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# Fuzzy Modeling of User Behaviors and Virtual Goods Purchases in Social Networking Platforms

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**Abstract**: An important aspect of managing social platforms, online games and virtual worlds is the analysis of user characteristics related to subscriptions and virtual goods purchases. The results of such a process could be adopted in decision support applications that build on top of users' behavior provide efficient strategies for the virtual world's management. One of the research questions in this area is related to the factors affecting purchases and their relation to the activity within social networks as well as the ability to use past data to make reasoning about future behaviors. Complex online systems are hard to analyze when adopting legacy methodologies due to the huge amount of data generated by users' activity and changes in their behavior over time. In this paper, we discuss an analysis of the characteristics of users performing purchases for virtual products. We adopt a Neuro-Fuzzy system which has the ability to process data under uncertainty towards better decisions related to parameterization of the virtual retail system. The proposed Fuzzy Logic (FL) inference model focuses on the analysis of purchases based on the types of past transactions and social activity as inputs. The proposed system results values for specific parameters affecting/depicting users' behavior like own purchases, gifting and virtual products usage as output. Our results could be adopted for decision support of online platform operators and show the relations between less and more experienced users in terms of frequency and value of purchases, engagement with the use of virtual goods and gifting behaviors. Models based on the social activity with distinguished inbound and outbound social connections show increased interest in virtual goods among users with a higher number of inbound connections as a possible tool for building social position.

**Keywords:** fuzzy modeling, virtual goods; user behavior; social networks; decision support
**Categories:** H.4, I.2.1, M.4, M.8, H.5.1

## 1 Introduction

In the past years, virtual worlds, social networks and massively multiuser online systems have attracted significant interest of the research community in various domains [Messinger 2009, Moor and Weigand 2007]. Introducing new features, acquiring new participants and providing community growth are important issues towards the effective commercial social network ventures. In these environments, virtual marketplaces, where users can purchase products, are becoming increasingly attractive. The reason is that such places can become sources of revenue involving various business models e.g., subscriptions or purchases of virtual goods [Hamari 2015, Hamari and Lehdonvirta 2010]. These platforms allow users to purchase and use virtual products, usually equivalents of products from the real-world. A market analysis presented in [Piper Jaffray 2009] indicates that more than 100% of annual growth in the number of virtual objects , with sales growing from 621 million dollars to 2.5 billion dollars a year. Barnes [Barnes 2007] cites virtual world expenditure levels to be between 1 and 2 million dollars a day while Gartner [Gartner Research 2010] argues that a key problem facing social network and virtual world entrepreneurs is in understanding users' behavior and developing an attractive value proposition: "*business models and compelling business cases remain problematic, while effective metrics are still under development*". As a result, virtual retail systems can constitute an added value to the operating income of business ventures. However, this depends on the effectiveness of the distribution systems. Problems in this area are related to changing preferences and factors related to various aspects of the users' behavior within digital communities that, consequently, affect purchasing decisions.

In this paper, we present a model for identifying user characteristics that influence purchasing actions for the purpose of decision making in the parameterization of virtual retail system. We propose an inference system based on *Fuzzy Logic* (FL) [Zadeh 1965, Zadeh 1994] that focuses on the identification of users' characteristics and the analysis of important parameters which affect the realization of purchases. FL is the appropriate technique for handling the uncertainty present in virtual marketplaces. For instance, we cannot be sure about the preferences of the users concerning the desired virtual products and, consequently, the realization of purchases. Allowing a degree of fuzziness, we can adopt FL to provide a decision making mechanism infer purchasing behavior based on a set of parameters. The adoption of FL involves representation of the users preferences knowledge and the inference on the purchases. The proposed approach can be the basis for a decision support system targeted to decisions related to the selection of target groups for new products, the identification of parameters affecting purchases, pricing strategies and better digital resources management within the online platform. Our experiments aim to highlight the potential adoption of the FL inference model and delivers interesting results that show possible relations between users' activity, historical transactions and purchases towards better decisions related to system parameterizations and effective utilization of potential of virtual goods. More specifically, we take into consideration users' activity in terms of: (i) *the realized past purchases*; (ii) *the purchases realized to serve as gifts*; (iii) *the usage of the purchased virtual products*. In addition, the users' social activity model incorporates both inbound and outbound social connections based on the degree measures with the ability to show the output as a number of purchases.

The proposed model aims to reveal the hidden parameters that affect users in performing purchases. Users' activity in a virtual world can provide the necessary data to reveal these parameters. We do not aim to provide a single system that proposes products to users but a tool for evaluating the parameters that affect the purchasing behavior of users. Our model could be easily combined with other systems that perform product recommendations to users. Such a combination could enhance the intelligence of recommender systems and lead to more efficient results. In general, the contributions of our paper is as follows:

- A new approach for modeling users' behavior and preferences in virtual retail systems;
- An inference model that outputs insights on future virtual goods purchases involving the user status, transactional (historical data on past purchases) and social activity. It should be noted that the proposed model does not aim to perform prediction but to provide an inference mechanism for identifying the hidden parameters that affect the purchasing behavior of users. When adopting the term 'future virtual goods purchases' we do not refer to a prediction scheme but to the capability of the model to derive the inferred purchasing behavior of users. In our future research agenda is the involvement of a prediction scheme for basic parameters of our system (e.g., number of purchases as gifts) that will result future estimates fed into our FL model. This combination will connect the current state (current parameters realization) with future estimates (predicted values on the same parameters) and, thus, it will lead to a more efficient system.
- A comprehensive analysis for real data retrieved by a virtual world; these detain corporate relations between users and reveal how users' relationships affect future purchases and the use of virtual products (e.g., for own purposes or gifts);
- A comprehensive analysis for virtual products usage and characteristics like pricing; the analysis is performed in relation to user status within the virtual community and historical transactions.

The rest of this paper is structured as follows. Section 2 presents the related work while Section 3 describes our conceptual framework, including the fuzzy modeling approach. This is followed by an overview of the virtual world and social and transactional variables used in the analysis (Section 4). In Section 5, we present the analysis and our results. Finally, in Section 6, we conclude our paper by giving some implications and future insights in the discussed research domain and it is followed by summary in Section 7.

## 2 Related Work

When determining the functional scope of virtual retail systems, it is important to identify, analyze and understand those user characteristics that contribute to user uptake of payable services or subscriptions [Bhattacherjee 2001]. Knowledge of behavioral patterns and preferences allows managers to influence and maximize revenues by targeting groups that are responsive to these kinds of offers [Hernandez-Ortega 2008]. The influence of consumer experience on their transactional behavior to illustrate the importance of consistent and loyal consumers in online social systems was studied [Liao et al. 2006]. Further, consumers change their consumption and purchasing preferences over time and as they are adapted to the system [Denguir-Rekik et al. 2009, Kamis et al. 2008]. Managing and responding to these changes is also important as customers of the online services may easily switch to alternative providers [Chang and Chen 2008, Flavián et al. 2006]. While recent work has also examined the uptake of social and virtual communities [Cheung et al. 2011, Jang et al. 2008] and their influence on brands [Hinz et al. 2010], the design and retail of virtual goods has received little prior research attention [Lehdonvirta 2009]. Ongoing financial viability is a problem affecting managers and developers of online social platforms [Clemons 2009a]. Virtual worlds and social networks provide many possibilities for implementing a variety of business and revenue models [Grimes and Feenberg 2009] based on subscription fees, sales of virtual objects [Hamari 2015, Hamari and Lehdonvirta 2010], advertising campaigns, sales of ancillary goods (e.g., branded clothing and accessories), usage data from social networks for recommendations [Ting 2012, Sabucedo et al. 2014] or external partnerships [Clemons 2009b, Zott et al. 2011]. However, determining the appropriate revenue sources remains a problem not only for managers but also for potential partner firms who are considering to adopt such media for promotion, customer interaction and client support [Warr 2008]. One possible revenue source could come from virtual product transaction systems. In this model, members use real-world currency to purchase virtual products to use them within the virtual environment [Guo and Barnes 2007]. Virtual products differ from material products in that they exist only within the confines of the virtual world [Lehdonvirta 2009]. As with material goods, virtual products may have various functional, social and hedonic attributes. However, such attributes are environment depended and they typically cannot be used within other virtual economies. Shin provides evidence that some users are prepared to spend substantial amounts of money on improving their virtual experience, including purchasing virtual items, to maintain and change their virtual appearance [Shin 2008]. Mäntymäki and Salo report a relationship between continuous use and purchases [Mäntymäki and Salo 2011]. A number of online applications are experimenting with this type of virtual commerce by integrating micro transaction and virtual product distribution systems. For instance, Second Life [Shelton 2010] allows members to trade in virtual products for virtual currency. Facebook and MySpace have implemented their own payment platforms, Hi5 introduced its own virtual currency and systems like Habbo Hotel and Tencent offer a number of direct micropayment methods for purchasing virtual products and services [Ba et al. 2010, Lehdonvirta and Virtanen 2010]. Taking advantage of the virtual product retail systems, managers of novel online worlds may want insight into a number of user-related phenomena and specific characteristics in these online networking platforms. For instance, a manager may want to know the relationship between friendship invitations (given and received) and the propensity to purchase virtual products, either for their own consumption, or to be used as gifts. Similarly, a manager may want to understand how amenable particular user groups are to purchasing premium or prestige products over standard items, and how the level of system use affects this behavior [Hinz et al. 2010]. In particular, the understanding of the role of contextual factors of the virtual world to understand how product attributes are affected by the virtual world environment [Lehdonvirta 2009] in order to set performance goals [Wu and Chou 2011] is crucial. However, some idiosyncratic properties of online social environments make it difficult to analyse and, thus, monetize these platforms [Clemons 2009b]. For instance, virtual world systems are highly dynamic, affected by a variety of internal and external conditions. Applying analytical methods that assume deterministic input data may not faithfully reflect the true character of the environment. Assuming precise values for input parameters can lead to over-specified models and be characterized by lack of generalizability. Often, in such situations, precise boundaries between values may not exist and allows us to categorize customers to different segments due to small differences in parameters [Meier and Werro 2007].

This paper proposes a method that can deal with large amounts of data yielding useful and comprehensible insights for real world systems. FL inference can handle the uncertainty related to users' behavior and setup the basis for an efficient decision mechanism that results insights on future purchases on top of a set of parameters. These parameters are related with the users' characteristics, e.g., past transactions / purchases, relationships with other users. A number of analytical methodologies (e.g., experimental analysis, economic modeling and social network analysis) can be used to determine user preferences in these circumstances. These analytical methods make significant use of statistical data analysis techniques, data mining and extraction of associative rules for user segmentation. While these approaches are useful, real world systems generate significant amounts of data; analysis of these data is not always suited to purely deterministic methods. However, at the same time, these data are useful for the purposes of decision-making and shaping the developmental initiatives while it may be more useful to employ linguistic values, such as *small, medium* and *high* (e.g., user activity) based on fuzzy sets theory [Zadeh 1965]. Previously, this theory has been applied in fields of decision making [Zadeh and Bellman 1970], linguistic reasoning [Zadeh 1975], artificial reasoning systems [Mamdani and Gaines 1981] and sequential and multi-criteria decision making [Iwamoto and Sniedovich 1998]. Emerging applications that could adopt FL in decision making include behaviour adaptation [Kolomvatsos and Hadjiefthymiades 2012], user preference analysis [Zenebe et al. 2010] and supply chain management [Chen et al. 2010]. In general, FL models are useful in cases where imprecise data are present [Tam et al. 2002]. By using a multi-dimensional approach to fuzzy modeling, systems can be adopted for the management decision-making in large data sets [Jiang and Chen 2005]. Adaptive fuzzy modeling has been applied in recent real world business problems [Xie and Baldwin 2007, Abraham et al. 2009] as well as in online applications such as the analysis of navigation patterns [Zehraoui et al. 2010], environmental monitoring [Park Cho 2011] and network data traffic [Schuler et al. 2009, Wang et al. 2005].

## 3 Conceptual and Methodological Framework

The main goal of the proposed approach is to build a model of users preferences and characteristics as the basis for an efficient decision making system that will result insights on user behaviors and purchases. The proposed model takes as inputs historical data related to users' activity within virtual communities. Input data can be based on various sources including activity within system, gathered experience or past purchases. In addition, our model considers social activity in terms of users' relationships (i.e., inbound and outbound connections, number of purchases as gifts, number of friends invitations) in the virtual world. The model results insights on purchasing behavior, preferable product prices or the usage of purchased objects. For instance, the usage of a product could be for own use or to serve as a gift. An FL inference mechanism is particularly suitable because it addresses large, dynamic datasets with uncertainty based on imprecise information about users' preferences. In this paper, we propose a *FL System* (FLS) that aims to provide decisions on users' behavior when interacting in a virtual environment. The FLS builds on top of an *Adaptive FL Model* (AFM) and tries to handle the uncertainty related to users' activities. The AFM is updated every time new data are realized into the virtual world. On the other hand, the FLS takes prior events and behaviors into account in order to infer purchasing behavior. This approach assists in determining the probability of purchasing activities based on previous behavior and can adjust model parameters to input data. The proposed method allows the use of linguistic terms rather than crisp values. In general, linguistic terms are easier to be handled and, thus, can efficiently be adapted to inputs. For building the proposed adaptive FLS, we adopt the *Adaptive Neuro Fuzzy System* (ANFIS) as presented in [Jang 1993]. FL rules allow elements of interest to be categorized into sets, by inferring characteristics of the elements according to relevant sets of membership criteria [Zadeh 1965]. Memberships represent the degree of truth for a specific fuzzy set and they are governed by rules which are typically of the following form: *IF antecedent THEN consequent*. A set of rules define the *FL rule base* adopted to derive the output of the FLS. For each rule, if the antecedent is satisfied, then the consequent dictates the relevant fuzzy set. The antecedent and the consequent involve linguistic variables to describe the corresponding fuzzy sets. FL rules are the basis of the *FLS inference system* that determines the membership degree for input and output variables. The inference system typically consists of five component layers or blocks. Fig. 1 presents the layered architecture of fuzzy inference model integrated with the online social platform.

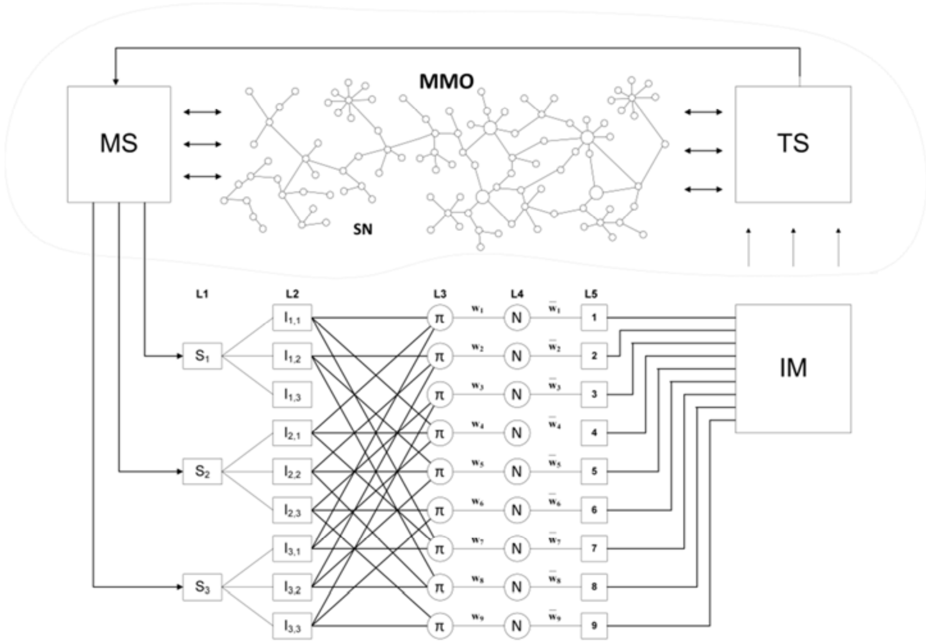


*Figure 1: Integration of an ANFIS inference system with the MMO platform.*

The system is based on the ANFIS model [Jang 1993] with adopted the inference mechanism [Takagi and Sugeno 1985] with five layer structure. The first layer, *L1*, processes the input data for each input $S_i$, a parameterization and the introduction of premises. The second layer, *L2*, generates the support product $I_{i,j}$ and the level of each rule. The third layer, *L3*, sends normalized rules πto the output. The fourth layer, *L4*, determines the inference parameters *N*, and the fifth layer, *L5*, produces a crisp, deffuzificated output. The output is defined as the linear combination of the input parameters. The inference system is integrated with a *Massively Multiplayer Online* (*MMO*) system where users are connected within social networks *SN* and perform transactions over virtual products in a transactional system denoted by *TS*. A *Monitoring System* (*MS*) is responsible to aggregate data while the *Inference Module* (*IM*) is responsible to adjust system parameters. Furthermore, we adopt a training algorithm to enhance system's parameterization and produce the FLS fully aligned with the virtual world characteristics. The goal of the training algorithm is to build the model's parameters and membership functions aligned with the real-world data. For generating the membership functions, we adopt the Mamdani's model [Dweiri and Kablan 2006, Mamdani 1974, Mamdani 1977, McCloskey et al. 2006] that involves linguistic expressions for the adopted fuzzy sets. The functional basis of this model is to handle inputs in the form of a vector *X* corresponding to the output *Y*. The orientation is on the minimization of the *Mean Square Error* (MSE) [Mamdani 1977]. In the initial phase, some expert knowledge may be required to parameterize the system and define the adopted fuzzy sets. Moreover, each fuzzy rule determines a fuzzy point in the area of a Cartesian product $X×Y$. Membership functions $\mu_{Ai}$ and $\mu_{Bj}$ denote belonging to the sets $A_i$ and $B_j$ of input values $x_1^*$ and $x_2^*$ and they determine the model output $y*$ with the *MIN* operator(see Eq(1)).

$$MIN(\mu_{Ai}(x_1^*), \mu_{Bj}(x_2^*)) \quad (1)$$

Another possible solution adopts the algebraic product operator [Larsen 1980]. We also adopt the back propagation gradient descent as the learning algorithm. The method calculates squared errors with respect to each output in the recursive process from the output layer back to the input elements.

# 4 Analyzing Social and Transactional Behavior

## 4.1 The Adopted Virtual World

The implemented prototype virtual product distribution system is based on the ANFIS model, using a neuron back-propagation algorithm. The model was designed to analyse user purchasing behavior in the context of a virtual world and examine user interest in virtual products and their propensity to participate in transactions. The system was integrated with an existing virtual world Timik.pl located in Poland, containing 850,000 registered users. In this virtual world, principle user activities include: (a) communication; (b) establishing social bonds; (c) meeting other users; and (d) chatting. Within the system, users are represented by graphical avatars and they have the opportunity to be engaged in the life of an online society performing various actions and interactions. Avatars may also possess decorative adornment elements comprising selectable clothing styles and virtual products. Users enter and communicate in public spaces throughout the virtual world, represented by graphical rooms that are associated with different themes. It should be noted that users may also activate their own private virtual rooms for particular groups and themes, choosing the decoration, furniture and adornment. They can also activate different types of products such as dedicated packages, special effects and units of virtual currency. For each user in the virtual world, we gather a number of variables of interest. Table 1 shows the discussed variables.

## 4.2 Virtual Products Description

Within the analysed system users can purchase a variety of virtual products. After the purchase, each virtual object can be used by the user's avatar or it could be given to another user as a gift. For instance, the user's avatar may be seen to hold in their hand a drink, a cake, or bouquet of flowers as they move around the virtual world and interact with other users. Prices of these virtual products vary depending on the appearance of the product and its potential attractiveness to a user. Pricing for individual product groups reflect pricing proportions in the real world e.g., the lowest prices are assigned to cool drinks and fruit juices, while the highest prices are allocated to mascots and toys. To show the relation of virtual goods to their real representation, Table 2 presents the set of the virtual products available to users in virtual world divided into several categories together with label for each product.

| Name | Definition | Description |
|---|---|---|
| $S_i$ | Status of a user *i* | The more time he/she uses the system, the greater the user's status. It increases with the number of logins but is limited to three logins per day and a maximum of 21 per week. |
| $A_i$ | Number of activations of premium services by user *i* | Premium services include VIP accounts, premium accounts, and digital currency. The most popular payment method is SMS payment via mobile phone. |
| $P_i$ | Number of purchases of virtual products by user *i* | Users may purchase virtual products such as mascots, toys and drinks. |
| $F_{out,i}$<br><br>$F_{in,i}$ | Number of friend invitations sent by user *i*<br><br>Number of friend invitations received by user *i* | As in many online social networks, users may send and receive invitations to be friends with other users. |
| $G_i$ | Number of gifts sent by user *i* to other users | Once a user has purchased a virtual product, they may send that item as a gift to another user in the virtual world. |
| $V_i$ | Total transactions value for user *i* | This variable represents the total value of transactions undertaken by the user, including purchases of virtual products and activation of premium services. |
| $L_i$ | Number of system logins by user *i* | This variable describes the number of times the user has logged into the virtual world. |
| $U_i$ | Number of object calls by user *i* | After buying a virtual object, the user's avatar can use it (for example, in the avatar can hold it in their hands to show to other users). The virtual object can be called multiple times. |

*Table 1: User interaction variables.*

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| Product Group | Visual representation |
|---|---|
| Mascots | $m_1$ $m_2$ $m_3$ $m_4$ $m_5$ $m_6$ $m_7$ $m_8$ |
| Beverages | $n_1$ $n_2$ $n_3$ $n_4$ $n_5$ |
| Energy drinks | $e_1$ $e_2$ $e_3$ $e_4$ $e_5$ |
| Bouquets | $k_1$ $k_2$ $k_3$ |
| Desserts | $d_1$ $d_2$ $d_3$ $d_4$ $d_5$ |
| Fruit juices | $o_1$ $o_2$ $o_3$ $o_4$ |
| Toys | $z_1$ $z_2$ $z_3$ |

*Table 2: Virtual products and categories.*

### 4.4 Implementation of the FL Inference System

In order to develop the proposed FL inference system, we distinguish two main areas related to the transactional activity of the platform and the social characteristics of users. The model that is based on the transactional activity can be integrated with the selling platform and connected with the transactional database. The main goal is to infer about user preferences and purchasing behaviors. The model based on social characteristics of users can be integrated with the internal communication module where social activity and communications with friends take place. To develop both models, we adopt two groups of input parameters: (i) transactional activity parameters; and (ii) social activity parameters. These parameters are related to the inputs into the proposed system. The outputs include the parameters depicted in Table 1, such as:

i. the number of purchases denoted by *P*;
ii. the number of times the virtual products are used denoted by *U*;
iii. the number of products used as gifts denoted by *G*;
iv. the total value of transactions denoted by *V*;
v. the price of the virtual products *PP*.

The first group of parameters contains the transactional activity parameters which describe the patterns of the system use and account transactions. Two groups of users' activity variables are considered: (i) the user status $S_i$ and (ii) transactions related to the premium service activation $A_i$. Both are used as elements of a data supply vector $[A_i, S_i]$ fed to the transaction activity fuzzy inference sub-model. The specific sub-model is responsible to result insights on *P* and can be adopted to infer purchase behavior. This approach makes possible the examination of the users' behavior and experiences w.r.t. their virtual product transactions and system use. Values for input variables are acquired from the data gathered in analysed virtual world. Input data are grouped into several intervals and average output values are, then, calculated for each parameter. For instance, we adopt four sets of values for $A_i$, as follows: $A_1$Interval$_1$:

(1,2], $A_2$Interval$_2$:(2,3], $A_3$Interval$_3$:(3,10], $A_4$Interval$_4$:(10,∞) from two transactions to more than 20 transactions, and for $S_i$, we adopt six intervals as follows: $S_1$Interval$_1$: (0,20], $S_2$Interval$_2$:(20,50], $S_3$Interval$_3$:(50,100], $S_4$Interval$_4$:(100,200], $S_5$Interval$_5$: (200,500], $S_6$Interval$_6$: (500, ∞). We consider Gaussian membership functions which are ultimately selected to be applied in the final model. In our system, the number of membership functions for each input is analyzed, and the final result is presented for three membership functions for each individual entry. Finally, the adopted fuzzy sets are depicted by the linguistic variables Low, Medium, High and divided proportionally in the range from 0 to more than 20 virtual product purchases. We also adopt the same linguistic descriptors as in the $A_i$ variable.

The second group of parameters is related to users' social activity and uses degree within network. We consider two parameters: (i) the parameter $F_{in}$ represents the number of inbound friendship requests; and (ii) the $F_{out}$ related to outbound friendship requests. Within the structure of the ANFIS inference model for the social activity of users the input of the sub-model is the vector [$F_{in}$, $F_{out}$] (i.e., the inbound and outbound interactions) while the output is related to average number of gifts sent to other users *G*. Input values for the social activity sub-model are divided into six intervals for both parameters. The adopted intervals for $F_{in}$ are as follows: $F_{in}$Interval$_1$: (0, 50], $F_{in}$Interval$_2$: (50, 100], $F_{in}$Interval$_3$: (100, 200], $F_{in}$Interval$_4$: (200, 300], $F_{in}$Interval$_5$: (300, 400], $F_{in}$Interval$_6$: (400, ∞) and the same for $F_{out}$, where each interval involves the number of inbound or outbound connections (requests). It should be noted that, in the following, we denote with $F_{in,i}$ or $F_{out,i}$, $i \in \{50, 100, 200, 300, 400, \infty\}$ each interval presented for parameters $F_{in}$ and $F_{out}$ to represent the upper value for each. Linguistic values are assigned to both inbound and outbound connections in the interval (0, 600]. We consider the linguistic terms Low, Medium, High.

# 5 Empirical Results

## 5.1 The Training Process of the proposed FLS

Our experiments are performed adopting Matlab$^{TM}$. We train the proposed ANFIS with a dataset retrieved from virtual world platform. At first, we focus on the first sub-model (i.e., the transactions activity model). For model calibration, we use the average values for different intervals of input parameters. Each block in the ANFIS model is trained using both the back-propagation gradient descent method and a hybrid approach. The hybrid approach involves the least-squares method combined with the back-propagation gradient descent method. It should be noted that better results are achieved using the back-propagation method. Once trained, the model is tested using the user data retrieved from the virtual world. The membership functions are determined using input measures of aggregate transaction values according to each user's parameters. The model is tested for 10, 20 and 50 epochs, however, training beyond 20 epochs did not yield significant improvements. In Fig. 2 we can see the interface of the inference system for the discussed model. Recall that the first sub-model determines estimated values for the parameter *P* adopted to estimate users' purchase behaviour. As we can see in Fig. 2 (A), *P* takes values in the interval

[0.6597, 5.472] representing the average number of purchases. A similar approach is also adopted to define sub-models for outputs *U*, *G*, *V*.

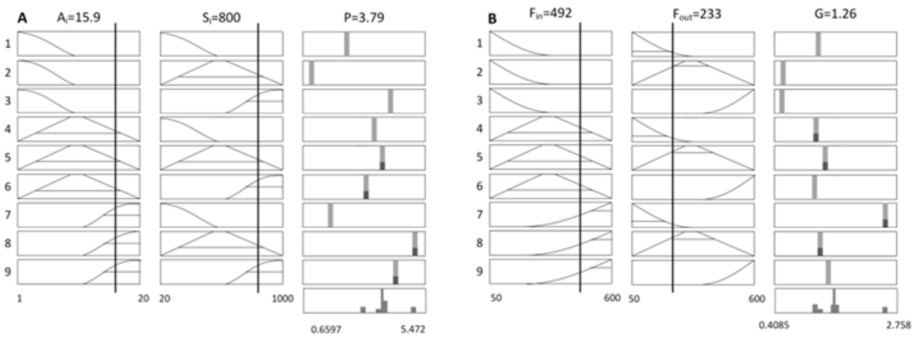


*Figure 2: Fuzzy reasoning and system interface for purchases P (A) and gifting behaviors G (B).*

In Fig. 2 (B), we present the result of the inference system concerning the social activity of users. Recall that in this sub-model, the output is related to the parameter *G*. For a chosen input level for $F_{in}$ and $F_{out}$ parameters, this model determines values for the output *G* in the interval [0.000, 2.758] for the output value. The sub-model based on $F_{in}$ and $F_{out}$ inputs for products usage *U* as output is designed with similar structure.

### 5.2 The Virtual World Statistics

We perform an analysis for data collected in a two month period. The data are related to 1,322 users who had activated and used virtual products in analysed virtual world. We taste 3,935 virtual product transactions that consider 128,962 units of virtual currency. The average total value is 97 units of virtual currency for an average of three transactions per user. Data related to virtual products are analyzed w.r.t. the number of transactions and purchases number. Intraday transaction levels remain reasonably consistent. However, users purchase more objects to provide them as gifts on weekends. Table 3 shows the number of transactions for the considered products.

A large number of transactions are observed for bouquets of flowers. Most of the transactions are realized for virtual mascot products $m_1$ and $m_2$. Users appear to be less interested in objects representing toys or fruit juices compared to virtual energy drinks. Predictably, due to their low price, beverages $n_1$-$n_5$ are very popular. There is significant diversity of users' interest in the available virtual products. The highest total aggregate sales number is observed for mascot products $m_1$, $m_2$ and $m_5$, and the most expensive bouquet of flowers $k_3$. Mascots comprised 33% of all transactions, where 21% of purchases are related to virtual equivalents of the cheapest beverages, as well as flowers and energy drinks. With regard to sale values, 58% of shops' income comes from mascots sales, 16% from of flower bouquets, and 16% from energy drinks. Furthermore, in Table 3, we depict the number of purchases of products that will serve as gifts. 72% of the transactions are realized for own usage purposes and 28% of expenses are incurred for gifts. Of those products purchased as gifts, 33% are mascots and 22% are flowers. Purchases are almost exactly evenly divided between genders. Some relations represent behavior similar to real world activity like mascots like $m_2$ and $m_5$ are typical for purchases for gifts while $m_3$ and $m_8$ are with the highest rate for own usage. Table 4 presents sample and descriptive statistics for the observed data. This analysis shows that only a fraction of users conclude purchases of virtual products. This finding is similar to other online payable services, in which the percentage of users willing to make payments may be a very low proportion of the total audience [Clemons 2009b, Enders et al. 2008].

| **Products** | | | | | **Transactions** | | | **Gifts** | |
|---|---|---|---|---|---|---|---|---|---|
| **Group** | **Group %** | **L** | **Name** | **Price** | **N** | **% in group** | **total %** | **N** | **%** |
| Mascots | 26% | $m_1$ | Pink bunny | 45 | 433 | 25.09% | 6.60% | 130 | 30.02% |
| | | $m_2$ | Pink heart | 45 | 649 | 37.60% | 9.89% | 250 | 38.52% |
| | | $m_3$ | Yellow duckling | 45 | 78 | 4.52% | 1.19% | 19 | 24.36% |
| | | $m_4$ | Red hair doll | 45 | 112 | 6.49% | 1.71% | 38 | 33.93% |
| | | $m_5$ | Teddy bear | 45 | 170 | 9.85% | 2.59% | 70 | 41.18% |
| | | $m_6$ | Gingerbread man | 45 | 83 | 4.81% | 1.26% | 27 | 32.53% |
| | | $m_7$ | Fluffy toy | 45 | 147 | 8.52% | 2.24% | 51 | 34.69% |
| | | $m_8$ | Rubber duck | 45 | 54 | 3.13% | 0.82% | 16 | 29.63% |
| Beverages | 23% | $n_1$ | Bottle of milk | 5 | 252 | 16.69% | 3.84% | 58 | 23.02% |
| | | $n_2$ | Cup of coffee | 5 | 378 | 25.03% | 5.76% | 97 | 25.66% |
| | | $n_3$ | Red lemonade | 5 | 274 | 18.15% | 4.18% | 47 | 17.15% |
| | | $n_4$ | Red can of drink | 5 | 336 | 22.25% | 5.12% | 77 | 22.92% |
| | | $n_5$ | Yellow lemonade | 5 | 270 | 17.88% | 4.11% | 59 | 21.85% |
| Energy drinks | 19% | $e_1$ | Blue energy drink | 25 | 203 | 16.14% | 3.09% | 41 | 20.20% |
| | | $e_2$ | Green energy drink | 25 | 202 | 16.06% | 3.08% | 31 | 15.35% |
| | | $e_3$ | Red energy drink | 25 | 413 | 32.83% | 6.29% | 80 | 19.37% |
| | | $e_4$ | Yellow energy drink | 25 | 200 | 15.90% | 3.05% | 30 | 15.00% |
| | | $e_5$ | Pink energy drink | 25 | 240 | 19.08% | 3.66% | 47 | 19.58% |
| Bouquets | 12% | $k_1$ | Small pink rose | 15 | 307 | 37.17% | 4.68% | 155 | 50.49% |
| | | $k_2$ | Five roses | 25 | 278 | 33.66% | 4.24% | 130 | 46.76% |
| | | $k_3$ | Seven roses | 55 | 241 | 29.18% | 3.67% | 124 | 51.45% |
| Desserts | 8% | $d_1$ | Red dessert | 15 | 124 | 22.63% | 1.89% | 14 | 11.29% |
| | | $d_2$ | Big red dessert | 15 | 115 | 20.99% | 1.75% | 19 | 16.52% |
| | | $d_3$ | Orange dessert | 15 | 167 | 30.47% | 2.54% | 31 | 18.56% |
| | | $d_4$ | Green dessert | 15 | 92 | 16.79% | 1.40% | 17 | 18.48% |
| | | $d_5$ | Big green dessert | 15 | 50 | 9.12% | 0.76% | 8 | 16.00% |
| Fruit juices | 6% | $o_1$ | Orange juice | 10 | 37 | 8.92% | 0.56% | 2 | 5.41% |
| | | $o_2$ | Pink raspberry juice | 10 | 170 | 40.96% | 2.59% | 34 | 20.00% |
| | | $o_3$ | Green kiwi juice | 10 | 81 | 19.52% | 1.23% | 26 | 32.10% |
| | | $o_4$ | Blackcurrant juice | 10 | 127 | 30.60% | 1.94% | 25 | 19.69% |
| Toys | 4% | $z_1$ | Green car | 40 | 30 | 10.75% | 0.46% | 12 | 40.00% |
| | | $z_2$ | Red car | 40 | 178 | 63.80% | 2.71% | 55 | 30.90% |
| | | $z_3$ | An airplane | 40 | 71 | 25.45% | 1.08% | 17 | 23.94% |

*Table 3: Experimental Results from Virtual Product Retail System.*

| Variable | Variable Description | Sum | Min | Max | Mean | SD |
|---|---|---|---|---|---|---|
| $S_i$ | Status of user *i* | 320,645 | 1 | 2,099 | 242.55 | 312.63 |
| $A_i$ | Number of activations of premium services | 7,443 | 1 | 97 | 5.63 | 7.04 |
| $P_i$ | Number of purchases of virtual product | 3,967 | 1 | 28 | 3 | 2.92 |
| $F_{in,i}$ | Number of invitations sent by user *i* | 105,502 | 0 | 2,603 | 79.8 | 153.76 |
| $F_{out,i}$ | Number of invitations received by user *i* | 153,352 | 0 | 1,923 | 116 | 184.94 |
| $G_i$ | Number of gifts given by users *i* other users | 1,211 | 0 | 14 | 0.92 | 1.59 |
| $V_i$ | Total transaction value for user *i* | 128,962 | 5 | 915 | 97.55 | 113.46 |
| $L_i$ | Number of system logins by user *i* | 166,689 | 0 | 3,156 | 126.09 | 227.82 |
| $U_i$ | Number of objects calls by a user *i* | 7,199 | 0 | 129 | 5.45 | 12.6 |

*Table 4: Aggregated data sample and descriptive statistics.*

### 5.3 Modeling Purchases in relation to User Transactional Activity

In order to study the effect of user parameters, the proposed inference model is used to analyze different relations of the adopted parameters and, thus, to infer users' behavior. In the following, our experimental results show the outcome of the proposed reasoning models that illustrate the system's output for various combinations of input variables. Fig. 3 illustrates the response surface for the relationship between the individual user characteristics and the average number of purchases. These results are retrieved in relation to the status of each user $S_i$ and the number of premium activations $A_i$. Users with low experience, as represented by $S_i$, are less interested in purchasing virtual products. Comparing users with different $S_i$ statuses, with $A_i = 10$, we get an increased number of purchases, i.e., about 50%. This finding becomes more intense for users with higher status e.g., $S_i = 650$ and increasing premium service activations up to $A_i = 20$. New users may be aware of new products but they are not yet sufficiently involved in the activities of the community to appreciate the advantages related to these objects. Experienced users know that some objects are expensive and it can be fashionable or prestigious to possess them. For new users without knowledge of the mechanics of the virtual world, it is hard to evaluate these advantages and, thus, they have no clearly defined preferences for virtual goods because of the lack of knowledge about insider's behaviors. Fig. 4 shows the model's response surface for the number of items usage $U$. The maximum usage is equal to 6 for $A_i = 10$ and $S_i = 1{,}000$. The number of objects calls increases as users are eager to buy premium services. For users with $A_i \geq 15$, we get $U \rightarrow 2$, but a strong relation can be observed for users with high status $S_i$. Such users are more interested in using virtual objects. The highest number of object usage is observed for $S_i > 700$.

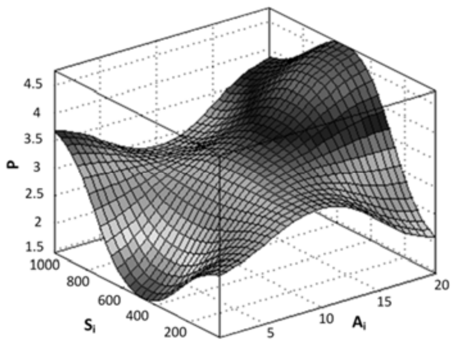


Figure 3: The inference plot for products purchases P.

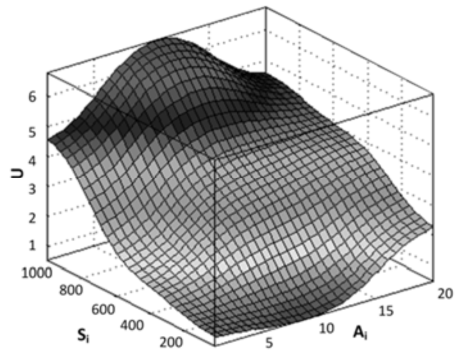


Figure 4: The inference plot for products usage U.

Fig. 5 shows the response surface for the number of premium service purchases concerning the average number of gifts. We observe that the most activity is performed between users with $S_i \in [600, 1000]$ and $A_i > 20$. Our analysis shows that for high levels of premium service activation, there are some low levels of user status and gift giving. The figure also shows that users with $A_i \in [15, 20]$ and $S_i \rightarrow 1{,}000$ are buying more products for gifts. A relatively high number of gifts is realized by users with $S_i > 800$ even with $A_i \rightarrow 0$.

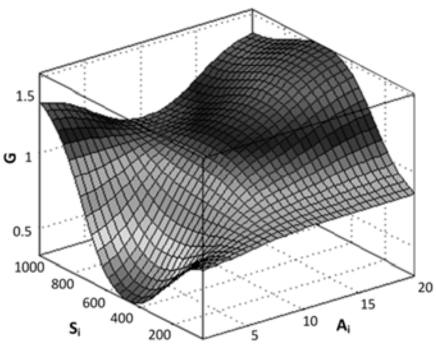


Figure 5: The inference plot for gifts purchases G.

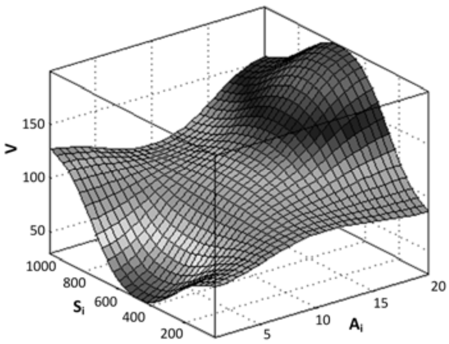


Figure 6: The inference plot for total transaction value V.

We report on the relationship between $A_i$ and $S_i$ and the total number of transactions and products prices for *V* and *PP*. The parameter *V* depicts the purchases value while the parameter *PP* depicts the virtual product price. Fig. 6 shows the model's response surface for the average total transaction values. We observe that users with $S_i \in [250, 600]$ are more interested in purchasing virtual products. New users with $S_i < 200$ are less interested even with high buying potential due to premium activations. The average transactions are observed as reduced even for experienced users with $S_i > 800$ (no matter the value of $A_i$). However, users with high $S_i$ and low $A_i$ are more willing than new users to spend more units of virtual currency for purchases. Obtained relation between $S_i$ and $A_i$ and the average product price $PP$ shows that the average price of purchased products grows together with buying power as depicted by $A_i$. Users with high $S_i$ are more willing to buy more expensive products. Average price for high $S_i$ and low $A_i$ is in the interval [30, 40] units of the virtual currency. The proposed FLS could be adopted to support a decision making mechanism that will deliver specific strategies related to pricing policies and so on. For instance, a tool could feed our system with the necessary values for inputs parameters and the proposed FLS could result an estimate for e.g., users' purchases. The FLS could retrieve values in pre-defined intervals e.g., every week and the decision making mechanism could build on top of the proposed FLS and its results. Hence, we could deliver an efficient framework that is adaptive on the users' behavior as the derived strategies will be fully aligned with the dynamics of the virtual environment.

### 5.4 Modeling Purchases in Relation to User Social Activity

Fig. 7 illustrates the response surface for modeling the number of object calls $U$ w.r.t. $F_{in}$ and $F_{out}$. For users with few outbound friendship connections, $U$ increases as the number of inbound friendship connections increases ($F_{in} \in [0, 300]$). However, $U$ stabilizes after achieving a value of 4. The highest values (i.e., $U = 7$) are observed for users with $F_{in} = 600$ and $F_{out} = 300$. Users maintaining a high number of connections may be more interested in making impression and to distinguish among other users with account extensions and additions like virtual goods. A high $F_{out}$ may represent users that are active in looking for new social connections. This type of users can use virtual objects as an additional tool to build their personal reputation with the virtual community. Similarly, users with a high $F_{in}$ are very popular and they are possibly less interested in using objects showing them to others in order to acquire positive impressions.

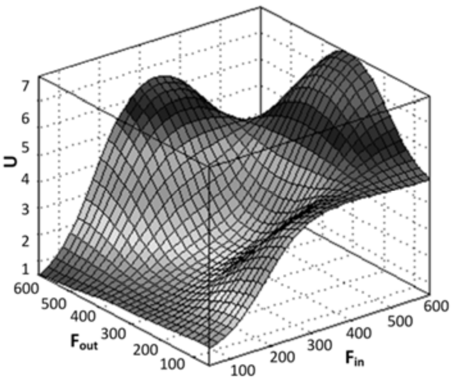


*Figure 7: The inference plot for product usage U w.r.t. the social activity.*

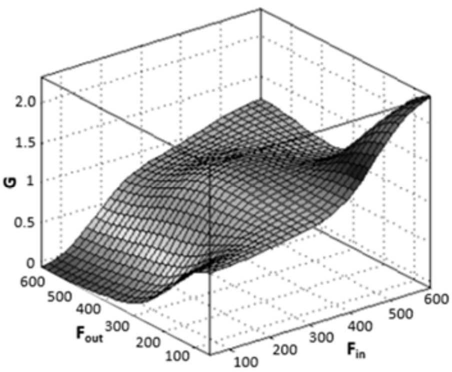


*Figure 8: The inference plot for gifts purchases G w.r.t. the social activity.*

Fig. 8 shows the response surface for the parameter $G$ w.r.t. the users' social activity. When a user has a high $F_{in}$ is more willing to send gifts compared to users with high $F_{out}$. For users with low $F_{in}$ and relatively high $F_{out}$ only a small amount of gift-giving actions occurs. When $F_{out} > 400$, a high percentage of user's virtual product purchases is given as gifts. The effect of the number of gifts and its relation to $F_{out}$ and $F_{in}$ indicate the importance of gift–giving, especially for users engaged in community with many connections.

## 6 Discussion

Despite the popularity of virtual worlds and social platforms significant importance have activities targeted to finding viable sources of revenue including business models based on virtual goods. Virtual object platforms can complement existing business models; however, they require the appropriate integration of a variety of complex technologies and adequate planning for payment systems, virtual currencies and electronic content. Companies wishing to implement virtual object distribution systems also require an ongoing understanding of the user characteristics that lead to virtual object purchases. This study applied a neuro-fuzzy inference model to explore the preferences and characteristics of virtual product purchasers. The fuzzy approach allowed the introduction of unclear boundaries between clusters, which in the case of supplies of real systems with big dynamics, is a more natural approach than strict assignment of objects to individual clusters. The results indicate potential areas of fuzzy modeling appliance in services focused on societies and distribution of virtual objects. Those results can be used in downstream analytical systems. These systems analyze a demand for individual objects, and determine characteristics of users who are potentially willing to participate in transactions; all based on the users characteristics. During model construction it is useful to know the occurrences that appear in a given social platform.

Applying fuzzy input values allows managers to determine their variable characteristics and to have a more natural description of variable relationships than those afforded by crisp values. For example, the number of transactions can be perceived as moderate when it is equivalent to approximately 15 transactions, with different membership to this set of values, from 10 to 20. This type of description is more natural than crisp, with a discrete indication to 15 transactions.

Analysis of the example data indicates that consumers' behavior in this online environment is also reflected in actions observed on traditional markets. There are determined purchase preferences, demand and supply rights. The shaping of pricing policy for virtual goods and detecting consumer needs play a crucial role for the success of commercial ventures. The integration of new possibilities can provide many direct and indirect advantages and strengthens the social bond within Web applications. New technologies give possibility to introduce alternative strategies and search for business models, of which the potential has not been fully explored.

This study may be open to a number of limitations. Depending on the characteristics of input data the model may require additional modification. In order to obtain precise modeling results the model's structure should be tailored to the input data. With regard to the generalizability of our modeling results it is possible that different virtual communities will exhibit different outcomes because of varying user bases, interaction levels and contextual factors.

Our model also applies to any site that makes use of social relationships and interaction. Many sites are now incorporating 'friending' mechanisms into their operations, either by developing their own proprietary social network mechanism or integrating Facebook or MySpace [Ganley and Lampe 2009]. This friendship behavior can generate significant amounts of data as news flows through the community. Proposed modeling approach allows managers to examine this friendship behavior in order to determine the market stimuli that results in expenditure and purchasing outcomes. This knowledge of needs and preferences could then form part of an effective recommendation platform for both virtual and material products. The suggested system also records more immediate reactions to the introduction of new products and allows managers to quickly eliminate products that are unattractive. At this stage some extensions can be planned. Future work assumes applications of dynamic models and takes into account more social aspects related to social network structures and social influence within the network.

This study suggests a number of implications. The introduction of products into a service requires that they are consistent with users' expectations and needs. With this in mind, the results suggest several possible applications of fuzzy models in online environments where environmental variability and data uncertainty make deterministic methods less useful. The approach may be useful for a variety of problems seen in virtual worlds and online communities. For example, some virtual communities see a high turnover of users and new members do not stay on to become long-term members of the community [Goel and Mousavidin 2007, Hou et al. 2011]. Our approach would also be useful in preserving the memory of prior user behavior, as shown in earlier research [Dweiri and Kablan 2006], allowing managers to glean insight into these briefer memberships and better understand member retention. The graphical outcomes of our approach could also be used to demonstrate the mechanics of the online social network to business partners, such as advertisers. Because of the significant level of online competition it is important to be able to demonstrate value for money to partners like advertisers and media managers [Clemons 2009b]. Our approach can effectively illustrate the value of particular marketing strategies to advertising partners. The ability to model these types of large information clusters would also assist in the introduction and evaluation of viral marketing efforts where individual consumers spread news of events of products through their social networks [Valck et al. 2009]. This diffusion can generate significant amounts of user data in a very short amount of time [Kiss and Bichler 2008], which is harder to implement using traditional deterministic analysis methods.

## 7 Conclusions

Virtual worlds and the data that they convey related to users' activities could be very important when analyzing users' behavior in the real world. In these environments, virtual marketplaces, where users can purchase products, are becoming increasingly attractive as they can become sources of revenue involving various business models. In this paper, we try to reveal the hidden parameters that affect users' purchasing behavior. As those parameters are characterized by uncertainty, we adopt Fuzzy Logic to infer the purchasing behavior of users. The proposed mechanism could be adopted for decision making as its results could give us an indication and estimate on the realization of purchases. Our model builds on top of the Fuzzy Logic and the data observed in the virtual environment and models the users preferences knowledge and the inference on the purchasing behavior. To be adapted in the underlying data, a Neuro-Fuzzy model is included into our mechanism for depicting users' characteristics. The analysis of the collected data and the application of the proposed system indicate that consumers' behavior in online environments is also reflected in traditional markets. This is very important as our model could become the basis for delivering a high quality decision making mechanism for real markets that will be related to the definition of significant parameters like prices. Finally, the proposed system outcomes could be efficiently adopted in real systems (e.g., recommenders) to increase their performance and produce results that will maximize users satisfaction levels.

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