

T5ModelsForAfricanLanguages

1 University of Waterloo
2 University of Washington
3 Masakhane
4 University College London
aooldip@uwaterloo.ca

Abstract

In this study, we highlight the importance of emphasizing the quality of pretraining data in multilingual language models. Existing web draws have demonstrated quality issues, particularly in the context of low-resource languages. Consequently, we introduce a new multilingual pretraining corpus for 16 African languages, designed by carefully auditing existing pretraining corpora to understand and rectify prevalent quality issues. To compile this dataset, we undertake a rigorous examination of current data sources for thirteen languages within of the most extensive multilingual web crawls, mC4, and extract cleaner data through meticulous auditing and improved web crawling strategies. Subsequently, we pretrain a new T5-based model on this dataset and evaluate its performance on multiple downstream tasks. Our model demonstrates better downstream effectiveness over existing pretrained models across four NLP tasks, underscoring the critical role data quality plays in pre-training language models in low-resource scenarios. Specifically, on cross-lingual QA evaluation, our new model is more than twice as effective as multilingual T5. All code, data and model are publicly available at <https://github.com/castorini/AfriTeVa-keji>.

1 Introduction

As language models have scaled up in size and multilingual capability in recent years, commensurate effort has followed to curate pretraining data (Raffel et al., 2020) to support this growth and improve the alignment of language models.

Earlier multilingual models such as mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019) were trained on monolingual data from Wikipedia and/or other large-scale web crawls which included only a few African languages. The introduction of mC4 (Xue et al., 2021), a document-level dataset spanning 101 languages helped alleviate this cover

2 Wura means Gold in Yoruba

with more refining, the quality of our data and model improves. the respective languages. We consolidate the result of our efforts (cleaning and crawling) with data from other sources, notably Wikipedia, and include four high-resource languages - Arabic, English, French & Portuguese.

To evaluate the quality of our new corpus, we pretrain a new T5-based LM on the collected dataset and benchmark its performance on multiple downstream tasks. Our model demonstrates improved effectiveness over existing pretrained LMs further highlighting the importance of carefully curated datasets for pretraining language models in low-resource scenarios. Our model was significantly better than the baseline mT5 models across four different downstream tasks. Specifically, on cross-lingual QA evaluation, our new model achieves more than double the performance of multilingual T5.

3 WURA Dataset

We present WURA, a multilingual dataset comprising 16 African languages and 4 high-resource languages popularly spoken on the African continent - Arabic, English, French, and Portuguese.

The curation of WURA was carried out in a three-part process: - (i) Auditing and cleaning mC4 (ii) Crawling indigenous websites and (iii) Combination with existing language resources.

3.1 Auditing and Cleaning mC4

3.1.1 Language Contamination

Kreutzer et al. (2022) reports mC4’s high ratio of non-linguistic content and sentences in incorrect languages, with African languages being of particular concern. The authors report significant loss (up to 50%) in recall of correct in-language sentences as they increased precision of their automatic language classification.

Our manual audit of mC4 corroborates the documented issues. We highlight three important findings: (1) The distribution of mC4 document sources has a long tail. Many individual news publications yield thousands of documents in the mC4. (2) Documents from news publications are more likely to be of higher quality i.e., both in-language and grammatical compared to documents from other web sources. (3) Some documents are from websites which translate content using online translation tools. Such documents are often a mix of in-language and noisy or non-linguistic text, and may best be filtered at sentence-level. Noting all of these issues and findings, we filter at three levels:

Corpus-level. We first rank unique websites in descending order of the number of documents they contribute to the mC4 corpus for each language. Then, we select the top 20% of websites for each language and collect documents sourced from websites in this list. This preserves high potential sources for further document level filtering.

Document-level. At document level, we filter out documents that do not contain at least 5 stopwords in them (Caswell et al., 2020) using stopwords from Stopword Lists for African Languages dataset.³

Passage-level. After document-level filtering, we chunk the dataset into passages of roughly 512 tokens. Finally, we filter out passages that contain fewer than 4 unique words or contain repetition for more than 20% of its word length; have more than 40% of its characters are numeric or contain markers of possibly offensive content such as included in the Toxicity-200 dataset (NLLB Team et al., 2022) for the relevant language.

While Kreutzer et al. (2022)’s audit of mC4 did not yield a significant amount of offensive content (0.06% of sentences they audited) and our web crawls mainly focused on verified news publications, these filters ensure that non-linguistic and offensive contents are removed at the passage level.

3.1.2 mC4 is a Great Source!

Xue et al. (2021)’s inclusion of the URL each document is sourced from makes the mC4 corpus even more useful as a data source. Commonly, multiple articles are collected from the same base website, e.g., news publications. For many news publications that provide a sitemap, we find that there are fewer articles in mC4 than is actually available on the websites. Further, mC4 only covers up to August, 2020 so updating the crawls up to the current day yields more data.

We initiate focused crawls for such websites and this leads to significant increase ($> 100\%$ for Hausa and Somali) in the amount of articles available per language. For all languages we consider except Chichewa, Sesotho, Xhosa and Zulu, we collect 1.39M articles (see Table 6) from credible sources found in mC4.

3.2 Combination with Existing Language Resources and Non-African Languages

Following previous works (Alabi et al., 2022; Adebara et al., 2022), we include certain non-African languages in our pretraining data. Specifically, we include over 240,000 articles newly crawled from 10 African news websites reporting in English, French and Portuguese. We also include a sample of 1.5M Wikipedia articles for English and French, as well as Wikipedia articles written in Egyptian Arabic. For the African languages, we include all Wikipedia articles. Finally, we deduplicate using the document URLs. In doing this, we prioritize news articles in our focused crawls over their existing counterparts in mC4.

Final Dataset Statistics Table 6 presents a statistical summary of our dataset. The combined dataset from crawling, combining with existing sources and deduplication amounts to $\sim 30\text{GB}$ of data across all languages and $\sim 19\text{GB}$ for African languages.

4 Experimental Setup

4.1 Model

Using t5x and seqio (Roberts et al., 2022), we pretrain a T5 (Shazeer, 2020; Raffel et al., 2020) model with a subword-tokenizer of vocabulary size 150,000. We pretrain for 524,288 steps on the span-corruption objective using the Adafactor optimizer. Each training batch consists of 512 examples, each with an input of 512 tokens and an output of 114 tokens. Our new model is known as AfriTeVa V2, a 428M parameter model.

4.2 Downstream Tasks

4.2.1 Cross-lingual Question Answering

We evaluated our models on the test set of AfriQA Ogundepo et al. (2023), a cross-lingual question answering dataset with questions in 10 African languages and gold passages in English or French. We evaluated in zero-shot generative cross-lingual QA settings using in-lang queries and the provided gold passages in English.

4.2.2 Machine Translation

We evaluated using MAFAND-MT (Adelani et al., 2022) - a machine translation benchmark in the news domain. MAFAND-MT contains few thousand parallel training sentences (2,500-30,000 sentences) for 16 African languages, ideal for evaluating the effective adaptation of pretrained LMs to new languages and domains.

4.2.3 Summarization

For summarization, we use XL-Sum (Hasan et al., 2021), an abstractive summarization dataset which covers 44 languages, including 9 African languages. The authors establish strong baselines on both low and high-resource languages in the dataset through multilingual finetuning of mT5.

4.2.4 Text Classification

We use the news topic classification dataset recently introduced by Adelani et al. (2023) for 16 African languages, MasakhNews. The authors establish multiple baselines on the dataset using both classical machine learning models and finetuning or prompting language models.

4.3 Baseline Models

We compare our new model, AfriTeVa V2, with the base variants of existing multilingual T5 models: mT5 (Xue et al., 2021), ByT5 (Xue et al., 2022) and FlanT5 (Chung et al., 2022), as well as African metric models: AfriTeVa (Ogundepo et al., 2022), AfriMT5 & AfriByT5 (Adelani et al., 2022).

mT5 was pretrained on the mC4 corpus which is the starter point for this work while ByT5 is the byte-level adaptation of the mT5 model. FlanT5 is T5 instruction-finetuned for improved performance. AfriTeVa, AfriMT5 and AfriByT5 models provide a closer comparison given the nature and focus of our research. While AfriTeVa is a T5 model pretrained on a small corpus ($\sim 1\text{GB}$), AfriMT5 &

AfriByT5 are adapted from mT5 and ByT5 models using continual pretraining. Apart from AfriTeVa, AfriTeVa V2 has $\sim 26\%$ less parameters than the other baseline models.

5 Result and Discussion

5.1 Downstream Performance

In this section, we compare AfriTeVa V2 to baseline models on selected tasks. For each downstream task, we evaluate under the same conditions. We performed per-language finetuning for machine translation & text classification, multilingual finetuning over 35K steps for summarization.

5.1.1 Cross-lingual Question Answering:

AfriTeVa V2 achieves very impressive results in the cross-lingual question-answering task, especially for languages in our pretraining data. We finetune on the train set of Squad 2.0 Rajpurkar et al., 2016 dataset and evaluate the models performance on the test set AfriQA. We compare performance on generative gold passage answer prediction, with in-language queries and English passages. Table 4 shows that AfriTeVa V2 achieves much better F1 scores and Exact Match accuracies ($\sim 2\times$) across 6 out of 7 languages compared to using mT5-Base as the back-bone model.

5.1.2 Machine Translation

We observe higher BLEU scores when translating from African languages into English than in the reverse direction. According to Table 2, we achieve a better score on average, topping mT5 and AfriMT5 base models by $\sim 1 - 3$ points. While both ByT5-style models show greater effectiveness over the mT5 models, AfriTeVa V2 consistently improves over both results for all languages except ibo and pcm, an English-based creole language.

5.1.3 Summarization

We perform multilingual training for 35,000 steps and sample each batch from a single language. Table 3 shows we match the performance of mT5 on orm & pcm and gain improvements over baseline Rouge scores for the other languages we consider, with yor benefiting the most.

5.1.4 Text Classification

Our results for the news classification task are presented in Table 1. We finetune AfriTeVa V2 on MasakhaNews for each language, framing it as a text-to-text task by predicting the class of each article in the decoding sequence and report results of 3 random seeds. On average, AfriTeVa V2 yields better F1 scores across all languages and has the best F1 score on 10 out of 16 languages.

5.2 Discussion

5.2.1 Results for Nigerian Pidgin

AfriTeVa V2 does not outperform baselines for text classification, machine translation and summarization on Nigerian Pidgin (pcm). We note that AfriTeVa V2 was not pretrained on Nigerian Pidgin. As Nigerian Pidgin is an English-based creole, models pretrained on large amounts of English text are expected to be performant for the language. However, AfriTeVa V2 was pretrained on far less English text than the baselines we compare to, save for AfriTeVa. Still, we obtain results for Nigerian Pidgin that are competitive with the best baselines across the evaluation tasks.

5.2.2 Impact of Data Quality on LMs

Previous works have shown the correlation between the quality of the data used in pretraining a model and the performance of the trained model (Rae et al., 2021; Kreutzer et al., 2022; Hernandez et al., 2022). AfriTeVa V2’s improvement over baselines in downstream tasks suggests that this is true. We note that AfriTeVa V2 outperforms the larger AfriMT5 & AfriByT5 (Alabi et al., 2022) which were trained on unfiltered mC4 corpus.

However, our pretraining dataset, WURA, contains $\sim 1.5\times$ more data than mC4 contains across 16 African languages. Thus, more experiments are needed to separate the effects of scale from that of data quality.

6 AfriTeVa V2 Large Model

We also pre-train a large variant of AfriTeVa V2 using the same configuration of the T5-large model except for the vocabulary size which we set to be 150,000, similar to the configuration of AfriTeVa V2 (base) as detailed in subsection 3.1. We present the effectiveness of scaling to a large model size on summarization and news topic classification tasks in Appendix C.4

7 Related Work

Absence of a large monolingual corpus has always been the major challenge of leveraging the benefits of self-supervised pretraining for building representation and language models for African languages. The most available corpus are mostly from religious corpus like Bible (Resnik et al., 1999) or JW300 (Agić and Vulić, 2019), Wikipedia and Common Crawl archive. The latter often has significant quality issues (Kreutzer et al., 2022).

Earlier works on building word representation models for African languages showed the importance of developing FastText embeddings with small high-quality data (Alabi et al., 2020) over pretrained FastText embeddings developed from noisier common crawl data. Obtaining such high-quality data is tedious since it involved curating several verified sources manually. Thus, previous works have prioritized filtering of the common crawl data to produce better quality dataset for pretraining (Conneau et al., 2020; Ortiz Suárez et al., 2019; Xue et al., 2021; Bapna et al., 2022). However, quality issues still persist in those filtered corpora. An alternative to this is basically aggregating high quality data for African languages mostly from verified sources (Ogueji et al., 2021; Leong et al., 2022; Palen-Michel et al., 2022). However, this often results in smaller sized corpus.

The current models with impressive performance on African languages simply aggregate both low-quality data and high-quality data for pretraining (Alabi et al., 2022; Adebara et al., 2022). The quality of these models implies that there must be significant portions of the data that are of good quality. To this end, we systematically and rigorously filtered these low-quality data from mC4 corpus for African languages, similar to the OSCAR dataset approach. To the best of our knowledge, no previous work has done this. OSCAR dataset only has few documents for African languages e.g., 37.2MB for Afrikaans dataset while our filtered corpus has more than 4.5 GB.

8 Conclusion

In this work, we look to address the lack of large, quality pretraining dataset for African languages. While previous works have highlighted quality issues in existing pretraining dataset such as mC4, we demonstrate how these datasets can be enhanced by auditing their document sources and incorporating rigorous data filtering methods. To highlight the effectiveness of our approach and the relevance of this new dataset, we train a new T5 model, AfriTeVa V2, on our dataset. Our experiments show significant improvements across existing NLP benchmarks for African languages underscoring the impact of qualitative pretraining data in training language models.

9 Limitations

The representativeness of our dataset poses a potential limitation. Despite our efforts to collect data from multiple African news websites, it is possible that our dataset does not fully capture the breadth and diversity of African news articles. The reliance on specific websites and the utilization of the mC4 dataset, along with existing corpora, may introduce inherent bias that our work does not address.

Furthermore, our implementation of several-level filtering techniques, including the removal of non-linguistic content in the target language, does not guarantee the complete removal of all text in different languages or other toxic contents that may be present in the existing corpus.

Lastly, we acknowledge the need for future work to include more African languages. Our dataset only covers 16 languages, limiting the generalizability of our findings across the wide range of languages spoken in Africa.

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References

References

- [1] Julien Abadji, Pedro Ortiz Suarez, Laurent Romary, and Benoit Sagot. 2022. Towards a Cleaner DocumentOriented Multilingual Crawled Corpus. ArXiv, abs/2201.06642.
- [2] Ife Adebara, AbdelRahim Elmadany, Muhammad Abdul-Mageed, and Alcides Alcoba Inciarte. 2022. SERENGETI: Massively Multilingual Language Models for Africa. ArXiv, abs/2212.10785.
- [3] David Ifeoluwa Adelani, Jesujoba Oluwadara Alabi, Angela Fan, Julia Kreutzer, Xiaoyu Shen, Machel Reid, Dana Ruiter, Dietrich Klakow, Peter Nabende, Ernie Chang, Tajudddeen Rabiu Gwadabe, Freshia Sackey, Bonaventure F. P. Dossou, Chris C. Emezue, Colin Leong, Michael Beukman, Shamsuddeen Hassan Muhammad, Guyo Dub Jarso, Oreen Yousuf, Andre Niyongabo Rubungo, Gilles Hacheme, Eric Peter Wairagala, Muhammad Umair Nasir, Benjamin Ayoade Ajibade, Tunde Oluwaseyi Ajayi, Yvonne Wambui Gitau, Jade Z. Abbott, Mohamed Ahmed, Millicent A. Ochieng, Anuoluwapo Aremu, Perez Ogayo, Jonathan Mukiibi, Fatoumata Ouoba Kabore, Godson Kalipe, Derguene Mbaye, Allahsera Auguste Tapo, Victoire Memdjokam Koagne, Edwin Munkoh-Buabeng, Valencia Wagner, Idris Abdulkummin, Ayodele Awokoya, Happy Buzaaba, Blessing K. Sibanda, Andiswa Bukula, and Sam Manthalu. 2022. A Few Thousand Translations Go a Long Way! Leveraging Pre-trained Models for African News Translation. In North American Chapter of the Association for Computational Linguistics.
- [4] David Ifeoluwa Adelani, Marek Masiak, Israel Abebe Azime, Jesujoba Oluwadara Alabi, Atnafu Lambebo Tonja, Christine Mwase, Odunayo Ogundepo, Bonaventure F. P. Dossou, Akintunde Oladipo, Doreen Nixdorf, Chris C. Emezue, Sana Sabah Al-Azzawi, Blessing K. Sibanda, Davis David, Lolwethu Ndolela, Jonathan Mukiibi, Tunde Oluwaseyi Ajayi, Tatiana Moteu Ngoli, Brian Odhiambo, Abraham Toluwase Owodunni, Nnaemeka C. Obiefuna, Shamsuddeen Hassan Muhammad, Saheed Salahudeen Abdullahi, Mesay Gemedu Yigezu, Tajudddeen Rabiu Gwadabe, Idris Abdulkummin, Mahlet Taye Bame, Oluwabusayo Olufunke Awoyomi, Iyanoluwa Shode, Tolulope Anu Adelani, Habiba Abdulganiy Kailani, Abdul-Hakeem Omotayo, Adetola Adeeko, Afolabi Abee, Anuoluwapo Aremu, Olanrewaju Samuel, Clemencia Siro, Wangari Kimotho, Onyekachi Raphael Ogbu, Chinedu E. Mbonu, Chiamaka Ijeoma Chukwuneke, Samuel Fanijo, Jessica Ojo, Oyinkansola F. Awosan, Tadesse Kebede Guge, Sakayo Toadoum Sari, Pamela Nyatsine, Freedmore Sidume, Oreen Yousuf, Mardiyyah Oduwole, Ussen Kimanuka, Kanda Patrick Tshinu, Thina Diko, Siyanda Nxakama, Abdulmejid Tuni Johar, Sinodos Gebre, Muhidin A. Mohamed, Shafie Abdi Mohamed, Fuad Mire Hassan, Mogens Ahmed Mohamed, Evrard Ngabire, and Pontus Stenetorp. 2023. MasakhA NEWS: News Topic Classification for African languages. ArXiv, abs/2304.09972.
- [5] Željko Agić and Ivan Vulić. 2019. JW300: A WideCoverage Parallel Corpus for Low-Resource Languages. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3204–3210, Florence, Italy. Association for Computational Linguistics.
- [6] Orevaoghene Ahia, Sachin Kumar, Hila Gonen, Jungo Kasai, David R. Mortensen, Noah A. Smith, and Yulia Tsvetkov. 2023. Do All Languages Cost the Same? Tokenization in the Era of Commercial Language Models. ArXiv, abs/2305.13707.
- [7] Jesujoba Alabi, Kwabena Amponsah-Kaakyire, David Adelani, and Cristina Espana-Bonet. 2020. Massive vs. Curated Embeddings for Low-Resourced Languages: The Case of Yoruba and Twi. In Proceedings of the Twelfth Language Resources and Evaluation Conference, pages 2754–2762, Marseille, France. European Language Resources Association.
- [8] Jesujoba Oluwadara Alabi, David Ifeoluwa Adelani, Marius Mosbach, and Dietrich Klakow. 2022. Adapting Pre-trained Language Models to African Languages via Multilingual Adaptive Fine-Tuning. In International Conference on Computational Linguistics.
- [9] Ankur Bapna, Isaac Caswell, Julia Kreutzer, Orhan Firat, Daan van Esch, Aditya Siddhant, Mengmeng Niu, Pallavi N. Baljekar, Xavier Garcia, Wolfgang Macherey, Theresa Breiner, Vera Axelrod, Jason Riesa, Yuan Cao, Mia Xu Chen, Klaus Macherey, Maxim Krikun, Pidong Wang, Alexander Gutkin, Apurva Shah, Yanping Huang, Z. Chen, Yonghui Wu, and Macduff Hughes. 2022. Building Machine Translation Systems for the Next Thousand Languages. ArXiv, abs/2205.03983.

- [10] Isaac Caswell, Theresa Breiner, Daan van Esch, and Ankur Bapna. 2020. Language ID in the Wild: Unexpected Challenges on the Path to a Thousand-Language Web Text Corpus. ArXiv, abs/2010.14571.
- [11] Hyung Won Chung, Le Hou, S. Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Dasha Valter, Sharan Narang, Gaurav Mishra, Adams Wei Yu, Vincent Zhao, Yanping Huang, Andrew M. Dai, Hongkun Yu, Slav Petrov, Ed Huai hsin Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. Scaling Instruction-Finetuned Language Models. ArXiv, abs/2210.11416.
- [12] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzman, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised Cross-lingual Representation Learning at Scale. In Annual Meeting of the Association for Computational Linguistics.
- [13] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzman, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised Cross-lingual Representation Learning at Scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440-8451, Online. Association for Computational Linguistics.
- [14] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In North American Chapter of the Association for Computational Linguistics.
- [15] Cheikh M. Bamba Dione, David Ifeoluwa Adelani, Peter Nabende, Jesujoba Oluwadara Alabi, Thapelo Sindane, Happy Buzaaba, Shamsuddeen Hassan Muhammad, Chris C. Emezue, Perez Ogayo, Anuoluwapo Aremu, Catherine Gitau, Derguene Mbeye, Jonathan Mukibi, Blessing K. Sibanda, Bonaventure F. P. Dossou, Andiswa Bukula, Rooweither Mabuyu, Allahsera Auguste Tapo, Edwin Munkoh-Buabeng, Victoire Memdjokam Koagne, Fatoumata Ouoba Kabore, Amelia Taylor, Godson Kalipe, Tebogo Macucwa, Vukosi Marivate, Tajuddeen Rabiu Gwadabe, Mboning Tchiaze Elvis, Ikechukwu E. Onyenwe, Gratien Gualbert Atindogbe, Tolulope Anu Adelani, Idris Ak-inade, Olanrewaju Samuel, Marie-Rosette Nahimana, Théogene Musabeyezu, Emile Niyomutabazi, Ester Chimhenga, Kudzai Gotosa, Patrick Mizha, Apetele Agbolo, Seydou T. Traore, Chinedu Uchechukwu, Aliyu Yusuf, Muhammad Abubakar Abdulla, and Dietrich Klakow. 2023. Masakha-pOS: Part-of-Speech Tagging for Typologically Diverse African Languages. In Annual Meeting of the Association for Computational Linguistics.
- [16] Guillaume Lample and Alexis Conneau. 2019. Crosslingual Language Model Pretraining. In Neural Information Processing Systems.
- [17] Tahmid Hasan, Abhik Bhattacharjee, Md. Saiful Islam, Kazi Samin, Yuan-Fang Li, Yong-Bin Kang, M. Sohel Rahman, and Rifat Shahriyar. 2021. XL-Sum: Large-Scale Multilingual Abstractive Summarization for 44 Languages. In Findings.
- [18] Danny Hernandez, Tom Brown, Tom Conerly, Nova DasSarma, Dawn Drain, Sheer El-Showk, Nelson Elhage, Zac Hatfield-Dodds, Tom Henighan, Tristan Hume, et al. 2022. Scaling Laws and Interpretability of Learning from Repeated Data. ArXiv, abs/2205.10487.
- [19] Julia Kreutzer, Isaac Caswell, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Allahsera Tapo, Nishant Subramani, Artem Sokolov, Clayton Sikasote, Monang Setyawan, Supheak-mungkol Sarin, Sokhar Samb, Benoit Sagot, Clara Rivera, Annette Rios, Isabel Papadimitriou, Salomey Osei, Pedro Ortiz Suarez, Iroro Orife, Kelechi Ogueji, Andre Niyongabo Rubungo, Toan Q. Nguyen, Mathias Muller, Andre Muller, Shamsuddeen Hassan Muhammad, Nanda Muhammad, Ayanda Mnyakeni, Jamshidbek Mirzakhelov, Tapiwanashe Matangira, Colin Leong, Nze Lawson, Sneha Kudugunta, Yacine Jernite, Mathias Jenny, Orhan Firat, Bonaventure F. P. Dossou, Sakhile Dlamini, Nisansa de Silva, Sakine Cabuk Balli, Stella Biderman, Alessia Battisti, Ahmed Baruwa, Ankur Bapna, Pallavi Baljekar, Israel Abebe Azime, Ayodele Awokoya, Duygu Ataman, Orevaoghene Ahia, Oghenefego Ahia, Sweta Agrawal, and Mofetoluwa Adeyemi. 2022. Quality at a Glance: An Audit of Web-Crawled Multilingual Datasets. Transactions of the Association for Computational Linguistics, 10:50-72.

- [20] Taku Kudo and John Richardson. 2018. SentencePiece: A Simple and Language Independent Subword Tokenizer and Detokenizer for Neural Text Processing. In Conference on Empirical Methods in Natural Language Processing.
- [21] 1. Colin Leong, Joshua Nemecek, Jacob Mansdorfer, Anna Filighera, Abraham Owodunni, and Daniel Whitenack. 2022. Bloom Library: Multimodal Datasets in 300+ Languages for a Variety of Downstream Tasks. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, pages 8608-8621, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- [22] NLLB Team, Marta R. Costa-jussa, James Cross, Onur Celebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, Anna Sun, Skyler Wang, Guillaume Wenzek, Al Youngblood, Bapi Akula, Loic Barrault, Gabriel Mejia-Gonzalez, Prangtip Hansanti, John Hoffman, Semarley Jarrett, Kaushik Ram Sadagopan, Dirk Rowe, Shannon Spruit, Chau Tran, Pierre Andrews, Necip Fazil Ayan, Shruti Bhosale, Sergey Edunov, Angela Fan, Cynthia Gao, Vedanuj Goswami, Francisco Guzman, Philipp Koehn, Alexandre Mourachko, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, and Jeff Wang. 2022. No language left behind: Scaling human-centered machine translation. ArXiv, abs/2207.04672.
- [23] Kelechi Ogueji, Yuxin Zhu, and Jimmy J. Lin. 2021. Small Data? No Problem! Exploring the Viability of Pretrained Multilingual Language Models for Low-resourced Languages. Proceedings of the 1st Workshop on Multilingual Representation Learning.
- [24] Odunayo Ogundepo, Tajuddeen R. Gwadabe, Clara E. Rivera, Jonathan H. Clark, Sebastian Ruder, David Ifeoluwa Adelani, Bonaventure F. P. Dossou, Abdou Aziz DIOP, Clayton Sikasote, Gilles Hachem, Happy Buzaaba, Ignatius Ezeani, Roeweither Mabuyu, Salomey Osei, Chris Emezue, Albert Njoroge Kahira, Shamsuddeen H. Muhammad, Akintunde Oladipo, Abraham Toluwase Owodunni, Aftauf Lambebo Tonja, Iyanoluwa Shode, Akari Asai, Tunde Oluwaseyi Ajayi, Clemencia Siro, Steven Arthur, Mofetoluwa Adeyemi, Orevaoghene Ahia, Aremu Anuoluwapo, Oyinkansola Awosan, Chiama Chukwuneke, Bernard Opoku, Awokoya Ayodele, Verrah Otiente, Christine Mwase, Boyd Sinkala, Andre Niyongabo Rubungo, Daniel A. Ajisafe, Emeka Felix Onwuegbuzia, Habib Mbow, Emile Niyomutabazi, Eunice Mukonde, Falalu Ibrahim Lawan, Ibrahim Said Ahmad, Jesujoba O. Alabi, Martin Namukombo, Mbonu Chinedu, Mofya Phiri, Neo Putini, Ndumiso Mngoma, Priscilla A. Amuok, Ruqayya Nasir Iro, and Sonia Adhiambo. 2023. AfriQA: Cross-lingual Open-Retrieval Question Answering for African Languages.
- [25] Odunayo Jude Ogundepo, Akintunde Oladipo, Mofetoluwa Adeyemi, Kelechi Ogueji, and Jimmy Lin. 2022. AfriTeVA: Extending Small Data Pretraining Approaches to Sequence-to-Sequence Models. In Proceedings of the Third Workshop on Deep Learning for Low-Resource Natural Language Processing, pages 126-135.
- [26] Pedro Javier Ortiz Suarez, Benoit Sagot, and Laurent Romary. 2019. Asynchronous Pipelines For Processing Huge Corpora on Medium to Low-Resource Infrastructures. Proceedings of the Workshop on Challenges in the Management of Large Corpora (CMLC-7) 2019. Cardiff, 22nd July 2019, pages 9 - 16, Mannheim. Leibniz-Institut fur Deutsche Sprache.
- [27] Chester Palen-Michel, June Kim, and Constantine Lignos. 2022. Multilingual Open Text Release 1: Public Domain News in 44 Languages. In Proceedings of the Thirteenth Language Resources and Evaluation Conference, pages 2080-2089, Marseille, France. European Language Resources Association.
- [28] Aleksandar Petrov, Emanuele La Malfa, Philip H. S. Torr, and Adel Bibi. 2023. Language Model Tokenizers Introduce Unfairness Between Languages. ArXiv, abs/2305.15425.
- [29] Jack W Rae, S Borgeaud, T Cai, K Millican, J Hoffmann, HF Song, J Aslanides, S Henderson, R Ring, S Young, et al. 2021. Scaling Language Models: Methods, Analysis & Insights from Training Gopher (2021). ArXiv, abs/2112.11446.
- [30] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the Limits of Transfer Learning With a Unified Text-to-Text Transformer. The Journal of Machine Learning Research, 21(1):5485-5551.

- [31] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In Conference on Empirical Methods in Natural Language Processing.
- [32] Philip Resnik, Mari Broman Olsen, and Mona T. Diab. 1999. The Bible as a Parallel Corpus: Annotating the ‘Book of 2000 Tongues’. Computers and the Humanities, 33:129-153.
- [33] Adam Roberts, Hyung Won Chung, Anselm Levskaya, Gaurav Mishra, James Bradbury, Daniel Andor, Sharan Narang, Brian Lester, Colin Gaffney, Afroz Mohiuddin, Curtis Hawthorne, Aitor Lewkowycz, Alexandru Salcianu, Marc van Zee, Jacob Austin, Sebastian Goodman, Livio Baldini Soares, Haitang Hu, Sasha Tsvyashchenko, Aakanksha Chowdhery, Jasmijn Bastings, Jannis Builan, Xavier Garcia, Jianmo Ni, Andrew Chen, Kathleen Kenealy, J. Clark, Stephan Lee, Daniel H Garrette, James Lee-Thorp, Colin Raffel, Noam M. Shazeer, Marvin Ritter, Maarten Bosma, Alexandre Passos, Jeremy B. Maitin-Shepard, Noah Fiedel, Mark Omernick, Brennan Saeta, Ryan Sepassi, Alexander Spiridonov, Joshua Newlan, and Andrea Gesmundo. 2022. Scaling Up Models and Data with t5x and seqio. ArXiv, abs/2203.17189.
- [34] Noam M. Shazeer. 2020. GLU Variants Improve Transformer. ArXiv, abs/2002.05202.
- [35] 2019. Asynchronous Pipeline for Processing Huge Corpora on Medium to Low Resource Infrastructures.
- [36] Linting Xue, Aditya Barua, Noah Constant, Rami Al-Rfou, Sharan Narang, Mihir Kale, Adam Roberts, and Colin Raffel. 2022. ByT5: Towards a TokenFree Future with Pre-trained Byte-to-Byte Models. Transactions of the Association for Computational Linguistics, 10:291-306.
- [37] Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 483-498, Online. Association for Computational Linguistics.
- [38] Judit Acs. 2019. Exploring BERT’s Vocabulary.

A Data

A.1 mC4 Audit

We aim to tease out heuristics that are guaranteed to help us quickly and reliably extract high-quality monolingual text across the African languages in mC4. First, we reduce the source URL of each document to its hostname and keep a list of unique hostnames that exist for each language. For each language, we first sample a hostname then sample 20 documents sourced from the sampled hostname. This sampling strategy not only allows to audit more documents and sources faster, it allows us trace existing quality issues to the source URLs that produced the documents. We follow non-expert auditing strategies proposed by Kreutzer et al. (2022). Additionally, we also visit the hostname URL to ascertain its purpose for speakers of the language and translate paragraphs in the document using Google Translate.

A.2 Web Crawling

We open-source Otelemyue, an extensible framework for large scale web-crawls. In our work, we crawl at a safe pace that does not degrade the website’s performance and respect the rules websites publish in their robots.txt. Where possible, we include the category under which each article was published. This information may be useful for identification of the domains in our dataset. We also release a list of the top document URLs for each language and invite native speakers to audit these sources to help us improve the quality of WURA.

B Tokenization

In multilingual settings, the design of tokenizers has great impact on the downstream utility and cost of inference of language models across languages (Petrov et al., 2023; Ahia et al., 2023). We characterize the

performance of our tokenizers using fertility (Acs., 2019), defined as the number of subwords created per word (or per dataset) by the tokenizer. We compute fertility on the languages covered by MasakhanePOS (Dione et al., 2023).

We train multiple unigram language models on our dataset using Sentencepiece (Kudo and Richardson, 2018) with vocabulary sizes ranging from 100,000 to 250,000. As shown in Table 6 above, our dataset sizes varies over orders of magnitude between languages. To alleviate unfair treatment of the lowest-resourced of the languages we consider, we follow Guillaume Lample and Alexis Conneau (2019) to learn the unigram language models on sentences sampled according to a multinomial distribution with probabilities $q_{i,i=1\dots N}$ calculated as follows:

$q_i = \frac{p_i^\alpha}{\sum_{j=1}^N p_j^\alpha}$ where $p_i = \frac{n_i}{\sum_{k=1}^N n_k}$ and $\alpha = 0.3$ N denotes the number of languages and n_i , the number of sentences in language i . We denote this as sampling configuration . We also investigate a sampling configuration in which we further up sample languages which still do not have adequate representation after sampling sentences with the calculated probabilities. Simply, after calculating probabilities using O , we upsample by a factor of 10 for ibo, kin, nya, sna, sot, tir, xho, and a factor of 5 for amh, arz, mlg, som. We make this choice of upsampling factor taking into consideration the maximum amount of data we can train with given our CPU resources. The fertility of tokenizers trained on the sentences obtained by both sampling configurations are presented in Table 5.

Across both configurations O & O , we obtain the best tradeoff between fertility distributions across the languages and vocabulary size at 150,000. Tokenizers obtained from O perform better across board, improving fertility markedly for ibo, kin, nya, sna, xho, yor and zul without affecting fertility for hau and swa negatively.

C AfriTeVa V2 Large

We also pretrain a large variant of AfriTeVa V2 and present its effectiveness on summarization (Table 7) and classification (Table 8). For summarization, we finetune both models for 10 epochs and make inference using beam search with width of 4. We gain improvements over the base model across both tasks, particularly for summarization where iob benefits the most.