



The 2015 International Conference on Soft Computing and Software Engineering (SCSE 2015)

Knowledge representation through graphs

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Abstract

Due to the increasing amount of data, knowledge aggregation, representation and reasoning are highly important for companies. In this paper, knowledge aggregation is presented as the first step. In the sequel, successful knowledge representation, for instance through graphs, enables knowledge-based reasoning. There exist various forms of knowledge representation through graphs; some of which allow to handle uncertainty and imprecision by invoking the technology of fuzzy sets. The paper provides an overview of different types of graphs stressing their relationships and their essential features. An example is included for didactical reasons.

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Peer-review under responsibility of organizing committee of The 2015 International Conference on Soft Computing and Software Engineering (SCSE 2015).

Keywords: fuzzy cognitive maps; fuzzy graphs; fuzzy hypergraphs; graphs; hypergraphs

1. Introduction

Nowadays, companies are established in an environment characterized by increasing amounts of data, which make knowledge aggregation, representation and reasoning [1], [2] highly important for handling this data. Creativity techniques are useful for acquiring knowledge. As human reasoning and its environment are uncertain and imprecise, especially in contexts where creativity is applied, fuzzy logic can enhance the process of knowledge aggregation and representation. Graphs are a useful formalism to represent knowledge in a computer-understandable way. Some types of graphs can account for imprecision and uncertainty by introducing fuzziness. Because of their

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great variety, the aspiration of this paper is to offer a classification of different types of graphs. Section 2 elaborates on knowledge aggregation and representation and explains the importance of creativity techniques, fuzzy logic and fuzzy set theory. Section 3 presents a classification of various graphs (e.g., fuzzy cognitive maps (FCMs), fuzzy graphs (FGs), hypergraphs (HGs) and fuzzy hypergraphs (FHGs)). Although FCMs, FGs and especially HGs are individually a well-known subject addressed in many research papers ([3], [4], [5], [6], [7], [8], [9]), classifications and connectivity of such, which would help nonprofessionals in this field to learn the roots, is hard to come by. The final section concludes the paper and provides an outlook for further research.

2. Knowledge aggregation and representation

Knowledge aggregation, representation and reasoning are difficult tasks for many employees, who are often not experts in this respect. Creativity techniques are simple to use and understand, and they make it possible to take advantage of people's creativity [10], [11]. Thus, the process of knowledge acquisition (as part of knowledge aggregation) can be facilitated by applying suitable creativity techniques such as brainstorming or mind mapping (e.g., see [1]).

Human reasoning occurs in an imprecise and uncertain environment, especially if creativity is involved. Moreover, natural language, which is the basis of human communication and human reasoning, is imprecise and subjective [12]. The aim of fuzzy logic is to model the ability of humans to reason in an environment with imprecise concepts [12], which are treated by fuzzy set theory [13]. Hence, fuzzy logic and fuzzy set theory might be useful for aggregating and representing knowledge (e.g., [14]), especially if creativity techniques are applied (e.g., see [1]).

The aggregated knowledge must be represented in a way that allows information systems to actively process knowledge, rather than only to represent it, and thus to enable knowledge-based reasoning [1]. As graphs can easily be understood by users, and the underlying concepts can be directly used for reasoning without transforming them first, they are a powerful tool for knowledge representation (e.g., see [15]). They can represent knowledge explicitly, on a logical basis, and in a structured way. Thus, users can understand how the knowledge base is being built, how it is used, and they have control over every step of building the knowledge base [15].

3. Classification of different graphs

Fig. 1 is a visualization of the relationships among different kinds of graphs according to our understanding. Fig. 1b provides a simple overview, and Fig. 1a offers a broader context. The goal of this paper is to provide a clear and concise analysis of the relationships among different types of graphs, including an example. Thus, to keep the picture ascertainable, not all types and definitions of graphs are included and the focus lies on some main features (e.g., orientation of the edges, existence of weights). Following this approach, the core of Fig. 1a and 1b consists of the sets of directed (DGs) and undirected graphs (UGs) with a finite set of nodes [16]. These classes could be further categorized, for instance by distinguishing between cyclic and acyclic [17], or between simple graphs and

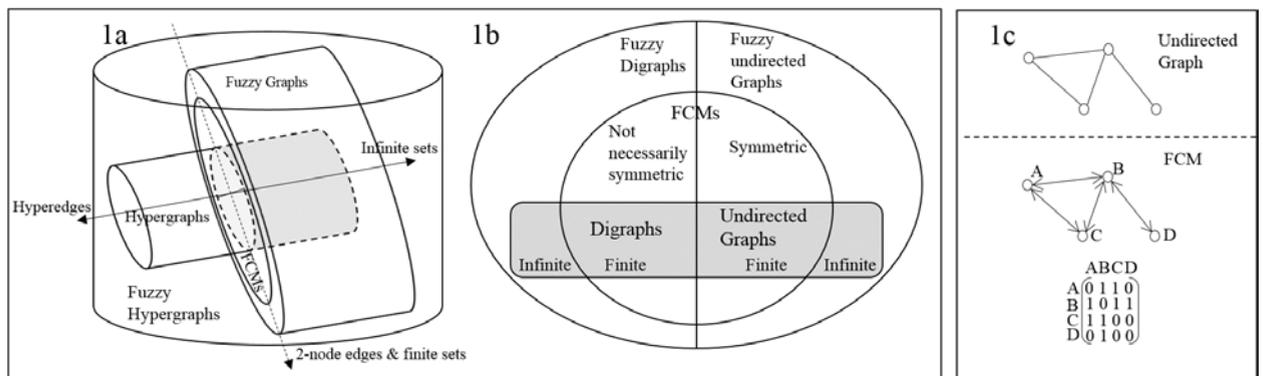


Fig. 1 Visualization of the relationships among different graphs and an illustrative example

multigraphs [16], which are neglected. Thus, UGs can be understood as symmetric DGs by replacing an undirected edge with a directed edge and its inverse.

As depicted in Fig. 1b, both DGs and UGs with finite sets can be interpreted as FCMs [18] by taking an unweighted edge with the value 1 and an UG as a symmetric FCM (for instance, see Fig. 1c, where first, the nodes of the UG are labeled, and second, the symmetric adjacency matrix of the FCM is built such that it becomes obvious that the UG belongs equally to the set of UGs as well as to the set of FCMs). It clearly illustrates that – in this way – only a portion of all FCMs can be described, as the edges of a FCM can have real values coming from $[-1,1]$, and the adjacency matrix of a FCM does not have to be symmetric. Nevertheless, as can be seen in Fig. 1b, not every DG or UG can be transformed into a FCM, as they may have an infinite set of nodes. A similar argument can be made for the relationship of FCMs and FGs. As shown in Figure 1a, every FCM can be seen as a fuzzy (i.e., weighted) DG or even a fuzzy UG, depending on whether the adjacency matrix of the FCM is symmetric or not. However, in general, FGs do not have to be finite (i.e., having a finite set of nodes).

An even larger picture of the relationships is displayed in Fig. 1a. Starting again with the core, it can be seen that the cylinder of DG and UG – both with finite and infinite sets of nodes (i.e., the backward cylinder) – is the set of special cases of HGs, containing only edges that connect just two nodes. Furthermore, the FCMs are represented as a disk because, as already seen in Fig. 1b, a FCM cannot have an infinite set of nodes, and in addition, an edge in a FCM is always a directed edge between only two nodes (or a loop) but never a hyperarc. To avoid misinterpretation, the set of FGs is not exclusively drawn as the cylindrical continuation of the set of FCMs, as would follow from Fig. 1b, but is drawn a little wider than the FCMs, even though every FG with a finite set of nodes can be understood as a FCM. The same holds for the FHGs, which contain every other mentioned type of graphs. Restricted to non-hyperedges (i.e., edges between just two nodes or loops), they would be the same set as the FGs but are depicted larger to keep the picture clear.

4. Conclusions and Outlook

Graphs can represent aggregated knowledge in such a way that knowledge-based reasoning becomes possible. Because of the variety of graph types, the aim of this paper was to provide an overview of the relationships between them. This work is not exhaustive and it could be enhanced by many more definitions (e.g. see [16], [17]). Additionally, further research could include directed HGs and intuitionistic fuzzy directed HGs. It is shown that both DGs and UGs with finite sets of nodes can be understood as FCMs. Only FGs with finite sets are FCMs. HGs allow for hyperedges and thus generalize the concept of a conventional graph. Every considered class of graphs is a special case of a FHG. FGs and FHGs are especially useful because they can account for uncertainty and imprecision. There already exist applications with FCMs (e.g., see [1], [19]). Further research should investigate the usefulness of other types of graphs and possible applications for knowledge aggregation, representation and reasoning. Because FHGs allow for edges that connect more than two concepts, they might be useful not only for binary but also for more complex problems.

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