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Rough Cognitive Networks

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ABSTRACT

Decision-making could informally be defined as the process of selecting the most appropriate actions among a set of possible alternatives in a given activity. In recent years several decision models based on Rough Set Theory (e.g. three-way decision rules) and Fuzzy Cognitive Maps have been introduced for addressing such problems. However, most of them are focused on decision-making problems with discrete attributes or they are oriented to specific domains. In this paper we present a decision model called Rough Cognitive Networks that combines the abstract semantic of the three-way decision model with the neural reasoning mechanism of Fuzzy Cognitive Maps for addressing numerical decision-making problems. The contribution of this study is two-fold. On one hand, it allows to explicitly handle decision-making problems with numerical features, where the target object could activate multiple regions at the same time. On the other hand, in such granular networks the three-way decision rules are used to design the topology of the map, addressing in some sense the inherent limitations in the expression and architecture of Fuzzy Cognitive Maps. Moreover, we propose a learning methodology using Harmony Search for adjusting the model parameters, leading to a parameter-free decision model where the human intervention is not required. A comparative analysis with standard classifiers and recently proposed rough recognition models is conducted in order to show the effectiveness of the proposal.

1. Introduction

Over the last few years, decision-making problems have become an active research area due to their impact on solving real-world problems. Decision-making could informally be defined as the task of determining and selecting the proper actions that allow solving a specific problem. Making a decision implies that there are alternative choices to be considered, hence experts regularly have to choose the action with the highest probability to maximize the efficacy and efficiency of a given process. This is supported by the available knowledge, which should justify the selected decision. However, the knowledge acquired from the experts could exhibit inconsistent patterns, therefore affecting the accuracy of the underlying reasoning process (e.g. different perceptions for the same observation).

The Rough Set Theory (RST) is a mathematical theory [1] for handling inconsistency, which has been used to tackle decision-making and pattern classification problems [2–5]. This approach uses two crisp sets (called the lower and upper approximations) to describe a given set. Such crisp sets are entirely based on the collected data [6], hence further information is not required. The lower approximation consists on those objects that *certainly* belong to the concept, whereas the upper approximation consists on the objects that only *possibly* belong to the concept [7]. These approximations divide the universe of discourse into three pair-wise disjoint regions, that is: the lower approximation is the positive region, the complement of the upper approximation is the negative region, while the difference between the upper and lower approximations defines the boundary region.

These regions can be suitably employed to derive classification rules when facing decision-making problems. For instance, Grzymala-Busse [8] defined two categories of rules: *certain* rules from the lower approximation and *possible* rules from the upper approximation. Nevertheless, since the lower approximation is in fact a subset of the upper approximation, there is an overlap between these rules [9] leading to confusing interpretations for the decision model. Wong and Ziarko [10] proposed two types of decision rules: *deterministic* decision rules for positive regions and *non-deterministic* decision rules for boundary regions. Since the three regions are mutually exclusive, the derived rule sets no longer have an overlap [9] and so a higher degree of interpretability is achieved.

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One may associate probabilistic measures, such as accuracy and confidence to rules [11] where the accuracy and confidence of a deterministic rule is 1, whereas for nondeterministic rules they take values between 0 and 1. In [12] the author referred to them as *certain* and *uncertain* decision rules, respectively. In point of fact, Pawlak focused on the positive region and certain rules [7] since they characterize objects on which we can make confident decisions, so they ensure highest consistency when selecting the decision. Despite this fact, uncertain rules often contribute relevant information that could be used in order to improve the accuracy of the decision model.

More recently Yao [13] introduced the three-way decision model. Rules constructed from the three regions are associated to different actions. A positive rule suggests a decision of *acceptance*, a negative rule implies a decision of *rejection*, whereas a boundary rule advocates for *abstaining*. The three-way decisions play a central role in decision-making problems in the sense that experts usually make a decision based on available knowledge and evidence. However, if the evidence is insufficient, then they cannot make a positive or negative decision, instead experts could choose an alternate decision that often denotes non-commitment. For instance, during the discussion of policies at the United Nations sessions, members vote in agreement if the project matches the interests of their country or corresponds to international laws; they could vote against if they consider the project as inadmissible, or they could abstain if there are not enough reasons for accepting or declining the proposal.

In the three-way decision model the interpretation is not so critical since the classical Rough Set Theory does not involve any uncertainty. In order to overcome this issue, Wong and Ziarko [14] considered a probabilistic association between equivalence classes and the target object, leading to the probabilistic three-way decisions. Therefore, an object in the probabilistic positive region does not certainly belong to the decision class, but it belongs with a high probability. It implies that the acceptance and rejection decisions are made in light of certain error tolerance levels. The probabilistic three-way decision rules proved to be more accurate [15] regarding the classical approach. However, such models are mainly focused on solving discrete decision-making problems with high uncertainty.

More explicitly, most decision-making approaches based on RST (e.g. the three-way decision model) are focused on discrete domains. To deal with numerical problems, we must replace the equivalence relation by a weaker binary relation (e.g. a similarity relation). This approach induces a soft covering of the universe, and so the evidence could activate several regions simultaneously. In such scenarios, computing the preference degree of each decision could be hard, that is why using a neural inference rule could be convenient. Furthermore, in most RST-based decision models the target instance must necessarily be observed at least once, otherwise the equivalence class – based on the whole set of attributes – will be an empty set and the decision-making process is not possible.

On the other hand, in recent years Fuzzy Cognitive Maps (FCM) have become a suitable knowledge-based methodology for modeling and simulating complex systems [16]. From the structural viewpoint FCM can informally be defined as causal recurrent neural networks with learning abilities, consisting of nodes and weighted edges. Concepts are equivalent to neurons in connectionist models and denote variables, entities, states or objects related to the system under investigation. The weights on the graph edges denote the *causality* strength among concepts/neurons. The sign of causal connections involves a relevant meaning for the physical system since a positive causal relation implies a direct correlation between the cause and the effect concepts, a negative relation implies an inverse correlation between the neurons, whereas zero values suggest that there is no relation between them.

Therefore, the central advantage of using these neural models in decision-making problems relies on their interpretability since FCM-based models are capable of explaining the inference result by using causal relations, but unfortunately FCM are problem-dependent. It means that two decision-making problems cannot be modeled through the same FCM since they probably involve dissimilar physical interpretations. On the other hand, although FCM-based models are capable to solve decision-making problems with numerical attributes, they are not appropriate for handling inconsistent scenarios where similar observations could involve quite different system responses.

The first goal of this study is the introduction of a novel decision model to cope with decision-making problems with high uncertainty arising from inconsistency, where attributes could be either numerical or discrete. It should be noticed that our model does not attempt to classify new objects into a set of decision classes, instead it attempts to compute the preference degree of each decision. This feature is highly desirable in decision-making scenarios where decision-makers have to consider further factors such as availability, reliability, cost, and so on. The second objective of this proposal is to introduce a heuristic learning methodology for automatically adjusting the required parameters from historical data, where human intervention is not required. As a result, we obtain a parameter-free granular decision model with interpretability features that allows computing the preference degree of each decision, instead of spitting the most likely alternative.

In order to address the above goals, we introduce the Rough Cognitive Networks, which combine the basic semantic of the three-way decision rules with the neural reasoning ability of FCM. This granular model involves three main steps: (i) the information granulation, (ii) the network design, and (iii) the network exploitation using a new instance. The first step consists of granulating the input space by using an extended RST scheme for handling numerical domains in which the equivalence class is replaced by a similarity class. The equivalence relation induces a hard partition of the universe, but this is not necessarily true if we use a similarity relation since an object could simultaneously belong to different similarity classes. This suggests that input patterns could activate different regions and making a precise decision based on the available evidence could be non-trivial. The second step is concerned with building the network topology by using the three-way decision rules. In the third step, we provide an inference model for exploiting the network by using the pattern as the initial stimulus.

This granular neural model not only allows solving mixed-attribute or numerical problems, but it also preserves the interpretability of the three-way decision model. The recurrent reasoning law of sigmoid-activated FCM could compute accurate results by propagating an initial stimulus, therefore leading to the most appropriate group of decisions. The use of the abstract semantic of the three-way decision rules allows to effortlessly design the network topology, which in some sense addresses the limitations in the expression and architecture of FCM. This means that the human intervention is only required when analyzing the response vector computed by the granular model, since in the analysis phase decision-makers generically make the decision based on additional factors.

The rest of the paper is organized as follows: in Section 2 the theoretical background about Rough Set Theory and the three-way decision model is described. Section 3 discusses the principles of sigmoid Fuzzy Cognitive Maps. In Section 4 we present Rough Cognitive Networks and the three-phased aforementioned approach. Section 5 introduces a learning methodology based on the Harmony Search metaheuristic for automatically adjusting the model parameters, therefore leading to a parameter-free granular decision model. Section 6 elaborates on synthetic and real-world experiments illustrating the model behavior when solving decision-making problems. As a final point, in Section 7 we discuss some relevant remarks and further research aspects to be considered.