

## Research Article

# Analysis of Consumer Behavior Data Based on Deep Neural Network Model

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This paper divides the research modes of consumer purchase behavior characteristics into three categories: experience-driven mode, theory-driven mode, and data-driven mode. An analysis algorithm based on customer consumption behavior is proposed, and the idea of combining customer consumption behavior factors such as satisfaction and loyalty is proposed. Through comparison, it is pointed out that the data-driven model is most suitable for analyzing the characteristics of online consumers' purchasing behavior. Using the decision support of knowledge base, different service schemes for customers with different evaluation degrees are realized. In order to improve the accuracy of sample classification and maximize the output function, genetic algorithm is used to optimize the samples. A deep neural network structure algorithm is proposed to classify customer transaction data samples. In this algorithm, the sheep nodes are not fixed, but the number of hidden layers and unit nodes of the neural network are dynamically determined according to the sample training. The research excavates various kinds of valuable information such as consumer preferences and consumption structure from the huge consumption data of consumers. It is not only helpful for enterprises to analyze consumers' consumption behavior and organize production but also helpful for enterprises to realize the concept of personalization.

## 1. Introduction

At present, the consumption concept of consumers has undergone great changes [1]. Nowadays, consumers no longer pay attention to the price of goods but pay more attention to the quality of goods, after-sales service of merchants, service attitude of sales departments, etc. [2]. Traditional commodity trading methods are now being affected by online consumption. The visual communication between merchants and customers has been interrupted. Customers can place orders without going to the store to compare goods, which greatly improves efficiency [3]. Western research on consumer behavior originated from "consumer analysis" [4]. However, most consumer behavior patterns are driven by experience or theory [5]. With the intensification of market competition, enterprises must focus on customer needs, strive to collect consumer information, mine customer consumption characteristics, formulate marketing strategies that meet market conditions, and improve market competitiveness [6].

It is mentioned in the science of consumer behavior that the consumption behavior of consumers has great volatility, and it is difficult to quantify with mathematical or logical rules [7]. The idea of data mining is to find hidden rules from irregularities [8]. This paper analyzes the consumption characteristics of users and finds out the consumption preferences of users in different places by tracking different consumption records. Because the offline stores cannot effectively conduct data statistics on consumers, they cannot well grasp the challenges they face [9]. At present, China's e-commerce is booming. With the implementation of the home broadband project, more and more consumers have access to the Internet and surf the Internet through the home network, which will increase the possibility of consumers' online shopping. In order to succeed in online shopping, consumers' support and participation are urgently needed. If you want to stimulate or motivate consumers to do online shopping, it will not work if you cannot clearly understand consumers' behavior [10].

Based on the idea of data mining, this paper considers two kinds of problems of consumers: consumption factors and consumption research objects.

## 2. Related Work

Shang et al. pointed out that online shopping itself has the advantages of convenience and quickness, which is favored by more and more consumers [11]. According to Boston Consulting Group's prediction, the current average level of 1,000 dollars in the United States exceeds [12]. Ke et al. pointed out that with the rapid development of the online shopping market, online shopping is no longer an optional supplement for consumers in addition to traditional shopping but has become an important shopping way for many consumers. The attention to online shopping behavior, especially the convenience provided by the Internet, and the variety of commodity types make a special purchase behavior—impulsive buying behavior likely to occur [13]. Zheng et al. pointed out that people would find ways [14]. Based on online word of mouth, Hong JL and others have a large number [15]. The fundamental reason for the uneven views of some consumers lies in the problem of consumers' decision-making. Different consumers have different consumption views, which leads to the difficulty of common consumption [16]. From this, it can be seen that online marketing is a way of direct targeting to convey specific marketing information to specific individuals, including one-to-one marketing through rich database content analysis and identification of online consumers' behavior patterns or their preferences [17]. Therefore, the network is an ideal medium with great potential for manufacturers to contact with potential customers and consumers and conduct relationship marketing. Based on the traditional model, Olan et al. and Sayeed et al.'s analysis and prediction of consumer behavior is only in the qualitative stage. Now, big data analysis can be used to track consumer shopping behavior and improve consumers' awareness of shopping platforms. loyalty to gain greater market share [18, 19].

Nik PG based on the key link, from the perspective of consumer behavior process problems [20]. This paper discusses the marketing strategy and marketing strategy combination that enterprises should adopt to carry out online marketing, aiming to provide guidance for enterprises to carry out online marketing.

## 3. Methodology

**3.1. Customer Behavior Analysis Model.** The consumption pattern evolves with the changes of productivity and production relations. The main reasons for the change of natural consumption patterns are the ecological environment, the degree of scientific development, and the situation of population and resources. The main reason for the change of consumption social model is the change of social needs based on consumption needs. In recent years, with the changes in the ecological environment, the degree of scientific development, and the situation of population and resources, China's consumption pattern has undergone unprecedented changes. This change reflects the change of social demand

dominated by consumption needs and the subtle influence of consumers on consumption patterns. The consumption pattern has undergone a revolutionary change. Now, customers do not have to go to the mall, just go to the homepage of the mall, and click the "Buy" button to buy the goods they want. The credit of shopping malls, even the credit problems of customers, the service attitude and quality of shopping malls, and so on, also appear. Building the model is done. Different algorithms are used for model training, and a unified evaluation standard is used to evaluate the effectiveness of the model, and then, the optimal model is selected to predict the product recommendation in the product subset to improve the accuracy of the recommendation. BP neural network has strong learning ability and nonlinear parallel processing and reasoning ability. A consumption behavior research model based on BP neural network. Before exploring the traditional prediction model, this section first designs the basic process of building the prediction model, which is applicable to the establishment of various models discussed in the paper, as shown in Figure 1.

Whether the customer is satisfied with the product includes three indicators: these data should be obtained through customer feedback information, that is, through questionnaire survey. Finally, the customer satisfaction is obtained by weighted summation:

$$M = \sum_{i=1}^m DC_i * ci, \quad i = (1, 2, \dots, m). \quad (1)$$

Among them,  $DC_i$  represents the weight of the  $i$ -th survey item, and  $ci$  represents the weight that the customer thinks the  $i$ -th survey item occupies in all survey items. Whether consumers are loyal to a product mainly includes the following indicators: the number of visits per week, the retention rate, and the number of purchases, where retention rate = number of visits/average number of visits per week. Based on the above, consumer loyalty can be expressed as

$$L = \sum_{i=1}^m ZC_i * ci | i = (1, 2, \dots, m). \quad (2)$$

According to the above definition, combined with the training and verification capabilities of the BP neural network, the customer behavior analysis model is obtained:

$$y_b^k = f \left( \sum_{i=0}^{N_1} \omega_{\vartheta} * x_i^k + \theta_k \right). \quad (3)$$

Among them,  $\omega_{\vartheta}$  is the weight corresponding to the analysis factor (satisfaction, loyalty, etc.)  $v_h^k$  in the output node  $x_h^k$ .

Typically, consumers are different in the likelihood of transacting with a business in a year versus a month. Then, the retention of the consumer is

$$B = \frac{N}{C * R}. \quad (4)$$

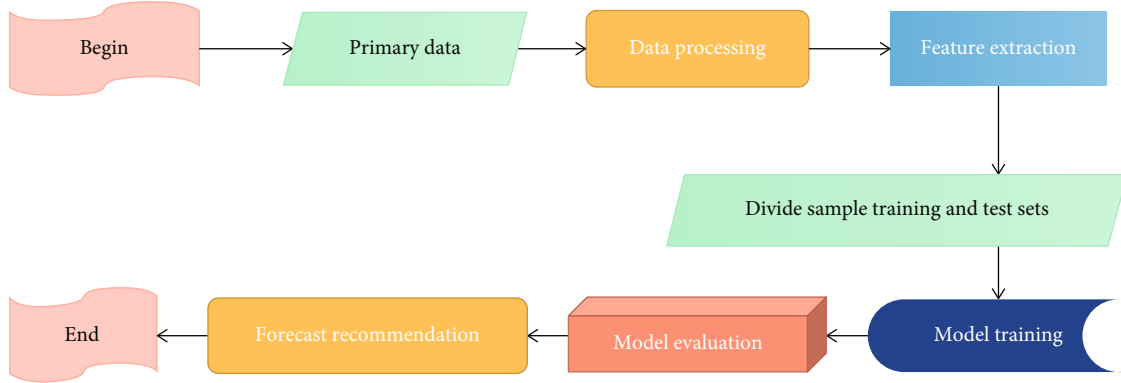


FIGURE 1: Flow chart of building prediction model.

According to the above definition, combined with the training and verification ability of BP neural network, the customer behavior analysis model is obtained: the output of the output layer node is

$$\begin{aligned}
 Z &= f \left( \sum_{i=0}^{N_2} \omega_{hj} * y_h^k + \gamma_j \right) \\
 &= f \left( \sum_{i=0}^{N_2} W_{hj} * F \left( \sum_{i=0}^{N_1} \bar{\omega}_{ih} * x^k + \theta_k \right) + \gamma_j \right), \quad (5)
 \end{aligned}$$

where  $\omega_{hj}$  is the weight of the output node  $Z$  corresponding to the hidden layer output node  $y_h^k$ .  $Z$  is the general evaluation of consumers. It reflects the error size function between the expected output and the calculated output of the network. The following is the output error of the  $i$ -th cell node:  $E_k = 1/2 \sum_{k=1}^n (y_{ik} - T_{ik})^2$ . The total error is

$$E = \frac{1}{2N} \sum_{k=1}^N E_k. \quad (6)$$

$y_{ik}$  is the actual output value of the  $I$  node. For the neural network model, the hidden layer features are

$$h^{(1)} = \sigma \left( w^{(1)} h^{(i-1)} + b^{(1)} \right). \quad (7)$$

After training, the predicted value is close to the actual value, and the difference between them is defined as the loss function. Assuming that the training set is  $\{(X^{(1)}, y^{(i)})\}_{i=1}^N$ ,  $n$  is the sample size, the overall loss function of the neural network model is

$$J(x, b) = \left[ \frac{1}{N} \sum_{i=1}^N \|h_{wb}(x_i) - y(i)\|^2 \right] + \frac{\lambda}{2} \sum_t \sum_i \sum_j (w_{ij}^i)^2. \quad (8)$$

The first term is the mean square, which aims to control the error between the model output and the target, and the second term is the weight decay term, which prevents the model from overfitting through the weight decay magnitude.

Businesses get customer data from multiple channels, including consumption records, questionnaires, and feedback information, which contain a lot of important data, but also mixed with a lot of miscellaneous data that are not helpful for analysis. Therefore, it is necessary to use BP network model to analyze the information screening data after integration and cleaning. The whole process is shown in Figure 2.

Combined with the above figure, the whole process can be summarized into the following steps: (1) obtaining customer information, (2) integrate data from different sources through data migration and other ways and store them in another data warehouse, (3) using customer behavior analysis model for data analysis, and (4) after the analysis result is obtained, according to the degree of consumers and the knowledge base, the consumption strategy for this customer is obtained.

**3.2. Consumer Behavior Data Processing Architecture.** Recommend products to consumers with high accuracy and speed, focusing on designing effective analysis and prediction models. Before building a model, data processing and feature engineering are the basis for constructing a predictive model. Data processing refers to the analysis, calculation, sorting, and other processing of raw data. Feature engineering refers to the extraction of data features that are most suitable for the objectives of this research project on the basis of data processing. Consumer Internet behavior data is usually stored in the form of logs, and the logs related to consumer behavior analysis include consumer behavior logs, behavior event logs, and commodity category logs. Firstly, the interaction log is extracted from the user commodity interaction system to prepare the data related to the analysis and prediction of consumer behavior. Secondly, data preprocessing includes data cleaning, filling in missing values and removing outliers, removing duplicate data, ensuring the uniqueness of data, and dividing data sets according to time. The missing values of the paper are filled by the average. Thirdly, based on the overall description of the sample data in the form of charts and other forms, random sampling treatment is made according to the characteristics of unbalanced distribution of consumer behavior categories. Based on the original data, the data training set and test set are divided, shallow features are extracted

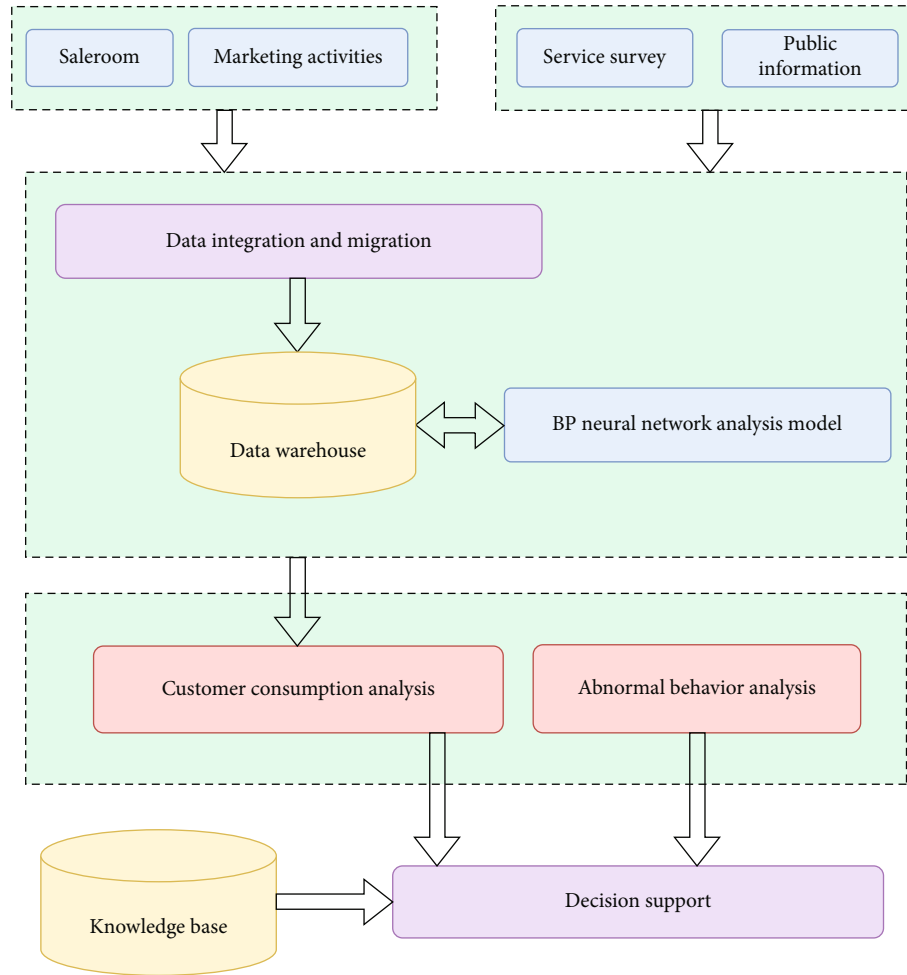


FIGURE 2: Customer behavior analysis model application model.

manually, the feature dimension is expanded, and then, the features are processed by methods such as normalization; finally, the prediction model is constructed and evaluated. In the construction of deep learning models, this paper makes a comparative study of prediction models. And identify the advantages and disadvantages of the model, so as to achieve recommendation prediction.

The flow chart of deep learning model construction is shown in Figure 3.

According to the characteristics of unbalanced category data, R DNN model and KM DNN model are introduced. Different models adopt early stop strategy. When the training times increase but the value of loss function no longer decreases, the training is stopped. Finally, the same AUC and  $F$  values are used as the method of effect evaluation. Data clustering is a Mini Batch KMeans clustering algorithm in sklearn-cluster module based on Python. Random sampling is based on Python's random module, and random generates random numbers to randomly extract negative samples from data. DNN is designed by using the deep learning library Keras based on Theano. Keras is modular and easy to expand, and it is guided by simple Chinese documents. It is easy for beginners of deep learning to get started, and it is also the foundation for researchers in the

field of deep learning to conduct in-depth research and excavation. In the user-product interaction log, there is very little data on consumer purchase behavior (marked as 1), and most of the data is the data that consumers have not purchased (marked as 0). There is a phenomenon of extreme imbalance between data categories. In classification problems, category imbalance often occurs, which is mainly reflected in the fact that there is less data in a certain category or several categories of samples. In real life, a small number of category samples are often the focus that deserves more attention. For example, the problem of advertising clicks. Users click on a small number of advertisements. Most users just browse without clicking. Focusing on advertisements with high click counts can help websites accurately put advertisements. The traditional classification model is built on the basis that the category samples are nearly balanced, and the classification model is more inclined. Therefore, when the categories are extremely unbalanced, the model may treat the data with less category samples as noise. Samples with few categories of data contain more important information. For example, in the identification of credit card fraud, if the fraud information is mistaken for normal information, the user will suffer heavy losses; in the medical diagnosis and treatment, if the patient is mistaken for a healthy

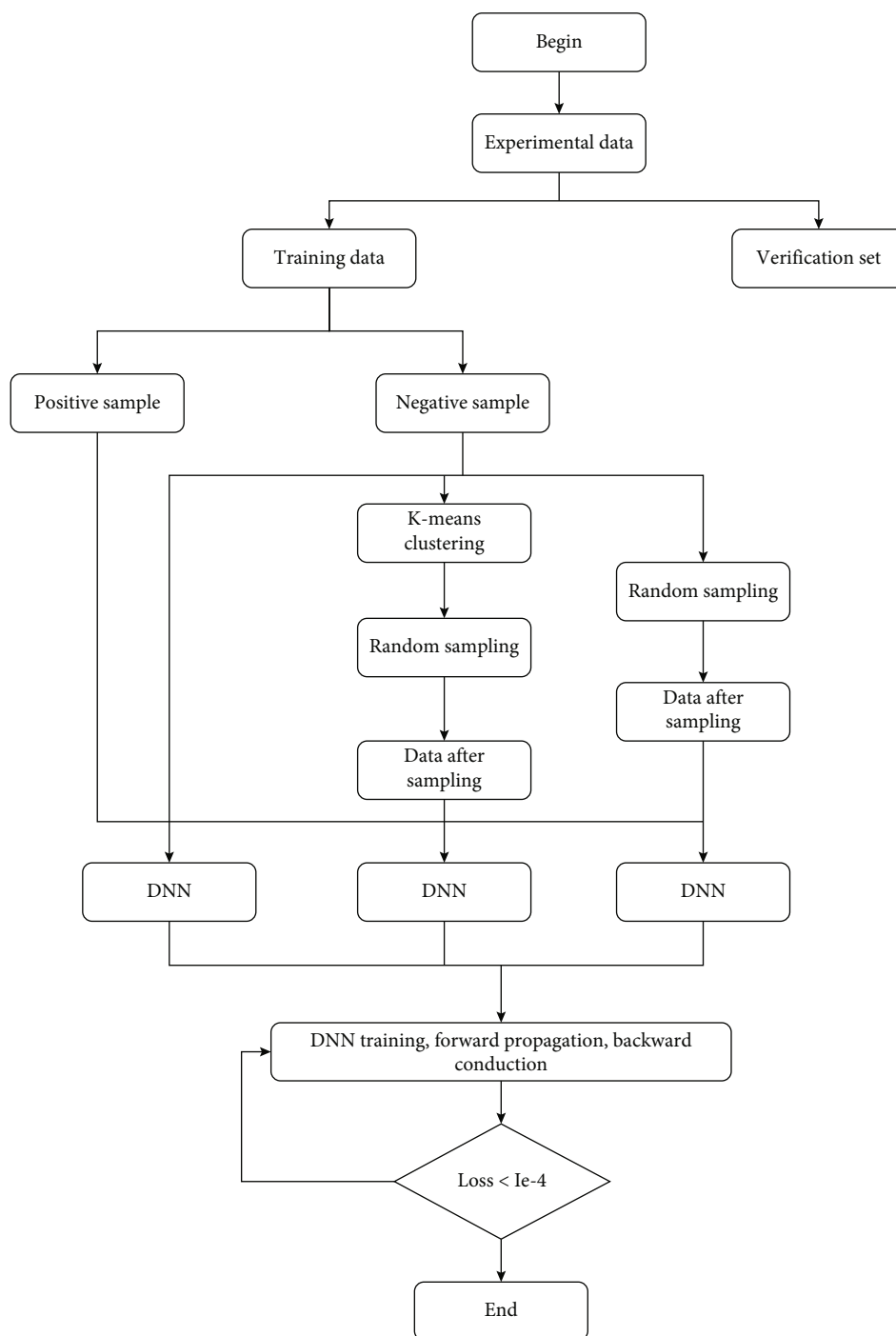


FIGURE 3: Flow chart of deep learning model construction.

person, delaying the diagnosis and treatment time may lead to serious losses and lead to aggravation or even life-threatening. Therefore, solving the problem of data class imbalance is our focus.

#### 4. Result Analysis and Discussion

This paper selects a large retail enterprise as the experimental object, which has two ways of sales department and online sales, and has a complete examination paper investi-

gation mechanism. This paper selects its customers' consumption records and examination papers as sample data for analysis. It includes customers' personal information and historical consumption records, which has two ways: sales department and online sales, and has a complete test paper investigation mechanism. In this paper, the consumption records and examination papers of 50 customers are selected as sample data for analysis. This includes the customer's personal information and 10-month consumption records. Consumer data that is not of numerical type should

TABLE 1: Weights between the input layer unit node and the hidden layer unit node.

Hidden layer	Input layer									
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
H1	-4.1446	6.14784	-0.2854	5.3598	0.5466	-2.7655	3.454	-1.5866	-3.594	-3.4589896
H2	-0.5566	-4.56899	5.5956	3.5966	4.7486	2.45555	1.7578	-1.56456	-2.4988	2.49854
H3	-3.4846	0.498452	3.54152	-0.355	3.4884	3.4885	0.556	0.5456	4.15416	-1.98874
H4	3.4984	1.18545	-1.54485	-2.5845	0.54984	-3.4555	-0.569	2.9684	2.1685	-1.85858
H5	2.8451	-1.84556	-2.54865	-3.4554	-2.478	6.4552	-1.5866	-5.4854	-0.485556	1.9845

TABLE 2: Weights between hidden layer unit nodes and output layer unit nodes.

Output node	Input layer				
	H1	H2	H3	H4	H5
Y1	-9.4561	9.456156	-1.455696	-0.949856	1.94856
Y2	9.45664	-9.41568	0.4884523	1.258956	-1.55656

be converted into numerical type by defining data, that is, weight allocation. Lasagna used in this paper is based on Theano library, and Keras can use either TensorFlow or Theano. These libraries provide more flexible interfaces, which can be used to build neural networks and track the rapid development of deep learning research. All popular deep learning libraries also allow the use of high-performance graphics processing units (GPUs). For example, the conversion of consumer occupation  $\rightarrow$  weight: {laid-off or unemployed  $\rightarrow$ 0.3; General staff  $\rightarrow$ 0.5; Director  $\rightarrow$ 0.6; Department Manager  $\rightarrow$ 0.8 and so on}. According to the algorithm of the above dynamic neural network, the neural network can construct nine different network structures:  $I = 10, J1 = 4, k = 2$ ;  $I = 10, J1 = 5, k = 2$ ;  $I = 10, J1 = 6, k = 2$ ;  $I = 10, J1 = 12 = 4, k = 2$ ;  $I = 10, J1 = 12 = 5, k = 2$ ;  $I = 10, J1 = 12 = 6, k = 2$ ;  $I = 10, J1 = 12 = 13 = 4, k = 2$ ;  $I = 10, J1 = 12 = 13 = 5, k = 2$ ; and  $I = 10, J1 = 12 = 13 = 6, k = 2$ . The iterative termination conditions of the algorithm are as follows: the correct classification ratio of training samples is 0.05, and the learning rate is 0.53. After 21,000 iterations, the algorithm satisfies the iterative termination condition. The neural network structure is  $I = 10, J1 = 5$ , and  $k = 2$ . Tables 1 and 2 are the input layer unit node to the hidden layer unit node and the hidden layer unit, respectively.

In order to select the optimal individual  $X_i$ , let the population size be 10, the probability. According to the fitness, excellent chromosomes are retained. Classify and store purchased computers and non purchased computers according to the output value of the vector. When the output corresponding to the chromosome is to the salt element Y1 or only reaches the maximum function value 1, the information contained in the chromosome is the customer purchase behavior rule that should be extracted. Implicit nodes are the consumption factors such as satisfaction and loyalty. After processing and calculating the data in the above table, the trend chart of customer evaluation index is obtained, as shown in Figure 4.

The algorithm of dynamic neural network is proposed. According to the training results of neural network, the dynamic network structure is constructed. At the same time, this paper uses genetic algorithm to optimize the sample input disk of the neural network, looking for excellent individuals to make the objective function  $\eta$ , achieve the maximum value, then realize the classification of customer transaction sample data, and extract the behavior rules that represent the characteristics of customer consumption. In the data of computer samples purchased by customers given in this paper, the correct classification ratio of training samples is obtained. By synthesizing the weights, iteration times, and extraction rules of nodes in each layer of neural network, it can be seen that the algorithm proposed in this paper has the characteristics of small computation and high accuracy.

The results of the second statistical survey on the development of my country's Internet show that at this stage, the number of Internet users and the number of Internet computers in China have reached 137 million, respectively. The rapid growth of the total number of Chinese netizens has been noticed by the world, but the 137 million netizens only account for 10.5% of China's total population of 1.31 billion, an increase compared to 8.5% in the same period last year. This shows that although the total number of netizens in China is large and growing rapidly, the popularity of the Internet is still very low at present, but the future development space is relatively large, as shown in Figure 5.

Besides neural network can be used for sample data classification, decision tree is also a common method for data classification. ID3 is an algorithm that selects attributes as the split nodes of decision tree based on information gain. However, this algorithm is only effective relatively, resulting in lower accuracy. The results of this survey show that among netizens, those aged 31-35 account for 10.4% and those over 35 and those aged 36-40 account for a relatively low proportion. Netizens aged 35 and below accounted for 82.5%, and netizens over the age of 35 accounted for 17.5%. The age structure of netizens was still younger. From the perspective of the penetration rate, the penetration rate of netizens between the ages of 18 and 24 is the highest, reaching 38.8%, which is 10.2 percentage points higher than that of the previous year. The penetration rate of Internet users between the ages of 25 and 30 ranks second with 25.0% as shown in Figure 6.

Second, the educational background of Internet users can be seen from the educational level distribution map of Internet users. Figure 7 shows that Internet customers

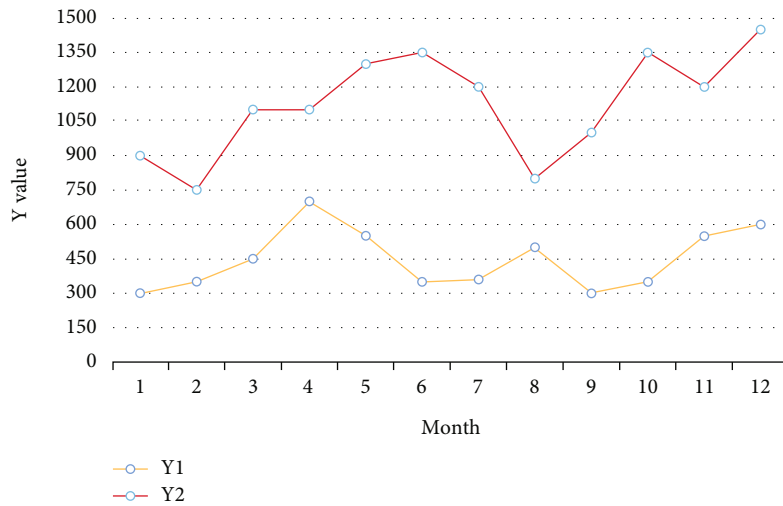


FIGURE 4: Change trend diagram of evaluation index Y.

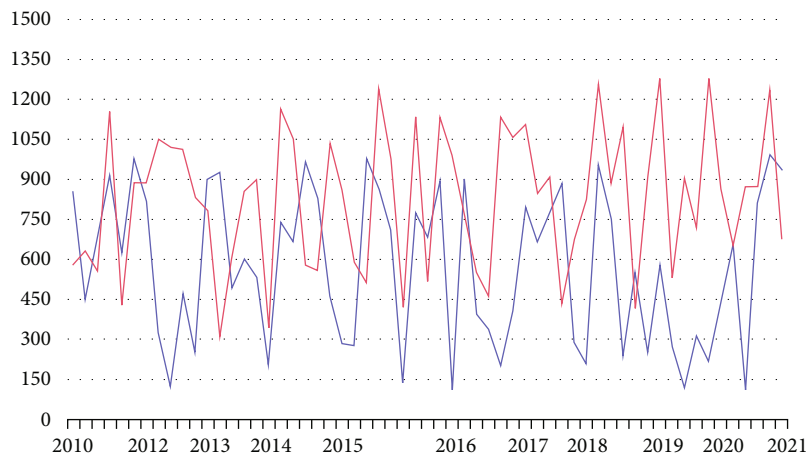


FIGURE 5: The total number of netizens in previous surveys.

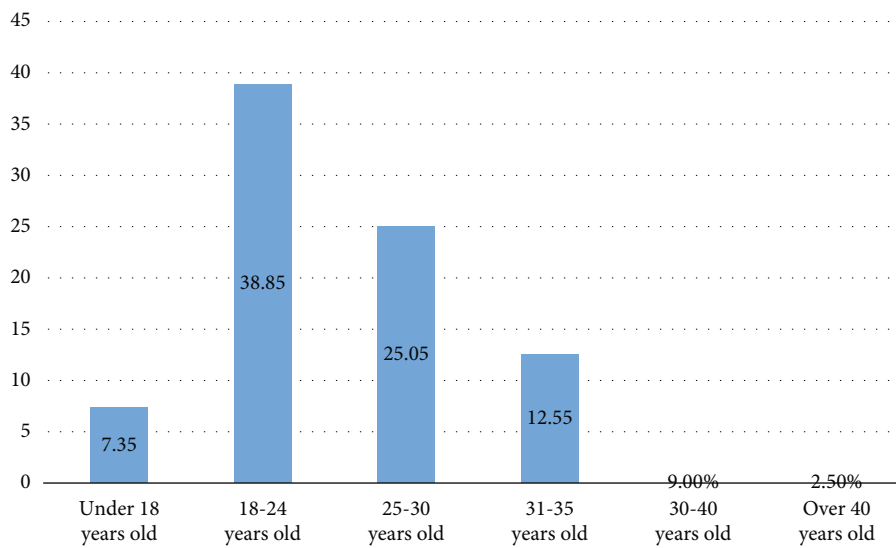


FIGURE 6: Internet users in different age groups.

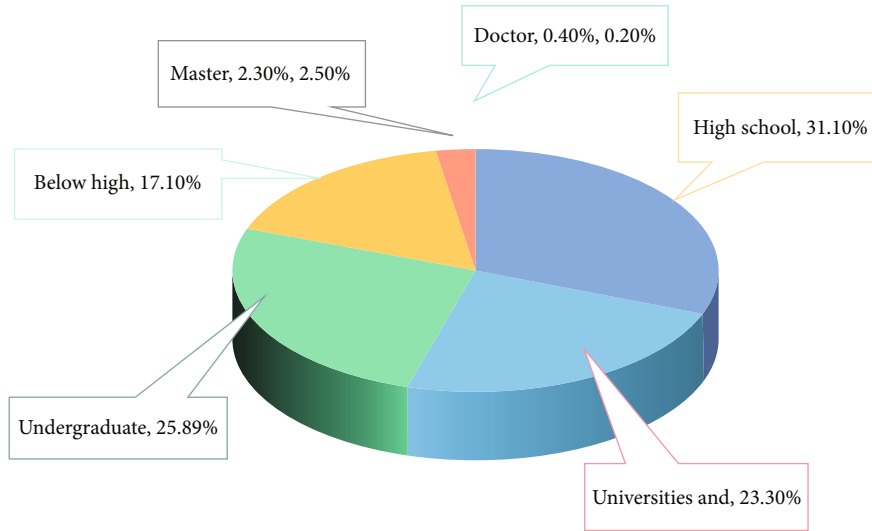


FIGURE 7: Distribution of education level of Internet users.

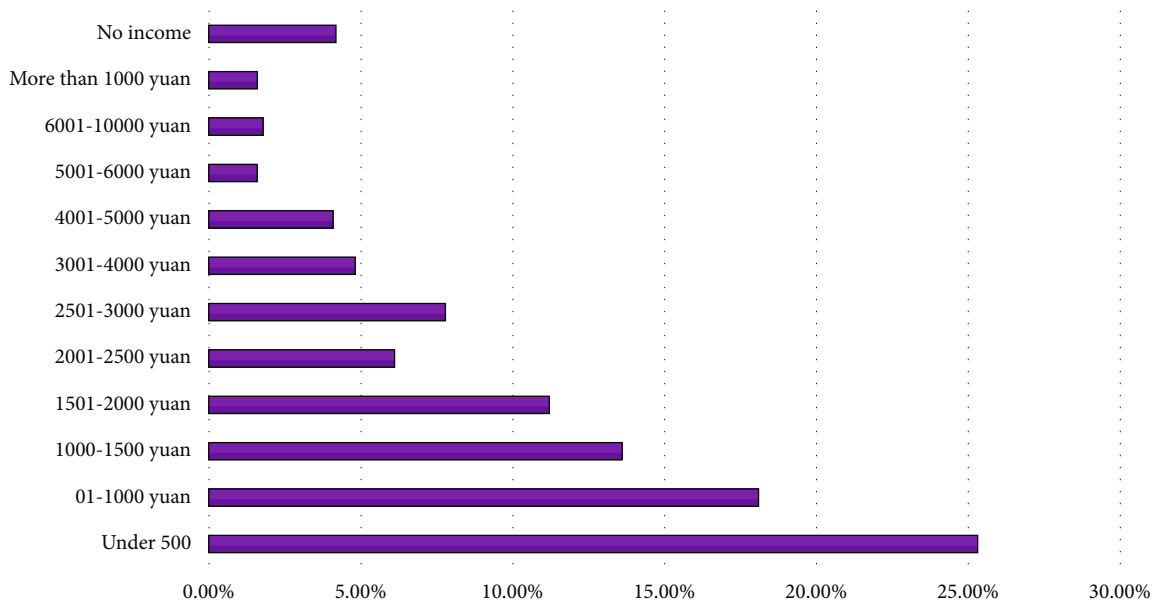


FIGURE 8: Monthly income distribution of Internet users.

generally have higher educational background. Among them, 17.1% have a high school education or below, 31.1% have a high school education, 23.3% have a college education, 25.8% have a bachelor’s degree, and 2.7% have a graduate degree. This shows that the use of the network is related to educational background. With the improvement of educational background, the use of the network is also improving, as shown in Figure 7.

Third, the monthly income of Internet users in this survey shows that the proportion of family Internet users whose monthly income is less than 500 yuan (including no income) is the highest, reaching 29.5%, followed by Internet users whose monthly income is 501~1000 yuan and 1001~2000

yuan (18.1% and 13.6%, respectively), 11.2% of Internet users whose monthly income is 1501~2000 yuan, and the proportion of Internet users whose monthly income is more than 2000 yuan is 27.6%. Low-income Internet users still occupy the majority, as shown in Figure 8.

The whole purchasing process of consumers is related to the products, prices, channels, promotion, and credit of enterprises, and any one of them will make the potential customers decide whether to buy or not. Therefore, it is necessary to closely link the purchasing process of consumers with the marketing strategy of network enterprises, so as to promote the occurrence of potential consumers’ purchasing behavior. Starting from the characteristics of online



consumers, this paper analyzes the purchase decision-making process of online consumers. Get the main factors that affect the purchase behavior of online consumers. Then, according to the research results, formulate effective marketing countermeasures for online enterprises. Reduce the blindness of enterprise network marketing and improve the possibility of success of online enterprises. In contrast, the algorithm proposed in this paper is suitable for the data set with large sample size, less affected by noise, and more suitable for mining the purchase information of customers with large sample size and extracting behavior rules. The monthly (or quarterly) consumption analysis of consumers can not only obtain the consumption level and ability of consumers but also understand the changes of customers in time. For example, if there is a downward trend in the Z value of consumers, you can find out which degree has changed and then take measures; for consumers with high potential, once the consumption level is found to increase, you can provide profitable services and so on.

## 5. Conclusions

This paper discusses the analysis and prediction of consumer behavior and explores the prediction of commodity recommendation based on consumer behavior. In order to improve the classification accuracy, genetic algorithm is used to optimize the samples, and customer purchase behavior rules are extracted by mining case data. Analyze the behavior characteristics of consumers, accurately identify and capture real online consumers (especially 20% VIP consumers), and carry out targeted online marketing activities according to the purchase behavior characteristics of these consumers. The research has far-reaching significance for online advertising and accurate recommendation, and its results also reflect consumers' consumption habits and consumption behavior rules to a certain extent. However, due to the small number of case samples, larger samples should be used to further verify the effectiveness of the algorithm in future research.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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