Towards Geolocation of Millions of IP Addresses*

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ABSTRACT

Previous measurement-based IP geolocation algorithms have focused on accuracy, studying a few targets with increasingly sophisticated algorithms taking measurements from tens of vantage points (VPs). In this paper, we study how to scale up existing measurement-based geolocation algorithms like Shortest Ping and CBG to cover the whole Internet. We show that with many vantage points, VP proximity to the target is the most important factor affecting accuracy. This observation suggests our new algorithm that selects the *best few* VPs for each target from many candidates. This approach addresses the main bottleneck to geolocation scalability: minimizing traffic into each target (and also out of each VP) while maintaining accuracy. Using this approach we have currently geolocated about 24% of the allocated, unicast, IPv4 address-space (about 55% of the addresses in the Internet that can be directly geolocated).

1. INTRODUCTION

IP geolocation is the process of finding geographic locations of Internet Protocol addresses. IP geolocation is widely used today. For example, companies use IP geolocation to limit the content to certain countries (for example, television and movies that are often licensed differently by the viewer's country) and to customize advertising based on location. Internet researchers use IP geolocation to relate network phenomena to countries, such as studying the cultural impacts on social networking, or rates of computer crime by country and policy. Moreover, IP geolocation is essential in law enforcement to identify the appropriate jurisdiction to handle enforcement of computer crime statues.

Several research and commercial geolocation systems exist, exploring many different approaches. They can be roughly divided into three categories: systems driven by databases (such as NetGeo [9] and GeoCluster [12]), measurement based geolocation such as Geoping [12], Shortest Ping [8], CBG [5], TBG [8], and target-assisted geolocation such as Skyhook [14]. We focus on measurement-based systems here, since they provide better coverage and accuracy than database approaches and are independent of the target. Measurement-based algorithms all depend on *vantage points* (VPs) to actively probe the geolocation *targets*. We study both Geoping- and CBG-like algorithms.

Our goal is not to invent a new geolocation algorithm, but to understand how existing algorithms can *scale up* to many millions of targets and the entire IPv4 address space. We encounter several problems in scaling-up existing algorithms to the whole Internet. First, all existing work uses a relatively small set of VPs, typically tens of VPs [5, 8]. Second, existing work is tested on a relatively small set of targets, typically hundreds of targets. Typical targets are selected with known ground truth to evaluate algorithm accuracy. With a dozens of VPs and hundreds of targets, current algorithms each have all VPs send many probes to each target. While this product is reasonable when both are small, with hundreds of VPs and a billion targets, the product is large. The result is a huge amount of traffic out of each VP, burdensome traffic into each target, where hundreds of probes arrive to *each* IP address in a target block, and a heavy load to bring this data together.

To scale geolocation to the entire Internet, our first contribution is *to study what factors affect geolocation scalability and accuracy* for the measurement-based geolocation protocols. We show that *traffic*, both outbound from VPs and inbound to targets, is a significant limitation to full-Internet geolocation, and show that fewer VPs can make inbound traffic manageable. We then show that most VPs provide little benefit to geolocation, suggesting that one can select only a few VPs to geolocate each IP address, getting reasonable accuracy while greatly reducing traffic. We develop three conjectures factors that affect accuracy and show that good accuracy with a few VPs is possible (Section 4.1).

Our second contribution is to define *new algorithms to choose the right few VPs* (Section 4.2). Our idea is to select the closest VPs to the target, since closer VPs provide stronger constraints on location. We show
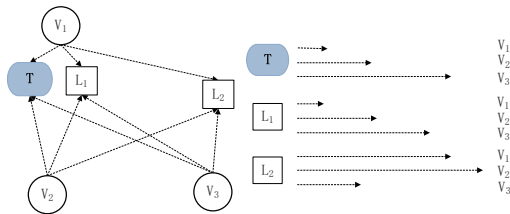
Figure 1: Vantage points (VP), targets and landmarks in Geoping (left), with RTT vectors for Geoping (right).

that VP selection using trial measurements to each /24 address block works well (Section 4.2). Our experimental results show that representatives can identify close VPs and provide accuracy almost as good as many VPs. For Shortest Ping, the median error is the same with 10 close VPs compared to all 400 VPs, and for CBG median error is only 11% worse.

2. PROBLEM STATEMENT

Our goal is to geolocate every allocated, unicast IPv4 address, with similar accuracy as basic Shortest Ping and CBG. While geolocation algorithms are well known, the main constraint in scaling them up to cover the entire Internet is probing traffic. We next review geolocation elements and these constraints.

2.1 Geolocation terminology

Measurement-based geolocation systems send probes from *vantage points* to geolocate *targets* in the Internet. Some systems also probe *landmarks* at known reference location. Figure 1 shows those entities: V_1, V_2 and V_3 are VPs, T is the target, L_1, L_2 are landmarks.

Targets are IP addresses on the Internet that we wish to geolocate. In this paper we assume targets have fixed physical locations (for example, if associated with a mobile phone), although with mobile IP and wireless networks they can have multiple locations.

Vantage points (VPs) are hosts in the Internet, always with known locations. They send messages (probes) to targets to determine the targets locations.

Landmarks are IP addresses with known locations used by some IP-geolocation algorithms such as Geoping. Unlike VPs, landmarks do not actively send messages. Since VPs are usually in known locations, they often also serve as landmarks.

Address blocks, (or *blocks*), are groups of consecutive addresses. Block size is usually identified as the number of leading bits in common, so all addresses in a /24 block have the same leading 24 bits. Because of IP address allocation policies, blocks are usually managed by the same organization and often have similar characteristics [1], presumably including physical location [12].

2.2 Problem Constraints

Unfortunately, it is intractable to probe billions of addresses from hundreds of VPs. Assume we have 500 VPs and each VP probes every IP address 10 times to get the minimum round-trip time (RTT). The number of all allocated, unicast IPv4 addresses is about 3.7 billion. Simple probing of all addresses 10 times by all VPs therefore would generate 1.8×10^{13} records, too many to process centrally a large amount of traffic. Covering this number of targets is difficult because of the the amount and diversity of incoming traffic at the targets, and the amount of traffic required from the VPs, combinined with the need to probe relatively quickly so that observations can be combined. We expore each of these constraints below.

The primary challenge is *incoming traffic to the targets*, partially because of its size and moreso because it can be misinterpreted. The amount of traffic for geolocation is not huge, but can be noticed. Ten probes from 500 VPs is only 320 kB of traffic, equal to about a 10 seconds of a Skype video call (at 250 kb/s). While not a huge amount of traffic by itself, the network administrator of a /24 network (or her users) can easily be alarmed at this traffic rate as it covers all 256 addresses over much of an hour. Even a few percent of very vigilant network operators can result in abuse complaints due to concerns of denial-of-service attacks; we must minimize complaints in our use of a shared measurement infrastructure.

The challenge of *outgoing traffic at the VPs* is that it requires sustained, high-rate traffic. While sustaining 1 Gb/s of traffic for 5 hours is not impossible, geolocation requires *geographically* distributed VPs. Current public measurement infrastructure, such as PlanetLab, caps sustained outgoing traffic to less than 10 Mb/s, thus pushing measurement time to more than 500 hours, or much longer when the nodes are shared. A simple solution to traffic problems is to spread probes out in time. Slowing probing can reduce traffic arbitrarily, potentially to the same level as "background radiation" [16].

Potentially probing traffic could be spread out in time to reduce the negative effects on VPs and targets. However, measurements must be *coherent*, that is consistent in the face of path or target chagnes. Probes cannot easily be combined if they cross changes in routing or target movement. According to Paxon, most paths have routes that are stable for days [13]. In our experiment, we assume that most paths are stable for more than two days (48 hours), so we keep measurements of each address to 48 hours or less.

2.3 Our Approach

To make our goal tractable, we must reduce the workload by using fewer targets or fewer VPs. Prior work such as GeoCluster selects a single target to represent an entire cluster of IP addresses [12], which can signifi-

cantly reduce the number of targets. However, Gueye et al. [4] show that the geographic area spanned by blocks can be far larger than the typical distance between any two IPs within a block, so we choose not to reduce the number of targets.

We therefore instead focus on reducing the number of VPs. Ethan et al. [8] shows that geolocation rarely works better than the distance to the nearest landmark. Our approach is based on one similar observation: although one needs *many potential observation points* for accurate IP geolocation, *only a few add information*[1].

In the next section we formalize this observation as three conjectures and develop a geolocation system around it. Reducing the number of VPs also addresses each of our constraints, lowering the demand on each individual VP, the inbound traffic to each target, and the amount of data we must process.

3. RELATED WORK

Three general approaches to geolocation have been proposed. The earliest is *database-driven*, using WHOIS [9, 11] or DNS [12] to infer location, although with generally poor accuracy. Recent work has explored *target-assisted* geolocation, such as with GPS and Wifi-based method such as Skyhoook [14]. These approaches require geolocation code to run on the target, an approach incompatible with covering the entire Internet.

The focus of this paper is on *measurement-based* geolocation: systems that measure network delay from VPs to target to estimate location.

Geoping [12] is based on the assumption that hosts exhibiting similar network delays to other fixed hosts tend to be co-located. In Geoping, all VPs probe RTT to many landmarks at known locations, building a set of distance fingerprints (Figure 1). To geolocate an address, all VPs actively probe the target and compare the resulting fingerprint against known landmark fingerprints using Euclidian distance, placing the target at the best matching landmark. Shortest Ping is a simplification of Geoping where targets are mapped to the closest VP (effectively making VPs the only landmarks) [8]. We use Shortest Ping to approximate Geoping because of its efficiency, and its similar accuracy [8].

Constraint-based Geolocation (CBG) instead uses multilateration [5]. The geographic location of a given point is estimated by measuring distances from multiple vantage points at known locations. Each VP draws a circle with its location as center and the distance (estimated from measured network delay by "bestline") to the target as radius. CBG locates the target in the overlap of all circles. Topology-based Geolocation (TBG) improves CBG accuracy by considering network topology and using a better latency-to-distance estimate [8]. Oc-

tant extends CBG by using both positive constraints (which the target might satisfies) and negative constraints (which the target doesn't satisfy) to reduce the estimated region for the target [15]. We explore basic CBG as representing a second class of algorithms.

Yong et al. propose a three-tiered geolocation algorithm which takes advantage of a massive landmark database and the fact that relative distances are preserved in delay measurements at small scales [17]. In the first tier, the algorithm utilizes the same idea of CBG to geolocate a target IP into a region. In the second tier, the algorithm employs the landmarks in the region of tier 1 to narrow down the possible region, with the distance constraint-based method. In the final tier, the target is mapped to the closest landmark found in the region of tier 2. We do not examine this algorithm because of the difficulty of generating a landmark database with sufficient detail.

Although we focus on Shortest Ping and CBG as representatives of the two main classes of measurement-based geolocation, we expect that other approaches that also use VPs can also benefit from our evaluation.

4. METHODOLOGY

To address the problem of scaling current geolocation approaches (Section 2), we next describe how selecting a few, good VPs can reduce inbound traffic on each target while preserving accuracy. This section outlines our approach: first we identify three conjectures that must be satisfied for our approach to work, then specific VP selection algorithms, and finally we describe our overall system to geolocate the world.

4.1 Three Conjectures

To minimize traffic on each target, we probe each target only from a few VPs. In this section we explore three conjectures required to minimize traffic while maintaining accuracy:

1. A few VPs *can be as accurate* as many VPs
2. *Certain small subsets* have good accuracy
3. The *closest* VPs generally maximize accuracy

4.1.1 A Few VPs Can Be Accurate

We begin with our first conjecture: a few VPs *can be as accurate* as many VPs. If all VPs are important to accuracy, then there is no way to reduce traffic.

To evaluate this conjecture we begin with 400 vantage points and select non-exact subsets of 2 to 150 VPs. We do not go with more VPs, because the result has already converged with less than 150 VPs. For each trial we geolocate 24 targets with known locations, using both Shortest Ping and CBG. We repeat each trial 100 times with a different, random subsets of VPs. Our VPs are 400 PlanetLab nodes, the targets are 24 university sites from around the world.

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[1]We thank Bill Woodcock of Packet Clearing House for suggesting this observation.

Figure 2a reports median and standard deviations of Shortest Ping accuracy. With more than 60 VPs, median error is small and stable. With less than 60 VPs, median error rises and standard deviation is high—some random subsets do well, but some do poorly. This experiment shows that many VPs add no information to geolocation—we can certainly reduce the number of VPs, but few are used affects accuracy.

We repeated this experiment with CBG. CBG results are shown in Figure 3a. The affects of number of VPs are qualitatively similar as Shortest Ping: moderate numbers of VPs are stable, and use of only a few VPs shows very large variance in accuracy.

4.1.2 Certain Small Subsets Have Good Accuracy

We have shown that subsets can generally have good accuracy, but variance increases greatly as the number of VPs gets very small: some instances do well, but many cases result in large error. We next explore, for a given number of VPs, how different instances perform.

We use the same 400 possible VPs, 25 targets as Section 4.1.1. However, here we look at the distribution of accuracies for several specific sizes of VP subsets. Ideally, for each size we would study all possible combinations, but that is computationally infeasible. (There are about 83×10^{12} possible combinations of 5 VPs selected from 400.) Instead, we evaluate Shortest Ping and CBG on each of 10,000 randomly chosen subsets.

Figures 2b (Shortest Ping) and 3b (CBG) show the cumulative distribution of median location error across all 24 targets for all 10,000 trials for the two algorithms. The result supports our second conjecture: different instances of same-size VP sets get different accuracy.

With fewer VPs, a small number of cases have very large error (about 5% of cases with 10 to 50 VPs, and 20% of cases with 5 VPs). However, many of the *best instances* have similar accuracy. For example, in Figure 2b, with 5 VPs, the worst instance has errors larger than 4000 km, error in the best instance is less than 42 km, close to the best instance with 50 VPs (about 30 km). (Using *all* 400 VPs is closer still, at about 12 km, so full exploration of all VPs and $80\times$ greater traffic does provide some improvement.) This experiment indicates that if we can select the *right* VP subset, we can achieve fairly good accuracy with just a few VPs.

4.1.3 The Closest VPs Generally Maximize Accuracy

Since we know some combinations of a few VPs provide good results; presumably some VPs provide more information than others. Our final step is to predict which few those are.

Our assumption is that *close* VPs provide stricter constraints than far away VPs. To quantify this intuition, we next explicitly compare VP distance and ge-

olocation error. We fix the number of VPs to 10, drawn from the same 400, and geolocate our 25 targets. We carry out 800 trials, each with a different, randomly selected subset of 10 VPs. In each case, we plot the minimum RTT across all VPs with the geolocation error.

Figures 2c and 3c show our study for a single target (a computer at New York University in New York City, USA). This example is representative of all 25 targets. Each point in the figure represents one set of randomly chosen VPs. The line shows the mean geolocation error for all observations in each 5 ms bin of minimum RTTs.

This experiment shows that geolocation error for Shortest Ping has an almost linear relationship with minimum RTT. For CBG, the linear relation between geolocation and minimum RTT holds when the minimum RTT is small (less than 25ms); for larger values of minimum RTT the relationship is much noisier. The correlation coefficient value is 0.88 for the example with Shortest Ping and 0.71 for the example with CBG. In both graphs, we can see that small geolocation errors usually have small minimum RTTs, supporting our claim that we can select a good set of VPs by estimating the closest VPs.

4.2 VP Selection and Geolocation

From these conjectures we next propose our VP selection algorithm. We work on /24 blocks, typically consider groups of 6 /8s, processing 150k–217k /24 blocks a time to spread load on the targets (Section 4.4). Although we select VPs by only several representatives of the block, we geolocate every IP address in the block with those selected VPs to understand how often and which /24 blocks have multiple locations.

Our algorithm has four steps:

1. Using Internet census histories, select several *representatives* for the block.

2. Probe those representatives from all VPs to *select nearby VPs* for the block.

3. Probe all addresses in the block from nearby VPs to generate *raw geolocation input*.

4. Centralize this input and process it with Shortest Ping (or CBG) to identify *IP geolocation*.

Finding Representatives: We begin by finding representatives for each block. Prior work studied IP hitlists and approaches to select representatives, IP addresses most likely to respond [3]. For geolocation, we *require* at least one representative that responds; we use three to provide some redundancy. If all three representatives do not respond, we just ignore the block. As with hitlist discovery, we use the results of prior IPv4 censuses and the hitlist prediction algorithm to select representatives.
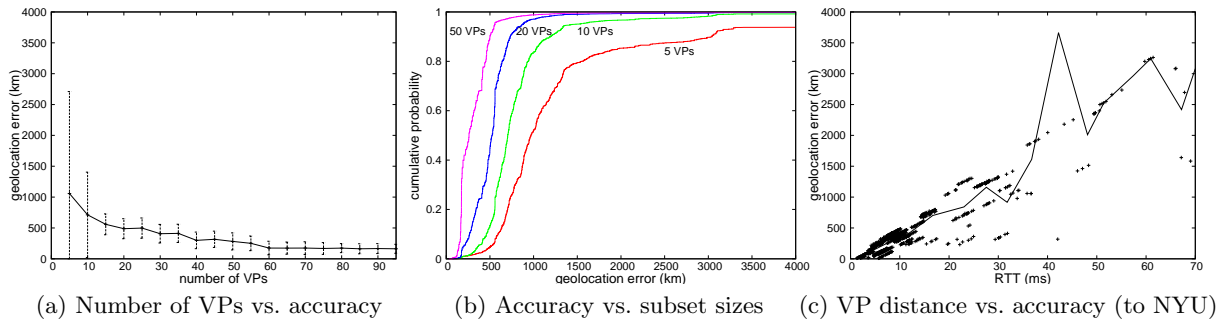
(a) Number of VPs vs. accuracy   (b) Accuracy vs. subset sizes   (c) VP distance vs. accuracy (to NYU)

Figure 2: Evaluation of three conjectures for Shortest Ping.

(a) Number of VPs vs. accuracy   (b) Accuracy vs. subset sizes   (c) VP distance vs. accuracy (to NYU)
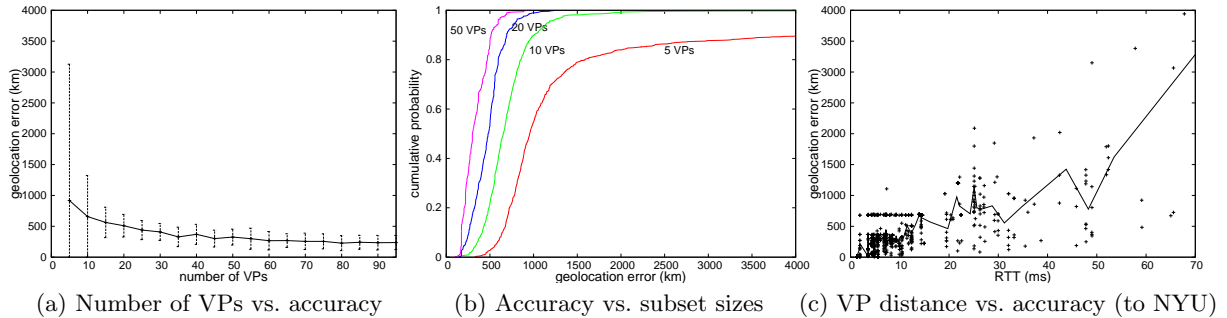
Figure 3: Evaluation of three conjectures for CBG.

Because census histories are public, this step requires no network traffic. We distribute a list of representatives to all VPs for the next step.

Selecting Nearby VPs: To select close VPs, we probe representatives for each block from all possible VPs. With only a few representatives per block, we probe fairly slowly (200 probes/s) in parallel across all VPs. We probe each representative 10 times, typically taking about 16 hours.

We use our own high-rate probing software, first developed for IPv4 census collection [7]. It probes each address on a target list in a pseudorandom order, spreading probes in time and space to minimize impact on the target networks.

After the representatives are probed, we retrieve all data in parallel to a central site. We estimate VP-representative RTT using the second-to-minimum measurement to reduce occasional measurement noise. Finally, we select the closest VPs for each target block.

Given representatives for each block, we centrally compute target lists unique to each VP and distribute them.

Probing Blocks: VPs then probe targets using the same software. We use a higher probing limit of 500 probes/s, since with $85\times$ more targets, traffic to each block is still limited. After probing, we copy the raw geolocation data to a central site.

Retrieving Data and Geolocating: Finally, with the raw data centralized, we first extract second-to-minimum RTT for each target, then run standard Shortest Ping and CBG.

4.3 VP Selection and Accuracy

We next examine how our VP selection affects geolocation accuracy. We know geolocation will have some error; our question is: does VP selection increase that error? We randomly select 18 /24 blocks from our ground truth dataset, each block with about 100 responsive IP addresses. We then compare the distribution of accuracy of 10 VPs selected by our algorithm against use of all 400 VPs, using both Shortest Ping and CBG.

Figure 4 shows accuracy for both Shortest Ping and CBG. For Shortest Ping, accuracy of our 10 VPs is basically indistinguishable from use of all VPs. Median error is 105 km for both 10 close VPs and all VPs. This similarity is because the geolocation algorithm depends only on shortest VPs, but it shows that our assumptions about representatives hold here. For CBG, accuracy of using our selected 10 VPS is slightly worse than using all VPs: median error is 231 km instead of 208 km, 11% worse. We conclude that our approach is successful, adding no or only slight error while using only about 2% the number of VPs.
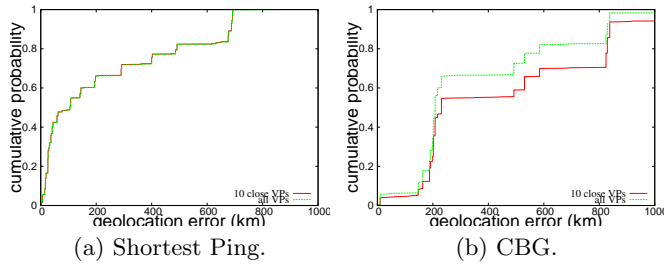
(a) Shortest Ping. (b) CBG.

Figure 4: geolocation error with 10 close VPs VS. with all VPs

4.4 Managing Probing Rates

Our approach must manage probing rate, going as fast as we can (to maximize coherence) but not so fast as to generate traffic that harms or worries the targets. Our main constraint is the amount of traffic arriving at each target. We evaluate incoming traffic per /24 block, with a goal of being no more than the Internet background radiation [16], that is 0.5 to 0.9 packets/s per /24 block. The traffic rate we generate is:

$$addr\_rate = \frac{probes\_per\_VP \times VPs \times tx\_rate\_per\_VP}{target\_blocks \times targets\_per\_block}$$

$$block\_rate = targets\_per\_block \times addr\_rate$$

Since probes-per-VP and number of VPs are fixed, we control our block-rate by capping the transmit rate and increasing the number of blocks. Our probing software sends probes for a given run in a pseudorandom order, so with a fixed transmit rate, adding targets spreads probes out over more time, decreasing the traffic to each target per unit time.

In our current practice we study 393k /24 blocks per run (6 /8s). For VP selection, we probe only 3 targets per block, so we cap each VPs transmit rate at 200 probes/s. With fewer VPs and more targets per block for geolocation we are able to probe at a greater rate of 500 probes/s, so we estimate that each /24 receives at most 0.64 probes/s.

Experimental verification: The above analysis assumes steady state and smooth flow; we expect traffic will be burstier in practice. To verify our analysis we recorded all incoming probes to one target over 16 hours for VP selection and about 12 hours for geolocation.

Because VPs are not synchronized and probe rates vary due to response, we see that traffic is moderately bursty. If we normalize time to one probe per interval, most periods see no traffic and a few see two or three probes. If we project to block probe rates, the mean observed probe rate is 0.13 probes/s (standard deviation: 0.20) during VP selection, and 0.48 probes/s (standard deviation: 0.79) during geolocation.

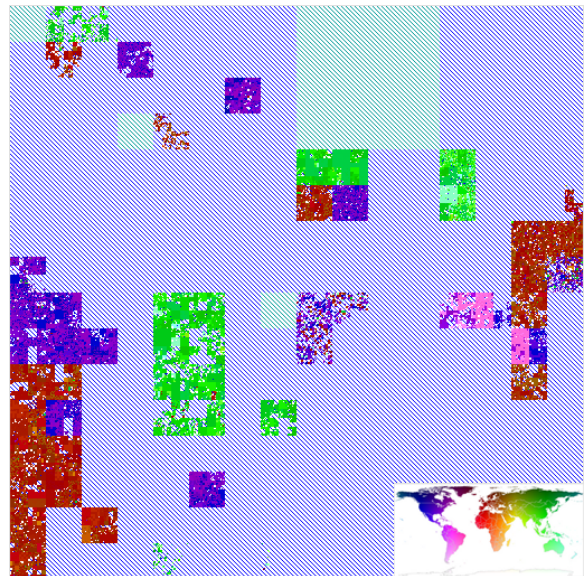Our early use of PlanetLab generated traffic at about

Figure 5: The IPv4 address space placed on a Hilbert curve, with colors corresponding to geolocation (hue follows longitude; lightness, latitude).

double our current rate and drew some complaints. However, after limiting probing as described above, the complaints have stopped.

4.5 Visualization of Geolocation Data

Picturing the results of geolocating the entire IPv4 address space requires new visualization methods. We cannot simply project blocks onto the globe.

Several prior efforts have plotted the IPv4 address space on a Hilbert curve [10, 6, 1, 2]. A Hilbert curve keeps numerically close addresses physically close in two dimensions, and as a fractal it is easy to zoom in or out to control detail. We use it here to show the geographic location of IP addresses, rendering location as color.

To date we have geolocated 54 /8s, about 24% of the allocated, unicast, IPv4 address-space with our proposed techniques. We can only geolocate addresses that respond to probes. From IPv4 censuses we know that those addresses are unevenly distributed; our best estimate is that our progress so far corresponds to about 55% of the addresses in the Internet that can be directly geolocated. Figure 5 shows the map of our geolocation results. Each of the large squares corresponds to a /8 address block (for example, the redish block near the top left is 2/8). The light green hatched regions are private or multicast address space, the blue hatched regions have not yet been geolocated. Areas that have been geolocated are colored by their location; colors are keyed to latitude and longitude, with hue corresponding to longitude and lightness to latitude, as shown in the country color map at the right bottom of Figure 5.

Code for our color conversion function is freely available at our website.

Because of limited resolution, in this figure each pixel is colored to show the mean latitude and longitude of all addresses in a /18 block. We are evaluating different aggregation methods. While using the mean is our current method, we are considering the use of the modal location, the most common value, although that is sensitive to jitter.

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