

Commodity Dynamic Pricing and Replenishment Decision Model Based on Cosine Annealing

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Abstract. The purpose of this paper is to analyze the relationship between commodity sales volume, commodity types, sales time, etc., and propose a decision model to predict future sales data through historical sales data to determine a reasonable pricing strategy. First, the collected data is preprocessed. Through correlation analysis, the most important influencing factors of commodity sales are obtained. Through the construction of XGBoost model to model the influence factors obtained, the wholesale prices of chili products (yuan/kg) from July 1 to 7, 2023 are 3.63, 6.68, 6.90, 5.44, 6.62, 6.90, 5.44, respectively. In order to further develop a reasonable pricing strategy, this paper constructs a model based on cosine annealing algorithm combined with dynamic pricing algorithm. Through this model, it is calculated that from July 1 to 7, 2023, the restocking quantity (kg) of chili products is 234.20, 95.85, 110.04, 179.77, 176.60, 110.04, respectively. 179.77. Profit (Yuan) is 148.81, 298.96, 347.82, 370.75, 287.54, 356.33, 383.00. By comparing the model with the actual data, the error of the model is small and the robustness is high, which provides an effective decision-making model for supermarkets to formulate commodity sales strategy.

Keywords: XGBoost, Cosine annealing, Dynamic pricing decision.

1. Introduction

Due to its perishable characteristics, vegetable products decrease with the passage of time, and the next day's goods are often difficult to sell. However, due to the early purchase transaction time and diverse sources of vegetable commodities, the supermarket needs to make purchase decisions in advance according to the demand and supply situation. In order to maximize profit, the supermarket usually determines the purchase quantity according to the correlation between time and sales volume and adopts discount sales strategy for goods with transportation loss and product phase change difference. From the perspective of supply side, limited by sales space, supermarkets in the face of rich vegetable supply types, choose a reasonable sales mix is also crucial [1].

Existing relevant studies have deeply studied the reasonable pricing strategy of fresh commodities from the aspects of value loss caused by transportation and preservation [2]. Or refer to the concept of complementarity in economic theory to consider the impact of overpurchase categories on pricing results in actual situations [3]. However, these studies did not consider the effects of both. In view of this, this paper collected the relevant transaction data of a supermarket and established a model reflecting the impact of total sales volume of vegetable categories on pricing. In order to further optimize the model and make it better reflect the actual sales situation, the total number of sales and the quantity of purchase are limited. The sales mix optimization strategy under the goal of maximizing the profit of supermarket is obtained.

2. Materials and methods

2.1. Data acquisition and processing

Through market research, this paper collected the relevant data of a supermarket from July 1, 2020, to June 30, 2023, including commodity information of vegetable categories, transaction details and purchase prices of each commodity, and data of the recent loss rate of the commodity. In order to reduce the impact of wrong data on the results, this paper preprocesses the data first. After statistical

analysis, the probability of return is 0.0005, which is a very small probability event, so this part of data is removed.

2.2. Method introduction

In order to facilitate the study, this paper makes the following assumptions:

(1) All purchases in the early morning are sold out on the same day, and there is no impact of goods accumulation

(2) It is assumed that the price of frequently changing vegetable products has no effect on consumer satisfaction

(3) The rate of vegetable loss is not affected by the seasonal change and the mode of transportation

In the process of predicting the future sales volume and price of each vegetable category, this study first obtained the quantitative index of each vegetable category by analyzing the sales volume and price of each single product. On this basis, the statistical analysis results of various vegetable related indicators such as wholesale price and transportation loss rate over time were obtained by comprehensively considering the influencing factors of sales volume and price. The XGBoost model was used to predict the size of relevant indicators from July 1 to 7.

Then, the relationship between the total sales volume and the price of each category of vegetables is predicted by various methods, and the forecasting effect is compared. Then, this paper takes the profit of the supermarket as the optimization objective, takes the wholesale price and sales price of the commodity as the constraint conditions, adopts cosine simulated annealing algorithm to solve iteratively, and establishes a single objective optimization model to solve the maximum profit and optimal pricing of the supermarket from July 1 to 7, 2023. The XGBoost model is used to predict the sales volume by referring to the relationship between the selling price of vegetable category, wholesale price and sales volume. The flow chart of the forecast of excess replenishment and selling price is shown in Figure 1.

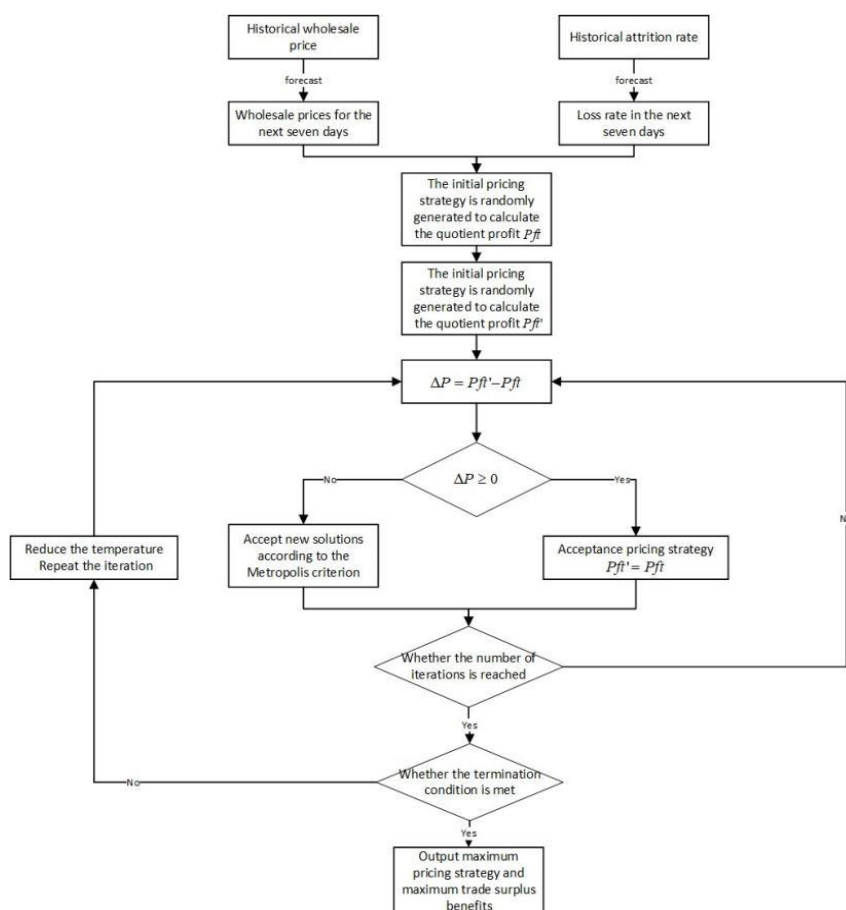


Figure 1 Flowchart

2.2.1 Cosine annealing

Simulated annealing algorithm is a random optimization algorithm based on Monte Carlo iterative solution strategy. As an extension of the local search algorithm, it accepts parameters with low fitting accuracy with a certain probability to avoid the algorithm falling into the local optimal, and with the iterative decline of temperature parameters, the simulated annealing algorithm gradually tends to the global optimal [4].

In the traditional training process, it is necessary to set the learning rate to train the model. However, if a constant learning rate is used for training, the model will oscillate near the optimal solution and fail to reach the optimal solution at the lowest point of the loss function. Therefore, by using the decayed learning rate, near the optimal solution, the gradient gradually decreases, corresponding to a decrease in the learning rate, so that the model can smoothly converge to the correct desired position [5].

However, in practice, due to the complexity of the model, it is difficult to correctly describe the location of the optimal solution and the structure of the loss function due to the multi-modal characteristics of the optimized objective function, which makes the model often converge to a local optimal solution. Finally, due to the attenuation of learning rate, the model eventually falls into a local optimal solution rather than a global optimal solution.

In order to optimize the model, cosine annealing algorithm is selected. The learning rate is adjusted periodically by using the cosine function. After it decays to a certain value, the recovery learning rate is re-adjusted. Based on the Metropolis criterion, the current local optimal solution is removed, and the global optimal solution is re-found [6]. The Metropolis criteria are as follows:

$$P_t(x_{new} = x_{new'}) = \begin{cases} 1 & f(x_{new'}) \leq f(x_{old}) \\ e^{-\frac{f(x_{old}) - f(x_{new'})}{t}} & f(x_{new'}) > f(x_{old}) \end{cases} \quad (1)$$

Based on this criterion, a larger initial temperature is set when the model is established in this paper to increase the probability of the algorithm accepting the poor solution, thereby improving the global search capability of the model and gradually reducing the sales value through 1000 iterations. At the same time, in the process of gradually decreasing learning rate, the learning rate is periodically increased, and the learning rate is recovered by hot restart random gradient descent, so as to better break through the local optimal solution and eventually approach the global optimal. Cosine annealing is a relatively simple hot restart method, and its principle is as follows:

$$\eta_t = \eta_{\min}^i + \frac{1}{2}(\eta_{\max}^i - \eta_{\min}^i)(1 + \cos(\frac{T_{cut}}{T_i} \pi)) \quad (2)$$

Where, i indicates the number of hot restarts, $\eta_{\min}^i, \eta_{\max}^i$ limit the variation range of the i -learning rate. $\eta_{\min}^i, \eta_{\max}^i$ decreases gradually as the number of times increases. T_{cut} represents the number of current learning experiences, and T_i represents the period of cosine annealing.

2.2.2 XGBoost algorithm

XGBoost model is an algorithm to improve GBDT model. This model is based on boosting ensemble idea and adopts forward distribution algorithm for greedy learning during training, learning a single classification tree in each iteration to fit the residual difference between the prediction results of the previous $t-1$ tree and the true value of the training sample [7]. The advantage of XGBoost is that it performs second-order Taylor expansion of the loss function, which increases the accuracy; In addition, regularization term is added to the objective function to prevent overfitting, and it also has a good processing of missing value data, and supports parallelization calculation, which improves the training speed.

2.3. Model evaluation index

2.3.1 Mean absolute percentage error.

In order to obtain the forecast results of vegetable loss rate and wholesale price from July 1 to 7, a variety of methods were used to analyze, and the average absolute percentage error (MAPE) was used to compare the analysis results. MAPE is a measure of the accuracy of model prediction and is often used to evaluate the performance of time series prediction models. In time series analysis, we usually need to make predictions about future trends and changes. The MAPE value reflects the difference between the predicted value and the actual value, expressed as a percentage. The smaller the value of MAPE, the higher the prediction accuracy of the model. The calculation formula is as follows:

$$(\sum (\frac{V_{actual} - V_{predicted}}{V_{actual}}) * 100\%) / N \quad (3)$$

Where, V_{actual} represents the actual value, $V_{predicted}$ represents the predicted value, N indicates the number of samples.

2.3.2 Sensitivity analysis

In order to increase the probability of the cosine-annealed model to accept the bad solution and improve the global search ability of the model, a higher initial temperature is selected in this paper. Considering the possible influence of subjective selection on the result, the initial value is now made to fluctuate within the 10% range, and the model is trained repeatedly to obtain the prediction result, and the fluctuation range of the model prediction result is observed.

3. The establishment and solution of the model

3.1. Quantitative index of daily sales volume and selling price of various types of vegetables

When considering the overall quantitative value of vegetable category, this paper holds that the sales volume of each vegetable item reflects the contribution of that item to this category. Therefore, this paper weighted various indicators of vegetable products based on sales volume, took the weighted average of daily data of vegetable products of the same category as the evaluation index of that category of vegetables on that day, quantitatively analyzed the total daily sales volume, average selling unit price, wholesale price and transportation loss rate of each category of vegetables, and obtained the statistical results of the changes of relevant indicators of each category of vegetables over time.

Based on the sales volume of a single product, this paper assigns weight to the sales volume and selling price of all vegetable items of the same category, and regards the average weighted value as the quantitative value of the corresponding index of vegetables of the same category on the same day, that is:

$$P_{mi} = \frac{1}{n} \left[\sum_{k=1}^n \alpha_{mk} P_{mk} \right] \quad (4)$$

$$x_{mi} = \frac{1}{n} \left[\sum_{k=1}^n \alpha_{mk} x_{mk} \right] \quad (5)$$

Where, α_{mk} represents the weight of the k vegetable item on the m day, P_{mk} , x_{mk} respectively represents the price and sales volume of the k vegetable item on the m day, P_{mi} , x_{mi} Represents the quantitative value of the price and total sales volume of the i vegetable category on the m day, respectively.

Based on the above quantitative methods, this paper obtains the quantitative values of daily sales volume and selling price of each vegetable category. Taking Mosaic vegetables as an example, the quantified values of their total sales and selling prices from July 1 to 5, 2020 are shown in Table 1:

Table 1 Sales and prices of flowers and leaves from July 1 to 5, 2020

Sale date	Total sales (kg)	Price(yuan/kg)
July 1, 2020	205.40	7.60
July 2, 2020	198.36	7.24
July 3, 2020	190.78	7.43
July 4, 2020	236.59	7.84
July 5, 2020	223.90	7.11

3.2. XGBoost prediction

This paper uses cosine simulated annealing algorithm to solve the problem by taking the profit of commercial surplus as the optimization objective and the commodity wholesale price and transportation loss rate as the constraint conditions.

Therefore, this paper first needs to predict the wholesale prices and loss rates of various types of vegetables from July 1 to 7, 2023. Referring to the quantitative method of sales volume and selling price of each category of vegetables, this paper quantifies the wholesale price and loss rate of vegetable categories. For each vegetable category, this paper takes the weighted average sum of the daily wholesale price and transportation loss rate of each vegetable as the quantitative value of the corresponding index of the category.

In order to predict the wholesale price and loss rate of various types of vegetables, various methods were used to analyze and compare the analysis results. The comparison results are shown in Table 2:

Table 2 Analysis effect comparison

method	Mean absolute percentage error
Random forest	0.18725
Support vector machine	0.40021
XGBoost	0.12018
LightGBM	0.38880

As can be seen from the above table, XGBoost has the best prediction effect. Based on the statistical results of wholesale price and transportation loss rate over time, this paper uses XGBoost model to construct a three-step long time series for forecasting. The model construction steps are as follows:

Suppose that the selling price P and sales volume D_m of vegetable are analyzed, and the selling price of vegetable can be expressed as:

$$P = \varphi(x_1, x_2, x_3, \dots, x_m) \quad (6)$$

XGBoost model uses regular function, quadratic Taylor expansion and other methods to optimize GBDT model, and its optimization function is as follows:

$$P_j = \varphi(x_1, x_2, x_3, \dots, x_n) = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) + \text{constant} \quad (7)$$

Where, l is the loss function, $\Omega(f_t)$ is the regular term, constant is the regular item, the function is built as follows:

Firstly, based on the concept of ensemble learning, this paper integrates multiple decision trees and establishes K regression trees to make the predicted value of the tree group with high accuracy and maximum generalization ability. Then the model can be written as:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (8)$$

where f_k is the k th decision tree.

Based on the core idea of XGBoost, feature splitting is performed to add a tree, that is, learning a new function $f(x)$ to fit the residual of the last prediction. At step t , the model can be expressed as:

$$\hat{y}_i^t = \sum_{k=1}^t f_k(x_i) = \hat{y}_i^{t-1} + f_t(x_i) \quad (9)$$

In this case, the objective function of the model can be expressed as:

$$P_j^t = \sum_{i=1}^n l(y_i, \hat{y}_j^t) = \sum_{i=1}^n l(y_i, \hat{y}_i^{t-1} + f_t(x_i)) \quad (10)$$

Optimization objective function based on Taylor quadratic expansion:

$$P_j^t = \sum_{i=1}^n \left[l(y_i, \hat{y}_i^t) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] \quad (11)$$

Let $f(x_i)$ be a single decision tree with T leaf nodes. In order to prevent overfitting of the model, regular terms are introduced into the original model for optimization.

The model complexity can be represented by the regular term:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (12)$$

Bring in the objective function and group all nodes to get:

$$P_j^t = \sum_{i=1}^n \left[g_i w_q(x_i) + \frac{1}{2} h_i w_{q(x_i)}^2 \right] + \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 = \sum_{j=1}^T \left[\left(\sum_{i \in I_j} g_i \right) w_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) w_j^2 \right] + \gamma T \quad (13)$$

In each iteration, the maximum return of splitting is selected to generate a new decision tree and the predicted value is calculated. New decision trees are added to the value model and iterated continuously. The newly generated model is trained based on the last round of model residual until the result reaches the expected accuracy [8].

Because the statistical results are too long, only the forecast results of vegetable loss rate and wholesale price of chili from July 1 to 7 are given in this paper, as shown in Table 3.

Table 3 Forecast of wholesale price and loss rate

Date	Price(yuan/kg)	Attrition rate(%)
July 1, 2023	3.63	4.952
July 2, 2023	6.68	6.486
July 3, 2023	6.90	7.227
July 4, 2023	5.44	9.504
July 5, 2023	6.62	11.514
July 6, 2023	6.90	4.938
July 7, 2023	5.44	6.486

3.3. Cosine annealing

The simulated annealing model is constructed with the profit of the optimization quotient as the objective function, and the preliminary optimization objectives are as follows:

$$Pft = (P_{mi} - I_{mi}) * x_{mi} * (1 - \delta) \quad (14)$$

Among them, Pft represents the profit of commercial super, Pmi, Imi, xmi, δ represent the selling price, purchase price, sales volume and loss rate of Category i vegetables on day m respectively.

Using this model to forecast, the selling price and corresponding profit of each category of vegetables from July 1 to 7 were obtained. Considering the correlation between the sales volume of vegetable products and the selling price and the purchase price in the previous question, this paper adopts XGBoost algorithm to predict the sales volume of each vegetable category from July 1 to 7 based on the predicted price value of simulated annealing and the predicted purchase price of time series. Among them, the forecast results of the best-selling price, replenishment volume and maximum profit of chili are shown in Table 4.

Table 4 Statistical chart of the best-selling price and replenishment of chili

Data	Price(yuan/kg)	replenishment(kg)	profit(yuan)
July 1, 2023	4.27	234.20	143.81
July 2, 2023	10.01	95.85	298.96
July 3, 2023	10.30	110.04	347.82
July 4, 2023	7.72	179.77	370.75
July 5, 2023	8.46	176.60	287.54
July 6, 2023	10.30	110.04	356.33
July 7, 2023	7.72	179.77	383.00

3.4. Discount quantitative indicators

Considering the characteristics of vegetable perishability, the supermarket will discount the vegetables with transport damage and poor phase change over time [9]. This paper takes this factor into account and quantifies its effect on the profit of supermarket. By changing the selling price, the objective function of the cosine annealing model is optimized.

Considering that vegetables deteriorate with time, the likelihood of discount processing is related to time. In this paper, the time of all transactions in the transaction details is counted by hour. In order to analyze the distribution law of discount processing over time, this paper calculates the total number of discount processing in each time period and normalizes the data. The distribution of discount processing over time after normalization is shown in Figure 2.

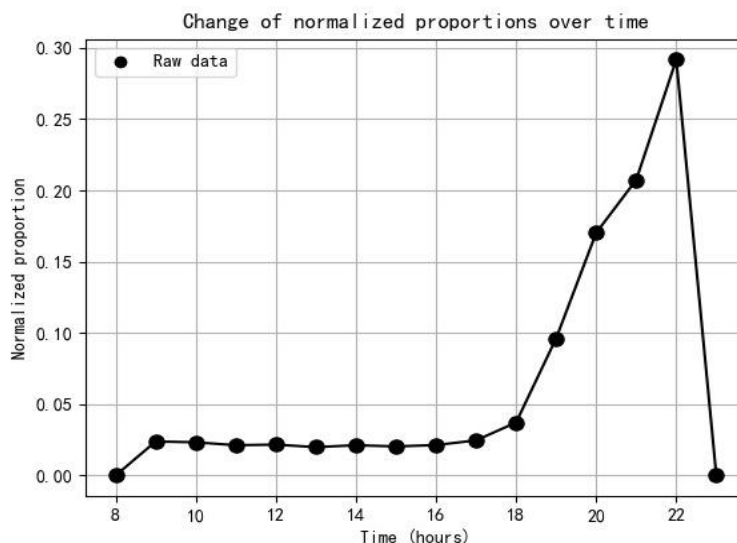


Figure 2 Distribution of discounting proportion

The discount strength of all discounted vegetables in the collected data is collected, and the average value is used as the base value. Based on the results of the proportion distribution, the discount intensity of different periods was weighted, and the weighted average and the quantified value of the impact of discount treatment on the price of a certain category of vegetables were calculated.

The price of vegetables is optimized, namely:

$$\hat{p} = \frac{P}{(1 - p * \chi)} \quad (16)$$

Where, $\hat{p}$ represents the price optimization value, p is the discount probability, χ represents the quantitative index of discount strength of a certain category of vegetables. Bring the optimized price into the model and see Table 5 for the prediction results of 7-day replenishment volume and price of chili.

Table 5 Replenishment volume and selling price forecast table.

Data	Price(yuan/kg)	replenishment(kg)	profit(yuan)
July 1, 2023	5.41	127.50	216.38
July 2, 2023	8.77	165.84	324.90
July 3, 2023	10.02	221.57	643.98
July 4, 2023	8.14	102.16	249.04
July 5, 2023	8.93	227.76	465.13
July 6, 2023	10.03	221.57	660.05
July 7, 2023	8.14	102.16	257.74

3.5. Category restriction

In order to make the model better reflect the actual sales situation, the total number of sales and the quantity of purchase are limited. Based on the profit value of each item, this paper first screened out the sales item mix on July 1, statistically analyzed the daily purchase price, sales unit price, loss rate and sales volume of the salable items from June 24 to 30, 2023, and quantified the profit index of each item by calculating the total profit value of each item during this period, namely:

$$Pft_k = \sum_{i=1}^6 (P_{mk} - I_{mk}) * x_{mk} * (1 - \delta_{mk}) \quad (17)$$

Where, Pft_k represents the total profit of the k item, P_{mk} , I_{mk} , x_{mk} , δ_{mk} represents the selling price, purchase price, sales volume and loss rate of the k vegetable item on the m day respectively.

According to the profit value, 49 kinds of merchantable single products were screened, and 33 kinds of single products with the highest profit value were selected, and the screening results were shown in Table 6.

Table 6 Filtering results

Capsicum frutescence	broccoli	Xixia mushroom	Yunnan Lettuce (1)	Yunnan romaine vegetable	Wuhu green pepper
Screw Pepper (1)	Purple eggplant	Lotus root (1)	Solanum japonicum	Baby Chinese cabbage	Bamboo leaf
Screw Pepper (2)	Agaricus bisporus	Ginger, garlic, millet and pepper combo	Shanghai blue	Branch Jiang green stalk scattered flowers	Milk cabbage
Black fungus	rugosa	amaranth	Red pepper	Brassica chinensis	Honghu lotus root belt
Sweet potato tips	spinach	Water caltrop	Seafood mushroom	Needle mushroom	Colorful Pepper (2)
Yunnan Lettuce (2)	Green Eggplant (1)	Green and red Hangzhou pepper combination			

Among them, the number after the vegetable indicates that there are multiple import sources of the vegetable single product.

With reference to the cosine annealing prediction model for sales volume and selling price above, maximizing the profit of merchants on July 1, 2023, as the objective function, and adding the

restriction condition of minimum sales volume of 2.5kg to predict the sales volume and pricing of each single product. Among them, the sales volume and price forecast results of the five categories of single products with the largest profit are shown in Table 7.

Table 7 Forecast of replenishment quantity and selling price of vegetable items.

Vegetable item	Price(yuan/kg)	replenishment(kg)	profit(yuan)
Xixia mushroom	45.68	21.15	228.90
Lotus root (1)	43.24	12.55	170.70
broccoli	40.58	11.90	140.40
Branch Jiang green stalk scattered flowers	34.30	13.19	91.90
Yunnan lettuce	38.17	8.39	90.40

4. Discussion

4.1. Model advantages

The model used in predicting sales volume effectively avoids the problem of overfitting. Using traditional decision trees for prediction is prone to model overfitting problems. This model uses Taylor quadratic expansion, introduces regular term functions and other methods to suppress the complexity of decision trees, and then integrates multiple decision trees by gradient lifting to effectively avoid model overfitting problems.

The cosine annealing model is used to train the model by constantly adjusting the learning rate of the model periodically. The influence of the position selection of the optimal solution of the function and the description deviation of the loss function on the result is reduced, and the model prediction results tend to the global optimal solution.

The model used in this paper has low requirements for data characteristics. Different from the traditional statistical prediction model, this model does not put forward specific requirements for correlation and collinearity between variables and does not require complex feature engineering and feature transformation. The workload of data preprocessing is greatly simplified.

The prediction effect of various models is compared in this paper. In the end, the prediction effect of the model used is the best, and the prediction accuracy is increased by more than 6% compared with other models.

4.2. Model improvement

4.2.1 Model robustness

Model robustness refers to the ability of the model to maintain stable performance and accurate prediction ability in the face of changes in inputs or parameters. The robustness of the annealing model can be improved by the following methods [10]:

In the training process of the model, a new training set can be generated by collecting adversarial samples, so as to improve the sensitivity of the model to these adversarial samples. In addition, data enhancement methods such as Patch Gaussian can also be used to improve the adaptability of neural networks to general perturbations through the enhancement of training sets.

Before the input samples are incorporated into the model, they are first pre-checked and processed to exclude potentially adversarial samples. For example, a sample can be detected by compressing and simplifying the input sample and judging whether it is an adversarial sample based on the detection result.

4.2.2 Parameter optimization

The cosine annealing of the same period makes the learning rate change too fast, and the model repeatedly jumps out of the local optimal, resulting in the failure to find a stable local optimal model, which will affect the accuracy of the result integration. Because the periodic cosine annealing method may lead to the lack of network learning stability, we optimize the learning rate adjustment period

and introduce a periodic increasing cosine annealing strategy. This method makes the learning process smoother and helps to obtain more stable locally optimal models in the later stage of learning, thus improving the accuracy of the result integration.

5. Conclusions

In this paper, by applying XGBoost machine learning algorithm and combining the relationship between product sales volume, product quality, sales time and other influential factors, a forecasting model is constructed to predict future sales data by using historical data. In order to further optimize the pricing strategy of supermarket, a model based on cosine annealing algorithm combined with dynamic programming pricing algorithm is constructed to calculate the best replenishment volume, selling price and profit of commodity in the future. Compared with the actual data, the model constructed in this paper has small error and strong robustness, which provides an effective decision-making model for the supermarket to make a reasonable sales strategy.

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