JABER: Junior Arabic BERT
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Abstract
Language-specific pre-trained models have proven to be more accurate than multilingual ones in a monolingual evaluation setting. Arabic is no exception. However, we found that previously released Arabic BERT models were significantly under-trained. In this technical report, we present JABER, Junior Arabic BERT, our pretrained language model prototype dedicated for Arabic. We conduct an empirical study to systematically evaluate the performance of models across a diverse set of existing Arabic NLU tasks. Experimental results show that JABER achieves the state-of-the-art performances on ALUE, a new benchmark for Arabic Language Understanding Evaluation, as well as on a well-established NER benchmark.

1 Introduction
Transformer-based (Vaswani et al., 2017) pre-trained language models (PLMs) such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), XLNET (Yang et al., 2019), T5 (Raffel et al., 2019) have shown great success in the field of natural language understanding (NLU). These large-scale models are first pre-trained on a massive amount of unlabeled data, and then fine-tuned on downstream tasks.

Recently, it has become increasingly common to pre-train a language-specific model such as for Chinese (Wei et al., 2019; Sun et al., 2019, 2020, 2021; Zeng et al., 2021), French (Martin et al., 2019; Le et al., 2020), German (Chan et al., 2020), Spanish (Canete et al., 2020), Dutch (de Vries et al., 2019), Finnish (Virtanen et al., 2019), Croatian (Ulčar and Robnik-Šikonja, 2020), and Arabic (Antoun et al., 2020; Safaya et al., 2020; Abdul-Mageed et al., 2021), to name a few. These models have been reported more accurate than multilingual ones, like mBERT (Devlin et al., 2019) and XLM-RoBERTa (Conneau et al., 2020), when evaluated in a monolingual setting.

However, the abundant emergence of such models has made it difficult for researchers to compare between them and measure the progress without a systematic and modern evaluation technique (Gorman and Bedrick, 2019; Schwartz et al., 2020). To address this issue, there has been a number of efforts to create benchmarks that gather representative set of standard tasks, where systems are ranked in an online leaderboard based on a private test set. GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019) were first proposed for English, which were expanded later to other languages like CLUE (Xu et al., 2020) and FewCLUE (Xu et al., 2021) for Chinese, RussianSuperGLUE (Shavrina et al., 2020), and ALUE (Seelawi et al., 2021) for Arabic. These benchmarks have played a critical role for driving fields forward by facilitating the comparison between models (Ruder, 2021).

In this technical report, we revisit the standard pre-training recipe of BERT (Devlin et al., 2019) by exploring recently suggested tricks and techniques such as BBPE tokenization (Wei et al., 2021) and substantial data cleaning (Raffel et al., 2019; Brown et al., 2020). We introduce JABER, a Junior (12-layer) Arabic BERT model.

Through extensive experiments, we systematically evaluate five Arabic BERT models by assessing their performance on the ALUE benchmark. The results can serve as an indicator to track the progress pre-trained models for Arabic NLU. Experimental results show that JABER outperforms ARBERT¹ (Abdul-Mageed et al., 2021) by 2% on ALUE and reports the new state-of-the-art perfor-

¹The best existing 12 layers Arabic BERT model of the same size and architecture as JABER.
AraBERT and MARBERT didn’t provide their data duplication factor.

The remainder of the report is organized as follows. We discuss topics related to our work in Section 2. We describe the process for pre-training JABER in Section 3. An evaluation of six Arabic BERT models on the ALUE benchmark, as well as on a NER benchmark is described in Section 4, thus before concluding and discussing future works in Section 5.

## 2 Related Work

BERT (Devlin et al., 2019) was the leading work to show that large PLMs can be effectively fine-tuned for natural language understanding (NLU) tasks. During the pre-training phase, BERT is trained on both Masked Language Modelling (MLM) and Next Sentence Prediction (NSP) unsupervised tasks. MLM refers to predicting randomly masked words in a sentence. In real implementation, training data is duplicated by $n$ times (duplication factor) with different token masking. NSP is a binary classification task for predicting whether the second sentence in a sequence pair is the true successor of the first one. The author experimented on English with a 12-layer BERT-base and the 24-layer BERT-large Transformer (Vaswani et al., 2017) models respectively.

RoBERTa (Liu et al., 2019) proposed multiple improvements on top of BERT. First, it is trained on over 160 GB of textual data compared with 16 GB for BERT. RoBERTa corpora includes English Wikipedia and the BOOK CORPUS (Zhu et al., 2015) of BERT, in addition to the CC-NEWS (Nagel, 2016), OPEN WEB TEXT (Gokaslan and Cohen, 2019) and STORIES (Trinh and Le, 2018) corpora. Compared to BERT, RoBERTa is pre-trained with a larger batch size, more training steps on a longer sequences (512 vs. 128). It was shown that the NSP task was not beneficial for end task performances, and that MLM dynamic masking (mask change at epoch epochs) works better than static masking.

mBERT (Pires et al., 2019) and XLM-RoBERTa (Conneau et al., 2020) are multilingual PLMs that follow the pre-training procedure of BERT and XLM-RoBERTa. The first is BERT-base model that was pre-trained on concatenation of 104 Wikipedia languages. The latter is pre-trained on 2.5 TB data of cleaned Common Crawls (Wenzek et al., 2019) from 100 languages. Also, XLM-R uses an extra Translation Language Modeling (TLM) pre-training objective, which is similar to MLM but it expects concatenated parallel sequences as input.

Despite the all-in-one advantage of multilingual models, there have been particular needs to have language-specific BERT models. This is because monolingual PLMs have been found to outperform multilingual ones in language-specific evaluations on multiple languages (Wei et al., 2019; Martin et al., 2019; Canete et al., 2020; de Vries et al., 2019), where Arabic is not an exception (Safaya et al., 2020; Antoun et al., 2020; Abdul-Mageed et al., 2021).

Table 1 shows the configuration used by popular publicly available Arabic BERT models, as well as those of JABER (this work). Arabic-BERT (Safaya et al., 2020) is a 12 layer BERT model trained on 95GB of common crawl, news, and Wikipedia Arabic data. AraBERT (Antoun et al., 2020) used a larger vocab size of 64k WordPieces and performs text normalization. On one hand, they used 3.3 less textual data, while on the other hand, they increased the duplication factor by 3.3 times.

![Table 1: Configuration comparisons of various publicly available Arabic BERT models and JABER (ours). AraBERT and MARBERT didn’t provide their data duplication factor.](image-url)
Recently, Abdul-Mageed et al. (2021) proposed two 12-layers Arabic pre-trained BERT models named ARBERT and MARBERT. The first model is meant to be tailored for Modern Standard Arabic (MSA) NLU tasks, while the latter is dedicated to tasks that include Arabic dialects (especially tweets). They differ from the two prior works by performing light data processing, and training MARBERT on 128GB of Arabic tweet text data.

ARBERT and MARBERT outperform AraBERT and multilingual models on 37 out of 48 classification tasks (they called ARLUE) that contain both MSA and Arabic dialect datasets. Although both models are made publicly available, the authors didn’t provide their train/test split for most of the task, so unfortunately we couldn’t perform a direct comparison with their models on ARLUE.

In this work, we perform a systematic and fair evaluation of the aforementioned Arabic BERT models and our JABER using the ALUE (Seelawi et al., 2021) benchmark. We differ from prior works by using strict data filtering methods that reduce the pre-training corpus size from 514GB to 115GB. This allows us to perform efficient pre-training with fewer data and fewer training epochs, still obtaining higher scores than all existing Arabic BERT models.

3 Pre-training

3.1 Data Collection and Processing

We collected our pre-training corpus from 4 sources:

- **Common Crawl (CC)** This data was downloaded from 10 shards of monthly Common Crawl covering March to December 2020. It includes 444GB of plain text after filtering non-Arabic text. Also, we use the November 2018 monthly shard of Common Crawl provided by the OSCAR (Suárez et al., 2019) project. We downloaded the un-shuffled version of the Arabic corpus from HuagainFace, which is 31GB of plain text.

- **NEWS** We used the links provided by the OSIAN corpus (Zeroual et al., 2019) to crawl 21 GB of Arabic textual data from 19 popular Arab news websites.

- **EL-KHEIR** (El-Khair, 2016) provides a collection of 16GB articles collected between 2002 to 2014 from 10 Arabic news sources.

- **WIKI** We use June 2021 Arabic Wikipedia dump, and extract the text using wikiextractor (Attardi, 2012).

Recent studies (Raffel et al., 2019; Brown et al., 2020) suggest that cleaning up the raw pre-training data (especially Common Crawl) is crucial for end-task performances. Therefore, we developed our in-house methods for Arabic that aggressively filter-out gibberish, noisy, short, and near duplicated texts. we used the heuristics described in Appendix A for cleaning up our corpora.

| Source   | Original | Clean   |
|---------|----------|---------|
| CC      | 475GB    | 87GB (18%) |
| NEWS    | 21GB     | 14GB (67%) |
| EL-KHEIR| 16GB     | 13GB (82%) |
| WIKI    | 1.6GB    | 1GB (72%)  |
| **Total** | **514GB** | **115GB (22%)** |

Table 2: Size of the pre-training corpora before (Original) and after (Clean) applying data cleaning methods. Figures between parenthesis indicate the percentage of the remaining data after cleaning.

It is worth mentioning that our pre-training corpus has comparable size with the one of prior works like Arabic-BERT and MARBERT (95GB and 128GB respectively). Finally, We apply the Arabic text normalization procedure of AraBERT which includes removing emoji, tashkeel, tatweel, html markup. We refer the readers to (Antoun et al., 2020) for more details.
### 3.2 Model and Implementation

We use byte-level byte pair encoding (BBPE) (Wei et al., 2021) tokenizer to process sub-tokens. BBPE first converts the text to a sequence of bytes and then builds BPE vocabulary (Sennrich et al., 2016) on top of the byte-level representations. The authors show that BBPE eliminates the out-of-vocabulary problem and improves the learning of the representations of rare words. We set the vocabulary size to 64k, double than Arabic-BERT, same as AraBERT, and 36% less than ARBERT and MARBERT.

JABER has the same architecture and pre-training tasks as BERT-base (Devlin et al., 2019). A hidden size of 768, 12 hidden layers, and 12 attention heads. We pre-trained JABER on both Masked Language Modelling (MLM) and Next Sentence Prediction (NSP) unsupervised tasks. In MLM, we use whole word masking with a probability of 15%. The original tokens are replaced with the [MASK] special tokens in 80% of the times, 10% by a random token, while we keep the original token in 10%. We used a duplication factor of 3 during data generation, meaning that each sequence has 3 random sets of masked tokens.

We perform pre-training on 16 servers\(^7\) for 15 epochs. Each server contains 8 NVIDIA Tesla V100 GPUs with 32 GB of memory. The distributed training is achieved through Horovod (Sergeev and Del Balso, 2018) with full precision. We set the initial learning rate to 1e-4, with 10000 warm-up steps, and used AdamW (Loshchilov and Hutter, 2017) optimizer with learning rate linear decay. We only train with the maximum sequence length of 128, while setting the per GPU batch size to 64. It takes about 16 hours to finish one epoch.

### 4 Experiments

#### 4.1 Datasets

We run experiments on eight tasks from the ALUE benchmark (Seelawi et al., 2021). It is a newly proposed benchmark that gathers a diversified collection of Arabic NLU tasks: 4 single-sentence, 2 sentence-pair, and one multi-label classification tasks, as well as a single regression task. The final score is the unweighted average over the eight tasks. We refer the readers to (Seelawi et al., 2021) for detailed descriptions of ALUE datasets.

As shown in Table 3, 5 (out of 8) ALUE tasks are sourced from Tweets, and 6 (out of 8) tasks contains Arabic dialect data. This makes ALUE a suitable tool to identify useful models and keep track of the progress in the Arabic NLU field. However, ALUE training datasets and their sentence lengths are relatively small compared to English GLUE (Wang et al., 2018). In addition, three tasks

\(^7\)On Huawei Cloud [https://www.huaweicloud.com/product/modelarts](https://www.huaweicloud.com/product/modelarts)
Table 4: DEv performances on the ALUE benchmark. Bold entries describe the best results. * indicates that the results are on our own MQ2Q dev set.

(FID, MQ2Q, XNLI) are not supported by a dev set, and the test set labels are publicly provided for three tasks (MDD, FID, XNLI).

We use a simple yet generic method to obtain a dev set for the MQ2Q task. First, we translated the development set of QQP task from English to Arabic using an online translation service. Then we randomly selected 2k positive and negative samples (4k in total). In order to ensure a high-quality corpus, we only select sentence pairs that don’t contain English alphabet letters. This set is inclusively used as a proxy to evaluate models and select the best one for test submission.

Furthermore, we consider ANER (Benajiba and Rosso, 2007) for evaluation, it is a well-established benchmark for Arabic Named Entity Recognition (NER) which includes 4 types of named-entities. We run experiments on the train/test split provided by (Obeid et al., 2020) and report mention-level F1 scores using the official CoNLL-2003 (Tjong Kim Sang and De Meulder, 2003) evaluation script.

4.2 Implementation Details

We run extensive experiments in order to fairly compare JABER with Arabic-BERT, AraBERT, ARBERT and MARBERT on the ALUE tasks. For all these models, we use AdamW optimizer with learning rate with linear decay. We search the learning rate from \{7e-6, 2e-5, 5e-5\}, batch size from \{8, 16, 32, 64, 128\}, hidden dropout from \{0.1, 0.2, 0.3, 0.4\}, and fixed the epoch number to 30. The aforementioned HP search strategy is applied to all models, and the best hyper-parameters are listed in Table 7 in Appendix B.

In order to validate the statistical significance of our results, we run all experiments 5 times with different random seeds, and we report average scores and standards deviations. For JABER test submissions, we use the models performing the best on the dev set for each task. Our fine-tuning code is based on the PyTorch (Paszke et al., 2019) version of the HuggingFace Transformers (Wolf et al., 2020) library. We run all experiments on a single NVIDIA Tesla V100 GPU.

4.3 Results

Table 4 shows the dev set performance of models trained on ALUE tasks. For each model, we report the averages and standard deviations of 5 runs. First, we notice that variance in performances of multiple runs is roughly the same on average for all models. The variance is within an acceptable range (0.6-0.7 on average), except on OHSD where all models suffer from high variance.

Second, we notice that Arabic-BERT and AraBERT perform roughly the same with 72.4% and 72.5% on average respectively. This might be because both models have similar training data sizes. Arabic-BERT had 95GB of text data that were duplicated 3 times (285GB), while AraBERT had 27GB duplicated 10 times (270GB). Third, we observe that MARBERT performs well on Tweets tasks, but fails to maintain good performance on MSA tasks and vice versa for ARBERT.

JABER significantly outperforms ARBERT and...
Table 5: Leaderboard test results (as of 01/09/2021) of experiments on ALUE tasks. Bold entries show the best results.

| Model   | MQ2Q | MDD  | SVREG | SEC  | FID  | OOLD | XNLI  | OHSD | Avg. |
|---------|------|------|-------|------|------|------|-------|------|------|
| mBERT   | 83.2 | 61.3 | 33.9  | 14.0 | 81.6 | 80.3 | 63.1  | 70.5 | 61.0 |
| Arabic-BERT | 85.7 | 59.7 | 55.1  | 25.1 | 82.2 | 89.5 | 61.0  | 78.7 | 67.1 |
| JABER   | 93.1 | 64.1 | 70.9  | 31.7 | 85.3 | 91.4 | 73.4  | 79.6 | 73.7 |

MARBERT by 2.1% and 2.3% on overall average ALUE score respectively. MARBERT reported a higher score than JABER on SVREG (88.0% vs. 87.4%) and SEC (47.6% vs. 46.8%). However, JABER significantly outperforms this particular model on MSA tasks by +9.1% and +6.0% on XNLI and MQ2Q respectively. Furthermore, it shows better performances on the remaining dialect and tweet based tasks.

The results are promising, especially when we consider that our pre-training data did not contain tweets data, and we pre-trained our model with fewer data and fewer epochs compared to MARBERT. Moreover, the fact that a single model (JABER) works well on MSA, dialect, and tweets tasks is an indicator that our models have potential to generalize well independent from the source data.

Table 6: Test set mention Level F1 scores of Arabic BERT models fine-tuned on ANERcorp.

| Model   | F1 score  |
|---------|-----------|
| Arabic-BERT | 82.05±0.28 |
| AraBERT  | 82.72±0.23 |
| ARBERT   | 84.03±0.22 |
| MARBERT  | 80.50±0.35 |
| JABER    | 84.20±0.32 |

Table 5 shows the performances of the top 3 models submitted to ALUE leaderboard by 01/09/2020. JABER outperforms Arabic-BERT 12 by 6.6% on average compared with 3.2% on the dev set. JABER astonishingly outperforms Arabic-BERT on SVREG, XNLI, MQ2Q and SEC by 15.8%, 12.4%, 7.5% and 6.6% respectively. This can be because the private sample sets were collected at different time frames from train and dev set (Seelawi et al., 2021), and also are designed to be harder. Unfortunately, we could not submit the remaining baselines to the leaderboard due to the rules defined by the ALUE toolkit owners.

To further validate our approach, we perform an evaluation on a sequential labeling task, namely named entity recognition (NER). Table 6 shows models F1 mention level score on the test set of ANERcorp corpus over 5 runs. Consistent with the results obtained on ALUE, JABER reports the highest score of 84.2% and outperforms all its counterpart, while their standard deviation indicate that the improvement is significant. Expectedly, MARBERT is the worst model on this task (80.5%) because the data was sourced from MSA news articles.

5 Conclusion and Future Work

In this work, we provide detailed information of the steps we follow to pre-train 2 new Arabic BERT models. We also performed a systematic evaluation with previously existing models in the field. Our experiment shows that JABER significantly outperforms several baselines which are pre-trained under similar settings and sets a new state-of-the-art on the ALUE benchmark, a collection of 8 diversified Arabic NLU tasks.

In future, we will work on enhancing the dialect awareness of JABER by pre-training it on a massive amount of Tweets data as done by MARBERT (Abdul-Mageed et al., 2021). Also, we would like to explore more pre-training architectures and task formulations like T5 (Raffel et al., 2019) and GPT-3 (Brown et al., 2020) for Arabic NLU. We make the source code and pre-trained weights of JABER freely available at https://github.com/huawei-noah/Pretrained-Language-Model/JABER-PyTorch.

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12Submitted by the authors of the ALUE paper.
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A Filtering Heuristics

1. Remove sentences with HTML or Javascript code (Raffel et al., 2019).
2. Remove sentences if it has less than 70% Arabic characters.
3. Remove sentences with less than 8 words.
4. Remove sentences with more than 3 consecutive punctuation (excluding dot).
5. Remove document less than 64 words.
6. We remove long spans of non-Arabic text (mostly English) inside a sentence. We observe that most of these sentences where garbage text and not related with the content.
7. We represent each sentence by the concatenation of the first and last 3 words. We de-duplicate the corpus by only keeping the first occurrence of sentences with the same key.
8. We discard a document if more than 30% of its sentences are discarded by the last step.

B ALUE Hyper-parameters

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14We considered only words that do not include digits and has more than 3 characters.
| Model     | MQ2Q | MDD | SVREG | SEC | FID | OOLD | XNLI | OHSD |
|-----------|------|-----|-------|-----|-----|------|------|------|
| **Arabic-BERT** |      |     |       |     |     |      |      |      |
| batch size | 64   | 16  | 16    | 16  | 32  | 32   | 64   | 16   |
| hidden dropout | 0.1  | 0.1 | 0.1   | 0.1 | 0.1 | 0.1  | 0.1  | 0.1  |
| learning rate | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 |
| **AraBERT** |      |     |       |     |     |      |      |      |
| batch size | 128  | 32  | 8     | 8   | 8   | 32   | 32   | 16   |
| hidden dropout | 0.1  | 0.1 | 0.2   | 0.1 | 0.1 | 0.1  | 0.3  | 0.1  |
| learning rate | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 |
| **ARBERT** |      |     |       |     |     |      |      |      |
| batch size | 64   | 16  | 32    | 8   | 32  | 128  | 32   | 32   |
| hidden dropout | 0.1  | 0.1 | 0.3   | 0.3 | 0.1 | 0.1  | 0.1  | 0.3  |
| learning rate | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 7e-06 |
| **MARBERT** |      |     |       |     |     |      |      |      |
| batch size | 64   | 64  | 16    | 8   | 64  | 64   | 64   | 64   |
| hidden dropout | 0.3  | 0.2 | 0.1   | 0.3 | 0.1 | 0.2  | 0.2  | 0.1  |
| learning rate | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 |
| **JABER** |      |     |       |     |     |      |      |      |
| batch size | 64   | 32  | 8     | 16  | 32  | 128  | 16   | 32   |
| hidden dropout | 0.3  | 0.2 | 0.1   | 0.1 | 0.1 | 0.2  | 0.1  | 0.3  |
| learning rate | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 2e-05 | 7e-06 |

Table 7: For each ALUE task, the value of Hyperparameters for Arabic BERT models.