Expert Systems with Applications 39 (2012) 11435–11442

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Improving customer retention in financial services using kinship network information

Dries F. Benoit *, Dirk Van den Poel

Department of Marketing, Faculty of Economics and Business Administration, Ghent University, Tweekerkenstraat 2, B-9000 Ghent, Belgium

ARTICLE INFO

Keywords:
Network based marketing
CRM
Predictive analytics
Social network analysis (SNA)
Kinship network
Financial services
Random forests

ABSTRACT

This study investigates the advantage of social network mining in a customer retention context. A company that is able to identify likely churners in an early stage can take appropriate steps to prevent these potential churners from actually churning and subsequently increase profit. Academics and practitioners are constantly trying to optimize their predictive-analytics models by searching for better predictors. The aim of this study is to investigate if, in addition to the conventional sets of variables (socio-demographics, purchase history, etc.), kinship network based variables improve the predictive power of customer retention models. Results show that the predictive power of the churn model can indeed be improved by adding the social network (SNA-) based variables. Including network structure measures (i.e. degree, betweenness centrality and density) increase predictive accuracy, but contextual network based variables turn out to have the highest impact on discriminating churners from non-churners. For the majority of the latter type of network variables, the importance in the model is even higher than the individual level counterpart variable.

1. Introduction

1.1. Customer Relationship Management (CRM)

In the past, companies had close relationships with their customers. They knew each customer individually and offered them personal customized service. As a result, they earned loyalty and a large share of their customers' business. Over the years, through increased competition and mass marketing, customers interchanged personalized service for anonymity, reduced variety and lower prices (Peppard, 2000).

The current business environment is characterized by intense competition and saturated markets. Mutanen, Ahola, & Nousiainen (2006) remarks that the mass marketing approach, where each customer gets the same treatment of the company, cannot succeed in the diversity of consumer business today. Therefore, companies are practicing an approach to marketing that uses continuously refined information about current and potential customers to anticipate and respond to their needs. This marketing strategy is called Customer Relationship Management (CRM) (Peppard, 2000).

CRM is about structuring and managing the relationships with customers (Kim, Suh, & Hwang, 2003). CRM covers all the processes related to customer acquisition, customer cultivation, customer retention and the reactivation of defected customers. This study can be situated in the customer retention domain. The goal is to identify the customers with a high churn probability in order to target them with appropriate actions and consequently try to keep them within the company. These actions may include targeting these customers with appropriate "next-product-to-buy" (NPTB) as shown in Prinzie and Van den Poel (2006) for financial services.

1.2. Customer attrition in financial services

Personal retail banking is characterized by customers who typically spread their assets over only one or two companies and stay with a company for long periods of time (Mutanen et al., 2006). From the point of view of the financial services company, this produces a stable environment for CRM. It is argued that these companies need to operate on a long-term "cradle-to-grave" customer management strategy (Li, Sun, & Wilcox, 2005). This means that they recognize that young customers are often unprofitable in their earlier years, but become profitable at a later stage. The longer customers stay with the bank, the more they become tied to such an extent that the perceived cost of defection outweighs the benefits of shifting their banking business to another provider.

Although the process of attracting new customers is important, most financial services companies make customer retention a top priority for several reasons: in general, the longer a customer stays with a bank, the more that customer is worth (Benoit & Van den

* Corresponding author.
E-mail addresses: Dries.Benoit@UGent.be (D.F. Benoit), Dirk.VandenPoel@UGent.be (D. Van den Poel).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.04.016

Poel, 2009). Long-term customers buy more, take less of a company's time, are less sensitive to price differences, and bring in new customers (Ganesh, Arnold, & Reynolds, 2000; Reichheld, 1996). Long-term customers become less costly to serve because of the banks' greater knowledge of the existing customer base and reduced servicing costs (Ganesh et al., 2000). In addition, the cost of winning a new customer is about five times greater than the cost of keeping an existing one (Colgate & Danaher, 2000). A study by Reichheld and Sasser (1990) showed that reducing defections by just 5% can generate 85% more profits for a bank. The latter findings corroborate the results of a study of Van den Poel and Larivière (2004), which illustrated how increasing retention by just 1% resulted in substantial profit gains.

1.3. Network based marketing

A limitation of traditional direct marketing is that it assumes that customers act independently. In reality, a customer's decision to buy a product is strongly influenced by his or her friends, family, business partners, etc. (Domingos & Richardson, 2001). Ignoring these network effects when deciding which customers to market to can lead to suboptimal decisions. For example, an unprofitable customer may be worth marketing to when this customer is likely to influence a lot of peers. In contrast to traditional direct marketing, network based marketing recognizes that links between consumers exist. As a result of the availability of gigantic databases of customer information today, companies now are able to target their customers taking into account their interrelatedness. Traditional marketing research does not reveal these social connections between consumers and thus cannot take advantage of links between customers.

Network based marketing assumes some kind of interdependency among customer preferences (e.g. purchase patterns, shopping habits, ...). These interdependencies are measured through implicit links (e.g. matching on demographic attributes, geographic links, etc.), or through explicit links (e.g. communications between actors, family ties, etc.) (Hill, Provost, & Volinsky, 2006).

Although network based marketing offers clear advantages over direct marketing, the use of social network information in prediction modeling is a very recent phenomenon (e.g. Hill et al., 2006; Manchanda, Xie, & Youn, 2008; Subelj, Furlan, & Bajec, 2011). This study contributes to the literature by investigating if social network information can improve the accuracy of churn detection. Moreover, this is, to the best of our knowledge, the first study that investigates different types of network effects in the same research setting.

The reminder of this paper is organized as follows: Section 2 delves into the methodological aspects of social network analysis. In order to get acquainted with the prevailing concepts and terminology, we first give a brief introduction to the field. Next, we show how the different effects that come into play in a social network can be quantified and how this data can be used in a modeling context. Finally, Section 2 is concluded with a discussion of the classifier and the evaluation criteria used in this study. Section 3 explains the dataset that was used to test the proposed methodology and gives an overview of the results that were obtained. Finally, Section 4 concludes the study with a discussion on the main findings.

2. Methodology

2.1. Social networks

A crucial insight in network analysis is that actors and their actions are viewed as interdependent rather than as independent and autonomous units (Wasserman & Faust, 1994). Typically, a cross-sectional CRM dataset contains a single row for every customer and columns for the information on that customer, where we assume that all rows are independent of each other. However, the information embedded in social networks is not of this standard form where attributes can easily be linked to individuals. To make this clear, consider the simple graphical representation of a kinship network in Fig. 1.

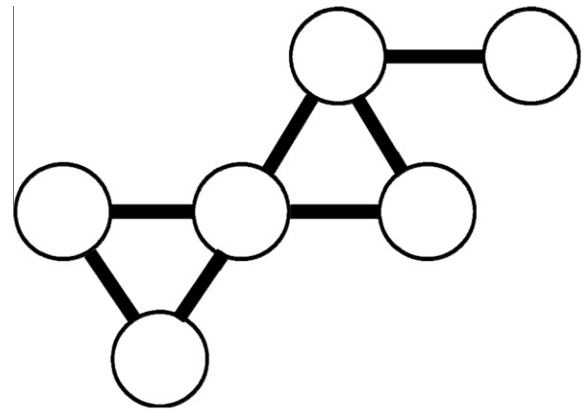

Fig. 1. Simple network graph

This way of representing a network is called a graph. Several dots (or '*nodes*') can be seen, which correspond to the individuals or any other unit of analysis. Some nodes are linked to other nodes by lines (or '*ties*'). Two nodes sharing a link are '*adjacent*' nodes. Together, all ties and nodes form a graph.

Nowadays we are facing a new trend in network research that is largely driven by the availability of powerful computers and the fast growing number of relational databases available to researchers (Chen, Yan, Zhu, Han, & Yu, 2009). The last couple of years, the focus is shifting away from the analysis of small-scale networks and the properties of individual ties towards large-scale statistical properties of networks (Newman, 2003). Previous studies used to look at small networks of only ten to several hundreds of nodes. However, in recent studies, it is not unusual to see networks with millions of nodes (e.g. Hill et al., 2006). Due to the dimensions of these new datasets, some specific approaches have emerged.

The data warehouse of the anonymous financial services company used for this study contains information on three categories of kinship links, i.e. parent–child relations, sibling relations and finally spouse relations. Using this information on the ties, the kinship networks of the customers were constructed. More specific, we built the networks by means of the egocentric network approach (e.g. Bar-Yossef, Guy, Lempel, Maarek, & Soroka, 2008). This means that a given customer or '*ego*' is focused on and then all other customers with whom the '*ego*' shares a kinship link (the '*alters*') are identified (see Fig. 2). The network for this given ego is now defined. Next, we zoom in on another customer (who now becomes '*ego*') and construct his/her network. This process continues until all customers' egocentric networks are identified.

The egocentric network approach has the distinct advantage that its analysis is related to the traditional attribute-based methodology, in that the typical predictors (socio-demographics, purchase history, etc.) are augmented with network measures that are deduced from the ego network (Knoke & Yang, 2007). Moreover, other methods that emerged from social network analysis are only suitable for networks up to a few dozen to a few hundred customers, whereas the egocentric network approach is able to handle the typical CRM datasets with hundreds of thousands of customers (Hill et al., 2006). The egocentric network created in this research, contains all alters no more than two ties removed from ego. The network that emerges from this method is thus a 2nd order egocentric network.