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Retraction

Retracted: Research on Intelligent Recommendation Model of E-Commerce Commodity Based on Feature Selection and Deep Belief Network

Security and Communication Networks

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Security and Communication Networks has retracted the article titled "Research on Intelligent Recommendation Model of E-Commerce Commodity Based on Feature Selection and Deep Belief Network" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

The authors do not agree to the retraction.

References

[1] Y. Li, G. Wu, and C. Liu, "Research on Intelligent Recommendation Model of E-Commerce Commodity Based on Feature Selection and Deep Belief Network," *Security and Communication Networks*, vol. 2022, Article ID 6469217, 11 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

Research on Intelligent Recommendation Model of E-Commerce Commodity Based on Feature Selection and Deep Belief Network

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Due to the complexity and uncertainty of customer demand behavior, it was often difficult to obtain satisfactory recommendation results by using the existing online commodity recommendation systems. Therefore, a network commodity intelligent recommendation model based on feature selection and deep belief network was proposed. Based on the basic structure and function of the existing recommendation systems, this paper expounded the interaction process between customers, e-commerce platforms, enterprises, and the recommendation system. By analyzing the internal relationship between customer demand and commodity recommendation, the relationship model between customer demand and commodity recommendation was established. After analyzing the characteristics of customers' demand for goods, a data mining method was used to classify the characteristics of customers' demand behavior, and a feature selection method based on deep belief network (DBN) was proposed to obtain the main information conducive to commodity recommendation. Finally, an e-commerce commodity recommendation algorithm based on feature selection and deep belief network was proposed. The experimental results showed that the network commodity recommendation model proposed in this paper can not only provide customers with satisfactory recommendation results but also has better performance than other traditional recommendation models. The recommendation model proposed in this paper can support different e-commerce website recommendation systems.

1. Introduction

With the improvement of IT technology and network communication level, the e-commerce industry has developed rapidly. The commodity recommendation system provided on the e-commerce website not only provides convenience for customers but also provides strong support for merchants to promote product sales and improve enterprise benefits. A network commodity recommendation system mainly uses customer demand behavior data to establish the corresponding relationship between customers and commodities to predict the potential demand information of customers for commodities [1]. The recommendation system can provide customers with effective recommendation services for online goods. The service provided by the recommendation system can not only stabilize the existing customer market but also meet customers' more needs for goods. Due to the huge network data processing tasks and many data types involved in e-commerce websites, the accuracy, timeliness, and effectiveness of the recommendation system to provide customers with commodity promotion services have attracted the attention of researchers at home and abroad in recent years.

The commodity recommendation system provided by e-commerce websites generally uses customers' previous demand or transaction records for commodities to recommend as many commodities as possible for customers' reference or purchase [2]. Using the recommendation system and network platform, e-commerce enterprises can fully mine the commodity information to meet the needs of customers and provide customers with the commodities they may need to choose and buy at will, which can not only meet the needs of customers but also make profits for businesses. The recommendation system not only provides customers with the goods they need but also provides customers with valuable commodity information [3]. The recommendation system can effectively analyze the customer's historical demand behavior, construct the customer's demand preference model for goods, and use the model to provide customers with accurate commodity recommendation services. Therefore, the network commodity recommendation system can not only meet the needs of customers for commodities but also provide fast commodity sales for merchants to realize the rapid development of e-commerce industry.

From the demand behavior characteristics of customers for online goods, it is very important to use data mining technology to classify a large amount of data and obtain valuable relevant information. In recent years, scholars at home and abroad have proposed different recommendation models or algorithms. These models mainly filter out the data that can support customers' demand behavior from a large number of sparse data information, so as to meet customers' personalized needs for goods [4]. The network commodity recommendation system mainly extracts effective features from the customer's commodity demand behavior characteristics and associates the customer with the commodity information, which not only saves the time for the customer to search the required commodities but also meets the customer's actual demand for commodities. The main function of the recommendation system is to provide customers with feasible demand information, and the recommendation algorithm determines the performance of the recommendation system to a great extent. A good recommendation algorithm can fully meet the needs and interests of different customers and improve the accuracy of the recommendation system. Through the network platform, the recommendation model can not only promote the required commodity information for customers but also obtain the demand intention of different customers for commodities. It is of great significance for stabilizing the customer market and realizing the win-win situation between customers and merchants.

2. Related Works

The function of most recommendation systems is to use some recommendation algorithms to establish the relationship between customer demand objects and recommendation objects. Therefore, an effective recommendation algorithm is an important part of the recommendation system. The idea of recommendation algorithm is to analyze and predict the collection of goods that customers may need to buy according to the collected customer demand behavior information. Common recommendation algorithms mainly include the following four kinds: content-based recommendation algorithm (CRA), collaborative filtering recommendation algorithm (CFRA), association rule-based recommendation algorithm (ARRA), and hybrid recommendation algorithm (HRA) [5–7]. Among them, the recommendation algorithm based on collaborative filtering is one of the most concerned algorithms in recent years. The algorithm can be divided into user-based collaborative filtering algorithm and model-based collaborative filtering algorithm.

In addition to using the commodity recommendation algorithm based on collaboration and content filtering, some scholars have proposed a knowledge-based recommendation algorithm, which can be applied to the recommendation system to effectively analyze customers' demand preferences and purchase behavior. The knowledge-based recommendation algorithm can recommend goods that meet customers' needs according to customers' demand behavior, so customers can really experience the goods and services they are interested in. In addition, some scholars have proposed a utility-based recommendation algorithm. Compared with the traditional content-based recommendation method, the utility-based recommendation algorithm is better than the traditional recommendation algorithm in prediction accuracy, time cost, and customer satisfaction [7, 8]. From the practical application, the performance of utility-based recommendation algorithm usually depends on the context-related information of recommended commodity.

With the continuous development of e-commerce industry, especially the increasing demand of customers and the amount of commodity information, it is necessary to extract the potential information hidden in big data through relevant methods and use relevant recommendation systems to promote the commodities they need for customers [9]. The traditional recommendation algorithm usually cannot obtain the required feature data from a large amount of information, which makes the recommendation results difficult to meet the needs of customers. In addition, the characteristics of many customer demand behaviors are analyzed, and data mining and analysis methods are used to provide customers with accurate product promotion services. In recent years, due to the great progress of data mining technology and deep learning methods, some scholars began to use deep learning methods to study recommendation systems [10]. Many customer demand behavior characteristics are analyzed, data mining and analysis methods are used to screen the characteristics of customer demand for goods, and then an effective recommendation model was used to provide customers with accurate commodity promotion services.

According to the analysis of the recommendation system provided on the existing e-commerce platform, the relevant recommendation models have their own advantages and disadvantages in realizing different customer needs. Because it is difficult to produce good recommendation ability and effect by using a single recommendation algorithm, how to generate recommendation results according to different types of data processing needs and integrate relevant algorithms in order to achieve the best recommendation effect is one of the problems widely concerned by scholars at home and abroad in the construction of recommendation systems. Aiming at the problem of online commodity recommendation, due to the complex change of customers' demand behavior for online commodities and the heavy workload of data processing, this paper proposes an e-commerce commodity recommendation algorithm based on feature selection and deep belief network.

3. Network Commodity Recommendation Theory

3.1. Common Structure of Recommendation System. With the continuous development of e-commerce industry, the use of online commodity recommendation systems has become one of the main tools for communication between merchants and consumers. The design of recommendation system is mainly based on user demand behavior information and goods and services provided by e-commerce enterprises. According to many customers online demand behavior logs, designers can use data mining and analysis methods to obtain customers' demand preferences for different goods and recommend the required goods for different users. Through the recommendation system service, users can improve the click-through rate of online goods to complete commodity transactions or services. It can not only let customers experience the goods they need to buy in advance but also enable businesses to stabilize potential consumer groups and expand the commodity demand market. In order to meet customers' demand for goods, the recommendation system can not only save customers' purchase time to a great extent but also improve the purchase quality and efficiency of goods. Figure 1 shows the relationship between customer demand and e-commerce commodity information established through the recommendation system.

E-commerce companies provide online product recommendation services to customers, usually using media attention to products and using data mining methods to analyze demand behaviors based on customers' past consumption records, and then make suggestions to customers' potential consumption needs. Online commodity recommendation systems mainly customize customers' demand behavior and provide customers with real-time online commodity recommendation services. The main task of online commodity recommendation systems is to recommend appropriate commodities to customers by using different recommendation models according to the needs of users. The structure of online commodity recommendation systems is usually composed of information collection, data preprocessing and analysis, recommendation model, commodity selection, and recommendation. Figure 2 shows the interaction between customers, e-commerce platforms, enterprises, and the recommendation system.

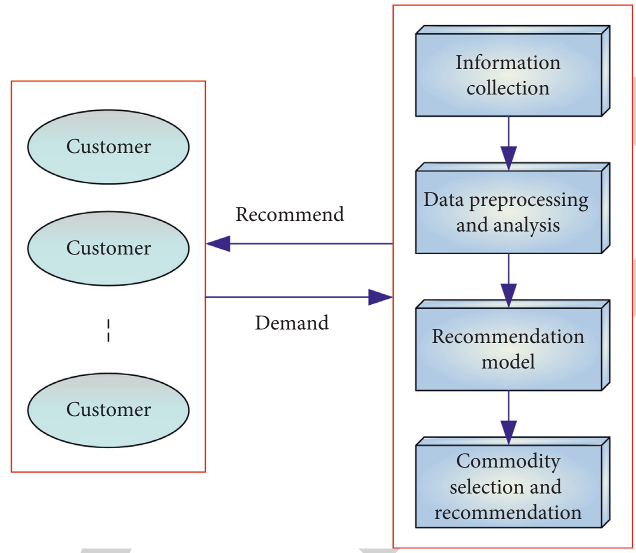

Figure 1: Relationship between customer demand and commodity recommendation.

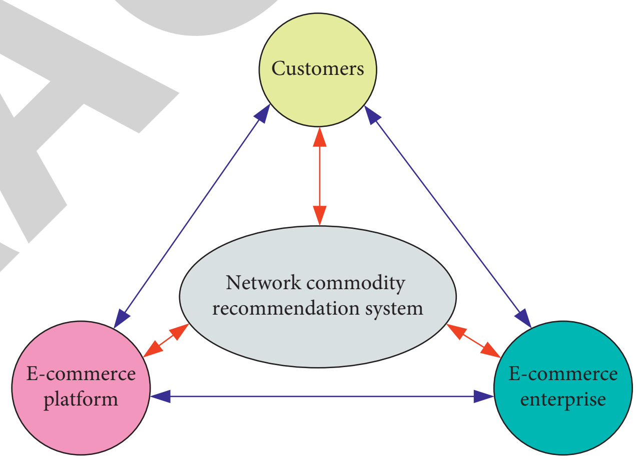

Figure 2: The interaction between customers, e-commerce platforms, enterprises, and the recommendation system.

3.2. Main Functions of Recommendation System. Through the online recommendation system, various networks or mobile platforms can be used to record the merchant website information visited by customers and customers' attention to goods in real time. Based on the data preprocessing of the recommendation system, combined with the user's consumption demand behavior and its associated commodity information warehouse, the original customer demand behavior data set can be constructed. At the same time, the website information or browsing product information visited by the customer is mapped to the recommended candidate product sequence and fed back to the customer as recommendation information [11]. According to the different composition of the online recommendation function, the online recommendation function module can be further divided into customer front-end, background server, backup recommended product collection, and interaction between customers and merchants. The schematic diagram of the personalized online product recommendation process is shown in Figure 3.

Based on the user consumption demand data set obtained in the early stage, the online commodity recommendation system classifies all kinds of commodities by using the method of data mining and forecasts and estimates the user's demand behavior by establishing the customer demand model to realize the online recommendation of different commodities. Firstly, the relevant records of customers and data information such as commodity demand behavior are extracted from the data warehouse, and the irrelevant data are screened and deleted through operations

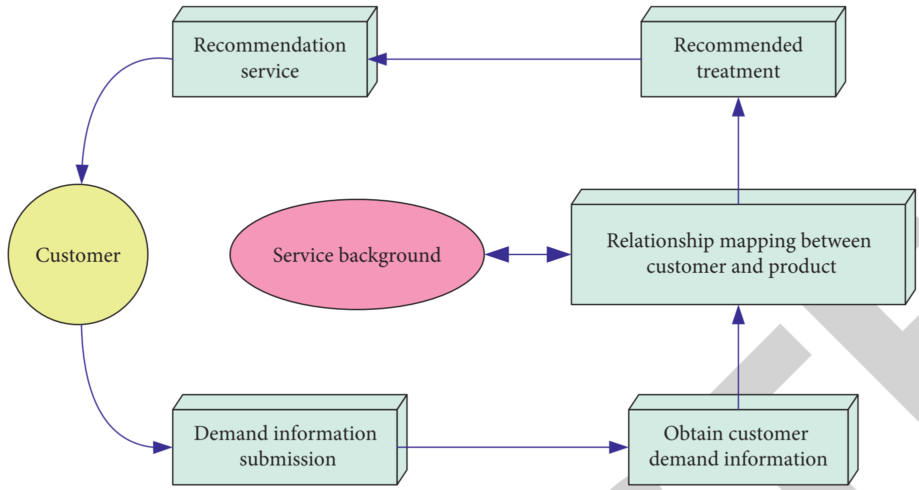

Figure 3: Schematic diagram of personalized online product recommendation process.

such as data preprocessing and feature extraction to retain the required data. Secondly, according to the characteristics of customer demand, the user's demand intention model for goods is established, and the goods required by users are added to the data warehouse. Finally, based on data analysis and in-depth learning methods, the mapping relationship of customers' demand for goods is established, and the goods they intend to buy are recommended to relevant customers.

From the above analysis of online commodity recommendation function, it is known that a typical recommendation system is mainly composed of different customer groups, various e-commerce services, and various website systems including recommendation function. Taking the online product recommendation process as an example, when consumers are willing to demand online products, they need to visit various e-commerce websites containing recommendation functions [12]. E-commerce enterprises generally provide product recommendation services for customers through different e-commerce platforms. The website recommendation system is used to analyze customers' previous demand behavior or purchase transaction records, establish the mapping relationship of customers and corresponding commodities through feature matching, and then recommend appropriate commodities to relevant customers according to customers' demand wishes. A reliable recommendation system should not only provide satisfactory products for customers to choose according to customers' demand behavior but also enable customers to trust the commodity recommendation services provided by the website system. Therefore, a good recommendation system can not only increase the operating revenue for e-commerce enterprises but also effectively meet the actual needs of customers for goods.

3.3. Relationship Model between Customer Demand and Commodity Recommendation. The acquisition of customer demand information is the premise of building a recommendation system model. The acquisition methods of customer demand information data usually adopt active and passive methods. Taking the initiative to obtain customer demand data information generally depends on the active participation of customers, and the participation process may make customers not active enough or even produce boredom and emotion for various reasons. Therefore, this proactive approach is not only easy to lose customers but also difficult to obtain the required customer demand information through big data and artificial intelligence processing methods due to the lack of data. Acquiring customer demand data information in a passive way does not require the direct participation of customers but uses data mining and analysis methods to model the demand behavior of customer history log and commodity transaction information and then put forward the corresponding recommended commodity feature information according to the customer demand behavior data. In recent years, most scholars generally use a passive way to obtain customer demand information when establishing the recommendation system model [13, 14].

In order to build a network commodity recommendation system to meet customer needs, it is necessary to establish a relationship model reflecting customer needs and commodity recommendation, as shown in Figure 4. The relationship model mainly includes customer data information collection and preprocessing, customer demand behavior analysis for goods, establishing the mapping relationship of customer demand for goods, commodity recommendation function, and other modules.

(1) *Collect and preprocess customer data information.* The customer data information to be collected usually includes the customer's purchase history log of goods and various online business activities or transaction behavior information. Based on these data information, we can effectively analyze customers' commodity demand behavior and establish the mapping relationship of customers' commodity demand. Because the collected original data are generally rough and there is lack of correlation between the data, the collected customer's original purchase information can be preprocessed by online

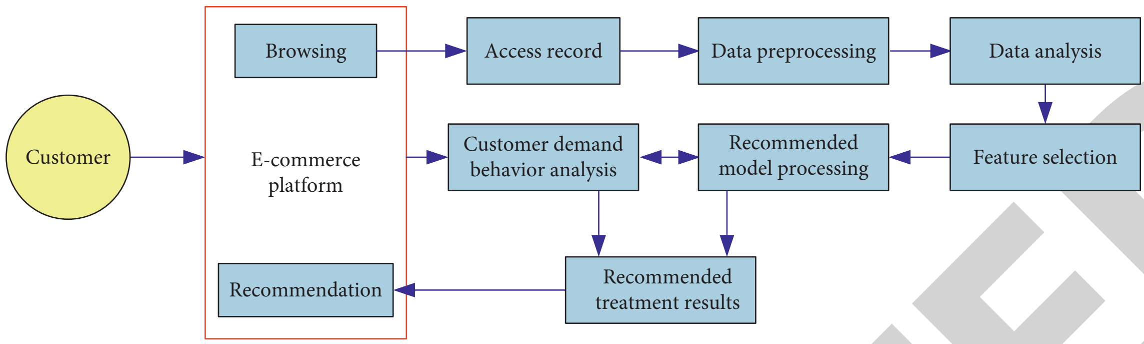

Figure 4: Relationship model reflecting customer needs and commodity recommendation.

detection of transaction records, and the data conducive to completing commodity recommendation for customers can be screened by data mining and feature extraction methods.

(2) *Analyze the customer's demand behavior for commodities*. Use the customer interaction center to obtain the customer's demand behavior data information for commodities, analyze the user's demand for commodities and purchase intention, mine the customer's demand preference for different commodities, and store the associated commodity information in the warehouse center, to provide a data basis for establishing the mapping relationship of customers' demand for commodities.

(3) *Establish the* mapping relationship of *customers' demand for goods*. Generally, by analyzing customers' demand behavior for goods, using deep learning and feature matching methods, combined with the constructed associated commodity information warehouse, customers' demand mapping relationship for different commodities can be established.

(4) *Recommend commodities*. According to the mapping relationship of customers' commodity needs, search for commodities that are greatly related to customers' needs in the related commodity information warehouse, and feedback through the customer interaction platform.

4. E-Commerce Commodity Intelligent Recommendation Model

4.1. Customer Demand Characteristics and Identification. The premise of a good online commodity recommendation system in e-commerce websites is not only to obtain the effective demand information of customers but also to analyze or judge the relevant data to provide the basis for commodity recommendation. For the data information of different objects, it is necessary to mine the potential information hidden in the data through in-depth data analysis [15]. As the recommendation system mainly provides services for customers to select and purchase goods, mastering customers' demand behavior for goods is the prerequisite for building an effective recommendation system. According to the demand behavior characteristics of customers for goods, the relevant information of users and goods can be obtained through data collection and preprocessing. This information reflects the customer's demand for different types of goods or services. Based on the analysis and preprocessing of these data, we can further understand and master customers' demand behavior and purchase intention to provide support for the establishment of an appropriate recommendation system.

Customers' demand or feedback information on goods can be collected through different channels. At present, most e-commerce enterprises mainly obtain it through customers' evaluation of purchased goods and questionnaire survey. This part of information usually reflects the satisfaction of the commodities to the customer according to the customer's objective score or evaluation on the commodities. For example, through the scoring system, customers can score and evaluate the purchase or use of goods, or additional scores can be taken to indicate customers' attitude toward the continuous use of goods. This explicit scoring method can not only obtain the preference of customer groups for goods but also grasp the satisfaction of different consumer groups with different types of goods [16]. Some e-commerce website platforms not only provide customers with scoring mechanisms but also allow customers to comment on commodity needs. No matter using commodity evaluation methods such as comment or scoring mechanism, e-commerce enterprises can timely understand the demand intention of different customers for various commodities, which will provide data support for further obtaining customers' demand behavior.

Affected by the uncertainty of customer demand and the diversification of online commodity types, some feedback information of customers on commodities cannot directly reflect customers' demand intention or satisfaction with the purchase and use of commodities; for example, the number of times customers browse or visit e-commerce websites and customers' attention to businesses or goods. Although this information does not directly reflect customers' demand or purchase intention for goods, it can express customers' various preferences for goods. This kind of information is often referred to as the indirect feedback information of customers to goods. Different from the direct feedback information, although the indirect feedback information has the problems of large amount of data information and difficult to obtain, the data obtained from the indirect feedback information will more truly reflect the customer's demand and preference for goods through data mining and deep learning [17]. From the different behavior characteristics of customers' demand for goods, we can compare the direct feedback information and indirect feedback information from customers, as shown in Table 1.

When analyzing the feedback information of customers on goods, it is usually necessary to analyze the data in combination with the contextual information of customers' demand behavior for goods to deeply understand the changes of customers' demand intention for goods. Generally, different customers have different contextual information about various commodity demand behaviors, and most of the contextual information about customers' online commodity demand behaviors includes customers' access time, place, and mood of e-commerce websites. Therefore, according to the relevant information of customers' demand behavior for online goods, data mining and deep learning methods can be used to extract the time, place, and other characteristics of customers' demand behavior for goods to obtain the information representing customers' demand preference for goods [18].

According to the analysis of customer demand feedback information on different e-commerce websites, it is known that there are certain potential laws in the change of customer demand behavior and online commodity marketing mode. For users, in addition to paying attention to commodity information on e-commerce websites, customers may also pay attention to news and other information. Therefore, in the e-commerce website recommendation system, it is generally difficult for customers to maintain high access frequency and click-through rate for a long time. For online goods, since the newly launched goods are often paid more attention by customers, the visit frequency or click volume of such goods are relatively large at the initial stage of launch, but the attention of goods also decreases with the passage of time. Therefore, when designing e-commerce commodity recommendation system, we should not only consider the changes of customers' demand behavior for commodities but also consider the changing characteristics of commodities and their attributes over time.

4.2. Feature Selection of Customer Demand Behavior Based on Deep Belief Network (DBN). When designing the online commodity recommendation model, there may be some interference data in the customer demand behavior characteristics as the input of the model, which will increase the training time of the model and reduce the efficiency of the recommendation algorithm. Therefore, selecting the characteristics of customer demand behavior is conducive to improve the efficiency and accuracy of the recommendation model [19]. In many customer demand behavior data, the feature processing objects mainly come from customer the demand data set, commodity data set, and the mapping relationship data set between customer and commodity. Because the customer demand data set has the characteristics of discrete distribution, the customer demand data set can be preprocessed by feature reorganization to obtain the required feature set. For the mapping relationship data set between customer and commodity, the data set can be preprocessed according to the customer's demand intention for commodity to obtain the required feature set. In order not to affect the implementation effect of the subsequent recommendation algorithm, because the features extracted from the customer demand behavior are used as the input data of the recommendation model, it is very important to select an appropriate method to extract an effective feature data set.

When completing the task of feature extraction, it is necessary to detect many customer demand behavior data sets, commodity data sets, and mapping relationship data sets between customers and commodities, because the deep belief network model reduces the dimension of the input initial feature set while generating effective features through model training. The deep belief network model contains multilayer neurons, and the bottom layer is the neuron that provides input data for the model, which is called the explicit layer. Other layers except the bottom layer are called hidden layer, which is mainly used to extract data features. Each neuron in the hidden layer represents a kind of features.

Deep belief network is a hybrid model composed of undirected graph model and directed graph model, as shown in Figure 5. Among them, the undirected graph model is an associative memory composed of the top layer and hidden layer of the network, while the directed graph model is composed of restricted Boltzmann machines (RBMs) stacked layer by layer. The features in the directed graph model are trained continuously by the adjacent restricted Boltzmann machine, and finally the selected features are output to the undirected graph model for storage.

The data set of customers' demand behavior for goods includes the operation time of customers' access, click, and transaction, which shows that customers' demand behavior for online goods often changes over time. Therefore, when extracting and selecting the characteristics of customers' demand behavior for goods through the deep belief network model, we need to consider the time context-related information, that is, we need to add the time factor to the feature set based on the deep belief network model. The classification and extraction of different features after model processing are shown in Table 2.

The low-level features of deep belief network can be transferred to the higher-level features after learning and training. Through the continuous learning of features layer by layer in the deep belief network, the high-dimensional complex input features can be trained into low-dimensional features that can not only reflect the information contained in the input data but also clearly reflect the data differences. Therefore, when there are many characteristics of customer demand behavior and the dimension of input data characteristics is high, the use of deep belief network can not only

Table 1: Comparison between direct feedback information and indirect feedback information.

Item	Direct feedback information	Indirect feedback information
Data size	More	Less
Real-time data	Poor real-time performance	Good real-time performance
Customer demand preference	Vague	Clear
Information transparency	Not transparent	Transparent
Information reference value	Necessary	Important

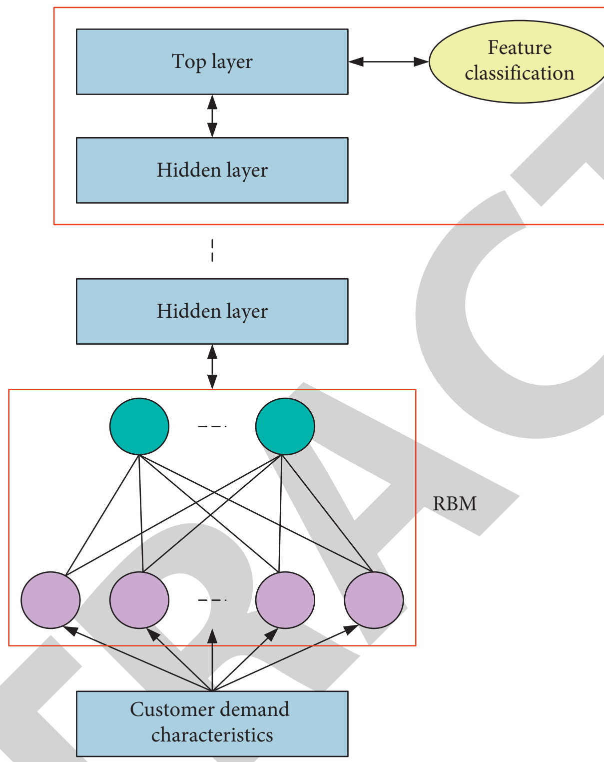

Figure 5: Feature selection process based on deep belief network.

Table 2: Different category features and their attribute extraction.

Feature type	Characteristic content	Feature attribute extraction
*S*1	Customer information	Customer network name, occupation, preference, etc
*S*2	Customer characteristics	Customers click, browse, collect, etc
*S*3	Commodity trading characteristics	Such commodities are clicked, browsed, collected, purchased, etc
*S*4	Characteristics of customers and commodity trading places	Location attributes such as distance between customer and commodity
*S*5	Behavioral characteristics of customer demand for goods	Customer's click, browse, collection, purchase times, and other attributes of goods
*S*6	Commodity characteristics	Commodity click, browse, collection, purchase volume, etc

select the effective features conducive to the recommendation system from many complex features but also improve the efficiency of model training and the accuracy of commodity recommendation.

4.3. E-Commerce Commodity Recommendation Algorithm. According to the design requirements of online commodity recommendation system, based on the construction of customer demand behavior data set, commodity data set, and customer commodity mapping relationship data set, feature detection, extraction, and selection of the customer demand behavior data set based on deep belief network, an e-commerce commodity recommendation algorithm model can be established, as shown in Figure 6.

Firstly, according to the customer demand and the design requirements of the online commodity recommendation system, through the feature extraction and selection of different data sets, combined with the requirements of online commodity recommendation and evaluation, the

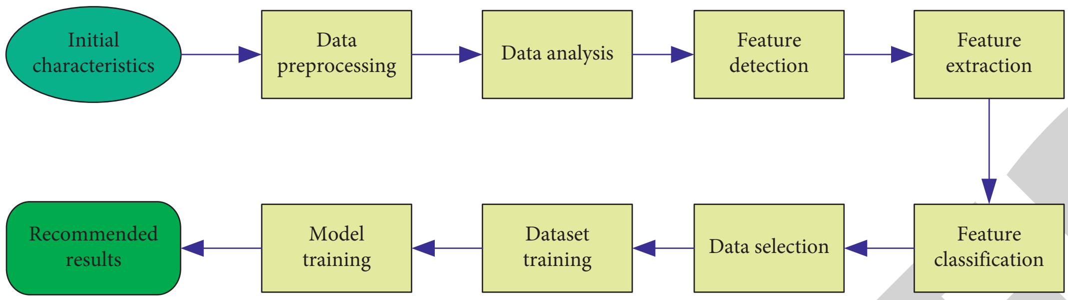

Figure 6: Construction process of e-commerce commodity recommendation algorithm.

original data such as customer demand behavior can be preprocessed [20, 21]. Then, in order to ensure that the feature set can support the recommendation system of the e-commerce platform, some key feature information in the feature set needs to be counted and analyzed in the form of charts. At the same time, in order to improve the accuracy and coverage of online commodity recommendation system and make the recommendation results consistent with customer needs, we also need to consider various factors affecting customer demand behavior. For example, based on the existing data sets, when constructing the recommendation system, we also need to fully consider the information related to context and the information based on the mobile e-commerce platform related to time and geographical location. Therefore, it is necessary to add some additional features to the feature information extracted by the deep belief network. Finally, different data sets are used to strengthen the learning and training of the recommendation algorithm model, and the recommendation algorithm model is optimized by adjusting the model parameters to make the recommendation algorithm consistent with the customer demand behavior.

The performance of online commodity recommendation algorithm largely depends on the processing of customer demand behavior data set, and the results of data processing not only affect the training effect of recommendation model but also directly affect the accuracy and efficiency of the recommendation algorithm. Normal data processing can not only ensure that the algorithm can effectively fit the data set but also mine the internal data relationship in the data set to obtain effective recommendation results. On the contrary, poor data set processing will lead to exceptions in the data trained by the recommended algorithm. For example, the training error of the algorithm means that the customer demand result obtained by the recommendation algorithm is wrong, which affects the accuracy of the recommendation algorithm. Therefore, when constructing the recommendation algorithm model, we need to fully preprocess different data sets to ensure the effectiveness of the recommendation algorithm.

Not all the features in the feature set obtained by feature processing can be used by the recommended algorithm model because, when training the model, these characteristics not only increase the complexity of algorithm implementation but also may affect the implementation effect of the model. Therefore, in the process of feature processing, it is necessary to screen out the features that are conducive to the implementation of commodity recommendation. In order to make the commodity recommendation model meet the needs of different customers, when training the recommendation model with different data sets, it is necessary to screen the feature information that is not conducive to the recommendation results and use the weighted combination method to process the features in different data sets [22]. In order to avoid the overlap between different features, when training different data sets, it is necessary to classify the feature sets and analyze the impact of different types of features on the recommendation model. For those features that can produce better recommendation results for the recommendation algorithm model, the training of these features should be strengthened during model training. When using the deep belief network model to select the features of different data sets, it is necessary to strengthen the learning of training data sets on different feature sets to obtain effective feature sets, which can not only reduce the complexity of the recommendation model but also make the recommendation model obtain better recommendation effect.

5. Results and Analysis

5.1. Model Evaluation Method. In the evaluation of recommendation system, multiple evaluation indexes can be taken from different angles to evaluate the performance of the recommendation system. Different evaluation indicators have different evaluation results on the recommendation system. For example, some indicators describe the performance of the recommendation system in a quantitative way, while some indicators are evaluated in a qualitative way.

The accuracy of the model can reflect the proximity of the recommendation model to the customer demand behavior. This index is mainly used to describe whether the recommendation algorithm can accurately predict the customer demand preference. At present, most recommendation systems use this evaluation index to evaluate the accuracy of the model. In offline calculation of model accuracy, data sets need to be classified differently, including training set, test set, and verification set. When the recommendation algorithm model is used to simulate customer demand behavior, the training set is used to train the recommendation algorithm model, and the test set is used to obtain the recommendation results of the model. Finally, the similarity between the model prediction results and the verification set is used as the accuracy of the model.

In the e-commerce website recommendation system, the commodities recommended to customers according to the law of customer demand behavior are usually given in the form of list. These commodities mainly adopt different recommendation algorithms and are arranged in a certain order. The accuracy of online product recommendation results generated by the recommendation system is mainly reflected by two indicators: recall rate and accuracy rate [7].

The recall rate of the recommendation algorithm can be calculated as follows:

$$\text{recall} = \frac{\sum_{i=1}^{N} f(i) \cap r(i)}{\sum_{i=1}^{N} r(i)}, \tag{1}$$

where N denotes the customer data set, $f(i)$ represents the prediction set of recommendation results obtained by using the recommendation algorithm model trained through the test set, and $r(i)$ shows the actual result set of customer online commodity transaction, that is, the verification set.

At the same time, the accuracy of the recommended algorithm can be calculated as follows:

$$\text{accuracy} = \frac{\sum_{i=1}^{N} f(i) \cap r(i)}{\sum_{i=1}^{N} f(i)}. \tag{2}$$

From the above calculation formula of accuracy and recall, the recall and accuracy used to describe the performance of the recommended algorithm are inversely proportional to each other, that is, the higher the accuracy, the lower the recall. In order to weigh the relationship between the two indicators, a comprehensive trade-off indicator $F1$ can be used to describe the accuracy of online commodity recommendation results of the recommendation algorithm. The calculation formula of $F1$ is as follows:

$$F1 = \frac{2 \times \text{recall} \times \text{accuracy}}{\text{recall} + \text{accuracy}}. \tag{3}$$

Many data feature sets are used to strengthen the training of the recommended model, and the model is optimized by repeatedly adjusting relevant parameters. In order to verify the effectiveness and reliability of the recommended algorithm, the feature test sets of different categories are used as the input values of the model to calculate the corresponding prediction results, and then the feature test sets are used to calculate the recall rate, accuracy rate, $F1$, and other evaluation index values of the model.

In order to judge whether the commodity prediction results obtained by the recommendation system include all commodities that should be recommended, the coverage index can be used to describe. Coverage can better reflect whether the recommendation results cover all recommended commodities to explain the probability of commodities being recommended. Coverage can be expressed by the ratio of the number of all recommended products to the total number of products. Due to the complex demand behavior of customers for goods, in order to meet the various demand behaviors of customers for online goods, the commodity prediction results obtained by using the recommendation algorithm should meet the different needs of customers. Therefore, the recommendation algorithm should usually be diverse. For example, if there is no product that meets the customer's needs in the product prediction result obtained by the recommendation algorithm, the customer is not satisfied with the recommendation result [8]. If the recommendation algorithm can better predict the goods required by customers according to different customer demand behaviors, to meet customers' various needs for online goods, the recommendation algorithm has diversity.

Diversified recommendation algorithms can ensure that customers can choose their own satisfactory products in the product prediction results. For nondiversified recommendation algorithms, there may be products that cannot meet customers' needs in the generated product prediction results, reducing customers' attention and demand interest in online products. Therefore, the diversity of recommendation algorithms can better evaluate the advantages and disadvantages of recommendation algorithms.

5.2. Result Analysis. In order to evaluate the prediction effect of the recommendation model on different characteristics, five different characteristics are selected from the customer demand behavior data set, and the recommendation model is used to predict these different characteristics. According to the different features shown in Table 2, combined with the prediction results of the recommended model, $F1$ values corresponding to these five different characteristics are obtained, as shown in Figure 7.

From the impact of different category features on the recommendation results shown in Figure 7, among the six feature categories, the F1 value obtained when using the recommendation model to predict the $S1$ category features is the largest, indicating that the $S1$ category features have the greatest impact on the recommendation results. The $F1$ value obtained when using the recommendation model to predict the characteristics of $S5$ category is the smallest, indicating that the characteristics of $S5$ category have the least impact on the recommendation results. In the data set of customers' demand behavior for goods, the impact of different categories of features on recommendation results is different, which needs to be determined according to specific different feature categories. Therefore, dividing the customer demand behavior data set into multiple different types of feature sets and using these different types of feature sets to strengthen the training of the model can not only continuously improve the accuracy of the recommendation model but also optimize the effect of the recommendation algorithm.

This paper observed the feature selection process based on the depth belief network model through experiments and analyzed the influence of the number of hidden layer nodes of the model on the recognition accuracy and running time of the model through data statistics, as shown in Figure 8. The experimental results showed that the running time of the model increased linearly with the increase of the number of hidden layer nodes. For the recognition accuracy of the

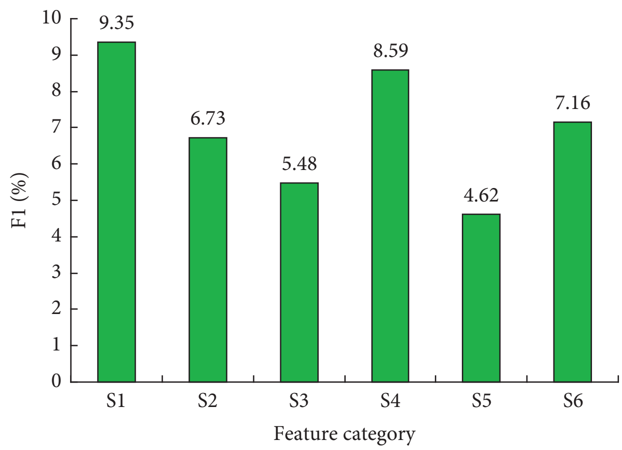

Figure 7: Comparison of accuracy of recommendation results for different types of features.

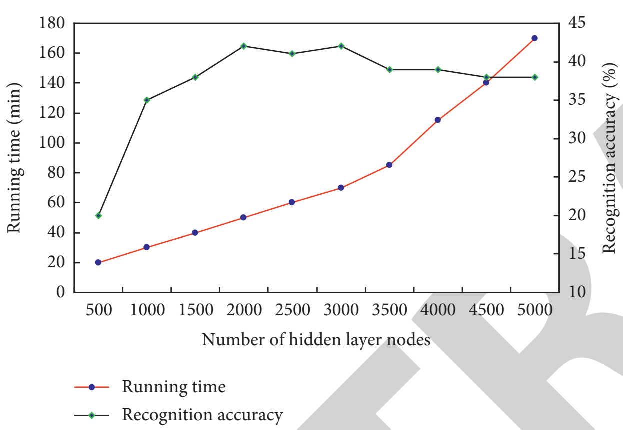

Figure 8: Influence of the number of hidden layer nodes of deep belief network model on recognition accuracy and running time.

model, when the number of hidden layer nodes changed between 500 and 2000, the recognition accuracy showed an upward trend. When the number of hidden layer nodes changed between 2000 and 3000, the recognition accuracy decreased slightly. When the number of hidden layer nodes changed between 3000 and 5000, the recognition accuracy basically did not change.

The performance of different common recommendation models in terms of commodity recommendation time overhead was compared, as shown in Figure 9. The experimental results showed that the recommendation time cost of various models increased with the increase of the number of recommended items, but the recommendation time cost of the model proposed in this paper was lower than that of other relevant models, indicating that the model proposed in this paper had good intelligence for commodity recommendation.

At present, the common recommendation algorithms are mainly collaborative filtering-based recommendation algorithm, association rule-based recommendation algorithm, knowledge-based recommendation algorithm, user behavior analysis-based recommendation algorithm, user

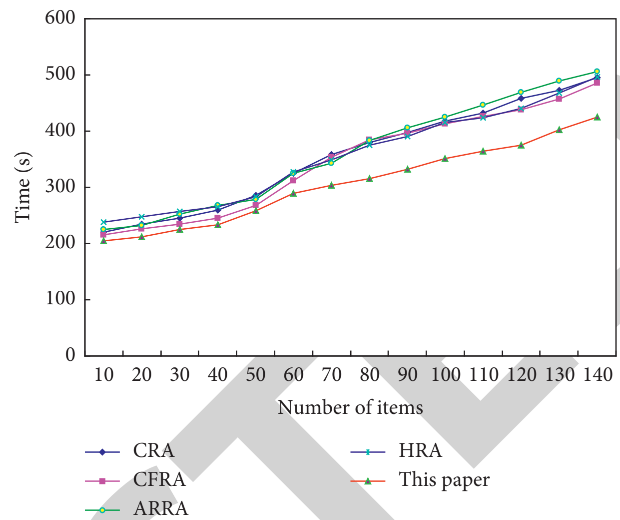

Figure 9: Comparison of recommended time cost of various models.

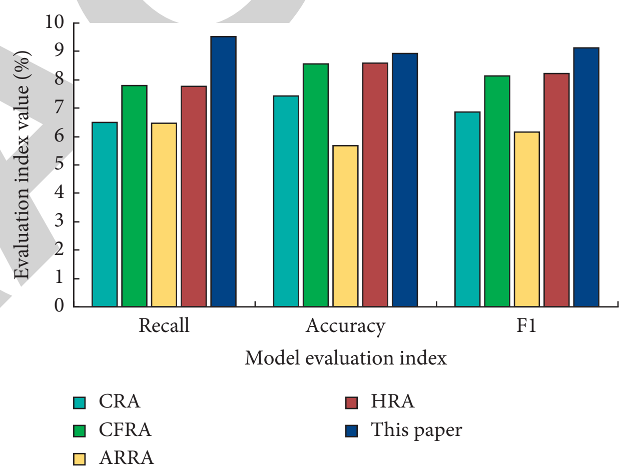

Figure 10: The comparison between this model and other commodity recommendation models.

statistical information-based recommendation algorithm, and utility-based recommendation algorithm. In order to describe the performance of different recommendation algorithms, the recommendation algorithm proposed in this paper are compared with these common recommendation algorithms, as shown in Figure 10. According to the prediction results and actual results of various algorithms, the evaluation index values such as recall, accuracy, and *F*1 of different recommendation models can be calculated. From the comparison results of various algorithms, the recommended algorithm proposed in this paper is superior to other related algorithms in all performance indexes.

6. Conclusion

The traditional recommendation system was difficult to meet the actual needs of customers for goods due to the lack of screening the characteristics of customer demand behavior, and the relevant recommendation models were also difficult to provide customers with the expected recommendation results. Therefore, this paper proposed a network commodity intelligent recommendation method based on feature selection and deep belief network, which aimed to provide customers with effective commodity recommendation results. According to the basic structure and function of the existing recommendation system, the interaction process between customers, e-commerce platforms, enterprises, and the recommendation system was analyzed. By exploring the internal relationship between customer demand and commodity recommendation, the mapping relationship model between customer demand and commodity recommendation was established. Using data mining technology to screen the characteristics of customer demand, a feature selection method based on deep belief network (DBN) was given, and a network commodity recommendation algorithm based on feature selection and deep belief network was proposed. The experimental results showed that the commodity recommendation model proposed in this paper not only had better performance than other traditional recommendation models but also can meet the actual needs of customers. The network commodity recommendation model proposed in this paper can provide a reference for the better design and development of e-commerce platform recommendation systems.

Data Availability

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

Conflicts of Interest

The authors declare that they have no competing interests.

Acknowledgments

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References

[1] C. Ju, J. Wang, and G. Zhou, "The commodity recommendation method for online shopping based on data mining," *Multimedia Tools and Applications*, vol. 78, no. 21, pp. 30097–30110, 2019.

[2] T. V. R. Himabindu, V. Padmanabhan, and A. K. Pujari, "Conformal matrix factorization based recommender system," *Information Sciences*, vol. 467, pp. 685–707, 2018.

[3] Z. Wei and L. Wei, "The new algorithm of commodity recommendation based on MapReduce," *Agro Food Industry Hi-Tech*, vol. 28, no. 3, pp. 3188–3191, 2017.

[4] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, no. 6, pp. 734–749, 2005.

[5] M. A. Mazurowski, "Estimating confidence of individual rating predictions in collaborative filtering recommender systems," *Expert Systems with Applications*, vol. 40, no. 10, pp. 3847–3857, 2013.

[6] C. Feng, J. Liang, P. Song, and Z. Wang, "A fusion collaborative filtering method for sparse data in recommender systems," *Information Sciences*, vol. 521, pp. 365–379, 2020.

[7] Z. Zhang, Y. Kudo, and T. Murai, "Neighbor selection for user-based collaborative filtering using covering-based rough sets," *Annals of Operations Research*, vol. 256, no. 2, pp. 359–374, 2017.

[8] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, "Recommender system application developments: A survey," *Decision Support Systems*, vol. 74, pp. 12–32, 2015.

[9] A. Wulam, Y. Wang, D. Zhang, J. Sang, and A. Yang, "A recommendation system based on fusing boosting model and DNN model," *Computers, Materials & Continua*, vol. 60, no. 3, pp. 1003–1013, 2019.

[10] M. Spiliopoulou, B. Mobasher, B. Berendt, and M. Nakagawa, "A Framework for the evaluation of session reconstruction heuristics in Web-usage analysis," *INFORMS Journal on Computing*, vol. 15, no. 2, pp. 171–190, 2003.

[11] H. L. Pan and Z. J. Zhang, "Research on context-awareness mobile tourism E-commerce personalized recommendation model," *Journal of Signal Processing Systems*, vol. 93, no. 2, pp. 147–154, 2021.

[12] T. Bellotti, Z. Luo, A. Gammerman, F. W. Van Delft, and V Saha, "Qualified predictions for microarray and proteomics pattern diagnostics with confidence machines," *International Journal of Neural Systems*, vol. 15, no. 4, pp. 247–258, 2005.

[13] T. Yang and Q. Li, "Reduction about approximation spaces of covering generalized rough sets," *International Journal of Approximate Reasoning*, vol. 51, no. 3, pp. 335–345, 2010.

[14] N. Capuano, G. R. Mangione, A. Pierri, and S. Salerno, "Learning Goals recommendation for self regulated learning," *International Journal of Engineering Education*, vol. 28, no. 6, pp. 1373–1379, 2012.

[15] J. J. Jung, "Attribute selection-based recommendation framework for short-head user group: An empirical study by movielens and imdb," *Expert Systems with Applications*, vol. 39, no. 4, pp. 4049–4054, 2012.

[16] S. K. Shinde and U. Kulkarni, "Hybrid personalized recommender system using centering-bunching based clustering algorithm," *Expert Systems with Applications*, vol. 39, no. 1, pp. 1381–1387, 2012.

[17] C. Wei, J. Niu, and Y. Guo, "DLGNN: A double-layer graph neural network model incorporating shopping sequence information for commodity recommendation," *Sensors and Materials*, vol. 32, no. 12, pp. 4379–4392, 2020.

[18] M. Jalali, N. Mustapha, M. N. Sulaiman, and A. Mamat, "WebPUM: A Web-based recommendation system to predict user future movements," *Expert Systems with Applications*, vol. 37, no. 9, pp. 6201–6212, 2010.

[19] J. K. Kim, H. K. Kim, H. Y. Oh, and Y. U. Ryu, "A group recommendation system for online communities," *International Journal of Information Management*, vol. 30, no. 3, pp. 212–219, 2010.

[20] N. Capuano, M. Gaeta, P. Ritrovato, and S. Salerno, "Elicitation of latent learning needs through learning goals recommendation," *Computers in Human Behavior*, vol. 30, pp. 663–673, 2014.

[21] A. Gunawardana and G. Shani, "A survey of accuracy evaluation metrics of recommendation tasks," *Machine Learning Research*, vol. 10, pp. 2935–2962, 2009.

[22] L. Hu, Y. Wang, Z. Xie, and F. Wang, "Semantic preference-based personalized recommendation on heterogeneous information network," *IEEE Access*, vol. 5, pp. 19773–19781, 2017.