Contextual Text Embeddings for Twi

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Abstract

Transformer-based language models have been changing the modern Natural Language Processing (NLP) landscape for high-resource languages such as English, Chinese, Russian, etc. However, this technology does not yet exist for any Ghanaian language. In this paper, we introduce the first of such models for Twi or Akan, the most widely spoken Ghanaian language. The specific contribution of this research work is the development of several pretrained transformer language models for the Akuapem and Asante dialects of Twi, paving the way for advances in application areas such as Named Entity Recognition (NER), Neural Machine Translation (NMT), Sentiment Analysis (SA) and Part-of-Speech (POS) tagging. Specifically, we introduce four different flavours of ABENA – A BERT model Now in Akan that is fine-tuned on a set of Akan corpora, and BAKO - BERT with Akan Knowledge only, which is trained from scratch. We open-source the model through the Hugging Face model hub and demonstrate its use via a simple sentiment classification example.

1 Introduction

Natural Language Processing (NLP) is a subfield of artificial intelligence that is primarily concerned with developing systems that can read and process spoken or written human language to perform intelligent tasks. In order to capture the meaning encoded in a sentence or a phrase, a language model can be employed to extract such information.

A language model is a core component of NLP, accurately placing distributions over sentences to decode the complexities of a language – such as grammatical structure and semantics (Jozefowicz et al., 2016). Over the years, there have been many attempts at developing language models that fully capture the context of a sentence and also better models for the observed distributions of a language. Recent advances in transformer (Vaswani et al., 2017) neural language models such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2018) (Radford et al., 2019) has stimulated significant progress in performance for high-resource languages such as English, Chinese, etc. These models are typically trained on billions of words. While text data and other computational resources are easily accessible for some languages, text data resources in many low-resource languages remain almost non-existent. In this work, we contribute to closing this gap by developing the first transformer language model for the low-resource Ghanaian language Twi or Akan.

Human languages share some similarities in both acoustic and phonetic aspects. Features extracted from some languages can be shared with other languages at some levels of abstraction (Chung et al., 2018; Jia et al., 2020). Inspired by that, the main idea is to first train a high-resource language model, and then use the resulting trained
network (the parent or source model) to initialize and fine-tune a low-resource language model (the child or target model) (Nguyen and Chiang, 2017). This process is typically referred to as transfer learning (Ruder et al., 2019; Azumre, 2020).

In this paper, we develop several pretrained transformer language models for the Akuapem and Asante dialects of Twi, paving the way for advances in application areas such as Named Entity Recognition (NER), Neural Machine Translation (NMT), Sentiment Analysis (SA) and Part-of-Speech (POS) tagging. We introduce four different flavors of ABENA – A BERT model Now in Akan. We first employ transfer learning to fine-tune a multilingual BERT (mBERT) model on the Akuapem Twi subset of the JW300 dataset. Subsequently, we fine-tune this model further on the Asante Twi Bible data to obtain an Asante Twi version of the model. Additionally, we perform both experiments using the DistilBERT architecture instead of BERT. This yields smaller and more lightweight versions of the Akuapem and Asante ABENA models. Finally, we introduce BAKO – BERT with Akan Knowledge Only. This is essentially the same as ABENA, but trained from scratch. We open-source the model through the Hugging Face model hub, and demonstrate its use via a simple sentiment classification example.

2 Related Work

Global matrix factorization methods, such as Latent Semantic Analysis (LSA) (Deerwester et al., 1990) learn vector space representation of words and transform textual data into numerical representations which uses mathematical models to learn dependencies between each word, phrase and document (Gu, 2018). The process of turning text into numbers is commonly known as vectorization or word embedding. These techniques are functions which map words into vectors of real numbers. The vectors form a vector space – an algebraic model where all the rules of vector addition and measures of similarities apply.

2.1 Language Modeling

Language modeling is formulated as the task of predicting the \((n+1)^{th}\) token in a sequence given the \(n\) preceding tokens (Merity et al., 2018). Mathematically, a language model may be expressed as \(P(x^{n+1} | x^n, ..., x^1)\) where \(P(x^T, x^{T-1}, ..., x^1) = P(x^1) \cdot P(x^2 | x^1) \times ... \times P(x^T | x^{T-1}, ..., x^1) = \prod_{t=1}^T P(x^t | x^{t-1}, ..., x^1)\).

Language models can operate at various granularities, with tokens formed from either words, sub-words, or characters (Merity et al., 2018) which can be used to accurately predict the next word in a sentence. Further, when trained on vast amounts of data, language models compactly extract meaning encoded in the training data (Jozefowicz et al., 2016).

Primarily, there are two types of language models: statistical language models and neural language models. The difference between the two lies in their mode of operation and architecture.

2.1.1 Statistical Language Models

Statistical language models are based on the concepts of assigning a probability distribution to words and sentences (Popov et al., 2018) where each sentence is an ordered sequence of words. Every word \(w\) is taken from a set \(D\) also called a dictionary.

The goal of a statistical language model is to build a probabilistic distribution over all possible sentences in a language (Raychev et al., 2014). That is, given a sentence \(S\), the language model estimates its probability \(P(S)\).

For a sentence \(S = w_1, w_2, ..., w_m\), many language modeling approaches estimate its probability as follows:

\[
P(S) = \prod_{i=1}^m P(w_i | h_{i-1}) \quad \forall i : \quad 1 \leq i \leq m,
\]

where we refer to the sequence \(h_i = w_1, w_2, ..., w_i\) as the history. A sentence likelihood is calculated by generating it word by word using conditional probabilities on the already generated words. Furthermore, a statistical language model is usually built on a finite amount of training data that is used to estimate the true probabilities of sentences.

There are several variants of the statistical language model, like the \(n\)-gram models and count-based models. Almost all these variants of the statistical language model decompose the probability of a sentence into a product of conditional probabilities, i.e., instead of modeling the probability of each sentence independently, the probability is composed of probabilities of its sub-parts or words.

Statistical language models are also regarded as knowledge-improvised data-optimal techniques (Rosenfeld, 2000) which fail to capture long-term dependencies and linguistic structure in
their architecture. Owing to this, statistical language models inherently suffer from data sparsity. Some solutions have been exploited like the Good-Turing (Church and Gale, 1991), Kneser-Ney (Heafield et al., 2013) and the Witten-bell (Giwa and Davel, 2013) algorithms. Aside these, domain specific and domain adaptive statistical language models have been used (Rosenfeld, 1996), but these solutions are computationally expensive and still fail to fully capture context in sentences with long-term dependencies.

Statistical language models also have a fundamental problem known as the curse of dimensionality which limits modeling on larger corpora for a universal language model (Ranjan et al., 2016). For example, if one wants to develop an n-gram language model with a vocabulary of size 1000, there are potentially $1000^n - 1$ possible dimensions in the resulting vector space.

In view of these challenges, we turn our attention to neural language models.

2.1.2 Neural Language Models - Static

Neural Networks are a class of machine learning algorithms that learns to perform a task by modeling probabilities using continuous internal representations of the input feature. Some of these network architectures are employed in language modeling, and the resulting models are known as neural language models (Ahn et al., 2016). Neural language models (Xu and Rudnicky, 2000) traditionally used convolutional neural networks (CNNs) (O’Shea and Nash, 2015) and recurrent neural networks (RNNs) (Mikolov et al., 2010) – like LSTMs (Hochreiter and Schmidhuber, 1997; Gers et al., 2002; Sundermeyer et al., 2012) and GRUs (Cho et al., 2014; Chung et al., 2014) – with transformations becoming more popular recently.

Unlike statistical language models, the conditional probabilities $P(x_t | x_{1:t-1})$ can be specified using a neural network in which the context $x_{1:t-1}$ at each time $t$ is represented using a hidden state vector $h_t \in \mathbb{R}^d$. This is defined recursively via $h_t = f(x_{t-1}, h_{t-1}; \theta)$, where $f$ is a non linear map with a trainable parameter $\theta$. The conditional probabilities are then defined using a softmax function as $P(x_t | x_{1:t-1}; \theta, \omega) = \text{softmax}(X_t, \omega, h_t)$ where $\omega = \omega_i \subset \mathbb{R}^d$ is the softmax coefficient. $\omega_i$ can be viewed as an embedding vector for word $i \in V$ and $h_t$ the embedding vector of context $x_{1:t-1}$ which is converted into a probability using the softmax function.

Key to neural language modeling are word embeddings which represents words in the form of vectors (Chen and Sokolova, 2018). It is a form of learning representation which is primarily concerned with representing each word using an $N$-dimensional vector such that the cosine similarity of any two terms corresponds to their semantic similarity (Speer and Chin, 2016). The next section discusses some techniques that are used to learn word embedding from text data.

Word2vec

Word2vec is a method of unsupervised shallow two-layer neural network modeling (Goldberg and Levy, 2014) that captures word embeddings from a text corpus. Word2vec produces embeddings based on the contextual semantics of words in a text such that words with similar linguistic contexts are mathematically grouped together in a vector space, preserving the semantic relationship between words. It then uses these word embeddings to produce predictions on a word.

There are two model architectures of word2vec that can be used:

- Skip-Gram Model
- Continuous Bag-of-Words Model (CBOW)

FastText

FastText embeddings exploit subword information to construct word embeddings. Representation are learnt of character $n$-grams and words represented as the sum of the $n$-grams vectors (Bojanowski et al., 2017). This extends the word2vec type of models with subword information and helps the embeddings understand suffixes and prefixes. Once a word is represented using character $n$-grams, a skip-gram model is trained to learn the embeddings.

Sent2vec

Sent2vec is an efficient unsupervised word embedding architecture that seeks to train distributed representations of sentences (Pagliardini et al., 2017). The model is further augmented by also learning source embeddings for not only unigrams but also $n$-grams of words present in each sentence, and averaging them along with the words. It can be thought of as an extension of fastText
and word2vec.

**Doc2vec**
Doc2vec (Lau and Baldwin, 2016) is an extension of word2vec. The model aims to create a numerical representation of a document rather than individual words (Chen and Sokolova, 2018). It functions on the logic that the meaning of a word is largely dependent on the document that it occurs in. The vectors generated by doc2vec are generally used to find the similarities between documents.

### 2.1.3 Neural Language Models - Contextual

Unlike the static embeddings like word2vec and fastText, transformer-based language models have the ability to dynamically adapt to changing contexts. For instance, consider the following two English sentences:

- He examined the *cell* under the microscope.
- He was locked in a *cell*.

The same word *cell* here means two completely different things. A human would look at the context, i.e., the words surrounding our target word, for cues about the exact meaning. The word *microscope* clearly brings up biological connotations in the first sentence. The word *locked* clearly brings up connotations of a prison in the second sentence.

To make a Twi example, consider the following two sentences.

- *akraman no so paa* — the dog is very *big*.
- *akra no da mpa no so* — the cat is sleeping *on* the bed.

The word *so* means *big* in the first sentence and *on* in the second sentence. Transformer-based models possess the ability to dynamically analyze the context for meaning cues, and adapt to it. They do this using the so-called *self-attention mechanism*, which we do not discuss in detail here. BERT is arguably the most popular model from this class. It is typically trained with a “*fill-in-the-blanks*” objective which is very practical to implement and does not require labeled data — just randomly drop some words and try to predict them. It is also trained with the task of predicting if the next sentence is a plausible one to follow the current one, i.e., *next sentence prediction*.

These models are equipped with the ability to be adapted or fine-tuned to new tasks, scenarios and languages. As already mentioned earlier, this adaptation process is also referred to as transfer learning. Nowadays, it is a lot less common to train any model from scratch — instead, models trained to fill-in-the-blanks (and other tasks) on billions of words are shared openly and fine-tuned to new scenarios using very little additional data. This is more representative of how humans learn, as we typically make associations to what we already know when faced with new challenges.

Since BERT is a very large model, its large variant being approximately 179 million parameters in size, a number of recent efforts have been aimed at making them smaller and more lightweight. These include ALBERT (Lan et al., 2020), RoBERTa (Liu et al., 2019) and DistilBERT (Sanh et al., 2020). Here, we utilize DistilBERT, which employs a technique known as *knowledge distillation*, to produce smaller distilled versions of ABENA. We also experiment with RoBERTa for training models from scratch.

### 2.2 Static Word Embeddings for Twi

The work by Alabi et al. (2020) constructed static word embeddings for the Twi language. In their work, the researchers made use of two main architectures which analyzed representation of words of the Twi language at both word and character levels, in order to explore the semantics of the language. The two main architectures used were fastText (Bojanowski et al., 2017) and Character Word Embedding (CWE) (Chen et al., 2015). They noted that there is a large amount of ambiguity in the Twi language, hence the decision to choose a CWE architecture.

The authors performed experiments which checked how these architectures performed on three different classes of corpora for the Twi language: i) a clean corpora (Asante Bible), ii) clean plus some noisy corpora (Asante Bible and Twi Wikipedia) and iii) all clean and all noisy corpora (Bible, Wikipedia and JW300 (Agic and Vulić, 2020)). For evaluation, researchers and linguists translated the wordsim-353 (Finkelstein et al., 2001) dataset from English to Twi, with the resulting dataset being a notable contribution. The Spearman $\rho$ correlation between human judgement encoded in this dataset and cosine similarity scores on the wordsim-353 dataset were used as the metric to evaluate these embeddings.

It was discovered that the “clean plus some...
noisy” Twi data gave the best result, as evident by the best correlation with human judgements ($\rho_{\text{CWE}}^2 = 0.437$ vs. $\rho_{\text{fastText}}^2 = 0.388$). As a precursor to the work we report in this paper, we first worked on replicating the fastText component of their results$^1$. While results from training directly on their data was comparable, we were able to improve on the value of $\rho_{\text{fastText}}^2$ by training on the large noisy JW300 corpus only. This yielded a $\rho$ value of 0.421 that is close to the value they achieved with CWE.

3 Dataset

JW300 is a parallel corpus of over 300 languages with around 100 thousand parallel sentences per language pair on average. It spans across 343 languages, and comprises a total of 1,335,376 articles – with a bit over 109 million sentences, and 1.48 billion tokens (Agic and Vulić, 2020). It is a thorough mine of all the publications from the jw.org website. A vast majority of texts come from the magazines Watchtower and Awake! Although the articles emanate from a religious society, they encompass a various range of topics.

JW300 plays a vital role in low-resource language coverage (Orife et al., 2020). For example, OPUS (Tiedemann, 2012), another massive parallel text collection, offers over 100 million English-German parallel sentences, and 1.48 billion tokens (Agic and Vulić, 2020). It is a thorough mine of all the publications from the jw.org website. A vast majority of texts come from the magazines Watchtower and Awake! Although the articles emanate from a religious society, they encompass a various range of topics.

Table 1: Convergence info for ABENA models. All models were trained on a single Tesla K80 GPU on an NC6 Azure VM instance.

| Model            | Epochs/Time | Loss |
|------------------|-------------|------|
| Akuapem (cased)  | 3 epochs, 35 hrs | 0.56 |
| Asante (uncased)| 3 epochs, 1.8 hrs  | 0.95 |

4 ABENA Training Experiment

First, we initialize a BERT neural architecture and corresponding tokenizer to the multilingual BERT (mBERT) checkpoint$^2$. This model checkpoint was trained on over 100 languages simultaneously. Although these did not include any Ghanaian languages, it does include another “Niger-Congo” language — Nigerian Yoruba. It is thus reasonable to expect that this model contains some knowledge useful for constructing a Twi embedding.

We transfer this knowledge by fine-tuning the initialized mBERT weights and tokenizer on the monolingual Twi subset of the JW300 corpus. The convergence info is shown in Table 1. All models were trained on a single Tesla K80 GPU on a single NC6 Azure Virtual Machine instance.

The time to run 3 epochs is significantly shorter for the Asante model because the Asante Twi Bible is significantly smaller than JW300 (25k+ samples versus 600k+ samples). Moreover, note that we further made the Asante model uncased due to this smaller training data size. This just means that the model does not distinguish between upper and lower cases of letters, while the Akuapem model does. We present the final loss value attained for all models, in the absence of any other benchmarks available for the Twi languages. In the final section we will outline some of the things we are doing to address this lack of benchmarks. Recall that the BERT loss is the sum of the “fill-in-the-blanks” and next sentence prediction losses.

Next, we perform the same experiments using the DistilBERT architecture (Sanh et al., 2020) instead of BERT. This yields smaller and more lightweight versions of both the Akuapem and Asante ABENA models. DistilBERT employs a technique known as knowledge distillation to reduce the size of the model while sacrificing little of the performance. If DistilBERT is the distilled version of BERT, then DistilABENA is the distilled version of ABENA.

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$^1$Introducing ABENA (Medium article)

$^2$BERT github repo
Table 2: Convergence info for DistilABENA models. All models were trained on a single Tesla K80 GPU on an NC6 Azure VM instance. “V2” models have tokenizers trained from scratch.

| Model     | Epochs/Time  | Loss |
|-----------|--------------|------|
| Akuapem   | 3 epochs, 26.9 hrs | 0.65 |
| Asante “V2” | 5 epochs, 26.7 hrs | 2.2  |
| Akuapem   | 3 epochs, 1.4 hrs | 1.05 |
| Asante “V2” | 5 epochs, 1.5 hrs | 3.5  |

Table 3: Convergence info for RoBAKO models trained from scratch. All models were trained on a single Tesla K80 GPU on an NC6 Azure VM instance.

| Model     | Epochs/Time  | Loss |
|-----------|--------------|------|
| Akuapem   | 5 epochs, 15.3 hrs | 2.2  |
| Asante    | 5 epochs, 1 hrs  | 3.5  |

6 Simple Examples

6.1 Fill-in-the-blanks

We present two (2) example masked sentences and resulting completions by our model. Several other examples could be experimented within minutes using our Kaggle ABENA usage demo.

```python
# First Sentence
print(fill_mask("Saa tebea yi maa me [MASK]."))
# In English the above sentence reads ("This situation made my father [mask].")

# Second Sentence
print(fill_mask("Eyi de ohaw kese baa [MASK] ho. "))
# In English the above sentence reads ("This presented a difficult problem for [mask]")
```

As you can see, having hosted this on the Hugging Face model repo, the code required to do this is only a few lines. Table 4 and Table 5 display the top 5 completions for the two (2) example masked sentences.

The religious bias is clearly evident. For instance, when completing the sentence “Eyi de ohaw k "bba h", you get completions such as “Eyi de ohaw k "bba Adam h" and/or “Eyi de ohaw k "bba Satan h" among the most likely completions. These indicate a strong level of religious bias as the training dataset emanates from a religious society. Otherwise the completions seem to be reasonable.

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1ABENA usage demo on Kaggle
| Completed Sentence | Score |
|--------------------|-------|
| Saa tebea yi maa me papa no | 0.228 |
| Saa tebea yi maa me papa boom | 0.068 |
| Saa tebea yi maa me papa bio | 0.057 |
| Saa tebea yi maa me papaapa | 0.038 |
| Saa tebea yi maa me papa da | 0.027 |

Table 4: Top five completions for first example sentence

| Completed Sentence                                      | Score |
|---------------------------------------------------------|-------|
| Eyi de ṣhaw krse baa ḥō                                    | 0.171 |
| (This presented a difficult problem for me)              | 0.171 |
| Eyi de ṣhaw krse baa Adam ḥō                               | 0.149 |
| (This presented a difficult problem for Adam)            | 0.149 |
| Eyi de ṣhaw krse baa ne ḥō                                 | 0.113 |
| (This presented a difficult problem for him)             | 0.113 |
| Eyi de ṣhaw krse baa ṣie ḥō                                | 0.053 |
| (This presented a difficult problem for the house)       | 0.053 |
| Eyi de ṣhaw krse baa Satan ḥō                              | 0.047 |
| (This presents a difficult problem for Satan)             | 0.047 |

Table 5: Top Five Completions for the Second Sentence

6.2 Sentiment Classification

In the context of sentiment classification, we built a simple sentiment analysis dataset of just 20 samples and experimented with the features of our model above to solve a classification problem. Detailed Python code and results of the sentiment analysis can be obtained from our ABENA usage demo.

Briefly, we created a balanced dataset of 20 samples – 10 indicating positive sentiment, such as *M’ani agye papa* (I am very happy), and 10 indicating negative sentiment, such as *Sister Akosua adu-ane no nnye dre* (Sister Akosua’s food isn’t good). We train a simple kNN classifier on 14 random subsamples with *sklearn* and test on the remaining 6. In our testing of many repeated runs, we found the accuracy to consistently fall in the 83% to 100% range, and always outperform 50% random chance. Although testing on a bigger dataset is required – an effort currently underway – these results are very promising.

7 Discussion and Conclusion

As we already mentioned, the models show a varying degree of religious bias. For instance when completing a sentence like “Eyi de ṣhaw krse baa ____ ḥō”, you may see completions such as “Eyi de ṣhaw krse baa *Adam* ḥō” and/or “Eyi de ṣhaw krse baa Satan ḥō” among the most likely completions. While these are not technically wrong – they can be useful for understanding sentence structure, part of speech likely to appear in that location, etc. – the fact that these are among the top 5 completions indicates a strong religious bias in the model. This is obviously at least partly due to the religious bias in the data used to train/fine-tune them.

This is the best we could do at the moment, due to the extreme low-resource nature of Twi, and it is clearly already a useful set of models. However, it is very important to communicate that this is a work in progress, and the models should be used with care and awareness of their religious bias.

In an ongoing attempt to reduce the religious bias in the JW300 dataset to a minimum, we have recently curated an English to Akuapem Twi parallel machine translation corpus with 25,421 sentence pairs. The purpose of this dataset is to fine-tune the model further after training it on the JW300 dataset. We are in the process of creating even larger datasets on which we can fine-tune these models further to reduce the bias.

The work we have presented opens up a number of research directions for us to pursue in order to further improve these models, and enable many critical applications. In no particular order, the following list describes these research efforts, some of which are already ongoing.

1. Fine-tuning on cleaner, higher-quality and less-biased Twi data
2. Developing a Twi version of the labeled GLUE Dataset *Wang et al. (2018)* for fine-tuning on many other tasks, such as entailment, sentiment analysis, sentence similarity, etc.
3. Training ALBERT *Lan et al. (2020)* for Twi and comparing with presented models. This architecture promises an even greater size saving than RoBERTa.
4. Unsupervised spell-checking methods based on these models
5. Unsupervised Named Entity Recognition (NER) methods based on these models
6. Developing a Twi version of the GPT *Radford et al. (2018) Radford et al. (2019)* causal transformer-based text generator
7. Developing a labeled Named Entity Recognition (NER) dataset, e.g., a translation of CONLL 2003, and fine-tuning these models on it

8. Incorporating all of the above developments into an open Python API to make all of these Ghanaian NLP tools readily available to NLP developers and practitioners

9. Extending all of the above to other overlooked Ghanaian and African languages

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References

Željko Agic and Ivan Vulic. 2020. Jw300: A wide-coverage parallel corpus for low-resource languages. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3204—3210.

Sungjin Ahn, Heeyoul Choi, Tanel Pärnamaa, and Yoshua Bengio. 2016. A neural knowledge language model. arXiv preprint arXiv:1608.00318.

Jesujoba Alabi, Kwabena Amponsah-Kaakyire, David Adelani, and Cristina Espana-Bonet. 2020. Massive vs. curated embeddings for low-resourced languages: the case of yoruba and twi. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 2754–2762.

Paul Azunre. 2020. Transfer Learning for Natural Language Processing. Manning Publications.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5:135–146.

Qufei Chen and Marina Sokolova. 2018. Word2vec and doc2vec in unsupervised sentiment analysis of clinical discharge summaries. arXiv preprint arXiv:1805.00352.

Xinxiong Chen, Lei Xu, Zhiyuan Liu, Maosong Sun, and Huanbo Luan. 2015. Joint learning of character and word embeddings. In Twenty-Fourth International Joint Conference on Artificial Intelligence.

Kyunghyun Cho, Bart Van Merrienboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1259.

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Yu-An Chung, Wei-Hung Weng, Shrasing Tong, and James Glass. 2018. Unsupervised cross-modal alignment of speech and text embedding spaces. In Advances in neural information processing systems, pages 7354–7364.

Kenneth W Church and William A Gale. 1991. A comparison of the enhanced good-turing and deleted estimation methods for estimating probabilities of english bigrams. Computer Speech & Language, 5(1):19–54.

Scott Deerwester, Susan T Dumais, George W Furnas, Thomas K Landauer, and Richard Harshman. 1990. Indexing by latent semantic analysis. Journal of the American society for information science, 41(6):391–407.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 4171—4186.

Lev Finkelstein, Evgeniy Gabrilovich, Yossi Matias, Ehud Rivlin, Zach Solan, Gadi Wolfman, and Eytan Ruppin. 2001. Placing search in context: The concept revisited. In Proceedings of the 10th international conference on World Wide Web, pages 406–414.

Felix A Gers, Nicol N Schraudolph, and Jürgen Schmidhuber. 2002. Learning precise timing with lstm recurrent networks. Journal of machine learning research, 3(Aug):115–143.

Oluwapelumi Giwa and Marelie H Davel. 2013. N-gram based language identification of individual words. In Pattern Recognition Association of South Africa (PRASA), pages 3204—3210.

Yoav Goldberg and Omer Levy. 2014. word2vec explained: deriving mikolov et al.’s negative-sampling word-embedding method. arXiv preprint arXiv:1402.3722.

Mandy Gu. 2018. Introduction to natural language processing. https://towardsdatascience.com/introduction-to-natural-language-processing-part-1-777f972cc7b3.
Kenneth Heafield, Ivan Pouztyrevsky, Jonathan H Clark, and Philipp Koehn. 2013. Scalable modified kneser-ney language model estimation. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 690–696.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

Xueli Jia, Jianzong Wang, Zhiyong Zhang, Ning Cheng, and Jing Xiao. 2020. Large-scale transfer learning for low-resource spoken language understanding. arXiv preprint arXiv:2008.05671.

Rafal Jozefowicz, Oriol Vinyals, Mike Schuster, Noam Shazeer, and Yonghui Wu. 2016. Exploring the limits of language modeling. arXiv preprint arXiv:1602.02410.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. Albert: A lite bert for self-supervised learning of language representations. In Proceedings of the International Conference on Learning Representations.

Jey Han Lau and Timothy Baldwin. 2016. An empirical evaluation of doc2vec with practical insights into document embedding generation. arXiv preprint arXiv:1607.05368.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Stephen Merity, Nitish Shirish Keskar, and Richard Socher. 2018. An analysis of neural language modeling at multiple scales. arXiv preprint arXiv:1803.08240.

Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černocký, and Sanjeev Khudanpur. 2010. Recurrent neural network based language model. In Eleventh annual conference of the international speech communication association.

Toan Q. Nguyen and David Chiang. 2017. Transfer learning across low-resource, related languages for neural machine translation. arXiv preprint arXiv:1708.09803.

Iroro Orife, Julia Kreutzer, Blessing Sibanda, Daniel Whitenack, Kathleen Siminyu, Laura Martinus, Jamii Toure Ali, Jade Abbott, Vukosi Marivate, Salomon Kabongo, et al. 2020. Masakhane—machine translation for africa. arXiv preprint arXiv:2003.11529.

Keiron O’Shea and Ryan Nash. 2015. An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458.

Matteo Pagliardini, Prakhar Gupta, and Martin Jaggi. 2017. Unsupervised learning of sentence embeddings using compositional n-gram features. arXiv preprint arXiv:1703.02507.

Mikhail Popov, Boris Kuhlitskiy, Igor Perezzhogin, Vladimir Mordkovich, Danila Ovsyannikov, SergeiPerfilov, Ludmila Borisova, and Vladimir Blank. 2018. Catalytic 3d polymerization of c60. Fullerenes, Nanotubes and Carbon Nanostructures, 26(8):465–470.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI Technical Report.

Alex Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. OpenAI Technical Report.

Nihar Ranjan, Kaushal Mundada, Kunal Phaltane, and Saim Ahmad. 2016. A survey on techniques in nlp. International Journal of Computer Applications, 134(8):6–9.

Veselin Raychev, Martin Vechev, and Eran Yahav. 2014. Code completion with statistical language models. In Proceedings of the 35th ACM SIGPLAN Conference on Programming Language Design and Implementation, pages 419–428.

Ronald Rosenfeld. 2000. Two decades of statistical language modeling: Where do we go from here? Proceedings of the IEEE, 88(8):1270–1278.

Roni Rosenfeld. 1996. A maximum entropy approach to adaptive statistical language modeling. Computer Speech & Language, 10:187–228.

Sebastian Ruder, Matthew Peters, Swabha Swayamdipta, and Thomas Wolf. 2019. Transfer learning in natural language processing tutorial. In Proceedings of NAACL HLT 2019: Tutorial Abstracts, pages 15–18.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2020. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Robyn Speer and Joshua Chin. 2016. An ensemble method to produce high-quality word embeddings (2016). arXiv preprint arXiv:1604.01692.

Martin Sundermeyer, Ralf Schlüter, and Hermann Ney. 2012. Lstm neural networks for language modeling. In Thirteenth annual conference of the international speech communication association.

Jörg Tiedemann. 2012. Parallel data, tools and interfaces in OPUS. In Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC-2012), pages 2214–2218, Istanbul, Turkey.
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

A Wang, A. Singh, J. Michael, F. Hill, O. Levy, and S.R. Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP*, pages 353–355.

Wei Xu and Alex Rudnicky. 2000. Can artificial neural networks learn language models? In *Sixth international conference on spoken language processing.*
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