E-commerce logistics management cargo volume prediction research: a cargo volume prediction system constructed based on LSTM models

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Abstract. With the booming development of the Internet economy, the e-commerce market continues to expand, the importance of the e-commerce logistics industry has become increasingly prominent, and the continuous optimization of its level of service is imperative. Sorting link as the "main force" of e-commerce logistics, reasonable prediction of the amount of goods and analyze the transportation route can effectively reduce costs and improve efficiency. In this paper, the LSTM neural network model is used to predict the future operation of cargo volume for the historical cargo volume of the sorting center. By debugging the parameters and structure of the model for many times, it successfully predicts the cargo volume for the next 30 days and every hour, which provides effective support for the management of the logistics industry.

Keywords: logistics management, LSTM model, shipment prediction.

1. Introduction

In the context of the Internet economy era, the logistics industry continues to develop, people's habits began to quietly change, the real economy on the Internet to deepen the degree of dependence, which puts forward higher requirements for the development of e-commerce logistics enterprises. [1] This is a rare opportunity for development. This is a rare opportunity for development, but also a huge challenge, consumers not only focus on the price and quality of goods, but also put forward higher expectations of the shopping experience, looking forward to fast and convenient to receive the goods purchased. Therefore, the reasonable adjustment of the management strategy of e-commerce logistics network, and improve the quality and speed of the logistics network transportation is the current study of the express transportation process of the top priority. [2] The following are some of the most important issues in the study of express transportation process.

With the continuous progress of science and technology and changes in consumer demand, the e-commerce logistics industry must continue to innovate and change, requiring each link to cooperate with each other and seek common development [3] The sorting center is one of the important links in the logistics network. The sorting center, as one of the important links in the logistics network, undertakes the task of sorting parcels according to different flow directions and sending them to the next station. Sorting centers, as one of the important links in the logistics network, undertake the task of sorting parcels in different flow directions and sending them to the next station, and the advantages and disadvantages of their service level will, to a certain extent, affect the choice of consumers for e-commerce platforms, thus indirectly affecting their economic benefits.[4] In order to maximize the economic benefits, the service level will be better or worse to a certain extent affect the consumers' choice of e-commerce platform, thus indirectly affecting its economic benefits. To maximize the economic benefits, it is necessary to improve the service quality and transportation efficiency while meeting the diversified needs of consumers.

In terms of logistics cargo volume prediction, Chen Guo mentioned that the application of big data technology in cross-border logistics management can help enterprises to realize the full visualization of logistics, effectively monitor the various links in the supply chain, accurately predict the demand, delivery time and transportation costs, and make timely adjustments to optimize operational efficiency.[5] The optimization of operational efficiency. Wang Yuxin pointed out that the use of gray correlation analysis method, the amount of goods transported as the output indicator of logistics demand, logistics demand forecasting in Liaoning Province.[6] Zhang Xuebing believes that the LMST model has a high prediction accuracy for analyzing a large amount of given data [7].

In this paper, the selected data are from http://mathorcup.org/, and the cargo volume prediction system is constructed by using LSTM model to accurately predict the cargo volume of 57 sorting centers in the data source for the next 30 days and every hour, and the results are analyzed in depth to draw relevant conclusions.

2. LSTM prediction model based on data analysis

2.1. LSTM Neural Network Model

The LSTM algorithm is more widely used and reliable, it can be used as a complex nonlinear unit for the construction of larger deep neural networks, more adaptable, wide coverage, and suitable for datasets of time-series data for cargo volume prediction [8]. When selecting the data source, the default data of the current logistics network is reliable and accurate; assuming that the collected logistics cargo volume data is continuous and consistent, and the data collection method is uniform throughout the time series; assuming that the logistics network is not affected by external factors, such as: epidemic factors and other unexpected factors; assuming that the circulation of goods in the logistics network will be affected by seasonal factors.

Based on the daily shipment volume in the past 4 months and the hourly shipment volume in the past 30 days of the 57 sorting centers, a reasonable and effective prediction model is built using the LSTM network model to forecast the shipment volume in the next 30 days and hourly.

Since the LSTM model is a special kind of recurrent neural network model, it is very important to choose the parameters. The LSTM network model can solve the dependency problem over long distances, which cannot be handled by the RNN, but the LSTM neural network model predicts the data that needs to be predicted later, based on the predicted values as a basis. Therefore, LSTM neural networks are also known as long- and short-term memory models [9] LSTM Neural Networks are also known as Long Short-Term Memory Models.

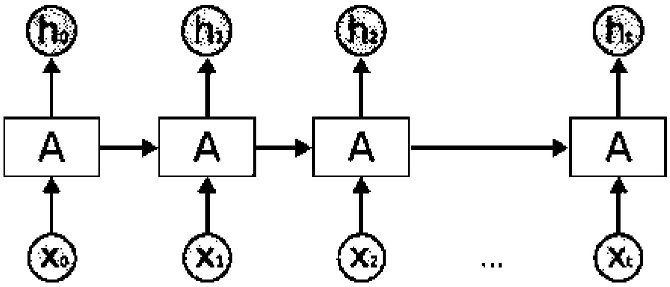

Figure 1. RNN neural network model

As shown in Fig. 1 RNN neural network model, the hidden layer of the original RNN model has only one state l, and therefore, it is very sensitive to short-term data inputs. At the same time, an additional state is added to keep the model in a long-term state to make long-term predictions using short-term data.

LSTM adds a gating mechanism to control the rate of information accumulation, which selectively accumulates and rejects information. The LSTM network model is allowed to compute the cell state of the current input based on the last output and the current input. To understand the proposed LSTM model more easily, the details of all the network parameter tables of the LSTM model are explained in the following table:

Table 1. LSTM neural network model grid parameters

Grid parameters	hidden meaning
m_t	Input at the current moment
f_t	Oblivion gate control signal
i_t	Input door control signal
o_t	Output gate control signal
s_{t-1}	Previous Momentary Memory Unit
s_t	current moment memory cell
$\hat{s}_t$	Information Candidate Status
l_t	Current external state
l_{t-1}	The external state of the previous moment
y_i	Daily cargo volume at sorting centers
x_i	Summed total 24-hour cargo volume at sorting centers
a	1 to 57 sorting centers
b	1 to 30 days in the future

As can be seen from Table 1 LSTM Neural Network Model Grid Parameters table, at time t, there are three inputs to the LSTM network model which are: the network input value at the current moment, the memory unit at the previous moment and the external state at the previous moment.

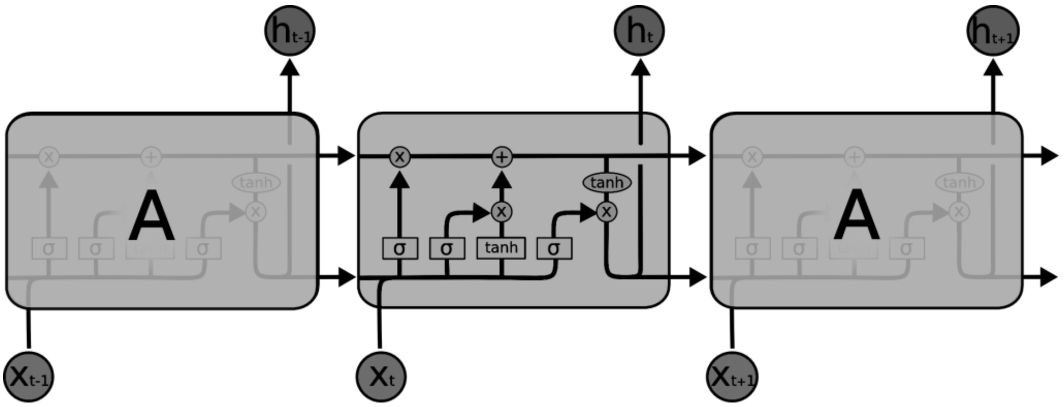

Figure 2. LSTM neural network structure

As shown in Fig. 2 LSTM neural network structure, the LSTM network model has two output values: the current moment memory unit and the current moment external state. To keep the prediction for a long period of time, therefore, the LSTM network model has three gating control switches, which are: "Forgetting Gate", "Input Gate" and "Output Gate".

(1) Oblivion gate f: It determines how much of the state of the memory cell in the previous moment is retained in the memory cell in the current moment when the in and how much information needs to be forgotten. Partial selective memorization and forgetting is performed by the sigmoid function. The criterion is: the closer it is to 0, the more it should be forgotten, and conversely, the closer it is to 1, the more it should be retained.

$$f_t = \sigma\left(W_f\left[l_{t-1,}m_t\right] + b_f\right) \quad (1)$$

(2) Input gate i: It determines how much of the input of the LSTM network model network at the current moment can be saved into the current moment memory cell.

$$i_t = \sigma(W_i[l_{t-1}, m_t] + b_i) \quad (2)$$

$$\hat{s}_t = \tan l\,(W_i[l_{t-1}, m_t] + b_s) \quad (3)$$

The results obtained from the above two methods are added together, and the redundant information can be forgotten or deleted. At the same time, new input data can be added to obtain the predicted data for the next state.

$$s_t = f_t s_{t-1} + i_t \hat{s}_t \tag{4}$$

(3) Output gate o: can control how much of the current moment's memory cell state can be output to the current moment's external state of the LSTM.

$$o_t = \sigma(W_i[l_{t-1}, m_t] + b_o) \tag{5}$$

$$l_t = o_t \times \tan l(s_t) \tag{6}$$

The above network parameters of the LSTM network model enable the LSTM network model to perform long term time series prediction as well as short term time series data prediction.

2.2. LSTM hyperparameters and neural network structure setting

There are usually two types of parameters in a machine learning model: those that need to be learned and estimated from data, called model parameters, and those that are tuning parameters in a machine learning algorithm that need to be set by humans, called hyperparameters. Model hyperparameters are configurations external to the model, and the values of the hyperparameters need to be set manually.

In machine learning, we have been talking about "parameter tuning", which is not tuning "parameters", but tuning "hyperparameters". The learning rate α in gradient descent method, the number of iterations epoch, the batch-size, k (the number of closest points) in k-nearest neighbor method, the depth of the tree in decision tree model, etc. are all hyperparameters. If there is a deviation in the hyperparameter settings, it will lead to overfitting or poor fitting of the model, therefore, the structure of the LSTM neural network model and its hyperparameter settings are shown in the table below after several debugging sessions:

Table 2. LSTM neural network model hyperparameter settings

parameters	numerical value
numFetures	1
numResponses	1
numHiddenUnits	175/360
MaxEpochs	300
GradientThreshold	1
Initial LearnRate	0.002
LearnRateDropPeriod	100
LearnRateDropFactor	0.25

According to Table 2, the hidden layers of the LSTM model for the daily shipment volume in the past 4 months are 175 layers, and the hidden layers of the LSTM model for the hourly shipment volume in the past 30 days are 360 layers. After several adjustments and setting the above hyperparameters, the prediction results for the next 30 days and every hour can be obtained.

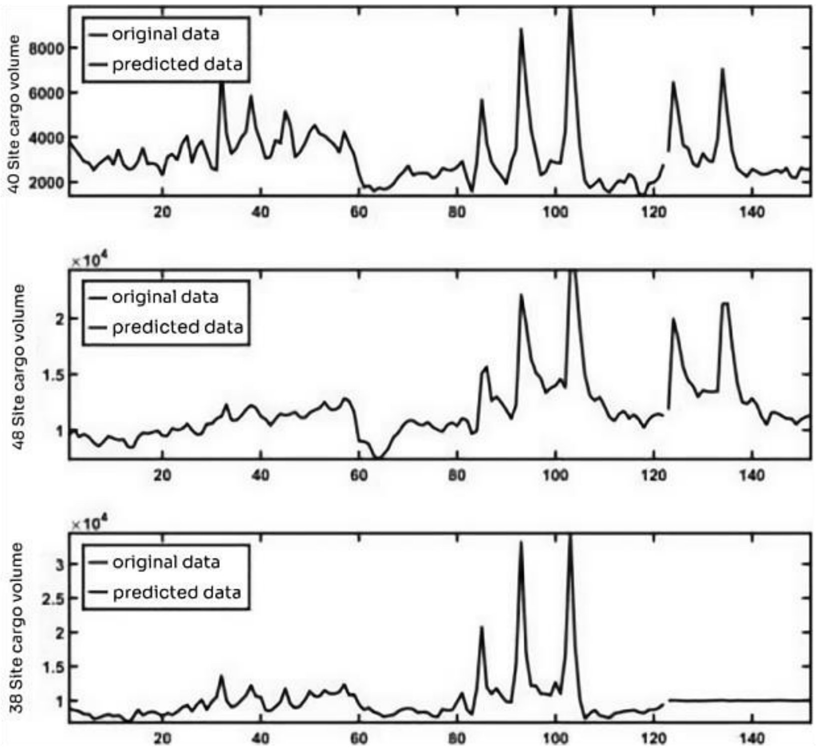

Figure 3. LSTM predicted daily cargo volume for randomly selected stations

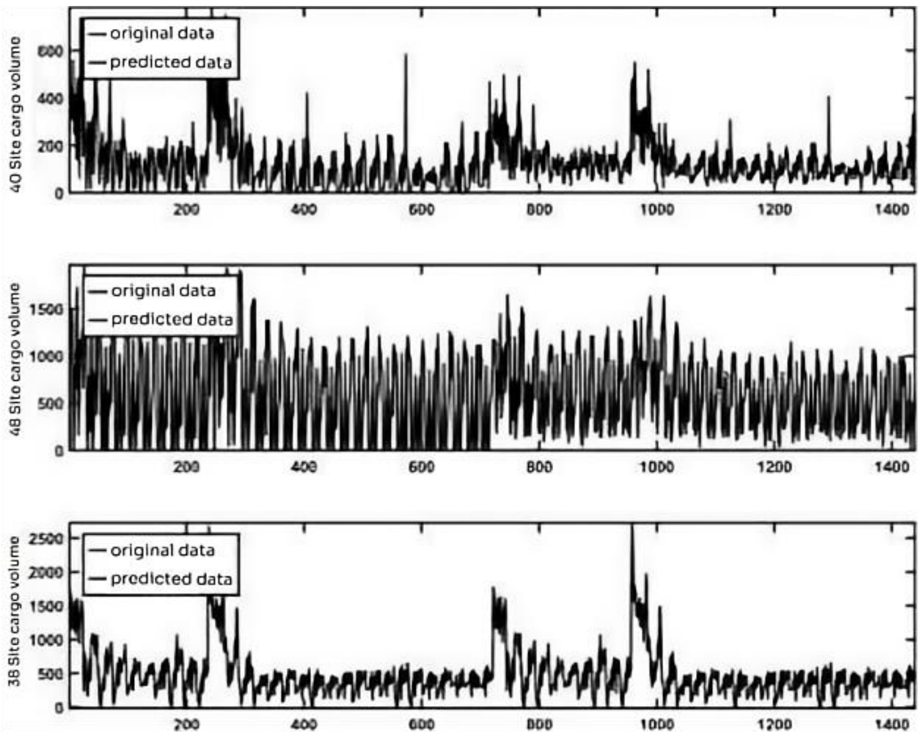

Figure 4. LSTM randomly selected stations to predict hourly cargo volume

It can be seen from Fig. 3 and Fig. 4 that: as the shopping frenzy of "Double 11" faded, the logistics sites quickly ushered in the peak of cargo handling of "Double 12". Some sites have regular fluctuations in cargo flow, while others are constantly busy and running at high speed, just like a giant ship that never stops in the logistics ocean. Our in-depth analysis of the past 90 days and forecast 30 days and daily shipment data shows that these two shopping nodes are extremely active, and highlights the differences in the ability of different sites to cope with the pressure of the peak period. Specific 30-day daily shipments and hourly shipment results are shown in Tables 3 and 4:

Table 3. LSTM Prediction Results for 30-Day Shipments per Site (Partial)

sorting center	dates	quantity of goods
SC1	2023-12-1	61246
SC1	2023-12-2	69133
SC1	2023-12-3	77866
SC1	2023-12-4	76320
SC1	2023-12-5	67622
SC1	2023-12-6	59907
SC1	2023-12-7	57337
SC1	2023-12-8	58189
SC1	2023-12-9	63074
SC1	2023-12-10	71774
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Table 4. LSTM Predictions of 30-Day Hourly Shipments per Site (Partial)

sorting center	dates	hourly	quantity of goods
SC1	2023-12-1	0	3024
SC1	2023-12-1	1	3154
SC1	2023-12-1	2	2987
SC1	2023-12-1	3	2697
SC1	2023-12-1	4	2965
SC1	2023-12-1	5	2502
SC1	2023-12-1	6	698
SC1	2023-12-1	7	808
SC1	2023-12-1	8	1627
SC1	2023-12-1	9	1523
SC1	2023-12-1	10	1414
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2.3. LSTM secondary prediction model based on line change

2.3.1. Data analysis of line changes

All other things being equal, we make some changes to the transportation routes between the 57 sorting centers for the next 30 days. Based on the average cargo volume of each transportation route at each sorting center over the past 90 days, we fine-tuned the data for the daily cargo volume over the past four months and the hourly cargo volume over the past 30 days. Specifically, for the daily volume data for the past four months, subtraction is applied to the volume of cargo at the originating station and addition is applied to the volume of cargo at the destination station to facilitate the smooth flow of cargo. For the hourly volumes for the past 30 days, the operation is the same as the previous one, but the data are evenly distributed over a 24-hour period. Eventually, the adjusted data will be used as input to the LSTM prediction model for secondary prediction to obtain more accurate predictions [10].

Table 5. Eliminated routes and cargo volumes

outgoing sorting center	Arrival at the Sorting Center	quantity of goods
SC36	SC8	97
SC19	SC15	336
SC4	SC15	15
SC51	SC15	12
SC36	SC47	133
SC55	SC7	128
SC24	SC5	138
SC28	SC4	8
SC18	SC51	14
SC54	SC25	182
SC1	SC25	254
SC2	SC19	356
SC61	SC10	228
SC39	SC60	119

According to Table 5, the total number of original cargo circulation routes is 134, and the following cargo routes are canceled: SC36→SC8, SC19→SC15, SC4→SC15, SC51→SC15, SC36→SC47, SC55→SC7, SC24→SC5, SC28→SC4, SC18→SC51, SC54→SC25, SC1→SC25, SC2→SC19, SC61→SC10, SC39→SC60, and the changes are SC5→SC4, SC31→SC9 cargo transportation routes. SC25, SC2→SC19, SC61→SC10, SC39→SC60, changing to SC5→SC4, SC31→SC9 cargo transportation routes. The total amount of all the above transport routes is 2020, and the above cargo volume is evenly distributed among the above updated transport routes to optimize the cargo transport routes and maintain a balanced transport capacity of the cargo routes as much as possible.

2.3.2. LSTM Neural Network Modeling

The LSTM neural network model is a special type of recurrent neural network (RNN) designed to solve the long-term dependency problem in traditional RNNs. The LSTM neural network model can be used to predict the secondary route cargo transportation by fine-tuning the data source, and after substituting the relevant data, the same model prediction as the previous one is carried out, and the specific 30-day daily shipments and hourly shipments are shown in Table 6 and Table 7:

Table 6. LSTM Predictions of 30-Day Shipments per Site (Partial)

sorting center	dates	quantity of goods
SC1	2023-12-1	59846
SC1	2023-12-2	61908
SC1	2023-12-3	64524
SC1	2023-12-4	64361
SC1	2023-12-5	62083
SC1	2023-12-6	60228
SC1	2023-12-7	60089
......	......	......

Table 7. LSTM Predictions of 30-Day Hourly Shipments per Site (Partial)

sorting center	dates	hourly	quantity of goods
SC1	2023-12-1	0	3018
SC1	2023-12-1	1	3199
SC1	2023-12-1	2	3028
SC1	2023-12-1	3	2701
SC1	2023-12-1	4	2969
SC1	2023-12-1	5	2514
SC1	2023-12-1	6	734
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3. Conclusion

As the e-commerce logistics industry is paid more and more attention to, the sorting link which plays a key role in e-commerce logistics also needs to be optimized continuously, this paper proposes the problem of future cargo volume prediction of the sorting center, and the daily cargo volume of the sorting center in the past four months and the hourly cargo volume in the past 30 days are predicted for the future operation of the cargo volume by using the LSTM neural network model. By debugging the model parameters and structure for many times, the future 30 days and hourly cargo volume are successfully predicted, which provides effective support for the management of logistics industry.

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