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# DEEP LEARNING BASED SEMANTIC TEXTUAL SIMILARITY FOR APPLICATIONS IN MACHINE TRANSLATION DOMAIN

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A thesis submitted in partial fulfilment of the requirements of the University of  
Wolverhampton for the degree of Doctor of Philosophy

2021

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## ABSTRACT

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An abstract is a synopsis of the thesis, and it goes in the file `abstract.tex`.



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## ACKNOWLEDGEMENTS

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Your acknowledgements should go in `ack.tex`.

We would like to acknowledge Donald Craig at Memorial University, Newfoundland who published the meta-thesis on which this template is based. You can find Donald's work on his web site, here: <http://www.cs.mun.ca/~donald/metathesis/>.



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## LISTINGS

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## INTRODUCTION

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## **Part I**

# **Semantic Textual Similarity**



# CHAPTER 1

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## INTRODUCTION

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### 1.1 Semantic Textual Similarity Approaches

Over the years, researchers have proposed numerous STS methods. Most of the early approaches were based on traditional machine learning and involved heavy feature engineering [1]. With the advances of word embeddings, and as a result of the success neural networks have achieved in other fields, most of the methods proposed in recent years rely on neural architectures [2, 3]. Neural networks are preferred over traditional machine learning models as they generally tend to perform better than traditional machine learning models. They also do not rely on explicit linguistics features which have to be extracted before the ML model is learnt. Determining the best linguistic features for calculating STS is not an easy task as it requires a good understanding of the linguistic phenomenon and relies on researchers' intuition. In addition, calculating these features is usually not an easy task, especially for languages other than English. Therefore, in contrast to traditional ML methods, models based on word embeddings and neural networks can be easily applied to other languages.

As stated in the Chapter 1 the machine learning algorithms we experimented can be classified in to two min categories: Unsupervised STS methods and Su-

pervised STS methods. In the Chapter 2 we evaluate the current STS state of the arts methods that uses word embeddings and we improve state of the arts STS methods using contextual embeddings.

In Chapter 3 we explore another unsupervised STS method using sentence encoders. We use three different sentence encoders analyse their performance in various aspects of English STS and also evaluate their portability to different languages and domains.

Siamese Neural Networks are a special kind of neural network that are being used commonly in STS tasks. It is a supervised STS method which we discuss comprehensively in Chapter 4. We evaluate the existing Siamese Neural Network architectures in STS datasets and propose a novel Siamese Neural Network architecture, MAGRU: an efficient and more accurate Siamese Neural Network architecture for STS tasks. We also asses its performance on different languages and different domains.

In the final chapter of the Part I of this thesis, we explore the newly released transformers in STS tasks. We bring together various transformer architectures like BERT [4], XLNet [5], RoBERTa [6] etc and investigate their performance in various STS datasets in Chapter 5.

The remainder of this chapter is structured as follows. Section 1.2 discuss the various datasets we used in "*Semantic Textual Similarity*" part of the thesis. We also briefly analyse the datasets for common properties. In the Section 1.4 we discuss the main contributions we have to the community with the "*Semantic Textual Similarity*" part of the thesis. The chapter concludes with the conclusions.

## 1.2 Datasets

We experimented with several datasets throughout the experiments in the Semantic Textual Similarity Section. In order to maintain the versatility of our methods we experimented with several English datasets as well as several non English datasets and several datasets from different domains which we will introduce in this section. All of the datasets which are described here are publicly available and can be considered as STS benchmarks.

### 1.2.1 English Datasets

1. **SICK dataset**<sup>1</sup> - The SICK data contains 9927 sentence pairs with a 5,000/4,927 training/test split which were employed in the SemEval 2014 Task1: Evaluation of Compositional Distributional Semantic Models on Full Sentences through Semantic Relatedness and Textual Entailment [7]. The dataset has two types of annotations: Semantic Relatedness and Textual Entailment. We only use Semantic Relatedness annotations in our research. SICK was built starting from two existing datasets: the 8K ImageFlickr data set<sup>2</sup> [8] and the SemEval-2012 STS MSR-Video Descriptions dataset<sup>3</sup> [9]. The 8K ImageFlickr dataset is a dataset of images, where each image is associated with five descriptions. To derive SICK sentence pairs the organisers randomly selected 750 images and sampled two descriptions from each of

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<sup>1</sup>The SICK dataset is available to download at <https://wiki.cimec.unitn.it/tiki-index.php?page=CLIC>

<sup>2</sup>The 8K ImageFlickr data set is available at <http://hockenmaier.cs.illinois.edu/8k-pictures.html>

<sup>3</sup>The SemEval-2012 STS MSR-Video Descriptions dataset is available at <https://www.cs.york.ac.uk/semeval-2012/task6/index.html>

## 1.2. DATASETS

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them. The SemEval2012 STS MSR-Video Descriptions data set is a collection of sentence pairs sampled from the short video snippets which compose the Microsoft Research Video Description Corpus<sup>4</sup>. A subset of 750 sentence pairs have been randomly chosen from this data set to be used in SICK.

In order to generate SICK data from the 1,500 sentence pairs taken from the source data sets, a 3-step process has been applied to each sentence composing the pair, namely *(i) normalisation*, *(ii) expansion* and *(iii) pairing* [7]. The *normalisation* step has been carried out on the original sentences to exclude or simplify instances that contained lexical, syntactic or semantic phenomena such as named entities, dates, numbers, multiword expressions etc. In the *expansion* step syntactic and lexical transformations with predictable effects have been applied to each normalized sentence, in order to obtain *(i)* a sentence with a similar meaning, *(ii)* a sentence with a logically contradictory or at least highly contrasting meaning, and *(iii)* a sentence that contains most of the same lexical items, but has a different meaning. Finally, in the *pairing* step each normalised sentence in the pair has been combined with all the sentences resulting from the expansion phase and with the other normalised sentence in the pair. Furthermore, a number of pairs composed of completely unrelated sentences have been added to the data set by randomly taking two sentences from two different pairs [7].

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<sup>4</sup>The Microsoft Research Video Description Corpus is available to download at <https://research.microsoft.com/en-us/downloads/38cf15fd-b8df-477e-a4e4-a4680caa75af/>

Each pair in the SICK dataset has been annotated to mark the degree to which the two sentence meanings are related (on a 5-point scale). The ratings have been collected through a large crowdsourcing study, where each pair has been evaluated by 10 different annotators. Once all the annotations were collected, the relatedness gold score has been computed for each pair as the average of the ten ratings assigned by the annotators [7]. Table 1.1 shows examples of sentence pairs with different degrees of semantic relatedness; gold relatedness scores are expressed on a 5-point rating scale. Given a test sentence pair the machine learning models require to predict a value between 0-5 which reflects the relatedness of the given sentence pair.

Sentence Pair	Relatedness
1. A little girl is looking at a woman in costume. 2. A young girl is looking at a woman in costume.	4.7
1. Nobody is pouring ingredients into a pot. 2. Someone is pouring ingredients into a pot.	3.5
1. Someone is pouring ingredients into a pot. 2. A man is removing vegetables from a pot.	2.8
1. A man is jumping into an empty pool. 2. There is no biker jumping in the air.	1.6

Table 1.1: Example sentence pairs from the SICK dataset with their gold relatedness scores (on a 5-point rating scale). **Sentence Pair** column shows the two sentence and **Relatedness** column denotes the annotated relatedness score.

Figure 1.1

Figure 1.2

Figure 1.3



## 1.2. DATASETS

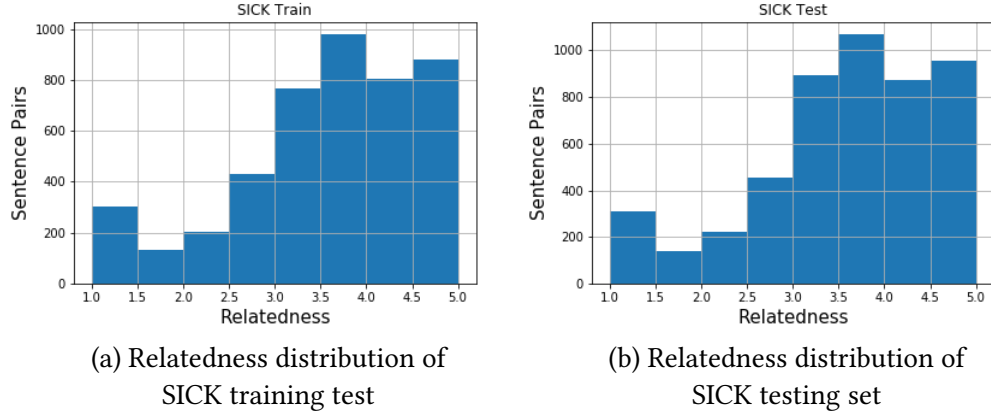


Figure 1.1: Relatedness distribution of SICK train and SICK test. *Sentence Pairs* shows the number of sentence pairs that a certain *Relatedness* bin has.

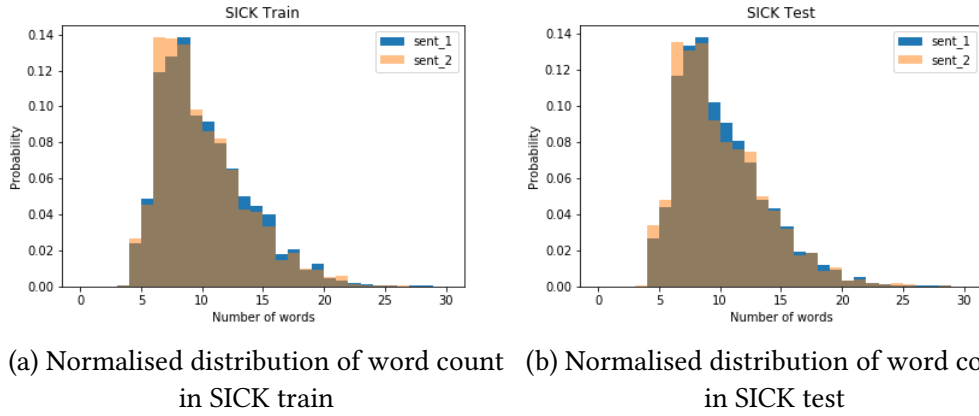


Figure 1.2: Normalised distribution of word count in SICK train and SICK test. *Number of words* indicates the word count and *Probability* shows the total probability of a sentence with that word count appearing in the dataset.

Measure	SICK Train		SICK Test	
	<b>Sent_1</b>	<b>Sent_2</b>	<b>Sent_1</b>	<b>Sent_2</b>
<i>Word Count Mean</i>	9.73	9.52	9.69	9.53
<i>Word Count STD</i>	3.66	3.70	3.69	3.65
<i>Word Count MAX</i>	28	32	28	30
<i>Word Count MIN</i>	3	3	3	3

Table 1.2: Word count stats in SICK training and SICK testing. *STD* indicates the standard deviation and the other acronyms indicate the common meaning

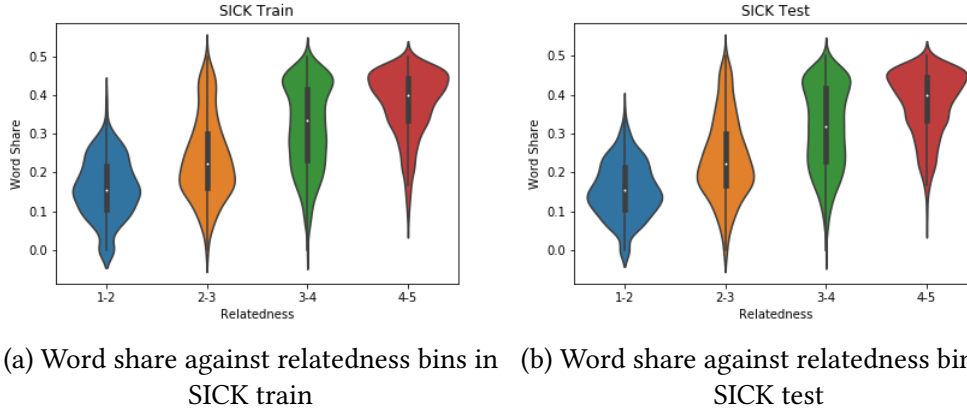


Figure 1.3: Word share against relatedness bins in SICK train and SICK test. *Word Share* indicates the ratio between number of common words in the two sentences to total number of words in the two sentences against each *Relatedness* bins

2. **STS 2017 English Dataset**<sup>5</sup> STS 2017 English Dataset was employed in SemEval-2017 Task 1: Semantic Textual Similarity Multilingual and Cross-lingual Focused Evaluation which is the most recent STS task in SemEval [10]. As the training data for the competition, participants were encouraged to make use of all existing data sets from prior STS evaluations including all previously released trial, training and evaluation data from SemEval 2012 - 2016 [9, 11, 12, 13, 14]. Once combined we had 8277 sentence pairs for training. More information about the datasets used to build the training set is available in Table 1.3.

On the other hand, a fresh test set of 250 sentence pairs was provided by SemEval-2017 STS Task organisers [10]. The Stanford Natural Language Inference (SNLI) corpus [15] was the primary data source for this test set.

<sup>5</sup>The STS 2017 English Dataset is available to download at <http://ixa2.si.ehu.es/stswiki/>

## 1.2. DATASETS

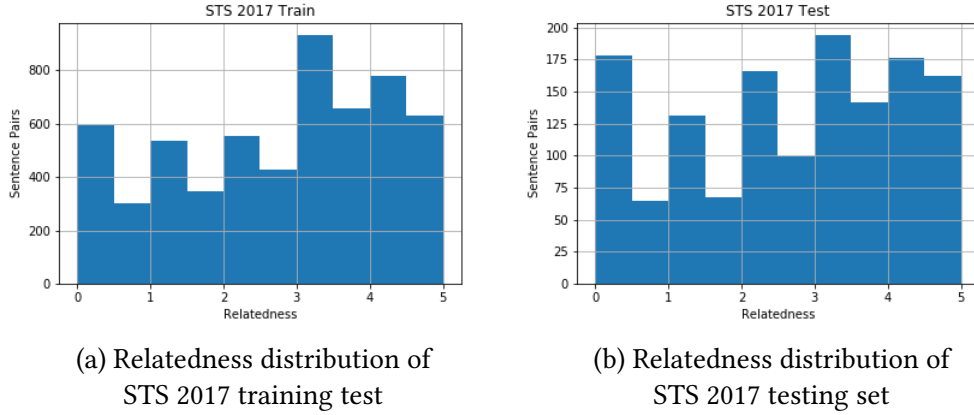


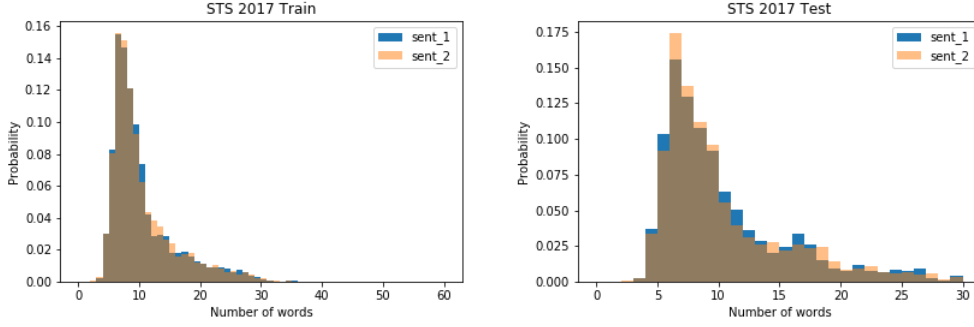
Figure 1.4: Relatedness distribution of STS 2017 train and STS 2017 test. *Sentence Pairs* shows the number of sentence pairs that a certain *Relatedness* bin has.

Similar to the SICK dataset, Each pair in the STS 2017 English Test set has been annotated to mark the degree to which the two sentence meanings are related (on a 5-point scale). The ratings have been collected through crowdsourcing on Amazon Mechanical Turk<sup>6</sup>. Five annotations have been collected per pair and gold score has been computed for each pair as the average of the five ratings assigned by the annotators. However, unlike the SICK dataset, the organisers has a clear explanations for the score ranges. Table 1.4 shows some example sentence pairs from the dataset with the gold labels and their explanations. Similar to the SICK dataset, the machine learning models require to predict a value between 0-5 which reflects the similarity of the given sentence pair.

### 3. Quora Question Pairs<sup>7</sup> The Quora Question Pairs dataset is a big dataset

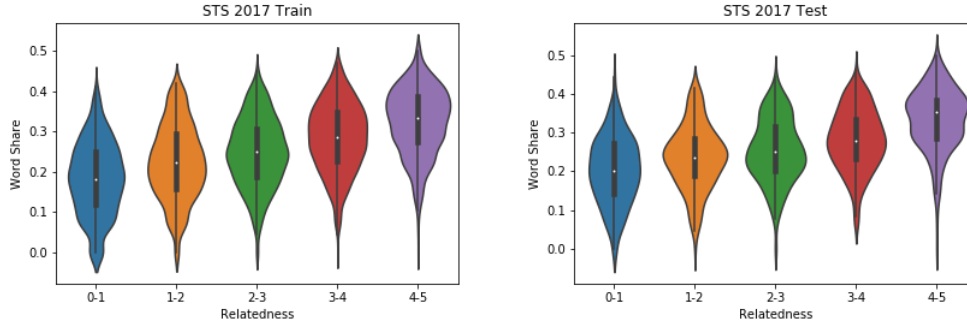
<sup>6</sup>Amazon Mechanical Turk is a crowdsourcing website for businesses to hire remotely located *crowd workers* to perform discrete on-demand tasks. It is available at <https://www.mturk.com/>

<sup>7</sup>The Quora Question Pairs Dataset is available to download at [http://qim.fs.quoracdn.net/quora\\_duplicate\\_questions.tsv](http://qim.fs.quoracdn.net/quora_duplicate_questions.tsv)



(a) Normalised distribution of word count in STS 2017 train (b) Normalised distribution of word count in STS 2017 test

Figure 1.5: Normalised distribution of word count in STS 2017 train and STS 2017 test. *Number of words* indicates the word count and *Probability* shows the total probability of a sentence with that word count appearing in the dataset.



(a) Word share against relatedness bins in STS 2017 train (b) Word share against relatedness bins in STS 2017 test

Figure 1.6: Word share against relatedness bins in STS 2017 train and STS 2017 test. *Word Share* indicates the ratio between number of common words in the two sentences to total number of words in the two sentences against each *Relatedness* bins

## 1.2. DATASETS

Year	Dataset	Pairs	Source
2012 [9]	MSRpar	1500	newswire
2012 [9]	MSRvid	1500	videos
2012 [9]	OnWN	750	glosses
2012 [9]	SMTnews	750	WMT eval.
2012 [9]	SMTeuroparl	750	WMT eval.
2013 [11]	HDL	750	newswire
2013 [11]	FNWN	189	glosses
2013 [11]	OnWN	561	glosses
2013 [11]	SMT	750	MT eval.
2014 [12]	HDL	750	newswire headlines
2014 [12]	OnWN	750	glosses
2014 [12]	Deft-forum	450	forum posts
2014 [12]	Deft-news	300	news summary
2014 [12]	Images	750	image descriptions
2014 [12]	Tweet-news	750	tweet-news pairs
2015 [13]	HDL	750	newswire headlines
2015 [13]	Images	750	image descriptions
2015 [13]	Ans.-student	750	student answers
2015 [13]	Ans.-forum	375	Q&A forum answers
2015 [13]	Belief	375	committed belief
2016 [14]	HDL	249	newswire headlines
2016 [14]	Plagiarism	230	short-answer plag.
2016 [14]	post-editing	244	MT posteditits
2016 [14]	Ans.-Ans.	254	Q&A forum answers
2016 [14]	Quest.-Quest.	209	Q&A forum questions
2017 [10]	Trial	23	Mixed STS 2016

Table 1.3: Information about the datasets used to build the English STS 2017 training set. The **Year** column shows the year of the SemEval competition that the dataset got released. **Dataset** column expresses the acronym used describe a dataset in that year. **Pairs** is the number of sentence pairs in that particular dataset and **Source** shows the source of the sentence pairs.

which was first released for a Kaggle Competition<sup>8</sup>. Quora is a question-and-answer website where questions are asked, answered, followed, and

<sup>8</sup>Kaggle is an online community of data scientists and machine learning practitioners that hosts machine learning competitions. The Quora Question Pairs competition is available on <https://www.kaggle.com/c/quora-question-pairs>

Sentence Pair	Relatedness
<i>The two sentences are completely equivalent as they mean the same thing.</i> 1. The bird is bathing in the sink. 2. Birdie is washing itself in the water basin.	5
<i>The two sentences are completely equivalent as they mean the same thing.</i> 1. The bird is bathing in the sink. 2. Birdie is washing itself in the water basin.	4
<i>The two sentences are roughly equivalent, but some important information differs/missing.</i> 1. John said he is considered a witness but not a suspect. 2. “He is not a suspect anymore.” John said.	3
<i>The two sentences are not equivalent, but share some details.</i> 1. They flew out of the nest in groups. 2. They flew into the nest together.	2
<i>The two sentences are not equivalent, but are on the same topic.</i> 1. The woman is playing the violin. 2. The young lady enjoys listening to the guitar.	1
<i>The two sentences are completely dissimilar</i> 1. The black dog is running through the snow. 2. A race car driver is driving his car through the mud.	0

Table 1.4: Example sentence pairs from the STS2017 English dataset with their gold relatedness scores (on a 5-point rating scale) and explanations. **Sentence Pair** column shows the two sentence and **Relatedness** column denotes the annotated relatedness score.

edited by internet users, either factually or in the form of opinions. If a particular new question has been asked before, users merge the new question to the original question flagging it as a duplicate. The organisers used this functionality to create the dataset and did not use a separate annotation process. Their original sampling method has returned an imbal-

## 1.2. DATASETS

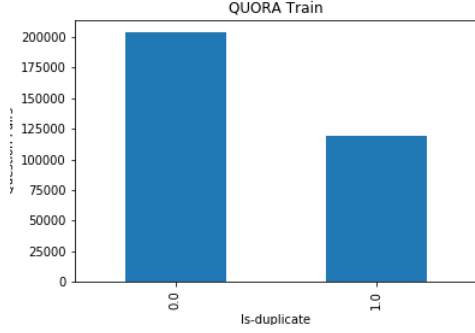
Measure	SICK Train		SICK Test	
	<b>Sent_1</b>	<b>Sent_2</b>	<b>Sent_1</b>	<b>Sent_2</b>
<i>Word Count Mean</i>	10.01	9.94	9.83	9.80
<i>Word Count STD</i>	5.52	5.36	5.14	5.14
<i>Word Count MAX</i>	57	48	30	30
<i>Word Count MIN</i>	3	2	3	2

Table 1.5: Word count stats in STS 2017 training and STS 2017 testing. *STD* indicates the standard deviation and the other acronyms indicate the common meaning

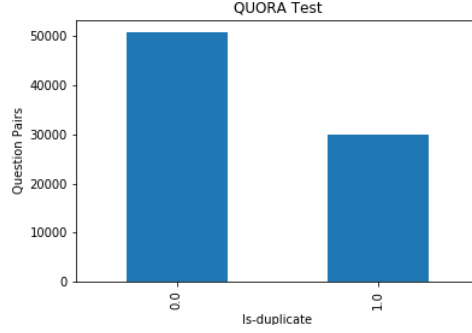
anced dataset with many more true examples of duplicate pairs than non-duplicates. Therefore, the organisers have supplemented the dataset with negative examples. One source of negative examples have been pairs of *related question* which, although pertaining to similar topics, are not truly semantically equivalent.

The dataset has 400,000 question pairs and we used 4:1 split on that to separate it into a training set and a test set resulting 320,000 questions pairs in the training set and 80,000 sentence pairs in the testing set. The machine learning models need to predict a value between 0 and 1 that reflects whether it is a duplicate question pair or not. 1 indicates that a certain question pair is a duplicate and 0 indicates it is not a duplicate.

This is different to the previous datasets since it is not artificially created and use day to day language. Since it has more than 300,000 training instances deep learning systems will benefit more when used on this dataset.

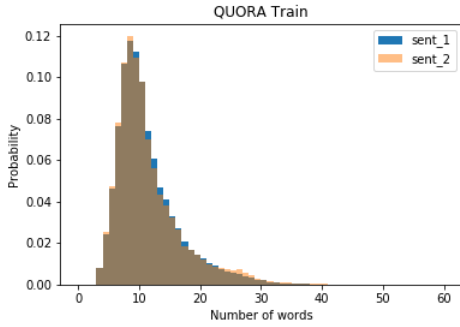


(a) Is-duplicate distribution of QUORA training test

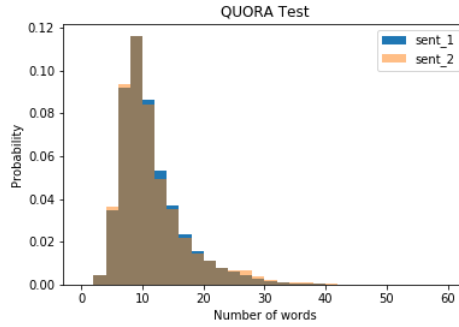


(b) Is-duplicate distribution of QUORA testing set

Figure 1.7: Is-duplicate distribution of QUORA train and QUORA test. *Sentence Pairs* shows the number of sentence pairs that a certain *Is-duplicate* has.



(a) Normalised distribution of word count in QUORA train



(b) Normalised distribution of word count in QUORA test

Figure 1.8: Normalised distribution of word count in QUORA train and QUORA test. *Number of words* indicates the word count and *Probability* shows the total probability of a sentence with that word count appearing in the dataset.



## 1.2. DATASETS

Question Pair	is-duplicate
1. What are natural numbers? 2. What is a least natural number?	0
1. Which Pizzas are most popularly ordered in Dominos menu? 2. How many calories does a Dominos Pizza have?	0
1. How do you start a bakery? 2. How can one start a bakery business?	1
1. Should I learn Python or Java first? 2. If I had to choose between learning Java and Python what should I choose to learn first?	1

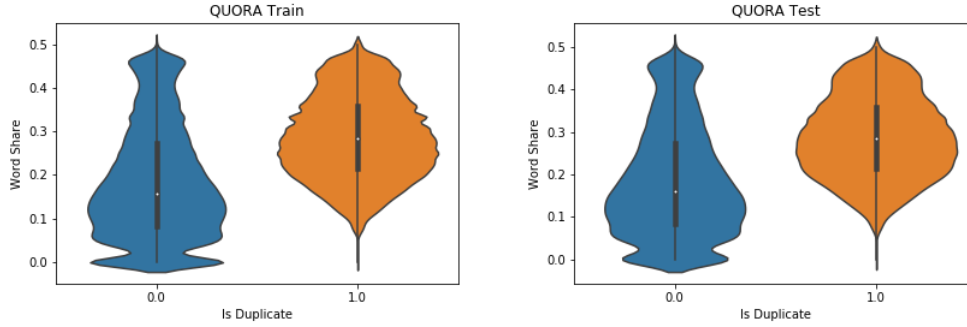
Table 1.6: Example question pairs from the Quora Question Pairs dataset with their gold is-duplicate value. **Question Pair** column shows the two questions and **is-duplicated** column denotes whether it is a duplicated pair or not.

Measure	QUORA Train		QUORA Test	
	Ques_1	Ques_2	Ques_1	Ques_2
<i>Word Count Mean</i>	10.95	11.20	10.92	11.14
<i>Word Count STD</i>	5.44	6.31	5.40	6.31
<i>Word Count MAX</i>	125	237	73	237
<i>Word Count MIN</i>	1	1	1	1

Table 1.7: Word count stats in QUORA training and QUORA testing. *STD* indicates the standard deviation and the other acronyms indicate the common meaning

### 1.2.2 Datasets on Other Languages

One of the main requirements in our research was to build a STS method without depending on the language. Therefore through out our research we worked on several datasets from different languages. Those non-English datasets are described below.



(a) Word share against relatedness bins in QUORA train (b) Word share against relatedness bins in QUORA test

Figure 1.9: Word share against relatedness bins in QUORA train and QUORA test. *Word Share* indicates the ratio between number of common words in the two sentences to total number of words in the two sentences against each *Is-duplicate*

1. **Spanish STS Dataset**<sup>9</sup> - Spanish STS dataset that we used was employed for Spanish STS subtask in SemEval 2017 Task 1: Semantic Textual Similarity Multilingual and Cross-lingual Focused Evaluation [10]. The training set has 1250 sentence pairs annotated with a relatedness score between 0 and 4. The training set combined several datasets from previous SemEval STS shared tasks also[10]. Table 1.8 shows more information about the training set. There were two sources for test set - Spanish news and Spanish Wikipedia dump having 500 and 250 sentence pairs respectively [10]. Both datasets were annotated with a relatedness score between 0 and 4. Table 1.9 shows few pairs of sentences with their similarity score. The machine learning models require to predict a value between 0-4 which reflects the similarity of the given Spanish sentence pair.

<sup>9</sup>The Spanish STS dataset can be downloaded at <http://alt.qcri.org/semeval2017/task1/index.php?id=data-and-tools>

## 1.2. DATASETS

Year	Dataset	Pairs	Source
2014 [12]	Trial	56	NR
2014 [12]	Wiki	324	Spanish Wikipedia
2014 [12]	News	480	Newswire
2015 [12]	Wiki	251	Spanish Wikipedia
2015 [13]	News	500	Sewswire
2017 [10]	Trial	23	Mixed STS 2016

Table 1.8: Information about the datasets used to build the Spanish STS training set. The **Year** column shows the year of the SemEval competition that the dataset got released. **Dataset** column expresses the acronym used describe a dataset in that year. **Pairs** is the number of sentence pairs in that particular dataset and **Source** shows the source of the sentence pairs.

2. **Arabic STS Dataset**<sup>10</sup> The Arabic STS dataset we selected was also used for the Arabic STS subtask in SemEval 2017 Task 1: Semantic Textual Similarity Multilingual and Cross-lingual Focused Evaluation [10]. Unlike Spanish, no data from previous SemEval competitions were available since this was the first time an Arabic STS task was organised in SemEval. More information about the extracted sentences will be shown in the Table 1.10.

To prepare the annotated instances, a subset of the English STS 2017 dataset has been selected and human translated into Arabic. Sentences have been translated independently from their pairs. Arabic translation has been provided by native Arabic speakers with strong English skills in Carnegie Mellon University in Qatar . Translators have been given an English sentence and its Arabic machine translation<sup>5</sup> where they have performed post-editing to correct errors. STS labels have been then transferred to the

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<sup>10</sup>The Arabic STS dataset can be downloaded at <http://alt.qcri.org/semeval2017/task1/index.php?id=data-and-tools>

Sentence Pair	Similarity
<p>1. Amás, los misioneros apunten que los números d'infectaos puen ser shasta dos o hasta cuatro veces más grandess que los oficiales.  <i>(Furthermore, missionaries point out that the numbers of infected can be up to two or up to four times larger than the official ones.)</i></p> <p>2. Los cadáveres de personas fallecidas pueden ser hasta diez veces más contagiosos que los infectados vivos.  <i>(The corpses of deceased people can be up to ten times more contagious than those infected alive.)</i></p>	0.6
<p>1. La policía abatió a un caníbal cuando devoraba a una mujer Matthew Williams, de 34 años, fue sorprendido en la madrugada mordiendo el rostro de una joven a la que había invitado a su hotel.  <i>(Police killed a cannibal while devouring a woman Matthew Williams, 34, was caught early in the morning biting the face of a young woman he had invited to his hotel.)</i></p> <p>2. La policía de Gales del Sur mató a un caníbal cuando se estaba comiendo la cara de una mujer de 22 años en la habitación de un hotel.  <i>(South Wales police killed a cannibal when he was eating the face of a 22-year-old woman in a hotel room.)</i></p>	2
<p>1. Ollanta Humala se reúne mañana con el Papa Francisco.  <i>(Ollanta Humala meets tomorrow with Pope Francis.)</i></p> <p>2. El Papa Francisco mantuvo hoy una audiencia privada con el presidente Ollanta Humala, en el Vaticano.  <i>(Pope Francis held a private audience today with President Ollanta Humala, at the Vatican.)</i></p>	3

Table 1.9: Example sentence pairs from the Spanish STS dataset. **Sentence Pair** column shows the two sentences. We also included their translations in the table. The translations were done by a native Spanish speaker. **Similarity** column indicates the annotated similarity of the two sentences.

translated pairs. Therefore, annotation guidelines and the template will be similar to the English STS 2017 dataset. 1103 sentence pairs were available for training and 250 sentence pairs were available in the test set. Table

## 1.2. DATASETS

Dataset	Pairs	Source
Trial	23	Mixed STS 2016
MSRpar	510	newswire
MSRvid	368	videos
SMTeuroparl	203	WMT eval.

Table 1.10: Information about the datasets used to build the Arabic STS training set. **Dataset** column expresses the acronym used describe the dataset. **Pairs** is the number of sentence pairs in that particular dataset and **Source** shows the source of the sentence pairs.

1.11 shows few pairs of sentences with their similarity score. The machine learning models require to predict a value between 0-5 which reflects the similarity of a given Arabic sentence pair.

### 1.2.3 Datasets on Different Domains

In order to experiment how our STS methods can be adopted in to different domains we have used two datasets from different disciplines which we introduce in this section.

1. **Bio-medical STS Dataset: BIOSSES** <sup>11</sup> - BIOSSES is the first and only benchmark dataset for biomedical sentence similarity estimation. [16]. The dataset comprises 100 sentence pairs, in which each sentence has been selected from the TAC (Text Analysis Conference) Biomedical Summarisation Track- training dataset containing articles from the biomedical domain <sup>12</sup>. The sentence pairs have been evaluated by five different human experts that judged their similarity and gave scores ranging from 0 (no

<sup>11</sup>Bio-medical STS Dataset: BIOSSES can be downloaded from <https://tabilab.cmpe.boun.edu.tr/BIOSSES/DataSet.html>

<sup>12</sup>Biomedical Summarisation Track is a shared task organised in TAC 2014 - <https://tac.nist.gov/2014/BiomedSumm/>

Sentence Pair	Similarity
1. أحدهم يقلي لحماً. <i>Someone is frying meat.</i> 2. أحدهم يعزف البيانو. <i>Someone plays the piano.</i>	0.250
1. امرأة تنظيف المكونات في الإناء. <i>A woman cleaning ingredients in the bowl.</i> 2. امرأة تكسر ثلاثة بيضات في الإناء. <i>A woman breaks three eggs in a bowl.</i>	1.750
1. طفلة تعزف القيثارة. <i>A Child is playing harp.</i> 2. رجل يعزف القيثارة. <i>A man plays the harp.</i>	2.250
1. المرأة تقطع البصل الأخضر. <i>The woman chops green onions.</i> 2. امرأة تقشر بصلة. <i>A woman peeling an onion.</i>	3.250
1. الأيل قفز فوق السياج. <i>The deer jumped over the fence.</i> 2. أيل يقفز فوق سياج الإعصار. <i>Deer jumps Over Hurricane Fence</i>	4.800

Table 1.11: Example question pairs from the Arabic STS dataset. **Sentence Pair** column shows the two sentences. We also included their translations in the table. The translations were done by a native Arabic speaker. **Similarity** column indicates the annotated similarity of the two sentences.

relation) to 4 (equivalent). The score range was described based on the guidelines of SemEval 2012 Task 6 on STS [9]. Besides the annotation instructions, example sentences from the bio-medical literature have been also provided to the annotators for each of the similarity degrees. To represent the similarity between two sentences we took the average of the

scores provided by the five human experts. Table 1.12 shows few examples in the dataset. The machine learning models require to predict a value between 0-4 which reflects the similarity of the given bio medical sentence pair.

A dataset as small as this one can not be used by to train a supervised ML method, requiring alternative approaches such as unsupervised methods and transfer learning techniques which we will be exploring in the next few chapters.

2. **Clinical STS Dataset: MedSTS** <sup>13</sup>. MedSTS is another important STS benchmark dataset built on electronic clinical records (EHR). MedSTS contains 1,642 sentence pairs which were employed in Track 1 of National NLP Clinical Challenges (n2c2): Clinical Semantic Textual Similarity. Out of the 1,642 sentence pairs, 1,068 pairs were from the BioCreative/OHNLP 2018 shared task [17] <sup>14</sup> as well as 1,006 new pairs from two EHR systems, GE <sup>15</sup> and Epic <sup>16</sup>. Sentence pairs for BioCreative/OHNLP 2018 shared task have been extracted from Mayo Clinic’s clinical data warehouse [18].

The creators of the dataset have removed protected health information (PHI) in the sentences by employing a frequency filtering approach [19].

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<sup>13</sup>Clinical STS Dataset: MedSTS can be downloaded from <https://n2c2.dbmi.hms.harvard.edu/track1>.

<sup>14</sup>BioCreative/OHNLP shared task is available on <https://sites.google.com/view/ohnlp2018/home>

<sup>15</sup>GE Healthcare provides IT healthcare solutions that also includes EHR solutions and can be accessed from <https://www.gehealthcare.sa/products/healthcare-it/electronic-medical-records>

<sup>16</sup>Epic is a cloud-based EHR solution. More information can be viewed from their website <https://www.epic.com/>

Sentence Pair	Similarity
1. It has recently been shown that Craf is essential for Kras G12D-induced NSCLC. 2. It has recently become evident that Craf is essential for the onset of Kras-driven non-small cell lung cancer.	4
1. Up-regulation of miR-24 has been observed in a number of cancers, including OSCC. 2. In addition, miR-24 is one of the most abundant miRNAs in cervical cancer cells, and is reportedly up-regulated in solid stomach cancers.	3
1. These cells (herein termed TLM-HMECs) are immortal but do not proliferate in the absence of extracellular matrix (ECM) 2. HMECs expressing hTERT and SV40 LT (TLM-HMECs) were cultured in mammary epithelial growth medium (MEGM, Lonza)	1.4
1. The up-regulation of miR-146a was also detected in cervical cancer tissues. 2. Similarly to PLK1, Aurora-A activity is required for the enrichment or localisation of multiple centrosomal factors which have roles in maturation, including LATS2 and CDK5RAP2/Cnn.	0.2

Table 1.12: Example question pairs from the Arabic STS dataset. **Sentence Pair** column shows the two sentences. We also included their translations in the table. The translations were done by a native Arabic speaker. **Similarity** column indicates the averaged annotated similarity of the two sentences.

Once the sentence pairs have been selected two clinical experts have being asked to annotate each sentence pair on the basis of their semantic equivalence. The annotation guideline is similar to the annotation guidelines of the STS 2017 English dataset [9]. Table 1.13 and Table 1.14 shows some example sentence pairs from the dataset with the gold labels and their explanations. The machine learning models require to predict a value between



## 1.2. DATASETS

0-5 which reflects the similarity of the given sentence pair.

Sentence Pair	Relatedness
<p><i>The two sentences are completely equivalent as they mean the same thing.</i></p> <p>1. Albuterol [PROVENTIL/VENTOLIN] 90 mcg/Act HFA Aerosol 2 puffs by inhalation every 4 hours as needed.</p> <p>2. Albuterol [PROVENTIL/VENTOLIN] 90 mcg/Act HFA Aerosol 1-2 puffs by inhalation every 4 hours as needed 1 each.</p>	5
<p><i>The two sentences are completely equivalent as they mean the same thing.</i></p> <p>1. Discussed goals, risks, alternatives, advanced directives, and the necessity of other members of the surgical team participating in the procedure with the patient.</p> <p>2. Discussed risks, goals, alternatives, advance directives, and the necessity of other members of the healthcare team participating in the procedure with the patient and his mother.</p>	4
<p><i>The two sentences are roughly equivalent, but some important information differs/missing.</i></p> <p>1. Cardiovascular assessment findings include heart rate normal, Heart rhythm, atrial fibrillation with controlled ventricular response.</p> <p>2. Cardiovascular assessment findings include heart rate, bradycardic, Heart rhythm, first degree AV Block.</p>	3

Table 1.13: Example sentence pairs from the MedSTS dataset with their gold relatedness scores (on a 5-point rating scale) and explanations - Part I. **Sentence Pair** column shows the two sentence and **Relatedness** column denotes the annotated relatedness score.

Sentence Pair	Relatedness
<p><i>The two sentences are not equivalent, but share some details.</i></p> <p>1. Discussed risks, goals, alternatives, advance directives, and the necessity of other members of the healthcare team participating in the procedure with (patient) (legal representative and others present during the discussion).</p> <p>2. We discussed the low likelihood that a blood transfusion would be required during the postoperative period and the necessity of other members of the surgical team participating in the procedure.</p>	2
<p><i>The two sentences are not equivalent, but are on the same topic.</i></p> <p>1. No: typical 'cold' symptoms; fever present (greater than or equal to 100.4 F or 38 C) or suspected fever; rash; white patches on lips, tongue or mouth (other than throat); blisters in the mouth; swollen or 'bull' neck; hoarseness or lost voice or ear pain.</p> <p>2. New wheezing or chest tightness, runny or blocked nose, or discharge down the back of the throat, hoarseness or lost voice.</p>	1
<p><i>The two sentences are completely dissimilar</i></p> <p>1. The risks and benefits of the procedure were discussed, and the patient consented to this procedure.</p> <p>2. The content of this note has been reproduced, signed by an authorized</p>	0

Table 1.14: Example sentence pairs from the MedSTS dataset with their gold relatedness scores (on a 5-point rating scale) and explanations - Part II. **Sentence Pair** column shows the two sentence and **Relatedness** column denotes the annotated relatedness score.

## 1.3 Evaluation Metrics

While training a model is a key step, how the model generalizes on unseen data is an equally important aspect that should be considered in every machine learning model. We need to know whether it actually works and, consequently, if we can trust its predictions. This is typically called as *evaluation*. All of the datasets that we introduced in the previous section has what we call a *test* set. The machine learning models need to provide their predictions for the test set and the predictions will be evaluated against the true values of the test set.

There are three common evaluation metrics that are employed in Semantic Textual Similarity tasks, which we explain in this section. We will be using them to evaluate our models through out the first part of our research.

In the equations presented for each of the evaluation metrics, we represent the gold labels with  $X$  and predictions with  $Y$ . Therefore, a gold label in  $i^{th}$  position will be represented by  $X_i$  and a prediction in  $i^{th}$  position will be represented by  $Y_i$ .

1. **Pearson's Correlation Coefficient** - Correlation is a technique for investigating the relationship between two quantitative, continuous variables. Pearson's correlation coefficient ( $\rho$ ) is a measure of the strength of the linear association between the two variables. A value of +1 is total positive linear correlation between the variables, 0 is no linear correlation, and -1 is total negative linear correlation.

Pearson's Correlation Coefficient is one of the most common evaluation

metrics in STS shared tasks [7, 9, 11, 12, 13, 14]. A machine learning model with a Pearson's Correlation Coefficient close to 1 indicates that the predictions of that model and gold labels have a strong positive linear correlation and therefore, it is a good model to predict STS. Pearson's Correlation Coefficient equation is shown in Equation 1.1 where  $cov$  is the covariance,  $\sigma_X$  is the standard deviation of  $X$  and  $\sigma_Y$  is the standard deviation of  $Y$ .

$$\rho = \frac{cov(X, Y)}{\sigma_X \sigma_Y} \quad (1.1)$$

2. **Spearman's Correlation Coefficient** - Spearman's Correlation Coefficient ( $\tau$ ) is another common evaluation metric in STS shared tasks [7, 9, 11, 12, 13, 14]. It assesses how well the relationship between two variables can be described using a monotonic function. A monotonic relationship is a relationship that does one of the following:

- (a) as the value of one variable increases, so does the value of the other variable, *OR*,
- (b) as the value of one variable increases, the other variable value decreases.

But not exactly at a constant rate whereas in a linear relationship the rate of increase/decrease is constant. The fundamental difference between Pearson's Correlation Coefficient and Spearman's Correlation Coefficient is that the Pearson Correlation Coefficient only works with a linear relation-

ship between the two variables whereas the Correlation Coefficient works with the monotonic relationships as well. Spearman's Correlation Coefficient equation is shown in Equation 1.2 where  $D_i$  is the pairwise distances of the ranks of the variables  $X_i$  and  $Y_i$  and  $n$  is the number of elements in  $X$  or  $Y$ .

$$\tau = 1 - \frac{6 \sum D_i^2}{n(n^2 - 1)} \quad (1.2)$$

3. **Root Mean Squared Error** - Both Pearson's Correlation Coefficient and Spearman's Correlation Coefficient works only when both gold labels( $X$ ) and predictions ( $Y$ ) are continues. Therefore, in the datasets like Quora Question Pairs where the gold labels are discrete values, Root Mean Squared Error (RMSE) is preferred for evaluation than Correlation Coefficient values. RMSE measures the distance between the gold labels and the predictions. RMSE equation is shown in Equation 1.3 where  $n$  is the number of elements in  $X$  or  $Y$ .

$$rmse = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^n (Y_i - X_i)^2} \quad (1.3)$$

## 1.4 Contributions

The main contributions of this part of the thesis are as follows.

1. In each chapter, we cover various techniques to compute semantic similarity at the sentence level that can benefit the applications in the machine

translation domain.

2. We propose a novel unsupervised STS method that outperforms current state of the arts unsupervised STS methods in all the English datasets, non-English datasets and datasets in other domains.
3. We propose a novel Siamese neural network architecture model which is efficient and outperforms current Siamese neural network architectures in all STS datasets.
4. We provide important resources to the community. The code of the each chapter as an open-source GitHub repository and the pre-trained STS models will be freely available to the community. The link to the GitHub repository and the models will be unveiled in the introduction section of the each chapter.



## CHAPTER 2

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### STATE OF THE ART METHODS

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The biggest challenge that the neural based architectures face when applied to STS tasks is the small size of datasets available to train them. As a result, in many cases the networks cannot be trained properly. Given the amount of human labour required to produce datasets for STS, it is not possible to have high quality large training datasets. As a result researches working in the field have also considered unsupervised methods for STS. Recent unsupervised approaches use pretrained word/sentence embeddings directly for the similarity task without training a neural network model on them. Such approaches have used cosine similarity on sent2vec [20], InferSent [21], Word Mover’s Distance [22], Doc2Vec [23] and Smooth Inverse Frequency with GloVe vectors [24]. While these approaches have produced decent results in the final rankings of shared tasks, they have also provided strong baselines for the STS task.

This chapter explores the performance of three unsupervised STS methods - cosine similarity using average vectors, Word Mover’s Distance [22] and cosine similarity using Smooth Inverse Frequency [24] and how to improve them using contextual word embeddings which will be explained more in Section 2.1. The main contributions of this part of the thesis are as follows.



1. In the Related Work Section (Section 2.1), we cover three unsupervised STS techniques to compute semantic similarity at the sentence level.
2. We propose an improved unsupervised STS method based on contextual word embeddings.
3. The code with the experiments conducted will be publicly available to the community<sup>1</sup>.
4. We published the findings in this chapter in Ranasinghe et al. [25].

The rest of this chapter is organised as follows. Section 2.1 describes the three unsupervised STS methods we experimented in this section. In section 2.2 we present the methodology, the contextual word embeddings we used followed by the results to the English datasets comparing with the baselines. Section 2.3 and Section 2.4 shows how our method can be applied to different languages and domains and their results. The chapter finishes with conclusions and ideas for future research directions in unsupervised STS methods.

## 2.1 Related Work

Given that a good STS metric is required for a variety of natural language processing fields, researchers have proposed a large number of such metrics. Before the shift of interest in neural networks, most of the proposed methods relied

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<sup>1</sup>The public GitHub repository is available on <https://github.com/tharindudr/simple-sentence-similarity>

heavily on feature engineering. With the introduction of word embedding models, researchers focused more on neural representation for this task. The three unsupervised STS methods explored in this paper: Cosine similarity on average vectors, Word Mover’s Distance and Cosine similarity using Smooth Inverse Frequency are the most common unsupervised methods explored in STS tasks. Apart from them cosine similarity of the output from Infsent [? ], sent2vec [? ] and doc2vec [? ] have been used to represent the similarity between two sentences which we discuss in the next chapter.

### 2.1.1 Cosine Similarity on Average Vectors

The first unsupervised STS method that we used to estimate the semantic similarity between a pair of sentences, takes the average of the word embeddings of all words in the two sentences, and calculates the cosine similarity between the resulting embeddings. This is a common way to acquire sentence embeddings from word embeddings. Obviously, this simple baseline leaves considerable room for variation. Researches have investigated the effects of ignoring stopwords and computing an average weighted by tf-idf in particular.

### 2.1.2 Word Mover’s Distance

The second STS state of the arts method that we have considered is Word Mover’s Distance introduced by Kusner et al. [22]. Word Mover’s Distance uses the word embeddings of the words in two texts to measure the minimum distance that the words in one text need to “travel” in semantic space to reach the words in the other text as shown in Figure 2.1. Kusner et al. [22] says that this is a good

approach than vector averaging since this technique keeps the word vectors as it is through out the operation. We have investigated the effects of considering/ ignoring stop words before calculating the word mover's distance.

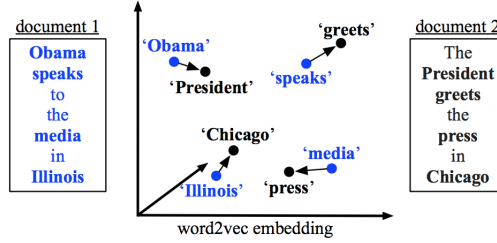


Figure 2.1: The Word Mover's Distance between two sentences

### 2.1.3 Cosine Similarity Using Smooth Inverse Frequency

The third and the last unsupervised STS method we have considered is to acquire sentence embeddings using Smooth Inverse Frequency proposed by Arora et al. [24] and then calculate the cosine similarity between those sentence embeddings. Semantically speaking, taking the average of the word embeddings in a sentence tends to give too much weight to words that are quite irrelevant. Smooth Inverse Frequency tries to solve this problem in two steps.

1. **Weighting:** Smooth Inverse Frequency takes the weighted average of the word embeddings in the sentence. Every word embedding is weighted by  $\frac{a}{a+p(w)}$ , where  $a$  is a parameter that is typically set to 0.001 and  $p(w)$  is the estimated frequency of the word in a reference corpus.
2. **Common component removal:** After that, Smooth Inverse Frequency com-

putes the principal component of the resulting embeddings for a set of sentences. It then subtracts their projections on first principal component from these sentence embeddings. This should remove variation related to frequency and syntax that is less relevant semantically.

As a result, Smooth Inverse Frequency downgrades unimportant words such as *but*, *just*, etc., and keeps the information that contributes most to the semantics of the sentence. After acquiring the sentence embeddings for a pair of sentences, the cosine similarity between those two vectors were taken to represent the similarity between them.

All of these STS methods are based on word embeddings/vectors. The main weakness of word vectors is that each word has the same unique vector regardless of the context it appears. For an example, the word "play" has several meanings, but in standard word embeddings such as GloVe [26], FastText [27] or Word2Vec [28] each instance of the word has the same representation regardless of the meaning which is used. As an example the word 'bank' in two sentences - "I am walking by the river bank" and "I deposited money to the bank" would have the same embeddings which can be confusing for machine learning models. The recent introduction of contextualised word representations solved this problem by providing vectors for words considering their context too. In this way the word 'bank' in above sentences have two different embeddings. Therefore, we explore how the contextualised word representations can improve the above mentioned unsupervised STS methods. The following contextualised word representation models were considered for the experiments. We will explain the

neural network architectures of these contextual word embeddings in Chapter 5. For this chapter, we considered these architectures as a black box where we just feed the words to get the embeddings. We considered these contextualised word representations mainly considering the popularity they had by the time we were doing the experiments.

1. **ELMo**<sup>2</sup> introduced by Peters et al. [29] use bidirectional language model (biLM) to learn both word (e.g., syntax and semantics) and linguistic context. After pre-training, an internal state of vectors can be transferred to downstream natural language processing tasks. ELMo vectors have been successfully used many natural language processing tasks like text classification [30], named entity recognition [31] which motivated us to explore ELMo in unsupervised STS methods. Also, we were aware about the fact that ELMo has been pre-trained on different languages [32] and different domains [33] which will be easier when we are adopting our methodology for different languages and domains in Sections 2.3 and 2.4.
2. **BERT**<sup>3</sup> introduced by Devlin et al. [4] might probably be the most popular contextualised word embedding model. In contrast to ELMo which uses a shallow concatenation layer [4], BERT employs a deep concatenation layer. As a result BERT is considered a very powerful embedding architecture. BERT has been successfully applied in many natural language processing

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<sup>2</sup>More details about ELMo can be viewed on <https://allennlp.org/elmo>

<sup>3</sup>The GitHub repository of BERT is available on <https://github.com/google-research/bert>

tasks like text classification [34], word similarity [35], named entity recognition [36], question and answering [37] etc. Similar to ELMo, BERT too has been widely adopted to different languages such as Arabic [38], French [39] etc. and different domains such as SciBERT [40] and BioBERT [41] etc.

3. **Flair**<sup>4</sup> is another type of popular contextualised word embeddings introduced in Akbik et al. [42]. It takes a different approach by using a character level language model rather than the word level language model used in ELMo and BERT. Flair also has been used successfully in natural language processing tasks such as named entity recognition [43], part-of-speech tagging [42] and has been widely adopted in to different languages and domains [42, 44].

Apart from using these contextual word embedding models individually we also considered **Stacked Embeddings** of these models together. Stacked Embeddings are obtained by concatenating different embeddings. According to Akbik et al. [42] stacking the embeddings can provide a powerful embeddings to represent words. Therefore, we experimented with several combinations of Stacked Embeddings.

Even though these contextual word embedding models have shown promising results in many natural language processing tasks, to the best of our knowledge none of these contextual word representations has been applied on unsupervised STS methods.

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<sup>4</sup>The GitHub repository of Flair is available on <https://github.com/flairNLP/flair>

## 2.2 Improving State of the Art STS Methods

As mentioned before we applied different contextual word embeddings on three unsupervised STS methods and their variants. First we experimented with English STS datasets we explained in Section 1.2. Our implementation was based on *Flair-NLP* Framework [45] which makes it easier to switch between different word embedding models when acquiring word embeddings. Also *Flair-NLP* has their own model zoo of pre-trained models to allow researchers to use state-of-the-art NLP models in their applications. For English, all of these contextualised word embedding models come with different variants like *small*, *large* etc.. Usually the larger models provide a better accuracy since they have been trained on a bigger dataset compared to the smaller models. However, this comes with the disadvantage that these larger models are resource-intensive than the smaller models. In order to achieve a better accuracy, we used the largest model available in each contextual word embedding models. We will describe them in the following paragraphs.

For ELMo we used the 'original (5.5B)' pre-trained model provided in Peters et al. [29] which was trained on a dataset of 5.5B tokens consisting of Wikipedia (1.9B) and all of the monolingual news crawl data from WMT<sup>5</sup> 2008-2012 (3.6B). Peters et al. [29] mentions that ELMo original (5.5B) has slightly higher performance than other ELMo models and recommend it as a default model. Using this model we represented each word as a vector with a size of 3072 values.

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<sup>5</sup>WMT: Workshop on Statistical Machine Translation is a leading conference in NLP that is being organised annually.

For BERT we used the 'bert-large-cased' pre-trained model. Compared to the 'bert-base-cased' model, this model provided slightly better results in all the NLP tasks experimented in Devlin et al. [4]. We represented each word as a 4096 lengthened vector using this model.

As suggested in Akbik et al. [42] the recommended way to use Flair embeddings is to stack pre-trained 'news-forward' flair embeddings and pre-trained flair 'news-backward' embeddings with GloVe [46] word embeddings. We used the stacked model to represent each word as a 4196 lengthened vector.

In the following list we show the performance of each unsupervised STS method with contextual word embeddings on different English STS datasets.

1. **Cosine Similarity on Average Vectors** - The first unsupervised STS method we tried to improve using contextual word embeddings is Cosine Similarity on Average Vectors which we explained on Section 2.1.

## 2.3 Portability to Other Languages

## 2.4 Portability to Other Domains

## 2.5 Conclusions





## CHAPTER 3

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### SENTENCE ENCODERS

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#### **3.1 Introduction**

[21]

#### **3.2 Related Work**

#### **3.3 Exploring Sentence Encoders in English STS**

#### **3.4 Portability to Other Languages**

#### **3.5 Portability to Other Domains**

#### **3.6 Conclusions**



## CHAPTER 4

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### SIAMESE NEURAL NETWORKS

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#### **4.1 Introduction**

[47]

#### **4.2 Related Work**

#### **4.3 MAGRU: Improving Siamese Neural Networks**

##### **4.3.1 Portability to Other Languages**

##### **4.3.2 Portability to Other Domains**

#### **4.4 Conclusions**



## CHAPTER 5

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### TRANSFORMERS

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#### **5.2 Related Work**

#### **5.3 Exploring Transformers in English STS**

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#### **5.5 Exploring Transformers for STS in Other Domains**

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# **Part II**

## **Applications - Translation Memories**





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#### **1.1 What is Translation Memory?**

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## **Part III**

# **Applications - Translation Quality Estimation**



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#### **2.1 Introduction**

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#### **2.2 Methodology**

#### **2.3 Results and Evaluation**



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