Soft Computing as a Methodology to Risk Engineering

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Abstract: Methods for risk engineering is a bundle of engineering tools including fundamental concepts and approaches of soft computing with application to real issues of risk management. In this talk fundamental concepts and soft computing approaches of risk engineering will be introduced. As the term of *risk* implies both advantageous and hazardous uncertainty in its origins, a fundamental theory to describe uncertainties is introduced that includes traditional probability and statistical models, fuzzy systems, as well as less popular modal logic. In particular, modal logic capabilities to express various kinds of uncertainties are emphasized and relations with rough sets and evidence theory are described. Another topic is data mining related to problems in risk management. Some risk mining techniques including fuzzy clustering are introduced and a recently developed algorithm is overviewed. A numerical example is shown.

1 Introduction

Many kinds of risks are now surrounding us and it is believed that risks are becoming more and more threatening to us. For such a reason, new organizations with the name of risk and security are being established: the author's department of risk engineering which has been established in 2001. The department of risk engineering is small: it has 20 staffs, 60 students in Master Program, and 15 students in the Ph.D. Program. Although it is a small department, its research and educational activities are very active.

This report describes only a small part of many research aspects in risk engineering, that is, a fundamental aspect of soft computing related to risk engineering.

We first overview general concepts of 'risk' whereby why the approach of soft computing to risk engineering is adequate is shown. Second, two specific subjects in risk engineering for which soft computing methodology is employed are discussed. One is modal logic approach to discuss uncertainties in its fundamental aspects; the other is data mining including issues of risks.

2 Risks in General

The word of *risk* refers to different meanings depending on a variety of situations and applications. There is a book edited by Ansell and Wharton [1] in which the first sentences in the preface saids: 'Risk is unavoidable feature of human existence. Neither man nor the organizations and societies to which he belongs can survive for very long without taking risks.' This is the fundamental standpoint of them and many other professionals engaging in risk management: we cannot avoid risks forever and have to be a risk taker to survive.

In the first chapter of this book, Wharton [17] considers risks in general. He saids that evolution of risks is with humans' evolution, and types of risks surrounding us have been changed with the human history. He then mentions two different origins of this word: one implies fortune and the other means hazard. These two aspects of 'risk' last until today, where *risk* in finance means profit and loss at the same time, while in other fields of engineering *risk* mainly implies loss and hazard.

General definitions of risks are given therein: many professionals defines a *risk* to be a measurement of the chance of an outcome (good or bad), the size of the outocme, or the combination of both. Although professional literature generally uses probabilistic measures, he suggests an older interpretation: 'a risk is any unintended or unexpected outcome of a decision or course of action'.

At the same time he emphasizes the interdisciplinary nature of risk analysis and risk management. Contributions from different fields of sciences and engineering are expected.

In spite of such growing concern to the issues of risks, organizations or departments of 'risk engineering' have not been found in universities (an exception is an insurance company which uses this term over years), while risk management organizations exist in many places. The reason is mainly due to historical use of this term: risk management has been studied in social sicences and medical siences, while fields of engineering have been concentrated on safety issues rather than risks. Moreover information engineers are interested in security issues instead of risk management. However, the rapid growth of the society with risks are requesting us to consider risk, security, and safety issues in a unified framework of engineering and sciences. For this reason the department of risk engineering meets the request from the society nowadays.

2.1 Fundamental methodology of risk engineering

An important question is what the fundamental methodology in risk engineering is. To answer this question, let us consider again the definitions and concepts of risks. Since risks mean uncertainty and its measures, the basic methodology should describe uncertainties in a variety of mathematical frameworks. Although the probabilistic risk analysis (e.g. [2]) is popular, other methods such as fuzzy systems [19], neural networks, evidence theory [16], rough sets [14], and modal logic [4, 15] should also be included in the methodology. There is a convenient and flexible term of *soft computing* (see e.g. [8]) for emcompassing all these *soft methods* handling various uncertainties in systems. Therefore we consider soft computing as the fundamental methodology to risk engineering.

3 Soft Computing with Applications to Risk Issues

It is impossible to review all methods in soft computing here. We hence describe relatively unknown methods of modal logic with applications and data mining for risk issues.

3.1 Modal logic applications

Generally modal logic is not recognized as a method of soft computing. It encompasses most methods dealing with uncertainties, however. In other words, rough sets and measures in evidence theory are derived from modal logic systems with additional structures and/or variations. Even probabilistic measures can be derived from modal logic. Studies of modal logic should thus be essential to system analysis including risk issues. Among many systems of modal logic, polymodal systems [15] have stronger capabilities to describe uncertainties and have been used to uncover fundamental theoretical properties in computer languages and programming.

In relation to uncertainties, Miyamoto [13] discusses a family of polymodal logic having modalities

$$\langle\alpha\rangle \mathrm{A}, \qquad \alpha \in \Lambda \tag{1}$$

$$[\alpha]\mathrm{A}, \qquad \alpha \in \Lambda \tag{2}$$

which are read as 'sentence A is possible (resp. necessary) with the parameter α,' where the parameter set Λ is a lattice. He considers the Kripke semantics where truth and falsity in possible worlds are discussed; on the other hand a family of axiomatic systems are introduced. The soundness and completeness between the two are proved [13].

Two applications of polymodal logic have been considered by the same author. First, the possibility and necessity measures can be derived from the polymodal system as the special case of $\Lambda = [0,1]$ (the unit interval); in other words, the possibility theory is generalized into lattice-valued possibility theory on the basis of the polymodal system [13]. Second, change of environment from a normal state to an abnormal state has been considered using the same framewwork of polymodal logic [11]; how the possible worlds in the Kripke semantics are correspondent to states of the real world in applications is studied therein.

3.2 Rough sets and modal logic

It is known that the rough set theory [14] is based on the S5 system [4] of modal logic. Moreover generalized rough sets [18] having neighborhoods to each objects instead of classifications of the universe can be handled in the framework of KBT system of modal logic [4]. Let us briefly see how the two are related. For this purpose assume W is the universal set of objects and $\mathcal{U}(\alpha) = \{U_1(\alpha), \ldots, U_K(\alpha)\}$ is a partition (i.e., a family of mutually exclusive subsets such that the union of all sets of the family is equal to the unversal set). The partition is assumed to be dependent on the parameter α in Λ for the discussion below.

According to the theory of rough sets, the upper and lower approximations of a set, say A, are considered. That is, the upper approximation is

$$R^*(\alpha)A = \{\, U_j(\alpha) \in \mathcal{U}(\alpha) \;:\; U_j(\alpha) \cap A \neq \emptyset \,\}; \tag{3}$$

the lower approximation is

$$R_*(\alpha)A = \{\, U_j(\alpha) \in \mathcal{U}(\alpha) \;:\; U_j(\alpha) \subseteq A \,\}. \tag{4}$$

Suppose a sentence A corresponds to the set A of the same symbol without confusion. Note also that the set of possible worlds where B is true is denoted by $\|\mathrm{B}\|$.

We then can prove

$$\|\langle\alpha\rangle \mathrm{A}\| = R^*(\alpha)A, \tag{5}$$

$$\|[\alpha]\mathrm{A}\| = R_*(\alpha)A, \tag{6}$$

although we omit the detail.

The above equations hold for generalized rough sets in which the partition is replaced by neighborhoods for each objects of W. That is, we assume

$$\mathcal{U}(\alpha) = \{\, U(x;\alpha) \subseteq W \;:\; x \in U(x;\alpha),\ \forall x \in W \,\} \tag{7}$$

instead of a partition.

It is not difficult to see that the evidence measures can be derived from modal systems by assuming a measure for subsets in $\mathcal{U}(\alpha)$. When we consider the trivial case of $U(x;\alpha) = \{x\}$ for all $x \in W$, we have the ordinary probability measure.

We thus can show relations among modal logic semantics, possibility theory, rough sets, evidence theory, and probability measure.

It is also easy to see that $\mathcal{U}(\alpha)$ forms a hierarchical classification when Λ is a totally ordered set, and moreover a hierarchical classification is closely related to agglomerative clustering [9] when such a classification should be generated from a data set.

3.3 Data mining from information table

A major application of rough sets is knowledge discovery from an information table. Let us briefly see what it means in the present context. An information table can be written in an abstract manner using relational database terms. Let $\mathcal{A} = \{a_1, \dots, a_m\}$ be a schema of attributes and $a_1, \dots, a_m$ are individual attributes. Each attribute a_j has a corresponging set D_j of a domain. Assume $D \subseteq D_1 \times \cdots \times D_m$ is a finite relation: it is a set of tuples $t = (t(a_1), \dots, t(a_m)) \in D$ where $t(a_j) \in D_j$. Assume also that for $A = (a_i, \dots, a_j) \subseteq \mathcal{A}$,

$$t(A) = (t(a_i), \dots, t(a_j)),$$

that is, $t(A)$ is a subsequence of t corresponding to the subset A. For a subset $T \subseteq D$, we can define

$$T(A) = \{t(A) : t \in T\}.$$

In ordinary rough approximations, we are given a subset T of D and consider $R^*(T)$ and $R_*(T)$ using all attributes. In contrast, we can explicitly show dependence on the set of attributes using the polymodal framework. For this purpose let $\Lambda = 2^{\mathcal{A}}$, the set of all subsets of $\mathcal{A}$. Then, each element $\alpha \in \Lambda$ is a set of attribute, e.g., $\alpha = A$. We define

$$R^*(A)T = \{t \in D : t(A) \in T(A)\}, \quad (8)$$
$$R_*(A)T = \{t \in D : t(A) \in T(A) - T^C(A)\}. \quad (9)$$

We have several other theoretical properties but they are omitted here (see [13]). These investigations show that the theory of relational database also has intrinsic relations to rough sets and polymodal logic, although this observation does not seem to have been discussed elsewhere.

3.4 Data clustering in risk engineering

Data clustering tools are now becoming standard techniques in different fields of sciences and engineering. In particular, it is viewed as an adequate tool for data mining, since this method is employed in the initial stage of data analysis when knowledge on data sets is insufficient. Fuzzy clustering [9, 8] has extensively been studied among which most known techniques are fuzzy c-means and their variations [3, 10, 7].

In this paper we show a fuzzy c-regression model applied to a data set of cancer risks and smoking. The fuzzy c-regression model means that c different regression models

$$y = \sum_l \beta_i^l x^l + \beta_i^{p+1}, \qquad i = 1, \dots, c$$

which are hidden in a data set $\{(x_k^1, \dots, x_k^p, y_k)\}$ ($k = 1, \dots, n$) are derived at the same time and each object has fuzzy membership values to all regression models.

In fuzzy c-regression models using an entropy function [12], the following objective function should be minimized.

$$J(U, B, A, S) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ki}(y_k - \sum_l \beta_i^l x_k^l - \beta_i^{p+1})^2 / S_i + \lambda^{-1} \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ki} \log \frac{u_{ki}}{a_i}$$

where $U = (u_{ki})$, $B = (b_i^l)$, $A = (a_i)$, $S = (S_i)$, and λ is a positive constant. In these variables (U, B, A, S), U is the fuzzy membership matrix which describes the degree of belongingness of an object to a cluster. The membership should be nonnegative and satisfy $\sum_i u_{ki} = 1$ for all $1 \leq k \leq n$.

The objective function is minimized using an alternate optimization algorithm using each of U, B, A, and S while other variables are fixed. Iterative solutions for these variables are obtained and iterations are continued until convergence. In a rigorous sense no strict optimization is guaranteed but empirically the alternate optimizaiton algorithm works well for many data.

We omit detailed description of the optimal solutions here (see e.g.[6, 10]) and we observe an example.

Figure 1 shows data of the numbers of death (unit is 10^5) by four different types of cancers in 44 states in USA in 1960. The horizontal line shows the average number of smoking cigarettes (unit is 100). The distinction by different marks have been neglected and all data have been handled by the fuzzy c-regression model as the whole data set. The result with $c = 4$ is shown in Fig. 2, where four clusters are clearly observed and the difference with the original classification is small.

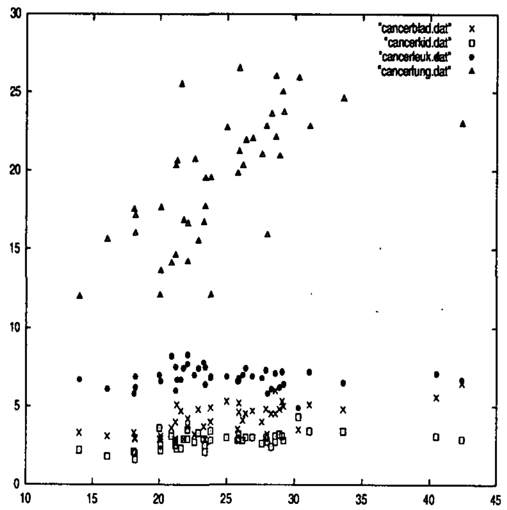

Figure 1: Data of smoking and cancer.

4 Concluding Remarks

We have overviewed the concept of risks in general, where interdisplinary characeristics of risk engineering and the fundamental role of soft computing have been

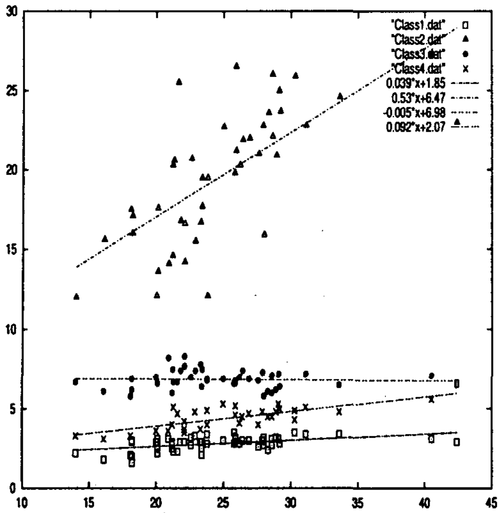

Figure 2: Results from the algorithm of fuzzy c-regression models with the size and variance variables based on entropy (four clusters are assumed).

emphasized. It has also been shown that polymodal systems are a fundamental tool having capabilities to be a unified framework that connects different theories theoretically. Moreover rough sets and data mining are mentioned and a clustering technique have been discussed with a numerical example.

As this paper is an overview of soft computing methods in risk engineering, many other activities in the department of risk engineering have been omitted here. There are important application studies and educational activities, which will be mentioned in the presentation.

There are also many problems to be studied in risk engineering and risk management. Collaborations among scientists in different fields and international cooperations will be useful.

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