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Creating Profitable Customers through the Magic of Data Mining

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Abstract: In the early days of Relationship Marketing, its proponents argued for customer retention on the grounds that this would increase the lifetime value of the customer and, by extension, that this would increase overall corporate profitability. However, recent research has indicated that, for many organisations, a high proportion of customers is unprofitable. This raises a question about the retention proposition. Increasing the retention of unprofitable customers may be damaging, not beneficial, to organisations. This paper discusses some common data analysis techniques used to identify the most and least profitable customers so that marketing managers can develop effective, appropriately targeted customer management strategies.

Key words: customer profitability, data mining, customer risk, relationship marketing.

Relationship Marketing: the value of Lifetime Relationships with Customers

The emergence of Relationship Marketing has seen an increased emphasis on customer retention[1,2] Influential voices have insisted that the relationship with the customer is a fundamental driver of business success and that companies need to trade-off their investment in creating value for customers with the shareholder value that those customer relationships create for the company.[3] What is, or has become, controversial is the role that customer retention may play in the creation of shareholder value.

One reason that this is a contentious topic is the growing criticism of marketing for its lack of measurement and, by implication, of tangible returns. In particular, an undue emphasis on customer satisfaction may result in strategies that do nothing to generate shareholder value.[4] Doyle and others[5] argue that the key role of marketing is to create shareholder value. Targeted marketing and relationship management have an important role to play in creating shareholder value[6, 7]

The early position of Relationship Marketing was to argue that increasing overall customer retention will improve corporate performance.[8] This position was exemplified by Reichheld's much-cited 1996 book with its statistics for the impact of a 5% increase in customer retention on the lifetime value of those customers.[9] In Reichheld's examples, the reason that customer retention increases customer lifetime value is because customer acquisition costs are high, making new customers unprofitable, whereas there are underlying profits from these customers in future years. Therefore, increasing customer retention will allow these customers to mature into profitability; as Reichheld says:

> "In most businesses, the profit earned from each individual customer grows as the customer stays with the company" ([10]p.37).

If customers are profitable once acquisition costs are disregarded then it is a truism that increasing customer retention will increase customer lifetime value. Adding an extra year of profit to the lifetime value of a customer will of course increase the lifetime value of that customer. Unfortunately, there is a growing body of research showing that a high proportion of customers are unprofitable and the reasons are not to do with customer acquisition costs.[11, 12,13] These customers are unprofitable because the company's cost of servicing them is too high or the prices that it charges are too low, or both.[14,15,16,17] No amount of increased retention will make these customers profitable; in fact, increasing the retention of unprofitable customers may actually destroy shareholder value. This more recent research demonstrates that Reichheld errs in recommending retention across the board; the real payback is in targeting marketing efforts to attracting and retaining those customers who are more profitable.[18]

This paper argues that, to be effective at creating value for the company, relationship management must focus on attracting and retaining those customers that are most profitable for the organisation. So relationship management has three objectives: to develop strategies that increase customer value and, hence, satisfaction; to identify the most valuable customers or segments and target them successfully with retention strategies; and to reduce the risk that valuable customers defect to competitors. In all three objectives, customer information is key. This is where the magic of data mining comes in.

Magic trick 1: Finding the penny behind the ear - Identifying the sources of customer value

The first task for relationship management is to identify offers that create value for customers. One technique for identifying what customers really want is cross-buying analysis. Cross-buying analysis identifies which products or services tend to be bought together.[19] A simple form of cross-buying analysis is cross tabulation ('cross tabs'). Cross tabs can be used to analyse purchase data from groups of like customers to search for purchasing patterns that may suggest new strategies. One application of cross tabs is in developing promotions. Cross tabs can suggest what offers may be more likely to succeed with certain customer groups, thereby increasing multiple product holding which is known to be linked with customer retention.[20] Knowing what combinations of products customers are more likely to buy can also prevent companies discontinuing products with low sales that are an important part of the purchasing mix from the customer's point of view. This can be particularly important when combined with customer lifetime value analysis: one supermarket that was considering dropping an expensive, low sales cheese found that many of its most profitable customers bought the product. It might well be that the exclusive cheese was an important reason for these valuable shoppers to shop there; more research would be needed to ensure that dropping this product line would not jeopardise the entire relationship.

A step on from cross tabs is collaborative filtering. The premise underlying collaborative filtering is that customers who have similar purchasing patterns will share similar tastes. Thus, if one customer starts buying a new product, it is likely that other customers with similar previous purchasing patterns will also be attracted to the new product. Perhaps the most well-known user of collaborative filters is Amazon ("Other customers who bought this product also bought….").

Another powerful way in which customer information can be mined to help develop CRM strategies uses a combination of trade-off and cluster analysis. Trade-off analysis is a form of analysis that has its origins in mathematical psychology.[21] The idea is that purchasers have to make trade-offs in their purchasing decisions between the availability and the cost of certain product or service offerings. The results of a trade-off exercise allow managers to identify where there are clusters of customer preferences around certain combinations of factors.[22] These can be used as the basis for developing value propositions and tailored relationship strategies for customer segments.

The marketing managers for a direct insurance company had always believed that motor insurance was sold overwhelmingly on price. In fact, their trade-off exercise revealed that the purely price-sensitive segment comprised just 14% of the customer base. Using customer data the insurer profiled this so-called 'Economy' segment and found that customers in this segment were willing to buy other products, resulting in a cross-selling programme. A large segment of 'Security Seekers' revealed by the analysis preferred to buy from a reputable company which had been recommended to them; this finding led to brand advertising in targeted publications, and member-get-member promotions to increase positive word of mouth.[23]

Magic trick 2: Vanishing and reappearing customers – predicting customer relationship lifetimes and defection probabilities

Henry Ford may have thought that history was bunk but, for most organisations, the history of a customer relationship is the best guideline to its future. This principle applies not only to purchasing behaviour but also to customer relationship lifetimes. Reasonable estimates of a customer relationship lifetime can be obtained from data analysis. Grouping customers according to their length of relationship lifetime and then cross-analysing the results by customer profile may reveal indicators of long (or short) relationship lifetimes. One bank, for example, found that although younger customers had theoretically longer relationship lifetimes they were, in fact, more likely to defect so that certain older customers had longer actual relationship lifetimes.[24] Information about which customers are most likely to vanish early can be used to calculate the net present value of customer acquisition campaigns.

A problem that has received far less attention than it merits is that of calculating the relationship lifetime of customers who vanish and then reappear, sometimes months or years later. A personal loans organisation suspected that it had customers who might take out a loan for a car, perhaps, and then return months or years later to take out another loan when they wanted to change their car again. Unfortunately, the loan company identified loans by the loan number, not by customer, so returning customers were issued with a new loan number and treated as though they had never before done business with the company. Data managers used a sophisticated tool, fuzzy logic, to deal with this problem. Fuzzy logic works by matching qualitative concepts (such as 'young, female') and language concepts (such as slightly differently spelled names that are in fact the same person) and indicating how probable it is that a match has been found. The loan company discovered that many of its customers did apparently return for additional loans, making them substantially more valuable than one-time customers. The fuzzy matching process identified one customer who had taken out no fewer than nine loans over the course of her relationship lifetime with this organisation, each loan larger and hence more profitable than the one before! [25] This

demonstrated to the personal loans organisation that its current method of calculating customer lifetime value based purely on existing product holdings was inaccurate. An additional implication was that it was worth keeping customer details on the database for longer and trying to match them to incoming 'new' customers; in this way, the service to returning customers could be improved. Finally, it would be possible to profile the returning customers and compare their characteristics with those of other, similar but non-returning customers; in this way, the company would be able to spot higher-potential customers earlier and ensure that the received follow-up loan offers.

Customers also vanish because they are dissatisfied or attracted by the offer of a competitor. The magic of data mining can identify customer behaviour patterns that warn of imminent defection. Using a technique called micro pattern matching, historic data about customers who have defected are compared with a control group of retained customers to identify the distinctive behaviours of the defectors (for example, taking longer to pay their bills; buying less often; buying fewer products). Then, the analysis is applied to the existing customer database to identify customers with defecting behaviour patterns. Wesleyan Insurance is an innovator in this field. Its customer database is continually searched for patterns of behaviour that indicate that the customer may be considering leaving. These accounts are flagged as 'in danger', and the customer records transferred automatically to a relationship management team tasked to find out what the problem is and to rescue the relationship.[26]

Magic trick 3: How many rabbits in the hat? Forecasting Revenues and Costs over the Relationship Lifetime

Revenues and direct product or service costs will depend on the product mix. Selling more products to existing customers is the first rabbit out of the data mining hat. Best practice companies are using predictive modelling techniques to help their marketing people forecast likely product mix and purchasing levels at various points in a customer's lifecycle stage. A major UK bank uses neural networks to try to identify what products it would expect its customers to buy at a given stage in their lives; the bank then matches this to the products it knows its customers hold. The resulting gaps may mean that the customer does not have products that they might need or want, which is an immediate opportunity for cross-selling; or perhaps that the customer does own these products, but through a competitor. In the latter case the bank may decide to try to win the customer over to its own product[i].

A truly startling finding from recent research has been the impact of indirect costs, the costs of serving customers, on the relative profitability of different customers. Some customers are far more expensive to serve than others. One study [27] found that:

> "At the individual customer level, the service costs vary from 3.6% to 306.5% of revenues, and the customer profitability varies from -251.7% to 59.6% of sales revenue." ([28,] p8)

Using traditional tools such as activity-based costing to identify indirect costs, customer by customer, can be an expensive and time-consuming exercise. Even apparently small matters such as customer-specific packaging can mean extra resources and costs: higher wastage rates, the need for specialised warehousing and transport etc. Fortunately, there are IT tools

[i] Private conversation between the Marketing Director of this bank and the author.

that help companies to collect, analyse and understand the costs of doing business with their customers. For example, sales time can be estimated, costed and shown against the specific customer using sales force automation software. New call centre systems may also automatically identify time spent, customer-by-customer.

Customer-specific costs can differ significantly between different customers or segments, yet managers may fail to take these costs into account. The information may be used for pricing or to adjust service levels. A high-tech company began to itemise the notional costs of service to some of its more costly customers on their monthly statement. Although it continued to provide the service for free, customers' perception of the value they received was enhanced. The company found that this practice reduced the focus on price during contract renewal negotiations. Zurich London insurance used information about customer-specific costs to identify where account managers were 'giving away free' valuable services. [29]

Magic trick 4: Sawing the Customer [Risk] in half.

Risk scoring is a standard procedure in the sale of consumer durables such as mobile phones, furniture, household appliances or cars where credit is to be given, as well as in retail financial services when customers apply for a mortgage, loan or credit card. Risk scoring is an effective way of evaluating certain specific types of customer risk, normally the risk of default. Traditionally, risk scoring has been done on application. However, the risk of the customer may change dramatically over the course of the relationship. An individual's ability to meet repayments might be dramatically influenced, for example, by a promotion or a redundancy. Data manipulation can cut the risk associated with these changes by monitoring risk on an ongoing basis. At least one leading UK bank has developed a dynamic risk evaluation process that enables it to view the changing risk of its customers and adjust its risk exposure accordingly. Other banks, like Virgin, use their total view of the customer to offer combined current account and mortgage products. Detailed management of individual customer risk in this way allows Virgin to offer its customers convenient products at very competitive prices.[30] Dynamic risk monitoring is also used by MBNA to adjust its pricing.[31]

Discussion

This paper has argued that a key role of marketing is to identify the customers or segments with the greatest value-creating potential and target them successfully with retention strategies to reduce the risk of these high lifetime value customers defecting to competitors. The managerial implications are extremely interesting. Firstly, managers have to recognise that some customers or segments are more valuable than others. Failing to carry out the kind of analysis outlined above could lead a company to overvalue certain customers or segments and perhaps to invest disproportionate time and resources in them whilst other, more profitable or less risky segments are neglected. Second, companies will do better by learning about their customers through transactional data than through satisfaction surveys that reflect attitudes not actual purchasing behaviours.

Third, managers must understand that there are certain customers who can never create value for that organisation – in other words, customers that the firm would be better off without, or better off not attracting in the first place. It can be hard for some organisations to recognise that not all customers are a good thing. Both acquisition and retention activities should be focused on the more valuable customers.

The fourth managerial implication concerns risk. New data analysis techniques allow companies to understand the risk in their customer relationships. All other things being equal, if two customers or segments have the same level of expected future returns but one is more risky, the riskier segment will be less valuable to the company. If they understand risk, managers can develop new strategies to manage it.

Best practice demands that marketers develop their understanding of new data mining and analysis techniques and use the output to develop marketing strategies creatively to maximise shareholder value.

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