A promising method of knowledge acquisition using a Rough set theory

Ying Xin

SHU-UTS SILC Business School, Shanghai University, Shanghai, China;

jennyxin1982@163.com

Abstract

The determinant of survival in the knowledge-based economy is knowledge development and management, which usually starts with knowledge acquisition followed by knowledge organization and utilization. Although several studies demonstrate that data mining techniques and the rough sets theory (RST) are useful to knowledge acquisition, few people really enjoy or benefit from them in daily work and life. This is primarily because we lack a practical way of implementing them, a method which can reliably provide us with certain results in knowledge acquisition. This paper proposes a knowledge acquisition process that enables us to gain knowledge useful for decision support through the RST. An empirical study is presented to illustrate the application of the proposed method. According to the findings of this study, management implications and conclusions are discussed.

Keywords

Knowledge acquisition, Rough set theory.

1. Introduction

With the development of an ever more competitive business environment in the knowledge economy, knowledge management is increasingly regarded as a key source of sustainable competitive advantage (Holsapple & Singh 2001; Liao, 2003). Knowledge management is the organizational optimization of knowledge to achieve enhanced performance through the use of various methods and techniques (Kamara et al., 2002), a systematic way to manage the organizationally specified process of acquiring, organizing and communicating knowledge (Benbya et al., 2004). Nowadays, knowledge management and related strategic concepts are promoted as important components in the struggle of organizations to survive (Martensson, 2000).

Furthermore, knowledge management will play a fundamental role in transforming individual knowledge into organizational knowledge (Liebowitz, 2001). Benbya et al. (2004) stress that knowledge development cycle is a process of knowledge generation, knowledge storage, knowledge distribution, and knowledge application. Lee et al. (2005) note that the knowledge circulation processes includes five components, namely, creation, accumulation, sharing, utilization, and internalization of knowledge. In fact, the several different frameworks proposed have significant similarities, for example, they are often articulated in four phases where the first one is the ‘knowledge acquisition’ phase (Benbya et al., 2004). In other words, knowledge development and management usually starts with knowledge acquisition.

There are a number of characteristics peculiar to knowledge: it is intangible, is difficult to measure, and sometimes increases through use (Wiig et al., 1997). More importantly, with the addition of value, data becomes information, and with the addition of insight, information becomes knowledge (Spiegler, 2003). According to Martensson (2000), data is first organized to produce information; individuals then assimilate the information and transform it into knowledge. In fact, data is largely considered as raw numbers: data mining is, nonetheless, an essential first step in knowledge acquisition. Several studies have demonstrated that data mining techniques and the rough sets theory (RST) are useful for knowledge acquisition. It is also true, however, that few people really enjoy or benefit from them in daily work and life. This is primarily because we lack a practical way of implementing them, a method which can reliably provide us with certain results in knowledge acquisition.

In order for data mining techniques and implementation of related theories to make real contributions, it is essential that we find a system of knowledge acquisition which promises to really enable us to create and generate useful knowledge. This paper therefore proposes a knowledge acquisition process which, through a combination of Bayesian classifiers and the RST, truly facilitates our efforts to acquire valuable knowledge for decision support. The remainder of this paper is organized as follows. In section 2, the knowledge acquisition process is proposed. In section 3, Bayesian networks and the RST are discussed. In section 4, an empirical study is presented to illustrate implementation of the method. Finally, from the findings of this research project, we derive some conclusions and implications for management.

2. The Knowledge Acquisition Process

Successful knowledge development and management relies on the availability of a systematic way to acquire, share, and utilize knowledge. That is, knowledge acquisition is the starting point of knowledge development and management. Thus, how to make knowledge acquisition practical and fruitful is a critical issue. To address this issue, a data mining system is called for. According to Liebowitz (2001), one of the key building blocks for developing and advancing the field of knowledge management is artificial intelligence. Data mining, as an artificial intelligence powered tool, can help people discover the useful knowledge hidden in a database.

Data mining methodologies have been developed for exploration and analysis of large quantities of data in order to discover meaningful patterns and rules. It is discovery-driven, not assumption-driven (Chien & Chen, 2008). Data mining involves several tasks associated with different mining purposes. These include association rule mining, clustering, classification, prediction, and time-series analysis (Liu et al., 2008). Essentially, data mining can be regarded as an analytic process designed to explore data in search of consistent patterns and/or systematic relationships between variables with the purpose of obtaining knowledge useful for decision support. For example, CRISP (Cross-Industry Standard Process for data mining) was proposed in the mid-1990s by a European consortium of companies to serve as a standard process model for data mining. It comprises a sequence of phases, as follows: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. In addition, another framework called SEMMA (Sample, Explore, Modify, Model, and Assess) has been proposed by SAS Institute.

Although these data mining frameworks (CRISP, SEMMA) are comprehensive and practically applicable, few people actually make use of them. For instance, researchers whose works are published in ‘Expert Systems With Applications’ – with the exception of Liao et al. (2008) – rarely employ either the SPSS Clementine with analytic process of CRISP, or the SAS Enterprise Miner with analytic process of SEMMA. On the other hand, there are some studies on work performed by various types of software targeting specific research purposes. Deng et al. (2008) use the software ‘NeuroSolutions’ to build the BPNN prediction model, and Wu (2008) uses the software ‘ROSE’ to explore core competencies for R&D technical professionals. The paucity in use of these tools probably reflects the fact that the comprehensive analytic process is too abstract, and therefore more specific processes targeted for particular purposes are needed. This paper proposes a knowledge acquisition process (KAP) that can enable us to grasp “macro-level knowledge” and “micro-level knowledge” within data tables. As shown in Fig. 1, the knowledge acquisition process (KAP) consists of four phases: Data preparation, Macro-level knowledge, Micro-level knowledge, and Knowledge synthesizing and application.

Data preparation: this is a preparation phase for data mining. In this stage it is required that we cleanse and format the data. This is because some of the mining functions only accept data in a certain format. With regard to software preparation, there are many free software packages available and these can readily be downloaded from various websites. In fact, “software mining” is prior to data mining.

Macro-level knowledge: this is a kind of snapshot. It outlines knowledge, involving all data classes, characterized by condition attributes (independent variables) and class attributes (dependent variables or decision attributes), and it can be displayed using a causal relationship diagram.

Micro-level knowledge: this is a kind of detailed portrait that depicts knowledge about one data class, described by some specific condition attributes. It is a subset of macro-level knowledge. We may say that macro-level knowledge provides a holistic view allowing us to see generally, while micro-level knowledge enables us to think deeply. For the former we can utilize the software ‘WEKA’ to obtain a directed acyclic graph (DAG) through Bayesian networks, while, for the latter we can employ the software ‘ROSE’ to get decision rules based on the RST.

Knowledge synthesizing and application: this requires synthesizing macro-level knowledge and micro-level knowledge with the purpose of giving support to better decision-making and problem-solving.

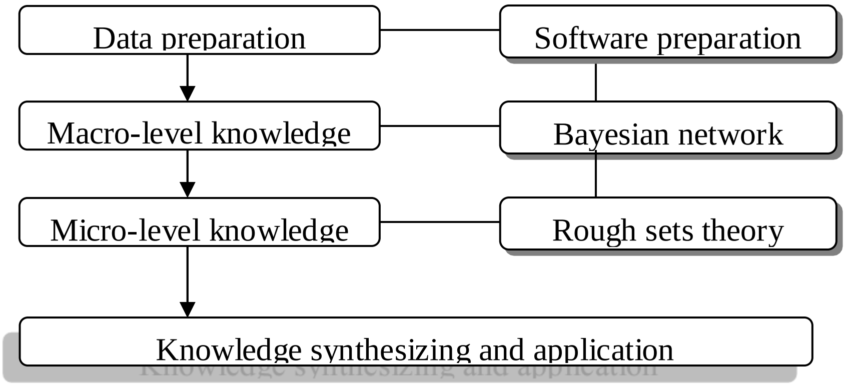

Fig. 1. Knowledge acquisition process

3. Rough set theory

The most commonly used techniques in data mining include K-means clustering, decision trees, Bayesian networks, regression models, and neural networks. Such data mining techniques are supported by the software ‘WEKA’ which contains a wide variety of machine learning algorithms for data mining tasks. WEKA provides comprehensively practical utilities, under headings such as: Preprocess, Classify, Cluster, Associate, Select attributes, Visualize. Among data mining techniques, the use of the Bayesian network can produce a DAG that models causal relations between attributes. The RST-based software ‘ROSE’ can perform a standard and an extended rough set based analysis, such as: searching for the core and reducts of attributes in order to achieve attribute reduction, and inducing decision rules from rough approximations of decision classes. In particular, decision rule generation can be viewed as a combination that implements functionally both Associate and Select attributes. More details are given as follows.

3.1 Rough set theory

The RST is effective in data reduction for qualitative analysis. Unlike a conventional data analysis, which uses statistical inference techniques with rigorous statistical assumptions, the RST is usually used as a data-mining technique whose object is to obtain knowledge through direct analysis of original data with either quantitative or qualitative attributes. Especially, the RST needs no additional information or statistical assumption (Goh & Law, 2003; Su & Hsu, 2006).

The RST has been successfully applied in a variety of fields such as: business failure prediction (Slowinski & Zopounidis, 1995; Dimitras et al., 1999; Ahn et al., 2000; Beynon & Peel, 2001; Tay & Shen, 2000), rough neural expert system (Yahia et al., 2000), maximally general fuzzy rules (Hong et al., 2000), customer and product fragmentation (Changchien & Lu, 2001), rules from incomplete training examples (Hong et al., 2002), stock price mining (Wang, 2003), hierarchical decision rules from clinical databases (Tsumoto, 2003), case-based reasoning application (Huang & Tseng, 2004), travel pattern generation (Witlox & Tindemans, 2004), credit scoring (Ong et al., 2005), bank credit ratings (Griffiths & Beynon, 2005), rule discovery from noisy data (Wang, 2005), group decision (Huang et al., 2006), classification rules (Tsai et al., 2006), customer relationship management (Tseng & Huang, 2007), insurance market (Shyng et al., 2007), drug utilization knowledge (Chou et al., 2007), supplier selection (Xia & Wu, 2007), location based services (Sikder & Gangopadhyay, 2007), neighborhood classifiers (Hu et al., 2008) cross-level certain and possible rules (Hong et al., 2008), feature selection (Chen et al., 2008), and so on. The basics of RST are explained below.

3.1.1. Lower and upper approximation

The RST was originally introduced by Pawlak in 1982 (Pawlak, 1982), and is particularly useful for dealing with problems such as attribute reduction, rule generation, and data classification in qualitative analysis (Hong et al., 2008). Any imprecise information or vague concept can be treated by the RST with a pair of precise concepts that consist of the lower and upper approximation. The difficulty in distinguishing objects on the basis of imprecise information is the starting point of RST (Pawlak, 1997). In other words, the imprecise information causes the objects to be indiscernible in terms of the available data. To deal with this indiscernible relation, two operations are available, namely, the lower and the upper approximations of a set, a pair that enables us to define the accuracy and the quality of approximations (Pawlak, 1984). The lower approximations set $\underline{P}Y$ is the set of all objects which can be certainly classified by values of attributes, while the upper approximation set $\overline{P}Y$ consists of the lower approximation set and the fuzzy boundary region, so that it cannot be completely distinguished.

Using lower and upper approximations of a set, the accuracy and the quality of approximation are defined. Referring to Pawlak (1984), we can use $\mu_P(Y) = (\underline{P}Y)/(\overline{P}Y)$ to measure the accuracy of approximation $\mu_P(Y)$ for any class, in which $0 \le \mu_P(Y) \le 1$. Furthermore, the total quality of classification $\eta_P(Y)$ can be measured by $\eta_P(Y) = \text{all } \underline{P}Y / \text{all objects}$, while the total accuracy of classification $\beta_P(Y)$ can be measured by $\beta_P(Y) = \text{all } \underline{P}Y / \text{all } \overline{P}Y$. Through use of the lower and upper approximation, the knowledge hidden in a data table may be discovered and expressed in the form of decision rules (Mi et al., 2004).

3.1.2. Decision rule and Covering Index

Data analysis based on the RST starts from the data table called an information system, which contains data about objects characterized by a set of certain attributes (Pawlak, 2002). The information system is used to construct the approximation space. If the information system divides attributes into condition attributes and decision attributes, then it is called the decision table. The condition attributes can be regarded as independent variables, while the decision attributes may be regarded as class attributes or dependent variables. The decision table constitutes an attribute-value system, which is a basic knowledge representation framework, comprising a table with columns designating attributes and rows designating objects featured by the values of attributes. Furthermore, each cell of the decision table denotes the value of a specific attribute for a particular object.

According to Witlox and Tindemans (2004), the main merit of using RST is its ability to produce the decision table and the decision rules which are often presented in an ‘IF condition(s) THEN decision(s)’ format. That is, the decision rule reflects a relationship between the condition attributes and the decision attributes. Moreover, a decision rule is always accompanied by the Covering Index (CI). The CI presents a covering ratio, i.e., the ratio of A: how many objects with the same attribute value there are in a class, to B: how many objects belong to that same class (Huang et al., 2008). Commonly, a decision rule of shorter path and higher CI is regarded as superior. Through the process of discovering the CI, the uniquely valuable attributes and attribute values can be extracted from a set of complex attributes and attribute values, and thus the quality of decision-making can be augmented.

4. Empirical study

In this section, an empirical study is presented to illustrate the application of the proposed knowledge acquisition process (KAP), whose purpose is to grasp and utilize certain knowledge.

Phase 1 is data preparation. This study adopts the Car Evaluation Data Set, selected from the UCI Machine Learning Repository, provided by Bohanec and Rajkovic. As shown in Table 1, this dataset has 1728 instances, in which each instance is featured by six conditions (“buying”, “maint”, “doors”, “persons”, “lug_boot”, and “safety”) and one class attribute (acceptability). These seven attributes are all categorical.

Table 1 Attribute information

Attribute	Type	Description	Attribute values
buying	condition	buying price	vhigh, high, med, low
maint	condition	price of the maintenance	vhigh, high, med, low
doors	condition	number of doors	2, 3, 4, 5more
persons	condition	capacity in terms of persons to carry	2, 4, more
lug_boot	condition	the size of luggage boot	small, med, big
safety	condition	estimated safety of the car	low, med, high
acceptability	class	car acceptability	unacc, acc, good, vgood

In phase 2, the Bayesian network classifier with the TAN search algorithm was implemented through WEKA, using a test mode of 10-fold cross-validation. As a result, the causal relationship diagram (Fig. 2) was obtained, which displays macro-level knowledge. In Fig. 2, it is clear that (1) price factor (buying price and price of the maintenance) is at upper while non-price factor is at lower, and this reveals that car acceptability is highly dependent on price factors rather than non-price factors; (2) maintenance price is the most considered factor, followed by buying price; (3) among non-price factors, safety is the object of most concern; and (4) the linkage of “maint” → “buying” → “safety” is critical to the enhancement of car acceptability.

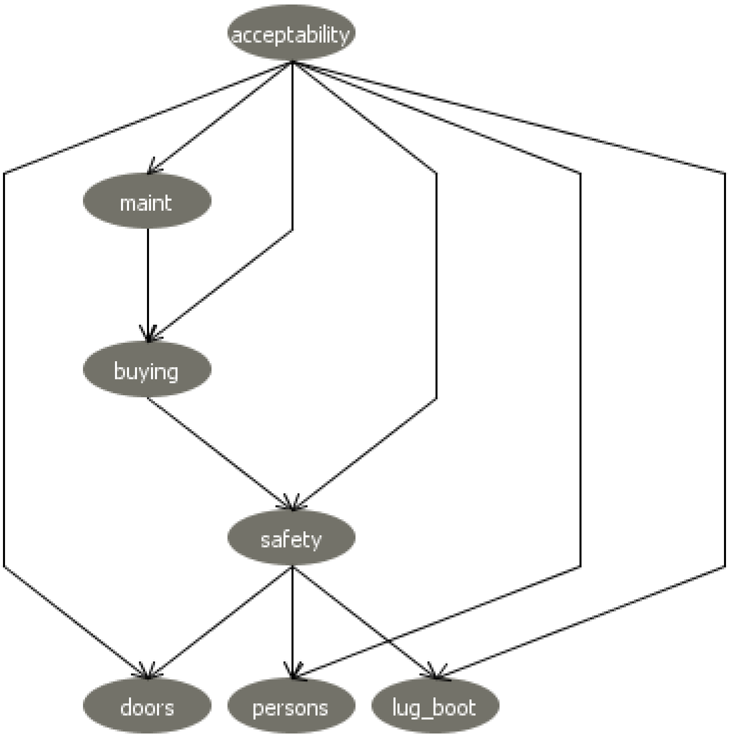

Fig. 2. The causal relationship diagram

In phase 3, the analysis results using the RST show that (1) both the total quality of classification and the total accuracy of classification are 100%; (2) the six condition attributes are significant and it is not advisable to omit any in this case, because they are all core attributes; and (3) a total of 77 decision rules are obtained, however, only 5 decision rules (see Table 2) exhibit shorter path (less than six attributes) and higher CI.

Furthermore, for ‘acceptability = unacc’ referring to rule 1 and rule 2, this implies that 47.60% of respondents do not accept the car owing to ‘persons = 2’ or ‘safety = low’. For ‘acceptability = acc’ referring to rule 21, this means that 6.25% of respondents would accept the car because ‘buying = high’, ‘maint = med or low’, ‘persons = 4’, and ‘safety = high’. For ‘acceptability = good’ referring to rule 58, this indicates that 11.59% of respondents consider the car acceptability is good because ‘buying = med or low’, ‘maint = low’, ‘persons = 4’, ‘lug_boot = small’, and ‘safety = high’. Finally, for ‘acceptability = vgood’ referring to rule 73, this reveals that 49.23% of respondents consider the car acceptability is very good because ‘buying = med or low’, ‘maint = med or low’, ‘persons = 4 or more’, ‘lug_boot = big’, and ‘safety = high’.

Table 2 Decision rule and CI

rule 1. (persons = 2) => (acceptability = unacc); CI= 47.60%;
rule 2. (safety = low) => (acceptability = unacc); CI= 47.60%;
rule 21. (buying = high) & (maint in {med, low}) & (persons = 4) & (safety = high) => (acceptability = acc); CI= 6.25%;
rule 58. (buying in {low, med}) & (maint = low) & (persons = 4) & (lug_boot = small) & (safety = high) => (acceptability = good); CI=11.59%;
rule 73. (buying in {med, low}) & (maint in {med, low}) & (persons in {more, 4}) & (lug_boot = big) & (safety = high) => (acceptability = vgood); CI= 49.23%.

5. Implications and conclusions

Effective knowledge acquisition is the starting point for successful knowledge development and management. However, to date we have been without a convenient method for obtaining reliable and constructive knowledge. This paper, therefore, proposes a knowledge acquisition process (KAP) which, through a combination of the Bayesian network and the RST, allows us to obtain useful knowledge for decision support. Using the proposed KAP, the analysis results of our Car Evaluation Data Set can be clearly seen as beneficial and fruitful. In this process, firstly, the Bayesian network classifier with the TAN search algorithm was implemented to acquire macro-level knowledge, and it resulted in a causal relationship diagram. This causal relationship diagram enabled us to bring out insights in a profound manner. For example, it shows that the price factor is not the main thing enhancing a product’s competitive advantage or affecting a customer’s purchase attitude, but, in this case, price factors (buying price and price of the maintenance) are more important than non-price factors. Furthermore, it shows that, among non-price factors, safety is the factor that has the most influence on car acceptability.

For the purpose of understanding more details about car acceptability, some related micro-level knowledge is needed. The analysis results using the RST offer several implications for management. For example, 47.60% of respondents consider a car unacceptable due to ‘persons = 2’ or ‘safety = low’ while 49.23% of respondents consider it very good because ‘buying = med or low’, ‘maint = med or low’, ‘persons = 4 or more’, ‘lug_boot = big’, and ‘safety = high’. This implies that, in this case, unacceptable factors are low safety and low capacity in terms of passengers, while acceptable factors are: price of buying and maintenance should not be high, while others (passenger capacity, the size of luggage boot, and safety of the car) must be high. In addition, note that the number of doors is not of much concern relative to car acceptability. These kinds of macro and micro-level knowledge are needed to effectively synthesize strategies for application in marketing and new product development.

In sum, the proposed KAP successfully integrates the Bayesian network and the RST, and that it really performs well in the task of acquiring insightful knowledge. Hence, the proposed method achieves its purpose and is a promising means of knowledge acquisition.

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