Traffic Prediction Based on P-ConvLSTM in Optical Transport Networks

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Abstract: Based on Prophet-guided neural network, P-ConvLSTM is proposed for traffic prediction. Proved by multi-group real traffic data in OTN, P-ConvLSTM has high accuracy and strong generalization. © 2022 The Author(s)

1. Introduction

With the accelerated development of digital transformation, network traffic has shown characteristics of explosive growth, high complexity and high burst. Therefore, accurate traffic prediction in intelligent optical networks is essential for network operators to realize dynamic resource allocation, predict traffic abnormal conditions, and improve the quality [1]. Traffic prediction methods can be divided into statistical analytic model-based methods and data-driven machine learning methods [2]. Statistical model-based linear methods such as auto regressive integrated moving average (ARIMA) [3] are based on scientific knowledge, but they are usually difficult to be used to predict data with complex randomness. Prophet and its variants based on an additive model where non-linear trends are fit with annual, weekly, and daily seasonality, plus holiday effects are widely used for traffic prediction in networks [4]. However, Prophet lacks local perspective, which is vital for forecasting the near-term future [5]. Machine learning methods have also exhibited excellent performance in the field of traffic prediction. Exiting machine learning models include deep neural networks (DNNs) [6], convolutional neural networks (CNNs) [7], support vector machines (SVMs) [8], reinforcement learning [9], etc. Since CNNs can extract the spatial-temporal characteristics of traffic data, many traffic prediction methods combined CNNs with other machine learning models [10]. Specially, the long short-term memory networks (LSTMs) combined with CNNs, i.e., ConvLSTM for traffic prediction have been a research hotspot. However, these deep learning methods are purely data driven, and they are difficult to handle emergent data streams which may hinder their deployment in actual networks.

In this paper, the Prophet-guided ConvLSTM (P-ConvLSTM) which integrates the output and physical characteristics of Prophet model into the ConvLSTM is proposed to traffic prediction. The P-ConvLSTM method can not only use the powerful fitting ability of machine learning, but also use the analytical model to predict data trends and emergencies. The traffic data sets of different time interval and different ports in real optical transport network (OTN) private line services are predicted. Experimental results show that supported by the analytic model, P-ConvLSTM has strong generalization ability which can accurately predict all the test traffic data sets and reduce normalized deviation (ND) of predicted traffic data by 69%.

2. Traffic Prediction Based on P-ConvLSTM

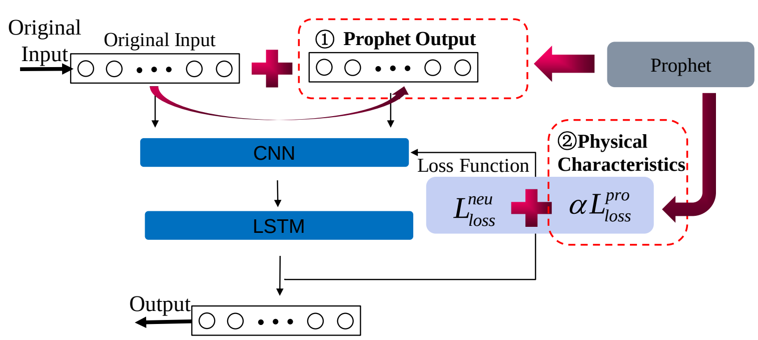

Fig. 1. The structure of P-ConvLSTM.

The P-ConvLSTM method makes use of the modeling ability of Prophet and the nonlinear fitting ability of ConvLSTM. The structure of P-ConvLSTM is shown in Fig.1. For the input of P-ConvLSTM, the original input of the neural network is converted into the output based on the Prophet model and then the feature vectors combined it with original input.

The loss function of P-ConvLSTM is denoted as

$$L_{loss} = (1-\alpha)L_{loss}^{neu} + \alpha L_{loss}^{pro}, \tag{1}$$

where α is the weight coefficient. A smaller value of α indicates a stronger randomness of traffic data. L_{loss}^{neu} is the ND which is generally used for traditional traffic prediction [6] and it can be represented as

$$L_{loss}^{neu} = \frac{(\sum_{u\in\Omega_{test}} |\hat{u}-u|)/|\Omega_{test}|}{(\sum_{u\in\Omega_{test}} |u|)/|\Omega_{test}|}, \tag{2}$$

where Ω_{test} is the testing set and $|\Omega_{test}|$ is the number of elements in Ω_{test}. u is the actual value of traffic data in Ω_{test} and $\hat{u}$ is the predicted value. L_{loss}^{pro} is used to ensure the consistency of Prophet model which can extract physical features from characteristics of the time series and it can be represented as

$$L_{loss}^{pro} = \frac{\sum_{u\in\Omega_{test}} |\hat{u}-u|}{(\sum_{u\in\Omega_{test}} |\hat{u}+u|)/2} + \frac{\sum_{u\in\Omega_{test}} (u \ge \hat{u}_{lower} \,\|\, u \le \hat{u}_{upper})}{|\Omega_{test}|}. \tag{3}$$

The left of (3) is the symmetric mean absolute percentage error which can reflect Bi-directional prediction deviation. The right of (3) is the bound function where $\hat{u}_{lower}$ is the lower bound and $\hat{u}_{upper}$ is the upper bound. It can reflect the prediction trend.

The partition of training set and testing set is shown in Fig.2. The Software Defined Network (SDN) controller collects the number of sent and received bytes at different ports in day interval, hour interval, minute interval and second interval. The Intelligent management and control system stores them in the format shown in Fig. 2. Then, the existing traffic data is divided into training set, verification set and testing set according to a certain proportion. The training set consists of N samples based on sliding window. The testing set also consists of M sets based on sliding window. The previous predicted traffic is the input of the latter prediction, and the final predicted traffic data is the output of all the testing sets.

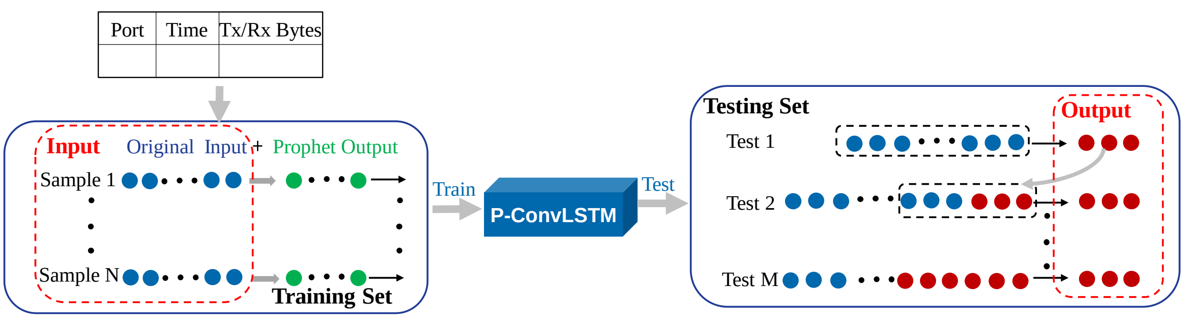

Fig. 2. The partition of training set and testing set.

3. Experimental Results

In order to verify the accuracy of network traffic prediction model, three real network traffic data sets in OTN were selected for experiment. For the traffic prediction based on ConvLSTM and P-ConvLSTM, the length of sliding window is set to 60, the batch size is set to 30, and the total 1000 epochs are trained.

Table 1. ND of Different Methods

	Data Set A	Data Set B	Data Set C
Prophet	0.00496	0.00932	0.09631
ConvLSTM	0.00470	0.00568	0.06674
P-ConvLSTM	0.00196	0.00294	0.03085

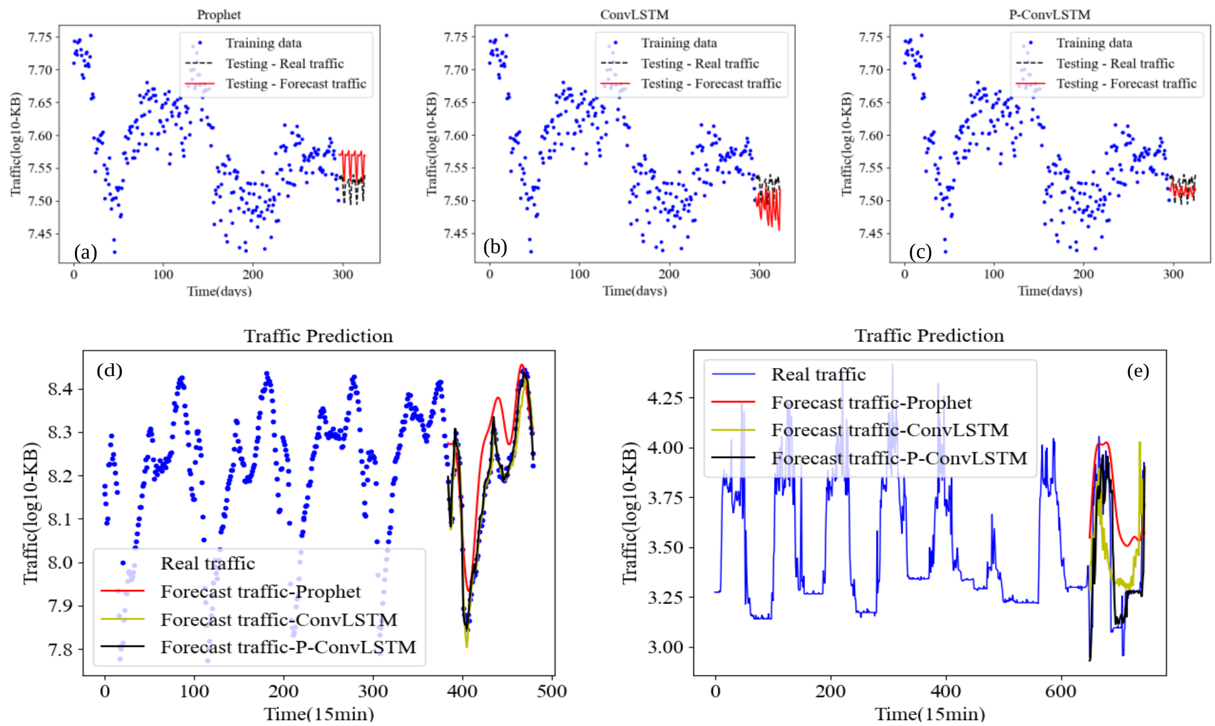

Fig. 3. The real and predicted traffic for data set A, data set B and data set C.

Data set A consisting of 326 traffic samples is collected from 00:00 on January 1, 2020 to 00:00 on November 1, 2020 every day. The traffic data of first ten months is the training set and the last month is the testing set. The real and predicted traffic based on Prophet, ConvLSTM and P-ConvLSTM is shown in Fig.3(a)-(c). The ND of different methods is shown in Table 1. For the data set A, Prophet overestimates the value of traffic data and ConvLSTM underestimates the value of traffic data. The P-ConvLSTM proposed in our paper can predict the traffic accurately and both reduce the ND of Prophet and ConvLSTM by nearly 60%.

Data set B comes from total traffic of multiple services in OTN and has obvious periodicity. Data set B consisting of 480 traffic samples is collected from 00:00 on May 13, 2021 to 23:45 on May 17, 2021 every 15 minutes. Data set C comes from traffic of private line service in OTN and has obvious traffic peak. Data set C consisting of 745 traffic samples is collected from 05:15 on September 20, 2022 to 07:30 on September 28, 2022 every 15 minute. The traffic prediction for data set B and data set C is shown in Fig.3(d) and Fig.3(e) where the traffic of last day is the testing set. The ND of different methods is shown in Table 1. For the data set B, ConvLSTM and P-ConvLSTM can reduce the ND of Prophet by about 40% and 69%, respectively. For the data set C, Prophet and ConvLSTM cannot predict the peak and valley of traffic. However, the P-ConvLSTM with both physical modeling ability of Prophet and the nonlinear fitting ability of machine learning can predict the traffic of whole day accurately. And it is helpful for operators to early warn the traffic peak in this scenario. The P-ConvLSTM method is considered to be embedded in the management and control system to realize intelligent operation and maintenance of the optical networks later.

4. Conclusions

Compared with Prophet and ConvLSTM, the proposed P-ConvLSTM can predict the traffic of different services for long-term and short-term data in real OTN accurately, which demonstrated that P-ConvLSTM has the ability of high accuracy and strong generalization.

5. References

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