

Domain Specific Complex Sentence (DCSC) Semantic Similarity Dataset

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Abstract—Semantic textual similarity is one of the open research challenges in the field of Natural Language Processing. Extensive research has been carried out in this field and near-perfect results are achieved by recent transformed based models in existing benchmark datasets like STS dataset and SICK dataset. In this paper, we study the sentences in these datasets and analyze the sensitivity of various word embeddings with respect to the complexity of the sentences. We propose a new benchmark dataset- the Domain Specific Complex Sentences (DSCS) dataset comprising of 50 sentence pairs with associated semantic similarity values provided by 15 human annotators. Readability analysis is performed to highlight the increase in complexity of the sentences in the existing benchmark datasets and those in the proposed dataset. Further, we perform a comparative analysis of the performance of various word embeddings and the results justify the hypothesis that the performance of the word embeddings decrease with an increase in complexity of the sentences.

Index Terms—Natural Language Processing, Semantic similarity, word embeddings, dataset

1 INTRODUCTION

ONE of the core components of Natural Language Processing (NLP) is assessing the semantic similarity between text data. The versatility of natural languages has made it a challenging task for researchers to capture the semantics of text data using numerical representations. Measuring the semantic of text data is essential in various NLP tasks like text summarization [1], topic modelling [2], text simplification [3], machine translation [4], question answering tasks [5], information retrieval [6] and so on. Extensive research has been carried out in the past decade in the field of semantic similarity to construct vector representations that preserve the syntactic and semantic properties of words. Word embeddings like *word2vec* [7] and *GloVe* [8] exploit the principle of the distributional hypothesis [9] “similar words occur together frequently”. These methods use the advancements in machine learning techniques to capture the semantics of the words using large text corpora. Recent language models like BERT [10], RoBERTa [11], and ALBERT [12] use transformers to build vector representations of text data from underlying corpora by traversing through the corpora in both directions. Over the years various benchmark datasets have been used for comparing the performance of models in measuring semantic similarity between text data. Two of the most popular datasets are the STS benchmark dataset [13] and the SICK dataset [14] on which BERT models have achieved near-perfect results. Analyzing the readability of the sentences in these datasets, we find that the sentences in these datasets have a low readability index which is a measure of complexity of sentences. However, various real world

applications of semantic similarity involves more complex sentences to be analysed [15]. We hypothesize that the performance of the existing word embedding models will decrease with the increase in the complexity of sentences. In this paper, we investigate the sensitivity of the existing word embeddings to the complexity of sentences, by providing a new benchmark dataset, the Domain-specific complex sentence (DSCS) dataset with sentences of a higher degree of complexity than the existing datasets. The DSCS dataset comprises of 50 pairs of sentences from the computer science domain, with corresponding similarity scores provided by 15 human annotators. We determine the correlation of the similarity values obtained using existing word-embeddings with the human-annotated similarity values and the results clearly prove our hypothesis indicating a decrease in the performance of the models that achieved the state of the art results in the existing datasets. The remaining of the paper is organised as follows. Section 2 of this paper provides a brief description of the existing research works carried out in the field of semantic similarity. Section 3 describes in detail two of the existing benchmark datasets and five different word-embeddings chosen for the comparative analysis. Section 3 discusses in detail the methodology adopted to construct the new benchmark dataset and provides a detailed description of the readability analysis that compares the complexity of sentences in the existing datasets to the sentences in the proposed dataset. Section 5 provides a comparative study of the performance of various word embeddings and provides an insight into the inferences made that would guide the future scope of this research.

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2 RELATED WORK

Similarity between text data does not always attribute to the lexical or syntactic similarity between text. While two sentences that contain exactly the same words may mean

completely different, it is possible that sentences with different sets of words provide the same meaning. Hence while assessing the similarity between text data, it is of importance to understand the meaning conveyed by the text. The similarity between the meaning of the text is known as semantic textual similarity (STS). For the past three decades, various semantic similarity methods have been proposed to measure semantic similarity. These methods are widely classified as knowledge-based methods and corpus-based methods. The knowledge-based methods use structurally strong ontologies like Wordnet [16], DBpedia [17], Wikipedia¹, Wiktionary², etc. These ontologies are often used like graphs and various edge counting methods, consider the words in the taxonomy as nodes, and calculate the distance between the words using the edges between them. The greater the distance between the words the lower their similarity value [18]. However, these methods assume that the length of these edges to be similar which is not always the case. Another type of knowledge-based approach, called the feature-based methods, assess the similarity based on features of the words, like their dictionary definition, neighboring concepts, etc. derived from the underlying ontologies [19]. Knowledge-based methods are computationally simple and are efficient in distinguishing the different meanings of words solving the problem of ambiguity with concepts like polysemy and synonymy. However they are heavily dependent on the underlying taxonomies, they do not account for the versatility of natural language, and structured taxonomies for languages other than English are not common [20]. Corpus-based semantic similarity methods use statistical principles to capture the contextual semantics of data using large underlying corpora. The principle of distributional hypothesis states that words with similar meanings occur together in documents and this principle forms the basis of most corpus-based methods, while these methods do not take into account the actual meaning of individual words. Word vectors, also called word embeddings, are constructed using corpus-based methods and the similarity is measured based on the angle or distance between these vectors. The dimensionality of these embeddings depends on the size of the corpus. While using significantly large corpora various dimensionality reduction techniques like Singular Value Decomposition (SVD), Principal Component Analysis (PCA), and filtering techniques are used to achieve computational efficiency. These word embeddings are the fundamental components of recent techniques that use the advancements in deep neural networks to achieve a significant increase in performance in semantic similarity tasks. word2vec proposed by Mikolov et al. [7] and GloVe vectors proposed by Pennington et al. [8] have proven to be major breakthroughs in the field of semantic similarity and they are two of the most widely used word embeddings to date. In 2019, Devlin et al. [10] proposed the Bidirectional Encoder Representation from Transformers (BERT) language model which used transformers to build word embeddings, which were further used for various downstream NLP applications. Variations of BERT models like, ALBERT [12] and RoBERTa [11] were also published in 2019 and have outper-

formed the existing semantic similarity models achieving state of the art results [21]. Raffel et al. [22] proposed the T5: text-to-text transformer model which used the principle of transfer learning and was trained on a custom build corpus called “Colossal Clean Crawled Corpus” or C4. This model tied for the first place with ALBERT by achieving a Pearson’s correlation of 0.925 on the STS dataset. In the following section, we describe in detail the two most widely used benchmark datasets for assessing the performance of semantic similarity methods, and five of the most popular word embeddings that we have chosen for comparison in this paper.

3 DATASETS AND WORD EMBEDDING MODELS

3.1 Semantic similarity Datasets

The first and the most widely used word-to-word similarity dataset, the R&G dataset [23], was proposed by Rubenstein and Goodenough in 1965 with 65 English noun pairs annotated by 51 native English speakers with similarity values ranging between 0 and 4. Some of the prominent datasets used are compiled in Table 6 in Appendix C. While many datasets were published over the years as the benchmark for models measuring sentence level semantic similarity, the SICK dataset, and the STS datasets are those that gained significance. For our analyses and comparison, we choose these two datasets owing to their wide usage and popularity.

3.1.1 SICK Dataset [14]

Marelli et al. [14] compiled the SICK dataset for sentence level semantic similarity/relatedness in 2014 composed of 10,000 sentence pairs obtained from the ImageFlickr 8 and MSR-Video descriptions dataset. The sentence pairs were derived from image descriptions by various annotators. 750 random sentence pairs from the two datasets were selected, followed by three steps to obtain the final SICK dataset: sentence normalisation, sentence expansion and sentence pairing. Initially all the sentences were normalised by removing unwanted syntactic or semantic phenomena. This process was carried out by two different annotators and checked for compatibility. In instances of contradiction, a third annotator made the choice by analysing the two alternatives, and if both were correct a random choice was made. From the normalised sentences, 500 pairs were chosen for expansion. The process of expansion involved generating three different versions of the normalised sentence pairs - a similar sentence using meaning preserving transformation, a completely opposite version using negative transformation, and a sentence with same words but different meaning using random shuffling. Fig. 1 shows an example as presented by the authors. Finally, each normalised sentence was paired with all its expanded version, along with some random pairing. A survey was then conducted on Amazon Mechanical Turk where the workers were requested to rank the similarity/relatedness over a scale of 1 to 5 with 1 representing that the sentences were highly dissimilar and 5 representing that the sentences were highly similar. Ten unique responses for each sentence pair were collected and the average of the ten ratings was assigned as the gold standard. Each sentence pair is associated with a relatedness score and a text entailment relation as well. The three

1. <https://www.wikipedia.org/>

2. <https://www.wiktionary.org/>

entailment relations are "NEUTRAL, ENTAILMENT and CONTRADICTION."

3.1.2 STS Dataset [13]

In order to encourage research in the field of semantic similarity, semantic textual similarity tasks called SemEval have been conducted from 2012. The organizers of the SemEval tasks collected sentences from a wide variety of sources and compiled them to form a benchmark dataset against which the performance of the models submitted by the participants in the task was measured. While the dataset contains different tracks with sentences from different languages, we focus on the English component of the dataset. The English component of the dataset contains 8,295 sentence pairs of which 5,720 are provided as training samples and the remaining 2,575 sentences form the test set. The dataset is built over the years and contains the sentences that were used from 2012 to 2017. Table 1 provides a breakdown of the source of the sentences in the dataset and the year they were appended to form the current version of the dataset. The sentences were annotated using Amazon Mechanical Turk. The quality of the annotators was assessed using the 'masters' provided by the platform and five unique annotations were obtained for each sentence pair. The similarity values ranged between the values 0 and 5, with 5 indicating that the sentences are completely similar and 0 indicating the sentences are completely dissimilar. The final similarity score was obtained by taking an average of the five unique responses from the annotators.

TABLE 1: STS English language training dataset (2012-2017) [24]

Year	Dataset	Pairs	Source
2012	MSRPar	1500	newswire
2012	MSRvid	1500	videos
2012	OnWN	750	glosses
2012	SMTNews	750	WMT eval.
2012	SMTeuroparl	750	WMT eval.
2013	HDL	750	newswire
2013	FNWN	189	glosses
2013	OnWN	561	glosses
2013	SMT	750	MT eval.
2014	HDL	750	newswire headlines
2014	OnWN	750	glosses
2014	Deft-forum	450	forum posts
2014	Deft-news	300	news summary
2014	Images	750	image descriptions
2014	Tweet-news	750	tweet-news pairs
2015	HDL	750	newswire headlines
2015	Images	750	image descriptions
2015	Ans.-student	750	student answers
2015	Ans.-forum	375	Q & A forum answers
2015	Belief	375	committed belief
2016	HDL	249	newswire headlines
2016	Plagiarism	230	short-answers plag.
2016	post-editing	244	MT postedit
2016	Ans.-Ans	254	Q & A forum answers
2016	Quest.-Quest.	209	Q & A forum questions
2017	Trail	23	Mixed STS 2016

3.2 Word-embedding models

Distributed semantic vector representations of words called word embeddings have gained significant attention in the past decade, and a wide variety of word embeddings have been proposed over the years [25]. Word embeddings are constructed by analysing the distribution of words in any text data and are well known to capture the semantics of the words thus making them a significant component of a wide variety of semantic similarity algorithms. *word2vec* model uses neural networks to construct word embeddings and it has been one of the most widely used word-embeddings [25]. *Glove* vectors employ word co-occurrence matrices to identify the distribution of words, which is then statistically used to build word vectors that capture the semantics of the target word with respect to its neighboring words. Pre-trained word embeddings provided by recent transformer based models achieved state of the art results in a wide range of NLP tasks, including semantic similarity. In this section we discuss in detail five of the popular word embeddings that are publicly available.

3.2.1 word2vec [7]

Mikolov et al. proposed a word embedding called word2vec 2013, using a simple neural network that converted the given input word to a dense vector representation. Two different models of word2vec were proposed namely the Skip-gram model and the Continuous Bag of Words (CBOW) model. In the skip-gram model, the neural network is optimized to predict a target word given its context words, whereas in the CBOW model, the neural network predicts the neighboring words given a target word. The value vector in the hidden layer of the optimized neural network is used as the vector representation of the word. The number of neurons in the hidden layer of the neural network determines the dimension of the word vector. The models are trained using Google News corpus, which contains 1 million words. The model produced state of the art results in 2013, and is used widely among researchers owing to the simplicity in construction of the neural network. The major claim of the authors was that when simple algebraic operations were performed on these vectors the results were closely related to human understanding. For example, as shown in Fig. 2 the difference between V_k (vector representation for the word 'king') and V_m (vector representation for the word 'man') added to V_w (vector representation for the word 'women') provides a vector that is close to vector V_q (vector representation for the word 'queen'). This can be mathematically represented as,

$$V_q \simeq (V_k - V_m) + V_w \quad (1)$$

3.2.2 Glove [8]

Researchers at Stanford University proposed a vector representation for words using the word to word co-occurrence matrices. Given a corpus, a global co-occurrence matrix is built where each row and column represents the words in the corpus. The underlying principle for the construction of these vectors is that similar words occur together. The model proposed uses 'log-bilinear regression' to create a word

Original pair	
S0a: <i>A sea turtle is hunting for fish</i>	S0b: <i>The turtle followed the fish</i>
Normalized pair	
S1a: <i>A sea turtle is hunting for fish</i>	S1b: <i>The turtle is following the fish</i>
Expanded pair	
S2a: <i>A sea turtle is hunting for food</i>	S2b: <i>The turtle is following the red fish</i>
S3a: <i>A sea turtle is not hunting for fish</i>	S3b: <i>The turtle isn't following the fish</i>
S4a: <i>A fish is hunting for a turtle in the sea</i>	S4b: <i>The fish is following the turtle</i>

Fig. 1: Example of SICK dataset sentence expansion process [14]

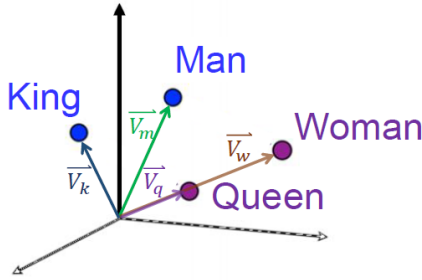


Fig. 2: Word vectors in word2vec models[cite]

vector space with substructures that provide meaningful word-vector representations. Glove vectors were trained on five different corpora like common web crawled corpus and the Wikipedia data dump resulting in 400,000 unique words to form the co-occurrence matrix. Pretrained word vectors of 3 different dimensions (50, 100 and 300) were released by the authors and they claimed that Glove vectors outperformed word2vec and achieved the state of the art results in 2014.

3.2.3 BERT [10]

In 2019, the BERT transformer model surpassed the state of the art results in 11 different NLP tasks, including semantic similarity. BERT uses the transformer model proposed by Vaswani et al [26]. The BERT models follow two distinct steps to adapt to specific NLP tasks namely pretraining and fine-tuning. The transformer contains an encoder and decoder module, the encoder containing 6 identical layers stacked above each other. Each layer consists of sublayers comprising of a multi-head attention mechanism followed by a fully connected feed-forward neural network. The decoder is similar to the encoder, with one additional sub-layer of multi-head attention, which captures the attention weights in the output of the encoder. The model is pre-trained using the Book corpus [27] and Wikipedia dump comprising of nearly 3300 million words. Pre-training is carried out with the help of two tasks namely 'Masked Language Model (MLM)' and 'Next Sentence Prediction (NSP)'. In the first task, random words in the corpus are masked and the model is optimized to predict the masked tokens. In the second task, the model is optimized to predict

whether or not a sentence follows another given sentence. BERT models thus produce bidirectional representations of words taking into consideration the context of the word in both directions. In general, the BERT model is fine-tuned using labeled training data to accommodate a specific NLP task. The model was fine-tuned with STS dataset and achieved state of the art results.

3.2.4 RoBERTa [11]

Liu et al. [11] proposed a robustly optimized version of BERT, by replicating the work of Devlin et al. [10] and adding to it an improved training procedure. They added more training data and trained for a longer period of time achieving state of the results which proved the BERT architecture was equipped to perform better than many later models, but it was under trained. While BERT was trained on Book Corpus and Wikipedia corpus, RoBERTa model was trained on four different corpora namely Book Corpus, Common Crawl News dataset, OpenWebText dataset and the Stories dataset. RoBERTa uses variations of the pretraining tasks used by BERT model. It uses both static and dynamic masking, and by performing dynamic mask the training data is duplicated ten times thus enabling the model to encounter each masked tokens four times over the forty epoch training. The authors study the effect of 'Next Sentence Prediction' task by replacing it with prediction of subsequent segments or sentences in a document and prove that the performance increased by removing the NSP task. The model outperforms the BERT model and achieves state of the art results in 11 NLP tasks including semantic similarity.

3.2.5 ALBERT [12]

One of the major challenges in the BERT model is the time and resource requirement to pretrain a complex transformer model. Lan et al. [12] proposed a Lite version of BERT by employing two different parameter reduction techniques to aid in scaling the pre-trained models, namely Factorized Embedding Parameterization (FEP) and Cross-layer Parameter Sharing (CPS). Using FEP, the authors split the vector embedding matrix of the vocabulary into two smaller matrices thus making the size of the vector independent of the hidden layer of the model. Using CPS enables the sharing of parameters across layers thus preventing the increase in number of parameters as the depth of the layers increase.

ALBERT also replaces one of the pretraining tasks - next sentence prediction in BERT with inter-sentence coherence loss that focuses on the coherence between two consecutive sentences. ALBERT has outperformed all the existing models and hold the highest Pearson's correlation in STS dataset.

TABLE 2: STS English language training dataset (2012-2017) [24]

SNo	Topic	SNo	Topic
1	Computer science	10	Pseudo code
2	Computer program	11	Programming language
3	Algorithm	12	Data analytics
4	Data structures	13	Computer Security
5	Artificial Intelligence	14	Computer virus
6	Computer program- ming	15	Cloud computing
7	Operating systems	16	Server
8	Database	17	Firewall
9	Computer Architecture	18	Outlier.

4 METHODOLOGY

In this section, we discuss the methodology followed in building the proposed benchmark DSCS dataset. We follow three steps in the construction of the dataset namely 1) Selection of domain, 2) Selection of sentences 3) Annotation of similarity values. Owing to our familiarity and current research topic, we chose the domain of interest to be computer science. Our dataset comprises of 52 unique sentences, which are definitions of widely known topics in the field of computer science. The list of the topics chosen is shown in Table 2. In order to extract sentences with similar meanings we used three different sources namely the Wikipedia³, Simple English Wikipedia⁴ and the Merriam Webster Online dictionary⁵. The single sentence definitions of the chosen topics are selected from these sources resulting in fifty two unique sentences. Fig. 3 shows an example of the definitions from various sources. In order to obtain dissimilar sentence pairs the sentences are paired among each other to form fifty final sentence pairs with no two sentences repeated more than twice.

4.1 Human Annotation

The sentence pairs were then marked with a binary annotation as "Similar" and "Dissimilar" based on whether they are the definition of the same topic. Then two separate surveys were conducted to obtain the human annotation of the similarity value between the sentence pairs. The initial survey was conducted among five graduate students pursuing a Masters in Computer Science. The students were requested to mark the similarity between provided sentence pairs over a range of values between 0 and 5, where 0 indicates that the sentences are completely dissimilar and 5 indicates that the sentences are completely similar. The survey was then extended to Amazon Mechanical Turk

3. 1

4. https://simple.wikipedia.org/wiki/Main_Page

5. <https://www.merriam-webster.com/>

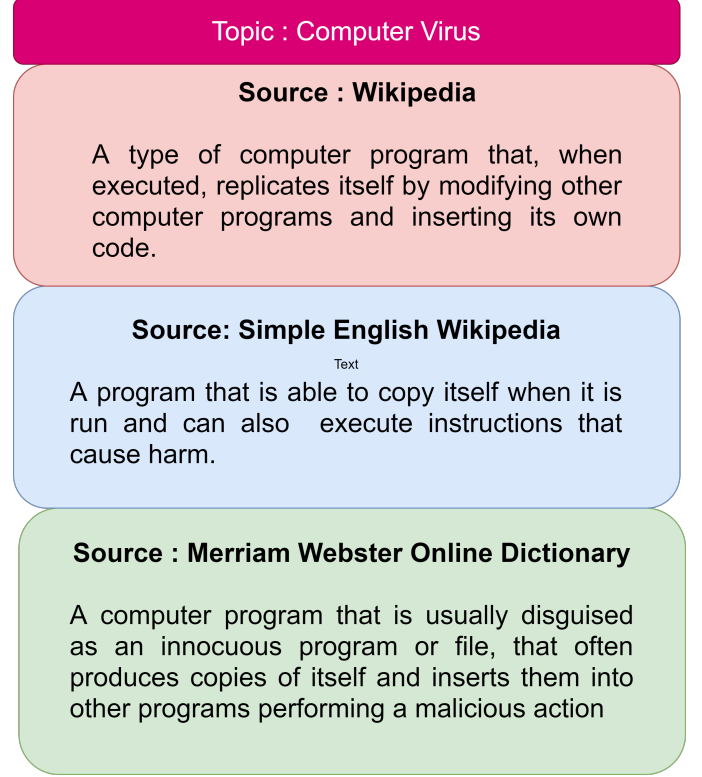


Fig. 3: Example of Sentences in DSCS dataset

(MTurk) requesting 10 unique responses for each sentence pair. The survey environments of both surveys are depicted in Fig. 5 and Fig. 6 in Appendix B. The survey in MTurk was restricted to North America for language expertise and the Turker was required to have US graduate level of expertise for domain expertise. Specific instructions were provided to the workers that sufficient domain knowledge is required to participate in the survey. However, since the actual qualification of the user cannot be determined or restricted in MTurk the responses of the workers were collected and examined for grave irregularities. The responses of all the workers were compared to the existing binary annotation of the dataset. If more than 80% of the similarity values provided by a worker contradicted the binary annotation then the user's responses were removed. By repeating this process 10 unique responses for 50 sentence pairs were obtained. The results of the two surveys were combined to obtain 15 unique values for each sentence pair and the similarity score was calculated using the weighted average of the 15 unique responses using the formula below.

$$S = \frac{\sum_{i=0}^{i=5} (w_i \times s_i)}{\sum_{i=0}^{i=5} w_i} \quad (2)$$

where,

s_i represent the values from 0 to 5 respectively and w_i represent the corresponding weights and are calculated as,

$$w_i = \left(\frac{\text{No of responses with } i \text{ similarity score}}{\text{Total number of responses}} \right) \quad (3)$$

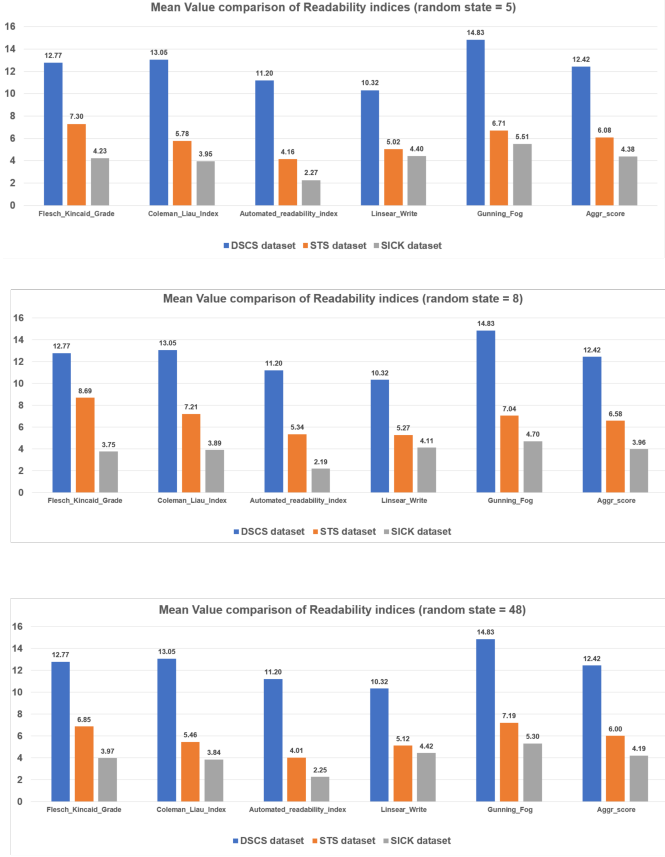


Fig. 4: Comparison of mean readability indices among three given datasets

4.2 Readability Analysis

Readability indices are used by researchers to measure the complexity of text data mostly in text simplification tasks [28], [29]. In order to prove that the sentences chosen for building this dataset are more complex than the existing gold standard datasets a comparative readability analyses is conducted between the two existing benchmark datasets and the proposed dataset. The below-mentioned readability grade-level scores indicate the grade level of education required by the reader to comprehend the given text which in turns reflects the complexity of the sentences. For example, a readability index of 10.4 indicates that a student of grade 10 would be able to read the given text. Various readability indices used and the formula for determining the scores are provided below.

- **Flesch-Kincaid Grade Level [30]**

$$= 0.39 \left(\frac{\text{total words}}{\text{total sentences}} \right) + 11.8 \left(\frac{\text{total syllables}}{\text{total words}} \right) - 15.59 \quad (4)$$

- **Coleman-Liau Index [31]**

$$= 0.588L - 0.296S - 15.8 \quad (5)$$

where,

L denotes the number of characters per 100 words

and

S denotes the number of sentences per 100 words.

- **Automated readability Index [30]**

$$= 4.71 \left(\frac{\text{characters}}{\text{words}} \right) + 0.5 \left(\frac{\text{words}}{\text{sentences}} \right) - 21.43 \quad (6)$$

- **Linsear Write**

For each sample of 100 words,

$$r = \frac{1 * (\text{Easy words}) + 3 * (\text{Hard words})}{\text{No of sentences in sample}} \quad (7)$$

where,

Easy words = words with less than 2 syllables and
Hard words = words with more than 3 syllables.

$$LW = \begin{cases} \left(\frac{r}{2} \right), & \text{if } r > 20 \\ \left(\frac{r}{2} - 1 \right) & \text{if } r \leq 20 \end{cases} \quad (8)$$

- **Gunning fog index [32]**

$$= 0.4 \left[\left(\frac{\text{words}}{\text{sentences}} \right) + 100 \left(\frac{\text{complex words}}{\text{words}} \right) \right] \quad (9)$$

where,

complex words = words consisting more than or equal to three syllables

- **Text Standard:**

An aggregated score based on all the above readability indices.

The STS training dataset contains 10,818 unique sentences and the SICK dataset contains 6,076 unique sentences. On analysing the complexity of these sentences using the above mentioned readability indices we find that 70% of sentences in STS dataset and 90% of sentences in SICK dataset have a aggregate readability score below 10, while only 25% of the sentences in the proposed dataset are below the index 10. This clearly indicates that the two existing datasets have predominantly simpler sentences. In order compare the complexity of the datasets, we select the readability indices of 52 random sentences from the the two benchmark datasets and 52 sentences from DSCS dataset. This process is repeated with three different seeds for random selection. Fig. 4 shows the results of the comparison between the mean value of six different readability indices among the three datasets repeated thrice and we can clearly see a significant increase in the complexity of the sentences. The results show us that while sentences in STS dataset and SICK dataset can be interpreted by 6th graders and 4th graders respectively, DSCS requires the knowledge of a 12th grader to comprehend the meaning of the provided sentences clearly indicating the increase in complexity in the sentences of the proposed dataset.

5 COMPARATIVE ANALYSIS

5.1 Experimental setup

We perform a comparative analysis between the five chosen word embeddings, to assess the sensitivity of the word embeddings to the complexity of the sentences, by comparing

TABLE 3: Configuration of BERT, RoBERT, and ALBERT models compared in this paper.

Model Name	Trans former Blocks	Hidden Layers	Attention heads	Total Param- eters
BERT _{BASE}	12	768	12	110M
BERT _{LARGE}	24	1024	16	340M
RoBERTa _{BASE} and RoBERTa _{LARGE}	24	1024	16	340M
ALBERT _{XLARGE}	24	2048	32	60M
ALBERT _{XXLARGE}	12	4096	64	235M

their performance across the two benchmark datasets and the proposed dataset. Since this research experiment focuses on the sensitivity of the word embeddings themselves, the sentence vectors are formed by simply taking the mean of the word vectors. In transformer based models a mean pooling is added to the model to form the sentence vectors. Initially we replicate the results provided by the authors of each model using the STS dataset, and use the same models to measure the similarity scores for both SICK dataset and the proposed DSCS dataset. In the first model, the pre-trained *word2vec* model, trained on the Google News dataset containing 300 dimensional vectors with a vocabulary of 3M words provided by *gensim* python library is used for building the word vectors. Then, the 300 dimensional *GloVe* vectors pre-trained on a Wikipedia dump corpus with 6B tokens provided by the *gensim* library is used to build the word vectors. However, since the proposed dataset is from the computer science domain, we use a specific corpus - the computer science corpus to train the word2vec and GloVe models initialized with the pretrained weights using transfer learning. The PetScan⁶ tool that traverses through the Wikipedia categories and subcategories based on provided keywords is used for building the corpus. Using ‘computer_science’ as the category and a depth ‘2’ which indicates the level of subcategories to be included, the ‘computer science corpus’ containing 4M tokens is used to train both the word2vec and GloVe models. Since the different BERT models do not provide explicit word embeddings, we use Sentence-BERT framework proposed by Reimer’s et al. [33] to compare their performance. The various BERT models selected for comparison and their configuration is listed above in Table 3. We use the SentenceTransformer python library to initialize the model with the weights of pretrained BERT models followed by a mean pooling layer to form the sentence vectors. In order to factor in the effect of ‘fine-tuning’ one of the prominent characteristic of transformer based models we fine tune the BERT models, with the AllNLI dataset. To estimate the impact of supervised learning in the quality of the word vectors provided by transformer based models we experiment with BERT models fine tuned with both AllNLI dataset and the STS dataset on all three datasets included in the comparison. While the T5 model proposed by Raffel et al. [22] is one of the models that achieved the best performance in the STS dataset, due to computational constraints we were not able to replicate the model hence it is not included in our comparison.

6. <https://petscan.wmflabs.org/>

5.2 Results and Discussion

The correlation between the similarity scores provided by human annotators and the similarity scores calculated by the models is used as the measure to estimate the performance of the word embedding models. Since both Pearson’s correlation and Spearman’s correlation are used by the authors of the models chosen for comparison, we depict our results using both the correlations. The results are categorized as three different sections based on the level of supervision used for the models. The first section records the performance of the unsupervised word embedding models, the word2vec and GloVe and their variations trained on the ‘computer science corpus’. The second section shows the performance of the two variants of BERT, RoBERTa and ALBERT models, fine tuned using AllNLI dataset, we consider this as partial supervision since the text entailment tasks are similar to semantic similarity tasks, but the model has not been trained on sentences from any of the three datasets used for comparison. The third section comprises the results of the same models trained (fine-tuned) using both AllNLI and the STS dataset. The results are provided in Table 4.

The performance of the word-embeddings decrease considerably when tested on the proposed dataset, which proves our initial hypothesis that performance decreases with increase in complexity. While ALBERT-xxlarge model achieves the best performance in the proposed dataset with 73.67% Pearson’s Correlation and 67.54% Spearman’s correlation, we can see that these results are sub-par in comparison to the 92.58% correlation achieved in the existing benchmark dataset. It is important to note that, though the sentences in the proposed dataset are definitions of topics from a particular domain, they are derived from sources that are commonly used by everyone. Hence these sentences are comparatively simpler than the sentences that we might encounter in scientific or academic articles. Hence, we confer that there is an imminent need to explore venues to improve the quality of these word embeddings to capture the semantics in complex documents. Next, we see that the correlation in the proposed dataset increased in word2vec and Glove models trained using a custom built domain-specific corpus than the models trained on general corpora indicating the need for custom built efficient corpora for domain specific tasks. We also see that the BERT models fine-tuned to a specific NLP task like semantic similarity do not perform as effectively in the proposed dataset indicating the impact of the training data used in the fine-tuning process. With the insights we have gathered through the experiments we described in this paper, we propose to focus our future research on two aspects. We intend to repeat the process and add more number of sentences to the dataset and accommodate more domains thus building a large complex sentence dataset which can in turn be used by transformer-based models for fine tuning. Secondly, we intend to focus on building more complex domain specific corpora compared to the common crawl dataset which predominantly contains simpler text, thus training word embedding models to capture semantics in more complex sentences.

TABLE 4: Pearson’s correlation and Spearman’s correlation percentages of the word embedding models in STS Benchmark Dataset, SICK dataset, and DSCS dataset.

Supervision	Model	Pearson’s Correlation			Spearman’s Correlation		
		STS - test	SICK - Test	DSCS	STS - test	SICK - Test	DSCS
Unsupervised	word2vec	62.61	72.67	48.30	58.71	62.13	49.04
	Glove	45.42	63.53	43.90	46.88	55.59	50.14
	word2vec + CS Corpus	56.77	67.75	52.35	53.27	59.38	46.79
	Glove + CS Corpus	41.09	60.44	48.02	42.85	54.20	42.52
Partially supervised	BERT large + NLI + Mean Pooling	76.17	73.65	54.78	79.19	73.72	54.47
	BERT base + NLI + Mean Pooling	74.11	72.95	50.91	76.97	72.89	47.73
	RoBERTa large + NLI + Mean Pooling	76.26	74.35	54.54	78.69	74.01	46.36
	RoBERTa base + NLI + Mean Pooling	74.58	76.05	37.74	77.09	74.44	39.48
	ALBERT xxlarge + NLI + Mean Pooling	78.56	77.78	45.44	79.55	75.37	41.33
	ALBERT xlarge + NLI + Mean Pooling	77.68	73.90	54.90	80.12	74.78	57.68
Supervised	BERT large + NLI + STSB+ Mean Pooling	84.63	80.97	71.11	85.25	78.48	66.78
	BERT base + NLI + STSB+ Mean Pooling	84.18	82.16	67.79	85.04	78.43	64.02
	RoBERTa large + NLI + STSB+ Mean Pooling	85.54	82.32	64.69	86.42	78.40	60.48
	RoBERTa base + NLI + STSB+ Mean Pooling	84.26	81.78	50.57	85.26	77.43	46.46
	ALBERT xxlarge + NLI + STSB + Mean Pooling	92.58	85.33	73.67	90.22	80.03	67.54
	ALBERT xlarge + NLI + STSB + Mean Pooling	91.59	83.28	71.45	90.73	81.52	66.97

6 CONCLUSION

Measuring semantic similarity between text data has been one of the most challenging tasks in the field of Natural Language Processing. Various word embedding models have been proposed over the years to capture the semantics of the words in numeric representations. In this paper we propose a new benchmark dataset, that contains sentences that are more complex than the existing dataset and measure the sensitivity of the existing word embedding models to the increase in complexity of the sentences. On performing a comparative analysis between five different word embedding models we prove our hypothesis that the performance of word embeddings models in semantic similarity tasks decreases with increase in complexity.

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APPENDIX A**DOMAIN SPECIFIC COMPLEX SENTENCE DATASET**

Sno	Sentence_1	Sentence_2	Final Similarity
1	The study of computation and information.	The study of manipulating, managing, transforming and encoding information.	3.60
2	The study of computation and information.	A branch of science that deals with the theory of computation or the design of computers	3.67
3	A program can be a plan of how to do something	A branch of science that deals with the theory of computation or the design of computers	0.87
4	A finite sequence of well-defined, computer-implementable instructions, typically to solve a class of problems or to perform a computation	A specific set of instructions or steps on how to complete a task.	4.00
5	A finite sequence of well-defined, computer-implementable instructions, typically to solve a class of problems or to perform a computation	A procedure for solving a mathematical problem in a finite number of steps that frequently involves repetition of an operation	3.20
6	A data organization, management, and storage format that enables efficient access and modification.	A specific set of instructions or steps on how to complete a task.	0.87
7	A set of instructions used to control the behavior of a machine.	A program can be a plan of how to do something	2.13
8	A set of instructions used to control the behavior of a machine.	A sequence of coded instructions that can be inserted into a mechanism	3.27
9	The study of manipulating, managing, transforming and encoding information.	A sequence of coded instructions that can be inserted into a mechanism	1.87
10	A data organization, management, and storage format that enables efficient access and modification.	The organization and implementation of values and information.	2.47
11	A procedure for solving a mathematical problem in a finite number of steps that frequently involves repetition of an operation	Various methods or formats for organizing data in a computer	0.60
12	The organization and implementation of values and information.	Various methods or formats for organizing data in a computer	2.53
13	The intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals.	The ability of a computer program or a machine to think and learn.	3.67
14	The intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals.	A branch of computer science dealing with the simulation of intelligent behavior in computers	3.07
15	The ability of a computer program or a machine to think and learn.	A branch of computer science dealing with the simulation of intelligent behavior in computers	3.67
16	The process of designing and building an executable computer program to accomplish a specific computing result.	A software that controls the operation of a computer and directs the processing of programs	2.40
17	The process of designing and building an executable computer program to accomplish a specific computing result.	The process of preparing an instructional program for a device	3.00
18	The process of telling a computer to do certain things by giving it instructions.	The process of preparing an instructional program for a device	3.40
19	A system software that manages computer hardware, software resources, and provides common services for computer programs.	A group of computer programs, including device drivers, kernels, and other software that lets people interact with a computer.	2.80
20	A system software that manages computer hardware, software resources, and provides common services for computer programs.	The process of telling a computer to do certain things by giving it instructions.	1.73
21	A group of computer programs, including device drivers, kernels, and other software that lets people interact with a computer.	A software that controls the operation of a computer and directs the processing of programs	3.27
22	An organized collection of data, generally stored and accessed electronically from a computer system.	A system for storing and taking care of data	3.67
23	An organized collection of data, generally stored and accessed electronically from a computer system.	A set of rules and methods that describe the functionality, organization, and implementation of computer systems.	1.60
24	A system for storing and taking care of data	A large collection of data organized especially for rapid search and retrieval	2.87
25	A set of rules and methods that describe the functionality, organization, and implementation of computer systems.	The conceptual design and fundamental operational structure of a computer system.	3.27
26	A large collection of data organized especially for rapid search and retrieval	The manner in which the components of a computer or computer system are organized and integrated	1.13
27	The conceptual design and fundamental operational structure of a computer system.	The manner in which the components of a computer or computer system are organized and integrated	3.93
28	An informal high-level description of the operating principle of a computer program or other algorithm.	A description of the source code of a computer program or an algorithm in a language easily understood by humans.	3.93

Table 5 continued from previous page

Sno	Sentence_1	Sentence_2	Final Similarity
29	An informal high-level description of the operating principle of a computer program or other algorithm.	a formal language comprising a set of instructions that produce various kinds of output.	2.07
30	A description of the source code of a computer program or an algorithm in a language easily understood by humans.	A program code unrelated to the hardware of a particular computer and requiring conversion to the code used by the computer before the program can be used.	2.80
31	a formal language comprising a set of instructions that produce various kinds of output.	a type of written language that tells computers what to do in order to work.	3.60
32	A program code unrelated to the hardware of a particular computer and requiring conversion to the code used by the computer before the program can be used.	various high-level languages used for computer programs	2.33
33	a type of written language that tells computers what to do in order to work.	various high-level languages used for computer programs	3.80
34	The discovery, interpretation, and communication of meaningful patterns in data.	The process of discovering, interpreting, and communicating significant patterns in data to get meaningful information.	4.27
35	The discovery, interpretation, and communication of meaningful patterns in data.	A branch of information technology which is intended to protect computers.	0.60
36	The protection of computer systems and networks from the theft of or damage to their hardware, software, or electronic data.	A branch of information technology which is intended to protect computers.	3.73
37	The protection of computer systems and networks from the theft of or damage to their hardware, software, or electronic data.	The process of discovering, interpreting, and communicating significant patterns in data to get meaningful information.	0.33
38	A type of computer program that, when executed, replicates itself by modifying other computer programs and inserting its own code.	A program that is able to copy itself when it is run and can also execute instructions that cause harm.	4.27
39	The practice of storing regularly used computer data on multiple servers that can be accessed through the Internet	A computer program that is usually disguised as an innocuous program or file, that often produces copies of itself and inserts them into other programs performing a malicious action	0.13
40	The on-demand availability of computer system resources, especially data storage and computing power, without direct active management by the user.	Computing services provided by a company or place outside of where they are being used.	2.73
41	The on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user.	The practice of storing regularly used computer data on multiple servers that can be accessed through the Internet	2.60
42	Computing services provided by a company or place outside of where they are being used.	A type of computer program that, when executed, replicates itself by modifying other computer programs and inserting its own code.	0.47
43	A program that is able to copy itself when it is run and can also execute instructions that cause harm.	A computer program that is usually disguised as an innocuous program or file, that often produces copies of itself and inserts them into other programs performing a malicious action	4.33
44	A piece of computer hardware or software that provides functionality for other programs or devices, called "clients".	A computer that serves many kinds of information to a user or client machine.	3.60
45	A piece of computer hardware or software that provides functionality for other programs or devices, called "clients".	A computer in a network that is used to provide services to other computers in the network	2.87
46	A network security system that monitors and controls incoming and outgoing network traffic based on predetermined security rules.	A piece of software that monitors the network traffic between the inside and outside.	4.20
47	A network security system that monitors and controls incoming and outgoing network traffic based on predetermined security rules.	A computer hardware or software that prevents unauthorized access to private data by outside computer users	3.40
48	A computer that serves many kinds of information to a user or client machine.	A piece of software that monitors the network traffic between the inside and outside.	1.20
49	A computer in a network that is used to provide services to other computers in the network	A computer hardware or software that prevents unauthorized access to private data by outside computer users	0.87
50	A data point that differs significantly from other observations.	A statistical observation that is markedly different in value from the others of the sample	4.13

TABLE 5: Domain-Specific Complex Sentence Dataset

APPENDIX B

SURVEY ENVIRONMENTS

Sentence pair 5 *

Sentence A: A finite sequence of well-defined, computer-implementable instructions, typically to solve a class of problems or to perform a computation

Sentence B: A procedure for solving a mathematical problem in a finite number of steps that frequently involves repetition of an operation.

To what extent are the above sentences similar

0 1 2 3 4 5
Completely dissimilar ☐ ☐ ☐ ☐ ☐ ☐ Completely similar

Fig. 5: Survey using Google forms

Fig. 6: Survey using Amazon Mechanical Turk

APPENDIX C

SEMANTIC SIMILARITY DATASETS

TABLE 6: Popular Benchmark datasets for Semantic similarity [20]

Dataset Name	Word/Sentence pairs	Similarity score range	Year	Reference
R&G	65	0-4	1965	[23]
M&C	30	0-4	1991	[34]
WS353	353	0-10	2002	[35]
LiSent	65	0-4	2007	[36]
SRS	30	0-4	2007	[37]
WS353-Sim	203	0-10	2009	[38]
STS2012	5250	0-5	2012	[39]
STS2013	2250	0-5	2013	[40]
WP300	300	0-1	2013	[41]
STS2014	3750	0-5	2014	[42]
SL7576	7576	1-5	2014	[43]
SimLex-999	999	0-10	2014	[44]
SICK	10000	1-5	2014	[14]
STS2015	3000	0-5	2015	[45]
SimVerb	3500	0-10	2016	[46]
STS2016	1186	0-5	2016	[47]
WiC	5428	NA	2019	[48]