Diacritization of Maghrebi Arabic Sub-Dialects

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Abstract
Diacritization process attempts to restore the short vowels in Arabic written text; which typically are omitted. This process is essential for applications such as Text-to-Speech (TTS). While diacritization of Modern Standard Arabic (MSA) still holds the lion’s share, research on dialectal Arabic (DA) diacritization is very limited. In this paper, we present our contribution and results on the automatic diacritization of two sub-dialects of Maghrebi Arabic, namely Tunisian and Moroccan, using a character-level deep neural network architecture that stacks two bi-LSTM layers over a CRF output layer. The model achieves word error rate (WER) of 2.7% and 3.6% for MOR and TUN respectively and is capable of implicitly identifying the sub-dialect of the input.

1 Introduction
Arabic is typically written without diacritics (short vowels)1, which require restoration during reading to pronounce words correctly given their context. For MSA, diacritics serve dual function, namely: word-internal diacritics dictate pronunciation and lexical choice; and end of word diacritics (aka case endings) indicate syntactic role. Conversely, dialects overwhelmingly use sukun, which typically indicates the absence of a vowel, as case endings, eliminating the need for syntactic disambiguation. Thus, DA diacritic recovery mostly involves restoring word-internal diacritics. Diacritic restoration is crucial for applications such as text-to-speech (TTS) to enable the proper pronunciation of words. Though sub-dialects could be orthographically identical, regional phonological variations necessitate specific tuning for sub-dialects.

In this paper we present new state-of-the-art Arabic diacritization of two sub-dialects of Maghrebi, namely Moroccan (MOR) and Tunisian (TUN). We employ a character-level Deep Neural Network (DNN) architecture that stacks two bi-LSTM layers over a Conditional Random Fields (CRF) output layer. The model achieves word error rate (WER) of 2.7% and 3.6% for MOR and TUN respectively. Further, the model is capable of implicitly identifying the sub-dialect of the input enabling joint learning and eliminating the need for specifying the sub-dialect of the input. We compare our approach to an earlier work based on CRF sequence labeling (Kareem et al., 2018). Our contributions are:

• Our novel work on Maghrebi diacritization shows some traits of Maghrebi (e.g. effective out-of-context diacritization) and provides strong results.
• Improve earlier results of using CRF.
• We explore cross dialect and joint training between MOR and TUN. Our DNN approach can effectively train and test on multi-dialectal data without explicit dialect identification.

2 Background
Most research on Arabic diacritization was devoted to MSA for a number of reasons among which the availability of resources. Till recent, written dialects was very scarce. Since dialects have mostly eliminated case endings, we focus on word-internal diacritization. Many approaches have been explored for word-internal diacritization of MSA such as Hidden Markov Models (Gal, 2002; Darwish et al., 2017), finite state transducers (Nelken and Shieber, 2005), character-based maximum entropy based classification (Zitouni et al.,

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1List of Arabic diacritics: fatha (a), damma (u), kasra (i), sukun (o), shadda (~).
2006), and deep learning (Abandah et al., 2015; Belinkov and Glass, 2015; Rashwan et al., 2015). Darwish et al. (2017) compared their system to others on a common test set. They achieved a WER of 3.29% compared to 3.04% for Rashwan et al. (2015), 6.73% for Habash and Rambow (2007), and 14.87 for Belinkov and Glass (2015).

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Azmi and Almajed (2015) survey much of the literature on MSA diacritization. For dialectal diacritization, the literature is rather scant. Habash et al. (2012) developed a morphological analyzer for dialectal Egyptian, which also performs diacritization using a finite state transducer that encodes manually crafted rules. They report an overall analysis accuracy of 92.1% without reporting diacritization results specifically. Khalifa et al. (2017) developed a morphological analyzer for dialectal Gulf verbs, which also attempts to recover diacritics. Again, they did not specifically report on diacritization results. Jarrar et al. (2017) annotated and diacritized a corpus of dialectal Palestinian containing 43k words. (Kareem et al., 2018) used a collection of 8,200 verses from Moroccan and Tunisian dialectal Bible to build a Linear Chain CRF to recover word diacritics. They achieved a word level diacritization error of 2.9% and 3.8% on Moroccan and Tunisian respectively.

3 Data

We used the same data for (Kareem et al., 2018) that is composed of two translations of the New Testament into two Maghrebi sub-dialects, namely Moroccan\(^2\) and Tunisian\(^3\). Both contains 8,200 verses each with 134,324 and 131,923 words for MOR and TUN respectively. Table 1 gives a sample verse from both dialects with English translation. The data has two distinguishing properties, namely: it is religious in nature; and spelling is mostly consistent. Other dialectal text from social media differ in both of these aspects. For future work, we plan to extend this work to social media text.

We split the data into 5 folds for cross validation, where training splits were further split 70/10 for training/validation. Given the training portions of each split, Table 2 shows the distribution of the number of observed diacritized forms per word. As shown, 89% and 82% of words have one diacritized form for MOR and TUN respectively. We further analyzed the words with more than one form. The percentage of words where one form was used more than 99% of time was 53.8% and 55.5% for MOR and TUN respectively. Similarly, the percentage of words where the most frequent form was used less than 70% was 6.1% and 8.5% for MOR and TUN respectively. We looked at alternative diacritized forms and found that the less common alternatives involve: omission of default diacritics (ex. 

| Lang. | Verse (Matthew 10:12) |
|-------|-----------------------|
| MOR   | وَالَّذِينَ آخَذُوْا لَفْتًا دَارَ فَسَاطَ غَلِيْقَ مَحْلُوْلاً |
| TUN   | وَكَذَٰلِكَ أَدْخَلَوْاهُمَّ غَلِيْقَ مَحْلُوْلَةَ |
| MSA   | وَجَنَّ أَدْخَلَوْاهُمَّ ضَيْغَ مَحْلُوْلَةَ |
| EN    | As you enter the home, greet those who live there |

Table 1: Sample verse from Bibles

Further, we used the most frequent diacritized form for each word, and we automatically diacritized the training set (“Most Freq” line in Table 2). The accuracy was 99.1% and 98.9% for MOR and TUN respectively. This indicates that diacritizing words out of context may achieve up to 99% accuracy. We compared this to the MSA version of the same Bible verses (132,813 words) and a subset of diacritized MSA news articles of comparable size (143,842 words) after removing case-endings. As Table 2 shows, MSA words, particularly for the Bible, have many more possible

\[2\] Translated by Morocco Bible Society

\[3\] Translated by United Bible Societies, UK
diacritized forms, and picking the most frequent diacritized form leads to significantly lower accuracy compared to dialects.

We compared the overlap between training and test splits. We found that 93.8% and 93.4% of the test words were observed during training for MOR and TUN respectively. If we use the most frequent diacritized forms observed in training, we can diacritize 92.8% and 92.0% of MOR and TUN words respectively. Thus, the job of a diacritizer is primarily to diacritize words previously unseen words, rather than to disambiguate between different forms. We also compared the cross coverage between the MOR and TUN datasets. The overlap is approximately 61%, and the diacritized form in one dialect matches that of another dialect less than two thirds of the time. This suggests that cross dialect training will yield suboptimal results. Other notable aspects of MOR and TUN that set them apart from MSA are: both allow leading letters in words to have sukun (MOR: 34% and TUN: 26% of words); MOR uses a shadda–sukun combination; and both allow consecutive letters to have sukun (ex. all letter in the MOR word ‘wolloboloAyoSo – “and places”) have sukun save one).

4 Proposed Approach

Capitalizing on the success of neural approaches (Belinkov and Glass, 2015; Abandah et al., 2015) and more precisely biLSTMs and CRF (Lample et al., 2016; Ling et al., 2015), we implemented the architecture shown in Figure 1 with four layers: one input, one output, and two hidden layers. At the input, a look-up table of randomly initialized embeddings maps each input character to a d-dimensional vector. The output from the character fixed-dimensional embeddings is used as input to the two hidden layers containing two stacked Bidirectional Long Short Term Memory (biLSTM) (Schuster and Paliwal, 1997) layers. BiLSTMs have shown their effectiveness in processing sequential data as they capture long-short term dependencies within the characters (Graves, 2012). At the output layer, a CRF layer is applied over the hidden representation of the two stacked biLSTMs to obtain the probability distribution over all labels. Since biLSTMs produce probability distribution for each output independently from other outputs, CRFs help overcome this independence assumptions and impose sequence labeling constraints. In our scenario, this was 12 possible tags representing one of the possible diacritics or none. We used Adam (Kingma and Ba, 2014) to optimize for the cross entropy objective function. Side experiments with stochastic gradient descent with momentum, AdaDelta (Zeiler, 2012), and RMSProp (Dauphin et al., 2015) did not lead to improvements. To avoid overfitting, we applied dropout (Srivastava et al., 2014) and early stopping. Dropout prevents co-adaptation of the hidden units by randomly setting a portion of hidden units to zero during training. We used early stopping with patience equal to 10. If validation error did not improve enough after this number of times, training is stopped. We tuned hyper-parameters on the development dataset by using random search resulting in the following parameters:

| Layer   | Hyper-Parameters | Value |
|---------|------------------|-------|
| Bi-LSTM | state size       | 200   |
|         | initial state    | 0.0   |
| Dropout | dropout rate     | 0.25  |
| Characters Emb. | dimension | 100   |
|         | batch size       | 5     |
|         | learning rate    | 0.01  |
|         | decay rate       | 0.05  |

The baseline results provided by (Kareem et al., 2018) used CRF sequence labeling (Lafferty et al., 2001), which has shown effectiveness for many sequence labeling tasks. CRFs effectively combine state-level and transition features. CRF++ implementation of a CRF sequence labeler with L2 regularization and default value of 10 for the generalization parameter “C$

https://github.com/taku910/crfpp
... $c_{-2}, c_{-1}, c_0, c_1, c_2 ... c_m$, we used a combination of character n-gram features, namely unigrams ($c_0$), bigrams ($c_0 c_{-1}$; $c_1 c_{-2}$; $c_2 c_{-3}$), trigrams ($c_0 c_{-2} c_{-1}$; $c_1 c_{-3} c_{-2}$; $c_2 c_{-4} c_{-3}$), and Brown Clusters (Brown et al., 1992). Given that the vast majority of dialectal words have only one possible diacritized form, the CRF is trained on individual words out of context. (Kareem et al., 2018).

5 Results and Discussion

We conducted three sets of experiments in contrast to previous results using CRF which achieved WER of 3.1% and 4.0% for MOR and TUN respectively (Table 3). The DNN model edged the CRF approach with 0.4% drop in WER for both dialects (Table 4 (a)).

| Training Set | Test Set | Error Rate |
|--------------|----------|------------|
| (a) Uni-dialectal Training | | |
| Moroccan | Moroccan | 1.1 | 2.9 |
| Tunisian | Tunisian | 1.7 | 3.8 |
| (b) Cross Training | | |
| Moroccan | Tunisian | 20.1 | 47.0 |
| Tunisian | Moroccan | 20.8 | 48.9 |
| (c) Combined Training | | |
| Combined | Moroccan | 12.6 | 34.2 |
| Combined | Tunisian | 9.5 | 23.8 |

Table 3: CRF Results with Brown clusters reported by (Kareem et al., 2018)

| Training Set | Test Set | Accuracy |
|--------------|----------|----------|
| (a) Uni-dialectal Training | | |
| MOR | MOR | 1.0 | 2.7 |
| TUN | TUN | 1.6 | 3.6 |
| (b) Cross Training | | |
| MOR | TUN | 21.4 | 48.2 |
| TUN | MOR | 22.3 | 49.4 |
| (c) Combined Training | | |
| Joint | MOR | 1.3 | 3.7 |
| Joint | TUN | 2.1 | 4.9 |

Table 4: DNN Results – Average Across All Folds

Second, we tested if sub-dialects can learn from each other. Tables 3 (b) and 4 (b) show that cross-dialectal results were significantly lower than mono-dialectal ones, confirming that dialects are phonetically divergent. Identical words with different diacritized forms in both dialects abound. Examples include \{ manoToqapo} (region) and \{ Tofulo, Tofalo} (boy) in MOR and TUN respectively.

Third, we combined training data from both dialects, and we tested on individual dialects. Tables 3 (c) and 4 (c) show the results of joint training. While the CRF baseline results were significantly worse, DNN WER increased by 1% and 1.3% for MOR and TUN respectively. The results suggest that unlike CRFs, our DNN model was implicitly identifying the sub-dialect.

| T | P | R | Examples |
|---|---|---|----------|
| ~ | ~u | 8.8% | \{ Aln ~baho \rightarrow Aln ~ubaho \} |
| ~a | ~u | 2.5% | \{ Alm ~daqap \rightarrow Alm ~udaqap \} |
| o | ~ | 3.4% | \{ toEaT ~lo \rightarrow toEaT ~lo \} |

Table 5: Most common diacritic prediction errors (T: Truth, P: Predicted, R: Ratio)

| T | P | R | Examples |
|---|---|---|----------|
| o | ~ | 14.3% | \{ Alj ~mal \rightarrow Alj ~mal \} |
| ~i | ~ | 2.1% | \{ gal ~toha \rightarrow gal ~toha \} |
| a | ~a | 3.0% | \{ Dny ~aAf \rightarrow Dny ~aAf \} |

Table 5: Most common diacritic prediction errors (T: Truth, P: Predicted, R: Ratio)

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Figure 2: Confusion Matrix for Moroccan using Combined approach.
manly errors involve shadda (~) or sukun (o); Table 5 details the most common errors for both sub-dialects with error examples. The most common errors involved fatha (a), shadda (~), sukun (o), and kasra (i). We also looked at the percentage of errors for individual diacritics (or combinations in which they appear) using mono-dialectal and joint training. The break-down was as follows:

|          | MOR Mono | MOR Joint | TUN Mono | TUN Joint |
|----------|----------|-----------|----------|-----------|
| fatha (a)| 68.4     | 58.1      | 83.0     | 51.0      |
| sukun (o)| 63.3     | 64.9      | 55.8     | 56.1      |
| shadda (~)| 48.5      | 42.7      | 30.4     | 29.0      |
| kasra (i)| 14.6     | 14.6      | 52.7     | 43.7      |
| damma (u)| 11.8     | 13.4      | 20.5     | 19.1      |

The breakdown shows that error types in MOR and TUN were rather different. For example, kasra error were more pronounced in TUN than MOR. Also, joint training affected different diacritics differently. For example, joint training for TUN caused a very large drop in errors for fatha.

Given our results, we suggest that an effective strategy for robust dialectal diacritization would involve: a) building, with the help of our model, a large lookup table for the most common words with one possible diacritized form for each dialect, which would account for 99% of the words, and using simple lookup for seen words in the lookup table and using the diacritization model otherwise; and b) using a mono-dialectal model in application where the sub-dialect is known (ex. chat app in a specific country) and resorting to the combined model otherwise (ex. tweets of unknown source).

6 Conclusion

In this paper, we have presented the diacritization of Maghrebi Arabic, a dialect family used in Northern Africa. This work will help enable NLP to model conversational Arabic in dialog systems. We noted that dialectal Arabic is less contextual and more predictable than Modern Standard Arabic, and high levels of accuracy can be achieved if enough data is available. We used a character-level DNN architecture that stacks two biLSTM layers over a CRF output layer. Mono-dialectal training achieved WER less than 3.6%. Though sub-dialects are phonetically divergent, our joint training model implicitly identifies sub-dialects, leading to small increases in WER.

References

Gheith A Abandah, Alex Graves, Balkees Al-Shagoor, Alaa Arabiyat, Fuad Jamour, and Majid Al-Taee. 2015. Automatic diacritization of arabic text using recurrent neural networks. *International Journal on Document Analysis and Recognition (IJDAR)*, 18(2):183–197.

Aqil M Azmi and Reham S Almajed. 2015. A survey of automatic arabic diacritization techniques. *Natural Language Engineering*, 21(03):477–495.

Yonatan Belinkov and James Glass. 2015. Arabic diacritization with recurrent neural networks. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 2281–2285, Lisbon, Portugal.

Peter F Brown, Peter V Desouza, Robert L Mercer, Vincent J Della Pietra, and Jenifer C Lai. 1992. Class-based n-gram models of natural language. *Computational linguistics*, 18(4):467–479.

Kareem Darwish, Hamdy Mubarak, and Ahmed Abdellali. 2017. Arabic diacritization: Stats, rules, and hacks. In *Proceedings of the Third Arabic Natural Language Processing Workshop*, pages 9–17.

Yann Dauphin, Harm de Vries, and Yoshua Bengio. 2015. Equilibrated adaptive learning rates for non-convex optimization. In *Advances in neural information processing systems*, pages 1504–1512.

Ya’akov Gal. 2002. An HMM approach to vowel restoration in arabic and hebrew. In *Proceedings of the ACL-02 workshop on Computational approaches to Semitic languages*, pages 1–7. Association for Computational Linguistics.

Alex Graves. 2012. *Supervised sequence labelling with recurrent neural networks*, volume 385. Springer.
Nizar Habash, Ramy Eskander, and Abdelati Hawwari. 2012. A morphological analyzer for egyptian arabic. In Proceedings of the twelfth meeting of the special interest group on computational morphology and phonology, pages 1–9. Association for Computational Linguistics.

Nizar Habash and Owen Rambow. 2007. Arabic diacritization through full morphological tagging. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers, pages 53–56. Association for Computational Linguistics.

Mustafa Jarrar, Nizar Habash, Faeq Alrimawi, Diyam Akra, and Nasser Zalmout. 2017. Curras: an annotated corpus for the palestinian arabic dialect. Language Resources and Evaluation, 51(3):745–775.

Darwish Kareem, Abdelali Ahmed, Mubarak Hamdy, Samih Younes, and Attia Mohammed. 2018. Diacritization of arabic dialects. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).

Salam Khalifa, Sara Hassan, and Nizar Habash. 2017. A morphological analyzer for gulf arabic verbs. WANLP 2017 (co-located with EACL 2017), page 35.

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. CoRR, abs/1412.6980.

John Lafferty, Andrew McCallum, and Fernando CN Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. Proceedings of the 18th International Conference on Machine Learning 2001 (ICML 2001), pages 282–289.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. Neural architectures for named entity recognition. arXiv preprint arXiv:1603.01360.

Wang Ling, Yulia Tsvetkov, Silvio Amir, Ramon Fernandez, Chris Dyer, Alan W Black, Isabel Trancoso, and Chu-Cheng Lin. 2015. Not all contexts are created equal: Better word representations with variable attention. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1367–1372.

Rani Nelken and Stuart M Shieber. 2005. Arabic diacritization using weighted finite-state transducers. In Proceedings of the ACL Workshop on Computational Approaches to Semitic Languages, pages 79–86. Association for Computational Linguistics.

Mohsen Rashwan, Ahmad Al Sallab, M. Raafat, and Ahmed Rafea. 2015. Deep learning framework with confused sub-set resolution architecture for automatic arabic diacritization. In IEEE Transactions on Audio, Speech, and Language Processing, pages 505–516.

Mike Schuster and Kuldip K Paliwal. 1997. Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing, 45(11):2673–2681.