Comparing Resources for Spanish Lexical Simplification

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Abstract. In this paper we study the effect of different lexical resources and strategies for selecting synonyms in a lexical simplification system for the Spanish language. The resources used for the experiments are the Spanish EuroWordNet, the Spanish Open Thesaurus and a combination of both. As for the synonym selection strategies, we have used both local and global contexts for word sense disambiguation. We present a novel evaluation framework in lexical simplification that takes into account the level of ambiguity of the word to be simplified. The evaluation compares various instances of the lexical simplification system, a gold standard, and a baseline. On the basis of our results we recommend different resources and word sense disambiguation methods depending on the ambiguity level of the target word to be simplified.

Keywords: Lexical Simplification, Text Simplification, Spanish, Word Sense Disambiguation, Word Vector Model, Lexical Simplification Evaluation

1 Introduction

Lexical Simplification aims at replacing difficult words with easier synonyms, while preserving the meaning of the original text segments. It is usually considered as an essential part of text simplification, which might target other aspects of textual complexity, such as the syntactic complexity of sentences. Text Simplification can be used as a linguistic preprocess in order to improve other NLP tasks [9, 23], but it can potentially help people with various types of reading comprehension problems [1, 7, 21].

Lexical simplification requires the solution of at least two tasks: First, the finding of a set of synonymic candidates for a given word generally relying on a dictionary and, second, replacing the target word by a synonym which is easier to read and understand in the given context. For the first task different resources are generally used such as WordNet [18]. For the second task, different strategies of word sense disambiguation (WSD) and simplicity computation are requited.

Even if there is a considerable number of approaches to lexical simplification in different languages, an estimation of how different lexical resources and WSD strategies impact the task have not yet been studied. There is also no previous work which addresses the question in how far the level of ambiguity of a word influences the degree of success in automatic lexical simplification. The goal of this paper is to address these gaps using LexSiS [5], a system for Spanish lexical simplification which uses as parameter a lexical resource which provides word senses and lists of synonyms. Hence, the main contributions of this paper are:

- A comparison of the performance of our lexical simplification system with two different lexical resources (Open Thesaurus and EuroWordNet), in addition to a combined version of the two.
- A comparison of two different strategies for word sense disambiguation, one which only considers the local context of a target word and another which assumes that each target word has only one meaning per text and takes all local contexts for a given target into account.
- An evaluation that assesses the performance of the system depending on different levels of the ambiguity of target words.

The rest of the paper is organized as follows: In Section 2 we discuss the related work and the context in which our proposal has to be seen. In Section 3 we describe our system, including the alternative resources it can work with and alternative strategies to perform word sense disambiguation. Section 4 explains the evaluation framework and presents the experimental results while Section 5 draws some conclusions on the use of different lexical resources and disambiguation method. Section 6 concludes the paper with a summary of the main results and an outlook on future work.

2 Related Work

In this paper, we are only interested in lexical simplification as one of the various aspects of text simplification. Lexical simplification requires, at least, two things: a way of finding synonyms (or, in some cases, hyperonyms), and a way of measuring lexical *complexity* (or simplicity). Many approaches to lexical simplification [6, 7, 16] used WordNet in order to find appropriate word substitutions. Bautista *et al.* [3] use a dictionary of synonyms. De Belder *et al.* [11] apply explicit word sense disambiguation, with a Latent Words Language Model, in order to tackle the problem that many of the target words to be substituted are polysemic. As a measure of lexical simplicity most of the cited approaches [6, 7, 16] have relied on word frequency, with the exception of Bautista *et al.* [3], who use word length as a predictor for lexical simplicity. Since both word frequency and word length have been shown to correlate to the cognitive effort in reading [20], Bott *et al.* [5] use a weighted simplicity metric which combines length and frequency.

More recently, the availability of the Simple English Wikipedia (SEW) [10], in combination with the "ordinary" English Wikipedia (EW), made a new generation of text simplification approaches possible, which use primarily machine learning techniques [10, 28–30, 32]. This includes some new approaches to lexical simplification, which are the most important points of reference for our work.

Yatskar *et al.* [31] use edit histories for the SEW and the combination of SEW and EW in order to create a set of lexical substitution rules. Biran *et al.* [4] also rely on the SEW/EW combination (without the edit history of the SEW), in addition to the explicit sentence alignment between SEW and EW. They use WordNet as a filter for possible lexical substitution rules but do not apply explicit word sense disambiguation, their approach is *context-aware*, since they use a cosine-measure of similarity between a lexical item and a given context, in order to filter out possibly harmful rule applications which would select word substitutes with the wrong word sense.

Finally, there is a recent tendency to use statistical machine translation techniques for text simplification (defined as a monolingual machine translation task). Coster and Kauchak,[10] and Specia [24], drawing on work by Caseli *et al.*[8], use standard statistical machine translation machinery for text simplification. In this case lexical simplification is treated as an implicit part of the machine translation problem. The former uses a dataset extracted from the SEW/EW combination, while the latter is noteworthy for two reasons: first, it is one of the few statistical approaches that targets a language different from English (namely Brazilian Portuguese); and second, it is able to achieve good results, although for a limited range of phenomena, with a surprisingly small bi-data-set of only 4,483 sentences.

3 Spanish Lexical Simplification in LexSiS

LexSiS tries to find the best substitution candidate (a word lemma) for every word which has an entry in a lexical resource which is a parameter of the simplification process. The substitution operates in two steps: first the system tries to find the most appropriate sense for a given word, and then it tries to find the best substitution candidate within the list of synonyms of this sense. Here the *best* candidate is defined as the simplest and most appropriate synonym word in the given context. In order to perform word sense dissambiguation we rely on a word vector space model while for the simplicity criterion we apply a combination of word length and word frequency. In the rest of this section we provide the details of the resources and methods used by LexSiS.

3.1 Lexical Resources

As already mentioned, some approaches to lexical simplification make use of WordNet [18] in order to measure the semantic similarity between lexical items and to find an appropriate substitute. Spanish is one of the languages represented in EuroWordNet [27], although its scope is more modest[1]. We have tried three lexical resources in LexSiS: the **Spanish Open Thesaurus** (SOT), the **Spanish**

[1] The Spanish part of EuroWordNet contains only 50,526 word meanings and 23,370 synsets, in comparison to 187,602 meanings and 94,515 synsets in the English WordNet 1.5.

EuroWordNet (SWN), and **combination of SWN and SOT** (SWN+SOT). We describe each of them below.

The Spanish Open Thesaurus lists 21,831 target words (lemmas) and provides a list of word senses for each word. Each word sense is, in turn, a list of substitute words (and we shall refer to them as *substitution sets* hereafter). There is a total of 44,353 such word senses. The substitution candidate words may be contained in more than one of the substitution sets for a target word. The entry in SOT for the word *hoja* is as in (a).

(a) hoja|3
- |acero|espada|puñal|arma blanca
- |bráctea|hojilla|hojuela|bractéola
- |lámina|plancha|placa|tabla|rodaja|película|chapa|lata|viruta|loncha|lonja|capa|...

The first line of the entry represents the target word and states that there are three different meanings. The three lines that follow list synonyms for the three word meanings (*blade*, *leaf* and *sheet* in English).

A second resource we use is the Spanish EuroWordNet. However, for its use with LexSiS we represented synset of SWN in the same format as the Spanish Open Thesaurus, additionally enriching each entry with hyperonymes (e.g. *organo_de_una_planta/plant organ* in the last sense below) of the word. The SWN entry for *hoja* is given in (b)[2].

(b) hoja|4
- |instrumento_cortante
- |folio|cuartilla|pliego|hoja_de_papel|papel
- |folio|folio|cuartilla|pliego|hoja_de_papel
- |follaje|órgano|órgano_de_una_planta|órgano_vegetal

The word *hoja* is also semantically ambiguous here and can mean *blade*, *leaf* or *sheet of paper*. Here the sense for *sheet of paper* is represented by two synsets (second and third lines).

Finally, we are interested in whether a combination of SWN and SOT is able to produce better substitutions since this combination provides more substitution candidates to choose from. For this end we used a union of SWN synsets and SOT substitution sets and let LexSiS choose freely from the alternative lists of synonym words stemming from the two resources. The combined (SOT+SWN) representation for *hoja* contains all the lines contained in (a) and in (b).

3.2 Word Vector Space Model

In order to measure lexical similarity between words and contexts, we used a Word Vector Space Model [22]. Word Vector Space Models are a good way of modelling lexical semantics [26], since they are robust, conceptually simple

[2] It can be seen in this example that SWN lists many multi-word expressions. At the moment we do not have a module that can detect the same kind of multi-word expressions in the linguistic pre-process, so we have to ignore these entries.

and mathematically well defined. The 'meaning' of a word is represented as the contexts in which it can be found. A word vector can be extracted from contexts observed in a corpus, where the dimensions represent the words in the context, and the component values represent their frequencies. The context itself can be defined in different ways, such as an n-word window surrounding the target word. Whether two words are similar in meaning can be measured as the cosine distance between the two corresponding vectors. Moreover, vector models are sensitive to word senses. For example, vectors for word senses can be built as the sum of word vectors which share one meaning.

We trained a vector model on a 8M word corpus of Spanish online news. We lemmatized the corpus with FreeLing [19] and for each lemma type in the corpus we constructed a vector, which represents co-occurring lemmas in a 9-word (actually 9-lemma) window (4 lemmas to the left and to the right). The vector model has n dimensions, where n is the number of lemmas in the lexicon. The dimensions of each vector in the model (i.e. the vector corresponding to a target lemma) represent the lemmas found in the contexts, and the value for each component represents to number of times the corresponding lemma has been found in the 9-word context. In the same process, we also calculated the absolute and relative frequencies of all lemmas observed in this training corpus.

3.3 Word Sense Dissambiguation in LexSiS

We implemented two different methods to carry out word sense disambiguation, which we call the *local* and the *global* method. The local method only looks at the local context of a target word assuming that the local context provides enough information for disambiguation [15], while the global method takes all the occurrences of each target word within a text and constructs a combined representation of the contexts in which they are found, assuming the one sense per discourse hypothesis [14].

For the **local method**, we check for each lemma if it has alternatives in our lexical resource. If this is the case, we extract a vector from the surrounding 9-word window. Since each word is a synonym to itself (and might actually be the simplest word among all alternatives), we include the original word lemma in the list of words that represent the word sense. We construct a common vector for each of the word senses listed in the thesaurus by adding all the vectors of the words listed in each word sense. Then, we select the word sense with the lowest cosine distance to the context vector. In the second step, we select the best candidate within the selected word sense, assigning a simplicity score and applying several thresholds in order to eliminate candidates which are either not much simpler or seem to differ too much from the context.

The **global method** works largely like the local method, with one difference. We assume that each target word has only one meaning in each text it appears. So, instead of extracting a local context vector for each target instance of a word w, we extract all of the local vectors for w found in the text. Then we sum over all of these local vectors, and obtain a global vector for w and compare it to the vectors representing word senses.

3.4 Simplicity Computation and Filtering in LexSiS

As a measure for simplicity we use the metric proposed by Bott et al. [5], which combines word length and word frequency. This metric weights scores for length and frequency and combines them into a single simplicity score. The authors give arguments for the inclusion of word length into the calculus on the basis of a corpus study.

We also apply three thresholds in order to reduce the amount of bad simplification candidates proposed by LexSiS. First of all, we do not want to simplify frequent words, even if our resources (SOT or SWN) list them. So we set a cutoff point for frequent words, such that LexSiS does not try to simplify words with a frequency higher than 0.001% (calculated on the training corpus we used to build the vector model). We also discard substitutes where the difference in the simplicity score with respect to the original word is lower than 0.5, because such words can be expected not to be significantly simpler. We achieved this latter value through experimentation. Since many of the alternatives proposed by LexSiS are not acceptable substitutes, we try to filter out words that do not fit into the context by discarding all candidates whose word vector has a distance with a cosine inferior to 0.013, another value achieved through experimentation. This last threshold is also an attempt to remedy some shortcomings of the lexical resource, especially SOT, which often has entries which are far from being perfect.

4 Evaluation

In this section we present the experimental set-up employed to evaluate the different resourses and word sense disambiguation strategies for LexSiS. The evaluation was conducted thoroughly, rating the degree of simplification and the preservation of meaning of the substitutions.

Baseline: As baseline we use the method of [12]. It replaces a word with its most frequent synonym, presumed to be the simplest. This frequency baseline was also used in SemEval-2012 shared task for lexical simplification [25].

Gold Standard: We have an in-house corpus of parallel texts, consisting of 160 news texts (718 sentences) and manually simplified versions of these text, aligned on the sentence level. As the gold standard we used the manual lexical simplifications we found in this corpus.

Evaluation Dataset: The dataset is composed of the total of lexical simplification substitutions from our gold standard (55), together with the corresponding synonyms generated by LexSiS using the different resources (55 lexical substitutions each), giving a total of 275 lexical substitutions: baseline substitutions (**FREQ**), **SWN** substitutions, **SOT** substitutions, **SWN+SOT** substitutions, **Gold** manual lexical substitutions.

For each of the methods we used two different WSD strategies, having as a result 275 simplifications using a local strategy (**Local WSD**) and 275 simplifications using a global strategy (**Global WSD**).

Since we wanted to evaluate the meaning presentation as well as the simplification, each of the substitutions were inserted in their original sentences. In total we had 550 lexical substitutions to be compared with the original target words. We manually corrected the ungrammatical examples[3] and deleted the duplicated lexical substitutes giving a total of 456 unique lexical substitutions. We believe this is a reasonable size for an evaluation dataset, in [31] they use a total of 200 simplification examples, and in [4] 130 sentences were used. Below, we show two examples of a sentence with its original word (O) and the lexical substitution proposed by our system using SWN+SOT.

> (O) Se encuentra a favor de la lucha contra la DESIGUALDAD y la pobreza.
> *'It is in favor of the fight against inequality and poverty.'*
> (SWN+SOT) Se encuentra a favor de la lucha contra la IRREGULARIDAD y la pobreza.
> *'It is in favor of the fight against irregularity and poverty.'*

Ambiguity Bands: We divided the target words of the dataset in three levels of difficult depending on their degree of ambiguity. For measuring the degree of ambiguity we considered the average of senses per word given by WordNet and Open Thesaurus. Hence, our dataset has three ambiguity bands, low (from 0.5 to 1.5 senses, 49.08% of the dataset), medium (from 2 to 2.5 senses, 25.09 % of the dataset) and high (3 senses or more, 25.84% of the dataset).

Design: We created a multiple choice questionnaire presenting two sentences for each item. The test included all the unique lexical substitutions. Each item contained one sentence with a simplification example and the same sentence with the original word. These sentences were presented in counterbalanced order to the annotator (i.e., either as Original *vs.* SYSTEM or SYSTEM *vs.* Original). For each pair of sentences, the annotators were asked two questions to choose one option in each of then, one regarding the meaning preservation: "the sentences above have the same meaning" vs. "the sentences above do not have the same meaning", and another one regarding the simplicity degree: "the first of the sentence above is simpler than the second" vs. "the first of the sentence above is not simpler than the second". Five annotators with no previous annotation experience performed the tests using an on-line form. They were all Spanish native speakers, frequent readers and were not the authors of this paper. The five participants annotated all the instances of the datasets, achieving a Fleiss' kappa score of 0.332. Hence, we can assume we have a fair agreement [13, 17], comparable with other inter-annotator agreements in related work, where kappa score was between 0.35 and 0.53 [4].

4.1 Results

Table 1 shows a direct comparison of the performance of LexSiS with different resources and the two different WSD methods, the baseline and the gold standard. In Table 2 we show the results for WSD and simplicity by ambiguity level. The scores for simplicity were calculated over those data points which were judged

[3] The correction only affected inflections and agreement errors, since we could not use a morphological generator in the experimental setting.

as being synonymous in order to be able to achieve independent scores for synonymity and simplicity. The WSD methods of *local* and *global* correspond to the two ways of constructing context vectors described in Section 3.

Method	**WSD**	**Synonym**	**Simpler**
SWN	Local	**63.2**	68.2
SWN	Global	62.2	**69.2**
SOT	Local	62.0	66.7
SOT	Global	62.0	66.7
SWN + SOT	Local	58.6	66.4
SWN + SOT	Global	60.6	68.2
Baseline	-	52.6	**71.1**
Gold	-	**75.9**	69.3

Table 1. Results for the different resources using local and global WSD.

Ambig.		Meaning preservation			Simpler synonyms		
Band	**WSD**	**SWN**	**SOT**	**SOT+SWN**	**SWN**	**SOT**	**SOT+SWN**
Low	Local	60.0	62.5	56.0	70.0	**70.0**	68.7
Low	Global	61.0	62.5	56.9	70.3	**70.0**	68.9
Med.	Local	65.5	51.1	56.9	72.2	60.9	70.3
Med.	Global	61.7	51.1	63.1	**73.0**	60.9	**70.8**
High	Local	**67.4**	**70.4**	**66.7**	60.6	65.8	58.3
High	Global	65.3	**70.4**	66.1	62.5	65.8	64.1

Table 2. Results for meaning preservation for different ambiguity levels.

5 Discussion

We observe (Table 1) that LexSiS shows consistently much higher synonymity scores than the baseline. For the whole dataset, without distinction of levels of ambiguity LexSiS with SWN achieves a score of 63.16% in comparison to 52.59% produced by the baseline. When LexSiS uses other resources (SOT or SWN+SOT) the scores are only slightly lower. The score for the gold standard is higher (75.92%), but surprisingly it does not even get close to 100%, which shows that human judges are reluctant to accept alternatives as being fully synonymous and gives an idea of the difficulty of the task. A surprise is that the combination of the two resources (SWN+SOT) performs much worse than the two resources on their own. We hoped that the word disambiguation component would perform better with the availability of more synonym sets, because the cosine distance between the vectors for these sets should lead to a selection of the set with the most coherent meaning, penalising sets which include words that are not coherent with the rest of the set. This expectation was not met. A possible alternative would be to align the resources so that equivalent synsets are merged together providing additional synonym choices for equivalent senses. We will investigate this in future work.

Turning to the question whether the use of SOT shows a worse performance than that of SWN, we can observe a slightly better performance of LexSiS+SWN than LexSiS+SOT in both categories (Table 1), but none of the differences is statistically significant. This is an interesting result, because it suggests that a simpler resource like SOT can lead to nearly the same level of performance than the use of a more sophisticated resource like SWN, whose quality is controlled in a much stricter way. In SOT we often observed incoherent synonyms sets, cases in which more than one synonym sets appear to represent the same word sense and word senses which are not represented by a single synonym set. Nevertheless, we think that the use of the word sense disambiguation component in combination with the threshold that filters out candidates with a high cosine distance to the context can partially remedy the shortcomings of the thesaurus.

The left part of Table 2 (meaning preservation) suggests that words with a higher degree of ambiguity are easier to disambiguate, which might come as another surprise. We suspect that this reveals a possible shortcoming of the resources used: words which are listed with only one word sense are often still ambiguous, while the entries of words with many listed senses tend to be disambiguated better in the dictionary entry.

Turning to the production of synonyms which are perceived as being actually simpler than the original, again SWN outperforms SOT and SWN+SOT (cf. Table 1). In right part of Table 2 (simpler synonyms) we can observe that the success of producing simpler synonyms depends very much on the level of ambiguity of the target word. Highly ambiguous words are harder to simplify, while words with low ambiguity are easier. Words with a medium level ambiguity show a curious behaviour: for SWN and the combination of SWN and SOT these words appear to be easier to simplify.

Table 2 also shows that the global method of choosing synonyms (one synonym for each target per text) systematically outperforms the local method in its ability to produce simpler substitutes. We attribute this to the fact that the summed vectors for target word contexts are present much richer context information and are much more reliable than the rather sparse vectors for individual contexts. The assumption that each target word has only one meaning per text proves to be quite helpful. For example, in the following sentence the original word *noción* (*notion*) has been substituted with the word *representacíon*(*representation*) with the local method and the more acceptable word *idea* with the global method, using SWN+SOT.

(O) ... vivimos en un mundo en el que se ha perdido la NOCIÓN de autoridad.
'... we live in a world where the NOTION of authority has been lost'

In Table 1 the baseline outperforms LexSiS and even the gold standard in the simplification task, but it has to be taken into account that the simplicity scores were calculated only over those data instances that were actually perceived by the annotators as being synonymous. This amounts to saying that the frequency baseline would perform extraordinarily if all the non-synonym productions were filtered out, which is first impossible and would result in a much lower coverage (i.e. much less substitutions produced) than LexSiS. As a curious matter of fact, only 51.85% of the gold standard cases were both judged as being synonymous and being simpler, which illustrates the difficultly of the combined task.

Turning to significance, we only found a significant effect between different methods on the meaning preservation; the gold standard preserved significantly more meaning in their substitutions that the rest of the methods, ($F(9, 2262) = 4.062, p < 0.01$). This finding is hardly surprising, given the difficulty of the word sense disambiguation task. It is probably more interesting to note that, while the gold standard achieves higher scores for simplicity, this score is not much higher than the score for LexSiS with the use of SWN. Also, even if the scores for LexSiS with different configurations are lower, the difference to the gold standard could not be shown to be statistically significant.

6 Conclusions and Outlook

In this paper we compared the effect of using different lexical resources and disambiguation strategies in a lexical simplification system for the Spanish language. In particular we have instantiated experiments with the Spanish WordNet and the Spanish Open Thesaurus as lexical resources. Where disambiguation methods are concerned, we have tried local and global disambiguation strategies.

The comparison of two different lexical resources shows how far the quality of the resource used influences the quality of the lexical simplifications the system produces. Since Open Thesaurus is an open collaborative effort, the quality of the thesaurus entries is not strongly controlled, a factor which we could see reflected in poorly separated word senses and even missing representation for some senses. We could find differences in the performance depending on the lexical resource used, but it was surprisingly low and not statistically significant. This is a good result because the main bottleneck for the most language dependent part of a lexical simplification system like LexSiS is the availability of lexical resources. Our evaluation suggests that thesauri may be a good substitute for more sophisticated lexical ontologies.

Another contribution of this paper is the comparison of two WSD methods: one based on local context and the second global method based on summed local context on the text level. We could show that the global method performs better for the lexical substitution task. The choice of the lexical resource is only one of a list of possible optimizations for the LexSiS system. There are other possibilities we would like to explore in the future, such as the use of TF*IDF weights and the investigation of in how far the size of the window which represents the context influences the system performance. Our lexical simplification system could also help to normalize paraphrases to the simplest word choice, which could be useful in plagiaism detection [2].

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