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 and SABER, Junior and Senior Arabic BERt respectively, our pre-trained language model prototypes 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 and SABER 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; Inoue 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, FLUE (Le et al., 2020) for French, RussianSuperGLUE (Shavrina et al., 2020), and ALUE (Seelawi et al., 2021) for Arabic. These benchmarks have played a critical role for driving the field forward by facilitating the comparison of 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 and SABER, Junior (12-layer) and Senior (24-layer) Arabic BERt models respectively. Through extensive experiments, we systematically compare seven Arabic BERT models by assessing their performance on the ALUE benchmark. The results can serve as an indicator to track the progress of pre-trained models for Arabic NLU. Experimental results show that JABER outperforms AR-BERT1 (Abdul-Mageed et al., 2021) by 2% on

1The best existing, based on our evaluation on ALUE, 12
Table 1: Configuration comparisons of various publicly available Arabic BERT models and ours (JABER and SABER). AraBERT and MARBERT didn’t provide their data duplication factor.

| Model          | #Params (w/o emb) | Vocab Size | Tokenizer | Normalization | Data Filtering | Textual Data Size | Duplication Factor | Training epochs |
|----------------|-------------------|------------|-----------|---------------|----------------|-------------------|--------------------|-----------------|
| Arabic-BERT    | 110M (85M)        | 32k        | WordPiece | ✓             | ✓              | 95GB              | 3                  | 27              |
| AraBERT        | 135M (85M)        | 64k        | WordPiece | ✓             | ✓              | 27GB              | 10                 | 27              |
| CAMeLBERT      | 108M (85M)        | 30k        | WordPiece | ✓             | ✓              | 167GB             | 10                 | 2              |
| ARBERT         | 163M (85M)        | 100k       | WordPiece | ✓             | ✓              | 61GB              | -                  | 42              |
| MARBERT        | 163M (85M)        | 100k       | WordPiece | ✓             | ✓              | 128GB             | -                  | 36              |
| JABER          | 135M (85M)        | 64k        | BBPE      | ✓             | ✓              | 115GB             | 3                  | 15              |
| SABER          | 369M (307M)       | 64k        | BBPE      | ✓             | ✓              | 115GB             | 3                  | 5               |

ALUE. Furthermore, SABER improves the results of JABER by 3.6% on average, and reports the new state-of-the-art performances of 77.3% on ALUE.

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 seven 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 $n$ 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 160GB of textual data compared with 16GB for BERT. RoBERTa corpora includes English Wikipedia and the BOOK CORPUS (Zhu et al., 2015) used by 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 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 over 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 RoBERTa respectively. The former is a 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-RoBERTa 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, 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; Inoue 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 vocabulary 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 a factor of 3.3.

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 do not provide their train/test split for most of the task, which prevent us to perform a direct comparison with their models on ARLUE.

Recently, Inoue et al. (2021) performed a comparative study between Arabic BERT-base models called CAMeLBERT-MSA, CAMeLBERT-DA, CAMeLBERT-CA that are pre-trained on MSA, dialect, and classic Arabic text data respectively. Furthermore, the authors proposed CAMeLBERT-MIX, which is pre-trained on a mix of 167GB of the aforementioned 3 text genres. We hereafter use the latter model as a representative for (Inoue et al., 2021) work, and we refer to it as CAMeLBERT.

In this work, we perform a systematic and fair comparison of the aforementioned Arabic BERT models and our JABER model, while also reporting results with our BERT-large SABER model, 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).

| 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 in parentheses indicate the percentage of the remaining data after cleaning.

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.
Table 3: Task descriptions and statistics of the ALUE benchmark. Test sets shown in bold use labels that have been made publicly available. The average sequence length, and standards deviation, are calculated based on the word count of the tokenized text of the training set.

and 128GB respectively). Finally, we apply the Arabic text normalization procedure of AraBERT\(^6\) which includes removing emoji, tashkeel, tatweel, and html markup. We refer the readers to (Antoun et al., 2020) for more details.

### 3.2 Model and Implementation

We use a 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, twice the one of Arabic-BERT and CAMeLBERT, similar to AraBERT, and 36% less than ARBERT and MARBERT.

JABER and SABER has the same architecture and pre-training tasks as BERT-base and BERT-large (Devlin et al., 2019) respectively. We pre-trained the models 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 with 80% of the times, 10% by a random token, while we keep the original token in the remaining 10%. We used a duplication factor of 3 during data generation, meaning that each input sequence has 3 random sets of masked tokens.

We perform pre-training on 16 servers\(^7\) for 15 and 5 epochs for JABER and SABER respectively. Each server contains 8 NVIDIA Tesla V100 GPUs with 32GB 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 a learning rate linear decay. We only train with the maximum sequence length of 128, while setting the per GPU batch size to 64 and 32 for JABER and SABER respectively. It takes about 16 and 32 hours to finish one epoch for JABER and SABER respectively.

### 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 fi-
nal 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 Table 3 shows, 5 (out of 8) ALUE tasks are sourced from Tweets, and 6 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 (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\(^8\). First, we translated the development set of QQP task\(^9\) 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 also consider ANER\(_{corp}\) (Bennajiba 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\(^{10}\).

### 4.2 Finetuning Details

We run extensive experiments in order to fairly compare JABER\(^{11}\) with Arabic-BERT, AraBERT, CAMeLBERT, ARBERT and MARBERT on the ALUE tasks. For all these models, we use AdamW optimizer with learning rate with linear decay. We search\(^{12}\) 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 and SABER 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 average and standard deviation of the official CoNLL-2003 (Tjong Kim Sang and De Meulder, 2003) evaluation script\(^{10}\).

| Arabic-BERT | AraBERT | CAMeLBERT | ARBERT | MARBERT | JABER | SABER |
|-------------|---------|------------|--------|---------|-------|-------|
| MQ2Q* | 73.3±0.6 | 73.5±0.5 | 68.9±1.1 | 74.7±0.1 | 69.1±0.9 | 75.1±0.3 | 77.7±0.4 |
| MDD | 61.9±0.2 | 61.1±0.3 | 62.9±0.1 | 62.5±0.2 | 63.2±0.3 | 65.7±0.3 | 67.7±0.1 |
| SVREG | 83.6±0.8 | 82.3±0.9 | 86.7±0.1 | 83.5±0.6 | 88.0±0.4 | 87.4±0.7 | 89.3±0.3 |
| SEC | 42.4±0.4 | 42.2±0.6 | 45.4±0.5 | 43.9±0.6 | 47.6±0.9 | 46.8±0.8 | 49.0±0.5 |
| FID | 83.9±0.6 | 85.2±0.2 | 84.9±0.6 | 85.3±0.3 | 84.7±0.4 | 84.8±0.3 | 86.1±0.3 |
| OOLD | 88.8±0.5 | 89.7±0.4 | 91.3±0.4 | 90.5±0.5 | 91.8±0.3 | 92.2±0.5 | 93.4±0.4 |
| XNLI | 66.0±0.6 | 67.2±0.4 | 55.7±1.2 | 70.8±0.5 | 63.3±0.7 | 72.4±0.7 | 75.9±0.3 |
| OHSD | 79.3±1.0 | 79.9±1.8 | 81.1±0.7 | 81.9±2.0 | 83.8±1.4 | 85.0±1.6 | 88.9±0.3 |

Avg. | 72.4±0.6 | 72.6±0.6 | 72.1±0.6 | 74.1±0.6 | 73.9±0.7 | 76.2±0.7 | 78.5±0.3 |

\(^8\)Following ALUE paper, we treat FID and XNLI test set as a dev set.

\(^9\)https://www.quora.com/q/quoradata/First-Quora-Dataset-Release-Question

\(^{10}\)https://www.clips.uantwerpen.be/conll2000/chunking/conlleval.txt

\(^{11}\)as well as for fine-tuning SABER

\(^{12}\)We used grid search with multiple runs
Table 5: Leaderboard test results (as of 03/01/2022) of experiments on ALUE tasks. Bold entries show the best results among all models.

| 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 |
| SABER    | 93.3 | 66.5 | 79.2  | 38.8 | 86.5 | 93.4 | 76.3 | 84.1 | 77.3 |

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 less so on MSA tasks and vice versa for ARBERT.

Although CAMeLBERT significantly outperforms Arabic-BERT, AraBERT, and ARBERT on 6, 5, and 4 tasks respectively, its overall performance is not competitive to the other baselines (72.1% on average). This overall lower performance can be attributed to the lower performance of CAMeLBERT on MQ2Q (68.9) and XNLI (55.7), which are sentence pair classification tasks and consists of MSA data.

JABER significantly outperforms ARBERT and 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. Expectedly, SABER significantly outperforms JABER by a margin of 3.6% on average, as well as all other BERT-base models on all the ALUE 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 independently from the source data.

Table 5 shows the performances of the top 4 models submitted to ALUE leaderboard\(^\text{13}\) by 03/01/2022. JABER outperforms Arabic-BERT\(^\text{14}\) 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 may 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.

Similar to the dev set scores, SABER significantly outperforms JABER by 3.6% on the average test results as well, therefore SABER reports state-of-the-art results on ALUE. Unfortunately, we could not submit the remaining baselines to the leaderboard due to the rules\(^\text{15}\) defined by the ALUE toolkit owners.

Table 6: Test set mention Level F1 scores of Arabic BERT-base models fine-tuned on ANER\(_{corp}\).

| Model     | F1 score       |
|-----------|----------------|
| MARBERT   | 80.50±0.35     |
| Arabic-BERT | 82.05±0.28   |
| CAMeLBERT | 82.53±0.21     |
| AraBERT   | 82.72±0.23     |
| ARBERT    | 84.03±0.22     |
| JABER     | 84.20±0.32     |

To further validate our approach, we perform an evaluation on a sequential labeling task, namely

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\(^{13}\)https://www.alue.org/leaderboard

\(^{14}\)Submitted by the authors of the ALUE paper.

\(^{15}\)https://www.alue.org/FAQ
named entity recognition (NER). Table 6 shows models F1 mention level score on the test set of ANER corp corpus over 5 runs. Consistent with the results obtained on ALUE, JABER reports the highest score of 84.2% and outperforms all its counterpart BERT-base models, 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 followed to pre-train 2 new Arabic BERT models. We 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. Also, SABER 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 our models 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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References

Muhammad Abdul-Mageed, Abdellrahim Elmadany, and El Moatez Billah Nagoudi. 2021. ARBERT & MARBERT: Deep bidirectional transformers for Arabic. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 7088–7105, Online. Association for Computational Linguistics.

Wissam Antoun, Fady Baly, and Hazem Hajj. 2020. Arabert: Transformer-based model for arabic language understanding. In LREC 2020 Workshop Language Resources and Evaluation Conference 11–16 May 2020, page 9.

Giuseppe Attardi. 2012. Wikiextractor.

Yassine Benajiba and Paolo Rosso. 2007. Anersys 2.0: Conquering the ner task for the arabic language by combining the maximum entropy with pos-tag information. In ICAI, pages 1814–1823.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165.

José Canete, Gabriel Chaperon, Rodrigo Fuentes, and Jorge Pérez. 2020. Spanish pre-trained bert model and evaluation data. PML4DC at ICLR, 2020.

Branden Chan, Stefan Schweter, and Timo Möller. 2020. German’s next language model. arXiv preprint arXiv:2010.10906.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Édouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451.

Wietse de Vries, Andreas van Cranenburgh, Arianna Bisazza, Tommaso Caselli, Gertjan van Noord, and Malvina Nissim. 2019. Bertje: A dutch bert model. arXiv preprint arXiv:1912.09582.

Ibrahim Abu El-Khair. 2016. 1.5 billion words arabic corpus. arXiv preprint arXiv:1611.04033.

Aaron Gokaslan and Vanya Cohen. 2019. Openwebtext corpus. URL: https://skylion007.github.io/OpenWebTextCorpus.

Kyle Gorman and Steven Bedrick. 2019. We need to talk about standard splits. In Proceedings of the 57th annual meeting of the association for computational linguistics, pages 2786–2791.

Go Inoue, Bashar Alhafni, Nurpeiis Baimukan, Houda Bouamor, and Nizar Habash. 2021. The interplay of variant, size, and task type in arabic pre-trained language models. In Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 92–104.

16https://www.mindspore.cn/
Hang Le, Loïc Vial, Jibril Frej, Vincent Segonne, Maximin Coavoux, Benjamin Lecouteux, Alexandre Al-lauzen, Benoît Crabbé, Laurent Besacier, and Didier Schwab. 2020. Flaubert: Unsupervised language model pre-training for French. In Proceedings of The 12th Language Resources and Evaluation Conference, pages 2479–2490.

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.

Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.

Louis Martin, Benjamin Muller, Pedro Javier Ortiz Suárez, Yoann Dupont, Laurent Romary, Eric Villemonte de la Clérgerie, Djamé Seddah, and Benoît Sagot. 2019. Camembert: a tasty french language model. arXiv preprint arXiv:1911.03894.

Sebastian Nagel. 2016. Ce-news. URL: http://web.archive.org/save/http://commoncrawl.org/2016/10/newsdatasetavailable.

Ossama Obeid, Nasser Zalmout, Salam Khalifa, Dima Taji, Mai Ouadah, Bashar Alhafni, Go Inoue, Fadhil Eryani, Alexander Erdmann, and Nizar Habash. 2020. CAMeL tools: An open source python toolkit for Arabic natural language processing. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 7022–7032. Marseille, France. European Language Resources Association.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. Advances in neural information processing systems, 32:8026–8037.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual bert? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharon Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683.

S Ruder. 2021. Challenges and opportunities in nlp benchmarking.

Ali Safaya, Moutasem Abdullatif, and Deniz Yuret. 2020. Kuisail at semeval-2020 task 12: Bert-cnn for offensive speech identification in social media. In Proceedings of the Fourteenth Workshop on Semantic Evaluation, pages 2054–2059.

Roy Schwartz, Jesse Dodge, Noah A Smith, and Oren Etzioni. 2020. Green ai. Communications of the ACM, 63(12):54–63.

Haitham Seelawi, Ibraheem Tuffaha, Mahmoud Gzawi, Wael Farhan, Bashar Talafha, Riham Badawi, Zayed Sober, Oday Al-Dweik, Aied Alhakim Freihat, and Hussein Al-Natsheh. 2021. Alue: Arabic language understanding evaluation. In Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 173–184.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725.

Alexander Sergeev and Mike Del Balso. 2018. Horovod: fast and easy distributed deep learning in tensorflow. arXiv preprint arXiv:1802.05799.

Tatiana Shavrina, Alena Fenogenova, Anton Emelyanov, Denis Shevelev, Ekaterina Artemova, Valentin Malych, Vladislav Mikhailov, Maria Tikhonova, Andrey Chertok, and Andrey Evlampiev. 2020. Russiansuperglue: A russian language understanding evaluation benchmark. arXiv preprint arXiv:2010.15925.

Pedro Javier Ortiz Suárez, Benoît Sagot, and Laurent Romary. 2019. Asynchronous pipeline for processing huge corpora on medium to low resource infrastructures. In 7th Workshop on the Challenges in the Management of Large Corpora (CMLC-7). Leibniz-Institut für Deutsche Sprache.

Yu Sun, Shuohuan Wang, Shikun Feng, Siyu Ding, Chao Pang, Junyuan Shang, Jiaxiang Liu, Xuyi Chen, Yanbin Zhao, Yuxiang Lu, et al. 2021. Ernie 3.0: Large-scale knowledge enhanced pre-training for language understanding and generation. arXiv preprint arXiv:2107.02137.

Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. 2019. Ernie: Enhanced representation through knowledge integration. arXiv preprint arXiv:1904.09223.

Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifang Wang. 2020. Ernie 2.0: A continual pre-training framework for language understanding. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 8968–8975.

Erik F Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. In Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4, pages 142–147. Association for Computational Linguistics.
Trieu H Trinh and Quoc V Le. 2018. A simple method for commonsense reasoning. *arXiv preprint arXiv:1806.02847*.

Matej Ulčar and Marko Robnik-Šikonja. 2020. Finest bert and cross-lingual bert: less is more in multilingual models. *arXiv preprint arXiv:2006.07890*.

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.

Antti Virtanen, Jenna Kanerva, Rami Ilo, Jouni Luoma, Juhani Luotolahti, Tapio Salakoski, Filip Ginter, and Sampo Pyysalo. 2019. Multilingual is not enough: Bert for finnish. *arXiv preprint arXiv:1912.07076*.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2019. Super-glue: A stickier benchmark for general-purpose language understanding systems. *arXiv preprint arXiv:1905.00537*.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355.

Junqiu Wei, Qun Liu, Yinpeng Guo, and Xin Jiang. 2021. Training multilingual pre-trained language model with byte-level subwords. *arXiv preprint arXiv:2101.09469*.

Junqiu Wei, Xiaozhe Ren, Xiaoguang Li, Wenyong Huang, Yi Liao, Yasheng Wang, Jiashu Lin, Xin Jiang, Xiao Chen, and Qun Liu. 2019. Nezha: Neural contextualized representation for chinese language understanding. *arXiv preprint arXiv:1909.00204*.

Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. 2019. Ccnet: Extracting high quality monolingual datasets from web crawl data. *arXiv preprint arXiv:1911.00359*.

Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Morgan Funtowicz, Joe Davison, Sam Shleifer, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45.

Liang Xu, Hai Hu, Xuanwei Zhang, Lu Li, Chenjie Cao, Yudong Li, Yechen Xu, Kai Sun, Dian Yu, Cong Yu, et al. 2020. Clue: A chinese understanding evaluation benchmark. *arXiv preprint arXiv:2004.05986*.
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 successive punctuation (excluding dot).

5. Remove document with less than 64 words.

6. Remove long spans of non-Arabic text (mostly English) inside a sentence. We observe that most of these sentences were garbage text and not related with the content.

7. Represent each sentence by the concatenation of the first and last 3 words\textsuperscript{17}. We de-duplicate the corpus by only keeping the first occurrence of sentences with the same key.

8. Discard a document if more than 30% of its sentences are discarded by the last step.

B ALUE Hyper-parameters

\textsuperscript{17}We 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   | 32  | 32   | 16   |      |
| hidden dropout| 0.1  | 0.1 | 0.2   | 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 |
| **CAMeLBERT** |     |     |       |     |     |      |      |      |
| batch size  | 16   | 8   | 8     | 32  | 8   | 128  | 32   | 8    |
| hidden dropout| 0.2  | 0.2 | 0.2   | 0.1 | 0.2 | 0.2  | 0.1  | 0.1  |
| learning rate| 5e-05 | 2e-05 | 2e-05 | 2e-05 | 5e-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 |
| **SABER** |      |     |       |     |     |      |      |      |
| batch size  | 32   | 32  | 8     | 8   | 32  | 32   | 32   | 32   |
| hidden dropout| 0.1  | 0.1 | 0.2   | 0.2 | 0.3 | 0.2  | 0.2  | 0.1  |
| learning rate| 7e-06 | 2e-05 | 7e-06 | 2e-05 | 2e-05 | 7e-06 | 7e-06 | 7e-06 |

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