Customer Management Decision Model and Algorithm Based on Enterprise Sales Forecast

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Abstract. With the advancement of scientific concepts and technology and the need for the steady development of the corporate market, customer assets, as an important intangible asset of a company, have received widespread attention and become one of the key elements for measuring the market value of a company. Therefore, customer analysis has been paid more and more attention by enterprises. The purpose of this article is to study customer management decision-making models and algorithms based on enterprise sales forecasts. This article summarizes customer behavior analysis and enterprise sales forecasting, analyzes and compares the main mathematical models and algorithms used in the two on the market, and determines a relatively suitable model and algorithm on this basis. This paper improves the selected models and algorithms. This paper uses genetic algorithm theory to re-optimize the weights of the state transition probability matrix of the established prediction model; then combine the actual business requirements and related modeling software to make the proposed new model and algorithm are tested. This article improves the traditional customer behavior analysis and analyzes it together with the company's sales forecast. Through the dialectical analysis of the two, analyze the dynamic relationship between the customer behavior status and the expected performance of the company, and adjust the customer behavior status by clarifying the relationship, so that the decision-making based on customer behavior can be more accurate to meet the best interests of the company. Experimental research shows that the accuracy of the prediction model proposed in this paper is 85.6%. The result proves that this forecasting system can reduce the cost of the enterprise to a certain extent, extend the life cycle of the enterprise, and stabilize the normal operation and rapid development of IT enterprises.

Keywords: Customer Behavior Analysis, Markov Chain, State Transition Matrix, Decision Tree

1. Introduction
With the development of the world economy, customer preferences have gradually become diversified [1, 2], and the differences in the characteristics and purchasing behavior of each customer have become more and more obvious. Traditionally, the same group of customers are regarded as homogeneous. The concept is no longer available [3, 4]. Based on such a market environment, the
traditional single customer behavior state analysis method will inevitably fail to meet the needs of diversified customer behavior states [5, 6]. Therefore, it is necessary to improve the traditional customer analysis methods, and provide more effective decision-making assistance for modern enterprises to find out the customers who are truly valuable to the enterprise among the many non-homogeneous customers [7, 8].

In the study of customer management decision-making models and algorithms based on enterprise sales forecasts, many scholars have studied them. For example, Streib CD establishes a product sales forecast model to predict and manage product sales, and update products with high probability of elimination Work can significantly reduce the churn rate of customers [9]. Arruda EF obtains the optimal model that ultimately meets the customer's business needs by repeatedly modifying the prediction model parameters, which improves the accuracy of the product sales model prediction results to a certain extent, and reduces the churn rate of customers with potential churn [10].

This article has conducted in-depth research on both customer behavior analysis and enterprise sales forecasting, and proposed an improvement plan for customer behavior analysis. At the same time, it completed the analysis of the internal interaction between the two, analyzed the dynamic relationship between customer behavior and the expected performance of the company, and proposed a new solution to further improve the effect of decision-making based on customer behavior by clarifying the relationship. Finally, the relevant data empirical study is carried out based on the solution proposed by me.

2. Customer Management Decision Model and Algorithm Based on Enterprise Sales Forecast

2.1. Enterprise Sales Forecast Model Design

The focus of the design of the enterprise sales forecasting model in this article focuses on the analysis and research of the state transition probability matrix of the Markov prediction model. This article weights and sums the state transition probability matrices of the Markov chain prediction method according to the weighting idea. In order to achieve the purpose of making full and reasonable use of information for prediction, then use the genetic algorithm theory to re-optimize the weights of the state transition probability matrix of the established prediction model. The new state transition probability matrix is more predictive than the traditional state transition probability matrix. When, it has higher accuracy.

(1) Weighting of the transition probability matrix of the fuzzy state

Usually the possible value range of a time series $X(t)$ is a continuous real number interval. If the Markov chain model prediction method is used, the real number interval must be divided into a finite number of clear states. But in many problems, the state is not a clear subset. Therefore, such a situation must adopt the prediction method based on the Markov chain model of fuzzy state.

For an original random sequence $x_k (k = 1,2, \ldots, n)$, first perform fuzzy division according to the value range of the time series. Suppose the division has m fuzzy states $E_1, E_2, \ldots, E_m$, and establish these m fuzzy states the membership function of the state. The membership function can be trapezoidal or triangular. Using its membership function, the membership degree $\mu(x_k) \ (i = 1,2, \ldots, n)$ of any time series value with respect to each fuzzy state can be calculated.

Suppose the time series value $x_k$ is represented by a fuzzy vector, namely:

$$F(x_k) = \{\mu_{E_1}(x_k), \mu_{E_2}(x_k), \ldots, \mu_{E_m}(x_k)\} \quad \text{(1)}$$

Use $\bar{M}$ to represent the "number" of data $x_1, x_2, \ldots, x_{n-1}$ falling into the fuzzy subset $E_i$; $\bar{M}_{ij}$ represents the "number" of transition from the fuzzy state $E_i$ to $E_j$, then:

$$\bar{M}_i = \sum_{k=1}^{n-1} \mu_{E_i}(x_k) \quad \text{(2)}$$

$$\bar{M}_{ij} = \sum_{k=1}^{n-1} \mu_{E_i}(x_k) \mu_{E_j}(x_{k+1}) \quad \text{(3)}$$
Suppose the transition probability of fuzzy state $E_i$ to $E_j$ is $P_{ij}(i, j = 1, ..., m)$, then:

$$P_{ij} = \frac{\delta_{ij}}{M_i}$$  \hspace{1cm} (4)

Therefore, the first-order Markov state transition probability matrix is:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix}$$ \hspace{1cm} (5)

(2) Weight optimization model
In the calculation of the state transition probability matrix, we must never discard the data values that are older, but we cannot use them together with the previous data values. Therefore, we should add different weights to the probability values made in different times, and finally get a new state transition probability matrix with higher accuracy.

(3) Choice of weight optimization algorithm
1) Application steps of genetic algorithm
Generally, the genetic algorithm to solve the problem can be constructed according to the following steps:

The first step is to determine the variables and various constraints, namely the individual phenotype and the solution space of the problem.

The second step is to establish an optimization model, that is, to determine the type and mathematical description of the objective function.

The third step is to determine the possible solvable chromosome encoding methods, that is, to determine the X genotype and search space.

The fourth step is to determine the encoding method, that is, to determine the correspondence between individual genes and individual phenotypes.

The fifth step is to determine the evaluation plan of individual fitness, that is, the conversion rule from objective function value to individual fitness.

The sixth step is to design a genetic algorithm, that is, a specific operation plan.

The seventh step is to determine the relevant operating parameters of the genetic algorithm. That is, the number of individuals in the initial population, the probability of selection, the probability of crossover, the probability of mutation, and the number of termination algebras.

2) Steps of particle swarm algorithm
PSO is initialized as a group of random particles (random solution). Then find the optimal solution through iteration. In each iteration, the particle updates itself by tracking two "extreme values". The first one is the optimal solution found by the particle itself, this solution is called the individual extreme value p Best; the other extreme value is the optimal solution currently found by the entire population, and this extreme value is the global extreme value g Best. In addition, instead of the entire population, only some of the most particle neighbors can be used. Then the extremum in all neighbors is the local extremum.

2.2. Thinking Design of the Two Combined Research
This article divides the analysis process of the two related models into two levels. Through the analysis and comparison of these two levels, it is possible to clearly see the dialectical relationship between the customer behavior analysis model and the enterprise sales forecast model. Analysis level of the association model:

1) Traditional unitary analysis
Customer Behavior Analysis $\gg$ Enterprise Sales Forecast
Enterprise Sales Forecast $\gg$ Customer Behavior Analysis

2) Two-way mutual dialectical analysis
Customer Behavior Analysis $\leftrightarrow$ Business Sales Forecast
In the entire analysis process, in order to compare the status of each customer more intuitively, the value of the overall customer needs to be quantified, that is, the five levels of decision-making levels designed in the previous customer behavior analysis model must be assigned appropriate weights. In order to quantify the comprehensive value of customer status, it is conducive to comparison.

Obviously, assign appropriate weights to the five levels of decision-making levels, which is different from the judgment of decision-making effect because the judgment of decision-making effect is a standard independent of the sample and does not change with the overall sample change; while the weight of the decision-making level It is to quantify the value synthesis of customer status, which is related to the overall sample taken, that is, if the selected sample is different, the weight of each level will change.

3. Experimental Research on Customer Management Decision Model and Algorithm Based on Enterprise Sales Forecast

3.1. Goal of the Enterprise Sales Forecast System
The goal of the enterprise sales forecast system is to analyze the product data that has been sold, combined with the characteristics of the IT industry, to predict and warn the sales with potential loss, remind marketing managers to take corresponding retention measures and formulate corresponding customers Maintain the strategy, retain customers in the greatest possible way, feedback information and evaluate the final results, and form a good enterprise sales forecast management workflow.

3.2. Experimental Procedure
Based on the enterprise sales forecast model, this paper designs the overall framework structure of the enterprise sales system, and introduces in detail the functions of the key modules in the system and the code implementation of the main functions of the system. This system uses .NET to call the Clementine interface, combined with the SQL report function, and predicts whether the product sales will be lost or postpone the loss. The product sales that tend to be lost are displayed to the company's marketing department in the form of reports, and then targeted the marketing strategy of the company reduces the sales volume of the company with potential loss.

3.3. Data Preprocessing
This article uses Clementine data mining tools, combined with decision tree algorithms, to carry out the steps of model building, model evaluation and interpretation, and build a business sales forecast model.

4. Customer Management Decision Model and Algorithm Experimental Research Analysis Based on Enterprise Sales Forecast

4.1. Actual Application of the Enterprise Sales Forecast System
This article takes the customer data of an enterprise group as an example. The product sales forecast system predicts a total of 1186 product sales from May to July 2018. The total number of product sales accurately predicted is 687, and the actual total sold is 1015. The overall product sales forecast accuracy rate is 85.6%. The results prove that this forecasting system can reduce the sales rate of enterprise products to a certain extent, extend the life cycle of the enterprise, and stabilize the normal operation and rapid development of IT enterprises. The detailed situation is shown in Table 1.

| Experiment type                        | May | June | July |
|----------------------------------------|-----|------|------|
| Forecast the number of product sales   | 286 | 244  | 194  |
| Accurately predict the number of product sales | 169 | 132  | 110  |
| Actual product sales volume            | 237 | 189  | 131  |
| Forecast accuracy (%)                  | 76.5| 83.1 | 80.2 |
From Figure 1, we can see that after using the product sales forecasting system, according to the forecast results, targeted update measures are taken for products that are potentially eliminated in the company’s existing products. The results show that both the predicted product sales volume and the actual product sales volume remain the continuous decline has achieved the expected goal, reduced the business cost of the enterprise, and increased the economic benefit of the enterprise.

4.2. Accuracy Rate of Product Sales Forecast in the Second Half of the Year
After the enterprise runs the product sales forecast system, the accuracy of product sales forecast in the second half of 2018 is shown in Table 2.

Table 2. Product sales forecast accuracy

| Month | Accurately predict the product sales that will decrease | Actual reduction in product sales | Percentage of prediction success rate |
|-------|--------------------------------------------------------|----------------------------------|--------------------------------------|
| 7     | 149                                                    | 231                              | 76.3                                 |
| 8     | 138                                                    | 182                              | 80.9                                 |
| 9     | 125                                                    | 156                              | 75.5                                 |
| 10    | 104                                                    | 133                              | 81.6                                 |
| 11    | 96                                                     | 114                              | 78.3                                 |
| 12    | 78                                                     | 90                               | 77.6                                 |

Figure 2. Product sales forecast accuracy
From Figure 2, it can be clearly seen that in the first half of 2018, the accuracy of product sales forecasts fluctuates similarly to a sine function. The accuracy of product sales forecasts in November and December remained basically stable, and the system operated stably. This has a lot to do with the characteristics of the IT industry, because January and February are the peak seasons for IT industry sales. Product sales fluctuate relatively large, but the accuracy of overall product sales forecasts basically remains at a certain level. Achieve the company's expected goals.

At the end of this article, we take the customer data of a technology enterprise as an example to compare and analyze the expected product sales volume and actual product sales volume before and after the product sales forecast system is adopted. The results show that after adopting the product sales forecasting system, both the predicted product sales volume and the actual product sales volume remained declining, basically reaching the expected goal of the IT enterprise, reducing enterprise operating costs to a certain extent, extending the life cycle of the enterprise, and increasing the economic benefits of the enterprise, to maintain the healthy and sustainable development of the enterprise.

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