Reviewer #1

Summary: This paper considers the routing data when viewed through the lens of the recently-proposed routing state distance metric, or RSD (from Sigcomm 2012). It shows that the metric enables new ways of visualizing routing data that lends interesting insights into the existence of clusters called "local atoms"; this is a group of ASes that have distinctive forwarding behavior toward a particular collection of destination prefixes. The paper shows that RSD is amenable to new clustering algorithms and presents a theoretically-ground scheme for clustering routing information on the basis of RSD to derive local atoms. It presents a study of the local atoms derived using this approach. It also presents an enhanced clustering algorithm that helps derived richer groupings of routing data (overlapping clusters). On the whole, a nice contribution to research on understanding and visualizing routing.

Strengths:
- Very well written
- Nice combination of theory and empirical analysis
- Interesting results

Weaknesses:
- Not entirely clear if the insights derived using RSD could not have been derived using other simpler techniques.
- Parts of the writing are too vague.
- Some aspects of the proposal are not clearly explained or poorly evaluated.
- There is no real comparison of the clustering schemes.

Comments to authors: Congratulations on an extremely well written draft and on your deft execution! I really don’t have any significant comments to offer. I do have some thoughts, and some issues with lack of clarity in parts.

At the highest level: I was wondering if the local atoms you saw could also be explained or derived by looking at the structure of the AS graph. I am not sure if this is possible as there is insufficient detail in the paper explaining the local atoms. To elaborate: You say that the local atoms arise due to synchronized choices of a set of source ASes in how they reach certain destination prefixes. But you never explain if the source ASes did have other choices to reach these destinations. My gut feeling is that they didn’t (in other words, the region of the AS graph you are exploring has limited path diversity). If this ends up being true, it somewhat weakens your claim about the unique usefulness of RSD. Would be nice to see further discussion or analysis along these lines.

You should also more clearly explain your contributions relative to your recent work on RSD. The paragraph toward the end of the intro is very vague and unsatisfactory.

Digging deeper:
Section 2: You say that RSD satisfies triangle inequality in the basic case, but enhancements to it may not. While you say that empirically such violations don’t happen too often, you don’t tell us what the implications are when the violations do happen.

Is this section essentially repeating content from [10]. It seems to be. If so please be clear about this.

You that a metric like hop distance will have discrete increases. Why is this bad? Can you give a concrete example?

Section 4: D is an \text{n x n} matrix \rightarrow did you mean \text{m x n}?

You say that an interesting local atom should have a significant number of ASes and destination prefixes. What is significant? You never make this clear. The results you show in table 1 have a variety of different sizes, especially for the number of source ASes, but it is not clear if these are significant or not.

Section 5:
You say that existing clustering schemes need to know the number of clusters beforehand. This is not true for schemes, e.g., star clustering. Is there another reason beyond knowing the number of clusters due to which existing schemes are inapplicable? Is *NO* existing clustering scheme applicable? If so, state this clearly. If not, you need to quantitatively and qualitatively compare your clustering scheme against these alternatives.

What are the practical implications of the 3-approximation? Does the factor of 3 gap mean that you eventually have to rely on heuristics in practice, such as trying different values of \(\tau\), to derive meaningful local atoms?

Section 6: Based on what you said in Section 5.1 about there being an optimal number of clusters (The para starting “Observe that”), I would have expected the graphs in figure 11 to have a different shape with a unique optimum. Can you explain why you see a monotonic trend instead?

The next hop density numbers you show in table 1 seem pretty low, with no significant skew (meanings that the ASes outside the top three may be contributing enough weight and hence need to be considered, too).

Section 7:
I found the description of algorithm 2 to be very vague. E.g., What is the complexity of the two steps in the inner "for" loop in algorithm 2? (NNLS and Boolean)? More importantly, you state earlier that you need to scale RSD by the number of ASes and quasi routers, but algorithm 2 depends on comparison with a metric in [0, 1]. There is something wrong here. There is a hidden parameter "p" in this algorithm. What is its impact? How to choose it?

The conclusion of this section was vague and quite unsatisfactory. Also, why not compare your clustering scheme against those in [2]?

**Reviewer #2**

**Summary:** This paper describes routing state distance (RSD), a new metric to characterize BGP paths. The paper shows that RSD can uncover interesting information from BGP data, such as local atoms - sets of prefixes that are routed similarly by a subset of ASes. RSD is simple to understand and calculate and can be efficiently visualised in few dimensions. Using RSD the authors uncover interesting cases of "collective" routing decisions towards certain prefixes in Asia or America.

**Strengths:** I liked this paper quite a bit. It is very easy to read and understand, and I believe it could be useful to many people. The problems are well defined and the solutions clearly explained. The results are interesting.

**Weaknesses:** I would have liked to hear more about how we can use RSD. Ideally, one of the ideas in the discussion section could be expanded as another application of the RSD metric. Also, local atoms are quite interesting as a phenomenon, but its unclear straightaway how such information can be used and for what.

Evaluation of the scaling properties of your proposed algorithms would make your paper stronger.

**Comments to authors:** Please elaborate more on the effect of missing nhop information in your data. You said you have performed extensive studies and please include some convincing results. This assumption is very important for the whole paper.

Why didn’t you run the analysis for all the prefixes, but only for small-ish random samples? You say it looks very similar for other random samples - but I would assume the 1/100 random sampling you performed (a few thousand prefixes out of 100K prefixes) would bias the clusters you find quite a bit.

The above observation naturally makes me wonder how well your algorithms scale with the number of prefixes. Can you please tell us both what are the theoretical scaling properties and what you can do in practice. That way, we can better gauge the applicability of your algorithms.

Your analysis in section 4.2 mentions percentages of prefixes in Asia, etc - are these percentages out of the total number of prefixes, or percentages out of the subset you analyzed? (i assume the latter, but you don’t say).

It took me a while to understand why the datapoints are different in Figure 10 and 12; 12 is showing a subset of the datapoints in 10, because only the first 5 out of many clusters are shown; in 10, all clusters are shown. Is this the case? Can you please explain it, it can be very confusing!

It would be very nice to hear a bit more about the proof the RSD-clustering is NP-hard - please point the reader to a technical report with the proof!

You can gain some space by compressing (or plain ditching) figure 13 - it doesn’t say that much.

You keep mentioning a toolbox - when (if) will your tools be released?

**Reviewer #3**

**Summary:** This paper describes routing state distance (RSD), a new metric that can help analyze BGP data. RSD is defined as the number of ASes that have different next hops to two prefixes. The authors show that RSD obeys triangle inequality, and can be used to cluster prefixes that are routed via the same next hop in some part of the Internet. The paper presents two clustering algorithms. One divides prefixes into non-overlapping clusters and the other into overlapping clusters.

**Strengths:** The paper is well written, and the idea of using RSD to analyze BGP data is intriguing.

**Weaknesses:** The applications of RSD seem to be limited. It is not clear whether the formalism presented in this paper is necessary. Also RSD is not a new concept, and has appeared in the author’s recent SIGCOMM paper.

**Comments to authors:** I enjoyed reading the paper and found the idea really intriguing. However, although mathematically speaking, RSD is a nice metric, obeying the triangle inequality, it is not an intuitive metric to me. I kept on thinking whether it is an overkill for the applications you proposed: discovering local atoms. Can one simply compare the next hops used by ASes that are close to each other?

It’d also be useful to explain why discovering local atoms is an interesting or important application. Policy atoms can be used to compress BGP routing tables. So one naturally wonders what local atoms can be used for.

Section 2: I am guessing that RSD’s triangle inequality feature is essential for the clustering algorithms to work. If so, it’d be helpful to forecast this application in this section.

Section 3: You randomly picked 1000 prefixes to draw figure 2, and 3000 to draw figure 3. These numbers look arbitrary to me. It’d be useful to explain why you picked those numbers. Have you validated whether 1000 and 3000 are a large enough subset so that the resulting graphs are representative? Why not use all prefixes in your datasets to draw those figures?

4.2 “The fact that Internet prefixes cluster into two distinct groups...” I am surprised to see that there are only two clusters. What is special about ASN 6939? Who owns it? And why does it become such a hub AS between Far East and US? Have you tried to validate the data using routing registries?

Figure 4: What are the x-axis and y-axis?

Section 5 & 7: Here you presented two clustering algorithms. I find the overlapping clustering algorithm not easy to understand. What do overlapped clusters indicate? How are the two clustering algorithms related to each other? Can one replace the other? When should one apply one clustering algorithm vs the other?
Reviewer #4

Summary: This paper proposes a new metric based on how many ASes differ in next-hop choice for a given prefix. The metric is a simple aggregate that can be used to group ASes based on routing decisions, and its simplicity is appealing. My rationale for a lower score is the concern that it may be good for a very small number of visualizations and not much else.

Strengths: The paper proposes a fairly interesting way of examining routing decisions, boiling down differences to a simple number. In that sense, the new metric gets rid of a lot of complexities in the routing decisions and provides something that is easier to use in many scenarios. The paper then shows various analyses using this metric and the underlying causes that give rise to these analyses.

Weaknesses: It wasn’t clear to me exactly how useful this metric would be going forward. The authors showed a clustering in figures 6 and 8, and the main determining factor in generating those clusters seems to be the effect of one AS, Hurricane Electric. So, while the clusters do show some interesting behavior, my concern is whether the metric is really relevant in the sense that one AS (and hosting service) has such a large effect on it.

Comments to authors: The paper is interesting in that routing decisions are fairly complex and contain a lot of information, but this metric is able to reduce it and still produce interesting results. The "problem" as a reviewer is that the results, while interesting at a cerebral level, aren’t as convincing at a practical level. In particular, while the clusterings show a marked difference between clusters and a clear separation, the question is whether the groupings really mean anything.

Saying that it boils down to the decisions made regarding Hurricane Electric is a "technically correct" answer, but it doesn’t seem satisfying in the sense that one would expect that this relatively minor detail would be one way of thinking of how to split the Internet into two. I admit that I’m not the most knowledgeable person when it comes to knowing all the players in the transit business, but it took me a search to remember why I’d ever heard of Hurricane Electric at all. Doesn’t the fact that the groupings revolve around this relatively minor AS suggest a problem with the metric? Maybe I’m being unfair in that I’ve got an IPv4 bias, and Hurricane Electric is actually important in the IPv6 space, but again, doesn’t reality also have an IPv4 bias at this point?

The rest of the paper performs various other slices and dices, and the concept of local routing atoms was an interesting one, in the sense that I could see more utility from the metric than the earlier part of the paper. However, it’s still got a long way to go to be broadly applicable, it seems. So, the strength of the paper, as far as I can tell, is not in proposing what I think will be a definitive and long-lasting metric, but rather the first steps toward something that will be more useful as it gets modified over time. It may be that the modifications, including various weightings, etc., dilute its character as a pure metric, and introduce various inequalities, but that would seem logical, given that there are already so many inequalities in the underlying data.

Reviewer #5

Summary: The authors discuss their RSD metric, which they introduced in a SIGCOMM ‘12 paper. In this paper, the analyze its properties and show that it may be useful for determining ‘local atoms’, namely prefixes that are routed similarly for a particular portion of the Internet.

Strengths: The paper is well written, and provides a thorough analysis of what is a clear and intuitive metric. The authors show that the theoretical results map to real, technical aspects of how forwarding works. The particular aspects uncovered by the clustering where new to this reviewer, although perhaps not to one more familiar with the state of IPv6 transit providers.

Weaknesses: The RSD metric itself was proposed elsewhere, which takes considerable sheen off the contribution of this manuscript. Rather, this manuscript purports to further analyze the utility of the metric and discuss its properties. Since the SIGCOMM ‘12 paper is essentially concurrent, it would have been nice had the authors provided a greater discussion of the prior work and how this manuscript differs.

Comments to authors: Nice paper. It was unusual in that I enjoyed reading what was essentially a theoretical manuscript—that is rarely the case for me. It’s a bit out of my area of expertise, so I don’t have a lot of concrete suggestions to make, but I found some of the discussion a bit too vague, in that it wasn’t always clear what the utility of the particular clustering task was.

You made a big deal about the Hurricane Electric cluster which was, admittedly, new to me. I wonder, however, how many other local atoms can be similarly explained. It would have been nice if you had tried to identify any other such known phenomena using RSD. Conversely, one wonders if there are alternate methods to discover the same thing?

Technically, I was bothered by the "missing nexthop" information. Since RSD is all about next hop information, the fact that you had to synthesize this for a significant portion of your dataset is somewhat worrisome. I would have appreciated more discussion on this issue.

Why are the cluster locations continually moving? In particular, aren’t Figures 10 and 12 showing the same random path pairs, just clustered differently? I’m sure it’s my confusion, but further discussion would seem necessary.

Why did you pick random path pairs at all? If the clusters really are so fundamental, it would seem the graphs should look similar regardless of the number of points? Or is the data so scattered that a full dataset plot would simply be a black box? If true, that seems to contradict your argument?

Response from the Authors

We thank the anonymous reviewers for their comments and suggestions, which have improved the paper considerably.

We have addressed the following comments:

A reviewer asked whether ASes that constitute the source sets of local atoms had other next-hop choices. In the revised version of the paper, we explore in detail the reasons for the Hurricane Electric local atom. We show that the local atom occurs not because
of topological restrictions, but because of the particular policies of Hurricane Electric. We were not able to explore the smaller local atoms in detail, but at least in the case of this largest local atom, the issue does not seem to be topology.

We have also added text to explain the relationship of this paper to our paper in SIGCOMM 2012.

We have clarified the difference between Figures 10 and 12, and extended the range of data in Figure 11 to better illustrate the behavior of the P-Cost objective function.

We have released our toolbox of RSD related code and data at csr.bu.edu/rsd.

A reviewer asked "what is special about ASN 6939"? As mentioned above, we have made progress toward answering that question in the revision. In particular, based on contacting operators involved, we now understand why ASN 6939 is the preferred next hop for the specific set of prefixes in the Hurricane Electric local atom. This is explained in Section 4.2.