INTELLIGENT ELECTRONIC CATALOGS BASED ON SELF-ORGANIZING MAPS: FROM CONCEPTION TO EMPIRICAL VALIDATION

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Abstract— This paper introduces and validates empirically a novel pro- posal of automatic personalized product catalogs for E-commerce based on topological ordering. The main goal is the construction of interactive intelligent interfaces (intelligent catalogs) that minimizes user search time and effort on choosing products in electronic catalogs on the Inter- net. The topological ordering is realized by Self-Organizing Maps (SOM) neural networks. The conception of personalized catalogs considers the degrees of importance (preference) of each product attribute which are provided by the user and define a weighted Euclidean distance metric. The proposed system achieves product clustering by employing users personal criteria and, therefore, enables the discovery of interesting prod- uct regions from the user perspective. Comparisons are conducted by recording user interactions in two virtual stores: traditional shop with hierarchical catalogs (clustering by product brands and models) and intelligent shop with topological organized catalogs (clustering by user preferences of product attributes and SOM). Descriptive and inferential statistical analyses of the collected data indicate promising results in fa- vor of the proposed system when users are familiar with the interface, since differences are significant (at 5%) in terms of search time (session duration) and selected product quality.

Keywords— Self-Organizing Maps (SOM), electronic catalogs.

1 Introduction

E-commerce is trying to adapt traditional businesses progressively (Steckel, 2005). In traditional businesses, attendants interact with customers to help them find the desired product. In virtual shops, however, interactions with clients are accomplished by electronic catalogs. The organization (classification, clustering and sorting) and publication (representation, presentation, personalization, segmentation, navigation and search) of product information are important features to build intelligent interactive interfaces and to allow the minimization of effort and navigation time on searching for products in electronic catalogs.

2 Problem, Hypothesis and Variables

The approached problem is summarized by the question 'How can the product search in electronic catalogs on the Internet be enhanced?' Hypotheses states that intelligent catalogs based on SOM networks should reduce effort and search time, leading to higher user satisfaction, and behavioral changes when they are compared with traditional catalogs.

The format of electronic catalog organization is the independent variable to test and it classifies catalogs in intelligent (with topological ordering) and traditional (hierarchical brand-model ordering) classes. The observed and measured dependent variables are time spent on product search and selection, searching effort (mouse clicks and keyboard inputs), user satisfaction after shopping (measured by questionnaires), and consumer behavior.

3 Theoretical Foundations

3.1 Artificial Neural Networks

Several adaptation techniques to problem solving exist in Artificial Intelligence (Russell and Norvig, 1995), including Artificial Neural Networks (McCulloch and Pitts, 1943)(Rumelhart et al., 1987)(Fausett, 1994). Among them, Self-Organizing Maps (SOM) (Kohonen, 1982) were chosen for the composition of intelligent electronic catalogs. SOM are the subject of many studies from theoretical advances to application developments (Kohonen, 1995)(Martins et al., 2004). They have competitive and unsupervised learning and, the most important, they create topological maps. Therefore, their main feature is the ability to topologically project multidimensional data on spaces with fewer dimensions (typically on 2-dimensional spaces) and, simultaneously, they cluster data and ease visualization of data relations (similarity, in particular) (Haykin, 1998).

In the (self-organizing) training process, output neurons, which are fully connected to all inputs, learn to encode cluster prototypes in their synaptic weights after iterative example (data) presentation. SOM parameters can be grouped in two sets basically: structure definition parameters (dimensions, neighborhood relations) and learning control parameters (online or batch mode, epoch number, learning and neighborhood decrease rate, training phases and input data normalization). In order to produce good mappings, heuristics have been proposed based on map evolution behavior to define quality metrics. Two quality metrics are usually employed: quantization average error (that focus on local representational ability) and topological error (responsible to measure global organization) (Kaski, 2001).

In the SOM standard learning algorithm, topological relations and the number of neurons are fixed from beginning (Kohonen, 1995). This quantity of neurons defines scale or granularity of the resulting model. Scale selection affects model accuracy and generalization capability. It should be considered that generalization and accuracy are contradictory goals. By improving the first goal, the second is left behind, and vice versa.

An important requirement of SOM networks is the similarity function that measures input-prototype distances. The employment of Euclidean distance metrics is typical. More recently, however, the employment of weighted Euclidean metrics to express user viewpoints have been reported (Martins, Nalini, Oliveira and Guedes, 2006).

3.2 Electronic Catalogs

The organization and publication of high volume of information are hard tasks and involve concepts of several areas, such as Data Mining (Lin et al., 1999), Human-Machine Interfaces (Callahan and Koenemann, 2000)(Espen, 2006), Marketing etc. These areas cope directly with functional and structural problems of catalogs (Yen and Kong, 2002)(Palmer, 1997), which have become popular along the years. The style and uses have evolved based on the supporting media (paper, CDROM etc). With the advent of the Internet, catalogs have migrated to the World Wide Web environment.

To locate product (and service) information on the Web has become a time-consuming activity (Lawrence and Giles, 2005). When consumers look for information, they do expect to find not only the most appropriate product for their needs but also they want this information as sooner as possible (Lee and Lee, 2003). Conventional search techniques, already present on many Internet sites, require key-words searching and the navigation on many product pages in the catalog. Search results are shown in simplistic formats that employ ordered lists of predefined classes most of the time (Stanoevska-Slabeva and Schmid, 2000)(Segev et al., 1995)(Keller and Genesereth, 1997).

Needs and desires differ significantly from one person to another. The processes of decision making and product search take important fraction of the psychological activity of human beings when they are consumers (**?**). Therefore, the knowledge of such processes, which includes the verification of the effect of different consumer scenarios, is very important to the technological development of many areas related to the comprehension and controlling of the purchase behavior of products and services.

The satisfaction of virtual consumers depends on their expectations and experiences during site navigation (Lee and Joshi, 2006). Due to these reasons, it is necessary to integrate statistical data on user navigation with qualitative and quantitative data on site structure and dynamics. Purely quantitative data, such as log files and path statistics, are considered insufficient to compare site performances, since they records only what consumers did and ignores the underlying conditions (except for the site specifications).

The Behavioral Perspective Model (BPM) proposes to identify and to consider discriminative stimuli of each specific consumer situation by defining the consequences of consummation based on the properties of chosen product and service. The frequency of consumer behaviors is a complex function of the consumer learning personal history, the openness degree of the consumer scenario, the utilitarian or informative reinforcers of available products, and the aversive consequences of consuming in each situation (Foxall, 1995)(Foxall, 2005).

In the proposed system, catalogs are organized and personalized in topological groups based on user preferences of attributes. Besides the catalog organization, satisfaction aspects and consumer behavior are evaluated to identify the effects of catalog organizations. The satisfaction is indicated by the consumer at the end of shopping when a specific questionnaire is answered. The behavior analysis is implemented along with the time and effort employed on product searching and choosing in the electronic catalogs.

4 Proposed System - Conception and Implementation

The proposed system (see Figure 1 for global dynamics) uses the automatic unsupervised classification (SOM) to organize (cluster) a product catalog where each product is described by a multi-dimensional array. The catalog customization is carried out based on weights (in the [0,1] range) provided by the user to each of product attribute. Such weights define a weighted Euclidean metric that is employed to conduct the SOM training. In other words, the consumer states the importance of each product attribute based on his/her specific needs and desires and these preferences are used to define the similarity among products in the SOM context.

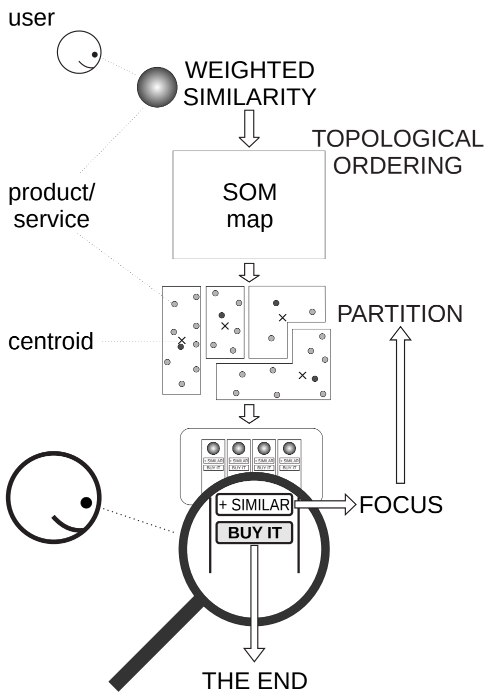

Figure 1: Dynamics of the proposed system.

The resulting topological map is divided in k regions (based on k-means algorithm (Murty et al., 1999)) and a product is selected (the closest product to the region centroid based on the weighted Euclidean distance) to represent each of the k regions. These k 'distant' (very different) representative products are shown side by side to the customer with the attributes sorted on decreasing order by the user weight such as that the most important features are presented on the top. Then, the user is in the position to buy one of them or to search similar products to one of the k products by clicking on buttons just below the product image labeled as 'buy' and '+ similar', respectively. If customer decides to inspect for similar products, the area related to the selected product is divided again in k regions and the process repeats itself until the user buys a product or the product area is too small, when the process starts all over from the beginning with the removal of the shown products.

The proposed system (as well as the referential traditional e-commerce website) has been implemented with Matlab (The MathWorks, n.d.) Web Server with SOM toolbox (Alhoniemi, 2005), Macromedia Flash, PHP and MySql.

5 Empirical Validation

5.1 Experiments

In order to observe variables properly, three questionnaires were developed to deal with demographic data, attribute weighting, and user (participant) satisfaction, besides two virtual shops (traditional and intelligent formats).

The neural network parameters were defined according to product features and selected tests. Inputs were composed by 29 attributes (to represent the cellphone scenario) with normalization in the range -1 and +1. The vector which describes the relative importance of cellphone features promotes the weighted Euclidean distance as the similarity measure. Therefore, it has been used an online training that takes place after the ranking of cellphones' features.

In practical terms, it has been employed random weight initialization. The network structure uses 25 neurons in a 5x5 matrix and a hexagonal neighbouring with gaussian function which decreses from 4 to 1. The neural network is trained in 100 epochs, that is, all training set is shown 100 times to the network, one example after the other sequencially. The learning rate starts in 0,5 to decrease to 0,1 as training progresses to the end.

In each virtual shop, information about time and navigation (mouse clicks and keyboard inputs) were registered to every user. On each participant iteraction (event) at the virtual shop, the following data were recorded: user identification, event date and time, mouse position on the screen, selected object and current shop identification. The experiment has simulated the purchase/selling of a cellular phone in two virtual shops. There were 150 cellular phones and 20 participants in total. In these simulations, participants have visualized, inspected, compared available information and decided which cellular phone is the best for themselves. In order to avoid occasional time delays, data collection has taken place in a corporative intranet that resembles the Internet. The experiment has been divided in two phases (see Figure 2):

- **Phase 1** - Demographic data survey, where experiment participants (sample) have been chosen from personal data of HumaniDATA (Martins, Moraes and Nalini, 2006) members. The desired participant profile is composed of: age from 18 to 60 years old, proficiency on basic resources of Informatics and Internet usage.

- **Phase 2** - Purchase simulations. They were subdivided in four stages:

  1. user identification and attribute weighting,
  2. first purchase,

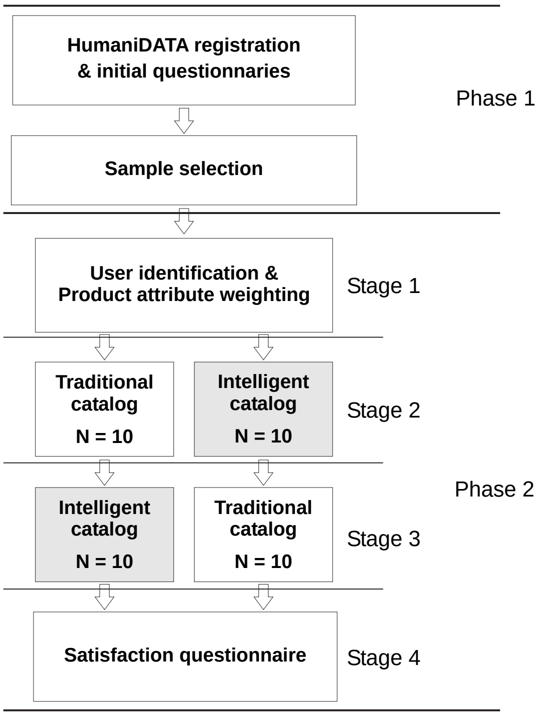

Figure 2: Experiment design.

3. second purchase, and
4. satisfaction questionnaire.

Note that the main sample is divided in two subsamples in order to study the effect of purchase order. In the last stage, participants indicate their perceptions on satisfaction, time (session duration), comfort, pleasure, efficiency and autonomy related to the shopping experiences on the two virtual shops (see Figure 2).

5.2 Results

Generally, results indicate good performance of the proposed system in terms of reducing the session time for product selection and purchase. The time reduction observed at the second purchase too. This fact is certainly connected with the increasing of familiarity with the interface.

In Phase 1, the questionnaire has assessed the importance of some aspects of virtual shops (Table 1) by employing direct questions on each feature. Data have shown that security is the most essential item in virtual shops. The ease of navigation has emerged as the second most important item. Layout and help areas are the least important features according to users.

Demographic features of the sample ensure participants with high level of instruction and reasonable computer and Internet experience. All participants had previous purchase experience on virtual shops. Despite the familiarity with the Internet, collected data has shown high variability.

Table 1: Importance percentual of virtual shops' aspects. S: security, N: navigation, L: layout, A: search, H: help, R: recommendation system, N: not important, R: rarely important, E: eventually important, V: very important, I: indispensable.

	N	R	E	V	I
S	-	-	-	20%	80%
N	-	-	5%	80%	15%
L	-	15%	30%	45%	10%
A	-	-	15%	60%	25%
H	-	15%	30%	45%	10%
R	-	-	15%	60%	25%

Table 2: Session time (s) in traditional and intelligent shops

situation	min	max	average
traditional shop:	**39**	**640**	**259**
1st purchase	115	589	282
2nd purchase	39	640	236
intelligent shop:	**4**	**527**	**148**
1st purchase	13	527	209
2nd purchase	4	259	86

Descriptive statistical analysis is used to highlight some important differences between the two experimental conditions based on sample data. To present significant differences, the t-Student test (at significance of 5%) was employed in inferential statistical analysis.

5.2.1 Analysis of session time (duration).

As it can be seen in Table 2, in the second purchase, the average session time of the traditional shop is much higher when compared to the intelligent shop (236s compared to 86s). This fact is also observed in the first purchase but with lower intensity. By using the inferencial analysis based on t-Student test, the order in which each shop is visited has shown significant effect (observed value of 2.14 and critical value of 1.75). This fact has lead to the definition of two contexts for analysis. During the first purchase, no significant difference has been found, but the proposed system has lead to significant reduction of session time when compared to traditional system during the second purchase (observed value of 3.48 and critical value of 1.83).

5.2.2 Analysis of user effort.

As with the session duration (see Table 3), during the second purchase, the average number of clicks of the traditioal shop is higher than the intelligent one (22 compared to 25 clicks). Similarly, the average number of clicks is lower during shopping in the intelligent shop when compared to the

Table 3: User effort (clicks) in traditional and intelligent shops

situation	min	max	average
traditional shop:	**8**	**58**	**28**
1st purchase	22	46	31
2nd purchase	8	58	25
intelligent shop:	**4**	**104**	**25**
1st purchase	4	90	28
2nd purchase	4	104	22

traditional shop (25 compared to 28 clicks). The order of shop visit, by using inferential analysis, is not significant. This fact justifies a joint analysis which has resulted in no significant differences on user effort in intelligent and traditional shopping (observed value of 0.35 and critical value of 1.73). Despite descriptive results, observed differences in populational terms should be considered casual.

5.2.3 Analysis of user satisfaction.

User satisfaction has been understood as the composition of seven factors: layout, comfort, perceived satisfaction, efficiency, autonomy, pleasure, and time perception. Each factor has been evaluated in terms customer's degree of agreement with respect to presented comparative statements such as 'Buying in the first shop is more pleasurable than in the second shop'. Graphic information was given to ease shop identification. As for the layout, 90% has perceived differences between shops clearly. In the next shopping experience, 70% of them would choose the intelligent shop. In terms of comfort, 85% agrees that the intelligent shop is more comfortable than the traditional shop.

By using correlation measures (see Table 4), it could be seen that the perceived time is not correlated with any other variable (such as layout, comfort, efficiency, autonomy, and pleasure) in particular, despite the fact that it is correlated with the global satisfaction. In all factors, it could be noted the user preference for the intelligent shop since questionnaire items have been formatted as comparative statements. Although a qualitative factor, pleasure is correlated with all other factor, but time. Layout, on the other hand, has little correlation with other factors. Those findings support the development of more pleasurable E-commerce sites which do not mean sites with outstanding layout effects.

5.2.4 Analysis of user behavior.

The satisfaction of the virtual consumer depends on the expectation (what does he/she intend to do?) in the website, and on the experience during the navigation process. By analyzing the prod-

Table 4: Correlated satisfaction factors ('x' indicates significant correlation) L: layout, C: comfort, S: satisfaction, E: efficiency, A: autonomy, P: pleasure, and T:time.

	L	**C**	**S**	**E**	**A**	**P**	**T**
L		x				x	
C	x		x	x		x	
S		x				x	
E		x	x			x	
A						x	
P	x	x	x	x	x		
T							

uct attribute weights and the purchased products from the intelligent and traditional shops, it has been verified that products selected in intelligent shops present, in general, more similarity with the user importance and needs than products selected in traditional shops.

As it was mentioned before, there is a tendency of lower session time and user effort in the intelligent shop. This fact shows that, in some aspect, the user has changed his/her behavior in the interaction with the electronic catalog in such a way to reduce the time and effort of searching and choosing. Behavior changes affect directly user satisfaction as it is evidenced by the collected data.

6 Conclusions

This work has presented a novel electronic catalog suited for E-commerce environments where the topological organization (based on SOM neural networks) and personalization (based on a weighted Euclidian similarity metric with user preferences on product attributes) turns the analysis and selection of products easier when compared to traditional catalogs (with hierarchical clustering by product brands and models). The proposed system can contribute to new generation of electronic catalogs that facilitate user search and evaluation of products.

As a new research subject (Lavene and Poulovassilis, 2004), much work is still waiting to be done in the future. Among many ideas to improve this initial setting, it could be mentioned: new methods to choose and divide topological maps, new presentation formats of products (lists versus matrixes) (**?**), new ways to define user preferences on attributes and studies on satisfaction factors.

Finally, this work has demonstrated the applicability of self-organizing maps in the organization of electronic catalogs. Based on descriptive and inferential analyses of collected data, it can be objectively said that the proposed system should be taken as responsible for the observed differences and be considered as more beneficial for human usage. Significant smaller session time have been observed when participants are at the second purchase moment, that is, when they are familiar with the task. Advantages in term of participant effort and satisfaction have also been recorded along with behaviour changes.

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