Can Multilingual Language Models Transfer to an Unseen Dialect?
A Case Study on North African Arabizi

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Abstract
Building natural language processing systems for non-standardized and low resource languages is a difficult challenge. The recent success of large-scale multilingual pretrained language models provides new modeling tools to tackle this. In this work, we study the ability of multilingual language models to process an unseen dialect. We take user-generated North-African Arabic as our case study, a resource-poor dialectal variety of Arabic with frequent code-mixing with French and written in Arabizi, a non-standardized transliteration of Arabic to Latin script. Focusing on two tasks, part-of-speech tagging and dependency parsing, we show in zero-shot and unsupervised adaptation scenarios that multilingual language models are able to transfer to such an unseen dialect, specifically in two extreme cases: (i) across scripts, using Modern Standard Arabic as a source language, and (ii) from a distantly related language, unseen during pretraining, namely Maltese. Our results constitute the first successful transfer experiments on this dialect, paving thus the way for the development of an NLP ecosystem for resource-scarce, non-standardized and highly variable vernacular languages.

1 Introduction
Accurately modeling low resource and non-standardized languages exhibiting a high degree of variation is extremely challenging. Recent releases of multilingual language models trained on large corpora (Devlin et al., 2019; Lample and Conneau, 2019) provide an interesting opportunity to address this challenge in new ways. We frame our work as a cross-lingual transfer learning analysis; we study the capacity of a system trained as a language model on a source set of languages to transfer to a target language and task. More precisely, we investigate the ability of multilingual language models to process a language that is absent from their pre-training set. For brevity, we simply refer to such languages as unseen.

Our work focuses on the multilingual version of BERT (mBERT) (Devlin et al., 2019). The cross-lingual modeling ability of mBERT has been recently studied by Pires et al. (2019), who show that cross-lingual transfer is very efficient between pretrained languages. In our work, we address a different and more challenging question: can mBERT transfer to an unseen and non-standardized dialect? We take North-African Arabizi, hereafter Narabizi, as our case study. We define Narabizi as the Arabic dialect spoken in Algeria, found ubiquitously on social media and written in Latin script, although with no standard spelling and no standard transliteration of Arabic letters. It is a non-standardized dialect and shows a high degree of code-mixing with French (Amazouz et al., 2019). This makes Narabizi highly variable across users and therefore very challenging for Natural Language Processing.

For our experiments, we use the Narabizi raw corpus and treebank recently released by Seddah et al. (2020) and focus on two tasks, namely part-of-speech (POS) tagging and dependency parsing. After a detailed cross-lingual performance analysis, our results show that multilingual models are able to transfer to unseen, highly variable data. More precisely, we make the following contributions:

- We push the zero-shot cross-lingual abilities of mBERT to the extreme and show that it can transfer to unseen Narabizi in POS tagging and parsing, even when the source is another unseen and related language such as Maltese.
- By running comparison across source languages and diverse BERT models, we demonstrate that mBERT is using its multilingual representations to process Narabizi.
- We show the positive impact of unsupervised fine-tuning on cross-lingual transfer and demonstrate its ability to make transfer possible, even across scripts, in a scenario where
the target language is not in the pre-training corpora.

2 Related Work

Word embedding & Cross lingual Transfer

Recently, cross lingual transfer has benefited from multilingual language models. We refer to (Lample and Conneau, 2019; Eisenschlos et al., 2019; Vania et al., 2019; Wu et al., 2019; Conneau et al., 2019; Wu and Dredze, 2019) who demonstrate the efficiency of language models in zero-shot transfer settings for a variety of tasks. In this regard, Pires et al. (2019) analyze in detail the zero-shot transfer ability of mBERT on sequence labeling. Wang et al. (2019) suggest that cross-lingual transfer of multilingual models rely on structural properties of languages. Both studies focus on transfer between languages that are part of the pretraining corpora. In our work, we study the ability of mBERT to transfer to an unseen language.

Code-Switching

is a hard challenge for NLP as shown in the myriad of works that have tackled this phenomenon for more than 10 years, see for example (Solorio and Liu, 2008; Vyas et al., 2014; Çetinoğlu and Çöltekin, 2016; Lynn and Scannell, 2019). Ball and Garrette (2018) and Pires et al. (2019) analyzed the performance of neural models for sequence labeling showing that those approaches can cope with such a complexity. In our work, we face both code-switched and highly variable data.

Unsupervised Adaptation of Language Models

Han and Eisenstein (2019) show that fine-tuning BERT in an unsupervised way using its masked language objective brings significant improvement to downstream sequence labeling tasks for out-of-domain Old English. Studying the specific case of English-Spanish code-mixing, Gonen and Goldberg (2018) show how to adapt bilingual language models to code-mixed data. In our work, we focus on unsupervised adaptation and analyze its impact on the even more challenging case of Narabizi.

3 Narabizi

Arabic varieties are often classified into three categories (Habash, 2010): (i) Classical Arabic, as found in the Qur’an and related canonical texts, (ii) Modern Standard Arabic (MSA), the official language of the vast majority of Arabic speaking countries and (iii) Dialectal Arabic. This work focuses on North-African dialectal Arabic in its Algerian form, understood and spoken by more than 40 million people in the Maghreb (Sayahi, 2014). In its written form, it is mostly found online and in Latin script. For simplicity we refer to this North-African Arabic dialect as North-African Arabizi (Farrag, 2012) or Narabizi, illustrated here:

source: Mrhba, Ana 3rbi mn dzaye
translation: “Hey, Im Arab from Algeria”

Like other written languages found on social media and even more importantly as it is not standardized, Narabizi shows a high degree of variability across writers. As part of its variability, Narabizi frequently involves code-switching with French.

Moreover, Narabizi does not belong to the pretraining corpora of mBERT. For this reason, we take Narabizi as our case study to analyze the ability of mBERT to handle an unseen, highly variable and code-mixed dialect.

Data

The data we use comes from two main sources. The first one, described by Cotterell et al. (2014), is a collection of 9000 raw Algerian romanized Arabic sentences, a sample of which has been annotated with Universal Dependency trees (McDonald et al., 2013) and word-level language identification by Seddah et al. (2020) totalling 1,434 (1172/146/178) annotated sentences. Our second source, also released by Seddah et al. (2020), is a collection of 49,546 raw Narabizi sentences.

Baselines

To grasp the complexity of Narabizi, we run some preliminary experiments. We take Qi et al. (2019)’s tagger and parser as our strong baselines (named StanfordNLP), and as our bottom lines the majority class predictor for POS tagging and the left predictor for dependency parsing. Competitive taggers perform on datasets of similar size above 90%. StanfordNLP only reaches 84.20% on our data for POS tagging and 52.84% for parsing, as measured by the unlabeled attachment score (UAS; cf. Table 1).

4 Model

mBERT is a Transformer (Vaswani et al., 2017) trained as a joint masked-language and a next sentence prediction task.
stance prediction model on sub-word level tokenized sentences. More details can be found in (Devlin et al., 2019). We use the multilingual cased version of BERT. mBERT was trained on the concatenation of the Wikipedia corpora for 104 languages.

**POS tagging and dependency parsing with mBERT** Following Devlin et al. (2019), we turn mBERT into a POS tagger by appending a softmax on top of its last layer. For parsing, we append the biaffine graph parser layers described by Dozat and Manning (2016). In both cases, we fine-tune the overall model by backpropagating only through the first sub-word token of each word. We call these architectures mBERT+POS and mBERT+PARSE, and use them in our zero-shot learning experiments by applying models trained on a source language to data in our target language.

**Unsupervised Adaptation** We call unsupervised adaptation the process of fine-tuning mBERT in an unsupervised manner using its Masked-Language Model (MLM) objective trained on raw sentences. We refer to mBERT fine-tuned on raw data as mBERT+MLM. We define as mBERT+MLM+TASK, with TASK referring to POS, resp. PARSE, to point to mBERT+MLM fine-tuned as a POS tagger, resp. parser.

5 Experiments

Our goal is to measure how well mBERT makes use of its multilingual pre-training on an unseen dialect. We defined a source language as a language on which a POS tagger or a parser are trained, and will report the performance of the resulting models when applied to Narabizi data.

5.1 Source Languages

We study transfer along two independent directions. The first one is the relatedness of the source language to Narabizi. The more different they are, the worse we expect the transfer to be. Our second direction distinguishes between source languages included in mBERT pre-training corpora and those that are not. We expect the transfer to be better when the source language is included in the pre-training corpora. To cover the full scope of cases, we pick Modern Standard Arabic, French, English and Vietnamese.

As recalled in (Habash, 2010; Čeplö et al., 2016), Maltese is related to the Arabic continuum of languages. It is standardized and written in an extended Latin script. This makes Maltese a promising candidate for transferring to Narabizi.

We also use French in order to study the impact of code-mixing. In addition, we experiment with English as another European language written in Latin script, but which is not code-mixed with Narabizi. Finally, we use Vietnamese as the most unrelated language to test the cross-lingual power of the model in the most extreme case. We refer the reader to the Appendix (Table 3) for an overview of the source languages. We sample the training datasets to have 1,200 sentences for each source language. Additionally, we report results in the standard supervised setting in which we fine-tune mBERT+TASK on Narabizi and evaluate on Narabizi. This provides us with an upper bound on how we can expect mBERT to perform on such a language.

5.2 Optimisation

For supervised fine-tuning, we use the same range of hyper-parameters as Devlin et al. (2019). For unsupervised adaptation, we run preliminary experiments to measure the impact of the raw corpus among the 49,000 sentences Narabizi corpus, and Narabizi mixed with a sub-sample extracted from mBERT pre-training corpora. As reported by Gonen and Goldberg (2018), we found that, if carefully optimized, fine-tuning mBERT with its masked language objective directly on the target data leads to the best models.6

6 Results and Discussion

We present our results in Table 1. We report the accuracy for POS tagging and the Unlabeled Attachment Score (UAS) for parsing.7 Any performance above the bottom line demonstrates that transfer is happening from the pre-training or fine-tuning stages to process Narabizi. For both POS tagging and parsing, mBERT+TASK performs outperforms the baselines by a large margin when the source is Maltese, French and English. This shows that mBERT is able to transfer to Narabizi even without having been trained on any Narabizi tokens at any stage of the training process.

We report an average boost with mBERT+MLM+TASK of +10.15 points in

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6 We pick the first 1,200 training sentences. More information on the datasets used is given in Appendix 5.1.

7 Cf. Appendix § A.2 for details on hyper-parameters.
6.2 Impact of code-mixing

We hypothesize that the high level of transfer when the source is French is due to the high code-mixing proportion of Narabizi. To test our hypothesis, we present in Figure 1 the performance of the model with respect to the code-mixing ratio.

We split the dataset into four buckets of around 25% of the full dataset, according to the ratio of native Narabizi tokens in each sentence (between less than 60% to strictly 100%) as opposed to French tokens. We compare French and Maltese as source languages. We confirm our intuition that code-mixing explains the good performance of the model trained on French. Indeed, on sentences that have 100% Narabizi tokens, mBERT+Task trained on French performs poorly (cf. fig. 1 (E) for POS and (L) for parsing). On the other side, for sentences that include at least 40% of French tokens, scores reach 54% (cf. (A)) for POS tagging and 47% for parsing (cf. (I)). Moreover, for French, mBERT+MLM+Task leads to an impressive 21.2% error reduction compared to mBERT+Task for POS tagging (33.12 vs. 47.32) and an 8.5% error reduction for parsing (cf. Table 1). We observe in Fig. 1 (cf. (B) and (K)) that this improvement mostly comes from a better accuracy on Narabizi tokens. Interestingly, we observe that unsupervised fine-tuning leads to the closing of the gap between the performance of the models tuned on French and Maltese on native Narabizi tokens (+15: (B)-(E) vs. +2.4: (B)-(C) for POS tagging and +5.6: (K)-(L) vs. +2.2: (J)-(K) for parsing). This demonstrates the capacity of unsupervised fine-tuning to close lexical mismatch between distant languages such as native Narabizi and French.

6.3 Transfer between unseen languages

Surprisingly, mBERT+Task tuned on Maltese does not perform poorly. It leads to the best performance for mBERT+Task for both POS tagging and parsing. It outperforms StanfordNLP in the zero-shot scenario by 5 points in POS tagging and 6 points in parsing. As seen in Figure 1 (C) and (J), it performs the best on native Narabizi sentences (with no code-mixing). This result is surprising as Maltese is absent from the pre-training corpora. It shows that mBERT is able to capture structural properties shared by related languages even if they are absent from the pre-training corpora, thereby extending the observations described by Wang et al. (2019).

Is the multilingualism of mBERT at play? Finally, we want to show that the ability of mBERT to achieve cross-lingual transfer is related to the 104 languages it is pre-trained on, rather than because a pre-trained Transformer is an inherently

Table 1: Cross-Lingual performance averaged on 5 seeds on the Narabizi test set. Baselines are described in Section 3.

Table 2: Zero-shot transfer from French (fr) and Maltese (mt) to Narabizi. 5 averaged seeds.

7 Conclusion

Our work on Narabizi reveals novel properties of multilingual language models. We have shown that transfer learning approaches can be used successfully on this language, both in zero-shot scenarios, where no target language data is used at any stage of the training process, and in unsupervised adaptation scenarios, where only raw target language data is used.

This is remarkable, because Narabizi, an increasingly used language on social media, is an extremely challenging language for NLP in general and transfer learning approaches in particular, for at least three reasons: (i) it is written in a script different to its closest resourced relative (Modern Standard Arabic), (ii) it displays a high degree of variation because of the lack of spelling standard, and (iii) it involves frequent code-switching with an unrelated language (French, in our case).

Our results pave the way to using transfer learning approaches to build NLP tools not only for Narabizi but also for other vernacular varieties of Arabic written in Latin script, and more generally for any low resource language, even when it displays some of the challenging properties listed above. Our paper therefore sheds light on a way to initiate the development of NLP ecosystems for languages and language varieties that are increasingly used online, for which NLP is badly needed, but for which few resources, if any, are available to date.

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Appendix

A.1 Source Languages

| Language      | Script      | Relatedness | $\in \Omega_{mBERT}$ |
|---------------|-------------|-------------|----------------------|
| Narabizi      | Latin       | -           | no                   |
| French        | Latin       | code-mixed  | yes                  |
| English       | Latin       | none        | yes                  |
| Maltese       | Latin       | shared root | no                   |
| MS Arabic     | Arabic      | shared root | yes                  |
| Vietnamese    | Latin       | none        | yes                  |

Table 3: Source language in regard to Narabizi based on languages relatedness and inclusion in model pre-training corpora ($\in \Omega_{mBERT}$ for languages included in the 104 pre-training languages of mBERT).

| Language   | Script     |
|------------|------------|
| French     | fr_gsd     |
| MS Arabic  | ar_padt    |
| English    | en_ewt     |
| Maltese    | mt_mudt    |
| Vietnamese | vi_vib     |

Table 4: Universal Dependencies (Nivre et al., 2016) Datasets used for cross-lingual experiments

A.2 Fine-tuning hyper-parameters

We list here all the hyper-parameters used for fine-tuning in a supervised way on POS tagging and in an unsupervised way on raw Narabizi data (cf. Table 5 and 6). For the supervised setting, we run a grid search on all the combination of hyper-parameters and select the best model on the validation set of the source language for both POS tagging and parsing.

| Hyper-parameters | Values            |
|------------------|-------------------|
| Batch size       | {32, 16}          |
| Learning rate    | {1e-5, 5e-5, 1e-4} |
| Optimizer        | Adam              |
| Epochs (best of)| 10                |

Table 5: Supervised fine-tuning hyper-parameters.

| Hyper-parameters | Values            |
|------------------|-------------------|
| Batch size       | 64                |
| Learning rate    | 5e-5              |
| Optimizer        | Adam              |
| Warmup steps     | 10% total         |
| Epochs (best of)| 10                |

Table 6: Unsupervised fine-tuning hyper-parameters

A.3 Buckets: Detailed data and scores

| Proportion Arabizi | % of word in sentence | Train set number sents |
|--------------------|------------------------|------------------------|
| $<$60              | 60-78-100              | 78-100                 | =100                   |
|                    | 322                    | 286                    | 283                    | 276                    |

Table 7: Code-mixed Buckets