Rule-Based FCM: A Relational Mapping Model

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Abstract. Rule-Based Fuzzy Cognitive Map (RBFCM) is proposed as an evolution of Fuzzy Causal Maps (FCM) to allow more complete and complex representation of cognition so that relations other than monotonic causality are made possible. This paper shows how RBFCM can be viewed in the context of relation algebra, and proposes a novel model for representing and reasoning causal knowledge relation. The mapping model and rules are introduced to infer three kinds of causal relations that FCM can't support. Capability analysis shows that our model is much better than FCM in emulating real world.

1 Motivation

Fuzzy Conceptual Maps have become an important means for drawing a graphical representation of a system , and connecting the state concepts (variables) in the system by links that symbolize cause and effect relations, and have been used in simulating process, forecasting or decision support, etc. Though FCMs have many desirable properties, they have some major limitations [4]. For example, .FCMs can't provide the inference of sequential relations or time-delay causal relations because all the interaction of FCMs' concepts is synchronous, and can't provide the inference of conditional probabilistic causal relations. Their inference results in some intelligent systems are usually distorted.

Some authors have tried to extend FCMs to include time, and they developed systems such as "Extended FCMs" (Hagiwara [2]) and rule-based FCMs (Carvalho [3]).But they can't support conditional probabilistic causal relations. Neural Cognitive Map (NCM [5]) are presented to solve complex causal relations, but NCM needs much training data that are difficult to be obtained in some intelligent systems, and time-delay causal relations as well as sequential relations are difficult to be found by neural networks.

Our model proposes a novel model for representing and reasoning causal knowledge relation. The mapping model and rules are introduced to infer three kinds of causal relations including sequential relation, time-delay causal relations, and conditional probabilistic causal relations that FCM can't support.

2 The Mathematical Model

In our model, causal knowledge is in the form of concepts, relations, directional connections and weights. Fig.1 describes the cause-effect relation mapping about terror

A. Hoffmann, H. Motoda, and T. Scheffer (Eds.): DS 2005, LNAI 3735, pp. 389 – 391, 2005.

events represented by RBFCM. The hostage, explosion and casualty are the subsequences of terrorists, and the terrorists are the subsequence of the foreign policy and the striking power. The foreign policy has not an immediate effect because it needs days or months to make a full impact on terrorists. The striking power also needs hours or days to make a full impact on terrorists. Our model is the map that can represent and infer more complex and complete casual knowledge than FCM.

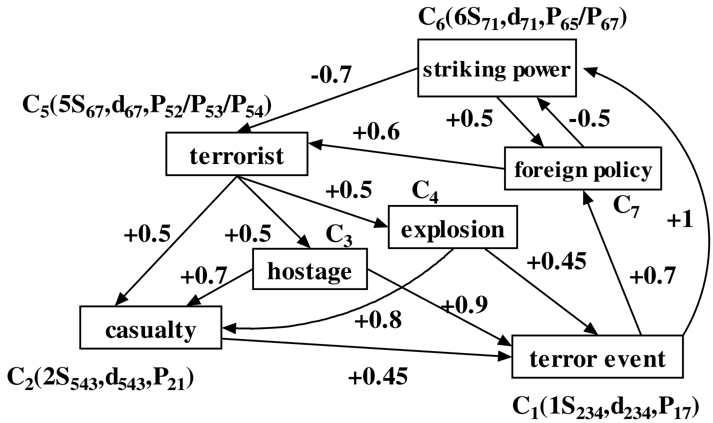

Fig. 1. The cause-effect relation mapping terror events represented by RBFCM

Definition. Let S_{ci} and S_{cj} be the state values of concept C_i and C_j, $f(x)$ be the reasoning function of C_j. R_{ij} and w_{ij} are the relation type and the weight from C_i to C_j respectively, and are the elements of the relation matrix $\boldsymbol{R}$ and the adjacency matrix $\boldsymbol{A}$. The mapping model can be determined by the following operations of **Rule 1- 3**:

1. If there exist conditional probabilistic causal relations from different concepts C_i to C_j, $f(x)$ is a computing function of all the concepts C_i occurrences leading to the increase / decrease probability of concept C_j. Here $f(x) = \tanh(x) \in [-1,1]$. **2**. If there exists time-delay causal relation from C_i to C_j, then reserve the primary value of C_i during the time delay, and all values of the i^{th} row are zero in the adjacency matrix $\boldsymbol{A}$, then set $S_{ci}(t)$ equal to the original value of C_i. Here $f(x) = 1/(1+e^{-x}) \in [0,1]$. **3.** The $(i\text{-}1)^{th}$ sequential relation should be reasoned before the reasoning of the i^{th} sequential relation. if the concept value interval is [-1, 0], Then $f(x) = 1/(1-e^{x})$.

The effect concept's state value at time (t+1) should partly depend on its own state value at time t. ϕ and φ are allotted coefficient. $\phi + \varphi = 1$. The computing of effect concept's state value is as follows: $S_{cj}(t+1) = f(\phi \sum_{i=1}^{n} w_{ij} S_{ci}(t) + \varphi \sum_{j=1}^{n} w_{ij} S_{cj}(t))$.

The relation matrix $\boldsymbol{R}$ and the adjacency matrix $\boldsymbol{A}$ describe the relation types and the weights between concepts of directional connections respectively. And all of their interactions among concepts, relations, directional connections and weights compose a dynamic network. In Fig.1, the cause-effect causal relation and the conditional probabilistic causal relation are denoted as R_{ce} and R_{cp} respectively. If there does not exist causal relation between concepts, it is denoted as N in $\boldsymbol{R}$. The m^{th} subsequence is denoted as mS and the time-delay causal relation is denoted as d_n. For example, $\boldsymbol{R2}$ (2, 1) = ($2S$, d_{543}) represents that there exists first sequential relation and the time-delay causal relation from C_2 to C_1.. The denotation C_5 ($5S_{67}$, d_{67}, P_{52}/ P_{53}/ P_{54}) in Fig.1 represents that there exists first sequential relation and the time-delay causal relation from C_6 and C_7 to C_5, and there also exists conditional probabilistic causal relation from C_5 to C_2, from C_5 to C_3 and from C_5 to C_4 .

$$R=\begin{pmatrix} N & N & R_{ce} & R_{cp} & N & N \\ R_{ce} & R_{cp} & R_{cp} & (6S,d_{71}) & N & N \\ R_{ce} & N & (5S,d_{67}) & R_{cp} & R_{cp} & R_{cp} \\ N & R_{ce} & R_{cp} & N & N & N \\ N & R_{ce} & R_{cp} & N & N & N \\ R_{ce} & R_{ce} & R_{ce} & (2S,d_{543}) & N & R_{cp} \\ R_{ce} & R_{ce} & R_{ce} & (1S,d_{432}) & N & R_{cp} \end{pmatrix} \qquad A=\begin{pmatrix} 0 & 0 & +0.7 & +0.6 & 0 & 0 \\ +1 & -0.7 & +0.5 & +0.7 & 0 & 0 \\ +0.6 & 0 & -0.7 & +0.5 & +0.5 & +0.5 \\ 0 & +0.45 & +0.5 & 0 & 0 & 0 \\ 0 & +0.7 & +0.5 & 0 & 0 & 0 \\ +0.5 & +0.7 & +0.8 & +0.45 & 0 & +0.45 \\ +0.45 & +0.9 & +0.45 & +0.7 & 0 & +1 \end{pmatrix}$$

3 Conclusions and Future Work

In this paper, RBFCM represent a very promising inference structure that is able to capture the causal reasoning processing present in most human decision making activities. We present our formal definitions and theoretical results for the analysis of the inference mechanisms of RBFCM. Although in real-world applications, FCM can be extremely complex, we can regularly divide a given FCM into basic FCM modules. The ongoing work is to use the mapping model to share and understand causal knowledge in Knowledge Grid environment.

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