Research Article

Core Technology Optimization of Intelligent Financial Technology Based on Collaborative Filtering Algorithm in Big Data Environment

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With the improvement of people’s economic level, people pay more attention to financial investment. At present, the financial industry provides customers with a variety of investment services, but it has always been unable to provide targeted services for customers. Based on this, this paper studies the optimization of intelligent financial technology core technology based on collaborative filtering algorithm in the big data environment. On the basis of a simple analysis of the application of financial core technology and the research status of collaborative filtering algorithm, this paper constructs an application model of intelligent financial collaborative filtering algorithm. In view of the shortcomings of collaborative filtering algorithm, it uses user-based clustering algorithm to improve the collaborative filtering algorithm. According to the frequency of customers’ access to financial products, the attention model is established and simulated. The results show that the collaborative filtering optimization algorithm used in this paper can reduce the absolute error of recommendation and improve the accuracy.

1. Introduction

With the development of information technology, various financial products are emerging. In addition to common banking products, other financial products have also attracted the attention of many investors [1]. The core business of the financial industry includes the following three aspects: (1) liability business refers to the business that forms the source of funds, and its funds mainly come from its own funds and foreign investment; (2) asset business refers to the business in which the bank uses the funds raised through liability business; (3) intermediary business refers to the business in which a bank does not need to use its own funds but only undertakes entrusted matters such as payment on behalf of customers and charges corresponding handling charges. In the core business of the financial industry, in addition to the traditional deposit business, the sales of financial products have also become one of the core businesses [2, 3]. However, the quality of a wide variety of products in the financial industry is not exactly the same. It is also accompanied by many financial risks. How to avoid risks is crucial to the development of the financial industry. Improving the accuracy of product recommendation is a good way. In financial product recommendation, collaborative filtering algorithm is widely used at present. It can recommend corresponding financial products according to the characteristics of users [4]. However, this collaborative filtering algorithm only recommends according to the scoring data in the application, and the accuracy is not particularly high. There is a cold start problem in the application of the algorithm. There are missing values when analyzing the user matrix. Whether it is deleted directly or the average value will affect the accuracy of the results.

Based on this background, this paper studies and analyzes the optimization of the core technology of intelligent financial technology based on collaborative filtering algorithm in the big data environment, which is mainly divided into four chapters. The first chapter briefly introduces the recommendation status of financial core business and the chapter arrangement of this study. Chapter 2 introduces the application of recommendation algorithm and collaborative filtering algorithm at home and abroad and the
research status of improved algorithms and summarizes the shortcomings of the current research. In Chapter 3, the optimization model of intelligent financial technology core technology based on collaborative filtering algorithm in big data environment is constructed. Aiming at the shortcomings of collaborative filtering algorithm, cluster analysis algorithm is used to improve it. The improved collaborative filtering algorithm only focuses on the shortcomings on user scoring, improves the accuracy of algorithm recommendation, and reduces errors. In Chapter 4, the optimization model of collaborative filtering algorithm constructed in this paper is simulated and analyzed to measure the performance of the algorithm under different number of clusters and nearest neighbors. The experimental results show that when the number of clusters is 25, the performance of the algorithm is the best. Compared with the traditional collaborative filtering algorithm, the accuracy and product diversity have been significantly improved.

The main point of this paper is the improvement of collaborative filtering algorithm. In the improvement of collaborative filtering algorithm, generally only based on the user rating data, using clustering to improve also has this problem. In this paper, the clustering analysis is carried out from the two aspects of initial class center and distance. After improving the clustering algorithm, the collaborative filtering algorithm is used to achieve product recommendation and improve the quality of recommendation.

2. State of the Art

The financial industry has the characteristics of customer intensive, so it is inevitable to use data mining technology in financial institutions. As an important part of the financial industry, banks have added many investment products in addition to time deposits in their core business. Accurately recommending products for customers plays a great role in the development of banks. At present, the core technology of the financial industry has widely used intelligent algorithms to mine information. In their research and analysis, Shang et al. determined the frequent fuzzy option set through fuzzy clustering method, parallel rules, and parallel mining algorithm, so as to obtain the fuzzy association rules that meet the minimum fuzzy reliability and analyze the financial risk [5]. In the bank telemarketing analysis, Moro et al. used data-based sensitivity analysis to extract feature correlation and also used expert evaluation to decompose and describe the telemarketing contact to sell bank deposits [6]. Tang et al. used the method of fuzzy subset selection in their research to characterize the relevant indicators that have a great impact on the trading history, automatically customize the indicators of different financial products in different markets, and the selection algorithm runs in the frequency domain to identify and match the peak value and technical indicators in the key patterns and trading volume [7]. Collaborative filtering algorithm is widely used in financial product recommendation. This algorithm has also been improved in different fields in recent years. In their research, Yu et al. proposed a cross domain collaborative filtering algorithm to expand the user and project features through the potential factor space of the auxiliary domain. The recommendation problem is described as a classification problem in the target domain. Taking the user and project location as the feature vector, funk SVD decomposition is used to extract additional user and project features from the user and project side auxiliary domains, respectively, so as to expand the two-dimensional location feature vector [8]. Pan et al. proposed an improved collaborative filtering algorithm, which uses the confidence coefficient to distinguish the reliability of the score. The program recommends items by comprehensively considering the predicted score and predictability of the items and converts the program into a 0-1 knapsack problem, so as to select the optimized recommendation list [9]. Li et al. proposed the collaborative filtering algorithm based on category priority K-means (cpckcf) and proposed the definition of user item category preference ratio (uicpr) to calculate the uicpr matrix [10].

To sum up, it can be seen that the application of intelligent algorithms in the core businesses of the financial industry has been relatively common at present. It can mine and analyze data and improve the efficiency. However, the intelligent core technology also has its own limitations. With the increasing data, it has been unable to meet the development needs of customers. On the other hand, there are many improvements in the recommendation algorithm, but there are not many research results applied to the financial industry. Therefore, it is of great significance to carry out the research on the optimization of the core technology of intelligent finance based on collaborative filtering algorithm in the big data environment.

3. Methodology

3.1. Intelligent Financial Technology Core Recommendation System. Among the core technologies of science and technology in the financial industry, product sales and financial risk technology are the core technologies. Collaborative filtering algorithm is widely used in product sales. As a recommendation system, collaborative filtering algorithm has many similarities with other recommendation systems. It is to find potential customers and provide personalized product sales services to improve customer satisfaction [11]. Compared with other recommendation algorithms, collaborative filtering algorithm mines information according to the association between users and products, not just users themselves. In application, it has low requirements for data and does not need to extract text information. In recommendation, it can mine many similar products according to the calculation of user similarity, with simple technical operation and strong scalability [12]. Collaborative filtering algorithm is widely used in various fields of customer recommendation, as shown in Figure 1.

In the field of financial product sales, collaborative filtering algorithm is established in the unified processing, storage, and analysis of various financial systems. In customer analysis, it is necessary to make a detailed mining of customer basic information, product information, and historical transactions [13]. The financial database needs to store the product-related data extracted from the core system
and data and also covers the basic information of users, product information, and so on. In the data mining module, the data mining algorithm is used to classify customers and realize cluster analysis. In the data analysis module, products are combined and classified to provide customers with corresponding product services.

When providing users with personalized products and services, collaborative filtering method has many advantages compared with other algorithms, such as filtering the content that is difficult to analyze by the machine, summarizing the previous experience, avoiding inaccurate analysis, and filtering some complex content [14]. Collaborative filtering algorithm has the ability of recommendation information, can provide users with completely unknown information, and can realize automatic recommendation and improve efficiency. However, collaborative filtering algorithm also found many deficiencies in the application. In the collaborative filtering algorithm, there is basically no evaluation of customers, so it is impossible to accurately analyze customers’ preferences and realize accurate recommendation [15]. With the increase of user scale, the number of items and products is increasing sharply, but the user score is always sparse. In this case, the collaborative filtering algorithm is difficult to provide users with more recommendation information and will affect the accuracy of the algorithm [16]. From the perspective of data analysis, collaborative filtering algorithm only uses part of the information to mine, and the recommendation accuracy and scalability are not completely solved. Therefore, it is necessary to optimize the collaborative filtering algorithm.

3.2. Optimization Design of Collaborative Filtering Algorithm. Combined with the actual situation of the financial industry, collaborative filtering algorithms mostly use collaborative filtering algorithms based on user needs. It is mainly divided into two steps: establishing the similarity model and then establishing the interest model [17]. The similarity model mainly views the set of customers’ interests, and the degree of interest is to recommend new financial products based on the financial products purchased by users [18]. In the construction of similarity model, the core part is the calculation of user similarity. In the calculation of collaborative filtering algorithm, similarity mainly focuses on user interest. Cosine similarity measures the similarity between two vectors by measuring the cosine of the angle between them. The cosine value of 0 degree angle is 1, and the cosine value of any other angle is not greater than 1. And its minimum value is -1. Thus, the cosine value of the angle between the two vectors determines whether the two vectors point roughly in the same direction. When two vectors have the same direction, the value of cosine similarity is 1. When the angle between two vectors is 90°, the value of cosine similarity is 0. When two vectors point in completely opposite directions, the value of cosine similarity is -1. This result is independent of the length of the vector, but only related to the direction of the vector. Cosine similarity is usually used in positive space, so the value given is between -1 and 1. The interest similarity is calculated by cosine formula, which is expressed as

\[
Z(u, V) = \frac{|I(u) \cap I(v)|}{\sqrt{|I(u)||I(v)|}},
\]

where \(Z\) represents the interest similarity of users, \(I\) represents the collection of financial products purchased, and \(u, v\) represents users. Combined with this formula, the user interest model is constructed. The formula is expressed as

\[
P(Rui) = \sum_{v \in Nu \cap S(u)} RviS(u, v),
\]

where \(Nu\) represents the set of users interested, \(U\) represents the set of users who buy financial products, and \(S\) represents
the similarity. In the recommendation algorithm, binary tagging is widely used in the tagging evaluation matrix. Therefore, for users who have purchased products, the RVI value is 1. The traditional collaborative filtering algorithm does not pay attention to the time data in the calculation, but the time information can also reflect many problems. Using these rules, users can mine the connection of products purchased by users, and the financial products purchased by customers may affect the purchase interest of other customers [19]. In this paper, the attention model is established according to the product access frequency of different attributes to carry out cluster analysis. Considering that the traditional clustering algorithm has the problems of distance calculation and initialization center, this paper improves it in the research, introduces K-means clustering algorithm and Mahalanobis distance, and generates user cluster classification based on scoring data. The attention model is established according to the user access, which makes up for the deficiency of the clustering model [20, 21]. Based on user clustering analysis, collaborative filtering recommendation algorithm is used to further mine users’ interests and narrow the search space.

When customers access some financial products, they may access different categories of products. If a customer purchases a certain type of financial products many times, it indicates that the customer pays high attention to this kind of financial products; he thinks that the customer likes this kind of financial products and has a high degree of preference. He will also give priority to viewing this kind of financial products when purchasing financial products next time. Therefore, based on the project category matrix, this paper introduces the user’s view records and constructs the attention model. The formula is as follows:

\[ \text{Att}_{ug} = \frac{|I(u) \cap I(g)|}{|I(u)|}, \]

where \( I \) represents the project collection accessed by the user and \( \text{Att} \) represents the degree of concern. In the construction of this attention model, the scoring information is not introduced, because the input data of the algorithm selects the user clustering results, and the clustering analysis can be realized only by reflecting the customer preference. After clustering analysis, the search scope of collaborative filtering algorithm can be greatly reduced. The introduction of scoring information can further increase the amount of calculation. Suppose that the user set is represented by \( U \), the matrix is composed of \( L \)-dimensional vectors, the number of users is represented by \( n \), and the number of categories is represented by \( l \). According to the essence of the algorithm, each class is a subset of users. In the process of clustering, the membership degree needs to be updated continuously. Taking the membership degree and class center as constraints, the objective function is established. The formula is

\[
J(Q^*, C^*) = \sum_{i=1}^{n} \sum_{j=1}^{l} q_{ij} (d_{ij})^2,
\]

where \( J \) represents the sum of squares from the user to the cluster center and \( d \) represents the distance from the user to the cluster center. This distance is generally calculated by Euclidean distance, but the distance measure function needs to be changed in the calculation of different data sets. Smooth the membership of customers to each class, divide users into cluster classes, and have corresponding class centers. The membership matrix can be expressed as

\[
Q = \begin{bmatrix}
q_{11}, q_{12}, \cdots, q_{1c} \\
\cdots \\
q_{n1}, q_{n2}, \cdots, q_{nc}
\end{bmatrix},
\]

where \( k \) represents the number of clusters, \( q \) represents the degree of membership, and \( c \) represents the number of class centers. When the membership range is 0 ~ 1, the membership of all users is within this range. In essence, this algorithm belongs to unsupervised local search algorithm. When \( \rho > 1 \), the algorithm can converge, and the membership matrix and central matrix are calculated iteratively. Under constraints, calculate the minimum value of the objective function. The formula is

\[
\min \{J(Q^*, Q^*)\} = \sum_{i=1}^{n} \min_{j=1}^{k} \left( q_{ij} \right)^{\rho} \left( d_{ij} \right)^2 \]

where \( \min \) represents the minimum value of the objective function. Lagrange multiplier method is used in the solution:

\[
F = \sum_{i=1}^{n} \sum_{j=1}^{k} q_{ij} \rho d_{ij}^2 + \sum_{i=1}^{n} \lambda \sum_{j=1}^{k} (q_{ij} - 1),
\]

\[
\frac{\partial F}{\partial q_{ij}} = \rho (q_{ij})^{\rho-1} (d_{ij})^2 - \lambda = 0.
\]

Reach the optimal constraint condition, expressed as

\[
q_{ij} = \frac{1}{\lambda} \left( \frac{d_{ij}}{d_{ik}} \right)^{2/(\rho-1)}.
\]

In the application of clustering algorithm, the initial class center and distance are important factors. In order to fully reflect the user type, these two problems need to be solved. In this paper, we consider that before the mean clustering analysis, we first carry out a K-means clustering analysis and then take the clustering results as the initial class center to optimize the algorithm and improve the clustering results. The customer is regarded as an object requiring binary division, and the clustering results either belong to this category or not. The objective function is established, and the formula is expressed as

\[
J = \sum_{j=1}^{K} \sum_{i=1}^{n} ||u_i - c_j||^2,
\]
where $n$ represents the number of users, $k$ represents the number of cluster classes, and $c$ represents the class center. The value of the class center is the mean value of the user vector of the cluster center, and the formula is expressed as

$$ c_j = \frac{1}{n} \sum_{i=1}^{n} u_i, $$

where the value range of $j$ is $1 \sim k$. The K-means algorithm is relatively easy to initialize, so it is less difficult to use in the operation of K-means algorithm. The Mahalanobis distance is used to calculate the cluster analysis distance. The core idea is to use the overall covariance matrix to calculate the sample distance. This measure function takes into account the internal characteristic relationship of customers and can calculate the location samples. Assuming that the mean vector of the sample is expressed by the distance from the set sample to the center can be expressed as

$$ D(x_i, u) = \sqrt{(x_i - u)^T T^{-1} (x_i - u)}, $$

where $T$ is the covariance matrix and $D$ is the Mahalanobis distance.

The distance between samples is expressed in $d_N$ and the Mahalanobis distance is taken as the standard of distance measure, assuming that the user attention matrix is a population, covering a total of $n$ user samples, the Mahalanobis distance from the user to the population can be expressed as

$$ d_N(u_i, U^*) = \sqrt{(u_i - u)^T T^{-1} (u_i - u)}, $$

where $u$ represents the mean vector, $d$ represents the Mahalanobis distance, and $U$ represents the bank user, and the covariance matrix can be expressed as

$$ T = \frac{1}{n} \sum_{i=1}^{n} (u_i - u)(u_i - u)^T, $$

where $T$ represents the covariance matrix.

On this basis, the collaborative filtering algorithm is optimized based on user clustering analysis. The process is shown in Figure 2. Input the scoring data set, build the customer attention model, calculate the attention of different financial product categories, and generate the attention matrix. The K-means clustering algorithm is used to cluster the matrix, the class center matrix is output, and the matrix is clustered by Mahalanobis distance, and the clustering results are obtained. Determine the category of target customers, calculate the similarity, and select the user with the highest similarity to generate a neighbor set. When the neighbor set is generated, the score matrix of target customers is obtained according to the matrix and clustering results, and then, the similarity is calculated. The prediction scores of financial products that the customer has not consulted are analyzed by the scores of the nearest neighbor set users. The calculation formula is expressed as

$$ Y_{ui} = R_{ui} + \frac{\sum_{j \in K(u_i)} sim_p(u_i, u_j) \times (r_j - \bar{R}_{ui})}{\sum_{j \in K(u_i)} sim_p(u_i, u_j)}, $$

where $p$ represents the prediction score, sim represents the similarity, and $K$ represents the nearest neighbor set. After completing the user’s prediction score, select the financial product with the highest score and recommend it to the customer.

### 4. Result Analysis and Discussion

#### 4.1. Simulation Analysis of Optimized Collaborative Filtering Algorithm

The financial product database is used for simulation analysis. These data are from stock information. The file covers the scoring records of more than 6000 users on stocks, and the stock information covers hundreds of kinds. The data were randomly divided into two groups, 60% of which were used as test data and 40% as training set. The average absolute error MAE commonly used in the recommendation algorithm is used for scoring. The smaller the value, the better the classification effect. The average absolute error of the improved algorithm first decreases and then increases with $K$ value. When $K$ value is 25, the average absolute error
is the smallest. The improved algorithm is better than the collaborative filtering algorithm.

In the improvement of the algorithm, the K-means clustering algorithm is used to classify users, so the $K$ value is changed to discuss the impact on the algorithm. The $K$ value determines the size of the search space of the target user, and the appropriate number of classifications can get higher similarity. In the simulation, the number of nearest neighbors is 40, and the size of the number of clusters $K$ is changed. The measurement results are shown in Figure 3. From the data changes in the figure, it can be seen that the error decreases continuously and the accuracy is improved at $5 \sim 25$. When it continues to increase, the change is not obvious. At this time, because $K$ is small, the distinction is obvious, and the difference is large. It is impossible to accurately analyze the nearest neighbors. The number of users’ nearest neighbors is too large, and the analysis of users’ nearest neighbors is not necessarily accurate. Therefore, the value of $K$ is 25.

Analyze the impact of the improved algorithm on the effectiveness of the financial product recommendation algorithm. The nearest neighbor value is 40, and the number of clusters is 25. The traditional algorithm and the improved collaborative filtering algorithm are used for simulation analysis. The measurement results are shown in Figure 4. It can be seen from the data changes in the figure that the improved algorithm has significantly improved the recommendation efficiency and shortened the running time.

By comparing and analyzing the accuracy of the algorithm, change the number of nearest neighbors and take the value of $K$ as 25. The measurement results are shown in Figure 5. It can be seen from the figure that the accuracy has been improved with the increase of the number of nearest neighbors. In comparison, the accuracy of the algorithm proposed in this paper is higher.

There are many types of financial products. When providing products to customers, we need to ensure the diversity of products. Therefore, we also need to consider the diversity of different algorithms. The measurement results are shown in Figure 6. It can be seen from the data in the figure that with the increase of parameter values, the diversity is increasing. In comparison, the diversity of the algorithm proposed in this paper is richer.
4.2. Simulation Analysis on Core Technology of Financial Product Recommendation. Taking the stock recommendation of financial products as an example, the simulation analysis is carried out. The original data covers the stock code, recent trading date, rise and fall range, turnover rate, closing price, and other data of thousands of Shanghai stock exchanges. In order to facilitate the calculation, the missing value of stocks is supplemented by inserting the average value. Convert the data into values of the same dimension for comparative analysis. The stock data is sorted and normalized. Considering the high complexity of data and inconvenient for rapid processing, dimensionality reduction is needed. PCA is used as the dimensionality reduction scheme to retain the amount of information, and the information can be concentrated in the first few dimensions. Calculate the cosine similarity of data after dimension reduction. Figure 7 shows the results of data cosine similarity, absolute error, and retained information. From the data in the figure, we can see that the similarity range is 0.9 ~ 1.1, the similarity is very high, and the average absolute error does not exceed 1.5%.

Calculate the cosine similarity and average absolute error ratio of the data. The measurement results are shown in Figure 8. It can be seen from the figure that this value is constantly changing. When the dimension is 3, the ratio reaches the maximum. Therefore, the financial data indicators can be reduced to 3 dimensions for analysis, which can retain more information and reduce the amount of information processing. The similarity and average absolute error are both small.
5. Conclusion

The average absolute error of collaborative filtering algorithm does not change significantly with $K$ value. The average absolute error of the improved algorithm first decreases and then increases with $K$ value. When $K$ value is 25, the average absolute error is the smallest. The improved algorithm is better than the collaborative filtering algorithm. The K-means clustering algorithm is used to classify users, so change the $K$ value to discuss the impact on the algorithm. The value of $K$ is 25. The improved algorithm significantly improves the recommendation efficiency and shortens the running time. The accuracy increases with the increase of the number of nearest neighbors. The accuracy of the algorithm proposed in this paper is higher. The results of data cosine similarity, absolute error, and retained information show that the similarity range is 0.9 – 1.1, the similarity is very high, and the average absolute error is not more than 1.5%. Calculate the cosine similarity and average absolute error ratio of the data. When the dimension is 3, the ratio reaches the maximum.

With the development of the era of big data, in the core technology of finance, information recommendation algorithm has become one of the necessary application technologies for the main business. As the most commonly used big data mining algorithm, collaborative filtering algorithm shows a lot of value in application and also finds many deficiencies. Based on this, this paper studies the optimization of the core technology of intelligent financial technology based on collaborative filtering algorithm in the big data environment, improves the existing recommendation model of the financial industry, and uses the improved clustering algorithm to optimize the recommendation algorithm. The number of clusters is optimized through simulation test, which shows superiority in accuracy, diversity, and error of product recommendation. In view of the huge amount of
financial data and the difficulty of processing, the dimension reduction processing is carried out in the simulation, which reduces the complexity of data processing. It should be pointed out that there are many factors affecting the clustering effect. In addition to the number of clusters proposed in this simulation, there is also the degree of fuzziness. With the increase of data scale, the cold start problem is still not well solved, and it may also affect the running time of the algorithm. These need to be further studied.

Data Availability

The figures used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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