Entity-aware ELMo: Learning Contextual Entity Representation for Entity Disambiguation

Abstract

We present a new local entity disambiguation system. The key to our system is a novel approach for learning entity representations. In our approach we learn an entity aware extension of Embedding for Language Model (ELMo) which we call Entity-ELMo (E-ELMo). Given a paragraph containing one or more named entity mentions, each mention is first defined as a function of the entire paragraph (including other mentions), then they predict the referent entities. Utilizing E-ELMo for local entity disambiguation, we outperform all of the state-of-the-art local and global models on the popular benchmarks by improving about 0.5% on micro average accuracy for AIDA test-b with Yago candidate set. The evaluation setup of the training data and candidate set are the same as our baselines for fair comparison.

1 Introduction

Named Entity Disambiguation (NED) is an essential task in natural language processing that resolves mentions in a document to their referent entities in a Knowledge Base (KB). A notable differentiating factor between NED systems is whether the global joint inference is used to resolve all the mentions in the same document collectively, separating the local and global NED models.

Local NED systems disambiguate a mention individually by utilizing the local compatibility between the mention (and its textual context) and its candidate entities. Global NED models further consider the global coherence between assigned entities via structured prediction. Empirically, they have been shown to consistently outperform local models as they capture long-range document-wise information. Nevertheless, in this work, we demonstrate that a simple local model, when equipped with the right context and entity representation, can achieve competitive, even superior performance compared to the state-of-the-art global models.

There are several limitations with the existing local models [He et al., 2013; Sun et al., 2015; Hu et al., 2015; Yamada et al., 2016; Yamada et al., 2017; Ganea and Hofmann, 2017; Sil et al., 2018; Le and Titov, 2018] in capturing contextual dependencies between mention and candidate entities. Yamada et al. [Yamada et al., 2016; Yamada et al., 2017] and Ganea et al. [Ganea and Hofmann, 2017] learn entity representations by encoding the co-occurrence statistics between the entity and the words in their context. Each word is considered individually and hence its syntactic and semantic roles in the sentence are overlooked.

In another effort, Sil et al. [Sil et al., 2018] propose a model in which a recurrent neural network is utilized to compare the context of the query mention with the canonical pages of all candidate entities. To make their approach practical, their method is limited to only consider the first paragraph in each canonical page, which may not provide sufficient information for representing an entity throughout a large corpus. A convolutional architecture has also been explored for encoding sentence-level contextual information [Sun et al., 2015]. However its fixed-length windows limit the scope of the context.

Recently, Embedding for Language Model (ELMo) [Peters et al., 2018] is introduced to produce context-sensitive representation of words as a function of the entire sentence. Although ELMo produces context-sensitive representations for words in a sentence, its learning objective is unaware of the entities. For instance in the phrase “Jordan as a member of the Tar Heels’ national championship team,” the language model predicts ambiguous mention Jordan, instead of the entity Michael Jordan.

There are many virtues in ELMo which make it a suitable choice to be used for learning entity representations: 1) Each token is represented as a function of its surrounding context via bi-directional RNNs which can potentially capture the dependencies between a mention and all the surrounding context as well as other named entity mentions in the context. 2) Deep layers of ELMo capture syntactic and semantic dependencies both of which are required for NED, and 3) ELMo is trainable on un-annotated corpora which is an important means to transfer information.

In this work we introduce a novel approach for learning contextual entity representations by learning an entity-aware extension of ELMo, which is surprisingly effective. The learning mechanism which we call E-ELMo trains the language model to predict the grounded entity when encountering its mentions, as opposed to the words in the mentions. This modification affords us context-rich entity representa-
tions that are well-suited for disambiguation of the named entities with just local contexts. Incorporating E-ELMo’s representations into a very simple local model, we achieve a superior or competitive performance on popular benchmarks compared to the state-of-the-art global models. Here we need to mention that in a similar work [Yamada et al., 2020] (published few days after this work) the effectiveness of incorporating entities into BERT [Devlin et al., 2019] is experimentally analysed and verified for entity linking.

2 Entity-ELMo (E-ELMo)

Here we first briefly review ELMo (Sec 2.1) and then explain E-ELMo (Sec 2.2). As an example, we will consider an instance paragraph, which is a sequence of \( T \) tokens containing two mentions with three tokens each, as shown in Figure 1. Here mentions \([x_{i-1}, x_i, x_{i+1}]\) and \([x_{j-1}, x_j, x_{j+1}]\) refer to entities \( e_i \) and \( e_j \) respectively. Tokens \( x_{i-2} \) and \( x_{i+2} \) are the preceding and succeeding tokens of the first mention respectively. Note that a paragraph might include any number of mentions, each may contain any number of tokens.

2.1 ELMo Review

For a given sequence, ELMo produces word representations on top of a 2-layer bi-RNN with character convolutions as input. For each direction, ELMo first computes a context-independent representation for each token at position \( k \) by applying a character-based CNN. It then passes the token representations through a 2-layer LSTMs. As a result, each LSTM layer outputs a context-dependent representation

\[
\text{E-ELMo's target layer}
\]

\[
\begin{array}{cccccc}
\text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} \\
\text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} & \text{CNN-RNN} \\
\end{array}
\]

Figure 1: Bidirectional language model predicts different targets in ELMo and E-ELMo.

2.2 E-ELMo Model

As shown in Figure 1, E-ELMo is in fact ELMo with entities incorporated in the target layer, replacing the targets from the mention words to the grounded entity. In particular, the target for position \( k \in I_i = \{i - 2, i - 1, i\} \) for the forward and \( k \in J_i = \{i, i + 1, i + 2\} \) for the backward directions should be entity \( e_i \). The log likelihood objective of the E-ELMo is the sum of the log likelihood for both words and entities as follows:

\[
ll_{E-ELMo} = ll_w + ll_e
\]

where

\[
ll_e = \sum_{i,k} \left( \sum_{k \in I_i} \log p(e_i | \mathbf{x}_{k-1,l}, \Theta_{LM}, \Theta_B, \Theta_k) + \sum_{k \in J_i} \log p(e_i | \mathbf{x}_{k+1,l}, \Theta_{LM}, \Theta_B, \Theta_k) \right)
\]

where \( ll_w \) is equal to \( ll_{ELMo} \) minus the terms predicting entities and \( \Theta_h \) is the entity parameters. Note that it is important to optimize the entity vectors on the unit sphere to yield qualitative embeddings for NED. To maximize Eq. 1, we consider several different configurations of E-ELMO:

- **Config-a:** We freeze all parameters except for \( \Theta_h \).
- **Config-b:** All the parameters are fine-tuned.
- **Config-c:** All the parameters are fine tuned but we redefine Eq. 1 to be \( ll_{E-ELMo} = ll_e \).

3 Local Entity Disambiguation Model

To evaluate the effectiveness of the learned entity representations, we consider a simple local entity disambiguation model to rank the candidate entities. Given a query mention \([x_{i-1}, x_i, x_{i+1}]\) with its local context \( x_1, \ldots, x_{i-2}, x_{i-1}, x_i, x_{i+1}, x_{i+2}, \ldots, x_T \), the context is fed into the E-ELMo corresponding to one of the config-a, b and c to produce \( \mathbf{x}_{k,l} \) and \( \mathbf{x}_{k,l} \) for all positions \( k \in 1 \ldots T \). The context representation for the mention is given by concatenating \( \mathbf{f}_c = \frac{1}{|I_i|} \sum_{k \in I_i} (\mathbf{x}_{k,l}) \) and \( \mathbf{f}_c = \frac{1}{|J_i|} \sum_{k \in J_i} (\mathbf{x}_{k,l}) \).

We also utilize the following basic features introduced by prior work [Yamada et al., 2016; Yamada et al., 2017; Sil et al., 2018; Ganea and Hofmann, 2017, Le and Titov, 2018].

- **Prior Compatibility (\( f_p \)):** We consider \( p(e|m) \), the prior probability that an entity \( e \) is linked to a mention string \( m \) as prior evidence.
- **String Matching (\( f_s \)):** We use ten lexical features \( f_s[1] \ldots f_s[10] \) listed in [Shahbazi et al., 2018] to
We evaluate our NED on the following benchmarks:

- AIDA-CoNLL [Hoffart et al., 2011]: This dataset which is one of the biggest dataset for NED, contains training (AIDA-train), validation (AIDA-A) and test (AIDA-B) sets.
- MSNBC (MSB), AQUAINT (AQ) and ACE2004 (ACE) datasets [Guo and Barbosa, 2016].
- WNED-WIKI (WW) and WNED-CWEB (CWEB): These datasets are bigger and are built from the ClueWeb and Wikipedia corpora by [Guo and Barbosa, 2016; Gabrilovich et al., 2013]
- TAC 2010 [Hoffart et al., 2011] and TAC 2010 [Ji et al., 2010]: This dataset is very popular with the baselines for both local and global model.

To follow similar setup to our baselines [Ganea and Hofmann, 2017; Le and Titov, 2018] we use the train, test, validation splits and also candidate sets and also prior values $p(e|m)$ for all the the datasets from [Ganea and Hofmann, 2017].

Table 1 presents the results of our models as well as baseline local and global models on AIDA-CoNLL and TAC 2010. Our baselines include a large number of state-of-the-art local (seven) and global (eight) models proposed in recent years. In addition, we also consider an alternative NED system based on the original ELMo. In particular, this model, referred to as ELMo, is identical to our local NED model except that E-ELMo is replaced with the original ELMo.

Table 3 presents the results of our models as well as baseline local and global models on AIDA-CoNLL and TAC 2010. Our baselines include a large number of state-of-the-art local (seven) and global (eight) models proposed in recent years. In addition, we also consider an alternative NED system based on the original ELMo. In particular, this model, referred to as ELMO, is identical to our local NED model except that E-ELMo is replaced with the original ELMo.
Table 2: Results on five out-domain test sets

<table>
<thead>
<tr>
<th>models</th>
<th>MSB</th>
<th>AQ</th>
<th>ACE</th>
<th>CWEB</th>
<th>WW</th>
</tr>
</thead>
<tbody>
<tr>
<td>global: [Guo and Barbosa, 2016]</td>
<td>92</td>
<td>87</td>
<td>88</td>
<td>77</td>
<td>84.5</td>
</tr>
<tr>
<td>global: [Ganea and Hofmann, 2017]</td>
<td>93.7 ± 0.1</td>
<td>88.5 ± 0.4</td>
<td>88.5 ± 0.3</td>
<td>77.9 ± 0.1</td>
<td>77.5 ± 0.1</td>
</tr>
<tr>
<td>global: [Le and Titov, 2018]</td>
<td>93.9 ± 0.2</td>
<td>88.3 ± 0.6</td>
<td>89.9 ± 0.8</td>
<td>77.5 ± 0.1</td>
<td>78.0 ± 0.1</td>
</tr>
<tr>
<td>local: E-ELMo_0</td>
<td>92.3 ± 0.1</td>
<td>90.1 ± 0.3</td>
<td>88.7 ± 0.1</td>
<td>78.4 ± 0.2</td>
<td>79.8 ± 0.2</td>
</tr>
<tr>
<td>local: E-ELMo_c</td>
<td>92.0 ± 0.1</td>
<td>89.6 ± 0.1</td>
<td>87.6 ± 0.1</td>
<td>77.5 ± 0.3</td>
<td>78.4 ± 0.1</td>
</tr>
</tbody>
</table>

Table 3: Results on TAC 2010 and AIDA test-b

The ablation rows in Table 3 present the performance of our models versus the local attention based models [Ganea and Hofmann, 2017] without using the prior and lexical features. As shown in the table our models see only slight reduction in performance when prior and lexical features are removed. In contrast, the local attention based model suffered a substantial performance dip. This suggests that the contextual dependencies captured by E-ELMo are significantly richer, possibly because E-ELMo not only captures syntactic and semantic dependencies but also captures lexical and prior dependencies between the mention and the entity with the help of the char CNN in the first layer.

Table 2 presents the performance of E-ELMo_0 compared to state-of-the-art global models on five additional open domain datasets. Because these datasets are not widely used in prior studies, we can only compare to three prior methods, all of which are global methods. As can be seen from the table, E-ELMo_0 is very competitive compared to the prior state-of-the-art results achieved by global models on these datasets as well.

4.5 Analysis of Results

We take a closer look at the performance of our method in comparison with a popular global model [Ganea and Hofmann, 2017] (referred to as M) on the AIDA-CoNLL dataset (YAGO+KB), focusing on the 4400 test queries with gold in the candidate set. In particular we are interested in how entity frequencies and the number of entities in the same document influence the performance of our local model in comparison with the global model.

As shown in Table 4, E-ELMo has substantially higher performance compared to $M_g$ in dealing with entities with low frequency in the Wikipedia, suggesting that by unifying the entity representations with the word representation through E-ELMo, we can learn effective representations for rare entities. It is also observed that E-ELMo performs consistently well on documents with different number of mentions, but the performance gap with $M_g$ is small for documents with over 20 mentions. This is consistent with expectation because such documents tend to benefit more from the global models.

5 Conclusions

We introduced a novel approach for learning deep contextual entity representation by learning an entity aware extension of ELMo called E-ELMo. We also proposed a local entity disambiguation model which utilizes E-ELMo as its key component. The results demonstrate that our local model with very basic features achieves the best reported performance on AIDA-CoNLL and TAC-2010 with an improvement of about .5% over the latest global model on AIDA-CoNLL. The model is also competitive to the global models on open domain datasets.

References


