Building a User-Generated Content North-African Arabizi Treebank: Tackling Hell

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Abstract

We introduce the first treebank for a romanized user-generated content variety of Algerian, a North-African Arabic dialect known for its frequent usage of code-switching. Made of 1500 sentences, fully annotated in morpho-syntax and Universal Dependency syntax, with full translation at both the word and the sentence levels, this treebank is made freely available. It is supplemented with 50k unlabeled sentences collected from Common Crawl and web-crawled data using intensive data-mining techniques. Preliminary experiments demonstrate its usefulness for POS tagging and dependency parsing. We believe that what we present in this paper is useful beyond the low-resource language community. This is the first time that enough unlabeled and annotated data is provided for an emerging user-generated content dialectal language with rich morphology and code switching, making it an challenging testbed for most recent NLP approaches.

1 Introduction

Until the rise of fully unsupervised techniques that would free our field from its *addiction* to annotated data, the question of building useful data sets for under-resourced languages at a reasonable cost is still crucial. Whether the lack of labeled data originates from being a minority language status, its almost oral-only nature or simply its programmed political disappearance, geopolitical events are a factor highlighting a language deficiency in terms of natural language processing resources that can have an important societal impact. Events such as the Haïti crisis in 2010 (Munro, 2010) and the current Algerian revolts (Nossiter, 2019)[1] are massively reflected on social media, yet often in languages or dialects that are poorly resourced, namely Haitian Creole and Algerian dialectal Arabic in these cases. No readily available parsing and machine translations systems are available for such languages. Taking as an example the Arabic dialects spoken in North-Africa, mostly from Morocco to Tunisia, sometimes called *Maghribi*, sometimes *Darija*, these idioms notoriously contain various degrees of code-switching with languages of former colonial powers such as French, Spanish, and, to a much lesser extent, Italian, depending on the area of usage (Habash, 2010; Cotterell et al., 2014; Saadane and Habash, 2015). They share Modern Standard Arabic (MSA) as their matrix language (Myers-Scotton, 1993), and of course present a rich morphology. In conjunction with the resource scarcity issue, the code-switching variability displayed by these languages challenges most standard NLP pipelines, if not all. What makes these dialects especially interesting is their widespread use in user-generated content found on social media platforms, where they are generally written using a romanized version of the Arabic script, called *Arabizi*, which is neither standardized nor formalized. The absence of standardization for this script adds another layer of variation in addition to well-known user generated content idiosyncrasies, making the processing of this kind of text an even more challenging task.

In this work, we present a new data set of about 1500 sentences randomly sampled from the romanized Algerian dialectal Arabic corpus of Cotterell et al. (2014) and from a small corpus of lyrics coming from Algerian dialectal Arabic Hip-Hop and Raï music genre that had the advantage of having already available translations and of being representative of Algerian vernacular urban youth language. We manually annotated this data set with morpho-syntactic information (parts-of-speech and morphological features), together with glosses and code-switching labels at the word

[1] https://www.nytimes.com/2019/03/01/world/africa/algeria-protests-bouteflika.html

level, as well as sentence-level translations. Furthermore, we added an additional manual annotation layer following the Universal Dependencies annotation scheme (Nivre et al., 2018), making of this corpus, to the best of our knowledge, the first user-generated content treebank in romanized dialectal Arabic. This treebank contains 36% of French tokens, making it a valuable resource to measure and study the impact of code-switching on NLP tools. We supplement this annotated corpus with about 50k unlabeled sentences extracted from both Common Crawl and additional web crawled data, making of this data set an important milestone in North-African dialectal Arabic NLP. This corpus is made freely available under a Creative Commons license.[2]

2 The Language

As stated by Habash (2010), Arabic languages are often classified into three categories : (i) Classical Arabic, as found in the *Qur'an* and related canonical texts, (ii) Modern Standard Arabic, the official language of the vast majority of Arabic speaking countries and (iii) Dialectal Arabic, whose instances exhibit so much variations that they are not mutually understandable across geographically distant regions. As space is missing for an exhaustive description of Arabic language variations, we refer the reader to Habash (2010), Samih (2017) and especially to Saadane and Habash (2015) for a thorough account of Algerian dialectal Arabic, which is the focus of this work. In short, the key properties of North-African dialectal Arabic are:

- It is a **Semitic language**, non codified, mostly spoken;
- It has a **rich-inflexion system**, which qualifies this dialect as a morphologically-rich language (Tsarfaty et al., 2010), even though Saadane and Habash (2015) write that many properties present in Classical Arabic are absent from this dialect (*e.g.* it has simplified nominal and verbal case systems);
- It displays a **high degree of variability** at all levels: spelling and transliteration conventions, phonology, morphology, lexicon;
- It exhibits a **high degree of code-switching**; due to historical reasons and cultural influence of French in the media circles, the Algerian dialect, as well as Tunisian and Morocco, is known for its heavy use of French words.

Gloss	Attested forms	Lang
why	wa3lach w3alh 3alach 3lache	NArabizi
all	ekl kal kolach koulli kol	NArabizi
many	beaucoup boucoup bcp	French

Table 1: Examples of lexical variation in *NArabizi*

As stated above, this dialect is mostly spoken and has even been dubbed with disdain as a *Creole* language by the higher levels of the Algerian political hierarchy.[3] Still, its usage is ubiquitous in the society and, by extension, in social media user-generated content. Interestingly, the lack of Arabic support in input devices led to the rise of a romanized written form of this dialect, which makes use of alphanumeric letters as additional graphemes to represent phonemes that the Latin script does not naturally cover. Not limited to North-African dialectal Arabic, this non-standard "transliteration" concurrently emerged all over the Arabic-speaking world, and is often called *Arabizi*. Whether or not written in *Arabizi*, the inter-dialectal divergences between all Arabic dialects remain.

The following list highlights some of the main properties of *Arabizi* compared to MSA written in the Arabic script.

- Unlike in MSA written in the Arabic script, where short vowels are marked using optional diacritics, all vowels are explicitly written;
- Digits are used to cope with Arabic phonemes that have no counterpart in the Latin script; for instance, the digit "3" is often used to denote the *ayin* consonant, because it is graphically similar to its rendition in Arabic script;
- No norms exist, resulting in a high degree of variability between people writing in *Arabizi*.

From now on, we will call *NArabizi* the Algerian dialect of Arabic when written in *Arabizi*, thereby simultaneously referring to the language variety and to the script itself. Table 1 presents several examples of lexical variation within *NArabizi*. Interestingly, this variability also affects the code-switched vocabulary, which is mostly French in the case of *NArabizi*. A typical example of *NArabizi* that also exhibits code-switching with non-standard French spelling can be seen in Example 1.

(1)

Source: salem 3alikoum inchalah le pondium et les midailes d'or

[2] http://almanach-treebanks.fr/NArabizi

[3] https://www.lesoirdalgerie.com/articles/2010/02/17/article.php?sid=95823&cid=2

Norm.: *Assalamu alaykum inshallah le podium et les médailles d'or*
Trans.: *Peace be on you God willing [we will get] the podium and the gold medals*

3 Corpus

As other North-African Arabic dialects, *NArabizi* is a resource-poor language, with, to the best of our knowledge, only one available corpus developed by Cotterell et al. (2014) for language identification purposes.

3.1 Data Collection

Cotterell et al. (2014)'s corpus was collected in 2012 from an Algerian newspaper's web forums and covers a wide range of topics (from discussion about football events to politics). We collected the 9973 raw sentences from its GitHub repository[4] and sampled about 1300 sentences. In addition, because they were available with translations in French and English, we included lyrics from a few dozen recent popular songs of various genres (Raï, hip-hop, etc.), leading to an additional set of 200 sentences. These 1500 sentences form the core of our *NArabizi* treebank annotation project. In order to make our corpus usable by modern, resource-hungry natural language processing techniques, we also used data-driven language identification models to extract *NArabizi* samples among the whole collection of the Common-Crawl-based OSCAR corpora (Ortiz Suárez et al., 2019) as well as 2 millions sentences of additional crawled web-data, resulting in 50k *NArabizi* sentences of high quality, to date the largest corpus of this language. This makes this collection a valuable test bed for low-resource NLP research.

3.2 Annotation Layers

Our *NArabizi* treebank contains 5 annotations layers: (i) tokenization, (ii) morphology, (iii) code-switching identification, (iv) syntax and (v) translation.

Tokenization Following Seddah et al. (2012) and their work on the French Social Media Bank, we decided to apply a light tokenization process where we manually tokenized only the obvious cases of wrongly detached punctuations and "missing whitespaces" (*i.e.* cases where two words are contracted into one token).[5]

Morphological Analysis This layer consists of two sets of part-of-speech tags, one following the Universal POS tagset (Petrov et al., 2011) and the other the FTB-cc tagset extended to deal with user-generated content (Seddah et al., 2012). In cases of word contractions, we followed their guidelines and used multiple POS as in `cetait (`itwas')/PRON+VERB/CLS+V`. In addition, we added several morphological features following the Universal Dependency annotation scheme (Nivre et al., 2018), namely `gender`, `number`, `tense` and verbal `mood`. Note that instead of adding lemmas, we included French glosses for two reasons: firstly for practical reasons, as they helped manual corrections done by non-native speakers of *NArabizi*, and secondly because of the non-formalized nature of this language, which makes lemmatization very hard, almost akin to etymological research as in the case of *garjouma/the throat* which can either originate from French *gorge* or be of Amazigh root.

Code-Switching identification Unlike other works in user-generated content for minority languages (Lynn and Scannell, 2019), we do not distinguish between inter- and intra-sentential code-switching and consider word-level code-mixing as lexical borrowing. We annotate code-switching at the word level with information about the source language, regardless of the *canonical-ness* of spelling.

Syntactic Annotations Here again we follow the Universal Dependencies 2.2 annotation scheme (Nivre et al., 2018). When facing sequences of French words with regular French syntax, we followed the UD French guidelines; otherwise, we followed the UD Arabic guidelines, following the Prague Arabic Dependency UD Treebank.

Translation Layer Our final layer is made up for sentence-level translations in French. It shall be noted that the validation of these translations often led to massive rewording, as the annotators came from different regions of Algeria and could diverge in their interpretations of a given sentence.

[4] https://github.com/ryancotterell/arabic_dialect_annotation

[5] We corrected in average one tokenization error (less frequently two) per sentence on the web forum parts. We noticed a high degree of variance. Some users displayed this behavior much more than others. This led some of our annotators to believe it resulted from an ill-functioning input device.

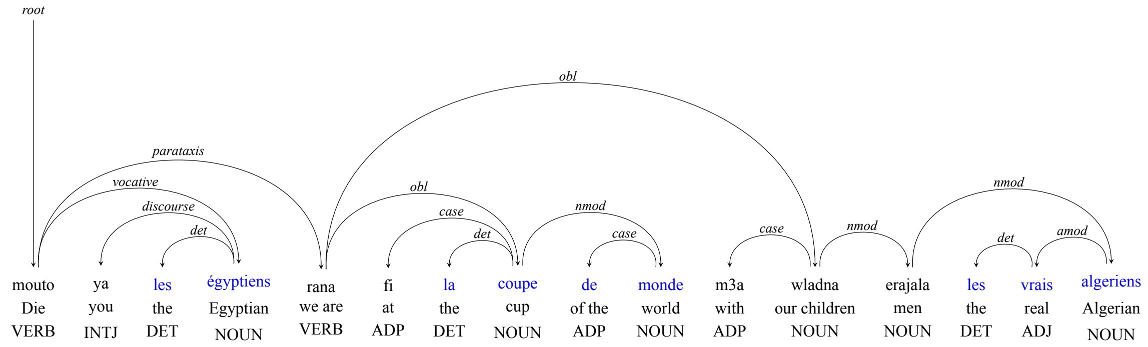


Figure 1: Annotation example: "mouto ya les égyptiens rana fi la coupe de monde m3a wladna erajala les vrais algeriens" [*Die Egyptians! We are at the world cup with our children of Algeria, the real men!*]. Code-switching is highlighted in blue.

A sample of 200 sentences was blindly translated (without access to the morpho-syntactic analysis) in order to favor further research on the fluency of machine translation for this dialect.

All annotations layers are displayed in Figure 1.

4 Extending Our Data Set With Noisy Unlabeled Data

The need for more data has never been more striking as they are needed for important tasks such as handling lexical sparseness issues via word embeddings, lexicon acquisition, domain adaptation via self-training, or fine-tuning pre-trained language models, its modern incarnation. The trouble with *NArabizi* is that it is a spoken language whose presence can be mostly found in informal texts such as social media. More importantly, the *Arabizi* transliteration process is also used by other Arabic dialects, making the data collection *a needle in a haystack* search task. We therefore present in this section the process we used to mine an additional set of 50k *NArabizi* sentences from two large corpora, one based on search query-based web-crawling and the other from a cleaned version of the CommonCrawl corpora, developed by Ortiz Suárez et al. (2019).

4.1 First method: SVM-based classifier

Using keywords-based web scrapping tools, we collected a raw corpus of 4 million sentences, called CrawlWeb, that *in fine* contained a mixture of French, English, Spanish, MSA and *Arabizi* texts. Since we are only interested in *NArabizi*, we designed a classifier to extract proper sentences from that raw corpus. The corpus we used as gold standard is made of 9k sentences of attested *NArabizi* from our original corpus and 18k of French and English tweets. Using language identification (Lui and Baldwin, 2012), we convert each sentence from the gold-standard corpus to a feature vector containing language-identification scores and use it as input to a SVM classifier with a classical 80/10/10 split. With a precision and recall score of 94%, we filtered out 173k code-mixed sentences out of the CrawlWeb corpus. Preliminary experiments showed promising initial results, but further analysis pointed out a high level of noise in this initial set, both in terms of erroneous language identification and on the amount of remnant ASCII artifacts that could not easily be removed without impacting the valid *NArabizi* sentences.

4.2 Second method: Neural-based classification

The objectives of this method are twofold: (i) selecting data from CommonCrawl using a neural classifier and (ii) using this data set to intersect the data collected with the previous method. The idea is to ensure the quality of the final resulting unlabeled corpus.

Given the large number of noisy data in CommonCrawl, a "noise" class is added to the language classification model and is built according to several heuristics.[6] That "noisy" class corpus is made of 40k sentences randomly selected among the result of the application of these rules to a short, 10M-sentence sample of CommonCrawl. We then trained a classifier using Fasttext (Joulin et al., 2016) on 102 languages, 40k sentences each, extracted from the CommonCrawl-based, language-classifed OSCAR corpus, to which we added the 9k sentences of the *NArabizi* original corpus and

[6] These heuristics are presented in the Appendix for reproducibility.

the "noise" class. The final dataset is composed of 4,090,432 sentences and is split into 80% train, 10% development and 10% test sets. The classifier consists in a linear classifier (here logistic regression) fed with the average of the n-gram embeddings. n-grams are useful in this case as they enables the model to capture specific sequences of *NArabizi* characters such as `lah`, `llah`, `3a`, `9a`, etc. We choose to embed 2- to 5-grams. These parameters lead to precision and recall scores of 97% on the *NArabizi* test set.

After an intensive post-processing step (cf. Appendix A.2), this process results in a dataset of 13,667 sentences extracted from half the CommonCrawl corpus.[7] To evaluate the quality of the resulting data set, we randomly picked 3 times 100 sentences, and genuine *NArabizi* sentences were manually identified, which allowed us to assess the accuracy of our corpus as reaching 97%. Table 2 presents the results of the evaluation of the two classification methods performed on both the development and test sets of the original *NArabizi* corpus.[8] Results show that the fastText classifier and its n-gram features is more precise than its non-neural counterpart and its language-id feature vectors.

4.3 Corpus intersection

When applied to the CrawlWeb corpus, the Fasttext model extracted 44,797 unique Arabizi sentences while the SVM model extracted 83,295 unique Arabizi sentences. The intersection of both extractions amounts to 39,003 Arabizi sentences (with a 99% precision). This means that 44,292 sentences were classified as Arabizi by the SVM model and not by Fasttext. Among them, by random sampling, it can be stated approximately that 55% are indeed *NArabizi*. Mistakes are misclassified sentences (Spanish and English sentences, for instance) or sentences with only "noise" (such as symbols). 5,794 sentences were classified as *NArabizi* by the Fasttext model and not SVM. Among them, by random sampling, it can be stated that approximately 60% are indeed Arabizi. Errors are long sentences with only figures and numbers or sentences with many symbols (e.g. " { O3 } " or "!!!! !!!!").

	F1-Score Arabizi
Fasttext	0.97
SVM Classifier	0.94

Table 2: F1-scores of both language classification models on the Arabizi class.

In order to ensure that the collected corpus contains as little non-*NArabizi* data as possible, we only release the intersection of the data we classified, to which we add the original *NArabizi* corpus (Cotterell et al., 2014) (after having removed the annotated data we extracted from it). Table 3 provides quantitative information about our corpora.

Dataset	#Sentences	#Tokens
Original source data	9,372	203k
Manually Annotated	1,434	22k
Unlabeled *NArabizi*	46,941	1.02M

Table 3: Corpus statistics

5 Pre-annotation Tool Development via Noisy Transliteration of an Arabic UD Treebank

In order to speed up the annotation process of our data, we decided to create a pre-annotation morphosyntactic and syntactic annotator trained on quasi-synthetic data obtained by "transliterating" a pre-existing Arabic (MSA) treebank, the Prague Arabic Dependency Treebank (PADT), into the *NArabizi* Latin script, together with data from the French GSD UD treebank. Both are taken from the UD treebank collection (Nivre et al., 2018).

Before it can be used as training data, the PADT needs to first be transformed into a form similar to *NArabizi*. Since the PADT corpus is a collection of MSA sentences with no diacritics, it is impossible to directly "transliterate" into *NArabizi*. We first diacritized it, in order to add short-vowel information, and then "translitterated" it into an *Arabizi*-like corpus. We describe this process in this Section. The results of the pseudo-*NArabizi* parser trained on the "translitterated" corpus are then presented in Section 6.2.

Random diacritics As vowels are always written in *Arabizi*, the PADT corpus needs to be diacritized before transliteration. Using an equiprobable distribution, diacritics were added randomly, and the text then transliterated using the probabil-

[7] Due to computing power limitation, we were not able to run our selection on the whole CommonCrawl.

[8] Note that the precision and recall are slightly different in both methods, but the rounding at the second decimal made them equal.

ity distributions we describe below. The BLEU score (Papineni et al., 2002) of this method on the small parallel corpus provides a baseline of 0.31.

Proper diacritization Using the Farasa software (Abdelali et al., 2016), PADT sentences are diacritized with 81% precision rate,[9] then tokens aligned with corresponding diacritized words. The text is then transliterated the same way as before. The BLEU score of this version is 0.60. An example showing how this system visibly improves the transliteration can be seen in the "Prop. Diac." output in Example 2.

(2)

Source: berlin tarfoudhou 7oussoul charika amrikia 3ala ro5sat tasni3 dabbabat "léopard" al almania
Trans.: Berlin refuses to authorize an American firm to produce the "Leopard" German tank.

Random diac.: brouliyani trfidh 7iswla chiroukou amiyirikyoui 3alia rou5soui tasaniya3i dhabouaboui louyiwibiaridha alalmaanouyou

Proper diac.: birlin tarfoudhou 7ousolou charikatin 2amiriqiatin 3alaa rou5sati tasni3i dabbatin " lyuberid " el2almeniati

System	BLEU score
Random diacritization	0.31
Proper diacritization	0.60

Table 4: BLEU score of both transliteration systems.

Transliteration Once diacritized, the corpus can be properly transliterated. Arabic letters are either consonant sounds or long vowels, each one may have several different transliterations in *NArabizi*, depending on the writer's age, accent, education and first learned Western language. For example, the letter ث[10] can be transliterated as "t" or "th". A probability must be assigned for each possibility, and to make it as close as possible to what is produced by *NArabizi* speakers, a small parallel corpus of PADT sentences and their transliteration by ten *NArabizi* speakers was assembled, and then each letter aligned with all its possible matches to get probability distributions.

6 Usability

In this section we describe preliminary experiments on part-of-speech tagging and statistical dependency parsing that show promising results while highlighting the expected difficulty of processing a low-resource language with a high level of code-switching and multiple sources of variability.

6.1 POS Tagging

The baseline POS tagger we used is alVWTagger,[11] a feature-based statistical POS tagger, which ranked 3rd at the 2017 CoNLL multilingual parsing shared task (Zeman et al., 2017). It is briefly described in (de La Clergerie et al., 2017). In short, it is a left-to-right tagger that relies on a set of carefully manually designed features, including features extracted from an external lexicon, when available, and a linear model trained using the Vowpal Wabbit framework.[12] In our case, we simply created an "external" lexicon by extracting the content of the training set. It contributes to improving the POS accuracy because it provides the tagger with (ambiguous, partial) additional information about words in the right context of the current word.[13]

	Dev		Test	
	All	OOV	all	OOV
OOV %		*32.28*		*32.75*
UPOS (a)	78.74	55.85	80.37	57.42
MFEATS (b)	88.10	70.04	87.17	69.12
(a)+(b)	72.61	40.94	73.87	43.50

Table 5: POS tagging results.

6.2 Early Parsing experiments

As stated earlier in this paper, *NArabizi* contains a high-level of code-switching with French and is closely related to MSA. We described in Section 5 how we built a mixed treebank based on the

[9] Other diacritization systems have better performances (Belinkov and Glass, 2015) but are either not maintained with the proper python packages, or come with a fee.

[10] Theh, U+062B.

[11] Note that we performed a set of baseline experiments with UDPipe 2.0 (Straka and Straková, 2017) as well on a previous version of this data set. It reached only 73.7 of UPOS on the test set.

[12] `https://github.com/VowpalWabbit/vowpal_wabbit/wiki`

[13] Without this endogenous lexicon extraction step, the tagger performed slightly worse, although the difference is small.

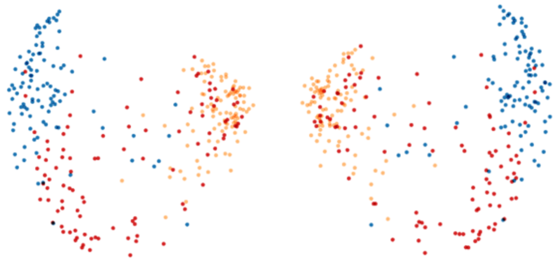
French GSD UD treebank and our *Arabizi* version of the Prague Arabic Dependency Treebank. We trained the UDPipe parser (Straka and Straková, 2017) on various treebanks obtained by combining different proportions of the French GSD and our PADT-based pseudo-*Arabizi* treebank. We ran these parsers with already annotated gold parts-of-speech. The best scores were obtained with a model trained on a mix 30% of pseudo-*Arabizi* and 70% of French, which we call the MIX treebank, totaling 5,955 training sentences. We split this treebank into training, development and test sets, called MIX$_{\text{train/dev/test}}$, following a 80/10/10 split. We used a very small manually annotated *NArabizi* development dataset of 200 *NArabizi* sentences, called Arabizi$_{\text{dev}}$, to evaluate our parser. As shown in Table 6 (line "Mix"), despite good results on MIX's development and training sets, MIX$_{\text{dev}}$ and MIX$_{\text{test}}$ respectively (see Table 6), this first parser did not performed very well when evaluated on Arabizi$_{\text{dev}}$. This performance level proved insufficient to speed up the annotation task. We therefore manually annotated 300 more *NArabizi* sentences (Arabizi$_{\text{train300}}$), to be used as additional training data. When added to MIX$_{\text{train}}$, parsing performance did improve, yet not to a sufficient extent, especially in terms of Labeled Attachement Score (LAS). It turned out that training UDPipe on these 300 manually annotated *NArabizi* sentences only (Arabizi$_{\text{train300}}$) produced better scores, resulting in a parser that we did use as a pre-annotation tool in a constant bootstrap process to speed up the annotation of the remaining sentences.

Training corpus	Dev		Test		Test *Arabizi*	
	LAS	UAS	LAS	UAS	LAS	UAS
MIX	**87.67**	**89.42**	87.69	89.44	39.28	51.52
MIX+*Arabizi* 300	87.42	89.20	87.44	89.22	55.54	65.36
Arabizi 300	39.11	49.62	39.14	49.65	**63.03**	**71.21**

Table 6: Results of UDPipe (trained 100 epochs) on the preliminary test set.

7 Discussion

How interleaved are French and *NArabizi*? As stated before, *NArabizi* takes its root in Classical Arabic and in multiple sources of integration of French, MSA and Berber, the *Amazigh* language. As the *NArabizi* treebank contains more than 36% of French words, it is of interest to use recent methods of visualization to see how interleaved it is with some of its source languages. To this end, we extract words embeddings using fastText (Joulin et al., 2016) from a corpus made of the "translitterated" PADT described in Section 5, the French UD GSD and *NArabizi* original corpus (Cotterell et al., 2014). Two-dimensional representations of the resulting embeddings space for 300 selected words are shown in Figure 2 for embeddings of size 50 and 100.



(a) dim: 50

(b) dim: 100

Figure 2: Two-dimensional representation of Fasttext word embeddings for 300 words (100 for transliterated MSA - blue -, French - yellow - and *NArabizi* - red -) after PCA analysis

We notice that the overall shapes of both representations are very similar, apart from a non significant x-axis reversal. On the first components, increasing the embedding size does not provide more information.

We also see that French and transliterated Arabic words are clearly separated into two clusters of low standard deviation, while *NArabizi* words are very spread out. Some fall within the French cluster, they correspond to French words present in this Algerian dialect. Others are in the middle of the Arabic cluster, these are the purely Arabic words of the dialect. Between the two, there are *Amazigh* words (*rak*, *mech*), arabized French words (*tomobile* < French *automobile*), Arabic words whose Berber pronunciation has resulted in an unexpected *NArabizi* rendering (*nta* instead of expected *enta* 'you', *mchit* instead of expected *machayt* 'to go-2SING').

What is the Impact of Code-Switching in POS--tagging performance? Given the large degree of interleaving between French and *NArabizi*, it is interesting to assess the impact of the French vocabulary on the performance of a POS-tagger trained on French data only. For these experiments, we use the StanfordNLP neural tagger (Qi et al., 2019), which ranked 1st in POS tagging at the 2018 UD shared task, trained on the UD French

ParTUT treebank, using French fastText vectors (Mikolov et al., 2018). In order to perform a meaningful evaluation, we split the *NArabizi* training set into 4 buckets of approximately 25% of it size in tokens, with a increasing proportion of identified *NArabizi* tokens. Results in Table 7 show a clear drop of performance between the sentences that contain more code-switching (59.55% of UPOS accuracy) and those with none (16.84%). This suggests that low-resource languages with a high-level of code-switching such as *NArabizi* can benefit from NLP models trained on the secondary language. The level of performance to expect from these cross-language approaches is yet to be determined.

% of *NArabizi* per sent.	<60	60-78	78-100	100
bucket set size (sent.)	322	286	283	276
StanfordNLP (French)	59.55	35.93	25.41	16.84

Table 7: POS tagging Performance with regard to code-mix proportion trained on UD French Partut treebank

8 Treebanking Costs

Following Martínez Alonso et al. (2016), we provide here the cost figures of this annotation campaign. We do not include the salaries of the permanent staff, nor do we include the overhead. These figures are meant as an indication of the effort needed to create an annotated data set from scratch. It shall be noted that even though the inter-annotator agreement gave us early indications on the difficulty of the tasks, it also acted as a metric in terms of language variability among annotators. None of them come from the same part of North-Africa and none of them has the same familiarity with the topics discussed in the web-forums we annotated. We had to constantly re-annotate sentences and update the guidelines every time new idiosyncrasies were encountered and most importantly accepted as such by the annotators. Compared to what was reported in (Martínez Alonso et al., 2016), the figures are here much higher (about 5 times higher), because unlike their work on French treebanks, we could not use preexisting guidelines for this language and because we could not keep the same team all along the project, so that new members had to be trained almost from scratch or to work on totally different layers.

Phase	1st	2nd	3rd	4th	5th	p.m	Costs (k€)
Annotators	8	2	2	3		15	45
Jr Researcher		2	5			7	21
Confirmed					6	6	21
total	8	4	7	3	6	28	87

Table 8: Treebanking costs. The annotation phases are (i) Morphology/tokenization, (ii) Translation, (iii) Pre-annotation Syntax, (iv) Correction, (v) Final Syntax. P.M stands for person.month

9 Related Work

Research on Arabic dialects is quite extensive. Space is lacking to describe it exhaustively. In relation to our work regarding North-African dialect, we refer to the work of (Samih, 2017) who along his PhD covered an large range of topics regarding the dialect spoken specifically in Morocco and generally regarding language identification (Samih et al., 2016) in code-switching scenario for various Arabic dialects (Attia et al., 2019).

Unlike *NArabizi* dialects, the resource situation for Arabic dialects in canonical written form can hardly be qualified as scarce given the amount of resources produced by the Linguistic Data Consortium regarding these languages, see (Diab et al., 2013) for details on those corpora. These data have been extensively covered in various NLP aspects by the former members of the *Columbia Arabic NLP team*, among which Mona Diab, Nizar Habash, and Owen Rambow, in their respective subsequent lines of works. Many small to medium scale linguistics resources, such as morphological lexicons or bilingual dictionaries have been produced (Shoufan and Alameri, 2015). Recently, in addition to the release of a small-range parallel corpus for some Arabic dialects (Bouamor et al., 2014), a larger corpus collection was released, covering 25 city dialects in the travel domain (Bouamor et al., 2018).

Regarding the specific NLP modeling challenges of processing Arabic-based languages, as part of the morphologically-rich languages, recent advances in joint models have been addressed by Zalmout and Habash (2019) that recently efficiently adapted a neural architecture to perform joint word segmentation, lemmatization, morphological analysis and POS tagging on an Arabic dialect. Recent works on cross-language learning using the whole massively multilingual pre-trained language models artillery have started to emerge

(Srivastava et al., 2019). If successful, such models could help to alleviate the resource scarcity issue that plagues low-resources languages in the *more-than-ever* data hungry modern NLP.

10 Conclusion

We introduced the first treebank for an Arabic dialect spoken in North-Africa and written in romanized form, *NArabizi*. More over, being made of user-generated content, this treebank covers a large variety of language variation among native speakers and displays a high level of code-switching. Annotated with 4 standard morpho-syntactic layers, two of them following the Universal Dependency annotation scheme, and provided with translation to French as well as glosses and word language identification, we believe that this corpus will be useful for the community at large, both for linguistic purposes and as training data for resource-scarce NLP in a high-variability scenario. In addition to the annotated data, we provide around 1 million tokens (over 46k sentences) of unlabeled *NArabizi* content, resulting in the largest dataset available for this dialect. Our corpora are freely available[14] under the CC-BY-SA license and the *NArabizi* treebank is also released as part of the Universal Dependencies project.

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A Appendix

A.1 Class-noise for our language classifier

Given the large number of noisy data in Common Crawl, a class noise is added to the classification model we presented section 4.2 and is built according to the following empirical rules :

- If the word ”url” appears more than two times, the sentence is added to class noise.
- If the sentence has more than four ” [” , the sentence is added to class noise.
- The same rule as above works for ” ”, ” ”, ” { ” or ” } ” symbols.
- If the word ”http” appears more than two times, the sentence is added to class noise.
- If more than two ”@” character, the sentence is added to class noise in order to capture sentences with email address or tweets with only mentioned people.
- If the phrase ”WARC-Refers-To” appears, the sentence is added to class noise.

A.2 Post-processing steps

- Get unique sentences (about 20K sentences).
- The model is likely to classify as Arabizi sentences which contain any letter repeated a lot of times in a row (e.g. ”iiiiiii..”, ”uuuuuuu..”, ”ffffff...”). These sentences are deleted from the dataset.
- Due to the n-gram embeddings, ”lah” is considered as a marker of Arabizi, so a lot of sentences containing ”blah” are classified as Arabizi. If this phrase appears more than 5 times, the sentence is deleted.
- Figures and numbers are widespread in Arabizi (particularly ”3” and ”9”), so the model classifies too many sentences which contains only numbers. Therefore, sentences which have more ”number of figures” characters than 80% of the number of characters (excluded figures) are deleted.