Discovery of CPA's Tacit Decision Knowledge Using Fuzzy Modeling

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Abstract

The discovery of tacit knowledge from domain experts is one of the most exciting challenges in today's knowledge management. The nature of decision knowledge in determining the quality of a firm's short-term liquidity is full of abstraction, ambiguity, and incompleteness, and presents a typical tacit knowledge extraction problem. In dealing with knowledge discovery of this nature, we propose a scheme that integrates both knowledge elicitation and knowledge discovery in the knowledge engineering processes. The knowledge elicitation component applies the Verbal Protocol Analysis to establish industrial cases as the basic knowledge data set. The knowledge discovery component then applies fuzzy clustering to the data set to build a fuzzy knowledge based system, which consists of a set of fuzzy rules representing the decision knowledge, and membership functions of each decision factor for verifying linguistic expression in the rules. The experimental results confirm that the proposed scheme can effectively discover the expert's tacit knowledge, and works as a feedback mechanism for human experts to fine-tune the conversion processes of converting tacit knowledge into implicit knowledge.

Keywords:

Tacit knowledge discovery; knowledge management; knowledge engineering; fuzzy modeling; financial statement analysis

Introduction

Knowledge has increasingly being regarded as the most critical resources of firms and economies [1, 2, 3]. A survey of Fortune 500 and Post 300 CEOs, CFOs, and chairman of Board has found that knowledge is regarded as their company's most critical resource for competitive advantage. Nations worldwide are emphasizing the importance of knowledge as a meaningful resource in boosting management performance [4], and organizations are struggling, with all possible means, to maintain and/or develop highly intelligent and competitive capability in this ever-changing and turbulent market [5]. Knowledge management has hence emerged as a major theme of modern management arena, and established its domain in the creation, storage, sharing, and reuse of the organization's knowledge [5].

The current interest in knowledge and knowledge management has its root in organizational learning [4]. Organizational learning emphasizes the development of systems or establishment of culture that could both retain expertise and transfer ideas to new individuals. The requirements of an organization in providing quality products or services to its customers have generally led its employees to develop expertise for fulfilling his/her responsibility, and continue to accumulate expertise in the form of problem solving skills under different situations. These different kinds of expertise represent the knowledge of a company, and the ultimate goal of knowledge management is to be able to reuse the knowledge by providing the right information to the right people, so that effective actions can be taken efficiently.

The heart of knowledge management is knowledge, which, as widely recognized, exists in two forms – explicit and tacit [6]. Explicit knowledge is fact-based knowledge that can be articulated in formal language and transmitted among individuals, hence is easily spoken about, and easy to state and record in form of rules or to write in written form. In contrast, tacit knowledge is intangible; it represents the kind of personal knowledge embedded in individual experience, intuition, personal belief, perspective, and values [5]. This knowledge is difficult to communicate to others as information, and is non-codified, disembodied know-how that is acquired via informal take-up of learned behavior and procedures [1]. As a result, this form of knowledge is wholly embodied in the individual, rooted in practice and experience, expressed through skillful execution, and transmitted by apprenticeship and training through watching and doing forms of learning [1]. It is this kind of knowledge that is used to perform a task, and is, in the business context: practical, action-oriented, experience-based, and context-linked. A great amount of knowledge in an organization exists in a form of highly personal and context-dependent one that belongs to tacit knowledge, and it plays a key role in the way people work especially when collaborating with others. In terms of management of tacit knowledge, one can always adopt the approach of conversion tacit knowledge into explicit form [5] by applying methods, such as information map, knowledge map, cognitive map, rule-based approach, data mining, etc. Alternatively, one can reuse decision-making experience by storing expertise in a knowledge base, and reuse it properly for relevant decision-making problems. Case-based reasoning [5] represents a major method in this category.

This research focuses on the knowledge extraction of decision processes in determining quality of short-term liquidity of a firm from an experienced CPA. The decision factors employed in the processes and the situations that warrant certain decision chain, in most cases, may be characterized as uncertain, incomplete, or even ambiguous [7, 8, 9]. In dealing with this type of tacit knowledge, we propose a scheme that consists of three components: knowledge elicitation for extracting knowledge data from CPA, fuzzy modeling for expressing knowledge data in terms of fuzzy rules, and knowledge refinement for further fine-tune the decision rules. Section Approach and Methods describes the fuzzy nature of decision process of short-term liquidity. It also explains the methodologies used in the scheme, which is followed by the explanation of the scheme. Section Results and Discussion details the results of the experiment, and is followed Section conclusion.

Approach and Methods

Tacit Nature of Short-Term Liquidity Problems

The short-term liquidity of a company represents its ability to meet its short-term financial commitments. Short-term financial commitments are current liabilities, which are typically trade creditors, bank overdrafts PAYE, VAT and any other amounts that must be paid within the next twelve months. The short-term liquidity of a company is an important indicator for both investors and management. To investors, this indicator points toward the prospect of the immediate future of the company. A company, despite of its excellent long-term future, could be forced into bankruptcy, if it does not have the ability to pay employees, suppliers, and holders of short-term notes. To management of the company, this indicator can be used to measure the achievements of management initiatives of the past, and at the same time, it can indicate the what-will-be performance of the company for its immediate future.

The decision processes in determining the quality of short-term liquidity of a company can be quite complicated [10]; it is normally determined by the combination of a set of decision factors. Our CPA has indicated that he relies on six decision factors: Current Ratio (CR), Account Receivable Collection Period (AR), Inventory Turnover Period (INV), Operation Cycle (OC), Net Operation Cycle (NOC), Sales (S), and Operation Income (OI). The decision knowledge involved includes evaluation of given problem situation, determination of what factors and their relative importance for consideration in the decision chain, and the extent of the decision chain deemed necessary for the given case. The CPA, during the whole process, evaluates each factor in terms of range and expresses the corresponding grade in five categories. Thus, the fuzzy element has been introduced into the decision process at the very beginning. In addition, the relativity plays an important role during the decision process; a company with good CR and bad AR could be in the same ranking with a company with an average CR and good AR, if AR of the latter is much better than AR of the former. Even decision chains may be different for different companies in order to arrive at a final ranking; the ranking for a company may be decided if both CR and AR are good, while more factors may need to be examined if one of them is either average or bad. It is very clear that this decision knowledge depends very much on personal experience, and is a typical form of tacit knowledge.

Verbal Protocol Analysis and Fuzzy Modeling

The verbal protocol analysis has been a well recognized method in knowledge elicitation that uses verbal data to study cognitive processes of human experts in many areas of science [10], where knowledge and experience cannot be easily assessed by traditional observations. This method requires subjects of domain expert to verbalize his/her thinking process – thinking aloud – while performing a task simultaneously. There are in general two types of instruction for subjects. The first type is to ask subjects to verbalize their thoughts only, which simply verbalizes the information they attend to while generating answers. The second type requires subjects to provide their thoughts as well as analysis of meaning, which may include explanations, justifications, and rationalizations. In essence, the first type only consists of inputs and conclusions, and treats the decision knowledge as a black box; while the second type, in addition to inputs and conclusions, aims to unearth the details of the box.

The first part of our scheme is to establish a set of basic knowledge data through our CPA, which consists of only important profile of a company and the conclusion of quality rating of its short-term liquidity, so that the fuzzy model in the second part can analyze it. Hence we apply the first type of verbal protocol analysis in this study.

Fuzzy modeling originates from the classic fuzzy logic theory that deals with incomplete and imprecise information linguistically [11]. For a given specific domain, it has been shown that it can be very effective and realistic in modeling human expertise [12]. A fuzzy model is a rule-based system that employs fuzzy logic to reason about data. A generic fuzzy model (will be hereafter interchangeably called fuzzy knowledge base system, FKBS) consists of five components: a fuzzifier that converts crisp values of inputs to fuzzy values; a fuzzy rule base that contains a set of fuzzy rules; a database that contains membership functions for the fuzzy rules; an inference engine that derives a fuzzy consequent given the fuzzy inputs and fuzzy rules; and a defuzzifier that converts the fuzzy consequent to a crisp output value. Each rule in the rule base has the following format:

R : If x_1 is $\widetilde{A}_R^1$ and x_2 is $\widetilde{A}_R^2$ and ... and x_p is $\widetilde{A}_R^p$ Then y is $\widetilde{B}_R$

where $\widetilde{A}$ and $\widetilde{B}$ are linguistic values defined by fuzzy sets on input and output variables, x and y, respectively. The If-part is called the premise of the rule whereas the Then-part is the conclusion of the rule. Depending on the format of the consequent part, many fuzzy models have been developed [12]. In this paper, zero-order TSK fuzzy model [13] is employed, in which the output y is a constant, since the short-term liquidity is evaluated as a integer number ranging from 1 to 5. Each fuzzy set $\widetilde{A}$ can be represented as $\widetilde{A} = \{(x, \mu(x)) \mid x \in X\}$, where $\mu(x)$ is the membership function of A, which denotes what degree the value of x belongs to A. Triangle, trapezoidal, and bell-shaped are three commonly used membership functions.

We apply fuzzy clustering to construct a FKBS from a data set, which is one of the most promising techniques in obtaining an initial approximation to the fuzzy rules without any assumption about the structure of the data [14, 15]. Fuzzy clustering partitions a data set into a number of overlapping clusters such that the inter-distance in each cluster is minimized and the intra-distance among clusters is maximized. The output of fuzzy clustering is a set of cluster prototypes and membership degrees of each cluster each datum belongs to. If the provided data set is representative of the model it comes from, one can assume that each cluster represent a rule. Therefore, one can derive fuzzy rules by projecting each cluster to the input coordinate spaces correspondingly [11]. The fuzzy rules have the following form:

If x_1 is μ_k^1 and ... and ... and x_p is μ_k^p Then y = r_k, $k = 1,2,\Lambda\ ,c$

where c is the number of clusters, μ_k^i is the membership function of the i-th variable in cluster k, and r_k is the class number cluster k belongs to.

A Scheme for Discovering CPA's Tacit Decision Knowledge

Figure 1 shows the proposed scheme, which consists of three parts: knowledge elicitation, knowledge discovery, and knowledge refinement. We apply Verbal Protocol Analysis in the first part to elicit decision knowledge from our CPA, when industrial cases are presented to him for evaluation and generate the knowledge data set. The knowledge discovery part then takes the data set as input information for generating fuzzy clusters through fuzzy clustering module and fuzzy rule through fuzzy rule generation module, and builds a corresponding FKBS. The so constructed FKBS model should represent the underlying decision knowledge of the earlier data set. In order to verify its performance, the knowledge refinement part compares the predictions of FKBS with that of the earlier protocol model. For those discrepant cases, the feedback branch of the scheme takes them back to the CPA, he then investigates and identifies the causes for further fine-tuning of the decision knowledge.

Results and Discussion

From the financial statements of 746 selected companies for our research, our CPA starts the think-aloud procedure by rating each of the six decision factors into one of the five grade categories: good (rating 5), above-average (rating 4), fair (rating 3), below-average (rating 2) and bad (rating 1). Based on these ratings and his own weighting system of the six factors, the CPA then applies his reasoning process to derive the overall quality rating of a company. Upon the completion of the verbal recordings, a research assistant developed the script of the recordings, which was further modified until it became satisfactory with the CPA. This knowledge elicitation part built a knowledge data set of 746 cases, which forms the basis of knowledge discovery for the second part.

In the second part, we develop a fuzzy modeling tool in Matlab 5 to extract the tacit decision knowledge, which is expressed in terms of fuzzy rules. Then, we apply k-fold cross-validation to evaluate the performance of the discovered knowledge. The 746 cases are evenly divided into five ($k = 5$) subsets, of which four subsets (497 cases) are in turn assigned as the training set and the remaining set (149 cases) as the test data for validation. In order to reduce the experimental bias during the process, 20 experiments are conducted. Using mean-square-error as the measurement of differences in ratings between FKBS and CPA, we found that the so constructed FKBS is within satisfactory accuracy.

With the 746 cases, the system has identified 17 clusters that represent the CPA's decision knowledge in 17 fuzzy rules. Due to space limitation, we present and illustrate only one of them in Figure 2. Each rule is represented graphically as fuzzy sets that can be easily interpreted by the CPA in linguistic terms. As shown in the figure, each factor is represented as a fuzzy variable, with grade being the x-axis and the corresponding weight in y-axis. The combination of the six fuzzy factors leads to the final Rating; that is fair (=3) in this case.

Our CPA interprets the rule in Figure 2 as follows:

If CR is above-average and **AR** is fair and **INV** is below-average and **NOC** is

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below-average and S is fair and OI is
below-average Then Rating = 3
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In addition to the fuzzy rules, our system is able to uncover the membership functions for each factor. These membership functions represent subjective recognition about the quality of each factor by the CPA. Figure 3 shows eight membership functions of CR (variable 1), with V*n*MF*m* being membership function *m* of variable *n*. While V1MF3 and V1MF6 both centering at 3, the distribution of the latter is much more condense than the former, one thus can express it linguistically in more precise terms than the former; roughly fair vs. very fair.

The fact that the system is required to apply all six variables to represent a fuzzy decision rule may lead to cumbersome expressions of decision knowledge, comparing with that of CPA. To CPA, there are cases where a conclusion can be made by applying only a subset of the six factors. In order to tackle this issue, a knowledge-refinement procedure is conducted, where fuzzy rules were presented to the CPA who used the earlier knowledge data to fine-tune rules. For the above rule, our CPA reasoned that with CR close to 4 ("above-average") and NOC close to 2 ("below average"), the final Rating could be 2, 3, or 4, depending the quality of S and OI. With S close to 3 ("fair") and OI close to 2 ("below average"), he then concluded that Rating is 3 ("fair"); the rule is thus simplified as:

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If  CR  is  above-average  and  NOC  is
    below-average and S is fair and OI is
    below-average
    Then Rating = 3
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Conclusion

We proposed a scheme for discovering the tacit decision knowledge from human experts, and applied it to the problem of quality evaluation of short-term liquidity of firms from an experienced CPA. The scheme is composed of knowledge elicitation, knowledge discovery, and knowledge refinement. We applied verbal protocol analysis to elicit the CPA's decision procedure to establish knowledge data, and applied fuzzy clustering to the knowledge data to develop a fuzzy knowledge based system. With the linguistically expressed fuzzy rules and their membership functions, the knowledge system is then further refined with the involvement of CPA. Experimental results demonstrate that the proposed scheme can systematically uncovered the CPA's tacit knowledge with satisfactory accuracy, and provide a feedback mechanism for CPA to refine the knowledge system to improve its interpretation and computational efficiency.

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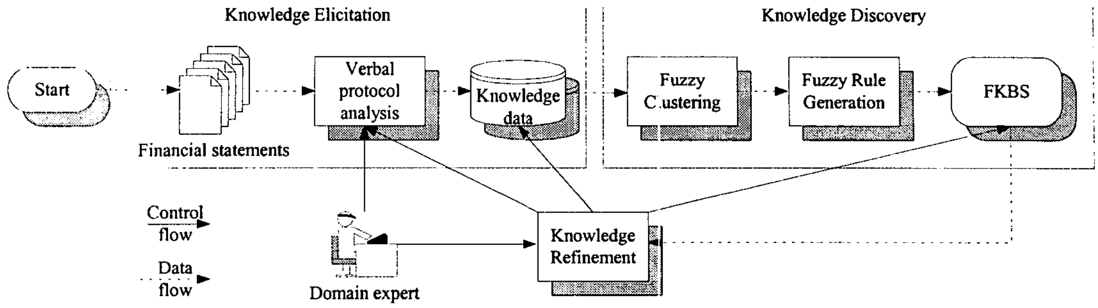

Figure 1 - The proposed scheme for discovering tacit knowledge

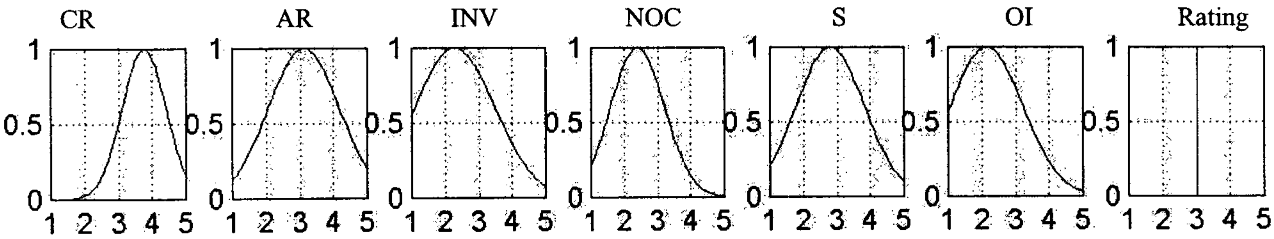

Figure 2 - One fuzzy rule

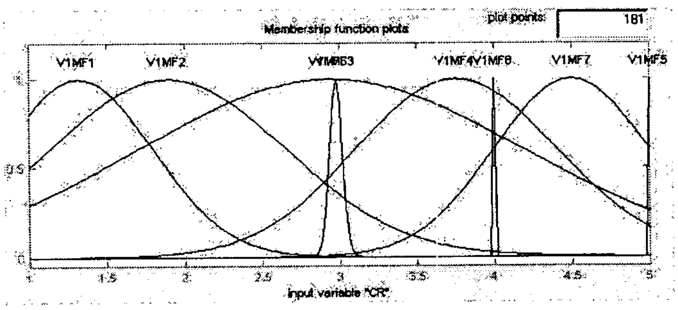

Figure 3 - The eight membership functions of CR