An Improved Dissimilarity based Approach to Semantic Similarity Calculation

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***Abstract*-With the trend that the computational process of semantic similarity more and more mimics the human thought process, it becomes very important to consider the difference between semantics. In this paper, we review commonly used semantic similarity models, discuss the limitations of our previous models, and improve the information content (IC) computation model based on wordnet ontology. In turn, different strategy is employed. The results show that the model proposed in this paper has high computational accuracy.**

Keywords-semantic similarity; WordNet; dissimilarity; antisense

I. INTRODUCTION

With the rapid development of the Internet, information processing has become more and more important, especially the processing of text information has become more complex. Therefore, improving the accuracy of semantic similarity calculation is of great significance to the processing of text information. The semantic similarity calculation method has developed from initially only using the "is-a" relationship [1-4] to count the path length between concepts, the amount of information and depth of the concept itself, then，more multiple semantic relation-based approaches. [5-7] have been proposed by considering more relations such as “part-of”.

With the deepening of ontology research and the wide application of ontology technology, more and more scholars propose to use structured domain ontology to calculate concept similarity, especially the semantic information in WordNet ontology is widely used in the calculation of semantic similarity [8]. WordNet-based computing methods are mainly divided into four categories: path distance [1,2,9-14], information content [3,15-20] and features [21-24], followed by multiple relation-based metrics that consider multiple computational factors [6,25-29].

In the calculation of semantic similarity, these studies mainly calculate the semantic similarity from the forward direction, that is, the correlation between concepts is calculated through the path length between concepts, the amount of information contained and the characteristics, so as to obtain higher similarity. Calculated results, which tend to deviate significantly from human-assessed results.

This paper believes that the current researches on WordNet-based similarity calculation haven’t considered the structure of WordNet very comprehensively, especially the use of antisense relationship. Fewer existing research about antisense [25,29] are only limited to the direct antisense relationship of the concepts to be compared or the antisense relationship is simply calculated as a negative impact.

Based on our previous work [29], this paper proposes an improved approach to maximize the use of antisense relationship by combining the information (depth, information content) contained in the node itself in the antisense path based on the Node to Least Common Ancestor Path (NLAP) to improve the accuracy of the calculation.

II. RELATED RESEARCH

In this section, the existing WordNet-based similarity calculation methods will be introduced and analyzed in detail.

A. Similarity measures based on path distance

The method based on path distance relies on the WordNet is_a relational classification tree, and the semantic similarity between two concepts is represented by the shortest distance in the relational tree between two concepts.

Rada [1] proposed to calculate the similarity of two concepts according to the minimum length path in the paths linking two concepts, that is, use the number of edges to calculate.However, Rada's method suffers from a drawback that all two concepts with the same semantic distance are equally similar. In some cases, the above inferences drawn from Rada's method do not match human judgment. This is a limitation of the path-based approach.

Li et al. [2] exploited two structural factors of concepts, namely local density and LCA depth, to compute semantic similarity.

Hao et al. [9] proposed a new model to combine path distance and depth of LCA through imitating the thought process of humans.

Wu [10] improved on Rada's work by considered the depth of LCS (Least Common Subsumer).

B. Similarity measures based on information content (IC)

Resnik [15] was the first person to combine

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ontology and corpus. He argues that the similarity between two concepts depends on the amount of information shared between them,he proposes an information content-based similarity method that uses the IC of the least common subclass LCS (c_i, c_j) between two concepts.

Jiang [16] fused the path-based method (using only the shortest path) and the information content method to reflect the similarity between concepts,

Lin et al. [17] improved Resnik's method by using the ratio of commonality between concepts and all the information they need as the similarity score between concepts，On the basis of the Lin method,

Meng [3] proposed a nonlinear similarity model with the Lin metric result as the index for similarity calculation.

Seco et al. [18] proposed an intrinsic computational method that only relies on the number of concept hyponyms in the taxonomy ontology.

C. Similarity measures based on features

Feature-based methods utilize common features between concepts to measure semantic similarity and avoid the consistency of edge lengths between concepts. Two concepts are considered semantically more similar if they share more common information, and vice versa.

Tversky et al. [21] believe that the similarity between concepts is asymmetric, and usually the features of the concept's parent and child classes will play a greater role than when they are compared backwards.

Sánchez et al. [22] present an attribution-based approach which only uses taxonomic relationships in WordNet to calculate the normalized dissimilarity between concepts. It can avoid corpora-dependency or parameter-tuning and improve the generality in compare with the original measure.

Wasti et al. [23] combine feature-based and statistics-based methods to form a new weighted feature-based method to solve the problem that feature-based methods treat all features equally in similarity evaluation and ignore the basic statistical information of features.

D. Similarity measures based on Multiple Relationships

Hirst and St-Onge [25] believe that there are concept words c1 and c2 with shorter paths, and the less the number of times the direction changes in the process of traversing the path, the stronger the correlation between the two concept words.

Saif et al. [28] treat the semantic representation of a concept as a set of concepts that are extracted from the concepts of the same name in the semantic taxonomy, and then they propose four weighting mechanisms by using the Topological parameters (edges, depth, descendants, and density) to measure the relevance of features.

Guan et al. [29] propose a method to add the dissimilarity between semantics to the calculation of semantic similarity,The method deeply mines the antisense relationship between concepts through the unique hierarchical structure of WordNet, and then uses the antisense relationship to represent the dissimilarity and combines with the existing methods to obtain the final semantic similarity result.

The method considers introducing a new approach to improve existing methods incorporating antisense relationships. On this basis, we also consider the structural information of WordNet. Due to the different depths and amounts of information in different positions of concepts, simply calculating the semantic similarity of concepts on the NLAP path will lead to inaccurate similarity results, thereby improving the original similarity calculation model.

III. PROPOSED MODEL

In most cases, when people use the inherent structure of WordNet to calculate the similarity between them, they can consider the commonalities of concepts, such as their domain, class and species. However, the differences between them are ignored. In our previous research [29], in order to examine the effect of dissimilarity on the calculation results of similarity, we first introduced a new calculation factor called the Antisense Coefficient (AC) as the representation of dissimilarity between concepts, and proposed a new calculation factor called Node to Least Common Ancestor Path (NLAP) to consider the negative impact of antonyms of concept ancestors and the positive impact of concept ancestors, but in previous experiments, We have not considered the influence of different conceptual nodes in the NLAP path on the experimental results due to their different depths and densities, resulting in different amounts of information.

Although we proposed the use of NLAP before, we did not consider the difference in information carried by different nodes on the NLAP path. For example, in Figure 1, when calculating the similarity between school boy#1#1 and monk#1#2, it is first known that their LCA node is person#1#3, and the concept of school boy is in the node The extension of the concept is male#2#6 and male child#1#1, and their corresponding antonyms are female#2#5 and female child#1#1. So the nodes on NLAP(school boy#1#1) are female#2#5 and female child#1#1.But in the same hypernymy/hyponymy relationship of WordNet, each child node contains the information contained in the parent node, and contains more information than the parent node, so we believe that the deeper the level of the concept node, the higher its IC value.So the IC value of female child#1#1 node is greater than female#2#5. Therefore, we have the following definition for the node *Nc* in NLAP.

Definition 1.IC(*Nc*) Information content of nodes on NLAP. The IC of concept *Nc* is calculated in (1):

$$IC(Nc) = (1 - \frac{\log(hypon(Nc)+1)}{\log(\max\_nodes)} \times \frac{e^{\gamma \times D(Nc)} - e^{-\gamma \times D(Nc)}}{e^{\gamma \times D(Nc)} + e^{-\gamma \times D(Nc)}}) \quad (1)$$

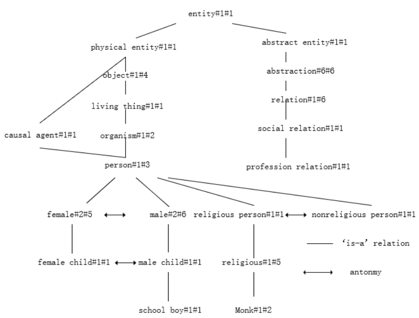

Figure 1 An excerpt of the field relationship in WordNet

where γ is the smoothing factors($0 < \gamma < 1$), Where *hypon(Nc)* is the hyponym number of concept *Nc* and *max_nodes* is the number of the nodes in a taxonomic ontology. *D(NC)* represents the depth of concept nodes in Wordnet.

When NLAP is used to calculate AC, $NLAP(c_i)$ and $NLAP(c_j)$ are used to represent the set of hidden antonyms in c_i and c_j,When calculating the $simNlap(c_i,c_j)$,the similarity results of the existing path distance-based methods are linearly fitted. At this time, the similarity formula is presented in (2):

$$sim_{Nlap}(c_i,c_j) = sim_{path}(c_i,c_j) - antisim(c_i,c_j) \quad (2)$$

Where *simpath* is the result of existing similarity calculation methods related to path distance, c_i and c_j are a pair of concepts to be compared, $antisim(c_i,c_j)$ is a function representing the AC of c_i and c_j, and to examine the effect of antonymy on the correction of similarity, When calculating $antisim$ (c_i, c_j), it is necessary to consider the location information of different nodes on his NLAP path, The similarity formula is presented in (3):

$$antisim(c_i,c_j) = (\sum_{Nci \in NLAP(c_i)} e^{-(\alpha \times L(path) + \beta \times L(IC))} + \sum_{Ncj \in NLAP(c_j)} e^{-(\alpha \times L(path) + \beta \times L(IC))}) / N \quad (3)$$

where α and β are the smoothing factors(0 < α, β <1),*N* represents the number of nodes on both NLAPs, and Nc_i represents the nodes on $NLAP(c_i)$ and $NLAP(c_j)$,The antisense coefficient between concepts is equal to the mean of the similarity of all nodes on NLAP between one of the concepts to be compared and the other.

L(path) is the distance function related to the shortest path, *L(IC)* is the distance function related to IC.

The definition of *L(IC)* is the same as Jiang [16], *L(path)* and *L(IC)* are calculated as (4) and (5):

$$L(path) = \frac{\log(dis(Nc_i, Nc_j)+1)}{\log(2 \times d\max + 1)} \quad (4)$$

$$L(IC) = IC(Nc_i) + IC(Nc_j) - 2 \times IC(LCS(Nc_i, Nc_j)) \quad (5)$$

Where *dis* (Nc_i,Nc_j) represents the distance between two concept nodes, and dmax represents the maximum depth of WordNet.

IV. Experiment

A. Experimental dataset and evaluation criteria

In order to verify the effectiveness of the method model, the datasets and evaluation criteria selected in this paper are widely selected from other papers and have high authority.

(1) Rubenstein and Goodenough (RG65) [30]: RG65 contains 65 pairs of common English words, and in 1965, 51 college students scored these 65 pairs of words, ranging from 0 to 4 representing words Pairs range from completely unrelated to very consistent, meaning that the higher the similarity score of the word pair, the higher the similarity.

(2) Miller and Charles (MC30) [31]: MC30 is a re-improvement of RG65 25 years after its launch. 30 representative word pairs were selected from RG65, namely 10 completely unrelated word pairs, 10 relatively related word pairs and 10 very related word pairs. And the 30 word pairs were manually scored again after selection.

(3) Pearson Correlation Coefficient: As with most choices of existing methods, this paper uses the Pearson correlation coefficient to compare the set of similarity results of the method with the set of similarity results judged by humans. The obtained Pearson correlation coefficient ranges from 0 to 1, and the closer the value is to 1, the closer the similarity result obtained by the method model is to human judgment. The formula for calculating the Pearson correlation coefficient is as (6) :

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 * \sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (6)$$

Where x represents the dataset composed of human judgment results, y represents the similarity result dataset obtained from the experiment, x_i and y_i represent the i-th element in x and y, respectively, $\overline{x}$ and $\overline{y}$ represent the mean of x and y, respectively, and n is the number of word pairs in the dataset.

B. A comparative analysis of the model and existing path-based methods

First, this paper reproduces the existing method of calculating factors such as path distance, depth and density, and uses it to combine with our model in the same way to compare how close the test results are to human judgment on the same test dataset. Experiments show that when the antisense model proposed in this paper is combined with the existing methods based on the upper and lower relationship, the model in this paper can make the similarity results of the existing methods closer to human judgment. Table 1 shows the comparison results between the model in this paper and the existing path-based methods. From Table 1, it can be concluded that, the proposed model can significantly improve the partial path-based Pearson correlation coefficient on WordNet, including methods based only on path distance [1], methods based on path distance and depth [2,10], and methods based on path distance, depth, and density, and a method of weighted path length [6].

TABLE I
Comparison results with existing path-based methods

Method for counting path distances	**Similarity calculation model**	**calculating factors**	**MC30**	**RG65**
Rada's method	Wu[10]	path length,depth	0.741	0.786
	Leacock[13]	path length	0.779	0.838
	Liu[14]	path length,depth	0.796	0.842
Zhu's method	Li[2]	path length,depth	0.792	0.852
	Hao[9]	path length,depth	0.827	0.856
	Wu_PD[10]	path length,depth,density	0.872	0.857
	Leacock_PD[13]	path length,depth,density	0.833	0.844
	Li_PD[2]	path length,depth,density	0.839	0.849
Guan's method	Wu[10]	path length,depth	0.809	0.810
	Leacock[13]	path length,depth	0.784	0.846
	Liu[14]	path length,depth	0.845	0.855
	Li[2]	path length,depth	0.841	0.864
	Hao[9]	path length,depth	0.883	0.860
	Wu_PD[10]	path length,depth,density	0.887	0.857
	Leacock_PD[13]	path length,depth,density	0.855	0.845
	Li_PD[2]	path length,depth,density	0.870	0.849
our method	Wu[10]	path length,depth	0.813	0.814
	Leacock[13]	path length	0.792	0.848
	Liu[14]	path length,depth	0.853	0.859
	Li[2]	path length,depth	0.852	0.867
	Hao[9]	path length,depth	0.890	0.863
	Wu_PD[10]	path length,depth,density	0.891	0.860
	Leacock_PD[13]	path length,depth,density	0.863	0.849
	Li_PD[2]	path length,depth,density	0.874	0.853

The above existing path-based similarity methods generally improve the correlation by about 6.2% on MC30, and generally improve the correlation by about 0.8% on RG65. In the original method, the higher the original Pearson correlation coefficient, the lower the improvement effect of the Pearson correlation coefficient. Compared with our previous method, the correlation is generally improved by about 1% on MC30 and 0.3% on RG65, and the best correlations on MC30 and RG65 are 0.891 and 0.867, respectively.

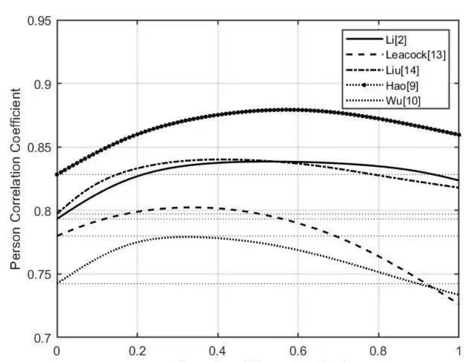

Figure 2 Comparison of five existing path distance-based methods improved by our model.

Figure 2 is the comparison result of five existing path-distance-based methods improved by our model, where γ is set in the range of 0 to 1.

It can be seen from Figure 2 that the Pearson correlation value of Li [2], Hao [9], Liu [12] combined with our model will increase when $0<\gamma<0.99$. The correlation value of each model will decrease after reaching the extreme value. For example, after Wu [8] and Leacock [13] are combined with our model, their Pearson correlation value is compared with the original method. When $\gamma>0.7$ and $\gamma>0.9$, it decreased and was lower than the original Pearson correlation value, At the same time, this also shows that compared with our previous model, considering the information of the nodes on the path in NLAP will optimize the experimental results. And the scope of optimization has also been improved (from 0.6 to 0.7, and 0.85 to 0.9, respectively), which indicated that the correction effect of the antisense coefficient would not improve the Pearson correlation value when the parameter took any value. When the Pearson correlation value is lower than the original Pearson correlation value of the method, it means that the antisense coefficient at the moment is too large, and there is no improvement effect on the original method.

C. A comparative analysis of the model and existing methods

This section compares the results of our model with existing similarity algorithms (information content-based methods, feature-based methods, hybrid methods) to evaluate the effectiveness of our model.

TABLE Ⅱ

Results compared with various existing methods

Type	Similarity model	MC30	RG 65
Feature	Sánchez [22]	0.830	0.857
	Wasti [23]	0.840	0.853
Edge-counting	Wu [10]	0.741	0.786
	Leacock [13]	0.779	0.838
	Liu [14]	0.796	0.842
	Li[2]	0.792	0.852
	Hao [9]	0.827	0.856
	Wu_PD [10]	0.872	0.857
IC — IC calculated in Seco's method	Li [12]	0.863	0.871
	Resnik [15]	0.741	0.794
	Lin [17]	0.841	0.844
	Meng [3]	0.838	0.848
IC — IC calculated in Meng's method	Resnik [15]	0.838	0.831
	Lin[17]	0.849	0.862
	Meng [3]	0.858	0.876
Hybrid	Zhou [6]	0.866	0.872
	Cai [26]	0.901	0.852
	Saif [28]	0.852	0.862
Edge-counting	Hao [9] (our)	0.890	0.863
	Wu_PD [10] (our)	0.891	0.860

It can be seen from Table 2 that the accuracy of the distance-based semantic similarity calculation methods is low, and the hybrid calculation method has a relatively higher correlation coefficient. The test results of the method proposed in this paper on the MC30 and RG65 datasets better than most methods.

From the above analysis, it can be seen that the proposed method can improve other path-based methods and obtain higher correlation values with standard benchmarks (our model has the highest correlation of 0.891 with the MC30 dataset and the highest correlation with the RG65 dataset is 0.867.

V. Conclusion And Future Work

This paper proposes an improved WordNet-based concept similarity calculation method. This method is suitable for improving other methods for calculating semantic similarity between concepts based on path distance. Compared with our previously introduced NLAP model experimental model, quantifying the amount of information contained in the node's own position on the NLAP path makes the similarity calculation result more accurate and can also correct the over-similarity of the existing path distance-based model. The existing methods are reproduced and the corresponding experiments are carried out on the combination of the antisense relationship and the existing methods. The experimental results show that the model proposed in this paper has a high correlation on the data sets MC30 and RG65. are 0.891 and 0.867, respectively.

In the future work, in the application of concept similarity, it can be considered to combine the similarity calculation method based on concept dissimilarity proposed in this paper with strings according to part of speech to calculate the similarity of sentences.

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