Aggregating Procedure for Fuzzy Cognitive Maps

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Abstract

In the field of Knowledge Engineering and Representation, a typical struggle encompasses transferring the Subject Matter's expertise into computational descriptions that could be used to create digital-twin representations of a given real-world scenario. Fuzzy Cognitive Maps (FCMs) have recently gained relevant attention among multiple techniques developed with this aim. However, one issue remains, when numerous of these representations need to be combined into a unique aggregated structure, it is essential to weigh factors (such as quality) into the final form to ensure its veracity, making the process not too straightforward. This paper proposes an aggregation procedure to combine FCMs into one that represents best its contributors. The technique was utilized for solving a real-life problem, and several configurations were explored. The results are compiled and reported in this paper.

Introduction

A digital twin is a virtual representation of a physical object or system that can be used for various purposes, including simulation, analysis, and control. The importance of creating automated models of reality lies in the ability to test and evaluate the design of a product or system before it is built and to monitor and optimize the performance of an existing product or system in real time. FCMs are applied in this study to simulate individuals' decision-making processes (Leon, 2009). The application of FCMs is not only used to understand people's travel behaviors and their actions due to some factors in their decision atmosphere and to discover hidden patterns. Recent studies (Hoitsma, 2020) employ the robust mechanism present in FCMs to derive conclusions from classical classification problems.

This paper specifically focuses on the open challenge of combining knowledge representation into one that can best represent the group. This technique is highly needed in clustering problems when finding centroid elements, among others. The paper is organized as follows: the rationale behind FCMs for modeling knowledge, a novel aggregation method to combine FCMs based on their credibility, experiments to find the best possible configuration in a real-life domain, concluding remarks, and references.

FCMs as a Modelling Technique

FCMs are weighted Cognitive Maps; the weights are associated with fuzzy sets (Nápoles, 2020). So, the degree of the relationship among concepts in an FCM is either a linguistic term, such as: often, extremely, exceptionally or a degree of activation/causality in [-1, 1]. Modeling the graphical representation of the FCM is a much more precise mathematical way consisting in a 1×n state vector A which includes the values of the n concepts and an n×n adjacency matrix W, which gathers the weights W_{ij} of the interconnections among the n concepts (Kandasamy, 2007). So, the value A_i for each concept C_i can be calculated as expressed in (1),

$$A_i = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n}[A_j \times W_{ji}]\right) \quad (1)$$

where A_j is the activation level of concept C_j and W_{ji} is the weight of the interconnection between C_j and C_i, the value of A_i depends on the weighted sum of its input concepts, and f is a threshold or normalization function. The most widely used function is the sigmoid function. In most seen applications, FCMs links have only positive signs; for illustration purposes, we choose the normalization function given in expression (2) that best fits our task.

$$f(x) = \frac{1}{1+e^{-c(x-0.5)}} \quad (2)$$

So, the new state vector Anew is computed by multiplying the previous state vector A_{old} by the weight matrix W, as shown in (3). The new vector shows the effect of the change in the value of one concept in the whole FCM (Carlsson, 1996).

$$A_{new} = f(A_{old} \times W) \quad (3)$$

When constructed, an FCM can model and simulate the system's behavior. Firstly, the FCM should be initialized, the activation level of each map node takes a value based on the expert's opinion of the current state, and then the concepts are free to interact. This concept interaction continues until a fixed equilibrium is reached or other variants (Nápoles, 2018).

Aggregating Fuzzy Cognitive Maps

Several characteristics make FCMs peculiar compared to other techniques. Tree structures are not dynamic systems because they lack edge cycles or closed inference loops (Glykas, 2010). Moreover, combining several trees does not produce a new tree in general. However, combining FCMs into a new FCM is possible. The combined FCM averages the FCMs, their corresponding causal descriptions, and much of their dynamics.

The average operator is an example of a basic aggregation procedure, but other operators could be considered depending on the data distribution. Combining various FCMs into one is a technique that can be used to represent and analyze complex systems. This can be done by merging the individual FCMs into a single, larger map that captures the relationships and interactions between the different components of the system.

The fusion or aggregation of FCMs is considered an advantage over other methods, where combining the structures becomes problematic for several reasons. For example, the user can mix any number of FCMs, merging them into a single FCM by the simple artifice of "adding" their scaled and augmented (zero-padded) adjacency edge matrices (Banini, 1998). Aggregating maps from multiple experts can improve the credibility of modeling with FCMs. The aggregation of FCMs aims to improve the final model's reliability, which is less susceptible to potentially erroneous beliefs of a single expert (Leon, 2014). Commonly, experts evaluate a different set of concepts.

Consequently, the sizes of the corresponding matrices may not be the same, and/or the corresponding rows/columns may refer to different concepts. To aggregate a set of FCMs given by experts with different credibility, the proposed maps are multiplied with a nonnegative "credibility" weight. So, combining these different FCMs will produce an augmented FCM.

Experimentation, analysis, and discussion

In the study, 221 FCMs were built, and their performances were calculated. These measures could be considered a quality index for combining the different maps. This criterion allows us to use the accuracy percentage to estimate how good a map is. Thus, instead of a simple average of the map links, we obtain a weighted average using the credibility of each map. In the proposed model, a new parameter is introduced besides a credibility index per map, restricting the inclusion of concepts for the final map based on the number of times a concept was present in the maps to be aggregated.

So, the user, before executing the procedure for making a new map from several ones, could specify the desired appearance percentage for each type of variable so that the variables that appear only in a few maps are not going to be present in the final map because they did not pass a specified threshold. By default, the model considers all sets of variables. Table 1 summarizes the comparison; in the rows, we have the four clusters and, by columns, a different configuration of the experiment.

Cluster	A	B	C	D	E	F	G	H
1	85	88	89	91	88	90	90	**92**
2	88	86	88	89	88	84	90	**94**
3	81	82	82	85	84	86	84	**89**
4	70	72	75	77	76	78	75	**86**

Table 1. Accuracy of aggregated maps.

The different configurations are as follows:

- A: Averages all links from selected maps; credibility is "1" by default for all maps. All variables are considered.
- B: Weighted average. Each map has a credibility index taken from its classification accuracy.
- C: Like in A, situational variables (S) must be considered in more than 30% of maps (S: 30%). No check on the attribute (A) and benefit (B) variables.
- D: Like in B, but S: 30%, A: 30%, B: 30%.
- E: Like in A, but S: 50%, A: 50%, B: 50%.
- F: Like in B, but S: 50%, A: 50%, B: 50%.
- G: Like in A, but S: 50%, A: 70%, B: 30%.
- H: Like in B, but S: 50%, A: 70%, B: 30%.

For example, the configuration described in A, cluster 1, reported 85% accuracy, while the configuration in H reported 92%, etc. Automated credibility of maps based on their classification skills and user's criteria about the importance of variables is considered for aggregating FCMs into a single structure, constituting a promising centroid construction due to its predicting capabilities.

Conclusions

FCMs have proven an effective modeling technique to represent knowledge and create systems depicting complex real-life scenarios. Experimental results based on simulations verified the proposed approach's effectiveness, validity, and good behavior. The area dealing with the learning, clustering, and aggregation of Fuzzy Cognitive Maps is still up-and-coming because humans' obtained maps are directly interpretable and help extract information from data about the relations among concepts or variables.

This paper introduced a procedure for generating maps, considering each map's credibility degree, depending on its actual performance when assessing user scenarios in machine learning tests. The idea of obtaining one map representing a specific group resulted conveniently because the prototype map represents its contributors, which is still easier to deal with.

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