WikiMulti: a Corpus for Cross-Lingual Summarization

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Abstract. Cross-lingual summarization (CLS) is the task to produce a summary in one particular language for a source document in a different language. We introduce WikiMulti - a new dataset for cross-lingual summarization based on Wikipedia articles in 15 languages. As a set of baselines for further studies, we evaluate the performance of existing cross-lingual abstractive summarization methods on our dataset. We make our dataset publicly available here: https://github.com/tikhonovpavel/wikimulti

1 Introduction

Automatic summarization is one of the central problems in Natural Language Processing (NLP) posing several challenges relating to understanding (i.e. identifying important content) and generation (i.e. aggregating and rewording the identified content into a summary). Of the many summarization paradigms that have been identified over the years, single-document summarization has consistently garnered attention. Given an input text (typically a long document or article), the goal is to generate a smaller, concise piece of text that conveys the key information of the input text. There are two main approaches to automatic text summarization: extractive and abstractive. Extractive methods chop out one or more segments from the input text and concatenate them to produce a summary. These methods were dominant in the early era of summarization, but they suffer from some limitations, including weak coherence between sentences, inability to simplify complex and long sentences, and unintended repetition. Abstractive text summarization is the task of generating a short and concise summary that captures the salient ideas of the source text.

Despite the presence of a large number of datasets for abstractive summarization \cite{14,11,12}, the vast majority of them are focused on mono-lingual summarization.

However, there exists a number of summarization datasets including several languages. The task for summarization on several languages could be stated in two significantly different ways. The one is called cross-lingual and other is multi-lingual. In the case of multi-lingual datasets, the corpus is collected in several languages, but there is no requirement for an alignment, in the sense that the documents in one language may not correspond to the documents in any other language. The systems trained on such corpora are targeted to produce summary of a document of the same language, e.g. a system should make summaries for Portuguese documents in form of the paragraphs in
Portuguese. *Multiling'13 and '15 [4,5], MLSUM [15], and XL-Sum [6] are examples of a multi-lingual datasets.*

In the case of a cross-lingual dataset, the corpus have to be aligned between the languages. For example, the document in English should have a summary in Portuguese. The systems trained on such datasets should be able to make a summary in another language regarding the language of the input document.

There were a few attempts for addressing the problem of cross-lingual summarization [7,13]. Among them, only [7] is the only one of the datasets which is large and addresses the problem of cross-lingual summarization. However, this dataset contains only short articles for a few topics.

This further opens up avenues to explore new approaches for cross-lingual summarization, which are currently understudied. We present a novel dataset WikiMulti consisting of Wikipedia articles and summaries in 15 languages. With the dataset in hand, we evaluate several approaches for cross-lingual summarization to establish the baselines.

This paper is structured as follows: in Sec. 2 we review existing datasets on multi- and cross-lingual summarization; in Sec. 3 we describe WikiMulti, the presented dataset; Sec. 4 is devoted to the description of the baselines for this dataset; Sec. 5 contains the results for the baselines, while Sec. 6 concludes the paper.

## 2 Existing Datasets

In this section, we take a closer look at the multi- and cross-lingual summarization datasets. The statistics on these datasets provided in Tab. 1.

| Dataset       | Num languages | Avg num summaries | Avg summary length | Avg article length |
|---------------|---------------|-------------------|--------------------|--------------------|
| MultiLing’15  | 40            | 30                | 185                | 4,111              |
| MLSUM         | 5             | 314,208           | 34                 | 812                |
| Global Voices | 15            | 1,456             | 51                 | 359                |
| WikiLingua    | 18            | 42,783            | 39                 | 391                |
| WikiMulti     | 15            | 10,467            | 112                | 1078               |

*Table 1. Statistics for existing multi-lingual (top) and cross-lingual (bottom) datasets.*

### 2.1 Multi-lingual datasets

*Multiling’13 [4,5] and Multiling’15 [5] have been collected at MultiLing Workshops by organizers. The MultiLing’13 dataset includes summaries of 30 Wikipedia articles per language, describing a given topic. For MultiLing’15, an additional 30 documents were collected for evaluation purposes.*

*MLSUM [15]: A dataset obtained from online newspapers. It contains 1.5 million article/summary pairs in five different languages, namely, French, German, Spanish, Russian, and Turkish.*
XL-Sum [6]: A dataset containing 1 million article-summary pairs in 44 languages, being the first publicly available abstractive summarization dataset for many of them. The dataset covers 44 languages ranging from low to high-resource.

2.2 Cross-lingual datasets

Global Voices [13]: authors collected descriptions of news articles provided by Global Voices site creators (it’s an international, multilingual community of writers, translators, academics, and digital rights activists.). This dataset supports 15 languages, however, 10 of them have less than 1,000 articles.

WikiLingua [7]: authors crawled WikiHow site (is an online resource of how-to guides where each page includes multiple methods for completing a multi-step procedural task along with a one-sentence summary of each step).

3 WikiMulti Dataset

The well-known community collected encyclopedic resource of Wikipedia is a source for many datasets [11,17,16] to name a few, due to on the one hand the massive contents with a variety of topics and languages, curation of the content (for the most popular languages), and on the other hand, the permissive Creative Common license[3] used throughout the whole Wikipedia.

Wikipedia project has a concept of so-called Good Article, i.e. the article which is approved by the community as the one describing a specific topic in full detail and well written. One point of this article structure includes the summary as the first paragraph of an article. We decided to build our dataset on this basis. To produce the corpus, we take a list of Wikipedia’s Good Articles[4] and get a corresponding article in 14 other languages for each article in the list.

Each article belongs to some categories and subcategories. For example category “Language and literature” divided into “Ancient texts”, “Comics”, “Novels”, “Characters

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[3]: Text is available under the Creative Commons Attribution-ShareAlike License 3.0”, https://en.wikipedia.org/wiki/Main_Page
[4]: https://en.wikipedia.org/wiki/Wikipedia:Good_articles/all
https://en.wikipedia.org/wiki/Wikipedia:Good_articles/Social_sciences_and_society
https://en.wikipedia.org/wiki/Wikipedia:Good_articles/Sports_and_recreation
https://en.wikipedia.org/wiki/Wikipedia:Good_articles/Video_games
https://en.wikipedia.org/wiki/Wikipedia:Good_articles/Warfare
Outer space, commonly shortened to space, is the expanse that exists beyond Earth and its atmosphere and between celestial bodies. Outer space is not completely empty - it is a hard vacuum containing a low density of particles, predominantly a plasma of hydrogen and helium, as well as electromagnetic radiation, magnetic fields, neutrinos, dust, and cosmic rays. The baseline temperature of outer space, as set by the background radiation from the Big Bang, is 2.7 kelvins (−270.45°C; −454.81°F). The plasma between galaxies is thought to account for about half of the baryonic (ordinary) matter in the universe, having a number density of less than one hydrogen atom per cubic metre and a temperature of millions of kelvins. Local concentrations of matter have condensed into stars and galaxies. Studies indicate that the majority of the mass-energy in the observable universe is dark energy, a type of vacuum energy that is poorly understood. Intergalactic space takes up most of the volume of the universe, but even galaxies and star systems consist almost entirely of empty space.
Our final dataset consists of 22,061 unique English articles. Other languages have, on average, 9,639 articles that align with an article in English. From the Wikipedia list, those with more than 1 million articles were selected. From the list of Wikipedias[^1], those with more than 1 million articles were selected. Several of such Wikipedias were skipped (namely, Waray, Cebuano, Egyptian Arabic) due to the most articles in them have one or two paragraphs.

More detailed statistics for our dataset is shown at Tab. 3 while its comparison to other existing cross-lingual datasets is shown in Tab. 1.

| Language | Language code | Articles |
|----------|---------------|----------|
| English  | EN            | 22061    |
| French   | FR            | 14625    |
| Spanish  | ES            | 13068    |
| Italian  | IT            | 11847    |
| Russian  | RU            | 11703    |
| German   | DE            | 11228    |
| Portuguese | PT        | 10441    |
| Japanese | JA            | 8922     |
| Polish   | PL            | 8875     |
| Chinese  | ZH            | 8711     |
| Swedish  | SV            | 8007     |
| Dutch    | NL            | 7681     |
| Arabic   | AR            | 7476     |
| Ukrainan | UK            | 7216     |
| Vietnamese | VI         | 5153     |
| **Average** |             | **9639** |

Table 3. Number of articles on different languages in WikiMulti.

### 4 Experiments

In all the experiments we used classic ROUGE scores described in [8] for evaluation in our experiments. We use all the most common variances of ROUGE scores, namely, Precision, Recall, and F-measure for ROUGE-1, ROUGE-2, and ROUGE-L.

#### 4.1 Baselines

We evaluate the following baseline approaches for cross-lingual summarization on our data:

- **TextRank+Translate**: we have used TextRank[^10] tool to automatically get a summary of the text without using complex models, and then translate summary to target

[^1]: https://en.wikipedia.org/wiki/List_of_Wikipedias
language. Following the recommendation from [7] we used Amazon translating tool\footnote{https://aws.amazon.com/translate/} to perform translation.

Also we fine-tuned several models to perform cross-lingual summarization task to do direct cross-lingual learning. Fine tuning on different models might give a better idea of which architectures are best suited. We’ve used the following models:

**mBART** [9] is a multi-lingual language model that has been trained on large, monolingual corpora in 25 languages. The model uses a shared sub-word vocabulary, encoder, and decoder across all 25 languages, and is trained as a denoising auto-encoder during the pre-training step. mBART is trained once for all languages, providing a set of parameters that can be fine-tuned for any of the language pairs in both supervised and unsupervised settings, without any task-specific or language-specific modifications or initialization schemes.

**M2M100** [3] is a multilingual encoder-decoder (seq-to-seq) model primarily intended for translation task. It was originally pre-trained on a dataset that covers thousands of language directions with supervised data, created through large-scale mining. One of the main goals stated by the authors is to focus on a non-English-centric approach: the model can translate directly between any pair of 100 languages.

**mT5** [18] is a massive model, a multilingual variant of T5 that was pre-trained on a Common Crawl-based dataset covering 101 languages. The model was trained with “Text-to-Text Transfer Transformer” paradigm which means casting every task, including translation, question answering and classification as feeding the model text as input and training it to generate some target text. This allows to use the same model, loss function, hyperparameters, etc. across diverse set of tasks.

To train M2M100 and mBART we took a one-directional approach: train 14 different models using English as source language and summarize English text into one of 14 languages. I.e. for a French-English pair, all texts will be in English and the model will summarize them into French.

To train mT5 we took a different two-directional approach: train 14 different models, but use both English and non-English articles as text to summarize and as summaries 50% of time. In this case for the same French-English pair, half of the texts will be in English, and the model will summarize them in French, and the other half of the texts will be in French, and the model will summarize them into English.

Figure 1 illustrates these two kinds of approaches.

### 4.2 Experiment Parameters

We fine-tuned mT5, M2M100 and mBART models for 20k steps on a distributed cluster of 7 Nvidia Tesla P100 GPUs. We used AdamW with cosine learning rate schedule with a linear warmup of 500 steps.

### 5 Results and Analysis

Tab. 4 shows ROUGE scores for the evaluated baselines.
M2M100 showed the highest performance on average, especially compared to mBART and mT5. However, all three M2M100, TextRank+Translate, and mBART have problems with Japanese and Chinese languages, where mT5 is better than all the others.

Also, it is interesting that for the Dutch language, all models show on average a larger ROUGE score than in other languages.

6 Conclusion

We proposed a novel dataset for cross-lingual summarization. It is comparable in size to the existing largest one, while being more broad in topics and including longer documents and summaries. We have evaluated several well known models for abstractive summarization on this dataset and found out that the performance is stronger correlated with the language itself than the model. E.g. the Dutch language has better scores on average for all the models. We hypothesize that this reflects the culture of Wikipedia writing in Dutch language, rather than the language structure.

We hope that this dataset will ease the way for other researchers in the field of cross-lingual summarization.

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| Model       | Language | ROUGE-1 |         | ROUGE-2 |         | ROUGE-L |         |
|-------------|----------|---------|---------|---------|---------|---------|---------|
|             |          | F      | P      | R       | F      | P      | R       |
| TextRank+   | AR       | 0.10   | 0.13   | 0.15    | 0.02   | 0.01   | 0.02    |
| Translate   | DE       | 0.10   | 0.14   | 0.16    | 0.04   | 0.02   | 0.03    |
|             | ES       | 0.11   | 0.13   | 0.15    | 0.03   | 0.02   | 0.03    |
|             | FR       | 0.21   | 0.17   | 0.28    | 0.04   | 0.03   | 0.06    |
|             | IT       | 0.17   | 0.19   | 0.31    | 0.04   | 0.03   | 0.06    |
|             | JA       | 0.18   | 0.15   | 0.24    | 0.03   | 0.02   | 0.02    |
|             | NL       | 0.18   | 0.14   | 0.31    | 0.04   | 0.03   | 0.07    |
|             | PL       | 0.10   | 0.07   | 0.19    | 0.02   | 0.01   | 0.04    |
|             | PT       | 0.18   | 0.15   | 0.25    | 0.02   | 0.02   | 0.04    |
|             | RU       | 0.08   | 0.06   | 0.14    | 0.01   | 0.01   | 0.02    |
|             | SV       | 0.15   | 0.11   | 0.26    | 0.02   | 0.01   | 0.04    |
|             | UK       | 0.07   | 0.05   | 0.12    | 0.01   | 0.01   | 0.02    |
|             | VI       | 0.21   | 0.18   | 0.30    | 0.04   | 0.03   | 0.06    |
|             | ZH       | 0.00   | 0.00   | 0.00    | 0.00   | 0.00   | 0.00    |
| M2M100      | AR       | 0.20   | 0.31   | 0.16    | 0.08   | 0.11   | 0.07    |
|             | DE       | 0.29   | 0.42   | 0.24    | 0.13   | 0.17   | 0.11    |
|             | ES       | 0.34   | 0.46   | 0.30    | 0.17   | 0.22   | 0.16    |
|             | FR       | 0.28   | 0.49   | 0.22    | 0.13   | 0.22   | 0.10    |
|             | IT       | 0.25   | 0.44   | 0.19    | 0.09   | 0.17   | 0.07    |
|             | JA       | 0.08   | 0.10   | 0.07    | 0.03   | 0.03   | 0.03    |
|             | NL       | 0.38   | 0.48   | 0.34    | 0.20   | 0.24   | 0.19    |
|             | PL       | 0.31   | 0.37   | 0.29    | 0.17   | 0.19   | 0.16    |
|             | PT       | 0.31   | 0.43   | 0.26    | 0.14   | 0.19   | 0.13    |
|             | SV       | 0.31   | 0.40   | 0.28    | 0.14   | 0.18   | 0.14    |
|             | UK       | 0.27   | 0.36   | 0.25    | 0.14   | 0.17   | 0.14    |
|             | VI       | 0.33   | 0.42   | 0.30    | 0.16   | 0.20   | 0.15    |
|             | ZH       | 0.03   | 0.04   | 0.03    | 0.01   | 0.01   | 0.01    |
| mBART       | AR       | 0.15   | 0.17   | 0.14    | 0.10   | 0.12   | 0.08    |
|             | DE       | 0.19   | 0.23   | 0.18    | 0.05   | 0.06   | 0.05    |
|             | ES       | 0.32   | 0.44   | 0.29    | 0.16   | 0.20   | 0.15    |
|             | FR       | 0.30   | 0.50   | 0.24    | 0.14   | 0.24   | 0.12    |
|             | IT       | 0.16   | 0.22   | 0.14    | 0.02   | 0.03   | 0.02    |
|             | JA       | 0.04   | 0.05   | 0.03    | 0.00   | 0.00   | 0.00    |
|             | NL       | 0.41   | 0.47   | 0.39    | 0.23   | 0.26   | 0.23    |
|             | PL       | 0.21   | 0.23   | 0.21    | 0.09   | 0.09   | 0.08    |
|             | PT       | 0.19   | 0.23   | 0.18    | 0.06   | 0.07   | 0.06    |
|             | RU       | 0.26   | 0.32   | 0.24    | 0.11   | 0.14   | 0.11    |
|             | SV       | 0.30   | 0.37   | 0.27    | 0.13   | 0.15   | 0.12    |
|             | UK       | 0.21   | 0.27   | 0.20    | 0.08   | 0.11   | 0.08    |
|             | VI       | 0.16   | 0.17   | 0.17    | 0.03   | 0.03   | 0.03    |
|             | ZH       | 0.01   | 0.00   | 0.01    | 0.00   | 0.00   | 0.00    |
| MT5         | AR       | 0.17   | 0.37   | 0.12    | 0.05   | 0.10   | 0.04    |
|             | DE       | 0.30   | 0.44   | 0.25    | 0.13   | 0.17   | 0.12    |
|             | ES       | 0.29   | 0.49   | 0.23    | 0.13   | 0.21   | 0.10    |
|             | FR       | 0.28   | 0.47   | 0.22    | 0.11   | 0.19   | 0.09    |
|             | IT       | 0.29   | 0.49   | 0.23    | 0.14   | 0.22   | 0.11    |
|             | JA       | 0.16   | 0.25   | 0.13    | 0.06   | 0.08   | 0.05    |
|             | NL       | 0.32   | 0.49   | 0.26    | 0.13   | 0.20   | 0.11    |
|             | PL       | 0.23   | 0.39   | 0.18    | 0.08   | 0.13   | 0.07    |
|             | PT       | 0.29   | 0.42   | 0.25    | 0.13   | 0.17   | 0.12    |
|             | SV       | 0.28   | 0.43   | 0.23    | 0.12   | 0.18   | 0.10    |
|             | UK       | 0.22   | 0.38   | 0.18    | 0.08   | 0.13   | 0.07    |
|             | VI       | 0.27   | 0.43   | 0.23    | 0.11   | 0.17   | 0.10    |
|             | ZH       | 0.13   | 0.22   | 0.10    | 0.04   | 0.06   | 0.03    |

Table 4. Evaluation on different models
| Category                                      | Num of articles | Num of subcategories |
|-----------------------------------------------|-----------------|----------------------|
| Agriculture, food, and drink                  | 298             | 10                   |
| Albums                                        | 1350            | 13                   |
| Architecture                                  | 1062            | 11                   |
| Art                                           | 368             | 3                    |
| Biology and medicine                          | 1889            | 21                   |
| Chemistry and materials science                | 184             | 14                   |
| Classical compositions                        | 137             | 2                    |
| Computing and engineering                     | 383             | 11                   |
| Earth science                                 | 1357            | 15                   |
| Film                                          | 1157            | 18                   |
| Geography                                     | 666             | 9                    |
| Language and literature                       | 1308            | 17                   |
| Mathematics and mathematicians                | 110             | 3                    |
| Media and drama                               | 657             | 6                    |
| Other music articles                          | 878             | 7                    |
| Philosophy                                    | 216             | 6                    |
| Physics and astronomy                         | 398             | 11                   |
| Places                                        | 533             | 10                   |
| Religion                                      | 424             | 5                    |
| Royalty, nobility, and heraldry               | 684             | 4                    |
| Songs                                         | 2246            | 23                   |
| Television                                    | 2586            | 113                  |
| Transport                                     | 2404            | 17                   |
| World history                                 | 1629            | 14                   |
| Armies and military units                     | 384             | 4                    |
| Baseball                                      | 431             | 2                    |
| Basketball                                    | 251             | 2                    |
| Battles, exercises, and conflicts             | 1051            | 10                   |
| Cricket                                       | 139             | 2                    |
| Culture, sociology, and psychology            | 381             | 8                    |
| Economics and business                        | 317             | 5                    |
| Education                                     | 280             | 3                    |
| Football                                      | 1394            | 7                    |
| Hockey                                        | 264             | 3                    |
| Law                                           | 543             | 10                   |
| Magazines and print journalism                | 151             | 2                    |
| Military aircraft                             | 151             | 2                    |
| Military decorations and memorials            | 24              | 2                    |
| Military people                               | 797             | 7                    |
| Military ranks and positions                  | 7               | 1                    |
| Motorsport                                    | 317             | 2                    |
| Multi-sport event                             | 421             | 5                    |
| Other sports                                  | 841             | 31                   |
| Politics and government                       | 654             | 11                   |
| Pro wrestling                                 | 344             | 5                    |
| Recreation                                    | 278             | 9                    |
| Video games                                   | 1639            | 20                   |
| Warships and naval units                      | 1761            | 3                    |
| Weapons, equipment, and buildings             | 336             | 4                    |

*Table 5. English Good articles divided into categories*