Multilingual Open Text 1.0:
Public Domain News in 44 Languages

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Abstract
We present a new multilingual corpus containing text in 44 languages, many of which have limited existing text resources for natural language processing. The first release of the corpus contains over 2.7 million news articles and an additional 1 million short snippets (photo captions, video descriptions, etc.) published between 2001–2021 and collected from Voice of America’s news websites. We describe our process for collecting, filtering, and processing the data. The source material is in the public domain, our collection is licensed using a creative commons license (CC BY 4.0), and all software used to create the corpus is released under the MIT License. The corpus will be regularly updated as additional documents are published.

Keywords: multilingual corpora, text data, low resource NLP, open access text

1. Introduction
This work describes the first release of Multilingual Open Text (MOT), a collection of permissively licensed texts created with a goal of improving the amount of high-quality text available for lower-resourced languages.

In this release, MOT v1.0, the corpus consists of data collected from Voice of America (VOA) news websites. Our broader goal is a corpus of open access multilingual text, and we plan to include data from other sources in future releases. As part of the development of this corpus, we created infrastructure to continue to scrape new documents as they are published in order to provide subsequent releases with newly published and updated documents. We have been using this infrastructure for several months to expand the corpus. The corpus contains documents in many different languages, many of which are lower resourced.

In this paper, we explain our process for collecting, filtering, and processing the data from VOA new websites in multiple languages and describe the resulting corpus. In Section 2, we motivate the need for this corpus and compare with similar lower-resourced language dataset creation efforts. In Section 3, we describe the content of MOT v1.0. In Section 4, we detail our process for creating the corpus. Finally, in Section 5, we discuss future directions and conclude. The corpus is available via GitHub.

2. Related Work
A multilingual collection of unlabeled text can be useful for many tasks, especially for lower-resourced languages with limited freely-available text. An unlabeled non-parallel corpus is typically the starting point for further annotation work and dataset creation work. Additionally, much of modern NLP relies on either static pre-trained word embeddings or pre-trained transformer models. In either case, these rely on large quantities of text data, which lower-resourced languages lack.

Even with the existence of multilingual transformer models, like multilingual BERT (Devlin et al., 2019) or XLM-R (Conneau et al., 2020), unlabeled data from lower-resourced languages can be useful for adaptation of these models (Adelani et al., 2021; Pfeiffer et al., 2020). It is also possible to train a multilingual transformer model without relying heavily on higher resourced languages (Ogueji et al., 2021).

There have been plenty of other works which have scraped news data for lower-resourced languages (Adelani et al., 2021; Niyongabo et al., 2020). Adelani et al. (2021) also includes partial scrapes of sections of VOA news sites. Gezmu et al. (2021) used random samples of VOA news sites to create a spelling correction corpus for Amharic. Unlike these data collection efforts, MOT intends to be a complete collection of VOA’s documents rather than just enough data to meet the goals of a specific annotation effort. Our resulting corpus also preserves metadata for each document which was discarded by other datasets.

There are a number of other existing resources that can be used as unlabeled data for lower-resourced languages. The DARPA LORELEI program (Strassel and Tracey, 2016; Tracey et al., 2019; Tracey and Strassel, 2020) produced datasets for a number of lower-resourced languages. However, these datasets require payment or an LDC subscription which can be prohibitively expensive for speakers of those languages to access. At the time of publication—over six years after the start of the program—many of the datasets planned for publication have not yet been released.

Many text collections for lower-resourced languages focus on parallel text for the purposes of machine trans-
The OPUS website hosts a number of parallel text datasets and related tools (Tiedemann, 2012). These parallel text datasets are also sometimes treated as unlabeled monolingual text. Among its many sources, OPUS contains data from the Christian Bible. While the Christian Bible has been translated into more than 1,000 languages, it covers a very narrow domain that is not representative of most modern texts, is often translated into more archaic forms of each language, and reflects the perspective of its religious content.

JW300 (Agic and Vulic, 2019) is a corpus containing data in 300 different languages. It was extracted from jw.org, the website of the Jehovah’s Witnesses (Watch Tower Bible and Tract Society of Pennsylvania). While JW300 has been a useful resource for lower-resourced NLP, at the time of writing, it is not currently available due to it being distributed without permission from the copyright holders. While we began work on MOT before JW300 became unavailable, the challenges of working with restrictively licensed source materials were one of the many factors that motivated us to create MOT.

3. Dataset Description

3.1. Source: Voice of America Online News

Copyright. VOA was founded in 1942 and produces content for digital, television and radio platforms in more than 40 languages. It is the largest U.S. international broadcaster and has a weekly audience of an estimated 300 million people (Voice of America, 2021a). Because VOA’s content is produced by employees of the United States government, it is in the public domain under U.S. federal law (17 U.S.C. § 105). VOA’s copyright statement in their terms of use also explicitly states that all content produced by VOA is in the public domain (Voice of America, 2016). All documents not in the public domain were filtered out of this corpus. The VOA copyright statement specifies that VOA has a license with the Associated Press (AP) to use AP content which is not in the public domain. Although the VOA copyright statement does not explicitly mention them, we identified content written by Agence France-Presse (AFP) and Reuters appearing on VOA news websites. We used automated methods to ensure that we did not include any articles from AP, AFP, and Reuters in our corpus.

Independent Journalism. Because VOA is funded by a government, it is worth discussing its independence as a news source and accordingly, the ethical considerations of using it in a corpus. VOA maintains independence from U.S. political influences through the 1994 U.S. International Broadcasting Act, which prohibits any U.S. government official from interference in the objective reporting of news (Voice of America, 2021b). The VOA’s journalistic code also requires accuracy, balance, fairness, and context in documents. For example, the code requires all staff who prepare content to not use negative terms to describe persons or organizations unless those individuals use those terms to describe themselves (Voice of America, 2021a). These rules and standards ensure that the VOA operates independently, and thus a corpus derived from VOA content should be similar in its biases to corpora derived from other newswire sources.

3.2. Corpus Contents

This dataset contains paragraph-segmented data collected from 51 VOA news websites in the following 44 languages: Albanian, Amharic, Armenian, Azerbaijani, Bambara, Bangla, Bosnian, Burmese, Cantonese, Dari Persian, English, Farsi, French (African), Georgian, Greek, Haitian Creole, Hausa, Indonesian, Khmer, Kinyarwanda, Korean, Kurdish, Lao, Lingala, Macedonian, Mandarin Chinese, Ndebele, Oromo, Pashto, Portuguese (African), Russian, Serbian, Shona, Somali, Spanish, Swahili, Thai, Tibetan, Tigrinya, Turkish, Ukrainian, Urdu, Uzbek, and Vietnamese. As noted, the French and Portuguese data is written primarily for African audiences.

The counts of articles for each language are given in Figure 1. While we have released the Bambara data for completeness, it contains essentially no articles, only short descriptions of other content (for example, photo captions, descriptions of audio stories, etc.). This is largely due to how new the inclusion of Bambara is to VOA. Currently the focus for the Bambara section of VOA is on radio and multimedia, and therefore has essentially no text news articles. As shown in Figure 2, the corpus is comprised of articles published starting in 2001 up until December 31, 2021. As recent years have more data than older ones, continuing to collect data will allow the corpus to steadily grow.

The corpus is organized by VOA site and further organized by content type. Some languages in VOA are further divided into separate domains. For example, English includes VOA News (global news), VOA Zimbabwe, Editorials, and an English Learning site. Pashto, Kurdish, and Khmer also have more than one domain, where the distinction is typically a differing region or dialect (for example, Sorani and Kurmanji for Kurdish). The content types found in VOA pages’ metadata consist of article, audio, video, photo, poll, quiz, index, author, schedule, subscribe, upload, account, and comment.

We focus on extracting data from content type article which is a typical news article. However, we also in-

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4 https://www.insidevoa.com/a/6241315.html

Documents with a timestamp prior to 2001 in the time_published field were removed from the corpus. This includes 4 articles dated as 1899, 1900, 1997, and 1998 whose timestamps we believe to be incorrect.

4 https://www.voanews.com/a/2020-usa-votes_bidens-cabinet-picks-include-some firsts/6198990.html
exclude audio, video, and photo pages as they contain some usable text data in the form of titles, short captions, or descriptions. The content type audio includes documents associated with audio media. The content type video includes documents associated with video media. The content type photo includes documents that mainly include a series of images. The counts of documents in each content type can be seen in Table[1]. Most languages have more content of type article, yet some languages, like Swahili, may have more of a focus on radio, and thus contain more audio files.

For some languages, we have few or no documents for certain content types like audio or video. This is typically not because there is no audio or video in that language, but because the audio and video in that language did not contain captions from which to extract text data, the captions were too short to be kept as quality text extractions, or the captions were in an unexpected format that caused our extraction to miss it. Pages of content type poll, quiz, index, author, schedule, subscribe, upload, account, and comment are not included in our final data release. These typically contained little or no data, were more complicated to extract from, or in the case of content type index, duplicated descriptions from other pages where we were able to secure more complete extractions.

All content provided in this corpus is text, so for media like photos and videos, the data is the text description or a caption; it is not extracted from the media itself. To preserve paragraph breaks from the original HTML, sentences are stored as a list of paragraphs, where each paragraph contains a list of sentences as strings. Tokens similarly are stored as a list of paragraphs containing lists of sentences which each contain a list of the tokens. Each site is provided as a separate .tgz file, and an all langs.tar file is included which combines each of the individual .tgz files into a single tarball.

All languages are identified using ISO 639-3 codes. Each file contains the following fields:

[1] https://www.voanews.com/t/60.html
[2] https://www.voanews.com/a/episode_nuclear-power-cautiously-embraced-bidens-green-goals-4711476/6117084.html
[3] https://www.voanews.com/a/2808902.html
| Language          | Code | Article | Audio | Photo | Video | All   |
|------------------|------|---------|-------|-------|-------|-------|
| Albanian         | sqi  | 86,061  | 5,000 | 229   | 15,022| 106,312|
| Amharic          | amh  | 10,867  | 9,182 | 207   | 1,224 | 21,480|
| Armenian         | hye  | 19,184  | 0     | 63    | 5,928 | 25,175|
| Azerbaijani      | aze  | 81,722  | 1,636 | 1,118 | 10,898| 95,374|
| Bambara          | bam  | 1       | 7,567 | 13    | 1,255 | 8,836 |
| Bangla           | ben  | 31,333  | 3,521 | 11    | 612   | 35,477|
| Bosnian          | bos  | 63,282  | 7     | 453   | 9,645 | 73,387|
| Burmese          | mya  | 51,088  | 9,171 | 462   | 16,852| 77,573|
| Cantonese        | yue  | 71,176  | 28,402| 443   | 17,516| 117,537|
| Dari Persian     | prs  | 44,878  | 19,343| 299   | 6,876 | 71,396|
| English          | eng  | 351,455 | 170,655|1,544 | 6,416 | 530,070|
| Farsi            | fas  | 140,724 | 0     | 1     | 0     | 140,725|
| French (African) | fra  | 41,236  | 36,299| 490   | 9,833 | 87,858|
| Georgian         | kat  | 39,494  | 5,752 | 279   | 5,240 | 50,765|
| Greek            | ell  | 30,671  | 147   | 31    | 64    | 30,913|
| Haitian Creole   | hat  | 13,795  | 8,794 | 297   | 5,928 | 28,814|
| Hausa            | hau  | 31,792  | 15,156| 1,166 | 2,461 | 50,575|
| Indonesian       | ind  | 135,024 | 80,318| 1,394 | 17,023| 233,759|
| Khmer            | khm  | 27,664  | 5,450 | 281   | 2,878 | 36,273|
| Kinyarwanda      | kin  | 17,461  | 9,391 | 271   | 451   | 27,574|
| Korean           | kor  | 124,132 | 5     | 304   | 7     | 124,448|
| Kurdish          | kur  | 87,484  | 14,221| 1,527 | 5,622 | 108,854|
| Lao              | lao  | 30,605  | 3,397 | 266   | 960   | 35,228|
| Lingala          | lin  | 1,644   | 2,522 | 15    | 1,247 | 5,428 |
| Macedonian       | mkd  | 24,705  | 2     | 84    | 4,584 | 29,375|
| Mandarin         | cmn  | 294,411 | 47,856| 1,298 | 17,192| 360,757|
| Ndebele          | nde  | 21,546  | 5,097 | 43    | 3,104 | 29,790|
| Oromo            | orm  | 8,307   | 324   | 82    | 346   | 9,059 |
| Pashto           | pus  | 73,572  | 44,105| 302   | 14,797| 132,776|
| Portuguese (African) | por | 40,790  | 5,185 | 507   | 5,861 | 52,343|
| Russian          | rus  | 102,146 | 566   | 455   | 10,788| 113,955|
| Serbian          | srp  | 67,378  | 173   | 163   | 6,120 | 73,834|
| Shona            | sna  | 16,814  | 7,017 | 10    | 2,715 | 26,556|
| Somali           | som  | 21,583  | 14,087| 194   | 77    | 35,941|
| Spanish          | spa  | 107,205 | 22    | 5     | 81    | 107,313|
| Swahili          | swh  | 6,180   | 9,746 | 452   | 5,084 | 21,462|
| Thai             | tha  | 23,038  | 7,654 | 136   | 1,090 | 31,918|
| Tibetan          | bod  | 13,592  | 21,448| 4     | 7,207 | 42,251|
| Tigrinya         | tir  | 9,830   | 2,184 | 169   | 815   | 12,998|
| Turkish          | tur  | 100,716 | 168   | 734   | 15,522| 117,140|
| Ukrainian        | ukr  | 47,083  | 14    | 635   | 16,001| 63,733|
| Urdu             | urd  | 80,341  | 7,707 | 2,481 | 12,276| 102,805|
| Uzbek            | uzb  | 23,384  | 6,676 | 2,714 | 9,371 | 42,145|
| Vietnamese       | vie  | 152,359 | 7,333 | 673   | 19,581| 179,946|
| **Total**        |      | 2,767,753| 623,300 |22,305 | 296,570| 3,709,928|

Table 1: Counts of documents by content type and ISO 639-3 codes for each language included in MOT.

*filename:* the name of the file derived from the URI.

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*File names sometimes contain abbreviated headlines, but occasionally the headline used for the file name is in a different language than the actual headline and text appearing in the document. This is likely the result of editorial errors and may reflect that the document was adapted or translated from a document in another language.*
• url: the URL from which the document was retrieved
• url_origin: the sitemap from which the URL was retrieved
• content_type: the type of content (e.g., article, audio, photo, video) of the document
• site_language: the language of the VOA site
• time_published: the timestamp for when the document was published
• time_modified: the timestamp for when the document was last modified
• time_retrieved: the timestamp for when the document was retrieved from the sitemap
• title: the title of the document
• authors: the author(s) of the document
• paragraphs: the text extracted from the document
• n_paragraphs: the number of paragraphs in the document
• n_chars: the number of characters in the document
• cld3_detected_languages: the language(s) identified by CLD3 from the full extracted text of the document (see Section 4.3)
  - language: the language outputted by CLD3
  - probability: the probability that the language identified is correct (passed directly from CLD3)
  - is_reliable: if probability is above 0.7 (passed directly from CLD3)
  - proportion: the proportion of the text identified as the language (passed directly from CLD3)
• predicted_language: the language that we predict that the document is in, based on rules that take into account the site, the CLD3 predictions, and whether the site language is supported by CLD3
• keywords: the terms relating to the text content of the document
• section: the subpage the document falls under

These additional fields are included only for subset of languages:

• sentences: the text extracted from the document segmented into sentences
• n_sentences: the number of sentences in the document
• tokens: the text extracted from the document segmented into tokens
• n_tokens: the number of tokens in the document
• parallel_english_article: the English document from which the current document was translated from into the site language (This is currently only available for Lao)

3.3. How Low Resourced?

While there is no single way of classifying lower-resourced languages due to the large number of intersecting factors that contribute to such a designation, Joshi et al. (2020) created a taxonomy of resource availability for languages based on the amount of labeled and unlabeled data. The scale goes from 0 (lowest resources) to 5 (highest resources). While this is an oversimplification of the state of resources for a language, it is still a useful taxonomy.

Of the 44 languages included in version 1.0 of MOT, only 4 are considered “winners” at level 5. 16 of the languages are classified as level 1, “scraping-bys,” which is described as having essentially no labeled data and very little existing unlabeled data. MOT also includes 3 languages classified as level 0, “left-behinds,” Hatian Creole, Ndebele, and Dari.

Another way of evaluating the low-resourced-ness of MOT is to compare with article counts in Wikipedia. Because Wikipedia is a commonly used resource for multilingual text, languages that have poor representation in Wikipedia could be considered more lower-resourced. As seen in Table 2, MOT contains more articles than Wikipedia in 14 languages, demonstrating MOT’s potential value in providing more unlabeled text data for lower resourced languages. While we are unable to evaluate this quantitatively and at scale, from our examination of Wikipedia articles of the languages appearing in Table 2, articles in MOT in these languages are typically longer than Wikipedia articles in the same languages.

While it is true that the highest-resourced languages such as English or French contained in MOT initially do not appear to be much of a contribution when plenty of resources exist for these languages, we include them for completeness and also because much of the text in the VOA documents has a regional focus that may not be present in existing datasets.

For example, portions of the English data focus on news in Zimbabwe while a portion of the Portuguese data is centered around Mozambique. This can matter for annotation projects that may wish to use monolingual data that is region specific\(^9\). While there is existing Mozambique-focused Portuguese data available from Davies and Ferreira (2006), we are not aware of any usable data for Zimbabwe-focused English. We were only able to identify one partial English corpus with a focus on Zimbabwe textbooks. However, we were not able to locate a copy as it is described as being on magnetic tapes and it is unclear whether a usable copy exists (Louw and Jordan, 1993).

\(^9\) As an example, one early adopter of our corpus wished to translate news data focused on Mozambique from Portuguese into eMakhuwa to create a parallel corpus.
Wayback CDX Server API

addition to the sitemaps, we used the Internet Archive’s modification date, and content type for each page. In an attempt to collect the canonical link, publication date, and author(s) from the HTML meta tags. We also attempt to collect the title, description, keywords, and sentences that consist of the equivalent of “login.” If the page contains no valid text, it is not included in the output. However, not all data that is extracted and paragraph breaks from the HTML are maintained in the output. While this process of extracting text data from paragraph tags or the usual div tags is automated, there are sentences that were translated into the site language, this is provided in the parallel_language_article field. However, this is currently only available in Lao. The filename is derived from the URL and includes everything following the top-level domain. If the name of the file is too long, the filename has been shortened to only the last 100 characters.

4.4. Language Identification and Filtering

Not all of the documents in VOA are consistently in one language. While code switching exists, most of the mixed language use that we observed in the corpus were sentences that were translations of other content in the document rather than instances of natural code

dated scrape. We have scraped periodically[11] since begin-ning our collection effort in summer 2021. This will allow us to continue to release future versions of the corpus with the most recently published documents. We store the raw HTML and metadata of each scraped page in a database so that future scrapes can be compared against prior scraping for purposes of de-duplication, as well as updating existing documents that may have different URLs but have the same canonical link in their metadata. The gains in numbers of previously unseen URLs in roughly a month’s time varies from a few hundred to about 2,000 for languages other than English.

The Greek section of VOA is no longer being updated, so there are never new URLs for that section. We also notice some URLs are no longer found in the sitemaps between our scraping efforts; however, the number of URLs lost is quite small. For example, only 720 URLs went missing in Persian Farsi between December 1, 2021 and January 1, 2022, which is relatively small compared to the 141,060 documents we extracted. For the same time period, 25 languages had not lost any URLs in the sitemaps. We can also report anecdotally that many of these lost URLs are either video clips with little or no caption content or are sites that were updated and have a newer URL, which we attempt to de-duplicate if a canonical link was present.

4.2. Extracting Text from HTML Documents

We now turn to the process of extracting text data from the raw HTML scraped from VOA. All relevant text content from each document is extracted and paragraph breaks from the HTML are maintained in the output. However, not all data that is extracted from paragraph tags or the usual div tags is actually part of the document content. We remove repetitive and meaningless content, such as user comments and sentences that consist of the equivalent of “login.” If the page contains no valid text, it is not included in the output.

Some pages contain sections that are easily identifiable as translations of the main content. If the document has a parallel document in English from which it was translated into the site language, this is provided in the parallel_language_article field. However, this is currently only available in Lao. The filename is derived from the URL and includes everything following the top-level domain. If the name of the file is too long, the filename has been short-ened to only the last 100 characters.

| Lang. | Wikipedia | MOT |
|-------|-----------|-----|
| bod   | 5,968     | 13,592 |
| hau   | 13,696    | 31,792 |
| khm   | 8,608     | 27,664 |
| kin   | 2,883     | 17,461 |
| kur   | 85,737    | 87,484 |
| lao   | 3,902     | 30,605 |
| nde   | 0         | 21,546 |
| orm   | 1,070     | 8,307  |
| prs   | 0         | 44,878 |
| pus   | 12,974    | 73,572 |
| sna   | 7,489     | 16,814 |
| som   | 7,366     | 21,583 |
| sqi   | 84,220    | 86,061 |
| tir   | 218       | 9,830  |

Table 2: Counts of Wikipedia and MOT articles for lower resourced languages where MOT provides a larger count.
switching. Unfortunately, these translated portions of such documents did not appear to be systematic enough to extract parallel text in most cases. In some cases, this is because the document is a translation, but the captions remain in the reported language. In other cases, the document may contain the English translation or may be a part of VOA’s language learning site that was miscategorized. We attempt to filter out heavily multilingual text along with documents that erroneously contain mostly English despite claiming to be written in another language.

CLD3. We use CLD3 for our language ID in the filtering process. Compact Language Detector version 3 (CLD3) (Salcianu et al., 2016) is a neural network model for language identification that supports over 100 languages and scripts. The model outputs the languages identified as BCP-47-style language codes, along with its corresponding probability, reliability, and proportion (see Section 3.2 for more information about these fields). CLD3 does not support the following languages from MOT: Azerbaijani, Bambara, Cantonese, Dari Persian, Kinyarwanda, Lingala, Ndebele, Oromo, Tibetan, and Tigrinya. Because these languages are unsupported, we do not use the language ID predictions for our predicted_language field and instead rely on VOA’s reported language based on which domain the site is from. We do include the main CLD3 prediction information, but end users should take note that certain languages are likely to be misrecognized. For example, Tigrinya is regularly classified as Amharic by CLD3 since it is not supported.

Filtering Process. CLD3 was used to identify the language present in the extracted text with a maximum of 5 languages. This was used to determine the predicted language of the document. We filter at the paragraph level and at the document level. At the paragraph level, we filter only for confidently English paragraphs in non-English sections of VOA. If the probability is greater than 0.7 and the proportion of the paragraph is greater than 0.25, the English paragraph is discarded. Because URLs in text tend to get identified as English by CLD3, this also helps to filter out URLs. This paragraph level filtering is useful as there are some documents that will be almost entirely in one language with just one or a few paragraphs in English. Typically, these paragraphs in English are also redundant with the main language of the document. It is also common for the English contamination to be a translation of just a few quotes in the document.

At the document level, we also run language ID on the original text before paragraph level filtering. If CLD3 is confident in one language, the predicted language is assumed to be either the original sitemap language or English as CLD3 does not predict all of the languages encountered in the corpus. If CLD3 is confident that the majority of the document is either English in a non-English section, or non-English in an English section, the document is filtered out. If CLD3 has identified multiple languages with a probability above 0.9 and a proportion above 0.05, the predicted language is listed as “mul.” All documents include a prediction of the language expected from the output of CLD3. Every document is predicted to be written in the site language unless CLD3 has identified more than one language from the text (‘mul’) or CLD3 has identified only English present in the document (‘eng’), in which case the document is not included.

4.4. Sentence Segmentation and Tokenization

Segmentation. We primarily use Ersatz (Wicks and Post, 2021) for sentence segmentation; however, off-the-shelf monolingual models provided for Ersatz do not cover all of the languages in MOT. We attempted to use the multilingual model provided by Ersatz, but it had unsatisfactory performance in some languages.

| Language | Documents | Sentences | Tokens |
|----------|-----------|-----------|--------|
| amh      | 21,480    | 82,613    | 1,753,470 |
| cmn      | 360,757   | 2,121,159 | 218,501,393 |
| ell      | 30,913    | 156,827   | 6,150,949  |
| eng      | 530,070   | 4,416,079 | 189,104,698 |
| fas      | 140,725   | 881,837   | 35,929,832 |
| fra      | 87,858    | 499,635   | 19,641,240 |
| hye      | 25,175    | 144,533   | 4,881,903  |
| ind      | 233,759   | 1,205,022 | 38,957,338 |
| khm      | 36,273    | 379,431   | 10,187,019 |
| kor      | 124,448   | 1,434,722 | 39,528,919 |
| lao      | 35,228    | 520,873   | 21,119,153 |
| mya      | 77,573    | 606,165   | 33,397,338 |
| pus      | 132,776   | 777,899   | N/A      |
| ruz      | 113,955   | 1,014,345 | 49,809,558 |
| spa      | 107,313   | 846,178   | 30,910,897 |
| srp      | 73,834    | 598,176   | 25,731,979 |
| tha      | 31,918    | 245,055   | 10,182,982 |
| tir      | 12,998    | 69,162    | 1,615,438 |
| tur      | 117,140   | 832,242   | 30,147,461 |
| ukr      | 63,733    | 358,379   | 17,041,316 |
| vie      | 179,946   | 1,120,083 | 58,846,555 |
| yue      | 117,537   | 711,537   | 57,943,075 |
| Total    | 2,655,409 | 19,021,952 | 899,410,233 |

Table 3: Counts of documents, sentences, and tokens for languages with sentence segmentation and tokenization.
boundaries in Greek, likely because Ersatz was not trained on any language using the Greek alphabet. It also did not contain any Ge’ez script punctuation as candidates for sentence splits and was therefore unusable for Amharic or Tigrinya. Thai and Lao, which do not have sentence ending punctuation, were also challenges. Because the multilingual segmentation model had sub-optimal performance for languages it was not trained on, we have chosen to only release sentence breaks and tokenization for those languages that have more reliable sentence segmentation or tokenization. We used PyThaiNLP (Phatthiyaphaibun et al., 2016) for Thai and amseg (Yimam et al., 2021) for Amharic and Tigrinya. amseg is a rule-based Amharic segmenter, but as it is based on whitespace and Ge’ez script punctuation, we used it for Tigrinya in addition to Amharic. While Wicks and Post (2021) provides a test suite for segmentation, it does not cover Thai, Amharic or Tigrinya. Parsivar (Mohaj et al., 2018) was used for Persian, khmer-nltk for Khmer, LaoNLP for Lao, and razdel for Russian. We also use Stanza (Qi et al., 2020) for Armenian, Burmese, Greek, Indonesian, Korean, Serbian, Ukrainian, and Vietnamese. As Wicks and Post (2021) point out, there tends to be a lack of reliable test sets for sentence segmentation, so we have not yet independently vetted the performance of these segmenters though many of the segmenters have been compared and evaluated by others in previous work. For languages in which we do not yet have satisfactory sentence segmentation, we do not provide sentence breaks. In Table 3 we provide counts of sentences and tokens for the languages where we are able to provide segmentation and tokenization. We hope to provide more robust sentence segmentation in future releases.

**Tokenization.** We used spaCy (Honnibal et al., 2020) for tokenization in English, Cantonese, French, Mandarin Chinese, Russian, Spanish, and Turkish. PyThaiNLP (Phatthiyaphaibun et al., 2016) is used to tokenize Thai, and amseg (Yimam et al., 2021) to tokenize Amharic and Tigrinya. khmer-nltk (Hoang, 2020) was used for Khmer tokenization. Stanza (Qi et al., 2020) is also used for tokenization in the same languages it is used for sentence segmentation. Pashto is the only language for which we were able to provide segmentation but not tokenization. Ersatz supports Pashto, but we were not able to find a tokenizer for Pashto that was proven to be reliable.

5. Limitations and Future Work

Extracting text from HTML from a site with as many domains as VOA is non-trivial and although we have done our best to ensure complete and clean extractions, it is likely that issues will be discovered as the dataset is used. There are still a number of languages where we do not have sufficient sentence segmentation and tokenization or are unable to properly evaluate the performance due to lack of labeled segmentation datasets. Similarly, we would like to improve language identification to better identify documents with multiple languages, as CLD3 does not cover all of the languages within MOT. We also plan to continue to increase the size of the corpus as more documents are published by VOA. Additionally, we plan to expand MOT by adding other permissively-licensed texts to expand our coverage of lower-resourced languages. There are also many future directions that MOT could be used in later work. MOT could be a good source of text data for ensuing labeled dataset creation work. For lower-resourced languages, even human annotation of tasks normally considered simple, such as sentence segmentation and tokenization, would be useful. Sections of MOT could also be used for annotation projects to get labeled data for specific tasks like document classification, sequence labeling tasks such as NER, and syntactic or semantic parsing. Because MOT includes metadata for time_published, it may be possible for future work to make use of MOT for work in alignment to create semi-parallel text. While we do not include audio or images as part of our release, others may want to make use of the included source URL and employ the captions on the photo content type for image captioning in lower-resourced languages.

6. Conclusion

We have presented a new corpus containing unlabeled text data in 44 languages, many of them lower-resourced languages for which this represents a substantial increase in the amount of available text data. The data in this corpus is in the public domain and is positioned to grow in size in future releases as new documents are published. We look forward to the opportunity to further refine the extraction and increase the usefulness of the corpus as speakers of the languages contained in MOT begin to make use of the corpus.

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8. Bibliographical References

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