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# <sup>3</sup> Computing semantic similarity between biomedical concepts using new information content approach

Mohamed Ben Aouicha, Mohamed Ali Hadj Taieb  $*$ 

8 Multimedia InfoRmation system and Advanced Computing Laboratory, Sfax University, 3021, Tunisia

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#### **ABSTRACT**

The exploitation of heterogeneous clinical sources and healthcare records is fundamental in clinical and 26 translational research. The determination of semantic similarity between word pairs is an important 27 component of text understanding that enables the processing and structuring of textual resources. 28 Some of these measures have been adapted to the biomedical field by incorporating domain information 29 extracted from clinical data or from medical ontologies such as MeSH. This study focuses on Information 30 Content (IC) based measures that exploit the topological parameters of the taxonomy to express the 31 semantics of a concept. A new intrinsic IC computing method based on the taxonomical parameters of 32 the ancestors' subgraph is then assigned to a biomedical concept into the "is a" hierarchy. Moreover, 33 we present a study of the topological parameters through the MeSH taxonomy. This study treats the 34 semantic interpretation and the different ways of expressing the parameters of depth and the descen- 35 dants' subgraph. Using MeSH as an input ontology, the accuracy of our proposal is evaluated and com- 36 pared against other IC-based measures according to several widely-used benchmarks of biomedical 37 terms. The correlation between the results obtained for the evaluated measure using the proposed 38<br>approach and those from the ratings of human' experts shows that our proposal outperforms the previous 39 approach and those from the ratings of human' experts shows that our proposal outperforms the previous measures. 40

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## 45 1. Introduction

 Clinicians are confronted with increasing amounts of medical data from multiple sources housed in electronic format. The huge amounts of clinical and scientific documents in digital libraries and the digitized records assigned to patient health are valuable resources for clinical and translational research. Translational research includes medical information on patient health that comes from various sources and systems, including empirical observations, visits, and worksheet. The provided information is often heterogeneous and unprocessed. There is increasing interest in recent research in the search for variable strategies to manage and process this huge flow of data. The literature indicates that semantic technology offers promising opportunities for the devel- opment of efficient approaches to the interpretation of data from multiple origins and for determining the relationship between 60 them.

61 The estimation of the semantic similarity between words is one 62 of the major tools employed in semantic technology for text pro-63 cessing and understanding. It has been widely applied in several natural language processing tasks, such as word sense disambigua- 64 tion  $[1,2]$ , document categorization or clustering  $[3,4]$ , word spel- 65 ling correction  $\boxed{5}$ , automatic language translation  $\boxed{4}$ , ontology 66 learning  $[6]$ , and information retrieval  $[7,8]$ . 67

In the biomedical field, the computation of the similarity 68 between words can improve the performance of information 69 retrieval from biomedical sources [\[8,9\],](#page--1-0) integration of heteroge- 70 neous clinical data [\[10\],](#page--1-0) automation of semantic grouping of clini-<br>
71 cal word pairs [\[11\],](#page--1-0) and clustering of clinical models from local 72 electronic health records [\[12\].](#page--1-0) 73

Semantic similarity is a computational method used to identify 74 and quantify likeness between words using the common character- 75 istics shared between them. For example, bronchitis and flu are 76 similar because they are both disorders of the respiratory system. 77 The semantic similarity is based on the evaluation of the semantic 78 evidence observed in a knowledge source (such as ontologies or 79 domain corpora). According to the type of domain knowledge 80 exploited, different families of functions can be identified: those 81 based on the taxonomical structure of an ontology and those rely-<br>82 ing on the intrinsic Information Content (IC) of concepts [13-18]. 83

⇑ Corresponding author. E-mail address: [mohamedali.hadjtaieb@gmail.com](mailto:mohamedali.hadjtaieb@gmail.com) (M.A.H. Taieb).

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 These measures perform poorly with biomedical terms if they 85 are exploited with general purpose knowledge [\[19\]](#page--1-0), such as 86 WordNet<sup>1</sup> [\[20\].](#page--1-0) The problem with WordNet is not the quality of the semantic relations between the present biomedical concepts, but with its coverage capacity (only 25.1% of MeSH terms are cov-89 ered in WordNet  $[19]$ ). Therefore, there are a number of relevant biomedical ontologies, knowledge repositories and structured vocabularies that model and organize concepts in a comprehensive way. Well-known examples are MeSH (Medical Subject Headings) for indexing literature, the ICD taxonomy (International Classifica- tion of Diseases) for recording causes of death and diseases, and SNOMED CT (Systematized Nomenclature of Medicine-Clinical Terms) the most comprehensive and precise clinical health terminol- ogy product, owned and distributed around the world by The Inter- national Health Terminology Standards Development Organisation (IHTSDO). Several similarity computation approaches have been compared using the biomedical knowledge source and evaluated over particular datasets or in the context of a concrete application, such as document clustering [\[3,21\]](#page--1-0), assessment of similarity 103 between words  $[8,22-24]$ , and providing a useful basis for assessing the structure of terminological systems and the content of medical records [\[25\].](#page--1-0)

 In this paper, we first review and discuss the IC-based semantic similarity measures commonly referenced in the literature and provide details of their potential adaptation to the biomedical domain. We also analyze the taxonomic parameters used for the quantification of intrinsic information content of biomedical con- cepts to determine their semantic interpretations. In order to over- come some of the problems identified in this study, we present a new intrinsic IC computing method based on the exploitation of the ancestors' subgraph and the quantification of the specificity of each hypernym. Finally, the paper evaluates and compares the results obtained by our measure against those reported by other 117 similarity functions when applied to the biomedical domain. The results show that our proposed method, coupled with Lin's similar- ity measure, displays a high level of correlation and outperforms other IC computing approaches.

121 The rest of the paper is organized as follows. Section 2 presents a survey about the IC-based semantic similarity measures, includ- ing the IC computing methods and the similarity measures. Sec- tion [3](#page--1-0) provides a study of the topologic parameters extracted from the MeSH taxonomic knowledge resource for the computa-126 tion of semantic similarity between biomedical concepts. Section [4](#page--1-0) describes the new intrinsic IC-computing method of a biomedical concept based on its ancestors' subgraph and the taxonomic parameters. Section [5](#page--1-0) reports on the evaluation and comparison of our approach against currently available ones using known benchmarks and the biomedical resource MeSH. The final section is devoted to presenting our conclusions and recommendations for future research.

## 134 2. Related works: information content-based semantic 135 similarity measures

 The measurement of semantic similarity based on Information 137 Content (IC) was first introduced by Resnik [\[1\].](#page--1-0) The basic idea of IC is that general and abstract entities found in a discourse present less IC than more concrete and specialized ones. This principle is 140 inspired from the work of Shannon  $[26]$ . The more probable a con- cept appears, the less information it conveys. In other words, speci- fic words are more informative than general ones. IC-based semantic similarity measures [\[27–29\]](#page--1-0) consist of two parts: the **computing IC method** and the **IC-based measure**. There are two ways for quantifying IC: the first exploits corpora, and the second, 145 which is often described as *intrinsic*, uses topological parameters 146 from the hierarchical knowledge structure: descendants (hypo- 147 nyms), depth, leaves, and ancestors (hypernyms), for quantifying 148 the IC of a concept. The terms ''hypernym/hyponym", ''ancestors/ 149 descendants" and "subsumers" are used as follows: 150

- Hypernym/hyponym: In the ''is a" relation linking two concepts, 151 such as "Animal" and "Pet", "Animal" is called hypernym of "Pet", 152 and "Pet" is an hyponym of "Animal". 153
- Ancestors/descendants: ancestors of a concept pertaining to ''is a" 154 hierarchy refer to direct and indirect hypernyms. Descendants 155 refer to direct and indirect hyponyms. The mass of the state of th
- Subsumer: a concept  $c_1$  is a subsumer of  $c_2$  if  $c_2$  is a descendant 157 of  $c_1$ . 158

IC-based similarity measures exploit the IC-values assigned to 160 concepts  $c_1$  and  $c_2$  to provide the semantic similarity estimation 161 between them. A complete survey of IC-based similarity measures 162 is presented in the next paragraph. 163

### 2.1. Similarity measures exploiting the IC 164

Several semantic similarity measures, which are based on the 165 exploitation of the information content, have been proposed. The 166 similarity estimation between two concepts  $c_1$  and  $c_2$  is computed 167 using their ICs and the IC of the Lowest Common Subsumer (LCS) 168 which is extracted from the "is a" hierarchy. Some measures are 169 presented in next paragraphs: 170

• *Resnik:* Guided by the idea that the similarity between a pair of 172 concepts may be judged by "the amount of shared information", 173 concepts may be judged by "the amount of shared information", Resnik  $[1]$  defined the similarity between two concepts as the IC 174 of their Lowest Common Subsumer  $LCS(c_1,c_2)$  as follows:

$$
Sim_{Res}(c_1, c_2) = IC(LCS(c_1, c_2))
$$
\n(1) 178

• *Jiang-Conrath:* This approach subtracts the IC of the LCS from the  $\frac{180}{180}$ <br>sum of the IC of the individual concents [30] It provides the dis-sum of the IC of the individual concepts [\[30\]](#page--1-0). It provides the dissimilarity estimation between two terms, because the more dif- 182 ferent the terms are, the higher the difference between their ICs 183 and the IC of their LCS will be. The dissimilarity measure is 184 expressed as follows:

$$
DisJC(c1, c2) = (IC(c1) + IC(c2)) – 2IC(LCS(c1, c2))
$$
 (2) 188

 $\bullet$  Lin: The similarity measure described by Lin [\[31\]](#page--1-0) is defined as Dice coefficient:

$$
Sim_{Lin}(c_1, c_2) = \frac{2 \times IC(LCS(c_1, c_2))}{IC(c_1) + IC(c_2)}
$$
\n(3)

• *Pirro:* He proposes a similarity measure  $[23]$  that is conceptually in  $\frac{1}{2}$  is similar to the IC and Lin measures. However, it is based on the 197 similar to the JC and Lin measures. However, it is based on the feature-based theory of similarity described by Tversky [\[32\].](#page--1-0) 198 According to Tversky, the similarity between two concepts  $c_1$  199 and  $c_2$  is a function of the features common to  $c_1$  and  $c_2$ , those 200 in  $c_1$  but not in  $c_2$ , and those in  $c_2$  but not in  $c_1$ . The semantic 201 similarity between concepts can be computed as an aggregation 202 between the ICs of  $c_1$ ,  $c_2$ , and their LCS:

$$
Sim_{\text{tvr}}(c_1, c_2) = 3 \times IC(LCS(c_1, c_2)) - IC(c_1) - IC(c_2) \tag{4}
$$

Finally, the measure is defined as follows:

$$
Sim_{P\&S}(c_1, c_2) = \begin{cases} Sim_{\text{tvr}}(c_1, c_2) & \text{if } c_1 \neq c_2 \\ 1 & \text{if } c_1 = c_2 \end{cases}
$$
(5) 210

• Meng: This measure  $\left[33\right]$  used Lin's measure. It increases monotonically with  $Sim_{Lin}$  as follows:

$$
\frac{1}{1} \frac{\text{https://wordnet.princeton.edu/}}{\text{https://wordnet.princeton.edu/}} \qquad \frac{\text{Sim}_{\text{Meng}}(c_1, c_2)}{\text{Sim}_{\text{Meng}}(c_1, c_2)} = e^{\text{Sim}_{\text{Lin}}(c_1, c_2)} - 1 \qquad (6)
$$

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