Extractive approach for text summarization using graphs

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Natural language processing is an important discipline with the aim of understanding text by its digital representation, that due to the diverse way we write and speak, is often not accurate enough. Our paper explores different graph related algorithms that can be used in solving the text summarization problem using an extractive approach. We consider two metrics: sentence overlap and edit distance for measuring sentence similarity. Relevant structures have been implemented and the code can be obtained in this link (1).

While the quantity of information is growing exponentially, there's a need to compress the content in condensed versions. The summarization of information is a problem that deals with presenting the main idea of the text without the need to read all the content of the text. Such task is heavily relied on the calculation of sentence similarity, and in that regard, various methods have been tried. Two methods for automatic text summarization are considered: extractive and abstractive. Extractive summarization is based on the identification of important sections of the text and producing a subset of the sentences from the original text, whereas abstractive summarization tries to reproduce the important content in a new way after interpretation and examination of text using more advanced techniques.

Supervised summarization models are built by treating the problem as a classification task, and by classifying which features in a sentence are relevant for summarization. Those models aren’t very reliable because of the unpredictable nature of language, from which it is not easy to generate a classification pattern. In addition, such models require training data which worsen the data acquisition problem which is already a challenge on its own.

Task summarization problem concerns itself with representing data in such way that the importance of each sentence and their terms is properly considered. Text should be represented in such ways that the inter-word and inter-sentence dependency is kept.

The task is challenged by a sustainable data source for validation and subsequently, an efficient metric for evaluating it and other text-understanding tasks. The challenges are topics of Document Understanding Conference, which later became Text Analysis Conference. A domain-independent evaluation is also complex to be achieved. For example, a model reporting a high accuracy in summarizing news articles might not perform with the same accuracy when summarizing, let’s say, Reddit posts.

Generally, best performing models are deep learning based. The construction of such models is faced with challenges of its own mainly regarded with computational resources. For that reason, it’s important to consider more simpler approaches like the ones that are presented in this paper.

Our contribution includes a direct implementation of graph-based algorithms for computing relevant data that could summarize the test documents the best. The respective algorithms help us extract the most important sentences that will constitute the summary. We test two different metrics for computing sentence similarity, and in one of them we employ a notion of graph similarity - edit distance - Figure 1.

Related work

Text summarization is an open problem. There hasn’t been report of an official model who can achieve a decent data-independent accuracy. Current state-of-art models achieve accuracy of around 50% percent. Those models are usually deep learning models. (6) achieves state-of-the-art results on the CNN/Daily mail dataset. The model presented there is the Reinforced Neural Extractive Summarization (RNES) model. (5) presents a general overview of two ranking algorithms - PageRank and HITS, and an agnostic overview of building a graph representation of text to be used for summarization by extraction. In addition, for smoother outputs, shortest path algorithm is suggested. This paper lacks concrete results tested on some dataset.

(2, 15) dive deeper in the use of PageRank algorithm for text summarization, whose use in such cases is referred to as TextRank. Sentences are extracted using the respective algorithm in a weighted graph built with nodes representing the sentences to be summarized, and weighted edges represent the similarity those sentences have with each other. Similarity between sentences is calculated as their overlap which can be determined as the number of common words between their lexical representation. The resulting model is an unsupervised model that has achieved 47% accuracy, as evaluated by the ROGUE metric, on 567 news articles provided by the Document Understanding Evaluations (DUC) 2002. The paper also explores the use of TextRank in keyword extraction. The paper introduces the respective algorithm very well but could benefit by the computation of a larger batch of test data.

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(8) implements the TextRank algorithm and expands on
the pre and post-processing part. The data (sentences) is en-
coded and different methods are considered such as tf-idf and
Word2vec. Moreover, the implementation is tested on Malay-
ian content, demonstrating the domain independence of the
algorithm. Another extractive text summarization algorithm
is LexRank, which is based on computing the importance of
a sentence by the concept of eigenvector centrality presented
in (10). The similarity between sentences, also represented
as nodes, is calculated as the cosine similarity between the
vector of their words mapped as their idf values.

Topic based approaches are seen on (11, 13, 14). They are
based on the distribution of words accross documents from
which it is possible to derive topics that later constitute sums-
aries. (17) treats the problem of summarization as a com-
pression problem that could be integrated in both extractive
and abstractive summarization approaches, and (4) builds a
small world network to summarize biomedical articles.

Results

Native structures have been implemented with the aim of
supporting experiments. Graphs have been created using
NetworkX (23), whereas linguistic processing has been done
with nltk (22) and stanza (16).

The aim of our experiments was to test how well different
centrality measures are able to identify the most important
parts of the text. For that reason, we consider pagerank,
hits, closeness, betweenness and degree measures. In addition,
when construction the edges of the graph, we use two different
metrics for measuring how similar two sentences are, thus
determing the weight of the link between those two nodes:
word overlap and edit distance. The edge candidates are then
ranked based on their weight, and then, by a threshold value,
the edges with the top weights are created.

The model has been evaluated using 3500 documents from
the CNN/Dailymail (18, 19) dataset - Table 1, which is a
collection of news articles with their highlights serving as our
summarization tests.

Various methods have been tested with two different met-
rics: sentences overlap and sentences edit distance (TED).
After employing strategies described in the Methods section,
top five sentences, number which is based on the average
summary length, are extracted that represent the generated
summary with our method(s). The summary is then compared
with the ground truth summary provided in the dataset using
the ROGUE metric.

Edit distance for sentence similiarity is more time consuming
because it adds three extra steps in our pipeline: word depen-
dency parsing, tree construction and edit distance calculation.
We report on recall and F1 score values. We are using recall to
evaluate how much of the ‘correct’ content is included in sum-
maries, and F1 score to give a balanced evaluation score that
is not based on the attributes that recall takes into account
such as the summary length.

The results from Table 2, 3, 4 and 5 might not have very
seductive numbers but they are standard numbers across sum-
marization models and are actually comparable with the state-
of-the-art models, like the one in (6), although we can not
make direct comparisons because their model has been tested
in a greater batch of testing data than ours. Rogue-1 tells us
the number of golden tokens found in the summary. Rogue-2
tells us the number of bigrams that were matched between
test and ground truth summary but the values here aren’t
expected to be high as the ordering of the sentences (and
words, although since our approach is extractive, that’s not a
big issue for our case) matters. Rouge-L is an important value
to consider as it measures the relation of the two contents in
a wider context.

Discussion

The performance of closeness, betweenness and degree centrality
measures is approximate with each other. It is completely
affected by the threshold value that determines the number of
edges to be created. Hypothetically, if the threshold is 1,
the output of the summary would be the first 5 lines of the
article. In addition, using those methods, there is a limitation
on the possibilities for fine tuning the results.

Pagerank and hits perform the most consistently, and that
is based on the fact that those algorithms take into account
the weight of the edges. Those methods aren’t affected by the
number of generated edges, as long as the weights are properly
accounted for. Those methods are in the same spirit, they
both formalise link analysis as eigenvector problems. Pager-
ank reports higher accuracy because it is able to operate in
the complete graph, unlike Hits which operates on a smaller
subgraph. In addition, those methods work well because they
do not rely on the isolated information regarding the node

| Method      | Rogue-1 | Rogue-2 | Rogue-L |
|-------------|---------|---------|---------|
| Pagerank    | 0.50    | 0.19    | 0.44    |
| Hits        | 0.48    | 0.19    | 0.42    |
| Closeness   | 0.50    | 0.20    | 0.45    |
| Betweenness | 0.50    | 0.20    | 0.44    |
| Degree      | 0.50    | 0.19    | 0.45    |
| Clusters    | 0.47    | 0.18    | 0.42    |

| Method      | Rogue-1 | Rogue-2 | Rogue-L |
|-------------|---------|---------|---------|
| Pagerank    | 0.48    | 0.17    | 0.426   |
| Hits        | 0.48    | 0.17    | 0.423   |
| Closeness   | 0.51    | 0.19    | 0.45    |
| Betweenness | 0.51    | 0.19    | 0.45    |
| Degree      | 0.51    | 0.19    | 0.45    |
| Clusters    | 0.43    | 0.14    | 0.38    |
The clustering method could be favorable as we can incorporate a hybrid approach towards summarization by turning the problem into a graph compression problem after finding the relevant clusters, where for each cluster we try to compress it into a single sentence by linking the most important part of sentences. Other than text summarization, the findings in this paper can also be referenced as proposals for solving classification problems using graphs.

The work on text summarization problem needs to be supported by a standard dataset that covers a more diverse textual content. Future work should also approach new metrics for content evaluation that could overcome ROGUE limitations. Such metrics should account for the relation that words have with each other, preferably through an embedding methodology and based on an external corpus, although in the first sight it already looks computationally heavy and that’s another issue that would need to be taken care off.

**Methods**

**Pre-processing.** Sentences of a document have been tokenized, cleaned up and the next processes have been executed depending on the metric. For the sentence similarity, the words in sentences are represented by their lemmas so that the context is not missed even if words are in different forms. For the edit distance, we build dependency parsed trees for each sentence using the stanford parser (stanza).

**Metrics.** One metric used for measure sentence similarity is by checking their overlapping words (2). To avoid bias on long sentences, the number of overlapping words is normalised by the lengths of both sentences.

\[
Sim(S_i, S_j) = \frac{|\{ w_i, w_k \in S_i \land w_j, w_k \in S_j \}|}{\log(|S_i| + \log(|S_j|))}
\]

The other metric used to measure how similar two sentences are is the edit distance, in our case since the sentences are represented as tree, we work with tree edit distance. The tree edit distance (TED) (21) is calculated using the algorithm proposed by Zhang and Shasha in (20). TED is a more accurate metric because it is able to account for the number of words in a sentence needed to be changed to match the other sentence, as compared to string based distance metrics that report on character changes, and such metric would be totally incorrect when comparing sentences of different lengths. The similarity of two sentences based on their distance is calculated as:

\[
Sim(i, j) = \frac{1}{1 + d(T_i, T_j)}
\]

**Graph construction.** After the document has been processed into sentences, we construct the undirected graph by generating a node for each sentence. Then, similarities between each pair of sentences is calculated. Afterwards, the similarities are sorted from highest to lowest, and based on a user defined threshold \( \alpha \) we pick the top \( \alpha \) percent of similar pairs to serve as the edges of the graph.

**Algorithms.** The implementation of PageRank, Hits, Closeness, Betweenness and degree measures is straightforward - after the scores for each node(sentence) have been computed, they are ranked and top \( N \) sentences are picked where \( N \) is a user defined parameter symbolizing the desired summary length. Whereas, for the clustering method, after the cliques in the graph have been found we process them in the following way:

| Method | Rogue-1 | Rogue-2 | Rogue-L |
|--------|---------|---------|---------|
| Pagerank | 0.26 | 0.10 | 0.28 |
| Hits | 0.26 | 0.10 | 0.28 |
| Closeness | 0.28 | 0.12 | 0.30 |
| Betweenness | 0.28 | 0.11 | 0.29 |
| Degree | 0.28 | 0.11 | 0.29 |
| Clusters | 0.27 | 0.10 | 0.27 |

| Method | Rogue-1 | Rogue-2 | Rogue-L |
|--------|---------|---------|---------|
| Pagerank | 0.24 | 0.08 | 0.244 |
| Hits | 0.24 | 0.08 | 0.246 |
| Closeness | 0.24 | 0.09 | 0.25 |
| Betweenness | 0.24 | 0.09 | 0.25 |
| Degree | 0.24 | 0.09 | 0.25 |
| Clusters | 0.25 | 0.08 | 0.25 |

but instead, they take into account the entire graph and the relationships within.

The clustering method offers more room for tuning the results. The clustering process is based on finding cliques which is a hard problem. It is more computationally expensive compared to other algorithms. It performs best with the tree edit distance as this measure is able to represent the similarity of sentences for clustering purposes. It is affected by the threshold parameter.

The lack of higher numbers in the results is not necessarily because of the actual quality of our summaries, rather than the limitation that ROGUE metric has. ROGUE address content selection between the test and the ground truth content without accounting for other quality aspects such as coherence, grammaticality or fluency. The content selection is relied on lexical overlap but a good summary isn’t always expressed without accounting for other quality aspects such as noun, verbs or adjectives.

To be able to account for the number of words in a sentence needed to be changed to match the other sentence, as compared to string based distance metrics that report on character changes, and such metric would be totally incorrect when comparing sentences of different lengths. The similarity of two sentences based on their distance is calculated as:

\[
Sim(S_i, S_j) = \frac{|\{ w_i, w_k \in S_i \land w_j, w_k \in S_j \}|}{\log(|S_i| + \log(|S_j|))}
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![Sentence similarity graphs generated using t=0.1 and t=0.5 respectively.](image)
• we ignore cliques with one item
• for cliques with more than two items, we consider their closeness scores from which we pick the one item with the highest scores
• in case one item is found to be the highest scoring item in more than one clique, we pick that as the representative for the cluster with the bigger clique, and the selection moves onto the second highest scoring item in the remaining clique

Evaluation. Our extracted summaries are evaluated using the Recall-Oriented Understudy for Gisting Evaluation - ROGUE metric. We have incorporated three types of ROGUE evaluation metric, Rogue-1, the overlap of unigrams (each word) between extracted summary and ground truth summary provided in the dataset, Rogue-2, the overlap of bigrams in the respective relation, and Rogue-L which reports on the longest common subsequence statistics.

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