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Reinterpreting Interpretability for Fuzzy Linguistic Descriptions of Data

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Abstract. We approach the problem of interpretability for fuzzy linguistic descriptions of data from a natural language generation perspective. For this, first we review the current state of linguistic descriptions of data and their use contexts as a standalone tool and as part of a natural language generation system. Then, we discuss the standard approach to interpretability for linguistic descriptions and introduce our complementary proposal, which describes the elements from linguistic descriptions of data that can influence and improve the interpretability of automatically generated texts (such as fuzzy properties, quantifiers, and truth degrees), when linguistic descriptions are used to determine relevant content within a text generation system.

Keywords: fuzzy sets, linguistic summarization, fuzzy linguistic descriptions of data, interpretability, natural language generation, data-to-text

1 Introduction

Among the different tools that fuzzy sets theory encompasses, the generation of linguistic summaries or descriptions on data (LDD) provides a way to synthesize numeric datasets into compact sentences (protoforms), such as *"Most days of the year the energy consumption is high"* from the corresponding raw data. These descriptive techniques, whose origins can be found in the works of Yager and Zadeh more than three decades ago [17, 18], have been extensively researched from a formal perspective, but also many different use cases have been proposed in more recent years [2].

Among the main advantages of LDD, we can highlight the management of imprecision in human language through the modeling of linguistic terms as fuzzy sets, and their compositionality (an inherent feature of fuzzy sets in general), which allows to aggregate and summarize data from different numeric variables into a single description. However, today there exists a general consensus about the limited expressiveness of these linguistic descriptions [7, 10, 14]. In short, the linguistic realization of the protoforms is poor for being presented to human users in a real context. Therefore, in order to improve the applicability of LDD in the real world, an important effort oriented to enhance its linguistic quality must be made.

In order to address this challenge, some authors have proposed to incorporate a natural language generation (NLG) layer that converts the instanced protoforms into texts [7]. Others take this interpretation one step further, and understand fuzzy linguistic descriptions of data not in isolation, but rather as a tool that can be used as part of the content determination stage of an NLG system [10, 14]. This means that such linguistic descriptions need to be integrated with other tasks within the system, such as lexicalization or referring expression generation.

Be it as standalone descriptions or integrated as one of the many parts of an NLG system, the interpretability of LDD is one of the less explored characteristics of this tool beyond the initial discussion about their adequacy for human users in their original form. In fact, interpretability is one of the features that differentiates fuzzy systems from other types of computational intelligence approaches, and research on interpretable fuzzy systems (IFS) has been extensive in this regard, especially for fuzzy rule-based systems.

In this context, the aim of this paper is to approach the interpretability of LDD from an end-user's perspective, with a special focus on the crucial task that involves converting the original protoform structures into texts adapted to end-users. For this, in Sec. 2 we will describe the essential concepts about linguistic descriptions of data and their use in different contexts, and Sections 3 and 4 will respectively discuss the problem of their interpretability from a classic point of view and from our own perspective.

2 Linguistic Descriptions of Data in a Real Application Context

Linguistic descriptions of data are collections of short linguistic propositions used to quantify certain properties on numeric datasets that follow the structure of a protoform, such as *"Q Xs are A"* in its simplest form (also known as type-1 fuzzy quantified sentence), where Q is a (fuzzy) quantifier, X is the reference set to be described, and A is a linguistic label that represents a fuzzy property used to describe the reference set. For instance, in "A few men are short", $Q =$'A few', $X =$'men', and $A =$'short'. Likewise, linguistic variables represent the partitioning of a numeric domain into several fuzzy properties, e.g., "height"$=\{$*short, medium, tall*$\}$.

Starting with the simplest type of fuzzy quantified sentence, more complex linguistic descriptions can be composed, for instance, by relating two different properties using type-2 quantified sentences *"Q DXs are A"* (e.g. "Some cold days are very humid") or quantifying over time (e.g., "most patients have a constant heart-rate most of the time"). In fact, time series data have been a recurring target of many use cases in LDD.

In addition to fuzzy quantifiers and linguistic labels, another important element to consider in linguistic descriptions is the truth degree associated to each sentence which is computed. This degree is calculated through the use of a fuzzy quantification model, such as Zadeh's [18] or the F^A [4] model, among many others [3]. In short, these models take into account the aggregation of truth degrees resulting from evaluating the fuzzy properties against the dataset, and then apply a fuzzy quantifier to provide a single truth degree that characterizes the whole sentence. For instance, T(*"Most days of the year the energy consumption is high"*)=1 means that 'most' values of the reference set fulfill the property 'high' in the highest degree.

In their original conception, protoforms were proposed as a more human-friendly approach to perform queries on databases. However, their later application in the generation of LDD has raised some questions about their adequacy as a descriptive tool *per se*. As Fig. 1 (left side) shows, typical use cases of LDD involve the researcher alone. This means that the knowledge base (i.e., the definition of quantifiers and linguistic terms based on fuzzy sets, among others), the types of protoforms that are used, and even the datasets that are described are all selected by the researcher, whose purpose is to illustrate how the LDD technique works and provide some insights about its potential. Thus, in such cases, there does not exist a communicative act, and other actors such as domain experts or end-users are not considered at all.

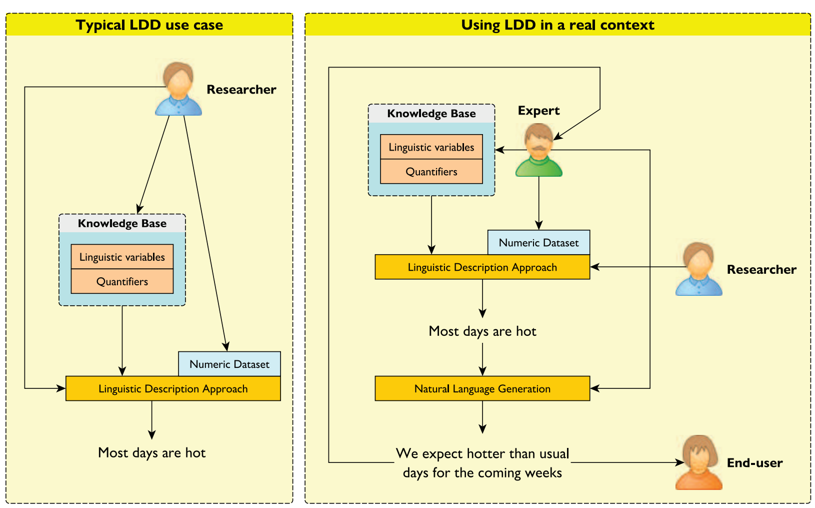

Fig. 1. Contexts of use for linguistic descriptions of data: use cases and use in a real setting.

When other actors such as end-users were finally considered, the direct utility of LDD was put into question. Despite their use of linguistic terms, it is a major consensus nowadays that the language that protoforms convey is too restricted and generic to be provided directly to other users [7, 10, 14]. In contraposition to the use case scenario, Fig. 1 (right side) shows the schema of a setting where LDD would be applied in a real problem, and there exists an actual need for providing textual descriptions of data.

The first consideration in such case is ensuring that the language we are using to convey the information that the linguistic descriptions hold is adapted to the domain requirements and fit for end-users [6, 14, 10]. This can be achieved through a natural language generation layer that transforms the linguistic description into an actual text. The second forethought consists in the more than likely presence of an expert and/or specific domain guidelines. These will determine our knowledge, and will also provide the kind of input data to be used and set the language requirements of the generated texts [15]. A third consideration is that the role of the researcher or developer is to determine whether using LDD is suitable for addressing the problem (or some of its parts) and, if so, to implement this technique and devise how to convert the protoform-like linguistic descriptions into texts that match the target language [13]. This scenario actually describes the setting of the GALiWeather system [15], which generates textual short-term weather forecasts.

Of course, other scenarios are also possible. For instance, the end-users of the generated texts might be the experts themselves (suppose that they need a tool to easily generate reports from data, to help them save time for other duties), the knowledge base could be built based on the preferences of the readers rather than the writers (because in some cases the language of experts is too technical for end-users). However, the presence of actors that need to interpret the textual information that is given by the system is common for all real context scenarios.

Although this more realistic scenario has not been considered until recent times, one of the main concerns of research on LDD has addressed how to devise criteria that allows to ensure the quality of the protoforms in their intrinsic form, leading to the concept of interpretability. Despite not having a clear definition, interpretability in fuzzy systems has been studied quite extensively, and it has been under this same light that interpretability on LDD has been discussed.

3 Interpretability of Linguistic Descriptions of Data

The traditional conception of interpretability in fuzzy sets theory has its roots in fuzzy rule-based systems, such as those built on Mamdani rules "if X_1 is P_1 and X_2 is P_2 ... then Y is R". In this case, there are several properties that are considered important to improve the interpretability of the rule-sets, such as compactness (a system with less rules will be easier to interpret), completeness (the system rules should cover all possible cases) and consistency (the definitions of the fuzzy sets should be the same for all the rules). However, this idea of interpretability is rather intrinsic and closer to the concept of legibility, and its influence is rather limited to the system designer (who, of course, should be able to unpack what is being designed and implemented).

In the case of LDD, interpretability has been explored mainly in [8]. This study provides an interesting explanation of several properties that should be taken into account in order to assess the quality of the linguistic descriptions. More interestingly, the authors distinguish between features that are important for determining the interpretability of individual protoforms and properties that are useful when considering a set composed of several protoforms.

For instance, for single protoforms, truth degrees are interpreted as "quality degrees". Thus, if T(*"Some cold days are very humid"*)=1 and T(*"Some hot days are dry"*)=0.8, then the quality of the first sentence is higher. However, in [8] it is also acknowledged that a truth degree is not the only property that determines the quality of a protoform, and other quality measures are also described. Among them, the degree of appropriateness, the relevance, the degree of informativeness or the differentiation score appear as additional features that can prove useful to refine the filtering of good linguistic descriptions.

Linguistic descriptions often involve over-generation, i.e., given several linguistic variables composed of several fuzzy properties each, a fuzzy quantifier partition and different types of target protoforms, one needs to generate all possible sentence combinations and then filter those with the highest quality. In this context, [8] also describes properties that a set of sentences should fulfill as a whole. For example, the properties of non-contradiction and double negation are described to ensure the consistency among the different sentences. Likewise, redundancy among the different sentences is also an issue that is related to the double negation property, the inclusion (when quantifiers, or properties are included in others) or the similarity.

4 Interpretability from a text generation perspective

Recent works in fuzzy rule-based systems extend the classical idea of interpretability to consider not only researchers or designers, but experts or non-specialized users. In short, the objective is to provide systems whose decisions can be understood by those mainly affected by them. For this, research on interpretable fuzzy systems has already been made at an explanation level [11, 12, 1].

In the case of linguistic descriptions of data, users do not need to understand how the descriptions are computed. Instead, they need to properly interpret the result itself, i.e., the information represented by protoform-based sentences. In [8], this view is also briefly considered from a standalone perspective. Namely, users defining the vocabulary of the descriptions and the "linguistic rendering" of the sentences (their verbalization) are depicted to have a positive influence on the interpretability of the descriptions.

Our approach to the interpretability of LDD is made under a different, albeit complementary, view, which corresponds to the real setting context shown in Fig. 1. First of all, we assume that there exists a communicative purpose and that the act of communication is made in the form of an automatically generated text [6]. Secondly, we assume that the mechanisms of linguistic descriptions of data are tools meant to be used as part of an NLG system, and thus cannot be studied only in isolation [14]. Thirdly, under this light, users are meant to receive textual information fully adapted to their language, and not just descriptions composed of protoform-like sentences. This means that any information gathered by linguistic descriptions could be mixed within the text with other kinds of information (numerical, statistical, etc.) in order to fulfill the users' information needs, as was the case in [15].

Under these assumptions, the actual entities which are subject to an interpretation from users are the texts that NLG systems generate, instead of the raw linguistic descriptions. Thus, the problem shifts from focusing just on the intrinsic interpretability of the linguistic descriptions towards the problem of how to use LDD in the generation of textual explanations for an end-user. In other words, we need to devise how to translate the semantic depth that linguistic descriptions hold (the relations between their components, e.g., quantifiers, fuzzy labels, truth degrees...) into a textual element that can ultimately help users understand the whole text and the underlying data that is being described.

Some questions and ideas regarding the use of fuzzy sets and LDD within an NLG system have already been given in [13]. However, these were not considered strictly from an interpretability perspective. Thus, our purpose in what follows is to discuss and illustrate how some of the different elements that compose a linguistic description can be verbalized to improve the interpretability of an automatically generated text. Namely, we will consider the role that the following elements play:

- Fuzzy properties.
- Fuzzy quantifiers.
- Truth degrees.
- Fuzzy quantification mechanisms.

For reasons of clarity we will refer in what follows to the simplest type of linguistic descriptions, composed of type-I quantified sentences, as the issues described in this paper relate to elements that are common for all different kinds of protoforms.

4.1 Interpretability from fuzzy properties

As we said, in LDD, a linguistic variable categorizes a numerical domain in concepts, which are modeled by means of fuzzy sets. For instance, the notion of "temperature" could be divided into the fuzzy sets "cold","mild" and "warm", whose membership functions cover the temperature numeric domain. For enhancing the interpretability of the output text containing these concepts (and in this we coincide with [9]), their definition is not just a decision of the designer of the system, but it must follow an expert's criteria, as NLG systems do, in order to suit in addressees' background.

In many occasions, it is not possible to use fuzzy properties if there exist strict guidelines to follow, but in others it might be necessary to capture the meaning of words and model their imprecision. For instance, when there are several experts with different perceptions and understandings it can be useful to aggregate them by creating fuzzy models. Likewise, if the aim of the NLG system is to provide texts whose meaning is more adapted to what readers understand, surveys can be made to ascertain the semantics of the words to be used.

Furthermore, in our context it is possible that the terms defined for a specific linguistic variable do not end up being reflected in the output text in their original form. For example, a fuzzy property "mild" related to the temperature could be expressed in the final text using a synonym as "soft". This kind of changes help improve the final text with richer style and variation, as long as the semantic similarity between the synonyms is high (and thus the conveyed concept remains the same).

4.2 Interpretability from quantifiers

The case of fuzzy quantifiers is similar to the fuzzy properties in linguistic variables in the sense that both quantifiers and properties are assigned a specific linguistic term or expression, which can be included in the generated text. However, quantifiers in protoforms provide richer alternatives for text purpose generations, because they can lead to sentences that do not express the quantifier explicitly, but improve the interpretability for end-users thanks to the use of a more adapted language.

For instance, the GALiWeather system makes use of type-I fuzzy quantified sentences to create a description of the cloud coverage variable. However, the information represented by the protoforms using linguistic terms and quantifiers is further processed to be adapted to the target language requirements. In some cases, quantifiers are also included in the generated text (although different words are used to convey them), and sometimes they are omitted, as the text itself conveys the same meaning implicitly. Figure 2 shows four different linguistic descriptions (composed of three protoforms) that GALiWeather can produce, and their corresponding realization in text.

The decision of when to make quantifiers implicit or explicit will largely depend on the requirements of the target language, as was the case in GALiWeather. For instance, if the NLG system generates technical reports to be reviewed by experts, providing explicit numerical quantifiers such as "around 40%" can provide enough information to the expert and improve the interpretability of the text compared to showing raw numbers. In more casual settings, quantifiers that indicate a wide coverage can be omitted, in order to improve the fluidity of the texts, e.g., a protoform like "most days last month were cold" could be realized as "last month was cold".

Linguistic description (set of protoforms)			Generated text
Most values are very cloudy	**A few** values are partly cloudy	**A few** values are clear	Very cloudy skies **in general** for the coming days [, **occasionally** partly cloud/clear].
Several values are very cloudy	**Several** values are partly cloudy	**A few** values are clear	Skies **alternating** very cloudy and partly cloudy moments [, **occasionally** clear].
A few values are very cloudy	**A few** values are partly cloudy	**Several** values are clear	There will be clear skies, with partly cloudy [and very cloudy] **moments**.
A few values are very cloudy	**A few** values are partly cloudy	**A few** values are clear	Very variable cloudiness throughout the coming short term.

Fig. 2. Examples of linguistic descriptions obtained by GALiWeather and associated verbalizations (translated from Spanish). Optional parts that depend on the coverage criterion of the protoforms are displayed in square brackets.

4.3 Interpretability from truth degrees

One of the main differences between LDD and other kinds of techniques that can be used for content determination in NLG resides in the truth degree which is associated to each computed protoform. As we have reviewed in Sec. 3, the truth degree of a protoform is considered its main quality indicator, so in general it is assumed that sentences with higher truth degrees are better than others with a lower degree. In this sense, the truth degree is also the first criterion which is usually taken into account to filter sentences. However, to our knowledge its influence on how the protoform can be linguistically realized has never been taken into account.

From our perspective, the truth degree should also be considered an important part of the underlying semantic of the protoform, even though it is not originally associated to a linguistic term. For this, we present a more general interpretation of this element, that understands a truth degree not as a degree of quality, but as a metric that measures the level of evidence that supports a sentence or, in other words, that provides a measure of how certain the system can be about the statement.

In order to provide a proper interpretation of the truth degree of a protoform, one must understand what a fuzzy quantification model actually does to calculate the truth degree. Particularly, we will focus on Zadeh's model for type-I fuzzy quantified sentences, which is shown in Eq. 1, where Q is a fuzzy quantifier, X is the data referential to be evaluated, A is a fuzzy property (summarizer), μ a membership function (different for Q and A), and v_i a data value in a data set in the referential, which is composed of n elements.

$$T(Q\ X's\ are\ A) = \mu_Q\left(\frac{1}{n}\sum_{i=1}^{n}\mu_A(v_i)\right) \tag{1}$$

We can determine this model involves obtaining the cardinality of the fuzzy property that is being evaluated. This cardinality is then evaluated against a fuzzy quantifier. This means that truth degrees corresponding to single data values aggregate into a single value. For instance, if we interpret *T(few cities have high population)* from a logical point of view, we could say that T it is "the degree in which the 'high population' cities fulfill that they are 'few' within all cities". However, this can also be interpreted from a language use perspective which can be useful for our purpose: to generate texts that are more interpretable.

Our interpretation of T, which is meant to have an influence on deciding how to realize protoforms linguistically, is that the fuzzy nature of the linguistic terms that compose them (both fuzzy properties and quantifiers) ends up causing a lack of certainty about the statement, which is reflected in the truth degree. For example, under this interpretation T*(few cities have high population)=0.4* would mean that we can not be quite certain (or, alternatively, that there does not exist a strong evidence) that "few cities have high population".

This fact led us to conclude that truth degrees can be useful in one of the current challenges in NLG systems: generating texts from non-linguistic input data (commonly known as data-to-text systems) that communicate *uncertainty about the reliability of the input or the system's analysis* [16]. Thus, an NLG system can use the truth degree obtained from a protoform as an indicator for applying a modal operator (i.e., *might*, *can*, *must*, etc.) or selecting a different quantifier (i.e., *most* - *in general*, *several* - *alternating*, etc.) for the generation of the final statement. For example, suppose that there are CO_2 sensors in every room of a house, and an intelligent assistant is able to retrieve their data in real time and inform us about their current state using text-to-speech. The assistant could communicate the information from a single protoform in different ways depending on its truth degree, as Fig. 3 shows. A simple syntactical-semantical structure like a protoform can actually lead to generating more sophisticated sentences with different variations.

Protoform	T	Generated text
Most places in the house have a low CO2 concentration	1	The concentration of CO2 is low in most parts of the house.
	0.8	Based on the data gathered from the sensors, I am quite certain that the concentration of CO2 is low in most parts
	0.6	The sensors show there is some evidence that the concentration of CO2 is low in most parts of the house.
	0.4	I can not say for certain that the concentration of CO2 is low in most parts of the house.
	0.2	There is little evidence of a low concentration of CO2 in most parts of the house currently.
	0	I have no evidence about the concentration of CO2 being low in most parts of the house.

Fig. 3. Examples of verbalizations of the same protoform according to different truth degrees.

Although in a real context the assistant would be likely to provide information associated to high truth degrees and high coverage quantifiers, there can appear situations where a statement can be considered relevant despite having a low degree (e.g., a protoform that includes a fuzzy property which is considered very important or exceptional). Likewise, situations of conflict or ambiguity could also be communicated, when two competing sentences end up having similar truth degrees, in a similar fashion to what occurs when two rules of a fuzzy rule-based system with different consequents activate at the same time.

For our ultimate purpose, using the truth degree as a means to adding information about certainty or evidence in the generated texts can help provide a more familiar language that improves the interpretability of the texts for end-users [16], since these elements are usually present in our daily language use. Furthermore, this can also be useful for specialized users in some domains, where the NLG system can generate texts that indicate different possibilities to guide experts for the interpretation of the input data (e.g. in health domains, where there is a strong dependence on the expertise of doctors and strict guidelines are not always followed).

4.4 Influence of fuzzy quantification models

The existence of different fuzzy quantification models means that the truth degree of a protoform can be calculated in several ways with different results depending on the model we choose. While we have not considered this in the truth degree discussion above, this issue will undoubtedly influence how one can interpret the truth degree of a protoform in order to achieve a proper linguistic realization afterwards.

It is not the purpose of this paper to enter into technical details about fuzzy quantification models or their use. For this, the reader can find very useful the extensive review of models in [3] and a behavioral guide with some practical guidelines in [5]. However, to illustrate the importance of the influence of a quantification model in the interpretation of truth degrees we will refer to the issue of aggregative behavior which is present in some models.

Referencing [5], *aggregative behavior makes reference to the tendency of a model to confuse one 'high degree' membership element with a large quantity of 'low degree' membership elements*. For instance, suppose a protoform "a few men are tall" and a dataset with 100 height values from different men. Under Zadeh's model, which is affected by this issue, the truth degree resulting from having 10 values with a truth degree of 1 is the same as the one that results from having all 100 values with a truth degree of 0.1. Thus, for both cases we could obtain that T*(a few men are tall)=1*, despite that all values in the second case fulfill the property 'tall' in an extremely low degree. Such cases would hurt the interpretability of the generated text and result in a misleading interpretation of the original data.

5 Conclusions

In this paper we have proposed a novel understanding of interpretability in the context of fuzzy linguistic descriptions of data. Instead of focusing on the classical notion of interpretability for fuzzy systems and LDD, we have approached this concept from an NLG perspective, where the end-user is key. We have discussed how the different elements in a protoform could be taken into account during the text generation process to improve the interpretability of the output texts.

The ideas here described are based on previous experiences of using LDD and fuzzy sets in the development of NLG systems, but still represent a starting point in this regard. As future work, we believe that the concepts here discussed should be further explored under an empirical setting. For instance, small controlled experiments with subjects could be done to verify whether different truth degrees for a same protoform should result into different verbalizations. Also, it would be interesting to study the influence of using different quantification models when calculating truth degrees for protoforms. Under this setting, evaluating the interpretability of the texts could be achieved through intrinsic evaluation methods to assert if the generated texts can be properly understood by users [14].

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