A promising method of knowledge acquisition using a combination of Bayesian network and Rough set theory

Xin Ying

SHU-UTS SILC Business School, Shanghai University, China

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 a combination of Bayesian networks and 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, Bayesian network, 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.

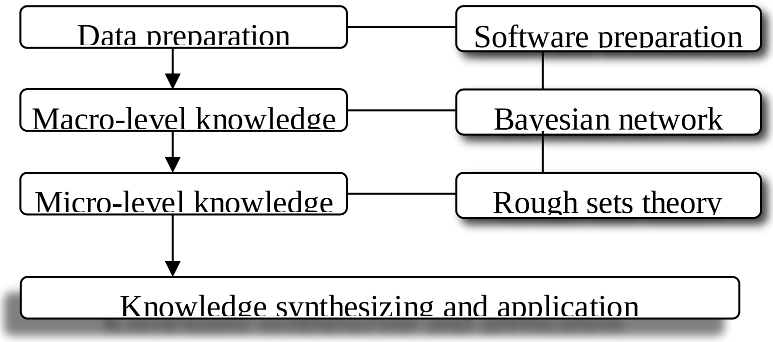

Fig. 1. Knowledge acquisition process

3. Bayesian classifiers and 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 Bayesian networks

The Bayesian network has many practical applications due to its ability to compactly represent joint probability distribution in many variables (Klopotek, 2002). According to Wang et al. (2004), a Bayesian network is a graphical representation of probabilistic relationships between multiple variables, and it is more robust for inferring structure because it is resistant to noise in data. The Bayesian networks are probabilistic inference engines that support reasoning under uncertainty (Hruschka & Ebecken, 2007). Moreover, a Bayesian network is an outcome of a machine learning process that finds the network's structure and its associated parameters, and it can provide diagnostic reasoning, predictive reasoning, and intercausal reasoning (Lauria & Duchessi, 2007).

In general terms, the Bayesian network is a graphical representation of probabilistic relationships between multiple attributes/variables, which is more robust for inferring structure since it is better resistant to noise in data than other methods. It can be stated, additionally, that a Bayesian network is a DAG that consists of a set of nodes/vertices linked by arcs, in which the nodes represent the attributes and the arcs stand for a relationship among the connected attributes (Hruschka & Ebecken, 2007). Moreover, In a DAG, the arcs designate the existence of direct causal relations between the linked variables, and the strengths of these relationships are expressed in terms of conditional probabilities.

Inferring Bayesian structure from expression data can be viewed as a search problem in the network space (Wang et al., 2004). Thus, to heuristically search the Bayesian network space, it is necessary to employ search methods such as: simulated annealing algorithm, genetic algorithm, and tree augmented Naïve Bayes (TAN). For structure learning through Bayesian networks, the 'WEKA' offers various algorithms such as: hill climbing, K2, simulated annealing, genetic, tabu, TAN, and so on. Among these algorithms, the TAN is notable in that it can produce a causal-effect graph (not just a tree-like graph) in which the class attribute is located at the top in the DAG (Friedman et al., 1997). The causal-effect graph of the TAN is formed by calculating the maximum weight spanning tree using Chow and Liu's method (1968).

The TAN is an extension of the Naïve Bayes, which removes the Naïve Bayes assumption that all the attributes are independent. Moreover, the TAN finds correlations among the attributes and connects them in the network structure learning process. According to Friedman et al. (1997), the TAN allows additional edges between attributes that capture correlations among them, and it approximates the interactions between attributes by using a tree structure imposed on the Naïve Bayes structure. Davis et al. (2004) note that (1) the Naïve Bayes is straightforward to understand as well as easy and fast to transmit through training, while the TAN, on the other hand, allows for more complex network structures than the Naïve Bayes; and (2) the TAN achieves retention of the basic structure of Naïve Bayes, permitting each attribute to have at most one other parent, and allowing the model to capture dependencies between attributes.

Bayesian network classifiers in WEKA such as the Bayesian network with the TAN search algorithm, have shown excellent performance in data mining (Cerquides & De Mantaras, 2005). Due to the fact that the conditional independence assumption of Naïve Bayes is not real, the TAN was developed to make up that deficit and, in fact, achieves significant improvement in terms of classification accuracy, efficiency and model simplicity (Jiang et al., 2005). Although the TAN do not certainly perform with the best possible classification accuracy, this study adopts the TAN because it can create a causal-effect graph that facilitates and stimulates our powers of conceptualization and insight.

3.2 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.

3.2.1. 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 $\bar{P}Y$ 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 $\mu_P(Y)=(\underline{P}Y)/(\bar{P}Y)$ 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 $\beta_P(Y)=\text{all }\underline{P}Y/\text{all }\bar{P}Y$. 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).

3.2.2. 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. 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.

References

[1] Ahn, B. S., Cho, S. S., & Kim, C. Y., 2000. The integrated methodology of rough set theory and artificial neural network for business failure prediction. Expert Systems with Applications, 18(2), 65-74.

[2] Benbya, H., Passiante, G., & Belbaly, N. A., 2004. Corporate portal: a tool for knowledge management synchronization. International Journal of Information Management, 24(3), 201-220.

[3] Beynon, M.J., Peel, M. J., 2001. Variable precision rough set theory and data discretisation: an application to corporate failure prediction. Omega: International Journal of Management Science, 29(6), 561-576.

[4] Cerquides, J., De Mantaras, R. L., 2005. TAN Classifiers Based on Decomposable Distributions. Machine Learning, 59, 323-354.

[5] Changchien, S. W., Lu, T. C., 2001. Mining association rules procedure to support on-line recommendation by customers and products fragmentation. Expert Systems with Applications, 20(4), 325-335.

[6] Chen, W. C., Tseng, S. S., & Hong, T. P., 2008. An efficient bit-based feature selection method. Expert Systems with Applications, 34(4), 2858-2869.

[7] Chien, C. F., Chen, L. F., 2008. Data mining to improve personnel selection and enhance human capital: A case study in high-technology industry. Expert Systems with Applications, 34(1), 280-290.

[8] Chow, C. K., Liu, C. N., 1968. Approximating Discrete Probability Distributions with Dependence Trees. IEEE Transactions on Information Theory, 14(3), 462-467.

[9] Chou, H. C., Cheng, C. H., & Chang, J. R., 2007. Extracting drug utilization knowledge using self-organizing map and rough set theory. Expert Systems with Applications, 33(2), 499-508.

[10] Davis, J., Costa, V. S., Ong, I. M., Page, D., & Dutra, I., 2004. Using Bayesian Classifiers to Combine Rules. In 3rd Workshop on Multi-Relational Data Mining, Seattle, USA.

[11] Deng, W. J., Chen, W. C., & Pei, W., 2008. Back-propagation neural network based importance–performance analysis for determining critical service attributes. Expert Systems with Applications, 34(2), 1115-1125.

[12] Dimitras, A. I., Slowinski, R., Susmaga, R., & Zopounidis, C., 1999. Business failure prediction using rough sets. European Journal of Operational Research, 114(2), 263-280.

[13] Friedman, N., Geiger, D., & Goldszmidt, M., 1997. Bayesian Network Classifiers. Machine Learning, 29(2-3), 131-163.

[14] Goh, C., Law, R., 2003. Incorporating the rough sets theory into travel demand analysis. Tourism

Management, 24(5), 511-517.
[15] Griffiths, B., Beynon, M. J., 2005. Expositing stages of VPRS analysis in an expert system: Application with bank credit ratings. Expert Systems with Applications, 29(4), 879-888.
[16] Jiang, L., Zhang, H., Cai, Z. , & Su, J., 2005. Learning Tree Augmented Naive Bayes for Ranking, DASFFA 2005: database systems for advanced applications, Lecture Notes in Computer Science, 3453, 688-698, Springer Berlin.
[17] Holsapple, C. W., Singh, M., 2001. The knowledge chain model: activities for competitiveness. Expert Systems with Applications, 20(1), 77-98.
[18] Hong, T. P., Lin, C. E., Lin, J. H., & Wang, S. L., 2008. Learning cross-level certain and possible rules by rough sets. Expert Systems with Applications, 34(3), 1698-1706.
[19] Hong, T. P., Tseng, L. H., & Wang, S. L., 2002. Learning rules from incomplete training examples by rough sets. Expert Systems with Applications, 22(4), 285-293.
[20] ong, T. P., Wang, T. T., Wang, S. L., & Chien, B. C., 2000. Learning a coverage set of maximally general fuzzy rules by rough sets. Expert Systems with Applications, 19(2), 97-103.
[21] Hruschka, E. R., Ebecken, N. F. F., 2007. Towards efficient variables ordering for Bayesian networks classifier. Data & Knowledge Engineering, 63(2), 258-269.
[22] Hu, Q., Yu, D., & Xie, Z., 2008. Neighborhood classifiers. Expert Systems with Applications, 34(2), 866-876.
[23] Huang, C. C., Tseng, T. L., 2004. Rough set approach to case-based reasoning application. Expert Systems with Applications, 26(3), 369-385.
[24] Huang, J. J., Ong, C. S., & Tzeng, G. H., 2006. Interval multidimensional scaling for group decision using rough set concept. Expert Systems with Applications, 31(3), 525-530.
[25] Huang, Y. F., Wu, W. W., & Lee, Y. T., 2008. Simplifying Essential Competencies for Taiwan Civil Servants by Using the Rough Set Approach. Journal of the Operational Research Society, 59(2), 259-266.
[26] Kamara, J. M., Anumba, C. J., & Carrillo, P. M., 2002. A CLEVER approach to selecting a knowledge management strategy. International Journal of Project Management, 20(3), 205-211.
[27] Klopotek, M. A., 2002. A new Bayesian tree learning method with reduced time and space complexity. Fundamenta Informaticae, 49(4), 349-367.
[28] Lauria, E. J. M., Duchessi, P. J., 2007. A methodology for developing Bayesian networks: An application to information technology (IT) implementation. European Journal of Operational Research, 179(1), 234-252.
[29] Lee, K. C., Lee, S., & Kang, I. W., 2005. KMPI: measuring knowledge management performance. Information & Management, 42(3), 469-482.
[30] Liao, S. H., 2003. Knowledge management technologies and applications-literature review from 1995 to 2002. Expert Systems with Applications, 25(2), 155-164.
[31] Liao, S. H., Hsieh, C. L., & Huang, S. P., 2008. Mining product maps for new product development. Expert Systems with Applications, 34(1), 50-62.
[32] Liebowitz, J., 2001. Knowledge management and its link to artificial intelligence. Expert Systems with Applications, 20(1), 1-6.
[33] Liu, D. R., Ke, C. K., Lee, J. Y., & Lee, C. F., 2008. Knowledge maps for composite e-services: A mining-based system platform coupling with recommendations. Expert Systems with Applications, 34(1), 700-716.
[34] Kamara, J. M., Anumba, C. J., & Carrillob, P. M., 2002. A CLEVER approach to selecting a knowledge management strategy. International Journal of Project Management, 20(3), 205-211.
[35] Martensson, M., 2000. A critical review of knowledge management as a management tool. Journal of Knowledge Management, 4(3), 204-216.
[36] Mi, J. S., Wu, W. Z., & Zhang, W. X. 2004. Approaches to knowledge reduction based on variable precision rough set model. Information Sciences, 159(3-4), 255-272.
[37] Ong, C. S., Huang, J. J., & Tzeng, G. H., 2005. Building credit scoring models using genetic programming. Expert Systems with Applications, 29(1), 41-47.

[38] Pawlak, Z., 1984. Rough Classification. International Journal of Man-Machine Studies, 20(5), 469-483.
[39] Pawlak, Z., 2002. Rough sets, decision algorithms and Bayes' theorem. European Journal of Operational Research, 136(1), 181-189.
[40] Pawlak, Z., 1997. Rough Sets. In: Lin, T. Y. & Cercone, N. (Eds.). Rough Sets and Data Mining: Analysis for Imprecise Data. Norwell, MA: Kluwer Academic Publishers.
[41] Pawlak, Z., 1982. Rough sets. International Journal of Computer and Information Science, 11(5), 341-356.
[42] Shyng, J. Y., Wang, F. K., Tzeng, G. H., & Wu, K. S., 2007. Rough Set Theory in analyzing the attributes of combination values for the insurance market. Expert Systems with Applications, 32(1), 56-64.
[43] Sikder, I. U., Gangopadhyay, A., 2007. Managing uncertainty in location services using rough set and evidence theory. Expert Systems with Applications, 32(2), 386-396.
[44] Slowinski, R., Zopounidis, C., 1995. Application of the rough set approach to evaluation of bankruptcy risk. International Journal of Intelligent Systems in Accounting, Finance and Management, 4(1), 27-41.
[45] Spiegler, I., 2003. Technology and knowledge: bridging a “generating” gap. Information & Management, 40(6), 533-539.
[46] Su, C. T., Hsu, J. H., 2006. Precision parameter in the variable precision rough sets model: an application. Omega: International Journal of Management Science, 34(2), 149-157.
[47] Tay, F. E. H. ,Shen, L., 2000. Economic and financial prediction using rough sets model. European Journal of Operational Research, 141(3), 641-659.
[48] Tsai, Y. C., Cheng, C. H. , & Chang, J. R., 2006. Entropy-based fuzzy rough classification approach for extracting classification rules. Expert Systems with Applications, 31(2), 436-443.
[49] Tseng, T. L. & Huang, C. C., 2007. Rough set-based approach to feature selection in customer relationship management. Omega: International Journal of Management Science, 35(4), 365-383.
[50] Tsumoto, S., 2003. Automated extraction of hierarchical decision rules from clinical databases using rough set model. Expert Systems with Applications, 24(2), 189-197.
[51] Wang, F. H., 2005. On acquiring classification knowledge from noisy data based on rough set. Expert Systems with Applications, 29(1), 49-64.
[52] Wang, T., Touchman, J. W., & Xue, G., 2004. Applying two-level simulated annealing on Bayesian structure learning to infer genetic networks. Computational Systems Bioinformatics Conference, 2004. CSB 2004. Proceedings. Publication Date: 16-19, 647- 648.
[53] Wang, Y. F., 2003. Mining stock price using fuzzy rough set system. Expert Systems with Applications, 24(1), 13-23
[54] Wiig, K. M., Hoog, R. D., & Spek, R. V. D., 1997. Supporting Knowledge Management: A Selection of Methods and Techniques. Expert Systems with Applications, 13(1), 15-27.
[55] Witlox, F. , Tindemans, H., 2004. The application of rough sets analysis in activity-based modeling: Opportunities and constraints. Expert Systems with Applications, 27(1), 585-592.
[56] Wu, W. W., 2009. Exploring core competencies for R&D technical professionals, Expert Systems with Applications, 36(5), 9574–9579.
[57] Xia, W. , Wu, Z., 2007. Supplier selection with multiple criteria in volume discount environments. Omega: International Journal of Management Science, 35(5), 494-504.
[58] Yahia, M. E., Mahmod, R., Sulaiman, N. , & Ahmad, F., 2000. Rough neural expert systems. Expert Systems with Applications, 18(2), 87-99.