

AraBERT: Transformer-based Model for Arabic Language Understanding

Wissam Antoun*, Fady Baly*, Hazem Hajj

American University of Beirut
{wfa07, fgb06, hh63}@aub.edu.lb

Abstract

The Arabic language is a morphologically rich and complex language with relatively little resources and a less explored syntax compared to English. Given these limitations, tasks like Sentiment Analysis (SA), Named Entity Recognition (NER), and Question Answering (QA), have proven to be very challenging to tackle. Recently, with the surge of transformers based models, language-specific BERT based models proved to have a very efficient understanding of languages, provided they are pre-trained on a very large corpus. Such models were able to set new standards and achieve state-of-the-art results for most NLP tasks. In this paper, we pre-trained BERT specifically for the Arabic language in the pursuit of achieving the same success that BERT did for the English language. We then compare the performance of AraBERT with multilingual BERT provided by Google and other state-of-the-art approaches. The results of the conducted experiments show that the newly developed AraBERT achieved state-of-the-art results on most tested tasks. The pretrained araBERT models are publicly available on github.com/aub-mind/araBERT hoping to encourage research and applications for Arabic NLP.

Keywords: Arabic, transformers, BERT, AraBERT, Language Models

1. Introduction

Pretrained contextualized text representation models have enabled massive advances in Natural Language Understanding (NLU) tasks, and achieved state-of-the-art performances in multiple Natural Language Processing (NLP) tasks (Howard and Ruder, 2018; Devlin et al., 2018). Early pretrained text representation models aimed at representing words by capturing their distributed syntactic and semantic properties using techniques like Word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). However, these models do not incorporate the context in which a word appears into its embedding. This issue was addressed by generating contextualized representations using models like ELMO (Peters et al., 2018)).

Recently, there has been a focus of applying transfer learning by fine-tuning large pretrained language models for downstream NLP/NLU tasks with a relatively small number of examples, resulting in a notable performance improvement on these tasks. This approach takes advantage of the language models that can be pre-trained in an unsupervised manner (or sometimes called self-supervised). However, this advantage comes with drawbacks, particularly the huge corpora needed for pre-training, in addition to the high computational cost of days of training (latest models required 500+ TPUs or GPUs running for weeks (Conneau et al., 2019; Raffel et al., 2019; Adiwardana et al., 2020)). These drawbacks limited the availability of such models to English mainly (and a handful of other languages). To remedy this gap, multilingual models were trained to learn representations for +100 languages simultaneously, but still fall behind single-language models due to low data representation and small language specific vocabulary. While languages with similar structure and vocabulary can benefit from the shared representations (Conneau et al., 2019), this is not the case for other

languages, like Arabic, which differ in morphology and syntactic structure and share very little with other abundant Latin-based languages. This, as a result, handicapped Arabic NLP systems and research.

In this paper, we describe the process of pretraining the BERT transformer model (Devlin et al., 2018) for Arabic language, and which we name ARABERT. We evaluate ARABERT on three Arabic NLU downstream tasks that are different in nature: (i) Sentiment Analysis (SA), (ii) Named Entity Recognition (NER), and (iii) Question Answering (QA). The experiments results show that ARABERT achieves state-of-the-art performances for most tasks, compared to several baselines including previous multilingual and single-language approaches. The datasets that we considered for the downstream tasks demonstrate the superiority of our model in handling dialects that were not seen during the pretraining stage.

Our contributions can be summarized as follows:

- We present a methodology to pretrain the BERT model on a large-scale Arabic corpus.
- We evaluate ARABERT and show its superiority on three NLU downstream tasks: Sentiment Analysis, Named Entity Recognition and Question Answering.
- To elevate the state of Arabic NLP research, we will release ARABERT on popular NLP libraries.

The rest of the paper is structured as follows. Section 2. provides a concise literature review of previous work on language representation for English and Arabic. Section 3. describes the methodology that was used to develop ARABERT. Section 4. describe the downstream tasks and benchmark datasets that are used for evaluation. Section 5. presents the experimental setup and discusses the results. Finally, section 6. concludes and points to possible directions for future work.

*Equal Contribution

2. Related Works

2.1. Evolution of Word Embeddings

Research to finding the most meaningful representations for words started with the word2vec model developed by (Mikolov et al., 2013). Since then, research started moving towards that direction with variations of word2vec of the likes of GloVe (Pennington et al., 2014) and fast-Text (Mikolov et al., 2017), where these embeddings were meant to be fed as inputs to neural networks models. Whereas these models lacked contextualized information, the issue was tackled by ELMO (Peters et al., 2018) providing contextualized word representations. The performance over different tasks improved noticeably, leading the research to building larger structures that have superior word and sentence representations. Ever since, language understanding models have been developed such as ULM-Fit (Howard and Ruder, 2018), BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019), ALBERT (Lan et al., 2019), and T5 (Raffel et al., 2019)

2.2. Non-contextual Representations for Arabic

Following the success of the English word2vec (Mikolov et al., 2013), the same feat was sought by NLP researchers to create language specific embeddings. Arabic word2vec was first attempted by (Soliman et al., 2017), it was then followed by a Fasttext model (Bojanowski et al., 2017) trained on wikipedia data, showing even better performance than what was achieved with word2vec. To tackle dialectal variations in Arabic (Abu Farha and Magdy, 2019) provided the largest Arabic word embeddings trained on 250M tweets.

2.3. Contextualized Representations for Arabic

Walking in the footsteps of English language understanding models, same structures were also used to train Arabic models such as done by hULMonA (ElJundi et al., 2019) using the ULMfit structure. Google then released a multilingual BERT (Devlin et al., 2018) supporting 100+ languages with decent performance boost for most languages included. Although a multilingual model was provided for the public, pre-training monolingual BERT for other languages proved to provide better performance over the multilingual BERT such as Italian BERT Alberto (Polignano et al., 2019) and other publicly available BERTs (Martin et al., 2019; de Vries et al., 2019). However, to the best of our knowledge and at the time of writing, there is no Arabic specific BERT released, which motivates the investigation of pretraining such model.

3. ARABERT: Methodology

In this paper, we develop an Arabic language representation model –leveraging recent advances in language modeling techniques originally developed for English– to improve the state-of-the-art in several Arabic NLU tasks. In particular, we create ARABERT based on the BERT model, a stacked Bidirectional Transformer Encoder (Devlin et al., 2018). This model is widely considered as the basis for most state-of-the-art results in different NLP tasks in several languages. In particular, we use the

BERT-base configuration that has 12 encoder blocks, 768 hidden dimensions, 12 attention heads, 512 maximum sequence length, and a total of $\sim 110M$ parameters¹. We also introduced additional preprocessing prior to the model’s pre-training, in order to better fit the Arabic language. Below, we describe the the pre-training setup, the pre-training dataset that we used to pre-train ARABERT, the proposed Arabic-specific preprocessing, and the fine-tuning process.

3.1. Pre-training Setup

Following the original BERT pre-training objective, we employ the *Masked Language Modeling* (MLM) task by adding whole-word masking; 15% of the N input tokens were selected for replacement. Those tokens are replaced 80% of the times with the [MASK] token, 10% with a random token, and 10% with the original token. Whole-word masking improves the pre-training task by forcing the model to predict the whole word instead of getting hints from parts of the word. We also employ the *Next Sentence Prediction* (NSP) task that helps the model understand the relationship between two sentences, which can be useful for many language understanding tasks such as Question Answering.

3.2. Pre-training Dataset

The original BERT was trained on 3.3B words extracted from English Wikipedia and the Book Corpus (Zhu et al., 2015). Since the Arabic Wikipedia Dumps are small compared to the English ones, we manually scraped Arabic news websites for articles. In addition, we used two publicly available large Arabic corpora: (1) the 1.5 billion words Arabic Corpus (El-Khair, 2016), which is a contemporary corpus that includes more than 5 million articles extracted from ten major news sources covering 8 countries, and (2) OSIAN: the Open Source International Arabic News Corpus (Zeroual et al., 2019) that consists of 3.5 million articles ($\sim 1B$ tokens) from 31 news sources in 24 Arab countries.

The final size of the pre-training dataset, after removing duplicate sentences, is 70 million sentences, corresponding to $\sim 24GB$ of text. This dataset covers news from different media in different Arab regions, and therefore can be representative of a wide range of topics discussed in the Arab world. It is worth mentioning that we preserved words that include Latin characters, since it is common to mention named entities, scientific or technical terms in their original language, thus excluding will result in significant information loss.

3.3. Sub-Word Units Segmentation

Arabic language is known for its lexical sparsity, i.e., words can have different forms and share the same meaning, which is mainly due to the complex concatenative system of Arabic (Al-Sallab et al., 2017). For instance, while the definite article “ال - Al”, which is equivalent to “the” in English, is always prefixed to another word, it is not an intrinsic part of that word. Hence, when using a BERT-compatible tokenization, tokens will appear twice, once

¹Further details about the transformer architecture can be found in (Vaswani et al., 2017)

with “*Al-*” and once without it. For instance, both “*كتاب-kitAb*” and “*الكتاب-AlkitAb*” need to be included in the vocabulary, leading to a significant amount of unnecessary redundancy.

To avoid this issue, we segmented the words using Farasa (Abdelali et al., 2016) into stems, prefixes and suffixes. For instance, “*اللغة - Alloga*” becomes “*Al+ log +a*”. Then, we trained the SentencePiece (Kudo, 2018), in unigram mode, on the segmented pre-training dataset to produce a vocabulary of $\sim 60K$ tokens. To evaluate the impact of the proposed tokenization, we also trained SentencePiece on non-segmented text to create a second version of ARABERT (AraBERTv0.1) that does not require any segmentation. The final size of vocabulary was 64k tokens, which included nearly 4K unused tokens to allow further pre-training, if needed.

3.4. Fine-tuning

To fine-tune AraBERT for sequence classification, we take the final hidden state of the first token, which corresponds to the word embedding of the special “[CLS]” token prepended to the start of each sentence. We then add a simple feed-forward layer with standard Softmax to get the probability distribution over the predicted output classes. During fine-tuning, the classifier and the pre-trained model weights are trained jointly to maximize the log-probability of the correct class.

4. Evaluation

We evaluated ARABERT on three Arabic language understanding downstream tasks: Sentiment Analysis, Named Entity Recognition, and Question Answering. As a baseline, we compared ARABERT to the multilingual version of BERT, and to other state-of-art results on each task.

4.1. Sentiment Analysis

We evaluated ARABERT on the following Arabic sentiment datasets that cover different genres, domains and dialects.

- **HARD:** The Hotel Arabic Reviews Dataset (Elnagar et al., 2018) contains 93,700 hotel reviews written in both Modern Standard Arabic (MSA) and in dialectal Arabic. Reviews were split into positive and negative reviews, where a negative review has a rating of 1 or 2 over 5, positive review has a rating of 4 or 5, and neutral reviews with rating of 3 were ignored.
- **ASTD:** The Arabic Sentiment Twitter Dataset (Nabil et al., 2015) contains 10,000 tweets written in both MSA and Egyptian dialect. We tested

on the balanced version of the dataset, referred to as ASTD-B.

- **ArSenTD-Lev:** The Arabic Sentiment Twitter Dataset for LEVantine (Baly et al., 2018) contains 4,000 tweets written in Levantine dialect with annotations for sentiment, topic and sentiment target. This is a challenging dataset as the collected tweets are from multiple domains and discuss different topics.
- **LABR:** The Large-scale Arabic Book Reviews dataset (Aly and Atiya, 2013) contains 63,000 book reviews written in Arabic. The reviews are rated between 1 and 5. We benchmarked our model on the unbalanced two-class dataset, where reviews with ratings of 1 or 2 are considered negative, while those with ratings of 4 or 5 are considered positive.
- **AJGT:** The Arabic Jordanian General Tweets dataset (Alomari et al., 2017) contains 1,800 tweets written in Jordanian dialect. The tweets were manually annotated as either positive or negative.

Baselines Sentiment Analysis is a popular Arabic NLP task. Early approaches relied on sentiment lexicons such as ArSenL (Badaro et al., 2014), which is a large-scale lexicon of MSA words that is developed using the Arabic WordNet in combination with the English SentiWordNet. Recurrent and recursive neural networks were explored with different choices of Arabic-specific processing (Al Sallab et al., 2015; Al-Sallab et al., 2017; Baly et al., 2017). Convolutional Neural Networks (CNN) were trained with pre-trained word embeddings (Dahou et al., 2019a). A hybrid model was proposed by (Abu Farha and Magdy, 2019), where CNNs were used for feature extraction, and LSTMs were used for sequence and context understanding. Current state-of-the-art results are achieved by the hULMonA model (ElJundi et al., 2019), which is an Arabic language model that is based on the ULMfit architecture (Howard and Ruder, 2018). We compare the results of ARABERT to those of hULMonA.

4.2. Named Entity Recognition

This task aims to extract and detect named entities that are mentioned in the text. It is framed as a word-level classification (or tagging) task, where the classes correspond to pre-defined categories such as names, locations, organizations, events and time expressions. For evaluation, we use the Arabic NER corpus (ANER-corp) (Benajiba and Rosso, 2007). This dataset contains 16.5K entity mentions distributed among 4 entities categories, *person* (39%), *organization*: (30.4%), *location*: (20.6%), and *miscellaneous*: (10%).

Baselines Advances in the NER task have been focusing on English, namely on the CoNLL 2003 (Sang and De Meulder, 2003) dataset. Initially, NER was tackled with Conditional Random Fields (CRF) (Lafferty et al., 2001). Later on, CRFs were used on top of Bi-LSTM models (Huang et al., 2015; Lample et al., 2016) presenting significant improvements

over standalone CRFs. Bi-LSTM-CRF structures were then used with contextualised embeddings that even displayed further improvements (Peters et al., 2018). Lastly, large pre-trained transformers showed slight improvement, setting the current state-of-the-art performance (Devlin et al., 2018). As for Arabic, We compare ARABERT performance with Bi-LSTM-CRF baseline that set the previous state-of-the-art performance (El Bazi and Laachfoubi, 2019), and with BERT multilingual.

4.3. Question Answering

Open-domain Question Answering (QA) is one of the goals of artificial intelligence, this goal can be achieved by leveraging natural language understanding and knowledge gathering (Kwiatkowski et al., 2019). English QA research has been fueled by the release of large datasets such as Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al., 2016). On the other hand, research in Arabic QA has been hindered by the lack of such massive datasets, and by the fact that Arabic presents its own challenges such as:

- Inconsistent name spelling (ex: Syria in Arabic can be written as “سوريا - *sOriyA*” and “سورية - *sOriyT*”)
- Name de-spacing (ex: The name is written as “عبدالعزیز - *AbdulAzIz*” in the question, and “عبدالعزیز - *Abdul AzIz*” in the answer)
- Dual form “المثنى”, which can have multiple forms (ex: “قلمان” - “*qalamAn*” or “قلمين” - “*qalamyn*” meaning “two pencils”)
- Grammatical gender variation: all nouns, animate and inanimate objects are classified under two genders either masculine or feminine (ex: “كبير” - “*kabIr*” and “كبيرة” - “*kabIrT*”)

We evaluate ARABERT on the Arabic Reading Comprehension Dataset (ARCD) (Mozannar et al., 2019) , where the task is to find the span of the answer in a document for a given question. ARCD contains 1395 questions on Wikipedia articles along with 2966 machine translated questions and answers from the SQuAD dubbed (Arabic-SQuAD). We follow the authors, and train on the whole Arabic-SQuAD and on the training set of ARCD (50% split) and test on the remainig 50% of ARCD.

Baselines The authors reports that Multilingual BERT achieved state of the art results on ARCD.

5. Experiments

5.1. Experimental Setup

Pretraining In our experiments, we used the original implementation of BERT on TensorFlow. The data for pre-training was sharded, transformed into TFRecords, and

then stored on Google Cloud Storage. We used a duplication factor of 10, a random seed of 34, and a masking probability of 15%. We pre-trained our model on a TPUv2-8 pod for 1,250,000 steps. To speed up the training time, we trained the first 900K steps on sequences of 128 tokens, and the remaining steps are trained on sequences of 512 tokens. The decision of stopping the pre-training was based on performance on downstream tasks (we follow the same approach taken by the open-sourced German BERT (DeepsetAI,)), We use Adam optimizer with learning rate of 1e-4, batch size of 512 and 128 for sequence length of 128 and 512 respectively. Training took 4 days, for 27 epochs over all the tokens.

Fine-tuning We independently fine-tune using the same configuration for all tasks (we do not run extensive grid search for the best hyper-parameters due to computational and time constraints). We use the splits provided by the dataset’s authors when available. and the standard 80% and 20% when not².

5.2. Results

Table 1 illustrates the experimental results of applying AraBERT to multiple Arabic NLU downstream tasks, compared to state-of-the-art results and the multilingual BERT model (mBERT).

Sentiment Analysis For Arabic sentiment analysis, the results in Table 1 show that both versions of AraBERT outperform mBERT and other state-of-the-art approaches on most tested datasets. Even though AraBERT was trained on MSA, the model was able to preform well on dialects that were never seen before.

Table 1: Performance of AraBERT on Arabic downstream tasks compared to mBERT and previous state of the art systems

Task	metric	prev. SOTA	mBERT	AraBERTv0.1/ v1
SA (HARD)	Acc.	95.7*	95.7	96.2 / 96.1
SA (ASTD)	Acc.	86.5*	80.1	92.2 / 92.6
SA (ArsenTD-Lev)	Acc.	52.4*	51.0	58.9 / 59.4
SA (AJGT)	Acc.	92.6**	83.6	94.1 / 93.8
SA (LABR)	Acc.	87.5 [†]	83.0	85.9 / 86.7
NER (ANERcorp)	macro-F1	81.7 ^{††}	78.4	84.2 / 81.9
QA (ARCD)	Exact Match	mBERT	34.2	30.1 / 30.6
	macro-F1		61.3	61.2 / 62.7
	Sent. Match		90.0	93.0 / 92.0

* (ElJundi et al., 2019)

** (Dahou et al., 2019b)

[†] (Dahou et al., 2019b)

^{††} Previous state of the art performance by BiLSTM-CRF model

Named Entity Recognition Results in Table 1 show that AraBERTv0.1 improved results by 2.53 points in F1 score scoring 84.2 compared with the Bi-LSTM-CRF model, making AraBERT the new state-of-the-art for NER on ANERcorp. Testing AraBERT with tokenized suffixes and prefixes, we got results similar to that of the Bi-LSTM-CRF model. We believe that the reason this happened is because the start token (B-label) is referenced to the suffixes most

²The scripts used to create the datasets are available on our Github repo <https://github.com/aub-mind/arabert>

of the time. An example of this, “الجامعة” with a label B-ORG becomes “ال”, “جامعة” with labels B-ORG, I-ORG respectively, providing misleading starting cues to the model. Testing multilingual BERT, it proved inefficient as we got results lower than the baseline model.

Question Answering While the results in Table 1 show an improvement in F1-score, the exact match scores were significantly lower. Upon further examination of the results, we noticed that the majority of the erroneous answers differed from the true answer by one or two words with no significant impact on the semantics of the answer. Examples are shown in Tables 2 and 3. We also report a 2% absolute increase in the sentence match score over mBERT, which is the previous state-of-the-art. Sentence Match (SM) measures the percentage of predictions that are within the same sentence as the ground truth answer.

Table 2: Example of an erroneous results from the ARCD test set: the only difference is the preposition “في - In”.

Question	أين تأسست منظمة الأمم المتحدة؟ where was the united nations established?
Ground Truth	في سان فرانسيسكو - In San Francisco
Predicted Answer	سان فرانسيسكو - San Francisco

Table 3: Another example of an erroneous results from the ARCD test set: the predicted answer does not include “introductory” words.

Question	ما هو النظام الخاص بدولة النمسا؟ What is the type of government in Austria?
Ground Truth	النمسا هي جمهورية فيدرالية - Austria is a federal republic
Predicted Answer	جمهورية فيدرالية - A federal republic

5.3. Discussion

AraBERT achieved state-of-the-art performance on sentiment analysis, named entity recognition, and the question answering tasks. This adds truth to the assumption that pre-trained language models on a single language only surpasses the performance of a multilingual model. This jump in performance have many explanations. First, data size is a clear factor for the boost in the performance. AraBERT used around 24GB of data in comparison with the 4.3G Wikipedia used for the multilingual BERT. Second, the vocab size used in the multilingual BERT is 2k tokens in comparison with 64k vocab size we used for developing AraBERT. Third, with the large data size, the pre-training distribution has more diversity. Fourth, the pre-processing applied on the pre-training data took into consideration the complexities of the arabic language. Hence, reducing the required vocab size by excluding unnecessary redundant tokens that come with certain common prefixes, and help the model learn better by reducing the language complexity. We believe these factors helped reaching state-of-the-art results on 3 different tasks and 8 different datasets. Obtained results indicate that the advantage we got in the datasets

considered are better understood in a monolingual model than of a general language models trained on Wikipedia crawls such as multilingual BERT.

6. Conclusion

AraBERT sets new state-of-the-art for several downstream tasks for Arabic language. It is also 300MB smaller than multilingual BERT. By publicly releasing our AraBERT models, we hope that it will be used to serve as the new baseline for the various Arabic NLP tasks, and hope that this work will act as a footing stone to building and improving future Arabic language understanding models. We are currently working on publishing an AraBERT version that won’t depend on external tokenizers. We are also in the process of training models with better understanding of the various dialects that the Arabic language have across different Arabic countries.

7. Acknowledgments

We would like to express special thanks to Dr. Ramy Baly (Massachusetts Institute of Technology) for the useful discussions and suggestions, to Dr. Dirk Goldhahn (Universität Leipzig) for access to the OSIAN dataset, to TFRC for the free access to cloud TPUs, and to As-Safir newspaper, and Yakshof for providing us with their news articles.

8. References

- Abdelali, A., Darwish, K., Durrani, N., and Mubarak, H. (2016). Farasa: A fast and furious segmenter for arabic. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations*, pages 11–16.
- Abu Farha, I. and Magdy, W. (2019). Mazajak: An online Arabic sentiment analyser. In *Proceedings of the Fourth Arabic Natural Language Processing Workshop*, pages 192–198, Florence, Italy, August. Association for Computational Linguistics.
- Adiwardana, D., Luong, M.-T., So, D. R., Hall, J., Fiedel, N., Thoppilan, R., Yang, Z., Kulshreshtha, A., Nemade, G., Lu, Y., and Le, Q. V. (2020). Towards a human-like open-domain chatbot.
- Al Sallab, A., Hajj, H., Badaro, G., Baly, R., El-Hajj, W., and Shaban, K. (2015). Deep learning models for sentiment analysis in arabic. In *Proceedings of the second workshop on Arabic natural language processing*, pages 9–17.
- Al-Sallab, A., Baly, R., Hajj, H., Shaban, K. B., El-Hajj, W., and Badaro, G. (2017). Aroma: A recursive deep learning model for opinion mining in arabic as a low resource language. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, 16(4):1–20.
- Alomari, K. M., ElSherif, H. M., and Shaalan, K. (2017). Arabic tweets sentimental analysis using machine learning. In *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pages 602–610. Springer.
- Aly, M. and Atiya, A. (2013). LABR: A large scale Arabic book reviews dataset. In *Proceedings of the 51st Annual*

- Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 494–498, Sofia, Bulgaria, August. Association for Computational Linguistics.
- Badaro, G., Baly, R., Hajj, H., Habash, N., and El-Hajj, W. (2014). A large scale arabic sentiment lexicon for arabic opinion mining. In *Proceedings of the EMNLP 2014 workshop on arabic natural language processing (ANLP)*, pages 165–173.
- Baly, R., Hajj, H., Habash, N., Shaban, K. B., and El-Hajj, W. (2017). A sentiment treebank and morphologically enriched recursive deep models for effective sentiment analysis in arabic. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, 16(4):1–21.
- Baly, R., Khaddaj, A., Hajj, H., El-Hajj, W., and Shaban, K. B. (2018). Arsentd-lev: A multi-topic corpus for target-based sentiment analysis in arabic levantine tweets. In *OSACT 3: The 3rd Workshop on Open-Source Arabic Corpora and Processing Tools*, page 37.
- Benajiba, Y. and Rosso, P. (2007). Anersys 2.0: Conquering the ner task for the arabic language by combining the maximum entropy with pos-tag information. In *IICAI*, pages 1814–1823.
- Bojanowski, P., Grave, E., Joulin, A., and Mikolov, T. (2017). Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146.
- Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., and Stoyanov, V. (2019). Unsupervised cross-lingual representation learning at scale.
- Dahou, A., Elaziz, M. A., Zhou, J., and Xiong, S. (2019a). Arabic sentiment classification using convolutional neural network and differential evolution algorithm. *Computational intelligence and neuroscience*, 2019.
- Dahou, A., Xiong, S., Zhou, J., and Elaziz, M. A. (2019b). Multi-channel embedding convolutional neural network model for arabic sentiment classification. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, 18(4):1–23.
- de Vries, W., van Cranenburgh, A., Bisazza, A., Caselli, T., van Noord, G., and Nissim, M. (2019). Bertje: A dutch bert model. *arXiv preprint arXiv:1912.09582*.
- DeepsetAI.). Open sourcing german bert.
- Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- El Bazi, I. and Laachfoubi, N. (2019). Arabic named entity recognition using deep learning approach. *International Journal of Electrical & Computer Engineering* (2088-8708), 9(3).
- El-Khair, I. A. (2016). 1.5 billion words arabic corpus. *arXiv preprint arXiv:1611.04033*.
- ElJundi, O., Antoun, W., El Droubi, N., Hajj, H., El-Hajj, W., and Shaban, K. (2019). hulmona: The universal language model in arabic. In *Proceedings of the Fourth Arabic Natural Language Processing Workshop*, pages 68–77.
- Elnagar, A., Khalifa, Y. S., and Einea, A. (2018). Hotel arabic-reviews dataset construction for sentiment analysis applications. In *Intelligent Natural Language Processing: Trends and Applications*, pages 35–52. Springer.
- Howard, J. and Ruder, S. (2018). Universal language model fine-tuning for text classification. *arXiv preprint arXiv:1801.06146*.
- Huang, Z., Xu, W., and Yu, K. (2015). Bidirectional lstm-crf models for sequence tagging. *arXiv preprint arXiv:1508.01991*.
- Kudo, T. (2018). Subword regularization: Improving neural network translation models with multiple subword candidates.
- Kwiatkowski, T., Palomaki, J., Redfield, O., Collins, M., Parikh, A., Alberti, C., Epstein, D., Polosukhin, I., Kellecey, M., Devlin, J., Lee, K., Toutanova, K. N., Jones, L., Chang, M.-W., Dai, A., Uszkoreit, J., Le, Q., and Petrov, S. (2019). Natural questions: a benchmark for question answering research. *Transactions of the Association of Computational Linguistics*.
- Lafferty, J. D., McCallum, A., and Pereira, F. C. (2001). Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *ICML*.
- Lample, G., Ballesteros, M., Subramanian, S., Kawakami, K., and Dyer, C. (2016). Neural architectures for named entity recognition. *arXiv preprint arXiv:1603.01360*.
- Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., and Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations.
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., and Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach.
- Martin, L., Muller, B., Suárez, P. J. O., Dupont, Y., Romary, L., Éric Villemonte de la Clergerie, Seddah, D., and Sagot, B. (2019). Camembert: a tasty french language model.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.
- Mikolov, T., Grave, E., Bojanowski, P., Puhersch, C., and Joulin, A. (2017). Advances in pre-training distributed word representations. *arXiv preprint arXiv:1712.09405*.
- Mozannar, H., Maamary, E., El Hajal, K., and Hajj, H. (2019). Neural arabic question answering. In *Proceedings of the Fourth Arabic Natural Language Processing Workshop*, pages 108–118.
- Nabil, M., Aly, M., and Atiya, A. (2015). ASTD: Arabic sentiment tweets dataset. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 2515–2519, Lisbon, Portugal, September. Association for Computational Linguistics.
- Pennington, J., Socher, R., and Manning, C. (2014). Glove: Global vectors for word representation. In *Pro-*

- ceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.
- Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. (2018). Deep contextualized word representations. In *Proceedings of NAACL-HLT*, pages 2227–2237.
- Polignano, M., Basile, P., de Gemmis, M., Semeraro, G., and Basile, V. (2019). ALBERTo: Italian BERT Language Understanding Model for NLP Challenging Tasks Based on Tweets. In *Proceedings of the Sixth Italian Conference on Computational Linguistics (CLiC-it 2019)*, volume 2481. CEUR.
- Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., and Liu, P. J. (2019). Exploring the limits of transfer learning with a unified text-to-text transformer.
- Rajpurkar, P., Zhang, J., Lopyrev, K., and Liang, P. (2016). Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*.
- Sang, E. F. and De Meulder, F. (2003). Introduction to the conll-2003 shared task: Language-independent named entity recognition. *arXiv preprint cs/0306050*.
- Soliman, A. B., Eissa, K., and El-Beltagy, S. R. (2017). Aravec: A set of arabic word embedding models for use in arabic nlp. *Procedia Computer Science*, 117:256–265.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need.
- Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R., and Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding.
- Zeroual, I., Goldhahn, D., Eckart, T., and Lakhouaja, A. (2019). OSIAN: Open source international Arabic news corpus - preparation and integration into the CLARIN-infrastructure. In *Proceedings of the Fourth Arabic Natural Language Processing Workshop*, pages 175–182, Florence, Italy, August. Association for Computational Linguistics.
- Zhu, Y., Kiros, R., Zemel, R., Salakhutdinov, R., Urtasun, R., Torralba, A., and Fidler, S. (2015). Aligning books and movies: Towards story-like visual explanations by watching movies and reading books.