Abstract

Advances in English language representation enabled a more sample-efficient pre-training task by Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA). Which, instead of training a model to recover masked tokens, it trains a discriminator model to distinguish true input tokens from corrupted tokens that were replaced by a generator network. On the other hand, current Arabic language representation approaches rely only on pretraining via masked language modeling. In this paper, we develop an Arabic language representation model, which we name ARAELECTRA. Our model is pretrained using the replaced token detection objective on large Arabic text corpora. We evaluate our model on two Arabic reading comprehension tasks, and we show that ARAELECTRA outperform current state-of-the-art Arab ic language representation models given the same pretraining data and with even a smaller model size.

1 Introduction

Recently, pre-trained language representation models have demonstrated state-of-the-art performance on multiple NLP tasks and in different languages. Pre-training is commonly done via Masked Language Modeling (MLM) (Devlin et al., 2019; Liu et al., 2019; Conneau et al., 2019), where an input sequence has some of its tokens randomly hidden and the model is tasked to recover the original masked tokens. While this approach has proven successful, recent works have shown that MLM is not sample-efficient (Clark et al., 2020b), since the network only learns from the small subset of masked tokens per sequence (15% of the tokens in BERT). Clark et al. (2020b) proposed an approach called Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA). The method uses a pre-training technique based on replaced token detection (RTD) task is more efficient than MLM, and thus achieved state-of-the-art results on English benchmarks. Replaced token detection is a pretraining task where a model is tasked to distinguish true input tokens from synthetically generated ones. RTD solves the issue of the mismatch created in MLM, where the model only sees the [MASK] token during pretraining but not during fine-tuning. In ELECTRA, a small masked language generator network \( G \) is used to generate used to generate the corrupted tokens, and BERT-based discriminator model \( D \) predicts for whether a token is an original or a replacement.

Current state-of-the-art language representation models for Arabic employ MLM as a pretraining objective (Antoun et al., 2020; Safaya et al., 2020; Lan et al., 2020; Abdul-Mageed et al., 2020; Chowdhury et al., 2020). In this paper, we describe the process of pretraining a transformer encoder model for Arabic language understanding using the RTD objective, which we call ARAELECTRA. We also evaluate ARAELECTRA on Arabic reading comprehension and show empirically that ARAELECTRA outperforms current state-of-the-art Arabic pretrained models.

Our contributions can be summarized as follows:

- Pretraining the ELECTRA model on a large-scale Arabic corpus.
- Reaching a new state-of-the-art in Arabic question answering.
- Publicly releasing ARAELECTRA on popular NLP libraries.

The rest of the paper is organized as follows. Section 2 provides a review of previous Arabic language representation literature. Section 3 details the methodology used in developing ARAELECTRA. Section 4 describes the experimental setup, evaluation procedures, and experiment results. Finally, we conclude in Section 5.
2 Related Works

Recently, work on Arabic language representation have been on the rise due to the performance benefits that transfer learning approaches have achieved. Early transfer learning approaches in Arabic relied on using pre-trained word embeddings i.e. AraVec (Soliman et al., 2017). Model-level transfer learning was shown to work on Arabic with hULMonA (ElJundi et al., 2019), a recurrent neural network based language modeling approach. Antoun et al. (2020) and Safaya et al. (2020) improved on hULMonA, and pre-trained transformer-based models with MLM with large scale Arabic corpora. Other approaches addressed issues with the early BERT-based models such as, training on code-switched English-Arabic corpora to improve performance on information retrieval tasks (Lan et al., 2020), and training on dialectal Arabic (DA) corpora to address the domain miss-match between MSA and DA during pretraining and fine-tuning (Abdul-Mageed et al., 2020; Chowdhury et al., 2020).

We hence propose an Arabic ELECTRA-based language representation model pretrained using the RTD objective on large MSA corpora.

3 ARAELECTRA: Methodology

In this paper, we develop an ELECTRA-based Arabic language representation model to improve the state-of-the-art in Arabic reading comprehension. We create ARAELECTRA a bidirectional transformer encoder model with 12 encoder layers, 12 attention heads, 768 hidden size and 512 maximum input sequence length for a total of 136M parameters. The pretraining setup and dataset of ARAELECTRA are described in the following sections.

3.1 Pre-training Setup

While ARABERT was trained using the MLM objective, ARAELECTRA is pretrained using the RTD objective. The RTD approach trains two neural network models, a generator $G$ and a discriminator $D$ or ARAELECTRA, as shown in Figure 1. $G$ takes a corrupted input sequence, where random tokens are replaced with the $[\text{MASK}]$ token, and learns to predict the original tokens that have been masked. The generator network $G$ is in our case a small BERT model with 12 encoder layers, 4 attention heads, and 256 hidden size\(^1\). The discriminator network $D$ then takes as input the recovered sequence from the output of $G$ and tries to predict which tokens were replaced and which tokens are from the original text.

While this approach may look like a generative adversarial network (GAN) (Goodfellow et al., 2014), the generator network is trained with maximum-likelihood instead of adversarial training to fool the discriminator, and the input to the generator is not a random noise vector.

3.2 Pretraining Dataset

We chose to pretrain on the same dataset as ARABERTv0.2 (Antoun et al., 2020), which makes the comparison between models fair. The dataset is a collections of the Arabic corpora list below:

- The OSCAR corpus (Ortiz Suárez et al., 2020), with inappropriate content filtering.
- The 1.5B words Arabic Corpus (El-Khair, 2016).

\(^1\)in the generator, the input embeddings of size 768 are first projected into the generator hidden size with the addition of a linear layer.
The Arabic Wikipedia dump from September 2020.

• The OSIAN corpus (Zeroual et al., 2019).
• News articles provided by As-Safir newspaper.

The total size of the training dataset is 77GB or 8.8 billion words, and comprises of mostly news articles. For validation, we use new Wikipedia articles that were published after the September 2020 dump.

For tokenization, we use of the same wordpiece vocabulary from AraBERTv0.2.

3.3 Fine-tuning

Since the discriminator network has the same architecture and layers as a BERT model, we add a linear classification layer on top of ELECTRA’s output, and fine-tune the whole model with the added layer on new tasks.

We chose question answering as a fine-tuning task since this task represents the model’s reading comprehension capabilities. The datasets of choice are ARCD (Mozannar et al., 2019) and the TyDiQA (Clark et al., 2020a). Both datasets follow the SQuAD (Rajpurkar et al., 2016) format where the model is required to extract the span of the answer given a question and a context.

We evaluate our model against a collection of Arabic transformer models that were trained on the same datasets.

• AraBERTv0.1&v1 (Antoun et al., 2020).
• AraBERTv0.2&v2-base, large (Antoun et al., 2020).
• Arabic-BERT base, medium, large (Safaya et al., 2020).
• Arabic-ALBERT base, large, xlarge².

4 Experiments and Evaluation

4.1 Experimental Setup

Pretraining For pretraining, we mask 15% of the 512 input tokens. We pretrain the model for 2 million steps with a batch size of 256. Pretraining took 24 days to finish on a TPUv3-8 slice. Learning rate was set to 2e-4, with 10000 warm-up steps.

Fine-tuning We fine-tuned all the models with batch size set to 32, maximum sequence length of 384, and a stride of 128. We only experimented with the following learning rates [2e-5, 3e-5, 5e-5], since model specific hyper-parameter optimization is computationally expensive.

4.2 Evaluation

The ARCD (Mozannar et al., 2019) training set consists of 48344 machine translated questions and answers from English, with 693 questions and answers from the ARCD set. We test on the remaining 702 questions from the ARCD set.

From the TyDiQA (Clark et al., 2020a) we chose the Arabic examples from the training and development sets of subtask 2, for a total of 14508 pairs for training and 921 pairs for testing.

4.3 Results

Experiments results are shown in Table 1, where it shows that AraELECTRA achieved much higher exact match and F1-score on both datasets than AraBERTv0.2-base pretrained on the same data. AraELECTRA also greatly improved on AraBERTv0.2-large and all Arabic-ALBERT variants on TyDiQA, but only fell short to Arabic-ALBERT-xlarge, a model 4 times its size, in exact match scores on ARCD.

These results clearly demonstrates that ELECTRA’s RTD objective achieves higher accuracy and improved semantic representation compared to MLM.

5 Conclusion

In this paper, we showed that pretraining using the RTD objective on Arabic text is more efficient and produces pretrained language representation models better than the MLM objective. Our AraELECTRA model improves the state-of-the-art for

Table 1: Results on TyDiQA and ARCD

| Model | TyDiQA | ARCD |
|-------|--------|------|
|       | EM     | F1   | EM   | F1   |
| AraBERTv0.1 | 58.31  | 78.91| 31.62| 67.45|
| AraBERTv1 | 61.11  | 79.36| 31.7 | 67.81|
| AraBERTv0.2-base | 60.67  | 79.63| 32.76| 66.53|
| AraBERTv2-base | 61.67  | 81.66| 31.34| 67.23|
| AraBERTv2-large | 59.61  | 80.16| 33.62| 66.59|
| Arabic-BERT-base | 57.00  | 77.53| 30.48| 62.24|
| Arabic-BERT-large | 59.17  | 80.86| 33.33| 67.28|
| Arabic-ALBERT-base | 56.13  | 77.91| 30.91| 61.33|
| Arabic-ALBERT-large | 57.33  | 77.02| 34.19| 65.41|
| Arabic-ALBERT-xlarge | 61.02  | 80.56| 37.75| 68.03|
| AraELECTRA | 65.91  | 83.65| 35.33| 68.57|

²https://github.com/KUIS-AI-Lab/Arabic-ALBERT/
Arabic Question Answering, and achieves higher performance compared to other models pretrained with the same dataset and with larger model sizes. Our model will be publicly available, along with our pretraining and finetuning code, in our repository github.com/aub-mind/arabert/araelectra.

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