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USING LSTM NETWORKS TO TRANSLATE FRENCH TO SENEGALESE LOCAL LANGUAGES: WOLOF AS A CASE STUDY

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1 PROBLEM STATEMENT

Nowadays, internet applications are changing people’s life all over the world. Applications such as Google-Map allow people to locate themselves. Facebook, Snapchat, Instagram allow people to be connected with their friends. Amazon, Alibaba allow people to do effortless online shopping. Netflix allows people to watch video contents. For smooth interaction, these applications require an understanding of internet dominant languages such as English, Spanish, Chinese, Arabic, French, etc. Others languages, spoken in Africa, such as Eastern Ethiopian Amharic, Southern African Swahili, Western African Fulani or Wolof can not be used with these applications. The main reason being that compared to English, for instance, many of these languages are spoken by small sized populations.

In machine learning, natural language processing models have been developed to extract relevant information from electronic documents on the internet. These models mostly address documents written in well-resource languages such as English, Mandarin, Spanish, Arabic, French, etc. Apart from rare cases, low-resource language, such as Eastern Ethiopian Amharic, Southern African Swahili, Western African Fulani or Wolof, are seldom addressed. Having machine learning models such as machine translation systems that are able to transform information from high to low resource languages would have great impact. This will allow population speaking low-resource languages to make full use of internet contents and applications.

In this paper, we present investigations we conduct toward developing a long short-term memory (LSTM) neural network machine translation model to translate French into Wolof (Hochreiter & Schmidhuber, 1997; Sutskever et al., 2014). Up to our knowledge, this is the first time such task is being addressed. First, we gathered a dataset of seventy thousand aligned French-Wolof sentences. Then, we trained LSTMs (bi-directional networks, and bi-directional LSTM with attention) to translate French sentences into Wolof. Evaluation of our models using BLEU scores show promising results. In the remainder of this article, we give details about the corpus, the models, and conducted experimental validation.

2 A CORPUS FOR FRENCH TO WOLOF TRANSLATION

Wolof language is mainly spoken in West Africa (Gamble, 1950). It’s usage is mainly centered around Senegal and it’s neighboring countries such as Gambia, Mauritania, Mali, and Guinea. Historically, Wolof is the language of the Jolof Kingdom which was located inside the modern Senegambian region. Approximately, Wolof is spoken by about 10 million people. In Senegal, Gambia, and Mauritania, Wolof has an official language status, together with French, English, and Arabic. Because of France’s historical influence in Senegal, and also because Wolof and French are two Senegalese official languages, bilingual French-Wolof documents are available.

We constructed a French-Wolof parallel corpus according to the following steps. First, appropriate corpus data sources (pdf, text, html and doc) are identified. Then, text content is extracted from the sources. Next, raw text data are split into monolingual and bilingual texts. Finally, monolingual texts are translated from French into Wolof. Likewise, bilingual texts are manually corrected by

Domains	Languages	Tokens	Average Length	Vocabulary	Sentences
Education	French	36467	7.0129	7603	5200
	Wolof	27869	5.3594	6597	
Religion	French	831972	23.5040	49764	35397
	Wolof	739375	20.8881	44301	
General	French	169666	6.5915	15925	25740
	Wolof	161921	6.2906	10731	
Laws	French	10016	17.6028	2738	569
	Wolof	9951	17.4886	2461	
Legend	French	27780	12.8492	6460	2162
	Wolof	26051	12.0495	5292	
Society	French	25391	12.9151	6398	1966
	Wolof	26266	13.3601	5412	

Table 1: Statistic summary of the French-Wolof parallel corpus

expert linguists. The output of this stage consists of bilingual (or multilingual) parallel documents. During the data collection process, special emphasis was placed on the quality of the content and translation.

One of the most challenging tasks for creating a parallel corpus is sentence alignment. This consists in extracting from parallel French and Wolof corpora sentence pairs that are translations of one another. In this work, we used semi-automatic methods to align Wolof and French texts at the sentence level. First, using Python scripts, we extracted the bilingual texts contained in all documents. Then, paragraphs of texts are split into sentences using a script-based sentence-splitter. Three widely used open-source tools were benchmarked: *hunalgn* (Varga et al., 2007), *yasa* (Lamraoui & Langlais, 2013) and *champollion* (Ma, 2006). *hunalgn* is a hybrid algorithm that combines the dictionary and length based methods. In contrast, *yasa* and *champollion* use lexical-based approaches. The final results indicated that *hunalgn* achieves satisfactory performance.

As showed by Table 1, the final corpus content can be categorized in six major domains : education, general, laws, legend, religion, and society. Corpus content statistics are showed in Table 1. *Religion* contains the most sentences, followed by *General*. The smallest portion are *Society* and *Laws*. The final corpus comprises 71034 phrases. Nguer et al. (2020) provides more details about the corpus content.

3 LSTM MODELS FOR TRANSLATION

To assess the quality of the corpus we trained three word embedding models on the Wolof monolingual corpus: a continuous bag of words model (CBOW), a Skip-gram model and a Global vector for word representation model (GloVe) (Mikolov et al., 2013; Pennington et al., 2014). Conducted evaluations about word analogy tasks show that constructed embedding capture words semantic relatedness despite the moderated corpus size (Lo et al., 2020).

In addition to developing word embedding models, we used the corpus to train and evaluate four LSTM based models to translate French sentences into their corresponding Wolof version: baseline LSTM, bidirectional LSTM, LSTM+attention, bidirectional LSTM+attention (Hochreiter & Schmidhuber, 1997; Sutskever et al., 2014).

For the translation task, we split the dataset into two disjoint sets of 50% each (i.e. 34805 parallel sentences) for training and validation, respectively. The data split was done randomly. The sentences in the corpus have different lengths. Some are short (e.g. length 20-30 words), but there are very long ones (> 100 words). We filter out sentence pairs whose lengths exceed 50 words and used padding to compensate for the empty slots in shorter sentences.

Models	Accuracy	BLEU 1	BLEU 2	BLEU 3	BLEU 4
LSTM	56.69	26.36	44.24	47.46	39.73
LSTM + attention	63.89	23.63	41.93	45.97	37.78
LSTM + bidirectional	68.03	25.29	43.36	46.90	39.34
LSTM + bidirectional + attention	72.27	23.49	41.81	45.90	38.65

Table 2: Models BLEU scores (in percentage) on French-Wolof translation task.

Across experiments, the following models hyper-parameters are kept constant: number of LSTM units, embedding size, weight decay, dropout rate, shuffle size, batch size, learning rate, max gradient norm, optimizer, number of epochs and early stopping patience. We used a baseline encoder-decoder LSTMs with 300 cells and 128 dimensional word embeddings. All models are composed of a single LSTM layer with a dropout layer for the decoder, dropout rate and weight decay regularization parameters for both the encoder and decoder. It has to be noted that word embeddings are learned together with the LSTM networks parameters.

Models are trained using Adam stochastic gradient descent with a learning rate set to 10^{-3} (Kingma & Ba, 2014). We perform early stopping based on the validation set accuracy. Our shuffled mini-batch contains 128 training sentences.

The quality of our translations are evaluated by comparing the predictions and ground truth using BLEU (Papineni et al., 2002). We use cumulative BLEU scores Brownlee (2017) by calculating the weighted geometric mean of individual n-gram scores from 1 to 4 orders. The weights for BLEU-1 are (1.0, 0, 0, 0) or 100% for 1-gram. BLEU-2 assigns a weight of 0.50 to each of the 1-gram and 2-gram. BLEU-3 assigns a weight of 0.33 to each of the 1-, 2- and 3-gram scores. The weights for the BLEU-4 are 0.25 for each of the 1-gram, 2-gram, 3-gram and 4-gram scores. For each model, we report cumulative BLEU scores (BLEU 1 to 4) combined with the smoothing function suggested by Chen & Cherry (2014). This function assigns smaller smoothed counts to shorter translations as they tend to have inflated precision values due to having smaller denominators.

Table 2 shows that the best BLEU scores are achieved by the baseline unidirectional non-attentional model. Our experiments showed that adding bidirectional LSTMs and the attention mechanism did not necessarily improve BLEU scores. The most likely explanation is the noticeable difference in the number of parameters. In other words, part of this improvement is likely due to the fact that the baseline model has fewer parameters and therefore require less training data. However, despite the lower BLEU scores, qualitative analysis of the results shows that the bidirectional attentional LSTM produces better qualitative translations with less repeated words.

4 CONCLUSION

Research presented in this paper are preliminary investigations we are conducting about analyzing Wolof language using deep neural networks. In this work, words were consider as basic token exploited LSTM networks for the translation task. Our aim is to make our corpora and models publicly available to the machine learning community to advance research about low-resource African languages.

In the future, we plan to consider byte pair encoding (BPE) tokenization (Sennrich et al., 2016) to account for Wolof’s morphological and compositional structure. We also plan to investigate the use of transformer models for the translation task as transformer have stated most latest state of the art natural language processing performances (Devlin et al., 2019).

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REFERENCES

Jason Brownlee. *Deep Learning for Natural Language Processing: Develop Deep Learning Models for your Natural Language Problems*. Machine Learning Mastery, 2017.

- Boxing Chen and Colin Cherry. A systematic comparison of smoothing techniques for sentence-level bleu. *Workshop on Statistical Machine Translation*, pp. 362–367, 2014.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv:1810.04805*, 2019.
- David P. Gamble. The wolof of senegambia: Western africa part xiv (ethnographic survey of africa). *Routledge*, 1950.
- Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 1997.
- Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- Fethi Lamraoui and Philippe Langlais. Yet another fast, robust and open source sentence aligner. time to reconsider sentence alignment. *XIV Machine Translation Summit*, 2013.
- Alla Lo, Cheikh M. Bamba Dione, Elhadji Mamadou Nguer, Sileye O. Ba, and Moussa Lo. Building word representations for wolof using neural networks. *Colloque National sur la Recherche en Informatique et ses Applications (CNRIA): in press*, 2020.
- Xiaoyi Ma. Champollion: A robust parallel text sentence aligner. In *Language Resources and Evaluation Conference (LREC)*, 2006.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems (NIPS)*, 2013.
- Elhadji Mamadou Nguer, Alla Lo, Cheikh M. Bamba Dione, Sileye O. Ba, and Moussa Lo. SEN-CORPUS: A multilingual parallel corpus between senegalese languages and western languages. *Language Resources and Evaluation Conference (LREC): in press*, 2020.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. *Annual meeting on association for computational linguistics (ACL)*, 2002.
- Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2016.
- Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. *Advances in neural information processing systems (NIPS)*, 18:1527–1554, 2014.
- Dániel Varga, Péter Halácsy, András Kornai, Viktor Nagy, László Németh, and Viktor Trón. Parallel corpora for medium density languages. *Amsterdam Studies In The Theory And History Of Linguistic Science Series 4*, 2007.