TEL AVIV UNIVERSITY אוניברסיטת תל-אביב
FACULTY OF ENGINEERING הפאקולטה להנדסה

THE IBY AND ALADAR FLEISCHMAN FACULTY OF ENGINEERING
The Zandman-Slaner School of Graduate Studies

Near-Deterministic Inference of AS Relationships

A thesis submitted toward the degree of
Master of Science in Electrical and Electronic Engineering

by

Udi Weinsberg

August, 2007

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This research was carried out in the
Department of Electrical Engineering - Systems,
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Abstract

The discovery of Autonomous Systems (ASes) interconnections and the inference of their commercial Type-of-Relationships (ToR) has been extensively studied during the last few years. The main motivation is to accurately calculate AS-level paths and to provide better topological view of the Internet. An inherent problem in current algorithms is their extensive use of heuristics. Such heuristics incur unbounded errors which are spread over all inferred relationships. This work proposes a near-deterministic algorithm for solving the ToR inference problem. The proposed algorithm uses as input the Internet core, which is a dense sub-graph of top-level ASes. We evaluate several methods for creating such a core, and demonstrate the robustness of the algorithm to the core's size and density, the inference period, and errors in the core.

In this thesis we evaluate the proposed algorithm using AS-level paths collected from RouteViews BGP paths and DIMES traceroute measurements. Our proposed algorithm deterministically infers over 95% of the approximately 58,000 AS topology links. The inference becomes stable when using a week worth of data and as little as 20 ASes in the core. The algorithm infers 2–3 times more peer-to-peer relationships in edges discovered only by DIMES than in RouteViews edges, validating the DIMES promise to discover periphery AS edges.

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Chapter 1

Introduction

Today's Internet consists of thousands of networks administrated by various Autonomous Systems (ASes). ASes are assigned with one or more blocks of IP prefixes and communicate routing information to each other using Border Gateway Protocol (BGP). Each AS uses a set of local policies for selecting the best route for each reachable prefix. Typically, these policies are based on the Type-of-Relationship (ToR) that exists between ASes and on a shortest path criteria. In order to calculate the paths between ASes, one needs to obtain the ToR between all neighboring ASes. Since ToRs are regarded as proprietary information, deducing them is an important yet difficult problem.

Typically [18], there are three major commercial relationships between neighboring ASes: customer-to-provider (c2p), peer-to-peer (p2p), and sibling-to-sibling (s2s). In the c2p category, a customer AS pays a provider AS (usually larger than the customer) for traffic that is sent between the two. In the p2p category, two ASes freely exchange traffic between themselves and their customers, but do not exchange traffic from or to their providers or other peers. In s2s, two ASes administratively belong to the same organization and freely exchange traffic between their providers, customers, peers, or other siblings.

Gao [12] was the first to study the AS relationships inference problem and deduced that every BGP path must comply with the following hierarchical pattern: an uphill segment of zero or more c2p or s2s links, followed by zero or one p2p links, followed by a downhill segment of zero or more p2c or s2s links. Paths with this hierarchical structure are called *valley-free* or valid. Paths that do not follow this hierarchical structure are called invalid and may result from BGP misconfigurations or from BGP policies that are more complex and do not distinctly fall into the above classification. Most work in this field (section 1.1) follows the valley free routing principle.

Current relationships inference algorithms attempt to solve the ToR problem either by using heuristic assumptions or by optimizing some aspects of the ToR assignments. Optimization is usually achieved by minimizing the number of paths that violate the valley free routing property [22] while not allowing cycles to be created [8, 19] in the resulting directed relationships graph.

Using heuristic assumptions throughout the relationships inference process causes the erroneous ToRs to be spread over all interconnecting ASes links. The optimization models fail to capture the true Internet hierarchy [10] and have a relatively low p2p inference accuracy [24]. The result is that both solutions fail to provide an insight, or a bound on the inference errors.

Typically, AS relationships are not published by AS operators, hence the validation of such results is done either by sending queries to the operators of a small subset of ASes [9] or by comparing the results to partial information that is available on the Internet [24]. Although these methods can give a good approximation on the correctness of the results, one cannot assume a bounded mistake.

This work aims to improve on existing methods by providing a near-deterministic inference algorithm for solving the ToR problem. The input for our algorithm is the Internet *Core*, a sub-graph that consists of the globally top-level providers of the Internet and their interconnecting edges with their already inferred relationship types. Theoretically, given an accurate core with no relationships errors, the algorithm *deterministically* infers most of the remaining AS relationships using the AS-level paths relative to this core, without incurring additional inference errors. In real-world scenarios, where the core and AS-level paths can contain errors (due to misconfigurations or measurements mistakes), the algorithm introduces minimal inference errors. The core can be approximated in several ways, as described in section 2.5, or extracted from public databases. We show that our algorithm has relaxed requirements from the core, and proves to be robust under changes in its definition, size and density. Since the top-level ASes are a small and stable group, accurately revealing the core members and their mutual types of relationships is fairly easy. For the remaining set of relationships that cannot be inferred deterministically, a heuristic inference method is deployed. Since this group is relatively small, it is possible to provide a strict bound on the inference error. In order to increase the number of vantage points from which we see the Internet, we use both RouteViews (RV) [2] BGP data and DIMES [21] AS-level traceroutes.

We expect that over time, the group of non-deterministic inferred relationships will even further decrease.

The remaining of this paper is organized as follows. Section 1.1 provides several related works concerning AS relationships inference. Section 2 provides a detailed description of our deterministic inference algorithm and discusses the methods used to infer on the remaining unclassified edges. Section 3 provides a detailed evaluation of the proposed algorithms and Section 4 concludes the paper and discusses future work.

1.1 Related Work

As mentioned above, Gao's pioneering work [12] was the first to study the AS relationships inference problem. Gao proposed an inference heuristic that identified top providers and peering links based on AS size, which is proportional to its degree (the number of immediate neighbors of a vertex), and the valley-free nature of routing paths. Gao used this heuristic to infer relationship between ASes in the Internet by traversing advertised BGP routes, locally identifying the top provider for each path, and classifying edges (i.e., inferring the relationships represented by the edges) as going uphill to the top provider and downhill afterwards. Xia and Gao [24] later proposed to use partially available information regarding AS relationships in order infer the unknown relations. It is not clear that this information can be obtained and validated periodically, unlike our suggestion to use the almost constant relationships in the Internet core. Our sole reliance on the core produces simpler inference rules that are less prone to inference errors.

Following Gao's work, Subramanian *et al.* [22] formally defined the Type-of-Relation (*ToR*) maximization problem that attempts to maximize the number of valid (valley-free) routing paths for a given AS graph. Their approach takes as input the BGP tables collected at different vantage points and computes a rank for every AS. This rank is a measure of how close to the graph core an AS lies (equivalent to vertex coreness [3]), and is heuristically used to infer AS relationships by comparing ranks of adjacent ASes. If the ranks are similar, the algorithm classifies the link as p2p, otherwise it is classified as c2p or p2c.

Battista *et al.* [6] showed that the decision version of the ToR problem (*ToR-D*) is an NP-complete problem in the general case. Motivated by the hardness of the general problem, they proposed approximation algorithms and reduced the ToR-D problem to a 2SAT formula by mapping any two adjacent edges in all input AS-level routing paths into a clause with two literals, while adding heuristics based inference.

Dimitropoulos *et al.* [10] addressed a problem in current ToR algorithms. They showed that although ToR algorithms produce a directed Internet graph with a very small number of invalid paths, the resulting AS relationships are far from reality. This led them to the conclusion that simply trying to maximize the number of valid paths (namely improving the result of the ToR algorithms) does not produce realistic results. Later in [9] they showed that ToR has no means to deterministically select the most realistic solution when facing multiple possible solutions. In order to solve this problem, the authors suggested a new objective function by adding a notion of "AS importance", which is the AS degree "gradient" in the original undirected Internet graph. The modified ToR algorithm directs the edges from low importance AS to a higher one. The authors showed that although they have high success rate in p2c inference (96.5%) and in s2s inference (90.3%), the p2p inference success rate (82.8%) is relatively low. Moreover, the authors surveyed some ASes operators and mention that for some of them, the BGP tables, which are the source for AS-level routing paths for most works in this research field, miss up to 86.2% of the true relationships between adjacent ASes, most of which are of p2p type.

Cohen and Raz [8] follow previous works [14, 13] and describe an algorithm that attempts to minimize the number of invalid paths, while capturing the true hierarchal structure of the Internet. Following the fact that the real Internet graph cannot contain cycles, they defined the Acyclic Type of Relationship (*AToR*) problem as an attempt to maximize the number of valid paths from a given set of routing paths, while keeping the directed graph acyclic. A parallel work that provided a very similar definition to the AToR problem, but was very focused on the theoretical aspects of the problem was published by Kosub *et al.* [19]. It was later applied to the Internet [17], showing that the acyclicity assumptions are valid on the Internet graph.

The observations made by the works listed in this section, highly motivate our work. They drive us not only to seek an algorithm that better captures the true AS relationships in the Internet while reducing the usage of heuristics for inference, but also adding a complementary data source, that has the ability to capture much of the missing links.

Chapter 2

AS Relationships Inference

In this section we describe our ToR inference algorithm in details. We start with explaining the deterministic algorithm, and proceed with the heuristics we employ for edges that the deterministic algorithm fails to classify.

2.1 Deterministic Classification

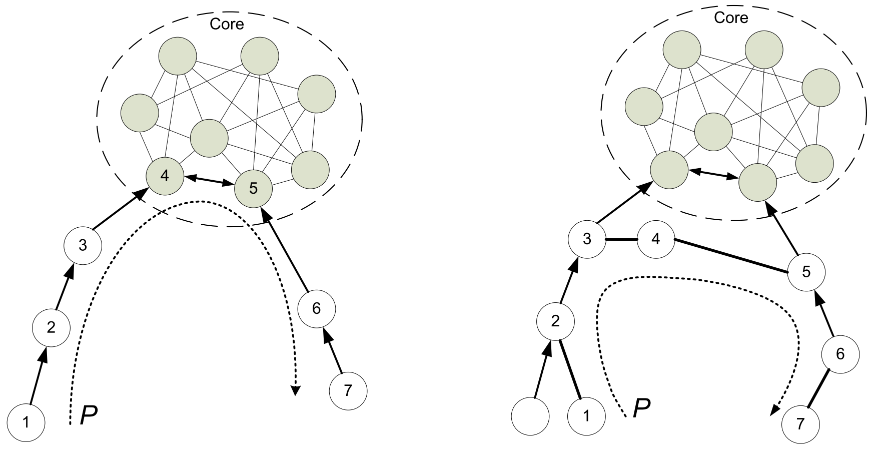
Our deterministic algorithm receives as input two undirected AS-level graphs and a set of AS-level routing paths, denoted by S. The first graph, denoted by $G(V_G, E_G)$, contains the set of vertices that represent all ASes, and the interconnecting edges that need to be classified. The second graph, denoted by $Core(V_C, E_C)$, holds the vertices and interconnecting edges that represent the core of G, and is assumed to contain all the top-level ASes.

Prior to starting the relationships inference algorithm, we infer s2s relationships, since ignoring these relationships might cause proliferation of erroneous inference [9]. We use s2s data collected from [1]. These s2s classifications are obtained from IRR databases, namely RIPE, ARIN and APNIC. Although these databases are not always up-to-date, they are reasonably steady and accurate for the s2s inference. Once classified, the s2s edges are removed from the edges set E_G, and the two adjacent vertices are united to form a single vertex that inherits the connectivity of both.

Following the assumption that the input core consists of all the global top-level ASes and using the valley-free model of Internet routing, the algorithm classifies most of the edges in $G(V_G, E_G)$ without using heuristic assumptions:

Phase 1. All paths that *pass through the core* are split into a segment of zero or more uphill c2p edges towards the core, at most one p2p edge in the core and a downhill segment of zero or more p2c edges from the core.

The algorithm, shown in Algorithm 0, traverses only paths that pass through the core. It starts with the uphill segment of the path, classifying each edge as c2p, until reaching the core. Once reached the core, the uphill segment finishes and the core segment starts. Inside the core the algorithm classifies edges that are not already classified as p2p (the default type for core edges). The downhill segment starts with an AS that does not belong to the core, and is traversed until the end of the path. Invalid paths are detected when an edge is directed towards the core (uphill) during the downhill segment. Each path that is classified in this phase is removed from the set of paths S. Note that the algorithm does not use direct inference but a voting technique, which is explained in section 2.2.



(a) Phase 1 (b) Phase 2

Figure 2.1: Deterministic ToR inference algorithm

An example for edges that are classified during this phase is illustrated in Figure 2.1(a). Path P traverses the core and consists of seven AS hops, numbered 1 to 7. The segment between hop 1 and hop 4 is identified as an uphill segment, resulting in the classification of the edges (1,2), (2,3), and (3,4) as c2p (illustrated as an arrow pointed from the customer to the provider). ASes 4 and 5 are inside the core, therefore are already classified (by default to p2p). The segment starting in AS 5 and ending in AS 7 is considered as a downhill segment, resulting in the classification of the edges (5,6) and (6,7) as p2c.

Since the remaining paths in S do not traverse the core, they do not provide us with a direct method for classification. However, amongst these, there are

Algorithm 1 Phase 1 of ToR Inference Algorithm

Input: Graphs $G(V_G, E_G)$, $Core(V_C, E_C) \subset G$, Paths set S

Output: Edges E_G with votes for relationship types

```
 1: foreach $path \in S$ do
 2:     if $\exists e \in path \mid e \in E_C$ or $\exists v \in path \mid v \in V_C$ then
 3:         $upHill \leftarrow TRUE$
 4:         $downHill \leftarrow FALSE$
 5:         $inCore \leftarrow FALSE$
 6:         foreach $edge \in Path$ do
 7:             $AS1 \leftarrow edge.firstAS$
 8:             $AS2 \leftarrow edge.secondAS$
 9:             if $edge \in E_C$ then
10:                 $upHill \leftarrow FALSE$
11:                 $inCore \leftarrow TRUE$
12:             else if $AS1 \in V_C$ and $AS2 \notin V_C$ then
13:                 $upHill \leftarrow FALSE$
14:                 $inCore \leftarrow FALSE$
15:                 $downHill \leftarrow TRUE$
16:             else if $downHill$ and $AS2 \in V_C$ then
17:                 $voteForInvalid(edge)$
18:             end if
19:             if $upHill$ then
20:                 $voteForCustomerToProvider(edge)$
21:             else if $inCore$ and $notClassified(edge)$ then
22:                 $voteForPeerToPeer(edge)$
23:             else
24:                 $voteForProviderToCustomer(edge)$
25:             end if
26:         end for
27:         $S \leftarrow S \setminus path$
28:     end if
29: end for
```

paths that partly overlap other paths that traverse the core. Meaning that some of the remaining paths already contain edges that were classified as either c2p or p2c in the first phase of the algorithm. We use these edges for the second phase of the algorithm:

Phase 2. For a given path, edges that precede a c2p edge must reside in an uphill segment, and be of type c2p. Edges that follow a p2c edge must be in a downhill segment, and be of type p2c. The algorithm, listed in Algorithm 0, traverses one path at a time, and looks for an already inferred c2p or p2c edges. If a c2p edge is detected, all unclassified edges in the path before this edge, temporarily stored in the *suspectC2P* list, are classified as c2p. If a p2c edge is detected, all unclassified edges in the path after this edge, temporarily stored in the *suspectP2C* list, are classified as p2c.

Since this phase uses classified edges in order to classify unclassified edges, it is repeated for all paths in S that still have unclassified edges, until there are no more edges that can be classified using this method.

Figure 2.1(b) illustrates an example for a path that contains edges that will be classified during Phase 2 of the algorithm. Path P does not traverse the core but contain edges that are already classified. The edge (1,2) precedes the edge (2,3) which is classified as c2p, therefore is classified as c2p. The edge (6,7) follows a p2c edge, therefore is classified as p2c. The edges (3,4) and (4,5) cannot be classified, since we are unable to determine which AS is the top-level provider and whether the edges (3,4) and (4,5) represent a p2p relationship.

2.2 Assigning Type-of-Relationship to Edges

The data we use might be ”noisy” and reflect transient routing effects or changes in the commercial relationships between ASes, especially when performing relationships inference over a long time frame. To avoid incorrect inferences resulting from these effects, we use voting technique [12] instead of direct relationship inference. Meaning, that the above methods vote for the ToR of each traversed edge. Once the algorithm is finished, we count the votes and assign each edge with the type that received a relative votes count that passes a given threshold. The pseudo-code of this vote counting technique is provided in Algorithm 0. The algorithm simply calculates the relative vote count for each type of relationship and returns the one that exceeds the

Algorithm 2 Phase 2 of Classification Algorithm

Input: Graph $G(V_G, E_G)$, Remaining set of paths S

Output: Edges E_G with votes for relationship types

```
1: foreach $path \in S$ do
2:     $suspectC2P \leftarrow \emptyset$
3:     $suspectP2C \leftarrow \emptyset$
4:     $passedP2C \leftarrow FALSE$
5:     foreach $edge \in Path$ do
6:         if $maxVotesC2P(edge)$ and $suspectC2P \neq \emptyset$ then
7:             foreach $e \in suspectC2P$ do
8:                 $voteForCustomerToProvider(edge)$
9:             end for
10:            $suspectC2P \leftarrow \emptyset$
11:        else if $maxVotesP2C(edge)$ then
12:            $suspectC2P \leftarrow \emptyset$
13:            $passedP2C \leftarrow TRUE$
14:        end if
15:        if $noClassificationVotes(edge)$ then
16:            if $passedP2C = FALSE$ then
17:                $suspectC2P \leftarrow suspectC2P \cup edge$
18:            else
19:                $suspectP2C \leftarrow suspectP2C \cup edge$
20:            end if
21:        end if
22:    end for
23:    if $suspectP2C \not\equiv \emptyset$ then
24:        foreach $e \in suspectP2C$ do
25:            $voteForProviderToCustomer(edge)$
26:        end for
27:    end if
28: end for
```

provided threshold.

The deterministic algorithm does not attempt to classify edges that have a vote count that does not pass the threshold, but rather it employs the non-deterministic methods discussed in section 2.3. The exact value of the threshold is set to avoid incorrect inferences that can be the result of a relatively close vote count, and is discussed in section 3.2. at received a relative votes count that passes a given threshold.

Algorithm 3 Type-of-Relationship inference using vote count

```
Input: Edge $e$, $threshold$
Output: Type-of-Relationship for edge $e$
1: $p2c \leftarrow 0$
2: $c2p \leftarrow 0$
3: $p2p \leftarrow 0$
4: $sum \leftarrow (e.p2p + e.p2c + e.c2p)$
5: if $sum \neq 0$ then
6:     $p2c \leftarrow e.p2c/sum$
7:     $c2p \leftarrow e.c2p/sum$
8:     $p2p \leftarrow e.s2s/sum$
9:     if $p2c \geq threshold$ then
10:        Return $provider - to - customer$
11:    else if $c2p \geq threshold$ then
12:        Return $customer - to - provider$
13:    else if $p2p \geq threshold$ then
14:        Return $peer - to - peer$
15:    else
16:        Return $heuristicsInference(e)$
17:    end if
18: else
19:    Return $unclassified$
20: end if
```

2.3 Non-Deterministic Inference of Remaining Relationships

The deterministic algorithm fails to classify several types of edges. The first type are edges that appear in paths that do not traverse the core, and reside between a c2p edge and a p2c edge (see Figure 2.2(a)). This can be a result of a path that does not traverse the core and has no overlapping edges with other paths, or overlaps other paths in edges that are close to the beginning or end of the path. Alternatively, the path may have a p2p relationship between its two top-level vertices.

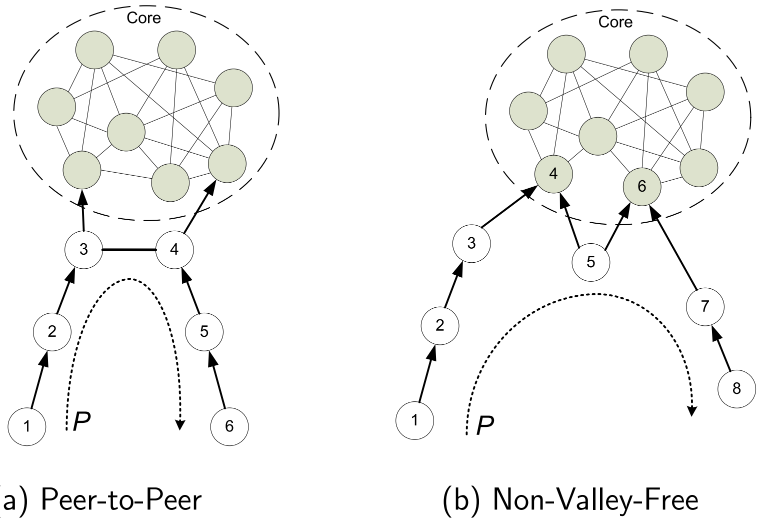


Figure 2.2: Non-Deterministic ToR inferences

In order to infer relationships related to these edges we use the following assumption (which is backed from observations, as we show in section 3.5): a c2p or p2c edges should participate in, at least, one path that pass through the core. For this not to happen the following should occur: 1) a client will rarely route through a certain edge to its provider and thus may not expose this link in a DIMES measurement path that passes through the core, and 2) at the same time the paths through the core that contain this edge will be filtered by BGP in the direction of the speakers sampled by RouteViews. Thus, we assume that most c2p and p2c edges are already classified by our deterministic algorithm. Following this assumption we can infer that in paths that do not pass through the core, and have a *single* remaining unclassified edge (which must reside between a c2p and a p2c edges), this edge should be classified as a p2p edge (this is illustrated as the edge between ASes 3 and 4 in Figure 2.2(a)). In case there is more than a single edge between the c2p and the p2c (as illustrated in Figure 2.1(b)), we leave the edges unclassified, since we cannot determine which of the vertices is the provider.

The second type of unclassified edges are the ones that have a similar number of votes for two or more types of relationships. This can be the result of changes in the commercial relationship between adjacent ASes over the measurements period, or due to more complex peering agreements that can cause the same edge to behave differently as seen from different view points in the Internet [9].

To resolve these ambiguities, we use heuristic-based methods suggested by other works. Although we chose to use the AS degree in the graph [12], and the k-shell index [23, 7], any other method can be employed. Analysis of this inference technique is further discussed in the experimental results in section 3.

The third type of unclassified edges are edges that appear in non-valley-free paths (Figure 2.2(b)), possibly the result of valid paths that pass a malformed core, or invalid paths that pass an accurate core. Since these invalid paths occur in only a small fraction of paths (less than 1% on average from the investigated paths per week), we leave the classification of these "valley edges" to future work.

2.4 Internet Exchange Points Classification

An Internet exchange point (IXP) is a physical infrastructure that allows different ASes to exchange traffic between them by means of mutual peering agreements. IXPs operate either in Layer-2, as a switching fabric, or in Layer-3 as a router. In the first case, the IXP does not have an AS number, therefore it will not be visible in our set of paths and the AS-graph. Although traditionally IXPs were used to allow transit between peering ASes with no cost, nowadays IXPs are a convenient method to create other types of interconnections between ASes, namely p2c and c2p.

The main challenge that IXPs pose when performing ToR inference, is that the edges connecting an IXP to adjacent ASes can exhibit different ToR depending on the AS-level path they participate in. An example to this difficulty is given in Figure 2.3. The figure shows two paths, P1 and P2, that traverse the same edge (IXP,6). In P1 this edge appears to be a valley edge since in goes downhill from AS4 to the IXP and then uphill to AS6. On the other hand, in P2 this edge is simply a c2p edge. However, realizing that the IXP is an exchange point, we result in two "virtual" edges - (4,6) and (10,6), the first should be classified as p2p while the latter should be classified as c2p.

ASes that indirectly interconnect via an IXP have a *virtual edge* that connects the two. These virtual edges exhibit quite quite complex relationships, since IXPs route at different networking layers. Although it is claimed that

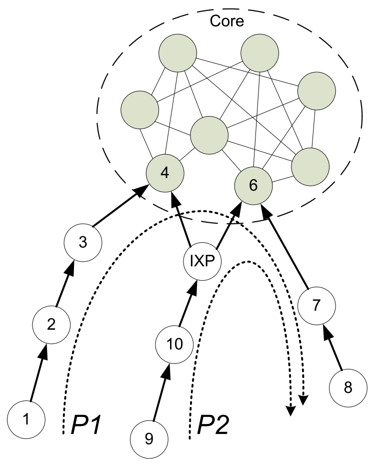


Figure 2.3: Internet Exchange Point edges classification

IXPs should not be visible in either BGP or traceroutes paths, our observations shows otherwise. We are able to see IXPs in various paths, both in BGP and traceroutes that we collect. However, since there are no previous works that attempt to infer these relationships, it is impossible to compare results in order to determine their accuracy. Thus, we leave the analysis of these complex relationships to future work.

2.5 Core Graph Construction

Motivated by the need to capture the true global hierarchal structure of the Internet we looked for an accurate global decomposition of the Internet AS-level graph. There have been several attempts to characterize the core of the Internet AS graph [22, 23, 7, 16, 15]. We use three core construction methods, that result in cores that vary in size and density. We analyze the effect that each core has on the classification algorithm.

Tauro *et al.* [23] proposed the *Jellyfish* conceptual model in which they identified a topological center and classified vertices into layers with respect to the center. The authors defined core as a clique of high-degree vertices, and constructed it by sorting the vertices in non-increasing degree order. The first vertex in the core is the one with the highest degree. Then, they examine each vertex in that order; a vertex is added to the vertex only if it forms a clique with the vertices already in the core. The resulting core is a clique but not necessarily the maximal clique of the graph. We refer to this core as

GreedyMaxClique .

Carmi *et al.* [7] indicated that using the popular vertex's degree (which was encouraged by the finding of the Internet's power-law distribution [11]) as an indicator of the vertex's importance can be misleading. The authors presented the new *Medusa* model, that uses a k-pruning algorithm to decompose the Internet AS graph and extract a nucleus (the K_{max}-Core) which is a very well connected globally distributed subgraph. Note that this algorithm extracts a core by looking at the entire graph, unlike GreedyMaxClique that takes a local approach. The properties listed for this model are useful for AS relationship inference, mainly due to the finding that the nucleus plays a critical role in BGP routing, since its vertices lie in a large fraction of the paths that connect different ASes. We refer to this core as k-Core.

The last core we use is constructed from most of the ASes and interconnecting edges that exhibit p2p relationship under the inference method in [9]. We use the Automated AS ranking provided by CAIDA [1] and constructed a graph that contains all the edges classified as p2p (tagged with 0 in the files downloaded from $http://as-rank.caida.org$) and their adjacent AS vertices. We then selected the largest connected component that contains some of the largest tier-1 ASes, namely AS701 ($UUNET$) and AS7018 (*AT&T*). We refer to this core as *CP* (CAIDA Peers).

The three core types vary in size and density as an attempt to capture different inference behaviors. Using a small, dense core reduces the probability that a non-top-level AS is wrongfully considered as a top-level AS for all paths that pass through it, thus causing incorrect inferences. However, a small core might miss top-level ASes, thus cause non-valley-free paths. On the other hand, when using a large core, a trace might have several hops in the core. In this case we follow [22] and assume that two ASes may have an "indirect peering" relation, meaning they have p2p relationship through an intermediate AS, such as an exchange point. Traces with more than three hops in the core are considered invalid.

Chapter 3

Experimental Results

In this section we evaluate the deterministic algorithm and the additional heuristics inferences using data from the first five weeks of 2007. We evaluate its accuracy by comparing the results to the classification algorithm proposed in [9], referred to as $CAIDA$. We start by discussing the data sources, and the three different type of cores we use as inputs to the algorithm. We then analyze the effect of the core size (number of vertices) and density (the number of edges divided by the full clique size) on the algorithm, and check the transient effects caused by aggregating data for changing time frames. Finally we check the sensitivity of the algorithm to increasing mistake in the core.

3.1 Data Sources

For this work we combined data from the RouteViews (RV) [2] and DIMES [21] projects to maximize the size of our AS topology. We used BGP paths collected by the RV project, similar to most other previous work [10, 13, 14, 23, 11, 22, 20]. We created weekly batches of AS-level paths by downloading one RV file that was generated daily at 20:00, and merged all 7 files, making sure that each path appears exactly once. We parse RV's files and use only AS paths marked as "valid". Some of the paths advertised in BGP contain a repeating AS. This is caused due to routers that prepend their AS number multiple times to make the route longer, thus discourage the route being selected as the best route [20]. We process these paths and drop repeating ASes.

Since BGP paths miss many of the actual links (primarily of type p2p) caused by non-advertised links in BGP [9, 8] we use additional data from DIMES. DIMES is a large-scale distributed measurements effort that measures and tracks the evolution of the Internet from hundreds of different view-points, in an attempt to overcome the "law of diminishing returns" [5]. DIMES daily collects over 2 million traceroute and ping measurements targeted at a set of over 5 million IP addresses, which are spread over all the allocated IP prefixes.

In order to create AS-level paths from the IP-level traceroutes provided by DIMES agents, we preform AS resolution for each hop in all paths. AS resolution is done by first performing longest-prefix-matching against BGP tables obtained from RV archive. This resolves approximately 98% of the IP addresses. For the remaining 2%, we query against two WhoIs databases, namely RIPE and RADB, that resolves additional 1.5% of the IP addresses. The remaining 0.5% unresolved IP addresses are discarded and do not participate in the inference algorithm.

It is reasonable to assume that the resulting AS-level traceroutes behave according to the valley-free model, since, except unique routing schemes, they mostly follow the routing paths determined by the advertised BGP paths (shortest paths) or by manually configured (and not advertised) routes.

The raw DIMES data was filtered in order to reduce inference mistakes and inclusion of false links. We filtered for some measurements artifacts by only including edges which were seen from at least two agents. In addition we trimmed all traces that exhibit known traceroute problems [4], namely routing loops and destination impersonation, keeping only the section of the path preceding the identified problem.

Using AS paths gathered from DIMES gives us the ability to identify and classify edges that might not be advertised in BGP, thus enabling us to obtain a complete AS-level Internet graph, as seen by numerous vantage points, located at various types and sizes of ASes.

Using this data, we have the ability to construct the inputs required by our algorithm: the path set, S, consists of all paths from both data sources gathered in the examined time frame and passed the filtering rules; the AS Internet graph, G, is the directed graph consists of both directions of every edge that is contained in some RouteViews or DIMES path during the examined time frame; the core graph $Core$ construction is discussed in the following section.

Table 3.1 shows the number of ASes and interconnecting links gathered during the first five weeks of 2007, obtained by using both RouteViews and DIMES. On average, the data set consists of over 24,000 AS vertices and approximately 58,000 links (undirected edges). Approximately 44% of the edges exist only in RV paths, about 12% exist only in the filtered DIMES paths and the remaining 44% of the edges exist in both RV and DIMES. In section 3.5 we analyze the edges seen only by DIMES in order to understand the type of these additional links.

Table 3.1: ASes and links collected by Dimes and RouteViews during the first five weeks of 2007

Week	ASes	Links	RV links	DIMES links	RV&DIMES links
1	24391	57875	24282	6964	26629
2	24451	57920	24313	6986	26621
3	24492	57921	24609	6630	26682
4	24581	59058	24913	7288	26857
5	24716	59779	25528	7331	26920

On a weekly average, we filtered approximately 5,100 DIMES edges that were measured only once, which is over 15% of the edges measured by DIMES. Around half of these edges appear in RouteViews, providing a testimony to our conservatism.

3.2 Voting Threshold

In order to validate the usage of the voting technique described in section 2.2 and set a proper threshold value, we tested the distribution of votes to inference types. For each edge we calculated the ratio of p2c votes. Figure 3.1 shows the number of edges for each p2c ratio. Clearly, the vast majority of the edges are uniquely classified as either p2c or c2p. This remains true when running the algorithm on longer time frames.

Looking at the data backing up this graph, we see that on average over 94% of the edges have votes for exactly one relationship type, and almost 99% of the edges have over 80% of the votes casted for a single relationship type, which provides a very high level of confidence for this selected type. Thus, a threshold value of 0.8 covers almost 99% of the edges, and leaves approximately 1% of the edges to be classified using heuristic methods, or remain unclassified.

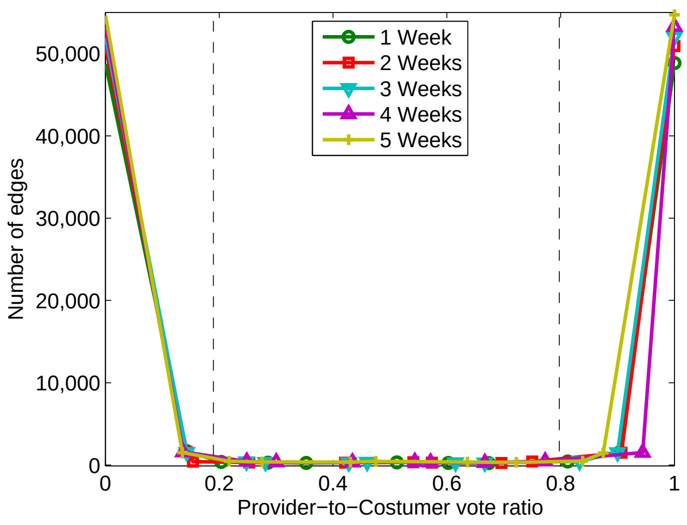


Figure 3.1: Types-of-Relations voting distribution

3.3 Sensitivity Analysis

Since the construction of the core graph is a major building block for the algorithm, we evaluate the effect that the core has on the inference process. We start by examining the overall algorithm performance and stability over consecutive weeks. We then evaluate the optimal core size, i.e., a core that results in a minimal inference mistake while achieving a high classification percentage. Finally, we test the sensitivity of the algorithm to errors in the core by randomly replacing core vertices.

We start by looking at the result of executing the algorithm using the first five weeks of 2007, each time with a different core type. As expected, most of the AS relationships are inferred in phase 1 of the deterministic algorithm using paths that traverse the core. These paths comprise a large percentage of all available paths, ranging from over 98% for k-Core and CP to 81% for the smaller GreedyMaxClique core.

Table 3.2 shows the structure of the different core types used and the effect it has on the deterministic inference algorithm. The percent of classified edges and edges matching CAIDA's inference is calculated out of the total number of edges (including edges that are unclassified by CAIDA). It shows that the smallest GreedyMaxClique core results in the lowest deterministic inference percentage while the largest CP core have the highest percentage. This is the result of the larger cores having more paths that traverse them, therefore can be deterministically inferred. k-Core provides an excellent overall inference percentage (over 95% deterministically inferred and around 75% matching CAIDA). Additionally, the results are stable over the measured fix weeks period. The drop in the percentage of edges matching CAIDA in week 5 is caused due to a decrease in the number of edges classified by CAIDA.

Table 3.2: Structure of input cores and its effect on the deterministic inference algorithm

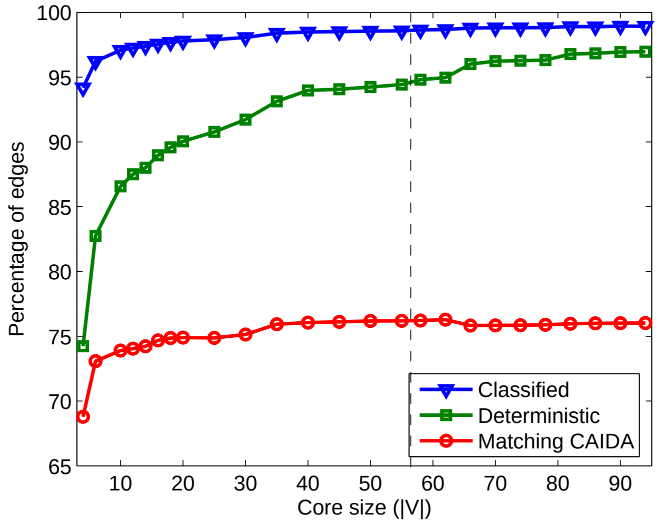
Core	Week→	1	2	3	4	5
k-Core	Core Vertices	57	56	54	58	54
	Core Edges	2260	2198	2076	2344	2134
	Classified	95.59%	95.76%	95.34%	95.24%	94.22%
	Match CAIDA	75.23%	75.32%	75.08%	73.76%	62.76%
Greedy Max Clique	Core Vertices	17	17	17	18	17
	Core Edges	272	272	272	306	272
	Classified	89.64%	89.87%	89.77%	89.62%	88.87%
	Match CAIDA	73.73%	73.82%	73.60%	72.56%	61.68%
CP	Core Vertices	1067	1053	1068	1056	1087
	Core Edges	6158	6110	6012	5844	6138
	Classified	98.29%	98.55%	98.45%	98.0%	97.39%
	Match CAIDA	79.77%	79.78%	79.43%	77.93%	67.19%

Although CP core seems to result in the best overall performance, constructing the CP core revealed that only a few p2p edges out of the approximately 6,000 edges were not a part of the largest connected component. This suggests that CAIDA incorrectly infers AS relationships as p2p, since it is highly unlikely that all p2p edges are connected. This causes a bias, resulting in more inference errors.

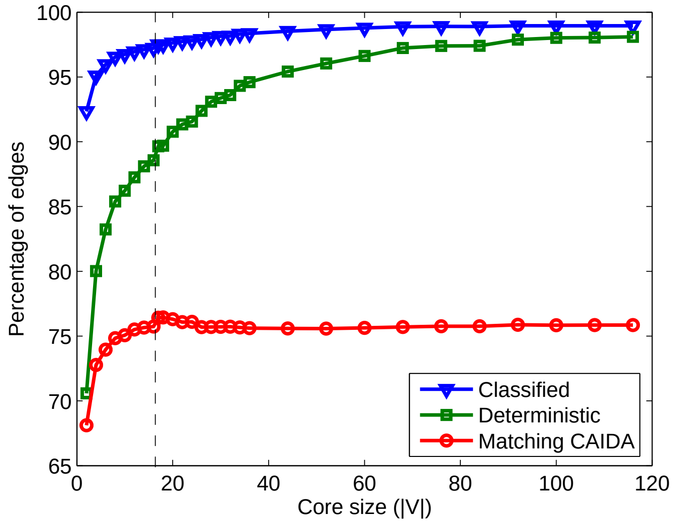
Table 3.3 shows that less than 6% of the edges were differently classified using two cores in each week, and the difference between k-Core and GreedyMaxClique is much smaller. This shows that the algorithm results are relatively consistent regardless of the input core.

Table 3.3: Percentage of edges that change classification comparing different core types

Cores | Week→	1	2	3	4	5
k-Core - GreedyMaxClique	1.77%	1.66%	1.58%	1.8%	1.64%
k-Core - CP	5.94%	5.89%	5.84%	5.7%	5.81%
GreedyMaxClique - CP	3.53%	3.45%	3.37%	3.34%	3.51%



(a) *k*-Core



(b) GreedyMaxClique

Figure 3.2: Robustness of the algorithm to changes in the size of the core

In order to find the best core size, we run the algorithm with a growing core size starting at four vertices. We do this for two of our core types - k-Core and GreedyMaxClique, using the first week of 2007. We start with the highest degree vertices and add vertices in a non-increasing degree order. Using k-Core, we first add vertices from the $K_{max} - Core$ and then proceed to shells with lower indexes.

Figure 3.2 shows the robustness of the algorithm relative to the size of the input core. The vertical dashed line marks the true core size. For both cores, it shows that for more than 20 vertices in the core the algorithm classification success and similarity to CAIDA do not significantly change, while the number of deterministically classified edges increases. However, this increase comes with an increase in the percentage of non-valley-free paths as shown in Figure 3.3. This implies that the core must be kept small enough to decrease the number of invalid paths.

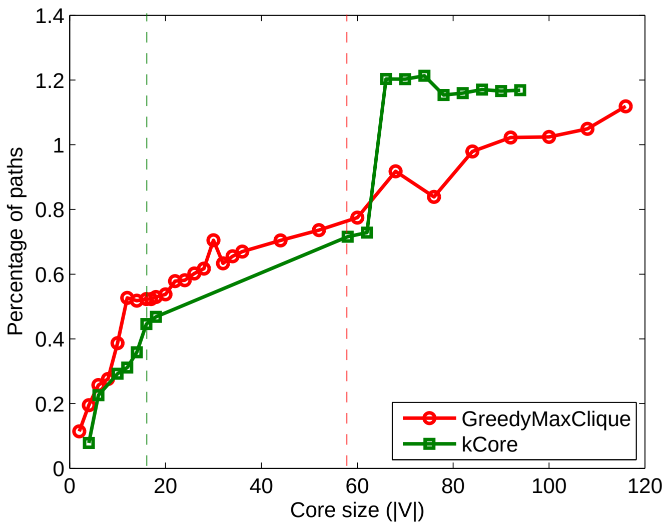


Figure 3.3: Non-Valley-Free paths

Overall we showed that the algorithm is consistent over time and various cores. Additionally, a core containing approximately 20 top-level ASes is sufficient to obtain excellent inference results.

3.4 Time Aggregation Analysis

We wish to find a time frame for which the algorithm captures best the relationships between ASes. A short time frame results in a fast running algorithm but might miss AS links and AS paths, especially in the DIMES data. This results in a low vote count, possibly decreasing the success of the algorithm. On the other hand, a long time frame captures two effects that can also cause a decrease in the algorithm's success: 1) commercial relationships can change and complex routing behaviors may occur over long durations, and 2) possible measurements mistakes can pile up and skew the results.

We executed the algorithm on an increasing time frame. We started with the first day of 2007 and aggregated single days until the end of the first week (for this experiment we took three RouteViews files a day). Then, we aggregated a week at a time, until reaching 10 consecutive weeks. DIMES provides approximately 1.5M non-unique tracroutes each day, reaching over 100M traceroutes for the 10 weeks period. RouteViews provides approximately 1.2M *unique* paths regardless of the time frame used.

The percentage of deterministically inferred edges over the aggregated time frame is shown in Figure 3.4. Using data from a single week (marked as the vertical dashed line) results in over 90% of the edges being classified for all core types, having CP obtaining the best percentage and GreedyMaxClique the worst. This is directly related to the size of the core, since a larger core results in more paths that traverse through it, yielding more deterministically inferred relationships.

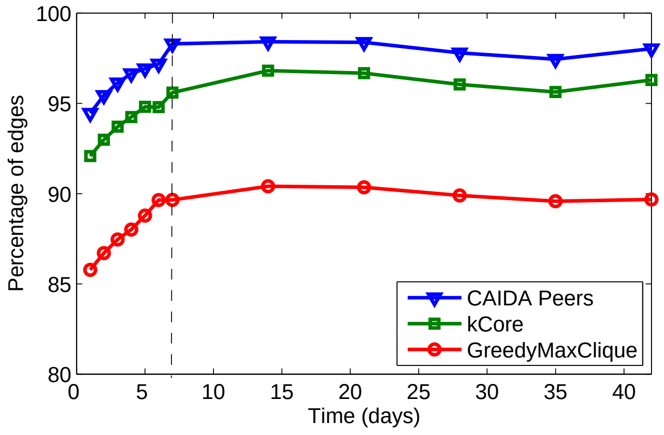


Figure 3.4: Deterministically classified edges over an increasing time frame

We evaluate the deterministic algorithm over this time frame by looking at the edges that are identically classified by the deterministic algorithm and CAIDA, out of the edges that are classified by both. Figure 3.5 shows that for all cores and any time frame, the algorithms agree on over 92% of the edges. Obviously, using CP gives the best match to CAIDA's inference. It is interesting to see that although k-Core has better overall deterministic inference success than GreedyMaxClique (shown in Figure 3.4), it results in a lower match rate. This is probably due to the relatively small, local and degree-based GreedyMaxClique core, which is more related to the heuristic used by CAIDA's inference methods.

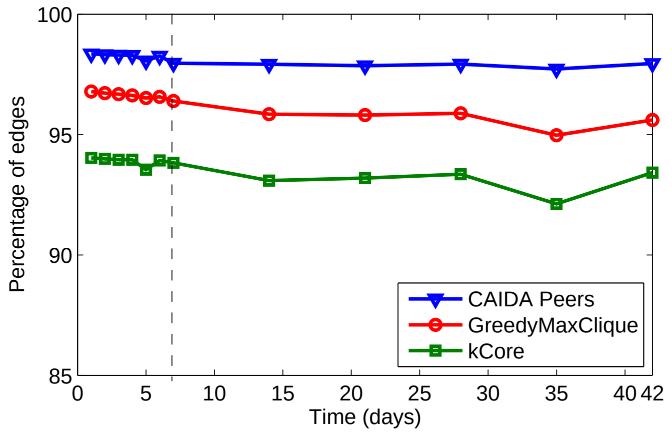


Figure 3.5: Percentage of deterministically inferred edges matching CAIDA out of edges that are inferred by both algorithms

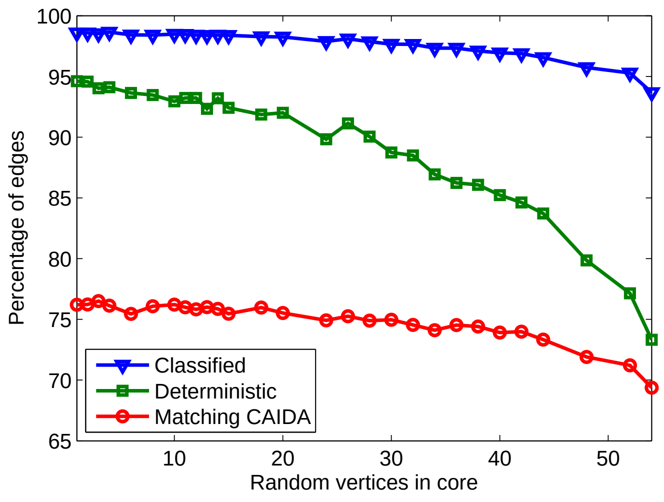
Finally, we looked at the consistency of the inference results over the time frame by comparing edges that are classified in both time frames. We found that over 98% of the inferences remain constant between consecutive time frames. This suggests that there are only a few commercial relationships that change over time. Short-term routing changes have very little effect, since they statistically "disappear" as the more common routes become dominant over time.

3.5 Analysis of Non-Deterministically Inferred Relationships

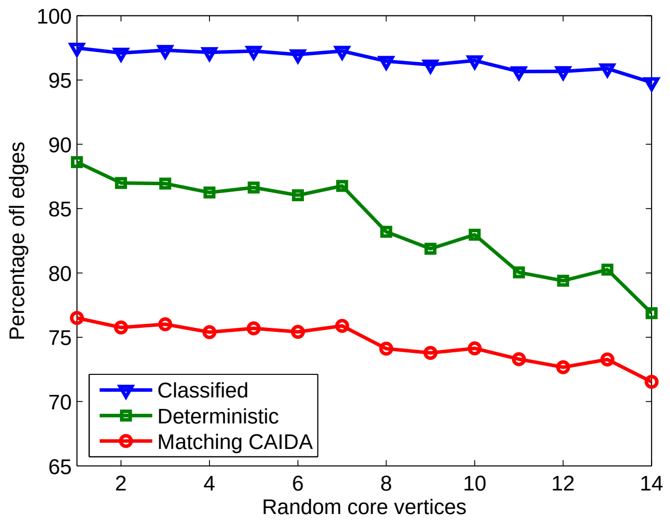
Edges that the deterministic algorithm fails to classify are classified using the two heuristic-based inference methods described is section 2.3. The first method breaks voting ties and the second infers p2p relationships.

To break voting ties we compared adjacent AS degrees (similar to [12]) and inferred the relationship between them as p2p if the degrees ratio is between 0.8 and 1.2, or p2c otherwise (marking the provider as the AS with the higher degree). For k-Core we also compared the k-Shell index, and inferred the relationship to be p2p if the two ASes have the same k-Shell index, or p2c otherwise (marking the provider as the AS with the higher k-Shell index) and note very little difference between the two heuristics.

We estimate the accuracy and robustness of the algorithm by intentionally increasing the mistake in the core. We do this by randomly replacing ASes in the core and see how the number of relationships inferred and their correlation with CAIDA's inference change. We start by replacing one core AS with one random AS (that is connected to at least one of the remaining core ASes) and gradually replace more ASes until we have a core that consists of completely random but still connected ASes.



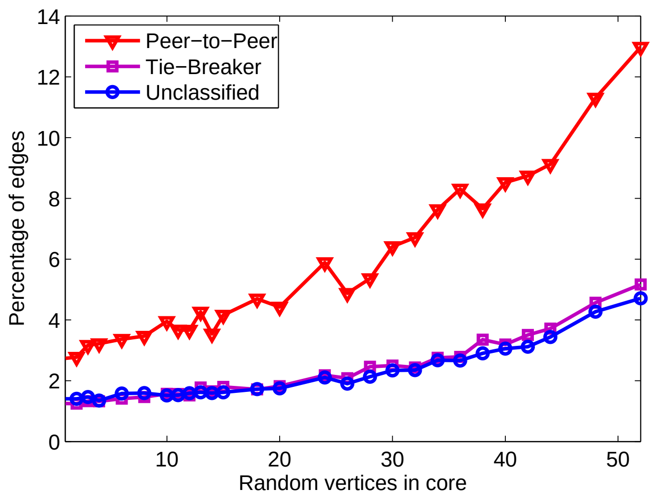
(a) *k*-Core



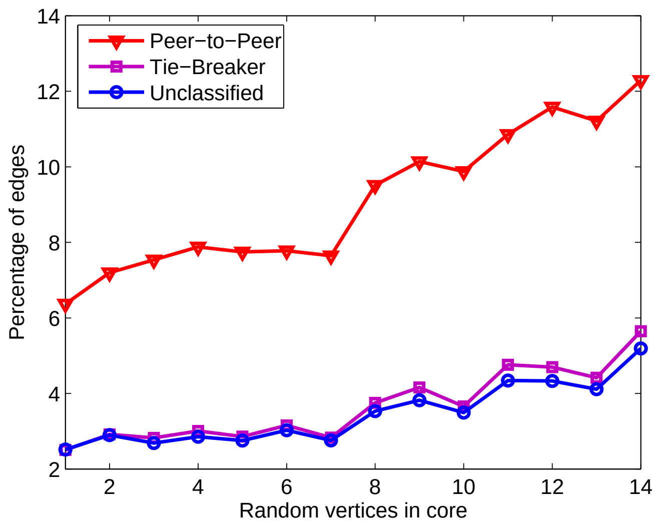
(b) GreedyMaxClique

Figure 3.6: Robustness of the algorithm to errors in the core

Figure 3.6 shows the percentage of classified edges, deterministically classified edges and the percentage of edges that match CAIDA's inference using k-Core and GreedyMaxClique. Interestingly, while the algorithm's performance decreases as we increase the randomness of the core, the overall degradation is not as high as one would expect. However, Figure 3.7 shows a rising trend of the percentage of unclassified, p2p and tie-breaking heuristic edges as we inject errors to the core. As more errors are injected, the algorithm needs to use more heuristics. Particulary, when there are approximately 50% random vertices in the core, the effect of the increasing mistake becomes more noticeable. However, even with a completely random core, the overall heuristically inferred edges account for less than 20% of all edges.



(a) *k*-Core



(b) GreedyMaxClique

Figure 3.7: Percentage of p2p, heuristically classified and unclassified edges

These results indicate that although the algorithm seems quite robust to the mistake in the core, it is still significantly affected once there are more than 50% incorrect core vertices. Figure 3.8 provides a focus on p2p edges. It shows us that as we inject more errors, the percentage of p2p edges that are classified differently by CAIDA increases from around 16% to over 40%.

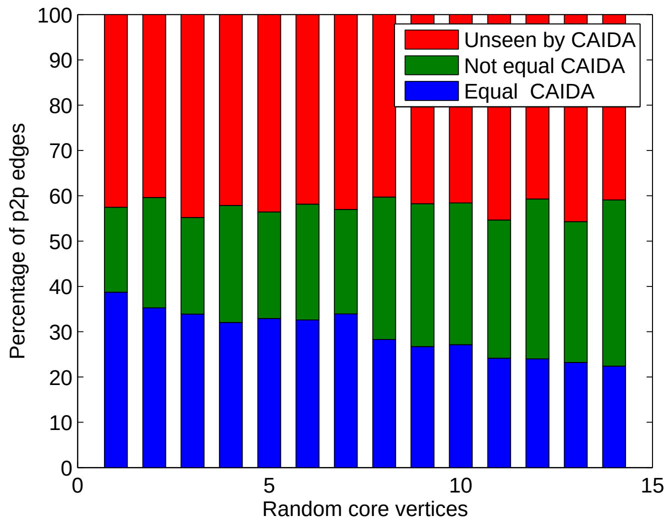


Figure 3.8: P2P inference method using GreedyMaxClique core

Finally, we analyzed the distribution of relationship types for edges that appear only in DIMES, and are not seen in the BGP routing tables, to understand what are the types of relationships that DIMES discovers. We found that while on average the p2p relationships comprise 4-5% of the total number of edges, it goes up to around 12% of the edges that appear only in DIMES. Moreover, approximately 40% of the p2p edges inferred by our algorithm, do not appear in the RV tables. This means that utilizing DIMES significantly improves the ability to detect p2p links between ASes, mainly since DIMES agents are spread over the Internet and contribute AS links that are either not collected by the RouteViews routers or even not published in the BGP protocol.

Chapter 4

Conclusion and Future Work

The common weakness of previously proposed AS relationships inference algorithms is their lack of guarantee on inference errors introduced during the process. This work improves on existing methods by providing a near-deterministic algorithm that, given a classified error-free input core, does not introduce additional inference errors. We investigate various input cores and show that the proposed algorithm provides accurate inferences that are robust under changes in the core's size and creation technique. We show that a core containing as little as 20 almost fully-connected ASes is sufficient for good inference results. Additionally, we show that heuristic methods can still play an important role in inferring the remaining relationships. Using data collected from a single week (containing approximately 1.2M BGP paths and over 10M DIMES AS-level traceroutes), the algorithm runs for only about 2 hours and yields over 95% deterministically inferred relationships.

As the Internet grows larger, many providers interconnect at multiple locations for traffic engineering and embrace the usage of exchange points. The relationships and policies used in these interconnection points might not conform to either provider-to-customer or peer-to-peer relationships. Moreover, it might not even conform to the valley-free property. The data provided from the DIMES project can reveal these complex relationships and seed other large scale Internet analysis work.

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