Graph Convolutional Network based Link State Prediction

Sungwoong Yeom, Chulwoong Choi, Shivani Sanjay Kolekar, Kyungbaek Kim
Department of Artificial Intelligence Convergence
Chonnam National University
Gwangju City, South Korea
yeomsw0421@gmail.com, sentilemon02@gmail.com, shivanikolekar@gmail.com, kyungbaekkim@jnu.ac.kr

***Abstract*—Because of the activation of IoT (Internet of Things) devices due to the rapid development of recent communication technology, network traffic is currently fluctuating and increasing explosively. As existing network resource management policies are not sophisticated enough to cope with network conditions that change constantly, resource utilization can be lowered and costs can be higher. With the recent advances in deep learning techniques, network operators can manage networks intelligently. For the intelligent network, there is a technique which predict the state of network links. However, when the scale of the network increases, overall network management can be complicated. In addition, as the models of link state prediction are affected by the states of adjacent links, it is necessary to consider the spatio-temporal characteristics between links. In this paper, we propose a GCN(Graph Convolutional Neural Network)-GRU(Gated Recurrent Unit) based link state prediction technique. The proposed GCN-GRU model predicts network traffic by considering the spatio-temporal characteristics of each link state such as bandwidth, delay, and packet loss rate. Through extensive experiments on actual network traffic, the proposed GCN-GRU based link state prediction technique has shown to achieve 1.5% lower a mean absolute percentage error (MAPE) compared to a LSTM (Long Short term Memory) based link state prediction technique.**

***Index Terms*—Software-Defined Networking, Graph Convolutional Network, Gated Recurrent Unit, Link State Prediction**

I. Introduction

Depending on the activation of devices such as sensors, mobiles, wearables and other IoT devices, the amount of IoT data moving over the network is exploding. However, as the amount of data is increasing explosively, the current Internet infrastructure is not suitable for adjusting the network resource allocation. When the network resources are wasted by the resource allocation techniques such as static threshold, the resource utilization is generally low and the network costs increase. Making cost effective resource allocation while optimizing network and resource utilization, network state prediction techniques help to dynamically plan network resources.

In order to dynamically plan the network resources, the traffic volume prediction techniques using network traffic seasonality was studied [1, 2]. However, because of unexpected behavior of network users, network traffic reveals many features such as high jitter and non-linearity [3]. In non-linear network traffic [4], burstiness [5] and randomness are easily observed, and the performance of traffic volume prediction techniques using seasonality are degraded. Recently, with the activation of deep learning neural networks, the network traffic volume prediction techniques using a time series neural network achieves a low error rate [6]. However, as only using the information of traffic flows for the management of overall network resources is not sufficient, the representation of network states is needed. In order to predict the network state, a traffic matrix including bandwidth, delay, and packet loss rate is estimated using the time series neural network [7, 8].

However, in the case of a large-scale network interconnected between multiple sites linking overseas sites, the global management for network state prediction models are needed [9, 10]. In order to manage multiple models, the prediction model for aggregated traffic using time series neural network was studied [11]. However, even if the general time-series neural networks can learn spatial dependencies, it may be inevitable to capture some amount of noise and spurious relationships that are likely not to represent causal structures in graph-structured networks. In order to forecast traffic in the complex graph-structured network, a GCN (Graph Convolutional Network) that captures the spatial and temporal dependency is studied [12]. This GCN model predicts the network state by using the adjacent matrix representing the graph structure consisting links and features of links.

In this paper, we propose a GCN-GRU based link state prediction technique. In order to manage a network and predict each of link(equals to one hop) state, the proposed technique constructs the direction of graph representing the one hop links as the vertex and connection between the links (the link between nodes is two hops) as edge, and collects the link state information such as bandwidth, delay and the packet loss rate from the each links. For efficient representation for link state, the aggregated link state information is used to calculate link utilization. The proposed GCN-GRU model uses link utilization of each link as inputs and predicts the states of each links. In order to verify the effectiveness of the proposed technique, the model was evaluated using real network traffic data.

The rest of this paper is arranged as follows. Chapter II describes the work associated with network traffic prediction for managing graph-structure network efficient. Chapter III describes the proposed GCN-GRU based based link state prediction model. Chapter IV presents the results of the experiment. Chapter V provides conclusions and future research directions.

II. Related Work

The rapid development of data center networks and the explosive growth of cloud-driven applications are continuously generating the tremendous amounts of traffic. These traffic exhibit highly dynamic, heterogeneous, and asymmetric characteristics, so that the broker plane should have robust traffic engineering methods to improve network throughput. a SDN (Software-Defined Networking) [13] provides more dynamic, manageable and adaptive network control logic to handle high bandwidth and modern applications, making networks more flexible and efficient. Additionally, network administrator can use SDN to dynamically adjust the flow of traffic across the network to meet new application requirements [14]. Aiming at improving network performance on evolving scenarios, we consider the statistical characteristics of traffic observed on the network are time dependent, self-similarity, seasonality, non-linearity, randomness and burstiness.

In a stable network, traffic characteristics such as time-dependency, self-similarity and seasonality are observed. Moayedi et al. [15] suggest a ARIMA (Autoregressive Integrated Moving Average) based traffic prediction model to increase the accuracy of prediction. However, because of irregular usage patterns of network users [3], the amount of traffic characteristics such as non-linearity [4], randomness, and burstiness [5] are observed. Lu et al. [16] suggest a real-time network traffic prediction model based on LSTM to cope with network traffic burstiness and uncertainty. In this time, if network traffic trend is distinguished in same embedding spaces to express relationship between the traffic trends, LSTM can be efficiently customized [8]. However, in order to solve the problem of long time learning due to the complex structure of LSTM, a GRU (Gated Recurrent Units) model with a relatively simple structure, fewer parameters, and fast learning ability has been studied [17]. However, when the state of the large-scale network are predicted, it is difficult to manage a lot of link state prediction models located in the links constituting the network. In addition, the state of each link can be affected by the states of neighbor links.

Recently, a GNN (Graph Neural Network) have been activated to model correlations between links and generate representations in networks of graph structures. In particular, for large-scale network graphs, GNN requires eigenvalue decomposition of Laplacian matrices, which is a computationally complex procedure. Yu et al. [18] developed a GNN which considered spatial correlation to predict traffic flow, but did not consider temporal correlation of data simultaneously. In this paper, we propose a GCN-GRU based link state prediction technique that considers spatiotemporal correlation in large-scale networks.

III. GCN-GRU based Link State Prediction

With the recent advances in the Software Defined Networking paradigm, research to consider the network as a black box and optimize it by operating through a control loop to provide automation, recommendations, optimization, verification, and estimation is being activated [13]. In order to optimize autonomously network resource in large-scale network, it is necessary to predict and manage the overall network state. In this paper, we use link-level prediction to make the network respond early to congestion events and avoid packet loss and delay increase.

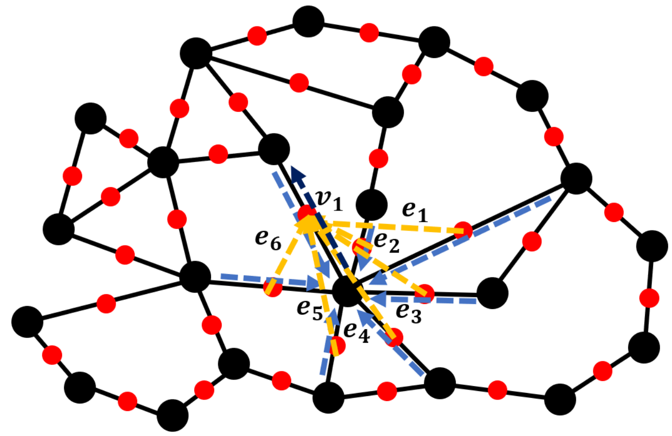

Fig. 1. Link State Aggregation from GEANT2 Network Topology

Figure 1 show a link state aggregation for updating the specific link state from the adjacent links. For example, we predict the state of a one-hop-level link, and aggregate information of the adjacent link e connected to the target link v to predict the link state of overall network. For the representation of complex link relationship in graph-structure network, an adjacency matrix AM that represents the connection between links and an feature matrix FM that manages link information $Link$ from all links are used. At this time, if the number of links is N, the shape of the adjacency matrix AM becomes $2N \times 2N$ considering the link direction. The elements of the adjacency matrix AM are represented in binary. When the target links and adjacent links are interconnected, the element of the adjacency matrix is 1, conversely, the element of the adjacency matrix is 0.

In order to collect link state information $Link$ by direction of the link, the shape of the feature matrix FM becomes $2N \times Link$. In this time, we define link utilization lu_i to simplify link state by using link state information $Link$ such as bandwidth utilization bwu_i, delay d_i, packet loss rate pl_i observed on time i as shown in equation 1.

$$lu_i = \frac{w_1 * \ddot{bwu}_i + w_2 * \ddot{d}_i + w_3 * \ddot{pl}_i}{w_1 + w_2 + w_3} \quad (1)$$

In this time, the weight w represent Importance of the specific element in link utilization. The weight is represented as shown in equation 2.

$$w_1 + w_2 + w_3 = 1, w_1, w_2, w_3 \in [0, 1] \quad (2)$$

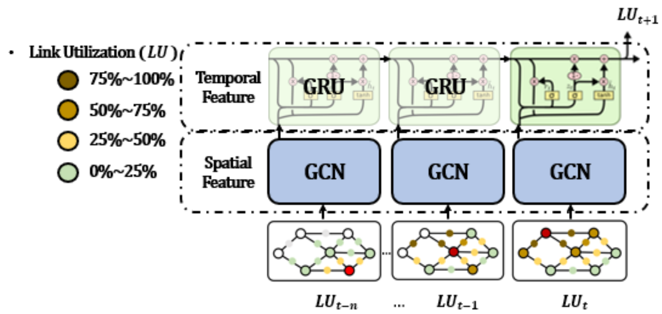

Fig. 2. Architecture of GCN-GRU based Link State Prediction Model

Because of each link state element composed of a different unit, the Min-Max method is used to normalize each element. The normalization is shown in equation 3.

$$\ddot{x}_i = \frac{x_i - min(X)}{max(X) - min(X)}, \ddot{x}_i \in X \tag{3}$$

The link utilization lu_i can be represented as one of the bandwidth utilization bwu_i, one of the delay d_i, and one of the packet loss rate pl_i according to weights w_1, w_2, w_3. However, we set each weight w to $1/3$ in order to equally represent the importance of the elements constituting the link utilization.

For the prediction of next the link utilization from a complex graph-structured network, it is necessary to learn spatio-temporal features in the graph convolution neural network. Figure 2 shows the architecture of GCN-GRU based link state prediction model. This model consists of GCN layer and GRU layer. First, in order to acquire the spatial dependence of complex graph-structured network links, the GCN layer trains link utilization as input. Given an adjacency matrix and the feature matrix, the GCN layer constructs a filter in the fourier domain. The filter of GCN model captures spatial features between the nodes by its first-order neighborhood. Second, in order to capture temporal features of link utilization, the GRU model train time series data that obtained spatio feature as input. The GRU layer learns the link utilization from the past to the present and predicts the next link utilization.

IV. Evaluation

In this section, we evaluate the accuracy of GCN based link state prediction. In order to evaluate the performance of GCN model, we built a ground truth with one of delay simulator with queues using OMNeT++. In this environment, we simulate with the variable link capacities in a GEANT2 and NSFNET topology. By applying more than 200 different routing schemes on the GEANT2 and NSFNET topology, we compute the mean delay, sparse bandwidth and packets drop for every links along time units. The link capacities range the following values: 10, 40 or 100 kbps. We generates 50,000 link state matrices that consist of bandwidth, delay and packet drops. For the evaluation of proposed model, we use 40,000 samples to train and 10,000 samples to test. In order to minimize the loss function between the prediction results and the ground truth during training, we use the adam optimizer and set an initial learning rate to 0.001. And, we use a MAPE (Mean Absolute Percentage Error) to evaluate the prediction quality of each prediction model. Because sparse bandwidth changes according to traffic intensity, the MAPE of model can be changed according to traffic intensity.

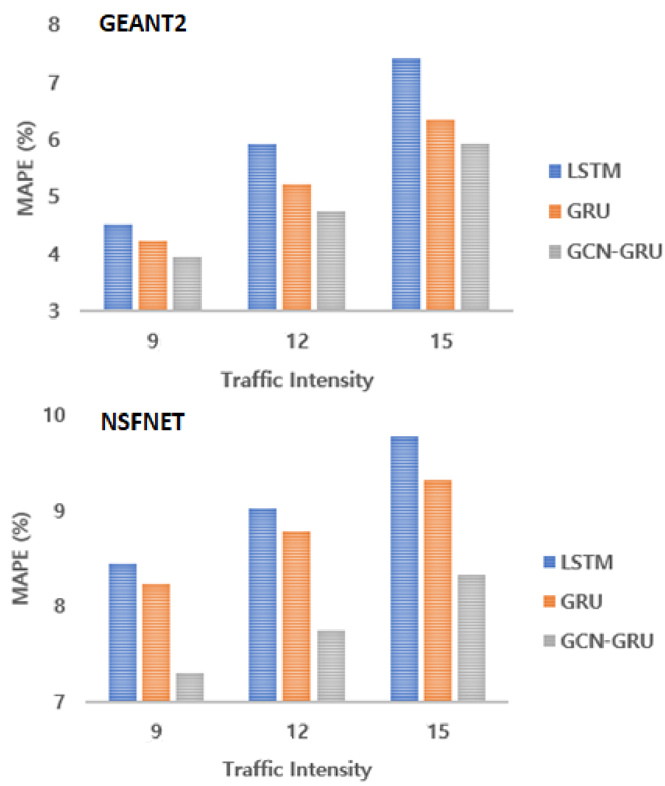

Fig. 3. Performance Comparison of Link State Prediction under different Traffic Intensity in GEANT2 and NSFNET topology

Figure 3 show the performance comparison of link state prediction model under the traffic intensity in GEANT2 and NSFNET. In case of the GEANT2 topology, it consists of 25 nodes and 37 links (e.g. 74 link direction). The GEANT2 topology shows a relatively complex graph structure with 9 adjacent links on some link. If the traffic intensity increases, the burst rate and randomness increase. When the traffic intensity is 9 which shows relatively low burst rate and low randomness, the performance of LSTM, GRU, and GCN-GRU model are similar. However, when the traffic intensity is 12 which shows relatively high burst rate and high randomness, the performance of models is highest in order of GCN-GRU, GRU, and LSTM. The LSTM and the GRU use gated mechanism to memorize as much long-term information as possible. However, because of complex graph structure network, LSTM has a longer training time while the GRU model show the relatively simple structure and faster training time. And, because the GCN-GRU learns the correlation between each link state and neighbor link state, the GCN-GRU shows lower MAPE than the LSTM and the GRU. In case of the NSFNET topology, it consists of 14 nodes and 21 links (e.g. 42 link direction). The NSFNET topology shows a relatively simple graph structure with 4 adjacent links on some link. In this NSFNET topology, when the traffic intensity increases, MAPE of LSTM, GRU and GCN-GRU also increases. However, regardless of traffic intensity, the performance of models is highest in order of GCN-GRU, GRU, and LSTM.

V. Conclusion

In this paper, we propose a GCN-GRU based link state prediction technique. We use the graph convolutional network to model a graph network in which the nodes on the graph represent of network links, the edges represent the connection relationships between links, and the link state information on the network is described as the attribute of the links on the graph. In the proposed model, GCN is used to capture the spatial network structure of the graph for obtaining the spatial dependence; GRU is introduced to capture the dynamic change of node attribute for obtaining the temporal dependence. In order to verify the effectiveness of the proposed technique, we evaluate that the GCN-GRU model was compared with the LSTM model and the GRU model using the network simulation dataset, and it showed 1.5% lower MAPE compared to the conventional LSTM model. In the future, we will study reinforcement learning-based routing using the proposed GCN-GRU based network link state prediction model.

Acknowledgment

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program (IITP-2021-2016-0-00314) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation).

References

[1] S.-N. Nguyen, V.-Q. Nguyen, G.-T. Nguyen, J. Kim, and K. Kim, "Source-side detection of drdos attack request with traffic-aware adaptive threshold," *IEICE Transactions on Information and Systems*, vol. 101, no. 6, pp. 1686–1690, 2018.

[2] G.-T. Nguyen, V.-Q. Nguyen, S.-N. Nguyen, and K. Kim, "Traffic seasonality aware threshold adjustment for effective source-side dos attack detection." *KSII Transactions on Internet & Information Systems*, vol. 13, no. 5, 2019.

[3] M. Candela, V. Luconi, and A. Vecchio, "Impact of the covid-19 pandemic on the internet latency: a large-scale study," *arXiv preprint arXiv:2005.06127*, 2020.

[4] S. Mukherjee, R. Ray, R. Samanta, M. H. Khondekar, and G. Sanyal, "Nonlinearity and chaos in wireless network traffic," *Chaos, Solitons & Fractals*, vol. 96, pp. 23–29, 2017.

[5] H. Jiang and C. Dovrolis, "Why is the internet traffic bursty in short time scales?" ser. SIGMETRICS '05. New York, NY, USA: Association for Computing Machinery, 2005, p. 241–252. [Online]. Available: https://doi.org/10.1145/1064212.1064240

[6] G.-T. Nguyen, V.-Q. Nguyen, H.-D. Nguyen, and K. Kim, "Lstm based network traffic volume prediction," in *Proceedings of 2018 KIPS Spring Conference*, 2018.

[7] A. Azzouni and G. Pujolle, "Neutm: A neural network-based framework for traffic matrix prediction in sdn," in *NOMS 2018-2018 IEEE/IFIP Network Operations and Management Symposium*. IEEE, 2018, pp. 1–5.

[8] S. Yeom, C. Choi, and K. Kim, "Source-side dos attack detection with lstm and seasonality embedding," in *Proceedings of the 36th Annual ACM Symposium on Applied Computing*, 2021, pp. 1130–1137.

[9] D. L. Mills and H.-W. Braun, "The nsfnet backbone network," in *Proceedings of the ACM workshop on Frontiers in computer communications technology*, 1987, pp. 191–196.

[10] M. Yampolskiy and M. K. Hamm, "Management of multidomain end-to-end links-a federated approach for the pan-european research network geant 2," in *2007 10th IFIP/IEEE International Symposium on Integrated Network Management*. IEEE, 2007, pp. 189–198.

[11] A. Lazaris and V. K. Prasanna, "Deep learning models for aggregated network traffic prediction," in *2019 15th International Conference on Network and Service Management (CNSM)*. IEEE, 2019, pp. 1–5.

[12] J. Bruna, W. Zaremba, A. Szlam, and Y. LeCun, "Spectral networks and locally connected networks on graphs," *arXiv preprint arXiv:1312.6203*, 2013.

[13] K. Kirkpatrick, "Software-defined networking," *Communications of the ACM*, vol. 56, no. 9, pp. 16–19, 2013.

[14] I. F. Akyildiz, A. Lee, P. Wang, M. Luo, and W. Chou, "Research challenges for traffic engineering in software defined networks," *IEEE Network*, vol. 30, no. 3, pp. 52–58, 2016.

[15] H. Z. Moayedi and M. Masnadi-Shirazi, "Arima model for network traffic prediction and anomaly detection," in *2008 international symposium on information technology*, vol. 4. IEEE, 2008, pp. 1–6.

[16] H. Lu and F. Yang, "Research on network traffic prediction based on long short-term memory neural network," in *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*, 2018, pp. 1109–1113.

[17] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.

[18] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting," *arXiv preprint arXiv:1709.04875*, 2017.