MULTILINGUAL LANGUAGE MODEL ADAPTIVE FINE-TUNING: A STUDY ON AFRICAN LANGUAGES

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ABSTRACT

Multilingual pre-trained language models (PLMs) have demonstrated impressive performance on several downstream tasks on both high resourced and low-resourced languages. However, there is still a large performance drop for languages unseen during pre-training, especially African languages. One of the most effective approaches to adapt to a new language is *language adaptive fine-tuning* (LAFT) — fine-tuning a multilingual PLM on monolingual texts of a language using the pre-training objective. However, African languages with large monolingual texts are few, and adapting to each of them individually takes large disk space and limits the cross-lingual transfer abilities of the resulting models because they have been specialized for a single language. In this paper, we perform *multilingual adaptive fine-tuning* (MAFT) on 17 most-resourced African languages and three other high-resource languages widely spoken on the continent – English, French, and Arabic to encourage cross-lingual transfer learning. Additionally, to further specialize the multilingual PLM, we removed vocabulary tokens from the embedding layer that corresponds to non-African writing scripts before MAFT, thus reducing the model size by 50%. Our evaluation on two multilingual PLMs (AfriBERTa and XLM-R) and three NLP tasks (NER, news topic classification, and sentiment classification) shows that our approach is competitive to applying LAFT on individual languages while requiring significantly less disk space.

1 INTRODUCTION

Recent advances in the development of multilingual pre-trained language models (PLMs) like mBERT (Devlin et al., 2019), XLM-R (Conneau et al., 2020), and RemBERT (Chung et al., 2021) have led to significant performance gains on a wide range of cross-lingual transfer tasks. Due to the *curse of multilinguality* (Conneau et al., 2020) – a trade-off between language coverage and model capacity – and non-availability of pre-training corpora for many low-resource languages, multilingual PLMs are often trained on about 100 languages. Despite the limitations of language coverage, multilingual PLMs have been shown to transfer to several low-resource languages unseen during pre-training. Although, there is still a large performance gap compared to languages seen during pre-training.

One of the most effective approaches to adapt to a new language is *language adaptive fine-tuning* (LAFT) — fine-tuning a multilingual PLM on monolingual texts in the target language using the pre-training objective. This has been shown to lead to big gains on many cross-lingual transfer tasks (Pfeiffer et al., 2020), and low-resource languages (Muller et al., 2021; Chau & Smith, 2021), including African languages (Alabi et al., 2020; Adelani et al., 2021). Nevertheless, African languages with large monolingual texts are few and adapting a model to each of them individually takes large disk space, and limits their cross-lingual transfer abilities because they have been specialized for one language.

An orthogonal approach to improve the coverage of low-resource languages is to include them in the pre-training data. An example for this approach is AfriBERTa (Ogueji et al., 2021), which trains on 11 African languages from scratch. A downside of this approach is that it is resource intensive in terms of data and GPU compute.

Another alternative approach is parameter efficient fine-tuning like Adapters (Pfeiffer et al., 2020) and sparse fine-tuning (Ansell et al., 2021), with the drawback that their cross-lingual transfer ability

is dependent on having a source language with the same task and label configuration (e.g number of labels and label names) as the target language. This iss however not true in many settings.

In this paper, we propose *multilingual adaptive fine-tuning (MAFT)*. We perform language adaptation on the 17 most-resourced African languages and three other high-resource language widely spoken on the continent – English, French, and Arabic – *simultaneously* to provide a single model for cross-lingual transfer learning for African languages. To further specialize the multilingual PLM, we follow the approach of Abdaoui et al. (2020) to remove vocabulary tokens from the embedding layer that corresponds to non-Latin and non-Ge'ez (used by Amharic) scripts before MAFT, thus effectively reducing the model size by 50%. Our evaluation on two multilingual PLMs (AfriBERTa and XLM-R) and three NLP tasks (NER, news topic classification and sentiment classification) shows that our approach is competitive to performing LAFT on the individual languages, with the benefit of having a single model instead of a separate model for each of the target languages.

As an additional contribution, and in order to cover more diverse African languages in our evaluation, we create four novel news topic classification datasets for Lingala, Nigerian-Pidgin, Somali, and isiZulu from pre-defined news categories of VOA, BBC and Isolezwe newspapers. To further the research on AfricaNLP, we will make our code, models and data publicly available.

2 Related Works

Multilingual PLMs for African languages. The success of multilingual pre-trained language models (PLMs) such as mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) for cross-lingual transfer in many natural language understanding tasks has encouraged the continuous development of multilingual models (Luo et al., 2021; Chi et al., 2021; Ouyang et al., 2021; Chung et al., 2021; He et al., 2021). Most of these models cover 50 to 110 languages and only few African languages are represented due to lack of large monolingual corpora on the web. To address this under-representation, regional multilingual PLMs have been trained from scratch such as AfriBERTa (Ogueji et al., 2021) or adapted from existing multilingual PLM through LAFT (Alabi et al., 2020; Pfeiffer et al., 2020; Muller et al., 2021; Adelani et al., 2021). AfriBERTa is a smaller multilingual PLM (126M parameters) trained using RoBERTa architecture on 11 African languages. It produces competitive performance on NER task when compared with XLM-R, which has more than twice as many parameters. However, it lacks coverage of languages from the southern region of the African continent, specifically the southern-Bantu languages.

In our work, we extend to those languages since only a few of them have large (>100MB size) monolingual corpus. We applied MAFT that allows multilingual adaptation and preserves downstream performance on both high-resource and low-resource languages.

Adaptation of multilingual PLMs. It is not unusual for a new multilingual PLM to be initialized from an existing model. For example, Chi et al. (2021) trained InfoXLM by initializing the weights from XLM-R before training the model on a joint monolingual and translation corpus. Although they make use of a new training objective during adaptation. Similarly, Tang et al. (2020) extended the languages covered by mBART (Liu et al., 2020b) from 25 to 50 by first modifying the vocabulary and initializing the model weights of the original mBART before fine-tuning the it on a combination of monolingual texts from the original 25 languages in addition to 25 new languages. Despite the increasing the number of languages covered by their model, they did not observe a significant performance drop on downstream tasks. We take inspiration from these works for applying MAFT on African languages, but we do not modify the training objective during adaptation nor increase the vocabulary.

Compressing PLMs. One of the most effective methods of creating smaller PLMs is distillation where a small student model is trained to reproduce the behaviour of a larger teacher model. This has been applied to many English PLMs (Sanh et al., 2019; Jiao et al., 2020; Sun et al., 2020; Liu et al., 2020a) and a few multilingual PLMs (Wang et al., 2020; 2021). However, it often leads to drop in performance compared to the teacher PLM. An alternative approach that does not lead to drop in performance has been proposed by Abdaoui et al. (2020) for multilingual PLM where unused vocabulary tokens are removed from the embedding layer. This method significantly reduce embedding parameters thus reducing the overall model parameter size since the embedding layer contributes the

most to the total number of model parameters. In our paper, we combine MAFT with the method proposed by Abdaoui et al. (2020) to reduce the overall size of the resulting multilingual PLM for African languages. This is crucial because especially people from under-represented communities in Africa may not have acces to powerful GPUs in order to run these models. Also, Google Colab[1], which is widely used by individuals from under-represented communities without access to other compute resources, cannot run large models like XLM-R and RemBERT. Hence, it is important to provide models for these communities that have strong downstream task performance and are small.

Evaluation corpora in African languages. One of the challenges of developing (multilingual) PLMs for African languages is the lack of evaluation corpora. There have been many efforts by communities like Masakhane to address this issue (∀ et al., 2020; Adelani et al., 2021). We only find two major evaluation benchmark datasets that cover a wide range of African languages: one for named entity recognition (NER) (Adelani et al., 2021) and one for sentiment classification (Muhammad et al., 2022). In addition, there are also several news topic classification datasets (Hedderich et al., 2020; Niyongabo et al., 2020; Azime & Mohammed, 2021a) but they are only available for few African languages. In our work contributes novel news topic classification datasets for 4 African languages: Lingala, Nigerian-Pidgin, Somali, and isiZulu.

3 DATA

3.1 ADAPTATION CORPORA

We perform MAFT on 17 African languages (Afrikaans, Amharic, Hausa, Igbo, Malagasy, Chichewa, Oromo, Naija, Kinyarwanda, Kirundi, Shona, Somali, Sesotho, Swahili, isiXhosa, Yorùbá, and isiZulu) covering the major African language families and 3 high resource languages (Arabic, French, and English) widely spoken in Africa. We selected the African languages based on the availability of a sizeable amount of monolingual texts. We obtain the monolingual texts from three major sources: the mT5 pre-training corpus which is based on Common Crawl Corpus[2] (Xue et al., 2021), British Broadcasting Corporation (BBC) News, Voice of America News[3] (Palen-Michel et al., 2022), and some other news websites based in Africa. Table 6 provides a summary of the monolingual data, including their sizes and sources. We pre-processing the data by removing lines that consist of numbers or punctuation only and lines with less than 6 tokens.

3.2 EVALUATION TASKS

We run our experiments on two sentence level classification tasks: news topic classification and sentiment classification and one token level classification task: NER. We evaluate our models on English as well as African language datasets.

3.2.1 EXISTING DATASETS

NER. For the NER task we evaluate on the MasakhaNER dataset (Adelani et al., 2021), a manually annotated dataset covering 10 African languages (Amharic, Hausa, Igbo, Kinyarwanda, Luganda, Luo, Nigerian Pidgin, Swahili, Wolof, and Yorùbá) with texts from the news domain. For English, we use data from the CoNLL 2003 NER task (Tjong Kim Sang & De Meulder, 2003) also containing texts from the news domain. For isiXhosa, we use the data from Eiselen (2016).

News topic classification. We use existing news topic datasets for Amharic (Azime & Mohammed, 2021b), English – AG News corpus – (Zhang et al., 2015), Kinyarwanda – KINNEWS – (Niyongabo et al., 2020), Swahili – new classification dataset– (David, 2020), and both Yorùbá and Hausa (Hedderich et al., 2020). For dataset without a development set, we randomly sample 5% of their training instances and used them as a development set.

[1] https://colab.research.google.com/
[2] https://commoncrawl.org/
[3] https://www.voanews.com

Domain	Number of sentences			Number of classes
	Train	Dev	Test	
Newly created datasets				
Lingala (lin)	1,536	220	440	5
Naija (pcm)	1,165	167	333	5
Somali (som)	10,072	1,440	2879	6
isiZulu (zul)	2,961	424	847	5
Existing datasets				
Amharic (amh)	36,029	5,147	10,294	6
English (eng)	114,000	6,000	7,600	4
Hausa (hau)	2,045	290	582	5
Kinyarwanda (kin)	16,163	851	4,254	14
Swahili (swa)	21,096	1,111	7,338	6
Yorùbá (yor)	1,340	189	379	7

Table 1: Number of sentences in training, development and test splits.

Sentiment classification. We use the NaijaSenti multilingual Twitter sentiment analysis corpus (Muhammad et al., 2022). This is a large code-mixed and monolingual sentiment analysis dataset, manually annotated for 4 Nigerian languages: Hausa, Igbo, Yorùbá and Pidgin. Additionally, we evaluate on the Amharic, and English Twitter sentiment datasets by Yimam et al. (2020) and Rosenthal et al. (2017), respectively. For all the datasets above, we only make use of the positive, negative and neutral tweets.

3.2.2 Newly Created datasets

News topic classification We created novel dataset for 5 African languages. We obtained data from three different news sources: VOA, BBC[4] and isolezwe[5]. From the VOA data we created datasets for Lingala and Somali. For Pidgin and isiZulu we scraped news topics and their categories from BBC Pidgin and isolezwe websites, respectively. We obtained the topics from data released by Palen-Michel et al. (2022) and used the provided urls to get the news category from the websites. For pidgin and isiZulu, we scrapped news topic from the respective news website directly base on their category. We noticed that some news topics are not mutually exclusive to their categories, therefore, we filtered such topics with multiple labels. Also, we ensured that each category has atleast 200 news topic, this is an heuristic we decided to work with. The pre-processed datasets were divided into training, development, and test sets using stratified sampling with a ratio of 70:10:20.

4 Models and Methods

4.1 Pre-trained Masked Language Models

For our experiments, we make use of different multilingual PLMs that have been trained using only the masked language model objective on large collections of monolingual texts from several languages. Table 2 shows the number of parameters as well as the African languages covered by each of the models.

1. XLM-R (Conneau et al., 2020) has been pre-trained on 100 languages including eight African languages. We make use of the XLM-R-base model with 200M parameters because it was easier to adapt to more languages due to its smaller size than the XLM-R-large.
2. AfriBERTa (Ogueji et al., 2021) has been pre-trained only on African languages. Despite its smaller parameter size (110M), it gives competitive performance to XLM-R on African language datasets (Adelani et al., 2021; Hedderich et al., 2020).
3. XLM-R-miniLM (Wang et al., 2020) is a distilled version of XLM-R with only 117M parameters.

[4] https://www.bbc.com/pidgin
[5] https://www.isolezwe.co.za

4. RemBERT (Chung et al., 2021) scales up mBERT (Devlin et al., 2019) to a larger model size (559M) and makes use of a larger output embedding size during pre-training, resulting in better downstream performance. RemBERT has similar or better performance to XLM-R-large and we chose to evaluate on it to compare the performance of our approach to a larger multilingual model and also because it has been pre-trained on more African languages than XLM-R.

PLM	PLM size	# Lang.	African languages covered
XLM-R-base	270M	100	afr, **amh**, **hau**, mlg, orm, **som**, **swa**, **xho**
AfriBERTa-large	126M	11	**amh**, **hau**, **ibo**, **kin**, kir, orm, **pcm**, **som**, **swa**, tir, **yor**
XLM-R-miniLM	117M	100	afr, **amh**, **hau**, mlg, orm, **som**, **swa**, **xho**
RemBERT	575M	110	afr, **amh**, **hau**, **ibo**, mlg, nya, sna, **som**, **swa**, **xho**, **yor**, **zul**
Ours	117M-270M	20	afr, **amh**, **hau**, **ibo**, **kin**, kir mlg, nya, orm, **pcm**, **sna**, **som**, sot, **swa**, **xho**, **yor**, **zul**

Table 2: Language coverage and size for pre-trained language models. Languages in **bold** have evaluation datasets for either NER, news topic classification or sentiment analysis.

4.2 MULTILINGUAL ADAPTIVE FINE-TUNING (MAFT)

We introduce MAFT as approach to adapt a multi-lingual PLM to a new set of languages. Adapting (multilingual) PLMs has been shown to be effective when adapting to a new domain (Gururangan et al., 2020) or language (Pfeiffer et al., 2020; Alabi et al., 2020; Adelani et al., 2021). While previous work on multilingual adaptation has mostly focused on autoregressive sequence-to-sequence models such as mBART (Tang et al., 2020), in this work, we adapt non-autoregressive masked PLMs on monolingual corpora covering 20 languages. Crucially, during adaptation we use the same training objective that was also used during pre-training. The models resulting from MAFT were then fine-tuned on supervised NLP downstream tasks.

4.3 PRE-TRAINED LM VOCABULARY REDUCTION

Multilingual PLMs come with various parameter sizes, the larger ones having more than hundred million parameters, which makes fine-tuning and deploying such models a challenge due to resource constraints. One of the major factors that contributes to the parameter size of these models is the embedding matrix whose size is a function of the vocabulary size of the model. While a large vocabulary size is essential for a multilingual PLM trained on hundreds of languages, some of the tokens in the vocabulary can be removed when they are irrelevant to the domain or language considered in the downstream task, thus reducing the vocabulary size of the model. Inspired by Abdaoui et al. (2020) we experiment with reducing the vocabulary size of the XLM-R-base model before adapting via MAFT. To perform vocabulary reduction, we concatenate the monolingual texts from the 20 languages we which to adapt to. Then, `sentencepiece` is applied to the concatenated texts using the original XLM-R-base tokenizer. The frequency of all tokens in the resulting corpus is computed and we select the top-k most frequent tokens. We assume that the top-k most frequent tokens should be representative of the vocabulary of the whole 20 languages. We chose $k = 50.000$ and $k = 70.000$ which covers 99.0% and 99.8% of our multilingual adaptation corpus, respectively. In addition, we include the top 1.000 tokens from the original XLM-R-base tokenizer in the new vocabulary to include frequent tokens that were not present in the new top-k tokens.[6] We note that our assumption above may not hold in the case of some very distant and low-resourced languages as well as when there are domain differences between the corpora used during adaptation and fine-tuning. We leave the investigation of alternative approaches for vocabulary compression for future work.

[6]This introduced just a few new tokens which are mostly English tokens to the new vocabulary. For $k = 50.000$ and $k = 70.000$ we end up with 50.136 and 70.039 tokens, respectively.

Method	Size	amh	eng	hau	ibo	kin	lug	luo	pcm	swa	wol	xho	yor	avg
Finetune														
XLM-R-miniLM	117M	69.5	91.5	74.5	81.9	68.6	64.7	11.7	83.2	86.3	51.7	69.3	72.0	68.7
AfriBERTa	126M	73.8	89.0	90.2	87.4	73.8	78.9	70.2	85.7	88.0	61.8	67.2	81.3	78.9
XLM-R-base	270M	70.6	92.3	89.5	84.8	73.3	79.7	74.9	87.3	87.4	63.9	69.9	78.3	79.3
RemBERT	575M	68.9	**92.8**	90.0	87.1	76.2	82.7	71.8	88.9	87.9	61.9	71.7	79.7	80.0
MAFT + Finetune														
XLM-R-miniLM	117M	69.7	91.7	87.7	83.5	74.1	77.4	17.5	85.5	86.0	59.0	72.3	75.1	73.3
AfriBERTa	126M	72.5	90.1	89.7	87.6	75.2	80.1	69.6	86.5	87.6	62.3	71.8	77.0	79.2
XLM-R-base	270M	76.1	**92.8**	91.2	87.4	78.0	82.9	75.1	89.6	88.6	67.4	71.9	82.1	81.9
XLM-R-base-v50k	125M	63.8	91.3	89.8	87.3	**78.1**	83.3	**77.3**	89.2	86.0	66.0	72.0	81.5	80.5
XLM-R-base-v70k	140M	67.8	90.6	90.7	87.4	77.1	83.1	77.2	89.8	88.6	66.0	72.0	81.2	81.0
XLM-R-base+LAFT	3240M	**78.0**	91.3	**91.5**	**87.7**	77.8	**84.7**	75.3	**90.0**	**89.5**	**68.3**	**73.2**	**83.7**	**82.6**

Table 3: NER model comparison, showing F1-score on the test sets after 50 epochs averaged over 5 runs. Results are for all 4 tags in the dataset: PER, ORG, LOC, DATE/MISC. For LAFT, we multiplied the size of XLM-R-base by the number of languages as LAFT results in a single model per language.

5 RESULTS

5.1 BASELINE RESULTS

For the baseline models (top rows in Tables 3, 4, and 5), we directly fine-tune on each of the downstream tasks in the target language: NER, news topic classification[7] and sentiment analysis.

Effect of languages seen during pre-training. For NER and sentiment analysis we find RemBERT to give the best overall. We attribute this to the fact that it has been pre-trained on the largest number of African languages and has a larger model capacity compared to the other PLMs. Similarly, we find AfriBERTa and XLM-R to give better results on languages they have been pre-trained on, and in most cases AfriBERTa tends to perform better than XLM-R on languages they are both pre-trained on, for example `amh`, `hau`, and `swa`. However, when the languages are unseen by AfriBERTa (e.g. `eng`, `wol`, `lin`, `lug`, `luo`, `xho`, `zul`), it performs much worse than XLM-R and in some cases even worse than the XLM-R-miniLM. This shows that it may be better adapting to an new African language from a PLM that has seen numerous languages than one built on a subset of African languages.

LAFT is a strong baseline. Here, we applied LAFT to the XLM-R-base model (last row in Tables 3, 4, and 5). As our results show, applying LAFT on each language individually provides a significant improvement in performance across all languages and tasks we evaluated on. Sometimes, the improvement is very large, for example, ($+7.4$) F1 on Amharic NER and ($+9.5$) F1 for Zulu news-topic classification. The only exception is for English since XLM-R has already seen large amounts of English text during pre-training. Additionally, LAFT tends to hurt the performance especially when training on a smaller corpus Pfeiffer et al. (2020).[8]

5.2 MULTILINGUAL ADAPTIVE FINE-TUNING

While LAFT provides an upper bound on downstream performance for most languages, our new approach is often competitive to LAFT. On average, the difference on NER, news topic and sentiment classification is (-0.7), ($+0.1$), and (-0.3) F1, respectively. Crucially, comapred to LAFT, MAFT results in a single adapted model which can be applied to many languages while LAFT results in a new model for each language. Below, we discuss our results in more detail.

PLMs pre-trained on many languages benefit the most from MAFT. We found all the PLMs to improve after we applied MAFT. The improvement is the largest for the XLM-R-miniLM where, the

[7]RemBERT results is not available yet due to the long training time of the model. We will include them in an updated version.

[8]We performed LAFT on English using VOA news corpus with about 906.6MB

Method	Size	amh	eng	hau	kin	lin	pcm	som	swa	yor	zul	avg
Finetune												
XLM-R-miniLM	117M	70.4	94.1	77.6	64.2	41.2	67.6	74.2	86.7	68.8	56.9	70.2
AfriBERTa	126M	70.7	93.6	90.1	75.8	55.4	81.5	**79.9**	87.7	**82.6**	71.4	78.9
XLM-R-base	270M	71.1	94.1	85.9	73.3	56.8	77.3	78.8	87.1	71.1	70.0	76.6
MAFT + Finetune												
XLM-R-miniLM	117M	69.5	94.1	86.7	72.0	51.7	78.1	77.7	87.2	74.0	60.3	75.1
AfriBERTa	126M	68.8	93.7	89.5	76.5	54.9	**82.2**	**79.9**	87.7	80.8	76.4	79.0
XLM-R-base	270M	71.9	**94.6**	88.3	**76.8**	**58.6**	78.9	79.1	87.8	80.2	**79.6**	**79.6**
XLM-R-base-v50k	125M	63.8	94.4	87.7	76.5	56.1	76.8	79.3	87.7	77.2	79.7	77.9
XLM-R-base-v70k	140M	70.4	94.2	87.7	76.1	56.8	76.1	79.4	87.4	76.9	77.4	78.2
XLM-R-base+LAFT	2700M	**73.0**	94.3	**91.2**	76.0	56.9	77.4	79.4	**88.0**	79.2	79.5	79.5

Table 4: News Topic Classification, showing F1-score on the test sets after 25 epochs averaged over 5 runs. For LAFT, we multiplied the size of XLM-R-base by the number of languages as LAFT results in a single model per language.

Model	Size	amh	eng	hau	ibo	pcm	yor	Avg
Finetune								
XLM-R-miniLM	117M	51.0	62.8	75.0	78.0	72.9	73.4	68.9
AfriBERTa-large	126M	51.7	61.8	81.0	**81.2**	75.0	80.2	71.8
XLM-R-base	270M	51.4	66.2	78.4	79.9	76.3	76.9	71.5
RemBERT	575M	50.1	**67.3**	79.0	79.9	**78.4**	78.0	72.1
MAFT+Finetune								
XLM-R-miniLM	117M	51.3	63.3	77.7	78.0	73.6	74.3	69.7
AfriBERTa	126M	53.6	63.2	81.0	80.6	74.7	80.4	72.3
XLM-R-base	270M	53.0	65.6	80.7	80.5	77.5	79.4	72.8
XLM-R-base-v50	125M	51.8	65.4	81.1	80.8	77.4	78.3	72.5
XLM-R-base-v70	140M	50.7	64.5	80.8	80.7	76.8	78.6	72.0
XLM-R-base+LAFT	1620M	**55.0**	65.6	**81.5**	80.8	74.7	**80.9**	**73.1**

Table 5: Sentiment Classification, showing F1 evaluation on test sets after 20 epochs, averaged over 5 runs. We obtained the results for the baseline model results of "hau", "ibo", "pcm", and "yor" from Muhammad et al. (2022). For LAFT, we multiplied the size of XLM-R-base by the number of languages as LAFT results in a single model per language.

performance improved by ($+4.6$) F1 for NER, and ($+4.9$) F1 for news topic classification. Although, the improvement was lower for sentiment classification ($+0.8$). Applying MAFT on XLM-R-base gave the overall best result. On average, there is an improvement of ($+2.6$), ($+3.0$), and ($+1.5$) on NER, news topic and sentiment classification, respectively. The main advantage of MAFT is that it allows us to use the same model for many African languages and cross-lingual transfer tasks instead of many models specialiced to individual languages. This significantly reduces the required disk space to store the models, without sacrificing performance. Interestingly, there is no strong benefit of applying MAFT to AfriBERTa. In most cases the improvement is (< 0.4). We speculate that this is probably due AfriBERTa's tokenizer having a limited coverage. We leave a more detailed investigation of this for future work.

More efficient models using vocabulary reduction. Applying vocabulary reduction helps to reduce the model size by more than 50% before applying MAFT. We find a slight reduction in performance as we remove more vocabulary tokens. Average performance of XLM-R-base-v70k reduces by (-1.6) and (-1.4) F1 compared to XLM-R-base+LAFT, and even lower (-2.1 and 1.4 F1) for XLM-R-base-v50k. Despite, the reduction in performance compared to XLM-R-base+LAFT, they are still better than XLM-R-miniLM, which has a similar model size, with and without MAFT. We also find that their performance is better than that of the PLMs that have not undergone any adaptation. We find the largest reduction in performance on `amh` which makes use of the Ge'ez script while other languages make use of Latin. The vocabulary reduction significantly reduced the number of `amh` subwords that are covered by our `tokenizer`. XLM-R-base-v50k gave the worst result for `amh` with performance dropping by (-16.2) F1 and (-9.2) F1 on NER and news topic classification

when compared with LAFT. The performance difference is smaller in sentiment classification (-3.2 F1). If we exclude amh in the evaluation, XLM-R-base-v50k and XLM-R-base-v70k perform very similar.

In summary, we recommend XLM-R-base+MAFT for all languages on which we evaluated, including high-resource languages like English, French and Arabic. If there are GPU resource constraints, we recommend using XLM-R-base-v50k+MAFT for languages that use the Latin script (which is the dominant script among African languages) and AfriBERTa without adaptation for amh, since it has the best model size vs. performance trade-off.

6 CONCLUSION

In this work, we proposed and studied MAFT as an approach to adapt multilingual PLMs to many African languages with a single model. We evaluated our approach on 3 different NLP downstream tasks and additionally contribute novel news topic classification dataset for 4 African languages. Our results show that MAFT is competetive to LAFT while providing a single model compared to many models specialized for individual languages. We went further to show that combining vocabulary reduction and MAFT leads to a 50% reduction in the parameter size of a XLM-R while still being competitive to applying LAFT on individual languages. We hope that future work improves vocabulary reduction to provide even smaller models with strong performance on distant and low-resource languages.

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A APPENDIX

Language	Source	Size (MB)	No. of sentences
Afrikaans (afr)	mC4 (subset) (Xue et al., 2021)	752.2MB	3,697,430
Amharic (amh)	mC4 (subset), and VOA	1,300MB	2,913,801
Arabic (ara)	mC4 (subset)	1,300MB	3,939,375
English (eng)	mC4 (subset), and VOA	2,200MB	8,626,571
French (fra)	mC4 (subset), and VOA	960MB	4,731,196
Hausa (hau)	mC4 (all), and VOA	594.1MB	3,290,382
Igbo (ibo)	mC4 (all), and AfriBERTa Corpus (Ogueji et al., 2021)	287.5MB	1,534,825
Malagasy (mlg)	mC4 (all)	639.6MB	3,304,459
Chichewa (nya)	mC4 (all), Chichewa News Corpus (Siminyu et al., 2021)	373.8MB	2,203,040
Oromo (orm)	AfriBERTa Corpus, and VOA	67.3MB	490,399
Naija (pcm)	AfriBERTa Corpus, and VOA	54.8MB	166,842
Rwanda-Rundi (kin/kir)	AfriBERTa Corpus, KINNEWS & KIRNEWS (Niyongabo et al., 2020), and VOA	84MB	303,838
Shona (sna)	mC4 (all), and VOA	545.2MB	2,693,028
Somali (som)	mC4 (all), and VOA	1,000MB	3,480,960
Sesotho (sot)	mC4 (all)	234MB	1,107,565
Swahili (swa)	mC4 (all)	823.5MB	4,220,346
isiXhosa (xho)	mC4 (all), and Isolezwe Newspaper	178.4MB	832,954
Yorùbá (yor)	mC4 (all), Alaroye News, Asejere News, Awikonko News, BBC, and VON	179.3MB	897,299
isiZulu (zul)	mC4 (all), and Isolezwe Newspaper	700.7MB	3,252,035

Table 6: Monolingual Corpora (after pre-processing – we followed AfriBERTa Ogueji et al. (2021) approach) , their sources and size (MB), and number of sentences.