Interactivity and Personalization of Digital Television Advertisements

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Abstract

Interactive digital television (iDTV) combines the appeal and mass audience of traditional TV with the interactive features such as those currently available on the Web and offers new possibilities for the viewer, who can directly access relevant information and other services being just 'one-click' away. While interactivity and personalisation is a practice used widely on the Internet, the design of interactive services for digital television presents a number of obstacles. In this paper we focus on the requirements that guide the design of interactive and personalized advertisements. The requirements are mainly associated with the personalization technique applied and the domain characteristics. The results that can be drawn from the literature review as well as a consumer survey show that interactivity features may be kept at a minimum provided that an appropriate personalization approach is selected.

Introduction

The ability to deliver personalized advertising messages has long been a major objective in marketing since it allows marketers to meet heterogeneous consumer needs and target their messages more effectively (Arens and Bovee, 1994). However, traditional one-to-many marketing approaches applied in mass media suffer from their inability to meet this objective (Hoffman and Novak, 1997; Dibb, 1998). In order to increase the efficiency of their strategy, marketers identify homogeneous groups of consumers (*market segmentation*), which they target according to their marketing objectives. Thus, market segmentation has become the most important marketing tool for targeting purposes (McBurnie and Clutterbuck, 1998), also utilized in the TV advertising domain in conjunction with domain-specific features such as time zones and/or program typologies.

However, this strategy has admittedly little to offer towards the ultimate goal of one-to-one communication, since the targeted unit is the segment rather than the individual consumer, and therefore individual needs cannot be satisfied. In the broadcasting television advertising domain, media coverage either exceeds the targeted market segment or leaves potential customers without exposure to the message, thus reducing its cost effectiveness (Belch and Belch, 1995). At the same time, TV viewers have to deal with a vast amount of available advertising information. The issue of *information overload*, typical in information theoretic terms, is also experienced in the case of TV advertisements as *advertising clutter*, which has been identified as one of the significant factors associated with the negative attitude of viewers towards advertising and can have a negative impact on television advertisement recall or recognition (Mord and Gilson, 1985). Relevant surveys reveal that 80% of the viewers feel that there is "too much advertising in television" (Elliott and Speck, 1998), while more than 75% of consumers are not happy with the broadcasted advertisements (Hawkins et al., 1998).

Current target marketing methods are limited in their ability to efficiently target consumers at the individual level – particularly in mass media such as television. Thus, personalization of advertisements provides marketers with the opportunity to increase advertising effectiveness by targeting consumers who are most likely to respond positively to the advertising message.

The present article investigates an appropriate personalization method for the domain of digital television advertisements by examining relevant methods utilized for personalized Web applications. In addition, it is concerned with the design of the interactive elements of a typical 30-second advertisement in support of the personalization process. The two objectives of this article are interrelated: the selection of a personalization technique affects the design of interactive advertisements since it indicates the type of interaction data that should be collected in order to enable personalization.

The next section of this article opens up the discussion on personalization from a theoretical point of view leading to the selection of a suitable for the domain personalization method presented in the following section. Then, the types of interaction data required to achieve personalization are discussed and coupled in the following section with the viewer requirements as drawn from a relevant survey presented. The article concludes at the final section with further discussion and conclusions.

Personalization Research

Adaptive hypermedia and adaptive Web-based systems are systems that adapt their content, structure or presentation to the goals, tasks, interests, and other features of individual users or groups of users (Brusilosvsky and Maybury, 2002). The term hypermedia denotes interactive systems that allow users to navigate a network of linked objects (for example web pages). However, the usefulness of these systems extends to any application area with diverse users and reasonably large space of possible options (Brusilovsky, 1996; 2001). Indeed, adaptive hypermedia systems provide the scientific framework for the personalization research (Ardissono and Goy, 2000; Kobsa et al., 2001).

In the personalization process, user data are collected either implicitly (by observing interactive behavior) or explicitly (provided directly by the users) (Breese et al., 1998). Subsequently, they are utilized in the user model that describes the user in terms of the various features such as knowledge, goals, or interests. The user model is then processed to infer predictions concerning the user's future actions or preferences (Kobsa, 1993) and produce the desired adaptation effect (for example, presenting different content, restructuring the presentation or recommending items relevant to the user's information needs).

User modeling, which lies in the heart of the adaptation process, can be either knowledge-based or behavior-based (Middleton et al., 2001). In the knowledge-based user modeling approaches, typically some form of domain model is matched against the user model contents. Then, relationships between domain concepts are exploited to make inferences about the user (for example Milosavljevic, 1997; Ardissono and Goy, 2000). However, the inherent uncertainty in user modeling concerning the prediction of a user's behavior (Zukerman and Albrecht, 2001) and the inability of knowledge-based methods to accommodate changes in the user model (Kobsa et al., 2001) have boosted the use of machine learning techniques for the prediction of interests, preferences, goals, and actions upon observations of the user's behavior (Webb et al., 2001). Indeed, beyond observing interactive actions in order to build and update the user model, the user's behavior may also serve as a direct basis for personalization. The task in such behavior-based approaches is to find regularities (patterns) in a user's behavior instead of inferring the values of the user model features.

Since the personalization task in our domain refers to the prediction of a user's interest for unobserved advertisements, behavior-based approaches provide a suitable solution to the above problem. However, the amount of available interaction data is restricted given the domain requirement that the level of interaction should be kept at a minimum. Interactivity in TV, in particular in interactive advertising, should not be confused with the extended interactive sessions in applications in other media, such as over the Web. Lee and Lee (1995) suggest that extended interactivity should not be adopted by interactive services since it contradicts with the current viewing patterns (for example, relaxing home atmosphere, low involvement, and so on). Similar results are supported by ethnographic studies in households (O'Brien et al., 1999). Television is not a personal computer (Nielsen, 1997;). The main objective of television viewers is to get entertained or informed in a relaxing atmosphere rather than get engaged into long interactive sessions such as those that occur in a work environment or over the Web. Moreover, TV viewing is experienced mainly as a passive (Belch and Belch, 1995) group activity, possibly surrounded by other noisy factors. The input devices, such as the remote control, are not suitable for extended interactions, while the viewing distance can be a few meters away from the TV set, rather than just in front of it (as for the PC). In addition, the short duration of a typical 30-second commercial leaves only a very short period of time for prompt and impulse reaction.

Traditional adaptation approaches require a significant amount of data before they start adapting to the user and therefore "they *are only useful in application domains where users engage in extended (and in most cases even repeated) sessions of system use. They may not be appropriate for infrequent users with typically short sessions*" (Kobsa et al., 2001). However, the emergence of *recommender systems* provides a solution that overcomes the above limitations, as will be discussed in the next section.

Recommender Systems

Recommender systems (Resnick and Varian, 1997), a sub-class of adaptive systems, meet both the personalization objective in our domain as well as the low-interactivity requirement described above. Recommender systems have been widely and successfully used (Schafer et al., 2001) in order to make personalized recommendations for information, products or services (). They operate upon data such as the explicit or implicit expression of a user's interest on observed items (documents, products, or advertisements). User-driven data are provided in the form of ratings either in binary format denoting interest/non-interest or in a Likert scale (for example, one-to-five). Ratings are processed using machine learning techniques and the produced output is a prediction concerning the user's interest on unobserved items.

Two major approaches are utilized for the processing and prediction tasks in recommender systems: *Collaborative filtering (CF)* and *Content-based filtering (CBF)*. Collaborative filtering is employed by many successful commercial recommender systems, such as Amazon.com and MovieFinder.com (Schafer et al., 2001). Collaborative filtering is based on the assumption that users who exhibit similar behavior can serve as recommenders for each other on unobserved data items (Resnick et al., 1994).

On the other hand, content-based filtering relies solely on a user's previous preferences upon specific item features to infer predictions for his/her future behavior (for example, Mooney and Roy, 2000). Content-based filtering requires a textual description of items to achieve a machine-parsable form (Balabanovic and Shoham, 1997) and cannot capture attributes, such as aesthetics and the overall taste of a user for a given item (Herlocker et al., 2002; Balabanovic and Shoham, 1997; Resnick et al., 1994). Furthermore, content-based filtering restricts the spectrum of recommendations to items that are similar to the ones that the user has previously evaluated (Herlocker et al., 2004). In addition, collaborative filtering has been shown to be more accurate in its predictions (Alspector et al., 1997). Thus, collaborative filtering offers a suitable approach that can serve as the basis for personalization in the domain of TV advertisements.

User Input and Interaction design

The primary and most important input in the collaborative filtering process is the user's rating on observed items. Taking into account that collaborative filtering is suggested by the review above as an appropriate method for personalization of advertisements, it is important to analyze the notion of rating and the implications of the rating collection methods on the design of interactive advertisements.

In information retrieval and information science research, a rating is defined as a quantification of the human judgment of *relevance* in evaluating the effectiveness of information retrieval (Schamber and Bateman, 1996). Numerous factors affect human judgment resulting into large differences in the evaluation of relevance (Greisdorf, 2000). In Recommender Systems research the notion of rating is associated to the overall taste of a user for a specific piece of information. Similar to the notion of relevance, "overall taste" is a quite generic concept which embraces a number of factors which may affect the evaluation of an item. For example, in the domain of TV advertising an expression of interest may be associated to the user's information needs which are met by the advertised product but also because of the "aesthetic quality" that an advertisement bears. It must be noted that in the application of the collaborative filtering technique we are not interested in the factors that affect the viewers' interest on an advertisement but in the overall evaluation as expressed through a rating.

Acquisition Methods

Following the acquisition methods in adaptive hypermedia systems, user ratings can be collected either implicitly or explicitly. Implicit acquisition methods include the monitoring of user's interactive behavior, such as the browsing activities, page viewing time, and so on. Data acquired implicitly are typically represented by binary ratings denoting the presence or absence of user's interest on the observed items and can be coded either symbolically (interesting/uninteresting) or assigned a numeric value (e.g. 1=interesting, 0 = uninteresting). An exception to the representation of implicit rating in binary form stems from the relationship between a document's reading time (e.g. time spent on a news article) to numerical rating, enabling the representation of this form of evaluation into numerical ratings (Konstan et al., 1997). Explicit acquisition methods refer to the direct request for provision of ratings. For example, Amazon.com™ (www.amazon.com) and citeseer.org (http://citeseer.comp.nus.edu.sg/cs) request users to provide their ratings on read books or papers/articles on a 1-5 numerical scale. Ratings can also be requested explicitly upon icons (for example, "thumbs-up"/"thumbs-down" or "smiling faces" as in Syskill and Webert (Pazzani and Billsus, 1997) and *represented* directly by numerical values on a Likert scale or by binary ratings.

Implicit and explicit rating acquisition methods present a number of advantages and disadvantages, which should be evaluated with respect to the application domain characteristics.

It has been argued that it is rather obtrusive to the users' main goal in using a system to ask them to explicitly evaluate items (Brusilovsky, 1996) while this additional effort beyond the scope of the system usage, introduces an additional cognitive cost (Nichols, 1997). These may result into the unwillingness of users to provide explicit ratings, thus reducing the amount of collected data, in contrast to implicit acquisition in which almost any interaction can be interpreted in some sort of expression of interest (Konstan et al 1997). However, despite the ability of implicit methods to acquire interaction data, the value of such information is limited (Nichols, 1997). A first limitation is the unreliability associated with the interpretation of certain types of interaction data into evidence about the interests of the user (Brusilovsky, 1996; Kobsa et al, 2001). Secondly, even though some types of interaction data can be regarded as strong indicators of the user's interest for specific items (e.g. purchases), it is hard to acquire data denoting negative attitude. Herlocker et al (2004), uses the term "unary" instead of binary to refer to implicitly acquired ratings, denoting that the ability of implicit methods is restricted to the collection of "positive" behavior. However, both "positive" and "negative" ratings are necessary for the application of machine learning techniques. Therefore some form of explicit feedback provided directly by the users is required even in "rich" interaction systems (Brusilovsky, 1996) and seems rather unavoidable in low-interactivity environments. It is clear that the requirement for accuracy urges the use of explicit acquisition methods and recent surveys have found that users are willing to provide such ratings in order to get more accurate recommendations (Swearingen K. and Sinha R., 2002) as long as a certain number of interactions (such as one or two clicks) is not exceeded (Brusilovsky, 1996).

Finally, the utilization of a measurement scale in explicit rating enables the measurement of the degree of relevance of the selected item to the users information need. Indeed, from an information-theoretic perspective it is argued that relevance has a middle range (Spink and Greisdorf, 1997) contrary to strictly dichotomous evaluations. However, it must be noted that a user's perception of rating scales is subjective in the sense that a rating of "3" in a 5-point scale may be denoting interest for a certain user while the same rating could be regarded as "neutral" for another user (Herlocker et al, 2004; Resnick et al, 1994). Most prediction algorithms take into account this difference in perceptions and adjust their prediction accordingly.

The main advantages and disadvantages of the two rating acquisition methods are summarized in Table 1.

Rating Acquisition Method	**(+)**	**(-)**
Explicit	– Results into more accurate user's profile – Expressed in numerical scale which is appropriate for measuring relevance – Appropriate for low-level interactive environments – Flexible in processing	– Requires some effort from user which may result into reduced amount of collected ratings
Implicit	– Unobtrusive to user's main task – In rich interactive environments an increased number of interaction data can be collected	– In most cases result into inaccurate user's profile – Interest inference based on assumptions – Hard to infer "non-interest"

Table 1: Advantages and disadvantages of rating acquisition methods

Viewers' Requirements

As a result of the above discussion, the design of interactive elements that support either explicit or implicit acquisition of ratings presents certain trade-offs. For example, asking explicitly the user to rate an advertisement on a 1-to-5 Likert scale that appears in the form of numbered buttons on top of the advertisement video may lead to fewer interaction data affecting the accuracy of collaborative filtering. On the other hand, the implicit capturing of users' interests on advertisement seems more natural when interactive features provide direct benefits for the user. Such features that enhance the functionality of a television advertisement include browsing (in web-like style) the advertisement for more info, requesting off-line additional information (through brochures or personal contact), or purchasing the advertised product.

In order to collect actual consumers' perception a consumer survey was conducted to estimate (among other) the popularity of the above features. The survey was quantitative and the sample consisted of 479 respondents, aged between 15-55 years old with the method of personal interviews at home.

The viewers' requirements concerning the desired type of interactivity are depicted in Table 2.

I would like to be able to browse more information about the content of the advertisement	51,0%
I would like to request on-line a presentation meeting	54,0%
I would like to request more information to be sent to me	65,0%
I would like to purchase the product/service which is being advertised	43,0%

Table 2 Viewer requirements for Interactive Advertisements

The above data indicate that viewers are skeptical about on-line purchases concerning the advertised product. However, they would like to get more information for the product as well as to request off-line communication with the vendor (either personally or through a brochure mailing). These options may provide good indications about viewer's interests and comply with the domain requirements for short interactive sessions (in contrast to the browsing option).

The options concerning the functionality of interactive advertisements were further examined as depicted in Table 3.

Pause the program flow and view more information about the specific advertisement and then return on the program flow exactly the moment you quit	55,7%
Stop the program flow and view more information about the specific advertisement and then return on the normal program flow	15,7%
Mark the advertisement and after the advertisement break or any time after you wish, view more information about the specific advertisement	43,4%
View more information on a part of the screen while keeping on watching the program flow	43,4%
None of the above	13,1%

Table 3 Viewer requirements on functionality of interactive advertisements

Viewers prefer to browse the content of the interactive advertisements and get back to the point where the browsing was initiated. However, this type of interactivity requires time-shifting capabilities from the digital television system. As a consequence, the activation of such functionality would eventually lead to advertisement skipping creating significant problems to the entire business model. The significance of this problem should certainly be considered by technology providers (e.g. PVR manufacturers) and it is not considered as a plausible alternative type of interactivity. Nevertheless, the percentage of the 'Bookmark' interaction type (43%) is not insignificant while in combination with the 'Contact me' type (Table 2) provide an appropriate – for the domain form – of interactivity.

Discussion & Conclusions

The above analysis suggests that a 'Bookmark' and a 'Contact me' button hardwired on the remote control (or assigning specific functions to the existing colored buttons) as shown in Figure 1, represent suitable interaction elements. The 'Bookmark' feature provides the possibility to store an advertisement in the 'favorites' folder for viewing at any time, enabling the downloading of additional informational content for the stored advertisements. The 'Contact me' button forwards request to the product supplier for a personal contact or

Figure 1: ***Bookmark and contact me functionality***

brochure mailing to the viewer.

The design of the 'Bookmark' and 'Contact me' interactive features is supported by successful cases of interactive advertising implemented by enhancing the 30-second advertisement video with an interactive button that simply overlays the video. For example, the Ford motor's interactive advertisement aired at UK's BSkyB satellite network prompts viewers to press the "select" button on their remote control to get more information on the advertised car type. The advertisement has led to a 2,4% of viewers launching the interactive application and an impressive 64% who requested a brochure (OpenTV, 2004).

As an alternative design the direct use of 1-to-5 Likert scale buttons would provide explicit information concerning the users' interest on an advertisement but at the cost of collecting fewer interaction data that may harm the final personalization result. Empirical findings concerning the application of the two different design strategies report that the use of explicitly acquired numerical ratings may lead to more accurate personalization results (Lekakos and Giaglis, 2006; Lekakos and Giaglis, 2005).

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List of terms

Interactivity: a two-way communication model providing users with power over the presented content.

Personalization: the process of providing content tailored to individuals

User model: a representation of user features

User modeling: the development or updating of the user model

Adaptive hypermedia systems: systems that adapt their content, structure, or presentation to the features of their users

Rating: a quantification of a user's evaluation on observed information items

Recommender Systems: systems that provide personalized recommendations according to the user's interests

Collaborative filtering: a recommendation method that exploits similarities between the users of a recommender system