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A New Method for Semantic Similarity Assessment using Fuzzy Formal Concept Analysis & Fuzzy Set Similarity Measure

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Abstract**: *Measuring the accurate semantic similarity between the words is a major issue in various applications of artificial intelligence and computational linguistics areas such as natural language processing, text-mining, information retrieval and for development of semantic web. In the past, many approaches have been proposed and adopted to evaluate similarity by using the knowledge based systems such as WordNet and MeSH ontology. In this paper we have proposed a new method; based on hybridization approach in knowledge based system. In this we have used feature based method and fuzzy Set theory. In feature based approach, properties or features are used for measuring the similarity as compare to edge and content information approaches. Our approach is investigated on standard dataset like R&G, M&C and 353-TC, which shows prominent improvement in the judgment of semantic similarity score between the words. This approach can be further used among cross ontology and fuzzy ontology as it is based on the feature based measure and fuzzy set theory.***

Index Terms: Semantic Similarity Measures, Formal concept Analysis, Fuzzy Formal Concept Analysis, Word Net

I. INTRODUCTION

Research is drowning interest towards the semantic web[1]. The semantic web has a shared understanding, a defined structural and extension of current World Wide Web[2]. Ontology play's an extremely important role for the development of a semantic web. Ontology is defined by the Author Gurber et al [3] "it is a formal specification of a shared conceptualization". All-though ontologies are created for the different aspects and domains, they regularly contain overlapping data and the information. This information can be further used to evaluate the similarity among the words[4] .Semantic similarity; measures a numerical value that specify the closeness among the words/concepts. The idea of similarity or likeness is to identify the concepts having common characteristics. Appropriate assessment of similarity improves the understanding of textual data[5].More semantically close words are those that share same idea or terms, specified by the synonym in the English language like "pain and hurt", two different words but can be used inter-changeably. To measure the accurate similarity among the words/concepts is the open research problem in the area of computational linguistic[6] and natural language processing[7]. In the fig1 Car, ship and bus which are different class, having 'is-a' relation with Automobile, in a travel ontology. Similarity can be computed between the {automobile, car},{automobile, bus},{bus, car} and so on..Semantic closeness shows how taxonomically near two Terms are, as they share some common attribute of their meaning. Two terms highly associated with the concept of semantic similarity is semantic distance and semantic relatedness.

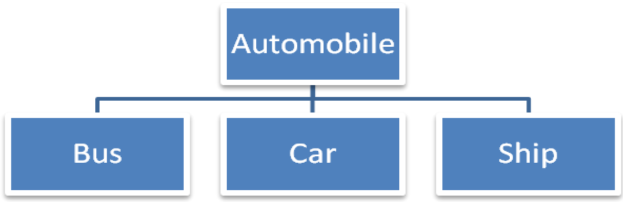

Figure 1: Showing "is-a" Relationship on Travel Ontology

Semantic distance [8] is computed as edge or link difference between the two terms, how far the two terms; like dist(bus, car)=dist(car, ship) but sim(bus, car) ≠ sim(car, ship). Another term associated with semantic similarity is ' semantic relatedness' , which does not only rely on the taxonomic relation "is-a" more relations to be considered like part –of, antonym relationship's that are present in the WordNet [9] can be considered. Words {ink, pencil} are less related to each other as compared to {pencil, paper} in terms of semantic relatedness.

In this paper, proposed a new method for feature based approaches. In this WordNet is used for taxonomical information, Formal Concept Analysis (FCA) is exploit for extraction of features for given concept or words. Linguistics value to each feature is assigned to show how much an attribute/feature is related to the corresponding concept/word/class accordance with fuzzy logic and mapped into fuzzy formal concept Analysis. A multi-attribute features table is constructed for the concepts. A fuzzy set similarity measure is used to compute similarity among the words. The overall process yields us a better result in terms of accuracy on benchmark datasets. The same approach can be applied in Global ontologies, cross ontologies and fuzzy ontology.

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The paper is organized in following sections. Section 2 describes the related work in the area of semantic similarity. Section 3 describes the proposed approach and different preliminary for the proposed approach.

Section 5, 6 presents the step followed in our approach and evaluation respectively. Result section shows the result on TC-353 similarity data-set and comparison with other methods. Last division illustrates the conclusion and future work.

II. RELATED WORK

In general two words can be similar lexically or semantically. Lexical similarity represents, words having similar string sequence like in {"Man", "Lan" and "Van"} and also in DNA sequence matching {"ADCGTDCGTC" and "ADCCGTCGCA"}. Lexical similarity has a wide application in the areas of medical sequence matching [10] and pattern recognition[11]. Various measures are proposed in this area[12]. Whereas semantic similarity deals with the meaning of the two words, how the linguistic meanings of two words are similar such as how much similar the words {"mango" and "orange"} as both words belongs to class "Fruit". For calculating the semantic similarity among the words diverse similarity measures have been proposed by different researchers groups. In literature two common approaches "Corpus-Based Approaches" and "Knowledge-Based Approaches" are presented by the researchers [13]. In corpus based approaches large amount of text context is used for calculating the similarity among the words. Latent Semantic Approach (LSA) [14] and Pointwise mutual information(PMI)[15] are the most used methods for computing the semantic similarity.

The major related work on semantic similarity measures utilizing the taxonomy knowledge by the Global ontologies like WordNet, MeSH[16] a medical oncology and SUMO ontology. Knowledge-based Methods [17] are an effort to figure out the semantic similarity without human intervention, it uses a vast amount of environment knowledge about the concepts. Ontologies have been extensively used in the area of knowledge-base systems. WordNet is a domain free and all-purpose thesaurus of common English words. It formulates approximately 10000 English words in a semantic structure that looks like ontology. The resultant of WordNet concepts forms a network of significantly related words. A graph prototype is generated in form of network and used for forming the meaning of concepts. WordNet is exploited as background ontology in largely associated areas of the knowledge-based system. Broadly classified Knowledge-based technique has three approaches [5], [13][18]and the last one is hybrid approaches which can be combination of any of these method. The approaches are (1)Edge/path based Approaches (2) Information Content approaches (3) Features Based Approaches (4)Hybrid Approaches. Edge-Counting approach introduced by Author et al Lin [19] after that many measures was introduced by the different researchers[20], [21],[22] it is a straight-forward technique to measure the similarity, it calculates the minimum path-distance from end to end connection with their related ontological models through a "is-a" link. As the path length increases the distance is also increased and less similar the word are. The drawback of these measures are that; they only work on the "is-a" link and works in the single ontology structure. In information Content Approach, it is based on the theory that every concept has a large extent of information in WordNet. In a multidimensional space where a node represents a unique concept it contains definite amount of information and an edge represents direct liking between the two concepts. The similarity among these two concepts is computed on the basis of information they have shared in that space. It assumes if the concepts share more common information, the concepts are more similar. Resnik et al [23] introduced the information content theory in year 1995. In this many resent researches are also taking place presented by different researcher group [24][24], [25].These approaches are corpus dependent it accuracy dependent on the size of the corpus and if same Lcs (least common subsumer) not exist they can't compute the similarity among the words.

Feature based methodology described by the Author Tversky [26], similarity among the concepts as a factor of their properties. It rely upon the extent of common and un-common features of compared concepts. Common features increase the similarity and exceptional features tend to weaken it. It is established on the theory that every concept is depicted through a set of keywords representing their properties and features. As represented in the WordNet through definitions and glosses values. Glossary of the word "automobile" describe through the WordNet as "a motor vehicle with four wheels; usually propelled by an internal combustion engine". Two words are more similar if they contain more common characteristics of words and fewer exceptional characteristics. Tversky measure is represented as;

$$Sim_{Tversky}(C_1, C_2) = \frac{|c_1 \cap c_2|}{|c_1 \cap c_2| + k(|c_1 \setminus c_2|) + (k-1)\{|c_2 \setminus c_1|\}} \quad (1)$$

K is adjustable factor and K can be $\in [0,1]$

Rodriguez and Egenhofer [27] In this computation is done on the basics of the individual sum of likeness between the "synsets", their "features" and "neighborhood concept" of the estimated terms as;

$$Sim_{Res}(C_1,C_2) = w.S_{synsets}(C_1,C_2)+u.S_{feature}(C_1,C_2)+v.\ S_{neighborhood}(C_1,C_2) \quad (2)$$

$S_{synsets}, S_{feature}$ and $S_{neighborhood}$ are the similarity among the "synonym set" their "features" and corresponding "semantic neighborhood" of the computed terms. According to this (w, u, v>=0) value of w, u and v depends on the particular similarity weights of every specific component. The value relies upon the individuality of the taxonomy. Here S symbolizes the coinciding between the dissimilar features, which are computed by the equ. 1.

In the latest research [28] used the Wikipedia as an ontology and similarity is computed on the basic of synonyms, glosses, anchors and categories among the concepts. Main shortcoming of this study is that computational space and huge amount of knowledge is required as for each word; have to search many Wikipedia articles.

In this research paper, we have utilized the WordNet knowledge i.e. already utilized the textual knowledge about the concepts and computation is low in this case.

III. PROPOSED APPROACH

a. Process flow

The motivation behind this paper is to present a new method in the area of features based similarity measures to tackle the limitation of past methods applied. The current paper focuses on the learning of semantic similarity between the concept / words or terms using fuzzy formal concept analysis, fuzzy membership show how close the word to a particular attribute in a context, as in example the words (car, road, ship) comes in travel ontology but the feature road is more associated with concept car as compared to ship. If a word having more associative with an attribute we define high membership to that attribute as specified by fuzzy set theory given by the researcher Lofti Zadeh [29].We apply the Fuzzy set similarity measure to calculate the similarity among the words inside the ontology. Extracted the features from WordNet a Global Ontology, features usually depict the taxonomic and non–taxonomic information present in ontology. Overall process is shown in Fig.2

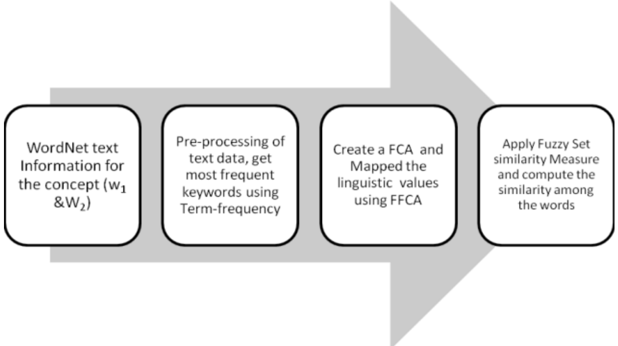

Figure 2. Process flow diagram

B. Preliminaries

Formal concept analysis was introduce by a mathematician Willy et al [30] based on the lattice theory; a group containing same set of objects and attributes. In a defined domain a concept (word) is a set of objects, describes the instances of the concept. FCA is a well established theoretical structure for construction, evaluation and visualization of data for the information used in data mining, knowledge representation and for the development of ontology. FCA based techniques describes formal contexts to symbolize the relationships among the objects and attributes in a given domain. Formal concepts correspond to concept lattice. Concept lattice can be further used for presenting information accurately and effectively[31], [32] .

Fuzzy Formal Concept Analysis (FFCA) proposed by the Author et al Quan in 2004 [33] by introducing the FOGA framework, merging the two theories FCA and fuzzy theory. In this membership value is define among the attributes according to the fuzzy set theory in a particular context. FFCA is a generalization of FCA for defining the degree of fuzzy membership between the object and the attributes. In FCA if a concept is related to some attribute having only two values, if it is related then showing through (・) otherwise that column is blank, FCA has only two values are (0, 1). FFCA is used for dealing the vagueness and uncertainty present in data. FFCA permits us to quantify the terms how much they are related within a formal context. It shows the closeness between the particular instances with their attributes. "How much" association is illustrated by the membership grade values. For every formal concept a membership value is specified for each attribute values. This information can be used in categorize each formal concept more accurately [34].

Different researchers proposed different similarity measure for fuzzy sets .Fuzzy similarity measures are used to compute the similarity among the fuzzy sets. For this research study, for the similarity computation among the words we have choose a similarity measure introduce by the researcher[35], compute a good accuracy in all fields of application like image processing , fuzzy information retrieval[36] and feature extraction . Fuzzy Similarity between two fuzzy set (A, B) is computed by the given formula.

$$Sim_{(A,B)} = \frac{\sum_{i=1}^{n} min(\mu^i A, \mu^i B)}{\sum_{i=1}^{n} max(\mu^i A, \mu^i B)} \qquad (4)$$

If $\mu^i A + \mu^i B = 0$ then $Sim_{(A,B)} = 1$

IV. PROCESS DEVELOPMENT

Extraction of feature is a difficult task among the ontologies. In this paper, utilized a Global ontology WordNet having gloss, hypernymy / holonymy, antonym and many more relationships of a particular word {w} in WordNet {WN} is present. Using these information, extracted the keyword or the feature /attribute of that particular concept. We construct a multi-feature/attribute row for a single word in the same manner we can construct the multi-features value for another words. Formal definition of a Context; it is comprise of three parameter, one is a concept, other-one are its attributes and last one is the relationship present among the concept and attributes. A formal lattice is drawn using these concepts; one is known as intent and other known as extent for the lattice. It is used for the transforming of data in to lattice. Lattice shows the inheritance relationship "is-a" between the two concepts. Taking an example of travel ontology in WordNet. Let it has only three classes/words {Car, Bus, Ship} which are all automobiles. Random features are represented by {f1, f2 f3….fn} in Formal Concept Analysis. In this, also take an example of another word/class pencil which is not described in above context. Attributes are shown by the features and terms are concepts. Different attributes are depicted in Table 1. for the concepts car, bus, ship and pencil.

Table No-1 Concept/Attribute represented by FCA.

Attribute / Concept	On road	On water	Wheels	Fuel used	price	Fuel consumed	Speed	Produce heat
Car	•		•	•	•	•	•	•
Bus	•		•	•	•	•	•	•
Ship		•	•	•	•	•	•	•
Pencil					•		•	

Drawn a lattice diagram using an open excess tool; Concept Explore[37] for this context. In this, features {speed, price} is common to all concepts, that's why it is most generalized features. In lattice diagram {ship, car, bus} are on same level and pencil which is not part of this context is on another level. Up-to this point we can say class ship, bus, car are more similar to each other as compared to pencil. From the fig. 3, it can be depicted that words bus, car are most similar words but how much similar we can't compute.

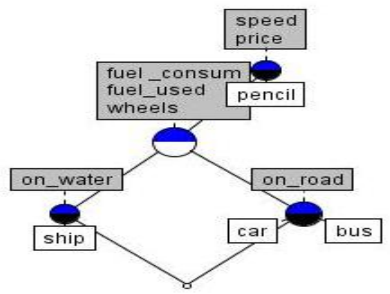

Figure No 3- : Lattice diagram of above example using Concept Explorer Tool

In FFCA fuzzy membership is defined among the objects and attributes. This knowledge can be exploited for measuring the similarity between the formal concepts. In the same example, we can assign the linguistic value to each feature for a particular concept. As we can say that word/concept car is having a high membership towards road as compare to ship having low membership value. We have defined the linguistic value to each attribute/feature according to "how much" it is related to a specific object. Like in word ship has more price as compared to word car and bus, in the same manner linguistic values are defined.

Table No-2: Assigning the Linguistic Values to each feature

Attribute	On -road	On-water	Wheels	Fuel used	Price
Car	High	Very low	Moderate	Moderate	High
Bus	High	Very low	High	Moderate	Very high
Ship	Very low	Very _high	Very high	High	Very very high
Pencil	No	No	No	No	Low

After that we have assign the membership range to each feature. We have used an expert opinion to define the membership values to the features set.

Table No-3: Shows the membership assignment for the different features.

Attribute	On –road	On-water	Wheels	Fuel Used	Price
Car	[0.7-0.9]	[0.01-0.1]	[0.4-0.6]	[0.5-0.6]	[0.5-0.8]
Bus	[0.7-0.8]	[0.01-0.1]	[0.5-0.7]	[0.6-0.7]	[0.6-0.8]
Ship	[0.01-0.1]	[0.8-1]	[0.7-0.8]	[0.7-0.8]	[0.8-0.9]
Pencil	[0]	[0]	[0]	[0]	[0.05-0.1]

Now we can compute the similarity using the fuzzy set similarity measure among any of these two words as (car, bus), (car, ship),(ship, bus) and(car, pencil) by the similarity measure given in the equation(3)

V. EVALUATION AND IMPLEMENTATION

We have taken the information about the concepts (i.e. car, chair) using WordNet Api, where word information, relationship information & gloss information is show in fig. 4. Using R language, pre-processed the textual information. Pre-processing of text-data means removing stop-word for a given language, remove punctuations & stemming process. Using tm, NLP package in R we are able to extract the most frequent word as features of the concepts. In this we select the keywords, whose frequency is greater than 10. Constructed a multi-feature table for the different words using WordNet api.

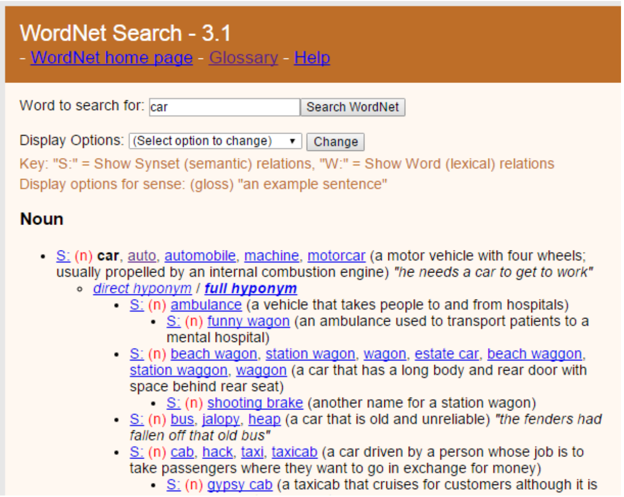

Figure No-4 Word Net Api for the concept "car"

For assigning the membership expert opinion is used. Now we have fuzzy feature vector table (FFVT) for all the concepts, after applying the fuzzy similarity measures we get the final semantic similarity score between the words.

Taking the same example extracted features for word "car". Features are (automobile, travel, wheels, fuel, battery, patrol car, fuel car , speed, machine…….)

Features for the word "bus" (vehicle, public transport, passengers, wheels, ……..).

Table No-6: FFVT for "Car" and "Bus"

Feature	Road	Water	wheels	Fuel	cost	Speed	travel	Heat_ production
Car	0.96	0.023	0.755	0.623	0.53	0.711	0.93	0.81
Bus	0.84	0.011	0.833	0.73	0.72	0.867	0.754	0.76
Pencil	0	0	0	0	0.01	0.012	0	0

Semantic similarity is computed by equ. 3 as " ***Car* and "*Bus*" is 0.69** and between "***car and pencil***" =**0.012**

$$Sim_{(Car,Bus)} = \frac{0.84+0.011+0.755+0.623+0.53+.711+0.754+0.76+0.31}{0.96+0.023+0.833+0.73+0.72+0.867+0.754+0.81+0.82} =$$

$$\frac{4.534}{6.517} = 0.\ 699$$

Sim(car, pencil)=0.012

VI. RESULT

We have applied this similarity measure on various benchmark dataset like M&C [5], R&G[38] and word-similarity TC-353[39] .Pearson correlation method is used to compute correlation between human judgment and our method.

$$\rho(X,Y)=cov(x,y)/\ \sigma X.\sigma Y \qquad (4)$$

Table No-7 Computed Similarity for different words from TC-353 dataset.

Word 1	Word 2	Human (mean)	(Proposed approach)
Love	sex	6.77	0.8
Tiger	cat	7.35	0.9
Tiger	tiger	10	1
Book	paper	7.46	0.8
Computer	keyboard	7.62	0.85
Computer	internet	7.58	0.92
Plane	car	5.77	0.12
Train	car	6.31	0.78
Telephone	communication	7.5	0.87
Television	radio	6.77	0.89
Media	radio	7.42	0.87
Drug	abuse	6.85	0.34
Bread	butter	6.19	0.51
Cucumber	potato	5.92	0.5
Bank	money	8.12	0.89
Wood	forest	7.73	0.85
Money	cash	9.15	0.97

Proposed method has given higher accuracy on different dataset. This method computes the similarity 0.84, 0.83 and 0.82 for the Miller and Charles, R& G and TC-353 dataset respectively. Also compares the results with the other measures in this area.

Table No-8:Comparison Table with other measures.

Measures	Type	M&C	R& G	353 word similarity
Path length[40]	Edge –Method	0.59	N/A	N/A
Wu & Palmer[41]	Edge –Method	0.74	N/A	N/A
Lin[19]	IC(Corpus)	0.7	0.72	N/A
Jiang &Conrath[8]	IC(Corpus)	N/A	0.82	N/A
Tversky[26]	Feature	0.71	N/A	N/A
Feature based Approach using Wikipedia [28]	Feature	0.78	0.8	0.82
Proposed approach	Feature	0.84	0.83	0.84

VII. CONCLUSION

Semantic similarity judgment is a key issue for the development of semantic web. Semantic web is the future of the current World Wide Web. Now a day's web is used for connecting people and their information's. Semantic web is the extension of Web used to share knowledge among the machines. Ontologies are essential part of Semantic web. To deal with the vagueness and uncertainty among the ontologies, requires the fuzzy ontology. FCA techniques applied in various dimensions as in ontology merging, knowledge discovery and in the field of data mining, without much dealing in the field of semantic similarity. In this paper we have used FCA to compute the similarity among the different words. If two classes/words (that are part of that particular ontology) having the similar features are more related to each other. For similarity computation fuzzy membership is used to describe the proximity towards that attribute. For any two classes (words) having the same attributes and membership towards that attribute are nearly equal or computed more similar word. Through fuzzy formal concept analysis and fuzzy set similarity measure it computes the exact similarity between the concepts/words.

Utilizing the word information, we are able to get all the relationship present in Global ontology Word Net. Our experimental result shows that in most cases computed value gives us a better result on various datasets. As this measure is based on Fuzzy formal concept and fuzzy similarity measure this can be further applied for the cross ontologies and in fuzzy ontologies.

This approach can be further modified using neural network for defining the fuzzy membership among the concepts and its feature set.

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