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Analysis of the Internet's Structural Evolution

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***Abstract*—**

In this paper we study the structural evolution of the AS topology as inferred from two different datasets over a period of seven years. We use a variety of topological metrics to analyze the structural differences revealed in the AS topologies inferred from the two different datasets. In particular, to focus on the evolution of the relationship between the core and the periphery, we make use of the weighted spectral distribution.

We find that the traceroute dataset has increasing difficulty in sampling the periphery of the AS topology, largely due to limitations inherent to active probing. Such a dataset has too limited a view to properly observe topological changes at the AS-level compared to a dataset largely based on BGP data. We also highlight limitations in current measurements that require a better sampling of particular topological properties of the Internet. Our results indicate that the Internet is changing from a core-centered, strongly customer-provider oriented, disassortative network, to a soft-hierarchical, peering-oriented, assortative network.

I. INTRODUCTION

The Internet continuously evolves: new networks are created, old ones disappear, and existing ones grow or merge. At the same time, business dynamics cause interconnections between networks to change. Both these effects cause the underlying topology of the Internet to be in a constant state of flux. Studying the evolution of this topology is important as it impacts a variety of factors relevant to network users and application designers, such as scalability and performance. For example, different network structures affect the propagation of both legitimate (e.g., routing) and illegitimate (e.g., viruses) information.

Most efforts to understand the structure of the Internet have focused on the Autonomous System (AS) topology. There are over 30,000 ASes, each representing a single administrative authority with its own network and peering policies. Thus, the AS topology is a graph reflecting the interconnections between the networks that compose the Internet. Relationships between ASes are typically classified as either customer-provider, sibling-sibling or peer-peer. Note that as the Internet has grown, many larger networks have come to be represented as more than one AS (i.e., to advertise more than one AS number). As a result, the AS topology may contain edges that do not directly represent a business relationship between two distinct networks. However, the AS topology serves as an available, albeit approximate, measure of the complexity of the Internet's structure at the network level.

Characterising the structure of the AS topology has proved difficult, but it is usually simplified to: a richly connected core, including the fully meshed tier-1 Internet Service Providers (ISPs), providing connectivity for the huge number of smaller ISPs and customer networks at the periphery of the network. These edge ISPs may connect to only a single upstream provider, or may connect to many for resilience, performance and cost reasons. Recent work has shown that the trend is for networks to try to connect directly in the periphery of the Internet, rather than to the core, bypassing the largest providers [8]. However, no direct evidence of a corresponding large-scale change in the topological structure had been shown.

In this paper we analyse the evolution of the AS topology using two significant datasets, each generated by a different measurement technique: the Skitter dataset using traceroute, and the UCLA dataset using BGP. We are aware that there are problems with biased measurements in both data sets. However, it is still our aim to draw conclusions mindful of these drawbacks. We focus on the overall structure of the topology, rather than local features such as node degree, using a recently introduced metric called the *weighted spectral distribution* (WSD) [7]. This allows us to distinguish topologies with different mixing properties, i.e., how much the core can be differentiated from the periphery of the topology. A clear distinction between the core and the periphery is believed to be one of the strongest features of the Internet topology [18], [21].

This paper makes three contributions. First, we explain how the WSD depicts the mixing between core and periphery in the AS topology (Section III). Second, we find that the AS topology has evolved from a highly hierarchical graph with a clearly distinct core towards a "softer" hierarchy where the core and non-core parts of the topology are less distinct (Section IV). Third, we show how the two different measurement techniques, traceroute and BGP, both provide limited but complementary coverage of the AS topology: the traceroute dataset has increasing difficulty sampling the periphery, while the BGP dataset can improve its sampling of the transit part of the Internet (Section V).

II. THEORETICAL BACKGROUND

The *weighted spectral distribution* (WSD) is a graph theoretic metric based on the random walk cycles in a graph. A random walk starts at a node, u say, with degree d_u, and transitions to the a connected node with probability $1/d_u$. After several such steps, say N, if the random walk returns to the starting node, then this is called a random walk cycle of length N. The WSD takes the struture of the graph to be all such random walk cycles as expressed via the normalised Laplacian (roughly speaking, how the graph appears over short walks taken from every node). The normalised Laplacian matrix of a graph, G, defined as:

$$L(G)(u,v) = \begin{cases} 1, & \text{if } u = v \text{ and } d_v \neq 0 \\ -\dfrac{1}{\sqrt{d_u d_v}}, & \text{if } u \text{ and } v \text{ are adjacent} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Expressing L using the eigenvalue decomposition,

$$L(G) = \sum_i \lambda_i e_i e_i^T \quad (2)$$

where e_i and λ_i are the eigenvalues and eigenvectors of L resp [1]. The WSD is based on the following theorem from [7]:

Theorem 2.1: The eigenvalues, λ_i, of the nomalised Laplacian matrix for an undirected network are related to the random walk cycle probabilities as:

$$\sum_i (1 - \lambda_i)^N = \sum_C \frac{1}{d_{u_1} d_{u_2} \ldots d_{u_N}} \quad (3)$$

where d_{u_i} is the degree of node u_1 and $u_1 \ldots u_n$ denotes a path from node u_1 of length n ending at node n, i.e. an n-cycle. For a proof see [7]. Theorem 2.1 states that the probability of taking a random walk of length N that returns to the original node, is directly related to the weighted eigenvalues of L. This probability is the 'local structure' of a node, i.e. its local connecivity. Noting that the λ_i are unique [2] to a graph it can be seen that the WSD gives a 'thumbprint' for the structure of a graph. As shown in [7] this can be used for estimating the parameters of a topology generator that produce graphs which are close (in the WSD sense) to the target graph however, in this paper we apply the technique for tracking the evolution of the AS level graph.

A. Examples

After the fairly theoretical previous section, we aim at giving the reader a better intuition behind the WSD with a simple example. Figure 1 shows a small network, called G_1, with 7 nodes and 8 links. As can be seen there are 2 cycles of length 3 in this network and one of length 4. We will take $N = 3$ in this example for convenience and without loss of generality. The random walk probabilities are labeled in Figure 1. For example, node 3 has a degree of 5 resulting in a probability of $1/5^{th}$ for each edge. The total probability of taking a random walk around each 3-cycle is: $6 \times 1/2 \times 1/3 \times 1/3 = 0.33$, also shown.[3]

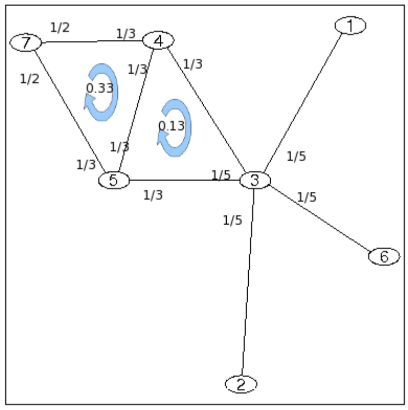


Fig. 1. A simple example network G_1.

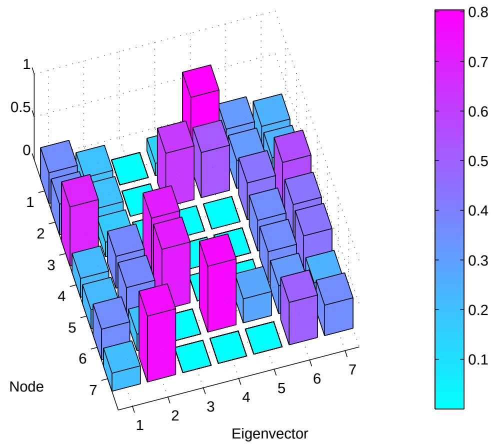


Fig. 2. Eigenvectors of the simple example network.

Figure 2 shows a 3-D plot of the absolute value (for clarity) of the eigenvectors of the normalized Laplacian. The corresponding eigenvalues are shown in Table I.

As is well known, the eigenvectors of the normalised Laplacian perform a partitioning of the nodes in a graph. In this example nodes 4 and 5 are grouped into eigenvector 3, nodes 1,2 and 6 into eigenvectors 4 and 5, node 7 into eigenvector 2 and node 3 into eigenvector 1 (Figure 2). Note that for each partition the nodes in the partition are the same; i.e. we could swap the labels between nodes 4 and 5 and the network would not change (i.e. an isomorphism). Eigenvector and eigenvalue 7, e_7 and $\lambda_7 = 0$, are special and partitions all the nodes in the network with the most central nodes having

[1]These are in general different from the eigenpairs of the walk Laplacian

[2]This is not strictly true but the proportion of co-spectral graphs is thought to be insignificant

[3]The six comes from the fact that the random walk can start in one of three nodes and go in one of two directions. It can be viewed in our case as really just a nuisance scaling factor.

TABLE I
EIGENVALUES, WSD AND DOMINANT NODES OF EXAMPLE NETWORK.

e_7	Eigenvector	λ	$1-\lambda$	$(1-\lambda)^3$	Dominant nodes
0.2500	1	1.8615	-0.8615	-0.6394	3,1,2,6
0.2500	2	1.3942	-0.3942	-0.0612	7,4,5
0.5590	3	1.3333	-0.3333	-0.0370	4,5
0.4330	4	1.0000	0.0000	0.0000	6,2
0.4330	5	1.0000	0.0000	0.0000	1,2,6
0.2500	6	0.4110	0.5890	0.2043	7,3
0.3536	7	0.0000	1.0000	1.0000	3,4,5,7
	$\sum_{i=1}^{7}(1-\lambda_i)^3$			0.4667	

the highest coefficients (see Table I, column 1). In general the number of eigenvalues that are zero is equal to the number of components, arguably the most important structural property in a graph. This graph contains 1 connected component and so has a single zero eigenvalue (λ_7). Note that the highest possible weighting in the WSD is given at zero (i.e. 1 = 1-0); the number of components in the graph.

Note that the sum of the eigenvalues taken to the power of N is indeed the same as the sum of the probabilities of taking N random walk cycles in the graph. This is shown in Table I, last row, $\sum_{i=1}^{7}(1-\lambda_i)^3 = 0.4667$ which can be easily verified by adding the cycle probabilities from Figure 2 $(0.3333 + 0.1333 = 0.467)$. What is interesting is how this sum is constructed. In Table I the main contributions to the sum are from eigenvalues 1,2,3 and 6 (we ignore eigenvalue 7 as it merely reflects that the graph is connected) which are dominated by the nodes which form the cycles; 3, 4, 5 and 7.

However, this does not mean that the information provided by the WSD is confined to N-cycles in the graph. For example in Figure 4 we take the edge linking nodes 1 and 3 and rewire it so that 1 and 6 are now connected. Note that while the right cycle is still in place its probabilities have now changed, as the degree of node 3 is now 4. The corresponding eigenvalues have also changed as seen in Figure 3. [4]

In conclusion, the WSD can roughly be seen as an amalgamation of *local* views (i.e. walks of length N) taken from all the nodes. As $(1-\lambda_i) \leq 1\ \forall i$, $(1-\lambda_i)^N$ will suppress the smaller eigenvalues more and more as N increases [5]. We consider 3 and 4 to be suitable values of N for the current application: $N = 3$ is related to the well-known and understood clustering coefficient; and $N = 4$ as a 4-cycle represents two routes (i.e., minimal redundancy) between two nodes. For other applications, other values of N may be of interest. Also note that in section II we propose using the *distribution* of the eigenvalues for large networks; unfortunately it is not instructive to talk about a distribution for a small number of eigenvalues (7 in this example).

[4]Note that if we had used the adjacency matrix instead of the normalised Laplacian the re-wiring would have no effect on the sum of the eigenvalues.

[5]This is closely related to the settling times in Markov chains which are often expressed in terms of the largest non-trivial eigenvalue. It differs in that the Walk Laplacian and not the normalised Laplacian is used.

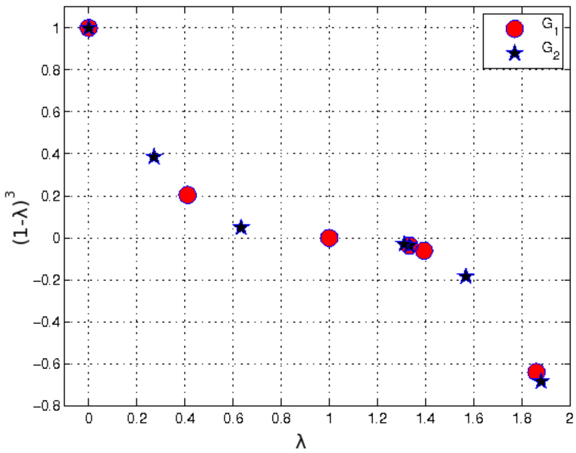


Fig. 3. WSD of the example network.

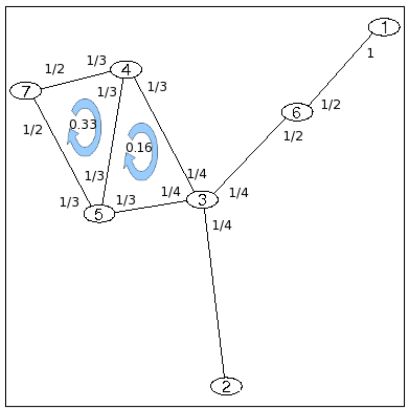


Fig. 4. The second example network, G_2.

III. MIXING PROPERTIES OF NETWORKS

The synthetic topology generator introduced in this section is intended as a strawman tool [6] that can be adjusted to show the effect of different parts of a topology on the resulting WSD. These topologies are generated using a simple model

[6]i.e. purely for demonstration purposes

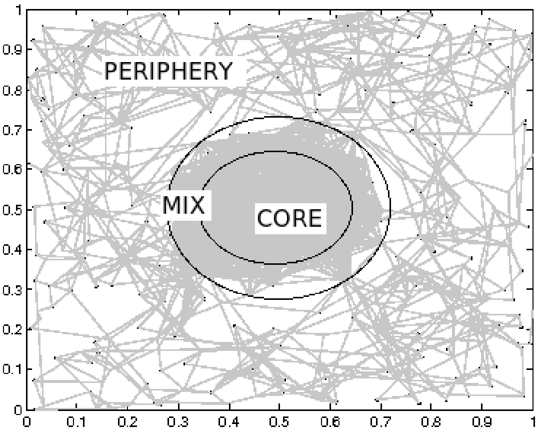


Fig. 5. Synthetic topology.

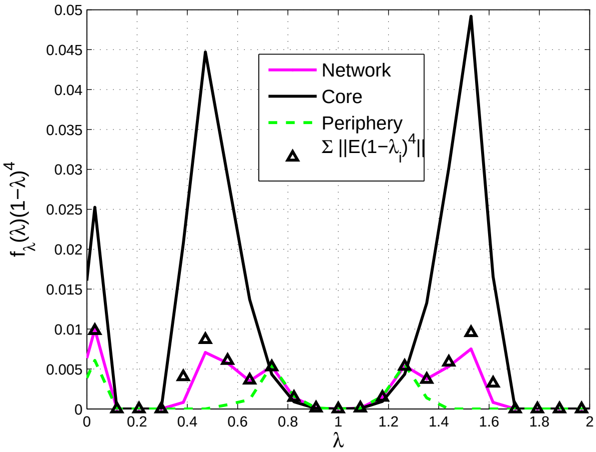


Fig. 6. Synthetic topology spectra.

based on the existence of a network core and a periphery, as do most generative models of the Internet. Figure 5 shows a small topology of 500 nodes. All M nodes within the graph are first assigned locations using a uniform distribution. Nodes within a circle of diameter D are then defined as the *core* and nodes outside a circle of diameter $D\times(1-m)$ as the periphery, where $m \leq 1$ is a factor called the *mixing factor*. Links are then assigned between the core nodes using a Waxman model:

$$P(u \to v) = \alpha_{core} \exp^{\frac{-d\beta_{core}}{D}} \tag{4}$$

where α_{core} and β_{core} are the Waxman coefficients for the core, and d is the distance between two nodes u and v. Subsequently, links are also assigned in the periphery[7] using a Waxman model but one with different coefficients, α_{per} and β_{per}. After this process, isolated nodes are connected to their nearest neighbour.[8] Figure 6 shows the WSD (using $N = 4$) for a topology generated with $M = 2000$ nodes, $D = 0.25$, $\alpha_{core} = 0.08$, $\beta_{core} = 0.08$, $\alpha_{per} = 0.06$, $\beta_{per} = 0.7$, and $m = 0.95$ (i.e., 5% mixing), resulting in a small (relatively) meshed core with a less well connected periphery. There are several things to note in Figure 6. Ignoring the asymmetrical part of the curve, which is caused by a small number of disconnected components, the peak of the weighted spectrum of the periphery alone lies at $\lambda = 0.7$ while that for the core lies at 0.5. The spectrum for the overall network has *two peaks* at these points. This is a direct consequence of the spectrum of a graph being the union of the spectra of its disconnected subgraphs [3]. In terms of the WSD, the union of spectra is equivalent to a weighted average of the WSD. That is, for a graph $G+H$ composed of two disconnected subgraphs G and H:

$$\omega(G + H, N) = |G + H| \left(\frac{\omega(G, N)}{|G|} + \frac{\omega(H, N)}{|H|} \right) \tag{5}$$

where $|.|$ denotes volume (number of vertices). Although there is 5% mixing between the core and periphery $\omega(G + H, N)$ results in an close estimate of the network WSD (see Figure 6, denoted $\Sigma||E(1 - \lambda_i)^4||$). As $m \to 0$ (i.e., the core and periphery become less and less connected) this estimate becomes more accurate and is exact at m = 0.

Figure 7 shows the effect of increasing the mix between the periphery and the core.[9] As can be seen the core becomes less distinct in the resulting spectrum, and has practically disappeared with 40% mixing. By increasing the mix we are effectively adding edges connecting the core and periphery, which results in a spreading of the eigenvalues and thus a spreading of the WSD, resulting in less-distinct peaks. In the current context, the new edges in the mix are being added to t nodes causing the eigenvalues to spread by at most t places. It should be noted that although this makes the core peak less distinct this does not mean that the core is more difficult to detect, rather that the core itself is now less distinct from the periphery.

IV. Evolution of the Internet

In this section we look at the evolution of the Internet seen through the two datasets, over a period of more than 3 years. We rely on a number of topological metrics presented in Section II. Section IV-A studies the evolution of the AS topology seen in the Skitter dataset, and Section IV-B then studies the evolution of the AS topology seen in the UCLA dataset. We compare these views of the AS topology in Section V, where we also discuss the likely evolution of the ”real” AS topology. We are aware of the problems associated with traceroute sampling and we are also aware of the efforts

[7]Note that nodes lying between D and $D \times (1 - m)$ are members of the core *and* the periphery and will be connected twice.

[8]Note that there are likely to be some disconnected components in the resulting graphs, leading to asymmetrical spectra, but this does not affect the main results.

[9]Again the large peaks before 0.2 represent isolated subgraphs and are ignored.

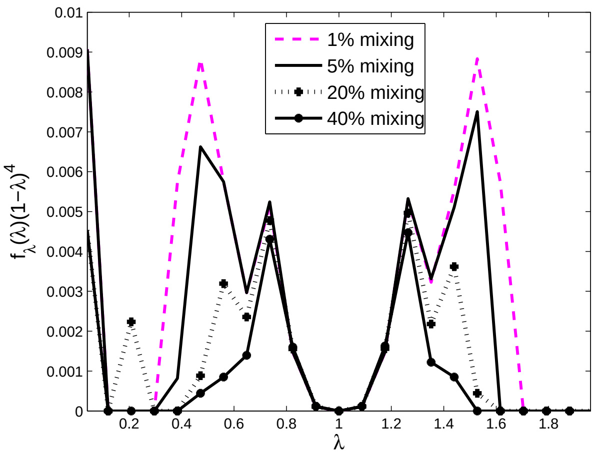


Fig. 7. Effect of a change in m on the spectrum of the overall network.

in DIMES project to remedy these issues[10], however this data is currently only available since January 2007 and hence not long enough for a thorough comparison of Internet topology evolution.

A. Skitter topology

The first dataset we study consists of 7 years of traceroute measurements, starting in January 2001, collected by the CAIDA Skitter project [12]. Traceroutes are initiated from several locations in the world toward a large range of destination IP addresses. The IP addresses reported in the traceroutes are mapped to AS numbers using RouteViews BGP data. We use a monthly union of the set of all unambiguous links collected on a daily basis by the project.[11]

Figure 8 presents the evolution over the 7 years of a set of topological metrics computed on the AS topology of Skitter.

The number of ASes seen by Skitter exhibits abrupt changes during the first 40 months. At the end of those 40 months, changes were made in the way probing was performed.[12] The large increases in the number of ASes, observed during the first 40 months, are due to new monitors being added to the system. After each increase in the number of ASes a smooth decrease follows, corresponding to a subset of the IP addresses of the Skitter list that no longer respond to probes, e.g., because a firewall starts blocking the probes. The variations in the number of ASes seen by Skitter are not caused by changes in the AS topology itself, but are artifacts of the probing. Such artifacts should be reported and accounted for in topological studies.

The number of AS edges and the average node degree both follow the behavior of the number of ASes seen. We only observe a large increase in the number of links during the first few months, during which new monitors are added resulting in new regions of the Internet being covered by Skitter measurements. Given the difficulty of building a list of destination IP addresses that will answer probes and cover most of the ASes, especially at the edge [2], a new monitor will typically discover new ASes close to its location.

The AS edges that Skitter no longer observes probably still exist but can no longer be seen by Skitter due to its shrinking probing scope. To be effective in observing topology dynamics, traceroute data collection must update destination lists constantly to give optimal AS coverage. This limitation of Skitter is visible in the decreasing average node degree. We would expect to see a net increase in the average node degree as ASes tend to add rather than remove peerings, and the results of the BGP data support this view. If the sample of the AS topology of the Skitter measurements was not worsening, we should see an increasing average node degree.

The lower three graphs of Figure 8 present the evolution of the clustering coefficient, the assortativity coefficient,[13] and the weighted spectrum with $N = 3$, $\omega(G, 3)$ (related to the topology's clustering)[14]. We observe that changes were made to the way Skitter probes the Internet around month 40: the metrics take an unusual value, very small for the clustering and very high for assortativity. The values of the clustering and the assortativity coefficients fluctuate wildly over the 7 years, as if the sampling of the AS topology by Skitter at the AS-level is not stable. Neither the clustering nor the assortativity seem to decrease or increase over the 7 years. The value of $\omega(G, 3)$ shows a long-term increasing trend, similar to the decreasing trend in the average node degree. Although related to the clustering, $\omega(G, 3)$ gives different weights to different parts of the topology. The subset of the topology that corresponds to duplicated topological structures, e.g. different ASes at the periphery that connect to the same set of upstream providers, receives a smaller weight than the rest. The increasing $\omega(G, 3)$ is likely to be caused by the shrinking network sampled by Skitter, that contains more 3-cycles on average.

Figure 9 presents four WSDs sampling the entire duration of the Skitter dataset. Notice the eigenvalues at zero, indicating the presence of several disconnected components. The WSD in January 2002 shows a single peak at $\lambda = 0.4$. As time passes, a second peak appears around $\lambda = 0.3$. The sampling from the Skitter data shows an Internet moving from a less hierarchical to more hierarchical topology, i.e. the core becoming more dominant. This contradicts current observations that

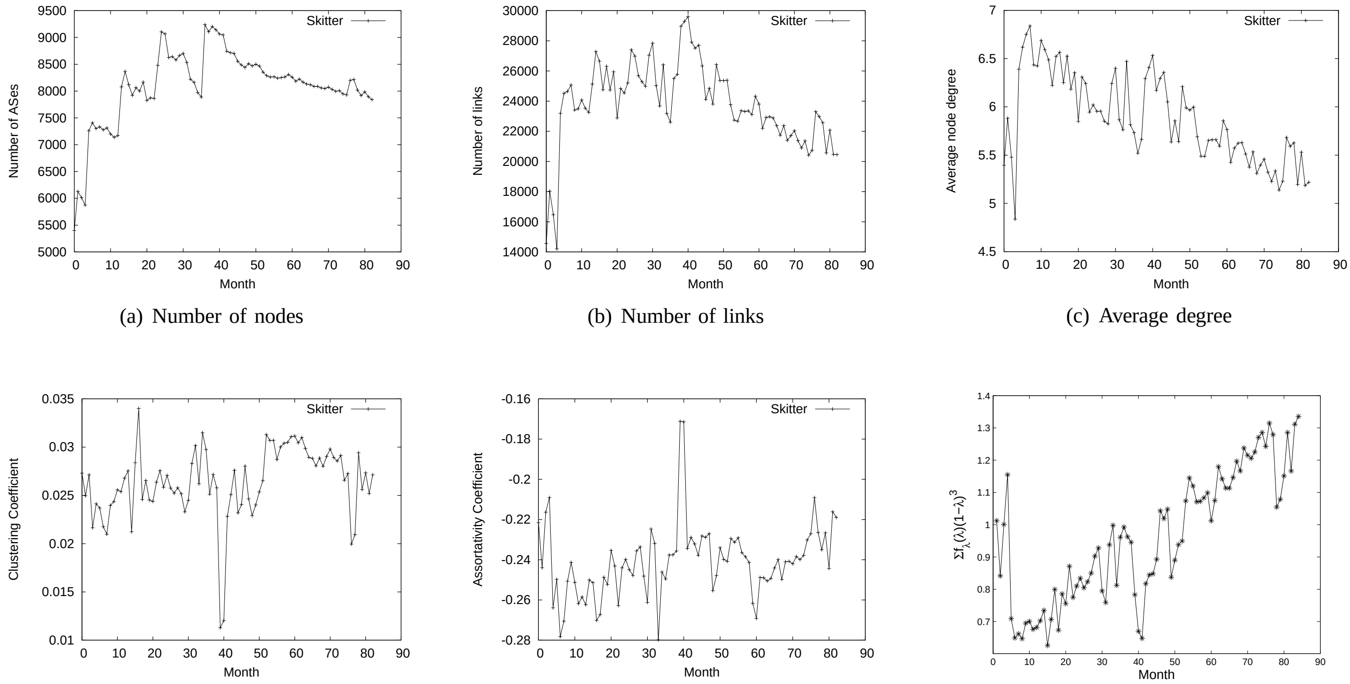
[10] http://www.netdimes.org

[11] A link may be ambiguous for a variety of reasons, principally due to problems resolving an IP address to an AS number. The Skitter IP address list includes some IP addresses which matched a prefix with two or more origin ASes. This can happen for a number of reasons such as a provider stripping the customer AS from the AS path. Since it is not known which AS is the true origin, the dataset lists both ASes. We filter out such instances as it is not possible to identify the authenticity of such links.

[12] These changes were subject to caveats and bugs affecting measurements, and, thus, the resulting metrics, at month 40. For more information refer to http://www.caida.org/data/active/skitter_aslinks_dataset.xml/

[13] Assortativity is a measure of the likelihood of connection of nodes of similar degrees [13]. This is usually expressed by means of the *assortativity coefficient* r: assortative networks have $r > 0$ (disassortative have $r < 0$ resp.) and tend to have nodes that are connected to nodes with similar (dissimilar resp.) degree.

[14] See [9] for a detailed explanation on the mathematical measures and different datasets



(a) Number of nodes

(b) Number of links

(c) Average degree

(d) Clustering coefficient

(e) Assortativity coefficient

(f) $\omega(G, 3)$

Fig. 8. Topological metrics for Skitter AS topology.

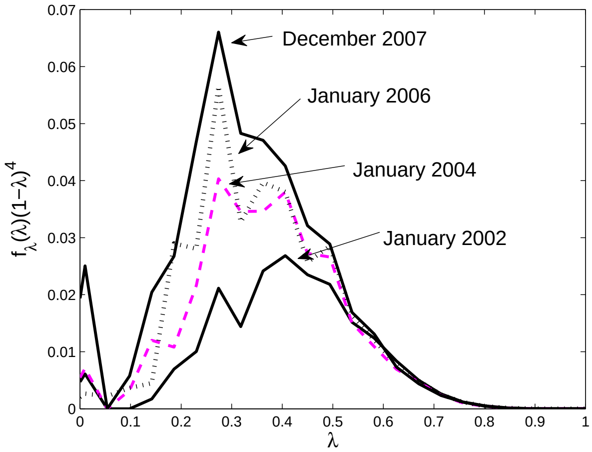


Fig. 9. Weighted Spectral Distribution, Skitter AS topology.

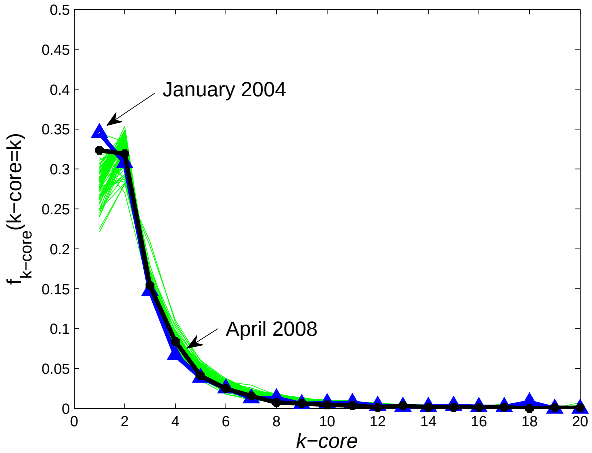


Fig. 10. k-core proportions, Skitter AS topology

the AS topology is becoming less hierarchical, with increasing numbers of ASes peering at public Internet Exchange Points (IXPs) to bypass the core of the Internet.

To further investigate this unexpectedly dominant core seen in the Skitter dataset, we introduce supporting evidence using the k-core metric. A k-core is defined as the maximum connected subgraph, H, of a graph, G, with the property that $d_v \geq k \; \forall v \in H$. As pointed out by Alvarez-Hamelin *et al.* [1] the k-core exposes the structure of a graph by pruning nodes with successively higher degrees, k, and examining the maximum remaining subgraph; note this is not the same as simply pruning all nodes with degree k or less. Figure 10 shows the proportion of nodes in each k-core as a function of k. There are 84 plots shown, but as can be seen there is little difference between each of them, demonstrating that the proportion of nodes in each core is not changing over time. The nature of the sampling performed by Skitter explains this behavior: the Skitter data set is composed of traceroutes rooted at a limited set of locations, so the k-core is expected to be similar to *peeling the layers from an onion* [1]. From a topology evolution point of view, this result shows that, although the number of nodes being sampled by Skitter is decreasing, the hierarchy of the Internet as observed by Skitter is actually not changing. Skitter is not sampling the periphery of the Internet and so cannot see evolutionary changes there.

We insist on the fact that the purpose of this paper is not to blame the Skitter dataset for its limited coverage of the AS topology, as it aims at sampling the router-level topology.

Datasets like Skitter that rely on active probing do provide topological information not visible from BGP data, as will be shown in Section V.

B. UCLA

We now examine the evolution of the AS topology using 52 snapshots, one per month, from January 2004 to April 2008. This dataset, referred to in this paper as the UCLA dataset, comes from the Internet topology collection[15] maintained by Oliviera *et al.* [15]. These topologies are updated daily using data sources such as BGP routing tables and updates from RouteViews, RIPE,[16] Abilene[17] and LookingGlass servers. Each node and link is annotated with the times it was first and last observed.

Figure 11 presents the evolution of the same set of topological metrics as Figure 8, over 4 years of AS topologies in the UCLA dataset.

The UCLA AS topologies display a completely different evolution compared to the Skitter dataset, more consistent with expectations. As the three upper graphs of Figure 11 show, the number of ASes, AS edges, and the average node degree are all increasing, as expected in a growing Internet.

The increasing assortativity coefficient indicates that ASes increasingly peer with ASes of similar degree. The preferential attachment model seem to be less dominant over time. This trend towards a less disassortative network is consistent with more ASes bypassing the tier-1 providers through public IXPs [8], hence connecting with nodes of similar degree. Another explanation for the increasing assortativity is an improvement in the visibility of non-core edges in BGP data. We will see in Section V that the sampling of core and non-core edges by UCLA and Skitter biases the observed AS topology structure. Contrary to the case of Skitter, $\omega(G, 3)$ for UCLA decreases over time. As a weighted clustering metric, $\omega(G, 3)$ indicates that the transit part of the AS topology is actually becoming relatively sparser over time compared to the periphery. Increasing local peering with small ASes in order to reduce the traffic sent to providers decreases both the hierarchy induced by strict customer-provider relationships, and in turn decreases the number of 3-cycles on which $\omega(G, 3)$ is based.

If we look closely at Figure 12, we see a spectrum with a large peak at $\lambda = 0.3$ in January 2004, suggesting a strongly hierarchical topology. As time passes, the WSD becomes flatter with a peak at $\lambda = 0.4$, consistent with a mixed topology where core and non-core are not so easily distinguished.

Figure 13 shows the proportion of nodes in each k-core as a function of k. There are 52 plots shown as a smooth transition between the first and last plots, emphasized with bold curves. The distribution of k-cores moves to the right over time, indicating that the proportion of nodes with higher connectivity is increasing over time. This adds further weight to the conclusion that the UCLA dataset shows a weakening hierarchy in the Internet, with more peering connections

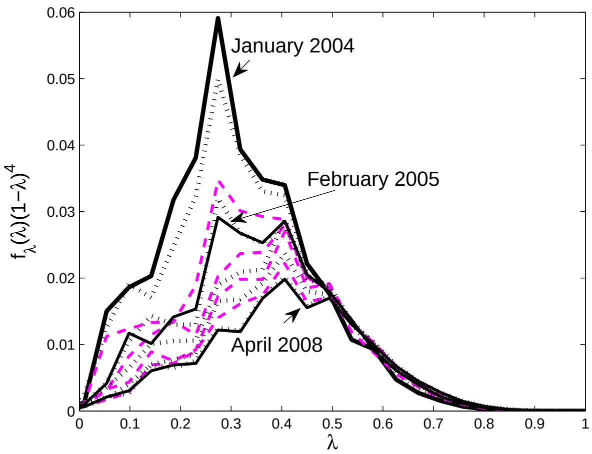


Fig. 12. Weighted Spectral Distribution, UCLA AS topology.

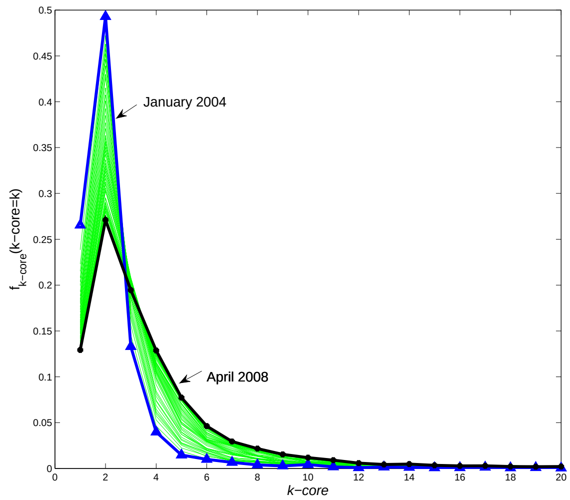


Fig. 13. k-core proportions, UCLA AS topology.

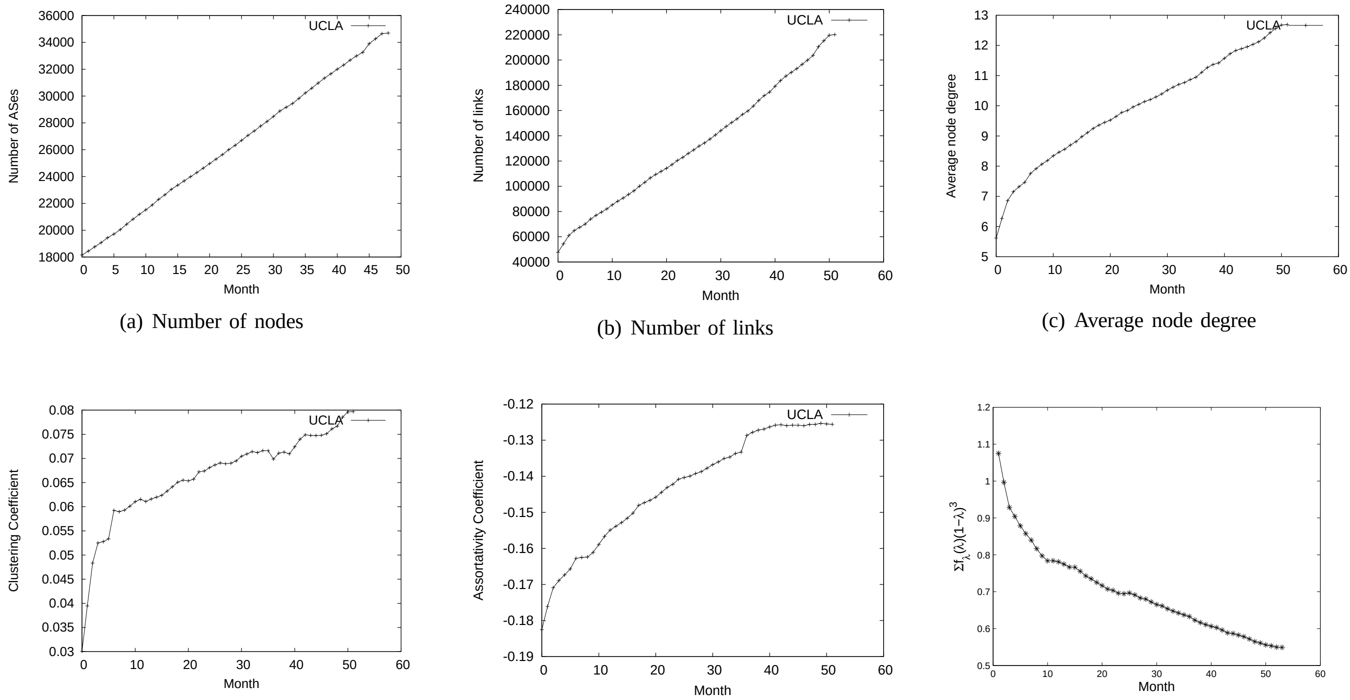
between nodes on average. Note that the UCLA data set was not examined in [1].

V. Reconciling the Datasets

The respective evolutions of the AS topology visible in the Skitter and UCLA datasets differ, as seen from topological metrics. Skitter shows an AS topology that is becoming sparser and more hierarchical, while UCLA shows one that is becoming denser and less hierarchical. Why do these two datasets show such differences? The explanation lies in the way Skitter and UCLA sample different parts of the AS topology: Skitter sees a far smaller fraction of the complete AS topology than UCLA, and even UCLA does not see the whole AS topology [14]. A far larger number of vantage points than those currently available are likely to be necessary in order to reach almost complete visibility of the AS topology [16].

To check how similar the AS topologies of Skitter and UCLA are, we computed the intersection and the difference between the two datasets in terms of AS edges and ASes. We used a two-year period from January 2006 until December 2007. In Table II we show the number of AS edges and ASes that Skitter and UCLA have in common during some

[15] http://irl.cs.ucla.edu/topology/
[16] http://www.ripe.net/db/irr.html
[17] http://abilene.internet2.edu/



(a) Number of nodes (b) Number of links (c) Average node degree

(d) Clustering coefficient (e) Assortativity coefficient (f) $\omega(G, 3)$

Fig. 11. Topological metrics for UCLA AS topology.

of these monthly periods (labelled ”intersection”), as well as the number of AS edges and ASes contributed to the total and coming from one of the two datasets only (labelled ”Skitter-only” or ”UCLA-only”). We observe a steady increase in number of total ASes and AS edges seen by the union of the two datasets. At the same time, the intersection between the two datasets decreases. In late 2007, Skitter had visibility of less than 25% of the ASes and less than 10% of the AS edges seen by both datasets. As Skitter aims at sampling the Internet at the router-level, we should not expect that it has a wide coverage of the AS topology. Such a limited coverage is however surprising, given the popularity of this dataset. Note that Skitter sees a small fraction of all AS edges, which is not seen by the UCLA dataset. This indicates that there is potential in active topology discovery to complement BGP data.

From Table II, we may conclude that the Skitter dataset is uninteresting. To the contrary, the relatively constant, albeit decreasing, sampling of the Internet core by Skitter gives us a clue about which part of the Internet is responsible for its structural evolution.

In Table III we show the number of AS edges belonging to the tier-1[18] mesh (labelled ”T1 mesh”) as well as other AS edges where a tier-1 appears. More than 30% of the AS edges sampled by Skitter cross at least a tier-1 AS, against about 15% for UCLA. Both dataset see almost all AS edges from the tier-1 mesh. Note that the decrease in the number of AS edges in which a tier-1 appears in Skitter is partly related to IP to AS mapping issues for multi-origin ASes [8].

The evolution of the AS topology observed by the Skitter and UCLA datasets is not inconsistent. Rather, the two datasets sample differently, the AS topology, leading to different bias. A large fraction of the AS topology sampled by Skitter relates to the core, i.e., edges containing at least a tier-1 AS. With its wider coverage, UCLA observes a different evolution of the AS topology, with a non-core part that grows more than the core. The evolution seen from the UCLA dataset seems more likely to reflect the evolution of the periphery of the AS topology. The non-core part of the Internet is growing and is becoming less and less hierarchical. We wish to point out that, despite a common trend towards making a *union* of datasets in our networking community, such simple addition is not appropriate for the UCLA and Skitter datasets. Each dataset has its own biases and measurement artifacts. Combining them bindly will only add these biases together, potentially leading to poorer quality data. More data is not always better data. Further research is required in order to devise a correct methodology that takes advantage of different datasets obtained from different sampling processes.

The above observations suggests that the Internet, once seen as a tree-like, disassortative network with strict power-law properties [6], is moving towards an assortative and highly inter-connected network. Tier-1 providers have always been well connected, but the biggest shift is seen at the Internet's periphery where content providers and small ISPs are aggressively adding peering links among themselves using IXPs to avoid paying transit charges to tier-1 providers. However, a different view of the Internet evolution can be

[18]We rely on the currently accepted list of 12 tier-1 ASes that provide transit-only service: AS174, AS209, AS701, AS1239, AS1668, AS2914, AS3356, AS3549, AS3561, AS5511, AS6461, and AS7018.

Time	Autonomous Systems Total	Intersection	Skitter-only	UCLA-only	AS Edges Total	Intersection	Skitter-only	UCLA-only
Jan. 2006	25,301	32.6%	0%	67.4%	114,847	15.4%	5.3%	79.3%
Mar. 2006	26,007	31.6%	0%	68.4%	118,786	14.9%	4.4%	80.7%
May. 2006	26,694	30.5%	0%	69.5%	124,052	13.8%	4.6%	81.5%
Jul. 2006	27,396	29.5%	0%	70.5%	128,624	13.2%	3.7%	83.1%
Sep. 2006	28,108	28.7%	0%	71.3%	133,813	12.6%	3.4%	84.0%
Nov. 2006	28,885	27.9%	0%	72.1%	139,447	12.4%	3.4%	84.2%
Jan. 2007	29,444	27.2%	0%	72.8%	144,721	11.6%	3.1%	85.3%
Mar. 2007	30,236	26.5%	0%	73.5%	151,380	11.2%	3.0%	85.8%
May. 2007	30,978	25.6%	0%	74.4%	157,392	10.5%	2.7%	86.8%
Jul. 2007	31,668	25.9%	0%	86.1%	166,057	10.0%	3.8%	86.2%
Sep. 2007	32,326	24.5%	0%	75.5%	168,876	9.7%	2.5%	87.8%
Nov. 2007	33,001	23.9%	0%	76.1%	174,318	9.5%	2.2%	88.3%

TABLE II

STATISTICS ON AS AND AS EDGE COUNTS IN THE INTERSECTION OF BOTH SKITTER AND UCLA DATASETS, AND FOR EACH DATASET ALONE.

Time	Skitter Total	T1 mesh	Other T1	UCLA Total	T1 mesh	Other T1
Jan. 2006	23,805	66	7,498	108,720	64	19,149
Mar. 2006	22,917	66	7,289	113,555	64	19,674
May. 2006	22,888	64	7,504	118,331	64	20,143
Jul. 2006	21,740	65	7,192	123,842	64	20,580
Sep. 2006	21,400	65	6,974	129,228	64	21,059
Nov. 2006	22,034	66	7,159	134,636	65	21,581
Jan. 2007	21,345	65	6,898	140,216	65	22,531
Mar. 2007	21,366	65	6,774	147,000	65	23,194
May. 2007	20,738	65	6,694	153,156	65	23,769
Jul. 2007	22,972	65	6,838	159,792	65	24,310
Sep. 2007	20,570	64	6,510	164,770	65	24,888
Nov. 2007	20,466	64	6,430	170,431	65	25,480

TABLE III

COVERAGE OF TIER-1 EDGES BY SKITTER AND UCLA.

obtained using the WSD, shown in Figures 9 and 12. As seen in Section III, one possible cause for this behavior is increased mixing of the core and periphery of the network, i.e. the strict tiered hierarchy is becoming less important in the network structure. This is given further weight by studies such as [14] which show that the level of peering between ASes in the Internet has greatly increased during this period, leading to a less core-dominated network. Given that a fraction of AS edges are not visible from current datasets and that visibility is biased towards a better visibility of customer-provider peerings, we believe that our observations actually underestimate the changes in the structure of the AS topology. Using a hierarchical and preferential attachment-based model to generate synthetic AS topologies is likely to be less and less justified than ever. The AS topology structure is becoming more complex than in the past.

VI. RELATED WORK

In this section we outline related work, classified into three groups: evolution of the AS topology, spectral graph analysis of the AS topology, and analysis of the clustering features of the AS topology.

Dhamdhere and Dovrolis [4] rely on available estimation methods for type of relationships between ASes in order to analyze the evolution of the Internet ecosystem in last decade. They believe the available historic datasets from RouteViews and RIPE are not sufficient to infer the evolution of peering links, and so they restrict their focus to customer-provider links. They find that after an exponential increase phase until 2001, the Internet now grows linearly in terms of both ASes and inter-AS links. The growth is mostly due to enterprise networks and content/access providers at the periphery of the Internet. The average path length remains almost constant mostly due to the increasing multihoming degree of transit and content/access providers. Relying on geo-location tools, they find that the AS ecosystem is now larger and more dynamic in Europe than in North America. In our paper we have relied on two datasets, covering a more extensive set of links and nodes, in order to focus on structural growth and evolution of the Internet. We use a large set of graph-theoretic measures in order the focus on the behavior of the topology. Due to inherent issues involved with inference of node locations and types of relationships [11], we treat the AS topology as an undirected graph.

Shyu *et al.* [17] study the evolution of a set of topological metrics computed on a set of observed AS topologies. The authors rely on monthly snapshots extracted from BGP RouteViews from 1999 to 2006. The topological metrics they study are the average degree, average path length, node degree, expansion, resilience, distortion, link value, and the Normalized Laplacian Spectrum. They find that the metrics are not stable over time, except for the Normalized Laplacian Spectrum.

Oliveira et al. [15] look at the evolution of the AS topology as observed from BGP data. Note that they do not study the evolution of the AS topology structure, only the nodes and links. They propose a model aimed at distinguishing real changes in ASes and AS edges from BGP routing observation artifacts. We use the extended dataset made available by the authors, in addition to 7 years of AS topology data from an alternative measurement method.

Vukadinovic *et al.* [19] were the first to investigate the properties of the AS topology based on the normalized Laplacian spectrum. They observe that the normalized Laplacian spectrum can be used to distinguish between synthetic topologies generated by Inet [20] and AS topologies extracted from BGP data. This results indicates that the normalized Laplacian spectrum reveals important structural properties of the AS topology. However, as noted by Haddadi *et al.* [10], the spectrum *alone* cannot be used directly to compare graphs as it contains too detailed information about the network structure. We expand on this work by demonstrating how appropriate weighting of the eigenvalues can reveal the structural differences between two topologies.

VII. Conclusions

In this paper we presented a study of two views of the evolving Internet AS topology, one inferred from traceroute data and the other from BGP data. We exposed discrepancies between these two inferred AS topologies and their evolution. We reconciled these discrepancies by showing that the topologies are not directly comparable as *neither* method sees the entire Internet topology: BGP data misses some peerings in the core which traceroute observes; traceroute misses many more peerings than BGP in the periphery. However, traceroute and BGP data do provide complementary views of the AS topology.

To remedy the problems of decreasing coverage by the Skitter traceroute infrastructure and the lack of visibility of the core by UCLA BGP data, significant improvements in fidelity could be achieved with changes to the existing measurement systems. The quality of data then collected by the traceroute infrastructure would benefit from greater AS coverage, while the BGP data would benefit from data showing intra-core connectivity it misses today. We acknowledge the challenges inherent in these improvements but emphasize that, without such changes, the study of the AS topology will forever be subject to the vagaries of imperfect and flawed data. Availability of traceroute data from a larger number of vantage points, as attempted by the Dimes project, will help remedy these issues. However, even such measurements have to be done on a very large scale, and ideally performed both from the core of the network (like Skitter), as well as the edge (like Dimes). Efforts in better assessment of the biases inherent to the measurements are also necessary.

To provide an objective analysis of the changing structure of the AS topology, we used a wide range of topological metrics, including the newly introduced weighted spectral distribution. We find that the core of the Internet is becoming less dominant over time, and that edges at the periphery are growing instead. The practice of content providers and content distribution networks seeking connectivity to greater numbers of ISPs at the periphery, and the rise of multi-homing, both support these observations. Further, we observe a move away from a preferential attachment, tree-like disassortative network, toward a network that is flatter, highly-interconnected, and assortative. These findings are also indicative of the need for more detailed and timely measurements of the Internet topology, in order to build up on works such as [5], focusing on the economics of the structural changes such as institutional mergers, dual homing and increasing peering relationships.

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