MUSE – A Multilingual Sentence Extractor

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Abstract-MUltilingual Sentence Extractor (MUSE) is aimed at multilingual single-document summarization. MUSE implements the supervised language-independent summarization approach based on optimization of multiple statistical sentence ranking methods. The MUSE tool consists of two main modules: the training module activated in the offline mode, and the on-line summarization module. The training module can be provided with a corpus of summarized texts in any language. Then, it learns the best linear combination of user specified sentence ranking measures applying a Genetic Algorithm to the given training data. The summarization module performs real-time sentence extraction by computing sentence rankings according to the weighted model induced in the training phase. The main advantage of MUSE is its language-independency - it can be applied to any language given a gold standard summaries in that language. The performance of MUSE in our previous works was found to be significantly better than the best known state-of-theart extractive summarization approaches and tools in the three different languages: English, Hebrew, and Arabic. Moreover, our experimental results in a cross-lingual domain suggest that MUSE does not need to be retrained on each new language, and the same weighting model can be used across several languages.

Index Terms—automated summarization, multi-lingual summarization, language-independent summarization, genetic algorithm, optimization, linear combination

I. INTRODUCTION

DOCUMENT tools should identify a minimum number of words and/or sentences to express a document's main ideas. In this way, high quality summarization tools can significantly reduce the information overload faced daily by many professionals in a variety of fields.

The publication of information on the Internet in an everincreasing variety of languages amplifies the importance of developing multilingual summarization tools. There is a particular need for language-independent statistical tools that can readily be applied to text in any language without depending on language-specific linguistic analysis. In the absence of such tools, the only alternative to language-independent summarization is the labor-intensive translation of the entire document into a common language.

Since a pure statistical method usually characterizes only one sentence feature, various attempts were made to use a combination of several methods as a ranking function [1], [2]. MUSE continues this effort by learning the best linear combination of 31 statistical language-independent sentence ranking features using a Genetic Algorithm (GA). With this approach, MUSE can be easily applied to multilingual extractive summarization. All sentence features comprising the linear combination are based on either a vector or a graph representation using a mere word and sentence segmentation of a document.

MUSE implements the multilingual summarization¹ approach introduced in [4].² Evaluation of MUSE on three monolingual (English, Hebrew and Arabic) and one bilingual corpora of English and Hebrew documents has shown the following:

- MUSE performance is significantly better than TextRank [5] and Microsoft Word's Autosummarize tool in all tested languages, as demonstrated in Table II.

- In English, MUSE outperforms such known summarization tools as MEAD [1] and SUMMA [2].

- MUSE does not need to be retrained on each language and the same model can be used across at least three–English, Hebrew, and Arabic–different languages.

Table I demonstrates the results of training and testing comprising the average ROUGE values obtained for English³, Hebrew⁴ and bilingual corpora using 10-fold cross validation and reported in [4].

Table II shows the comparative results, also reported in [4], (ROUGE mean values) for three corpora, with the best summarizers on top. Results contain comparisons between: (1) a multilingual version of TextRank (denoted by

 $^{\rm l}Multilingual$ summarization is defined by [3] as "processing several languages, with summary in the same language as input"

²A web application of the MUSE-based summarizer will soon be made available at http://www.cs.bgu.ac.il/~litvakm/

 3 We used the corpus of summarized documents available at the Document Understanding Conference, 2002 [6] for English. This benchmark dataset contains 533 news articles, each accompanied by two to three human-generated abstracts of approximately 100 words each.

⁴For the Hebrew language we generated a corpus of 50 summarized news articles of 250 to 830 words each from the Website of the *Haaretz* newspaper (http://www.haaretz.co.il)

ML_TR) (Mihalcea, 2005), (2) Microsoft Word's Autosummarize function (denoted by MS_SUM), and (3) the best single scoring method in each corpus. As a baseline, we compiled summaries created from the initial sentences (denoted by POS_F). MUSE performed significantly better than TextRank in all three corpora and better than the best single methods COV_DEG in English and D_COV_J in Hebrew corpora respectively.

 TABLE I

 Results of 10-fold cross validation (Litvak et al., 2010b)

| | ENG | HEB | MULT |
|-------|--------|--------|--------|
| Train | 0.4483 | 0.5993 | 0.5205 |
| Test | 0.4461 | 0.5936 | 0.5027 |

TABLE II SUMMARIZATION PERFORMANCE. MEAN ROUGE-1 (LITVAK ET AL., 2010b)

| Metric | ENG | HEB | MULT |
|---------|--------|--------|--------|
| MUSE | 0.4461 | 0.5921 | 0.4633 |
| COV_DEG | 0.4363 | 0.5679 | 0.4588 |
| D_COV_J | 0.4251 | 0.5748 | 0.4512 |
| POS_F | 0.4190 | 0.5678 | 0.4440 |
| ML_TR | 0.4138 | 0.5190 | 0.4288 |
| MS_SUM | 0.3097 | 0.4114 | 0.3184 |

II. MULTILINGUAL SENTENCE EXTRACTOR (MUSE): Overview

A. 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 document 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 timeconsuming.

Using MUSE, the user can choose the subset of totally 31 sentence metrics that will be included in the linear combination. All metrics are based on different 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 sub-category contains group of metrics using the same scoring method.

A detailed description of sentence metrics used by MUSE can be found in (Litvak et al., 2010b).

We found the best linear combination of the metrics depicted in Figure 1 using a Genetic Algorithm (GA). GAs are categorized as global search heuristics. Figure 2 shows a simplified GA flowchart. 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.



Fig. 2. Simplified flowchart of a Genetic Algorithm (Litvak et al., 2010b)

We represent each solution as a vector of weights for a linear combination of sentence scoring 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 the number of metrics used in the combination.

Defined over the genetic representation, the fitness function measures the quality of the represented solution. We use ROUGE-1 and ROUGE-2, Recall (Lin & 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 used 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, summarization computation time, given a trained model, is also linear (at factor of 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—selection and reproduction before reaching convergence.

B. Architecture

The current version of MUSE tool can be applied only to text documents or textual content of the HTML pages. It consists of two main modules: the *training module* activated in offline, and the real-time *summarization module*. Both modules utilize two different representations of documents described in (Litvak et al., 2010b): vector- and graph-based.



Fig. 1. Taxonomy of language-independent sentence scoring metrics (Litvak et al., 2010b)

Algorithm 1 Step 1: Training

| Input: Gold Standard - a corpus of summarized documents |
|---|
| D, N chosen metrics |
| Output: 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 |

The *preprocessing module* is responsible for constructing each representation, and it is embedded in both modules.

The *training module* receives as input a corpus of documents, each accompanied by one or several gold-standard summaries—abstracts or extracts—compiled by human assessors. The set of documents may be either monolingual or multilingual and their summaries have to be in the same language as the original text. The *training module* applies a genetic algorithm to a document-feature matrix of precomputed sentence scores with the purpose of finding the best linear

Algorithm 2 Step 2: Summarizing a new document

Input: A document d, maximal summary length L, a trained weighted model W**Output:** 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 sentense $s \in d$ do Calculate N metrics using R_1 , R_2 , and R_3 Calculate a score as a linear combination according to ${\cal W}$ 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 $S = S \bigcup s_i$ **until** S exceeds max length Lreturn S

combination of features using any ROUGE metric (ROUGE-1 Recall as a default or specified by end-user) as a fitness function. The output/model of the training module is a vector of weights for user-specified sentence ranking features. In the current version of the tool, the user can choose from 31 vectorbased and graph-based features. The recommendation for the best 10 features one can find in (Litvak et al., 2010a).

The *summarization module* performs summarization of input text/texts in real time. Each sentence of an input text obtains a relevance score according to the trained model, and the top ranked sentences are extracted to the summary in their original order. The length of resulting summaries is limited by a user-specified value (maximum number of words in the text extract or a ratio). Being activated in real-time, the *summarization module* is expected to use the model trained on the same language as input texts. However, if such model is not available (no annotated corpus in the text language), the user can choose the following: (1) the model trained on some other language/corpus can be used (in (Litvak et al., 2010b) we show that the same model can be efficiently used across different languages), or (2) user-specified weights for each sentence feature (from 31 provided in the system) in the linear combination can be used for summarization.

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 sentencebased 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 is implemented using Strategy Design Pattern (Freeman et al., 2004) and 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. Figure 4 presents a small text example and its word-based graph representation.

Figure 3 shows the general architecture of the MUSE system.



Fig. 3. MUSE architecture

C. Use Case

MUSE has five possible use cases demonstrated in Figure 9 and briefly described in Table III: Configure, Train, Summarize, Rouge, and Evaluate.

In the **Configure** use case, the user is required to specify the following parameters: folder paths to input documents being

- 0 Hurricane Gilbert Heads Toward Dominican Coast
- Hurricane Gilbert swept toward the Dominican Republic Sunday, and the Civil Defense alerted its heavily populated south coast to prepare for high winds, heavy rains and high seas.
- 2 The storm was approaching from the southeast with sustained winds of 75 mph gusting to 92 mph.



Fig. 4. Text document (top) and its graph representation (bottom)

summarized, gold standard, output summaries, maximal length of a summary, preprocessing settings. The advanced user can change the default settings for a GA: population size, crossover and mutation probabilities, etc., training settings: splitting to the training and test data, preprocessing settings: maximal size of a graph representation, etc.. All specified settings can be used in the next user actions aka training and/or summarization or stored for the later use.

In the **Train** use case, the user trains genetic algorithm on the training corpus of annotated documents, where the optimal weights for the linear combination of sentence scoring metrics are determined. The weighted model can be used in the subsequent **Summarize** use case or stored for the later use.

The MUSE system can be evaluated on a new annotated dataset in the **Evaluate** use case.

In the **Summarize** use case, the user can get a summary for a single input document or set of summaries for a set of input documents. The pre-specified, new or modified settings can be used. The pre-trained or a new trained weighted model can be used.

In the fifth, **Rouge** use case, the user can apply ROUGE evaluation toolkit on existing—just produced or stored in advance—summaries. The ROUGE-1 Recall metric is applied by default, but it can be changed in the configuration use case.

D. Features

MUSE software has the following unique features:

• **Multilingual summarization.** The way in which MUSE processes a text is fully *multilingual*. All statistical metrics for sentence ranking used by MUSE do not require any language-specific analysis or knowledge, that allow MUSE to process texts in any language. Figures 6, 7, and 8 demonstrate the documents and their summaries—in a source language and translated to English—generated

| Summarizer (De | mo) | | |
|--|---|---|-------------------|
| processing Summ | ary Algorithm (MUSE) Configuration Summary | v Content | |
| hoose file to presen | 6 | | |
| P880508-0070.sen | ts | × | Display |
| Colored Sentences | Sentences ranked Sentences sortes by scores | 8 | |
| A 3 year campaign Northinastern anno. The degree is to be the degree is to be the degree is to be the degree of the degree the degree of the degree south Alinca's while the degree of the degree South Alinca's while South even know "Yourd think al leas "This stated out a "We are very, very it want meant to be invirsitiv spokesm However, Northeas | the has ucceeded in getting Notheasten III and Janus III available dagets incoming Mana experiodic biggin a cancelar of demonstrations incomes second lists in the law Rever Mark as incomes and hiddyeas law aludent. Such Dings with an oxida dagets and and the second second encode government aget a will here Marcelao on the administration along it may have and such an along many Back. have what drive is spontoining k ⁺ and kells Moley. In the administration along it may need in use and such as long in they need in use and such as a long it may need in the administration along it may have and kells the first on a law bits in the administration of the in along the Marceles dation is any to port their and January and Marceles dation is any to port their and January and Marceles dation is any to port their and January and Marceles dation is any to port their and January and Marceles dation is any to port their and January and Marceles dation is any to port their and January and Marceles dation is any to port their and January and the second approval from the Mark and have and the second approval from the Mark and have and the second approval from the Mark and their second approval from | viensity to evend an homorary degree to jaied 5 south African nationalities leader Netron Mandde has raired object glorin May 13, and when a long that is built to a benefit driver. and vipio in the campus, is "Homo Netion Mandda s, "Netion Mandda was an | pris from some fe |
| () | | | 8 |
| og files deleted in CAD files deleted in CAD files deleted in CAD ummarizer module p BS_VALUE_WORE VPUT_VALUE_WORE VPUT_SENTS_DIR | EMQ_EXPERIMENTS\S\ EMQ_EXPERIMENTS\SS\servinces EMQ_EXPERIMENTS\SS\servinces exempler: IS_MAX_100 USENQ_EXPERIMENTS\S\ CLOEMQ_EXPERIMENTS\S\Servinces | | |
| | | Próceed | |

Fig. 5. Input file (AP880228-0097 from DUC 2002 collection) and its extract by MUSE.



(c) Translated summary

Fig. 6. Arabic document titled "America: an unprecedented step in the "International (Monetary Fund)"" and its summary.

by MUSE for Arabic, Hebrew and English languages, respectively. Figures 6, 7 and 8 demonstrate extracts produced by MUSE for Arabic, Hebrew and English texts, respectively.

• Flexible pre-processing. User is allowed to add the following language-specific analysis to the MUSE processing: stopwords removal, stemming, sentence segmen-

tation and POS tagging, by configuring the system and providing necessary tools or data. For example, the user can decide that he/she wants to remove stopwords by providing the stopwords list in the processed language and turning on the "remove stopwords" parameter. Also, many parameters for constructing a document representation are configurable.

| נתניהו ואבו מאזן הסכימו: לסיים מו"מ תוך שנה | | | | |
|--|--|--|--|--|
| לפי דיווח ב"ניו יורק טיימס", מזכירת המדינה האמריקאית קלינטון תודיע היום על חידוש השיחות הישירות בין ישראל לפלסטינים. | | | | |
| עוד נאמר בדיווח כי ראש הממשלה ויו"ר הרשות הפלסטינית הסכימו לסיים את השיחות בתוך שנה. | | | | |
| על הפרק: כל סוגיות הסדר הקבע | | | | |
| תגיות: הקוורטט ברק אובמה אבו מאזו משא ומתו ישיר בקרוב שוב בבית הלבו? אבו מאזו עם אובמה ייענה להזמנה? | | | | |
| נתניהו עם אובמה | | | | |
| מזכירת המדינה האמריקאית הילרי קלינטון צפויה להודיע היום (שישי) על כר שישראל והפלסטינים יחדשו בתחילת החודש הבא את השיחות | | | | |
| הישירות ביו הצדדים. לאחר הפסקה של כשנה וחצי. לפי הדיווח ב"ניו יורק טיימס". נתניהו ויו"ר הרשות הפלסטינית אבו מאזו. הסכימו לסיים את | | | | |
| השיחות בתור שנה. עוד נתחר בי במשא נותו השיר יודונו כל תוניות החדר הפרט ובהו מעמדה של ירושלים. נבולות המדיות הפלתנוניות החדשה | | | | |
| ערכוות בינוק שהיו לאראל ווכות השורה של הפלונויה הפלתווונים | | | | |
| עד ביות בסווד וול למור היות היות ביו הבווריום והרע הווה להשבעל והלהווויוה להתהול המשע ומהו משור הומשונים ורשהווה התהומרה. הנורה עווי | | | | |
| מוקד היות אמו העדדום וענו להנותם יקרא היום לישו אל נעסטיבו לחותי ל במשאתום עד היות אלו בהיים בטפטבבו האח בניין כן הכווברב הוא שאנו העדדום וענו להנותם אלואו אכפ"ר בכל עובתי שמתם את היא כמולי | | | | |
| כי התינימודים שניים להנות המנות התירים ענישא אחד בבוק אבמודים מיותף אף האג בשיות בעובים ביונים ביונים ביונים ב | | | | |
| אמש הוה כי בסיסת ההוה עה שבפר לפו טב הקוה טכו המו כב במארה ב, האידור האידופי חיסיה - לא יהיה מתכו באופן מפורש הבוד | | | | |
| בהקפאת הבנייה בהתנותיות, כפי שהופיע בהצהרות הקוח סט הקם מתכ עד דוחר כי בהודעה יצרן ששיחות השלום צפויות להגיע לסיומן בתו | | | | |
| כשנה. | | | | |
| עם זאת, המקורות דיווחו כי בטיוטת ההודעה נכתב כי "הקוורטט מאשרר את מחויבותו המלאה להצהרותיו הקודמות", בהן נקראה ישראל לעצור | | | | |
| את הבנייה בהתנחלויות. על פי המקורות, בטיוטה נכתב עוד כי "משא ומתן ישיר ודו צדדי שיפתור את כל נושאי הליבה יוביל להסדר שנידון בין | | | | |
| הצדדים, שיסיים את הכיבוש, ותוצאותיו יהיו מדינה פלסטינית שחיה בשלום לצד ישראל". עוד דווח, שבטיוטה נכתב כי "המשא ומתן יכול להסתיים | | | | |
| בהצלחה תוך שנה", וכן כי "הצלחתו תדרוש את תמיכתם של מדינות ערב." | | | | |
| ביום ראשון החליטו שרי השביעייה להתעלם מהצהרת הקוורטט הבינ"ל, בנושא פתיחת המשא ומתן הישיר בין ישראל והפלסטינים. את הצהרת | | | | |
| הקוורטט, הגדירו שרי השביעייה כ"עלה תאנה" של הפלסטינים לדחות את המהלך. בנוסף, הוחלט להמתין לזימון של האמריקאים, שאמור | | | | |
| להתקבל אצל הצדדים בימים הקרובים, לפתוח בשיחות ישירות במצרים או בוושינגטון. | | | | |
| | | | | |
| (a) Summarized document | | | | |
| | | | | |

לפי הדיוות בינו יזרקט ייתפי", עניתו וירי הרשות המלסטינית אנו מאון, הספימו לסיים את השיחות בתוך שנה. אמש דוחי כי בטויות התודעה שפעול מפרם הקורטינט המוכרב מאחרי, הקולים, האיחוד האירופי ורוסיה - לא יהיה מוזכר באופן מפודש הצרך בהקטאת הבניית בהתנגליות, כפי שהופיע בתורחה הקודיטט הקודמות על פי המקורות, בטיטה נכתב עוד כי ימש ומתוך יאירד וצדי ישימוןי ואת כל נושאי הליבה יוביל להסדר שנידון בין הצדיים, שיסיים את הכיבוש, ותנצאותיו יהיו מדינה פלסטינית שחיה בשלום לצד ישראל.

(b) Original summary

According to a report in The New York Times, Netanyahu and Palestinian Authority Chairman Mahmoud Abbas, agreed to complete the talks within a year. Last night it was reported that the draft notification that is expected to be published by the Quartet consisting of U.S., UN, EU and Russia - will not explicitly mention the need to freeze settlement construction, as appeared in the previous Quartet statements. According to the sources, the draft stated that "direct and bilateral negotiations that will solve the core issues will lead to an agreement between the parties, and will end the occupation, and its results will be a Palestinian state living in peace alongside Israel."

(c) Translated summary

Fig. 7. Hebrew document titled "Netanyahu and Abbas agreed to complete negotiations within a year" and its summary.



(b) Summary

Fig. 8. English document titled "Images reveal Indonesian tsunami destruction" and its summary.

- A rich choice of statistical sentence features. User can choose from 31 sentence features provided by MUSE for summarization by configuring their weights in a linear combination. Our recommendation for 10 best metrics identified by cluster analysis of their performance on English and Hebrew corpora can be found in (Litvak et al., 2010a).
- Easy to use. Text and HTML documents can be summarized with just one click. Figure 5 shows extract produced by MUSE for one of the DUC 2002 (DUC, 2002) documents.
- Cross-lingual use of multiple ranking models. MUSE allows to use the same trained model across different languages. As result, no need in retraining on a new

| Use Case | Goal | Precondition | Postcondition | Brief |
|-----------|-----------------|----------------------|-------------------------|--|
| Configure | Specify | None | Stored configuration | User specifies all necessary parameters as: |
| | preprocessing | | file for later use | path to the input document/s, summary length, |
| | and summarizer | | | gold standard folder, etc. User can store |
| | settings | | | his settings for the later use. |
| Train | Train a | Parameters settings, | Trained model - weights | Train the genetic algorithm on the training |
| | model | train and test data | for linear combination | document set. The trained model can |
| | | | | be stored for the later use. |
| Evaluate | Evaluate the | Parameters settings, | Average train and test | Evaluate the system on the given document set |
| | system | gold standard | scores (ROUGE) | using 10-fold cross-validation. The average |
| | | summaries | | ROUGE score is presented to the user. |
| Summarize | Summarize | Settings and | Summary for each | User can get a summary for each input document |
| | the input | a weighted model | input document | and store it in the file system. Also, different |
| | document/s | | | output representations are provided to the user: |
| | | | | sentence scores, highlighted and sorted sentences. |
| Rouge | Calculate ROUGE | Settings, input and | ROUGE score | User can get a ROUGE score for the input |
| | score for the | gold standard | | summaries given gold standard summaries |
| | input summaries | summaries | | for the document set. |

TABLE III USE CASE DESCRIPTION



Fig. 9. Use case diagram of MUSE

corpus, language or genre. User is allowed to store the trained model in the file system for later use.

- Storing summaries for later use. The final summary can be exported to a file according to the user's settings.
- Storing statistics for later analysis. The results for the future statistical analysis (like summaries per individual metric, ROUGE score per document, etc.) can be stored in the file system for later use.
- Summary options. The size of the summary can be assigned according to specific goals: a cursory examination or a detailed survey. Specify the summary length by either the number of words/sentences in the summary or a percentage of the original text.
- **Output interpretability.** User can obtain various output representations: input document with colored extracted sentences, scores per sentence, and sentences sorted by their score.
- **High-level configuration.** MUSE has flexible preprocessing and optimization options. The user can work in the default mode as well as in advanced one. Advanced users can configure the settings of the genetic algorithm, pre-processing, etc.

III. CONCLUSIONS AND FUTURE WORK

In this article we described MUSE—a *supervised* languageindependent summarizer for the text documents based on sentence extraction.

We described and detailed the MUSE architecture, approach and use cases.

MUSE does not require any language-specific knowledge and can be applied to any language with a minimum amount of text pre-processing. Moreover, our experiments show that the same weighting model is applicable across multiple languages.

In general, we can conclude that combination of as many independent statistic features as possible can compensate the lack of linguistic analysis and knowledge for selecting the most informative sentences to a summary. More features can be added to our system, and/or another supervised model can be used for the learning and optimization of a linear combination. We believe that such an approach generally works when retrained on different genres and languages.

We can recommend the following: If a corpus in the target language exists, the best approach is to train MUSE on the target-language corpus, while periodically updating the trained model when new annotated data becomes available. If there is a corpus in any source language, but no high-quality targetlanguage corpus is available, we would recommend to use the model trained on the source language corpus for summarizing documents in the target language.

In future work, MUSE may be evaluated on additional languages and language families, incorporate threshold values for threshold-based metrics into the GA-based optimization procedure, improve performance of similarity-based metrics in the multilingual domain, apply additional optimization techniques like Evolution Strategy (Beyer & Schwefel, 2002), which is known to perform well in a real-valued search space, and extend the search for the best summary to the problem of multi-objective optimization, combining several summary quality metrics.

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