Poster: Prediction of Mobile-App Network-Traffic Aggregates using Multi-task Deep Learning

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ABSTRACT

Modeling and predicting network traffic have become essential to many diverse practical contexts, ranging from security and network planning to QoS optimization. Nonetheless, modeling such processes is challenging due to the complexity and variability of the network traffic. Several modeling approaches have been proposed to improve classification and forecasting performances, spanning different objectives, excluding the prediction of aggregated network traffic generated by mobile applications. In this poster, we aim at filling this gap by exploring the suitability of several Deep learning (DL) and Machine Learning (ML) models to such aim. In particular, we used multi-task deep learning to predict several aggregate traffic features, including downstream and upstream traffic volumes, on different window sizes, showing promising performances.

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1 INTRODUCTION

Modeling network traffic is of utter importance to understand traffic peculiarities and predict its characteristics. Predicting traffic features has become essential for diverse practical contexts, such as enforcing traffic engineering, managing the QoS, detecting anomalies, and emulating real traffic for testing purposes. In particular *Traffic Prediction* (TP) task refers to forecasting network traffic given historical measurements or related data, passed as input to a properly trained system. We addressed the TP problem by predicting future aggregated traffic features at short-time scales (milliseconds) and leveraging multi-task deep learning. We considered the number of packets and volume (i.e., the sum of application-layer payload bytes) for each flow direction (i.e., upstream and downstream). Recent works investigated the usage of Neural Networks (NNs) to deal with the aggregates prediction problem, proving that NNs outperform the ARIMA models [3–5]. Authors in [2] compared NNs and Random Forest Regression (RFR) algorithm to the prediction problem applied on aggregated CAIDA dataset and showing that RFR outperforms DL approaches in short-term bandwidth estimation. Nonetheless, since there is no best method to deal with traffic prediction, it remains a hot topic. Also, none of those works attempted to predict aggregated traffic generated by mobile video applications.

We compared state-of-art NNs and ML models and examined their suitability to predict mobile video application traffic, showing that model performances strongly depend on the application traffic profile. Furthermore, in this work, we go beyond the previous approaches by evaluating how smaller aggregation windows impact the prediction of the next larger ones. We observe that a finer observation granularity achieves better results for most traffic profiles by revealing undiscovered mobile traffic patterns.

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2 METHODOLOGY

Our approach focuses on four aggregate features: upstream volume, downstream volume, upstream packets, and downstream packets. These features (i) are extracted from bidirectional flows (i.e., biflows), which constitute the traffic objects under investigation and (ii) are evaluated aggregating packets lying in pre-defined aggregation windows. In general terms, our system aims at observing these features over a T_M time period and at predicting them over a T_P period. In detail, packets within T_M are aggregated considering non-overlapping windows of size W. Formally, we call Δ_M size of the aggregation window so that $T_M = W\Delta_M$. We leveraged a human-generated dataset collected via a recently proposed architecture for capturing mobile-app traffic with related ground truth [1]. Traffic traces have been grouped in biflows (i.e., *bidirectional* flows), then the aggregated features are obtained through pre-processing operations constisting in

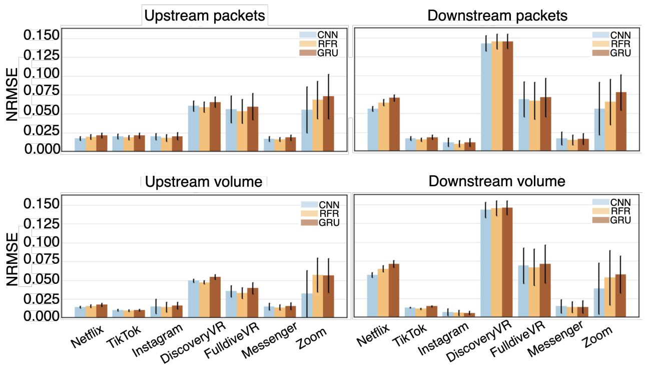

Figure 1: NRMSE comparison between CNN, RFR and GRU for $\Delta_M = 100$ ms and $T_M = 500$ ms.

sliding a time aggregation window over each biflow. The window leverages application-level raw payload along with timestamp information of packets to compute the aggregated statistics. Specifically, the biflows of each application are submitted to the aggregation module. Within the aggregation module, upstream and downstream application-layer payload bytes are considered to compute the traffic volume for each Δ_M along with the number of packets. The resulting four features constitute the aggregated dataset. We leveraged Multi-Task Learning which consists in learning tasks in parallel while using a shared representation, thus reducing computational overhead with respect to multiple single-task learning. We compared CNN and GRU as deep learning models and RFR as a machine learning model with a fixed aggregation window (100 ms). Then we used CNN to evaluate performances using different aggregation windows Δ_M (25 and 50 ms) and fixing a larger prediction time T_P (100 ms).

3 EVALUATION RESULTS

Our experiments involved applications from different categories, specifically, as labeled in the used dataset: *Cloud Virtual Reality (or CloudVR)* (`DiscoveryVR`, `FulldiveVR`), *Short-Video* (`Instagram`, `TikTok`), *Video Chat* (`Zoom`, `Messenger`) and *Video On-Demand* (`Netflix`). We predicted four different aggregated features: the number of packets and the traffic volume in upstream and downstream. Figure 1 shows that our prediction performance in terms of Normalized Root Mean Square Error (NRMSE) is heavily dependent on the application. In our initial results, we found a higher prediction accuracy for `Netflix`, `DiscoveryVR` and `Zoom` applications, where CNN outperform the other models. Consider Figure 2 where we show a synthetic analysis using CNN: for each application, we set T_M to be 500 ms, 1000 ms, or 1500 ms. The green boxes represent a growing trend of performances when considering aggregation windows, from the smallest (i.e., 25ms) to the largest (i.e., 100ms). For most application

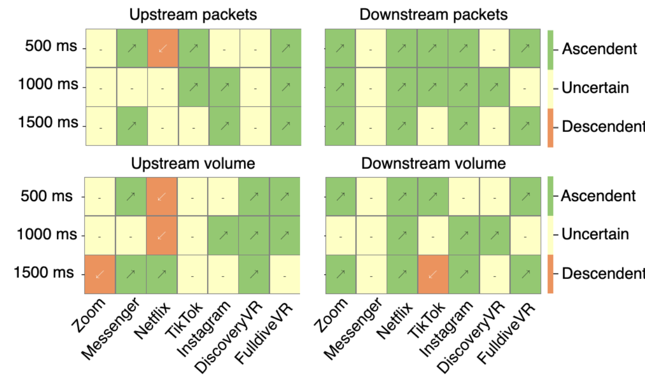

Figure 2: Performance trends heatmap varying T_M and fixing $T_P = 100$ ms.

categories, our predictor shows an improvement in prediction performances when using smaller aggregation window (Δ_M). Nonetheless, such improvement does not apply to all T_M values except for `Netflix` and `DiscoveryVR`. These two classes instead show rising performance trends regardless of the size of the model memory, which was arguably unexpected. We noticed that `Netflix` and `DiscoveryVR` have similar traffic profiles in terms of flow packet rate and number of packets.

4 CONCLUSION

In this poster, we presented a Multi-Task Deep Learning approach to solve the aggregated mobile-app traffic prediction problem. We analyzed the suitability of state-of-art models for the prediction task, showing that the traffic profile of some specific applications affects the performance of our training models. Our approach is promising when considering smaller observation granularity to aggregate flow packets with a fixed prediction time. Furthermore, in our initial results, we observed how reducing the granularity leads to improved prediction performances.

ACKNOWLEDGMENT

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REFERENCES

[1] G. Aceto, D. Ciuonzo, A. Montieri, V. Persico, and A. Pescapé. 2019. MIRAGE: Mobile-app Traffic Capture and Ground-truth Creation. In *IEEE ICCCS*.

[2] M. Labonne, J. López, C. Poletti, and J.-B. Munier. 2020. Short-Term Flow-Based Bandwidth Forecasting using Machine Learning. *arXiv preprint arXiv:2011.14421* (2020).

[3] A. Lazaris and V. K. Prasanna. 2019. Deep learning models for aggregated network traffic prediction. In *IEEE CNSM*.

[4] N. Ramakrishnan and T. Soni. 2018. Network traffic prediction using recurrent neural networks. In *IEEE ICMLA*.

[5] H. D. Trinh, L. Giupponi, and P. Dini. 2018. Mobile traffic prediction from raw data using LSTM networks. In *IEEE PIMRC*.