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Using context to improve the effectiveness of segmentation and targeting in e-commerce

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ABSTRACT

In e-commerce, where competition is tough and customers' preferences can change quickly, it is crucial for companies to segment customers and target marketing actions effectively. The process of segmentation and targeting is effective if the customers grouped into the same segment show the same behavior and reaction to marketing campaigns. However, the link between segmentation and targeting is often missing. Some research contributions have recently addressed this issue, by proposing approaches to build customer behavior models in each segment. However customers' behavior can change with the context, such as in many e-commerce business applications. In these cases, building contextual models of behavior would provide better predictive performance and, in turn, better targeting. However, the problem of including context in a segmentation model and building predictive behavior model of each segment consistently is still an open issue. This research aims at providing an answer to the following research issue: how to include context in a segmentation model in order to build an effective predictive model of customer behavior of each segment. To this aim we identified three different approaches and compared them by a set of experiments across several settings. The first result is that one of the three approaches dominates the others in certain conditions in our experiments. Another important result is that the most accurate approach is not always the most efficient from a managerial perspective.

1. Introduction

Today's marketing professionals are being pressured to keep their companies competitive as significant changes are taking place in the business environment. On the one hand globalization, technological advances in information and communication technology (ICT), increasing competition, fragmentation of markets, have compelled companies to rethink their marketing strategies and processes. This is especially true on the web, where teradata of information are available every day and the search costs are low, thus making competition just "a mouse click away" (Jiang & Tuzhilin, 2009b). Therefore, in such increasingly competitive environment, it is crucial to segment customers and target marketing actions effectively. The process of segmentation and targeting is effective if the customers grouped into the same segment show the same behavior and reaction to marketing campaigns.

E-commerce provides companies with the unprecedented opportunity to record data on customers behavior in richer way, thus making it possible to adopt better segmentation models and targeting marketing actions more effectively. Several studies have addressed this issue by using different techniques (Chan, 2008; Hwang, Jung, & Suh, 2004; Jonker, Piersma, & Poel, 2004; Kim, Jung, Suh, & Hwang, 2006). Some scholars have proposed to build predictive models of customer behavior in each segment in order to enable an effective targeting (Apte et al., 2001; Jiang & Tuzhilin, 2009a, 2009b).

Customers' behavior can change with the context and keeping segmentation and targeting linked can remain challenging. In these cases, building contextual models of behavior would provide better predictive performance and, in turn, better targeting. The marketing literature (Bettman, Luce, & Payne, 1998; Lilien, Kotler, & Moorthy, 1992) has recognized the importance of considering contextual information because it can induce important changes in customer purchasing behavior, thus challenging traditional approaches to segmentation (Firat & Shultz, 1997; Peltier & Schribrowsky, 1992; Tsai & Chiu, 2004). Research has shown that including the context in which a transaction occurs in customer behavior models, improves the ability of predicting their behavior (Gorgoglione, Palmisano, & Tuzhilin, 2006; Palmisano, Tuzhilin, & Gorgoglione, 2008).

However, no systematic study has been done before to empirically address the issue of how to incorporate context into segmentation and targeting and it still is an open issue.

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In this paper, we contribute to filling this gap. In particular, we present a conceptual framework to incorporating context into a segmentation model and building predictive models of customer behavior in each segment to improve targeting. We identified three possible approaches, namely contextual pre-filtering, contextual post-filtering and contextual profiling, and performed a comparative analysis across a wide range of experimental conditions. Each approach differs from the others in how context is considered along the entire process of building segment-based behavior models. Each type of contextual model is compared with an un-contextual segmentation, which does not take into consideration any contextual information. Some managerial implications arising when using different approaches are discussed.

2. Background work

The problem of aggregating customers by an effective segmentation has long been studied by scholars in marketing. The evolution of technology, particularly the development of data mining techniques for the analysis of large data sets and the growth of online markets, provides companies with the unprecedented opportunity to gather much data on customers' behavior and build accurate predictive models of behavior in order to target the marketing actions effectively. Much research has dealt with this opportunity.

Recent research on segmentation has questioned the use of demographic, attitudinal, and psychographic attributes of a customer to segment markets (Lee & Park, 2005), and recognized the effectiveness of using transactional and behavioral data, i.e. variables describing customer purchasing behavior (Sinha & Uniyal, 2005; Tsai & Chiu, 2004; Yankelovich & Meer, 2006).

Several approaches have been investigated to deploy segmentation by using behavioral information and several techniques have been used. (Chan, 2008) reviewed this variety by classifying the customer segmentation methods into methodology-oriented and application-oriented approaches. The methodology-oriented approaches use statistic methods or other mathematical techniques (e.g., fuzzy sets, genetic algorithms, neural networks) to segment the market (Hwang et al., 2004; Kim et al., 2006; Tsai & Chiu, 2004; Vellido, Lisboa, & Meehan, 1999). In the application-oriented approaches the method used to segment the market depends on the specific application domain (Kuo, An, Wang, & Chung, 2006; Shin & Sohn, 2004; Woo, Bae, & Park, 2005) and often it is a combination of multiple methods.

A model of segmentation based on a recency, frequency and monetary model (RFM model) has also proposed by (Hsieh, 2004). Several authors have used the customer life time value (CLTV) as a criterion to improve the effectiveness of a segmentation model (Chan, 2008; Hwang et al., 2004; Kim et al., 2006). Jonker et al. (2004) proposed a joint optimization framework which makes use of a RFM model to segment customers and CLTV to optimize the marketing actions.

Several studies as in Apte et al. (2001) and Jiang and Tuzhilin (2009a, 2009b) have focused on building predictive models of customer behavior when the target audience is split into customer segments and predictive models are built for each of these segments, in order to overcome the pitfalls related to 1-to-1 marketing and personalization applications. However, since each customer may show different behavioral patterns associated with specific contexts, a behavioral segmentation may be ineffective if context is not considered. Both marketing scholars and practitioners have highlighted traditional market segmentation problems (Herman, 2007; McKechnie, 2006), however no systematic research empirically studying the effect of using context in market segmentation has been done before.

Scholars in marketing have maintained that the purchasing process is contingent upon the context in which a transaction takes place. The same customer can adopt different decision strategies and prefer different products or brands depending on the context (Bettman et al., 1998; Lussier & Olshavsky, 1979). According to Lilien et al. (1992), "consumers vary in their decision-making rules because of the usage situation, the use of the good or service (for family, for gift, for self) and the purchase situation (catalog sale, in-store shelf selection, and sales person aided purchase)".

The convergence between the evolution of data mining models and that of e-business have make the research areas dealing with context grow quickly. Several factors have been used to capture contextual information. In the context-aware systems literature, context has been represented by the location of the user, the identity of people near the user, the objects around, and the changes in these elements (Schilit & Theimer, 1994). Further factors include the date, the season and the temperature (Brown, Bovey, & Chen, 1997), the physical and conceptual status of interest for a user (Greenberg, 2001), and the user's emotional status (Dey, Abowd, & Salber, 2001). Several research contributions have demonstrated that including context in customer behavior models improves the ability of predicting their behavior (Adomavicius & Tuzhilin, 2010; Palmisano et al., 2008).

In this paper, we contribute to fill the aforementioned gap by presenting a conceptual framework to incorporating context in a segmentation model, in order to build accurate predictive models of customer behavior in each market. This can allow companies to better target marketing actions. We identify three possible approaches and compare them across a wide range of experimental conditions. In Section 3 we present the framework and describe the problem formulation. Section 4 reports the experimental setup, while Section 5 discusses the results of the experimental analyses.

3. Problem formulation

In order to identify the possible approaches by which context can be incorporated in a segmentation model, it is useful to describe the logical steps a business analyst has to follow in order to segment customers and build a predictive model of customer behavior in each segment. The process is described in Fig. 1. The three steps are the following: (1) collecting transactional (and possibly demographic) data about customers, (2) computing customer profiles and grouping customers into segments, (3) learning predictive models on each segment. The steps are described more formally in the following subsections.

3.1. Transactional data

The first step towards building segment-based behavioral models is the collection of both transactional and demographic data of customers in time. More formally, let C be the customer base represented by N customers. Each customer C_j is defined by a set of m demographic attributes $A = \{A_1, A_2, \ldots, A_m\}$, and a set of r transactions $Trans(C_j) = \{TR_{j1}, TR_{j2}, \ldots, TR_{jr}\}$, where each transaction TR_{ji} performed by customer C_j, is defined by a set of transactional attributes $T = \{T_1, T_2, \ldots, T_p\}$. In addition, we also have contextual information K associated with each transaction TR_{ji} of the form shown in Fig. 3(a) or Fig. 3(b). For example, customer C_j can be defined by the demographic attributes $A = \{IDuser, Age, Income\}$, by a set of three transactions $Trans(C_j) = \{TR_1, TR_2, TR_3\}$, each transaction defined by the transactional attributes $T = \{ProductID, Price, TransactionTime\}$, and by a set of contextual attributes K describing the context associated with each purchase, specifying the contextual hierarchy $K = (K^1, \ldots, K^q)$, where q represents the degree of contextual knowledge (i.e., rough or fine).