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THE INTEGRATION AND INNOVATION OF SPORTS SOCIAL PLATFORMS AND INFORMATION TECHNOLOGY

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Abstract. In order to better achieve the integration and innovation of sports social platforms and information technology, the author proposes an SFD (Sport Friend Discover) sports friend recommendation model based on physical testing big data. The core idea of this model is to use physical measurement data to match the similarity between athletes and recommend suitable exercise partners. Specifically, we collected a large amount of physical measurement data, including height, weight, body fat percentage, muscle mass, etc. Then, through data mining algorithms, these data are transformed into feature vectors of the movers. Next, we use a similarity algorithm to calculate the similarity between different athletes and find the most matching motion partner with the user. The results show that the SFD method outperforms the other two traditional recommendation methods on the dataset, with P @ 10, P @ 20, P @ 30, and P @ 40 of SFD reaching 0.099, 0.095, 0.085, and 0.591, respectively. SFD not only utilizes more neighboring information than FOAF based on local graph structure, but also compared to TRW based on global graph structure method, at the same time, the importance of the node itself is also considered, resulting in higher accuracy. It has been proven that the SFD sports friend recommendation model based on physical testing big data has achieved good results in recommending sports partners. Users can quickly find sports partners with similar body types and health conditions, improving the fun and effectiveness of exercise.

Key words: Recommendation algorithm, Sports and social interaction, Integrated innovation

1. Introduction. With the continuous development and popularization of information technology, sports social platforms are playing an increasingly important role in today's society. Sports social platform refers to a platform that combines sports and socializing through the internet and mobile applications. They provide a convenient way for people to share their sports experiences, challenges, and achievements, and interact and communicate with other sports enthusiasts. In the past few years, the number of users on sports social platforms has grown rapidly, attracting more and more people to join [1]. These platforms provide a virtual community where people can find like-minded partners and share their sports experiences and insights. By posting their own exercise records and achievements, users can receive praise and encouragement from others, which is crucial for improving their motivation to exercise and persevere [2]. In addition, sports social platforms also provide many useful features, such as sports data analysis, training plan development, and health advice, to help users better manage and improve their exercise status.

However, there are currently some issues and limitations with sports social platforms in the market. Firstly, for users, existing platforms often lack personalized and customized functions, which cannot meet the needs of different users. Everyone has different sports hobbies and goals. Some people like running, some like cycling, and some like exercising. Existing platforms often only provide some basic functions and cannot meet the personalized needs of users. Users hope to customize their exercise plans and training content based on their interests and goals [3]. Therefore, future sports social platforms need to strengthen the development of personalized and customized functions to meet the diverse needs of users. Secondly, for platform operators, there are difficult to solve privacy protection and data security issues. Sports social platforms involve users' personal information and exercise data, which are very important to users. However, due to the lack of effective privacy protection mechanisms, users' personal information and exercise data may be abused or leaked. In addition, data security is also an important issue.

Sports social platforms store a large amount of user data, which may be exploited by hackers or criminals without appropriate security measures. For platform operators, protecting user privacy and data security is an

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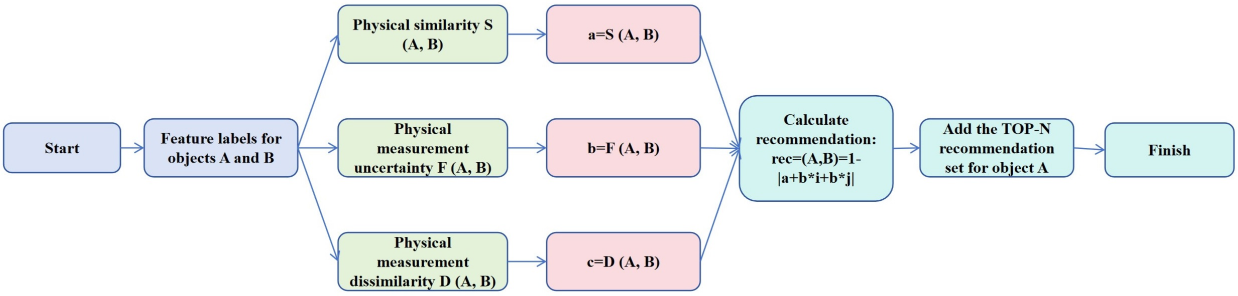

Fig. 2.1: Algorithm flow of college student physical examination

important responsibility, and they need to strengthen technical and management measures to ensure that user information is fully protected.

In addition, due to technological limitations and operational strategies, the functionality and experience of sports social platforms still need further improvement and innovation. At present, sports social platforms mainly focus on user interaction and sharing, but often overlook the needs of users for professional knowledge and guidance. Many users hope to receive professional sports advice and guidance to help them better engage in sports training. Future sports social platforms can strengthen cooperation with professional sports coaches and health experts, providing users with more comprehensive and professional services. In addition, sports social platforms can also combine virtual reality and augmented reality technology to provide a richer and more immersive sports experience [4].

In summary, sports social platforms play an important role in today's society, providing people with a convenient way to share sports experiences, challenges, and achievements, and interact and communicate with other sports enthusiasts. However, there are currently some problems and limitations with sports social platforms in the market, such as a lack of personalized and customized functions, privacy protection and data security issues, as well as limitations in functionality and experience [5].

Future sports social platforms need to strengthen the development of personalized and customized functions, as well as measures to protect privacy and data security, simultaneously enhancing functionality and experience to meet the diverse needs of users. Only in this way can sports social platforms better play their role in promoting health and social interaction.

2. SFD Sports Friend Recommendation Algorithm.

2.1. Overall Algorithm Design. The college student physical testing recommendation algorithm is specifically designed based on the big data of college student physical testing, and the algorithm process is shown in Figure 2.1. The concept of set pair analysis was introduced in this study to transform the traditional similarity. In the recommendation process, the first step is to calculate the similarity, uncertainty, and dissimilarity between two objects. Then, based on the theory of set pair analysis, the set pair recommendation degree rec (A, B) needs to be calculated. Finally, the set pair recommendation degree is used to select suitable recommended objects and make recommendations [6].

2.2. Data preprocessing. Before designing the recommendation algorithm, in order to calculate the physical fitness recommendation between two objects, it is necessary to rate the physical fitness test items of college students according to the National Physical Fitness Standards, standardize the data of student physical test items into percentages, and classify the physical condition of students: The scores for explosive, endurance, flexibility, and strength categories are calculated based on the scores of student physical testing items with different weights [7].

Then, through threshold grading, different groups of strong, medium, and weak students are determined. Finally, it is necessary to fit the textual sports characteristics and give definitions: {"Strong": 1, "Medium": 2, "Weak": 3}.

Assuming the existence of objects A and B, their motion features are represented as feature vectors, that is $A =< a_1, a_2, a_3, a_4 >, B =< b_1, b_2, b_3, b_4 >$, the difference between the features of A and B can be represented by $|a_k - b_k|$, where $k \in \{1, 2, 3, 4\}$,

$|a_k - b_k|$=0, indicating that A and B have similarity

$|a_k - b_k|$=1, indicating that A and B have uncertainty

$|a_k - b_k|$=2, indicating that A and B have a degree of dissimilarity.

This study will design the similarity, dissimilarity, and uncertainty of physical measurements in the context described above[8].

2.3. Set pair recommendation . Unlike traditional similarity calculation recommendation algorithms, it is necessary to consider the similarity between users, the differences between users, and the uncertain factors between users. Therefore, the concept of set pairs is introduced in the similarity calculation of recommendation algorithms, and the following definitions exist:

$$rel(A, B) = a + b \times i + c \times j \tag{2.1}$$

Among them, rel (A, B) represents the correlation between A and B, $rel \in [-1, 1]$, the larger the rel, the higher the similarity, and vice versa, the lower the dissimilarity. a represents the physical similarity between A and B, that is a=S (A, B); B represents the measurement uncertainty between A and B, that is b=D (A, B); c represents the physical measurement dissimilarity between A and B, that is c=F (A, B), and satisfies a+b+c=1. i is the uncertainty marker and j is the dissimilarity marker. During the operation, i and j are both coefficients involved in the operation, and a constant value of -1 is specified for j, the value of i in the range of [-1,1] depends on the situation[9]. Set pair recommendation is a transformation based on the correlation degree rel, which comprehensively considers the factors of similarity, difference, and uncertainty to avoid errors caused by high similarity or difference, and is defined as follows:

$$rec(A, B) = 1 - |a + b \times i + c \times j| \tag{2.2}$$

rec (A, B) represents the set pair recommendation degree between A and B, $rec \in [0, 1]$, the closer rec approaches 0, the less likely it is to be recommended; The closer it approaches 1, the easier it is to be recommended[10].

(1) Physical similarity. Similarity is a numerical measure of the degree of similarity between two objects, and is an important reference indicator in personalized recommendation systems. Traditional similarity is calculated based on user ratings of items and recommendations using relevant formulas. The calculation method of physical similarity in this study is different from traditional methods[11]. It refers to obtaining student physical measurement data, analyzing and processing the data to extract and describe the movement characteristics of students, calculate similarity by comparing the eigenvalues of different students through certain methods. If there are objects A and B in the recommendation system, the recommended objects A and B have the following similarity:

$$S(A, B) = \frac{N(a_k = b_k)}{n} \tag{2.3}$$

Among them, S (A, B) represents the physical similarity between objects A and B, n is the total number of feature attribute types, and a_k and b_k represent the feature values of the two objects, respectively. By using certain rules, students' grades are divided into different levels. When two students have equal levels of physical education grades, it is considered that they have a certain degree of similarity, that is, $N(a_k = b_k)$ is the number of features that two objects have the same characteristic value[12].

(2) Physical measurement dissimilarity. Dissimilarity is a numerical measure that describes the degree of difference between two objects. In the recommendation problem based on physical fitness test scores, it is often unreasonable to only recommend based on similarity, if the two recommended parties only have similarity, it means that there is very little knowledge that both parties can learn from each other, so there needs to be a certain degree of difference between them. Only when there are two different parties can there be the possibility of learning from each other[13]. If there are two objects A and B with dissimilarity in the recommendation

system, then the recommended objects A and B have the following dissimilarity:

$$D(A,B)=\frac{\sum_{k=1}^{n}||a_k-b_k|-1|-N(a_k=b_k)}{n} \tag{2.4}$$

In the formula, D (A, B) represents the degree of dissimilarity between objects A and B, n is the total number of feature attribute types, and ak and bk represent the feature values of the two objects, respectively. It $\sum_{k=1}^{n}||a_k-b_k|-1|-N(a_k=b_k)$ is the number of distinct features that two objects have, among them, $\sum_{k=1}^{n}||a_k-b_k|-1|$ is the sum of the number of similar and different features of two objects, $N(a_k=b_k)$ is the sum of similar features of two objects, and n is the type of feature attribute[14].

(3) Physical measurement uncertainty. If there are objects A and B in the recommendation system, when one party's sports performance is average and the other party's performance is strong or weak, it cannot be used to determine whether the gap between the two parties is really large enough to teach the other party, thus there is uncertainty. In set pair theory, the sum of similarity, dissimilarity, and uncertainty is 1, that is, a+b+c=1. Therefore, there are the following uncertainties for recommended objects A and B:

$$F(A,B)=1-\frac{\sum_{k=1}^{n}||a_k-b_k|-1|}{n} \tag{2.5}$$

(4) Determination of connectivity i. The value of the difference uncertainty coefficient i corresponding to the set pair recommendation degree of objects A and B in the recommendation system is a key point that needs to be determined. As the value of i approaches 1, the similarity between the two objects increases. Therefore, using cosine similarity, a method for determining the value of i using computational value method is proposed, which has the following definitions:

$$i=\frac{1}{1+d/s} \tag{2.6}$$

where s is the cosine similarity of objects A and B, the formula is as follows:

$$S=\frac{\sum_{k=1}^{n}(a_k\times b_k)}{\sqrt{a_k}\sqrt{b_k}} \tag{2.7}$$

d is the cosine dissimilarity of objects A and B. Under certain conditions, cosine dissimilarity can be transformed from cosine similarity. Use the following formula to transform similarity:

$$d=e^{-s} \tag{2.8}$$

d represents the degree of dissimilarity between two objects, s represents the degree of similarity between two objects. The larger the value of s, the smaller the value of d, and the closer i approaches 1; On the contrary, the further i moves away from 1 [15].

(5) Calculation of Top-N Recommendation Set and Friend Recommendation. The Top-N recommendation algorithm sorts data according to certain rules and selects the largest or smallest N data from the sorting list for recommendation. Different rules can be formulated for different social environments to filter the data in the recommendation set. Based on the study of university student groups, multiple factors need to be considered when making friend recommendations. Based on the obtained user set for the recommendation set, the average recommendation degree between the user and the recommended user is calculated as the threshold r. Recommendations greater than the threshold are stored in the user's Top-N recommendation set, as shown in Figure 2.2.

Due to the fact that in the process of friend recommendation, not only do we need to consider the recommendation level between users, but there are also some practical issues that need to be considered, such as the user's class, gender, and distance between living areas. When recommending, we filter based on the user's needs [16].

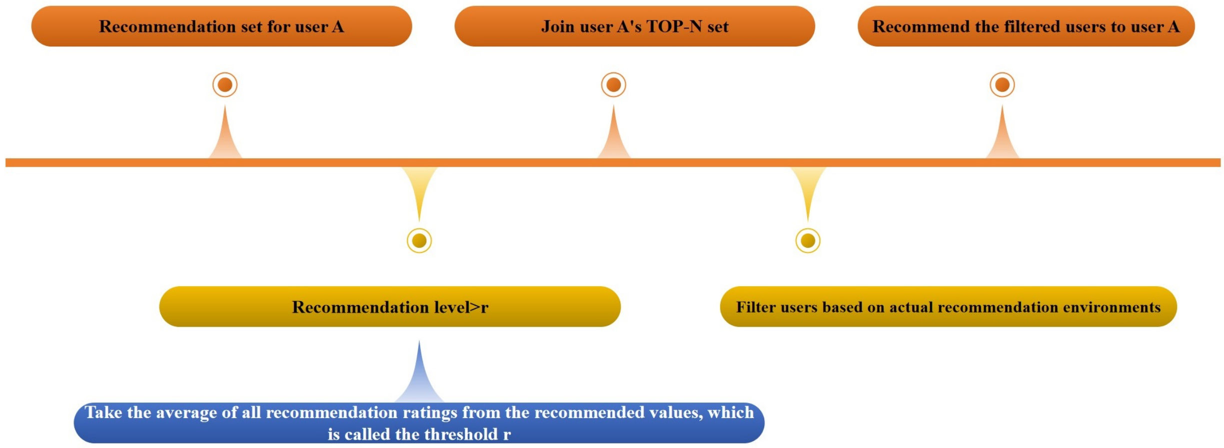

Fig. 2.2: Determination of Top-N recommendation set and friend recommendation

Table 3.1: Partial Physical Examination Data for Male Students

number	height /cm	weight /kg	vital capa- -city /ml	long ju- -mp /cm	sit-and- -reach /cm	50 m/s	1 km/s	Pull up /piece
Male 1	173.5	55.2	3235	252	8.6	7.3	213	7
Male 2	177.3	74.4	3902	210	19	8.7	285	0
Male 3	174.4	68	4464	250	10.1	6.8	201	7
Male 4	174.2	64.2	4111	224	3.7	8.1	360	15
Male 5	175.5	62.7	3176	240	13.2	7.8	255	17

Table 3.2: Partial Physical Examination Data for Female Students

number	height /cm	weight /kg	vital capa- -city /ml	long ju- -mp /cm	sit-and- -reach /cm	50 m/s	800 m/s	Sit ups /piece
Female 1	159.4	69.7	3012	154	18.5	10.2	270	33
Female 2	156.8	45.8	2462	176	14.8	9.5	246	26
Female 3	151.6	41.7	2063	160	19.9	10.2	300	32
Female 4	157.5	50.7	3035	194	26.8	8.6	227	44
Female 5	152.4	45.6	2323	186	23	8.4	237	45

3. Experimental results. The selected data is taken from the physical examination results of college students in a certain university, which are true and reliable, and only the part of the physical examination results is retained, the identification information such as name and student ID have been deleted. The student physical examination results are shown in Tables 3.1 and 3.2.

According to the National Physical Fitness Standards, calculate the physical test scores of students in Tables 3.1 and 3.2, as shown in Tables 3.3 and 3.4.

Based on the actual situation, provide the weight coefficients of the physical testing project for the features, and calculate the four major feature scores of students according to the weights, as shown in Figure 3.1.

In order to evaluate the effectiveness of the newly proposed SFD friend recommendation algorithm, the author compared SFDH with some typical local and global methods: FOAF: If two vertices have more com-

Table 3.3: Partial Physical Examination Results for Male Students/score

number	BMI	vital capacity	long jump	sit-and--reach	50m	1km	pull-up
Male 1	18.34	60.58	81.25	66.29	77	84.38	20
Male 2	23.67	71.7	60	82.35	63	52.5	0
Male 3	22.36	81.28	80	68.43	90	94	20
Male 4	21.16	75.18	67	55 69	15	76	
Male 5	20.36	58.59	75	72.86	72	66	85

Table 3.4: Female Partial Physical Examination Results/score

number	BMI	vital capacity	long jump	sit-and--reach	50m	800m	Sit ups
Female 1	27.43	79.24	64	78.46	60	60.8	66
Female 2	18.63	68.24	108	72.77	67	70.4	55
Female 3	18.14	60.26	76	81.33	60	32	65
Female 4	20.44	79.7	88.57	100	76	78	77
Female 5	19.63	65.46	82.86	91.5	78	74	78

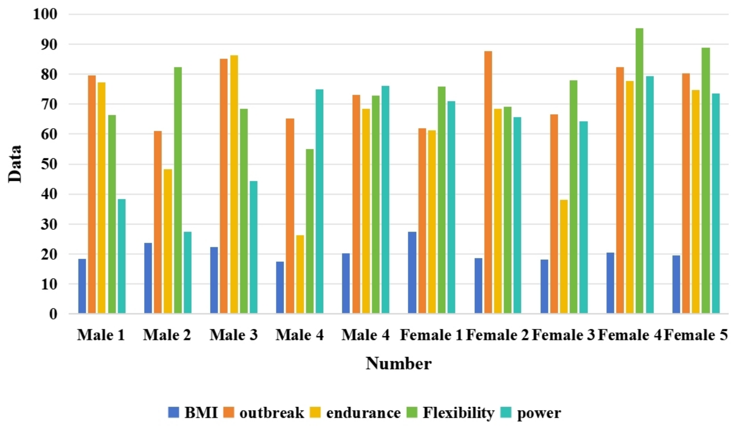

Fig. 3.1: Male and female partial feature scores/score

mon friends, they are more likely to become friends. Global Walkthrough Algorithm (TRW): Preserves all path structures in the network, investigates all structural information, and calculates node similarity. The performance of the three algorithms on the mathematical data of ScienceNet is shown in Figure 3.2.

As shown in Figure 3.2, the SFD method outperforms the other two traditional recommendation methods on the dataset, with P @ 10, P @ 20, P @ 30, and P @ 40 of SFD reaching 0.099, 0.095, 0.085, and 0.591, respectively [17,18,19].

SFD not only utilizes more neighboring information than FOAF based on local graph structure, but also considers the importance of nodes themselves, resulting in higher accuracy compared to TRW based on global graph structure method.

4. Conclusion. The author proposes a friend recommendation model based on set pair theory, which innovates extensively in the formulas of similarity, dissimilarity, and uncertainty. The cosine similarity calculation method and its transformation are used to determine the value of connectivity i, ultimately obtaining the rec-

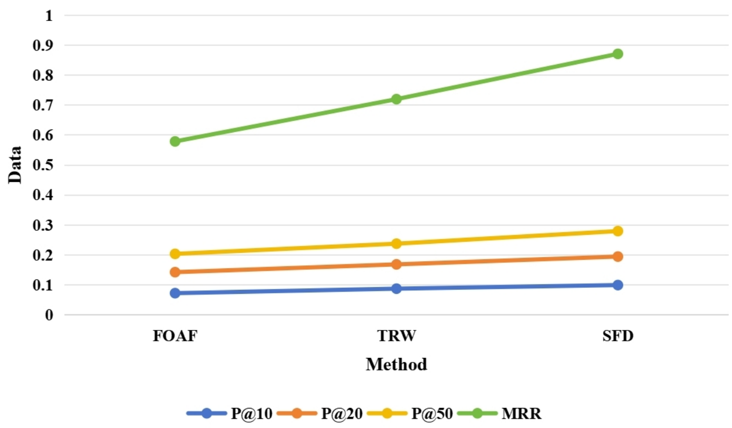

Fig. 3.2: Performance comparison of methods on the Science Network dataset

ommendation degree between users. The experimental results demonstrate that the designed recommendation method is more targeted and complementary, and the quality of recommended users is improved. Due to the relatively small number of feature attribute types and feature grading levels, the degree of difference between users is not significant, which has a better effect on users with larger differences. Therefore, in future research, more feature attributes will be added, such as user gender, user grade, and other personal information, and the formula will be further improved to further improve recommendation accuracy and rationality.

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