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Automatic Fuzzy Cognitive Map Building Online System

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Abstract
Under the present-day global crisis, global economy regionalization and technological areas redistribution there has been seen an unprecedented uncertainty growth along with various risks, which makes it harder to take managing decisions. The scenario approach appears to be one of the most popular when it comes to modelling weakly-structured subject fields and complex problems. Fuzzy cognitive maps have good prospects in the field, as they enable us to describe both the structure and the dynamic of the area under study. This paper goes along the topical automated data science and focuses on developing the OCAM (Online Cognitive Automated Mapper) system that allows to automatically-build cognitive maps without turning to experts. The cognitive map building data source of this system is website logs. The article features the main algorithms, the system architecture and some of the system work results.

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1 Introduction

Modern managing processes require taking decisions within weakly-structured dynamic systems where interconnected parts ties cannot be described functionally. In order to carry out business-modelling of such systems that show qualitative nature of interconnected parts ties, analysts use special system models called cognitive maps [1]. A cognitive map is a model that shows experts' knowledge on the developing principles and features of the situation under analysis. A cognitive map can be formally represented as a directed graph G = (V, E) with aligned weights to each arc $E_i \in E$. The vertices V of a cognitive map correspond to the factors (concepts) that define the situation. The arcs E correspond to the cause-effect (casual) relations between factors. A cognitive map building process if influenced by the way an expert sets the power of cause-effect relations and values.

A fuzzy cognitive map (FCM) in general is a directed graph where the weights of oriented edges can have values of [-1; +1], or the values that characterize the influence power of a corresponding tie

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and belong to a linguistic scale {very weak, weak, average, strong, very strong} [5]. If the weight wij of the arc (Vi, Vj) is more than zero, then Vj increases along with the increase of Vi and Vj decreases along with the decrease of Vi. If the weight wij of the arc (Vi, Vj) is less than zero, then Vi. Fuzzy cognitive maps were first time developed by B. Kosko as the extension to symbolic cognitive maps with the use of fuzzy casual functions [4].

Cognitive maps represent one of variants of representation of some domain knowledge, along with semantic maps and frames. The main specificity of this tool is the ability to represent dynamic processes with the aim of modelling and forecasting development of those processes. Latest years have seen experts and analysts researching deep into cognitive map modelling system methodology, for example [2]. The cognitive map-based automatic modelling system software is called cognitive mapper [1]. The Kanva [1] system and Mental Modeler [3] are widespread as well.

Still there are some situations when we cannot get "hand-made" fuzzy cognitive maps: there is no expert to build one; experts have diverse knowledge of the field and build different cognitive maps; the number of concepts and ties is so huge that experts can easily make mistakes. All these cases ask for algorithms that allow us to automatically single out concepts and ties, thus building cognitive maps.

2 Main approaches to the problem

The ultimate goal of the automatic algorithms that build cognitive maps is to single out concepts and to define the ties between them. Different data types (numerical, character or mixed) require different cognitive map building algorithms. If an algorithm lacks subject field knowledge, singling concepts out automatically turns into the hardest task.

Machine-learning algorithms are successfully used for the numerical data type. Character data type requires logic-based classification methods, when Bayesian networks, decision trees and fuzzy decision trees are used for fuzzy cognitive maps. In case there is numerical and character data combined, we use neuro-fuzzy systems[6], cognitive decision trees[7] and association rules[8]. The taller three are of special interest, as they are universal and enable us to get man-readable rules as a rearsult, which is vital for such fields like medicine, economy and sociology.

A fuzzy decision tree is an extended classical decision tree concept from the field of artificial intelligence. The latest researches in fuzzy decision trees development covered the ID3 algorithm modification.

Sison and Chong offered a fuzzy version of the ID3 algorithm, that automatically generated a basic set of fuzzy rules for an object. The basic fuzzy rule set was based on a set of input-output data[9]. Umano offered his ID3 version as well. The modified algorithm could generate a man-readable fuzzy decision tree based on fuzzy sets, set by the user[10]. Janikow considers a fuzzy decision tree building algorithm that used a directly entered set of data and is called FID (Fuzzy Induction on Decision Tree)[11]. This algorithm is based on different types of fuzzy rules, described here [12]. Such an approach enables us to get cause-effect ways and fuzzy rules for linguistic weights. It also helps to build a dynamic fuzzy cognitive map to support decision-making process.

Neuro-fuzzy systems combine the methods of artificial neural networks and fuzzy logic systems [13,14]. Tahmasebi looks deeper [15] into different neuro-fuzzy systems, analyzes them and other approaches to assessment prediction.

The algorithms to single out association rules are currently the most used tools of data-mining aimed at rules extraction. The field counts a lot of methods, still all of them have two common steps. The first step features the search for a frequency set of elements occurrences, which is followed by an algorithm generating association rules. The appropriate algorithm is chosen according to the structure and the size of the data under analysis, as well as to the subject field.