Similarity Fuzzy Semantic Networks and Inference. An application to analysis of radical discourse in Twitter

Juan Luis Castro[1 [0000−0003−0501−0139]] and Manuel Francisco[1 [0000−0001−9748−2269]]

Department of Computer Science and Artificial Intelligence, University of Granada, 18071 Granada, Spain {castro,francisco}@decsai.ugr.es
https://decsai.ugr.es/

Abstract. In this paper we introduce a new Knowledge Representation model, the Similarity Fuzzy Semantic Networks. It is an extension of Fuzzy Semantic Networks that incorporates *reasoning by similarity* through a Similarity Inference Rule. Moreover, we show as it can be effectively applied to a trending and complex problem like the analysis of radical discourse in Twitter.

Keywords: Fuzzy Semantic Networks · Similarity Fuzzy Reasoning · Social Network Analysis · Knowledge Engineering · Semantic Network

1 Introduction and motivation

Semantic Networks are one of the first models proposed for Knowledge Representation, and they have been effectively applied over the years [**?**,**?**]. Later, graduations were introduced to obtain Fuzzy Semantic Networks, that have interesting and relevant applications [**?**,**?**]. Moreover, it is an effective approach to use reasoning by similarity in fuzzy systems [**?**]. Thus, it would be interesting to extend the Fuzzy Semantic Network model to include similarity reasoning.

In this paper, we propose a new model of knowledge representation which extend Fuzzy Semantic Network model, and incorporate an *inference by similarity* rule.

The rest of this paper is organised as follows. Sections 2 and 3 present a brief introduction to Semantic Networks and Fuzzy Semantic Networks models, respectively. Section 4 proposes our Similarity Fuzzy Semantic Network model, jointly with the similarity inference rule. Section 5 shows an inference strategy for an effective application of the model. Lastly, section 6 applies it to a trending and complex problem: the analysis of radical discourse in social networks.

2 Semantic Networks

Semantic Networks represent knowledge with directed labelled graphs, where vertices represent concepts, which can be individuals or classes (sets of individuals), and labelled edges represent semantic relations between concepts, such that:

$$\mathbf{A} \xrightarrow{relationS} \mathbf{B} \tag{1}$$

represents the assertion " **A** *relationS* **B** ". Consequently, we can represent knowledge as "Bird has-part Wings", "Animal has-part legs" or "Bird is-an Animal".

We can distinguish between two types of semantic relations:

- Hierarchical semantic relations:
  - *instance-of* (an individual is an instance of a class)
  - *is-a* (a class is a subclass of another class)
- Domain-specific semantic relations, such as *is-an-opponent-of*, *owns*...

Hierarchical semantic relations are universal, in the sense that they are present in any semantic network, meanwhile each semantic network introduces its own domain-specific relations.

The main inference rule in a Semantic Network is *inference by inheritance*. It consists on deducing new assertions in accordance with the following scheme:

$$\frac{\begin{array}{l}\mathbf{A}\ \ \textit{is-a}\ \ \mathbf{B}\ \vee \mathbf{A}\ \ \textit{instance-of}\ \ \mathbf{B}\\ \mathbf{B}\ \ \textit{relationS}\ \ \mathbf{C}\end{array}}{\mathbf{A}\ \ \text{relationS}\ \ \mathbf{C}} \tag{2}$$

3 Fuzzy Semantic Networks

It has been proposed to use graduations to obtain Fuzzy Semantic Networks [**?**,**?**]. These models represent knowledge as graded labelled directed graphs. Classes are now defined as fuzzy sets of individuals, and the degree of the relation *instance-of* is the membership function of the correspondent fuzzy set. Analogously, edges represent graded semantic relations:

- *instance-of* : α stands for an instance with grade α
- *is-a* : α stands for a class that inherits from other in grade α
- Domain-specific fuzzy semantic relations, such that each relation has a an associated degree in which the assertion meets.

In this way,

$$\mathbf{A} \xrightarrow{relationS:\alpha} \mathbf{B} \tag{3}$$

represents the fuzzy assertion

$$\mathbf{A}\ \textit{relationS}\ \mathbf{B} \text{ in } \alpha \text{ degree.} \tag{4}$$

that can be abbreviated as

$$\mathbf{A}\ \textit{relationS:}\alpha\ \mathbf{B} \tag{5}$$

We can now define the *fuzzy inference by inheritance rule*. It consists on deducing new fuzzy assertions by the following scheme:

$$\frac{\begin{array}{l}\mathbf{A}\ \textit{is-a:}\alpha\ \mathbf{B} \vee \mathbf{A}\ \textit{instance-of:}\alpha\ \mathbf{B} \\ \mathbf{B}\ \textit{relationS:}\beta\ \mathbf{C}\end{array}}{\mathbf{A}\ \textit{relationS:}t(\alpha,\beta)\ \mathbf{C}} \tag{6}$$

being t a t-norm chosen to model the connective "and".

Obviously, the fuzzy inference by inheritance is a generalisation of the (non fuzzy) inference by inheritance: if we have crisp semantic relations in the premises ($\alpha = \beta = 1$), then we obtain the same crisp consequence ($t(1, 1) = 1$).

3.1 Combining inferences

After applying fuzzy inference by inheritance (or any other reasoning method), it is possible to obtain the same semantic relation between two given concepts but with different degrees. We can use an aggregation function [**?**] to combine both assertions in the following *combining inference rule*:

$$\frac{\begin{array}{l}\mathbf{A}\ \ \text{relationS:}\alpha\ \mathbf{B} \\ \mathbf{A}\ \ \text{relationS:}\beta\ \mathbf{B}\end{array}}{\mathbf{A}\ \ \text{relationS:}g(\alpha,\beta)\ \mathbf{B}} \tag{7}$$

were g is a previously chosen aggregation function.

4 Similarity Fuzzy Semantic Networks

In the same way that classes extend its semantic relations to its sub-classes and instances by inheritance, individual or classes may transmit properties, by similarity semantic relations, to similar individual or classes [**?**,**?**]. For example, if two persons have similar opinions about political topics, then it will be reasonable to think that the properties with political sense would affect one another.

In order to enrich the model of fuzzy semantic relation with this idea, we propose a new model for knowledge representation that we call *Similarity Fuzzy Semantic Networks*. It consist on fuzzy semantic networks with a specific family of semantic relations between classes or individuals, which we call *Similarity semantic relations*.

4.1 Similarity semantic relations

Similarity semantic relations are fuzzy semantic relations that represent that two individuals or two classes are similar in some sense or aspect:

$$\mathbf{A}\ \textit{is-similar-in-sense-D} : \alpha\ \mathbf{B}, \tag{8}$$

where D may be any topic or aspect, and it represents the assertion that concepts A and B are similar in the sense D in α degree.

We can have similarity relations between classes and also between individuals. Additionally, for every sense D, each concept will have a fuzzy neighbourhood of similar concepts in sense D.

On the other hand, we only might transmit by *similarity-in-sense-D* those semantic relations that are related to D. Thus, we introduce relations between *senses* and *semantic relations of the network*.

4.2 Meta-relations

Semantic relations of the network can be considered *second order concepts*, therefore it is possible to think in *second order relations* where relations between *semantic relations of the network* are established. We call them *meta-relations*.

Particularly, we introduce in our Similarity Fuzzy Semantic Networks model a meta-relation that will be used for the Similarity inference. It is a relation that goes from domain-specific semantic relations to *is-similar-in-sense-D* relations:

$$\textbf{relationS}\ \textit{is-related-to:}\gamma\ \textbf{senseD}, \tag{9}$$

representing the assertion that *relationS* is related to *senseD* and thus, it can be transmitted by *is-similar-in-sense-D*.

The similarity semantic relation specifies a correspondence between concepts in an specific aspect D, meanwhile *is-related-to* delimits the domain in which similarity relations apply. In fact, when using meta-relations, we are defining a new semantic network of a higher level in which concepts are similarity relations of the principal semantic network.

4.3 Similarity inference

These new relations enable a new kind of reasoning based on similarity. New knowledge may be extracted upon propagation of semantic relations through the *is-similar-in-sense-D* by means of the *Similarity Inference Rule*:

$$\frac{\begin{array}{l}\textbf{A}\ \textit{is-similar-in-sense-D}:\alpha\ \textbf{B}\\ \textbf{B}\ \textit{relationS:}\beta\ \textbf{C}\\ \textbf{relationS}\ \textit{is-related-to:}\gamma\ \textbf{senseD}\end{array}}{\textbf{A}\ \textit{relationS:}(\gamma * t(\alpha,\beta))\ \textbf{C}} \tag{10}$$

where t is a triangular norm (t-norm).

5 Inference Strategy

In the proposed similarity fuzzy semantic network, the properties of the concepts may be deduced by fuzzy inheritance and/or by similarity inference. Moreover, each reasoning process results in new knowledge that may lead to new inferences. Hence, we might to establish an inference strategy.

First of all, we may choose the prevalence between inheritance and similarity inference rules. Inheritance is a *depth reasoning*, while similarity can be considered a *breadth inference*, since it is based on the neighbourhood of similar concepts. Therefore, we can use the classical Z and N models of reasoning strategy:

– Z model: first similarity, then inheritance.
– N model: first inheritance, then similarity.

Lastly, we establish iterations or cycles, as it is usual when dealing with these kind of systems. In each step, we update the degree of every semantic relation by applying inheritance and similarity reasoning rules in the chosen order, and then applying the combining inference rule.

6 Application to radical discourse in Twitter

There are several cases in which it may be interesting to infer knowledge using similarity fuzzy semantic networks. In this case, we applied it to represent and infer new knowledge about radical discourse in Twitter.

Radical propaganda is disseminated through Social Networking Sites (SNS) such as Twitter, blogs and other platforms [**?**,**?**]. Recruitment and radicalisation of SNS users is due to diverse factors which radicals take advantage of [**?**]. Identifying these radical accounts and others that are susceptible of being radicalised are important tasks in order to deal with extremism.

We used Twitter API to obtain tweets about some specific topics that are frequently found in the radical discourse. The challenge that we are facing is to detect radical users in the social network, and its main handicap is that most of the users and tweets are not radical in any form.

Given a *twitter user* U, we consider a domain-specific fuzzy semantic relation *is-radical* to represent whether a user is radical or not:

$$U \xrightarrow{\textit{is-radical}:\alpha} Yes \tag{11}$$

$$U \xrightarrow{\textit{is-radical}:\beta} No \tag{12}$$

being α and β the degrees in which U is radical or not, respectively.

When two users, A and B, share opinions regarding the selected topics, we represent it by the similarity semantic relation *is-similar-in-sense-opinion-share*:

$$\mathbf{A}\ \textit{is-similar-in-sense-opinion-share} : w\ \mathbf{B} \tag{13}$$

where w stands for the degree in which they share opinions. This enables us to propagate knowledge from user A to B and vice versa. However, we still need to determine a way in which properties defined by the semantic fuzzy relation *is-radical* can be propagated using the similarity relation. Let us define a meta-relation such that

$$\textbf{is-radical}\ \textit{is-related-to} : \gamma\ \textbf{is-similar-in-sense-opinion-share} \tag{14}$$

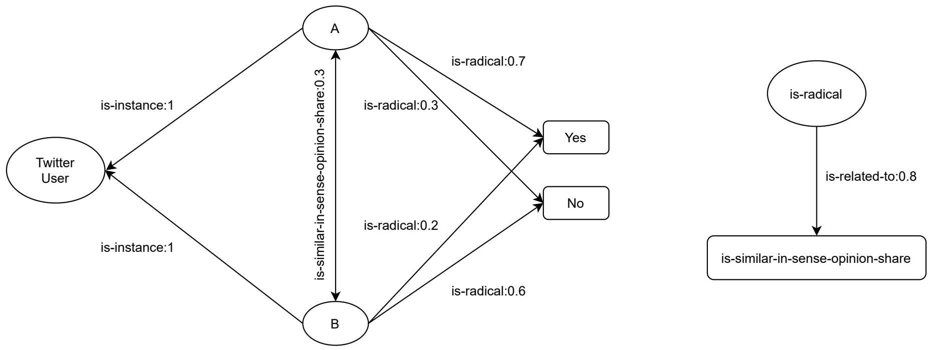

Fig. 1. Graphical representation of a similarity fuzzy semantic network for the radical discourse in Twitter.

Figure **??** shows the graphic representation of the fuzzy semantic network.

Let us exemplify the results of the inference in this similarity fuzzy semantic network. We use the product t-norm and the sum aggregation.

First, we apply the similarity inference rule for every pair of similar users (users that share opinions about the selected topics):

$$\frac{\begin{array}{l}\textbf{A} \text{ is-similar-in-sense-opinion-share:w } \textbf{B}\\ \textbf{B} \text{ is-radical:p } \textbf{Yes}\\ \textbf{is-radical} \text{ is-related-to:}\gamma \textbf{ is-similar-in-sense-opinion-share}\end{array}}{\textbf{A} \text{ is-radical:}\gamma * w * p \textbf{ Yes}} \tag{15}$$

Then, using the combination inference rule, we obtain the degree in which every twitter user *is radical*:

$$\frac{\begin{array}{l}\textbf{A} \text{ is-radical:}p_1 \textbf{ Yes}\\ \textbf{A} \text{ is-radical:}p_2 \textbf{ Yes}\end{array}}{\textbf{A} \text{ is-radical:}p_1 + p_2 \textbf{ Yes}} \tag{16}$$

For each cycle, the similarity inference is fired for every similar user to A, and since summation is an associative operator, the order in the combination inference rule is not relevant. Thus, we may conclude that, when the cycle i ends, it is possible to deduct that:

$$\textbf{A} \text{ is-radical: } \left(radical^{(i)}(A)\right) \textbf{ Yes} \tag{17}$$

being

$$\text{radical}^{(i)}(A) = \text{radical}^{(i-1)}(A) + \gamma * \sum_{U|w_u \in neighbours(A)} w_u * \text{radical}^{(i-1)}(u) \tag{18}$$

where *neighbours*(A) is the fuzzy set of twitter users similar to A in the sense that they share opinions about the selected topics:

$$neighbours(A) = \{U | w_u : \mathbf{A} \text{ is-similar-in-sense-opinion-share} : w_u \ \mathbf{U}\} \tag{19}$$

and being

$$radical^{(0)}(A) = \alpha \tag{20}$$

where α is the initial degree (if any) for **A** is-radical : α **Yes**.

6.1 Determining degrees for the fuzzy relations

The similarity inference process is conditioned to the initial degrees of at least one of the instances of Twitter users. Determining these values is not a trivial task, but it can be done in several manners.

is-radical is defined for a particular user and, initially, it can be calculated taking into account only the information available for such user (in this case, their tweets). It is possible to use an *oracle* that, given a tweet, returns a binary answer (yes or no) to the question "*is this tweet radical?*". In our case, we used a human expert as an oracle, which answer this question for some tweets. The initial degree p would be the result of the aggregation of the answers. We used the *mean*, that result in the ratio between user's radical tweets an the total number of them.

is-similar-to-in-sense-opinion-share is defined between two users and it needs to be determined taking into account the information available for both of them. We used a predictor H using Twitter mechanics as proposed in [**?**]:

$$\begin{aligned}\forall u, v \in T, H(u,v) = \ & cocopies(u,v) + cofavourites(u,v) + \|\{m : m \in M \wedge \\ & \wedge author(u,m) \wedge \exists n \in M : [author(v,n) \wedge \\ & \wedge (copy(m,n) \vee favourite(u,n))]\}\|\end{aligned} \tag{21}$$

where:

- M is the set of all the tweets.
- *cocopies*(u,v) stands for the number of retweets that both users have in common (which can be translated to the number of tweets that both users agree with).
- *cofavourites*(u,v) stands for the number of favourites that both users have in common (analogously to *cocopies*).
- *author*(u,m) checks if the tweet m belongs to the user u.
- *copy*(m,n) checks if the tweet n is a retweet of m.
- *favourite*(u,n) checks if the tweet n is marked as favourite by u.

After applying normalisation to H, we obtain a degree in which both users share opinions.

Table 1. Results of the expert evaluation of the deductions made by the model. 3537 of the 4114 deductions were accepted, that yields 85.97% of accuracy.

Accepted Deductions	3537
Rejected Deductions	549
Undetermined Deductions	28
Total Deductions	4114

is-related-to is a context-dependant degree that should be decided after an analysis of the specific problem. It may be defined using statistical measures such as percentiles or centrality measures.

6.2 Real-world experiments

We effectively conducted real-world experiments with a dataset that involve more than 430000 tweets authored by more than 30000 users using a human oracle to establish initial degrees for 778 tweets. Later, since our model implements an approximate reasoning, we evaluated the result of the inference process with the help of human experts to check for the soundness of these conclusions, and we obtained good results as shown in table **??**. We obtained 85.97% of accuracy, which is a better result than a baseline non-deductive model such as Support Vector Machines (SVM). Particularly, we trained a SVM model over the same dataset and we obtained a 68.97% accuracy in a cross-validation scheme.

7 Conclusions

Semantic Networks are widely used to represent Knowledge, and they have been specialised to Fuzzy Semantic Networks with useful applications. Throughout this paper, we extended these to provide them with similarity reasoning. In order to do so, we introduced a new family of semantic relations and a higher order meta-relation that allows to develop an *inference by similarity* rule, along with an inference strategy. We also showed how it can be applied to radical discourse in Twitter and how knowledge is inferred in a practical manner. This example illustrates that our proposal can be applied to complex problems and that it has great potential. We obtain effective and sound results that shows that deductions are precise in 85.97% of the cases, that is better than a baseline non-deductive machine learning model.

We intend to pursue further research in the future, both at a theoretically and at application level. In particular, we want to explore dissimilarities as a manner to complement similarity measures in order to better determine fuzzy memberships.

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