

Using Part-of-Speech Tags as Deep-Syntax Indicators in Determining Short-Text Semantic Similarity

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Abstract. This paper presents POST STSS, a method of determining short-text semantic similarity in which part-of-speech tags are used as indicators of the deeper syntactic information usually extracted by more advanced tools like parsers and semantic role labelers. Our model employs a part-of-speech weighting scheme and is based on a statistical bag-of-words approach. It does not require either hand-crafted knowledge bases or advanced syntactic tools, which makes it easily applicable to languages with limited natural language processing resources. By using a paraphrase recognition test, we demonstrate that our system achieves a higher accuracy than all existing statistical similarity algorithms and solutions of a more structural kind.

Keywords: short-text semantic similarity, statistical similarity, corpus-based measures, part-of-speech tags, POS weighting, syntactic information, bag-of-words model, natural language processing.

1. Introduction

Determining the semantic similarity of short texts means assigning a certain metric to a given pair of texts based on the level of semantic matching between them. Semantic similarity systems provide a standard score between zero and one, where zero denotes complete semantic dissimilarity, and one full semantic equivalence. Short-text semantic similarity (STSS) is especially important since short texts are widely used on the Internet as search queries and results, comments on social networks, news headlines and snippets, product tags, etc.

The use of some measure of semantic similarity is vital in many problems within the field of natural language processing (NLP), such as text summarization, text categorization, question answering and information retrieval, machine translation, etc. For instance, in extractive text summarization, selecting the sentences to be included in the final text is a crucial phase. During this phase, particularly in multi-document summarization, it is essential to avoid choosing a sentence that carries the same information as the already selected ones [1]. In information retrieval or question answering systems, the information from the query can be phrased in a way different

from the one used in the document that contains the answer. Hence, taking those variations into account can lead to improvements in system performance [2].

There are two basic approaches to determining the semantic similarity of two words: the *topological* or *knowledge-based* one, which uses expert knowledge, and the *statistical* or *corpus-based* one, which uses a text corpus. Topological similarity determines the semantic relatedness between words by using hand-crafted ontologies like *WordNet* [3]. Since such structures are created by using expert human knowledge, they are able to model the degrees of semantic relatedness between words quite successfully when suitable distance metrics are applied. However, significant human effort is required to create resources of this kind, rendering the topological approach inapplicable to many minor languages or languages with scarce NLP resources. A recent study [4] found that there are currently around 40 projects to build wordnets for various languages. Only about a third of them are available under a free, open-source license, while a further third are free solely for academic research. In comparison, there are over 7000 languages spoken in the world today [5], 1300 of which are spoken by more than 100,000 people. Moreover, many existing wordnet projects are still in inception, with a rather limited number of words and synsets included, making them unsuitable for complex NLP tasks like STSS.

On the other hand, the only resource required in the implementation of statistical methods is a text corpus, which makes them widely and easily applicable. Statistical approaches to semantic similarity rely on the distributional hypothesis, which states that words with similar meanings tend to appear in similar contexts [6]. By applying this hypothesis to a large text corpus, it is possible to create a semantic space in the shape of a co-occurrence matrix. In this matrix every word found in the corpus has its own row and every context its own column. Cells of the matrix specify how many times each word appeared in each context. A context can usually be either a document from the corpus, or another word in whose proximity the given word appeared. In this way each word is assigned a context vector, which makes it possible to compare word meanings by comparing their vectors.

A newer statistical viewpoint is based on the probabilistic approach to semantics, which originates in the field of topic modeling [7]. Topic models treat each document within a text corpus as a mixture of corpus-wide topics, and each topic as a distribution over a certain vocabulary. Topic modeling algorithms use the textual documents to infer the distribution of topics in the corpus, the per-document topic proportions, and the per-word topic assignments. Since words can occur in multiple topics with different probabilities, they can be viewed in terms of their topic contributions. By comparing those contributions it is possible to compare word meanings.

Part-of-speech (POS) tags are probably the most commonly used type of syntactic information. Part-of-speech tagging is the process of labeling each word in a text as belonging to a particular part of speech, based both on its definition, as well as its surrounding context. Various other syntactic and semantic procedures for text analysis, such as chunking, parsing, and semantic role labeling, depend on the results of POS taggers. Determining a word's part of speech is a classification problem, which is why POS taggers are usually constructed by applying supervised machine learning to a text corpus that had been hand-annotated with the correct POS tags. English language POS taggers typically differentiate between 36 parts of speech (excluding the punctuation mark tags) which were standardized in the Penn Treebank Project [8].

This paper is organized as follows: in Section 2 we give an overview of current STSS systems. Section 3 outlines the main ideas of our approach and the motivation behind it, and presents certain existing algorithms and tools used within it. In Section 4 we describe the corpus processing procedures which we employed. Section 5 contains a detailed explanation and an example of the operation of our proposed system and the way it utilizes POS tags. In Section 6 we elaborate on the procedure used to train and optimize our model. Section 7 presents an evaluation of our method and a comparison to other approaches. Finally, in Section 8 we summarize our work and point towards possible system improvements and directions for future research.

2. Related Work

Numerous STSS solutions, both topological and statistical, already exist, and many of them use some form of syntactic information. In terms of their approach toward syntax, there are two main types of STSS systems:

1. Systems which ignore sentence structure by employing a *bag-of-words* technique. In this model, a sentence is treated as an unordered set of words, thereby ignoring the organization and interdependence of words within a sentence. These systems sometimes use shallow syntactic information, such as POS tags, but mostly in a superficial manner.
2. Systems which adopt a more structural approach to semantics by harnessing deep syntactic information. These systems use more advanced NLP tools like parsers and semantic role labelers.

In relation to STSS systems, there also exists an entire family of algorithms which deal with the issue of paraphrase identification, i.e. of determining whether sentences in a given pair are paraphrases of each other or not. Such algorithms commonly employ advanced machine learning classifiers and a wealth of features, oftentimes including syntactic ones, to arrive at a binary decision ([9], [10]). However, it should be pointed out that the task of generating a binary classification is a much more limited and easier one than the task of interval-based semantic gradation performed by STSS methods.

2.1. Bag-of-Words Models

Mihalcea et al. [11] proposed a notable bag-of-words approach which combines six knowledge-based metrics that use WordNet for determining the word-to-word similarities with two corpus-based algorithms into a unified measure. Since most of the word-to-word knowledge-based metrics cannot be applied across parts of speech, their method uses POS tags to prevent the pairing of words that do not belong to the same part of speech. The same POS tag usage can be found in the model of Fernando and Stevenson [12], who experimented with five different WordNet metrics. Similarly, Lintean and Rus [13] considered a bag-of-words model with which they tested LSA (*Latent Semantic Analysis*), a statistical algorithm, and a set of WordNet measures. They utilized POS tags in the same manner as [11] and [12], but they also considered a

weaker form of this restriction which relies only on basic word classes, e.g. verbs, and not on their subtypes like infinitives, past tenses, participles, etc.

Rus et al. [14] experimented with the same LSA algorithm alongside LDA (*Latent Dirichlet Allocation*), a topic modeling method, within a syntactically simpler approach in which no POS information is utilized. Quan et al. [15] devised another approach based on topic modeling, called TBS (*Topic Based Similarity*). It compares short texts on the basis of their common words, as well as the probabilities of their distinguishing terms under each probabilistic topic.

Ramage et al. [16] proposed a method that does not compare two bags-of-words directly but instead compares the distributions induced by each text when used as the seed of a random walk over a graph, which is constructed by using both WordNet and a text corpus. POS information is utilized during the graph construction phase, and as a part of text preprocessing, thus allowing the model to more accurately match the words in the given text with the nodes in the graph on which it operates.

Guo and Diab [17] also use POS tagging as a corpus preprocessing step within a latent semantic model of sentences called WTMF (*Weighted Textual Matrix Factorization*). Their method explicitly models the words that are not present in the sentences, but takes into account the fact that the missing words are not as informative as the observed ones.

The approach devised by Islam and Inkpen [18] does not employ POS tags but instead combines string similarity with corpus-based semantic similarity. They also experimented with the inclusion of a measure of the common-word order between the two given texts. Furlan et al. [19] modified their model to utilize the more advanced COALS (*Correlated Occurrence Analogue to Lexical Semantic*) statistical algorithm. Furlan et al. [20] further developed this method into a language-independent, corpus-based approach called LInSTSS which relies on term frequency weighting.

2.2. Structural Models

Structural solutions of the second kind include the one from Li et al. [21] which uses shallow parsing to divide each sentence into noun phrases (*NP*), verb phrases (*VP*), and preposition phrases (*PP*). Their method then compares the meanings of sentences by comparing the appropriate phrases within them, while individual word meanings are acquired through the use of WordNet. In addition, Li et al. experimented with a similar approach [22] in which sentences are compared based on the objects that appear in them, as well as the properties of those objects and their behavior. Shallow parsing is used to extract noun and verb phrases from each sentence. Their method groups the nouns from noun phrases as objects, the adjectives and adverbs from noun phrases as object properties, while verb phrases are grouped as object behaviors. The final similarity of sentences is determined as a sum of the similarities of these three groups, while the word-to-word similarities are calculated by using WordNet.

Oliva et al. [23] created SyMSS (*Syntax-based Measure for Semantic Similarity*) – a more complex topological model which utilizes a joint dependency parser and semantic role labeler to perform a deep syntactic analysis of each sentence. SyMSS is able to semantically compare words or phrases that have the same syntactic function in both sentences, and to reduce the final similarity score in situations where one sentence

contains certain syntactic structures not present in the other. Like [11], [12], and [13], Oliva et al. also experimented with various WordNet metrics, and employed POS information in a similar way.

Lee et al. [24] considered a combination of string similarity metrics similar to the ones used in [18] and a syntactic pattern matching mechanism which identifies subject-verb-object structures in each sentence. This mechanism relies on the use of a parser, while the word-to-word semantic similarities are determined by using WordNet. Lee et al. [25] also proposed a different topological method that treats a sentence as a sequence of links, each of which contains a specific meaning and connects a pair of words. In order to extract such links it uses a syntactic parser called Link grammar.

Furlan et al. [19] described a knowledge-based algorithm that employs a semantic net called *ConceptNet* as the word data model. They use a semantic role labeling module to extract subject-verb-object tuples from each sentence. Achananuparp et al. [26] proposed a way to address the syntactic variability of language expression by measuring the similarity of sentences via verb-argument structures. Such structures are obtained through semantic role labeling and the final similarity score is calculated as a sum of the similarities of verbs, determined by using WordNet, and their corresponding arguments.

Several structural solutions employ a weighting scheme of some kind, in which the similarities of different constituents are given different weights. This is accomplished by weighting according to semantic roles ([19], [23]), phrase types [21], or a combination of phrase types and word types [22]. In some methods weighting is an optional component whose effects were not explored [24]. Other authors concluded that their methods perform best when equal weighting is utilized [26].

3. Proposed Method

The central idea of our proposed method is that certain parts of speech and certain relationships between different parts of speech are semantically more important than others, not only inherently, but also due to the roles they commonly play within a sentence. By taking account of this notion, our STSS system is able to utilize POS tag information as an indicator of the deeper underlying syntactic structure.

3.1. Motivation

It is rather intuitive that not all elements of a sentence carry the same amount of semantic information. For instance, let us consider the following sentences:

1. *I drank some coffee.*
2. *I drank some milk.*
3. *I bought some milk.*

Most people would agree that the semantic distance between the first and the second sentence is smaller than the one between the second and the third. This is because human similarity is strongly affected by verb similarity and less so by object similarity [27]. This difference in semantic salience also exists between other constituents.

Hence, the use of weighting strategies in some of the existing STSS systems does have a sound justification. However, such a strategy has, so far as we know, never been implemented solely on the part-of-speech level. All existing STSS systems that employ weighting are structural ones. They use advanced syntactic tools – parsers and semantic role labelers – to delineate constituents by harnessing deeper syntactic information.

As far as the existing bag-of-words methods are concerned, almost all of them either do not utilize POS tags at all, or they do so rather superficially and usually in order to prevent the pairing of words belonging to different parts of speech. This usage, though logical at first glance, can in fact easily lead to errors. Let us consider, for example, the following sentence pair:

- *He is a diligent worker.*
- *He works diligently.*

Although these two sentences carry the same meaning, the combination of an adjective and a noun from the first sentence (*diligent worker*) is replaced by a combination of a verb and an adverb in the second (*works diligently*). In such cases, it would be a mistake to forbid the pairing of words (*worker, works*) and (*diligent, diligently*), even though the words comprising those pairs belong to different parts of speech. Similar examples can be found in pairs of sentences where one sentence is in the active and the other in the passive voice:

- *They finished constructing the bridge.*
- *The construction of the bridge was finished.*

The words *constructing* and *construction* do not belong to the same part of speech, but it is clear that the pairing of those words is appropriate and should not be prohibited.

3.2. POST STSS

Our method, which we call POST STSS (*POS-tag-supported STSS*), combines a weighting strategy based on POS tags with a bag-of-words approach. Although POS tags offer only a shallow representation of sentence structure, we argue that through their use it is possible to obtain much of the information usually provided by the more complex, but also more error-prone NLP tools. In addition, we recognize the merits of allowing the coupling of certain parts of speech and disallowing the pairing of others, but we handle such rules much more carefully than did the previous STSS solutions.

Since we aimed at creating a general STSS method that could be applied even to languages with scarce NLP resources, we opted for a statistical similarity model. We chose to base our method on the approach proposed by Islam and Inkpen [18], since the string similarity measure which they included in the final similarity score allows their model to perform better when dealing with different forms of infrequent proper nouns. Furthermore, we decided to utilize the COALS algorithm for determining the word-to-word semantic similarity, as suggested by Furlan et al. [19], since it is able to better predict human similarity judgments than older algorithms like LSA [28]. An integral part of COALS is an algebraic operation called SVD (*Singular Value Decomposition*) which, through matrix factorization and decomposition, is able to reduce the generated semantic space to a lower dimension, rendering the whole algorithm more scalable. We

utilized the algorithm implementation provided by the *S-Space* package [29], with the default setting of 14000 for the initial size of the co-occurrence matrix. Its dimensionality is then reduced to 800 through SVD.

For text preprocessing we used the Stanford *CoreNLP* package [30]. This suite encompasses many NLP tools, including a tokenizer, a sentence splitter, a lemmatizer, a POS tagger, a named entity recognizer, a dependency parser, and a coreference resolution tool. They are all tied together in a modular fashion, making it easy to take advantage of the more advanced functions, if needed. In our system we utilized only the tokenizer, the sentence splitter, the lemmatizer, and the POS tagger. The POS tagger is based on a log-linear approach and achieves an accuracy of over 97% [31].

4. Corpus Processing

The text corpus chosen for the creation of the POST STSS system needed to be sufficiently large, topically diverse, and publicly available, which is why we selected the English Wikipedia abstract corpus. This corpus contains short text summaries of all the articles present in the English Wikipedia. Its size, at the time, was around 3.7 GB. Since the corpus is available as an XML file which, aside from the abstracts, also includes other irrelevant information, we had to scan through the file to extract the useful data. We then cleaned the text by eliminating all numbers and words that contain numbers, by removing all punctuation marks, and by normalizing all letters into lower case.

We tested two text preprocessing procedures on our system: stemming and lemmatization. Stemming is a transformation in which a given word is stripped of its suffixes, thereby reducing it to its *stem*. In this manner, multiple different words can be normalized into a single morphological form, thus reducing the overall number of different words. Hence, the application of stemming to a text corpus ultimately leads to the creation of a smaller semantic space. This can, in effect, reduce the overall computational costs. In our system we utilized the standard Porter stemmer [32].

Despite their advantages, stemmers also have their drawbacks, like their inability to cope with prefixes. However, the biggest issue concerning stemmers is their propensity to make mistakes. For instance, the words *animal*, *animation*, and *animism*, although semantically diverse, will all be reduced to a single stem – *anim*. While such errors are the exception rather than the rule, numerous other examples can be found. In a semantic space, these mistakes can trigger the merger of words which have completely unrelated meanings, consequently having a detrimental effect on system performance. These problems are further exacerbated when working with highly inflectional languages.

That is why we also considered lemmatization, a more advanced word transformation. Lemmatization is the process of determining the *lemma*, or dictionary form, of a given word. This allows different inflected forms of a word to be treated like a single item. For example, lemmatization reduces the past participle, present participle, and all other inflected forms of a verb to its base form. This can be of particular value when dealing with words with irregular inflections, like the verb *to be*, for which a stemmer would generate multiple stems. Due to their different approach, lemmatizers are not limited to dealing with suffixes, and do not lead to the merger errors that stemmers can produce.

Still, unlike stemmers, which operate on individual words with no knowledge of the surrounding context, lemmatizers have to be able to discriminate between words that can have different meanings depending on their part of speech. Thus, a POS tagger is required for their operation. Since we devised our STSS model around using POS tags, it was simple to add lemmatization to it, via the appropriate Stanford CoreNLP module.

After stemming or lemmatizing our text corpus, we created the semantic space by supplying the processed corpus to the COALS algorithm. The produced semantic space was saved to the hard drive in the Sparse Text format, defined in the S-Space package.

5. System Operation

The POST STSS approach employs the method proposed in [18] of matching each word in the shorter text P to its most similar counterpart in the longer text R , and then adding up the individual similarity scores, based on both the string and the semantic similarity, into a unified measure. We improve this method by weighting word similarity scores using values determined on the basis of both words' POS tags.

Determining the semantic similarity of two short texts begins by creating annotation modules from the Stanford CoreNLP package for tokenizing, sentence splitting, part-of-speech tagging, and lemmatizing, and applying them to both texts. Properly identifying the placement of sentence boundaries in a given short text is important for the proper functioning of POS tagging. Words are tokenized, and POS tagging is subsequently performed. Tokens are then either stemmed or lemmatized. Finally, all tokens containing numbers or other non-alphabetic characters are excluded from further consideration, thus generating the processed texts and their POS tag sequences. The number of tokens in the shorter text P will hereafter be referred to as m , while the number of tokens in the longer text R will be n .

We then identify the words which appear in both texts, whose count we will refer to as d . Since those words are identical in both P and R , both their string and semantic similarities are maximal. Hence, their final similarity measures depend only on their POS tags. We describe the precise manner of POS weighting in Section 5.3. The scores of all of the words appearing in both texts are added up into a similarity sum S_{same} .

The remaining $m - d$ and $n - d$ words from both texts are used to construct three $(m - d) \times (n - d)$ matrices in which the remaining words from the shorter text P are assigned to the rows of the matrix, whereas the columns of the matrix represent words from the longer text R . These matrices are:

1. The string similarity matrix;
2. The semantic similarity matrix;
3. The POS weighting matrix.

5.1. String Similarity

In the *string similarity matrix* each cell has a value between zero and one that represents the level of string similarity between the row-word and the column-word, where zero indicates completely different string contents, and one full string equality. In the same

way as [18], we calculate this similarity score by combining the following three modifications of the LCS (*Longest Common Subsequence*) metric:

- NLCS – Normalized Longest Common Subsequence;
- NMCLCS₁ – Normalized Maximal Consecutive Longest Common Subsequence starting at character 1;
- NMCLCS_N – Normalized Maximal Consecutive Longest Common Subsequence starting at character N.

Unlike the LCS where consecutiveness is not required, the second and the third modification only search for the longest *consecutive* common subsequence. The second algorithm searches for the maximal consecutive portion of the shorter string that consecutively matches with the longer string, where matching starts from the first character in both strings. The third algorithm does the same, but allows the matching to start at any character in both strings. In all three modifications the basic similarity value is divided by the length of both strings compared, thereby normalizing the score. The final string similarity score is gained by summing the individual scores of these three metrics, while giving each an equal weight.

5.2. Semantic Similarity

In the *semantic similarity matrix* each cell has a value that represents the level of semantic similarity between the row-word and the column-word. We obtain this score by taking the context vectors of the two words being compared and calculating their cosine similarity. The context vectors are extracted from the semantic space generated by COALS. A score of zero indicates total semantic dissimilitude while a score of one signifies a complete semantic match. COALS can also produce negative similarity scores for certain vector pairs, as a side effect of the SVD operation, but this occurs relatively rarely [28]. As far as we have noticed, such scores tend to have low absolute values. We experimented with setting those scores to zero, but found no performance benefit from doing so and, hence, we ultimately retained them.

5.3. POS Weighting

In the *POS weighting matrix* each cell has a value given by our POS weighting method to the POS tags of the word pair which consists of the row-word and the column-word. This value reflects the relative importance/unimportance of the given parts of speech, as well as the significance of their interaction in determining short-text semantic similarity. Given the number of POS tags used in English, as well as the considerably higher number of combinations of interactions between them, it is infeasible to manually compile an optimal list of such values. Although a solution based on certain linguistic intuitions and general approximations could be constructed, a set of training data is required in order to optimize system performance on a given task. This learning process is described in detail in Section 6.

Our POS weighting method uses a set of weights for different POS tags and a POS interaction matrix. The POS interaction matrix is a symmetric matrix which consists of binary values specifying for any two diverse tags whether the coupling of words that have those tags assigned to them should be allowed or not. In other words, the POS interaction matrix determines which diverse part-of-speech couplings are allowed and which are forbidden.

When comparing two words that belong to the same part of speech we simply place the weight for that part of speech in the appropriate cell of the POS weighting matrix. On the other hand, in situations when the words being compared belong to different parts of speech, a lookup is performed within the POS interaction matrix. If the binary value assigned to a given coupling is zero, a zero weight is written to the appropriate cell of the POS weighting matrix, which effectively prohibits that coupling. Conversely, if the binary value is one, the POS weighting matrix cell is given a value determined by a *POS weighting function* which uses the respective POS weights. We experimented with the following five forms of this function:

1. Choosing the higher POS weight of the two;
2. Choosing the lower POS weight of the two;
3. Calculating the arithmetic mean of the two POS weights;
4. Calculating the geometric mean of the two POS weights;
5. Calculating the harmonic mean of the two POS weights.

The exact form of this function is chosen during the training process. This selection is elaborated upon in Section 6.3.

The same method of POS weighting is also applied to words that appear in both given texts. However, in their case the POS weighting score is not written to a matrix cell but instead represents their final similarity score.

5.4. Final Similarity Calculation

The string similarity, the semantic similarity, and the POS weighting matrices are then combined into one as follows: We first combine the string and the semantic similarity matrices by multiplying their values with the relative weights given to the word-to-word string and semantic similarities and then adding them up. These relative weights are global, i.e. not word-specific, they add up to one, and their optimal values are determined during the training phase. Afterwards, we multiply each cell of this new matrix with its corresponding cell in the POS weighting matrix. Thus, we gain a similarity measure for each word pair according to the following expression:

$$Sim(i, j) = (w_{str} \times String(i, j) + w_{sem} \times Semantic(i, j)) \times POS(i, j) \quad (1)$$

where $String(i, j)$ represents the string similarity score of the words in the i -th row and the j -th column, $Semantic(i, j)$ stands for their semantic similarity score, and $POS(i, j)$ represents the POS weighting score assigned to them based on their respective POS tags. The relative weights w_{str} and w_{sem} are given to the word-to-word string and semantic similarities, where $w_{str} + w_{sem} = 1$.

Once we have created the final similarity matrix, we proceed to extract the best word pairs on the basis of it. We do so by finding the matrix cell with the highest score and adding it to a similarity sum $S_{different}$. We then pair the row-word and the column-word of that cell, after which we discard the entire row and column from the matrix. By doing this, we remove from further consideration all other word pairs in which words from the chosen pair appeared. Hence, we only allow a word from text P to be paired with a word from text R once. We repeat this procedure until there are no more matrix rows left.

To obtain the final similarity score of texts P and R we add up the scores S_{same} and $S_{different}$. As in [18], we then normalize them by using the reciprocal harmonic mean of m and n , the lengths of the two texts:

$$S(P, R) = \max\left((S_{same} + S_{different}) \frac{m+n}{2mn}, 1 \right) \quad (2)$$

In addition, in order to gain a final similarity between zero and one, we place an upper limit on the score value. We do this because the similarity score can theoretically exceed the value of one if we are comparing texts containing only those words whose POS weights are higher than one. However, no such instances occurred in practice during our evaluation since real-life examples always include function words and other word types whose lower POS weights decrease the similarity score.

5.5. Example

We will demonstrate the functioning of the POST STSS method on a pair of sentences from the *Microsoft Research Paraphrase Corpus* [33]. Table 1 contains the original sentences, their preprocessed and lemmatized forms, and their POS tag sequences.

Table 1. An example sentence pair from the Microsoft Research Paraphrase Corpus

1	Houston	fourth-graders	also	performed	similarly
	houston	fourth grader	also	perform	similarly
	NNP	JJ NNS	RB	VBD	RB
1	to	national	peers	in	writing
	to	national	peer	in	write
	TO	JJ	NNS	IN	VBG
2	New	York	City	and	Houston
	new	york	city	and	houston
	NNP	NNP	NNP	CC	NNP
2	fourth-graders	were	at	the	national
	fourth grader	be	at	the	national
	JJ NNS	VBD	IN	DT	JJ
2	average	in	writing		
	average	in	write		
	NN	IN	VBG		

These sentences were classified by human annotators as semantically different. Their meanings are actually rather similar, though worded differently, but the second sentence includes information about New York City students, which is not present in the first one.

All system parameters used in this example are the ones gained by training our model on the training part of the Microsoft Research Paraphrase Corpus. We describe this training process in detail in Section 6.

For the sake of convenience, we listed all POS weights used in this example and their respective POS interaction values in Table 2. The entire list of POS weights that our trained model utilizes is shown in Table 11, Section 7.3, while the entire configuration of the POS interaction matrix is given in Figure 1, in the same section. The chosen POS weighting function is the calculation of the arithmetic mean of the two POS weights.

Table 2. POS weights and POS interaction values used in this example

	CC	DT	IN	JJ	NN	NNS	NNP	RB	TO	VBD	VBG
	0.7	0.7	0.7	0.7	0.8	1.0	0.8	1.3	0.8	1.2	1.1
CC	1	1	0	0	0	0	0	0	1	1	1
DT	1	1	0	1	0	0	0	0	1	1	0
IN	0	0	1	0	1	0	0	1	1	1	0
JJ	0	1	0	1	0	0	0	1	0	1	1
NN	0	0	1	0	1	0	1	1	0	1	1
NNS	0	0	0	0	0	1	1	1	0	1	1
NNP	0	0	0	0	1	1	1	1	0	1	1
RB	0	0	1	1	1	1	1	1	0	0	0
TO	1	1	1	0	0	0	0	0	1	1	1
VBD	1	1	1	1	1	1	1	0	1	1	1
VBG	1	0	0	1	1	1	1	0	1	1	1

After preprocessing and lemmatization, the first sentence contains 11 tokens and the second 14. Hence, $n = 14$ and $m = 11$. There are 6 identical tokens in both sentences – *houston, fourth, grader, national, in, write*. Therefore, $d = 6$.

The scores of these words depend only on their POS tag weights. If such a word has the same POS tag in both sentences, then its score is equivalent to the weight of its tag. Otherwise, its score is either equal to zero, if the pairing of the two different tags assigned to the word is prohibited, or is equal to the POS weighting function of its two tags, if the pairing of those tags is permitted.

To illustrate, the score of the word *write* is 1.1, since it appears in both sentences with a VBG tag, whose weight is 1.1. On the other hand, it could have been the case that in one of the sentences the word *write* appeared as a verb in the past tense (tag VBD), and in the other as a gerund/present participle (VBG). The POS interaction value for these two tags is one, meaning that their coupling is permitted. Since the weight of the VBD tag is 1.2 and the weight of the VBG tag is 1.1, the score of the word *write* would have been calculated as the arithmetic mean of these two values, which is 1.15.

The scores of all the words appearing in both sentences are then added up into a similarity sum S_{same} . In this example, that sum would be $S_{same} = 5.0$.

For the remaining words in both sentences we create three 5×8 matrices in which the words from the shorter sentence are assigned to the rows of the matrix, whereas the

columns of the matrix represent words from the longer sentence. These matrices are: the string similarity matrix, shown in Table 3; the semantic similarity matrix, shown in Table 4; and the POS weighting matrix, shown in Table 5. The actual values in the matrices always depend on the particular words being considered. The semantic similarity scores also depend on the text corpus chosen to create the semantic space.

These matrices are then combined into a final similarity matrix, shown in Table 6. The values in each cell of the final matrix are calculated according to formula (1). Our trained model utilizes the same weight of 0.5 for both the string and the semantic similarity, which is also the value used in this example.

Table 3. The string similarity matrix

	new	york	city	and	be	at	the	average
also	0.000	0.041	0.000	0.083	0.000	0.124	0.000	0.035
perform	0.031	0.094	0.000	0.000	0.047	0.000	0.031	0.054
similarly	0.000	0.018	0.046	0.024	0.000	0.037	0.000	0.026
to	0.000	0.083	0.083	0.000	0.000	0.165	0.165	0.000
peer	0.055	0.041	0.000	0.000	0.083	0.000	0.055	0.094

Table 4. The semantic similarity matrix

	new	york	city	and	be	at	the	average
also	-0.033	0.023	0.052	0.100	0.240	0.018	-0.003	-0.058
perform	-0.097	-0.045	-0.031	0.225	0.031	0.106	-0.010	0.074
similarly	-0.051	-0.070	-0.032	0.081	0.018	0.047	0.006	0.080
to	-0.053	-0.142	-0.085	0.170	0.067	0.016	0.007	0.152
peer	-0.052	-0.056	-0.101	0.149	0.071	-0.003	-0.063	0.025

Table 5. The POS weighting matrix

		new	york	city	and	be	at	the	average
		NNP	NNP	NNP	CC	VBD	IN	DT	NN
also	RB	1.05	1.05	1.05	0.00	0.00	1.00	0.00	1.05
perform	VBD	1.00	1.00	1.00	0.95	1.20	0.95	0.95	1.00
similarly	RB	1.05	1.05	1.05	0.00	0.00	1.00	0.00	1.05
to	TO	0.00	0.00	0.00	0.75	1.00	0.75	0.75	0.00
peer	NNS	0.90	0.90	0.90	0.00	1.10	0.00	0.00	0.00

Table 6. The final similarity matrix

	new	york	city	and	be	at	the	average
also	-0.017	0.034	0.027	0.000	0.000	0.071	0.000	-0.012
perform	-0.033	0.024	-0.016	0.107	0.047	0.050	0.010	0.064
similarly	-0.027	-0.027	0.008	0.000	0.000	0.042	0.000	0.056
to	0.000	0.000	0.000	0.064	0.033	0.068	0.064	0.000
peer	0.001	-0.007	-0.045	0.000	0.085	0.000	0.000	0.000

We extract the best word pair from the final similarity matrix by finding the maximum-valued matrix element. We add the value of that element to a similarity sum $S_{different}$ and then we remove the entire row and the entire column of that element from the matrix. The process is repeated as long as there are matrix rows left. The values extracted from the final similarity matrix are marked in bold script. The $S_{different}$ sum would in this case be $S_{different} = 0.383$.

Our approach is based on a bag-of-words model, so it is incapable of pairing entire phrases, such as “*similarly to national peers*” and “*at the national average*”. However, since our trained model mostly allows the pairings of words belonging to different parts of speech, it is able to pair the adverb “similarly” in the first phrase with the noun “average” in the second phrase, which is, arguably, the most appropriate choice here.

The final similarity score is found by using the formula (2) and its value is $S(P, R) = 0.437$. Our trained model utilizes a paraphrase detection threshold of 0.5, which means that this sentence pair has correctly been identified as one in which sentences are highly related, but not to the extent that they could be viewed as paraphrases. As an illustration, the score of this sentence pair would have been 0.519 had POS weighting not been used, leading to its misclassification by the system. This highlights the importance of POS weighting in giving a more realistic assessment of semantic similarity.

6. Parameter Optimization

In order to obtain an optimal configuration of parameters for a given task, it is necessary to train the POST STSS model on a particular dataset. The optimization procedure must be performed only once for any given task, after which the system can function indefinitely using the obtained optimal parameters. Our training algorithm optimizes three types of parameters:

1. POS weights;
2. POS interaction matrix values;
3. Relative weights of the string and the semantic similarities.

We sought to keep the average similarity score around the mean value of 0.5 in an effort to prevent the general distribution of scores from becoming unbalanced. Since our model multiplies a similarity score by a weighting value, we used a POS weight range of [0.7, 1.3], which is both centered on the neutral value of one and symmetrical with regard to it. In effect, our POS weighting can increase or decrease the similarity score of a word pair by 30% at most. This particular choice was a trade-off between the preference for a broad range of weights and the need to keep the length of the training process manageable.

The relative weights of the string and the semantic similarities always add up to one. As a result, they can actually be optimized in terms of a single value in the range of [0, 1]. We chose to optimize the string similarity weight w_{str} while the semantic similarity weight w_{sem} was calculated as $w_{sem} = 1 - w_{str}$.

In order to avoid overfitting to the training data we decided to utilize a relatively coarse step value of 0.1 in altering both the POS weights and the string similarity weight. This step value is used throughout our algorithm.

6.1. Dimensionality

The main problem in optimizing our model lies in its dimensionality. The Penn Treebank Project defined 36 different POS tags for the English language, which means that the POS interaction matrix contains $36 \times 36 = 1296$ cells. However, since semantic similarity is a symmetric relation, the POS interaction matrix is symmetric as well. Furthermore, it is logical to always permit the coupling of words belonging to the same part of speech, rendering the values along the main diagonal irrelevant. Consequently, there are 630 distinct binary values within the POS interaction matrix that ought to be determined. Taking into account the number of variables and their respective ranges of values, the size of the search space is given by the following expression:

$$\text{Full Search Space Size} = 7^{36} \times 2^{630} \times 11 \quad (3)$$

Clearly, an exhaustive search is impossible, given the enormous number of combinations. We tackled this problem by partially optimizing the parameters in a lower-dimensional search space and then continuing on from that semi-optimized point in the full-sized search space.

The lower-dimensional search space we used was based on aggregating several related POS tags into broader classes. We utilized six such categories:

1. Nouns – includes common nouns in the singular (*NN*) and the plural (*NNS*), as well as proper nouns in the singular (*NNP*) and the plural (*NNPS*). We also put nouns tagged as numerals (*CD*) in this category. Still, this does not include numeric tokens, since they are discarded in the preprocessing steps.
2. Verbs – includes verbs in their base form (*VB*), the past tense (*VBD*), and the present tense (*VBP*, *VBZ*), as well as present participles/gerunds (*VBG*), past participles (*VBN*), modals (*MD*), and particles (*RP*).
3. Adjectives – includes adjectives in their base (*JJ*), comparative (*JJR*), and superlative (*JJS*) forms.
4. Adverbs – includes adverbs in their base (*RB*), comparative (*RBR*), and superlative (*RBS*) forms, as well as Wh-adverbs (*WRB*).
5. Pronouns – includes personal (*PRP*) and possessive pronouns (*PRP\$*), as well as their Wh- counterparts (*WP*, *WP\$*).
6. Others – includes the remaining 12 tags (*CC*, *DT*, *EX*, *FW*, *IN*, *LS*, *PDT*, *POS*, *SYM*, *TO*, *UH*, *WDT*).

The reasoning behind this approach is that the model should first be allowed to learn the relative importance of and interactions between general word classes. Only then should the focus shift toward the specificities of individual POS tags. For instance, it ought to be possible to detect whether, generally speaking, nouns are semantically more salient than adjectives and whether the pairing of these word classes in the context of STSS is sensible. These general conclusions can then be particularized with regard to the individual tags within these broader categories.

Our lower-dimensional search space uses 6 different POS weights instead of 36, and its POS interaction matrix contains 15 distinct binary values that ought to be optimized. Hence, the size of the reduced search space is as follows:

$$\text{Reduced Search Space Size} = 7^6 \times 2^{15} \times 11 \quad (4)$$

Although this reduction significantly contains the combinatorial explosion, an exhaustive search still remains intractable. Therefore, our training procedure consists of the following two phases:

1. Pseudo-exhaustive searching in the lower-dimensional search space;
2. Steepest ascent hill climbing with momentum in the full-sized search space.

6.2. Pseudo-exhaustive Search

The idea of pseudo-exhaustive searching is to search exhaustively only among those parameter values which have some likelihood of being the optimal ones. We begin by choosing a single initial value for all POS weights, as well as a starting binary value for all the cells within the POS interaction matrix. An initial string similarity weight is also chosen. Finally, we select a POS weighting function among the five described in Section 5.3. We note the performance of the system on the training data with these initial settings, via a chosen metric.

We then explore all possible pairings of POS categories. We sequentially select a pairing and iterate over all combinations of POS weights for the word classes in the pair. While doing this, we fix to their initial values the weights of other word classes, the POS interaction matrix contents, and the string similarity weight. We then invert the POS interaction matrix bit of the pair that is being considered and repeat the process. In other words, we freeze the model in its initial state and only iterate over the changes of POS weights of the two given word classes and the changes of their respective POS interaction bit. Once a word class pairing has been explored, we reset the model to its initial state and start exploring another one. We do this for all possible pairings.

While iterating, we evaluate the model on the training data. For each pairing we note the POS weights and the respective POS interaction bit that maximized system performance. Since there are 15 different pairings possible in our lower-dimensional model, the size of the search space is quite manageable:

$$\text{Word Class Pairing Search Space Size} = 7^2 \times 2 \times 15 \quad (5)$$

The motivation for this procedure is to observe in isolation the interplay between any two word classes and the relative importance of one with regard to the other. If a particular POS weight for a particular word class was not detected as optimal in any of the pairings, then it is highly unlikely that such a value would ultimately lead to optimal system performance. Consequently, we discard it from further consideration, thereby reducing the number of combinations to explore in the next step of the search process. Similarly, if a certain POS interaction value leads to worse performance than the other, we simply remove it from further consideration. Still, there can be more than one optimal combination of parameters for many pairings. For instance, a {0.7, 1.1} combination of POS weights with a POS interaction value of zero might perform just as well as a {0.8, 1.0} combination with a POS interaction value of one.

This approach presupposes that it is possible to accurately observe the interaction between two word classes in isolation. In effect, we assume that the choice of optimal weights and POS interaction bits for the entire model can be divided into a number of entirely separate decisions for each word class pairing. This assumption is obviously problematic, but it allows us to significantly reduce the search space and, ultimately, leads to promising results.

We then compile a list of candidate weights for each word class by going through the pairings in which it participated and collecting its optimal weights. The candidate values for each POS interaction matrix cell are simply the optimal POS interaction bit(s) from the respective word class pairing.

We exhaustively iterate over all combinations of candidate values for all POS weights and POS interaction bits. We do this while still keeping the string similarity weight fixed to its initial value. In each iteration we evaluate the model on the training data. At the end of the search we select those POS parameters which maximized system performance. The exact size of the search space in this stage is impossible to determine in advance, since it depends on the results of the previous step, but in our experience it can range from as low as 50 to as high as a couple of thousand. Nevertheless, this is still much smaller than the entire reduced search space whose size is on the order of $\sim 10^{10}$.

In the final step of our pseudo-exhaustive search, we iterate over all possible values of the string similarity weight (from zero to one, with a step of 0.1) for each of the best-performing POS parameter sets from the previous stage. Since there are usually only one or two of them, this process is executed quickly. Again, in each iteration we evaluate the model on the training data. The full parameter combination(s) which maximized system performance is/are presented as the output of the pseudo-exhaustive search and is/are used as a starting point in the second phase of our training procedure – hill climbing.

We also experimented with applying a *value minimization* process to that output before starting the climb. The idea is that, depending on the set of initial conditions used in the search, certain POS weights might remain needlessly high and certain POS interactions might remain needlessly permitted, thereby obscuring the truly relevant POS interactions and weight values. To remedy this, our value minimization iterates over all POS weights and attempts to lower their values, if they are not already at the 0.7 minimum and if such changes do not diminish system performance on the training data. It also iterates over all bits of the POS interaction matrix and attempts to set them to zero, prohibiting the pairing of the respective word classes, if such modifications do not diminish system performance. The decision whether to use value minimization was one of the hyperparameters, which are described in the following subsection.

6.3. Hyperparameters

Our pseudo-exhaustive search relies on several hyperparameters – parameters that have an impact on the functioning of the process but cannot be optimized by the training algorithm itself. Instead, they must be manually set in advance. In order to both determine the optimal configuration of these hyperparameters and to avoid overfitting our model to the training data we used a three-fold stratified cross-validation. The more usual choice of a ten-fold cross-validation could have, perhaps, yielded even better results. Still, due to the time constraints, we opted for a lower number of folds.

Hence, we divided the training data into three folds and repeatedly trained our model via a pseudo-exhaustive search on two of them and tested its final performance on the third while cyclically switching which fold is used for testing. We executed this procedure for all hyperparameter combinations. Finally, we adopted the combination that led to the best average test result on all three folds. In Table 7 we present a list of all hyperparameters, the different options we considered, and the optimal options that were chosen as final. The cross-validation was performed on the training portion of the Microsoft Research Paraphrase Corpus [33], which is described in detail in Section 7.

The selected POS weighting function is used not only during the pseudo-exhaustive search, but in the remainder of the training process and in the general functioning of the POST STSS method as well. Therefore, it can be regarded as a hyperparameter of the entire POST STSS model.

Table 7. Hyperparameters used in the pseudo-exhaustive search

Hyperparameter	Options considered	Optimal option
Initial POS weights	0.7 / 1.0 / 1.3	0.7
Initial POS interaction values	0 / 1	0
Initial string similarity weight	0.3 / 0.4 / 0.5 / 0.6 / 0.7	0.5
Usage of the value minimization process	Yes / No	No
POS weighting function	Choose the higher weight	Arithmetic mean of the two weights
	Choose the lower weight	
	Arithmetic mean of the two	
	Geometric mean of the two	
	Harmonic mean of the two	

6.4. Steepest Ascent Hill Climbing

The task of the second phase of our training process is to take the parameter set produced by the first phase and fine-tune it within the full-sized search space. We expand the parameter set from the lower-dimensional search space into the full-sized one as follows: each individual part of speech in the full-sized space is assigned a weight according to its broader category in the lower-dimensional space. For instance, the weight given to the class of adjectives is copied onto the specific POS weights for adjectives in their base (*JJ*), comparative (*JJR*), and superlative form (*JJS*). Moreover, the POS interaction matrix is expanded so that all relations between parts of speech stay the same. For example, if the pairing of adverbs and adjectives was permitted in the lower-dimensional space, then the pairing of adjectives in their base form (*JJ*) and adverbs in their comparative form (*RBR*) would remain permitted in the full-sized space. The same would be true for all other combinations of individual parts of speech from these two word classes. The interactions among the individual parts of speech within a single, broader category are all allowed. For instance, all specific adjective forms can be freely paired with all the others. Finally, as in the lower-dimensional space, we automatically allow the pairing of words belonging to the same part of speech. The only

difference is that now this rule refers to individual parts of speech instead of broader word classes. Regardless, in such instances the POS interaction matrix is not consulted.

In the second phase of the training procedure we utilize a variation of the steepest ascent hill climbing algorithm. As the full-sized space is so large, hill climbing is one of the few viable options. We employ three kinds of moves:

1. An increase/decrease of a single POS weight;
2. An inversion of a single bit within the POS interaction matrix;
3. An increase/decrease of the string similarity weight.

In each step of the climb we evaluate the effect of every possible move on the entire training data. The typical steepest ascent reasoning would be to select the move which leads to the largest increase in system performance. Instead of always following this logic, we add a momentum to each move which alters the string similarity weight or a POS weight. If a certain weight change has the largest positive impact on system performance, then it is perpetuated as long as the performance keeps increasing, even if, at some point, there appears another move which would lead to a greater performance increase. The momentum feature allows our algorithm to escape from certain local maxima and not only leads to better final results, but speeds up the hill climb as well. Once the repeated weight increase/decrease no longer improves system performance, we resume the climb using the standard steepest ascent method.

To speed up the climb, we allow a move which alters a POS weight to simultaneously invert one POS interaction bit. This added inversion is permitted only on the bits that pertain to the POS whose weight is being modified. Furthermore, we allow the climb to include *jumps* – moves in which a weight is changed not by the usual step of 0.1, but by twice as much. We also let the POS weight jumps to invert a related POS interaction bit.

If multiple moves lead to the same level of performance improvement, our algorithm randomly picks one of them. Thus, each run of the climb can produce different results. This allows multiple runs of our algorithm to explore a larger portion of the search space than would have otherwise been the case.

The hill climbing can be sustained as long as there are moves which lead to better performance on the training data. However, this would likely result in an overfitted model. To prevent this, we used a simple heuristic – we first ran the hill climbing algorithm several times, finishing the climb only when all the moves leading to superior system performance are exhausted. In each run we noted how many moves it took to reach that final stage. Our analysis showed that the maximum length of this process is around 50 moves. We chose to stop the climb after 25 moves, i.e. half of the maximum. Although this heuristic is rather crude, it actually performed quite well in practice. Therefore, the parameters acquired after 25 moves are the ones we adopt as final. They are used in the evaluation of the POST STSS method described in Section 7.

If a certain hyperparameter combination leads to multiple starting points for the hill climb, we can simply repeat the climb from each point. Then we can pick the final parameter combination which performs best on the training data. However, this situation did not occur with our optimal hyperparameter options.

In principle, the aforementioned value minimization can also be applied to the parameters obtained through hill climbing. Since the cross-validation already showed that such a technique does not improve performance in the lower-dimensional space, we did not employ it in the full-sized space either.

Although our training procedure is not guaranteed to find the global optimum, it still leads to good results. One of main strengths of the proposed training algorithm is that almost all of its stages can be effectively parallelized, leading to a significant reduction in the length of the procedure.

7. Evaluation

We evaluated our model by using a paraphrase recognition test on the *Microsoft Research Paraphrase Corpus* (MSRPC) [33]. The MSRPC is a corpus containing 5801 pairs of sentences which are all semantically related to some extent. However, only some sentence pairs are paraphrases, i.e. semantically equivalent, while others have only partly overlapping semantic information. The entire corpus was hand-annotated with binary scores indicating for each pair if it is a paraphrase or not. 3900 pairs (67%) were deemed semantically equivalent, while the remaining 1901 (33%) were classified as semantically diverse. Two human raters examined each pair, while a third cast the deciding vote in cases of disagreements. The average inter-rater agreement was 83%, which is therefore the maximum accuracy an STSS system can reach.

The task of STSS systems is to match the sentence-pair scores of human annotators, thereby testing the systems' ability to accurately assess the level of semantic similarity between two sentences. To do so, a threshold between zero and one has to be chosen, so that any score above it is treated as recognition of semantic equivalence and any below it as indication of semantic divergence.

The MSRPC dataset was originally split into a training portion consisting of 4076 sentence pairs, and a test portion encompassing 1725 pairs. The training part is used to determine the optimal threshold value, while the evaluation is performed on the testing part. We changed the threshold in 0.1 increments in order to limit the possibility of overfitting to the training data. In addition, we used the training set in the parameter optimization process described in the previous section. During training, a new optimal threshold value was determined whenever a performance evaluation was required. This was done so as to maximize system performance at each point in the process.

7.1. Performance Metrics

The most important metric used to determine a system's performance is system accuracy, which is defined as the ratio of the number of correctly identified sentence pairs and the total number of pairs in the corpus. By definition, accuracy is calculated as the sum of true positives and true negatives divided by the sum of all positives and negatives. True positives (TP) are sentence pairs which are paraphrases and are correctly identified by an algorithm as such. False positives (FP) are sentence pairs that are semantically diverse, but are misclassified as semantically equivalent. False negatives (FN) represent the reverse case – sentence pairs which are paraphrases but are mistakenly labeled as semantically different. Finally, true negatives (TN) are properly recognized pairs of semantically dissimilar sentences.

However, there are other metrics, taken from the information retrieval theory, which are also frequently employed. Precision is the ratio of true positives and all pairs classified as paraphrases. Therefore, precision reflects the level of false positive errors, while ignoring false negative ones. Recall is calculated as the ratio of true positives and all paraphrase pairs from the corpus. Recall measures the level of false negatives, but ignores the false positive errors. This is why it is easy to optimize a system to have either high precision or high recall, at the expense of the other. The F-measure was introduced as a standard way of combining these measures into a unified, balanced score, and is defined as the harmonic mean of precision and recall. The mathematical formulas for calculating all these metrics are given by the following expressions:

$$A = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

$$P = \frac{TP}{TP + FP} \quad (7)$$

$$R = \frac{TP}{TP + FN} \quad (8)$$

$$F = \frac{2PR}{P + R} \quad (9)$$

As shown in expressions 7–9, the F-measure fails to take into account the level of true negatives an STSS system produces. This makes accuracy the predominant parameter of system evaluation since it measures not only false positive and false negative types of errors, but also the level of performance on both true positives and true negatives. Such a broad scope of evaluation is essential for problems in which the level of true negatives is not to be ignored. This is the case in all situations where measuring semantic *dissimilarity* is important (e.g. in extractive text summarization STSS is used to calculate semantic dissimilarity between the already selected summary sentences and a set of potential candidates). Thus, we decided to train the model and to pick the optimal threshold value according to the maximal system accuracy.

7.2. Results

An overview of POST STSS behavior on the MSRPC paraphrase recognition test with regard to different threshold values is given in Table 8. As shown, the optimal threshold value for our system is 0.5.

Table 9 shows a comparison between the results of the existing STSS solutions and our proposed method. Solutions which require both a knowledge base and a text corpus, such as the ones proposed by Mihalcea et al. [11] or Ramage et al. [16], were listed as topological, since a suitable knowledge base is much harder to find. We sorted the results in each category in increasing order according to their accuracies.

Some previously devised methods were presented in a number of variants. In such cases, the version with the highest accuracy was chosen for comparison. Lintean and Rus [13] presented both a topological and a statistical similarity variant of their approach, so we included both in the table.

In addition, we implemented a slight modification of the LInSTSS approach of Furlan et al. [20] which does not use stop-word removal. This was done in order to compare that algorithm to our own on equal terms, since our model does not use a stop-word list. The LInSTSS implementation utilized the same text corpus and stemming technique described in Section 4.

Table 8. An overview of POST STSS performance on the MSRPC paraphrase recognition test with regard to different threshold values

Threshold	Accuracy	Precision	Recall	F-measure
Training set				
0	67.54%	67.54%	100.00%	80.63%
0.1	67.54%	67.54%	100.00%	80.63%
0.2	67.57%	67.56%	100.00%	80.64%
0.3	67.62%	67.61%	99.93%	80.65%
0.4	69.09%	69.01%	98.44%	81.14%
0.5	74.34%	75.87%	90.92%	82.72%
0.6	68.40%	82.69%	67.31%	74.21%
0.7	53.70%	92.62%	34.18%	49.93%
0.8	36.21%	97.52%	5.70%	10.78%
0.9	32.56%	100.00%	0.15%	0.29%
1.0	32.46%	NaN	0%	NaN
Test set				
0	66.49%	66.49%	100.00%	79.87%
0.1	66.49%	66.49%	100.00%	79.87%
0.2	66.49%	66.49%	100.00%	79.87%
0.3	66.55%	66.53%	100.00%	79.90%
0.4	68.87%	68.46%	98.61%	80.81%
0.5	74.09%	75.74%	89.80%	82.17%
0.6	66.78%	81.89%	64.25%	72.01%
0.7	51.42%	88.92%	30.78%	45.73%
0.8	36.93%	96.83%	5.32%	10.08%
0.9	33.51%	NaN	0%	NaN
1.0	33.51%	NaN	0%	NaN

The results of our POST STSS method are presented stepwise, in four variants. The first one is the direct application of COALS, with no stemming, lemmatization, or POS weighting performed. The results of this version can be considered a baseline for evaluating the proposed improvements. The second and the third variation depict the changes in system performance when either stemming or lemmatization is used. The fourth variant shows the results of our final POST STSS model, obtained by utilizing the proposed POS weighting strategy in conjunction with lemmatization as the preprocessing step.

The POST STSS method outperforms the current state-of-the-art statistical similarity algorithms in terms of accuracy. Its F-measure is also higher than most other statistical solutions. Only TBS [15], a topic modeling approach, performs slightly better in terms of the F-measure, but with a considerably lower accuracy. The topological similarity measures of Fernando and Stevenson [12] and Lintean and Rus [13] attain similar or better results than we do, but at the cost of having to use a hand-crafted knowledge base in the form of WordNet. This makes their solutions unsuitable for a broad range of languages in which such resources are nonexistent. Moreover, the POST STSS method achieves a significantly better accuracy than all structural models, including the algorithms ([19], [21], [22], [23]) which employ a weighting mechanism in conjunction with (shallow) parsing and/or semantic role labeling to detect constituents. This result validates our view that POS tags are well suited to be used in such weighting schemes as indicators of the deeper syntactic information.

Table 9. A comparison between the results of the existing STSS solutions and our proposed method on the MSRPC paraphrase recognition test

Algorithm	Accuracy	Precision	Recall	F-measure
<i>Topological similarity</i>				
Lee et al. [24]	/	75.30%	55.60%	63.90%
Achananuparp et al. [26]	67.56%	67.53%	97.58%	79.82%
Furlan et al. [19] – ConceptNet	68.23%	/	/	/
Mihalcea et al. [11]	70.30%	69.60%	97.70%	81.30%
Ramage et al. [16]	70.80%	/	/	80.10%
Li et al. [21]	70.80%	70.30%	97.40%	81.60%
SyMSS [23]	70.87%	74.47%	84.17%	79.02%
Lee et al. [25]	71.02%	73.90%	91.07%	81.59%
Li et al. [22]	72.10%	71.30%	97.30%	82.30%
Fernando and Stevenson [12]	74.10%	75.20%	91.30%	82.40%
Lintean and Rus [13] – LCH	75.70%	78.30%	87.90%	82.80%
<i>Statistical similarity</i>				
TBS [15]	69.90%	100%	69.90%	82.30%
LInSTSS [20]	70.03%	78.43%	75.76%	77.07%
Furlan et al. [19] – COALS	70.32%	/	/	/
WTMF [17]	71.51%	/	/	/
Islam and Inkpen [18]	72.64%	74.70%	89.10%	81.30%
Lintean and Rus [13] – LSA	73.00%	77.30%	84.00%	80.50%
Rus et al. [14]	73.56%	75.34%	89.53%	81.83%
<i>Our proposed method</i>				
Plain COALS	71.77%	74.02%	88.67%	80.68%
COALS + Stemming	72.17%	73.64%	90.58%	81.24%
COALS + Lemmatization	72.87%	74.23%	90.67%	81.63%
POST STSS	74.09%	75.74%	89.80%	82.17%

When compared to the existing solutions of Islam and Inkpen [18] and Furlan et al. – COALS [19], which were a foundation for our approach, it is evident that the POST STSS method outperforms them by all standards. More detailed statistics of this

comparison, alongside our Plain COALS baseline, are shown in Table 10. We also included the LInSTSS algorithm [20] in the comparison, because it is a modification of the same two methods we used as our starting point. We presented the error rates of all algorithms, given that the maximal possible accuracy on the task is 83%. In addition, we calculated the relative error reduction of our approach, when compared to the existing solutions and our baseline. The relative error reduction is computed as:

$$RER = \frac{Error_{ES} - Error_{POST\ STSS}}{Error_{ES}} \quad (10)$$

where $Error_{ES}$ is the error rate of one of the existing solutions or the baseline, and $Error_{POST\ STSS}$ is the error rate of the POST STSS method.

Table 10. Improvements of the POST STSS method with regard to related methods and the existing solutions which were used as a starting point for our approach

Algorithm	Accuracy	Error rate	RER
Furlan et al. – COALS	70.32%	12.68%	29.73%
Islam and Inkpen	72.64%	10.36%	14.00%
LInSTSS	70.03%	12.97%	31.30%
Plain COALS baseline	71.77%	11.23%	20.66%
POST STSS	74.09%	8.91%	/

Surprisingly, the LInSTSS approach actually performed the worst. We found several factors which could have had a detrimental effect on it. To begin with, in order to avoid overfitting to the training data we had decided to use a 0.1 increment when searching for the optimal threshold. This did not degrade the performance of POST STSS since the values of the POS weights it uses also change in steps of 0.1, i.e. rather coarsely. On the other hand, the method of term frequency weighting implemented in LInSTSS uses a finely differentiated range of weights between 0.5 and 1.0. This means that the 0.1 step is much too coarse for choosing a threshold in LInSTSS. We tested this hypothesis by lowering the threshold step to 0.001, as was suggested by Furlan et al. [20]. The results validated our finding since the accuracy rose to 71.48%.

Nonetheless, even this result is still slightly below our COALS baseline. In fact, it would be more appropriate to compare LInSTSS to our COALS + Stemming variant, since LInSTSS uses stemming as a text preprocessing step. This comparison is even worse for LInSTSS and indicates that term frequency weighting decreased system performance instead of increasing it, as was the case in the original system constructed for Serbian. The precise cause of this effect in English is somewhat unclear, but it has been previously detected by other researchers ([12], [13]). It is possibly linked to the size of the corpus used to create a semantic space and generate term frequencies. The English-language corpus is significantly larger than the Serbian one, leading to generally lower min-max TF weights for frequently found words. Hence, all sentence pairs which contain a number of such words will have their similarity score noticeably reduced, lowering the overall system accuracy.

7.3. Optimal Parameters

The final results of the POST STSS method were achieved by using the POS weights shown in Table 11. Entries in the table are sorted alphabetically according to their POS tag [8]. We obtained these specific weights by training the model on the MSRPC training set in the manner described in Section 6. The final optimal weights for the string and the semantic similarities were both 0.5.

Table 11. Optimal part-of-speech weights

Part of speech	Tag	Weight
Coordinating conjunction	CC	0.7
Cardinal number	CD	0.8
Determiner	DT	0.7
Existential there	EX	0.7
Foreign word	FW	0.7
Preposition or subordinating conjunction	IN	0.7
Adjective	JJ	0.7
Adjective, comparative	JJR	0.7
Adjective, superlative	JJS	0.8
List item marker	LS	0.7
Modal	MD	1.2
Noun, singular or mass	NN	0.8
Noun, plural	NNS	1.0
Proper noun, singular	NNP	0.8
Proper noun, plural	NNPS	0.8
Predeterminer	PDT	0.7
Possessive ending	POS	0.7
Personal pronoun	PRP	0.7
Possessive pronoun	PRP\$	0.7
Adverb	RB	1.3
Adverb, comparative	RBR	1.2
Adverb, superlative	RBS	1.0
Particle	RP	1.2
Symbol	SYM	0.7
To	TO	0.8
Interjection	UH	0.7
Verb, base form	VB	1.2
Verb, past tense	VBD	1.2
Verb, gerund or present participle	VBG	1.1
Verb, past participle	VBN	0.8
Verb, non-3rd person singular present	VBP	1.2
Verb, 3rd person singular present	VBZ	1.2
Wh-determiner	WDT	0.7
Wh-pronoun	WP	0.7
Possessive wh-pronoun	WP\$	0.7
Wh-adverb	WRB	1.3

Our system gives the highest weight to verbs and adverbs, reflecting the claim of Wiemer-Hastings that humans are more strongly affected by the similarities of verbs than that of the other constituents [27]. This also corresponds to the findings of other researchers ([19], [23]) who showed that actions, i.e. verbs, are semantically more salient than subjects/objects involved in them. Interestingly, it is two of the adverb tags (RB and WRB) that actually have the highest weight assigned to them. Apart from the inherent importance of adverbs as modifiers of verbs, this effect likely stems, at least in part, from the distribution of examples in the paraphrase corpus. The MSRPC contains numerous instances where both sentences in a pair describe the same basic action but performed in different manners. In such situations giving more weight to adverbs is an elegant way of detecting these dissimilarities.

In addition to verbs and adverbs, nouns are also given higher weights than most other parts of speech. This showcases their syntactic significance since nouns often play the roles of subjects and objects in a sentence. The remaining parts of speech are mostly given lower weights, indicating their reduced impact on STSS due to the limited amount of semantic information they carry.

The optimal POS interaction matrix configuration is depicted in Figure 1. Values within it are ordered according to the alphabetical ordering of tags in both the left-to-right and the top-to-bottom direction [8]. Therefore, the first row and the leftmost column correspond to the tag CC, while the last row and the rightmost column correspond to the tag WRB. A value of one means that the pairing of the parts of speech that correspond to a particular row and column is permitted. A value of zero means that such a coupling is forbidden.

Even though the starting value of all matrix cells was zero, as set via a hyperparameter described in Section 6.3, the final matrix mainly contains values of one. This means that disallowing the pairing of words with different POS tags can be beneficial only in a limited number of situations. Hence, the impact of POS weights is even larger, since most POS interactions are allowed.

Most values are grouped in uniform rectangular portions of the matrix, since they were chosen jointly, by allowing/disallowing pairings on the level of broader word classes. Many groupings have a linguistically understandable backing, if considered within a bag-of-words model. For instance, verbs can be paired with any word class except for adverbs. Nouns can, in general, only be paired with verbs and adverbs. Most adjectives cannot be paired with nouns and words in the “other” category. It is permitted to pair adverbs with adjectives, nouns, and pronouns, but not with verbs and words in the “other” category. There are also certain matrix values that are somewhat surprising. For example, pronouns can be paired with any word class, except for nouns. Since nouns and pronouns often have similar syntactic roles, this indicates that aligning words solely on the basis of their syntactic properties might not be the correct choice for STSS, at least within a bag-of-words model. Finally, words in the “other” category can be paired with pronouns and verbs. Of course, words within a broader word class can, by and large, be paired with other words in the same class.

Still, there are exceptions to these general rules which break the rectangular patterns in the POS interaction matrix. For instance, the system found that disallowing the pairing of common nouns in the singular and common nouns in the plural leads to better

performance. Such fine-grained decisions are made during the hill-climbing part of the training process, described in Section 6.4.

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101110000110000111100011111111111110
010000000011111000011110001111110001
101110100110000111100011111101111110
101110000110000111100011111111111110
101111000110000111100011111111111110
000011000101000111111011111101101010
001000110010000001111110001111110111
000000111010000001111110001111110111
000000011010000001111110001111110111
101111000110000111100011111111111110
111110111110111111100011111111111110
010001000001011000011110001111110001
010000000010111000011110001111110001
010000000011111000011110001110110001
010000000011111000011110001111110001
101111000110000111100011111111111110
101111000110000111100011111111111110
101111111110000111111111111111111011
101111111110000111111111111111111111
010001111001111001111000000001000111
010001111001111001111100000000000111
010000111001111001101100000000000111
111111111111111111110001111111111110
101111000110000111100011111111111110
101111000110000111100011111111111110
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111111111111111111110001111111111110
1111111111111111111100011111111011110
1101101111111111111100011111111101110
111111111111110111111001111111111110
1111111111111111111100011111011111110
1111101111111111111100011111101111110
101111000110000111100011111111111110
101110111110000110111111111111111111
101111111110000111111111111111111111
010000111001111001111100000000000111

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Fig. 1. The optimal configuration of the POS interaction matrix

8. Conclusion

In this paper we have presented POST STSS, a bag-of-words approach to measuring the semantic similarity of short texts based on using part-of-speech tags as indicators of the deeper syntactic information. We have described our proposed system's operation, including the central POS tag weighting technique, as well as the parameter optimization procedure. We have trained the model and evaluated its performance by using a paraphrase corpus. We have concluded that our method achieves a higher accuracy than current state-of-the-art statistical similarity algorithms. In this respect it also outperforms the methods which utilize more advanced syntax-processing tools. Since our approach does not require either hand-crafted knowledge bases or advanced syntactic tools like parsers and semantic role labelers, it is more easily applicable to languages with scarce natural language processing resources.

A potential avenue of future research could focus on integrating our POS weighting strategy with shallow parsing, which groups several words/POS tags into noun, verb, or preposition phrases. By weighting both the phrases and the POS tags within them, it may be possible to develop an even better representation of the relative semantic importance of different constituents.

An alternative research direction would be the verification of our approach on another language. Serbian is an interesting potential candidate since it differs from English in many respects, particularly morphosyntactic ones. Despite the scarcity of NLP resources for Serbian, there are existing corpora in this language in which every word has been annotated with a POS tag and a lemma ([34], [35], [36]). Research has shown that these corpora can be successfully utilized to create POS taggers and lemmatizers for Serbian ([35], [37]).

Still, the usefulness of our STSS method largely depends on the cardinality of the utilized set of POS tags and the accuracy of the tagging process. If there are too many different tags our method becomes essentially inapplicable since it is not possible to learn the relative importance of each part of speech from the usually limited amount of training data. A large tag set also has a negative impact on tagger accuracy, which could render our POS weighting mechanism much less effective. Earlier annotation schemes for Serbian are especially problematic in this respect since they use hundreds of different morphosyntactic labels, due to the complexity of the language itself [34]. Nevertheless, the need for a more compact and practical set of tags has been recognized in the recently developed corpora where sets of 16 [35] or 45 [36] POS tags are employed. These figures are on a par with the number of tags used in the Penn Treebank Project [8]. Taggers trained on these corpora achieve accuracies comparable to those of the English-language taggers, which should therefore enable the implementation and proper functioning of our STSS method.

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