Enhancing Deep Learning with Embedded Features

for Arabic Named Entity Recognition

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Overview

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1. Introduction
    - NER Task for Arabic
    - Related Work
    - The Arabic Language
2. Proposed model
3. Experiments
4. Error Analysis
5. Conclusion

NER Task for Arabic

The most used corpora

- ANERcorp: 150,268 tokens
  Benajiba et al. (2007)
- AQMAR: 73,910 tokens
  Mohit et al. (2012)

Class	Train	Test
Person	2724	882
Location	3778	656
Organization	1579	450
Miscellaneous	889	229
All	8970	2217

Table 1: Number of Entities in the ANERcorp

Class	Train	Test
Person	1048	424
Location	1117	325
Organization	354	102
Miscellaneous	1763	721
All	4282	1572

Table 2: Number of Entities in AQMAR corpus

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- Machine learning approaches.
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- Hybrid of machine learning and rule based.
  Shaalan and Oudah (2014)
- Deep learning using word embeddings and Neural Networks.
  Youssef et al. (2020)

The Arabic Language

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- Lack of capitalization: letters has one case.
- Unwritten diacritics.

  مصر

  مِصْر: Egypt

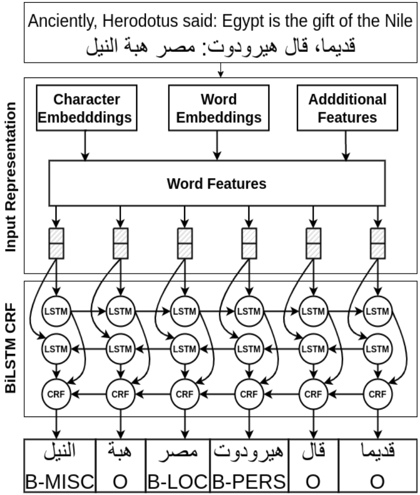
  مُصِرّ: insisting

  مَصَّرَ: divide to provinces

Overview

Model Architecture

- Input is fed to one layer of Bi-LSTM followed by a layer of CRFs.
- Input combines the advantages of deep learning and traditional machine learning by combining word embedding, character embedding, and additional features.



Input Representation

Input consists of three parts:

- Word embeddings are : Glove, Word2Vec, Fastext, AraBert.
- Character embeddings using Convolutional Neural Networks.
- Additional features By Madamira
  - Part of speech.
  - Capitalization from the English translation.
  - Word analysis feature.
    - Suffixes and prefixes.
    - Otehr morphological and syntactical features.

Overview

Model Performance

Training the model using different word embeddings along with features and character embeddings.

Embedding	Alone	+Features	+CE	+Features & CE
One Hot	54.90	59.70	60.00	61.80
GloVe	61.52	72.33*	72.27*	75.22*
AraVec	73.46	77.668*	77.09*	78.10*
FastText	78.34	79.85*	78.87 *	79.44*
AraBert	85.97	**86.47***	85.89	86.00

Table 3: Average F1-scores of 6 runs on ANERcorp in (%)

Embedding	Alone	+Features	+CE	+Features & CE
FastText	70.66	71.77*	71.63	71.95*
AraBert	77.82	**78.51***	77.42	77.56

Table 4: Average F1-scores of 6 runs on AQMAR in (%)

Features Analysis

Training the model using different word embeddings along with every feature.

Embedding	None	+POS	+Capitalization	+Word Analysis	+Quote
GloVe	61.52	67.97*	64.97 *	69.82 *	61.43
AraVec	73.46	76.31*	75.01*	77.46*	73.90*
FastText	78.34	79.29*	79.13*	80.16*	78.23
AraBert	85.97	86.17	85.87	86.26	86.04

Table 5: Average F1-score of 3 runs in (%) after adding features one at a time

* indicates statistical significance on the test set against mere embeddings by a paired sample t-test at level $\alpha = 0.05$.

Performance of Best Model

Class	Recall	Precision	F1
Location	95.59	89.08	92.22
Miscellaneous	64.83	74.63	69.39
Organization	74.00	83.04	78.26
Person	89.75	92.03	90.88
All	85.66	87.77	86.71

Table 6: Performance measures in (%) of the best model on the ANERcorp

Class	Recall	Precision	F1
Location	90.49	84.05	87.15
Miscellaneous	66.90	72.63	69.65
Organization	75.25	71.70	73.43
Person	91.96	89.63	90.78
All	79.07	79.88	79.48

Table 7: Performance measures in (%) of the best model on AQMAR

Comaprison with Previous Models

Model	F1-Score
Benajiba and Rosso (2008)	79.21
Antoun et al. (2020)	83.10
Obeid et al. (2020)	83.00
Our model	**86.71**

Table 8: Comparison with previous taggers results in (%) on the ANERcorp

Model	F1-Score
Helwe and Elbassuoni (2019)	67.22
Bazi and Laachfoubi (2018)	61.80
Liu et al. (2019)	75.82
Youssef et al. (2020)	77.62
Our model	**79.48**

Table 9: Comparison with previous taggers results in (%) on the AQMAR

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  university, institute, neighbourhood.
- Nested Entities: 7.11%
  - Bank of France بنك فرنسا.

Error Analysis

- Remianing Failures: 15.14%
  - Miscellaneous class is too broad
  - Entities with conflicting tags
  - Entities that require deep understanding or prior knowledge.

We have published the ANERcorp with correct annotation at the repository: https://github.com/CSabty/ANERcorp-Correction

Overview

Conclusion

- Our model outperforms previous models by:
  3.6 % for ANERcorp.
  1.86% for AQMAR.
- Additional knowledge can improve deep learning by utilizing it in the input layer.
- Data of higher quality can enhance NER Performance.

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