東海大學資訊工程研究所

碩士論文

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基於 AHP 之網路商品推薦系統

An AHP-Based Recommendation System for Online Stores

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中華民國 一〇一 年 一 月 五 日

東海大學碩士學位論文考試審定書

資訊工程 研究所

研究生 阮 皇 維 所提之論文

基於 AHP 之網路商品推薦系統

經本委員會審查，符合碩士學位論文標準。

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中華民國 101 年 1 月 5 日

感 謝 函

能夠順利完成此篇論文，真的要大力的感謝羅文聰老師與許瑞愷老師，沒有兩位老師的鼎力協助與教導，我可能需要多花十倍的力氣在寫這篇論文，一開始真的要好好得感謝這兩位老師給予好的方向跟想法，還提供了一些學校沒有辦法得到的業界想法，衷心的感謝。

此外，在研究所的三年內要感謝的人數都數不清，當然最重要的是我的家人，提供給我一個無虞的生活環境，可以好好的在學校學習。這一路走來感謝我的父母對我在情緒上的包容，感謝我的父母不嫌棄他的兒子需要三年才能完成碩士學位，也感謝我的父母一直以來的栽培，我知道這一切都是很非常的辛苦。我也很感謝我伯父，在台灣這段時間他很照顧我讓我可以專心念完大學又鼓勵我升研究所。我真的很幸運才有這麼好的機會完成我的學業。

校內生活上，得先感謝兩個人，一個是智彬同學他在我最痛苦想題目的時候都把實驗室裡面的大小事情都承擔，讓我有更多時間完成題目。也感謝他在我碰到瓶頸的時候拍拍我肩膀鼓勵我，另外個人是我的學弟小光，感謝他每周四都與我一起去學吉他讓我可以放鬆並找回平衡點。也感謝很多我認識的朋友已在我背後鼓勵我。

感謝人：阮皇維

中文摘要

隨著網路的發展，電子商務也逐漸變成新的趨勢。許多種線上購物中心的出現，使得買賣不同種類商品變的更簡單，更快速。但此刻出現一個問題，因為網路的發達，購物中心陳列了大量資訊，使得消費者在找商品的時候反而更困難、更花時間與更費力。

因此，為了幫助消費者省時間，推薦系統誕生了。許多推薦技術已經被提出例如：content based、collaborative filtering 和 knowledge based。這些技術都以商品、消費者購物資訊來進行推薦運算。但是，它不能告訴消費者商品是否適合。除此之外，這些推薦技術也有一些問題如 cold start 等問題。

為了幫助消費者找出一件適合的商品，我們推出一種推薦方法，是基於 AHP 以及結合商品知識、專家經驗，此方法不但解決 cold start 問題，也改善傳統 AHP 的方法。消費者只需提供少數個人資訊，再經過系統運算後就可以找出一件適合的商品。此方法適合給專賣店或是專業店，因為他們對商品有足夠了解，同時也懂消費者的需求，因此很快就可以幫助消費者找到他們要找的商品。

最後，我們會以羽毛球推薦系統來當作我們方法的例子。

關鍵詞：Recommender system、cold start problem、Analytic Hierarchy Process、E-Commerce

Abstract

Recommendation system is an important method of solving the problem of information overload. It also helps consumers to save time while searching for goods. Numerous recommendation techniques are proposed. However, they still have to confront some weaknesses such as cold-start, gray sheep and matrix sparsity problems.

The purpose of this research is to propose a method to overcome the cold-start problem and recommend a fit item for consumers to improve the personalized service. The proposed method can be applied in the e-commerce websites of exclusive or specialty stores. It is a combination of the product knowledge and Analytic Hierarchy Process (AHP) method. There are two phases in the proposed method. Phase 1 is to calculate the weight between product attributes and create a candidate product set. Phase 2 is to conduct the recommendation from the candidate set.

This research also introduces the implementation experiences by taking the badminton racket recommendation as a case study example.

Keyword: Recommender system、cold start problem、Analytic Hierarchy Process、E-Commerce.

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Chapter 1

Introduction

1.1 Introduction

Internet has changed our world since it was born in 1980s. It has brought to us a different way to search information or connect with people. As the original purpose of the internet was the sharing of information among scientists in academic and government institutes. So, the efficiency and accuracy were emphasized and user friendliness was not a priority. Until the incompatible documents on different computer systems occurred, it prompted CERN to establish the WWW (World Wide Web) in 1989. From that WWW starts its revolution to change our lifestyle.

Along with the development of the internet [1] the ecommerce appeared and grown up quickly. It made the traditional markets behaviors changed. By the exploitation of e-commerce, a large number of data were produced. As a result, consumers spent more time to search for goods from different kinds of categories. So, the recommender system was developed [2] in order to help consumers save time and to simplify purchasing decision.

The recommendation technique is a core of the recommender system which is classified into content based, collaborative filtering, demographic, knowledge based and hybrid categories [3], [4]. The advantage of the recommender system is to generate recommendations based on customer interests, hobbies, and habits.

Most of the techniques have to confront a problem called “cold-start”. This term actually discusses two problems: New user and new item. The new user cold start problem is caused by the fact that the recommendations use the comparison between the target user and other users based on the accumulation of ratings, so a user with very little ratings will become difficult to categorize. The new item cold start problem results from a new item not having many ratings, and thus it cannot be recommended easily. However, these techniques are applied in many applications [5], [6] and [7].

Beside the recommender techniques, there is a common statistical method which is used to make the decision. It is known as Analytic Hierarchy Process (AHP) – an intuitively easy method for formulating and analyzing decisions [8], [9]. It is applied in many applications [10], [11] and [12].

In the end, this research also introduces the badminton racket recommendation as a case study example.

1.2 Motivation and Purpose

During the research, beside the classical problems of recommendation techniques, we found that most of the recommendations are based on user habits or hobbies. In some cases they are not good recommendation. Besides that, many exclusive or specialty stores in Taiwan need a suitable recommendation system for their business. In order to help these stores and improve the recommendation technique, we proposed a recommendation system which based on AHP and product knowledge that:

1. Solve the cold start problem.
2. Recommend an appropriate item for specialty or exclusive store consumers.
3. Improve the AHP method by reducing the amount of questionnaire questions.
4. Provide a simple and low cost recommendation system

The product knowledge in our system comes from the expert who is managers, product designers etc…they were serving in the sales department and have valuable knowledge about the products, customer requirements and preferences.

Chapter 2

Background

2.1 E-Commerce

2.1.1 What Is E-commerce?

What is E-commerce? The answer can be found on Google. But, we hope to give a clearly definition, in [13] it briefly defines electronic commerce or e-commerce. For a better understanding, let distinguish between e-commerce and electronic business. E-commerce is the buying and selling happen on the internet. Electronic business is all the electronic transaction, so it includes e-commerce. Another word, e-commerce is a part of electronic business. Electronic business includes a host of related activities such as: online shopping, sales force automation, supply chain management, electronic payment systems…etc.

E-commerce site is not only a pure electronic business, like amazon.com, but also is a site sells services. A company could have an e-commerce site but not necessarily need an electronic business.

Summary, Electronic commerce consists of the buying and selling of products and services over the internet. It is not only a buying and selling products online but also provides the entire online process of developing, marketing, selling, delivering and paying for products or services.

2.1.2 Models of E-commerce

As e-commerce has an explosive growth and helps many business organizations to increase their profit [14]. It causes the e-commerce transformation of many business organizations. There are numerous researches about how to transform into e-commerce [15]. And in [16], ecommerce is defined as a part of business and categorized into 4 models [17]:

1. Business to business (B2B): describes commerce transactions between businesses such as: the transactions between manufacturer and wholesaler or a wholesaler and a retailer.

2. Business to consumer (B2C): describes the activities of transactions between businesses and end consumer. B2C is the most basic trading patterns in the e-commerce with variety services such as: online banking, travel service, online auctions, health information and real estate sites.

3. Consumer to consumer (C2C): refers to two or more transactions between customers. These transactions necessarily have or do not necessarily have third-party presence.

4. Government to consumer (G2C)/ Government to business (G2B): G2C is the communication link between a government and private individuals. G2B is the online non-commercial interaction between local and central government and the commercial business sector.

There are advantage and disadvantage in e-commerce [13]. Table 2.1 - 1 is the summary of the advantage, and table 2.1 - 2 is the summary of disadvantage.

Table 2.1 – 1. The advantage of e-commerce

The Possible Advantages of E-Commerce
Open 7 days a week, 24 hours a day
Gaining additional knowledge about potential customers
Improved customer involvement
Improved customer service
Improved relationships with suppliers
Improved relationships with the financial community
Increased flexibility and ease of shopping
Increased number of customers
Increased return on capital and investment, since no inventory is needed
Personalized service
Product and service customization

Table 2.1 – 2. The disadvantage of e-commerce

Some Disadvantages of E-Commerce
Possible capacity and bandwidth problems
Security issues
Accessibility
Acceptance
A lack of understanding of business strategy and goals

2.1.3 Category of Ecommerce Service

Among the models of ecommerce, B2C is often used. In [18], based on the service of e-commerce website, it categorizes B2C into three kinds of role, they are: Supplier-oriented which includes content provider model, e-tailer model and manufacturing. Support-oriented which includes affiliate model, brokerage model and trust intermediary model. The last kind of role is consumer-oriented which includes community model and user creating model.

Although business models have been defined and categorized in many different ways, but it is a try to present a comprehensive and cogent taxonomy of business models observable on the web. And internet business models continue to develop; it should appear new and interesting variations in the future. Table 2.1 - 3 is the summary of the basic services.

Table 2.1 – 3. The Summary of Services

Type of Model	Description
Brokerage	They bring buyers and sellers together and facilitate transactions.
Advertising	The web advertising model is an extension of the traditional media broadcast model. The broadcaster provides content and services mixed with advertising messages in the form of banner ads.
Infomediary	Data about consumers and their consumption habits are valuable, especially when that information is carefully analyzed and used to target marketing campaigns.
Merchant	Wholesalers and retailers of goods and services. Sales may be made based on list prices or through auction.
Manufacturer	Another name is "direct model", it is predicated on the power of the web to allow a manufacturer to reach buyers directly and thereby compress the distribution channel.
Affiliate	Provides mechanisms or techniques to build memberships and share profit between allied websites.
Community	Provides a platform of people with a common interest enabling sharing information and service provision via the internet
Subscription	Users are charged a periodic fee (daily, monthly or annual) to subscribe to a service.

2.1.4 Recommendation in E-Commerce

During surveying the recommendation in e-commerce website, we find that e-tailing is the most common which is used in B2C. E-tailing has succeeded since 1997 [23]. Then, it pushed the traditional business organizations transform into e-commerce so, how to transform and how to satisfy the consumer on e-commerce website also are the research issues. In [24], it showed that there are five factors we have to notice in order to satisfy the consumer, they are: website design, information quality, customer service, website security and website intelligent. In [25], it showed that how many modules that e-commerce website needs to attract consumer.

During our survey about the approach to increase the intelligent for e-commerce website, we found that most of the researches focus on the recommender system of the auction sites [26], [27] and [28]. These recommendation techniques based on the "favorite" attribute of consumer.

But, our method is based on the "suitability" of the product for user, it is when consumer wants to purchase, he or she needs a "suggestion" of expert in order to buy the suitable product. Table 2.4 - 1 is a survey of the recommender techniques which are applied in B2C models.

Table 2.1 – 4. Survey of recommender system in e-commerce

B2C business model	Example website	Recommender system	Suggestion
Auction	amazon.com	Combination of collaborative and content base	1. Similar item 2. Item accessories
Clicks and bricks	walmart.com sears.com	Collaborative	Similar item
Catalog merchant	llbean.com landsend.com	Collaborative	Similar item
Exclusive store	missionbicycle.com	Not available	Not available
Specialty store	shop.wimbledon.com centralsports.co.uk	Not available	Not available

From our survey, the successful ecommerce website likes Amazon, Walmart… They have used a huge computation from many computers to build up their web services, including recommendation system. But, there are many smaller shop, they also want to improve their services so they have to apply the recommendation system.

2.2 Recommendation Technique

2.2.1 What Is Recommender System?

Recommender system analyzes the profile of users and the relationship between user and target item to help user purchase on the interest. With the power of computer, recommender systems can analyze huge collection of data of user's preference and give good recommended items. Recommender system also can help online companies to sell their products better.

In [19] we learn that elements of the recommender system are:

1. Background data: it is the information which required by system before the recommendation is made.

2. Input data: the user must provide system with their information in order to generate a recommendation.

3. Algorithm: an algorithm that is used to combine background data and input data to arrive at suggestions.

Based on these elements recommendation technique is categorized into different kinds. They are: collaborative filtering, content based, demographic, knowledge based and hybrid. Table 2.2 - 1 is a summary of the recommendation techniques which is modified by [19].

Table 2.2 – 1. Recommendation techniques

Technique	Background	Input	Process
Collaborative	Ratings from **U** of items in **I**	**u**'s ratings of items in **I**	Identify users that are similar in ratings to **u**, and extrapolate from their ratings of **i**
Content based	Features of items in **I**	**u**'s ratings of items in **I**	Generate a classifier that fits **u**'s rating behavior and use it on **i**
Knowledge based	Features of items in **I**. Knowledge of how these items meet **u**'s needs.	A description of **u**'s needs or interests	Infer a match between **i** and **u**'s need.
Demographic	Demographic information about **U** and their ratings of items in **I**	Demographic information about **u**	Identify users that are demographically similar to **u**, and extrapolate from their ratings of **i**

U is the set of users whose preferences are known, **u** belong to **U** is the user for whom recommendations need to be generated, and **i** belong to **I** is an item for which we would like to predict **u**'s preferences.

2.2.2 Collaborative Filters

A recommender system may use correlations between users as a basis for creating the predicted ratings of recommended items. It is mean the user will be recommended items that people with similar behaviors (i.e. buying, watching and listening) liked in the past.

Let make an example for explaining how this recommendation technique works. Table 2.2 - 2 is the summary of the rating from users set to the items.

Table 2.2 – 2. Example for collaborative filtering

	User 1	User 2	User 3	User 4	User 5
Item 1	–	+	+	+	–
Item 2	+	+	+	–	+
Item 3	+	–	+	–	+
Item 4	–	+	–	+	–
Item 5	+	–	+	–	?

We can see that user 1 and user 5 have previously rated on items in the same way, so this is likely to influence user 5’s prediction for the item 5 positively. We can also see that user 4 and user 5 tend to disagree in their ratings, and again it seems that user 5 will rate the item 5 highly.

The *similarity* between users is often computed by using Pearson’s correlation [19]. After computing the degree of *similarity* between the target user and other users, the system predicts a rating for a given item.

2.2.3 Content-based Filters

Content-based recommender systems are based on user ratings and similarity between items. It is mean, while collaborative filtering are based on correlations between users, content-based filters are based on correlations between items.

Let make an example for explaining how this recommendation technique works. Table 2.2 - 3 is the summary of the rating from user set to the items and their key words.

Table 2.2 – 3. Example for content-based filtering

	Genre 1	Genre 2	Genre 3	Genre 4	Genre 5	User 1
Movie 1	Y	Y				–
Movie 2			Y	Y		+
Movie 3					Y	+
Movie 4	Y					–
Movie 5					Y	?

We can see that each movie has several keywords (maybe are genres). User 1 does not like movies with genre 1, and she likes the other movie with genre 5. Then the weight for genre 1 would be negative, and the weight for genre 5 would be positive. The movie only belong to genre 5 has a high score and is recommended, and the movie only belong to genre 1 has a low score and is not recommended. The predicted rating for a movie would be lower if it belongs to two genres. How much lower would depend on the relative weighting of the genre.

The *similarity* between items is also computed by using Pearson's correlation [3].

2.2.4 Knowledge-based

The recommendation relies on product knowledge. Knowledge-base can be seen as particular types of content-based filters. In other words, item properties are used in order to make recommendations.

Knowledge-based approaches are distinguished in that it has functional knowledge: it has knowledge about how a particular item meets a particular user need, and the relationship between a need and a possible recommendation. The user profile can be a knowledge structure supports inference.

The knowledge used by a knowledge-based recommender can also take from many forms such as: Google uses information about the links between website to infer the popularity and authoritative value.

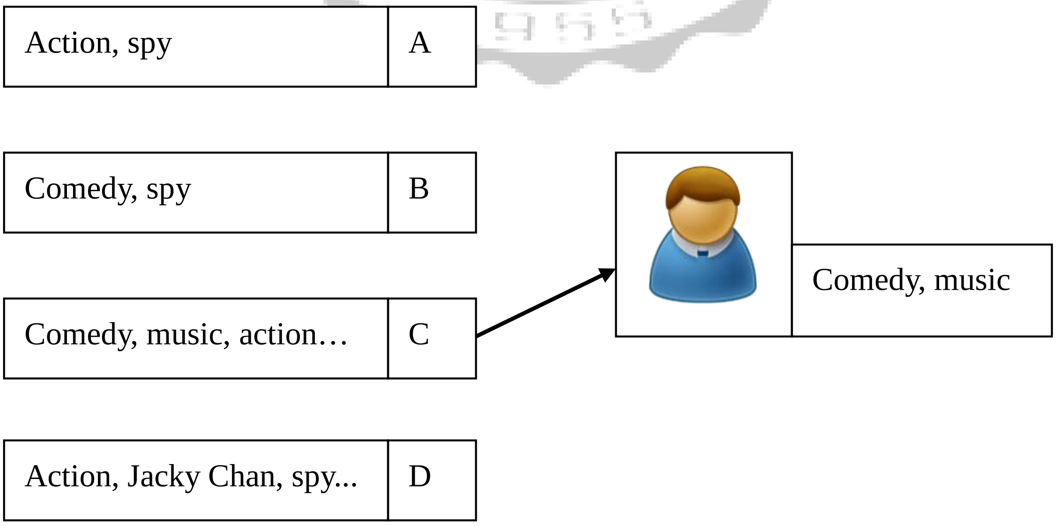


Figure 2.2 – 1. Knowledge-based approach

2.2.5 Demographic-based Filters

Demographic-based filter use the known user characteristics in order to classify users and model user preferences into classes. Could say that demographic-based filter works similarly to collaborative filter as they use the similarities between users, but the different is they use the different types of data. One is based on demographic information of users and the other is based on the rating patterns of users.

Demographic information of user can be used to identify the type of user. Table 2.2 - 4 shows information on the age, gender, education, etc. of people that rated a certain restaurant. With this data, system might learn the type of person that likes a certain restaurant.

Table 2.2 – 4. Example of demographic data

	Gender	Age	Education	Employed	Restaurant A
User 1	M	17	HS	0	+
User 2	F	19	HS	0	–
User 3	M	35	C	1	+
User 4	F	10	E	0	?

Figure 2.2 -2 is the explanation about the categorization of the exist user into a class.

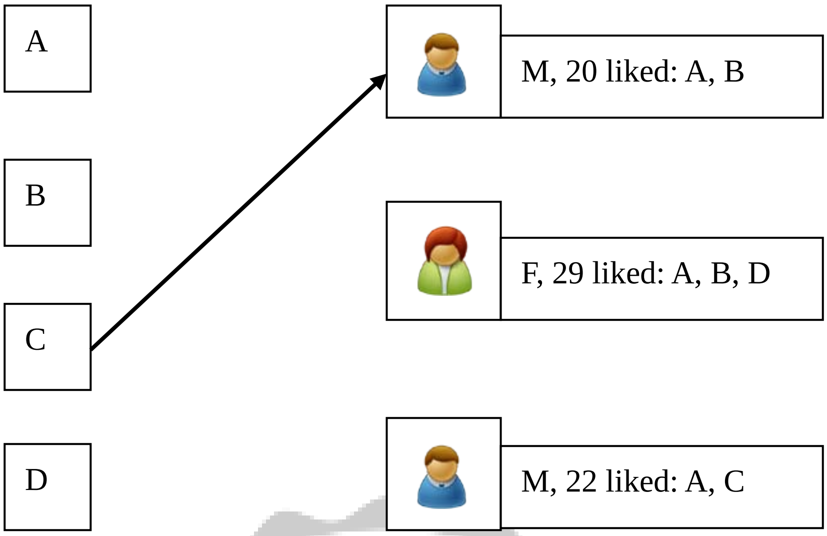


Figure 2.2 – 2. Demographic-based recommendation based on popularity

2.2.6 Hybrids

Many recommender systems use a combination or called hybrid to overcome the weaknesses in each algorithm. There is a discussion in [19] about the different types of hybrids used, and discusses how algorithms can be combined. In these hybrids, one recommender refines the recommendations which are given by another. The table 2.2 – 5 shows some of the combination methods that are used in hybrid recommender systems.

Hybridization can reduce several problems associated with collaborative filtering and other recommendation techniques. As, the cold-start problem occurs because there is a need of database of ratings. So, the hybrids are popular, because the ratings can be compressed from many examples, then can be more easily compared across users.

Table 2.2 – 5. Hybrid method categories

Hybridization method	Description
Weighted	The ratings of several recommendation techniques are combined together to produce a single recommendation
Switching	The system switches between recommendation techniques depending on the current situation
Mixed	Recommendations from several different recommenders are presented at the same time
Feature combination	Features from different recommendation data sources are thrown together into a single recommendation algorithm
Cascade	One recommender refines the recommendations given by another
Feature augmentation	Output from one technique is used as an input feature to another
Meta-level	The model learned by one recommender is used as input to another

2.2.7 Recommender Techniques and Classical Problems

All of the techniques that we concerned suffer from the cold-start problem. Also, there is a problem between stability and plasticity for these techniques. Once a user's profile is built up, it is hard to change the preferences. Example, a fan of BMW sport car that becomes a fan of Ferrari sport car will continue to get BMW car recommendation from a content-based or collaborative recommender for some time.

For improving one of the classical problems – cold start, there are numerous scholars were seeking different approaches to solve it such as:

1. Andrew et al [20] with the solution is to find out the other users whose preference are similar to the target users in collaborative filtering system, and take the favorite items as the basis for recommendation.

2. Paolo and Booby [21] by using 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.

3. Hyung Jun Ahn [22] with the same idea about cluster usage by establishing a new similar cluster to solve the new user's cold-start problem.

The table 2.2 – 6 summarizes the trade-off between the recommender techniques.

Table 2.2 – 6. Trade-offs between recommendation techniques

Technique	Strengths	Weaknesses
Collaborative filtering	A. can identify cross-genre niches B. Deep domain knowledge not needed C. Adaptive: quality improves over time D. Implicit feedback sufficient	I. New user cold-start J. New item cold-start K. “Gray sheep” problem L. Quality dependent on large historical dataset M. Stability vs. plasticity problem
Content-based	B, C, D	I, L, M
Knowledge-based	E. No cold start F. Sensitive to changes of preference G. Can include non-product features H. Can map from user needs to products	N. Suggestion ability static O. Knowledge engineering required
Demographic	A, B, C	I, K, L, M P. Must gather demographic information

2.3 Similarity Computation and Prediction

2.3.1 Similarity Computation

Similarity computation between items or users is a critical step in collaborative filtering and content based. In item-based of collaborative filtering, the similarity between two item *i* and *j* is first work on the set of users who have rated both of item *i* and *j*. Then, the Pearson correlation between items *i* and *j* is:

$$w_{i,j} = \frac{\sum_{u \in U}(r_{u,i} - \overline{r_i})(r_{u,j} - \overline{r_j})}{\sqrt{\sum_{u \in U}(r_{u,i} - \overline{r_i})^2}\sqrt{\sum_{u \in U}(r_{u,j} - \overline{r_j})^2}} \tag{1}$$

Where:

$w_{i,j}$ is the similarity between item *i* and *j*

$u \in U$ is the set of users who have rated both of item *i* and *j*

$\overline{r_i}, \overline{r_j}$ is the average rating of the i^{th}, j^{th} item

In user-based of collaborative filtering, we calculate the similarity $w_{u,v}$ between the user *u* and *v* who have both rated on the same items. Then, the Pearson correlation between user *u* and *v* is:

$$w_{u,v} = \frac{\sum_{i \in I}(r_{u,i} - \overline{r_u})(r_{u,j} - \overline{r_v})}{\sqrt{\sum_{i \in I}(r_{u,i} - \overline{r_u})^2}\sqrt{\sum_{i \in I}(r_{u,j} - \overline{r_v})^2}} \tag{2}$$

Where:

$w_{u,v}$ is the similarity between users *u* and *v*

$i \in I$ is the set of items which are both rated by users *u* and *v*

$\overline{r_u}, \overline{r_v}$ is the average rating of the user u and user v

2.3.2 Prediction Computation

This is the most important step in recommendation system. The predictions are generated from the subset of nearest neighbors of active user whose the similarity are in an acceptable range.

To make a prediction for the active user a, on a certain item i we can take a weighted average of all the ratings on that item, and then apply into the equation below:

$$P_{a,i} = \overline{r_a} + \frac{\sum_{u \in U}(r_{u,i} - \overline{r_u})w_{a,u}}{\sum_{u \in U}|w_{a,u}|} \tag{3}$$

Where:

$\overline{r_a}$,$\overline{r_u}$ are the average ratings for the user a, user u on all other rated items.

$w_{a,u}$ is the weight between user a and user u.

$u \in U$ is set of user who have rated the item i.

2.3.3 Example of Prediction for an Item

In this example, we will make the prediction of I_2 for U_1. Firstly, we have to calculate the weight between users. Secondly, we predict the rate for item I_2.As (3) required, we now start to calculate $w_{1,2}$, $w_{1,4}$ and $w_{1,5}$.

Table 2.3 – 1. A Simple example of ratings matrix

	I_1	I_2	I_3	I_4
U_1	4	?	5	5
U_2	4	2	1	
U_3	3		2	4
U_4	4	4		
U_5	2	1	3	5

To calculate the weight between users, we use equation (2). The table below is the result of the weights.

Table 2.3 – 2. The weights between users

$w_{1,2}$		
$\bar{r}_1$	Item	$r_{1,i} - \bar{r}_1$
4.5	I_1	-0.5
	I_3	0.5
$\bar{r}_2$	Item	$r_{2,i} - \bar{r}_1$
2.5	I_1	1.5
	I_3	-1.5
$w_{1,2}$	-1	

$w_{1,4}$		
$\bar{r}_1$	Item	$r_{1,i} - \bar{r}_1$
4	I_1	0
$\bar{r}_4$	Item	$r_{4,i} - \bar{r}_4$
4	I_1	0
$w_{1,4}$	0	

$w_{1,5}$		
$\bar{r}_1$	Item	$r_{1,i} - \bar{r}_1$
	I_1	-0.667
4.667	I_3	0.333
	I_4	0.333
$\bar{r}_5$	Item	$r_{5,i} - \bar{r}_5$
	I_1	-1.333
3.333	I_3	-0.333
	I_4	1.667
$w_{1,5}$	0.63	

Now we make the prediction rate of item 2 for user 1. In table 2.3 -1 we see that there are only user 2, user 4 and user 5 both rated item 2, so we take these users into account for the equation (3).

$$P_{1,2} = \bar{r_1} + \frac{\sum_{u \in U}(r_{u,2} - \bar{r_u}) w_{1,u}}{\sum_{u \in U} |w_{1,u}|}$$

$$= \bar{r_1} + \frac{(r_{2,2} - \bar{r_2}) w_{1,2} + (r_{4,2} - \bar{r_2}) w_{1,4} + (r_{5,2} - \bar{r_2}) w_{1,5}}{|w_{1,2}| + |w_{1,4}| + |w_{1,5}|}$$

$$= 4.667 + \frac{(2-2.5)(-1)+(4-4)(0)+(1-3.333)(0.63)}{1+0+0.63}$$

$$= 4.072$$

2.4 Analytic Hierarchy Process

2.4.1 What Is Analytic Hierarchy process?

Analytic Hierarchy Process (AHP) is developed by Saaty to provide a tool for solving different types of multi-criterion decision problems. It based on the relative priorities assigned to each criterion’s role in achieving the original goal.

2.4.2 Fundamental Elements of Analytic Hierarchy Process

The fundamental elements of the AHP 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 specific set of evaluation criteria. For each alternative was given 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 structured in hierarchical.

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

Figure 2.5 - 1 is AHP hierarchy structure, and figure 2.5 - 2 is pair-wise matrix, table 2.5 - 1 is Saaty fundamental scale.

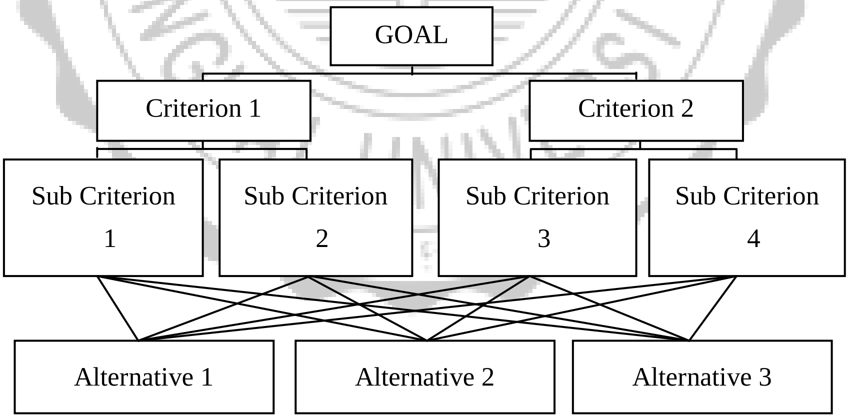


Figure 2.4 – 1. AHP hierarchy structure

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

Figure 2.4 – 2. Pair-wise matrix

Table 2.4 – 1. Satty fundamental scale

Importance scale	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 above

Saatty scale is used in factors comparisons an element must be assigned a number to define how much it is better or more important than the other.

2.4.3 Basic Steps in Analytic Hierarchy Process

The basic steps involved in analytic hierarchy process 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. Do the calculations to find the maximum Eigen

6. Find the maximum Eigen value, consistency index CI, consistency ratio CR.

7. If the maximum Eigen value, C.I, C.R is suitable then decision is taken or everything should be repeated till these values are in a desired range.

2.4.4 Analytic Hierarchy Process Operations

After the pairwise comparison is done, we need to calculate the Eigen value. We can use the equation (4) below for this purpose.

$$W_i = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i, j = 1, 2, \ldots, n \tag{4}$$

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

$$\mathrm{C.I} = \frac{\lambda - n}{n-1} \tag{5}$$

$$\lambda = \frac{\sum_{i=1}^{n} (\sum_{j=1}^{n} w_j a_{ij}) / w_i}{n} \quad i, j = 1, 2, \ldots, n \tag{6}$$

$$\mathrm{C.R} = \frac{C.I}{R.I} \tag{7}$$

Equation (7) will use the value of R.I for the computation. Table 2.5 – 2 is the values of R.I

Table 2.4 – 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

2.5 Facebook Platform

Because my implementation is developed on Facebook, so there is a need to make a short introduction about Facebook platform. Facebook first launched in 2004 with the name is thefacebook.com, the original purpose was only for student of Harvard university. And in 2005 it was re-launched with the name which is used now, Facebook. In 2006, it was opened for all users around the world.

The process of Facebook is not as same as the traditional process of website. Figure 2.5 – 1 is traditional website processes and figure 2.5 – 2 is Facebook processes.

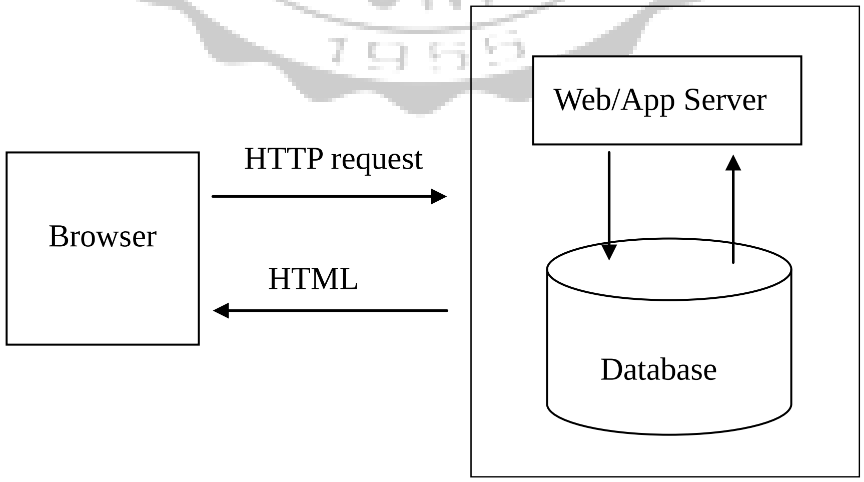


Figure 2.5 – 1. Traditional processes

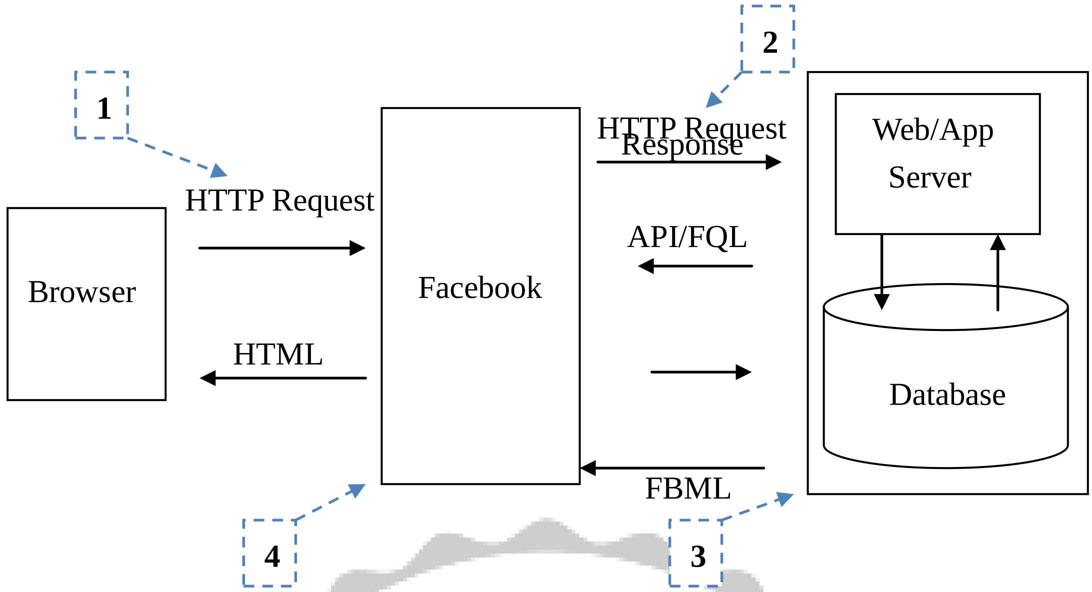


Figure 2.5 – 2. Facebook processes

1. Facebook server receives a URL request for your application
2. Facebook calls the callback URL on your server.
3. Your application processes the request, getting Facebook data via the API or FQL and returns FBML for display to the user.
4. Facebook takes FBML response, presents it within the Facebook canvas, and returns HTML to the requesting browser.

Facebook released a lot of APIs for developer, for the details of APIs, we can find all at http://developers.facebook.com/docs/.

Chapter 3

Methodology

In this section, we will introduce our methodology. Firstly, it is an introduction of some sets that will be used. Secondly, the introduction of the recommendation process, there are two phases: phase 1 is a process that calculates weight of product attribute, and creates candidate product set. Phase 2 is a process that calculates the weight for candidate products and generates the recommendation.

3.1 Basic Definition

In the traditional system which is based on AHP, consumer needs to answer a lot of questionnaire questions to help service provider understand what consumer exactly need. But now, consumer is not willing to spend much time to answer questions. With the purpose in reducing the number of questionnaire question, experience of expert and product knowledge are included into our method, by letting expert decides what kind of questions the system will ask users, and define the relationship between user attribute and product attribute etc. To achieve that we defined product set, product profile domain, user profile domain and matching set.

3.1.1 Product Profile Domain

Let *Prod* is a set of product which is defined:

$$\forall \mathrm{prod} \in \mathrm{Prod}, \exists \mathrm{prod} = [\mathrm{prod_{id}}, \mathrm{att_{name}}, \mathrm{att_{val}}] \quad (8)$$

Where:

$prod_{id}$ is the series number

att_{name} is the name of an attribute

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

The purpose of this set is to create a data of product with the whole product attributes and their value.

3.1.2 User Product Profile

Let *P* is a set of user product profile which its elements are the product attributes, listed in AHP, in identifying the criteria. We have:

$$\forall \mathrm{p} \in \mathrm{P}, \exists \mathrm{p} = [\mathrm{p_{name}^{Att}}] \quad (9)$$

Where:

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

The purpose of this set is to create the set of product attributes which are going to use in computing the product attribute Eigen value.

3.1.3 User Profile Domain

Let *U* is a set of user profile domain which is used to ask user for getting their personality attributes. In this data set, there are relative product attribute and the weight of relationship. We have:

$$\forall \mathrm{p} \in \mathrm{P}, \exists \mathrm{p} = [\mathrm{u}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{w}_{\mathrm{p}}^{\mathrm{u}}] \tag{10}$$

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}

The purpose of this set is to create user attributes which are used to ask for the user attribute value. The relationship between product attribute and user attribute, and their weight are also defined here.

3.1.4 Matching Set

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

$$\forall \mathrm{m} \in \mathrm{Matc}, \exists \mathrm{m} = [\mathrm{u}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{u}_{\mathrm{range}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{name}}^{\mathrm{Att}}, \mathrm{p}_{\mathrm{range}}^{\mathrm{Att}}] \tag{11}$$

Where:

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

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

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

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

The purpose of matching set is to define the relationship between user attribute and product attribute. The relationship between *U* and *P* are shown in figure 3.1 - 1.

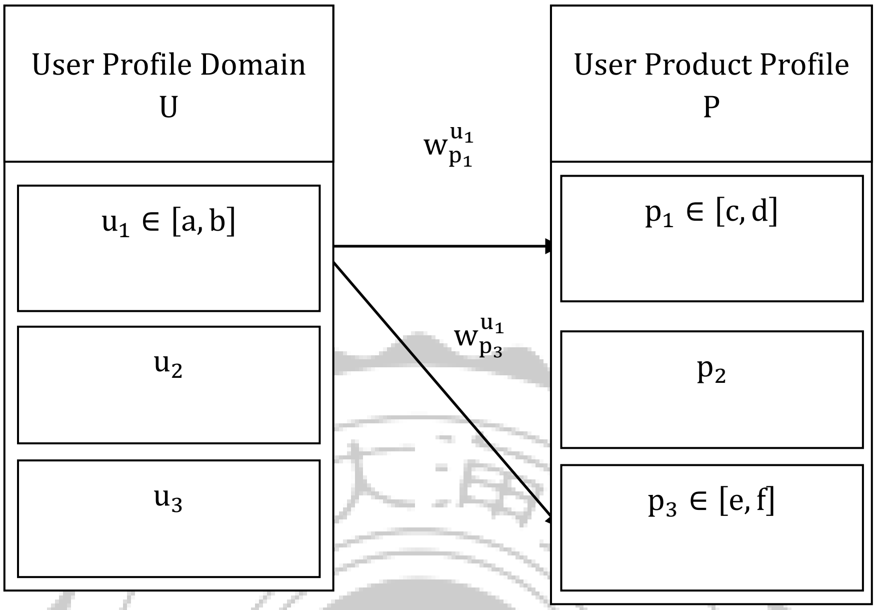


Figure 3.1 – 1. The relationship between *U* and *P*

3.2 Recommender Process

3.2.1 Phase 1 – Weight Calculating for Product Attributes, and Candidate product Set Generation

In set P, the weight of these attributes are calculated, it is required by AHP method. In this process, there are many pair-wise comparisons need to be done before the comparison matrix is made.

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

Then, the priority vector can be found by using:

$$W_i = \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}} \quad i, j = 1,2 \dots n \tag{12}$$

Now, it is the explanation about how to choose product from *Prod* set by using the matching from *U* to *P*.

$$U \rightarrow P \rightarrow Prod$$

As defined in *Matc*, for each attribute in *U*, there's a corresponding attribute in *P*, when users input their reality value of an attribute in *U*, the corresponding point in *P* is found, that point is called $idealpoint_p$. Let r_j is the value of user attribute u_j. $u_j, p_i \in Matc$, $u_j.max$, $u_j.min$, $p_i.max$ and $p_i.min$ are the range of u_j and p_i. $idealpoint_{p_i}$ is calculated by:

$$idealpoint_{p_i} = \frac{\sum_{j=1}^{n}(cor_{p_i}^{u_j} * w_{p_i}^{u_j})}{\sum_{j=1}^{n}(w_{p_i}^{u_j})} \tag{13}$$

Where:

$$cor_{p_i}^{u_j} = \frac{(r_j - u_j.min)(p_i.max - p_i.min)}{(u_j.max - u_j.min)} + p_i.min \tag{14}$$

Make an example. Let $p_1, u_1 \in Matc$, $[a, b]$ and $[c, d]$ are the ranges of p_1 and u_1. p_1 relates to u_1. Then the $idealpoint_{p_1}$ is calculated by:

$$idealpoint_{p_1} = \frac{(cor_{p_1}^{u_1} * w_{p_1}^{u_1})}{w_{p_1}^{u_1}} \text{ where } cor_{p_1}^{u_1} = \frac{(u-a)(d-c)}{(b-a)} + c$$

From idealpoint_{p_i} the candidate product set is found. Candidate product set is a set of the products which their attribute i is close to the idealpoint_{p_i}. This step is shown in figure 3.2 - 1.

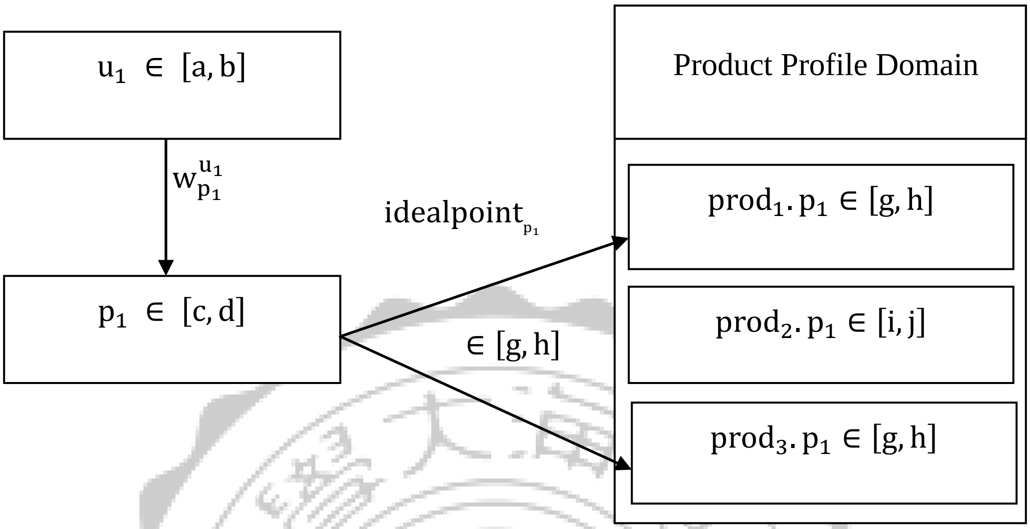


Figure 3.2 – 1. Finding candidate products from idealpoint

3.2.2 Phase 2 - Weight setting for Candidate Product, and Recommendation Generating

The relation between products and idealpoint_{p_i} is described in figure 3.2 - 2.

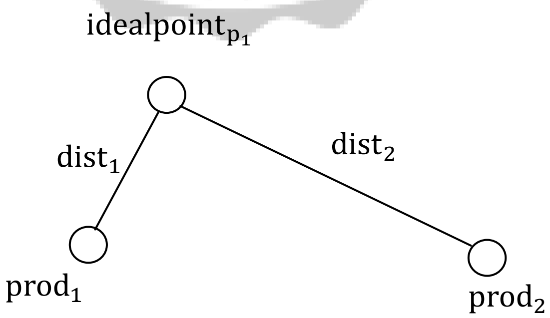


Figure 3.2 – 2. Relationship between idealpoint and products

The closer distance to $\mathrm{idealpoint}_{p_i}$, the more important that product is. So, dist_1 is closer than dist_2, it means product 1 is more important than product 2.

In other hand, the comparison of their distances is created to compare their distance to *idealpoint*:

$$k = \frac{\mathrm{dist}_2}{\mathrm{dist}_1}, k > 0, \mathrm{dist}_2 > \mathrm{dist}_1 \tag{15}$$

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

$$\mu_{A_i}(k) = \begin{cases} 0, k < a \\ 1 \quad , a \le k < b \\ 0, k \ge b \end{cases} \quad a, b \in N; i = 1,2, \ldots, 5 \tag{16}$$

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

$$\alpha = \mu_{A_i}(k) \text{ where } \mu_{A_i}(k) = 1, i = 1,2, \ldots, 5 \tag{17}$$

From table 2.4 - 1 the value of α can be found, then table 3.2 - 1, is product pair-wise comparison is created.

Table 3.2 – 1. Products 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 (12) into table 4, the priority vector of each product can be calculated. The final recommendation is calculated by:

$$\mathrm{result}_i = \sum_{j=1}^{m} w_j * \mathrm{candiatePrioVect}_{ji},\ i = 1,\ 2 \ldots n;\ j=1,\ 2 \ldots m \qquad (18)$$

Where w_j is product attribute priority vector which is calculated in (12) and *candiatePrioVect* is candidate product priority vector. The highest result is the final recommendation.

3.2.3 The Summary of the Methodology

The purpose of this methodology is to help consumers get the suitable item recommendation from their attributes. To achieve this goal, we create four kinds of data set: product set, product profile domain, user profile domain and matching set. They have their own usage. By the matching set, we convert consumer attribute values into corresponding product attribute values then, we put these data into AHP to make the decision.

During the process of AHP, there is a need that to make the pairwise comparison between products to measure the importance level of each. So, we use the distance of each product attribute value to an ideal point to decide the level of importance, the closer to an ideal point the more important the product get. Figure 3.3 – 2 is a summary.

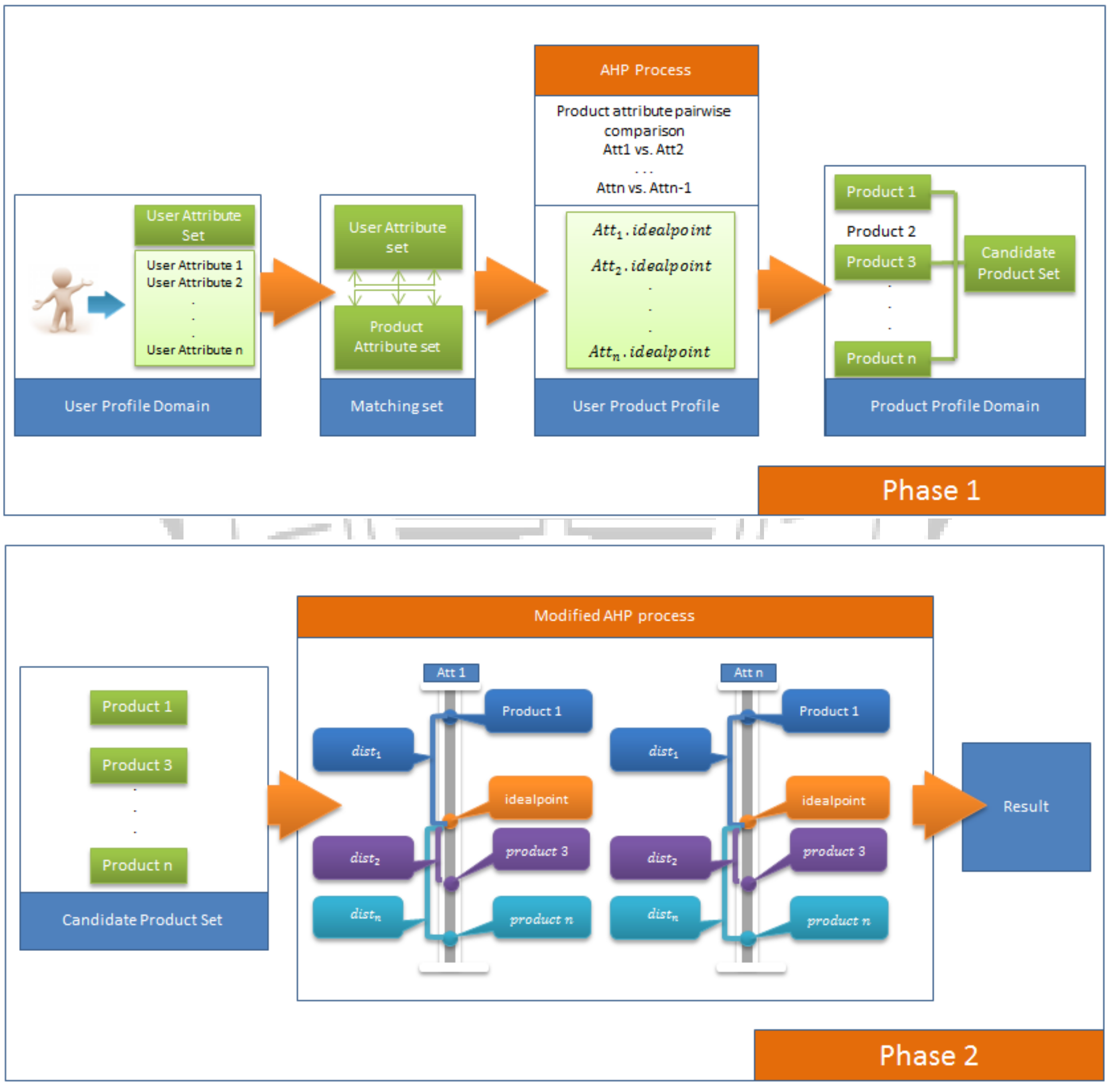


Figure 3.2 – 3. Summary of Recommendation Processes

Chapter 4

Implementation

4.1 The Structure of Recommender System

There are user interface, data collector, recommendation engine, get data engine, feedback collector and system database. The system is simple; figure 4 – 1 is structure of the system.

User interface is used to let user interacts with system. User can read and answer the questions then user can leave feedback about the recommendation result.

Data collector is used to collect user information, and user feedback information. So, system can provide expert more information to increase system performance.

Recommendation engine is used to process the recommendation. From the information which received from user interface system process phase 1 and phase 2.

Get data engine plays the role of a bridge between recommendation engine and System database. All queries which are created by recommendation engine through get data engine the needed information can be retrieved.

Feedback controller is used to integrate the information about user which are given by data collector then store at System database.

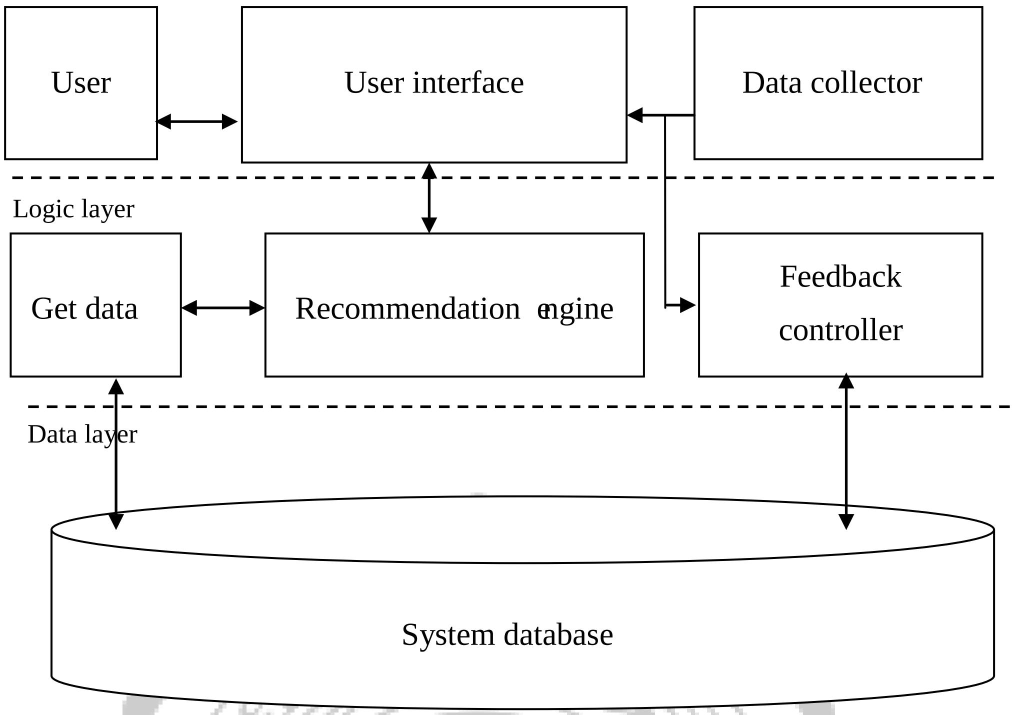


Figure 4.1 – 1. The structure of recommender system

4.2 Recommendation Engine

Figure 4.2 – 1 is the detail of recommendation engine structure. In *recommendation engine*, *user attribute/product attribute converter* and *product searcher* are our phase 1 and *product comparator* is our phase 2. *Product searcher* through *get data engine* retrieves the information that phase 1 and phase 2 requested.

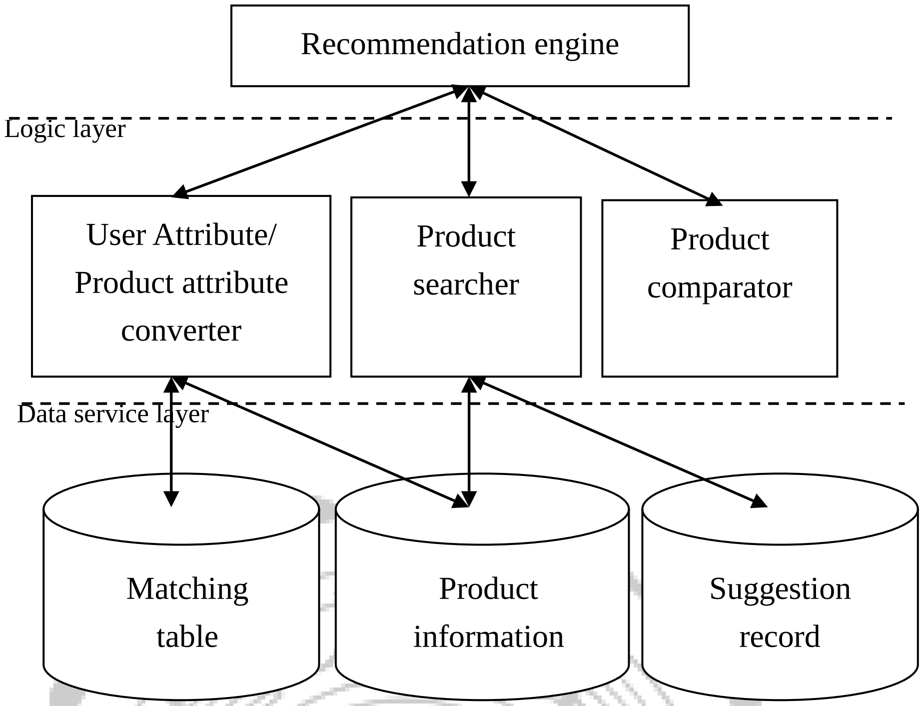


Figure 4.2 – 1. Recommendation engine

During the development of the badminton recommendation, there are many issues that we have to take notice, from the design of database to the user interface. As we have decided to develop this application on Facebook, so it is needed to make interface style as same as Facebook style. And, we also need to use dynamic memory disposing during the computation.

In our implementation, we used HTML+javascript on client side, php+MySQL on server side and XML is the data transfer from client to server or from server to client.

4.3 Case study – Badminton Recommendation

For a person who loves to play badminton, the suitable racket is a basic need in improving playing skill. But, it is difficult to choose, because badminton racket has numerous properties such as length, weight, tension... some kinds of badminton racket are designed for offensive player and some are for defensive player, and the usage is also different. So, although there are many advices from people about racket but it is still hard for new players to choose a suitable one.

Bonny [29] is a sport equipment manufacture which was founded in Taiwan area in 1982. They have more than 26 years of experience in manufacturing composite materials and have a deep experience in products such as: tennis rackets, badminton rackets, squash rackets, ski poles, and hockey sticks and so on.

In a project which we had a chance to cooperate with, Bonny gave us a lot of valuable knowledge about badminton racket. It is very helpful in taking into our badminton recommendation system.

4.3.1 Player Attribute and Product Attribute Analysis

In table 4.3 – 1, the styles of player decide their racket frame shape and racket frame.

Table 4.3 – 1. The relationship between player property 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 4.3 – 2. Relationship between height, weight 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 upper	78 – 100	91±1

Table 4.3 – 3. Relationship between height, weight 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 – 185 upper	66 – 83	88±1

Table 4.3 – 2 and table 4.3 – 3 showed that the racket weight belongs to different user height and weight values.

Table 4.3 – 4. Relationship between playing technique, balance, flex and gender

Male	Offensive		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

Table 4.3 – 4 showed that the player level also decides the balance and flex of a racket.

4.3.2 Implementation of Badminton Racket Recommendation

From the information which is given by expert, now we make an example to understand how our system works. Table 4.3 – 5 is a matching table for intermediate player in specific case.

Table 4.3 – 5. 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 (13), (14) we can get the $\text{idealpoint}_{\text{weight}}$ is 86, and $\text{idealpoint}_{\text{balance}}$ is 288. From this, we can find a set of products which their attributes are close to these ideal points. Table 4.3 – 6 is a list of six products which are chosen and table 4.3 – 7 is the distance to the ideal points.

Table 4.3 – 6. Product candidate set

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

Table 4.3 – 7. Distance to the ideal points

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

By (8), (9) and (10) we create the product pair-wise comparison and find out the priority vector of each product. Table 4.3 – 8, table 4.3 – 9 is the pair-wise comparison in case of weight and balance

Table 4.3 – 8. Pair-wise comparison in 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

λ= 5.14; C.I = 0.04; C.R = 0.03

Table 4.3 – 9. Pair-wise comparison in 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

λ= 5.15; C.I = 0.04; C.R = 0.03

As expert calculated priority of weigh is 0.75, balance is 0.25; by (11) we can find the recommendation. Table 4.3 – 10 is the results.

Table 4.3 – 10. Result

A	B	C	D	E
0.084	0.097	0.367	0.381	0.072

That we can see the racket D which has the highest value is our recommendation.

4.3.3 The Screenshot of Badminton Recommendation System

Our system is developed as an application on Facebook [30]. In figure 4.3 – 1 when user chooses recommendation feature, the first sight is some questions that user need to answer. After get these information, the system starts to process the recommendation and the result is shown in figure 4.3 – 2 and figure 4.3 – 3

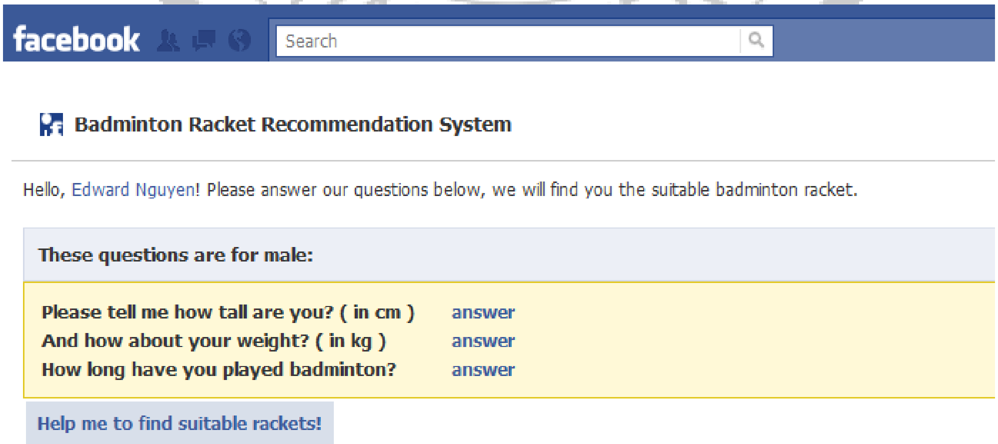


Figure 4.3 – 1. System Interface

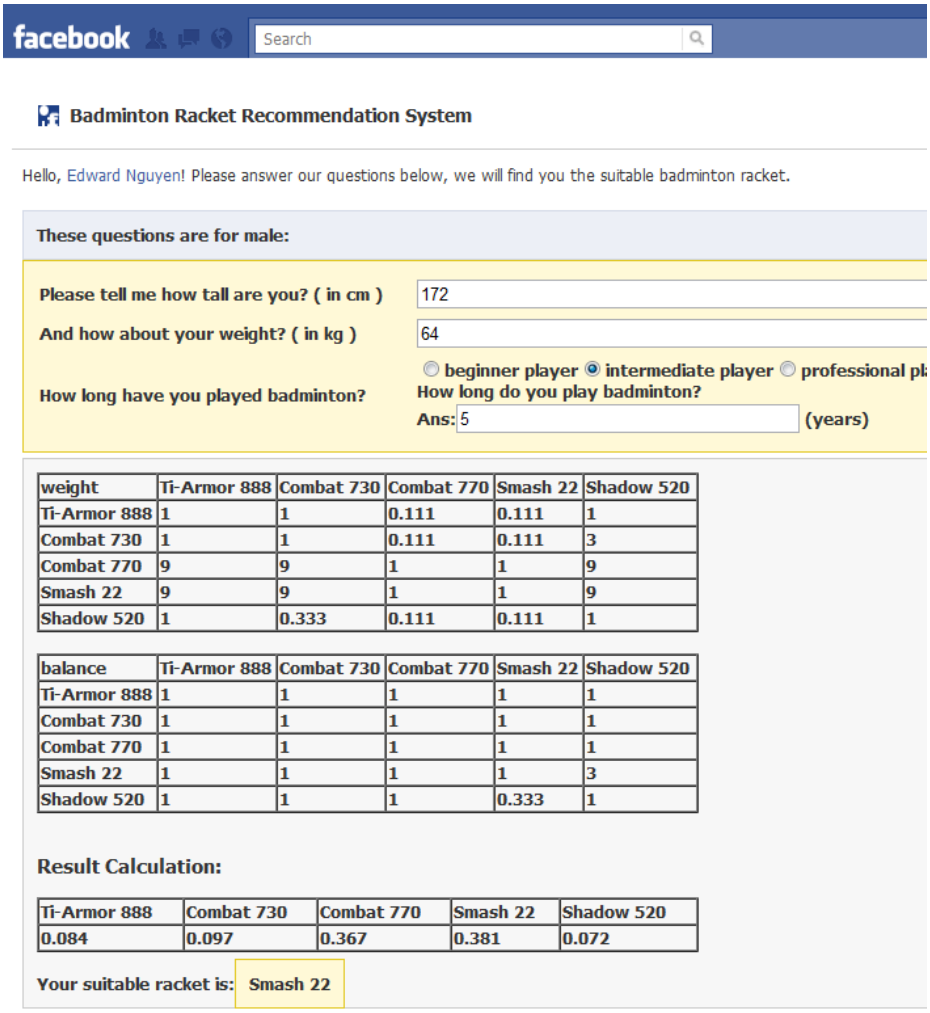


Figure 4.3 – 2. The result

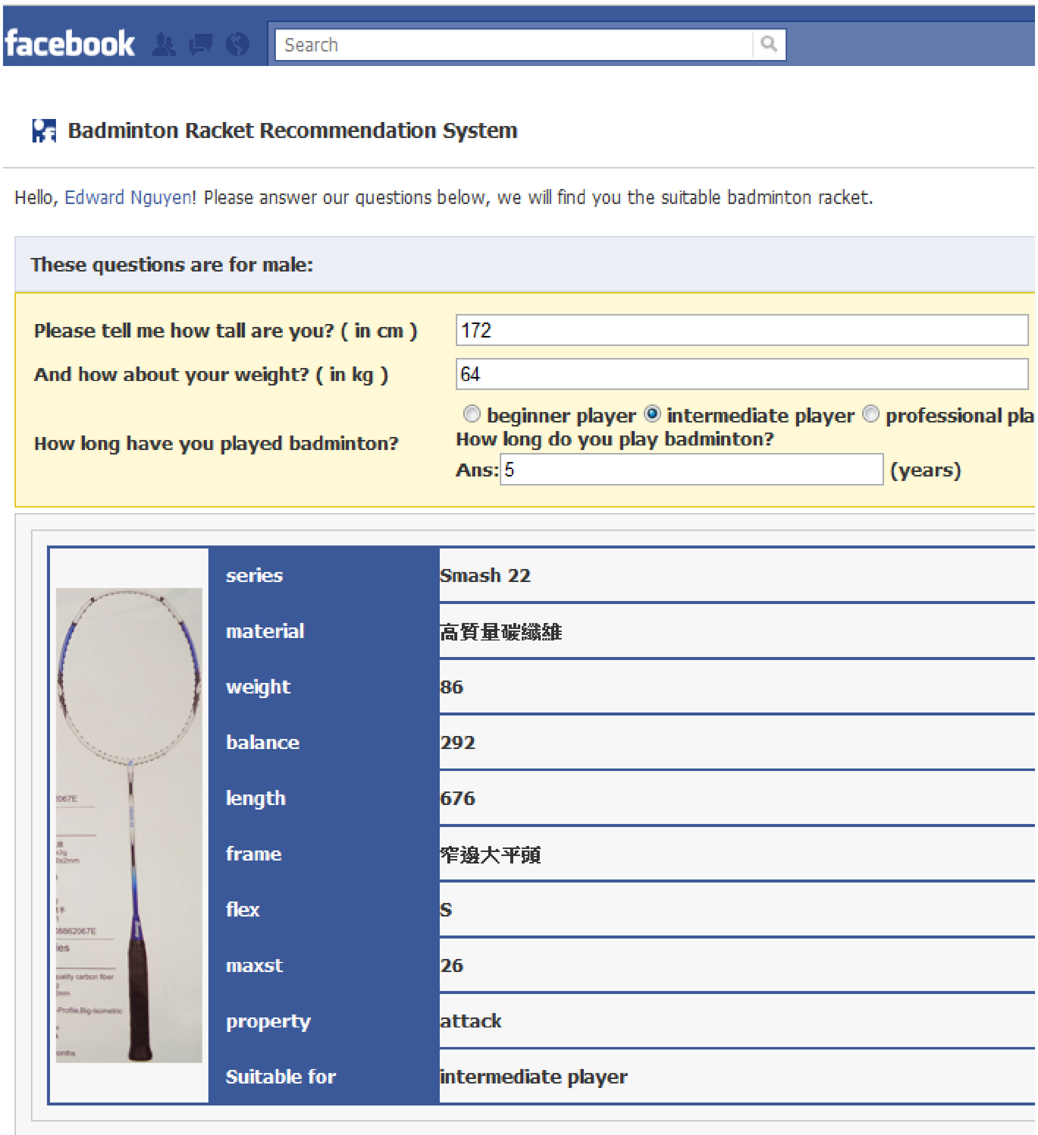


Figure 4.3 – 3. The recommendation racket

Figure 4.3 – 4 is the interface of management. There are: Product Database and Recommendation Process. Product Database is used to create and manage new production, and Recommendation process is used to create and manage the recommendation conditions.

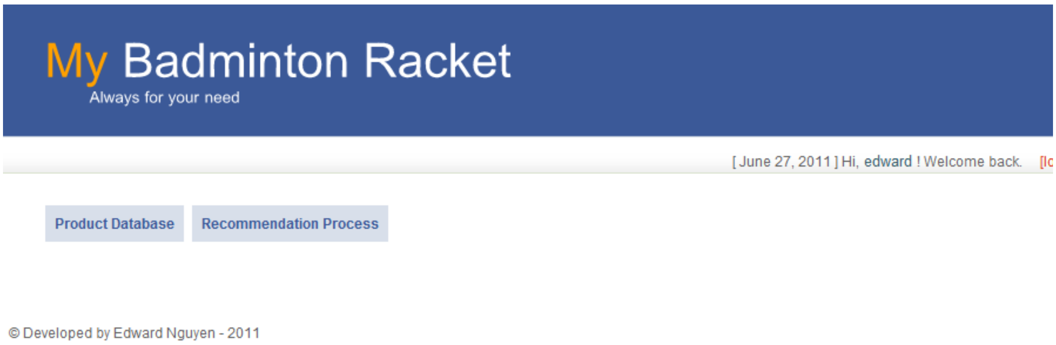


Figure 4.3 – 4. The interface of management

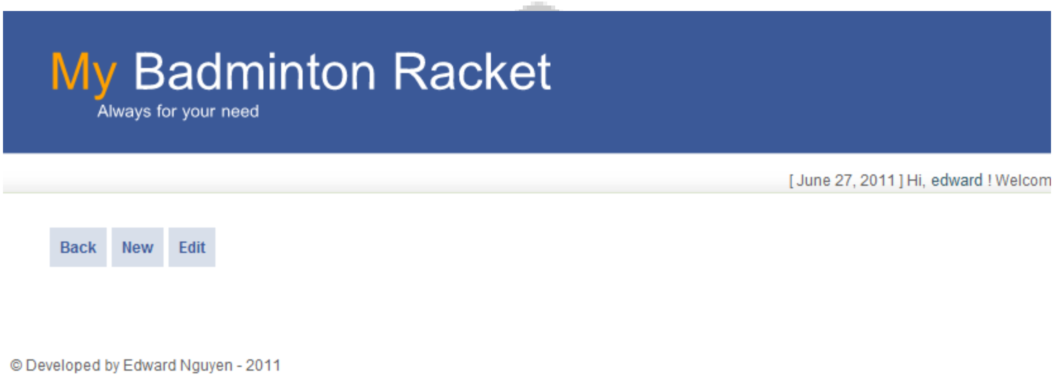


Figure 4.3 – 5. Items of Product Database

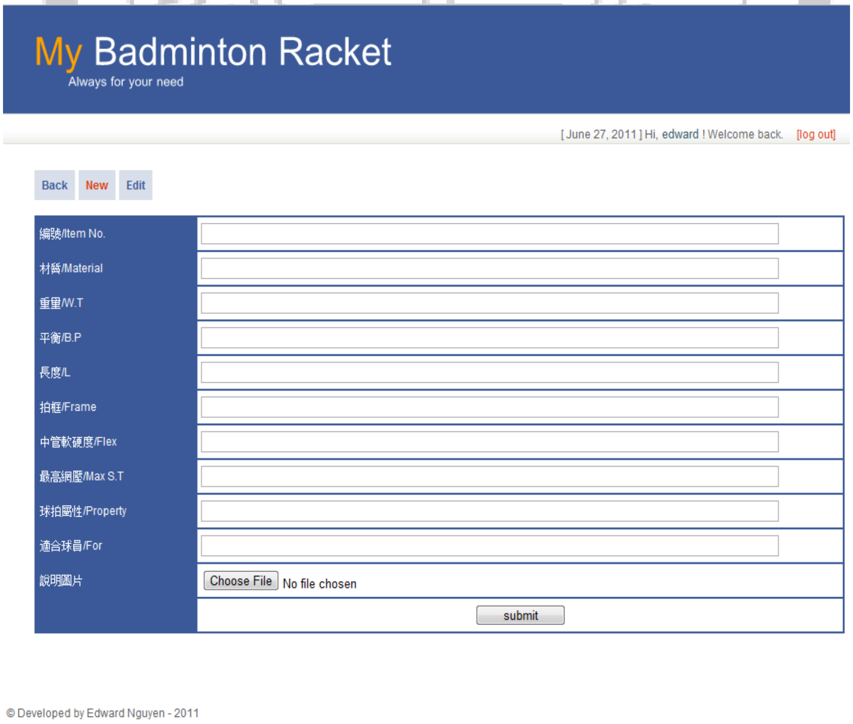
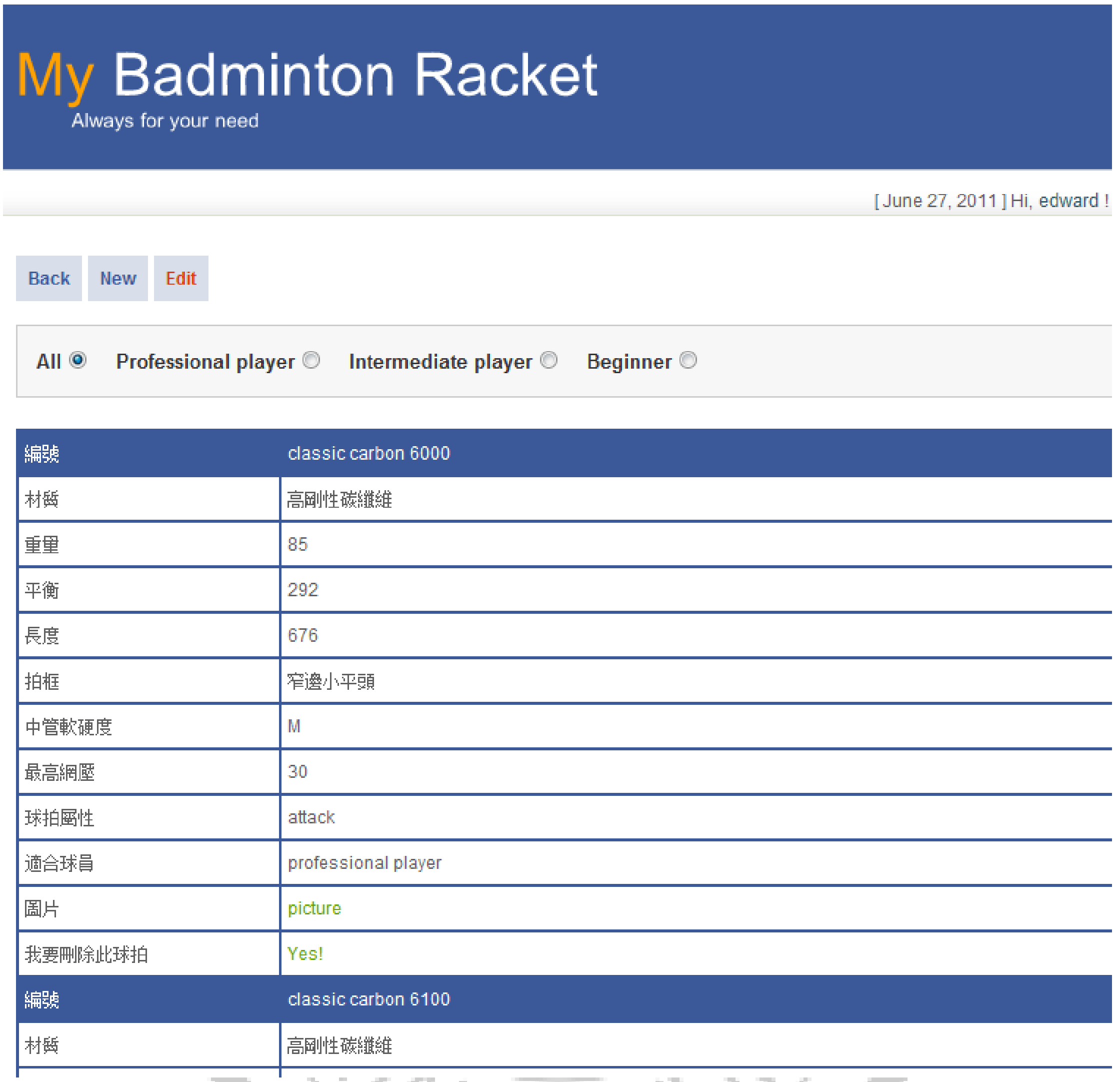


Figure 4.3 – 6. Create new product



編號	classic carbon 6000
材質	高剛性碳纖維
重量	85
平衡	292
長度	676
拍框	窄邊小平頭
中管軟硬度	M
最高網壓	30
球拍屬性	attack
適合球員	professional player
圖片	picture
我要刪除此球拍	Yes!
編號	classic carbon 6100
材質	高剛性碳纖維

Figure 4.3 – 7. Product management

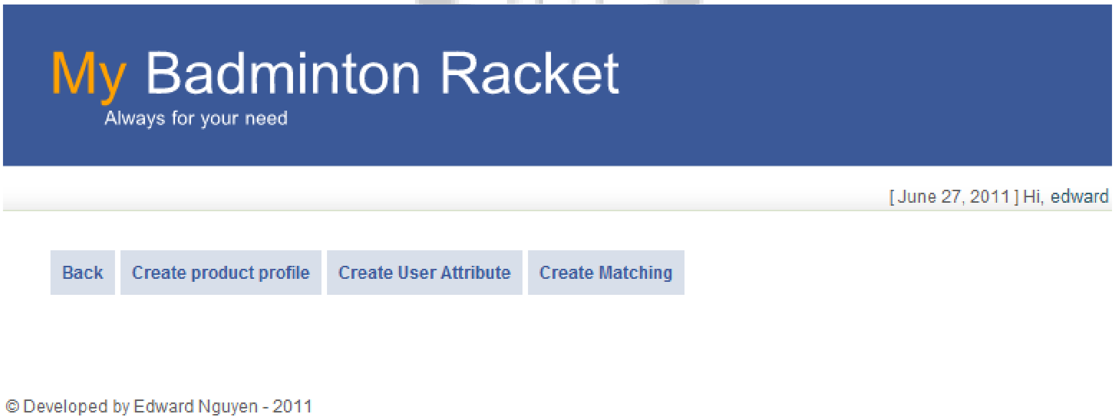


Figure 4.3 – 8. Management of recommendation process

Figure 4.3 – 9. Create product profile

In figure 4.3 – 9, a list of product attribute will be shown. Manager just only choose which kind of product attribute will be used in recommendation process. After the attributes are chose, AHP for product attributes is started to find the weights of these product attribute. Then they are saved in database.

Figure 4.3 – 10. AHP for product Attribute

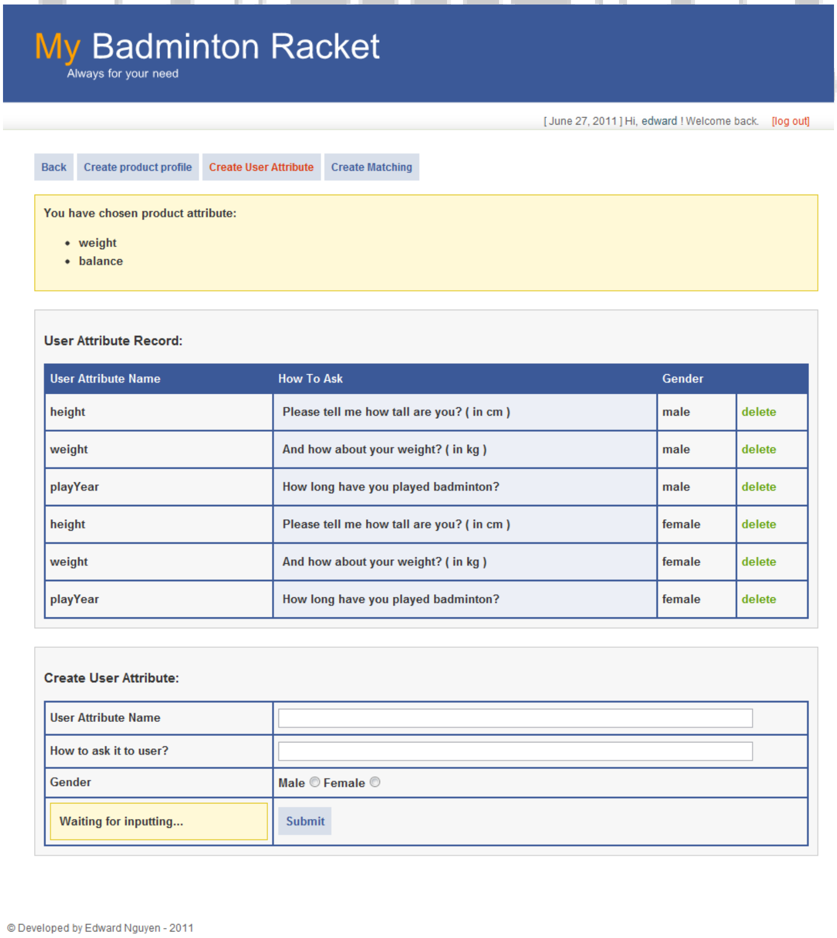


Figure 4.3 – 11. Create user attribute and management.

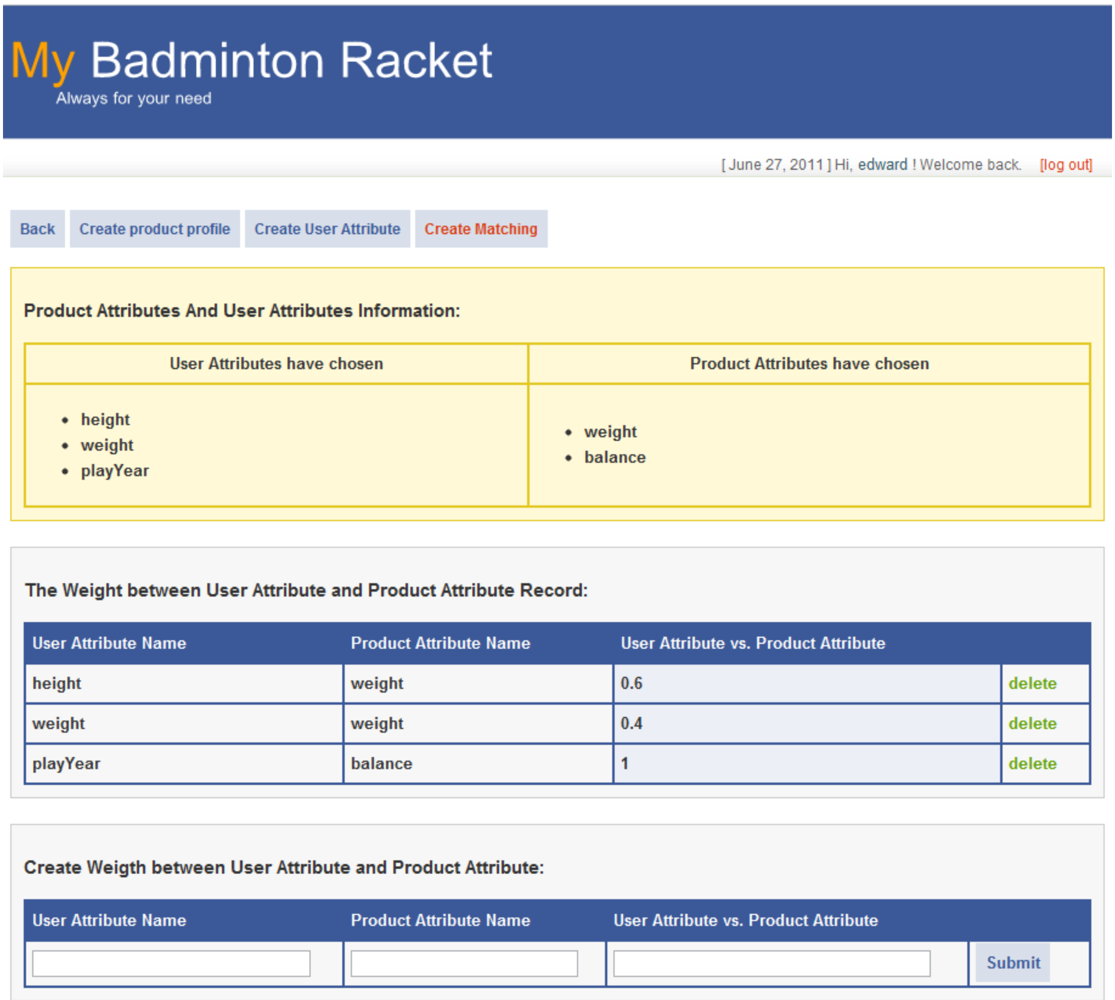


Figure 4.3 – 12. Weight setting for user and product attribute

User Attribute Name	User Attribute Min Value	User Attribute Max Value	Product Attribute Name	Product Attribute Min Value	Product Attribute Max Value	Gender	
height	140	150	weight	82	85	male	delete
height	151	155	weight	84	86	male	delete
height	156	165	weight	85	87	male	delete
height	166	169	weight	86	88	male	delete
height	170	174	weight	87	89	male	delete
height	175	179	weight	88	90	male	delete
height	180	185	weight	89	92	male	delete
weight	36	55	weight	82	85	male	delete
weight	56	60	weight	84	86	male	delete
weight	61	71	weight	85	87	male	delete
weight	72	76	weight	86	88	male	delete
weight	77	81	weight	87	89	male	delete
weight	82	87				male	delete
		12	balance	280	290		
playYear	13	60	balance	280	290	female	delete
playYear	61	240	balance	280	290	female	delete

Figure 4.3 – 13. Matching condition between user attributes and product attributes

Chapter 5

Discussion

5.1 Online Purchasing Behavior Investigation

During on the project with Bonny corp. we have made a questionnaire to survey behaviors of the online purchasing of consumer. We have randomly asked 100 people about their online purchasing behavior, and some interesting results are found.

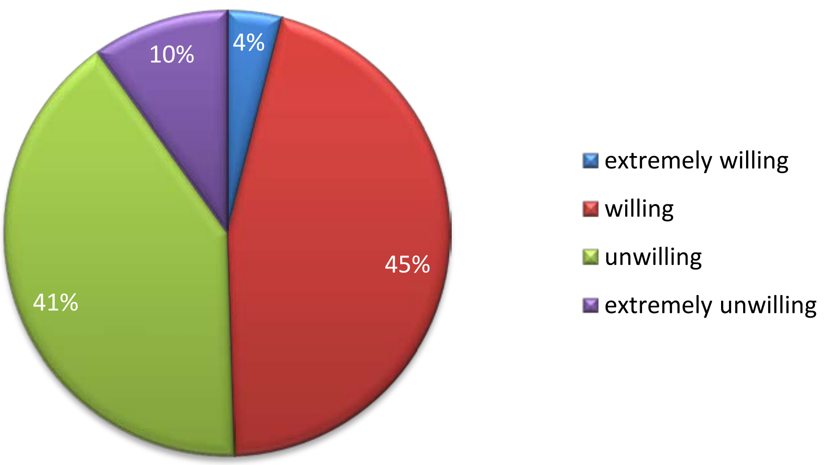


Figure 5.1 – 1. Willing to answer online questionnaire

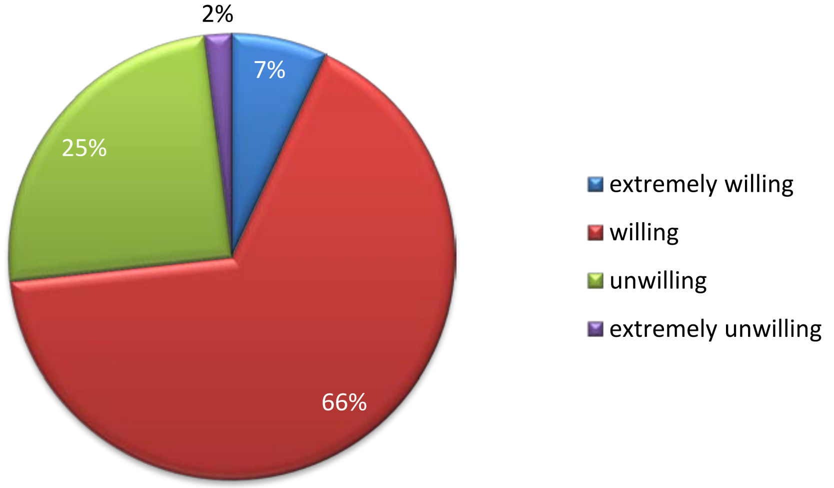


Figure 5.1 – 2. Willing to answer questionnaire before getting the suitable product

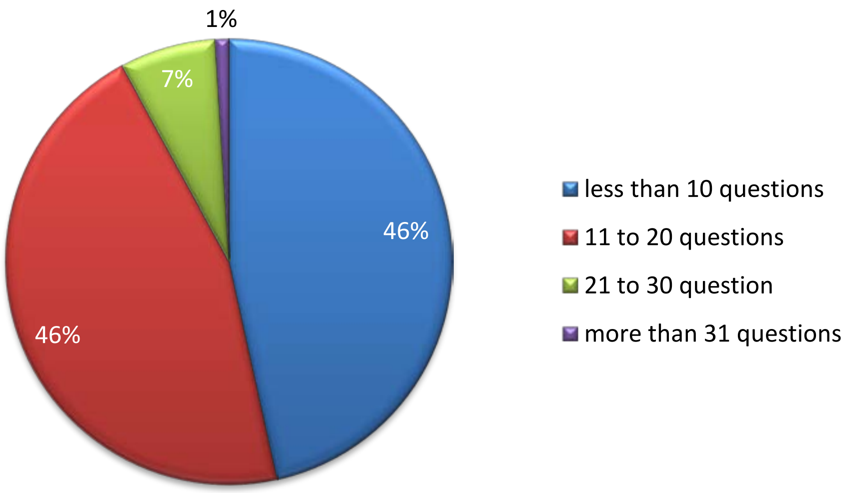


Figure 5.1 – 3. The number of questionnaire question that can be accepted

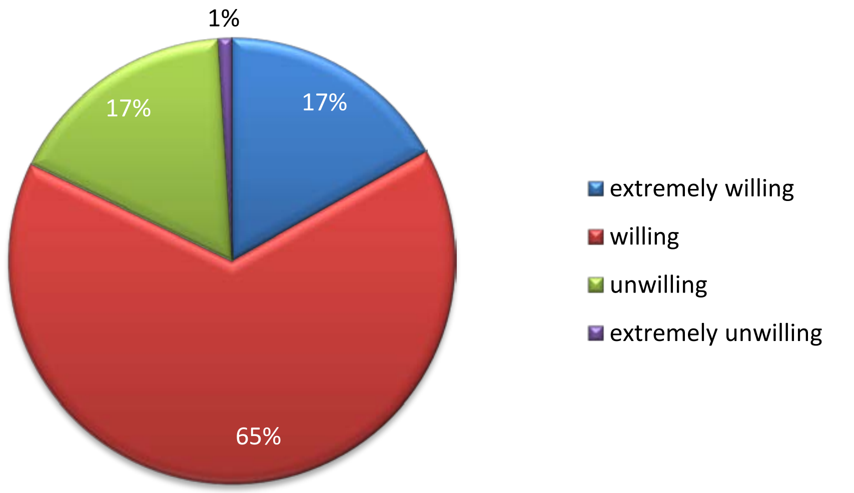


Figure 5.1 – 4. Willing to follow the suggestion of expert before purchasing

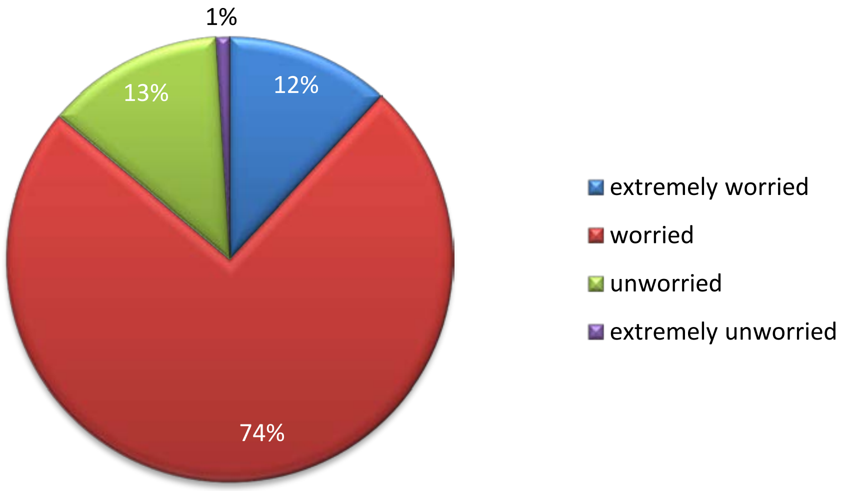


Figure 5.1 – 5. The feeling of consumers when purchase unsuitable goods

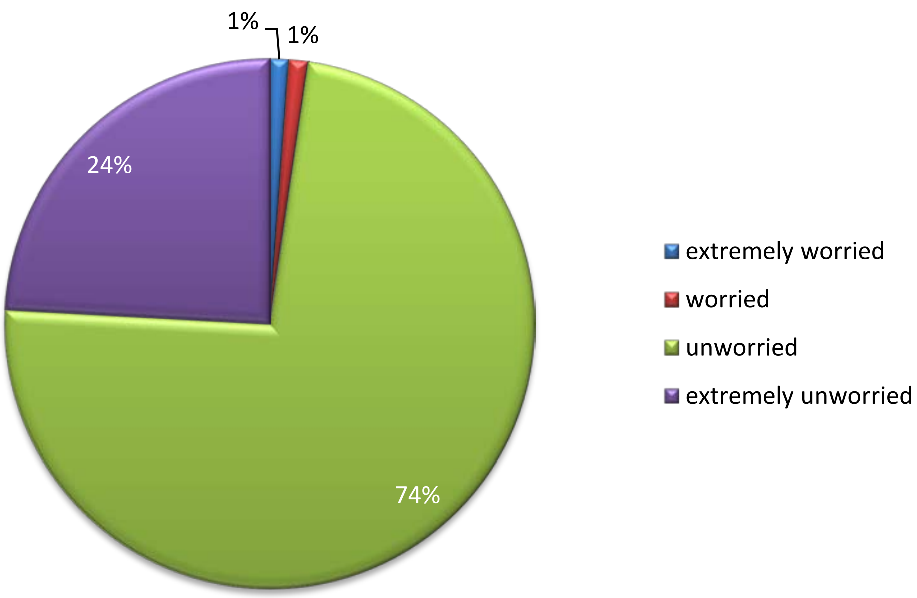


Figure 5.1 – 6. The feeling of consumers after receive suggestion from expert

From these surveys, we found that when people want to buy a product, especially sport equipment, they worry about if they purchase a wrong item, then they cannot use it or they are injured if they try to use it. So, there is a need of a recommender system that tells the consumer which product is suitable and which one is not.

5.2 The Lessons from the Research

We use amazon.com as a successful example of e-commerce website. Recommendation technique is used as a target marketing tool. If you click on the “your recommendations” link, it leads you to an area where the recommendations can be filtered by product line and subject area, rate the recommended products, rate their previous purchases and you can see why the items are recommended. By the different kind of service, the different recommendation technique is applied. It’s very helpful in helping consumer saving time and increasing the sales volume of the accessories.

But we found that, although the recommender system is applied in some popular e-commerce websites like amazon.com and ebay.com, their recommendations can still be improved. Most of the recommendations were integrated from the habits and hobbies of the registered members, so the recommendations can be helpless for unregistered visitors – potential customer. And with some kinds of items, the recommendations come from experts are better, such as: recommendations for sports equipment, clothes.

In the randomized investigation of the online purchasing behaviors of 100 people, interesting result emerged. 55% of people are willing to answer online questionnaires, 44% of people are willing to answer about 10 questions, 86% of people are worried about purchasing wrong or unfit sports equipment, and 74% of people are unworried if they have suggestions from experts before purchasing sports equipment.

The proposed method can be applied to the sports equipment specialty stores or sports equipment exclusive stores, because it adopted the product knowledge and the customer knowledge to make the recommendations, and it does not need much time to build up. By adopting the experiences of experts and human characteristics, it can solve the new user cold-start problem and provide the appropriate recommendation for not only registered members but also new visitors.

Chapter 6

Conclusion and Future Work

In order to help the exclusive or specialty store to satisfy their online customer, we introduce a recommendation technique which combined their experiences. The cost for our recommendation system is low. It does not need to own a huge computing hardware like the other recommendation techniques does, so, exclusive or specialty store can completely apply for their web-service.

By using human characteristic to make the recommendation, the cold start problem can be solved, because system does not need historical information of user or item at the initial time. The recommendation is coming from the experience of expert who has product knowledge and customer knowledge, so the recommendation is easily accepted by customer. And, this research also improves AHP method, it reduces the questionnaire questions so, user just answers fewer questions, and the process is done.

In the further study, a mechanism which is used to quantity the non-quantifiable factors such as color and decorative design can be considered, a faster way to set weight for candidate products and the feedback mechanism will be applied into the system.

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