Routing without Routing Algorithms: an AI-Based Routing Paradigm for Multi-Domain Optical Networks

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Abstract: We first propose a novel multi-domain routing paradigm that transforms the routing problem from heuristic-algorithm-based computation to artificial-intelligence-based data analytics. Numerical results prove that our proposal can achieve excellent routing accuracy, and significant signaling reduction.

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1. Introduction

The global communication networks are composed of multiple network domains dominated by different countries and companies. The network status inside the domain is protected from exterior access for security considerations [1]. The control plane design is an important problem in such heterogeneous multi-domain networks [2]. Path Computation Element (PCE) and the Backward Recursive PCE-based Computation (BRPC) algorithm were proposed to calculate an end-to-end route by multiple domain collaborations preserving domain privacy (Fig. 1a) [3-7]. There are also some other studies tried to solve the problem by domain information abstraction which transform the intra-domain topology into a virtual topology and calculate the end-to-end inter-domain path with abstracted information. Basically, these methods fulfill the task of inter-domain routing under the condition of limited domain information visibility, paying the cost of increased control signaling complexity. On the other hand, if we can envision a centralized controller (Fig. 1b) that can collect all the information from network domains regardless of domain privacy, calculating an inter-domain route is a simple traffic-engineering task by shortest-path algorithms without complicated signaling interactions. *In short, the core idea of conventional heuristic-algorithm-based methods is to find a constrained shortest path on a graph knowing the weights of every links.* The limited visibilities of link weights in different domains raise a trade-off between domain privacy and coordination complexity (knowing more links reduces coordination complexity, but compromises domain privacy).

Can we get rid of this zero-sum balance, and design a new routing paradigm combining the advantages of both methods? The answer is positive if we reconsider the inter-domain routing problem with Artificial Intelligence (AI) and data analytics techniques. Our work are built on the fact that sparse route trajectories of historical inter-domain requests can shed light on future routing decisions [8]. Moreover, combinatory optimization problems (e.g., routing) have been proved to be solved by machine learning techniques [9]. *Therefore, if we can collect and train a machine-learning model that can associate the traffic request and public inter-domain link capacities with route trajectories, the inter-domain routing problem will be addressed elegantly*.

In this paper, we renovate the way to deal with inter-domain routing problem with state-of-the-art machine learning techniques. *In our proposal, we apply data-analytical method to learn from sparse historical route trajectories and train a deep-learning model that can directly return a feasible inter-domain route when being requested*. All the data in both training and testing stages are public available (traffic requests, historical route trajectories, inter-domain link capacities), and the complicated relationship among these three items are deeply hidden inside the layers of the neural network that enables the model, thus will not divulge the protected domain information. We believe this work paves the way for future AI-driven autonomous network control and management.

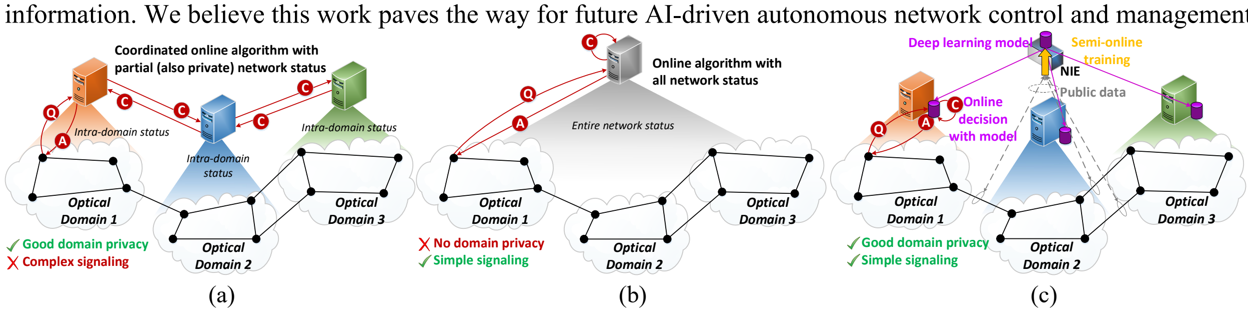

Fig. 1, different control plane architectures for inter-domain routing, where **Q** means traffic request, **A** means routing result, **C** means path computation. (a) Distributed collaborative routing, (b) centralized routing, (c) AI-based data-analytical routing.

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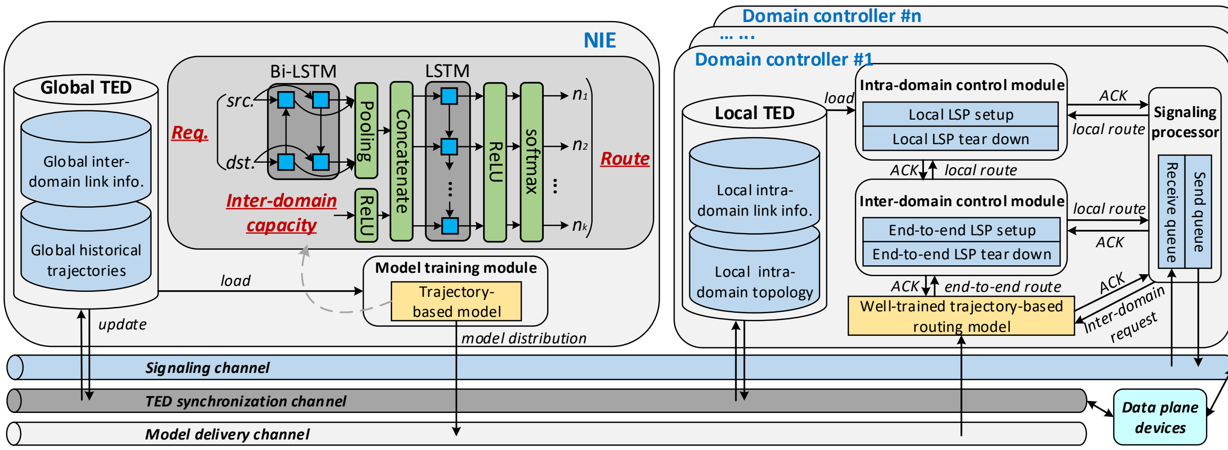

Fig. 2, functional modules of a NIE in control plane for AI-based data-analytical routing.

2. Enabling Control Plane Technologies for AI-Based Multi-Domain Routing

Compared with conventional heuristic-algorithm-based routing, there are two major enabling technologies for AI-based data-analytical routing, as Fig. 1c depicts.

1) Network Intelligence Element (NIE)

Network Intelligence Element (NIE) is first proposed to fulfill the task of model training with data analytics techniques. The NIE operates in a centralized manner and is equipped with enough computation capability for training machine learning models. As Fig. 2 depicts, the NIE maintains a global Traffic Engineering Database (TED) which collected public global information in the multi-domain network (e.g., global inter-domain link information, and global historical route trajectories). The information inside the global TED is loaded to train the AI-based data-analytical model. After the training process, the data-analytical model is broadcasted and distributed to all domain controllers via the model delivery channel.

For a traffic demand requesting an inter-domain path, the *well-trained trajectory-based routing model* is used to generate an end-to-end inter-domain path. Then, the end-to-end path is sent to the *inter-domain control module* to split it into several local paths in different domains. The local paths are forwarded to corresponding domain controllers, and the *intra-domain control module* in each domain controller is responsible for setting up a local path. All these local paths make up an end-to-end inter-domain path, and terminates the inter-domain path setup procedure.

2) Long Short-Term Memory (LSTM)-Based Deep Neural Networks

Long Short-Term Memory (LSTM) is well-suited with sequential learning problems. The inter-domain routing can be formulated as a sequential learning problem, as the input and output are both sequences of network nodes. We have successfully developed the model training module that enables NIE. This model is built upon state-of-the-art LSTM deep neural networks, which can learn from sequential data (sparse historical route trajectories) and generate output (inter-domain route) in a sequential manner, too. Due to space limitations, we only plot the schematic structure which shows the core architecture of the neural networks in Fig. 2.

To formulate the routing problem as a sequence learning task, we set the input of LSTM to be two sequences: traffic requests (a vector composed of source node and destination node) and inter-domain link capacities (a vector composed of the capacity value of each link). The inter-domain link capacities is put into the neural networks because they can influence the routing result when some of them are fully-occupied and a detour route may be returned. The output is set to be the inter-domain route (a vector composed of traversed nodes that the inter-domain route goes through). We use one-hot encoding to transform a node value into a binary vector to be processed in neural networks. Dropout method is used to prevent overfitting.

3. Numerical Evaluations

We evaluate the performance of the AI-based data-analytical routing on a sample multi-domain network topology in Fig. 3(a). All fiber links are assumed to have 200 Gb/s capacity. Each inter-domain traffic request requires 10 Gb/s bandwidth. Historical route trajectories are acquired by running the BRPC algorithm for evenly-distributed traffic requests. The total number of historical trajectories is 1000000. We classify all trajectories by its source and destination node pairs. Trajectories between certain node pairs are selected as training data, while the remaining trajectories are testing data. We train the model on training dataset, which contains historical route trajectories between 55% node pairs on the graph, as Fig, 3(b) depicts. During training, we use Adam optimizer to minimize the categorical crossentropy loss function. We build the model on *Keras* using *Tensorflow* backend, and the hardware platform for NIE is a commercial server with 32G memory, Xeon E5 2630 CPU and Nvidia GTX1080Ti GPU.

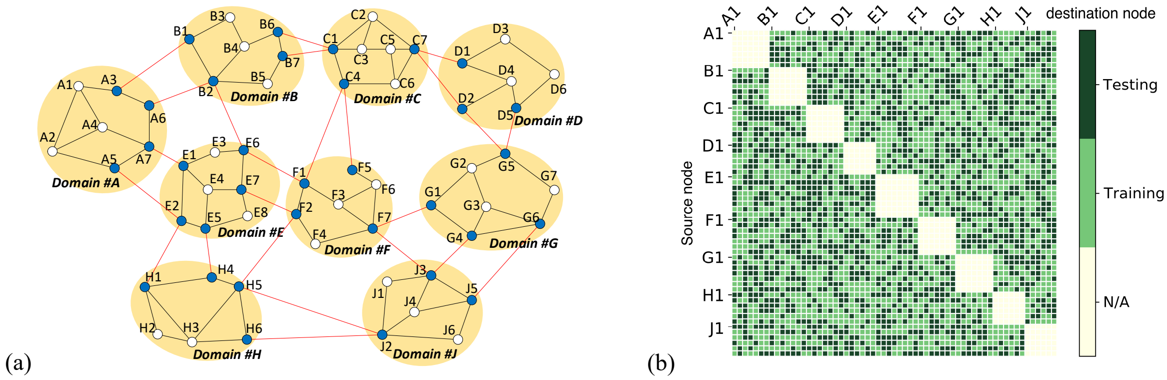

Fig. 3, (a) a multi-domain network topology, (b) an example distribution of training and testing data (training/testing=0.55/0.45).

Fig. 4(a) shows the prediction accuracy of the AI-based data-analytical routing on different testing datasets under the same training/testing distribution as Fig. 3(b) indicates. Note that the training and the testing datasets have the same blocking probability. We set two different criteria for accuracy. First, "*same route*" means that the predicted route must be absolutely the same as the target one in testing dataset. While the "*good route*" will return true as long as the predicted route can be routed in the network successfully. We see that the prediction accuracy declines when there are larger traffic blockings in testing dataset. We find that most negative predicted routes are caused by resource crunch when a detour path is supposed to be selected. Fig. 4(b) shows the amount of inter-domain signaling messages for setting up inter-domain connections with different traversed domain numbers. The reduced signaling volume is because AI-based routing do not need multi-domain collaboration to compute an end-to-end route.

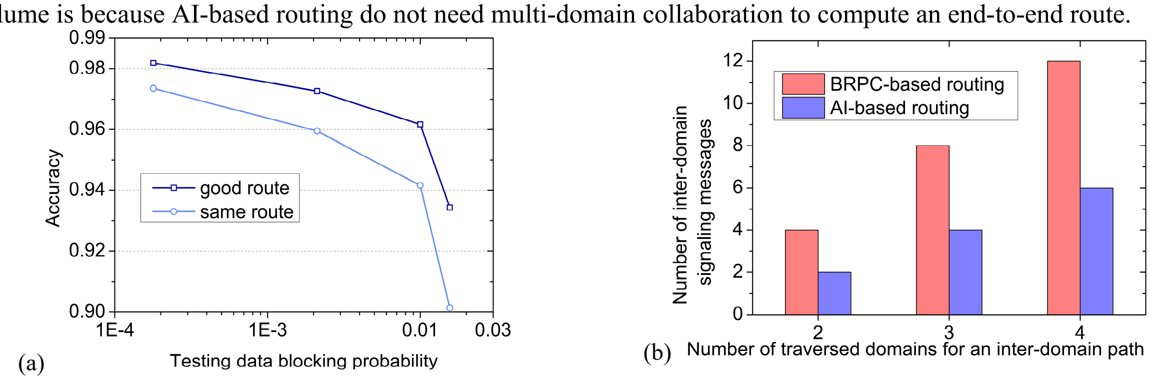

Fig. 4, (a) testing accuracy under different testing dataset blocking probabilities, (b) number of inter-domain signaling messages.

4. Conclusion

In this paper, we transform the inter-domain routing paradigm from conventional algorithm-based routing to AI-based data-analytical routing. We proposed the control plane architecture that enables the AI-based routing. NIE is first introduced as the venue for training the LSTM-based deep neural networks, which can directly generate an inter-domain route under the input of traffic request and inter-domain link capacities. Numerical evaluations show that with 55% historical route trajectories as training data, the model can achieve over 98% prediction accuracy for traffic requests between the rest 45% node pairs under sufficient network resources (low blocking probability). This proves the feasibility of applying machine learning and data analytics techniques to inter-domain routing problems. Future work on an enhanced version of AI-based routing considering wavelength continuity [7] is under developing.

5. References

[1] M. Chamania, and A. Jukan, "A survey of inter-domain peering and provisioning solutions for the next generation optical networks," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, 2009.

[2] N. Ghani, Q. Liu, A. Gumaste, D. Benhaddou, N. S. V. Rao and T. Lehman, "Control plane design in multidomain/multilayer optical networks," *IEEE Communications Magazine*, vol. 46, no. 6, 2008.

[3] F. Paolucci, F. Cugini, A. Giorgetti, N. Sambo, and P. Castoldi, "A survey on the path computation element (PCE) architecture," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 4, 2013.

[4] R. Muñoz, R. Casellas, R. Martínez, and R. Vilalta, "PCE: What is it, how does it work and what are its limitations?" *Journal of Lightwave Technology*, vol. 32, no. 4, 2014.

[5] J. P. Vasseur, R. Zhang, J. L. Le Roux, and N. Bitar, "A backward recursive PCE-based computation (BRPC) procedure to compute shortest inter-domain traffic engineering label switched paths," *IETF RFC*: 5441, 2009.

[6] F. Paolucci, F. Cugini, L. Valcarenghi, and P. Castoldi, "Enhancing Backward Recursive PCE-based Computation (BRPC) for Inter-Domain Protected LSP Provisioning," *OFC*, 2008.

[7] R. Casellas, R. Martínez, R. Muñoz, and S. Gunreben, "Enhanced backwards recursive path computation for multi-area wavelength switched optical networks under wavelength continuity constraint," *Journal of Optical Communications and Networking*, vol. 1, no. 2, 2009.

[8] C. Guo, B. Yang, J. Hu, and C. S. Jensen, "Learning to route with sparse trajectory sets," *Proc. ICDE*, 2018.

[9] H. Dai, E. B. Khalil, Y. Zhang, B. Dilkina, and L. Song, "Learning combinatorial optimization algorithms over graphs," *Proc. NIPS*, 2017.