Fuzzy Classification of Online Customers

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Abstract

The following paper presents a case study conducted for a non profit organisation (BSU). BSU is a student organisation from Fribourg, Switzerland that regularly organises stock market simulations for students. The purpose of this case study was to analyse participants using a hierarchal fuzzy classification. After a brief overview of BSU, different methods for analysing online customers are analysed. Fuzzy set are presented next and finally a hierarchical fuzzy classification of online participants is presented.
1 Introduction

1.1 Objective

The growing importance of electronic business in today’s economy forces businesses to adapt their behaviour towards the different actors on the market [3]. The fact that online customers surf from one site to the next looking for interesting products means that a competitor is just one click away [6]. Successful customer relationship management has therefore become more important than ever.

The objective of this paper is to present a case study of an analysis of online customers, using a hierarchical classification. The case study was carried out at Börsenspiel der Schweizer Universitäten (BSU), a non profit organisation which organises online stock market simulations for students at Swiss Universities.

BSU was chosen because it has organised stock market simulations since the early nineteen nineties, and playing has taken place exclusively online for over a decade. This means that BSU has a large corpus of data on participants, but has never made any attempt to analyse it for the purpose of customer relationship management (CRM). BSU therefore presented the perfect challenge: a lot of data on customers, no existing CRM strategy, and limited resources.

1.2 Aim

The aim of this paper is to answer the follow questions:

1. What is BSU exactly and how does it operate?
2. What information is available about online participants
3. Can a hierarchical fuzzy classification be used to analyse online participants to maximise their longterm value to BSU?
4. What are the advantages of such an approach?
1.3 Outline

The rest of this paper is organised as follows, first in Section 2 a brief overview of BSU and its activities is given. In Section 3 online customer portfolios are discussed. First a general overview of information that can be obtained and how it can be used to manage customer relationship is given. Specific applications for BSU are introduced next. Fuzzy logic and its uses are introduced in Section 4. This section covers fuzzy sets their operations as well as linguistic variables. Finally, in section 5 a hierarchical fuzzy classification is presented an its uses will be discussed.

2 Börsenspiel der Schweizer Universitäten

Börsenspiel der Schweizer Universitäten (BSU) is a non-profit organisation based in Fribourg, Switzerland. Every year BSU organises several stock exchange simulations on behalf of various organisations. In recent years the association developed various game concepts including:

- **Stock Exchange Training** (1995 & 1996) behalf the HWV
- **Magic Fonds Cup** (1995-1997) of the Schweizer Bankvereins (UBS today)
- **Real Banking Adventure** (1998-2005) on behalf of the apprentice training for the Regional Banks (RBA)
- **Effektenforum** (2007) on behalf of the University of St-Gallen.

Since 1998 SSU’s flagship product, the anual stock exchange simulation for the Swiss Universities, is called Portfolio Management Simulation (PMS). The number of participants in the PMS has grown steadily of the years, from a handful originally to over 1600 participants this year.

Since the mid 1990s, all stock market simulations organised by BSU are carried out online via BSUs website \(^1\). This means that a wealth of information can be gleaned from thousands of online participants of nearly a decade. This makes BSU an ideal candidate for online analysis of customer profiles.

Until now, BSU has made very little effort to analyse or cluster participant profiles. This is unfortunate as participants vary greatly in their value to

\(^1\)http://www-bsu.unifr.ch/
BSU. On the one extreme are those players who have played regularly for many years and who encourage their friends to play, and on the other extreme are those players who sign up, but never pay their membership fee. By encouraging their friends to join, the first group increase the number of participants (critical for attracting sponsors) while the second use up valuable resources, notably the time of BSU volunteers who have to remind them to pay and the amount of computer processing power (generously donated by the Service Informatique of the University of Fribourg) to calculate the value of their stock portfolio.

For the rest of this paper, we will focus on the PMS stock simulation. The reasoning behind this is that this is the longest running game and there is therefore of data available.

3 Online Customer Portfolios

Compared to traditional brick and mortar stores, online customers leave a trail of information that can be exploited. A number of customer profiles can be derived (where profile is defined as being a set of data ‘describing specific characteristics of a customer’ [5] and grouped into explicit and implicit profiles [4, 5] as shown in Figures 1 and 2.

Explicit profiles are derived from data that the customer provides explicitly. These include information given when registering, information stored in his or her online profile and feedback given via e-mail.

Implicit profiles are derived implicitly from customer actions. Every action of an online customer, such as links followed, is stored and can be used.

Of particular interest to us are the identification profile and the interaction profile.

The identification profile contains information that the participant entered upon registration. Of particular interest is the question asking “how did you hear about PMS”. One option is “from a member”. This helps BSU to identify which members contact their friend and encourage them to participate. This year, as an incentive, BSU offers member who convince at least five of their friends to play (and pay) a gift.

The interaction profile contains information that is derived from a participant’s interactions with the system. Of particular interest here is the partic-
<table>
<thead>
<tr>
<th>Profile</th>
<th>Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification Profile</td>
<td>user name, role, contact information, personal browser settings, address, payment information, IP-address, etc</td>
</tr>
<tr>
<td>Preference Profile</td>
<td>self-revealed preferences (product meta data)</td>
</tr>
<tr>
<td>Socio-economic Profile</td>
<td>self-categorization in predefined classes (age, gender, hobbies, etc.)</td>
</tr>
<tr>
<td>Ratings</td>
<td>three types of ratings: of products, of reviews, of pages [scale e.g.: I like it – not for me]</td>
</tr>
<tr>
<td>Relationships</td>
<td>Relationships to other users/customers [e.g. “soul sisters”]</td>
</tr>
<tr>
<td>Reviews/Opinions</td>
<td>Plain text, images, videos and other material</td>
</tr>
</tbody>
</table>

Figure 1: Explicit user profiles, taken from [5]
<table>
<thead>
<tr>
<th>Profile</th>
<th>Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transaction Profile</td>
<td>transaction log, product purchases linked to product meta data (purchases, inquiries, payment, etc.)</td>
</tr>
<tr>
<td>Interaction Profile</td>
<td>click stream (pages viewed are linked to product meta data [preference categories])</td>
</tr>
<tr>
<td>External data</td>
<td>Information procured from other sources [e.g. weather report, local news, events, credit rating]</td>
</tr>
</tbody>
</table>

Figure 2: Implicit user profiles, taken from [5]

**ipation**, i.e. how many times this particular participant has participated in stock market simulations organised by BSU.

A mentioned previously, this years PMS attracted over 1600 participants. Each participant was asked to pay a membership fee of 15 CHF, which some payed immediately, other payed with some delay and some failed to pay at all. A sample of some of these participants is shown in Figure 3 (The names have been modified to preserve the anonymity of the participants). The **peration** shows in absolute number how many times a player has participated in the PMS. The **commended** column show how often the people recommended the game to other who also played (and payed). The **ayment delay** column show how long a player took to pay his membership fee. Please not that payment are checked a irregular intervals (usually two weeks). Also note that some players, despite numerous warnings, fail to pay their membership fee and have their account cancelled.

Figure 3 show a selection of participants in the most resent edition of the PMS. Suter is a new player, this is his first participation and has never recommend participating to anyone. Huber has participated a total of three times and recommended PMS to 12 other players. Müller is the most regular participant, having participated in 6 editions of the game. He has also recommended the game to 6 of his friends. Finally Sieber has played four times and recommended the stock market simulation 6 times.
<table>
<thead>
<tr>
<th>Participant</th>
<th>Participation</th>
<th>Recommended</th>
<th>Payment delay (weeks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suter</td>
<td>1</td>
<td>0</td>
<td>never</td>
</tr>
<tr>
<td>Huber</td>
<td>3</td>
<td>12</td>
<td>4</td>
</tr>
<tr>
<td>Müller</td>
<td>6</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Sieber</td>
<td>4</td>
<td>6</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 3: Participant in the 2008 edition of PMS

4 Fuzzy Classification

4.1 Fuzzy Sets

Fuzzy set theory was first proposed by Lofti Zadeh as a precise mathematical tool for dealing with classes of objects without precisely defined criteria of membership [10]. In classical set theory, the membership of elements in a set is defined in binary terms, an element either belongs or does not belong to the set. A classic subset $A$ of a set $U$ is defined by an *indicator function* $\mu_A(x)$ defined by [1]:

$$\mu_A(x) = \begin{cases} 
1 & \text{if } x \in A \\
0 & \text{if } x \notin A 
\end{cases}$$

Fuzzy sets, on the other hand, to have varying degrees of membership, expressed by a *membership function* over a continuous domain between 0 and 1[10, 7]. A fuzzy sub set $A$ of a set $U$ is defined as a set of ordered pairs

$$\{(x_i, \mu_A(x_i))\}$$

where $x_i \in U$, $\mu_A : U \rightarrow [0, 1]$ is the *membership function* of $A$ and $\mu_A(x) \in [0, 1]$ is the degree of membership of $x$ in $A$ [8].

Many classes encountered in the real world cannot be defined in terms of crisp sets. Notions such as a ‘young person’, a ‘tall man’ or ‘warm weather’ cannot be sharply defined. The notion of ‘regular participants’, for instance, is ambiguous because it is unclear where the cut off between the irregular and regular participants is.
As an example, we shall consider the set of participants of the PMS shown in Figure 4, a sharp classification would for instance set the boundary of the set regular participants at four or more participations. This would leave Huber you falls just short of this criteria upset as he will now be treated no better than a first time participant. Müller is likely to be equally unhappy as he will be given the same advantage as somebody who has far fewer participations.

A fuzzy classification would give a much fairer decomposition. If we for instance, define a linear membership function:

\[ \mu_{\text{regular participant}}(x) = \begin{cases} 
1 & \text{if } x \geq 6 \\
\frac{x}{6} & \text{if } 1 < x < 6 \\
0 & \text{if } x = 1 
\end{cases} \]

we would get the following fuzzy subset regular participants:

\[ \text{regular participants} = \{ (\text{Suter},0),(\text{Huber},0.5),(\text{Sieber},0.66),(\text{Müller},1) \} \]

Suter, a first time participant, would intuitively not be considered to be a regular participant, is assigned a membership degree of 0. Huber and Sieber, who have a similar number of participations, are assigned a similar membership degree. Finally, Müller, the most regular amongst the regular participants is assigned by far the highest membership coefficient. If membership privileges are assigned according to a member’s participation record, all member will have the impression of being treated fairly.
4.2 Operations on Fuzzy Sets

The set complement, set intersect and set union operators from classical set theory can be generalised and applied to fuzzy sets. While different definitions of this operator exist [8], we will base ourselves on the definition proposed in Zadeh’s original paper [10].

The complement of a fuzzy sub set A of a set U is defined as follows:

\[-A = 1 - \mu_A(x), x \in U\]

The intersection of two fuzzy sets A and B is defined as follows:

\[A \cap B = \mu_A(x) \land \mu_B(x) = \min(\mu_A(x), \mu_B(x)), x \in U\]

The union of two fuzzy sets A and B is defined as follows:

\[A \cup B = \mu_A(x) \lor \mu_B(x) = \max(\mu_A(x), \mu_B(x)), x \in U\]

In order to show how these operators work, we will consider an example consisting of the set of regular players, used in the previous example as well as the set of players who recommended the game to their friends. First of all we must calculate the membership degree of each player to the set great ambassador. To do this we will use the data in Figure 5 and the membership function:

\[\mu_{ambassadors}(x) = \begin{cases} 
1 & \text{if } x \geq 12 \\
\frac{x}{12} & \text{if } 0 < x < 12 \\
0 & \text{if } x = 0
\end{cases}\]

This gives the following fuzzy subset great ambassadors:
great ambassadors = \{ (Suter,0),(Huber,1),(Sieber,0.5),(Müller,0.83) \}

We can now calculate the complement of the sub set regular participants:

\[ \neg \text{ regular participants} = \{ (Suter,1),(Huber,0.5),(Sieber,0.44),(Müller,0) \} \]

The intersection of the two fuzzy sets regular participants and great ambassadors is:

\[ \text{regular participants} \cap \text{great ambassadors} = \{ (Suter,0),(Huber,0.5),(Sieber,0.5),(Müller,0.85) \} \]

The union of the two fuzzy sets regular participants and great ambassadors is:

\[ \text{regular participants} \cup \text{great ambassadors} = \{ (Suter,1),(Huber,1),(Sieber,0.5),(Müller,1) \} \]

### 4.3 Linguistic Variables

Fuzzy logic unlike probability theory allows fuzzy quantifiers and fuzzy probabilities [9]. This allows users to work at a semantic level using linguistic variables [3]. A customer can be described a being ‘loyal’ or ‘likely’ to pay on time. Such fuzzy quantifier are especially important in management decisions dealing with uncertainty and values that can not be quantified [2, 1]

Linguistic variables are variables whose value is expressed in natural language [1]. Certain variables such as for instance the loyalty of a customer can not be assigned a numerical value. If we consider an example from everyday life, described by [1], is that of the age a person. While is possible to give a numerical answer to this question, people frequently describe themselves as young, old or middle aged. This is further complicated by the fact that a person may be considered to be young, yet someone of exactly the same age old.

Bojadiev [1] for instance, describes the linguistic variable age by the linguistic terms, very young, young, middled aged, old and very old. This is shown in Figure 6.

The membership functions for the terms are are:
If we take a person aged 45 years old, for instance, we see that this person is young to the degree of 0.25 and middle aged to the degree of 0.75. This particular person can therefore be described as young (degree 0.25) and middle aged (degree 0.75).
5 Hierarchical Classification

In the simple examples shown in Section 4.1 customers were only evaluated based on two criteria. This simple classification is not sufficient when evaluating real customers. Evaluating customers on more than two criteria leads to a multi dimensional classification that is difficult to interpret. This same problem afflicts sharp classification and can be partially solved by introducing linguistic variables [8]. While linguistic variables representing smooth transitions can reduce the number of classes, the problem of an excessively large number of dimensions remains.

One solution to this problem is to decompose our multidimensional fuzzy classification hierarchically into sub classes. From the previously mentioned participant information, a hierarchical fuzzy classification can be created based on the model established by Werro et al. [3]. A the top, we have the participant lifetime value, the concept which we wish to optimise. The participant lifetime value can be decomposed into the loyalty and the profitability concepts.

![Figure 7: Customer lifetime decomposition for BSU](image.png)

The proposed decomposition is shown in Figure 7. The decomposition has two main perspectives, the profitability and the loyalty perspective. The loyalty perspective measures how attached a participant has been to BSU over a number of years. It is determined by the number of times a contestant has participated, and the number of friends that he has recommended the game to. The profitability dimension show how profitable a player’s participation has been to BSU for this particular year. It is determined by the speed at which participants pay. The combination of these two measures a participants value to BSU over a range of years, and provides an accurate predication for future behaviour of the participants.

The hierarchical decomposition ensures that we can precisely measure a participants value to BSU while at the same remaining comprehensible. A
marketing analysis of participants might for instance begin at the highest level, the *participant lifetime value*. At this level it can be determined if a particular participant represents a problem from either the *loyalty* or the *profitability* concept. The affected concept can then be decomposed, and the process repeated iteratively until the problem has been discovered.

For the remainder of this section we will progress in the opposite direction, building complex concepts expressing higher semantics from simpler ones. We begin by composing the *loyalty* concept from the *participation* and the *recommended* attributes. We will then compose the *participant lifetime value* concept from the *loyalty* and the *profitability* concepts.

### 5.1 Decomposing the loyalty concept

The loyalty concept show attached a participant is to the game. It has a deeper meaning than just the *profitability* concept as it measures a participants loyalty to BSU over a number of years, as well as the willingness to share his experience with his friends. It can be defined in terms of the number of times that a player has participated in the PMS, his *participation* and the number of other players that he has recommended the PMS to, his *recommended* value.

For *participation*, the domain has been restricted to the interval [1,6], the lower limit representing the initial participation, and the upper limit reflecting the fact that the simulation is aimed at students. The domain for the *recommended* value has been fixed over the interval [0,6] and the upper and lower bounds of the the interval reflect those of the participants shown in this paper.

![Figure 8: Customer loyalty concept for BSU](image)
The results of the loyalty concept are shown in Figure 8. The participants belong to various degrees in four fuzzy classes: C1, C2, C3 and C4 based on their attachment to BSU.

- **Class C1**: This is the class of participants who can be described as being ‘very loyal’. These are the members who participate regularly and who encourage others to join. Such participants have an extremely high value for BSU as their continued participation demonstrates their approval of BSU and they are eager to share their experience. From a marketing perspective, these are the participants who need to be rewarded for their loyalty, to ensure their continued participation in BSU games and to ensure that once they are no longer eligible to play, they continue to recommend BSU.

- **Class C2**: This is the class of participants who can be best described as ‘good ambassadors’ for BSU. Their recommendation to friends demonstrates their approval of BSU and encourages others to join the game. Because this is often their initial participation, measures need to be taken to ensure that they continue to play in years to come.

- **Class C3**: These participants are a paradox. On the one hand, their regular participation indicates that they enjoy the games organised by BSU, but on the other hand, they are unwilling to share their experience with others. From a marketing perspective, these players have the potential to become ‘very loyal’ provided that they are given the right incentive.

- **Class C4**: These participants are those who have no loyalty. They participate infrequently, sometimes because this is their initial participation, and their lack of recommendations indicates their unhappiness with BSU. Their lack of loyalty can have multiple causes, either genuine lack of interest or lack of communication between BSU and the participants.

As can be seen clearly in Figure 8, Huber, Sieber and Müller have an almost equal membership degree in multiple classes. This clearly shows the power of fuzzy classification. If a sharp classification had been used, these participants would have belonged exclusively to one set. Sieber, for instance, would find himself in the same set as Suter, even though their differences are great in their loyalty.

By assigning grades of loyalty to each class, it is now possible to calculate each participant’s individual loyalty grade using the following definition [8]:

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The personalised value $V(I_i|C)$ of an object $O_i$ with membership degrees $M(O_i|C_k)$ in the set of fuzzy classes $C = \{C_1...C_n\}$ each fuzzy class having a definite grade $gr(C_k)$ expressing a concept, is defined as:

$$V(I_i|C) = \sum_{k=1}^{n} M(O_i|C_k)gr(C_k)$$

The result depend on the values chosen for $gr(C_k)$. An example result is shown in Figure 9.

<table>
<thead>
<tr>
<th>Participant</th>
<th>Participation</th>
<th>Recommended</th>
<th>Loyalty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suter</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Huber</td>
<td>3</td>
<td>12</td>
<td>0.8</td>
</tr>
<tr>
<td>Müller</td>
<td>6</td>
<td>5</td>
<td>0.6</td>
</tr>
<tr>
<td>Sieber</td>
<td>4</td>
<td>6</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Figure 9: Calculation of the loyalty concept

### 5.2 The profitability concept

<table>
<thead>
<tr>
<th>Participant</th>
<th>Payment delay (weeks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suter</td>
<td>never</td>
</tr>
<tr>
<td>Huber</td>
<td>4</td>
</tr>
<tr>
<td>Müller</td>
<td>6</td>
</tr>
<tr>
<td>Sieber</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 10: Payment delay for participants in the 2008 edition of PMS

A participants profitability to BSU depends solely on one factor, his annual membership fee. Figure 10 shows, all participants have to pay the same fee (15 CHF) and can be differentiated only in the amount of time they take to pay. Please note that payment are checked only at two week intervals.
so all units are multiples of two. Player who delay payment represent an additional charge for BSU as they need to be constantly reminded of the fact that payment is mandatory. Of course some players never pay. These represent a total loss for BSU.

We decided to model the *profitability* concept as the linguistic variables *profitable* and *unprofitable* over the domain of \(x\) (the amount of time a player took to pay). Giving the membership function of the class:

\[
\mu_{\text{profitable}}(x) = \begin{cases} 
\frac{6-x}{5} & \text{if } 0 \leq x \geq 6 \\
0 & \text{if } x > 6 
\end{cases}
\]

\[
\mu_{\text{unprofitable}}(x) = \begin{cases} 
\frac{x}{6} & \text{if } 0 \leq x \geq 6 \\
1 & \text{if } x > 6 
\end{cases}
\]

This means that Suter is profitable (degree 0) and unprofitable (degree 1); Huber is profitable (degree 0.3) and unprofitable (degree 0.7); Müller is profitable (degree 0) and unprofitable (degree 0.3) and Sieber is profitable (degree 0.3) and unprofitable (degree 0.6).

### 5.3 Participant Lifetime Value Classification

The concepts of *loyalty* and *profitability* can now be combined to create the concept of *participant lifetime value* that precisely measures each participant value to BSU. A graphical representation of the *participant lifetime value* is shown in Figure 11.

The results of the *participant life time* concept are shown in Figure 11. The participants belong to various degrees in four fuzzy classes: C1, C2, C3 and C4 based on their value to BSU.

- **Class C1**: These are the highest value participants. Not only does their continued loyalty to BSU ensure that they will remain a source of revenue for the foreseeable future, but their prompt payment ensures that they remain lucrative for BSU.

- **Class C2** These participants are those who pay promptly yet participate rarely. From a marketing point of view, it would be useful to encourage these players to participate more regular in years to come via a targeted marketing campaign.
Figure 11: Participant lifetime value for BSU

- **Class C3** These participants have demonstrated a long time loyalty to BSU but have difficulties in paying promptly. Their loyalty demonstrates that they feel a certain attachment and their delayed payments indicate that they are given insufficient incentives to pay rapidly.

- **Class C4** These participants are those who have neither loyalty nor do they represent a particularly lucrative source of income. They are infrequent players and have great difficulties paying on time.

As can be seen clearly in Figure 11 many participants are in class C4, they represent a loss for BSU. What is particularly troublesome is that they have such a strong degree of membership to this class because of their unwillingness to pay on time. Upon further analysis, it became clear that BSU has a major problem when it comes to payment processing. Participants are given very generous deadlines for payment, and because all payments are processed infrequently by hand, these deadlines are rarely enforced.

Please note once again Sieber has an equal membership degree to class C4 (loss inducing customers) and C3 (payment needs to be accelerated). If we had performed a sharp classification, Sieber might have found himself exclusively in class C4. This would have been unfortunate for him as he would be treated like a loss, and equally unfortunate for the organisers as they would have risked losing a loyal player who simply needed to be reminded to pay on time.
6 Conclusion and Outlook

6.1 Summary of findings

The purpose of this paper was to analyse the online participants of the BSU Portfolio Management Simulation with the aim of maximising their long term value. We began by looking at ways in which information can be gathered about online customers in both explicit and implicit ways. For BSU, we decided to use the explicit information given at registration, notable the question as to who recommended the game to them. We also considered the passive information concerning their participation over a number of year as well as the speed at which they paid their membership fees.

Next, we looked at how this data can be classified using fuzzy sets. We discovered the usefulness of being able to assign a participant to more than one class and the advantages of describing certain concepts using fuzzy variables.

Finally we took the fuzzy variable of participant lifetime value and decomposed it into the simpler concepts of loyalty and profitability. Such a hierarchical decomposition ensured that we could precisely measure a participants value to BSU while at the same remaining comprehensible.

An initial analysis of this hierarchical fuzzy classification showed that BSU had a problem with participant delaying payment of their membership fee. At the level of the loyalty concept, it was further noted that more could be done to encourage frequent participants to encourage others to play.

6.2 Outlook

The participant value carried out was limited in scope to a few participants and very analytical in nature. We nonetheless demonstrated the soundness of such an approach. The next step would be to extend this approach by including data from more participants.
References


