Cross-AS (X-AS) Internet Topology Mapping

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Abstract

The global communication infrastructure of the Internet is formed by tens of thousands of Autonomous Systems (ASes) connecting various organizations and individuals together. In the last two decades researchers have developed many techniques to infer the topology of individual ASes as well as the whole Internet at the interface, router, subnet, point of presence and AS levels. In this study we extend the AS level Internet topology maps by introducing cross-AS (X-AS) topology maps. X-AS maps capture both ASes and cross connections between the ASes observed at the network layer. We propose a set of techniques to infer X-AS topology maps by employing datasets obtained through common tools such as traceroute, ping and BGP data collectors. X-AS maps allow us to go beyond the simple AS level graphs and abstract the topology of the Internet as a multigraph supporting multiple connections among the ASes. We verify the proof of concept using several research and commercial networks and investigate various features of the Internet's X-AS map and its multigraph representation. We believe that X-AS Internet topology maps will allow us to (i) gain further insight into the structural and operational characteristics of the Internet; (ii) enhance current and future IP stack protocols; (iii) optimize networking infrastructures; and (iv) improve synthetic network generators and simulation tools.

Keywords: Internet Topology Mapping, Cross-AS Topology Maps, AS level Multigraphs

1. Introduction

The Internet is a highly engineered, large scale, decentralized network of networks serving billions of people worldwide. Individuals, companies, educational institutions and government agencies use the Internet for communication, entertainment, marketing, distance education, citizen participation and administration. The advent of new applications and enabling technologies such as cloud computing and Internet of Things clearly demonstrate that this trend will only grow in the future.

Having a global topology map of the Internet allows network researchers to understand the dynamics of the Internet in practice; guides network operators to enhance the reliability and security of their networks; allows network engineers to improve the efficiency of their systems; and helps developers to develop topology aware applications, among others [1]. Therefore, the communication infrastructure of the Internet has received a great deal of attention from the researchers over the last decades [1, 2]. Internet's communication infrastructure is formed by tens of thousands of autonomous systems connected to each other. A group of networks managed by one or more operators under a well defined routing policy is called an Autonomous System (AS) in the Internet. Autonomous Systems (ASes) are identified by unique AS numbers. They are connected to each other in different forms, i.e., customer-toprovider (c2p), peer-to-peer (p2p) and sibling-to-sibling (s2s), to achieve the "global" Internet communication [3, 4]. Individual users, small businesses and ASes located at the edge of the Internet participate in the global infrastructure by means of other ASes called Internet Service Providers (ISPs). Typically,

ISPs are business entities providing Internet access service to their customers while getting the same service from one or more upstream ISPs. At the core of the Internet, a small number of ISPs peer with each other through settlement-free interconnections to glue the whole communication infrastructure together.

The ASes forming the communication infrastructure of the Internet *cooperate* with each other to carry traffic from one host to another. Typically, the traffic passes through several independent ASes until it reaches to the final destination. However, these ASes also compete with each other to increase their market share by providing better services and expanding into new regions. Each AS independently oversees its own network, yet achieving a global level of surveillance requires an Internet map capturing both ASes and the cross connections among them. Mapping cross-AS connections is particularly important because it allows us (i) to detect congestion points which mostly occur on the links between ASes [5]; (ii) to analyze failures and determine reliability bottlenecks in the Internet [6]; (iii) to mitigate the impact of attacks targeting BGP speaking routers [7]; (iv) to make provisions for attacks targeting inter-AS connections [8, 9]; (v) to leverage the quality of VoIP services and reduce the traffic overhead [10]; and (vi) to optimize server deployment in content delivery networks [11].

On the contrary, AS level Internet topology maps abstract the topology as a graph G = (V, E) where the vertex set, V, corresponds to the ASes and the edge set, E, represents the logical relations between the ASes. Figure 1a shows an example AS level Internet topology graph consisting of ten ASes along with their logical links. Although AS level graphs, annotated with



Figure 1: Simple graph and multigraph derived from an example cross-AS (X-AS) topology map

business relationships, are suitable for studying the economics of the Internet, they often fall short in analyzing reliability, routing, efficiency and robustness of the Internet. Because, reducing the Internet topology to a simple graph simply misses parallel (multiple) connections among the ASes [1, 12, 2]. In reality, the ASes in the Internet span over various geographic regions and often, cover the same regions in part or in whole. Moreover, they physically connect to each other at multiple colocation centers or Internet eXchange Points (IXPs) to exchange traffic and routing information.

A proper abstraction of the Internet topology would be a multigraph G = (V, E, f) where the vertex set, V, corresponds to the ASes, the edge multiset, E, represents the cross connections between the ASes and $f: E \rightarrow \{(v_i, v_i) : v_i, v_i \in V, v_i \neq v_i\}$ is a function returning the endpoints of the edges to support parallel edges between two ASes. Figure 1b shows a multigraph demonstrating cross-AS connections for the same ASes given in Figure 1a. Obviously, deriving the multigraph in Figure 1b requires constructing a topology map that includes ASes, the cross-connections between the ASes and an abstraction for the endpoints of the connections. Figure 1c shows an example Internet topology map where the ten ASes in Figures 1a and 1b are connected to each other via multiple border/edge routers at various facilities. Note that the topology map in Figure 1c can be used to generate both the simple graph in Figure 1a and the multigraph in Figure 1b.

In this study, we introduce cross-AS (X-AS) Internet topology maps which capture both ASes and cross-AS connections observed at the network layer in the Internet. Multiple inter-AS connections between pairs of ASes have been studied in different contexts. In [13] the authors use DNS-based geolocation to map the PoPs of 65 ISPs to their corresponding cities to study the impact of intra and inter-connections on path inflation. In [14] the authors use a geographical database to map the external links of routers to develop a model describing the US Internet backbone topology. In [15] the authors use traceroute and reverse DNS to map IP addresses to IXPs to reveal the participants of IXPs and study their characteristics. In [16] the authors use DNS-based geolocation and a geolocation database to determine inter-domain links in path traces to study hybrid and partial business relations among ASes. Moreover, multigraph representation of the Internet topology is pointed in different survey works [1, 12]. However, this is the first study solely focusing on the cross-AS Internet topology maps and their multigraph representations, to the best of our knowledge.

In this study, we systematically combine traceroute data analysis, BGP advertisements, DNS-based geolocation, Round-Trip Time (RTT) delays and geolocation databases to map multiple connections between ASes and achieve a multigraph representation of the Internet at the AS level. We define a cross-border interface (X-BI) as an interface (or an IP address) that belongs to a border/edge router of an AS. We use traceroute datasets and IP address to AS mapping tools to extract X-BIs that appear in path traces where the paths switch from one AS to another. Then, we apply a set of techniques based on DNS names, geolocation databases, BGP advertisements and traceroute datasets to accurately cluster X-BIs into X-BI nodes. We define an X-BI node as a set of X-BI interfaces located in the same facility within a particular AS regardless of the border routers accommodating the X-BIs. X-BI nodes allow us to represent the endpoints of parallel connections between the pairs of ASes. In this study, our main objective is to capture multiple connections between pairs of ASes. Therefore, grouping the X-BIs into X-BI nodes rather than individual routers serves for the purpose without complicating the process. Lastly, we exploit traceroute and BGP datasets to discover cross connections between the X-BI nodes. Note that the techniques used in this study are based on the network layer data. Therefore, the cross connections between the X-BI nodes are network layer (layer-3) abstractions of the physical connections implemented as point-to-point links or Local Area Networks (LANs) via switches at the lower layers. The final X-AS map, X = (N, C), consists of a set of X-BI nodes, N, and a multiset of X-BI connections, C.

We conducted several experiments not only to validate our approach but also to analyze various features of X-AS maps and the resulting multigraphs. We used three research networks, Internet2, GÉANT and ULAKNET and nine large scale commercial networks belonging to Cox, AT&T, CenturyLink, Cogent, Cox, Deutsche Telekom, Hurricane Electric, Level3 and Tata Communications to validate our approach. Our experimental results show that the X-AS map successfully captures the X-BI nodes belonging to both research and commercial networks. The X-AS topology map covers 84.9% relationships among 43,386 ASes where the coverage is 100% for 78% of the ASes. Our X-AS Internet topology map consists of 69,573 X-BI nodes distributed over 43,386 ASes. Majority of the ASes have only one X-BI node whilst the maximum number of X-BI nodes per AS is 506. We demonstrated that X-BI node distribution follows power law in the tail with a statistically significant p-value. The X-BI nodes in the X-AS map has 558,840 connections between 69,573 X-BI nodes. The X-BI node degree (number of connections to other X-BI nodes) changes between 1 to 4,171 and follows power law in the tail as well. Finally, we extracted an AS level multigraph from our X-AS Internet topology map. We analyzed both AS degree distribution and assortative mixing by degree in the multigraph. Our results show that there is a strong correlation between low degree and high degree ASes whereas medium degree ASes are correlated to both low degree and medium degree ASes.

The rest of the paper is organized as follows. Section 2 presents the background and motivation. We introduce the details of our approach in Section 3. In Sections 4, 5 and 6 we validate our approach, present experimental results and discuss the limitations of our approach, respectively. Finally, Sections 7 and 8 present the related work and conclude the study, respectively.

2. Background and Motivation

In spite of the known benefits of having a global scale topology map of the Internet, many network operators do not share their topologies due to security and/or business concerns. Nevertheless, researchers have developed many techniques to infer the topology maps of individual ASes as well as the whole Internet at the interface, router, subnet, PoP and AS levels in the last two decades [1, 2, 17, 18, 19].

A router is a device that forwards a packet toward its destination in packet switching networks. Routers are connected to multiple networks through different interfaces. Usually each interface is assigned a unique IP address. *Interface level* topology mapping aims to discover the connectivity between IP interfaces. Figure 2a shows an example interface level topology map. In the figure, the circles show IP addresses and the links present connections between the routers hosting these IP addresses. Although this type of maps are easy to construct, they do not have much use.

Identifying the interfaces that belong to the same router through their IP addresses allows us to construct Internet topology maps at the router level. *Router level* mapping groups the interfaces according to their routers and infers the connections between these routers. Figure 2b shows an example router level topology map. In the map, the ovals represent the routers and each link represents a connection between two routers. Many techniques have been suggested in the literature to discover the IP addresses assigned to the same router [20]. However, the problem is still an open problem due to the limited network support, rate limiting practices and scalability issues [21, 22].

A Point of Presence (PoP) in the Internet is defined as a set of cooperating routers that belong to the same AS located in the same facility [18]. PoPs create the backbone infrastructures of ISPs and allow those networks to extend their services geographically. As shown in figure 3, PoPs contain several types of routers including core, distribution, access, service and border [23]. Core routers mediate the traffic between the routers in a single facility as well as transit the traffic between the PoPs of the same AS. Access routers connect user networks to the rest of the Internet through the distribution routers. Distribution routers distribute the traffic coming from/to core



(1) A-AS level

Figure 2: Illustrative topology maps at different levels



Figure 3: Typical PoP structure

routers to/from access routers. Service routers transmit the traffic from/to service hosts such as web hosting, email and DNS servers. Lastly, BGP speaking border routers connect different autonomous systems to each other by carrying data and/or control traffic. PoP level Internet topology maps cluster the routers/interfaces located in the same facility per AS. Figure 2c shows an example PoP level topology map. In the map, each heptagon corresponds to a PoP and each link represents a connection between two PoPs whether those PoPs belong to the same AS or not. PoP level mapping studies typically employ path traces to find the interface IP addresses and geolocation databases to assign those interfaces to their locations. Nevertheless, capturing the backbone connections within an AS is a challenging task because it requires carefully crafted traceroute queries per AS to increase coverage while reducing the probing overhead [17, 24] and probing the backbone topology of ISPs is more prone to packet filtering [25].

AS level topology maps represent autonomous systems as nodes and the business relations between them as links. These maps typically label the links according to the business relations between their induced ASes as customer-to-provider, peer-topeer and sibling-to-sibling [3]. Figure 2d shows an example AS level topology map. In the map, each cloud corresponds to an AS and the links represent the business relations between the ASes. AS level maps hide the connection details between the ASes because a business relation can be implemented by multiple connections at different geographic locations and between multiple routers/PoPs. On the other hand, AS level maps are suitable for BGP path analysis as well as Internet economics.

Figure 2e superimposes all maps to provide an integrated network view. In the figure clouds, heptagons, ovals and small circles represent ASes, PoPs, routers and interfaces, respectively. The interfaces belonging to border routers are shown in dark color.

An example X-AS topology map, introduced in this study, is shown in Figure 2f. In the figure, rhombuses correspond to X-BI nodes, dark circles inside the rhombuses represent X-BIs and the links between the XBI nodes show the cross-AS connections observed at layer-3. A cross-border interface (X-BI) is an interface, represented by an IP address, which belongs to a border/edge router of an AS. An X-BI node is a set of X-BI interfaces located in the same facility within a particular AS re-



Figure 4: An outline of the methods

gardless of the border routers accommodating the X-BIs. The main focus of X-AS maps is the cross connections between the ASes rather than the backbone connections within the individual ASes. In the following we present the details of X-AS Internet topology mapping.

3. X-AS Internet Topology Mapping

In this section, we present several techniques to infer crossborder interfaces (X-BIs), cluster them into cross-border interface nodes (X-BI nodes) and finally construct cross-AS (X-AS) maps. We construct X-AS maps in five steps as shown in Figure 4.

1. **IP to AS Mapping:** In this step, we map the IP addresses collected in traceroute and BGP datasets to their corresponding ASes.

Algorithm 1 X-BI Identification

Inp	out: traceDatasets	▹ traceroute datasets
Ou	tput: X-BI S et	▹ Set of X-BIs
1:	for all traces from traceDatasets	do
2:	trace is an array of IP addre	sses in a traceroute
3:	$IP_1 = trace.get(0)$	
4:	$AS_1 = findASN(IP_1)$	
5:	for $i = 1$ to trace.length -1 of	lo
6:	$IP_2 = trace.get(i)$	
7:	$AS_2 = findASN(IP_2)$	
8:	if AS_1 and AS_2 not equal to	o 'NA' then
9:	if AS_1 not equal to AS_2	2 then
10:	X-BI S $et.add(IP_1)$	
11:	X-BI S et. $add(IP_2)$	
12:	end if	
13:	end if	
14:	$IP_1 = IP_2$	
15:	$AS_1 = AS_2$	
16:	end for	
17:	end for	

- 2. **X-BI Identification:** In this step, we extract the X-BI IP addresses that appear in BGP advertisements and switch from one AS to another AS in path traces.
- 3. **X-BI Geolocation:** In this step, we geolocate the X-BIs extracted from the previous step by applying the following techniques.
 - (a) DNS-GeoDB based geolocation
 - (b) Majority GeoDB based geolocation
 - (c) Sandwich method geolocation
 - (d) RTT-based geolocation
 - (e) Singular GeoDB based geolocation
- AS Based X-BI Node Clustering: In this step, we cluster the X-BIs of ASes into X-BI nodes with respect to their geolocations.
- 5. X-AS Map Construction: In this step, we use traceroute and BGP datasets to find the links between the X-BI nodes generated in the previous step. The final X-AS map, X = (N, C), consists of a set of X-BI nodes, *N*, and a multiset of X-BI connections, *C*.

In step 1, we map all unique IP addresses observed in traceroute and BGP datasets to their corresponding ASes. We use IPv4 Routeviews prefix to AS mappings dataset (pfx2as) obtained from CAIDA [26]. In step 2, we identify the IP addresses that represent the cross-border interfaces (X-BIs). Remember that an IP address is an X-BI if it appears immediately before or after an IP address that belong to another AS in path traces. Put in other words, it is part of a connection between two ASes. We process the successive IP address pairs that appear in path traces and label them as X-BIs if the pair switches from one AS to another AS. We use iPlane [27] and CAIDA [28] traceroute datasets collected from multiple vantage points.

Algorithm 1 presents X-BI identification using traceroute datasets. The algorithm requires a set of path traces as input. It returns the IP addresses that are X-BIs. The algorithm parses each path trace into a path trace array at line 2. At lines 3-4,

the algorithm gets the first IP address in the array and finds its AS number. At lines 6-7, the algorithm gets the next IP address and finds its AS number. At lines 8-13, the algorithm adds the IP addresses as X-BIs in case their AS numbers change. Lines 14 and 15 advance the IP addresses in the array.

After identifying X-BIs from traceroute datasets, we expand the list using the BGP datasets. We extract IP addresses given in the "NEXT HOP" fields in our BGP datasets. Since the next hop IP addresses typically belong to border routers, they are X-BIs as well. We use RIS RIPE [29] and RouteViews [30] BGP datasets.

In step 3, we geolocate X-BIs by applying multiple techniques in the following order: DNS-GeoDB based geolocation, majority GeoDB based geolocation, sandwich method geolocation, RTT-based geolocation and singular GeoDB based geolocation.

DNS-GeoDB based geolocation: Although DNS has limited support, it is still one of the most valuable information that directly comes from the ASes. ASes typically encode geographic information in their DNS naming conventions. To illustrate, SprintLink uses the naming convention 'sl-gw5fw.sprintlink.net' for its gateways which denotes 'SprintLink Gateway 5 router in Fort Worth, TX' [31]. On the other hand, DNS naming conventions are not enforced and may vary from one ISP to another. UNDNS is a tool for extracting geolocation information from DNS names. It is developed as part of the RocketFuel project [17] and improved further by the iPlane project [32]. During this study, we improved their key dataset to extend the coverage of the DNS names. We extract geolocation information from DNS names by using UNDNS. In addition, we verify the DNS geolocation information via our geolocation databases to reduce the potential DNS misnaming distortion [33]. We use the commercial version of "DB-IP IP address to location" database [34] and the free versions of "Maxmind GeoLite2 City" [35] and "IP2Location DB5 Lite" [36] databases.

Majority GeoDB based geolocation: The unresolved X-BIs are resolved by geolocation database majority voting. Basically, we collect the geolocation from all three databases and assign a geolocation to an X-BI if at least two databases agree on the geolocation.

Sandwich Method geolocation: We apply our sandwich method to resolve the remaining X-BIs. The sandwich method locates unresolved X-BIs appearing in path traces and checks the two IP addresses that immediately appear before and after an X-BI. If these two IP addresses are at the same location then the X-BI is at the same location as well. We assume that it is unlikely for a packet to visit a city and then come back to the same city after traversing an intermediate city.

RTT-based geolocation: To resolve the geolocation of the remaining unresolved X-BIs, we collect the resolved IP addresses that appear before or after each X-BI in all path traces. We assume that if the RTT time difference between the X-BI and a resolved IP address is shorter than a threshold, 3 ms, they both are located in the same city. However, if any other resolved IP address suggests a different location, we ignore this method and leave the X-BI as unresolved.

Algorithm 2 R1 1-based Geoloca	ation
Input: traceDatasets	▹ traceroute datasets
Input: X-BI	⊳ unresolved X-BI
Input: threshold	
Output: X-BI Location	▹ resolved or unresolved X-BI
1: get all IP pairs $(IP_1, X-BI)$ and	d (X-BI, IP_2) from traceDatasets
where IP_1 and IP_2 locations are	known
2: for all pairs do	
3: if $\dot{\mathbf{X}}$ -BI.RTT – $IP_1.RTT < t$	hreshold then
4: $loc.insert(IP_1.location)$	
5: end if	
6: if $IP_2.RTT - X - BI.RTT < th$	areshold then
7: $loc.insert(IP_2.location)$	
8: end if	
9: if loc contains different location	tions then
10: unable to resolve X-BI	
11: else	
12: if loc contains same plac	e more than once then
13: resolve X-BI	
14: else	
15: unable to resolve X-I	31
16: end if	
17: end if	
18 end for	



Figure 5: Example X-BI node connection decisions w.r.t. the BGP dataset

Algorithm 2 gives the pseudocode for the RTT-based geolocation method. It requires the traceroute datasets, an unresolved X-BI and a threshold value. It returns the geolocation of the X-BI if the algorithm successfully resolves it. At line 1, the algorithm extracts the IP pairs $(IP_1, X-BI)$ and $(X-BI, IP_2)$ involving the input X-BI such that the preceding or succeeding IP addresses are resolved. At line 2, the algorithm iterates through IP pairs. It checks the RTT time difference between each pair at lines 3 and 6. If the RTT difference is less than the threshold, the algorithm inserts the location into the 'loc' vector. At line 9, it checks if the 'loc' vector contains different locations. If the same location is reported by more than one IP addresses, the algorithm returns the location. Our empirical results suggest that a 3ms threshold value reduces false positives while allowing false negatives to be resolved later (Section 5).

Singular GeoDB based geolocation: Lastly, we use one of the extensive geolocation databases to locate the remaining unresolved X-BIs. We use Maxmind database [35] because it is publicly available, extensive and frequently used in the literature.

In step 4, we cluster X-BIs of individual ASes into X-BI

Algorithm 3 X-AS Map link discovery by traceroute Input: traceDatasets ▹ traceroute datasets Input: X-AS Map 1: for all traces from traceDatasets do trace is an array of IP addresses in a traceroute 2: for i = 0 to trace.length - 1 do 3:

	0
4:	$IP_1 = trace.get(i)$
5:	$IP_2 = trace.get(i+1)$
6:	if IP_1 and IP_2 are X-BIs then
7:	$XBINode_1 = retrieveXBINode(IP_1)$
8:	$XBINode_2 = retrieveXBINode(IP_2)$
9:	if map.containsLink(XBINode ₁ , XBINode ₂) then
0:	doNothing
1:	else
2:	$map.insertLink(XBINode_1, XBINode_2)$
3:	end if
4:	end if
5:	end for
6:	end for

Algorithm 4 X-AS Map link discovery by BGP

Inp	ut:	тар	X-AS Map created by traceroute
Inp	ut:	BĜP	▶ BGP datasets
1:	for	each link in BGP dataset do	
2:		obtain AS_1 and AS_2	
3:		if map.containsAS $Link(AS_1, AS_2)$	then
4:		doNothing	
5:		else	
6:		$XBINodes_1 = retrieveAllXBING$	$des(AS_1)$
7:		$XBINodes_2 = retrieveAllXBING$	$des(AS_2)$
8:		findIntersectingGeolocations(XI	$BINodes_1, XBINodes_2)$
9:		if there is only one intersecting a	geolocation then
10:		insert link between the corre	sponding X-BI nodes
11:		end if	
12:		end if	
13:	enc	l for	

nodes with respect to their geolocations. Our assumption is that each AS has at most one PoP in a city which contains border router(s) to connect to other AS PoPs. Hence, if two or more X-BIs belonging to the same AS are located in the same city, then they are grouped into the same X-BI node. We created the X-BI nodes of ASes by clustering their X-BIs according to their city information.

Once we build the X-BI nodes, we find the layer-3 links between those nodes by using traceroute and BGP datasets in step 5. First, we use traceroute datasets to construct the initial map. We check each X-BI pair. If we discover a traceroute link between two X-BI addresses, then we insert a link between the related X-BI nodes in the X-AS map.

Algorithm 3 shows the pseudocode for X-AS Map link discovery by traceroute. It requires the traceroute datasets as well as the current X-AS map. Note that, initially the X-AS map consists of only X-BI nodes without any links between them. The algorithm uses traceroute to discover and insert the links between X-BI nodes. At lines 1-2, the algorithm parses each path trace into a trace array. At lines 4-5, the algorithm gets an IP pair. It checks if the pair is an X-BI pair or not at line 6. If both of them are X-BIs, then the algorithm retrieves their X-BI nodes at line 7 and 8. At lines 9-13, the algorithm inserts a link between the X-BI nodes accommodating the X-BI pairs if there is no link between them.

In addition to the traceroute datasets, we incorporated BGP datasets [29, 30] to improve the accuracy and coverage of our

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(a) Internet2 layer-3 PoPs

Figure 6: Internet2 backbone map comparison

Figure 7: GÉANT backbone map comparison



(b) Internet2 X-BI nodes



(a) GÉANT backbone map





maps by additional links. If a non-existing connection between two ASes is reported in the BGP dataset, these two ASes should have at least one connection at their X-BI nodes. We assume that if the two ASes have at most one X-BI node in the same city then, the connection should have been between these two X-BI nodes. To illustrate, Figure 5 shows three ISPs, AS1, AS2 and AS3, providing Internet access service at the West Coast, South and East Coast regions of the US. When we observe a link between AS1 and AS2 in a BGP advertisement, we assume that the connection occurs at the Phoenix X-BI nodes, because the other X-BI nodes are located at distinct cities. On the contrary, when we observe a link between AS2 and AS3 in a BGP advertisement, we cannot be conclusive. In Figure 5, AS2 and AS3 have X-BI nodes at more than one cities, Atlanta and Miami, and the actual connection(s) might be at either one of the cities or at both cities.

Algorithm 4 presents X-AS Map link discovery using the BGP datasets. The algorithm requires the partial map produced by algorithm 3 as input. At line 3, the algorithm checks if the map contains a link between two ASes: AS_1 and AS_2 . At lines 6 and 7, the algorithm retrieves the X-BI node sets of AS_1 and

 AS_2 , respectively. At line 8, the algorithm finds the intersecting geolocations of the X-BI node sets. At lines 9-11, the algorithm inserts a new link between the corresponding X-BI nodes if there is only one intersecting geolocation.

4. X-AS Map Validation

One major challenge for network measurement and analysis community has been research outcome validation. Most of the validation methods in the literature are partial or indirect, because ISPs do not share the complete details of their networks, mainly due to security and business concerns. In the following, we designed two experiments to validate our X-AS topology maps. The first experiment uses PoP level maps of major research networks and commercial ISPs to validate the X-BI nodes only. The second experiment uses AS level maps to validate the existence of the links between the X-BI nodes.

4.1. X-BI Node Validation

We acquired PoP level topology maps of major research networks and several large scale ISPs from their official websites.





(a) ULAKNET backbone map







(a) Cox national backbone map





These maps demonstrate the backbone infrastructures of their networks, hence they do not show any cross-AS connections. However, the X-BI nodes mapped to geographic locations in X-AS maps correspond to PoPs that accommodate border routers. Therefore, we compare the X-BI nodes to the PoPs of several networks, below.

We first examined Internet2 (AS11537, AS11164), an academic network based in the United States. Figure 6a presents Internet2 network infrastructure map. In the figure, the blue circles present Internet2's layer-3 service PoPs. Figure 6b shows the Internet2 X-BI nodes that we inferred as part of our X-AS Internet topology map. The figures verify that our X-AS mapping approach successfully identified the X-BI nodes of Internet2 except for the two overlapping PoPs in New York and Los Angeles. Remember that our approach assumes that an AS has at most one X-BI node at a city. That is, if an AS has more than one PoP accommodating border routers in a city, their X-BIs will be merged into a single X-BI node in our approach (Please see Section 6 for the limitations).

Next, we examined the network infrastructure of GÉANT (AS20965, AS21320), an academic network based in Europe. Figure 7a shows GÉANT's backbone topology

map. Figure 7b shows the X-BI nodes that we were able to find in our X-AS map. This was the only topology map that we experienced a significant amount discrepancy between the published and inferred nodes. Investigating the case further revealed that GÉANT reports its associate European National Research and Education Networks (NRENs) in its backbone topology map [37]. Moreover, some national research networks which have no physical GÉANT presence are shown in the map. These networks connect to remote GÉANT PoPs through leased circuits [37]. The PoPs belonging to Finland, Iceland, Norway, Belarus and Sweden are part of NORDUnet (the Nordic regional network) which is viewed as an extension of GÉANT. The other PoPs such as Turkey, Israel, Cyprus and Serbia belong to national research networks connected to GÉANT PoPs through leased circuits. Hence, the corresponding X-BI nodes do not appear as part of GÉANT in the X-AS map. Nevertheless, our X-AS map captures all X-BI nodes listed in the PoP decode table document that is publicly available on GÉANT's Network Operations website [38].

Third, we compared our map to ULAKNET (AS8517) belonging to Turkish academic network and information center. ULAKNET provides high speed Internet service to universi-



Figure 10: Discrepancy between X-AS map links and AS level map relations

ties and research institutions in Turkey. Figure 8a presents ULAKNET backbone map. In the figure, there are 82 PoPs scattered in Turkey. The map also shows that only three of these PoPs connect ULAKNET to the rest of the Internet: Ankara, Istanbul and Izmir PoPs. Figure 8b shows ULAKNET X-BI nodes that we inferred as part of our X-AS Internet topology map. Our X-AS topology map includes only the three X-BI nodes having cross-AS connections.

In addition to the research networks, we compared our map with several commercial ISPs. We examined AS22773 belonging to Cox Communications based in the US. Figure 9a presents Cox national IP backbone map. In the figure, there are 33 PoPs scattered around the US. Figure 9b shows the Cox X-BI nodes that we inferred as part of our X-AS Internet topology map. We were able to find 30 X-BI nodes that geographically match the PoPs of Cox. In figure 9a, there are three PoPs that do not appear in our X-AS map. Either those three PoPs do not connect to any other AS or they are our false negatives. Unfortunately, Cox operators did not respond to our inquiry to validate our results.

We conducted the same experiment for the US maps of AS7018 (AT&T), AS209 (CenturyLink), AS174 (Cogent), AS6939 (Hurricane Electric), AS3356 (Level3), AS6453 (Tata Communications) and AS3320 (Deutsche Telekom). We found 101, 69, 60, 27, 146, 15 and 18 X-BI nodes, respectively. Due to space constraints, we provide these map visualizations along with their X-BI node comparisions on our project website [39].

4.2. X-BI Link Validation

In this part, we compare the X-BI node connections against the AS relationships dataset that we obtained from CAIDA [40]. The AS relationships dataset contains inferred business relations, customer-to-provider and peer-to-peer, between the ASes in the Internet. These business relations are implemented as physical connections at one or more facilities to exchange traffic and routing information. X-BI to X-BI links in X-AS maps also represent these connections observed at the network layer of the IP stack. Our experimental setup assumes that if there is an X-BI to X-BI link between two ASes in the X-AS map, then



Figure 11: Discrepancy between X-AS map links and AS level map relations

there must be a reported relationship in CAIDA's AS relationships dataset. We are aware that this experimental setup is not ideal, yet it is practical for validating our proof of concept given that ISPs do not publish their detailed, ground-truth topologies.

Figure 10 shows an equal-width binned histogram of the discrepancies (in terms of percentages) between CAIDA's AS level map and our X-AS map connections. The X-AS map is 100% in agreement with CAIDA's AS level map for 78% of the ASes. The average cross-AS link agreement is 84.9% for the entire X-AS topology map. The maximum discrepancy that we observed is 50%. Analyzing the cases further shows that the majority of these ASes have only two relations and we were able to capture only one of the two relations in our X-AS maps. Yet, only 3% of ASes have a discrepancy of 40% or more. We observed a similar behavior at 33% discrepancy band which constitutes 6.2% of the ASes. Further analysis has revealed that most of these ASes have three relations in CAIDA's AS level map and we were able to capture only two of the three relations.

In addition, we separately examined the links incident on the research and commercial networks that we analyzed in the previous section. Figure 11 presents the discrepancy between CAIDA's relationships and our X-AS map cross con-We observed 100%, 97.8% and 93.8% agreenections. ment for Internet2 (AS11537, AS11164), GÉANT (AS20965, AS21320) and ULAKNET (AS8517), respectively. As for large scale commercial networks, we observed 100% agreement for AS7018 (AT&T) and AS2273 (Cox), 98.8% agreement for AS3320 (Deutsche Telekom), 98.5% agreement for AS6453 (Tata Communications), 96.8% agreement for AS6939 (Hurricane Electric), 95.8% agreement for AS209 (CenturyLink), 93.1% agreement for AS3356 (Level3) and 90.5% agreement for AS174 (Cogent).

5. Empirical Analysis

In this section, we first present the datasets used for constructing an X-AS Internet topology map. In the second part, we investigate various features of the X-AS map. In the last part, we build an AS level multigraph using the X-AS map and examine the connectivity structure of the multigraph.



Figure 12: X-BI taxonomy w.r.t. different data sources

5.1. Analysis of the Datasets

In the following we present the datasets used in this study and examine the techniques introduced in Section 3.

Traceroute Datasets: We used iPlane [27] and CAIDA [28] traceroute datasets in this work. IPlane and CAIDA datasets contain more than 11 million (11,266,865) and 19 million (19,275,509) path traces, respectively. We found 856,184 unique IP addresses in both datasets.

BGP Datasets: We used RouteViews [30] and RIS RIPE [29] BGP datasets in this work. We were able to get 3,918 IP addresses from the RIPE dataset and 3,032 IP addresses from the RouteViews dataset. Among those IP addresses, we observed 1,618 in both datasets.

IP2AS Mapping: We used RouteViews prefix to AS mapping dataset (pfx2as) obtained from CAIDA [26]. We were able to map 92% percent of the unique IP addresses (791,073) to their corresponding AS numbers. We removed the remaining 8% because our techniques, presented in Section 3, do not apply to them.

X-BI Identification: We found 251,597 and 329,929 X-BIs in iPlane and CAIDA datasets, respectively. Moreover, we observed 5,332 X-BIs from the BGP datasets. Figure 12 shows the taxonomy of X-BIs with respect to different data sources. In total, we observed 397,124 unique X-BIs.

Geolocation Methods

DNS: We were able to resolve the geolocations of 16,650 X-BIs which mostly belong to large scale ISPs. Although it corresponds to 4.19% of all X-BIs, it nicely complements other geolocation techniques.

Geolocation Databases: In this work, we used three different commercial geolocation databases. We applied majority voting to resolve the remaining unresolved X-BIs. All three databases agreed on 168,881 X-BIs out of 397,124 X-BIs. Only two databases agreed on 139,326 X-BIs. In total, majority voting successfully resolved 308,207 X-BIs which corresponds 77.61% of all X-BIs. DNS-GeoDB and majority GeoDB methods together resolved 81.8% of the X-BIs.

In order to resolve the remaining X-BIs, we found the geolocations of all non-XBI IP addresses in our traceroute datasets using the previous two geolocation techniques. Remember that, our dataset consists of 856,184 unique IP addresses. We were able to resolve the geolocations of 651,397 IP addresses (76%).



Figure 13: RTT difference distribution

Sandwich Method Geolocation: The sandwich method locates unresolved X-BIs appearing in path traces and checks the two IP addresses that immediately appear before and after an X-BI. If these two IP addresses are at the same location, then so is the X-BI. This technique resolved 14,314 X-BIs out of the remaining 71,389 unresolved X-BIs.

RTT-based Geolocation:

We assume that if the round trip time difference between a resolved IP address and an X-BI is less than a 3ms threshold, then they are at the same location. Figure 13 shows the distribution of the RTT differences between consecutive traceroute IP addresses that are known to be located in the same cities via our previous geolocation techniques. The distribution is positive skewed with a median of 3.21 ms which is rounded to 3 ms in our experiments. In an earlier work, Feldman and Shavitt use 5 ms RTT difference to extract IP subgraphs located in PoPs [18]. We use a more conservative threshold value to decrease false positives, because false negatives are resolved further in our last step. We were able to resolve an additional 47,138 X-BIs using this method.

Singular GeoDB based Geolocation: Lastly, we used Maxmind [35] geolocation database to resolve the remaining 9,937 (2.5%) unresolved X-BIs. At the end, all X-BIs were mapped to a geolocation.

5.2. X-AS Map Analysis

In the following, we analyze the main components of the X-AS map that we constructed using the datasets presented earlier. The final X-AS topology map X = (N, C) consists of a set of X-BI nodes, N, and a multiset of X-BI connections, C.

5.2.1. X-BI Node Analysis

Once we identify the X-BIs of the ASes and map them to their geolocations, we cluster them into X-BI nodes with respect to their geolocations as explained in Section 3. We found 69,573 X-BI nodes distributed over 43,386 ASes.

Figure 14 shows the X-BI node distribution over the ASes in log-log scale due to the skewness in the tail. The x-axis shows



Figure 14: X-BI node distribution over ASes

the number of the X-BI nodes per AS and the y-axis shows their frequencies. The red line presents the power law in the tail. In the figure, 34,995 (80.7%) ASes have only one X-BI node (Please see Section 5.3 discussing stub ASes and backup links), 4,678 (10.8%) ASes have two X-BI nodes, 1,685 (3.9%) ASes have three X-BI nodes and the remaining 2,028 (4.7%) ASes have four or more X-BI nodes. In addition, Table 1 shows the minimum, first quartile, second quartile (median), third quartile, maximum, mean and standard deviation for the X-BI node distribution.

Table 1: Summary statistics for the X-BI node distribution over ASes

Q_0	Q_1	Q_2	Q_3	Q_4	Mean	S tdDev
1	1	1	1	506	1.56	5.33

The linear pattern in Figure 14 suggests that the X-BI node distribution follows power law in the tail. Formally, a quantity follows power law if it is drawn from a probability distribution p(x) such that $p(x) \propto x^{-k}$ where 2 < k < 3 is called the scaling parameter [41]. Power law distributions frequently appear in man-made and natural networks. In general, power law indicates that the observations with low values are much more frequent compared to the observations with high values with a proportional relative change. Figure 14 suggests that the majority of the ASes in the Internet have a very small number of X-BI nodes, while only a small number of ASes have larger numbers of X-BI nodes. This finding is consistent with the previous studies in the sense that the majority of the ASes in the Internet are stub ASes [4] that do not span geographically (single X-BI node), while a relatively small number of ASes span over multiple geographical regions (many X-BI nodes).

However, power law distributions appearing in works using traceroute datasets should be viewed with healthy skepticism for statistical and measurement-based reasons [42]. Moreover, the linearity in log-log plots is a necessary but not sufficient condition for power law distributions. Therefore, we applied power law hypothesis testing suggested in [41]. The hypothesis test combines maximum-likelihood fitting methods along with goodness-of-fit tests based on the Kolmogorov-Smirnov statistic and likelihood ratios [41]. The hypothesis testing suggests



Figure 15: X-BI node degree distribution

Table 2: Summary statistics for the X-BI node degree distribution

Q_0	Q_1	Q_2	Q_3	Q_4	Mean	StdDev
1	1	2	4	4171	6.41	43.38

that there is not enough evidence to reject the power law tail in the X-BI node distribution for $x_{min} = 2$ with p-value 0.475.

5.2.2. X-BI Link Analysis

In this part, we analyze the degree distribution of the X-BI nodes in our X-AS map. We define the degree of an X-BI node as the number of the links that it has to other X-BI nodes. Note that, we discovered 434,924 X-BI node links using the traceroute datasets and an additional 123,916 connections using the BGP datasets.

Figure 15 shows the X-BI node degree distribution in log-log scale. The x-axis shows the X-BI node degree and the y-axis shows the frequency. The red line presents the power law in the tail. In the figure, 21,358 (30.7%) X-BI nodes have degree one, 16,499 (23,7%) X-BI nodes have degree two, 8,744 (12.6%) X-BI nodes have degree three and 22,972 (33%) X-BI nodes have degree four or more. In addition, Table 2 shows the minimum, first quartile, second quartile (median), third quartile, maximum, mean and standard deviation for the X-BI node degree distribution.

Again, the X-BI node degree distribution exhibits power law in the tail with scaling parameter k = 2.0049. Applying power law hypothesis testing shows that there is not enough evidence to reject the power law tail in the X-BI degree distribution for $x_{min} = 3$ with p-value 0.563. Figure 15 suggests that the majority of the X-BI nodes have very low degree, while only a small number of X-BI nodes have higher degrees. The low degree X-BI nodes can be attributed to the stub ASes which do not have any customers or peers as well as no more than a few providers. On the other hand, higher degree X-BI nodes belong to large scale ISPs and content providers and they are located at major cities including San Francisco, Stockholm and London. These X-BI nodes have presence at significant colocation centers and IXPs located in major cities which provide more opportunities to establish transit and peer business links with other ASes.



Figure 16: AS degree distribution

5.3. Analysis of AS level Multigraph

Using the X-AS Internet topology map X = (N, C), we generated a multigraph representation, G = (V, E, f), of the topology map where the endpoints of the edges correspond to the X-BI nodes. In the following we first analyze the degree distribution of the multigraph *G*. Next, we investigate assortative mixing by degree in the multigraph.

5.3.1. AS Degree Distribution

We define the degree of an AS as the number of the connections it has to other ASes including the parallel (multiple) connections. Note that AS degree is different from X-BI node degree because an AS may have more than one X-BI nodes. Unlike simple graphs, the degree of a vertex in a multigraph does not necessarily correspond to its unique neighbors due to potential parallel edges. Yet, the degree is an upper bound for the number of neighbors of a vertex.

Table 3: Summary statistics for the AS degree distribution

Q_0	Q_1	Q_2	Q_3	Q_4	Mean	StdDev
1	1	2	5	26418	10.02	193.37

Table 3 shows the summary statistics for the AS level multigraph degree distribution. The median degree is two for the ASes in our multigraph. 26.7% of the ASes have degree one which means they are single-homed. Despite the exceptions, ASes are required to be multi-homed with at least two providers. However, the second connections to alternative ASes are typically backup links and more often they are not visible [12]. Although majority of the ASes are stub ASes in the Internet and they do not have high degrees, we observe a small number of large degree ASes up to 26,418.

Figure 16 shows the AS level multigraph degree distribution in log scales. The x-axis shows the AS degree and the y-axis shows the frequency. The red line presents the power law in the tail. Figure 16 also suggests that the majority of the ASes have very low degrees, while only a small number of ASes have higher degrees. The low degree ASes correspond to the stub ASes which do not have any customers or peers as well as no



Figure 17: AS Assortativity

more than a few providers. On the other hand, a small number of ASes span multiple geographical locations and have many customers, providers and peers at multiple colocation centers and IXPs. These ASes belong to major market players such as Telianet, Level3 and Cogent Communications. The distribution also has a power law tail for $x_{min} = 3$ with p-value 0.369.

5.3.2. AS Assortativity

Assortative mixing in graphs shows the preferences for a graph's vertices to attach to other vertices. In complex systems assortativity is often examined in terms of degree. If high (low) degree nodes prefer to attach high (low) degree nodes in general, the graph is said to be assortative. If high (low) degree nodes prefer to attach low (high) degree nodes in general, the graph is said to be disassortative. One way of looking at the assortativity in graphs is examining the conditional degree-degree distribution plots.

Figure 17 shows the conditional degree-degree distribution using a heat map. In the figure x and y axes show the AS degrees in the multigraph denoted by k and k', respectively. The color encoded z axis shows the conditional distribution P(k'|k). In the graph, all axes are given in logarithmic scales due to the skewness toward large values. The conditional probability increases from cold colors toward the warm colors. Figure 17 clearly shows that the ASes are not connected to each other uniformly at random. We can visually break the figure into five consecutive sections: [0, 1], (1, 1.6], (1.6, 2.8], (2.8, 3.7], (3.7, 4.4]. The first section shows the ASes of degree 1 and 10. These ASes prefer to connect to low degree and high degree ASes while slightly disfavoring medium degree ASes. The ASes having degree 10 and 40 in the second section show a stronger preference toward the low degree and high degree ASes while avoiding connections to the medium degree ASes. The ASes having degree 40 and 631 in the third section exhibit preference toward lower degree ASes. They also have a stronger tendency toward connecting to medium degree ASes while they do not drastically prefer high degree ASes. The ASes in the fourth section show a pattern similar to the ASes in the third region; they have a stronger preference toward the low degree and high degree ASes. The very high degree ASes in the fifth section are connected to the lower degree ASes and some higher degree ASes while avoiding the medium degree ASes.

The patterns we observe on the left and right sections can be explained by high degree, large scale ASes offering better services and competitive prices to lower degree, stub ASes. These stub ASes prefer them as their main providers. The medium size ASes in the middle on the other hand, are regional ASes providing service to stub ASes in their regions as well as peering with similar size ASes to reduce their overall traffic costs.

6. Limitations and Discussions

Similar to other topology mapping works in the literature, X-AS mapping has its own limitations. First, the accuracy and coverage of the X-AS maps depend on the accuracy and coverage of the datasets used in X-AS map construction. In order to increase our coverage, we used two distinct traceroute datasets and two BGP datasets. To enhance our accuracy rate, we used three different geolocation databases in addition to IP sandwich, DNS and RTT-based geolocation techniques. Second, we assume that an AS has at most one X-BI node at a city. In case an AS has more than one PoP accommodating border routers in a city, our approach merges them into a single X-BI node. Third, X-AS maps capture connections observed at the network layer (layer-3) which may be implemented as point-to-point links or Local Area Networks (LANs) via switches at the lower layers.

ISPs use MPLS tunnels, typically in their backbone infrastructures, for traffic engineering, QoS assurance and/or remote peering provisions. Although MPLS tunnels spanning over two or more ISPs are technically possible, they are not adopted in practice. Because, they complicate network management and troubleshooting processes. However sibling ISPs, formed by company buyouts and merges, may implement MPLS tunnels spanning over the cross links between the sibling ASes. Donnet et al. categorize MPLS tunnels into four types; explicit, implicit, opaque and invisible [43]. Explicit and implicit tunnels do not purposefully hide the IP addresses in the tunnels, hence they do not introduce any peculiarities into path traces. On the other hand, opaque and invisible tunnels purposefully hide the IP addresses in the tunnels. Regardless of their types, MPLS tunnels implemented in the backbone infrastructures of ISPs do not affect X-AS maps. Because, X-AS maps focus on the cross connections between ASes rather than the connections within the backbone infrastructures of the ASes. On the other hand, opaque and invisible MPLS tunnels spanning over cross links or involving border/edge routers may introduce invisible subpaths in path traces. These invisible subpaths result in false positive cross connections in X-AS maps while missing the true cross connections.

Lastly, we were unable to map 8% (68,788) of the IP addresses in our dataset to their corresponding ASes. Please remember that the main objective of this study is to generate X-AS maps which capture X-BI nodes and the cross connections between them. Among these unmapped IP addresses, the ones that are not X-BIs do not affect the accuracy or coverage of X-AS topology maps. The ones that are part of the alreadyinferred X-BI nodes or cross connections also do not affect the accuracy and coverage of X-AS maps. On the other hand, the unmapped IP addresses that belong to the endpoints of unknown cross connections will be reflected as missing connections in X-AS maps. Although it is very unlikely, the ones that collectively represent an unknown X-BI node will be reflected as a missing X-BI node in X-AS maps.

Finally, the approaches presented in this work can be used for PoP level Internet topology mapping as well. PoP level topology maps require finding the backbone connections between the PoPs of a single AS as well as the cross-AS connections between the PoPs of different ASes. Capturing the backbone connections within an AS is a more challenging task because (i) it requires path traces entering into an AS through every PoP and leaving the AS through every PoP [24] (ii) it necessitates carefully crafted traceroute queries per AS to increase coverage while reducing the probing overhead [17] and (iii) it is reported that probing the backbone topology of ISPs is more prone to packet filtering [25].

7. Related work

Many approaches have been introduced to derive the Internet topology maps at the interface, router, subnet, PoP and AS levels [1, 2]. Traceroute, ping and their variants are commonly used to discover the IP addresses in the Internet [17, 44, 45].

Router level maps group the IP addresses according to their routers along with the connections between these routers. Grouping IP addresses based on the accommodating routers is called IP alias resolution [20, 46]. Mercator [44] is a probebased IP alias resolver that depends on the similarity in source IP addresses in probe responses. Ally [17] extends Mercator by utilizing the IP identifiers in probe response packets to decide on aliases. Radargun [47] employs velocity modeling scheme to reduce Ally's quadratic probing complexity. APAR [48] is an inference-based alias resolver to resolve aliases among IP addresses collected via traceroute.

A PoP is defined as a set of cooperating routers that belong to the same AS and located in the same facility. PoP level maps focus on the physical locations of the facilities as well as the connections between these facilities. Rocketfuel project defines a PoP as a collection of routers located in the same place [17]. Hence, they group routers into their geolocations by using DNS information. Madhyastha et al. [32] improved Rocketfuel's DNS project by extending their key dataset. Shavitt and Zilberman have suggested a graph-based approach to infer PoPs [18]. Their idea is to find network motifs repeated in traceroute datasets. In their work, they define a PoP as a set of IP interfaces. Yoshida et al. proposed a delay-based PoP finder method for ISPs in Japan [25]. Rasti et al. [49] used eyeball ASes which directly provides services to end-users to infer PoPs in an area. Topology Zoo [50] and the Internet Atlas [51] projects suggest using topology information provided by ISPs for mapping.

AS level topology maps capture ASes and the business relations among the ASes. The related topology mapping techniques can be categorized based on the source(s) that they em-

ploy. Path trace based approaches use traceroute to collect path traces and employ IP address to AS number mapping techniques to build the links between the ASes. Chang et al. proposed a method for discovering AS level connectivity by inferring individual connections from the router level topology of the Internet [19]. Mao et al. suggested heuristics to fix inaccurate IP-to-AS mappings by using BGP and traceroute paths collected from multiple vantage points [52]. Later, they proposed a new approach based on dynamic programming to iteratively improve IP-to-AS mappings [53]. More recently, Faggiani et al. showed that using multiple traceroute infrastructures helps with improving the completeness of AS level topology maps [54]. He et al. developed an approach which identifies additional AS links by cross-reference and synthesis of BGP routing tables, path traces and IRRs [55]. Khan et al. constructed an AS level Internet topology map using BGP looking glasses [56]. Mahadevan et. al [57] combine traceroute, BGP and WHOIS measurements to create more accurate AS level maps. BGP routing table based approaches passively collect BGP updates and use the advertised paths to construct an AS level topology map of the Internet. Most of the studies in this category not only focus on mapping but also inferring the types of business relations between the ASes. In her influential work [3], Gao classified business relations between ASes into three groups (customerto-provider, peer-to-peer and sibling-to-sibling) based on the assumption that AS level paths are valley-free, i.e., hierarchical. Other studies focused on the formalization of relation inference and its complexity [58, 59]. More recently, Giotsas et al. suggested a new algorithm to infer partial and hybrid relations between ASes [16].

In this study, we introduce Cross-AS (X-AS) Internet topology maps which capture both ASes and the parallel connections between the ASes observed at the network layer. Such maps allow us to abstract and study the topology of the Internet as a multigraph. Although constructing router level and PoP level Internet topology maps is more difficult and error prone, they ideally provide a richer set of information compared to the X-AS topology maps. X-AS maps neither capture individual routers, their interfaces and the connections among them nor do they capture the backbone infrastructures of the ASes. Compared to the AS level Internet topology maps, X-AS maps capture multiple links among ASes instead of logical relations among them.

8. Conclusions

The Internet is a highly engineered, large scale, decentralized network of networks serving billions of people worldwide. In the last two decades researchers have developed many techniques to infer the topology of individual ASes as well as the whole Internet at the interface, router, subnet, PoP and AS levels. In this study, we introduced *cross-AS* (*X-AS*) *Internet topology maps* which capture both ASes and the cross-AS connections observed at the network layer. We presented a set of techniques that exploit multiple data sources (path traces, BGP advertisements, geolocation databases and DNS datasets) to construct X-AS topology maps. We used three research networks, Internet2, GÉANT and ULAKNET and nine large scale commercial networks belonging to Cox, AT&T, CenturyLink, Cogent, Cox, Deutsche Telekom, Hurricane Electric, Level3 and Tata Communications to validate our approach. Our experimental results show that the X-AS map successfully captures the X-BI nodes belonging to both research and commercial networks and covers the links between the ASes with high accuracy. We investigated various features of the Internet's X-AS map and its multigraph representation. Particularly, we demonstrated the existence of power law tails in the X-BI node distribution over ASes, X-BI node degree distribution and AS degree distribution with statistically significant p-values. Lastly, we investigated assortative mixing in AS level multigraphs. Our results show that there is a strong correlation between low degree and high degree ASes, whereas medium degree ASes are correlated to both low degree and medium degree ASes.

In the near future, we plan to investigate alternative geolocation techniques to improve the accuracy of X-AS maps and differentiate between multiple X-BI nodes that belong to the same AS and located in the same city. In addition, we plan to examine the unresolved IP addresses using alternative data sources to improve the accuracy and coverage of X-AS maps further. Moreover, we plan to investigate private and public peering practices at IXPs to distinguish between point-to-point links and LANs in X-AS maps. Finally, the source code of our implementation is available at our project website [39].

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