THE PRACTICE OF TWO-PHASE RECOMMENDER SYSTEM FOR SPORTING GOODS

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ABSTRACT

Recommendation systems are majorly developed based on relationships of product features or between consumer attributes. Most of them need a lot of analysis of historical shopping transactions and statistical user or product features to come out good suggestions for consumers to make right decisions. However, it does not fit into the users' shopping experiences for specialty stores of sporting goods. The characteristics of sporting goods specialty stores are less products and less volume of customers than other types of stores. It is hard for recommender systems to help users making the shopping decisions with limited product information and users' historical shopping behaviors. It is the purpose of this paper to propose a two-phase recommendation technique based on the AHP methodology to improve the selling of sporting goods specialty stores. We also implemented a practice system for a specialty store selling badminton-related goods. The results show that it is easier for sporting goods stores to promote products, and help consumers to choose products based on their own features.

Keywords:Recommender system, Analytic Hierarchical Process, Sporting Goods, Badminton

1.0 INTRODUCTION

Consumer buying decisions vary with product types. Generally speaking, the buying decision process of a consumer is highly related to the purchasing frequency or familiarity of products. For instance, buying a loaf of bread is easy, and buying a smart-phone is more deliberate and time consuming. It is because the purchasing frequency of a loaf of bread is more than that of a smart-phone, and consumers have more knowledge or familiarities of breads than smart-phones. That is the reason why product companies try to promote products with explicit selling points using easily understood terminologies. Once consumers get enough product information or knowledge, they can make buying decisions quickly.

To solve the purchasing decision making problems, recommender systems are proposed for stores to suggest products to consumers[1,2,3,4]. Recommendation technique is the core of a recommendation system. In [5], it shows that the foundation elements of the recommendation system are background data, input data and the algorithm. Background data is the information which is required by the system before the recommendation is made. Input data is the information which is provided by users in order to generate a recommendation. The algorithm is used to combine background data and input data to arrive at a suggestion. Based on the foundation elements, the recommendation techniques can be categorized into collaborative filtering, content based, demographic, knowledge based and hybrid recommender systems. Collaborative filtering methods are based on collecting and analyzing a large amount of information on users' behaviors, activities or preferences and predicting what users will like based on their similarity to other users [6]. A key advantage of the collaborative filtering approach is that it does not rely on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an "understanding" of the item itself. Content-based filtering methods are based on the textual information of an item, and users will be recommended items similar to the ones which are preferred in the past. The similarity between items is also calculated by the Pearson's correlation [7,8]. Recommender systems belong to Demographic type use personal attributes to categorize users or items, and make the recommendation based on demographic categorizations [9]. Knowledge-based systems recommend items relying on specific product knowledge about how certain item features meet users' needs and preferences and, ultimately, how the item is useful for the user [10,11]. Hybrid recommender systems combine the above-mentioned techniques, and try to leverage advantages and fix disadvantages from them [12]. Although there are so many recommender systems trying to help the decision making for consumers while buying goods, most of them have the problems of cold start, scalability and sparsity[13].

For specialty stores of sporting goods, the cold-start would be a common feature because systems with cold-start problems need a large amount of existing data on a user in order to make accurate recommendations. There are still numerous scholars seeking different approaches to solve cold-start problems. For instance, Schein et al. [14] find out that other users whose preferences are similar to the target users in collaborative filtering systems, and take the favorite items as the basis for recommendation. Paolo and Booby [15] use Trust Network means to convene the cluster being given trust label to establish their own trust network and then find out other trust group's favorite items as the basis for recommendation, and Jung [16] used the same idea about cluster usage by establishing a new similar cluster to solve the new user's cold-start problem. However, no feasible recommender system is used for specialty stores, especially for sporting goods stores. It is the purpose of this paper to propose a two-phase recommendation algorithm by extending the famous analytical hierarchical process to help specialty stores, especially for the sporting goods stores, to recommend products for consumers. To verify the accuracy, and feasibility of the proposed algorithm, a prototype recommender system is also developed for a badminton store to demonstrate the feasibility of the two-phase recommendation algorithm, and share the implementation experiences of the proposed technique.

2.0 THE BASIS OF ANALYTIC HIERARCHICAL PROCESS

Analytic Hierarchy Process (AHP) is developed by Saaty to provide a tool for solving different types of multi-criterion decision problems [17,18,19]. Based on mathematics and psychology, AHP is a structured technique for organizing and analyzing complex decisions. Rather than prescribing a "correct" decision, the AHP helps decision makers find one that best suits their goal and their understanding of the problem. It also provides a comprehensive and rational framework for structuring a decision problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions.

There are five fundamental elements in AHP, and they are:

1. Goal: The purpose or the problem that we want to solve or want to be reached.
2. Alternatives: The finite set of options to be chosen. They represent the possible candidates to the solution.
3. Criteria: The alternatives comparison is made taking into account a specific set of evaluation criteria. For each alternative, it can be better or worse, depending on the adopted set of criteria. A criterion represents one property to be evaluated in each alternative.
4. Hierarchy: The set of criteria is organized hierarchically as shown in Fig. 1.

5. Pair-wise Comparison: The comparisons are made pair by pair to show which alternative is preferable in relation to another. As shown in Fig. 2, comparisons are registered in a pair-wise matrix, where element a_{ij} represents a comparison between alternative*i* and alternative *j*.

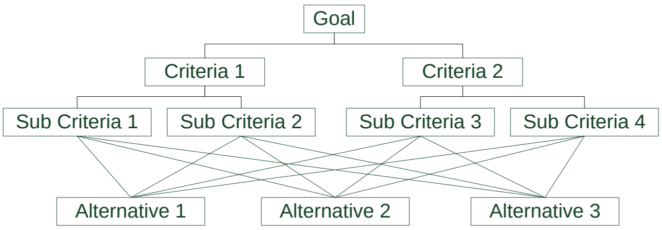

Fig. 1. AHP Hierarchical Structure

$$\begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ & 1 & a_{23} & a_{24} \\ & & 1 & a_{34} \\ & & & 1 \end{bmatrix}$$

Fig. 2. Pair-Wise Matrix for AHP

Table 1. Saaty Scales for AHP

Importance	Explanation
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	The intermediate values of adjacent judgments

Table 1 is the Saaty scaleused in factors comparisons.An element must be assigned a number to define how much it is better or more important than the others.

2.1. AHP Process Steps

The basic steps in AHP processes are:
1. Identify the problem.
2. Extend the objectives of the problem or consider all factors and the outcome.
3. Identify the criteria.
4. Structure the problem in a hierarchy of different levels including goal, criteria, sub-criteria and alternatives.
5. Do the comparison for each element in the same level, set them to the numerical scale. There are n(n-1)/2 comparisons, n is the number of elements. The diagonal elements are always "1". The others are the reciprocals of the earlier comparisons.
6. Do the calculations to find the maximum Eigen value, consistency index C.I, consistency ratio C.R.
7. If the maximum of Eigen value, C.I, and C.R is suitable, then a decision is taken or everything should be repeated till these values are in a desired range.

2.2. AHP Operations

After the pair-wise comparison of step5 is done, we need to calculate the Eigen value. We can use the equation (1) below for this purpose.

$$W_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} i, j = 1, 2, \dots, n \tag{1}$$

To verify the Eigen values, we need to find the *C.I* and *C.R* values.If*C.R*< 0.1, the result of Eigen values would be accepted.

$$C.I = \frac{\lambda - n}{n - 1} \tag{2}$$

$$\lambda = \frac{\sum_{i=1}^{n}(\sum_{j=1}^{n} w_j a_{ij})/w_i}{n} i, j = 1, 2, \dots, n \tag{3}$$

$$CR = \frac{C.I}{R.I} \tag{4}$$

Equation (4) will use the value of *R.I* for the computation. R.I which stands for random index,is the average value of C.I for random matrices using Saaty scale obtained by Forman and Saaty, only accepts a matrix as a consistent one iff C.R < 0.1 [17].Table 2 showsthe values of *R.I.*

Table 2. R.I values

N	1	2	3	4	5	6	7	8
R.I	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41

3.0 TWO-PHASE RECOMMENDATION ALGORITHM

3.1. Basic Definitions

For traditional AHP-based applications, consumers are requested to answer many questions in questionnaires to help the service provider understand what consumers exactly need. In reality, consumers are not willing to spend time to answer questions. Consequently, reducing the number of questionsis the key factor of a successful recommender system. To meet the requirement, our algorithm proposes to consult experienced experts or professionals with product knowledge in advance to figure out the relationships between product attributes and user features.

The proposed algorithm uses four types of data set, and they are product set, product profile domain, user profile domain and matching set. Each data set represents the products with specified features, and collects user attributes for further matching process. Based on the matching set, we convert consumer attribute values into corresponding product attribute values which will be used as the input data tothe AHP algorithm. By applying the AHP algorithm, there is a need to make the pair-wise comparison between products to measure the importance levels. Again, we use the distance of each product attribute value to compute the level of importance. The product with the minimum distance will be the one with themost important level, and will be the target product to suggest to consumers.

3.1.1 Product Profile Domain

Let Prod bea set of products:

$$\forall \mathrm{prod} \in \mathrm{Prod}, \exists \mathrm{prod} = [\mathrm{prod}_{\mathrm{id}}, \mathrm{att}_{\mathrm{name}}, \mathrm{att}_{\mathrm{val}}] \quad (5)$$

where

$prod_{id}$ is the series number

att_{name} is the name of an attribute

att_{val} is the value of att_{name}

3.1.2 User Product Profile

Let Pbea set of user product profiles. Its elements are product attributes which are listed in AHP in identifying the criteria. We have:

$$\forall \mathrm{p} \in \mathrm{P}, \exists \mathrm{p} = [\mathrm{p}_{\mathrm{name}}^{\mathrm{Att}}] \quad (6)$$

where

p_{name}^{Att} is the name of a product attribute

The purpose of this set is to create the set of product attributes used to calculate the Eigen value.

3.1.3 User Profile Domain

Let Ubea set of user profile domains which represent the personality attributes of each user. This dataset consists of relative product attribute and the weight of relationship. By extending equation (6), it can be represented as:

$$\forall \mathrm{u} \in \mathrm{U}, \exists \mathrm{u} = [\mathrm{u}_{\mathrm{name}}^{\mathrm{Att}}] \quad (7)$$

$$\forall \mathrm{p} \in \mathrm{P}, \exists \mathrm{p} = [\mathrm{u}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{w}_{\mathrm{p}}^{\mathrm{u}}]$$

where

u_{name}^{Att} is the name of user attribute

p_{name}^{Att} is the name of related product attribute

w_p^u is the weight of the relationship between u_{name}^{Att} and p_{name}^{Att}

User attributes form the user profile which arebasic information such as gender, age, weight, height, and so on. The relationship between product attribute and user attribute, and their weight are also defined here.

3.1.4 Matching Set

Let *Matc*be amatching set. It defines the matching condition between *U* and *P*. We have:

$$\forall \mathrm{m} \in \mathrm{Matc}, \exists \mathrm{m} = [\mathrm{u}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{u}_{\mathrm{range}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{range}}^{\mathrm{Att}}] \quad (8)$$

where

u_{name}^{Att} belongs to *U*, is the user attribute,

u_{range}^{Att} is the range of user attribute,

p_{name}^{Att} belongs to *P*, is the product attribute,

p_{range}^{Att} is the range of the product attribute.

The purpose of the matching set is to define the relationship between user attribute and product features. The relationship between U and Pisshown in Fig. 3. It would be the key of the proposed two-phase recommendation algorithm to convert the user attributes into the product features, which will help to identify the best suggestions to users.

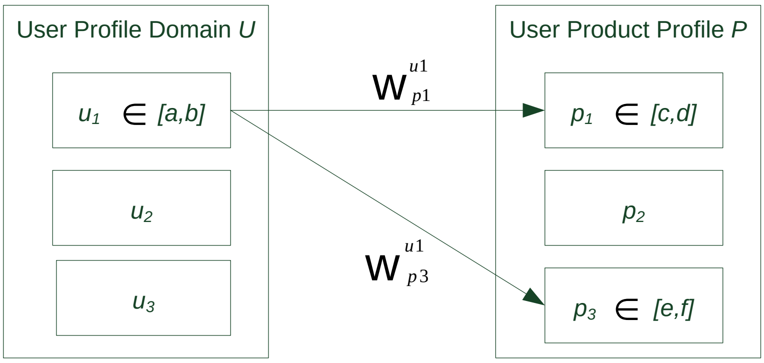

Fig. 3. The Relationship between *U* and *P*

3.2. Recommendation Phases

3.2.1 Phase I: Weight Calculating and Candidate Product Set Generation

In set *P*, the weights of these attributes are calculated based on the AHP method. In this process, there are many pair-wise comparisons to come out a comparison matrix.

$$P = (p_{ij}) = \begin{bmatrix} 1 & p_{12} & \cdots & p_{1n} \\ 1/p_{12} & 1 & & p_{2n} \\ \vdots & & \ddots & \vdots \\ 1/p_{1n} & 1/p_{2n} & \cdots & 1 \end{bmatrix}$$

Based on the above matrix, the priority vector can be worked out by equation 9.

$$W_i = \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}} \quad i, j = 1,2 \ldots n \tag{9}$$

It is the major task of phase I which tries to choose products from Prod set by using the matching from U to P.As defined in *Matc*, for each attribute in U, there isa corresponding attribute in P.When users input their reality value of an attribute in U, the corresponding point in P would be found. We name the corresponding point the $\mathrm{idealpoint}_p$. Let r_j bethe value of user attribute u_j. $u_j, p_i \in \mathrm{Matc}$, $u_j.\max$, $u_j.\min$, $p_i.\max$ and $p_i.\min$ are the range of u_j and p_i. $\mathrm{idealpoint}_{p_i}$ can be calculated by:

$$\mathrm{idealpoint}_{p_i} = \frac{\sum_{j=1}^{n}(\mathrm{cor}_{p_i}^{u_j} * w_{p_i}^{u_j})}{\sum_{j=1}^{n}(w_{p_i}^{u_j})} \tag{10}$$

where

$$\mathrm{cor}_{p_i}^{u_j} = \frac{(r_j - u_j.\min)(p_i.\max - p_i.\min)}{(u_j.\max - u_j.\min)} + p_i.\min \tag{11}$$

Takethe following case as the example. Let $p_1, u_1 \in \mathrm{Matc}$,$[a, b]$ and $[c, d]$ bethe ranges of p_1 and u_1. p_1 relates to u_1.Then the $\mathrm{idealpoint}_{p_1}$ could be calculated by:

$$\mathrm{idealpoint}_{p_1} = \frac{(\mathrm{cor}_{p_1}^{u_1} * w_{p_1}^{u_1})}{w_{p_1}^{u_1}} \text{ where } \mathrm{cor}_{p_1}^{u_1} = \frac{(u-a)(d-c)}{(b-a)} + c \tag{12}$$

Based on the $\mathrm{idealpoint}_{p_i}$, the candidate product set could be foundeasily. The candidate product set is a set of the products with attribute *i* close to the $\mathrm{idealpoint}_{p_i}$.Fig.4 represents the processes about how to find the candidate products.

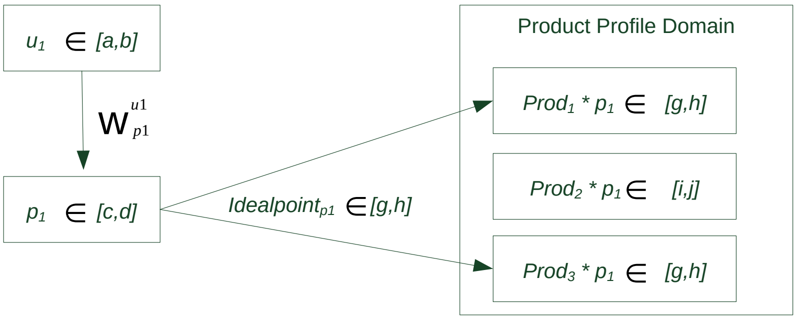

Fig. 4. Finding Candidate Products from Ideapoint

3.2.2 Phase II: Weight Settings for Candidate Products, and Generating Recommendations

The relation between products and $\mathrm{idealpoint}_{p_i}$ is described in Fig.5.

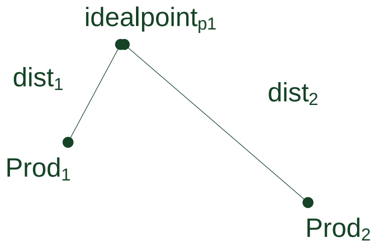

Fig. 5. Relationship between Ideapoint and Products

The closer distance to$\mathrm{idealpoint}_{p_i}$, the more important that product is. As shown in Fig. 5, dist_1 is closer to ideapointthan dist_2.It means product 1 is more important than product 2. Onthe other hand, the comparison of products equals to the comparison of their distance to idealpoint:

$$\mathrm{k} = \frac{\mathrm{dist}_2}{\mathrm{dist}_1}, \mathrm{k} > 0, \mathrm{dist}_2 > \mathrm{dist}_1 \qquad (13)$$

Let A = ("equal importance", "moderate importance", "strong importance","very strong importance", "extreme importance") be a fuzzy set which represents the level of importance. The membership function of set A is:

$$\mu_{A_i}(\mathrm{k}) = \begin{cases} 0, \mathrm{k} < a \\ \quad 1 \quad , \mathrm{a} \le \mathrm{k} < b \quad \mathrm{a,b} \in \mathrm{N}; \mathrm{i} = 1,2,\ldots,5 \\ 0, \mathrm{k} \ge \mathrm{b} \end{cases} \qquad (14)$$

Let α be an importance level of a product in product pair-wise comparison. We have:

$$\alpha = \mu_{A_i}(k) \text{ where } \mu_{A_i}(k) = 1 \text{ , } i = 1,2,\dots,5 \qquad (15)$$

The value of α can be found in Table 1, and the product pair-wise comparison is created as shown in Table 3.

Table 3. Product Pair-Wise Comparison

p_i	Product 1	Product 2	…	Product n
Product 1	1	$\alpha_{1,2}$	…	$\alpha_{1,n}$
Product 2	$\frac{1}{\alpha_{1,2}}$	1	…	$\alpha_{2,n}$
…	…	…	…	…
Product n	$\frac{1}{\alpha_{1,n}}$	$\frac{1}{\alpha_{2,n}}$	…	1

By applying equation (9), the priority vector of each product can be calculated. The final recommendation could be calculated by:

$$\text{result}_i = \sum_{j=1}^{m} w_j * \text{candiatePrioVect}_{ji} \quad i = 1, 2, \dots, n; j = 1,2,\dots,m \qquad (16)$$

where w_j is the product attribute priority vector which is calculated in equation (12) and candidatePrioVect is candidate product priority vector. The product with the highest valuewould be the final recommendation.

4.0 IMPLEMENTATION OF THE TWO-PHASE RECOMMENDER SYSTEM

4.1. System Architecture

The idea of the Two-Phase recommendation algorithm is to reduce the number of questionsfor consumers, and try to leverage the advantage of AHP to calculate the best-fit suggestion to them. To meet the goal, we asked users to input their basic profiles with attributes of weight, height, gender and years of playing badminton to replace the questions. As shown in Fig. 6, users input their profiles, and then the system will automatically convert them into product features which are created by surveying badminton professionals and players in advance. In Fig. 7, during the second phase process, the recommender system will calculate the distance for each product, and then suggest the best-fit product to users.

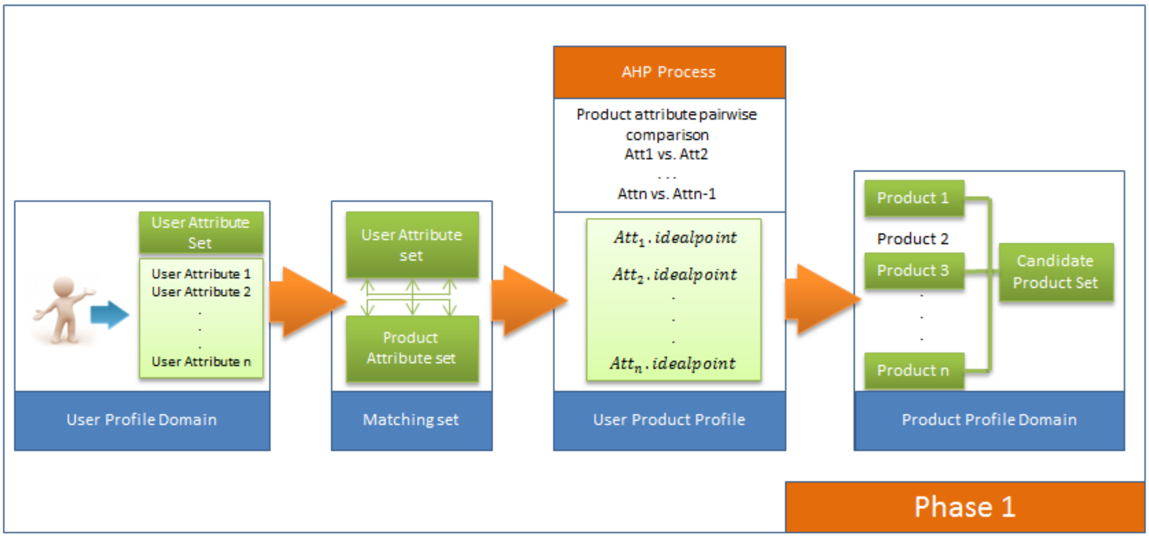

Fig. 6. Phase 1 of Two-Phase Recommendation

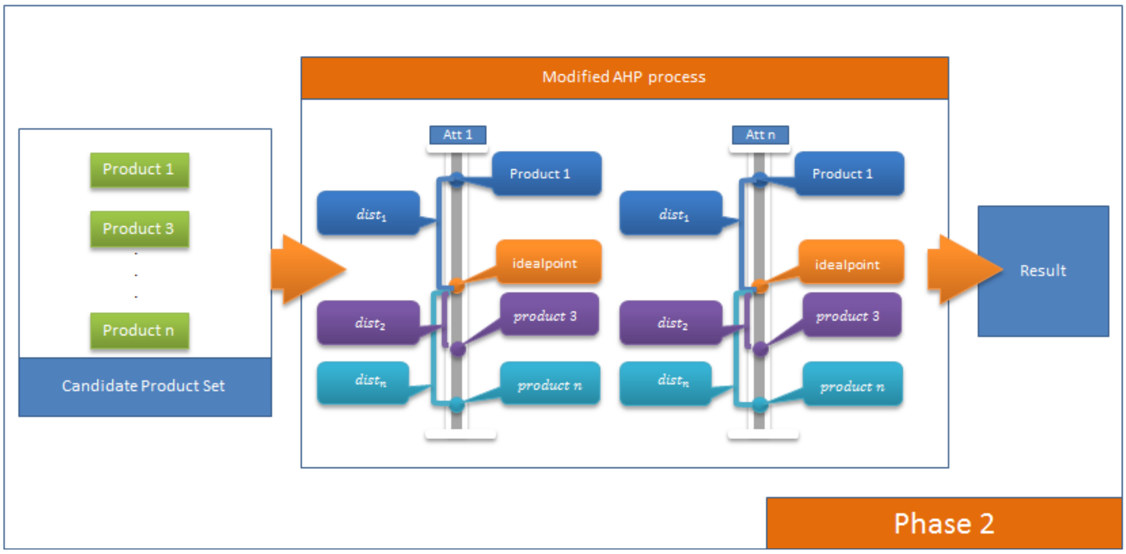

Fig. 7. Phase II of Two-Phase Recommendation

The badminton recommender system is implemented using web interface, and http protocols. The web interface is integrated with Facebook system [20]. In our implementation, we used HTML and javascripts in the client side, php and MysQL on the server side. XML is used to be the data format for the transmission of data or control logic back and forth between the server and clients.

There are user interface, data collector, recommendation engine, get data engine, feedback collector and system database. Fig. 8 shows the structure of the system. User interface is used to let the user interact with the system. The user can read and answer the questions then leave feedback about the recommendation result. The data collector is used to collect user information, and user feedback information. So, the system can provide the expert with more information to increase system performance. The recommendation engine is used to process recommendations. From the information received from the user interface system, phase 1 and phase 2 can be sequentially conducted. The get data engine plays the role of a bridge between the recommendation engine and system database. By creating the queries from recommendation engine,relevant information can be retrieved from the database system. The feedback controller is used to integrate the information about the user which is given by the data collector, then store at the system database.

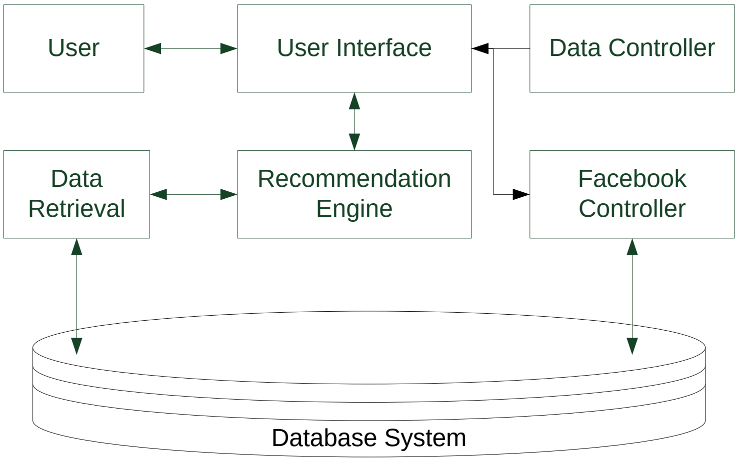

Fig. 8. System Architecture of the Two-Phase Recommender System

4.2. Recommendation engine

Fig. 9 is the detailed implementation of the recommendation engine. It is the key component of the badminton recommender system. Its major function is to convert user attributes to product features.After the phase 1 process, products with the same features will be collected, and as the input of the second phase. The main function of the phase 2 process is to calculate the best-fit product to users.

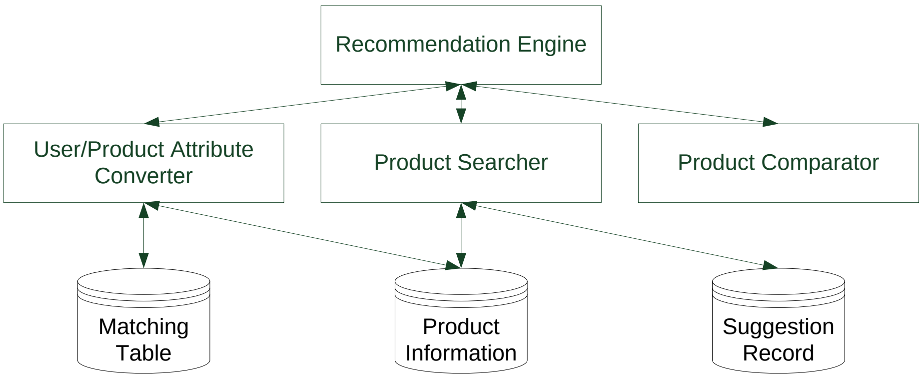

Fig. 9. Architecture of Recommendation Engine

The recommendation engine converts user attributes to product features, and search products with the same features in phase 1. It also computes the distance of each product, and calculatesthe ideapoint for the final recommendation.

5.0 CASE STUDY WITH BADMINTON SPECIALTY STORES

For users who love to play badminton, asuitable racket is a basic need for improving playing skills or just for fun. It is really difficult for them to choose a good racket because badminton rackets have numerous properties such as length, weight, tension, and the like. Some typesof badminton rackets are designed for offensive players and some are for defensive players. The purpose of each design has its own target players or consumers.Besides, there will be too many advices while buying rackets, and users do not know how to choose a suitable one. Bonny Inc. (www.bonny.cn) is a sport equipment manufacturer which was founded in Taiwan in 1982. Ithasmore than 26 years of experience in manufacturing composite materials and hasextensive experience in racket design. During the past 26 years, Bonny has manufactured tennis rackets, badminton rackets, squash rackets, ski poles, and hockey sticks and so on. During the development of the two-phase recommender system, Bonny plays the roles of professional player, and well-known ledged expert. Itdefined the relationships between user profiles, and product features. It would be a good reference for other sporting goods recommender system design.

5.1. Player Attribute and Product Attribute Analysis

In the following tables, there are the styles of suggestions from players about the relationships between racket frame shape, racket frame, user profiles and product features.

Table 4. The Relatiohship between Player attributes and Racket Frame Shape

Defensive	Frame shape	Small-isometric/Medium-isometric/ Big-isometric
	Frame	Medium-profile/Narrow-profile
Offensive	Frame shape	Small-isometric/Medium-isometric/ Traditional frame
	Frame	Medium-profile/Wide-profile

Table 5. The Relationship between Weight, Height of Male, and Weight of Racket

Height (cm)	Weight (kg)	Racket weight (g)
140 – 149	36 – 54	83±1
150	45 – 55	84±1
151 – 155	46 – 60	85±1
156 – 165	51 – 71	86±1
166 – 169	59 – 76	87±1
170 – 174	63 – 81	88±1
175 – 179	68 – 87	89±1
180 – 185	72 – 93	90±1
>185	78 – 100	91±1

Table 6. The Relationship between Weight, Height of Female, and Weight of Racket

Height (cm)	Weight (kg)	Racket weight (g)
140 – 142	27 – 35	77±1
143 – 145	30 – 38	78±1
146 – 148	32 – 42	79±1
149 – 150	35 – 44	80±1
151 – 154	37 – 48	81±1
155 – 164	41 – 60	82±1
165 – 169	50 – 65	83±1
170 – 172	54 – 68	84±1
173 – 176	57 – 72	85±1
177 – 179	61 – 76	86±1
180 – 182	64 – 79	87±1
>183	66 – 83	88±1

Table 7. The Relationship between Play Experience, Balance, Flex and Gender

Male	Offensive	N/A	Balance (mm)	290
			flex	M
	Defensive	beginner	Balance (mm)	280 – 286
			flex	S
		Intermediate	Balance (mm)	280 – 288
			flex	M
		Professional	Balance (mm)	285±1
			flex	M
Female	Offensive	beginner	Balance (mm)	285 – 290
			flex	S
		Intermediate	Balance (mm)	285 – 290
			flex	S
		Professional	balance	285 – 290
			flex	M
	Defensive	beginner	Balance (mm)	280 – 285
			flex	S
		Intermediate	Balance (mm)	280 – 285
			flex	S
		Professional	Balance (mm)	280 – 285
			flex	M

5.2. Implementation of Badminton Racket Recommendation

Based on the above tables, we can now convert user profiles into product features, and then match the relationships into ideapoints. Table 8shows a matching table for an intermediate player in a specific case.

Table. 8. Matching Table for Intermediate Player

U	Range	Weight of U and P	P	Range
Height (cm)	170	0.6	Weight	87
	174			89
Weight (kg)	61	0.4	Weight	85
	71			87
Years	1	1	Balance	280
	5			288

For an intermediate player with 172 cm in height, 64 kg in weight, he has played badminton for 5 years. By (11) and (12), we can get theidealpoint$_{weight}$ as86, and idealpoint$_{balance}$ as288. From this, we can find a set of products with attributes close to these ideal points. Tables9-11are lists of six products which are chosen and Table 12 shows the distances to the ideal points.

Table. 9. Product Candidate Set

Series	A	B	C	D	E
Weight	83	84	86	86	91
Balance	297	295	295	292	300

Table. 10. Distance to the Ideapoint

Series	A	B	C	D	E
Weight	3	2	0	0	5
Balance	9	7	7	4	12

Based on the equations of (13), (14) and (15) we create the product pair-wise comparison and find out the priority vector of each product. Table 11and Table 12 are the pair-wise comparisons in the case of weight and balance.

Table. 11. Pair-Wise Comparison in the Case of Weight

Weight	A	B	C	D	E	PV
A	1	1	0.11	0.11	1	0.05
B	1	1	0.11	0.11	3	0.06
C	9	9	1	1	9	0.42
D	9	9	1	1	9	0.42
E	1	0.33	0.11	0.11	1	0.05

whereλ= 5.14; C.I = 0.04; C.R = 0.03

Table. 12. Pair-Wise Comparison in the Case of Balance

Balance	A	B	C	D	E	PV
A	1	1	1	1	1	0.19
B	1	1	1	1	1	0.19
C	1	1	1	1	1	0.19
D	1	1	1	1	3	0.25
E	1	1	1	0.33	1	0.18

whereλ= 5.15; C.I = 0.04; C.R = 0.03

As the expert calculated the priority of weigh as0.75, balance as0.25,based on the equation (16), we can find the recommendation. Table 13shows the recommendation results. The racket D with the highest value is the final suggestion to consumers.

Table. 13. Recommendation Results

A	B	C	D	E
0.084	0.097	0.367	0.381	0.072

6.0 DISCUSSION AND CONCLUSION

6.1. Lack of Recommender System For Sporting Goods Specialty Stores

In addition to the design and implementation of the two-phase recommender system, during the development period, we triedto understand the revenue distribution of sporting goods stores. It is interesting that half of the revenue comes from the products of remarkable brands. For badminton rackets, consumers buy the products of the first 3 brands (i.e., YY, Victory and Wilson) in the world. But, there is still a half of the revenue that comes from other products of infamous brands. Consumers buying worldwide products are mostly well-educated experts or professional players. They know how to choose rackets, and which racket to buy. As for the other half of consumers, they seldom buy rackets and do not know how to select the best-fit product for themselves. Based on the long tail theory, it is worth to have a good recommender system to automate and speed up the decision making process of buying a badminton racket which will strongly increase the revenue. It is really a pity that currently no suitable recommender system can be used to help the business of badminton specialty stores.

6.2. Just-in-Time Computation Is Necessary For Recommendations

It is important to regularly introduce new products of new technology, new features or improved quality to market for consumer product market. Once a new product is rolling out to the market, all consumers are new to it. It is difficult for the recommendation systems to compute the similarities for discovering the relationships between users and the new items. On the other hand, there will be a short-term trend for some events. For example, a new winner of an Olympic game will attract the eyes of audiences, and they are willing to buy the same products used by the winner. During the event, the recommender system should give the right suggestions to buyers. For stores of large volume of consumers or products, it will take too much time to calculate the suggestions before the end of the event. That is, the capability of just-in-time recommendation is necessary for sporting goods stores.

6.3. Feedbacks are the Key to Success

Although there exist several customer satisfaction collection mechanisms [21], [22], [23], it is still the hardest part for us to get feedbacks from consumers while verifying the correctness and improving thequality of the design and implementation of our system. In our experiments, we get two of threepositive feedbacks from 100 consumers. It seems that the proposed algorithm works well in badminton specialty stores. The key factor of the result would be the good design of our algorithm or the mapping of user attributes to product features given by experts or professional players. We need to have further investigations by applying the algorithm to different product domains such as table tennis or something like that. In addition, a good mechanism to verify the customer satisfactions from feedbacks is another important factor for us to improve the current version of two-phase recommendation algorithm.

6.4. Conclusion

Simple recommender systemsare already applied in some popular e-commerce websites like amazon.com and ebay.com. Most of the recommendations were calculated from the habits and hobbies of the registered members.That is to say, the recommendations can be helpless for unregistered visitors or new products.The proposed recommendation algorithm can be applied to the sporting goods specialty stores or sports equipment exclusive stores easily and solve the cold-start problems. Itdoes not onlyintegrate the knowledge of experts and professional players, the product features and the consumer attributes, but also leverage the advantages of AHP methodology to recommend best-fit products to consumers. Besides the design of the two-phase recommendation algorithm based on AHP, we also implemented a recommender system and applied it to the badminton specialty stores. From the feedbacks of consumers, the proposed algorithm works well by meeting the requirements from the users.

In the near future, we will have other practices[24,25,26,27] for different products such as table-tennis, and bicycles. We are also planning to designanother consumer satisfaction mechanism to verify the results from the proposed system.

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