Consolidated Review of

AS Relationships, Customer Cones, and Validation

1. Strengths:

This paper is one of the first I have seen (probably the first?) to openly acknowledge that inter-AS relationships are more complicated than monolithic AS-level business relationships, and to recognize that some noise in the data (e.g., poisoning) can interfere with inference. Business relationships are useful for understanding the Internet's topology and routing, but existing datasets / algorithms have limitations. AS classification methods developed by authors directly address existing classifications problems, with success.

I imagine I'll use this dataset in the future (and, in fact, have already used the website to check some paths I was looking into). Most significant validation of AS relationship data; data (in as far as is possible) will be made public. The data will be publicly available and actively maintained, which will serve as an important resource for the research community.

Also, neat techniques to gather the validation data. Very good validation with a novel "ground-truth" dataset. Better validation than previous work in this area, and good results in the validation.

The domain knowledge that this paper brings to the discussion of inter-AS relationships is quite useful.

Observation of possible increased stature of tier 1s seems interesting.

2. Weaknesses

Customer cone section raises some questions. Ignores sibling links and does not properly deal with how this affects AS relationships or cones. Not clear how sensitive AS relationship classifications are to various details of the classification algorithm; some better explanations of inaccuracies were missing. No attempt to validate the customer cone inference, except to say that "provider-peer ... seems to be the most robust"

The methods used are not new, some missing citations.

Some of the methods, such as the method to discard poisoned paths and the methods to infer regional business relationships, are bogus or incomplete.

The validation results show that the inference algorithm is only incrementally better than existing techniques, making the work quite incremental. Given that the coverage of the ASes that were validated is relatively small, it is not clear that the improvement over previous approaches is really all that significant (it is perhaps within the margin of error). When the validation fails, there is no real insight as to the causes of the failed inference. The inference data---and how it was computed---is likely useful, but it doesn't warrant a 14-page paper. Section 5 (the "longitudinal analysis") is underwhelming and shows no clear trends.

3. Comments

Very nice paper on a good problem. I enjoyed reading it and look forward to using the data. I found this paper enjoyable to read, particularly the motivation, which sheds light on some of the more "modern" challenges with inferring inter-AS relationships.

Intro: 2nd paragraph was a very nice explanation that I can imagine using to introduce AS relationships in a class, say. Intro: I wasn't sure what to make of the challenges you present: - First challenge of removing artifacts seems pretty minor - Second challenge of missing peering links, you are still missing them, but you show that they don't trip you up. But, I didn't notice strong evidence that they affecting existing approaches any more - Third challenge of valley-free. Neat that you don't have to assume this. It didn't come across in 4.7 whether this was affecting existing approaches. - Fourth challenge of regional/prefix specific. Is this where the tier-1 visibility assumption trips up UCLA? - Fifth challenge of siblings: you ignore, whereas some previous work uses them. I didn't understand your decision to completely ignore sibling links. How do they end up classified in your results? Why not use the results from [16] as siblings, if nothing else? Do you no longer buy your previous work? Why it is hard to differentiate leaks from siblings? I would think that leaks are short-lived and siblings are not, so you could use time to differentiate, but maybe I'm missing something. How is ignoring siblings impacting your customer cones? The discussion in 5.3 focuses on what seem to me to be essentially meaningless shifting of customers from one sibling to another. Why is this interesting? When I've tried to build customer cones using existing CAIDA/UCLA relationship data with siblings, they did blow up, but I wonder if your approach is too conservative. What distinction are you drawing vs. existing work? Mainly the third challenge, or do the other challenges trip them up more than you too?

2: I think you should probably cite iPlane Nano. It also uses observed triples to infer policy, although towards a very different end, and it also differentiated between links/triples seen in transit vs. those only seen at the end of paths, which seems similar to what you do in places. Am I correct to think that triples will allow only valley-free paths if all triples are valley-free, but you relax the valley-free assumption by using all observed triples, some of which may not be valley free? It wasn't clear to me how your link classification deals with leaks. The only place I see them mentioned is briefly in step 10. I would think that the % of ASes (transitively) single-homed beneath a single tier 1 must be decreasing. Are we getting closer to it being possible for an AS to go transit-free without peering with the full mesh? What if they peer with some large tier 2s? Just curious how much connectivity they would miss. (Not really anything you need to get into in the paper) I was confused by all the attention to poisoning. - Is it used frequently in practice? I'm surprised! Or are you just observing a small number of research systems using Georgia Tech's Transit Portal? If the latter, can you just filter out their prefix/AS? If most of the poisoning is them, you might want to cite them / PECAN / LIFEGUARD / PoiRoot. If it is not them, you might want to characterize the poisoning you see, as I don't think many people think of it as a major issue on the Internet. - You mention the number seen in April 2012. Was this meant as a peak or as a representative month? Was it just some researchers running an experiment? - Fig 6 Path 6 is mentioned as potential poison. Does anyone announce poison like that, rather than like 2629 27065 2629, to avoid confusing the neighbor? Why do you have to deal with poison in step 7 if you removed it is step 1? To identify IXPs, can you borrow earlier data / techniques from the Sidewalk Ends paper and the IXPs:Mapped paper? Can you look up the IX prefix space on IX websites and map those prefixes to AS? Does PCH have good data? In step 8, how do you know W--X rather than W < X? Do you verify that all the provider-less ASes make sense, like TransitRail? Table 2: Step 7 seems unreliable (48.2%), but I don't see discussion of what is going on.

4.: The assumptions in Section 4.1 are never justified, and I can think of many recent "peering battles" that might cause some of these to be (at least temporarily) violated. Also, the paper does not clearly explain how it deals with some of the more complex relationships; while some are covered superficially in Section 4.6, many (e.g., regional peering relationships) are not really addressed. Given the introduction's fanfare, I was really hoping for a more careful treatment of the material in this section, which would represent a quantum leap forward if it were solved.

4.5: Since your final step is to assume anything left over is p2p, we'd like some confidence that your set of steps is complete. How do we know that?

4.6: Can hybrid relationships etc. cause violations of your assumption of no p2c cycles? 4.7: Great that you did validation and compared to previous results. Too bad that you could not get a few earlier techniques. With more time, can you at least get [26] and [32] (before camera ready, say)? It would be nice if this paper can be definitive by including all major existing techniques.

4.7: add more detail about why your technique makes mistakes when it does, and same with other techniques. More details like this: "The UCLA algorithm often infers c2p links to be p2p because it uses the visibility of a link from tier-1 VPs to draw inferences, and defaults to a p2p inference for links it cannot see (see section 2). We agree with the intuition behind this visibility heuristic and use a variant of it in our algorithm, but we use additional heuristics to accommodate for phenomena that inhibit visibility through tier-1 VPs, e.g., traffic engineering, selective announcements"

5: Given that many ASes are multi-homed, it seems like saying that the customer cone is the ASes that might be disrupted is a bit of an overstatement. How do backup links affect the PP counts? For example, a large AS may be transit free with a backup provider link to guarantee global connectivity in case of a depeering (I know of such a case in practice). If you observe that transit link but it isn't usually used for the large AS's customers, they will count in recursive but not in PP. Isn't that undercounting the scope of the transit provider? Part of this might come down to what exactly you mean by customer cone, which might not be stated that clearly.

The relative rise of tier-1 providers isn't really a new observation (Labovitz discussed this in his SIGCOMM 2011 paper), and beyond that, I did not find Section 5 particularly interesting, general, etc. Many of the other phenomena (e.g., flattening) have also been described in previous papers, including a paper by one of the authors of this paper.

5.2: Unless I am misreading, the text seems to be referring to some other version of Table 4: it says that the top 5 are the same for all algorithms, but the table seems to show, for example, 3257 in the top 5 only for PP. And, it says 2828 and 3491 are exceptions to BGP>PP, but, in the table, they are not exceptions (but are close). I decided to try out your customer cone data using your website. I had IP pairs where IP1 was a client served by an Akamai-style cache node with IP2. Since an AS hosting a cache server would only want to serve its customers, we'd expect IP1 to be in the customer cone of IP2. However, 10% of the time this was not the case, which seemed VERY high to me. It could be problems with IP->AS mapping, it could be mistakes in how the DNS mapping for the serving is happening, or it could problems with your customer cones. Whatever the problem, it would be nice to validate that section as well as you validated the AS relationships, and it would be nice to discuss how the 3 approaches break down.

5.2: Your discussion mainly deals with large ASes. Do you expect the technique to also work well for small ASes?

5.4: This section was interesting; especially the drop in fraction of paths using a non-clique peering link, but some of it confused me. Why did you just look at paths within a single AS's cone, instead of also looking at paths that start in X's cone and end in Y's cone (but could take a shortcut peering link instead of going via X-Y)? What if, in addition to X, they are also both in large AS Y's cone and transit via Y? Will that count against X's fraction in the graph? In other words, is greater redundancy a possible explanation for part of the effect, or did you eliminate it? When you say "the fraction of observed paths crossing a peering link between a clique AS and a lower tier AS," do you mean a P2P link, or could it be a P2C link? In general, this part was interesting and could use further discussion about what is going on, which types of paths are changing, do all VPs see this sort of change (I didn't look into what the 8 VPs you used are), etc.

The customer cone inference techniques and analysis were the weakest sections of the paper. Some aspects are not well explained, there is little discussion of the accuracy of the inferences made, and there are some inconsistencies in presentation. - For example, in 5.3, the cone size is examined as a fraction of "topology size". Although it becomes clear later that this is the fraction of the total number of ASes, you should be more explicit than "topology size". Similarly, the Table 4 caption should indicate what the numbers actually refer to --- there's nothing in the caption to explain what the percentages mean. - I found the explanations in section 5.4 to be confusing. For example, the third sentence if paragraph 2 in that section is hard to parse, and paragraph 3 in that section is extremely dense and difficult to read. - There's some inconsistency with the time frame considered. Some analyses look at 15 years, but others look at 11. In 5.2, paragraph 3 indicates that Fig 8 considers 11 years of history, but the figure shows 15 years. In Fig 11, the timeline shows 11 years, but all others go back to 1998.

The main strength of the paper is the validation dataset, and it is indeed far more comprehensive than anything reported before. However, the methods used for inference are not new, thus I find the contribution in this area very marginal.

I also found the thoroughness of the validation extremely refreshing. This is a model for how validation should be done for this type of inference work; I particularly liked how the paper used three different (and independent) datasets to validate the approach. Some of the techniques, such as that used to remove poisoned paths, seem somewhat bogus/incomplete: Simply because an AS is repeated in the path does not mean that the AS path is poisoned: sender-side loop detection could be disabled, for other reasons (e.g., acquisition). Also, there could be poisoned paths that do not exhibit this property.

The authors have done a pretty nice job in explaining all the steps of algorithm 1. One thing that stood out, however, was that for some of the inferences that were apparently inaccurate (i.e., as shown in Table 2, specifically steps 7, but also step 10 and other low-ish accuracy steps), there was not much or any discussion on why the proposed inference algorithm was so inaccurate.

Key issues:

1. Looking at the acyclic nature of the AS-graph is not new, and was done before in Infocom'07 (http://www.cs.technion.ac.il/~ramic/publication/CR07.pdf) and IMC'07 (http://conferences.sigcomm.org/imc/2007/papers/imc97.pdf). I am not sure why you ignored these citations.

2. You used a simple max-clique core, whereas a more comprehensive study of the selection of ASes in the core was done by Shavitt et al (your [32]) - it seems like k-core is a better way to choose a core, but you completely ignored other methods.

3. I am not convinced that the way you sanitize your data is sufficient (looking manually at ASes). Both IXP Mapped? and "Where the sidewalk ends [12]" have much more rigorous analysis of IXPs. Can you use their methods?

4. Another citation that you should add is from TMA'13 (http://www.eng.tau.ac.il/~shavitt/pub/TMA2013.pdf), where the authors study complex relationships using PoP-level analysis.

5. Overall, the method relies mostly on the same heuristics that was used in previous work. So I am not sure what are the new insights that this work brings. The major contribution to the community is the dataset -- the actually annotated links.

4. Summary from PC Discussion

The PC found that this paper added to the (relatively large) body of existing work on this topic, and that the public release of the dataset would be of significant value to the community. The dataset was one of the more redeeming aspects of the work; all of the reviewers agreed that the dataset was a useful contribution. The PC was also impressed with the thorough validation.

The PC was less impressed with the discussion of customer cones, and some of the techniques (e.g., the one to remove poisoned ASes) seemed extraneous and perhaps not correct. The paper could be strengthened with more discussion/emphasis on validation and methods, and less on the longitudinal study. Or, more work needs to be put into the cones section to make it stronger.

5. Authors' Response

We added substantially more material to 4.6 (complex relationships) to explain how siblings, mutual transit, partial transit, backup transit, leaks, and poisoning manifest in our data. We also added text that describes clique complexities: backup transit for clique de-peerings and mergers between clique ASes. Finally, we further discussed challenges in accurately inferring customer cones due to hybrid relationships. While preparing our IMC submission in May we accidentally introduced a bug in step 7 which caused that step to perform poorly, and also accidentally included IPv6 AS paths in our BGP dataset. We resolved both of these which improved the accuracy of our inferences.