A Study of Geolocation Databases

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ABSTRACT

The geographical location of Internet IP addresses has an importance both for academic research and commercial applications. Thus, both commercial and academic databases and tools are available for mapping IP addresses to geographic locations.

Evaluating the accuracy of these mapping services is complex since obtaining diverse large scale ground truth is very hard. In this work we evaluate mapping services using an algorithm that groups IP addresses to PoPs, based on structure and delay. This way we are able to group close to 100,000 IP addresses world wide into groups that are known to share a geo-location with high confidence. We provide insight into the strength and weaknesses of IP geolocation databases, and discuss their accuracy and encountered anomalies.

1. INTRODUCTION

Geolocation services have become in the recent years a necessity in many fields and for many applications. While the end user is usually not aware of it, many websites visited by him every day use geolocation information. Some of the common uses of geolocation information is for targeted localized advertising, localized content (such as local news and weather), and compliance with local law.

Perhaps the most highlighted purpose of geolocation information is for fraud prevention and various means of security. Banking, trading, and almost any other type of business that handles online money transactions are exposed to phishing attempts as well as other schemes. Criminals try to break into user accounts to transfer money, manipulate stocks, make purchases and more. The geolocation information provides means to reduce the risk, for example by blocking users from certain high-risk countries, cross-referencing user expected and actual location and more. Organizations that handle national security find geolocation information useful as well, like the DHS cyber security center [37]. Even simple emergency services, such as dispatching emergency responders to the location of emergency use it.

Geolocation information is also important in many research fields. It improves internet mapping and characterization, as it ties the internet graph to actual node positions, and allows exploring new aspects of the network that are otherwise uncovered, such as the effect of ISP location on its services and types of relationships with other service providers.

Many previous papers have discussed the usage of geolocation information in day-to-day applications. They vary in fields from law [22, 43, 44] through information security and fraud prevention [27, 11] to various economic aspects [23, 25]. However, not many works have focused on the accuracy of geolocation databases.

In 2008, Siwpersad et al. [40] examined the accuracy of Maxmind [29] and IP2Location [17]. They assessed their resolution and confidence area and concluded that their resolution is too coarse and that active measurements provide a more accurate alternative. Gueye et al. [15] investigated the imprecision of relying on the location of blocks of IP addresses to locate Internet hosts and showed that the geographic area spanned by blocks can be far larger than the typical distance between any two IPs within a block. Thus it indicated that geolocation information coming from exhaustive tabulation may contain an implicit imprecision.

The IETF has also commenced in defining standards for geolocation and emergency calling. The IETF GEO-PRIG working group [19] discusses internet geolocation standards and privacy protection for geolocation. Some examples are DHCP location, as in RFC3825 and RFC4776, and defining protocols for discovering the local location information server [45].

Muir and Oorschot [31] conducted a survey of geolocation techniques used by geolocation databases and examined means for evasion/circumvention from a security standpoint.

Improving location accuracy by measurements has been addressed by several works in the recent years. IP2Geo [32] is one of the first to suggest a measurement-
based approach to approximate the geographical distance of network hosts. A more mature approach is constraint based geolocation [16], which uses several delay constraints to infer the location of a network host by a triangulation-like method. Later works, such as Octant [16] use a geometric approach to localize a node within 22 mile radii. Yoshida et al. [34] suggested topology based geolocation using link delay to improve the location of nodes. Yoshida et al. [34] used end-to-end communication delay measurements to infer PoP level topology between thirteen cities in Japan. Laki et al. [34] increased geolocation accuracy by decomposing the overall path-wise packet delay to link-wise components and were thus able to approximate the overall propagation delay along the measurement path. Eriksen et al. [7] apply a learning based approach to improve geolocation. They reduce IP geolocation to a machine learning classification problem and use Naive Bayes framework to increase geolocation accuracy.

In this paper we study the accuracy of geolocation databases. The main problem in such a study is the lack of ground truth information, namely a large and diverse set of IP addresses with known geographic location to compare the geolocation databases against. We avoid this need using a different approach, we use an algorithm, whose main features are summarized in Section 3.1 for mapping IP addresses to PoPs (Points of Presence). The algorithm, which is based both on delay measurements and graph structure, has a very small probability to map two IP addresses, which are not co-located, to the same PoP. Thus, while we do not know the location of the PoP we know that all the IP addresses within a PoP should reside in the same location. This serves as a mean to check a geolocation database coherency: if two IP addresses in the same PoP are mapped to different locations the database has a problem, and we can use the distances among the various locations of IP addresses in the same PoP as a measure of database accuracy. The results are presented in Sec. 4.1.

We take a step further and compare multiple databases results for the same PoP (Sec. 4.2). In case a majority of the results in each database are identical we can expect that for each database a majority vote will give us the correct location of the PoP, and the spread of the locations will give us the confidence measure of the result. This will help us to identify cases where a database reports for a large portion of the IP addresses of some ISP the same default location (usually the ISP headquarters).

2. GEOLOCATION SERVICES

Geolocation services range from free services, through services that cost a few hundreds of dollars and up to services that cost tens of thousands of dollar a year. This section surveys most of these services, focusing on the main players.

Free geolocation services differ from one another in nature. Three representative of such sources are discussed here: DNS resolution, Google Gears and HostIP-Info. DNS resolution was probably the first source for geolocation information, being free and available to all users. In 2002 Spring et al. [11] used DNS names to improve location information as part of the Rocketfuel project. The UnDNS tool they provided is still used to uncover location from DNS name. However, DNS suffers from several problems: many interfaces do not have a DNS name assigned to them, and incorrect locations are inferred when interfaces are misnamed [45]. In addition, rules for inferring the locations of all DNS names do not exist, and require some manual adjustments. As part of Google Labs Gears API, Google provides a set of geolocation API [12] that allows to query a user’s current position. The position is obtained from on-board sources, such as GPS, a network location provider, or from the user’s manual input. When needed, the location API also has the ability to send various signals that the devices has access to (nearby cell sites, WIFI nodes, etc.) to a third-party location service provider, who resolves the signals into a location estimate [13]. Thus, the service granularity is based on a single IP address granularity and not on address blocks. HostIP.Info [18] is an open source project, with many of its API contributed by its community. The data is collected from users participating in direct feedback through the API, as well as ISP’s feedback. In addition, website visitors are updating their location, which in turn is updated as a database entry. The city data comes from various sources, such as data donation and US census data (for the USA). The data is provided as /24 CIDR blocks.

Another type of geolocation services emerges from universities and research institutes. These services tend to use measurements, entirely or on top of other methodologies, in order to improve geolocation data quality. While many of the measurement based geolocation services that we discussed in Section 1 do not provide the ability to query specific IP addresses [24] [40] [37], one online geolocation service that does allow it is Spotter [35], which is based on a work by Laki et al. [34]. Spotter uses a detailed path-latency model to determine the overall propagation delays along the network paths more accurately, which in turn translates to more accurate geographic distance estimation. The evaluation process also takes into account the discovered topology between the measurement points, and end-to-end latency measurements as well. One-way delay measurements further increase the accuracy of router geolocation techniques.

Mid-range cost geolocation services include databases such as Maxmind GeoIP, IPiligence, and IP2Location.
All these databases cost a few hundreds of US Dollars and provide the user a full database, typically as a flat file or MySQL dump. Some of the companies, such as MaxMind, also provide a geolocation web service.

MaxMind [29] is one of the pioneers in geolocation, founded in 2002, and it provides a range of databases: from country level to city level, longitude and latitude. Information on ISP and netspeed can be retrieved as well. In addition to all the above, MaxMind suggests to enterprises a database with an accuracy radius for its geolocation information. In this work, the MaxMind GeoIP City database is being used for geolocation information. IPInfoDB [1] is a free geolocation service that uses MaxMind GeoIP lite database and adds on top of it reserved addresses and optional timezone. Hexasoft development maintains IP2Location [17], a geolocation database with a wider range of geolocation information: from IP to country conversion, to retrieving information such as bandwidth and weather. For this study, we used their DB5 database, which maps IP addresses to country, region, city, latitude, and longitude. In all the above products, the IP addresses’ location is given in ranges, which vary in size and reach the granularity of a handful of addresses per range.

High end geolocation services are often priced by the number of queries and their cost may reach tens of thousands of dollars a year for large websites. Amongst these services, and based on their pricing level, are Quova, Akamai Edge Platform, Digital Element’s NetAcuity Edge and GeoBytes. Each of these companies praise themselves with large tier-1 customers from different fields, who use their services for target advertising, fraud prevention, and more.

Quova [2], founded in 1999, provides three levels of data information, bronze, silver, and gold. The advanced services contain attributes such as location confidence level, Designated Market Area (DMA), and status designations for anonymized Internet connections. Quova’s database is based on random forest classifier rules, synthesis rules, approved location labels, hand-labeled hostnames, and research notes, with 6 patents issued and 9 patents pending.

Akamai [3] was founded in 1998 and launched its commercial service in 1999, provides through its Edge Platform product IP location information. Its IP location services are a part of a much larger package of tools and applications used for traffic management, dynamic sites accelerations, performance enhancement and more.

Digital Element [6], founded in 2005, provides under the products NetAcuity and NetAcuity Edge two levels of geolocation information, with over thirty nine data points, including demographics, postal code, and business type. The IP geolocation data source is anonymous data gathered from interactions with users. One source for this user information is partner companies that use the product. The information is validated using a proprietary clustering analysis algorithm. The data collection and analysis are protected by more than 20 issued and pending patents.

GeoBytes [9] launched in 2002 its GeoSelect product, which provides geolocation information. The data provided by GeoBytes matches mid-range companies in its wealth, but it is part of a broader package of services, including reports, users redirection, etc. While in the past GeoBytes used ICMP packets to create an infrastructure map, current methods include also gathering information from websites that require users to enter their location information and then processing this data onto GeoBytes’ infrastructure map of the Internet [30]. No DNS information is used by GeoBytes for their location resolution.

In this work, databases from all three groups are being used. From the no-charge databases: HostIP.info, Spotter and DNS (partial). Mid-range databases used are MaxMind GeoIP City, IPligence Max, and IP2Location DB5. GeoBytes and NetAcuity are the last two databases used in this work. Unfortunately, we failed to reach a collaboration with Quova and Akamai for this project.

### 2.1 Databases Accuracy

The geolocation service provider is, in many cases, the sole source for database accuracy information. Some vendors do not publish accuracy figures at all, such as IPligence, while others provide accuracy figures without explaining how they were obtained. A few geolocation services, such as Akamai and Quova provide accuracy figures obtained by external auditors. Table 1 provides a summary of accuracy figures, as given by the geolocation service providers on their websites [2] [3] [6] [9] [29] [17]. The table includes information on country level accuracy, city level accuracy world wide and city level accuracy in the USA.

All the databases claim to have 97% accuracy or more at the country level and 80% or more at the city level.

| Database  | Country Level | City Level | USA City Level |
|-----------|---------------|------------|----------------|
| IP2Location | 99%          | 80%        |                |
| MaxMind    | 99.8%         | Varies     | 83%            |
| GeoBytes   | 97%           | 85%        |                |
| NetAcuity  | 99.9%         | 95%        |                |
| Akamai     | 99.9%         | 97.22%     | 100%           |
| Quova      | 99.9%         |            | 97.2%         |

Table 1: Geolocation Database Accuracy

†State level accuracy
MaxMind provides detailed expected accuracy on city level based on country [25]. The accuracy ranges from 40%–44% in countries like Nigeria and Tunisia to 94%–95% in countries like Georgia, Qatar and Singapore. An accurate resolution here is considered one within 25 miles from its true location. NetAcuity accuracy figures are based on a test by Keynote Systems, which resulted in an exact match for every IP address at the country level, and state level for those IP addresses located in the United States. At the city level NetAcuity delivered 97% accuracy. Quova’s accuracy figures are based on an audit by Pricewaterhouse Cooper [26], which used 3 reference third party databases. Here 99.9% accuracy was achieved at the country level and 97.2% to 98.2% were achieved at the state level.

The accuracy of the figures in Table 1 cannot be easily evaluated. For example, neither the means by which Keynote Systems tested NetAcuity nor the reference databases used to test Quova are revealed. Akamai claims for 97.2% accuracy at the city level worldwide and 100% accuracy at the city level in the USA. The source for this is a report by Gomez [20], which defined a node location to be unique on /23 CIDR subnets. In addition, a Census Metropolitan Area (CMA) is the basis of the naming convention used by Gomez to identify the physical location of its measurement nodes. The accuracy of this method is thus debateable, as described in Sec. 1.

Assessing the accuracy of geolocation databases is therefore a hard question, since a large scale ground truth does not exist (or is hard to obtain). In this work a structural approach is taken to evaluate the accuracy of databases, gaining greater knowledge on each IP address by locating it as part of a PoP-level map.

3. THE EVALUATION MODEL

3.1 Building PoP Maps

We define a PoP as a group of routers which belong to a single AS and are physically located at the same building or campus. In most cases [20, 14] the PoP consists of two or more backbone/core routers and a number of client/access routers. The client/access routers are connected redundantly to more than one core router, while core routers are connected to the core network of the ISP. The algorithm we use for PoP extraction was first suggested by Feldman and Shavitt in [8] and later improved in [29]. The algorithm looks for bi-partite subgraphs with certain weight constraints in the IP interface graph of an AS; no aliasing to routers is needed. The bi-partites serve as cores of the PoPs and are extended with other close by interfaces.

The initial partitioning removes all edges with delay higher than $PD_{max}^{th}$, PoP maximal diameter threshold, and edges with number of measurements below $PM_{min}^{th}$, the PoP measurements threshold. $PM_{min}^{th}$ is introduced in order to consider only links with a high reliable delay estimation to avoid false indication of PoPs. The result non-connected graph $G'$ contains induced sub graphs, each is a candidate to become one or more PoPs. There are two reasons for a connected group to include more than a single PoP. The first and most obvious reason is geographically adjacent PoPs, e.g., New York, NY and Newark, NJ. The other is caused by wrong delay estimation of a small amount of links. For instance a single incorrectly estimated link between Los Angeles,CA and Dallas,TX might unify the groups obtained by such a naive method.

Next, the algorithm checks if each connected group can be partitioned to more than one PoP, using parent-child classification according to the measurement direction in the bipartite graph. Further localization is achieved by dividing the parents and children groups into physical collocations using the high connectivity of the bipartite graph. If parent pair and child pair groups are connected, then the weighted distance between the groups is calculated (If they are connected, by definition more than one edge connects the two groups); if it is smaller than a certain threshold the pair of groups is declared as part of the same PoP. Last, a unification of loosely connected parts of the PoP is conducted. For this end, the algorithm looks for connected components (PoP candidates) that are connected by links whose median distance is very short (below $PD_{max}^{th}$).

In the original algorithm [8], an additional step was implemented, called Singleton Treatment, in which nodes with only one or two links are assigned to PoPs based on their median distance. This step may add to the PoP IP addresses that are not necessarily part of it. Thus, in this work, two PoP level maps were generated: one map without any singletons, which is considered to be accurate looking at the PoP IP addresses only, and a second map that includes singletons. The aim of the second map is to improve location estimation where PoP location is undetermined based on the first map only. As the singletons are necessarily in the vicinity of the PoP, using them does not harm the locations estimation.

In a previous work [29], the stability and correctness of the PoP extraction algorithm were discussed, as well as the effect of threshold settings. For this paper’s purposes, the thresholds sensitivity should be mentioned, as they may affect the geolocation accuracy. Figure 1 explores the PoP extraction algorithm’s sensitivity to $PD_{max}^{th}$. In the figure five ISPs are explored: Level 3, AT&T, Comcast, MCI, and Deutsche Telekom. The figure presents the number of IP’s included in PoPs when changing $PD_{max}^{th}$. Neither the number of discovered PoPs nor the number of IPs within the PoPs are sensitive to the delay threshold, as long as the threshold is $3mSec$ or above. $PD_{max}^{th}$ was selected to be $5mSec$. 


as it presents a good tradeoff between delay measurement’s error and location accuracy. The number of IPs included in PoPs decreases as the minimal number of required measurements, \( PM_{\min_{th}} \), increases, as can be expected (see [39]). In our extracted PoP maps, \( PM_{\min_{th}} \) was selected to be 5.

### 3.2 Data Evaluation Method

The geolocation databases evaluation is conducted using the classification of IP addresses into PoPs as described above. Since the classification is based on both structure and delay measurements, the chances that two IP addresses, which our algorithm maps to the same PoP, are not located in the same geographical location are slim. We do recognize that when two PoPs are very close (within a few tens of kilometers) our algorithm may unify them to one. However, in this case the median of their location is half their distance, namely not far.

To identify the geographical location of a PoP, we use the geographic location of each of the IPs included in it. As all the PoP IP addresses should be located within the same campus, or within its vicinity if singletons are considered, the location confidence of a PoP is significantly higher than the confidence that can be gained from locating each of its IP addresses separately. The algorithm, introduced in [39], operates as follows:

**Initial Location** Each of the evaluated geolocation databases is queried for the location (longitude, latitude) of each IP included in the PoP. Next, the center weight of the PoP location is found by calculating the median of all PoP’s IP locations. Unlike average calculation, where a single wrong IP can significantly deflect a location, median provides a better suited starting point. Median is certainly not a guarantee for good results. If there is complete disagreement between geolocation databases as for the location of a PoP, e.g., if one of them places all the PoP IPs in London, and the other in New-York, the median may be far away from any of the suggested locations. However, since geolocation databases are typically reliable in country-level assignment, such an example is highly unlikely. We consider this assumption later in section 4.

**Location Error Range** Every PoP location is assigned a range of convergence, representing the expected location error range based on the information received from the geolocation databases. As the PoP location is given as [latitude, longitude], in units of degrees, so does the range of convergence. This stage is done iteratively, looking for a majority vote for the PoP location. For every IP address in a PoP and for every geolocation database we collect the geographic coordinates, thus if there are \( N \) IP addresses and \( M \) databases, and for each of the IP addresses, all the databases suggest a location, then \( N \times M \) IP address elements are being considered for the vote. The algorithm starts at the median location, and checks if there is a majority vote for the PoP location within a radius 0.01 degrees (one latitude/longitude degree is roughly equivalent to 111km). If the circle includes less than 50% of the located IP elements, we continue and increase the radius of the circle, by 0.01 degrees each step, until the PoP location has a majority vote. Alternatively, the algorithm stops when the circle radius reaches a predefined threshold, typically 1 or 5 degrees, which we define as the maximal range of error. If one of the geolocation databases lacks information on an IP address, this IP element is not counted in the majority vote. With a majority vote we ensure most of the geolocation databases agree on the PoP location.

**Location Refinement** After a range of convergence is found, the PoP location accuracy is further improved. A new median location of the PoP is calculated, based only on IP elements that are located within the range of convergence. This ensures that deviations in the PoP location caused by a small number of IP elements outside the range of convergence are discarded, and the PoP is centered based only on credible IP addresses.

The result of the PoP geolocation algorithm includes per PoP the following new parameters: longitude, latitude, range of convergence, the percentage of IP addresses within convergence range out of all IP addresses, and the percentage of IP addresses within the convergence range considering only IP elements with location information.

To validate the PoP geolocation generated maps correctness, results were compared against PoP maps published by the ISPs, such as Sprint [42], Qwest [33], Global Crossing [10], British Telecom [5], AT&T [1], and others. In addition, we reported [39] a limited small
scale testing of the geolocation accuracy based on 50 known university locations. The test was based only on three databases: Maxmind, IPligence and HostIP.info. For 49 out of 50 universities, the location was accurate within a 10 kilometer radius. The last PoP, belonging to The University of Pisa, was located by the algorithm in Rome, due to an inaccuracy in the MaxMind and IPligence databases. Only Hostip.info provided the right coordinates for this PoP. Each PoP location was also validated against its DNS name, whenever a DNS name was assigned to the interface.

3.3 Dataset

The collected dataset for PoP level maps is taken from DIMES [38]. We use all traceroute measurements taken during March 2010, totaling 126.7 million, namely an average of 4.2M million measurements a day. The measurements were collected from over 1750 vantage points, which are located in 74 countries around the world, as shown in Figure 2. About 16% of the vantage points are mobile.

The 126.7 million measurements produced 7.85 million distinct IP level edges (no IP level aliasing was performed). Out of these, 1.3 million edges were measured five times or more, thus above $P_{M_{\text{min},th}}$, and 642K edges had less than $P_{D_{\text{max},th}}$ median delay, and were therefore considered by the PoP extraction algorithm. As described above, two PoP level maps were generated by the PoP extraction algorithm, with and without singletons addition. A total of 3800 PoPs were discovered, containing 52K IP addresses from the first run, and 104K IP addresses from the second run, meaning with singletons. Although the number of discovered PoPs is not large, as the algorithm currently tends to discover mainly large PoPs while missing many access PoPs, the large number of IP addresses and the spread around the world (see below) allow a large scale and meaningful geolocation databases evaluation.

Figure 2 shows the geographical location (as calculated by our algorithm) of the PoPs discovered by the PoP algorithm. The PoPs are spread all over the world, in all five continents, with high density of PoPs in Europe and North America. As can be seen, PoPs are located even in places such as Madagascar and Papua New Guinea, which comes to show the vast range of location information required from the geolocation databases in this evaluation.

The following databases were studied in this work: MaxMind GeoIP, IPligence Max, IP2Location DB5, HostIP.info, GeoBytes, NetAcuity, DNS and Spotter. For most of the databases, the data which was used, was updated on the first week of April 2010. NetAcuity database was obtained on the third week of April and Spotter located the IP addresses during April and the beginning of May 2010.

4. RESULTS

4.1 Basic Tests

4.1.1 Null Replies

The first question asked for each database is "How many NULL replies are returned for IP address queries?". There are four flavors for this question. First it is asked only on IPs which are in the core of the PoPs and then it is asked for all IP addresses, including singletons addresses. As some databases may have better information on end users or access interfaces than on core routers and main PoPs, this can be meaningful. The next observation regards NULL replies that apply to all the IP addresses within a certain PoP: does the database fail to cover a range of addresses or a physical location range, or are the NULL replies a matter of a single IP address lack of information? This too is considered both with and without singletons. Table 2 shows for each of the databases the percentage of IP addresses which returned a NULL reply for each of these questions.

NetAcuity and IP2Location where the only databases to return a reply for all the queried IP addresses. For IP2Location database there are a few hundreds of NULL entries in the entire database (for IP addresses not in this study). This alone does not come to indicate that the returned addresses are correct, only that an entry
exists. The location correctness is discussed later on in this section. On the other end of the scale, HostIP.info failed to locate most of the IP addresses, however on the PoP level this percentage drops by half. It can be assumed that HostIP.info nature of the failure is lack of information on specific IP addresses and not IP ranges. Further more, in most cases HostIP.info does return a reply with country information, but without longitude and latitude. Spotter did not locate about a third of the IP addresses. The reason for such a failure can be either that the IP did not respond to ping or the IP responded to ping, but the roundtrip-times were too high to provide approximations for the algorithm. Only core PoP IP addresses, without singletons, where tested here. For MaxMind, the percentage of Null replies refers to events where no specific location information was available. In most of these cases, MaxMind does return longitude and latitude information, which are the center of the country where the IP is located. A list of these coordinates is available to the users, and though we choose in this work to refer to this information as a NULL reply, a general notion of location is provided by the database. DNS NULL replies are less than 15% for core PoP IP adresses, and almost 29% when taking into account singletons. This is caused mostly due to lack of information on IP addresses, as many PoPs do not have even a single IP with location information inside a PoP. The case of Spotter here is different. As this information is acquired by measurements, having almost a third of the PoPs converge within one kilometer is an indication of good performance. In addition, over 82% of the PoPs converge within 100 km, and close to 98% within 500 km, which is similar or better than most of the other databases. The slow accumulation is expected due to measurements errors. Maybe the most important graph here is the All graph, showing the range of convergence when combining the information from all databases. Though all databases, have most of their PoPs located within the minimal range, less than 30% of the All PoPs converge within this range, meaning that between the databases there is disagreement, though as the range grows so does the percentage of converged PoPs. This does not necessarily mean that all the databases have agreed on the same location, as databases which reply with a location for every IP have more influence that databases

### Table 2: Null IP Address Information

| Database      | Core PoP IP | With Singletons |
|---------------|-------------|-----------------|
|               | Null IP     | Null PoP        | Null IP | Null PoP |
| IP2Location   | 3.0%        | 1.5%            | 2.9%    | 1.4%    |
| MaxMind       | 0%          | 0%              | 0%      | 0%      |
| HostIP.Info   | 84%         | 10.6%           | 64%     | 29%     |
| GeoBytes      | 20.7%       | 4.3%            | 17.8%   | 2.7%    |
| NetAcuity     | 0%          | 0%              | 0%      | 0%      |
| Spotter       | 37%         | 18.1%           |         |         |
| DNS           | 14.3%       | 12.2%           | 28.4%   | 2%      |

### Figure 4: Range of Convergence Within Databases

By nature, IP addresses belonging to the same PoP reside in the same area. One can leverage this information to evaluate the accuracy of a geolocation database: if IP addresses that belong to the same PoP are assigned different geographical location, then the accuracy of this information should be questioned. This statement is based on the assumption that the PoP algorithm is correct and does not assign IP addresses from different locations to the same PoP. We already discussed why it is true based on design and previous limited evaluation. Our experiments here further support the assumption: in all the PoPs evaluated, with no exception, there are always databases that support the PoP vicinity requirement.
with some NULL replies. We further explore this question in section 4.2. An important observation is that even if a certain database indicates that the range of convergence of a PoP is minimal, i.e., 1km, it does not necessarily imply accuracy, or in our case that all other databases will agree with this location.

Figures 5 and 6 present a CDF of the agreement within databases without singletons. The X axis marks the percentage of IP addresses in PoPs that represent the majority, and the Y axis presents the probability for this majority vote. For Figure 5 we set a radius of 100km and in Figure 6 the used radius is 500km, within which a majority is required. In some cases no majority is found, i.e., less than 50% of the IP addresses are within any circle with the given radius. Remember that the algorithm selects in such a case the location based on the largest group of votes.

Note that for all databases there are PoPs that had no majority vote, meaning the locations diverged by more than 100km or 500km. IPLigence and IP2Location have the highest probability to reach an agreement within a PoP, while HostIP.Info, and Geobytes grow at the slowest pace. For a radius of 100km, Spotter does not reach full agreement for almost 60% of the PoPs, probably due to measurement accuracy limitations. Interestingly, for less than 4% of the PoPs there is 100% agreement by all databases, which once again does not correlate with single-database observations and points to a mismatch between databases.

4.2 Comparison Between Databases

4.2.1 Accuracy

So far, we have discussed results that depend only on the database itself. Next we compare the databases based on the data collected from all databases. First, we assess the accuracy of a database by comparing an IP location in every database to the location of its PoP as voted by all databases.

Figure 7 depicts for each database the CDF of the deviation from PoP majority - 500km Range. Figure 8 breaks down the deviation from PoP majority CDF By region - 500km Range.
is a city range, and 500\( \text{km} \) range, which can be referred to as a region. IPligence, MaxMind and IP2Location have a probability of 62% to 73% to place a IP within 40\( \text{km} \) from the PoP majority vote, with IPligence and MaxMind placing over 80% of the IP addresses within 500\( \text{km} \) radius. Geobytes, HostIP.Info and Netacuity place 33% to 47% of the IP addresses within a city range, and 48% to almost 60% within 500\( \text{km} \) from the majority. Spotter places only 10% within 40\( \text{km} \) range and 30% within the same region.

Some of the databases, like HostIP.Info, Netacuity, Geobytes and Spotter, deviate less in Europe than in the USA and the rest of the world, as depicted in Figure 8. Other databases, as IP2Location, have greater deviation in Europe than the rest of the world. For clarity, only two of the databases are shown in Figure 8. A drawback of all databases is that there is a long tail of IP addresses locations which are placed 5000\( \text{km} \) or more from the majority of the vote. Figure 8 shows that in some databases this tail can hold 15% of the IP addresses. Although the majority vote may be incorrect, this points that at least one of the databases is very far off from the real IP address location.

Figure 10 depicts for each database a scatter plot of the range of convergence (X axis) versus the deviation of the IP location from its PoP location based on all databases (Y axis). The figure demonstrates that in many cases the range of convergence is small, yet the deviation from the PoP majority location is very large. This can indicate, as is demonstrated next, that large groups of IP addresses are assigned a single false location.

For MaxMind and HostIP there are many PoPs at the far end of the graph, with a large range of convergence. This is caused by lack of information on specific IP addresses which does not allow them to reach a majority vote. Netacuity and Spotter demonstrate a scattered behavior, meaning the range of convergence and the deviation from the PoPs majority both change. For Netacuity this means that IP addresses are assigned distinct locations within the same area, as with different users in the same city. Spotter suffers from large range of convergence for some PoPs due to NULL replies, however there is an obvious trend that places most PoPs IP addresses within 300\( \text{km} \) range from each other, with a small number scattered at larger range of convergence, as can be expected in a triangulation based method.

### 4.2.2 Correlation Between Databases

While some of the databases have proprietary means to gather location information, a large portion of geolocation databases is likely to come from the same source, such as getting country information from ARIN. To examine this theory we calculate the cross correlation between every pair of databases, on the entire IP address location vector, and display it as a heatmap, shown in Figure 11.

The strongest correlation is between IPligence and
IP2Location. As was shown in previous results, the trends of these two databases look very similar. The correlation between these two databases is over 0.99. Maxmind and HostIP.Info also have very high correlation with IP2Location and IPligence as well as between themselves. The correlation figures above do not take into account NULL replies. Considering those, IPligence’s and IP2Location’s correlation with Maxmind drops to 0.8 and with HostIP.Info below 0.6. Comparing all the databases, Netacuity and Geobytes correlate the least: 0.89. Spotter has over 0.94 correlation with most databases, expect Geobytes, with 0.97 correlation to Netacuity. Considering that the location given by Spotter is never a landmark, rather a result of delay measurement, this is a high figure. The high correlation between the databases indicates that in most cases the location addresses returned by all the databases will be very much alike. In cases where it is difficult to obtain the location address, the answers may vary significantly between services.

4.3 Database Anomalies

Though the results above may indicate that some databases have superb location information, this is not the case. In many cases the returned data is deceiving, and actually may represent lack of information in the database. For example, we identified 266 IP addresses in the PoPs that belong to Qwest Communications. Out of those, 253 IP addresses are located by IPligence in Denver, Colorado. Looking at the raw IPligence database, there are 20291 entries that belong to Qwest communications. Out of those, 20252 are located in Denver, which is the location of Qwest’s headquarters. The phenomenon was first detected by our algorithm last year, in July/2009: 70 Qwest PoPs where detected. Maxmind assigned them to 55 different locations, HostIP.info to 46 locations, IP2locations to 35 locations and IPligence located them all in Denver. In response to a query back then, IPligence have replied that "In some occasions you could find records belonging to RIPE or any other registrar, these are most likely not used IP addresses but registered under their name, anything else should be empty or null".

Quite a similar case exists with IP2Location. For Cogent, 2365 out of 2879 IP addresses were located in Washington DC, which is Cogent’s headquarters location. Out of 57 PoPs belonging to Cogent, only one was not placed by IP2Location in these exact same coordinates. For IPligence, all the PoPs were located in the same place, too. However, Maxmind placed the PoPs in 13 locations, Geobytes in 23 locations and Netacuity in 31 locations (only a handful in Washington’s area). In the Akamai audit by Gomez [20] a similar case is described: A node in Vancouver, Canada was reported to be in Toronto, and a node in Bangalore, India was reported to be in Mumbai. In both cases those were ISP headquarters known locations.

Sometimes differences between databases may be very acute, with a reported node location being far off by thousands of kilometers and even countries far apart. In Figure 12 one such example is shown. We take a 4-nodes PoP in ASN 703 (Verizon/ UUNET / MCI Communications) and display on a map the location of the PoP based on each of the geolocation database. IPligence, IP2Location, Geobytes, Netacuity and DNS all internally have the PoP four IP addresses at the same location, however each of the databases locate it differently: IPligence and IP2Location in Australia, Netacuity and DNS in Singapore and Geobytes in Afghanistan. MaxMind and Spotter lack information on these nodes and HostIP.Info places the PoP with 66% certainty in China. Extending our PoP view to include singletons, thus including 10 nodes, the picture does not change. MaxMind and Spotter have location on one of the IPs and they place it in Singapore. IPligence and IP2Location place 9 out of 10 IPs in Australia, and one in Singapore. Geobytes places this last IP address in Singapore too, yet 6 out of 10 IP locations still point to Kabul. The rest three nodes are located in Australia. Geobytes does give low certainty rate to the location, being 50 or less to both country and region. Netacuity places 8 out of 10 IPs in Singapore and 2 in Australia. HostIP.Info has location information on 6 IPs, 3 of them are placed in China and 3 in Australia, but in Melbourne, far from IPligence and IP2location designated location. Notably, all the edges in this PoP have less than 3.5mS delay and are measured five to 173 times each.

The mismatch between databases is not uncommon. Some examples exist inside the United States, too: in Figure 13 we show one PoP in ASN 3549, Global Crossing, as it is placed by the different geolocation databases across the country. This PoP has over 160 IP ad-
addresses, counting singletons, and as such a majority in each database has more substance. IPligence places the PoP with more than 90% majority in Springfield, Missouri. MaxMind and IP2Location point to Saint Louis, Missouri with 92% and 82% accordingly. NetAcuity indicates that the PoP is in San-Jose, California with 100% certainty, while DNS and Spotter place the PoP in this vicinity, in a radius of a few tens of kilometers. GeoBytes has somewhat above 59% of the locations pointing to New York, with other common answers being spread across California (25%). GeoBytes country certainty here was 100% with 42% region certainty for the IP addresses it located in New York. HostIP.Info placed the PoP in Chicago with 65% majority (28% of the locations had pointed to Santa Clara, California).

The above are not single incidents. Similar cases have been found in other AS as well, such as REACH (AS 4637), where IPligence, IP2Location and Maxmind located a PoP in China, GeoBytes located it in Australia, while NetAcuity and Spotter put it in the silicon valley, USA. Other cases range from AS16735 (CTBC/Algar Telecom) where PoP locations in Brazil were set thousands of kilometers apart, to Savvis (AS3561) which is another case of locations spread across the USA.

4.4 Database Changes

One of the motivations to update geolocation databases is the claim that they change significantly over time. Maxmind [29] claim that it loses accuracy at a rate of approximately 1.5% per month. IP2Location [17] state that on average, there are 5%-10% of the records being updated in the databases every month due to IP address range relocation and new range available. Based on the PoPs dataset, we compare this information versus the databases at our disposal. For IPligence, an average of approximately one percent of the addresses changes every month, with some minimal changes in some consecutive months, such as 0.6% between November and December 2009. In HostIP.Info, 18% of the IP addresses changed their location within nine months, meaning an average of 2% a month. IP2Location changed only 1% of the locations over 4 months, meaning 0.25% per month, however the reference set here included only 10K IP addresses. For Netacuity, running only on our dataset of 104K IP addresses, we observe that 2.4% of the IP addresses have changed in less than a month.

5. DISCUSSION

Interpretation of the results in Section 4.2 should be done with care. Placing a PoP at the majority center of gravity may not always yield the true results, e.g., in cases where a single wrong information source is used by multiple databases.

IPligence and IP2Location share several similar characteristics as well as strong cross correlation. This is exhibited by the high probability for a small range of convergence and by the fast rate their probability grows to reach a high level of agreement. However, the various anomalies found in their databases shed a different light on these results. For example, if for a certain ISP all the IP addresses are assigned to a single location, then the immediate effect will be a small range of convergence and high level of agreement. Further more, lack of NULL replies in this case may be misleading as the returned reply may be false. As in the cases of MCI/UUNET and Global Crossing, as well as other investigated cases, IP2Location and IPligence located IP addresses far from Spotter’s estimated location, it is likely that their geolocation information, in these cases, was wrong.

Judging MaxMind performance has to be done carefully, as they do not claim to have high accuracy for router interfaces. This is manifested in the high number of returned NULL replies. MaxMind seems to have a lot in common with IPligence and IP2Location, as the cross correlation shows, however unlike these databases MaxMind prefers to return NULL or country center reply when a location is unknown and thus returns less false locations.

We find it hard to analyze GeoBytes performance.
The database returns relatively a lot of NULL replies, which are significantly reduced by PoP level aggregation. Further more, the granulality of the database is /24 CIDR, thus grouping every 256 address block to a single location. Though this is a common practice, it has some degradation effect. The oddity here is that there are many cases where the range of convergence is about 250km, which means the database located the IP addresses within each others’ area, but did not consider them to be at the exact same city. However, as Geobytes indicate that they focus on the service area of a PoP rather then the location of that PoP, this can be expected. An advantage of Geobytes is that no assignment to a single location or ISP headquarters were detected so far.

The main drawback of HostIP.Info is the lack of information. As most of the IP addresses and over a third of the PoPs did not have any location information, the knowledge gained on this database is limited. The limited location information led HostIP.info to perform worst on almost all test cases. In addition, in more than a single case the location information indicated by the database was far off from any other database or measurement based location.

Netacuity is probably the most expensive and highly claimed database used in this research. The results of the tests however may not stand up to expectations. Though one may assume that majority location is affected by errors in other databases, it can be expected that when compared to itself the performance will be high. The results show that for over 40% of the cases, same PoP IP addresses are not all located within 100km radius, which is in fact 200km diameter, and close to 20% are not located within 500km radius either. The strength of Netacuity is that ISP IP addresses are rarely assigned to a single location, unless this is indeed a true single place. In addition, in the several anomalous cases that were investigated, Netacuity majority pointed to the most probable correct location. Note that a minority of IP location votes still pointed to different locations, even in different countries.

5.1 Active Measurement Accuracy

Active measurements are used by many geolocation services [24, 46, 35] and by other projects for different localization tasks, most notably for assigning IP addresses to PoPs [11]. Spotter geolocation is based solely on active measurements, thus we selected to study its performance to a greater depth due to the importance of understanding the limitations of this approach.

Figures 14 and 15 show Spotter’s overall performance compared with its performance for PoPs located only in Europe or in the USA. It is clear from both figures that in Europe Spotter perform much better than in the USA and slightly better than the world average. For example, for 40km radius (which is frequently used as a city diameter) Spotter reach about 78% convergence in Europe compared to 67% convergence worldwide, and only 44% for the USA. The difference can be explained by the spread of vantage points used by Spotter, which are almost entirely based on PlanetLab nodes. While in Europe PlanetLab nodes are well spread geographically, in the USA, most PlanetLab nodes are located along the coasts making localization of IP addresses in the middle of the USA less accurate. Interestingly, other databases which are based on other means also achieve better results for European addresses than for USA addresses (see Fig. 16).

Spotter convergence (Fig. 4) starts as the lowest which is an outcome of the measurement error that tend to spread the results for different IPs around the ‘true’ location. However, at a radius of 100km it closes the gap with most databases and reaches over 80% convergence (and close to 90% for Europe). However, 20% ‘error’ may make distance measurements unfit as the sole method for assigning IP address to PoPs.

6. CONCLUSION

This paper presented a comprehensive study of geolocation databases, comparing a large number of databases

*We consulted Peter Haga and Peter Matray from the Spotter project on this aspect.
of different types. The results show that while some of the databases provide results that are well aggregated and have a small number of NULL replies, the accuracy of the returned location cannot be trusted. There is a strong correlation between all databases, which indicated that the vast majority of location information replies are correct. However, in some cases there are errors in the databases in the range of thousands of kilometers and countries apart. The use of geolocation database should therefore be careful and its information cannot be considered as ground truth.

Our results also show that measurement based geolocation can achieve good results that compete with geolocation information gathered by other means and that the achieved accuracy of geolocation using such tools can be fairly high. However, this accuracy may not be high enough to be used as the sole tool to map IP addresses to PoPs. Future research in this field should focus on means to decide on ground truth when there is a disagreement between the databases.

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