Applying Data Mining Techniques for Customer Relationship Management: A Survey

AHMED M. El-ZEHERY, HAZEM M. EL-BAKRY
Faculty of Computer Science & Information systems
Mansoura University, EGYPT

Mohamed S. El-KSASY
Faculty of Engineering
Mansoura University, EGYPT

NIKOS MASTORAKIS,
Technical University of Sofia, Bulgaria

Abstract:- Data mining has various applications for customer relationship management. In this proposal, I am introducing a framework for identifying appropriate data mining techniques for various CRM activities. This Research attempts to integrate the data mining and CRM models and to propose a new model of Data mining for CRM. The new model specifies which types of data mining processes are suitable for which stages/processes of CRM. In order to develop an integrated model it is important to understand the existing Data mining and CRM models. Hence the article discusses some of the existing data mining and CRM models and finally proposes an integrated model of data mining for CRM.

Key-Words:- Data Mining, CRM**,** integrated model

1. Introduction

Value Creation for the customer is the key determinant of a successful business. Customer satisfaction ensures profitability for businesses in the long run. Customer bases built over a period of time proved to be of immense help in increasing the reach of a particular business's product or service. However, the recent increase in the operating costs of business made it more compelling for businesses to increase loyalty among existing customers while trying to attract new ones. The processes by which an organization creates value for the customer, is often referred to as Customer Relationship Management (CRM) [1]. According to Microsoft, CRM is "a customer-focused business strategy designed to optimize revenue, profitability, and customer loyalty. By implementing a CRM strategy, an organization can improve the business processes and technology solutions around selling, marketing, and servicing functions across all customer touch-points (for example: Web, e-mail, phone, fax, in-person)". The overall objective of CRM applications is to attract, retain and manage a firm's profitable ("right") customers [1].

Business intelligence for CRM applications provides a firm with actionable information from the analysis and interpretation of vast quantities of customer/market related data. Databases for business intelligence include customer demographics, buying histories, cross-sales, service calls, website navigation experiences and online transactions. Through the appropriate use of analytical methods and software, a firm is able to turn data into information that leads to greater insight and development of fact-based strategies which in turn helps the firm gain competitive advantage by creating greater value for the customer [1].

Analogous to traditional mining, which involves searching for an ore in a mountain, data mining involves searching for valuable information in large databases. Both these processes involve either groping through a vast amount of material or intelligently probing the data to find the true value that lies hidden in data. Data mining involves not only the extraction of previously unknown information from a database but also the discovery of relation-ships that did not surface in the previous methods of data analysis. The "jewels" discovered from the data mining process include these non-intuitive hidden predictive relationships between variables that explain customer behavior and preferences. The predictive capabilities of data mining enable the businesses to make proactive, knowledge-driven decisions. Data mining tools facilitate prospective analysis, which is an improvement over the analysis of past events provided by the retrospective tools. The emergence of large data warehouses and the availability of data mining software is creating opportunities for businesses to find innovative ways to implement effective customer relationship strategies [1].

The automation of data collection and the relative decrease in the costs of operating huge data warehouses has made customer data more accessible than ever. The analysis of data, which until a few years ago was associated with high-end computing power and algorithms decipherable by only professional statisticians, is increasing to become more popular with user-friendly tools available on desktops [Berger, 1999 #2]. Data mining plays an important role in the analytical phases of the CRM life cycle as well as the CRM process [1].

2. Research methodology

As the nature of research in CRM and data mining are difficult to confine to specific disciplines, the relevant materials are scattered across various journals. Business intelligence and knowledge discovery are the most common academic discipline for data mining research in CRM. Consequently, the following online journal databases were searched to provide a comprehensive bibliography of the academic literature on CRM and Data Mining:

_ ABI/INFORM Database;
_ Academic Search Premier;
_ Business Source Premier;
_ Emerald Fulltext;
_ Ingenta Journals;
_ Science Direct; and
_ IEEE Transaction.

The literature search was based on the descriptor, ‘‘customer relationship management” and ‘‘data mining”, which originally produced approximately 900 articles. The full text of each article was reviewed to eliminate those that were not actually related to application of data mining techniques in CRM. The selection criteria were as follows:

_ Only those articles that had been published in business intelligence, knowledge discovery or customer management related journals were selected, as these were the most appropriate outlets for data mining in CRM research and the focus of this review.

_ Only those articles which clearly described how the mentioned data mining technique(s) could be applied and assisted in CRM strategies were selected.

_ Conference papers, masters and doctoral dissertations, textbooks and unpublished working papers were excluded, as academics and practitioners alike most often use journals to acquire information and disseminate new findings. Thus, journals represent the highest level of research. Each article was carefully reviewed and separately classified according to the four categories of CRM dimensions and seven categories of data mining models. Although this search was not exhaustive, it serves as a comprehensive base for an understanding of data mining research in CRM.

3. Data Mining Challenges & Opportunities in CRM

In this section, we build upon our discussion of CRM and Life Sciences to identify key data mining challenges and opportunities in these application domains. The following is a list of challenges for CRM [2].

3.1. Non-trivial results almost always need a combination of DM techniques. Chaining/composition of DM, and more generally data analysis, operations is important. In order to analyze CRM data, one needs to explore the data from different angles and look at its different aspects. This should require application of different *types* of DM techniques and their application to different “*slices*” of data in an interactive and iterative fashion. Hence, the need to use various DM operators and combine (chain) them into a single “exploration plan” [2].

3.2. There is a strong requirement for data integration before data mining.

In both cases, data comes from multiple sources. For example in CRM, data needed may come from different departments of an organization. Since

ISBN: 978-960-474-361-2

many interesting patterns span multiple data sources, there is a need to integrate these data before an actual data mining exploration can start [2].

3.3. Diverse data types are often encountered.

This requires the integrated mining of diverse and heterogeneous data. In CRM, while dealing with this issue is not critical, it is nonetheless important. Customer data comes in the form of structured records of different data types (e.g., demographic data), temporal data (e.g., weblogs), text (e.g., emails, consumer reviews, blogs and chat-room data), (sometimes) audio (e.g., recorded phone conversations of service reps with customers) [2].

3.4. Highly and unavoidably noisy data must be dealt with.

In CRM, weblog data has a lot of "noise" (due to crawlers, missed hits because of the caching problem, etc.). Other data pertaining to customer "touch points" has the usual cleaning problems seen in any business-related data [2].

3.5. Privacy and confidentiality considerations for data and analysis results

are a major issue. In CRM, lots of demographic data is highly confidential, as are email and phone logs. Concern about inference capabilities makes other forms of data sensitive as well—e.g., someone can recover personally identifiable information (PII) from web logs [2].

3.6. Legal considerations influence what data is available for mining and what actions are permissible.

In some countries it is not allowed to combine data from different sources or to use it for purposes different from those for which they have been collected. For instance, it may be allowed to use an external rating about credit worthiness of a customer for credit risk evaluation but not for other purposes. Ownership of data can be unclear, depending on the details of how and why it was collected, and whether the collecting organization changes hands [2].

3.7. Real-world validation of results is essential for acceptance.

In CRM, as in many DM applications, discovered patterns are often treated as hypotheses that need to be tested on new data using rigorous statistical tests for the actual acceptance of the results. This is even more so for taking or recommending actions, especially in such high-risk applications as in the financial and medical domains. Example: recommending investments to customers (it is actually illegal in the US to let software give investment advice) [2,3].

3.8. Developing deeper models of customer behavior:

One of the key issues in CRM is how to understand customers. Current models of customers mainly built based on their purchase patterns and click patterns at web sites. Such models are very shallow and do not have a deep understanding of customers and their individual circumstances. Thus, many predictions and actions about customers are wrong. It is suggested that information from all customer touch-points be considered in building customer models. Marketing and psychology researchers should also be involved in this effort. Two specific issues need to be considered here. First, what level should the customer model be built at, namely at the aggregate level, the segment level, or at the individual level? The deciding factor is how personalized the CRM effort needs to be. Second is the issue of the dimensions to be considered in the customer profile. These include demographic, psychographic, macro-behavior (buying, etc.), and micro-behavior (detailed actions in a store, e.g. individual clicks in an online store) features [2,3].

3.9. Acquiring data for deeper understanding in a non-intrusive, low-cost, high accuracy manner:

In many industrial settings, collecting data for CRM is still a problem. Some methods are intrusive and costly. Datasets collected are very noisy and in different formats and reside in different departments of an organization. Solving these pre-requisite problems is essential for data mining applications [2].

3.10. Managing the "cold start/bootstrap" problem:

At the beginning of the customer life cycle little is known, but the list of customers and the amount of information known for each customer increases over time. In most cases, a minimum amount of information is required for achieving acceptable results (for instance, product recommendations computed through collaborative filtering require a purchasing history of the customer). Being able to deal with cases where less than this required minimum is known is a therefore a major challenge [2].

3.11. Evaluation framework for distinguishing between correct/incorrect customer understanding:

Apart from the difficulty of building customer models, evaluating them is also a major task. There is still no satisfactory metric that can tell whether one model is better than another and whether a model really reflects customer behaviors. Although there are *some* metrics for measuring quality of customer models (e.g., there are several metrics for measuring the quality of recommendations), they are quite rudimentary, and there is a strong need to work on better measures. Specifically, the recommender systems community has explored this area [2,3,6,7].

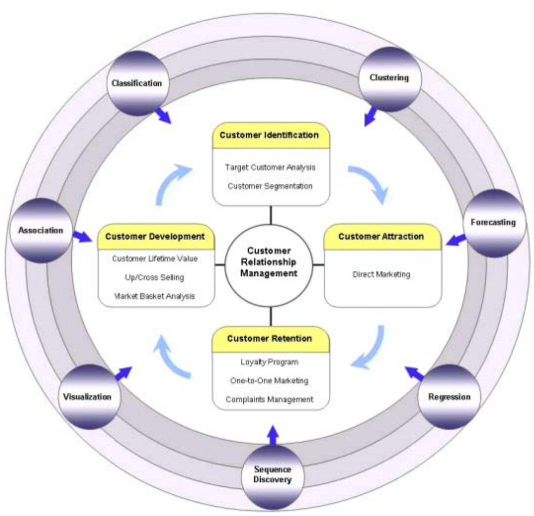

Fig. 1. Classification framework for data mining techniques in CRM.

In the previous figure we can see how Data mining stages used with all CRM lifecycle.

(1) Association rule;
(2) Decision tree;
(3) Genetic algorithm;
(4) Neural networks;
(5) K-Nearest neighbour;
(6) Linear/logistic regression.

A graphical classification framework on data mining techniques in CRM is proposed and shown in Fig. 1; it is based on a review of the literature on data mining techniques in CRM.Critically reviewing the literature on data mining in CRM helped to identify the major CRM dimensions and data mining techniques for the application of data mining techniques in CRM. It describes CRM dimensions as: Customer Identification, Customer Attraction, Customer Retention and Customer Development. In addition, described the types of data mining model as Association, Classification, Clustering, Forecasting, Regression, Sequence Discovery and Visualization. We provide a brief description of these four dimensions and some references for further details, and each of them is discussed in the following sections.[6]

4. Classification framework – CRM Dimensions

In this study, CRM is defined as helping organizations to better discriminate and more effectively allocate resources to the most profitable group of customers through the cycle of customer identification, customer attraction, customer retention and customer.

(i) Customer identification: CRM begins with customer identification, which is referred to as customer acquisition in some articles. This phase involves targeting the population who are most likely to become customers or most profitable to the company. Moreover, it involves analyzing customers who are being lost to the competition and how they can be won back . Elements for customer identification include target customer analysis and customer segmentation. Target customer analysis involves seeking the profitable segments of customers through analysis of customers' underlying characteristics, whereas customer segmentation involves the subdivision of an entire customer base into smaller customer groups or segments, consisting of customers who are relatively similar within each specific segment .

(ii) Customer attraction: This is the phase following customer identification. After identifying the segments of potential customers, organizations can direct effort and resources into attracting the target customer segments. An element of customer attraction is direct marketing. Direct marketing is a promotion process which motivates customers to place orders through various channels. For instance, direct mail or coupon distribution are typical examples of direct marketing.

(iii) Customer retention: This is the central concern for CRM. Customer satisfaction, which refers to the comparison of customers' expectations with his or her perception of being satisfied, is the essential condition for retaining customers . As such, elements of customer retention include one-to-one marketing, loyalty programs and complaints management. One-to-one marketing refers to personalized marketing campaigns which are supported by analysing, detecting and predicting changes in customer behaviours Thus, customer profiling, recommender systems or replenishment systems are related to one-to-one marketing. Loyalty programs involve campaigns or supporting activities which aim at maintaining a long term relationship with customers. Specifically, churn analysis, credit scoring, service quality or satisfaction form part of loyalty programs.

(iv) Customer development: This involves consistent expansion of transaction intensity, transaction value and individual customer profitability. Elements of customer development include customer lifetime value analysis, up/cross selling and market basket analysis. Customer lifetime value analysis is defined as the prediction of the total net income a company can expect from a customer. Up/Cross selling refers to promotion activities which aim at augmenting the number of associated or closely related services that a customer uses within a firm. Market basket analysis aims at maximizing the customer transaction intensity and value by revealing regularities in the purchase behaviour of customers

4.1 Good action mechanisms:

Once data mining has been conducted with promising results, how to use them in the daily performance task is critical and it requires significant research effort. It is common that after some data results are obtained, the domain users do not know how to use them in their daily work. This research may require the participation of business and marketing researchers.

Another way to accommodate actioning mechanisms is to integrate them into the knowledge discovery process by focusing on the discoveries of actionable patterns in customer data. This would make easier for the marketers or other domain experts to determine which actions should be taken once the customer patterns are discovered [2].

4.2 Incorporating prior knowledge

This has always been a problem in practice. Data mining tends to find many pieces of patterns that are already known or redundant. Incorporating prior domain knowledge can help to solve these problems, and also to discover something novel. However, the difficulties of incorporating domain knowledge result in little progress in the past. There are a number of reasons for this. First of all, knowledge acquisition from domain experts is very hard. This is well documented in AI research, especially in the literature of expert systems building. Domain experts may know a lot but are unable to tell. Also, many times, domain experts are not sure what the relevant domain knowledge is, which can be very wide, although the data mining application itself is very narrow. Only after domain experts have seen some discovered patterns then they remember some domain knowledge. The second reason is the algorithmic

ISBN: 978-960-474-361-2

issue. Many existing methods have difficulty to incorporate sophisticated domain knowledge in the mining algorithm. Also, once the new patterns are discovered, it is important to develop methods that integrate the newly discovered knowledge with the previous knowledge thus enhancing the overall knowledge base. Although there is some general work on knowledge enhancement, much more needs to be done to advance this area and adapt it to CRM problems. Also, integration of these methods with existing and novel Knowledge Management approaches constitutes a fruitful area of research [2].

Customer relationship management in its broadest sense simply means managing all customer interactions. In practice, this requires using information about your customers and prospects to more effectively interact with your customers in all stages of your relationship with them. We refer to these stages as the customer life cycle.

The customer life cycle has three stages:

1. Acquiring customers
2. Increasing the value of customers
3. Retaining good customers

Data mining can improve your profitability in each of these stages when you integrate it with operational CRM systems or implement it as independent applications [4].

4.3. Acquiring new customers via data mining [4]

The first step in CRM is to identify prospects and convert them to customers. Let's look at how data mining can help manage the costs and improve the effectiveness of a customer acquisition campaign.

Big Bank and Credit Card Company (BB&CC) annually conducts 25 direct mail campaigns, each of which offers one million people the opportunity to apply for a credit card. The conversion rate measures the proportion of people who become credit card customers, which is about one percent per campaign for BB&CC.

Getting people to fill out an application for the credit card is only the first step. Then, BB&CC must decide if the applicant is a good risk and accept them as a customer or decline the application. Not surprisingly, poor credit risks are more likely to accept the offer than are good credit risks. So while six percent of the people on the mailing list respond with an application, only about 16 percent of those are suitable credit risks; approximately one percent of the people on the mailing list become customers.

BB&CC's six percent response rate means that only 60,000 people out of one million names respond to the solicitation. Unless BB&CC changes the nature of the solicitation – using different mailing lists, reaching customers in different ways, altering the terms of the offer it is not going to receive more than 60,000 responses. And of those 60,000 responses, only 10,000 are good enough risks to become customers. The challenge BB&CC faces is reaching those 10,000 people most efficiently.

BB&CC spends about $1.00 per piece, for a total cost of $1,000,000, to mail the solicitation. Over the next couple of years, the customers gained through this solicitation generate approximately $1,250,000 in profit for the bank (or about $125 each), for a net return of $250,000 from the mailing.

Data mining can improve this return. Although data mining won't precisely identify the 10,000 eventual credit card customers, data mining helps focus marketing efforts much more cost effectively.

First, BB&CC sent a test mailing of 50,000 prospects and carefully analyzed the results, building a predictive model showing who would respond (using a decision tree) and a credit scoring model (using a neural net). BB&CC then combined these two models to find the people who were both good credit risks and were most likely to respond to the offer.

BB&CC applied the model to the remaining 950,000 people in the mailing list, from which 700,000 people were selected for the mailing. The result? From the 750,000 pieces mailed (including the test mailing), BB&CC received 9,000 acceptable applications for credit cards. In other words, the response rate rose from one percent to

1.2 percent, a 20 percent increase. While the targeted mailing only reaches 9,000 of the 10,000 prospects – no model is perfect – reaching the remaining 1,000 prospects is not profitable. Had they mailed the other 250,000 people on the mailing list, the cost of $250,000 would have resulted in another $125,000 of gross profit for a net loss of $125,000.The following table summarizes the results.

Table 1: Results

	Old	New	Difference
Number of pieces mailed	1,000,000	750,000	(250,000)
Cost of mailing	$1,000,000	$750,000	($250,000)
Number of responses	10,000	9,000	(1,000)
Gross profit per response	$125	$125	$0
Gross profit	$1,250,000	$1,125,000	($125,000)
Net profit	$250,000	$375,000	$125,000
Cost of model	0	40,000	$40,000
Final profit	$250,000	$335,000	$85,000

Notice that the net profit from the mailing increased $125,000. Even when you include the $40,000 cost of the data mining software and the computer and employee resources used for this modeling effort, the net profit increased $85,000. This translates to a return on investment (ROI) for modeling of over 200 percent, which far exceeds BB&CC's ROI requirements for a project.

4.4 Increasing the value of your existing customers [4]

Cannons and Carnations (C&C) is a company that specializes in selling antique mortars and cannons as outdoor flower pots. It also offers a line of indoor flower pots made from large caliber antique pistols and a collection of muskets that have been converted to unique holders of long-stemmed flowers. The C&C catalog is sent to about 12 million homes.

When a customer calls C&C to place an order, C&C identifies the caller using caller ID when possible; otherwise the C&C representative asks for a phone number or customer number from the catalog mailing label. Next, the representative looks up the customer in the database and then proceeds to take the order.

C&C has an excellent chance of cross-selling, or selling the caller something additional. But C&C discovered that if the first suggestion fails and the representative suggests a second item, the customer might get irritated and hang up without ordering anything. And, there are some customers who resent any cross-selling attempts.

Before implementing data mining, C&C was reluctant to cross-sell. Without a model, the odds of making the right recommendation were one in three. And, because making any recommendation is unacceptable for some customers, C&C wanted to be extremely sure that it never makes a recommendation when it should not. In a trial campaign, C&C had less than a one percent sales rate and received a substantial number of complaints. C&C was reluctant to continue cross-selling for such a small gain.

The situation changed dramatically once C&C used data mining. Now the data mining model operates on the data. Using the customer information in the database and the new order, it tells the customer service representative what to recommend. C&C successfully sold an additional product to two percent of the customers and experienced virtually no complaints.

Developing this capability involved a process similar to what was used to solve the credit card customer acquisition problem. As with that situation, two models were needed.

The first model predicted if someone would be offended by additional product recommendations. C&C learned how its customers reacted by conducting a very short telephone survey. To be conservative, C&C counted anyone who declined to participate in the survey as someone who would find recommendations intrusive. Later on, to verify this assumption, C&C made recommendations to a small but statistically significant subset of those who had refused to answer the survey questions. To C&C's surprise, it discovered that the assumption was not warranted. This enabled C&C to make more recommendations and further increase profits. The second model predicted which offer would be most acceptable.

ISBN: 978-960-474-361-2

In summary, data mining helped C&C better understand its customers' needs. When the data mining models were incorporated in a typical cross-selling CRM campaign, the models helped C&C increase its profitability by two percent.

4.5 Increasing the value of your existing customers personalization via data mining [4]

Big Sam's Clothing (motto: "Rugged outdoor gear for city dwellers") developed a Web site to supplement its catalog. Whenever you enter Big Sam's site, the site greets you by displaying "Howdy Pardner!" However, once you have ordered or registered with Big Sam's, you are greeted by name. If you have a Big Sam's ordering record, Big Sam's will also tell you about any new products that might be of particular interest to you. When you look at a particular product, such as a waterproof parka, Big Sam's suggests other items that might supplement such a purchase.

When Big Sam's first launched its site, there was no personalization. The site was just an online version of its catalog nicely and efficiently done but it didn't take advantage of the sales opportunities the Web presents.

Data mining greatly increased Big Sam's Web site sales. Catalogs frequently group products by type to simplify the user's task of selecting products. In an online store, however, the product groups may be quite different, often based on complementing the item under consideration. In particular, the site can take into account not only the item you're looking at, but what is in your shopping cart as well, thus leading to even more customized recommendations.

First, Big Sam's used clustering to discover which products grouped together naturally. Some of the clusters were obvious, such as shirts and pants. Others were surprising, such as books about desert hiking and snakebite kits. They used these groupings to make recommendations whenever someone looked at a product.

Big Sam's then built a customer profile to help identify customers who would be interested in the new products that were frequently added to the catalog. Big Sam's learned that steering people to these selected products not only resulted in significant incremental sales, but also solidified its customer relationships. Surveys established that Big Sam's was viewed as a trusted advisor for clothing and gear.

To extend its reach further, Big Sam's implemented a program through which customers could elect to receive e-mail about new products that the data mining models predicted would interest them. While the customers viewed this as another example of proactive customer service, Big Sam's discovered it was a program of profit improvement.

The personalization effort paid off for Big Sam's, which experienced significant, measurable increases in repeat sales, average number of sales per customer and average size of sales.

4.6 Retaining good customers via data mining [4]

For almost every company, the cost of acquiring a new customer exceeds the cost of keeping good customers. This was the challenge facing KnowService, an Internet Service Provider (ISP) who experiences the industry-average attrition rate, eight percent per month. Since KnowService has one million customers, this means 80,000 customers leave each month. The cost to replace these customers is $200 each or $16,000,000 – plenty of incentive to start an attrition management program.

The first thing KnowService needed to do was prepare the data used to predict which customers would leave. KnowService needed to select the variables from its customer database and, perhaps, transform them. The bulk of KnowService's users are dial-in clients (as opposed to clients who are always connected through a T1 or DSL line) so KnowService knows how long each user was connected to the Web. KnowService also knows the volume of data transferred to and from a user's computer, the number of e mail accounts a user has, the number of e-mail messages sent and received along with the customer's service and billing history. In addition, KnowService has demographic data that customers provided at sign-up.

Next, KnowService needed to identify who were “good” customers. This is not a data mining question but a business definition (such as profitability or lifetime value) followed by a calculation. KnowService built a model to profile its profitable customers and unprofitable customers. KnowService used this model not only for customer retention but to identify customers who were not yet profitable but might become so in the future.

KnowService then built a model to predict which of its profitable customers would leave. As in most data mining problems, determining what data to use and how to combine existing data is much of the challenge in model development. For example, KnowService needed to look at time-series data such as the monthly usage. Rather than using the raw timeseries data, it smoothed the data by taking rolling three-month averages. KnowService also calculated the change in the three-month average and tried that as a predictor. Some of the factors that were good predictors, such as declining usage, were symptoms rather than causes that could be directly addressed. Other predictors, such as the average number of service calls and the change in the average number of service calls, were indicative of customer satisfaction problems worth investigating.

Predicting who would churn, however, wasn’t enough. Based on the results of the modeling, KnowService identified some potential programs and offers that it believed would entice people to stay. For example, some churners were exceeding even the largest amount of usage available for a fixed fee and were paying substantial incremental usage fees. KnowService offered these users a higher-fee service that included more bundled time. Some users were offered more free disk space to store personal Web pages. KnowService then built models that would predict which would be the most effective offer for a particular user.

To summarize, the churn project made use of three models. One model identified likely churners, the next model picked the profitable potential churners worth keeping and the third model matched the potential churners with the most appropriate offer.

The net result was a reduction in KnowService’s churn rate from eight percent to 7.5 percent, which allowed KnowService to save $1,000,000 per month in customer acquisition costs.

KnowService discovered that its data mining investment paid off – it improved customer relationships and dramatically increased its profitability.

5. Conclusion

Customer relationship management is essential to compete effectively in today’s marketplace. The more effectively you can use information about your customers to meet their needs, the more profitable you will be. We can conclude that operational CRM needs analytical CRM with predictive data mining models at its core. The route to a successful business requires that you understand your customers and their requirements, and data mining is the essential guide [4].

References

[1] Savitha S kadiyala , Georgia State University, Alok Srivastava, Georgia State University , Data Mining Techniques for Customer Relationship Management

[2] Jaideep Srivastava, Data Mining for Customer Relationship Management (CRM)

[3] E.W.T. Ngaia, Li Xiub, D.C.K. Chaua , Application of data mining techniques in customer relationship management

[4] Herb Edelstein, President , Two Crows Corporation , Building profitable customer relationships with data mining .

[5] Lee, S. C., Suh, Y. H., Kim, J. K., & Lee, K. J. (2004). A cross-national market segmentation of online game industry using SOM. Expert Systems with Applications, 27, 559–570.

[6] Application of data mining techniques in customer relationship management:
A literature review and classification E.W.T. Ngai , Li Xiu , D.C.K. Chau , 2592-2605

[7] Lee, T. S., Chiu, C. C., Chou, Y. C., & Lu, C. J. (2006). Mining the customer credit using classification and regression tree and multivariate adaptive regression splines. Computational Statistics and Data Analysis, 50, 1113–1130.