# 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

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# ABSTRACT

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

#### ACKNOWLEDGEMENTS

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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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# Part I

Semantic Textual Similarity

#### INTRODUCTION

#### 1.1 What is Semantic Textual Similarity?

#### 1.2 Related Work

#### 1.3 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 republicly available and can be considered as STS benchmarks.

#### 1.3.1 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 En-

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

tailment [1]. 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> [2] and the SemEval-2012 STS MSR-Video Descriptions dataset <sup>3</sup> [3]. 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 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 [1]. 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,

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

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

<sup>&</sup>lt;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/

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 [1].

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 [1]. 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.	4.7
2. A young girl is looking at a woman in costume.	4.7
1. Nobody is pouring ingredients into a pot.	3.5
2. Someone is pouring ingredients into a pot.	0.0
1. Someone is pouring ingredients into a pot.	2.8
2. A man is removing vegetables from a pot.	2.0
1. A man is jumping into an empty pool.	1.6
2. There is no biker jumping in the air.	1.0

Table 1.1: Example sentence pairs from the SICK dataset with their gold relatedness scores (on a 5-point rating scale).

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 [4]. 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 [3, 5, 6, 7, 8]. Once combined we had 8277 sentence pairs for training. More information about the datasets used to build the training set is available in Table 1.2.

On the other hand, a fresh test set of 250 sentence pairs was provided by SemEval-2017 STS Task organisers [4]. The Stanford Natural Language Inference (SNLI) corpus [9] was the primary data source for this test set. Similar to the SICK dataset, Each pair in the STS 2017 En-

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

glish 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 1.3 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 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 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

<sup>&</sup>lt;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>&</sup>lt;sup>7</sup>The Quora Question Pairs Dataset is available to download at http://qim.fs.quoracdn.net/quora\_duplicate\_questions.tsv

<sup>&</sup>lt;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

Year	Dataset	Pairs	Source
2012 [3]	MSRpar	1500	newswire
2012 [3]	MSRvid	1500	videos
2012 [3]	OnWN	750	glosses
2012 [3]	SMTnews	750	WMT eval.
2012 [3]	SMTeuroparl	750	WMT eval.
2013 [5]	HDL	750	newswire
2013 [ <mark>5</mark> ]	FNWN	189	glosses
2013 [ <mark>5</mark> ]	OnWN	561	glosses
2013 [ <mark>5</mark> ]	SMT	750	MT eval.
2014 [6]	HDL	750	newswire headlines
2014 [6]	OnWN	750	glosses
2014 [6]	Deft-forum	450	forum posts
2014 [6]	Deft-news	300	news summary
2014 [6]	Images	750	image descriptions
2014 [6]	Tweet-news	750	tweet-news pairs
2015 [7]	HDL	750	newswire headlines
2015 [7]	Images	750	image descriptions
2015 [7]	Ansstudent	750	student answers
2015 [7]	Ansforum	375	Q&A forum answers
2015 [7]	Belief	375	committed belief
2016 [8]	HDL	249	newswire headlines
2016 [8]	Plagiarism	230	short-answer plag.
2016 [8]	post-editing	244	MT postedits
2016 [8]	AnsAns.	254	Q&A forum answers
2016 [8]	QuestQuest.	209	Q&A forum questions
2017 [4]	Trial	23	Mixed STS 2016

Table 1.2: 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.

and did not use a separate annotation process. Their original sampling method has returned an imbalanced dataset with many more true examples of duplicate pairs than non-duplicates. Therefore, the organisers have supplemented the dataset with negative examples. One

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

Table 1.3: Example sentence pairs from the STS2017 English dataset with their gold relatedness scores (on a 5-point rating scale) and explanations.

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.

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

Table 1.4: 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.

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.

#### 1.3.2 Datasets on Other Languages

In order to evaluate the potability of our STS methods we used several non-English datasets through out the experiments which we describe below. 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 [4]. 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[4]. Table 1.5 shows more information about the trainin set. There were two sources for test set - Spanish news and Spanish Wikipedia dump having 500 and 250 sentence pairs respectively [4]. Both datasets were annotated with a relatedness score between 0 and 4. Table 1.6 shows few pairs of sentences with their similarity score.

Year	Dataset	Pairs	Source
2014 [6]	Trial	56	NR
2014 [6]	Wiki	324	Spanish Wikipedia
2014 [6]	News	480	Newswire
2015 [6]	Wiki	251	Spanish Wikipedia
2015 [7]	News	500	Sewswire
2017 [4]	Trial	23	Mixed STS 2016

Table 1.5: 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.

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

Sentence Pair	Similarity
1. Amás, los misioneros apunten que los númberos	
d'infectaos puen ser shasta dos o hasta cuatro veces	
más grandess que los oficiales.	
(Furthermore, missionaries point out that the numbers of	
infected can be up to two or up to four times larger than	0.6
$the \ official \ ones.)$	0.0
2. Los cadáveres de personas fallecidas pueden ser hasta	
diez veces más contagiosos que los infectados vivos.	
(The corpses of deceased people can be up to ten times	
$more\ contagious\ than\ those\ infected\ alive.)$	
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.	
(Police killed a cannibal while devouring a woman Matthew	
Williams, 34, was caught early in the morning biting the	2
face of a young woman he had invited to his hotel.)	2
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.	
(South Wales police killed a cannibal when he was eating the	
face of a 22-year-old woman in a hotel room.)	
1. Ollanta Humala se reúne mañana con el Papa Francisco.	
(Ollanta Humala meets tomorrow with Pope Francis.)	
2. El Papa Francisco mantuvo hoy una audiencia privada	3
con el presidente Ollanta Humala, en el Vaticano.	0
(Pope Francis held a private audience today with President	
Ollanta Humala, at the Vatican.)	

Table 1.6: 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.

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

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

Textual Similarity Multilingual and Cross-lingual Focused Evaluation [4]. 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 1.7.

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

Table 1.7: 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.

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 translation5 where they have performed post-editing to correct errors. STS labels have been then transferred to the 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 1.8 shows few pairs of sentences with

their similarity score.

Sentence Pair	Similarity
أحدهم يقلي لحما1	
Someone is frying meat.	0.250
أحدهم يعزف البيانو2	0.200
Someone plays the piano.	
أمرأة تظيف المكونات في الإناء1	
A woman cleaning ingredients in the bowl.	1.750
إمرأة تكسر ثلاثة بيضات في الإناء2	1.750
A woman breaks three eggs in a bowl.	
طفلة تعزف القيثارة1	
A Child is playing harp.	2.250
رجل يعزف القيثارة2	2.250
A man plays the harp.	
المرأة تقطع البصل الأخضر1	
The woman chops green onions.	3.250
إمرأة تقشر بصلة2	5.250
A woman peeling an onion.	
رجل يرقص على صقف الغرفة1	
A man dancing on the roof of the room.	4.600
رجل يرقص رأسا على عقب على السقف2	4.600
A man is dancing upside down on the ceiling.	

Table 1.8: 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.

#### 1.3.3 Datasets on Different Domains

1. Bio-medical STS Dataset - [10]

2. Clinical STS Dataset [11]

# 1.4 Applications

#### STATE OF THE ART METHODS

#### 2.1 Introduction

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- 2.2 Related Work
- 2.3 Improving State of the Art STS Methods
- 2.3.1 Portability to Other Languages
- 2.3.2 Portability to Other Domains
- 2.4 Conclusions

#### SENTENCE ENCODERS

#### 3.1 Introduction

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- 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

#### SIAMESE NEURAL NETWORKS

#### 4.1 Introduction

[14]

- 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

## Transformers

# 5.1 Introduction

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- 5.2 Related Work
- 5.3 Exploring Transformers in English STS
- 5.4 Exploring Transformers for STS in Other Languages
- 5.5 Exploring Transformers for STS in Other Domains
- 5.6 Conclusions

# Part II Applications - Translation Memories

## INTRODUCTION

1.1 What is Translation Memory?

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- 1.2 Datasets
- 1.3 Related Work
- 1.4 STS for Translation Memories

SENTENCE ENCODERS FOR TRANSLATION MEMORIES

# 2.1 Introduction

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- 2.2 Methodology
- 2.3 Results and Evaluation

# Part III

# Applications - Translation Quality Estimation

## INTRODUCTION

- 1.1 What is Translation Quality Estimation?
- 1.2 Datasets
- 1.3 Related Work

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1.4 STS for Translation Quality Estimation

TRANSQUEST: STS ARCHITECTURES FOR QE

# 2.1 Introduction

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- 2.2 Methodology
- 2.3 Results and Evaluation

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