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Combined rough set theory and flow network graph to predict customer churn in credit card accounts

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A R T I C L E I N F O

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A B S T R A C T

Customer churn has become a critical issue, especially in the competitive and mature credit card industry. From an economic and risk management perspective, it is important to understand customer characteristics in order to retain customers and differentiate high-quality credit customers from bad ones. However, studies have not yet adequately introduced rules based on customer characteristics and churn forms of original data. This study uses rough set theory, a rule-based decision-making technique, to extract rules related to customer churn; then uses a flow network graph, a path-dependent approach, to infer decision rules and variables; and finally presents the relationships between rules and different kinds of churn. An empirical case of credit card customer churn is also illustrated. In this study, we collect 21,000 customer samples, equally divided into three classes: survival, voluntary churn and involuntary churn. The data from these samples includes demographic, psychographic and transactional variables for analyzing and segmenting customer characteristics. The results show that this combined model can fully predict customer churn and provide useful information for decision-makers in devising marketing strategy.

1. Introduction

Losing a customer is an opportunity for competitors to gain a customer. With so much competition, companies need to focus on keeping existing customers by satisfying their needs because the cost of attracting a new customer is usually considerably more than the cost to retain a current customer (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994; Reichheld & Sasser, 1990; Van den Poel & Lariviere, 2004). From the risk management perspective, retaining an existing customer lessens the need for a commercial bank to acquire a less credit-worthy customer or one whose ability or willingness to pay is uncertain. Customer characteristics become increasingly important in a competitive and mature credit card industry within which customers can easily switch their accounts and balances from one bank to another. In the past decade, with the help of business intelligence, databases have been growing rapidly. Commercial banks hold enormous amounts of their customers' transaction data in customer relationship management (CRM) databases, including data related to sales, servicing and marketing functions. This data provides abundant information about customers that decision-makers can use to characterize customers for strategic planning and decision-making purposes and to enhance their competitiveness. However, data is only as good as the system that turns it into usable information. Given the proclivity of some customers to switch credit card companies, there is a pressing need for an integrated system that will identify the customer characteristics that lead to churn before the customers are lost so appropriate action can be taken (Chiang, Wang, Lee, & Lin, 2003). This kind of information can also be used to identify and target customers for implementation of customer management strategies to maximize customer value.

The original rough set theory (RST) proposed by Pawlak (1982, 1984) is an effective approach for discovering hidden deterministic rules and associative patterns in all types of data and for handling unknown data distribution and information uncertainty or ambiguity. In other words, it can integrate learning-from-example technology, extract rules from data sets, and identify data regulations (Komorowski & Zytkow, 1997). Recently, RST has been applied in the marketing field because it is of benefit in analyzing and segmenting customer characteristics to formulate efficient and effective marketing strategies (Tseng & Huang, 2007), such as personal investment portfolio analysis (Shyng, Shieh, Tzeng, & Hsieh, 2009), video game customer purchase behavior (Tseng &

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Huang, 2007), insurance market attributes analysis (Shyng, Wang, Tzeng, & Wu, 2007), brand marketing (Beyon, Curry, & Morgan, 2001), supermarket customer loyalty (Lingras, Hogo, Snorek, & West, 2005) and travel demand analysis (Goh & Law, 2003).

Numerous studies have applied customer churn analysis to several areas, like the credit card industry (Kim, Shin, & Park, 2005; Kumar & Ravi, 2008; Lee, Chung, & Kim, 2001; Lee, Chung, & Shin, 2002), the wireless telecom industry (Hwang, Jung, & Suh, 2004; Wei & Chiu, 2002) and the financial services industry (Van den Poel & Lariviere, 2004). Customer churn analysis benefits for managers in decisions about the right marketing strategy to retain their customers. However, RST has not been widely used in predicting customer churn, especially in credit card industry. Therefore, the major objective of this study is to adopt RST to predict the characteristics of credit card customers so decision-makers can understand the rules of customer churn and use multiple indicators to formulate efficient and effective strategies for marketing of reducing churn.

This article is organized as follows. Section 2 provides an overview of previous relevant studies in the domain of customer churn. In Section 3 we use the RST to inducing the rule of credit card customer churn. In Section 4, we design and develop a flow network graph based on the decision rules extracted by RST, and Section 5 concludes.

2. Review of credit card customer churn

Customer churn occurs when customers switch vendors or cancel service altogether and can be categorized as: unavoidable churn, involuntary churn and voluntary churn (Modisette, 1999). Unavoidable churn occurs when a customer dies or moves out the provider's operating area. Involuntary churn occurs when a user fails to pay for service and the provider terminates services as a result. Termination of service resulting from theft, fraudulent service acquisition or fraudulent usage is also classified as involuntary churn. Involuntary churn is detectable, but not yet predictable and absolutely not actionable from a marketing perspective (Burez & Vand den Poel, 2008). Voluntary churn refers to service termination when the customer leaves one operator for another. Decreasing the churn rate is advantageous and should be a goal of marketers because the cost of retaining current customers is much less than the cost of obtaining new one; Karakostas, Kardaras, and Papathanassiou (2005) argued that a 5% increase in customer retention can result in an 18% reduction in operating costs. Therefore, if a customer starts acting in a way that manifests the intent to leave, management should have an anti-churn strategy prepared (Chu, Tsai, & Ho, 2007). Effective customer churn management also plays an important role in enhancing the quality of customer relationships.

Many studies have discussed customer churn management in various industries, especially in the mobile telecommunications industry. For instance, Estevez, Held, and Perez (2006) found that analyzing the customer antecedents at the time of application could prevent involuntary churn from subscription fraud in telecommunications, and Wei and Chiu (2002) argued that a mobile services provider needs to be able to predict which of its customers may be at risk of changing services in order to make those users the focus of customer retention efforts. However, there are relatively few studies the analyze customer churn among credit card holders. Customers usually carry one or two bank credit cards, along with other kinds of credit cards, so managing customer churn is a priority for most banks in the credit card sector.

Commercial banks provide credit card services that include account acquisition and activation, funding of receivables, card authorization, private label credit card issuance, statement generation, remittance processing, customer service functions, and marketing services. The tremendous competition among banks for providing these services has resulted in a significant increase in the reliability of and quality of service (Kumar & Ravi, 2008). Therefore, customers have become increasingly conscious of service quality. When a customer feels no particular loyalty to his or her bank, the customer will shift from one bank to another when greater service quality or better rates are perceived as being offered elsewhere.

Understanding what customer characteristics are likely to lead to this kind of churn is important to banks. Lee et al. (2001) described a fuzzy cognitive map approach to integrate explicit knowledge and tacit knowledge for churn analysis of credit card holders in Korea. Lee et al. (2002) compared the neural network approach with logistic analysis and C5.0 for churn analysis of credit card holders in Korea. However, although past research has applied customer churn analysis to discuss how to reduce credit card churn, little has been done to determine what customer characteristics will lead to the churn intention. In this study, we solve the customer credit card churn prediction via rough set theory and outline the most important predictor variables in solving the credit card churn prediction problem. The study determines what customer characteristics will lead to the churn intention, which can contribute to preparing effective anti-churn strategies to retain customers.

3. Rough set theory and flow network graph

The rough set theory was first introduced by Pawlak, 1982. RST has been used by many researchers, and the theory has a long list of achievement (Pawlak & Skowron, 2007). This section reviews the basic concepts of rough sets and flow network graph.

3.1. Information systems

RST may be described as an information table or decision table that can be represented by a set of objects dependent on the multi-valued attributes represented (Pawlak, 1982). Given an information system (IS), $IS = \langle U, Q, V, f \rangle$; $U = \{x_1, x_2, \ldots, x_m\}$, where U is the closed universe of IS, $A = \{a_1, a_2, \ldots, a_n\}$, where A is the set of attributes (features/variables), and for each attribute $a \in A$ (an attribute belonging to the considered set of attributes A), $V = \cup_{a \in A} V_a$, is a set of values of the attributes. According to Pawlak (2002), let $\rho : U \times A \to V$ be a description function, $\rho(x,a) \in V_a$ for each $a \in A$, and $x \in U$. Walczak and Massart (1999) expressed that a decision table T is any IS containing conditional attributes and decision attributes and is denoted $T = (U, A \cup D)$, where $D = \{d_1, d_2, \ldots, d_p\}$, $D \notin A$ is a decision variable or output feature, and the elements of A are condition variables or input features. For any application of RST, the first step is to transfer the original data into decision table.

3.2. Indiscernibility of object and classification

Discretization converts continuous attributes into discrete ones while removing redundant and irrelative attributes. Any set of all indiscernible objects is called an elementary set, and such a set forms a basic granule of knowledge about the universe. Some objects (e.g., a_1 and a_2, where $a_1, a_2 \in U$) in U can hardly be distinguished in an available set of attributes (let it be B in A). It is also said that a_1 and a_2 are indiscernible from a set of attributes B, so the relationship between a_1 and a_2 is determined to be an indiscernible relationship, $IND(B)$, defined as $a \in B$, if $\rho_{x_1}(a) = \rho_{x_2}(a)$ for every $a \in A$. $IND(B)$ divides the given universe U into equivalence classes; then any a_i of U can be determined so that the