TOWARDS END-TO-END TRAINING OF AUTOMATIC SPEECH RECOGNITION FOR NIGERIAN PIDGIN

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ABSTRACT

Nigerian Pidgin remains one of the most popular languages in West Africa. With at least 75 million speakers along the West African coast, the language has spread to diasporic communities through Nigerian immigrants in England, Canada and America, amongst others. In contrast, the language remains an under-resourced one in the field of natural language processing, particularly on speech recognition and translation tasks. In this work, we present the first parallel (speech-to-text) data on Nigerian pidgin. We also trained the first end-to-end speech recognition system (QuartzNet and Jasper model) on this language which were both optimized using Connectionist Temporal Classification (CTC) loss. With baseline results, we were able to achieve a low word error rate (WER) of 0.77% using a greedy decoder on our dataset. Finally, we open-source the data and code along with this publication in order to encourage future research in this direction.

Index Terms— Automatic Speech Recognition, Nigerian Pidgin, CTC, Convolutional networks.

1. INTRODUCTION

Automatic speech recognition (ASR) remains one of the most fundamental areas of natural language processing that enables the recognition and translation of spoken language into textual information. Currently, there are about 6,900 languages on earth [1] and Africa represents about 2,000 of them [2]. In retrospect, the interest of applying ASR systems on spoken languages has been remarkable [3] in recent years, but for most applications, the growing interest is seen majorly in western languages such as English, French, German and so on. This is relatively due to the substantial quantity [4] of linguistic resources available for these languages since the multitude of African languages are very low-resourced [2]. To combat this problem, we focus on Pidgin English as a case study.

Pidgin English is one of the most widely spoken languages in Africa with approximately 75 million speakers estimated in Nigeria and over 5 million speakers in Ghana [5]. Though variants of Pidgin English exist, the language is fairly uniform across the continent. In this work, we directed our research to the most commonly spoken variant of West African Pidgin English - the Nigerian Pidgin English [5].

[5] released the first monolingual Pidgin English text-to-text corpus and trained the first Pidgin word vectors, aligning these\(^1\) with English word vectors to create cross-lingual embeddings. [7] improved on their work by using English text in a target-domain as a pivot language to enhance Pidgin text fluency and relevance. While these are recent works on Pidgin English, they do not fall under the speech-to-text category.

Under the speech-to-text-category, [8] began the first effort in developing Human Language Technology (HLT) tools, precisely speech resources for Nigerian Pidgin. Their work focused on developing speech corpus for a tokenizer, an automatic speech system for predicting the pronunciation of the words and their segmentation. However, these resources were only integrated into a software tool and we are not aware of any discoverable platform where the data has been made readily available for research purposes.

In an attempt to provide further development on this language and category, we collected the first known speech-to-text dataset on Nigerian Pidgin. Even though building complex neural architectures for speech recognition tasks through the use of reusable components can somewhat be challenging, we use the Nemo toolkit [9] for training complex speech models on the speech data we have collected. Empirically, we achieved very low-error rates on our evaluation set and demonstrate this performance in the result section.

Our major contribution therefore, is to:

1. Introduce the first parallel (speech-to-text) data on Nigerian Pidgin Language as a bench-mark for further studies.
2. Build the first publicly available (end-to-end) ASR system on Nigerian Pidgin Language.
3. Open-source the code and data to encourage further research.

2. DATA COLLECTION

Developing an automatic speech recognition system requires an adequate amount of speech signals and corresponding text data. However, getting these two together is challenging because they are not readily or publicly available online. In this section, we describe the methodology used to collect the speech signals and textual data for building an automatic recognition system.

\(^*\) Both authors contributed equally to this work.
2.1. Textual Corpus

The conventional way of building substantial corpus of textual information for ASRs is the collection of texts from online websites. For many resourced languages, there exists, at the minimum, a wikipedia corpus. However, the case is different for Pidgin English [5]. Nonetheless, [5] crawled several news websites and publicly made available a Pidgin English text-to-text dataset. We leverage on this dataset and use it as a reference match to record our speech signals. In total, the crawled text data contained 56,695 sentences and 32,925 unique words including topics from sports, politics, entertainment and everyday life from which we selected 7,885 utterances for recording the speech data. Each utterance has an average of 8 to 14 words.

2.2. Speech Corpus

With the acquired text information, we proceed to collecting speech recordings to build the recognition system. Since there is no available speech corpus to work with, we carried out the task of recording and collecting our own speech data. These recordings were made with the LigAiKuma [10] android application developed by Steven Bird and the GETALP group of Grenoble’s Computer Science Laboratory. In total, we recorded over 14 hours of speech data, made by 10 native pidgin speakers (5 males and 5 females) within the age range of 20 to 28 years in a nearly noiseless environment. We split the data into training, validation and testing set. The training set is composed of 3 males and 3 females, and contained 6,107 utterances (about 10.92 hours of speech data), the development set is composed of 1 male and 1 female, that contained 759 utterances (about 1.64 hours of speech data) and the test set is composed of 1 male and 1 female, that contained 1,019 utterances (about 2.27 hours of speech data). We ensured that speakers who appeared in the test or development set do not appear in the training set. This is to avoid the problem of speaker overlapping during training, validation or testing. Finally, each set contained speakers from both genders.

| Set       | Male | Female | No. of Utterances | Duration (hrs) |
|-----------|------|--------|-------------------|----------------|
| Training  | 3    | 3      | 6107              | 10.92          |
| Development | 1    | 1      | 759               | 1.64           |
| Testing   | 1    | 1      | 1019              | 2.27           |
| Total     | 5    | 5      | 7885              | 14.83          |

2.2.1. Speech data preprocessing

Pre-processing speech data is considered a crucial step in building robust speech recognition systems [11]. Since audio information is more beneficial in the context of frequencies of sound over time, we explored Spectrograms and Mel Spectrograms. Spectrogram is a visual representation of the amplitude or soundness of a speech signal over time at various frequencies and this is done by breaking the signal into overlapping chunks and carrying out a short-time Fourier transform on each chunk [12].

Mel Spectrogram on the other hand, simply changes the scale of the frequencies from linear to mel scale [13]. With Mel Spectrogram, we have better feature representation such that differences in-between frequencies are more aligned to what humans perceive. Therefore, using the Mel Spectrogram to transform the scale of the frequencies to what we can hear is an important preprocessing step.

We plot the spectrogram of an example speech signal and show the corresponding Mel spectrogram. The audio recording is linked here and the reference Pidgin text is the following sentence:

"main thing bi say di education go make sense, to help reduce poverty."

![Fig. 1. Audio Spectrogram.](Image)

![Fig. 2. Mel Spectrogram.](Image)

2.2.2. Speech data augmentation

SpecAugment is a simple data augmentation technique for automatic speech recognition [14] and is applied directly on the feature inputs. We applied SpecAugment on the speech corpus and investigated the performance of the system if the size of the training set increases.

3. METHODS AND IMPLEMENTATION DETAILS

Several automatic speech recognition models have been implemented for different African languages [15]. However, nearly all of them use traditional approaches. These approaches are generative and contain pipelines that include language models, which determines the probability of a given sequence of words occurring in a sentence (e.g n-gram model), pronunciation model for each word in the sentence, or acoustic model that translates the pronunciations into distinct sounds (e.g. Gaussian Mixture Models) [16].

In recent time, deep neural networks have replaced the individual or whole components of traditional pipelines with end-to-end architectures. Such end-to-end architectures are trained at once and they simply take an audio input in order to predict corresponding textual outputs given a particular loss function. In this study, we
trained two state-of-the-art end-to-end ASR architectures, namely, Jasper [17] and QuartzNet [18]. We give an overview of both models and schematically highlight the blocks in these architectures.

3.1. Jasper Model

Jasper is a family of end-to-end ASR models that replace acoustic and pronunciation models with convolutional neural networks. The architecture consists of repeated block structures that use 1D convolutions, batch normalizations, ReLU, dropout and residual connections [17]. In a Jasper BxR model, R sub-blocks consisting of the 1D convolution, batch norm, ReLU and dropout, are grouped into a single block, which is later repeated B times. At the beginning, there is an extra block and few more at the end that are not part of B and R.

We trained a jasper model with k=4 blocks of single R=1 sub-block and a Connectionist Temporal Classification (CTC) decoder greedily. Since the model does not rely on temporally-aligned data, we trained using a CTC loss. The optimizer for the architecture was NovoGrad, a variant of the Adam optimizer [19] with a smaller memory footprint. We trained for 5 epochs on NVIDIA Tesla P4 with a learning rate of 0.001, sample rate of 16,000 and weight decay of 0.001.

3.2. QuartzNet Model

The QuartzNet design is similar to the Jasper architecture but with a key difference [18]. The 1D convolutions are replaced with 1D time-channel separable convolutions. This significantly reduces the number of trainable parameters while maintaining high performance.

We trained the model with k=4 blocks of single R=1 sub-block and a greedy CTC decoder. The optimizer for the architecture was NovoGrad with a learning rate of 0.001 and weight decay of 0.001. The model was trained for 5 epochs on NVIDIA Tesla P4 with a sample rate of 16,000.

4. RESULT

Word Error Rate (WER) [20] is a metric used to compute the similarity between a reference text and a prediction. It is computed as the ratio of the numerator and denominator for each pair.

$$WER = \frac{S+D+I}{N} = \frac{S+D+I}{S+D+C}$$

where:
- S is the number of substitutions
- D is the number of deletions
- I is the number of insertions
- C is the number of correct words.
- N is the number of words in the reference

(N = S+D+C)

To select the best model, we developed on a development set of 759 utterances and evaluated on a test set of 1,019 utterances from the dataset. The lower the WER, the better.

Table 2: Summary of the Word Error Rate (WER) for Jasper and QuartzNet.

| Model      | No Data Augmentation | With Data Augmentation |
|------------|----------------------|------------------------|
| Jasper     | 0.997                | 0.987                  |
| QuartzNet  | 0.777                | 0.772                  |

Hence, the model with the lowest WER was selected as the best. Table 2 presents the summary of results for the Jasper and QuartzNet model.

For the same amount of training, the Quartznet model outperformed the Jasper model both with data augmentation and
without data augmentation. Also, the results show that data augmentation improves performance albeit for few epochs. We therefore show the training WER and validation WER for the data augmented version of the models.

The data and code have been made publicly available on the project repository [21]. We hope to encourage more speech recognition research on Nigerian Pidgin Language.

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5. CONCLUSION

In this work, we introduced a parallel (speech-to-text) data on Nigerian Pidgin Language as a bench-mark for accessible, discoverable and reproducible research in ASR systems for Nigerian Pidgin. We also built and optimised the first (end-to-end) automatic speech recognition system on this language using a CTC loss.

Furthermore, we used the greedy or max decoding technique and studied word-level speech recognition. For further work, it would be interesting to study how a modified beam-search algorithm compared to the greedy approach could improve performance, as well as explore character-level recognition to see how it affects the learning of the system.

We also show qualitative results of the Quartznet model with the following examples.

Reference: "mosquito wey no dey hear word na im dey follow dead body enter grave"
Prediction: "muskito wey no dey hear word nam im dey follow dead body enter grave"

Reference: "okorocha folo am do the waka"
Prediction: "ookoroja folan du di waka "

The authors would like to thank generous volunteers who have contributed immensely to the data collection, and anonymous reviewers who have provided useful feedback on the writing.
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