Research on logistics supply chain optimization strategy based on machine learning

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ABSTRACT

With the process of globalization and the continuous development of the economy, the role of the logistics supply chain in corporate operations has become more and more prominent, and its optimization has become a core topic of modern management. This research aims to explore the optimization strategy of logistics supply chain through machine learning technology. First, based on an in-depth analysis of machine learning theory and supply chain processes, a specific machine learning model adapted to this scenario was selected, and empirical research was conducted to explore the problems and challenges that may be encountered in practical applications, and for this purpose, specific suggestions were put forward. sexual optimization plan. It is expected that through the application of machine learning, efficient, accurate and flexible management of the logistics supply chain can be achieved, bringing substantial benefit improvements to modern enterprises.

Keywords: machine learning; logistics supply chain; optimization strategy

1. INTRODUCTION

With the development of globalization and the booming economy, the logistics supply chain has become a core component of the daily operations of enterprises. Its efficiency and accuracy are directly related to the enterprise's cost control and customer satisfaction. However, with the explosive growth of data volume and the gradual increase in the complexity of supply chains, existing traditional methods are difficult to meet the requirements of efficiency, accuracy and real-time. In this context, machine learning, with its powerful data processing and pattern recognition capabilities, is regarded as a powerful tool for optimizing the logistics supply chain [1]. The research aims to explore the application potential and optimization strategies of machine learning in logistics supply chains. It is hoped that it can provide a new and effective optimization method for related fields of logistics supply chain, and provide reference and inspiration for future practice.

2. THEORETICAL FRAMEWORK OF MACHINE LEARNING IN SUPPLY CHAIN

2.1 Machine learning basics and algorithm classification

Machine learning, as a branch of artificial intelligence, mainly focuses on building algorithms to enable computers to discover patterns in data and learn autonomously [2]. As shown in Figure 1, these algorithms are usually classified according to their learning mechanism and task objectives. Supervised learning is one of the most commonly used methods, which relies on labeled data [3]. From this data, the algorithm learns and builds a model, which is then used to predict or classify unknown data. Unsupervised learning does not rely on labeled data. It attempts to discover hidden structures or patterns in data, such as clustering or association rules. Reinforcement learning focuses on how to make optimal decisions in interaction with the environment [4]. This type of learning is often used in scenarios that require continuous decision-making.

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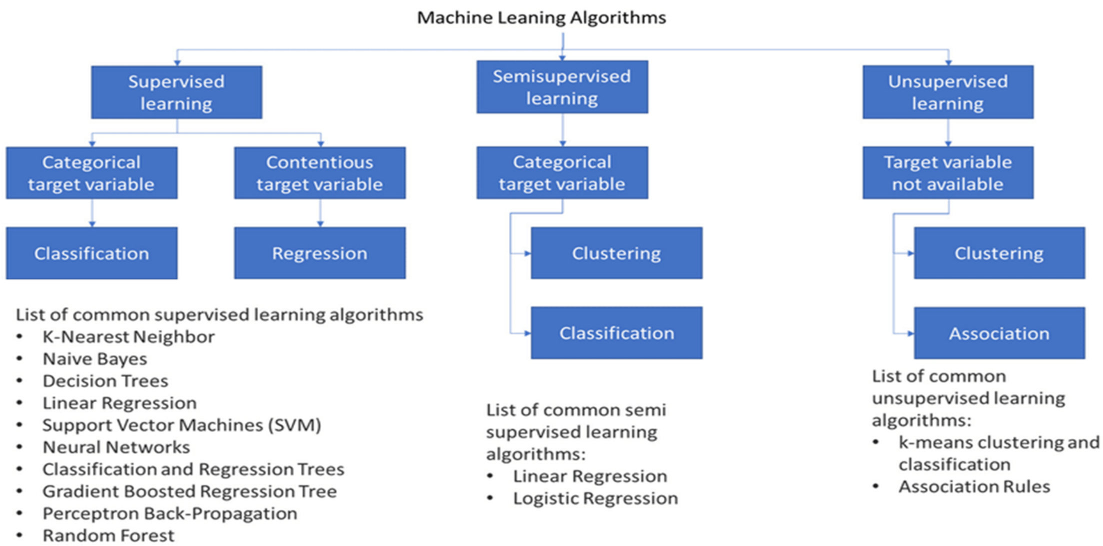

Figure 1 Classification and summary of machine learning algorithms

2.2 Operation process of logistics supply chain

The logistics supply chain management system provides efficient information flow channels for each link. As shown in Figure 2, from "purchasing" to "production" to "inventory" and "distribution", each step in the entire chain structure can achieve rapid transmission of information and accurate feedback. This process ensures that all links in the supply chain can operate synchronously, reducing redundancy and errors [3]. In the logistics supply chain network , logistics suppliers are at the core. They work closely with the financial department to ensure that capital flow and logistics operate simultaneously and efficiently. At the same time, a solid communication bridge has been established between logistics suppliers and customers, promoting real-time updates and exchanges of supply and demand information, thereby improving the transparency and response speed of the overall industry. This tight and orderly operating process not only ensures the high efficiency of the supply chain, but also brings a more stable and predictable operating environment to the enterprise.

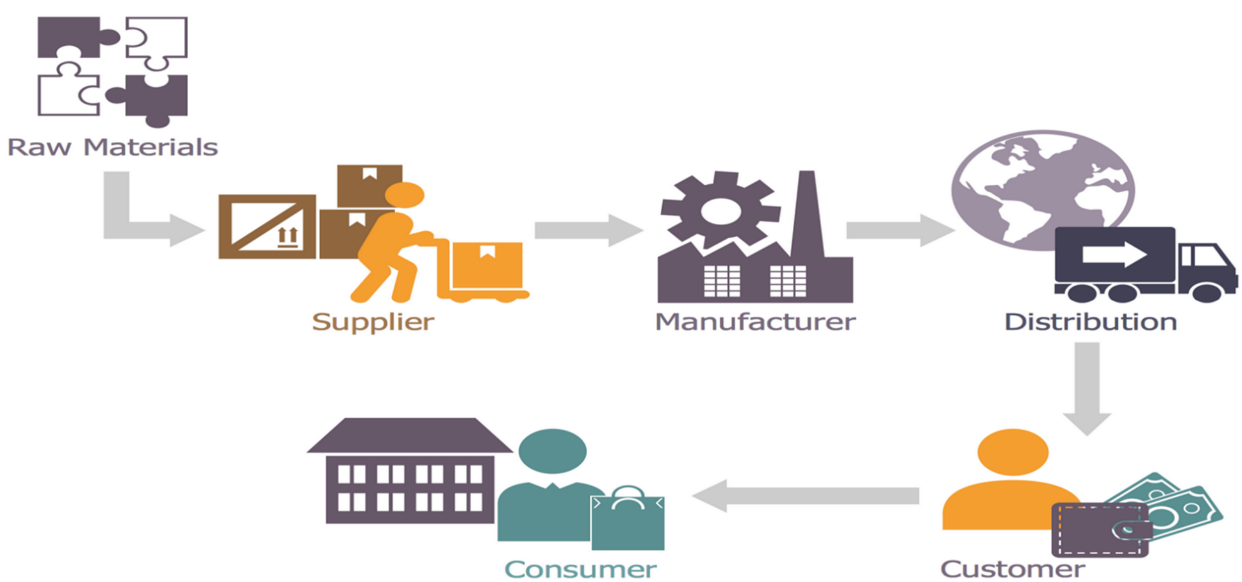

Figure 2 Logistics supply chain system operation flow chart

3. EXPERIMENTAL DESIGN

3.1 Dataset description and source

In order to deeply explore the practical application effect of machine learning in the logistics supply chain, the study used a data set specifically focused on user purchasing behavior, called "User Behavior Data Set". This data set comes from the logistics big data training data set platform.

Additional purchases and other behavioral information over a period of time. This data provides rich information for in-depth analysis of users' purchasing trends, preferences and patterns. Through in-depth mining of these data, we can better understand the actual needs of the market and provide powerful decision-making support for all aspects of the logistics supply chain.

3.2 Feature engineering and data preprocessing methods

After in-depth analysis of the "user behavior data set", in order to ensure the effectiveness and accuracy of the model, refined feature engineering and preprocessing were performed on the data.

(1) Feature extraction

Purchase frequency: $F = \frac{\Sigma \text{ Number of purchases}}{T}$, where F represents the purchase frequency and T represents the total number of days of observation.

Average spending amount: $M = \frac{\Sigma \text{ purchasing price}}{\Sigma \text{ Number of purchases}}$, where M represents the average consumption amount.

(2) Data preprocessing:

Handle missing values : For numeric data, use the mean of the data set μ to fill:

$$X_{i,\text{ new}} = X_{i,\text{ old}} \text{ if } X_{i,\text{ old}} \neq \text{ null else } \mu \tag{1}$$

Outlier handling: Use the Z-score method, where σ is the standard deviation: $Z = \frac{X-\mu}{\sigma}$. If $|Z|>3$, it is considered an outlier.

Data normalization: $X_{\text{norm}} = \frac{X-\mu}{\sigma}$, so that X_{norm} the mean is 0 and the standard deviation is 1.

3.3 Selected machine learning models and why

Based on the characteristics and business needs of the "user behavior data set", the study selected the decision tree model as the main machine learning algorithm. A decision tree is a tree-structured algorithm in which each internal node represents a test on an attribute, each branch represents a test output, and each leaf node represents a classification. Mathematically, the decision tree T is recursively defined by the following formula:

$$\begin{cases} c & \text{if } T \text{ is a leaf with label } c \\ T_k(x) & \text{otherwise} \end{cases} \tag{2}$$

where x is the input data sample and is T_k the subtree selected based on the test of x on the k-th attribute . The results of the decision tree are easy to interpret and understand, and are especially suitable for scenarios such as logistics supply chains that require clear decision-making basis. During the construction process, split points will be selected based on the importance of features, which means that for "user behavior data sets" such For high-dimensional data, decision trees can effectively reduce dimensions. In addition, decision trees do not need to assume the distribution of data, so for data such as "user behavior data sets" that may have various unknown distributions, decision trees have better robustness.

3.4 Development tools

Decision tree experiments were developed using the Python programming language. The main libraries used include Scikit-learn for machine learning model development, Pandas for data preprocessing, and Matplotlib for visualization. The entire experiment was conducted in the Jupyter Notebook environment, which provided an interactive platform for model training, testing, and evaluation.

3.5 Response test

In order to further verify the application effect of the decision tree model in actual supply chain scenarios, we conducted a response test.

(1) Scenario simulation:

Use decision tree models to predict user purchasing behavior. Based on the prediction results of the model, different scenarios of inventory management, distribution and supply and demand matching of the supply chain are simulated. The calculation formula is:

$$S = P \times I \tag{3}$$

Where S represents the supply chain status, P represents the prediction result of the model, and I represents the initial inventory.

(2) Feedback loop:

A feedback mechanism is implemented to feed actual supply chain performance indicators into the model. This allows the model to learn and adjust its predictions in real time, further optimizing the supply chain. Formula description:

$$F_n = F_{n-1} + \alpha \times (R - P) \tag{4}$$

In F_n Represents the nth feedback result, F_{n-1} it's the feedback from the previous time, R is the actual supply chain performance indicator, P is the prediction result of the model, α is a learning rate.

(3)Evaluate:

Use an optimized supply chain to measure based on key performance indicators such as inventory turns, distribution efficiency, and customer satisfaction. The formula is:

$$E = \frac{T_n}{T_0} \tag{5}$$

In E represents the evaluation index, T_n is the performance value after the response test, T_0 is the performance value before testing.

4. EXPERIMENTAL RESULTS AND EFFECT EVALUATION

4.1 Training process and convergence of the model

Based on the aforementioned decision tree model design, the study began model training. Cross- entropy was chosen as the loss function to measure the difference between model predictions and real data. The loss function is defined as follows: $L(y,\hat{y}) = -\sum_i y_i \log\left(\hat{y}_i\right)$. where y is the real label, but is the predicted output of the model. $\hat{y}$

Since the model is still in its "original" state, the loss drops faster. However, as the training progresses, the loss decreases gradually until it converges. The accuracy on the validation set also gradually improved during the iteration process, reflecting the enhanced generalization ability of the model. At the beginning of training, the value of the loss function is 1.75. Through iterative training, the model continuously optimizes its structure to minimize this loss . After the 50th iteration, the loss dropped to 1.25; by the 100th iteration, the loss was further reduced to 0.65. At the 150th iteration, the model converges and the loss stabilizes at 0.32.

Table 1 Summary of key indicators of the model in different training stages

Number of iterations	loss function value	Validation set accuracy	Model complexity (number of leaf nodes)
0	1.75	55%	10
50	1.25	65%	15
100	0.65	78%	18
150	0.32	85%	20

As can be seen from Table 1, as the number of iterations increases, the loss function value steadily decreases, while the accuracy on the validation set continues to improve. This shows that the model gradually adapts to the data during the learning process and can better capture its inherent patterns. At the same time, the complexity of the model also increased, but the growth rate gradually decreased, indicating that the model was gradually converging.

4.2 Analysis of key performance indicators

When validating model performance, a single accuracy often cannot fully reflect the true performance of the model. In order to deeply evaluate the effect of the decision tree model on the "user behavior data set", several key performance indicators were selected for evaluation, including precision, recall and F1 score. Precision, recall, and F1 score are calculated by the following formulas:

$$\text{(accuracy) Precision} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{(recall rate) Recall} = \frac{TP}{TP+FN} \tag{7}$$

$$F1 = 2\times\frac{\text{Accuracy} \times \text{Recall}}{\text{Accuracy} + \text{Recall}} \tag{8}$$

Among them, TP represents a true example, FP represents a false positive example , and FN represents a false negative example.

Table 2 Summary of key performance indicators of the model at different stages

Number of iterations	Accuracy	Recall	F1 score
50	63%	68%	65.5%
100	77%	79%	78%
150	85%	87%	86%

From Table 2, it can be seen that the precision rate, recall rate and F1 score of the model have been significantly improved during the iteration process. This not only shows that the model's performance in positive and negative classification is more balanced, but also that it can capture key data points more effectively, thereby more accurately predicting user purchasing behavior.

5. LOGISTICS SUPPLY CHAIN OPTIMIZATION STRATEGY BASED ON MACHINE LEARNING

5.1 Data enhancement and simulation technology

5.1.1 Application of Generative Adversarial Network (GAN) in data simulation

Generative adversarial network (GAN) consists of two parts: generator GG and discriminator DD. The generator's task is to produce data that is as realistic as possible, while the discriminator's task is to differentiate between real and generated data. The two compete with each other to continuously optimize the authenticity of the data generated. The objective function of the generative adversarial network is defined as:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] . \tag{9}$$

where x is the real data, z is the noise randomly sampled from some distribution p_z , and G(z) is the data generated by the generator.

In the scenario of logistics supply chain, GAN can be used to simulate possible user purchasing behavior or other related data, thereby enhancing the data set. For example, if you find that there is too little purchase data for certain items, you can use GANs to generate additional data to help the model better learn the underlying patterns of these items.

5.1.2 Use Bootstrap method to increase sample diversity

The Bootstrap method is a statistical resampling technique that aims to generate multiple new sample sets by randomly sampling from the original data set with replacement. This method can effectively increase the diversity of samples and help improve the stability of the model, especially when the amount of data is small or the data is unevenly distributed. The basic steps of Bootstrap are as follows:

Given an original data set D, which contains N samples . Randomly select N samples from D with replacement to form a new data set D'. Repeat the above steps M times to obtain M new data sets. Bootstrap's resampling formula can be expressed as: $D_i^{'} = \{d_1, d_2, \ldots, d_N\}$. Among them, each d_j is a sample randomly drawn from the original data set D, and i is the number of resampling, from 1 to M. In the context of logistics supply chain, if data in some key situations are scarce, the data representation of these situations can be enhanced through the Bootstrap method.

5.2 Dynamic adjustment and online learning strategy

5.2.1 Adaptive learning rate adjustment techniques

Adaptive learning rate adjustment is designed to automatically adjust the learning rate based on the model's training progress and validation performance. The most commonly used strategy is to multiply the learning rate by a coefficient less than 1 when the model verification performance does not improve significantly in consecutive epochs. The specific update strategy is as follows: $\alpha_{\text{new}} = \lambda \times \alpha_{\text{current}}$. Among them, α_{new} is the new learning rate, α_{current} is the current learning rate, and is a decay coefficient. $\lambda (0 < \lambda < 1)$ Assume the current learning rate is 0.01. When the performance of the model does not improve in 5 consecutive epochs, you can choose λ to be 0.5 and adjust the learning rate to 0.005 to accelerate the convergence of the model and improve the generalization ability of the model. The logic behind this strategy is that as the model gradually approaches the optimal solution, more refined parameter adjustments are needed to avoid excessive oscillation and missing the best performance. In the scenario of logistics supply chain, this adaptive learning rate adjustment method can help the model adapt to changes in data faster, thereby achieving more stable and accurate predictions.

5.2.2 Real-time decision-making optimization using reinforcement learning

Reinforcement learning models usually consist of the following core components: Agent, Environment, Action, State and Reward. Specific to the logistics supply chain, the intelligent agent can be regarded as a decision-making system. The status may include inventory levels, demand forecasts, transportation status, etc., while the actions may include order distribution, inventory replenishment, etc. Based on this, a Q learning model can be constructed for decision optimization. At each time step, the agent observes the current state s, selects an action a based on the Q value, and obtains the reward r returned by the environment and the new state s'. The update rule of Q value is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a^{'}} Q\left(s^{'}, a^{'}\right) - Q(s,a)\right) \tag{10}$$

Among them, α is the learning rate, which controls the update amplitude of the Q value; γ is the discount factor, which determines the degree of consideration of future rewards. In a logistics supply chain scenario, for example, when considering an order delivery strategy, status may include the quantity, destination, delivery deadline, etc. of the current order; actions may include selecting a specific delivery route or delivery method; rewards may be based on delivery. Determine the timeliness and cost of the goods.

5.3 Hybrid model combining traditional supply chain theory

5.3.1 Forecasting based on time series analysis

In the logistics supply chain, considering the seasonality, trend and cyclicality of orders, the ARIMA model can be used for prediction first. The specific ARIMA model can be expressed as: (p, d, q). Among them, p is the order of the autoregressive term, d is the order of the difference , and q is the order of the moving average.

Once you have the predicted value of ARIMA, it can be input into a machine learning model, such as random forest, neural network, etc., as a new feature together with other related features for further prediction. First, use historical data to fit the ARIMA model and make predictions, combine the ARIMA prediction values with other relevant features, then use the combined feature data to train the machine learning model, and finally use the machine learning model to make the final prediction. In this way, it not only leverages the expertise of time series analysis in processing time-dependent data, but also introduces the powerful ability of machine learning in processing high-dimensional, non-linear data.

5.3.2 Integrating network optimization technology and machine learning for resource scheduling

In the logistics supply chain, resource scheduling is a crucial link, which is related to the effective circulation of goods, minimization of costs and maximization of time efficiency. Traditional network optimization techniques, such as linear programming and integer programming, have long played a central role in resource scheduling. Machine learning, with its ability to analyze large amounts of data, provides a more accurate decision-making basis for resource scheduling. Consider a simplified resource scheduling problem: how to determine the quantity of goods each distribution center receives from the warehouse to minimize total cost . This problem can be expressed by the following linear programming model:

$$\min \sum_{i,j} c_{ij} x_{ij} \; ; \; \overset{s.t.}{\sum_{j} x_{ij} \le s_i, \quad \forall i} \; ; \; ; \; \sum_{i} x_{ij} \ge d_j, \quad \forall j \; ; \; x_{ij} \ge 0, \quad \forall i, j \tag{11}$$

Among them, x_{ij} represents the quantity of goods from warehouse i to distribution center j. c_{ij} is the unit cost from warehouse i to distribution center j. s_i is the supply of goods in warehouse d_j i . is the demand for goods in distribution center j. After obtaining the preliminary resource allocation, machine learning models, such as neural networks or support vector machines, can be further used to fine-tune the resource scheduling strategy. This requires taking various characteristics of the dispatch strategy (such as distance, traffic conditions, historical demand data, etc.) as input, and the prediction goal is demand or cost changes in the short term. Using the output of network optimization technology as the input of the machine learning model can achieve fine-grained adjustments to the scheduling strategy, thereby better coping with various uncertainties and changes in actual operations.

6. CONCLUSION

The research deeply explores the application potential and strategies of machine learning technology in logistics supply chain optimization. Through comparative analysis, the superiority of machine learning and traditional methods in processing large-scale and complex data is clarified. At the same time, the article also points out the challenges faced by machine learning in practical applications and proposes a series of targeted optimization solutions. Looking to the future, as technology further evolves and the complexity of supply chain management increases, the application space for machine learning will become even broader. Especially with the support of technologies such as the Internet of Things and big data, the data of the logistics supply chain will be richer and more accurate, providing a greater application space for machine learning.

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