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Deep learning-based prediction of base station traffic

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Abstract: *Nowadays, the development of 5G, edge computing, NFV and other technologies brought by the surge of network traffic will become a new challenge to the refinement, automation, intelligent operation and maintenance and management of the network. In order to meet this challenge, it is necessary to accurately perceive the application-level network traffic at multiple levels, such as edge network, MAN and backbone network. In order to reduce and reduce the error of predicting network flow data, a neural network algorithm prediction model based on machine deep learning, long and short memory network flow prediction model, which can predict the base station flow data according to the periodicity and volatility characteristics of base station flow data. After experimental verification, it shows that compared with the traditional time series prediction model AR model, ARIMA model also has the basic neural network model, that is, the fully connected neural network model. This method has higher accuracy and smaller experimental error in mobile communication traffic prediction. The MAE value is optimized by 21.6%, 33.4% and 12.5%.*

Keywords: *Mobile Communication Base Station, Traffic Forecasting, Long-Short-Term Memory Neural Network, Time series analysis*

1. Introduction

With the continuous development of Internet and communication technology, network heterogeneity and complexity also improve more users and data throughput is geometric number growing, thus to today's network planning caused many problems, and network planning and design management are based on prediction and analysis of network traffic characteristics as the premise. Therefore, the accurate network traffic prediction technology is increasingly valued by all parties and makes a lot of practices.

Studies in the literature [1] demonstrated the predictability of network traffic. At the same time, network traffic prediction itself has many difficulties. On the one hand, network traffic is widely distributed in time and space; on the other hand, network traffic features different traffic in different scenarios such as backbone network, data center and edge network. It is difficult to fully capture the feature difference of the traditional model alone, which affects the design, training and performance improvement of the prediction model. With the verification of a large amount of data and the practical efforts of researchers, two types of prediction model directions are summarized: (1) linear time series prediction model, and (2) non-linear time series prediction model. The linear time series model has two popular submodels: auto regressive (AR) model and the moving average (MA) model. They can also form an AutoRegressive Moving Average (ARMA) model. And there are many variants, and linear time series are the traditional method for network prediction. Literature [2] predicts the base station traffic based on ARIMA model and combining AR and MA model. Literature [3] proposed the improved PCA algorithm to monitor communication traffic data. Literature [4] proposed the prediction based on vector autoregressive VAR model and improves the accuracy of prediction data combined with Lasso. However, linear time series prediction is often accompanied by the calculation of huge data volume and the short board of long-term sequence prediction, so it is only applicable for short-term prediction. In recent years, the popularity of deep learning is increasing. Its power is that the input model can be transformed and extracted for many times. At the same time, deep learning is a supervised learning method. Only by obtaining a large number of trusted network traffic data, establishing an appropriate prediction model according to the important characteristics of network traffic, and making it fully trained, to master the complex characteristics contained in network traffic, can it accurately predict the future network traffic and give full play to its application value. Literature [5] proposes a time-series-based Adaptive Neuro-Fuzzy Inference System (ANFIS) for modeling and predicting Internet traffic. Literature [6] predicts network traffic based on Elman neural network, using wavelet transform to improve the prediction performance. Literature [7] predicts traffic congestion based on the long and short-term memory model.

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For the processing of long and short time series data in the accurate prediction of base station traffic, this paper puts forward the long and short time memory neural network model to complete the prediction of the base station traffic for the defined time period, at the same time, compare the prediction results of the neural network model with the MAE value of the conventional time series prediction model, it is concluded that the prediction effect by machine learning method is more accurate than the conventional AR model and ARIMA model value. Then comparing the parameters between the fully connected neural network model (DNN) and the LSTM model shows that the comprehensive parameter value of the LSTM model is better and more accurate than that of the fully connected neural network.The experimental results show that compared with other flow prediction models, this model has higher prediction accuracy and stronger anti-interference ability, and can be widely used. It provides an effective reference form for the operators to accurately plan their network resources in the future.

2. Correlation theory

2.1. DNN and LSTM

Fully connected neural network (DNN) is the most simple neural network, which has the most network parameters and the largest computation amount. The structure of DNN is not fixed. The general neural network includes the input layer, hidden layer and output layer. A DNN structure has only one input layer and one output layer, and the input layer and the output layer are all hidden layer. Each layer has several neurons, the layer is connected, the neurons are not connected to each other, and the next layer connects all the neurons in the upper layer. Hidden layer more (> 2) of the neural network called deep neural network (DNN network layer does not include input layer), the expression of deep neural network is stronger than shallow network, only a hidden layer of neural network can fit any function, but it requires a lot of neurons, its basic structure is shown in the figure 1 below.

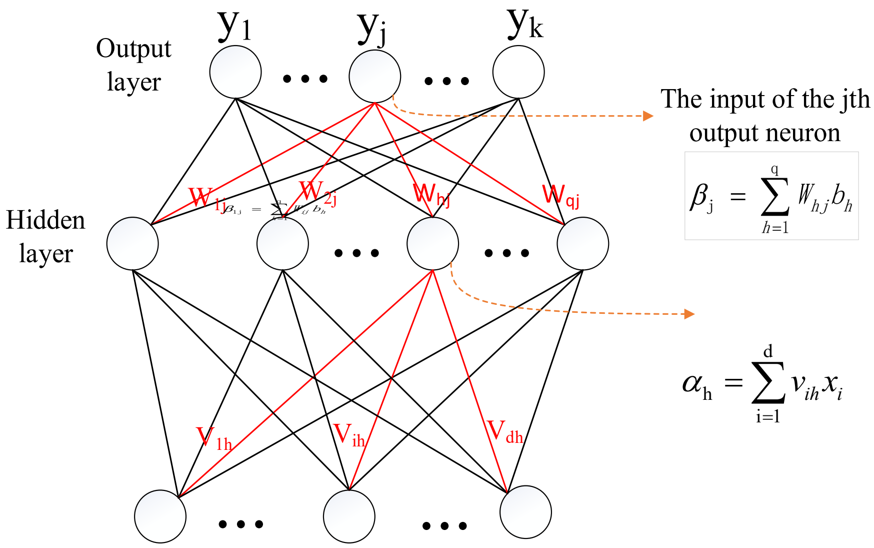

Figure 1: CNN Basic structure diagram

The advantage of DNN is that it can fit almost any function, so the nonlinear fit of DNN is very strong. Often deep and narrow networks are more resource-efficient. But its disadvantage is also very prominent, that is, DNN is not easy to train, need a lot of data, a lot of skills to train a deep network. So, better neural network models are introduced to solve this problem.

The long and short-time memory neural network (LSTM) is a modified version of the recurrent neural network (RNN), and the RNN is suitable for processing sequence data. As shown in Figure 2, the RNN has a reused neuron forming a circular chain structure with a cyclic chain length depending on the length of the input sequence. This chain allows the information contained in the sequence data at different stages to be retained in the neurons. The repetitive neuronal structure in the basic RNN is simple, as the RNN structure shown in Figure 3, with only one tanh layer within the nerve. In the formula h_{t-1} represents the output of the neuron at the preceding moment. x_{t-1} represents the input from the previous moment.

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h_t represents the output of the current moment. When the sequence length is too long, such a simple structure will make the distant information lost, accompanied by gradient disappearance, gradient explosion and other problems.

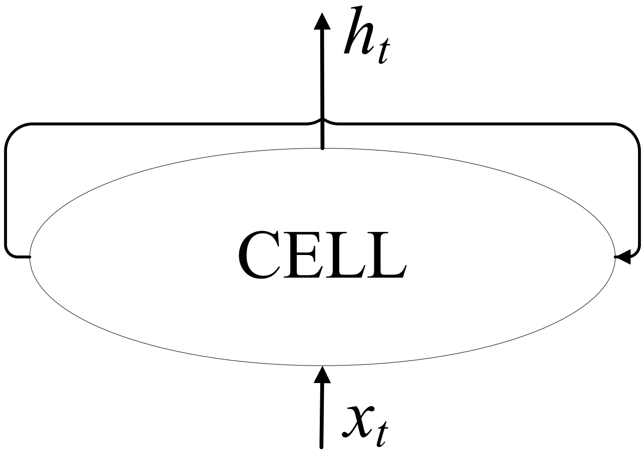

Figure 2: Schematic diagram of the RNN cycle

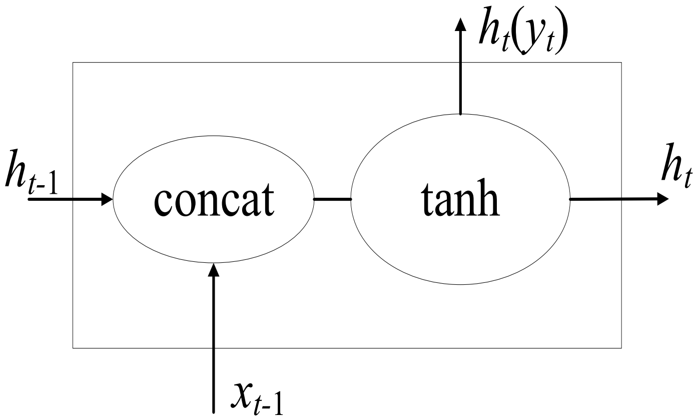

Figure 3: Internal structure diagram of the RNN

The LSTM neural network solves the problem of RNN backpropagation causing gradient explosion or disappearance, compared to conventional RNN, introducing cell state C to convey prior information. At the same time, the activation output value of the previous moment a_{t-1} and the input of the current moment X_t jointly determine the forgetting gate and the update gate. And then determines the choice between C and X_t information. The basic structure is shown in the figure 4 below.

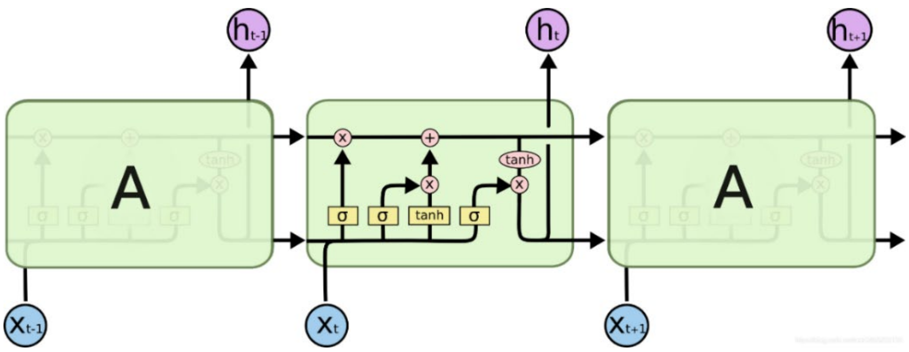

Figure 4: Basic structure diagram of LSTM

Where the forgetting matrix f_t is:

$$f_t = \sigma_1(W_f[a_{t-1}, X_t] + b_f) \tag{1}$$

The update matrix i_t is:

$$i_t = \sigma_1(W_i[a_{t-1}, X_t] + b_i) \tag{2}$$

i_t linear transformation of hidden layer a_{t-1} output by input X_t and at time t-1. Finally obtained after the Sigmoid activation function σ_1. i_t is a vector of element [0,1] used to control the amount of information flowing through the gate.

Current memory cell candidate values $\tilde{C}_t$ are:

$$\tilde{C}_t = tanh(W_c[a_{t-1}, X_t] + b_c) \tag{3}$$

The LSTM then determines the cell state information jointly through the forgetting gate and the update gate:

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \hat{C}_t \tag{4}$$

While the current output is controlled by the output gate, where the output function o_t is:

$$o_t = \sigma_1(W_o[a_{t-1}, X_t] + b_o) \tag{5}$$

And act on the cellular information C_t to jointly determine the current activation output a_t:

$$a_t = o_t \otimes tanh(C_t) \tag{6}$$

Finally, to output the result at time t, the output prediction $\hat{h}_t$ calculation:

$$\hat{h}_t = \sigma_2(W_y[a_t] + b_y) \tag{7}$$

Where: σ_2 is the Softmax activation function.

This is the LSTM internal information transfer process, where W_f, b_f, W_i, b_i; W_c, b_c; W_o, b_o; W_y, b_y are the weight and bias parameters of the forgetting gate, update gate, output gate and the output result value of LSTM. At the same time, by controlling the forgetting door, updating the door, the output door can flexibly choose effective information and invalid information. Non-linear functions can be simulated, while the transmission of cellular information can retain the past information for a long time. This design can solve the data dependence in the timing problem, and effectively improve the accuracy of prediction.

3. Experimental Verification

3.1. Data preprocessing

The mobile base station traffic data used in this paper from the actual data set in the game for simulation verification, collected a base station cell from August 28, 2021 to September 25,2021 base station traffic data for experimental training test, data collection interval of 1 h, extracted a cell 11832 data, first data pretreatment, cleaning data screening 696 sets of effective data, using 522 data to complete the training of the model, 174 data is used for test performance. The raw network traffic used in the experiment is shown in Figure 5.

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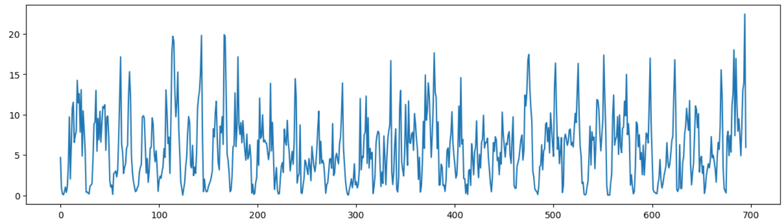

Figure 5: Raw flow data of the base station

Before the data enters the neural network, the data preprocessing should be carried out. Data standardization is one of the data preprocessing, and the purpose is to speed up the training speed of the neural network. The way is to subtract the mean value from the data, and then divide it by the variance:

$$z = (x - \mu) / \sigma \tag{8}$$

Where z represents the calculated value, x the raw data, μ the mean of the data and σ the variance of the data. Therefore, the data with mean 0 and standard deviation 1 are obtained. In data processing, the Z-score normalization (0-1 normalization) method is used to normalize the mean and standard deviation of the original data.

3.2. Evaluating indicator

MAE evaluates the accuracy of the common error index, and the formula is:

$$MAE = \frac{1}{T_y} \sum_{i=1}^{T_y} \left| \hat{y}_i - y_i \right| \tag{9}$$

3.3. Experimental result

In this paper, LSTM neural network is used to predict base station traffic, including multi-step prediction AR model and ARIMA model, and fully connected neural network. Table 1 gives the error evaluation index of MAE parameters. From Table 1, LSTM model compared with AR model, ARIMA model has the minimum MAE value, which shows that the proposed LSTM model is closer to the true value in base station traffic prediction, and better than that of the other three models.

Table 1: Comparison of MAE values between LSTM and the other three models

Model	AR	ARIMA	DNN	LSTM
MAE	3.55	4.18	3.18	2.78

In this paper, the above two best effective models are selected to draw the images of the MAE of the training test set. Figure 6 and Figure 7 are the images of the values of the base station traffic test set MAE and the MAE values of the fully connected neural network and LSTM model.

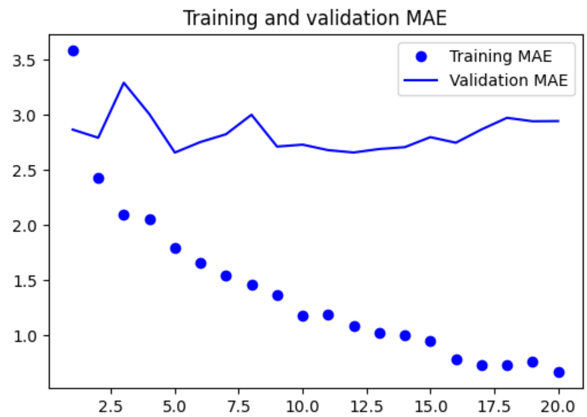

Figure 6: MAE values of the test set and validation set

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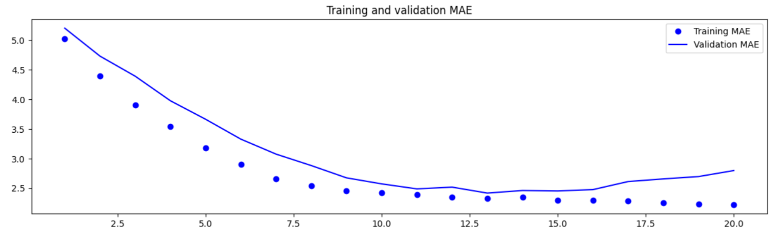

Figure 7: MAE values of LSTM models

By the above two images DNN at the 5th epoch, the loss of the validation set no longer drops. The LSTM converged at the 15th epoch. Moreover, the fit of the MAE values for LSTM is closer to the training set, and the loss of the validation set is more stable after the 10th epoch. It can be concluded that the LSTM model is closer to the true value and has less deviation than the fully connected neural network.

4. Conclusion

This paper for the problem of mobile base station traffic prediction, puts forward the LSTM neural network prediction model method. At the same time, it can better help operators to reasonably plan the allocation of network resources, so that users can feel more comfortable with the network experience, and provide an effective reference form for the future development of network technology.

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