Design procedure and improvement of a mathematical modelling to estimate customer satisfaction

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Abstract

A design procedure of the customer satisfaction model, which is required for an artificial adaptive service system action, is introduced. And the methods to improve the model are presented using a statistical analysis and selection of several clustering methods that form the mathematical service model from the surveyed quantitative data. Using a case-study about the hotel guest service, accuracies of those methods were evaluated by cross-validations. As a result, the Naive Bayes clustering method and the REPTree algorithm showed good estimation of the customer satisfaction as much as about 40 percent.

Keywords:

Customer satisfaction model, M-GTA, data clustering, hotel reception service.

1 INTRODUCTION

Although people tend to think that service is directly provided and received between service providers and customers, rate of such situation against whole service encounter is much smaller than people expect. Various types of artificial systems－such as computer systems, networked infrastructures, automated buildings, and mechatronics products－ transmit a service between service providers and service recipients [1]. Now, on the other hand, the service industry becomes most important position in the economy, and a ratio of the service in GDP in advanced countries reaches 70 percent [2]. Most of benefits of the service industry's development are given by the development of above-mentioned engineering technologies. These technologies are, however, mainly utilized as a tool to make a process of the sending or receiving of service more efficient. In other words, an artificial system created using the engineering technology has not provided a service adaptively and autonomously to a human customer.

Meanwhile researches on an adaptability of a machine to a human, such as Human Adaptive Mechatronics [3] and COGNIRON [4], are under active investigation. The enhancement of such adaptability of the artificial systems is also expected from the service field. Under the circumstance, an academic discipline, service engineering, was launched to generate new worth of service by integrating engineering, psychology, information-technology, and economics. In the service engineering, mathematical modelling and a design theory to provide a service are studied mainly using artificial systems such as robots and computer systems.

A behavior design model implementable into the artificial system providing adequate service is, however, quite difficult due to ambiguous characteristics of a service such as intangibility, simultaneity, heterogeneity, and perishability [5]. In order to know the level of the service provided from the system, what information should be measured from a human service recipient? How do we have to build the database to deal with the implicit knowledge about the target service? Little is known about a design procedure for the implementable model to provide service. To this issue, the present authors have opinion that mathematical model expressing satisfaction/values of the service receiver/provider is significant. Therefore, in our previous study, a feasibility study was executed by focusing on the following points [6] :

- Proposition of a mathematical modelling of customer satisfaction concerning service interaction
- Suggestion of a design procedure to obtain the mathematical model
- Verification of the modelling through a case-study of hotel service

In that study, although a procedure to derive the service model concerning the above-mentioned first and second items was shown, sufficient accuracy of the model could not be achieved. The insufficient result appears to have come from inadequate matching between characteristics of the hotel service and the SOM technique which was used there to form the mathematical data structure. Therefore in this study, various clustering algorithms except SOM were applied for the modelling, and the effectiveness was investigated. In short, the purpose of this study is to improve the mathematical modelling by using various types of clustering methods.

The latter sections are organized as follows: In Section 2, the concept of a customer satisfaction / evaluation model, which were reported by reference of [6], are introduced briefly. In Section 3, the design procedure is explained concretely using a case-study of a hotel reception service. Section 4 is main body of the presented paper, and a procedure to select information to build the service model is mentioned. Several types of clustering algorithms are explained there, and the results of the model verification are analyzed. Last Section 4 presents the conclusion.

2 CUSTOMER SATISFACTION MODEL

The reception service exists in various kinds of business, and it effects a creation of customer satisfaction and customer loyalty especially [7]. Therefore, in our previous feasibility study, reception service was focused on, and the mathematical model to evaluate customer satisfaction was presented. For the reception service, two types of models－a provider-worth model and a receiver-worth model－have to be considered separately. The concept is shown in Fig. 1.

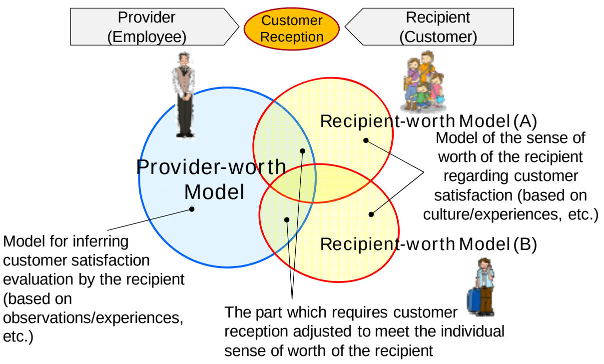

Fig.1 Hypothetical structure of reception service in a hotel

As shown in the figure, each one of customers has an own recipient-worth model. Based on his/her model, customer's satisfaction is determined depending on the provided service and other factors. On the other hand, the provider infers the customer satisfaction by referring own provider-worth model. The provider-worth model is formed by reflecting his/her experience and knowledge with estimation of the recipient-worth model. The provider behaves by referring the provider-worth model, and he/she provides adequately the service for the customer.

Based on this concept, a procedure to construct the customer satisfaction model was presented, as shown in Fig. 2. First step, Step 1, is clarification of the tacit knowledge, and sociological qualitative methods such as the interview analysis and the observational investigation are used to form a structure of the provider-worth model. Further, service factors manipulatable by the service provider, other factors reflecting the satisfaction of the recipient, and relation between them are elucidated. The second step (Step 2) quantifies the relation among the factors that were found in Step 1. For this, a survey methods by questionnaire resembling a marketing research is used. Since the data obtained at Step 2 are inevitably multidimensional and multivariate ones, multivariable analyses including a clustering method and statistical approach are applied to obtain quantified database-like model by reflecting the correlation of these variables. Then, a level of new customer's satisfaction and his/her sense of worth are predicted using the database-like model. This process belongs to Step 3. To wrap up, the customer satisfaction model is numerically constructed as a data-based clustering which was trained using the questionnaire data.

In our previous study, self-organizing map (SOM) [8], which is generally suitable for multivariate clustering, was used for Step 3; however, the accuracy of the obtained service model was low. Therefore, in the present study, we tried to improve the model accuracy using several clustering methods other than SOM. The details of their clustering methods will be explained in Section 4.

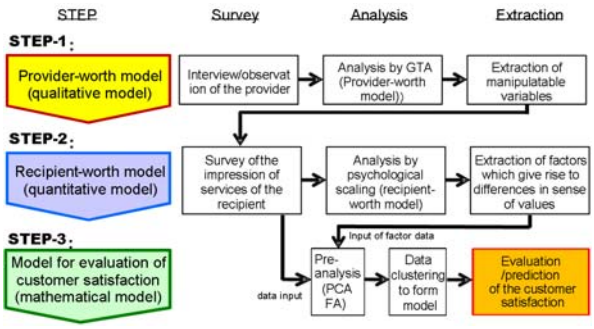

Fig.2 Design procedure of a mathematical model of service satisfaction evaluation

3 CASE STUDY: MODELLING OF HOTEL RECEPTION SERVICE

In this section, Step 1 and 2 of the design procedure are introduced briefly through the case study of hotel reception service, which was treated in our previous study.

3.1 Step 1: Provider-worth model

In Step 1, an implicit knowledge about the hotel reception service is clarified. For this aim the providers' empirical rules and comprehension mastered through his/her experience are investigated. Specifically the qualitative structure concerning the service is extracted by using the modified grounded theory approach (M-GTA) [9]. In case of the hotel service, we interviewed several hotel staffs, observed their treatment for customers, and investigated their action using an ethnography method. Important point on the interview is to clarify what the input and output information for the provider-worth model are. Specifically, we tried to find what of the customer the hotel service provider paid attention to and how the provider made his / her action.

With the help of Royal Park Hotel (Kanagawa, Japan) and Kobe Portopia Hotel (Hyougo, Japan), the group interview was conducted for the following types of work: reception staffs (three staffs who had 12, 10, and 1 years of work experience, respectively), doormen (two who had the 6 and 3 years of experience, respectively), and restaurant staff (two who had the 17 and 5 years, respectively). The duration of the group interview was approximately 90 minutes for each group. All the speech obtained in the interviews was recorded with permissions obtained from the participants. Qualitative analysis M-GTA was performed using the management software MAXQDA2007. Figure 3 shows the obtained chart that expresses association of service elements. As an input information for the provider-worth model, various elements written in the block of "observation of guest" in Fig.3 were found: for instance, types of guest car, entrance and route the guest used, number of accompanying person, clothes, and types of baggage. As the output, the following unique stances as a hotel staff were found:

- They, hotel staffs, are conscious to treat each customer as a special guest.
- They keep in mind that they propose proactively something good more than the guest requests.
- They try to treat the guest in a casual manner rather than in a formal way.

The extracted implicit knowledge and elements were utilized for the following Step 2.

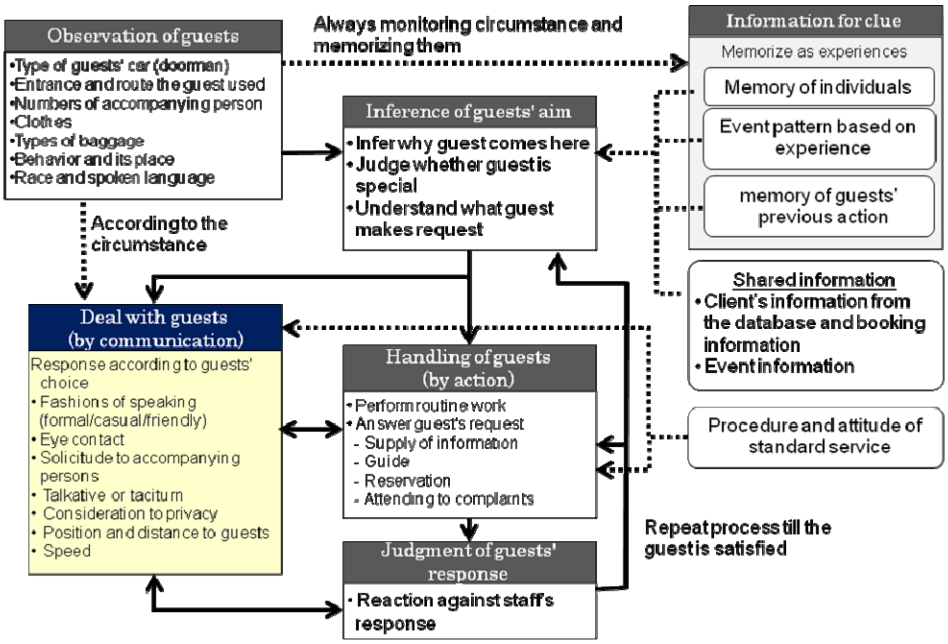

Fig.3 Provider-worth model in hotel reception services (qualitative model)

3.2 Step 2: Recipient-worth model

The service recipient evaluates a service given by the provider, and his/her evaluation is strongly affected by his/her own cultural and psychological background. To know the mutual relation concerning personal characteristics of the recipients, it is necessary to collect data from a certain number of recipients. Therefore, quantitative data are collected by a questionnaire using the psychological scale in this Step 2. The question items are made so as to measure the service factors that were confirmed in Step 1 via the qualitative analysis of the service providers. For it, web questionnaire method by an online panel was used.

In consideration of the results of the survey in Step 1, the items shown in Table 1 were surveyed. For the evaluation of the customer satisfaction to the hotel services, the survey items of JCSI (Japanese Customer Satisfaction Index) were utilized as a reference with partial revision [10]. The following instruction was given in order to make participant recall their experience as accurately as possible since the customer satisfaction evaluation of hotels is a retrospective evaluation with regard to his/her experience of each respondent:

"Please recall a single most memorable experience of a stay among your experiences within a year."

Table 1 Items of questionnaire survey

#	Survey Items	No. of Items	Measurement Scale
1	Experience of a stay at the lodging facilities	5	nominal scale
2	Reason to determine the hotel	4	nominal scale
3	Evaluation of customer satisfaction regarding hotel services (by reffering JCSI)	17	scoring method (out of 10)
4	Sense of worth of services (based on Step 1)	16	five-point rating scale
5	Evaluation of worth of customer reception patterns (based on Step 1)	5	five-point rating scale

* JCSI : Japan Costomer Satisfaction Index

Fourth item in Table 1, which is "the sense of worth of service", was asked by eight items as shown by S1-S8 in Table 2. The sympathy ratings of the respondents to these items were surveyed by the five-point rating scale. Fifth item in Table 1 was asked by other eight items as shown in Table 3

Table 2 Examples of items related to the sense of worth about services

#	item
S1	I (the participant to this questionnaire) think that a little selfishness is permissible because I paid the charge.
S2	Customer reception service should be as moderate as possible when I did not specially request it.
S3	Customer should complain if there is even a little difference from what I expected in advance.
S4	Regarding a small inconvenience, I can just bear with it.
S5	I say words of thanks to a hotel staff if I got pleasant service.
S6	I do not hesitate to give more tip to a hotel staff who provides good service.
S7	When a service is not provided on time, I ask a staff member about it before voicing complaint
S8	I feel sorry when I request a hotel staff to do something for me.

Table 3 Examples of items for evaluation of the worth of patterns of customer reception

#	item
1	When receiving services of a higher grade, I wish to get special personal treatment.
2	Recommendation provided by the hotel staff without my request is a good service.
3	Thorough reception services are not necessary if the expected level of service is being provided.
4	An informal and friendly speech in customer reception is better than polite treatment
5	Even when the staff is busy, they should pay attention to a guest with the highest priority.

6	I am pleased when the customer reception staff call me every time by my name.
7	I'm glad to receive simple reception since the customer reception is troublesome for me.
8	Quick response is better than thorough reception

The participants were sampled from persons having an experience of a stay in a hotel or an inn (Japanese "ryokan") within one year. Participants were allocated as shown in Table 4 in order to reduce biases by frequency of use and purpose of use. 10,054 samples of both genders and of ages 20～69 were extracted at random nationally from the registration panel. There were 4,339 responses (43.2% response rate) to the questionnaire for screening participants, and participants corresponding to the allocation were extracted for the latter analysis. Valid responses were received from 310 persons (male 72.6%, female 27.4%), and total 302 samples were obtained after an elimination of outlier data.

Table 4 Allocation of samples for hotel service questionnaire

	Frequencies of private use	
Frequencies of business use	High	Low
High (more than once in a half year)	75 samples	75 samples
Low (less than once in a year)	75 samples	85 samples

4 STEP 3: MODELLING FOR EVALUATION OF CUSTOMER SATISFACTION

4.1 Selection of the service input/output variables

Adequate decision of conditional variables (input variables) and satisfaction variables (output variables) is required for a better learning of the mathematical model. Concerning the input variables, the following items were chosen from Table 2 by considering their significant levels: all items of #1, #4, and #5, two items of #2, and two screening conditions (sex and age-group). At that time, nominal scales in item were coded into number data. For items answered by multiple selections, the data were reduced by integrating multiple answers into one variables through a binary-to-decimal conversion. Finally, 30 items were chosen for a service input variables vector, say x. Concerning the output variables, high-independent items among 17 items in Table 2-#3 were elected. As a result of correlation analysis among those items, the three items— "Total satisfaction level ($j1$)", "Level of goodness to your hotel selection ($j2$)", and "Effectiveness to your life by selection of the hotel ($j3$)"—have strong correlation ($r_{j1 \text{ vs } j2}$=0.86, $r_{j2 \text{ vs } j3}$=0.76, $r_{j3 \text{ vs } j1}$=0.72); hence, these were summed up into one variable J_1 $(=j1+j2+j3)$. Since items about an attitude to guests had high independency against other items, only this item was selected as the second input variable J_2. And the four items — "I want to use that hotel frequently", "I want to use it for other purpose", "Do you want to use it again?", and "Will this hotel be first candidate?" — had strong correlation as much as 0.86-0.91, and these items data were summarized into an output variable J_3.

Since decision tree algorithms, used in this study, can basically deal with only scalar data as discrimination information, three classifiers by each algorithm were learned using J_1, J_2, and J_3 respectively. That is, classifiers C_1, C_2, and C_3 were trained using datasets $\{x, J_1\}$, $\{x, J_2\}$, and $\{x, J_3\}$, respectively. Then, satisfaction indexes corresponding to J_1, J_2, and J_3 were predicted using C_1, C_2, and C_3, separately.

4.2 Pre-analysis by statistical approaches

Variables shown in Section 4.1 were chosen intuitively although several statistical processes were applied. In order to decrease the insufficient objectivity, further statistical analysis about sense of worth of a service was performed. Applying a principal components analysis (PCA) to items S1-S8 which were shown in Table 2, three components could be extracted. These components were named "concern to hotel staff", "patience", and "selfish", respectively. Their factors and contribution ratios are summarized in Table 5. The cumulative contribution ratio of these three components was 55.5%. Hence, the original eight items were converted into the three variables by a linear combination with proportion of the contribution rates. The new input vector variable x_p was defined by replacing the original eight items into above three elements.

Table 5 Contribution ratios obtained by PCA (about items of worth of service)

Item No in Table 2	1st componet "Concern to staff"	2nd componet "Patience"	3rd componet "Selfish"
S5	**0.78**	-0.11	-0.14
S7	**0.71**	-0.02	0.06
S6	**0.59**	-0.28	0.09
S2	**0.55**	0.24	0.16
S4	-0.01	**0.83**	-0.12
S8	-0.09	**0.68**	-0.02
S1	-0.12	0.09	**0.85**
S3	-0.03	-0.36	**0.66**

Moreover, factor analysis (FA) was applied to the items asking customer satisfaction. FA with a promax rotation against 17 questionnaire items found two factors, and they could be interpreted as "possibility of a repeat customer" and "customer's expectation". Representative items among these 17 items are shown in Table 6 with their factor loadings. The first factors of the top three items is as large as 1. This means that `Do you want to utilize the same hotel again?' reflects comprehensive satisfaction better than the original items, that are 'How happy are you with the hotel service comprehensively?' Therefore, these three factors were newly used for the service output variables and are described by J_a, J_b, and J_c, respectively. In short, classifiers C_a, C_b, and C_c were formed using datasets $\{x_p, J_a\}$, $\{x_p, J_b\}$, and $\{x_p, Jc\}$, respectively. Then, satisfaction indexes corresponding to J_a, J_b, and J_c were predicted using the trained C_a, C_b, and C_c, separately.

Table 6 Loading factors computed by FA against question about customers' satisfaction

	Questionnaire items	1st comp	2nd comp
Q.4-16	Do you want to keep utilizing this accommodation?	1.03	−0.16
Q.4-14	Do you want to utilize this accommodation more frequently?	1.02	−0.14
Q.4-17	Is this accommodation the first candidate next time?	1.01	−0.16
Q.4-12	Did total quality of the accommodation outweigh your laboriousness of the reservation?	0.79	0.16
Q.4-11	Do you agree the quality of the accommodation is adequate for cost you paid?	0.74	0.17
Q.4-2	Do you think you made the right decision to select this accommodation?	0.61	0.36
Q.4-1	How much did you receive satisfaction from the service in this accommodation?	0.41	0.54
	...		

4.3 Classifiers

Our approach to predict customer's satisfaction consists of two phases; a learning of the classifier and an estimation of other customer's satisfaction by the classifier. Hence, an accuracy of the prediction is affected depending on a combination between the types of classifier and characteristics of a target service. Although various types of classifiers are known [11,12], decision tree type classifiers were adopted in this study since it is orthodox. Decision tree analysis is a tree-like model of data produced by a data mining method and is principally used to choose between several courses of action. In the field of the machine learning, the decision tree has been utilized to determine the action under some conditions. The computation was executed by the WEKA machine learning algorithm toolkit [13]. From various classifiers provided by WEKA, the following algorithms which do not depend on a structure and property of data [14] are selected:

- C4.5 Tree (J48)
- Naive Bayes
- NBTree
- RandomForest
- RandomTree
- REPTree

C4.5 algorithm was developed by Ross Quinlan [15]. The decision trees computed by C4.5 have been often used for classification. For this reason, C4.5 is often referred to as a statistical classifier. This classifier is not so precise, but it is most popular method; hence, C4.5 was chosen for our analysis. In the Weka analysis, J48 algorithm which is almost equivalent to C4.5 was used. In the learning process for this classifier, confidence factor and minimum number of objects were specified as 0.25 and 2, respectively.

Naive Bayes classifier is a typical probabilistic classification method. This method is based on Bayes' theorem with naive independence assumptions. In spite of its naive design and apparently oversimplified assumptions, it is well known that this classifier is quite effective against many complex real-world problems. Although this classifier is not a decision tree, it was adopted since this algorithm is implemented in WEKA.

Naive Bayes Tree (NBTree) is an algorithm to make a decision tree using the naive Bayes classifier approach [16]. NBTree is a so-called hybrid type from Beyes classifier and decision tree.

RandomForest is one of a meta classifier algorithm by combining several decision trees that are generated by bootstrapped sub classes of data [17]. In other words, this is a group learning algorithm that utilizes a decision tree as a weak classifier. This method was selected as a bootstrap method that is popular technique in various classification approaches. Since it is known that this algorithm works well for a case involving many explanatory variables, this appeared to be feasible for our case-study of the customer satisfaction prediction. The number of trees, the seed, and the number of features were specified as 10, 1, and 0, respectively on the WEKA computation.

RandomTree is other type of decision tree, and this method chooses variable for bifurcation at random. The minimum number and the seed were specified as 1.0 and 1, respectively.

REPTree generates a tree structure using information of the gain and variance. Algorithm of REPTree resembles C4.5, but it differs from C4.5 on the pruning method. It is said that this method has a merit in a high-speed computation rather than the accuracy. In the learning process, the minimum number, the minimum variance, the number of the folding, and a seed were specified as 2.0, 0.001, 3, and 1, respectively.

Decision tree principally classifies objective variables into finite number of discrete bins. This means that decision tree does not have ability to output analog value. With consideration of this feature, values of customer satisfaction, which became pseudo analog information because of a use of scoring method in questionnaire, were discretized using several bins. It was predicted that difference in the number of bins affected to the estimation accuracy; hence, two cases (five-scaled and ten-scaled) were specified since five bins, i.e., five-scaled, was equivalent to the original scale of the questionnaire. In both cases, it was confirmed that their histogram of customer satisfaction were almost Gaussian, and there are no problem of the selection of the number of scales.

4.4 Result of verification

Estimation accuracies of each classifier were investigated by the 3-fold cross validation. Figure 4 summarizes the matching ratios of the predicted satisfaction in case of ten-scale, which was selected as double precise scale against original questionnaire scale. The matching ratio is a percentage of the predicted satisfaction level against the actual satisfaction level answered by the participants on the questionnaire. Blue bars in the graph indicate the mean value of the matching ratios in case of a use of data set consisting of x and J_1-J_3 (hereafter, normal-case). Words attached to each bar indicate types of the classifiers which were explained in Section 4.3. Red bars are another results in case of a use of preanalyzed data, x_p and J_a-J_c (heareafter, preanalysis-case). Upper and lower lines were drawn on each bar to express the maximum and minimum of the master data. From the figure, it is found that sufficient matching ratios could not be obtained in case of ten-scale since the maximum value given by NBTree is as low as 25.2%.

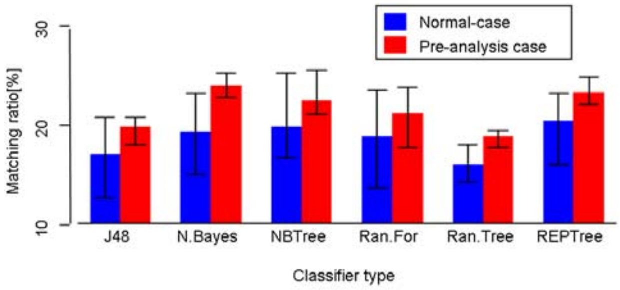

Fig. 4 Matching ratio of an estimation of customers satisfaction expressed by ten-scale (blue bars: normal-case, red bars: preanalysis-case)

Another results obtained using the five-scaled satisfaction are shown in Fig. 5. From the figure, it is confirmed that the matching ratios were more improved as 30-35% than the ten-scale case. This improvement might be no wonder since the resolution of the satisfaction level was reduced. The five-scale is, however, same as original scale used in the questionnaire; hence, it is reasonable to adopt the five-scale for the output variables of the service model.

Checking the difference in the normal-cases (blue bars) and the preanalysis-cases (red bars), it is found that any preanalysis-case is higher than normal case in all types of classifier in both five-scale and ten-scale cases. This fact indicates that pre-analysis, which was shown as Step 3 in Fig.2, is effective to enhance the accuracy of the service model.

Last, tendency of each classifier was investigated. From the figure, N.Bayes showed best accuracies in both cases of five-scale and ten-scale. (mean=45% in case of the five-scale, mean=24% in case of the ten-scale)

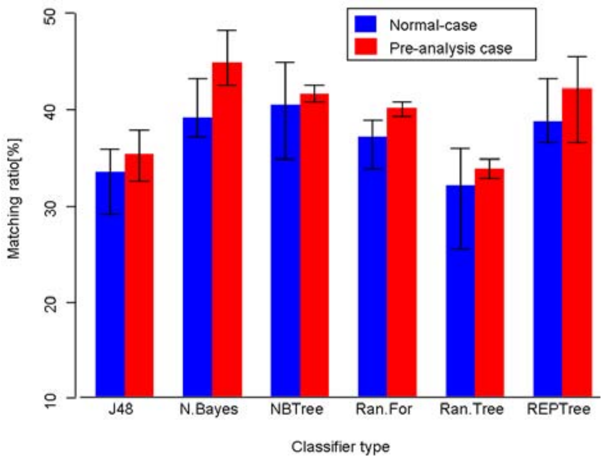

Fig. 5 Matching ratio of an estimation of customers satisfaction expressed by five-scale (blue bars: normal-case, red bars: preanalysis-case)

The second best is REPTree (mean=42%:five-scale, mean=23%:ten-scale). These results may show that Bayesian approach is better than decision-tree type in case of the hotel service modelling. This inference is also supported by other fact that Naive Bayes is superior to RandomForest, that is a meta-optimization of decision tree classifier. It can be guessed that satisfaction of hotel customers is decided by probabilistic correlation based on our experience rather than simple combination of the conditions, because Bayes approach can reflect subjective probabilistic relation. This inference might be helpful as a guideline to deduce model of customer's behavior.

5 CONCLUSION

Concerning a design procedure of the customer satisfaction model required to be implemented in artificial service systems, accuracies of the modelling were verified using several classifier algorithms. Through a case-study of the hotel guest service, a qualitative analysis of the hotel customer service was performed to the several hotel staffs. The result was reflected to items of the web questionnaire to obtain effectively information to build the customer satisfaction model. Unlike the authors' previous feasibility study, six types of classifiers were applied to form the customer satisfaction model with a stochastic pre analysis in this study. The accuracies of those models were evaluated by the cross-validations, and the following results and conclusion were obtained:

- Estimation accuracy of customer's satisfaction could be improved to about 40% by selection of an adequate clustering method in case of the hotel service.
- The naive Bayes clustering method was more effective than decision tree types. However, REPTree utilizing the variance and gain tuning depending on the raw data was effective although this was a type of decision tree algorithm.
- Pre-analysis by PCA and FA is effective to improve an accuracy of the mathematical service model. This effect is valid regardless of the type of clustering algorithm.

The estimation accuracy by the approach mentioned in this paper was able to be improved as much as maximum 45%. This result is better than previous feasibility study, where the accuracy was 16-22%. Although this comparison is not strictly fair since variable conditions for their clustering methods differ from each other, an improvement of the mathematical modelling of customer satisfaction could be achieved. In conclusion, effectiveness of the presented procedure of the design of the service modelling could be enhanced.

Future works are additional statistical analysis to obtain further accuracy and the improvement of design of the questionnaire for the modelling.

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