Research on Website Traffic Prediction Method Based on Deep Learning

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Abstract. Accurate prediction of website traffic can improve network management, improve service quality, and improve the end user experience. Using the neural network learning and memory function, we can predict the time series of network traffic flow. Based on short - and long-term memory, we design the structure of data and neural network model and select the nonlinear activation function. The experimental results show that the proposed prediction method obtains the higher accuracy, which can effectively predict the traffic of visiting websites. At the same time, this method can effectively reduce the training time. By accurate traffic prediction, the network manager can adjust scheduling strategy to guarantee the user experience.

Keywords: Network traffic prediction · Bidirectional LSTM · Deep learning · Activation function · Automatic polling

1 Introduction

With the development of emerging technologies such as artificial intelligence, big data, and 5G, some emerging network technologies and communication methods have been proposed [1, 2], and the quality and experience of the network are constantly improving [3, 4]. The WEB data is advancing the development of big data technology [5, 6]. Based on data mining, we can predict the network flow and reconstruct the traffic flow [7–10]. The machine learning is adopted to improve network scheduling and experience of end user [11]. Based on these emerging technologies, we can deploy new scheduling strategies in base station and mobile nodes to improve the energy efficiency [12–15]. By predicting future website visiting, grasping the network operation status in the future and taking more measures, the pressure of network congestion can be alleviated. According to the prediction results of website traffic, network resources are scheduled and allocated. Abnormal website traffic can also reflect the situation of network intrusion. If an abnormal phenomenon is detected in some key nodes on the website traffic, it is likely to have illegal behavior, and the administrator only needs to issue an alert, Taking preventive measures will ultimately protect user privacy, improve security and reliability,

D. Jiang and H. Song (Eds.): SIMUtools 2021, LNICST 424, pp. 432–440, 2022.
https://doi.org/10.1007/978-3-030-97124-3_32

and maintain a stable operating environment. Establish a suitable prediction model and use it to predict the size of website visits. Using the prediction results as a guideline can effectively reduce network congestion, prevent network attacks, maintain the normal operating environment of the website, reduce the possibility of failure, and improve security mechanism. From a higher perspective, it can have a very positive effect on website management and service performance.

2 Introduction

Information technology era, the Internet technology brought further changes to our lives, the network traffic as the amount of data transferred on the network, the actual situation of network indicators, through the website of network traffic analysis and forecasting, in network planning, network security, user experience, etc. have not kill the practical significance. In recent years, many methods and studies have emerged. In Literature [16], traffic prediction models are built in terms of text targets based on the characteristics of ever-growing pattern for attendance websites and business process objects. However, these models are relatively simple and their accuracy needs to be improved. In Literature [17], a network transmission point process based on deep mechanism is proposed to simulate network traffic characteristics, which can be used for effective mode prediction. It is suitable for large institutions such as data centers and has a good performance improvement. However, its architecture is complex and the actual application scenarios are limited. In Literature [18], based on layered network traffic, an efficient algorithm HTSIMPUTE was developed. In the time series of multivariable network traffic, the eigenvalues were predicted more accurately and had consistency constraints. The prediction model developed in literature [19] is enhanced by the general adaptive conditional scoring model, and can effectively deal with various load fluctuations by using the characteristics of regression. Its accuracy has been improved, and its practicability remains to be studied. Some scholars [20, 21] proposed a method based on request statistics and used vector machine classification to better predict traffic. In the face of the pattern and its statistical characteristics, an incremental learning method was proposed to improve the performance in terms of accuracy. Some scholars [22] also mark the characteristics of samples through a semi-unsupervised method, aiming at the abnormal HTTP traffic, providing a good foundation for the future development trend of traffic. The classification accuracy of traffic is improved [23, 24], which is conducive to reducing data resampling and improving the generalization ability of the system. By using Internet domain and sandbox analysis, logs can be correctly interpreted and weak supervision can be realized. Accurate detection channels can be obtained to provide a stable platform environment for improving prediction accuracy. Literature [25] evaluates the performance of eight machine learning algorithms in classification applications and traffic prediction, and compares the differences between different algorithms and models. Literature [26] proposes a network traffic encryption prediction method based on OQE, which has certain effect on the future expectation of video users. It further improves the model and analyzes the cause and time of the prediction error. In addition, the adaptive algorithm is studied. Therefore, from the perspective of experience quality, valuable insights are provided on the logical direction of strategy selection. This approach is also of certain significance for improving the future QoE algorithm and enhancing the core competitiveness. Scholars [27] estimate the future trend of network security problems by using the dark web crawling method of routers, and predict and evaluate high risk traffic. The model idea of this research is helpful to improve the accuracy of website traffic. Literature [28] proposed a TC engine, from the perspective of training and characteristics, the selection module and classifier, through the data plane, offline, to accurate classification of data packets, and then sent to the control plane, the effective mark packets implement resources and queue management, defined by the software point of view, the development trend of flow and main mark characteristic has the very good revelation function, however, the accuracy of future expected effect in site visits, needs further research. The traffic identification model in Literature [29] can automatically learn the nonlinear relationship between the original input and the predicted output, and it can effectively predict the traffic through classification and recognition. The method proposed in Literature [30] can provide abnormal interpretation of Web traffic, cope with traffic dynamics and future explosion, and the dimension-reduction technology based on neural network can extract the effective trend model of Web access data.The fuzziness and chaos of network traffic limit the precision of SVM prediction model. Wang et al. proposed a method to optimize model parameters, which improved the precision of SVM prediction model [31]. Literature [32] introduces the actual traffic data of enterprise network access points, and the temporal and spatial analysis of network traffic during actual operation. The results show that LSTM can effectively improve the prediction performance of access points. However, it is slightly insufficient in terms of versatility and cannot achieve the best results. In [33], for the 5G core network, a mechanism for predicting traffic load changes through LSTM is proposed, which can realize traffic load prediction. The results show that the scalability mechanism based on prediction is superior to other solutions in terms of responsiveness and resource integration. However, the choice of threshold needs to be improved. To sum up, in the field of web site network traffic prediction, a variety of methods and models, are put forward and continue to improve, to establish a suitable prediction model, and use it to predict the future, the size of the network traffic to improve network security, network management and network performance and so on can generate a very positive role, especially in the aspect of improving the end user experience, has a huge potential value.

3 Data Processing

The processing of website traffic-related data requires standardized processing to improve the accuracy of forecasts. The current predictive evaluation system often contains multiple indicators, among which the nature of the dimensions and the order of magnitude is different, resulting in huge differences. Such differences will cause poorer expected results. Therefore, in order to reduce this difference and ensure the standardization of traffic prediction related data and the rapid characteristics of cost function optimization, the original data of the training set and the test set are standardized here. In the training process, the use of dimensionless data features can improve the running speed of the model, and at the same time can avoid the influence of outliers on the overall calculation, improve the accuracy of the model, and ensure the reliability of the results.

Transform the sequence $P = \{p_1, p_2, p_3 \cdots p_n\}$ to obtain the dimensionless sequence $Q = \{q_1, q_2, q_3 \cdots q_n\}$, and the model is shown in Formula (1).

$$q_i = \frac{p_i - \min\limits_{1 \le j \le n} \{p_j\}}{\max\limits_{1 \le j \le n} \{p_j\} - \min\limits_{1 \le j \le n} \{p_j\}} \tag{1}$$

In Eq. (1), $\min\limits_{1 \le j \le n} \{p_j\}$ is the minimum value in the sequence and $\max\limits_{1 \le j \le n} \{p_j\}$ is the maximum value in the sequence, then the new sequence $Q = \{q_1, q_2, q_3 \cdots q_n\}$ is dimensionless. We selected a data set to carry out normalization processing on the data, and made images before and after normalization, as shown in Fig. 1 and Fig. 2.

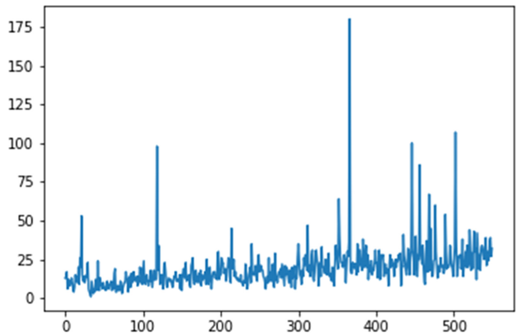

Fig. 1. Before regression.

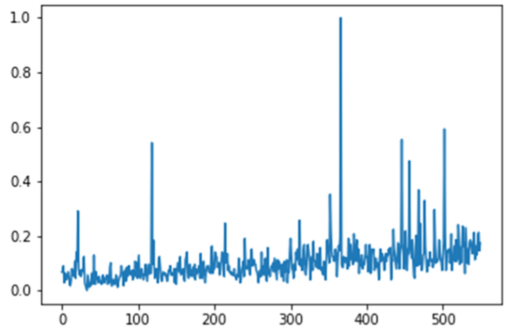

Fig. 2. After regression.

Figure 1 shows the data graph before regression, and Fig. 2 shows the data graph after regression. It can be seen that the shapes of the two graphs tend to show the same, and the range of the longitudinal axis is narrowed by regression processing, limiting it to 0–1. After data standardization processing, all indicators of the original data are in the same order of magnitude, which is suitable for comprehensive comparative evaluation. Among them, the most typical is the normalization of data processing.

4 Model

The input data of a one-way LSTM is unique, and these training data include the information of visited user. Bidirectional LSTM uses input data to run in two ways, one is from the past to the future, and the other one is from the future to the past. The difference between the two methods is that in the feedback operation, the future information is retained in both directions and the information before and after can be saved at any point in time. Bidirectional LSTM is composed of two LSTM cyclic layers with opposite information transmission. The two cyclic layers transmit information in time order and reverse order respectively, and the output results are calculated in combination with consideration of two directions. The model structure is shown in Fig. 3.

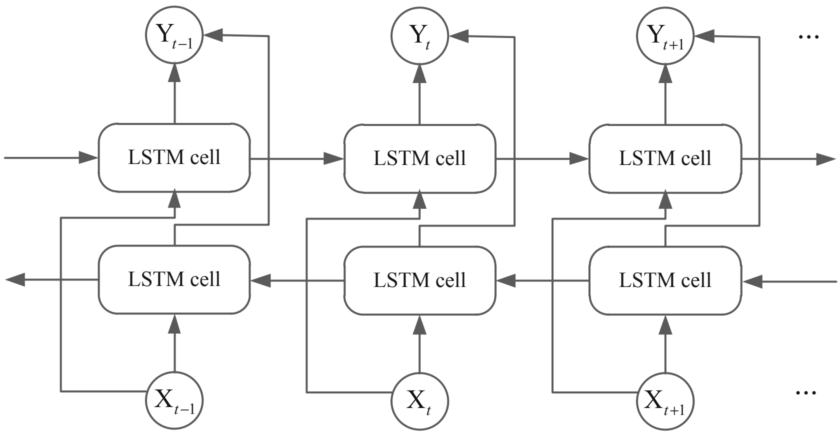

Fig. 3. Model structure.

In Fig. 3, $\{x_1, x_2, \cdots\}$ is the input layer, $\{y_1, y_2, \cdots\}$ is the output layer.

The ReLU activation function is adopted here to solve the nonlinear problem of neural networks. Using ReLU can more effective gradient descent and back propagation, thus avoiding the problems of gradient explosion and gradient disappearance. In terms of the calculation process, the process can be effectively simplified and the negative influence of other activation functions, such as the influence of the exponential function, can be shielded. In addition, its decentralized activity reduces the overall computational cost of the neural network and optimizes resource utilization.Automatic polling verifies universality, as shown in Table 1.

Table 1. Automatic polling algorithm.

Automatic algorithm
Input:Range1,Range2,Step
Output:figures
//Random generated parameter and run the model
for K=1 to Step.size do
P1 = random(Range1)
P2 = random(Range2)
Result.figures=LSTM(P1,P2)
end for
return Result.figures

In Table 1, an automated method is proposed to automatically poll and traversal the target, saving time cost and ensuring the comprehensiveness of data evaluation.

5 Assessment

In this case, the use of CUDNNLSTM acceleration is specifically implemented for CUDA parallel processing and can only be implemented in a GPU environment, otherwise it will not run. The faster execution time is due to the parallelism. Train_rmse and test_rmse values are obtained and plotted. It can be found that although the look_back value has changed, test_rmse and train_rese are basically stable. In order to prove the superiority of bidirectional LSTM in time series forecasting, the stacked and bidirectional LSTM are compared by error criteria, and RMSE (rootmeansquarederror) is selected for judgment, as shown in formula (2).

$$\text{RMSE} = \sqrt{\frac{\sum (y - y')^2}{n}} \tag{2}$$

In formula (2), y is the real result, y' is the predicted result, and n is the size of the data set. The evaluation index can unify the error, and the dimensions of the original data and the target data, compared with MAE (mean absolute error), make up for the defects of non-direction at some points. Randomly select 40 articles, use the bidirectional and stacked LSTM models to make predictions, and compare the RMSE of the results of the two models, as shown in Fig. 4.

It can be seen from Fig. 4 that the RMSE of the bidirectional LSTM is generally small, which is more suitable for time series forecasting analysis.

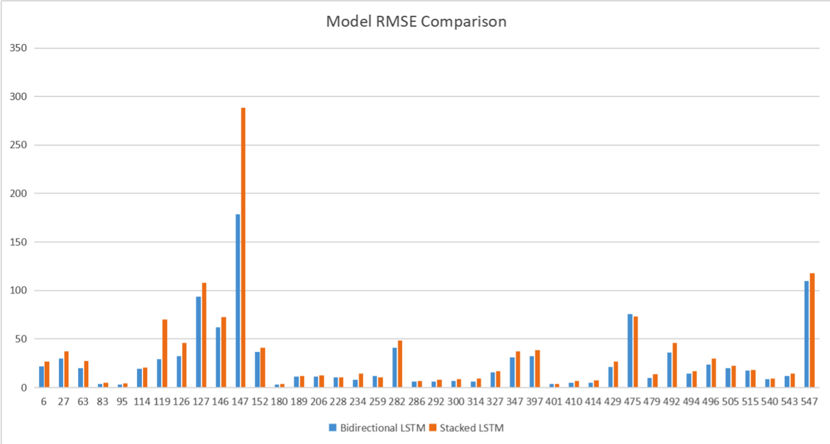

Fig. 4. Rmse comparison.

6 Assessment

This paper adopts neural network learning and memory function to predict website traffic. According to the time series of network traffic forecasting, we design a method to optimize the data structure. The nonlinear activation function of the enhanced neural network model is adopted, and automatic polling traversal is proposed to access the site prediction data of the specified target. The experimental results show that the method has certain practical value. On the other hand, the acceleration function can effectively reduce the running time of the model and save costs. Accurate website traffic forecasting can help better network management, improve service quality, optimize resource allocation, and improve user experience.

Acknowledgment. This work is partly supported by Jiangsu technology project of Housing and Urban-Rural Development (No. 2018ZD265) and Xu Zhou Science and Technology Plan Project (No. KC21309).

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