A Novel Model for Global Customer Retention Using Data Mining Technology

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1. Introduction

This chapter deals with how to use data mining technology to find interesting pattern, which can be organized for global customer retention. Customer relationship management (CRM) comprises a set of processes and enabling systems supporting a business strategy to build long term, profitable relationships with specific customers. Customer data and information technology (IT) tools shape into the foundation upon which any successful CRM strategy is built. Although CRM has become widely recognized as an important business strategy, there is no widely accepted definition of CRM. Parvatiyar (2001) defines CRM as the strategic use of information, processes, technology, and people to manage the customer relationship with the company across the whole customer life cycle. Kincaid (2003) defines CRM as a company approach to understanding and influencing customer behavior through meaningful communications in order to improve customer acquisition, customer retention, customer loyalty, and customer profitability. These definitions emphasize the importance of viewing CRM as a comprehensive process of retaining customers, with the help of business intelligence, to maximize the customer value to the organization.

According to (Swift 2001; Kim et al., 2003) CRM consists of four dimensions: Customer Identification, Customer Attraction, Customer Retention, and Customer Development. They share the common goal of creating a deeper understanding of customers to maximize customer value to the organization in the long term. Customer retention has a significant impact on enterprise profitability. Analyzing and understanding customer behaviors and characteristics are the foundation of the development of a competitive customer retention strategy, so as to acquire and retain potential customers and maximize customer value. Gupta et al. (2004) find that a 1% improvement in retention can increase enterprise value by 5%. 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 analyzing, detecting and predicting changes in customer behaviors. Loyalty programs involve campaigns or supporting activities which aim at maintaining a long term relationship with customers.

Customer satisfaction is the central concern for customer retention. Customer satisfaction, which refers to the comparison of customer expectations with his or her perception of being satisfied, is the essential condition for retaining customers (Chen et al., 2005). Bolton and Ruth N. (1998) have established the positive effect of customer satisfaction on loyalty and

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usage behavior. With comprehensive customer data, data mining technology can provide business intelligence to generate new opportunities. Brijs et al. (2004) and Wang et al. (2005) concern with the discovery of interesting association relationships, which are above an interesting threshold, hidden in local databases. These researches mainly aimed at regional customer retention.

Globalization is no longer choice for most marketers; any company with a Web site has instant global exposure. Players at all levels are being pulled into global marketing by customer interaction over the Web, but not all are prepared for it. The message to company is clear: If your business is incapable of handling global trade, you are missing the point of conducting business. Company needs an efficient approach to find the pattern of global customer retention. One of the most important reasons companies are failing to take advantage of new global marketing opportunities is that the effective pattern of customer retention needed to do is woefully lacking. That is especially problematic for companies wishing to implement the modern analytical and targeting techniques of global customer retention (Matthew et al., 2006). For example, success with global customer retention requires familiarity with cultural practices. A database of Korean customers needs to include not only date-of-birth but also another data element not usually included in western databases-the wedding anniversary date of customers so the company can send the expected card. These main problems of global customer retention can be summarized as follows:

- Customer retention on a global scale demands the ability to apply theory with systems that reflects local cultures, local attitudes, and the real needs of individual customers in each market.
- Customer retention on a global scale demands to identify the sources of customer data and ascertain that all data was obtained in a manner that complies with privacy laws.
- Customer retention on a global scale demands to judge the values of min-support and min-confidence when utilizing data mining technique to discovery the interesting pattern.
- Customer retention on a global scale demands to avoid the signals that sent by customers are noise and confusing.

This chapter presents a comprehensive and effective model to solve the facing problems of customer retention shown above. This chapter is organized as follows. Customer retention overview is described in section 2. Sections 3 to 4 describe our novel model for global customer retention. This proposed model combines data mining technology with intuitionistic fuzzy set theory (IFS), α-cuts, and expert knowledge to discovery the interesting pattern of global customer retention (sections 3); some definitions for global customer retention are defined in section 4. An example according to the proposed model is expatiated in section 5. Following sections show our experimental results of the proposed approach and model (section 6), discuss its properties and conclude (section 7) the chapter.

2. Customer retention overview

2.1 Customer retention

At the heart of any contractual or subscription-oriented business model is the notion of the retention rate. An important managerial task is to take a series of past retention numbers for a given group of customers and project them into the future in order to make more accurate predictions about customer tenure, lifetime value, and so on. Churn refers to the tendency

for customers to defect or cease business with a company. Marketers interested in maximizing lifetime value realize that customer retention is a key to increasing long-run enterprise probability. A focus on customer retention implies that enterprises need to understand the determinants of customer churn and are able to predict those customers who are at risk of defection at a particular point in time. Customer churn is the loss of existing customers to a competitor. The phenomenon has the potential to result in considerable profit loss for a company. As such the prevention of customer churn is a core.

Given the importance of customer retention, companies use a variety of mechanisms for reducing churn. These efforts can be grouped into three main areas: improving service quality, targeting interventions to prevent churn, and loyalty programs.

Firms' investment in improving service quality and customer satisfaction is based on the assumption that they improve customer retention. While some studies have found a link between satisfaction and retention (Rust & Zahorik, 1993), others have questioned this link. For example, Mittal & Kamakura (2001) find the link between customer satisfaction and retention to be moderated by customer characteristics.

Recent research finds that retention rates are affected by the channel utilized by the customer. Ansari et al. (2004) find that e-mails tend to drive persons to the Internet, and that purchases on the Internet lessen inertia in buying and loyalty. They conjecture that this arises from lower service levels and lower switching costs. Zhang & Wedel (2004) find the opposite effect in the context of grocery purchases, perhaps due to the use of e-shopping lists, which might actually raise switching costs. In light of these conflicting findings it would be desirable to better ascertain the role of optimal channel mix in retention.

Since the introduction of frequent flier program by American Airlines in the 1980s, loyalty programs have become ubiquitous in almost every industry. The interest in loyalty programs has increased over time as more and more companies use them for developing relationships, stimulating product or service usage, and retaining customers (Kamakura et al., 2000).

In spite of the pervasiveness of loyalty programs, their effectiveness is far from clear. Some studies find that loyalty programs increase customer retention and customer development (Bolton et al., 2000; Leenheer et al., 2004; Verhoef, 2003; Lixia Du et al., 2008); others find no impact on retention but improvement in share of wallet (Sharp & Sharp, 1997); and yet others find almost no difference in the behavior of loyalty program members and non-members (Dowling & Uncle, 1997). Kopalle and Neslin (2003) investigate the economic viability of frequency reward programs in a competitive environment, and find brands benefit from reward programs when customer's value future benefits, reward programs expand the market and if the brand has a higher preference.

Optimal targeting of loyalty programs is also an open issue. Conventional wisdom suggests that loyalty programs should be designed to reward a firm's best customers. However, Lal & Bell (2003) found that, in the context of grocery stores, loyalty programs do not affect the behavior of best customers. Instead, these programs have the biggest impact on a store's worst customers.

Several questions pertain to loyalty program design, including whether rewards should use cash or merchandise, offer luxury or necessity goods, be probabilistic or deterministic, or whether to use the firm's own products. Recent behavioral research provides some guidelines on these important issues (Kivetz, 2003; Kivetz & Simonson, 2002), and these findings have implications for modeling loyalty program design.

2.2 Data mining and customer retention

Data mining combines the statistic and artificial intelligence to find out the rules that are contained in the data, letters, and figures. The central idea of data mining for customer retention is that data from the past that contains information that will be useful in the future. Appropriate data mining tools, which are good at extracting and identifying useful information and knowledge from enormous customer databases, are one of the best supporting tools for making different customer retention decisions. There are many methods of data mining including classification, estimation, prediction, clustering, and association rules. Among these, association rules can discover the high frequency pattern and discover which things appear frequently and simultaneously.

Within the context of customer retention, data mining can be seen as a business driven process aimed at the discovery and consistent use of profitable knowledge from organizational data. Each of the customer retention elements can be supported by different data mining models, which generally include association, classification, clustering, forecasting, regression, sequence discovery.

- Association: Association aims to establishing relationships between items which exist together in a given record. Market basket analysis and cross selling programs are typical examples for which association modeling is usually adopted. Common tools for association modeling are statistics and apriori algorithms.
- Classification: Classification is one of the most common learning models in data mining. It aims at building a model to predict future customer behaviors through classifying database records into a number of predefined classes based on certain criteria. Common tools used for classification are neural networks, decision trees and if then-else rules.
- Clustering: Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters. It is different to classification in that clusters are unknown at the time the algorithm starts. In other words, there are no predefined clusters. Common tools for clustering include neural networks and discrimination analysis.
- Forecasting: Forecasting estimates the future value based on a record's patterns. It deals with continuously valued outcomes. It relates to modeling and the logical relationships of the model at some time in the future. Demand forecast is a typical example of a forecasting model. Common tools for forecasting include neural networks and survival analysis.
- Regression: Regression is a kind of statistical estimation technique used to map each data object to a real value provide prediction value. Uses of regression include curve fitting, prediction (including forecasting), modeling of causal relationships, and testing scientific hypotheses about relationships between variables. Common tools for regression include linear regression and logistic regression.
- Sequence discovery: Sequence discovery is the identification of associations or patterns over time. Its goal is to model the states of the process generating the sequence or to extract and report deviation and trends over time. Common tools for sequence discovery are statistics and fuzzy set theory.

2.3 Customer retention models

Many customer retention models are concerned churn models. Many aspects of churn have been modeled in the literature. First, whether churn is hidden or observable influence the overall approach to modeling. In some industries, customer defection is not directly

observed, as customers do not explicitly terminate a relationship, but can become inactive. In other industries, however, the defection decision is observable as customers cease their relationship via actively terminating their contract with the firm (Schmittlein et al., 1987; Fader et al., 2004).

Models that are better at explanation may not necessarily be better at prediction. The empirical literature in marketing has traditionally favored parametric models (such as logistic or regression or parametric hazard specifications) that are easy to interpret. Churn is a rare event that may require new approaches from data mining, and non-parametric statistics that emphasize predictive ability (Hastie et al., 2001). These include projection-pursuit models, jump diffusion models, neural network models, tree structured models, spline-based models such as Generalized Additive Models (GAM), and Multivariate Adaptive Regression Splines (MARS), and more recently approaches such as support vector machines and boosting (Lemmens & Croux, 2003).

The above models are mainly concerned on technology. To the real markets, more and more customer retention models integrate human nature and culture factors with technology to be built. The following models consider human nature and culture factors.

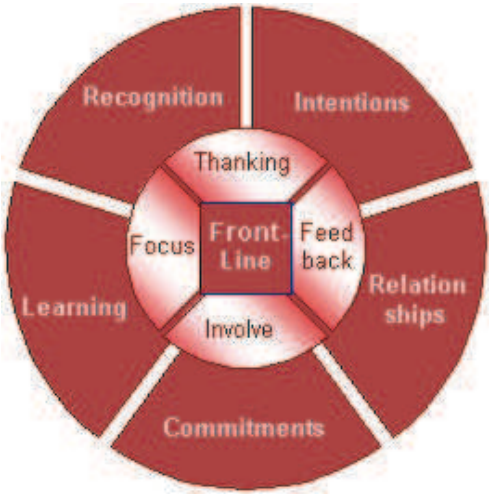

Fig. 1. Customer retention model architecture

This model (see Fig.1) is a bottom-up or user-centered approach based on leading workplace relationships and experiences to compliment your existing management of them. The model is based on a best practice combining two critical processes, or sets of actions, of cultures and human nature. Those processes being asking and thanking. Handling customer concerns, both complements as well as complaints, by asking the questions to get everyone on the service team involved. Retention customers by demonstrating intentions to continue to better serve them and increase value-beginning with those providing products and services. Working backwards, with the support of middle managers, to compliment and provide continuation for existing managerial efforts--especially for the "people" part of the enterprise. Cusomers may not remember what the employees said but they will always remember what how you made them feel. In other words, best pratice is important to customers (see URL: http://thankingcustomers.com/model.html).

We proposed a model on customer retention in 2007 (shown in Fig.2). The model contains two functions, i.e. classification and making policies parts. In the classification part, firstly, it constructs a database which concludes a number of satisfaction factors, then it forms a new database based on the original database by combining intuitionistic fuzzy set theory and α-cuts (see in section 3). Secondly, it gets the churn probability and classifies the customers into different groups. In the making policies part, it employs data mining technique to find the interesting pattern and association rules to each customer group. This is then used to create appropriate policies for different customer group. The most significant feature of this model is that it not only predicts churning but also makes proactive attempts to reduce it.

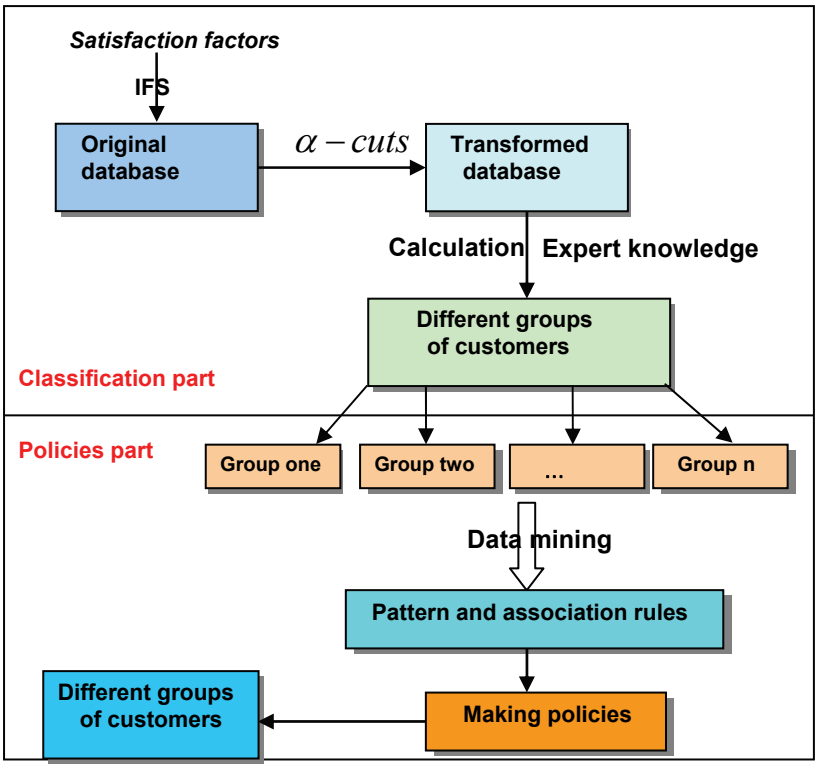

Fig. 2. Customer retention model-CP Model

Although exist a lot of customer retention models, there is a lack of comprehensive and effective approach and model to realize global customer retention by now. CP model has potential merits (such as churn probability, customer behavior character), but it cannot satisfy global customer retention problem. We combine potential merits of CP model to propose a novel global customer model (see section 3).

3. Global customer retention model

As the nature of research in global customer retention, data mining technology is difficult to confine to specific disciplines. In this section, intuitionistic fuzzy set theory, α-cuts, expert knowledge, and CP model are combined for the proposed global customer retention model.

3.1 Proposed global customer retention model

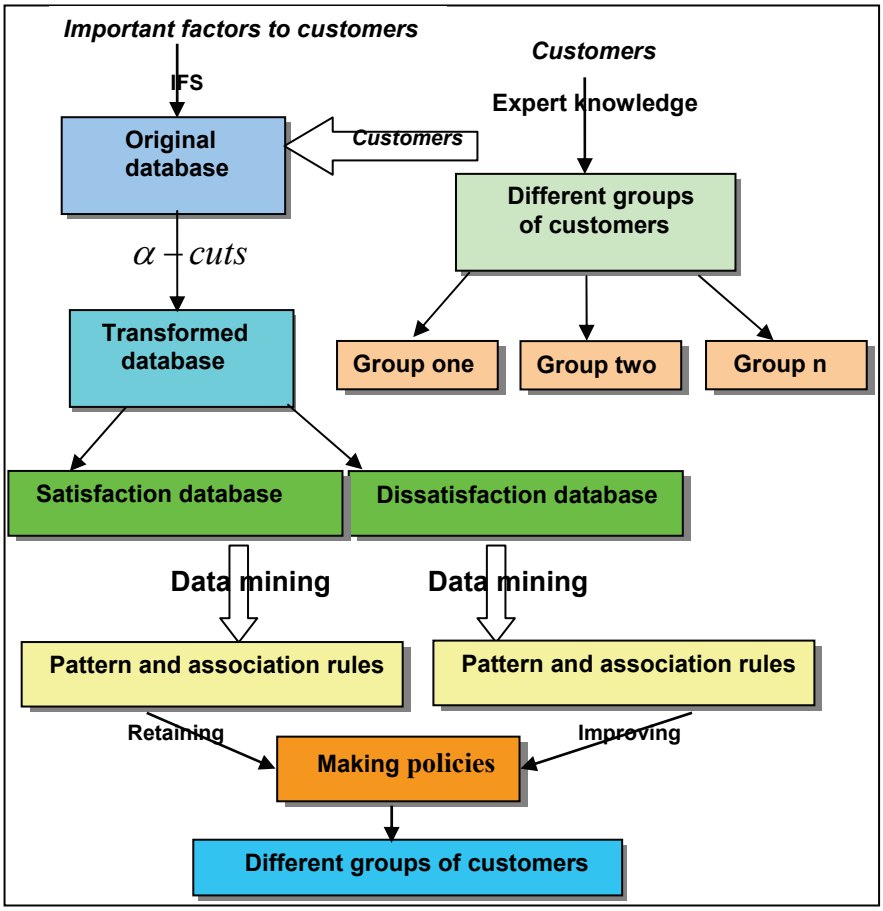

Fig. 3. Proposed global customer retention model-GCP Model

We proposed GCP Model (see Fig.3). Intuitionistic fuzzy set theory, α-cuts, and data mining technology are all employed in CP Model and GCP Model.The main differences between CP Model and GCP Model are that the function of expert knowledge and original customer database. GCP Model includes dissatisfaction database.

3.2 Intuitionistic fuzzy set theory

Fuzzy set theory was firstly presented by Professor L.A.Zadeh in California University in 1965. It transforms the meaning and spoken description into fuzzy set instead of general set, then studies and deals with subjective and undefined data with membership functions, qualifies the data then transforms it into useful information through systemic fuzzy operations.

Intuitionistic fuzzy set (IFS) is intuitively straightforward extensions of L.A.Zadeh's fuzzy sets. IFS theory basically defies the claim that from the fact that an element x ''belongs'' to a

given degree to a fuzzy set A, naturally follows that x should ''not belong'' to A to the extent 1-μ, an assertion implicit in the concept of a fuzzy set. On the contrary, IFS assign to each element of the universe both a degree of membership μ and one of non-membership v such that μ +v ≤1, thus relaxing the enforced duality v=1-μ from fuzzy set theory. Obviously, when μ +v = 1 for all elements of the universe, the traditional fuzzy set concept is recovered (Atanassov, 1986). IFS owe its name to the fact that this latter identity is weakened into an inequality, in other words: a denial of the law of the excluded middle occurs, one of the main ideas of intuitionism.

In CP and GCP Model, intuitionistic fuzzy set theory is an extension of fuzzy set theory that defies the claim that from the fact that an element x belongs to a given degree $\mu_{A(x)}$ to a fuzzy set A, naturally follows that x should not belong to A to the extent $1-\mu_{A(x)}$, an assertion implicit in the concept of a fuzzy set. On the contrary, IFS assigns to each element x of the universe both a degree of membership $\mu_{A(x)}$ and one of non-membership $v_{A(x)}$ such that

$$\mu_{A(x)} + v_{A(x)} \leq 1 \tag{1}$$

Thus relaxing the enforced duality $\mu_{A(x)} = 1 - v_{A(x)}$ from fuzzy set theory. Obviously, when $\mu_{A(x)} + v_{A(x)} = 1$ for all elements of universe, the traditional fuzzy set concept is recovered. Here, IFS builds the bridge between customer satisfaction and retention. The most important virtue is that IFS can express the customers' psychology and behavior exactly.

3.3 α-cuts

An element $x \in X$ that typically belongs to a fuzzy set A, when its membership value to be greater than some threshold $\alpha \in [0, 1]$. The ordinary set of each element is the α-cut A_α of A:

$$A_\alpha = \{x \in X, \mu_{A(x)} \geq \alpha\} \tag{2}$$

Didier Dubois and Henri Prade (2001) also define the strong α-cut:

$$A_\alpha = \{x \in X, \mu_{A(x)} > \alpha\} \tag{3}$$

CP and GCP Model all employ formula (2) to transform the original database.

The membership function of a fuzzy set can be expressed in terms of the characteristic function of its α-cuts according to the following expressions:

- $\mu_{A(\alpha)} = 1$ iff $x \in A_\alpha$
- Otherwise $\mu_{A(\alpha)} = 0$

With the help of α-cuts, the attribute values of database can be transformed to 0 or 1.

3.4 Database architecture

At the core of any sizable global trading effort is the database of information needed to guide and drive customer interactions through locally appropriate customer retention strategies. Customer satisfaction is the essential condition for retaining customers. Well-developed customer information base will smooth a path to the customer; a poorly assembled core of data might well compound global trading difficulties beyond repair. Customer retention is to stay abreast of data privacy rule making. The notion of privacy-preserving data mining is to identify and disallow such revelations as evident visible to the third parties in the kinds of patterns learned using traditional data mining techniques. So the essential factors of data privacy preserving are considered during the research. From the

architecture of the customer retention database, some expressions can be organized as the attributes of database (shown in Table 1).

Description of factors	Satisfaction and dissatisfaction reply
Enterprise offers competitive price (D_1)	[0,1.0]
Enterprise is abreast of developing new products (D_2)	[0,1.0]
Complains are taken by enterprise's employees (D_3)	[0,1.0]
It is easy to get enterprise's contact with the right person at call center (D_4)	[0,1.0]
The employees at enterprise's center are competent and professional (D_5)	[0,1.0]
The enterprise's sales representative understands the enterprise (D_6)	[0,1.0]
The enterprise's sales representative is competent and has profound knowledge (D_7)	[0,1.0]
The enterprise offers gifts to customers in special days (D_8)	[0,1.0]
The enterprise's society responsibility (D_9)	[0,1.0]

Table 1. The attributes of database

3.5 Expert knowledge

In CP Model, expert knowledge and percentage of customer satisfaction are combined to classify the customers. Experts of this field are employed to confirm the boundary of customer satisfaction. For example:

- 0 1 0 1 0 1 1 1 0, P=5/9=55.6%
- 1 1 1 1 1 1 0 0 0, P=6/9=66.7%
- 1 1 1 1 1 1 1 1 0, P=8/9=88.9%
- 1 1 1 1 1 1 1 1 1, P=9/9=100%

The customers can be divided into different groups according to the percentage of customer satisfaction and expert knowledge.

- Group one: P< 60%
- Group two: 60%≤P< 80%
- Group three: 80%≤P< 90%
- Group four: P=100%

In GCP Model, with regard to the levels of different customers, expert knowledge used to set the weights of the customers, such as customer categories combined with data privacy preserving principle, age, gender characters and regions. The value of α is related to the weights of customers, in other words, the weights of customers satisfy different criterion K_j , with j=1, 2,… , n, $\alpha = \max(K_j)$.

4. Proposed definitions

This section introduces the following definitions to discover the pattern of global customer retention.

- Definition 1 An association rule has the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$, I is a transaction set, and $X \cap Y = \Phi$.
- Definition 2 The support of the association rule $X \rightarrow Y$ is the probability that $X \cup Y$ exists in a transaction in the database D.
- Definition 3 The min-support is defined as follows, min-support=$C \cdot (N/P)$, where C denotes the weight of the region; N denotes the number of a special group of customers in the research; P denotes the number of all customers is involved in the research.
- Definition 4 The confidence of the association rule $X \rightarrow Y$ is the probability that Y exists that a transaction contains X, i.e., $Pr(Y/X) = Pr(X \cup Y)/Pr(X)$.

5. Example of GCP model

Practicing global customer retention demands the ability to apply strategies in a way that reflect local cultures, local attitudes, and the real needs of individual customers in each market. GCP Model is expatiated by an example in this section.

5.1 Steps of GCP model

The steps of GCP Model are described below:

- Construct the database of customer retention with support of IFS.
- Ascertain the value of α according to different group of customers and $\alpha = \max(K_j)$.
- Select the satisfaction reply whose value is one to form transaction tables with the help of α-cuts; select the dissatisfaction reply whose value is zero to form transaction tables with the help of α-cuts.
- Discover the pattern of customer retention combined with data mining technique and expert knowledge.

5.2 An example

In order to explain the proposed GCP Model and find the pattern of customers under globalization, the section takes the data (age: A_1 (20-29); gender: M_2) from the cooperative enterprise to set an example. Here we just show the example of satisfaction pattern based on GCP Model.

- Step one: Table 2 shows the original database according to IFS.
- Step two: M_2=0.6, A_1=0.3, according to $\alpha = \max(K_j)$, α=0.6. Table 3 shows the transformed table with the help of α-cuts.

D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
0.3	0.6	0.8	0.5	0.4	0.3	0.5	0.6	0.8
0.3	0.4	0.6	0.4	0.3	0.2	0.4	0.5	0.9
0.5	0.3	0.5	0.4	0.2	0.4	0.4	0.4	0.7
0.4	0.3	0.4	0.5	0.2	0.3	0.3	0.4	0.6
0.5	0.6	0.3	0.5	0.1	0.4	0.3	0.6	0.5
0.6	0.7	0.3	0.4	0.1	0.3	0.3	0.3	0.6
0.6	0.3	0.2	0.4	0.1	0.2	0.2	0.5	0.3
0.6	0.3	0.2	0.3	0.2	0.3	0.4	0.6	0.6
0.6	0.3	0.1	0.3	0.1	0.3	0.3	0.6	0.5
0.7	0.2	0.1	0.3	0.2	0.3	0.4	0.7	0.6

Table 2. Original database

D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
0	1	1	0	0	0	0	1	1
0	0	1	0	0	0	0	0	1
0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	1
0	1	0	0	0.	0	0	1	0
1	1	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	1
1	0	0	0	0	0	0	1	0
1	0	0	0	0	0	0	1	1

Table 3. Transformed database

- Step three: Select the satisfaction reply whose value is one to form transaction database. The transaction database is shown in table 4. Each transaction is a subset of I, and is assigned a transaction identifier (TID).

TID	Items	TID	Items	TID	Items	TID	Items
1	D_2D_3 D_8 D_9	2	D_3 D_9	3	D_9	4	D_9
5	D_2 D_8	6	D_1 D_2 D_9	7	D_1	8	D_1 D_8 D_9
9	D_1 D_8	10	D_1 D_8 D_9				

Table 4. Transaction database

- Step four: Calculate the appearing times of every transaction item and show in Table 5.
- Step five: Acquire the support of every appearing item, D_1=0.5, D_2=0.3, D_3=0.2, D_8=0.5, D_9=0.7.

Item	Appearing times	Item	Appearing times	Item	Appearing times
D_1	5	D_2	3	D_3	2
D_8	5	D_9	7		

Table 5. The appearing times of every item

- Step six: Compare the support of every appearing item with min-support (0.3). It is obviously to find frequent item set I_1, I_2. I_1= {D_1, D_2, D_8, D_9}, I_2= {D_1D_8, D_8D_9}.
- Step seven: The min-confidence is say, 60%, and then the association rules are shown in table 6.

Association rules	Confidence	Association rules	Confidence
$D_1 \rightarrow D_8$	60%	$D_8 \rightarrow D_1$	60%
$D_8 \rightarrow D_9$	60%		

Table 6. Association rules

However, to women customers whose age is between 20 and 29, the satisfaction patterns are presented below:

- If customers value the competitive price offered by the enterprise, they will like the gifts provided by the enterprise in special days.
- If customers like the gifts provided by the enterprise in special days, they will value the competitive price offered by the enterprise.
- If customers like the gifts provided by the enterprise in special days, they will concern social responsibility of the enterprise.

Dissatisfaction patterns of customers are also can be achieved by the same approach. Finally, the achieved patterns and rules are established for the decision makers.

6. Experiments analysis

The study of global customer retention under GCP Model with the cooperative enterprises started in 2007. Although the experiments of proposed approach are still in the early stage, some interesting pattern and rules are achieved in the research. For instance, the proposed approach can increase response rate of the customer loyalty by segmenting customers into groups with different characteristics; the proposed approach can predict how likely an existing customer is to take his/her business to a competitor. It is interesting to note that, dissatisfaction patterns of customers are mainly related to the enterprise call center. Owing to the different culture and location, the satisfaction patterns are almost different. For example, some (especially for western customers) care about the enterprise responsibility; some (especially for eastern customers) care about the gifts provided by the enterprise. All of these useful pattern and rules help the decision makers to make effective policies.

7. Conclusions

Study of global customer retention is an emerging trend in the industry. This chapter has proposed a novel model (GCP Model) to practice global customer retention. It aims to find the useful pattern with the combination of IFS, α-cuts, expert knowledge, and data mining technique. This proposed model might have some limitations, for instance, some sensitive data of customers are not involved in it, and this will be the future research direction. With respect to the research findings, in order to maximize an organization's profits, policy makers have to retain valuable customers and increase the life-time value of the customer. As such, global customer retention is so important to maintaining a long term and pleasant relationship with customers according to different cultures and locations.

8. Acknowledgements

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This book presents four different ways of theoretical and practical advances and applications of data mining in different promising areas like Industrialist, Biological, and Social. Twenty six chapters cover different special topics with proposed novel ideas. Each chapter gives an overview of the subjects and some of the chapters have cases with offered data mining solutions. We hope that this book will be a useful aid in showing a right way for the students, researchers and practitioners in their studies.

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