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RESEARCH ARTICLE

Pragma SUM: KEY WORD USE IN AUTOMATIC SUMMARIZATION

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ABSTRACT

As access to the Internet broadens and with the advent of tools that allow people to create content, the amount information to which we have access grows exponentially. Texts written about various subjects and by countless authors are produced every day. It is impossible to absorb all the information available or to select the most adequate piece of information for a certain interest or public. Automatic text summarization, in addition to presenting a text in condensed form, can simplify it, thus generating an alternative for saving time and widening access to contained information for many different types of readers. The automatic summarizers that currently exist in literature do not present personalization methods for each type of reader and, consequently, generate results that have limited precision. This article aims to use the automatic text summarizer PragmaSUM in educational texts with new summarization techniques using keywords. Personalization methods using keywords seek to increase precision and improve the performance of PragmaSUM and its summaries. In order to achieve that, a corpus was formed exclusively by scientific articles in the field of education in order to conduct tests and comparisons between different summarizers and summarization methods. The summarizers' performance was measured by the Recall, Precision and F-Measure metrics, all of which are present in the ROUGE tool. The results point towards improved performance when employing keywords in summarization with PragmaSUM, which suggests the importance of choosing keywords adequately for classifying the content of the source text.

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INTRODUCTION

With growing access to the Internet and the creation of tools that allow people to create content, the amount of information to which we have access increases exponentially. Textual documents about various subjects, written by countless authors, are produced every day. Absorbing all the information available is an impossible task, as is selecting the most adequate piece of information meant for a certain interest or public. According to Rocha and Guelpeli (2017), the huge flow of information generated todays makes it impossible to read all the texts available, given that human capacity is limited. A condensed presentation of this information becomes an alternate way of saving time and decreasing the effort required by the reader to absorb the whole content and decide the degree of importance of the text. After a preliminary analysis of a smaller and more simplified version of the text, the reader will decide if the information is useful to achieve her goals. One way of reducing difficulties and time spent creating text summaries is the use of automatic summarization (AS).

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AS seeks to remove more important information from a source text and present it in condensed form with a summary. AS is the summary of the source text produced automatically, seeking human efficiency in its creation. In academic texts, it is common to use summaries and keywords as classification tools for helping the reader make a reading decision. In other means, this practice is not that common. Even in the academic milieu, there is no consensus regarding how summaries and keywords of a scientific article should be used and selected. Poor use of these classification tools may frustrate the journey of a new undergraduate student. The type of language presented to the student, along with a misguided classification of its content, may pose difficulties to knowledge access. A clear and objective classification of how these terms can be created can aid access and recovery of the information contained in the text. Pragma SUM (Rocha, 2014; Rocha; Guelpeli, 2017) is an automatic text summarizer that uses keywords in building the summary. The choice of these words is made by the reader. The summarizer places more weight in sentences that contain these keywords, which increases the likelihood of it appearing in the summary. PragmaSUM achieved good results with its summarization of scientific articles using keywords of this article's authors in composing summaries. This work presents new summarization methods developed in PragmaSUM. An Educational corpus was used in

Portuguese (Aguiar *et al.,* 2017) and performance evaluation tests of automatic summarizers were conducted using the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) tool (Lin; Hovy, 2003). This article hopes to contribute to academic research mainly by presenting a new form of AS, employing a model that improves the precision of generated summaries. It also hopes, considering the circumstances suggested in this work, to enable future studies about the importance of choosing keywords in scientific articles.

State of the Art

Most scientific research is currently guided by language, writing being the most commonly used one, in various forms of documents existing today. The advancement of telecommunications changed the way information is viewed today. The amount of data generated daily, in addition to known human limitations, renders it impossible to conduct a manual analysis and subsequently extract succinct and reliable information. Summarization is a technique used to condense information contained in texts for a more generic presentation, thus reading becomes an easier and faster experience. Summarization is a common activity in everyday life. It is present in both informal conversation and scientific research, and causes our dialogues to be faster and accelerates decision-making. In general, summarization is the organization of data in condensed form, without loss of information and meaning, and may be about facts, texts, films, etc. According to Martins *et al.* (2001), summaries generated from texts are particularly useful and may function as indexes or be self-contained. In the former, summaries are read to reveal the subject of the corresponding source text and, in case of interest, the reader is forwarded to the complete text for more information. In the latter case, summaries are already considered informative enough and, therefore, the reader can dismiss the original text and still apprehend the main information contained in the text.

According to Pardo (2008), summaries can be constructed, mainly, by two approaches, which are defined according to the amount and level of linguistic knowledge they use: the superficial and the detailed approach. Both of them can also merge in a variety of ways, giving rise to a hybrid approach. The superficial approach makes little or no use of linguistic knowledge in order to produce summaries. In this approach, it is common to make use of statistical and empirical data. For example, a method employed to construct text extracts is based on the selection and juxtaposition of the sentences of the source text that contain the words that most often appear in the text. The detailed approach considers linguistic knowledge by using formal theories and models of the language used in the text. PragmaSUM (Rocha; Guelpeli, 2017) is an automatic text summarizer independent of the text's language and knowledge domain. PragmaSUM uses the technique for evaluating the sentences of the source text presented by Guelpeli (2012) in the Cassiopeia text clustering model, in which the technique for reducing high dimensionality and sparse data is presented, Luhn's curve (Luhn, 1958), which is based on the Zipf Curve. To give form to the summary, PragmaSUM uses five words that are chosen by the user, which are then graded according to their position. As shown in Table 1, the first word is given the highest value and the last one has the lowest value. Using these words to evaluate the sentences of the source text is important for the personalization of the generated summary, as it is able to produce summaries that are even more precise, according to the user's profile.

Table 1. Word Grading

Position	Value
1st	6
2nd	5
3rd	4
4th	3
5th	2

Salton and Buckley (1988) presented the information retrieval algorithm, which is currently a well-grounded study called *Term Frequency - Inverse Document Frequency* (TF-IDF). In its simplest version, the algorithm is calculated for each word in a set of texts. The frequency the word appears in the document is divided by the number of documents in which it appears. According to Antiquera (2007), it is a normalized frequency measure that seeks to put less emphasis on very frequent terms that do not help to discriminate between documents. Laroca Neto *et al*. (2002), replacing the idea of document for sentence, presented the algorithm *Term Frequency - Inverse Sentence Frequency* (TF-ISF). Its value is attributed to only one document and not a collection. The algorithm variation states that each sentence is given an associated score by the TF-ISF value of all its words. This value is considered a criterion for selecting the sentences that should form a summary. According to Martins *et al*. (2001), the importance of word w in sentence s, shown as TF-ISF(w, s), is calculated by the following formula:

$$TF-ISF(w,s)=TF(w,s)*ISF(w) \qquad \text{(1)}$$

Where TF (w, s) is the number of times that word w appears in sentence s, and the inverse frequency of the sentence is achieved through the following formula:

$$ISF(w)=\log\left(\frac{|S|}{SF(w)}\right) \qquad \text{(2)}$$

Where sentence frequency SF (w) is the number of sentences in which word w appears and |S| is the number of sentences in the text.

Rouge

In order to evaluate the summaries created by automatic summarizers, the tool selected was Recall Oriented Understudy for Gisting Evaluation - ROUGE (Lin and Hovy, 2003), which, according to Oliveira (2014), is an automatic summarization evaluation pack that compares the quality of summaries generated by automatic summarizers with those produced by human beings. This tool is adopted in international conferences dedicated to the subject, such as the Text Analysis Conference - TAC, held annually in the United States and supported by the U.S. Department of Defense. The use of automated evaluation is justified by the large quantity of texts undergoing analysis and by the high costs of having it performed by specialists. ROUGE conducts an evaluation considering the amount of n-grams; i.e., word sequences, in which automatically generated summaries overlap with manual summaries. Each gram is represented by a shared word sequence among summaries. For each new appearance, the n-gram is thus incremented by a four-word sequence in common. Then 4-grams are found, and so forth. The n-grams range from 0 to 1 and, the closer the calculated result is to 1, the more the automatic summary resembles the compared human-generated summary (Luchi and Ribeiro, 2011). ROUGE employs the statistical metrics Recall (coverage), Precision (accuracy) and F-Measure (harmonic mean). Recall indicates the amount of the manual summary that remains in the automatic summary, Precision indicates the degree in which the auto-summary overlaps the manual summary, and the F-Measure indicates the harmonic average between coverage and accuracy. Figure 13 shows a simplified structure of the evaluation process using ROUGE.

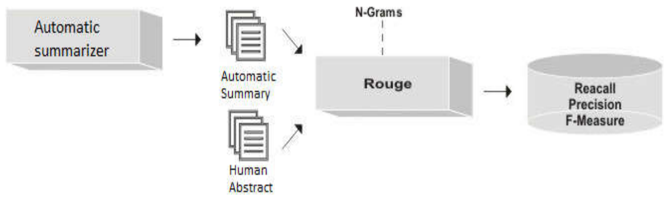

Figure 1. Simplified summary evaluation using the ROUGE tool (Delgado *et al.*, 2010)

MATERIALS AND METHODS

An educational corpus was employed in order to perform the tests (Aguiar *et al.,* 2017). The corpus is composed of scientific articles written in Portuguese and contains texts in ten fields of knowledge within the Education domain. Scientific articles were selected based on the summaries and keywords of the respective authors. The summaries were evaluated by ROUGE and the keywords in the text were summarized with PragmaSUM. All of the 500 articles were divided into ten fields of knowledge, each one containing 50 articles. The knowledge domains of the corpus include: Special Education; Permanent Education; Preschool Education; Teaching and Learning; Philosophy of Education; History of Education; Educational Policy; Educational Psychology; Sociology of Education and Educational Technology. Adequate representation of information contained in a given document is crucial for information recovery, as well as in the summarization conducted by PragmaSUM. The keywords presented by each author are used to influence the generation of automatic summaries. In order to make better use and assure the occurrence of the keywords in the source text, the text files, abstracts and keywords were separated from the original corpus only from the articles presenting the occurrence of at least five keywords created by the article's author. Table 2 shows the frequency in which the keywords appear in the body of the source text. As shown below, there was no occurrence of five keywords in 110 texts, which separated 390 texts for summarization.

Table 2. Frequency in which keywords appear in source text

Frequency of keywords in text	Number of texts
0	2
1	7
2	4
3	27
4	72
5	102
> 5	288
Total number of texts in Corpus	500
Total number of texts used	390
Difference	110

All the summarizers used are automatic and extracted from academic literature. They were selected due to their ability to summarize in Portuguese and due to their text compression rate of between 50% and 90%. BLMSumm (Oliveira and Guelpeli, 2011) is independent of language and domain of source text. In order to generate the summaries, it uses different methods for classifying sentences and algorithms for generating summaries. Since there are no studies about the best algorithm used by BLMSumm, the summaries generated by BLMSumm in this study originated from a combination of the TF-ISF sentence classification method with the algorithm Subida de Encosta, selected randomly. GistSumm (Pardo, 2002, 2005) is a summarizer based on the main idea of the text through which it is possible to identify the sentence which best represents the main idea of the text, which Pardo (2002) calls *gist sentence*. GistSumm uses a superficial approach; i.e., it uses statistical methods in order to identify hte gist sentence or the sentence that it most resembles.

Algorithm alteration

PragmaSUM uses a ranking system of the keywords selected for the profile. For improving the efficiency of these words, changes were made in the word selection during summarization. The summarization mode in batches, in which several texts are summarized at once, has been modified, as shown in Figure 2. The option of using files to remove the keywords and the number of words used in summarization was added.

Figure 2. Summarization in Batches Screen

The methods used for word selection and assessment were also modified. The Sequence Method is the original method, in which words are selected in the order they appear in the text file. The Classification Method sorts the words found in the file according to their frequency in the source text, using the most frequent words with the highest score. The first two methods use the original PragmaSUM grading system, which selects the five words and grades them from the first to the last word chosen. The TF-ISF Method uses the classification to select the words that will be used, and uses the TF-ISF algorithm for grading. It is important to note that the selected words do not assume a fixed value. Rather, each sentence is awarded a different score according to the word in question.

Automatic Summarization Process

The AS process can be presented in two stages: first, in the text summarization itself, and secondly, in the automated evaluation of summary evaluation through the ROUGE tool. Text summarization with PragmaSUM was conducted without using keywords with five words in each one of the previously presented methods (Sequence, Classification and TF-ISF). Four compression rates were used: 90%, 80%, 70% and 50%; that is, summaries were generated with sizes 10%, 20%, 30% and 50%, respectively, of the original text. In total, 9,360 summarizations were conducted (390 source texts* 4 compression rates* 6 (4 methods of PragmaSUM + BLMSumm + GistSumm)). In the second stage, ROUGE was used for assessing summaries. This tool generates individual spreadsheets for metrics F-Measure, Precision and Recall using results of individual comparisons with each automatic summary and its respective manual summary. Comparisons were made with each of the ten knowledge domains and with six types of summarizations.

RESULTS

Due to the large volume of data generated through tasks to attest the efficiency of summaries and with the goal of comparing accuracy obtained by PragmaSUM in using text keywords, only the comparative graphs of domains from Precision will be presented. All other achieved results, as well as the corpus created, are available at http://goo.gl/1i4wYv. According to Rocha and Guelpeli (2017), the Precision metric indicates how the automatic summary coincides with the manual summary and how using keywords aims to personalize the summary according to its incidence in the source text becomes the ideal metric for analyzing the algorithm performance used by PragmaSUM. The results achieved through PragmaSUM will be represented by sem_chave, 5_chave_v1, 5_chave_v2 and 5_chave_v3. The representation sem_chave presents the original method of PragmaSUM, without using keywords; 5_chave_v1 represents the original method using 5 keywords; 5_chave_v2 represents the Classification mode and 5_chave_v3 represents TF-ISF. With a 50% compression rate, the domain History of Education achieved the best results in Precision for all assessed automatic summarizers and the TF-ISF method (5_chave_v3) achieved the highest result, as can be observed in Table 3 and Figure 3.

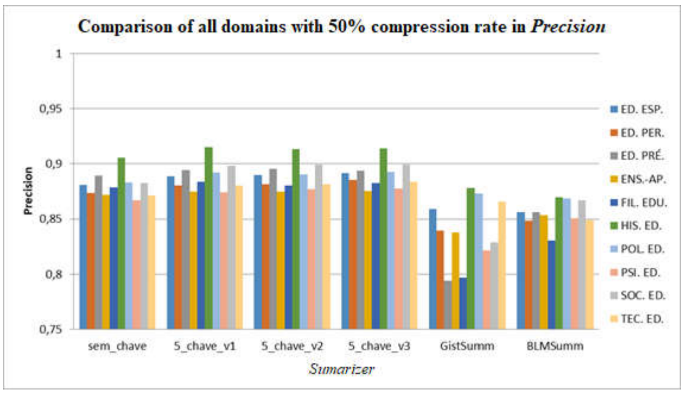

Figure 3. Comparison of all domains with 50% compression rate in *Precision*

With a 70% compression rate, the History of Education domain achieved the best *Precision* results for all automatic summarizers, except GistSumm, which obtained the highest value with the domain Educational Policy, as can be observed in Table 4 and Figure 4.

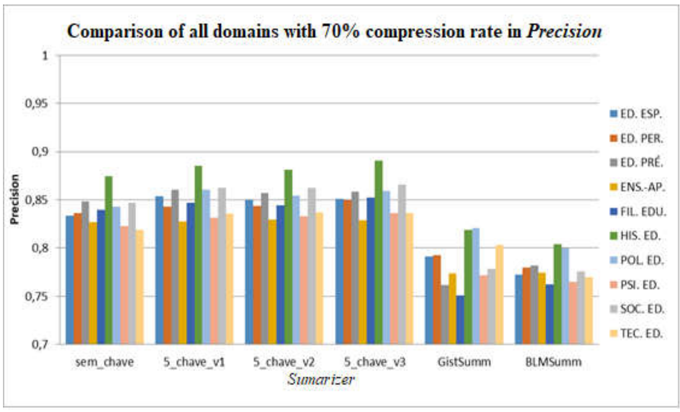

Figure 4 - Comparison of all domains with 70% compression rate in *Precision*

With an 80% compression rate, the History of Education domain achieved the best *Precision* results for all PragmaSUM methods. The Educational Policy domain achieved the best results with BLMSumm and GistSumm, as can be observed in Table 5 and Figure 5.

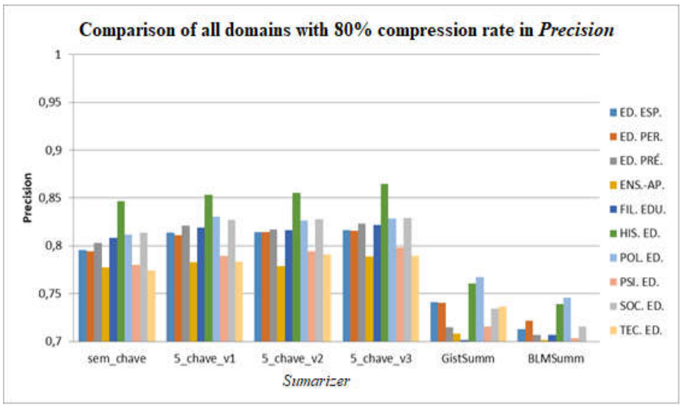

Figure 5. Comparison of all domains with 80% compression rate in *Precision*

With 90% compression, the History of Education domain achieved the best *Precision* results for all PragmaSUM methods. The Educational Policy domain presented the best results with BLMSumm and GistSumm, as observed in Table 6 and Figure 6, reproducing the performance of previous results.

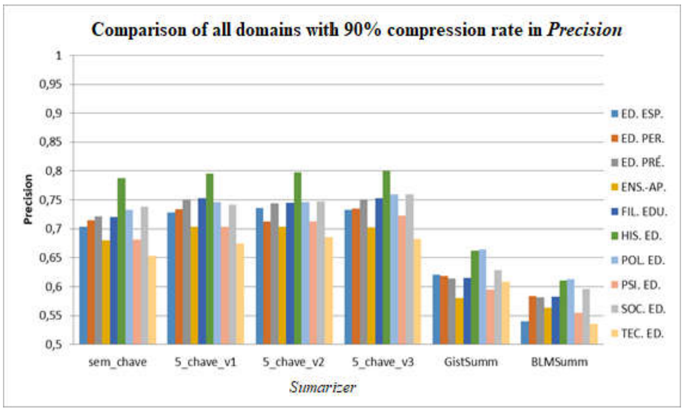

Figure 6. Comparison of all domains with 90% compression rate in *Precision*

Table 3. Comparison of all domains with 50% compression rate in *Precision*

	Sem_chave	5_chave_v1	5_chave_v2	5_chave_v3	GistSumm	BLMSumm
ED. ESP.	0.88093	0.88897	0.88967	0.8913	0.85891	0.8562
ED. PER.	0.87365	0.88047	0.88163	0.8852	0.83934	0.84852
ED. PRÉ	0.88923	0.89438	0.89537	0.89397	0.79394	0.85642
EN-APR.	0.87225	0.87453	0.87504	0.87545	0.83757	0.85361
FIL. EDU.	0.87847	0.88367	0.88036	0.88242	0.7968	0.83047
HIST. ED.	0.90541	0.91525	0.91356	0.91371	0.87829	0.8695
PO. EDU.	0.88316	0.89228	0.8904	0.89292	0.87331	0.86859
PS. EDU.	0.86681	0.87424	0.87697	0.87758	0.82166	0.85052
SOC. EDU.	0.88261	0.89836	0.89923	0.89918	0.82903	0.86672
TEC. EDU.	0.8716	0.88032	0.88154	0.88385	0.86557	0.84889

Table 4. Comparison of all domains with 70% compression rate in *Precision*

	sem_chave	5_chave_v1	5_chave_v2	5_chave_v3	GistSumm	BLMSumm
ED. ESP.	0.83379	0.85351	0.84966	0.85081	0.79093	0.77265
ED. PER.	0.83653	0.84318	0.84358	0.84948	0.79266	0.7801
ED. PRÉ	0.84809	0.86029	0.85742	0.85825	0.7616	0.78189
EN-APR.	0.82663	0.82725	0.82924	0.82911	0.77384	0.77452
FIL. EDU.	0.83984	0.84683	0.8446	0.8523	0.75117	0.76224
HIST. ED.	0.87472	0.88524	0.88099	0.89101	0.81905	0.80383
PO. EDU.	0.84294	0.86015	0.85433	0.8594	0.82053	0.80008
PS. EDU.	0.82306	0.83146	0.83289	0.83621	0.7717	0.76512
SOC. EDU.	0.84737	0.86274	0.86244	0.86583	0.77831	0.77585
TEC. EDU.	0.81854	0.83541	0.83698	0.836	0.80324	0.76955

Table 5. Comparison of all domains with 80% compression rate in *Precision*

	sem_chave	5_chave_v1	5_chave_v2	5_chave_v3	GistSumm	BLMSumm
ED. ESP.	0.79572	0.81361	0.81417	0.81603	0.74089	0.7125
ED. PER.	0.79435	0.81123	0.814	0.81551	0.7402	0.72166
ED. PRÉ	0.80282	0.82077	0.81714	0.82305	0.71484	0.70687
EN-APR.	0.77736	0.78266	0.77895	0.78886	0.70792	0.70168
FIL. EDU.	0.80809	0.81901	0.81638	0.82144	0.70166	0.70668
HIST. ED.	0.84651	0.85354	0.85511	0.86444	0.76055	0.73935
PO. EDU.	0.81129	0.83043	0.82628	0.82834	0.76733	0.74578
PS. EDU.	0.77991	0.78943	0.79403	0.79803	0.71534	0.70344
SOC. EDU.	0.81339	0.82699	0.82777	0.82926	0.73426	0.71548
TEC. EDU.	0.77371	0.78351	0.79098	0.78925	0.73662	0.67345

Table 6. Comparison of all domains with 80% compression rate in *Precision*

	sem_chave	5_chave_v1	5_chave_v2	5_chave_v3	GistSumm	BLMSumm
ED. ESP.	0.70333	0.72865	0.73597	0.73246	0.62067	0.53976
ED. PER.	0.71427	0.73367	0.71286	0.73489	0.6184	0.58375
ED. PRÉ	0.72147	0.75002	0.74431	0.74985	0.61367	0.58101
EN-APR.	0.67958	0.7037	0.70342	0.70217	0.57989	0.56363
FIL. EDU.	0.72093	0.75256	0.74543	0.75305	0.6156	0.58252
HIST. ED.	0.78747	0.79518	0.79801	0.80022	0.66253	0.61031
PO. EDU.	0.73303	0.746	0.74622	0.75928	0.66411	0.61256
PS. EDU.	0.68156	0.7035	0.71275	0.72278	0.59483	0.5545
SOC. EDU.	0.73796	0.74217	0.74676	0.76001	0.62901	0.5966
TEC. EDU.	0.65344	0.67494	0.68564	0.68276	0.6079	0.53553

Table 7. Variation of *Precision* values with compression rate increase of the History of Education domain

History of Education	sem_chave	5_chave_v1	5_chave_v2	5_chave_v3	GistSumm	BLMSumm
50%	0.90541	0.91525	0.91356	0.91371	0.87829	0.8695
90%	0.78747	0.79518	0.79801	0.80022	0.66253	0.61031
Variation	0.11794	0.12007	0.11555	0.11349	0.21576	0.25919

It is possible to state that PragmaSUM, by using keywords, achieved satisfactory results in all 40 analyzed samples; i.e., 100% of cases. The TF-ISF method (5_chave_v3) achieved the best results, with 25 samples and a 62.5% success rate, followed by the Sequence method (5_chave_v1), with 8 samples and 20% success rate, subsequently the Classification method (5_chave_v2) with 7 samples and 17.5% success rate. In addition to the advantage that the original method PragmaSUM held over BLMSumm and GistSumm, all methods using keywords achieved better results compared to the original text (sem_chave). It was observed that the results achieved by all PragmaSUM summarization methods were the most satisfactory. All the summarization methods that use keywords showed an advantage over the original PragmaSUM method and, when compared to GistSumm and BLMSumm, this advantage was even greater. It was also noted that, as the compression rate increased, the difference between the values obtained by PragmaSUM and the other summarized analysts became larger. As can be seen in Table 7, both GistSumm and BLMSumm suffered about twice the loss of information compared to all PragmaSUM methods. The TF-ISF method (5_chave_v3) obtained the lowest variation: 0.111349; GistSumm: 0.21576 and BLMSumm: 0.25919. Through the results obtained with PragmaSUM, the use of keywords in text summarization and new methods applied improved the performance of the Precision metric. This improvement was observed mainly by applying higher compression rates, as seen in Table 7. It is important to note that there was no previous analysis of the texts in relation to the influence of the keywords in their content, which can influence the results obtained through these metrics. A corpus that analyzes and provides proof of the influence of keywords in the source texts can improve the results of the methods that use them. There was a major gain in the use of keywords in most domains, especially when the compression rate reached 80% and 90%. With increase in compression rate, and consequent decrease in summary length, selecting a few sentences becomes necessary, and the chance of sentences containing the keywords replacing others becomes greater.

Conclusion

The main objective of this study was to evaluate the efficiency of using keywords in summarization with the automatic text summarizer PragmaSUM. To accomplish this objective, an Educational corpus (Aguiar *et al.,* 2017) was used for conducting tests on scientific articles written in Portuguese and with ten domains within the larger field of Education. BLMSumm, GistSumm and PragmaSUM summarizers were evaluated using the original method and using keywords with the Sequence, Classification and TF-ISF methods. In the tests conducted in this study, samples were generated displaying four stages of compression: 50%, 70%, 80% and 90%. The results were evaluated by the ROUGE tool with the *Precision* metric. When results were compared, the History of Education domain performed best using all PragmaSUM methods. GistSumm and BLMSumm obtained the best results with the Educational Policy domain, except when the compression ratio was 50%, in which case the History of Education domain was better. The TF-ISF method (5_chave_v3) presented the highest success rate of all methods, in 25 out of 40 samples, or 62.5%. Regarding the four applied compression rates, it was observed that the automatic summarizers achieved more homogeneous results when the compression rate was 50% and much variation when the rate was 90%. Moreover, results also showed that the automatic summarizers displayed a trend: the higher the compression rate applied, the lower the results. All PragmaSUM methods experienced less value variation with increased compression than GistSumm and BLMSumm, as shown in Table 6. According to Rocha and Guelpeli (2017), text size is another factor that can be considered in the performance of each domain. In general, larger domains (concerning their text size) obtained the best results, and the smallest domains obtained the worst results. This can be related to the fact that, with higher compression rates, there is a greater loss in results, since smaller texts consequently generate smaller summaries. According to Rocha and Guelpeli (2017), PragmaSUM performs well with the highest compression rates using keywords precisely because its summary consists of a larger number of important sentences in the text; i.e., sentences containing the keywords provided by the author.

Future Research

Future research may include using a corpus in different languages and in more domains for evaluation. It is subsequently possible to develop new summary personalization methods for keywords by employing machine learning. Another research possibility is creating new ways to select keywords by eliminating human iteration in the process. Still another is to carry out a study on the relevance of keyword use in the content of scientific articles, as well as a study of the number of these keywords in the indexation of scientific texts.

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