# A Review on Identification of Contextual Similar Sentences

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**Abstract—** The task of identifying contextual similar sentences plays a crucial role in various natural language processing applications such as information retrieval, paraphrase detection, and question answering systems. This paper presents a comprehensive review of the methodologies, techniques, and advancements in the identification of contextual similar sentences. Beginning with an overview of the importance and challenges associated with this task, the paper delves into the various approaches employed, including traditional similarity metrics, deep learning architectures, and transformer-based models. Furthermore, the review explores different datasets and evaluation metrics used to assess the performance of these methods. Additionally, the paper discusses recent trends, emerging research directions, and potential applications in the field. By synthesizing existing literature, this review aims to provide researchers and practitioners with insights into the state-of-the-art techniques and future avenues for advancing the identification of contextual similar sentences.

**Keywords**- *sentence semantic similarity, CNN, BERT, RNN, deep learning*

## I. INTRODUCTION

Sentence similarity is important in NLP and has been used for a variety of tasks, including question answering, text categorization, paraphrase recognition, and information retrieval. [5] sentence or short text similarity has come to be a popular topic in NLP due to the growing demand for these applications. The brief text, on the other hand, is distinct from conventional long text, such as news and periodicals. Because the brief text's information is so minimal, typical string-based measurements are no longer appropriate. As a result, determining the similarity of short texts necessitates certain solutions, and study in this area has extensive potential and research significance.

To cope with a variety of brief text similarity and other NLP difficulties, string-based similarity metrics such as Lowenstein Distance, Euclidean Distance, Cosine, Jaccard, and Hash were proposed early in the study. String-based similarity tests, on the other hand, are unable to account for semantic difficulties like polysemous and synonyms. Furthermore, because the most noticeable feature of phrases is a lack of string-based similarity, context metrics are difficult to calculate correctly. As a result, one of the most difficult problems in similarity computation is getting the machine to comprehend the meaning provided by a brief sentence. We've found that relying solely on string measures isn't always reliable. By recognizing the semantic information of the text, semantic similarity compensates for the inadequacies of older approaches and calculates the similarity more correctly. In fact, a sound theoretical basis and application requirements for similarity computation can be laid by a correct grasp of semantic information. Because the meaning of the text will be better recognised, the similarity can be assessed more accurately than traditional string-based assessments by recognising the context information. As a result, semantic similarity has emerged as a fundamental NLP technology. Many applications currently utilize semantic similarity technologies and have produced positive outcomes. Text classification, attitude analysis, [10-12] social network and information retrieval, are just a few examples. [14-16]

The extraction technique of semantic information has improved because of the growing interest in neural networks, particularly the emergence of deep learning models. [17-19]
Semantic similarity measurements are separated into non-deep learning and deep learning measures in the following sections. There are two types of non-DL measurements: corpus-based and knowledge-based.. In addition, we use popular DL methods to summarise the DL similarity data. General model, [20,21]

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attention model, [22,23], and hybrid model are the three forms of DL similarity measures. [24,25]

The following is how the rest of the article is structured. In Section 2, the approaches for non-deep learning and deep learning measures are discussed. The applications of semantic similarity are discussed in Section 3. Section 4 wraps up our research and makes recommendations for future work.

| Model | Method | Year | Published |
|---|---|---|---|
| Corpus based | VSM [28] | 1975 | ACM |
| | LSA [29] | 1990 | JASIS |
| | LDA [30] | 2003 | JMLR |
| | Word2Vec [31] | 2013 | ICLR |
| | Doc2Vec [32] | 2014 | ICML |
| | NGD [33] | 2007 | IEEE Transactions |
| | SH [34] | 2006 | IWWW |
| | CODC [35] | 2006 | COLING |
| Knowledge based | Shortest Path [36] | 1989 | IEEE Transaction |
| | Resnik [37] | 1995 | IJCAI |
| | Resk [26] | 1998 | ICML |
| | Li [38] | 2013 | IEEE Transaction |
| | WikiRelate [39] | 2006 | Artificial Intelligence |
| | ESA [40] | 2007 | IJCAI |

## II. SEMANTIC SIMILARITY MEASURES

Sentence similarity has gotten a lot of attention in NLP, because accurately comprehending semantics is a significant challenge in understanding ambiguity and lexical diversity. This is likewise the case with most effective method for dealing with the intricacy of brief texts. Short text similarity faces the following issues.

1. Short texts lack sufficient context and semantic content, resulting in sparsity. Because short sentences have fewer significant words, it's more difficult to extract useful feature words. "How are you?" for example, has far too few keywords. As a result, the initial challenge of semantic similarity is to improve the machine's ability to discern the proper meaning of short sentences.
2. Textual noise is increased using irregular and Internet keywords in brief sentences. Text communications frequently contain polysemous terms and synonyms. It's possible that the same word can have several meanings. It's possible that different terms have the same meaning. Information identification becomes more challenging because of these complex properties.

As a result, for these two objectives, we'll focus on assessing semantic similarity measurements. As previously stated, semantic similarity measurements are classified as either non-DL or DL. Based on these metrics, In Figure 1, the classification system is broadened and subdivided.

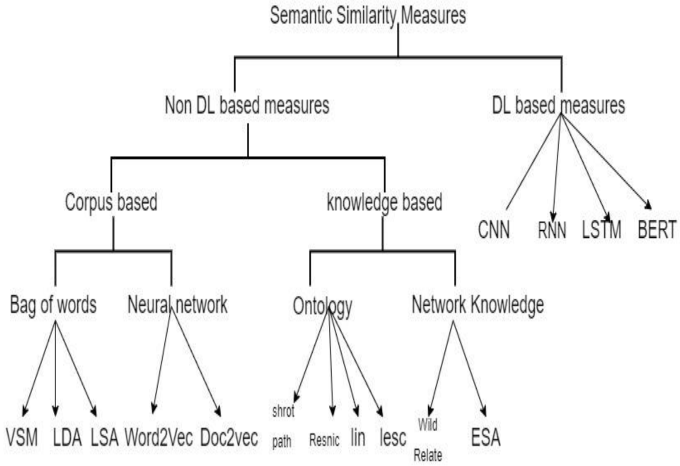


Fig 1 Classification of Semantic Similarity Measures

**Non-Deep learning Measures: -** knowledge-based and Corpus-based measures are examples of non-DL measures. The resemblance between two or more texts retrieved from the corpus is calculated using corpus-based methods. Domain specialists build a knowledge base based on their experience. In knowledge-based measurements, the semantic network's information is employed to determine the similarity between two words. Table 1 also contains a summary of the full information about semantic similarity metrics based on non-DL measure.

**Table 1**

**2.1 DL Measures: -** To overcome some of the problems associated with non-deep learning measures, deep learning is utilized to sentence pairings. Deep learning technology has made significant advances in the fields of speech recognition and image processing, as well as in NLP. DL is now being used by an increasing number of research institutions to address more difficult and abstract NLP jobs.

Other DL similarity measures have been devised, in fact. The following are the most common and popular models among them:

1. Measures based on Convolutional Natural Networks (CNNs) To get a vector representation of question pairs, [43,44] The retrieved data characteristics should be fed into the fully connected layer. The classic similarity measurement is used to determine the similarity of the question pairings.
2. The RNN model can be considered as a collection of clones of the similar neural network, each transmitting a message to the next. [45] Because of the model, the gradients may vanish and burst. As a result, the concept of LSTM [40] was established. LSTM-based measures

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[18,23,46] prevent the gradient trouble that RNNs have, have a higher "memory ability," and extract context information more effectively.

2.1.1 **CNN based metric: -** Kalchbrenner et al [20] proposed a dynamic CNN that extracts crucial semantic information from words via dynamic k-max pooling. He et al [21] introduced a CNN-based model for model sentences, in the network captures features at different levels of granularity and uses multiple types of pooling to make future similarity computations easier. To capture all semantic information, Wang et al [48] focus on the relevance of dissimilar sections of two phrases and utilize a two-channel CNN to separate comparable and different components.

2.1.2 **RNN-based metric:** The problem of gradient vanishing and gradient ballooning is, however, one of RNN's most fundamental flaws. Because of this, RNN has a hard time training in long texts. As a result, LSTM and its derivatives were proposed. Not only did the LSTM model overcome flaws, but it also excelled in NLP-related tasks. [42] Mueller and Thyagarajan [50] proposed comparing the similarity of two texts of varied lengths using Siamese Recurrent Architectures. To encode the embedding of the pre-processed phrases, the Siamese architecture employs two shared weighted LSTM. The bidirectional LSTM (BiLSTM) model, which consists of a forward and backward calculation, was introduced by Neculoiu et al [51]. This allows it to acquire bidirectional semantic information from two sources of incoming text.

2.1.3 **CNN and RNN-based hybrid measurement: -** The most utilized semantic synthesis models for sentence similarity are CNN and LSTM. For concise text representation, the hybrid model can capture many levels of feature information. To obtain fine-grained features, semantic representation, and important contextual and grammatical characteristics, Zheng et al [25] developed BiLSTM, a hybrid bidirectional recurrent convolutional neural network that captures contextual and lengthy text information. Furthermore, the model made advantage of CNN's maximum pool layer, which uses context information to identify which words are important in the text. The hybrid model beats not just standard machine learning models, but also CNN and RNN, according to all the results.

2.1.4 **Attention mechanism-based measurement: -** In recent years, the attention mechanism has been widely applied to a variety of NLP applications based on DL. [49-54] Researchers have offered numerous attentions based on their in-depth examination of the attention mechanism. Keywords are frequently weighted using the attention mechanism. Attention weights were computed directly on the input representation, the output of convolution, and both directions by Yin and Schütze [22] to analyse experiment effects. Three corpora and three linguistic tasks were used to demonstrate the method's effectiveness. Google made extensive use of the self-attention mechanism [47] to learn text representation in 2017. The self-attention mechanism pays extra attention to the sequence and looks for a link. It has been proven to work with text summaries, machine reading, and image description generation. Cheng et colleagues [55] coupled an LSTM model with a self-attention mechanism to outperform previous models in machine reading.

2.1.5 **BERT-based computation: -** BERT performs NLP tasks in two steps: fine-tuning and pre-training. Word embedding is akin to pre-training. It trains a language model using an existing unlabeled corpus. To fulfil sentence similarity challenges, fine-tuning use pre-trained language models. A new structured language model was proposed by Zhang et al [56]. The model contains structured semantic information in addition to a simple context, resulting in rich semantics for language representation. Using the BERT model, Sakata et al [57] Identify the degree of similarity among the client's query and the response. In terms of retrieval, their strategy is both dependable and effective. Many more BERT-based NLP tasks have been proposed [58,59], with promising results.

Table 2 also contains a summary of the deep learning models results of state of the arts method till now.

**Table 2**

| **DL Model** | **Method** | **Year** | **ACC** | **Precision** | **Recall** | **F1** |
|---|---|---|---|---|---|---|
| CNN | ABCNN [22] | 2017 | 86.2 | | | 84.7 |
| | Two-channel [48] | 2017 | 78.4 | | | 82.3 |
| | CNN [43] | 2018 | 74.2 | | | |
| RNN | Siamese LSTM [50] | 2016 | 84.2 | | | |
| | AttSiaLSTM [23] | 2018 | | 65.68 | | |

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| | | | | | | |
|---|---|---|---|---|---|---|
| | AttSiaBiLSTM[23] | 2018 | | 63.19 | | |
| Hybrid | CNN-LSTM [52] | 2018 | | 74.8 | 60.4 | 72 |

## III. APPLICATION

Semantic similarity is used in a variety of applications, including text classification and clustering, information retrieval, social networks, sentiment analysis, academic plagiarism detection, and specific domain detection. Table 3 summarizes each application area.

**Table 3**

| S.No. | Application Domain | Year | Published | Method used |
|---|---|---|---|---|
| 1. | Text Classification | 2014 | EMNLP [60] | CNN |
| | | 2016 | ACL [61] | BiLSTM |
| | | 2017 | King University-Computer and Information Science [9] | LSI |
| | | 2019 | IEEE Access [25] | BRCAN |
| 2. | Text clustering | 2014 | Information Sciences [62] | GA |
| | | 2019 | IEEE Access [63] | WVDD |
| | | 2019 | Knowledge and Information Systems [64] | FGTM |
| 3. | Sentiment analysis | 2016 | IJCNN [11] | LDA |
| | | 2019 | Knowledge-Based Systems [12] | word embeddings |
| 4. | Information retrieval | 2009 | Expert Systems with Applications [13] | Ontology |
| | | 2012 | World Congress on Intelligent Control and Automation [5] | Ontology |
| | | 2013 | Expert Systems with Applications [65] | WordNet |
| | | 2015 | ICLR [66] | LSTM |
| | | 2017 | J Intell Inf Syst [67] | LSTM |
| 5. | Academic plagiarism detection | 2016 | MIPRO [67] | WordNet |
| | | 2018 | COLING [68] | CNN |
| 6. | Specific Domain | 2012 | BMC Bioinformatics [69] | Ontology |
| | | 2019 | BioMed Research International [70] | Ontology |
| | | 2019 | International Joint Conference on Artificial Intelligence [37] | Resnik |

## IV. CONCLUSION AND FUTURE WORK

The methodologies and applications of sentence semantic similarity measurements are presented in this study. In the field, a variety of approaches for determining the similarity of sentences or short texts are proposed. HAN et al. [13-16] Knowledge-based, corpus-based, and DL-based measures are the three types of metrics. The fundamentals of these measures are described.

We think there are dual important study avenues in the realm of semantic similarity: application in professional sectors and cross-linguistic information.

Monolingualism accounts for most of the cross-linguistic information in the present work on semantic similarity. However, as the degree of economic globalization has increased, cross-national interactions and cooperation have grown increasingly common. Semantic similarity between languages could be beneficial.

Application in professional fields: Most current semantic similarity studies or contests are focused on people's daily lives. Most of the datasets come from Google News. However, many other subjects, such as geology, medicine, astronomy, and other specialized fields, apply to text similarity.

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