

# GENERIC ARCHITECTURE FOR INCOORPORATING CLUSTERING INTO e-COMMERCE APPLICATIONS

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**Keywords:** User modelling, e-Commerce, e-Shopping, Adaptivity, Clustering, Stereotypes, Animated agents.

**Abstract:** Today product recommending applications use many techniques in order to achieve personalization. These techniques may prove successful but lack in portability. This means that it is very difficult to apply the same architecture and techniques that have been used on one system to a totally different one. In this paper we propose a generic architecture that can be used to achieve personalization to a product recommending system. The main advantage of this architecture is that every system can use it, even if it is built on php, asp.net or a different web technology. In this paper we present a case study that we applied this architecture. This case study proves the independency of our architecture and that it can be applied easily to any kind of remote recommending system

## 1 INTRODUCTION

E-commerce applications have become very popular since they provide easy access to all kinds of products. However, most of existing applications are generic and do not address specific needs, preferences and attributes of individual customers. A remedy to this problem can be achieved by web personalization techniques. As De Pessemier et.al. (Pessemier et.al. 2008) suggests, new technologies such as Internet, iDTV, and mobile applications create the possibility to advertise in a different, more attractive manner than the traditional commercial breaks. This leads to a rise of interactive commercials on websites, banners on the internet, and commercials on mobile devices. Thus the market moves towards more converged architectures corresponding to different types of mediums such as mobile phones, internet. Despite the fact that there are many techniques in order to achieve personalization, there is a lack in the effort to produce frameworks that can be applied to any product recommending application without concerning the product that sells or the medium that this application uses. Also as Veruska R. Aragao suggests, (Aragao et.al. 2001) there is no widely-available mechanism to allow users to personalize their interaction with web data and services meaning that as years pass the need for general personalization architectures is becoming more and

more imperative. The difficulty of making such a framework is high and it's reinforced by the fact that product brokering requires assisting users in finding information in a complex multidimensional space (Pu & Faltings, 2002). In this paper we present a generic architecture for e-commerce applications that incorporates a clustering algorithm in order to create groups of similar users, concerning their needs and interests.

## 2 RELATED WORK

There are many e-shops applications that try to make recommendations using many techniques. These techniques usually involve the construction of user models that are either based on explicit user information or on data about the user behaviour that is collected implicitly by the system. An interesting approach in the field of e-commerce has been made by Choi, et al. (Choi et.al. 2006). They chose a multi-attribute decision making method to find similar products. The procedure of finding a similar product is based on a weighted attribute theory that can fill incomplete specifications of a similar product if these specifications do not exist.

Another interesting approach in the same field that uses clustering techniques in order to group products is the system created by Guan et al. (Guan et.al., 2005) . In their system they use an explicit

method of ranking to acquire generic attributes from products and then cluster new attributes into the different groups of generic attributes using the k-NN algorithm. A very interesting technique also, based on a rating system has been conducted by Q. Li and B. M. Kim (Li & Kim, 2004). The system acquires rates and then calculates fuzzy inferences and extracts similarities between users. Their method proved very successful according to the evaluation presented. Another interesting research has been proposed by Kazienko and Kolodziejski (Kazienko & Kolodziejski, 2005). Their system is called WindOWls and is a recommending system that uses user modelling techniques to propose products to individual users. Windowls uses association rules to calculate weights in order to group acquired tastes together.

Despite the fact that all the above systems provide users with recommendations, they are so domain and problem depended that lose the ability to be applied with easy in different fields or products. In this way every time a new application is built a new architecture must be constructed from scratch in order to address the specific application's problems. The framework presented here is product and domain independent. The main advantage is that it can be applied on any product recommending application without consideration of the domain or the products used such as personal computers, mobile phones or even cars.

### 3 THE PROPOSED ARCHITECTURE

The main architecture of our framework is divided into two general sections (figure 1). The first section contains elements that do not interact with the users directly and the second section contains elements that users can understand and interact with. The elements included in the first section are: Explicit Information User Profiles, Observing Behaviour Agent, Clustering Algorithm Process, Double Stereotypes and User Model Server. The Explicit Information User Profiles element contains all the information in a database that users have provided the system in an explicit way. Either, by answering interest questions or rating products. The next element is Observing Behaviour Agent. This element plays a key role in the construction of the User Model and contains all the information about the user interactions with the system. Also observes users' actions throughout the usage of the system.

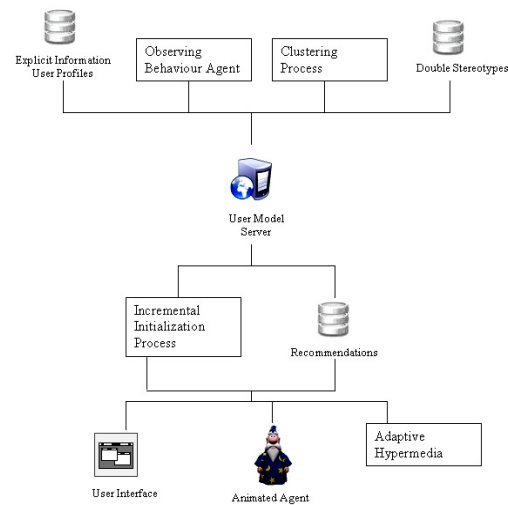


Figure 1: The General Architecture.

For example, this element contains information about the categories a user has visited, products that s/he visited, products that s/he moved in or out of his cart and products that s/he bought. The Clustering Process Algorithm element contains the clustering algorithm that the system uses to group similar users and extract representative users of these groups. The clustering algorithm takes as input the statistical data of all the explicit and implicit information that the system measures about users. Every category and product characteristic is a feature measured by the algorithm. The clustering algorithm processes these data and provides the system with groups based on similarity. From these groups representative feature vectors are extracted. After this procedure the Double Stereotypes element calculates dynamic double stereotypes from these representatives. These stereotypes follow a general to specific hierarchy, meaning that the system constructs a low number of generic stereotypes at first and then continues to construct more specific stereotypes until it reaches a certain point of complexity. These four elements mentioned above contribute to the construction of the User Model Server component. The User Model Server component contains all the information, implicit and explicit, about a specific user, the stereotype that s/he belongs to and his/her more similar representatives and manages all the above elements. The second section contains elements interacting directly with the user. The Incremental Initialization Process element acquires information from the user model and tries to provide the best recommendations to new users or users that the system has little information about. This element uses mostly stereotypic information from the Double

Stereotypes element and makes assumption about where the user should belong to according to the moves that s/he made so far. The Recommendation element communicates with the User Model element and provides the users with recommendation about products and system usage. The Recommendation element contains all system recommendations about products, mistakes or other recommendations in a database. This element can use many techniques in order to make recommendations such adaptive hypermedia, dynamic annotations and the animated agent. The Recommendation element also takes feedback from the users and provides the User Model with more useful information. The next element is the Animated Agent. It's a system component that manages an animated agent that can help users throughout the navigation of the system. This agent can provide useful information about the usage of the system and make recommendation about products by acquiring information from the user model. Next, we have the User Interface element. We use a dynamic user interface that not only adjusts to the medium used automatically, but also changes according to the users' interests. The Recommendation and Incremental Initialization elements can change the User Interface according to the User Model of every user. In this way if a user uses a mobile phone or an interactive tv the experience would be different. We must note here that despite the fact that user interface experience is different for every medium, it contains its basic characteristics in order to avoid user confusion. Last but not least, we have the Adaptive Hypermedia element that is used to annotate user interface elements according to the users' needs or preferences. All these elements communicate with each other using the User Model Server as passage from one to another. The diagram below shows a schematic representation of the proposed architecture and how the above elements are connected together. The main interaction between the user and the intelligent system is made through the dynamic user interface.

#### 4 CASE STUDY

Our first case was video store application called Vision.Com (Virvou et.al. 2007). Vision.Com is an e-commerce video store that learns from customers' preferences. Its aim is to provide help to customers choosing the best movie for them.

For every user the system creates a different record at the database. There are two types of

information saved for every user, the explicit and implicit. The explicit information is saved on the Explicit Information User Profiles and the implicit are saved by the Observing Behaviour Agent. In Vision.Com every customer can visit a large number of movies by navigating through four movie categories.

All navigational moves of a customer are recorded by the system in the statistics database by the Observing Behaviour Agent. In this way Vision.Com saves statistics considering the visits in the different categories of movies and movies individually, movies that were moved to buyers' cart and bought movies. Each user's action contributes to the individual user model by implying degrees of interest into one or another movie category or individual movie. Apart from movie categories that are already presented, other movie features that are taken into consideration by Vision.Com are the following: price range, leading actor and director. The price of every movie belongs to one of the five price ranges: 20 to 25 €, 26 to 30 €, 31 to 35 €, 36 to 40 € and over 41 €.

Vision.Com incorporates an AIN clustering algorithm (Cayzer & Aickelin, 2002), (Morrison & Aickelin, 2002). This algorithm was built by D.N Sotiropoulos et.al. (Sotiropoulos et.al 2006) This algorithm takes as input feature vectors that contain all the statistical data of all users. Then AIN algorithm processes this information and provides the system with representatives. This process is being conducted by the Clustering Process Element of our architecture. We used these representatives in order create double stereotypes that are saved in the Double Stereotypes element of our general architecture. The stereotypes concern both users and movies. In order to find similar movies to a users' interest through the stereotypical information we use the Euclidean distance. The hierarchy of the stereotypes follows the complexity of the stereotypes. Levels 1 are the more general stereotypes and level 5 the more complex ones, depending on the information the system has about a user. After level 5 the system uses an individual user model about this user. This process also helps the Incremental Initialization Process to provide better results about new users. Moreover, Vision.Com uses an Animated Agent (figure 2) to inform and help the users and provide general recommendations.

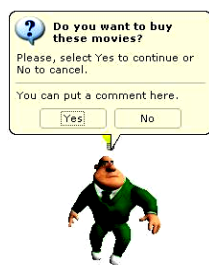


Figure 2: The animated agent.

## 5 CONCLUSIONS

In this paper we proposed a generic architecture that can be used to achieve personalization to a remote recommending system. The main advantage of this architecture is that its medium independent meaning that every system can use it, even if it is built on a mobile phone, a pc or a tv. We presented two case studies that we applied this architecture that use entirely different products, mediums and kinds of recommendations. These two cases prove the independency of our architecture and how easily it can be applied to any kind of remote recommending system.

## ACKNOWLEDGEMENTS

Travel fund support for this work was provided by the University of Piraeus Research Center.

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