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TECHNOLOGY PERCEPTIVE OF INTELLIGENT MACHINE LEARNING DATA ANALYTICS METHOD USING FUZZY LOGIC SYSTEMS

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Abstract

The instinct of human beings is very complex. The understanding of this instinct needs a strong dimensional analysis of the knowledge of discourse. The computer systems are now trained to realize how things operate in a real-time environment for intelligent analysis. This effort although very progressive has a restriction. There is an intelligence gap which makes human one step above the machine. The fuzzy logic system can be employed to make a machine understand this intelligence gap in a better way. In other words, fuzzy logic is a computational Intelligence technique that makes a computer understand and think the way humans do. The fuzzy logic system is now attracting scientists and engineers around the world since by integrating its abilities with soft computing techniques like neuro and chaos computing, genetic algorithm, probability reasoning, and immune networks, it can handle the problems that had not been solved before. Not only has the fuzzy system significantly enhanced knowledge-based or expert system technology, but it has also primarily changed the granularity of intelligence. For example, with the help of the fuzzy logic system, industrialists of home appliances are today embedding intelligence in specific productsThe aim of this study is two folds: first, to understand the fuzzy logic system for effective decision making and second, to demonstrate the presence of this intelligence gap through real-time examples. The examples are selected cautiously to illustrate and demonstrate the applications of the fuzzy logic system for every reader.

Key Terms: Intelligent Data Analysis, Fuzzy Logic Systems, Machine Learning, Genetic Algorithms, Probability Modelling

1. Introduction

The fields of science and technology enable us to develop applications that help us in a real world. In this context, the fuzzy logic system is a gift for us that is acceptable in a wide range of various industry applications. The fuzzy logic system concept is based on the idea of relative membership degree, as inspired by the processes of human insight and perception. Lotfi A. Zadeh published his first renowned research article on fuzzy sets in 1965. The fuzzy logic system can handle data arising from computational perception and cognition, that is, uncertain, imprecise, vague, partially true, or without crisp values. The fuzzy logic system allows for the inclusion of vague human analysis in computing problems. Similarly, it gives an effective means for conflict resolution of multiple criteria and better analysis of options [1].

Of late, new computing methods based on fuzzy logic system have become one of the most effective technologies utilized in the development of intelligent systems for sophisticated control and reasoning, optimization, identification, decision making, pattern recognition, control, and inference systems [2, 3] The reason for its success lies in the fact that the system based on fuzzy logic system carefully resembles human decision making with the capacity to handle problems and provides accurate solutions. It is also significant that fuzzy models are transparent and easily adaptable. Moreover, fuzzy logic system methods exploit the sub-symbolic data existing in the universe of discourse providing the context to the given model and solution [4, 5]. The fuzzy logic system generates reasonably good solutions from imprecise data, by decreasing the computational overhead vastly, compared to conventional methods.

The gap in engineering design which is left vacant by purely mathematical approaches is often filled by the fuzzy logic system and other computational intelligence methods. Other methods need hardcore mathematical calculations to simulate real-time complex problems. On the other hand, fuzzy logic-based systems can handle the uncertainties of the real-time scenario more suitably owing to the generation of soft or vague boundaries, rather than crisp values [6]. The problem specifications are transformed into automatic systems by intuitive design approaches. The applications of the fuzzy theory were primarily industrial, such as the very first one: the process control of cement kilns. Nevertheless, as the technology was further embraced, fuzzy logic systems were employed in several applications, some of them relatively sophisticated.

2. System Model

Reasoning with uncertain and imprecise information is of central concern in both the fuzzy logic system and general Artificial Intelligence (AI). However, for a long time, the fuzzy logic system was not considered as being a part of mainstream AI. The reasons for this are many and complex. First, the fuzzy logic system is different from traditional AI methodologies. Most AI systems are based on conventional predicate logic and are symbolic in nature. In contrast, fuzzy logic system systems are based on multi-valued logic and are numerical in nature [7]. Second, questions about the underlying theoretical bases of the fuzzy logic system were raised by some investigators [8]. Third, for most of the 1970s and the 1980s, the dominant emphasis within AI was the building of knowledge-based systems by means of traditional rule-based technology [9].

Although largely ignored in the USA (both by industry and academia) for about two decades after its invention, the fuzzy logic system was embraced and developed by investigators in Asian and European countries. Independent of mainstream AI research, fuzzy logic system acquired a large following of dedicated researchers around the world and developed into a major academic field with its associations (such as the International Fuzzy Systems Association), journals (such as the International Journal of Fuzzy Sets and Systems and the International Journal of Approximate

Reasoning), and conferences (organized by IEEE and the International Fuzzy Systems Association). The fuzzy logic system has also been applied in many other fields including mathematics, operations, research, medicine, and transportation [10].

The western industry has recently turned its attention to the fuzzy logic system and its commercial potential. The fuzzy logic system is also slowly gaining acceptance from the mainstream AI community. The first practical application of the fuzzy logic system to the control of industrial processes was pioneered in Europe by Mamdani and Assilian in 1974 in connection with the regulation of a steam engine [11]. In 1980, F. L. Smidth and Co. of Copenhagen started marketing the first commercial fuzzy expert system to control the fuel intake rate and gas flow of a rotating kiln employed to make cement. While academic interest in the fuzzy logic system in Japan started quite early, it was only during the early 1980's that Japanese industries recognized the commercial potential of the fuzzy logic system and started investing in it seriously.

3. Representational Concepts Using Fuzzy Sets

Fuzzy logic system aims to model the imprecise modes of reasoning that play a significant role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision. Zadeh proposed that rather than regard human reasoning processes as themselves "approximating" to some more refined and exact logical processes that could be performed with mathematical accuracy, the essence, and power of human reasoning lies in its ability to grasp and use vague theory directly. For example, we are usually quite comfortable dealing with questions (like those give below) based on a store of knowledge that is inaccurate, partial, or not completely consistent:

Most wealthy actors live in Beverly Hills. Mary is a rich actress. What can be said about the location of Mary's residence?

Most players on the basketball team are quite tall. George is on the basketball team. How tall is George?

Conventional logical systems are typically based on Bivalent logic. In the bivalent logic system, any proposition can be either true or false. This brings an intrinsic limitation in its ability to denote "vague" and "imprecise" notions like "wealthy" and "tall." To understand this better, consider the concept "tall." Most peoples would agree that a person whose height is more than 7' is surely tall while someone whose height is below 5' is definitely short. In order to quantify the distinction between tall and short peoples, a common methodology is to employ a predefined value (above which everybody is tall and below which everybody is not tall). Let us select the predefined value of height to be 6'. This predefined value appropriately categorizes the height of 7' as tall and of 5' as short. Next consider two persons A and B, with heights of 5'11" and 6'1" correspondingly.

The use of linguistic variables makes it much easier for humans to express statements or conditions linguistically. The use of linguistic variables in fuzzy reasoning procedures is explained below. Note that a linguistic variable can be viewed as a generalization of a conventional variable. Though some formal procedures have been proposed in the literature for obtaining these distributions [19], no theoretically correct method exists. These distributions are essentially context-dependent and are usually defined by subjective estimates.

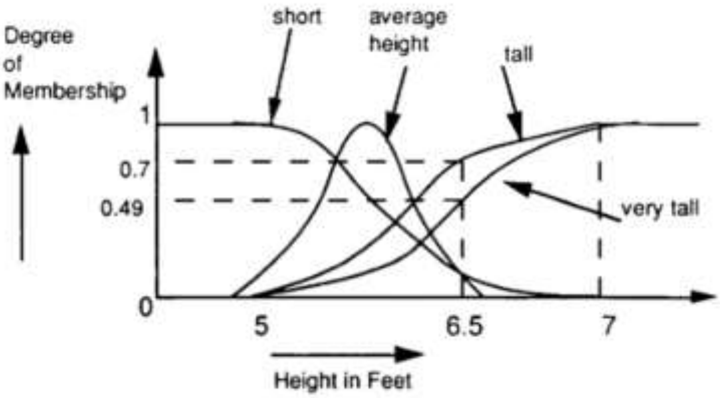

Figure 1: Representation of the concept “tall” using fuzzy sets

For example, while a height of 6' would be considered average in Scandinavian countries, the same would be considered “very tall” among Indians. Thus the distributions defining the same concept “tall” would vary depending upon the context of the problem solution. In most cases, it is the responsibility of the domain expert to define the shapes of the distributions. This subjectivity in the procedure for obtaining the distributions has often been criticized by opponents of the fuzzy logic system.

In order to understand how these partial matches are calculated and how the fuzzy inference process works, it is required to know about some fundamental mathematical operations on fuzzy sets. Fuzzy sets are defined as extensions of conventional sets. Therefore, it is possible to describe the operations of union, intersection, and complementation for fuzzy sets. These operations are described by means of the membership degrees of the different elements in the corresponding fuzzy sets.

- **Union:** The possibility distribution of the union, XUY, of two fuzzy sets X and Y is given by taking the maximum of the membership degrees of the elements in X and Y.

- **Intersection:** The possibility distribution of the intersection, X∩Y, of two fuzzy sets X and Y is given by taking the minimum of the membership degrees of the elements in X and Y. Note that only elements common to both sets are retained in their intersection.

- **Complement:** The possibility distribution of the complement of a fuzzy set X is obtained by subtracting from 1 the membership degrees (in the fuzzy set X) of the different elements in the domain.

4. Fuzzy Logic System – Intelligent Data Analytics Process

The min-max operators used for defining the fuzzy set theoretic operations were first proposed by Zadeh in his seminal paper on fuzzy sets. There is nothing inherently unique about the min-max operators, and over the years several new operators for fuzzy sets have been proposed by different researchers. A description of these other operator categories is beyond the scope of this paper. This paper focuses on the min-max operators as they remain the most popular operators used in commercial applications due to their simplicity and appealing properties. For simplicity, let the fuzzy sets Low, Medium, and High used in rules 1 and 2 have similar representations for both Voltage and Current as shown in Figure 3 (X-axis scales would be different for voltage and current).

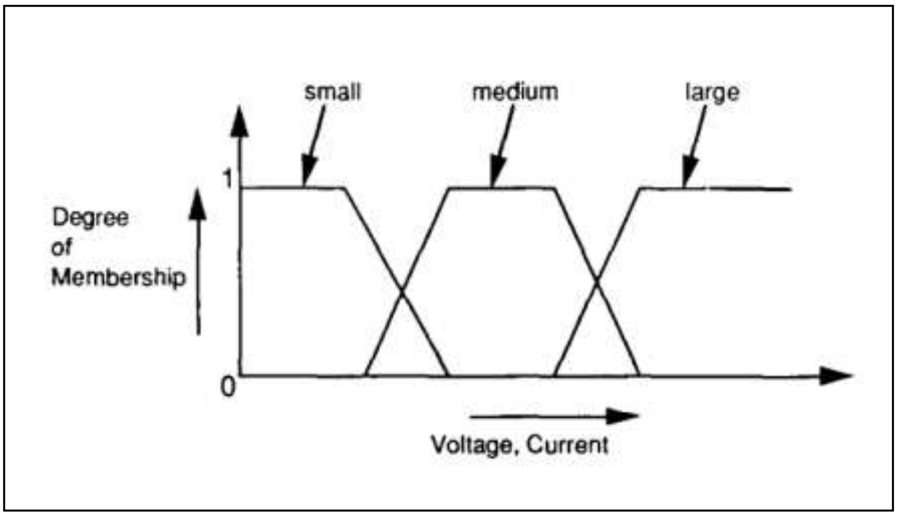

Figure 2: The fuzzy sets Low, Medium, and High

Though there is not a direct match between the premises of the two fuzzy rules and the input fact, note that a partial match with each rule does exist. Thus intuitively one can expect each of the two rules to contribute partially to the output answer. The desired value of Current is computed as follows:

1. The intersection of the input fact with each of the fuzzy premises is computed. The intersections are shown by the striped regions in the input premises in Figure 4.

2. The contribution of each rule to the output answer is determined by taking the portion of the output fuzzy distributions (shown shaded in the conclusions in Figure 4) which are contained within the intersections computed in the above step.

3. A union is taken of the contributions of the conclusions of each rule to give the final desired output value of Current (shown by the shaded region in the bottom right-hand corner of Figure 3). Sometimes, a linguistic answer may be desired, especially if the output answer is to be given to a human.

A fuzzy logic system generally comprises four components namely fuzzifier, defuzzifier, fuzzy rules and fuzzy inference engine, which is shown in Figure 3.

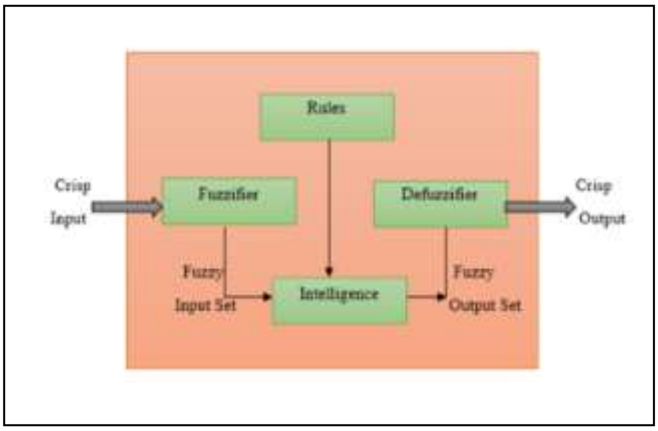

Figure 3: Components of a fuzzy logic system

The main objective of the fuzzifier is to transform the real crisp input variables into linguistic variables. In Mathematics, the variable age can assume any number, whereas in fuzzy logic the value of age variable can be “tall” or “short”. This is known as a linguistic variable. Fuzzy rules are generally in the form of If-Then rule. The main purpose of using a fuzzy rule in a fuzzy logic system is that it will be used to control the output variable. A fuzzy implication rule will represent the correlation between input and output. A fuzzy inference engine is used to convert the input to the output using the If-then fuzzy rules. In a defuzzifier of a fuzzy logic system, a fuzzy inference engine’s output is converted to crisp variables with the help of fuzzy membership functions. The most commonly used defuzzifiers are the mean of maximum, largest of maximum, the bisector of area, centroid of the area and smallest of maximum. A fuzzy knowledge base contains the rule base used along with a database. The entire list of If-then fuzzy rules is accommodated in the rule base and the database defines the membership function.

5. System Implementation – Process Modeling

The inverted pendulum is one of the conventional systems used for studying control procedures. The problem consists of applying a suitable force to balance an inverted pendulum. In principle, it is very similar to balancing a stick on one’s hand by moving the hand forward or backward as necessary. Figure 7 describes a simple inverted pendulum in which a motor gives the necessary force for balancing the pendulum. In this system, there are two inputs (the angular displacement of the bob, θ, and the angular velocity of the bob ω (i.e., $\omega=d\theta/dt$)) and one output (the force applied by the motor).

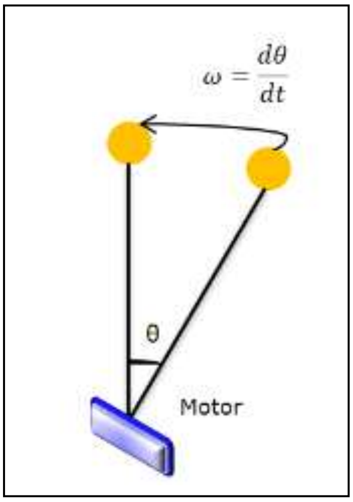

Figure 4: An inverted pendulum.

In spite of its simplicity, the inverted pendulum is a non-linear system (i.e., the required current strength varies as a nonlinear function of θ and ω). The system can be represented precisely but needs the solution of a second-order differential equation. As anticipated, some generalizations (e.g., the approximation of sin θ by θ) are used for solving the equation quickly. These generalizations are not always effective and can be violated (e.g., the approximation of sin θ by θ is not valid for large θ, i.e., for large displacements). An optimum solution would involve the utilization of distinct numerical methods (which are computationally intensive). Also, a solution of the equations to balance the pole is not easily possible as the solution point it unstable regarding the system's initial conditions. The solutions are also sensitive to different factors like the mass of the bob, the length of the shaft and the strength of the motor. Precise and robust control of such a system can be achieved using a set of fuzzy rules of the following form:

IF θ is zero **AND** ω is zero **THEN** Force-applied is zero

Table 1 describes a set of 12 rules which can be employed to control a simple inverted pendulum [21]. The angular displacement and the angular velocity of the pendulum are represented by θ and ω, correspondingly. It is also expected that an electric motor is being employed to produce the required force to balance the inverted pendulum.

Table 1: Fuzzy rules implemented to control an inverted pendulum

IF	θ	is negative-	**AND**	ω	is zero	**THE**	Curren	is positive-
IF	θ	is negative-small	**AND**	ω	is zero	**THE**	Curren	is positive-small
IF	θ	is zero	**AND**	ω	is zero	**THE**	Curren	is zero
IF	θ	is positive-small	**AND**	ω	is zero	**THE**	Curren	is negative-small
IF	θ	is positive-	**AND**	ω	is zero	**THE**	Curren	is negative-
IF	θ	is zero	**AND**	ω	is negative-	**THE**	Curren	is positive-
IF	θ	is zero	**AND**	ω	is negative-small	**THE**	Curren	is positive-small

IF	θ	is zero	**AND**	ω	is zero	**THE**	Curren	is zero
IF	θ	is zero	**AND**	ω	is positive-small	**THE**	Curren	is negative-small
IF	θ	is zero	**AND**	ω	is positive-	**THE**	Curren	is negative-
IF	θ	is positive-small	**AND**	ω	is zero	**THE**	Curren	is zero
IF	θ	is negative-small	**AND**	ω	is positive-small	**THE**	Curren	is zero

Figure 4 illustrates the shapes of these fuzzy sets. Note that the input values of θ and ω are crisp. Moreover, a crisp value has to be given to the motor as the recommended value of current to balance the inverted pendulum.

4. Conclusion

Fuzzy logic has been implemented in several applications including facial pattern recognition, vacuum cleaners, antiskid braking systems, air conditioners, washing machines, transmission systems, control of subway systems and unmanned aerial vehicles, knowledge-based systems for multi-criteria optimization of power systems, weather forecasting systems, models for new product pricing or project risk assessment, medical diagnosis and treatment plans, and stock trading. Fuzzy logic has been effectively implemented in several domains including control systems engineering, image processing, power engineering, industrial automation, robotics, consumer electronics, and optimization. This branch of mathematics has instilled new life into scientific domains that have been dormant for a long time. According to most indications, the full commercial impact of the fuzzy logic system is only starting to be felt. The long-term implications for industry and business are enormous. While the fuzzy logic system does not provide a panacea for all problems facing the industry, it does provide proven benefits. The need to market more innovative products and to do it cheaply and quickly is being increasingly seen as an important determinant of a company's ability to survive in the global market

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