On Fuzziness in Relationship Value Segmentation: Applications to Personalized e-Commerce

MIGUEL-ÁNGEL SICILIA
and
ELENA GARCÍA

Relationship marketing strategies focus on the construction and maintenance of tailored relationship with customers. Consequently, electronic commerce systems following the relationship approach may benefit from Web personalization techniques in tailoring the interaction with its users according to an evolving customer model. 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. In this paper, a fuzzy approach to value segmentation is described, allowing more flexible customer segments. Fuzzy models of value estimations are represented by fuzzy triangular numbers, and two segmentation approaches, *directed* and *discovery-oriented* are briefly described. The usefulness of the approach is then illustrated through concrete personalization techniques based on those fuzzy categories.

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1. INTRODUCTION

Relationship marketing [23] is nowadays considered a paradigm shift from previous production-oriented marketing approaches, in spite of controversies about its novelty [18]. The focus of this approach is on building and maintaining relationships with customers (or suppliers), giving each of them a personalized treatment, including in some cases targeted promotions and even tailored prices, among other adaptations. In consequence, electronic commerce systems following a relationship approach may benefit from a variety of Web personalization technologies [19], which are a subset of the more general category of *adaptive hypermedia* technologies [5]. These technologies provide support to relationship maintenance through adapted contents and navigation, based on some form of evolving customer model obtained from the interaction between the users and the commerce Web site. The activities oriented towards refining, revising and augmenting the customer model (or more generally, the *user model*) are commonly referred to as *user modeling* activities in the research literature regarding the topic [4]. In the just described context, market segmentation in its various forms [29] can be considered as one of the essential user modeling activities that will serve as the basis for subsequent personalization.

Authors' addresses: Miguel-Ángel Sicilia, Computer Science Department, Carlos III University, Avda. Universidad, 30 – 28911 Leganés (Madrid), Spain, msicilia@inf.uc3m.es. Elena García, Computer Science Department, University of Alcalá, Ctra. Barcelona, km. 33600 – 28871 Alcalá de Henares (Madrid), Spain, elena.garciab@uah.es.

Customer segmentation activities (we will use here the terms "market segmentation" and "customer segmentation" interchangeably) in the context of relationship marketing make an special consideration to value-segmentation among the possible *bases* [29] (the term "bases" refer to analysis criteria). This is due to the fact that the principles of relationship marketing give emphasis to retention of the most "valuable" customers. But the term "valuable" can be considered as vague at least to some extent, since the frontier between valuable and non-valuable customers does not posses sharp and clear boundaries. Moreover, customer value is a long-term measure that entails predictions of future transaction records, thus entailing some degree of subjective or statistically inferred uncertainty. Vagueness and uncertainty are two different forms of information imperfection – according to Smets [26] – that occur simultaneously in value analysis.

In this paper, we describe a model to characterize vagueness in customer value segmentation, and a straightforward mathematical method to assess value segments that allow for some degree of flexibility. Although a similar approach can be applied to classic general and product-specific bases, we have focused on value segmentation since it entails a higher degree of uncertainty and imprecision derived from the difficulty of characterizing traits like loyalty, and of predicting long term value and retention plausibility. In addition, some concrete personalization techniques based on the resulting fuzzy categories are sketched to illustrate the benefits of the approach. The rest of this paper is structured as follows. Section 2 describes the fuzzy model for value-based market segmentation. Section 3 provides example personalized interactions based on such vague user model. Finally, Section 4 gives conclusions and some possible future directions for research.

2. A FUZZY APPROACH TO VALUE SEGMENTATION

Relationship marketing emphasizes the importance of customer relationships as one of the key assets of the business [2]. Once this importance has been recognized, the problem of *which* customers are more beneficial to build closer relationship arises. The concept of customer value (or better, of relationship value) is an attempt to solve this problem. Once value has been determined, the most valuable customers will be given priority, and less valuable ones will be subject to scrutiny in search of improvement. Approaches using customer profitability as the measure of consumer value have several shortcomings [21] that have fostered the development of more comprehensive and forward-looking approaches, encompassing relationship lifetime, risk of volatility and relationship-maintenance costs as additional aspects of valuing relationships. Since the inception of the market segmentation concept by Smith [27], it has been recognized that segments are derived from the heterogeneity of customer wants, but they are also modeled after managers' conceptualization about the structure of each concrete market. In value segmentation, the higher degree of uncertainty about customer estimates makes the importance of managers' conception critical. According to previous on cognitive psychology research initiated by Rosch [20], human categories are vague and organized around prototypical examples, thus making Fuzzy Set Theory [13] a good candidate to model manager conceptions about relationship value. In fact, uncertainty is considered an important element in recent methodologies for the assessment of relationship value [11]. Nonetheless, although some previous work has applied fuzzy clustering to concrete attitude and interest segmentation settings [17], and to give support to decision in marketing [14], a fuzzy model of relationship value has not been approached yet.

In the rest of this section, we first provide a generic fuzzy model for relationship value, based on triangular fuzzy numbers, and then discuss two approaches to segmentation considering imprecision. Some classical effectiveness criteria for segmentation are then briefly discussed with regards to imprecise segmentation.

2.1. A Generic Fuzzy Value Model

Relationship value is an emerging concept subject to revision and extension for which commonly accepted formulations are not still firmly established. Here we will deal with a generic formulation adapted from Martha Rogers'[1], which estimates the net present value of the future stream of profits from a given customer (1).

$$V = \sum_i (1+d_i)^{-i} \cdot p_i \qquad (1)$$

The expression in (1) aggregates the value for each period i of a given customer, where d is the discount rate and p_i is a factor of (a) the expected incremental contribution on purchases, (b) estimated duration and 'trajectory' of the relationship, and (c) other costs and contributions, financials or not. The integration of fuzziness in this formulation of relationship value will follow the approach described by Abdel-Kader and Dugdale [1], that considers both financial and intangible benefits in a model of investment evaluation. Following the work of Laarhoven and Pedrycz [15], triangular fuzzy numbers will be used for practical computation purposes. A fuzzy number M in $\Re$ is a triangular number if its fuzzy membership function $m_M:\Re\rightarrow[0,1]$ is in the form:

$$m_M(x) = \begin{cases} 0 & x \le a \\ (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & x \ge c \end{cases} \qquad (2)$$

Expression (2) is often abbreviated in the form $M=(a,b,c)$. Triangular fuzzy numbers are a simple way to allow for imprecision derived from uncertainty or subjectiveness. For example, an estimated duration of 'approximately fifteen months' may be represented by (13, 15, 17), while an exact estimation of a maintenance cost for a customer may be represented by (0, 200, 0). Imprecision can be added to the customer value expression (1) by considering each of its factors as a fuzzy triangular number specified as the lowest possible estimate, the best estimate, and the largest possible estimate, following the approach use to measure financial returns in [1]. Since p_i and d_i (and also the factors required to compute p_i) are triangular fuzzy numbers, respectively (p_{i1}, p_{i2}, p_{i3}) and (d_{i1}, d_{i2}, d_{i3}), the value V is also a triangular fuzzy number (V_1, V_2, V_3). Expression (1) can be extended to its fuzzy counterpart as follows:

$$(V_1, V_2, V_3) = \left(\sum_i (1+d_{i1})^{-i} \cdot p_{i1}, \sum_i (1+d_{i2})^{-i} \cdot p_{i2}, \sum_i (1+d_{i3})^{-i} \cdot p_{i3} \right) \quad d_{i1} \ge 0 \qquad (3)$$

In consequence, the membership function of V is approximated by the triangular shape:

$$m_V(x) = \begin{cases} (x-V_1)/(V_2-V_1) & V_1 \le x \le V_2 \\ (V_3-x)/(V_3-V_2) & V_2 \le x \le V_3 \\ 0 & otherwise \end{cases} \qquad (4)$$

Table 1 provides data for a simple numerical example about the application of the formulas (values are scaled in the [0, 1] interval), assuming a fixed crisp discount rate of

[1] Available at http://www.1to1.com/.

0.05, and p_i is computed as the product $a_i(\times)b_i(\times)c_i$, with the three factors corresponding to rough fuzzy scaled estimations of the elements (a), (b) and (c) described above. The final values obtained according to (3) have been multiplied by a factor of 10^3 to obtain an output range above one. Since the selection of the fuzzy numbers is carried out by the expert, different degrees of imprecision are assigned to different customers, and the degree of imprecision also varies from period to period.

$a_{i1(A)}$	$a_{i2(A)}$	$a_{i3(A)}$	$b_{i1(A)}$	$b_{i2(A)}$	$b_{i3(A)}$	$c_{i1(A)}$	$c_{i2(A)}$	$c_{i3(A)}$	$V_{i1(A)}$	$V_{i2(A)}$	$V_{i3(A)}$
0,20	0,30	0,35	0,60	0,80	1,00	0,05	0,10	0,20	**5,71**	**22,86**	**66,67**
0,20	0,30	0,35	0,50	0,70	0,90	0,05	0,10	0,20	**10,25**	**41,90**	**123,81**
0,25	0,30	0,35	0,50	0,70	0,90	0,05	0,15	0,25	**15,65**	**69,12**	**191,84**
0,15	0,20	0,20	0,50	0,70	0,90	0,00	0,01	0,10	**15,65**	**70,27**	**206,65**
0,15	0,20	0,20	0,40	0,70	0,90	0,00	0,00	0,15	**15,65**	**70,27**	**227,80**
0,05	0,10	0,10	0,30	0,50	0,70	0,05	0,10	0,15	**16,21**	**74,00**	**235,64**
0,05	0,10	0,10	0,20	0,40	0,60	0,05	0,10	0,10	**16,56**	**76,84**	**239,90**
0,05	0,10	0,10	0,10	0,20	0,25	0,00	0,00	0,00	**16,56**	**76,85**	**239,93**
0,05	0,05	0,06	0,05	0,10	0,15	0,00	0,00	0,00	**16,56**	**76,86**	**239,93**
0,05	0,05	0,06	0,00	0,10	0,10	0,00	0,00	0,00	**16,56**	**76,86**	**239,94**
0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	**16,56**	**76,86**	**239,94**
0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	**16,56**	**76,86**	**239,94**

$a_{i1(B)}$	$a_{i2(B)}$	$a_{i3(B)}$	$b_{i1(B)}$	$b_{i2(B)}$	$b_{i3(B)}$	$c_{i1(B)}$	$c_{i2(B)}$	$c_{i3(B)}$	$V_{i1(B)}$	$V_{i2(B)}$	$V_{i3(B)}$
0,20	0,30	0,35	0,60	0,80	0,90	0,05	0,10	0,20	**5,71**	**22,86**	**60,00**
0,20	0,30	0,40	0,50	0,75	0,90	0,05	0,10	0,25	**10,25**	**43,27**	**141,63**
0,25	0,30	0,40	0,50	0,70	0,90	0,05	0,15	0,30	**15,65**	**70,48**	**234,93**
0,30	0,40	0,50	0,65	0,70	0,75	0,10	0,20	0,25	**31,69**	**116,55**	**312,06**
0,35	0,40	0,60	0,75	0,80	0,85	0,19	0,20	0,20	**70,77**	**166,69**	**391,98**
0,40	0,50	0,60	0,75	0,80	0,85	0,19	0,20	0,20	**113,30**	**226,39**	**468,09**
0,50	0,60	0,70	0,75	0,80	0,85	0,19	0,20	0,20	**163,94**	**294,62**	**552,66**
0,55	0,60	0,65	0,75	0,80	0,85	0,35	0,40	0,45	**261,66**	**424,57**	**720,94**
0,65	0,70	0,75	0,79	0,80	0,81	0,35	0,40	0,45	**377,51**	**568,96**	**897,16**
0,65	0,70	0,70	0,79	0,80	0,81	0,30	0,30	0,32	**472,08**	**672,10**	**1008,55**
0,68	0,70	0,70	0,79	0,80	0,81	0,30	0,30	0,32	**566,31**	**770,32**	**1114,63**
0,69	0,70	0,71	0,79	0,80	0,81	0,30	0,30	0,35	**657,37**	**863,87**	**1226,71**

Table 1. Example numerical data about customers *A* and *B*

The values in Table 1 are computed according to the following definitions of addition, multiplication and scalar multiplication on triangular fuzzy numbers:

$$M(+)N = (a+e, b+f, c+g) \qquad (5)$$

$$M(\cdot)N = (a \cdot e, b \cdot f, c \cdot g) \qquad (6)$$

$$\forall k > 0, \qquad M(\cdot)k = (a \cdot k, b \cdot k, c \cdot k) \quad (7)$$

given two triangular fuzzy numbers $M=(a, b, c)$ and $N=(e, f, g)$ and an ordinary positive number $k \in \Re$.

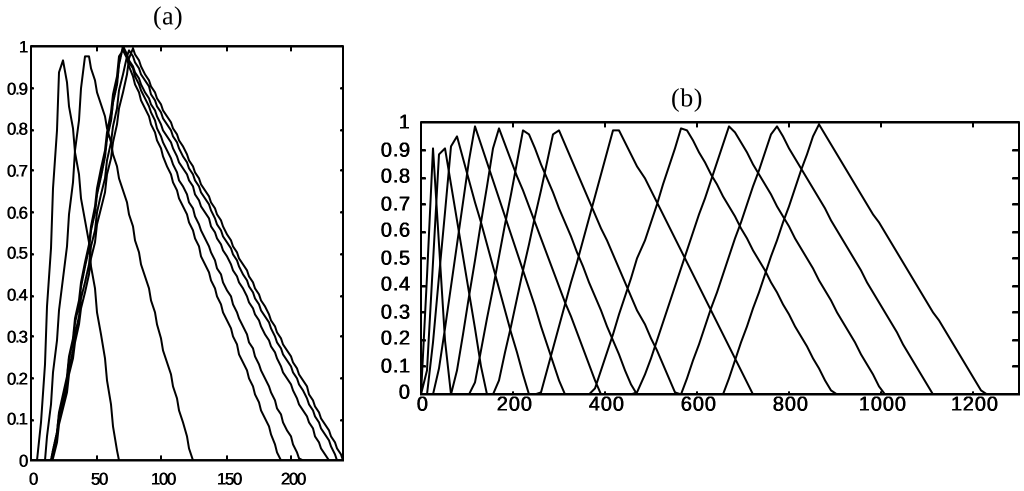

Figure 1. Evolution of fuzzy net present value of customers *A* and *B*

Figure 1(a) depicts the net value of the seven first periods of customer A. The small shifts of the triangular fuzzy numbers reflect a decrease in estimated customer value after an initial increase in the three initial periods. This analysis, that can be easily computed as a function of the degree of overlapping of the fuzzy numbers across periods, may lead to a marketing action to attempt to improve the relationship with customer A. Figure 1(b) shows the evolution of net present value of customer B. In this case, the evolution of the customer in the twelve periods analyzed evolves continuously, and ends in the higher end of the value scale. This clearly indicates a continuous and progressive relationship improvement, ending with the customer positioned as one of the most valuable. Subsequent marketing programs should start considering this excellent positioning in initial value estimations. The evolution of imprecision for each period in the case of customer B is depicted in Figure 2. The points reflect changes in the degree of imprecision regarding estimations. It should be noted that this imprecision may be due to an increase in optimistic estimations about the trajectory of the customer, so that often marketing actions may lead to a consideration of wider triangular fuzzy numbers, reflecting expectations of increased value. An interesting fact that arises when examining imprecise marketing estimates is that the fuzzy numbers representing net present value tends to increase its spread, reflecting higher propagated imprecision as time evolves.

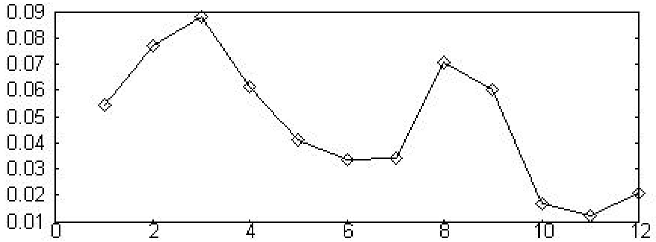

Figure 2. Evolution of imprecision in p_i of customer *B*

As the numerical examples have illustrated, three aspects are interrelated in customer value analysis: the rate of grow of the net value (i.e. shifts of the triangular fuzzy numbers), the increase in the spread of the fuzzy numbers, that provide a relative estimation of the degree of uncertainty of the calculated values, and the absolute positions of the fuzzy numbers in the value scale. Stable growing rates combined with relatively moderate uncertainty degrees are positive indicators of interesting relationships, even in the case that the aggregated net present value were relatively small. In any case, these evidences require further study to come up with reliable analysis methods.

2.2. Fuzzy Value Segmentation

Once the (fuzzy) relationship value of each customer is available, segments can be obtained by using linguistic terms regarding value. In the simplest setting, users are categorized in three groups: "most valuable customers" (MVC), "most growable customers" (MGC) and "below zero customers" (BZ). In idealized terms, given a distribution of customers according to relationship value, a shift of the distribution to the right – as depicted in Figure 3 – results in an increase of MVC and a decrease of BZ, which in turn results in an overall aggregate grow of relationship value.

In Figure 3, the two vertical lines represent a given crisp frontier dividing the three pre-established customer segments. This approach suffers from the well-known crisp-boundary effect that have originated the application of fuzzy techniques to many practical situations. For example, it is difficult to determine whether a customer positioned very close to the frontier between the BZ and MGC categories should be subject to marketing tactics typical of MGC or not. If a fuzzy value model as the one described above is used, this kind of situations become even more common, since customer values may actually span across several value segments to some extent. This rationale calls for research on the introduction of fuzziness as a central concern in customer segmentation.

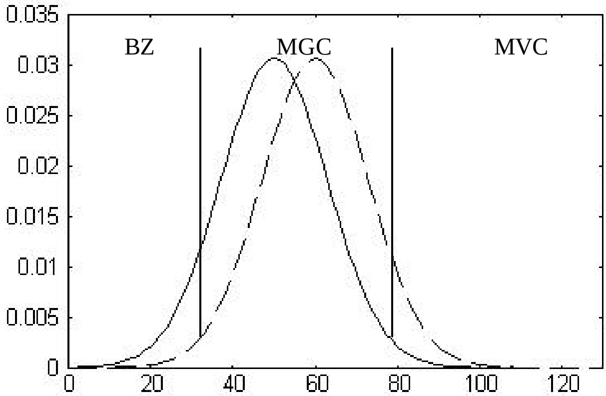

Figure 3. Illustrative representation of the desired improvement regarding customer distribution

Two kinds of value segmentation processes may be approached. On the one hand, if the marketing expert has some pre-established assumptions about value segments for the concrete business, we have a directed method. On the other hand, it is possible that not such clear assumptions are at hand, so that some form of discovery process is required (this categories are often called *a priori* and *post hoc* respectively in marketing literature

[3]). Here we will restrict ourselves to the aprioristic approach, since fuzzy clustering has been applied yet to conventional market segmentation scenarios.

When using a directed method, the type and number of segments are determined in advance by the expert. A straightforward directed approach may proceed by eliciting [3] one fuzzy set for each of the pre-established value categories, and then using some form of similarity or compatibility measure to determine the degree to which the value of a given customer matches each of the categories. For example, a small experiment with three experts using a straightforward membership exemplification technique (as described in [3]) resulted in the three categories f-BZ, f-MGC, f-MVC showed in Figure 5. It was obtained by regression of the example memberships taken for twenty sample customer value characterizations following the expression (1), and according to the computation used for the data in Table 1. Although the small amount of experimental data is not sufficient to take the functions in Figure 5 as definitive, and their definition may vary depending on the sector or situation, they serve as an illustration of the flexible approach taken. It should be noted that the f-MGC category has been approximated by a Gaussian function having different left and right slopes. The higher decrease rate in the right slope may be interpreted as a belief of lower sensitivity to growing actions for customers of present large values. In addition, the f-BZ category is non-normalized in the sense that no element attains full membership in it, perhaps reflecting the belief that every relationship has a chance to be improved at least to some extent.

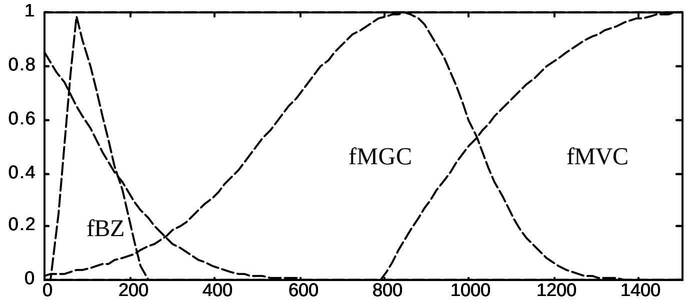

Figure 4. Fuzzy categories BZ, MGC, MVC and its overlapping with a concrete fuzzy customer value

In Figure 4, a triangular fuzzy value of a customer is showed using dashed lines. It becomes clear that its degree of overlapping with f-MVC is zero, while the degree of overlapping with f-BZ is large, and it also overlaps in a small region with f-MGC. Of course, other common a priori techniques like contingency tables, regression or cross-tabulation may be studied and extended for fuzziness, but this is left to future work.

Discovery-oriented methods require using clustering algorithms to find underlying relationships between customers. Although fuzzy clustering has been applied yet to customer segmentation [12], further research should address the specifics of imprecise values.

2.3. Segmentation Effectiveness Criteria Revisited

The assessment of a market segmentation approach requires an examination of its effectiveness and manageability from the viewpoint of marketing activity. A number of criteria have been proposed for that assessment, being the most frequently put forward those described in [9]: identifiability, substantiality, accessibility, stability, responsiveness and actionability. *Identifiably* can be defined as the extent to which the expert can recognize distinct groups of customers by using specific segmentation bases. As a consequence, the explicit introduction of fuzziness entails the need for a measure of the degree of identifiably – i.e. the degree of fuzziness – for a given situation. The concept of *entropy* of fuzzy sets [7], that has been also studied with regards to arithmetic operations [28] can be used for that purpose. *Responsiveness* can be defined as the extent to which segments respond uniquely to marketing efforts directed at them. This concept requires a re-formulation in the presence of fuzzy segments, considering partial memberships. An straightforward approach to measure responsiveness may be that of compensating a given crisp measure of the concept with the degree of membership to the given segment. For a given segment *S*, overall responsiveness may be computed as the aggregation of the crisp responsiveness compensated with fuzzy membership to *S*, relative to the responsiveness of the same individuals to other segments, since a single customer may (partially) belong to more than one segment. A relative degree of *stability* in time is required, at least for a period long enough to implement targeted marketing strategies. Conversely, marketing actions can be tailored to detected change degrees in the evolution of customers. When fuzzy methods are used, approximate rates of change can be extracted from the analysis of the evolution of customer value as depicted in Figure 1. This form of analysis would produce a fuzzy time frame limiting the effectiveness of marketing actions. The spread of such a frame can be interpreted as a risk estimation. *Substantiality* (the fact that the segments represent a large enough proportion of the market), *actionability* (the degree to which the identification of the segments provides guidance for marketing decisions) and *accessibility* (the degree to which managers are able to reach the targeted segments) are not directly affected by the use fuzzy techniques.

3. PERSONALIZATION BASED ON FUZZY SEGMENTS

Once value segments are determined, a marketing strategy must provide differentiated treatment to customers in different segments. This includes providing tailored interactions through the commerce Web site. A number of research efforts [4] and also a variety of commercial personalization frameworks has been constructed to date [8]. One of the most used paradigms for personalization is the rule-based approach, offered by big commerce players like ATG[2] and BEA [3] (the other widespread paradigm is *collaborative filtering* – see, for example [22] –, but it focuses on the concrete marketing action of *cross-selling* through prediction of user likes). According to this approach, marketing staff is responsible for defining personalization rules targeted to subsets of users with an appearance like the one described informally in Figure 5(a):

```
Include these customers:
   <<logical expression>>
Exclude these customers:
  <<logical expression>>
Action:
  <<user model update>>
  | <<show content>>
  | <<apply marketing action>>
```

(a)

```
Include these customers:
  MGC and annualIncome > 1000
  And interest includes Cars
Action:
  Engage  in  02_Summer_Campaign
and Show:
  offerings   where   price   is
medium and product is sport_car
```

(b)

Figure 5. Syntax and example of personalization rule

[2] http://www.atg.com
[3] http://www.bea.com

In Figure 5(b) a simple example rule is provided that applies a campaign and enables some context to a subset of the MGC category. More complicated scenarios can be devised, but the essence of all of them is explicit of implicit categorization of users, and using these categories to target content, promotions, prices or to make tailored updates to the user model. When using fuzzy segments, the application of such rules becomes a matter of degree, so that their triggering may be specified through some form of activation threshold. Nonetheless, fuzzy categories also open new possibilities to implement personalization. For example, the actions may depend on the degree of membership to one or several (possibly overlapping) categories, e.g., in:

```
Include:fMGC and not fBZ Action:Apply high discount on Promotion1
```

So that if customer *c1* is positioned at value point 300, according to the functions in Figure 4, and using the standard product as the interpretation of 'and', and the negation as the complement, he/she will trigger the rule to an extent of 0.18*(1-0.14) = 0.15, while a customer *c2* at point 1125 (at the right slope of fMGC), will do it to the extent of 0.18*(1-0)=0.18. If 'high discount' is described also as a fuzzy set, slightly different discounts would be applied to *c1* and *c2*. This an other kinds of approximate rules [24] make more flexible the application of marketing actions, and interface-related interactions can also be adjusted to fuzzy degrees. For example, link annotation actions, like changing the size of fonts, can be achieved by analogous rules, as described in [25].

4. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Relationship marketing strategies face a big challenge in the characterization of the central notion of relationship value. The lack of a precise and reliable single measurement method and the vagueness included in the term itself point out the necessity of flexible, fuzzy modeling frameworks. We have described how fuzzy arithmetic can be used to extend a concrete, simple notion of relationship value, and also how value segmentation can be also generalized to its fuzzy counterpart. In addition, some examples of personalized Web technologies that can make use of the resulting customer segments have been described. This work has only set the scene for further research on fuzziness in relationship marketing. Fuzzy models in this area are capable of making explicit the diverse forms of uncertainty [26] that are inherent to market analysis and the measure of highly abstract notions like relationship value. Nonetheless, the appropriateness of such models require revisiting goodness criteria for segmentation and also the empirical assessment of the methods for capturing and using degrees of vagueness or uncertainty. Future research should address both the modeling and the segmentation problem in deeper detail. Advanced models of relationships and interactions should be considered [10], along with the role of flexible aggregation [6] in the elements driving the formulas for relationship value. Furthermore, comparative studies of segmentation approach effectiveness should be carried out, and choice theory, conjoint analysis and other marketing engineering decision approaches [16] should be revisited to provide them an explicit support to fuzziness.

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