

Deep RNN-based Traffic Analyzation Scheme for Detecting Target Applications

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Abstract—This letter proposes a deep RNN-based traffic alayzation scheme for detecting target applications. The proposed scheme improves the classification performance in telecommunication networks with heavy traffic. In this work, we design a novel classification learning method where input features and output labels are two-dimensional image with traffic packet and target applications, respectively. Specifically, traffic packets are provided through universitat politecnica de catalunya barcelonatech as the training data[1]. Then, the proposed scheme provides a fast and exact traffic alayzation from the produced inferred function by analyzing the training data. We implement the proposed scheme using a commercial deep long short-term memory system. Simulation-based experiments show that the proposed scheme achieves almost xx% accuracy performance with low complexity, requiring only xx ms elapsed time.

Index Terms—LSTM, Deep Learning, Network Traffic, Traffic Analyzation.

I. INTRODUCTION

VARIOUS types of applications and services are operating in recent networks. It also provides easy access to the network from anywhere, including the smartphone, laptop, and desktop users. As the quality of demand increases, larger and more diverse traffic data is occurring. Therefore, the scope of human data analysis and management is greatly expanding[2]. Therefore, it is necessary to establish a lightweight and automated network[3]. In addition, the application of Deep Learning, which is gaining attention recently, is increasing. Some of deep learning technologies include Multilayer Perceptron (MLP), CNN, and Recurrent Neural Network (RNN). The MLP is a basic deep learning model consisting of approximately one or more hidden layers. CNN, which is a neural network that is comprised of three levels of local reception area, convolutional layer, and pooling layer, is a deep learning technique that is typically used in image analysis. RNN is a circular neural network suitable for processing random sequential data, and its characteristics are influenced by previous computational results. In this paper, RNN is used among deep learning techniques to classify network traffic based on flow. The flow is a collection of the same traffic by 5-tuple, which in turn contains network packets. Therefore, RNN, which is suitable for training sequential data, is used for flow-based network traffic classification. This requires a process of converting flow data collected on the network into a form that can be learned using RNN. To this end, through the traffic data preprocessing process, the learning data generation step makes the raw traffic data divided by each application into traffic split and splited network traffic set easy to learn. The RNN learning will then categorize the flow. Chapter 2 of this paper describes the system model, and Chapter 3 suggests deep RNN-based traffic analyzation scheme, and Chapter 4 conducts

performance evaluation. Chapter 5 describes conclusions and future research plans.

II. SYSTEM MODEL

We need to express a system model that is behind the proposed scheme.

III. PROPOSED DEEP RNN-BASED TRAFFIC ANALYZATION SCHEME (DR-TAS)

This chapter describes traffic data preprocessing and deep RNN model for Proposed deep RNN-based traffic analyzation scheme.

A. traffic data preprocessing

The traffic data used to perform traffic classifications is a preprocessing packet capture (PCAP) files supplied by universitat politecnica de catalunya barcelonatech (UPC) [1] suitable for RNN learning. PCAP is a file that captures network packets and stores them in the form of PCAP files using programs such as Wireshark and TCPdump. PCAP provided for flow-based network traffic classification using RNN suggested in this letter need to be pre-processed into data sets classifiable in RNN traffic analyzation. This requires a data pre-processing process to filter and shorten the PCAP files. The original PCAP file is approximately 59GB in size and has 769507 flows. In the packet_default.info file provided with the PCAP file, there is labeling for the traffic data. Labeling is divided into classes, such as the application type, protocol, and application name for the corresponding traffic flow. The labeling file gave us the correct label for ground truth in the flow-based traffic classification with RNN suggested in this letter.

For the data pre-processing process, eight types of applications were selected based on the number of flows. The top eight label names were Remote Desktop Protocol (RDP), Skype, SSH, Bittorrent, HTTP-face-Govert, HTTP-Doki, HTutube, and only the corresponding label selection flow. Only the payload of the application layer was filtered out of the selected flow internal packet, and the extracted payload data was placed and eight application layer Payload data files were generated. And for HTTP-facebook-Google, HTTP-Web, HTTP-Doki, HTTP-Youtube, we finally combined the label with the label Web to create a total of five data sets. Through the integration process, the application layer Payload data files of RDP, Skype, SSH, Bittorrent, and Web were completed. The data file has header information for each flow, and the payload separated by a # delimiter for each packet. That is, each file is a collection of flows with the same label, with packets having only a payload and the payload being separated by a packet. The payload is also a string, with a size of four bits per one

TABLE I
STATISTICAL INFORMATION OF EACH APPLICATION

	rdp	skype	ssh	bittorrent	http-web
Total number of filtered flows	153,349	2,041	38,831	96,222	21,715
Total number of packets(K)	6,876K	3,015K	173,911K	207,306K	47,136K
Average number of packets in a flow	44	1,477	461	2,154	2,483
Total packet size (GB)	131.3	12.0	321.7	2,170	698.4
Average packet size over all flows (KB)	20.0	4.2	18.8	11.3	15.9
Min packet size over all flows (B)	8.0	8.0	8.0	8.0	8.0
Max packet size over all flows (MB)	5.5	0.3	6.6	0.8	40.0

character. Figure 1 shows statistical information on the finished application layer Payload data file.

This step describes the process of converting LSTM into learning data using the application layer payload data generated in the previous step. A data set for learning will have flight data with 8,750 flows, 1,250 validation data, and 2,500 test data. Each label data equal to the number of each transaction, validation, test data set. Each application flow in the application layer payload data file goes through a conversion process into data for LSTM learning. The conversion job removes the head information that indicates the flow id, start time, and end time of each flow, and imports the data portion of the application layer only the payload in the flow unit and creates a data set. The LSTM models should have the same number of data input at a time to perform the learning in flow units. That is, a flow should have the same size packets. For this purpose, the user can specify as many packets per flow as P. In addition, one packet in the flow has a user-designed size, which can be set by the user to N, and it has a one-dimensional array size. The pixels of a packet's pixel have a 2^n bit size and a character-type value replaced by a floating point value. That is, the data in one flow will be the same size as the equation (1).

$$N_{\text{flow}} = N \times 2^n \times P \quad (1)$$

Fig.1 shows the payload of a packet in one of the completed flows in an two-dimentional image, a element of four bits in size, and a value between zero and fifteen floating point. In addition, due to the nature of the LSTM network structure, all flows should have the same number of packets.Because the length of sequence is set in advance, the number of packets per flow should be the same by that length. However, since not all Applicatoin flows can have the same number of packets, if the number of packets per flow is smaller than the N set, then the packet is generated by zero. Train, Validation and Test Label have labels for a total of five applications, which can be expressed as one-hot vectors of five lengths. A one-hot vector label having a value of only one element, can be defined as a label on which an index of one points to an application name. Table 2 shows the structure represented by the Train, Validation, and Test labels as on-hot vectors.

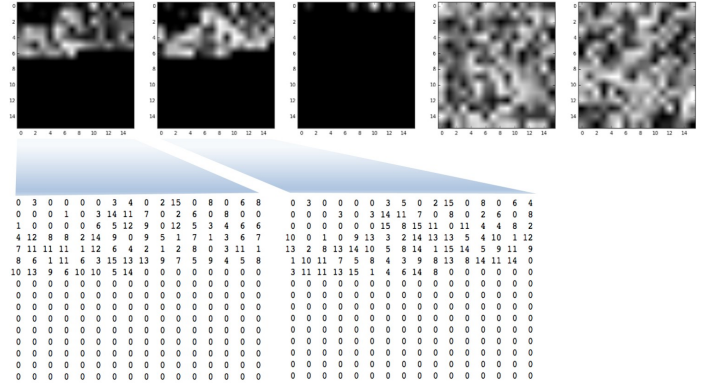


Fig. 1. Input features of flow packet

TABLE II
OUTPUT LABELS OF APPLICATION ONE-HOT VECTOR

Application	RDP	Skype	SSH	Bittorrent	Web
label	[1,0,0,0,0]	[0,1,0,0,0]	[0,0,1,0,0]	[0,0,0,1,0]	[0,0,0,0,1]

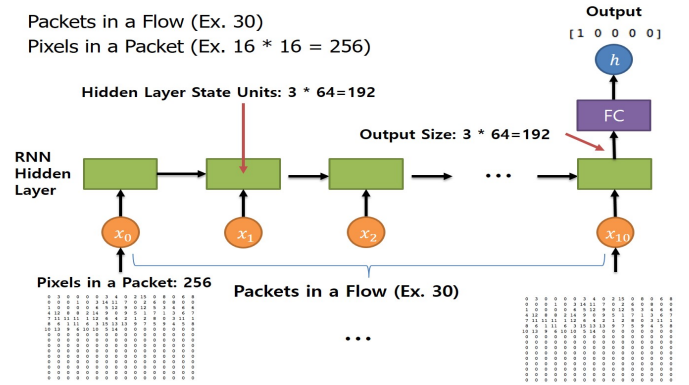


Fig. 2. Proposed deep RNN-based traffic analysis scheme

B. Proposed deep RNN model

This subsection describes the LSTM models that will be used for flow based network traffic classification using the proposed LSTM. LSTM shows great performance for various natural language processing (NLP) issues, especially LSTM is able to learn sequential data over CNN, which is used more by Deep Learning. Therefore, we believe that the network traffic classification through LSTM will be accurate in analyzing the flow that contains sequential information of packets. Fig.2 shows the learning structure of the Proposed deep RNN-based traffic analysis scheme used to classify traffic, and the learning model consists of a single layer. The time step for learning LSTM is to preset the number of packets throughout the flow to be learned. Time steps represent the number of inputs a flow enters sequentially from a single layer to an LSTM. Therefore, the form of learning data sets is represented in the train data set (number of flows, number of packets per flow, and payload size per packet), and the label data (number of flows, number of labels). The data sets of tests and validation are also inputted in the same form and learned through LSTM. The problem with the existing vanilla RNN is that of long-term dependency if the length of sequence is longer. Thus, this network architecture utilizes LSTM, a solution to long-term dependency problems.

TABLE III
HYPER-PARAMETERS USED IN DR-TAS AND DC-TAS

Hyper-Parameter	Value
Units	payload size $\times 2$
Filter	payload size $\times 1/2$
Kernel size	3×3
Activation	Softmax
Optimizer	Adam
Batch size	100
Epoch	200

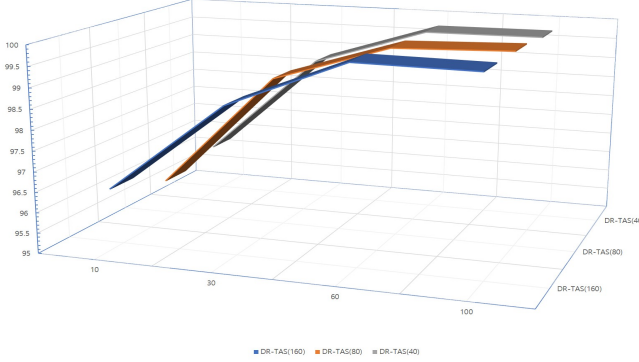


Fig. 3. Accuracy of deep RNN-based traffic analysis scheme

IV. PERFORMANCE EVALUATION

In this section, we present the results of classification of traffic data through the DR-TAS and DC-TAS experiments, and compare the network traffic classification results of DR-TAS with the ones of DC-TAS.

A. Experiments environment

Our experiments were conducted on Ubuntu 16.04 LTS, using 32GB of RAM and two NVIDIA GTX 1080Ti 11GB. We also used Tensorflow 1.8 in Python 3.6 environment to configure the LSTM and CNN deep learning models. For the experiments, we have 2000 flows for each application in train data, and the number of packets per flow is set to 10, 30, 60, and 100. In addition, the payload size of each packet was set to 40, 80, and 160. Table. III shows the Hyper-parameters used in DR-TAS and DC-TAS.

B. Experiments Results

For five applications, we examine the overall accuracy of the DR-TAS with regard to various numbers of packets per flow and payload size of each packet, and the results are shown in Fig. 3. As shown in the figure, the more the number of packets per flow, the higher the accuracy, and the accuracy becomes high as the payload size increases. If particular, when the number of packets per flow is 100 and the payload size is 160, the overall accuracy is the highest (i.e., 99.85%). The lowest accuracy is 96.00% when the corresponding values are 10 and 40, respectively.

Fig. 4 show the accuracy of DR-TAS for five applications, respectively. The accuracy of each application increases as the number of packets per flow increases. It is noted that, in the case of *Web* and *Bittorrent*, the accuracy is not high particularly when the number of packets per flow are 10 and

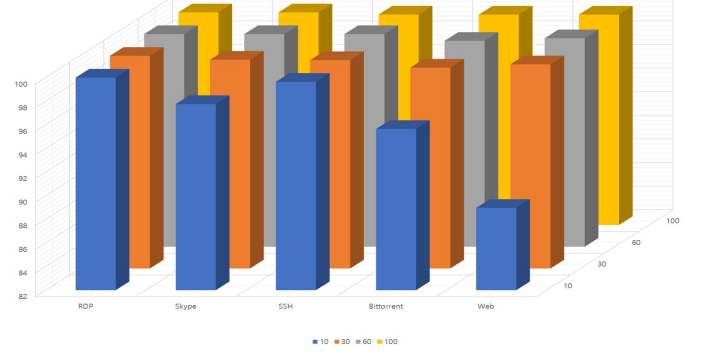


Fig. 4. Accuracy of DR-TAS for each target application

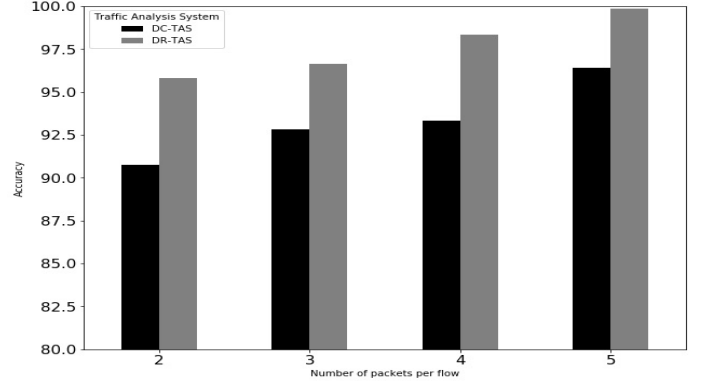


Fig. 5. Comparison on accuracy of DR-TAS vs. DC-TAS

payload size is 40. When the *Web* is classified using DR-TAS, the lowest accuracy is 88.97%. In case of *bittorrent*, the accuracy is 95.65%. Therefore, if the number of packets per flow is 10 and the payload size is 40 in fig3, the total accuracy is the lowest. The reason is that *Bittorrent* and *Web* are usually composed of image or video data. So, if the number of packets per flow and the payload size increases the accuracy of the LSTM model for *web* and *Bittorrent* is 99.81% and 99.82%, respectively.

The following is an experiment to compare DR-TAS and DC-TAS. For a detailed comparison of the two TASs, we compare the accuracy of each application with regard to four sets of applications:

$$\text{Set I} = \{\text{Bittorrent}, \text{Web}\} \quad (2)$$

$$\text{Set II} = \{\text{Bittorrent}, \text{Web}, \text{Skype}\} \quad (3)$$

$$\text{Set III} = \{\text{Bittorrent}, \text{Web}, \text{Skype}, \text{SSH}\} \quad (4)$$

$$\text{Set IV} = \{\text{Bittorrent}, \text{Web}, \text{SSH}, \text{Skype}, \text{RDP}\} \quad (5)$$

Fig. 5 shows the accuracy comparison results for the number of applications of DC-TAS and DR-TAS. Both DC-TAS and DR-TAS show that accuracy is lowered when TASs learned *Set I*. But, as applications are added, the amount of data to learn increases and overall accuracy improves. In addition, the overall accuracy of the DR-TAS is higher than that of DC-TAS. In other words, DR-TAS is a flow-based packet classification, it is more suitable for the characteristics of network traffic.

We compare elapsed time from data preprocessing of DC-TAS and DR-TAS to result prediction. The elapsed time is the

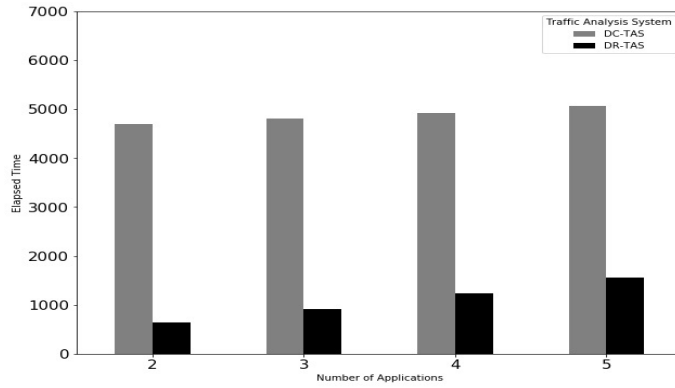


Fig. 6. Comparison on preprocessing elapsed time of DR-TAS vs. DC-TAS

sum of the preprocessing time for generating the appropriate data for each model and the time taken to train the CNN and LSTM model. Fig. 6 shows the elapsed time taken in the experiment of DR-TAS and DC-TAS comparing experiment. As the number of applications increases, the elapsed time increases. The elapsed time has increased because the amount of data to train has increased. It is noted that, in the case of DR-TAS, the elapsed time is less than elapsed time of DC-TAS as a whole. In the case of DC-TAS, elapsed time is long because data preprocessing reads arbitrary packets of each application flow. On the other hand, in the case of DR-TAS, preprocessing time is less than CNN preprocessing because it reads and generates data in each application flow unit.

V. CONCLUSION

As a result of learning from the LSTM model using network traffic data as a unit of flow, its accuracy was over 99%. This confirmed that the classification was nearly 100%. Future research will explore the classification of network traffic through deployment in a real network and also how new packets, other than those already learned, will be classified as they enter the real network.

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