Hierarchical Aggregation of Dialectal Data for Arabic Dialect Identification

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Abstract

Arabic is a collection of dialectal variants that are historically related but significantly different. These differences can be seen across regions, countries, and even cities in the same countries. Previous work on Arabic Dialect identification has focused mainly on specific dialect levels (region, country, province, or city) using level-specific resources; and different efforts used different schemas and labels. In this paper, we present the first effort aiming at defining a standard unified three-level hierarchical schema (region-country-city) for dialectal Arabic classification. We map 29 different data sets to this unified schema, and use the common mapping to facilitate aggregating these data sets. We test the value of such aggregation by building language models and using them in dialect identification. We make our label mapping code and aggregated language models publicly available.

Keywords: Arabic Dialects, Dialect Identification, Language Models

1. Introduction

Dialect identification (DID) is a natural language processing (NLP) task that aims at automatically determining the dialect of a given speech fragment or text (Erman and Beex, 2015). Since dialectal difference tend to be more subtle in relative terms to language differences, the DID task is harder than language identification. In this paper we focus on Arabic dialect identification, but we believe that our techniques and insights are extensible to other languages and dialect groups.

Arabic is a collection of dialectal variants that are historically related but significantly different. Arabic dialects are often classified in terms of geography at different levels of granularity: at the regional, country, province and city levels (Zaidan and Callison-Burch, 2012; Bouamor et al., 2019; Abdul-Mageed et al., 2020; Abdul-Mageed et al., 2021). Dialects are different from each other and Modern Standard Arabic (MSA) in terms of phonology, orthography, morphology, and the lexicon. Arabic speakers tend to code-switch between their dialect and MSA, creating sentences with different levels/percentages of "dialectlessness" (Habash et al., 2008; El-Faridy et al., 2013; El-Haj et al., 2018; Ali et al., 2021). That said, many of the differences are not observed in the written forms since in Arabic orthography, writing vowel diacritics is optional.

Several efforts have targeted creating different resources at different hierarchical levels going from cities to regions (Zaidan and Callison-Burch, 2011; Smaili et al., 2014; Jarrar et al., 2016; Al-Twaresh et al., 2018; Bouamor et al., 2018; Abdul-Mageed et al., 2020). Most of these resources were built in independent efforts using different labeling schemas, making the joint use and comparison of these data sets impractical.

In this paper, we address this issue by defining a unified hierarchical schema for dialectal Arabic identification; and demonstrate its use by mapping a number of data sets to it, and building aggregated language models at different hierarchical levels.

The main contributions of our work are as follows:

- We define a unified 3-level hierarchical schema for labeling dialectal text from different sources: region-country-city.
- We map the various labels from 29 different data sets into our unified schema. We make our mapping code, which is tailored to the different data sets, available.
- We create aggregated n-gram language models (LM) at the region, country, and city levels in character and word spaces from all of the data sets we worked with. We make the LMs publicly available.
- We demonstrate the value of our aggregated dialectal LMs on a standard DID test set for city level identification extending on a well-established state-of-the-art approach for Arabic DID.

The paper is organized as follows. We present some basic facts about the challenges of processing Arabic dialects in Section 2. In Section 3 we provide an overview of related work. Section 4 details our approach and its implementation from selecting the data sets, to building the aggregated LMs. We evaluate the use of the aggregated LMs in Section 5. We conclude the work in Section 6.

https://github.com/CAMEL-Lab/
HierarchicalArabicDialectID
2. Arabic Linguistic Challenges

Arabic is a collection of dialectal variants that are historically related but significantly different. Arabic dialects are often classified in terms of geography at different levels of granularity. Typical regional groupings cluster the dialects into Levantine Arabic (Lebanon, Syria, Jordan and Palestine), Gulf Arabic (Qatar, Kuwait, Saudi Arabia, United Arab Emirates and Bahrain), with Arabic and Omami Arabic included sometimes, Egyptian Arabic (which may include Sudan), North African Arabic (vaguely covering Morocco, Algeria, Tunisia, Libya and Mauritania), and Yemeni Arabic ([Habash, 2010]). However, within each of these regional groups, there is significant variation down to the country, province, and city levels. Although we acknowledge that there are various dimensions of classifying them (i.e., social class and religious), the automatic regional dialect identification, or less granular classification, has shown to achieve strong results ([Zaidan and Callison-Burch, 2012] [Althoabati, 2020]). But city level identification has been shown to be very challenging ([Bouamor et al., 2019] [Abdul-Mageed et al., 2020] [Abdul-Mageed et al., 2021]). The differences among the dialects, and between the dialects and MSA extend over the phonological, morphological and lexical dimensions. For example, the Levantine word لقبطية about the tomatoes is morphologically and lexically different from its MSA phrase الميتشة. The word for 'tomato' varies widely across Arabic dialects, e.g., معائبة in Moroccan Arabic, and قطة in Egyptian Arabic.

Such differences suggest that the task of dialect identification should be easy. But in fact, distinguishing among different Arabic varieties is quite difficult for a number of reasons. Because short vowels are optional, the automatic regional dialect identification, or less granular classification, has shown to achieve strong results ([Zaidan and Callison-Burch, 2012] [Althoabati, 2020]). But city level identification has been shown to be very challenging ([Bouamor et al., 2019] [Abdul-Mageed et al., 2020] [Abdul-Mageed et al., 2021]). The differences among the dialects, and between the dialects and MSA extend over the phonological, morphological and lexical dimensions. For example, the Levantine word لقبطية about the tomatoes is morphologically and lexically different from its MSA phrase الميتشة. The word for 'tomato' varies widely across Arabic dialects, e.g., معائبة in Moroccan Arabic, and قطة in Egyptian Arabic.

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2Arabic transliteration is in the HSB scheme ([Habash et al., 2007]).

3. Related Work

Recently, there has been an active interest in developing automatic Arabic dialect processing systems working at a different levels of representation and in exploring different dialectal data sets ([Shoufan and Alameri, 2015] [Jauhiainen et al., 2019] [Althoabati, 2020]). This has been facilitated by the newly developed monolingual and multilingual dialectal corpora and lexicons. Several mono-dialectal corpora covering different Arabic dialects were built and made available ([Gadalla et al., 1997] [Diab et al., 2010] [Zaidan and Callison-Burch, 2011] [Al-Sabbagh and Girju, 2012] [Salama et al., 2014] [Sada et al., 2014] [Smaïli et al., 2014] [Cotterell and Callison-Burch, 2014] [Jarrar et al., 2016] [Khalifa et al., 2016] [Al-Twaresh et al., 2018] [Abu Kwaik et al., 2018] [El-Haj, 2020]).

The expansion into multi-dialectal data sets was initially done at the regional level ([Zaidan and Callison-Burch, 2011] [McNeil and Faiza, 2011] [Elfardy et al., 2014] [Bouamor et al., 2014] [Salama et al., 2014] [Meftouh et al., 2015]). Then, several efforts for creating finer grained parallel dialectal corpus and lexicon has been presented. These include labeling country-level data from similar regions ([Sawalha et al., 2019] [Jarrar et al., 2016] [Meftouh et al., 2015] [Zaghouani and Charfi, 2018] [Al-Twaresh et al., 2018] [Abu Kwaik et al., 2018] [El-Haj, 2020] [Shom et al., 2020] [Abdelali et al., 2020] [Abdul-Mageed et al., 2018]) and introducing larger-scale data sets covering between 5 and 21 countries ([Mubarak and Darwish, 2014] [Bouamor et al., 2018] [Abdul-Mageed et al., 2018] [Zaghouani and Charfi, 2018] [Al-Twaresh et al., 2018] [Abu Kwaik et al., 2018] [El-Haj, 2020]) with a much more varying label sets. [Bouamor et al., 2015] introduced MADAR, the first city-level dialectal data set including dialects from 25 cities. Following this effort, [Abdul-Mageed et al., 2020] presented NADI, a large scale data set of Arabic varieties annotated with provinces in addition to cities, countries and regions, covering up 21 countries and 100 provinces.

However, most of these efforts focus primarily on a number of varieties corresponding generally to those spoken in major cities ([Cairo, Amman, Baghdad, Tunis, Rabat, etc.]), or study different dialects independently. All these data sets have different dialect labeling schema at different hierarchical levels, making their use in any research work impractical.

To the best of our knowledge, our work is the first aiming at aggregating several Arabic dialectal data sets.
from different sources and different levels: region, country, province and city levels, defining a unified hierarchical schema for labeling dialectal text from different sources, and building the largest-scale dialectal Arabic resource, mapped to their MSA, English, and French versions, when available.

In terms of dialect identification, a number of Arabic dialect identification shared tasks were organized first as part of the VarDial workshop. These focused on regional varieties such as Egyptian, Gulf, Levantine, and North African based on speech broadcast transcriptions and integrated acoustic and phonetic features extracted from raw audio (Malmasi et al., 2016; Zampieri et al., 2017; Zampieri et al., 2018). Then, shared tasks dedicated to Arabic dialect identification specifically were created: The MADAR shared task (Bouamor et al., 2019) and the NADI shared task in its two editions (Abdul-Mageed et al., 2020; Abdul-Mageed et al., 2021).

A variety of methods have been introduced to classify the dialectal texts in MADAR and NADI. Most of the work have shown that shallow n-gram based approaches are the state-of-the art in terms of performance for this task (Salameh et al., 2018; Bouamor et al., 2019; Abdul-Mageed et al., 2020; Abdul-Mageed et al., 2021), while using deep learning architectures such as RNN, CNN, or BERT do not achieve a comparable accuracy. Recently, Inoue et al. (2021) compared fine-tuning 12 different BERT models for Arabic and none of them improved over Salameh et al. (2018)’s model. Since fine-tuning tends to be more robust to limited training/tuning, we hypothesize that the BERT-like masked LMs are trained towards modeling deeper semantic similarity and less so towards modeling shallow signals of phonology and spelling differences that can help the task of dialect identification (i.e. in comparison to n-gram features and models).

In this work, we improve on the DID results reported in (Salameh et al., 2018) by adopting the same approach and adding a few additional features.

## 4. Unified Labeling of Arabic Dialect Data Sets

We discuss next the various data sets we worked with, and the process to unify their dialectal id labels.

### 4.1. Data Selection

There are numerous data sets for Arabic NLP. In this effort, we selected 29 data sets that fit the following criteria. First, the data sets is primarily or exclusively written in Arabic script. We do not consider Arabizi data sets in this effort. Second, The data sets are primarily or exclusively in Arabic dialects. We do not

| Corps ID | Corpus Name | Reference |
|----------|-------------|-----------|
| ADEPT  | LDC2012T09: Arabic-Dialect/English Parallel Text | (BBN Technologies et al., 2012) |
| AMDTC  | Arabic Multi Dialect Text Corpus | (Almemani and Lee, 2013) |
| AOG    | Arabic Online Commentary Dataset | (Zaidan and Callison-Burch, 2011) |
| ARAP-T | Arap-Tweet: The Arabic Author Profiling Project Twitter Corpus | (Zaghoubani and Charf, 2018) |
| BOLT-SMS | LDC2017T07: BOLT Egyptian SMS | (Chen et al., 2017) |
| CALLHOME | LDC2017T19: CALLHOME Transcripts | (Gadalla et al., 1997) |
| CALLHOME-EX | LDC2002T38: CALLHOME Supplement Transcripts | (Linguistic Data Consortium, 2002) |
| CURRAS | Curras: A corpus for the Palestinian Arabic dialect | (Jarar et al., 2016) |
| GULF-TRANS | LDC2006T15: Gulf Arabic Transcripts | (Appen Pty Ltd, 2006a) |
| GUUMAR | Guammar: A Gulf Arabic Internet Novel Corpus | (Khaila et al., 2018) |
| HABIBI | Habibi: A multi Dialect multi National Arabic Song Lyrics Corpus | (El-Haj, 2020) |
| IRAQ-TRANS | LDC2006T16: Iraqi Arabic Transcripts | (Appen Pty Ltd, 2006b) |
| LEV-BABYLON | LDC2005S08: Babylon Levantine Arabic Transcripts | (BBN Technologies, 2005) |
| LEV-CTS | LDC2005S14: CTS Levantine Arabic Transcripts | (Maamouri et al., 2005) |
| LEV-FISHER | LDC2007T04: Fisher Levantine Arabic Transcripts | (Maamouri et al., 2007) |
| LEV-TRANS-1 | LDC2006T07: Levantine Arabic Transcripts | (Maamouri et al., 2006) |
| LEV-TRANS-2 | LDC2007T01: Levantine Arabic Transcripts | (Appen Pty Ltd, 2007) |
| MADAR-EX | MADAR Corpus 6 Extra | (Bouamor et al., 2019) |
| MADAR-ST1 | MADAR Shared Task 1 | (Bouamor et al., 2019) |
| MADAR-ST2 | MADAR Shared Task 2 | (Bouamor et al., 2019) |
| MDCPC | Multi-dialect parallel corpus | (Bouamor et al., 2014) |
| MMIC-N | Multi-dialect, multi-genre informal corpus news | (Cotterrell and Callison-Burch, 2014) |
| MMIC-T | Multi-dialect, multi-genre informal corpus twitter | (Cotterrell and Callison-Burch, 2014) |
| NADI | NADI: Nuanced Arabic Dialect Identification Shared Task | (Abdul-Mageed et al., 2020) |
| PACID | PADIC: Parallel Arabic Dialect Corpus | (Metrouk et al., 2015) |
| QADI | QCRI Arabic Dialects Identification Corpus | (Abdelali et al., 2020) |
| SHAMI | Shami: A Corpus of Levantine Arabic Dialects | (Abu Kwaik et al., 2018) |
| SUAR | SUAR: Saudi Corpus for NLP Applications and Resources | (Al-Twaresh et al., 2018) |
| YOUDACC | Youtube Dialectal Arabic Commentary Corpus | (Salama et al., 2014) |

Table 1: The list of dialectal data sets used in this work.
Furthermore, the data sets vary widely in how the di-
gional (e.g., G
UMAR
 to a single country (e.g. CALLHOME), others are re-
region level. It terms of spread, some are specific
labels: city, province, country and region. Some data sets
include multiple regions and countries, but are only la-
els: city, province, country and region and spread. In terms of granularity, we found four lev-
s: city, province, country and region. Some data sets
include multiple regions and countries, but are only la-
s: city, province, country and region.

4.2. Data Variability
Table compares the data sets we worked with. As can
be seen, the data sets cover a wide range of genres: speech transcripts, social media texts (tweets, news
comments, youtube comments), SMS, forum novels,
travel phrases, and song lyrics. The data set labels vary widely in terms of granularity and spread. In terms of granularity, we found four levels: city, province, country and region. Some data sets include multiple regions and countries, but are only labeled at the city or province levels. Some only specify the region level. It terms of spread, some are specific to a single country (e.g. CALLHOME), others are regional (e.g., GUMAR and SHAMI) or pan-Arab (e.g., MADAR-ST2 and NADI). Some data sets included and marked MSA texts explicitly. Furthermore, the data sets vary widely in how the dialect label is identified in terms of textual units. The lowest level of identification is at the sentence/line level. The speech transcript data sets were created by targeting a specific speech community. The MDPC, MADAR-ST1, and MADAR-EX data sets were commissioned translations, so they were created in the target dialect at the sentence level. The MADAR-ST2 data set was labeled by identifying the country of the Tweeter and assigning the label to all their tweets. The GUMAR data set was labeled at the document level. The NADI data set was annotated automatically using Tweet location as proxy for dialect.

Finally, these data sets also vary in terms of size, as well as whether standard (i.e. non-random, and replicable) experimental train-dev-test splits already exist for them.

4.3. Data Preprocessing and Splitting
We minimally processed the data sets using simple
punctuation based sentence segmentation and white
space tokenization using (Obeid et al., 2020).

If a data set does not have a standard train-dev-test split, we manually divided it as follows: 80% for training, 10% for development, and 10% for testing. Table 3 shows the aggregated counts for the splits. In this pa-

| Corpus ID          | Genre/Domain    | Region | Country | Province | City | MSA | Split  | # Lines (1000s) | # Words (1000s) | # Chars (1000s) |
|--------------------|-----------------|--------|---------|----------|------|-----|--------|----------------|----------------|-----------------|
| MADAR-ST1          | travel domain   | (mix)  | (mix)   | (mix)    | 25   | X   | original | 112            | 800            | 3,351           |
| MADAR-EX           | travel domain   | (mix)  | (mix)   | (mix)    | 6    | X   | original | 48             | 285            | 1,473           |
| NADI               | twitter         | (mix)  | (mix)   | (mix)    | 100  | -   | original | 31             | 408            | 2,553           |
| MADAR-ST2          | twitter         | (mix)  | 22      | -        | -    | -   | original | 188            | 2,240          | 12,235          |
| HABIBI             | song lyrics     | (mix)  | 18      | -        | -    | -   | new     | 412            | 2,525          | 12,637          |
| QADI               | twitter         | (mix)  | 18      | -        | -    | -   | original | 499            | 6,260          | 32,628          |
| ARAP-T             | twitter         | (mix)  | 16      | -        | -    | -   | new     | 1,607          | 18,827         | 119,548         |
| LEV-FISHER         | speech transcript | (mix) | 6      | -        | -    | -   | new     | 61             | 326            | 1,307           |
| MDPC               | web mixed       | (mix)  | 5       | -        | X    | new | 6       | 58             | 275            |
| PADIC              | speech transcript | (mix) | 5       | -        | -    | X   | new     | 45             | 301            | 1,424           |
| GUMAR              | forum novel     | (1)    | 6       | -        | -    | -   | original | 9,097          | 85,615         | 452,570         |
| LEV-CTS            | speech transcript | (1)  | 4       | -        | -    | -   | new     | 192            | 968            | 3,648           |
| LEV-TRANS-1        | speech transcript | (1)  | 4       | -        | -    | -   | new     | 359            | 1,841          | 7,052           |
| LEV-TRANS-2        | speech transcript | (1)  | 4       | -        | -    | -   | original | 60             | 499            | 2,035           |
| SHAMI              | web mixed       | (1)    | 4       | -        | -    | -   | new     | 66             | 1,050          | 4,706           |
| GULF-TRANS         | speech transcript | (1)  | 3       | -        | -    | -   | original | 58             | 479            | 1,926           |
| BOLT-SMS           | sms             | (1)    | 1       | -        | -    | -   | original | 67             | 310            | 1,421           |
| CALLHOME           | speech transcript | (1)  | 1       | -        | -    | -   | original | 29             | 147            | 669             |
| CALLHOME-EX        | speech transcript | (1)  | 1       | -        | -    | -   | new     | 3              | 14             | 63              |
| CURRAS             | web mixed       | (1)    | 1       | -        | -    | -   | original | 5              | 57             | 267             |
| IRAQ-TRANS         | speech transcript | (1)  | 1       | -        | -    | -   | original | 27             | 228            | 927             |
| LEV-BABYLON        | speech transcript | (1)  | 1       | -        | -    | -   | new     | 76             | 336            | 1,725           |
| SUAR               | web mixed       | (1)    | 1       | -        | -    | -   | new     | 11             | 121            | 565             |
| MMIC-N             | news comments   | 5      | -       | X        | new  | 91   | 2,999   | 11,307         |
| YOU/DACC           | youtube comments | 5      | -       | -        | X    | original | 510           | 8,317          | 44,468          |
| MMIC-T             | twitter         | 5      | -       | -        | -    | new | 40      | 578            | 3,114          |
| AMDTC              | web mixed       | 4      | -       | X        | new  | 5,183| 50,323  | 273,545        |
| AOC                | news comments   | 3      | -       | X        | new  | 108  | 1,976   | 10,221         |
| ADEPT              | web mixed       | 2      | -       | -        | -    | new | 176     | 1,689          | 7,755          |

Table 2: Corpora domain, region, province and city level details and statistics in terms of lines, words, and characters. We indicate whether original publish train-dev-test splits are used or new ones defined in this work.
Table 3: Aggregated Data Splits

| Level   | Split | # of lines (1000s) |
|---------|-------|--------------------|
| City    | Train | 591                |
|         | Dev   | 53                 |
|         | Test  | 55                 |
| Country | Train | 11,154             |
|         | Dev   | 1,474              |
|         | Test  | 2,023              |
| Region  | Train | 14,805             |
|         | Dev   | 1,903              |
|         | Test  | 2,454              |

Figure 1: Hierarchical classification of the Arabic dialect labels in our data set. Country labels follow the ISO 3166 standard.

4.4. Unified Hierarchical Labeling

Our next step is to unify the labeling for the various data sets discussed above. Not only did the data sets come at different levels of annotation, but they used different naming conventions for the labels. Since these data sets were created in different research efforts for different original purposes, they did not have a common format or representation. As such, our challenge was to process the data from each data set into a common unified representation.

In order to create our labeling schema, we first went through all the collected data sets and created a list of all unique terms they used for region, country, province, and city labels. We then created a mapping from each label to a unified set of corresponding labels for region, country, and city. We intentionally ignored the province level because only one data set had...
In total, our label space comprises 113 city labels, 22 country labels and 6 region labels, which we organize hierarchically. At each level we include MSA as an additional dialect label, i.e., the city, country and region are all msa. The full list of labels for each level in our hierarchy is provided in Figure 1. Obviously this is not a complete list, but it covers the data points in our data sets.

Finally, we assign the missing hierarchical labels to all the data set points when possible. Basically, a specific fine granularity label identifies all of the higher level labels, e.g., the city label ‘Abu Dhabi’ identifies its country (‘The United Arab Emirates’) and its Region (‘Arabian Gulf’). However, for the country label ‘Syria’, we cannot identify the specific cities, but can identify the region as ‘Levant’. As such, some data set points will be under-specified for lower levels of the hierarchy. For all the data points from all the sets, we keep a record of their original corpus, data source, splits, etc. An example of our hierarchical labeling of a sentence extracted from the MADAR-ST1 data set and originally labeled with the Rabat city label is shown in Figure 2.

### 4.5. Aggregated Language Models

Using the hierarchical labels, we create aggregated data sets for each city, country and region, by combining all the data points from the 29 data sets with shared city, country or region labels, accordingly. These aggregations were done separately for training, development, and test subsets.

From each aggregated training set, we created two n-gram language models at the character and word levels using KenLM (Heafield, 2011) with an order of 5 and discount fallback. We make all the models publicly available.

We demonstrate the use of these models in the next section.

### 5. Evaluation

We assess the value of our aggregated language models on a difficult public shared task.

#### 5.1. Experimental Settings

**Task and Data** We report our results on the MADAR Shared Task 1, which targets labeling 25 city dialects and MSA (26 labels) (Bouamor et al., 2019). The task makes use of data in the travel phrase domain (Bouamor et al., 2018) consisting in commissioned translations from the English and French versions of the Basic Traveling Expression Corpus (BTEC) (Takezawa et al., 2007).

The official shared task allows the use of training data for the 26 labels (Corpus-26), a larger data set (Corpus-6) which has more examples labeled for five cities and MSA, in addition to unlabeled external data. We use the same labeled data for our baseline and all of our training. We make use of our training split aggregated LMs only to provide features to other machine learning classifiers in a pretrained LM manner. As such it should be noted that indeed our use goes beyond the restrictions of the official shared task since technically our aggregated data was labeled, even if not for the same target set of labels of the shared task. That said, we still think there are very useful insights from these experiments.

**Metrics** We evaluate our model’s outputs in terms of accuracy and F1 score at the city, country and region level. We classify only at the city level, and generate the country and region labels by simple deterministic mapping from the finer grained city labels using our label hierarchy.

#### 5.2. Dialect Identification Approach

**Previous Efforts** The MADAR Shared Task 1 is quite a hard task. To our knowledge, the best results reported on it is that by (Salameh et al., 2018), which precedes the shared task itself. (Salameh et al. (2018) used a Multinomial Naive Bayes classifier with a set of engineered n-gram features. (Salameh et al. (2018) reported worse results using a number of models, including neural model without success. They attributed the weaker performance on the limited training data. Recently, Inoue et al. (2021) compared fine-tuning 12 different BERT models for Arabic and none of them improved over [Salameh et al. (2018) s model.

In the rest of this paper we discuss the (Salameh et al. (2018) approach and describe how we extend it using our aggregated LMs.

**Baseline Classifier** As a baseline, we consider the Camel Tools implementation (Obeid et al., 2020) of...
| Classifier Setup | City |  | Country |  | Region |  |
|------------------|------|---|---------|---|--------|---|
| (Salameh et al., 2018) | 67.75 | 67.89 | 76.44 | - | 85.96 | - |
| Baseline | 67.69 | 67.83 | 76.33 | 74.10 | 85.75 | 82.60 |
| +City | 67.69 | 67.87 | 76.50 | 74.09 | 85.94 | 82.68 |
| +Country | 67.90 | 68.10 | 77.12 | 74.83 | 86.46 | 83.52 |
| +Region | 68.13 | 68.27 | 76.92 | 74.65 | 87.06 | 83.80 |
| +City +Country | 67.13 | 67.46 | 76.33 | 73.75 | 86.02 | 82.90 |
| +City +Region | 67.48 | 67.64 | 76.46 | 73.97 | 86.38 | 83.17 |
| +Country +Region | 67.54 | 67.76 | 76.77 | 74.39 | 86.56 | 83.40 |
| +City +Country +Region | 67.23 | 67.51 | 76.50 | 73.79 | 86.38 | 83.27 |

Table 4: Dialect identification results on MADAR Shared Task 1 data (MADAR 26 Test). The results for (Salameh et al., 2018) are as reported in (Bouamor et al., 2019).

Salameh et al. (2018)’s best model for dialect identification. This is the only available implementation of Salameh et al. (2018). This implementation is slightly below the reported results in the shared task paper: 0.06% at the city-level accuracy and F1.

The Salameh et al. (2018) best model uses two classifiers: main and supporting. Both classifiers use word unigram and character uni-, bi-, and trigram features with TF-IDF scores in addition to 5-gram LM scores, all trained on the same training MADAR data set. The supporting classifier is trained on Corpus-6 and classifies into its corresponding six labels. The main classifier is trained on Corpus-26 and classifies into its corresponding 26 labels. Most importantly, the main classifier uses the supporting classifier probabilities as additional features.

Aggregated Classifiers We build three new classifiers to use as additional supporting classifiers to the main classifier design mentioned above. The three classifiers use the Corpus-26 training data and n-gram features, but replace the 5-gram LM scores with those from our aggregated models at the city, country and region levels.

In all of these classifiers, the number of additional LM features is equal to two times the number of the labels in the hierarchy level. For example, in the city classifier, we use 113 word 5-gram features and 113 character 5-gram features. But, in all cases, we only classify into the 26 labels of the MADAR 26 Shared Task 1; and we only pass the 26 classification probabilities to the main classifier.

We experimented with the use of all combinations of the aggregated classifiers. For example, in Baseline+City+Region, we use the exact Baseline setup, but add the classifier output probabilities from City and Region.

5.3. Results and Discussion

The results of our experiments are presented in Table 4.

The best results at the city level come from using the aggregated region classifier to support the baseline classifier with an increase of 0.44% in accuracy and 0.43% in F1. However, these results are not statistically significant against the baseline using McNemar’s test (p = 0.07) (McNemar, 1947). The aggregated region classifier setup also has the best region-level performance with an increase of 1.31% in accuracy and 1.20% in F1. These results are statistically significant (p < 0.01). The setup with the aggregated country classifier outperforms on the country-level labels, with an increase of 0.79% in accuracy and 0.73% in F1. These results are also statistically significant (p < 0.05). The setup with the aggregated city classifier did not help the city-level classification; and did not do well, in general. The combinations of aggregated classifiers did worse than the single aggregated classifiers.

The simple interpretation of the results is that the larger aggregated models, for region and country, help more because they have more data in them. The aggregated region set has 32% more lines of training than the aggregated country set; and 25 times the number of lines in the aggregated city training. Furthermore, most of the data in the aggregated city LMs come from the MADAR data, any way. It’s unclear why the combinations of aggregated classifiers do not help; perhaps this is due to noisy signals from the different components.

While our use of the aggregated data for DID is similar to what Salameh et al. (2018) did with the Corpus-6 classifier, there is an important difference. The Corpus-6 contained the same in-domain data as Corpus-26 and included labels all of which appear in the basic Corpus-26 set. The regional aggregated data comes from a much wider variety of genres and domains, and it contains a limited number of low granularity labels. But it is much bigger in size; which is the biggest advantage it has.
6. Conclusion and Future Work

In this work, we defined a general hierarchical dialectal labeling schema and mapped 29 different dialectal data sets into it. We created a number of n-gram language models for specific cities, countries and regions and demonstrated the use of such models in city-level dialect identification task. We make our models and code publicly available.

In the future, we would like to use the aggregated language models in other Arabic dialect NLP tasks, such as speech recognition. We would like to use these models as part of systems for downstream applications such as user-aware (dialect-wise) generation, and text normalization. We also look forward to extending the label set to cover more Arab cities.

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