Multilingual Single-Document Summarization with MUSE

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Abstract

MUltilingual Sentence Extractor (MUSE) is aimed at multilingual single-document summarization. MUSE implements a supervised language-independent summarization approach based on optimization of multiple sentence ranking methods using a Genetic Algorithm. The main advantage of MUSE is its language-independency—it is using statistical sentence features, which can be calculated for sentences in any language.

In our previous work, the performance of MUSE was found to be significantly better than the best known state-of-the-art extractive summarization approaches and tools in three different languages: English, Hebrew, and Arabic. Moreover, our experimental results in the cross-lingual domain suggest that MUSE does not need to be retrained on a summarization corpus in each new language, and the same weighting model can be used across several languages (Last and Litvak, 2012).

MUSE participated in the MultiLing 2013 single document summarization task on three languages: English, Hebrew and Arabic. Due to a very limited time that was given to the participants to run their systems on the MultiLing 2013 data, the results submitted to evaluation were obtained by summarizing the documents using models pre-trained on different corpora. As such, no training has been performed on the MultiLing 2013 corpus.

1 MUltilingual Sentence Extractor (MUSE): Overview

1.1 Methodology

MUSE implements a supervised learning approach to language-independent extractive summarization where the best set of weights for a linear combination of sentence scoring methods is found by a genetic algorithm trained on a collection of documents and their summaries. The weighting vector thus obtained is used for sentence scoring in future summarizations. Since most sentence scoring methods have a linear computational complexity, only the training phase of our approach is time-consuming.

Using MUSE, the user can choose the subset of totally 31 sentence metrics that will be included in the linear combination. The available metrics are based on various text representation models and are language-independent since they do not rely on any language-specific knowledge. Figure 1 demonstrates the taxonomy of all 31 metrics. We divided them into three main categories—structure-, vector-, and graph-based—according to their text representation model, where each subcategory contains group of metrics using the same scoring method.

A detailed description of sentence metrics used by MUSE can be found in (Last and Litvak, 2012).

A typical genetic algorithm requires (1) a genetic representation of the solution domain, (2) a fitness function to evaluate the solution domain, and (3) some basic parameter settings like selection and reproduction rules.

We represent each solution as a vector of weights for a linear combination of sentence scor-
ing metrics—real-valued numbers in the unlimited range normalized in such a way that they sum up to 1. The vector size is fixed and it equals to the number of metrics used in the combination.

Defined over the genetic representation, the fitness function measures the quality of the represented solution. We can use ROUGE-1 and ROUGE-2, Recall (Lin and Hovy, 2003) as a fitness functions for measuring summarization quality—similarity with gold standard summaries, which should be maximized during the training (optimization procedure). We use an annotated corpus of summarized documents, where each document is accompanied by several human-generated summaries—abstracts or extracts, as a training set.

The reader is referred to (Litvak et al., 2010b) for a detailed description of the optimization procedure implemented by MUSE.

Algorithms 1 and 2 contain the pseudo-code for two independent phases of MUSE: training and summarization, respectively. Assuming efficient implementation, all metrics have a linear computational complexity relative to the total number of words in a document - $O(n)$. As a result, the summary extraction time, given a trained model, is also linear (in the number of metrics in a combination). The training time is proportional to the number of GA iterations multiplied by the number of individuals in a population times the fitness evaluation (ROUGE) time. On average, in our experiments the GA performed $5 - 6$ iterations—

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**Algorithm 1**

**Step 1: Training**

**Require:** Gold Standard - a corpus of summarized documents $D$, $N$ chosen metrics

**Ensure:** A weighted model $W$ - vector of weights for each of $N$ metrics

**Step 1.1: Compute $M$ - sentence-score matrix**

For all $d \in D$ do

Let $R_1$, $R_2$, and $R_3$ are $d$ representations

For all sentences $s \in d$ do

Calculate $N$ metrics using $R_1$, $R_2$, and $R_3$

Add metrics row for $s$ into $M$

End for

End for

**Step 1.2: Compute a vector $W$ of metrics weights**

Run a Genetic Algorithm on $M$, given $D$:

Initialize a population $P$

Repeat

For all solution $g \in P$ do

Generate a summary $a$

Evaluate $a$ by ROUGE on summaries of $D$

End for

Select the best solutions $G$

$P$ - a new population generated by $G$

Until convergence - no better solutions are found

Return a vector $W$ of weights - output of a GA
Algorithm 2 Step 2: Summarizing a new document

Require: A document \( d \), maximal summary length \( L \), a trained weighted model \( W \)

Ensure: A set of \( n \) sentences, which were top-ranked by the algorithm as the most important.

Step 2.1: Compute a score of each sentence

Let \( R_1 \), \( R_2 \), and \( R_3 \) are \( d \) representations for all sentence \( s \in d \) do

- Calculate \( N \) metrics using \( R_1 \), \( R_2 \), and \( R_3 \)
- Calculate a score as a linear combination according to \( W \)

end for

Step 2.2: Compile the document summary

Let \( S = \emptyset \) be a summary of \( d \)
repeat

- get the top ranked sentence \( s_i \)
- \( S = S \cup s_i \)
until \( S \) exceeds max length \( L \)

return \( S \)

The preprocessing module performs the following tasks: (1) sentence segmentation, (2) word segmentation, (3) vector space model construction using \( tf \) and/or \( tf-idf \) weights, (4) a word-based graph representation construction, (5) a sentence-based graph representation construction, and (6) document metadata construction, including such information like frequency (\( tf \) and \( tf-idf \)) for each unique term, its location inside the document, etc. The outputs of this submodule are: sentence segmented text (SST), vector space model (VSM), the document graphs, and the metadata stored in the xml files. Steps (1) and (2) are performed by the text processor submodule, which consists of three elements: filter, reader and sentence segmenter. The filter works on the Unicode character level and performs such operations like identification of characters, digits, punctuations and normalization (optional for some languages). The reader invokes the filter, constructs word chunks from the input stream and identifies the following states: words, special characters, white spaces, numbers, URL links and punctuation marks. The sentence segmenter invokes reader and divides the input space into sentences. By implementing different filters, the reader can work either with a specific language (taking into account its intricacies) or with documents written in arbitrary language (in this case, a general filtering according to UTF-8 encoding is performed).

Figure 3 shows the general architecture of the MUSE system.
2 Training of MUSE

Since a very limited time was given to participants to run their summarizers on the MultiLing 2013 dataset, we did not perform training on a new data. The models obtained from training MUSE on monolingual corpora of English, Hebrew, and Arabic texts in 2011 (Last and Litvak, 2012), have been used for summarization in three languages. Both ROUGE-1 and ROUGE-2 have been used for building the models. In the current settings, ROUGE-1-based models were utilized. The English text material used in the experiments comprised the corpus of summarized documents available for the summarization task at the Document Understanding Conference 2002 (DUC, 2002). This benchmark dataset contains 533 news articles, each accompanied by two to three human-generated abstracts of approximately 100 words each.

For the Arabic language, we used a corpus compiled from 90 news articles. Each article was summarized by three native Arabic speakers selecting the most important sentences into an extractive summary of approximately 100 words each.

For the Hebrew language, we used a corpus where 120 news articles of 250 to 830 words are summarized by five human assessors each.

The documents from all corpora have a title as the first sentence.

ROUGE-1 and ROUGE-2 metrics (Lin, 2004) have been used as a fitness function during the training of MUSE. The same metrics have been used for evaluation of generated summaries in three languages. In order to use the ROUGE toolkit on Hebrew and Arabic, it was adapted to these languages by specifying the regular expressions for a single “word” using Hebrew and Arabic characters.

Figure 4 present models learned by MUSE on different monolingual corpora using ROUGE-1 and ROUGE-2, respectively. The actual results in the trained models include some negative values.

The evaluation results of MUSE on three monolingual corpora using 10-fold cross validation showed its significant superiority over TextRank (Mihalcea, 2005), the best known language-independent unsupervised approach.

3 Experimental Results

According to the results of automated evaluation in MultiLing 2013 (N-gram graph methods: AutoSummENG, MeMoG, NPowER), MUSE took fourth place in English corpus (out of 7 systems), third place in Hebrew (out of 5 summarizers), and the first place in Arabic (out of 6 participants). We believe, that training MUSE on the original data and using correct titles\(^1\) (by parsing xml documents) may significantly improve its results.

\(^1\)Due to the time constraints of the single-document summarization task, we used a simple txt format of summarized documents in the published dataset, where the title is not separated from the first sentence by punctuation marks.
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