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# On the Geographic Location of Internet Resources

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*Abstract*— One relatively unexplored question about the Internet’s physical structure concerns the geographical location of its components: routers, links and autonomous systems (ASes). We study this question using two large inventories of Internet routers and links, collected by different methods and about two years apart. We first map each router to its geographical location using two different state-of-the-art tools. We then study the relationship between router location and population density; between geographic distance and link density; and between the size and geographic extent of ASes.

Our findings are consistent across the two datasets and both mapping methods. First, as expected, router density per person varies widely over different economic regions; however, in economically homogeneous regions, router density shows a strong superlinear relationship to population density. Second, the probability that two routers are directly connected is strongly dependent on distance; our data is consistent with a model in which a majority (up to 75-95%) of link formation is based on geographical distance (as in the Waxman topology generation method). Finally, we find that ASes show high variability in geographic size, which is correlated with other measures of AS size (degree and number of interfaces). Among small to medium ASes, ASes show wide variability in their geographic dispersal; however, all ASes exceeding a certain threshold in size are maximally dispersed geographically. These findings have many implications for the next generation of topology generators, which we envisage as producing router-level graphs annotated with attributes such as link latencies, AS identifiers and geographical locations.

## I. INTRODUCTION

Despite the Internet’s critical importance in society, surprisingly little quantitative information is known about its physical structure and about the dynamic processes that drive its rapid growth. Developing a better understanding of the Internet’s structure is of interest from a purely scientific standpoint, but is also of immediate practical interest, since knowledge of the network’s properties enables researchers to optimize network applications and to conduct

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more representative network simulations.

Previous attempts to model Internet structure have often made implicit or explicit assumptions about the network’s geometry. For example, the Waxman model [38] makes two such assumptions: 1) that network nodes are placed uniformly at random in the plane; and 2) that the likelihood two nodes are directly connected is an exponentially declining function of separation distance. On the other hand, other models have implicitly assumed that there is *no* important underlying geometry to the network, and the patterns of connectivity are only influenced by topological factors [9], [41], [2].

Despite these prevalent assumptions about network geometry, very little work to date has actually examined the geometry of the Internet’s infrastructure. In this paper, we present initial results bearing on these questions. For example, with respect to the Waxman assumptions, we find that assumption 1 (uniform distribution of routers) is very inaccurate — the actual distribution pattern of routers is highly irregular. On the other hand, we find evidence that supports assumption 2 — the connectivity patterns of routers show a strong relationship to distance.

In the process of obtaining these results, we ask a number of basic questions. Regarding router placement, we ask: Where are the routers comprising the Internet physically located? and: What factors drive the geographic placement of routers? Turning to connectivity, the key questions we wish to answer are: Where are the links between Internet routers physically located? and: To what extent does router connectivity appear to be sensitive to physical distance? Our third set of questions concerns the autonomous system (AS) structure of the network: How does geographical size (number of locations) relate to previously studied measures of AS size? How do ASes disperse their resources geographically? and: How do interdomain links differ from intradomain links geographically? The answers we find to our main questions are consistent across three different regions of the world, across two very different sources of data, and across two different geographic mapping techniques.

The choice of these questions is motivated by current problems in network topology generation. We turn to

geography for inspiration because a number of unsolved problems in topology generation appear much easier to solve given an underlying geographical model. For example, an accurate geometric model of router placement and link formation would make the labelling of links with latency values a straightforward matter.

Although the questions we pose are relatively simple, providing reasoned and justifiable methods to answer them is surprisingly difficult. The foremost difficulty is that there does not exist a recent “snapshot” of the Internet that provides geographical location of routers, links, and ASes.<sup>1</sup> To build such snapshots, we took two large inventories of Internet routers and links, collected by different methods about two years apart, and processed them in two stages: first, by mapping each router to its associated AS number, and second, using two different state-of-the-art tools to determine each router’s geographical location.

We present our main results in Sections IV to VI. In Section IV we show that router density per person varies widely over different economic regions, but that router density per “online user” (defined in Section IV) shows much less variability — suggesting that the number of network users in a geographic region (as determined, *e.g.*, by surveys) can be used to roughly size the amount of network infrastructure expected in the region. When we restrict our focus to economically homogeneous regions, we find that router density shows a strong superlinear relationship to population density; that is, the number of routers per person is higher in highly populated areas. (This may reflect the superlinear scaling of the number of communication paths needed as a function of the number of network users in an area.) These results justify the use of population distribution (which is well studied, with easily accessible datasets [6]) as an effective proxy for the actual distribution of routers.

Next, in Section V, we show that the probability that two routers are directly connected is strongly dependent on the distance between them. In fact, our data is consistent with a model in which a surprisingly large majority (up to 75-95%) of link formation is influenced by geographical distance. As mentioned above, this is the assumption made in the Waxman model [38] but it is explicitly *not* an assumption in more recent and more sophisticated topology models. In fact, we even find that the functional form of distance dependence used by Waxman (*i.e.*, an exponentially declining connection probability) is in agreement with our data. Of course, the Waxman method produces topologies very different from reality; but our results highlight the relative importance in examining the point distribution as-

sumptions in the Waxman model in assessing the sources of its inaccuracy.

Finally, in Section VI, we turn to questions of how to use geographical information to assign nodes to Autonomous Systems. We find that ASes show remarkable variability in geographic extent. We show that the number of distinct locations in which an AS places routers has a long-tail distribution similar to that previously reported for AS degree [12] and number of routers in an AS [36]. We also show that all three of these measures of AS size are clearly correlated. In examining the geographic area covered by the routers of an AS, we show evidence for two distinct types of ASes: smaller ASes show a wide range of variation in the geographic dispersion of their infrastructure. On the other hand, there is an upper cutoff in size (in terms of degree, number of routers, or number of locations) beyond which all ASes are maximally dispersed geographically. In examining the AS-crossing properties of links, we find that intradomain links constitute the majority of links in our dataset (generally over 80%) and that they are on average only half as long as interdomain links.

We conclude in Section VII with a review of our findings and a look to the future, including the implications of our work for representative topology generation.

## II. RELATED WORK

Early work in generating test topologies focused on simple and natural methods for producing interconnections between a set of nodes on the plane. The widely studied Erdős-Rényi random graph model [10] includes each possible connection with a fixed probability  $p$ , but typically yields a graph which is not connected when  $p$  is chosen so that the resulting graph is sparse. Waxman [38] created topologies in which the probability that a connection between a pair of nodes is made decays exponentially as the distance between the nodes increases, emphasizing *spatial* considerations in topology generation. Structural models such as Tiers and GT-ITM [9], [41] chose a different tack, building an explicit *hierarchy* into their topologies.

Following the discovery of then-unexplained power laws in Internet topologies of Faloutsos *et al.* [12], subsequent methods, notably the Barabási-Albert model [2], and topology generators such as Inet [20] and generation models in BRITe[25], measured success primarily in terms of graph connectivity properties, such as node degree distributions. An active debate about the merits and limitations of these approaches is ongoing [20], [22], [7], [5]; the jury is still out on which models are best and studies have shown varying conclusions depending on the generators used [29].

Our goal is not to propose a new topology generation

<sup>1</sup>The most recent geographical map of the entire Internet we have been able to find dates from 1982 (ARPANET).

method in this paper, but to suggest a wider set of bases for the construction of topology generation tools. To this end, we study the geographic location of Internet links, routers and ASs. CAIDA’s NetGeo [13] is a database that contains mappings from IP addresses, domain names and AS numbers to latitude/longitude values. NetGeo’s database is built using *whois* lookups to the ARIN, RIPE, and APNIC servers. Ixia’s IxMapper [19] database, extends NetGeo by using other data sources and heuristics, including geographically-based hostname conventions. Padmanabhan and Subramanian [28] show that this hostname based mapping is accurate up to the granularity of a city. Another mapping tool is Akamai’s EdgeScape [1] which uses geographical information gathered from ISPs along with hostname conventions to resolve IPs to their geographical locations. Besides Ixia and Akamai, other commercial providers include Matrix NetSystems [24].

To our knowledge, the only other work which measures and models geographic location of Internet resources is recent work of Yook, Jeong and Barabási [40]. That paper demonstrated the similar fractal dimension ( $\approx 1.5$ ) of routers, ASes, and population density; our work, not shown in this paper, confirms this result for our datasets as well (via the box-counting method [23], [11]). However, our goals differ with respect to links and distance: while [40] studied the distribution of link lengths, we are concerned with the likelihood that two nodes are directly connected as a function of the distance between them.

### III. METHODOLOGY

We use router level topology snapshots from two sources, collected by different methods and about two years apart. For each router interface IP address in the datasets, we obtained a geographical coordinate and the AS that originated that address.

#### A. Datasets

Our first topology dataset is a large collection of ICMP forward path (traceroute) probes. This data was collected by Skitter, a measurement tool run on more than 20 monitors around the world by CAIDA [14]. Skitter sends hop-limited probes to a list of destination nodes located worldwide. Intermediate routers which respond to packets with expired TTL values transmit an ICMP message back to the source. Contained within this packet is the IP address of an *interface* on the router; thus a successful Skitter probe reports a sequence of interfaces along contiguous routers on the path from the source to the destination. In this study, we treat interfaces as virtual nodes, and define a link to mean a connection between two adjacent interfaces. The destination lists are created with the aim to cover all blocks

of 256 addresses ( $/24$ s) in the IPv4 space [4]. Destinations are selected by several methods, among which are: results of searches for several hundred thousand geographic names and popular science articles from the top five search engines, Squid web cache logs [39], CAIDA’s IP geography server [13], and UCSD web server and traffic logs. Our particular dataset was gathered between December 26, 2001 and January 1, 2002 and is the union of traceroute paths from 19 monitors, each probing a destination list of varying size. This dataset contains 704,107 router interfaces and 1,075,454 incident links. To our knowledge, this is one of the largest and most recent router level dataset studied to date. On this dataset, we followed the methods of [4] and discarded anomalies such as self-loops. We further discarded all interfaces appearing in the destination lists (18%). This was motivated by the fact that many destinations in these lists are end-hosts and we are interested only in routers.

Our second dataset is another router level topology snapshot collected during August 1999 by the Scan Project’s [34] Mercator tool. Mercator also uses hop-limited probes to discover and map routers and links. Unlike Skitter, Mercator is run from a single host to a heuristically determined destination address space [15]. Further, Mercator employs loose source routing to discover lateral connectivity and therefore limits the tree-like properties commonly found in single-source router mapping efforts such as [31]. Our Mercator dataset is considerably smaller than our Skitter dataset, at 268,382 router interfaces and 320,149 links. Mercator employs published techniques [30] to collapse interface IP addresses belonging to the same router to a canonical IP address for that router. After this disambiguation process, we are left with 228,263 routers and 320,149 links.

An important distinction between maps generated by Mercator and Skitter is that the former generates a map of routers, while the latter generates maps of interfaces. Routers often have multiple interfaces, thus maps that are unable to resolve which interfaces are present on which routers are prone to inaccuracies described elsewhere in the literature [3]. The primary method to resolve interfaces [30] is to send UDP probe packets to unknown ports for every interface in the dataset. When two interfaces are on the same router, the router will respond with two ICMP Port unreachable messages, both of which have the same source IP address. Unfortunately, this technique suffers from numerous limitations, especially because probe packets now frequently trigger network intrusion detection systems, and routers may not respond correctly to the probes. Because of these reasons, we were not able to perform interface disambiguation on the Skitter datasets. Despite this

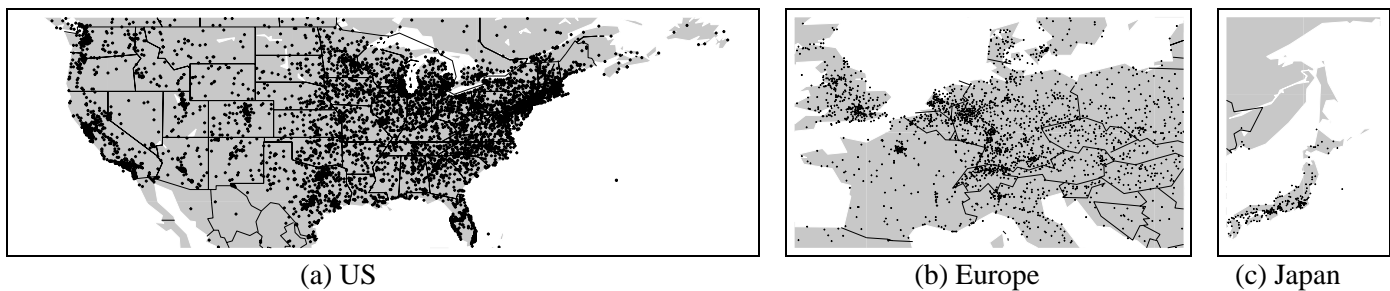


Fig. 1. Regions Studied (Not to Same Scale).

Dataset	No. of Nodes	No. of Links	No. of Locations
IxMapper, Mercator	214,498	258,999	7,696
IxMapper, Skitter	563,521	862,933	12,610
EdgeScape, Mercator	216,116	269,484	7,076
EdgeScape, Skitter	570,761	881,618	13,767

TABLE I  
SIZES OF PROCESSED DATASETS

difference, our conclusions seem robust whether expressed in terms of routers or interfaces. But to emphasize this difference, we will always keep the terms “router” and “interface” distinct in this paper.

### B. Geographical Mapping

We draw on two different state-of-the-art geographic mapping tools to identify IP addresses with their geographical longitude and latitude: Ixia’s *IxMapper* [19] and Akamai’s *EdgeScape* [1].

*IxMapper* extends NetGeo’s [26] methods for location mapping by using several data sources and a library of heuristics to infer the geographical location of an IP address. The primary technique employed by *IxMapper* is hostname based mapping. This technique exploits the fact that ISPs usually adhere to a strict naming convention for each of their routers in which some sense of geographical location (such as city name or airport codes) is specified. For instance, 0.so-5-2-0.XL1.NYC8.ALTER.NET maps to New York City. *IxMapper* also uses other techniques, parsing whois records [16] and DNS LOC records [8]. The whois lookup method is generally accurate for small organizations but may fail in cases where geographically dispersed hosts are mapped to an organization’s registered headquarters. DNS LOC records, while accurate, are not required and are therefore not always available. *IxMapper* always tries to use hostname based mapping, defaulting to DNS LOC records if available and finally to whois records.

Akamai’s *EdgeScape* service supplements hostname

Name	North	South	West	East
US	50° N	25° N	150° W	45° W
Europe	58° N	42° N	5° W	22° E
Japan	60° N	30° N	130° E	150° E

TABLE II  
BOUNDARIES OF REGIONS STUDIED

based mapping techniques with internal ISP geographical information. Akamai’s many relationships with networks coupled with its extensive server deployment give it access to such information.

Our principle results are consistent across both mapping tools. However, due to space limitations and to avoid confusion, we only present results obtained from *IxMapper* in the next sections. Results from *EdgeScape* are provided in the Appendix.

Our results of geographic mapping the router/interfaces from both datasets are encouraging. After discarding private addresses originating from misconfigured routers, only 1% of Mercator’s routers and 1.5% of Skitter’s interfaces could not be located by *IxMapper*. Similarly, only 0.6% of Mercator’s routers and 0.3% of Skitter’s interfaces could not be identified by *EdgeScape*. All unmapped interfaces were discarded. For the Mercator dataset, we determined the location of a router by the location most commonly reported across all its interfaces. We discarded routers with ties for the most commonly reported interface location (2.9% for *IxMapper* and 2.5% for *EdgeScape*). Table I summarizes the final number of geographically mapped interfaces/routers and links for both datasets.

For reasons described in the next section, the majority of our results are based on analysis of three regions, delineated by the latitude and longitude lines shown in Table II. These regions, along with the results of our *IxMapper* mapping for the Skitter dataset, are shown in Figure 1.

	Population (Millions)	Interfaces	People Per Interface	Online (Millions)	Online per Interface
Africa	837	8,379	100,011	4.15	495
South America	341	10,131	33,752	21.9	2,161
Mexico	154	4,361	35,534	3.42	784
W. Europe	366	95,993	3,817	143	1,489
Japan	136	37,649	3,631	47.1	1,250
Australia	18	18,277	975	10.1	552
USA	299	282,048	1,061	166	588
World	5,653	563,521	10,032	513	910

TABLE III  
VARIATION IN PEOPLE/INTERFACE DENSITY ACROSS REGIONS

### C. Mapping to Autonomous Systems

We next label all nodes in both datasets with their parent AS. This was done by identifying the longest advertised prefix in a BGP table that matches the IP address and recording the AS which originated that prefix. While there are several publicly available sources of raw and processed BGP data [32], [18], [33], we used the RouteViews data from the University of Oregon’s Advanced Network Technology Center which has been the most comprehensive public source since 1997. RouteViews data is the union of many BGP backbone tables contributed by several dozen participating ASes. We used BGP tables from August 10, 1999 and January 1, 2002 to map the routers in the Mercator and Skitter datasets, respectively. For the Mercator dataset, we again determined the parent AS of a router by choosing the AS most commonly reported by its interfaces. A small fraction of IP addresses (2.8% for Mercator and 1.5% for Skitter) were not mapped. We grouped these into a separate AS, which was omitted in our analysis of Autonomous Systems (Section VI).

## IV. ROUTERS AND POPULATION

It is natural to assume that demand for Internet services is greater in areas of higher population. All of the drivers for Internet service would seem to have a connection to population: *e.g.*, end-user demand, content availability, and switching capacity. What is less obvious is what precise relationship we should expect between population density and density of network infrastructure. In this section we explore that relationship quantitatively; the results then form a foundation for subsequent sections.

### A. Variation Across Economic Regions

While a relationship between population and network infrastructure density is natural, it is also obvious that this relationship is not the same in all parts of the world. We

explore the variation in degree of Internet development in Table III. This table shows various regions of the world, including both less developed regions and highly developed regions.<sup>2</sup> The *Interfaces* column shows the number of interfaces from our Skitter dataset that were mapped into this region. *Population* numbers are from Columbia University’s CIESIN database [6], and the number of *Online Users* per region is from the extensive repository of survey statistics gathered and maintained by Nua, Inc [27].<sup>3</sup>

Looking at the first three columns of the table, it is clear that penetration of Internet infrastructure varies dramatically across regions; the ratio of people to interfaces varies by a factor of over 100 from less developed to highly developed regions. This makes it clear that studying population vs. interface density over the entire world will be misleading. On the other hand, the last two columns provide a different perspective: the ratio of online people to interfaces shows *much* less variability — only about a factor of four across the regions studied. This is encouraging for two reasons: first, it suggests that the number of online users in an area may provide a rough indicator of the amount of network infrastructure present; and second, it suggests that our datasets are not excessively biased in favor of any particular geographical area. We note that we found the same ranges of variation in our Mercator dataset — a variation of a factor over 100 in people per router, and only about a factor of 4 in online people per router.

Thus it is important to restrict our study to regions that are roughly homogeneous in terms of development of Internet infrastructure. Using simple tests we can easily ver-

<sup>2</sup>Regions in this table, and throughout this paper, are delineated by simple latitude/longitude boundaries. The names assigned to such regions are only approximate, since we are not working with precise political boundaries.

<sup>3</sup>According to Nua, an online user is defined as an adult or child who has accessed the Internet at least once during the last 3 months, although not all of their data is strictly based on this definition.

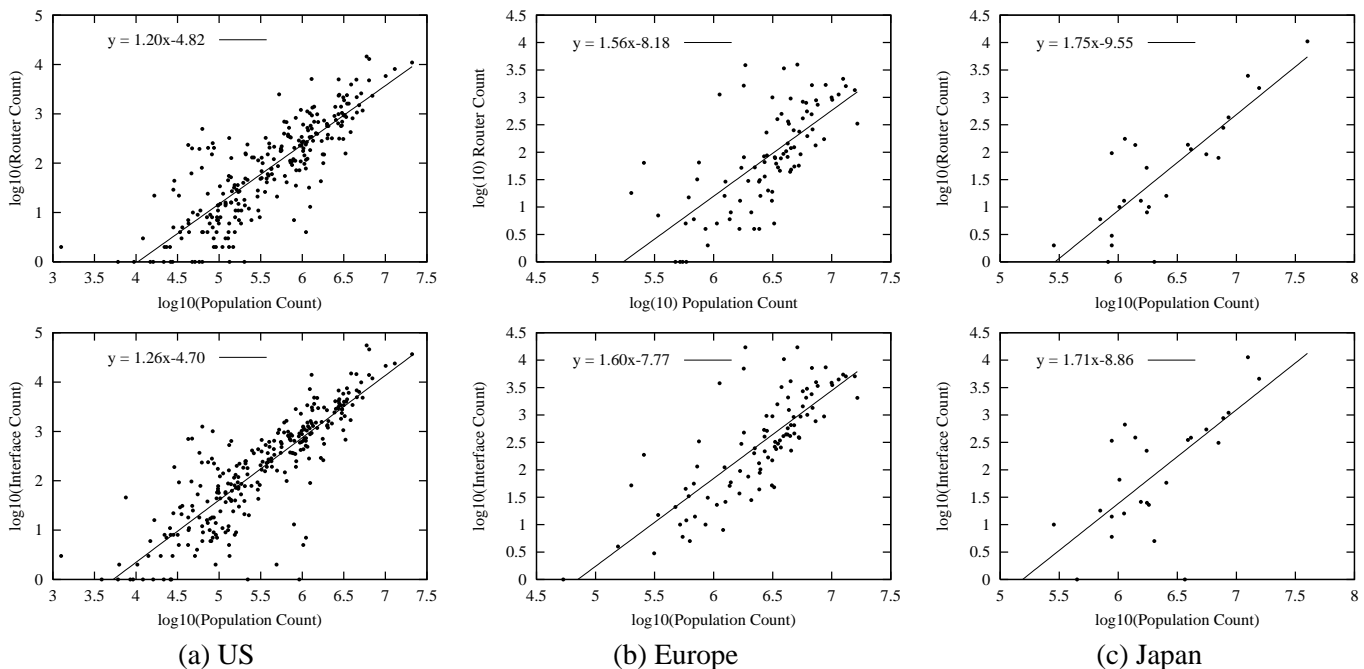


Fig. 2. Router/Interface Density vs. Population Density: Upper, Mercator (Routers); Lower, Skitter (Interfaces). Corresponding results using EdgeScape can be found in the Appendix (Figure 11).

ify whether a region meets this criterion. For example, consider the case of the continental US. We can test its homogeneity by dividing it into two subregions, as shown in Figure 3. We also include a portion of Central America as a third region for comparison. The statistics for these three regions are shown in Table IV. It is clear that the two subregions of the US are quite similar in deployment of network infrastructure, and that the Central American region is dramatically different.

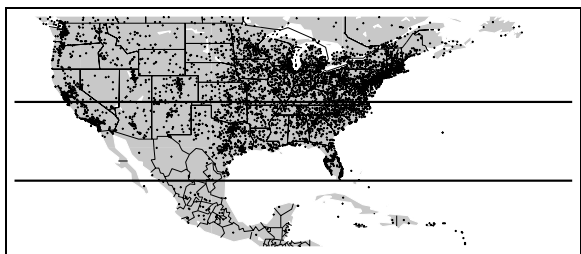


Fig. 3. Regions Used to Test for Homogeneity

	Population (Millions)	Interfaces	People Per Interface
Northern US	168	182,846	991
Southern US	132	101,102	1305
Central Am.	154	4,361	35,533

TABLE IV  
TESTING FOR HOMOGENEITY

### B. Infrastructure vs. People in Homogeneous Regions

Focusing on the economically homogeneous regions shown in Figure 1 and delineated in Table II allows us to ask how router density relates to population density. To answer this question, we subdivided each region into patches of size  $75 \text{ arc-minutes} \times 75 \text{ arc-minutes}$ . At the latitudes studied, this creates patches about 90 miles on a side. This size is much larger than the median location error reported by Padmanabhan and Subramanian [28] for their toolset, which employs techniques similar to (and a subset of) those used by IxMapper and EdgeScape. Within each patch, we tally the population and the number of routers or interfaces.

The results are plotted on log-log scale in Figure 2, for the two datasets and three regions. Each plot includes a least-squares fitted line for comparison purposes. The figure shows that within each region, the plots for routers and interfaces are qualitatively quite similar, as are the properties of the fitted lines. This similarity is striking given the considerable time difference of collection between the two datasets, and the very different collection methods.

All the plots show a strong relationship between infrastructure and population density. Although these plots appear roughly linear on these log-log axes, the precise functional relationship between population density and router density is difficult to identify from these data because of the significant amount of noise, and the relatively limited range of scales available. For example, it would be hard

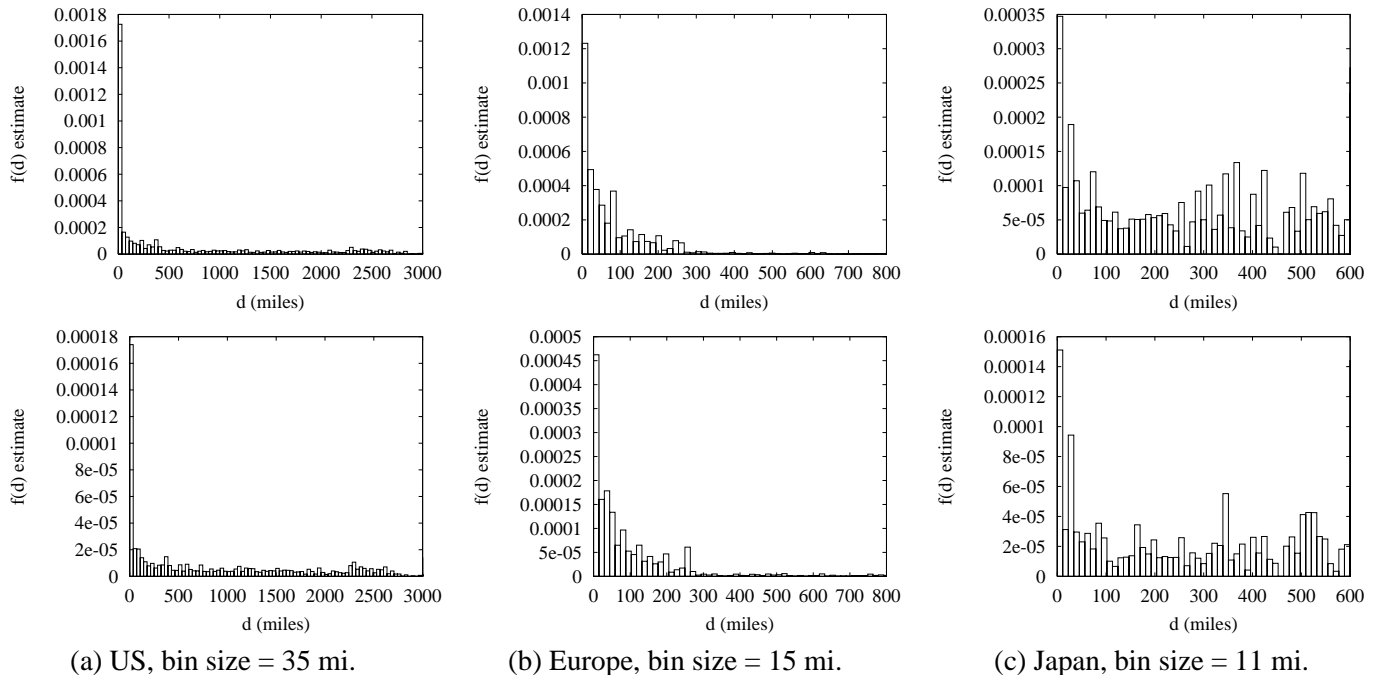


Fig. 4. Empirical Distance Preference Function: Upper, Mercator; Lower, Skitter. Corresponding results using EdgeScope can be found in the Appendix (Figure 12).

to distinguish a  $n \log n$  relationship from a power law relationship for the data in Figure 2(a).

Nonetheless, we conclude that in each plot, router/interface density clearly bears a *superlinear* relationship to population density (slope of the fitted line is larger than 1). This surprising result indicates that the number of routers or interfaces per person is *higher* in areas of high population density (population centers).

Furthermore, it seems reasonable to use a simple power law relationship as an approximation for the trends seen in these plots; that is, over the limited range of data studied, we can approximately model router or interface density  $R$  and population density  $P$  as related by

$$R \sim P^\alpha$$

with  $\alpha$  varying from 1.2 to 1.7 across the regions studied, based on the slopes of the fitted lines.

This result may be interpreted as a consequence of simple scaling effects: as the number of network users  $n$  in a region grows, the number of potential connections between pairs of users grows via an  $n^2$  law. If the capacity of individual switches does not scale accordingly, then in order to provide acceptable service it becomes necessary to add switches in a superlinear fashion. Thus, *e.g.*, multistage interconnection networks for multiprocessor computers are often designed to scale in  $n \log n$  fashion [21], [17].

## V. LINKS AND DISTANCE

Given an understanding of how routers are distributed over the Earth's surface, we next proceed to examine the geographical properties of node-node links. As described in Section II, early work in topology generation used a distance-sensitive function for link creation, while later work has focused on different features, such as overall network structure and node degree distribution.

Our data provides an opportunity to examine the sensitivity of router connections to distance. To do so we proceed as follows: we measure the empirical probability that two routers separated by great-circle distance  $d$ , are directly connected.

Note that this is not the same as assuming that link creation is in fact dependent on distance; more detailed data would be needed to verify that claim. However, evidence of distance-sensitivity in router connectivity is suggestive of factors influencing link creation, and provides an important characteristic to be taken into account in constructing and validating topology generators.

For any pair of routers separated by distance  $d$  let  $C$  be the event that the two routers are directly connected. Then we are interested in estimating the likelihood function:

$$f(d) = P[C|d].$$

We call this the *distance preference function*. We estimate this function by placing the data into bins of size  $b$ . Then



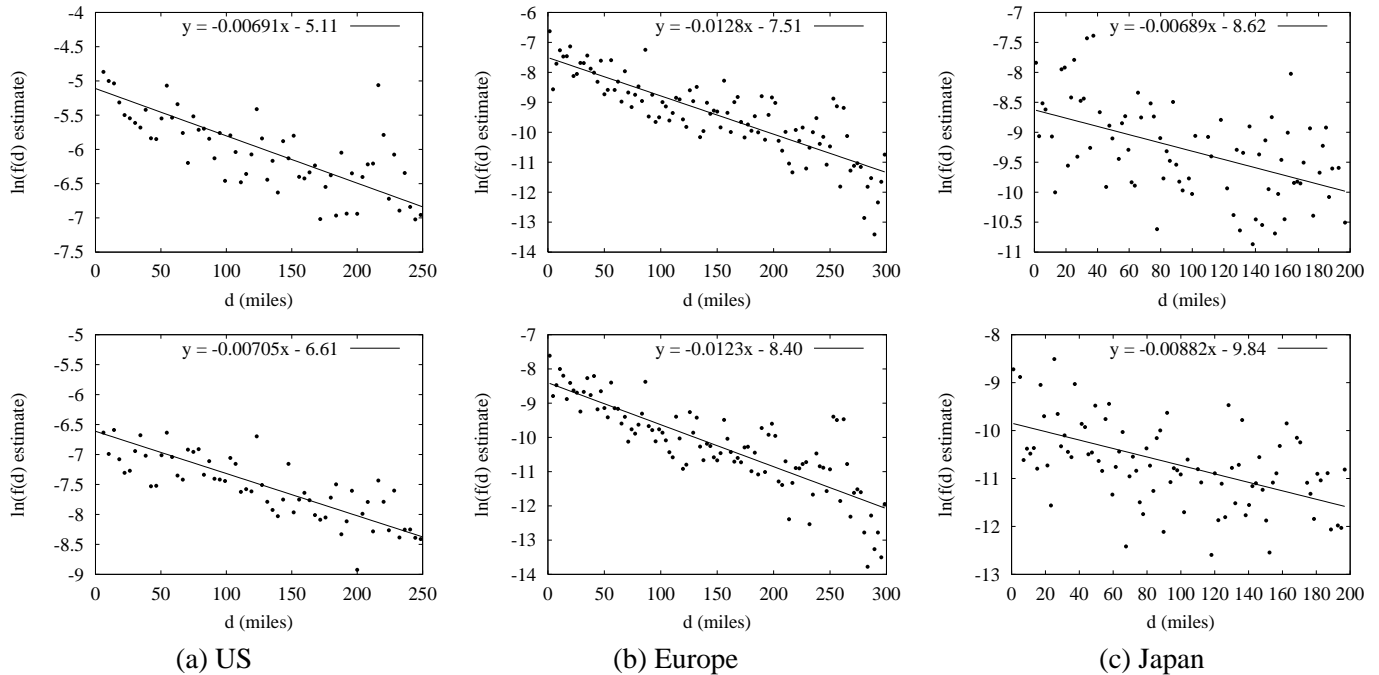


Fig. 5. Empirical Distance Preference Function, Small  $d$ , Semi-Log: Upper, Mercator; Lower, Skitter. Corresponding results from EdgeScape can be found in the Appendix (Figure 13).

we form the empirical distance preference function as:

$$\hat{f}(d) = \frac{\# \text{ links with length in } [d, d + b]}{\# \text{ node pairs with distance in } [d, d + b]} \quad (1)$$

for values of  $d$  that are multiples of  $b$ .

The resulting estimates for our three regions are shown in Figure 4. The maximum value of  $d$  varies with size of the region considered; in each case we use 100 bins (the bin sizes are noted on the figure). Note that for large distances the number of links and router pairs grows small, making the estimate based on (1) noisy, so we omit the very largest distances from these plots.

Broadly speaking, these plots appear to show two regimes: for short distances,  $f(d)$  declines with distance; while for longer distances,  $f(d)$  seems nearly constant. To explore this relationship further, we break the data up into two regions, “small  $d$ ” and “large  $d$ ”, and plot the two regions separately. We motivate how to choose the cut-off point momentarily.

Focusing first on small  $d$ , we plot  $\ln(f(d))$  vs.  $d$ . These plots are shown in Figure 5. Surprisingly, these plots show a linear tendency on the semi-log axes, suggestive of an exponentially declining function.<sup>4</sup> In fact, these fits can be characterized in terms of Waxman’s method for topology generation [38]. In the Waxman model, the probability that

<sup>4</sup>Note again that the much smaller number of routers and links for the Japan region means that the method results in more noisy estimates.

two nodes are connected  $f_W(d)$  is:

$$f_W(d) = \beta \exp(-d/\alpha L)$$

where  $L$  is the maximum distance between nodes,  $0 < \alpha \leq 1$  is the sensitivity of link formation to distance, and  $0 < \beta \leq 1$  controls link density.

In terms of the Waxman model, we find estimates of  $\alpha L \approx 140$  miles for the US and Japan, and 80 miles for Europe. This is not to suggest that the Waxman model is a correct model for the growth of the Internet over these distance ranges, but rather that it is surprisingly descriptive of the end result.<sup>5</sup>

In the other region (large  $d$ ), the function  $f(d)$  appears nearly constant, *i.e.*, insensitive to distance. Because of the noise in the data, we study the cumulated distance preference function,

$$F(d) = \sum_{d' < d} f(d').$$

Summing the data smooths out noise, and if the original function  $f(d)$  is constant, then the cumulated function  $F(d)$  will be linear.

The results are shown in Figure 6. In each plot, a fitted least square line is also shown for comparison. Again, for large distances the number of links and router pairs

<sup>5</sup>It is important to note that the Waxman topology generator places points randomly in the plane, which is very far from the case for our data.

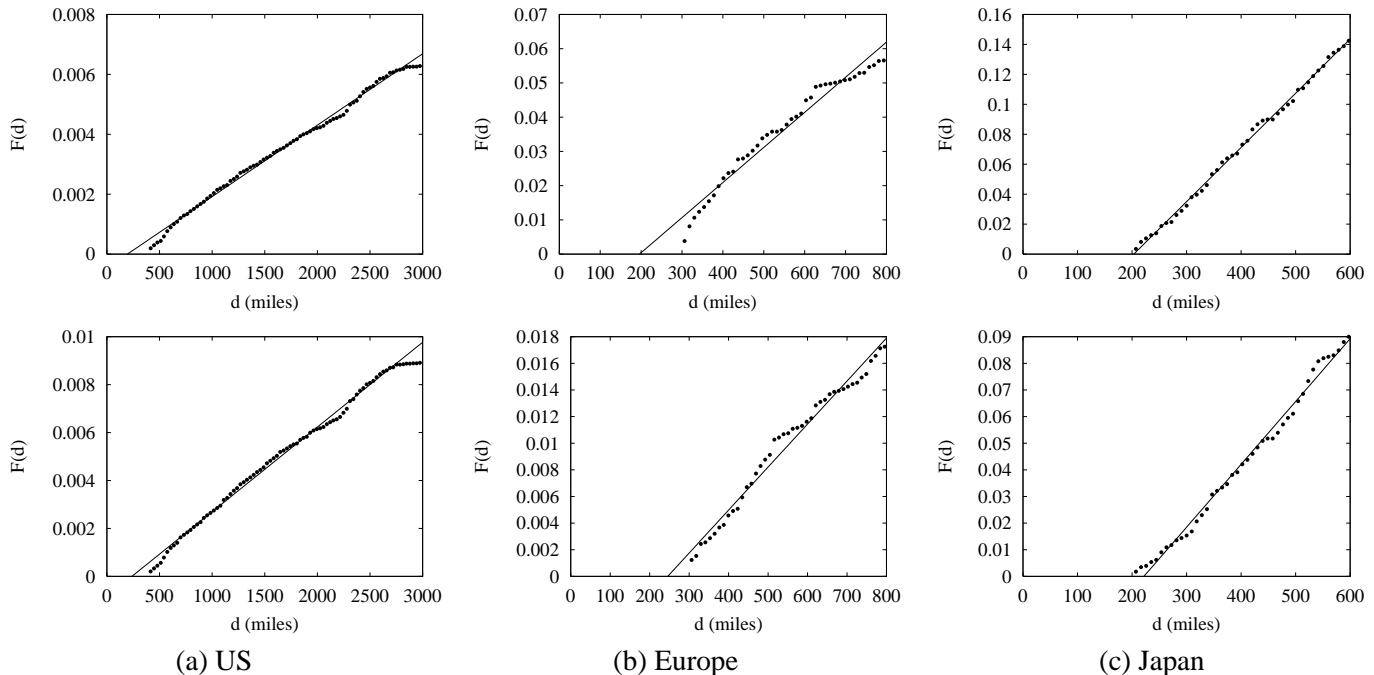


Fig. 6. Cumulated Empirical Distance Preference Function, Large  $d$ : Upper, Mercator; Lower, Skitter. Corresponding results obtained from EdgeScope can be found in the Appendix (Figure 14).

	Mercator		Skitter	
	Limit	% Links < Limit	Limit	% Links < Limit
USA	820 mi.	82.1%	818 mi.	77.2%
Europe	383 mi.	97.3%	366 mi.	95.4%
Japan	165 mi.	91.5%	116 mi.	92.8%

TABLE V  
LIMITS OF DISTANCE SENSITIVITY

grows small, so the trailing off of the points from the fitted line may not be significant. All of these plots but one (Mercator, Europe) show good agreement with the linear fit line, suggesting that the probability two routers are directly connected for large  $d$  is independent of their separation distance.

By setting the exponential functional fits in Figure 5 equal to the average  $f(d)$  value for large  $d$ , we obtain a value for each plot that approximately demarcates the limit of the distance-sensitive portion of the empirical preference function. Roughly speaking, links between router pairs that are further apart than this limit can be considered distance-independent, while links with length less than the limit are consistent with a distance-dependent model.

The limit values are shown in Table V. The table also shows the fraction of links whose length is less than the limit in each case. The table shows that values across

datasets are strikingly consistent, but across regions are not. The variation across regions is a consequence of the differences in overall density of links and different distance sensitivity parameters ( $\alpha L$ ) in each region.

Even more notable is the fraction of links in each dataset with length less than the sensitivity limit. Most links (from 75% to 95%) fall within the range of link lengths considered distance-sensitive. We conclude that distance sensitivity of router connectivity applies to the vast majority of router-router links in our datasets.

On the other hand, we note that although a small fraction of routers are connected in a manner insensitive to distance, they are clearly not randomly connected, and their connections doubtless play an important structural role. In fact, work in [37] has shown that only a very small fraction of non-local links is needed to dramatically reduce the average diameter of an otherwise locally-connected graph.

## VI. AUTONOMOUS SYSTEMS

Having developed an understanding of how properties of routers and links relate to geography, we now turn to the properties of autonomous systems. A significant, unsolved problem common to all current topology generators is their inability to label routers with autonomous system information in a representative way. This prevents topology generators from being able to assign IP addresses automatically to routers for simulating interdomain routing. In this section we study two geographic properties of ASes

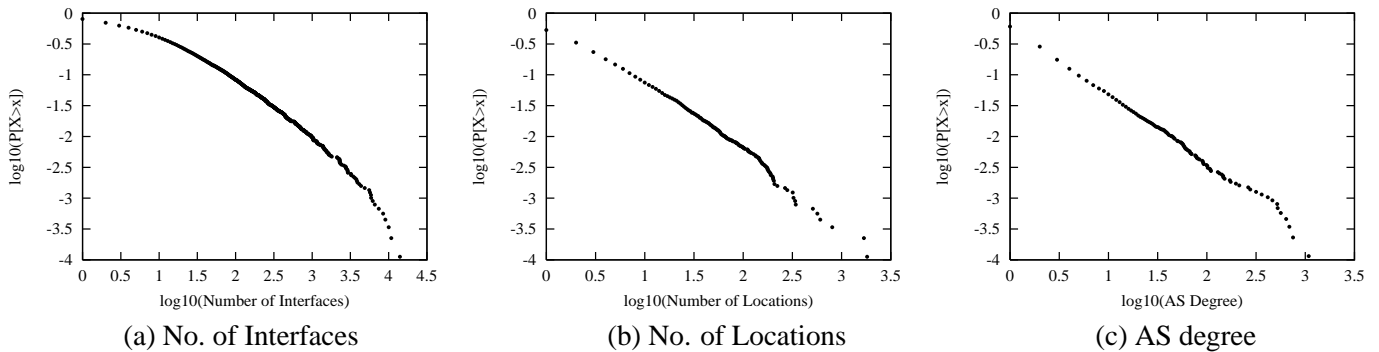


Fig. 7. Distributions of AS Sizes (World). Corresponding results using EdgeScope can be found in the Appendix (Figure 15).

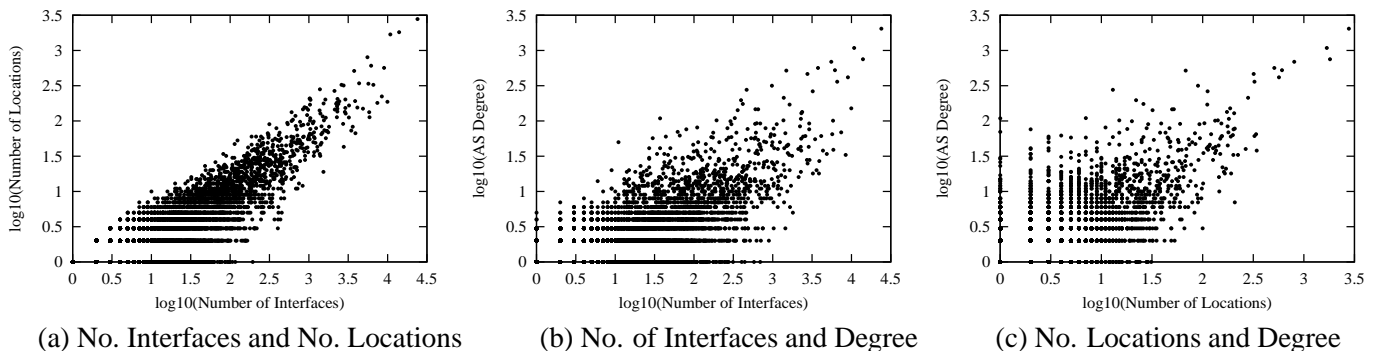


Fig. 8. Scatterplots of AS Size Measures (World). Corresponding results using EdgeScope can be found in the Appendix (Figure 16).

that can help guide the assignment of routers to ASes: the number of distinct locations spanned by an AS, and the geographical dispersion of an AS’s components.

Due to space limitations, this section uses data from Skitter (with IxMapper) only, but our results in this section are consistent across the two datasets and both mapping methods.

#### A. AS Size: Number of Locations

Previous work has documented the distribution of AS sizes measured in degree in the AS-graph [12] and measured in the number of routers within the AS [36]. In both cases, the observed distribution is highly variable, with a long tail spanning many orders of magnitude. In this section we show that a similar property holds for AS size when measured as the *number of distinct locations* in which an interface for the AS is present.

In Figure 7 we show log-log complementary distribution plots of three measures of AS size in our skitter data: (a) the number of interfaces contained in an AS; (b) the number of distinct geographic locations contained in an AS; and (c) the degree of the AS in the AS-graph (the number of other ASes directly connected to an AS).

Figures 7(a) and (c) generally agree with previous work suggesting that these AS size measures have long-tail dis-

tributions. Figure 7(b) broadens this understanding by showing that the same is true for the number of distinct locations spanned by an AS.

In [36], the authors point out that the number of routers in an AS and the degree of the AS are strongly related. Our data shows that in the *three-way* relationship among (1) number of interfaces, (2) number of locations, and (3) degree, each pair of measures shows correlation. This is shown in Figure 8, which shows scatter plots of (a) number of interfaces and number of locations; (b) number of interfaces and degree; (c) number of locations and degree.

These plots show that the correlation between number of locations and degree (Figure 8(c)) is as strong or stronger than the previously documented correlation between the number of interfaces and degree (Figure 8(b)). The strongest correlation (tightest scatterplot) appears to be that between number of interfaces and number of locations (Figure 8(a)), suggesting that ASes with a large number of interfaces (routers) tend to place those resources in many distinct locations.

Figure 8(a) also reveals that there is surprising geographic diversity in how ASes place routers. For example, it shows that some ASes with hundreds of interfaces have placed them in only *two* locations distinguishable by our methods (lowest line of points in plot).

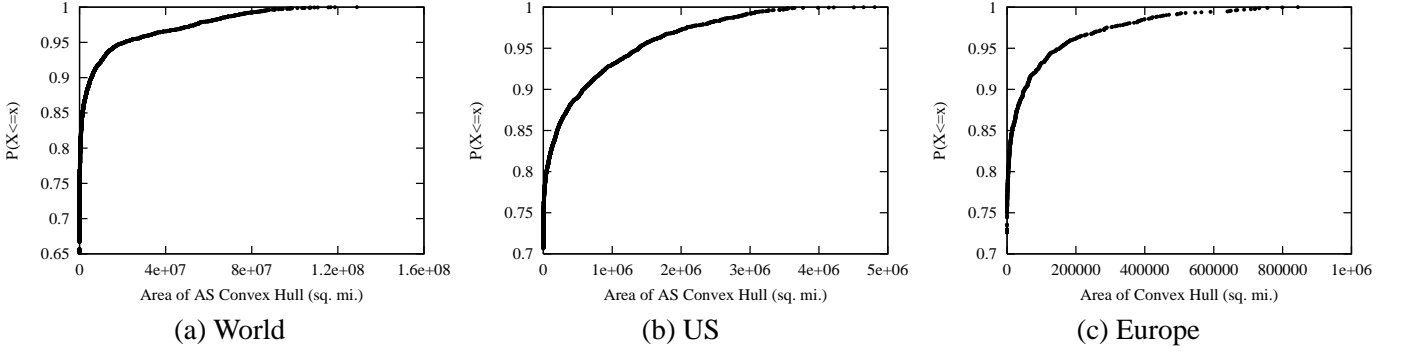


Fig. 9. CDFs of AS Convex Hull Size

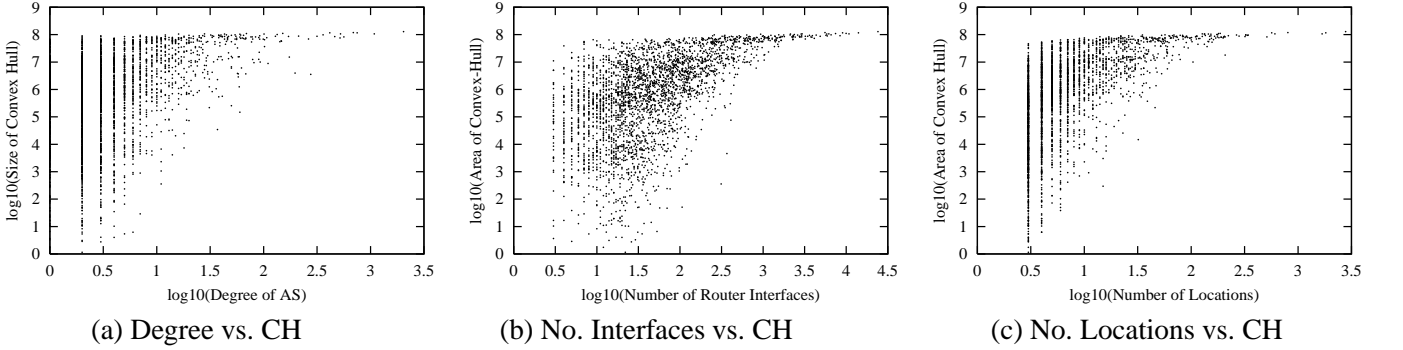


Fig. 10. Scatterplots of Size Measures vs. Convex Hull (World). Corresponding results using EdgeScope can be found in the Appendix (Figure 17).

### B. AS Size: Geographical Extent

The results in the last subsection suggest that topology generators that label routers with AS numbers should do so in a manner that creates many geographically distinct locations for large ASes, while creating a more variable number of distinct locations for medium and small ASes. However, it is not clear from this data *where* such locations should be chosen relative to each other. To answer this question we examine the geographical extent of ASes — the degree to which an AS’s routers are dispersed over the Earth’s surface.

To assess this property we measured the convex hull of each AS’s interface set. The standard definition of convexity of a point set is not applicable on a manifold such as the globe, so we adopted the following simple approach: we mapped each point onto the plane using the Albers Equal Area projection [35]. This conic projection does not preserve areas perfectly (no projection can) but since our goal in this section is primarily qualitative, this approach was deemed sufficient. The globe is unfolded at the poles and the International Date Line, thus yielding a standard planar geometry in which convexity of a set is well defined.

Figure 9 shows CDFs of convex hull size for the World, and for portions of the map restricted to the US and Europe regions. These plots show that the vast majority of

ASes have no extent at all: around 80% of ASes in each dataset have either one or two locations (and thus zero area). However, among the remaining ASes, there is considerable variability in geographical dispersion.

To understand what drives geographical dispersion, we compare the size measures from the last section to the convex hull measure. The results are shown in Figure 10. These plots expose two distinct strategies or regimes for AS interface placement, depending on AS size.

For smaller ASes, the minimum convex hull size grows with other size measures, but there is a maximum size that is often attained even for the smallest ASes. That is, even small ASes (*e.g.*, those with only three or four locations, or two or three connections to other ASes) may be very widely dispersed geographically (in fact, worldwide).

For the largest ASes, there is no relationship between other size measures and geographical extent; all these ASes are fully dispersed geographically. This can be seen for ASes with degree greater than about 100 (Figure 10(a)), with more than about 1000 interfaces (Figure 10(b)), or with more than about 100 locations (Figure 10(c)).

	Interdomain		Intradomain	
	Count	Mean Length	Count	Mean Length
World	146,936	1664 mi.	715,997	757 mi.
US	77,367	762 mi.	354,593	421 mi.
Europe	15,365	88.6 mi.	99,023	29.1 mi.
Japan	3,651	181 mi.	44,701	54.5 mi.

TABLE VI  
INTRADOMAIN VS. INTERDOMAIN LINKS

### C. Domains and Link Lengths

A final question bearing on the geographic arrangement of ASes regards the properties of AS-AS connections. To study this question we make the distinction between *interdomain* links and *intradomain* links. We label a link as interdomain if the routers it connects are assigned to different ASes, and intradomain otherwise.

The domain-crossing properties of the links in the Skitter dataset are shown in Table VI. This table shows that about half of all links in our dataset lie within the continental US. With respect to length, the table shows that for our dataset, interdomain links tend to be about twice as long as intradomain links, and that the majority of links (83% or more) are intradomain. Comparing this table with Table V shows that the mean length of intradomain links is well within the limits of distance sensitivity, while for the US and Japan, the mean lengths of interdomain links approaches or exceeds the limits of distance sensitivity.

## VII. CONCLUSIONS

In this paper we have described a wide range of geographical properties of the Internet, focusing on routers, links, and autonomous systems. We are specifically motivated to develop results to guide the development of geographically-driven topology generation methods.

We believe that geographically-based topology generation has some advantages over existing methods. To be useful, network topologies must be labeled with link latencies; these can be approximated in a straightforward manner when nodes have geographical location. Second, network topologies must be labeled with link bandwidths; such labeling might also be more tractable when starting from a geographical placement of nodes. Finally, routers need autonomous system labels in order to assign IP addresses to them in a realistic manner, *e.g.*, to simulate interdomain routing; we believe that knowledge of geography provides leverage here as well.

Given the evident promise of geographically-based topology generation, we have presented in this paper a

collection of results intended to bring that goal closer. First, we have described the quantitative relationship between population density, and the corresponding density of routers (or router interfaces). We have shown that, within economically homogeneous regions, there is a systematic relationship between these two densities that appears *superlinear*, so that router density per person is higher in population centers.

Second, we have shown that the connection patterns between routers are strongly related to geographical distance. For our data, between 75% and 95% of all links are consistent with a distance-based model for link formation.

Finally, we have shown that the number of distinct locations spanned by an AS is strongly correlated with two other measures of size: number of interfaces, and degree in the AS graph. Among small to medium ASs, these locations show wide variability in their geographic dispersal. However, all ASs exceeding a certain threshold in size are maximally dispersed geographically.

Beyond and apart from these implications for topology generation, we believe that understanding the relationship between physical geography and the Internet’s resources is an important component of *Internet science* (loosely, the study of laws and patterns in Internet structure); we anticipate that understanding the relationship between network structure and geography will have broad applicability across disciplines and for future problems.

### Acknowledgements

This work benefitted significantly from the help and comments of a number of people, and we thank them. CAIDA provided facilities and support for part of this work. David Moore and k claffy (CAIDA) provided important guidance and advice in using IxMapper. Andre Broido (CAIDA) helped us understand Skitter data and how to use it. Bruce Maggs (CMU/Akamai) helped map our datasets using EdgeScape. Ramesh Govindan (ICSI) and Hongsuda Tangmunarunkit (USC/ISI) provided the Mercator data and advice on AS mapping. We benefitted from extensive discussions about the importance of geo-

graphical location of Internet resources with Albert-László Barabási and Hawoong Jeong (both at University of Notre Dame) which helped shape our interest in this topic. In addition, we've benefitted from discussions on this work with Avi Freedman (Akamai), Gregory Yetmen (CIESIN), and Larry Landweber (U. Wisconsin).

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## APPENDIX

### RESULTS FROM EDGESCAPE MAPPING

The results presented in this Appendix were obtained from Akamai's EdgeScape mapping and are provided as a comparison point against plots presented in the paper using IxMapper.

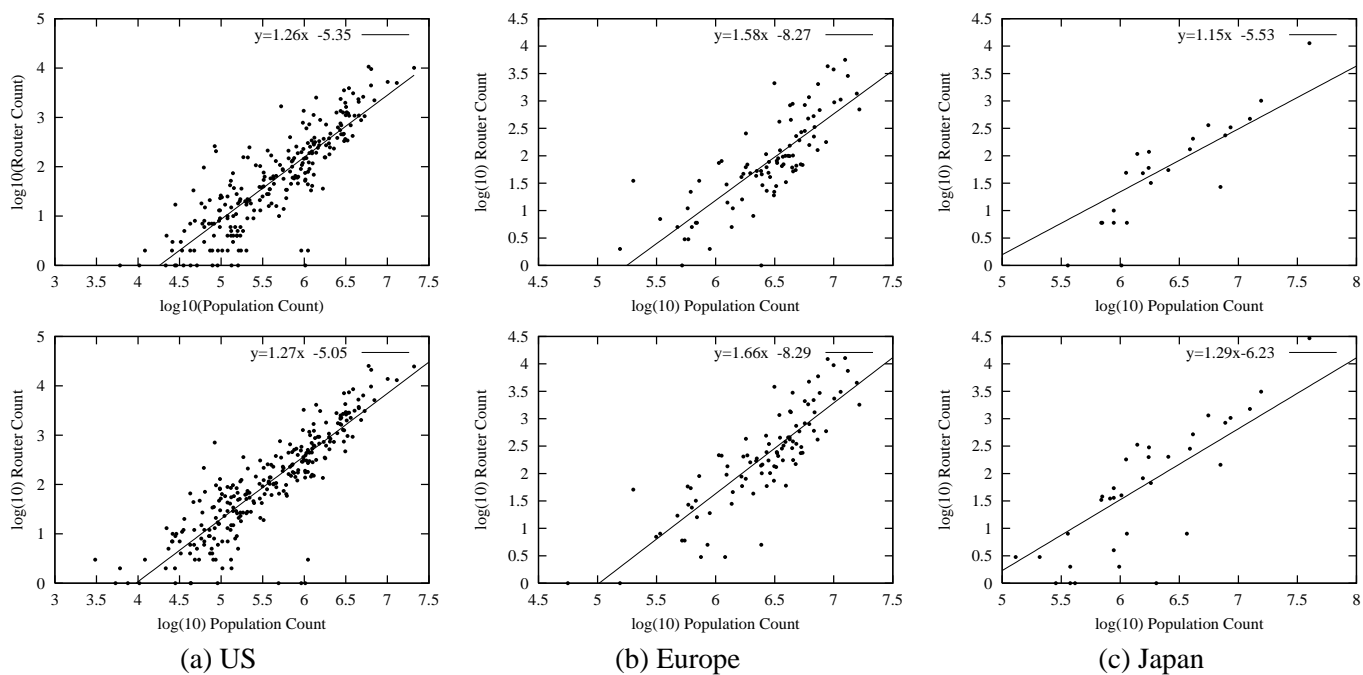


Fig. 11. Router/Interface Density vs. Population Density: Upper, Mercator (Routers); Lower, Skitter (Interfaces). Compare with Figure 2.

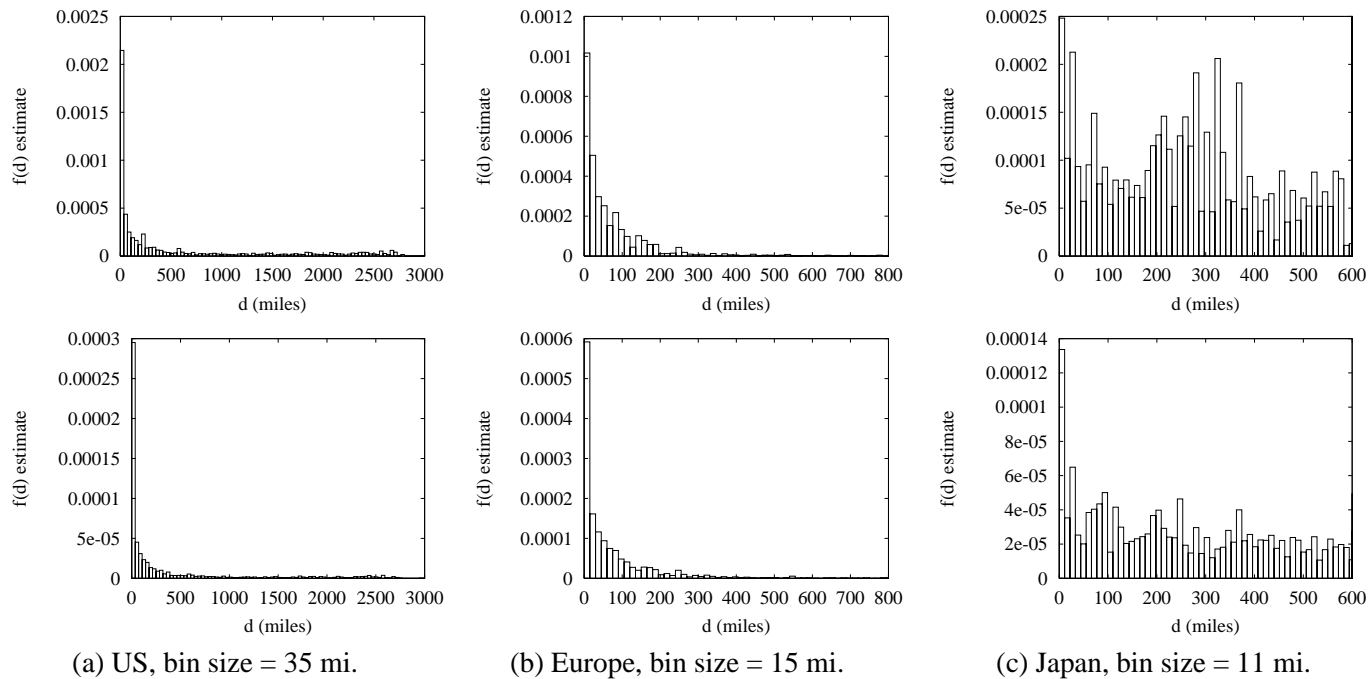


Fig. 12. Empirical Distance Preference Function: Upper, Mercator; Lower, Skitter. Compare with Figure 4.

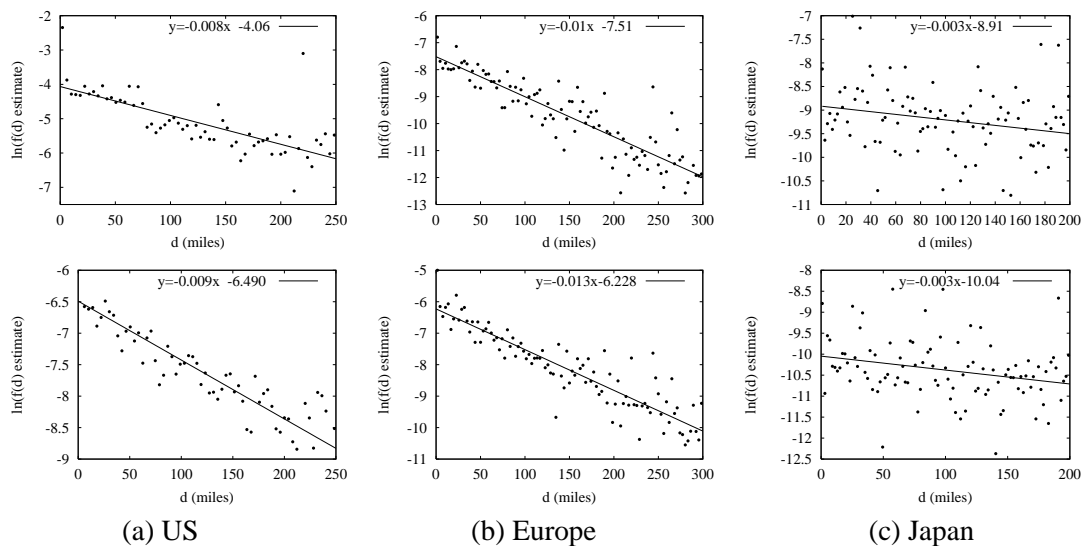


Fig. 13. Empirical Distance Preference Function, Small  $d$ , Semi-Log: Upper, Mercator; Lower, Skitter. Compare with Figure 5.

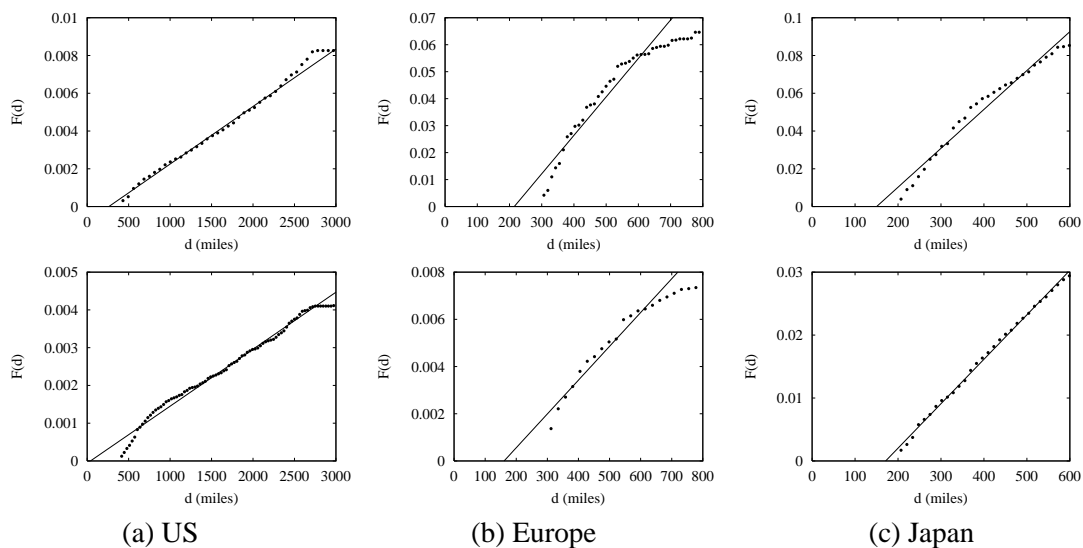


Fig. 14. Cumulated Empirical Distance Preference Function, Large  $d$ : Upper, Mercator; Lower, Skitter. Compare with Figure 6.

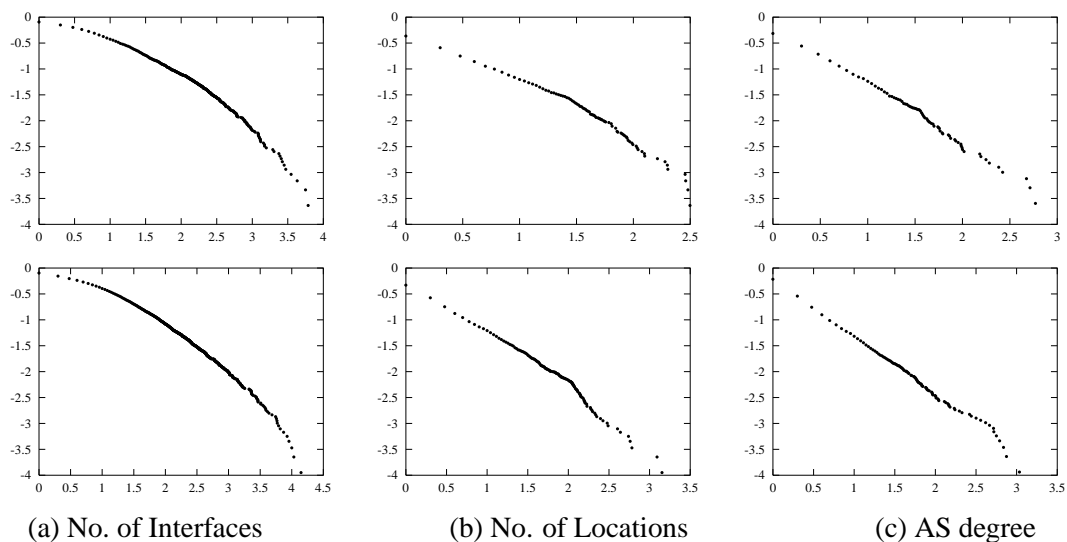


Fig. 15. Distributions of AS Sizes (World): Upper, Mercator; Lower, Skitter. Compare with Figure 7.



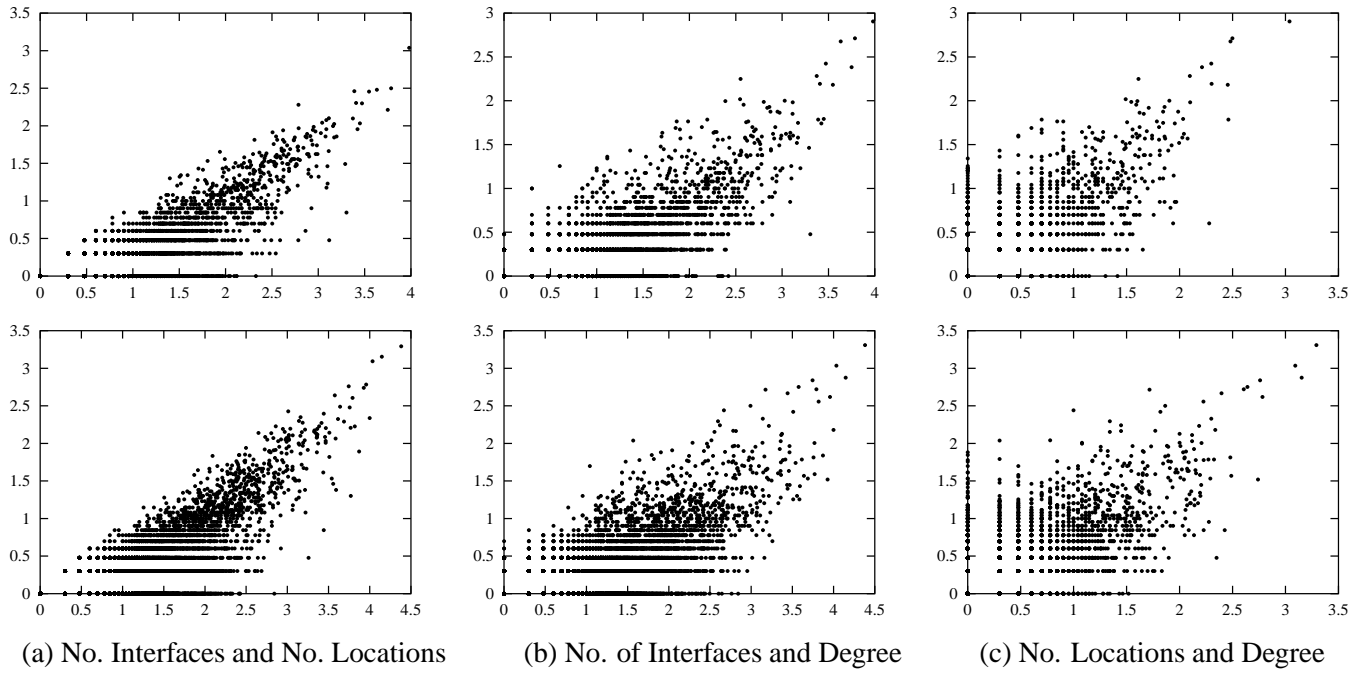


Fig. 16. Scatterplots of AS Size Measures (World): Upper, Mercator; Lower, Skitter. Compare with Figure 8.

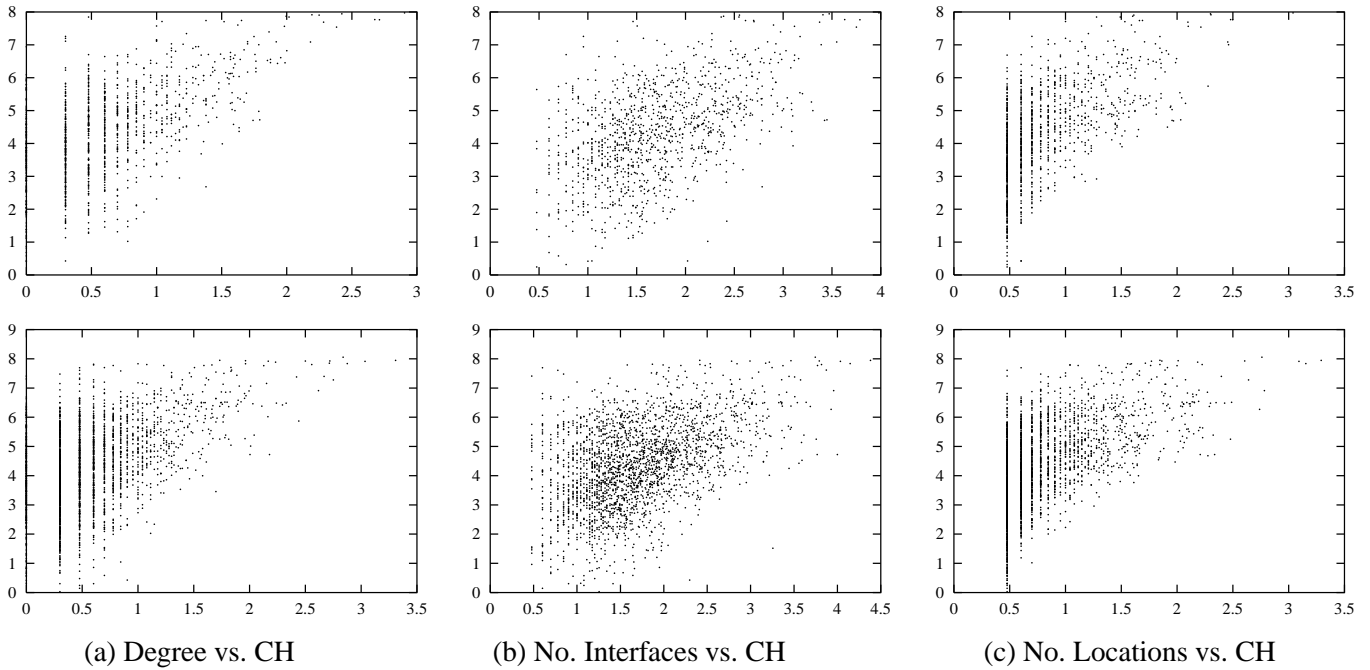


Fig. 17. Scatterplots of Size Measures vs. Convex Hull (World): Upper, Mercator; Lower, Skitter. Compare with Figure 10.