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A Fuzzy Decision System Using Shoppers' Preferences for Recommendations in E-Commerce Applications

Zhengping Wu
Department of Computer Science and Engineering
University of Bridgeport
Bridgeport, CT, USA
zhengpiw@bridgeport.edu

Hao Wu
Department of Computer Science and Engineering
University of Bridgeport
Bridgeport, CT, USA
wuhao@bridgeport.edu

***Abstract*—In e-commerce applications, the magnitude of products and the diversity of venders cause confusion and difficulty for common consumers to choose the right product from a trustworthy vender. Although people have recognized the importance of feedbacks and reputations for the trustworthiness of individual venders and products, they still have difficulties when they have to make a shopping decision from a huge number of choices. This paper introduces fuzzy logic into rule definition for preferences of venders and price for products, and designs a novel agent-based decision system using fuzzy rules and reasoning mechanisms to find the right product from a trustworthy vender according to users' preferences.**

Keywords: E-Commerce; Decision-making; Fuzzy Recommendation; Preference-based shopping.

I. INTRODUCTION

Trustworthiness has been discussed in the e-commerce environment for many years. From common users' points of views, the trust or trustworthiness toward a vender includes many factors [1]. Due to the diversity of these factors, management of this trustworthiness in the e-commerce environment is very difficult. The research for the management of trustworthiness in related areas such as the studies in the context of access control [2], public key architecture [3], and reputation systems for peer-to-peer networks [4] can help us understand key points in management of trustworthiness for e-commerce. In e-commerce environments, a consumer needs to deal with product descriptions from shopping sites/venders, the sites/venders' reputations from Better Business Bureau (BBB) or other sources, and the reputation for that product from a consumer-reporting agency. Even if the shopping site/vender is honest, reading the product description from site/vender could still raise concerns about the accuracy of this summarization of the original product specification from its manufacturer. Because this information is indirect, uncertainty in this factor is unavoidable. Meanwhile the user's (consumer's) response always includes some level of fuzziness, because the user's decision is based on subjective judgment from knowledge of the brand, previous experience with that brand, and possibly previous experience with that site/vender. Furthermore consumers need to compare the product among different e-commerce sites to see which site provides the most attractive offer. It is impossible to do all these things manually. We introduce an agent-based system following users' preferences to provide personalized shopping recommendations.

II. RELATED WORK

Trust is a complex subject related to belief in honesty, trustfulness, competence, and reliability of an entity. In McKnight et al.'s "The Meanings of Trust" [6], the most tangible aspects of trust are trust behavior and trust intention. In the context of e-commerce, trust is usually specified in terms of a temporary relationship between a consumer and a vender or product. In this relationship, trust intention formed from a number of fuzzy factors in the decision process leads to the actual trust behavior (purchases). In today's e-commerce environment, the management of trust needs to handle many factors over multiple websites or domains. Beth et al. [7] categorize the inter-domain trust relationships into two classes: direct trust and recommended trust. Based on the expectation for an entity being able to finish a task, the system can calculate the probability of whether the entity will complete the task based upon positive and negative experience, measure the trustworthiness using this probability, and create a formula for calculating a number value of the trustworthiness with a set of derivation and integration rules. But this mechanism simplifies real life by modeling trustworthiness based only on probability, and equates the subjectivity and uncertainty to the randomness. At the same time, it uses the mean value of multiple sources of trustworthiness as the indicator of the aggregate trust and final trust value number, which omits possible weights on each trust source. In [8], Josang proposed a trust model based on subjective logic, which introduces the concepts of evidence space and opinion space to describe and measure trustworthiness. Based upon the Beta distribution function that describes the posteriori probability for binary events, the author calculates the trustworthiness for every possible event from every entity. Meanwhile, Josang defines a set of operators for the calculation of trustworthiness. Josang's

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model literally equates the subjectivity and uncertainty to the randomness also. But as a cognitive activity, the subjectivity and uncertainty of trustworthiness is mainly expressed in its fuzziness. How to model this fuzziness and apply this model to the management of multiple factors in e-commerce activities is the problem.

III. Model of uncertainty and trustworthiness

A. Categorization of uncertainty

To manage a collection of trust-related activities across e-commerce domains, we need to understand trust itself. From different points of views, trust can be categorized into different classes. Following the categorization described by Beth et al. [7], we categorize trust into two classes - direct trust and indirect trust. A trust relationship formed from direct experience or negotiations can be characterized as direct trust; a trust relationship or a potential trust relationship built from recommendations by a trusted third party or a chain of trusted parties, which create a trust path, is called indirect trust. Indirect trust is derived from direct trust. Indirect trust is a function of direct trust(s). It may add new values to direct or indirect trust from a trusted party. The added values are uncertain at some level and tend to be fuzzy.

From another point of view, trust is a concept everybody understands at some personal level, but most people will have trouble providing a specific definition of the concept. Some people will have objective measures they use to evaluate their level of trust in a person or company, while others rely on a more subjective feeling for determining whether to trust somebody. So trust can be either derived from one's belief/feeling or based on an evaluation of certain measurements.

An entity's (brand's or vender's) trustworthiness is associated with the quality of services/products it provides to others. The quality of a service/product can be objectively measured or subjective measured. Intuitively, if the quality of a service/product can be objectively measured, then the trustworthiness toward that service/product reflects some intrinsic property, which should be independent of the source of the trust evaluation. However, the subjective trust may vary greatly when different sources of trust evaluation are considered. Due to this variation, subjective trust is uncertain at some level, and therefore needs special representations and enforcement processes to handle this aspect of trust management for federation activities.

B. Fuzzy model of uncertainty

The trust relationships in multi-domain e-commerce applications are hard to assess due to involved uncertainty. If a trust relationship relies upon a subjective judgment based on indirect information, it will be very uncertain and any operations related to that trust relationship may cause unexpected results.

Fuzzy logic is a suitable way to represent uncertainties, especially when they need to be handled quantitatively. Two advantages of using fuzzy logic to quantify uncertainty in trust management are: (1) Fuzzy inference is capable of quantifying imprecise data or uncertainty in measuring different levels of trust. (2) Different membership functions and inference rules could be developed for different trust relationships, without changing the fuzzy inference engines and enforcement mechanisms.

L. Zadeh first introduced fuzzy logic in the development of the theory of fuzzy sets. The theory of fuzzy logic extends the ontology of mathematical research to a composite that leverages quality and quantity and contains certain fuzziness. We try to solve the issues associated with uncertainty in trust management using fuzzy logic. First, we need to identify the subjects of those issues. These subjects are either the sources of trust-related information needed in trust management or the entities with which trust relationships are built. This subject set can be defined as follows.

Definition 4.1 Set of subjects in trust management

The set of subjects in trust management is all the subjects that are either the sources of trust-related information or are the entities with which trust relationships are built. This set is represented as X in this paper.

Then we need to define a general fuzzy set in trust management.

Definition 4.2 Fuzzy set for trust management

For every element x in the set of subjects X, there is a mapping $x \mapsto \delta(x)$*, in which* $\delta(x) \in [0,1]$*. The set* $\Delta = \{(x, \delta(x))\}$ *for* $\forall x \in X$ *is defined as a fuzzy set for trust management.* $\delta(x)$ *is defined as the membership function for every X in* Δ .

All the fuzzy sets on X are represented as Z(X). Then we can use a group of fuzzy sets from Z(X) to group all the elements of X into several sets with different levels of uncertainty. For example, we can use a group of three sets $Z_i \in Z(x)$ to categorize of uncertainty in trust management.

Z_1 *represents not recommended;*

Z_2 *represents normally recommended;*

Z_3 *represents highly recommended.*

In real life, the level of uncertainty cannot be limited to only one set, and the degrees to these sets are not simply 'total' or 'none'; additionally, it is sometimes difficult to determine which set or sets should be used for certain kinds of uncertainty. In other words, these sets are not exclusive to each other. So when we deal with certain kinds of uncertainty, a vector consisting of the degrees of belongingness to each set $D=\{d_1, d_2, d_3\}$ is more appropriate for describing the actual trustworthiness-based judgment from daily life, in which $d_i (i=1,2,3)$ is the degree of belongingness to set $Z_i (i=1,2,3)$. Meanwhile, there are several ways to determine or calculate the degrees d_i. One way is direct judgment that determines the degree from direct experience or evaluation. Another one is indirect inference that determines the degree via an analysis of an indirect source. For example, reputation is relatively subjective while the evaluation method may be very objective, and recommendation is relatively objective while the source of information may be subjective.

IV. FUZZY REPRESENTATION OF UNCERTAINTY

To reason among the degrees of uncertainty in trust management for further inference or decision-making, we need to represent uncertainty formally. Direct trust is formally described as $a \xrightarrow{D} b[Z]$, which means entity a is willing to rely upon entity b to degree D for the categorized uncertainty Z. D is a vector with corresponding degrees of belongingness for each set in categorization Z. Direct trust is from direct experience of the trustworthiness of the other entity or from a judgment with subjective/objective evaluation. Indirect trust is described as $a \underset{P}{\xrightarrow{D}} b[Z]$, which means entity a is willing to rely upon b to degree D following P's recommendation for the categorized uncertainty Z. P is one or more entities constructing a path that gives a recommendation to entity a for entity b. D is a vector with corresponding degrees of belongingness for each set in categorization Z. Indirect trust is derived from the recommendation passed through one or more intermediate entities. There are also two types of recommendations. One type is that the recommender had direct experience with the recommended entity so that the P has only one entity; the other is that the final recommender formed the recommendation from further recommendations of other recommenders so that the P has more than one entity constructing a chained recommending path or a compound recommending graph. But from the recommendee's (entity a's) point of view, there is no big significance related to with the number of entities forming the recommending path; the recommendee (entity b) only cares about the final recommender's capability to make accurate recommendation based on its own experience and trustworthiness.

The use of fuzzy rules to describe uncertain rules in trust management can involve rules in which we have antecedent terms of the form:

"*If the probability of (some event) is high, then a certain action is performed.*"

Here, we will incorporate PBG probability distribution for evaluating the uncertainty level of this type of antecedent by comparing alternative events for this case. In order to formalize the antecedent in the above example rule, we use Y to represent a fuzzy subset of $Z(X)$ in the domain of X. This corresponds to a general fuzzy event. We also use a fuzzy probability H corresponding to the description of "high" in the previous example. Then the rule becomes:

"*If the probability that (X is Y) is H, then a certain action is performed.*"

If we use W to indicate the variable corresponding to the "probability of the event is," the rule can be represented as:

"*If W is H, then a certain action is performed.*"

We will apply this general form to describe fuzzy rules in a trustworthiness-based decision system for e-commerce to express real life uncertainty in trust management and decision making with human linguistics. Here different formats of the probability function W introduce different types of rules. If W is a threshold function, the rule becomes a binary decision rule; if W has a fuzzy definition, the rule is a fuzzy rule; if W uses a granular probability distribution, the rule becomes most suitable for uncertainty description in human linguistics. Detailed comparison of these three probability functions can be found in [9].

V. ENFORCEMENT OF FUZZY POLICY FOR UNCERTAINTY MANAGEMENT

Currently, most people use Zadeh operators $\wedge$ and $\vee$ to perform calculation and analysis with fuzzy logic. But these operators are too imprecise in that too much information will be lost if these are the only operators used. Thus several general class fuzzy operators are proposed [10]. To adapt to different sources of uncertainties in trust management, a parameterized general intersection operator and union operator are needed. They are also called T-norm and S-norm. With different values of the parameters, these operators can maximize the expressiveness and flexibility of the system to capture people's intentions toward these uncertainties. Here we choose a general class of parameterized fuzzy operators proposed by Dubois and Prade [5] to perform further calculation and analysis. Because these operators are suitable for policy analysis and have clear semantic meanings, the intention embedded in fuzzy sets can be easily enforced. So we define T-norm and S-norm as follows.

Definition 5.1 T-norm
For fuzzy set A,B ∈Z(X) andα ∈[0,1],

$$(A \cap B)(x) = T(A(x), B(x), \alpha) = \frac{A(x)B(x)}{\max\{A(x), B(x), \alpha\}},$$

in which $A(x)$ *and* $B(x)$ *represent x's degrees of member function to fuzzy sets A and B.*

Definition 5.2 S-norm
For fuzzy set A,B ∈Z(X) and α *∈[0,1],*

$$(A \cup B)(x) = S(A(x), B(x), \alpha) = \frac{A(x) + B(x) - A(x)B(x) - \min\{A(x), B(x), (1-\alpha)\}}{\max\{1 - A(x), 1 - B(x), \alpha\}}$$

in which $A(x)$ *and* $B(x)$ *represent x's degrees of member function to fuzzy sets A and B.*

Then we define two calculators on vectors of fuzzy values. Suppose we have two fuzzy value vectors $D_1 = \{d_{11}, d_{12}, ..., d_{1P}\}$ and $D_2 = \{d_{21}, d_{22}, ..., d_{2P}\}$.

Definition 5.3 Connection calculator

$D_1 \otimes D_2 = \{T(d_{11}, d_{21}, \alpha), T(d_{12}, d_{22}, \alpha), \ldots, T(d_{1P}, d_{2P}, \alpha)\}$ *Definition 5.4 Union calculator*

$$D_1 \oplus D_2 = \{S(d_{11}, d_{21}, \alpha), S(d_{12}, d_{22}, \alpha), \ldots, S(d_{1P}, d_{2P}, \alpha)\}$$

After we define the above calculators, we can perform formal analysis on fuzzy sets and fuzzy rules used for uncertainty expressions. Here we define two sets of derivation rules (deduction rules and consensus rules) to handle different types of uncertainty. Below are the formal descriptions of deduction rules.

Definition 5.5 Deduction rules

$$a \xrightarrow{D} b[Z] \wedge b \xrightarrow{D'} c[Z] \Rightarrow a \xrightarrow[P'']{D''} c[Z] \wedge (P'' = \{b\}) \wedge (D'' = D \otimes D')$$

$$a \xrightarrow{D} b[Z] \wedge b \xrightarrow[P']{D'} c[Z] \Rightarrow a \xrightarrow[P'']{D''} c[Z] \wedge (P'' = \{b, P'\}) \wedge (D'' = D \otimes D')$$

$$a \xrightarrow[P]{D} b[Z] \wedge b \xrightarrow[P']{D'} c[Z] \Rightarrow a \xrightarrow[P'']{D''} c[Z] \wedge (P'' = \{P, P'\}) \wedge (D'' = D \otimes D')$$

Deduction rules are used for a recommendation's connection to construct a whole recommendation chain that allows the trustworthiness to be transferred from one end to the other end. For the trust relationships from the same categorization, deduction rules can form a new connection using the trust relationship between the recommender and the recommendee and embed the content of that recommendation into the new connection. Below are the formal descriptions of consensus rules.

Definition 5.6 Consensus rules

$$a \xrightarrow{D_1} b[Z] \wedge a \xrightarrow{D_2} b[Z] \wedge \ldots \wedge a \xrightarrow{D_n} b[Z] \Rightarrow a \xrightarrow{D''} b[Z] \wedge (D'' = D_1 \oplus D_2 \oplus \ldots \oplus D_n)$$

$$a \xrightarrow[P_1]{D_1} b[Z] \wedge a \xrightarrow[P_2]{D_2} b[Z] \wedge \ldots \wedge a \xrightarrow[P_n]{D_n} b[Z] \Rightarrow a \xrightarrow[P'']{D''} b[Z] \wedge$$
$$\left(P'' = \{P_m \mid |P_m| = \min\{|P_i| (i = 1 \ldots n)\}\}\right)$$
$$\wedge \, (D'' = D_1 \oplus D_2 \oplus \ldots \oplus D_n)$$

Consensus rules are used for combining of multiple recommendations for the same kind of categorization. When two or more recommendation paths appear simultaneously, consensus rules can synthesize the opinions to form a comprehensive recommendation. The shortest recommending path is the easiest path to verify that indirect information, even if the value of the trust degree vector is not as high as others. We use this path as the recommending path for verification of that recommendation. But more likely we will only use the unified trust degree vector alone after the composition.

With the help of the fuzzy operations and rules defined above, we can form a formal decision-making process to handle uncertainty in personalized recommendation involving the management of trustworthiness. Users need to define the categorization of uncertainty. Then the decision-making process uses fuzzy operations to combine uncertain information from different sources. After defuzzification of the trustworthiness degrees, users need to judge whether the final degree is consistent with their own rules. If not, the parameters of the fuzzy operations need to be adjusted

VI. IMPLEMENTATION

A. System architecture

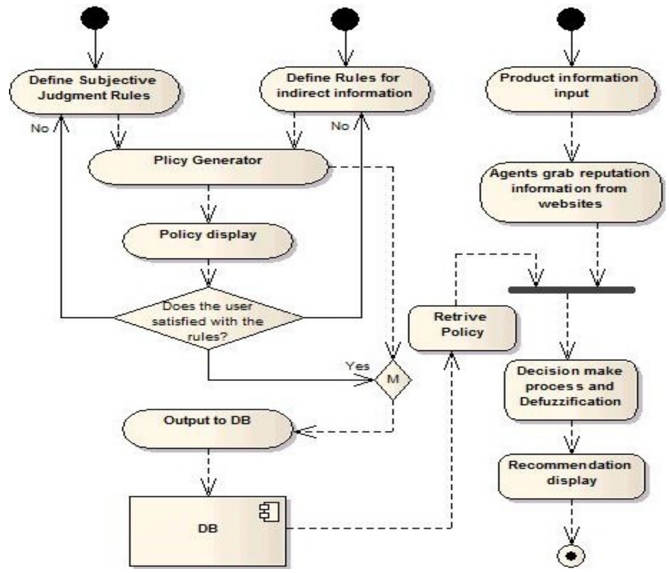

Fig.1. System Architecture

Figure 1 illustrates the system architecture of our prototype system. After users defining their fuzzy policies, the system stores these policies in a database. Then, when users use the system to select products, the system retrieves policies from the policy database and applies these policies onto the decision process based on the information grabbed from ecommerce sites and consumer reporting agencies by a number of agents. Our system grabs product information and venders' reputation through e-commerce sites where we can apply our agents. Each agent corresponds to one e-commerce site. If reputation information is not directly available from these websites, our agents will grab such information from consumer-reporting websites such as BBB or epinion.com. Finally a list of recommendations is returned to users.

B. User interface

Following the decision process and system architecture described above, we illustrate some practical fuzzy policies, the user interface to input fuzzy policies, and the enforcement mechanism to enforce these policies for e-commerce applications. Since the shopping decision of a product involves both indirect information and subjective judgment, we generate our policies using both indirect information from reputations and subject judgment for price of the product. All policies follow the general rule (policy) format discussed in section 4. One example fuzzy policy is illustrated below.

- If the reputation of the vendor is excellent/average/below average and(or) the reputation of the product is good/average/poor and(or) the price of the product is expensive/average/cheap then the product is highly /normally/not recommended.

We also provide a user interface to assist users to input these policies consistent with the accurate rules or intentions in their minds. It allows users to change the flexible parts in fuzzy policies according to their own shopping needs. Furthermore users can modify membership functions rather than use default functions, and combine membership functions using and/or operator between any two of the factors. The system also allows users to add e-commerce sites to the search list, from which is used by agents to grab product information and vender's/ product's reputation.

Default membership functions follow general shopping practices. But the system still allows consumers to modify all the membership functions by changing sampling points, which are used to sketch the shape for the fuzzy membership functions if the default membership functions do not accurately capture consumers' own rules or intentions. Once the definitions of fuzzy polices are finally determined, the system uses a policy generator to translate the fuzzy policies into XACML format, and store them in a policy database. Then consumers need to input information of the products. Then agents will grab price from e-commerce sites and reputation information from BBB, epinion, or other consumer reporting agencies. Once the agents get all needed information, system will list top 5 recommendations through the decision process described in section 6.1. Users can also refine system's accuracy by following this decision process. Figure 2 illustrate the policy definition, membership function and recommendation interfaces.

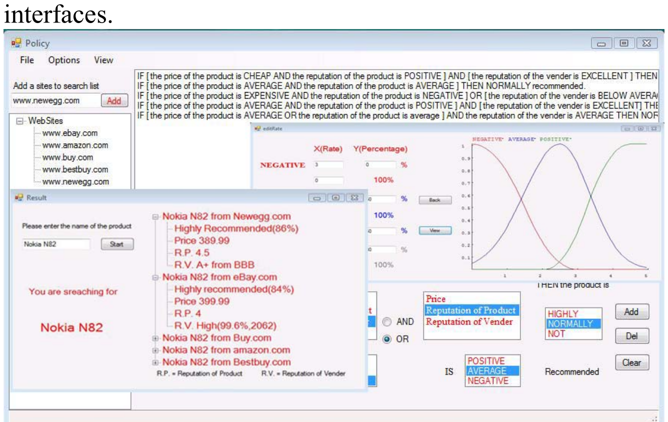

Fig.2. User Interface

VII. Experiments and Discussion

To exam the performance and adaptability of the system, we select a Nokia N82 cell phone as the target of shopping activities. Then we run the system on two different sets of policies to compare the recommendations for different sites, and compare the recommendations with user's own decisions. Furthermore we searched the same product on websites that provide product comparisons and compared our recommendations to their results. We also did a survey on 30 different people to confirm the usability of our system. Most of them confirmed the usability of the system and willing to use the system.

A. Experiments on different policies & different e-commerce sites

We run our system on two different policy sets. The first policy set follows a common sense, which prefers the balance of reputation and price. The second policy set prefers high price. The first policy set is defined as below:

-IF [the price of the product is CHEAP AND the reputation of the product is POSITIVE] AND [the reputation of the vender is HIGH] THEN HIGHLY recommended.

-IF [the price of the product is AVERAGE AND the reputation of the product is AVERAGE] AND the reputation of the vender is AVERAGE THEN NORMALLY recommended.

-IF [the price of the product is EXPENSIVE AND the reputation of the product is NEGATIVE] OR [the reputation of the vender is LOW] THEN NOT recommended.

The policies of policy set 2 are defined below.

-IF the price of the product is CHEAP AND the reputation of the vender is HIGH THEN NOT recommended.

-IF the price of the product is AVERAGE AND the reputation of the vender is HIGH THEN NORMALLY recommended.

-IF the price of the product is EXPENSIVE AND the reputation of the vender is HIGH THEN HIGHLY recommended.

Table.1. Results of Final Decisions and Recommendations for Different E-commerce Sites

E-commerce site	Price	R.P.	R.V.	Final decision (1)	Final decision (2)
Newegg	389.99	4.5	A+(BBB)	Highly(86%)	Normally(50%)
eBay(V1)	399.99	4	High(99.6%, 2062)	Highly(84%)	Normally(50%)
Buy.com	371.54	5	B+(BBB)	Normally(97%)	Normally(73%)
Amazon	372.38	4.5	B-(BBB)	Normally(91%)	Normally(50%)
Bestbuy	599.99	4	A-(BBB)	Normally(53%)	Highly(75%)
eBay(V2)	399.99	4	LOW(93.1%, 12)	Not(53%)	Not(69%)

(R.P. represents "reputation of product"; R.V. represents "reputation of vender". Final decision 1 and 2 are made based on policy set 1 and2. R.V. is directly got from BBB.org, R.V. of eBay are calculated from positive feedbacks and the number of feedbacks. Final decisions use percentage to represent the reliability of the recommendation.)

From table 2 we can see that in final decision (1), the most recommended shopping target site is neither the cheapest nor the most reputable, but its excellent vender reputation (A+). This satisfies the common sense defined in policy set 1. In the final decision (2), we can clearly tell that just one cell phone, the most expensive one from bestbuy.com, is highly recommended by our system. This result is consistent with the second policy set that prefers the most expensive offer. So our system can clearly capture the preference of a user through defined policies and recommend the right e-commerce sites following the user's preferences.

B. Comparison with other recommendation systems

When consumers search products from the Internet, there are several recommendation websites that can provide a list of product information, which contains price and feedbacks of the vender. We searched our target product Nokia N82 cell phone from 3 such websites. Table 2 illustrates the top 5 recommended e-commerce sites of each recommendation websites. From the table we can clearly tell that each of these websites has different recommendations. However users can hardly tell which vender is most recommended or even cannot find any particular rankings from the results. Furthermore, users are not specified how these websites calculate the result. Some venders even have no reputation are still recommended by these websites. Compared with our system, our system always recommends the sites which match users' intensions most and ranks them according to the recommendation level that calculated by the system. Thus users can clearly identify which sites are most recommended by the system. So the results indicate that our recommendation reflects more users' preferences, while other using their own unknown default rules.

VIII. CONCLUSION

This paper proposes a model of uncertainty based on fuzzy logic to handle uncertainty and fuzziness in decision process for e-shopping activities based on trustworthiness. Compared with the trust management model proposed by Josang [9], this paper identifies different sources of uncertainty in trustworthiness, and finds that this uncertainty cannot be simply treated as a probability and thus cannot be described by a simple probability model. This paper introduces a general categorization to describe various types of trustworthiness in practical e-commerce environments. In addition, the derivation rules proposed in this paper incorporate a parameter to allow users to adjust the membership function through a feedback mechanism in order to make the system adapt to users' changing intentions and preferences. The model proposed in this paper can be used in evaluation, analysis, and derivation of policies in management of trustworthiness directly. As illustrated in section 6, application of this model in an agent-based e-commerce recommendation application can help consumers make right online shopping decisions following their own preferences using indirect information and their subjective price judgments. The experiments in section 7 confirm the accuracy, flexibility, usability, and adaptability of the system.

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Table.2. Result from Other Recommendation Websites

	Dealtime			**PriceGrabber**			**MSN shopping**			**Our System**		
	Sites	**R.V.**	**Price**	**Sites**	**R.V.**	**Price**	**Sites**	**R.V.**	**Price**	**Sites**	**R.V.**	**Price**
1	Dell	3	377.99	Dell	4.5	377.99	Dell	4.5	377.99	Newegg	A+	389.99
2	QVC.com	4.5	418.96	Buy.com	2	371.54	Buy.com	3.5	371.54	eBay	High	399.99
3	amazon.com	3.5	372.38	Icellx	N/A	439.99	NothingButSoftware	N/A	410.44	Buy.com	B+	371.54
4	onsale.com	3.5	361.49	unbeatableSale	4	458.75	icellx	N/A	439.99	Amazon.com	B-	372.38
5	macMall	3.5	371.19	TechforlessStore	4.5	472.51	unbeatableSale	3	458.75	bestbuy	A-	599.99