PERSONALIZED DISCOUNT - A FUZZY LOGIC APPROACH

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Abstract: A growing challenge for the companies in the e-business era is customer retention. In today's global economy this task is getting, at the same time, more difficult and more important. In order to retain the potentially good customers and to improve their buying attitude this paper proposes to calculate personalized discounts. This calculus is based on a fuzzy classification which can derive the customers' value for an enterprise. This approach allows the company to drive the customer equity which treats the customers according to their real value in order to maximize its profit.

Key words: CRM, Discount Management, Customer Equity, Fuzzy Classification, Query Language, Relational Databases

1. INTRODUCTION

The growing importance of the e-business in today's economy forces the enterprises to adapt their behavior towards the different actors of the market. This is particularly true for the customer relationship management (CRM) as the traditional means based on the human relationship are no more available. In this area, the customer retention is a special issue because the global economy enabled by the Internet allows, on the one hand, the companies to offer their products or services worldwide and, on the other hand, also allows the customers to easily compare the different products/services and their prices.

When buying on the Internet the price is certainly one of the most important decision factors. For this reason companies are using different discount strategies in order to attract and retain their customers. Standard discount methods are based either on the *customer* (fixed discount per customer sometimes calculated for customer segments), on the *quantity* (scale price in regard to the quantity of the purchased items), on the *time* (promotional price for a given timeframe), on the *region* (discount depending on the region) or on *other products* (special price for a bundle of items).

A company can combine those different methods in order to fit its price strategy (see Inoue et al., 2001). By doing so, the company may encounter the following difficulties:

- Each method has to be defined manually and independently of the other chosen methods.
- The maintenance and adaptation of the discount methods can be difficult since new customers and products are regularly added.
- The combination of several methods may lead to discount collisions which have to be solved.
- With several independent discount methods it is almost impossible to maintain a consistent price strategy on the long run.

To avoid the mentioned problems and to improve the customer retention, a global discount method considering all the aspects of the customers, including the customer's buying attitude and potential, is needed.

This article presents a simple way of calculating personalized discounts in order to improve the retention rate of the potentially good customers. Based on a fuzzy classification, our approach can derive the customers' value according to an enterprise and, this way, can give each customer the discount he deserves. This approach, often called customer equity (see Blattberg et al., 2001; Rust et al., 2000), allows the company to reinforce the customers' loyalty and also encourages the customers to improve their buying attitude.

The reminder of the present paper has the following structure: Section 2 introduces the fuzziness with relational databases as well as the fuzzy classification concept, query language and implementation. Based on a fuzzy classification, the concept of customer equity and the calculation of personalized discounts are explained in section 3, which also presents the aggregated concept of customer loyalty and discusses the combination of the personalized discount approach with other discount methods in order to include the customer acquisition problematic. Finally, section 4 gives a conclusion and an outlook.

2. FUZZY CLASSIFICATION

2.1 Databases & Fuzziness

In practice, information systems are often based on very large data collections, mostly stored in relational databases. Due to an information overload, it is becoming increasingly difficult to analyze these collections and to generate marketing decisions.

In this context, a toolkit for the analysis of customer relationships which combines relational databases and fuzzy logic is proposed. Fuzzy logic, unlike statistical data mining techniques such as cluster or regression analysis, enables the use of non-numerical values and introduces the notion of linguistic variables. Using linguistic terms and variables will result in a more human oriented querying process.

The proposed toolkit reduces the complexity of customer data and extracts valuable hidden information through a fuzzy classification. The main advantage of a fuzzy classification compared to a classical one is that an element is not limited to a single class but can be assigned to several classes. Furthermore, each element has one or more membership degrees which illustrate to what extend this element belongs to the classes it has been assigned to. The notion of membership gives a much better description of the classified elements and also helps to find out the potential or the possible weaknesses of the considered elements.

In everyday business life, many examples can be found where fuzzy classification would be useful. In the customer relationship management for instance, a standard classification would sharply classify customers of a company into a certain segment depending on their buying power, age and other attributes. If the client's potential of development is taken into account, the clients often cannot be classified into only one segment anymore, i.e. customer equity. Other examples are risk management in an insurance company or client's credit worthiness in a bank. In the last case, studies have shown that with a sharp classification, clients with almost similar risks were classified very differently. The opposite happened too, that is with clearly different properties the clients' overall judgment was very similar.

The fuzzy classification is achieved by extending the relational database schema with a context model. A fuzzy Classification Query Language (fCQL) can directly operate on the underlying database so that no migration of the raw data is needed. In addition, fCQL allows marketers to formulate unsharp queries on a linguistic level. To implement this, an fCQL interpreter which transforms fCQL queries into SQL (Structured Query Language) statements for the sharp databases has been developed.

2.2 Fuzzy Classification with Linguistic Variables

In order to define classes in the relational database schema, we extend the relational model by a context model proposed by Chen (1998). This means that to every attribute A_j defined by a domain $D(A_j)$, we add a context $K(A_j)$. A context $K(A_j)$ is a partition of $D(A_j)$ into equivalence classes. A relational database schema with contexts R(A,K) is then the set $A=(A_1,\ldots,A_n)$ of attributes with associated contexts $K=(K_1(A_1),\ldots,K_n(A_n))$ (see Shenoi, 1995).

Throughout this paper, a simple example of relationship management is used. In this example, customers will be evaluated by only two attributes, turnover and payment time. In addition, these two qualifying attributes for customer equity will be partitioned into only two equivalence classes. The pertinent attributes and contexts for relationship management are:

- *Turnover* in dollars per month: The attribute domain is defined by [0,1000] and divided into the equivalence classes [0..499] for low turnover and [500..1000] for high turnover.
- *Payment time* in days: The domain of the attribute is defined by [-9,10] with its equivalence classes [-9..0] for a positive payment time and [1..10] for a negative one. A payment time of -3 means that the customer pays bills three days before the payment deadline.

To derive fuzzy classes from sharp contexts, the qualifying attributes are considered as linguistic variables, and verbal terms are assigned to each equivalence class (see Zimmermann, 1992). With the help of linguistic variables, the equivalence classes of the attributes can be described more intuitively (see Fig. 1). In addition, every term of a linguistic variable represents a fuzzy set. Each fuzzy set is determined by a membership function μ over the domain of the corresponding attribute (see Fig. 2).

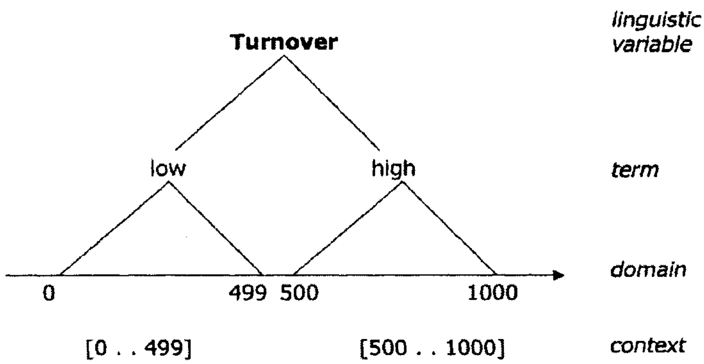

Figure 1. Concept of linguistic variable

The definition of the equivalence classes of the attributes turnover and payment time determines a two-dimensional classification space shown in Fig. 2. The four resulting classes C1 to C4 could be characterized by marketing strategies such as 'Commit Customer' (C1), 'Improve Loyalty' (C2), 'Augment Turnover' (C3), and 'Don't Invest' (C4).

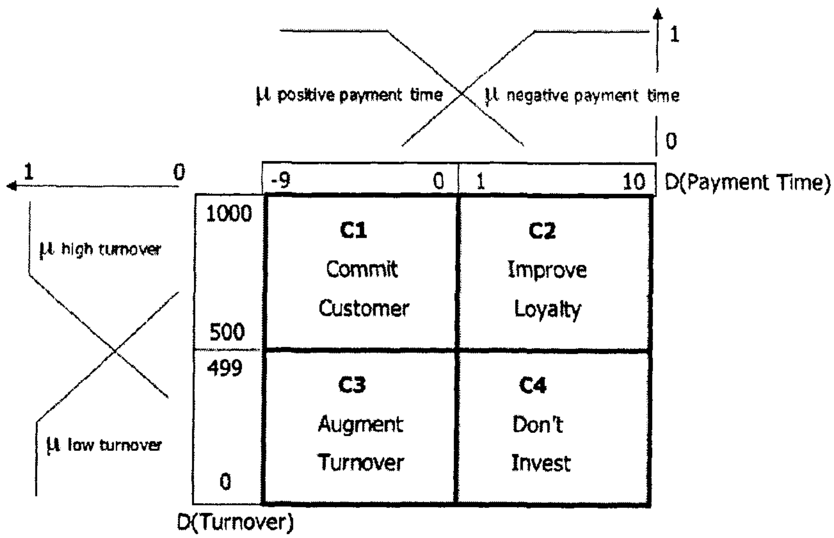

Figure 2. Fuzzy classification space defined by turnover and payment delay

With the context model, the usage of linguistic variables and membership functions, the classification space becomes fuzzy. This fuzzy partition has an important outcome, it implies the disappearance of the classes' sharp orders, i.e. there are continuous transitions between the different classes. This means that a customer can belong to more than one class at the same time and that his membership degrees in the different classes can be calculated. This precise information on the customers allows a company to correctly judge its customers and to apply the customer equity by treating the customers according to their real value (see section 3.1).

The selection of qualifying attributes, the introduction of equivalence classes and the choice of appropriate membership functions are important design issues. Database architects and marketing specialists have to work together in order to define an adequate fuzzy classification which will correctly express the company's viewpoint.

2.3 Fuzzy Classification Query Language fCQL

The Structured Query Language SQL is the standard for defining and querying relational databases. By adding to the relational database schema a context model with linguistic variables and fuzzy sets, the query language has to be extended. The proposed extension is the fuzzy Classification Query Language fCQL, originally described by Schindler (1998).

The classification language fCQL is designed in the spirit of SQL. Instead of specifying the attribute list in the select-clause, the name of the object column to be classified is given in the classify-clause. The from-clause specifies the considered relation, just as in SQL. Finally, the where-clause is changed into a with-clause which does not specify a predicate for a selection but a predicate for a classification. An example in customer relationship management could be given as follows:

```
classify    Customer
from        CustomerRelation
with        Turnover is high
            and PaymentTime is positive
```

This classification query would return the class C1, i.e. the class with the semantic 'Commit Customer'. This class was defined as the aggregation of the terms 'high' and 'positive'. The chosen aggregation operator is the γ-operator which was suggested as compensatory and was empirically tested by Zimmermann and Zysno (1980).

In this simple example, specifying linguistic variables in the with-clause is straightforward. In addition, if customers have to be classified on three or more attributes, the capability of fCQL for a multi-dimensional classification space is increased. This can be seen as an extension of the classical slicing and dicing operators on a multidimensional data cube.

2.4 Architecture of the fCQL Toolkit

As noted above, the fuzzy classification is achieved by extending the relational database schema. This extension consists of meta-tables added to the system catalogue. These meta-tables contain the name and the definition of the equivalence classes, the description of the classes and all the meta-information regarding the membership functions.

The architecture of the fCQL toolkit shown in Fig. 3 illustrates the interactions between the user and the different fCQL components. The fCQL toolkit is an additional layer above the relational database system. This particularity makes fCQL independent of underlying database systems and thus enables fCQL to operate with every RDBMS. It also implies that the user can always query the database with standard SQL (see case 1 in Fig. 3).

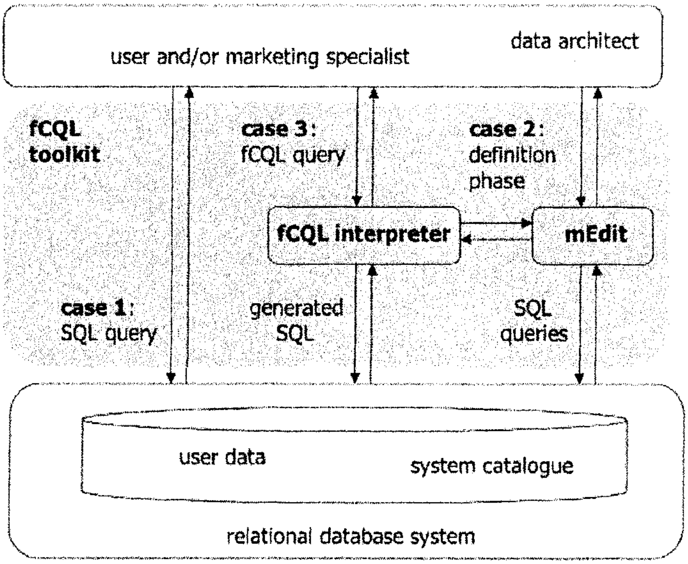

Figure 3. Overview of the fCQL toolkit

The architecture of the fCQL toolkit consists of two main components, the fCQL interpreter and the mEdit editor. mEdit, for membership function editor (see case 2), helps the data architect to select the appropriate attributes and to define the equivalence classes, the linguistic variables and the linguistic terms. Its main functionality is to allow the user to graphically define the membership functions by using linear and S-shaped functions (see Dombi, 1991). The mEdit editor finally communicates with the underlying database via classical SQL statements.

The fCQL interpreter allows the user to formulate unsharp queries (case 3). Those queries are analyzed and translated into corresponding SQL statements for the RDBMS. The interpreter also communicates with mEdit in order to retrieve the membership degrees of the classified elements regarding the previously defined membership functions. With the information returned by the database system and the mEdit data, the fCQL interpreter computes the membership degrees of the elements in the final classes and provides the fuzzy classification to the user.

For more details on the concept and the implementation of the fCQL toolkit, see Werro et al. (2005).

3. FUZZY CUSTOMER CLASSES

3.1 Customer Equity

Managing customers as an asset requires measuring them and treating them according to their real value (see Blattberg et al., 2001). With sharp classes, i.e. traditional customer segments, this is not possible. In Fig. 4 for instance, customers Brown and Ford have similar turnover as well as similar willingness to pay. However, Brown and Ford are treated differently: Brown belongs to the winner class C1 (Commit Customer) and Ford to the loser class C4 (Don't Invest). In addition, a traditional customer segment strategy treats the top rating customer Smith the same way as Brown, who is close to the loser Ford.

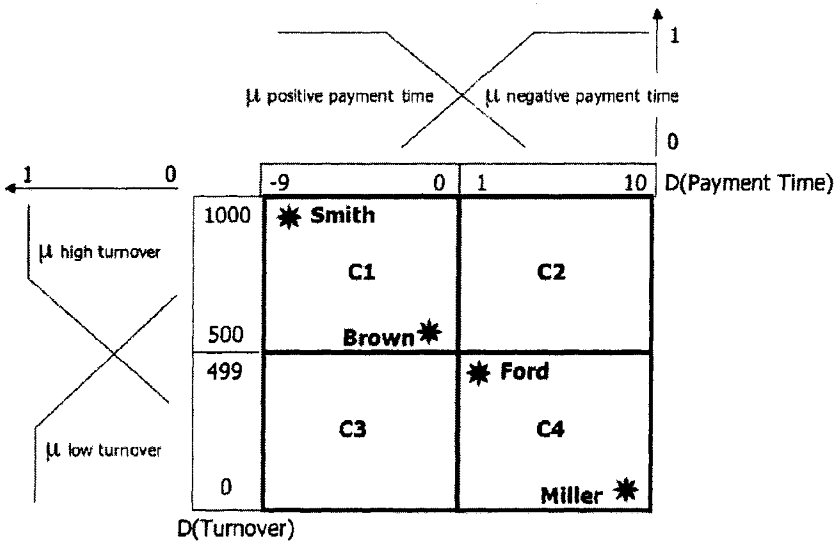

Figure 4. Customer equity example based on turnover and willingness to pay

With a sharp classification, the following effects may happen:

- Customer Brown has no advantage of improving his turnover or his payment time as he already gets the privileges of the class C1.
- Brown may also be surprised and disappointed to be suddenly treated very differently if his turnover and payment time would slightly decrease.
- Customer Ford, who is a potentially good customer classified in the loser class, may find better opportunities elsewhere.
- More critical for the company is the fact that Smith, the most profitable customer, not being treated accordingly to his value could leave the company.

Those dilemmas can be adequately solved by the use of a fuzzy classification where the customers can belong to several classes. The notion of membership functions brings the disappearance of the sharp borders between the customer segments. Fuzzy customer classes better reflect the reality and allow companies to treat customers according to their real value. By driving the customer equity, a company can significantly improve the retention rate of potentially good to top customers and, by this mean, maximize its profit.

3.2 Personalized Discount

According to the customer equity principle, customers personalized discounts can be easily derived from the fuzzy classification shown in Fig. 4. Indeed the membership degrees of the customers in the different classes can precisely determine the privileges they deserve, i.e. a personalized discount reflecting their real value for the enterprise. For that purpose, a discount rate can be associated with each fuzzy class: for instance C1 gets a discount rate of 10% (Commit Customer), C2 one of 5% (Improve Loyalty), C3 3% (Augment Turnover), and C4 0% (Don't Invest). The individual discount of a customer can then be calculated by the aggregation of the discount of the classes he belongs to in proportion to his membership degrees.

The top rating customer Smith belongs 100% to class C1 because he has the highest possible turnover as well as the best paying behavior; the membership of Smith in class C1 would be written as Smith (C1:1.0). Customer Brown belongs to all four classes and would be rated as (C1:0.28, C2:0.25, C3:0.25, C4:0.22). With fuzzy classification, the customers of Fig. 4 get the following discounts:

- Smith (C1:1.0, C2:0, C3:0, C4:0):
  (1.0 * 10%) + (0 * 5%) + (0 * 3%) + (0 * 0%) = 10%
- Brown (C1:0.28, C2:0.25, C3:0.25, C4:0.22):
  (0.28 * 10%) + (0.25 * 5%) + (0.25 * 3%) + (0.22 * 0%) = 4.8%
- Ford (C1:0.22, C2:0.25, C3:0.25, C4:0.28):
  (0.22 * 10%) + (0.25 * 5%) + (0.25 * 3%) + (0.28 * 0%) = 4.2%
- Miller (C1:0, C2:0, C3:0, C4:1.0):
  (0 * 10%) + (0 * 5%) + (0 * 3%) + (1.0 * 0%) = 0%

Using a fuzzy classification leads to a transparent and fair judgment: Smith gets the maximum discount and a better discount than Brown who belongs to the same customer class. Brown and Ford get nearly the same discount rate. They have comparable customer values although they belong to opposite classes. Miller, who sits in the same class as Ford, does not benefit from a discount.

Applying the customer equity with personalized discounts has two positive side effects apart being fair with the customers. The first one is to motivate all the customers to improve their buying attitude. For instance, with a sharp classification the customer Brown, being in the best class, has no interest of getting better. With a fuzzy classification he can on the one hand get better privileges by improving his buying behaviour and, on the other hand, he can concretely see his progression. The second side effect comes from the fact that only a small group of the customers in the winner class C1 (Commit Customer) gets the best discount. So if an enterprise gave 10% discount to all the customers in the sharp class C1, with a fuzzy classification it can give to its very best customers a greater discount (20% for example) within the same discount budget. By treating accordingly the top customers, this approach reinforces their loyalty toward the company.

3.3 Customer Loyalty

Customers can be classified based on several information or attributes. In the classification example shown in Fig. 4, customers were only evaluated regarding the turnover and the willingness to pay on time. This simple example cannot be effective in the real world. Some other perspectives like the number of items bought, the purchase intervals, the customer's age and region and so on can be included into the classification in order to reflect the customers' value. It is important to note that each company will consider different attributes to judge its customers depending on the data available and the company's definition of the value of a customer.

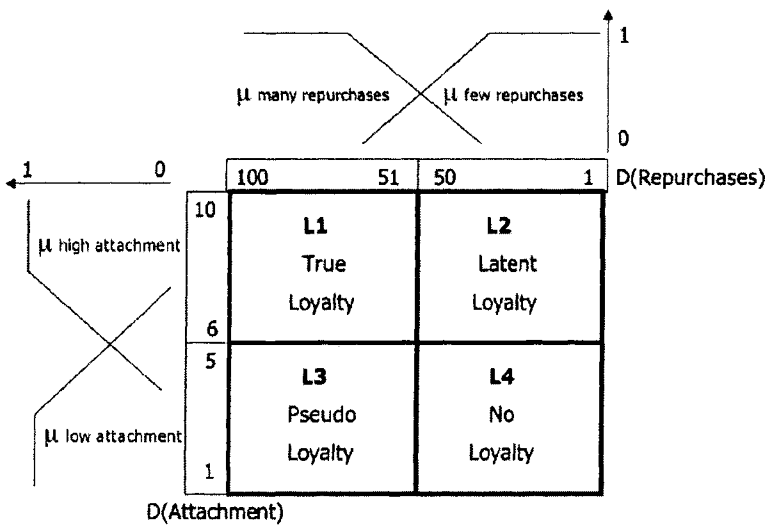

Figure 5. Fuzzy concept for loyalty

A specifically central perspective for a company is the customer loyalty. Many loyalty concepts have been proposed in the marketing literature. Harrison (2000), for instance, proposes two important dimensions, attachment and behavior of customers. For simplicity again, only two attributes (attachment, repurchases) and four classes will be considered: Class L1 (True Loyalty) with high attachment and numerous repurchases, class L2 (Latent Loyalty) with high attachment but few repurchases, class L3 (Pseudo Loyalty) with low attachment but many repurchases, and finally, L4 (No Loyalty) with low attachment and few repurchases. The four fuzzy classes for customer loyalty with appropriate membership functions are illustrated in Fig. 5.

This classification scheme can be used to improve the original customer classes of Fig. 2. For instance, the attribute payment time can be replaced by a loyalty rate calculated the same way as the personalized discount. This mechanism allows the companies to merge several attributes in order to build more consistent and valuable concepts. Those new dimensions can be then integrated in the final classification space (see Fig. 6).

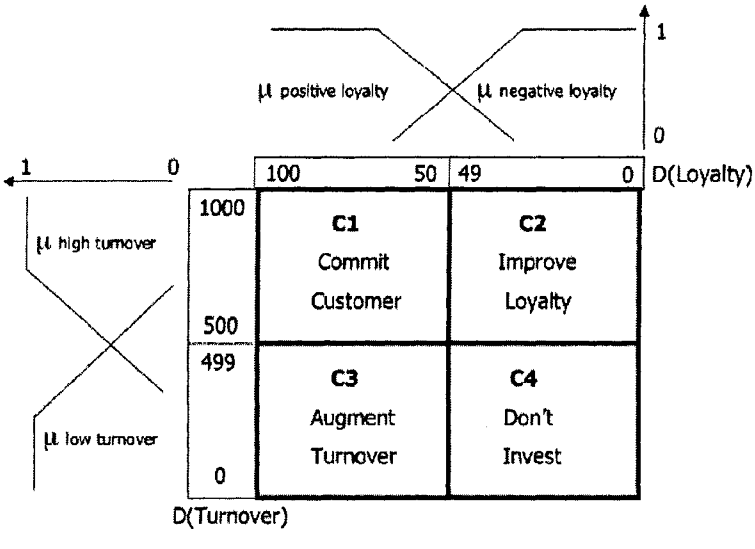

Figure 6. Fuzzy classification space integrating the concept of loyalty

The loyalty concept beneficially replaces the attribute payment time which was too weak to express the fidelity of the customers. Therefore, by combining attributes and calculated concepts, a company can effectively define a fuzzy classification scheme which will be able to calculate the real value of its customers.

3.4 Customer Acquisition

The personalized discount approach is primarily focused on the customer retention by trying to keep the best customer and by motivating them to improve their buying attitude. For this reason it is necessary to combine this approach with other strategies in order to integrate the customer acquisition process.

For this sake, the discount methods mentioned in the introduction based on the time or on bundle of products can be well combined with the personalized discounts in order to attract new customers and, at the same time, better retain the already loyal customers. The combination of other discount methods with the personalized discounts should not lead to discount collisions because all the resulting discounts should be simply summed.

By combining the time and bundle discounts with the personalized discount, a company can build and easily maintain a consistent and effective price strategy which will allow it to fully benefit from the opportunities offered by the e-business era.

4. CONCLUSION AND OUTLOOK

The personalized discount approach allows the companies to effectively retain the good customers by driving the customer equity. The main advantage of this approach is to have a fully automatic and fair discount method once the fuzzy classification has been set. This precise and transparent evaluation of the customers is made regarding the companies' criteria. By combining this approach with other discount methods which enable the customer acquisition, an enterprise can manage a consistent and effective price strategy in order to maximize its profit, especially through the digital channels.

The strength of a fuzzy classification is not limited to the calculation of a personalized discount. Some other CRM techniques taking advantage of a fuzzy classification like the selection of the most appropriate customers for a marketing campaign or the ability of precisely observe the customers' evolution, are foreseen. The objective is to achieve a CRM framework entirely based on a fuzzy classification.

The personalized discount will be implemented in the eSarine Webshop (see Werro et al., 2004) as alternative discount method. More generally, the fuzzy classification of customers is actually tested in a major Swiss company and will be compared to clustering methods. The results of this experimentation will show the advantages (resp. disadvantages) of a fuzzy classification versus the standard data mining methods.

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