Research And Improvement of E-Commerce Shipment Prediction Model Based on Neural Network

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Abstract. In this paper, for the problem of e-commerce shipment prediction, the first initial modeling and solving is based on BP neural network model. Through the construction and training of the neural network model, the relationship between the commodity shipments of each merchant in different warehouses and various properties is explored and predicted. Then, the irrationality of the initial model is improved, and the STL-LSTM deep learning algorithm is used for prediction model building to better capture the seasonal characteristics and trends of the time series data and improve the prediction accuracy. Finally, combined with the SARIMA neural network prediction model, the e-commerce shipments are predicted and analyzed more accurately to provide a scientific basis and reference for the merchants' demand for goods in different warehouses. Through the research and improvement of this paper, the accuracy and practicality of e-commerce shipment prediction can be effectively improved, which has certain theoretical and practical significance.

Keywords: BP neural network, STL-LSTM deep learning, SARIMA neural network, e-commerce shipment prediction.

1. Introduction

In today's e-commerce world, there is a large and diverse ecosystem of merchants [1]. In order to more effectively manage inventory and ensure on-time delivery of orders, e-commerce platforms centralize the goods of each merchant in specially equipped warehouses, building a large and complex supply chain system. This complex supply chain system requires scientific management and intelligent decision-making support to achieve efficient operation. Big data technology plays a critical role in this process, providing deeper insights and intelligent support for management decisions, which is expected to significantly reduce inventory costs and improve order fulfillment efficiency. In this multi-vendor ecosystem, the e-commerce platform manages merchandise from various merchants and stores it in warehouses equipped with advanced technology and management systems [2-3]. This approach not only allows for more efficient inventory management, but also ensures that orders are delivered on time. The operation of such a supply chain system requires scientific management tools to cope with the growing variety of goods and inventory, as well as intelligent decision-making to better predict future demand and supply chain changes. Big data technology plays an important role in the operation of e-commerce platforms. It provides comprehensive and in-depth insights to decision makers by analyzing massive amounts of data to identify market trends, consumer preferences, sales patterns, and more. This data-driven intelligent decision-making is expected to help e-commerce platforms lower inventory costs and reduce excess inventory, while improving the efficiency of e-commerce platform resource utilization. In enterprise marketing, the application of big data can greatly promote the development of precision marketing and bring unprecedented development opportunities [4].

This paper uses historical data from e-commerce platforms to forecast merchants' demand for different warehouses and different commodities in the coming period (May 16, 2023, to May 30, 2023), sourced from http://mathorcup.org/.

2. Initial establishment of the neural network model

First of all, we use the merged shipment information table to make the information corresponding to the shipment volume at each point in time more detailed. Since the effects of seller_no, product_no, and warehouse_no can be reflected by the contents of Annexes 2-4, we only study category1, category2, category3, seller_category, inventory_category, seller_level, warehouse_category, and warehouse_region on the shipment volume and forecast based on these properties. For the convenience of prediction, the daily shipments of each product for 166 days are summed and averaged using EXCEL, and then the neural network prediction model is used to explore the relationship between these properties and the average shipment value and to make a prediction.

Various properties such as merchant category, inventory category, warehouse category, and warehouse location are taken as inputs, average shipment is taken as output, hyperbolic tangent function is chosen for the hidden layer activation function, weights are computed iteratively, forward propagation is performed, and back propagation is performed after calculating the deviation, which ultimately leads to the optimal prediction.

The neural network prediction of the dataset using SPSS, due to the SPSS neural network prediction does not accept string data, so we first merged the dataset after the numbering process (mainly on the seller_category, category1, category2, and category3 number, the rest of the string data to take EXCEL): Find and Replace for numeric conversion. Find and Replace for digital transcoding): use python to read the Excel file - list of column names, including the columns to be coded - use a loop to create a numerical code for each column - save the data with the code to the new Excel file "Processing Data 3", and ultimately form the EXCEL file "Numbered processed data", after which we use the data for forecasting.

First of all, the numbered file imported into SPSS, because the variables have been numbered, so select the variable type for the number, and set the label, the label that is the number of variables corresponding to the information, for example, inventory_category has A, B, C, D four categories, respectively, with 1, 2, 3, 4 on their labels to explain:

Then, according to the analysis-neural network-multilayer perceptron, the average shipment volume is taken as the dependent variable, and category1, category2, category3, seller_category, inventory_category, seller_level, warehouse_category, and warehouse_region as covariates. In "Output", choose to highlight the weights, prediction-measurement plots, residual-prediction plots, and independent variable importance analysis to facilitate the analysis of the output data, and choose to save the predicted values or categories of each dependent variable in "Save". In "Save", choose to save the predicted value or category of each dependent variable, and finally complete the prediction of the neural network model.

The importance of the independent variables is shown in figure 1：

Importance of argument

	Importance	Importance of normalization
selleer_category	.155	100.0%
invntory_category	.098	63.5%
sellr_level	.109	70.6%
category1	.131	85.0%
category2	.145	93.5%
category3	.118	76.4%
whc	.145	93.9%
whr	.099	64.3%

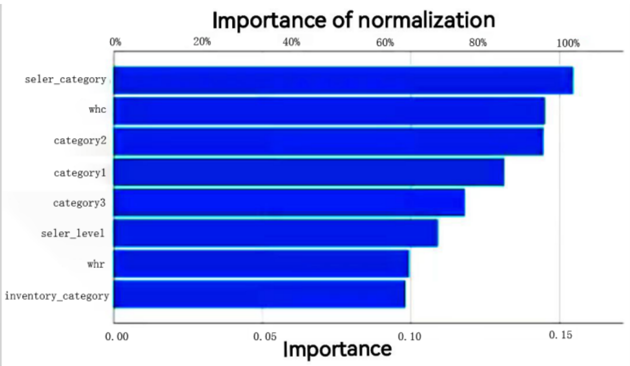

Figure 1 importance of argument and normalization

It can be found that the influence of seller_category, warehouse_category, category2, category1, category3, seller_level, warehouse_region, and inventory_category on the average shipment size decreases sequentially. Afterwards, we found that its predicted data appeared to be extremely irrational, so we improved it.

3. Improvement of neural network model

A new way was found to complete the neural network modeling and prediction, in order to predict the demand of the goods of each merchant in each warehouse from May 16, 2023, to May 30, 2023 and to improve the accuracy of the prediction, we modeled and analyzed the time series of the historical data of each merchant in each warehouse. Through the statistical analysis of the programming code in Python language, in which we used the compiler pycharm, we learned that the total number of merchants is 35, the total variety of products is 1212, the total number of warehouses is 54, and the number of combinations of different merchants, products, and warehouses in the consecutive time series is totaled to 1996. This means that we need to build 1996 time series prediction models and select parameters for each of these 1996 models to get the optimal parameters for each time series data and evaluate the models [5-6].

3.1. Prediction model based on STL-LSTM deep learning algorithm

The LSTM schematic is shown in figure 2:

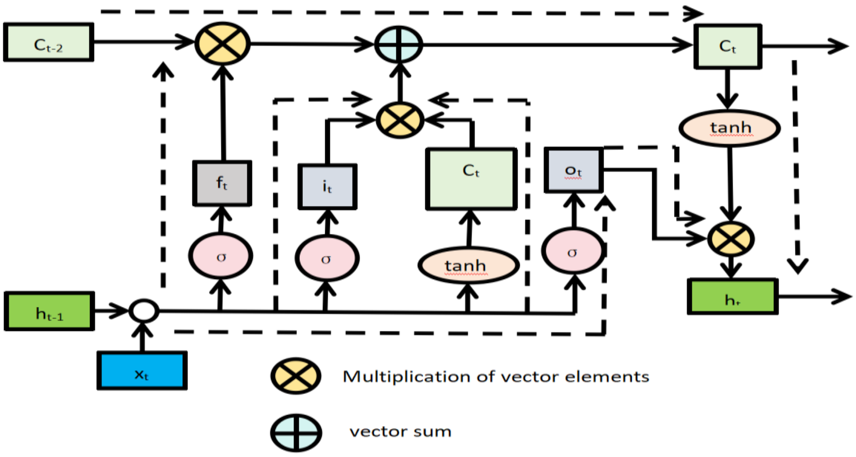

Figure 2 LSTM schematic

The core concept of LSTM lies in the state of the cell as well as the gate structure, where the cell state corresponds to the path of information transmission, which is controlled using a sigmoid activation function.

The STL model, Seasonal and Trend decomposition using Loess, is a time series decomposition algorithm based on locally weighted regression (LOESS) [7]. LSTM is a deep learning model for sequential data, while the seasonal decomposition model is a method used to decomposing time series data to identify trends, seasonality and residuals is a traditional statistical model.

The STL-LSTM model can utilize the advantages of both methods to better handle time series data with seasonality. We use the STL-LSTM model, a deep learning algorithm that incorporates a seasonal decomposition model, to complete the modeling of the forecasting problem.

3.2. Algorithm flow of STL-LSTM (Long Short Term Memory) neural network for time series prediction analysis

(1) Data preparation

The script first imports data from an Excel file containing information about the seller, product, warehouse, date and corresponding quantity. It filters the data based on a specific date range and retains the entries between '2022-12-01' and '2023-05-15'. This filtered dataset is then used for subsequent analysis.

(2) STL decomposition

A seasonal-trend decomposition is performed on the time series data. This decomposition can be achieved by the STL algorithm (Seasonal-Trend Decomposition using Loess), which decomposes the time series into trend, seasonal and residual components. The trend and seasonal components, and the residual term (residual) are obtained.

(3) Data Transformation

Prepare data for LSTM model training. Convert the trend, seasonal and residual data obtained from the STL decomposition into a format suitable for LSTM models. Create a supervised learning dataset that utilizes lagged observations to predict observations at the next time step.

(4) Time series transformation

To adapt the data for time series prediction, a function called series_to_supervised is used. This function prepares the dataset for supervised learning by creating lagged features. Its main goal is to reformat the data so that past values of quantities can predict future values.

(5) LSTM model configuration and training

The script builds an LSTM neural network using the Keras library and TensorFlow backend. It continues to loop through the unique combinations of sellers and warehouses in the filtered dataset. For each combination, if the amount of data is sufficient (more than 10 data points), the script further processes the data for LSTM model training.The steps to train an LSTM model are as follows:

1) Prepare the data for supervised learning, including the lag features required to create the LSTM inputs.

2) Divide the data into input features (x_train) and output/target (y_train) for model training.

3) Reshape the input data to match the structure expected from the LSTM model.

4) Train the LSTM model using the provided data with the number of training cycles set to 3000.

(6) Prediction and output generation

The script then starts predicting future quantities from '2023-05-16' to '2023-05-30' for each unique seller-warehouse combination. The predictions are generated iteratively using a trained LSTM model. These predictions are based on historical data and are updated incrementally for each subsequent date in the prediction.

(7) Exporting the results

The results of the demand forecasts for each merchant's goods at each warehouse for the period 2023-05-16 to 2023-05-30 are organized and stored in Results Table 1 - Forecast Results Table.

Part of the results, as shown below：

Table 1 Forecast Results Table.

result_graph_1			
seller_no	warehouse_no	date	forecast_qty
seller_21	wh_15	May 16, 2023	10.55762005
seller_21	wh_15	May 17, 2023	20.70213318
seller_21	wh_15	May 18, 2023	13.74939156
seller_21	wh_15	May 19, 2023	2.027481079
seller_21	wh_15	May 20, 2023	14.36472321
seller_21	wh_15	May 21, 2023	22.26498795
seller_21	wh_15	May 22, 2023	1.531583548
seller_21	wh_15	May 23, 2023	21.36212158
seller_21	wh_15	May 24, 2023	24.55774689
seller_21	wh_15	May 25, 2023	57.48078537
seller_21	wh_15	May 26, 2023	36.79756165
seller_21	wh_15	May 27, 2023	31.90729904
seller_21	wh_15	May 28, 2023	62.41589737
seller_21	wh_15	May 29, 2023	33.52414703
seller_21	wh_15	May 30, 2023	49.28968048

4. SARIMA neural network prediction model

Before building the ARIMA model, we need to make sure that the data series are smooth. For non-smooth series, we can make them smooth by exponential smoothing and then fit ARIMA(p,q,d) to the processed series.

The ARIMA model combines an autoregressive model (AR), a moving average model (MA), and a differencing operation (I for Integrated). The ARIMA model is usually denoted as ARIMA (p, d, q), where p, d, and q represent the order of the autoregressive model, the number of differencing operations, and the order of the moving average model, respectively.

Disregarding other relevant variables and trend terms, ARIMA (p,0, q) = ARIMA(p,q) when d=0.

These parameters need to be determined based on the mathematical features in the integrated big data set of e-commerce retailer merchant-warehouse-sales information. Since the e-commerce retail merchant-warehouse-sales information shows obvious periodicity and seasonality, the effect of the simple ARIMA model to predict the demand for each merchant's goods at each warehouse from May 16, 2023, to May 30, 2023, is not excellent enough. Therefore, in this paper, the SARIMA model is used to forecast the demand for each merchant's goods at each warehouse from May 16, 2023, to May 30, 2023.

Compared with the standard ARIMA model, the SARIMA model is more powerful and effective in dealing with time series data with obvious seasonal characteristics. It is better able to capture and predict seasonal patterns in the big data set of e-commerce retailer merchant-warehouse-volume information, enabling more accurate predictions of seasonal fluctuations. Similar to the standard ARIMA model, the SARIMA model is a tool for time series analysis and forecasting, but it takes into account the seasonality present in the big data set of e-commerce retail merchant-warehouse-sales information.

The SARIMA model consists of a seasonal ARIMA model that adds a seasonal autoregressive term (SAR), a seasonal difference operation (I), and a seasonal moving average term (SMA) to capture seasonal patterns in the big data set of time series e-commerce retailer-warehouse-sales information.The basic structure of the SARIMA model is ARIMA(p,d,q) (P,D,Q)s. In this formula, d is the number of non-seasonal differentials, p and q are the autoregressive and moving average steps, respectively, while P and Q are the seasonal autoregressive and moving average steps, D is the number of seasonal differentials, and s is the seasonal differential step size [8].

The model structure of SARIMA modeling is as follows:

$$\begin{cases} \varphi(B)\gamma^d X_t = \theta(B)\xi_t \\ E(\xi_t) = 0, Var(\xi_t) = \sigma^2, E(\xi_t\xi_s) = 0, t \neq s \\ E(\xi_t X_s) = 0, \wedge_s < t, \end{cases} \tag{1}$$

Where d is the non-seasonal difference order, s is the length of the seasonal cycle, p is the non-seasonal autoregressive order, q is the non-seasonal moving average order, and the structure of the SARIMA model with order (p,d,q)*(P,D,Q) is:

$$(1-B)^d(1-B^s)^D X_t = \frac{\theta_q(B)\gamma_P(B^S)}{\phi_p(B)\eta_Q(B^S)}\xi_t \tag{2}$$

$$\begin{cases} \phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p \\ \theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \\ \gamma_P(B^s) = 1 - \gamma_1 B^s - \cdots - \gamma_P B^{Ps} \\ \eta_Q(B^s) = 1 - \eta_1 B^s - \cdots - \eta_Q B^{Qs} \end{cases} \tag{3}$$

$(X_t)$is the original series, $(\xi_t)$is an independent zero-mean, same-variance white noise series, where P is the seasonal autoregressive order and Q is the seasonal moving average order ,$\theta_1, \theta_2, \cdots \theta_q$,$\eta_1, \eta_2, \cdots \eta_Q$,$\phi_1, \phi_2, \cdots \phi_p$,$\gamma_1, \gamma_2, \cdots \gamma_P$,is an unknown parameter in the model.

Finally, we chose to use the SARIMA model to forecast the shipments in the next 15 days for the 1996 models. Regarding the selection of the parameters of the SARIMA model, we used python's automatic optimization function and deposited the prediction results in the results table 2 - Prediction results table [9-10].

Some of the results, as shown below.

Table 2 Forecast Results Table.

result_graph_2				
seller_no	product_no	warehouse_no	Date	Predicted_Qty
seller_15	product_832	wh_1	2023/5/16	16.28078829
seller_15	product_832	wh_1	2023/5/17	15.2590488
seller_15	product_832	wh_1	2023/5/18	16.46582175
seller_15	product_832	wh_1	2023/5/19	15.48516377
seller_15	product_832	wh_1	2023/5/20	16.84246217
seller_15	product_832	wh_1	2023/5/21	16.14601394
seller_15	product_832	wh_1	2023/5/22	15.50498735
seller_15	product_832	wh_1	2023/5/23	15.70835804
seller_15	product_832	wh_1	2023/5/24	15.77786479
seller_15	product_832	wh_1	2023/5/25	15.80162037
seller_15	product_832	wh_1	2023/5/26	15.8097394
seller_15	product_832	wh_1	2023/5/27	15.81251427
seller_15	product_832	wh_1	2023/5/28	15.81346265
seller_15	product_832	wh_1	2023/5/29	15.81378678
seller_15	product_832	wh_1	2023/5/30	15.81389756

5. Conclusions

This study aims to explore the effectiveness of big data technology and neural network modeling in supply chain management in the field of e-commerce. By analyzing historical data and building prediction models, we find that big data technologies play an important role in supply chain management and can provide insights and intelligent support for management decisions, thus reducing inventory costs and improving order fulfillment efficiency. In particular, demand prediction using neural network models such as STL-LSTM and SARIMA can more accurately predict the demand for goods from different merchants in different warehouses, providing an important reference basis for supply chain management. The combination of these technologies and models brings more efficient and intelligent operation and decision-making support to e-commerce platforms and opens up new possibilities for development opportunities such as precision marketing. Therefore, big data technology and neural network model have a broad application prospect in e-commerce supply chain management, which is of great significance for the development of enterprises.

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