

Retraction

Retracted: Mining and Prediction of Large Sport Tournament Data Based on Bayesian Network Models for Online Data

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets 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 own 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. Wang, "Mining and Prediction of Large Sport Tournament Data Based on Bayesian Network Models for Online Data," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1211015, 8 pages, 2022.

Research Article

Mining and Prediction of Large Sport Tournament Data Based on Bayesian Network Models for Online Data

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In the modern society, competitive sports have an essential place in the world. Sports can reflect not only the comprehensive strength of a country to some extent but also the cohesion of a nation. Therefore, as China's overall strength and international influence continue to rise, sports are being given more and more importance. At the same time, research and exploration on the prediction of match results have also become a hot topic. In the large sport tournaments, there are many factors that influence the outcome of a match. In actual matches, the outcome is not only determined by the strength of the participants, but also by a number of unexpected factors. The randomness brought about by these unexpected factors makes it difficult to predict the outcome of a sporting event. In recent years, many researchers have sought to enhance the understanding of complex objects with the help of prediction of sporting outcomes. One of the more traditional methods of prediction is the probabilistic statistical method. However, the traditional prediction methods have low accuracy and do not provide satisfactory stability in the prediction results. In fact, since most sporting matches are played against each other, the ability values of the players often play a key role in the match. They can determine the winner of a match, but unexpected factors such as player play, playing time, and injury situations can also have an impact on the strength of a playing team, so these factors should not be ignored. This study establishes a reasonable causal relationship between the offensive and defensive situations in the game and the players' ability values and builds a complex Bayesian network model. A match prediction model is then built using the latent variables present during the match so that the various ability values of the match teams can be assessed.

1. Introduction

Athletics is one of the most watched and popular sports in the world. Apart from athletics' spectacle, its greatest characteristic is the unpredictability. It is because of this unpredictability that it becomes quite difficult to predict the outcome of a game when watching it [1]. In many major sporting events, the outcome of the game can change in a split second. In reality, there are many factors that can affect the outcome of a match. The outcome of a match is influenced by a number of factors including physical, psychological, technical, tactical, and environmental factors. Technical and tactical skills have a direct impact on the outcome of a match and are considered to be the core factors in winning a match. Although strength is the dominant factor, psychological factors, the play of the player, and other unexpected circum-

stances can also be important factors in determining the outcome of a match [2]. These factors are also random and uncertain, resulting in unpredictable results in competitive matches. Hence, uncovering key technical and tactical behaviors in the game in order to predict the outcome has been a central concern for coaches and players. In recent years, as competitive sport has become increasingly important, match analysis and prediction have turned into an important area [3]. In professional basketball, for example, team owners spend a lot of money on their teams each year. In order to avoid spending money on players who do not help the strength of their team, they will hire data analysts who spend much time trying to predict which team will win the championship each year, thus making a higher financial gain commercially. At the same time, many viewers want to be involved in predicting the outcome of games. In

the context of statistics, the prediction and analysis of competitive sporting outcomes have been transformed from a competition to a discipline [4]. Researchers have attempted to use a large number of technologies to analyze match data to predict the winner of a match, such as machine learning [5, 6], neural network [7], and efficacy model [8]. As much of sport is played between teams and the coordination between players is important, considering the individual statistics of the players can provide a more accurate analysis of the impact of the players on the win or loss and their contribution to the team.

With the continuous development of the Internet and big data technology, modern information technology has been widely used in the field of sports and has become a powerful driving force for the rapid development of sports. In today's sports research, it is important to find out how to deepen the interconnection between various factors from a large amount of game data [9, 10]. In sports competitions, a large amount of data about athletes is often generated, which can be applied for statistical and analytical purposes. Therefore, it is extremely necessary for sports training in today's sports research to dig deeper into the interconnections between various factors from the large amount of competition data so that it can accurately provide valuable information for people to use. The data mining techniques related to sports involve player training and field games, school sports management, sports industry, national fitness and national fitness research, and optimization [11]. The data mining techniques for player training include various physiological indicators, fitness test data, technical and tactical use statistics, and statistical analysis of opponent information [12]. Hence, the data analysis related to sports becomes essential in modern's sport tournaments.

In the large sport tournaments, there are usually only two outcomes, namely victory and defeat. A large number of techniques exist to compress the performance of athletes into the strength of a team [13]. These models approximate the parameters of multiple athletes as the overall strength of a team, i.e., the cooperation and confrontation between athletes is seen abstractly as a duel between teams as a whole. Among them, ELO rating model is one of the best-known forecasting models. It is a probabilistic model that approximates the probability of a team beating its opponent as a function of the difference in strength between the two teams, thus predicting the outcome of a match in probability [14]. Aldous improved Elo rating algorithms in order to track the changing strengths between two different teams in one match [15]. Angelini et al. developed the weighted Elo rating model, which not only considers the probability that a team can win in a match, but also how the victory can be achieved, and found that this new method outperforms other similar approaches [16]. After that, ELO rating model is optimized to the better predictive Bradley-Terry model [17]. Hankin used the Bradley-Terry model for risk aversion expressed through draw probabilities in chess tournaments and numerically optimized the resulting likelihood function with a number of chess tournament datasets [18]. Other win-loss prediction models, such as Glicko model, which applies logistic and statistical functions to model the probability of winning, are quite similar in distribution but have different convergence properties and differ in their tail distributions [19, 20].

In recent years, as predictive models have evolved, more and more models have involved team behavior and performance, and Bayesian networks have been introduced to combine multiple performance variables to infer the probability of victory. The Whole-History Rating model focuses on the dynamics of strength parameters over time, accounting for improvements in athletes' ability values as they gain experience and regressions with age [21, 22]. The TrueSkill model is adopted in both solo and team competitions and uses the Gaussian distribution as an a priori assumption of strength and performance [23, 24]. With the introduction of the TrueSkill model, the concept of athlete ability value assessment was introduced to predict the scoring of both sides of the encounter through the learning of player ability values. To be specific, the learning process for player ability values takes a Bayesian inference approach, using the Expectation Propagation algorithm in the TrueSkill model [25]. However, this algorithm does not refine the player's ability values, and there is only one player ability value variable on which all offensive and defensive situations on the field of play are shared and dependent [26]. Most sporting events are team competitions, and team competitions present additional key challenges to the field of Bayesian-based prediction. The outcome of a match is not simply the output of a win or a loss, and it is almost impossible to distinguish between players' ability values based on the outcome value of the match alone. Therefore, more complex factors need to be considered in the prediction model for practical predictions.

2. Bayesian Network

Bayesian networks are the graphical model for representing causal probability relationships between multi-attribute variables [27]. It is a network structure based on directed acyclic graphs to portray dependencies between attributes and uses conditional probability tables to describe joint probability distributions. Bayesian networks can reflect the state of some part of the world being modelled and describes how these states are associated with probabilities. It can be used in any areas that involve modelling an uncertain reality and are therefore very important in predictive modelling.

2.1. Concept of Bayesian Network. Assume that E is the set of elementary events and that the two events in E are X and Y , and $P(X) > 0$. Then, Equation (1) is expressed as the conditional probability of event Y conditional on the occurrence of event X :

$$P(X | Y) = \frac{P(XY)}{P(X)}, \quad (1)$$

After that, the Bayesian formula can be defined by the following equation:

$$P(Y_i | X) = \frac{P(Y_i) \times P(X | Y_i)}{\sum_{j=1}^n P(Y_j) \times P(X | Y_j)}. \quad (2)$$

Equation (2) can be used to determine the Bayesian probability. Bayesian probability is the degree of confidence

an observer has in whether an event is true or not, also known as subjective probability. The observer uses probabilistic methods to make predictions about the probability of an unknown event occurring, based on existing prior knowledge and the sample data obtained. The objective probability refers to the calculation of the probability of an event occurring by doing the same experiment several times. In contrast, Bayesian probability, or subjective probability, is the use of existing prior knowledge to predict unknown events.

The Bayesian network can be defined as a network that presents a series of random variables and the relationships between them in a graphical probabilistic model. Each variable represents a node in the network, and the nodes are connected to each other to form the network. To be specific, a directed acyclic graph is called a Bayesian network if it satisfies the following three conditions:

- (1) There exists a set of variables $X = \{X_1, X_2, \dots, X_n\}$ and also the set of directed edges between the nodes corresponding to the variables as S
- (2) All variables take on a finite number of discrete values
- (3) There exists a directed acyclic graph consisting of the nodes corresponding to the variables and the directed edges between the nodes

Thus, the Bayesian network can be expressed as $BN = (G, P)$, where $G = (X, E)$ is a directed acyclic graph, indicating the dependence between node variables. P is the conditional probability distribution table, showing the influence intensity between node variables. For a Bayesian network, the joint probability distribution in the set of discrete variables can be expressed as

$$P(X) = P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | Pa(X_i)), \quad (3)$$

where $Pa(X_i)$ refers to the set of parent nodes in the Bayesian network.

To better understand the principles of Bayesian networks, an example of a Bayesian network is given in Figure 1.

2.2. Graph Model. Graph models provide a framework for representing dependencies between random variables in statistical modelling puzzles and provide an intuitive way of representing the interactions between entities in a probabilistic system. Graph models use nodes to represent random variables and edges to represent dependencies between random variables. Graph models are divided into directed and undirected graphs, with undirected graphs also commonly referred to as Markovian random fields, and directed graph models, also commonly referred to as Bayesian networks. All edges, from parent to son nodes, represent the conditional dependencies of the corresponding random variables.

A directed graph model is a collection of probability distributions, dependent on the structure of a specific graph, decomposed in the manner of the above equation. An example of a directed graph model is shown in Figure 2. Nodes A,

B, C, and D represent different random variables, and each node represents a conditional probability that depends on its parent node. Using the chain rule for probabilities, the joint probabilities of Figure 2 are shown in Equation (4):

$$P(A, B, C, D; \alpha) = P(A; \alpha_a) \times P(B | A; \alpha_b) \times P(C | A, B; \alpha_c) \times P(D | A, B, C; \alpha_d). \quad (4)$$

In the graph models, random variables are divided into observable and non-directly observable hidden variables, which are usually used as sampling and computational steps in the middle of the calculation to eventually generate the observable variables. Graph models are classified as either parametric or nonparametric. If the model is nonparametric, i.e., the parameters are already fully known, then some inference problems can be applied. When calculating the marginal distribution of a subset of random variables, it is necessary to calculate the conditional distribution of a subset of variables given the remaining variables.

2.3. Latent Variable Model. In the Bayesian model, latent variables are introduced in order to keep the degree of freedom of the model manageable and to ensure its correlation. The objective of the latent variable model is to replace the variable y_1, \dots, y_d , which represents the distribution, with a smaller number of latent variables x_1, \dots, x_q . This process is achieved by first decomposing the joint probability distribution $P(y, x)$ into the product of the marginal distribution of the latent variable $P(x)$ and the conditional distribution giving the hidden variable $P(y | x)$ about the data variable. It is usually more convenient to assume that the conditional distribution is decomposed over the data variables so that the joint distribution becomes

$$P(y, x) = P(x) \times P(y | x) = P(x) \times \prod_{i=1}^d P(y_i | x). \quad (5)$$

The attributes of this decomposition can be graphically represented using a Bayesian network, as shown in Figure 3.

Next, Equation (6) shows the mapping from latent variables to the data variables:

$$y = f(x; m) + n, \quad (6)$$

where $f(x; m)$ refers to the function of the latent variable x and n is the noise process. Geometrically, the function $f(x; m)$ defines a manifold in the data space, as shown in Figure 4.

2.4. Modelling of Bayesian Network. There are three main approaches to modelling networks using Bayesian.

- (1) The nodal variables, structural model, and parameter distribution of the Bayesian network are determined by experts in the relevant field based on a priori knowledge. This approach is completely expert-driven and can lead to significant subjective bias

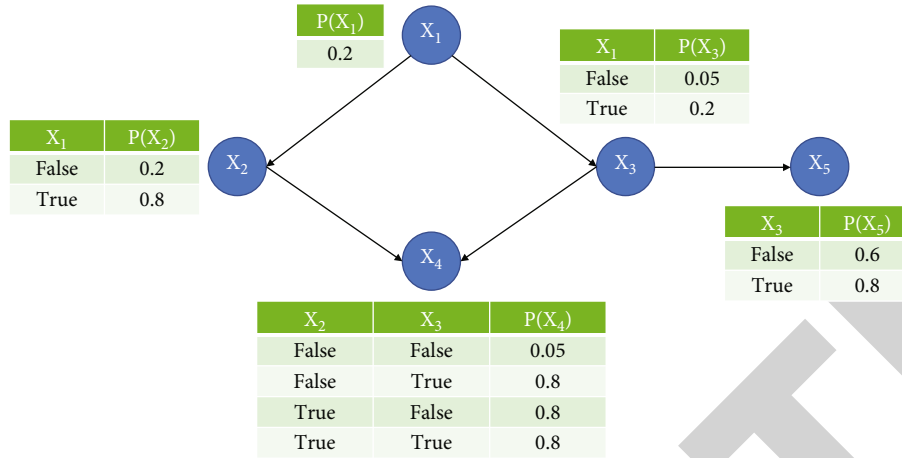


FIGURE 1: An example of the Bayesian network.

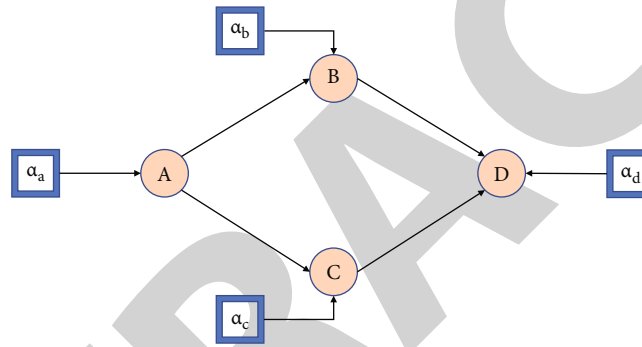


FIGURE 2: Framework of graph model.

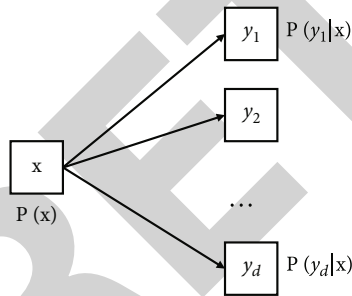


FIGURE 3: Bayesian network of latent variables.

the Bayesian network structure is also constructed through expert knowledge. However, the parameters of the Bayesian network are derived from sample data using machine learning methods through parametric learning algorithms. This approach is intermediate between the above two methods

2.5. Advantage of Bayesian Network. Compared to other data mining algorithms, Bayesian networks have the following advantages:

- (2) The node variables in the Bayesian network structure are determined by experts in the relevant field and the final Bayesian network structure, and some parameters are trained and learned by Bayesian network structure learning and parameter learning algorithms using sample data. This approach is a combination of expert experience and data-driven methods that are highly adaptable and effective in avoiding the subjective bias associated with having the network structure determined entirely by domain experts
- (3) The node variables in the Bayesian network are determined by the relevant domain experts, while
- (1) Bayesian networks consider both classification and regression problems for multiple input variables with dependent relationships. For other learning algorithms, the important problem they address is not the correlation between variables, and the predicted results can show large errors if there are missing values in the observations of the variables. Bayesian networks, on the other hand, represent probabilistic relationships between variables and conditional independence in a graphical and intuitive way
- (2) Bayesian networks can combine a priori information or expert knowledge with sample data to solve relevant domain problems. Prior information and

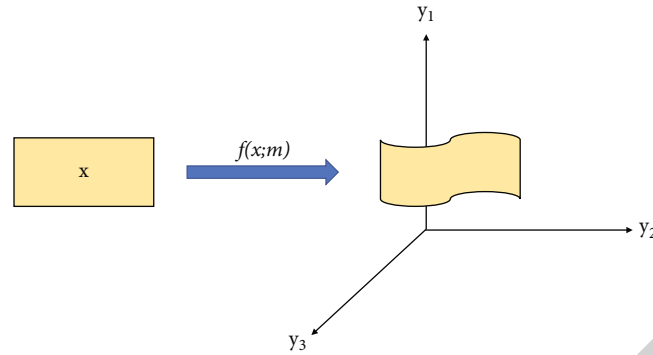


FIGURE 4: Mapping from latent variables to the data variables.

domain knowledge have an important role to play when modelling with small sample data

- (3) Bayesian networks do not require strict statistical assumptions
- (4) Bayesian networks can deal well with the problem of over-fitting of data
- (5) Bayesian networks are capable of causal learning, allowing incomplete and noisy sample data to reveal potentially useful models or relationships. In data analysis and data mining, causality can increase one's understanding of expert knowledge. In the presence of a high level of interference, Bayesian networks can likewise make accurate predictions. In addition, Bayesian networks have the ability to handle nonlinear relationships and are suitable for general nonlinear prediction and causal inference

3. Prediction Model

In this section, the football matches are used as an example for predictive analysis of the match outcome by creating a predictive model based on Bayesian networks.

3.1. Traditional Forecasting Model. Most traditional forecasting models lack a predictive model for the number of rounds played, instead predicting the score of a match directly on the basis of the players' abilities combined with other influencing factors. However, this type of model has obvious drawbacks, as often the combination of players on the pitch at different times of the game leads to significant differences in strength between teams at different times of the game, which has a significant impact on the scoring situation. The aim of this study is to develop a game model that can be broken down to each offensive and defensive turn of the team and then combine this with an estimate of the offensive and defensive efficiency to predict the total number of points scored.

As shown in Figure 5, there are a handful of traditional Bayesian network-based models that break down the course of the game as described above, down to each offensive and defensive turn. It is usually assumed that a player has an

offensive and a defensive ability value and fits a certain probability distribution. The team's strength value is then the sum of the players' ability values, and the players' ability value parameters are estimated using a Bayesian inference approach, trained using historical data from matches. The outcome of the match is then predicted based on the differences in the team's player ability values, combined with other factors affecting the match.

As can be seen from Figure 5, each team consists of a number of players, each with an offensive and defensive ability value, which determines the ability value of the teams playing against each other. The combination of players present then determines how many points are scored during the game.

3.2. Improved Forecasting Model. In fact, traditional match prediction models have a number of flaws. Specifically, in the current research in Bayesian-based ability differences in win-loss prediction models, there is a public common controversy regarding the logistic and Gaussian distributions of ability or performance. Thus, the traditional forecasting models are not suitable for more complicated situations. In this section, the improved forecasting model is proposed to adapt to the specific situations that occur in a football match. In addition, the improved model considers the multi-valued output results of each attack and defense in the game, the plausible causal relationship between the players' ability values and the scoring situation during the attack and defense, and the effect of the cooperation between players on the results.

In this model, the potential variables include the team's style and the coach's tactical system. The tactical styles and systems of different teams usually determine the number of attacking turns in a football match. Hence, it is necessary to consider team factors that may affect the number of attacking turns in a match by adding artificial priors for the teams involved in the match. These factors are assumed to be normally distributed here. In addition, the home and away factors can also have an impact on the number of attacking turns. Taking these factors into account, a match model is developed for the two teams involved in the match as shown in Figure 6 so that the number of attacking turns for both teams can be predicted.

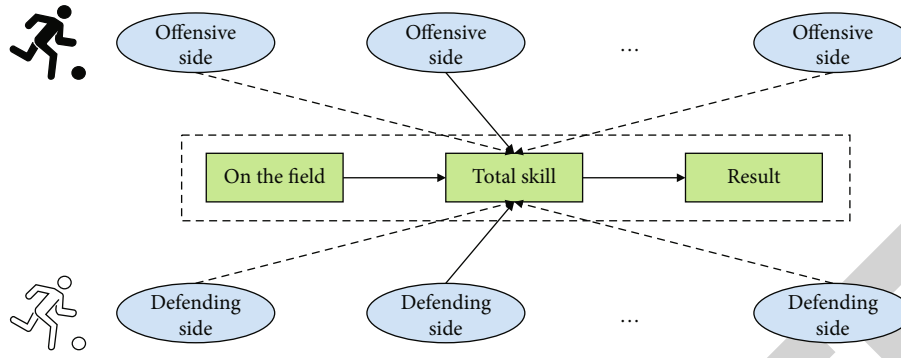


FIGURE 5: Bayesian networks of traditional forecasting models.

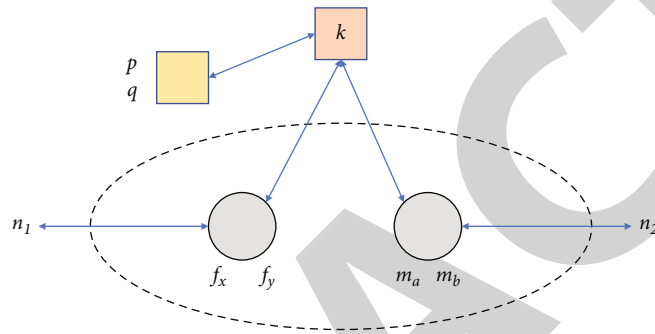


FIGURE 6: Framework of match model.

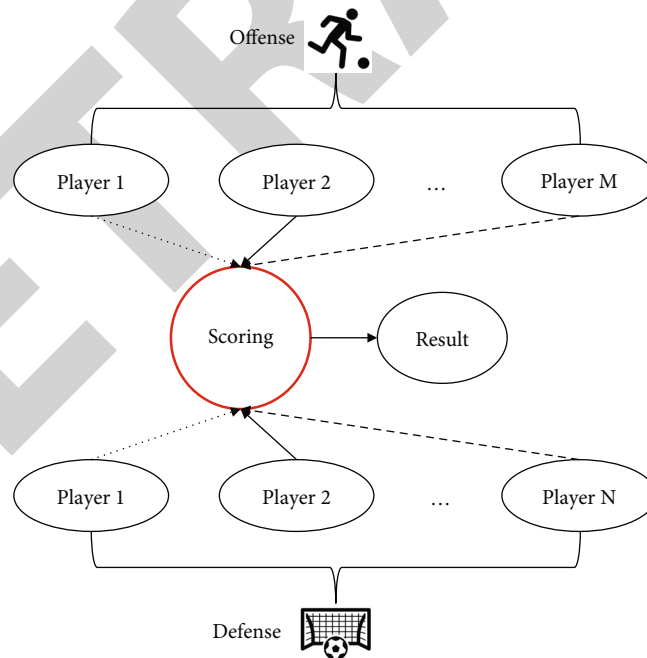


FIGURE 7: Bayesian model about football match.

Furthermore, the match model can be expressed by the following equations:

$$\begin{aligned} k_{x \rightarrow y} &= [p \ q] \times \begin{bmatrix} f_x & 0 \\ 0 & f_y \end{bmatrix} \times [m_a \ m_b]' \\ k_{y \rightarrow x} &= [p \ q] \times \begin{bmatrix} f_y & 0 \\ 0 & f_x \end{bmatrix} \times [m_a \ m_b]', \end{aligned} \quad (7)$$

where $k_{x \rightarrow y}$ indicates the number of rounds of attack by team x against team y , $k_{y \rightarrow x}$ indicates the number of rounds of attack by team y against team x , p refers to the home coefficient, and q refers the away coefficient. The vectors f_x and f_y indicate the team factors affecting the number of rounds played for team x and team y , respectively, and m_a and m_b refer to the offensive weighting factor and defensive weighting factor, respectively. Furthermore, by dynamically adjusting the number of factors influencing the team and using the dataset to learn the parameters of the potential variables and validate their prediction accuracy, a more accurate prediction of the number of attacking turns in the game can be conducted.

Next, the Bayesian network model can be constructed, as shown in Figure 7. Each attacking and defending session is divided into an attacking side and a defending side, with the attacking team having 11 players and the defending team also having 11 players. The random variables for the different scoring situations are not independent of each other, but are interrelated. The scoring result during the offense indicates the actual number of points scored during this offense and defense.

4. Conclusion

This paper provides a comprehensive overview of the current state of research in competitive sport prediction models and analyzes the prediction models that are currently available. The academic community is also constantly improving prediction models using new mathematical methods to improve their accuracy. A few of these representative mathematical methods are selected for detailed presentation in this article in order to facilitate an understanding of the shortcomings of traditional models as well as the advantages of improved models.

The prediction model proposed in this study is a latent variable model based on Bayesian networks, with the aim of simplifying some complex models by treating the possible factors affecting the match as latent variables using the historical battle report dataset for training. The learned latent variables are then used to predict the number of attacking turns in the match, thus avoiding the need to build overly complex models for these relevant factors. Furthermore, this research improves on the traditional prediction model by disentangling the scoring states in the number of attacking turns in a game, corresponding to the player's corresponding scoring ability, to establish a reasonable cause-and-effect relationship. The scoring states are also not independent of

each other, but interact with each other and together determine the scoring outcome in the offensive rounds.

Although the prediction model proposed in this study has better prediction results, there are many areas for improvement in this study in the future. The first one is to make a reasonable presentation of the players' ability values and to resume a reasonable evaluation model for the parameters of the players' ability values obtained in order to assess the value of the players to the team. The second one is that currently if training and prediction is done using games from different seasons, there is a deviation between the predicted and actual values due to the difference in offensive or defensive intensity from season to season, and this is also a target for future improvement.

Data Availability

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

Conflicts of Interest

The authors declare no competing interests.

Acknowledgments

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