Poster: ISOML: Inter-Service Online Meta-Learning for Newly Emerging Network Traffic Prediction

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ABSTRACT

The increasing utilization of newly emerging networks (e.g., private-5G) across industries underscores the need for accurate traffic prediction to manage network resources effectively. However, rapidly emerging networks face challenges in accurate prediction due to limited training data at the early stage and fluctuation in traffic load at the maintenance stage. In response, we propose *ISOML* (Inter-Service Online Meta-Learning), a novel traffic prediction pipeline designed for newly emerging networks. *ISOML* utilizes meta-learning to address data scarcity and employs the EWC (Elastic Weight Consolidation) for online learning to learn dynamics of traffic patterns. Experimental validation in real-world datasets demonstrates the efficacy of *ISOML* in predicting traffic for emerging network environments.

CCS CONCEPTS

• **Applied computing** → **Forecasting**; • **Networks** → **Data center networks**.

KEYWORDS

Private Networks, Private-5G, Traffic Prediction, Meta Learning, Online Learning

ACM Reference Format:

Migyeong Kang[1†], Juho Jung[1†], Minhan Cho[1], Daejin Choi[2*], Eunil Park[1],, Sangheon Pack[3], Jinyoung Han[1]. 2024. Poster: ISOML: Inter-Service Online Meta-Learning for Newly Emerging Network Traffic Prediction. In *The 22nd Annual International Conference on Mobile Systems, Applications and Services (MOBISYS '24), June 3–7, 2024, Minato-ku, Tokyo, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3643832.3661437

1 INTRODUCTION

Traffic prediction, which forecasts future network traffic from past patterns, is vital for efficient network management and resource allocation. With recent advances in communication technology, the frequency of newly emerging networks (e.g., private 5G) has increased. However, these networks face two distinct challenges in traffic prediction that are not encountered by networks that have been established for a longer period. These challenges include (i) scarce data resources at the early stages that interfere with accurate traffic prediction, and (ii) unstable dynamics of traffic patterns caused by the increase in usage or the influx of new service users at the maintenance stage, which leverages the need to adapt the prediction model to recent traffic patterns.

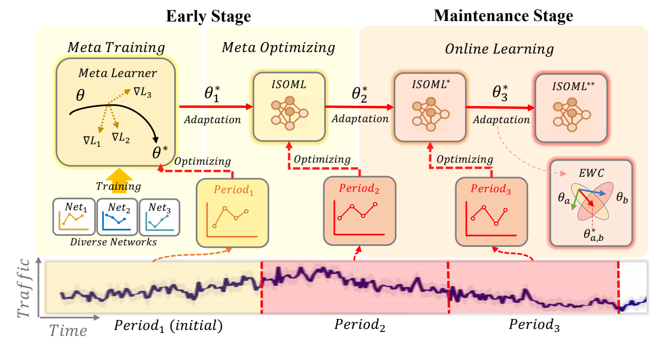

Figure 1: Design overview of the ISOML system.

To address these issues, previous research has proposed a method based on transfer learning and fine-tuning, which uses prior knowledge of traffic prediction for other networks to forecast traffic of the target emerging network at the early stage and update the model with the newly incoming traffic data at some time [2]. Unfortunately, the method requires a large amount of the data for pre-training before model transfer. Moreover, the method is exposed to the risk of catastrophic forgetting [4], where the model may lose its ability to recall past patterns as it learns from new data.

In this paper, we propose *ISOML* (Inter-Service Online Meta-Learning), a novel traffic prediction system for newly emerging networks, which has two different mechanisms in the early and maintenance stages. Adopting Model-Agnostic Meta-Learning (MAML) [1], ISOML overcomes the data scarcity problem at the early stage, by learning traffic patterns of other networks and refining model parameters with the small amount of traffic data from the target network. At the maintenance stage, the proposed model employs Elastic Weight Consolidation (EWC) [3], an online learning method to keep the model updating with up-to-date traffic patterns without catastrophic forgetting.

2 ARCHITECTURE

Figure 1 illustrates the overall architecture of the proposed system, which includes two main modules: MAML for the initial stage and EWC for the maintenance stage.

MAML for the early stage: In the early stage that suffers from data scarcity, *ISOML* first learns diverse traffic patterns of the other existing networks by employing MAML, a concept of meta learning

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MOBISYS '24, June 3–7, 2024, Minato-ku, Tokyo, Japan

ACM ISBN 979-8-4007-0581-6/24/06

https://doi.org/10.1145/3643832.3661437

Learning Type	Percentage of Training Dataset		
	3%	5%	10%
Direct Learning	4141.8	2250.5	1810.4
Transfer Learning	4697.2	2368.9	1360.9
ISOML	3312.7	2062.4	1351.2

Table 1: Performance with various sizes of training set

Learning Type	Time Period for Evaluation				
	0-20%	20-40%	40-60%	60-80%	80-100%
Full Training	2063.2	86456.2	1371.2	3096.9	1433.1
ISOML w/o EWC	9716.2	129027.8	1376.5	1277.4	1508.0
ISOML (ours)	5308.9	100710.3	1229.6	2753	1373.4

Table 2: Experiment results for the effects by EWC

designed to understand the process of solving the task itself [1]. Unlike the traditional transfer learning, which requires a large amount of traffic patterns from specific types of networks, MAML utilizes a smaller amount of diverse traffic patterns from various types of networks to find model parameter that can be quickly optimized for any new types of networks. The trained model parameter is then optimized with the traffic data of the target network. This approach allows ISOML to effectively predict traffic for newly emerging network that have a scarcity of historical traffic data.

EWC for the maintenance stage: With an assumption that the amount of the traffic data is sufficient at the maintenance stage, we propose a method for the prediction model to learn dynamics of traffic of the target network. Since a simple method that keeps updating models with the newly-incoming traffic can cause catastrophic forgetting, a phenomenon where the model forgets previously learned information, we employ EWC [3] that prioritizes the model parameters so that important parameters are preserved and only the parameters with lower priority are updated in the maintenance stage.

3 PRELIMINARY EVALUATION

We evaluate *ISOML* with the real-world traffic dataset provided by a cellular company in South Korea. The dataset consists of time-series of traffic volumes of four different services collected in every minutes for 27 days. Here, we select a target service, and traffic volumes of three services are used for pre-training. Based on the dataset, we evaluate *ISOML* from two different perspectives: (i) how accurate *ISOML* can predict traffic volumes in the situation of lack of the dataset for training and (ii) how EWC affects the model performance while online learning, whose results are shown in Table 1 and 2, respectively. Note that the training, validation, and test dataset is split with a 6:2:2 ratio, and LSTM is used as a base model for predicting traffic volume.

Table 1 shows the MAE values of traffic prediction with varying the size of the training dataset. Here, we also measure the performance of direct learning and transfer learning for a comparison purpose. *ISOML* achieves the lowest Mean Absolute Error (MAE) for less than 10% of data is trained, which demonstrates that *ISOML* can forecast future traffic even in the situation of data scarcity.

We also investigate how EWC affects the model performance, with detailed results presented in Table 2. Here, the entire dataset is divided into five sequential periods. Within each period, the data is separated into training, validation, and test sets. Considering that new traffic continuously accumulates over time under an online environment, the model is trained sequentially from the first period(0-20%) to the last period(80-100%). We report the performance of traffic prediction on the test dataset for each period, based on the model trained up to the last period(80-100%). This evaluation method is designed to assess how well the model retains knowledge from both past and recent periods. Note that we include the performance of the *full training* and *ISOML without EWC* case as a gold standard and a baseline case, respectively.

By 40% of the time periods, *full training* outperforms the others, indicating that sequential training leads to forgetting earlier periods. However, our method with EWC demonstrates superior performance compared to *ISOML without EWC*, illustrating that the EWC algorithm effectively alleviates catastrophic forgetting. Interestingly, after the period 40%, *ISOML* shows lower MAE values than *full training*, which trains uniformly across all periods, indicating that *full training* struggles to adapt to more recent traffic patterns. Additionally, *ISOML* consistently outperforms *ISOML without EWC* in all periods except 60-80%, which underscores the importance of EWC effectively preserving historical information while adapting to recent information. As a result, in situations where *full training* is considered impractical because it requires retraining the model from scratch every time new data is updated, *ISOML* can serve as an effective alternative or even a superior solution. Note that the performance of *ISOML without EWC* at period 60-80% is attributable to a similarity of the traffic pattern in the latter periods – traffic patterns between 60-80% and 80-100% are found to be similar, and since catastrophic forgetting of *ISOML without EWC* fortunately makes the model learn traffic patterns in 80-100%, leading to better performance in the 60-80%. In addition, exceptional fluctuation in traffic patterns during the 20-40% period resulted in high MAE values over all training methods.

4 CONCLUSION AND FUTURE WORK

We introduced *ISOML*, a novel traffic prediction pipeline for newly emerging networks, which showed great potential in both early and maintenance stages. Future research will enhance and generalize the models to more real-world datasets and scenarios.

5 ACKNOWLEDGMENTS

This research was supported by the National Research Foundation (NRF) of Korea Grant funded by the Korean Government (MSIT) (No. 2021R1A4A3022102) and the Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (IITP-2024-RS-2023-00259497, Research and Learning Program for Entertainment Data Science, Sungkyunkwan University).

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