CATS: A Tool for Customized Alignment of Text Simplification Corpora

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Abstract
In text simplification (TS), parallel corpora consisting of original sentences and their manually simplified counterparts are very scarce and small in size, which impedes building supervised automated TS systems with sufficient coverage. Furthermore, the existing corpora usually do not distinguish sentence pairs which present full matches (both sentences contain the same information), and those that present only partial matches (the two sentences share the meaning only partially), thus not allowing for building customized automated TS systems which would separately model different simplification transformations. In this paper, we present our freely available, language-independent tool for sentence alignment from parallel/comparable TS resources (document-aligned resources), which additionally offers the possibility for filtering sentences depending on the level of their semantic overlap. We perform in-depth human evaluation of the tool’s performance on English and Spanish corpora, and explore its capacities for classification of sentence pairs according to the simplification operation they model.

Keywords: text simplification, tools and resources, sentence similarity

1. Introduction
Automated text simplification (ATS) has the goal of automatically transforming sentence structure and lexical choices in a way that it provides better understanding and wider accessibility to large audiences. The main obstacle for successful supervised ATS is the scarcity and limited size of parallel TS corpora which would contain original sentences and their manual simplifications. The parallel TS corpus for Brazilian Portuguese, compiled for the purposes of the PorSimplex project (Aluísio et al., 2008) contains around 4,500 aligned sentences, and the parallel TS corpus for Spanish, compiled for the purposes of the SimpLext project (Saggion et al., 2015) contains only around 1,000 aligned sentences. The largest existing TS comparable corpora is the English Wikipedia – Simple English Wikipedia (EW–SEW), consisting of 170,000 sentence pairs (Kaufch, 2013), or 150,000 full matches and 130,000 partial matches in the newer version (Hwang et al., 2015). In both cases, the sentences were automatically aligned from comparable English Wikipedia and Simple English Wikipedia articles. However, the use of EW–SEW dataset for modeling TS has been disputed (Amancio and Specia, 2014; Štajner et al., 2015; Xu et al., 2015) for several reasons: (1) the simplified articles are not necessarily direct simplifications of the original articles; (2) the quality of simplifications is not checked; (3) the dataset does not cover sentence splitting which is one of the most common operations in text simplification. The Newsela corpora¹ of document-aligned news texts, manually simplified at four different simplification levels have been freely available for a few years for research purposes. These corpora have several advantages over the EW–SEW dataset (Xu et al., 2015; Štajner et al., 2017): (1) simplified texts present direct simplifications of the original articles; (2) simplification was performed by trained human editors, following strict guidelines; (3) by sentence-aligning those corpora one can get training material for simplifications at various levels, i.e. train different simplification models depending on the intended reader group; and (4) they provide comparable training material in two languages, English and Spanish. At the beginning of 2016, the Newsela corpora contained around 2,000 original news articles in English and around 250 original news articles in Spanish (both with their corresponding manually simplified versions at four different simplification levels).

The current state-of-the-art systems for automatic sentence-alignment of original and manually simplified text are the Greedy Structural WikNet (GSWN) method (Hwang et al., 2015) used for sentence-alignment of original and simple English Wikipedia, and the HMM-based (using Hidden Markov Model and Viterbi algorithm) method (Bott and Saggion, 2011) used for sentence-alignment of the Spanish Simplex corpus (Saggion et al., 2015). The HMM-based method can be applied to any language as it does not require any language-specific resources. It is based on two hypothesis: (H1) that the original order of information is preserved, and (H2) that every ‘simple’ sentence has a corresponding ‘original’ sentence. The GSWN method does not assume H1 or H2, but it only allows for ‘1-1’ sentence alignments (which is very restricting for TS) and it is language-dependent as it requires the English Wiktionary². In this paper, we present a freely available tool for sentence- and paragraph-alignment from document-aligned TS corpora, the CATS (Customized Alignment for Text Simplification) tool.³ The tool offers two main functionalities:

1. CATS-Align: sentence- or paragraph- alignment of parallel texts; and

¹https://newsela.com/
²https://www.wiktionary.org/
³The CATS tool and documentation can be downloaded from: https://github.com/neosyon/SimpTextAlign
2. CATS-Measure: three different sentence (or paragraph) similarity measures which can be further used to filter retrieved sentence/paragraph pairs for customised modeling of text simplification operations.

The CATS-Align has two main advantages over the state-of-the-art GSWN method:

- CATS is language-independent and resource light. Two out of three similarity metrics that CATS require only pre-trained word embeddings in the language for which it is to be used, while the third similarity metric does not even require word embeddings (it is based on character n-gram matching).
- The GSWN method only allows for ‘1-1’ sentence alignments, while CATS-aligns additionally offers a possibility for building a dataset which covers sentence splitting (‘1-n’ alignments).

Similarly to the HMM-based method, our alignment methods assume the hypothesis H2. We provide them in both variants, using the hypothesis H1 and without it (Section 2.2). The detailed human evaluation of our methods and the HMM-based method (Section 3) for both English and Spanish showed that our methods are significantly better, especially when aligning sentences from distant complexity levels.

The CATS tool was released together with our previous paper (Štajner et al., 2017). In that work, we were purely interested in augmenting the parallel datasets for training ATS systems and we performed an intrinsic evaluation of the tool only on the English part of Newsela corpora, and an extrinsic evaluation by using newly aligned dataset in a PBSMT approach to English ATS.

Here we build on our previous work by describing the full potential of the CATS tool: (1) for automatic sentence-alignment of both English and Spanish corpora; and (2) for automatic filtering of aligned sentence pairs according to the simplification operation: content deletion, information addition, and paraphrasing without significant semantic change.

In Section 2 we present different modes of the CATS tool. In Section 3, we present a detailed human evaluation and error analysis of the CATS-Align on both English and Spanish Newsela corpora. We evaluate CATS-Measure automatically on the ‘gold standard’ English Wikipedia dataset for classification of sentence pairs in three classes (full matches, partial matches, and no match) in Section 4. Finally, in Section 5, using the labels assigned by human annotators on the Newsela dataset during the human evaluation of CATS-Align, we test whether the CATS-Measure can be used to automatically classify the automatically-aligned sentence pairs (aligned by CATS-Align) into four classes depending on the type of simplification operation they model.

2. The CATS

Our CATS software can work in two different regimes:

- **CATS-Measure** for providing three different similarity measures that can be applied either on paragraph or sentence level;

- **CATS-Align** for choosing best paragraph or sentence alignments in a given document-aligned corpus.

2.1. CATS-Measure

CATS-Measure provides similarity measures for three different sentence/paragraph similarity methods:

1. **C3G**: The Character N-Gram (CNG) (Mcnamee and Mayfield, 2004) similarity model (with n set to 3) with log TF-IDF weighting (Salton and McGill, 1986).

2. **WAVG**: The continuous skip-gram model (Mikolov et al., 2013b) of the TensorFlow toolkit on the English Wikipedia. For each text snippet (i.e. sentence or paragraph, depending on the task) we average its word vectors to obtain a single representation of its content. This setting has shown good results in other NLP tasks (e.g. for selecting out-of-the-list words (Mikolov et al., 2013a), or for language variety identification (Franco-Salvador et al., 2015)).

3. **CWASA**: The Continuous Word Alignment-based Similarity Analysis (CWASA) model (Franco-Salvador et al., 2016) was initially proposed for plagiarism detection with excellent results. Unlike the WAVG method, CWASA does not average word vectors and was thus proposed as more adequate for long texts.

In all three methods, similarity between the vectors is calculated using the cosine similarity. In WAVG and CWASA methods we use 300-dimensional vectors calculated with the continuous skip-gram model. We use the September 2016 Wikipedia dumps as input to train the English vectors. The model uses negative sampling, context windows of size 10, and 20 negative words for each sample. For Spanish, we use the freely available pretrained 300-dimensional vectors obtained using the skip-gram model with negative sampling on a large collection of various Spanish corpora with a total of approximately 1.5 billion words (Cardellino, 2016).

2.2. CATS-Align

For aligning sentences or paragraphs from a document-aligned TS corpora, CATS-Align offers two different alignment strategies (MST and MST-LIS) depending on whether we assume the hypothesis H1 (see Section 1) that the simplified text presents the information in the same order as the original text:

- **Most Similar Text (MST)**: Having a set of ‘simple’ text snippets \( S \), a set of ‘complex’ text snippets \( C \), and one of the similarity methods (Section 2.1), MST compares similarity scores of all possible pairs \((s_i, c_j)\), and aligns each \( s_i \in S \) with the closest one in \( C \).

- **MST with Longest Increasing Sequence (MST-LIS)**: MST-LIS uses the hypothesis H1. It first uses the MST strategy, and then postprocess the output by extracting – from all obtained alignments – only those alignments \( l_i \in L \), which contain the longest increasing sequence of offsets \( j_k \in C \).

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4https://www.tensorflow.org/
original Spanish articles, together the four corresponding original English articles and 10

for building ATS systems (ˇStajner et al., 2017).

has shown best results in the extrinsic evaluation when used necessarily the same one. Two-step C3G alignment (C3G-2s)

In this option, paragraphs and sentences can be aligned by sentence-alignment within each pair of aligned paragraphs. Additionally, the CATS-Align offers two-step alignment option, by first performing paragraph-alignment, and then

2.2.2. Two-Step Alignment

Additionally, the CATS-Align offers two-step alignment option, by first performing paragraph-alignment, and then sentence-alignment within each pair of aligned paragraphs. In this option, paragraphs and sentences can be aligned by any of the six previously mentioned strategies (three similarity methods times two alignment strategies), and not necessarily the same one. Two-step C3G alignment (C3G-2s) has shown best results in the extrinsic evaluation when used for building ATS systems (ˇStajner et al., 2017).

3. Human Evaluation on Newsela Datasets

We randomly selected 10 original English articles and 10 original Spanish articles, together the four corresponding
simpler versions (at different levels of simplification) for each of them, and sentence-aligned them with seven different alignment strategies offered by the CATS tool: C3G, C3G*, CWASA, CWASA*, WAVG, WAVG*, C3G-2step, and the HMM-based alignment tool (Bott et al., 2012). Then we asked two native speakers of English (first trained on additional 3 original articles and their corresponding simplified versions) and two native speakers of Spanish (first trained in the same manner) to classify the obtained sentence pairs (a total of approx. 3,500 sentence-pairs for each language) in one of the four classes:

• 3: full match (full semantic overlap),

• 2: partial match (partial semantic overlap where the original sentence contains less information than the simplified sentence)

• 1: partial match (partial semantic overlap where the original sentence contains more information than the simplified sentence),

• 0: no match (no semantic overlap).

While sentence pairs with full matches can be used to model paraphrasing, sentence pairs with partial matches can be used to model deletions (class ‘1’ where the original sentence contains more information than the simplified sentence) or additions (class ‘2’ where the original sentence contains less information than the simplified sentence). Several examples from different classes are presented in Table 2. As can be seen, the CATS tool can successfully align sentences with full semantic overlap which differ only by one lexical/phrasal substitution (the second and the third example in Table 2), as well as those which are much stronger paraphrases of each other (the first example in Table 2). It can also align the sentences which have only partial semantic overlap (examples 4a, 4b, and 5 in Table 2).

3.1. Results of Human Evaluation

The results of this human evaluation are presented in Tables 3 and 4, as a percentages of different classes/matches. Given the human effort needed for such evaluation, we focused only on three level pairs: aligning the sentences from

| Ex. | Original | Simplified |
|-----|----------|------------|
| 1a  | Hand parts take up to 10 hours to print and another couple of hours to assemble with elastic cords to keep the hands open. | Hand pieces take up to 10 hours to print. |
| 1b  | Hand parts take up to 10 hours to print and another couple of hours to assemble with elastic cords to keep the hands open. | Putting them together takes another couple of hours. |
| 2a  | With one his wife bought him for Father’s Day, sheets of colored plastic, and free designs and advice found online, he made a hand for about $20 | Chi made his first 3-D hand with a printer his wife bought him for Father’s Day. He found free designs online. |
| 2b  | With one his wife bought him for Father’s Day, sheets of colored plastic, and free designs and advice found online, he made a hand for about $20 | With them, he printed a hand for about $20 |
| 2c  | With one his wife bought him for Father’s Day, sheets of colored plastic, and free designs and advice found online, he made a hand for about $20 | |

Table 1: Examples of ‘1-n’ alignments obtained by CATS-Align on the Newsela corpora (Newsela, 2016), which can be used either for modeling sentence compression (each example separately) or sentence splitting (by merging examples 1a–1b, and merging examples 2a–2c).
the Spanish dataset (up to 13.4% difference), while there is no much difference on the English dataset (only up to 3.3% difference). In aligning other level pairs (3-4 and 0-4) the differences in the percentages of partial matches modeling deletion were significant regardless the language.

3.1.2. The Influence of Hypothesis H1
We noticed that the use of hypothesis H1 reduces the percentage of full matches regardless of language, level pairs, and similarity measure. However, it sometimes increases the number of partial matches which model deletion (see Tables 3 and 4).

3.1.3. CATS Alignments across Languages
When comparing the performances of CATS alignments across the two languages, we find that alignment of 0-1 levels yields in slightly higher percentage of full matches on the English dataset than on the Spanish dataset, but at the cost of having lower percentage of partial matches modeling deletion (Part-Del). When aligning Level 3 with Level 4, we find similar percentage of full matches in both languages and a higher number of partial matches (deletions) on the English dataset. In the case of aligning Level 0 with Level 4, we also have a higher percentage of full matches on the English dataset than on the Spanish dataset, in addition to a higher percentage of partial matches. However, the differences in the percentage of full matches and partial matches between the two languages might not reflect the performances of the system on those languages but rather the nature of simplifications performed on the Newsela arti-

Table 2: Examples of different classes of alignments obtained by CATS-Align on the Newsela corpora (Newsela, 2016), together with their similarity scores obtained by C3G-2s alignment strategy. Differences between original and simplified sentences are presented in bold.

| Ex. | Original | Simplified | Class | Sim. |
|-----|----------|------------|-------|------|
| 1   | After focusing on the latest artificial limb technology, he began to hunt for more basic options. | He looked into the latest prosthetic limb technology and began hunting for cheaper, less complicated options. | 3 | 0.52 |
| 2   | Like many researchers, entrepreneurs and even artists in recent years, he turned to the 3-D printer. | Like many researchers, businesspeople and even artists in recent years, he turned to the 3-D printer. | 3 | 0.80 |
| 3   | With one his wife bought him for Father’s Day, sheets of colored plastic, and free designs and advice found online, he made a hand for about $20. | By using one his wife bought him for Father’s Day, sheets of colored plastic, and free designs and advice found online, he made a hand for about $20. | 3 | 0.95 |
| 4a  | A non-profit group called Women On 20s, formed to convince President Barack Obama to put a woman’s image on the $20 note, already has done some polling. | There is a group called Women On 20s. | 1 | 0.45 |
| 4b  | A non-profit group called Women On 20s, formed to convince President Barack Obama to put a woman’s image on the $20 note, already has done some polling. | It wanted a woman’s picture on the $20 bill. | 1 | 0.26 |
| 5   | The plastic comes out in layers. | They melt and the plastic comes out in layers. | 2 | 0.82 |
| 6   | Lew has said that Hamilton’s image will remain part of the new $10 bill. | The new $10 bill will have the picture of a woman, he said. | 0 | 0.47 |
| 7   | These are some of the candidates to be the first woman on U.S. currency notes in more than a century. | Who will be the first woman on American money in more than a 100 years? | 0 | 0.30 |

The original articles (Level 0) and the first simpler level (Level 1), aligning the sentences for the original articles (Level 0) and the simplest articles (Level 4), and aligning the sentences from the two simplest levels (Level 3 and Level 4). Due to the nature of simplification operations needed to be applied between levels 0 and 1, and those needed between levels 0 and 4, we expect a greater lexical and n-gram overlap between the sentences needed to align between levels 0 and 1, than those sentences needed to align between levels 0 and 4. Furthermore, we are interested in exploring whether the success rate of the alignment tool stays stable whenever we align two neighbouring levels, thus taking into account both 0–1 and 3–4 alignments. Finally, we investigate whether the success rate stays stable across the two languages.

3.1.1. Comparison with the State of the Art
In both languages and on all level pairs, the CATS alignments were able to find higher number of full and partial matches than the state-of-the-art HMM alignment method (Tables 3 and 4). The differences in the percentage of full matches found by the CATS alignments and the HMM method are particularly pronounced when we align 0-1 levels (up to 9.4% difference on the English dataset, and up to 10.8% difference on the Spanish dataset). The differences in the percentages of partial matches modeling deletion (Part-Del) between the CATS alignments and the HMM method while aligning 0-1 levels are noticeable on the Spanish dataset (up to 13.4% difference), while there is no much difference on the English dataset (only up to 3.3% difference). In aligning other level pairs (3-4 and 0-4) the differences in the percentages of full matches and partial matches modeling deletion were significant regardless the language.
Table 3: Distribution of different sentence-alignments according to the human evaluation on the English Newsela corpora. For each pair of levels, the highest percentage of full and part-del matches, and the lowest percentage of no matches are shown in bold.

| Align | Method | 0-1 | 0-4 | 1-3 | 2-4 | 3-4 | 4-5 |
|-------|--------|-----|-----|-----|-----|-----|-----|
|       |        | Full| Part-Add| Part-Del| No |
| 0-1   | C3G    | 69.6%| 2.8%| 23.8%| 3.9% |
| 0-1   | C3G*   | 67.4%| 2.8%| 24.3%| 5.5% |
| 0-1   | CWASA  | 69.1%| 2.8%| 24.3%| 3.9% |
| 0-1   | CWASA* | 66.9%| 2.8%| 24.3%| 6.1% |
| 0-1   | WAVG   | 69.6%| 2.2%| 24.3%| 3.9% |
| 0-1   | WAVG*  | 67.4%| 2.2%| 24.3%| 6.1% |
| 0-1   | HMM    | 60.2%| 2.8%| 21.0%| 16.0% |

| Align | Method | 0-4 | 0-1 | 1-2 | 2-3 | 3-4 | 4-5 |
|-------|--------|-----|-----|-----|-----|-----|-----|
|       |        | C3G | C3G*| CWASA| CWASA*| WAVG| WAVG*| HMM|
| 0-4   | C3G    | 44.5%| 0.9%| 32.7%| 21.8% |
| 0-4   | C3G*   | 42.7%| 0.9%| 33.2%| 23.2% |
| 0-4   | CWASA  | 45.5%| 1.4%| 31.3%| 21.8% |
| 0-4   | CWASA* | 42.7%| 0.9%| 31.3%| 25.1% |
| 0-4   | WAVG   | 44.1%| 1.4%| 32.2%| 22.3% |
| 0-4   | WAVG*  | 41.2%| 0.9%| 32.7%| 25.1% |
| 0-4   | HMM    | 38.9%| 0.9%| 23.7%| 36.5% |

| Align | Method | 0-1 | 0-4 | 1-3 | 2-4 | 3-4 | 4-5 |
|-------|--------|-----|-----|-----|-----|-----|-----|
|       |        | Full| Part-Add| Part-Del| No |
| 0-1   | C3G    | 10.0%| 0.5%| 43.6%| 46.0% |
| 0-1   | C3G*   | 6.2% | 0.0%| 48.8%| 45.0% |
| 0-1   | CWASA  | 9.5% | 0.5%| 33.6%| 56.4% |
| 0-1   | CWASA* | 6.6% | 0.0%| 35.1%| 58.3% |
| 0-1   | WAVG   | 9.5% | 0.5%| 45.0%| 32.7% |
| 0-1   | WAVG*  | 6.6% | 0.0%| 43.6%| 49.8% |
| 0-1   | HMM    | 4.7% | 0.0%| 20.1%| 74.4% |

Table 4: Distribution of different sentence-alignments according to the human evaluation on the Spanish Newsela corpora.

Table 4: Distribution of different sentence-alignments according to the human evaluation on the Spanish Newsela corpora. For each pair of levels, the highest percentage of full and part-del matches, and the lowest percentage of no matches are shown in bold.

| Align | Method | 0-1 | 0-4 | 1-3 | 2-4 | 3-4 | 4-5 |
|-------|--------|-----|-----|-----|-----|-----|-----|
|       |        | C3G | C3G*| CWASA| CWASA*| WAVG| WAVG*| HMM|
| 0-1   | C3G    | 44.8%| 1.0%| 26.7%| 27.6% |
| 0-1   | C3G*   | 41.9%| 1.0%| 25.7%| 31.4% |
| 0-1   | CWASA  | 43.8%| 1.9%| 21.0%| 33.3% |
| 0-1   | CWASA* | 41.9%| 1.9%| 24.8%| 31.4% |
| 0-1   | WAVG   | 41.9%| 1.9%| 21.9%| 34.3% |
| 0-1   | WAVG*  | 41.0%| 1.9%| 23.8%| 33.3% |
| 0-1   | HMM    | 38.1%| 0.0%| 18.1%| 43.8% |

| Align | Method | 0-4 | 0-1 | 1-2 | 2-3 | 3-4 | 4-5 |
|-------|--------|-----|-----|-----|-----|-----|-----|
|       |        | C3G | C3G*| CWASA| CWASA*| WAVG| WAVG*| HMM|
| 0-4   | C3G    | 3.8% | 0.0%| 37.1%| 59.0% |
| 0-4   | C3G*   | 1.9% | 0.0%| 43.8%| 54.3% |
| 0-4   | CWASA  | 3.8% | 1.0%| 35.2%| 60.0% |
| 0-4   | CWASA* | 1.0% | 0.0%| 35.2%| 63.8% |
| 0-4   | WAVG   | 3.8% | 1.0%| 35.2%| 60.0% |
| 0-4   | WAVG*  | 2.9% | 0.0%| 26.7%| 70.5% |
| 0-4   | HMM    | 1.0% | 0.0%| 10.5%| 88.6% |

Section 3.2. Error Analysis

We found that over 50% of original sentences from Level 0 get split into two or more (up to even five sentences) simple sentences when simplifying into Level 4. This sometimes results in low scores (no match) by human evaluation of isolated sentence pairs, although all simple sentences that correspond to the same original sentence, when seen together, perfectly match the original sentence (Table 5). In other words, when treated separately, some of the sentences aligned between levels 0 and 4 present false negatives, as they will later be merged together for training ATS systems, where they will then represent good training material for sentence splitting. These type of errors could be avoided by performing human evaluation on already merged sentences (those that together model sentence splitting), but in that case we would not have the count of correct deletions and additions, which might be useful for tasks other than simplification, or for modeling these specific text simplification operations.

Section 4. Automatic Evaluation on Wikipedia

The ‘gold standard’ Wikipedia dataset for sentence-alignment (Hwang et al., 2015) contains pairs of sentences and their ‘gold label’ (full match, partial match, or no match) with the same meaning as in our manual evaluation task. As the C3G, CWASA and WAVG methods output similarity score for each sentence pair, we use them to predict the labels for the sentence pairs in the Wikipedia dataset. Table 6 shows the $F_1$-measures obtained by our systems (using different combinations of sentence similarity measures and classification algorithms) and the state-of-the-art GSWN system, as well as several baselines used by Hwang et al. (2015) on two classification tasks: classifying between Good&GoodPartial matches vs. Others (Task 1), and between Good matches vs. Others (Task 2). The HMM-method requires full texts to use the H1 hypothesis and thus cannot be successfully applied to these tasks. Detailed results of our various classification methods on Tasks 1 and 2, presenting precision (P), recall (R) and $F_1$-measure (F) on the Good & GoodPartial class (Task 1) or Others (Task 2), are presented in Table 7. We observe similar behaviour of our similarity metrics in both tasks; the C3G method obtains significantly better recall than the word-embedding-based methods (CWASA and WAVG), while CWASA and WAVG obtain better precision than the C3G. All three methods combined together significantly boost both recall and $F_1$-measure, significantly outperforming all previously proposed methods on Task 1, and
1. Todos los estudiantes tienen que hacer el examen SAT para ser admitidos en la universidad.

2. Algunas personas opinan que los estudiantes de color están menos preparados para entrar a la universidad.

3. Dicen esto cuando los estudiantes afroamericanos tienen calificaciones más bajas que las de sus compañeros blancos en ese examen.

4. También, cuando reciben calificaciones más bajas en la universidad o se cambian a carreras “menos difíciles”.

Table 5: An example of sentence pairs which obtained score 0 (no match) each, but in fact present a good example of an ‘1–n’ alignment obtained by CATS-Align C3G method on the Newsela corpora (Newsela, 2016).

| Approach                  | Task 1 | Task 2 |
|---------------------------|--------|--------|
| C3G+CWASA+WAVG            | .643   | .705   |
| C3G+CWASA                 | .621   | .680   |
| C3G+WAVG                  | .602   | .691   |
| CWASA+WAVG                | .506   | .664   |
| C3G                       | .612   | .695   |
| CWASA                     | .490   | .671   |
| WAVG                      | .481   | .650   |
| GSWN (Hwang et al., 2015) | .607   | .712   |
| Unconst. WordNet (Hwang et al., 2015) | .515 | .636 |
| Ordered Vec.Space (Hwang et al., 2015) | .415 | .564 |
| Unconst. Vec.Space (Hwang et al., 2015) | .431 | .550 |

Table 6: $F_1$-measures on Task 1 (Good & Good Partial vs. Others) and Task2 (Good vs. Others). The best results for each task are shown in bold.

obtaining comparable results to the state of the art on Task 2 (see Table 6). Here is important to mention that, unlike the current state-of-the-art method on Task 2 (Hwang et al., 2015), our methods are language-independent, resource-light, and allow for retrieving material for sentence splitting (allow for ‘1–n’ matches).

5. Automatic Classification of Alignments

Finally, we explore if the similarity measures provided by CATS-Measure can be used to classify the aligned sentence pairs according to the type of simplification operation they model.

5.1. Distribution of Similarity Scores

We first explore the distribution of similarity scores across different transformation types and different text levels on both English and Spanish human annotated datasets (Figure 1). As can be seen, all six sentence similarity metrics (C3G, C3G*, CWASA, CWASA*, WAVG, WAVG*) seem to have better discriminatory power between the four classes (0–3) on the Spanish dataset than on the English dataset (discriminatory power seen as the overlap of box-plots for different classes), with the C3G and C3G* being the best among the six metrics. Here is important to mention that the metrics do not have to be able to distinguish between the classes 1 (insertion) and 2 (deletion). To discriminate between those two classes (in the case of similar metrics scores) we can use the difference in the sentence length between the two sentences, i.e. deletions and insertions should lead to the opposite sign when we subtract the length of the original sentence (in words) from the length of the simplified sentence (in words). The distributions of sentence similarity scores (Figure 1) indicate that we can expect better classification results for Spanish than for English experiments.
Figure 1: Distribution of the six similarity scores across different classes, text levels, and languages.

5.2. Classification Experiments

For classification experiments, we use the labels assigned by human evaluators as the ‘gold standard’ labels. As features, we use the similarity metrics obtained by CATS-Measure (one metric at the time) and the differences in word count between the original and simplified sentence (in order to distinguish between additions and deletions) which achieve similar scores for semantic similarity by all our similarity metrics (see Figure 1). Given that we observed certain differences in distribution of similarity metrics across different text levels, we also experiment with adding the level pair as an additional (third) feature for the classification.

We used five different classifiers: Logistic (Le Cessie and van Houwelingen, 1992), SMOs – Weka implementation of SVM (Platt, 1998) with feature standardisation, JRip rule learner (Cohen, 1995), J48 – Weka implementation of C4.5 decision tree (Quinlan, 1993), and Random Forest (Breiman, 2001), in a 10-fold cross-validation setup with 10 repetitions in Weka Experimenter (Hall et al., 2009).

As can be seen from the classification results presented in Table 8 (only for the best classifier, logistic), although CATS-Align achieved lower performances on the Spanish dataset, the no matches can easier be automatically filtered for Spanish than for English (lower number of false positives for Spanish than for English). The percentage of false positives for the no match class (fPos) indicate that if we are interested only in filtering out no matches, we can successfully achieve this by training the classifiers on a small number of human annotated sentence pairs, especially for Spanish (where, in the best scenario, using the WAVG*, difference in sentence length, and the level pair, the percent-
Table 8: Results of automatic classification of sentence pairs into four categories (no match, deletions, additions, and full matches) presented as the weighted average F₁ measure (w-F) and the percentage of false positives for the no match class (fPos), i.e. cases in which no match was classified as any other category. The best scores achieved for each classification evaluation metric (w-F and fPos), and for each language, are presented in bold.

| Features       | English w-F | fPos (%) | Spanish w-F | fPos (%) |
|----------------|-------------|----------|-------------|----------|
| C3G + len + levels | 71.5        | 32.5%    | 82.6        | 16.7%    |
| C3G + len      | 74.9        | 32.0%    | 82.3        | 21.4%    |
| C3G* + len + levels | 75.3        | 32.2%    | 84.1        | 16.3%    |
| C3G* + len     | 75.3        | 32.2%    | 84.8        | 16.3%    |
| CWASA + len + levels | 70.1        | 27.5%    | 80.9        | 19.1%    |
| CWASA + len    | 70.2        | 30.2%    | 83.8        | 14.9%    |
| CWASA* + len + levels | 72.6        | 26.6%    | 80.5        | 15.3%    |
| CWASA* + len   | 72.3        | 27.0%    | 81.4        | 13.9%    |
| W AVG + len + levels | 65.0        | 45.5%    | 77.0        | 23.1%    |
| W AVG + len    | 65.1        | 52.5%    | 78.6        | 30.3%    |
| W AVG* + len + levels | 69.7        | 42.0%    | 82.9        | 13.6%    |
| W AVG* + len   | 69.6        | 42.0%    | 83.1        | 15.3%    |

Conclusions

One of the main problems of the state-of-the-art automatic text simplification systems is the absence and the small size of parallel datasets (pairs of original sentences and their manually simplified versions) which leads to insufficient coverage of supervised systems. The CATS tool presented in this paper offers several different ways of sentence- and paragraph-aligning of document-aligned texts on different text complexity levels. It additionally offers three sentence similarity metrics which can be applied on sentence pairs into four categories (no match, deletions, additions, and full matches) presented as the weighted average F₁ measure (w-F) and the percentage of false positives for the no match class (fPos), i.e. cases in which no match was classified as any other category. The best scores achieved for each classification evaluation metric (w-F and fPos), and for each language, are presented in bold.

age of false positives for the no match class is only 13.6). If we are interested in classifying sentence pairs by different transformation operations, this can again be successfully achieved with classifiers trained on the small number of instances, with better results for Spanish than for English (weighted F-measure of 84.8 for Spanish, and 75.3 for English).

The results in Table 8 also indicate that specifying the level pair from which sentences were aligned improves the F-measure on the Spanish classification task (though not necessarily decreases the number of false positives for the no match class), but has no effect on the English classification task.

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