# ARBERT & MARBERT: Deep Bidirectional Transformers for Arabic

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## Abstract

Masked language models (MLM) have become an integral part of many natural language processing systems. Although multilingual MLMs have been introduced to serve many languages, these have limitations as to their capacity and the size and diversity of non-English data they are pre-trained on. In this work, we remedy these issues for Arabic by introducing two powerful deep bidirectional transformer-based models, ARBERT and MARBERT, that have superior performance to all existing models. To evaluate our models, we propose ArBench, a new benchmark for multi-dialectal Arabic language understanding. ArBench is built using 41 datasets targeting 5 different tasks/task clusters, allowing us to offer a series of standardized experiments under rich conditions. When fine-tuned on ArBench, ARBERT and MARBERT collectively achieve new SOTA with sizeable margins compared to all existing models such as mBERT, XLM-R (Base and Large), and AraBERT on 37 out of 45 classification tasks on the 41 datasets (%82.22). Our models are publicly available for research.

## 1 Introduction

Language models (LMs) exploiting self-supervised learning such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019a) have recently emerged as powerful transfer learning tools that help improve a very wide range of natural language processing (NLP) tasks such as part of speech tagging, named entity recognition, text classification, natural language inference, and question answering. Given the success of monolingual LMs, researchers have developed multilingual versions for application on 100+ languages. Examples are multilingual BERT (mBERT) (Devlin et al., 2019) and XLM-RoBERTa (XLM-R) (Conneau et al., 2020). Although multilingual models are effective, they are usually outperformed by monolingual models trained using larger vocabulary and more sizable language-specific datasets.

Many dedicated language models have been developed. These include AraBERT for Arabic (Antoun et al., 2020), Bertje for Dutch de Vries et al. (2019), CamemBERT Martin et al. (2020) and FlauBERT (Le et al., 2020) for French, PhoBERT for Vietnamese (Nguyen and Nguyen, 2020), and the models presented by Virtanen et al. (2019) for Finnish, Dadas et al. (2020) for Polish, and Malmsten et al. (2020) for Swedish. (Pyysalo et al., 2020) also create monolingual LMs for 42 languages exploiting Wikipedia data.

The model developed for Arabic, AraBERT (Antoun et al., 2020), yields promising performance. However, it suffers from a number of issues some of which are serious. **First**, in spite of the prominently positive impact of data size on model performance, AraBERT does not make full use of available and/or easily accessible data. **Second**, it is pre-trained with only Modern Standard Arabic (MSA) data. This largely limits AraBERT's applicability to tasks involving dialects. Arabic dialects vary from MSA at various linguistic levels, thus rendering a model that only serves MSA significantly sub-optimal. The critical need for an Arabic LM that serves dialects also arise from the explosive use of these dialects on social media. **Third**, AraBERT was evaluated on only three tasks: named entity recognition, question answering, and named entity recognition. Hence it is not clear how much it would perform on more diverse datasets and a wider range of tasks. **Fourth**, AraBERT has not been compared to the current SOTA multilingual model XLM-R (Conneau et al., 2020), making it hard to decide which model to choose when working on Arabic.

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In this work, we introduce **ARBERT** and **MARBERT**, two Arabic-focused MLMs exploiting large-to-massive scale datasets. For evaluation, we also introduce a novel **Ar**abic natural language understanding **Bench**mark (**ArBench**) comprising a very wide range of NLP tasks/task clusters. Namely, we evaluate on sentiment analysis (SA), a cluster of social meaning prediction tasks (SM), topic classification (TC), dialect identification (DI), and named entity recognition (NER). For each of these tasks/task clusters, we collect multiple datasets from published research and provide standard splits for comparisons whenever appropriate. ArBench comprises 41 datasets from MSA and Arabic dialects, making it by far the largest and most diverse Arabic NLP benchmark. Our goal is for ArBench to serve the existing critical need for measuring progress on Arabic, making it easier to compare models across tasks.

To summarize, our contributions are as follows:

1. **We develop ARBERT and MARBERT**, two novel Arabic-specific Transformer-based MLS pre-trained on very large diverse datasets to facilitate transfer learning on MSA as well as Arabic dialects.[1]

2. **We introduce ArBench**, a new benchmark developed by collecting and standardizing splits on a large number of datasets across 5 different NLU tasks/task clusters, thereby facilitating measuring progress on Arabic NLU across models and tasks.

3. We fine-tune our new powerful models on our new benchmark and provide an extensive set of comparisons to available models. **Our models achieve new SOTA** on all tasks/task clusters on the majority of the datasets.

The rest of the paper is organized as follows: In Section 2, we provide an overview of related work. Section 3 describes our Arabic pre-tained models. In Section 4, we present the datasets comprising our new benchmark, ArBench, across 5 different tasks/task clusters, and evaluate our models against other models. We conclude in Section 5.

[1]Our models are available for research at: https://github.com/UBC-NLP/marbert.

## 2 Related Work

Distributed representations of words, as in Word2Vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014) and FastText (Mikolov et al., 2017), have brought significant improvements to NLP. Contextualized word embeddings such as ELMo (Peters et al., 2018) and Flair (Akbik et al., 2018) have made it possible to provide more context-sensitive (hence more accurate) representations of words, and a growing list of embeddings (Akbik et al., 2019) followed. More recently, models exploiting a self-supervised objective with masking such as BERT (Devlin et al., 2019) have brought even more powerful representations. Better hyper-parameter optimization, such as in RoBERTa (Liu et al., 2019b), have resulted in further improvements. Multilingual versions of MLMs such as mBERT and XLM-Roberta (Conneau et al., 2019) were also trained. Other models with different objectives and/or architectures such as ALBERT (Lan et al., 2019), T5 (Raffel et al., 2019) and GPT3 (Brown et al., 2020) were also introduced. We briefly describe each of these models next.

### 2.1 BERT

BERT (Devlin et al., 2019) stands for **b**idirectional **e**ncoder **r**epresentations from **T**ransformers, and is trained with a masked language modeling as well as a next sentence prediction objective. Authors use WordPiece embeddings (Wu et al., 2016), with learned positional embeddings and a sequence length up to 512 tokens. Devlin et al. (2019) present two architectures. Denoting the number of layers as $L$, the hidden size as $H$, the number of self-attention heads as $A$, vocabulary size as $V$, these two models are as follows:

- **BERT$_{\textbf{Base}}$**: L=12, H=768, A=12, V=30K, Total Parameters=110M.

- **BERT$_{\textbf{Large}}$**: L=24, H=1,024, A=16, V=30K, Total Parameters=340M.

BERT models are trained on English Wikipedia [2] (2.5B words) and BooksCorpus (Zhu et al., 2015). The mBERT model is the multilingual version of BERT and is trained on Wikipedia for 104 languages (including Arabic), with L=12 layers, A=12, H=768, V=110K, making up 110M parameters.

[2]https://www.wikipedia.org/

### 2.2 XLM-RoBERTa

Liu et al. (2019a) introduce RoBERTa, a model similar to BERT but with better optimized hyper-parameters. Conneau et al. (2019) extend RoBERTA to the multilingual setting by creating XLM-RoBERTa (XLM-R). XLM-R is trained on more than 2TB of filtered CommonCrawl data in 100 languages. and comes in two sizes and architectures:

- **XLM-R$_{\text{Base}}$**: L=12, H=768, A=12, V=250K, Total Parameters=270M.
- **XLM-R$_{\text{Large}}$**: L=24, H=$1,024$, A=16, V=250K, Total Parameters=550M.

While both XLM-R models use the same masking objective as BERT, they do not include the next sentence prediction objective used in BERT. Conneau et al. (2019) report SOTA performance on several tasks, including sequence labeling, cross-lingual classification, and question answering.

### 2.3 ALBERT

Lan et al. (2019) present ALBERT, **A L**ite **Bert** for self-supervised learning of language representations. ALBERT is a Transformer-based neural network architecture (similar to BERT, RoBERTa and XLM-R) with two parameter reduction techniques proposed to increase the training speed and lower memory consumption of the BERT model (Devlin et al., 2019). The first one is the factorization of the embedding parameterization by decomposing the vocabulary embedding matrix into two small matrices. ALBERT uses an input-level embeddings with a relatively-low dimensionality (e.g., 128) and hidden-layer embeddings with higher dimensions (768 as in the BERT case, or more). The second technique is cross-layer parameter sharing (i.e., the same layer is applied such that similar layers are used on top of one another). Implementing these two techniques significantly reduces the number of parameters for BERT without considerably impacting performance. For instance, ALBERT$_{\text{Base}}$ model has only 12M parameters (i.e., 89% parameter reduction compared to the ALBERT$_{\text{Large}}$ model, which is as large as BERT$_{\text{Base}}$, yet still achieves good performance across 3 natural language understanding benchmarks: GLUE (Wang et al., 2018), SQuAD (Rajpurkar et al., 2016), and RACE (Lai et al., 2017). Moreover, Lan et al. (2019) show that ALBERT$_{\text{Large}}$ can be trained $\sim$ 1.7x faster with $\sim$ 18x fewer parameters.

### 2.4 T5

Raffel et al. (2019) propose **T**ext-**t**o-**T**ext **T**ransfer **T**ransformer model (T5). The main idea of T5 is to treat every text-based language task as a "text-to-text" problem. That is, T5 takes text format as input and produces new text format as output. T5 applies multi-task learning with the same model, objective, training procedure, and decoding process to several English NLP tasks. Tasks included are question answering, document summarization, machine translation, and sentiment classification. T5 is essentially an encoder-decoder Transformer (Vaswani et al., 2017) with some architectural modifications including applying a normalization layer before a sub-block and adding a pre-norm (i.e., initial input to the sub-block output). The encoder and the decoder are similar in configuration and size to a BERT$_{\text{Base}}$ (Devlin et al., 2019). T5 is trained on the "Colossal Clean Crawled Corpus" (or C4 for short), which is a $\sim$ 750 GB clean and natural English text extracted from CommonCrawl web data. T5 achieves SOTA on many benchmarks.

### 2.5 Arabic LMs

A few Arabic LMs have been developed. The most notable among these is AraBERT (Antoun et al., 2020). AraBERT is trained with the same BERT architecture (Devlin et al., 2019) and uses the same BERT$_{\text{Base}}$ configuration. The second version of AraBERT, AraBERTv1, employs the Farasa tool (Abdelali et al., 2016) to segment input text before training. AraBERT is trained on 23GB of Arabic text, comprising more than 70M sentences and 3B words. To train AraBERT, Antoun et al. (2020) use Arabic Wikipedia, the Open Source International dataset (OSIAN) (Zeroual et al., 2019) (3.5M news articles from 24 Arab countries), and 1.5B words Corpus from (El-Khair, 2016) (5M articles extracted from 10 news sources). Antoun et al. (2020) evaluate AraBERT on 3 Arabic downstream tasks. These are (1) sentiment analysis from 6 different datasets: HARD (Elnagar et al., 2018), ASTD (Nabil et al., 2015), ArsenTD-Lev (Baly et al., 2019), LABR (Aly and Atiya, 2013), and ArSaS (Elmadany et al., 2018). (2) NER, with the ANERcorp (Columbia University, 2016), and (3) Arabic QA, on Arabic-SQuAD (Mozannar et al., 2019) and ARCD (Mozannar et al., 2019) datasets. We now introduce our models.

## 3 Our Models

### 3.1 ARBERT

ARBERT is a large scale pre-training masked language model focused on Modern Standard Arabic (MSA). To train ARBERT, we use the same architecture as $\text{BERT}_{\text{Base}}$: 12 attention layers, each has 12 attention heads and 768 hidden dimensions, a vocabulary of 100K WordPieces, making $\sim$ 163M parameters. We now describe ARBERT's pre-train dataset, vocabulary, and pre-training setup.

#### 3.1.1 Training Data

We train ARBERT on a collection of Arabic datasets comprising 61GB of text. We list each of these datasets next, and provide data size and the number of tokens per dataset in Table 1.

| Source | Size | #Tokens |
|---|---|---|
| Books (Hindawi) | 650MB | 72.5M |
| El-Khair | 16GB | 1.6B |
| Gigawords | 10GB | 1.1B |
| OSIAN | 2.8GB | 292.6M |
| OSCAR-MSA | 31GB | 3.4B |
| OSCAR-Egyptian | 32MB | 3.8M |
| Wiki | 1.4GB | 156.5M |
| **Total** | **61GB** | **6.5B** |

Table 1: ARBERT 's pre-train resources.

- **Books (Hindawi)**. We collect and pre-process 1,800 Arabic books from the public Arabic bookstore Hindawi.[3]
- **El-Khair**. This is a 5M news articles dataset from 10 major news sources covering 8 Arab countries from El-Khair (2016).
- **Gigaword**. We use Arabic Gigaword 5th Edition (LDC2011T11) from the Linguistic Data Consortium (LDC).[4] The dataset is a comprehensive archive of newswire text from multiple Arabic news sources.
- **OSCAR**. This is the MSA and Egyptian Arabic portion of the Open Super-large Crawled Aalanach coRpus (Suárez et al., 2019),[5] a huge multilingual subset from Common Crawl[6] obtained using language classification and filtering.

[3] https://www.hindawi.org/books/

[4] https://catalog.ldc.upenn.edu/LDC2009T30

[5] https://oscar-corpus.com/

[6] https://commoncrawl.org

- **OSIAN**. The Open Source International Arabic News Corpus (OSIAN) (Zeroual et al., 2019) consists of 3.5 million articles from 31 news sources in 24 Arab countries.
- **Wikipedia Arabic**. We download and use the December 2019 dump of Arabic Wikipedia. We use WikiExtractor [7] to extract articles and remove markup from the dumb.

#### 3.1.2 Training Procedure

**Pre-processing.** To prepare the raw data for pre-training, we perform light pre-processing. This helps retain a faithful representation of the naturally occurring text. We only remove diacritics and replace URLs, user mentions, and hashtags that may exist in any of the collections with the generic string tokens URL, USER, and HASHTAG. We do not perform any further pre-processing of the data before splitting the text off to wordPieces (which we explain next).[8]

Multilingual models such as mBERT and XLM-R have 5K (out of 110K) and 14K (out of 250K) Arabic subwords, respectively, in their vocabularies. AraBERT employs a larger vocabulary of 60K (out of 64K)[9]. For ARBERT , we use a larger vocabulary of 100K WordPieces (Schuster and Nakajima, 2012). For subword tokenization, we use the WordPiece tokenizer (Wu et al., 2016) provided by Devlin et al. (2019).

**Pre-training.** To pre-train ARBERT, we follow Devlin et al. (2019)'s pre-training setup. To generate each training input sequence, we use the whole word masking, where 15% of the $N$ input tokens are selected for replacement. These tokens are replaced 80% of the time with the [MASK] token, 10% with a random token, and 10% with the original token. We use the original implementation of BERT in the TensorFlow framework. [10]. As mentioned, we use the same network architecture as $\text{BERT}_{\text{Base}}$: 12 layers, 768 hidden units, 12 heads, for a total of 110M parameters. We train ARBERT with a batch size of 256 sequences and a

[7] https://github.com/attardi/wikiextractor

[8] For example, we do not normalize variants of Arabic letters such as "Alif", "Yeh", "TaMarbota" to generic forms as is usually undertaken in order to reduce sparsity. We also are not concerned with sparsity since our datasets are large. In addition, this normalization could increases ambiguity and so we avoid it.

[9] The additional 4K vocabulary bin is reserved to allow for additional wordPieces if needed.

[10] https://github.com/google-research/bert

maximum sequence length of 128 tokens (256 sequences $\times$ 128 tokens = $32,768$ tokens/batch) for 8M steps, which is approximately 42 epochs over the 6.5B tokens. We train the model on 1 Google Cloud TPU with 8 cores (v2.8) from TensorFlow Research Cloud (TFRC) [11]. Training took 16 days, for 42 epochs over all the tokens. Table 2 shows a comparison of ARBERT with mBERT, XLM-R, AraBERT, and MARBERT (see next section) in terms of data sources and size, vocabulary size, and model parameter size.

### 3.2 MARBERT

Arabic has multiple varieties. Many of these varieties are understudied due to rarity of resources. Multilingual models such as mBERT and XLM-R are trained almost exclusively on MSA data, which is also the case for AraBERT and ARBERT[12]. As such, these models are not best suited for downstream tasks involving dialectal Arabic. To treat this issue, we use a large Twitter dataset to pre-train a new model, MARBERT , from scratch. For this new model, we also use the $\text{BERT}_{\text{Base}}$ architecture listed in Section 3.1. We now describe MARBERT 's pre-training dataset, vocabulary, and settings.

#### 3.2.1 Training data

To train MARBERT, we randomly sample 1B Arabic tweets from a large in-house dataset of about 6B tweets. We only include tweets with at least 3 Arabic words, based on character string matching, regardless whether the tweet has non-Arabic string or not. That is, we do not remove non-Arabic so long as the tweet meets the 3 Arabic word criterion. The dataset makes up 128GB of text (15.6B tokens).

#### 3.2.2 Training Procedure

**Pre-processing.** Again, we remove diacritics and replace URLs, user mentions, and hashtags with the generic string tokens URL, USER, and HASHTAG.
**Pre-training.** We use the same network architecture as $\text{BERT}_{\text{Base}}$, but *without* the next sentence prediction (NSP) objective since tweets are short. NSP were also shown not to be crucial for model performance (Conneau et al., 2019). We use the same vocabulary size (100K wordPiece) as ARBERT. We train MARBERT for 36 epochs with a batch size of 256 and a maximum sequence length of 128. Training took 40 days on 8 Google Cloud TPUs. We now present a comparison between our models and popular multilingual models as well as AraBERT.

[11] https://www.tensorflow.org/tfrc

[12] We note that, as explained earlier, ARBERT is trained on a small portion of Egyptian Arabic of text (32MB, making up 3.8M tokens).

### 3.3 Model Comparison

ARBERT and MARBERT compare to multilingual MLMs and AraBERT across 3 primary dimensions: (1) training data size, (2) vocabulary size, and (3) language varieties. Table 2 shows a comparison between all theses models across these 3 dimensions.
**Data size**. mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) use a small Arabic text collection from Wikipedia (153M tokens) and CommonCrawl (2.9B tokens), respectively. AraBERT (Antoun et al., 2020) is $\text{BERT}_{\text{Base}}$ pre-trained model for Arabic. As explained, Antoun et al. (2020) use two newswire datasets to train AraBERT (Zeroual et al. (2019) and El-Khair (2016)) comprising more than 70M sentences, corresponding to 24GB of text (2.5B tokens). Our ARBERT and MARBERT are trained on 61GB of Arabic text (6.2B tokens) and 128GB of Arabic tweets (15.6B tokens), respectively.
**Arabic Vocabulary size**. Each of ARBERT and MARBERTis trained with 100K Arabic subwords. The mBERT, XLM-R, and AraBERT models have 5K, 14K, and 60K subwords, respectively
**Language Variety**. Devlin et al. (2019) train mBERT with Wikipedia Arabic data, which is MSA. XLM-R (Conneau et al., 2020) is trained on Common Crawl data, hence conceivably comprises some dialectal Arabic data. However, it is not clear how much dialects are part of the XLM-R Arabic data. The datasets AraBERT is trained on are also only MSA. Our ARBERT model is trained on a collection of large MSA datasets and small amount of Egyptian data. The data we train MARBERTon is from Twitter, and comprises both MSA and diverse dialects. We now introduce our performance on downstream tasks.

## 4 Downstream Tasks

We evaluate our models on a wide range of natural language understanding tasks. To facilitate presentation, we thematically organize these tasks into the following 5 categories: (1) sentiment analysis, (2) social meaning (e.g., age and gender, dangerous and hateful speech, emotion, irony, sarcasm), (3) topic classification, (4) dialect identification, and

| Models | Training Data | | Vocabulary | | | Configuration | |
|---|---|---|---|---|---|---|---|
| | **Source** | **Tokens** (ar/all) | **Tokenization** | **Size** (ar/all) | **Cased** | **Arch.** | **#Param.** |
| mBERT | Wikipedia | 153M/1.5B | WordPiece | 5K/110K | yes | base | 110M |
| XLM-$R_B$ | CommonCrawl | 2.9B/295B | SentencePiece | 14K/250K | yes | base | 270M |
| XLM-$R_L$ | CommonCrawl | 2.9B/295B | SentencePiece | 14K/250K | yes | large | 550M |
| AraBERT | Several (3 sources) | 2.5B/2.5B | SentencePiece | 60K/64K | no | base | 135M |
| **ARBERT** | Several (6 sources) | 6.2B/6.2B | WordPiece | 100K/100K | no | base | 163M |
| **MARBERT** | Arabic Twitter | 15.6B/15.6B | WordPiece | 100K/100K | no | base | 163M |

Table 2: Configuration comparisons for AraBERT (Antoun et al., 2020), mBERT (Devlin et al., 2019), XLM-R (Conneau et al., 2020), ARBERT, and MARBERT.

(5) named entity recognition (NER).In each case, we fine-tune our models and all other models we compare to on the training data for each task, and evaluate on both development and test data. We typically use the exact data splits provided by original author(s) of each dataset. Whenever no clear splits are available, or in cases where expensive cross-validation was used by original authors, we divide the data following a standard 80% TRAIN, 10% DEV and 10% TEST split. Similar to our pre-processing for model pre-training, we slightly normalize the text as remove Arabic diacritics, replace hyperlinks and user mentions with URL and USER, respectively. For Twitter hashtags, we remove the hash sign and replace any underscore with a space. For all tasks, we fine-tune mBERT, XLM-$R_{Base}$, and AraBERT. Although XLM-$R_{Large}$ is much bigger (in terms of architecture) than our models, we also compare to it. For all models, including ARBERT and MARBERT, we use the same settings. We typically identify the best checkpoint for each model on the development set, and report its performance on both development and test data.

**Baselines.** Whenever applicable, we consider SOTA results for each task as our baseline. Otherwise, we consider AraBERT results as a strong baseline. We now introduce the different tasks.

### 4.1 Sentiment Analysis

We evaluate our models on all publicly available sentiment analysis datasets in addition to datasets we could acquire directly from authors. In total, we fine-tune our models on the following 17 MSA and DA sentiment datasets:

#### 4.1.1 Datasets

- **AJGT.** The Arabic Jordanian General Tweets (AJGT) dataset (Alomari et al., 2017) involves MSA and Jordanian tweets, with a balanced split of 900 *positive* posts and 900 *negative* posts (total=1, 800).

- **AraNET$_{\textbf{Sent}}$**. Abdul-Mageed et al. (2020b) collect 15 datasets in both MSA and dialects from Abdul-Mageed and Diab (2012) (AWATIF), Abdul-Mageed et al. (2014) (SAMAR), Abdulla et al. (2013); Nabil et al. (2015); Kiritchenko et al. (2016); Aly and Atiya (2013); Salameh et al. (2015); Rosenthal et al. (2017); Alomari et al. (2017); Mohammad et al. (2018), and Baly et al. (2019). These datasets involve varying numbers of sentiment categories: **binary** (*negative* and *positive*), **3-way** (*negative*, *neutral*, and *positive*). Some of the datasets also have a *subjective* language label. Abdul-Mageed et al. (2020b) combine the datasets for binary sentiment classification by reducing the different tags into the binary case (i.e., *negative* and *positive*) and removing data from all other labels, acquiring 126, 766 samples, which they split into 80% (100, 599), 10% (14, 344) and 10% (11, 823) for training, development, and test respectively.

- **AraSenTi-Tweet.** This is a collection of MSA and Saudi Arabic tweets by Al-Twairesh et al. (2017). The 17, 573 dataset is manually annotated. The distribution of labels is as follows: 4, 957 *positive*, 6, 155 *negative*, 4, 639 *neutral*, and 1, 822 *mixed* sentences.

- **ArSarcasm$_{\textbf{Sent}}$** Farha and Magdy (2020) introduce ArSarcasm, a sarcasm dataset labeled with sentiment tags. ArSarcasm has 10, 547 tweets, of which 2, 472 taken from ASTD (Nabil et al., 2015) and 8, 075 from SemEval-2017 Task 4 (Rosenthal et al., 2017). Farha and Magdy (2020) evaluate on the 3 sentiment labels *negative*, *neutral*, and *positive*.

| Dataset (#classes) | Classes | TRAIN | DEV | TEST |
|---|---|---|---|---|
| AJGT (2) | {neg, pos} | 1.4K | - | 361 |
| AraNET$_{\text{Sent}}$ (2) | {neg, pos} | 100.5K | 14.3K | 11.8K |
| AraSenTi-Tweet (3) | {neg, neut, pos} | 11.1K | 1.4K | 1.4K |
| ArSarcasm$_{\text{Sent}}$ (3) | {neg, neut, pos} | 8.4K | - | 2.1K |
| ArSAS (3) | {neg, neut, pos} | 24.8K | - | 3.7K |
| ArSenD-LEV (5) | {neg, neut, pos, neg$^{+}$, pos$^{+}$} | 3.2K | - | 801 |
| ASTD (3) | {neg, neut, pos} | 24.8K | - | 664 |
| ASTD-B (2) | {neg, pos} | 1K | - | 267 |
| AWATIF (4) | {neg, neut, obj, pos } | 2.3K | 288 | 284 |
| BBN (3) | {neg, neut, pos} | 960 | 125 | 116 |
| HARD (2) | {neg, pos} | 75K | - | 18.7K |
| LABR (2) | {neg, pos} | 13.2 | - | $3,3$K |
| SAMAR (5) | {mix, neg, neut, obj, pos} | 2.5 | 310 | 316 |
| SemEval (3) | {neg, neut, pos} | 24.8K | - | 6.1K |
| SYTS (3) | {neg, neut, pos} | 960 | 202 | 199 |
| Twitter$_{\text{Abdullah}}$ (2) | {neg, pos} | 1.6K | 202 | 190 |
| Twitter$_{\text{Saad}}$ (2) | {neg, pos} | 47K | 5.8K | 5.8 |

Table 3: Sentiment analysis datasets. **neg$^{+}$**: "very negative"; **pos$^{+}$**: "very positive".

- **ArSAS**.The Arabic Speech Act and Sentiment (ArSAS) corpus (Elmadany et al., 2018) consists of $21,064$ tweets annotated with four labels: *positive*, *negative*, *neutral*, and *mixed*.

- **ArSenD-Lev**. The Arabic Sentiment Twitter Dataset for LEVantine dialect (ArSenD-Lev) (Baly et al., 2019) has $4,000$ tweets retrieved from the Levant region (i.e., Jordan, Lebanon, Palestine, and Syria). Sentiment is labeled on a 5-point scale, with 835 *positive*, 397 *very positive*, 885 *neutral*, $1,253$ *negative*, and 630 *very negative*.

- **ASTD.** This is a collection of $10,006$ Egyptian tweets annotated with the labels positive (n=799), *negative* (n=$1,684$), *objective* (n=832), and *neutral* (n=$6,691$) by Nabil et al. (2015).

- **AWATIF**. A multigenre MSA dataset (Abdul-Mageed and Diab, 2012) consisting of $2,855$ sentences of newswire stories from Part 1, V3 of the Penn Arabic TreeBank,[13] $5,342$ sentences from 30 Wikipedia talk pages, and $2,532$ threaded conversations from 7 web forums.

- **BBNS & SYTS**. The **BBN** blog posts **S**entiment (BBNS) and **S**yria **T**weets **S**entiment (SYTS) are introduced by Salameh et al. (2015). BBNS comprises $1,200$ Levantine dialectal sentences extracted from the BBN Arabic-Dialect/English Parallel Text.[14] SYTS consist of $2,000$ Levantine Arabic tweets. Both BBNS and SYTS are manually annotated with tags from the set {*negative, positive, neutral*}.

- **CAMel$_{\text{Sent}}$**. Obeid et al. (2020) merge training and development data from ArSAS (Elmadany et al., 2018), ASTD (Nabil et al., 2015), SemEval (Rosenthal et al., 2017), and ArSenTD (Al-Twairesh et al., 2017) to create a new training dataset ($\sim$ 24K). For evaluation, they report performance on the independent test set from each of these sources.

- **HARD**. The Hotel Arabic Reviews Dataset (HARD) (Elnagar et al., 2018) consists of $93,700$ hotel reviews, each with a rating of 1-5 stars. The reviews are written in MSA and DA. Reviews with 1 and 2 stars are treated as *negative* and those with 4 and 5 stars as *positive*. Reviews with 3 stars reviews are removed from the dataset. Overall, there are 46.8K for each of the *positive* and *negative* classes.

- **LABR**. The Large Arabic Book Review Corpus (Aly and Atiya, 2013) has $63,257$ book reviews from Goodreads, the book readers social network.[15] The reviews are rated with a

[13] https://catalog.ldc.upenn.edu/LDC2005T20

[14] https://catalog.ldc.upenn.edu/LDC2012T09

[15] www.goodreads.com

1-5 stars scale. Posts with 1-2 stars are treated as *negative*, those with 3 starts as *neutral*, and those with 3-5 as *positive*.

- **Twitter$_{\text{Abdullah}}$.**[16] This is a dataset of 2,000 MSA and Jordanian Arabic tweets manually labeled by Abdulla et al. (2013). The dataset is balanced, with 1,000 *positive* and 1,000 *negative* tweets.
- **Twitter$_{\text{Saad}}$.** This dataset is released by Moatez Saad in 2019 and is available on Kaggle.[17] The dataset is collected using an emoji lexicon as a proxy for sentiment. In total, it has 29.8K *positive* and 28.7K *negative* tweets.
- **SemEval-2017**. The SemEval-2017 sentiment analysis in Arabic Twitter task (Rosenthal et al., 2017) provides data for 3 sentiment analysis sub-tasks. These included on 2 classes (*negative* and *positive*) with 9,500 tweets, 3 classes (*negative*, *positive*, and *neutral*) with 3,400 tweets, and 5 classes (*strongly negative*, *negative*, *neutral*, *positive* and *strongly positive*) with 9,450 tweets.

### 4.1.2 Baselines

For sentiment analysis, we compare our results to the following STOA:

- **Antoun et al. (2020).** The authors fine-tune two versions of AraBERT: AraBERTv0.1, which employs no Arabic segmentation nor pre-possessing, and AraBERTv1, which is based on segmentation nor pre-possessing. They fine-tune these two versions on 5 sentiment datasets. These are HARD (Elnagar et al., 2018), the balanced data for ASTD (which we will refer to as ASTD-B) (Nabil et al., 2015), ArSenTD-Lev (Baly et al., 2019), AJGT (Alomari et al., 2017), and the unbalanced positive and negative classes for LABR (Aly and Atiya, 2013). Antoun et al. (2020) split the data into 80/20 for training/test, respectively and report results in accuracy using the best epoch identified on test data. For a valid comparison, we use the same data splits and evaluation set up as (Antoun et al., 2020). Their best results are obtained by fine-tuning AraBERTv1.
- **Obeid et al. (2020).** The authors fine-tune mBERT and AraBERT on the merged CAMel$_{\text{sent}}$ datasets and compared their results with Mazajak (Farha and Magdy, 2019). Obeid et al. (2020) use $F_1{}^{PN}$ score for evaluation, which was defined by SemEval-2017 and also used by Majazak (Farha and Magdy, 2019). $F_1{}^{PN}$ is the macro $F_1$ score over the positive and negative classes only, while neglecting the neutral class.
- **Abdul-Mageed et al. (2020b).** The authors fine-tune mBERT on the AraNET$_{\text{Sent}}$ data and report results in $F_1$ score on test data.

### 4.1.3 Sentiment Analysis Results

To facilitate comparison to previous works with the appropriate evaluation metric, we split our results into two tables: We show results in accuracy and $\text{F}_1^{PN}$ in Table 5 and accuracy and $\text{F}_1$ in Table 4. We typically **bold** results acquired with the best model in the metric adopted in previous work on each dataset. As Table 5 shows, our models achieve best results in 10 out of 12 datasets. More specifically, MARBERT achieves best results on 9 datasets, ARBERT is best on one dataset, and XLM-R$_{\text{Large}}$ is best on 2 datasets. We also note that XLM-R$_{\text{Large}}$ outperforms AraBERT on 10 datasets out of the 12 datasets. Our models achieve new SOTA on all the datasets, outperforming cases where there is previous published SOTA (as by to Obeid et al. (2020) and Abdul-Mageed et al. (2020b), both marked in Table 5). On average, our models are 2.8 $\text{F}_1$ better than any next best model on the 12 datasets.

Of the 5 datasets in Table 4, MARBERT and ARBERT achieve best results on 4 datasets. MARBERT, again, compares favorably to ARBERT. In all except one case (ArsenTF-LEV), ARBERT is better than XLM-R$_{\text{Large}}$. Across all datasets, our models are consistently better than our own fine-tuned AraBERT baseline and AraBERT results published by Antoun et al. (2020), which we consider SOTA.[18]

To summarize, compared to SOTA on the 5 datasets HARD, ArsenTD-LEV, LABER, and ASTD-B reported by Antoun et al. (2020), ARBERT and MARBERT achieve new SOTA (exceeding AraBERT, mBERT and XLM-R models).

[16] For ease of reference, we assign a name to this and other unnamed datasets.

[17] www.kaggle.com/mksaad/arabic-sentiment-twitter-corpus

[18] Our own fine-tuned AraBERT results are all lower than those reported in Antoun et al. (2020) in spite of us using a wide set of hyper-parameters including those described in Antoun et al. (2020). However, as noted, we also compare to AraBERT results published by Antoun et al. (2020).

Compared to SOTA reported by Obeid et al. (2020) on the 3 datasets ArSAS CAMel, ASTD CAMel, and SemEval CAMel datasets, our models achieve new SOTA (on all 3 datasets) with an average improvement of 4% $F_1^{PN}$. Compared to Abdul-Mageed et al. (2020b) on $\text{AraNET}_{\text{Sent}}$ data, both of our models outperform $\text{AraNET}_{\text{Sent}}$ but our new SOTA is achieved by $\text{XLM-R}_{\text{Large}}$ (which is $\sim 1\%$ higher than MARBERT on $\text{AraNET}_{\text{Sent}}$ data).

For all other datasets ($n = 8$), we consider published AraBERT results in Antoun et al. (2020) a strong baseline (calling it SOTA, although we find that $\text{XLM-R}_{\text{Large}}$ outperforms it in most cases). Both of our models outperform AraBERT on all datasets except on AraSenTi-Tweet (where both $\text{XLM-R}_{\text{Large}}$ and AraBERT obtain better results than our models). Overall, experiments on the the sentiment datasets show our fine-tuned ARBERT and MARBERT models are better in 14 out of the 17 datasets ($\% =\sim 82.4$). These results also clearly show that MARBERT is superior to ARBERT, outperforming it on 16 out of the 17 datasets.

| Data (#classes) | SOTA | LM | TEST Acc. | TEST F1 |
|---|---|---|---|---|
| AJGT (2) | 93.8 | mBERT | 86.67 | 86.59 |
| | | XLM-R$_B$ | 89.44 | 89.43 |
| | | XLM-R$_L$ | 91.94 | 91.87 |
| | | AraBERT | 92.22 | 92.19 |
| | | ARBERT | **94.44** | 94.43 |
| | | MARBERT | **96.11** | 96.10 |
| HARD (2) | 96.2 | mBERT | 95.54 | 95.54 |
| | | XLM-R$_B$ | 95.74 | 95.74 |
| | | XLM-R$_L$ | 95.96 | 95.96 |
| | | AraBERT | 95.89 | 95.89 |
| | | ARBERT | **96.12** | 96.12 |
| | | MARBERT | **96.17** | 96.17 |
| ArsenTD-LEV (5) | 59.4 | mBERT | 50.50 | 47.98 |
| | | XLM-R$_B$ | 55.25 | 49.89 |
| | | XLM-R$_L$ | **62.00** | 59.99 |
| | | AraBERT | 56.13 | 54.30 |
| | | ARBERT | 61.38 | 58.06 |
| | | MARBERT | **60.38** | 59.04 |
| LABR (2) | 86.7 | mBERT | 91.20 | 81.98 |
| | | XLM-R$_B$ | 91.23 | 82.70 |
| | | XLM-R$_L$ | 92.20 | 83.82 |
| | | AraBERT | 91.97 | 84.89 |
| | | ARBERT | **92.51** | 84.98 |
| | | MARBERT | **92.49** | 85.20 |
| ASTD-B (2) | 92.6 | mBERT | 79.32 | 79.30 |
| | | XLM-R$_B$ | 87.59 | 87.55 |
| | | XLM-R$_L$ | 77.44 | 77.41 |
| | | AraBERT | 83.08 | 83.07 |
| | | ARBERT | **93.23** | 93.21 |
| | | MARBERT | **96.24** | 96.24 |

SOTA are results reported in Antoun et al. (2020) based on Acc.

Table 4: Performance of models on SA tasks (I).

| Dataset (#classes) | SOTA | LM | TEST Acc. | TEST $F_1^{PN}$ |
|---|---|---|---|---|
| ArSAS (3) | 92* | mBERT | 89.65 | 87.50 |
| | | XLM-R$_B$ | 91.76 | 90.00 |
| | | XLM-R$_L$ | 92.85 | 91.50 |
| | | AraBERT | 91.76 | 91.00 |
| | | ARBERT | 93.12 | **92.00** |
| | | MARBERT | 93.85 | **93.00** |
| ASTD (3) | 73* | mBERT | 59.54 | 67.00 |
| | | XLM-R$_B$ | 63.96 | 60.67 |
| | | XLM-R$_L$ | 71.38 | 67.67 |
| | | AraBERT | 63.78 | 72.00 |
| | | ARBERT | 68.73 | **76.50** |
| | | MARBERT | 71.02 | **78.00** |
| SemEval (3) | 69* | mBERT | 58.02 | 57.00 |
| | | XLM-R$_B$ | 64.62 | 64.00 |
| | | XLM-R$_L$ | 68.01 | 67.00 |
| | | AraBERT | 62.37 | 62.00 |
| | | ARBERT | 68.08 | **69.00** |
| | | MARBERT | 69.35 | **71.00** |
| AraNET$^{\text{Sent}}$ (2) | 76.2** | mBERT | 84.80 | 84.00 |
| | | XLM-R$_B$ | 92.40 | 91.93 |
| | | XLM-R$_L$ | 93.50 | **93.11** |
| | | AraBERT | 87.14 | 86.44 |
| | | ARBERT | 89.55 | 88.95 |
| | | MARBERT | 92.77 | 92.31 |
| ArSarcasm$^{\text{Sent}}$ (3) | - | mBERT | 70.43 | 60.50 |
| | | XLM-R$_B$ | 72.89 | 63.50 |
| | | XLM-R$_L$ | 75.92 | **70.00** |
| | | AraBERT | 70.71 | 63.50 |
| | | ARBERT | 75.12 | 68.00 |
| | | MARBERT | 77.35 | **71.50** |
| AraSenTi (3) | - | mBERT | 89.93 | 89.50 |
| | | XLM-R$_B$ | 92.40 | 92.00 |
| | | XLM-R$_L$ | 93.34 | **93.50** |
| | | AraBERT | 90.95 | 91.00 |
| | | ARBERT | 90.80 | 90.00 |
| | | MARBERT | 90.59 | 90.00 |
| BBN (3) | - | mBERT | 52.17 | 55.50 |
| | | XLM-R$_B$ | 66.96 | 69.50 |
| | | XLM-R$_L$ | 47.83 | 46.50 |
| | | AraBERT | 66.96 | 70.00 |
| | | ARBERT | 71.30 | **76.50** |
| | | MARBERT | 73.91 | **79.00** |
| SYTS (3) | - | mBERT | 73.30 | 67.00 |
| | | XLM-R$_B$ | 78.01 | **78.00** |
| | | XLM-R$_L$ | 68.59 | 40.50 |
| | | AraBERT | 78.53 | 75.50 |
| | | ARBERT | 79.06 | **79.00** |
| | | MARBERT | 78.53 | 76.50 |
| Twitter$^{\text{Saad}}$ (2) | - | mBERT | 79.08 | 79.00 |
| | | XLM-R$_B$ | 95.19 | 95.00 |
| | | XLM-R$_L$ | 95.29 | **95.00** |
| | | AraBERT | 80.90 | 81.00 |
| | | ARBERT | 89.85 | 90.00 |
| | | MARBERT | 95.72 | **96.00** |
| SAMAR (5) | - | mBERT | 42.54 | 22.50 |
| | | XLM-R$_B$ | 54.92 | 54.00 |
| | | XLM-R$_L$ | 56.83 | **57.00** |
| | | AraBERT | 49.21 | 36.50 |
| | | ARBERT | 48.57 | 43.50 |
| | | MARBERT | 57.46 | **55.50** |
| AWATIF (4) | - | mBERT | 66.16 | 60.50 |
| | | XLM-R$_B$ | 67.68 | 63.50 |
| | | XLM-R$_L$ | 71.10 | 68.50 |
| | | AraBERT | 71.10 | 66.50 |
| | | ARBERT | 73.00 | **71.50** |
| | | MARBERT | 75.67 | **72.50** |
| Twitter$^{\text{Abdullah}}$ (2) | - | mBERT | 82.01 | 81.50 |
| | | XLM-R$_B$ | 91.01 | 91.00 |
| | | XLM-R$_L$ | 92.06 | 92.00 |
| | | AraBERT | 89.42 | 89.50 |
| | | ARBERT | 91.53 | **91.50** |
| | | MARBERT | 94.71 | **95.00** |

* Obeid et al. (2020), ** Abdul-Mageed et al. (2020b) based on $F_1$, otherwise we consider AraBERT Antoun et al. (2020) as SOTA.

Table 5: Performance of models on SA tasks (II).

### 4.2 Social Meaning Tasks

We evaluate on a host of tasks to which we collectively refer to as **social meaning**. These are age and gender detection; dangerous, hateful, and offensive speech detection; emotion detection; irony detection; and sarcasm detection. We now describe datasets we use for each of these tasks.

#### 4.2.1 Tasks & Datasets

**Age and Gender**. For both age and gender, we use the *Arap-Tweet* dataset (Zaghouani and Charfi, 2018). This dataset covers 17 different countries from 11 Arab regions. For each region, authors crawl data from 100 Twitter users based on an initial list of seed words characteristic of each region. Zaghouani and Charfi (2018) assign gender from the set $\{$*male, female*$\}$ and age group labels from the set $\{$*under-25, 25-to-34, above-35*$\}$. We follow the 80% $(1,285,795)$, 10% $(160,724)$, and 10% $(160,725)$ data split of AraNet (Abdul-Mageed et al., 2020b).

**Dangerous Speech.** We use the dangerous speech *AraDang* dataset from Alshehri et al. (2020a). This data is extracted from Arabic Twitter and consists of $4,445$ manually annotated tweets. Of these, $3,225$ are labelled as *safe* and $1,220$ as *dangerous*.

**Offensive Language and Hate Speech**. We use the dataset released in the shared task of offensive speech by Mubarak et al. (2020).[19] The shared task is divided into two sub-tasks: **sub-task A**: detecting if a tweet is *offensive* or *not-offensive*, and **sub-task A**: detecting if a tweet is *hate-speech* or *not-hate-speech*. The offensive content dataset consists of $10,000$ manually annotated tweets, of which $1,991$ are *offensive* and rest (n=$8,009$) is *not-offensive*. The same tweets are also labeled with hate speech tags ($9,494$ *hate-speech* and $8,009$ *not-hate-speech*).

**Emotion.** For this task we use the *AraNeT$_{emo}$* dataset from Abdul-Mageed et al. (2020b). To create this data, the authors merge the two datasets LAMA-DINA and LAMA-DIST from Alhuzali et al. (2018). AraNeT$_{\text{emo}}$ consist of 192K tweets (split into 190K TRAIN, 911 DEV, and 942 TEST), and labeled with the Plutchik 8 primary emotions classes in the set $\{$*anger, anticipation, disgust, fear, joy, sadness, surprise, and trust*$\}$.

**Irony**. We use the irony identification dataset for Arabic tweets released by IDAT@FIRE2019 shared task (Ghanem et al., 2019). This dataset contains $5,030$ tweets and involves both MSA and Egyptian, Gulf, and Levantine dialects. IDAT@FIRE2019 (Ghanem et al., 2019) is set up as a binary classification task with *ironic* and *non-ironic* labels. A total of $4,024$ and $1,006$ tweets were released by organizers as training and test data. In our experiments, we use the same split of Abdul-Mageed et al. (2020b), where they split the $4,024$ released training data into 90% TRAIN (n= $3,621$ tweets; *ironic*= $1,882$ and *non-ironic*= $1,739$) and 10% DEV (n= 403 tweets; *ironic*= 209 and *non-ironic*= 194).

**Sarcasm**. We use the *ArSarcasm* dataset developed by (Farha and Magdy, 2020). *ArSarcasm* contains $10,547$ tweets, $2,472$ of these are from ASTD (Nabil et al., 2015) while the rest (n=$8,075$) are from SemEval2017 (Rosenthal et al., 2017). The tweets are labeled with *sarcasm* and *not-sarcasm* tags.

#### 4.2.2 Baselines

We compare our results with the STOA on each task, as follows:

- **Age and Gender**. We compare to AraNET Abdul-Mageed et al. (2020b) age and gender models, trained by fine-tuning mBERT. The authors report 51.42 and 65.30 $F_1$ on age and gender, respectively.

- **Dangerous Speech**. We compare to Alshehri et al. (2020b), who report best results with an mBERT model fined-tuned on emotion data on 8 emotion classes from Twitter. They report 59.60 $\text{F}_1$ on test data.

- **Emotion**. We compare to Abdul-Mageed et al. (2020b), who acquire 60.32 $F_1$ on test with a fine-tuned mBERT.

- **Hate Speech**. The best results on the offensive and hate speech shared task (Mubarak et al., 2020) are reported by (Husain, 2020). The authors employ heavy feature engineering with SVMs exploiting emoticons, emojis, and hashtags. They also convert dialectal tokens to MSA and perform word clustering. They report 95 $\text{F}_1$ score. Since our goal is to advance methods exploiting language models without need for heavy hand-crafted features, we do not compare to (Husain, 2020). Rather, we compare our models to (Djandji et al., 2020) who rank $2^nd$ in the shared task since they use AraBERT in a multi-task setting. They report 83.41 $\text{F}_1$ score on test data.

- **Irony**. We compare to Zhang and Abdul-Mageed (2019a) who fine-tune mBERT on

[19] http://edinburghnlp.inf.ed.ac.uk/workshops/OSACT4/

| Task | Dataset (#classes) | Classes | TRAIN | DEV | TEST |
|---|---|---|---|---|---|
| Age | Arap-Tweet (3) | { $\leq$ 24 yrs, 25 $-$ 34 yrs, $\geq$ 35 yrs } | 1.3M | 160.7K | 160.7K |
| Dangerous | AraDang (2) | {dangerous, not-dangerous} | 3.5K | 616 | 664 |
| Emotion | AraNET$_{\text{Emo}}$ (8) | {ang, anticip, disg, fear, joy, sad, surp, trust} | 190K | 911 | 942 |
| Gender | Arap-Tweet (2) | {female, male} | 1.3M | 160.7K | 160.7K |
| Hate Speech | HS@OSACT (2) | {hate, not-hate} | 10K | 1K | 2K |
| Irony | FIRE2019 (2) | {irony, not-irony} | 3.6K | - | 404 |
| Offensive | OFF@OSACT (2) | {offensive, not-offensive} | 10K | 1K | 2K |
| Sarcasm | AraSarcasm (2) | {false, true} | 8.4K | - | 2.1K |

Table 6: Social Meaning datasets.

the irony task. The authors use multi-task learning, where they employ an auxiliary author profiling task along with the main irony task. They report 82.4 $F_1$ score on the test set.

- **Offensive Language**. The best results on the offensive shared task (Mubarak et al., 2020) are reported by Hassan et al. (2020). They propose an ensemble of SVMs, CNN-BiLSTM, and mBERT with majority voting. They report 90.51 $F_1$. We compare to their results.

- **Sarcasm**. We compare to Farha and Magdy (2020) who train a BiLSTM model using the AraSarcasm dataset, reporting 46.00 $F_1$ score.

#### 4.2.3 Social Meaning Results

Results of social meaning tasks are reported in Table 7. As the table shows, our models acquire best results on all 8 tasks. MARBERT acquires best performance on 7 tasks, while ARBERT is best on on one task (irony@FIRE2019). We also note that XLM-R outperforms AraBERT on 6 out of the 8 tasks. On average, our models are 12.5 $F_1$ better than all previous SOTA.

### 4.3 Topic Classification

Classifying documents by topic is a classical task. Work in this area generally pre-dates the more recent focus on teasing apart texts by their more nuanced semantic and pragmatic attributes. Most of the topic classification work we identified in the Arabic NLP literature involves some focus on preprocessing techniques, dimensionality reduction, data transformation, etc. (Altınel and Ganiz, 2018). We include this task since categorizing documents by topic is still a useful task of practical value. We now describe each of the topic classification datasets we collected.

#### 4.3.1 Datasets

We fine-tune on the following datasets:

- **Arabic News Text.** Chouigui et al. (2017) build the Arabic news text (ANT) dataset from transcribed radio broadcasts of the Tunisian radio channel *Jawhara FM*. ANT has 10K documents divided into 5 categories: *Culture*, *economy*, *international news*, *technology*, and *sports*. ANT comes with a title field and so we run our experiments on this dataset under 3 settings pertaining input on which we fine-tune the language models: *Title only*, *text only*, and *title+text*.

- **Khaleej**. Abbas et al. (2011) created the Khaleej dataset from Gulf Arabic websites. Khaleej comprises 5,690 documents from 4 topical categories: *economy*, *international news*, *local news*, and *sports*.

- **OSAC.** Saad and Ashour (2010) collect the OSAC corpus, a total of 22,429 articles covering 10 categories: *economy*, *family*, *health*, *history*, *law*, *recipes*, *religion*, *space*, *sports*, and *stories*.

#### 4.3.2 Baselines

For topic classification, to the best of our knowledge, there are no published results exploiting deep learning models. Therefore, we consider fine-tune AraBERT a strong baseline.

### 4.4 Topic Classification Results

Table 9 shows our results on the topic classification datasets. As the table shows, ARBERTacquires best results on both OSAC and Khaleej, and the title-only setting of ANT. AraBERT slightly outperforms our models on the text-only and title+text settings of ANT. We also note that, on average, MAR-

| Task | Dataset (#classes) | SOTA | LM | TEST Acc. | TEST F1 |
|---|---|---|---|---|---|
| Age | ArapTweet (3) | 51.42‡‡ | mBERT | 56.19 | 56.35 |
| | | | XLM-R$_B$ | 59.73 | 59.73 |
| | | | XLM-R$_L$ | 53.39 | 53.60 |
| | | | AraBERT | 57.55 | 57.72 |
| | | | ARBERT | 58.82 | 58.95 |
| | | | MARBERT | 62.10 | **62.27** |
| Dangerous | AraDange (2) | 59.60† | mBERT | 80.09 | 62.66 |
| | | | XLM-R$_B$ | 80.84 | 62.76 |
| | | | XLM-R$_L$ | 80.84 | 65.01 |
| | | | AraBERT | 81.30 | 64.37 |
| | | | ARBERT | 81.00 | 63.21 |
| | | | MARBERT | 81.00 | **67.53** |
| Emotion | AraNET$_{Emo}$ (8) | 60.32‡‡ | mBERT | 67.41 | 65.79 |
| | | | XLM-R$_B$ | 72.20 | 70.67 |
| | | | XLM-R$_L$ | 75.72 | 74.89 |
| | | | AraBERT | 67.20 | 65.68 |
| | | | ARBERT | 69.86 | 67.73 |
| | | | MARBERT | 77.42 | **75.83** |
| Gender | Arab_Tweet (2) | 65.3‡‡ | mBERT | 68.59 | 68.06 |
| | | | XLM-R$_B$ | 71.15 | 71.00 |
| | | | XLM-R$_L$ | 71.46 | 71.14 |
| | | | AraBERT | 68.58 | 67.75 |
| | | | ARBERT | 70.18 | 69.86 |
| | | | MARBERT | 72.90 | **72.62** |
| Hate Speech | OSACT-B (2) | 82.28** | mBERT | 96.15 | 72.81 |
| | | | XLM-R$_B$ | 95.15 | 71.33 |
| | | | XLM-R$_L$ | 96.35 | 79.31 |
| | | | AraBERT | 95.80 | 78.89 |
| | | | ARBERT | 96.85 | 83.02 |
| | | | MARBERT | 97.00 | **84.79** |
| Irony | FIRE2019 (2) | 60.32‡ | mBERT | 81.12 | 80.96 |
| | | | XLM-R$_B$ | 82.11 | 81.97 |
| | | | XLM-R$_L$ | 82.86 | 82.52 |
| | | | AraBERT | 83.23 | 83.01 |
| | | | ARBERT | 85.84 | **85.59** |
| | | | MARBERT | 85.59 | 85.33 |
| Offensive | OSACT-A (2) | 90.51* | mBERT | 90.70 | 84.25 |
| | | | XLM-R$_B$ | 91.00 | 85.26 |
| | | | XLM-R$_L$ | 92.80 | 88.28 |
| | | | AraBERT | 91.80 | 86.57 |
| | | | ARBERT | 93.85 | 90.38 |
| | | | MARBERT | 95.20 | **92.41** |
| Sarcasm | AraSarcasm (2) | 46.00†† | mBERT | 81.80 | 68.20 |
| | | | XLM-R$_B$ | 86.26 | 66.76 |
| | | | XLM-R$_L$ | 86.68 | 69.23 |
| | | | AraBERT | 85.31 | 72.23 |
| | | | ARBERT | 86.73 | 75.04 |
| | | | MARBERT | 87.63 | **76.30** |

Dataset has only TRAIN and TEST splits or SOTA system only reported on TEST.
* Hassan et al. (2020), ** Djandji et al. (2020), ‡ Zhang and Abdul-Mageed (2019a)
† Alshehri et al. (2020b), †† Farha and Magdy (2020), ‡‡ Abdul-Mageed et al. (2020b)
$F_1$ score is the evaluation metric

Table 7: Results on social meaning tasks.

BERT is $\sim 1\%$ $F_1$ less than both ARBERT and AraBERT.

### 4.5 Dialect Identification

Available Arabic dialect identification datasets carry labels of varying granularity, from binary (i.e., MSA-DA) (Elaraby and Abdul-Mageed, 2018), AOC (Zaidan and Callison-Burch, 2014) to regional (Farha and Magdy, 2020), country-level (Bouamor et al., 2018; Abdul-Mageed et al., 2020a; Abdelali et al., 2020), and recently province level (Abdul-Mageed et al., 2020a). We introduce these next.

#### 4.5.1 Datasets

We introduce each dataset briefly here, and provide a description summary of all datasets in Table 10.

- **Arabic Online Commentary (AOC).** This

| Dataset (#classes) | Classes | TRAIN | DEV | TEST |
|---|---|---|---|---|
| ANT (5) | {culture, economy, inter news, middle east, sports, technology} | 25.2K | 3.2K | 3.2K |
| OSAC (10) | {economy, family, health, history, law, recipes, religious, space, sports, stories} | 18K | 2.2K | 2.2K |
| Khallej (4) | {economy, inter news, local news, sports} | 4.6K | 570 | 570 |

Table 8: Topic Classification datasets.

| Data (#classes) | LM | TEST Acc. | TEST $F_1$ |
|---|---|---|---|
| OSAC (10) | mBERT | 98.17 | 96.84 |
| | XLM-$R_B$ | 98.31 | 97.15 |
| | XLM-$R_L$ | 98.84 | 98.20 |
| | AraBERT | 98.35 | 97.03 |
| | ARBERT | 98.44 | **97.50** |
| | MARBERT | 98.48 | 97.23 |
| Khallej (4) | mBERT | 94.20 | 92.81 |
| | XLM-$R_B$ | 93.15 | 91.87 |
| | XLM-$R_L$ | 94.73 | 93.56 |
| | AraBERT | 95.25 | 93.83 |
| | ARBERT | 95.43 | **94.53** |
| | MARBERT | 94.73 | 93.63 |
| $ANT_{Text}$ (5) | mBERT | 85.66 | 84.89 |
| | XLM-$R_B$ | 86.42 | 85.77 |
| | XLM-$R_L$ | 86.90 | 86.72 |
| | AraBERT | 88.58 | **88.17** |
| | ARBERT | 87.25 | 86.87 |
| | MARBERT | 85.12 | 85.27 |
| $ANT_{Title}$ (5) | mBERT | 79.57 | 78.29 |
| | XLM-$R_B$ | 81.00 | 79.96 |
| | XLM-$R_L$ | 81.82 | 81.25 |
| | AraBERT | 82.20 | 81.03 |
| | ARBERT | 81.54 | **81.70** |
| | MARBERT | 80.87 | 81.19 |
| $ANT_{Title+Text}$ (5) | mBERT | 85.53 | 84.67 |
| | XLM-$R_B$ | 86.64 | 86.21 |
| | XLM-$R_L$ | 87.50 | 86.96 |
| | AraBERT | 87.56 | **87.22** |
| | ARBERT | 87.02 | 87.21 |
| | MARBERT | 85.72 | 85.60 |

SOTA ($F_1$) are results reported in Antoun et al. (2020).

Table 9: Performance of models on TC tasks.

is a repository of 3M Arabic comments on online news sites developed by (Zaidan and Callison-Burch, 2014). AOC is labeled with MSA and the 3 **regional** dialects *Egyptian*, *Gulf*, and *Levantine*.

- **ArSarcasm$_{\textbf{Dia}}$**. This dataset is developed by Farha and Magdy (2020) for sarcasm detection but also carries **regional** dialect labels from the set {*Egyptian*, *Gulf*, *Levantine*, and *Maghrebi*}. ArSarcasm$_{\text{Dia}}$ comprises $10,547$ tweets, $2,472$ of which are taken from ASTD (Nabil et al., 2015) while the rest (n=$8,075$) come from SemEval 2017 (Rosenthal et al., 2017).

- **MADAR**. Sub-task 2 of the MADAR shared task (Bouamor et al., 2019)[20] is focused on user-level dialect identification with **country** labels. The dataset is composed of $\sim$ 265K manually-curated Tweets. In this paper, we evaluate our models on MADAR at the tweet level and compare to the shared task top ranking system's (Zhang and Abdul-Mageed, 2019b) tweet-level results.

- **NADI.** The first Nuanced Arabic Dialect Identification shared task (NADI 2020) (Abdul-Mageed et al., 2020a)[21] targets **country** level as well as **province** level dialects. The dataset is composed of $21,000$ tweets, covering 21 Arab countries and 100 respective provinces.

- **QADI**. The QCRI Arabic Dialect Identification (QADI) dataset (Abdelali et al., 2020) is labeled at the **country** level and has 540K tweets from $2,525$ Twitter users.

#### 4.5.2 Baselines

We compare our models to the following dialect identification SOTA:

- **Elaraby and Abdul-Mageed (2018)** report 3 levels of classification on the AOC dataset (Zaidan and Callison-Burch, 2014). These are *MSA* vs. *DA*, where they acquire 87.23 accuracy, regional (i.e., *Egyptian*, *Gulf*, and *Levantine*), where they report 87.81 accuracy, and *MSA*, *Egyptian*, *Gulf*, and *Levantine* accuracy of 82.45. (Elaraby and Abdul-Mageed, 2018) acquire best models with either BiLSTMs or a simple Naive Bayes classifier.

- **Abdelali et al. (2020)** fine-tune AraBERT on the QADI dataset. They report 60.6 $F_1$.

- **Zhang and Abdul-Mageed (2019b)** developed the top ranked system in the MADAR sub-task 2 shared task (Bouamor et al., 2019). Although the sub-task is focused on user level dialect identification, their system is based on tweet level modeling where they first identify the dialect of a tweet then port the label at the

[20]https://sites.google.com/view/madar-shared-task/home.

[21]https://sites.google.com/view/nadi-shared-task/home.

| Task (#classes) | Dataset | Classes | TRAIN | DEV | TEST |
|---|---|---|---|---|---|
| AOC (2) | Binary | {DA, MSA} | 86.5K | 10.8K | 10.8K |
| AOC (3) | Region | {Egypt, Gulf, Levnt} | 35.7K | 4.5K | 4.5K |
| AOC (4) | Region | {Egypt, Gulf, Levnt, MSA} | 86.5K | 10.8K | 10.8K |
| ArSarcasm$_{\text{Dia}}$ (5) | Regoin | {Egypt, Gulf, Lev, Magreb, MSA} | 8.4K | - | 2.1K |
| MADAR-TL (21) | Country | {Algeria, Bahrain, Djibouti, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Palestine, Qatar, KSA, Somalia, Sudan, Syria, Tunisia, UAE, and Yemen} | 193.1K | 26.6K | 44K |
| NADI (21) | Country | {Algeria, Bahrain, Djibouti, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Palestine, Qatar, KSA, Somalia, Sudan, Syria, Tunisia, UAE, and Yemen} | 2.1K | 5K | 5K |
| QADI (18) | Country | {Algeria, Bahrain, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, KSA, Sudan, Syria, Tunisia, UAE, and Yemen} | 497.8K | - | 3.5K |

Table 10: Dialect datasets.

user level. They report 48.76 accuracy and 34.87 $F_1$ on the tweet-level task.

- **Talafha et al. (2020).** We compare to the NADI sub-task 1 (**country level**) winning team, Mawdoo3 AI (Talafha et al., 2020). They further pre-train AraBERT on 10M unlabeled tweets released by the NADI 2020 organizers (Abdul-Mageed et al., 2020a) for 3 epochs. They report 26.78 $F_1$ for this country level sub-task.
- **El Mekki et al. (2020).** NADI sub-task 2 (**province level**) and was won by El Mekki et al. (2020). They clean and normalized the data by remove diacritization, URLs, hashtags, retweets, emojis, Latin letters, and numbers. They then augment the original data (i.e., before normalization) with the normalized data and use a combination of word and character n-grams TF_IDF vectors to fine-tune AraBERT. El Mekki et al. (2020) report 6.08 $F_1$ on this province level sub-task.
- **AraBERT.** For ArSarcasm$_{\text{Dia}}$, where there is no dialect identification system previously reported, we fine-tune AraBERT on the dataset and consider it a strong baseline. We report results in both accuracy and macro $F_1$, but treat $F_1$ as the metric for comparison to align with results on other datasets.

### 4.6 Dialect Identification Results

Our models on the dialect datasets (Section 4.5) can be viewed as performing identification on 5 different levels: **binary** (*MSA* vs. *DA*), **regional** (e.g., *Egyptian*, *Gulf*, *Levantine*, and *Maghrebi*), **country** (e.g., *Algeria*, *Egypt*, *Morocco*, *Saudi Arabia*), and **province** levels (e.g., the Egyptian provinces of *Cairo* and *Alexandria*, the Saudi Arabia provinces of *Al-Madinah* and *Ar-Riyad*). As Table 11 shows, MARBERT outperforms all SOTA as well as AraBERT with an average of 5% $F_1$ across all classification levels. These results reflect the powerful and diverse dialectal representation capacity of MARBERT. Although ARBERTis mainly developed for MSA, it outperforms AraBERT, mBERT, and XLM-R with an average of 3% $F_1$ across the different dialect classification levels. This is a function of overlap (e.g., lexical) between MSA and dialects and demonstratesARBERT's ability to transfer knowledge on what may be referred to as a "zero-shot" setting (i.e., going from MSA to dialects).[22]

### 4.7 Named Entity Recognition

NER is usually carried out as a sequence labeling task with the objective of predicting which words refer to categories of real-world objects such *persons*, *locations*, and *organisations*. We fine-tune our models on 5 datasets, which we now introduce.

#### 4.7.1 Datasets

We evaluate on the Automatic Context Extraction (ACE)'s 2003 Broadcast News (ACE-BN 2003) and Newswire (ACE-NW 2003) (Mitchell et al., 2004), ACE's 2004 Newswire datasets (Mitchell et al., 2005), ANERcorp (Benajiba and Rosso, 2007), and Twitter Social Media NER (TW-NER) (Darwish, 2013). Table 12 shows the distribution of named entity classes and the total number of tokens across the 5 datasets as presented by (Khalifa and Shaalan, 2019).

[22]This applies only in the wider sense of the term, due to cited overlap between MSA and dialects.

| Dataset (#classes) | Task | SOTA | LM | TEST | |
|---|---|---|---|---|---|
| | | | | Acc. | F1 |
| ArSarcasm$_{\text{Dia}}$ (5) | Regoin | 47.54 | mBERT | 76.30 | 43.81 |
| | | | XLM-R$_{\text{B}}$ | 77.44 | 41.71 |
| | | | XLM-R$_{\text{L}}$ | 77.96 | 41.83 |
| | | | AraBERT | 79.00 | 47.54 |
| | | | ARBERT | 76.87 | 51.27 |
| | | | MARBERT | 78.29 | **54.70** |
| MADAR-TL (21) | Country | – | mBERT | 48.89 | 34.92 |
| | | | XLM-R$_{\text{B}}$ | 49.48 | 35.91 |
| | | | XLM-R$_{\text{L}}$ | 50.17 | 35.14 |
| | | | AraBERT | 49.26 | 34.87 |
| | | | ARBERT | 51.78 | 37.90 |
| | | | MARBERT | 53.77 | **40.40** |
| AOC (4) | Region | 82.45* | mBERT | 49.11 | 36.02 |
| | | | XLM-R$_{\text{B}}$ | 50.02 | 34.59 |
| | | | XLM-R$_{\text{L}}$ | 50.72 | 35.77 |
| | | | AraBERT | 50.22 | 36.44 |
| | | | ARBERT | 51.38 | 37.84 |
| | | | MARBERT | 86.19 | **82.37** |
| AOC (3) | Region | 78.81* | mBERT | 86.17 | 85.76 |
| | | | XLM-R$_{\text{B}}$ | 86.87 | 86.39 |
| | | | XLM-R$_{\text{L}}$ | 88.02 | 87.56 |
| | | | AraBERT | 88.15 | 87.68 |
| | | | ARBERT | 89.51 | 89.06 |
| | | | MARBERT | 91.27 | **90.85** |
| AOC (4) | Binary | 87.23* | mBERT | 86.81 | 86.19 |
| | | | XLM-R$_{\text{B}}$ | 87.34 | 86.85 |
| | | | XLM-R$_{\text{L}}$ | 87.87 | 87.30 |
| | | | AraBERT | 88.25 | 87.76 |
| | | | ARBERT | 88.94 | 88.46 |
| | | | MARBERT | 89.08 | **88.59** |
| QADI (18) | Country | 60.6** | mBERT | 66.92 | 66.57 |
| | | | XLM-R$_{\text{B}}$ | 76.61 | 77.00 |
| | | | XLM-R$_{\text{L}}$ | 82.58 | 82.73 |
| | | | AraBERT | 72.00 | 72.23 |
| | | | ARBERT | 88.60 | 88.63 |
| | | | MARBERT | 90.88 | **90.89** |
| NADI (21) | Country | 26.78†† | mBERT | 32.38 | 13.32 |
| | | | XLM-R$_{\text{B}}$ | 34.18 | 16.36 |
| | | | XLM-R$_{\text{L}}$ | 35.16 | 17.17 |
| | | | AraBERT | 36.06 | 17.46 |
| | | | ARBERT | 41.02 | 22.56 |
| | | | MARBERT | 48.40 | **29.14** |
| Province (100 ) | Province | 6.08†† | mBERT | 3.32 | 2.13 |
| | | | XLM-R$_{\text{B}}$ | 4.76 | 4.12 |
| | | | XLM-R$_{\text{L}}$ | 2.14 | 0.32 |
| | | | AraBERT | 3.86 | 3.13 |
| | | | ARBERT | 6.94 | 6.10 |
| | | | MARBERT | 8.48 | **6.28** |

* Elaraby and Abdul-Mageed (2018), ** Abdelali et al. (2020),
†† Abdul-Mageed et al. (2020a), † Zhang and Abdul-Mageed (2019b).
SOTA evaluation metric is $F_1$ score

Table 11: Dialect Identification Tasks.

### 4.7.2 Baseline

We compare our results with SOTA presented by Khalifa and Shaalan (2019) and follow them in focusing on person (PER), location (LOC) and organization (ORG) named entity tags, and setting other tags to the unnamed entity (O). Khalifa and Shaalan (2019) apply a character Convolutional Neural Networks (WC-CNN) and character-level bidirectional Long Short-Term Memory (WC-BiLSTM) on the 5 listed NER datasets. They use an $80-10-10$ train-dev-test split and report $\text{F}_1$ scores of 88.77, 91.47, 94.92, 91.20, and 65.34 on test on the ANERcorp, ACE-NW 2004, ACE-BN 2003, ACE-NW 2003, and TW-NER datasets, respectively. We use their exact data splits.

| Dataset | #Tokens | #PER | #LOC | #ORG |
|---|---|---|---|---|
| ANERCorp | $150K$ | $6,504$ | $5,018$ | $3,437$ |
| ACE-2003_BN | 15K | 832 | $1,223$ | 288 |
| ACE-2003_NW | 27K | $1,146$ | $1,147$ | 893 |
| ACE-2004_BN | $70K$ | 3201 | $3,921$ | $2,239$ |
| TW-NER | $81K$ | $1,252$ | $1,300$ | 765 |

Table 12: Distribution of classes and token size of the Arabic NER datasets (Khalifa and Shaalan, 2019).

| Dataset (#classes) | SOTA | LM | TEST | |
|---|---|---|---|---|
| | | | Acc. | $\text{F}_1$ |
| ANERcorp. | 88.77 | mBERT | 97.69 | 86.78 |
| | | XLM-R$_{\text{B}}$ | 88.06 | 87.24 |
| | | XLM-R$_{\text{L}}$ | **98.73** | **89.94** |
| | | AraBERT | 98.41 | 89.13 |
| | | ARBERT | 97.85 | 84.38 |
| | | MARBERT | 9756 | 80.64 |
| ACE-NW 2004 | **91.47** | mBERT | 96.82 | 86.37 |
| | | XLM-R$_{\text{B}}$ | 97.94 | 89.93 |
| | | XLM-R$_{\text{L}}$ | 98.16 | 89.89 |
| | | AraBERT | 97.74 | 89.03 |
| | | ARBERT | 97.65 | 88.24 |
| | | MARBERT | 97.45 | 85.02 |
| ACE-BN 2003 | 94.92 | mBERT | 98.08 | 91.23 |
| | | XLM-R$_{\text{B}}$ | 92.97 | 83.97 |
| | | XLM-R$_{\text{L}}$ | 97.77 | 85.41 |
| | | AraBERT | 98.64 | 91.94 |
| | | ARBERT | **99.21** | **96.18** |
| | | MARBERT | 97.02 | 79.05 |
| ACE-NW 2003 | **91.2** | mBERT | 96.03 | 81.40 |
| | | XLM-R$_{\text{B}}$ | 97.31 | 87.24 |
| | | XLM-R$_{\text{L}}$ | 98.10 | 90.62 |
| | | AraBERT | 97.88 | 88.09 |
| | | ARBERT | 97.90 | 90.09 |
| | | MARBERT | 97.67 | 87.76 |
| Twitter | 65.34 | mBERT | 90.80 | 36.83 |
| | | XLM-R$_{\text{B}}$ | 92.22 | 49.16 |
| | | XLM-R$_{\text{L}}$ | 92.80 | 54.44 |
| | | AraBERT | 88.61 | 41.26 |
| | | ARBERT | 95.50 | 59.17 |
| | | MARBERT | 96.57 | **67.39** |

SOTA are results reported in Khalifa and Shaalan (2019) based on $\text{F}_1$.

Table 13: Performance of our models on NER task.

## 4.8 NER Results

As Table 13 shows, we outperform SOTA on 3 out of the 5 datasets for NER. Namely, our MARBERT model outperforms SOTA on ACE-NW 2004 and Twitter datasets with $+1.26\%$ and $+2.05\%$ $\text{F}_1$, respectively. Our model ARBERTalso outperforms SOTA on ACE-BN 2003, with $+1.26\%$ $\text{F}_1$. XML-R$_{\text{Large}}$ acquires best $\text{F}_1$ (89.94) on ArERcop. We also note that our models outperform AraBERT on ACE-NW 2003, ACE-BN 2003, and Twitter datasets. Again, these reults reflect the transfer learning strength of our models.

## 5 Conclusion

In this paper, we reported our efforts to develop two powerful Transformer-based language models for Arabic. Our moddels are trained on large datasets from MSA (ARBERT) or both MSA and DA (MARBERT). We also traced, collected, and benchmarked 45 models on the 41 comprising AraNLU across 5 tasks/task clusters. When fine-tuned on the various labeled datasets, our models achieve new SOTA on all the tasks on the majority of the datasets. More precisely, out of the 45 models we train, our models acquire SOTA in 37 cases (%=82.22).

Compared to multilingual models such as mBERT and XLM-R, our models have better representation of Arabic and yield better performance. Even when compared to XLM-R$_{\text{Large}}$ model, which is larger, our models compare more favorably (in addition to being less computationally costly at inference time). Compared to Arabic-specific models such as AraBERT, ARBERT has generally better MSA representation and performs better in most cases. Compared to both ARBERT and AraBERT, MARBERT covers DA and is much more powerful. Our models are publicly available for research. In the future, we plan to evaluate our models on more Arabic NLP tasks and further pre-train them to improve their performance on the datasets where they are currently outperformed.

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# Appendices

In the majority of our tasks, we either use the train/dev/test splits of a given work we compare to or split existing data for which we identified no clear splits into the standard train/dev/test. We present results on the DEV splits across the different tasks here, noting that a few of the works we compare to (namely Antoun et al. (2020), Abdelali et al. (2020), Obeid et al. (2020), and Farha and Magdy (2020)) did not have a DEV split and hence do not show in our appendices.

## A Sentiment Analysis

| Data (#classes) | LM | Dev | | |
|---|---|---|---|---|
| | | Acc. | F1 | $F_1^{PN}$ |
| AraNET sentiment (2) | mBERT | 84.80 | 83.84 | 84.00 |
| | XLM-$R_B$ | 92.40 | 91.93 | 92.00 |
| | XLM-$R_L$ | 93.50 | **93.11** | 93.00 |
| | AraBERT | 87.14 | 86.44 | 86.50 |
| | ARBERT | 89.55 | 88.95 | 89.00 |
| | MARBERT | 92.77 | 92.31 | 92.00 |
| AraSenTi-Tweet (3) | mBERT | 93.05 | 92.94 | 93.00 |
| | XLM-$R_B$ | 94.25 | 94.10 | 93.50 |
| | XLM-$R_L$ | 95.44 | 95.34 | **95.00** |
| | AraBERT | 92.75 | 92.60 | 91.50 |
| | ARBERT | 92.60 | 92.49 | 92.00 |
| | MARBERT | 93.87 | 93.81 | 93.50 |
| BBN(3) | mBERT | 64.52 | 56.08 | 68.00 |
| | XLM-$R_B$ | 71.77 | 62.55 | 75.00 |
| | XLM-$R_L$ | 46.77 | 31.30 | 47.00 |
| | AraBERT | 66.13 | 46.69 | 70.00 |
| | ARBERT | 75.00 | 66.45 | **79.50** |
| | MARBERT | 75.81 | 68.57 | **78.50** |
| SYTS(3) | mBERT | 70.78 | 41.34 | 62.00 |
| | XLM-$R_B$ | 79.87 | 67.93 | **80.50** |
| | XLM-$R_L$ | 66.88 | 26.72 | 40.00 |
| | AraBERT | 72.73 | 43.22 | 65.00 |
| | ARBERT | 69.48 | 45.86 | **69.00** |
| | MARBERT | 76.62 | 48.39 | 72.50 |
| Saad2019 (2) | mBERT | 79.81 | 79.76 | 80.00 |
| | XLM-$R_B$ | 95.60 | 95.60 | 95.50 |
| | XLM-$R_L$ | 95.53 | 95.53 | **95.50** |
| | AraBERT | 81.24 | 81.24 | 81.50 |
| | ARBERT | 89.90 | 89.90 | 90.00 |
| | MARBERT | 96.02 | 96.02 | **96.00** |
| SAMAR(5) | mBERT | 46.60 | 24.22 | 26.00 |
| | XLM-$R_B$ | 55.02 | 50.30 | 54.50 |
| | XLM-$R_L$ | 59.22 | 50.29 | **61.00** |
| | AraBERT | 49.84 | 36.06 | 42.50 |
| | ARBERT | 56.31 | 40.19 | 50.50 |
| | MARBERT | 58.58 | 52.18 | **62.50** |
| AWATIF(4) | mBERT | 65.84 | 59.01 | 63.50 |
| | XLM-$R_B$ | 68.33 | 59.83 | 62.00 |
| | XLM-$R_L$ | 70.82 | 65.35 | 67.50 |
| | AraBERT | 71.53 | 61.99 | 65.00 |
| | ARBERT | 73.31 | 66.89 | **70.50** |
| | MARBERT | 75.09 | 65.51 | **72.00** |
| Abdullah2013 (2) | mBERT | 87.56 | 87.41 | 87.50 |
| | XLM-$R_B$ | 91.04 | 90.96 | 91.00 |
| | XLM-$R_L$ | 95.52 | 95.47 | 95.50 |
| | AraBERT | 92.54 | 92.52 | 92.50 |
| | ARBERT | 99.00 | 98.99 | **99.00** |
| | MARBERT | 97.01 | 96.98 | **97.00** |

Table A.1: Results of sentiment analysis models on DEV.

## B Sentiment Analysis Results

| Dataset (#classes) | Task | LM | DEV | |
|---|---|---|---|---|
| | | | Acc. | F1 |
| OSACT-A (2) | Offensive | mBERT | 91.10 | 84.04 |
| | | XLM-$R_B$ | 91.70 | 85.26 |
| | | XLM-$R_L$ | 92.40 | 86.72 |
| | | AraBERT | 92.70 | 87.21 |
| | | ARBERT | 93.50 | 88.77 |
| | | MARBERT | 95.10 | **91.68** |
| OSACT-B (2) | Hate Speech | mBERT | 96.70 | 75.91 |
| | | XLM-$R_B$ | 96.40 | 76.56 |
| | | XLM-$R_L$ | 96.50 | 78.00 |
| | | AraBERT | 95.00 | 72.09 |
| | | ARBERT | 96.30 | 75.01 |
| | | MARBERT | 97.00 | 82.91 |
| AraDange (2) | Dangerous | mBERT | 78.05 | 67.35 |
| | | XLM-$R_B$ | 78.21 | 65.09 |
| | | XLM-$R_L$ | 81.30 | 69.95 |
| | | AraBERT | 80.98 | 67.73 |
| | | ARBERT | 80.33 | 68.58 |
| | | MARBERT | 83.25 | **75.50** |
| $\text{AraNET}_{\text{Emo}}$ (8) | Emotion | mBERT | 62.93 | 61.34 |
| | | XLM-$R_B$ | 73.05 | 72.09 |
| | | XLM-$R_L$ | 73.71 | 72.78 |
| | | AraBERT | 67.22 | 65.46 |
| | | ARBERT | 69.20 | 68.05 |
| | | MARBERT | 75.80 | **75.18** |
| FIRE2019 (2) | Irony | mBERT | 81.14 | 81.08 |
| | | XLM-$R_B$ | 83.13 | 83.12 |
| | | XLM-$R_L$ | 81.39 | 81.29 |
| | | AraBERT | 79.16 | 79.12 |
| | | ARBERT | 84.86 | **84.83** |
| | | MARBERT | 86.85 | 86.77 |
| Arab_Tweet (3) | Age | mBERT | 56.19 | 56.33 |
| | | XLM-$R_B$ | 59.73 | 59.70 |
| | | XLM-$R_L$ | 53.45 | 53.63 |
| | | AraBERT | 57.51 | 57.67 |
| | | ARBERT | 58.48 | 58.60 |
| | | MARBERT | 62.05 | **62.19** |
| Arab_Tweet (2) | Gender | mBERT | 68.60 | 68.06 |
| | | XLM-$R_B$ | 71.25 | 71.10 |
| | | XLM-$R_L$ | 71.54 | 71.23 |
| | | AraBERT | 68.49 | 67.61 |
| | | ARBERT | 70.30 | 69.97 |
| | | MARBERT | 73.07 | **72.81** |

Table B.1: Results of social meaning models on DEV.

## C Social Meaning

| Data (#classes) | LM | DEV | |
|---|---|---|---|
| | | Acc. | $F_1$ |
| OSAC (10) | mBERT | 98.75 | 97.87 |
| | XLM-$R_B$ | 98.80 | 97.75 |
| | XLM-$R_L$ | 98.80 | 97.61 |
| | AraBERT | 98.93 | **97.94** |
| | ARBERT | 98.66 | 97.56 |
| | MARBERT | 98.80 | 97.66 |
| Khallej (4) | mBERT | 94.55 | 94.48 |
| | XLM-$R_B$ | 95.43 | 95.32 |
| | XLM-$R_L$ | 96.31 | 96.09 |
| | AraBERT | 95.96 | 95.65 |
| | ARBERT | 96.13 | 96.16 |
| | MARBERT | 96.31 | **96.31** |
| $\text{ANT}_{\text{Text}}$ (5) | mBERT | 85.79 | 85.04 |
| | XLM-$R_B$ | 86.96 | 86.74 |
| | XLM-$R_L$ | 88.30 | 87.41 |
| | AraBERT | 88.55 | **87.98** |
| | ARBERT | 87.25 | 87.06 |
| | MARBERT | 86.30 | 85.80 |
| $\text{ANT}_{\text{Title}}$ (5) | mBERT | 80.08 | 79.46 |
| | XLM-$R_B$ | 81.70 | 80.77 |
| | XLM-$R_L$ | 82.62 | 82.04 |
| | AraBERT | 83.67 | **83.56** |
| | ARBERT | 81.29 | 81.10 |
| | MARBERT | 81.73 | 82.36 |
| $\text{ANT}_{\text{Title+Text}}$ (5) | mBERT | 87.41 | 87.24 |
| | XLM-$R_B$ | 87.25 | 86.36 |
| | XLM-$R_L$ | 88.71 | 88.45 |
| | AraBERT | 88.68 | **88.76** |
| | ARBERT | 87.41 | 87.27 |
| | MARBERT | 64.08 | 85.99 |

Table C.1: Results of TC models on DEV.

# D Dialect Identification

| Dataset (#classes) | Task | LM | DEV | |
|---|---|---|---|---|
| | | | Acc. | F1 |
| MADAR-TL (21) | Country | mBERT | 48.07 | 33.75 |
| | | XLM-R$_{base}$ | 48.91 | 34.54 |
| | | XLM-R$_{large}$ | 49.34 | 33.28 |
| | | AraBERT | 48.84 | 33.47 |
| | | ARBERT | 51.84 | 39.24 |
| | | MARBERT | 53.48 | **40.61** |
| AOC (4) | Region | mBERT | 48.54 | 35.38 |
| | | XLM-R$_{base}$ | 49.15 | 33.50 |
| | | XLM-R$_{large}$ | 49.82 | 36.31 |
| | | AraBERT | 49.61 | 35.89 |
| | | ARBERT | 51.53 | 39.14 |
| | | MARBERT | 87.15 | **83.56** |
| AOC (3) | Region | mBERT | 87.46 | 87.07 |
| | | XLM-R$_{base}$ | 87.24 | 86.80 |
| | | XLM-R$_{large}$ | 88.58 | 88.21 |
| | | AraBERT | 88.94 | 88.46 |
| | | ARBERT | 89.98 | 89.57 |
| | | MARBERT | 91.93 | **91.56** |
| AOC (4) | Binary | mBERT | 88.36 | 87.89 |
| | | XLM-R$_{base}$ | 88.03 | 87.63 |
| | | XLM-R$_{large}$ | 88.81 | 88.38 |
| | | AraBERT | 89.15 | 88.76 |
| | | ARBERT | 89.72 | 89.32 |
| | | MARBERT | 90.06 | **89.66** |
| NADI (21) | Country | mBERT | 33.17 | 14.49 |
| | | XLM-R$_{base}$ | 35.34 | 17.30 |
| | | XLM-R$_{large}$ | 37.44 | 18.62 |
| | | AraBERT | 36.51 | 16.18 |
| | | ARBERT | 42.87 | 23.73 |
| | | MARBERT | 48.86 | **26.40** |
| Province (100 ) | Province | mBERT | 4.10 | 2.32 |
| | | XLM-R$_{base}$ | 4.70 | 3.91 |
| | | XLM-R$_{large}$ | 2.78 | 0.65 |
| | | AraBERT | 4.12 | 3.04 |
| | | ARBERT | 7.16 | **6.05** |
| | | MARBERT | 7.91 | 5.23 |

Table D.1: Results of dialect identification models on DEV.

# E NER

| Dataset (#classes) | LM | DEV | |
|---|---|---|---|
| | | Acc. | $F_1$ |
| ANERcorp. | mBERT | 97.74 | 86.20 |
| | XLM-R$_B$ | 88.06 | 87.24 |
| | XLM-R$_L$ | 98.63 | **89.64** |
| | AraBERT | 98.51 | 90.24 |
| | ARBERT | 97.77 | 83.32 |
| | MARBERT | xx | xx |
| ACE 2004 NW | mBERT | 96.77 | 86.57 |
| | XLM-R$_B$ | 97.64 | 88.21 |
| | XLM-R$_L$ | 97.93 | 90.49 |
| | AraBERT | 97.76 | 89.76 |
| | ARBERT | 97.31 | 86.17 |
| | MARBERT | xx | xx |
| ACE 2003 BN | mBERT | 96.46 | 80.35 |
| | XLM-R$_B$ | 91.55 | 40.36 |
| | XLM-R$_L$ | 97.01 | 83.39 |
| | AraBERT | 96.84 | 81.05 |
| | ARBERT | **98.38** | **90.91** |
| | MARBERT | xx | xx |
| ACE 2003 NW | mBERT | 96.63 | 87.21 |
| | XLM-R$_B$ | 97.78 | 90.08 |
| | XLM-R$_L$ | 98.12 | 91.94 |
| | AraBERT | 97.65 | 89.70 |
| | ARBERT | 97.23 | 89.33 |
| | MARBERT | xx | xx |
| Twitter | mBERT | 96.21 | 52.60 |
| | XLM-R$_B$ | 98.01 | 73.48 |
| | XLM-R$_L$ | 98.29 | 77.70 |
| | AraBERT | 97.59 | 73.61 |
| | ARBERT | 97.91 | 70.78 |
| | MARBERT | xx | xx |

Table E.1: Results of NER models on DEV.