

TOWARDS NEURAL MACHINE TRANSLATION FOR EDOID LANGUAGES

Iroko Fred Ònòmè Orife

Niger-Volta Language Technologies Institute
iroko@alumni.cmu.edu

1 INTRODUCTION

Many of the 500 plus languages spoken in Nigeria today have relinquished their previous prestige and purpose in modern society to English and Nigerian Pidgin, notably amongst the younger generations. Unlike numerous East and South Asian populations, which preserved the socio-linguistic status of their indigenous languages under colonial rule (e.g. India), Nigerian communities with primarily oral traditions have been the most susceptible to language endangerment (Rolle, 2013; Omo-Ojugo, 2004).

For tens of millions of speakers, language inequalities manifest themselves as unequal access to information, communications, health care, security along with attenuated participation in political and civic life. These inequities are further exacerbated in a technological age, where only the most highly resourced (i.e. colonial) languages become the milieu for economic advancement (Odoje, 2013; Awobuluyi, 2016; Ganagana & Ogboru, 2019). Finally, there have been practical and technical challenges in language technology for indigenous languages like orthographic standardizations and consistent diacritic representation (Unicode) in electronic media and across device types.

For almost-extinct languages, machine translation offers hope for language documentation and preservation. For speakers of minority Nigerian languages, it can facilitate good governance, national development and offers a path for technological, economic, social and political participation and empowerment to those with unequal access (Odoje, 2016; 2013). Using the new JW300 public dataset, we trained and evaluated baseline Neural Machine Translation (NMT) models for four widely spoken Edoid languages: Èdó, Ésán, Urhobo and Isoko.

2 EDOID LANGUAGES

Belonging to the eastern sub-branch of the Volta-Niger family within the Niger-Congo phylum, and spoken by approximately 5 million people, the Edoid languages of Southern Nigeria (Edo and Delta states) comprise over two dozen so-called “minority” languages. The term *Edoid* stems from Èdó, the most broadly spoken member language and the language of the famed Kingdom of Benin. Èdó, Ésán are members of the North-Central branch while Urhobo and Isoko belong to the South-Western family (Eberhard et al., 2019). These languages were selected based on the availability of text and because they are the most widely spoken.

Edoid languages generally employ the SVO constituent order type, open syllable systems with very few consonant clusters. Each language has at least two basic tone levels, high (H) and low (L) with kinetic, downstepped or contour tones variously utilized. As tone patterns serve different lexical and grammatical functions, “the phonetic and phonological implementation of this system is in fact complex and difficult to pin down” (Rolle, 2013; Ogie, 2009; Adeniyi, 2010; Iloilo, 2013). Finally, nasalisation is very common for both vowels and consonants (Elugbe, 1989; Donwa-Ifode, 1986; Ikoyo-Eweto, 2018).

Within Nigeria there is scholarship on rule, phrase and statistical machine translation systems for majority tongues of Yorùbá, Igbo and Hausa (Odoje, 2013). The present study is the first work known to the authors done in computational linguistics for any of the Edoid languages, specifically for machine translation.

3 METHODOLOGY

We first built baseline models using the Transformer architecture, the dominant modeling approach for NMT. The Transformer uses an encoder-decoder structure with stacked multi-head self-attention and fully connected layers (Vaswani et al., 2017). Given the performance of Byte Pair Encoding (BPE) subword tokenization for low-resourced South African languages, and the size of our datasets, we trained baseline models based on the ablation study results by Martinus et al., some 4000 BPE tokens (Martinus & Abbott, 2019). Models were then re-trained for all four languages using the standard word-level tokenization.

Dataset: The recently published JW300 dataset is a large-scale, parallel corpus for Machine Translation (MT) comprising more than three hundred languages of which 101 are African (Agić & Vulić, 2019). JW300 text is drawn from the Watchtower and Awake! religious magazines by Jehovah’s Witnesses (JW). The test set contains sentences with the highest coverage across all other languages in the corpus. The cardinality of the training set in number of tokens and sentences is listed in Appendix Table 1.

Models: The open-source, Python 3 machine translation toolkit `JoeyNMT` was used to train Transformer models (Kreutzer et al., 2019). Our training hardware was the free-tier configuration on Google Colaboratory, a single core Xeon CPU instance and a Tesla K80 GPU. Model training elapsed over multiple days, as experiments were repeated for the different tokenizations.

4 RESULTS

Qualitative: Urhobo and Isoko with larger training texts unsurprisingly had higher BLEU scores which generally correlated with the translation quality when reviewed by L1 speakers. BPE tokenization provided approximately a 37% boost across dev and test sets for Èdó and Ésán, a 32% boost for Urhobo but was flat to slightly worse than word-level tokenization for Isoko. Full scores and examples are listed in the Appendix.

Table 1: Per-language BLEU scores by BPE or word-level tokenization

Language	BPE		Word		Tokens	Sentences
	dev	test	dev	test		
Èdó	7.92	12.49	5.99	8.24	229,307	10,188
Ésán	4.94	6.25	3.39	5.30	87,025	4,128
Urhobo	15.91	28.82	11.80	22.39	519,981	25,610
Isoko	32.58	38.05	32.38	38.91	4,824,998	214,546

Error Analysis: While studying the models’ predictions, we observed that the training data requires significantly more preprocessing, notably to remove prevalent scriptural book, chapter and verse number annotations. Cleaner data will simplify the training task and generate models which generalize better on non-Biblical texts. Dialects of a singular language can also exhibit variance in the expression of concepts, so it would be advantageous to capture multiple references in different dialects. Finally, based on the performance of the Isoko models, with BLEU scores in the range {32, 39}, we have an estimate of how much additional clean text is required to achieve a similar performance with Èdó and Ésán.

5 FUTURE WORK AND CONCLUSIONS

Fertile avenues for future work include investigations using unsupervised machine translation and back-translation, a full ablation study with different (subword) tokenization approaches as well as specific consideration of linguistic knowledge. A human evaluation study accompanied by a more

extensive error analysis will also be crucial to better understand the linguistic features where NMT models under-perform.

We hope this initial effort will assist translators and the lay-person alike, bootstrap development and sustenance of literary traditions and energize interest in language technology for socio-linguistic and economic empowerment. Ultimately, languages with predominantly oral traditions will benefit most from (audio) speech-to-speech language technologies (Jia et al., 2019). This present work is but one step towards that goal. All public-domain datasets, pre-trained translation models and their training and evaluation configurations are available on GitHub.¹

ACKNOWLEDGMENTS

The authors thank Dr. Ajovi B. Scott-Emuakpor, MD and Dr. John Nevboyeri Orife for their encouragement and qualitative critiques of the translations.

REFERENCES

- Harrison Adeniyi. Tone and Nominalization in Edo. *California Linguistic Notes*, 35(1):1–22, 2010.
- Željko Agić and Ivan Vulić. JW300: A Wide-Coverage Parallel Corpus for Low-Resource Languages. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 3204–3210, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1310. URL <https://www.aclweb.org/anthology/P19-1310>.
- Ọládélé Awobuluyi. Why We Should Develop Nigerian Languages. *Issues in Contemporary African Linguistics: A Festschrift for Oladele Awobuluyi*, 11:347, 2016.
- Shirley Donwa-Ifode. Phonetic Variation in Consonants (Isoko). *Anthropological Linguistics*, 28(2):149–160, 1986. ISSN 00035483, 19446527. URL <http://www.jstor.org/stable/30028405>.
- David M. Eberhard, Gary F. Simons, and Charles D. Fennig (eds.). *Ethnologue: Languages of the World*, 2019. URL <http://www.ethnologue.com>.
- Ben Ohiomamhe Elugbe. *Comparative Edoid: phonology and lexicon*. University of Port Harcourt Press, 1989.
- D. E. Peter Ganagana and Lawrence Efe Ogboru. Contrastive Study Of The Morphological Differences Between English, Izon And Isoko Languages. 2019.
- Evarista Ofure Ikoyo-Eweto. Phonetic Differences between Esan and Selected Edoid Languages. *Journal Of Linguistics, Language and Culture*, 4(1), 2018.
- AKPOGHENE ONORIEVARIE Ilolo. *Vowel Reduction in Educated Isoko English*. PhD thesis, 2013.
- Ye Jia, Ron J Weiss, Fadi Biadisy, Wolfgang Macherey, Melvin Johnson, Zhifeng Chen, and Yonghui Wu. Direct speech-to-speech translation with a sequence-to-sequence model. *arXiv preprint arXiv:1904.06037*, 2019.
- Julia Kreutzer, Joost Bastings, and Stefan Riezler. Joey NMT: A Minimalist NMT Toolkit for Novices. To Appear in *EMNLP-IJCNLP 2019: System Demonstrations*, Nov 2019.
- Laura Martinus and Jade Z. Abbott. A Focus on Neural Machine Translation for African Languages. *CoRR*, abs/1906.05685, 2019. URL <http://arxiv.org/abs/1906.05685>.
- Clement Odoje. Language Inequality: Machine Translation as the Bridging Bridge for African languages. 4, 01 2013.
- Clement Odoje. The Peculiar Challenges of SMT to African Languages. *ICT, Globalisation and the Study of Languages and Linguistics in Africa*, pp. 223, 2016.

¹<https://github.com/Niger-Volta-LTI/edoid-nmt>

Ota Ogie. *Multi-verb constructions in Edo*. Norges teknisk-naturvitenskapelige universitet, Det humanistiske fakultet, 2009.

MO Omo-Ojugo. Esan language endangered. *Implications for the Teaching and Learning of Indigenous Languages in Nigeria*, 2004.

Nicholas Rolle. Phonetics and Phonology of Urhobo. *UC Berkeley PhonLab Annual Report*, 9(9), 2013.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is All you Need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (eds.), *Advances in Neural Information Processing Systems 30*, pp. 5998–6008. Curran Associates, Inc., 2017. URL <http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf>.

A APPENDIX

Table 2: Example Translations

Èdó	
Source:	Reading and meditating on real - life Bible accounts can help us to do what ?
Reference:	De vbené okha ni rre Baibol ya ru iyobó ne ima hẹ ?
Hypothesis:	De emwi ne ima gha ru ne ima mieke na gha mwẹ irenmwi nọ gbae vbekpae Jehova ?
Source:	What are the rewards for being humble ?
Reference:	Ma ghaa mu egbe rrioto , de afgangbe na lae miẹn ?
Prediction:	De emwi nọ khẹke ne omwa nọ dizigha oyẹvbu ru ?
Ésán	
Source:	I WAS raised in Graz , Austria .
Reference:	AGBAEBHO natiọle Graz bhi Austria , ọle mẹn da wanre .
Prediction:	Mẹn da ha khian ọne isikulu , mẹn da dọ ha khian ọne isikulu .
Source:	We should also strive to help others spiritually .
Reference:	Ahamiẹn mhan re eghe bhi otọ rẹ ha lue iBaibo
Prediction:	Mhan dẹ sabọ rẹkpa mhan rẹ sabọ ha mhọn ureọbhọ bọsi eria .
Urhobo	
Source:	But freedom from what ?
Reference:	Èkẹvuọvo , ẹdia vọ yen egbomọphẹ na che si ayen nu ?
Prediction:	(1 Pita 3 : 1) Èkẹvuọvo , die yen egbomọphẹ
Source:	Today he is serving at Bethel .
Reference:	Nonẹna , ọ ga vwẹ Bẹtẹl .
Prediction:	Nonẹna , ọ ga vwẹ Bẹtẹl asaọkiephana .
Isoko	
Source:	Still , words of apology are a strong force toward making peace .
Reference:	Ghele na , eme unu - uwou u re fi obọ họ gaga evaọ eruọ udhedhe .
Prediction:	Ghele na , eme unu - uwou yọ egba ologbo nọ ma re ro ru udhedhe .
Source:	We can even ask God to ‘ create in us a pure heart . ’
Reference:	Ma rẹ sae tubẹ yare Oghenẹ re ọ ‘ kẹ omai eva efuafo . ’
Prediction:	Ma rẹ sae tubẹ yare Oghenẹ re ọ ‘ ma omai eva efuafo . ’