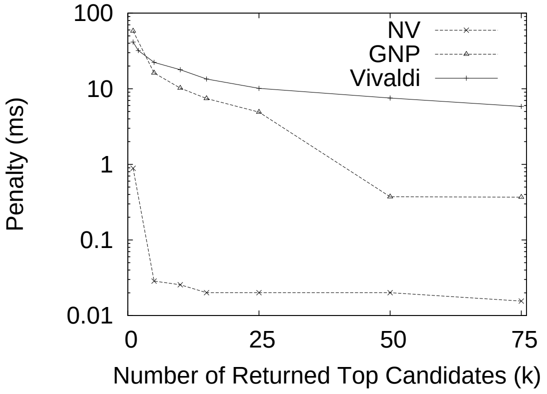


Figure 10: Penalty of Netvigator, GNP, and Vivaldi in PlanetLab.

as the DHT key to report themselves to the global information table. The global information table then instructs nodes to measure to a set of milestones that the global information table has identified to be close to each of the nodes, using a landmark clustering scheme such as GNP.

3.4 Latency Estimation Results

In this section, we present a subset of our results on latency estimation on PlanetLab. The results for the enterprise network are similar and are omitted for the sake of brevity. We use the same datasets on which proximity estimation was tested. As mentioned before, only the min_sum clustering technique produces a distance estimate in Netvigator. We compare the accuracy of the distance estimation of Netvigator (L=12 landmarks) with that of GNP (L=12 landmarks, G=7 dimensions) and Vivaldi (3-dimensions) on the same PlanetLab measurement dataset. As mentioned before, in the real world, obtaining a complete set of measurements on a platform such as PlanetLab is not guaranteed. Thus, for a small fraction of node pairs (less than 12%) we do not have the actual measured latency and these pairs are omitted from the evaluation of distance estimation accuracy.

Figure 11 contain plots of the estimated delay versus the actual measured delay for Netvigator, Vivaldi and GNP. The units for the axes are in microseconds. In these scatter plots, the closer the points plotted are to the diagonal, the better is the estimation. In each case, the mean and standard deviation of the absolute error (E) as defined earlier is listed with the corresponding plot. The estimation with Netvigator is the best, with a mean absolute estimation error of 23 msec, followed by Vivaldi and GNP in this order.

The directional relative errors (DRE) for Netivagor, Vivaldi and GNP are plotted against the actual measured delay in Figure 12. The mean and variance of the relative error (RE) computed over all node pairs with available measurements is also listed with each plot. For Netvigator, the DRE ranges between -30 and 60, whereas for both Vivaldi and GNP, the DRE range is much larger. For the sake of easy visual comparison, all three plots are shown with the same range of the axes as used in the Netvigator plot. Again, it is clear that Netvigator exhibits much better latency estimation performance than the other two schemes with an average RE of just 0.56. Vivaldi is the next best performer with an average RE of 2.19. For this dataset, GNP performs very poorly with an average RE of 114.29.

3.5 S^3 Service on PlanetLab

Since January 23, 2006, we have been running a network measurement service called the Scalable Sensing Service (S^3) on PlanetLab [16]. As part of the service, we publish a snapshot of data for approximately 400 nodes (latency estimated by Netvigator, available bandwidth and capacity) every 4 hours. In Figure 13, we present Netvigator latency estimation results on the snapshots generated over a 7-day period between March 23 15:49:37 PST 2006 and March 30 19:12:05 PST 2006 and compute various statistics of the absolute estimation error.[8] These statistics are the mean, the 25th, 50th, 75th and 90th percentile of the absolute error. The absolute error is computed over about 5% of the dataset for which we have the actual measured latency. The main observation is that the 25th, 50th and 75th percentile absolute error is fairly low and stable across the entire time period, with 75% of the measured latency having estimation error less than 25 msec. The error exhibits a heavy tail. We intend to continue studying the accuracy of Netvigator over a long period of time from the data obtained using S^3.

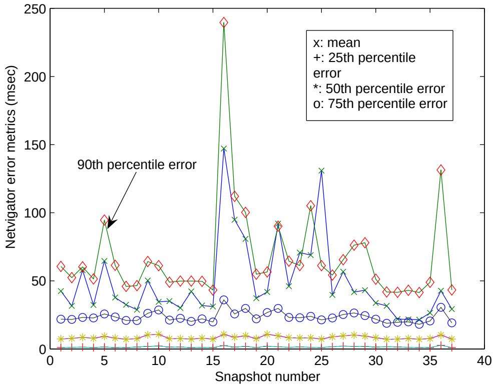


Figure 13: Netvigator error statistics.

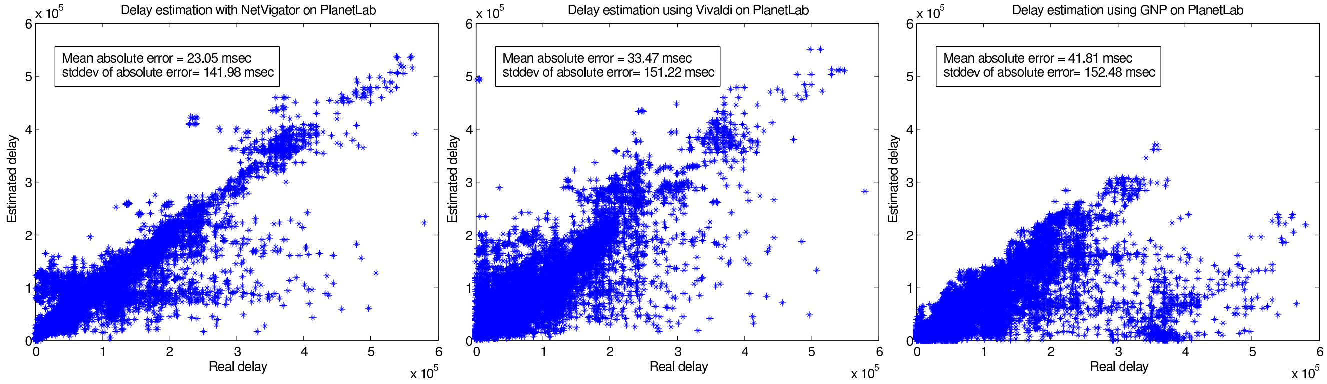
4. DISCUSSION

In this section, we first discuss issues relating to the crucial issue of scalability. We have done a limited scalability study in [27] using simulations with synthetic topologies. Preliminary results indicate that Netvigator technique scales with the number of end hosts without the loss of accuracy and without increasing the number of landmarks. We are currently experimenting with our PlanetLab prototype to further understand the issues and are considering the reducing the measurement overhead and a distributed querying mechanism as described in the next two subsections. The remaining three subsections deal with deployment issues and refinements to the original scheme.

4.1 Reducing Measurement Overhead

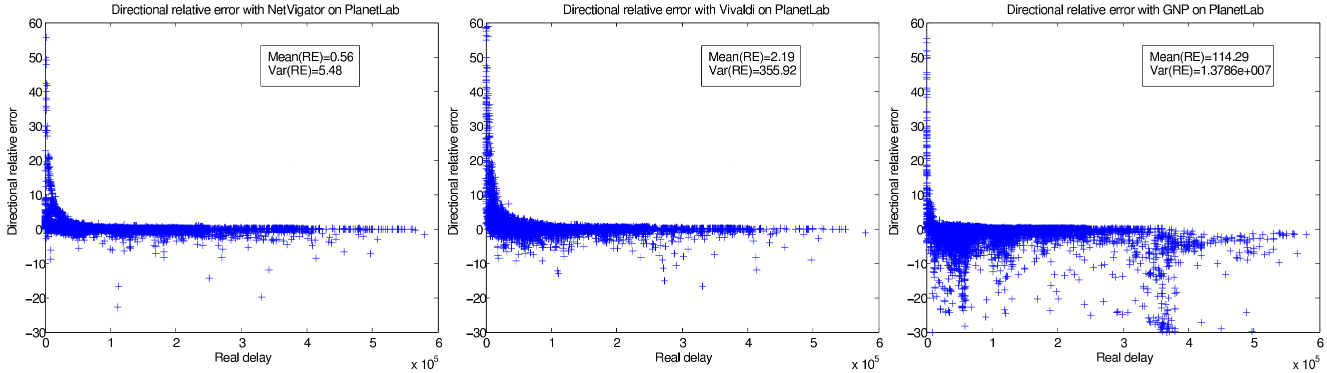
As discussed earlier, each `traceroute` probe incurs message overhead proportional to the length of the probed path. To reduce the measurement overhead we propose "smart-traceroute," a smarter version of `traceroute` that does not probe every hop. Instead of incrementing the TTL of the ICMP probe packet by 1, smart-traceroute intelligently skips intermediate hops. It exploits the fact that fine grained delay information is primarily needed for the milestones closer to the node. We used two heuristics *exp* and *hop* as skipping patterns for smart-traceroute. The *exp* exponentially increases `traceroute` TTL and probes only hops 1, 2, 4, 8, etc., whereas the *hop* mimics the hierarchical network structure and uses slowly increasing probing TTL (1, 2, 3, 6, 9, 12,. . .). If the largest path is 32, the message overhead for each smart-traceroute probe is less than 6 for *exp* and 12 for *hop*. Figure 14 compare

[8] During this time, our service suffered a few outages and a few snapshots are missing.



(a) Netvigator (L=12). (b) Vivaldi. (c) GNP (L=12, G=7).

Figure 11: Estimated vs. actual delay on PlanetLab.



(a) Netvigator (L=12). (b) Vivaldi. (c) GNP (L=12, G=7).

Figure 12: Directional relative error on PlanetLab.

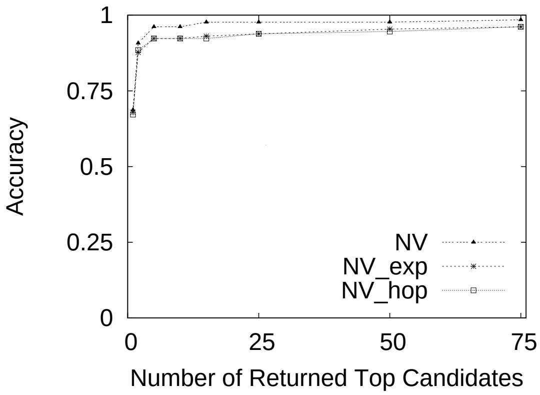


Figure 14: Accuracy of NV, NV_exp, and NV_hop.

these two smart hop skipping techniques, along with the baseline Netvigagor on PlanetLab with 12 landmarks.

We observe from the graph that with less measurement overhead, both *exp* and *hop* perform similarly and are only slightly less accurate than the baseline Netvigator. This implies that the information not used in *exp* and *hop* was not adding much value.

We plan to explore this further to find how the skipping patterns for smart-traceroute can be adapted to given topologies. In addition, we will enable smart-traceroute to probe multiple targets simultaneously. This smart version will have the following features: (i) Using heuristics, it avoids probing the common paths multiple times. (ii) It reports data incrementally as it becomes available. (iii) It groups consecutive routers that are close to each other into super-routers to increase the probability of capturing common subpath among different clients.

4.2 Distributed Querying

Using a centralized server to store all information is not scalable as it requires all nodes to report and query a central unit. This can cause a concentration of network traffic and single point of failure. We are working on a distributed Internet distance information service to make Netvigator more robust and scalable. Our solution takes advantage of the locality of interest since nodes usually are interested in finding resources or services that are close by in network proximity. We propose to distribute the position data among a set of infrastructure nodes, and have used a heuristics based approach for partitioning and querying this data [6]. Simulation results show that distributed approach is not only accurate but also results in shorter response time and better network resource utilization.

4.3 Blocking of ICMP Probe Messages

The widespread deployment and availability of traceroute made it the measurement tool of choice for our experiments. At the same time, we observed that traceroute is not a perfect path probing tool. Some network administrators disable the ICMP responses originat-

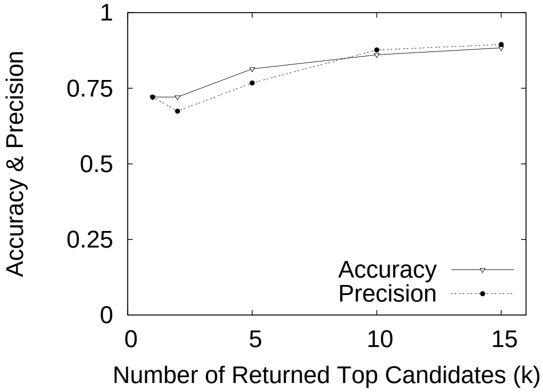


Figure 15: Precision and Accuracy of Netvigator on HP Intranet using traceroutes initiated at the landmark nodes.

ing from their routers. This is more common in the open Internet to shield the routers from denial-of-service attacks. Hence, it was not always possible to get complete path information between the clients and the landmark nodes. Some routers are also configured to filter or rate control the ICMP responses to reduce the load on the routers. These configuration and policy changes result in specious data such as the case where the delay to the next hop in the path does not increase monotonically. Also, several routers do not process ICMP message in the fast path, leading to incorrect hop latencies. Some routers do not correctly decrement time-to-live field of the packet. Duplicate hops in the path are the result of such behavior. We also found that several routers in the enterprise intranet were configured to block ICMP packets. This is especially a problem for traceroute tool for the Windows operating system that uses ICMP request packets for probing the path instead of UDP packets.

4.4 Measurements Initiated at the Landmark Nodes

The current Netvigator assumes that the traceroutes are initiated by the end client nodes to the landmark nodes. This is a good approach in a loosely managed heterogeneous/P2P environment where the identity of all nodes in the system is not known. Thus the end nodes have the onus of deploying the measurement scripts and running them periodically to probe the advertised well known landmark nodes. However, in a well managed enterprise network environment, from a deployment standpoint it is easier to give the identity of the end clients to a few infrastructure management nodes that can act as landmarks and carry out periodic traceroutes to the end clients. Netvigator can work well in the enterprise paradigm.

For the enterprise network, we ran experiments with the traceroutes being initiated at the landmark nodes instead of at the clients. Figures 15 and 16 contain results of the proximity as well as distance estimation using 7 landmark nodes and the traceroutes initiated at the landmark nodes. It is clear from these figures that initiating traceroutes at the landmark nodes does not cause deterioration of either the proximity estimation or the distance estimation. We plan on exploring this thread of work in more detail in the future.

4.5 Path Symmetry

In network coordinate-based systems (such as GNP and Vivaldi) that compute Euclidean distance metrics, the distances computed between any two nodes n and c is the same in either direction. However, path asymmetry exists in the real world. Netvigator does not a priori assume asymmetric paths and can provide different distance estimates in the two directions. This is because the common closest landmark/milestone may be different when computing from node n or from node c. Netvigator can be modified to take directional input, provided traceroutes to/from landmark nodes are available. Thus instead of $N \times L$ traceroutes, $2 \times N \times L$ traceroutes would need to be conducted. This aspect of our work is ongoing.

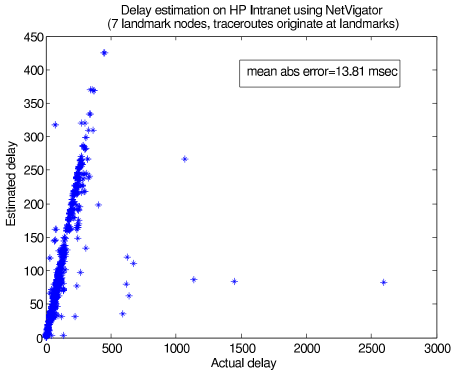


Figure 16: Estimated vs. actual delay on HP Intranet using Netvigator with traceroutes initiated at the landmark nodes.

5. RELATED WORK

Several schemes have been proposed to estimate Internet distances. Internet Distance Maps (IDMaps) [7] places tracers at key locations in the Internet. These tracers measure the latency among themselves and advertise the measured information to the clients. The distance between two clients A and B is estimated as the sum of the distance between A and its closest tracer A', the distance between B and its closest tracer B', and the distance between the tracers A' and B'. An algebraic approach can be used complementary to IDMaps to compute distances between intermediate hops without extra probing [18]. The accuracy of IDMaps improves as the number of tracers increases. One problem with IDMaps is that a client node has to measure distances to all tracers to identify the closest tracer. Dynamic Distance Maps (DDM) [23] is similar to IDMaps. DDM organizes the tracers into a hierarchy, and a client node traverses the hierarchy top-down to locate the closest tracer.

M-coop [20] utilizes a network of nodes linked in a way that mimics the autonomous system (AS) graph extracted from BGP reports. Each node measures distances to a small set of peers. When an estimate between two IP addresses is required, several measurements are composed recursively to provide an estimate. King [8] is similar in spirit to IDMaps and M-coop. It takes advantage of the existing DNS architecture and uses the DNS servers as the measurement nodes. King, M-coop, IDMaps, and DDM all require that the IP addresses of both the source and the destination are known at the time of measurement. Therefore, they cannot be used when the IP address of the target node is unknown. In scenarios where a client attempts to locate close-by Internet services, the target IP addresses of these local service nodes are usually not known in advance, and must be discovered. Furthermore, storing and retrieving the measurement information is a non-trivial task.

There are schemes that use landmark techniques for network distance estimation. Landmark clustering [11, 15] uses a node's distances to a common set of landmark nodes to estimate the node's physical position. The intuition behind this technique is that if two nodes have similar latencies to the landmark nodes, they are likely to be close to each other. There are several variations of landmark clustering. In landmark ordering [15], a node measures its round-trip time to a set of landmarks and sorts the landmark nodes in the order of increasing round-trip time (RTT). Therefore, each node has an associated order of landmarks. Nodes with the same (similar) landmark order(s) are considered to be close to each other. This technique however, cannot differentiate between nodes with the same landmark orders.

Another variation is GNP (Global Network Positioning) [11] and its sequel NPS (Network Positioning Systems) [12]. In this scheme, landmark nodes measure RTTs among themselves and use this information to compute the coordinates in a Cartesian space for each landmark node. These coordinates are then distributed to the clients. The client nodes measure RTTs to the landmark nodes and compute the coordinates for itself, based on the RTT measurements and the coordinates of the landmark nodes it receives. The Euclidean distance between nodes in the Cartesian space is directly used as an estimation of the network distance. Internet Iso-bar [3] also requires each node to measure distance to landmarks. It uses the distance information to form clusters. For each cluster, it assigns a monitoring agent for the center node. Each monitor measures the distance to all other cluster-heads and this latency is used to estimate distances between two hosts in different clusters.

GNP and Internet-Iso-bar require all client nodes contact the same set of landmarks nodes, and the scheme may fail when some landmark nodes are not available at a given instant of time. To address this problem, Lighthouse [13] allows a new node joining the network to use any subset of nodes that is already in the system (i.e., *lighthouses*) as landmarks to compute a global network coordinate based on measurements to these lighthouses. Mithos [25] and PCoord [24] are similar to lighthouse in that they do not require each node to measure distances to all the predetermined landmarks. PIC (Practical Internet Coordinates) [4] has been proposed to use a security test based on triangular inequality to filter out wrong coordinates/measurements from the malicious landmarks.

Virtual landmarks [22] and ICS (Internet Coordinate System) [10] are also landmark-based schemes. They however, use the PCA (Principal Component Analysis) of Lipschitz embedding, instead of Euclidean embedding, to obtain network positions. Compared with GNP, these schemes are computationally more efficient and require less dimensionality. BBS (Big-Bang Simulation) [19] on the other hand reduces Euclidean embedding error by iteratively simulating the error as potential force fields.

Despite the variations, current landmark clustering techniques share one major problem. It causes *false clustering* where nodes that have similar landmark vectors but are far away in network distance are clustered near each other.

Vivaldi [5] is another scheme that assigns coordinate space for each host, but it does not require any landmarks. Instead of using probing packets to measure latencies, it relies on piggybacking when two hosts communicate with each other. With the information obtained from passively monitoring packets (e.g., RPC packets), each node adjusts its coordinates to minimize the difference between estimates and actual delay. Although Vivaldi is fully distributed, it takes time to converge, requires applications to sample all nodes at relatively same rate to ensure accuracy, and packets need to add Vivaldi-specific fields.

Meridian [26] network location service is similar in intent to Netvigator and is also focused on proximity estimation. Meridian forms a loosely-structured overlay network of concentric rings based on direct measurements. A gossip protocol is used for exchanging information amongst the nodes. The query matching is performed by forwarding it towards the most appropriate node.

6. CONCLUSIONS

We presented *Netvigator*, a network proximity estimation tool that uses an enhanced landmark clustering technique to accurately locate the closest node to a given node. Our clustering algorithms for finding the closest nodes utilize distance information from the landmarks as well as milestones encountered en route. This approach provides high accuracy as well as robustness to bad measurements. We developed a prototype of our scheme and evaluated it in the real world including on planet-lab as well as HP intranet. Our experiments show that with 90% confidence, our algorithm identifies the actual closest node.

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