JHU System Description for the MADAR Arabic Dialect Identification Shared Task

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Abstract

Our submission to the MADAR shared task on Arabic dialect identification (Bouamor et al., 2019) employed a language modeling technique called Prediction by Partial Matching, an ensemble of neural architectures, and sources of additional data for training word embeddings and auxiliary language models.[1] We found several of these techniques provided small boosts in performance, though a simple character-level language model was a strong baseline, and a lower-order LM achieved best performance on Subtask 2. Interestingly, word embeddings provided no consistent benefit, and ensembling struggled to outperform the best component submodel. This suggests the variety of architectures are learning redundant information, and future work may focus on encouraging decorrelated learning.

1 Introduction

While Modern Standard Arabic (MSA) is used across many countries for formal written communication, regional Arabic dialects vary substantially. Dialect identification has traditionally been performed at the level of broad families of dialects—for instance grouping many dialects across the Arabian Peninsula together. However, even within a single country there is often noticeable variation from one city to another. The MADAR dataset and corresponding shared task aim to perform dialect identification at a finer-grained level. Subtask 1 aims to distinguish travel phrases produced between Arabic dialect speakers from 25 different cities, as well as MSA. Subtask 2 aims to distinguish Twitter users from different Arabic-speaking countries. Along with the inherent difficulty of classifying short documents, highly-correlated modalities like topic and proper names can lead to overfitting, particularly for user-directed content like Twitter. Our method attempts to address the former by using a language modeling technique that has empirically been found to perform well on extremely short documents. For the latter, we employ ensembles of heterogeneous neural architectures and aggressive dropout, with the goal of finding a broad range of features that support the task without overfitting.

2 Data

In addition to the data provided by the MADAR subtasks, we used the following data sets to train embeddings or auxiliary language models:

1. Preexisting collections of the Arabic Dialect Corpus (ADC) of 150k comments from three Arabic-language newspaper sites focused on Saudi Arabia, Jordan, and Egypt (Zaidan and Callison-Burch, 2011)

2. The Twitter LID corpus of 70k Tweets in 70 languages [2].

3. Crawled posts from Reddit and the Twitter 1% sample either tagged as Arabic, or having a majority of Arabic characters, amounting to 11k and 100m posts, respectively, are used.

The ADC and Twitter LID corpora were also used to train additional PPM language models,

[1] Code available at https://bit.ly/2Kouo5X

[2] https://bit.ly/2KlITre

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though these proved to be ineffective in our ensembles (see Section 5)

Split	Missing
Train	13076 (6%)
Dev	1607 (5%)
Test	5763 (12%)

Table 1: Missing tweets from the Subtask 2 data splits, absolute number and percent of total.

Table 1 shows how many tweets were still available when we initialized Subtask 2.

3 System

3.1 PPM Language Models

Prediction by Partial Matching (PPM) was first introduced as a sequence compression algorithm (Cleary and Witten, 1984) but has been found to be particularly effective as a character language model for classifying short documents (Frank et al., 2000; McNamee, 2016), using the probabilities directly rather than as input to a numeric encoding.

PPM is based on a variable-order Markov model that contains a parameter N known as the *maximal order*. When compressing data files or training a classification model, observations from previously seen data are used to estimate the likelihood of observing a symbol following a given context of up to N characters. Longer contexts are used when available, starting with the maximal order N. However, PPM automatically backs off to use shorter contexts when a symbol has never been observed in a longer context. A context-dependent penalty, also known as an escape probability, is applied when backing off is required.

As an example, in English, an 'n' is the most likely character observed after the sequence "t i o". Other letters are observed less frequently, such as 'l', 'm', and 'p'. However, a 'z' is not observed. To account for a 'z' after "t i o" it is necessary to back off using the estimates from shorter contexts such as "i o". If a 'z' has never been observed after "i o" then the process continues, with an additional penalty and further recursive backoff for 'z' using the context of the single symbol ('i').

To use PPM for classification rather than compression, models $M_1, M_2, ..., M_n$ are trained for each discrete class. Then for a given textual sample t, choose the model that encodes t in the least number of bits. In reality the text is not compressed and the probabilities from the model are used to choose the model which best fits the text.

N	Subtask 1	Subtask 2
2	0.430	0.431
3	0.576	0.543
4	0.591	0.402
5	0.586	0.287

Table 2: Performance of PPM models on the subtask dev sets using different values of N.

For each labeled corpus, we trained PPM language models for distinguishing among the labels. This included each of the two subtasks, as well as the ADC and Twitter LID corpora that have a way to divide the instances into categories.

These models can either be used directly for their "native" task, or produce probabilities that may contain useful signal for a downstream task. Table 2 shows how the native models for each MADAR subtask perform with different values of maximal order N on dev data. $N = 4$ was best for Subtask 1, and $N = 3$ was best for Subtask 2.

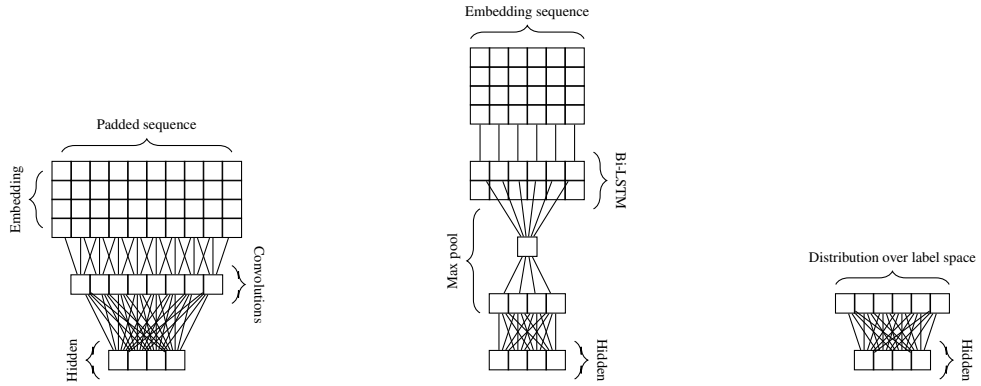
3.2 Word Embeddings

For the word-based neural models, we use 300-dimensional word embeddings trained on different amounts of data as input representations. First, we use randomly initialized embeddings. Then, we train fastText continuous bag of words (cbow) models with default parameters on the MADAR data (Bojanowski et al., 2017).[3] Finally, we utilize additional data, training on MADAR in addition to the datasets mentioned above (MADAR+). We provide final results (Macro-Average F1) from the ensemble model using each of these variants in Table 3. We see that utilizing additional data provided marginal performance gains, helping more in Subtask 2 where much of our additional data was also Twitter data, making it in-domain.

Embedding	Subtask 1	Subtask 2
Random	0.632	0.399
MADAR	0.626	0.397
MADAR+	0.634	0.411

Table 3: Effect of different word embeddings, Macro-Average F1 for final ensemble models on dev data.

[3] https://fasttext.cc/



(a) CNNs over sequences (b) RNNs over sequences (c) MLPs over distributions

Figure 1: The three basic types of submodels combined into the final ensemble, where the top layer is the input representation. They all produce the same-sized final hidden representation that can either be mapped directly to the target value with a final linear layer (for individual training) or concatenated into an ensemble.

3.3 Ensemble Models

In what follows, all layers other than the final fully-connected input to softmax employ ReLU non-linearity.

We experimented with an ensemble model that combines submodels to extract signal from different features or incorporate information from non-neural methods. Figure 1 shows the three types of submodels: CNNs and RNNs over character and word sequences, and MLPs over probability distributions from language models and metadata. We integrate the metadata provided with Subtask 2 as additional distributions: the probabilities from the organizers' 26-class model are incorporated the same way as LM scores, while the Twitter label is treated as a one-hot distribution and also incorporated alongside the LM scores.

Each submodel, regardless of architecture, eventually produces a same-sized hidden representation, which are initially mapped to the target output via cross-entropy to train as an individual model. Once the submodels have converged, their parameters are frozen, their hidden layers are detached from the target output, and instead concatenated into a single representation. This representation is then the input to the shared ensemble architecture, as shown in Figure 2. Note that the "Step-down FCs" layer is actually composed of several fully-connected layers, each dividing the representation size in half until it is one factor larger than the output label space.

Other specific choices for the models in this paper are: 100-dim char embeddings, char/word CNN filter sizes 1,2,3,4,5, bidirectional 2-layer LSTMs with 32-dim states, and SGD with LR=0.1, momentum=0.9, patience of 10 for LR decay, early stop patience of 20, and minibatch size of 512.

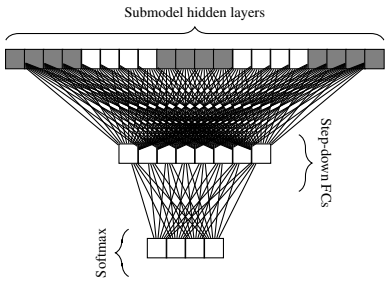


Figure 2: The ensemble model concatenates the hidden representations produced by the submodels and stacks one or more dense, non-linear layers, stepping down in size to a final softmax output over the label space.

Due to a misreading of the task description, our models were designed to classify tweets individually: this was handled at the submission deadline by taking a majority vote over each user's tweets.

4 Results

Table 4 reports the final precision, recall, and F1 scores for the best-performing model on each subtask.

The ensemble for Subtask 1 incorporates the best-performing (PPM-4) language model (see Table 2). The PPM-3 model for Subtask 2 performed text normalization to only include Arabic characters, followed by prepending the user name.

Subtask	Model	Prec	Rec	F1
Subtask 1	Ensemble	63.7	63.4	63.4
Subtask 2	PPM-3	74.9	46.5	54.3

Table 4: Precision, recall, and f-score of the best model for each subtask.

5 Discussion

Table 5 shows the final performance (Macro-Average F1) of the *submodels* of the ensemble on Subtask 1, before they were frozen, and the performance of the final ensemble model (which used the submodels). The modest 4-point improvement of the ensemble over the PPM submodel, and the fact that the Subtask 2 ensemble under-performed the PPM-3 model, suggests poor coordination of the representational power of the constituents. Distributions from language models trained on our other data sets unfortunately provided no benefit under the ensemble, and were not included.

Submodel	F1 Score
CNN	0.545
RNN	0.554
MLP-PPM	0.591
Ensemble	0.634

Table 5: F1 Scores of the submodels of the best ensemble for Subtask 1.

Figures 3 and 4 show the confusion matrices of the best models on Subtask 1 and 2, respectively. Our Task 1 misclassifications closely track those reported in (Salameh and Bouamor, 2018), e.g. TUN/SFX and BAS/BAG.

For Task 2, the preponderance of Saudi Arabian documents dominates the misclassifications, but also striking is how asymmetric the heatmap is compared to Subtask 1. This may largely be due to the small number of instances (half of the classes have counts in the single digits), but even better-represented pairs like Oman (14) and Iraq (10) are largely unidirectional, with Iraq much likelier to be misclassified as Oman than the reverse.

6 Conclusion

We experimented with a non-standard character language model (PPM) designed for classifying short text sequences, and an ensemble model that combined several neural architectures and input

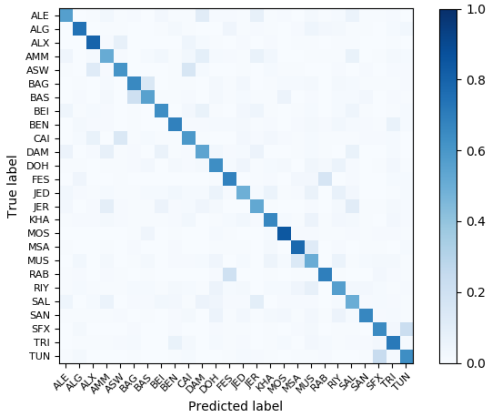


Figure 3: Confusion matrix for the Subtask 1 dev set using an ensemble model with word embeddings and language model scores constructed from the full suite of MADAR and external data sets

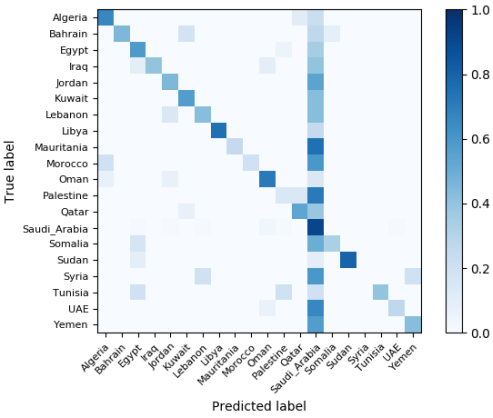


Figure 4: Confusion matrix for Subtask 2 dev set using a 3-gram PPM model constructed from the train set

features. The language model proved difficult to beat, even by ensembles that include the LM itself: this under-performance indicates the ensembling is not optimally leveraging its inputs. Future work might focus on techniques for encouraging uncorrelated training, perhaps by sequential submodel training that modifies the data as a function of previous submodel predictions.

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