



# Using Multi-granular Fuzzy Linguistic Modelling Methods to Represent Social Networks Related Information in an Organized Way

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## Abstract

Social networks are the preferred mean for experts to share their knowledge and provide information. Therefore, it is one of the best sources that can be used for obtaining data that can be used for a high amount of purposes. For instance, determining social needs, identifying problems, getting opinions about certain topics, ... Nevertheless, this kind of information is difficult for a computational system to interpret due to the fact that the text is presented in free form and that the information that represents is imprecise. In this paper, a novel method for extracting

information from social networks and represent it in a fuzzy ontology is presented. Sentiment analysis procedures are used in order to extract information from free text. Moreover, multi-granular fuzzy linguistic modelling methods are used for converting the information into the most suitable representation mean.

**Keywords:** Multi-granular fuzzy linguistic modelling methods, fuzzy ontologies, sentiment analysis.

## 1 Introduction

Internet is now the preferred mean for sharing information. Thanks to it, high tons of people are connected and can share knowledge of all kind. In its first years, Internet was a closed platform where a reduced set of experts provided data and the users were only able to consume this information without providing anything new. Nevertheless, with the appearance of Web 2.0 technologies [3, 7], this situation has completely changed. Nowadays, users are, at the same time, source and consumers of all the information that is present on the Internet. Thanks to social networks, each user can contribute and provide his/her own knowledge to the net. All this information can be of great use to other users.

Although there is no doubt that high tons of information are available on the Web, it is difficult for the system to make use of the available information. This is because it is imprecise, and is represented in an unstructured way. When users provided it, they were not thinking about providing information in a way easily understandable by systems. On the contrary, they were just trying to make other humans to understand what they were sharing. Therefore, there is a need of designing novel methods that allow computational systems to obtain useful knowledge from all the data that users provide to the Internet.

In this paper, a novel method for processing social networks information in order to provide a structure to the knowledge is presented. Sentiment analysis procedures [2, 10] are going to be used in order to obtain information from the social networks' posts. Afterwards, multi-granular fuzzy linguistic modelling methods [4] are used in order to structure the information. Finally, the obtained information is stored on a fuzzy ontology [5, 8]. Thanks to this, any computational system can make use of this knowledge in order to perform any kind of analysis over the data. Fuzzy ontologies introduce a query system that allows any computational system to search specific information on the fuzzy ontology.

The paper is organized as follows. In section 2, basis needed to comprehend the presented approach are exposed. In section 3, the presented method is thoroughly exposed. In section 4, a brief example whose purpose is to improve the comprehension of the method is presented. Finally, some conclusions are pointed out.

## 2 Preliminaries

### 2.1 Fuzzy ontologies

Fuzzy ontologies can be formally defined using the following elements:

- **Concepts:** They are characteristics that the elements that conform the ontology can or not fulfill.
- **Axioms:** They are certain rules that all the fuzzy ontology elements must follow.
- **Relations:** They create connections between concepts and individuals and also between two individuals. Each relation determines if a certain individual is related or not with a certain concept or individual.
- **Individuals:** They are entities that are described using concepts by means of the relations.
- **Fuzzy relations:** They work in a similar way as the relations. Nevertheless, instead of marking two elements as  $\{related, not\ related\}$ , they establish a relation degree. This relation degree can be represented as a fuzzy set. Thanks to fuzzy relations, it is possible to represent imprecise information in a fuzzy ontology.

Fuzzy ontologies is a field that is quite present in the recent literature. For instance, in [6], a decision support system driven by a fuzzy ontology is presented. In [9], a recommendation system that uses ontologies and neuro-fuzzy classification is presented. Finally, in [1], a sentiment analysis procedure that uses word-embedding and ontologies is presented.

## 2.2 Multi-granular fuzzy linguistic modelling

Linguistic modelling provides an interesting framework for representing imprecise information. It uses linguistic label sets and the fuzzy sets' mathematical framework in order to carry out operations. Thanks to this, experts can express themselves using words and the system can interpret and work with this kind of imprecise information. The main issue of using linguistic label sets is that they have a fixed granularity value. Therefore, the number of labels of a set cannot be modified. In order to solve this, it is possible to use multi-granular fuzzy linguistic modelling methods. Thanks to them, it is possible to convert information expressed using a linguistic label set with a certain granularity value into information expressed using a linguistic label set whose granularity value is different.

One of the most flexible methods available in the literature use 2-tuple representation value in order to represent and transform the information. A linguistic 2-tuple is a tuple  $(s_i, \alpha)$  where:

- $s_i$  is a label belonging to a linguistic label set  $S = \{s_1, \dots, s_n\}$ .
- $\alpha$  is called the symbolic translation and consists on a number located on the following interval:  $[-0.5, 0.5]$ .

It is possible to transform a linguistic 2-tuple in a numerical value,  $\beta$ , by aggregating  $i$  and  $\alpha$ . The opposite operation can be performed as follows:

$$\alpha = \beta - \text{round}(\beta) \quad (1)$$

Therefore,  $\alpha$  can be considered as the distance between  $\beta$  and  $s_i$ . In order to convert a  $\beta$  value into a 2-tuple value  $(s, \alpha)$ , it is possible to use the following expressions. For converting  $\beta$  into  $(s, \alpha)$ :

$$\begin{aligned} \Delta : [0, g] &\rightarrow S \times [-0.5, 0.5] \\ \Delta(\beta) = (s_i, \alpha) &\text{ with } \begin{cases} s_i & i = \text{round}(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0.5] \end{cases} \end{aligned} \quad (2)$$

For converting  $(s, \alpha)$  into  $\beta$ :

$$\begin{aligned} \Delta^{-1} : S \times [-0.5, 0.5] &\rightarrow [0, g] \\ \Delta^{-1}(s_i, \alpha) &= i + \alpha = \beta \end{aligned} \quad (3)$$

## 3 Representing information in fuzzy ontologies using sentiment analysis and multi-granular fuzzy linguistic modelling methods

In this section, the designed method is described in detail. The overall set of actions that must be carried out can be summarized in three different steps:

- **Extract useful information from social networks:** Sentiment analysis procedures are used in order to extract information from social networks. A linguistic label set of 3 labels is used for representing the information.
- **Transforming the information into the desired representation:** The obtained information is transformed into the desired representation mean. Depending on how the data should be stored, it is possible to choose among different linguistic label sets.
- **Storing the information in the fuzzy ontology:** Once that the information is correctly represented, it is possible to store it on a fuzzy ontology.

In the following subsections, the process will be described in detail.

### 3.1 Extracting information from social networks

This main goal of this step is to obtain information from users' opinions on the Internet. In order to perform this task, first of all, it is necessary to focus on the topic that we want our fuzzy ontology to depict. For this purpose, the following steps can be followed:

1. **Defining the set of individuals:** First of all, the sets of elements that users are discussing about is listed. This way, the methods will center in retrieving and storing individuals' related information leaving aside irrelevant data. By using this information, the set  $E = \{e_1, \dots, e_n\}$  is defined.
2. **Defining the set of concepts:** The descriptions that users employ when referring to the individuals are defined. Using this information, the set  $C = \{c_1, \dots, c_m\}$  is defined.

Once that the elements that we want information for have been defined, it is possible to extract the information following the next steps:

1. **Defining the lists of words:** The fuzzy ontology will try to elucidate if the individuals fulfill or not the different defined concepts. In order to perform this task, it is possible to define several word lists that will help us to determine if there are relations between each individual and the concepts and their strength. For this purpose, three different lists of words are defined:
  - **Positive list of words:** This list of words is form by expressions typically used when the relation between an individual and a concept is fulfilled.
  - **Negative list of words:** This list of words is defined by expressions that are used when the relation between an individual and a concept is not fulfilled.
  - **Similar list of words:** This list of words contains expressions determining that it is not clear if an individual fulfills a concept or not.
2. **Obtaining the sentiment information:** The retrieved texts from social networks are analyzed in order to find expressions from the word lists. Three different values are calculated:
  - $npositive_i^j$ : This value indicates the number of matches that a certain set of related texts have when compared to the positive list of words.
  - $nnegative_i^j$ : This value indicates the number of matches that a certain set of related texts have when compared to the negative list of words.
  - $nneutral_i^j$ : This value indicates the number of matches that a certain set of related texts have when compared to the neutral list of words.
3. **Representing the information using a preference value:** Initially, a preference value belonging to each of the labels of the linguistic label set  $S_{c_i} = \{low\_c_i, medium\_c_i, high\_c_i\}$  can be calculated. For this purpose, the following expressions can be used:

$$\mu(low\_c_i) = \frac{nnegative_i^j}{nnegative_i^j + nneutral_i^j + npositive_i^j} \quad (4)$$

$$\mu(medium\_c_i) = \frac{nneutral_i^j}{nnegative_i^j + nneutral_i^j + npositive_i^j} \quad (5)$$

$$\mu(high\_c_i) = \frac{npositive_i^j}{nnegative_i^j + nneutral_i^j + npositive_i^j} \quad (6)$$

### 3.2 Converting the information into the desired representation

The information obtained in the previous step can be directly stored over a fuzzy ontology. Nevertheless, if we do not apply any further conversion, all the information will be represented using the same 3-label linguistic label set. In order to improve the representation flexibility of the method and to allow the use of different linguistic label sets, it is possible to convert the 3-label data into g-label data by using the following procedure:

1. **Selecting the required granularity value:** First of all, the target granularity is selected. If high precision is needed, it is possible to select a linguistic label set that has a high granularity value. On the contrary, if the information is imprecise, it is possible to select a low granularity value in order to better represent it.
2. **Obtaining a 2-tuple  $\beta$  value from a 3-label one:** Once that the desired target linguistic label set has been selected, it is possible to apply a multi-granular linguistic modelling transformation function in order to obtain the information in the required representation mean. First of all, the 3-label data is converted into a  $\beta$  value. This can be done by applying the following expression:

$$\beta = \mu(Low\_c_i) * 1 + \mu(Medium\_c_i) * 2 + \mu(High\_c_i) * 3 \quad (7)$$

3. **Obtaining the g-label representation from the  $\beta$  value:** Using the  $\beta$  value, it is possible to carry out a domain conversion from interval  $[0,3]$  to  $[0,g]$ . The following expression can be applied:

$$\beta_g = \frac{\beta_3 - 1}{3 - 1} \cdot (g - 1) + 1 \quad (8)$$

Finally, membership values for each of the labels should be obtained. For this purpose, the following expression can be applied:

$$\begin{aligned} \mu(s_i) &= 1 - (\beta - i) \\ \mu(s_{i+1}) &= 1 - ((i + 1) - \beta) \end{aligned} \quad (9)$$

In cases where the distance between the  $\beta$  value and the label is higher than one, the membership value is zero.

### 3.3 Storing the information in the fuzzy ontology

Once that the required conversions have been performed, the information is ready for being stored in the fuzzy ontology. For this purpose, a concept is generated per each label and element in  $C$ . For instance, imagine that  $C = \{prize, size\}$  are the set of concepts, and  $S^3$  and  $S^5$  are respectively used for representing the information. Then, there is a total of 8 concepts in the generated fuzzy ontology. For each defined individual in  $E$  and all the generated concepts, a fuzzy relation whose value is the membership value of the individual to the label of the concept is defined. Finally, there is no need of axioms in the definition of the target fuzzy ontology. Nevertheless, it is possible to include them manually if the tackled problem requires it.

## 4 Example

In this section, a brief application example is presented. Imagine that a set of users are debating about a set of wines. We want to retrieve information about price and acidity of five of them. First of all, information about them is retrieved. This can be done by finding text that includes certain keywords.

Once that the texts are retrieved, it is possible to search them in order to calculate the *npositive*, *nnegative* and *nneutral* values. Once that this process has been performed, results shown in Tables 1 and 2 are obtained.

<b>Wines</b>	<i>nnegative</i>	<i>nneutral</i>	<i>npositive</i>
$e_1$	10	4	2
$e_2$	1	13	2
$e_3$	16	1	2
$e_4$	1	1	12
$e_5$	1	0	7

Table 1: Word lists results for price.

<b>Wines</b>	<i>nnegative</i>	<i>nneutral</i>	<i>npositive</i>
$e_1$	0	14	1
$e_2$	0	1	15
$e_3$	1	1	11
$e_4$	1	0	17
$e_5$	18	0	11

Table 2: Word lists results for acidity.

<b>Wines</b>	<i>Low_price</i>	<i>Medium_Price</i>	<i>High_Price</i>
$e_1$	0.125	0.25	0.625
$e_2$	0.125	0.8125	0.0625
$e_3$	0.105	0.0526	0.8421
$e_4$	0.8571	0.0714	0.0714
$e_5$	0.875	0	0.125

Table 3: 3-labels representation for price.

<b>Wines</b>	<i>Low_Ac</i>	<i>Medium_Ac</i>	<i>High_Ac</i>
$e_1$	0	0.933	0.066
$e_2$	0	0.0625	0.9375
$e_3$	0.0769	0.0769	0.8561
$e_4$	0.555	0	0.9444
$e_5$	0.6206	0	0.3793

Table 4: 3-labels representation for acidity.

<b>Wines</b>	<i>VL_P</i>	<i>L_P</i>	<i>M_P</i>	<i>H_P</i>	<i>VH_P</i>
$e_1$	0	0	0	1	0
$e_2$	0	0.125	0.875	0	0
$e_3$	0	0	0	0.521	0.479
$e_4$	0.5718	0.4282	0	0	0
$e_5$	0.5	0.5	0	0	0

Table 5: 5-label representation of the individuals for the description price.

Next, 3-label representation is calculated. After applying expressions (4), (5) and (6), the results exposed on Tables 3 and 4 are obtained.

For calculation showing purposes, now we will transform prize related information into data represented by a linguistic label set of 5 labels. First of all,  $\beta$  values are calculated for each individual. For this purpose, expression (7) is used as follows:

$$\begin{aligned}\beta_{e_1} &= 0.125 \cdot 1 + 0.25 \cdot 2 + 0.625 \cdot 3 = 2.5 \\ \beta_{e_2} &= 0.125 \cdot 1 + 0.8125 \cdot 2 + 0.0625 \cdot 3 = 1.9375 \\ \beta_{e_3} &= 0.105 \cdot 1 + 0.0526 \cdot 2 + 0.8421 \cdot 3 = 2.7365 \\ \beta_{e_4} &= 0.8571 \cdot 1 + 0.0714 \cdot 2 + 0.0714 \cdot 3 = 1.2141 \\ \beta_{e_5} &= 0.875 \cdot 1 + 0 \cdot 2 + 0.125 \cdot 3 = 1.25\end{aligned}$$

Once that  $\beta$  values have been calculated, expressions (8) and (9) can be used in order to convert the 3-label information into a 5-label representation. Computations are done as follows:

$$\begin{aligned}\beta_5^{e_1} &= \frac{2.5 - 1}{3 - 1} \cdot (5 - 1) + 1 = 4 \\ \beta_5^{e_2} &= \frac{1.9375 - 1}{3 - 1} \cdot (5 - 1) + 1 = 2.875 \\ \beta_5^{e_3} &= \frac{2.7365 - 1}{3 - 1} \cdot (5 - 1) + 1 = 4.479 \\ \beta_5^{e_4} &= \frac{1.2141 - 1}{3 - 1} \cdot (5 - 1) + 1 = 1.4282 \\ \beta_5^{e_5} &= \frac{1.25 - 1}{3 - 1} \cdot (5 - 1) + 1 = 1.5\end{aligned}$$

The final obtained representation is shown on Table 5.

Once that all the required information is calculated, the fuzzy ontology can be built. For this purpose, the set of wines is used as individuals, labels that represent concepts are used as the concepts of the generated ontology. Finally, membership values of each of the individuals to the labels of the concepts are used as fuzzy relation values.

## 5 Conclusion

In this paper, a novel method that is capable of analyzing and obtaining real knowledge from social networks is presented.

Sentiment analysis is used in order to obtain knowledge from social networks users' opinions.

Multi-granular fuzzy linguistic modelling methods are used in order to obtain the more adequate representation for each piece of information. Finally, fuzzy ontologies are used in order to store the information in an organized way.

Thanks to fuzzy ontologies queries, it is possible for any kind of computational system to retrieve information and performed any required analysis.

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## Author contributions. Conflict of interest

The authors contributed equally to this work.

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