Nation-State Routing: Censorship, Wiretapping, and BGP

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ABSTRACT

The treatment of Internet traffic is increasingly affected by national policies that require the ISPs in a country to adopt common protocols or practices. Examples include government enforced censorship, wiretapping, and protocol deployment mandates for IPv6 and DNSSEC. If an entire nation's worth of ISPs apply common policies to Internet traffic, the global implications could be significant. For instance, how many countries rely on China or Great Britain (known traffic censors) to transit their traffic? These kinds of questions are surprisingly difficult to answer, as they require combining information collected at the prefix, Autonomous System, and country level, and grappling with incomplete knowledge about the AS-level topology and routing policies. In this paper we develop the first framework for country-level routing analysis, which allows us to answer questions about the influence of each country on the flow of international traffic. Our results show that some countries known for their national policies, such as Iran and China, have relatively little effect on interdomain routing, while three countries (the United States, Great Britain, and Germany) are central to international reachability, and their policies thus have huge potential impact.

1. INTRODUCTION

Internet routing is typically studied at the Autonomous System (AS) level. This is by design. Traditionally, ASes control their own internal networks and set their own policies for the routing, filtering, and monitoring of traffic, placing policy in the hands of the organizations that own them. Recently, groups of ASes have begun to act under common policies, issued by their country's government. Examples include Internet censorship [1], wiretapping [2], and protocol-deployment mandates [3, 4]. For instance, Chinese, British, and Pakistani ISPs are required (or strongly encouraged) to filter content deemed socially offensive. Although censoring techniques differ, all three countries are known to block traffic at the IP level (e.g., by filtering based on IP addresses and URLs in the data packets, or performing internal prefix hijacks [5, 6, 7]), which could affect the international traffic they transit. Some countries, such as the United States and Sweden, wiretap international traffic, where even encrypted traffic is vulnerable to traffic-analysis attacks [8]. Finally, governments can attempt to force the deployment of protocols, such as the deployment of IPv6 and DNSSEC in federal agencies of the United States.

It is unclear what effect any particular country's policies have on the rest of the Internet. Typically, censorship is applied to prevent domestic users from reaching disagreeable content. However, some censorship techniques (such as filtering based on IP addresses or URLs) may affect all traffic traversing an AS. In addition, ASes might intentionally, or accidentally as in the recent YouTube outage [6], apply censorship policies to international traffic. How many networks outside of the country would be prevented from viewing Web pages simply because their traffic traverses one of these networks? Which international traffic is vulnerable to warrantless wiretapping by the United States or Sweden? And, finally, how feasible is it to avoid directing traffic through a given country with objectionable policies by using alternative routes?

To answer these questions, we must study the aggregate effect of national policies on the flow of international traffic, rather than analyzing individual ASes in isolation. In this paper we take initial steps toward understanding interdomain routing at the nation-state level. We are particularly interested in understanding the influence that each country's ASes have over reachability between other countries. The resulting data and measurement techniques could be useful to many communities. First, those regions of the world with strong dependencies on particular countries could use our result to guide changes in how they connect to the rest of the Internet. Second, overlay networks (such as Resilient Overlay Networks [9]) could use our results to determine how best to circumvent specific countries, helping to ensure that data are delivered intact, and avoid snooping. Third, our results would be helpful to policy makers to understand what impact their decisions could have on the global Internet.

There are two primary challenges in this work. The first is to define suitable metrics for quantifying the importance, or centrality, of each country to Internet reachability. The second is to accurately infer the data needed to compute these metrics, and validate them. We adapt the *betweenness centrality* metric from statistical physics as a first approximation of country centrality. Betweenness centrality is typically used as a naive traffic estimator at each node in a graph. We adapt betweenness centrality to estimate the impact each country has on reachability between other countries, defining country centrality (CC) in Section 4.

Our metrics take as input the country-level paths between each pair of IP addresses in the Internet. This is a significant challenge because of the many levels of inference required to produce a country-level interdomain path. First, ASes select routes using the Border Gateway Protocol (BGP) [10], which chooses routes based on undisclosed routing policies, rather than simply using the shortest path. Fortunately, this is a well-studied problem and several inference algorithms exist for inferring AS-level routes. A second challenge arises because an individual AS may span many countries. This leads us to consider routing at the IP prefix level, which requires understanding how packets traverse each AS. Finally, each path must be converted to a country-level path by mapping IP addresses to prefixes, and then prefixes to countries (e.g., using routing registry data). There is a risk of introducing significant, and possibly compounding, error in each step of the process. However, we present empirical evidence to suggest that our centrality metric is robust to the measurement noise, and that our results are meaningful.

Our inference techniques allow us to estimate the centrality of each country, where CC values range from 0 (implying no influence) to 1 (the theoretical maximum). Our results show that countries known for censorship, such as Great Britain, China, Australia, and Iran, have CC values of 0.29, 0.07, 0.07, and 1.12e-05 respectively. These results suggest that, of the countries that censor Internet traffic, only some have significant impact on global routing. In particular, the countries that have received the most publicity for their censorship, such as China, have significantly less impact on international traffic than, say, Great Britain, which also censors traffic. We also show that the United States and Sweden (nations known to permit warrantless wiretapping) have CC values of 0.74 and 0.02; even if ASes actively prefer BGP routes that avoid the United States, the CC value only drops from 0.74 to 0.55.

With national policies on the rise, we believe that researchers, ISPs, and policy makers will soon need to understand the impact that these policies can have on other countries, networks, and even individual IP prefixes. Our major contribution is the development of a framework for studying interdomain routing at the nation-state level. This includes identifying and addressing the many challenges of inferring the country-level paths, developing network centrality metrics appropriate for the problem, validating the methods, and reporting initial results.

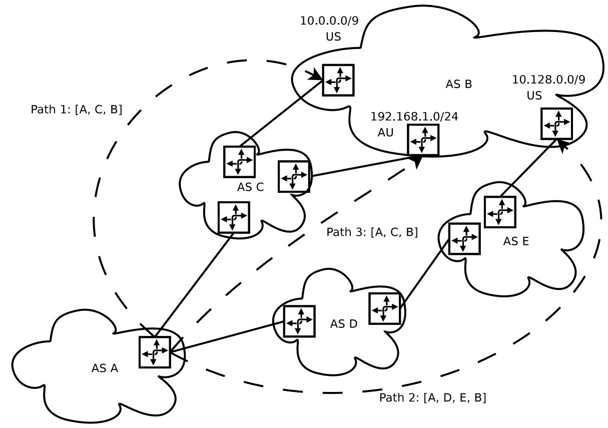

Figure 1: Example AS topology with AS paths. Paths 1 and 2 both route between the same pair of ASes (A and B), but their AS paths are different, depending on the destination prefix. The same AS path can also have distinct country-level paths, for example paths 1 and 3.

The paper is organized as follows. In the next section we briefly discuss the Internet's topology and the correct granularity for measuring country paths. In Section 3 we design, implement, and validate the *Country Path Algorithm* (CPA) for inferring country-paths from a pair of source and destination IP addresses. The algorithm has several stages, as it must first infer the interdomain path, and then intradomain paths, and finally determine the country path. Next, Section 4 reviews betweenness centrality and presents two extensions for measuring a country's influence over global reachability. These metrics take as input the global measurements produced by the CPA. In Section 5, we apply our inference techniques to sample data sets of traceroutes and AS paths, as well as inferred paths between all known IP prefixes. This helps validate that our metrics are robust to inference error. We also present initial results characterizing the data produced by the CPA. Next, we discuss future work and other possible challenges in country level analysis in Section 6, we review related work in Section 7, and finally conclude in Section 8.

2. AN APPROPRIATE GRANULARITY FOR ANALYZING COUNTRY-LEVEL PATHS

The Internet is currently comprised of roughly 30,000 Autonomous Systems, which are typically independently operated, multi-homed networks. Each AS is allocated IP address space, which is a contiguous blocks of IP addresses called IP prefixes. The interdomain routing protocol that allows ASes to reach one another's prefixes is called the Border Gateway Protocol (BGP). BGP is a policy based protocol that selects and propagates AS paths according to local policies (e.g., economic relationships), rather than path performance (e.g., shortest path routing). Example policies include customer-provider in which the customer pays the provider for transit, and peer-peer in which the participating ASes transit each other's customer traffic to their own customers. Lixin Gao showed that these policies can affect routing propagation [11]. For instance, most customers would not be willing to provide transit from one of their providers to another. Gao observed that ASes typically follow the *valley-free* rule, which states that routes received from a provider or peer should only be propagated to customers.

For our experiments it is necessary to inference all of the country-paths between each pair of IP addresses. Since IP addresses are allocated to ASes, we could determine the country-paths between each pair of ASes and use that information to determine all paths between each pair of IP addresses. One immediate problem is that some ASes span more than a single country. A second issue is that in many cases there are multiple paths between two ASes, depending on where traffic enters the AS and on the destination prefix in question. For example, in Figure 1 AS A uses path 1 to reach prefix 1 at AS B, but uses path 2 to reach prefix 2 at the same destination AS. AS B might split its traffic like this to balance its traffic load between two providers (ASes C and E).

A second possible approach would cluster together the prefixes with the same AS paths between AS pairs, and infer a path for one prefix from each cluster. This is known as a *BGP Atom* [12, 13]. Although this approach can enumerate the best AS-paths between AS pairs, it does not encompass the full diversity of country-level paths. Two destination prefixes with the same AS path may have different underlying country-level paths. For instance, in Figure 1 AS paths 1 and 3 are the same, however they terminate in different countries (United States in path 1 Australia in path 3).

After ruling out the first two approaches, we resorted to inferring the country-level paths between each pair of IP prefixes, the finest level of measurement available. There are over 290,000 prefixes in today's routers, resulting in over 84 billion country paths that need to be inferred and analyzed. We also study all of the available alternate paths that exist from one prefix to another, resulting in more than 465 billion country path inferences that need to be performed. The large number of inferences places significant constraints on the inference algorithm's complexity. For instance, simply running Dijkstra's shortest path algorithm to determine the intradomain path of each AS in each path is too slow.

$$traceroute = \overbrace{ip_{src}, ip_2, ip_3}^{C_1}, \overbrace{ip_4, ip_5, ip_6}^{C_2}, \overbrace{ip_{dst}}^{C_3}$$

$$traceroute = \underbrace{ip_{src}, ip_2}_{AS_1}, \underbrace{ip_3, ip_4, ip_5}_{AS_2}, \underbrace{ip_6, ip_{dst}}_{AS_3}$$

Country-path Inference Algorithm:
$(ip_{src}, ip_{dst}) \rightarrow (AS_1, AS_2, AS_3) \rightarrow (C_1, C_2, C_3)$

Figure 2: Traceroutes, AS-paths, and country-paths. A traceroute is the list of IP addresses of the routers that a packet traverses from ip_{src} to ip_{dst}. Each router belongs to an AS, and each router is in a country C. The Country Path Algorithm takes a source and destination IP address as input, infers the interdomain AS-path between the two addresses, and then infers the country-path between them.

3. THE COUNTRY PATH ALGORITHM

The metrics described in Section 4 analyze country-level paths to determine which countries can potentially interfere with the communication of others. In this section we present the Country Path Algorithm (CPA) for inferring the country-level paths between any two IP addresses. There are two steps to the procedure. The first infers the interdomain path between the addresses, and the second step predicts the country-path from the AS-path. We use a slightly modified version of Qiu et al.'s [14] AS-path heuristic for the first step which is described in 3.1, and introduce the first country path predictor in the second step, presented in 3.3. An overview of the CPA algorithm is shown in Figure 2. The AS-path to country-path heuristic requires information about known traceroutes and their corresponding AS-paths and country-paths as input. We show how to infer these paths from a traceroute in Subsection 3.2.

3.1 Prefix Pair to AS-path

The first step in the country path algorithm is to map prefix source/destination pairs to their appropriate AS paths. Of the recent AS-path inference methods [14, 15, 16, 17], only Qiu's provides prefix-level predictions and is fast enough for our needs.

3.1.1 A Modified Version of Qiu's Heuristic

Qiu's heuristic simulates the propagation of BGP routes across an AS topology, as if each AS had a single router. The propagation model is a simplified model of the actual BGP protocol. In it, each router selects its best path to the destination prefix after receiving a route

```
1: KnownPath(p, G, prePaths):
2: while queue.length > 0 do
3:    u ← POP(queue,0)
4:    for all v ∈ peers(u) do
5:       P_u ← ribIn(u)[p][0]
6:       if legitimatePath((v)+P_u) then
7:          tmppath ← ribIn(v)[p][0]
8:          update ribIn(v)[p] ← with (v) + P_u
9:          sort(ribIn(v)[p])
10:         if tmppath = path(v)[p][0] and v ∈ queue then
11:            append(queue,v)
12: return ribIn
```

Figure 3: Pseudo-code of Qiu's inference algorithm. Line 6 was modified to propagate paths to pre-determined ASes.

```
1: ComparePath(P_1 = (u, v1, ...), P_2 = (u, v2, ...)):
2: if P_1.ulen ≠ P_2.ulen then
3:    return P_1.ulen - P_2.ulen
4: if |P_1| ≠ |P_2| then
5:    return |P_1| − |P_2|
6: if P_1.freq ≠ P_2.freq then
7:    return P_2.freq - P_2.freq
8: return P_1 − P_2
```

Figure 4: Pseudo-code of Qiu's path comparison heuristic. Lines 2-4 have been switched with lines 5-7 from the original algorithm.

announcement, and propagates the path to its neighbors (obeying the valley-free rule) if its best path has changed. The largest contribution that her work made was to include known BGP paths from routing table dumps (known as RIBs) to improve the accuracy of the heuristic. Essentially, ASes are primed with known paths for each prefix at the beginning of the algorithm. Then, as the paths are propagated, paths that are the fewest hops from a known path are given preference.

The original Qiu algorithm does not propagate paths to ASes that have pre-determined paths, since they will never select an alternate path. Therefore, many ASes will only have a best path, and no selection of alternative paths available. Our centrality metrics require a list of all possible alternate paths for each AS to each prefix as well as the best path. This is needed to estimate the ability of networks to route around (or avoid) particular countries using alternate paths. Therefore, we modified Qiu's algorithm to propagate paths to all ASes, even those that were primed with a known path. Our changes to the original algorithm, are shown in Figures 3 and 4. The purpose of our alterations is to predict alternate paths, not to increase the algorithm's accuracy. In the validation section we show that our changes appear to have no significant effect on the predictive accuracy of the algorithm.

3.1.2 Pre-processing the Data

Qiu's algorithm takes as input a list of known BGP routes and a topology of known ASes, the edges between ASes, and the economic relationship of each edge. We retrieved the first RIB of 2009 (BGP routing table) from RouteViews [18] and RIPE RIS servers [19]. In total there are paths for 290,691 prefixes. We divided the data in half, into a testing and training set. All routes from each observation point are kept together, and all observation points in the same AS are also kept together.

The topology was extracted from the AS paths found in the BGP RIBs. We developed a topology for use in testing and the total set for use in our final experiments. The training set topology has 29,580 vertices (ASes) and 68,396 edges while the total set has 29,607 vertices and 77,683 edges.

The edges of the topology must be labeled as one of customer-provider, peer-peer, or sibling-sibling (two AS numbers that represent the same network). We implemented the relationship inference algorithm described in [11] and labeled the edges of our topologies with the results. In total, the testing topology has 6,616 peer-peer edges, 61,037 customer-provider edges, and 743 sibling-sibling edges. The total topology has 12,623 peer-peer edges, 64,050 customer-provider edges, and 1,010 sibling-sibling edges.

3.1.3 Validation

To ensure that our implementation of the heuristic was working correctly, we downloaded RouteViews and RIPE RIBS from the beginning of 2005, which is close in time to the data used for Qiu et al.'s original paper. We split the data into testing and training sets proportional in size to the data sets used in [14] (we used the RIPE data for training, and tested on the RouteViews data), and then fed the testing topology and paths as input to the heuristic for prediction of paths in the testing set. The heuristic was able to predict 60% of the testing paths, exactly as stated in the original paper. This shows that the alterations had little effect on the algorithm, and suggests that our implementation is correct.

On our 2009 data set, the algorithm is able to predict the exact path found in the training set of the RIB correctly 54% of the time. However, the exact path is often in the routing table, but not selected as the best path. We show that the exact path is in the routing table 80% of the time.

Our results suggest that the routing table of each AS is relatively accurate, however the best path is not reliably selected. We return to this point in Section 4 and show experimentally that the heuristic is accurate enough for the reachability analysis that we perform.

3.2 Mapping Traceroutes to AS and Country Paths

The next step is to map an AS-path into a country-path. This requires information about known country-level paths and their respective AS-paths. In this subsection we describe how we extract country-level and AS-level paths from traceroutes, and the next section shows how the data can be used for inference country-level paths.

3.2.1 Challenges

Traceroutes show the router-level path between two IP addresses. By converting the routers' IP addresses to countries, we can determine the countries that a packet traverses.

There are many impediments to this process. First, a router can mask its existence in traceroutes by not decrementing packet TTLs, but we assume that this is a rare practice. A router could also be configured to not respond to traceroutes, which happens relatively frequently. Such traceroutes are incomplete, but we can still extract useful information from them.

The next challenge is to understand the location (country and AS) of each IP addresses found in the traceroutes. IP addresses are allocated to ASes by the regional routing registries (ARIN, RIPE, AFRINIC, APNIC, and LACNIC). Each regional registry publishes a database of allocated IP space, the ASes they were allocated, and the country of the organization. Once allocated, it is up to the ASes to update the registry databases of any changes. For instance, if an ISP delegates a portion of its prefix to a customer AS, that customer should be registered for the particular subprefix. This is not always done, and the registries are known to be incomplete and often inaccurate [20, 21].

3.2.2 Algorithm and Data

We collected traceroutes from the iPlane project [22] on December 17th of 2008. The data set contains roughly 26 million traceroutes, that were collected from 198 observation points (the majority of which are PlanetLab [23] nodes), with an average of 133,580 traceroutes each.

To convert the traceroutes to country-paths, we first had to obtain registry information for each IP address in the traceroutes. Team Cymru [24] keeps track of registry allocated prefixes and associated country code and AS mappings. For each IP in the traceroutes (as well as each prefix in the RIBs), we queried Team Cymru's server to obtain the country code. In the case that the lookup failed, or that the response was vague, such as "EU" (Europe) or "AP" (Asia Pacific), we ran a normal whois request (version 4.7.27) and extracted country and AS information where possible (whois responses vary, some contain more information than others). Our only tweak to the data was to replace the Hong Kong country code with China since they are now the same country. In total, we were able to determine a specific country code for 99% of the IPs found in traceroutes.

3.2.3 Validation

To verify the accuracy of our IP to country code and AS lookups, we compared our results to known ASes and countries for particular routers. One method of extracting the actual location of a given router is to extract it from its DNS hostname. For instance, the router with hostname, 143.ATM3-0.XR2.LAX2.ALTER.NET, is located in Los Angeles, which is in the United States. Two projects have developed hostname to location heuristics, RocketFuel's undns [25] and the sarangworld project [26], and the iPlane project has applied them to the routers in the traceroute data set. The locations were further verified by the iPlane project by timing analysis and known topology information.

For each IP address that was resolved to a country and AS using undns and sarangworld (9% of IPs in the traceroutes), we compared the values to our inferenced data from routing registries. We found that we could correctly infer the country of a router 96% of the time, and the AS 92% of the time. Our verification suggests that we have relatively accurate data sets with which to build our AS Path to country-path heuristic.

3.3 AS-path to Country-path

The last piece of our IP address pair to country-path algorithm involves inferring a country-path from an AS path. In total, the final algorithm takes a pair of IP addresses as input, determines their longest matching prefixes (like a routing table lookup), finds the best inferred AS path between them, and finally uses the algorithm in this sub-section to infer the countries along the path.

3.3.1 Challenges

It is difficult to infer intradomain routes. An Autonomous System is so called because it has complete control over its intradomain network. It can use whatever protocols it likes, even experimental ones, with its own policies, to determine how packets traverse its own network. This makes it very difficult for an outsider to determine how a packet might route through an AS. We do know that common intradomain protocols (e.g. OSPF [27] and IS-IS [28]) will typically choose the shortest path between any two points in the network. The difficulty is that the definition of shortest path can change between networks. For some networks, a short path might be low latency, where for others it might be one that follows a high-bandwidth path.

Since we are provided with an inferred AS path, the next step is to determine where the route will enter (ingress router) and exit (egress router) each AS. A simply heuristic for finding the exit router might be to find

$$\underbrace{ip_{src}, ip_2}_{AS_1}, \underbrace{ip_3, ip_4, ip_5}_{AS_2}, \underbrace{ip_6, ip_{dst}}_{AS_3}$$

Figure 5: Example annotated traceroute. ip_{src}, ip_3, and ip_6 are AS ingress points, and ip_2 and ip_5 are AS egress points.

```
predictCountries(AS-path):

for each ASN in the AS-path do
  if (a known ingress point exists for the next ASN from this ingress) then
    Select countries and next ingress point from known-ingress
  else if (a known ingress point exists for the next ASN from this ASN in this country) then
    Select most frequented ingress point (and corresponding country path)
  else if (a known ingress point exists for the next ASN from this ASN) then
    “”
  else if (a known ingress point exists for the next ASN from this country) then
    “”
  else if (a known ingress point exists for the next ASN) then
    “”
```

Figure 6: Pseudo-code of AS-path to country-path prediction

the the nearest router to the ingress router that is connected to the next hop AS. But again, nearness is not well defined.

Finally, the algorithm has to be fast enough to infer a country-path for 465 billion interdomain paths (one inference for each pair of prefixes over each AS path in each router's RIB) in a reasonable amount of time. Performing Dijkstra's shortest path across large ASes with tens of thousands of routers billions of times is simply too slow, and most AS paths include at least one AS of that size.

3.3.2 The Algorithm

We present a linear time (relative to the size of the AS path) algorithm to inference country-paths from AS-paths. The insight of the algorithm, similar to Qiu's AS-path algorithm, is to use known intradomain paths as often as possible, rather than infer our own.

The algorithm is broken down into two phases, initialization, and path inference. In the initialization phase, the (traceroute, country-path, AS-path) triples of known data are parsed for two particular features. First, each AS's ingress point is stored, relative to the ingress point of the previous AS in the path. For instance, Figure 5 shows an example triple in which we learn that when AS_2 is entered at ip_3, and AS_3 is the next AS, with ingress point ip_6. Therefore, when AS path AS_2, AS_3 is seen in the future, and AS_2 was entered at ip_3, then we infer that ip_6 is AS_3's ingress point and will have the country-path inferred from ip addresses ip_3, ip_4, ip_5,and ip_6. To increase accuracy, we also look two ASes ahead to determine the next AS's ingress point. For instance, we learn that when AS_1 is entered at ip_{src} and AS_2 and AS_3 are next, then ip_3 is the ingress point to AS_2. We store this information in a hash table referred to as the known-ingress table.

We will not have a value in the known-ingress table for every combination of ASes and ingress points. Therefore, it is sometimes necessary to to guess ingress points for the next AS. To aid in our guesses, the initialization algorithm also keeps track of the frequency of each AS's ingress points. For instance, we might learn that ip_3 is the ingress point for AS_2 75% of the time, or 50% of the time when coming from an AS in Canada, or 90% of the time when coming from anywhere in AS_1. We keep track all of these frequencies, and their relationships to previous ASes and countries.

The prediction algorithm is shown in Figure 6. For each AS in the AS path, it searches the known data for the current context (e.g. next AS, current country, current ingress point), progressively becoming less specific, until a match is found. A match provides information about the next ingress point and the list of countries between the current and next ingress points. This proceeds until the final ingress point is found. At which point, the country of the destination prefix is appended to the country-path and the path is returned.

3.3.3 Validation

To validate our algorithm, we selected roughly 1.4 million complete traceroutes from the testing set in which every router along the path has been determined the country and AS are known for each router, and the source and destination IP addresses are from different countries. Then, we initialized the prediction algorithm with the training set and predicted country paths for the test routes. Our algorithm predicted the exact set of countries 78% of the time. Another way of comparing the agreement of the predicted results to the known set of paths is to take the intersection of the sets over the union $\frac{Predicted \cap Actual}{Predicted \cup Actual}$, as seen in [17]. The agreement between our predicted paths and the actual paths is 92%, suggesting that when the predictor is wrong, it is usually close.

4. REACHABILITY METRICS

There are many ways to quantify the importance (or centrality) of a node in a network. Network centrality is a well studied problem [29, 30, 31] in statistical physics that has recently been applied to the AS-level Internet [32, 33, 34]. In this section we discuss the be-

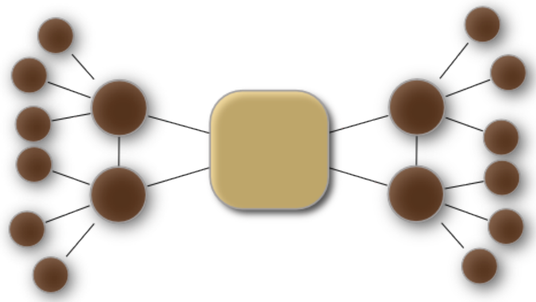

Figure 7: Betweenness centrality. The middle node does not have the greatest degree, but it is along the greatest number of shortest paths.

tweenness centrality metric, which is a centrality metric that we adapt for our own experiments. From betweenness centrality, we derive two metrics for measuring the centrality of a country at the BGP level.

4.1 Background on Betweenness Centrality

The simplest centrality metrics measure the degree of a node and the average shortest-path distance from a node to any other in the network. More advanced metrics, such as betweenness centrality, directly incorporate the importance of a node to network routing.

Betweenness centrality is an estimator of the importance of a node for communication flow in a network. It assumes that traffic flows equally along the shortest paths between two points, that each node has unit traffic, and that each node's traffic is uniformly distributed to the other nodes. It then estimates how much traffic flows through each node with the following formula:

$$Betweenness(v) = \sum_{\substack{s \neq v \neq t \in V \\ s \neq t}} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$$

where $\sigma_{s,t}$ is the number of shortest paths between s and t and $\sigma_{s,t}(v)$ is the number of shortest paths between s and t that transit through v. Nodes that transit lots of traffic have higher betweenness values than those that transit little. Figure 7 depicts an example network in which the middle node has the highest betweenness, even though four nodes have greater degree.

If each pair of nodes in the network had a single shortest path between them, then the betweenness centrality of a node could be interpreted as the number of shortest paths that pass through the node. In a network like the Internet, there are typically many shortest paths between two nodes. When multiple shortest paths exist, betweenness centrality splits the traffic equally among the shortest paths (by dividing it by $\sigma_{s,t}$). A node's betweenness centrality then represents the total amount of traffic it transits, given the stated assumptions.

4.2 Country Centrality

In this study, we are interested in determining each country's influence over global reachability. This is not the same as determining how much traffic a country transits. Although a country might transit 50% of all Internet traffic, that does not necessarily imply that 50% of country-pairs rely upon that country to communicate with one another. But, traffic estimates can still be useful for determining influence over reachability.

Because we are concerned with global reachability, we assume that all countries are equally important, and wish to communicate with one another uniformly. We then want to determine how much influence each country has over the communication paths. This can be thought of as a traffic estimation problem in which all countries have unit traffic, and all countries split that traffic equally to each destination. Then, to determine influence, we measure how much traffic each node transits. This is similar to the problem that betweenness centrality tries to solve.

There are three significant differences between country centrality and betweenness centrality. The first is that in country centrality, network nodes are countries, and each country is comprised of many prefixes. Therefore, the paths between any two nodes in our graph is actually the collection of paths between each pair of prefixes between the source and destination countries. Second, the path between a pair of prefixes is not the shortest path, but instead the country level path of the best AS-path inferred using the techniques found in Section 3. The final difference is that prefixes can be of varying size. A prefix 12.0.0.0/8 has 2^{24} IP addresses while 192.168.0.0/16 has 2^{16} IP addresses. Since we assume that each country has unit traffic, we then assume that each prefix in a country sends and receives traffic proportional to its fraction of the country's total IP address space.

We address the above differences with the Country Centrality metric. We changed the σ function to work on the best inferred path between prefixes instead of shortest path between vertices. We also changed the betweenness algorithm to sum over all of the prefixes for each country, and weight each path according to its prefix size. The CC value of a country v can be determined with the following formula:

$$CC(v) = \sum_{\substack{s \neq v \neq t \in V \\ s \neq t}} \sum_{\substack{\rho_s \in P_s \\ \rho_t \in P_t}} (W_{\rho_s} W_{\rho_t})\, \sigma_{\rho_s,\rho_t}(v)$$

where v is a country, P_s is the set of prefixes for country s, and W_{ρ_s} is equal to ρ_s 's fraction of country s's prefix space $\frac{|\rho_s|}{\sum_{p_i \in P_s} |\rho_i|}$. Here, the function $\sigma_{\rho_s,\rho_t}(v)$ equals the number of best paths between ρ_s and ρ_t that transit country Since there is only one best country path between each pair of prefixes in this function, σ is either 1 or 0. If each country had a single prefix, then the CC value of v would be the number of shortest paths that transit v, which represents the number of country-pairs that transit v to communicate. Since countries have many prefixes, and traffic between prefixes is proportional to prefix size, a country's CC value represents the total amount of traffic that it transits, given the stated assumptions.

To simplify CC values, we present them in this paper as normalized values from $[0, 1]$ by dividing it by the sum of traffic (with end-points other than the country itself) that it does not transit. Therefore, a value of one is the theoretical maximum value, suggesting that the country transits all traffic for every country pair. Similarly, a value of zero suggests that the country has no influence on reachability.

4.3 Strong CC

The CC metric estimates reachability influence based upon the best path between each pair of prefixes. BGP routers typically have multiple available routes to select from for each destination. Therefore, it is possible that a country in the best path could be avoided by using an alternate path. A network operator might intentionally try to avoid routing through a particular country, because it is known to filter or wiretap their data. In this subsection, we try to understand how central countries are when alternative routes are considered.

We consider a country to be strongly between a source and destination prefix if all of the source's available paths include the country. Once a router selects an alternate path, that change is propagated throughout the network, potentially changing the tables of thousands of other routers. Rather than attempt to measure all of the possible network states when alternate routes are selected, we look at a snapshot of the network's state, and determine how hard it is to avoid a country given each router's currently available paths. The resulting measure is called the strong country centrality SCC (SCC) metric.

$$SCC(v) = \sum_{\substack{s \neq v \neq t \in V \\ s \neq t}} \sum_{\substack{\rho_s \in P_s \\ \rho_t \in P_t}} (W_{\rho_s} W_{\rho_t}) \, \tau_{\rho_s,\rho_t}(v)$$

In the SCC measure, $\tau_{\rho_s,\rho_t}(v)$ is 1 (strongly central) when all all available paths from from ρ_s to ρ_t include v, otherwise it is 0. Once normalized, a value of one suggests that a country is completely unavoidable for all paths of all country-pairs. A SCC value should be strictly less than or equal to the same country's CC.

5. COUNTRY CENTRALITY RESULTS

In this section we quantify the influence that countries have on Internet reachability. We begin by determining country centrality (CC) values from the incomplete view we have from the raw traceroute and BGP paths described in Section 3. Then, we test our algorithm for mapping prefix pairs to country-paths by using the same prefixes seen in the traceroute set, but with the inferred country-paths that provide a more complete view of the Internet topology. This experiment shows that our metrics are robust to the error introduced in the paths. Finally, we infer country-paths between all pairs of prefixes and report on the CC and SCC values for the highest-ranked countries and countries known for pervasive censorship.

	TR	**BGP**
United States	0.335762 (1)	0.349493 (1)
Great Britain	0.240520 (2)	0.187967 (2)
Germany	0.149530 (3)	0.165787 (3)
Netherlands	0.079117 (4)	0.070454 (4)
France	0.059566 (5)	0.061420 (5)
Sweden	0.049587 (6)	0.013672 (15)
Hungary	0.042618 (7)	0.036281 (7)
China	0.033759 (8)	0.045443 (6)
Canada	0.033422 (9)	0.034070 (8)
Italy	0.032357 (10)	0.025297 (10)
Japan	0.024164 (11)	0.016592 (14)
Denmark	0.022172 (12)	0.165787 (21)
Russia	0.019994 (13)	0.023872 (11)
Singapore	0.017008 (14)	0.032938 (9)
Spain	0.016551 (15)	0.013413 (16)
Austria	0.016277 (16)	0.011704 (17)
South Africa	0.014977 (17)	0.002211 (20)
Australia	0.010235 (18)	0.007424 (12)
Serbia	0.007689 (19)	0.007488 (19)
Norway	0.006837 (20)	0.006769 (22)

Table 1: Country Centrality (CC) computed directly from traceroute (TR) and BGP paths

5.1 Analysis on Directly-Observed Paths

To start our analysis, we focus on statistics computed directly from the paths observed in the raw traceroute and BGP data. On the plus side, these paths are directly observed by some source, reducing the possibility of inference errors. On the negative side, these data sets provide only a partial (and potentially biased) view of paths through the Internet, depending on the locations of iPlane monitors (mostly PlanetLab nodes) and the vantage points where publicly-available BGP feeds are collected. In addition, these raw data sets do not provide information about alternate paths, precluding us from computing the Strong CC (SCC) metric.

Computing the CC value of the traceroute data set was straight-forward—we simply converted the traceroutes into country-paths using the method described in Section 3.2, and fed those paths into the algorithm for computing the CC metric. The results for the top 20 countries are listed in the "TR" column of Table 1. Similarly, for the BGP data, we inferred country-paths for each of the AS paths in the routing-table dumps described in Section 3. These results are listed in the "BGP" column of Table 1. (Notice that the sum of the CC values can be greater than one since multiple countries can lie on the same path.) The top five countries are the same in both data sets; the remaining 15 countries in the table are mostly the same, though slightly rearranged as one might expect given the relatively small differences in values across these countries.

The results show that three countries—the United States, Great Britain, and Germany—have very high CC values, while many of the commonly mentioned countries that employ censorship (e.g., China and Iran) have relatively little influence over global reachability. European countries are heavily represented in the table, including some countries with higher rankings than we expected—such as the Netherlands, Sweden, and Hungary. We suspect that the relatively large number of (small) countries in Europe cause a large number of European countries to rely on other countries in the same region for connectivity to the rest of the Internet. In addition, these results may be, at least in part, an artifact of the incomplete perspective of the raw traceroute and BGP data; as seen in the next section, these three countries drop somewhat (though admittedly not dramatically) in the ranking when we use the more complete, inferred paths.

5.2 Validation of Inference of Country Paths

The CC results from the raw traceroute and BGP data, while interesting, represent only a tiny sample of the Internet's country-paths. Still, these data sets are useful for validating our country-path inference technique. The validation experiment compares the CC results of real country-paths (directly mapped IP addresses to countries) to inferred country-paths (country-paths inferred from only the source and destination IP addresses). The inference algorithm was trained on the training sets of traceroutes and BGP RIBs. Then, we used the primed country-path inference algorithm to infer paths between the (source,destination) IP address pairs in the testing traceroute set. It is possible that the testing traceroute may have a source IP from an AS in the RIB training set. The algorithm would then have a known AS-path to inference, which would invalidate the experiment. To prevent such overlap from affecting our results, we ignored such traceroutes in the experiment.

We plot the results of the inferred paths against what are believed to be accurately inferred "real" country-paths in Figure 8. Both axis are log scaled to show the countries with low centrality in greater detail. Ideally,

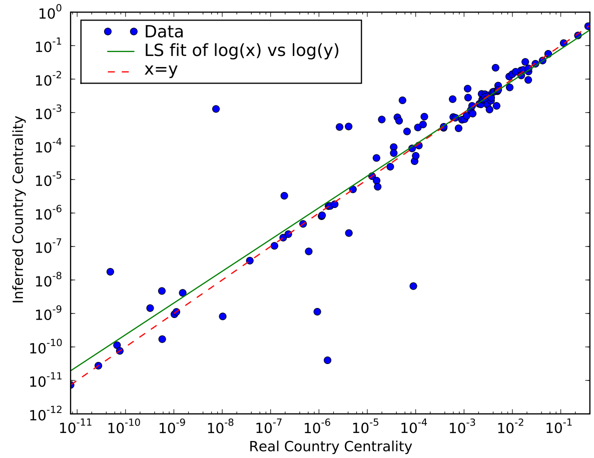

Figure 8: Actual versus Predicted Country Centrality. Predicted Country Centrality (CC) (log-scaled y-axis) is plotted against the actual CC for the same countries (log-scaled x-axis). Because there are so many small values, the data is fit in log(y) vs log(x) space to prevent overfitting the large values. The least squares linear fit is a solid line and the ideal $x = y$ line is dashed.

the data points would reside along the dotted $x = y$ line, suggesting that the CC of the real paths and inferred paths are the same. Many of them, especially the larger values, do lie closely along that line. Only a few extreme outliers exist, and they have relatively low CC values. We produced a least squares linear fit of $log(x)$ vs $log(y)$. It is plotted as a solid line, and has slope 0.94, with an R^2 of 0.84. This experiment leads us to believe that while there is inference error, the CC measurement is robust enough to the noise that the resulting values are meaningful.

5.3 Analysis on More Complete Country Paths

Because our inferred results match the CC values of the real paths so well, we inferred the entire set of country paths between all 290,682 routable prefixes found in our collection of RIBs. The country-path inference algorithm was trained on the full traceroute and RIB data sets. In total, the entire computation took two days to run when spread over 14 processors. Figure 9 plots the CC values of all countries, sorted by their CC values. Not surprisingly, the vast majority of countries have very small CC values. We list the top 20 countries in the ranking in the "CC" column in Table 2. The list of countries has a significant overlap with Table 1. The top five countries are the same, with just France (#4) and the Netherlands (#5) swapped in ranking between the two lists.

Surprisingly, the U.S. has a significantly higher CC

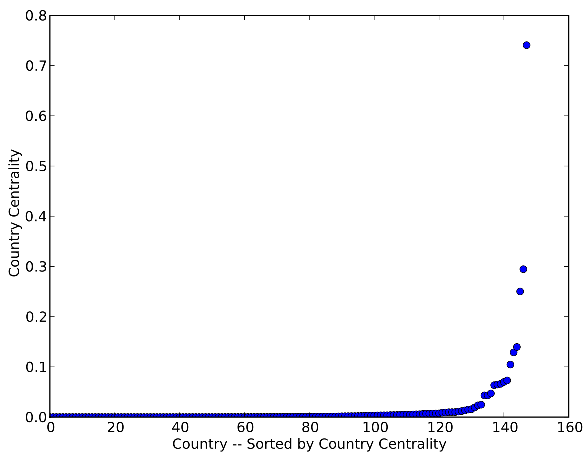

Figure 9: Country Centrality (CC) on more complete, inferred country-paths. Countries are displayed on the x-axis, sorted by their CC values, and CC values are displayed on the y-axis.

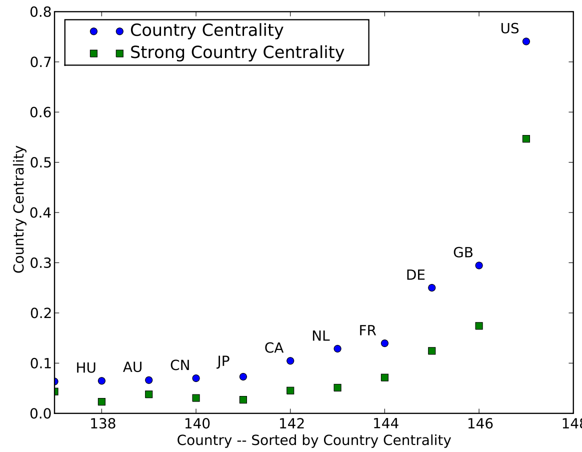

Figure 10: Strong CC (Zoomed). The top 10 countries (in terms of CC value) are displayed on the x-axis, sorted by their CC values. The CC values are displayed on the y-axis. The squares represent the Strong CC values of each respective country and have the same scale as the CC data.

	CC	SCC
United States	0.740695 (1)	0.546789 (1)
Great Britain	0.294532 (2)	0.174171 (2)
Germany	0.250166 (3)	0.124409 (3)
France	0.139579 (4)	0.071325 (4)
Netherlands	0.128784 (5)	0.051139 (5)
Canada	0.104595 (6)	0.045357 (6)
Japan	0.072961 (7)	0.027095 (11)
China	0.069947 (8)	0.030595 (10)
Australia	0.066219 (9)	0.037885 (8)
Hungary	0.064767 (10)	0.023094 (14)
Singapore	0.063522 (11)	0.043445 (7)
Italy	0.047068 (12)	0.027088 (12)
Spain	0.043248 (13)	0.025370 (13)
Russia	0.043228 (14)	0.035191 (9)
Austria	0.024632 (15)	0.010501 (17)
Sweden	0.023350 (16)	0.009785 (19)
South Africa	0.019294 (17)	0.013778 (15)
Denmark	0.015684 (18)	0.008101 (21)
Serbia	0.014935 (19)	0.012312 (16)
Switzerland	0.013302 (20)	0.003865 (35)

Table 2: Country Centrality (CC) and Strong Country Centrality (SCC) computed using inferred country paths

value in Table 2—nearly *double* the CC value in Table 1. We suspect that this is caused by the sampling bias in the traceroute and BGP data sets. For instance, the incomplete data sets likely over sample the routes from countries that have well-distributed connections to the Internet (such as European countries) and under sample countries with less rich connectivity (such as those in South America) that often rely on the United States for reachability to the rest of the Internet. This disparity points out the importance of having a more complete view of country-paths—possible because of the inference algorithms we used to compute paths from vantage points that do not run iPlane monitors or provide BGP measurement feeds.

Next, we investigate the Strong CC (SCC) of each country. This is an estimate of the difficulty in circumventing a given country, even if alternate routes are used. The results are shown in the "SCC" column of Table 2. The table shows that the top three countries have high SCC values, suggesting that they are hard to avoid even using alternate paths. We also show the top 10 CC and SCC countries in Figure 10. Not surprisingly, the U.S. is especially difficult to avoid, especially for countries (e.g., in South America) that connect directly to the U.S. for connectivity to the Internet.

Finally, we consider the countries that are known for significant censorship. When Internet censorship is discussed, China, Iran, Saudi Arabia, and Pakistan are commonly mentioned as countries that filter Internet traffic. According to the OpenNet Initiative [35], these

	CC	SCC
China	0.069947 (8)	0.030595 (10)
Vietnam	0.007087 (30)	0.003916 (34)
South Korea	0.003548 (44)	0.001044 (54)
Saudi Arabia	0.003286 (47)	0.001722 (49)
U.A.E.	0.000839 (65)	0.000541 (63)
Pakistan	0.000274 (81)	0.000265 (74)
Iran	1.12e-05 (105)	9.48e-06 (101)
Yemen	1.06e-07 (131)	7.50e-08 (130)
Oman	2.64e-08 (138)	2.64e-08 (133)
Myanmar	0	0
North Korea	0	0
Sudan	0	0
Syria	0	0

Table 3: CC and SCC values of countries with pervasive censorship. Countries with 0 values were not found to transit *any* international traffic.

four countries along with eight others partake in pervasive traffic filtering. The CC values of each of these countries is shown in Table 3. Aside from China (with a CC of 0.07), these countries appear to have very little influence over global reachability. We were initially surprised to see that South Korea has a relatively low CC value (0.004), given the significant penetration of the Internet in the country. However, the large deployments of broadband connectivity for end users need not relate to whether Korean ISPs play an important role in transit service for other countries.

6. DISCUSSION AND FUTURE WORK

There are several potential sources of bias in the data sets we used, which could potentially impact the results.

First, it is believed that the Internet's topology is significantly larger than what can be observed in BGP RIBs [36]. For example, peer-peer connections are only visible to customers of the peers (due to the valley-free rule) and are thus difficult to find [37]. Fortunately, it is believed that customer-provider edges are well represented in the observed RIBs. The topologies that we extracted from the RIBs support these suppositions. As shown in 3.1, the number of peer-peer edges increases by 90% between the testing set and the total set while customer-provider edges only increased by 5%. Peer-peer edges typically have less impact on routing than customer-provider edges, since only the downstream customers of the two peers can route through peer-peer edges. In addition, we suspect that peer-peer edges, for the most part, arise between ASes in the same country, or at least the same small geographic region (e.g., between two countries in Europe), which would also limit their influence on the international flow of traffic through the Internet. Still, the missing edges could have impact on the results of our measurements. To test this, we plan to run our algorithms on multiple inferred and generated [38, 39] topologies, including traceroute measurements collected from larger number of vantage points [40].

Beyond the question of bias, we would also like to study the evolution of country centrality over time. It has been suggested that the United States transits a smaller fraction of total traffic than in the past. It would be interesting to know if the United States has also become less central in terms of reachability, and if so why. Which countries are becoming more central over time and which less so? It would also be interesting to know how our results would change if we incorporated more realistic models of interdomain traffic [41]. A more long-term question involves understanding the economically-driven strategies that single countries or small groups of countries could adopt, either to enhance their own centrality or to reduce the centrality of other countries (e.g., such as overlay routing). There may also be other network measures that are of interest. Deletion impact or measures that incorporate some component of traffic are two obvious directions.

Finally, the paths traversed by domestic traffic would also be interesting to study. What fraction of domestic paths (those that have a source and destination within the same country) are actually routed through another country? Answering this question would provide insight into the influence that foreign nations have over a country's domestic routing and security, and would shed light on a question posed in [2] concerning whether warrantless wiretapping on links connecting one country to another might inadvertently capture some purely domestic traffic. The framework developed in this paper could be extended to address that question.

7. RELATED WORK

We are unaware of previous work measuring the impact individual countries have on the flow of international traffic in the Internet. However, our results rely on earlier work on network centrality, Internet topology measurement, AS-relationship inferencing, AS-path inferencing, and studies of Internet censorship. In this section we briefly review the projects most relevant to this paper.

In addition to Qiu et al.'s work [14] discussed earlier, there are at least two other methods for inferring AS-paths that are prefix specific. Mühlbauer et al. [16] showed that when an AS has multiple routers distributed across many locations, more than one router needs to be simulated to capture all of the routing diversity within the AS. By simulating multiple quasi-routers per AS, they were able to predict AS-paths with relatively high accuracy (reported 65%); however, the high overlap between their testing and training data sets makes it difficult to compare the accuracy of their technique with ours. and more computationally efficient. This allowed us to study all 290,000 prefixes rather than the 1000 prefixes reported in Mühlbauer et al.

Another AS-path inference algorithm was developed by Madhyastha et al., [17] who used a structural approach to AS-path prediction. They began with known traceroutes from the iPlane project and used them to infer IP-level paths for chosen src/dest pairs. The algorithm works by searching for the closest observation point to the source prefix (by examining a few sample traceroutes from the source) and then uses the known iPlane paths to infer the remaining paths from the source. They do not report the accuracy of the IP-level paths, but we are interested in investigating this technique in future work as an alternate way to infer country paths.

Finally, there has been an enormous amount of work developing statistical measures of network properties [29, 30, 31], including preferential attachment models [42] and many models of the AS network [43, 39, 38, 44, 45]. Some of this work measures node centrality by the impact it would have on network connectivity if the AS was deleted, known as deletion impact [46, 39]. A parallel can potentially be made between node deletion and censorship. For example, deleting a country from the network is conceptually similar to all other ASes collectively routing around that country.

8. CONCLUSIONS

As government control over the treatment of Internet traffic becomes more common, many people will want to understand how international reachability depends on individual countries and to adopt strategies either for enhancing or weakening the dependence on some countries. The work presented in this paper is an initial step towards providing the algorithms and tools that will be needed to understand and manage nation-state routing.

In particular, we discussed the problems associated with understanding routing patterns at the country level, which is the level at which most censorship and wiretapping policies are mandated. We then described algorithms and data sources to infer country-level paths from traceroute probes and AS-level BGP data, and we validated those algorithms against different samples of the same kinds of data. Next we discussed metrics for comparing the relative importance of different countries in current routing topologies. Finally, we used the algorithms to infer a country path between each pair of IPv4 prefixes and then applied the metrics to the paths to obtain initial results.

It is not surprising that the results show the dominance of the U.S. at the country routing level. However, other countries appear to have either more or less importance than one might expect. For example, both Great Britain and Germany are second only to the U.S. in centrality, while Japan, China, and India are only 8th, 10th, and 32nd respectively. Collectively, these results show that the "West" continues to exercise disproportionate influence over international routing, despite the penetration of the Internet to almost every region of the world, and the rapid development of China and India. Beyond what the results tell us about the Internet today, we see the methods described in this paper as helping network designers, policy makers, and researchers better understand the likely impact of national policies on user privacy and the access to politically or socially sensitive content.

9. REFERENCES

[1] R. J. Deibert, J. G. Palfrey, R. Rohozinski, and J. Zittrain, *Access Denied: The Practice and Policy of Global Internet Filtering (Information Revolution and Global Politics)*. MIT Press, 2008.

[2] S. M. Bellovin, M. Blaze, W. Diffie, S. Landau, P. G. Neumann, and J. Rexford, "Risking communications security: Potential hazards of the Protect America Act," *IEEE Security and Privacy*, 2008.

[3] "Securing the federal government's domain name system infrastructure." `http://www.whitehouse.gov/omb/memoranda/fy2008/m08-23.pdf`, 2008.

[4] "Transition planning for Internet protocol version 6 (IPv6)." `http://georgewbush-whitehouse.archives.gov/omb/memoranda/fy2005/m05-22.pdf`, 2005.

[5] R. Clayton, "Anonymity and traceability in cyberspace," Tech. Rep. UCAM-CL-TR-653, University of Cambridge, 2005.

[6] RIPE, "YouTube hijacking: A RIPE NCC RIS case study." `http://www.ripe.net/news/study-youtube-hijacking.html`, 2008.

[7] J. R. Crandall, D. Zinn, M. Byrd, E. Barr, and R. East, "ConceptDoppler: A weather tracker for internet censorship," 2007.

[8] X. Wang, S. Chen, and S. Jajodia, "Tracking anonymous peer-to-peer VoIP calls on the Internet," in *ACM Conference on Computer and Communications Security*, 2005.

[9] D. Andersen, H. Balakrishnan, F. Kaashoek, and R. Morris, "Resilient overlay networks," in *ACM Symposium on Operating Systems Principles*, pp. 131–145, 2001.

[10] Y. Rekhter, T. Li, and S. Hares, "A Border Gateway Protocol 4 (BGP-4)." RFC 4271, Jan. 2006.

[11] L. Gao, "On inferring autonomous system relationships in the Internet," *IEEE/ACM Trans. on Networking*, vol. 9, December 2001.

[12] A. Broido and kc claffy, "Analysis of RouteViews BGP data: Policy atoms," in *Proceedings of the NRDSM workshop*, 2001.
[13] A. Broido and K. Claffy, "Complexity of global routing policies," in *IMA*, 2001.
[14] J. Qiu and L. Gao, "AS path inference by exploiting known AS paths," in *Proceedings of IEEE GLOBECOM*, 2005.
[15] Z. M. Mao, L. Qiu, J. Wang, and Y. Zhang, "On AS-level path inference," in *SIGMETRICS*, (New York, NY, USA), pp. 339–349, ACM, 2005.
[16] W. Mühlbauer, A. Feldmann, O. Maennel, M. Roughan, and S. Uhlig, "Building an AS-topology model that captures route diversity," *SIGCOMM*, 2006.
[17] H. V. Madhyastha, T. Anderson, A. Krishnamurthy, N. Spring, and A. Venkataramani, "A structural approach to latency prediction," *IMC*, 2006.
[18] U. of Oregon, "Routeviews project." `http://www.routeviews.org`, 2005.
[19] RIPE. `http://www.ripe.net/`.
[20] R. Mahajan, D. Wetherall, and T. Anderson, "Understanding BGP misconfiguration," in *Proc. ACM SIGCOMM*, pp. 3–16, 2002.
[21] K. Sriram, O. Borchert, O. Kim, P. Gleichmann, and D. Montgomery, "A comparative analysis of BGP anomaly detection and robustness algorithms," *to appear in the Proceedings of CATCH*, 2009.
[22] H. V. Madhyastha, T. Isdal, M. Piatek, C. Dixon, T. Anderson, A. Krishnamurthy, and A. Venkataramani, "iplane: An information plane for distributed services," *OSDI*, 2006.
[23] B. Chun, D. Culler, T. Roscoe, A. Bavier, L. Peterson, M. Wawrzoniak, and M. Bowman, "Planetlab: An overlay testbed for broad-coverage services," in *SIGCOMM*, 2003.
[24] "Team Cymru." `http://www.cymru.com/`.
[25] N. Spring, R. Mahajan, D. Wetherall, and T. Anderson, "Measuring ISP topologies with Rocketfuel," *IEEE/ACM Transactions on Networking*, 2004.
[26] "Sarangworld project." `http://www.sarangworld.com/TRACEROUTE/`.
[27] J. Moy, "OSPF version 2." RFC 2328, 1998.
[28] R. Callon, "Use of OSI IS-IS for routing in TCP/IP and dual environments." RFC 1195, 1990.
[29] L. Freeman, "A set of measures of centrality based on betweenness," *Sociometry*, vol. 40, pp. 35–41, 1977.
[30] L. C. Freeman, "Centrality in social networks: Conceptual clarification," *Social Networks*, vol. 1, no. 3, pp. 215–239, 1979.
[31] G. Sabidussi, "The centrality index of a graph," *Psychometrika*, vol. 31, pp. 581–603, 1966.
[32] P. Holme, J. Karlin, and S. Forrest, "Radial structure of the Internet," *Proceedings of the Royal Society A*, vol. 463, pp. 1231–1246, 2007.
[33] P. Mahadevan, D. Krioukov, M. Fomenkov, X. Dimitropoulos, Claffy, and A. Vahdat, "The Internet AS-level topology: Three data sources and one definitive metric," *SIGCOMM Comput. Commun. Rev.*, vol. 36, no. 1, pp. 17–26, 2006.
[34] S. Zhou and R. J. Mondragón, "Accurately modeling the Internet topology," *Phys. Rev. E*, vol. 70, p. 066108, Dec 2004.
[35] "Opennet initiative." `http://opennet.net`.
[36] R. V. Oliveira, D. Pei, W. Willinger, B. Zhang, and L. Zhang, "In search of the elusive ground truth: the internet's AS-level connectivity structure," *SIGMETRICS Perform. Eval. Rev.*, vol. 36, no. 1, pp. 217–228, 2008.
[37] H. Chang, R. Govindan, S. Jamin, S. J. Shenker, and W. Willinger, "Towards capturing representative AS-level internet topologies," in *Computer Networks Journal*, pp. 737–755, 2004.
[38] H. Chang and S. Jamin, "To peer or not to peer: Modeling the evolution of the internet's as-level topology," *In INFOCOM*, 2006.
[39] P. Holme, J. Karlin, and S. Forrest, "An integrated model of traffic, geography and economy in the internet," *ACM SIGCOMM CCR*, 2008.
[40] The DIMES Project. `http://www.netdimes.org`.
[41] A. Feldmann, N. Kammenhuber, O. Maennel, B. Maggs, R. D. Prisco, and R. Sundaram, "A methodology for estimating interdomain web traffic demand," in *Internet Measurement Conference*, pp. 322–335, 2004.
[42] A.-L. Barabási and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, pp. 509–512, October 1999.
[43] J. I. Alvarez-Hamelin and N. Schabanel, "An Internet graph model based on trade-off optimization," *Eur. Phys. J. B*, vol. 38, pp. 231–237, 2004.
[44] A. Fabrikant, E. Koutsoupias, and C. H. Papadimitriou, "Heuristically optimized trade-offs: A new paradigm for power laws in the Internet," in *Proceedings of the 29th International Conference on Automata, Languages, and Programming*, vol. 2380 of *Lecture notes in Computer science*, (Heidelberg), pp. 110–122, Springer, 2002.
[45] S.-H. Yook, H. Jeong, and A.-L. Barabási, "Modeling the Internet's large-scale topology," *Proc. Natl. Acad. Sci. USA*, vol. 99, pp. 13382–13386, 2002.

[46] R. Cohen, K. Erez, D. ben Avraham, and S. Havlin, “Resilience of the Internet to random breakdowns,” *Phys. Rev. Lett.*, vol. 85, pp. 4626–4628, 2000.