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Forecasting customer behaviour in a multi-service financial organisation: A profitability perspective

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ABSTRACT

This paper proposes a novel approach to the estimation of Customer Lifetime Value (CLV). CLV measures give an indication of the profit-generating potential of customers, and provide a key business tool for the customer management process. The performances of existing approaches are unsatisfactory in multi-service financial environments because of the high degree of heterogeneity in customer behaviour. We propose an adaptive segmentation approach which involves the identification of "neighbourhoods" using a similarity measure defined over a predictive variable space. The set of predictive variables is determined during a cross-validation procedure through the optimisation of rank correlations between the observed and predicted revenues. The future revenue is forecast for each customer using a predictive probability distribution based on customers exhibiting behavioural characteristics similar to previous periods. The model is developed and implemented for a UK retail bank, and is shown to perform well in comparison to other benchmark models.

1. Introduction

Customer Lifetime Value (CLV), an indicator of the expected future customer profitability for an organisation, is a well established concept in the academic and business literature. It is of particular interest to organisations which aim to maximise the value of a customer relationship over a particular time period.[1] In contrast to the prevailing practice of setting separate performance objectives for different business functions (which may conflict with each other), CLV offers a holistic decision support tool which gives "the same focus throughout the different decision making areas of the organisation" (Thomas, 2000). Applications of this concept include customer relationship management (CRM), which seeks to improve the long-term retention and profitability of both those customers who are currently highly profitable and those who are currently less profitable, or even unprofitable, but have the capacity to increase their profitability in the future (Zeithaml, Rust, & Lemon, 2001). Measuring the customer profit generating potential, along with credit scoring, which is an established decision support tool, is increasingly becoming an integral part of companies' lending decisions, providing a focus which is truly relevant to a company's objective of profit maximisation (Finlay, 2010; Fishelson-Holstine, 1998; Oliver, 1993; Thomas, 2000). Another important application of customer lifetime value modelling is in customer segmentation, where it facilitates the differentiation of levels and the volume of customer servicing in line with the revenue-generating levels and cost optimisation (Zeithaml et al., 2001). The implementation of our CLV modelling approach in a UK

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[1] Despite the name, Customer Lifetime Value models do not estimate the value over the entire lifetime of a relationship in a situation where the length of the relationship is indeterminate.

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bank led to a better understanding of the needs and preferences of some customer groups, and to the development of tailored customer propositions.[2]

Companies have been wrestling with the concept of CLV for a long time, as it is fraught with complexity in the context of a multiservice financial organisation. Firstly, the multidimensional nature of customer behaviour introduces challenges for behavioural models, as not only future purchase decisions but also their volumes need to be predicted (Donkers, Verhoef, & de Jong, 2007). Secondly, customers often purchase more than one product, and these purchasing decisions are not independent; these interdependencies should be taken into account when modelling the customer lifetime value (Kamakura, Ramaswami, & Srivastava, 1991; Kamakura, Wedel, de Rosa, & Mazzon, 2003; Knott, Hayes, & Scott, 2002; Li, Sun, & Wilcox, 2005). Thirdly, retail financial services organisations offer a wide variety of financial products (some rather complex) which differ in both their nature and their revenue generating pattern. Finally, a customer can switch between products or even between product providers at any point in time (Kamakura et al., 2003). Intense competition and technological advances have enabled historically "monogamous" retail bank customers (i.e., those conducting business only with one provider) to move increasingly towards the "always a share" relationship, in which a customer conducts business with several financial services providers simultaneously and can switch between them relatively easily. Due to these specifics of the retail financial industry, only a limited number of existing modelling approaches can be applied in this context.

A number of approaches to forecasting CLV have been discussed in the literature; for example, those focusing on the absolute level of individual customer values, the relative ordering of the individual customer values, and the aggregate CLV of all of the company's customers. The main focus of this paper is to differentiate between individual customers with high versus low profit generating potentials. This addresses a business need, as noted by Donkers et al. (2007), who stress that retail financial companies are interested mainly in identifying customers with high CLVs, rather than predicting the precise levels of their CLVs. We propose a novel approach to the modelling of the customer lifetime value which is based on adaptive customer segmentation using a neighbourhood concept. Our approach identifies customer neighbourhoods (local segments) which are (1) small enough to ensure customer homogeneity by capturing only customers who have similar characteristics and past behaviour, and (2) sufficiently large to ensure robust forecasts of customers' future behaviour. We use a *similarity measure* which is defined over a predictive variable space to establish a customer's neighbourhood. The customers' neighbourhoods are chosen so as to include customers who had predictive characteristics in a given past period which are similar to the most recently observed characteristics of the customer in question. The optimal local segment size and set of predictive variables are determined using a cross-validation procedure which employs the rank correlation between the observed and predicted profitability as the optimisation criterion. The one-period-ahead profitability is forecast for each customer using a predictive probability distribution estimated over the population from her neighbourhood. Multi-period forecasts are produced by the convolution of one-period predictive probability distributions, which is implemented using bootstrap simulations. Our segmentation approach can be applied to a range of predictive tasks, such as the forecasting of the conditional profitability (given some other customer characteristics, e.g., credit risk) or the prediction of other customer-related characteristics (e.g., product purchasing decisions or account balances). Thus, it provides a powerful tool in the development of tailored customer acquisition and retention strategies. The ranking approach has benefits during times of significant economic change.

Our model is applied to predict and validate the customer profitability using customer data for a UK retail bank for the period 2005–2008. We also compare our results with those obtained using various benchmark models: simple and multiple linear regression models for predicting the revenues from individual customers, and a probit model for identifying customers whose revenues are likely to increase, decrease or remain stable in the future. Our model performs better than the benchmark models. We are able to make robust predictions of individual customer revenues using a small number of variables.

The remainder of this paper is structured as follows. Section 2 offers a short review of the previous literature on modelling approaches in the context of a multi-service financial organisation. The details of our modelling approach are provided in Section 3. Section 4 offers an implementation algorithm which enhances the computational efficiency of our approach. The estimation results and a discussion of potential applications are given in Sections 5 and 6, respectively. Finally, Section 7 concludes.

2. Review of previous approaches in the context of a multi-service financial organisation

Gupta et al. (2006) and Jain and Singh (2002) provide comprehensive overviews of the existing lifetime value models. In the context of a multiservice financial organisation, the empirical evidence suggests that there is no advantage of complex service-level models of customer behaviour over simple models when predicting the individual customer lifetime value (Donkers et al., 2007). These simple models use aggregate customer data and make the restrictive assumption that the customer profitability is constant over time, or else exhibits a linear trend in profitability (e.g. Berger & Nasr, 1998; Malthouse & Blattberg, 2005). In the context of retail banking, this assumption can only be satisfactory if profitability margins do not vary over time and revenues are generated by regular payments from

[2] A segment of the over-50s customer age group was identified as having a high future revenue generating potential, which was subsequently recognised by the organisation as being a prime target for product cross-sale and customer acquisition and retention activities. This understanding has also contributed to the organisation's compliance with the UK Financial Services Agency's regulatory requirements for treating customers fairly.