DATA MINING OF CRM KNOWLEDGE BASES FOR EFFECTIVE MARKET SEGMENTATION
A Conceptual Framework

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Abstract: This paper illustrates the linkages between CRM systems, data mining techniques, and the strategic notions of market segmentation and relationship marketing. Using the hypothetical example of a consumer bank, the data in a relationship based marketing environment are illustrated and guidelines for knowledge discovery, data management and strategic marketing are developed.

1 INTRODUCTION

The importance and benefits of customer relationship management (CRM) have been well recognized (Kotler, 1997; Reichheld and Sasser, 1990). Customer acquisition costs exceed customer retention costs by factors of 5 to 7 (Kotler, 1997). A mere 5% reduction in customer defections can improve profits by 25 to 85% (Reichheld and Sasser, 1990).

Besides cost savings, CRM technologies, other allied information technologies, and data mining techniques offer amazing possibilities for creating and sustaining ideal, highly satisfying customer relationships (Goodhue, 2002; Ives, 1990).

The processes of implementing and executing CRM, however, are complex (Abbott, 2001; Winer, 2001). According to a Gartner Group study, 55% of CRM projects during 2002-2006 may fail.

Given high costs of deployment and maintenance (Caulfield, 2001), such drastic failure rates represent huge financial risks for CRM adopters. What is worse, 20% of long-standing customer relationships are soured by these CRM failures (Mello, 2002).

Without understanding who the valuable customers of a company are, what CRM is, and how it works, the huge investments in CRM resources simply push up the level of risk.

A major premise of CRM is that it could help companies leverage the continuous stream of customer-related data collected through various touchpoints, facilitating individual-level marketing decisions (Libai, Narayandas, & Humby, 2002).

Therefore, analytical CRM techniques using data mining and knowledge discovery in databases (KDD) play important roles. Not much research has been done, however, about data mining from the perspective of understanding customers better for CRM practice.

This paper investigates how data mining can be used to understand customers better, from CRM perspectives. It explores ways to use data mining to find segments of customers who want a relationship with a firm and who have potential for loyalty. The bases of segmentation are the customers' needs and wants implied in their transactions with a firm. Starting with the review of channel preference of customers, a framework for market segmentation is developed. A pivotal point of data mining is its ability to discover previously unknown and unsuspected patterns. Here we leverage this ability by using data mining algorithms to perform the customer segmentation rather than performing the segmentation based on some preconceived notions.

The next sections are brief reviews of CRM and KDD, followed by a framework for data mining technique for effective market segmentation.

2 CRM: BRIEF REVIEW AND EMERGING CHALLENGES

To define CRM, we need to first address the customer. The broad definition of customer includes suppliers, buyers, consumers, and employees – as internal customers (Gamble, 1999). In the proposed framework, however, the definition of customer is

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limited to buyers of the product or service that a firm provides.

Having narrowed the scope of the term "customer" to the product/service buyer, understanding what is CRM and what elements constitute CRM is the next step.

CRM represents a variety of things to different groups (Goodhue, Wixom, and Watson, 2002; Winer, 2001; Wright, 2002); hence CRM implementations tend to vary also. For example, to some, CRM means direct email or database marketing. For others, it refers to OLAP (online analytical processing) and CICs (customer interaction centers). Wright (2002) argued that the understanding of concepts such as 'customer retention' and 'cross-selling' and their application in practice is often weak (Wright, 2002).

Even though the definition of CRM is not consistent among researchers, based on the review of previous frameworks of CRM, three core dimensions characterize a buyer-focused CRM system:

- ***Customers*** at the center (CMO 2002; Gamble, Stone and Woodcock, 2002; Greenberg, 2002; Newell, 2003)
- ***Management***'s articulation and tracking of customer relationship goals, plans, and metrics (Ang and Buttle, 2002; Day and Van den Bulte, 2002; Greenberg, 2002)
- ***Technologies*** for facilitating collaborative, operational, and analytical CRM activities (Goodhue, 2002)

First, as an organizational strategy (Ang and Buttle 2002; Smith 2001; Day and Van den Bulte 2002), CRM systems should deal with various management levels. Strategies should be established to accomplish corporate-level goals. Specific plans have to be crafted and the performance of these plans has to be tracked and evaluated thoroughly. These goals, strategies, and plans should reflect the corporate philosophy regarding customer orientation and inculcate a customer-responsive corporate culture.

Second, the technological structure needs to be worked out, including analytical CRM systems, operational CRM systems, and collaborative CRM systems.

Analytical CRM systems help a firm to analyze the huge amount of customer data so that the firm can find some patterns of customers' purchasing behavior (Goodhue, Wixom, and Watson, 2002). Operational CRM systems entail the integration of all the front-end customer-facing functions of the business. For example, since the sales process depends on the cooperation of multiple departments performing different functions, the systems to support the business processes must be configurable to meet the needs of each department (Earl, 2003; Greenberg, 2002). Collaborative CRM systems refer to CRM functions that provide points of interaction between the customer and the channel – the so-called "touchpoints" (Greenberg, 2002).

Third and finally, the raison d'être of any CRM system is the customer. Customer service and related issues must be included in the design, implementation, and operation of any CRM system. Davids (1999) emphasized that viewing CRM as a sales or customer service solution is the surest way to fail. The only way to benefit the organization is to first benefit their customers (Davids, 1999). CRM software needs to pay attention to not only users within the implementing organization, but also to the end customer (Earl, 2003). While enhancing the operational efficiency of the organization is an important goal of using CRM technology, servicing and delighting the customers are the ultimate end-goals as well as the ultimate determinants of success.

Each level has to be coordinated for successful CRM implementation and performance outcomes. It is important to note that placing customers in the center should be the first. And then every other activity can be done to understand and satisfy the customers.

With these components in place, CRM can be defined as follows:

> CRM is a core business strategy that integrates internal processes and functions and external business networks to interact, create, and deliver value with personalized treatment to targeted customers to improve customer satisfaction and customer retention at a profit. It is grounded in high quality customer data and enabled by information technology (Day and Van den Bulte, 2002; Ang and Buttle, 2002).

With this CRM definition, we turn next to a review of how new technologies and techniques are used to understand customers in the CRM practices.

3 CRM-FOCUSED KDD

With improving technologies of information collection, transmission, processing and storage, companies can obtain timely, valid, and reliable information for solving important customer relationship problems (Moorman, Zaltman, & Deshpande, 1992). Hardware and database technologies allow efficient, inexpensive, and reliable data storage and access (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). The web – the emergent channel for promotion, transactions, and business process coordination – is an important and convenient source of customer data (Shaw *et al*., 2001). Huge warehouses of customer data exist, and companies face the challenge of generating insightful customer knowledge for competitive advantage (Kim *et al*., 2002).

Many useful marketing insights into customer characteristics and their purchase patterns, however, remain hidden and untapped (Shaw *et al.*, 2001). New computational techniques and tools for extraction of useful knowledge from the rapidly growing volumes of data are emerging. It is increasingly critical for companies to be acquainted with what, when, and how to use such data and tools.

As a tool to analyze CRM-related customer data, data mining has received the most attention (Mackinnon, 1999; Fayyad, Piatetsky-Shapiro, and Smyth, 1996). Systematic combining of data mining and knowledge management techniques can be the basis for advantageous customer relationships (Shaw *et al.*, 2001).

Data mining can be seen as one step of knowledge discovery in databases (KDD): the iterative process of data selection, sampling, pre-processing, cleaning, transformation, dimension reduction, analysis, visualization, and evaluation (Mackinnon, 1999). Data mining is often defined as the process of searching and analyzing data in order to find hidden and potentially valuable, information (Shaw *et al.*, 2001).

Data mining methods allow marketers to understand better their customers from the increasing volumes of data. Kim, Kim, and Lee (2002) found that companies are eager to learn about their customers by using data mining technologies, but due to the diverse situations of such companies, it is very difficult to choose the most effective algorithm for their specific problems. In their study, they proposed a methodology to enhance the accuracy in predicting the tendency of customer purchase behavior by combining multiple classifiers based on genetic algorithms, which can be considered to be a data mining techniques (Kim *et al*., 2002).

Shaw *et al.* (2001) introduced three major areas of application of data mining for knowledge-based marketing – (1) customer profiling, (2) deviation analysis, and (3) trend analysis.

- Customer profiling: It is a model of the customer. The marketer decides on the right strategies and tactics based on the customer profiles. Data mining tools can be dependency analysis, class identification, and concept description.
- Deviation analysis: It is an analysis of deviation from norms. Data mining tools provide powerful means such as neural networks for detecting and classifying such deviations.
- Trend analysis: Trends are patterns that persist over a period of time. Data mining tools such as visualization can be used to detect trends, sometimes very subtle and hidden in the database.

Also, Jackson (2002) noted that data mining can be used as a vehicle to increase profits by reducing costs and/or raising revenue. Some of the common ways to use data mining are eliminating expensive mailings to customers who are unlikely to respond to an offer during a marketing campaign and facilitating one-to-one marketing and mass customization opportunities in customer relationship management.

In sum, many organizations use data mining to help manage all phases of the customer lifecycle, including acquiring new customers, increasing revenue from existing customers, and retaining good customers. CRM systems can benefit from well-managed data analysis based on data mining.

4 REQUIREMENTS FOR EFFECTIVE MARKET SEGMENTATION

Data mining studies have mainly focused on strategies based on customers' purchasing behaviors (Berry and Linoff, 2000):

- Profiling: By determining characteristics of "good" customers, a company can target prospects with such characteristics.
- Cross-selling: By profiling customers who bought a particular product, a firm can focus attention on similar customers who have not bought that product.
- Reducing churn or attrition: Profiling also enables a company to identify customers who are at risk for leaving and act to retain them.

Based on the high failure rate of CRM, however, critics have raised questions about how companies define customers and how they manage the relationship.

Newell (2003) argues that relationship building must start with an understanding of the customer's needs. A firm should make customers manage the relationship, rather than try to manage customers (Newell, 2003).

In line with this notion, Fournier, Dobscha, and Mick (1998) have pointed out that consumers may not be willing to enter into a relationship with many businesses, because most relationships are initiated by the businesses. If consumers target the businesses and control the relationship, it will more likely increase involvement and participation (Fournier, Dobscha, & Mick, 1998).

In fact, three different possible situations of forming a relationship between the businesses and customers are identified in the consumers and the businesses relationship (Dowling, 2002):

- First, some consumers may associate a personality with a brand and want a relationship with the brand.
- Second, consumers may still value a relationship with the retailer that sells the product or service even though they don't want a relationship with the brand.
- Third, consumers may not want any relationship at all. If a company tries to provide the best value to them, they would respond to the offers with such type of loyalty as repeat purchase and positive recommendations to others. These 'transaction' customers will also cost less to serve than many other 'relationship' customers.

Therefore, clear understanding about who the customers are, whether they want from any relationship with a business, and, if yes, what they want from the relationship – these should be the cornerstones of CRM systems and customer service policies. Therefore, the proposed framework attempts to find a way to understand customers best by using data mining techniques based on the customers' perspective of relationship.

One of the chief ways of understanding customers is segmentation. Market segmentation has been used as a good way to find a group of consumers to target. Many studies have been conducted to find superior ways of segmenting customers. Consumers' decision-making styles (Walsh, Henning-Thurau, Wayne-Mitchell, & Wiedmann, 2001), consumers' shopping styles (Papatla & Bhatnagar, 2002), and consumers attitudes towards unsolicited direct mail and telesales (Mitchell, 2003) have recently been used as bases for segmentation.

Not many studies, however, have been conducted for deep understanding of customers from their perspectives and preferences even though Dowling (2002) argued that the simple way to check the relationship and a nature of a brand is to segment customers according to the strength of relationship customers would like to have with the brand (from strong to none) and then for the "willing" segments, determine the type of relationships they have with the brand.

Identifying valuable customers and their needs and wants is critical for successful CRM, and the proposed approach attempts to provide a framework to find the customer segments in terms of their perspectives. Data mining techniques are shown as paths to better market segmentation based on the channel and mode preferences as well as permissions.

5 TOWARDS BETTER CONCEPTUAL INTEGRATION

5.1 Data Mining for Effective Market Segmentation

From the previous literature review, it is clear that – before analyzing any patterns in the purchasing behaviors – a company should be sensitive to the very basic questions such as who its valuable customers are, how they want to structure their relationships with the businesses, what they want from any relationship, and what they like.

Since profitable customers and prospects may not be apparently revealed, there have been many studies focused on customer lifetime value (CLV). CLV is defined as the present value of all future profits generated from a customer (Gupta and Lehmann, 2003). Based on the assumptions that the information about how long a customer will be with a firm is known, one common approach is generate a discounted cash flow for that time period (Gupta and Lehmann, 2003).

Since the focus of the proposed framework, however, is on showing how data mining can be used to find the hidden, valuable customers in terms of their willingness to get involved in a relationship, rather than calculating financial value of customers, the study investigates only current status of transaction record (financial record), and the interaction mode (banking transaction, support, education, promotion) and channel preferences (branch, online, etc.) form the core bases for segmentation.

A relationship could start with any interaction, and the importance of managing multi-channel marketing has increased since the Internet and other technologies provide many more touchpoints than before.

Butler (2000) pointed out that companies use the online channel to increase their visibility, accessibility, and sales to the growing customer base on the Internet, and to enhance customer relationships. It is possible, however, that the online channel can suffocate the growth of other channels

(Butler, 2000). Therefore, while most companies use a variety of distribution and service channels, companies should skillfully manage potential channel conflicts in ways that allow channels to complement one another (Johnson, 2002).

Berry and Britney (1996) argued that small banks can use several combinations of segmentation themes to segment customers instead of using one theme. One of the themes is channel preference, which classifies customers into segments based on their relative use of the bank's services and sales channels.

Therefore, segmenting the customers based on their implied channel preferences and interaction modes is the first essential step towards building any type of relationship with valuable customers. Here, we propose that this essential step can be accomplished using data mining techniques.

A retail banking scenario is used to illustrate the procedures of market segmentation. CRM in financial services is exceptionally challenging (Rigley, 2003). Therefore, benefits from data mining would be correspondingly large. Financial services are very data intensive, complex businesses and traditional financial services business models are product-centric rather than customer-centric. Rigley (2003) argued that focusing the organization on customers in addition to the products, focusing targeted marketing efforts on the customer rather than "pushing" products, and understanding which customers are most profitable and taking action to grow and retain these relationships are the ways to improve CRM practice in the financial services arena. The retail banking scenario sets up the operating context of a typical financial service firm.

Channel preference is usually the starting point and therefore the data used for the analysis should be collected through all touchpoints and integrated into a single integrated data warehouse.

We turn next to the scenario to illustrate the market segmenting process.

5.2 Illustrative Scenario

Let us consider the hypothetical case of a retail bank, Gemstone Bank, with 15,000 customers each having at least one bank account. Gemstone provides ATMs, online banking services, 1-800 call center, and many branches in its geographical market area.

In the past, Gemstone Bank has rolled out several campaigns that involved getting a priori permissions. Each campaign used different set of channels to interact with customers. The bank collected permission consents from the customers. Some customers have been contacted several times through multiple campaigns while some others may not have been contacted at all. Now Gemstone has the information about customers and the permission related data.

Gemstone maintains a data warehouse for the information collected on all the touch points. The structure of such data is shown in Table 1.

Gemstone would like to use the information deposited in the data warehouse to find out who the valuable customers are and how to interact with them.

Table 1 includes four different channels – call center, online, walk-in, and ATM – and interaction modes such as banking transaction, support, or promotional interaction. Each interaction mode by each channel has different sets of activities, and therefore, different data are collected. Such data comprise the data warehouse. The data shown has been simplified to visibly illustrate this analysis.

As shown, various interaction channels can be used and the data collected through such channels are rich and diverse, and yet it is possible that some customers may use only one or two specific channels while others may want to use them all.

Therefore, it is important to note that the analysis based solely on the data collected with a subset of channels may be limited and biased and that the analysis needs to take all available channels into account.

5.3 Framework

With the scenario provided above, a framework is developed and proposed for customer segmentation. We argue that although the bank might have some intuitive understanding and insight of which customers to target and how, it is worthwhile to explore the channel preferences and interaction modes in greater depth. We propose a two tiered clustering scheme to segment the customer base as follows:

(1) Compute individual customer summary information based on the interaction records in the data warehouse which includes channel usage, most frequent transactions, mode preferences, etc. In general, only use attributes which describe customer/bank interactions.

(2) Based on this summary information, segment customer base using clustering. Standard data mining algorithms such as self-organizing maps or k-means seem appropriate here (Berry & Linoff, 1997).

Table 1: Channels and Data collected

ATM	Online	Call Center	Walk-in
Interaction Mode *Banking Transaction: *Withdraw* *Deposit* *Inquiry* *Transfer* *Maintain*	Interaction Mode *Banking transaction: *Transfer* *Inquiry* *Maintain* *Bill paying* *Portfolio mgt.* *Support: *_Transfer problem* *_General support* *.Location of banks* *.Products* *.ATM/Online* *.Credit card support* *Educational *Promotional	Interaction Mode *Banking transaction: *Transfer* *Inquiry* *Maintain* *Support: *_Transfer problem* *_General support* *.Location of banks* *.Products* *.ATM/Online* *.Credit card support*	Interaction Mode *Banking transaction: *Transfer* *Inquiry* *Maintain* *Deposit/ Withdrawal* *Portfolio* *Bank checks* *Travelers' check* *Support: *_Transaction* *_General* *Educational *Promotional
Information *Transactn: Date/ Time/c_ID/ Transaction Type/ Transaction related data	Information *Transaction: Date/c_ID/Transaction Type/data *Promotion/ Education: Date/c_ID/ promotionID/ Response *Support: Date/c_ID/ categories of questions – FAQ/ live chat	Information *Transaction: c_ID/Time/Type/ data *Support: c_ID/Time/ Categories (Transaction vs. support)	Information *Transaction: c_ID/Time/Type/ data
*c_ID: customer ID			

(3) Break out the obtained clusters, enrich the above summary information with bank product information such as average running account balances, mortgage or personal loan principals, etc. and perform yet another cluster analysis on each of the previously obtained clusters. Here we consider only attributes which describe the customer in terms of financial characteristics.

(4) Enrich the obtained clusters with previously obtained permissions data.

(5) Use customer profiling (including the permission related information) to investigate the final clusters.

As one can see in Figure 1, we postulate that individuals within the clusters obtained in the first analysis share strong channel and mode preferences, in other words interaction preferences. It is postulated that each of the clusters obtained in the second analysis describes a set of customers with varying degrees of value to the bank but who share the same interaction preferences. Some of these clusters describe high-value customers; others describe customers that are not interesting from the banks point of view.

Furthermore, the degree of permissions data available for customers within the nested clusters is expected to vary substantially. Some customers may have given very recent positive responses to permission requests; for other customers no permissions data may exist. Also, for some customers there may be recent negative responses to permission requests. In Figure 1 permissions data is represented as a color coding.

Due to the fact that nested clusters represent customers of varying value with a particular set of channel and mode preferences, it should be possible to design particular relationship strategies, including the channels to use and the messages to send out, around the preferences of the customers within these clusters.

Customer profiling performed in each of the clusters will shed light on understanding customers in terms of their value to the bank as well as the willingness to accept permissions based offers.

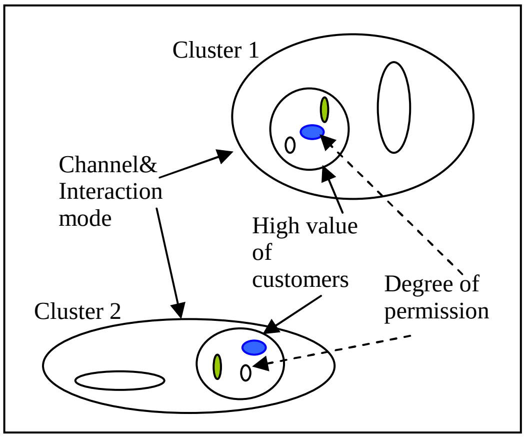

Figure 1

For example, even the valuable customers – those who have a record of good running balance in their account, have a mortgage with the bank, and use online banking most often – may exhibit low willingness to accept the bank's offers through emails. Rather, they may show higher acceptance level when the bank approaches them by face-to-face methods. Or they may not want any message asking for their permission at all.

Therefore, the clustering and profiling analyses based on the value and permission responses provide insights about the relationship strategy necessary for effective CRM.

Questions about to whom a message should be sent out, which channel should be used to contact, whether and what promotional incentive to offer, whether and how to ask for permissions – these could be answered by finding the channel used most often when a bank got the permission from the customers. For future campaigns, an immediate consequence of this approach is that permissions based relationships can be initiated by the bank via the customers' preferred channels and modes of contact, thereby reducing the chances that the customer will perceive the communication by the bank as unwanted and inappropriate.

The strength of this approach lies in the fact that we use the knowledge discovery abilities of data mining algorithms to guide the CRM strategy rather than using preconceived ideas about ideal or not-so-ideal customers.

5.4 Data analysis

We need to test our propositions and at the preliminary stage we propose to test it in an idealized setting. We will generate the customer database. The data for each field in the database will be preset with certain statistical properties such as mean, standard deviation, skewness, kurtosis, etc., so that the generated data represents approximations to real customers both ideal and not-so-ideal. By using such data with known patterns, it should be possible to confirm whether the data mining techniques and algorithm used for the customer segmentation are effective in finding the hidden patterns.

Once we acquire an actual dataset we expect the same kind of patterns to emerge as in the idealized setting. If not, we will have to investigate how the idealized setting differs from the actual dataset and adjust our data mining strategy accordingly.

We feel that these two tests would provide sufficient evidence of employing data mining methods for making CRM systems more customer-centric. Such testing is currently under way.

Here we do not consider performance characteristics of the CRM system, we are really only interested if the system can reconstruct the artificial population of customers segments generated for our testing purposes. Once we have shown that the theoretical underpinnings of our framework are intact we will consider looking at other performance characteristics. A true measure of our framework will be if we can discern customers more successfully with our staged clustering, rather than with a single segmentation step.

6 CONCLUDING REMARKS

Relationship marketing and CRM have been popular issues in business settings due to their strategic importance and customer service benefits.

With the advent of new technologies, companies are able to collect a variety of data about customers and to analyze such data to understand customers. CRM could help companies leverage the continuous stream of customer-related data collected through various touchpoints (Libai *et al.*, 2002). Data mining techniques offer strong possibilities for creating and sustaining ideal, highly satisfying customer relationships.

Companies should be careful, however, in conducting any analysis on customers, since it is reported that sometimes the analysis is not insightful enough and may result in letting valuable customers slip away, while not attracting new prospects. The critical issue for successful CRM is to understand customers and their preferences based on the customers' perspectives. Marketing approaches relying solely on preferences for products, without understanding anything about relationships and interactions, may not yield fruitful results. Given the high cost of CRM, such shot-in-the-dark misadventures become risky.

In this framework, it is argued that companies should be aware of the importance of comprehensive knowledge about their customers for successful CRM. By using data mining, effective market segmentation is possible especially via in-depth understanding of customers.

A retail banking scenario is provided to illustrate a situation for such datamining-based CRM practice. The scenario also indicates that there may be many different channels used by customers, and that the richness of data collected through all the channels needs to be tapped into. A framework was proposed along with this scenario to show how data mining can be used to obtain better understanding about customers.

This study is ongoing and will provide insights on how data mining can be used for effective market segmentation. The study highlights the importance of basic understanding of customers and segmentation based on such understanding. Also, the importance of managing multi-channel interactions becomes evident, even in the relatively simple scenario that was presented.

The major benefits of the proposed framework to the managers would be closer matching of CRM technology and CRM goals. In order to satisfy customers it is argued that better understanding about customers should precede service and CRM strategy formulation, and data mining can have the potential to discover the hidden patterns from the behaviors and reported preferences of customers. The results will provide guidelines for using data mining to design customized/personalized services that delight the customers.

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