Internet Topology over Time

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Abstract—There are few studies that look closely at how the topology of the Internet evolves over time; most focus on snapshots taken at a particular point in time. In this paper, we investigate the evolution of the topology of the Autonomous Systems graph of the Internet, examining how eight commonly-used topological measures change from January 2002 to January 2010. We find that the distributions of most of the measures remain unchanged, except for average path length and clustering coefficient. The average path length has slowly and steadily increased since 2005 and the average clustering coefficient has steadily declined. We hypothesize that these changes are due to changes in peering policies as the Internet evolves. We also investigate a surprising feature, namely that the maximum degree has changed little, an aspect that cannot be captured without modeling link deletion. Our results suggest that evaluating models of the Internet graph by comparing steady-state generated topologies to snapshots of the real data is reasonable for many measures. However, accurately matching time-variant properties is more difficult, as we demonstrate by evaluating ten well-known models against the 2010 data.

I. Introduction

The Internet is growing rapidly, having more than tripled in size in the last decade, from 10,000 Autonomous Systems (ASes) in 2002 to 34,000 in 2010. However, few studies have looked carefully at the time evolution of the Internet topology at the AS-level. Most studies consider a snapshot of the AS-level topology of the Internet, derived from the latest data available at the time of the research, e.g. [1], [2], [3], [4].

In this paper, we are interested in how the topology of the AS-level Internet changes over time. We take the common approach of regarding the Internet as a graph, where the vertices are ASes and the edges are routing links between them. There are many properties of the Internet graph that can be investigated, from the simple degree distribution to more complex measures such as betweenness centrality. We select a set of eight commonly used measures that are relevant to the way the Internet functions. The measures are described in section II.

We investigate how the selected measures change over the period from January 2002 to January 2010, and present the results in section IV. We find that the distributions for most of the measures remain unchanged except average path length and clustering coefficient. Since 2005, the average path length has slowly and steadily increased and the average clustering coefficient has steadily declined. These results may signify changes in peering relationships in the Internet; we discuss this idea in section VI.

Our results imply that Internet topology models can be evaluated using single snapshots of the topology in time for many measures but not all. We can expect that models that matched invariant measures five years ago will still match today. To this end we include a brief summary of 10 well-known models and their performance on the latest data set in subsection IV-C. We find that models that were accurate when originally proposed, often many years ago, still accurately predict many time-invariant AS features (such as centrality), while doing a poorer job on the time-variant measures, such as clustering coefficient. In addition, the unchanging maximum degree of the Internet is often poorly predicted.

II. Topological properties of the Internet

We selected a set of eight measures for our analysis of Internet topology evolution. Although many more measures are available, e.g., [5], [6], [7], [8], we chose those most commonly used in the past to evaluate both generative models and data of the actual AS topology [9]. Further, we selected measures that seem most relevant to understanding the functioning of the Internet. Table I summarizes the measures and our rationales for choosing them. Given space limitations, we restrict our attention to graph-based measures, ignoring network operation constraints, traffic flow analysis, and distributions of AS relationship types.

The measures are divided into four categories: *Node Centrality*, *Path Length*, *Community Structure*, and *Scale Free Structures*. We also track simple properties such as the maximum and average degree of ASes.

A. Node Centrality

Node centrality measures are related to the prominence of ASes, which is important when evaluating the implications of ISP regulation [10] or the robustness of the Internet [11]. We use three measures of centrality: the node *degree*, the *betweenness*, which is the fraction of all shortest paths that pass through a node [12], and the *page rank*, which is the number of times that a node will be visited on a sufficiently long random walk on the graph [13]. The betweenness centrality is inversely related to the robustness of the graph to removal of nodes, because the more paths that pass through a node, the more damage will be done when that node is removed.

Measure	Rationale
Degree Centrality	Simplest way to measure AS prominence
Betweenness Centrality	AS prominence under best (shortest-path) routing. Inversely related to robustness to node deletion
Page Rank Centrality	AS prominence under average (random) routing.
Path Length	Related to routing efficiency (hops between source and destination)
Clustering Coefficient	Related to the peering structure of the Internet, and routing resilience (number of alternative routes)
K-Cores Decomposition	Related to tier structure of the AS Graph
Assortativity	Relevant to peering relations
S-Metric	Distinguishes among scale-free graphs, alternate measure of assortativity

TABLE I
SUMMARY OF MEASURES.

B. Path Length

The *average shortest path length* from a node to all other nodes in the graph (the geodesic distance)[1] is important because it relates to the number of routing hops between ASes. Not all packets travel along the shortest paths because of business agreements (such as the valley-free rule), but to a first approximation, routing distances (hops on the AS graph) are largely determined by the shortest paths.

Alternative path length measurements include diameter, which is the longest of the shortest paths between all pairs of nodes, and the effective diameter, which is the path length that defines the 90th percentile of all paths [15]. In the Internet, the distribution of path lengths has small variance, so diameter and effective diameter are only slightly larger than the shortest average path length and highly correlated with it. Hence we use only the average shortest path length.

C. Community Structure

Community structure measures how groups of nodes form substructures within the graph and is relevant to understanding various aspects of the Internet, such as the tiered structure and resilience to node deletions. Although there are many community structure measures [16], [17], we chose three that reveal important features of the AS graph. The first measure is the *local clustering coefficient*, which is the number of edges among the neighbors of a node as compared to the maximum possible number [18].[2] The clustering coefficient is related to the resilience of the routing infrastructure, because it reflects the number of alternative routes between pairs of nodes (for example, a tree has a coefficient of 0 and the removal of any edges will partition the graph). The second community structure measure is *degree assortativity*, which measures whether nodes tend to connect to others of similar degree [19]. The final measure is *k-cores decomposition*, which measures successive maximally connected subgraphs [20]. We report two measures for k-cores: the distribution of k-cores values, and the size of the maximum core, k-max.

D. Scale-free Structures

The power-law degree distribution of the AS graph is a scale-free property often cited as a distinguishing feature of the Internet, e.g., [3]. If the AS graph can be described as scale-free it may share properties with other scale-free networks, for example, the tendency to be 'robust yet fragile' or the preferential attachment growth dynamic. However, Li et al [21] showed that it is possible to construct graphs and general data sets that have similar scale-free properties but very different structures. To address this issue, Li et al. propose the *s-metric*—the sum over edges of the product of the degree of the two nodes an edge connects. This computation yields a single value that measures the extent to which a graph is actually scale-free.

III. DATA SETS

To investigate how the Internet changes over time, we collected a set of AS graphs covering the period from January 2002 to January 2010 by parsing monthly snapshots of BGP routing table dumps from Oregon Route Views and RIPE.[3] Although BGP routing tables are dumped every few hours, monthly snapshots were of sufficient temporal resolution given the long time scale of the analysis. The monthly snapshots were compiled by parsing all of the dumps from the first day of each month, taking every adjacent pair in the ASPATH and adding them to the graph for that month. We did not filter out self loops, private Autonomous Systems Networks (ASNs), or any other potential spurious or inaccurate results from the dumps, as it is generally assumed that the number of false positives of this type are small [22].

One potential problem with the BGP data is that nodes and edges disappear and reappear due to the way the data are sampled. While there are other ways of dealing with disappearing edges and nodes [15], we assumed that nodes and edges that temporarily disappear from the BGP tables actually exist throughout from first appearance to last. Our data set is available[4] in networkx[5] format.

To validate our results, we ran identical experiments using data collected from the Cooperative Association of Internet Data Analysis (CAIDA) [23], and obtained essentially identical results. The collectors of the CAIDA data sets went to great

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[1]This is sometimes referred to as *closeness centrality*, though there are other definitions for closeness centrality [14].

[2]We do not use transitivity, which is an alternative definition of the clustering coefficient, because it tends to be highly correlated with the average degree and so does not yield additional useful information.

[3]www.routeviews.org andwww.ripe.net
[4]https://ftg.lbl.gov/projects/asim/data-2/
[5]http://networkx.lanl.gov/

length to deal with various false-positive errors and the issue of nodes and edges that temporarily disappear, so the close agreement between the two data sets indicates that relatively simple preprocessing of the data is adequate for the purposes of our study.

Although false positives in the data are likely rare, false negatives (missing links) are likely common because the BGP dumps do not capture peering links between smaller ASes on the edge of the graph.[6] Although several studies have attempted to quantify the number of missing links (e.g. [22], [24], [25]), it is difficult to determine how exactly those hidden links could affect the structure of the AS-graph. Consequently, we focus on the *visible* Internet, in which we see subtle topological changes (see section IV) that we speculate could be caused by an increase in missing links.

IV. RESULTS

Most of the measures yield a distribution rather than a single value. Although we can plot the distributions together, year by year, it is also useful to have a single value for determining the changes over time. A common approach to this problem aggregates distributions, using measures of central tendency, extent, or spread [9]. However, studying the distributions as a whole before aggregating allows us to discover changes to the shape of the distribution (e.g. a transition from an exponential distribution to a power-law) that might not be revealed under aggregation. Consequently, we test whether the distributions between years differ using the Cramér–von Mises Criterion (CMC) [26]. The CMC tests the hypothesis that two samples of data are drawn from the same distribution. Although many alternative tests and measures exist [27], [28], [29], the CMC gives accurate comparisons and captures intuitive similarities between plots that can be seen visually.

We used the CMC to identify year by year changes in all of the measures that have distributions. Table II shows the changes from one year to the next from 2002 to 2010. For each year, we applied the measures to the AS-graph for June; varying the month of data collection does not vary the results. For measures that do not have distributions (k-max, assortativity and the s-metric), Table II reports the absolute values, rather than the year by year differences.

A. Unchanging Features

Table II shows that the node centrality measures (degree, betweenness and page rank) stay constant over time. Figure 1 illustrates this point, showing that the power-law degree distribution is virtually identical over time. We obtain similar results for betweenness and page rank—the distributions are stable over time (data not shown).

In Figure 1 not only is the slope of the distribution unchanging, but the *extent* (maximum degree) is nearly constant. Only three ASes have had the maximum degree in the years 2002 to 2010: MCI Inc., Level 3 Communications, and Cogent Communications (see Figure 2). MCI, which held the top

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[6]Roughan et al [22] estimate that an AS graph extracted from public BGP views is likely to miss 27% of links overall, and 70% of peer-to-peer links.
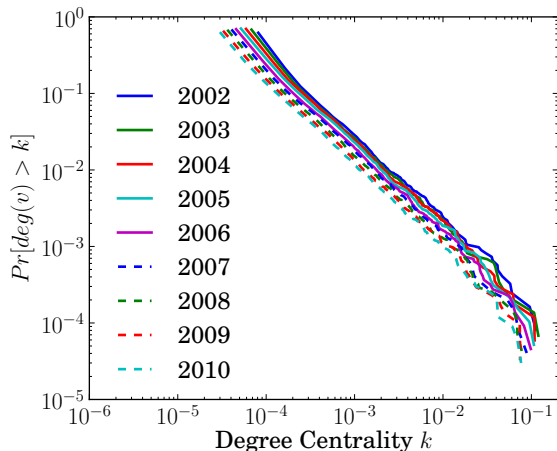

Fig. 1. Complement cumulative distribution of the degree of ASes between 2002-2010
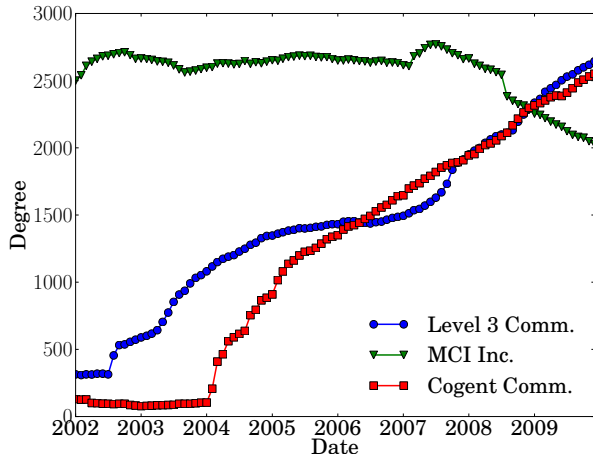

Fig. 2. Degree changes in the three largest degree ASes.

position until late 2008, maintained a nearly constant degree, while Cogent and Level 3 had a nearly monotonic increase in degree over the same time period. Growth is not guaranteed for an AS: 61% of all ASes experienced a month to month decline in degree at least once between 2002 and 2010 and fully 84% of ASes that have existed for five or more years experienced at least one monthly decline.

Other clearly unchanging features in Table II are the k-cores and the degree assortativity. The s-metric appears to gradually increase over the entire period, but this could be a meaningless change: According to Li et al. [21], graphs with low s-metric values (below 0.1) are likely "scale-rich" and difficult to differentiate from each other using the s-metric.

B. Changing Features

Two measures exhibit distinct changes over time: the average path length and the clustering coefficient. The changes in the distribution of path length, although statistically significant, are not easily visible on a plot. The clustering coefficient, on the other hand, has changes that are clearly visible, as can

Year	Nodes	Edges	Degree	Betweenness	Page Rank	Path Length	Clustering	K-Cores	K-max	Assort.	S-Metric
2002	13172	26695							16	-0.189	.0114
2003	15446	32089	NS	NS	NS	****	NS	NS	18	-0.188	.0121
2004	17722	39654	NS	NS	NS	****	NS	NS	22	-0.188	.0159
2005	20174	45505	NS	NS	NS	****	NS	NS	24	-0.196	.0176
2006	22708	50796	NS	NS	NS	****	*	NS	24	-0.189	.0183
2007	25691	58200	NS	NS	NS	****	NS	NS	26	-0.189	.0199
2008	28640	64111	NS	NS	NS	****	**	NS	25	-0.192	.0203
2009	31645	69938	NS	NS	NS	****	*	NS	25	-0.195	.0210
2010	34055	71544	NS	NS	NS	****	****	NS	21	-0.191	.0179

TABLE II

ANNUAL CHANGE OF MEASURES. WE REPORT COMPUTED VALUES FOR K-MAX, ASSORTATIVITY AND S-METRIC. FOR OTHER MEASURES, WE REPORT THE STATISTICAL SIGNIFICANCE OF THE CHANGE BETWEEN YEARS (NS: NOT SIGNIFICANT, *: $p < .1$, **: $p < .05$, ***: $p < .01$, **** : $p < .001$).

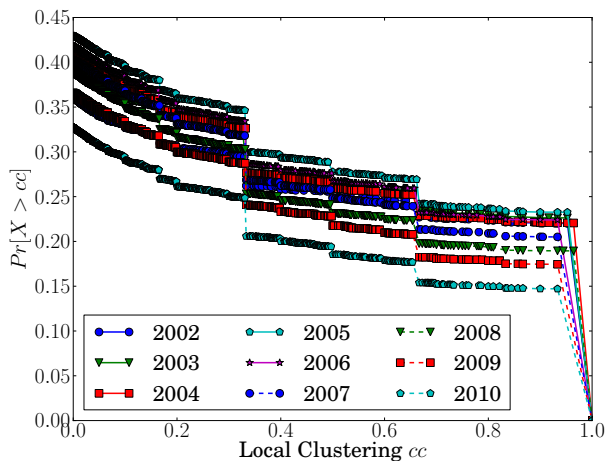Fig. 3. Complement cumulative distribution of the local clustering coefficient of the AS graph
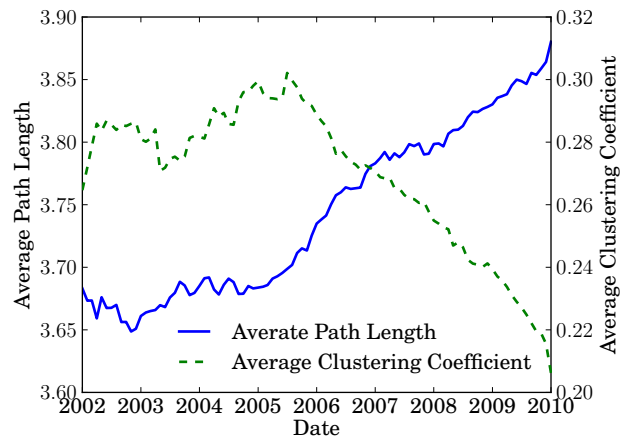

Fig. 4. The change in the average path length and the average clustering coefficient, plotted monthly. Both clustering coefficient and path length experience a nearly constant variance of .16 and .3 respectively, and so we do not report error bars in this figure.

be seen in Figure 3. Although the distribution changes little in shape, there is a distinct downward trend over time.

The trends in path length and clustering coefficient are evident in Figure 4, which plot averages over time. We can see that around 2005, the structure of the visible AS graph began to change. The average path length and average clustering coefficient do not exhibit any clear trend until mid 2005, when they began slowly increasing and decreasing respectively. In addition, the k-max value was steadily increasing up to 2005, after which it leveled off (see Table II). From these changes we can infer that both the efficiency of the *visible* Internet (as measured by number of hops on the shortest paths between locations) and resilience to router failure, have been decreasing since 2005. We discuss possible reasons for these changes in section VI.

The shift in topology beginning in 2005 indicates that the Internet has not reached steady-state. This observation contradicts many models of the AS graph, in which measures converge to a steady-state distribution. The next section studies how well different models of Internet topology match the AS graph on the different measures.

C. Topological Models of the Internet

The relatively slow changes we see in the Internet imply that generative models that give accurate results at one size should do so at most sizes. To check this we generated topologies from 10 different models and compared them to the AS graph from June 2010. Table III lists the models we considered. In each case, we generated a topology of 34,055 nodes, the same number as our latest snapshot of the AS graph.

The comparisons of the different models to the AS graph are shown in Figure 5. As expected, later models are more accurate than earlier models (the models are ordered from oldest at the top to most recent at the bottom). All models generate close matches to the degree distribution, which makes sense because this is typically the first measure authors use to evaluate a model, and it has not changed over time. Further, most models match the other measures of centrality quite well, presumably because they are also time-invariant.

It is notable that all the models perform worst on the measures that change the most, namely path length and clustering. In general, models match time-invariant measures better than time-varying measures, with the exception of maximum degree, which no model captures well.

| Name	Abbr.	Description	Reference
Barábasi-Albert	BA	Original preferential attachment model	[1]
Heuristically Optimized Trade-offs	FKP	Local optimization model	[30]
Generalized Linear Preference	GLP	Modified preferential attachment model	[31]
Univariate Heuristically Optimized Trade-offs	UFKP	Modified local optimization model	[32]
Bivariate Heuristically Optimized Trade-offs	BFKP	Modified local optimization model	[32]
Multivariate Heuristically Optimized Trade-offs	MFKP	Modified local optimization model	[32]
Interactive Growth	IG	Modified preferential attachment model	[33]
Positive Feedback Preference (1)	PFP1	Modified IG model	[33]
Positive Feedback Preference (2)	PFP1	Modified PFP1 model	[33]
ASIM	ASIM	Agent based topology generator	[10]

TABLE III
SUMMARY OF MODELS EVALUATED.
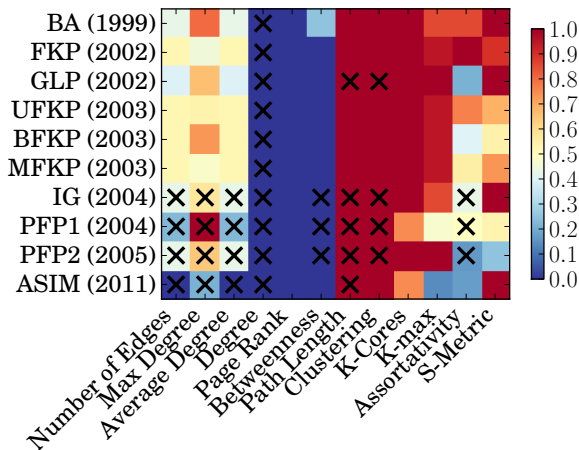
Fig. 5. Evaluating models. The color of each square corresponds to the statistical significance level for the Cramér-von Mises criterion when comparing the model to the January 2010 AS graph for a given measure. The number of stars (0 to 4) is scaled between 0 and 1 for consistency with the other measures. For k-cores, degree assortativity and the s-metric, the color corresponds to the relative error. Hence lower values mean more similar distributions. X's indicate that the measure was reported in the original publication of the model.

It is not surprising that most generative models we studied performed well on the time-invariant measures the models were originally tested on. However, most models perform much worse on measures they were not originally tested against. This indicates the importance of evaluating models against a wide variety of measures, because many different graphs can be similar in one measure, but it is much harder for different graphs to be similar in multiple measures.

V. RELATED WORK

There are few studies that look at changes in topological characteristics beyond the number of nodes and edges. Most of those that do focus on inter-AS relationships, for example, Chang et al [34] study the changes in customer-provider relationships and find that the number of providers is increasing over time. Another approach was taken by Oliveira et al [35], in which they investigate the changing relationship over time between stub ASes and transit providers. They find that the net growth of rewirings for transit providers levels off at the end of 2005, around the same time our results show subtle

changes in the Internet. Gill et al [36] look more closely at the evolution of peering relationships, and find that over time large content providers are relying less on Tier-1 ISPs, and more on peering with lower tiers. This finding is supported by Labovitz et al [37], who report a rapid increase in the traffic flow over peer links over time, resulting in a less hierarchical Internet topology. These observations could potentially explain some of our results, as we discuss in section VI.

In addition to studying business relationships, Dhamdhere el al [38] reported on changes in average degree and average path length over time. Their results on path length agree with ours, although their study included only data up to 2007, so the trends are less clear. Because the degree distribution does not change, it is likely that the shift they see in average degree is a result of a steadily increasing sample size. Another study [39] used spectral analysis to investigate clustering on the AS graph, and study coreness and changing path diversity. This analysis, however, covers short time spans (at most two and a half years), and only considers data before 2004.

The work of Zhang et al [40] is perhaps closest to ours. They study changes in several topological measures over the time period from 2001 to 2006. Because of this time period, their results do not capture the trends we report post-2005. However, the changes they document agree with what we observed in the earlier period: They find the assortativity and k-cores are stable over time and from 2004/2005 onwards, the k-max value changes little. Further, they find the average clustering coefficient starts declining around 2005, and the average path length starts increasing gradually.

VI. DISCUSSION

We have reported a distinct shift in the topology of the *visible* Internet since 2005: the average path length is increasing, and the average clustering coefficient is decreasing (Figure 4). On the surface, it would appear that the Internet is getting both less efficient and less resilient. But this may not actually be the case, because the the shift is likely caused by changes in peering policies that affect the hidden Internet and cannot be measured with public BGP dumps. As mentioned in section V, there are several studies showing that content providers are routing more traffic over hidden peer-to-peer links, and relying less on the more publicly visible Internet

infrastructure. Consequently they have less need to establish new customer-provider links, and a decreasing number of new customer-provider links increases the *observed* average path length of the graph.

Most models match topological measures that are invariant over time in the AS graph, particularly centrality. However performance degrades when examining time-variant measures such as average path length and clustering coefficient. Future modeling efforts will need to focus on incorporating mechanisms that can cope with such changing dynamics. For example, few existing models allow for the loss of links in the AS graph, a common feature according to our data. Agent-based models such as ASIM are potentially a promising direction for future AS topology modeling efforts because they can naturally model economic pressures that lead to link deletion. Further, robust statistical techniques such as the CMC will be needed to verify topological results.

In conclusion, it is surprising that so few of the common measures of Internet topology have changed over the past eight years, even though the number of ASes has tripled during this time period. Those measures that do change point to the increasing importance of understanding the role of policy and economics in determining Internet topology. Going forward, it will be increasingly important to find ways to reveal hidden links and evolving peering relationships.

VII. ACKNOWLEDGMENTS

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