# Arabic Diacritization with Recurrent Neural Networks

**Yonatan Belinkov, James Glass**

MIT Computer Science and Artificial Intelligence Laboratory, Cambridge, MA, USA

{belinkov,glass}@mit.edu

## 1. Overview

- Arabic, Hebrew, and similar languages are typically written without diacritics.
- Diacritization is important for core tasks like speech recognition and morphological analysis.
- Previous work relied on external resources (e.g. morphological analyzers)
- We develop a recurrent neural network (RNN) for diacritization, with long short-term memory (LSTM), trained solely from diacritized texts
- We achieve state-of-the-art results without relying on external resources.

## 2. Diacritization

### Problem Definition

- Given a training text with diacritics, learn a model that will predict diacritics in a test text without diacritics.

اعتبر المدير العام → اِعْتَبَرَ الْمُدِيرُ الْعَامُّ

AEtbr Almdyr AlEAm      AiEotabara Almudiyru AlEAm~

### Ambiguity

- Arabic words are highly ambiguous without diacritics:

| Word | Gloss |
|---|---|
| *Ealima* | he knew |
| *Eulima* | it was known |
| *Eal~ama* | he taught |
| *Eilomu* | knowledge (def.nom) |
| ... | ... |
| *EalamK* | flag (indef.gen) |

Possible diacritized forms for علم *Elm*.

### Arabic Diacritics

| Diacritic | Transliteration | Transcription |
|---|---|---|
| دَ | *a* | /a/ |
| دُ | *u* | /u/ |
| دِ | *i* | /i/ |
| دً | *F* | /an/ |
| دٌ | *N* | /un |
| دٍ | *K* | /in/ |
| دّ | ~ | Gemination |
| دْ | *o* | No vowel |

## 3. Approach

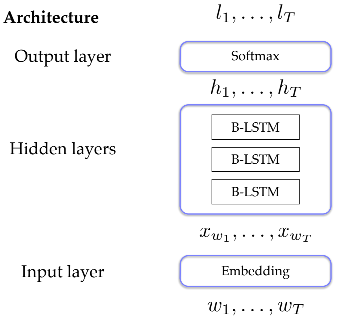
### Diacritization as sequence classification

- Map character sequence to label sequence

$$(w_1, \ldots, w_T) \rightarrow (l_1, \ldots, l_T)$$

- A label can be 0, 1, or more diacritics

### RNN Architecture



$l_1, \ldots, l_T$

Output layer: Softmax

$h_1, \ldots, h_T$

Hidden layers: B-LSTM, B-LSTM, B-LSTM

$x_{w_1}, \ldots, x_{w_T}$

Input layer: Embedding

$w_1, \ldots, w_T$

## 4. Experiments

### Data

- Diacritized texts extracted from the Arabic Treebank
- Diacritic combinations treated as separate label

| | Train | Dev | Test |
|---|---|---|---|
| Words | 470K | 81K | 80K |
| Letters | 2.6M | 438K | 434K |

Arabic diacritization corpus statistics.

### Results

- LSTM outperforms simple feed-forward networks
- Bidirectional LSTM is better than unidirectional
- Deeper models are better than shallow ones
- LSTM better at case endings (long dependencies)
- LSTM beats competitor lexical MaxEnt with access to same information
- LSTM rivals MaxEnt with access to a segmenter and part-of-speech tagger

| | DER | | |
|---|---|---|---|
| Model | All | End | # params |
| Feed-forward | 11.76 | 22.90 | 63K |
| Feed-forward (large) | 11.55 | 23.40 | 908K |
| LSTM | 6.98 | 10.36 | 838K |
| B-LSTM | 6.16 | 9.85 | 518K |
| 2-layer B-LSTM | 5.77 | 9.18 | 916K |
| 3-layer B-LSTM | 5.08 | 8.14 | 1,498K |

Diacrtic error rates (DERs) on the Dev set, over all diacritics and only at word ending.

| | |
|---|---|
| MaxEnt (only lexical) | 8.1 |
| MaxEnt (full) | 5.1 |
| 3-layer B-LSTM | 4.85 |

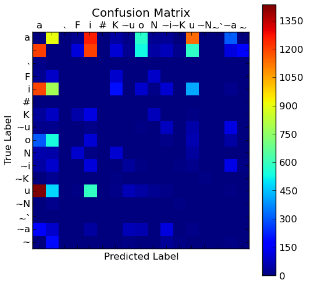
Results (DER) on the Test set. MaxEnt results from (Zitouni and Sarikaya, 2009).

### Error Analysis

- Most errors are from confusing short vowels
- Qualitative analysis shows how LSTM captures long-distance dependencies like case endings

| Model | Diacritization |
|---|---|
| Gold | AiEotabara Almudiyru AlEAm~u l " Aln~ahAri " juborAn tuwayoniy~ Aan Alt~a$okiylAti AlqaDA}iy~apa jA'at litamoyiyEi milaf~i [...] |
| Feed-forward | AiEotabara Almudiyru AlEAm~u l " Aln~ahAr_ " jaborAn tuwayoniy_ Aan Alt~a$okiylAti AlqaDA}iy~api jA'at litamayiyEi malaf~i [...] |
| B-LSTM | AiEotabara Almudiyru AlEAm~u l " Aln~ahAri " juborAn t_wayoniy_ Aan Alt~a$okiylAti AlqaDA}iy~apa jA'at litamoyiyEi milaf~i maHaT~api [...] |

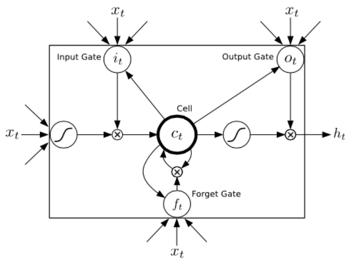
Errors by two diacritization models. Wrong diacritics underlined in red. Translation: "The editor [. . . ] thought that the judicial formations came to dilute the issue of [. . . ]".



A confusion matrix of errors made by our system.

## 5. Implementation Details

- Stack previous and future letter vectors in a context window
- Linear projection after input layer learns new representation
- Cross-entropy objective, optimized with SGD
- Hyper-parameters tuned on the development set
- Implemented with Currennt (Weninger et al. 2015)
- **LSTM hidden layers**: memory cells reuse long term dependencies over the sequence (Graves et al. 2013)



## 6. Future Work

- Experiment with other languages, genres, and dialects
- Incorporate diacritizer in a speech recognizer
- Replace external tools like MADA (Al Hanai and Glass 2014)

## References

- Graves et al. 2013. Speech recognition with deep recurrent neural networks. *ICASSP*.
- Weninger et al. 2015. Introducing CURRENNT. *JMLR*.
- Al Hanai and Glass. 2014. Lexical Modeling for Arabic ASR. *INTERSPEECH*.

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