Future Generation Computer Systems 95 (2019) 212–220

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

A data-driven method for future Internet route decision modeling

Zhihong Tian [a], Shen Su [a,*], Wei Shi [b], Xiaojiang Du [c], Mohsen Guizani [d], Xiang Yu [e]

[a] *The Cyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou, China*
[b] *School of Information Technology, Carleton University, Ottawa, Canada*
[c] *Department of Computer and Information Sciences, Temple University, Philadelphia, USA*
[d] *Electrical and Computer Engineering Department, University of Idaho, USA*
[e] *Taizhou University, China*

HIGHLIGHTS

- We propose a data-driven model for the inter-domain route decision process with deep learning method, which learns, understands, and models the route decision process without the priori knowledge.
- We propose a set of deep learning resolution to our model with structure, characterization, feature selection, and training data construction.
- We discuss the effectiveness of our paper with detailed cases, indicating that our model outperforms the AS business relationship model.

ARTICLE INFO

Article history:
Received 15 May 2018
Received in revised form 3 December 2018
Accepted 22 December 2018
Available online 4 January 2019

Keywords:
Deep learning
BGP route decision process
Data-driven modeling
Future Internet

ABSTRACT

Simulating the BGP routing system of Internet is crucial to the analysis of Internet backbone network routing behavior, locating network failure and, evaluating network performance for future Internet. However, the existing BGP routing model lacks in the coarse modeling granularity and the priori knowledge based model. The analysis of BGP routing data that reflects the routing behaviors, directly impacts the BGP routing decision and forward strategy. The efficiency of such analysis dictates the time it takes to come up with such a time-critical decision and strategy. Under the existing model, BGP routing data analysis does not scale up.

In this paper, we analyze the inter-domain routing decision making process, then present a prefix level route decision prediction model. More specifically, we apply deep learning methods to build a high-precision BGP route decision process model. Our model handles as much available routing data as possible to promote the prediction accuracy. It analyzes the routing behaviors without any prior knowledge. Beyond discussing the characteristics of the model, we also evaluate the proposed model using experiments explained in detailed cases. For the research community, our method could help in detecting routing dynamics and route anomalies for routing behavior analysis.

1. Introduction

Internet is composed of tens of thousands of Autonomous Systems (AS). Such ASes run their network individually, and exchange their routing information using inter-domain routing protocol, which is Border Gateway Protocol (BGP) in real-life deployment. In spite of the growing trend of discussing the next generation networking, the distributed management framework of Internet can hardly be changed due to its economic, political, geographical involvements.

Inter-domain routing protocol plays a dominant role in the maintenance and management of Internet. Appropriate protocol configurations could significantly improve network performance. On the contrary, inappropriate protocol configuration could be a disaster to the regional network, or even the whole Internet. It has been decades since the research community realized the importance of understanding, analyzing, and predicting the inter-domain routing behaviors, then modeling BGP network's route decision process. Unfortunately, modeling the route decision process is a non-trivial problem. An AS's BGP configuration involves its business secret, thus AS administrators never share their network's BGP configuration. The only way to conduct route decision modeling is to compare the input and output of the route decision process, then construct a general mapping from the input to the output. However, for BGP, the same route decision result could be reached after a series of equivalent configurations on the granularity of prefix. Due to different economic interest, traffic engineering objectives and political reasons, practical configurations of BGP are

* Corresponding author.
E-mail addresses: tianzhihong@gzhu.edu.cn (Z. Tian), sushen@gzhu.edu.cn (S. Su), wei.shi@carleton.ca (W. Shi), dxj@ieee.org (X. Du), mguizani@uidaho.edu (M. Guizani), 1267013@qq.com (X. Yu).

https://doi.org/10.1016/j.future.2018.12.054
0167-739X/

always different. Therefore, to form a general routing model for BGP's route decision process that satisfies most cases is always a challenge.

Generally, existing work models the route decision process based on prior experience, which means analyzing data, making assumptions, building a model, and finally verifying the correctness of the model. Such manner takes the route decision process as a white box, which explains explicitly how and why the model works. However, it leads to the following limitations of the route decision model:

First, researchers have to make the right assumption in the first place. Due to the reasons discussed above, such assumption can hardly fit all ASes de facto BGP configurations, thus limits the accuracy of the model. For example, AS business relationship model, the most famous routing model, assumes that the AS administrators always run their network based on their business relationships with their network's neighboring ASes. The model has been proven to be correct. However, recent work has found more and more counterexamples of this AS business relationship model. Growing amount of supporting BGP data has indicated that the de facto AS relationship is actually more complex than the AS business relationship. As a result, the AS business relationship model does not work for applications that need understanding of certain routing behaviors in a finer granularity (e.g. in prefix level).

Second, since adjustment on the model according to the input/output data is an inevitable , the structure of the white box (the model) must not be too complex to conduct any adjustment. As a result, the estimation of the model parameters can only be performed on a limited quantity of BGP data. Thus the accuracy of the route decision model can hardly be improved when the available BGP data increases. For example, since 2001, when the AS business routing model was first proposed, the amount of observable BGP data has been increased by 2 orders of magnitude, and the amount of BGP data is still growing. Such available data should reveal more detailed information of an inter-domain routing system. However, due to the limited expressiveness of the existing white box routing models, the accuracy and performance of the existing routing models are limited.

In recent years, deep learning technology is developing rapidly, which gives us an opportunity to model the BGP route decision process in a smarter way, i.e. to conduct data-driven modeling on the route decision process directly from the routing data, without understanding or explaining everything. With deep learning methods, we can form a general classification model to work as the route decision process. It learns from the available BGP data all by itself, then reveals possible configurations of BGP protocol. Intuitively, the accuracy of the route decision process model should be improved with the growing amount of BGP data, since theoretically, the more input data fed to the neural network structure, the more accurate the results. However, few existing works dedicate to model the route decision process by means of deep learning methods.

Considering the limitations of existing white box routing models, we propose to view the route decision process as a black box, and try to solve the route decision process modeling problem using deep learning methods. Since the route decision process takes the candidate routes as inputs, then outputs the optimal route, we model it as a classifier which distinguishes the optimal route from other candidate routes. Fundamentally, the challenges of this modeling problem include (1) model structure rationality discussion and, (2) parameter estimation for the model for each AS. In this paper, we focus on the former. We also discuss the model structure, the characterization of candidate routes, the training data set construction as well as the model evaluation.

The contributions of this paper are three folds:

(1) We propose to model the route decision process using a data-driven method, which enables us to focus on the efficiency of our networking model, without the explanation of model structure during the construction phase.

(2) We propose an efficient supervised learning resolution for the route decision process modeling, including the characterization, feature selection, and training data set construction modules. Our deep learning resolution ensures the scalability of the route decision process modeling, so that the model accuracy improves with the growth of the available BGP data.

(3) We investigate the feasibility of our model with open source BGP data based case study evaluation. We also compare our model with the AS business relationship model, proving its effectiveness for route decision modeling in finer granularity. We then discuss possible further applications of the proposed model in data analysis, network modeling and prediction.

The rest of the paper is organized as following. First we introduce related works in Section 2. Then we propose the general structure and details of our routing model, including the characterization, the training set construction, and how to tag the training data in Section 3. Next, we evaluate our model with comparison to the AS business relationship model using a case study presented in Section 4. Finally, we discuss the feasibility of our model in Section 5, then conclude the paper with future works to follow in Section 6.

2. Related works

2.1. Route decision process modeling

Researchers have been pursuing an appropriate model for inter-domain routing policy during the last two decades. Lixin Gao proposed AS business relationship [1], which is the first and most widely-used model on inter-domain routing policy. She partitioned routing policy into 3 classes: provider–customer, peer–peer, and sibling–sibling. Based on AS business relationship, she proved that a reasonable AS path should follow valley-free policy. Based on this model, there have been plenty of works on inferring AS business relationship [2–6]. Towards a finer granularity, works [7,8] use BGP atoms to represent groups of prefixes (originated by a given AS) that receive equivalent treatment by a set of BGP routers. Work [9] discusses the appropriate granularity of routing policy to model routing policy by comparing AS business relationships and BGP atoms. It also shows that a large fraction of path choices correspond to the selection of neighboring ASes choices. Work [10] proposes a SDN solution for the inter-domain routing of IXPs. Different from our work, they manage the inter-domain routing based on the management of virtual topology according to a manually predefined state machine.

Based on the above routing models, researchers [11–14] investigate both the intra-domain [11–13] and inter-domain [14] routing policies. For most cases, the AS business relationship works. However, due to reasons of the complex routing relationships, sibling ASes, prefix-specific policies, and filtering of more-specific prefixes, a non-trivial amount of incoherences exist in the Internet. Works [15–19] also contributes to related Internet and routing issues.

2.2. Feature selection methods

Based on the selection criterion, the feature selection methods can be roughly divided into three categories: filter, wrapper and embedded methods. A filter method [20–22] relies on the evaluation metrics such as correlation, dependency, consistency, distance and information to select features. A wrapper method [23] performs a forward or backward strategy in the space of all possible feature subsets, using a classifier to make choice among the subsets. Generally, this kind of method has high accuracy and is

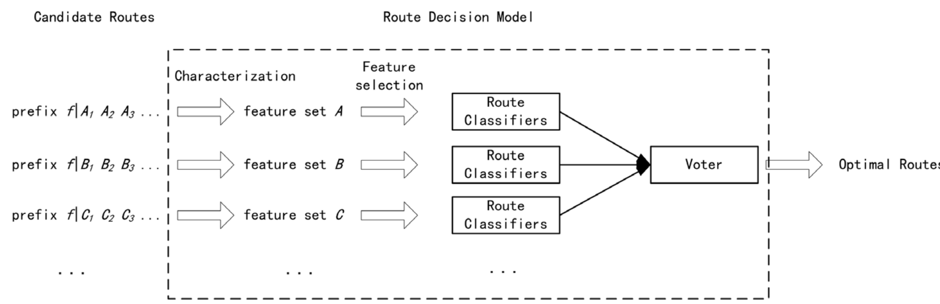

Fig. 1. Model structure.

about to find the features suitable for the predetermined learning algorithm. However, the exponential number of possible subsets makes this kind of methods computationally expensive. A embedded method [24–26] attempts to simultaneously maximize the classification performance and minimize the number of selected features by integrating the feature selection process into the model training process. It can provide suitable feature subset for the learning algorithm much faster than the wrapper methods, but the selected features may be not suitable for other learning algorithms.

3. Design of our route decision model

BGP's route decision process learns candidate routes from neighboring routers, ranking the preference of the candidate routes, and decides the optimal route. Herein, as a general model for the route decision process, our model takes the candidate routes information as input, and decides the optimal route as output.

Since BGP's route decision process decides the optimal for each prefix, our model also works in a per-prefix level. Since the route decision process ranks all candidate routes according to the same preference standard. We decompose the modeling problem to a set of sub problems which decides whether a candidate route is optimal. The structure of our route decision model works as following (shown in Fig. 1).

3.1. Model structure

For each prefix, our route decision model decides the optimal route among the set of candidate routes to the destination prefix. Since we aim at resolving our modeling problem in a deep learning way, we need to transform the origin samples (i.e. the candidate routes) to acceptable information for the neural networks. As a result, our route decision model first conducts characterization to generate a set of features of the candidate routes, which we will discuss in detail in Section 3.3. As a matter of fact, different ASes have various correlated features, which impact the effectiveness of the route decision modeling, thus we conduct further feature selection on the generated features. We will introduce our feature selection method in Section 3.4. The route classifier is a supervised training model, and we will discuss the generation of the labeled training data set in Section 3.2. The selected features are feed into the route classifier which determines whether the candidate route is optimal, more concretely, the possibility of the candidate route to be optimal. The voter collects the output of the route classifier for each candidate route, and decides the optimal routes for each prefix.

3.2. Labeled candidate route set construction

The route decision model works in a supervised way, i.e., we train our model with the labeled candidate routes. However, the BGP data we use for model construction is the public BGP data

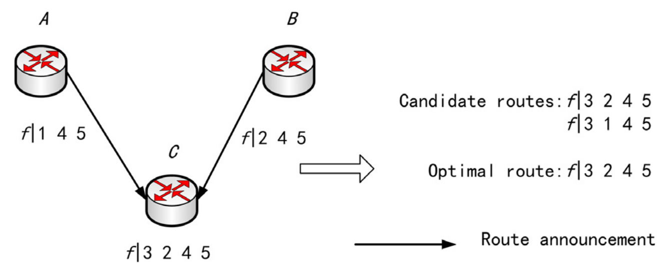

Fig. 2. Example of candidate route set construction.

set (e.g. Oregon data), which is routing table collected from BGP routers (i.e. the optimal route for each prefix). As a result, we need to generate the candidate route set ourselves together with the optimal-route labels.

Our idea for the data set construction is to rely on the data exchange between BGP monitors. Here, a BGP monitor refers the routers cited in an monitored AS which shares its routing table to the public data source. When monitors are cited in neighboring ASes, they would exchange their routing tables with each other, thus the candidate routes could be estimated according to the routing tables of monitors cited in neighboring ASes.

As shown in Fig. 2 is an example. Monitor A cites in AS 1; monitor B cites in AS 2, and monitors C cites in AS 3. Both AS 1 and AS 2 are neighboring ASes of AS 3. From the routing tables observed on monitor A and B, we observe the paths towards prefix f are "1 4 5" and "2 4 5" for AS 1 and AS 2 individually. Accordingly, AS 3 would receive the route announcement of "1 4" and "2 4 5" from AS 1 and AS 2 towards prefix f. Thus the candidate routes towards prefix f on monitor C should be "3 1 4 5" and "3 2 4 5".

Due to the existence of the out-bound filters, route announce from neighboring ASes could filtered, so that the corresponding candidate routes would not be received. For example, in Fig. 2, monitor A may set up filter rules which filter the out-bound route announcement of "1 4 5", so that the candidate route on monitor C would be just "3 2 4 5".

We resort to the historical routing updates to ensure the existence of candidate routes. Since the out-bound filter rules do not change frequently, we investigate the routing updates towards the same prefix during a recent period of time. If the candidate route could be observed in the routing updates, we consider that the candidate route exists.

To sum up, our methods to construct the labeled candidate route set of a target monitor works as following (shown in Alg. 1). The input of the algorithm includes the target monitor, the BGP monitor set, the snapshots observed on such monitors, and the historical routes derived by collecting the routing updates observed on the target monitor. The algorithm generates the labeled candidate route set for the target monitor. To that end, we search for the monitors cited in the neighboring ASes of the target monitor, and generate the candidate routes for each prefix of the target monitor according to the searched monitors. If the generated route could be observed during a recent historical period based on the routing updates observed on the target monitor, we add it to the candidate route set. To label the candidate route, we compare it with the snapshot of the target monitor, and label the candidate route observed in the target monitor's snapshot as the optimal route. The rest of generated candidate routes are labeled as non-optimal routes.

Algorithm 1 Labeled candidate route set construction algorithm.

Input:
a: The monitor cited in the target modeling AS;
M: BGP monitor set;
R: Snapshot observed on monitors;
H: Historical routes observed on monitors;
Output:
C: Candidate route set of the monitor a

Foreach m in M
  If a and m cite in a pair of neighboring ASes
    Foreach prefix p
      If "AS(a) $R(m, p)$" do not exists in $H(a, p)$ #AS(a) refers to the ASN of monitor a
        next;
      If "AS(a) $R(m, p)$" == $R(a, p)$
        label "AS(a) $R(m, p)$" as optimal
      Else
        label "AS(a) $R(m, p)$" as nonoptimal
      Add "AS(a) $R(m, p)$" to $C(p)$

3.3. Characterization

The labeled candidate route set is used for training the route classifier, which is realized by a neural network. Thus we need to extract a set of features from the candidate route to feed the route classifier. To ensure the effectiveness of the route classifier, the extracted features need to be impact factors of the route decision process.

On the perspective of network management motivations, there are mainly three impact factors for the route decision process control, including operating earnings, networks performance, and traffic engineering.

Operating earnings. The backbone of the Internet is composed of a number of ASes run by ISPs (Internet Service Providers). An ISP always want to make as much money as possible according to their business agreement. Thus the network administrators always prefer the routes which could bring more operating earnings. The AS business relationship model is based on such consideration, which classifies the AS relationships based on the charging mode of data transfer. For example, the traffic through customer networks usually makes more money than the traffic through provider networks.

Network performance. Data transferred on the Internet between hosts for communication usually need to traverse a number of ASes. The more ASes the transferred data traverse, the longer the round trip time would cost, leading to bad QoS (Quality of Service). To guarantee the network performance towards the target prefix, network administrators always prefer the routes with shorter AS path length.

Traffic engineering. For large scale ISPs, there are usually multiple next hop network access points. At the same time, a large amount of prefixes need to get through such access points after applying the above two principles. To conduct load balance to ensure none of the access points get congested. Network administrators usually conduct real-time traffic engineering, and configure the network to prefer different next-hop learned routes for different prefixes.

On the perspective of protocol configuration methods, the impacting factors are the route attributes considered (Local-pref, AS path length, Origin type, MED, etc.) in the route decision process for network configuration. Local-pref refers to the local configuration for the candidate route; AS path length refers to the quantity of the traversed ASes in the candidate route; Origin type refers to the origin of the candidate route (IGP > BGP). It also needs to be mentioned that the BGP route attributes could be configured based on BGP communities. BGP communities are declared by individual ASes, and marked on the routes traversing. A BGP router would configure the route attributes based on the BGP communities marked on the routes.

According to the above discussion, the next-hop ASes, the quantity of traversed ASes, the next hop access network point, and the target prefix are the dominant impacting factors in the route decision process. Since the candidate routes towards different target prefixes and the network access points usually traverse a set of different ASes. We believe we could represent the dominant impacting factors of each candidate route by the set of ASes the candidate route traversing.

Our method works as following, we first make a list of considered ASes as the feature vector for the candidate routes, noted as ASN digit list. Then we mark the feature vector for each candidate route, if the AS path of the route traverses certain AS in the list, we mark its corresponding ASN digit in the list.

3.4. Feature selection

The feature set we generate in the previous subsection could be at the length of tens of thousands. However, in most cases, there are no more than ten ASes in all candidate paths. The feature information content could be really sparse. A number of ASN digits are seldom used, and turn out to be noisy data to the route decision modeling. As a result, we conduct feature selection to improve the feature information content density.

Unlike the existing feature selection methods, which aim at improving the model prediction accuracy according to the training data, our objective is to select the most informative features (i.e., the ASN digits). The more frequently an AS shows up in the candidate routes, the more traffic it is likely to be responsible for, making it more important for the route decision process. Following this idea, our plan is to select the most frequently observed ASes in the candidate route set. Specifically, we calculate the frequency of all the observed ASes in the candidate route set, and rank the observed ASes according to the frequency from high to low. Finally, we select the top k ASes if the feature size is k.

3.5. Running example

Now we present a running example to construct the training and validating data set. As shown in Table 1 we list all the candidate routes. In our example, we train the route decision process for AS 1. AS 1 have 3 neighboring ASes (AS 2, AS 3, and AS 4). The candidate routes are observed from such neighboring ASes. The routing table of AS 1 includes 4 prefixes (p_1, p_2, p_3, p_4). Since AS 1 selects the path "1 2 5 9" for prefix p_1, the candidate path "2 5 9" from AS 2 is the optimal path, and the paths "3 7 9" and "4 8 9" are non-optimal paths (noted as ("2 5 9", 1), ("3 7 9", 0), and ("4 8 9", 0)). Similar for the other prefixes.

The next step is to rank the observed ASes according to their frequency. According to Table 1, AS 2, AS 3, AS 4, AS6, and AS 8 are observed for 4 times. AS 5, and AS 7 are observed for 2 times. AS 9, AS 10, AS 11, and AS 12 are observed for 3 times. Herein, the ranking for the observed ASes is (2, 3, 4, 6, 8, 9, 10, 11, 12, 5, 7). When the feature size is 5, we select AS 2, 3, 4, 6, and 8. When the feature size is 9, we select AS 2, 3, 4, 6, 8, 9, 10, 11, 12.

Table 1
Routing table of Fig. 3.

AS #	Prefix	AS path	AS #	Prefix	AS path
1	p_1	1 2 5 9	2	p_1	2 5 9
1	p_2	1 2 6 10	2	p_2	2 6 10
1	p_3	1 4 8 11	2	p_3	2 5 11
1	p_4	1 3 7 12	2	p_4	2 6 12
3	p_1	3 7 9	4	p_1	4 8 9
3	p_2	3 8 10	4	p_2	4 6 10
3	p_3	3 8 11	4	p_3	4 8 11
3	p_4	3 7 12	4	p_4	4 6 12

Suppose that the feature size is 5. We then extract characters from the candidate routes. Since the selected features are AS 2, 3, 4, 6, and 8, the candidate path "2 5 9" only traverses AS 2, and the extracted character is $(1, 0, 0, 0, 0)$. Similarly, the extracted character for the path "2 6 10" is $(1, 0, 0, 1, 0)$ since "2 6 9" traverses both AS 2 and AS 6.

4. Evaluation by case study

In this section, we investigate the feasibility of our proposed model. As a first step to the correctness of our method, we want to begin with case study of routing policy modeling, focusing on the detailed routing scenarios, and investigate the difference between our method and the previous proposed methods. To that end, we first introduce our used data set together with the topology of our example cases; we then compare the prediction accuracy of our method with the AS business relationship model with analysis of the model difference; next we investigate the feature selection and model parameter details to discuss the improvement of the model performance; finally, we analyze why our models works and the limitations of our model.

Our experiment environment is Ubuntu 16.04.1 LTS system, 64 bits, with 4 cores 1.8 GHz, 4G memory. Our deep learning tool is Keras using theano as backend.

4.1. Our data set

Our data set is learned from the open sourced BGP data of Oregon, which includes snapshot data every few hours and all routing updates. Since our aim is to train a routing policy model by learning the candidate paths and the optimal paths, we do not want to involve routing policy by using routing updates. Thus we download the snapshot data, and the data is generated during October, 2017. Totally, there are 54 full-table monitors in the Oregon data.

Our idea to generate the candidate routes set and the optimal route set is as following. When two monitors cite in neighboring ASes, and one AS provides data transmitting service for the other AS, the provider AS is likely to announce its entire routing table to the customer AS. As a result, the snapshot of the monitor in the provider AS could be observed as the candidate routes of the monitor in the customer AS. The snapshot of the monitor in the customer AS indicates its route choice among the candidate routes (i.e. the optimal routes). Herein, we could generate the candidate routes and optimal routes based on the monitors cited in neighboring provider–customer AS pairs; take the providers snapshot as the candidate route set; and take the customers snapshot as the optimal route set.

In the rest of this paper, we focus on the 3 following cases as shown in Fig. 3, which are used for modeling the routing policy of AS3356 and AS23673. For the case of AS3356, we have two monitors cited in AS2914 and AS1299 individually. AS2914 and AS1299 are both peering AS of AS3356, and are both Tier-1 AS in the Internet. For the case of AS23673, we have 3 monitors cited in AS1299, AS3257, and AS3356 individually, which are all provider AS of AS23673.

Since inferring AS business relationships is not our main objective in this paper, we utilize the AS business relationship provided by Caida data, their data is based on Luckie's method [27]. We also double check the AS business relationships involved in our paper with the AS business relationships combining Caida's data with the relationships inferred from Ark traceroute data [28].

According to our method introduced above, we generate the candidate route set and sign tags to the candidate route set to indicate the optimal route. For the monitor in AS3356, there are 847752 candidate routes for 423876 prefixes, taking about 50% of AS3356's entire routing table. For the rest 50% of AS3356's routes, there are no more than one candidate route for each prefix. It is meaningless to model the route decision process for such prefixes since there is only one route choice, and we ignore the candidate routes for such prefixes. Similar for AS23673, there are about 1297471 candidate routes for 436888 prefixes, taking about 67% of AS23673's routing table.

We then select and extract features with the candidate route set. Based on our method introduced above, we conduct statistics on the showing up frequency of each AS observed in the candidate route set, then select the most frequently observed ASes as the features, and generate the feature values for each candidate route. We split our tagged candidate route set into two parts as the training route set (90% of all routes) and the validating route set (10% of all routes).

4.2. AS business relationship model

As a comparison, we conduct route prediction for our cases based on the AS business relationship model, which always selects the shortest path from the optimal neighboring AS. Of course, all of the candidate routes in our training set comes from the same kind of neighboring AS, thus we simply select the shortest path. When there are multiple shortest paths, we make a random choice. When the optimal route is not selected from our candidate route set, we simply ignore that prefix. Out of 81389 prefixes in the candidate route set of AS3356, the AS business relationship model makes the correct route choice for 67373 prefixes with an accuracy of 82.78%. And out of 235594 prefixes in the candidate route set of AS23673, the AS business relationship model makes the correct route choice for 90413 prefixes, with an accuracy of 38.3%.

With no surprise, for 26996 of AS3356's prefixes (148566 for AS23673), there are more than one shortest path, and the route choice is made randomly. As a result, the traditional AS business relationship model performs terribly in our cases.

4.3. Prediction accuracy of our method

Utilizing the training data and validating data, we then model the route decision process for AS3356 and AS23673. Since our route decision model is composed with route classifier, we begin with the prediction accuracy evaluation of the route classifier. In our model, each route classifier is a neural network, taking the candidate route feature as input, and determining whether it is an optimal route. The neural network of our route classifier is composed with multiple layers of sequential models, and each layer includes as many neurons as the input feature number.

We also need to set a limitation to the feature size, we have two reasons for that. First, our experiment environment contains limited computation capability, and features more than 1000 would make the training procedure of the model take quite a long time period. Second, as shown in Fig. 4 is the AS show-up frequency of ASes in the candidate route set. Both axis are in log-scale,

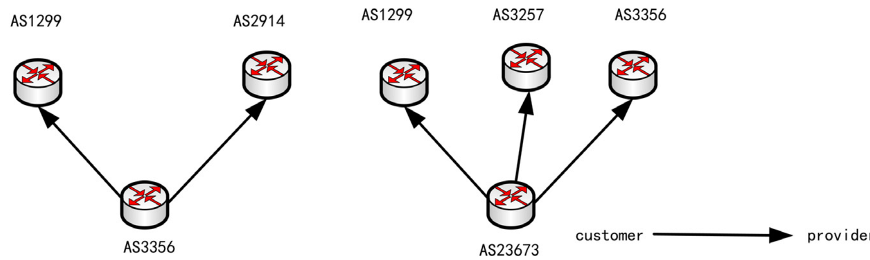

Fig. 3. Topology of our two modeling cases.

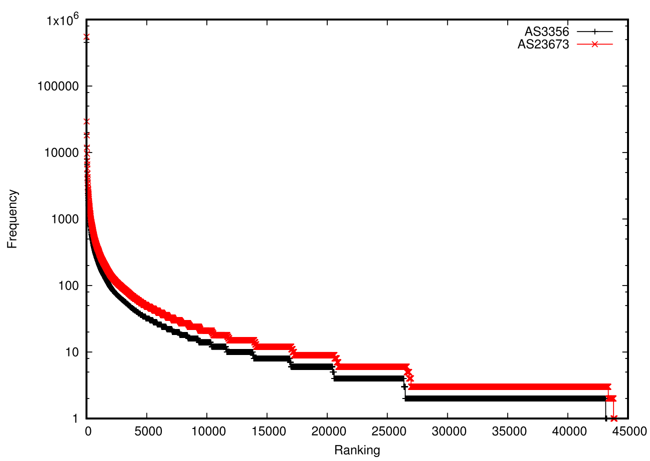

Fig. 4. Show-up frequency.

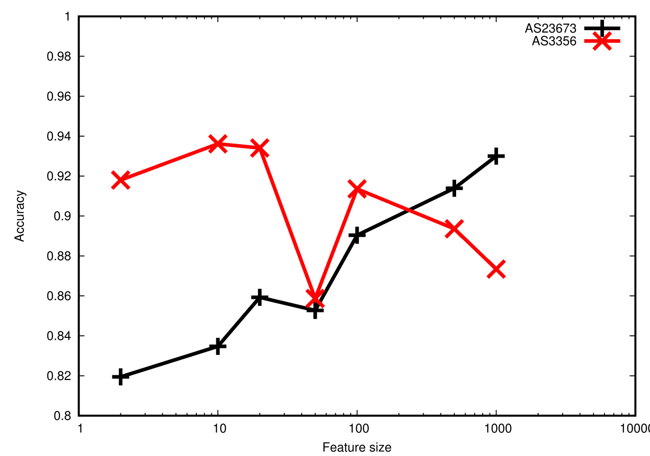

Fig. 5. Accuracy vs feature size.

and both curves have fat tale. For most of the ASes, the show-up frequency ranges from 0–100, and for the top 1000 ASes, the show-up frequency is at the level of 200–300. ASes showing up no more than 100 times usually cite at the edge of the Internet, and show up at the last 1–2 hops of the AS paths. For example, AS3356 has two candidate routes for the prefix of 181.189.248.024, the corresponding paths are "1299 6830 23520 27696" and "2914 6830 23520 27696". AS23520 and AS27696 both cite at the edge of the Internet. They seldom show up in AS3356's routes to other prefix, and cannot help in making the route choice since they appear on both candidate routes. To sum up, we believe 1000 could be an appropriate feature size up-limit.

As shown in Fig. 5 is the prediction accuracy of our route classifier with varying feature size. Here the neural networks contains 1 hidden layer. For all of the experiments of AS3356, the prediction accuracy is better than 82% (82% for AS23673). With appropriate feature size setup, the prediction accuracy could be improved by 8 percent for our cases. With the optimal feature size, we use the trained route classifier for route decision of our model, and achieve an accuracy of 94% (92% for AS23673). Compared to the AS business relationship model, our model performs much better.

For AS23673, the accuracy generally keeps improving, which indicates that the performance of our model could be improved when we consider more routing information. However, there exists counterexample, for which the accuracy decreases with the growing feature size (e.g. feature size = 20 and 50 for AS23673). This indicates that there should be other impacting factors for the feature selection, and selecting the most observed may introduce noise into the training data.

For AS3356, the accuracy could be improved when the feature size is expanded to 10. However, there is general a decreasing trend when we expand the feature size, indicating that the feature size should not be too big to induce too much noise.

As a matter of fact, a deep learning method should not consider only one hidden layer. Thus we evaluate the prediction accuracy for our cases with varies quantity of hidden layers in Fig. 6.

Generally, with the growing size of neural network, when the feature size is small (2 or 10), the prediction accuracy gets worse; when the feature size is bigger than 20, the prediction result is improving. We believe this is because a deeper neural network need more training data, and the limited training data for the small feature size setup makes the model under-fitting. The prediction accuracy improvement is not promising, because to neural network size and the training data size are both limited. However, compared to the AS business relationship model, we believe this is a promising result.

4.4. Limitations

In the previous section, the prediction accuracy can hardly be improved (93% at the best). Thus we are considering our model's limitations, or more specifically, the training data set's limitation. The problem is, when we extract the features for a selected set of frequently observed ASes, where would multiple routes with different optimal tags fell into the same feature value. For example, for AS3356, supposing the two selected ASes is AS1299 and AS2914. There are 2 candidate routes: "113.193.215.0/24 2914 9498 9730 45528" and "124.81.168.0/21 1299 4671 4795", the former one is tagged as optimal route. The feature value for the candidate route is "113.193.215.0/24 2914 9498 9730 45528" is (1, 0), and the feature value for the candidate route "124.81.168.0/21 1299 4671 4795" is also (1, 0). For such two cases, the input of our model, but they have conflict labels. If we let the model satisfy the former route, the prediction of the later route would endure errors since the validation route set is directly selected from the candidate route set. We believe that conflict routes play a dominant role in the inaccuracy of our prediction model.

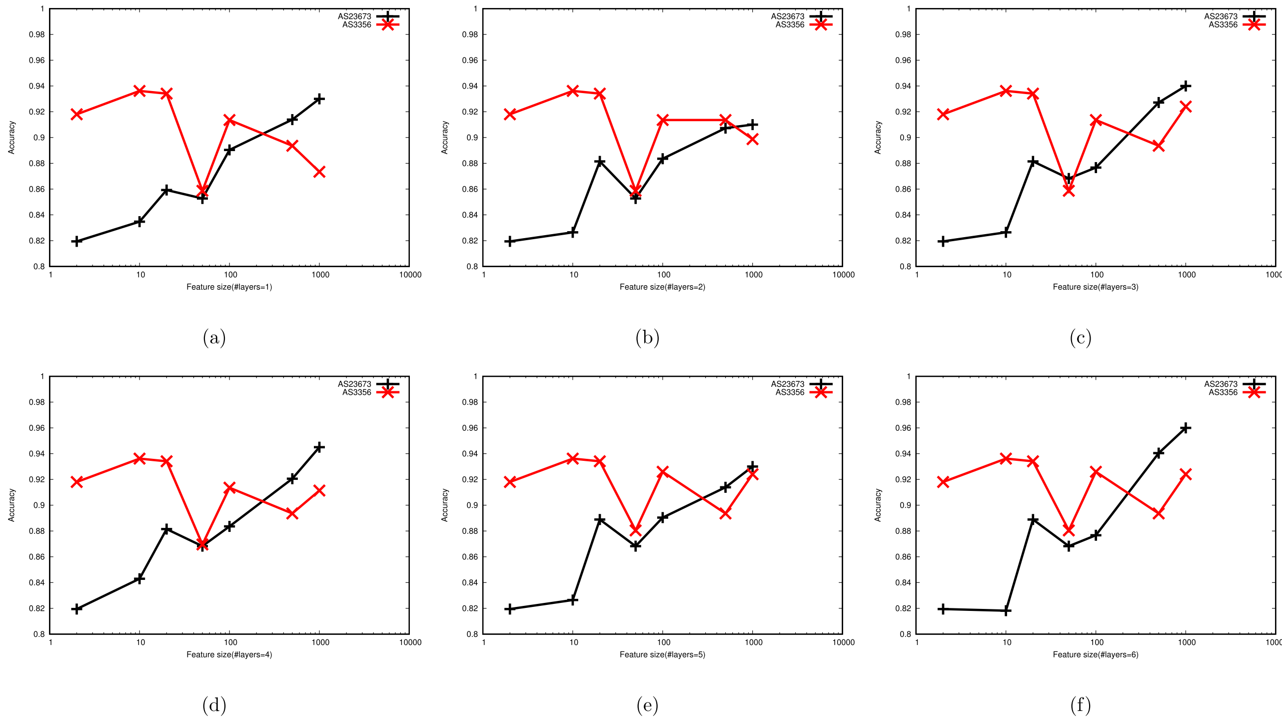

Fig. 6. Accuracy with varies # layers.

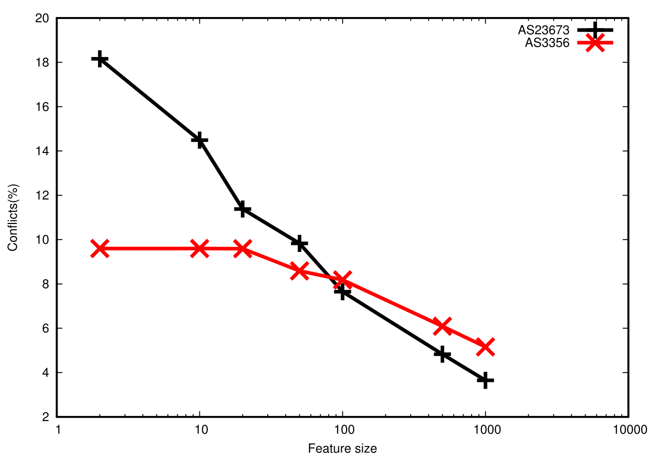

Fig. 7. Training data set conflict ratios.

As shown in Fig. 7 is the ratio of the conflict route set with various feature size. For AS3356, when the features just consider 2 ASes, the conflict routes take about 18% of all the candidate routes; when the features consider 1000 top observed ASes, the conflict routes could be decreased to 4% of all. Thus, on the perspective of avoiding conflict routes, it is better to consider more ASes as features.

It should be noticed that the feature size of Fig. 7 is in log-scale, thus the conflict ratio decreases very slow with the growing of the feature size. Thus with our method, it could be very hard exclude all the conflict routes.

The time consumption of our model generally relies on the layers used for the model. When the quantity of the layers is less than 4, the overall time consumption of the model always takes less than 10 s. When the quantity of the layers is 5, it generally will take a few minutes, and takes hours for 6 layers on our laptop.

5. Discussions

5.1. Model characteristic

The AS business relationship model make the route choice according to the next hop AS type, and the AS path length. We believe such two factors are both considered in our model. The neighboring ASes are the most frequently observed ASes in monitor's routing table, so they have first priority to be selected as features. With further appropriate training, the routes from the preferred neighboring ASes are more likely to be selected by our model since it simply speaks for the data.

Since our model considers a list of frequently observed ASes, the more ASes an AS path traverses, the more ASN digit will be tagged as 1. And such ASN digit correlates to the path length. As discussed in Section 4.3, the infrequently observed ASes usually cite at the edge of Internet, which would show up in all candidate routes. And ignoring such ASes will not impact the path length difference.

As a result, we believe our method is reasonable to outperform the AS business relationship model, because it considers all the factors of AS business and induce more detailed information in the route decision process.

A much more precise way for route decision modeling is to adjust the configuration of the BGP network to make its routing consist with the de facto BGP routing [9], on base of a per-prefix granularity. Our method is quite similar to theirs. Both let the data speak for the route decision. However, there is a semantic gap between the BGP protocol configuration and its routing policy. Simply adjust the protocol configuration could seriously impact the flexibility and the effectiveness of the routing model expression, and our method do not need to conduct detailed adjustment to the model, because we borrow the popular deep learning method to do it for us.

5.2. Modeling for all ASes

One may also argue that the utilization of our model could be very limited, since we need to feed our model with multiple routing tables for the modeling of one single monitor. Actually, the routing modeling of an AS merely need a candidate route set and its optimal route tags. This could be done by collecting routing updates of the modeled monitor, and ranking the path preference by calculating path usage time [29]. The path with longest life time is the optimal path. For the ASes without monitors, their routes and path usage time could be observed by other monitors, which we could use to conduct the modeling [30]. As a bigger picture, with the growing amount of BGP monitors deployed, the quantity of the ASes with available monitors is growing. In that case we could conduct precise route modeling for most ASes in the central part of the Internet.

5.3. Application

Another interesting problem is how could our model be used for the research and industry community. As a general picture, our vision is to model the internet. Generate a route decision model for each AS, and simulate the route transmission routing behaviors, so that we can analyze, control, and predict the Internet routings with detail. A potential application could be ISP traffic engineering.

For the current situation, our model could be used for analysis of routing dynamics. With modeling of routing decision process of each monitor with historical routing data, we are able to depict the monitors' routing policy. And feeding the latter routes to the model could check the consistence between the routing policy and the later routes, if not, there might be a route instability or a routing policy change.

Another possible application is to identify the fraud routings. Our model learns routing behaviors from the de facto routing updates. With accumulated training data, the fraud routings can merely take a small part of the overall training set. Herein, a fraud routing can hardly be selected as the best path. If there is a conflict in practice, the fraud routings could be easily detected.

6. Conclusion

In this paper, we introduce a data-driven method for the BGP network modeling, which sheds light on modeling the BGP route decision process as a black box. We discuss the modeling details including model structure, route set construction, characterization and feature selection. By comparison with the AS business relationship model in the form of a case study, we prove the effectiveness of our model. As a future work, it is necessary to conduct evaluation in more cases with more training data in order to further evaluate the effectiveness. To investigate the rout decision modeling for ASes with no sited monitors would also be a critical problem for the utilization of our model. We also believe that our route decision model could help in detecting routing policy changes and route anomalies for Internet routing prediction, routing behavior analysis, and route instabilities detection.

Acknowledgments

This work is supported by the National Natural Science Foundation of China under Grant No. 61572153, No. 61702220, and No. 61702223 and the National Key research and Development Plan (Grant No. 2018YFB0803504).

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Zhihong Tian Ph.D., professor, PHD supervisor, Dean of cyberspace institute of advanced technology, Guangzhou University. Standing director of CyberSecurity Association of China. Member of China Computer Federation. From 2003 to 2016, he worked at Harbin Institute of Technology. His current research interest is computer network and network security. E-mail: tianzhihong@gzhu.edu.cn.

Shen Su born in 1985, Ph.D., assistant professor, Guangzhou University. His current research interests include inter-domain routing and security, Internet of connected vehicles, and wireless sensor networks. E-mail: johnsuhit@gmail.com.

Wei Shi is an assistant professor at the University of Ontario Institute of Technology. She is also an adjunct professor at Carleton University. She holds a Bachelor of Computer Engineering from Harbin Institute of Technology in China and received her Ph.D. of Computer Science degree from Carleton University in Ottawa, Canada.

Xiaojiang Du Dept. of Computer and Information Sciences, Temple University, Philadelphia PA 19122, USA, email: dxj@ieee.org. His research interests are wireless communications, wireless networks, security, and systems.

Mohsen Guizani Dept. of Electrical and Computer Engineering, University of Idaho, Moscow, Idaho, USA, E-mail:mguizani@ieee.org. His research interests include wireless communications and mobile computing, computer networks, mobile cloud computing, security, and grid.

Xiang Yu born in 1978, Ph.D., Heilongjiang Institute of Technology. His current research interest is network and information security. E-mail: 1267013@qq.com.