

## *Retraction*

# **Retracted: Live Multiattribute Data Mining and Penalty Decision-Making in Basketball Games Based on the Apriori Algorithm**

### **Applied Bionics and Biomechanics**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1].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] J. Zeng and B. Jia, "Live Multiattribute Data Mining and Penalty Decision-Making in Basketball Games Based on the Apriori Algorithm," *Applied Bionics and Biomechanics*, vol. 2022, Article ID 6968789, 11 pages, 2022.

## Research Article

# Live Multiattribute Data Mining and Penalty Decision-Making in Basketball Games Based on the Apriori Algorithm

Jian Zeng<sup>1</sup> and Bao Jia <sup>2</sup>

<sup>1</sup>Mianyang Teacher's College, Sichuan, China

<sup>2</sup>Faculty Education College, Shaoxing University, Zhejiang 312000, China

Correspondence should be addressed to Bao Jia; 202121000939@stu.swpu.edu.cn

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The Apriori algorithm is used to conduct an in-depth analysis and research on the relationship between data mining and penalty decision of multiattribute data in the basketball game scene. The technical and tactical features are analyzed using an improved Apriori algorithm for association rule analysis of basketball game data. The algorithm generates association rules based on mining the set of frequent items among basketball technical actions. The improved algorithm can mine the technical moves that are more connected in the game data, and the analysis results are highly instructive. The technical and tactical directed analysis is divided into two parts: technical and tactical directed action analysis and technical and tactical directed cooperation analysis. The key action analysis uses Markov process-based data mining algorithm to analyze the basketball game data for key score transfer steps and key score loss transfer steps. The algorithm can find the key actions of scoring and key actions of conceding points in the game process, and the analysis results can guide basketball training and games, which has high practical value. Using the collated game data as the independent variable and the number of games won and lost as the dependent variable, logistic regression analysis is applied to derive the characteristics that affect winning. Again, the decision tree algorithm is used to select the significant features that affect winning and to make predictions of team performance. Finally, the technical statistics of the main players in the last three seasons are selected, and the association rule algorithm is applied to derive the degree of influence of player performance on the outcome of the game.

## 1. Introduction

Data mining is a key step in knowledge discovery in a database, which is the result of long-term research and development on database technology. International conferences on data mining have been gradually carried out, and major famous journals have added special issues on data mining, and the focus of research has gradually shifted from discovery methods to system applications, and the interpenetration of data mining and other disciplines, and the effective combination of various discovery strategies and techniques. In recent years, we have focused on the research and improvement of Bayesian methods and Boosting methods, the application of traditional statistical regression methods in KDD, and the close integration of KDD with databases [1]. The application side includes continuing to

generate and improve KDD commercial software tools, focusing on building an overall system for problem solving rather than an isolated process. Users are mainly concentrated in large banks, insurance companies, telecommunication companies, and the sales industry. In foreign countries, data mining technology has been widely used in finance, retail, telecommunication, government management, manufacturing, medical services, sports business, and other industries with a high degree of information technology. And its application on the web has become a hot spot [2]. The application of web information mining involves numerous aspects such as e-commerce, website design, and search engine services. In addition, many computer companies attach great importance to the development and application of data mining, and IBM and Microsoft have set up corresponding research centers to carry out work in this area [3]. In addition, some

companies' related software has started to be sold in China, such as Platinum, BO, and IBM. For different fields, R&D personnel has developed many special data mining tools. The diversity of data mining tasks determines that data mining faces many challenging topics. For data mining researchers, designing data mining languages, adopting efficient and useful data mining methods for system development, and building interactive and integrated data-mining environments are the main issues to be faced. With challenges come solutions, and this section looks at the trends in data mining from this perspective [4].

For data mining, it is an emerging technique invented to seek useful knowledge in a huge amount of data, and it is an important tool for knowledge discovery of our complex and large amount of data in the database. It targets various forms of data by using suitable algorithms to find the hidden knowledge behind the data. In data mining, the basic task is to analyze all or part of a large amount of data to extract previously unknown, useful, and interesting patterns. Data mining uses a variety of methods such as classification, clustering, association analysis, and other common methods [5]. The first algorithm proposed for obtaining frequent patterns in association analysis is the Apriori algorithm, which is also one of the classical methods for obtaining frequent patterns. Its origin comes from the story of two seemingly unrelated goods, diapers, and beer [6]. The Apriori algorithm has been a very interesting algorithm for researchers since its appearance until today. Its impact on association rules has been profound and on the advancement of data mining. Today, with the constant advancement of technology and the influx of Internet users, the scale of data involved in related problems has been different from the past, and the Apriori algorithm itself performs a scan traversal of the database in each iteration which is very time-consuming in terms of efficiency. It is difficult to meet my needs, and currently, the relatively popular research direction for the Apriori algorithm is to improve it or combine it with modern technology to compensate for its shortcomings.

Nowadays, the competitive level of basketball tournaments in the world is constantly improving, and the level of domestic basketball leagues has taken a place. With the rapid development of data mining technology, people's requirements for the degree of informationization of basketball games have gradually increased. After the data in the basketball game database is extracted, mined, and analyzed, there is a lot of valuable information hidden in the results, and these valuable data and information play a pivotal role in the further development of the domestic basketball career. To achieve the above idea, it is necessary to use data mining techniques to accomplish. By comparing data mining techniques such as association rule, genetic algorithm, and decision tree, association rule algorithm is selected to be more suitable for the field of a basketball game.

This paper uses the association rule Apriori algorithm for data mining to generate association rules and derive reliable analysis results based on association rules. It first focuses on the basic idea and key issues of the association rule Apriori algorithm in data mining. Then, it mainly studies that the association rule Apriori algorithm is improved

for basketball game mining data. Finally, the improved association rule Apriori algorithm is validated utilizing examples and experiments to verify that it can be effectively implemented and adapted to the important application area of basketball games.

## 2. Current Status of Research

The organizing committee of the American Professional Basketball League (MLB) began to collect data information related to basketball players. Initially, basketball game data was entered manually for statistical analysis [7]. The level of computer technology has improved substantially, and the collection, statistics, analysis, and management of data by the organizing committee of the American Basketball League became increasingly mature and stable, establishing specific basketball databases in which video analysis technology is used to introduce data information on details such as open shots hit rate, offensive scoring area, and turnover rate [8]. Since the 21st century, player metrics have been established by using fine-grained analysis of higher-order data, and data on the impact of a player's presence or absence on the overall team, the impact of psychological effects, and the degree of performance in critical moments have also been statistically analyzed [9]. From 2010 to date, researchers have set visual tracking data analysis techniques as a new development goal. However, the application of data mining and analysis techniques in basketball games is still in the exploration and research stage [10]. Two commonly held views on home-court advantage are also discussed; one view is venue perception, where the home team is more familiar with the venue of the game and can take better advantage of it. The other view is the journey, the interruption of family life, and the fatigue of living away from home due to the visiting team going away to play. Barsky oppose these two views and argue that home-court advantage is attributed to the enthusiastic support of hometown fans. The home players tend to elicit enthusiasm and cheer from the hometown fans, and this is what the players call energy [11].

Predicting game outcomes is particularly common in sports; for example, sportsbooks will set odds before a game based on the strength of both sides to predict the game-winner, coaches will adjust their tactics based on the predicted game outcome, and fans will likewise roughly predict the outcome of the game in their minds. Statistical prediction requires finding factors that affect the outcome of a game based on historical data and using the interaction of factors to make inferences to achieve a prediction [12]. Predictions are often flexible, with different prediction methods having different levels of accuracy and applicability. For statistical prediction, data completeness, factor accuracy, and model selection are crucial [13]. Güder et al. argue that the likelihood of a baseball win depends on various factors related to team strength, including the past performance of the two teams, the hitting ability of the two teams, and the starting pitcher [14]. These three factors form a relative strength parameter based on different contribution parameters and vary over time. They combined the relative intensity parameter with the home field advantage variable to form a two-

stage Bayesian model. A Markov chain-Monte Carlo algorithm is then used to make Bayesian inferences and simulate the outcome of the game—in the first stage, the probability of a team winning is assumed to be a random sample from a Beta distribution parameterized by the relative strength and home-field advantage variables [15]. In the second stage, the game outcome is assumed to be a random sample from the Bernoulli distribution parameterized by the probability of winning, i.e., a random sample from the Bernoulli ( $P$ ) distribution with probability  $P$  as a function of the relative strength variable and the home-field advantage.

The research background and research significance of the topic are described in the context of the actual needs of sports computing development. Different from the traditional statistical analysis methods, this paper proposes the use of data mining techniques to solve the problem of basketball technical and tactical analysis, solving the problems of the small data volume of statistical methods and the inability to conduct high-level analysis. On this basis, the current research status and development trend of data mining technology and the current situation of basketball technical and tactical analysis are outlined, and the research content and research methods of this paper are described. It mainly includes the relevant concepts of data mining technology, the data mining analysis method applied to this paper, and the introduction of the basketball game information collection system. Firstly, the data processing design of basketball script information is introduced, and on this basis, the key techniques for implementing the basketball technical and tactical analysis system are introduced in detail. Including association rule algorithm, clustering algorithm, and Markov process-based data mining algorithm, the detailed design of the application of the algorithm in basketball technical and tactical analysis system is presented, and the improved method of Apriori algorithm is proposed. It includes database design, system architecture, functional design, algorithm generalization design, and the design and application of each functional module. A case study approach is used to test each module of the basketball data mining tool for one game data.

### **3. Apriori Algorithm for Live Multiattribute Data Mining and Penalty Call Decision Analysis in Basketball Games**

*3.1. Improved Apriori Algorithm for Multiattribute Data Mining Design.* Association rule mining is an important topic in the field of data mining. It finds strong association rules by mining frequent itemsets. It uses an iterative approach to generate high-dimensional frequent itemsets by low-dimensional frequent itemsets. In this section, after a brief description of the design method of basketball scripting language, the design method of the Apriori algorithm in mining association rules of basketball technical moves is introduced, and the effectiveness of the Apriori algorithm is further demonstrated [16]. In the basketball technical and tactical analysis system, the improved Apriori algorithm is used to analyze the technical and tactical characteristics of

basketball games. The main purpose is to analyze the potential relationship between the technical actions of basketball games, find the association rules with high correlation and high confidence, and view the actual data of the game according to the analysis results, which can play a role in assisting the coaches' decision-making.

The Apriori algorithm is a typical algorithm for finding frequent itemsets in a transactional database. By frequent itemsets, we mean those itemsets whose support is greater than or equal to the minimum support. The implementation of this step requires multiple scans of the entire transactional database, which consumes a lot of time and space, so this is the key constraint on the efficiency of the Apriori algorithm operation. The implementation of the algorithm is briefly described below. The Apriori algorithm uses a recursive approach to find all the frequent itemsets present in the transaction database. First, each item in the transaction database is used as a candidate itemset, the database is scanned, the support of each itemset is counted, and the itemset whose support is greater than or equal to the minimum support becomes the set of frequent itemsets; then, the set of candidate itemsets is generated by connecting the frequent itemsets, and the set of items that satisfy the minimum support is greater than or equal to the set of frequent itemsets, and so on until it is empty, the algorithm stops. Among them, the generation of candidate itemset is done in two steps, and the candidate itemset is used as an example for illustration, as shown in Figure 1.

Apriori algorithm in the process of iteration, whenever to generate frequent itemset from candidate itemset, it must scan the database, and if the dimension of a frequent itemset is too large, doing Cartesian product will generate many candidate itemset; both above reasons will make the efficiency of the algorithm greatly reduced. In this paper, we address this problem and make necessary improvements to the algorithm. The improved idea of the algorithm is as follows. Firstly, the data in the database is read into the memory at one time to avoid the time and space overhead caused by scanning the database and to improve the operation efficiency of the algorithm. Take the basketball tactics analysis system as an example, the data to be read into the memory is the game script table. A game has about  $1000 \times 200 - 200000$  bytes [17]. Looking at the amount of data in a basketball game, it is perfectly feasible to read the basketball script data into memory. Each item in the transaction data table, the total number of transaction data, and the frequency of occurrence of the item are read into the vector container into memory at once. Perform algorithmic iteration on the transaction data in memory: Implement a generic algorithm to generate frequent itemset files for storage and generate association rules based on the file data. The results of association rule analysis are censored using business knowledge. A distinctive feature of association rule analysis is the uncertainty of the analysis results. Among the many association rules, there may be rules that do not match or even are contrary to the facts, which requires censoring the association rules based on business knowledge. In addition, the generation of association rules can also be controlled by setting the minimum value support and minimum

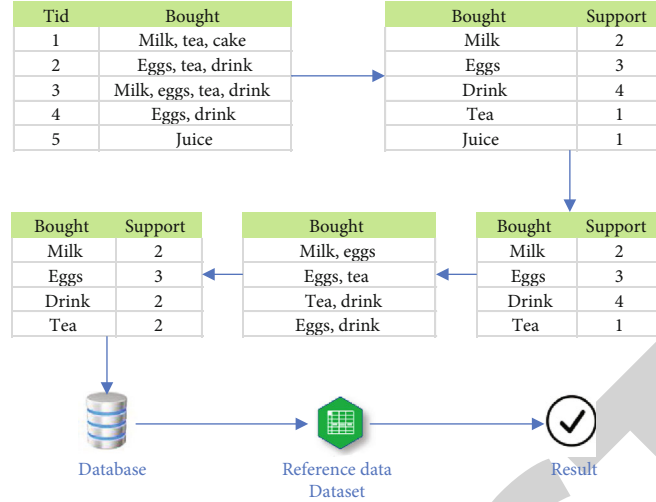


FIGURE 1: Flowchart of the improved Apriori algorithm.

confidence, and this paper will combine these two methods to control the generation of association rules and improve the usefulness of association rules in basketball technical and tactical analysis system.

$$S(x \Rightarrow Y) = \frac{\sigma(X \cap Y)}{D}. \quad (1)$$

The confidence level of the association rule is defined as follows:

$$D(x \Rightarrow Y) = \frac{\sigma(X \cap Y)}{\sigma(X \cup Y)}, \quad (2)$$

$$p = \frac{\sum_{i=1}^D |t_i^3|}{D \cdot I}. \quad (3)$$

This property, also known as the a priori principle, can be used in frequent itemset mining to reduce unnecessary computations and improve the efficiency of frequent itemset mining. If an itemset is nonfrequent, then all supersets of that itemset are nonfrequent. This property is also known as the inverse monotonicity of the support measure. In general, by association rule mining means mining of strong association rules. And to get the strong association rules, primarily, is to find the set of all frequent items in the transactional database  $D$  that satisfy the minimum support measure. Therefore, most association rule mining algorithms focus their main efforts on how to mine the frequent itemsets. Find all frequent itemsets that satisfy the minimum support and the frequency of this frequent itemset. The setting of the minimum support directly affects the speed of frequent itemset mining. Based on the found frequent itemsets, generate association rules and find the association rules that satisfy the conditions (usually to satisfy the minimum support and minimum confidence requirements), i.e., strong association rules. In these two steps, the first step is to mine the frequent itemset, and the second step is to generate asso-

ciation rules. The frequent itemset mined in the first step is a prerequisite for generating association rules, and the association rules generated in the second step can better reflect the interesting connections between items in the data set, thus providing better decision support for decision-makers.

$$\text{Support}(X) = \frac{\text{Number}(X)}{N^2}, \quad (4)$$

$$\text{Support}(X \Rightarrow Y) = \frac{\text{Number}(X \cup Y)}{N^2}. \quad (5)$$

The data in the transactional database are stored in external memory, and to avoid multiple accesses to the transactional database when mining association rules on the data in the transactional database using the Apriori algorithm, the data in the transactional database needs to be compressed so that it can be stored in memory. This makes it extremely important to design a suitable data structure for compressed storage representation of the data in the transactional database. Existing improvements to the Apriori algorithm have proposed a variety of data structures for the storage representation of transactional database data, but the compression of transactional data is limited, and some data structures are designed to be too complex and instead increase data redundancy. In this paper, a simple, easy-to-implement, chain table-based data structure is proposed to compress and store the data in the transactional database, as shown in Figure 2.

As you can see from the above definitions and the description of the specific example, the IList data structure makes it easy to decompose and merge transactional databases in either a horizontal or vertical format. For example, to divide the example list above into 2 pieces in a vertical format, simply remove half of the titles from the example IList and put it into another IList; to merge, do the opposite, remove all the TidList from one IList and add it to the other IList. In a similar manner, split and merge based on

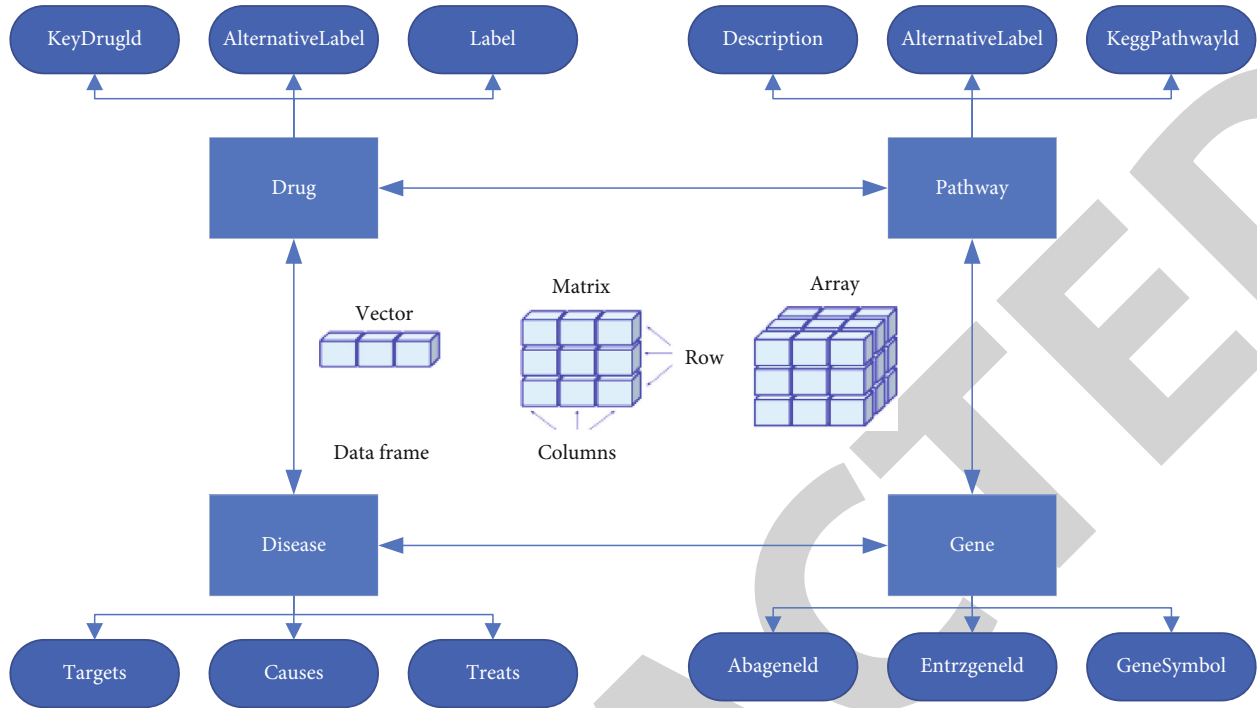


FIGURE 2: Schematic diagram of IList structure.

horizontal format simply changes the object of the operation to TidList.

$$X = \frac{x + \min}{\max + \min}, \tag{6}$$

$$L_S = \sum_{k=1}^m \ln \frac{\exp(W_{y_k}^T x_k - b_{y_k})}{\sum_{i=1}^n \exp(W_{y_i}^T x_k - b_{y_i})}. \tag{7}$$

The core idea of the cluster analysis method is to group data objects into clusters where objects in the same cluster have a high degree of similarity to each other, and objects in different clusters differ as much as possible. Cluster analysis can find intriguing patterns of data distribution in the underlying data. In basketball, there may be combinations of closely bound moves, that is, combinations of moves that are highly cohesive. In this section, cluster analysis will be used to analyze the matching movements of the specified actions. In this paper, the functional requirements of basketball technical and tactical analysis are considered while performing the cluster analysis; coaches want to discover what are the matching moves of a certain technical action, so they want to specify the technical action of interest, so that it is determined that there can be only one cluster, and the specified action is the center of the cluster. Therefore, this paper does not use any of the existing clustering algorithms but simply uses the core idea of cluster analysis.

**3.2. Experimental Design of Multiattribute Data Mining for Basketball Game Scene.** The basketball technical and tactical analysis system is another ball analysis system of the Software Architecture Laboratory after the research of volleyball

and table tennis game information collection and analysis system. The reason the Software Architecture Lab is dedicated to the development of ball information systems is that the information technology in the sports industry has not yet reached a level that matches the degree of information technology [18]. Although the number of game data in the database system is increasing, the technology for analyzing games still uses traditional statistical methods, and most coaches adjust their training and game strategies based on experience and statistics, without any substantial change in technology. The question of whether more techniques can be found to analyze data other than statistics has been answered. Data mining techniques can help with the day-to-day accumulation of match data. As we all know, the basketball game is the dominant sport in our country, especially women’s basketball. Traditional statistical methods can count the play of individual players on the court and the frequency of various technical moves, as well as the scoring of 2-pointers and 3-pointers, etc. All these indicators are important indicators to measure the win or loss of basketball games and to measure the overall ability of the team. However, when analyzing the potential correlation between technical moves in a game, analyzing the cooperation between technical moves, or even which technical moves determine the winner of a game through the basketball technical and tactical analysis system, the statistical method is no longer able to solve the problem, as shown in Figure 3.

The data mining approach can help to solve several of these problems, which are exactly the problems that need to be solved in the basketball technical and tactical analysis system from the characteristics of the basketball game. The following is a detailed analysis of the needs of basketball technical and tactical analysis systems [19]. To see, the

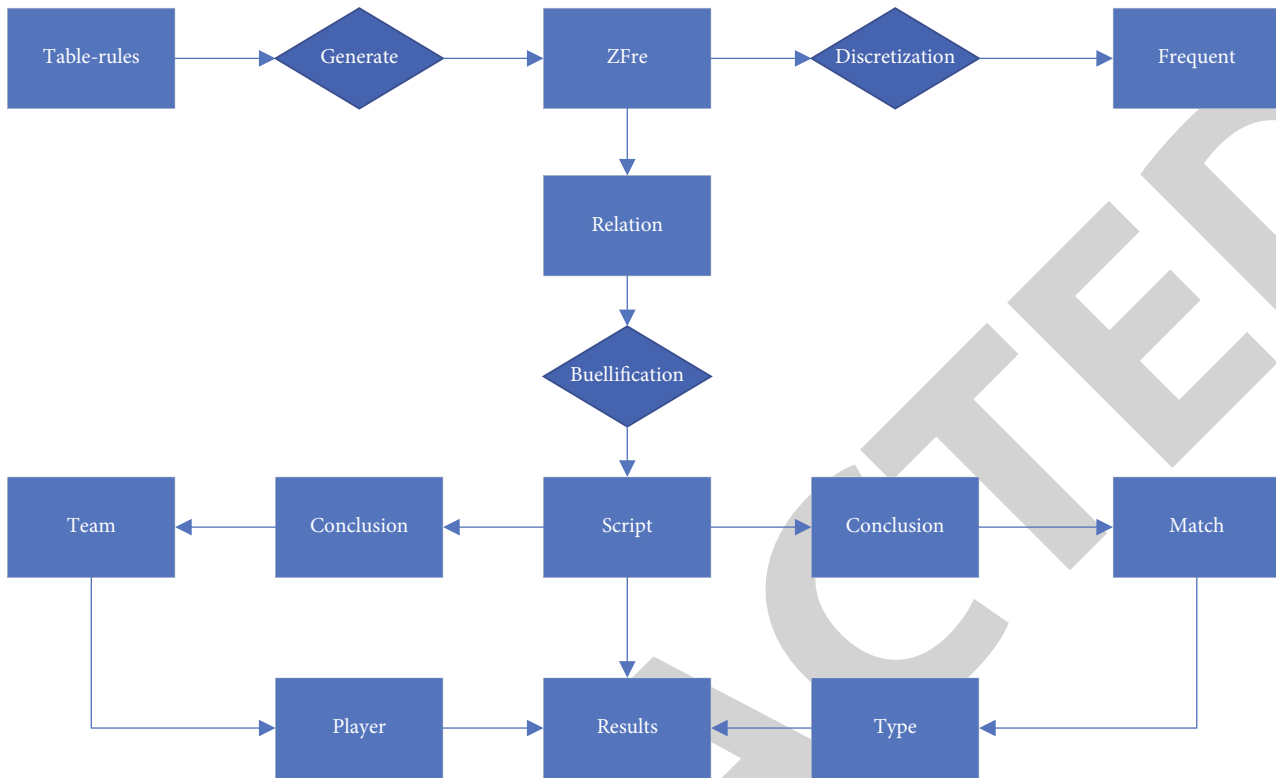


FIGURE 3: Database system diagram.

basketball game in the form of multiplayer cooperation sports, there are various cooperation between players if a link does not cooperate well, the whole offense or defense will fail. According to the requirements of the system in terms of performance and functionality, the architecture of the basketball technical and tactical analysis system can be derived. The data mining application in basketball technical and tactical analysis mainly uses five layers: database layer, data extraction, data conversion, data mining, user invocation, and visual interface display. The database layer provides data sources for this system; the data extraction and conversion layer mainly extracts basketball game data from the database and performs data preprocessing to provide mining data for the mining algorithm layer; the algorithm packaging layer mines the preprocessed data to produce useful information; for the user invocation layer, it invokes the specific mining algorithm in the mining tool according to the user's needs to generate the information required by the user. The display layer displays the user information generated by mining through visual graphics. Figure 4 shows the architecture of the basketball technical and tactical analysis system.

The analysis of technical and tactical characteristics is based on the association rule analysis method. The function mainly includes two parts: association rule analysis and association rule retraction, which are introduced in detail below. The association rules are arranged in order of confidence from highest to lowest. The whole process is smooth, and the data processing speed can reach the response time requirement of 5 s. To let users understand the association

rules found, an extension function is added to the system, namely, the association rule backtracking function. By double-clicking on an association rule of interest, the script records related to the association rule in the selected match can be listed, which is convenient for the user to understand and view the match process [20]. The analysis of technical and tactical directed actions uses the association rule analysis method combined with certain statistical methods. The function mainly includes the correlation analysis between the specified actions, the statistical analysis of the landing points of the specified actions, the statistics of the scores of the specified actions, and the statistical analysis of the follow-up actions of the specified actions.

As the competition of basketball techniques and tactics and the exchange of basketball culture become more intense, its influence does not make the basketball game towards the development path of technical and tactical play tends to be single [21]. Under the influence of this atmosphere, various basketball technical and tactical styles are constantly pushing out new ideas and advancing with the times in the intersection and collision and jointly promoting the rapid development and innovation of the world basketball, during which the new ideas, new features, and new trends, always impacting and challenging people's traditional thinking and traditional practices. Currently, the data in basketball is increasing rapidly, and increasingly valuable information is not easily accessible to people. Therefore, data mining techniques are needed to discover the relevant rules in the information.

The main task of this session is to clean out the incomplete, duplicate, wrong, or noisy data. For example, if the

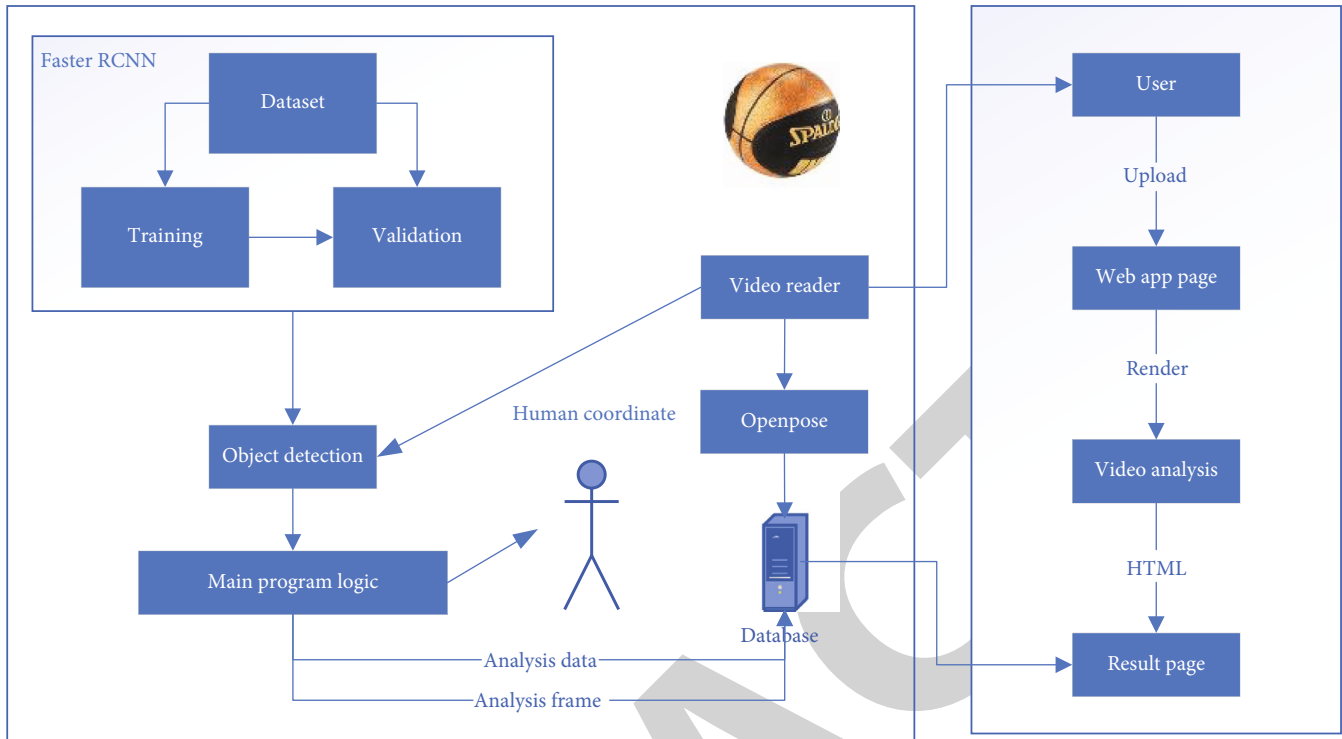


FIGURE 4: System structure of basketball technical and tactical analysis system.

extracted data does not contain how the players cooperate in passing, it can be directly deleted; for the case of missing data, it can be manually filled, or this data can be directly deleted. These data cannot be directly mined for association rules, or the mined results are not satisfactory. Therefore, to improve the quality of association rule mining, the data needs to be cleaned. Data transformation is to crawl and process all the data of basketball players playing with each other and getting scores and convert the foreign players' names into program-usable item identifiers by one-to-one association with corresponding items through a data transformation table, which aims to guarantee the mining of valid association rules.

#### 4. Analysis of Results

**4.1. Results of the Improved Algorithm.** Rebounding is the lifeline of every team, and for the Warriors, who lack a strong inside presence, protecting the front and backcourt rebounds can effectively increase the number of offensive and defensive transitions, improve the tempo of the game, and prevent the opponent's interior from playing into second-chance points and causing kills. The importance of rebounding cannot be overstated. Because the Warriors are a team with both superstars and a very mature tactical system that relies on team play, the number of assists in a game can greatly reflect whether the pace of the game is within the control of one's team and will have some impact on the outcome of the game. The number of turnovers is an important basis for considering a team's clinical performance and the level of team understanding. Steals and caps are important

indicators of the quality of a team's interior and exterior defense, respectively, and points allowed are a composite of a team's defensive quality. In addition, for the American court culture, the home and away game system can also cause some impact in terms of court atmosphere and players' mental combativeness. Therefore, some of the selected data are shown in Figure 5.

Logistic regressions were conducted to explore the winning indicators using the outcome of the game as the dependent variable, a binary variable with winning as 1 and not winning as 0. Logistic regressions were conducted using home and away, home as 1, and away as 0. Shooting percentage, 3-point field goal percentage, free throw percentage, rebounds, assists, steals, caps, turnovers, and points allowed per game as independent variables. Shooting percentage, three-point field goal percentage, free throw percentage, rebounds, assists, and steals all play a positive role in winning the game to varying degrees, especially the two items of shooting percentage and three-point field goal percentage. With other predictor variables held constant, each percentage point increase in shooting percentage will multiply the margin of victory ratio by 14.9 and 2.5, respectively, and the probability of winning the game will increase significantly. With the lack of a strong interior presence and most of the offense outside of the three-second zone, maintaining shooting consistency and sustaining a high level of shooting percentage become the most critical factor for the Warriors to win as the distance to the basket gets longer. The offense is fast, and the style of attack is small, fast, and agile. Securing rebounds can effectively increase the team's offensive and defensive turnovers and speed up the pace of the game.



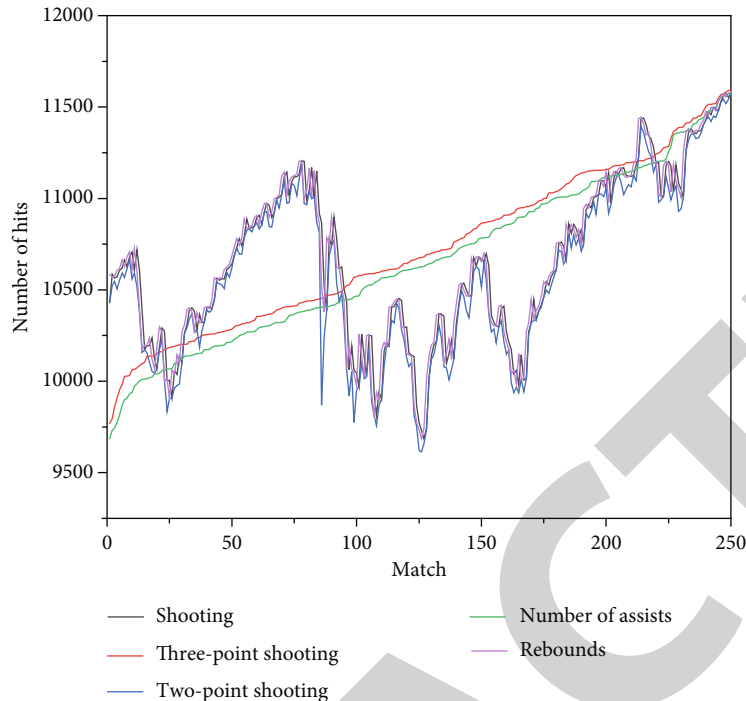


FIGURE 5: Competition data.

And securing the team's backcourt rebounds will also effectively organize the opponent's second close-court offense and reduce the opponent's kill on the team. Steals, on the other hand, are another great tool for securing the Warriors' offensive efficiency.

The player efficiency index (PER) is a product of player data collection and analysis. ESPN commentator John Hollinger developed it after years of experience covering basketball games and collecting and analyzing basketball data. It is now widely used by teams around the league as a measure of a player's value to the team. The index is calculated by weighting the player's basic statistics (e.g., points and assists) during a game and considering several technical indicators to calculate the player's efficiency index. The index allows for not only horizontal comparisons of players in the same position, team, and season but also annual vertical comparisons, thus providing an objective assessment of player value, as shown in Figure 6.

With different platforms and software giving different types of data, team management and coaching staff can not only grasp the dynamics of a player's level of play but also identify the competitive characteristics that different players possess, such as the player's common scoring style and offensive hot zone. These characteristics can either translate into strengths in the game or become bottlenecks that hinder a player's development. Therefore, the collection and analysis of player data provide the coaching team with relevant analysis of these characteristics, so that they can reasonably arrange offensive and defensive tactics, maximize the "chemistry" of the team, and improve the overall strength; with the sharing feature of the data platform, the coaching team can also analyze the technical and tactical styles of other teams

by referring to their data, to the data platform is shared, so that the coaching team can analyze the technical and tactical styles of other teams by referring to their data, to "know oneself and one's enemy."

**4.2. Data Mining and Sentencing Decision Results.** With the application of new technologies, the collection of basketball game statistics is no longer limited to basic data. Data such as rebounding average, points scored, turnovers, and assists are gradually replaced by data on breakdowns, potential assists, and propensity to make fouls when players and teams are evaluated for performance, and rating metrics regarding defense have been added to analyze data more relevant and comprehensive. The system can also collect unstructured data, such as the number of touches of a team in the restricted area, and further refine these data to produce more accurate ratings. For the team builder, the data collection and analysis technology of basketball undoubtedly bring an important basis for scientific decision-making, while for the audience of the professional basketball league, the attention to the game is not only limited to the playback of the game video but also more comments on the performance of players and teams, which increases the viewing appeal of professional basketball league and is conducive to the promotion and development of professional basketball league. The different stages of technical development mentioned above can be seen that the means of data collection and analysis of foreign basketball games are changing day by day, and more often than not, they rely on the collection and analysis of higher-order data to develop highly targeted and refined indicators that can be better applied to the evaluation of individual players' competitive ability, such as the

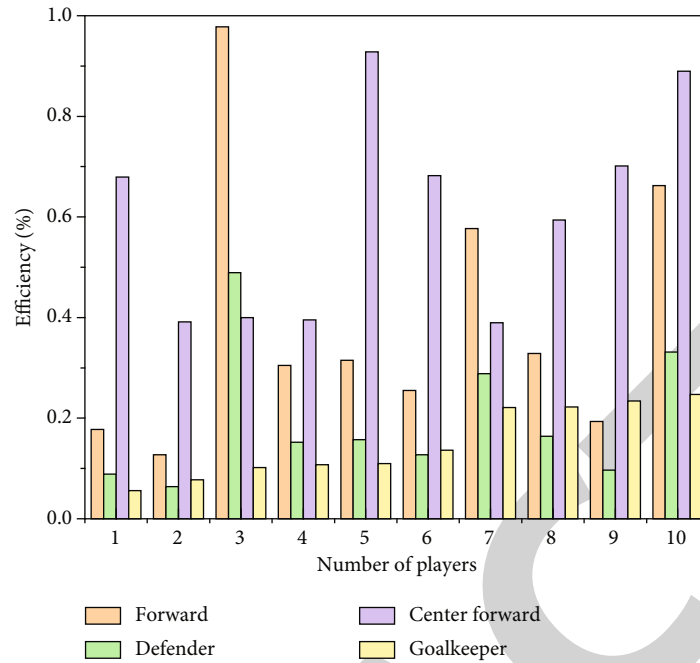


FIGURE 6: Statistical chart of player efficiency index.

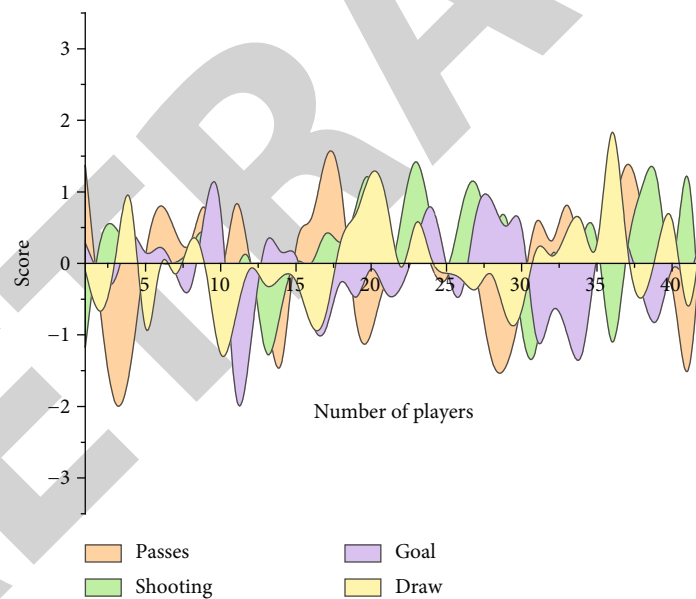


FIGURE 7: Graph of the results of the analysis of scoring key actions.

way players score in games, the correlation study between rest periods and team performance, and the analysis of win-making factors, as shown in Figure 7.

This paper improves the association rules Apriori algorithm from scanning database, storage of frequent itemsets, and filtering of association rules in three. Improvements are made to improve the efficiency of Apriori and to enhance the usefulness of association rules. The general design and implementation of the algorithm are also important to work completed in this paper. In this paper, the Apriori algorithm and the data mining method based on Markov process are

designed and implemented in general, and an application interface is provided. Only the corresponding data is needed to output the results of the algorithm operation, and the design is implemented in the basketball technical and tactical analysis system, and it is proved by the system operation that the algorithm can complete the analysis task well, as shown in Figure 8.

Firstly, we analyze the requirements of the association rule-based basketball player optimization combination system; secondly, we establish a data mining model for the system and describe the data collection and preprocessing

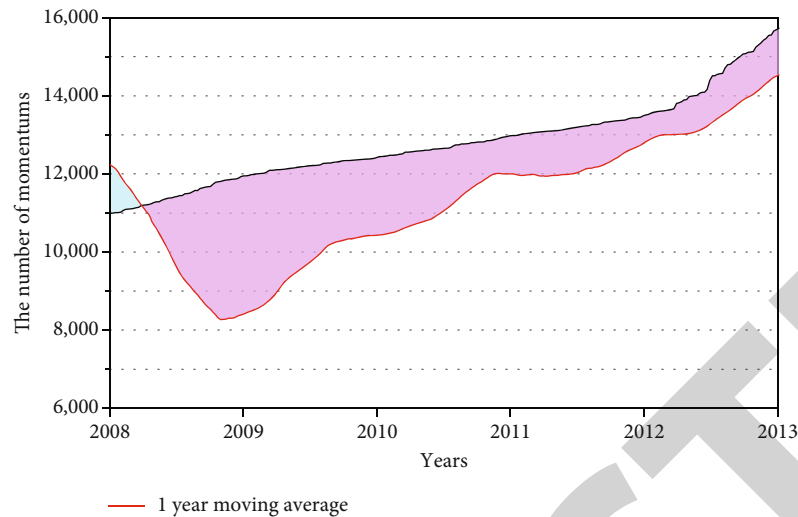


FIGURE 8: Time series plot of changes in.

process; finally, we elaborate on the application of the L-Apriori algorithm on basketball player optimization combination. Finally, the application of the L-Apriori algorithm on basketball players' optimal combination is elaborated, and the association rule mining results are presented in the form of visualization, while the association rule mining results are thoroughly analyzed and interpreted. Ultimately, the purpose of guiding coaches to make adjustments and decisions for players on the court is achieved.

## 5. Conclusion

By comparing the performance with the traditional Apriori algorithm for the different number of database transactions and different support thresholds, it is easy to find that the Apriori algorithm has better execution efficiency than the traditional algorithm for basketball player optimization portfolio. The presentation of the mining results is a very important part of the process. In the research process of this paper, the platform of basketball player optimization combination data mining system is built, the data mining model is established, the steps of data mining are given, and the results of data mining are displayed visually. Finally, the association rule mining results are analyzed so that people can have a better understanding of the analysis results. To adapt to the context of big data applications as well as to improve the applicability of the Apriori algorithm, two different task decomposition strategies based on the horizontal division of transaction database and vertical division of transaction database are chosen to apply the Apriori algorithm on the Hadoop framework for building distributed systems to meet the needs of big data mining. The transactional database horizontal partitioning strategy first mines the local frequent itemsets and then mines the global frequent itemsets from the local frequent itemsets, while the transactional database vertical partitioning strategy first mines the partial frequent itemsets, then performs the join operation on the partial frequent itemsets to construct the candidate itemsets, and then mines the remaining frequent

itemsets from the constructed candidate itemsets, to finally obtain the full frequent itemsets. The results of running the prototype system show the feasibility and practical value of the two different strategies for the application of the algorithm on distributed platforms.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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