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Detecting the migration of mobile service customers using fuzzy clustering

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ABSTRACT

Customer clustering is used to build customer profiles which make up the core of a customer centric information system. In this paper, we develop a method for extending the standard fuzzy c-means clustering algorithm using membership functions to detect how customers move between clusters over time. The study leads to the discovery of new usage and revenue patterns for customers, the identification of two groups of customers that exhibit migratory behavior over time, and the determination of specific usage and revenue attributes that impact customer migration. The findings provide insights to mobile services providers about how to detect temporal changes in customer behavior.

1. Introduction

Mobile technologies have entered the everyday life of people around the world. A report from the IDC group stated that the number of mobile devices accessing the Internet is predicted to reach 1.7 billion by 2017 [23]. However, a hot market also implies fierce competition. The mobile telecommunications industry is characterized by "considerable variability in customer behavior" and low commitment as "30% of the typical cellular providers' customers exit, either switching providers or discontinuing cellular usage, each year" [10]. The monthly churn rates of AT&T, Verizon Wireless, Sprint Nextel, and T-Mobile in 2007 were 1.7%, 1.1%, 2.7%, and 2.6%, respectively [34]. In fact, a 30% reduction in churn rate can effectively increase long-term revenues by 15% [10]. The key to survival in this competitive market lies in knowing customers better and preventing them from churning.

In the context of e-commerce, customer orientation is also regarded as indispensable for developing successful customer relationship management [42]. Knowledge about customers can give e-commerce companies a competitive edge [32]. Profiling of customers usually involves segmentation, which refers to all methods that group customers based on their similarities with respect to some characteristics [52]. For example, the Austrian mobile services provider Tele.ring performed segmentation to build customer profiles to help the company target and position customers and was able to generate a monthly profit of approximately US$ 25.20 per customer while attracting 200,000 new customers from their competitors [36]. Clustering algorithms are popular tools for segmentation and are used for customer profiling [41,52]. However, clustering was usually performed in a static fashion without consideration of the possible changes in customers' behavior over time. In contrast, the reality is that customers' behaviors do change over time [45]. For example, Song et al. discovered changes in customers' online shopping behavior such as frequency of visits, and number of orders in two consecutive temporal stages [50]. Lee et al. studied the Internet users' switching behavior across Internet portal websites based on their browsing record [29]. In e-commerce, customers respond to marketing activities much faster due to two techno-economic forces, micro-consumption enabler and micro-commodity enabler. The first force refers to technologies that can reduce the customers' effort in online shopping such as online payment services and search engines. The second force takes effect when traditional services or products are further dissected to come up with more specialized products or services that satisfy customers' needs. Without knowing the changes in customers' behavior caused by

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these forces, it is impossible to respond to new situations [20]. A feasible solution is to develop analytical techniques such as dynamic clustering algorithms or programs to discover the dynamics in consumers' preferences, and then use the analytical results as a basis to adjust market segmentation strategies accordingly and dynamically.

In this paper, we examine two issues in the process of multi-stage clustering: identification of new customer clusters and determination of migration path of customers. The determination of new customer clusters can be used as evidence to set up new market segmentation strategies. However, two practical conditions should be taken into consideration. First, the difference between the old segmentation and the new segmentation should be significant enough. Second, each segment should cover an acceptable portion of the customer population. Violation of these two conditions may make investing resources to create new marketing strategies unworthy. We develop a method that extends the standard fuzzy c-means clustering algorithm for identifying new customer clusters from data over multiple time periods. We determine membership functions for each customer that indicate how likely it is for a customer to belong to a cluster. By analyzing each customer's change of values of membership functions, we discover changes in individual behavior when monitoring the customers' migration paths. Our analysis also leads to determination of changes in group behavior through the discovery of new customers' usage and revenue clusters and determination of the relationship between them. We then provide recommendations to firms on augmenting their marketing strategies in response to changes in customers' behavior.

This paper provides a discussion of the related literature in the next section and moves on to a description of the research method in the section following that. Next, we describe the experimental results. The concluding section provides discussion of results, identifies limitations of this research, and lists some directions for extending this research in future.

2. Related literature

Firms spend large amounts of money to acquire new customers, and so they prefer to hold onto existing customers rather than to acquire new customers. It is known that "a 1% improvement in retention can increase firm value by 5%" [26], and at the same time "losing customers not only leads to opportunity costs because of lack of sales revenue, but also adds to the cost of attracting new customers" [3]. On the other hand, it would be more important to predict the value of customers in the future than just understand it in its current level because customers' value changes over time [17]. Some customers dissolve the relationship abruptly, while others make this decision gradually, exhibiting changes in their interactive behavior with the firm. This can take the form of a very active customer who becomes a totally passive customer or "a customer who alternates between active and non-active status" until the relationship is dissolved [30]. Therefore, understanding the temporal behavior could be important. Khan et al. [27] discovered that customization based on consumers' temporal heterogeneity could be more beneficial than customization based on the differences between customers. Service providers' actions may also influence customers' migration. Bansal et al. discovered that interaction between the 'push' factors of the current service providers that included satisfaction, trust, and commitment, and the 'pull' factors of the new service providers luring the customers through better financial or quality related benefits, had a significant impact on the customers' migratory behavior [5]. A timely detection of this migratory behavior of customers can enable firms to introduce strategies that are able to reduce the defection of such customers. It is worth noting that to study migration, we should observe the whole process of migration. "The time frame of the switching path covers the whole history of the process leading to the switching decision" rather than only the events that immediately preceded switching [46].

3. Statistical approaches for studying customer migration

In statistical approaches, the patterns of customers' behavior are captured with the help of probabilistic models. These models do not consider the change in the customers' behavior over time and use the same static (i.e., time-invariant) model throughout the time period under consideration. One of the earlier studies in the area of customer migration was that of Dwyer who studied customer migration, and predicted repeat purchase behavior and life time value (LTV) of customers using the knowledge of their recency of purchase [15]. An analytical formula for calculating the LTV of a migrating customer was obtained by Berger and Nasr [7]. A similar approach was adopted by Hwang et al. [22]. These papers studied customer migration as a static process. Pfeifer and Carraway modeled the dynamic nature of customer migration using Markov chains where the different situations representing a customer's possible relationship with the firm were referred to as states and the chance of migrating from one state to another was represented by transition probabilities [40]. Schweidel et al. proposed a hidden Markov chain-based approach for studying the migration of customers' services usage behavior for multiple services [48].

3.1. Clustering for studying customer migration

Clustering is a special class of statistical method that is used for understanding customer behavior. Customer clustering classifies customers into different groups so that special pricing and advertising policies targeted to these groups can be devised to satisfy their needs [44]. In addition to observable shopping behavior clustering, clustering can also be used to discover the differences existing in the attitude and intentions of customers [54]. On the basis of data assignment, two types of clustering techniques can be identified: hard clustering and soft clustering. Hard clustering algorithms assign a class label to each data item so that it is allocated to a single cluster. K-means and self-organizing maps (SOMs) belong to the class of hard clustering algorithms [25]. Soft clustering applies fuzzy logic when doing clustering. Fuzzy logic deals with situations that can be partially true. Usually, a continuous value between 0 and 1 is used to represent the truthfulness of the situation [55]. In the language of clustering, partial truth is represented by the degree of membership that associates each data item with all clusters that are discovered [25]. The changes in the degree of membership can be particularly useful for studying migratory behavior of customers. Hui and Jha suggested that hard clustering techniques such as unsupervised Kohonen networks could be used to identify customers that were likely candidates for cross-sell as well as to identify possible fraudulent behavior of customers [21]. Ozer [38] used the fuzzy c-means (FCM) algorithm for customer segmentation in online music services, and showed that the results obtained using the FCM algorithm provided insights about customer's attitudes, interests, and opinions about the services.

3.2. Conceptual frameworks for using clustering to study customer migration

The use of clustering techniques for studying migratory behavior of customers has been limited. In mobile telecommunications services related data, the frequency of update is high because mobile telecommunications users use mobile services