MPHAYANER: NAMED ENTITY RECOGNITION FOR TSHIVENḐA

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Named Entity Recognition (NER) is a natural language processing (NLP) task that involves identifying and classifying named entities such as person names, location names, and organization names in text (Mohit, 2014; Eiselen, 2016). NER is critical in various NLP applications, including information retrieval, text classification, and question answering. Identifying named entities is challenging, particularly in low-resource languages where annotated datasets and tools for NER are limited (Adelani et al., 2021). TshivenḐa is a minority language spoken by approximately 1.3 million[1] people, predominantly in South Africa and its northern neighbours of Zimbabwe, Mozambique and Botswana StatsSA (2016). Given the relatively small number of native speakers of the language, TshivenḐa has received limited attention in the NLP community, especially concerning NER. NER activity in TshivenḐa has been limited to SADiLaR corpus, which is primarily restricted to named entities in the government domain (Eiselen, 2016). The task of NER in TshivenḐa is complicated by the fact that TshivenḐa, like many other Bantu languages, is a morphologically rich language with complex morphological forms that can pose challenges for NER systems (van Huyssteen & Griesel, 2014; Adelani et al., 2022). Additionally, TshivenḐa has limited resources, including annotated datasets and pre-trained models, which are essential for developing NER systems. These challenges highlight the need to develop NER systems tailored to TshivenḐa, specifically designed to handle the language's morphological richness and resource-poor nature. We address the underrepresentation of TshivenḐa in NER by *fine-tuning* state-of-the-art pre-trained language models and further investigate cross-lingual zero-shot transfer between TshivenḐa and five other African languages.

TSHIVENḐA

TshivenḐa is part of the South-Eastern group of Bantu languages and is known for its similarities to the Karanga Dialect of Shona, as noted in (Cassimjee, 1992). TshivenḐa employs the Latin alphabet along with five letters that have accents. Four of these letters are dental consonants with a circumflex accent beneath them (ḓ, ḽ, ṋ, ṭ). One is a dot above the letter for the velar (ṅ). Seven vowels are represented using five vowel letters. J and Q are used exclusively for foreign words and names. TshivenḐa has a rich morphological structure featuring 21 noun classes (Musehane, 2014).

Like many Bantu languages, it only uses two tones - high (denoted by an acute accent) and low (no diacritic) (Reynolds, 1997). The population of TshivenḐa speakers is the second least in South Africa after isiNdebele speakers. As part of the minority speakers, there has been little attention to ensuring this language is included in digital platforms, particularly news media.

MPHAYANER CORPUS

We use data from Vuk'uzenzele [2], a monthly newspaper published in multiple languages, including TshivenḐa, by the communications unit of the South African Government. For this study, TshivenḐa Vuk'uzenzele news articles were used. The articles were originally in PDF format, they were converted to text files using py2PDF (Fenniak et al., 2022), cleaned and standardised by the Data Science for social impact (DSFSI) research group at the University of Pretoria Marivate et al. (2023)[3]. We manually preprocess the converted text file to minimise text extraction errors such as repeated phrases and erroneous word concatenation or splitting to create the MphayaNER corpus.

[1] http://salanguages.com/Tshivenda/index.htm
[2] https://www.vukuzenzele.gov.za/
[3] https://github.com/dsfsi/vukuzenzele-nlp/

Model	F1-score DATE	LOC	ORG	PER	AVG
mDeBERTaV3	39.2	76.6	67.6	96.2	66.4
AfriBERTa	37.4	60.2	54.8	84.2	58.7
AfroXLMR-small	41.0	77.4	62.4	**99.4**	66.1
AfroXLMR-base	43.4	**80.2**	62.6	97.0	67.3
AfroXLMR-large	**47.6**	77.2	**71.0**	98.8	**71.0**

(a) Benchmark results. F1 score

src lang	F1
swa	52.1
sna	**52.8**
tsn	50.0
xho	40.7
zul	36.2
M2.0	46.1

(b) Transfer Result: src lang → `ven`

Table 1: Benchmark and transfer learning results (F1-score). All results are averaged over 5 runs.

ANNOTATION

We make use of the same annotation guideline, scheme and tags as done by (Adelani et al., 2021). We also make use of ELISA annotation tool for labelling Tshivenḓa texts. We recruited 5 native speakers for the labelling and they were trained using the MasakhaNER guideline for labeling personal name (PER), organization (ORG), location (LOC), and dates (DATE). To speed up annotation effort, we assigned a sentence to be annotated by only two annotators. After annotation, we make use of the adjudication function of the ELISA tool to detect mistakes between annotators. Annotators met to resolve conflict, and for sentences that still had disagreement, we ask the lead Tshivenḓa annotator to decide the most appropriate tag for the token. Our new dataset is known as MphayaNER.

After annotation and verification, we divided the 1,359 sentences into TRAIN, DEV and TEST split based on 70%/10%/20% ratio. In total, the dataset consists of 40,778 tokens, where TRAIN, DEV and TEST splits have about 29,239, 4,212 and 7,327 tokens respectively. In MphayaNER, there are few entities in general, we found only 251 PER, 409 LOC, 702 ORG , and 504 DATE entities.

BASELINE MODELS AND RESULTS

We provide baseline NER models based on *fine-tuning* multilingual pre-trained language models (PLMs) – this is the state-of-the-art technique. We compared fine-tuning mDeBERTaV3 (He et al., 2021), one of the current state-of-the art PLMs and two Africa-centric PLMs i.e AfriBERTa(Ogueji et al., 2021) and AfroXLMR Alabi et al. (2022). We benchmark on several sizes of the AfroXLMR model (small, base, and large verions). All models are trained for 20 epochs, learning rate of $5e-5$.

Table 1(a) shows the result on MphayaNER, the AfriBERTa model has the worst result (58.7 F1) since Tshivenḓa and other related Southern Bantu languages were not covered during pre-training. mDeBERTaV3 had an impressive result (66.4 F1) despite seeing only two Bantu languages during pre-training(Kiswahili and isiXhosa). AfroXLMR has seen more Bantu languages, about eight. We found that the more the capacity/size of AfroXLMR increases, the better the performance — AfroXLMR-small (66.1 F1) , AfroXLMR-small (67.3 F1), and AfroXLMR-large (71.0 F1). In general, we found all the models to struggle with identifying DATE in the corpus.

Transfer result We examine how other Bantu languages adapt to Tshivenḓa in zero-shot setting. Similarly, we compared the adaptation of an NER model trained on 21 African languages (Adelani et al., 2022) (i.e MasakhaNER 2.0 or for shot M2.0) to Tshivenḓa. Our result on Table 1(b) shows there is a large gap when transfering to Tshivenḓa. The best result ($>$ 52.0 F1) was achieved by chiShona and Kiswahili. On further analysis, we found both languages are better able to identify DATE than MphayaNER training corpus reaching 71.0 F1 for DATE. **As a last experiment**, we combined **chiShona data** from M2.0 with **MphayaNER**, and we obtained a better result of (75.3) especially for DATE (47.6 $\rightarrow$ 56.0) F1. This result highlights the importance of increasing the training data of MphayaNER with sentences with more entities. We leave this as future work.

CONCLUSION

In this paper, we present first Tshivenḓa NER corpus in the news domain based on the Vuk'zenzele dataset. We establish baselines for this task by fine-tuning multilingual pre-trained state-of-the-art language models. We also investigate zero-shot transfer between Tshivenḓa and languages finding that chiShona and Kiswahili give the best results. Additional experiments show augmenting MphayaNER with chiShona data significantly improves model performance.

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