# Personalized Advertising Methods in Digital Interactive Television

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## 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 & Bovee, 1994). However, traditional one-to-many marketing approaches applied in mass media suffer from their inability to meet this objective (Dibb, 1998; Hoffman & Novak, 1997). 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 & 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 & 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 & Gilson, 1985). Relevant surveys reveal that 80% of the viewers feel that there is "too much advertising in television" (Elliott & Speck, 1998), while more than 75% of consumers are not happy with the broadcasted advertisements (Hawkins, Best, & Coney, 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 appropriate personalization methods 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 and in the following section specific personalization techniques are compared. Next, the types of interaction data required to achieve personalization are discussed and the article concludes 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

&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 & Goy, 2000; Kobsa, Koenemann, & Pohl, 2001).

In the personalization process, user data are collected either implicitly (by observing interactive behavior) or explicitly (provided directly by the users) (Breese, Heckerman, & Kadie, 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 (e.g., 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, De Roure, & Shadbolt, 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 (e.g., Ardissono & Goy, 2000; Milosavljevic, 1997). However, the inherent uncertainty in user modeling concerning the prediction of a user's behavior (Zukerman & 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, Pazzani, & Billsus, 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 (e.g., relaxing home atmosphere, low involvement, and so on). Similar results are supported by ethnographic studies in households (O'Brien, Rodden, Rouncefield, & Hughes, 1999). Television is not a personal computer (Nielsen, 1997). The main objective of television viewers is to be entertained or get informed in a relaxing atmosphere rather than become 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 & 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, p. 14). 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 & Varian, 1997), a subclass 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, Konstan, & Riedl, 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