Describing and Simulating Internet Routes

Jérémie Leguay[1], Matthieu Latapy[2], Timur Friedman[1], Kavé Salamatian[1]

[1] LIP6 – CNRS and Université Pierre et Marie Curie
8, rue du Capitaine Scott, 75015 Paris, France
Tel. +33 1 44 27 71 34, Fax +33 1 44 27 53 53
{jeremie.leguay,timur.friedman,kave.salamatian}@lip6.fr
[2] LIAFA – CNRS and Université Denis Diderot,
2, place Jussieu, 75005 Paris, France
Tel. +33 1 44 27 28 42, Fax +33 1 44 27 68 49
latapy@liafa.jussieu.fr

Abstract. This paper introduces relevant statistics for the description of routes in the internet, seen as a graph at the interface level. Based on the observed properties, we propose and evaluate methods for generating artificial routes suitable for simulation purposes. The work in this paper is based upon a study of over seven million route traces produced by CAIDA's *skitter* infrastructure.

Key words: Network measurements, graphs, statistical analysis, modeling, simulation.

1 Introduction

Realistic modeling of routes in the internet is a challenge for network simulation. Until now, one has had to choose one of the three following approaches to simulate routes: (1) use the shortest path model, (2) explicitly model the internet hierarchy, and separately simulate inter- and intra-domain routing, or (3) replay routes that have been recorded with a tool like `traceroute` [1]. All of these methods have serious drawbacks.

The first method does not reflect reality: routes do not in general have the same properties as shortest paths, as already pointed out by Paxson [2], because of routing policies [3,4] mainly at the autonomous system (AS) level. As described in detail recently by Spring et al. [3], and earlier by Tangmunarunkit et al. [5,4], this often induces a lengthening of paths, or *path inflation*, compared to shortest paths. The second method is limited by our ability to explicitly simulate the internet hierarchy. Much work [6,7] has been done in order to model the internet graph, and much progress has been made, but today's topology generators are still capable of being highly inaccurate in capturing some parameters while they strive to adhere to others. (See, for instance, the findings in Li et al.'s SIGCOMM 2004 paper [8].) Then, even if one is satisfied with the quality of the topology simulation, there is the question of simulating dynamic inter- and intra-domain routing. A non-negligible programming effort is required if the choice is made not to use a simulator, such as *ns* [9], that has these algorithms built in. Finally, the third method is not suitable if routes from a large number of sources are to be simulated. Today's route tracing systems employ at most a few hundred sources. CAIDA's *skitter* [10,11] infrastructure, for instance, produces an extensive graph suitable for simulations, but it is based on routes from just 30 sources.

Note that despite its well known drawbacks, and because of the lack of more accurate models, the shortest path model is generally used. Examples from recent years include Lakhina et al.'s Infocom 2003 paper [12], Barford et al.'s SIGCOMM 2002 paper [7], Riley et al.'s MASCOTS 2000 paper [13], and Guillaume et al.'s Infocom 2005 paper [14]. The ns network simulator documentation proposes simulating routes by shortest paths as an alternative to simulating routing algorithms [9, Chs. 26, 29].

This paper's principal contribution is a new approach to modeling routes in the internet, one that does not share the drawbacks just described. We suggest using an actual measured graph of the internet topology, such as the graph generated by skitter. From that topology, we suggest choosing sources and destinations as one wishes from the nodes of the graph. Between these sources and destinations, we suggest generating artificial routes with a model chosen to reflect statistical properties of actual routes.

Central to this contribution are two specific models that we propose for artificial route generation: the random deviation model and the node degree model. These models generate routes with relatively inexpensive calculations, and the routes that they generate better reflect the statistical properties of actual routes than does the shortest path model.

The remainder of this paper is organized as follows. Sec. 2 describes the data set that we have used and the context in which our work lies. Sec. 3 proposes a set of statistical properties to describe routes in the internet. Sec. 4 proposes the models we use to simulate routes based on these properties. Sec. 5 evaluates those models, and Sec. 6 concludes the paper.

2 The framework

The ideal perspective from which to characterize routes in the internet would be from a snapshot of the routing tables of routers throughout the network. Unfortunately, such a snapshot is impossible to obtain on the scale of the entire network. In this section, we describe the alternative that we opted for, and the hypotheses we made.

2.1 The internet as a graph

Efforts to map the internet graph take place at two levels. One is the autonomous system (AS) connectivity graph, which can be constructed from BGP announcements (captured for instance by The Oregon Route Views Project [15]). The other is the router and IP graph, which can be obtained using traceroute and similar tools from a number of different points in the network. To our knowledge, skitter, which conducts traceroutes from on the order of 30 servers to on the order of a million destinations, is the most extensive ongoing effort at the IP level.

Neither level is ideally suited to the task of modeling the behavior of routes at the router level. While the AS graph is directly based upon routing information, it is too coarse-grained to capture the details of path inflation. For this study, we therefore focussed on the IP and router level.

The main problem with this level is that what one actually sees is the graph of IP interfaces, while the graph of routers is more relevant. One single node in the router graph appears as several separate nodes, one or more for each of its interfaces, in the IP graph. Ideally, then, one would construct the router graph using methods to "disambiguate" IP addresses, such as the alias resolution techniques described by Pansiot et al. [16], and by Govindan et al. [17] for *Mercator*. There are also techniques, such as those used by Spring et al. [18,19], in *Rocketfuel*, and by Teixeira et al. [20], that take advantage of router and interface naming conventions to infer router-level topology.

We do not use the router graph, however. The disambiguation techniques, as applied for example in the *iffinder* tool from CAIDA [21], do not work by simple inspection of the IP graph; they require active probing, preferably simultaneously with graph discovery. This constraint makes extensive disambiguated router-level graphs much harder to obtain than IP interface graphs. At best, some core network topologies are available in this form thanks to Rocketfuel. But Rocketfuel is untested in stub networks. Finally, it is very difficult to judge the extent to which disambiguation is successful, and incomplete or incorrect disambiguation could introduce unknown biases.

To avoid these difficulties, we have restricted ourselves to the IP graph as obtained from skitter. The resulting caveat is that the graph may not be properly representative of the router graph. This caveat is however mitigated by the fact that the IP graph is a legitimate graph in its own right. As Broido et al. note [22], "interfaces are individual devices, with their own individual processors, memory, buses, and failure modes. It is reasonable to view them as nodes with their own connections." If a simulation does not require the explicit modeling of routers then a graph of interfaces can be perfectly adequate. Even more so since certain parameters, such as route lengths, are preserved. That is to say that a route that has a given length in the router graph has the same length in the corresponding IP graph. (Other parameters, such as node degree, will differ, and it is essential to take this into account when interpreting results.)

2.2 The data set

This study uses skitter data from July 2$^{\text{nd}}$ 2003. During that day, 23 servers targeting 594,262 destinations with 7,075,189 traceroutes. We merge these traceroutes to produce our IP graph. This graph captures the small-world, clusterized, and scale-free nature of the internet already pointed out in numerous publications, see for instance [23,24]. In particular, the average distance is approximately 12.54 hops, and the degree distribution is well fitted by a power law of exponent 1.97.

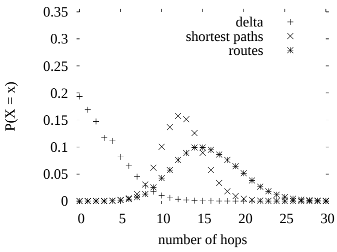
Notice that this graph is necessarily incomplete and biased due in particular to probing from a limited number of sources, to route dynamics, to tunneling and to erroneous or absent responses to traceroute probes. Biases of graphs induced by acquisition through a small number of traceroute monitors have been studied for instance in by Lakhina et al. [12]. However, recent studies by Dall'Asta et al. [25] and Guillaume et al. [14] show that one may be quite confident of the accuracy, using this kind of exploration, of distances and degrees, which are the main properties that we study here. We therefore consider the IP interface graph in this study, and in particular we use the skitter data as it represents the current state of the art in its extent and accuracy.

3 Statistical properties of routes

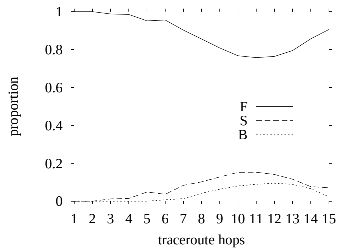
This section presents a set of properties for statistical description of internet routes. These properties motivate the models of Sec. 4. Several properties have already been studied in previous work, and the work here serves to evaluate and update them.

3.1 Route lengths

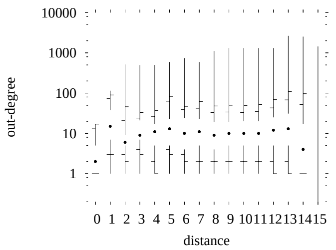
It is well known that routes are not shortest paths: they are not optimal in general. Fig. 1(a) shows the length distributions of the routes in our data set, and of the corresponding shortest paths. It also shows the distribution of the difference (*delta*) between the length of a route and the corresponding shortest path. The mean length of 15.57 hops for routes in this data set fits closely Paxson's observations [2] on a data set from nine years prior. The shortest paths have a mean length of 12.55 hops (11.4 hops if the graph is considered to be undirected).



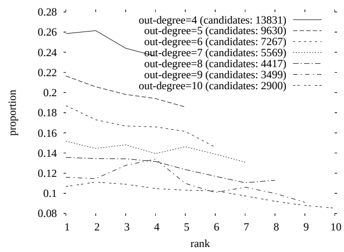
(a) Distributions of route lengths, shortest path lengths, and their differences



(b) Hop direction in 15-hop routes (F: Forward, S: Stable, B: Backward)



(c) Quantiles for the out-degree of nodes along routes of length 15. (See Footnote 1 for details.)



(d) Choice of next hop as a function of its degree ranking. Starting from nodes of degree 4 through 10.

Fig. 1: Statistical properties of internet routes.

The delta distribution confirms Tangmunarunkit et al.'s observation [5,4], mentioned at the beginning of this paper, that roughly 80% of routes are not shortest paths. In this data set, 19.34% of routes are shortest paths. Moreover, since the data is incomplete, there are undiscovered links, which implies that 19.34% is an overestimate.

3.2 Hop direction

When a packet travels from one router to another, it may move closer to its destination, but also it may move farther, or it may move to an interface that is at the same distance from the destination as one it just left. Likewise, the distance from the source may increase, decrease, or stay constant. We will call these behaviors the *hop direction*, considered with respect to either the destination or the source. In principle, a hop should always increase the distance from the source and decrease the distance to the destination; in such cases, the route is a shortest path. Note that hop directions in the router graph can be observed directly in the interface graph, since distances are preserved between the two graphs.

We determine hop direction by computing the shortest path from each traceroute source to all other nodes, using breadth-first search. This is feasible due to the small number of sources. It would also be natural to look at hop direction with respect to the destinations but, since they are much more numerous, it is computationally expensive.

We found that 87.3% of hops go forwards, 4.6% go backwards, and 8.1% remain at the same distance from the source (we call these *stable* hops). More precisely, Fig. 1(b) shows the portion of forward, backward, and stable hops at each hop distance for routes of 15 hops (the most numerous ones). Note that, as one would expect, the first and last few hops are generally forward because there are few alternatives. On the contrary, in the core of the network a significant proportion of the hops (more than one third) do not go closer to the destination. This type of behavior has already been described in the literature as the product of policy-based routing in the core of the internet. As Tangmunarunkit et al. [5,4] note, such behavior may be induced by load balancing, commercial considerations, etc.

3.3 Degree evolution along a route

Recent work has shown that many real-world complex networks tend to have very heterogeneous degrees, well fitted by power laws. This is in particular true for the internet, as observed by Faloutsos et al. [23] and others. Moreover, most of the short paths between pairs of nodes in these networks tend to pass through the highest degree nodes. Actually, almost all paths (not only short ones) tend to pass through these nodes, which make them essential for network connectivity, see for instance [26,27,28,29,30].

These observations lead us to ask how the node degree evolves along a route. If routes tend to pass through high degree nodes, where do they do so, and what degree nodes do they encounter? Furthermore, does this tendency to pass through high degree nodes imply that, when a choice exists between next hops, the next hop that leads to the highest degree node is generally chosen?

Fig. 1(c) shows[1] how node degree evolves for routes of length 15. It reveals that a typical route does not pass through the highest degree nodes, though a certain number of routes do pass through some very high degree nodes. There is a peak in median outdegree observable at distance 1. The median falls at distance 2, rises again, and then

[1] In Fig. 1(c), dots indicate the median. Vertical lines run from the min to Q1 and from Q3 to the max. Tick marks indicate the 5^{th}, 10^{th}, 90^{th} and 95^{th} percentiles.

stays fairly flat out to distance 13, with a median degree of about 10. This leads us to the following interpretation: the hosts have low degree, they are connected at their first hop router to relatively high degree nodes which play the role of access points, and then packets are routed in a core network where the degree (typically 10) does not depend much on the distance from the source or from the destination.

Can one observe a simple local rule governing degree evolution? In particular, if there is a choice of next hop interface along a route, is there a correlation between the degree rank of an interface and its probability of being chosen? For instance, are higher degree interfaces chosen preferentially over lower degree ones? Note that such a rule could be perfectly compatible with the observed flat degree evolution.

Fig. 1(d) plots the probability that a packet travels to an interface's i-th ranked neighbor, where the neighbors are ranked from highest out-degree to lowest. An interface's neighbors are its possible next hops in the directed graph. In order to preserve the greatest detail in this middle range, the figure does not show curves for degrees 2 or 3, or above 10, but the curves shown are typical. One can see a general bias towards higher degree nodes, though this bias is rather small, and sometimes is reversed.

4 Route models

The previous section provides a set of simple statistical tools to capture some properties of routes in the internet. We now propose three simple models (only two of which we eventually retain) designed to capture these features. Each model is based upon one statistical property studied in the previous section. Our approach is to model a property in a very simple way and then use other statistics to validate or invalidate the model.

Whereas our study of route properties was in the context of the directed graphs produced by traceroute, the models in this section are proposed for undirected graphs. The graphs available for simulation purposes, notably those produced by topology generators representing the router-level topology, are typically undirected graphs. Therefore, our models must be suitable for use in this context.

4.1 Path length model

The path length model is the simplest and the most obvious one conceptually, but it proves to be unusable in practice. The model aims at producing routes of the same lengths as real ones. As discussed in Sec. 3, a real route length typically exceeds that of the shortest known path by some small integer value $\delta \geqslant 0$.

In order to construct a route from a source s to a destination d, the path length model first computes the length ℓ of a shortest path from s to d. Then it samples a deviation δ from a distribution such as the one shown in Fig. 1(a), and a route is generated by choosing a path at random from s to d among the ones which are loop-free and have length $\ell + \delta$. This ensures that the difference between shortest path lengths and actual route lengths will be captured by the model.

To choose such a path at random implies however that one must construct all of the loop-free paths of length $\ell + \delta$ from s to d. In practice, the computation required to generate this number of paths may be prohibitive, since even in simple cases it is exponential in $\ell + \delta$. For example, in trying to generate all paths of length 21 between a pair of nodes in the skitter graph, we enumerated 1,206,525 possible paths. Therefore, despite its simplicity, we will not consider this model further.

4.2 Random deviation model

The random deviation model is based upon the idea that a route usually follows a shortest path, but might occasionally deviate from it. Our model uses a single parameter, p, the probability at any point of deviating from the current shortest path to the destination, if such a deviation is possible. We tuned the value of p to generate routes of realistic length. For the undirected version of the skitter graph, we found $p = 0.2$ to work well.

A random deviation route from source s to destination d is therefore based upon a shortest path u from s to d. At each hop, with probability $1 - p$, the route continues along u. But with probability p it will, if possible, deviate off u to another path. A deviation from current node x to a neighboring node y is deemed possible only if there is a shortest path w from y to d that does not pass through x. Should there be a deviation, the route continues along w to d (unless another deviation should occur). The model is precisely described by Algorithm 1.

Note that large numbers of routes to a destination d can be efficiently generated with the random deviation model once a shortest path tree rooted at d has been computed.

1: rand_dev_route (G,s,d,p)

```
Input    : A network G, a source s, a destination d, a deviation probability p.
Output   : An artificial route v from s to d in G, following the random deviation model.
Function: sp(x,y) returns the set of all the shortest paths from x to y in G.
begin
    u ← random element of sp(s,d);
    v ← empty list;
    copy the first element of u to the end of v;
    remove it from u;
    while the last element of v is not d do
        if rand[0,1] ⩽ p then
            C ← set of all the shortest paths from any neighbor of v to d;
            Remove from C the paths containing the last element of v;
            if C ≠ ∅ then
                u ← random element of C;
        copy the first element of u to the end of v;
        remove it from u;
    return v;
end
```

4.3 Node degree model

Several previous authors [31,27,32] have tried to use the heterogeneity of node degrees to compute short paths in complex networks. The basic idea is that a path which goes preferentially towards high degree nodes tends to see most nodes very rapidly (a node is considered to be seen when the path passes through one of its neighbors).

The node degree model is based upon a similar approach, as follows. Two paths are computed, one starting from the source and the other from the destination. The next node on the path is always the highest degree neighbor of the current node. The computation terminates when we reach a situation where a node is the highest degree neighbor of its own highest degree neighbor. One can show that this is the only kind of loop can occur. Then, one of two cases applies: either the two paths have met at a node, or they have not. In the first case, the route produced by the model is the discovered path (both paths are truncated at the meet up node, and are merged). In the second case, we compute a shortest path between the two loops, and then obtain the route by merging the two paths and this shortest path, removing any loops.

In work proceeding in parallel with this paper [32], the node degree model is shown to be an efficient way to compute short paths in complex networks in practice: the obtained paths are very close to shortest ones. Moreover, the computation of the tree-like structure where each node points to its highest degree neighbor is very simple and only has to be processed once. Likewise, the shortest paths between a small number of loops are computed only once. The overall model is described in Algorithm 2.

2: $\mathrm{node\_deg\_route}\ (G,s,d)$

Input : A network G, a source s, a destination d.
Output : An artificial route v from s to d in G, following the node degree route model.
Function: reverse(p): returns the path obtained by reading p from the end to the beginning.
climb_degrees(G,v): returns the path in G obtained from v by going to the highest degree neighbor at each hop, until it loops.

begin
    $p_s \leftarrow \mathrm{climb\_degrees}\ (G,s)$;
    $p_d \leftarrow \mathrm{climb\_degrees}\ (G,d)$;
    if p_s *and* p_d *meet up* **then**
        let u be the first node they have in common;
        remove from p_s all the nodes after u;
        remove from p_d all the nodes after u;
        $p \leftarrow (p_s,\mathrm{reverse}(p_d))$;
        return p;
    $q \leftarrow$ random shortest path from the last node of p_s to the one of p_d;
    $p \leftarrow (p_s,q,\mathrm{reverse}(p_d))$;
    remove loops from p;
    return p;
end

Fig. 2 is an example. There are three tree-like structures (the shaded areas). The source s belongs to the leftmost one, which is rooted at r_s, and the destination d to the rightmost one, with root at r_d. Each directed link goes from one node to its highest degree neighbor (the dotted lines are links which do not satisfy this). When one wants to build a route from s to d according to the node degree model, one first finds the path from s to r_s, and the one from d to r_d. One then has to compute a shortest path from r_s to r_d, which has length 5 in this example. The final route is obtained by merging these paths, and then removing the loops (which leads to the removal of a link, in our example). It has length 7 (while the shortest path has length 6).

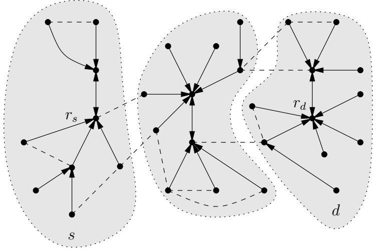


Fig. 2: The node degree model: example.

5 Evaluation

This section compares the performance of the random deviation and node degree models to that of the shortest path model. We use undirected version of the skitter graph described in Sec. 2.2, considered as an undirected graph. For each model, we chose at least 60,000 (source, destination) pairs at random from amongst the nodes of the graph and generated an artificial route from the source to the destination. We compute the same statistics on these routes as we had computed for actual routes in Sec. 3.

Fig. 3 shows the statistics for each model. We judge the quality of a model by how well its statistics mirror those for actual routes, shown in Fig. 1.

Comparing the route length distributions, we find that both models generate distributions that are symmetric, average somewhat higher than the shortest path distribution, and have tails similar to the actual route length distribution shown in Fig. 1(a). Mean route length is 15.15 for the random deviation model and it is 14.96 for the node degree model, whereas the mean shortest path is 12.93. (Note that, on the undirected skitter graph, shortest paths between random sources and destinations are longer on average than those between skitter sources and destinations, for which we had computed an average route length of 11.21.)

Lengths of paths generated with the node degree model tail off somewhat quicker than in reality (approaching zero closer to length 20 than length 25), but the degree of fidelity is nonetheless remarkable given that the length distributions are not explicitly part of the model. The random deviation model generates more routes that are shortest paths than in reality (roughly 30% compared to roughly 20%), whereas the node degree model generates somewhat fewer (roughly 26%). As is already known, the shortest path model does not capture the length properties.

Looking at the hop directions for the most frequent route length, we found that the curves for the random deviation model better match the shapes of the curves for real routes shown in Fig. 1(b). Hops are mostly forward near the source, but dip to around 80% roughly ten hops out (whereas in reality the portion of forward hops dips to around 80% at eleven or twelve hops out). This is in marked contrast to hop directions produced by the node degree model because forward hops dip much sooner and a bit less steadily. But overall portions of forward, stable, and backward hops closely match reality for both models: 89% forward, 7% stable, and 4% backward for the random deviation model, and 90% forward, 6% stable, and 4% backward for the node degree

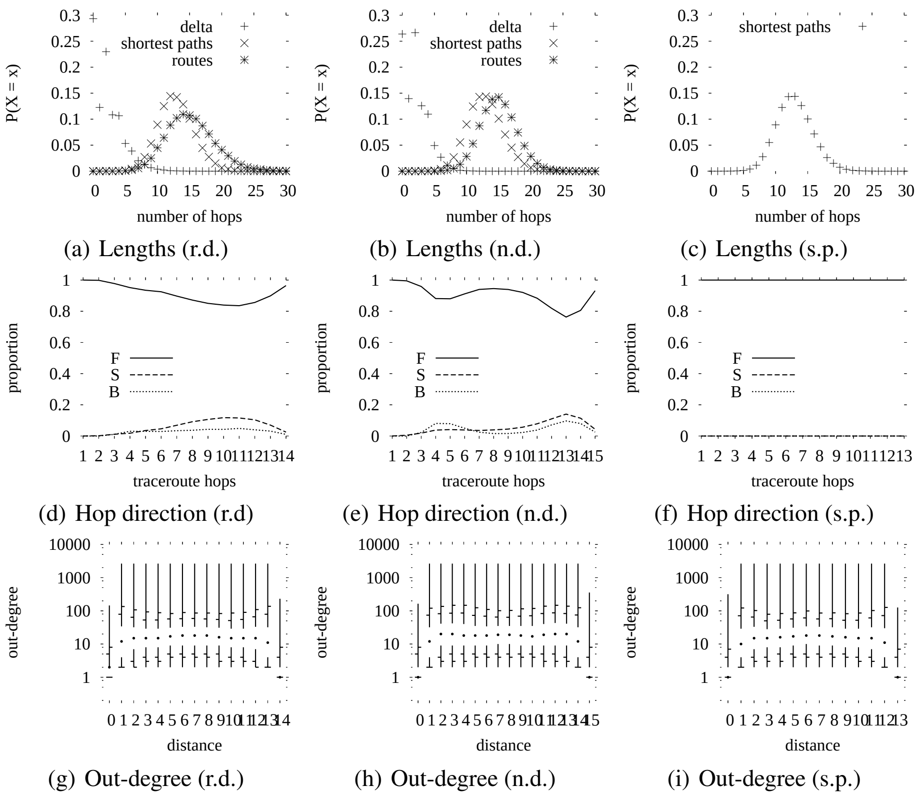


Fig. 3: Experiments using the *random deviation model* (left), the *node degree model* (center), and the *shortest path model* on the undirected skitter graph using sources and destinations chosen at random from amongst all the nodes in the graph.

model, compared to 87% forward, 8% stable, and 5% backward for true routes. The shortest path model fails to capture these proportions since all of its links are forward.

The node degree model does a better job than the random deviation model in capturing the evolution of the out-degree close to a route's source. Routes generated with this model show the peak in the out-degree before settling down to a median around 20 that we noticed in Fig. 1(c), though the peak is reached at distance 2 rather than at the first hop router. The random deviation model and the shortest path model also have a median around 20, but they arrive there through a smooth increase, with no clear peak.

Based upon this comparison to real routes, we can state that the random deviation and node degree models do a reasonable job of emulation, though each model captures some aspects better than others, and their strengths are different. Both models clearly out-perform the shortest path model.

6 Conclusion and future work

The main contribution of this paper has been to propose a new alternative for the simulation of routes in the internet: the use of simple models that capture non-trivial statistical properties of routes. The models proposed here have been found to reproduce a number of aspects of true internet routes, though neither fully captures all of the characteristics. Our goal was to introduce simple models that could serve as alternatives to the clearly unrealistic shortest path model. No model can be fully faithful to reality, and the key is to understand in what ways it is a true representation, and in what ways it diverges. Future work along these lines might include the development of models that explicitly incorporate some additional characteristics, such as the clustering coefficient. Other work might involve studying whether certain variants on the models, such as a hybrid of the random deviation and node degree approaches, would be more like real routes. Any such work must keep in mind the desirability of keeping the models conceptually simple, easy to implement, and computationally tractable.

Another area into which this work could be extended would be to capture something of the dynamics of internet routes. There are effectively random choices to be made in both the random deviation model (clearly) and the node degree model (when it comes to choosing among two or more neighbors of highest degree, or choosing a shortest path between two trees) but we have not touched on the timing of that variation.

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