Inferring Catchment in Internet Routing

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ABSTRACT

BGP is the de-facto Internet routing protocol for interconnecting Autonomous Systems (AS). Each AS selects its preferred routes based on its routing policies, which are typically not disclosed. Due to the distributed route selection and information hiding, answering questions such as "what is the expected catchment of the anycast sites of a content provider at the AS-level, if new sites are deployed?", or "how will load-balancing behave if an ISP changes its routing policy for a prefix?", is a hard challenge. In this work, we propose a framework and methodology to infer the routing behavior in existing or hypothetical routing configurations, and provide new capabilities and insights for *informative* route inference (e.g., isolating the effect of randomness that is present in prior simulation-based approaches). The proposed framework can be useful in a number of applications: measurements/monitoring, traffic engineering, network planning, Internet routing models, etc.

CCS CONCEPTS

• **Networks → Network performance analysis**; *Network performance modeling*; Network structure; Network management.

KEYWORDS

Border Gateway Protocol (BGP); Internet Routing; IP Anycast; Catchment Inference; Internet Measurements.

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1 INTRODUCTION

Networks establish routes at the level of Autonomous Systems (AS) using the policy-based, destination-oriented, path-vector Border Gateway Protocol (BGP). While ASes control their own routing decisions (by setting their BGP/routing policies), they typically *do not have control or even knowledge of how other networks route traffic to them.* However, this knowledge is important for many applications such as network planning, monitoring, IP anycasting, or traffic engineering. Specifically, for a destination network n_{dst}, it is of particular interest to know from which of its *ingress points* (*e.g.,* border routers) it should expect to receive traffic from other networks under a given routing configuration.

While a network n_{dst} can (partially) measure the *catchment* of an ingress point m (*i.e.,* the set of networks that route their traffic to n_{dst} via m) [3], *measurements can be used only for an existing deployment.* For network planning, traffic engineering, etc., it is important to be able to predict the catchment in hypothetical scenarios, *e.g.,* for evaluating a large number of possible routing configurations (*e.g.,* new anycast sites or peering links). A common approach to predict routes is to use BGP simulations on top of topology/routing models, such as the valley-free model [4] or other variants [5]. However, due to the coarse-grained knowledge of the real policies [2], many routing decisions are arbitrarily selected in simulations (*e.g.,* random tie-breaking); a simulation yields only one of all the possible outcomes. Thus, *simulation-based approaches can lead to a prediction that is heavily affected by the introduced randomness,* without revealing what is the effect of this randomness, *i.e.,* how many routes are affected by an arbitrarily chosen policy.

In this work, we revisit the challenging problem of route / catchment inference, and propose a framework and methodology that *enable an informative inference or prediction for the catchment of the ingress points of a network, under a given (existing or hypothetical) topological and routing configuration.* Our methodology can be applied on top of any given topology/routing model and set of policies (even when only coarse estimates of them are available). We infer with certainty or probabilistically the catchment under a routing configuration, while isolating the effect of randomness (*i.e.,* incomplete/inaccurate information) and revealing the important factors that affect the catchment (*e.g.,* specific networks or policies).

This paper is an extended abstract of [7], where we present in detail the inference methodology, evaluate it through simulations and real-world experiments, provide insights, and discuss its applicability in network management and operations. The code for an implementation of the proposed methods is available in [6].

2 MODEL & NOTATION

We assume a network with a set of nodes $\mathcal{N}$ and edges $\mathcal{E}$. A node n_{dst} announces a prefix to its neighbors through a set of *ingress points* $\mathcal{M}$. Nodes use BGP to establish routing paths to the destination; let $p_{i\rightarrow n_{dst}} = [i, j, ...n_{dst}]$ be a path from node i to n_{dst}. Nodes learn paths to n_{dst} from their neighbors, store them in their routing table (RIB), and select one of them as the best path $bp_{i\rightarrow n_{dst}}$.

Let $Q = \{q_{ij} \in \mathbb{R} : i, j \in \mathcal{N}, e_{ij} \in \mathcal{E}\}$ be the set of *local preferences* that nodes have for their neighbors. A node i selects as $bp_{i\rightarrow n_{dst}}$, the path in its RIB learned from the neighbor with the highest local preference. If the local preference for two neighbors j and k is equal ($q_{ij} = q_{ik}$), then the selection is based on other

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criteria ("tie-breakers"). Node i advertises (exports) $bp_{i \to n_{dst}}$ to all/some/none of its neighbors. We denote the set of export policies as $\mathcal{H} = \{h_{ijk} \in \{0,1\} : i,j,k \in \mathcal{N}, e_{ij}, e_{ik} \in \mathcal{E}\}$, where $h_{ijk} = 1$ denotes that i exports to k a path learned from j (and $h_{ijk} = 0$ otherwise). In practical setups it holds that $q_{ij} = q_{i\ell} \Rightarrow h_{ijk} = h_{i\ell k}$.
Eligible path *of i to n_{dst}, is a path $p_{i \to n_{dst}}$ that conforms to the routing policies $\mathcal{Q}$ and $\mathcal{H}$, and can be selected by i as its $bp_{i \to n_{dst}}$.*

If a neighbor j of n_{dst} is connected to n_{dst} through ingress point m, we denote $j \triangleright m$. For a node i with $bp_{i \to n_{dst}} = [i, ..., j, n_{dst}]$ (*i.e.,* through node j, $j \triangleright m$), we denote $bp_{i \to n_{dst}} \triangleright m$ and $i \triangleright m$.
Catchment *of an ingress point m is the node set $\{i \in \mathcal{N} : i \triangleright m\}$.*

In many cases we cannot determine a single best path for a node; we capture this uncertainty with the *route probability*:

$$\pi_i(m) = Prob\{bp_{i \to n_{dst}} \triangleright m\}, \ i \in \mathcal{N}, m \in \mathcal{M} \tag{1}$$

Furthermore, we define the *routing function* $f : \mathcal{N} \to \mathcal{M} \cup \{0\}$ that maps nodes ($i \in \mathcal{N}$) to ingress points ($m \in \mathcal{M}$) as:

$$f(i) = \begin{cases} \text{m} & \text{, if } \pi_i(m) = 1 \quad \text{(certainty)} \\ 0 & \text{, otherwise} \quad \text{(uncertainty)} \end{cases} \tag{2}$$

3 INFERENCE METHODOLOGY

The R-graph. We propose a graph structure, the R-graph (denoted as $\mathcal{G}_R$, with nodes $\mathcal{N}_R = \mathcal{N}$ and edges $\mathcal{E}_R$), which is a directed acyclic graph rooted at n_{dst} and encodes all the eligible paths $\forall i \in \mathcal{N}$. To construct $\mathcal{G}_R$, we simulate BGP with arbitrary tie-breaking , and $\forall i \in \mathcal{N}$ we retrieve its RIB and add in $\mathcal{E}_R$ directed edges from all nodes in the set $C_i = \{j \in P_i : q_{ij} = max_{k \in P_i} q_{ik}\}$ to i, where $P_i = \{j \in \mathcal{N} : \exists \, p_{i \to n_{dst}} = [i, j, ..., n_{dst}] \text{ } in \text{ } RIB_i\}$.

Theorem 1. *A path $p_{i \to n_{dst}}$ is eligible* iff *there is a sequence of directed edges in $\mathcal{G}_R$ that starts from n_{dst} and leads to i.*

Certain Inference. Leveraging the R-graph, we can infer for some nodes through which ingress point they route to n_{dst}. A certain inference is made when all the eligible paths of a node i are through the same ingress point, *i.e.,* $f(i) = m$ only when $f(j) = m, \forall j \in \{k : e_{ki} \in \mathcal{E}_R\}$. To calculate certain inferences efficiently (*i.e.,* without enumerating all eligible paths), we calculate a topological sort of $\mathcal{G}_R$, and check for each node (in that order) the above condition.

Probabilistic Inference. For some nodes a certain inference may not be possible (*i.e.,* $f(i) = 0$). However, we can still provide useful information about the possible routes, by calculating the probabilities $\pi_i(m), \forall i \in \mathcal{N}, m \in \mathcal{M}$. We can efficiently calculate these probabilities, by following a topological sort of $\mathcal{G}_R$, and calculating $\forall i$ the values $\pi_i(m)$ from the probabilities of its parent nodes:

$$\pi_i(m) = \textstyle\sum_{j \in C_i} \pi_j(m) \cdot \frac{1}{|C_i|}, \qquad C_i = \{k : e_{ki} \in \mathcal{E}_R\} \tag{3}$$

Inference under Oracles. In existing deployments, one can conduct measurements to determine the routes of the measured nodes $\mathcal{S}$, $\mathcal{S} \subseteq \mathcal{N}$. Using oracles/measurements for a node set $\mathcal{S}$, the R-graph enables inference for a set $\mathcal{S}'$, $\mathcal{S}' \supseteq \mathcal{S}$, *i.e.,* for more nodes than those measured, thus enhancing measurement techniques. This is done by checking recursively $\forall i \in \mathcal{S}$: (i) the condition of certain inference for all its children nodes (inference for i's children), and (ii) given that $i \triangleright m$, whether *only one* node j of i's parent nodes has $\pi_j(m) > 0$ (then $f(j) = m$; inference for i's parents).

Preference of Shorter Paths. $\mathcal{G}_R$ encodes all eligible paths, determined by the local preferences $\mathcal{Q}$. If nodes use the AS-path length to break ties for paths from neighbors of equal preference (this is a common practice [1]), we can incorporate this information in $\mathcal{G}_R$, by removing edges from $\mathcal{E}_R$ that correspond to eligible paths that are always longer and thus never preferred by a node.

4 DISCUSSION

We discuss some main insights, as well as results from the evaluation of our methodology in realistic simulations (with AS-relationships [2] and valley-free routing [4]) and real experiments.

Informative inference. The proposed methodology enables an informative inference. It goes beyond simulation-based approaches, which return only an instance of a possible catchment, *i.e.,* a sample from the distribution defined by the route probabilities $\pi_i(m)$, without revealing further information. Our methodology can identify whether a route inference is a result of randomness (uncertain inference) or not (certain inference), and also calculates the exact effect of this randomness (*i.e.,* the values $\pi_i(m)$).

Lightweight inference. Averaging the route of i over several simulation runs, gives a value that converges to $\pi_i(m)$. Our results show that around 100 runs are needed for convergence, while our methodology predicts this value in time almost equal to 1 simulation run. This reduced complexity becomes very important for applications where a large number of scenarios need to be evaluated (selection of ingress points, traffic engineering design, vulnerability analysis, network management with reinforcement learning, etc.).

R-graph structure. The R-graph encodes efficiently all the eligible paths, and enables a certain inference even for nodes with 1000*s* of eligible paths. A naive inference would infer the routes of one order of magnitude less nodes. Moreover, the structure of the R-graph reveals what are the important factors that affect the catchment and/or the inference: (i) Measurements can be targeted to the set of nodes that maximizes the inference (under oracles); our results show that an R-graph-based selection of measurements, can lead to much more complete inference (*e.g.,* 1000s of extra routes inferred). (ii) The edges appearing in the R-graph denote links/policies that affect catchment. Similarly, nodes with many children in the R-graph are more important than leaf nodes. Focusing on these edges/nodes, *e.g.,* when designing traffic engineering policies (such as path-prepending actions or deployment of new anycast sites) or building routing models, can lead to better decisions and higher accuracy; for example, "correcting" important links for the inference, yielded 10%-20% higher accuracy in our real-world experiments.

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