This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE INFOCOM 2010 proceedings

On the Diversity, Stability and Symmetry of End-to-End Internet Routes

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***Abstract*—The diversity of end-to-end (e2e) Internet routes has been studied for over a decade, dating back to Paxson's seminal work from 1995. This paper presents a measurement study of this issue and systematically evaluate the diversity of the Internet routes, while revisiting some of the conclusions previously made. Two large scale experiments are used for evaluation, one executed in late 2006 and the second in early 2009, both employ a set of more than 100 broadly distributed vantage points, actively measuring between each other.**

We find that although e2e routes are quite diverse, they are relatively stable, albeit with high variance between different vantage points, with strong dependency on the network type (academic vs. commercial). We show that while routes are mostly asymmetric, at the country level, which serves as a good indication for end-to-end propagation delays, the routes are highly similar. Finally, longitudinal analysis shows consistency of the diversity and stability, indicating trade-offs between the Internet growth and changing trends in its connectivity.

I. Introduction

The Internet has evolved rapidly in recent years and has grown to become an extremely complex communication network. This complexity resulted in work that attempt to quantify various aspects of the diversity, stability and symmetry of end-to-end (e2e) routes. These include both active measurements [12], [13], [11] and passive BGP collection [14], [7] techniques. Paxson [12] was the first to study this problem. However, this was done over a decade ago with data collected from a set of vantage points (VPs) that were mostly distributed in academic networks. Since then, the Internet has grown significantly, requiring more expert knowledge from operators which, when not available, results in routers misconfiguration which in turn causes various pathologies and instabilities [9]. Moreover, load-balancing devices and hot-potato routing are now more commonly deployed, resulting in an even harder to follow routing schemes.

In this work we perform a systematic analysis of several aspects of e2e diversity and stability in the Internet. We first introduce the methodology used to quantify diversity, based on detecting a set of dominant routes between a source and a destination hosts, quantifying their prevalence and comparing it to the remaining non-dominant routes. Several aspects of stability are analyzed – (a) the hop level, at five levels of granularity – IP address, IP prefix, autonomous system (AS), city and country; (b) symmetry of instability, i.e., how similar are the instabilities of a given pair when looked at in opposite directions, and (c) variations in observed stability as measured from different geographical locations and different AS types.

We evaluate these measures by conducting two large-scale experiments in late 2006 and in early 2009. Driven by the conclusions of Teixeira *et al.*[17], we use various techniques to extensively probe the diversity of routes. First, we use DIMES [15], a highly distributed community-based measurements infrastructure, to run two 96-hours experiments, using over 100 actively measuring VPs, located in a broad set of ASes and geographical locations. Each experiment provides us with more than 100k e2e routes. To avoid possible measurement artifacts, the data was filtered, resulting with 96 traceroute measurements per pair, using both ICMP and UDP protocols. Additionally, the ports in UDP packets were constantly changed to "induce" both per-packet and per-flow load-balancing, allowing us to detect hidden links.

The contributions of this paper are threefold. First, we use a distributed approach with a broad set of VPs located in end-user, commercial and academic Internet. Second, the two experiments spaced almost 3 years apart, give us the ability to perform a longitudinal analysis of the diversity and stability and observe changes resulted by the evolution of the Internet. Finally, analysis of routes with evidence to load-balancing devices is performed as an attempt to differentiate between diversity and instability.

Evaluation shows that the Internet e2e routes are diverse but relatively stable, with high variance between different VPs, strongly biased towards network type (academic vs. commercial). We show that stability properties are consistent for routes in opposite directions, i.e. routes are either both stable or unstable in opposite directions. We further show that while routes are asymmetric in most levels of aggregation, at the country level, which serves as a good indication for e2e propagation delay, routes are highly similar. Finally, longitudinal analysis shows that diversity and stability are consistent, indicating trade-offs between the Internet growth and changing trends in its connectivity.

II. Related Work

The diversity and stability of e2e routes has been studied for over a decade. Paxson [12] was the first to study the stability of e2e routes by conducting active probes from 37 VPs, back in 1994 and 1995, and found a relatively stable Internet. Our experiments differ from Paxson's since we use a broader set of VPs, fixed time interval between probes as opposed to exponentially distributed inter probe spacing, and attempt to probe the complete set of possible routes, whereas Paxson defined these per-packet fluctuations as pathologies.

He *et al.*[5], [6] found relatively low levels of routing asymmetry in the AS level, with a few end-points consistently being members of asymmetric pairs. Rexford *et al.*[14] further discovered that popular prefixes have an outstanding routing stability. Pathak *et al.*[11] focused mainly on the delay properties and found a strong correlation between changes in the one-way delay and a corresponding route change.

Labovitz *et al.*[7] studied AS-level routing instability in the Internet core using BGP updates and discovered that instability is equally spread across ASes and prefixes.

This paper extends and revisits existing work by leveraging a broad set of VPs located in a variety of networks that manage to capture the diversity of routes, contributing to better understanding of the stability and symmetry of routes.

III. Methodology

A. Definitions

Quantifying the diversity and stability of e2e routes begins with an input data of P of pairs, each $P_i = \{S_i, D_i\}$ is comprised of a source host S_i and destination host D_i. For each pair P_i, the set of traceroutes is partitioned into k_i equivalence subsets (i.e., any two traceroutes in each subset are the same). We denote the set of subsets by E^i. The exact method used for comparing traceroutes in order to group them is discussed later. The size of the subset $|E^i_j|$ is the total number of traceroutes that are contained in it. For a given pair P_i, each equivalence subset $E^i_j, 1 \leq j \leq k_i$ is represented by a single route $R(E^i_j)$ which represents a measured path between the source and the destination.

For each pair P_i we define the *dominant route* as the route $R(E^i_j)$ whose subset size, $|E^i_j|$, is the largest. This definition differs from [13] that defined the dominant routes as those that occupy a given significant fraction of the total duration. When several equivalence subsets have the same size, they are all considered dominant. The dominant route is determined in the IP level, but is used for all other levels as well. For brevity, we assume for now that each pair has only a single dominant route $R(E^i_r)$.

B. Measurement Setup

The data used in this paper was obtained from DIMES [15], a community-based Internet measurements system. DIMES performs active measurements using hundreds of software agents installed on users' PCs. For the purpose of this paper we performed two similar experiments that took place in December 2006 and April 2009. In each experiment, we selected over 100 globally distributed agents and designed 96-hours experiments in which each agent executed UDP and ICMP traceroutes to all other agents in a round-robin fashion. An agent probes each IP address roughly twice every two hours and repeat the same script for four days, yielding over one million traceroutes.

In order to capture path diversity, UDP traceroutes use per-packet port alternation and ICMP traceroutes have the sequence field modified per packet. This induce per-flow balancers and per-packet balancers to route the packets through different routes [3]. It should be noted that user applications usually generate packets in consistent flows [2], therefore this paper manages to capture route diversity but over-estimates user perceived instability.

C. Comparing Routes

Creating the equivalence set of traceroutes E^i requires the comparison of traceroutes. We check equality of two traceroutes using a simple hop-by-hop comparison of all hops in the traceroutes. In case we reach an unknown hop (marked by '*'), we refer to it as a "wild-card", meaning it matches any IP in the second traceroute. For example, the traceroutes (A,B,C) and (A,*,C) are considered equal, but are not considered equal to (A,C). This comparison method mandates that any two traceroutes in a given equivalence set E^i have the exact same length, with exact same hops, up to the unknowns. Since the number of unknown hops in the traceroutes is relatively low (on average, 1–2 unknown hops per traceroute after filtering) we flag an arbitrary traceroute in each equivalence set as the representative route for that set $R(E^i_j)$. Once selected, each representative route is resolved to higher levels of granularity.

To quantify the difference between two routes (at any level) we calculate their Edit Distance [8] (ED) value by counting the minimal number of insert, delete, and modify operations that are needed in order to make the two routes equal. Since ED is highly correlated with the length of the routes that it is calculated on, we normalized it by the length of the longest route of the two input routes (see Eq. (1)). This technique is an extension of the one described by He *et al.* [5] who used it for quantifying AS-level asymmetry, whereas we include stability issues at the various levels of granularity.

$$\widehat{ED}^i_{jk} = \frac{ED(R(E^i_j), R(E^i_k))}{\max\{|E^i_j|, |E^i_k|\}} \quad \forall j \neq k \tag{1}$$

Since the ED cannot be greater than the longest route, the normalized ED value is between 0 and 1, where 0 means that the two routes are identical and 1 means that they are completely different.

D. Quantifying Route Stability

We use two methods for quantifying the stability of a route. The overall appearance ratio (i.e., prevalence [12]) of a route $R(E^i_j)$, in pair P_i is the relative number of traceroutes in the set E^i_j (see Eq. (2)). The prevalence of the dominant route $R(E^i_r)$ is used as the first indication to the stability of routing for each pair.

$$Prevalence^i_j = |E^i_j| \Big/ \sum_{j=1}^{k_i} |E^i_j| \tag{2}$$

Second, for a pair P_i we find the normalized ED between the dominant route, $R(E^i_r)$, and all other non-dominant routes,

$R(E_j^i), j \neq r$. For pairs that have more than a single dominant route, we calculate the smallest normalized ED for each non-dominant route (i.e., using the dominant route that is closest to it in number of hops). We define the *Route Instability Measure* (RouteISM) of a pair as the weighted average of all normalized ED measures as depicted in Eq. (3). Thus, an ISM value close to 1 indicates high instability.

$$RouteISM_i = \sum_{j \neq r} \left(|E_j^i| \cdot \widehat{ED}_{jr}^i \right) / \sum_{j \neq r} |E_j^i| \qquad (3)$$

We use the RouteISM to quantify instabilities at the various levels of granularity by simply applying the normalized ED on depreciative routes that are resolved to higher levels. For example, we calculate $RouteISM_i^{AS}$ using the normalized ED between all non-dominant AS-level routes $R^{AS}(E_j^i), j \neq r$ and the dominant AS-level route $R^{AS}(E_r^i)$.

In previous work, He *et al.* [5] used string matching, a technique similar to our proposed ED. Pucha *et al.* [13], [11] defined a similarity coefficient for calculating AS level route symmetry as the number of similar elements divided by the total number of distinct elements in the two routes. We follow the first since ED better captures stability, as it takes into account the *order* of elements in each route.

RouteISM is used in conjunction with the prevalence of the dominant route, since RouteISM captures the "noise" that exists due to the existence of non-dominant routes. Consider the following two examples: in the first a pair that has a dominant route with high prevalence and high RouteISM and in the second a pair that has a dominant route with low prevalence and low RouteISM. These two routes are stable in different ways – the first is dominated by a single route but the non-dominant routes are very "noisy", while the other has many different routes but they are all quite similar. The combination of the two definitions can capture a view of stability which is more comprehensive than existing work.

E. Symmetry Analysis

Measuring between VPs enables us to do symmetry analysis of e2e routes. We study two measures of symmetry. First, we compare the instability measures of each pair as seen in opposite directions. This is done by taking the absolute value of the Route ISM difference between the opposing pairs Route ISM values, hence referred to as *Differential Route ISM*. This measure enables us to assess whether instabilities are consistent when looking at opposite directions.

Second, the dominant routes in opposite directions are compared by calculating the Route ISM between them. For each pair P_i, we find its symmetric opposite pair P_j and calculate the *SymRouteISM* as the normalized ED between the dominant route $R(E_r^i)$ and a reversed order $\overleftarrow{R}(E_r^j)$ as shown in Eq. (4).

$$SymRouteISM_i = \widehat{ED}(R(E_r^i), \overleftarrow{R}(E_r^j)) \qquad (4)$$

IV. Dataset Analysis

A. Distribution of VPs

In the 2006 experiment, 113 agents returned slightly more than a million traceroutes, providing us with 7040 source-destination directed pairs (an average of 142 measurements per source-destination pair). Most VPs are distributed in the USA and Canada (79), followed by West Europe (16), Russia (6), Australia and New Zealand (10) and Israel (2). In the 2009 experiment, 107 agents returned 1.05 million traceroutes, resulting in 10408 source-destination directed pairs (an average of 101 measurements per source-destination pair). VPs are distributed in numerous countries in West Europe (49), USA and Canada (35), Israel (9), Russia and the Ukraine (5), Australia (3), South America (3), and Far-East (3).

In both experiments, measurements were performed from a diverse set of VP types. Each VP was classified [4] as a large ISP (t1), a small ISP (t2) or an academic network (edu). Over 80% of the VPs in 2006 and 70% in 2009 were of type tier-2, while 16% of the VPs in 2006 and 7% in 2009 were tier-1. 48% of the agents that participated in the 2009 experiment were in academic PlanetLab nodes, providing us the ability to study the difference between the academic Internet and commercial Internet, as described in Sec. V-B.

The churn in the availability of DIMES agents resulted in only 15 VPs that appeared in both experiments. Additionally, measuring e2e routes between roughly 100 VPs is surely not a complete probing of the entire Internet, which contains over 25k ASes. However, since both experiments traverse a wide range of AS types and geographical regions, the results represent the broader Internet and comparing between the results can indicate the way its evolution affects diversity, stability and symmetry.

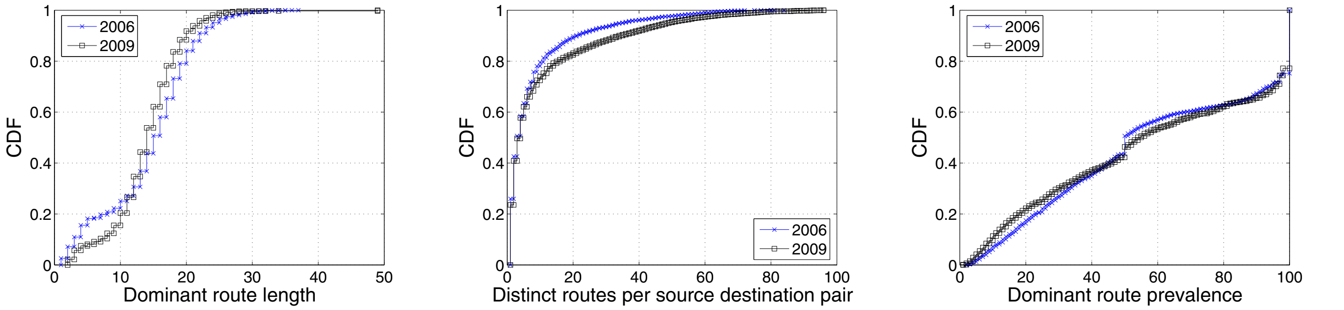
B. Data Filtering and Processing

Raw traceroute data is filtered by removing traceroutes that have only non-routable IP addresses. Additionally, to avoid any kind of measurement artifact we removed all traceroute pathologies [2], including repeating IPs, IP-level and AS-level loops. After filtering, roughly 400k traceroutes remained in 2006 and 800k in 2009. This extensive filtering guarantees that most, if not all anomalies caused by the traceroute process itself are mitigated from the dataset.

AS resolution is done using longest-prefix-matching against BGP announcements obtained from the RouteViews [18] archive (which resolves approximately 98% of the IP addresses) and two WhoIs databases, RIPE and RADB (resolves additional 1.5%). The remaining 0.5% unresolved IP addresses are discarded. Geographical resolution is achieved using the commercial MaxMind [10] database, and the few unresolved IPs were resolved manually using WhoIs databases.

C. Dataset Statistics

In both experiments, a variety of ASes were traversed (121 in 2006 and 195 in 2009). The majority of ASes are tier-2 (63% in 2006 and 60% in 2009), followed by tier-1 (28% in 2006 and 18% in 2009). In 2006 almost all agents resided



(a) Dominant route length (b) Distinct routes per pair (c) Dominant route prevalence

Fig. 1. Analysis of route statistics of the two experiments, showing (a) number of dominant routes per length, (b) the number of distinct routes per pair, and (c) the prevalence of the dominant route

in commercial ASes (109 out of 113 agents), while in 2009 new agents were installed on PlanetLab nodes, resulting in a significant increase in the number of academic ASes that were traversed in the 2009 experiment, reaching from 2% in 2006 to 13% in 2009.

The distribution of dominant route length is shown in Fig. 1(a). The figure shows that 2006 and 2009 experiments have roughly the same path lengths, with 2009 having slightly shorter routes. The median of the dominant route length is 14 for 2006 and 15 for 2009, while the majority of the routes (96%) traverse less than 25 hops. Interestingly, this result is remarkably similar to the one found by Paxson [12] in 1995, who found the mean route length to be between 15 and 16. Since the Internet has been growing at high rate since 1995, we assume that this relatively constant IP-level diameter is a result of richer connectivity among ASes and increased adoption of layer-2 tunnels, which can significantly reduce the number of IP-level hops.

V. Results

A. Diversity and Stability

Fig. 1(b) and Fig. 1(c) depict the diversity and stability by showing the number of distinct routes per pair and the prevalence of the dominant route. The figures show that roughly 25% of the pairs in both years have exactly one dominant route, which constitute to 100% prevalence of the dominant route. In both years, roughly 30% of the pairs have witnessed more than 10 different routes. Having less distinct routes in 2006 than 2009 is mostly attributed to the smaller set of measurements.

These results present a higher level of stability than the one reported by Pucha *et al.* [13]. The authors performed a longer experiment (20 days) with different probing policy (every 20 minutes probe all destinations), and showed that only 6% of the pairs witnessed exactly one route and 20% of the pairs witnessed 12 or more unique routes. However, as the experiments extend to longer time frames, the chances to see the exact same route over the entire duration decrease.

Fig. 1(b) shows that there are a few pairs that have over 90 different routes (out of the 96 possible routes per pair). Carefully examining these routes revealed that they are quite long (20–30 hops), traverse several ASes (over 6) and almost all ASes use different IP addresses along the different routes. These are clearly cases of heavily load-balanced routes, where a packet can traverse many different possible routes. Notice, that most applications will usually not sustain such high level of instability as they usually use consistent flows, however, since we analyze route stability and not flow stability, capturing these routes is needed.

In his 1995 experiment, Paxson [12] found that 30% of the pairs had a dominant route with prevalence of 60% or less with a median value of 82%. In our measurements, dominant prevalence of 60% or less is accounted for roughly 55% of the pairs, and the median has 50% in 2006 and 55% in 2009. This indicates a much lower stability than reported by Paxson. We attribute this to our broader set of VPs, in both the commercial and academic Internet, while Paxson measured mostly from academic networks (see Sec. V-B for discussion on measurement bias). Furthermore, the Internet has significantly evolved since 1995, which causes increased instability of routes.

Fig. 1(c) shows a clear 8% increase in 50% prevalence and a smaller increase in 25% prevalence. These can be explained by the common use of load-balancers that split traffic between two routes (50%) or four routes (25%), or by prolonged route flaps caused due to routing changes [19]. Augustin *et al.* [3] showed that 39% of their measured routes were load-balanced per-flow, and only 1.9% were load-balanced per-packet. Our experiments capture a mixture of the two. UDP traceroutes use changing port number, which causes load-balancers along the path to classify them into different flows and switch routes. ICMP traceroutes are balanced by per-packet load-balancers.

The 2006 and 2009 experiments exhibit similar diversity and stability properties. We assume that this is the result of a trade-off between the increasing topology size of the Internet and usage of load balancers, and on the other hand, the adoption of tunneling technologies that result in shorter and more stable IP-level routes.

Fig. 2(a) and Fig. 2(b) show the distribution of RouteISM in 2006 and 2009 respectively. The figures clearly show that the IP-level hops are the least stable. Additionally, for almost all

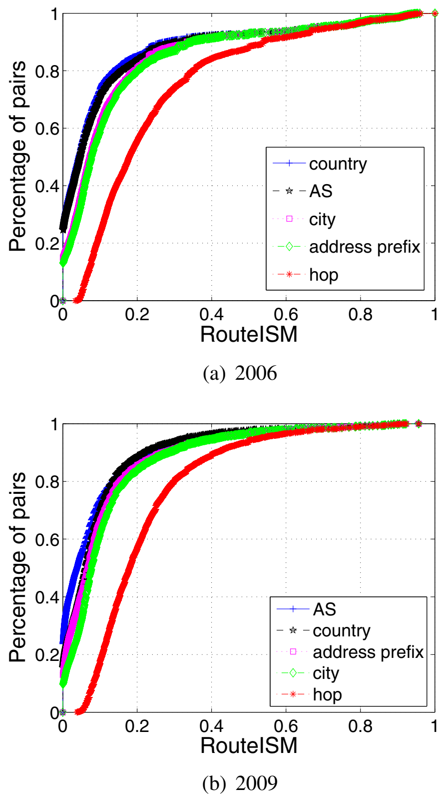


Fig. 2. Cumulative distribution of RouteISM

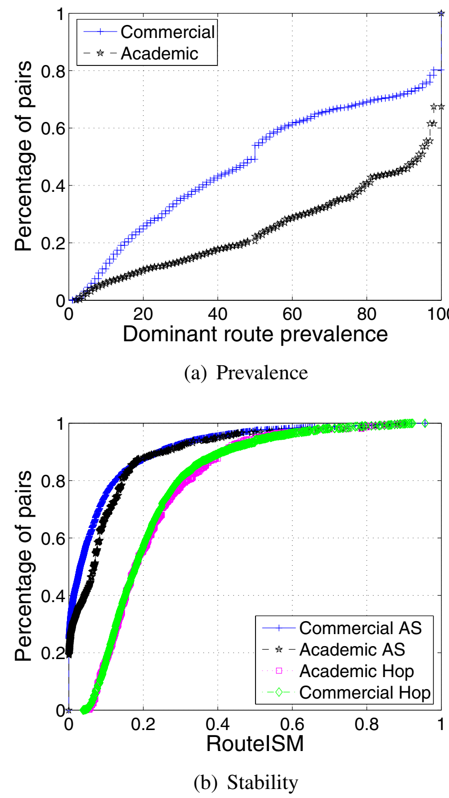


Fig. 3. Stability of academic and commercial pairs using the 2009 experiment

levels, but most obvious for the IP-level, the 2009 experiment witnessed higher stability. This indicates that although the Internet is increasing in topology size, the overall stability slightly improves over time.

B. Stability Measurement Bias

The stability which we measure can be biased due to several causes. Academic networks are reported [16], [11], [6] to be more stable than the commercial Internet. Additionally, measuring between different geographical locations can contribute to instability due to extreme physical paths lengths. The analysis in this section is performed only with the data from 2009, since it provides us with higher geographic and type diversity of VPs.

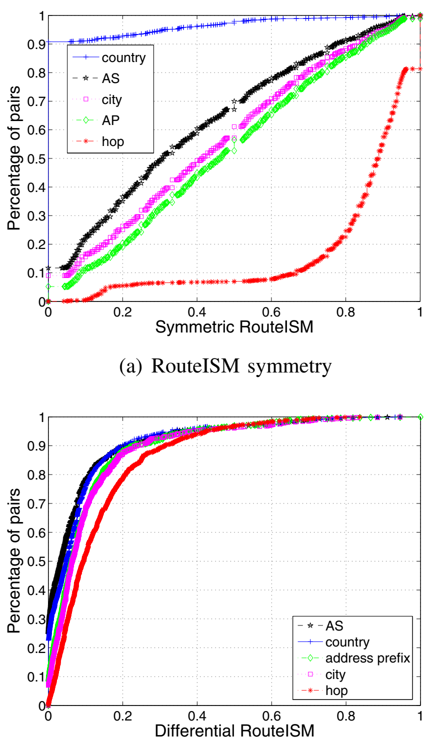
Previous work [11], [6] studying symmetry reported that academic networks exhibit more symmetric routing than commercial networks. We wish to validate whether these types of networks also exhibit different stability properties. Fig. 3(a) shows the prevalence of dominant routes measured between academic networks (often traversing mostly academic networks) and routes measured from or to non-academic networks. The figure clearly shows that routing in academic networks is much more stable: over 30% of the routes in the academic networks are stable compared to 20% in the commercial network. The stability of academic networks is even more profound when examining the median prevalence: 95% for academic networks while only 50% for the commercial networks. However, Fig. 3(b) shows that the RouteISM is not very different between the two types (the distribution is similar for prefix, city and county levels, but not shown for clarity of the figure). This shows that although the commercial Internet exhibits a larger route diversity between pairs, the "distance" between those routes and the dominant route is not much different than the one measured for academic networks, meaning that when instability occurs (more often in commercial networks), it has a similar affect on hop alternation.

Fig. 3(a) shows that dominant route prevalence of 50% exists in 5% of the commercial networks pairs but almost none of the academic networks pairs. This indicates that commercial networks use load balancers more than academic networks; note also the small jump at 25% in commercial networks which can be attributed to cascading of an additional load balancer after route forking in both sub-routes.

Considering bias in stability caused by geographic location of pair end-points, we found that cross-continent pairs are slightly more stable. This is expected, since often there are not many alternatives for these routes.

C. Routing Symmetry

Quantifying route symmetry has many applications, mainly when trying to deduce one-way-delay using RTT measurements. Fig. 4(a) shows the cumulative distribution of Symmetric RouteISM at different levels using the 2009 experiment. The IP-level is not symmetric since routers commonly have different interfaces with different IP addresses for the various networks. The address prefix and AS-level are affected by hot-potato routing mainly in large (tier-1) ASes that have multiple peering points. Interestingly, AS-level routes are more symmetric than city-level routes, indicating the existence of points-of-presence (PoPs) that belong to the same AS but reside in different cities. The country level being the most stable shows that even when routes are asymmetric in the AS-level, the different ASes usually reside in the same country.



(a) RouteISM symmetry

(b) Differential RouteISM

Fig. 4. Symmetry of routes

He *et al.*[5], [6] studied the routing asymmetry at the AS level and found that only 14% of the pairs displayed AS level routing asymmetry. Additionally, the authors found that 90% of the asymmetric routes had normalized asymmetry (analogous to our $SymRouteISM^{AS}$) of less than 0.1, which led them conclude that forward routes are highly similar to their reverse counterparts. This conclusion overlooks the existence of hot-potatoes routing in large ASes. Our results show that AS-level routes are highly not-symmetric, where almost 90% of the routes exhibit asymmetry and only 20% of the routes had $SymRouteISM^{AS} \leq 0.1$. The authors also quantified correlation between asymmetry and route length, and showed that longer routes have lower symmetry values. Although this conclusion makes sense, we suspect that their extensive usage in NLANR [1] VPs might be the cause to these conflicting conclusions.

Differential stability quantifies whether stability remains in opposite directions. As Fig. 4(b) shows, approximately 90% of the pairs have differential stability of less than 0.3 where the median is less than 0.05 for all except IP-level RouteISM. These figures show that when instability exists in one direction, it is likely to appear in the opposite direction as well. This is a non trivial observation, since tier-1 ASes that constitute 28% of the traversed ASes, are expected to use more hot-potato routing, which in turn changes the routes in different directions.

VI. Conclusion

This work presents a measurement study of the diversity of e2e paths in the Internet. We present a methodology used for quantifying the different measures of stability and symmetry and perform two wide-scale experiments.

We show that although the Internet today is less stable than the one studied by Paxson in 1995, it still exhibits different behavior depending on network type. Moreover, longitudinal analysis shows that e2e route properties did not significantly change in recent years. We attribute this to a trade-off between the increasing topology size of the Internet and usage of load balancers, and the adoption of tunneling technologies that result in more stable IP-level routes.

Acknowledgment. This work was partially funded by the OneLab II and the MOMENT consortia that are part of the EU FP7; and the Israeli Science Foundation, grant 1685/07.

References

[1] Active Measurement Project. Nlanr. http://watt.nlanr.net/.
[2] B. Augustin, X. Cuvellier, B. Orgogozo, F. Viger, T. Friedman, M. Latapy, C. Magnien, and R. Teixeira. Avoiding traceroute anomalies with paris traceroute. In *IMC*, pages 153–158, 2006.
[3] B. Augustin, T. Friedman, and R. Teixeira. Measuring load-balanced paths in the Internet. In *IMC*, 2007.
[4] X. Dimitropoulos, D. Krioukov, G. Riley, and kc claffy. Revealing the AS taxonomy: The machine learning approach. In *PAM*, 2006.
[5] Y. He, M. Faloutsos, and S. Krishnamurthy. Quantifying routing asymmetry in the internet at the AS level. In *GLOBECOMM*, 2004.
[6] Y. He, M. Faloutsos, S. Krishnamurthy, and B. Huffaker. On routing asymmetry in the internet. In *GLOBECOMM*, 2005.
[7] C. Labovitz, G. R. Malan, and F. Jahanian. Internet routing instability. *IEEE/ACM Transactions on Networking*, 6(5):515–528, 1998.
[8] V. I. Levenshtein. Binary codes capable of correcting deletions, insertions, and reversals. *Soviet Physics Doklady*, 10(8):707–710, 1966.
[9] R. Mahajan, D. Wetherall, and T. Anderson. Understanding BGP misconfiguration. In *SIGCOMM*, pages 3–16. ACM, 2002.
[10] MaxMind. http://www.maxmind.com.
[11] A. Pathak, H. Pucha, Y. Zhang, Z. M. Mao, and Y. C. Hu. A Measurement Study of Internet Delay Asymmetry. In *PAM*, 2008.
[12] V. Paxson. End-to-End Routing Behavior in the Internet. In *IEEE/ACM Transactions on Networking*, pages 601–615, 1996.
[13] H. Pucha, Y. Zhang, Z. M. Mao, and Y. C. Hu. Understanding network delay changes caused by routing events. In *SIGMETRICS*, volume 35, pages 73–84, 2007.
[14] J. Rexford, J. Wang, Z. Xiao, and Y. Zhang. BGP routing stability of popular destinations. *ACM SIGCOMM CCR*, pages 197 – 202, 2002.
[15] Y. Shavitt and E. Shir. DIMES: Let the internet measure itself. *ACM SIGCOMM CCR*, 35(5):71–74, 2005.
[16] Y. Shavitt and U. Weinsberg. Quantifying the importance of vantage point distribution in Internet topology measurements. In *Infocom*, 2009.
[17] R. Teixeira, K. Marzullo, S. Savage, and G. M. Voelker. In search of path diversity in ISP networks. In *IMC*, 2003.
[18] University of Oregon RouteViews Project. http://www.routeviews.org/.
[19] F. Wang, Z. M. Mao, J. Wang, L. Gao, and R. Bush. A measurement study on the impact of routing events on end-to-end Internet path performance. *ACM SIGCOMM CCR*, 36(4):375–386, 2006.