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Survey on Robust Learning and Accurate Prediction of Wireless Traffic

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ABSTRACT

Network traffic forecasting is typically performed based on current traffic conditions recorded over specific time intervals. If the time interval is short, you can assume that the current traffic conditions will continue for some time. Based on this existing research, this study proposes a neural network model that uses the traffic flow difference as an input parameter, applies dynamic roll prediction that was considered to design a new short-term traffic flow prediction method, and applies random roll prediction.

I. INTRODUCTION

Currently, most wireless traffic prediction approaches are focusing on a centralized learning strategy and involve transferring huge amounts of raw data to a data center to learn a generalized prediction model. However, the frequent transmission of training data and signaling overhead could easily exhaust the network capacity and yield negative impacts on payload transmissions. New wireless traffic prediction approaches that can cope with the above challenges are needed.

Recently, wireless traffic prediction has received a lot of attention as many tasks in wireless communications require accurate traffic modeling and prediction capabilities. Wireless traffic prediction is essentially a time series prediction problem. The methods to solve it can be roughly classified into three categories, i.e., simple methods, parametric methods, and non-parametric methods. Computer networks consist of nodes (routers and switches) connected by physical links (optical or copper wires). Data from one node (called a source) to another (destination) is sent over the network on predetermined paths or routes.

We will call the stream of data between a particular source/destination pair a flow. The so-called flow level traffic may traverse only a single link if the source and destination nodes are directly connected, or several links, if they are not. Also of interest is the aggregate data traversing each link. The traffic on a given link is the sum of the traffic of the various flows using the link.

Both flow-level and link-level traffic have been studied in the literature. Thread-level data is expensive to obtain and process but provides direct information about streams. Data, especially data regarding packet delay from source to destination, was used to do something. See some references. On the other hand, the link-level data is less expensive to obtain but provides less information about the underlying flows.

Current TCP/IP network infrastructures and management systems are facing a tough time in handling the unusual increase in network traffic due to the surge of typical real-time applications.

To solve this problem, the management system anticipates network traffic changes and manages them proactively.

The rapid growth of computing power and wireless technology has enabled the mass adoption of mobile devices, the proliferation of mobile content and services, and new technologies such as the Internet of Things (Internet of Things). Iodine). As a result, global internet traffic per month has grown from 122 exabytes (EB) in 2017 to 201 EB in 2019 and is expected to grow to 396 EB in 2022. combined with high quality of service (QoS) for users. requirements create new challenges for operators in managing their networks. Traditional traffic management technologies use threshold-based algorithms that react slowly to rapidly changing traffic. Therefore, traditional methods cannot maximize the use of network resources and do not guarantee QoS according to the new network traffic dynamics. A proactive approach is one way to overcome the weaknesses of traditional traffic management techniques.

II. LITERATURE SURVEY

[1]. Accurate traffic modeling and prediction based on (deep) machine learning is an integral part of future big data-driven smart mobile networks, as it can help control and manage autonomous networks and provide services. With this in mind, this paper proposes a new deep learning architecture, which is the Temporal Spatial Inter- Domain Neural Network (STC Net), to efficiently capture complex patterns hidden in mobile data. By applying a long-term memory convolutional network as a sub- component, STC Net has a powerful ability to model space-time

dependencies. In addition, three types of cross-domain datasets are actively collected and modeled by STC Net to capture external factors affecting traffic generation.

Due to the diversity and coexistence between the mobile traffic of different functional areas of the city, a clustering algorithm is proposed to divide urban areas into different groups, and thus Thereby, a sequential inter-cluster transfer learning strategy is proposed to improve knowledge reusability. Furthermore, the proposed STC-Net model also explores knowledge transfer between different types of mobile traffic. The performance of STC Net is validated against real mobile traffic data sets using three different metrics.

Test results prove that STC Net performs better than modern algorithms. In particular, transfer learning based on STC Net yields about 4% to 13% performance improvement. This work investigates intelligent traffic prediction based on deep-learning techniques for future mobile networks. To fully describe the various factors (spatial, temporal, and extrinsic) affecting mobile traffic generation, three types of cross-domain datasets, namely BS information, POI distribution, and social activity levels, were explored and their correlation with mobile traffic was explored. analyzed. analyzed in depth. Based on these data sets, a new deep neural network architecture, STC Net, was proposed to predict integration into mobile traffic.

[2]. Wireless mobile traffic prediction is an important issue for researchers and practitioners in the 5G/B5G field.

This is difficult, however, because wireless mobile traffic often exhibits high nonlinearities and complex patterns. Most current wireless mobile network traffic prediction methods cannot model dynamic spatial-temporal correlations of wireless mobile network traffic data and therefore cannot provide satisfactory prediction results. To improve the accuracy of 5G/B5G mobile network traffic prediction, more cross-domain data was reviewed and the learning strategy of unified handover between departments and regions (Unified handover) was based on the proposed space-time inter-domain neural network (STC-N) model. Several cross-domain datasets have been integrated.

The accuracy of training the target service domain based on the data characteristics of the source service domain based on the similarity between services and the similarity between different regions has been improved, so that the prediction performance of the model has been improved. The test results show that the predictive accuracy of the traffic prediction model is significantly improved after integrating multiple cross-domain datasets, and the RMSE performance of SMS, calls, and Internet services can be improved by about 8.39%, 13.76%, and 5.7. % co-responding. In addition, compared with the current forwarding strategy, the RMSE of the three services can be improved by about 2.48% ~ 13.19%.

[3]. Accurate path loss (PL) prediction is essential to predict transmitter coverage and optimize wireless network performance. Traditional PL models find it difficult to cope with the growing trend of diverse, time- varying, and mass wireless channels. In this work, the most widely used multilayer perceptual neural network (MLP) in artificial neural networks (ANN) is used for the accurate prediction of PL. Three types of environment features were identified and extracted, describing the propagation environment only by considering limited environment types instead of the complex 3D environment modeling. Principal component analysis (PCA) is used to generate low-dimensional environmental features and remove redundant information between similar types of environments. In addition, the base station (BS) and receiver (Rx) information including 3D position, frequency, BS transmit power, antenna information, line loss power

Supply and received power from all positions are obtained from measurements. The effects of the number of neurons in the hidden layer, the number of hidden layers, the number of training samples, and the environmental characteristics on the PL prediction models are explored by considering the absolute value of the error.

mean (AME), mean absolute error (MAE), standard deviation (STD) of error, correlation coefficient, and time ratio, respectively. This work aims to understand the propagation characteristics of radio waves, which can provide a theoretical basis for wireless network optimization and communication system design.

[4]. Network traffic prediction is a basic prerequisite for dynamic resource provisioning in wired and wireless networks, but it is known to be difficult due to its volatile and explosive nature and similarity. Itself. Predicting network traffic at the user level is particularly difficult because traffic characteristics emerge from the complex interaction between the user level and application protocol behavior.

In this work, we solve the problem of predicting network traffic at the user level for a short period, driven by its applications in mobile scheduling. Motivated by recent work on strong adversarial learning, we solve a prediction problem for non- stationary traffic in adversarial contexts and propose a hyper-learning scheme consisting of a set of predictors, each optimized to predict a specific type of traffic, and a master strategy trained to automatically select the most appropriate predictor based on near predictive performance this.

We have proposed a meta-learning scheme that automatically selects a predictor from a set of predictors and thus allows it to adapt to changing traffic characteristics. Our performance evaluation based on public and collected traffic traces shows that the proposed meta-learning scheme is significantly superior to independent predictors and can be an effective solution for short-term network traffic prediction despite changing traffic characteristics.

[5]. Considerable efforts have been and are being made on short-term traffic forecasting methods, especially for expressway traffic based on- site measurements. However, the literature on predicting the spatial distribution of traffic in urban intersections is very limited. This paper presents new data-driven prediction algorithm based on Random forest regression on aggregated spatial data on the number of vehicles in a grid.

The proposed method aims to estimate future media-to- everything (V2X) traffic demand distribution, providing valuable information for the dynamic management of radio resources in small cells. Radio access networks (RANs) operating in the terahertz band and deployed in small cells are expected to meet the high data rate requirements of connected vehicles.

We conclude that our method, designed from a grid perspective, is superior to other traffic prediction methods and the combined results of these predictions with the reaction-oriented algorithm. Dynamic radiation, as a use case application, helps to reduce the proportion of vehicles receiving only minimal signal strength.

The security of many critical V2X-based applications is highly dependent on the quality of service of the communication network. In general, the delivery of new communication solutions requires new advances in network resource allocation based on intelligent computing approaches toward the Q station with high data rates, high reliability, and high data rates.

[6]. With high and high reliability as a representative of wireless LAN (WLAN) traffic environment, this paper studies busy/idle (B/I) duration modeling and its predictability based on predictability theory. We first measure and model channel states in high-traffic environments on virtually all WLAN channels in the 2.4 GHz and 5 GHz bands during busy periods (peak hours).) and idle time.

Next, using two selected channels in the 2.4 GHz and 5 GHz bands, we analyze the upper limit (UB) and lower limit (LB) of busy/no-time predictability. works based on the theory of predictability. The analysis shows that the LB predictability of the durations can be easily increased by modifying their probability distributions.

[7]. City-level traffic speed predictions provide an important database for the intelligent transportation systems that enrich commuters with up- to-date information about traffic conditions. However, the speed of a vehicle on city roads is affected by many factors, making it difficult to accurately predict actual travel speed.

In this paper we propose a new Spatiotemporal model called L-U-Net based on U-Net and long-short-term memory architecture to develop an effective speed prediction model that can predict traffic conditions in urban areas. Experimental results show that our prediction model can effectively predict the speed of urban traffic. It uses LSTM neural networks in combination with U-Net architecture. The model can capture features in both temporal and spatial dimensions for traffic speed prediction, as well as extract features without extensive feature engineering. We have shown that our method can effectively reduce the feature engineering workload and predict future traffic conditions.

[8]. An accurate and reliable traffic flow prediction is of great significance, especially the long-term traffic flow prediction e.g., 24 hours, which can help the traffic decision-makers formulate the future traffic management strategy.

However, the long-term traffic flow prediction imposes great challenges for decision-makers due to the nonlinear and chaotic feature of traffic flow. Therefore, in this paper, we proposed a hybrid deep learning model based on wavelet decomposition, convolutional neural network-long, and short-term memory neural network (CNN-LSTM), called W- CNN-LSTM, to predict next- day traffic flow. The wavelet decomposition technology is used to decompose the original traffic flow data into high-frequency data and low-frequency data for the improvement of predictive accuracy.

IV. LITERATURE SURVEY TABLE

AUTHOR	PROPOSED METHOD	PRON	CONS	DATA SET	METRICS
Chaoyun Zhang, Paul Patras, and Hamed Haddadi	Spatial Tempor al Cross- domain neural Network (STCNet)	Effectively improve prediction accuracy	Fall into the local optimum, and a long training period.	SMS traffic dataset	13% extra performance improvement
Qingtian Zeng, Qiang Sun, Geng Chen	Regional fusion transfer learning strategy	Can scale in proportion to the amount of training data available	Difficult to be used in large-scale parallel computing	multiple cross-domain datasets	Improved about 2.48%~13.19%
Lina Wu, Danping He, Bo Ai, Jain Wang, Hang Qi, Ke Guan and Zhangdui Zhong	Artificial neural network	The prediction accuracy and the time consumptio n can be balanced.	High memory consumptio n during construction.	Rx to construct seven datasets	Improved about 18%
Qing He, Arash Moayyedi, Gyrgy Da, Georgios P. Koudouridid	Meta-learning scheme	Reveal the highly nonlinear Relationshi p	For high cardinality, the feature space can explode	BS construct seven datasets	Improved about 20.14%
Kun Niu, Huiyang Zhang, Tong Zhou, Cheng, Chao Wang	Novel data- driven	Reduce resource consumptio n while meeting reliability demands	Inaccurate models lead to systems that under- or over-perform	web-NotreDam e data set	Improved about 12.85%

Yafei Hou, Julian Webber, Kazuto Yano, Shun Kawasaki	The data categorizatio n (DC) method	Reveal the highly nonlinear Relationship	Computational intensive and require relatively large memory space	fitting modeling can provide realistic parameter s as dataset	Improved 18.25%
Yiqun Li , Songjian Chai , Zhengwei Ma and Guibin Wang	CNN	Problems existing in their respective network structures	Eliminating the huge workload of traditional methods	five benchmarks based on England traffic flow dataset	0.902 ACCURACY
Dong- Hoon Shin, Kyungyon g Chung and Roy C.Park	long short- term memory	Minimizes the workload on infrastructures	High computational expense in training models	England traffic flow dataset	IMPROVED approximate 5%.

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