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A Study on Reducing Churn Rate of telecommunication company using Case-based Reasoning

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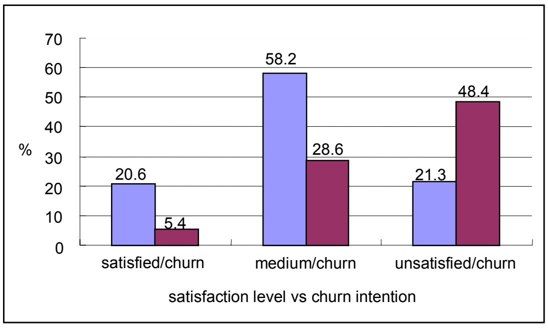
Abstract

In rapidly changing business environments, all business areas have stiff competition to a gain competitive edge. In the telecommunication service area, Churn is a serious problem. Data mining techniques are commonly used to predict churn probability. In this paper, we propose a hybrid approach, CBR with SAGA(Simulated Annealing and Genetic Algorithm) approach, for predicting the churn rate of a telecommunication service company. Case-Based Reasoning is rapidly emerging AI technology that can use past experiences to solve current problems. Genetic Algorithm can be described as a mechanism that mimics the genetic evolution of a species. The basic idea of simulated annealing originates from thermodynamics and metallurgy. This annealing process is mimicked by a local search strategy. In this hybrid approach, SAGA determines weight vector of CBR using SAGA learning. Churn rate prediction results are compared to other approaches - Logistic Regression and CBR with GA. An architecture of a decision support system which focuses on reducing the churn rate of telecom company, is also suggested.

1. Introduction

In the telecommunication service area, especially in Korea, 5 telecommunication companies compete with the others for expanding his market share. Figure 1 shows the survey result of J.D. PowerKorea. According to the result, Only 20.6% of customers are satisfied with the current service and 28.7% of service users want to change the current service company. Churn is a term for customers joining and then quitting within a short period of time. In the United States, the churn rate is nearly 30% a year.

Churn is an especially serious problem in the telecommunications industry where customers join a long distance calling plan or a cellular service for the introductory offer and then join a different company when the introductory offer expires. For example, in the cellular industry, the average churn rates approach 25 percent a year. With the customer growth rate slowing, it becomes increasingly important to control and reduce the churn rate.



[Figure 1] survey result of J.D. PowerKorea

The cause of churn is mainly due to the low national coverage, call density, in-house coverage [4]. Other research shows that churn probability is related to monthly expenditure and household income in the Internet Service provider market [16].

To predict the churn rate of a service company, 'Data Mining' technique is frequently used [4][7]. A number of studies have demonstrated that AI approach such as ANN(Artificial Neural Networks)[15] [17], Rule-based system[13] and Case-based Reasoning[5] are suitable tools for data mining.

In this paper, CBR with SAGA(Simulated Annealing and Genetic Algorithm) approach is proposed for predicting the churn rate of a telecommunication service company. Churn rate prediction results are compared with other approaches such as Logistic Regression and CBR with GA.

This paper is organized as follows: Section 2 provides a brief description of GA, SA, CBR and case indexing problem. Section 3 reviews on hybrid method using CBR and other techniques. Sections 4 reports on the experiments and results of predicting churn rate. Finally, Sections 6 and 7 review the conclusions and discuss future research issues.

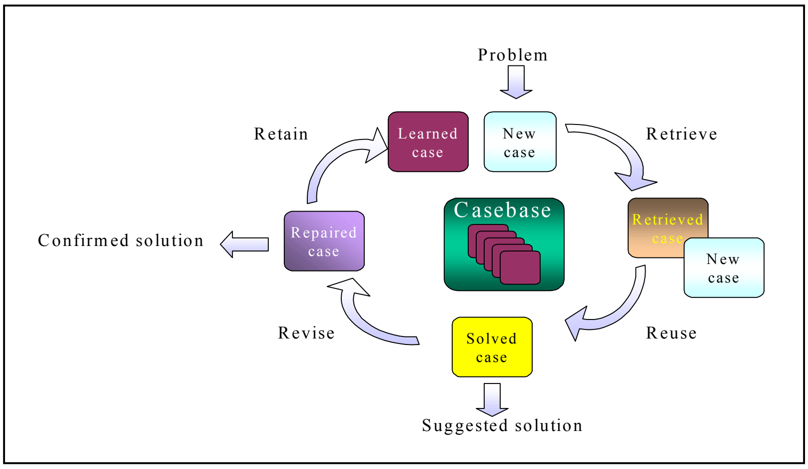
2. Literature Review

2.1 CBR

Case-Based Reasoning (CBR) is motivated by observing how human beings apply reason ability in practical situations. When faced with a problem situation, people often remember how they were able to solve a similar situation, rather than to re-think the entire problem. Case-Based Reasoning is rapidly emerging AI technology that can use past experiences to solve current problems. It can be defined as to solve a problem, remember a similar problem you have solved in the past and adopt the old solution to solve the new problem.

CBR methods can be divided into four steps, retrieve, reuse, revise, and retain - learn from the problem solving experience. This decomposition of methods depends heavily on the method suggested by Aamodt and Plaza [1], and is illustrated in figure 2.

The general procedure of CBR is shown in figure 2



[Figure 2] The general procedure of CBR

2.2 GA

A Genetic Algorithm may be described as a mechanism that mimics the genetic evolution of a species. The main difference between Genetic algorithm and Simulated Annealing, Tabu search is that GA deals with population of solutions rather than single solutions. A clear advantage is intrinsic parallelism but it goes beyond letting solutions evolve independently in parallel. This means that solutions interact, mix(crossover) together and produce their children that hopefully retain the good characteristics of their parents. In GA, the main operators used to generate and explore the neighborhood of a population and select a new generation are selection, crossover and mutation [20].

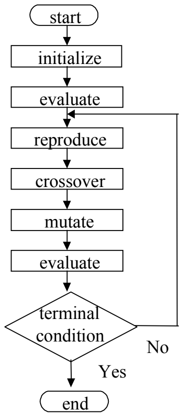
The pseudo code and flow chart is shown in figure 3.

2.3 SA

The basic idea of simulated annealing originates from thermodynamics and metallurgy. When molten iron is cooled slowly enough to solidify in a structure of minimal energy [20]. This annealing process is mimicked by a local search strategy. At the start, almost any directional move is accepted. It means that algorithm search the solution space. Then, gradually, the temperature decreases, and this implies that algorithm has become more and more selective in accepting new solutions [6].

A pseudo code of simulated annealing algorithm is shown in figure 4.

```
• procedure GA()
  initialize(Population);
  evaluate(Population);
  while not (terminal condition satisfied) do
      MatingPool = reproduce(Population);
      MutationPool = crossover(MatingPool);
      Population = mutation(MutationPool);
      evaluate(Population);
  end while
end procedure
```



[Figure 3] Pseudo code and flow chart of GA algorithm

```
□ procedure SA()
  initialize(best value F_best, x_best);
  while not (terminal condition satisfied) do
    generate x_n+1 at random in the neighborhood of N(x_n) of x_n;
   If F_best >= F(x_n+1), then x_n+1 <- X_best;
   else generated random number from [0, 1];
           if p<=p(n) then x_n+1 <- X_best;
  end while
end procedure
```

[Figure 4] A pseudo code of simulated annealing algorithm

2.4 Case indexing

Case indexing problems involve retrieving applicable cases at appropriate time. In building CBR system, the previous research proposes several guidelines for choosing indexes for particular cases [14]. indexes should be predictive, abstract enough to make a case useful in a variety of future situations, concrete enough to be recognizable in future cases, and useful to prediction

Both manual and automated methods have been used to select indices. Choosing indices manually involves deciding the purpose of a case with respect to the aims of the reasoner and deciding under what circumstances the case may be useful. The second issue of indexing cases is how to structure the indices so that the search through the case library can be done efficiently and accurately. An index used to retrieve cases from memory may fail even if there is a relevant case in memory [14]. This happens when the index does not correspond to the one used to index the case. The indexing problem refers to the task of storing cases for an effective and efficient retrieval [14].

3. Hybrid approach

3.1 Prior researches on the hybrid approaches

In many previous researches, GA and other local search heuristics have been increasingly applied in conjunction with other AI techniques such as neural networks, rule-based system, fuzzy theory, and CBR [22].

When combining GA with Neural Networks, GA is used to select relevant input variables, determine the optimal number of hidden layers, nodes and connectivity, and tune the learning parameters [3][8]. GA can also help to determine the weight vector of Neural Networks without the use of any gradient information by genetic learning [18].

GA are also used in conjunction with fuzzy logic systems to predict the interest rate[12], to provide an appropriate set of fuzzy IF THEN rules for classification problems [11].

SA is also used for optimizing other techniques. In a broad sense, SA performs the same function as GA in many researches. Jointed with neural Network, SA search the solution space to find out global optimum [23].

A few studies have dealt with hybridization of genetic and CBR, though there exists a great potential for useful applications in this area. Wang and Ishii applied GA to the method of similarity metrics based on the cases being represented by structured representations. In other research, GA has been used to search the weight space of nearest-neighbor indexing in CBR [22].

3.2 Hybrid systems with case-based reasoning and SAGA algorithm

The main focus of a hybrid system is that SAGA determines the weight vector of CBR using SAGA learning. In predicting the churn rate of a customer, the most similar cases need to be retrieved(case indexing problem) and it is also required to determine the nearest neighbor. SAGA wanders the weight space which maximizes the hit ratio (it is said to hit when a new given case and the most nearest-neighbor has same service status). In later part, a hybrid approach using SAGA to case indexing and retrieving process is explained in detail. The main difference between SAGA algorithm and other single local search heuristics is that in SAGA algorithm, each of the current solutions optimized rather than evolved [9].

Figure 5 shows a pseudo code of SAGA algorithm

```
STEP 1. Initialize the parameter of the GA
STEP 2. Generate initial population of solutions for the GA
STEP 3. Use the GA to produce k "good" solution
STEP 4. For each of the k solutions, do following:
        (a) Initialize the parameters of SA
        (b) Improve the "good" solution using SA, and
            return to the GA population
STEP 5. Repeat steps 3 and 4 needed
```

[Figure 5] A pseudo code of SAGA algorithm

The previous studies on the choice of indexing and retrieving method suggest some guidelines to choose an indexing technique. Inductive indexing is more appropriate when the retrieval goal is well defined while nearest-neighbor is preferred [2][5]. when the retrieval goal is subjective. In this regard, inductive approaches are suitable for business classification tasks, such as corporate bond rating and bankruptcy prediction. However, inductive indexing requires a large number of cases to form induction trees [2]. In addition, finding and maintaining an optimal induction tree for case-based retrieval is an expensive task [14].

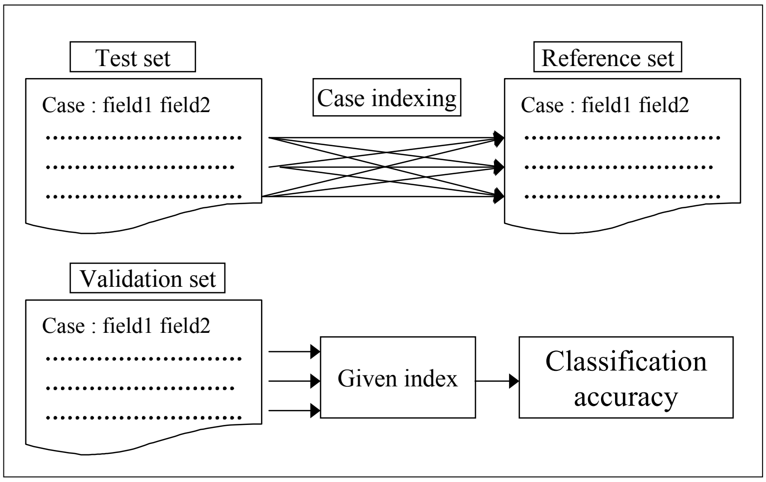
Among three indexing method, the nearest-neighbor approach is used in the paper. It is difficult to decide a set of feature weights that could accurately retrieve cases in a given situation [2]. As the feature weights for most problem domains are context dependent, each case should have its own set of feature weights for determining the relevance of that case to a new problem. So the accuracy of the system largely depends on the matching functions which include the weight vectors specified by the developer [22].

The importance of a dimension in judging similarity and degree of match should be considered in building matching functions [14]. Matching and ranking is the process of comparing two cases with each other and determining the extent of their of match and ordering cases according to the goodness of match or the usefulness for the application [14]. A good matching function takes into account which features of a case are more important and scores cases for the usefulness according to those criteria. A case that matches important features but not less important ones needs to be judged as a better match than one that matches less important features but does not match important ones. The easiest way to determine the similarity between two cases is to calculate the virtual distance between two cases. The shorter the distance, the more two cases are alike. The distance can be expressed in the following equation.

$$D_{ab} = \sqrt{\sum_{i=1}^{n} w_i \times (f_{ai} - f_{bi})^2} \qquad \textit{where n is the number of features}$$

$$w_i \textit{ is weight value of a feature i}$$

Every feature in the input case is matched to its corresponding feature in the stored case, and the degree of match of each pair is computed using the matching function. Based on the importance assigned to each dimension, an aggregate match score is computed. Ranking procedures order cases according to their scores, and higher scoring cases are used before lower scoring ones. Figure 6 represents the nearest-neighbor matching algorithm and calculation of classification accuracy. This match function is suggested by Shin & Han in 1999. In this study, the same method is used in calculating distance .



[Figure 6] The nearest-neighbor matching algorithm and calculation of classification accuracy.

Data is divided by three sets - the test set, reference set and validation set. Test set is used to determine the weight vector of CBR by calculating the distance suggested in this study. When case indexing is done, the classification accuracy is calculated using a validation set. The validation set has already target value, the current status of each user. Classification accuracy can be computed from the hit ratio - the predicted case has exactly the same status as target case. The hit ratio can be the most important performance measure in churn rate prediction, because the core of reducing the churning users is predicting the churning users and efficient churn prediction can be achieved through the proper selection of the weight vector. The weight vector which predict the churning users well should be determined by the highest hit ratio for effective prediction.

There are many possible combinations of algorithms, SAGA algorithm has a characteristic. In each GA iteration, population set is optimized via SA algorithm. The main difference between SAGA and GA is that GA algorithm evolve through crossover and mutation: make better offspring from selected good parents, and SAGA algorithm is optimized rather than evolved in each step. In this experiment, time complexity is very high and response will be take long time using single local search heuristics.

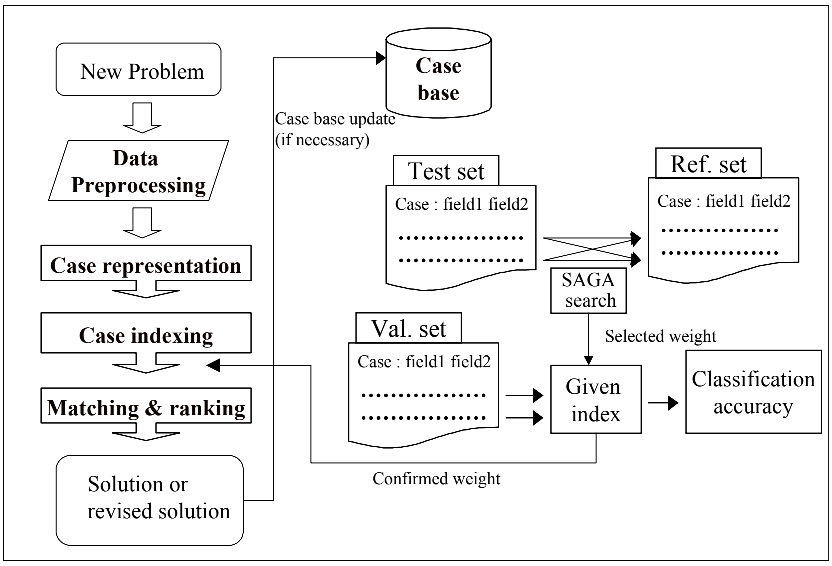
3.3 Hybrid structure of SAGA-CBR system

We set the range of the weights between 0 and 1 and do not apply particular constraints for this search. The task of defining a fitness function is always application-specific. In this case, the objective of the system is to retrieve more relevant cases that can lead to the correct solutions. The ability of case-based systems to achieve these objectives can be represented by the fitness function that specifies how well the matching function increases the classification accuracy. We apply the classification accuracy rate of the test set to the fitness function for this study. The test set consists of known cases where the classification outcome was determined and used to evaluate the fitness of different sets of feature weights. Mathematically, this fitness function is expressed as figure 7:

$$
\begin{gathered}
CR = \frac{1}{n} \sum_{i=1}^{n} CA_i \\
CA_i = \begin{cases} 1 & \text{if } O(T_i) = O(S_{j^*(i)}) \\ 0 & \text{otherwise} \end{cases} \\
S_{j^*(i)} = \underset{j \in R}{Min} \left[\sqrt{\sum_{k=1}^{l} w_k (T_{ik} - R_{jk})^2} \right] \\
\text{for given } i (i = 1, 2, 3, \cdots, n)
\end{gathered}
$$

[Figure 7] Fitness function of GA

The overall structure of hybrid approach is shown in figure 8.



[Figure 8] The overall structure of SAGA based CBR approach

As stated above, weight vector is determined by comparing test set and reference set. The weight vector is optimized by an SAGA algorithm and weight vector which induce highest hit ratio is selected. The selected weight is validated by statistical hypothesis test which compares the performance of a suggested method and other method such as Logistic regression and CBR with GA.

There has been much debate regarding the optimal population size for the problem. Generally, the population size is determined according to the size of the problem (a bigger population for a larger problem). The common view is that a larger population takes longer to settle on a solution, but is more likely to find a global optimum because of its more diverse gene pool. We use 50 organisms in the population for this study. The crossover and mutation rates are changed to prevent the output from falling into the local optima.

The controlling parameters are specified in table 1.

[Table 1] The controlling parameters of SAGA algorithm

parameter	Value & description
Population size	50
Crossover rate	0.5-0.7
Mutation rate	0.05-0.1
P_0	0.9
L	16 times the size of neighborhood
α	0.95

3.4 Determination of attributes affecting customer churn

When reducing the number of data in this study, it is difficult to determine which data have an influence on customer churn. Customer data has too many attributes - more than 200 attributes. Though it has many attributes, it is easy to reduce 200 attributes to 50. Data can be classified into two kinds. One is data gathered from users, the other is data generated by the company. Nearly all data gathered from users seem to affect customer churn. Fifty attributes are selected manually considering the description of expert.

[Table 2] Selected variables

variables	Description
SERVICE_ID	Service ID
MUST_MON	Compulsory usage period
ACCT_MON	Usage period
AGE	Age
SEX	Sex
S-VALUE	Bonus Point given by a company
TRAN_IND	Whether churn user or not

BAD_CRED	One's credit status
WEDDING	Whether one is married or not
BAD_MDL	Whether one's mobile phone is old or not
SUSP_CNT	Total number of suspension
INB_CNT	Total number of inquiry
SPECIAL_OPTION	Whether one has "family option" or not
OWN_TYPE	Whether phone is hired or not
DEL_MONEY	The total amount of arrears
BILL_MONEY	Average charge

4. Result and Analysis

4.1 selected variables and methods

Because there is no common churn rate prediction system and data set is different from case to case, it is difficult to measure the general performance of SAGA based CBR system. In this study GA-based CBR is selected to compare the performance. Logistic regression is also used as statistical model for predicting classification. The company of the study uses customer loyalty index which focuses mainly on the service charge, which is irrelevant to customer churn. This is index is also used for performance comparison.

Table 3 gives a brief description of selected method used for performance comparison

[Table 3] Selected method used for performance comparison

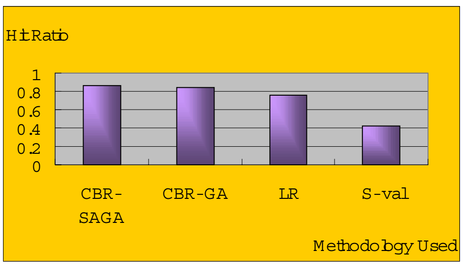
SAGA based CBR	Proposed approaches in this study
GA based CBR	Hybrid approach suggested in data mining area
Logistic regression	Statistical model generating possibility of including a certain classification category
S-value	Customer loyalty index in the company

The parameters related to GA algorithm have the same value in SAGA based CBR and GA based CBR except terminating conditions. Using a SAGA algorithm, it takes to much time if terminating condition is not tightly defined. 2500 GA iteration has internal iteration caused by SA algorithm and its time complexity is much bigger than general GA based CBR.

In logistic regression, after executing regression, the possibility with which a certain input data will be classified into category Ci. It is the choice of a decision maker at which point between [0, 1] is set up as the division point.

In this study division point is set up at the point which divide data into 2 category and maximize the hit ratio.

Figure 9 show the performance of each methodology



[Figure 9] The performance of each methodology

SAGA based CBR shows the highest prediction performance and GA based CBR and Logistic regression is better than S-value. It is natural that s-value has the lowest performance in predicting customer churn, because there is no concept of customer churn in s-value. S-value focuses on the service charge.

Classification accuracy is used as a performance index, because other indices such as response time and difficulty in performing of each methodology is less important than classification accuracy. The focus of this paper is predicting churn probability. Churn prediction need not to be preformed in real-time base. It is off-line batch job, namely, when it is required estimate churn probability, then this methodology is applied to service data and calculate churn probability. Other performance index doesn't have significant meanings.

4.2 Hypothesis test for performance comparison

In the previous section, the paper dealing with Genetic algorithm based CBR is reviewed and suggested methodology uses SAGA based CBR. It is meaningful to compare the performance of above two methodology. Because the main function of hybrid method is classifying customers with regarding to their data, it is also meaningful to compare suggested methodology with logistic regression - calculating the probability that given data is classified into given categories. As shown in the table 4, the hypothesis tests on two proportions, hit ratio, show that the two proportions have difference with a 5% level of significance.

$$\begin{cases} H_0: \ p_1 = p_2 & \textit{where } p_1 \textit{ is the hit ratio of proposed method} \\ H_1: \ p_1 > p_2 & \qquad p_2 \textit{ is the hit ratio of GA based CBR} \end{cases}$$

[Table 4] The performance comparison & hypothesis test between selected methods

Method	Prediction Accuracy	Hypothesis test
SAGA - CBR	86.64%	$1.96 = Z_{1-0.05/2} < Z = 4.11$
GA - CBR	83.72%	
Logistic regression	75.36%	
S-value	42.52%	

SAGA based CBR is better than GA base CBR and logistic regression. It is expected to predicting churn rate effectively using the suggested methodology.

5. Procedure of decision support using churn rate prediction

5.1 Churn analysis and OLAP

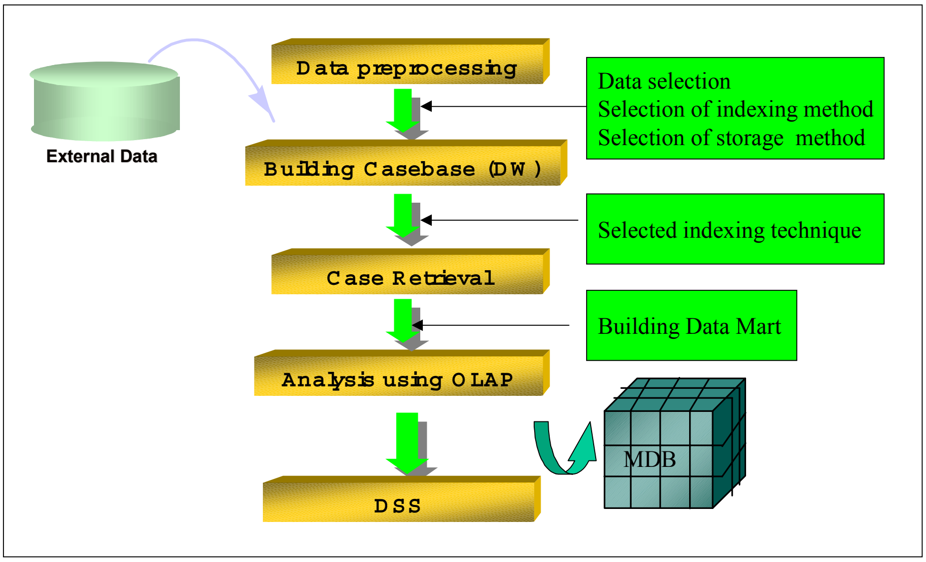
The characteristics of the data in this study can be summarized as:

- Huge amount (enough to build case base)
- Many attribute (50 dimensions)

Because the amount service data is very large and data has many attributes, it is not effective to build relational database to analyze service users. In many previous research, Data Warehousing and OLAP(On-Line Analytic Processing) are suggested as an alternative to OLTP(On-Line Transaction Processing - analysis tool for large database, in case of data in the database has subject-oriented and time-variant feature) [10].

5.2 Procedure of analyzing customer churn using Data Warehouse Technology

As mentioned above, it is much helpful to support decision making of a telecommunication company using Data Warehouse technology. The following figure 10 shows the procedure of analyzing customer churn using Data Warehouse technology.



[Figure 10] The procedure of analyzing customer churn using Data Warehouse technology

<u>External Data</u>

Originally many kinds of data are gathered and inserted to the Data Warehouse. In analyzing customer churn, however, main data source is service data and the source of data is mainly induced internally, it is still required to migration of external data. Because internal data is nearly composed of service data, there is no environmental data such as a rise in price, technological trends, and economic status. Though customer churn may be affected by service data itself, it is not negligible the influence of external data.

Data Preprocessing

In data preprocessing, data selection is needed as an input data of churn prediction system. Because the volume of service data is large, it is indispensable to select which data affects the churn rate. Statistical analysis and expert's experience is need to be considered together. In service data there is much categorical data and it is not easy to consider the categorical data and numeric data such as average charge, age, and average income at the same time. Expert's experience is helpful to reduce the number of attributes in this data. After reducing the number of data, statistical analysis should be applied to the data. It is already determined which indexing method will be used in data preprocessing, because an indexing method influences whether certain data is selected or not.

Case Retrieval

- In case retrieval step, a pre-determined case indexing method is adopted to retrieve a similar case in casebase, Data Warehouse. The retrieved case itself has significant meaning in analyzing customer loyalty. It is more meaningful when the result is analyzed using the OLAP tool. In this step, the preparation for data migration into Data Mart is fulfilled

Analysis using OLAP

Data in the Data Mart is retrieved and then, analyzed by OLAP tool. In the customer churn problem, OLAP is utilized for identifying patterns of data, dimensional difference, and unexpected relationships. When a query-based system cannot support ad hoc query adequately, it is difficult to analyze the data in various viewpoints [21].

DSS module

However the OLAP tool analyzes the current status or predicts customer churn, i.e., it gives decision maker some clues and helps, it cannot decide actions or alternatives for an analyzed problem. When the result of OLAP analysis is combined other DSS module such as financial system and sales system, it becomes a more useful DSS sub-module in a cellular service company.

6. Conclusion

In recent researches, many papers suggest hybrid approaches as alternatives for knowledge-based systems, and rule-based systems. Local search heuristics are widely used to solve combinatorial problems. In this study CBR with SAGA(Simulated Annealing and Genetic Algorithm) approach is proposed for predicting churn rate of a telecommunication service company. The result of predicting churn rate is compared to other approach - Logistic Regression and CBR with GA. SAGA is used to assign the weight vector of case indexing in CBR. Architecture of a decision support system which focuses on reducing churn rate of telecom co., is also suggested.

As mentioned above, churn rate is a hot issue in the telecommunication industry. Churn rate prediction will be more effective when it is mixed together with other decision support systems such as OLAP, DW, data mining and classical management information system.

7. Further study

When a hybrid method is used, it is generally said that if correlation of method used in hybridization is low, the method is more effective than each methodology [19][24][25]. In this study CBR impute its burden of determining weight vector to SAGA algorithm. It is required to research other methods mixed with each others which have synergistic effects or mutually complementary cooperation.

To enhance the performance of suggested methodology predicting churn rate of telecommunication company, it is helpful to regard the satisfaction level of a customer, how much a customer is satisfied with the current service level. When the satisfaction level of a customer is known or calculated from given data, it is possible to compute bayesian churn probability of the customer. If churn probability with regarding to satisfaction level is known and the satisfaction level of a new customer whose churn probability is needed to predicted can be calculated, it is expected to estimate the churn probability of a customer more accurately.

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