Automatic Summarization for Text Simplification: Evaluating Text Understanding by Poor Readers

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ABSTRACT
In this paper we present experiments on summarization and text simplification for poor readers, more specifically, functional illiteracy readers. We test several summarizers and use summaries as the basis of simplification strategies. We show that each simplification approach has different effects on readers of varied levels of literacy, but that all of them do improve text understanding at some level.

Categories and Subject Descriptors
I.2.7 [**Natural Language Processing**]: Language generation, Language parsing and understanding, Text analysis.

General Terms
Experimentation, Human Factors.

Keywords
Summarization, Text Simplification, Natural Language Processing.

1. INTRODUCTION
In Brazil, *letramento* (literacy) is a term used to designate people's ability to use written language to obtain and process information, express themselves, plan and learn continuously, i.e., to effectively use their reading and writing skills in several aspects of their social life [1].

Since 2001, INAF index (National Indicator of Functional Literacy) has been annually computed to measure the levels of functional illiteracy of Brazilian population. INAF 5-year report identifies four levels of reading/writing skills (i.e., four levels of literacy) for Brazilian population: illiteracy, rudimentary literacy, basic literacy and advanced literacy levels. Most of Brazilian population belongs to the rudimentary and basic literacy levels, which correspond to the ability of dealing with short texts and making simple inferences.

Text Simplification (TS) is the task of making texts easier to read and understand. It can be tailored to readers of different literacy levels, to people with cognitive disabilities (due to natural causes and/or diseases – like aphasia and dyslexia – and brain injuries, like stroke), and even to other machine applications (e.g. information retrieval and extraction). TS may include summarization strategies, elicitation of text structure and its organization, lexical and syntactic simplification, and presentation schemes. To our knowledge, no TS system exists for Portuguese.

In this paper we address an initial study on the Natural Language Processing (NLP) task of text summarization applied to TS in order to attend people at the rudimentary and basic literacy levels. We first conduct experiments to verify how good classical and state of the art summarization techniques are in identifying text main ideas and in producing good summaries. Then, we evaluate summarization impact in TS with readers of varied levels of literacy. We evaluate three simplification strategies and show that they have different effects on varied readers, but that all of them improve understanding at some level.

In the next section we overview the TS area and where our work fits. In Section 3, we briefly describe each summarization technique we tested and the results that we obtained. In Section 4 we report our simplification experiment and the conclusions we could draw. Section 5 presents some final remarks.

2. TEXT SIMPLIFICATION
It is well-known that long sentences, conjoined sentences, embedded clauses, passives, non-canonical word order, and use of low-frequency words, among other things, increase text complexity for language-impaired readers [9] [10] [11]. While [12] and [13] only consider syntactic knowledge to approach TS, using both rule-based systems and learned rules from a corpus,

respectively, [14], [15], [6], and [16] tackle the generation of simplified texts by focusing on choices at the discourse level. On the other hand, PSET (Practical Simplification of English Texts) project [11] investigated how lexical-level and syntactic level choices affect readability for a special kind of readers – aphasics – without considering discourse choices.

The kind of knowledge used to implement TS systems is also an important issue related to the final use and user a TS system is meant for. [12] and [13] design TS methods more appropriate to other language technology systems or systems with human post-processing. [10] focuses on TS to easy information seeking applications. [17], however, claim that heavily simplified sentences run the risk of being more difficult to comprehend, as they may have fewer linguistic cues of cohesion that specify how the sentences should be conceptually related. The approach followed by [16], [14] and [8] favors text accessibility to a wider audience of readers, and may be used for educational purposes.

Besides poor readers, that are the focus of our study, other users groups may benefit from TS systems: people making use of assistive technologies [18] [19] [20], as screen readers and translators; hearing-impaired people who communicate to each other using LIBRAS (Brazilian Sign Language), since they find difficult to understand complex texts in Portuguese, due to the structural differences between LIBRAS and Portuguese [21]; people with cognitive disabilities caused by medical conditions or interventions, e.g., people suffering from aphasia or dyslexia [22] [23] [7] [24] and traumatic brain injuries, strokes and aneurysms [25]; and last, but not least, people going through Distance Education, in which text understanding is important [26].

In spite of all the uses TS systems have, there are researchers, such as [27], that defend the use of simple accounts instead of simplified versions of texts, since the former consist in more natural and authentic texts for being directly produced for tailored audiences. While automating the generation of easy-to-read texts is computationally expensive (since it is needed to apply data-to-text generation) (see, e.g., [14], [28], [29]), manually written simple account texts can lead TS systems to generate more natural texts.

About using summarization strategies for text simplification, there are just a few works. [8] considers dropping parts from the text to favor understanding. The authors claim that extractive summarization methods (i.e., methods that build summaries by juxtaposing complete sentences from the source text) are useful, but that these methods alone are insufficient for simplification, since complex sentences may be chosen to be in the summary. The authors conduct a corpus analysis to show that summarization does happen in simplified texts, but do not evaluate its impact for poor readers. Another initiative, the Plain English, a movement in Britain and the USA that emerged in the late 1970's as a reaction to the unclear language used in government and business forms and documents, makes available guidelines that recommend the use of summaries and the removal of unessential information from texts.

To our knowledge, the work we report in this paper is the first one to effectively use summarization for TS and to evaluate its effectiveness for text understanding.

3. SUMMARIZATION METHODS AND EVALUATION

In order to find an good summarization method for TS, we implemented and compared several pre-existent summarization methods. Some methods are classical in the area, while others are the state of the art for Brazilian Portuguese. We overview each method in Subsection 3.1. Their evaluation is shown in Subsection 3.2.

3.1 Methods

For our experiments, we selected only extractive summarizers (the dominant technology for Portuguese). We selected representative methods for Portuguese based on varied strategies. The methods are briefly described below.

3.1.1 Summarization Methods Based on Keywords Extraction

Keywords-based summarization methods are the oldest and perhaps the most used ones in summarization history. They date back the 50's and inspired many methods that still exist.

The methods we selected (and reimplemented) were the ones presented in [3], which are fairly simple: given a text and its keywords, any sentence that contains at least one keyword is selected to be in the summary. Two algorithms for keyword selection were initially used (as defined in [4]): EPC-P (*Extração de Palavras-Chave por Padrão*, in Portuguese; or, in English, Keyword Extraction by Patterns) and EPC-R (*Extração de Palavas-Chave por freqüências de Radicais*, in Portuguese; or, in English, Keyword Extraction by Stem Frequency). EPC-P looks for word patterns classified as <Noun> and <Noun+Preposition+Noun> in the text, as well as the versions with adjectives (in any positions), which are assumed to be keywords. The most frequent ones are selected as keywords. EPC-R looks for frequent groups of stems from the words in the text. Besides frequency, groups that appear in the beginning of the text and groups composed by more than one stem have a higher weight in the computation that decides whether they are keywords. In this paper we will refer to the summarization methods above by simply the keyword extraction method they use: EPC-P and EPC-R. Two summarization methods based on the ones above were also implemented using EPC-P and EPC-R: instead of considering any sentence that contains a keyword part of the summary, all sentences are first ranked by the number of keywords they present and, then, the highest ranked ones are selected to form the summary. We will refer to these summarization methods as EPC-P2 and EPC-R2.

3.1.2 Summarization Method Based on Gist Identification

Another system we analyzed was GistSumm [5], which creates a summary based on a single sentence (the most important in the text), called "gist sentence". GistSumm is one of the first summarizers created for Brazilian Portuguese and, to the best of our knowledge, it is the system with the highest precision[1] for this language [2], i.e., it selects good sentences to be in the summary,

[1] Such measure refers to the traditional precision measure from the precision/recall pair.

but not necessarily selects all the information that should be in the summary.

For producing the summary, the system first computes the frequency of every stem in the text. Each sentence receives a score, which is the sum of the frequencies of every stem that belongs to it. Then, the sentence with the highest score is elected the gist sentence, which will necessarily be in the summary. To decide the rest of the sentences that will form the summary, there are two restrictions: the sentences must have at least one stem in common with the gist sentence and their scores must be above a threshold, which is the mean score of all sentences.

3.1.3 Summarization Method Based on Machine Learning

Based on a machine learning technique (a Naïve-Bayes approach), SuPor-2 [31] is the best summarizer for Brazilian Portuguese [2] [30]. It is important to notice that, differently from GistSumm that has a high precision, SuPor-2 has both good precision and recall.

The system uses several features to classify each sentence from the text according to its importance. Some features are very well known in summarization area, e.g., sentence length and position, word frequency, presence of importance signaling phrases, and occurrence of proper nouns; other features codify entire summarization methods, e.g., lexical chaining [32] and importance of topics-based summarization [33].

3.1.4 Summarization Methods Based on Graphs

New summarization methods based on graphs have received great attention in the area for their simplicity and elegance, since graph algorithms have been long studied.

Recently, [34] presented a language-independent summarization method based on Google PageRank algorithm [35]. The method, called TextRank, represents text sentences as nodes in a graph and adds edges codifying the similarity among the sentences, which is basically computed by a word overlap measure. TextRank and a version of it enriched with thesaurus synonym and antonym relations (to improve the word overlap measure) were evaluated for Portuguese and compared with SuPor-2. They achieved very good results, but could not outperform SuPor-2.

3.1.5 Baseline Summarization Methods

In order to verify how good the previous summarization methods are in the task we are to evaluate, we need some reference methods.

We implemented a very strong baseline, the First Sentences method, which selects the first sentences of the text to form the summary. As it is widely known in the area, news texts (which are the texts we use in our evaluation) present their main idea in the first sentences. In fact, for such texts, the First Sentences method is hardly outperformed. We also implemented a poor baseline method, which randomly selects sentences to be in the summary.

3.2 Evaluation

To evaluate all previous methods and define which one yields the best results, thus providing us with a summarization tool to be used for TS, we performed three different experiments.

The first experiment was to automatically determine the ability of each method to identify the main sentence of a text. To do so, we used a corpus of 187 texts in Brazilian Portuguese, all of them obtained from a national newspaper called *Folha de São Paulo*, to find out the percentage of success each of the methods achieved. Firstly, we assumed that the first sentence in each text is the most important one, since we are dealing with journalistic genre. Then, we generated one-sentence summaries for the 187 texts, which contain only what is considered the main sentence for each text according to each summarization method. The results achieved by the summarization methods are displayed in the second column of Table 1, where precision indicates the percentage of texts for which the methods selected the first sentence to form the one-sentence summaries.

The results show that EPC-P and First Sentences method have a clear advantage over all other methods, indicating that they would be good choices when summarizing news texts. It is important to notice that First Sentences method is heavily genre dependent. For other text genres, it may be very bad. For this reason, EPC-P may be the best choice among the methods.

Table 1. Performance of summarization methods

Method	Precision	Manually-checked precision	ROUGE
EPC-P	89%	85%	0.4722
EPC-P2	58%	60%	0.4640
EPC-R	60%	60%	0.4736
EPC-R2	39%	35%	0.4655
GistSumm	46%	50%	0.4185
SuPor-2	75%	85%	0,5839
TextRank	39%	50%	0,5426
TextRank+Thesaurus	27%	35%	0,5603
First Sentences	96%	90%	0.4369
Random	30%	25%	0.3121

Anyway, to verify the results and assure that the precision of EPC-P was not a mere coincidence (based on the strong assumption that text first sentences are the main ones), we randomly took a sample of 20 texts out of the corpus and manually performed the same evaluation, i.e., we manually looked for the main sentence of each text and compared it with the one-sentence summaries produced by the summarization methods. The more realistic results are displayed in the third column of Table 1. The results confirm what happens in the automatic evaluation and show that EPC-P has a very good performance. SuPor-2 achieved a precision similar to EPC-P in this evaluation. Both TextRank versions did not perform well. It is worth noticing that the Random method will have a different performance every time it runs, so these results are likely to be volatile. Other run cases for the Random method also resulted in performances between 10-30%.

Nevertheless, it is not enough to have a method that is capable of detecting the main sentence, since the quality of the whole summary may be compromised. Thus, we also need to compare the summaries in terms of informativeness. To do so, we used the set of metrics known as ROUGE [36]. ROUGE automatic evaluation compares an automatically generated summary with a manual summary created by a professional summarizer. The closest they are (in terms of common words), the best the score (among 0 and 1) the automatic summary achieves. ROUGE authors showed that it has a performance similar to human evaluation in ranking summaries by their content. Such automatic measure has been adopted in international summarization evaluation conferences and has become mandatory in any summarization experiment.

In this experiment, we used a different corpus, called TeMário [37], which has 100 texts from the newspaper *Folha de São Paulo*, and their respective manual summaries. The reason for not using the same corpus of the previous experiment is that it does not have manual summaries. We created our automatic summaries for each TeMário text using all the summarization methods with a 70% compression rate (i.e., the summary must have at most 30% of the text size – in terms of words). Such compression rate is a usual rate in the summarization area. It is also the summary size in TeMário corpus.

The results obtained are displayed in the fourth column of Table 1. We can see that SuPor-2 is the method that builds the best summaries, followed by both TextRank versions.

Overall, it is important to notice that all methods overcome the random method in all experiments. The experiments also show how strong First Sentences method is, specially for the text genre we used.

Finally, for selecting one summarization system for conducting our TS experiment, we took into consideration the following points: (i) the results for main sentence selection, (ii) the results for summary informativeness (based on ROUGE scores), and (iii) the availability, portability and possibility of use and embed the system in a TS application. For criterion (i), EPC-P is the best choice, followed by SuPor-2. For criterion (ii), SuPor-2 is the best one and is followed by both versions of TextRank; excepting the SuPor-2, TextRank and Random method, all other methods have similar performance in this criterion. For criterion (iii), excepting SuPor-2, all methods are good. SuPor-2 is an expensive summarizer in terms of necessary time to train it and for it to produce summaries.

Based on the above considerations, we chose EPC-P for our experiments. Criterion (iii) makes the use of SuPor-2 prohibitive, and criterion (i) excludes both versions of TextRank. First Sentences method was not considered a viable choice for being heavily genre dependent.

We present our experiment with TS in the next section.

4. EXPERIMENT WITH TEXT SIMPLIFICATION

Having a functional illiteracy reader as our target user, summarization can be used for TS purposes in varied ways. Some possibilities are: showing only the summary for the reader, showing the text with only the main sentence highlighted, showing the text with all important sentences highlighted, presenting the text with a headline for each paragraph (e.g., the main sentence of each paragraph), adding highlight sentences (which are sentences that express the most important facts about the text, but that do not constitute a summary) to the beginning of the text (as CNN does, for instance), and removing some irrelevant and redundant pieces of information from the text (a slightly shorter version of the text is produced, but it is still too big to be considered a summary).

For our experiment, we decided to evaluate the impact of the first three strategies from the possibilities above, i.e., presenting the summary for the reader, presenting the text with only the main sentence highlighted and presenting the text with all important sentences highlighted. These strategies are the more direct application of Portuguese summarization systems for our purposes. The remaining strategies will be investigated in future work. We selected two contemporaneous texts about different subjects: one about a famous American interviewer who has a serious disease and another one about border problems between Israel and Jordan, which at a first sight looks more difficult to read than the first one. For each text, we generated both the automatic 70% summary and the one-sentence summary with EPC-P method.

We carried out the experiment with 19 people with varied literacy levels: 3 had until 2 years of study and were almost illiterate; 5 had until 5 years of study and are in the rudimentary and basic literacy levels, which are the ones that we envision for this work; 6 had until 8 years of study; and 5 had more than 10 years of study. We collected these data by a form (in paper) that these people had to fill some days before the experiment. We used such data to plan the experiment better.

In the experiment, each person was presented to two pairs of texts, each pair containing an original text and the simplified version. The simplified version could be the 70% summary, the text with the sentences from the 70% summary in bold, or the text with the sentence from one-sentence summary in bold. After reading each pair of texts, the person had to fill a form (in paper) answering questions of multiple answers (‘yes’ or ‘no’ options): whether each text was difficult to read, whether the reading of each text was tiring, and whether the person understood each text. If the answer was ‘yes’ for the last question for some text, the person should write some lines (up to 5) stating what was the main idea of the text. This open question was intended to verify if the person had really understood the text. Finally, after reading the two texts in the group and answering the above questions for each one, the person should say (by questions with multiple answers) which text was more difficult to read, which text was more tiring to read and which text was easier to understand.

To perform the evaluation, we distributed the pairs in a way that all pairs of texts had the same amount of judgments and were judged by people from all literacy levels. The experiment was conducted in a computer laboratory. We decided to do it using computers (instead of using paper) to simulate a real situation in which TS would be performed according to what is presented in this paper. The interface for accessing the texts was developed by Human-Computer Interaction researchers and was a very simple and intuitive interface (which basically was a web browser with the texts and buttons to navigate between them).

After a demonstration of the use of the interface and of a fictional evaluation of a pair of texts, the experiment started. The experiment took almost 40 minutes to be conducted (with all people working in parallel) and counted with some computer specialists to help people that did not know how to use a computer.

From the people with until 2 years of study, 2 could not finish the experiment: 1 could not read and 1 got too tired after reading the first pair of texts. The only one that finished the experiment considered that the simplifications did not help et al.

About people with until 5 years of study: 66% considered that the summary was easier to understanding; 100% considered that the original text and the text with the important sentences in bold were equally understandable; and 60% considered that the text with the main sentence in bold was more difficult to understand. These results indicate that the summary helps, but that the information highlighted in texts do not. Our hypothesis for this fact is that the highlighted information is one more information to process, which, for these people, may be an extra burden.

About people with until 8 years of study: 100% considered reading the summary less tiring, but both original text and summary equally understandable; 75% considered the text with the important sentences in bold easier to understand; and 60% considered the text with the main sentence in bold more difficult to understand.

About the people with more than 10 years of study: 57% considered the text easier to understand than the summary, but the summary less tiring to read; 100% considered the original text easier to understand than the text with all the important sentences in bold; 80% considered the text with the main sentence in bold easier to understand.

In general, we could realize that people from each literacy level consider different simplification strategies useful: simplification could not help people with until 2 years of study, summaries helped people with until 5 years of study, the important sentences in bold helped people with until 8 years of study, and the main sentence in bold helped people with more than 10 years of study.

The above initial results showed that summarization is useful for TS purposes, but its application must be tailored to the literacy level one intends to deal with. We believe that bigger experiments with more people and more simplification strategies must be carried out. They could confirm our results until now and also indicate new strategies to follow. Particularly, we believe that summarization strategies combined with other TS approaches (like elicitation of text structure and syntactic simplification, for instance) may produce simpler texts that may be understood by more people with varied literacy levels.

5. FINAL REMARKS

To the best of our knowledge, we presented in this paper the first effort on text simplification for Brazilian Portuguese language. A comprehensive evaluation of classical and state of the art summarizers for Portuguese was presented and the impact of summarization for simplification was measured. In the future, we intend to run similar experiments with more simplification strategies and subjects.

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