E-Service Intelligence: An Introduction

Jie Lu[#], Da Ruan*, and Guangquan Zhang[#]

[#]Faculty of Information Technology, University of Technology, Sydney (UTS) PO Box 123, Broadway, NSW 2007, Australia. Email: {jielu, zhangg}@it.uts.edu.au

*Belgian Nuclear Research Centre (SCK•CEN), Boeretang 200, 2400 Mol, Belgium. Email: druan@sckcen.be

Abstract. *E-service intelligence* is a new research field that deals with fundamental roles, social impacts and practical applications of various intelligent technologies on the Internet based e-service applications that are provided by e-government, e-business, e-commerce, e-market, e-finance, and e-learning systems, to name a few. This chapter offers a thorough introduction and systematic overview of the new field e-service intelligence mainly based on computational intelligence techniques. It covers the state-of-the-art of the research and development in various aspects including both theorems and applications of e-service intelligence. Moreover, it demonstrates how adaptations of existing computational intelligent technologies benefit from the development of e-service applications in online customer decision, personalized services, web mining, online searching/data retrieval, and various web-based support systems.

1 E-Services

Electronic-services (e-services) involve various types, delivery systems, advanced information technologies, methodologies and applications of online services that are provided by e-government, e-business, e-commerce, e-market, e-finance, and e-learning systems, to name a few. The term e-services is typically used to describe a variety of internet based electronic interactions ranging from basic services, such as the delivery of news and stock quotes, to smart services, such as the delivery of context-aware emergency services (Chidambaram, 2001). In a fully web-enabled smart e-service environment, the services are likely to be composed of many interacting components and have the potential for "combinatorial

J. Lu et al.: *E-Service Intelligence: An Introduction*, Studies in Computational Intelligence (SCI) **37**, 1–33 (2007)
www.springerlink.com

explosion" described in cybernetics and systems theory. E-services are likely to push the limits of software engineering in terms of analysis, design, security, and testing. Moreover, it will have and is conducting long-term impacts of e-services on individuals, institutions, and society.

Over the last decade, many government and business online services have mainly gone through three stages in most industrialized countries: (a) online information presentation, (b) online transaction, and (c) online information integration. In the third stage, all possible related services that might be provided by the same agency, different agencies, agencies in other jurisdictions, and private partners have been integrated in an either vertical or horizontal way. Businesses and citizens can deal with online services as a single cohesive entity and for services to be delivered in a seamless manner-'one-stop shop.' Individuals wish to be able to get information and complete services without worrying whether it involves different agencies or layers of the business and government, and also wish to receive personalized services to avoid information overload problems. Clearly, the keyword *intelligence* will be the next paradigm shift in the e-services thanks to Internet technological advances (Lu et al., 2006). To provide intelligence for e-services, various intelligent technologies including fuzzy logic, expert systems, machine learning, neural networks, Bayesian network, game theory, optimization, rough sets, data mining, multi-agents and evolutionary algorithms etc. are being applied in various e-service approaches, systems, and applications. In the framework of intelligent technologies, government and business e-services will provide with a much higher quality for online information presentation, online information searching, personalized recommendation, website evaluation, and web based support systems. Some successful developments have appeared recently in applying various intelligent techniques to build intelligent e-service support systems, such as intelligent e-negotiation systems, intelligent e-shopping systems, intelligent online customer management systems, and intelligent online decision support systems. Literature has also showed some successful investigations based on intelligent approaches to evaluate e-service systems, conduct web user classification, help users' online trading and support users' online decision making. In the following we describe the application of intelligent techniques in the Internet based e-service development, implementation, and management. The chapter is organized as follows. Section 2 summarizes the role of intelligent techniques in e-service applications. Section 3 highlights applications of intelligent techniques in the web information presentation and online search. Section 4 presents how intelligent techniques are integrated with web mining. Section 5 discusses the implementation of e-service personalization supported by intelligent approaches. Section 6 presents how intelligent techniques

can help our e-service evaluation. Section 7 analyses several typical intelligent e-service systems with various intelligent techniques. Section 8 displays most available intelligent e-service models. Finally, Section 9 concludes the chapter and its related future research direction.

2 The Role of Intelligent Techniques in E-Services

Artifitial intelligent techniques incluing conventional intelligence, such as expert systems, machine learning, case based reasong, Bayesian network, and computational intelligence, such as artificial neural networks, fuzzy systems, evolutionary computation are playing important roles in e-service applications. The power of each technique or methodology as a design tool is limited only by the designer's imagination. Two features, in particular, stand out: (1) many of them are biologically inspired, and (2) they are all capable of solving non-linear problems (Ruan, 1997). The techniques and methodologies are for the most part complementary and synergistic rather than competitive. Intelligent techniques have already enjoyed considerable success in e-services, which have proven to be instructive and vital (Lu et al., 2006).

Computational intelligence (CI) research, closely assosiated with soft computing (SC), aims to use learning, adaptive, or evolutionary computation to create programs that are, in some sense, intelligent. Fuzzy logic (FL) (Zadeh, 1965) is designed to handle imprecise linguistic concepts such as *small, big, low, high, young*, or *old.* Systems based on FL exhibit an inherent flexibility and have proven to be successful in a variety of industrial control and pattern-recognition tasks ranging from handwriting recognition to traffic control. Central to the flexibility that FL provides is the notion of fuzzy sets. Fuzzy sets are the basic concept supporting fuzzy theory. The main research fields in fuzzy theory are fuzzy sets, fuzzy logic, and fuzzy measure. Fuzzy reasoning or approximate reasoning is an application of fuzzy logic to knowledge processing. Fuzzy control is an application of fuzzy reasoning to control. One of the main strengths of FL compared with other schemes to deal with imprecise data is that their knowledge bases, which are in a rule format, are easy to examine and understand. This rule format also makes it easy to update and maintain the knowledge base. Experts think in imprecise terms, such as *very often* and *almost never, usually* and *hardly ever*, *frequently* and *occasionally*, and use linguistic variables such as the above-mentioned *small, big, low* and *high* etc. FL provides a means to compute with words. In concentrates on the use of fuzzy values that capture the meaning of words, human reasoning

and decision making, and provides a way of breaking through the computational burden of traditional expert systems. As for the limitations of FL, the main shortcoming is that the membership functions and rules have to be specified manually. Determining membership functions can be a time-consuming, trial-and-error process. Moreover the elicitation of rules from human experts can be an expensive, error-prone procedure. As a new progress, fuzzy logic is moving its applications from computing with numbers to computing with words; and from manipulation of measurements to manipulation of perceptions (Zadeh, 1999). In particular, Fuzzy Logic and the Internet (FLINT) as an important topic has been proposed by Zadeh and has attracted many researchers to work on it (Loia et al., 2004). Zadeh (2003) also indicated that existing web search engines would need evolving into question-answering systems. Achievement of this goal requires a quantum jump in the web IQ of existing search engines. A view is that bivalent-logic-based methods have intrinsically limited capability to address complex problems which arise in deduction from information which is pervasively ill-structured, uncertain and imprecise. Web information is world knowledge that humans acquire through experience and education. Imprecision of perception-based information is a major obstacle to dealing with world knowledge through the use of methods based on bivalent logic and bivalent-logic-based probability theory. What is needed for this purpose is a collection of tools drawn from fuzzy logic-- a logic in which everything is, or is allowed to be, a matter of degree.

A neural network (NN), also called an artificial neural network (ANN) in computational intelligence, is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an NN is an adaptive system that changes its structure based on external or internal information that flows through the network. Two of its main areas of application are classification and decision problems (Anagnostopoulos et al., 2004). Neural networks are chosen mainly for computational reasons since, once trained, they operate very fast and the creation of thesauri and indices is avoided. Many experimental investigations on the use of NNs for implementing relevance feedback in an interactive information retrieval system have been proposed. In these investigations, the anticipated outcome was to compare relevance feedback mechanisms with NNs based techniques on the basis of relevant and non-relevant document segmentation (Crestani, 1994, Anagnostopoulos et al., 2004).

Evolutionary Computation (EC) is the general term for several computational techniques that are based to some degree on the evolution of biological life in the natural world. It is a subfield of CI involving

combinatorial optimization problems. It mostly involves metaheuristic optimization algorithms such as genetic algorithms, evolutionary programming, evolution strategy, learning classifier systems, ant colony optimization and particle swarm optimization and so on (http://en.wikipedia.org/wiki/Computational_intelligence). As a particular class of EC, a genetic algorithm (GA) is a search technique used to find approximate solutions to optimization and search problems. GAs are typically implemented as a computer simulation in which a population of abstract representations of candidate solutions to an optimization problem evolves toward better solutions.

As a broad subfield ofAI, machine learning is concerned with the development of algorithms and techniques, which allow computers to "learn" including inductive learning, and deductive learning. Extracting rules and patterns out from massive data sets is one of important tasks and has been widely used in the field of data mining. Machine learning research has also developed a set of useful inference algorithms. A wide spectrum of applications of machine learning such as search engines, stock market analysis, and object recognition have been well developed.

Data mining, also known as Knowledge-Discovery in Databases, is the process of automatically searching large volumes of data for patterns. Data mining is a fairly recent and contemporary topic in computing. It mainly applies many computational techniques from statistics, machine learning and pattern recognition and can be seen as a kind of intelligent techniques. Web mining refers to the use of data mining techniques to automatically retrieve, extract and evaluate information for knowledge discovery from web documents and services. Web mining can be divided into three categories: structure mining, usage mining, and content mining. Web structure mining is a research field focused on using the analysis of the link structure of the web, and one of its purposes is to identify more preferable documents. Web usage mining, also known as Web Log mining, is the process of extracting interesting patterns in web access logs. Analyzing the web access logs of different web sites can help understand the user behavior and the web structure, thereby improving the design of this colossal collection of resources. Web content mining is an automatic process that extracts patterns from on-line information, such as the HTML files, images, or E-mails, and it already goes beyond only keyword extraction or some simple statistics of words and phrases in documents. With more researchers continue to develop data mining techniques with intelligent functions, web mining intelligence is playing an increasingly important role in meeting the challenges of developing the intelligent e-services.

Expert systems apply reasoning capabilities to reach a conclusion. An expert system can process large amounts of known information and

provide conclusions based on them. Case based reasong and Bayesian network techniques are two main techniques used in expert systems.

With more and more applications of intelligent techniques in e-services, the integration between intelligence and web-based technology has been appeared. Some hybrid technologies of CI and web technology are dedicating to the improvement of e-service intelligence. Figure 1 shows main intelligent techniques and their applications in popular e-service fields with some typical examples.

As shown in Figure 1, intelligent techniques and methodologies as additional useful tools have nevertheless been successfully applied to some of the most interesting e-service areas. Typical e-service applications with the support of intelligent techniques will be briefly outlined over the rest of the chapter and will be detailed given by the rest chapters of this book.

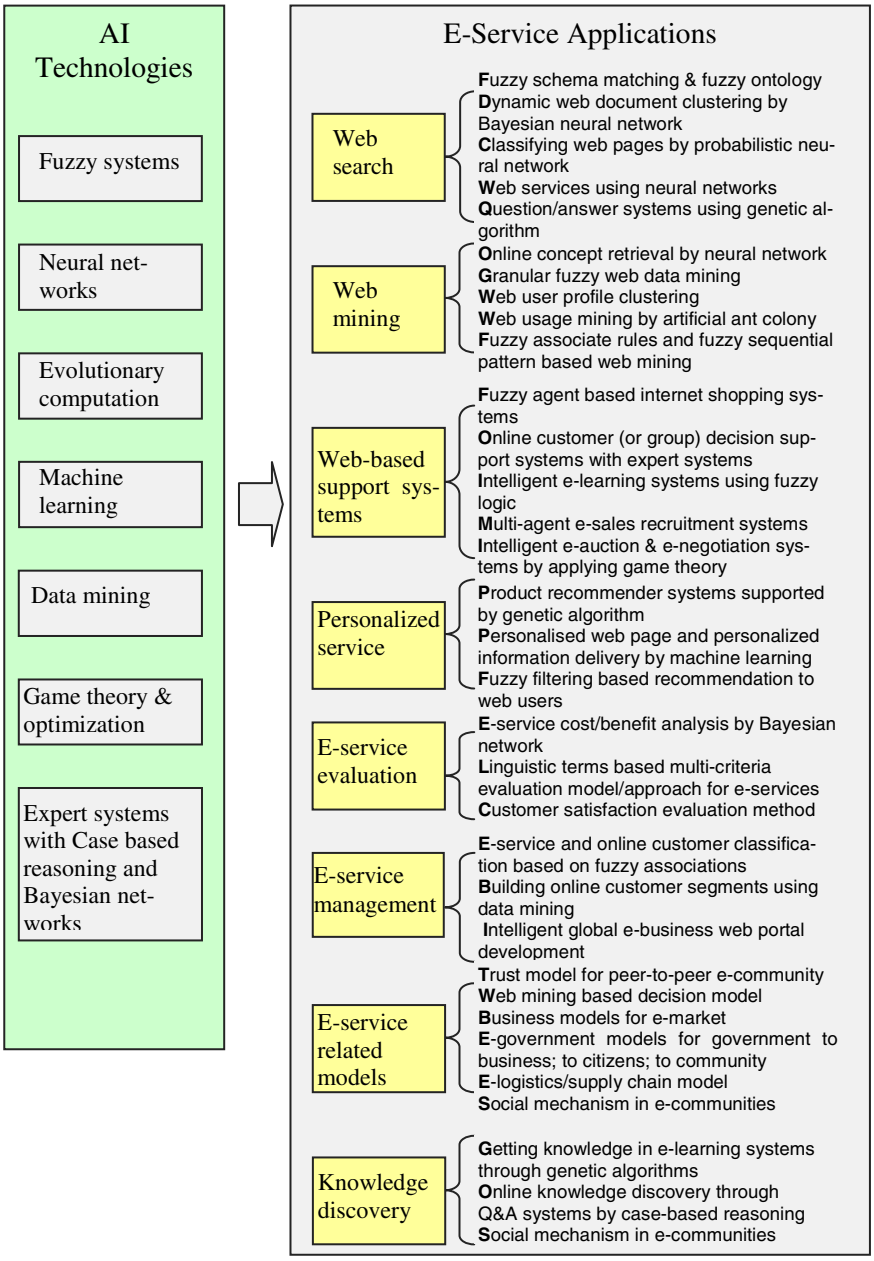

Figure 1 A list of intelligent techniques and web based applications

3 Intelligent Web Information Search and Presentation

E-service, e-commerce, e-government, e-business, e-learning, and e-science etc. -- the coining of such words reflects the growing importance of the web in all aspects of our lives. Consumers are spending more and more time on the web to search information and receive e-services. To provide these e-services, a typical web program involves three tiers. The front-end is the browser running on a user's computer. The middle-tier is a server, executing the logic that controls the user's interaction with the web site. The back-end is a database, providing the information the user wishes to access, such as a catalog of items for purchase, a collection of government records, or a store of learning materials.

AI techniques have abilities to provide a natural representation of human conceptualization and offer computational theory of perceptions (Zadeh, 2001). They are making many more contributions to each of the three tiers of web program to improve the presentation for online information and the searching on online products/services. With the requirement of semantic web from the facility of linguistic descriptions and partial matching, fuzzy systems, neural networks, machine learning and other intelligent approaches have shown a great potential for supporting such kinds of work (Nikravesh et al., 2002).

Applying AI techniques can improve the quality of web information search and retrieval in several ways. Schema matching plays a key role in data integration within e-services. Fuzzy logic and neural networks have been used in schema matching to deal with the issue of partial matching and similarity. In general, schema matching methods use a set of known rules. However, it is often hard to get such a set of rules. This is because the relationships of schema elements are usually uncertain and the availability of schema information may vary. Neural networks have emerged as powerful pattern recognition and can learn the similarities among data directly from its instances and empirically infer solutions from data without prior knowledge of regularities (Li et al., 2005). Neural network techniques have been applied in web page searching. For example, Anagnostopoulos et al. (2004) proposed a system that is capable of identifying, searching and categorizing web pages on the basis of information filtering. The system is a three-layer probabilistic NN with biases and radial basis neurons in the middle layer and competitive neurons in the output layer. The probabilistic NN scopes to identify e-commerce web pages and classify them to the respective type according to a framework, which describes the fundamental phases of commercial transactions in the web. Nikravesh and Azvin (2002) proposed a fuzzy conceptual-based search engine using

conceptual semantic indexing, and discussed fuzzy queries, search, and decision support systems. Fuzzy set techniques based conceptual search models and methods can be used for intelligent online information retrieval through conceptual matching of both text and images. Under the support of intelligent techniques, the selected query does not need to match the decision criteria exactly, which gives the system a more human-like behavior.

Existing web search engines have many remarkable capabilities. However, what is not among them is the deduction capability-the capability to answer a query by a synthesis of information which resides in various parts of the knowledge base. A question-answering (Q&A) system is by definition a system which has this capability. At current stage of e-service development, Q&A systems are important aiding tools for helping users effectively obtain information from the web. Such a system often finds answers by matching the features of previous questions to current ones, and considering the weights of the features. To improve the prediction accuracy, case-based reasoning approach, genetic algorithms, fuzzy logic, neural networks, and their combinations all have been applied in practice. Literature shows that case-based reasoning shows significant promise for improving the effectiveness of complex and unstructured decision-making. In a Q&A system, it can use a user's feed back gradually and make inferences using analogy to obtain similar experience for solving problems. It often combines with other intelligent methods such as fuzzy logic and neural networks to improve its performance. For example, Zhang et al. (2004b) used a genetic algorithm and case-based reasoning into a Q&A system and developed an interactive Q&A engine.

The semantic web (Berners-Lee et al., 2001) aims at creating a platform where information has its semantics and can be understood and processed by computers themselves with minimum human interference. Ontology theory and its related technology have been developed to help construct such a platform because ontology promises to encode certain levels of semantics for information and orders a set of common vocabulary for people or computers to communicate with. Fuzzy ontology has been developed to support schema and data integration for web-based applications (Parry, 2004, Widyantoro and Yen, 2001). For example, Widyantoro and Yen (2001) implemented a web-based, domain-specific search engine for searching abstracts of research papers. The system uses fuzzy ontology of term associations to support the feature**.** The fuzzy ontology is automatically generated from the information contained in its collection. The FOGA (Fuzzy Ontology Generation Framework) for automatic generation of fuzzy ontology on uncertainty information is developed by Quan et al. (2004a, b, c). The FOGA framework comprises fuzzy formal concept

analysis, fuzzy conceptual clustering and fuzzy ontology generation. First, fuzzy formal concept analysis incorporates fuzzy logic into formal concept analysis to form a fuzzy concept lattice. Fuzzy conceptual clustering then constructs the concept hierarchy from the fuzzy concept lattice. Finally, the fuzzy ontology generation generates the fuzzy ontology from the concept hierarchy.

The real way to get individualized interaction between a user and a website is to present the user with a variety of options and to let the user choose what is of interest at that specific time. If the information space is designed well, then this choice is easy, and the user achieves optimal information through the use of *natural intelligence,* that is, the choices are easy to understand so that users *know* what they will see if they click a link, and what they de-select by not following other links (Bonett, 2006). However, it is not easy to design a well information space. The **AI** approach is therefore used to help computers *guess* the user's needs, and find information and services the user needs to the user. This requirement needs more applications of intelligent techniques in web searching and information presentation.

4 Intelligent Web Mining

Classification and association-rule discovery are two of the most important tasks addressed in the web mining literature. The two tasks involve mining web data, web customers, web documents, web-based transactions and various web based applications and each has developed a set of approaches. Also, extensive research has been carried out to integrate approaches from both sides of the tasks to conduct high performance web mining. In the meantime, some intelligence techniques including neural networks, fuzzy logic (also its application in fuzzy associate rules and fuzzy sequential pattern), machine learning, genetic algorithms, Bayesian network, and case-based reasoning have also been applied into web mining. Some successful examples include web user profile clustering, web document classification, web document clustering, online concept retrieval, and web key information finding (Wang et al., 2006).

One of the main aims of web mining is to find out web consumers' customer behavior patterns. By these patterns, businesses and governments can target marketing, e.g. input patterns to a web server combining with web pages so that when pattern-related customers access the website corresponding ways of marketing can be created (Chen et al., 2004b). In general, web mining can help establish marketing patterns and customize mar-

keting to bring right products and services to right customers. It can also establish potential customers' list to help make decisions in customer relationship management. Intelligent techniques can be combined with traditional web mining approaches to improve the quality of mining. For example, by applying fuzzy set techniques to set up corresponding marketing patterns, businesses can better predict which kind of customers are loyal for a particular time being, and therefore can help businesses hold best customers and filter potential customers precisely. Fuzzy Adaptive Resonance (ART) has also been used for clustering customers in groups for targeting (Jain and Krishnapuram, 2001).

A related important aspect of web mining is the clustering of customer similar profiles to create customer "segments" (Mobasher et al., 2000). Clustered user profiles are a good option when there exist insufficient data to build individual profiles. Most customer attributes such as "quality-conscious" and "calorie-conscious" are inherently uncertain or fuzzy. Also, customer segments are not crisp. Thus, fuzzy set theory can play a major role in customer profile representations and clustering (Jain and Krishnapuram, 2001). Bautista et al. (2000) used a genetic algorithm to build an adaptive consumer profile based on documents retrieved by users. A fuzzy classification and a genetic term-selection process together provide a better utilization of valuable knowledge to learn the current and future interests of users. Granular computing techniques have been used in web mining applications to enhance the intelligent functionality of mining systems. For example, Zhang et al. (2003) used both fuzzy computing and interval computing techniques to design a fuzzy-interval data mining system for credit card companies with actual large data sets. Park (2000) also introduced a neural network-based data mining method to a company's internal customer data for target marketing. A fuzzy ART NN proposed in this study takes customer's purchasing history as input values and cluster similar customers into groups.

Web document and web pages classification as another important web mining aspect has used NN architectures (Kohonen et al., 2000). In the meantime, the use of evolution-based genetic algorithms, and the utilization of fuzzy function approximation, have also been presented as possible solutions for the classification problems (Rialle et al., 1997, Petridis and Kaburlasos, 2001, Haruechaiyasak et al., 2002). Also, Anagnostopoulos et al. (2004) described a probabilistic NN that classifies web pages under the concepts of business media framework. The classification is performed by estimating the likelihood of an input feature vector according to Bayes posterior probabilities.

Web usage mining has become very critical for effective website management, creating adaptive websites, business and support services, per-

sonalization, network traffic flow analysis and so on (Abraham and Ramos, 2003). Krishnapuram et al. (2001) introduced the notion of uncertainty in web usage mining, discovering clusters of user session profiles using robust fuzzy algorithms. In the approach, a user or a page can be assigned to more than one cluster. A dissimilarity matrix is created that is used by fuzzy algorithms presented in order to cluster typical user sessions. The study of ant colonies behavior and their self-organizing capabilities is of interest to information/knowledge retrieval, decision support systems sciences and also web mining, because it provides models of distributed adaptive organization, which are useful to solve difficult optimization, classification, and distributed control problems. Abraham and Ramos (2003) proposed an ant clustering algorithm to discover web usage patterns (data clusters) and a linear genetic programming approach to analyze the visitor trends.

5 E-Service Personalizations

E-service personalization (ESP) is the process of getting web users' information online, and using the information to tailoring web pages to individual users' preferences and deliver services to the user's needs. It is as an act of response according to the individual web user's characteristics, interest and preference. Personalised e-service is a means of meeting the web user's needs more effectively and efficiently; making online interactions with user faster and easier; and increasing online user satisfaction and repeat visits (Bonett, 2006, Riecken, 2000). It aims at delivering right information to right user at right time, so that to enhance e-service quality. In a marketing environment, the purposes of applying information technology to provide personalization are expressed as to (1) Better serve the customer by anticipating needs; (2) Make the interaction efficient and satisfying for both parties; and (3) and Build a relationship that encourages the customer to return for subsequent purchases including products and services (The PersonalizationConsortium, http://www.personalization.org/personalization.html Chen et al., 2004a).

E-service personalization is experiencing widespread adoption in the application areas such as e-commerce interaction, e-learning, online booking, and customer relationship management (Lu et al., 2006, Adomavicius and Tuzhilin, 2005). For example, given a customer, how to pick the right advertisement to target him/her? How to determine which product should be recommended to him/her? How to determine the content of a web page that he/she views? Therefore, personalization on the e-services is also re-

ferred as being about "building customer loyalty by building a meaningful one-to-one relationship." While creating user one-to-one relationships is to have its reflections on the web user satisfactions. User satisfaction is therefore the ultimate aim of personalization.

Many researchers have recently endeavored to provide personalization mechanisms, technologies and approaches for e-services (Adomavicius and Tuzhilin, 2005, Eirinaki and Vazirgiannis, 2003). Results involve five main aspects: (1) Profile based e-service personalization, (2) Link based e-service personalization, (3) Content based e-service personalization, (4) Structure based e-service personalization and (5) Recommendation based e-service personalization.

E-services will benefit from web personalization techniques in tailoring the interaction with their users according to an evolving customer model in both link based and content based personalization. In this context, relationship-value market segmentation becomes a central customer modeling activity. But value segmentation categories are inherently vague due to the use of imprecise linguistic categories, combined with a degree of uncertainty about customer behavior, and the difficulty inherent to estimating intangible variables. A fuzzy set approach to value segmentation is therefore developed, allowing more flexible customer segments. Fuzzy models of value estimations are represented by fuzzy triangular numbers for *directed* and *discovery-oriented* segmentation approaches. The usefulness of the approach has been illustrated through concrete personalization techniques based on those fuzzy categories (Sicilia and Garcia, 2003).

Recommender systems as the most typical personalization techniques have gained much attention in the past 10 years (Adomavicius and Tuzhilin, 2005). Recommender systems aim at filtering out the uninterested items (or predicting the interested ones) automatically on behalf of the users according to their personal preferences. A recommendation system considers user preferences, interests, or browsing behaviors when analyzing user behaviors for personalized services (Amoroso and Reinig, 2004). It therefore can either predict whether a particular user will like a particular item, or to identify a set of items that will be of interest to a certain user (Karypis, 2001).

Various approaches for recommender systems have been developed (Breese et al., 1998, Burke, 2000, Zeng et al., 2004). The main types of these approaches adopted in recommender systems are the content-based (CB) approach, the collaborative filtering (CF) approach, and the knowledge-based (KB) approach. The CB approach mainly relies on the content and relevant profiles to generate personalized recommendations. Using the approach, a recommender system recommends some web objects, to a user, which are similar to what the user has been interested in the past. The

CF approach offers recommendations based on the similarity of a group of users (Mobasher et al., 2000). The CF approach has been known to be the most popular recommendation approach. It has been used in various e-service applications such as recommending web pages, movies, articles and products. The CF approach can be divided into two types: user-based CF and item-based CF (Karypis, 2001). The user-based CF approach is implemented in two main steps: (1) a set of k-nearest neighbors of a target user is selected. This is performed by computing correlations or similarities between user profiles and a target user; (2) producing a prediction value for the target user on unrated (or unvisited) items, and generating recommendations to the target user. The item-based CF approach first considers the relationships among items. Rather than finding user neighbors, the system attempts to find k similar items that are rated (or visited) by different users in some similar ways. Then, for a target item, related predictions can be generated. For example, we can take a weighted average of a target user's item ratings (or weights) on these neighbor items. The third type is the KB approach. A knowledge-based recommender system attempts to suggest items based on inferences about a user's preferences. Such systems use knowledge in relevant to users and items to generate recommendations. In some sense, all recommendation techniques could be described as doing some kinds of inference. A knowledge-based recommender system avoids gather information about a particular user because its judgments are independent of individual taste (Burke, 2000).

There are still some spaces with current recommendation approaches to improve including the lack of scalability and sparsity, and the lack of the ability and accuracy to provide recommendations or predictions for new users and new items (Guo and Lu, 2006). Some intelligent techniques such as fuzzy approximate reasoning (Klir and Yuan, 1995), fuzzy matching, and fuzzy similarity, and case-based reasoning are being used in recommendation approaches to overcome these existing problems. Nasraoui and Petenes (2003) investigated the framework and provided a dynamic prediction in the web navigation space. Yager (2003) described a reclusive approach in which fuzzy set methods are used for the representation and subsequent construction of justifications and recommendation rules. Differing from CF, it is based solely on preferences of the single individuals for whom we provide the recommendation, without using preferences of other collaborators. It makes extensively use of an internal description of the items, and relies solely on the preferences of the target user. Carbo and Molina (2004) developed a CF-based algorithm in which ratings and recommendations can be linguistic labels represented by fuzzy sets. Perny and Zucker (1999, 2001) proposed a recommender system from a decision support perspective, noting that such applications position themselves be-

tween the archetypical problems of individual and group decision making. In that light, they pursued a hybrid approach that involves a number of fuzzy relations. Using appropriate fuzzy similarity measures, for each item i, and each user u, a neighborhood of k most similar elements is constructed. Also, based on a fuzzy similarity measure, a hybrid recommendation algorithm with fuzzy set theory was proposed. It is being used in a one-and-only item recommendation system in government e-services (Cornelis et al., 2005). Some of KB recommender systems employ the techniques of case-based reasoning for knowledge-based recommendation, such as Wasabi Personal Shopper (Burke, 1999) and a restaurant recommender system.

Personalization approaches have also been applied e-learning environments, which are mainly based on a range of delivery and interactive services. A personalized courseware recommendation system (PCRS) is proposed by Chen et al. (2004a). This system is developed based on the fuzzy item response theory to provide web-based learning services. In the proposed fuzzy item response theory, fuzzy set theory is combined with the original item response theory (Baker and Frank, 1992) to model uncertainly learning response. The PCRS can dynamically estimate learner ability based on the proposed fuzzy item response theory by collecting learner feedback information after studying the recommended courseware. Another example is a web-based personalized learning recommender system (Lu, 2004). This research aims to help students find learning materials they would need to read and therefore support students learn more effectively. Two related technologies are developed under the framework: one is a multi-attribute evaluation method to justify a student's need, and another is a fuzzy matching method to find suitable learning materials to best meet each student's needs.

The applications of intelligent techniques in e-service personalization also conduct some personalized e-service models. For example, Yang et al. (2004) combined genetic algorithms and k-nearest neighbor technology to model and reason a customer's personal preferences from a higher profile and then provide the most appropriate products to meet the user's higher needs. Genetic algorithms can help to obtain information more efficiently from the customers so that to help personalized products selection. Viswanathan and Childers (1999) considered online product categories as fuzzy sets. Products are said to have degrees of memberships in specific attributes. The memberships at the attribute level are then combined to obtain an overall degree of memberships of a product in a category. Fuzzy-set-based measures enable fine distinction among products and assist in the new product development, brand extension, and brand positioning. Fuzzy methods are also used in modeling market structure for e-business since

they can handle the uncertainty associated with consumers' choice and their next purchase (Nishio and Shiizuka, 1995).

6 Intelligent E-Service Evaluations

Since the mid-1990s, businesses have spent quite a bit of time, money and effort developing web-based e-service applications. These applications are assisting businesses in building more effective customer relationships and gaining competitive advantage through providing interactive, personalized, faster e-services to fulfill customer demands (Chidambaram, 2001). Businesses in the earlier stages of employing web-based applications had little data, knowledge and experience for assessing and evaluating the potential of e-services for organizational impacts and benefits. Organisational efforts were largely geared toward customer service provision with little to no thought identifying and measuring the costs involved in moving services online against the benefits received by adopting e-services. After several years experience of e-service provision, businesses now urgently need to plan their further development in e-services (Lu and Zhang, 2003). Importantly, businesses have obtained related e-service running data and knowledge, which makes it possible to identify in what items of investment for an e-service application effectively contribute to what benefit aspects of business objectives.

Recent reports concerning the success, quality, usability and benefit of e-services have led researchers to express increasing interest in evaluating and measuring the development of e-service applications (Wade and Nevo, 2005, Schubert and Dettling, 2002). Much research has been conducted to evaluate e-services from various views and using various methods. In general, the research in e-service evaluation can be classified under four major categories.

The first one is the evaluation for the features, functions or usability of e-service systems. It is often combined with the evaluation of the use of related websites. Typical approaches used in this category of research are testing, inspection and inquiry (Hahn and Kauffman, 2002). These approaches are often used together in analyzing a web search or a desk survey. For example, Ng et al. (1998) reported a desk survey of business websites and discussed the features and benefits of web-based applications. Smith (2001) proposed a set of evaluation criteria to New Zealand government websites. Lu et al. (2001) showed their assessment results for e-commerce development in the businesses of New Zealand. The quality of websites needs to be measured using criteria focused on the effective web-

site design (e.g., clear ordering of information, consistent navigation structure). However, from the information consumer's perspective the quality of a website may not be assessed independently of the quality of the information content that provides. Based on the information quality framework for the design of information systems defined in (Zadeh, 1975, Lee et al., 2002), Enrique et al. (2003) presented a computing-with-words based fuzzy-set method to measure the informative quality of Web sites used to publish information stored in XML documents.

The second category is the customer satisfactory evaluation. Meeting a web user's needs successfully is likely to lead to a satisfying relationship. Various evaluation criteria and factors about meeting users' needs and assessing user satisfactory degrees have been identified (Schubert and Dettling, 2002, Awan and Singh, 2006). Some evaluation systems have been designed for obtaining customers' feedback and measuring the degree of their satisfaction to current e-services provided (Lu and Lu, 2004). Questionnaire-based survey and multi-criteria evaluation systems are mainly used to conduct this kind of research. For example, Lin (2003) examined some customer satisfaction for e-commerce and proposed three main scales that play a significant role in influencing customer satisfaction: customer need, customer value, and customer cost. In the meantime, a related topic, customer loyalty, such as the antecedents and consequences of customer loyalty in e-commerce have been explored (Srinivasan et al., 2002). During the user satisfactory evaluation, fuzzy set techniques have been extended to discovery of fuzzy association rules (Kuok et al., 1998) and their extension to fuzzy sequential patterns (Hong et al., 1999). Fuzzy set theory provides a host of parameterized operators that can be used to model various aggregation strategies in web-based knowledge discovery (Jain and Krishnapuram, 2001). Setnes and Kaymak (2001) described an application of a fuzzy clustering algorithm to extract fuzzy rules from consumer response data collected by a sampling procedure. Such results will help e-service providers clear understanding their customers' satisfactory degrees to their e-services.

The third category is e-service investment analysis that has been conducted for evaluating and justifying investment in an e-service application. For example, Giaglis et al. (1999) presented a case-study of e-commerce investment evaluation. Furthermore, Drinjak et al. (2001) investigated the perceived business benefits of investing in e-service applications. While Amir et al. (2000) created a cost-benefit framework for online system management and evaluation. In particular, Lu and Zhang (2003) proposed a cost-benefit factor analysis model in e-services and conducted analysis for e-service development of businesses in Australia based on a questionnaire survey. Following the results, Zhang et al. (2004a) applied Bayesian

network techniques to analyze and verify the relationships among cost factors and benefit factors in the development of e-services. A cost-benefit factor-relation model is first proposed and considered as domain knowledge. Data collected through a questionnaire based survey is as evidence to the inference-based verification. This study first creates a graphical structure for cost-benefit factors. It then calculates conditional probability distributions among these factors. Based on the established Bayesian network, the Junction-tree algorithm is used to conduct inference. A set of useful findings have been obtained for the costs involved in moving services online against the benefits received by adopting e-service applications. For example, 'increased investment in maintaining e-services' would significantly contribute to 'enhancing perceived company image,' and 'increased investment in staff training' would significant contribute to 'realizing business strategies.' These findings have potential to improve the strategic planning of businesses by determining more effective investment items and adopting more suitable development activities in the development of e-services. Fuzzy set approaches have been used to summarize and analyze the survey results in e-service evaluation in the form of linguistic knowledge that can be understood by merchants easily. Fuzzy set techniques are known to be effective for analysis even with sparse data especially when application-specific knowledge is available in terms of fuzzy rules. Hsu et al. (2002) proposed a fuzzy clustering approach for segment structure analysis of customer response to surveys.

Significant results have also been reported in the fourth category, the establishment of evaluation models, frameworks and systems. For example, Lee et al. (1999) created a model for evaluating the business value of business-to-business e-service through five propositions. Zhang and Dran (2000) developed a two-factor model for the website design and evaluation. More generally, Hahn and Kauffman (2002) presented a value-driven framework for evaluating e-commerce websites. In general the quality of websites is often measured and evaluated using criteria focused on the effective website design such as clear ordering of information or consistent navigation structure. However, from the information consumer's perspective the quality of a website may not be assessed and evaluated independently of the quality of the information content that it provides. The evaluation of websites focusing on the quality of the information is a difficult task. One of the reasons is that users cannot express their judgments with an exact numerical value sometimes. Therefore, a more realistic approach may be to use linguistic assessments to express the evaluation judgments instead of numerical values. As mentioned above, the fuzzy linguistic approach is a tool to manage linguistic information; it is suitable to model qualitative values used in human communication for representing qualita-

tive concepts. Based on the principle, Herrera-Viedma et al. (2003) presented an evaluation model of informative quality of the websites based on fuzzy linguistic techniques. This model can be used by evaluators to use linguistic terms and finally can generate linguistic recommendations on quality websites by using information stored in multiple kinds of documents structured in the XML-format. A web-based fuzzy multi-criteria decision support system has been developed by Lu et al. (2005) to use for the website evaluation. A group of users can use the online decision support system to input linguistic terms such as '*good,*' '*very good*' for a set of selected websites respectively. Finally, evaluation results will show the level of the user satisfactory for each attribute of each website.

7 Intelligent E-Service Support Systems

As e-services become common, many Internet-based support systems such as software agents have been developed to assist users to receive high quality services in different aspects of e-services. These systems mainly perform tasks of intermediation and communication between users and the web (Yager, 2000), and many of them are developed under an intelligent framework.

One possibility to facilitate the communication processes between users and the web consists in the application of the fuzzy linguistic approach (Zadeh, 1975), which provides a flexible representation model of information by means of linguistic labels. The application of fuzzy linguistic techniques enables e-service providers to handle information with several degrees of truth and solving the problem of quantifying qualitative concepts. Some examples of the use of fuzzy linguistic techniques in the design of intelligent e-service systems, in particular multi-agent systems, can be found in (Delgado et al., 2001, Delgado et al., 2002, Herrera-Viedma et al., 2004). These papers presented some new models of fuzzy linguistic intelligent systems that involve the use of fuzzy set techniques and other intelligent approaches to improve the information access on the web. For example, a fuzzy linguistic multi-agent system can gather information on the web with a hierarchical architecture of seven action levels (Herrera-Viedma et al., 2004). E-negotiation, e-learning, e-decision, and e-shopping are the main forms of e-service support systems with a strong combination to intelligent techniques, which are displayed as follows.

E-negotiation as a kind of e-service support systems has well integrated with intelligent techniques. Kowalczyk and Bui (2000) presented some aspects of a customable fuzzy e-negotiation agents (FeNAs) system for

autonomous multi-issue negotiation in the presence of limited common knowledge and imprecise/soft constraints and preferences. The FeNAs use the principles of utility theory and fuzzy constraint-based reasoning in order to find a consensus that maximizes the agent's utility at the highest possible level of fuzzy constraint satisfaction subject to its acceptability by other agents (Dubois et al., 1994, Kowalczyk, 1999, Zadeh, 1973). Through applying the fuzzy set approaches, a variety of e-negotiation problems with incomplete common knowledge and imprecise/soft constraints can be handled. Genetic algorithms and Bayesian rule updating methods have also been used in e-negotiation systems. For example, Ouchiyama et al. (2003) proposed an experience based evolutionary negotiation agent that can conduct negotiation process in e-commerce on behalf of users it represents. By emulating human being, skills of an agent in negotiations can be improved with increasing knowledge and experience.

Another kind of e-service support systems is web-based e-learning systems. With the rapid growth of computers and Internet technologies, e-learning has currently become a major trend in the computer assisted teaching and learning field. Many researchers made efforts in developing web based e-learning systems to assist distance online learning. To promote learning efficiency and effectiveness, some systems have applied fuzzy sets and other intelligent approaches to fully consider learner's behaviors, interests, or habits, and also to assist learners in selecting subjects, topics, and materials through learners gives a 'linguistic' based response of understanding percentage for the learned courseware. Results show that applying the proposed fuzzy set approaches to e-learning can achieve personalized learning and help learners to learn more effectively and efficiently.

E-service activity in automated procurement will benefit from the kinds of web based decision support systems that can be constructed using intelligent technology. Ngai and Wat (2005) developed a fuzzy decision support system for risk analysis in e-commerce. Lu et al. (2005) developed a web-based fuzzy group decision support system (WFGDSS) based on the a fuzzy group decision-making method. This system first identifies three factors from web users that may influence the assessment of utility of alternatives and the deriving of the group satisfactory solution. The first one is an individual's role (weight) in the ranking and selection of the satisfactory solutions. The second factor is an individual's preference for alternatives. The third factor is criteria for assessing these alternatives. The above-mentioned three factors also derive a crucial requirement for linguistic information processing techniques in an online group decision-making practice. Any individual role in an online decision process, a preference for alternatives, and a judgment for assessment-criteria are often

expressed by linguistic terms. For example, an individual role can be described by using linguistic terms *important person* or *general decision person*. While a preference for an alternative can be described using linguistic terms *strong like it, just like ti,* or *don't like it any more.* Since these linguistic terms reflect the uncertainty, inaccuracy and fuzziness of decision makers, fuzzy set theory (Zadeh, 1965) is directly applied to deal with them. The WFGDSS uses a web environment as a development and delivery platform, and therefore allows decision makers distributed in different locations to participate in a group decision-making activity through the web. It manages the group decision-making process through criteria generation, alternative evaluation, opinion interaction and decision aggregation with the use of linguistic terms. This WFGDSS has a convenient and graphical user interface with visualization possibilities, and therefore is automatically available to many decision makers. Another example is a web based multi-objective decision support systems developed by Zhang and Lu (2005) and Lu et al. (2003). This system has a set of multi-objective decision-making methods. Some methods are more suitable than others for particular practical decision problems and particular decision makers. To help users choose a most suitable one in a particular situation, a linguistic term based intelligent guide is included in this system for selecting a desired method.

Intelligent e-shopping systems have been widely developed and used, because the Internet has been reaching almost every family in the world and anyone can build his/her own e-shops and also can purchase goods from any e-shops. Companies expect taking more benefit from online buying, selling, trading, etc and therefore continuing improve the functionality of their e-shopping systems. Some e-shopping systems applied traditional intelligent techniques such as multi-agent systems, rule-based or case-based process flows to coordinate communications for system automation. Some e-shopping systems propose fuzzy logic and neural networks or their combinations based approaches to tackle the uncertainties in practical online shopping activities such as consumer preferences, product specification, product selection, price negotiation, purchase, delivery, after-sales service, and evaluation (Liu and You, 2003). The fuzzy neural network provides an automatic and autonomous product classification and selection scheme to support fuzzy decision making by integrating fuzzy logic technology and the back propagation feed forward neural network. Fuzzy decision strategies are also proposed to guide the retrieval and evaluation of similar products that are used online shopping. For example, Liu and You (2003) presented a visualization approach to provide intelligent web browsing support for e-commerce using data warehousing and data mining techniques. This approach can overcome the limitations of the current web

browsers, which lack flexibility for customers to visualize products from different perspectives. By using fuzzy logic for a fuzzy neural network to support decision making, an agent-based fuzzy shopper system is developed to implement the strategy. Furthermore, Chau and Yeh (2005) presented how intelligent techniques facilitate the automatic development of multilingual web portal for e-business operating as a global enterprise. E-auction can be seen as a special kind of e-shopping. Byde (2003) applied evolutionary game theory to auction mechanism design. The main idea is using an evolution-based method for evaluating auction mechanisms and developing a multi-agent system to evolve good players for each mechanism.

Intelligent techniques have also been used in e-recruitment systems. For example, Khosla and Goonesekera (2003) reported an e-recruitment multi-agent application for recruitment and benchmarking of salespersons. This multi-agent e-sales recruitment system (e-SRS) integrates a selling behavioral model with expert systems and soft computing techniques like fuzzy- K-means for predicting the selling behavior profile of a sales candidate.

8 E-Service Models and Management

Management techniques and related models have long existed and are quite mature for every segment of service industries. In a growing competitive marketplace, e-services are under constant pressure to optimize their utilization of information resources. E-service administrators and planners have tried to use intelligent technologies and approaches to model and manage e-service applications. Some models developed under intelligent approaches include fuzzy association based e-service customer classification model, intelligent global e-business web portal development model, e-commence trust model, and web mining based decision model. These models involve both e-business and e-government. In the meantime, research on getting knowledge and online knowledge discovery in various e-service systems through genetic algorithms, case-based reasoning etc. has been shown in literature. The rest of the section will list some typical developments.

Goldszmidt et al. (2001) proposed an approach for defining and quantifying effective e-business capacity that allows to translate quality of service objectives into the number of users that a website can support. This approach is based on inducing online models using machine learning and statistical pattern recognition techniques. The concept of e-business capac-

ity allows us to naturally answer planning and operational questions about the information system infrastructure needed to support the e-business. The questions range from indicating which performance measures in the system are "important" to simulating "if-then" scenarios.

E-services have managed to place themselves in the society. However, there are many hindrance factors that cause them to fail to reach their full potential, mainly on the dissatisfaction of customers, such as a low level of personal data security and mistrust of the technology (Manchala, 2000). This has affected consumers' trust towards online business. Since the concept of trust is subjective, it creates a number of unique problems that obviate any clear mathematical result. Hence, fuzzy logic is currently being investigated as a possible best fit approach as it takes into account the uncertainties within e-commerce data and like human relationships, trust is often expressed by linguistic terms rather than numerical values. Nefti et al. (2005) identified two advantages of using fuzzy logic to quantify trust in e-commerce applications. (1) Fuzzy inference is capable of quantifying imprecise data and quantifying uncertainty in measuring the trust index of the vendors. For example, in the trust model, the community comments variable in the fulfillment factor has a wide range of values as we may have a small or large number of customers providing positive or negative feedback to the vendor; the number of comments will affect the decision made by the associated evaluation module. (2) Fuzzy inference can deal with variable dependencies in the system by decoupling dependable variables. The membership functions can be used to generate membership degrees for each variable. Any defined fuzzy rule set will be applied to the output space (trust index) through fuzzy '*and*' and '*or*' operators. Such a fuzzy trust module can describe more effectively users' trust behavior in e-services. Another trust model is developed under Peer-to-Peer e-commerce communities. A main way to minimize threats in such an open community is to use community-based reputations to help evaluating the trustworthiness and predicting the future behavior of peers. Xiong and Liu (2003) presented PeerTrust, a coherent adaptive trust model for quantifying and comparing the trustworthiness of peers based on a transaction-based feedback system. This study introduces two adaptive trust factors, the transaction context factor and the community context factor, to allow the basic trust metric to incorporate different contexts (situations) and to address common problems encountered in a variety of online e-commerce communities. Some studies have applied fuzzy-logic-based models to evaluate trust in e-commerce by taking into account the uncertainties within e-commerce data. For example, Chang et al (2005) demonstrated the application of a fuzzy trust model in an ecommerce platform. It aims to measure

trustworthiness, reputation or credibility of e-service consumers and e-service providers in loosely coupled, distributed e-commerce systems.

The potential for government using web to enhance services to its citizens, businesses and communities is now more evident than ever before. Thus, in the most of developed countries and some of developing countries, e-government applications are growing rapidly. E-government development promises to make governments more efficient, responsive, transparent, and legitimate. The challenge for governments is to continually embrace the opportunities that the web provides, and ensure that the needs and expectations of citizens, businesses and communities are met (Guo and Lu, 2004). As the amount of information available on the web is overwhelming, the users of e-government are constantly facing the problem of information overload. The increasing information overload would hinder government e-service effectiveness (Guo and Lu, 2005). In order to explore how e-government better face the challenge and developing next innovations, Hinnant and O'Looney (2003) conducted an exploratory study of e-service personalization in the public sector by examining pre-adoption interest of government in online innovations. This study proposes a revised model of technological innovation with an emphasis on socio-technical factors associated with electronic service delivery. This model focuses on three primary dimensions of online innovation: perceived need, technical capacity, and risk mitigation. This model is then used to examine a single online innovation, personalization of online government information and services.

9 Conclusions

E-service intelligence, like every new technology, provides solutions and challenges, along with a new set of research questions. The preliminary research seemed promising, but more research and developments should be followed soon. Intelligent technology plays an important role for dealing with e-services as already briefly outlined by many successful applications. We can speculate about the potential and problems of an integrated intelligent e-service economy, there is a lot we need to explore about the technological or organizational issues involved. We strongly believe the use of intelligent technologies in cope with web technologies will significantly enhance the current development of e-services in general and the future intelligent e-services in particular.

References

1. Abraham, A., Ramos, V. (2003) Web usage mining using artificial ant colony clustering and linear genetic programming. Proceedings of the 2003 Congress on Evolutionary Computation, 1384- 1391.
2. Adomavicius, G., Tuzhilin, A. (2005) Personalization technologies: a process-oriented perspective. Communications of the ACM, 48**:** 83-90.
3. Amir, Y., Awerbuch, B., Borgstrom, R.S. (2000) A Cost–Benefit framework for online management of a metacomputing system. Decision Support Systems, 28**:** 155-164.
4. Amoroso, D. L., Reinig, B.A. (2004) Personalization management systems: Mini-track introduction. Proceedings of the 37th Annual Hawaii International Conference on System Sciences (HICSS'04), Big Island, Hawaii, Track 7.
5. Anagnostopoulos, I., Anagnostopoulos, C., Loumos, V., Kayafas, E. (2004) Classifying Web pages employing a probabilistic neural network. Proceedings of IEEE Vol. 151, 139- 150.
6. Awan, I., Singh, S. (2006) Performance evaluation of e-commerce requests in wireless cellular networks. Information and Software Technology, Available online**:** 1-9.
7. Baker, Frank, B. (1992) Item Response Theory: Parameter Estimation Techniques*,* Marcel Dekker, New York.
8. Bautista, M.M., Vila, M.A., Larsen, H. (2000) Building adaptive user profiles by a genetic fuzzy classifier with feature selection. Proceedings of The Ninth IEEE International Conference on Fuzzy Systems, 308-312.
9. Berners-Lee, T., Hendler, J., Lassila, O. (2001) The semantic web. Scientific American, May 2001**:** 29--37.
10. Bonett, M. (2006) Personalization of Web Services: Opportunities and Challenges http://www.ariadne.ac.uk/issue28/personalization/.
11. Breese, J. S., Heckerman, D., Kadie, C. (1998) Empirical analysis of predictive algorithms for collaborative filtering. Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence, Madison, Wisconsin, USA, 43-52.
12. Burke, R. (1999) The Wasabi Personal Shopper: a case-based recommender systems. Proceedings of the 11th National Conference on Innovative Applications of Artificial Intelligence, Menlo Park, CA, 844-849.
13. Burke, R. (2000) Knowledge-based recommender systems. *Encyclopedia of Library and Information Systems*. Kent, A., Ed., Marcel Dekker, New York

14. Byde, A. (2003) Applying evolutionary game theory to auction mechanism design. Proceedings of IEEE International Conference on E-Commerce, 347- 354.
15. Carbo, J., Molina, J. M. (2004) Agent-based collaborative filtering based on fuzzy recommendations. International Journal of Web Engineering and Technology, 1**:** 414 - 426.
16. Chang, E. Schmidt, S. and Steele, R. and Dillon, T. (2005), Applying a fuzzy trust model to e-commerce systems, in Jarvis, R. and Zhang, S. (ed), *18th Australian Joint Conference on Artificial Intelligence (AI)*, Sydney, Australia, Dec. 2005, 318-329.
17. Chau, R., Yeh, C. H. (2005) Intelligent techniques for global e-business Web portal development. Proceedings of the 2005 IEEE International Conference on e-Technology, e-Commerce and e-Service, 334- 340.
18. Chen, C.M., Duh, L.J., Liu, C.Y. (2004a) A personalized courseware recommendation system based on fuzzy item response theory. Proceedings of 2004 IEEE International Conference on e-Technology, e-Commerce and e-Service (EEE'04), Taipei, Taiwan, 305-308.
19. Chen, Q. Z., Mao, K. J., Zhang, Y., Lu, L. Y. (2004b) Catching potential customers: an example of web-mining-aided e-commerce decision-making. Proceedings of the Fifth World Congress on Intelligent Control and Automation, 3986- 3990.
20. Chidambaram, L. (2001) The editor's column: Why e-Service Journal. e-Service Journal, 1**:** 1-3.
21. Cornelis, C., Guo, X., Lu, J., Zhang, G. Q. (2005) A fuzzy relational approach to event recommendation. Proceedings of the Second Indian International Conference on Artificial Intelligence (IICAI-05), Pune, India, 2231-2242.
22. Crestani, F. (1994) Comparing neural and probabilistic relevance feedback in an interactive information retrieval system. Proceedings of IEEE Int. Conf. on Neural Networks, Orlando, FL, 3426–3430.
23. Delgado, M., Herrera, F., Herrera-Viedma, E., Martín-Bautista, M. J., Martínez, L., Vila, M. A. (2002) A communication model based on the 2-tuple fuzzy linguistic representation for a distributed intelligent agent system on Internet. Soft Computing, 6**:** 320-328.
24. Delgado, M., Herrera, F., Herrera-Viedma, E., Martín-Bautista, M. J., Vila, M. A. (2001) Combining linguistic information in a distributed intelligent agent model for information gathering on the Internet. *Computing with Words*. Wang, P.P., Ed., John Wiley & Son, 251-276.

25. Drinjak, J., Altmann, G., Joyce, P. (2001) Justifying investments in electronic commerce. Proceedings of the Twelfth Australia conference on Information Systems, Coffs Habour, Australia, 187-198.
26. Dubois, D., Fargier, H., Prade, H., (1994) Propagation and Satisfaction of Flexible Constraints. *Fuzzy Sets, Neural Networks arid Sott Computing*. Yager, R. R. and Zadeh, L. A., Eds., 166-187
27. Eirinaki, M., Vazirgiannis, M. (2003) Web mining for web personalization. ACM Transactions on Internet Technology, 3**:** 1-27.
28. Enrique, H., Eduardo, P., Mar´ıa, D. O., Juan, C. H., Yusef, H. M. (2003) Evaluating the Informative Quality of Web Sites by Fuzzy Computing with Words. Proceedings of Atlantic Web Intelligence Conference. Madrid, Spain, Lecture Notes in Artificial Intelligence 2663: Springer, 62-72
29. Giaglis, G. M., Paul, R. J., Doukidis, G. I. (1999) Dynamic modelling to assess the business value of electronic commerce. International Journal of Electronic Commerce, 3**:** 35-51.
30. Goldszmidt, M., Palma, D., Sabata, B. (2001) On the quantification of e-business capacity. Proceedings of the 3rd ACM Conference on Electronic Commerce, Tampa, Florida, USA, 235-244.
31. Guo, X., Lu, J. (2004) Effectiveness of E-government Online Ser-vices in Australia. *Digital Government: Strategies and Implementation from Developing and Developed Countries*. Huang, Siau and Wei, Eds., Idea Group, Inc. 214-241.
32. Guo, X., Lu, J. (2005) Applying web personalization techniques in E-government services. Proceedings of the 11th Australian World Wide Web Conference, Gold Coast, Australia, 233-238.
33. Guo, X., Lu, J. (2006) Intelligent e-government services with recommendation techniques. International Journal of Intelligent Systems, Special issue on E-service intelligence**:** Accepted.
34. Hahn, J., Kauffman, R. J. (2002) Evaluating selling web site performance from a business value perspective. Proceedings of International conference on e-Business, Beijing, China, 435-443.
35. Haruechaiyasak, C., Mei-Ling, S., Shu-Ching, C., Xiuqi, L. (2002) Web document classification based on fuzzy association. Proceedings of the 26th Annual Int. Computer Software and Applications Conf., Oxford, UK, 487–492.
36. Herrera-Viedma, E., Herrera, F., Martínez, L., Herrera, J. C., López, A. G. (2004) Incorporating filtering techniques in a fuzzy multi-agent model for gathering of information on the Web. Fuzzy Sets and Systems, 148**:** 61-83.
37. E. Herrera-Viedma, E. Peis, M.D. Olvera, Y.H. Montero, J.C. Herrera (2003) Evaluating the informative quality of Web sites by Fuzzy

Computing with Words. Atlantic Web Intelligence Conference, AWIC'03. Madrid (Spain), Lecture Notes in Artificial Intelligence 2663, pp.62-72.
38. Hinnant, C. C., O'looney, J. A. (2003) Examining pre-adoption interest in online innovations: an exploratory study of e-service personalization in the public sector. IEEE Transactions on Engineering Management**:** 436- 447.
39. Hong, T., Kuo, C., Chi, S. (1999) Mining fuzzy sequential patterns from quantitative data. Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, 962-966.
40. Hsu, T., Chu, K.M., Chan, H.C. (2002) The fuzzy clustering on market segment. Proceedings of the Ninth IEEE International Conference on Fuzzy Systems, 62 1-626.
41. Jain, V., Krishnapuram, R. (2001) Applications of fuzzy sets in personalization for e-commerce. Proceedings of IFSA-NAFIPS 2001 Conference, 263-268.
42. Karypis, G. (2001) Evaluation of item-based top-N recommendation algorithms, Proceedings of the ACM 10th International Conference on Information and Knowledge Management, Atlanta, Georgia, 247-254.
43. Khosla, R., Goonesekera, T. (2003) An online multi-agent e-sales recruitment system. Proceedings of IEEE/WIC International Conference on Web Intelligence, 111- 117.
44. Klir, G. J., Yuan, B. (1995) Fuzzy Sets and Fuzzy Logic: Theory and Applications. Upper Saddle River*,* Prentice Hall, N.J.247-254.
45. Kohonen, T., Kaski, S., Lagus, K., Salojarvi, J., Honkela, J., Paatero, V., Saarela, A. (2000) Self organization of a massive document collection. IEEE Trans. Neural Network, 11**:** 574–585.
46. Kowalczyk, R. (1999) On Linguistic Fuzzy Constraint Satisfaction Problems *Computing with Words in Intelligent Information Systems*. Zadeh, L. A. and Kacprzyk, J., Eds., Kluwer, 166- 187.
47. Kowalczyk, R., Bui, V. (2000) FeNAs: A fuzzy e-negotiation agents system. Proceedings of the Conference on Computational Intelligence for Financial Engineering (CIFEr 2000), NY, 26-29.
48. Krishnapuram, R., Nasraoui, O., Joshi, A., L.M (2001) Low complexity fuzzy relational clustering algorithms for web mining. IEEE Transactions on Fuzzy Systems 9:595-607.
49. Kuok, C., Fu, A., Wong, M. H. (1998) Mining fizzy association rules in databases. SIGMOD Record, 27**:** 41-46.
50. Lee, C., Seddon, P., Corbitt, B. (1999) Evaluating business value of internet-based business-to-business electronic commerce. Proceedings of 10th Australasian Conference on Information Systems, Wellington, New Zealand, 2: 508-519.

51. Lee, Y. W., Strong, D. M., Kahn, B. K., Wang, R. Y. (2002) AIMQ: A methodology for information quality assessment. Inf.ormation & Managment, 40**:** 133-146.
52. Li, Y., Liu, D. B., Zhang, W. M. (2005) Schema matching using neural network. Proceedings of The 2005 IEEE/WIC/ACM International Conference on Web Intelligence, Paris, 743- 746.
53. Lin, C. (2003) A critical appraisal of customer satisfaction and e-commerce. Managerial Auditing Journal, 18**:** 202-212.
54. Liu, J., You, J. (2003) Smart shopper: an agent-based web-mining approach to Internet shopping. IEEE Transactions on Fuzzy Systems, 11**:** 226- 237.
55. Loia, V., Nikravesh, M., Zadeh, L. A. (2004) Fuzzy Logic and the Internet, Physica-Verlag, Springer.
56. Lu, J. (2004) Framework and approach for developing intelligent personalized learning recommender systems. Proceedings of the 2nd International Conference on Information Technology and Applications, Harbin, China, CDROM.
57. Lu, J., Lu, Z. (2004) Development, distribution and evaluation for online tourism services in China. Electronic Commerce Research Journal, 4**:** 221-239.
58. Lu, J., Ruan, D., Zhang, G. Q., Zimmermann, H. J. (2007) International Journal of Intelligent Systems, Special Issue on E-Service Intelligence.
59. Lu, J., Shi, C. G., Zhang, G. Q. (2003) Framework and implementation of a web-based WMODSS. Proceedings of Workshop on Applications, Products and Ser-vices of Web-based Support Systems, in conjunction with IEEE/WIC Inter-national Conference on Web Intelligence, Halifax, Canada, 7-11.
60. Lu, J., Tang, S., Mccullough, G. (2001) An assessment for internet-based electronic commerce development in businesses of New Zealand Electronic Markets: International Journal of Electronic Commerce and Business Media, 11**:** 107-115.
61. Lu, J., Zhang, G. Q. (2003) A model for evaluating E-commerce based on cost/benefit and customer satisfaction. Journal of Information Systems Frontiers, 5**:** 265-277.
62. Lu, J., Zhang, G. Q., Wu, F. (2005) Web-Based Multi-Criteria Group Decision Support System with Linguistic Term Processing Function. The IEEE Intelligent Informatics Bulletin, 5**:** 35-43.
63. Manchala, D. W. (2000) E-commerce trust metrics and models. IEEE Internet Comp. 4**:** 36-44.

64. Mobasher, B., Dai, H., Luo, M., Wiltshire, (2002) Discovery of evaluation of aggregate usage profiles for web personalization. Data mining and knowledge discovery, 6 (1): 61-82.
65. Nasraoui, O., Petenes, C. (2003) An intelligent web recommendation engine based on fuzzy approximate reasoning. Proceedings of the IEEE International Conference on Fuzzy Systems, St. Louis, MO, 1116-1121.
66. Nefti, S., Meziane, F., Kasiran, K. (2005) A fuzzy trust model for E-commerce. Proceedings of Seventh IEEE International Conference on E-Commerce Technology (CEC'05), 401-404.
67. Ng, H., Pan, Y. J., Wilson, T. D. (1998) Business use of the world wide web: A report on further investigations. International Journal of Management, 18**:** 291-314.
68. Ngai, E. W. T., Wat, F. K. T. (2005) Fuzzy decision support system for risk analysis in e-commerce development. Decision Support Systems, 40**:** 235-255.
69. Nikravesh, M., Azvin, B. (2002) Fuzzy queries, search, and decision support system. International Journal of Soft Computing-Special Issue on Fuzzy Logic and the Internet, 6:373-399.
70. Nikravesh, M., Loia, V., Azvine, B. (2002) Fuzzy logic and the Internet (FLINT), Internet, World Wide Web, and Search Engines. International Journal of Soft Computing-Special Issue in fuzzy logic and the Internet, 6:33-37.
71. Nishio, C., Shiizuka, H. (1995) Competitive market structures constructed from brand-switching data by fuzzy structural modeling. Proceedings of IEEE International Conference on Fuzzy Systems, 819-824.
72. Ouchiyama, H., Huang, R., Ma, J., Sim, K. M. (2003) An experience-based evolutionary negotiation model. Proceedings of the Fifth International Conference on Computational Intelligence and Multi-media Applications, 212- 217.
73. S. Park (2000), Neural Networks and Customer Grouping in E-Commerce: A Framework Using Fuzzy ART. AIWoRC 2000: 331-336
74. Parry, D. (2004) A fuzzy ontology for medical document retrieval. Proceedings of the Second Workshop on Australasian information security, Data Mining and Web Intelligence, and Software Internationalisation - Volume 32 CRPIT '04, 121-126.
75. Perny, P., Zucker, J. D. (1999) Collaborative filtering methods based on fuzzy preference relations. Proceedings of the EUROFUSE-SIC, 279 - 285.

76. Perny, P., Zucker, J. D. (2001) Preference-based search and machine learning for collaborative filtering: the 'Film-Conseil' movie recommender system. Revue I3, 1**:** 1-40.
77. Petridis, V., Kaburlasos, V. G. (2001) Clustering and classification in structured data domains using fuzzy lattice neurocomputing (FLN). IEEE Trans. Knowl. Data Eng., 13**:** 245-260.
78. Quan, T. T., Hui, S. C., Cao, T. H. (2004a) A Fuzzy FCA-based Approach to Conceptual Clustering for Automatic Generation of Concept Hierarchy on Uncertainty Data. CLA 2004. Proceedings of CLA 2004, 1-12.
79. Quan, T. T., Hui, S. C., Fong, A. C. M., Cao, T. H. (2004b) Automatic Generation of Ontology for Scholarly Semantic Web. Proceedings of International Semantic Web Conference 2004, 726-740.
80. Quan, T. T., Siu Cheung Hui, S. C., Cao, T. H. (2004c) FOGA: A fuzzy ontology generation framework for scholarly semantic Web. Proceedings of the Knowledge Discovery and Ontologies (2004), 37-48.
81. Rialle, V., Meunier, J., Oussedik, S., Nault, G. (1997) Semiotic and modeling computer classification of text with genetic algorithm: analysis and first results. Proceedings of Int. Conf. on Intelligent Systems and Semiotics (ISAS), Gaithersburg, 325–330.
82. Riecken, D. E. (2000) Personalized views of personalization. Communications of the ACM, 43**:** 27-28.
83. Ruan, D. (1997) Intelligent Hybrid Systems*,* Kluwer Academic Publishers, Boston.
84. Schubert, P., Dettling, W. (2002) Extended Web assessment method (EWAM) - evaluation of E-commerce applications from the customer's view-point, Proceedings of the 35th Annual Hawaii International Conference on System Sciences (HICSS'02)-Volume 7, 175-184.
85. Setnes, M., Kaymak, U. (2001) Fuzzy modeling of client preference from large data sets: an application to target selection in direct marketing. IEEE Trans. on Fuzzy Systems 9:153-163.
86. Sicilia, M., Garcia, E. (2003) On fuzziness in relationship value segmentation: applications to personalized e-commerce. SIGecom Exch., 4**:** 1-10.
87. Smith, A. G. (2001) Applying evaluation criteria to New Zealand government websites. International Journal of Information Management, 21**:** 137-149.
88. Srinivasan, S., Anderson, R., Ponnavolu, K. (2002) Customer loyalty in e-commerce: an exploration of its antecedents and consequences. Journal of Retailing, 78**:** 41-50.

89. Viswanathan, M., Childers, T. L. (1999) Understanding how product attributes inhence product categorization: development and validation of fuzzy set-based measures of gradedness in product categories. Journal of Marketing Research, XXXVI**:** 75-94.
90. Wade, R. M., Nevo, S. (2005) Development and validation of a perceptual instrument to measure E-commerce performance. International Journal of Electronic Commerce, 10**:** 123.
91. Wang, C., Lu, J., Zhang, G. Q. (2006) Mining key information of Web pages: a method and its application. Expert Systems with Applications**:** Accepted.
92. Widyantoro, D. H., Yen, J. (2001) Using fuzzy ontology for query refine-ment in a personalized abstract search engine. Proceedings of IFSA World Congress and 20th NAFIPS International Conference
93. Xiong, L., Liu, L. (2003) A reputation-based trust model for peer-to-peer e-commerce communities. Proceedings of IEEE International Conference on E-Commerce, 275- 284.
94. Yager, R. R. (2000) Targeted E-commerce marketing using fuzzy intelligent agents. IEEE Intelligent Systems, 15**:** 42-45.
95. Yager, R. R. (2003) Fuzzy logic methods in recommender systems. Fuzzy Sets and Systems, 136**:** 133-149.
96. Yang, H. W., Pan, Z.G., Wang, X.Z., Xu, B. (2004) A personalized products selection assistance based on e-commerce machine learning. Proceedings of the 2004 International Conference on Machine Learning and Cybernetics, 2629- 2633.
97. Zadeh, L. A. (1965) Fuzzy sets. Information and Control, 8**:** 338-353.
98. Zadeh, L. A. (1973) Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Man. and Cybernetics, 3**:** 28-44.
99. Zadeh, L. A. (1975) The concept of a linguistic variable and its applications to approximate reasoning. Part I, in Information Sciences 8, 199-249. Part II, in Information Sciences 8, 301-357. Part III, in Information Sciences 9, 43-80.
100. Zadeh, L. A. (1999) From computing with numbers to computing with words -- from manipulation of measurements to manipulation of perceptions. IEEE Transactions on Circuits and Systems, 45**:** 105-119.
101. Zadeh, A. L. (2003) Web Intelligence and Fuzzy Logic-The Concept of Web IQ (WIQ) keynote in Web Intelligence 2003.
102. Zadeh, L. A. (2001) A new direction in AI: towards a computational theory of perceptions. AI Magazine, 22**:** 73-84.

103. Zeng, C., Xing, C.X., Zhou, L.Z., Zheng, X.H. (2004) Similarity measure and instance selection for collaborative filtering. International Journal of Electronic Commerce, 8**:** 115 - 129.
104. Zhang, G. Q., Lu, J. (2005) A linguistic intelligent guide for method selection in multi-objective decision support systems. Special issue on Linguistic Decision Making: Tools and Applications, Information Sciences**:** Accepted.
105. Zhang, G. Q., Lu, J., Bai, C. G., Zhang, C. (2004a) Bayesian network based cost benefit factor inference in e-services. Proceedings of the 2nd International Conference on Information Technology and Applications, Harbin, China, CDROM.
106. Zhang, P., Dran, V. G. (2000) Satisfiers and dissatisfiers: a two-factor model for website design and evaluation Journal of American Association for Information Science (JASIS), 51**:** 1253-1268.
107. Zhang, T. Z., Fu, Y. G., Shen, R. M. (2004b) Improve question & answer system by applying genetic algorithm. Proceedings of the 2004 International Conference on Machine Learning and Cy-bernetics, 2317- 2321.
108. Zhang, Y. Q., Shteynberg, M., Prasad, S. K., Sunderraman, R. (2003) Granular fuzzy Web intelligence techniques for profitable data mining. Proceedings of the 12th IEEE International Conference on Fuzzy Systems, 1462- 1464.