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Tutorial on fuzzy logic in simulation

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Abstract

The objective of this tutorial is to introduce to the simulation community another tool that is now available. This tool is best known under the name of Fuzzy Set Theory. This tutorial contains a brief discussion of the current trends in simulation which we believe justify the need of this new tool. Kept to a minimum, the introduction to fuzzy sets will be strictly limited to the case of a finite number of elements. Most attention will be devoted to fuzzy logic. It is precisely fuzzy logic which lends itself to growth in the simulation of situations that arise in real life either because of the inexactness of the environment, or because of the inexactness/imprecision of the available data.

The state of the art in simulation

Although still young, the science of simulation developed through the years because of advances on two clearly recognizable, and roughly parallel tracks. On one track, computer languages have made progress through four or five generations so that a user now has only the embarassment of making a choice. On the other track, a multitude of problems of increasing complexity are recognized that can be solved by using the appropriate languages.

First encountered were problems with physical processes which were well understood, and for which known laws hold and good data can be obtained. These were basically problems of a deterministic nature. Then gradually more probabilistic features were introduced into the simulations, such as the Monte Carlo techniques. These were still applied primarily to problems with well defined, or well substantiated characteristics. An example is the class of simulation which depends on critical events. Optimization was often considered a suitable tool for many of these problems.

Clearly, as the physical processes became more involved and, at the same time less clearly understood or defined, success in simulation decreased. Furthermore, the quality of data which had to be used in some form or another for most of the current problems, for which simulation would be highly desirable, also worsened. The uncertainty associated with data has been partially alleviated by probability or randomness considerations. However, there exists another type of uncertainty for which probabilistic/randomness assumptions do not suffice.

Why? We believe a challenge exists to simulate real life situations for which imprecision/inexactness are a state of nature. Namely, one wishes to simulate within an inexact environment and with inexact data. For example, simulation in the usual sense of the word, does not yield good results when applied to the interesting sets of problems which operate on heuristics. It is precisely on this set of problems that the tools that stem from fuzzy set theory have begun yielding a great deal of successes.

Why fuzzy?

Simulation of real life situations is needed for cases involving an inexact environment with inexact data. But what does inexact, or uncertain, or vague mean?

Consider the the problems involved in the simulation of real life decision making among groups of people who are

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equally powerful, or equally expert, or in stressful situations. Such situations occur in goal oriented systems composed of a polity of local experts , i.e. in a committee at work, or during a corporate strategic planning , or during decision making situations under stress such as is encountered in a military command [6,7]. It is easy to recognize that each of the persons involved in a committee has a menu of acceptable behavior patterns and responses. These patterns and responses are quite general in nature, and they are selected as needed . This is an example wherein the local laws (behavior patterns),and the data (responses), of the system are fairly well known, but its global operations are not nearly so clearly definable.

To show that a probabilistic, or stochastic approach is not always sufficient in simulation, consider a group of people who are willing to referee papers which are submitted to a journal . To estimate the probability that anyone is called to referee a paper is one type of problem. To estimate the ability of this person to perform as a referee is quite another problem. Consider another example. A person is observed doing gardening in the backyard. We could try to estimate a probability measure that this person belongs to a garden club. This is a different kind of measure from that which specifies how active this person would be in the club. Medicine produces many applications as well. For instance, the probability that a symptom of a disease exists in a patient is different question from assessing the severity with which the symptom exists in a specific patient.

To conclude, there are real life situations with uncertainty for which probability and randomness do not suffice. What is needed is a systematic way to deal with reasoning under uncertainty. Fuzzy logic affords such a new approach.

What is a fuzzy set ?

The most attractive feature of fuzzy sets is that it affords an applicable rendition of the notion of belonging to complex situations for which " belonging " cannot be defined sharply. Since the publication of Zadeh's seminal paper in 1965 [20] , some four thousand articles and thirty books have been published on the topic of fuzzy sets and related areas. Two international journals and an international society are entirely devoted to the support and dissemination of the most recent advances in the field . Even popular press has recently paid attention to the notion of fuzziness , particularly as it applies to problem solving using the computer [11,15,18,23]. What has attracted all this attention ?

For simplicity , assume that B is a collection which has a finite number of members . For example , B is the set of people in this room . Suppose we want to determine the probability that each person in this room can perform a specific activity such as skiing.

We would collect data and make projections from known distributions. However , the foregoing would not answer another question of importance. If we ask each person whether or not they are able to ski , then to each person in this room we can attach a value that describes the ability to ski of this particular individual. What is each individual's ability to ski is the problem of context. This ability is a fuzzy concept.

Let s denote any individual in this room and let $a(s)$ denote the ability of s in skiing with its value calibrated in some fashion, usually between 0 and 1. Then the set of pairs $(s,a(s))$ is called a <u>fuzzy set</u> with support set B and <u>membership function</u> a . Such a set of pairs will be denoted B_f (f is for fuzzy !) while B simply denotes the support set .

Let's look more deeply. There are two types of skiing, downhill and cross-country. Let C_f be the set of people in this room who can ski cross-country, and who are not necessarily pros. Likewise, let D_f be the set of people who can ski downhill. <u>Equality</u> between the two sets is not possible unless each person in the room skis with the same ability both cross-country and downhill. In other words , equality between fuzzy sets holds if equality holds for the membership functions c and d ,

$$C_f = D_f \text{ if and only if } c(s) = d(s) \text{ for all } s \ .$$

If each person in this room is less good at cross-country than at downhill skiing, then the membership $c(s)$ is less or equal the membership $d(s)$. Thus <u>inclusion</u> is defined by

$$C_f \subseteq D_f \text{ if and only if } c(s) \leq d(s) \text{ for all } s \ .$$

So far, equality and inclusion have been defined. How about combining fuzzy sets ? The operation of <u>union</u> of the two fuzzy sets must yield a set that describes how good each s is at either of the two ways of skiing. The max-operation on the membership values satisfies the criterion. Similarly, an element s belongs to both sets, i.e. to the <u>intersection</u> , if the min-operation on the membership values is used. What is the <u>complement</u> of a fuzzy set ? Clearly, if s skis cross-country with ability $c(s)$ then $1 - c(s)$ describes what s needs to improve to reach perfection.

Many of the properties that hold for sets in the classical boolean case also hold for fuzzy sets. Fuzzy sets theory is a generalization of the ordinary set theory [13]. In fact, if the membership function can only equal 0 or 1 then the fuzzy set reduces to the ordinary case. The following shows that a simple property of ordinary sets does not hold for fuzzy sets. Recall that the intersection of an ordinary set with its complement is empty. Let D'_f denote the complement of the fuzzy set D_f. Then the $\min \{ d(s), 1 - d(s) \}$ may equal a value other than 0. For example , if the membership value $d(s) = 0.3$ then

$$d'(s) = 1 - 0.3 = 0.7 \ ,$$

$$\min\{d(s), d'(s)\} = \min\{0.3, 0.7\} = 0.3,$$

so that the intersection of D_f with D'_f contains the pair (s, 0.3). In other words, the set of pairs that belong to a fuzzy set and to its complement need not be empty. This fact turns out to yield some interesting methods to analyze inexactness [19], [12].

Languages

Having dealt with the rudiments of fuzzy set theory, let us turn to some more familiar computer languages which deal with context and logic. After all, this is the medium in which we will write our simulations. These are the tools which we will use to construct the fuzzy algorithms. For example, from these a global view of the interactions that arise among a group of decision makers is possible.

Recall that by object oriented programming is meant a programming style which permits descriptive and procedural attributes of an object to be associated directly with that object in a context (or in a frame as it is known in Artificial Intelligence circles). Incidentally, one definition characterizes an object as a set of operations, and also as a system component consisting of a set of private memory locations. In practice, this definition of object allows that sets of rules, and in fact whole programs, can be connected with the objects which are the subject of the simulation.

If the environment of the model with which the object must deal is fuzzy, then this object is provided with a set of fuzzy logic rules. Some programming tools which would seem particularly appropriate for coding fuzzy logic problems include the following. One of them is the KEE [10] software system which provides an example of a grab bag of tools. These tools facilitate object oriented programming of expert systems in a simulation environment. Another more famous, and more accessible example, is the SMALLTALK-80 language which has been implemented for mini-computers. It is well described in a text that bears the same name [9]. It is popular, particularly in Artificial Intelligence applications.

Yet, another example is ROSS, an acronym standing for Rule Oriented Systems Simulation [14]. It is a language that combines the twin evolutionary paths of SIMSCRIPT/SIMULA with the Artificial Intelligence approaches embodied in SMALLTALK, and in the much older language CONNIVER and micro-PLANNER. ROSS is interesting. It uses the following basic paradigm. This paradigm is referred to as the Actor-Message-Actor paradigm. It describes the process in which there is an entity, a person or a machine, sending a message to a receiver, also a person or a machine. ROSS directly maps people to people interactions. It achieves this goal by letting people (known as actors) talk through conventional messages with other people (actors). When the second actor receives the message, this entity (an actor in ROSS) consults the behavior list to discover what the response should be. The response is in the form of another message to the sender, or another actor. It may require only a simple pattern match to pick a right behavior. This can be compared to a boolean type of response. In other words, the result of the matching is perfect, or else it is denied. In fact, the use of fuzzy logic permits the response to be driven by external goals. An example is FLIP, i.e. Fuzzy Logic Interactive Program [4,5, 8,16]. Informally, it has been reported that a fuzzy logic chip has been constructed in Japan quite recently.

In the past few years much research has been directed to modify the boolean approach. This research has led to the use of certainty factors, of the theory of belief, and of fuzzy logic to decide the proper behavioral responses.

What is fuzzy logic ?

Fuzzy logic may be viewed as a generalization of multiple-valued logic in that it provides a wider range of tools for dealing with uncertainty and imprecision in knowledge representation, inference, and decision analysis. In particular, fuzzy logic allows:
(i) the use of fuzzy quantifiers exemplified by 'most', 'several', 'many', 'few', 'many more', etc. ;
(ii) the use of fuzzy probabilities exemplified by 'likely', 'unlikely', 'not very likely', etc. ;
(iii) the use of fuzzy truth-values exemplified by 'quite true', 'very true', 'mostly false', etc. ;
(iv) the use of predicate modifiers exemplified by 'very', 'more or less', 'quite', etc. ;
(v) the use of fuzzy possibilities exemplified by 'quite possible', 'almost impossible', etc..

What matters most about fuzzy logic is its ability to deal with fuzzy quantifiers as fuzzy numbers, which may be manipulated through the use of fuzzy arithmetic [21]. This ability depends on the existence - within fuzzy logic - of the concept of cardinality or, more generally, the concept of measure of a fuzzy set. This aspect of fuzzy logic makes it particularly well-suited for the management of uncertainty in expert systems [22], where in systems like MYCIN and PROSPECTOR the certainty factors are often fuzzy quantifiers, like 'many more'. More specifically, by employing a single framework for the analysis of both probabilistic and possibilistic uncertainties, fuzzy logic provides a systematic basis for inference from premises which are imprecise, incomplete, or not totally reliable. In this way, it becomes possible to derive a set of rules for combining evidence through conjunction, disjunction, and chaining [17]. In effect, such rules may be viewed as instances of syllogistic reasoning in fuzzy logic. However, unlike in most of the existing expert systems, they are not ad hoc in nature.

We have been talking about measurements. In order to include measurement in a fuzzy sense, the concept of cardinality is needed. Cardinality of a fuzzy set is related in an essential way to the concept of a fuzzy quantifier. The cardinality of a fuzzy set may be defined in a variety of ways. The simplest one is the sigma-count which will be defined by using again the fuzzy sets of the previous section. The sigma-count of the fuzzy set C_f of the people in this room who ski cross-country is defined as follows. Assume that there are n people in this room then

$$\text{sigma-count}(C_f) = c(s_1) + c(s_2) + \dots + c(s_n)$$

Given two fuzzy sets C_f and D_f, the relative sigma-count of C_f with respect D_f is interpreted as the proportion of the elements of C_f in D_f. It is denoted and defined by

$$\text{sigma-count}(C_f / D_f) = \frac{\text{sigma-count}(C_f \cap D_f)}{\text{sigma-count}(D_f)} ,$$

where the sigma-count of the intersection of C_f with D_f is computed in terms of the membership values according to

$$\text{sigma-count}(C_f \cap D_f) = \min\{c(s_1), d(s_1)\} + \dots \dots + \min\{c(s_n), d(s_n)\}.$$

The description of sigma-count just presented is next implemented in an application drawn from medical sources.

An application

A medical application of fuzzy logic is found in the CADIAG-2 system, a system that was developed at the University of Vienna [1,2,3]. This application has an additional objective. It aims to introduce the simulation community to an instance of a method whereby membership values are computed from observations. At the same time, it shows how rules of inference are used.

The basic rule on which the inference mechanism in CADIAG-2 relies is the compositional rule of inference. Let s be a patient. Let m(s,f) be the subjective evaluation of a physician expressing to what degree is f affecting s, i.e. it is a fuzzy description of a patient's finding. Two different kinds of relationships are taken into account:

(i) the frequency of occurrence of a finding f with a disease d;

(ii) the strength of confirmation of a finding f for a disease d.

Both relationships, denoted respectively $m_o(f,d)$ and $m_c(f,d)$ are computed by using the expression for the relative sigma-count. The formal representation of this rule then is given by

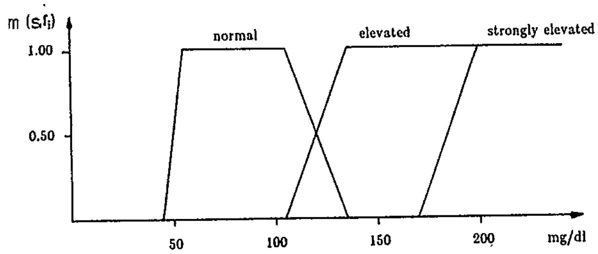
If s has f with m(s,f), and
If f implies d with $m_c(f,d)$,

Then s has d with m(s,d)

This fuzzy modus ponens syllogism is calculated using the max-min composition that provides very reliable inference values. If there are several findings for the patient s denoted f_i then m(s,d) is computed according to

$$m(s,d) = \max\min\{m(s,f_i), m_c(f_i,d)\},$$

where the max is found with respect to f_i. Results of this simulation which imbeds fuzzy logic define medical terms such as "normal", "elevated", and "strongly elevated" in terms of membership functions. See the sample curve below.



Summary

This tutorial began with the statement of a perceived problem dealing with imprecision/inexactness in simulation. This problem prevents extension of simulation into important areas of human behavior, e.g. human decision making. The problem is not solved by probability/randomness arguments alone. A complete treatment requires the use of a phenomenon known as fuzziness. A sketchy introduction to fuzzy sets has been given. Some computer techniques, and tools, capable of dealing with a fuzzy logic treatment of human behavior processes were identified. A fuzzy logic overview was presented. An actual example, taken from medical sources and which used fuzzy logic, closed this tutorial.

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