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레저산업의 고객관계관리 문제에서 기상예보의 정보가치를 최대화시키는 의사결정전략 분석*

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A Decision-making Strategy to Maximize the Information Value of Weather Forecasts in a Customer Relationship Management (CRM) Problem of the Leisure Industry

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■ Abstract ■

This paper presents a method for the estimation and analysis of the economic value of weather forecasts for CRM decision-making problems in the leisure industry. Value is calculated in terms of the customer's satisfaction returned from the user's decision under the specific payoff structure, which is itself represented by a customer's satisfaction ratio model. The decision is assessed by a modified cost-loss model to consider the customer's satisfaction instead of the loss or cost. Site-specific probability and deterministic forecasts, each of which is provided in Korea and China, are applied to generate and analyze the optimal decisions. The application results demonstrate that probability forecasts have greater value than deterministic forecasts, provided that the users can locate the optimal decision threshold. This paper also presents the optimal decision strategy for specific customers with a variety of satisfaction patterns.

Keywords : Customer Relationship Management(CRM), Cost-loss Model, Customer's Satisfaction Ratio Model; Value Score

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1. Introduction

Many decision-making problems in businesses (e.g., manufacturing, distribution, construction, electricity generation, etc.) are quite sensitive to weather information. A weather forecast has value if, and only if it can be used to make decisions that provide some benefit to the end user (Katz and Murphy, 1997; Mylne, 2002). Weather forecasts are generally provided to users with the best estimate as to whether a defined weather event of concern will occur, in a deterministic or probabilistic fashion. A decision maker attempts to determine the optimal action, which generates the maximum benefits from the provided weather information. Many studies have been conducted to evaluate the economic values of the applications of weather information on the basis of a user's prototypical decision-making models, the majority of which assume basic cost-loss ratio situations (Thompson, 1952, 1955; Murphy, 1976, 1977; Katz and Murphy, 1997; Stewart et al., 2004; Jolliffe and Stephenson, 2003).

The simple cost-loss ratio model assumes that a decision maker is obliged to decide whether or not to employ a protective action by considering the imperfect forecast information related with a particular adverse weather event. This protective action can reduce the loss of expenses with a smaller protection cost. However, an even larger loss will be incurred unless the protective action is taken with an occurrence of the adverse weather event. As the cost-loss ratio model has an advantage in describing realistically the situations faced by many forecast-sensitive decision makers via a considerably simple normative structure (Murphy, 1976), it has been utilized as a useful framework by which the use and the value of weather forecasts might be assessed.

Several studies have extended the basic cost-loss ratio situation to application in a variety of real world situations. Murphy (1985) proposed the generalized model with N actions and N events to augment a basic situation with two actions and two events. The dynamic or sequential models, in which assume that repetitive decision-makings are conducted, were discussed within the context of the basic situation (Murphy et al., 1985; Epstein and Murphy, 1988; Katz, 1993). Moreover, a considerable range of approaches have been conducted to investigate the relationship between forecast quality and forecast value for both the static and dynamic versions (Murphy et al., 1985; Katz and Murphy, 1990; Thornes, 2001; Wilks, 2001; Mylne, 2002; Zhu et al., 2002). Additionally, the study previously conducted by Murphy and Ye (1990) suggested a time-dependent version of the cost-loss ratio model to describe a situation in which the decision maker may delay the decision until forecasts of greater accuracy become available, despite the increased cost of protection inherent to the delay in action. Recently, Lee and Lee (2007) proposed a profit-loss model to estimate the economic value of forecasts for profit-oriented enterprise by expanding the traditional dichotomous actions to the continuous degree of actions.

This paper proposes a modified version of the cost-loss ratio model with the introduction of a customer's satisfaction index for the estimation of the economic value of weather forecasts of dichotomous events. One of two possible actions is determined by the expected degree of the customer's subjective satisfaction, which results from the accuracy of the provided forecast information. The decision maker considers the customer's satisfaction deriving from the action in addition to the degree of cost savings afforded as a benefit of the use of the weather information. In particular, the principal objective of customer relationship management (CRM) in most businesses is to maximize customer satisfaction, rather than to minimize expenses. This paper presents a positive-negative satisfaction ratio model adapted from the conventional cost-loss ratio model, designed to conform to the realistic situations faced by enterprise-based decision makers, whose principal concerns are the maximization of customer satisfaction. This approach is directly relevant to clients of the enterprise, and should also prove informative to forecast providers, who are most interested in the value of their forecasts, which may differ for different customer types.

In Section 2, a modified value score method for the calculation of forecast value is described via a CRM decision-making model to emphasize the maximization of customer satisfaction rather than the minimization of costs or losses. Section 3 provides a practical application of the proposed evaluation method for real forecast data. Finally, conclusions of this study are presented in section 4.

2. The Economic Value of Forecast for a CRM Related Decision-making Situation

From the viewpoint of decision makers in weather-sensitive businesses, forecasts are valuable only if an action is taken as a consequence of provided forecast information, and additionally only if that action proves profitable. This study modifies the basic cost-loss model initially introduced by Thompson (1952) and explained in details by Jolliffe and Stephenson (2003) such that it maximizes customer satisfaction rather than minimizing losses. The proposed approach considers the economic value for various customer types, thereby providing the more universal analysis required by forecast providers and users.

2.1 The Specific Decision-making Model for CRM service

The basic cost-loss model with a deterministic forecast for a binary weather event is extended to the decision-making model for the CRM service in a leisure industry. In this paper, it is assumed that a decision maker in charge of a CRM service in a resort must decide whether or not to undertake a specific customer service action, on the basis of the probability forecast provided for a specific precipitation event. The customer service, in this case, involves sending the subscriber a short message on a mobile phone, notifying the subscriber that it will rain on the day reserved, and encouraging the client to cancel her/his appointment. Therefore, this customer service action will be taken only if the chances of rain are judged to be considerably high.

The proposed decision-making model also assumes that the decision maker considers a customer's satisfaction index by utilizing the provided probability forecasts. Generally, the decision maker seeks to maximize the customer's satisfaction by forwarding appropriate short messages while minimizing her/his discontent due to the decision maker's misjudgment of the forecast information.

Assuming that the decision maker considers probability forecasts, a modified contingency table is provided in <Table 1>, which represents the degree of satisfaction and dissatisfaction associated with the CRM service. The value of the satisfaction index in the case of 'Correct Rejection' is 0, in a fashion similar to that of the basic cost-loss ratio model. It is supposed that the index value of the satisfaction in the case of 'Hit' is 1 for purposes of ease of calculation. On the other hand, the index values of two types of dissatisfaction in cases of 'False Alarm' and 'Miss' are assumed to be $-A$ and $-B$ ($A \geq 1$, $B \geq 1$). That is, the degree of dissatisfaction can be defined by a value relative to the satisfaction of 'Hit'. Additionally, the degree of dissatisfaction is not permitted to be less than the degree of satisfaction with 'Hit'. Accordingly, the expected degree of a customer's satisfaction from the CRM service consists of the entries in Table 1 weighted by the probabilities in <Table 2>, or

$$E_f = p_{11} - Ap_{01} - Bp_{10} \tag{1}$$

Detailed explanations of Eq. (1) and <Table 2> are provided in the following section.

〈Table 1〉 The 2×2 contingency table for CRM service

		Short Message Service	
		Yes-User sends short message	No-User does not send short message
Adverse Weather Observed	Yes	Hit (1)	Miss ($-A$)
	No	False Alarm ($-B$)	Correct Rejection (0)

〈Table 2〉 The 2×2 verification table for weather forecast

		Forecast Adverse Weather	
		Yes	No
Adverse Weather Observed	Yes	$p_{11} = \sum_{f_i > p_t} p(f_i, o_1)$	$p_{01} = \sum_{f_i \leq p_t} p(f_i, o_1)$
	No	$p_{10} = \sum_{f_i > p_t} p(f_i, o_0)$	$p_{00} = \sum_{f_i \leq p_t} p(f_i, o_0)$

2.2 Calculation of Forecast Value

The economic value of forecasts can be defined by the additional benefits (i.e., customer's positive satisfaction index) derived by the decision maker from the use of a forecast as opposed to not using one, and thus it is assumed that the decision criterion is to maximize the expected benefits. That is, the decision maker is postulated to select a CRM service strategy for which the expected satisfaction index of a customer is maximized, where the expected satisfaction index of the strategy is the probability-weighted average of the satisfaction indices, including the negative and positive indices resulting from the determined strategy and weather events.

2.2.1 Climatological Reference Profit

If decisions are based solely on the information regarding the climatological probability of adverse weather, or π, then the decision maker has two options : either always send the short message or never send the short message. Assuming that the decision maker selects the best strategy, the maximum expected climatological satisfaction index in the decision-making situation (shown in <Table 1>) is given by

$$E_{cl} = \max(-\pi A, \pi - (1-\pi)B) \quad (2)$$

Therefore, the expected satisfaction index when the climatological information is given can be defined as follows :

$$E_{cl} = \begin{cases} -\pi A & \text{if } \pi < \dfrac{B}{A+B+1} \\ \pi - (1-\pi)B & \text{otherwise} \end{cases} \quad (3)$$

2.2.2 Expected profit with perfect forecasts

Suppose that the decision maker has access to perfect forecasts. The decision to send the short message via SMS would then be taken only in cases in which forecasts warning of adverse weather (i.e., precipitation) would occur with the frequency π, thus making the customer's satisfaction index *one*. Otherwise, the strategy not to send a short message, which could lead to an index value of *zero*, would be taken with a frequency of $1-\pi$. Consequently, the expected profit attending perfect forecasts would be

$$E_p = \pi \cdot 1 + (1-\pi) \cdot 0 = \pi \quad (4)$$

2.2.3 Expected Profit with Pmperfect Forecasts

The expected satisfaction index when decisions are predicated on imperfect probability forecasts of adverse weather depends on the decision strategy, the particular customer's satisfaction pattern, and the performance characteristics of those forecasts. In order to make decisions from probability forecasts, the decision maker transforms each probability forecast to categorical (i.e., yes/no) forecasts of adverse weather, in accordance with the magnitude of the forecast probability f (Wilks, 2001). In effect, the decision to send a short message is made in cases in which the probability, p, of the precipitation exceeds a chosen threshold, p_t. Accordingly, the choice of p_t determines both the decision strategy and the value of the forecast.

As a consequence, it is expected that over a number of forecast occasions, the decision maker will experience average customer satisfaction, which will depend on the joint distribution of probability forecasts and the corresponding observations $p(f_i, o_j)$ (Murphy and Winkler, 1987; Wilks, 2001). Here f_i, i = 1, ⋯, I, are the allowable forecasts and o_j, j = 0, 1, are the possible observations for binary outcomes. This study supposes I = 11, with f_1 = 0.0, f_2 = 0.1, ⋯, and f_{11} = 1.0, assuming that the forecast probabilities are rounded to tenths. Although the number of allowable forecasts may be more or fewer than I = 11 depending on the forecast format, Wilks (2001) has previously demonstrated that the simplified model with I = 11 is sufficient to calculate the economic value of probability forecasts. Thus, the expected degree of customer satisfaction can be calculated by considering the decision pattern determined by p_t and the customer satisfaction-related parameters in accordance with the dichotomous weather events and actions provided in <Table 1>, which are weighted by the joint probabilities, $p(f_i, o_j)$, i = 1, ⋯, 11, j = 0, 1. Therefore, the expected satisfaction index obtained from the following specific decision patterns based on imperfect forecasts would be

$$E_f = \sum_{i=D}^{I} p(f_i, o_1) - A\sum_{i=1}^{D-1} p(f_i, o_1) - B\sum_{i=D}^{I} p(f_i, o_0) \quad (5)$$

in which D is the index of the smallest forecast probability that is larger than the threshold p_t (i.e., $D = \underset{i}{\arg\min}(f_i > p_t)$). From the definition of the index D, it can be deduced that precipitation is 'forecast', and thus a short message is sent to the customer for all forecasts with probability f_i, $i \geq D$. The proportion of occasions when this would occur in advance of precipitation would be $p_{11} = \sum_{i \geq D} p(f_i, o_1)$, and the proportion of occasions in which a short message would be needlessly sent would be $p_{10} = \sum_{i \geq D} p(f_i, o_1)$. The probability of precipitation following a 'no' forecast, p_{01}, and the probability of no precipitation following a 'no' forecast, p_{00}, are defined in a similar fashion, as is shown in <Table 2>.

From Eq. (5), we can observe that the expected satisfaction value depends on three features. The first is the particular decision maker's decision pattern determined by the choice of D or p_t. The second is the specific customer's satisfaction pattern represented by two parameters, A and B. The third is the performance characteristics of the forecasts used by the decision maker, as specified by the joint distribution of forecasts and observations $p(f_i, o_j)$. Note that it is quite important to select the most appropriate threshold p_t for the given characteristics of customer satisfaction and forecasts, on the grounds that only the first among three features can be controlled.

2.2.4 Value Score

With regard to the general utilization of forecast value assessments, some studies (Wilks, 2001; Mylne, 2002; Joliffe and Stephenson, 2003) have introduced the concept of a skill score, or value score, transforming the difference form to a normalized scale representing the relative increase in expected return to that of a perfect forecast. The relative economic value of a forecast, referred to as a value score (VS), is defined by

$$VS = \frac{E_f - E_{cl}}{E_p - E_{cl}} \tag{6}$$

3. Applications to Real Data Sets

The proposed skill score model for CRM service in a resort business has been applied to real forecast datasets in order to illustrate two simple verification examples with probability and deterministic forecasts, and was utilized to compare the verification results. The application was predicated on probability forecasts of precipitation in Seoul, South Korea made by the Korea Meteorological Administration (KMA) and deterministic or nonprobabilistic forecasts of precipitation in Shanghai, China produced by the China Meteorological Administration (CMA) for the period 2003~2005. In both cases, the event is defined as an occurrence if at least 0.254mm of precipitation is recorded over a forecast lead-time of 12 hours.

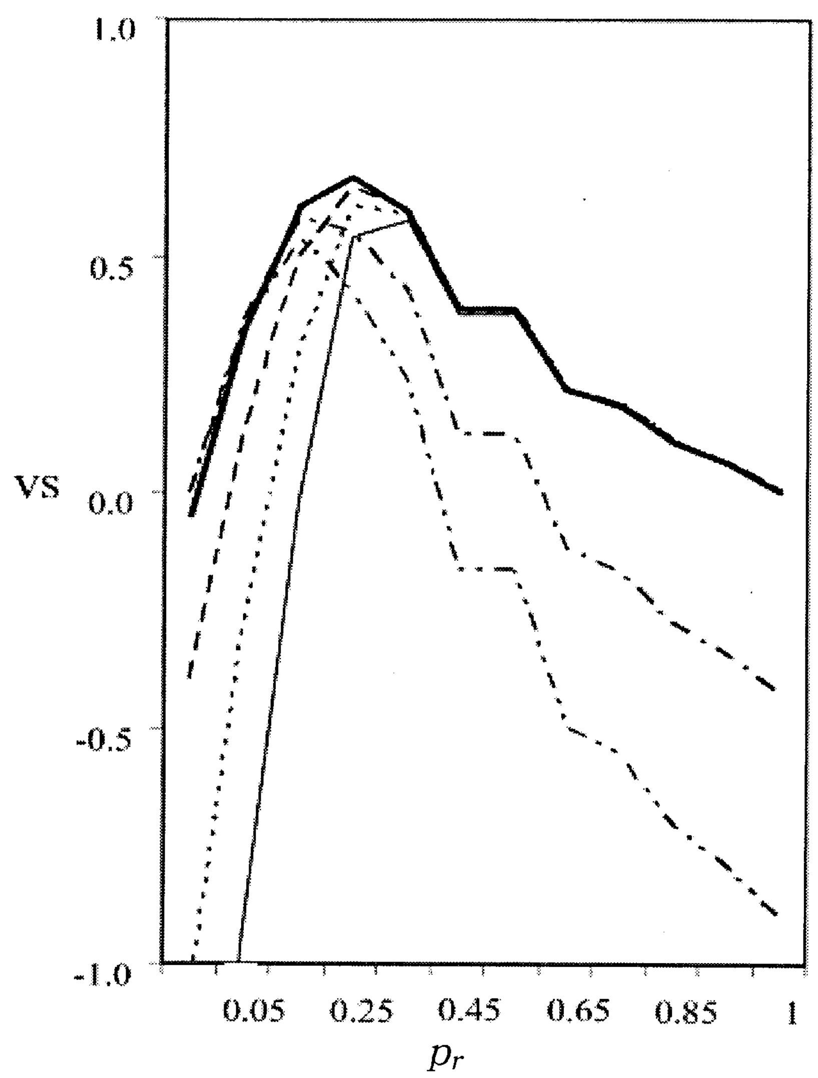
<Table 3> presents the joint distribution of forecasts and observations, $p(f_i, o_1)$, for the probability forecasts of 0, 0.1, 0.2, ⋯, 0.9, 1 provided for Seoul, and for the deterministic forecasts of 0 (no precipitation forecast) and 1 (precipitation forecast) provided for Shanghai. The summation of the joint probabilities $p(f_i, o_1)$ for all i = 1, 2, ⋯, I, constitutes the climatological probability, π.

〈Table 3〉 Joint distribution of forecasts and observations for Seoul and Shanghai

f_i	Seoul		Shanghai	
	$p(f_i, o_0)$	$p(f_i, o_1)$	$p(f_i, o_0)$	$p(f_i, o_1)$
0	0.26277	0.00547	0.56419	0.10473
0.1	0.21442	0.02281	-	-
0.2	0.15967	0.06022	-	-
0.3	0.03467	0.04015	-	-
0.4	0.00274	0.06843	-	-
0.5	0	0	-	-
0.6	0.00182	0.05566	-	-
0.7	0	0.01095	-	-
0.8	0.00091	0.02555	-	-
0.9	0	0.01460	-	-
1	0	0.01916	0.11486	0.21622
sum	0.67701	0.32299	0.67905	0.32095

3.1 Comparison of value scores for probability and deterministic forecasts

The economic values of forecasts as a function of the threshold, p_t, for selected customer satisfaction patterns with combinations of A and B, are calculated using the probability forecast data provided for Seoul. The results are provided in <Figure 1>. It can be observed from <Figure 1> that the value of a probability forecast is profoundly dependent on p_t. Also, as the degree of customer dissatisfaction is relatively larger (i.e., as the values of A and B are large), the interval of p_t with a positive VS value is smaller. Accordingly, the decision maker should deliberate on the CRM service for customers evidencing high levels of discontent. From <Figure 1>, however, we can note that the decision maker is able to obtain the maximum value by determining the optimal decision threshold, p_t, at which all the maximum values of the 6 cases shown in <Figure 1> have positive VS values. Consequently, the decision maker's principal requirement is to obtain maximum value from the forecast information, and therefore the practical value of the probability forecasts is given by the maximum of the curve at $p_t = p_{\max}$. By using $p_{\max}$ as a decision threshold, the decision maker can optimize future decision-making from the forecast information (provided only that past performance is representative of future performance).



〈Figure 1〉 VS curves plotted against decision threshold p_t for probability forecasts of precipitation in Seoul, South Korea. The combinations of parameter A and B are : A = 1, B = 1 (thick solid line); A = 1, B = 2 (dotted); A = 1, B = 3 (thin solid); A = 2, B=1 (dot-dash); A = 2, B = 2 (dashed); A = 3; B = 1 (dot-dot-dash)

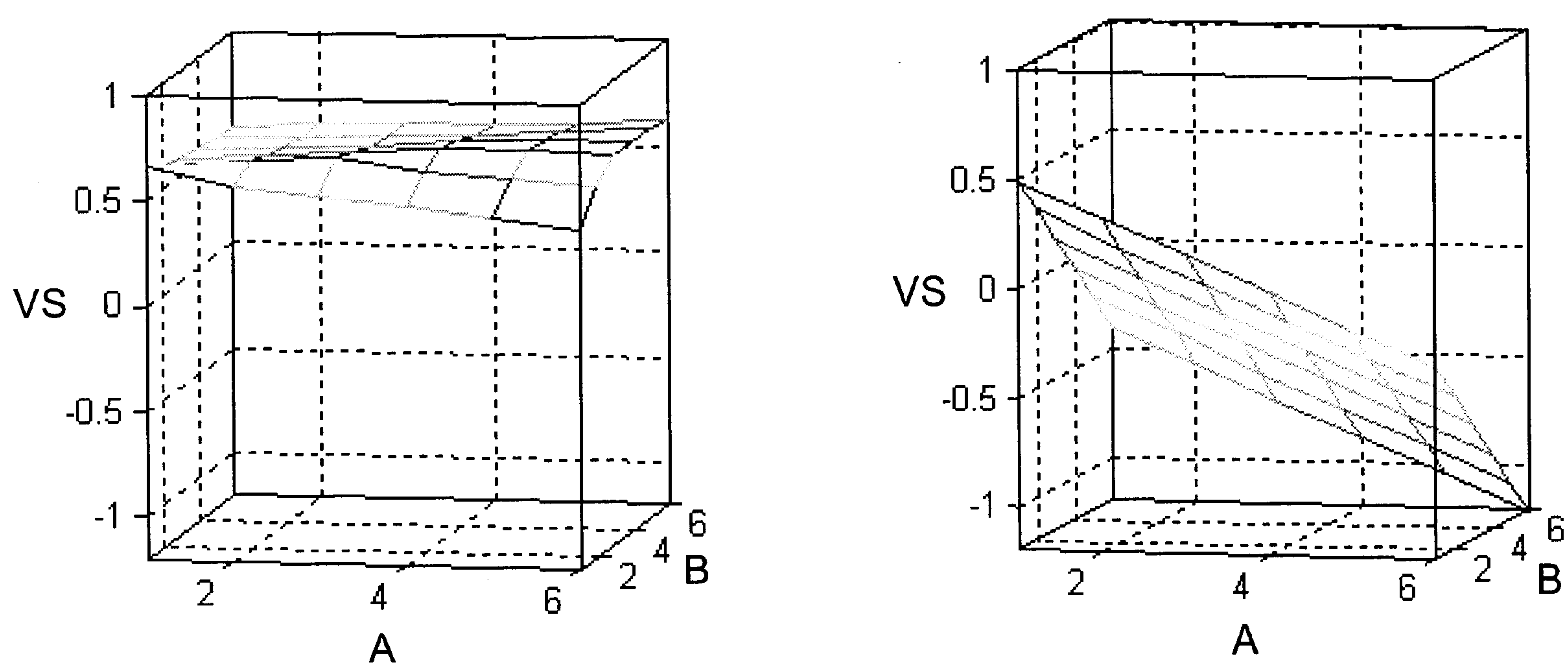
<Figure 2> shows the maximum value score (VS) acquired by the optimal decision threshold p_{max} for the probability forecast provided for Seoul and the value score for the deterministic forecast for Shanghai in the situations of value

combinations of A and B, given that the value of A and B can be 1, 2, ⋯, 6. As the values of A and B are defined as the degrees of two types of discontent relative to the satisfaction degree of 1, the value combinations of A and B can be considered to represent the various characteristics of customers. Thus, from <Figure 2> we can infer the expected degrees of satisfaction for various customers incurred by the CRM services. <Figure 2> shows that the Seoul probability forecasts are substantially more valuable for the CRM services in the resort business than are the Shanghai deterministic forecasts. However, the Shanghai forecasts evidence comparable values for small values of A and B, which illustrates that they can generate acceptable results in CRM services for customers whose dissatisfaction with false alarms and misses is not very large. It must also be noted that the forecast value may be negative for some customers with large A and B values, as in those cases the dissatisfaction associated with misses and false alarms is too high relative to the satisfaction deriving from a correct forecast. In this case, the decision maker's optimal strategy is to either always, or never send the short messages, whichever is better, rather than following the forecasts, as Mylne (2002) previously proposed.

In summary, it should be noted that the superiority of the probability forecasts to the deterministic forecasts is valid only if the decision maker can determine the most effective decision threshold p_{max}. <Figure 1> shows that the variation in the VS value is large according to the decision threshold p_t, and there exists a threshold interval with negative VS values which are even smaller than those of the deterministic forecasts. Consequently, it is important to analyze the optimal decision threshold for every particular customer type.

3.2 Analysis of the optimal decision strategy for the probability forecasts

The pattern of the graphs in <Figure 1> allows for the easy identification of p_{max} for each particular customer whose satisfaction pattern

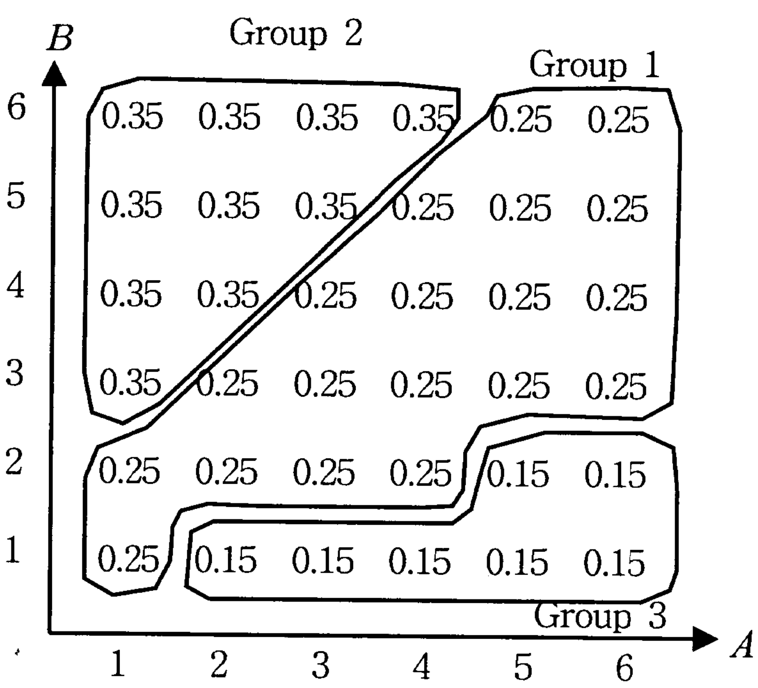


(a) Probability forecasts, Seoul (b) Deterministic forecasts, Shanghai

〈Figure 2〉 The maximum VS of precipitation forecasts for various customer satisfaction patterns. Similar VS values are represented by their corresponding colors in the contour.

is expressed in terms of A and B values. Figure 3 shows the p_{max} values for all possible combinations of A and B, given that the values of A and B can be 1, 2, ⋯, 6. By considering the values of the optimal decision threshold p_{max} and the combinations of the values of A and B, three groups can be considered. 'Group 1' would include customers with similar degrees of dissatisfaction for 'misses' and 'false alarms'. The customers in 'Group 2' have larger B values relative to A, which reflects their tendency to be more disappointed with 'false alarm' cases than with 'misses.' Conversely, the customers in 'Group 3' are more sensitive to 'misses' than to 'false alarms.'

Judging from 'Group 1' in <Figure 3>, it is evident that the optimal decision threshold p_{max} for the customer with similar A and B values is 0.25. This means that a customer who has similar degrees of dissatisfaction in cases of 'miss' and 'false alarm' is able to achieve maximum satisfaction if she or he receives a short message whenever the forecast probability is larger than 0.25 (in effect, whenever the forecast



〈Figure 3〉 Optimal policy (p_{max}) for customer's satisfaction patterns represented by A and B

probability is 0.3 or more). This result is identical to that reported by Mylne (2002). From 'Group 2' in <Figure 3>, we can also note that the optimal threshold is increased to 0.35 from 0.25 as the value of B is larger than that of A, which implies that the decision must be a conservative one when the customer tends to be more sensitive to 'false alarms' than 'misses'. The obverse of this interpretation can be applied to 'Group 3'.

4. Conclusion

This paper describes a method for the estimation of forecast value by introducing a modified cost-loss ratio situation coupled with a customer satisfaction index. The decision-making model was discussed to generalize the 2×2 cost-loss ratio contingency table and to conform the model to a real CRM decision-making situation in a Korean resort. The standard cost-loss ratio situation with two actions and two events was generalized to a satisfaction index model, considering the satisfaction and dissatisfaction incurred by the weather and the strategy for its CRM action. The satisfaction-dissatisfaction ratio situation assumes that the decision maker will attempt to maximize the expected customer satisfaction returns achieved as the result of optimally balancing the additional satisfaction and the incurred dissatisfaction.

The action taken to maximize a given customer's happiness can be determined in accordance with the degrees of content and discontent of the customer in relation to weather events. Thus, this paper uses the parameters A and B to parameterize customer satisfaction, in an effort to specify the relationship between the satisfaction and dissatisfaction following from the CRM decisions and the weather events. The appropriate CRM services are selected by choosing the optimal threshold for every customer satisfaction pattern.

In the proposed CRM decision-making situation, the concept of the value score (VS) was employed to represent the variations in scaled economic values as a function of the customer's satisfaction. The proposed economic valuation method with the VS curve in the CRM decision-making problem was applied to real-field forecast data for precipitation from Seoul and Shanghai, using probabilistic and deterministic formats, respectively. The verification results showed that the probability forecast source at Seoul is more valuable than that of Shanghai. The results of analysis demonstrate that the VS evaluation as a function of the decision threshold p_t is a useful method for determining the best decision strategies on the basis of forecast information for various customers.

In conclusion, the practical application for the maximization of customer satisfaction by using forecast information will require the fulfillment of certain prerequisites by the forecast users. The users (i.e., decision makers) must define the patterns of their customer's satisfaction and dissatisfaction following from the CRM services, that is, they must estimate the payoff structure (i.e., satisfaction and dissatisfaction) expected in each of the relevant contingencies. This study also provides an example showing that decision makers in a variety of enterprises can extract the greatest benefits from forecasts via possible extensions of the traditional cost-loss model. For example, we can elaborate the payoff relationship structure between the forecast-based decisions and events via the introduction of a satisfaction index. Another possible extension may involve the derivation not only of a theoretical, but also a practical decision parameter p_t, thereby reflecting an actual user's disposition toward the CRM decision-making.

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