A Fuzzy Classification Model for Online Customers

Andreas Meier and Nicolas Werro
University of Fribourg, Switzerland
E-mail: Andreas.Meier@unifr.ch, Nicolas.Werro@unifr.ch

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Building and maintaining customer loyalty are important issues in electronic business. By providing customer services, sharing cost benefits with online customers, and rewarding the most valued customers, customer loyalty and customer equity can be improved. With conventional marketing programs, groups or segments of customers are typically constituted according to a small number of attributes. Although corresponding data values may be similar for two customers, they may fall into different classes and be treated differently. With the proposed fuzzy classification model, however, customers with similar behavior and qualifying attributes have similar membership functions and therefore similar customer values. The paper illustrates how webshops can be extended by a fuzzy classification model. This allows webshop administrators to improve customer equity, launch loyalty programs, automate mass customization and personalization issues, and refine marketing campaigns to maximize the real value of the customers.

Povzetek: Razvit je model za določanje lojalnosti internetnih kupcev.

1 Motivation

Within what is now a global market, the attention span of the customer has decreased. The customer behaves more individually, and customer loyalty has become difficult to maintain. A successful company needs, therefore, to increase the value it provides to its customers. Furthermore, if a company cannot react quickly to changing customer needs, the customer will find someone else who can.

The World Wide Web has created a challenging arena for e-commerce: with a webshop, products and services can be offered to online customers. In this context, two specific strategic goals must be addressed. First, new online customers, or lost customers, have to be acquired; these customers should have attractive market and resource potential. The second strategic goal is to maintain and improve customer equity; this can be achieved by cross-selling and up-selling, and through programs aimed at lifetime customer retention (Blattberg et al. 2001).

Managing online customers as an asset requires measuring them and treating them according to their true value. With the sharp customer classes of conventional marketing methods this is not possible (see example in Section 3.1). Here a fuzzy model is proposed for the classification of online customers. With fuzzy classification, an online customer can be treated as a member of a number of different classes at the same time. Based on these membership functions, the webshop owner can devise appropriate marketing programs for acquisition, retention, and add-on selling.

A number of fuzzy classification approaches have been proposed in the marketing literature. Twenty years ago, Hruschka (1986) proposed a segmentation of customers using fuzzy clustering methods. A clusterwise regression model for simultaneous fuzzy market structuring was discussed by Wedel and Steenkamp (1991). Hsu's Fuzzy Grouping Positioning Model (2000) allows an understanding of the relationship between consumer consumption patterns, and a company's competitive situation and strategic positioning. The modeling of fuzzy data in qualitative marketing research was also described by Varki et al. (2000). Finally, a fuzzy Classification Query Language (fCQL) for customer relationship management was proposed by Meier et al. (2005). Most of the cited research literature applies fuzzy control to classical marketing issues. Up to now, fuzziness has not yet been adapted for e-business, e-commerce, and/or e-government. In our research work, the power of a fuzzy classification model is used for an electronic shop. Online customers will no longer be assigned to classical customer segments but to fuzzy classes. This leads to differentiated online marketing concepts and helps to improve the customer equity of webshop users.

This paper describes an extension of the webshop eSarine (see Werro et al. 2004) with a fuzzy classification model for online customers. The remainder of the paper is structured as follows: Section 2 presents the main processes and repositories of a webshop, introduces the fuzzy classification concept, model and query language, and briefly describes the architecture of the fCQL toolkit. In Section 3, aspects of customer equity, mass customization and online marketing campaigns based on fuzzy customer classes are illustrated with examples. Section 4 depicts a generic hierarchy of fuzzy classification and proposes a controlling loop for online customers. Finally Section 5 gives a conclusion.

2 Webshop with Fuzzy Classification

2.1 Business Processes and Repositories

A webshop (often called electronic shop or online shop) is a web-based software system that offers goods and services, generates bids/offers, accepts orders and carries out delivery and modes of payment. In principle, each webshop consists of a storefront and a backfront. The online customers only have access to the storefront and can seek information on products and services, order as required, pay and receive their product. Access to the backfront is reserved to the webshop administrator. Here, products and services are inserted into the product catalog and the different procedures for ordering, paying, and purchasing are specified.

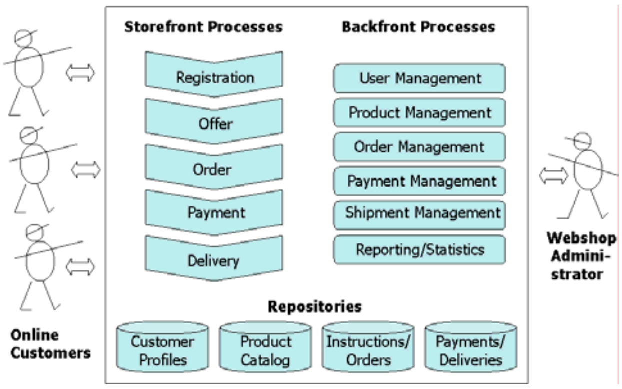

Figure 1: Logical Components of a Webshop

The most important processes and repositories of a webshop are presented in Fig. 1:

- Registration of online customers: a visitor to the electronic shop can find out about the products and services. Those intending to buy will communicate minimum data about themselves and establish user profiles along with payment and delivery arrangements.
- Customer profiles and customer administration: the data on customers is put into a database. In addition, an attempt is made to put together specific profiles based on customer behavior. This allows new, but relevant offers to be presented to the individual customer. However, the rules of communication and information desired by the user must be respected (e.g. customized push for online advertising).
- Product catalog: the products and services are listed in the catalog, grouped into categories so that the webshop can be clearly organized. Products may be listed with or without prices. With individual customer pricing, a quotation is computed and specified during the drawing up of the offer, which will also reflect the discount system selected.
- Offering and ordering: offers can be generated and goods and services bought as needed. The electronic shopping basket or cart is used by online customers to reserve the goods and services selected for possible purchase and show the total price with discount.
- Shipment options: where digital product categories are offered by webshops, goods and services can be delivered online.
- Measures for customer relationship management: online customer contact is maintained after a purchase by offering important after-sales information and services. These measures make customer contact possible when these goods and services are used, thus enhancing the customer connection.

To attract potential online customers of high quality and to retain and extend their customer value, a fuzzy classification model is helpful. The next sections present a model which allows companies to derive customer equity and treat online customers according to their real value.

2.2 Fuzzy vs. Sharp Classification

Fuzzy logic aims to capture the imprecision of human perception and to express it with appropriate mathematical tools. With the fuzzy classification model proposed in the next Section 2.3, marketers are able to use linguistic variables, such as ‘loyalty’, and linguistic terms like ‘high’ or ‘low’.

There are a number of advantages in using fuzzy classification for relationship management:

- Fuzzy logic, unlike statistical data mining, enables the use of non-numerical attributes. As a result, both qualitative and quantitative attributes can be used for marketing acquisition, retention, and add-on selling.
- With the help of linguistic variables and terms, marketers may describe equivalence classes more intuitively (excellent loyalty, medium loyalty, weak loyalty). The definition of linguistic variables and terms and the naming of fuzzy classes can be derived directly from the terminology of marketing and sales departments.
- Customer databases can be queried on a linguistic level. For example, the fuzzy Classification Query Language (Meier et al. 2005) allows marketers to classify single customers or customer groups by classification predicates such as ‘loyalty is high and turnover is large’.

An important difference between a fuzzy classification and a sharp one is the fact that a customer can belong to more than one fuzzy class. In conventional marketing programs, groups or segments of customers are typically constituted by a small number of qualifying attributes. If corresponding data values are similar for two customers, their membership functions are similar too. In the conventional case however, they may fall into different classes and be treated differently (see customers Brown and Ford in Fig. 4).

With fuzzy classification it is possible to treat each customer individually. This allows managers to allocate marketing budgets more precisely. In addition, cost savings can be achieved. For instance, when offering a discount (see Section 3.2), discount rates can be chosen according to the individual customer value. Companies can try to retain the more profitable customers by giving them individualized privileges.

Needless to say there are also drawbacks when applying fuzzy classification. The definition process of a fuzzy classification remains a challenging task. In our experience, the design of fuzzy classes requires marketing specialists as well as data architects and webshop administrators. Beyond this, a methodology is needed for the entire planning, designing, and testing process for appropriate fuzzy classes.

2.3 Fuzzy Classification Model

The relational database of online customers (see Customer Profiles in Fig. 1) is extended by a context model in order to obtain a classification space. To every attribute A_j defined by a domain $D(A_j)$ there is added a context $C(A_j)$. A context $C(A_j)$ of an attribute is a partition of $D(A_j)$ into equivalence classes (see Shenoi 1995). In other words, a relational database schema with contexts R(A,C) consists of a set $A=(A_1,\ldots,A_n)$ of attributes and the set $C=(C_1(A_1)),\ldots,C_n(A_n))$ of associated contexts.

Throughout this paper, an illustrative example from relationship management is used. For simplicity, online customers will be evaluated by only two attributes, turnover and loyalty. 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 Euro per month: the attribute domain is defined by [0..1000] and divided into the equivalence classes [0..499] for small and [500..1000] for large turnover.
- Loyalty: the domain {excellent, good, mediocre, bad} with its equivalence classes {excellent, good} for high and {mediocre, bad} for low loyalty behavior.

To derive fuzzy classes from sharp contexts, the qualifying attributes are considered as linguistic variables, and verbal terms are assigned to each equivalence class. With linguistic variables, the equivalence classes can be described more intuitively. In addition, every term of a linguistic variable represents a fuzzy set. Membership functions μ (see Zimmermann 1992) are defined for the domains of the equivalence classes.

As turnover is a numeric (sharp) attribute, its membership functions μ_{large} and μ_{small} are continuous functions defined on the whole domain of the attribute. For qualitative attributes like loyalty, step functions are used; the membership functions μ_{high} and μ_{low} define a membership grade for every term of the attribute's domain.

The selection of the two attributes 'turnover' and 'loyalty' and the corresponding equivalence classes determine a two-dimensional classification space (see 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).

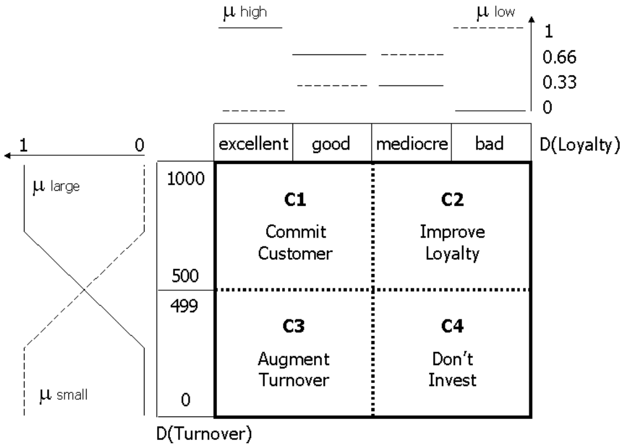

Figure 2: Fuzzy Classification Space defined by Turnover and Loyalty

The selection of qualifying attributes, the introduction of equivalence classes and the choice of appropriate membership functions are important design issues (Meier et al. 2001). Database architects and marketing specialists have to work together in order to make the right decisions.

With the proposed context model, the use of linguistic variables and membership functions, the classification space becomes fuzzy. A fuzzy classification of online customers has many advantages compared with common sharp classification approaches (see Section 2.2 and Section 3). Most importantly, with fuzzy classification a customer can belong to more than one class at the same time. This leads to differentiated marketing concepts and helps to improve customer equity.

2.4 Fuzzy Classification Query Language

The classification language fCQL is designed in the spirit of SQL (Schindler 1998). 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 specifies a classification predicate.

An example in customer relationship management could be given as follows:

```
classify Customer
from     CustomerRelation
with     Turnover is large and
         Loyalty is high
```

This classification query would return the class C1 (Commit Customer) defined as the aggregation of the terms 'large' turnover and 'high' loyalty. The 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. However, if customers are 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.

2.5 Architecture of the fCQL Toolkit

The architecture of the fCQL toolkit shown in Fig. 3 illustrates the interactions between the user (resp. the webshop), the fCQL toolkit and the relational database management system containing the different repositories of the webshop.

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 commercial product. It also implies that the user (resp. the webshop application) can always query the database with standard SQL commands (see case 1).

Before querying the fCQL toolkit, the data architect has to define the fuzzy classification (see case 2).

The user can now formulate unsharp queries to the fCQL toolkit (see case 3). Those queries are analyzed and translated into corresponding SQL statements for the database system. Then the classification results are displayed to the user or returned to the webshop software.

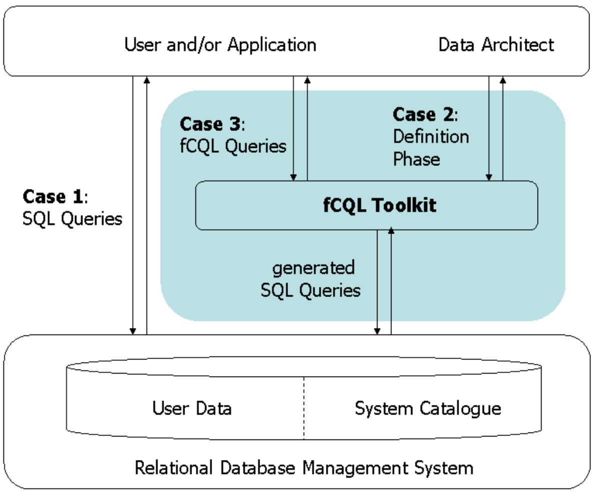

Figure 3: Architecture of the fCQL Toolkit

3 Fuzzy Classes for Online Customers

3.1 Customer Equity

Managing online customers as an asset requires measuring them and treating them according to their true value. 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 loyalty behavior. However, 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 in the same way as Brown, who is close to the loser Ford.

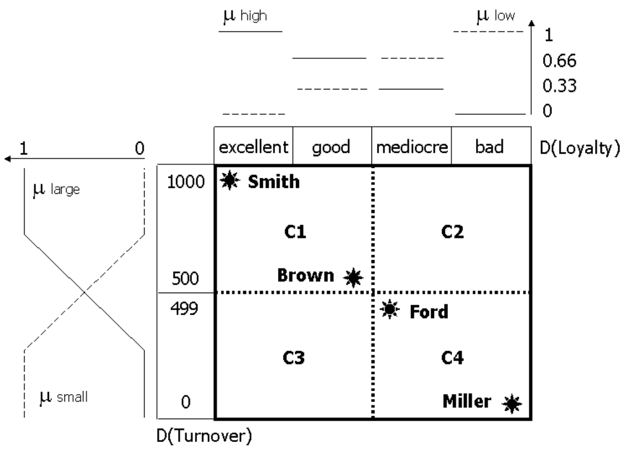

Figure 4: Customer Equity Examples based on Turnover and Loyalty

With a sharp classification, the following drawbacks can be observed:

- Customer Brown has no advantage from improving his turnover or his loyalty behavior as he already receives all the privileges of the premium class C1.
- Brown will be surprised and disappointed if his turnover or loyalty decreases slightly and he therefore falls into another class. He may even fall from the premium class C1 directly into the loser class C4.
- Customer Ford, potentially a good customer, may find opportunities elsewhere. As he belongs to the loser class C4, he is treated in the same way as Miller although he has higher turnover and better loyalty.
- The most profitable online customer with excellent loyalty is Smith. Sooner or later he will become confused. Although he belongs to the premium class C1, he is not treated according to his real value. In comparison with Brown, he might be disappointed by webshop offers or services.

The dilemmas described can be solved by applying a fuzzy classification as shown in Fig. 4: The main difference between a traditional classification and a fuzzy one is that in the fuzzy classification an online customer can belong to more than one class. Belonging to a fuzzy class implies a degree of membership. The notion of membership functions results in the disappearance of sharp borders between customer segments. Fuzzy customer classes reflect reality better and allow the webshop administrators to treat online customers according to their real value.

3.2 Issues of Mass Customization and Personalization

Customization and low cost is often mutually exclusive. Mass production provides low cost but at the expense of uniformity. Mass customization is defined as customization and personalization of products and services for individual customers at a mass production price (Pine and Davis 1999).

Digital goods and services are costly to produce but cheap to reproduce. In addition, versioning of products and services can easily be achieved. Another advantage of fuzzy classification, therefore, is its potential for personalized privileges. For instance, the membership degree of online customers can determine the privileges they receive, such as a personalized discount (Werro et al. 2005). Discount rates can be associated with each fuzzy class: in the following example C1 (Commit Customer) has a discount rate of 10%, C2 (Improve Loyalty) one of 5%, C3 (Augment Turnover) 3%, and C4 (Don't Invest) 0%. The individual discount of an online customer could be calculated by the aggregation of the discounts of the classes he belongs to in proportion to his various degrees of membership.

The top rating customer Smith belongs 100% to class C1 because he has the highest possible turnover as well as the best loyalty behavior; the membership degree of Smith in class C1 would be written as Smith (C1:1.0, C2:0.0, C3:0.0, C4:0.0). 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 online customers of Fig. 4 receive the following discounts:

- Smith (C1: 1.0, C2: 0.0, C3: 0.0, C4: 0.0):
  1.0*10% + 0.0*5% + 0.0*3% + 0.0*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: 0.0, C2: 0.0, C3: 0.0, C4: 1.0):
  0.0*10% + 0.0*5% + 0.0*3% + 1.0 * 0% = 0%

Using fuzzy classification for mass customization and personalization leads to a transparent and fair judgment: Smith gets the maximum discount and a better discount than Brown who belongs to the same class C1. Brown and Ford have nearly the same discount rate. They have comparable customer values although they belong to opposing classes. Miller, who is in the same class as Ford, does not benefit from a discount.

Applying the fuzzy classification model with personalized discounts has additional advantages: first, all online customers of a webshop are motivated to improve their buying attitude and/or loyalty behavior. Second, only a small group of the premium class C1 gets the 10% discount; the same is true for classes C2 and C3. In other words, the total budget for personalized discounts will be smaller compared with conventional discount methods. The savings can then be used for acquisition or retention programs, i.e. online marketing campaigns.

3.3 Online Marketing Campaign

Launching a marketing campaign can be very expensive. It is therefore crucial to select a customer group with potential. Fuzzy classification offers considerable advantages when planning and selecting customer subgroups.

An example of a fuzzy-controlled marketing campaign is given in Fig. 5. Here, the strategy is to select loyal customers with low turnover. Using membership functions, a subset of customers in class C3 can be chosen. The application of membership functions allows marketers to dynamically modify the size of the target group in relation to the available campaign budget. Modifying the size of the target group is also a valuable mean to increase or decrease the homogeneity between the targeted customers (Nguyen et al. 2003).

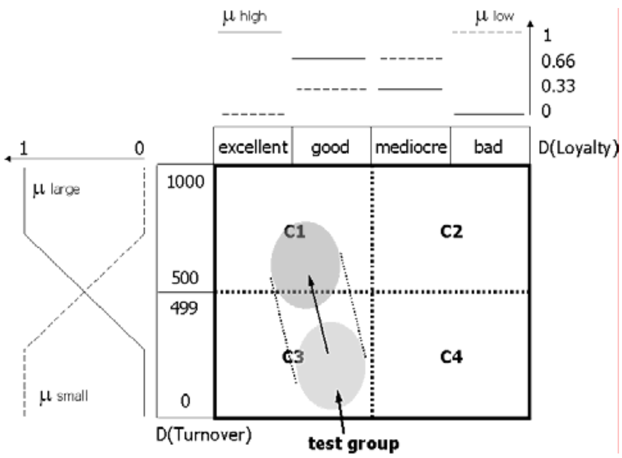

Figure 5: Development of the Target Group as a Result of a Marketing Campaign

Once the marketing campaign or testing process has been started, the fuzzy customer classes can be analysed again. It is important to find out if the money invested is moving the customers in the planned direction, i.e. improving their customer value.

With fuzzy classification, marketers can monitor the development of customers or customer groups (see Fig. 5). By comparing the value of a customer over time, it is possible to determine whether an online customer has increased, maintained, or decreased in customer value. The most useful application of monitoring customers could be the detection of churning customers: automated triggers can respond to the development of customer values; if a good customer begins to show churning behavior, an alert to the marketing department may help to retain this customer.

4 Hierarchical Fuzzy Classification

4.1 Analysis of Online Customers

The analysis of online customers compared to traditional ones has the advantage that a lot of information about the customers' behavior is automatically logged in the system.

In a webshop application, explicit and implicit information can be used for the analysis of the customer relationships. Explicit information is the data provided directly by the customer, like the orders or the product ratings and forum entries:

- Orders: the orders can determine the *turnover* and the *margin* of a customer as well as his *buying frequency*. Indirectly, the *payment delay* and the *return rate* can also be identified.
- Product ratings and forum entries: the ratings of products as well as forum entries can reveal the *involvement frequency*.

Implicit information is retrieved from the interaction and the behavior of the online user with the webshop:

- Clickstream: the clickstream information can establish the *visiting frequency* and the behavior of visitors.

The use of the order information is straightforward as most of the companies are using the turnover, margin, payment delay and return rate information in order to analyse and reward their customers. The clickstream data is a new source of information coming from the interaction of the users with the online shop. All the actions performed by the users are logged with a time stamp into the clickstream data allowing the system to determine the visiting frequency for each user (Lee et al. 2001). Many online shops provide their customers a way to communicate and to share knowledge by means of product ratings and forum entries. This social involvement can lead to a virtual community which increases the trust and the attachment towards the company (Rheingold 1993).

4.2 Hierarchy of Fuzzy Classification

In real applications, a fuzzy classification database schema can have a number of attributes, linguistic variables, and terms. This leads to a multi-dimensional classification space with a large number of classes. After combining all these attributes, it may not be possible to extract clear semantics for each resulting class. This problem, also present with sharp classifications, is partially resolved by the use of fuzzy classes. By having a continuous transition between the classes, fewer equivalence classes (linguistic terms) are required. The problem of complexity remains, however, if the number of dimensions (linguistic variables) increases exponentially with the number of classes.

In order to maintain classes with a proper semantic, a multi-dimensional fuzzy classification space can be decomposed into a hierarchy of fuzzy classification levels (Werro et al., 2006). By grouping attributes of a given context in sub-classifications, it is possible to derive meaningful definitions for each of the classes. The decomposition of a multi-dimensional fuzzy classification space also reduces the complexity and allows optimization during the modeling phase.

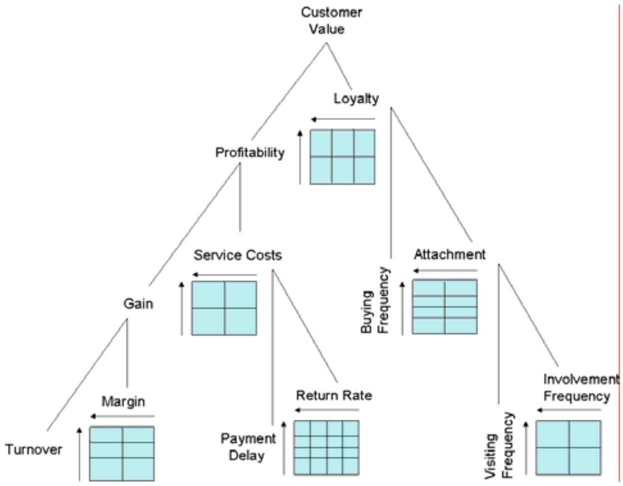

Figure 6: Customer Value as Hierarchical Fuzzy Classification

An example of a hierarchical fuzzy classification space could be the calculation and the controlling of customer equity. Customer equity not only has to deal with monetary assets (turnover, margins, service costs etc.) but also with hidden assets such as loyalty or attachment. Harrison (2000), for instance, proposes to express customer loyalty based on two dimensions, attachment and buying behavior. Taking these different aspects of customer equity into account, a hierarchy of fuzzy classes for the calculation of customer values could be derived (see Fig.6). In the proposed example, the customer value depends on the two linguistic variables profitability and loyalty, loyalty on buying frequency and attachment, attachment on visiting frequency and involvement frequency and so on. It is important to note that marketers can evaluate the fuzzy classification space in a more structured way and with clearly defined semantics at every level of the hierarchy. If, for instance, loyalty problems seem to occur for a given customer, then his buying, visiting and involvement behavior can be studied in more depth in order to evaluate retention programs.

4.3 Closed Loop for Controlling

In recent years, managers in a range of industries have been rethinking how to measure the performance of their businesses. They have recognized that a shift is needed towards treating financial statistics in the context of a broader set of measures. Edvinsson and Malone, for instance, propose the introduction of an intellectual capital report which brings together indicators from finance, customer base, process management, renewal, and development as well as from human resources

(Edvinsson & Malone 1997). The customer focus requires indicators such as market share, number of customers, customer equity, customers lost, average duration of customer relationship, ratio of sales contacts to sales responses, satisfied customer index and service expenses per customer.

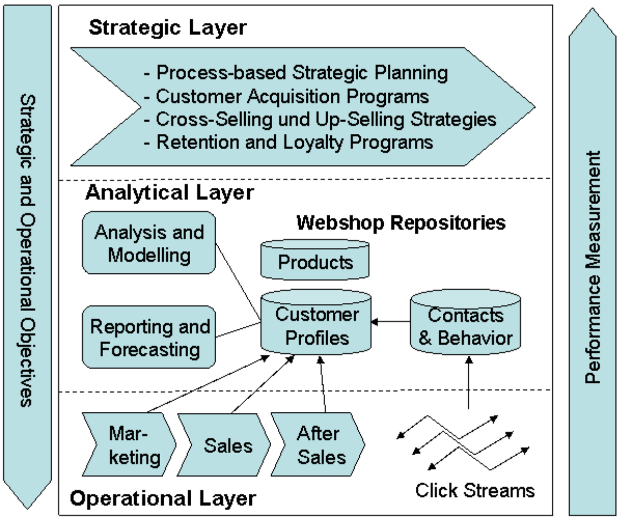

Figure 7: Closed Loop for Controlling Online Customers and their Behavior

Fig. 7 illustrates the closed loop for controlling online customer relationships. This loop has been implemented in the webshop eSarine with the help of a performance measurement system (Küng et al. 2001). At the strategic level, objectives for online customer acquisition, retention, and add-on selling must be defined, as must also the process and service quality goals of the webshop. The traditional tasks in marketing, sales and after-sales activities will be carried out. Applications for collaborative services such as customized push, personalized offers and care of e-communities will also be developed. In addition, all customer contacts information, i.e. click streams, has to be analyzed and stored in a contacts database.

The glue between the strategic and operational layer is the customer profile database with fuzzy classes, extended by the contacts database. The webshop administrator or a specialized team is responsible for a consistent customer database, and for analysis of the contacts and the behavior of online customers. The fuzzy classification model, with a corresponding query facility, allows the webshop owner to improve customer equity, launch loyalty programs, automate mass customization issues, and refine online marketing campaigns.

5 Conclusion

The fuzzy classification approach and the fCQL toolkit are more than just another concept and piece of software. Fuzzy classification can be seen as a management method and the fCQL toolkit is a powerful instrument for analysis and control of a business:

- *Strategic Management:* For the analysis of markets, fuzzy classification allows demographic, geographic, behavioral and psychographic market segmentations. It is more successful and realistic to fuzzily target markets and to fuzzily position brands or companies in their markets.
- *Customer Relationship Management:* For customer analysis and segmentation, fuzzy customer classes give the marketers a differentiated judgment of customers and customer groups. In addition, if customer value is calculated as an aggregated membership degree (see Section 4.2) then customer equity is based on both monetarily-based and hidden assets.
- *Supply Chain Management:* With a fuzzy approach, it is possible to classify, analyse and evaluate different suppliers and their delivery processes. A fuzzy supplier rating and/or fuzzy judgment of quality and time schedules of the delivery processes provides for more differentiated planning. For instance, improvements in the delivery system can be effected by observing moving targets in fuzzy classes.
- *Total Quality Management:* Quality measures are not only numeric; there are also qualitative measures. The equal treatment of quantitative and qualitative properties makes the fuzzy classification approach attractive for TQM. It is possible to fuzzily categorise, analyse and control materials, products, services and processes.
- *Risk Management:* In banking or insurance, individuals or companies have to be divided into risk classes. Very often, pricing components directly depend on risk levels. With a fuzzy classification, the calculation of risk degrees, creditworthiness or other indicators can be carried out with finer granularity.

Fuzzy classification helps to analyze and control qualitative and quantitative performance indicators in managerial application domains. If adequate data from marketing and finance is available in databases, fuzzy classification can be successfully used for performance measurement.

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