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Data Mining Techniques for Customer Relationship Management

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Abstract— Advancements in technology have made relationship marketing a reality in recent years. Technologies such as data warehousing, data mining, and campaign management software have made customer relationship management a new area where firms can gain a competitive advantage. Particularly through data mining—the extraction of hidden predictive information from large databases—organizations can identify valuable customers, predict future behaviors, and enable firms to make proactive, knowledge-driven decisions. The automated, future-oriented analyses made possible by data mining move beyond the analyses of past events typically provided by history-oriented tools such as decision support systems. Data mining tools answer business questions that in the past were too time-consuming to pursue. Yet, it is the answers to these questions make customer relationship management possible. Various techniques exit among data mining software, each with their own advantages and challenges for different types of applications. A particular dichotomy exists between neural networks and chi-square automated interaction detection (CHAID). While differing approaches abound in the realm of data mining, the use of some type of data mining is necessary to accomplish the goals of today's customer relationship management philosophy.

Keywords— Customer relationship management (CRM),Relationship, CHAID, Decision support system and Datamining

1. INTRODUCTION

A new business culture is developing today. Within it, the economics of customer relationships are changing in fundamental ways, and companies are facing the need to implement new solutions and strategies that address these changes. The concepts of mass production and mass marketing, first created during the Industrial Revolution, are being supplanted by new ideas in which customer relationships are the central business issue. Firms today are concerned with increasing customer value through analysis of the customer lifecycle. The tools and technologies of data warehousing, data mining, and other customer relationship management (CRM) techniques afford new opportunities for businesses to act on the concepts of relationship marketing. The old model of "design-build-sell" (a product-oriented view) is being replaced by "sell-build-redesign" (a customer-oriented view). The traditional process of mass marketing is being challenged by the new approach of one-to-one marketing. In the traditional process, the marketing goal is to reach more customers and expand the customer base. But given the high cost of acquiring new customers, it makes better sense to conduct business with current customers. In so doing, the marketing focus shifts away from the breadth of customer base to the depth of each customer's needs. The performance metric changes from market share to so-called "wallet share". Businesses do not just deal with customers in order to make transactions; they turn the opportunity to sell products into a service experience and endeavor to establish a long-term relationship with each customer. The advent of the Internet has undoubtedly contributed to the shift of marketing focus. As on-line information becomes more accessible and abundant, consumers become more informed and sophisticated. They are aware of all that is being offered, and they demand the best. To cope with this condition, businesses have to distinguish their products or services in a way that avoids the undesired result of becoming mere commodities. One effective way to distinguish themselves is with systems that can interact precisely and consistently with customers. Collecting customer demographics and behavior data makes precision targeting possible. This kind of targeting also helps when devising an effective promotion plan to meet tough competition or identifying prospective customers when new products appear. Interacting with customers consistently means businesses must store transaction records and responses in an online system that is available to knowledgeable staff members who know how to interact with it. The importance of establishing close customer relationships is recognized, and CRM is called for. It may seem that CRM is applicable only for managing relationships between businesses and consumers. A closer examination reveals that it is even more crucial for business customers. In business-to-business (B2B) environments, a tremendous amount of information is exchanged on a regular basis. For example, transactions are more numerous, custom contracts are more diverse, and pricing schemes are more complicated. CRM helps smooth the process when various representatives of seller and buyer companies communicate

and collaborate. Customized catalogues, personalized business portals, and targeted product offers can simplify the procurement process and improve efficiencies for both companies. E-mail alerts and new product information tailored to different roles in the buyer company can help increase the effectiveness of the sales pitch. Trust and authority are enhanced if targeted academic reports or industry news are delivered to the relevant individuals. All of these can be considered among the benefits of CRM. Cap Gemini conducted a study to gauge company awareness and preparation of a CRM strategy [1]. Of the firms surveyed, 65% were aware of CRM technology and methods; 28% had CRM projects under study or in the implementation phase;
12% were in the operational phase. In 45% of the companies surveyed, implementation and monitoring of the CRM project had been initiated and controlled by top management. Thus, it is apparent that this is a new and emerging concept that is seen as a key strategic initiative. This article examines the concepts of customer relationship management and one of its components, data mining. It begins with an overview of the concepts of data mining and CRM, followed by a discussion of evolution, characteristics, techniques, and applications of both concepts. Next, it integrates the two concepts and illustrates the relationship, benefits, and approaches to implementation, and the limitations of the technologies. Through two studies, we offer a closer look at two data mining techniques: Chi-square Automatic Interaction Detection (CHAID) and Neural Networks. Based on those case studies, CHAID and neural networks are compared and contrasted on the basis of their strengths and weaknesses. Finally, we draw conclusions based on the discussion.

2.DATA MINING: AN OVERVIEW

2.1. Definition

"Data mining" is defined as a sophisticated data search capability that uses statistical algorithms to discover patterns and correlations in data [2]. The term is an analogy to gold or coal mining; data mining finds and extracts knowledge ("data nuggets") buried in corporate data warehouses, or information that visitors have dropped on a website, most of which can lead to improvements in the understanding and use of the data. The data mining approach is complementary to other data analysis techniques such as statistics, on-line analytical processing (OLAP), spreadsheets, and basic data access. In simple terms, data mining is another way to find meaning in data. Data mining discovers patterns and relationships hidden in data [3], and is actually part of a larger process called "knowledge discovery" which describes the steps that must be taken to ensure meaningful results. Data mining software does not, however, eliminate the need to know the business, understand the data, or be aware of general statistical methods. Data mining does not find patterns and knowledge that can be generate hypotheses, but it does not validate the hypotheses. product information tailored to different roles in the buyer company can help increase the effectiveness of the sales pitch. Trust and authority are enhanced if targeted academic reports or industry news are delivered to the relevant individuals. All of these can be considered among the benefits of CRM. Cap Gemini conducted a study to gauge company awareness and preparation of a CRM strategy [1]. Of the firms surveyed, 65% were aware of CRM technology and methods; 28% had CRM projects under study or in the implementation phase; 12% were in the operational phase. In 45% of the companies surveyed, implementation and monitoring of the CRM project had been initiated and controlled by top management. Thus, it is apparent that this is a new and emerging concept that is seen as a key strategic initiative. This article examines the concepts of customer relationship management and one of its components, data mining. It begins with an overview of the concepts of data mining and CRM, followed by a discussion of evolution, characteristics, techniques, and applications of both concepts. Next, it integrates the two concepts and illustrates the relationship, benefits, and approaches to implementation, and the limitations of the technologies. Through two studies, we offer a closer look at two data mining techniques: Chi-square Automatic Interaction Detection (CHAID) and Neural Networks. Based on those case studies, CHAID and neural networks are compared and contrasted on the basis of their strengths and weaknesses. Finally, we draw conclusions based on the discussion.

2.2. The evolution of data mining

Data mining techniques are the result of a long research and product development process. The origin of data mining lies with the first storage of data on computers, continues with improvements in data access, until today technology allows users to navigate through data in real time. In the evolution from business data to useful information, each step is built on the previous ones. The evolutionary stages from the perspective of the user. In the first stage, Data Collection, individual sites collected data used to make simple calculations such as summations or averages. Information generated at this step answered business questions related to figures derived from data collection sites, such as total revenue or average total revenue over a period of time. Specific application programs were created for collecting data and calculations. The second step, Data Access, used databases to store data in a structured form at .m At this stage, company-wide policies for data collection and reporting of management in formation were established. Because every business unit conformed to specific on system regarding branch sales during any specified time period. Once individual figures were known, questions that probed the performance of aggregated sites could be asked. For example, regional sales for a specified period could be calculated. Thanks to multi-dimensional databases, a business could obtain either a global view or drill down to a particular site for comparisons with its peers (Data Navigation). Finally, on-line analytic tools provided real-time feedback and information exchange with collaborating business units (Data Mining). This Stage Business question Enabling technologies Product providers Characteristics Data "What was my average Computers, tapes, disks IBM, CDC Retrospective, Collection total revenue over the static data (1960s) last five years?" delivery Data Access "What were unit sales in Relational databases Oracle, Sybase, Retrospective, (1980s) New England last (RDBMS), Structured Informix, IBM, dynamic data March Query Language Microsoft delivery at record (SQL), ODBC level Data "What were unit sales in On-line analytic Pilot, IRI, Arbor, Retrospective, Navigation New England last processing (OLAP), Redbrick, dynamic data (1990s) March Drill down to multidimensional Evolutionary delivery at Boston" databases, data Technologies multiple levels Ware houses Data Mining "What's likely to happen Advanced algorithms, Lockheed, IBM, Prospective, (2000) in Boston unit sales next multiprocessor SGI, numerous proactive month Why?" computers, massive startups (nascent information data bases industry) delivery is useful when sales representatives or customer service persons need to retrieve customer information on-line and respond to questions on a real-time basis. Information systems can query past data up to and including the current level of business. Often businesses need to make strategic decisions or implement new policies that better serve their customers. For example, grocery stores redesign their layout to promote more impulse purchasing. Telephone companies establish new price structures to entice customers into placing more calls. Both tasks require an understanding of past customer consumption behavior data in order to identify patterns for making those strategic decisions—and data mining is particularly suited to this purpose. With the application of advanced algorithms, data mining uncovers knowledge in a vast amount of data and points out possible relationships among the data. Data mining help businesses address questions such as, "What is likely to happen to Boston unit sales next month, and why?" Each of the four stages were revolutionary because they allowed new business questions to be answered accurately and quickly [4]. The core components of data mining technology have been developing for decades in research areas such as statistics, artificial intelligence, and machine learning. Today, these technologies are mature, and when coupled with relational database systems and a culture of data integration, they create a business environment that can capitalize on knowledge formerly buried within the systems.

2.3. **Applications *of data mining***

Data mining tools take data and construct a representation of reality in the form of a model. The resulting model describes patterns and relationships present in the data. From a process orientation, data mining activities fall into three general categories_ ***Forensic Analysis***—the process of applying the extracted patterns to find anomalous or unusual data elements. Data mining is used to construct six types of models aimed at solving business problems: classification, regression, time series, clustering, association analysis, and sequence discovery [3]. The first two, classification and regression, are used to make predictions, while association and sequence discovery are used to describe behavior. Clustering can be used for either forecasting or description. Companies in various industries can gain a competitive edge by mining their expanding databases for valuable, detailed transaction information. Examples of such uses are provided below. Each of the four applications below makes use of the first two activities of data mining: discovery and predictive modeling. The discovery process, while not mentioned explicitly in the examples (except in the retail description), is used to identify customer segments. This is done through conditional logic, analysis of affinities and associations, and trends and variations. Each of the application categories described below describes some sort of predictive modeling. Each business is interested in predicting the behavior of its customers through the knowledge gained in data mining [5].

2.3.1. **Retail**

Through the use of store-branded credit cards and point-of-sale systems, retailers can keep detailed records of every shopping transaction. This enables them to better understand their various customer segments. Some retail applications include [5]: _ *Performing basket analysis*—Also known as affinity analysis, basket analysis reveals which items customers tend to purchase together. This knowledge can improve stocking, store layout strategies, and promotions. _ *Sales forecasting*—Examining time-based patterns helps retailers make stocking decisions. If a customer purchases an item today, when are they likely to purchase a complementary item?.

Database marketing—Retailers can develop profiles of customers with certain behaviors, for example, those who purchase designer labels clothing or those who attend sales. This information can be used to focus cost-effective promotions._ *Merchandise planning and allocation*—When retailers add new stores, they can improve merchandise planning and allocation by examining patterns in stores with similar demographic characteristics. Retailers can also use data mining to determine the ideal layout for a specific store.

2.3.2. Banking

Banks can utilize knowledge discovery for various applications, including [5]: *Card marketing*—By identifying customer segments, card issuers and acquirers

2.4.* Internal *considerations

For firms to integrate data mining into their decision-making process, the proper Skill sets and technology must be available. Skill sets will vary with the variety of Data mining stakeholders in the organization. While data mining is frequently done centrally or regionally, people on the front lines need to have the knowledge gained through data mining. These workers sell to and service customers, manage inventory, supervise employees, and work to correct and prevent loss. Information derived from data mining can be communicated to operational employees in several forms: an algorithm for scoring a score for a particular customer, employee, or transaction a recommended action associated with a particular customer, employee, or transaction [6].

2.5. DATA MINING TECHNIQUES

A top-level breakdown of data mining technologies is based on data retention. In other words, is the data retained or discarded after it has been mined? (see Fig. 2). In early approaches to data mining, the data set was maintained for future pattern matching. The retention-based techniques only apply to tasks of predictive modeling and forensic analysis, and not knowledge discovery since they do not distill any patterns, as shown earlier Approaches based on pattern distillation fall into three categories: logical, cross tabulation and equation. These technologies extract patterns from a data set and then use the patterns for various purposes. They ask, “What types of patterns can be extracted and how are they represented?” The logical approach deals with both numeric and non-numeric data. Equations require all data to be numeric, while cross tabulations work only on non-numeric data

User interactions with data mining technology and the user’s typical skill sets Stakeholder Skill set Miner Analytics, model building, statistics, neural net development, research Domain expert Intensive business and data knowledge, experience, decision maker Business user Understands business and data, decision maker, user of mining results IT Supports analytic environment, data model for new DM components, integrates DM (tools, processes, results, models) .

Pros and cons to data mining approaches Approach Pros Cons Logical Work well with multidimensional and Unable to work with smooth surfaces OLAP data that typically occur in nature Able to deal with numeric and nonnumeric data in a uniform manner Able to deal with numeric and nonnumeric data in a uniform manner Cross-tabulation Simple to use with small number of Not scalable nonnumeric values Ability to handle numeric values Ability to handle conjunctions Equation Works well on large sets of data Require all data to be numeric (nonnumeric must be coded) Works well with complex multi- System can quickly become a “black dimensional models box” Ability to approximate smooth surfaces [18].

3. CUSTOMER RELATIONSHIP MANAGEMENT: AN OVERVIEW

3.1. Definition

Customer Relationship Management is defined by four elements of a gay simple framework:Know, Target, Sell, Service [7]. CRM requires the firm to know and understand its markets and customers. This involves detailed customer intelligence in order 492 *C. Rygielski et al. / Technology in Society 24 (2002) 483-502* to select the most profitable customers and identify those no longer worth targeting. CRM also entails development of the offer: which products to sell to which customers and through which channel. In selling, firms use campaign management to increase the marketing department’s effectiveness. Finally, CRM seeks to retain its customers through services such as call centers and help desks CRM is essentially a two-stage concept. The task of the first stage is to master the basics of building customer focus. This means moving from a product orientation to a customer orientation and defining market strategy from outside-in and not from inside-out. The focus should be on customer needs rather than product features.Companies in the second stage are moving beyond the basics; they do not rest on their laurels but push their development of customer orientation by integrating CRM across the entire customer experience chain, by leveraging technology to achieve fucking time customer management, and by constantly innovating their value proposition to customers [7].

3.2. Components of customer relationship management

Customer relationship management is a combination of several components. Before the process can begin, the firm must first possess customer information. Companies can learn about their customers through internal customer data or they can purchase data from outside sources. There are several sources of internal data: that describe customers (e.g., billing records) customer surveys of a subset of customers who answer detailed questions, behavioral data contained in transactions systems (web logs, credit card records, etc)[8].

An enterprise data warehouse is a critical component of a successful CRM strategy. Most firms have massive databases that contain marketing, HR, and financial information. How cock, the data required for CRM can be limited to a marketing data mart with limited feeds from other corporate systems. Experience with CRM will dictate when to aggregate data for reasons of simplicity and when to keep the data granular. External sources of data or purchased databases can be a key source for gaining customer knowledge advantage [9]. Some examples of external data sources include lookups for current address and telephone number, household hierarchies,

Fair-Isaacs credit scores, and Webpage viewing profiles [8]. Next, the CRM system must analyze the data using statistical tools, OLAP, and data mining. Whether the firm uses traditional statistical techniques or one of the data mining software tools, marketing professionals need to understand the customer data and business imperatives. The firm should employ data mining analysts who will be involved but will also make sure the firm does not lose sight of their original reason for doing data mining. Thus, having the right people who are trained to extract information with these tools is also important. The end result is segmentation of the market, and individual decisions are made regarding which segments are attractive [9].

The last component of a CRM system is campaign execution and tracking. These are the processes and systems that allow the user to develop and deliver targeted messages in a test-and-learn environment. Implementation of decisions made as a result of data mining and OLAP is done through campaign execution and tracking. Today there are software programs that help marketing departments handle this complex feedback procedure. Campaign management software manages and monitors customer communications across multiple touchpoints, such as direct mail, telemarketing, customer service, point-of-sale, e-mail, and the Web [10]. While campaign management software may be part of the overall solution, it is primarily the people and processes that contribute to smooth interactions between marketing, information technology, and the sales channels [9].

4. DATA MINING AND CUSTOMER RELATIONSHIP MANAGEMENT

It should be clear from the discussion so far that customer relationship management is a broad topic with many layers, one of which is data mining, and that data mining is a method or tool that can aid companies in their quest to become more customer-oriented. Now we need to step back and see how all the pieces fit together.

4.1. The relationship

The term “customer lifecycle” refers to the stages in the relationship between a customer and a business. It is important to understand customer lifecycle because it relates directly to customer revenue and customer profitability. Marketers say there are three ways to increase a customer’s value: (1) increase their use (or purchases) of products they already have; (2) sell them more or higher-margin products; and (3) keep the customers for a longer period of time [8]. However, the customer relationship changes over time, evolving as the business and the customer learn more about each other. So why is the customer lifecycle important? Simply put, it is a framework for understanding customer behavior. In general, there are four key stages in the customer lifecycle:

1. ***Prospects***—people who are not yet customers but are in the target market
2. ***Responders***—prospects who show an interest in a product or service
3. ***Active Customers***—people who are currently using the product or service
4. ***Former Customers***—may be “bad” customers who did not pay their bills or who incurred high costs; those who are not appropriate customers because they are no longer part of the target market; or those who may have shifted their purchases to competing products. The customer lifecycle provides a good framework for applying data mining to CRM. On the “input” side of data mining, the customer lifecycle tells what information is available. On the “output” side, the customer lifecycle tells what is likely to be interesting [8].

4.2. Data mining and customer privacy

While data mining techniques help businesses address more questions than ever before, this capability may add to the risk of invading customer privacy. On one hand, mining customer data can help build an intimate relationship between businesses and their customers. On the other, databases can be used against customers’ wishes or to their detriment. However, personalization of CRM is far from invasion of an individual’s privacy. Personal information collected by businesses can be classified in two categories: data that are provided and accessible to the users, and data that are generated and analyzed by businesses. Before data mining became popular among businesses, customers’ data was generally collected on a self-provided or transactional basis. Customers themselves provide general descriptive data which contains demographic data about themselves. Transactional data refers to data obtained when a transaction takes place, such as product name, quantity, location, and time of purchase. These data are collected from registration forms, order forms, computer cookies, log files, surveys, and contests. The power of data mining helps turn customer data into customer profiling information. This kind of information belongs to the second category and is accessible to businesses, although this fact may not be known to consumers. It may include customer value, customer targeting information, customer rating, and behavior tracking. Once this information is obtained by marketers or businesses, consumers may periodically receive timely and personalized information. However, when abused, people may also suffer from certain forms of discrimination (such as insurance) or loss of career. Without proper scrutiny when applying and releasing profiling information, consumers may turn away from any effort to maintain a closer customer relationship. The central issue of privacy is to find a balance between privacy rights for consumer protection and while still providing benefits to businesses. Several advocacy groups and private efforts have been formed to promote the responsible use of technology for personalizing consumer and business relationships. However, privacy is more of a policy issue than a technology one. One basic principle for businesses using personalized technology is to disclose to their consumers the kinds of information they are seeking and how that information will be used. Some groups list objectives for ethical information and privacy management. Others have developed a Privacy Bill of Rights that includes fair access by individuals to their personal information, responsible linkage of online and off-line information, suitable criteria for opt-in and opt-out privacy options, standardizing the disclosure to consumers of any existing privacy policy, independent verification of implementation and execution of privacy and security policies, and fair mechanisms for resolving disputes by a trusted third party. Customer privacy can be better protected when customers do not have to reveal their identities and can remain anonymous even after data mining probing. One way to achieve this goal is to create an anonymous architecture for handling customer information. In this architecture, identity information is processed with an additional encryption procedure whenever data are fed into a data mining module for analysis.

The encrypted identity information remains unique for each individual but does not diminish the power of data mining while keeping the customer's identity information protected under a firewall. Some third-party organizations also take responsibility for handling identity information, becoming a surrogate for executing targeted marketing efforts, such as mail promotion messages to the targeted individual.

5. Case study: neural networks

Neo Vista Solutions, Inc. provides comprehensive, enterprise-level data mining solutions and professional services. Neo Vistas Solutions' Decision Series suite of knowledge discovery tools solves data mining challenges in a variety of markets, including retail, insurance, telecommunications, and healthcare. The Decision Series suite includes pattern discovery tools based on neural networks, clustering, genetic algorithms, and association rules to building and keeping trust. The nature of trust is so fragile that once violated, it vanishes. Current CRM solutions focus primarily on analyzing consumer information for economic benefits, and very little touches on ensuring privacy. As privacy issues become major concerns for consumers, surely an integrated solution that streamlines and enhances the entire process of managing customer relationships will become even more necessary.

6. Conclusion

We have chosen two particular data mining techniques, CHAID and neural nets, and will illustrate their use through two case studies. There are various data mining tool providers in the marketplace today, and each provider has a different combination of data mining tools that can be used to help their clients. There are no instances where one provider chose to use only one data mining technique; to the contrary, providers often choose a group of similar methods for accomplishing their goals. In this section we examine neural networks through Neo Vista Solutions Inc., and CHAID through Applied Matrix, Ltd. Both case studies come from the respective websites of Neo Vista and Applied Matrix, and the identities of their clients are withheld at the client's request.

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