

Fuzzy Ontologies in Semantic Similarity Measures

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Abstract—Ontologies are a fundamental part of the development of short text semantic similarity measures. The most known ontology used within the field was developed from the lexical database known as WordNet which is used as a semantic resource for determining word similarity using the semantic distance between words. The original WordNet does not include in its hierarchy fuzzy words – those which are subjective to humans and often context dependent. The recent development of fuzzy semantic similarity measures requires research into the development of different ontological structures which are suitable for the representation of fuzzy categories of words where quantification of words is undertaken by human participations. This paper proposes two different fuzzy ontology structures which are based on a human quantified scale for a collection of fuzzy words across six fuzzy categories. The methodology of ontology creation utilizes human participants to populate fuzzy categories and quantify fuzzy words. Each ontology is evaluated within a known fuzzy semantic similarity measure and experiments are conducted using human participants and two benchmark fuzzy word datasets. Correlations with human similarity ratings show only one ontological structure was naturally representative of human perceptions of fuzzy words.

Keywords—Fuzzy Ontology; Semantic Similarity Measures; Fuzzy Words

I. INTRODUCTION

An ontology is a structure that can be used to describe the hierarchical relationships between the entities that are contained within it [1]. In the development of word and short text similarity measures, the use of ontologies have been shown to be successful in both calculating word similarity [2] and semantic similarity between concepts in an ontology [3]. The ontological annotation of the lexical database WordNet provided an ideal resource for determining the semantic distance between words used in calculating their similarity [4,5]. However, the content of WordNet, did not include “fuzzy words” i.e. words with subjective meanings which are typically used in everyday human natural language dialogue and are often ambiguous and vague in meaning [6]. Examples of fuzzy words include “huge” and “small” which will have different meanings dependent on an individual in a given context. Hence, to develop fuzzy semantic similarity measures, domain specific fuzzy ontologies have to be developed in order to extract the semantic distance between fuzzy words contained within a short text.

Creation of fuzzy ontologies allows the relatedness between pairs of fuzzy words to be calculated and this value can be applied within an overall similarity measurement of short texts.

The motivation behind this work is to investigate the most suitable fuzzy ontological structure which can be applied in a fuzzy semantic similarity measure. Extensive research has been done on methods to create ontologies using tools such as protégé [7...11] and fuzzy ontologies [12...15]. There is no correct methodology to design an ontology [16], rather the method used is dependent on experience and the domain. The difficulty and challenge is how to evaluate the ontologies that are created by alternative methodologies [17]. In this paper, two different fuzzy ontological structures (known as FS-1 and FS-2) are developed where the methodology to develop the class hierarchy utilizes human participants to determine the domain and scope of the fuzzy ontologies. Humans first engage in a series of experiments to ascertain fuzzy categories i.e. “Size” and fuzzy words within them e.g. “Petite”. Secondly, a further set of participants perform quantification of fuzzy words within a set of predefined categories. Fuzzy words are assigned to different classes within the domain of the ontologies based upon type reduced fuzzy sets derived from the human quantification experiments. Each ontological structure is then evaluated by incorporating into a fuzzy semantic similarity measure (FAST [18]) and examining the correlation with human participant ratings on two benchmark fuzzy word datasets.

The value of semantic similarity measures within the natural language processing community is particularly relevant to the scripting of conversational agents [19]. The ability to replace thousands of patterns with just several prototypical short texts, removes the pattern matching component making scripting less complex and time-consuming [19]. However, current work in developing semantic conversational agents has only utilized non-fuzzy semantic similarity measures. The work in this paper is intended to explore different ontological structures to strengthen FAST so it can be incorporated into a future conversational agent.

The remainder of this paper is organized as follows. Section II, presents a review of ontologies. Section III describes the methodology used to create the two proposed ontological structures and the results of populating the domains and associated classes with

quantified fuzzy words. Section IV presents the experimental methodology and evaluation of each ontology and finally, section V concludes and discusses the impact of ontological selection on fuzzy semantic similarity measures.

II. ONTOLOGIES OVERVIEW

From the inception of ontological structures in computer science, they have played an important role in the area of knowledge representation and computer reasoning. In an early paper Clancey [20], described the use of ontology structures through establishment of hierarchical entity relations. The ontology, through use of a directed graph, classified various concepts into categories and sub-categories. Through the ontology, all the properties that an individual entity possessed could be determined based on the categories that it belonged to. Each entity could have more than one unrelated property i.e. to belong to more than one concept. The ontology structure also noted that all entities could be considered either as a singular or as part of a greater collective. In an example that was presented a collective of cows was a herd. To deal with this, the paper presented the idea of parallel ontological schemas, one for the entities as individuals and another that dealt with collectives that entities could belong to. Important work on the use of ontologies in the field of knowledge representation was done by Gruber [21]. In [21], a set of design criteria for ontologies was proposed to better facilitate their usefulness upon creation. The criteria were “clarity”, “coherence”, “extendibility”, “minimal encoding bias” and “minimal ontological commitment”. These criteria have since played a crucial role in the wider area of ontological creation [4].

A. Ontologies in Text Similarity

The development of ontologies has played an important role in the field of semantic similarity. This is particularly evident in measures that have been created to determine the level of semantic similarity between pairs of words (entity classes) in either the same or in different ontologies [2, 7, 8]. This work stemmed from the early work done on information retrieval from ontological structures [12] where a system of determining the conceptual closeness between Boolean queries and documents was proposed. Resnik [5] took a probabilistic approach to the problem of determining semantic similarity between entities in a taxonomy structure through information retrieval techniques. This was based on assigning probabilities to individual entities in the ontology based on their frequencies of occurrence in a corpus. The specific lexical ontology that Resnik used was adapted from the WordNet database. Subsequent tests of the system showed it to perform well against human results [13].

Determining similarity through ontologies is based on the fact that entities being more closely related ontologically to each other implies a higher level of similarity [14]. Therefore word and text similarity measures work through taking information about how

closely related words are to determine a semantic similarity value between them. As word similarity measures that use ontologies have been shown to be successful in representing word similarity [1], ontological structures present a framework through which the level of similarity between pairs of fuzzy words can be determined.

B. WordNet

WordNet is a large, widely used lexical database that was created by Miller [22]. WordNet was created to deal with the lack of machine readable lexical databases and was a linguistic database that could represent words conceptually rather than alphabetically. The latest version, WordNet 3.0 now contains 155287 words [23]. These words are organised into sets of synonyms (synsets) based on their shared meanings. This was achievable through the concept of a lexical matrices illustrating multiple word forms with a common meaning or a single word form that encompassed multiple meanings. A distinct feature of WordNet was in the lexical categories that contained the words. Specifically, it used Nouns, Verbs, Adjectives and Adverbs. Words could be present in more than a single category potentially leading to confusion [22]. WordNet also categorised the different relations between words based on synonymy, antonymy, hyponymy, meronymy and morphological relations. A synonym relation exists between two words if they share the same meaning (belong to the same synset), an antonym relationship exists between two words that have diametrically opposed meanings. Hyponym/hypernym (or conversely ISA) relations are transitive relations wherein one of the words is a subset of another word (for example car and vehicle). Meronym/holonym relations (or HASA) relations are transitive relations where one word is part of a grouping defined by the other. For example “dog” and “pack” would be an example of such a relationship. Morphological relationships are defined as the relationships between the different morphological forms of a particular word for example “car” and “cars”. This categorization of words makes WordNet far easier for a computer to extract information from other systems.

One of the most important features of WordNet, particularly in terms of ontological structures and the wider field of word similarity is what was accomplished with nouns and their relations. A lexical inheritance system was created for 117798 nouns [23] which categorizes the nouns in a vast lexical tree based on their lexical relationships with others. Superordinate (ISA) relations for each of the nouns towards single points were created which gave definition to the inter-relatedness of all nouns thus allowing inheritance of the various properties of all superordinate words.

The decision to use an inheritance based system came from work that was done in psycholexicology [24]. It was shown that lexical memory operated on an inheritance based system and that people were quicker to ascertain attributes from a closer superordinate than a more distant one. Therefore, through usage of the inheritance based model, the WordNet system worked

towards effectively emulating the naturalness of human thought allowing computers to process information in a similar manner to the human mind. This is a reason why it was such a suitable candidate to form the basis for the popular STASIS short text semantic similarity measure [25] and the conceptual ideas behind the creation of fuzzy ontologies reported in this paper.

C. Fuzzy Ontologies

A fuzzy ontology is an ontology which uses elements of fuzzy set theory to naturally represent imprecise and vague knowledge [12]. Significant research has been undertaken to address how fuzzy set theory could be integrated into the representation of the ontology [13]. One approach relevant to this research, is in the creation of a fuzzy linguistic variable ontology where for each linguistic variable, its name, set of its associated linguistic values, binary relations between these values are ordered and stored [13]. Qualifiers such as “not very” can also be used to extend the fuzzy linguistic variable ontology. Work has been undertaken to extend WordNet to allow for the representation of vague knowledge between terms [14]. This work involves the addition of new synsets and general axioms to allow for more natural fine natural language descriptors to be incorporated. The authors, acknowledge that it “requires considerable effort to define synset membership, similarity” etc. and experts would be required to assign such values. The issue of cost in developing ontologies and their reusability is also addressed by Amira et al. [15] who proposed an extension to the ontology editor Protégé based on fuzzy logic and formal concept analysis. Methodologies are often presented with no real world application and therefore are not evaluated. However, the new approach adopted in this paper, utilizes the quantification of fuzzy words by human participants in a number of categories to formulate both the classes and their relationships within the proposed ontological structures.

Evaluation of the proposed ontologies takes place through implementation in a fuzzy semantic similarity measure and measuring each’s success in contributing to how well the semantic similarity score correlates with human participants.

III. CREATING FUZZY ONTOLOGIES

A. Fuzzy Categories and Quantification

For the purpose of this work, the proposed fuzzy ontological structures, FS-1 and FS-2, (defined in Section III, B), were applied to 6 fuzzy categories. The categories that were used were selected based on the large number of fuzzy words they could contain and were Size, Goodness, Age, Temperature, Frequency, and Membership [8]. The process of quantifying sets of fuzzy words within each category required sets of fuzzy words to be collected that could be used to construct a scale for the sets of words (per category) to be quantified on. The procedure was conducted using human participants through two sets of empirical experiments that involved

1) Populating a set of categories with fuzzy words and 2) Quantifying the sets of fuzzy words.

The first empirical experiment asked a group of twenty native English speakers to complete questionnaires that asked them to write down as many words as they could think of from the different categories. Once the words were collected, it presented an opportunity to get an approximation of the impact of fuzzy words on the English language. For each fuzzy word, a set of synonyms were collected and statistics obtained from the Brown Corpus [26]. The fuzzy words represented 1.6 percent of all the words within the corpus and it was determined that 24% of all the sentences in the corpus contained at least one of the fuzzy words. This shows the influence even a very limited number of fuzzy words has and is a strong indication of the significance of fuzzy words in terms of sentence similarity.

The second experiment involved the quantification of all fuzzy words in each category. This was achieved by giving a group of participants a scale between 0 and 10 and asking them to quantify the words in each of the categories on that scale. Each participant was asked to provide a single value that they saw as representative of the point where the membership function of that word would be highest. For example, in the category “Distance”, one participant may assign the value 10 to the word “Gargantuan”, 9 to the word “Enormous” and 3 to the word “Petite”. The area of scale refers to the section of the 0 to 10 scale that these fuzzy words that human participants had assigned values within. Taking these values for all participants allowed the creation of a type reduced fuzzy set with domain representing the areas of scale for each fuzzy word. The standard deviation of these values reflects the level of uncertainty across human participants. Each fuzzy set was then defuzzified to create a single value to be used that is representative of that word. Table I shows the defuzzified words and associated standard deviation for fuzzy words in the Size/Distance category. The standard deviations were expected and reflects the level of uncertainty as identified by Mendel et al. [27].

TABLE I. SIZE/DISTANCE CATEGORY

Word	Defuzzified Value	Standard Deviation
Adjacent	2.22	1.52
Alongside	1.78	1.31
Average	4.89	1.08
Big	7.22	0.94
Close	2.39	1.85
Diminutive	1.94	2.22
Distant	7.89	1.53
Enormous	8.78	1.63
Far	8.28	1.07
Gargantuan	9.00	2.41
Giant	8.94	1.95
Gigantic	9.11	1.97
Great	8.22	1.56
Huge	8.39	1.65
Insignificant	1.86	1.66
Large	7.17	1.86
Little	3.17	1.86
Massive	8.11	1.32
Medium	4.67	1.37
Microscopic	0.94	1.21

Middle	4.72	1.02
Miniscule	1.11	0.90
Minute	1.67	1.19
Near	2.67	1.53
Nearby	3.00	1.08
Normal	4.67	0.69
Petite	2.06	0.94
Proximal	3.11	1.53
Proximate	3.11	1.45
Regular	4.44	0.92
Remote	8.11	1.75
Sizeable	7.11	1.97
Small	3.00	1.03
Standard	4.56	0.86
Substantial	7.33	1.57
Tiny	1.72	0.89

B. Building A Fuzzy Ontological Structure

This section describes the construction of two fuzzy ontological structures (FS-1 and FS-2) and the nature of the relationships of the entities contained within. These ontology structures would fill a role akin to the WordNet ontology used in Li's [25] similarity measure in terms of being used to provide distances between words as well as the subsumer depth distances from the lowest common subsumer to the top of the hierarchy. In creating the concepts of the fuzzy ontology, the first step was to divide each fuzzy category into nodes that were related to each other through subsumer relations to create the class hierarchy. With the division of categories in this manner, this allowed for sets of words from the categories to be stored within these nodes and hence allow for the relations between these words to be represented by their distances and subsumer depths. Each category was divided into five nodes (classes) with the central subsumer being representative of the area around the midpoint of the range. The issue therefore remained as to how many classes should exist within each fuzzy category and whether a greater or smaller number of classes would provide better results when applied within a fuzzy short text semantic similarity measure. Therefore two different ontological structures were designed with a different number of classes in each one (known as F-S1 and F-S2 respectively).

The creation of ontological classes in each structure was based on the areas of the scale for each fuzzy word. It was decided that each domain in F-S1 and F-S2 would contain five and ten classes respectively. The nature of FS-1 ensured that each class would contain relatively equal number of fuzzy words but contained a risk that some of the nuances in the different quantities between the fuzzy words would be lost. The nature of FS-2 on the other hand, created a risk that there would be empty classes but ensured by the fact classes covered smaller ranges of values that the fuzzy words contained within each class were close to each other in terms of the quantities they represented.

For FS-1, for each of the fuzzy categories the following domains were created which were characterized by a set of classes (e.g. Small, Average etc.).

- Size = {Very Small, Small, Average, Large, Very Large}
- Goodness = {Very Bad, Bad, Average, Good, Very Good}
- Age = {Very Young, Young, Average, Old, Very Old}
- Temperature = {Very Cold, Cold, Average, Hot, Very Hot}
- Frequency = {Very Often, Often, Average, Rarely, Very Rarely}
- Membership = {Nearly Empty, Hardly, Average, Mostly, Almost Full}

FS-2 is divided into "Neg" classes that contain words with values progressively lower on the scale than 0 and "Pos" classes that contain words with values progressively greater than 0 with the center point representing a single point on the scale where the value of 0 would be taken. Thus a domain was represented by the generic classes:

FS-2 Domain = {Neg5, Neg4, Neg3, Neg2, Neg1, Centre, Pos1, Pos2, Pos3, Pos4, Pos5}

The specific number of classes was determined by using numbers of domains that evenly divided the range of each category. However, the goal was to empirically test the effect of substantially increasing the number of classes for each domain. In FS-2 the areas of the scale for each fuzzy word per domain were equally split into classes. Therefore, the position of a fuzzy word in a domain in FS-1 could be different to that in FS-2 which would give different distances between fuzzy words as well as the subsumer depth distances from the lowest common subsumer to the top of the hierarchy.

C. Determining Relationships Between Classes

With the creation of the detailed categories (FS-2 domain) and associated classes, the next step of the methodology required determining the relationships between the classes. Given the nature of the classes that are being considered here, it was apparent that standard subsumer relations (ISA/HASA Relations) could not be used to map the relations between the classes. This is because of the nature of the classes occupying areas on a scale as opposed to one of them being a type or a property of another. Instead the relations that were used needed to reflect their differences in scale. Therefore another approach was required to represent their relationships. What is proposed instead is a "Surpasses" relationship which is defined as follows:

Given two words A and B within a fuzzy category and a Surpasses relationship Sur, the relationship B Sur A is defined as:

If A is in a positively aligned domain (a domain containing a range of values greater than 0), B is within a domain of greater positive alignment (containing a range of values greater than the range of the domain that contains A)

If A is in a negatively aligned domain (a domain containing a range of values less than 0), B is within a domain of greater negative alignment (containing a range of values less than the range of the domain that contains A)

If A is in a Neutral domain (the central domain in terms of values), B is in a non-Neutral domain.

For example, consider an evaluation of an exam paper. Whether a candidate performs better or worse than average (being classified as good or bad) their performance would exceed the requirements for being average. Then if the grade were very good then not only would it surpass average but also surpass good along that vector. Similarly on another vector, bad would also surpass average and be surpassed by very bad. Through the implementation of these relations the ontologies can provide a clear picture therefore of the differences and similarities between the classes in terms of the ontological distances between them and their subsumer depths. Each class is required to map onto a number of fuzzy words. The challenge is to therefore classify fuzzy words into the correct “classes” i.e. whether the word “Excellent” should be stored in “Good” or “Very Good”. To solve the classification issue, there were two stages. Firstly, given that both FS-1 and FS-2 structures required that the fuzzy words be classified according to ranges they occupied on a -1 to 1 axis based on human participant quantification scores, they had to be rescaled. This was because some of the words were positively orientated while others were negatively oriented. All fuzzy words were assigned to the appropriate classes (for either of the proposed structures FS-1 and FS-2) within their given domains based on the locations on the axis that they occupied. For example consider the word “tiny” which on the fuzzy category size scale takes a value of -0.76. This would allow it to be classified into the “Very Small” class in FS-1 and the “Neg4” class in FS-2. Tables II and III show how the fuzzy words were classified in the size domain using FS-1 and FS-2.

TABLE II. CLASSIFICATION OF SIZE/DISTANCE DOMAIN (FS-1)

Fuzzy Category	Fuzzy Word
Very Small	Microscopic
	Miniscule
	Minute
	Tiny
	Alongside
	Insignificant
	Diminutive
Small	Petite
	Adjacent
	Close
	Near
	Nearby
	Small
	Thin
Average	Proximal
	Proximate
	Little
	Regular
	Standard
	Medium
	Normal
Middle	

	Centre
	midpoint
	Average
Large	Sizeable
	Large
	Loads
	Thick
	Big
	Substantial
	Distant
Very Large	Massive
	Remote
	Long
	Great
	Far
	Huge
	oversized
	Immense
	Enormous
	mammoth
	Giant
	Gargantuan
	Gigantic

TABLE III. CLASSIFICATION OF SIZE/DISTANCE DOMAIN (FS-2)

Fuzzy Category	Fuzzy Word
Neg1	Microscopic
	Miniscule
Neg2	Minute
	Tiny
	Alongside
	Insignificant
	Diminutive
	Petite
Neg3	Adjacent
	Close
Neg4	Near
	Nearby
Neg5	Small
	Thin
	Proximal
	Proximate
	Little
	Regular
	Standard
Centre	
Pos1	Medium
	Normal
	Middle
Pos2	Average
	Sizeable
	Large
	Thick
	Big
Pos3	Substantial
	Distant
	Massive
	Remote
	Long
Pos4	Great
	Far
	Huge
Pos5	Enormous
	Giant
	Gargantuan
	Gigantic

D. Results of Populating Ontologies

Figures 1 to 6 show six ontologies which were created representing the six fuzzy categories using FS-1. Figure

7 shows the ontological structure FS-2 which was applied linearly to all six fuzzy categories.

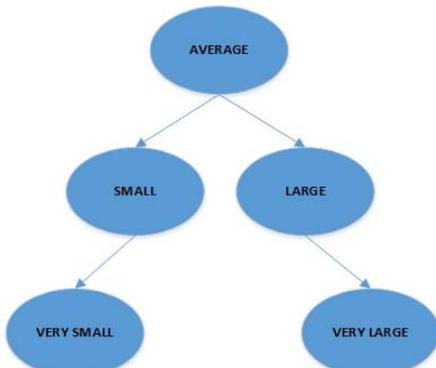


Fig. 1. Size/Distance Category (Structure 1)

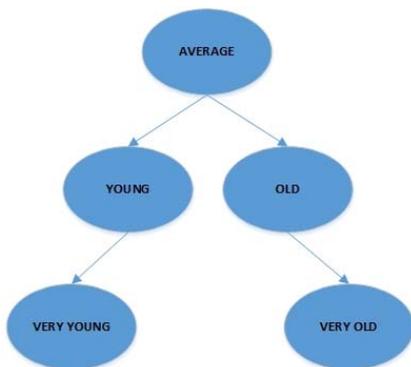


Fig. 2. Age Category (Structure 1)

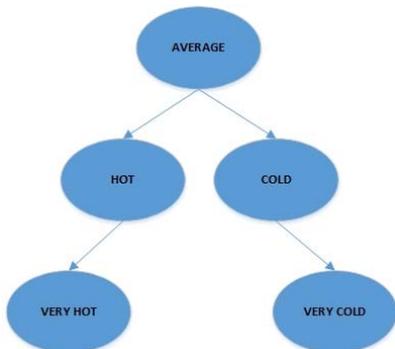


Fig. 3. Temperature Category (Structure 1)

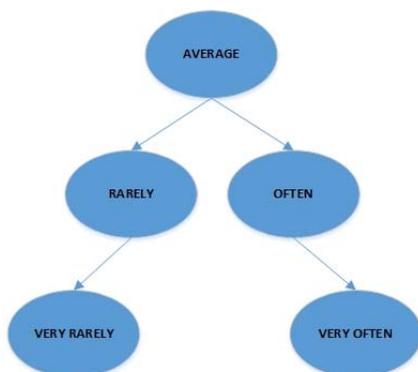


Fig. 4. Frequency Category (Structure 1)

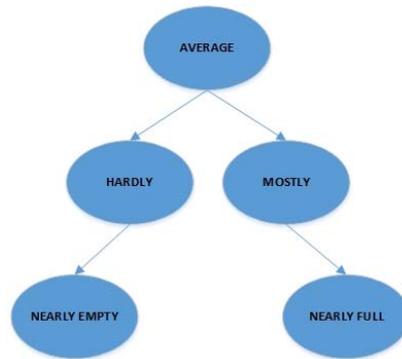


Fig. 5. Membership Category (Structure 1)

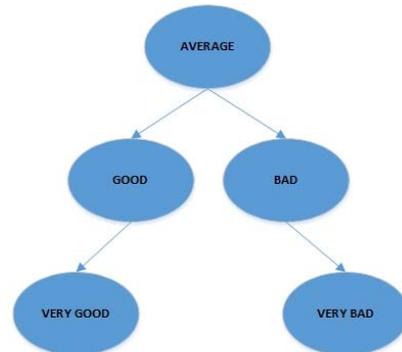


Fig. 6. Goodness Category (Structure 1)

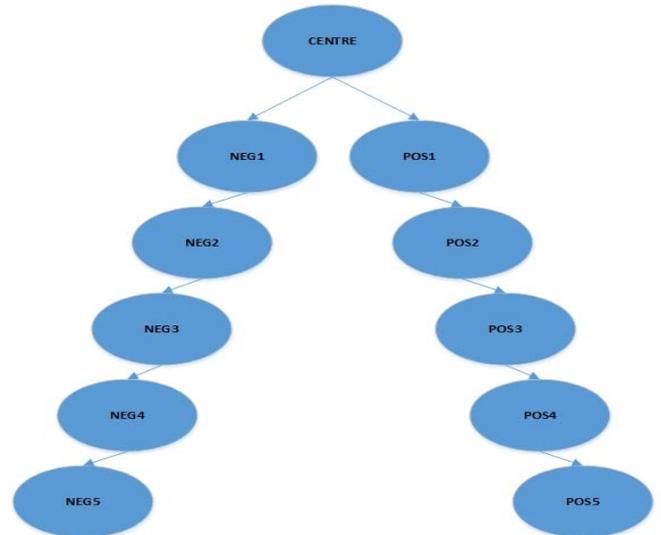


Fig.7. General Template for All Categories (F-S2)

As previously stated, the purpose of generating fuzzy ontological structures was to enable fuzzy words to contribute to determining the semantic similarity of short texts. However, it would be impossible to represent the relationships between all possible fuzzy words within a general unseen short text. If within an unseen short text, a fuzzy word (adjective or adverb) was identified that was not present in any domains classes, a search of WordNet Synsets was performed. If any word was found that was within one of the domain classes and of a similar type (i.e. adjective), its value in the WordNet Synset was taken instead. While this does expand the total number of words and add additional flexibility, it is not a suitable replacement for human quantification of the words, which is the ultimate goal.

IV. EVALUATION FUZZY ONTOLOGIES

In order to evaluate fuzzy ontologies, FS-1 and FS-2 had to be implemented within the fuzzy semantic similarity measure known as FAST [18] to ascertain the effect of each structure on the semantic similarity of the sentence pairs. To determine the best ontological structure the experiments needed to focus specifically on correlation with human similarity ratings in known benchmark fuzzy sentence similarity datasets. In order to evaluate FS-1 and FS-2, two fuzzy word benchmark datasets were used. The Single Fuzzy Word Dataset (SFWD) comprised of 30 pairs of the short texts containing one fuzzy words [28]. The Multiple Fuzzy Word Dataset (MFWD) contained 30 pairs of short texts containing at least two fuzzy words and was automatically generated from a corpus using a fuzzy sentence pairing algorithm [29].

Each sentence pair in both SFWD and MFWD contained a set of human ratings for each of the sentence pairs. Similarity ratings returned from the different FAST implementations (FS-1 and FS-2) for each of the sentence pairs could then be compared to the human ratings. Therefore the structure that is able to return results that are closer to the human ratings can be taken as more representative of human perceptions of sentence similarity. In particular, the MFWD was used to investigate if increasing the number of fuzzy words in a fuzzy sentence pair increases or diminishes the level of similarity between the sentences in a fuzzy pair then did the level of accuracy of FS-1 and FS-2 remain consistent? This required correlations of both FS-1 and FS-2 on both datasets to be examined. Table IV and V shows a comparison between FAST implementations with FS-1 and FS-2 on SFWD and MFWD respectively, where SP is the sentence pair number within SFWD and Human gives the average human participant rating for that sentence pair.

The results in Table IV show that while the correlation with human ratings for FS-1 remains high at 0.765, the correlation for FS-2 drops to 0.679. Fisher r to z transformation returns a p-value of 0.5 showing no significance between the results. However, at this point the difference in similarity between the two correlations has increased to 11.7%. Therefore, it is potentially the case that the FS-2 scale declines in accuracy when faced with sentences with fewer fuzzy words, in addition to not being adequate for sentences with large numbers of fuzzy words. This implies that equally splitting the areas of the scale for each class in each domain was not naturally representative of human perceptions of fuzzy words. This is potentially the result of sets of words clustering around particular ranges.

TABLE IV. EVALUATION OF F-S1 AND F-S2 ON SFWD

SP	Human	F-S1	FS-2
1	3.833	0.719	0.71
2	0	0.474	0.468
3	7.3	0.778	0.796
4	7.952	0.744	0.744
5	1.281	0.555	0.555
6	8.719	0.627	0.627
7	7.095	0.848	0.845
8	6.719	0.779	0.771
9	0.952	0.616	0.608
10	8.248	0.825	0.821
11	4.957	0.406	0.404
12	0.529	0.477	0.469
13	3.286	0.605	0.612
14	6.371	0.891	0.88
15	9.138	1	1
16	6.781	0.898	0.879
17	3.229	0.501	0.499
18	2.11	0.514	0.498
19	6.757	0.782	0.765
20	8.986	0.836	0.836
21	3.548	0.545	0.545
22	8.852	0.902	0.902
23	7.043	0.891	0.858
24	3.833	0.713	0.71
25	8.857	0.769	0.758
26	7.583	0.919	0.894
27	8.919	0.795	0.804
28	6.914	0.862	0.862
29	1.295	0.385	0.385
30	6.624	0.574	0.576

TABLE V. EVALUATION OF F-S1 AND F-S2 ON MFWD

SP	Human	FS-1	FS-2
1	5.623	0.904	0.897
2	1.715	0.588	0.656
3	3.769	0.944	0.898
4	0.75	0.21	0.198
5	3.708	0.901	0.892
6	8.35	0.997	0.997
7	5.677	0.937	0.92
8	3.842	0.978	0.973
9	4.873	0.822	0.808
10	6.865	0.969	0.962
11	1.223	0.577	0.575
12	7.127	0.996	0.967
13	5.285	0.97	0.93
14	5.938	0.967	0.94
15	7.381	0.943	0.923
16	3.238	0.76	0.826
17	4.312	0.965	0.934
18	1.446	0.362	0.329
19	7.792	0.975	0.968
20	7.815	0.792	0.593
21	2.112	0.625	0.625
22	6.25	0.993	0.989
23	8.162	0.996	0.996
24	7.215	0.844	0.845
25	7.485	0.854	0.732
26	6.331	0.859	0.809
27	3.842	0.967	0.961
28	1.269	0.438	0.435
29	6.069	0.913	0.909
30	6.488	0.965	0.967

V. CONCLUSION

This paper has proposed and evaluated two different fuzzy ontology structures (FS-1 and FS-2) which are

based on the areas of the scale determined through human quantification of fuzzy words across six fuzzy categories. The quantification experiments have provided a series of words across a number of categories that have been scaled against each other on individual scales pertinent to each category. In this work, it is important to note that the scaling is solely restricted at present to being *within* the categories and the words are not scaled *between* the categories. Developing a method for doing this is a potential area of future work.

Each ontology structure applied a different strategy for the partitioning of classes inside each ontological domain. Through implementation of the proposed ontologies within a fuzzy semantic similarity measure it was established that the natural partitioning of classes based upon quantification (FS-1) gave better correlations with human ratings on two benchmark datasets. The main benefit of using a natural ontology in fuzzy semantic similarity measure is that it allows the similarity measurement of fuzzy words to be determined which can then be incorporated into the final short text semantic similarity calculation. Further work is required to utilize the FS-1 structure to expand coverage to other fuzzy categories in not only English, but also modern standard Arabic.

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