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Variable Consistency Dominance-based Rough Set Approach to formulate airline service strategies

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ABSTRACT

This study differs from previous ones applying multivariate statistical analysis and multiple criteria decision-making (MCDM) methods. We use the Variable Consistency Dominance-based Rough Set Approach (VC-DRSA) to formulate airline service strategies by generating airline service decision rules that model passenger preferences for airline service quality. Flow graphs are applied to infer decision rules and variables. This combined method considers decision-maker inconsistency. The use of flow graphs to visualize rules makes them more reasonable and understandable than traditional methods. To validate the effectiveness of our model, a large sample is surveyed. Managerial improvements needed for carriers to achieve the aspired-to level of customer satisfaction are also discussed.

1. Introduction

Service quality can significantly affect customer satisfaction, loyalty, and retention. Higher service quality leads to higher passenger satisfaction, better branding, and higher passenger demand, which in turn leads to higher revenue [1]. Previous studies in airline service quality have either used multivariate statistical analysis [11–14] or multiple criteria decision-making (MCDM) methods [6–9]. In such surveys, natural language or linguistic variables are used to describe customer purchase patterns. Unfortunately, this can create an environment of imprecision, uncertainty, and partiality with regard to knowledge. These linguistic variables are then transformed into quantitative values, after which factor, cluster, and discriminant analyses are conducted. However, the semantic imprecision of natural languages leads to problems of computation, especially when the information described in a natural language is beyond the reach of existing bivalent logic and probability theory techniques [30]. The major problem with most multivariate statistical analysis or MCDM methods is that they rely on predetermined or fitting model measurements and it is not easy to derive managing implications directly from the results.

Although data mining methods have been applied in related fields [2–5,7], empirical analyses of airline service quality are relatively scarce in the existing literature. However, most machine learning techniques neglect the inconsistency of decision makes (e.g., if the service and food are "good," then the overall satisfaction rating is "poor"). This inconsistency is common in some human decision-making processes, especially airline service quality [5]. Therefore, our goal is to use the data mining technique, called the Variable Consistency Dominance-based Rough Set Approach (VC-DRSA), to analyze data from a survey on airline service quality. A set of "if *antecedent*, then *consequent*" decision rules are induced from the passenger preference data that express the relationships between attributes' values and the overall service ratings in the minds of the passengers. Although the Classical Rough Set Approach (CRSA) is a powerful tool for handling many problems, it is not able to deal with dominance-relationships originating from the criteria, e.g., attributes with preference-ordered domains (scale) like product quality, market share and debt ratio [20]. Dominance-based rough set analysis (DRSA) can handle the dominance-relationship within the decision making process. However, a completely consistent dominance-relationship within a large real-life data set is rare. As a result, decision rules derived from the lower approximations are very weak, that is supported by only a few objectives [20]. A modification of DRSA called Variable Consistency Dominance-based Rough Set Approach (VC-DRSA) is thus applied in this study. The VC-DRSA relaxes the conditions for assignment of objectives to lower approximations. With this technique, some inconsistent data can be assigned to the lower approximations but in a controlled way. The parameter controlling the inconsistency in VC-DRSA is

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named the consistency level [20]. The advantage of the VC-DRSA over the CRSA or DRSA is that it has access to an information table that displays comprehensive dominance relations. It is able to deal with the problem of inconsistency in large real-life data, by setting a consistency level to increase the objectives to lower approximations. There are several other advantages to using the VC-DRSA. First, the airline service decision rules are formulated in natural language and are easy to understand. Second, we may be able to eliminate some services associated with dispensable attributes without affecting the overall service rating. Third, we may be able to decrease some services to a minimum without lowering passenger perception of the airline service quality [5,7]. To visualize the cause-and-effect relationship derived from the VC-DRSA, the flow graph can be applied to illustrate the characteristics of airline service quality. In this study, we find VC-DRSA rules combined with flow graphs will provide greater insight for improving service quality.

The rest of this paper is organized as follows: Section 2 summarizes some important research on the airline service quality. Section 3 introduces the basic concepts of VC-DRSA. Section 4 describes our empirical data. Section 5 presents our results and analysis. Section 6 concludes the paper.

2. Airline service quality

Understanding exactly what customers expect is the most crucial step in defining and delivering high-quality service [10]. The most widely used customer-perceived service quality model is that advanced by Parasuraman et al. in 1985 [11]. Their model proposes 10 determinants of service quality: reliability, responsiveness, competence, assurance, courtesy of personnel, communications, credibility or trustworthiness of the organization, security or protection from risk, understanding of customers' needs, and tangibles or physical elements attesting to the service. Their model has been developed further and is now known as SERVQUAL (Service Quality). It contains 5 dimensions with 22 attributes of service quality [12]. Gronroos [13] suggested that measuring passenger experiences in an airline's service quality is a theoretically valid way of measuring perceived quality. This has led to the use of survey questionnaires to collect data for analysis. Based on SERVQUAL, Pakdil and Aydin [14] developed a 35-item questionnaire measurement to measure service quality survey in the airline industry. They used factor analysis to extract 8 factors from the 35-item questionnaire, which are employees, tangibles, responsiveness, reliability and assurance, flight patterns, availability, image, and empathy.

While most studies have used traditional statistical techniques to test some hypotheses, others apply MCDM models to investigate an airline's integrated service level and to make suggestions for improvement. Tsaur et al. [15] proposed a five-aspect measurement for service quality, which includes tangibility, reliability, responsiveness, assurance, and empathy. Each aspect includes two to four attributes. They concluded that the most important attributes are courtesy, safety, and comfort. Liou and Tzeng [16] applied a non-additive fuzzy integral model to investigate the service quality of eight international airlines.

Machine learning techniques have sometimes been applied in related fields. Wong and Chung [3] used a decision tree approach to manage valuable airline passengers. Verbeke et al. [4] applied a rule induction technique to build a model for customer churn. Liou [7] used the VC-DRSA method in their study of customer relationship management in the airline industry. However, they used only three decision levels in their model which is not sufficient of precisely develop management implications. Although their derived rules are more understandable than those obtained with traditional methods, too many individual rules make it difficult to capture an overall view of service quality. In a similar study conducted by Liou et al. [5], data mining was applied to determine how to improve airline service quality. Their work applied the DRSA with a 100% consistency level, which produced only a few useful rules and their sample size and decision levels were limited.

A different approach is taken in this current study. Instead of modeling passenger preferences explicitly in terms of importance weights, substitution rates, and other preference thresholds, the VC-DRSA induces a preference model through classification examples given by passengers in a survey rating airline services. This is an improvement over previous studies which applied a fixed consistency level and limited decision levels. To visualize the derived rules, flow graphs are drawn to infer rules and variables. The result is a set of decision rules and graphs that are easy for airline managers to put into action and can be used to formulate an airline's service strategy. The basic concepts of the VC-DRSA are presented in the next section.

3. The basic concepts of VC-DRSA

The classic rough set theory, first introduced by Pawlak in 1982 [17], is a valuable mathematical tool for dealing with vagueness and uncertainty [18]. However, the general use of the Classical Rough Set Approach (CRSA) as a data mining technique is restricted to classification problems where the data is either non-ordered or the ordinal nature of the data is ignored. Greco et al. [19] proposed an extension of the rough set theory based on the dominance principle to incorporate the ordinal nature of the preference data into the classification problem. The resulting Dominance-based Rough Set Approach (DRSA) essentially substitutes the dominance relation for the CRSA's indiscernibility relation in order to analyze preference-ordered data. However, the decision rules induced from the lower approximations of the DSRA are sometimes weak in that only a few objects support them. For this reason, a variant of DSRA, called VC-DRSA, has been proposed [20].

The basic concepts of VC-DRSA are summarized below. For more in depth discussion of the theory, see Refs. [21–28].

3.1. Data table

For algorithmic reasons, the information regarding the objects is supplied in the form of a data table, in which the separate rows refer to distinct objects (actions) and the columns refer to the different attributes or criteria (attributes with preference-ordered domains) to be considered. Each cell of this table indicates an evaluation (quantitative or qualitative) of the object placed in that row by means of the attribute/criterion in the corresponding column.

Formally, a data table is the 4-tuple information system $IS=(U, Q, V, f)$, where U is a finite set of objects (universe), $Q=\{q_1, q_2, \ldots, q_m\}$ is a finite set of attributes/criteria; V_q is the domain of attribute/criterion q; $V = \bigcup_{q \in Q} V_q$; and f: $U \times Q \rightarrow V$ is a total function such that $f(x, q) \in V_q$ for each $q \in Q, x \in U$, called the information function. The set Q is usually divided into a set C of condition attributes and a set D of decision attributes.

3.2. Rough approximation by means of the dominance relationship

Let $\succcurlyeq_q$ be an outranking relation to U with reference to criterion $q \in Q$, such that $x \succcurlyeq_q y$ means that "x is at least as good as y with respect to criterion q". Suppose that $\succcurlyeq_q$ is a complete preorder, i.e., a strongly complete (which means that for each $x, y \in U$, at least one of $x \succcurlyeq_q y$ and $y \succcurlyeq_q x$ is verified, and thus x and y are always comparable with respect to criterion q) and transitive binary relation. Moreover,