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Doctoral Dissertation

Development of Personalized Information Mining Techniques for product recommendation

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Abstract

In recent years, products' sense or design have been as a very important part for marketing, in other words, customers choose the right merchandise usually depending on their feelings about it, so an efficient products recommendation system would increase the desire to buy. This research is applied in Japanese traditional crafts, named “Kutani-ware”. As a Japanese traditional industry, there are many problems today, specifically, the scale of the industry has become smaller, and so as the employees of this industry. To revitalize this industry, the most important thing is to increase the sales, so an efficient recommendation system is urgent needed.

For the sense that from customers to the products, we can define many features to describe these products, and people can evaluate these features instead of evaluating the products. In this way, a complex and non-standard problem can be split into some easier problems. According to this, much Kansei data that can measure general feelings to the products is obtained; these data is treated as a database that can describe the products. With using some Kansei data analysis methods and computer technologies, an efficient recommendation system has been developed and more suitable products can be recommended to customers.

This research focuses on developing a new method to assist customers when they are making their purchasing, which will base on customer’s sense or feelings to the products. People always make their purchasing depending on their feels to the products, so how to abstract their desires according to their sense is an important way in marketing, the existing methods always focus on selecting and scoring features about a product, and have not concerned the differences between different kinds of features (in this research, there are two kinds of features: Kansei features and context features), and for collecting evaluation data, the uncertainty from the existing methods when evaluators have to face to a huge number of samples also have not been concerned. So in this research, we have made a new kind of structure to console the two kinds of features, in order to make a better way to take the relationship into account, which exists in different kinds of features. And we have also proposed a new kind of method on colleting the evaluating data, which is divided the evaluation issues into some simple comparison

issues. In the end of this research, we also made an evaluation between existing methods and the new method, from this way we could find which method is better and why it is, and also we could find some points to improve it.

The methods on collecting data and recommending products would be useful supplements of Kansei Engineering and Data Mining, which are the important parts of Knowledge Science. The new method on collecting data as general understanding, which is based on partial-comparison procedure, can be treated as a new aspect on Data Mining and Kansei Engineering. Especially, we have to face to a huge number of objects for evaluation. The ontological structure used for recommending products in this research is also a contribution of Kansei Engineering. With this special structure, the personal requirements of the consumer can be divided into several simple requirements, which can be easily measured.

For detail, the thesis focuses on the following points:

- Exploring of information personalization method.

The existing evaluation methods on collection the data of the general feelings of the product are mostly using the semantic differential method, which is executed with M-point approach. By this kind of method, evaluators may feel confused when the quantity of the evaluation samples is big. This research proposed a new method on evaluation the samples, which is based on the comparison procedure. Specifically, we select some samples randomly for evaluators, and make a comparison (sub-ranking list) on each attribute by them. Then an integration method is proposed for integrating the sub-ranking list into an integral ranking list, which is treated as the evaluation Database for the following research. With the evaluation Database, a new target-oriented method on personalizing consumer's requirements is also proposed.

- Adjusting of the algorithm using ontological structure.

Ontological structure have been justified as an useful method in many fields, with this structure, a complex and disordered problem can be described as many simple entities, and the relationship between these entities could also be concerned. This research takes this structure into account, specifically, we separate customer's desire into some small and simple entities, so customer's desire can be described by these entities, this kind of structure also has another advantage, because of the simple entities, we can concern the relationship between entities, and also between the features easily.

- Design of the recommendation system.

In the end of this research, a recommendation system is developed, and a subjective evaluation test on the comparison of the methods is also executed. The whole system includes two parts: recommendation part and comparison part. Firstly, we use the comparison system to collect Kansei data and Context data as general understanding on the products; and with using the data, the recommendation system can recommend a ranking list for consumer according to their special tastes.

Key word: Partial Comparison Process, Kansei Engineering, Kansei Evaluation, Decision Making Analysis, Target-Based Decision Making, Multi-Attribute Decision Making, Ontological Structure, Recommendation System.

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Chapter 1

Introduction

This chapter gives the background and the purpose of this research and gives a brief introduction of several related research areas, such as Decision making, Multi-Criteria Decision Analysis, Ontology, Multi-Criteria aggregation, Kansei Engineering. Then this chapter describes how these related researches can be used in this research and how this research contributes to Knowledge Science. The dissertation structure, originalities and the appropriateness of this research are given at last.

1.1 Background and Research Purpose

Nowadays, the design and sense of a product is increasingly important in marketing, since consumers put more attention to their sensibilities or feelings of the products, not only to the quality of the products. In today's increasingly competitive market, consumers usually have to face to a huge number of products with different designs but having the same use (Jiao et al., 2006). As internet technology developed, a new Commerce pattern, which so called E-commerce, has been more and more popular. Consumers can just purchase products in the internet, without going to any physical stores. Compare to traditional commerce pattern, E-commerce has shown many advantages, such as more convenient, less cost, etc., but there are also many disadvantage, like consumer cannot feel or touch the product before they buy it, the most significant disadvantage is that consumers may face to a huge number kinds of products with different designs, but they have no chance to communicate with seller for describing their desires. Therefore, how to simulate the purchase process of consumers online, and how to identify consumer's special tastes to recommend products would be an important research point in E-commerce.

1.2 Decision Making Analysis

When consumers face to a lot of products and want to make a purchase, it may be a decision making issues. Decision making analysis is a multi-discipline including psychology, business, engineering, operations research, system engineering and management science. It is a scientific discipline includes a collection of principles and methods aiming to help individuals, groups or organizations in the difficult decision issues. From the beginning of 40's, as the rapid development of social economy and science technology, social activities have become increasingly complex and changeable, decision making problems has become more and more important. Different from decision making in the part, modern decision making analysis has some new characteristics, as more complex, more accurate, more relative. There are two kinds of decision methods, the mathematical, modeling, computerized methods, such as System Engineering, Optimal Control, Linear Programming, Decision Tree and Game Theory; another kind of methods are based on psychology or sociology, such as Delphi method, Brainstorm, Strategic assumption analysis. Modern decision-making analysis usually face to more complex situations with massive information, therefore, the decision process integrating different kind of decision methods should be used to get the optimal decision. When you face to two optional choices, you may face to a decision problem.

Humans in society may have to face decision situations everyday; it is closely related to our daily life. Kast thinks that decision is to judge and make decision, when you face to two optional choices, you may face to a decision problems (Kast & Rosenzweig, 1974). Decision making does not only include the judgment and selection of the optimal choice, but also include all the efforts which can affect the final choice. Decision making also might be regarded as goal-driven problem solving activity, and can be terminated by selecting an optimal choice to make a solution. Therefore, decision making is a reasoning or emotional process which can be rational or irrational, and can be based on explicit or tacit assumptions (Simon, 1977).

Decision making process has a nature of dynamic. New information, new organizational forms and new technologies can usually affect the final decisions. When analyzing the situations related to the decision goals, new information or technologies or theories may change decision maker’s choice. As the environmental changes, the decision making process may turn into a more diversity situations, such changes as sex, race, experience, and many other personal characteristics, and the diversity of the process may leads to variable different consequences for decision makers. Particularly, in individual decision making process, the environmental changes maybe more affective to make a choice, includes the some emotional changes. Most theories about decision making think that decision making is about selection of optimal choices which can lead to an expected outcomes, with various options according to some kind of cost-benefit analysis. However, the effect of emotional changes is largely ignored, which is more important in individual decision making process. Individuals make decisions not only by cost-benefit analysis or other objective reasons, but also and even sometimes primarily at emotional situations. (Guzzo et al., 1995; Selbert, 1987; Johnston & Packer, 1987; Fugita & O’Brein, 1994; Bolick & Nestleroth, 1997).

The application data on decision making may be more imprecise and fuzzy in individual decision making process. When describing a phenomenon related to human concepts, people are often led to use words in natural language instead of numerical values (Herrera et al. 1996). This may lead to an uncertainty problem. Argote said, “There are as many definitions of uncertainty as there are treatments of this subject" (Argote, 1982). "The term uncertainty is so commonly used that it is all too easy to assume that one knows what he or she is talking about when using this term" (Downey & Slocum,1975). Therefore, uncertainty is one of the most crucial problems in decision making processs. Although different people may have different opinions or definitions on a subjective, which makes things uncertain, there should be some or partial common acknowledge on it. This part of common acknowledges should be some kind of general understandings on a subject, and decision making process can use them as some criterions. The preference or expected outcomes of individual may have more fuzzy or vague descriptions; even individual he/she may not know what really he/she wants. Therefor it is desirable to develop decision making methods to deal with those fuzzy data. It is equally important to evaluate the performance of these fuzzy decision making methods (Zimmermann, 2001; Triantaphyllou et al., 1990; Ben & Triantaphyllou, 1992; Bellman & Zadeh, 1970). The linguistic approach is an approximate technique, which represents qualitative aspects as linguistic values, and these values are measured by words or phrases instead of numeric values. Linguistic approaches are based on semantic differences by establishing linguistic expression domain to provide linguistic performance values according to different criteria; and establishing an appropriate aggregation operator of linguistic information to combine the linguistic performances; according to the aggregated linguistic performance, the best choice may be executed (Kacprzyk & Fedrizzi, 1990; Roubens, 1997).

Classical decision theory focused almost exclusively on automating the actual choice. The information was filtered and restructured by some criterions, according to the practical problems; and the information processing methods were modeled; the optional results were computed automatically and presented to decision makers. Simon defined essential phases of an analytical decision process (Simon, 1960): 1) Intelligence: information and data gathering. 2) Design: selecting or constructing a model of the decision situation. 3) Choice: examining decision options and choosing between them. This formalized process may be efficient on macro economics or corporate decision-making, which processes are based on numeric information, but it maybe not suitable in individual decision-making, especially when emotional factors and uncertainty are taken into account. Wierzbicki and Lewandowki proposed an intuitive decision processes as follow (Wierzbicki & Lewandowki, 1989): 1) Recognition: this starts with a subconscious feeling of uneasiness. This feeling is sometimes followed by a conscious identification of the type of problem. 2) Deliberation or analysis: if we feel confident as experts, a deep thought deliberation suffices. Otherwise an analytical decision process is useful, but with the final elements of choice delayed. 3) Gestation and enlightenment: this is an extremely important phase, and we must have time to forget the problem in order to let our sub-consciousness work on it. 4) Rationalization: this phase can be sometimes omitted if we implement the decision ourselves; however, in order to communicate our decision to others we must formulate our reasons. 5) Implementation: this might be conscious, after rationalization, or immediate and even subconscious. This kind of intuitive decision process maybe more efficient on handling individual decision-making processes or uncertainty problems.

1.3 Multi-Criteria Decision Analysis

In many decision-making problems, multi-attribute or multi-criteria maybe inevitable situations, such decision making issues are so called multi-attribute decision-making (MADM). The major part of MADM is concerned with analysis of a finite set of alternatives and ranking of these alternatives, each alternative is described in terms of different characteristics or criteria or attributes and to be taken into account simultaneously. MADM is an important part of decision making, which has attracted many researchers and practitioners. There are many methods in solving such MADM problems, such as value or utility based methods (MAUT), outranking methods and cost-benefit analysis (CBA) and so on. Different MADM methods aim at supporting complex planning and decision processes by providing a framework for collecting, storing and processing all relevant information. It is very difficult for any decision-aid method to satisfy all requirements in the ranking problems. All methods have their own inherent weaknesses (Lahdelma, 2000). Due to the different focuses of the MADM methods, the results may be quite different. This may leads to the formulation of a decision-making paradox (Dixon, 1966; Hwang & Masud, 1979; Triantaphyllou & Baig, 2005).

The problem setting of MADM can be typically described as: 1) Choose one or more best alternatives. 2) Complete or partial ranking of the alternatives. 3) Acceptability analysis of the alternatives (Lahdelma, 2000). For all these problem settings, the evaluations or information of the alternatives is known. The decision scheme of the problem settings of MADM may follow two steps: aggregation and ranking. The aggregation phase defines a relation, which indicates the global preference between alternatives; the ranking phase transforms the global information about the alternatives into a ranking of them, the most common methods being used of a ranking methods is to obtain a score function (Chiclana et. al, 1998; Chiclana et. al, 1996; Roubens, 1997). Decision-making in situations with multiple criteria or persons is a prominent area of research in normative decision theory. The topic has been widely studied (Arrow, 1976; Fodor & Roubens, 1994; Kacprzyk & Fedrizzi, 1990; Satty, 1980; Sen, 1970; Starr & Zeleny, 1977; Nijkamp, 1979)

1.4 Ontology Engineering

Ontology is originally the philosophical study of the nature of being, becoming, existence, or reality, as well as the basic categories of being and their relations. Traditionally listed as a part of the major branch of philosophy known as metaphysics, ontology deals with questions concerning what entities exist or can be said to exist, and how such entities can be grouped, related within a hierarchy, and subdivided according to similarities and differences (Harvey, 2006). This ancient study has been introduced and widely used in many areas, such as data mining, knowledge management, Artificial intelligence semantic web, systems engineering and library science. In computer science and information science, Gruber indicated that ontology formally represents knowledge as a set of concepts within a domain, using a shared vocabulary to denote the types, properties and interrelationships of those concepts (Gruber, 1993). Ontologies include some common components, such as individuals (or instances, objects), concepts which indicates the type of individuals, aspects which objects can have, relations which related the individuals and concepts, function terms (a complex structure to describe the individuals and the relations), restrictions which relations or individuals must follow, rules which means a logical relations among the individuals, events (changing of the attributes or relations). These components construct an integral Ontology system.

Ontology engineering aims at making explicit the knowledge contained within software applications, and within enterprises and business procedures for a particular domain. Ontology engineering offers a direction towards solving the inter-operability problems brought about by semantic obstacles. Ontology engineering is a set of tasks related to the development of ontologies for a particular domain (Pouchard et al., 2000). A significant development of ontological engineering occurred during last two decades, and it have been treated as tools on sharing knowledge about diverse domains, and play n important roles in many applications (Mizoguchi et al. 2000, Corcho et al. 2003, Pinto i Martins 2004, Bontas i Tempich 2006). However, there are diverse controversies also in ontological engineering, related to several opposite approaches to the construction, application and interpretation of ontologies (Wierzbicki et al., 2011). As the most advanced in ontological engineering, the works of Standard Upper Ontology Working Group (SUO WG) are often cited, aimed at *"forming an upper ontology whose domain is all of human consensus reality"* together with related CYC ontology (Curtis et al. 2006). The Upper Ontology (foundation ontology) is a model of the common objects that are generally applicable across a wide range of domain ontologies. It employs a core glossary that contains the terms and associated object descriptions as they are used in various relevant domain sets.

In MADM issues, Ontology Engineering might be a reasonable modeling tool. final choice or preference of consumers, as a factor of decision-making analysis, can be treated as an concepts, different attribute in multi-attribute preference can be treated as some domains, then the concept can be described by these domains. This modeling structure is just an ontological structure. Even the relations, another factor of Ontology Engineering, can be defined in MADM by setting the priorities of the domains (attributes or criteria). The rules of this ontological structure can be expressed by some common acknowledge of the alternatives, any domains need to follow the common acknowledge.

1.5 Kansei Engineering

"Kansei", is a Japanese word, means sensibility, and it is usually used to express the emotionally feeling of individual on the object, with using the sight, smell, taste and other sense approach; and it is also affected by the environment, mood, physiological status of the individual. In today's increasingly competitive market, the issues of describing the Kansei feelings of the customers to help them choose the right product are more and more important; even in design process of the product (Nagamachi, 1995; Nagamachi, 2002; Schütte, 2006), the "Kansei" issues are becoming more important.

According to Nagamachi (2002), there are two directions of flow in Kansei Engineering: one of which is from design to diagnosis and the other one is from context to design. The first one involves manipulating individual aspects of product's formal properties in order to test the effect of the alteration on a user's overall response to the product. The other one involves looking at the scenarios and contexts in which the product is used and then drawing conclusions about the implications of this for the design.

The researches related to Kansei is commonly called Kansei Engineering, which was invented by *Nagamachi* at Hiroshima University in the 1970s, and defined as "translating technology of a consumer's feeling and image for a product into design elements" (Nagamachi, 1995), has been proved as an efficient and successful approach in many fields (Nagamachi, 2002; Schütte, 2005), such as automotive, home electronics, office machines, cosmetics, food and drink, packaging, building products, and other sectors (Childs et al., 2001). The word Kansei expresses the subjective feelings of a product by people immanent phenomenological perception using all senses, viewing, hearing, touching, smelling and other ways (Schütte, 2005). In Kansei related researches, the most common method of the collection data is the semantic differential (SD) method (Huynh et al., 2010), which uses a set of adjectives and asks evaluators to express their feelings to an object with those words (Schütte, 2005; Grimsæth, 2005). The data used in Kansei Engineering is based on subjective estimations of objects and concepts and helps consumers to express their requirement on the objects.

1.6 Originalities of this research

The objective of this study is to explore the relationship between general understanding and personal preference, which is quite important in individual decision making. For this purpose, our research strategy is threefold. Firstly, extraction methods on obtaining general understanding about the alternatives will be studied, which can be treated as the database of this research. Secondly, single attribute preference decision making will be discussed to find a reasonable measurement method on matching general understandings and personal preference. At last, we will propose ontological structure based multi-attribute aggregation models to solve the multi-attribute decision-making issues, some ranking methods will also be introduced, which are suitable and reasonable to the aggregation models. The main contributions of this dissertation are shown as follow.

1) Contributions on Extracting general understandings

For extracting general understandings of the evaluation alternatives, we proposed a Partial Comparison Process based Semantic differential (SD) method. Comparing to traditional SD method in gathering information from alternatives, there may be some disadvantages: 1) Different evaluators may express quite different opinions on an object. With traditional SD method, the distribution of the evaluation values may be in polarization and inefficient. The Partial Comparison Process base SD method we proposed can solve this problem by getting a consecutive ranking list contains all objects. 2) Evaluation options (SD method with M-scale) are limited in traditional SD method; evaluators can only evaluate objects in M-point scale. It would be hard to evaluate a huge number of objects. However, in Partial Comparison Process, there are no limits in evaluation options, because the only thing evaluators need to do is to compare the partial group of objects and make a partial ranking list, instead of mark their feelings of the objects in M-point scale, and the system will combine the obtained partial ranking lists into a integral list with all objects.

2) Contributions on measurement of single attribute preference

This part of contribution includes two parts, the first one is about using the general understandings obtained from traditional SD method, the second one is about using the general understandings obtained from Partial Comparison Process based SD method.

1. Weighted fuzzy approach in measuring single attribute preference of consumers

The information of general understandings obtained from traditional SD method has some strange situations: the information may be distributed in polarization, some of the evaluators may think the object has the characteristic of the left side meanings of the bipolar attribute; and some of the evaluators may think the object has the characteristic of the other side meaning. To solve this problem, we will propose a weighted fuzzy approach, which takes some kind of support level into account. Specifically, the evaluation value of each side of bipolar attribute is affected by the supported evaluators of each side. One side attribute of the bipolar attribute get more evaluators approved the, then the significant of such side will be enhanced.

2. Linguistic variables approach in measuring single attribute preference of consumers

Linguistic variables approach is suitable for the information of general understandings obtained from Partial Comparison Process based SD method. A popular used Linguistic variables approach, which declares the different levels of bipolar attributes in equal scales, maybe lead to a problems when consumer select one of the level as his demand target: the effect area of the target is too small, the measurements of many objects will be invalid. Therefore, we proposed a modified Linguistic variables approach to solve it, which is take the natures of different levels into account. There approach assumes that the nature of the objects on a bipolar attribute can be divided into two parts according to the utmost of the bipolar attribute, and then effect area of consumer's target may be enlarged to half of the whole scale.

3) Contributions on aggregation of multi-attribute preference

The attributes used in this research have two types: Context attribute and Kansei attribute, which the former one expresses the application or purpose of the object, and the latter one expresses the consumer's emotional feelings. On multi-attribute aggregation problems, we will propose two aggregation models based on Ontological structure. This kind of aggregation models treats the demands of the consumers as ontology. And we treat the Context attributes selected by consumers as some kind of concepts, which is used for defining the demand ontology, and for each concept, we use the selected Kansei attributes to describe the concepts, which can also be treated as some kind of key words. The relations between ontology and concepts can be defined by consumer by his/her wish; the relations between concepts and key words is restricted by the internal natures of the attributes, moreover, the relations can also be adjusted by consumers in a certain range by his/her personal wishes, which range should be follow the restrictions discussed above.

The integration methods of the concepts for making a recommendation ranking list are also introduced. Different relations among different concepts of the ontology (consumer's demand) is optional according to consumer's preference: if they want the concepts have no difference on priority, the relations can be expressed by a logical operator "OR"; if they thought every concepts should meet their demands, a logical operator "AND" can express this relations. We also introduced two other integration techniques;

“*compensable criteria*” and “*essential criteria*”, which the former one is some kind of weighted average approach and the latter one is some kind of reference point approach. At last a subjective evaluation test will be executed for comparing the different aggregation models and ranking methods.

1.7 Contributions to Knowledge Science

Knowledge is a familiarity with someone or something, which can include facts, information, descriptions, or skills acquired through experience or education. It can refer to the theoretical or practical understanding of a subject. It can be implicit (as with practical skill or expertise) or explicit (as with the theoretical understanding of a subject); it can be more or less formal or systematic. Knowledge Science is a problem-oriented interdisciplinary field that takes as its subject modeling of the knowledge creation process and its application and carries out research in disciplines such as knowledge management; management of technology; support for the discovery, synthesis, and creation of knowledge; and innovation theory with the aim of constructing a better knowledge-based society (Nakamori, 2012). The methods or models proposed in this research may have contributions to Knowledge Science in the following aspects:

1) In Knowledge Creation process

For extracting general understandings, we propose a Partial Comparison Process based SD method, which can accumulate the common acknowledge of the public. The dissimilar acknowledges of humans can be weakened or canceled out, the same acknowledges can be strengthened and reserved as common acknowledge. This extracting method on obtaining common acknowledge maybe used for in Knowledge Creation process. In Knowledge Creation process, as the nature of knowledge, which is sometimes implicit and sometime explicit, the common acknowledge may be treated as a core part of the existing knowledge, from this core part, new knowledge related to the existing knowledge may be created or discovered, and the common acknowledge can also be treated as some restrictions in Knowledge Creation process.

2) Matching of common acknowledge and personal tacit preference

Multi-attribute decision-making methods, for matching common acknowledge and personal tacit preference, are proposed in this research. Problems in describing consumer’s personal preference, which usually have a nature of fuzzy or vague, are also proposed in this research. The methods or models can be treated as part of knowledge management, as Nakamori indicated: "a knowledge management approach by converting distributed (or tacit) knowledge into shared (or explicit) knowledge and using it effectively" (Nakamori, 2012).

1.8 Organization of this dissertation

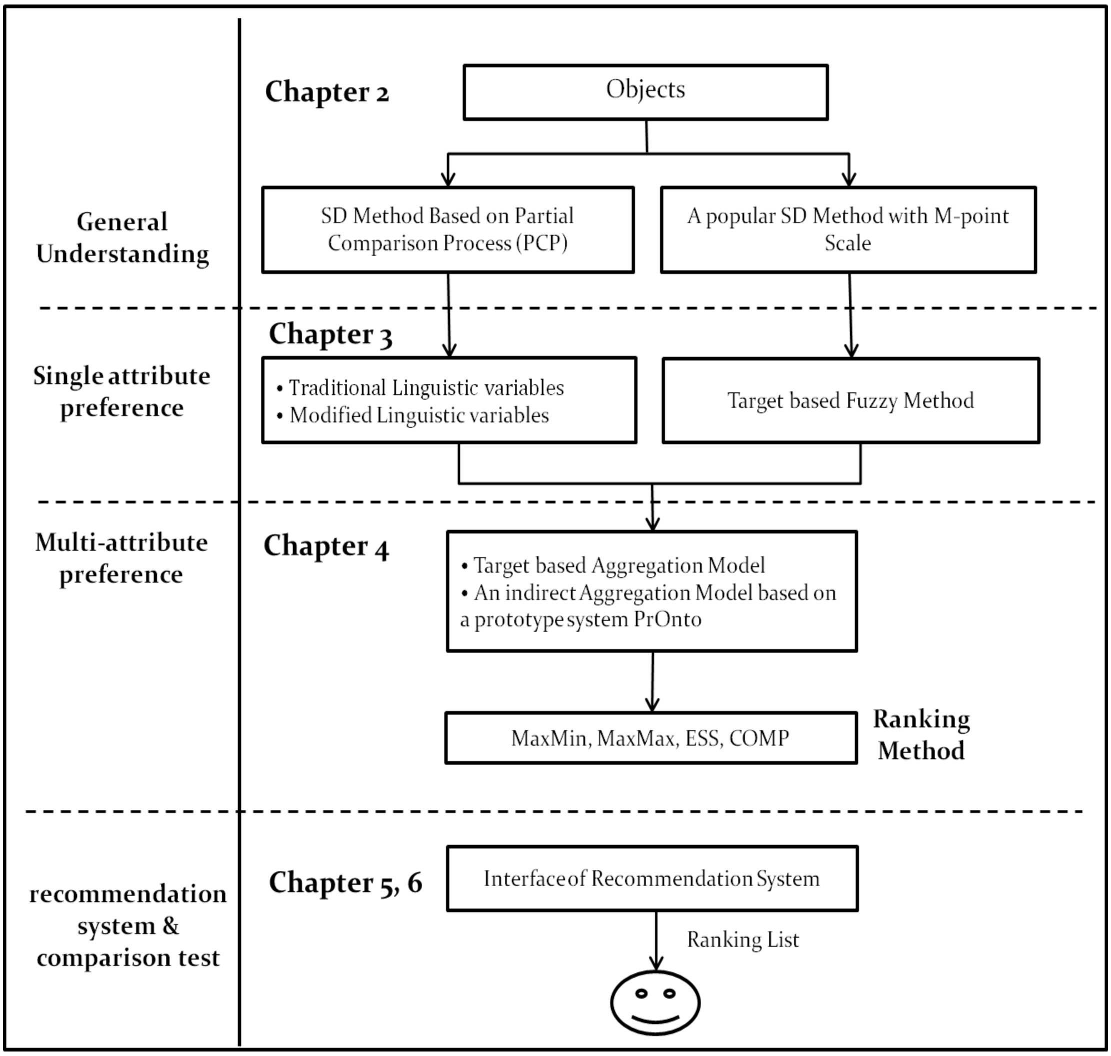

Figure 1.1 Overview of this thesis

The dissertation is composed of seven chapters. The overview of the organization of this dissertation except "*chapter 1 Introduction*" and "*chapter 7 Conclusion and future*" work is as Figure 1.1. The detailed explanation is shown as follow:

Chapter 1 describes the motivation and objective of this thesis, and introduces the related theories. Moreover, this chapter describes the relevance of this research and Knowledge Science.

Chapter 2 describes the gathering general understanding part, and proposed a Partial Comparison Process based SD method to do so. Also, this chapter discusses the difference of traditional SD method and the proposed method. At last, a Comparison system is developed for executing PCP based SD method.

Chapter 3 proposed a fuzzy approach in measuring single attribute preference using the general understanding data obtained from traditional SD method and a Linguistic variables approach in handling the data obtained from PCP based SD method. And also this chapter discusses the difference between the traditional fuzzy approach and proposed method, and between the classic Linguistic variables approach and the proposed method.

Chapter 4 proposed two aggregation models based on Ontological structure, for dealing with multi-attribute decision-making problem. And also some ranking methods are introduced, which take the relations among ontology concepts into account.

Chapter 5 & **chapter 6** illustrate our research by developing a Recommendation system; moreover a case study of traditional Japanese crafts is conducted. At last, an Evaluation test for comparing different aggregation models and ranking methods is also conducted.

Chapter 7 gives a summary of this thesis, and suggests some points of future work.

Chapter 2

Comparison Based Evaluation Modeling

This chapter is mainly about extracting general understandings by evaluating the alternatives, according to the attributes of them. A popular used Semantic (SD) differential method is introduced for gathering general understandings of the alternatives. A Partial Comparison Process (PCP) based SD method is proposed for solving the weakness of the traditional SD method. A Comparison system was developed for executing the PCP based SD method.

2.1 Problem Specification

When modeling a decision-making issue for the decision-maker's choice of the alternatives (objects, products), the first thing is to building an information system about the alternatives, corresponding to the attributes of the alternatives, which is defined or determined by the natures of them. The attributes used in this research is expressed by two kinds of attribute: Kansei and Context attributes. As preparations of personal preference measurement problem, we firstly conducted to collect Kansei data and Context data, which can express the general understandings of the alternatives. According to the natures of Kansei attributes and Context attributes, there is a popular method in gathering such information by assessing the products with their attributes, which is so called Semantic Differential (SD) method (Osgood et al., 1957), and also Linguistic variables approach is widely used (Zadeh, 1975, 2005). The attributes used in this research is some kind of bipolar-attribute. They are shown in Table 2.1. For a bipolar-attribute, such as [*Cold*, *Warm*], we also use the linguistic variables of [*very soft*, *normal soft*, *a little soft*, *neutral*, *a little hard*, *normal hard*, *very hard*], which are corresponding to 7-point scale of [*1*, *2*, *3*, *4*, *5*, *6*, *7*]. In addition, 5-point scale (Nakamori & Ryoke, 2006), 9-point scale (Lai, 2005), are also usually used in SD method.

Table 2. 1*: Kansei attributes and Context attributes*

Kansei attributes	*(Cute, Bitter), (Soft, Hard), (Feminine, Virile), (Bustling, Quiet),* *(Luxury, Simple), (Pale Whitish, Thick), (Calm, Exhilarated),* *(Sociable, Stately), (Dignified, Cordial), (Of momentum, Mild),* *(Friendly, Strong), (Traditional, Modern), (Rural, Urbanized),* *(Delicate, Exciting), (Fresh, Classic), (Sober, Flashy),* *(Dynamic, Static), (Cold, Warm), (Light, Heavy), (Rustic, Smart)*
Context attributes	*(For young, For senior), (For myself, For gift),* *(For guest, Ordinary use), (Souvenir, Wedding gift),* *(For male, For female), (Western style, Japanese style)*

As a common problem exists in Kansei engineering, evaluators may be confused on the Kansei or Context attributes, different evaluators may have different cognitions on the same Kansei attribute or adjective. This problem always exists in human cognition, and it would be impossible to solve, thus in Kansei engineering, what we need to do is just finding ways to weaken such problems. In this study, for weaken the effects of such problems, three methods are used in three different steps of this research: 1) The Kansei and Context attributes are selected by some experts, and the attributes are representative for describing the alternatives, and also for describing the attributes and for increasing the description strength, the attributes are designed as bipolar type. 2) For getting a common acknowledge, we also designed a partial comparison process based SD method, which can extract the general understandings of the alternatives on the attributes. 3) The requirements of consumers are reconstructed and divided into some simple sub requirements to simplify the fuzzy and vague requirements.

Figure 2.1: Research objects of Kutani-ware

The industry of Japanese traditional crafts, which is used as a study case, is a very important industry in Japan. These traditional industries are so closely connected to Japanese traditional culture. As explained in the Web-site of "*The association for the Promotion of Traditional Craft industries*", each of the traditional crafts is "*unique fostered through regional differences and loving dedication, and provides a continual* *wealth of pleasure*". However, as the rapidly changed lifestyles of younger generations and the rich diversity of the modern market products, traditional industries have shown some kinds of decadence, performance from the sales, scale of the employees and average age of the practitioners. Therefore, selection of this traditional industry as our research target is not only has the academic significance, but also has practical significance. Actually, the traditional crafts we focused are so-called Kutani-ware, which has almost 400 years' history, and now is an important traditional industry in Inshikawa prefecture, Japan. Figure 2.1 shows the Kutani-wares, which are our research objects. The following section will introduce a popular SD method for gathering Kansei and Context data.

2.2 Traditional SD Method with M-point scale

Semantic differential is a type of a rating scale designed to measure the connotative meaning of objects, events, and concepts. Osgood's semantic differential was an application of his more general attempt to measure the semantics or meaning of words, particularly adjectives, and their referent concepts. The respondent is asked to choose where his or her position lies, on a scale between two bipolar adjectives. Semantic differentials can be used to measure opinions, attitudes and values on a psychometrically controlled scale (Osgood et al., 1957). For gathering Kansei data in Kansei engineering issues, the most common used method is to choose Kansei words (treated as attributes, usually composed by adjective words) and ask people to express their feelings on the products according these Kansei words by means of semantic differential (SD) method or its modifications (Huynh, 2010). The SD method is treated as a measurement instrument, with using voting statistics on linguistic variables (Baldwin et al., 1996; Lawry, 2004; Zadeh, 1975).

	1 2 3 4 5 6 7	
Soft	□□□□□□□	Hard
Cold	□□□□□□□	Warm
Bustling	□□□□□□□	Quiet
Pale Whitish	□□□□□□□	Thick
Luxury	□□□□□□□	Simple
Calm	□□□□□□□	Exhilarated
Cute	□□□□□□□	Bitter
Sober	□□□□□□□	Flashy
Light	□□□□□□□	Heavy
Momentum	□□□□□□□	Mild
Friendly	□□□□□□□	Strong
Dynamic	□□□□□□□	Static
Rural	□□□□□□□	Urban
Delicate	□□□□□□□	Exciting
Fresh	□□□□□□□	Classic
Sociable	□□□□□□□	Stately
Traditional	□□□□□□□	Modern
Feminine	□□□□□□□	Virile
Dignified	□□□□□□□	Cordial
Rustic	□□□□□□□	Smart
For females	□□□□□□□	For males
Western-style	□□□□□□□	Japanese-style
For myself use	□□□□□□□	For gift
For guest	□□□□□□□	Ordinary use
Souvenir	□□□□□□□	Wedding gift

Figure 2.2: Questionnaire of SD method

The questionnaire using SD method with M-point scale for gathering general understandings of the objects consists of a listing Kansei attributes and Context attributes, which are bipolar type attributes. The questionnaire is shown as Figure 2.2. In this research, we use 7-point linguistic variables. The 7-point scale is symbolically denote by

$$V = \{v_1, v_2 \cdots, v_7\}$$

Where the left and right side word of the bipolar-attribute are respectively assumed to be at the ends of v_1 and v_7.

Generally, we can formulate our research. Let O as the set of the objects, where N is the cardinality of O, i.e., $N = |O|$. E is the set of evaluators, where $e_j \in E$, where $P = |E|$. And about the attirbutes, Let

$F = \{ F_k^l , F_k^r \mid k = 1, \ldots , K\}$ be the set of evaluated Kansei attributes. Where attributes F_k consists of a pair of Kansei words, F_k^l and F_k^r mean the left side Kansei word and right side Kansei word of bipolar-attribute F_k .

$C = \{ C_m^l , C_m^r \mid k = 1, \ldots , K\}$ be the set of evaluated Context attributes. attributes C_m consists of a pair of Context words, C_m^l and C_m^r mean the left side Context word and right side Context word of bipolar-attribute C_m.

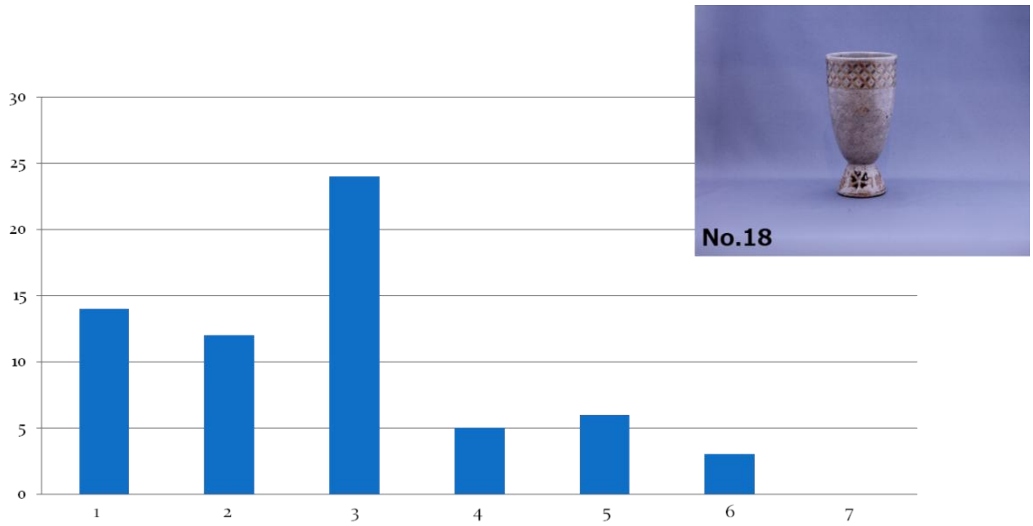

Figure 2.3: Distribution function of SD method

For a certain object $o_i \in O$, evaluator e_j express his/her feelings on the object according to attribute k and mark it in the questionnaire, we denote the mark as $x_{jk}(o_i)$, where $x_{jk}(o_i) \in V$. Then the distribution function of evaluator's feelings can be defined as:

$$f_{ik}(v_h) = \left| \left\{ e_j \in E : x_{jk}(o_i) = v_h \right\} \right| \tag{2.1}$$

As Figure 2.3 shown, the distribution function can be illustrated by it. Each rectangle in this figure means that how many evaluators think the object has the nature of the corresponding linguistic level. i.e., suppose the figure shows one objects distribution function on attribute [*Soft*, *Hard*], then this figure can show that there are 14 evaluators thought it is very soft, and 12 evaluators thought it is normal soft, and 24 evaluators thought it is a little soft, and 5 evaluators thought it is neutral, and so on. A certain object's assessment data can evaluated by people are shown in Table 2.2, which is expressed by $x_{jk}(o_i)$.

Table 2. 2: The Kansei or Context assessment data of object o_i (Huynh, 2012)

	Kansei or Context attributes			
evaluators	F_1	F_2	…	F_K
e_1	$x_{11}(o_i)$	$x_{12}(o_i)$	…	$x_{1K}(o_i)$
e_2	$x_{21}(o_i)$	$x_{22}(o_i)$	…	$x_{2K}(o_i)$
…	…	…	…	…
e_j	$x_{P1}(o_i)$	$x_{P2}(o_i)$	…	$x_{PK}(o_i)$

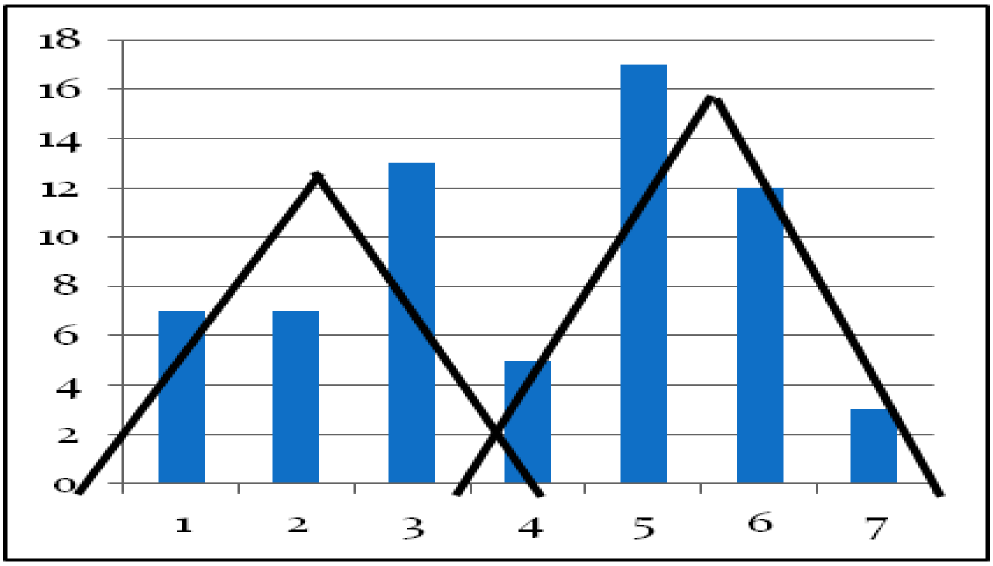

Figure 2.4: evaluations of inaccurate or vague attributes on an object

This popular classic SD method may have some limitations or inaccurate problem. Consider a situation: when there is a bipolar attribute defined not very accurate or this attribute is so vague on some objects for evaluators that they cannot get substantially similar feelings on the objects, then the assessment data may be inefficient on measuring the objects and will lead to inaccurate results for decision making (see Figure 2.4).

There is also a limitation in traditional SD method. The optional linguistic variables are not enough for distinguish all objects according to an attribute. Consider this situation, evaluators evaluate the objects on the attribute [*Soft*, *Hard*] one by one, when he/she evaluate object A, he/she may think it is very hard, and mark it in linguistic variables as level 7. Following object A, he/she start to evaluate object B, but he/she found it is more hard than object A (even the experiment is not include a comparison phase, the image of object A can stay in his/her mind for a while), how can he/she do then? Mark it also as level 7? That would be hard to distinguish object A and B, if he/she mark it as level 7 again.

2.3 A Partial Comparison Process based SD Method

In this section, we will propose a Partial Comparison Process Based SD Method to solve the problem and limitation existing in traditional SD method as we have mentioned in previous section. For solving such problems, a comparison process maybe a good choice, because the limitation of the number of optional linguistic variables does not exist in comparison process, evaluators just need to compare the objects and mark his/her feelings as a ranking list, instead of mark the feelings in optional linguistic variables. Moreover, the problem of obtaining substantially similar feelings on objects may be also solved in comparison process. The different opinions will be weakened or canceled in many time comparisons, and when the whole comparison process is finished, even the vague attributes for the objects can get a degree ranking list, the difference of this list and the list obtained from well-defined attributes is just express on a factor of weights (the objects in the ranking list is connected by some kind of edge and each edge has a weight to show the significant of this edge, we will introduce it in detail in the following part).

When the comparison process faces to a huge number of objects, the process maybe inefficient, because there is a limit of human's capability on recognizing things in one time. The number of objects an average human can hold in working memory is 7 ±2. It is about the concept of memory span. The memory span of young adults is approximately 7-items, where the items are some kind of meaningful units (Miller, 1956). We can call this theory as Magic-Seven (MS) for short, although this abbreviation is not expressing the theory accurately. Considering the comparison efficiency and taking the MS theory into account, we can randomly select 5 objects as a comparison group for evaluators to compare(evaluators can make a partial comparison list according to the group of the objects by a short time's glance), and then change to another randomly selected 5 objects' group and repeat the comparison process. Generally, we denote the group as g_i (i.e. $g_i = \{o_3, o_{16}, o_8, o_{15}, o_{17}\}$), and we denote the partial comparison list obtained from g_i as $l_i^k = \{ o_{15}, o_{16}, o_3, o_8, o_{17}\}$, where k means an attribute of F_k. And the left side attribute of bipolar-attribute "F_k^l" level is $o_{15}>o_{16}>o_3>o_8>o_{17}$, correspondingly, the right side attribute "F_k^r" level is $o_{15}<o_{16}< o_3<o_8<o_{17}$. The partial comparison list set can be denoted as L^k , where $L^k = \{ l_1^k, \ldots, \quad l_i^k, \ldots, l_I^k\}$.

To combine the partial comparison lists into a whole list containing all objects, Firstly, we need to do some necessary processes on the collected data. After these processes, the different opinions from different people will be weakened or cancelled out; the same opinions from different people will be strengthened and reserved. The remaining data can be expressed as the general understanding of the objects. As shown in Figure 2.5, for a certain attribute, we can map the corresponding comparison lists into a directed graphic to aggregate them, and we denote it as $G = (O, E, W)$, where O is the set of objects, shown as in Figure 2.5, O is the set of the point; E is the set of the edges which connect the points, the edges are directed links; W is the set of the weights regarding to set E, the values of the weights is determined by the connection times, i.e., w_i is the weight of edge e_i, which is the directed connection from o_m to o_n; when the value of w_i is 0, it means that there is no link from o_m to o_n. To map the list set L into a directed graphic, firstly, we set the points (each point indicates an object) in the graphic without any links, and then traversing all the lists contained in set L, when a directed connection from o_m to o_n appears, we add an directed edge from o_m to o_n, and the corresponding weight w_i should be added by 1; in case when a directed connection from o_n to o_m appears later, the weight w_i corresponding to the directed edge from o_m to o_n should be reduced by 1, if the weight w_i equals zero, the edge should be deleted. The reduced weights or the deleted edges do not mean that some of the opinions are lost; this process just follows the majority rules. The effects of the opinions (evaluation information) deleted in this process are reflected by enhancing the relative effects of other edges. Even when an edge is deleted by this process, e.g. there are two connections: *"a > b"* and *"b > a"*. The edge between *"a"* and *"b"* may be deleted, it does not mean that the two connections are invalid, we can just get *"a = b"* from the two connections.

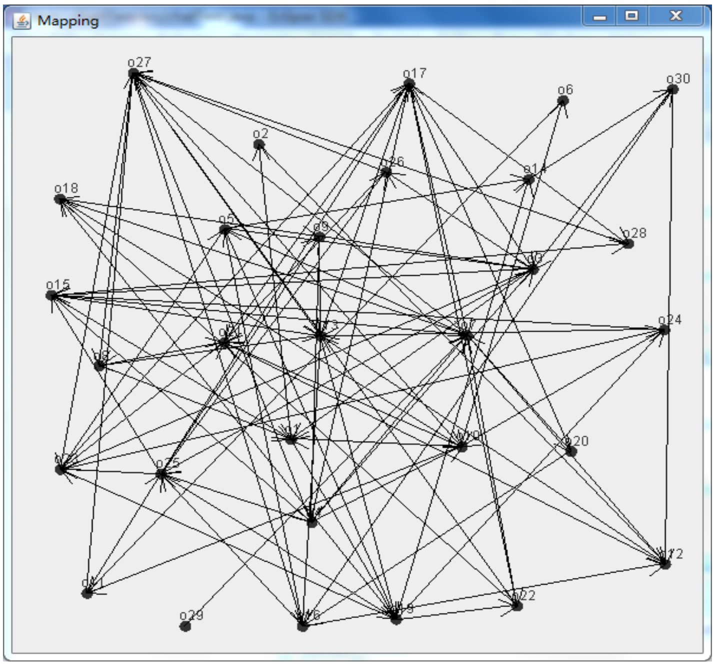

Figure 2.5: Mapped lists

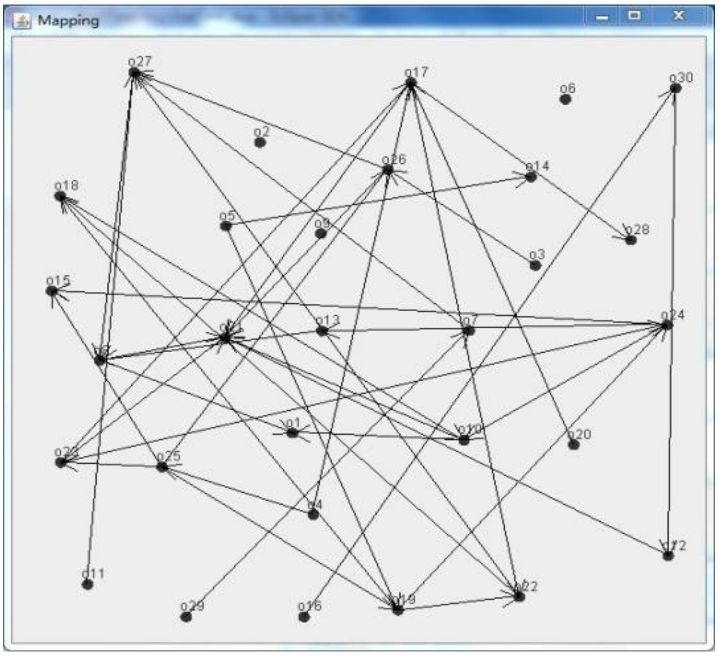

Figure 2.6: Mapped lists without loops

The directed graphic shows the entire information which is obtained from the partial comparison process, but there may be some contradictions in list set *L*, i.e., when lists contained in *L* compose some loops, the comparison relations contained in the loop will be in contradiction, i.e., considering a loop { $o_{15}>o_{16}>o_3>o_8>o_{15}$}. So the next step we need to do is to delete all the loops in *G*. For detail, traversing the directed graphic *G*, once we find a loop, we just reduce the weights of the edges contained in the loop by *1*, and we repeat this process until there is no loops in the directed graphic *G*, when the weight is reduced to 0, the corresponding edge should be deleted. The directed graphic *G* without loops is shown in Figure 2.6.

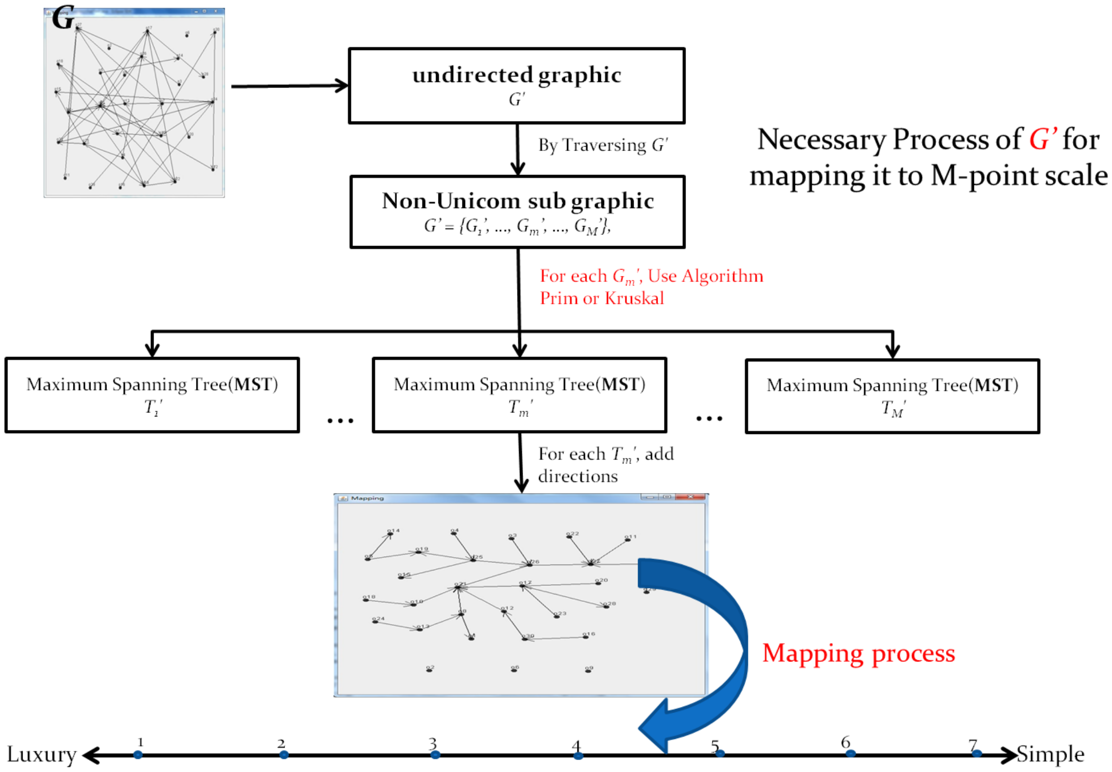

Figure 2.7: The entire process of PCP based MD method (The red colored words are the main processes of the following part)

The following discussion is mainly trying to combine the partial comparison lists into an integral list containing all objects according to an attribute, and map the integral list into 7-point scale as the general understandings. Figure 2.7 show the entire process of Partial Comparison Process based SD method. As the figure shown, after we map the partial comparison lists into a graphic and delete all loops of the graphic, we can get the graphics without any contradictions. With the graphic contained all evaluation information and without any loops and some necessary graphic techniques, we can a numeric measurement of general understandings about the objects.

The next step is to map this directed graphic G into the M-point scale. After this process, all objects will get a value $u(o_i)$ to show their levels on a Kansei attribute (or we can call it as distribution function), where $u(o_i) \in [1, M]$. The procedure is as follow:

(1) For any directed graphic, there is always an undirected graphic correspondingly, so we denote G' as the corresponding undirected graphic of G.
(2) Traversing G', we can find some sub graphic $G_m' = (O_m, E_m', W_m)$, where $G' = \{G_1', \ldots, G_m', \ldots, G_M'\}$, and we denote $C_m = |O_m|$ as the cardinality of O_m. All the sub graphics are Non-Unicom with each other.
(3) For each G_m', we need to find the maximum spanning tree, which is denoted as $T_m' = (O_m, TE_m', TW_m)$, and we add the directions of the edges which contained in T_m' according to G, we denoted the directed tree as $T_m = (O_m, TE_m, TW_m)$, where $O_m \in O$, $TE_m \in E$, $TW_m \in W$, the directed maximum spanning tree is shown as Figure 2.8.
(4) Traversing the directed tree T_m, we can calculate the value which shows the position of object o_i in T_m, we denote it as $d_m(o_i)$.

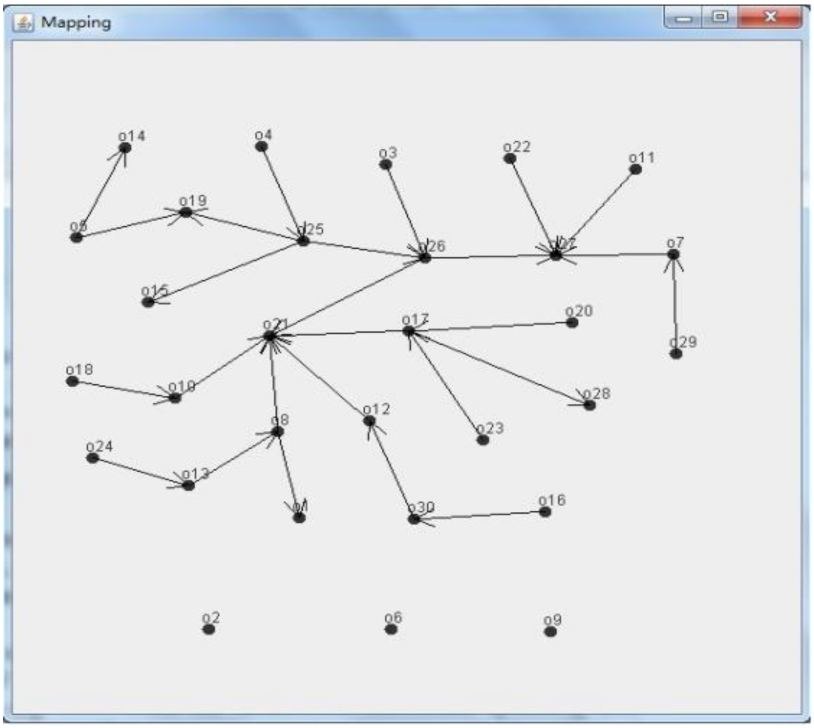

Figure 2.8: Maximum spanning tree

In this research, we use M-point method to evaluate the objects, so we need to map $d_m(o_i)$ into M-point scale, and we denote the mapped $d_m(o_i)$ as $u_m(o_i)$.

To get the maximum spanning tree T_m', we have to make some modification of G_m'. We denote $S = \sum_{j=1}^{J} w_j$ as the sum of weights W_m, where $W_m = \{w_1, \ldots, w_j, \ldots, w_J\}$. For each $w_j \in W_m$, $w_j = S - w_j$. Then we can find the minimum spanning tree of the undirected graphic G_m' with the algorithm of *Prim* or *Kruskal* (Prim, 1957; Kruskal, 1956). When we change every weight w_j to the original one, the maximum spanning tree of G_m' is just turned to the minimum spanning tree of the modified G_m'.

With the undirected maximum spanning tree T_m', we can get its correspondingly directed maximum spanning tree $T_m = (O_m, TE_m, TW_m)$. We define o_s is an start node (the node which has only one out-edge connected to it) of T_m, where $o_s \in O_m$, and define $d_m(o_s) = \varepsilon$. To calculate $d_m(o_i)$, *where* $o_i \in O_m$, we need to do a depth-first traversing on T_m, the procedure is as follow, for the sake of convenience, we denote it as *algorithm 1*, The main procedural of *algorithm 1* is that: when we visit an unvisited node y from node x, check the directed edge x-y, if x-y existed in edge set TE_m, $d_m(y)$ should be added by the weight of x-y, else it should be reduced by that value. Because the traversed tree is a Maximum Spanning Tree, this procedure will contain an optional entire comparison list with the most information.

Initialize Stack S; mark all $o_i \in O_m$ *unvisited;*
Visit o_s*; mark* o_s *as visited;* $d_m(o_s) = \varepsilon$*; S.push(*o_s*);*
while*(Stack S is not empty)* ***do****:*
    define *x = S.peek(); // not pop out from S.*
    if*(find a node w connected to x and w is unvisited)* ***do****:*
        visit w; mark it as visited; S.push(w);
        if*(directed edge xw is contained in* TE_m*)* ***do****:*
            $d_m(w) = d_m(x) + w_{xw}$;
        else do*:*
            $d_m(w) = d_m(x) - w_{xw}$;
        end if-else;
    else do*:*
        S.pop(x);//pop out node x from S.

14: end if-else;

15: end while;

With this procedure, we can get $d_m(o_i)$, where $i = 1, \ldots, C_m$. Then we should map the $d_m(o_i)$ into M-point scale as object's distribution function, which is denoted as $u(o_i)$. For each $G_m' \in G'$, there is correspondingly maximum spanning tree T_m and its $D_m(O_m)$, where $D_m(O_m) = \{d_m(o_1), \ldots, d_m(o_i), \ldots\}$. Generally, we define d_{max} and d_{min} for G_m' as:

$$d_{\min} = \min_i \{d_m(o_i)\} \tag{2.2}$$

$$d_{\max} = \max_i \{d_m(o_i)\} \tag{2.3}$$

We can also assume that the value $d_{scale} = (d_{max} - d_{min})$ of G_m' is bigger than the corresponding value of other sub graphic G_n', where $G_m' \in G'$, $G_n' \in G'$. Then the level of object o_i can be defined as follow, where $o_i \in O_m$:

$$u(o_i) = 1 + \frac{d_m(o_i) - d_{\min}}{d_{\max} - d_{\min}}(M-1) \tag{2.4}$$

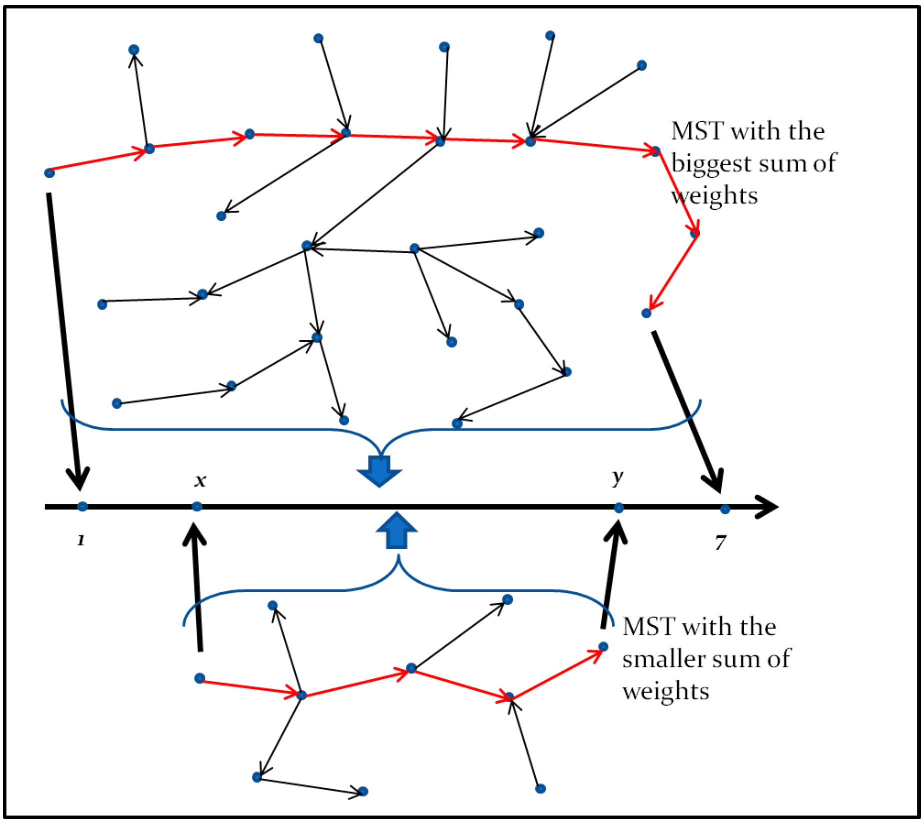

Figure 2.9: Processes of mapping MSTs to M-point scale

We also need to map $D_n(O_n)$ of the rest undirected graphic G_n' into M-point scale, where $G_n' \in G'$, because of that d_{scale} of G_n' is smaller than the corresponding value of G_m', the M-point scale should be narrowed from [$1, M$] to [x, y]. The mapping process from MSTs to M-point scale is shown if Figure 2.9. The red lines traces the longest lists with biggest sum of weights in MSTs, the objects on the pale position of longest list of the MST with biggest sum of weights, is positioned in the pale of [$1, M$]. Other objects in this MST are positioned according to the weights of their connection edges. For the MST with smaller sum of weights, the mapping scale need to be narrowed to [x, y], which has been shown in Figure 2.9. To do so, we have to make some definition firstly:

$$d'_{\min} = \min_i \{d_m(o_i)\} \tag{2.5}$$

$$d'_{\max} = \max_i \{d_m(o_i)\} \tag{2.6}$$

where $o_j \in O_n$. Then the scale can be narrowed from [1, M] to:

$$[\frac{M+1}{2} - \frac{d'_{\max} - d'_{\min}}{2(d_{\max} - d_{\min})}(M-1), \frac{M+1}{2} + \frac{d'_{\max} - d'_{\min}}{2(d_{\max} - d_{\min})}(M-1)]$$

Then the distribution function of object o_j can be defined as follow, where $o_j \in O_n$:

$$u(o_i) = \frac{M+1}{2} - \frac{d'_{\max} - d'_{\min}}{2(d_{\max} - d_{\min})}(M-1) + \frac{d_n(o_i) - d'_{\min}}{d_{\max} - d_{\min}}(M-1) \tag{2.7}$$

From (2.4) and (2.7), we can get all objects levels on every attribute, which are distributed in [1, M]. The following step is to personalize customer's requirements according to their personal profile. Equation (2.5-2.7), which is for mapping the smaller MST into 7-point scale, may not be used frequently. If the partial comparison makes enough times, all objects will appears in one MST, this means the objects were distinguished fully and precisely. The more times comparison executed the lower probability of existence of the Multi-MST. The gathered information of Kansei attributes and Context attributes is then stored in Database in the form of some kind of position values, which are shown as the objects' positions in the integral ranking list. This kind of distribution is fully positioned in 7-point scale and the distances of each position are determined by the weights of MST, which is obtained from the processes discussed above.

The MST used in this study may be not unique, thus when we use only one of the MST for getting the whole ranking list, some information may be ignored. Thus we need to find all of the MSTs by traversing the graphic from different starting points (*indegree* equals 0 and *outdegree* bigger than 0[1]). From different MSTs, we can calculate different distribution values of all objects, then for different distribution values of each object, we can calculate the average value of them.

In the following section, we will make an instance to illustrate PCP based SD method, and also, we will introduce a Comparison System for making those process executed automatically.

2.4 An Instance of PCP based SD method and the Comparison System

In this section, we will use an instance to illustrate PCP based SD method, firstly, we have developed an Online Comparison System[2], which can randomly select objects as a partial comparison group, and evaluators can compare these object and make a partial comparison list by clicking the corresponding buttons according to the attributes. As an instance, we will show what kind of data can we obtain in the partial comparison lists on a certain attribute, such as [*Cute*, *Bitter*], and after some necessary processes, we will see the position values of all the objects on the attribute.

Figure 2.10 shows the interface of the Comparison System, there are 5 randomly selected objects shown in the upper part of the interface; this system was developed by *FLEX* for interface, *JAVA* for internal process, *PostgreSQL* for database. According to the bipolar-attribute shown below the objects (the language of the attributes can be switched to Japanese or English by click "*EN/JP*"), evaluators should compare the 5 objects, find the most cute one, and click the corresponding "*SET*" button; then find the second cuter one, and click corresponding "*SET*" button. When people evaluate the objects in this system, they need compare them by the left side words (i.e. *Cute*) of the bipolar-attribute, and then the last object of the partial comparison list maybe the bitterest

[1] Indgree and outdegree are the terminologies of graphic theory. They express the situations of the connected edges of a node. Indegree means that the number of the edges ending at one node; outdegree means that the number of the edges starting from one node.

[2] *http://kutani.oicp.net:8080/evaluation_Kutani/run2/evaluation_Kutani.html*

one. After finish the partial comparison list, evaluators need to click "Confirm" button, and then the partial comparison list is stored in DB and the next bipolar-attribute will update in the area of "*Cute-Bitter*". After evaluate all attributes of this group, evaluators can click "Next" button, then the system will select another 5 objects for evaluators. Before comparison, the evaluators also asked to fill the blank in the lower left corner, which should contain the gender information, i.e. a code with the beginning alphabet of "m" indicates the evaluator is male; and a code with the beginning alphabet of "f" indicated the evaluators is "female". This gender information may be useful in our future research.

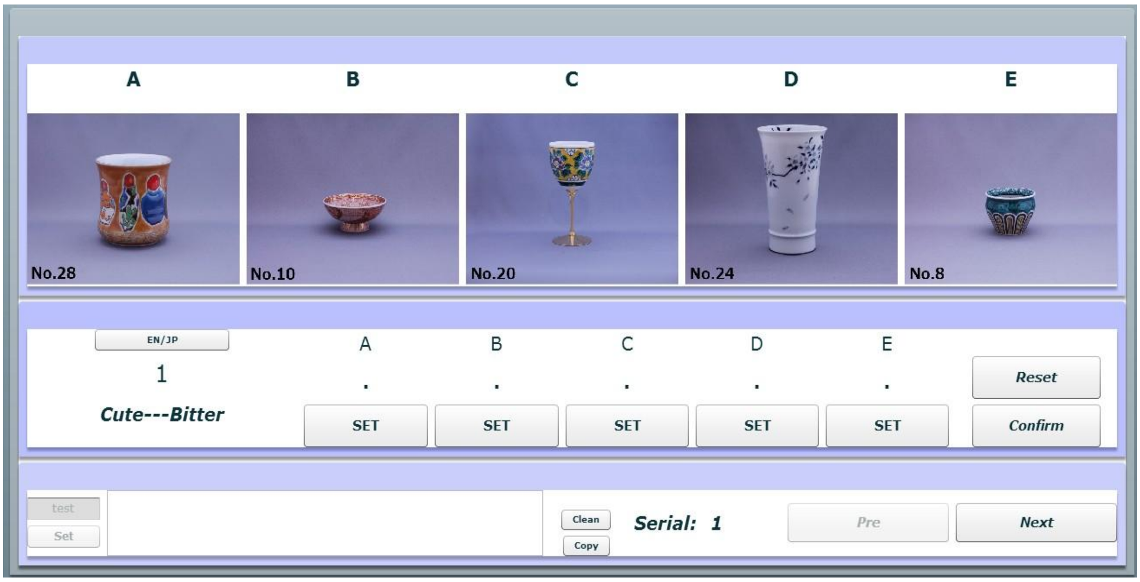

Figure 2.10: Interface of the Comparison System

The online Comparison System was distributed to about 20 evaluators, including several occupations (Students, Bank officers, Company staffs, teachers, housewives, private business man, et al.), and both males and females. Figure 2.11 shows part of the gathered information, the last column of the DB is the partial comparison lists, i.e. the red circled one {*10, 7, 29, 18, 21*}, it means evaluator "*m1260001*" (male) thought in this group ({*10, 7, 29, 18, 21*}) of objects, object 10 is the most cute one, and *object 21* it the bitterest one, specifically, it can be represented by $o_{10}>o_7>o_{29}>o_{18}>o_{21}$ on the attribute of "*cute*".

编辑数据 - localhost (localhost:5432) - postgres - collectiondata

文件(F) 编辑(E) 视图(V) 工具(T) 帮助(H)

不限制

	id [PK] integer	attributeid integer	attribute character varying	serial integer	evaluator character va	sublist integer[]
667	668	16	和やかな---厳かな	3	f1129	{3,4,27,13,26}
668	669	17	伝統的な---現代的な	3	f1129	{13,27,26,4,3}
669	670	18	女性的な---男性的な	3	f1129	{3,4,27,13,26}
670	671	19	威厳のある---親しみのあ	3	f1129	{26,13,27,4,3}
671	672	20	素朴な---おしゃれな	3	f1129	{13,26,27,3,4}
672	673	21	年配用---若者用	3	f1129	{26,13,27,4,3}
673	674	22	自分用---贈答用	3	f1129	{13,26,27,3,4}
674	675	23	男性用---女性用	3	f1129	{26,13,27,4,3}
675	676	24	洋室用---和室用	3	f1129	{3,4,26,13,27}
676	677	25	来客用---日常用	3	f1129	{3,4,27,13,26}
677	678	26	お土産用---引き出物用	3	f1129	{13,26,27,3,4}
678	679	1	Cute---Bitter	1	m1260001	{10,7,29,18,21}
679	680	2	Soft---Hard	1	m1260001	{10,7,29,18,21}
680	681	3	Cold---Warm	1	m1260001	{21,18,29,7,10}
681	682	4	Bustling---Quiet	1	m1260001	{7,21,18,29,10}
682	683	5	Pale Whitish---Thick	1	m1260001	{29,7,10,21,18}
683	684	6	Luxury---Simple	1	m1260001	{10,7,29,18,21}
684	685	7	Calm---Exhilarated	1	m1260001	{29,21,18,10,7}
685	686	8	Sober---Flashy	1	m1260001	{29,7,18,21,10}
686	687	9	Light---Heavy	1	m1260001	{10,7,29,18,21}
687	688	10	Of momentum---Mild	1	m1260001	{10,7,18,29,21}
688	689	11	Friendly---Strong	1	m1260001	{10,21,18,29,7}
689	690	12	Dynamic---Static	1	m1260001	{7,29,10,18,21}
690	691	13	Rural---Urbanized	1	m1260001	{21,18,29,10,7}

Figure 2.11: Gathered information by Comparison System

Then we can use these gathered information shown in Figure 2.11, and the necessary process of PCP based SD method to find the positions of all objects in the integral comparison list. As an instance, we use bipolar Kansei attribute "*Cute-Bitter*" as an example. When we have get enough data from the comparison system, we map them into the directed graphic *G*, which is shown as Figure 2.5, and for eliminating the contradictions, we delete all loops existed in *G*, the Kansei or Context data without any contradictions is shown as Figure 2.6. According to the Figure 2.6, some Non Unicom sub graphics are obtained by traversing the *G'*, which are $G' = \{G_1', G_2', G_3', G_4'\}$, specifically,

$$G_1' = (O_1, E_1', W_1)$$
$$G_2' = (O_2, E_2', W_2)$$
$$G_3' = (O_3, E_3', W_3)$$
$$G_4' = (O_4, E_4', W_4)$$

$$O_1 = \{o_1, o_3, o_4, o_5, o_7, o_8, o_{10}, o_{11}, o_{12}, o_{13}, o_{14}, o_{15}, o_{16}, o_{17}, o_{18}, o_{19}, o_{20}, o_{21}, o_{22}, o_{23}, o_{24}, o_{25}, o_{26}, o_{27}, o_{28}, o_{29}, o_{30}\}$$

$$O_2 = \{o_2\}$$

$$O_3 = \{o_6\}$$

$$O_4 = \{o_9\}$$

Because that set O_2, O_3, O_4 have only 1 element, set E_2', E_3', E_4', W_2, W_3 and $W_4 = \Phi$. According to G_1', with using the algorithm of Prim, the directed maximum spanning tree T_1 corresponding to G_1' could be obtained (see Figure 2.8). Then by doing a depth-first traversing on T_1 (*see the algorithm 1*), the objects' positions can be obtained, which is as follow. The value of ε can be any values, because ε will be offset in the processes and equations. Here ε is just a mark as a starting value in the depth-first traversing process (*algorithm 1*) to help reader to understand:

$$D_1(O_1) = \{\varepsilon-8, \varepsilon-3, \varepsilon-3, \varepsilon-1, \varepsilon-1, \varepsilon-2, \varepsilon+5, \varepsilon+1, \varepsilon+5, \varepsilon-4, \varepsilon, \varepsilon, \varepsilon-3, \varepsilon+3, \varepsilon+2, \varepsilon+1, \varepsilon-11, \varepsilon+6, \varepsilon+2, \varepsilon+1, \varepsilon-9, \varepsilon-2, \varepsilon+1, \varepsilon+3, \varepsilon+7, \varepsilon-7, \varepsilon+2\}$$

Then we can map these position values into M-point scale according to formula (2.2-2.4), for detail:

$d_{max} = \varepsilon+7$

$d_{min} = \varepsilon-11$

$d_{scale} = d_{max} - d_{min} = 18$

$u(O_1) = \{2, 3.67, 3.67, 4.33, 4.33, 4, 6.33, 5, 6.33, 3.33, 4.67, 4.67, 3.67, 5.67, 5.33, 5, 1, 6.67, 5.33, 5, 1.67, 4, 5, 5.67, 7, 2.33, 5.33\}$

For G_2', G_3', G_4', with formulas (2.5-2.7), we can calculate the level of the rest objects. Because there is only 1 element in the three sub graphics, the calculation process is quite easy, the result is $u(o_2) = u(o_6) = u(o_9) = 4$.

Considering other MSTs obtained by traversing from other starting points, we can find other kinds of distribution values of the objects. We can combine and merge them to get average distribution values, which are shown as follow:

$u(O_1) = \{2.31, 4, 3.88, 3.52, 4.1, 4, 4.25, 4.02, 4, 6.55, 5.21, 6.11, 3.33, 4.52, 4.65, 3.62, 5.55, 5.35, 4.98, 1.09, 6.68, 5.6, 5.2, 1.69, 4.1, 5.22, 5.99, 6.88, 2.1, 5.22\}$

The distribution of the objects can be shown in Figure 2.12. The same color of the objects in this figure mean that they are similar in the attribute, i.e. *object 20* and *24* are very cute, *object 10*, *12*, *28* are very bitter. Almost half of the objects have some kind of neutral characteristic on this attribute, this characteristic shows the difficulty of distinguish objects by semantic differential, because feelings or tastes always have a fuzzy or vague nature.

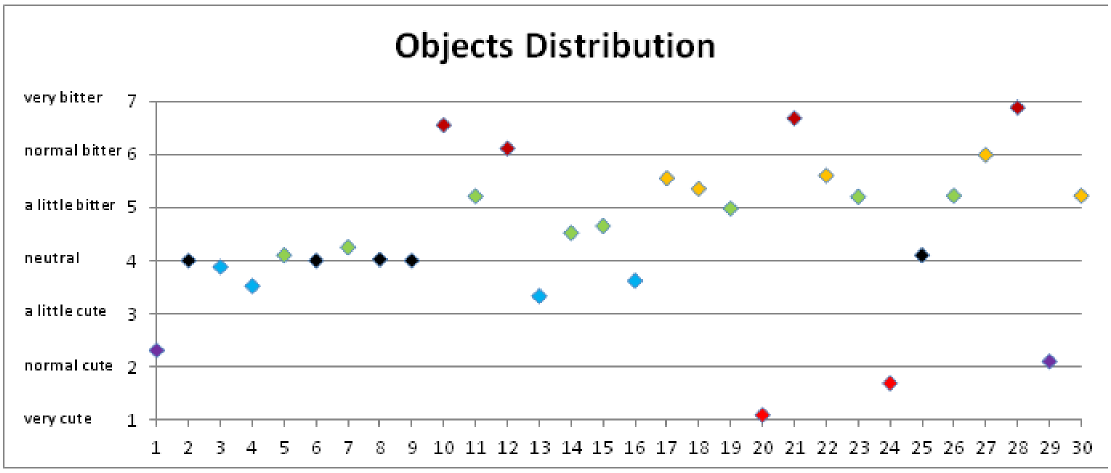

Figure 2.12: Distribution of the objects on attribute [Cute, Bitter]

The distributions of the objects in 7-point scale have been obtained from PCP based SD method and they can be treated as the general understandings of the objects, the next step is to use such information in the satisfaction measurement of single attribute requirement.

2.5 Conclusions

In this chapter, we have introduced a popular used traditional SD method in gathering Kansei and Context information, which information is expressed the general understandings of the objects. We also indicate the problems and limits of this popular SD method. To solve them, we have proposed a Partial Comparison Process Based SD method, which can solve the limits and problems exist in traditional SD method. To illustrate PCP based SD method, an instance and an online comparison System are executed and developed. In the following chapter, we will use the general understandings information, which is obtained from both traditional SD method and PCP based SD method, to measure the satisfaction the single attribute preference of consumer.

Chapter 3

Target-based Decision-making on Information Transformation

This chapter introduced a target-based fuzzy approach in matching personal preference and general understandings information, which information is obtained from traditional SD method, and also for solving the problems and limits of this method, we proposed an modified target-based fuzzy approach and a Linguistic variables approach for dealing with the information obtained from PCP based SD method.

3.1 Introductions

Simon proposed a behavioral model for rational choice, by expounding the theory of bounded rationality implying that due to the cost or the practical impossibility of searching among all possible acts for the optimal, the decision maker simply looks for the first “satisfactory” act that meets some predefined targets (Simon, 1955). However, there may be some problems, especially when the target is described by individual (consumer) on doing some purchases. The target described by consumer usually has a fuzzy or vague nature, i.e. “*I want a cute one*”, what kind of products is cute? Even consumer himself/herself does not know it clearly. It is now more and more widely acknowledged that the uncertainty of the target cannot be captured by a single probability distribution. Shown in many application, fuzzy subsets provides a very convenient object for representing the uncertain information, especially, the linguistic variables frequently represent the uncertain target by linguistically expressing the demands of consumer. Fuzzy decision analysis has received a lot of attraction since the pioneering work on fuzzy decision analysis by Bellman and Zadeh in 1970 (see Bellman & Zadeh, 1970).

Consumer’s fuzzy target on describing his/her demands is usually with compound fuzzy targets. For simplification, we will separate the compound fuzzy target into several single fuzzy target corresponding the semantic meanings of consumer’s demands, i.e., Consider this demands “I want a craft for my grandfather, with should be a little thick and traditional”, we analyze his demands by his words: the first target is “a gift”, and then “for seniors”, and then “for male”, and then “a little thick”, and then “traditional craft”. Thus the next section focuses on the single fuzzy target, and trying to measure the satisfactions of the single fuzzy target.

As we have obtained two kinds of general understandings information: obtained by traditional SD method and obtained by PCP based SD method, we will firstly introduce a classic target-based fuzzy approach dealing with the information obtained from traditional SD method, and then we will propose a modified target-based fuzzy approach for solving the weakness of the classic target-based fuzzy approach, secondly, we will propose a Linguistic variables approach in dealing with the information obtained from PCP based SD method. At last, we will discuss the advantage and disadvantage of these methods.

3.2 Target-based fuzzy method for dealing with the information obtained from traditional SD method.

In this section, we will introduce a traditional Target-based fuzzy method for dealing with the Linguistic fuzzy target. The information we have gathered in chapter 2 with traditional SD method on an attribute of a certain object can be express as Figure 2.3. The model of this fuzzy approach is defined by using the mean value w and the standard deviation $\boldsymbol{\sigma}$, utilizing an effective range of [w-3$\boldsymbol{\sigma}$, w+3$\boldsymbol{\sigma}$] (Nakamori, 2011). A triangle fuzzy membership function is described the general understandings of object i on attribute j, which is shown as Figure 3.1. The formula is defines by

$$f_{ij}(x)=\begin{cases}\dfrac{1}{3\sigma}\left\{x-\left(w_{ij}-3\sigma_{ij}\right)\right\} & (x\le w_{ij})\\ \dfrac{-1}{3\sigma}\left\{x-\left(w_{ij}+3\sigma_{ij}\right)\right\} & (w_{ij}\le x)\end{cases} \tag{3.1}$$

Consumer can select target in a fuzzy linguistic variables set as his/her demand, the linguistic variables are treated as a membership function, and are defined as follow and shown in Figure 3.1.

$$g_1(x)=-x-2 \qquad (-3\le x\le -2)$$
$$g_2(x)=\begin{cases}x+3 & (-3\le x\le -2)\\ -x-1 & (-2\le x\le -1)\end{cases}$$
$$g_3(x)=\begin{cases}x+2 & (-2\le x\le -1)\\ -x & (-1\le x\le 0)\end{cases}$$
$$g_4(x)=\begin{cases}x+1 & (-1\le x\le 0)\\ -x+1 & (0\le x\le 1)\end{cases}$$
$$g_5(x)=\begin{cases}x & (0\le x\le 1)\\ -x+2 & (1\le x\le 2)\end{cases}$$
$$g_6(x)=\begin{cases}x-1 & (1\le x\le 2)\\ -x+3 & (2\le x\le 3)\end{cases}$$
$$g_7(x)=x-2 \qquad (2\le x\le 3)$$

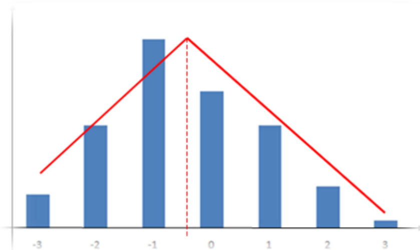

Figure 3.1: Triangle fuzzy membership function and Linguistic variables

The fitness value a single fuzzy target corresponding to single attribute preference can be given by the following formula and illustrate by Figure 3.2

$$fitness_{ij} = \max_x \min\{f_{ij}(x), g_v(x)\} \tag{3.2}$$

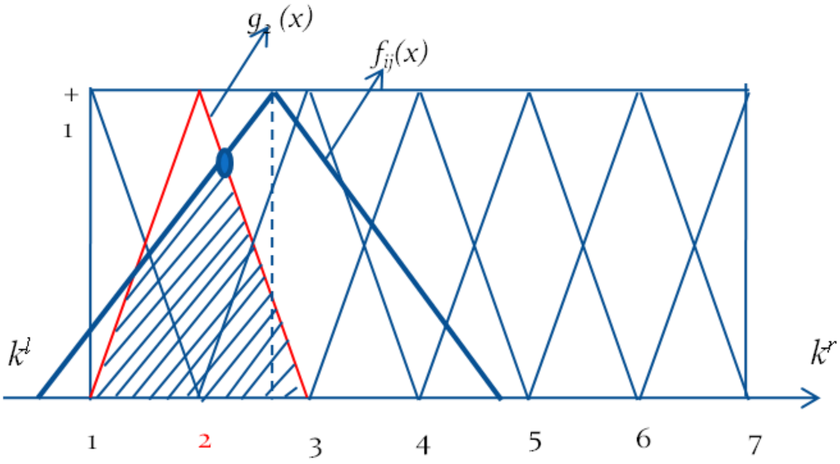

Figure 3.2: Target-based fuzzy approach

This target-based fuzzy approach is very efficient in dealing with the information obtained from traditional SD method when the information, as the general understandings expressed as Figure 3.1. However, it would be inaccurate and inefficient when the data expressed as Figure 3.3. Different evaluators express the quite different opinions on an attribute of an object, which make the general understandings information expresses some kind of symmetrical distributions. As shown in Figure 3.3, when we treat this kind of distributed information, there may be three kinds of triangle membership functions: 1) function 1 describes the general understandings of the evaluators, who thought the object is bustling, in this function the evaluators opinions, which been positioned in quiet side have been ignored. 2) In function 3, corresponding to function 1, the left side opinions have been ignored. 3) The function considered all evaluators opinion, but the mean value may equal *4* (means neutral), there might be another means: all opinions of the evaluators are ignored, or the attribute [*Bustling, Quiet*] is quite unsuitable for evaluating on this objects. Thus there are some questions: which function can express the reasonable general understandings? Are function 1 and 3 useless in measuring single attribute preference?

In the following part, we will propose a modified fuzzy target-based approach to solve this problem, which take both function 1 and function 2 into account. Actually, we can call this modified approach as a weighted target-based fuzzy approach.

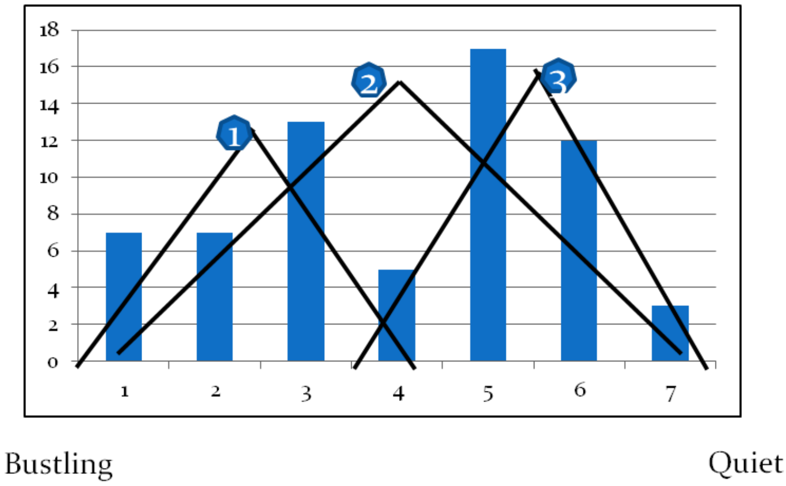

Figure 3.3: "Symmetrical distributions" of attribute [Bustling, Quiet]

For each attribute (generally, we use a Kansei attribute F_k as an example, where $k = 1, \ldots, K$), a different evaluator may have different feels on the same object. This means that some evaluators may mark the attribute F_k in the F_k^l area, but others may mark it in the F_k^r area (shown as Figure 3.3). Therefore, when we calculate the fitness value of an attribute for a certain object, we should separate the paired attribute into two single parts, which we call left part (F_k^l area) and right part (F_k^r area). We denote SC_{ik}^l as the significance coefficient of F_k when it is in the left part; relatively, SC_{ik}^r means the significance coefficient when F_k is in right part. Formula is as follow:

$$SC_{ij}^l = \frac{\sum_{h=1}^{(M-1)/2} v_h \cdot f_{ij}(v_h)}{\sum_{h=1}^{(M-1)/2} v_h \cdot f_{ij}(v_h) + \sum_{h=(M+1)/2}^{M} (v_h - (M+1)/2) \cdot f_{ij}(v_h)} \tag{3.3}$$

$$SC_{ij}^r = \frac{\sum_{n=(M+1)/2}^{M} (v_h - (M+1)/2) \cdot f_{ij}(v_h)}{\sum_{h=1}^{(M-1)/2} v_h \cdot f_{ij}(v_h) + \sum_{h=(M+1)/2}^{M} (v_h - (M+1)/2) \cdot f_{ij}(v_h)} \tag{3.4}$$

Formula (5) and (6) shows the some kind of percentage of the each side's supporter of evaluators. In this research, $M = 7$; so in formula (3.3), there are 3 levels ([*level 1, level 2, level 3*] corresponding to the linguistic variables of [*a little, normal, very*]); and in formula (3.4), there are also three levels (actually, there are 4 levels, but one of the level's score equals 0). This means the evaluators who thought this object is "*neutral*", they just seem like to make a abstention vote. These two significance coefficients not only consider the percentage of the supporter on each side, but also take the effects of different levels, actually, evaluators vote in the higher level express a stronger confidence than they vote the lower level.

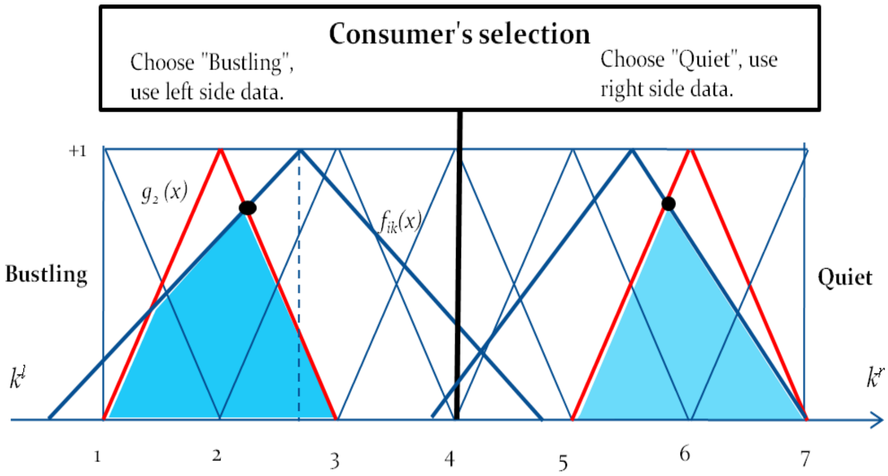

Figure 3.4: illustration of the modified target-based fuzzy approach

For each bipolar-attribute, we have cut it into left side and right side, the consumer can express his/her demands by selecting one side of the bipolar-attribute and set a linguistic variable as the target (in this situation, the linguistic variables can be express by [*very, normal, a little*]). As Figure 3.4 shown, when consumer select left side word of the bipolar-attribute, we just use function 1 (as we have discussed in Figure 3.3) and left side linguistic variables to calculate the fitness value, which value is also modified by the significance coefficient; correspondingly, when consumer select right side word as his target, we use function 3 (shown in Figure 3.3) to calculate the fitness value, and adjust the value by the corresponding significance coefficient. The formula for calculating the fitness value of consumer's single attribute preference is defined by

$$fitness_{ij} = SC_{ij}^{l} \max \min_{x} \{ f_{ij}(x), g_{v}(x) \} \qquad \textit{when consumer select left side word} \quad (3.5)$$

$$fitness_{ij} = SC_{ij}^{r} \max \min_{x} \{ f_{ij}(x), g_{v}(x) \} \qquad \textit{when consumer select right side word} \quad (3.6)$$

3.3 Linguistic variables approach for dealing with the information obtained from PCP based SD method

In chapter 2, we have proposed a Partial Comparison Process Based SD method, and have obtained the general understandings data expressed by some kind of position values. The target-based fuzzy approach proposed in the previous section may not be suitable for such kind of data. Therefore, we will propose a Linguistic variables approach to measure the satisfaction of consumer's single attribute preference with this special data. Customer can express his/her requirement on a Kansei or Context attribute by the set of linguistic variables represented by{*very, ordinarily, a little, neutral, a little, ordinarily, very*}, which is corresponding to {*1, 2, 3, 4, 5, 6, 7*}, i.e., for an typical Kansei attribute "*Cute-Bitter*", consumer can express his/her requirement by selecting one status from {*very cute, cute, a little, neutral, a little bitter, bitter, very bitter*}. A popular linguistic variables' definition on describing the requirement as a target is as Figure 3.1 (Nakamori, 2011), the triangles in the figure mean the targets; customer can select one of the triangle to describe his/her requirement. This definition of linguistic variables has a characteristic that the effect area of each linguistic variable is the same. However, this definition of linguistic variables maybe not suitable for the data obtained from PCP based SD method. Because the objects' levels are distributed in the scale of [1, 7], when customer's target is level 2, the objects level can be transferred to fitness value only when the objects' levels are between (1, 3), the other objects' fitness value would be zero (see Figure 3.5, as an instance, there are only three objects can get the values bigger than 0). This situation would be a big problem when the customer's requirement is composed by a multi-attribute, specifically, it would lose much useful information when we aggregate the multi-attribute. Therefore, we propose a modified definition of linguistic variables shown in Figure 3.6. The formula of this definition is also given in this figure. In this definition, each target, which will be selected by consumer to describe his/her preference, has equally effect area, but they have different effect pattern.

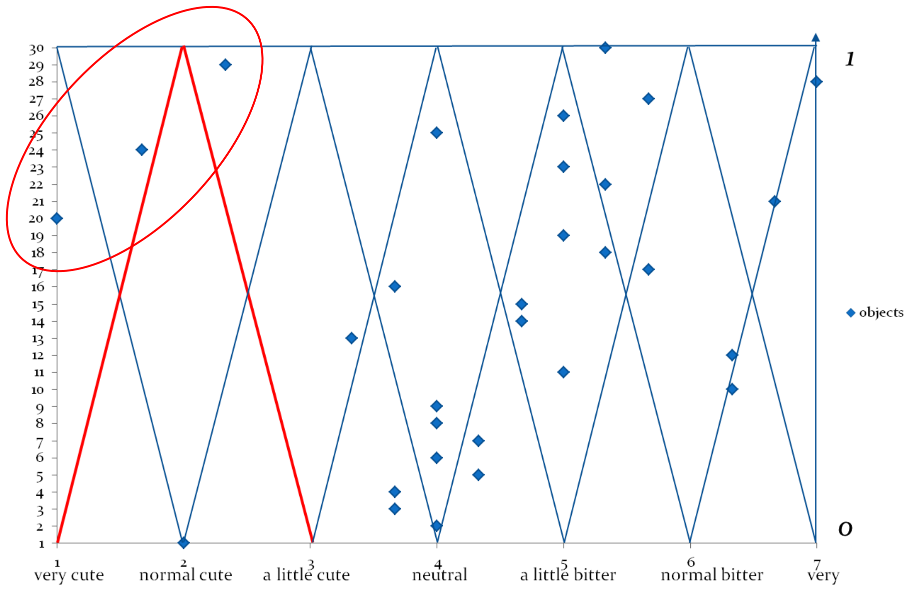

Figure 3.5: Measurement of satisfactions with classic definitions of linguistic variables

$$\mu_1(x)=\begin{cases}(5-x)/4 & 1\le x\le 5\\ 0 & 5<x\le 7\end{cases}$$

$$\mu_2(x)=\begin{cases}(x+1)/3 & 1\le x\le 2\\ (5-x)/3 & 2<x\le 5\\ 0 & 5<x\le 7\end{cases}$$

$$\mu_3(x)=\begin{cases}(x-1)/2 & 1\le x\le 3\\ (5-x)/2 & 3<x\le 5\\ 0 & 5<x\le 7\end{cases}$$

$$\mu_5(x)=\begin{cases}(x-3)/2 & 3\le x\le 5\\ (7-x)/2 & 5<x\le 7\\ 0 & 1\le x<3\end{cases}$$

$$\mu_6(x)=\begin{cases}(x-3)/3 & 3\le x\le 6\\ (9-x)/3 & 6<x\le 7\\ 0 & 1\le x<3\end{cases}$$

$$\mu_7(x)=\begin{cases}(x-3)/4 & 3\le x\le 7\\ 0 & 1\le x<3\end{cases}$$

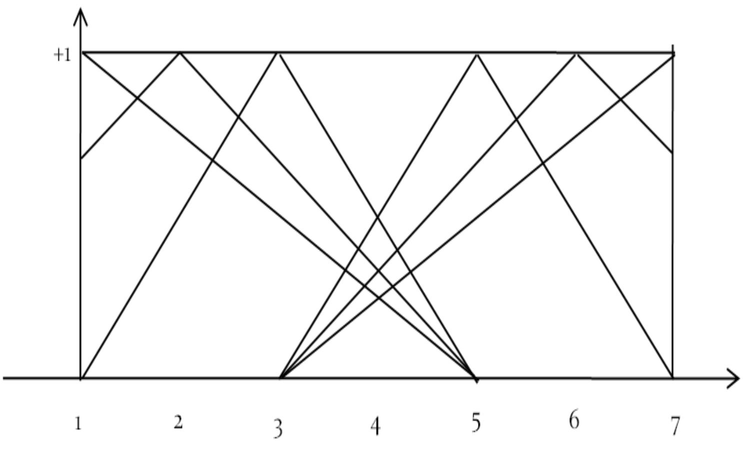

Figure 3.6: Modified linguistic variable for a Kansei attribute

Using this method, any object which is related to the customer's target would have a reasonable value. This method is based on such reasons:

1) Based on linguistic characteristic, the levels near to "neutral" is difficult to distinguish, so we can assume that levels between [3, 5] are indiscernible (level 4 means "neutral"), and we treat all these levels as "neutral".

2) As the first reason we discussed, for a certain Kansei attribute "Cute-Bitter", when the level is between [1, 5], there is possibility that it means "Cute", correspondingly, when the level is between [3, 7], there is also possibility that it means "Bitter".

3) When customer describes his requirement on a Kansei attribute, "neutral" would be a meaningless target, because "neutral" usually equals that the customer did not describe his requirement on this attribute.

We assume that the consumer's target on an attribute k is v. With modified linguistic variable and the Kansei data collected from PCP based SD method, we can calculate each object's fitness value on this attribute, denoted by $fitness_k(o_i, v)$, the algorithm is shown as Figure 3.7. With the traditional linguistic variable and the Kansei and Context data collected from partial comparison process, we can calculate each object's fitness value on this attribute shown as Figure 3.5.

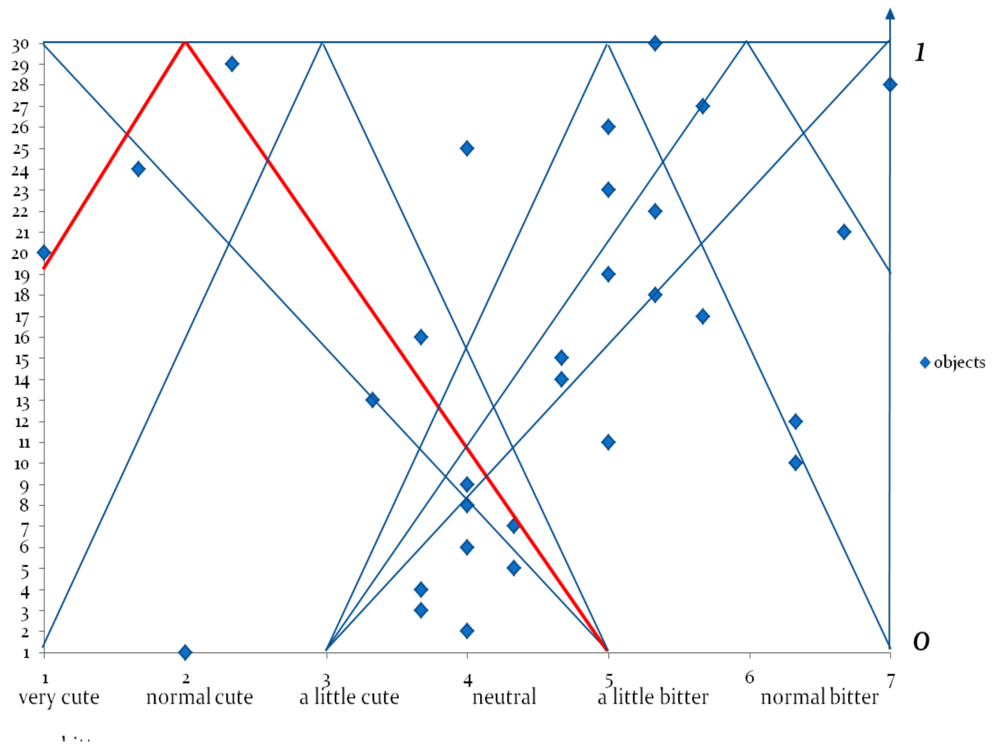

Figure 3.7: measurement of satisfactions with classic definitions of linguistic variables

As shown in Figure 3.5 and Figure 3.7, for an instance, the customer's target is level 2 (it means the customer wants a "normal Cute" object), then the fitness values of these four objects are expressed by the intersection of the abscissa of the points and the red folder line. The formula of the fitness is shown as follow, where v is target determined by customer, and function $u_k(o_i)$ is the distribution data obtained from PCP based SD method.

$$fitness_k(o_i, v) = \mu_v(u_k(o_i)) \tag{3.7}$$

For the convenience of describing the multi-aggregation models, which we will discuss in next chapter, we denote $fitness_k(o_i, v)$ as $fitness_{i,j}$, which is in the same form of the measurement method using information obtained from traditional SD method. We can see the differences between fitness values obtained from the two kind definitions of linguistic variables: with traditional linguistic variable, the target's affective area is narrower than the modified linguistic variable, so more objects' fitness value would be zero, when the objects' distribution is out of the target's affective area. So we strongly recommend the modified linguistic variable method.

3.4 Conclusions

In this chapter, we have proposed two kinds of approach for measuring the satisfaction of consumer's single attribute preference, for different kinds of data obtained from traditional SD method and PCP based SD method. The measurement approach for dealing with the data obtained from traditional SD method we have proposed is better than the classic target-based fuzzy approach in some aspects, the problem of "Symmetrical distribution" existed in the data obtained from traditional SD method is solved in a certain degree by proposing the significance coefficients. These coefficients are not only considering the percentage of the supporters, but also taking the different importance of different levels of the linguistic variables into account. We also proposed a modified Linguistic variables approach for dealing with the data obtained from PCP based SD method. Different from the classic definition of linguistic variables, the modified definition of the linguistic variables is more suitable in dealing with such data. Specifically, the effect areas of different linguistic variables are enlarged reasonably and efficiently. In next chapter, we will discuss the multi-attribute aggregation issues for handling the multi-attribute preference or requirement.

Chapter 4

Aggregation of Multiple Attributes Based on ontological Structure

In multi-attribute target-based decision models, the most important thing is aggregate the multi-attribute. The chapter will discuss the issues about multi-attribute aggregations based on ontological structure, which is a powerful and widely used methodology for describing things, aspects or concepts, and has been proved in many fields. The importance or priority information associated with different targets is a very important role in aggregate multi-attribute. This chapter will also discuss the priority or importance information of the targets for obtaining a more efficient structure of the multi-attribute.

4.1 Introduction

Target-based decision making analysis presumes that consumer's demand is usually met by the target (level) of an attribute. However, in many situations of decision making issues, multi-attribute is paid attentions by researches (Keeney & Lilien, 1987; Keeney & Raiffa, 1976), thus it is an important research topic about how a single attribute decision issues related to multi-attribute decision making problems. In previous chapter, we have discussed the measurement method of the satisfaction on consumer's preference of single attribute. In this chapter, we will propose multi-attribute aggregation models with using the results obtained from previous chapter.

In previous research of multi-attribute decision making analysis, Bordley and Kirkwood defined that the utility of a target-oriented decision maker for an attribute is only depend on whether the target of that attribute is achieved. They also extend this definition to multi-attribute area, which decision maker's utility for a multi-dimensional outcome depend only on the subset of attributes for which targets are met, and they developed a target-oriented approach to access a multi-attribute performance functions (Bordley & Kirkwood, 2004). Tsetlin and Winkler consider decision making in a multi-attribute target-oriented setting and study the impact on expected utility of changes in parameters of performance and target distributions (Tsetlin & Winkler, 2007).There are many approaches used in dealing with multi-attribute decision making analysis, such as attribute dominance utility functions (Abbas & Howard, 2005), equivalent target-oriented formulations for multi-attribute utility function (Tsetlin & Winkler, 2006).

For a multi-attribute decision making analysis, consumer usually expresses his/her demands by selecting several attributes, with targets of all the selected attributes. Moreover, some priority information of the selected attributes usually is hidden in their demands, or they usually associate the priority weights with different targets of the attributes. There are several approaches based on such situations (Calvo et al., 2002; Luo & Jennings, 2007; Torra, 1997; Torra & Narukawa, 2007; Yager, 1988 & 1996;). In practical decision making situations, the priorities of each attribute in multi-attribute is usually considered. As an instance, when consumer wants to buy a smartphone, the performance and design may be considered. If he/she focuses mare attention on performance and less attention in design, that means the smartphone's performance has highest priority, and the design has a lowest priority. There may be several strategies in handling this problem: 1) we will not tradeoff the design of the smartphone until the target of performance is achieved (Yan, 2008; Hyunh, 2009). 2) The measurements of the targets of both performances will be different according to the priorities of them, but will be considered in the same time. 3) The measurements of the targets of both performance an design will be considered in the same time with the same priorities, and we will modified the measurements by the priorities of the two attributes(Nakamori, 2011).

There are two kinds of approaches on priority Multi-attribute Decision Analysis in the previous researches. The first kind approach aims to use non-monotonic intersection operator and triangular norms to model the priority relationships existed among attributes (Luo et al., 2003; Yager, 1998). The second kind of approach used the weighted aggregation operators to model the prioritized MADA (Yager, 2008; Bellman & Zadeh, 1970). In this research, we will use the ontological structure for modeling the aggregation of the multi-attribute decision issues, which is some kind of hierarchical modeling approach.

The term *ontology* has its origin in philosophy, where it means *theory of being* (see, e.g., Heidegger 1927), and has been applied in many different ways. Computer science interprets differently this term as a classification of entities and words representing them. In information technology, we treat today the term *ontology* as an enriched taxonomy, vocabulary with a hierarchy and other (logical, semantic) relations of terms. (Chudzian et al., 2011). Today, Ontologies play important roles in many applications, when treated as tools of representation and shared understanding of knowledge about diverse domains, Such as development of information systems, organizing the content of internet pages, categorizing commercial products, standardizing vocabularies in given fields (Mizoguchi et al. 2000, Corcho et al. 2003, Pinto & Martins 2004, Bontas & Tempich 2006). There are many methods of constructing ontologies (Gómez-Pérez et al. 2003); we can speak about constructing *lightweight ontologies* with a simple hierarchical structure, or *heavyweight ontologies* including more detailed logical and semantic relations between terms. Another subdivision of the methods on the construction of the ontology is precisely related to the role of a human constructor. If we assume that the human constructor is "*on top*" and sovereign, then we should speak about a top-down way of ontology construction, which is starting with the intuitions as well as emotions of the human, while bottom-down way of ontology construction denotes an automatic construction based on broad textual content. The ontological structure used in this chapter for constructing the ontology is the *lightweight ontologies*, which divides the multi-attribute demands in to several layers according to the nature of different kind of the attributes, and it is also a top-down way of construction ontology. Actually, based on the nature of the attributes used in this research (Kansei attributes and Context attributes), we divide consumer's multi-attribute demands into several sub entities according to Context attributes, and use a lightweight ontologies with the selected Kansei attributes to construct the structure of the sub entities.

With using the ontological structure for constructing the ontologies (sub entities), the sub entities can be described by a hierarchical structure, which structure has three layers: 1) upper layer for the Context attribute; 2) lower layer for the selected Kansei attributes; 3) the middle layer for the relationships between upper layer and lower layer. Therefor, it is important to discuss the relationships existed in the middle layer of the sub entity. In this research, we will take both the internal relations between Kansei attribute and Context attribute, and consumer's personal wills into account. The internal relationships are expressed by the correlations between the two kinds of attributes, which is calculated by the mean values of each attribute. With this construction, both subjective and objective information can be taken into account, and makes the measurement of consumer's preference more reasonable. This kind of ontologies simulated the situations when consumers are making their purchases, specifically, when consumer wants to buy something, the first and the most important requirement is usually express by their purpose of buying this product, and then they may make some additional description of the product. For example, someone may express his/her requirement as "I want a Kutani-ware for my father as a gift, and it should be felt more heavy and traditional". The ontology used in this study is for constructing the consumer's requirement as "what is the consumer's requirement" or "what does the consumer really want". Actually, the concept of ontology is more like the theory of being in philosophy, and it maybe a little different with ontology used in computer science or information science.

For integrating the sub entities divided according to Context attributes, we then faced to a classic prioritized multi-attribute decision making issues. There are four kinds of approach to do so: 1) based on the logical operator "AND", which means all sub entities should meet consumer's preference; 2) based on the logical operator "OR", which means all sub entities have no differences for consumer; 3) Compensable criteria, which is a weighted average approach; 4) Essential criteria, which is a reference point approach (RPA).

The ranking of discrete options is a classical problem of multi-attribute decision analysis. However, most of the researches concentrate on subjective ranking (Keeney & Raiffa, 1976; Saaty, 1982; Keeney, 1992). Considering our research topic, the subjective information has been accessed in constructing ontologies as we have discuss above, so there should be an objective ranking method used in our research for dealing with the values we have obtained from the precesses of constructing the ontologies. The reference point approach is proposed by Wierzbicki, which is some kind of objective ranking method (Wierzbicki, 2008), and suggests the goal is to achieve a weakly or Pareto-optimal solution closest to a supplied reference point of aspiration level base on solving an achievement scalarizing problem (Wierzbicki, 1980). This kind of reference point methodology has been widely used by many researchers on handling the objective ranking issues or other decision making problems (Deb, 2006, Miettinen, 1999).

4.2 Discussion on the internal relationships in the attributes

As we use the ontological structure to construct the ontologies for multi-attribute decision making issues, the Context attribute can be treated as some kind of concepts of consumers, thus the Context attribute can be treat as an ontology or sub entity for describing part of the preference of consumer. And the Kansei attributes selected by consumer can be treated as some kind of key words for describing the sub entities. Therefore, the relations between the selected Kansei attribute and the sub entity should be considered. And then there may be 4 possibilities when consumer faces to the relationships:

(1) They want to decide the relations according to their preferences freely.

(2) They want to use the same relations for different Kansei attributes, and do not want to adjust them.

(3) They accept the relations calculated by the system, and do not want to adjust them.

(4) They partly accept the relations calculated by the system, but can adjust the relations in a certain range. Within this range, the personal tastes and the rules of the correlations between attributes can all be considered.

In this study, we will focus on the fourth possibility. When we use Kansei attributes to describe the Context attribute, we should know how important a Kansei attribute to a Context attribute is, we denote $f_{xy}(CC_{xy})$ as the importance coefficient between rc_x and rk_y, which is determined by their correlation coefficient; and we can use the correlation coefficient of attributes average values (*see formula (2)*) to describe a possible strength of their relationships.

Generally, we define CC_{xy} as the correlation coefficient between Kansei attribute y and Context attribute x, which is calculated by the mean values of each attribute (in dealing with the information obtained from traditional SD method), or by the position values of the objects on each attribute (in dealing with the information obtained from PCP based SD method). Table 4.1 shows the correlation coefficients obtained from mean values of the objects. All coefficient values, which are bigger than 0.5 or smaller than -0.5, are colored by green or red. The correlations are calculated according to the left side words of the bipolar-attribute. As the attribute we used in this research is bipolar-attribute, the minus correlations would be just turned to positive numbers, when we change one of the attribute's side of the bipolar-attribute, i.e., for Context attribute ["*Western style*", "*Japanese style*"] and the Kansei attribute ["*Rural*", "*Urbanized*"], the correlation coefficient is -0.8733, this means the correlation of ("*Western style*", "*Rural*") and ("*Japanese style*", "*Urbanized*") is -0.8733, correspondingly, the correlation of ("*Japanese style*", "*Rural*") and ("*Western style*", "*Urbanized*") is 0.8733.

Table 4. 1: Correlation coefficients obtained from the mean values

	For senior / For young	For male / For female	Western style / Japanese style	For myself / For gift	For guest / Ordinary use	Souvenir / Wedding gift
Soft / Hard	-0.2819	-0.684	0.0128	0.1732	-0.1433	0.1073
Cold / Warm	0.0714	0.2935	0.1509	-0.1233	0.155	-0.227
Bustling / Quiet	-0.0595	0.043	0.0976	-0.2676	0.1754	-0.0756
Pale Whitish, Thick	-0.3055	-0.4696	0.1309	0.3344	-0.2712	0.1139
Luxury, Simple	0.1667	0.1961	0.1841	-0.7441	0.6885	-0.576
Calm, Exhilarated	0.388	0.2185	-0.3832	0.2491	-0.1769	0.1655
Cute, Bitter	-0.651	-0.7622	0.4043	0.2138	-0.1893	0.0544
Sober, Flashy	0.3367	0.2046	-0.5556	0.5807	-0.5557	0.5371
Light, Heavy	-0.6178	-0.7092	0.295	0.4208	-0.3971	0.2141
Of momentum, Mild	-0.1451	0.1939	0.3338	-0.4678	0.4067	-0.3348
Friendly, Strong	-0.2546	-0.6731	0.0157	0.3138	-0.2516	0.1324
Dynamic, Static	-0.0522	0.1673	0.1216	-0.2521	0.1593	-0.1002
Rural, Urbanized	0.667	0.3793	-0.8733	0.4809	-0.5169	0.5899
Delicate, Exciting	0.0306	-0.4281	-0.107	-0.0662	0.1357	-0.1372
Fresh, Classic	-0.8962	-0.5708	0.908	-0.115	0.1494	-0.2897
Sociable, Stately	-0.4457	-0.5066	-0.0045	0.661	-0.651	0.5265
Traditional, Modern	0.0255	0.6275	-0.9121	0.2267	-0.0783	0.2486
Feminine, Virile	-0.5446	-0.9775	0.4354	0.0177	0.0359	-0.1806
Dignified, Cordial	0.5274	0.6145	-0.0771	-0.6726	0.6644	-0.5324
Rustic, Smart	0.6357	0.4543	-0.8567	0.5899	-0.6175	0.6866

Here are some definitions about the correlation coefficients:

If $0.8 \le CC_{xy} \le 1$*, there is a completely positive correlation;*
If $0.2 \le CC_{xy} < 0.8$*, there is a certain degree of positive correlation;*
If $-0.2 \le CC_{xy} < 0.2$*, there is no correlation;*
If $-1 \le CC_{xy} < -0.2$*, there is negative correlation;*

From these definitions, *we* can map the correlation coefficient to the importance coefficient. Specifically, when the correlation effect between a Kansei attribute and a Context attribute is significant, this means the Kansei attribute is important to describe the Context attribute. Correspondingly, if the correlation effect between the Kansei attribute and the Context attribute is not significant, or it appears a negative correlation effect, the Kansei attribute is not suitable to describe the Context attribute.

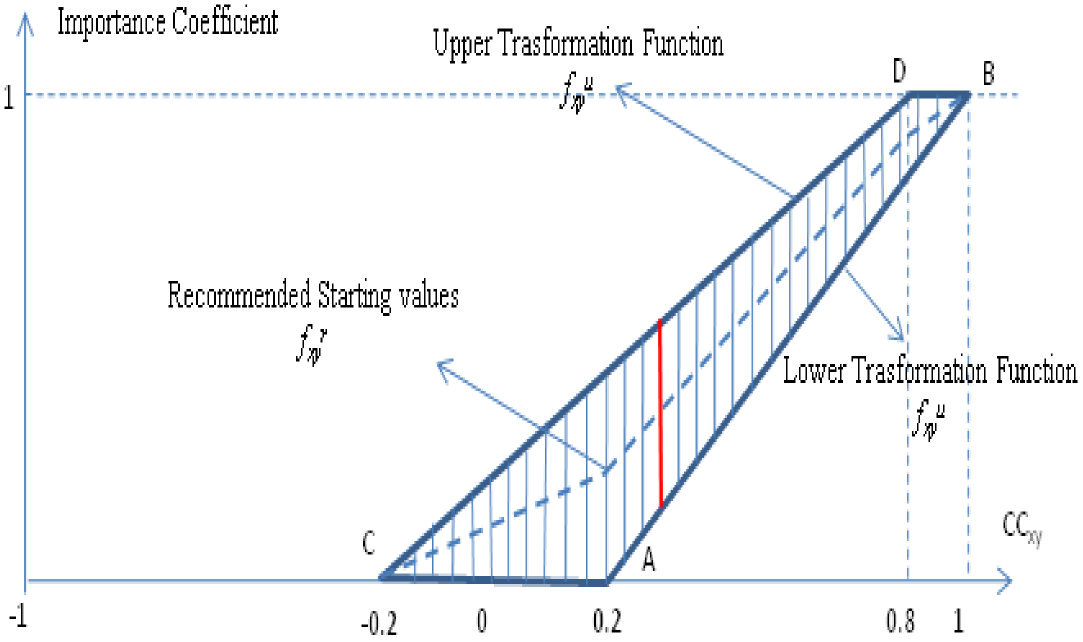

Figure 4.1: Conversion from correlation coefficient to importance coefficient.

We assume that the Kansei attribute is not suitable to describe the Context attribute when their correlation coefficient is smaller than *0.2* and we set then the importance coefficient of the Kansei attribute to the Context attribute as *0*. If their correlation coefficient is bigger than *0.2,* we assume that there is linear relationship between the importance coefficient and the correlation coefficient, the linear relationship is described by the segment *AB* in Figure 4.1. The composite line *CDB* indicates a reasonable upper limit to the importance coefficients set by a consumer; hence we define it as the upper recommended transformation line for an adjustment range, defined to meet consumer's personal requirements, which consumer can adjust the importance coefficient in a certain degree. This range is defined in a sense objectively, by taking into account the correlation coefficients obtained from the database. The lower limit of the range is expressed by the composite line *CAB*: specifically, if the correlation coefficient is bigger than *0.2,* we assume that line segment *AB* defines a reasonable lower limit for importance coefficients set by the consumer. To sum up, if the correlation coefficient is smaller than *-0.2*, we set the importance coefficient as *0*; if the correlation coefficient is bigger than *0.8*, we set upper limit of the importance coefficient as *1*; if the correlation coefficient is in the range *[-0.2, 0.8]*, we assume that there are limits to the importance coefficients set by the consumer, expressed by linear relationships between the correlation coefficient and the importance coefficient. The vertical lines in the shadowed area in Figure 4.1 are indicated the range of possible importance coefficients that can be selected by the consumer; as reasonable starting points, we can suggest to the consumer the middle values of these ranges, denoted on Figure 4.1 by a broken line.

Thus, consumers can set their preferred importance of a Kansei attribute y to a certain Context attribute x, which we denoted as s_{xy}. We define $f_{xy}{}^{l}$ and $f_{xy}{}^{u}$ as the recommended lower transformation function and upper transformation function (*see* Figure 4.1), and we define $f_{xy}{}^{r}$ as the middle value function which we recommend to a consumer as starting values, they are determined by the correlation coefficient of attributes x and y, in detail as follows:

$$f_{xy}{}^{l}(CC_{xy}) = \begin{cases} 0 & -1 \le CC_{xy} < 0.2 \\ 1.25CC_{xy} - 0.25 & 0.2 \le CC_{xy} \le 1 \end{cases} \tag{4.1}$$

$$f_{xy}{}^{u}(CC_{xy}) = \begin{cases} 0 & -1 \le CC_{xy} < -0.2 \\ CC_{xy} + 0.2 & -0.2 \le CC_{xy} < 0.8 \\ 1 & 0.8 \le CC_{xy} \le 1 \end{cases} \tag{4.2}$$

$$f_{xy}{}^{r}(CC_{xy}) = \begin{cases} 0.5CC_{xy} + 0.1 & -0.2 \le CC_{xy} \le 0.2 \\ 1.125CC_{xy} - 0.025 & 0.2 \le CC_{xy} < 0.8 \\ 0.625CC_{xy} + 0.375 & 0.8 \le CC_{xy} \le 1 \end{cases} \tag{4.3}$$

According to s_{xy} and formula (4.1-4.3), we can define f_{xy} as *in* (4.4), which means the importance coefficient concerned the correlation coefficient and the consumer’s personal will. The equation can make the adjusted importance coefficient in the shadow part of *Fig. 3*.

$$f_{xy} = \begin{cases} f_{xy}{}^{r} + s_{xy} \cdot (f_{xy}{}^{r} - f_{xy}{}^{l}) & -1 \le s_{xy} \le 0 \\ f_{xy}{}^{r} + s_{xy} \cdot (f_{xy}{}^{u} - f_{xy}{}^{r}) & 0 < s_{xy} \le 1 \end{cases} \tag{4.4}$$

With using this correlation based adjustable importance coefficients or priorities, the construction of the sub entities can not only follows consumer’s personal wills, but also take the internal rules of the attributes into account. In the following section, we will propose ontological structure based aggregation models, which take this correlation based adjustable priorities into account.

4.3 Ontological structure based aggregation models

Consumer can select some attributes of the product and set the importance coefficients of these attributes to describe his/her requirements in this recommendation problem. Therefore, we have to face to a situation that the consumer’s preference profile includes several attributes of the products, in other words, we face to a multi-attribute requirement, and we need to integrate the multi-attribute selection to obtain a scalar measure of consumer’s preference.

As we have discussed above, there are two kinds of attributes to describe a product: Kansei attributes and Context attributes. Kansei attributes are usually expressed by the adjective words; they are usually used to describe the sensibilities of a consumer about an object. These sensibilities usually have a vague nature for a human to describe, for example, “a little” or “very much” can express the degree of a Kansei word. Correspondingly, Context attributes usually express the product’s purpose of use or characteristic of users. They usually include some short phrases, and they are different from Kansei attributes: a Context attribute usually has an explicit meaning for a consumer. For example, for a Context attribute “for seniors” we cannot set a degree to describe this attribute as our requirement, and it just means that we want a product for seniors. According to these characteristics of Context attributes, we can use an ontological structure to describe them: specifically, we could use Context attributes as sub-requirement entities (selected Context attribute), and we use Kansei attributes to describe these sub-requirement entities, then we could integrate these sub-requirement entities as consumer's personal requirement.

The ontological structure used in this chapter for constructing the ontology is the lightweight ontologies, which divides the multi-attribute demands in to several layers according to the nature of different kind of the attributes, and it is also a top-down way of construction ontology.

4.3.1 Cnsumer target-based aggregation model

Given $R = R_c \cup R_k$ as the requirements set of consumer, where R_c means the Context requirements, R_k means the Kansei requirements: $R_c= \{rc_1, \ldots, rc_x\}$, $R_k = \{rk_1, \ldots, rk_y\}$. We have calculated how the object meets the selected attributes $r \in R$ separately, and then we will use a method to aggregate them to see how the object meets the consumer's preference. Here we use an ontological structure to describe consumer's preference. Specifically, we concentrate on the Context attributes, and use the selected Kansei attributes to describe them. We use the selected Kansei attribute set R_k to describe a selected Context attribute rc_x. This is some kind of enlarged Context attribute or we can say it is an enlarged concept, we denote it as $erc_x \in eR_c$, where $erc_x=\{ rc_x, R_k\}$, and eR_c is the set of enlarged Context attributes. For the enlarged context attribute erc_x, the fitness of the object o_i can be calculated by

$$fitness(o_i, erc_x) = fitness_{i,rc_x} + \sum f_{xy} \cdot fitness_{i,rk_y} \tag{4.5}$$

Where $fitness_{i,j}$ is the fitness value of single attribute, which we have discussed in chapter 3. f_{xy} is the importance coefficients, which considered both internal relationships of the attributes and the personal wills. As it is shown in Figure 4.2, each selected Context attribute can be treated as a sub-requirement entity, and for each sub entity, we use all selected Kansei attributes to describe it according to the importance coefficients and correlation coefficients. For example, see Figure 4.3, if there are 8 Kansei attributes (*k_1, k_2, …, k_8*) for describing the sub-requirement entity, and the consumer selects several Kansei attributes (e.g. *k_1, k_4* and *k_8* were selected.) to describe his/her requirements, then he/she can adjust the importance coefficients of the selected Kansei attributes within the adjustment range to meet his tastes.

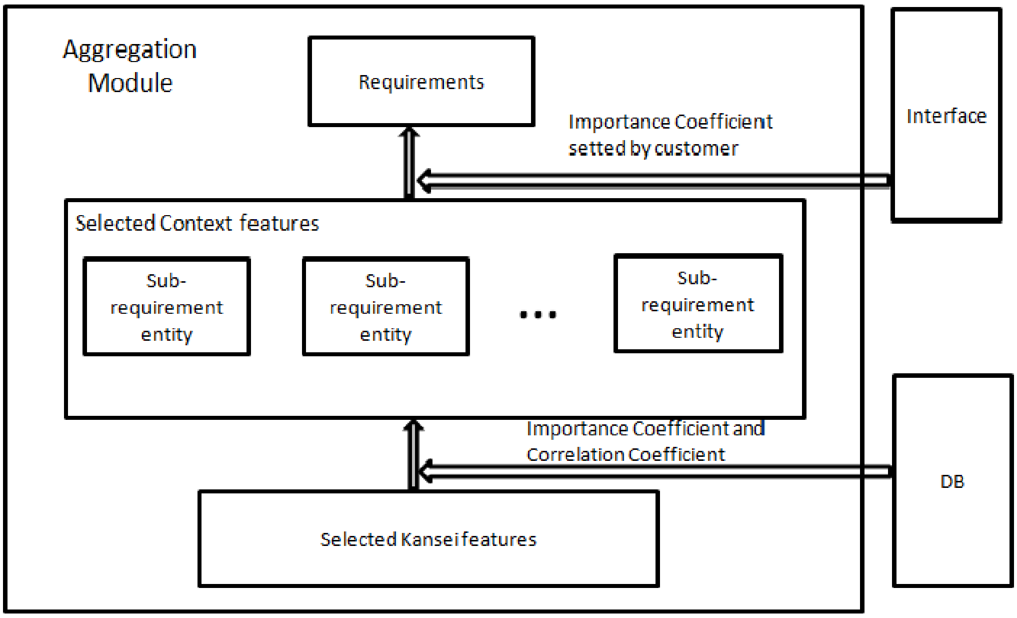

Figure 4.2: Multi-attribute aggregation process

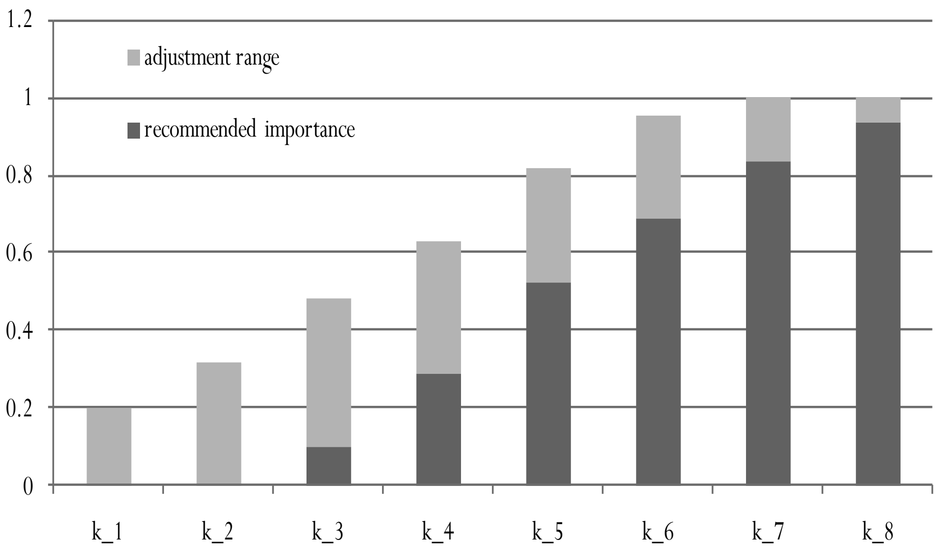

Figure 4.3: Adjustment range of the importance coefficients

4.3.2 Aggregation model based on a prototype system PrOnto

The prototype system *PrOnto* was developed in the *Requested Research Project of Poland* in the National Institute of Telecommunications, entitled *"Teleinformatic Services and Networks of Next Generation – Technical, Applied and Market Aspects"*, The system *PrOnto* is based on radically personalized ontological profiles of users, and takes into account the interaction with different users (Chudzian et al. 2011). If we use the idea of *PrOnto system* that a certain user-defined *concept* usually has a set of *key-words* to describe it, and a user can adjust the importance coefficients of these keywords, we can assume that for a certain Context attribute, treated as a *concept,* there is also a set of Kansei attributes, treated as a set of *keywords,* that can describe it commonly (we can call it a description set). And when we want to measure the satisfaction of a Context attribute, we can measure it by the related Kansei attributes, and personalize it by consumer's wishes. Specifically, we can make a set of Kansei attributes, which have higher correlations to that Context attribute, and instead of specifying the Context attribute by fuzzy method, we can use the fitness values of the set of Kansei attributes to describe the Context attribute indirectly, there is at least an advantage that we can distinguish different Context words in detail, because instead of using evaluation data only, there are many other Kansei attributes that can show their differences. If we want to take a typical selected Kansei attribute into account for the sub-requirement entity (a selected Context attribute), we can reset the correlation coefficient between this pair of Kansei attribute and Context attribute. The mechanism is shown in Figure. 4.4. This figure expresses the interior mechanism of a sub-requirement entity. As shown in Figure 4.4, a sub-requirement entity can be described by a set of Kansei attributes with higher correlation to this entity. Obviously, the consumer can also reset the correlation coefficient in a certain range (see *Figure 4.1*). For example, see Figure 4.5, the selected Kansei attributes were *k_2*, *k_4* and *k_5,* we can just reset the correlation coefficients in a rational range to meet consumer's special tastes.

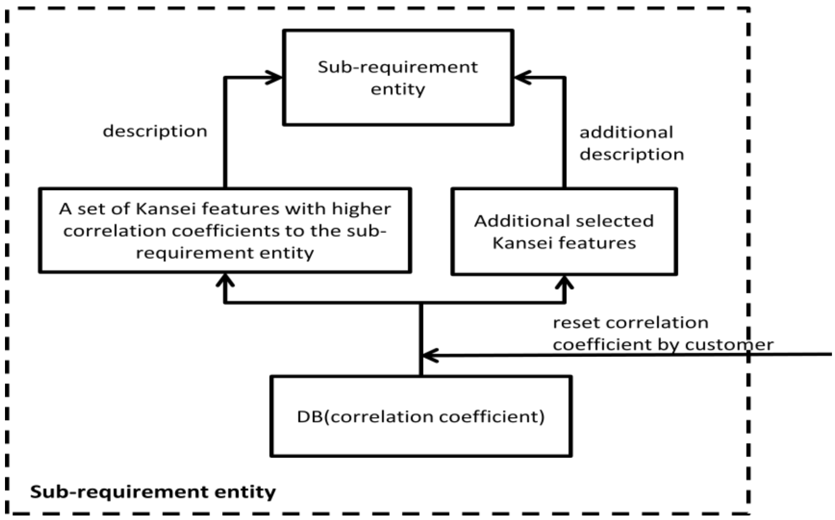

Figure 4.4: Interior of a sub-requirement entity

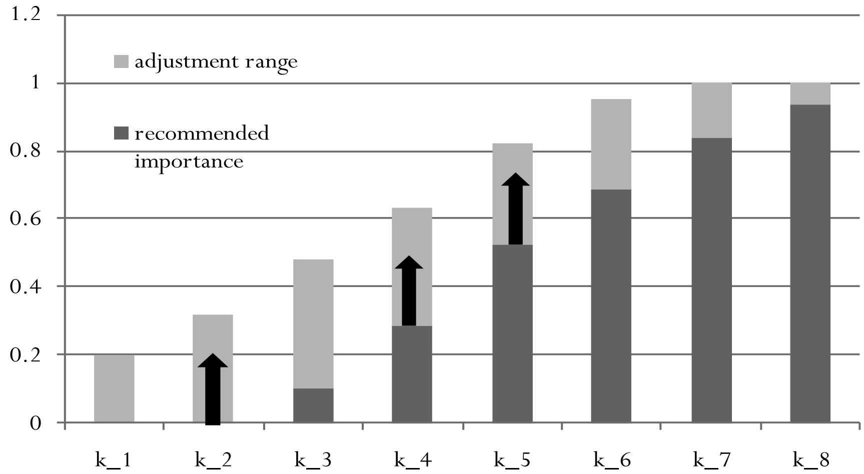

Figure 4.5. Interior of a sub-requirement entity

The algorithm is similar to the method we have mentioned above, the difference is that how to calculate the fitness of the enlarged context attribute erc_x. We just use the Kansei attributes to describe the enlarged context attribute in this model, and we will not take the fitness of selected Context attribute erc_x into account, the reason is that all Kansei attributes have special relationships with a certain context attribute, we can just use the Kansei attributes which have significant relations with that context attribute to distinguish context attributes. We denote K_{rc_x} as the Kansei attributes set, which have significant relations with rc_x, and as mentioned above, R_k is the selected Kansei attributes set. Then $fitness(o_i, erc_x)$ is given by

$$\begin{aligned} fitness(o_i, erc_x) = & \sum\nolimits_{ky \in K_{rc_x}, k_y \notin R_k} f_{xy}{}^{r} \cdot fitness_{i,rk_y} \\ & + \sum\nolimits_{rk_y \in R_k} f_{xy} \cdot fitness_{i,rk_y} \end{aligned} \tag{4.6}$$

The first part on the right side of the equation is the satisfaction of the selected Context attributes calculated by the description set; the second part on the right side of the equation is the satisfaction of the additional selected Kansei attributes, which are not included in the description set.

4.4 Ranking methods

We have constructed the ontological structure based sub requirement entities, with take the personal subjective priorities and the objective internal relationships existed between attributes into account. The next step is to find ways to integrate the sub requirement entities into an entire requirement of the consumer, to see how the object meets consumer's preference. For each selected Context attribute, the consumer can also set the importance which describe that how important of the Context attribute to his/her preference. We denote it by $f(erc_x)$. There are two kinds of relationships existed among sub requirement entities: "*AND*" and "*OR*", which shows consumer's preference on the sub requirement entities. The following part will discuss them and access them as ranking methods:

1) If we assume that all selected Context attributes have a fuzzy logical relation *"OR"*, it means all Context attributes have no difference of importance, actually, "have no difference" is simply means that the priorities of all sub requirement entities have the same values, then if we can treat this method as a weighted sum approach, thus consumer will concentrate on the sub requirement entity of highest fitness values. The aggregation method is as follow:

$$fitness(o_i) = \max_{erc_x \in eR_c} f(erc_x) \cdot fitness(o_i, erc_x) \tag{4.7}$$

2) If we assume the fuzzy logical relation *"AND"* rules all Context attributes, it means consumer wants every selected Context attribute to meet his/her requirements. "*All sub requirement entities meet ones taste*" means that consumer will focus on the sub requirement entity of lowest fitness value. Because when consumer focuses on the lowest fitness value, the other sub requirement entities' fitness values are reasonably bigger than the expected values. the aggregation method is:

$$fitness(o_i) = \min_{erc_x \in eR_c} f(erc_x) \cdot fitness(o_i, erc_x) \tag{4.8}$$

For the selected Context words, there might be some very small fitness value to an object, which will make the final score indiscernible, so we will introduce two other ranking methods to solve this problem. These two methods follow the *compensable criteria (COMP)* and *essential criteria (ESS).*

The first one means that a large value of criteria will compensate a small one, which is some kind of weighted average approach, it also means that the fitness values of sub requirement entities of an object will be distributed in the area near to the average value of all the sub requirement entities. Consider a situation: when the fitness values of some of the sub requirement entities are too small or even equal to zero, the final ranking list may appear a strange phenomenon: when we use formula (4.8) to calculate all objects' fitness values, many fitness values of the object may be equal to zero, and some part of the ranking list would be indistinguishable. When the fitness values of the sub requirement entities minus the statistic mean value of the average fitness value of all objects, the values bigger than mean value will compensate the values smaller than the mean value.

The second one means that all criteria should have reasonably large values, which is some kind of *reference point method* we have discussed in section 4.1. This approach is somewhat a combination approach of the logical operator "*AND*" and the *compensable criteria*, in which the operator "*AND*" will deal with compensable values.

First, we should compute the statistical mean to see the average fitness of all objects for a given selected Context attribute:

$$fitness_{av}(erc_x) = \frac{\sum_{o_i \in O} f(erc_x) \cdot fitness(o_i, erc_x)}{|O|} \tag{4.9}$$

Where $fitness(o_i, erc_x)$ is computed as in (4.5) or (4.6) and $|O|$ is the number of the objects. Then we can define the *compensable criteria* and the *essential criteria*:

$$fitness_{comp}(o_i) = \sum_{erc_x \in eR_c} (f(erc_x) \cdot fitness(o_i, erc_x) - fitness_{av}(erc_x)) \tag{4.10}$$

$$\begin{aligned} fitness_{ess}(o_i) = \min_{erc_x e R_c} (f(erc_x) \cdot fitness(o_i, erc_x) - fitness_{av}(erc_x)) \\ + \varepsilon \cdot fitness_{comp}(o_i) \end{aligned} \tag{4.11}$$

where $fitness(o_i, erc_x)$ is also computed as in (4.5) or (4.6), it is depending on that which kind of aggregation model we will use, the consumer target based aggregation model or indirect aggregation model. The coefficient $\varepsilon > 0$ in (4.11) indicates a compromise between interpreting the relations between the selected Context attributes as a fuzzy logical *"AND"* operation and interpreting them as compensable criteria. When $\varepsilon = 0$, formula (4.11) would be almost equivalent to (4.8), the difference is whether the fitness values are compensated. About the value of ε in formula (4.11), Chudzian et al. compared the different values of it (from *0.001* to *1.0*) by an objective comparison and indicated that method ESS with $\varepsilon > 0.2$ gives results practically identical to method COMP. Method ESS with $\varepsilon < 0.04$ gives results similar to, nevertheless different than method AND. The reason for this distinction is that method ESS analyzes differences from average values, while method AND analyzes absolute values (Chudzian et al., 2011). Therefore, if the average value is small for a given sub requirement entity, object with sufficiently high values of $fitness(o_i, erc_x)\text{-}fitness_{av}(erc_x)$ are ranked high by method ESS, while they might be ranked low by method AND because of low absolute value of $fitness(o_i, erc_x)$; in such situation; AND method would rank high only documents with exceptionally high values of $fitness(o_i, erc_x)$. It appears, therefore, that method AND has an essential drawback of neglecting the averages $fitness_{av}(erc_x)$ and method ESS with small values of parameter ε might be preferable. Actually, Chudzian suggest that $\varepsilon = 0.3$ in his research.

4.5 Conclusions

In this chapter, we discussed ontological structure based aggregation models for dealing with multi-attribute decision making problems. We use a lightweight ontologies to construct consumer's preference into several ontologies (sub requirement entities), which is considered both objective internal relationships existed in attributes and the subjective personal wills. The relationships is treated as the middle layer of the ontologies, and they indicate the relationships between sub requirement entities and the description set, which is constructed by the selected Kansei attributes with higher correlations to the sub requirement entities (selected Context attributes). For constructing the ontologies, we have proposed two kinds of structure: consumer target based aggregation model and indirect aggregation model base on *PrOnto*. Moreover, for integrating the sub entities into consumer's preference which means what they really, we introduce 4 ranking method: the logical operator "*AND*" based ranking method, the logical operator "*OR*" based ranking method, *Compensable Criteria*, and *Essential criteria*. The last two criteria are proposed for solving some limits or problems existing in the logical operator based ranking methods.

In next chapter, an instance and a recommendation system based on the methods we have proposed will be executed and developed to illustrate our research. The recommendation system uses both two kinds of information we have obtained in chapter 2, and executes the two aggregation models and the 4 ranking methods proposed in this chapter.

Chapter 5

A Case Study on Kutani-ware

In this chapter, we will used a traditional Japanese Crafts, which are so called "Kutani-ware", to make an instance for illustrating our research. There are two kinds of information on describing Kutani-wares in our research, firsly evaluation experiments will be executed for obtaining general understandings; secondly, we will use the measurement method for single attribute preference to get the fitness values of them; at last the multi-attribute aggregation models and ranking methods will be executed.

5.1 Introduction

Kutani-ware, as a Japanese traditional crafts, is an important industry of national cultural and historical value, which makes the country or nationality unique. However, as the rapid development of technology and the changes of lifestyle, this traditional industry has declined much, expressing by the decreasing of the employees, increasing of the average ages of the practitioners, less successors, and consequently decrease of the sales. Therefore, the purpose of promotion of this traditional industry is so important not only from the economic perspective, but also particularly important from the culture or historical perspective. In this chapter we will make an instance of Kutani-ware, which aims to make an efficient recommendation system for promoting this traditional industry. With this instance, the proposed method on gathering information of general understandings and the measurement method on single attribute preference and the multi-attribute aggregation models will be illustrated. The structure of this chapter is constructed according to the procedural of recommendation systems. Firstly, we will show the forms of information, as well as the general understandings, obtained from traditional SD method and PCP based SD method. Secondly, we will use these data and single attribute preference demand of consumer to measure the satisfactions of the object to consumer. At last, with using the satisfactions obtained in previous step, we will apply the aggregation models based on ontological structure.

5.2 Instance on Single Attribute Preference

The objects of Kutani-ware have been shown in chapter 2. For gathering general understandings, we applied two methods: the traditional SD method and the PCP based SD method. The part of the information obtained from the first method is shown in Figure 5.1. As discussed in chapter 2, i.e. for object 1 and the attribute of [*For young, For senior*], the height of the column on level 7 means how many evaluators thought object 1 is definitely for senior people use. We can see that some of the attributes for some objects are not distinguished very well: the distribution of object 3 on [*For gift, For myself*] is irregular (general understanding is quite different on this object of the attribute), and some of the attributes for some objects are distributed clearly: i.e., most of evaluators thought object 3 is warm and for female use (the feelings strength maybe different). The well distributed attributes on some objects will efficiently used in target-based fuzzy approach, on the contrary, the bad distributed attributes will be useless or inefficient on target-based fuzzy approach.

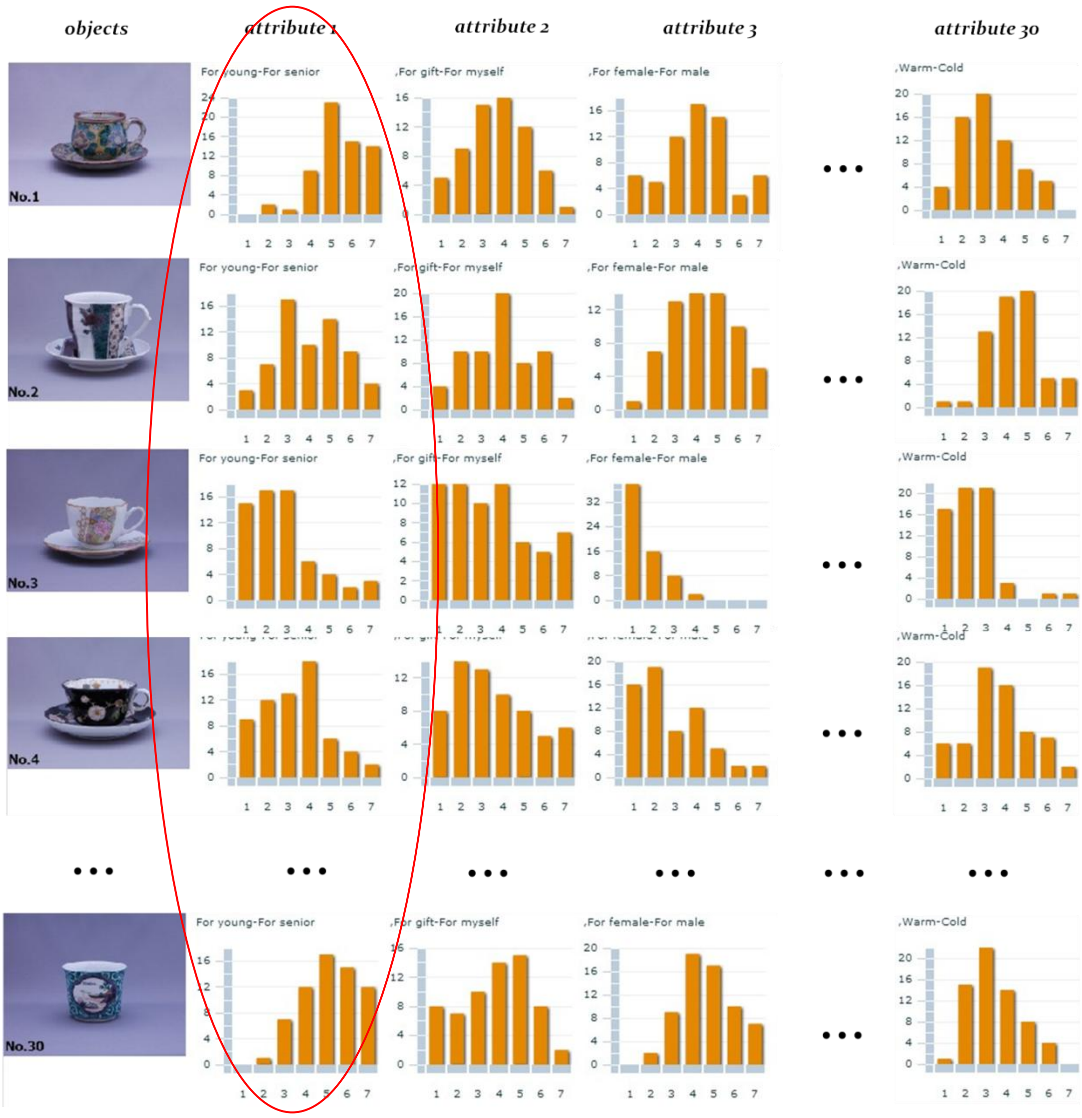

Figure 5.1: gathered information by traditional SD method.

With the general understandings information we have obtained, and the linguistic variable based single attribute target of consumers, we can use two target-based fuzzy approaches to measure the satisfaction of single attribute preference: traditional target-based fuzzy approach and weighted target-based fuzzy approach. Figure 5.2 shows the calculation procedural. As an instance, we assume consumer express his/her demands by a single attribute [*For young, For senior*] (the red circle in Figure 5.1 is the corresponding general understandings), and decide the target by linguistic variables as normal degree for young people use (as shown in Figure 5.2, the target is 2), and we shows how the measurement approach for single attribute preference works.

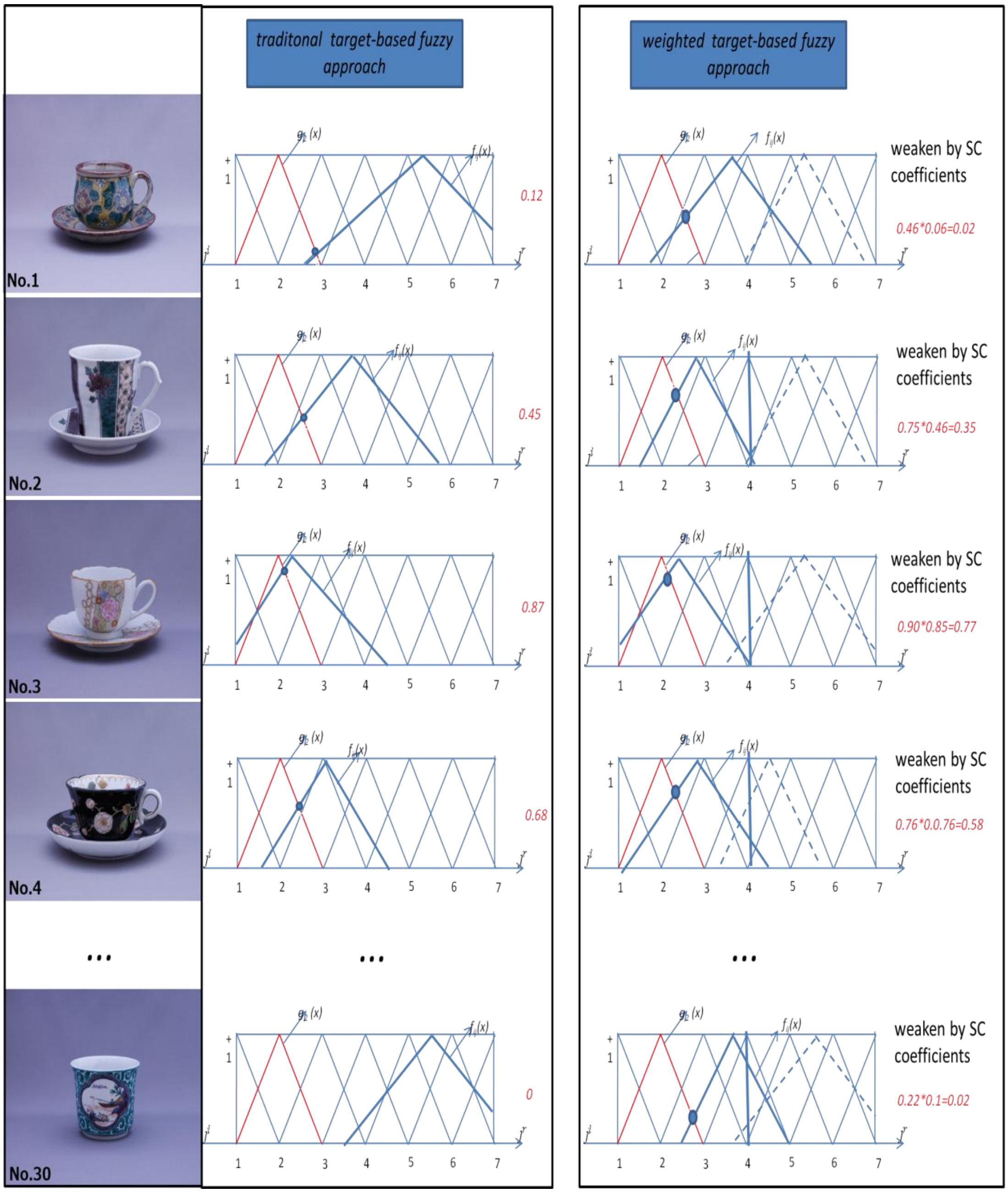

Figure 5.2: different target-based fuzzy approach

As Figure 5.2 shown, we describe two approaches for measure the satisfactions: the traditional target-based fuzzy approach and the weighted target-based fuzzy approach. The first approach uses the statistic mean values and the standard deviations to construct the general understandings of the information obtained from traditional SD method. The fitness value of the objects according to consumer's single attribute preference is shown as the points of the intersection. Correspondingly, the second one also uses the statistic mean values and the standard deviations, but the differences are that the data for calculating the mean values and the deviation values is from the evaluators, who support the target side of the bipolar-attribute, and the values are adjusted by some kind of weights, which indicates how many evaluators support the target side (the effect strength of different levels is taken into account). From the fitness values shown in Figure 5.2, we can see that the bigger values are weakened, and the small values are strengthened, which make all fitness values more reasonable.

Table 5. 1: Instance of dealing with the data obtained from PCP based SD method

objects	*Attribute [Cute, Bitter]*			
	Distributions	*Positions*	*Necessary processes*	*Partial Comparison lists*
1	*2*	*-8*	*1. Map all Partial Comparison lists* *into* *graphic G* *2. delete loops of G* *as G'* *3. according the connectivity* *divide G'* *into* *G'={G_1', ..., G_M'}* *4. Find MSTs* *as* *T={T_1, ..., T_M}* *5. depth-first traversing on each T_m* *find the positions of objects* *shown as the left cells*	*{10,13,24,8,21}* *{10,12,13,6,27}* *{19,12,30,14,21}* *{20,25,16,26,21}* *{17,23,3,26,21}* *{10,19,13,24,1}* *{23,3,13,15,26}* *{7,17,13,27,8}* *{5,12,16,25,15}* *{5,19,3,9,18}* *{2,12,7,22,18}* *{19,25,13,22,27}* *{8,1,26,27,2}* *{23,28,15,27,24}* *{10,13,16,11,27}* *{23,5,14,27,11}* *{7,3,5,1,15}* *{9,3,17,13,30}* *{17,16,4,12,15}* *{9,25,3,10,4}* *{13,17,30,16,21}* *{7,20,28,17,4}* *...* *{3,13,27,4,26}* *{10,7,29,18,21}* *{17,4,25,27,22}* *{7,6,24,13,2}* *{7,8,15,27,1}* *{3,28,14,1,4}*
2	*4*	***		
3	*3.67*	*-3*		
4	*3.67*	*-3*		
5	*4.33*	*-1*		
6	*4*	***		
7	*4.33*	*-1*		
8	*4*	*-2*		
9	*4*	***		
10	*6.33*	*5*		
11	*5*	*1*		
12	*6.33*	*5*		
13	*3.33*	*-4*		
14	*4.67*	*0*		
15	*4.67*	*0*		
16	*3.67*	*-3*		
17	*5.67*	*3*		
18	*5.33*	*2*		
19	*5*	*1*		
20	*1*	*-11*		
21	*6.67*	*6*		
22	*5.33*	*2*		
23	*5*	*1*		
24	*1.67*	*-9*		
25	*4*	*-2*		
26	*5*	*1*		
27	*5.67*	*3*		
28	*7*	*7*		
29	*2.33*	*-7*		
30	*5.33*	*2*		

In the following part of this section we will make an instance with using the data obtained from PCP based SD method. As shown in Table 5.1, the last column is the partial comparison lists, i.e., the first list {*10, 13, 24, 8, 21*} means a compared relation, which is *"10>13>24>8>2*1" on the left side attribute cute. With some necessary processes based on some graphic techniques, we can get the positions of the objects in the graphic (the positions of the object 2, 6 and 9 are "*", which means they are in the middle of the entire lists). As chapter 2 discussed, the positions is expressed by some kind of **ε** forms, here for simplification, we set **ε**=0. Then the positions of the objects are shown in the third column. The results obtained from formula (2.5) and (2.6) are shown as follow:

$$d_{max} = \varepsilon+7$$
$$d_{min} = \varepsilon-11$$
$$d_{scale} = d_{max} - d_{min} = 18$$

With using formula (2.7), the distributions of all the objects on the attribute [Cute, Bitter] are calculated in the second column. Table 5.1 shows the calculation procedural with one of the MSTs, the MST used in this study may be not unique, thus when we use only one of the MST for getting the whole ranking list, some information may be ignored. Thus we need to find all of the MSTs by traversing the graphic from different starting points (*indegree* equals 0 and *outdegree* bigger than 0). From different MSTs, we can calculate different distribution values of all objects, then for different distribution values of each object, we can calculate the average value of them.

5.3 Instance on Multi-attribute Preference

Consumer usually describes a multi-attribute preference when they are doing a purchase. Consider this situation: "I want a Kutani-ware of cups for my father, which should be traditional and a little hard." We can analysis from his semantic meanings as follow; the rest part of this section will always use this example.

"*For seniors use*"

"*For male*"

"*For gift*"

"*Normal traditional*"

"*A little hard*"

There are three Context attributes and two Kansei attributes for describing consumer's preference. As we have discussed in chapter 4, we can use ontological structure to construct the ontologies or sub requirement entities as;

Sub entity 1: For seniors with "traditional" and "a little hard".

Sub entity 2: For male with "traditional" and "a little hard".

Sub entity 3: For gift with "traditional" and "a little hard".

The consumer may also expresses the priorities of each attribute, i.e., he/she set the priority of "For senior" as 0.9, and "For male" as 0.9, "For gift" as 1.0, "traditional" as 0.8, "a little hard" as 0.6. Then we can express the ontologies by Figure 5.3. The priorities of each selected attributes are not usually described when consumer expresses his requirement by talking to the seller, but the priorities must exist in his mind. However in e-commerce, consumer usually expresses his/her demands in internet, and when he/she is asked to set the priorities of the selected attributes.

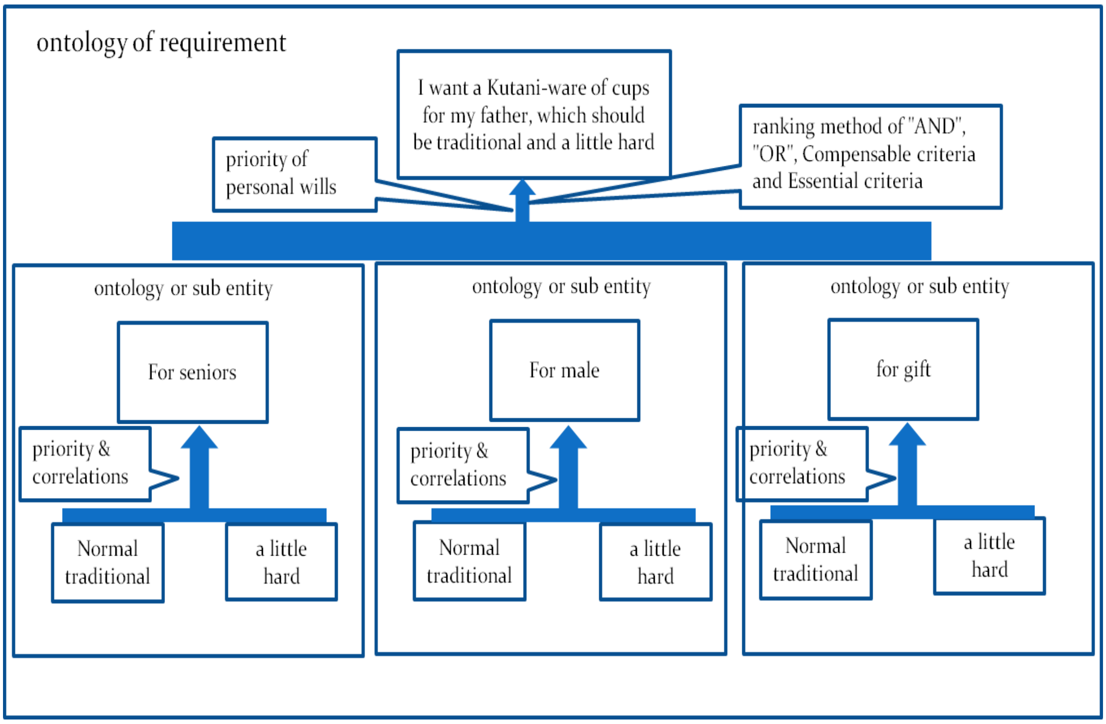

Figure 5.3: ontological structure based aggregation modeling

5.4 Conclusions

In this chapter we have used an instance of Kutani-ware with 30 objects to illustrate our research. Firstly, we have used traditional SD method and PCP based SD method for gathering general understanding information. Secondly, according to the data we obtained from different extracting method, we have also used a target-based fuzzy approach and a weighted target-based fuzzy approach to measure the single attribute preference, from the results of the measurements we have made a simple comparison of them, and we found the results obtained from weighted target-based fuzzy approach is more reasonable, where bigger values of the results is weakened, and smaller values of the results are strengthened. And we also assumed a demand of consumers to show how the ontological structure based aggregation model constructed. In next chapter, we will introduce the recommendation system, which we developed for test our research. And also a subjective comparison evaluation test will be executed for comparing different aggregation models and ranking methods.

Chapter 6

System Construction and Evaluation

We have used two kinds of method in gathering information, which can express the general understandings, and according to the different data we have obtained; we also proposed two measurement methods on single attribute preference. On multi-attribute decision making issues, we have proposed two aggregation models and 4 ranking methods. Therefor, it is important in comparing different method with different data, in this chapter we will discuss the advantage or disadvantage of the different data gathering method, and make a subjective comparison test to see which aggregation method and which ranking method are more suitable for our research. To do so, a recommendation system was developed.

6.1 Introductions

In the increasingly complex society, individuals or groups may face to a mass of information, when they are in the decision problems. Particularly, for personal purchasing decision making issues, there are more and more products with similar uses but different designs or performances, especially, in E-commerce. As the computer technology developed, to access mass of information for help individuals make a decision comes possible. Such kind of system is some kind of decision support system (DSS). The original DSS concept was most clearly defined by Gorry and Morton (Gorry & Morton, 1989), who integrated Anthony's (Anthony, 1965) categories of management activity and Simon's (Simon, 1960) description of decision types. Anthony described management activities as consisting of strategic planning, management control, and operational control. Simon described decision problems as existing on a continuum from programmed to non-programed. Gorry and Morton combined Anthony's management activities and Simon's description of the decision making process. Scott-Morton first articulated the concepts involved in DSS in the early 1970s under the term of management decision system. He defined such systems as interactive computer-based systems, which help decision makers utilize data and models to solve unstructured problems (McKenney & Morton, 1984). Another definition of DSS provided by Keen and Scott-Morton is as follows: DSS couple the intellectual resources of individuals which the capabilities of the computer to improve the quality of decisions. It is a computer-based support system for management decision makers who deal with unstructured problems (Keen & Scott-Morton, 1978). Information systems researchers and technologists have built and investigated decision support systems for more than 35 years. Building model-oriented DSS in the late 1960s, theory development in the 1970s, implementation of financial planning systems and group DSS in the early and middle 80s, and finally implementation of web-based DSS in the middle of 90s (Power, 2009).

Some researchers have extended the definition of DSS to include any system that might support decision making. Sprague defined DSS by its characteristics: 1) DSS tends to be aimed at the less well structured, underspecified problem that upper level managers typically face; 2) DSS attempts to combine the use of models or analytic techniques with traditional data access and retrieval functions; 3) DSS specifically focuses on features which make them easy to use by non-computer people in an interactive mode; 4) DSS emphasizes flexibility and adaptability to accommodate changes in the environment and the decision making approach of the user (Sprague, 1980). DSSs include knowledge-based systems. A properly designed DSS is an interactive software-based system intended to help decision makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems and make decisions.

In this chapter, we will develop a Decision Support System (DSS) to help individuals make decisions in E-commerce, which is so called a recommendation system. With this recommendation system, we will execute a comparison evaluation test for comparing the aggregation model and tanking methods.

6.2 Recommendation System

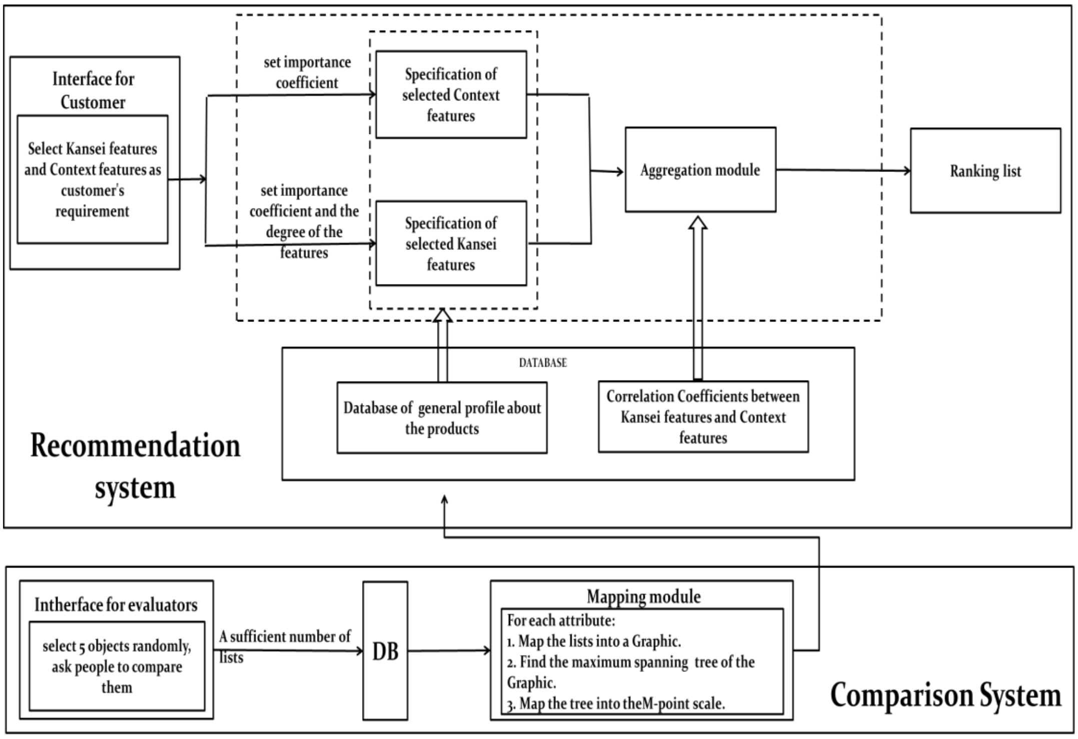

Figure 6.1: Overview of the recommendation system

This recommendation system is developed with three kinds of development tools: JAVA for core algorithm, PostgreSQL for the Database and Flex for the interface. The overview of this recommendation system is shown in Figure 6.1. There are 4 parts in this system: Interface, Specification module, Aggregation module, Database. The consumer can select attributes and set their levels and importance coefficients in the interface to describe his/her requirement; the specification module can measure the satisfaction of the selected single attribute, where the weighted target-based fuzzy approach for data obtained from traditional SD method and the linguistic variables approach for the data obtained from PCP based SD method are applied; the aggregation module can aggregate the selected attributes and make a recommendation list to consumer, where the aggregation models for constructing sub entities and the ranking methods for integrate the sub entities are optionally applied. The DB contains three kinds of data; 1) data obtained by traditional SD method; 2) data obtained from PCP based SD method; 3) the correlation coefficients existed between Kansei attributes and Context attributes.

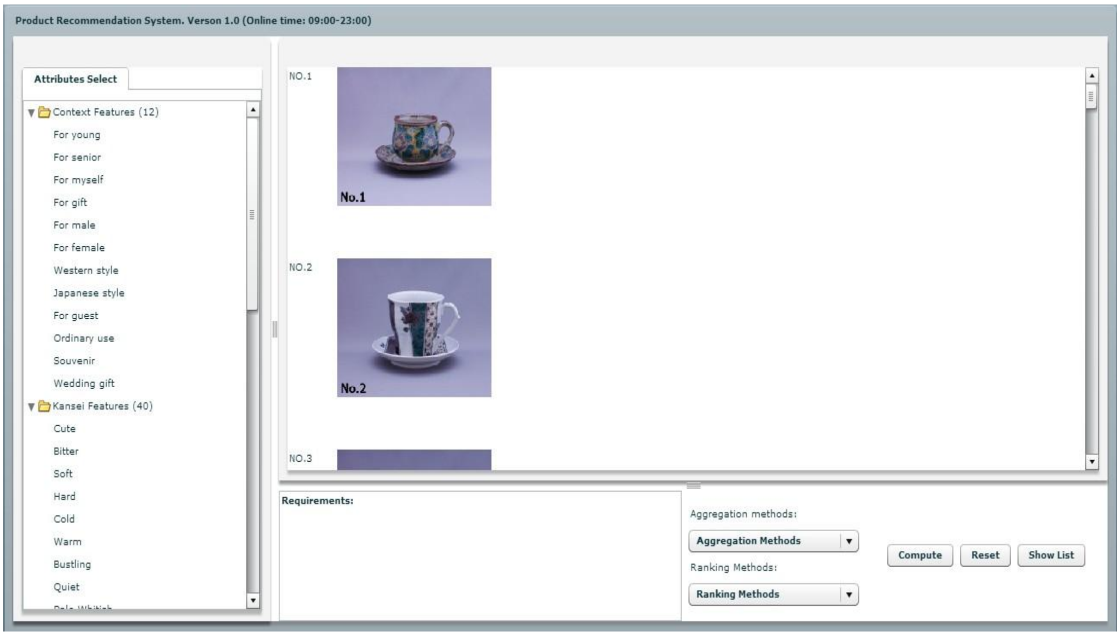

Figure 6.2 Interface of the recommendation system

Figure 6.3: A popup window for setting coefficients

The interface of the recommendation system is shown as Figure 6.2. Consumer can select attributes to describe his/her desires by click the words in the left side block. By clicking the attribute, a popup window for setting the linguistic target and importance (priority) coefficient will popped up, which is shown as Figure 6.3. Consumer can just slide the small triangles to do so. After selecting the attributes and setting the coefficients, the detail of the requirements will be shown in the requirements block (see Figure 6.2). Then they should select one of the aggregation models and ranking method to see the recommended objects, which is shown in the upper sub window (see Figure 6.4).

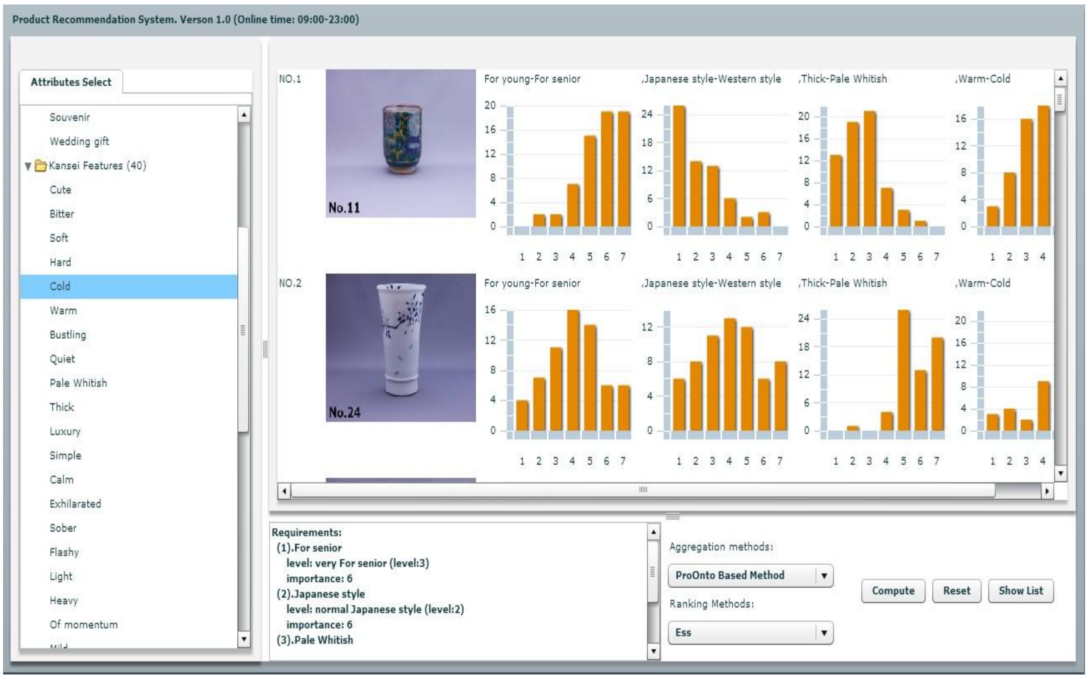

Figure 6.4: the results of the recommendation system

As shown in Figure 6.4, the requirements described by consumer are shown in the requirement window, which is {*for senior (target: very. Importance: 86%), Japanese style (target: normal. Importance: 86%), Pale whitish (target: very, importance: 100%), Cold (target: normal. Importance: 71%)*} (the importance level have 7 degrees for simplification). Consumer selected the indirect aggregation models based on PrOnto, and Essential criteria ranking method. The results are shown in the upper window: we can see that *object 11* is the most suitable one, and *object 24* is the second suitable one. For the general understandings information, we used the data obtained from PCP based SD method. Actually, in real E-commerce, users may not want to select the aggregation model and ranking method, because they may be confused by the meanings of them.

Therefore, a comparison test for finding the most efficient aggregation models and ranking method should be executed, actually, the button for selecting aggregation models and ranking methods is just for this purpose (it is a debug version, not the official version for real consumers). In next section, we will make a subjective comparison test for finding which aggregation model and ranking method is more efficient.

6.3 Subjective Comparison Evaluations

To make a comparison of different aggregation models and ranking methods, we will make an evaluation of the recommendation system to test the different aggregation models and ranking methods. In this evaluation, we had 25 volunteers for 49 times' test. Let them select some of Context attributes and Kansei attributes and set the level and importance of them as their requirements, then according to their selections, they should pick up the most preferred sample. We can use the recommendation system with these descriptions to test which models and which ranking methods are better.

Table 6. 1: Comparison results of different aggregation models and ranking methods.

No.	***Fuzzy target based aggregation model***				***Indirect PrOnto based aggregation model***			
	ESS	***COM***	***AND***	***OR***	***ESS***	***COM***	***AND***	***OR***
1	*10*	*9*	*10*	*9*	*13*	*13*	*13*	*14*
2	*10*	*19*	*25*	*15*	*3*	*4*	*19*	*3*
3	*3*	*2*	*2*	*4*	*4*	*4*	*4*	*6*
4	*14*	*13*	*12*	*16*	*5*	*5*	*4*	*5*
5	*5*	*2*	*9*	*1*	*2*	*5*	*3*	*8*
6	*15*	*11*	*4*	*17*	*12*	*12*	*4*	*13*
7	*2*	*1*	*4*	*1*	*4*	*3*	*11*	*1*
8	*5*	*4*	*7*	*1*	*2*	*2*	*4*	*1*
9	*8*	*7*	*6*	*7*	*7*	*7*	*7*	*7*
10	*3*	*5*	*2*	*7*	*4*	*6*	*2*	*6*
11	*4*	*4*	*5*	*3*	*3*	*3*	*3*	*3*
12	*9*	*2*	*1*	*11*	*7*	*3*	*1*	*9*
13	*9*	*9*	*9*	*8*	*11*	*12*	*9*	*10*
14	*7*	*7*	*10*	*5*	*6*	*4*	*12*	*5*
15	*1*	*1*	*13*	*1*	*1*	*1*	*11*	*2*
16	*5*	*2*	*8*	*3*	*3*	*2*	*3*	*5*
…	…				…			
49	*6*	*6*	*16*	*7*	*5*	*5*	*18*	*5*

There are 30 coffee cups in this test. With the recommendation system and consumer's special description of the requirement, we could get a recommendation list of the coffee cups for each time's test. Compare to this list with consumer's favorite coffee cup, we can know the position of the favorite coffee cup in this list. For example, if the number of the consumer's favorite cup is 23, and this cup is at the 3th position of the list, then we mark it as 3 (see Table 6.1). According to the marks, we can know the satisfaction of the recommendation results roughly, for example, if one of the marks in Table 6.1 is 5, the satisfaction can be calculated by (30-5)/30 = 0.83.

Table 6. 2: Comparison of different aggregation models.

Aggregation models	*Average Satisfaction*	*variance*	*t-test*
Consumer target based aggregation model	*0.72*	*18.53*	*0.097*
Indirect PrOnto based aggregation model	*0.77*	*12.49*	

As shown in Table 6.1, for each time of evaluation, there are two different aggregation models and 4 different ranking methods. At first, we compared the satisfactions of different aggregation models. Specifically, we have got the average marks of different aggregation models for each items of data, and then use *t-Test* to analyze the two series of data to find whether there is difference on their means, if so, we can compare their means to see which aggregation model is better (see Table 6.2).

As shown in Table 6.2, the mean values of the two aggregation models have a significant difference under the possibility of *90%* (*p-value of t-Test is smaller than 0.1*), and *PrOnto based aggregation mode (Indirect aggregation model)l* has a higher average satisfaction, it also has a lower variance, this means *Indirect PrOnto based aggregation model* is more efficient and stable. The reason might be that, consumers usually concentrate on the main attributes of a product (in this case, the main attributes should be Context attributes). The main attributes (Context attribute) are described by a group of Kansei attributes (description group) in *Indirect PrOnto based aggregation model*, and some of the selected Kansei attributes involved in the description group, will not be concerned again in the description group; correspondingly, the main attributes are calculated by target-based fuzzy method in *Consumer target based aggregation model*, in which the selected Kansei attributes are calculated separately. Therefore, a duplicate calculation would happen when selected Kansei attributes have higher correlations to the main attributes. That would make the main attributes more easily to be affected by selected Kansei attributes in *Consumer target based aggregation model*. The evaluation data of all attributes expresses the general understandings/feelings of the object, so there might be some deviations when we use them to calculate the satisfactions of consumers. In *Indirect PrOnto based aggregation model*, the satisfaction of the Context attribute is calculated by description set (a set of Kansei attribute with higher correlation to that Context attribute) instead of using the evaluation data of the Context attribute, it means we used several pieces of evaluation data to measure the satisfaction of the selected Context attribute, therefore, the deviations might be averaged. That may be the reason why *Indirect PrOnto based aggregation model* is more stable.

The index of stability is necessary, if the model is not stable enough, maybe, some-time the system could get a higher satisfaction, and some time get lower one. We use the variance to see which one is more stable, but we cannot use this value to see how stable the model is. According to the analysis above, we could say that *Indirect PrOnto based aggregation model* is better, then under this aggregation model, we will compare different ranking method.

As shown in Table 6.3, the two ranking methods with essential criteria (ESS) and compensable criteria (COM) have significant difference from the ranking method based on logical operation "AND" under the possibility of 95%. That means we can compare the mean value (the satisfaction values are calculated by mean values) of the ranking method ESS and the ranking method based on logical operation "AND" (including the ranking method COM and the ranking method based on logical operation "AND") to see which one is better.

Table 6. 3: Comparison of different ranking methods (1).

	ESS	*COM*	*AND*	*OR*
ESS		*0.5383*	*0.0059*	*0.3072*
COM	*0.5383*		*0.0481*	*0.7083*
AND	*0.0059*	*0.0481*		*0.1102*
OR	*0.3072*	*0.7083*	*0.1102*	

We can see that the ranking methods of *ESS*, *COM* and the ranking method based on logical operator *"OR"* have higher average satisfactions than the method based on logical operator *“AND”*(*see Table 6.4*), but from the analysis above, we can only say that *ESS* and *COM* is better than the ranking method based on logical operator *“AND”*. According to the variance value of each ranking method (*see Table 6.4*), we find that ranking method *ESS* has a lower variance; that means the ranking method *ESS* is more stable than others, so we can say ranking method *ESS* is better than other methods with using *Indirect PrOnto based aggregation model*.

Table 6. 4: Comparison of different ranking methods (2)

	Average Satisfaction	*variance*
ESS	*0.8051*	*13.8355*
COM	*0.7867*	*25.1769*
AND	*0.7153*	*30.9358*
OR	*0.7738*	*27.1458*

6.4 Conclusions

In this Chapter, we have developed a recommendation system, which applies, for single attribute preference, the different satisfaction measurement methods according to the data obtained from different from of general understandings; and also applies the different aggregation models and ranking methods optionally. And then we made a comparison test for comparing the different aggregation models and ranking methods, in which we found that the indirect aggregation model based on PrOnto is more efficient and the results of it is more stable, also the Essential criteria based ranking method is more stable and efficient.

Chapter 7

Conclusions and Future Work

Conclusions

The main focus of this thesis is to matching the personal preference and the general understandings on marketing. Actually, this matching process can be divided into three parts: 1) extracting the information of general understandings; 2) description or construction of consumer's preference; 3) matching the personal preference with the general understandings. A case study on Kutani-ware, a Japanese traditional crafts, was presented by using the knowledge we have acquired, for the purposed of both economic perspective and the national culture perspective. The main contributions of this thesis are as follow:

- **Method for extracting general understandings**

  - We have proposed a Partial Comparison Process based SD method for extracting general understandings in chapter 2, and compared this method to the traditional SD method. According to the comparison, we found the proposed PCP based SD method can solve the problems and limits existed in traditional SD method. Specifically, the problems and limits can be described by: 1) Different evaluators may express quite different opinions on an object. With traditional SD method, the distribution of the evaluation values may be in polarization and inefficient. 2) Evaluation options (SD method with M-scale) are limited in traditional SD method; evaluators can only evaluate objects in M-point scale. It would be hard to evaluate a huge number of objects.

  - The Partial Comparison Process based SD method we proposed can solve the problem by getting a consecutive ranking list contains all objects. In Partial Comparison Process, there are no limits in evaluation options, because the only thing evaluators need to do is to compare the partial group of objects and make a partial ranking list, instead of mark their feelings of the objects in M-point scale, and the system will combine the obtained partial ranking lists into an integral list with all objects.

- **Measurement of single attribute preference**

This part of contribution includes two parts, the first one is about using the general understandings obtained from traditional SD method, the second one is about using the general understandings obtained from Partial Comparison Process based SD method.

- Weighted fuzzy approach in measuring single attribute preference of consumers

  This measurement method can solve the problems existed in the data obtained from traditional SD method by taking some kind of support level into account. Specifically, the evaluation value of each side of bipolar attribute is affected by the supported evaluators of each side. One side attribute of the bipolar attribute get more evaluators approved the, then the significant of such side will be enhanced.

- Linguistic variables approach in measuring single attribute preference of consumers

  For dealing with the data obtained from PCP based SD method, we proposed a modified Linguistic variables approach. Compare to the classic linguistic variables definition, better than the classic one, the effect area of consumer's target can be enlarged to half of the whole scale for making more objects to have reasonable values in the modified linguistic variables approach.

➢ **Multi-attribute aggregation**

- The attributes used in this research have two types: Context attribute and Kansei attribute, which the former one expresses the application or purpose of the object, and the latter one expresses the consumer's emotional feelings. On multi-attribute aggregation problems, we have proposed two aggregation models based on Ontological structure. This kind of aggregation models treats the demands of the consumers as ontology. And we treat the Context attributes selected by consumers as some kind of concepts, which is used for defining the demand ontology, and for each concept, we use the selected Kansei attributes to describe the concepts, which can also be treated as some kind of key words. The relations between ontology and concepts can be defined by consumer by his/her wish; the relations between concepts and key words is restricted by the internal natures of the attributes, moreover, the relations can also be adjusted by consumers in a certain range by his/her personal wishes, which range should be follow the restrictions discussed above.

- The integration methods of the concepts for making a recommendation ranking list have also been introduced. Different relations among different concepts of the ontology (consumer's demand) have been taken into account according to consumer's preference: if they want the concepts have no difference on priority, the relations can be expressed by a logical operator "OR"; if they thought every concepts should meet their demands, a logical operator "AND" can express this relations. We have also introduced two other integration techniques; "*compensable criteria*" and "*essential criteria*", which the former one is some kind of weighted average approach and the latter one is some kind of reference point approach (RPA).

➢ **Ontological structure based DSS system**

- For Comparing different aggregation models and ranking methods, we have developed some kind of decision support system, which is so called recommendation system. And also a subjective comparison evaluation test has been executed to see which aggregation model and which ranking method is more efficient.

Future work

For the process of matching problem, we have discussed three steps of it: the phase of extracting general understandings; the phase of describing consumer's preference; the phase of matching the preference with the general understandings. This matching problem is occurred between consumers and products. There are also another matching problem between products and producers (or the designers of the products). With including this matching problem, we can get an entirely matching issue, such as from general understandings to consumer's preference, from consumers' satisfied products and corresponding preference to designers, from designers to products and from products to the general understandings of them. It would be a cycle process with feedback mechanism. So the possible research topic of our research may be the matching problems between the satisfied products and designers, as well as the feedback mechanism.

For the matching problems discussed in this thesis, there are also some future research topics Such as in PCP based SD method, a more efficient graphic process techniques should be developed for involving more weights contained in the graphic (in our research, we just simply calculate the average values of the distribution values obtained from different MSTs, there should be more efficient and more technical methods for take multi MSTs into account); and in measurement method of single attribute preference, we proposed a modified linguistic variables approach, there may be other method in dealing with such data; and in multi-attribute aggregation phase, ontological structure is used for constructing the ontologies (sub entities), the other aggregation models in dealing with the data obtained from PCP based SD method maybe an interesting topic.

Appendix

Table A: Comparison results of different aggregation models and ranking methods.

No.	***Fuzzy target based aggregation model***				***Indirect PrOnto based aggregation model***			
	ESS	***COM***	***AND***	***OR***	***ESS***	***COM***	***AND***	***OR***
1	*10*	*9*	*10*	*9*	*13*	*13*	*13*	*14*
2	*10*	*19*	*25*	*15*	*3*	*4*	*19*	*3*
3	*3*	*2*	*2*	*4*	*4*	*4*	*4*	*6*
4	*14*	*13*	*12*	*16*	*5*	*5*	*4*	*5*
5	*5*	*2*	*9*	*1*	*2*	*5*	*3*	*8*
6	*15*	*11*	*4*	*17*	*12*	*12*	*4*	*13*
7	*2*	*1*	*4*	*1*	*4*	*3*	*11*	*1*
8	*5*	*4*	*7*	*1*	*2*	*2*	*4*	*1*
9	*8*	*7*	*6*	*7*	*7*	*7*	*7*	*7*
10	*3*	*5*	*2*	*7*	*4*	*6*	*2*	*6*
11	*4*	*4*	*5*	*3*	*3*	*3*	*3*	*3*
12	*9*	*2*	*1*	*11*	*7*	*3*	*1*	*9*
13	*9*	*9*	*9*	*8*	*11*	*12*	*9*	*10*
14	*7*	*7*	*10*	*5*	*6*	*4*	*12*	*5*
15	*1*	*1*	*13*	*1*	*1*	*1*	*11*	*2*
16	*5*	*2*	*8*	*3*	*3*	*2*	*3*	*5*
17	*4*	*2*	*1*	*3*	*4*	*5*	*4*	*8*
18	*10*	*7*	*3*	*26*	*7*	*4*	*6*	*9*
19	*12*	*13*	*12*	*10*	*13*	*11*	*17*	*9*
20	*1*	*1*	*2*	*3*	*6*	*8*	*8*	*6*
21	*8*	*6*	*11*	*5*	*7*	*6*	*9*	*5*
22	*7*	*13*	*18*	*6*	*3*	*5*	*8*	*5*
23	*6*	*6*	*6*	*4*	*7*	*7*	*7*	*7*
24	*13*	*4*	*27*	*1*	*7*	*3*	*16*	*2*
25	*12*	*5*	*14*	*3*	*19*	*14*	*21*	*10*
26	*3*	*3*	*2*	*5*	*2*	*5*	*2*	*6*
27	*6*	*8*	*15*	*6*	*5*	*5*	*16*	*4*
28	*16*	*13*	*4*	*21*	*5*	*4*	*14*	*7*
29	*17*	*17*	*23*	*12*	*9*	*12*	*19*	*7*
30	*4*	*8*	*7*	*6*	*7*	*8*	*5*	*10*
31	*8*	*5*	*24*	*2*	*2*	*2*	*8*	*3*
32	*17*	*15*	*16*	*14*	*3*	*23*	*8*	*25*

33	*6*	*6*	*6*	*8*	*6*	*8*	*7*	*10*
34	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
35	*13*	*10*	*30*	*9*	*5*	*3*	*21*	*8*
36	*5*	*15*	*12*	*9*	*2*	*4*	*12*	*2*
37	*7*	*5*	*17*	*3*	*3*	*3*	*12*	*2*
38	*11*	*10*	*8*	*11*	*1*	*1*	*1*	*1*
39	*10*	*9*	*12*	*4*	*8*	*6*	*10*	*2*
40	*10*	*21*	*16*	*23*	*7*	*25*	*4*	*26*
41	*5*	*5*	*2*	*6*	*5*	*3*	*3*	*2*
42	*6*	*4*	*4*	*8*	*5*	*3*	*3*	*9*
43	*14*	*12*	*9*	*21*	*13*	*10*	*8*	*14*
44	*8*	*8*	*7*	*4*	*9*	*9*	*10*	*6*
45	*9*	*9*	*11*	*6*	*6*	*3*	*11*	*2*
46	*4*	*5*	*4*	*5*	*6*	*8*	*6*	*8*
47	*7*	*12*	*6*	*8*	*9*	*11*	*7*	*10*
48	*10*	*6*	*14*	*1*	*2*	*2*	*6*	*3*
49	*6*	*6*	*16*	*7*	*5*	*5*	*18*	*5*

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