Impact of Parallel vs. Non Parallel Corpora on the Identification of Arabic Dialects

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***Abstract*—In this paper, we conduct a study to evaluate the performance of statistical and neural methods to classify Arabic Dialects (AD). This evaluation is based on two kinds of corpora. The first one is a corpus named PADIC (Parallel Arabic DIalectal Corpus), which is a multi-dialectal corpus composed of six dialects: two Algerian dialects (of Algiers and Annaba cities), Palestinian, Syrian, Tunisian, and Moroccan, in addition to MSA. The second one (AraDial) is a manually collected corpus that contains the same dialects as well as the same number of sentences as PADIC (6412 sentences for each dialect). In our experiments, we used both statistical and neural classifiers, namely: Gaussian Naive Bayes, Bernoulli Naive Bayes, kNN, Logistic Regression, SGD Classifier, Passive Aggressive Classifier, Perceptron, Linear Support Vector, and Convolutional Neural Network Classifiers. We evaluated these classifiers in two setups: training on a parallel corpus (PADIC) and testing on the non-parallel corpus and vice versa. The obtained results have shown that training our system on a non-parallel corpus will give better results, as we achieved a mean score of 92.08%.**

***Index Terms*—Dialect Identification, Arabic, Parallel Corpus, PADIC, Non-Parallel Corpus**

I. Introduction

There are approximately 450 million Arabic speakers in the world, with a growing number of Internet users approaching 240 million, putting Arabic in the fourth position of the top ten languages used on the Web [1]. These users could be considered the primary sources of the Arabic content on the web, mostly written in Modern Standard Arabic (MSA) and also in dialectal Arabic that exists, in most cases, as social media content. Current research in Arabic Dialect Identification (ADI) is primarily concerned with the correct evaluation of linguistic information existing in the Arabic dialects and with the identification of their variations (22 Arab countries). Undoubtedly, the focus of research in this field is to strengthen further the techniques developed thus far, regarding their reliability and accuracy, especially for low-resourced languages like Arabic. The endeavour of this research paper is to primarily concentrate on the creation of new corpus for Arabic dialect identification, from scratch or from other tasks like the Machine Translation corpus.

Some efforts on ADI utilizing both text and speech corpora can be mentioned, such as those presented during the VarDial joint task [2]–[4]. The primary focus of ADI in this task is to identify between the five classes of Arabic dialects (Egyptian, Levantine, Gulf, North Africa, and MSA) based on geographical location, in both spoken and written forms.

Whereas to identify the written forms, many work have been done, as our previous work where we employed the first version of PADIC corpus [6] using two techniques based on word-level and sentence-level language identification, respectively [5]. We have concluded that for inter-country ADI, the sentence-level approach is more consistent than the word-level approach. The latter is more convenient with intra-country ADI (ex: Algerian dialects) [5].

In this paper, we investigate ADI at the sentence level using both machine learning and deep learning models. The classification models used are: Convolutional Neural Networks, Gaussian Naive Bayes, Bernoulli Naive Bayes, kNN, Logistic Regression, SGD, Passive Aggressive, Perceptron, Linear Support Vector Classifier.

As aforementioned, we first used PADIC corpus which is composed of six dialects namely: Syrian, Moroccan, Tunisian, Palestinian, Algiers and Annaba's dialect). Primarily PADIC was created for Machine Translation purpose, but it could well be used for other NLP topics like: dialect identification. In the second step, we collected a new non parallel named (AraDial) dataset having the same size of PADIC. We performed extensive experiments based on deep neural networks and traditional Machine Learning Classifiers for identifying the aforementioned Arabic varieties (dialects), using both parallel and non parallel corpora under various classification conditions, allowing us to perform well on the task, and we will carry out an analysis to uncover how the varieties in the data relate to one another based on shared lexical by using the Normalized Compression Distance.

Because in our previous study [5], we used PADIC (parallel corpus) as a training dataset and a manually collected corpus from the web as the test dataset, in this work, we will try the inverse. For this reason, it is desirable to have another corpus which is of the same size as PADIC (in the number of sentences). We also ask the empirical questions: to what extent can a parallel corpus influence the performance of an ADI system?. We can use the example in Figure 1, which shows two samples from the parallel PADIC and non-parallel AraDial corpora, to further understand this issue. We can see

[1] https://www.internetworldstats.com/stats7.htm

that while PADIC is made up of MSA phrases that have been translated into other dialects, the variety and vocabulary used in each dialect are not very different, which makes them harder to recognize. While in AraDial, the sentences in each dialect are significantly more distinct and simple to tell apart. In other words, which generalize better to new data, training on a parallel corpus or on a non-parallel corpus?

Corpus	Dialect/Lang	Sentence
PADIC	*Algeria*	كملت قرايتي في لافاك بالسيف
	Palestine	خلصت دراستي في المعهد بصعوبة
	MSA	أنهيت دراستي في المعهد بمشقة (I finished my studies at the institute with difficulty)
AraDial	*Algeria*	آه قالت لي مكانش عندي سوفل باه نعيط (She told me she ain't got no breath to scream)
	Palestine	ولما سمعها بتحكي هيك عرف انها هي (And when he heard her talk like that, he recognized that it was her.)

Fig. 1. Examples from PADIC and AraDial corpora.

The rest of the paper is organized as follows: in section II, we present the related state of the art. The datasets used are briefly described in sections III (PADIC and the manually collected dataset). In Section IV we describe the used classifiers. Section V presents the conducted experiments in details and analyses of our findings and results. Finally, we conclude in section VI.

II. Related Work

Research on ADI has been conducted on spoken and written forms. For spoken ADI, we mention, in a non exhaustive way, the works achieved by [8]–[11], [13], and those published recently in VarDial Shared Task 2018 by [14]–[17]. Whereas, for Arabic dialect identification based on texts, [18] have introduced a supervised approach for performing sentence level dialect identification between MSA and Egyptian dialectal Arabic using Naive-Bayes adopting token level labels as features. They achieved an accuracy of 85.5% on an Arabic online-commentary dataset. By using the same dataset, [19] applied linear support vector machines, and they achieved an accuracy of 89.1%. An improvement of 5% was recorded on the same dataset by [20], where they applied Conditional Random Field (CRF) that uses decisions from several underlying components such as language models, named entity recognition and morphological analysis to label each word in the sentence.

For Levantine dialect, [7] have collected a corpus named Shami which contains four dialects (Palestinian, Jordanian, Lebanese and Syrian). The accuracy recorded in identifying these dialects ranges between 52% and 90% using both binary and 3-class classification. For identifying (Levantine, Egyptian, Saudi and Iraqi) dialects, [21] applied a 4-class classification machine learning method. The training dataset they used consists of two corpora: a manually annotated dialect corpus (small) and a second one (bigger) grabbed from the Web and automatically annotated using word-marks. They used the most unique and frequent dialectal words as dialect identifiers. The best accuracy achieved by the authors using a Naïve Bayes classifier trained using character-based bigrams, tri-grams in addition to word-marks vocabulary was around 91%.

There is also the work done by [22], where they adopted a 5-class classification approach for the identification of four main categories of Arabic dialects (Egyptian, North African, Gulf and Levant) in addition to MSA. In fact, their approach is based on language bivalency and written code-switching. The authors have incorporated additional grammatical and stylistic features and defined a subtractive bivalency profiling approach to address issues of bivalent words across the examined Arabic dialects which obtained an accuracy more than 76%.

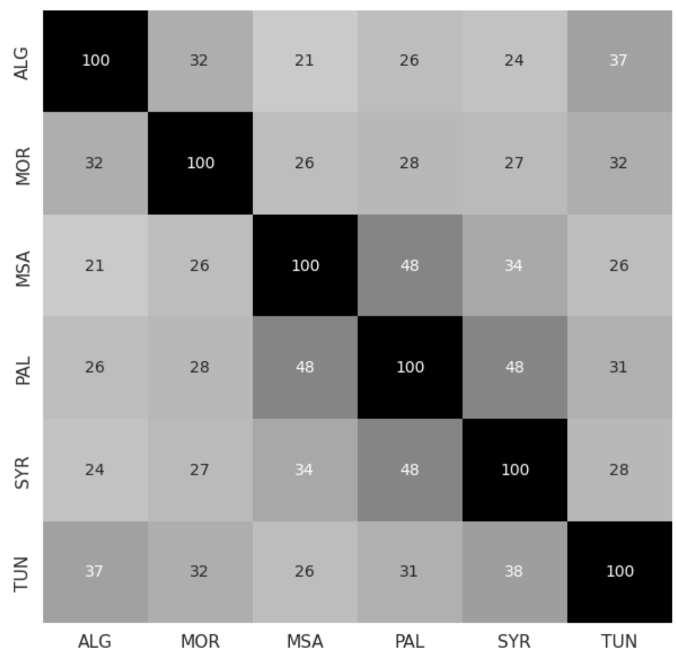

Fig. 2. Shared vocabulary between Arabic dialects -PADIC corpus-

III. Overview of the used Dialects

The first corpus that we used is PADIC (Parallel Arabic DIalectal Corpus) [2]. This corpus is a multi-dialectal corpus built in the framework of the National Research Project "TORJMAN"[3], funded by the Algerian Ministry of Higher Education and Scientific Research. PADIC is composed of 6 dialects: two Algerian dialects (Algiers and Annaba cities), Palestinian, Syrian, Tunisian, and Moroccan, in addition to MSA. The second corpus, which we called AraDial, was painstakingly compiled from articles on the internet, Facebook, discussion forums, and theatrical works. Even though

[2] https://sourceforge.net/projects/padic/
[3] https://sites.google.com/site/torjmanepnr/

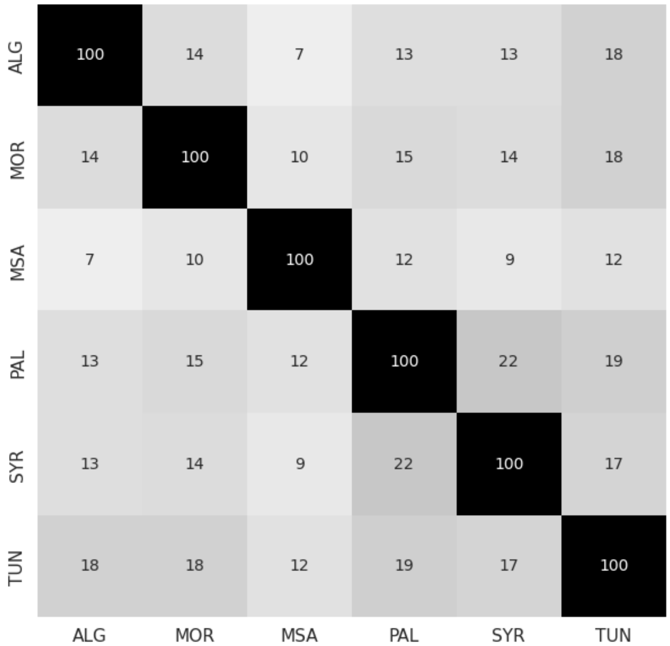

Fig. 3. Shared vocabulary between different dialects -AraDial corpus-

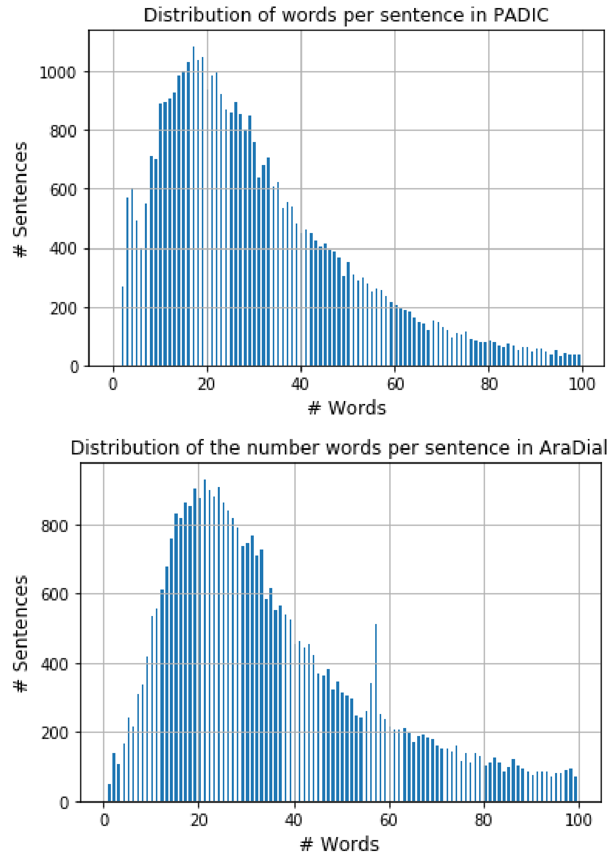

Fig. 4. Word per Sentence Distribution for PADIC (above), AraDial (below)

it is not Parallel like PADIC, the dialects are the same.
For the sake of understanding the similarity degree between all these dialects, we illustrate in Figure 2 the shared vocabulary between the different dialects. We note that Syrian dialect is lexically closer to Palestinian (48%) than to MSA (34%) and less close to Tunisian, Moroccan and Algerian (28%, 27% and 24% respectively), while Palestinian dialect is much closer to North African dialects than Syrian is.

In Figure 3, AraDial corpus, we notice the closeness between the different dialects which is almost the same as it is the case for PADIC (Figure 2), but with less shared vocabulary. Table I shows the distribution of sentences and words across the different datasets. Whereas, Figure 4 depicts the distribution of words per phrase across the PADIC and AraDial datasets. The maximum amount of words per phrase is over 100, while the average is around 30.

IV. Adopted Dialect Identification Approach

To investigate the impact of training on a parallel corpus or on a non-parallel corpus in ADI, we adopted a text classification approach that use seven statistical classifiers and one Neural Model. We used a set of classifiers of the sklearn tools [26], namely: Multinomial Naive Bayes, Bernoulli Naive Bayes, Linear Support Vector Classifier, Logistic Regression, Stochastic Gradient Descent Classifier, Passive Aggressive Classifier and the Perceptron.

The deep learning model (3 run) that we used is the freely available CNN classifier based on Keras and Tensorflow [4]. The inputs of the CNN models were the one-hot representation features. The output is a layer of seven values, each of them represents the probability that a given utterance belongs to the corresponding dialect. The different classifiers are evaluated in two setups (see Table II:

1) Train on 70% of PADIC, test on 30% of PADIC and evaluate on 30% of AraDial.
2) Train on 70% of AraDial, test on 30% of AraDial and evaluate on 30% of PADIC.

In these two setups, we consider it an internal test if the corpus used in the test is related to the one used in training. Otherwise, we consider it an external test. The aim of considering the external test is to see if our own model will generalize well in the presence of new external data. Because we compared the performance of many classifiers, we opted to use a simple feature extraction process where we applied a 1-gram TfidfVectorizer on a filtered corpora (we removed the Arabic stop words) in the case of a machine learning model. For the CNN, we used the tensorflow text tokenizer[5] process with a maximum number of words of 1000 to keep.

V. Experiments and Results

We performed our experiments using the models mentioned above (statistical and deep learning models). We first carried

[4]https://github.com/tensorflow/workshops/blob/master/extras/keras-bag-of-words/keras-bow-model.ipynb

[5]https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/text/Tokenizer

Arabic Dialects		ALG (Algeria)	MOR (Morocco)	MSA	PAL (Palestine)	SYR (Syria)	TUN (Tunisia)	ALL
PADIC	# Sentences	6,412	6,412	6,412	6,412	6,412	6,412	38,484
	# Words	40,731	42,536	44,145	42,154	40,190	38,876	248K
AraDial	# Sentences	6,412	6,412	6,412	6,412	6,412	6,412	38,484
	# Words	41,692	73,828	48,080	49,643	48,096	53,777	315K

TABLE I
DESCRIPTION OF PADIC AND ARADIAL DATASETS.

	Train data	Test data	
		Internal	External
Experiment 1	PADIC (70%)	PADIC (30%)	AraDial (30%)
Experiment 2	AraDial (70%)	AraDial (30%)	PADIC (30%)

TABLE II
DISTRIBUTION OF DATASETS ACROSS THE TWO EXPERIMENTS

Data	Results of Classification using a Parallel Corpus (PADIC)							
	MNB	BNB	L-SVC	LogReg	SGD	PassiveAgg	Perceptron	CNN
ALG-MSA	93.48	94.39	92.05	91.66	91.97	92.23	89.58	91.55
MOR-MSA	91.40	91.97	90.25	90.12	90.05	90.31	85.21	91
TUN-MSA	90.33	92.78	90.12	90.41	90.02	90.18	87.45	89.89
PAL-MSA	92.10	92.70	90.36	90.72	90.41	90.10	87.79	90.03
SYR-MSA	92.10	92.70	90.36	90.72	90.33	90.15	87.79	89.81
6-class	91.88	92.91	90.63	90.73	90.56	90.59	87.56	90.46

Data	Results of Classification using a non Parallel Corpus (AraDial)							
	MNB	BNB	L-SVC	LogReg	SGD	PassiveAgg	Perceptron	CNN
ALG-MSA	90.82	91.36	90.41	89.78	90.29	90.02	88.72	89.27
MOR-MSA	51.26	45.35	45.33	41.75	44.89	47.51	57.71	55.3
TUN-MSA	61.92	80.64	79.16	79.40	79.16	78.47	77.47	54.72
PAL-MSA	84.18	84.27	83.17	82.56	83.02	82.81	70.52	69.79
SYR-MSA	84.18	84.27	83.17	82.56	83.01	82.77	70.52	79.87
6-class	72.22	76.19	75.42	74.61	74.77	73.89	70.51	62.61

TABLE III
DIALECT IDENTIFICATION ACCURACY–EXPERIMENT 1

out a binary classification between each of the dialects and MSA: ALG-MSA, MOR-MSA, TUN-MSA, PAL-MSA, and SYR-MSA. Second, we achieved a multi-class classification of the given dialects in addition to MSA: ALG, MOR, PAL, SYR, and TUN. In addition, we will explore whether the task of dialect identification is easier using parallel (PADIC) or non-parallel (AraDial) corpora.

A. ADI based on Parallel Corpus

In this section, we present the results of experiment 1 using a parallel corpus (PADIC) for training. We show in Table III the accuracy obtained by both binary and multi-class classification tasks. Table III shows that for the evaluation using internal data (PADIC), the BNB classifier has achieved the overall best results in all cases, with a score ranging from 91.97% and 94.39%. However, using external data (AraDial), the BNB has also achieved the best results in almost all cases, except for MOR-MSA, for which Perceptron has obtained the best accuracy of 57.71%.

B. ADI based on a non parallel Corpus

We summarize in Table IV the accuracy achieved using AraDial (a non-parallel corpus) for training. It is noticeable that there is an improvement of at least 2%, compared to Experiment 1 -shown in Table III-. Indeed, in the case of testing using the internal dataset (AraDial), the best results are obtained by the MNB classifier, with a score ranging from 93.74% to 99.96% for binary classification. In the case of testing using PADIC as an external dataset, the best performance has been obtained by the MNB classifier for TUN-MSA: 83.57%, SYR-MSA: 84.79% and 6-class: 72.85%. Whereas for the ALG-MSA dataset, an accuracy of 87.51% was obtained by the BNB classifier and for PAL-MSA, Logistic Regression has achieved the best results of 81.93%.

However, We noticed, in this experiment that the parallel corpus, used as an external test dataset, led to a degradation of 6%, except for TUN-MSA and SYR-MSA where accuracy slightly improved by 3% and 0.5% respectively. We can conclude, in most cases, that the best results have been achieved through Experiment 2, where we used the non-parallel corpus in training and test (Internal Evaluation). Contrariwise, the best results are, in most cases recorded in Experiment 1, where a parallel corpus is used for training and AraDial as an external evaluation dataset -Table V-.

VI. CONCLUSION AND FUTURE WORKS

In this article, we compared the performance of convolutional neural networks and statistical classifiers. The impact of using parallel and non-parallel corpora on Arabic dialect identification was evaluated and reported. The results show that using a non-parallel corpus in the training phase improves results for the ALG and MOR dialects, whereas using a

Data	Results of Classification using a non Parallel Corpus (AraDial)							
	MNB	BNB	L-SVC	LogReg	SGD	PassiveAgg	Perceptron	CNN
ALG-MSA	96.16	95.02	95.5	94.93	95.5	95.28	90.3	95.03
MOR-MSA	99.96	99.96	99.96	99.96	99.96	99.96	99.96	99.95
TUN-MSA	93.74	87.18	93.26	93.22	93.33	92.93	91.39	89.41
PAL-MSA	94.54	86.93	93.37	91.68	93.04	92.93	86.51	91.96
SYR-MSA	94.72	91.53	93.89	92.75	93.48	93.53	89.92	92.15
6-class	72.47	78.81	77.77	76.78	77.20	77.56	74.21	68.53
Data	**Results of Classification using a Parallel Corpus (PADIC)**							
	MNB	**BNB**	**L-SVC**	**LogReg**	**SGD**	**PassiveAgg**	**Perceptron**	**CNN**
ALG-MSA	87.02	87.51	85.75	86.02	86	84.93	73.96	81.4
MOR-MSA	50	50	50	50	50	50	50	54.18
TUN-MSA	83.57	76.75	80.08	80.76	79.87	79.58	77.17	72.87
PAL-MSA	81.46	77.18	81.82	81.93	81.9	80.87	76.7	77.08
SYR-MSA	84.79	79.7	84.28	84.63	84.14	83.32	78.1	80.21
6-class	72.85	77.23	76.43	75.55	75.46	75.77	75.50	69.33

TABLE IV
DIALECT IDENTIFICATION ACCURACY–EXPERIMENT 2

	Test data	
	Internal	External
Experiment 1	88.24%	73.24%
Experiment 2	92.08%	71.57%

TABLE V
MEAN RESULTS OF EXPERIMENT 1 AND EXPERIMENT 2

parallel corpus improves results for the PAL, SYR, and TUN dialects. In addition to conducting a cross-corpus evaluation on the two well-known corpora, namely QCRI Arabic Dialects Identification (QADI) Corpus and Shami-corpus, we are eager to further investigate the pairing of the two corpora described above.

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