Research on the model of manufacturing product pricing strategy based on ConvLSTM

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ABSTRACT

As we all know, price is a very important factor that affects product sales. To a certain extent, price cuts will increase sales, and price increases within the acceptable range of users can increase manufacturers' profits. Therefore, for manufacturing companies, scientific product pricing has always been a tricky issue. The pricing strategy model of traditional manufacturing companies is generally based on traditional estimates and conduct price reduction promotions. At present, there are not many pricing strategy models with better scalability for manufacturing companies, especially there are not many quantitative models that can effectively evaluate the impact of competing products on this product. For manufacturing companies, the easiest way to affect sales is to modify product prices. Therefore, based on the relatively novel ConvLSTM eural network model, this article constructs a pricing strategy model for manufacturing companies. To build a pricing strategy model based on cross-domain and cross-brand data, the traditional LSTM model cannot capture the complex relationships between different dimensions of data. Therefore, this article introduces the improved ConvLSTM neural network model of the LSTM model into the field of pricing strategy, and first passes the relevant data through the convolutional layer before ConvLSTM to fully explore the hidden high-dimensional logical associations between the cross-manufacturer and cross-domain data. Therefore, this chapter uses the ConvLSTM model to predict sales based on cross-domain and cross-brand data. At the same time, statistical methods are used to check the confidence interval of the prediction results to enhance the reliability of the model. Finally, use the predictive model to traverse the reasonable pricing interval to obtain the simulated highest sales and optimal product pricing. This chapter finally verifies the superiority of the ConvLSTM-based pricing strategy model proposed in this chapter through design comparison experiments.

Keywords: Pricing strategy, ConvLSTM model, deep learning, LSTM

1. INTRODUCTION

As we all know, price is a very important factor that affects product sales. To a certain extent, price cuts will increase sales, and price increases within the acceptable range of users can increase profits of manufacture[1]. Therefore, for manufacturing companies, scientific product pricing has always been a difficult problem. The pricing strategy model of traditional manufacturing companies is generally based on traditional estimates and conduct price reduction promotions. At present, there are not many pricing strategy models with better scalability for manufacturing companies, especially there are not many quantitative models that can effectively evaluate the impact of competing products on this product. For manufacturing companies, the easiest way to affect sales is to modify product prices. Therefore, based on the relatively novel ConvLSTM[2] neural network model, this article constructs a pricing strategy model for manufacturing companies.

To build a pricing strategy model based on cross-domain and cross-brand data, the traditional LSTM[3-5] model cannot capture the complex relationships between different dimensions of data. Therefore, this paper introduces the improved ConvLSTM neural network model of the LSTM model into the field of pricing strategy, and first passes the relevant data through the convolutional layer before ConvLSTM to fully mine the hidden high-dimensional logical associations between the cross-manufacturer and cross-domain data[6].

Therefore, this chapter uses the ConvLSTM model to predict sales based on cross-domain and cross-brand data. At the same time, statistical methods are used to check the confidence interval of the prediction results to enhance the reliability

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of the model. Finally, use the predictive model to traverse the reasonable pricing interval to obtain the simulated highest sales and optimal product pricing. This chapter finally verifies the superiority of the ConvLSTM-based[7] pricing strategy model proposed in this chapter through design comparison experiments.

2. MATERIALS AND METHODS

Compared with the traditional use of single-domain data for pricing strategy recommendations, the amount of data that needs to be processed for cross-domain data sales will increase exponentially. The input of the traditional LSTM model is a two-dimensional matrix, so it cannot directly process cross-domain data. Usually, cross-domain data is mapped according to manually set weights or a fully connected layer is preset in front of the LSTM model, and the data is dimensionally reduced to make it a two- dimensional matrix that can be input to the LSTM model.

The above-mentioned traditional input data fusion method has certain limitations in the face of cross-domain data, especially considering the scalability of the cross-domain data model, setting the weight or total value between different domain data. The mixing method of the thickness of the connection layer is not reasonable enough. At the same time, the sales of manufactured products are exclusive, and the best-selling of a product is likely to affect the unsalable sales of similar products. Therefore, the pricing strategy model should also pay attention to the relevant information of similar products of different manufacturers. The LSTM model cannot solve this well. Therefore, this chapter introduces the ConvLSTM model to solve such problems.

For the construction of the ConvLSTM-based pricing strategy model, we divided into three steps[8]. The first step is to use the training set to shape the cross-manufacturer and cross-domain past product information and the current product price to make it a convolutional network suitable for ConvLSTM Input, further training, and train a sales forecast model that can set price changes; the second step is to use the test set to evaluate the confidence interval of the forecast results within a certain price fluctuation; the third step, the model automatically sets the price change of the current month, And predict the product sales data under different price fluctuations, and then check the confidence interval of the predicted result, remove the predicted value beyond the confidence interval, and use the prediction that meets the confidence interval to get the corresponding price and sales push Estimate the profit of the product, thereby constructing the mapping relationship between the product price and the total sales. The construction process of the pricing strategy model based on ConvLSTM and the execution process of the pricing strategy are shown in Figures 1-3.

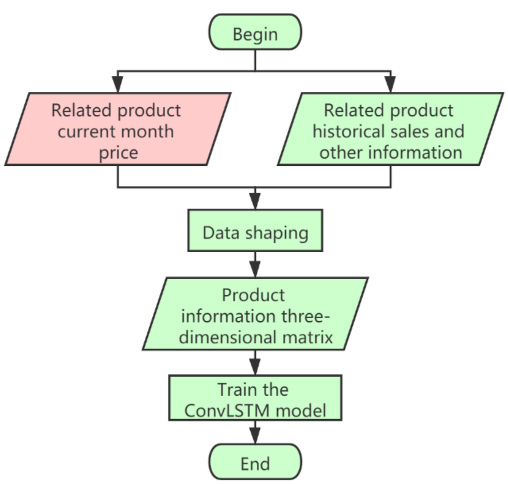

Figure 1. Training logic block diagram.

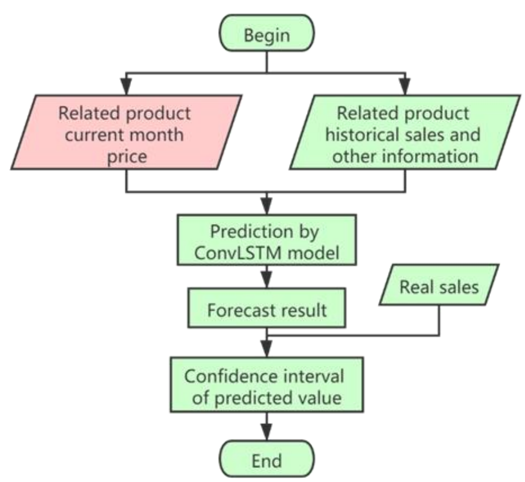

Figure 2. Test logic block diagram.

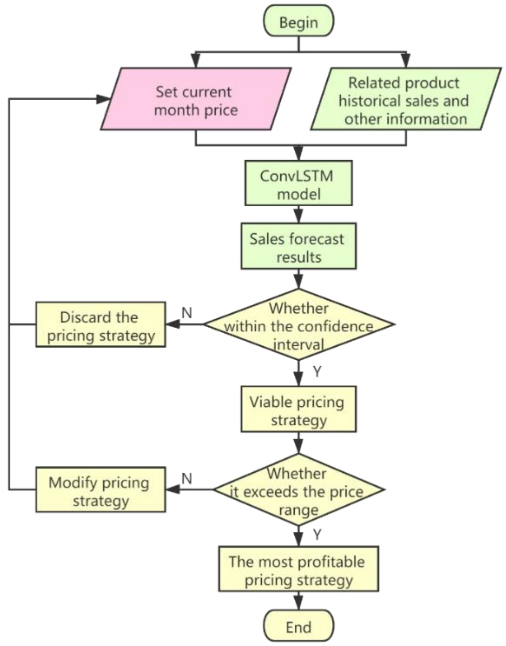

Figure 3. Logic block diagram of pricing strategy.

For the construction of the above model, this article first needs to solve two key issues, namely combining the characteristics of cross-domain and cross-manufacturer product information, and shaping the input data to make it conform to the corresponding characteristics of convolutional input; for a certain range of price fluctuations Confidence interval construction of sales forecast results. The solution to the above-mentioned key problems will be described in detail below.

2.1 Analysis and shaping of model input data

The ConvLSTM model was first proposed by scholars and applied to the field of weather prediction. The three-dimensional matrix of radar data is obtained through the radar characteristics of different areas at different times. Because the radar characteristics of different areas affect each other, the radar characteristics of different areas are analyzed. Convolution processing can dig out its inherent high-dimensional logical associations. The pricing strategy model required in this article has both similarities and differences with this model. The similarity is that for product information data, the factors that affect sales are not independent variables, but are interrelated. The difference is that the input of the above weather forecasting model is a three-dimensional matrix with a large length and width value. For the data of a single manufacturer, it is difficult to construct a three-dimensional matrix with a large length and width value as the input of the model.

In response to the above problems, this article proposes a reshaping method based on cross-domain and cross-brand data, so that the relevant data meets the input of the ConvLSTM model.

For product-related information of a single brand, this article first uses nine influencing factors including price, sales volume, evaluation index, attention index, company stock price, product cost, GDP index, CPI index, and A-share market index to form a 3*3 impact in the factor matrix, the price index has the greatest influence on sales, so the price is at the center of the influencing factor matrix. The matrix of influencing factors is shown in Figure 4.

Evaluation Index	Baidu Index	Product sales
Cost	Price	GDP
CPI	Stock index	Company stock price

Figure 4. The product influencing factor matrix.

On the one hand, the sales of manufactured products are often exclusive. Consumers tend to buy only one type of product at the same time. Therefore, the rise or fall of sales of other manufacturers in the same price range will often affect the sales of current products; on the other hand, For the input of the ConvLSTM model, the convolution of the 3*3 influencing factor matrix is often not ideal. Therefore, this article expands the input data to a 9*9 related manufacturer's influencing factor matrix and selects the 8 manufacturers A-H's influencing factor matrix that is closest to the manufacturer's product price. The matrix is arranged in the order of the manufacturer's data from high to low around.

The advantages of designing data input, as shown above, are as follows:

- By inputting the sales data of similar products of manufacturers in the same price range into the model, the model is closer to reality, and the high-dimensional logical relationship between the sales of products of different manufacturers can be mined.

- Using the feature of insufficient information extraction ability for the edge of the matrix by convolution, place the influencing factor matrix of related products around the pricing product, to use the characteristics of the convolutional network to naturally increase the weight of the pricing product information.

- Using the convolutional network to extract high-dimensional information between different domain data of the product itself, the model can theoretically obtain a better prediction effect.

2.2 Confidence interval for sales forecast

For pricing strategy models, the reliability of the sales forecast results is very important. Regardless of the training results, unconditional trust forecast results are unreasonable and unscientific. Therefore, this article will use the test set to construct the confidence interval of the sales forecast results under different degrees of price fluctuations, thereby increasing the robustness and reliability of the pricing strategy model.

To solve the above problems, this paper will use the test set to construct the confidence space of sales forecast and verify the reliability of the confidence space. Specific steps are as follows. The first step is to predict the sales of all the data in the test set; the second step is to classify the test set according to the price fluctuation range of the current month, and calculate the mean and standard deviation of the prediction result samples according to different classifications; the third step, artificial Set the confidence level and estimate the corresponding confidence space-based on this; the fourth step is to observe whether the real result is within the confidence interval. If it is not in the confidence interval, it means that the model training process is not perfect enough. Retrain the model. If the real results fall in the confidence interval Within the interval, it is considered that the model training results are better and meet the requirements of implementing the pricing strategy steps.

So far, this section has solved the key issues of the pricing strategy model, which are summarized as follows:

- To make better use of the relevant features of ConvLSTM's convolutional layer, this article fuses product data in the same price range and reshapes it to make the model have a better prediction effect.

- For the sales forecast results obtained by the pricing strategy model, traditional statistical methods are introduced to test the confidence interval, and the forecast results that do not conform to the statistical laws are discarded, which improves the scientificity and interpretability of the model[9].

3. RESULTS

In this section, we will conduct specific analysis and research on representative automobile sales data in manufacturing products. The source of the data is as follows: The relevant company provided data on automobile sales from January 2012 to June 2018. There are 18 products from different manufacturers, and the relevant data involves confidentiality.

Based on the data of nine domains, the current month's price, monthly sales data, cost, evaluation data, Internet attention index, manufacturer stock price, and macroeconomic indexes such as GDP, CPI, and A-share index, as well as the 8 closest product prices to the manufacturer Manufacturer's relevant product data, build models and verify them by experiments.

Because the dimensions of cross-domain data are different, this paper will normalize the cross-domain data according to their respective domains to ensure that the dimensions of the data are the same.

To verify the superiority of the pricing strategy model proposed in this article, this section will design experiments to conduct experiments on the monthly sales data of 18 kinds of manufacturers. The data of 14 manufacturers were randomly selected as the training set, and the data of the other 4 manufacturers were used as the test set. The length of the input data was six months. According to the model construction steps, a pricing strategy model based on ConvLSTM is constructed. In order to verify the advantages of the ConvLSTM model, this chapter will select the chapter will select ConvLSTM model, LSTM model, and SVR model for comparison experiments.

The experimental platform of this article uses the TensorFlow framework, which is the most commonly used framework in the field of machine learning. The code of this article is written in python language.

To compare the results of the above experiments, this article needs to select scientific evaluation indicators to evaluate the pros and cons of related models. In this paper, three commonly used evaluation indicators, mean absolute deviation rate (MAPE) are selected to evaluate the effect of the model.

$$\text{MAPE}(\%) = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{Y_t-F_t}{Y_t}\right|$$

where N is the total number of predictions, Y_t is the actual value at time t, F_t is the predicted value at time t, Y_h is the highest actual value, and Y_l is the lowest actual value. From the expression, this article can see that when the values of MAPE are smaller, the prediction effect of the model is better.

In this section, the ConvLSTM model, LSTM model, and SVR model will be compared and tested by the experimental design. Next, we will classify the data of the 4 manufacturers in the test set according to the degree of price fluctuation, and use a histogram to compare the average percentage error MAPE value of the prediction results of different models under different price fluctuations.

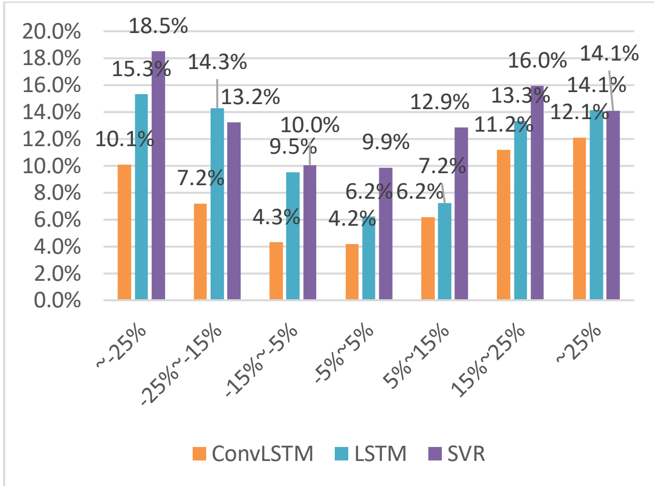

Figure 5. MAPE value of prediction results of ConvLSTM, LSTM, and SVR under price fluctuations.

From Figure 5 we can draw two preliminary conclusions intuitively. ConvLSTM model sales forecast accuracy is significantly better than the LSTM model and SVR model; for different price fluctuation ranges, the smaller the price fluctuation[10], the higher the prediction accuracy of the model. Therefore, in the following experiment, we only choose the ConvLSTM model to estimate the confidence interval and the output of the price strategy of the maximum sales.

This paper calculates the confidence interval of the corresponding sales volume change according to the different price fluctuation intervals of different ConvLSTM models. The confidence level used in this article is 95%. The specific confidence interval is shown in Table 1.

Table 1. An optimal parameter value of the prediction model.

Price fluctuation range	Confidence	Confidence interval of sales volume change
~-25%	95%	[80.3%, 133.4%]
-25%~-15%	95%	[75.3%, 126.9%]
-15%~-5%	95%	[73.2%, 123.4%]
-5%~5%	95%	[63.5%, 121.4%]
5%~15%	95%	[60.7%, 119.8%]
15%~25%	95%	[56.3%, 116.4%]
25%~	95%	[55.1%, 111.4%]
25%~	95%	[55.1%, 111.4%]

Through the determination of the above confidence interval, the result of the change in the sales forecast result caused by the price strategy change will be verified by the corresponding confidence interval. If the forecast result is not within the confidence interval, the forecast result is considered to be infeasible, and therefore the price change strategy is not recorded.

The following Table 2 will output the suggested pricing strategy for 78 test samples from 4 manufacturers. The output is based on the increase in sales based on the pricing strategy of this article and the actual sales.

Table 2. Increase in sales based on pricing strategy model.

Vendor number	Average increase in sales
Vendor A	5.16%
Vendor B	7.23%
Vendor C	3.12%
Vendor D	4.77%
Vendor A	5.16%

It can be seen that based on the pricing strategy model of this article, the total sales of manufacturing products in the four test sets have increased to a certain extent, with sales increasing by 5.07% on average.

So far, this article has proved through experiments that, for the pricing strategy model, the effect of the ConvLSTM model is better than that of LSTM and SVR, and the pricing strategy based on the ConvLSTM pricing strategy model proposed in this article can effectively increase the overall sales of manufacturing enterprises.

4. CONCLUSION

This chapter proposes a pricing strategy model based on ConvLSTM based on the product pricing issues of manufacturing companies. In view of the difficulties in the process of model construction, the ConvLSTM feature of ConvLSTM is used to perform cross-brand and cross-domain fusion and shaping of sales data, so that it can mine high-dimensional logical associations between cross-domain and cross-brand data; secondly, the traditional statistical method introduces the pricing strategy model, by estimating the confidence interval of changes in sales caused by price fluctuations and removing the predicted value that does not fall within the confidence interval, which improves the scientificity, interpretability and forecast accuracy of the model. This chapter is divided into two parts to describe the construction of the model, namely the construction of the sales forecast model based on ConvLSTM and the construction of the pricing decision model based on sales forecast, and then combine the two to construct the pricing strategy model based on ConvLSTM of this article. Design experiments to compare the performance of ConvLSTM neural network, LSTM neural network, and SVR algorithm in the model, and through experiments prove that the prediction accuracy of ConvLSTM model is 30.1% and 41.4% higher than that of LSTM model and SVR model respectively; ConvLSTM pricing strategy is used. The model priced the product, and the total monthly sales increased by an average of 5.07%.

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