TunBERT: Pretrained Contextualized Text Representation for Tunisian Dialect

Abir Messaoudi Hatem Haddad Moez BenHajhmida Malek Naski

iCompass

Ahmed Cheikhrouhou Nourchene Ferchichi Abir Korched Faten Ghriss Amine Kerkeni InstaDeep

Abstract

Pretrained contextualized text representation models learn an effective representation of a natural language to make it machine understandable. After the breakthrough of the attention mechanism, a new generation of pretrained models have been proposed achieving good performances since the introduction of the Transformer. Bidirectional Encoder Representations from Transformers (BERT) has become the state-of-the-art model for language understanding. Despite their success, most of the available models have been trained on Indo-European languages however similar research for under-represented languages and dialects remains sparse. In this paper, we investigate the feasibility of training monolingual Transformer-based language models for under represented languages, with a specific focus on the Tunisian dialect. We evaluate our language model on sentiment analysis task, dialect identification task and reading comprehension question-answering task. We show that the use of noisy web crawled data instead of structured data (Wikipedia, articles, etc.) is more convenient for such non-standardized language. Moreover, results indicate that a relatively small web crawled dataset leads to performances that are as good as those obtained using larger datasets. Finally, our best performing TunBERT model reaches or improves the state-of-the-art in all three downstream tasks. We release the TunBERT pretrained model and the datasets used for finetuning¹.

1 Introduction

In the last decade, natural language understanding has gained interest owing to the available hardware and data resources and to the evolution of the pretrained contextualized text representation models. These models learn an effective representation of a natural language to make it machine understandable. Word2Vec (Mikolov et al., 2013) has been one of the first proposed approaches where words were represented according to their semantic property. Next, ELMO (Peters et al., 2018) combined the previous model with BiLSTM in order to deal with the polysemy problem. Afterwards, the pretraining models have been firstly proposed with ULMFit (Howard and Ruder, 2018) where they were fine-tuned for downstream tasks. These models have achieved good performances but they did not support long-term and multiple contexts of the words.

After the breakthrough of the attention mechanism (Vaswani et al., 2017), a new generation of pretrained models have appeared. They have achieved tremendous performances since the introduction of the Transformers (Radford, 2018). Besides, the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) has been unleashed to become the state-of-the-art model for language understanding and gave new inspiration to further development in the Natural Language Processing (NLP) field. Accordingly, most languages have their own BERT-based language models. Specifically, the Arabic language has multiple language models: AraBERT (Antoun et al., 2020), GigaBERT (Wuwei et al., 2020), and multilingual cased BERT model (hereafter mBERT) (Pires et al., 2019) which was simultaneously pretrained on 104 languages.

Arabic language has more than 300 million native speakers around the world and it's used as a native language in 26 countries. The official form of Arabic is called Modern Standard Arabic (MSA). Although, each country has one or more locally Arabic spoken language, called Dialect. The people in Tunisia use the Tunisian dialect (Fourati et al., 2020) in their daily communications, most of their media (TV, radio, songs, etc), and on the internet (social media, forums). Yet, this

¹To preserve anonymity, a link to Github repository will be added to the camera-ready version if the paper is accepted.

dialect is not standardized which means there is no unique way for writing and speaking. Added to that, it has its proprietary lexicon, phonetics, and morphological structure as shown in Table 1.

The need for a robust language model for Tunisian dialect has become crucial to develop natural-language-processing-based applications (translation, information retrieval, sentiment analysis, etc). To the best of our knowledge, there is no such model proposed yet in literatures.

In this paper, we describe the process of pretraining a Pytorch implementation of NVIDIA BERT language model², called TunBERT (Tunisian BERT), trained on only 67.2 MB web-scraped dataset. We systematically compare our pre-trained model on three NLP downstream tasks; that are different in nature: (i) Sentiment Analysis (SA), (ii) Tunisian dialect identification (TDI), and (iii) Reading Comprehension Question-Answering (RCQA); against mBERT (Devlin et al., 2019), AraBERT (Antoun et al., 2020), GigaBERT (Wuwei et al., 2020) and the state of the art performances when available. Our contributions can be summarized as follows:

- First release of a pretrained BERT model for the Tunisian dialect using a Tunisian largescale web-scraped dataset.
- TunBERT application to three NLP downstream tasks: Sentiment Analysis (SA), Tunisian dialect identification (TDI) and Reading Comprehension Question-Answering (RCQA).
- Empirical evaluations illustrate that small and diverse Tunisian training dataset can achieve similar performance compared to several baselines including previous multilingual and single-language approaches trained on large-scale corpora.
- Publicly releasing TunBERT and the used datasets on popular NLP libraries³.

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

2 Related Works

Contextualized word representations, such as BERT (Devlin et al., 2019), RoBERTa (Delobelle et al., 2019) and more recently ALBERT (Lan et al., 2020), improved the representational power of word embeddings such as word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014) and fastText (Bojanowski et al., 2017) by taking context into account. Following their success, the large pretrained language models were extended to the multilingual setting such as mBERT (Pires et al., 2019). In (Conneau and Lample, 2019), authors showed that multilingual models can obtain results competitive with monolingual models by leveraging higher quality data from other languages on specific downstream tasks. Nevertheless, these models have used large scale pretraining corpora and consequently need high computational cost.

Recently, non-English monolingual models have been released: RobBERT for Dutch (Delobelle et al., 2020), FlauBERT (Le et al., 2020) and CamemBERT for French (Martin et al., 2020), (Canete et al., 2020) for Spanish and (Virtanen et al., 2019) for Finnish. In (Martin et al., 2020), authors showed that their French model trained on a 4 GB performed similarly to same model trained on the 138GB. They also concluded that a model trained on a Common- Crawl-based corpus performed consistently better than the one trained on the French Wikipedia. They suggested that a 4 GB heterogeneous dataset in terms of genre and style is large enough as a pretraining dataset to reach state-of-the-art results with the BASE architecure, better than those obtained with mBERT (pretrained on 60 GB of text). In (Virtanen et al., 2019), a Finnish BERT model trained from scratch outperformed mBERT for three reference tasks (partof-speech tagging, named entity recognition, and dependency parsing). Authors suggested that a language-specific deep transfer learning models for lower-resourced languages can outperform multilingual BERT models.

²https://github.com/NVIDIA/
DeepLearningExamples/tree/master/
PyTorch/LanguageModeling/BERT

³To preserve anonymity, a link to Github repository will be added to the camera-ready version if the paper is accepted.

Tunisian	MSA	English
محلاها هالغناية	ما أحلى هذه الأغنية	How nice is this song
ماتعجبنيش كيفاش تتصرف	لا تعجبني تصرفاتها	I don't like how she behaves
وقتاه يبدا الماتش	متى تبدأ المباراة	When does the match start

Table 1: Examples of Tunisian sentences with their MSA and English translation.

Compared to the increasing studies of contextualized word representations in Indo-European languages, similar research for Arabic language is still very limited. AraBERT (Antoun et al., 2020), a BERT-based model, was released using a pre-training dataset of 70 million sentences, corresponding to 24 GB of text covering news from different Arab media. AraBERT was pre-trained on a TPUv2-8 pod for 1,250K steps. It achieved stateof-the-art performances on three Arabic tasks: Sentiment Analysis, Named Entity Recognition, and Question Answering. Nevertheless, the pre-trained dataset is mostly a MSA based. Authors concluded that there is a need for pretrained models that can tackle a variety of Arabic dialects. Lately, Giga-BERT (Wuwei et al., 2020) customized bilingual language model for English and Arabic has outperformed AraBERT in several downstream tasks.

3 TunBERT

In this section, we describe the training Setup and pretraining data that was used for TunBERT.

3.1 Training Setup

TunBERT model is based on the Pytorch implementation of NVIDIA NeMo BERT ⁴. The model was pre-trained using 4 NVIDIA Tesla V100 GPUs for 1280K steps. The pretrained model characteristics are shown in Table 3. Adam optimizer was used, with a learning rate of 1e-4, a batch size of 128, a maximum sequence length of 128 and a masking probability of 15%. Cosine annealing was used for learning rate scheduling with a warm-up ratio of 0.01. Training took 122 hours and 25 minutes for 330 epochs over all the tokens.

The model was trained on two unsupervised prediction tasks using a large Tunisian text corpus: The Masked Language Modeling (MLM) task and the Next Sentence Prediction (NSP) task.

For the MLM task, 15% of the words in each sequence are replaced with a [MASK] token. Then,

#Uniq Words	#Words	#Sentences
8,256K	48,233K	500K

Table 2: Pretraining dataset statistics.

#Layers	Hidden Size	#self-attention heads
12	768	12

Table 3: Pretrained model configuration.

the model attempts to predict the original masked token based on the context of the non-masked tokens in the sequence. For the NSP task, pairs of sentences are provided to the model. The model has to predict if the second sentence is the subsequent sentence in the original document. In this task, 50% of the pair sentences are subsequent to each other in the original document. The remaining 50% random sample sentences are chosen from the corpus to be added to the first sentence.

3.2 Pre-training Dataset

Because of the lack of available Tunisian dialect data (books, wikipedia, etc.), we use a web-scraped dataset extracted from social media, blogs and websites consisting of 500k sentences of text, to pretrain the model. The extracted data was preprocessed by removing links, emoji and punctuation symbols. Then, a filter was applied to ensure that only Arabic scripts are included. Pretraining dataset statistics are presented in Table 2. The training dataset size is 67.2 MB.

4 Evaluation

We measure the performance of TunBERT by evaluating it on three tasks: Sentiment Analysis, Dialect identification and Reading Comprehension Question-Answering. Fine-tuning was done independently using the same configuration for all tasks. We do not run extensive grid search for choosing the best hyper-parameters due to computational and time constraints. We applied a configuration commonly used in the literature. We use the splits provided by the datasets authors when available

⁴https://github.com/NVIDIA/
DeepLearningExamples/tree/master/
PyTorch/LanguageModeling/BERT

Dataset	TSAC	TEC
#Negative	4175	1799
#Positive	3277	1244
#Train	4680	1947
#Dev	1170	487
#Test	1516	609

Table 4: TSAC and TEC Sentiment analysis datasets statistics.

and the standard 80 % and 20% when not.

4.1 Sentiment Analysis

For the sentiment analysis task, we used two manually annotated Tunisian Sentiment Analysis datastes:

- Tunisian Sentiment Analysis Corpus (TSAC) (Medhaffar et al., 2017) obtained from Facebook comments about popular TV shows. The TSAC dataset is composed of comments based on Latin scripts, Arabic scripts and emoticons. We use only the Arabic script comments.
- Tunisian Election Corpus (TEC) (Sayadi et al., 2016) obtained from tweets about Tunisian elections in 2014. Beside Tunisian content, TEC dataset content is also composed of MSA content.

Statistics of the TSAC and TEC are shown in Table 4.

4.2 Tunisian Dialect identification

This task focuses on identifying the Tunisian dialect of a given text from other Arabic dialects, especially on social media sources where there is no established standard orthography like MSA. First attempts to tackle the challenge identified 5 Arabic dialects categories in addition to MSA: Maghrebi, Egyptian, Levantine, Gulf, and Iraqi (Zaidan and Callison-Burch, 2011). (El-Haj et al., 2018) proposed 4 Arabic dialects categories by merging the Iraqi with the Gulf. Tunisian dialect was classified into the Maghrebi dialect along with the Algerian, Moroccan, and other dialects. Nevertheless, even if the Maghrebi vocabulary is pretty much similar throughout North African countries, many differences exist not only at the phonetic level (Harrat et al., 2018) but also at the lexical, morphological and syntactic levels (Horesh, 2019).

For evaluation, two sub-tasks were performed:

Dataset	TADI	TAD
#Train	40500	3200
#DEV	2396	400
#Test	7192	400

Table 5: TADI and TAD dataset statistics.

- Identification of Tunisian dialect from other Arabic dialects (TADI): this is a binary classification task: Tunisian dialect and Non Tunisian dialect from an Arabic dialectical dataset. We used the Nuanced Arabic Dialect Identification (NADI) shared task dataset with a total of 21,000 tweets, covering 21 Arab countries. NADI is an imbalanced dataset in which the training includes only 747 Tunisian tweets and the remaining tweets cover other dialects. Consequently, this dataset is unbalanced. To solve this issue, we created a new dataset TADI (Tunisian and Arabic Dialect Identification) by including a sub-set of TSAC dataset as Tunisian comments to have the same number of tweets for the Tunisian dialect as same as the other dialects as shown in Table 5.
- Identification of Tunisian dialect and Algerian dialect (TAD dataset): for this sub-task we used the Multi-Arabic Dialect Applications and Resources (MADAR) dataset (Bouamor et al., 2018). More specifically, we used the shared task dataset to target a large set of dialect labels at country level. We filtered the dataset of dialect labels at country level (Bouamor et al., 2019) to only keep Tunisia and Algerian labeled data as shown in Table 5.

4.3 Reading Comprehension Question-Answering

Open-domain Question-Answering (QA) task has been intensively studied to evaluate the language Understanding performances of the models. This task takes as input a textual question to look for correspondent answers within a large textual corpus. In (Mozannar et al., 2019), two MSA QA datasets has been proposed. However, to the best of our knowledge, no study was previously made for such a task for any Arabic dialect.

For this task, we built TRCD (Tunisian Reading Comprehension Dataset) as Question-Answering

Dataset	#Document	#Paragraph	#QA
#Train	114	342	1026
#Dev	15	45	135
#Test	15	45	135

Table 6: TRCD statistics.

Model	Accuracy	F1.macro
(Medhaffar et al., 2017)	78%	78%
word2vec (Mulki et al., 2020)	77.4%	78.2%
doc2vec (Mulki et al., 2020)	57.2%	61.7%
Tw-StAR (Mulki et al., 2020)	86.5%	86.2%
mBERT	92.21%	91.03%
GigaBERT	94.92%	93.39%
AraBERT	95.63%	94.91%
TunBERT	96.98%	96.98%

Table 7: TSAC results.

dataset for Tunisian dialect. We used a dialectal version of the Tunisian constitution following the guideline in (Chen et al., 2017). It is composed of 144 documents where each document has exactly 3 paragraphs and three Question-Answer pairs are assigned to each paragraph. Questions were formulated by four native speaker annotators and each question should be paired with a paragraph as shown in Figure 1).

To the best of our knowledge, this is the first Tunisian dialect dataset for the Question-Answering task. TRCD dataset statistics are showed in Table 6.

5 Experiments and Discussion

5.1 Tunisian Sentiment Analysis

The efficiency of TunBERT language model was evaluated against mBERT, AraBERT and Giga-BERT language models and the state of the art performances when available. The obtained performances of Tunisian Sentiment Analysis using TunBERT were further compared against the baseline systems that tackled the same datasets (word embeddings (word2vec), document embeddings (doc2vec) and Tw-StAR (Mulki et al., 2020)) and listed in Table 7 and Table 8.

The results in Table 7 illustrate the outperformance of the pretrained contextualized text representation models over the previous techniques namely word2vec and doc2vec. TunBERT achieved the best performance on the TSAC dataset.

Model	Accuracy	F1.macro
(Sayadi et al., 2016)	71.1%	63%
word2vec (Mulki et al., 2020)	61.9 %	58.4%
doc2vec (Mulki et al., 2020)	62.2%	56.4%
Tw-StAR (Mulki et al., 2020)	88.2%	87.8 %
mBERT	58.45%	36.89%
GigaBERT	71.75%	65.32%
AraBERT	79.14%	72.57%
TunBERT	81.2%	76.45%

Table 8: TEC results.

It reached 92.98% as F1.macro which is a high result comparing to to 78.2%, 61.7% and 86.2% scored by word2vec, doc2vec and Tw-StAR, respectively. The results show that TunBERT also outperform pretrained language models: mBERT, GigaBERT and AraBERT.

Likewise, Table 8 illustrates the outperformance of BERT-based LM against other techniques with the TEC dataset. Nevertheless, the best performances was achieved by Tw-StAR. For instance, the best achieved Tw-StAR F1.macro was in TEC dataset with a value of 87.8% compared to 76.45%, and 72.57% scored by TunBERT and AraBERT, respectively. This could be explained by the noisy nature of TEC dataset with a mixed Tunisian and MSA content. Results using mBERT achieved the worst performances could demonstrate that mBERT is not suitable for noisy data. The results showcase also the outperformance of TunBERT over the other pretrained language models.

5.2 Tunisian Dialect identification

For Tunisian Dialect identification, the results in Table 9 show that the TunBERT language model outperform other state-of-the-art language models. Indeed, our model achieved a F1.macro of 87.14% compared to 68.93% achieved by mBERT. TunBERT also outperforms the Arabic language pretrained BERT AraBERT. Likewise, it has achieved a F1.macro of 93.25% for the Tunisian-Algerian dialects identification task outperforming the other used language models as shown in Table 10.

5.3 Reading Comprehension Question-Answering

Fine-tuning TunBERT on the Tunisian Reading Comprehension Dataset did not give impressive results (Exact match of 2.17%, F1 score of 13.66% and a Recall of 22.59%). Comparable results

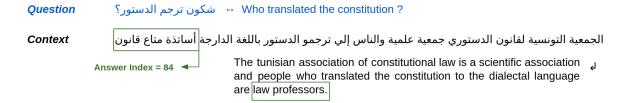


Figure 1: TRCD dataset example with its corresponding English translation.

Model	Accuracy	F1.macro
mBERT	75,21%	68.93%
AraBERT	79.57%	76.7%
GigaBERT	72.67%	65.3%
TunBERT	87.46%	87.14%

Table 9: TADI results

Model	Accuracy	F1.macro
mBERT	86.75%	86.4%
AraBERT	87.5% %	87.37%
GigaBERT		0%
TunBERT	93.3%	93.25%

Table 10: TAD results

were obtained for GigaBERT (Exact match of 0.7%, F1 score of 14.02% and a Recall of 21.65%). MBERT gave slightly better results (Exact match of 4.25%, F1 score of 22.6% and a Recall of31.3). Meanwhile, we noticed good results for AraBERT (Exact match of 26.24%, F1 score of 58.74% and a Recall of 63.96%).

Adding a pre-training step on an MSA reading comprehension dataset (In our case the Arabic-SQuAD dataset (Mozannar et al., 2019)) made great improvements in all of the models performances, especially for the TunBERT. The strategy was to use the pre-trained language model, fine-tune it for few epochs on the MSA dataset, then use the best checkpoint to train and test on the TRCD dataset. Following this stategy, TunBERT acheived great results with an Exact match of 27.65%, an F1 score of 60.24% and a Recall of 82.36%, as shown in Table 11.

5.4 Discussion

The experimental results indicate that the proposed pre-trained TunBERT model yields improvements, compared to mBert, Gigabert and AraBERT models as shown in Tables 7 and 8 for the

sentiment analysis sub-task, Tables 9 and 10 for dialect identification task, and Table 11 for the question-answering task.

Not surprisingly, GigaBERT as customized BERT for English-to-Arabic cross-lingual transfer is not effective for the tackled tasks and should be applied for tasks using code-switched data as suggested in (Wuwei et al., 2020).

As AraBERT was trained on news from different Arab media, it shows good performances on the three tasks as the datasets contain some formal text (MSA). The TunBERT was trained on a dataset including web text, which is useful on casual text, such as Tunisian dialect in Social media. For this reason, it performed better than AraBERT on all the performed tasks.

We show that pretraining Tunisian model on highly variable dataset from social media leads to better downstream performance compared to models trained on more uniform data. Moreover, results led to the conclusion that a relatively small amount of web-scraped dataset (67.2M) leads to downstream performances as good as models pretrained on a datasets of larger magnitude (24 GB for AraBERT and about 10.4B tokens for GigaBERT).

This is confirmed with the QA-task experiments where the created dataset contains a small amount of dialect texts. The Arabic-SQuAD dataset was used to help with the missing embeddings of the MSA and to permit the finetuned model to effectively learn the QA-task by providing more examples of question-answering. The TunBERT model has overcome all the other models in term of exact match and recall.

6 Conclusion

In this paper, we reported our efforts to develop a powerful Transformer-based language models for Tunisian dialect: TunBERT. Our models are

Finetuning	TRCD dataset		Arabic SQuAD			
datasets			and TRCD			
Language Models	Exact match F1 score Recall		Exact match	F1 score	Recall	
mBERT	4.25	22.6	31.3	29.07	60.86	62.18
AraBERT	26.24	58.74	63.96	24.11	63.53	70.43
GigaBERT	0.7	14.02	21.65	29.78	62.44	66.34
TunBERT	2.127	13.665	22.597	27.65	60.24	82.36

Table 11: TRCD results before and after pre-training on Arabic-SQuaD

trained on 67.2 MB Common-Crawl-based dataset extracted from social media consisting of 500k sentences of text. When fine-tuned on the various labeled datasets, our TunBERT model achieves new SOTA on all the tasks on all datasets. Compared to larger models such as GigaBERT and AraBERT, our TunBERT model has better representation of Tunisian dialect and yield better performances in addition to being less computationally costly at inference time. Our models are publicly available for research⁵. 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.

On social media, Tunisian people tend to express themselves using an informal way called "TUNIZI" (Fourati et al., 2020) that represents the Tunisian Arabic text written using Latin characters and numerals rather than Arabic letters. For instance, the word "sou2el" is the Latin based characters of the word "uniell". A natural future step would involve building a multi-script Tunisian dialect language model including Arabic script and Latin script based characters.

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⁵To preserve anonymity, a link to Github repository will be added to the camera-ready version if the paper is accepted. ⁶The word "Question" is the English translation.

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