Hindawi
Scientific Programming
Volume 2022, Article ID 6369074, 6 pages
https://doi.org/10.1155/2022/6369074

Research Article

Application of Clustering and Recommendation Algorithm in Sports Competition Pressure Source

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Received 12 January 2022; Revised 3 February 2022; Accepted 14 February 2022; Published 25 March 2022

Academic Editor: Ahmed Farouk

With the vigorous development of China's sports industry, the rules and number of events are increasing, and the competition pressure on the playground is also increasing. The increase of competition pressure will bring many negative effects to athletes. In order to relieve the pressure of athletes in sports competition and eliminate the negative significance of pressure to athletes, this paper mainly introduces the clustering algorithm of sports source and competition. The clustering algorithm uses the similarity of attributes between data objects to calculate the clustering structure of fractional clustering. In this paper, the original data of sports competition pressure are obtained through the questionnaire survey, using clustering and recommendation algorithms to calculate and analyze the original data, the data utilization rate is as high as 98%, and the analysis efficiency is as high as 97%. Dividing athletes into three categories, the magnitude and source of stress are analyzed, respectively, and application methods are recommended according to their respective stress distributions, so as to assist psychologists in the diagnosis, and the corresponding height is 80%; this enables athletes to receive good counseling advice and remain mentally healthy.

1. Introduction

1.1. Research Background and Significance. The competition in today's sports arena is quite fierce. Due to the development of sports science, sports technology is more advanced than before. It is not enough to have good technology alone. In the face of numerous internal and external pressures, what is tested is a player's ability to withstand pressure and psychological control. It is very important for an excellent athlete to be able to show the results of hard training in normal times on the field, to remain calm at critical moments, to stably exert one's skills, and to show a better competitive state and psychological quality.

With the vigorous development of sports in China, the rules and quantity of events are increasing, and the pressure on the sports field is increasing. Competition pressure comes from various aspects, among which the most lethal pressure is also psychological pressure. To play normally or abnormally on the field, psychological stress had to be surmounted. As a result, there has been an increasing focus on game stress by many psychologists and athletic coaches. In order to make athletes play normally and play for a long time in the competition, of course, the psychiatrists will give psychological guidance and conduct psychological diagnosis regularly. However, the psychological state of athletes is uncertain and fuzzy, and it is not possible to effectively understand and solve the pressure of athletes. Therefore, this paper proposes to apply clustering and recommendation algorithm to stress psychoanalysis and recommendation and give corresponding suggestions after cluster analysis, which can relieve the pressure of athletes and also provide athletes' data for psychological expert diagnosis. At the same time, it provides psychological treatment assistance information for psychologists and relieves stress for athletes.

1.2. Relevant Contents. In sports events, the sources of pressure on athletes are diverse. Liu et al. proposed a set of cognitive neuroscience evaluation systems for athletes' stressors to protect athletes in sports competitions. According to the stress of athletes, they designed questionnaires for many experts at home and abroad who study the stress of athletes and conducted in-depth and detailed investigations on the life process of athletes who often participate in sports events. At the same time, a cognitive neuroscience evaluation system in sports competitions is constructed by using the clustering algorithm and recommendation algorithm [1]. Their proposal is only aimed at the evaluation of cognitive nerves, and the stressors may also be reflected in the psychological and physical aspects, so they have a certain one sidedness [2]. Wang et al. proposed a clustering algorithm for fast searching and finding density peaks, which is a clustering algorithm for fast finding clustering centers. A method is suggested to automatically pull the baseline values through automatic threshold extraction using the potential entropy of the data fields in the original dataset. The accuracy of this method relies too much on the threshold value and there is no valid way to choose the proper value. The value is estimated empirically. For any dataset to be aggregated, the threshold value can be objectively calculated from the dataset rather than empirically estimated. Experimental results show that the algorithm clusters better compared to the empirical thresholds [3]. However, this algorithm has some prediction error with some bias. Hotta et al. proposed a new self-adaptive rate of change function integrating an index function with a linear function and applied this method to the SVD++ referral algorithm [4]. As a recommendation algorithm related to singular value decomposition (SVD), this algorithm is widely used and has good prediction performance. However, with the rapid growth of intelligent social data, the bad performance of the SVD++ referral algorithm becomes a salient drawback because of the long optimization time of the objective function in building the prediction model [5, 6]. Therefore, the study rate function is an important factor for prediction models based on SVD++ algorithm for recommendation. It directly affects the convergence rate and performance of the forecasting computer model [7]. However, the relative error of this algorithm will increase while improving the efficiency [8, 9].

1.3. Main Innovations. The innovations of this paper are as follows: (1) using clustering and recommendation algorithms to analyze the survey data of sports competition stressors; (2) using scientific calculation methods to calculate and analyze the data obtained from the survey; and (3) the research results are objective and reasonable. It uses the knowledge of computer theory and the pressure of sports competition. It also provides psychotherapy aids for future psychologists and stress relief for athletes.

2. Concept and Research Method

2.1. Concept of Pressure and Pressure Source. Pressure is a feeling caused by various aspects of oppression, which can be reflected in individual life continuously. Multiple stressors can cause the same stress response, and one stressor can cause multiple stress responses. The stress source is all the subjective and external stimuli that can cause people's stress response. By nature, stressors are divided into three categories: biological stressors, mental stressors, and socio-environmental stressors [10, 11]. Among them, biological stressors are a set of events that directly hinder and destroy the survival of the individual and the continuity of the race, including physical illness trauma or illness, hunger, sexual deprivation, sleep deprivation, noise, temperature changes, etc. Psychological stressors are a set of internal and external events that directly hinder and destroy the normal spiritual needs of an individual including wrong cognitive structure, bad personal experience, moral conflict and bad personality, and psychological characteristics caused by long-term life experience. Social environmental stressors are a set of events that directly hinder and disrupt an individual's social needs [12]. They are divided into two aspects: purely social, such as major social changes, the breakdown of important relationships, long-term family conflicts, war, incarceration, etc. The second category is interpersonal adaptation problems caused by their own conditions, such as personal mental disorders, infectious diseases, and anthropophobia. The pressure source of the sports competition studied in this paper is also described and studied from these three aspects. At the same time, stressors are divided into acute stressors and chronic stressors according to the degree of impact on life.

2.2. Clustering Algorithm and Recommendation Algorithm. With the development of human science and technology, the requirements for classification are getting higher and higher, so that sometimes it is difficult to classify accurately only by experience and professional knowledge. So, people gradually introduced mathematical tools to taxonomy, forming numerical taxonomy, and then introduced multivariate analysis technology to numerical taxonomy to form cluster analysis. This paper studies the hierarchical clustering method; its implementation principle is to use the similarity of attributes between data objects to calculate the clustering structure of fractional clustering. Cluster analysis, also known as group analysis, is a statistical analysis method for studying (sample or index) classification problems and is also an important algorithm for data mining [13, 14]. The process of clustering method is the process of merging and decomposing each layer structure [15–17]. Algorithms of cluster analysis can be divided into partition method, hierarchical method, density-based method, grid-based method, and model-based method. This paper divides athletes into three types by cluster calculation and analyzes each type. According to the calculation content and the athlete's pressure data, a model is established on the basis of analyzing the similarity, and then the prediction result of the pressure is calculated by the recommendation algorithm. The advantages of recommendation algorithms are that the recommendation results are intuitive, easy to interpret, and do not require domain-wide knowledge [18, 19]. However, there are sparse problems and new user problems, and complex attributes are difficult to deal with. There must be enough data to construct a classifier.

2.3. Questionnaire Survey. In order to understand the sources of sports competition pressure, the pressure sources of athletes are subdivided, and the pressure source questionnaire is used. In this paper, 100 athletes of different grades and ages are randomly selected from sports colleges and universities to fill in the questionnaire, and the recovery rate is 100%, which provides the original data for clustering algorithm and recommendation algorithm.

3. Clustering Evaluation and Recommendation Algorithm Flow

3.1. Clustering Evaluation Algorithm. In using clustering algorithms to process data, it is more critical to determine how good the clusters are, which is called cluster identification [20]. Generally speaking, the evaluation criteria of clustering algorithms are divided into the following categories: First, identify whether there is nonrandom structure or noisy data in the data; second, determine the number of cluster sets; third, pay attention to the quality of cluster analysis results, the degree of close separation, etc. fourth, compare the cluster results with known results [21, 22]. The first three are non-supervised evaluation, and the last is supervision evaluation. Generally, cluster sets are evaluated by the measurement standard of classification model. The common ones are pitch, accuracy, recall rate, F value, and so on [2, 23, 24]. The following describes several clustering evaluation criteria.

3.1.1. Contour Formula. Contour coefficient is a method to explain and verify the clustering results. It can display the advantages and disadvantages for a simple picture of any object present in the collection of data [25]. Assume that the data can be clustered into K clusters. To impose any object I of the data, $a(I)$ denotes the mean variance of object I from other objects in the same cluster. That is, it represents how favorably or unfavorably object I is allocated to the current cluster. The more similar I is to the other objects in the cluster, the more suitable I is to be allocated to the current cluster. $a(I)$ is specified below.

$$a(i) = \frac{\sum_{o' \in c_{i,o \neq o'}} \operatorname{dis}(o, o')}{|c_i| - 1}, \quad (1)$$

where $B(I)$ denotes the least distance, on average, between subject I and every other available cluster (not the one to which I is assigned), i.e., the object I's distance from its next best adjacent cluster. If object I is not effectively assigned, then the best cluster it should be assigned to should be the nearest available neutral neighborhood to that of the presently assigned cluster. B is given by the following formula:

$$b(i) = \min_{c_j: 1 \leq j \leq k, j \neq i} \left\{ \frac{\sum_{i' \in c_j} (o, o')}{|C_j|} \right\}. \quad (2)$$

So, the contour factor might be specified as follows:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (3)$$

or it can be written as follows:

$$s(i) = \begin{cases} 1 - \dfrac{a(i)}{b(i)}, & a(i) < b(i), \\ 0, & a(i) = b(i), \\ \dfrac{b(i)}{a(i)} - 1, & a(i) > b(i). \end{cases} \quad (4)$$

From the formula, $s(I)$ is taken as $[-1,1]$. As $a(I) < B(I)$, the smaller $a(I)$ is, the higher the distribution of I is, for $a(I)$ denotes the closeness of I to the targets within the cluster. The larger $B(I)$, the lower the distribution of I in the neighboring clusters. In this case, $s(I)$ near 1 indicates a better overall distribution level in the dataset; $s(I)$ near 0 indicates that object I is at the boundary of two clusters; $s(I)$ near -1 indicates that subject I is different from the objects in this cluster and object 1 is poorly assigned to a cluster. $s(I)$ means value in the set of data is used to rate the cluster results' quality. Therefore, the contour coefficient can serve as a useful reference point to choose the desired amount of clusters in the dataset. For example, if one chooses the k-means algorithm for clustering, the value of $s(I)$ can vary significantly if the value of k chosen is too large or too small.

3.2. Flow and Similarity Calculation in Recommendation Algorithm. The main principle of recommendation algorithm is to infer the most likely similar information of current customers according to the historical evaluation or opinion of existing customers. According to similar information to calculate the corresponding conclusion, the process is as follows.

As can be seen from Figure 1, the recommendation algorithm starts from obtaining user data, then establishes user information evaluation model to calculate the similarity, and then predicts the result by using similar user set according to the similarity.

At present, there are three common similarity calculation methods.

3.2.1. Cosine Similarity. The goal of the cosine similarity calculation method is to compute the value of the cosine of the degree of similarity among users or items based on the cosine value of the angle between the attribute vectors of the users or items. The larger the cosine value, the higher the similarity between them. The cosine similarity calculation formula is as follows (the similarity calculation formula of users and items is similar, and the subsequent formulas take the user similarity calculation as an example):

$$\operatorname{sim}(u_i, u_j) = \frac{\sum_{k=1}^{m} P_{ik} * P_{jk}}{\sqrt{\sum_{k=1}^{m} P_{ik}^2} * \sqrt{\sum_{k=1}^{m} P_{jk}^2}}, \quad (5)$$

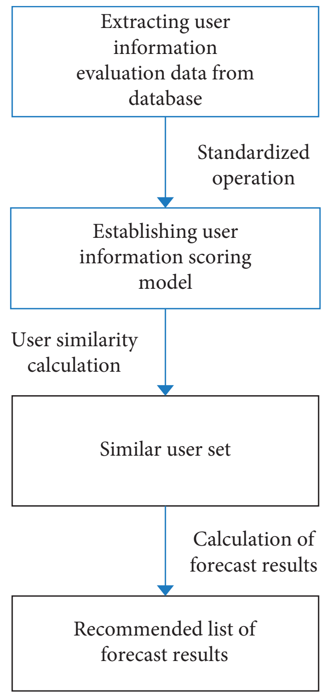

Figure 1: Flowchart of similarity calculation of recommendation algorithm.

where P_{ik} is the user I's score of item K. Formula (5) selects the customer's score information of all items in the database, including the data with a score of 0 and no score.

3.2.2. Adjusted Cosine Similarity. Cosine similarity calculation will have prediction error to a certain extent, especially when the amount of data is large, so some professionals put forward the adjusted cosine similarity formula.

$$\mathrm{sim}(i,j)=\frac{\sum_{k\in I_{ij}}\left(P_{ik}-\overline{P_i}\right)*\left(P_{jk}-\overline{P_j}\right)}{\sqrt{\sum_{k\in I_{ij}}\left(P_{ik}-\overline{P_i}\right)^2}*\sqrt{\sum_{k\in I_{ij}}\left(P_{ij}-\overline{P_j}\right)^2}}. \quad (6)$$

In this calculation method, the item set is used as the item set in which both users I and j have participated in scoring. P represents the average value of user I's rating of all over rated items, which can reflect the user's standard to a certain extent. The greater the similarity value is, the more similar they are.

3.2.3. Pearson Correlation Coefficient. Pearson correlation coefficient is set as the average score of the food set that users evaluate jointly. The formula is as follows:

$$\mathrm{sim}(i,j)=\frac{\sum_{k\in I_{ij}}\left(P_{ij}-\overline{P_{iI_{ij}}}\right)*\left(P_{ik}-\overline{P_{jI_{jk}}}\right)}{\sqrt{\sum_{k\in I_{ij}}\left(P_{ij}-\overline{P_i}\right)^2}*\sqrt{\sum_{k\in I_{ij}}\left(P_{jk}-\overline{P_j}\right)^2}}. \quad (7)$$

The greater the similarity value is, the more similar they are. The last step in the process is the calculation of the prediction results. The quality of the recommendation system lies in the accuracy of the final prediction results. The following formula is used to predict the score of user I on over rated thing K.

$$P_{ik}=\overline{P_i}+\frac{\sum_{j\in S_i}\mathrm{sim}(i,j)*\left(P_{ik}-\overline{P_{ik}}\right)}{\sum_{j\in s_i}\mathrm{sim}(i,j)}. \quad (8)$$

According to formula (8), we can get the target user's prediction score of the things that have not been rated too much, then sort the things according to the score value, and select the item with the highest score to form the user's recommended things.

4. Specific Analysis of the Prediction Results of Clustering and Recommendation Algorithm

4.1. Analysis of Clustering Algorithms in the Stressors of Physical Competitions. For the data analysis of the competition stress or questionnaire, the data are first clustered, and the questionnaire is divided into several parts, which are described in detail from the aspects of reduced sense of achievement, emotional support, social support, and negative sports evaluation. Thus, we can obtain a full range of data for analysis and obtain information on clustering. After calculation, the following final cluster centers can be obtained.

As can be seen from Table 1, 75 people belong to category 1, followed by category 2, with 25 people. The least number is category 3, with only 5 people. In Figure 2, the data of the first type are relatively stable, and the change is stable between 2 and 3. The range of the second type is also large, between 1 and 6. The change range of the third type is the largest, between 3 and 10. On the whole, we can draw the following conclusions:

(1) The third-type athletes have the largest change range, and there is a significant gap with the first category. This indicates that the athletes in the third category have a poorer mental level and a higher total score, suggesting a higher level of stress.

(2) The small range of variation in the first category suggests a relatively good mindset of the athletes. A low total rating indicates inconsistency with the stressor, indicating low stress. It indicates that mindfulness affects stress and that the athletes in the first group have a high level of self-happiness.

(3) Comparing the second type with the first category, the overall score is moderate, indicating that the pressure is moderate, but in terms of the mentality, it is not as good as the first type of athletes, so they will feel greater pressure.

In summary, the first type of athletes is worth training, and the overall mentality is good; for the second category, we should focus on the construction of mentality and relieving pressure. The third type of athletes is under great pressure, which is not conducive to the competition and is easy to get tired of the competition. Psychological and physical methods should be adopted to relieve the pressure.

Table 1: Final cluster center.

Serial number	The ultimate cluster center	Total data
1	(0.734 0.121 0.908 0.108)	75
2	(0.599 0.513 0.421 0.235)	20
3	(0.483 0.776 0.973 0.465)	5

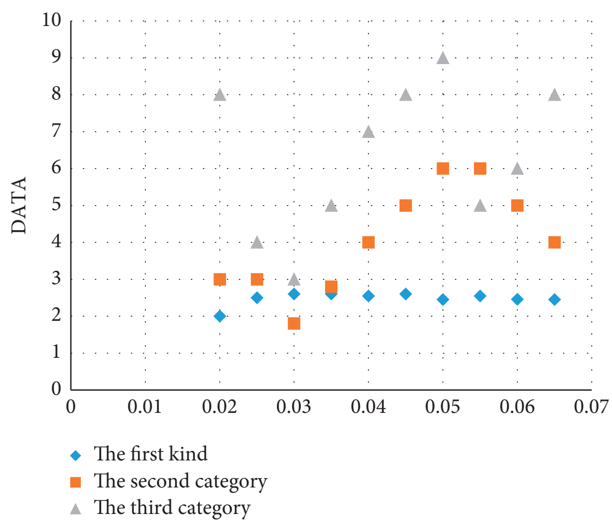

Figure 2: Variation of aggregation algorithm in pressure data of sports games.

4.2. Application of Recommendation Algorithm in Sports Competition. In the paper, we concentrate on analyzing the terms of stressor analysis in the questionnaire and calculate them by the recommended algorithm to obtain the following prediction results. Because the first type of pressure source is relatively small, this part of the pressure source analysis is only for the second and third types to predict the results.

From Table 2, it can be seen that the physical and mental fatigue of the second type athletes is high, and the athletes' burnout, goals, and development and social support are medium. This suggests that category 2 athletes are more likely to be physically and psychologically fatigued and have relatively inadequate social support. The athletes have not paid much attention to their own goals and development, and the stress and emotion are not enough, so they have been in such a state continuously, and the pressure and emotion are not enough. Therefore, the second type of athletes should pay attention to their own development, obtain higher social support, and relieve the current pressure with honor and social support.

It can be seen from Table 3 that the qualification selection, physical and mental fatigue, athlete burnout, and social support of the third kind of athletes are high. It shows that the ability of the third kind of athletes is excellent, and they have the highest degree of recognition and support in the society, but they are also faced with the greatest pressure, such as physical pressure, psychological pressure, and social pressure. Therefore, the third type of athlete should calm down and keep a relaxed and happy attitude to deal with the competition.

Table 2: Sources of the second type of athletes' stressors.

Similarity	Text theme	Grade
0.09	Athlete burnout	Secondary
0.07	Goals and development	Secondary
0.06	Social support	Secondary
0.05	Tired both physically and mentally	Higher

Table 3: Sources of the third type of athletes' stressors.

Similarity	Text theme	Grade
0.12	Qualification selection	Higher
0.05	Tired both physically and mentally	Higher
0.04	Athlete burnout	Higher
0.03	Social support	Higher

5. Discussion

Due to the rules, the contestants must deal with various situations in the competition alone on the field. Neither coaches nor other personnel may give any assistance or guidance to an athlete unless the athlete is in danger or forced to withdraw from the competition. This requires each player to have independent decision-making ability and the ability to solve problems on the spot. From another point of view, the pressure that individual sports athletes need to bear is much greater than that of team sports. Athletes suffer from serious disorders of their physical and psychological functions due to excessive competition pressure. The inability to effectively relieve pressure leads to the failure of the competition, athletes getting frustrated, and athletes doubting their own ability, which eventually leads to the athlete's injury or early retirement. Therefore, understanding and effectively judging the source of athlete's stress and taking effective coping strategies in a scientific and timely manner are crucial for the normal performance of windsurfers' competitive level. In this paper, a certain amount of sports competition pressure data are obtained through questionnaire survey, and then clustering and recommendation algorithm calculation and analysis are carried out according to the data. First, it is divided into three categories by clustering, and the corresponding results are obtained. Then, the similarity of the recommendation algorithm is calculated by combining different pressure sources, and the pressure sources of different types of athletes are obtained, and they are analyzed and corresponding recommendations were made. It can provide some auxiliary information for the relief of athletes' pressure and professional psychologists and promote the development of sports psychology in the future. Due to the limitations of technology and time, the research in this paper does not deeply explore the generation of stressors in sports competitions, and we will explore them in the future.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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