Intelligent Data Mining for Customer Relationship Management

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Abstract: *Customer Relationship Management (CRM) initiatives have gained much attention over the past few years. Although CRM involves technology, the important success factor involves the strategy of building your business around the customer. With the aid of data mining techniques, businesses can formulate specific strategies for different customer bases more precisely. Intelligent techniques such as neural networks allow complex functions relating customer behaviour to internal business processes to be learned more easily; and fuzzy theory allows industry expertise and experience from business managers to be integrated into the modelling framework directly, thus it is suggested that these techniques can be used in the CRM framework to enhance the creation of targeted strategies for specific customer bases.*

1. INTRODUCTION

Computational intelligence especially with the use of fuzzy rule based systems and Artificial Neural Networks (ANNs), is an emerging technology used to solve many problems of high complexity. This paper examines the use of intelligent techniques for data mining that can be used in Customer Relationship Management (CRM) to create specific targeted strategies for different customer bases. When businesses first used computers to store data, data mining technology started to evolve as a new technology in navigating through the database. Its purpose is mainly helping businesses to focus on important and useful information, by extracting the hidden predictive information from large databases. Basically, data mining techniques perform these predictive features based on modelling. The known situation is used to build the model, and then it is applied to another situation where it is not known. The objective of the data mining technique is to automate the detection of relevant patterns in a large database. The commonly used techniques in data mining are Artificial Neural Networks [4], decision trees [6,13], genetic algorithms [25, 27], nearest neighbour method [14], and rule induction [1].

In recent years, CRM initiatives have gained much attention. The International Data Corporation (IDC) expects the global market for CRM applications will exceed US$12 billion by 2004, from about US$3.3 billion in 2000. They have also indicated that in Australia about 65% of their survey respondents considered CRM to be either their first or second development priority.

Although CRM involves technology, the important success factor involves customer-focused strategy. A recent study in the US indicates that many businesses are dissatisfied with their current CRM initiative involving multi-function CMR software [8]. The report cited lack of customer focus and less adaptation to their unique requirements as reasons for their dissatisfaction. This paper posits that with the aid of data mining techniques, businesses can formulate specific customer focused strategies more easily and scientifically and therefore be more satisfied with their CRM initiatives. As the term CRM suggests, there are three main areas of focus: (1) the Customer, (2) the Relationship, and (3) Management of the relationship [McLaughlin,Nykamp]. Loyal customers are valuable assets for a business. Studies have shown that a 5% increase in customer retention can lead to a 25-100% increase in customer value [22]. Relationships with customers are driven primarily by the value the customer perceives from the relationship. Heskett et al. [15] have offered a model of customer value as shown below:

$$value_i = \frac{results + process\ quality}{price + aquisition\ \cos t} \quad (1)$$

From the above model, we can see that value for customer i has several components. The first component, results, refers to the idea that customers buy results and not products and services. To the extent a product or service enhances the desired result it increases customer value. Process quality also increases customer value. The way in which a service is delivered is often as important as the result itself. Price is also a component of customer value but not the only component. The costs of acquiring a product or service can sometimes overshadow the price itself. Data mining technology can enhance the understanding of different components of customer value as well as the needs and background of the customer [Thearling]. Different components of customer value provide opportunities for enhancement and management of the relationship with individual customers. From equation 1, we can see that value is defined at the individual level (hence the subscript i). Therefore it is important to identify the components of value that are unique to each customer or customer base in order to create unique value propositions to that customer base and manage those relationships appropriately.

One method of identifying components of value and opportunities for relationship enhancement is the identification of customer segments. In marketing research, this is normally known as market segmentation [Wedel]. Market segmentation breaks down a heterogeneous market into a number of smaller homogeneous markets where special treatment and care can be used to address a more precise satisfaction factor of the customer needs. Segmentation can normally be classified as a-priori and post-hoc approaches [30]. In CRM, the market to be segmented is the customer base. In this paper, data mining tool using ANN and fuzzy theory has been proposed in part of the CRM building block.

2. DATA MINING IN CRM

In order to understand a customer, it has to start from analysing all the relevant data belonging to the customer, thus data mining is the intelligence behind a successful CRM strategy [19]. This technology is to transform data into useful information for business to focus on customers. There are basically two main types of data mining: descriptive and predictive. Descriptive data mining generates information about the data so that we can realise some interesting underlying information. Predictive data mining makes use of past patterns and information in predicting what a customer will buy in the future. With most of the present techniques as mentioned in the introduction and those presented in [2], it is difficult to simultaneously perform these two analyses in the same model.

There are five main steps in the process of implementing a successful data mining solution for CRM [24]: setting goals, data collection, data preparation, analysis and prediction, and measurement and feedback. When setting the goals, identifying the market segmentation model is important. It can allow reasonable goals under each segment to precisely address the issues like retention, risk avoidance as well as possible cross selling [24]. In data collection and preparation, it is important to address the issues like feature selection, parameter identification and handling of missing data [24]. When building analysis and prediction models, different methods may have to be used in each different segment to meet the intended goals. A crucial point in gaining business confidence in establishing a model is to avoid a total "black box" method that eliminates the contributions of the expert in the business. In this paper, we make use of neural networks to learn the underlying function and use fuzzy rules to allow expert understanding.

3. ARTIFICIAL NEURAL NETWORKS

In the last decade, Artificial Neural Networks (ANNs) have emerged as an option for inferential data analysis and complex data analysis problem [11]. The observation sample that is used to derive the predictive model is known as training data in an ANN development. The independent variables, or the predictor variables, are known as the input variables and the dependent variables, or the responses, are known as the output variables.

In supervised learning [16], an ANN makes use of the input variables and their corresponding output variables to learn the relationship between them. Once found, the learned ANN is then used to predict values for the output variables given some new input data set.

Backpropagation Neural Network (BPNN) as shown in Figure 1 is the most widely used neural network system and the most well known supervised learning technique [23]. Back propagation is a systematic method for training multilayer ANN. It has been implemented and applied successfully to various problems. A basic BPNN consists of an input, an output and one or more hidden layers. Each layer is made up of a number of neurons that are connected to all the neurons in the next layers. However, the output layer will only generate the results of the network.

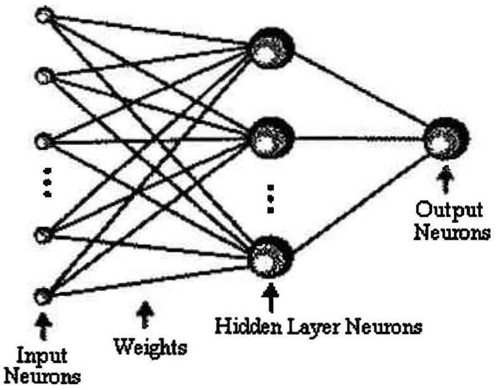

Figure 1: Backpropagation Neural Network

The objective of training BPNN is to adjust the weights so that application of a set of inputs will produce the desired set of outputs. A training set containing a number of desired input and output pairs is used. The input set is presented to the input layer of BPNN. A calculation is carried out to obtain the output set by proceeding from the input layer to the output layer. After this stage, feed forward propagation is done. At the output, the total error (the sum of the squares of the errors on each output cell) is calculated and then back propagated through the network. The total error, E, can be calculated using:

$$E=\sum_{k=1}^{K}\left(\frac{1}{2}\sum_{i=1}^{N_L}[T_i(k)-O_i^L(k)]^2\right) \qquad (2)$$

where K is the number of patterns, L is the layer number, T is the expect target, and O is the actual output

A modification of each connection weight is done and new total error is calculated. This back propagated process is repeated until the total error value is below some particular threshold. At this stage, the network is considered trained. After the BPNN has been trained, it can then be applied to predict other cases.

For unsupervised learning, an ANN will only make use of the input variables and attempts to arrange them in a way that is meaningful to the analyst.

Self-organising Map (SOM) is a popular unsupervised neural network technique mainly because it is a fast, easy and reliable unsupervised clustering technique [18]. SOM is designed with the intention to closely simulate the various organisations found in various brain structures and has a close relationship to brain maps. Its main feature is the ability to visualise high dimensional input spaces onto a smaller dimensional display, usually two-dimensional as shown in Figure 2. In this discussion, only two-dimensional arrays will be of interest. Let the input data space $\Re^n$ be mapped by the SOM onto a two-dimensional array with i nodes. Associated with each i node is a parametric reference vector $m_i=[\mu_{i1},\mu_{i2},\ldots,\mu_{in}]^T \in \Re^n$, where μ_{ij} is the connection weight between node i and input j. Therefore, the input data space $\Re^n$ consisting of input vectors $X=[x_1,x_2,\ldots,x_n]^T$, i.e. $X \in \Re^n$, can be visualized as being connected to all nodes in parallel via a scalar weight μ_{ij}. The aim of the learning is to map all the n input vectors X_n onto m_i by adjusting weights μ_{ij} such that the SOM gives the best match response locations.

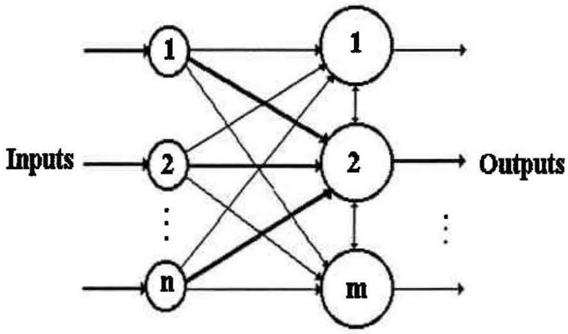

Figure 2a: Self Organising Map

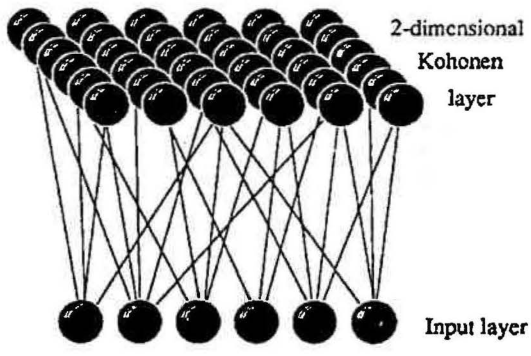

Figure 2b: Visualisation for Self Organising Map

SOM can also be said to be a nonlinear projection of the probability density function $p(X)$ of the high dimensional input vector space onto the two-dimensional display map. Normally, to find the best matching node i, the input vector X is compared to all reference vector m_i by searching for the smallest Euclidean distance $\| X - m_i \|$, indexed by c, i.e. $\| x-m_c \|=\min_i \| x-m_i \|$.

During the learning process the node that best matches the input vector X is allowed to learn. Those nodes that are close to the node up to a certain distance will also be allowed to learn. The learning process is expressed as:

$$m_i(t+1)=m_i(t)+h_{ci}(t)[X(t)-m_i(t)] \qquad (3)$$

where t is a discrete time coordinate, and $h_{ci}(t)$ is the neighbourhood function.

After the learning process has converged, the map will display the probability density function $p(X)$ that best describes all the input vectors. At the end of the learning process, an average quantisation error of the map will be generated to indicate how well the map matches the entire input vectors X_n. The average quantisation error is defined as:

$$E = \int \| X - m_c \|^2 \, p(X)dX \quad (4)$$

ANN analysis is quite similar to statistical approaches in that both have learning algorithm to help them realise the data analysis model. However, an ANN has the advantages of being robust with the ability to handle large amounts of data. Although the training of the ANN could takes a long time, but with configuration modification like Modular Neural Network [12,31] and the advancement of the computing power, it is normally acceptable. After training, the BPNNs should be able to produce output almost instantly without needing complicated mathematical calculation.

4. FUZZY THEORY AND FUZZY CLUSTERING

Fuzzy theory works on the basis derived from fuzzy sets [32,17]. A fuzzy set allows for the degree of membership of an item in a set to be any real number between 0 and 1, this allows human observations, expressions and expertise to be modelled more closely. The membership function of a fuzzy set A is denoted by:

$$A : X \rightarrow [0,1] \quad (5)$$

Once the fuzzy sets have been defined, it is possible to use them in constructing rules for fuzzy expert systems and in performing fuzzy inference. Fuzzy system can produce more accurate results based on the basic idea of the defuzzification. A defuzzification technique is used to calculate the conclusion by evaluating the degree of matches from the observation that triggered one or several rules in the model. This will lead to a better result by handling the fuzziness in the decision making. Thus, the fuzzy technique can improve the statistical prediction in certain cases.

Fuzzy sets allow human expertise and decisions to be modelled more closely, thus it is suggested in this paper that it can be used in the CRM model. A set of example data or knowledge from the business analyst is used as the basic knowledge available to build the fuzzy rule base. Using knowledge from the business analyst, fuzzy rules can be hand-coded into the CRM model. However, with the availability of the vast amount of data, it will be useful to extract knowledge from the data directly. This has the advantage of discovery new knowledge or relations underlying the data. In extracting fuzzy rules from the data, the first step is to translate all the available data into linguistic fuzzy rules using linguistic labels. The following algorithm outlines the steps in extracting the fuzzy linguistic rules from the available data. For k inputs, the given input-output data pairs with n patterns:

$$\begin{gathered} (x_1^1, \ldots, x_k^1; y^1) \\ (x_1^2, \ldots, x_k^2; y^2) \\ \vdots \\ (x_1^n, \ldots, x_k^n; y^n) \end{gathered}$$

The number of linguistics terms T and the distribution of data in the regions of the whole domain are first determined. For ease of interpretation and computational simplicity, the shape of the membership function used in this algorithm is triangular. In this case, we will obtain for every $x \in X$,

$$A_t \in F(x) \rightarrow [0,1] \qquad \text{for all } t \in T \quad (6)$$

After the fuzzy regions and membership functions have been set up, the available data set will be mapped. If the value cuts on more than one membership function, the one with the maximum membership grade will be assigned to the value:

$$R_n \Rightarrow [x_1^n(A_{t1}, \max), \ldots, x_k^n(A_{tk}, \max) : y^n(B_t, \max)] \quad (7)$$

After all the data sets have been assigned with a fuzzy linguistic label, Mamdani type fuzzy rules are then formed and centroid defuzzification is used.

After fuzzy rules have been generated from each data point, repeated rules are removed. In the event that there are repeated fuzzy rules, the number of repetitions of the fuzzy rules and the firing strengths of the rules will be examined to resolve conflicts.

Besides using fuzzy theory in the data mining process of the CRM model, fuzzy clustering can also be used. This provides a more precise measure to the company in delivering value to the customer and profitability to the company. Given a set of data, clustering techniques partition the data into several groups such that the degree of association is strong within one group and weak for data in different groups. Classical clustering techniques result in crisp partitions where each data can belong to only one partition. Fuzzy clustering extends this idea to allow data to belong to more than one group. The resulting partitions are therefore fuzzy partitions. Each cluster is associated with a membership function that expresses the degree to which individual data belongs to the cluster. Fuzzy C-Means (FCM) clustering has been very reliable and popular in performing fuzzy clustering [3].

Given a set of data, FCM clustering iteratively search for a set of fuzzy partitions and the associated cluster centres that represent the structure of the data. The FCM clustering algorithm relies on the user to specify the number of clusters present in the set of data to be clustered. Given the number of cluster c, FCM clustering partitions the data $X = \{x_1, x_2, \ldots, x_n\}$ into c fuzzy partitions by minimizing within group sum of squared error objective function using the following equation:

$$J_m(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (U_{ik})^m \parallel x_k - v_i \parallel^2, \qquad 1 \le m \le \infty \tag{8}$$

where $J_m(U,V)$ is the sum of squared error for the set of fuzzy clusters represented by the membership matrix U, and the associated set of cluster centres V. $\|.\|$ is some inner product-induced norm. In the formula, $\|x_k - v_i\|^2$ represents the distance between the data x_k and the cluster centre v_i. The squared error is used as a performance index that measures the weighted sum of distances between cluster centres and elements in the corresponding fuzzy clusters. The number m governs the influence of membership grades in the performance index. The partition becomes fuzzier with increasing m and it is proven that the FCM clustering converges for any $m \in (1,\infty)$.

5. CRM MODEL

In this part of the paper, part of a typical CRM model used by a business is proposed to show the use of the intelligent techniques as a data mining technique. The model was discussed and possible areas that neural and fuzzy can be used as a data mining technique was also investigated.

The building blocks of the CRM model provide a framework to deliver value to the customer and profitability to the company. This framework starts with differentiating customers along two dimensions, by their value to the firm, and by their wants and needs. The first dimension focuses on customer valuation measurement by understanding the value a customer represents to the company. This measurement identifies revenue growth potential from repeat purchases, referrals, and expanding scope of business. Customer loyalty is an important component of this first dimension. The second dimension looks at the customer preference to determine what are the wants and needs of customers, i.e., the customer value proposition. This measurement examines the results that a customer is trying to achieve, and determine whether the company can bundle products to deliver the results.

Basically, these two dimension form the basis for the CRM model [21] as shown in Figure 3. Please take note that in a CRM process, it is a cycle. Each time you repeat the cycle, more data and experience will be accumulated for the analysis model. This will put your company in a better position to meet customers' needs and increase revenue.

The investigation performed in this paper has proposed methods for understanding and differentiating customers using ANN and Fuzzy Logic which are the foundation for all other components of the CRM model in Figure 3.

FCM clustering is first used to perform an analysis on the available information and to perform unsupervised clustering. The FCM clustering identified different segments by using input parameters contributed by quantifying customers' needs, characteristics and behaviours. At the end of the clustering, each customer will be assigned to some fuzzy memberships that contribute to the whole distribution as well as to the different segments. After the FCM clustering has identified the segments with fuzzy partition, a set of fuzzy rules can also be extracted based on the clustering information. This will allow the business analyst to gain knowledge on how the segments are determined. Business analyst can examine the set of fuzzy rules to modify the behaviour of the clustering model, as well as to incorporate their own knowledge and experience. Beside the advantage of providing a set of understandable fuzzy rules, the fuzzy partitions together with the fuzzy memberships generated for each customer will allow next steps to be constructed easily and efficiently. With the extracted information, a customer's needs and expectations can be understood better. As a human, we do not always belong to a cluster. However, depending on the situations and circumstances, we may also have a certain degree of belonging in other segments at some time. With the assistance of fuzzy rules, fuzzy partition and fuzzy scores, this characteristic can be modelled more precisely.

In order to map to the existing marketing research knowledge base, SOM can first perform clustering in determining the behaviour of the customer. As we assume that this database is normally more complex and higher in input dimensional, SOM will be of favour to the FCM clustering. After the marketing research database has been separated into different cluster, BPNN can then use to map the two together to produce some meaningful interpretation of the two clusters. As business analyst will normally require understanding in the mapping, the fuzzy rule extraction technique can then used to extract fuzzy rules from the learned BPNN. This will enable the model to be understood and handle any vagueness in the data.

For customer loyalty management, an interesting application involves the use of call centre to enhance process quality through customer service. After a customer calls the call centre with a question or problem, an exit survey measures the satisfaction of the customer with the service performed. The data collected on customer satisfaction can be used as the basis for a decision support system which can be used to generate reports and alert managers of potential service quality problems.

The decision support system can be constructed using fuzzy memberships and fuzzy rules. In the very beginning, the business analyst has to hand-code the fuzzy rules based on their experience and knowledge. After more data have been collected, fuzzy rules can be constructed directly from the data. Business analyst will then need to verify the fuzzy rule base. The advantage of using fuzzy theory in mining the pool of surveyed customer is that, it will alert the client manager even though the warning signal is uncertain. The client manager can then decide on the seriousness of the warning signal based on the fuzzy firing strength and by examining relevant parameters.

Besides generating the warning signal, the overall customer voice data can be used in constructing segmented fuzzy rule bases to signal any change of trends in customer perception of service quality and product satisfaction. As the fuzzy rule bases work on fuzzy memberships, the

Understanding & Differentiate		Develop & Customise		Interact & Deliver		Acquire & Retain	
Examine customer's needs	Differentiate based on customer's needs, characteristics, and behaviours	Develop products to meet customer's needs	Customised by customer segment	Interact with customers and prospective customers	Deliver increased value to customer	Acquire customer and prospective customers	Retain valuable customers
Customer preference measurement		Customer valuation measurement		Customer loyalty measurement			

Figure 3: CRM Process Model

degree of changes can be model more closely to produce a more reliable analysis of the market.

6. CONCLUSION

This paper has examined the possibility of using intelligent techniques in the CRM model. The paper also highlighted two area in a typical CRM model where the use of intelligent techniques can improve the decision making process. The advantage of using fuzzy theory in CRM is that the business analyst can gain in-depth understanding into the data mining model. With the understanding of the model, the analyst can modify and add-on knowledge and experience into the model. Besides, fuzzy theory can handle uncertainties in the data more efficiently than traditional data mining techniques.

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