Prediction of port container throughput based on CNN and LSTM model

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Abstract

In order to improve the efficiency and accuracy of port container throughput prediction, deep learning algorithms are used for analysis and prediction to improve prediction accuracy. Taking Domestic Lianyungang port as an example, this paper USES convolutional neural network (CNN) and LSTM to analyze and predict the container throughput of its port. First, the characteristics related to the development trend of container throughput of Lianyungang port were collected, and then the container throughput prediction model of Lianyungang port was built based on CNN-LSTM, and compared with DNN and LSTM models. The results show that the container throughput prediction model based on CNN-LSTM has higher prediction accuracy and can well predict the development trend of port container throughput.

Keywords

CNN; LSTM; Port container throughput; Comparative analysis of prediction methods; Deep learning.

1. Introduction

With the development of the global integration process continuously, the port in the strategic position in the international transportation networks and trade exchanges continue to strengthen, and port throughput prediction is an important part of the port development strategy research, port throughput as a measure of a country or region economic development of important economic indicators, more and more get the attention of the people, how to correct and effective throughput forecast, according to the related influence factors to make for the development of logistics industry has the vital role. In the port throughput, container throughput takes up a large proportion, so accurate prediction of the growth trend of port container throughput is not only conducive to our reasonable planning and construction of logistics infrastructure, scientific layout optimization, but also of great significance to the sustainable and stable development of port cities and national economy.

At present, there are many forecasting methods for port throughput. The traditional forecasting methods mainly include linear regression\textsuperscript{[1]}, exponential smoothing method\textsuperscript{[2]}, gray model\textsuperscript{[3]}, BP neural network\textsuperscript{[4]} and so on. However, only a single factor (time dimension, etc.) is considered to affect port throughput, while other factors are ignored. At the same time, most of the traditional prediction methods (linear models) cannot well simulate the nonlinear relationship between variables in reality, which results in the decrease of prediction accuracy. With the continuous development of machine learning, deep learning theory and computing power of computers, the granularity and accuracy of port throughput prediction based on machine learning method are further improved, such as SVM\textsuperscript{[5]}, random forest, deep neural network, etc.
In this paper, firstly, the port container throughput and the characteristics related to the development trend of port container throughput are collected as modeling data, and then a prediction model based on CNN-LSTM for the port throughput is established and analyzed.

2. The data processing

2.1. The data source

Based on the existing research experience, this paper firstly screened and analyzed the data related to port container throughput of Lianyungang Statistical Bureau and China Port Statistical Yearbook from 2000 to 2016. Then, 11 characteristics including permanent resident population, GDP, total import and export, the added value of the first, second and third industries, fixed asset investment, railway freight volume, highway freight volume, waterway freight volume and the number of berths above 10,000 tons are selected as variables affecting container throughput, Z1-Z11 is used for simple subsequent representation. The specific explanation is as follows:

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Field meaning</th>
<th>Characteristics</th>
<th>Field meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z1</td>
<td>Permanent population (10,000)</td>
<td>Z7</td>
<td>Added Value of tertiary industry (100 million yuan)</td>
</tr>
<tr>
<td>Z2</td>
<td>GDP (100 million YUAN)</td>
<td>Z8</td>
<td>Railway freight volume (tons)</td>
</tr>
<tr>
<td>Z3</td>
<td>Total imports and exports (US $100 million)</td>
<td>Z9</td>
<td>Highway freight volume (tons)</td>
</tr>
<tr>
<td>Z4</td>
<td>Fixed Asset Investment (100 million YUAN)</td>
<td>Z10</td>
<td>Waterway freight volume (ten thousand tons)</td>
</tr>
<tr>
<td>Z5</td>
<td>Added value of primary industry (100 million yuan)</td>
<td>Z11</td>
<td>Number of berths above 10,000-ton class (per berth)</td>
</tr>
<tr>
<td>Z6</td>
<td>Added value of the secondary industry (100 million yuan)</td>
<td></td>
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</table>

2.2. Correlation analysis

It can be seen from the figure above that there is a high degree of linear correlation between most variables (>0.9). The correlation between Z1, Z2, Z5 and Z6 reached 0.99. If the traditional linear regression model is used, the effect of the model may be poor due to multicollinearity, resulting in the failure to simulate the real situation. Therefore, this paper uses the deep learning model.

2.3. Data set construction

According to the prediction task and data input requirements of the model in this paper, it is decided to use the data of the first five years to predict the data of the sixth year. Finally, the data is processed into a three-dimensional format (samples, timestep, features). The processed data set was divided into training data set and test data set. The data from 2000 to 2013 were selected as the training data set (80%) for the training model. 2014-2016 as a test data set (20%) to verify the validity of the model.
3. Model building

3.1. theory

3.1.1. CNN

Convolution operation is the key for the convolutional layer to extract image features. New feature images are generated by the input data through the convolution kernel dot product and slide. The convolutional layer is to carry out convolution operation on image data of multiple channels to obtain the feature image set with the same number of convolution kernels. The specific operation and structure are shown in Figure 2.

![Convolutional layer structure](image)

In this paper, 1-dimensional convolution (Conv1D) was used. The key difference between 1-dimensional convolution and 2-dimensional convolution lies in the shape of the convolution kernel (filter) and the sliding mode on the data. The figure 3 shows the specific operation mode. 

![Specific operation mode](image)
of Conv1D on the data. It can be seen from the figure that the size of Conv1D convolution kernel is only high, and the sliding direction slides from the first sample to the last sample.

3.1.2. LSTM

LSTM neural network is an improved structure of cyclic neural network (RNN). Traditional cyclic neural network (RNN) cannot solve the problem of long-term dependence and is prone to "gradient extinction". LSTM introduced the concept of gating mechanism on the structure of cyclic neural network (RNN), which controls the flow of data information in the network through input gate, forgetting gate and output gate. Among them, the input gate determines how much information is input and filters the input data once to remove the useless information. The forgetting door decides what information is discarded from the current unit, and the valuable information is retained. The output gate controls the data information of the current unit. The specific unit structure of LSTM is shown in Figure 4:

\[
i_t = \delta(w_i \cdot [h_{t-1}, x_t] + b_i)
\]

\[
f_t = \delta(w_f \cdot [h_{t-1}, x_t] + b_f)
\]

\[
o_t = \delta(w_o \cdot [h_{t-1}, x_t] + b_o)
\]

\[
c_t = f_t c_{t-1} + i_t \left( \tanh(w_o \cdot [h_{t-1}, x_t] + b_o) \right)
\]
\[ h_t = o_t \tanh(c_t) \]  

Where \( \delta \) is the Sigmoid function; \( c_t \) represents the memory state of the cell; \( h_t \) represents the hidden state of time \( t \); The input that \( x_t \) represents the moment \( t \); \( f_t \) represents the time \( t \) forgetting gate, which controls how much information will be discarded at any time.

### 3.2. Model structure

In this paper, a model based on CNN-LSTM structure is proposed. First, new features are extracted from the data through CNN, and then the new features are input into the LSTM to achieve the goal of improving the prediction effect of the model. The structure of the constructed port container throughput prediction model is shown in Figure 5. The model is mainly composed of a convolutional layer (32 filters) and an LSTM layer (32 units). Data were first extracted from 12 features by Conv1D (activation function Relu), and 32 features were output. The data passing over Conv1D is then fed into the LSTM layer; Finally, output data of LSTM layer into an output layer to get the predicted value of container throughput of the final port.

![Model Structure Diagram](image)

**Fig. 5 : Model Structure**

### 3.3. Model training

The processed training data set was input into the port container throughput prediction model built based on CNN and LSTM, and the prediction model was obtained by learning the training data set. When the model is trained, the value of iteration times has great influence on the accuracy of the final prediction model. With few iterations, the model cannot be fully trained, which results in the model underfitting. If there are too many iterations, the model will overlearn and waste computing resources, resulting in model overfitting and slower computing speed. The number of iterations set in this article is 3000, the model automatically saves the optimal model in the training process, and the learning curve is drawn as shown in Figure 6. It can be seen from the figure that the number of iterations is about 0 to 100, the MAE value drops rapidly, starting from 200 to stabilize.
The loss function used by the model is Mean Square Error, and the specific formula is as follows:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_{pred})^2 \tag{6}
\]

Where \( n \) is the number of samples, \( y_i \) is the true value of the sample \( i \), and \( y_{pred} \) is the predicted value of the sample \( i \). At the same time, the optimizer used by the model is Aadm, and the learning rate is 0.001.

3.4. Results analysis

3.4.1. The evaluation index

The evaluation indicators of regression prediction models generally include R-squared, mean square error, and mean absolute error. According to the prediction target, choose the average absolute error (MAE), the determination coefficient (R2) and the mean square error (MSE, see the loss function for the formula) as the indicators of the accuracy of the discriminant model. The calculation formula is as follows:

(1) MAE

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - y_{pred}| \tag{7}
\]

(2) Determination coefficient R2

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y_{pred})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} = 1 - \frac{RSS}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{8}
\]

Where \( y_i \), \( y_{pred} \) respectively represent the true value and predicted value of the sample \( i \), and \( \bar{y} \) represent the sample mean.

3.4.2. Analysis of model prediction results

In this paper, fully connected neural network (DNN) and LSTM are selected as comparison models. Based on the training data set constructed above, DNN, LSTM and CNN-LSTM port container throughput prediction models are respectively established to predict the test data set number and calculate different model accuracy evaluation indexes. The results are shown in Table 2:
Table 2: Feature number and interpretation

<table>
<thead>
<tr>
<th>Model</th>
<th>MSE</th>
<th>MAE</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>1516104.23</td>
<td>832.03</td>
<td>-0.27</td>
</tr>
<tr>
<td>LSTM</td>
<td>1111498.749</td>
<td>2544.91</td>
<td>-0.96</td>
</tr>
<tr>
<td>CNN-LSTM</td>
<td>2.83</td>
<td>1.42</td>
<td>0.99</td>
</tr>
</tbody>
</table>

It can be seen from the above table that the three evaluation indexes of CNN-LSTM model are superior to DNN and LSTM models. The MSE of THE CNN-LSTM model was 2.83, which was about 1516101 and 11114984 lower than DNN and LSTM, respectively. Meanwhile, MAE and R2 were also significantly reduced. The comparison curve between the prediction results of each model and the real value is drawn, as shown in Figure 7. It can be seen from the figure that the CNN-LSTM model well predicts the development trend of container throughput of Lianyungang Port, while the DNN and LSTM models do not well simulate the real situation.

Fig. 7: Container throughput forecast results

4. Conclusion

In this paper, a model based on CNN-LSTM structure is proposed, and features of the data are extracted by CNN, and then the predictive effect of the model is improved. The container throughput of the port of the case city (Lianyungang) is predicted, and the results show that the prediction model has high prediction accuracy, can well predict the container throughput and development trend of the port in the future period, and can provide scientific prediction data for relevant decision-making departments.

References


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