YELM: End-to-End Contextualized Entity Linking

Haotian Chen  
BlackRock  
haotian.chen@blackrock.com

Sahil Wadhwa  
BlackRock  
sahil.wadhwa@blackrock.com

Xi (David) Li  
BlackRock  
david.li@blackrock.com

Andrej Zukov-Gregoric  
BlackRock  
andrej.zukovgregoric@blackrock.com

Abstract

We propose yet another entity linking model (YELM) which links words to entities instead of spans. This overcomes any difficulties associated with the selection of good candidate mention spans and makes the joint training of mention detection (MD) and entity disambiguation (ED) easily possible. Our model is based on BERT and produces contextualized word embeddings which are trained against a joint MD and ED objective. We achieve state-of-the-art results on several standard entity linking (EL) datasets.

1 Introduction

Entity linking (EL) refers to the joint task of recognizing entity mentions in text through mention detection (MD) and assigning those mentions to corresponding entities in a knowledge base (KB) through entity disambiguation (ED). End-to-end EL is a difficult task because mentions must be recognized and disambiguated in a single pass. For example, in the sentence: “The Times began publication in London under its current name in 1788,” the words The Times must be recognized as belonging to an entity mention and then disambiguated to the correct corresponding entity, the British daily newspaper The Times. Due to the ambiguity of entity names, one can easily see how The Times could be assigned to any number of other newspapers which colloquially go by a similar name, such as The New York Times. As a result, EL models hinge on good: (1) mention detection, (2) local mention features, (3)

1MD is closely related to named entity recognition (NER), the key difference being that in NER words are classified as belonging to a class such as Person or Organization, whereas in MD there exist only two classes. MD and NER are sometimes used interchangeably in the literature since they can both be used to discover entity mentions in text.

2ED is also known as named entity disambiguation (NED).

global mention features, which model the relationship between mentions and (4) entity embeddings, the quality of which allow for easier disambiguation.

In this paper, we describe a new EL model jointly trained on MD and ED and based on BERT (Devlin et al., 2019). It takes in a sequence of words, binary mention indicators, and entity ids which index a pre-trained entity embedding matrix which we take from (Yamada et al., 2018). We represent the input words by their contextualized embeddings and train them on a joint MD binary classification and ED similarity maximization objective. Our model doesn’t explicitly model local and global mention features but instead relies on BERT’s ability to model word- and context-level features.

This paper introduces two main contributions:

(i) An end-to-end differentiable EL model that jointly performs MD and ED with state-of-the-art results. We use no separate local or global features and instead rely on BERT’s expressivity.

(ii) We study the impact of not using candidate sets at train and test time. Candidate sets limit a model to predicting across a predefined set of candidate entities.

2 Related Work

Neural-network based approaches to EL and ED have recently achieved strong results across standard datasets. Research into ED has focused on learning better entity representations and on extracting better mention-side features through novel model architectures.

Entity representation. Good KB entity representations are a key component of most ED and EL models. Representation learning has been tackled by (Yamada et al., 2016; Ganea and Hofmann, 2017; Cao et al., 2017; Yamada et al., 2017) and
(Sil et al., 2018; Cao et al., 2018) in the cross-lingual setting. These approaches trace their lineage back to conventional word embedding models such as (Mikolov et al., 2013). More recently, (Yamada and Shindo, 2019) propose learning entity representations using a model based on bidirectional transformer encoders which allow them to achieve state-of-the-art results in ED. To the best of our knowledge, our papers are the first to have applied transformer encoders to the ED and EL tasks.

**Mention features.** Recent work on the mention-side has focused on extracting global features (Ratinov et al., 2011; Globerson et al., 2016; Ganea and Hofmann, 2017; Le and Titov, 2018), extending the scope of ED to larger non-standard datasets (Eshel et al., 2017), and positing the problem in new ways such as building separate classifiers for KB entities (Barrena et al., 2018).

**Entity linking.** Early work on end-to-end entity linking (Sil and Yates, 2013; Luo et al., 2015; Nguyen et al., 2016) introduced models that do joint learning of NER and ED using hand-engineered features. More recently, (Kolitsas et al., 2018) proposed a model which considers all possible spans as potential mentions and learns contextual similarity scores over their entity candidates. As a result, MD is handled implicitly by only considering mention spans which have non-empty candidate entity sets. (Martins et al., 2019) propose jointly training a multi-task NER and ED objective using stack-LSTMs (Dyer et al., 2015). Our work differs from previous EL work in that it does not need candidate sets during training, it also focuses on MD instead of NER and swaps task-specific architectures with a more general BERT layer.

3 Model Description

Our EL model jointly solves MD and ED. It takes in a sequence of word tokens \( w = \{w_1, ..., w_n\} \), mention indicators \( y_{md} = \{I, O, B\}^n \), and entity ids \( y_{ed} = \{i \in \mathbb{Z} : i \in [1, k]\}^n \) which index a pre-trained entity embedding matrix \( E \in \mathbb{R}^{k \times d} \). The goal of the model is to tag words with their correct mention indicators and entity ids. The motivation behind

\[
\begin{align*}
\text{m}_{md} &= W_{md}h + b_{md} \\
\text{p}_{md} &= softmax(\text{m}_{md})
\end{align*}
\]

where \( b_{md} \in \mathbb{R}^3 \) is the bias term, \( W_{md} \in \mathbb{R}^{3 \times m} \) is a weight matrix, and \( \text{p}_{md} \in \mathbb{R}^3 \) is the predicted distribution across the \( \{I, O, B\} \) label set. The predicted label is then simply:

\[
\hat{y}_{md} = \arg\max_i \{\text{p}_{md}(i)\}
\]

3.1 Input Representations

The text input layers of our model are based on the BERT architecture (Devlin et al., 2019) which is formed of many bidirectional Transformers (Vaswani et al., 2017). We use the pre-trained weights for BERT-BASE released with the original BERT code. BERT uses WordPiece (Johnson et al., 2017) for unsupervised tokenization of the input text. The vocabulary is built such that it contains the most frequently used words or sub-word units. We use the representation of the first sub-word as the input to the word-level classifier over the MD label set. The output of the input layers are \( n \) contextualized WordPiece embeddings \( h_i \) which are grouped to form the embedding matrix \( H \in \mathbb{R}^{n \times m} \), where \( m \) is the embedding size and in the case of BERT-BASE is equal to 768.

On the entity-side we use pre-trained entity embeddings from (Yamada et al., 2018). The entities are trained on the 2018 version of Wikipedia and their embeddings are a function of the contexts in which they appear and where they sit in the Wikipedia link graph. We denote entity embeddings by \( E \in \mathbb{R}^{k \times d} \) where \( k \) is the number of entity embeddings we consider and \( d \) is their embedding size and in the case of (Yamada et al., 2018) is equal to 100.

3.2 Word-Level EL model

We train on a multi-task learning (Caruana, 1997) objective which combines the MD and ED tasks. Both our MD and ED predictions are based on the contextualized WordPiece embeddings.

**MD.** We model the MD task as a sequence labelling problem across the familiar inside-outside-beginning (IOB) label set (Ramshaw and Marcus, 1995). Contextualized embeddings \( h_i \) are taken and passed through a single feedforward neural network before being softmaxed:

\[
\begin{align*}
\text{m}_{md} &= W_{md}h + b_{md} \\
\text{p}_{md} &= softmax(\text{m}_{md})
\end{align*}
\]

where \( b_{md} \in \mathbb{R}^3 \) is the bias term, \( W_{md} \in \mathbb{R}^{3 \times m} \) is a weight matrix, and \( \text{p}_{md} \in \mathbb{R}^3 \) is the predicted distribution across the \( \{I, O, B\} \) label set. The predicted label is then simply:

\[
\hat{y}_{md} = \arg\max_i \{\text{p}_{md}(i)\}
\]
We model the ED task as a similarity maximization problem between transformed contextualized word embeddings and entity embeddings. We first apply a feedforward neural network to the contextualized word embeddings:

$$m_{ed} = \tanh(W_{ed}h + b_{ed})$$
$$p_{ed} = s(m_{ed}, E)$$
$$\hat{y}_{ed} = \arg\max_i \{p_{ed}(i)\} \quad (4)$$

where $b_{ed} \in \mathbb{R}^d$ is the bias term, $W_{ed} \in \mathbb{R}^{d \times m}$ is a weight matrix, and $m_{ed} \in \mathbb{R}^d$ is the same size as the entity embeddings. By $s$ we denote any similarity measure which relates $m_{ed}$ to every entity embedding in $E$. In our case, we use cosine similarity. Our predicted entity label is the index of $p_{ed}$ with the highest score.

## 4 Experiments

### 4.1 Dataset and metrics

We train and evaluate our model on the standard AIDA/CoNLL dataset (Hoffart et al., 2011). It is a collection of news wire articles from Reuters and split into a training set of 18,448 linked mentions in 946 documents, a validation set of 4,791 mentions in 216 documents, and a test set of 4,485 mentions in 231 documents.

### 4.2 Candidate selection

For each token we select entity candidates that might be referred to by the mention in which the token is in. We use the candidate sets generated by (Hoffart et al., 2011) using YAGO dictionaries. Importantly, we do not use any of the prior probabilities associated with candidate sets in any part of our model. We also set no limits on the size of the candidate sets.

### 4.3 Training details and settings

We minimize the following multi-task objective

$$J(\theta) = \lambda L_{md}(\theta) + (1 - \lambda)L_{ed}(\theta) \quad (5)$$

where $L_{md}$ is a cross entropy loss function and $L_{ed}$ a cosine similarity loss function.

We train with a batch size of 4 for 50,000 steps. We use the ADAM optimizer (Kingma and Ba, 2014). We use a learning rate of 1e-5, $\beta_1 = 0.9$, $\beta_2 = 0.999$, L2 weight decay of 0.01, learning rate warmup over the first 5,000 steps, and a linear decay of the learning rate. We use a dropout probability of 0.1 on all layers.

The training of our model was performed on single Tesla V100 GPUs with 16GB of memory. Models took around 6 hours to train.

### 4.4 Results

#### Comparison with other EL models

We compare the results of our model with four of the most recent EL models in Table 1. Our model which uses the candidate sets mentioned in Section 4.2 achieves state-of-the-art results. The small difference in micro and macro F1 suggest our model does not overfit (More detail here).

| System                        | Validation F1 | Test F1 |
|-------------------------------|---------------|---------|
|                               | Macro | Micro | Macro | Micro |
| Martins et al. (2019)         | 82.8  | 87.2   | 81.2  | 87.9   |
| Kolitsas et al. (2018)        | 86.6  | 89.4   | 82.6  | 82.4   |
| Cao et al. (2018)             | 77.0  | 79.0   | 80.0  | 80.0   |
| Nguyen et al. (2018)          | 81.3  | 83.5   | 81.3  | 83.5   |
| Our model (with candidate sets)| 92.0 ± 0.2 | 93.6 ± 0.2 | 87.5 ± 0.3 | 89.2 ± 0.3 |
| Our model (without candidate sets) | 82.6 ± 0.2 | 85.1 ± 0.2 | 70.7 ± 0.3 | 69.4 ± 0.3 |

Table 1: End-to-end EL results on validation and test sets in AIDA/CoNLL. The other models cited all use candidate sets.

Without candidate sets, and with 1 million entity embeddings to rank across, our model is not able to achieve similar results without using candidate sets, indicating that ranking over one million candidate entities is difficult.

#### Ablation tests

We perform ablation tests to try and identify components which contribute most to our final results. We find that by freezing BERT our results fall slightly when using candidate sets, but fall substantially when candidate sets are not used. This points to the importance of fine-tuning BERT for EL without candidate sets to be possible.

| Ablation Tests                          | Validation F1 | Test F1 |
|-----------------------------------------|---------------|---------|
|                                          | Macro | Micro | Macro | Micro |
| Without BERT fine-tuning (without candidate sets) | 85.3 ± 0.2 | 83.5 ± 0.2 | 87.5 ± 0.3 | 89.2 ± 0.3 |
| With random entity embeddings           | 93.6 ± 0.2 | 93.6 ± 0.2 | 87.5 ± 0.3 | 89.2 ± 0.3 |

Table 2: Ablation results on validation and test sets in AIDA/CoNLL.

We also look at the effect entity embeddings have on performance. We test random embeddings which are 100-dimensional embeddings sampled from a multivariate uniform distribution with a range of $-1$ to $1$. We also form fasttext entity embeddings which we define as the averaged 300-dimensional fasttext embeddings of entity titles.
The results show that with random embeddings, there is an expected substantial drop between validation and test sets. Nevertheless, test set results are still high which points to the helpfulness of candidate sets. Similarly, fasttext entity embeddings perform only slightly better than random embeddings pointing to the need for Wikipedia-specific entity embeddings.

5 Conclusion and Future Work

We proposed doing joint learning of MD and ED, in order to improve end-to-end EL results. Our results show our model achieves state of the art results. Furthermore, we show that training without candidate sets is possible and also present test results for when candidate sets are not used.

The model introduced in this paper focuses on the mention-side and it would be interesting to study how it performs given BERT-based entity embeddings such as the ones recently introduced in (Yamada and Shindo, 2019).

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