Modeling, comprehending and summarizing textual content by graphs

Vinicius Woloszyn\(^1\)\(^{0000−0003−3554−5580}\), Guilherme Medeiros Machado\(^1\)\(^{0000−0001−5283−9228}\), Leandro Krug Wives\(^1\)\(^{0000−0002−8391−446X}\), and José Palazzo Moreira de Oliveira\(^1\)\(^{0000−0002−9166−8801}\)

PPGC - Instituto de Informática - UFRGS, Porto Alegre RS, Brazil
\{vwoloszyn, guimmachado, wives, palazzo\}@inf.ufrgs.br

Abstract. Automatic Text Summarization strategies have been successfully employed to digest text collections and extract its essential content. Usually, summaries are generated using textual corpora that belongs to the same domain area where the summary will be used. Nonetheless, there are special cases where it is not found enough textual sources, and one possible alternative is to generate a summary from a different domain. One manner to summarize texts consists in using a graph model. This model allows giving more importance to words corresponding to the main concepts from the target domain found in the summarized text. This gives the reader an overview of the main text concepts as well as their relationships. However, this kind of summarization presents a significant number of repeated terms when compared to human-generated summaries. In this paper, we present an approach to produce graph-model extractive summaries of texts, meeting the target domain exigences and treating the terms repetition problem. To evaluate the proposition, we performed a series of experiments showing that the proposed approach statistically improves the performance of a model based on Graph Centrality, achieving better coverage, accuracy, and recall.

Keywords: Graph model · Summarization · Text modeling · Graph Centrality · Biased Summarization.

1 Introduction

Automatic Text Summarization (ATS) systems play a significant role by extracting essential content from textual documents. This is important given the exponential growth of textual information. Despite not being one of the newest areas of research, there are still open-ended summarization issues that pose many challenges to the scientific community \[21\]. One of the examples is when one summary must be generated prioritizing sentences that present terms of another specific domain (cross-domain summarization). Another example is the redundancy problem that occurs when a wrong text modeling leads to a repetition of content \[21\].

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The cross-domain summarization is a strategy to generate biased summaries, which generally favors a subject. The need for such bias happens in situations when a summary containing specific aspects must be extracted from general purpose documents. For instance, if a teacher wants to know better what are the educational aspects of a movie she is hoping to use in her class, and to do so, she is looking to other peoples’ comments about that movie. Another example: imagine a person who is shopping a new novel hoping to find one that also presents, for instance, historical facts of a city during the story.

Most works on summarization rely on supervised algorithms such as classification and regression \[29,32,30\]. However, the quality of results produced by supervised algorithms is dependent on the existence of a large, domain-dependent training dataset. One drawback of such strategy is that those datasets are not always available and their construction is labor-intense and error-prone since documents must be manually annotated to train the algorithms correctly.

Unsupervised models, conversely, are an interesting strategy for a situation where there are not enough textual sources since it does not need a large training set for the learning process. However, a common problem of these models is redundancy. It happens when a wrong text modeling can benefit from the generation of summaries that repeat the most central sentences or select a set of very similar ones in the documents. This causes a gain in accuracy but generates redundant summaries with poor coverage of text aspects.

To meet the cross-domain summarization needs and mitigate the redundancy problem, we propose an unsupervised graph-based model to generate cross-domain summaries. The generated graphs are able to uncover the main topics (concepts) of a document or a set of documents. To do so, the summarization algorithm focus on the most relevant, i.e., central, nodes using pre-determined domain corpora and nodes’ relationships. In our experiments, this combination of cross-domain generation avoiding redundancy, improves Graph-Based ATS system’s achieving better coverage, precision, and recall.

The contributions of this work are the following: 1) it is an unsupervised cross-domain summarization, i.e., it does not depend on specific annotated training set; 2) it address the redundancy problem performing a re-ranking of the initial centrality index to improve coverage and decrease redundancy; and 3) considering two distinct datasets, the results obtained in our experiments were significantly superior to the baselines analyzed.

The rest of this paper is organized as follows. Section 2 presents the background of the area and related work. Section 3 details the proposed model. Section 4 provides a case study, and Section 5 describes the design of our experiments. Section 6 discusses the results. Section 7 summarizes our conclusions and presents future research directions.

2 Background

Automatic Text Summarization (ATS) techniques have been successfully employed on user-content to highlight the most relevant information among documents \[10,11,21,23\]. Regarding techniques usually employed, several works have explored supervised learning strategies to predict text relevance \[29,30\]. Additionally, the use of regression algorithms consistently improves the prediction of
helpfulness [24]. However, these supervised techniques need annotated corpus for
the training process, which for the most of the cross-domains cases is unavailable.

Graph Centrality is also widely employed on unsupervised extractive
summarization systems where a graph representation of documents is used to weight
sentences relevance on a set of documents [10,10,27,25]. Based on that, central
nodes indicate that the sentence they represent is relevant in the group of doc-
uments. Let \( S \) be a set of all sentences extracted from the input document(s), a
graph representation \( G = (V,E) \) is created, where \( V = S \) and \( E \) is a set of edges
that connect pairs \( \langle u,v \rangle \in V \). Then, the score of each node is usually given by
an algorithm like PageRank [18] or HITS [12].

Figure 1 depicts the general steps of a summarization system based on Graph
Centrality: (a) it builds a similarity graph between pairs of sentences; (b) it
prunes the graph by removing all edges that do not meet a minimum threshold
of similarity; (c) it uses PageRank to calculate the centrality scores of each
node. Then a Greedy strategy is employed, where the centrality index produces a
ranking of vertices’ importance, which is used to indicate the ranking of the most
relevant sentences to compose the final summary. This a well-known strategy
used as the basis for many novel unsupervised approaches [28,6,27,2].

PageRank [18] computes the centrality of nodes, where each edge is consid-
ered as a vote to determine the overall centrality score of each node in a graph.
However, as in many types of social networks, not all of the relationships are
considered of equal importance. The premise underlying PageRank is that the
importance of a node is measured in terms of both the number and the im-
portance of vertices it is related to. The PageRank centrality function is given
by:

\[
PR(u) = \sum_{v \in B_u} \frac{PR(v)}{N_v}
\]  

where \( B_u \) is the set containing all neighborhood of \( u \) and \( N_v \) the number of
neighborhoods of \( v \).

However, this strategy is normally employed with no restrictions that ensure
an empty or a minimal intersection between sentences [10,28,6,27,2]. This lack
of restrictions would increase the overall redundancy on these approaches.
LexRank \cite{10}, which is a popular general-purpose extractive summarizer, relies on a graph representation of the document(s) building a complete graph, where each sentence from the document set becomes a node, and each edge weight is defined by the value of the cosine similarity between the sentences. Then the centrality index of each node is computed producing a ranking of vertices based on their importance, which indicates the ranking of the most relevant sentences to compose the summary.

This well-known strategy is used as the basis for many recent unsupervised approaches \cite{26,22,27,25}. Nevertheless, these approaches do not take into consideration the repetition problem that causes redundancy of words. Neither they present a conceptual model to meet the cross-domain summarization demands. Thus, next Section describes an unsupervised cross-domain summarization model and a post-processing algorithm to reduce repetition and improve the coverage of summaries.

3 Developed Model

The developed model structures a given text set in a graph model, and uses another specialized text set, from another domain, to put a bias in the extracted summary. As already described sometimes it is necessary to extract a specialized summary from a more general-purpose text set. The example given before is related to extracting educational aspects from user comments in movies. Besides the domain bias, the model also structures a post-processing that treats the problem of sentences repetition.

In Figure 2, it is shown how the cross-domain redundancy-free summary is extracted by using the Graph model. Since the first steps are the same of a general Graph-based summary (shown in Figure 1), this process starts with the output of the general process, i.e., a Graph where each node have a Page-Rank score that represents how central a determined sentence is (Figure 2(A)).

The initial Page-Rank scores are then recomputed by taking in consideration keywords found on an external corpus. Such keywords are used as a bias to compute the importance of each sentence. The final specialized summary is based on the centrality score of the sentences weighted by the presence of keywords from the external corpora.

Let \( S \) be a set of all sentences extracted from the \( R \) user’s reviews about a single movie; the first step is to build a graph representation \( G = (V, E) \), where \( V = S \) and \( E \) is a set of edges that connect pairs \( (u, v) \in V \). The score of each node (that represent a sentence) is given by the harmonic mean between its centrality score on the graph given by PageRank, and the sum of the frequencies of its specialized keywords (stated in equation \( 3 \)). The pseudo-code of the Cross-domain Re-scoring is given in Algorithm 1, where \( G \) is represented as the adjacency matrix \( W \).
Algorithm 1 - Cross-domain Re-scoring Algorithm $(S,B)$: $O$

- **Input**: a set of sentences extracted from a general purpose corpora (e.g., Amazon’s movies Reviews) $R$, and a corpora $B$ used as a bias
- **Output**: an extractive biased summary $O$ based on the general purpose corpora $R$.

1: for each $u, v \in S$ do
2: $W[u,v] \leftarrow \text{idf-modified-cosine}(u,v)$
3: end for
4: for each $u, v \in S$ do
5: if $W[u,v] \geq \beta$ then
6: $W'[u,v] \leftarrow 1$
7: else
8: $W'[u,v] \leftarrow 0$
9: end if
10: end for
11: $P \leftarrow \text{PageRank}(W')$
12: for each $u \in S$ do
13: $K \leftarrow \text{sim-keyword}(u, B)$
14: $O[u] \leftarrow \frac{||S|| P_u K}{P_u + K}$
15: end for
16: return $O$

The main steps of the Cross-domain Re-scoring algorithm are: (a) it builds a similarity graph $(W)$ between pairs of texts of the same product or subject (lines: 1-3); (b) the graph is pruned $(W')$ by removing all edges that do not meet a minimum similarity threshold, given by the parameter $\beta$ (lines 4-10);  

\footnote{The best parameter obtained in our experiments is $\beta = 0.1$}

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Fig. 2. Illustration of the cross-domain Graph centrality building, and the post-processing to avoid redundancy.
(c) using PageRank, the centrality scores of each node is calculated (line 11); (d) using the educational corpora, each sentence is scored according the presence of educational keywords (line 13); (e) The final importance score of each node is given by the harmonic mean between its centrality score on the graph, and the sum of its education keywords frequencies (line 14).

To get the similarity between the two nodes we define an adapted metric, that is the cosine difference between two corresponding sentence vectors [10]:

$$\text{idf-modified-cosine}(x, y) = \frac{\sum_{w \in x,y} tf_{w,x} tf_{w,y} (idf_w)^2}{\sqrt{\sum_{x_i \in x} (tf_{x_i, x} idf_{x_i})^2} \times \sqrt{\sum_{y_i \in y} (tf_{y_i, y} idf_{y_i})^2}}$$  \hspace{1cm} (2)

where $tf_{w,s}$ is the number of occurrences of the word $w$ in the sentence $s$. We employed the approach described by [16] to extract the keywords from the external corpora. The similarity between the sentences and the keywords extracted from the external corpora are given by the following equation:

$$\text{sim-keyword}(x, B) = \sum_{w \in x} tf_{w \in \text{keywords}(B)}$$  \hspace{1cm} (3)

To reduce the textual redundancy problem, it was developed an algorithm that employs a clustering technique to find groups of sentences from the graph of sentences that are both homogeneous and well separated, where entities within the same group should be similar and entities in different groups dissimilar. Then, it takes the most central sentence from each group to compose the final summary. While Graph-Centrality chooses the sentences based on their centrality, our algorithm divides the graph into $k$ groups of sentences and chose the most central sentence from each group Figure 2(C).

In the literature we find work employing clustering paradigms to provide a non-redundant multi-view of textual data [31,33]. The agglomerative hierarchical clustering method is one of them, and it creates a hierarchy tree, or Dendrogram, which can be used for sentence coverage searching purposes. Conceptually, the process of agglomerating documents creates a cluster hierarchy for which the leaf nodes correspond to individual sentences, and the internal nodes correspond to merged groups of clusters. When two groups are merged, a new node is created in this hierarchy tree corresponding to this bigger merged group.

In our work, we employed the Complete Link Hierarchical clustering algorithm [1] since it achieves better results on the experiments carried out, when compared with other clustering techniques, such as $k$-Means, $k$-Medoids, and EM [31]. By default, we remove stop words, and the remaining terms of the sentence are represented as uni-grams weighted by the known Term Frequency-Inverse Document Frequency (TF-IDF).

The pseudo-code for decreasing redundancy is displayed in Algorithm 2, where $G$ represents a complete graph obtained from the ATS approach based on Graph Centrality and cross-domain Re-scoring 2(B). $L$ represents the cluster labels extracted using the function $\text{cluster}(G)$ and $S$ the final solution containing $k$ sentences.
Algorithm 2 - Post-Processing Redundancy Algorithm \((G, P, K)\): \(S\)

- **Input**: a complete graph \(G = (V, E)\), where \(V\) are the sentences and \(E\) is a set of edges that represents the similarity between sentences; \(P\) the centrality score of each node; \(K\) number the sentences to extract.
- **Output**: ordered list \(S\) of sentences.

1. \(S \leftarrow \{\}\)
2. \(L \leftarrow \text{cluster}(G, K)\)
3. for each \(k \in K\) do
4. \(C \leftarrow L[k]\)
5. \(CS \leftarrow \text{sort_nodes_by_centrality}(C_k, P)\)
6. \(S[k] \leftarrow CS_k[0]\)
7. end for
8. return \(S\)

4 Case Study

As explained before, the goal of the presented approach was to build a graph representation of the main concepts of a document or set of documents. This representation works as a cross-domain summary avoiding redundancy. To do so, we selected two application domains, one to validate the cross-domain summary generation and other to validate the redundancy. The cross-domain generation was tested in the educational domain, and the redundancy control was tested in the news domain. Three datasets were employed to perform the experiments.

The first served as a word thesaurus to implement the educational bias in the cross-domain generation, and it was collected from an educational website, TeachWithMovies (TWM) where a set of movies are described by teachers with the goal to use them as learning objects inside a classroom. The second dataset is Amazon Movie Reviews (AMR) \[15\] which provides user comments about a large set of movies. Since we were interested in movies that appeared in both datasets, a filter was applied, and we ended up with 256 movies to perform our evaluation.

The third was used to evaluate the post-processing that treats the redundancy problem. CSTNews \[4\] is a novel corpus which comprises 140 news texts in Brazilian Portuguese divided into 50 groups, which has been successfully employed as gold-standard for many recent works on content selection and automatic production of summaries \[3,14,9,17,7\]. Next, we describe each dataset with more details.

4.1 Teaching with Movies

The TeachWithMovies dataset was collected through a crawler developed by us. Different teachers described the movies on the website, but each movie has only one description, this was a challenge while collecting the data because the information was not standardized or had associated metadata.

\[2\] http://www.teachwithmovies.org/index.html
\[3\] Public available on http://conteudo.icmc.usp.br/pessoas/taspardo/sucinto/cstnews.html
However, we have noticed that some movies presented common information such as: i) movie description; ii) rationale for using the movie; iii) movie benefits for teaching a subject; iv) movie problems and warnings for young watchers; and v) objectives of using this movie in class. The developed crawler extracted such information, and we have used the movie description since it contains the greatest amount of educational aspects. In the end, 408 unique movies and video clips were extracted, but after matching with the Amazon dataset, we could use 256 movies. This dataset was used as a Gold-standard to cross-domain summary generation.

4.2 Amazon Movie Reviews

The Amazon Movie Reviews was collected with a timespan of more than ten years and consists of proximately 8 millions of reviews that include product and user information, ratings, and a plain text review. In Table 1 is shown some statistics about the data.

| Dataset Statistics          |
|-----------------------------|
| Number of reviews           | 7,911,684         |
| Number of users             | 889,176          |
| Expert users (with >50 reviews) | 16,341      |
| Number of movies            | 253,059          |
| Mean number of words per review | 101           |
| Timespan                    | Aug 1997 - Oct 2012 |

4.3 CSTNews

In this dataset, each group of news has from 2 to 3 texts on the same topic, having in average 49 sentences and 945 words. It comprises clusters of news texts manually annotated in different ways to discursive organization, Rhetorical Structure Theory and Cross-document Structure Theory annotations. The corpus includes manual multi-document summaries (one for each cluster of news) with 70% compression rate (in relation to the longest text). The texts are manually annotated with high-level of agreement (more than 80%) of human judges using Cohen’s kappa coefficient, which is a statistic to measure inter-rater agreement for classification tasks [8]. That means the annotation agreement is reliable and similar to that in presented in other works [8] for other languages than Portuguese. For such reason, these human-generated summaries were used as a Gold-standard. Since this post-processing is not language dependent and the redundancy is also a problem observed in different languages [21], this corpus was used to evaluate this post-processing strategy.
5 Experiment Design

This section presents the experimental setting used to evaluate the cross-domain summary generation and the post-processing that reduces redundancy. It describes the methods employed as the baselines for comparison, the educational plans adopted as Gold-standard and the metrics applied for evaluation, as well as details of the experiment, performed to assess the approach.

5.1 First Baseline

The results obtained from our cross-domain summary are compared with Textrank [16] algorithm. Textrank was chosen because it is also a graph-based ranking algorithm and has been widely employed in Natural Language tools. Textrank essentially decides the importance of a sentence based on the idea of “voting” or “recommending”. Considering that in this approach each edge represents a vote, the higher the number of votes that are cast for a node, the higher the importance of the node (or sentence) in the graph. The most important sentences compose the final summary.

5.2 Second Baseline

Centrality-based ranking has been successfully on recent works to content selection and automatic production of textual summaries [28,12,27,2]. LexRank [10] is a well-know ATS system based on Graph Centrality that has been used many times in the literature for comparisons purposes, due to its good performance. Since the post-processing strategy aims to reduce redundancy in Centrality-based approaches, we employ LexRank as baseline due it uses only the sentence centrality index to the ranking task. We used MEAD’s implementation of Lexrank [20], which is a publicly available (for researching purposes) framework for text summarization that provides a set of Perl components for the summarization of texts written in English as well as in other languages such as Chinese.

5.3 Evaluation Metrics

ROUGE-\(n\) The evaluation was performed by applying ROUGE (Recall-Oriented Understudy for Gisting Evaluation) [13], which is a metric inspired on the Bilingual Evaluation Understuyd (BLEU) [21]. Specifically, we used ROUGE-\(n\) in the evaluation, this version of ROUGE makes a comparison of \(n\)-grams between the summary to be evaluated and the “gold-standard”; in our case, cross-domain summaries and TWM lesson plans, respectively. We evaluated the first 100 words of the summaries obtained by our approach and the baseline since it corresponds to the median size of the gold-standard. ROUGE was chosen because it is one of most used measures in the fields of Machine Translation and Automatic Text Summarization [19].
Redundancy An important aspect related to redundancy is lexical cohesion. Therefore, cohesive links between sentences is a positive component of the summary, and it has long been considered a key component in assessing content relevance in text summarization [21]. However, in some cases, it could improve mean redundancy in summaries. To show how redundancy would affect a multi-document summarizer, we perform a comparison between the baseline and human gold-standard summary.

Coverage It is the extent to which all words of the automatic summaries are found in the source documents. In other words, it is a global score assessing to what extent the candidate summary covers the text given as input.

6 Results

The next subsections present the evaluation results.

6.1 Cross-domain Summaries

In this section, we present cross-domain summaries evaluation regarding the adopted baselines concerning precision, recall, and f-Score obtained by using ROUGE-N.

The gold-standard utilized in the experiments, as already stated is the educational description extracted from the TWM website. Table 2 shows the mean Precision, Recall, and F-Score, considering both our cross-domain strategy and Textrank (the gold-standard used as the baseline).

The results presented in Table 2 show that our strategy outperformed the baseline in all measurements carried out. Regarding Precision, the differences range from 4.9 to 11.9 percentage points (pp) on all ROUGE-N analyzed, where N is the size of the n-gram used by ROUGE. Using Wilcoxon statistical test with a significance level of 0.05, we verified that our strategy is statistically superior when compared to the baseline. Regarding recall, the differences are also in favor of our strategy, ranging from 4.7 to 11.5 pp when compared to the baseline.

Regarding the distribution of Rouge’s results, in Fig 3 it is shown a boxplot indicating that our strategy results are not only better in mean, but also in terms of lower and upper quartiles, minimum and maximal values.

6.2 Post-processing

In this section, we will discuss the results obtained in our experiments regarding the adopted baselines in terms of Coverage, Redundancy, Precision, and Recall using CSTNews.

Redundancy and Coverage Figures 4 and 5 show that our post-processing strategy outperformed the unsupervised baseline generation summaries with less redundancy and more coverage, being closer to the human gold-standard summaries. The mean redundancy differences range from 5.42 to 6.75 percentage
Table 2. Mean of ROUGE results achieved by the Baseline (Column A) and our cross-domain strategy (Column B)

| ROUGE-n | Column A | Column B | p-values |
|---------|----------|----------|----------|
| Precision-1 | 0.65615  | 0.77028  | < 0.05   |
| Recall-1   | 0.65003  | 0.75611  | < 0.05   |
| F-score-1  | 0.65283  | 0.76296  | < 0.05   |
| Precision-2 | 0.22394  | 0.34350  | < 0.05   |
| Recall-2   | 0.22192  | 0.33744  | < 0.05   |
| F-score-2  | 0.22284  | 0.34037  | < 0.05   |
| Precision-3 | 0.06313  | 0.11268  | < 0.05   |
| Recall-3   | 0.06387  | 0.11102  | < 0.05   |
| F-score-3  | 0.06347  | 0.11182  | < 0.05   |

Fig. 3. Distribution of Rouge results.

points (pp) when compared to Lexrank. In terms of coverage, the mean difference is up to 3.96 pp. Using a Wilcoxon statistical test with a significance level of 0.05, we verified that our strategy results are statistically superior both in redundancy and coverage.

Precision and Recall Figure 6 and 7 show that our strategy also outperformed the unsupervised baseline in terms of Recall and Precision obtained using ROUGE-1. For Recall, the mean differences ranging from 3.12 to 9.39 pp when compared to Lexrank. For Precision, the mean differences ranging from 4.39 to 11.57 pp in all cases. Using the Wilcoxon statistical test with a significance level of 0.05, we verified that our strategy results are statistically superior in all cases.
In this paper, we presented an approach to generate cross-domain summaries based on graphs that are able to represent the main concepts of a document or set of documents. The proposed approach also reduces text redundancy in the generated summaries. We showed that our approach achieved statistically superior results than Textrank (a general summary algorithm) and Lexrank (another general summary algorithm).

The proposed algorithms require no training data, which avoids costly and error-prone manual training annotations. Compared to the baselines, our approach: a) outperforms the unsupervised techniques in terms of Precision and Recall; b) Statistically reduces redundancy and improves coverage; and c) is easy to plug into any standard Graph Centrality approach in any domain. Our experiments were performed in two domains, the educational and the news one, attesting the approach versatility.

Finally, it is also important to state that we found out a considerable number of highly helpful sentences with low centrality indexes which lead us to consider the investigation of other techniques to select the most relevant sentences to compose the movies’ educational description. It is also important to reaffirm the approach source language independence, for that reason, we consider, in the future, to extend the evaluation using different languages and summaries length.

Fig. 4. Mean Redundancy
Fig. 5. Mean Coverage
Fig. 6. Mean Recall
Fig. 7. Mean Precision

7 Conclusion
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