WHAT HAPPENS WHEN SMALL IS MADE SMALLER? EXPLORING THE IMPACT OF COMPRESSION ON SMALL DATA PRETRAINED LANGUAGE MODELS

Busayo Awobade[*], **Mardiyyah Oduwole**[*], **Steven Kolawole**[*]
ML Collective
{busayo.awobade, mardiyyah.oduwole, steven}@mlcollective.org

ABSTRACT

Compression techniques have been crucial in advancing machine learning by enabling efficient training and deployment of large-scale language models. However, these techniques have received limited attention in the context of low-resource language models, which are trained on even smaller amounts of data and under computational constraints, a scenario known as the "low-resource double-bind." This paper investigates the effectiveness of pruning, knowledge distillation, and quantization on an exclusively low-resourced, small-data language model, AfriBERTa. Through a battery of experiments, we assess the effects of compression on performance across several metrics beyond accuracy. Our study provides evidence that compression techniques significantly improve the efficiency and effectiveness of small-data language models, confirming that the prevailing beliefs regarding the effects of compression on large, heavily parameterized models hold true for less-parameterized, small-data models.

1 INTRODUCTION

One of the most challenging aspects of working with large language models (LLMs) is their computational complexity (Zhang et al., 2021). With 340M parameters, even the BERT-large model is impractical for deployment on low-end devices with inadequate computational power (Treviso et al., 2022). Several architectural changes to make the BERT model more efficient have been made (Jiao et al., 2019; Sanh et al., 2019; Lan et al., 2019). However, to achieve adequate performance on downstream tasks, LLMs require huge training corpora (billions of tokens), which are unavailable for most African languages (Nekoto et al., 2020). The omission of African languages from the pre-training phase of LLMs results in low performance in these languages, making NLP tasks participatory difficult (Kreutzer et al., 2022). Ahia et al. (2021) termed this situation the "low-resource double-bind" to describe the coexistence of data and computation limitations on resources. This is a popular NLP setting for low-resource languages, although the performance trade-offs are understudied.

One of the most promising attempts to mitigate the sparse presence of low-resource African languages in model training is the creation of AfriBERTa, the first multilingual language model trained purely and from scratch on African languages with $<$ 1GB of data. AfriBERTa (Ogueji et al., 2021) beats competitive models like mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) on text categorization and NER tasks. Instead of depending on high-resource languages for transfer learning, AfriBERTa takes advantage of linguistic similarities between languages from low-resource environments to yield promising results, which is critical in determining the sustainability of language models trained on small datasets. However, with 126M parameters, the AfriBERTa-large model is still impractical for deployment on low-end devices with inadequate computational power. Moreover, little is known about the ability of a small-data, low-resource-focused model like AfriBERTa to generalize to unseen-before languages, considering its small size, and its ability to get "smaller" for efficient usage by resource-constrained users.

[*]These authors contributed equally to this work.

This research attempts to bridge the gap between a low-resource, small-data, high-performance multilingual language model and an ultra-efficient, deployable model for double-bind users. Our experimental results demonstrate that pruning achieves $\approx 60\%$ reduction in model size with a minimal performance drop. Furthermore, generalization tests reveal varied outcomes, with some languages surpassing dense models even with extreme pruning. Distillation achieves compression rates between 22% and 33% with comparable performances. Additionally, quantization reduces the model size by 64.08%, inference time by 52.3%, and even outperforms the baseline model in the F1 score for certain languages. Our contributions address the following questions:

1. How tiny can we construct a small-data model using the knowledge distillation framework?
2. What are the efficiency and generalization limits of pruning on a small-data model?
3. What are the optimal reductions we can achieve in size and latency utilizing quantization?

Related work First introduced by Hinton et al. (2015), Sanh et al. (2019) demonstrated similar performances on downstream tasks with smaller language models pre-trained using distillation, which is faster at inference and suitable for edge devices. Jiao et al. (2019) proposed a transformer-specific distillation method, employing a two-stage learning framework with general and task-specific distillation using BERT. Han et al. (2015) reintroduced modern pruning as "network pruning." and the spotlight intensified with Frankle and Carbin (2019) suggesting the existence of subnetworks within a dense neural network that matches or surpass the dense model's performance—termed "winning tickets." Yu et al. (2019) and Renda et al. (2020) also found winning tickets early in training for Transformers and LSTMs. Chen et al. (2020) and Prasanna et al. (2020) also explored trainable subnetworks in pre-trained BERT models, locating matching subnetworks at 40% to 90% sparsity across various applications. Li et al. (2020) demonstrated that heavily compressing large models resulted in higher accuracy than lightly compressing small models. Bai et al. (2022) also introduced post-training quantization for language models, minimizing training time, memory, and data consumption, while Wang et al. (2022) achieved $16\times$ compression by quantizing transformer backbones to 4-bit and applying 50% fine-grained structural sparsity. Additionally, Xiao et al. (2022) enabled 8-bit weight, 8-bit activation quantization for large language models, addressing activation outliers, and Dettmers et al. (2022) used LLM.int8() on transformers with 16 or 32-bit weights for immediate inference using vector-wise quantization and mixed-precision decomposition. As far as we know, our work is the first to explore these techniques' efficacy in a low-resource double-bind setting.

2 APPROACH

This section details our experimental settings for the compression techniques we used to evaluate efficiency in our small-data, pre-trained model of choice. Further details on our training setup can be found in Appendix A, and all settings stay consistent for all our experiments.

Data We use the AfriBERTa corpus for distillation; it comprises 11 African languages. We use the MasakhaNER dataset (Adelani et al., 2021), a Named Entity Recognition dataset that spans 10 African languages, for task-specific compression evaluation.

Model Training This study uses the AfriBERTa models, *Base* and *Large*, which are based on the XLM-R architecture. For the different compression strategies we explore, we use either or both the large variant and base variant for our study. The final results were averaged over three training runs with different training seeds for all reported results. We notice an insignificant standard deviation and distribution between the results of the different seeds.

Tasks Evaluation The evaluation of the compressed models in this study focuses on the NER task due to its significant relevance in downstream applications such as question answering and information extraction (Tjong Kim Sang and De Meulder, 2003). We adopt the F1 score as our primary evaluation metric, and the evaluation dataset is the MasakhaNER dataset (Adelani et al., 2021).

Table 1: **Average results for the distilled models on NER task across 10 languages**. The best student variant for each teacher is highlighted, and the best variant for each strategy is underlined.

Distillation strategy	Teacher	#Layers	#Att. Heads	#Params	amh	hau	ibo	kin	lug	luo	pcm	swa	wol	yor	avg
Task-agnostic	AfriBERTa-base	4	4	83M	64.96	87.28	83.58	68.15	74.57	63.02	78.92	83.89	55.46	73.62	73.35
		4	6	83M	64.23	87.34	83.84	67.59	74.60	60.00	79.40	84.00	57.21	73.38	73.16
		6	4	97M	65.96	87.60	85.55	70.16	75.90	64.61	81.65	85.48	57.70	74.82	74.94
		6	6	97M	66.92	87.91	85.28	69.81	77.19	68.40	81.72	85.08	60.28	75.47	**75.81**
	AfriBERTa-large	4	4	83M	65.28	87.28	84.15	68.83	73.82	63.79	79.80	84.13	56.30	73.43	73.68
		4	6	83M	65.25	87.62	84.28	68.82	74.66	62.60	78.88	84.07	55.11	73.85	73.51
		6	4	97M	69.38	88.25	85.08	69.49	75.44	63.87	82.71	85.87	56.42	73.89	75.04
		6	6	97M	71.98	88.72	85.76	71.76	78.30	68.10	84.24	87.07	61.45	77.61	**<u>77.50</u>**
Task-specific	AfriBERTa-base	4	4	83M	65.04	87.12	83.13	67.62	75.01	62.90	78.19	83.96	54.04	69.22	72.62
		4	6	83M	65.52	87.27	83.93	68.18	75.56	63.78	79.03	83.70	57.46	69.98	73.44
		6	4	97M	67.28	87.27	85.72	71.68	77.18	66.58	81.85	84.92	60.20	74.78	**75.75**
		6	6	97M	69.45	88.23	85.47	69.88	74.90	65.79	82.27	85.36	59.12	76.25	75.67
	AfriBERTa-large	4	4	83M	65.66	87.60	83.42	67.38	74.28	62.37	79.62	83.78	55.72	72.89	73.27
		4	6	83M	71.20	88.27	84.66	70.70	77.11	65.58	82.09	86.06	58.00	76.21	75.99
		6	4	97M	69.38	88.25	85.08	69.49	75.44	63.87	82.71	85.87	56.42	73.89	75.04
		6	6	97M	72.58	88.33	86.05	71.16	78.56	69.87	84.03	86.32	61.49	76.66	**<u>77.51</u>**

2.1 Efficiency Evaluation

Distillation We apply both task-agnostic and task-specific distillation approaches on the base and large variants of the AfriBERTa model. We distil knowledge from the pre-trained AfriBERTa model into relatively smaller models for task-agnostic distillation and evaluate them for the NER downstream task. For the task-specific distillation, we distil knowledge from a model fine-tuned for the NER downstream task into smaller models.

Pruning Our pruning experiments at various sparsity levels range from 10% to 95%. We prune the model before, after, and during fine-tuning to examine the impact of pruning at each phase of the training process. We also examine the computational efficiency of the pruned models by measuring their inference time on the test data at all sparsity levels. Furthermore, we evaluate the generalization capabilities of the pruned models by fine-tuning and testing them on out-of-distribution (OOD) data. We compare the performance of the pruned models to the original dense model to assess any influence of pruning on cross-lingual knowledge transfer and the model's level of generalizability, using MasakhaNER 2.0 (Adelani et al., 2022) and MSRA NER (Feng et al., 2006) dataset.

Quantization We examine the effects of quantization on the large AfriBERTa model, which has been fine-tuned for Named Entity Recognition (NER) tasks. Our study utilizes two quantization approaches. The first is the **LLM.int8()** method, which uniformly converts the model's weights, activations, and attention mechanisms to an 8-bit integer (int8) format. The second approach is **dynamic quantization**, which dynamically converts the weights of linear layers from floating-point to integer data types at runtime and quantizes the activation layers during CPU-based inference.

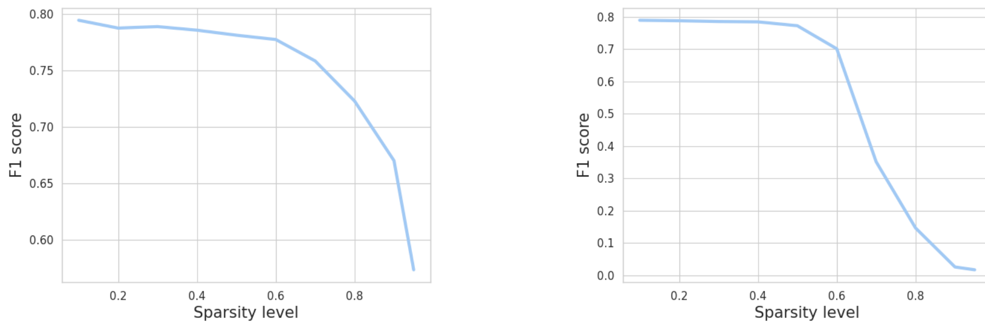
Table 2: **Comparison of NER results between the teachers and the best students.** The underlined scores are instances where the distilled model outperformed any of the teacher models.

Language	AfriBERTa-base (Teacher) <111M	AfriBERTA-large (Teacher) <126M>	Distiled AfriBERTa-base (Task agnostic) <97M>	Distiled AfriBERTa-base (Task specific) <97M>	Distiled AfriBERTa-large (Task agnostic) <97M>	Distiled AfriBERTa-large (Task Specific) <97M>
amh	71.8	**73.28**	69.45	66.92	71.98	<u>72.58</u>
hau	90.01	**90.17**	88.23	87.91	88.72	<u>88.33</u>
ibo	86.63	**87.38**	85.47	85.28	85.76	<u>86.05</u>
kin	69.91	**73.78**	69.88	69.81	<u>71.76</u>	<u>71.16</u>
lug	76.44	**78.85**	74.9	77.19	78.3	<u>78.56</u>
luo	67.31	**70.23**	65.79	68.4	68.1	<u>69.87</u>
pcm	82.92	**85.7**	82.27	81.72	<u>84.24</u>	<u>84.03</u>
swa	85.68	**87.96**	85.36	85.08	<u>87.07</u>	86.32
wol	60.1	**61.81**	59.12	60.28	<u>61.45</u>	<u>61.49</u>
yor	76.08	**81.32**	76.25	75.47	<u>77.61</u>	76.66
avg	76.688	**79.048**	75.672	75.806	77.499	<u>77.505</u>

3 Results and Discussion

3.1 How small can we make these language models?

Using our distillation methods, we achieve up to 31% compression while maintaining competitive results, with only a 7% performance drop for our least-performing model and only a 1.9% decline



(a) Pruning before fine-tuning

(b) Pruning after fine-tuning

Figure 1: Pruning **before vs after** fine-tuning: F1 score of sparsified models, averaged across languages.

compared to the best-performing AfriBERTa model at 22% compression, as shown in table 2. We notice only marginal differences between the teachers' and students' performances in some languages. We also see the student model trained by the large teacher outperform the base teacher in specific languages. Additionally, our task-agnostic models outperform the task-specific models in terms of F1 score, but with relatively minimal differences.

3.2 Which is the best teacher: Base vs Large?

Although there is a performance decline of roughly 1.9% from the AfriBERTa-large baseline, we discover that the AfriBERTa-large model produced the student with the best grade. However, the best-performing student by the base model only showed a performance decline of 1.3% between the original scores of the base model and the student scores (see Table 2). According to the results, the base model is comparatively better at imparting most of its knowledge to its students, even though the larger model creates the best overall student. Additionally, as the attention head and layer ratio reduce, the students being taught using the base model catch up to those taught by the larger model with no discernible difference in performance, as seen in Table 1. Our results suggest that the selected instructor model significantly influences the performance of student models.

3.3 How does pruning before and after fine-tuning affect model performance?

As seen in Figure 1, our results show that pruning before fine-tuning produces fairly consistent performance with the dense model up to a sparsity level of 60%. However, above this threshold, the model's performance gradually declines. Still, it remains competitive even at 80% sparsity, with an average F1 score of over 70% (detailed tables and charts in Appendix D.1). When fine-tuning is performed before pruning, however, our results demonstrate that the model's performance stays firmly on par with, and even exceeds, the performance of the dense model up to 50% sparsity. However, when the sparsity level increases, especially from the 70% sparsity, we find a dramatic deterioration in performance. It is worth mentioning that both methods have advantages and disadvantages. Pruning before fine-tuning results in more stable and predictable performance at greater sparsity levels, making it a feasible alternative for applications requiring high sparsity levels. On the other hand, pruning after fine-tuning can greatly improve the model's performance at lower sparsity levels, making it a better technique for applications that emphasize high accuracy.

3.4 Exploring the limits of pruning for small-data pre-trained Models

In our findings (see Appendix D.1), we notice that despite the limitations of AfriBERTa's training data and architecture, we find constant performance up to 50% and 60% sparsity. Notably, certain languages maintain a moderate degree of performance even at 95% sparsity, suggesting that the model might have a certain level of robustness to pruning. Nonetheless, we notice dramatic reductions in performance for several languages, such as Yoruba and Luganda, at this level. This might be

Table 3: F1 Scores by Language and Quantization Methods.

Language	Baseline	Dynamic	LLM.int8()
Amh	**73.36**	68.02	73.28
Hau	89.93	85.35	**89.95**
Ibo	**86.96**	82.21	86.88
Kin	**73.98**	61.58	73.91
Lug	79.78	68.94	**79.83**
Luo	**70.04**	42.40	69.77
Pcm	**85.23**	74.37	85.18
Swa	87.89	84.58	**87.93**
Wol	**61.73**	47.36	61.71
Yor	**80.76**	65.10	80.74

Table 4: Inference Time Comparison (ms) for the quantization Methods and the baseline model.

Language	Baseline	Dynamic	LLM.int8()
amh	26.01	**12.78**	13.27
hau	31.08	19.99	**13.31**
ibo	31.84	21.67	**15.03**
kin	27.19	20.95	**16.85**
lug	21.10	12.35	**10.62**
luo	22.40	5.53	**5.47**
pcm	41.70	17.96	**16.34**
swa	35.50	20.14	**17.37**
wol	25.38	20.95	**14.78**
yor	34.45	23.14	**18.36**

attributable to these languages' particular characteristics, such as their high inflectional complexity and the sparse nature of their datasets, which may make them more prone to pruning-induced degeneration. To confirm the robustness of our results, we also explored cross-lingual transfer on AfriBERTa leveraging pruning, as detailed in Appendix D.2. While our results show that aggressive pruning is possible for small-data pre-trained models, it is also critical to take into account the unique qualities of each language and dataset when calculating the ideal sparsity level for pruning.

3.5 How does Pruning affect Out-of-Domain Generalization?

Our findings (Figure 7) reveal that pruning can positively impact OOD generalization for some languages, while for others, the benefits are limited. Surprisingly, for many languages, including Swahili, the performance of the pruned models remains consistent with or surpasses that of the original dense model up to a sparsity level of 60%, with $\approx 90\%$ for Swahili. However, for languages such as Yoruba, which exhibit a higher level of linguistic complexity, the performance is lower even for the dense model, with an F1 score of around 60%, highlighting the challenge of compressing models with complex linguistic structures.

3.6 Effectiveness of Quantization on Model Efficiency

Our results, as shown in Table 3, show that the LLM.int8() quantization method generally outperformed the dynamic quantization method across all languages, with an average decrease in the F1-score of just 4.7%. Moreover, our findings suggest that for some languages, such as Swahili, Luganda, and Hausa, LLM.int8() may be preferable to the original dense model.

Model size reduced varyingly across languages, with dynamic quantization resulting in a 42.44% reduction and LLM.int8() resulting in a 64.08% reduction. There is no one-size-fits-all solution when it comes to quantization. The performance of quantized models depends on various factors, such as the language, the type of data being processed, and the adapted quantization technique.

Table 4 shows that quantization can significantly reduce inference time for all languages. For example, in the case of Amharic, quantization lead to a 50% reduction in inference time compared to the baseline model. Similarly, for Hausa and Swahili, quantization resulted in a 35% and 40% reduction in inference time, respectively. An average reduction of 40.9% for dynamic quantization and 52.3% for LLM.int8() was observed. These findings suggest that quantization effectively optimises small data-pre-trained models for deployment on devices with limited resources.

4 Conclusion and Future Work

This study investigates the effectiveness of pruning, knowledge distillation, and quantization on a small-data language model, AfriBERTa, trained on low-resource languages. Our findings indicate that compression techniques can significantly improve the efficiency and effectiveness of small-data language models. Also, we identify the importance of balancing the attention head and hidden layers when using knowledge distillation to compress small-data language models. Additionally, further experiments with different variations of quantization strategies yield results comparable to the original models. Our study balances compressed small-data language models' efficiency-accuracy tradeoff and generalization capabilities.

However, our work's novelty lies in applying existing compression techniques to a low-resource setting. We do not introduce new techniques or approaches but adapt and evaluate existing methods. Moreover, while NER is a crucial NLP task, a focus for future work is to explore the applicability of our findings to other NLP tasks.

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A Training Setup

A.1 Data

The AfriBERTa corpus is a multilingual dataset comprising 11 African languages. The data was primarily sourced from the BBC news[1] and the Common Crawl Corpus (Conneau et al., 2020). Although relatively small at 0.91 GB, it was specifically engineered to present a first-of-its-kind attempt to train a multilingual language model exclusively on low-resource languages. Table 5 shows language-specific information and token details.

The MasakhaNER dataset (Adelani et al., 2021) is used for task-specific compression and evaluation. It is a Named Entity ecognition dataset comprising PER, ORG, LOC, and DATE entities annotated for the 10 African languages. It was used to evaluate the original AfriBERTa model. The languages contained in the dataset are Amharic, Hausa, Igbo, Kinyarwanda, Luganda, Luo, Nigerian Pidgin, Swahili, Wolof, and Yorùbá. Table 7 summarizes the dataset's details, including the languages included in the dataset.

[1]https://www.bbc.co.uk/ws/languages (scraped up to January 17, 2021)

Table 5: AfriBERTa corpus (Ogueji et al., 2021): Size of each language in the dataset covering numbers of sentences, tokens, and uncompressed disk size.

Language	# Sent.	# Tok.	Size (GB)
Afaan Oromoo	410,840	6,870,959	0.051
Amharic	525,024	1,303,086	0.213
Gahuza	131,952	3,669,538	0.026
Hausa	1,282,996	27,889,299	0.150
Igbo	337,081	6,853,500	0.042
Nigerian Pidgin	161,842	8,709,498	0.048
Somali	995,043	27,332,348	0.170
Swahili	1,442,911	30,053,834	0.185
Tigrinya	12,075	280,397	0.027
Yorùbá	149,147	4,385,797	0.027
Total	**5,448,911**	**108,800,600**	**0.939**

Table 6: Model architecture details for AfriBERTa-base and AfriBERTa-large.

Model	#Params	#Layers	#Att. Heads
AfriBERTa-base	111M	8	6
AfriBERTa-large	126M	10	6

A.2 Data Preprocessing

Similar to the original preprocessing step for the AfriBERTa model (Ogueji et al., 2021), we use the AfriBERTa tokenizer. We also remove lines that are empty or contain only punctuations to ensure that the dataset is clean and contains meaningful text. We also enforce a minimum length restriction by retaining sentences with more than 11 tokens. This step helps to filter out concise sentences that may not provide enough context for the model to learn effectively. Furthermore, we take preprocessing steps significant to the performance of the AfriBERTa model and DistilBERT (Sanh et al., 2019). We use the entire pre-training corpus since it's already a small amount of data of 1GB in size.

A.3 NER

Adapted from the AfriBERTa experiment setup

learning rate: 5e-5

max sequence length: 164

batch size: 16

num‘ epochs:50

Tokenizer: ‘afriberta original tokenizer‘ (Ogueji et al., 2021)

optimizer: Adam (Kingma and Ba, 2014)

training seeds: [1, 3, 5]

B Distillation

We experiment using task-agnostic and task-specific distillation approaches on both the base and significant variants of the AfriBERTa model.

Task-Agnostic Distillation Task-agnostic distillation involves distilling a large pre-trained language model into a smaller model that is not optimized for any specific downstream task. Knowledge from the teacher model was used to pretrain the student model which is then further fine-tuned on a downstream task, in our case here, the NER downstream task.

Task-Specific Distillation The already fine-tuned teacher model was used to teach the already distilled student model on a downstream task. Task-specific distillation involves fine-tuning the

Table 7: Statistics of MasakhaNER datasets Adelani et al. (2021) including their source, number of sentences in each split, number of annotators, and number of entities of each label type, combined with information on language, family, number of speakers (Eberhard et al., 2019), and African regions. Adapted from (Adelani et al., 2021)

Language	Family	Speakers	Region	Data Source	Train/Dev/Test	# Anno	PER	ORG	LOC	DATE
Amharic	Afro-Asiatic-Ethio-Semitic	33M	East	DW & BBC	1750/250/500	4	730	403	1,420	580
Hausa	Afro-Asiatic-Chadic	63M	West	VOA Hausa	1903/272/545	3	1,490	766	2,779	922
Igbo	Niger-Congo-Volta-Niger	27M	West	BBC Igbo	2233/319/638	6	1,603	1,292	1,677	690
Kinyarwanda	Niger-Congo-Bantu	12M	East	IGIHE news	2110/301/604	2	1,366	1,038	2,096	792
Luganda	Niger-Congo-Bantu	7M	East	BUKEDDE news	2003/200/401	3	1,868	838	943	574
Luo	Nilo Saharan	4M	East	Ramogi FM news	644/92/185	2	557	286	666	343
Nigerian-Pidgin English	Creole	75M	West	BBC Pidgin	2100/300/600	5	2,602	1,042	1,317	1,242
Swahili	Niger-Congo-Bantu	98M	Central & East	VOA Swahili	2104/300/602	6	1,702	960	2,842	940
Wolof	Niger-Congo-Senegambia	5M	West & NW	Lu Defu Waxu & Saabal	1871/267/536	2	731	245	836	206
Yorùbá	Niger-Congo-Volta-Niger	42M	West	GV & VON news	2124/303/608	5	1,039	835	1,627	853

pre-trained model on the target task and distilling knowledge from the fine-tuned model into the already distilled pretrained student model.

B.0.1 Task agnostic

Adapted from HuggingFace distillation

temperature: [2, 3, 6]

B.0.2 Task specific

Adapted from TextBrewer.

temperature: 8

C Additional Results References for Distillation

See table 1 and figures 3 & 4 for references.

D Pruning

Unstructured magnitude pruning involves setting a binary mask, M, that determines which weights in the network are pruned based on their magnitude relative to a pruning threshold, t. Specifically, we define the mask M as:

$$M_{ij} = \begin{cases} 1 & \text{if } |W_{ij}| \geq t \\ 0 & \text{otherwise} \end{cases}$$

where $W_{i,j}$ is the weight at position (i, j) in the weight matrix, and t is a threshold determined by the desired sparsity level.

D.1 Average performances before and after fine-tuning

This section details the performance scores of all language tasks on all sparsity levels, before and after fine-tuning. See Tables 8 & 9 and Figures 5 & 6 for references.

D.2 The Impact of Pruning on Cross-Lingual Transfer

This section analyses the impact of pruning on the cross-lingual transfer learning capabilities of the AfriBERTa model.

Few-shot learning To evaluate the effectiveness of the AfriBERTa model in capturing linguistic intricacies in "unknown" languages, we fine-tuned it on two low-resource African languages - Fon and Bambara - from MasakhaNER 2.0. Results show that the performances when pruning after fine-tuning were comparable to the performances of the known languages. However, we observed

Table 8: **Pruning before Finetuning:** Performance metrics of each language at all sparsity levels

prune_rate	lang	loss	precision	recall	f1	inference_time	pruned_params
0.10	**amh**	0.38	0.71	0.76	0.74	1.36	7078579
	hau	0.15	0.88	0.93	0.90	1.83	7078579
	ibo	0.20	0.86	0.88	0.87	1.85	7078579
	kin	0.35	0.72	0.78	0.75	1.73	7078579
	lug	0.29	0.78	0.82	0.80	1.24	7078579
	luo	0.44	0.70	0.73	0.71	0.57	7078579
	pcm	0.15	0.84	0.87	0.86	1.76	7078579
	swa	0.20	0.86	0.90	0.88	1.76	7078579
	wol	0.37	0.66	0.60	0.63	1.52	7078579
	yor	0.24	0.78	0.83	0.81	2.01	7078579
0.20	**amh**	0.37	0.71	0.76	0.73	1.25	14157158
	hau	0.16	0.87	0.93	0.90	1.56	14157158
	ibo	0.20	0.85	0.89	0.87	1.80	14157158
	kin	0.34	0.70	0.78	0.74	1.73	14157158
	lug	0.29	0.78	0.82	0.80	1.12	14157158
	luo	0.46	0.67	0.72	0.69	0.58	14157158
	pcm	0.16	0.83	0.87	0.85	1.62	14157158
	swa	0.21	0.86	0.90	0.88	1.61	14157158
	wol	0.37	0.63	0.60	0.61	1.41	14157158
	yor	0.26	0.78	0.83	0.81	1.79	14157158
0.30	**amh**	0.37	0.69	0.76	0.72	1.24	21235738
	hau	0.16	0.88	0.93	0.90	1.57	21235738
	ibo	0.19	0.86	0.89	0.87	1.68	21235738
	kin	0.35	0.70	0.78	0.74	1.62	21235738
	lug	0.29	0.77	0.82	0.79	1.14	21235738
	luo	0.46	0.69	0.72	0.70	0.60	21235738
	pcm	0.15	0.83	0.86	0.85	1.62	21235738
	swa	0.21	0.86	0.90	0.88	1.80	21235738
	wol	0.36	0.64	0.60	0.62	1.38	21235738
	yor	0.25	0.79	0.83	0.81	1.80	21235738
0.40	**amh**	0.38	0.70	0.76	0.73	1.27	28314317
	hau	0.16	0.86	0.93	0.90	1.69	28314317
	ibo	0.19	0.86	0.89	0.87	1.66	28314317
	kin	0.35	0.70	0.78	0.73	1.63	28314317
	lug	0.28	0.77	0.82	0.79	1.12	28314317
	luo	0.44	0.68	0.71	0.70	0.53	28314317
	pcm	0.15	0.84	0.87	0.85	1.73	28314317
	swa	0.21	0.85	0.89	0.87	1.61	28314317
	wol	0.37	0.65	0.59	0.62	1.38	28314317
	yor	0.26	0.78	0.82	0.80	1.80	28314317
0.50	**amh**	0.37	0.69	0.76	0.72	1.36	35392896
	hau	0.17	0.87	0.93	0.90	1.56	35392896
	ibo	0.21	0.85	0.88	0.87	1.67	35392896
	kin	0.34	0.70	0.78	0.74	1.65	35392896
	lug	0.29	0.76	0.81	0.78	1.30	35392896
	luo	0.44	0.68	0.71	0.70	0.52	35392896
	pcm	0.16	0.82	0.86	0.84	1.74	35392896
	swa	0.22	0.84	0.89	0.86	1.63	35392896
	wol	0.37	0.64	0.59	0.61	1.38	35392896
	yor	0.26	0.78	0.82	0.80	1.79	35392896

prune_rate	lang	loss	precision	recall	f1	inference_time	pruned_params
0.60	**amh**	0.39	0.68	0.75	0.71	1.25	42471475
	hau	0.18	0.86	0.92	0.89	1.57	42471475
	ibo	0.19	0.85	0.88	0.87	1.63	42471475
	kin	0.36	0.69	0.78	0.73	1.60	42471475
	lug	0.29	0.76	0.81	0.78	1.20	42471475
	luo	0.43	0.68	0.70	0.69	0.58	42471475
	pcm	0.16	0.82	0.85	0.84	1.75	42471475
	swa	0.21	0.84	0.89	0.86	1.67	42471475
	wol	0.37	0.62	0.59	0.61	1.41	42471475
	yor	0.28	0.78	0.81	0.80	1.78	42471475
0.70	**amh**	0.40	0.66	0.73	0.69	1.30	49550054
	hau	0.19	0.85	0.92	0.88	1.55	49550054
	ibo	0.20	0.83	0.87	0.85	1.69	49550054
	kin	0.37	0.68	0.76	0.71	1.59	49550054
	lug	0.29	0.73	0.80	0.76	1.14	49550054
	luo	0.44	0.65	0.69	0.67	0.52	49550054
	pcm	0.17	0.80	0.85	0.83	1.76	49550054
	swa	0.21	0.83	0.88	0.86	1.77	49550054
	wol	0.38	0.57	0.56	0.56	1.43	49550054
	yor	0.29	0.76	0.79	0.77	1.85	49550054
0.80	**amh**	0.43	0.62	0.70	0.66	1.25	56628634
	hau	0.20	0.83	0.90	0.87	1.55	56628634
	ibo	0.21	0.81	0.84	0.83	1.67	56628634
	kin	0.41	0.62	0.71	0.66	1.63	56628634
	lug	0.32	0.69	0.76	0.72	1.14	56628634
	luo	0.47	0.58	0.63	0.60	0.59	56628634
	pcm	0.19	0.76	0.82	0.79	1.60	56628634
	swa	0.22	0.80	0.87	0.83	1.66	56628634
	wol	0.39	0.53	0.53	0.53	1.38	56628634
	yor	0.32	0.72	0.76	0.74	1.78	56628634
0.90	**amh**	0.50	0.55	0.64	0.59	1.24	63707213
	hau	0.22	0.80	0.88	0.84	1.61	63707213
	ibo	0.24	0.79	0.83	0.81	1.71	63707213
	kin	0.45	0.57	0.68	0.62	1.61	63707213
	lug	0.36	0.63	0.72	0.67	1.20	63707213
	luo	0.53	0.50	0.58	0.53	0.52	63707213
	pcm	0.24	0.69	0.77	0.73	1.76	63707213
	swa	0.24	0.77	0.85	0.81	1.70	63707213
	wol	0.44	0.43	0.46	0.45	1.50	63707213
	yor	0.39	0.62	0.70	0.66	1.96	63707213
0.95	**amh**	0.51	0.50	0.61	0.55	1.24	67246502
	hau	0.23	0.77	0.86	0.81	1.56	67246502
	ibo	0.25	0.75	0.81	0.78	1.66	67246502
	kin	0.44	0.53	0.65	0.59	1.62	67246502
	lug	0.37	0.58	0.69	0.63	1.15	67246502
	luo	0.54	0.42	0.52	0.47	0.53	67246502
	pcm	0.27	0.64	0.74	0.69	1.66	67246502
	swa	0.90	0.50	0.59	0.53	1.65	67246502
	wol	1.05	0.28	0.32	0.29	1.42	67246502
	yor	1.02	0.37	0.46	0.40	1.82	67246502

Table 9: **Pruning after Finetuning:** Performance metrics of each language at all sparsity levels

prune_rate	**lang**	**loss**	**precision**	**recall**	**f1**	**inference_time**	**pruned_params**
0.10	**amh**	0.37	0.72	0.76	0.74	1.88	7078579
	hau	0.17	0.87	0.93	0.90	1.93	7078579
	ibo	0.19	0.85	0.88	0.87	2.96	7078579
	kin	0.34	0.70	0.79	0.74	4.01	7078579
	lug	0.28	0.78	0.82	0.80	1.18	7078579
	luo	0.45	0.69	0.71	0.70	0.69	7078579
	pcm	0.15	0.84	0.87	0.85	1.76	7078579
	swa	0.20	0.86	0.90	0.88	1.76	7078579
	wol	0.36	0.63	0.60	0.61	1.64	7078579
	yor	0.25	0.78	0.83	0.80	2.35	7078579
0.20	**amh**	0.35	0.71	0.76	0.74	1.21	14157158
	hau	0.16	0.87	0.93	0.90	1.65	14157158
	ibo	0.19	0.85	0.88	0.87	1.75	14157158
	kin	0.32	0.70	0.79	0.74	1.71	14157158
	lug	0.27	0.77	0.82	0.80	1.18	14157158
	luo	0.43	0.68	0.71	0.69	0.55	14157158
	pcm	0.14	0.83	0.86	0.85	1.73	14157158
	swa	0.19	0.86	0.90	0.88	1.60	14157158
	wol	0.34	0.63	0.60	0.61	1.45	14157158
	yor	0.24	0.78	0.83	0.80	1.94	14157158
0.30	**amh**	0.32	0.72	0.76	0.73	1.21	21235738
	hau	0.14	0.87	0.93	0.90	1.66	21235738
	ibo	0.17	0.85	0.88	0.87	1.90	21235738
	kin	0.30	0.70	0.79	0.74	1.58	21235738
	lug	0.25	0.77	0.82	0.79	1.15	21235738
	luo	0.40	0.68	0.70	0.69	0.56	21235738
	pcm	0.13	0.82	0.86	0.84	1.58	21235738
	swa	0.18	0.85	0.90	0.88	1.73	21235738
	wol	0.32	0.63	0.59	0.61	1.51	21235738
	yor	0.22	0.78	0.83	0.81	2.04	21235738
0.40	**amh**	0.29	0.72	0.75	0.74	1.21	28314317
	hau	0.12	0.87	0.93	0.90	1.80	28314317
	ibo	0.15	0.85	0.88	0.87	1.62	28314317
	kin	0.26	0.69	0.78	0.74	1.57	28314317
	lug	0.22	0.77	0.81	0.79	1.18	28314317
	luo	0.36	0.69	0.69	0.69	0.51	28314317
	pcm	0.12	0.82	0.85	0.84	1.77	28314317
	swa	0.15	0.86	0.89	0.87	1.60	28314317
	wol	0.29	0.64	0.58	0.61	1.50	28314317
	yor	0.19	0.78	0.82	0.80	2.12	28314317
0.50	**amh**	0.23	0.71	0.74	0.72	1.32	35392896
	hau	0.10	0.86	0.93	0.89	1.51	35392896
	ibo	0.12	0.85	0.88	0.86	1.73	35392896
	kin	0.21	0.68	0.77	0.72	1.58	35392896
	lug	0.18	0.77	0.78	0.78	1.06	35392896
	luo	0.31	0.67	0.67	0.67	0.55	35392896
	pcm	0.11	0.81	0.83	0.82	1.68	35392896
	swa	0.12	0.85	0.89	0.87	1.66	35392896
	wol	0.25	0.64	0.55	0.59	1.49	35392896
	yor	0.17	0.79	0.80	0.79	1.95	35392896

prune_rate	lang	loss	precision	recall	f1	inference_time	pruned_params
0.60	**amh**	0.19	0.71	0.66	0.68	1.32	42471475
	hau	0.09	0.83	0.88	0.86	1.70	42471475
	ibo	0.10	0.84	0.84	0.84	1.75	42471475
	kin	0.19	0.67	0.65	0.66	1.72	42471475
	lug	0.21	0.72	0.60	0.66	1.08	42471475
	luo	0.36	0.52	0.47	0.49	0.50	42471475
	pcm	0.11	0.77	0.76	0.76	1.60	42471475
	swa	0.10	0.84	0.85	0.84	1.63	42471475
	wol	0.23	0.64	0.42	0.50	1.49	42471475
	yor	0.18	0.76	0.66	0.71	1.94	42471475
0.70	**amh**	0.38	0.45	0.23	0.30	1.35	49550054
	hau	0.30	0.66	0.58	0.62	1.71	49550054
	ibo	0.31	0.66	0.50	0.57	1.73	49550054
	kin	0.38	0.63	0.22	0.32	1.60	49550054
	lug	0.47	0.48	0.11	0.18	1.13	49550054
	luo	0.63	0.23	0.09	0.12	0.58	49550054
	pcm	0.31	0.49	0.27	0.35	1.60	49550054
	swa	0.32	0.64	0.50	0.56	1.77	49550054
	wol	0.30	0.59	0.13	0.21	1.53	49550054
	yor	0.42	0.57	0.20	0.29	1.89	49550054
0.80	**amh**	1.25	0.23	0.04	0.06	1.27	56628634
	hau	1.39	0.48	0.33	0.35	1.54	56628634
	ibo	1.29	0.64	0.18	0.28	1.78	56628634
	kin	1.31	0.59	0.13	0.21	1.71	56628634
	lug	1.25	0.35	0.02	0.04	1.20	56628634
	luo	1.57	0.15	0.05	0.05	0.57	56628634
	pcm	1.22	0.37	0.05	0.09	1.75	56628634
	swa	1.35	0.54	0.25	0.31	1.72	56628634
	wol	1.13	0.05	0.01	0.01	1.40	56628634
	yor	1.09	0.59	0.04	0.06	1.77	56628634
0.90	**amh**	2.02	0.01	0.02	0.06	1.24	63707213
	hau	2.02	0.03	0.05	0.18	1.75	63707213
	ibo	2.01	0.03	0.04	0.12	1.81	63707213
	kin	2.04	0.02	0.02	0.08	1.76	63707213
	lug	2.05	0.01	0.02	0.08	1.23	63707213
	luo	2.07	0.01	0.01	0.04	0.52	63707213
	pcm	2.04	0.02	0.03	0.11	1.65	63707213
	swa	2.02	0.03	0.04	0.14	1.82	63707213
	wol	2.01	0.01	0.02	0.07	1.43	63707213
	yor	1.96	0.02	0.02	0.06	1.99	63707213
0.95	**amh**	2.19	0.01	0.09	0.02	1.37	67246502
	hau	2.19	0.01	0.12	0.02	1.62	67246502
	ibo	2.19	0.01	0.13	0.03	2.02	67246502
	kin	2.19	0.01	0.15	0.02	1.80	67246502
	lug	2.20	0.01	0.13	0.02	1.13	67246502
	luo	2.21	0.01	0.10	0.01	0.60	67246502
	pcm	2.20	0.01	0.10	0.01	1.69	67246502
	swa	2.18	0.01	0.13	0.02	1.88	67246502
	wol	2.19	0.00	0.08	0.01	1.61	67246502
	yor	2.19	0.01	0.10	0.01	1.90	67246502

Figure 2: A chart of the F1 scores for the best-performing student models and the teacher models across each language in the NER task.

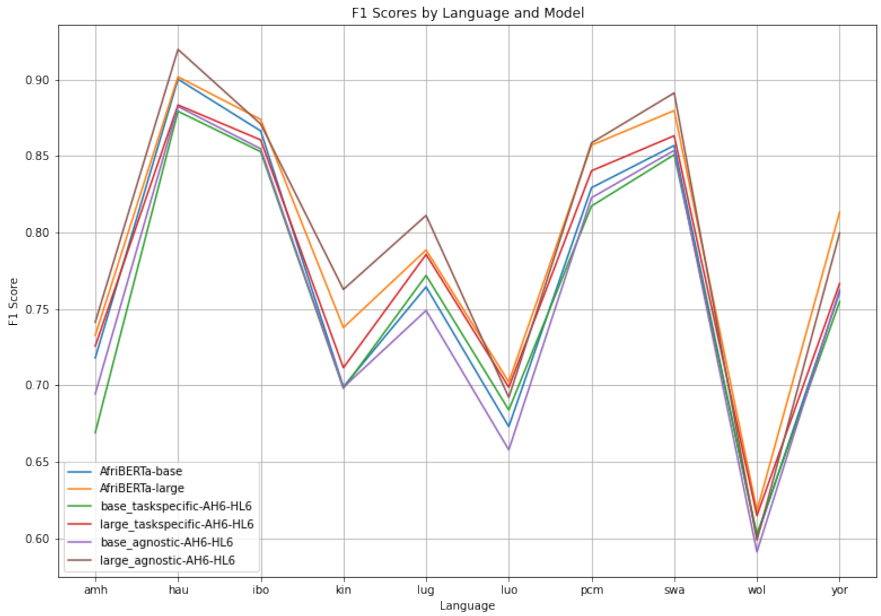
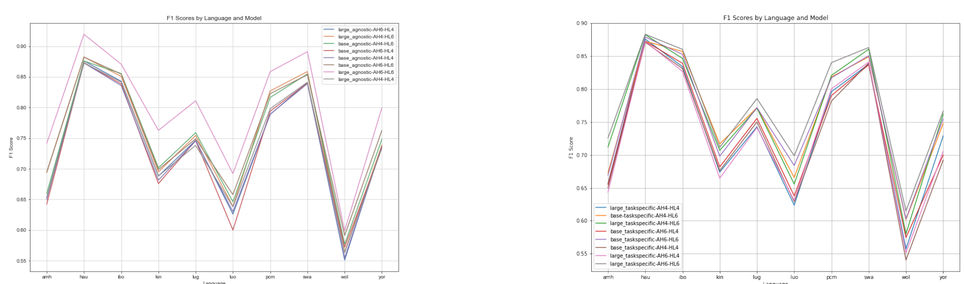


Figure 3: Performance (F1 score) during task agnostic and task-specific distillation across different languages in the NER task.

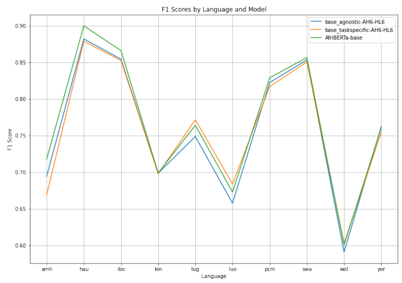


(a) Task agnostic

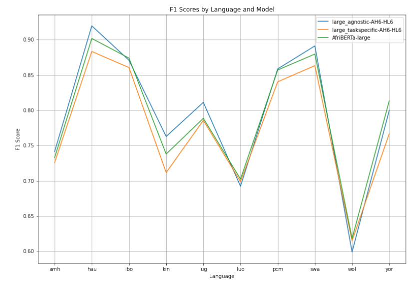
(b) Task specific

that inference time increased by 2 to 3 times the usual inference time, and performances deteriorated rapidly from 70% sparsity downwards. These observations suggest that the AfriBERTa model might have leveraged linguistic similarities and relationships inherent in languages sharing geographical regions.

Knowledge transfer from low-resource to high-resource Our results show that AfriBERTa leverages the linguistic similarities and relationships inherent in languages that share geographical regions (Ogueji et al., 2021). To test this assumption, we performed downstream on a high-resource language, Chinese, from the MSRA NER dataset (Feng et al., 2006). Surprisingly, AfriBERTa performed very strongly, implying that cross-lingual transfer is possible even between languages with

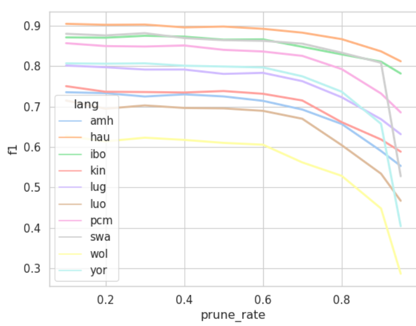


(c) Base teacher vs Students

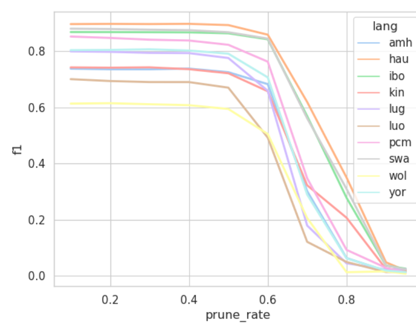


(d) Large teacher vs Students

Figure 4: Performance comparison between students and teachers (distillation).

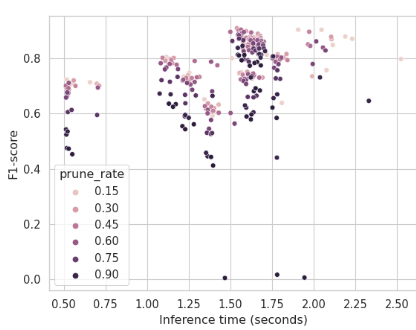


(a) Pruning before fine-tuning

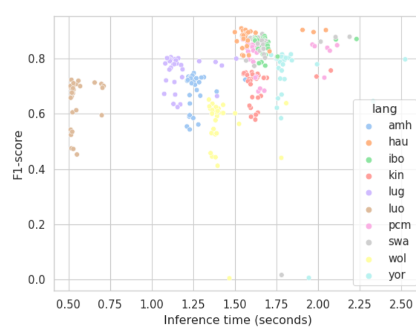


(b) Pruning after fine-tuning

Figure 5: Pruning **before vs after** fine-tuning: F1 scores averaged across the performances of each language.



(a) Inference Time wrt Sparsity Level

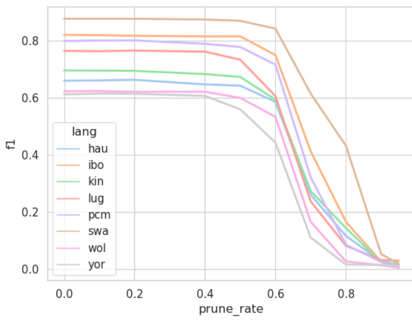


(b) Inference Time wrt Language Groups

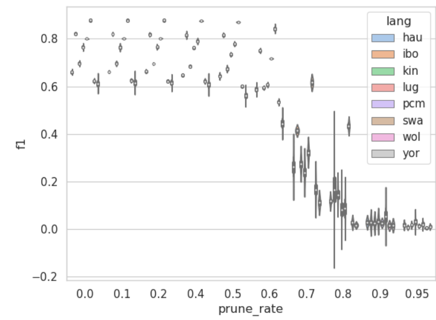
Figure 6: Comparison of how Sparsity Level and Language Groups affect Inference Time.

no known affiliation. However, inference time is about four times (5–7 sec) the usual time it takes to perform inference on familiar language data.

Zero-shot learning We further explored the zero-shot transferability of AfriBERTa on an unseen-before language at different levels of sparsity. Our findings reveal that F1 scores ranging between 40% and 60% remain competitive with MasakhaNER 2.0's zero-shot experiments on Afro-XLMR(Alabi



(a) Mean F1 scores of languages over sparsity levels



(b) Distribution of the languages F1-scores over sparsity levels

Figure 7: **OOD Generalization:** Performances stay consistent with dense models up till 50% sparsity.

et al., 2022), even at 50% sparsity. Predicting on a new language from models trained on languages from the same geographical region seems to perform zero-shot more confidently, consistent with findings in MasakhaNER 2.0's experiments (Adelani et al., 2022). However, we observed a considerable drop in performance at 70% sparsity, indicating that pruning might not be suitable for zero-shot learning in low-resource settings beyond a certain threshold.

D.3 Impact of pruning on inference time

The effect of pruning on inference time is a significant component of our research, and we discovered that when the sparsity level grows, inference time decreases noticeably. However, our investigation in Figure 6 indicated a wide range of inference time disparities, which might be related to variables other than the pruning rate itself. Our findings indicate that language-specific characteristics may have a considerable impact on inference time, as performance indicators showed no true connection with inference time. Further investigation is needed to study the language-specific aspects influencing inference time and to establish the ideal sparsity values for each language, taking both performance metrics and inference time into account.