

Retraction

Retracted: Research on Sports Training Decision Support System Based on Improved Association Rules Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Shao, "Research on Sports Training Decision Support System Based on Improved Association Rules Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 5561970, 6 pages, 2021.

Research Article

Research on Sports Training Decision Support System Based on Improved Association Rules Algorithm

Linhai Shao 

Mudanjiang Normal University, Mudanjiang 157011, China

Correspondence should be addressed to Linhai Shao; shaolinhai@mdjnu.edu.cn

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In my country, college students' physical exercise is mainly through physical exercise and amateur sports, which is basically in a state of disorder. Based on the improved association rules, this paper introduces the auxiliary decision support system for college students' sports training. First, we introduced a network security method and designed a sports training decision support system based on network security. Secondly, based on the Apriori algorithm, we have realized the organic integration of all aspects of college students' sports, applied scientific training theories and advanced training methods to the management of college students' sports training, and generated new knowledge rules through data mining technology, enriching knowledge. Finally, according to user input, select the corresponding model and combine with the rules in the knowledge base to generate a reasonable exercise training plan. After model simulation and example verification, the sports training decision support system based on the improved association rule prior algorithm designed in this paper has good applicability and efficiency.

1. Introduction

Sports is a comprehensive and very strong subject, which includes sports human science, sports humanities, and social sciences and so on [1, 2]. The research field of sports application decision support system is limited to sports training, sports evaluation, sports management, and other fields. Compared with the extensive research field of sports science, the application of DSS in the field of sports needs to be further expanded [1, 3]. The research shows that, in recent years, scholars of material movement field of intelligent management system, the national fitness information analysis, and decision support system are studied, which shows that more and more scholars have been aware of the strong support of all DSS functions, and applied to the sports field [4, 5]. With the rapid development of computer technology and in-depth application in various aspects, especially the development of artificial intelligence and data mining technology, to achieve the organic integration of different aspects of college students, the science training theory, advanced training method applied to college sports training management

has become a possibility, and the application of data mining in the assistant decision support system of College Students' sports training is feasible in theory [6, 7]. Many experts have proposed methods of applying technology in the field of scientific training centers, mainly for personalized information recommendation services in foreign university training halls, and these methods have achieved good results [8]. In recent years, foreign data mining technology has become more and more mature, and its application in the training hall has also been well studied [9].

At the same time, the understanding and application of data mining technology in university training hall is more and more profound. In view of the achievements made in foreign studies, this is relatively short of domestic research [10]. We will study the security solutions of next-generation mobile networks from the aspects of communication and network applications and establish, respectively, the NOMA anti-jamming offensive and defensive game and the secure mobile group intelligence perception game. We combine network security with sports training decision support system for program design [11].

2. Related Work

2.1. Network Security Overview. In the development of next-generation mobile networks, non-orthogonal multiple access technology provides efficient spectrum resource utilization for wireless communication systems, while mobile group intelligence sensing applications combine mobile cloud computing and Internet of Things technologies to monitor air quality and road conditions [12, 13] and provide real-time services such as many social works. However, due to the open nature of wireless networks and the development of intelligent network attacks, the reliability of wireless communication systems based on non-orthogonal multiple access and mobile group intelligence application networks has become an important challenge in the security research of next-generation mobile networks [14]. We will study the security solutions of next-generation mobile networks from the aspects of communication and network applications and establish, respectively, the NOMA anti-jamming offensive and defensive game and the secure mobile group intelligence perception game [15, 16]. We combine network security with sports training decision support system for program design.

2.2. Data Mining Overview. Data mining, which began in the 80s of last century, was originally used in the business and enterprise fields. By analyzing its database, the related characteristics of products can be understood, so as to provide decision support and enhance the competitive advantage of enterprises. A successful case is the classic “beer and diaper” example [17]. With a large number of scholars studying the scope of data mining applications, the application of data mining technology has become more extensive. The technology has involved financial data analysis, biological research, data analysis, telecom retail data analysis, and especially the development of electronic data. In the 90s, the international community training hall began to study the application of data mining technology to construct a personalized information recommendation system [18]. In recent years, foreign data mining technology is becoming more and more mature, and its application in the training hall has also been well studied [20].

3. Methods

3.1. Apriori Algorithm Elaboration. Apriori algorithm is a classical algorithm of American scholars in 1993 to solve the problem of association rules from customer transactional databases mining, and its core is the idea of frequent item sets mining based on the recursive algorithm of the two stages, which is the core algorithm of association rules [21]. Many researchers in the future have put forward a lot of improved algorithms, but they are based on this algorithm. In the process of optimizing the Apriori algorithm, all the frequent 1-item sets are obtained after the first scan of the transaction database [22]. If connection operation is used, a large number of candidate 2-item sets will be generated. At the same time, in order to count its support

count and get frequent 2-item sets, it is necessary to scan the entire database [23]. This step will cause great time and memory costs. Therefore, in order to reduce the number of candidate 2-item sets, the hash function (1) is used to generate frequent 2-item sets L_2 directly from frequent 1-item sets L_1 , and at the same time, it avoids the expense of counting the support count by scanning transaction databases.

$$h(x, y) = |L_1| * (\text{order}(x) - 1) - \frac{\text{order}(x) * (\text{order}(x) - 1)}{2} + \text{order}(y) - \text{order}(x). \quad (1)$$

In this, $|L_1|$ represents the number of items that are entered by frequent 1-items, $\text{order}(x)$ represents the index of the x in the entry, and the hash table is $(|L_1| * (|L_1| - 1)/2)$. Then, L_1 and L_2 are used to prune the original database, delete the irrelevant transactions, further compress the storage space, and build the hash table according to the width of the transaction/to the pruned database; the width of the hash table is $M-2$ (frequent 1-item sets and frequent 2 sets of items do not need to be added to the hash table), that is, using the hash function:

$$h(l) = l \bmod (M - 2). \quad (2)$$

M is the maximum width of the transaction, and the transaction identity with the width of l is stored in the node chain of the corresponding hash table [24]. In this way, when statistics support count is used, the transaction identifier can be used to store in hash table to directly find corresponding transactions in database, avoiding multiple scanning of database and saving a lot of contrast time. When the strategy of optimizing the original pruning method for the Apriori algorithm is described, the theoretical knowledge about the frequent item sets is firstly given. For a k -term set, if all its $k-1$ subsets are frequent item sets, it is a necessary condition for judging its frequent itemset where any one of the $k-1$ item sets of the k -term set X is infrequent; then, it can be judged that the set of X is an infrequent itemset. The most important theory is that if there is any element in the k -itemset, the frequency appearing in the frequent $k-1$ -item set L_{k-1} is less than $k-1$; then, the k -itemset X cannot be a frequent itemset. In the optimal pruning strategy, the frequency of the occurrence of the elements contained in the frequent k item set L_k is firstly dealt with:

$$|L_k(x)|, \quad x \in I' \setminus \{ \cup A | A \in L_k \}. \quad (3)$$

For those item elements that appear less than k as $I'' = \{i | |L_k(i)| < k-1\}$, then find out those frequent item sets containing L_k in any element of I' , remove them from L_k , and get a new k frequent item set L'_k , which contains fewer items. Then, you can use this smaller frequent k item set L'_k for its own connection to generate the next candidate $k+1$ project set C_{k+1}' . Under these circumstances, the candidate $k+1$ item set generated by reduced frequent

itemset L'_k connection is less than the number of candidate elements generated by C'_{k+1} generated by L'_k connection that has not been processed by reducing the number of C'_{k+1} . This can reduce the use of set X all $k - 1$ subsets, so that it can be judged that the set X is the nature of the infrequent itemset, and the infrequent itemset can also be filtered to determine, thus reducing the overhead in time [25].

3.2. The Steps of the Apriori-Hash Algorithm. Apriori-hash algorithm optimizes the database by hash table and integrates the optimized pruning strategy and optimized connection strategy mentioned before, which greatly improves the efficiency of mining association rules [26]. The basic steps of the algorithm are as follows: single pass scan loan database D calculates the support degree of each 1-itemset, gets frequent 1-item sets L_1 , and generates frequent 2-item sets L_2 through the hash function represented by formula (1), and uses the project in L_2 to trim the database. Because there are a lot of infrequent transaction records in the database, after scanning the database, the frequent 2 items are used to set generated by the first step to prune the database, and delete all transaction records that do not contain L2 items in the database. After pruning, if the length of the thing is less than 3, it is deleted. This can reduce transaction records in database, so as to compress the storage space needed to build hash tables. According to the width of transactions, we build hash tables for pruned databases [27].

In order to be able to quickly find all frequent item sets, after pruning set database by frequent 2, the width of data based on the transaction after pruning (i.e., the number of which contains the transaction record of the project) established the Hashim table; its approach is to determine the maximum width of the M transaction, the establishment of length header $M - 2$ Hashim (frequent 1-item sets and frequent 2-item sets do not need to be added to the hash table). The hash table is constructed by the zipper method. For the transaction record with a width of 1, function is used $H(1) = 1 \bmod (M - 2)$ to store the identification of the transaction with a width of 1 to the corresponding node chain of the hash table. This is equivalent to a transaction record for having different width to establish an index, when the need for statistical support of candidate item sets can be set length directly targeted to contain elements of the same number or more than the number of transaction records and items according to the item, and then compare whether the transaction contains the items. A set of candidate items is produced. Using an optimized pruning and connection strategy, an iterative loop is used to generate C_k by L_k ; frequent item sets are generated. When the support of the candidate item set C_k of k is calculated, it only needs to pass through the function:

$$h(k) = k \bmod (M - 2). \quad (4)$$

Function is used to locate the corresponding position in the hash table; the transaction ID of k width can be found to quickly scan the database; if $k < M$, then continue to calculate; there are

$$h(k + i) = (k + i) \bmod (M - 2), \quad (i = 1, 2, \dots, k + i \leq M). \quad (5)$$

To find the transaction identifier with a width greater than k to quickly scan the database, finally get the recognition support, and compare with the minimum support, and get the frequent K item set L_k . When L_k is generated, compute $|L_k|$; if $|L_k| < k + 1$, the algorithm ends. Otherwise, return to the last step. The detailed flow chart is shown in Figure 1.

4. Result Analysis and Discussion

4.1. Optimization of Performance Test of Apriori Algorithm. In order to verify the performance of the algorithm, this paper implements two kinds of Apriori algorithm and TMMFI algorithm which are widely used in sports training decisions under the same computer environment [28]. Figure 2 shows the execution time contrast under different minimum support degrees, and Figure 3 shows the memory utilization ratio under the sample data sets of different sizes. By contrast, the algorithm presented in this paper has better time complexity and space complexity [29]. The execution time comparison chart is shown in Figure 2. The comparison chart of memory utilization is shown in Figure 3.

4.2. The Practical Application of the Algorithm. First is clustering analysis for trainees by recording the sports training data in each trainee. The training record contains the following information: trainees, trainees' grade, number of trainees, and types of training information for each training implementation, etc. A variety of representative cluster clusters can be obtained by using different attribute information as feature research targets for clustering analysis. This article starts from the trainee sports training category to carry on the clustering analysis to the trainee, divides the trainee in the university physical education class into different groups, and then carries on the relevance association mining. Tether final clustering table is obtained by clustering analysis, and the cluster results are shown in Table 1.

First, extract the required information from transaction database. It only requires trainee number, training bar code, training items, and training time. What is considered here is the implementation of each trainee for each training. Secondly, the data is clustered according to the AKKMC clustering algorithm introduced before. During the process of clustering, researchers constantly adjust and optimize, and finally get the best clustering number of 7 categories. Finally, according to the results of clustering, the main attributes of data are analyzed in each cluster. In order to facilitate understanding of the specific circumstances of clusters, the borrowers' interest can be analyzed according to the classification profiles. Generally speaking, the trainees are low-grade freshmen, middle- and high-grade students, and graduates. They are also descriptions of the common interests of the three types of students. Here is a brief description of each cluster group in the training. All the

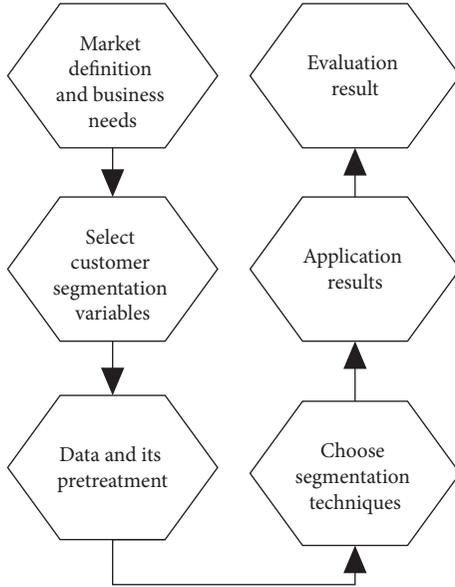


FIGURE 1: Basic process of customer segmentation.

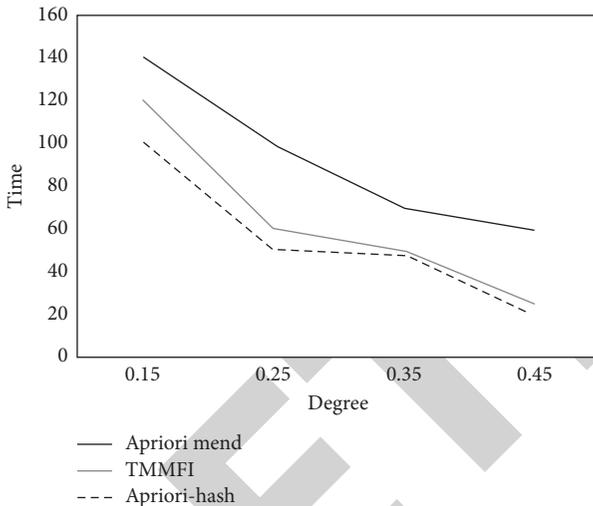


FIGURE 2: Execution time contrast diagram.

gymnasium categories give different categories corresponding content, so each cluster in the training category Class groups tend to be represented by classification. The trainees in group 1 mainly tend to complete the training of H, I, K, and T; the trainees in group 2 are mostly inclined to complete the training of B, J, O, Q, and T; the trainees in group 3 mainly tend to complete the training of B, C, and P; the trainees in group 4 are mostly inclined to complete D, N, U, and V.

Then, mining association rules for training data are to find out the interest preference of trainees, and the training mode related to training in training. Use the above-mentioned Apriori-hash mining algorithm for correlation analysis; on the one hand, train the trainees through borrowing the overall training, on the other hand, through the above-mentioned correlation clustering of the activity trainees.

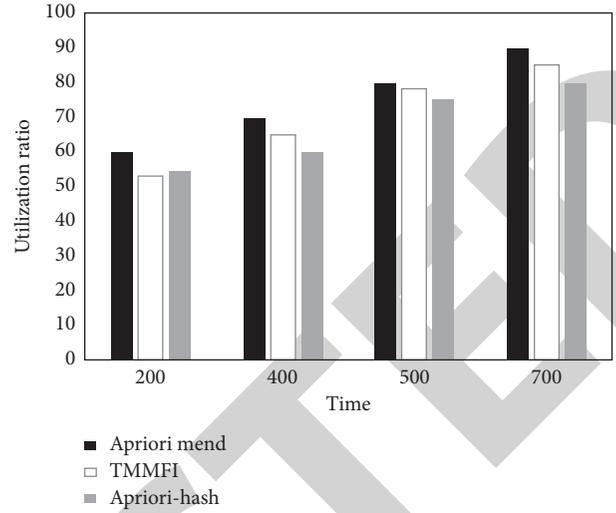


FIGURE 3: Memory utilization ratio contrast diagram.

TABLE 1: Cluster result table.

Reader ID	Cluster ID
26661005	Cluster-1
26661001	Cluster-4
26662066	Cluster-1
27661056	Cluster-3
26121102	Cluster-6
22462210	Cluster-6
25221455	Cluster-3
24621065	Cluster-6
26621058	Cluster-5
24125666	Cluster-7
26621058	Cluster-3
24156156	Cluster-6
25156122	Cluster-2
24411221	Cluster-7
26652129	Cluster-2
25662261	Cluster-4
26556664	Cluster-5
.....

The problem of mining association rules is to find out all the association rules that satisfy the minimum support and minimum confidence, that is, strong association rules. Setting the minimum support minisub of the association rules, before determining the value of the minisub, repeated tests are carried out, because if the minimum support minisub is too small, the final number of association rules will be too large, resulting in a lot of redundancies, which leads to the fact that the training mode cannot effectively respond to the trainees' interest preferences. With the support degree of 0.2 and the confidence level of 0.15, the final result obtained by mining algorithm is shown in Table 2.

If the minisub value is too large, the useful association rules data mining hidden may not be determined, leading to the inability to generate sufficient response to trainees training habits, to achieve the recommended service

trainee's association rules; there may be any valid association rules that cannot be generated, leading to the analysis of association rules being a waste of time and resources. In this paper, through constant debugging, the value of minisub is determined to be 0.2, and the confidence level is set to 0.15. That is to say, if training A, B's support degree and confidence level are greater than 0.2 and 0.15, it indicates that trainees can try to train B while training A. According to this rule, the trainees who have completed the training A can be trained. On the one hand, researchers select all training data for mining association rules and select the whole trainee to do all the training history data association analysis. Association mining results are shown in Figure 4.

Table 2 and Figure 4 show that, after completing the TP311.5/306, the trainee has a 44.444% probability to continue to finish H315/486 and, at the same time, 31.034% probability to continue to finish TP361.81/152. In addition to completing the TN710.43/313 trainee, there is a 41.167% possibility of continuing the TN710.43/5 87, and there is a 42.857% possibility of continuing to complete the TN405/17. But from the mining results, we can see that the confidence level of all the results is not more than 50%, so we can infer that the trustworthy strength of the obtained association rules is not enough. The degree of influence that can be provided in future recommendation is only at a certain level, and it can produce little effect in promoting the training decision-making level of physical education. Then, researchers do association rule mining in the clustered group and analyze the above results of the association rules mining for the whole trainee, researchers know that the result is not ideal, and the confidence level of all association rules is not more than 50%.

Research and analysis of the reasons for this deficiency may be related to the characteristics of the trainees in universities. Different trainers of sports interest will have different training behaviors when they finish training. Therefore, in order to optimize the training decision of the college physical education curriculum, it is necessary to find the characteristics of the sports interest of the different trainees. In summary, from the results of clustering group association mining, we can see that the results obtained in groups with similar training interest are ideal. In all trainees training records (selected transaction data set), trainees have strong correlation between different sports training in their respective majors and hobbies. When a trainee completes one of his training items, he can find out the rest of several sports items according to the rule set to recommend. When the trainee wants to choose different sports training items, it can also provide recommendation information for teachers or other trainees.

5. Conclusions

This paper studies the technology of association rule mining, introduces the basic principles and process of mining association rules, analyzes the advantages and disadvantages of the classic association rule Apriori algorithm, focuses on the optimization strategies for the shortcomings, and draws on the storage of hash tables. Hash table, memory saving, fast

TABLE 2: Association mining results.

Consequent	The aforesaid	Support degree %	Confidence degree %
TP311.5/306	H315/586	55.262	55.555
TP311.5/178	TN505/17	55.902	39.286
TP3 11.5/153	TM 133/87	50.82	29.032
022.52/557	029/53	350526	28.571
TN710.53/313	TN505/17	220951	52.857
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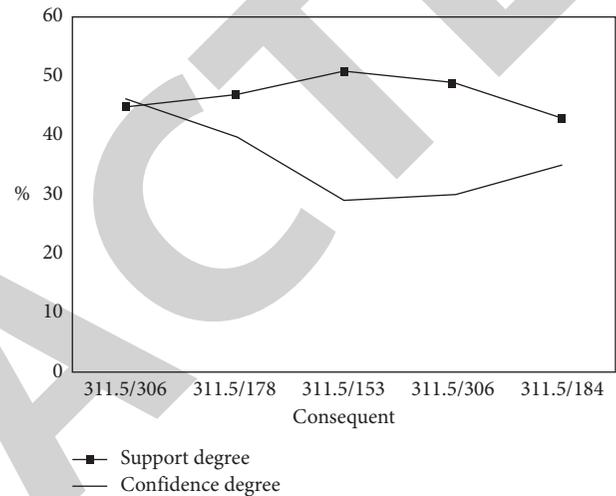


FIGURE 4: Association mining results.

search speed, etc. propose an improved Apriori algorithm, Apriori-hash algorithm, which is a basic hash table. And it is applied to the correlation analysis of sports training decisions. In the university sports training project, researchers extract training history data for a period of time, clean, transform, and integrate them to obtain a data set that meets the requirements.

The cluster analysis algorithm is used to cluster the trainees to form groups with different sports interests. Then, the new association rule mining algorithm proposed in this paper is used to mine association rules from two aspects. On the one hand, in all selected data sets for association mining, it shows that the results are not very satisfactory. On the other hand, according to the results of clustering, we can extract training information from the trainees, and the result is very ideal. It is possible to find patterns of rules, form a set of suggestions, and develop physical exercises for trainees who are more consistent with their interests and characteristics. In the future, we will continue to work on related research to promote the further development of the field of sports training.

Data Availability

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

Conflicts of Interest

The author declares that they have no conflicts of interest.

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