Global Entity Disambiguation with Pretrained Contextualized Embeddings of Words and Entities

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Abstract

We propose a new global entity disambiguation (ED) model based on contextualized embeddings of words and entities. Our model is based on BERT (Devlin et al., 2019) and trained with our new training task, which enables the model to capture both the word-based local and entity-based global contextual information. The model solves ED as a sequence decision task and effectively uses both types of contextual information. We achieve new state-of-the-art results on five standard ED datasets: AIDA-CoNLL, MSNBC, AQUAINT, ACE2004, and WNED-WIKI. Our source code and trained model checkpoint are available at https://github.com/studio-ousia/luke.

1 Introduction

Entity disambiguation (ED) refers to the task of assigning entity mentions in a text to corresponding entries in a knowledge base (KB). ED models typically rely on local contextual information based on words that co-occur with the mention and global contextual information based on the entity-based coherence of the disambiguation decisions. To improve the performance of ED, it is crucial to effectively combine both local and global contextual information (Ganea and Hofmann, 2017; Le and Titov, 2018).

In this study, we propose a new global ED model based on BERT (Devlin et al., 2019). Our model takes words and KB entities appearing in the document as input tokens (see Figure 1), and it is trained using a new training task based on the masked language model (MLM) of BERT. The task trains the model by predicting randomly masked entities in an entity-annotated corpus and enables the model to disambiguate masked entities based on words and non-masked entities. Based on the trained model, we solve ED as a sequence decision task (Yang et al., 2019; Fang et al., 2019). To disambiguate new mentions, we use local contextual information based on words, and global contextual information based on already disambiguated entities.

We conduct training using our training task with a large corpus obtained from Wikipedia. We achieve new state-of-the-art results on five standard ED datasets: AIDA-CoNLL, MSNBC, AQUAINT, ACE2004, and WNED-WIKI. Our source code and trained model checkpoint are available at https://github.com/studio-ousia/luke.

2 Related Work

Broscheit (2019) and Ling et al. (2020) recently proposed ED models based on BERT and trained with a large entity-annotated corpus obtained from Wikipedia. Broscheit (2019) trained an ED model based on BERT by classifying each word in the document to the corresponding entity, or the NIL entity if the word is not contained in an entity name. Ling et al. (2020) trained BERT by predicting entities in the document using the document-level representation. However, unlike our proposed model, these models address the task based only on local contextual information. Furthermore, it is difficult to model global contextual information based on these models because they do not output embeddings of entities in the document. BERT has also been used in recent studies to model latent entity type information (Chen et al., 2020) as well as the compatibility between the document and the entity descriptions (Fang et al., 2020).
Furthermore, past studies have captured global contextual information by solving ED as a sequence decision task (Yang et al., 2019; Fang et al., 2019). We address ED by adopting a similar method, with a training task designed to effectively implement the global ED model using BERT.

3 Model

Figure 1 illustrates the architecture of our model, which adopts a bidirectional transformer (Vaswani et al., 2017). It takes words and KB entities in the document as input tokens and outputs $H$-dimensional contextualized embedding for each token. Hereafter, we denote the number of words and the number of entities in the vocabulary by $V_w$ and $V_e$, respectively.

3.1 Input Representation

Similar to BERT (Devlin et al., 2019), the input representation of a word or an entity is constructed by summing the three $H$-dimensional embeddings:

- **Token embedding** is the embedding of the corresponding token. The matrices of the word and entity token embeddings are represented as $A \in \mathbb{R}^{V_w \times H}$ and $B \in \mathbb{R}^{V_e \times H}$, respectively.

- **Token type embedding** represents the type of token, namely word ($C_{\text{word}}$) or entity ($C_{\text{entity}}$).

- **Position embedding** represents the position of the token in a word sequence. A word and an entity appearing at the $i$-th position in the sequence are represented as $D_i$ and $E_i$, respectively. If an entity name contains multiple words, its position embedding is computed by averaging the embeddings of the corresponding positions, as shown in New York City in Figure 1.

Following BERT (Devlin et al., 2019), we insert special tokens [CLS] and [SEP] to the word sequence as the first and last words, respectively.

3.2 Masked Entity Prediction

We propose masked entity prediction (MEP), a new training task based on the MLM. The task randomly replaces some percentage of the entities with special [MASK] entities and then trains the model to predict masked entities. We adopt a model equivalent to the one used to predict words in MLM. Formally, we predict the original entity corresponding to a masked entity by applying softmax over all entities:

$$\hat{y} = \text{softmax}(Bm_e + b_o)$$

(1)

$$m_e = \text{layer_norm}(\text{gelu}(W_f h_e + b_f))$$

(2)

where $h_e \in \mathbb{R}^H$ is the output embedding corresponding to the masked entity, $W_f \in \mathbb{R}^{H \times H}$ is a matrix, $b_o \in \mathbb{R}^{V_o}$ and $b_f \in \mathbb{R}^H$ are bias vectors, $\text{gelu}(\cdot)$ is the gelu activation function (Hendrycks and Gimpel, 2016), and $\text{layer_norm}(\cdot)$ is the layer normalization function (Lei Ba et al., 2016).

3.3 ED Model

**Local ED Model** Given a document with $N$ mentions and their $K$ entity candidates, our local ED model takes words and $N$ [MASK] entities corresponding to the mentions in the document. The model then computes the embedding $m'_e \in \mathbb{R}^H$ for each mention using Eq. (2) and predicts the entity for each mention using softmax over its $K$ entity candidates:

$$\hat{y}_{ED} = \text{softmax}(B^* m'_e + b^*_o),$$

(3)

where $B^* \in \mathbb{R}^{K \times H}$ and $b^*_o \in \mathbb{R}^K$ consist of the entity token embeddings and the output bias values corresponding to the entity candidates, respectively. Note that $B^*$ and $b^*_o$ are the subsets of $B$ and $b_o$, respectively. This model is denoted as local in the remainder of the paper.
Global ED Model. Our global model addresses ED by resolving mentions sequentially for $N$ steps. The model is described in Algorithm 1. First, the model initializes the entity of each mention using the [MASK] entity. Then, for each step, the model predicts an entity for each mention, selects the mention with the highest probability produced by the softmax function in Eq.(3) in all unresolved mentions, and resolves the selected mention by assigning the predicted entity to the mention. This model is denoted as confidence-order in the remainder of the paper. Furthermore, we test a baseline model that selects mentions according to their order of appearance in the document and denote it by natural-order.

3.4 Modeling Details

We use the same transformer configuration adopted in the BERT\textsubscript{LARGE} model (Devlin et al., 2019). To reduce the training time, the parameters of our model that are shared with BERT are initialized using BERT. The other parameters are initialized randomly. The model is trained via iterations over Wikipedia pages in a random order for seven epochs. We treat the hyperlinks in Wikipedia as entity annotations and mask 30% of all entities at random. The input text is tokenized using BERT’s tokenizer with its vocabulary consisting of $V_w = 30,000$ words. Similar to Ganea and Hofmann (2017), we create an entity vocabulary consisting of $V_e = 128,040$ entities, which are contained in the entity candidates in the datasets used in our experiments. We optimize the model by maximizing the log likelihood of MEP’s predictions using AdamW. Further details are provided in Appendix A.

4 Experiments

Our experimental setup follows past work (Ganea and Hofmann, 2017; Le and Titov, 2018). In particular, we test the proposed ED models using six standard datasets: AIDA-CoNLL (CoNLL) (Hoffart et al., 2011), MSNBC, AQUAINT, ACE2004, WNED-CWEB (CWEB), and WNED-WIKI (WIKI) (Guo and Barbosa, 2018). We consider only the mentions that refer to valid entities in Wikipedia. For all datasets, we use the standard KB+YAGO entity candidates and their associated $p(e|m)$ (Ganea and Hofmann, 2017), and use the top 30 candidates based on $p(e|m)$. For the CoNLL dataset, we also test the performance using PPR\textsubscript{for}NED entity candidates (Pershina et al., 2015).\footnote{Results based on the PPR\textsubscript{for}NED candidates cannot be directly compared to those based on other candidates including the KB+YAGO because the candidates have high recall and very low ambiguity (Globerson et al., 2016).} We report the in-KB accuracy for the CoNLL dataset and the micro F1 score (averaged per mention) for the other datasets. Furthermore, we optionally fine-tune the model by maximizing the log likelihood of the ED predictions ($\hat{y}_{ED}$) using the training set of the CoNLL dataset with the KB+YAGO candidates. We mask 90% of the mentions and fix the entity token embeddings ($B$ and $B^*$) and the output bias ($b_o$ and $b_o^*$). The model is trained for two epochs using AdamW. Additional details are provided in Appendix B.

4.1 Results

Table 1 presents our experimental results. We obtain new state-of-the-art results on all datasets except the CWEB dataset, and achieve results superior to all BERT-based ED models described in Section 2, i.e., Broscheit (2019), Chen et al. (2020), Fang et al. (2020), and Ling et al. (2020). Furthermore, on the CoNLL dataset, our confidence-order model trained only on our Wikipedia-based corpus outperforms Yamada et al. (2016) and Ganea and Hofmann (2017) trained on its in-domain training set.
### Table 1: Our experimental results. **Fine-tune:** whether the model is trained using the CoNLL dataset.

| Name                          | Fine-tune | CoNLL | CoNLL (PRR&osNED) | MSNBC | AQUAINT | ACE2004 | CWEB | WIKI |
|-------------------------------|-----------|-------|-------------------|-------|---------|---------|------|------|
| Yamada et al. (2016)          | ✓         | 91.5  | 93.1              | -     | -       | -       | -    | -    |
| Ganea and Hofmann (2017)      | ✓         | 92.2  | -                 | 93.7  | 88.5    | 88.5    | 77.9 | 77.5 |
| Yang et al. (2018)            | ✓         | 93.0  | 95.9              | 92.6  | 89.9    | 88.5    | 81.8 | 79.2 |
| Le and Titov (2018)           | ✓         | 93.1  | -                 | 93.9  | 88.3    | 89.9    | 77.5 | 78.0 |
| Fang et al. (2019)            | ✓         | 94.3  | -                 | 92.8  | 87.5    | 91.2    | 78.5 | 82.8 |
| Broscheit (2019)              | ✓         | 87.9  | -                 | -     | -       | -       | -    | -    |
| Yang et al. (2019) (DCA-SL)   | ✓         | 94.6  | -                 | 94.6  | 87.4    | 89.4    | 73.5 | 78.2 |
| Yang et al. (2019) (DCA-RL)   | ✓         | 93.7  | -                 | 93.8  | 88.3    | 90.1    | 75.6 | 78.8 |
| Chen et al. (2020)            | ✓         | 93.5  | -                 | 93.4  | 89.8    | 88.9    | 77.9 | 80.1 |
| Fang et al. (2020)            | ✓         | 83    | -                 | 80    | 88      | 89      | -    | -    |
| Ling et al. (2020)            | ✓         | -     | 81.9              | -     | -       | -       | -    | -    |
| Ling et al. (2020)            | ✓         | -     | 94.9              | -     | -       | -       | -    | -    |
| **Our (confidence-order)**    | ✓         | 92.4  | 94.6              | 96.3  | 93.5    | 91.9    | 78.9 | 89.1 |
| **Our (natural-order)**       | ✓         | 91.7  | 94.0              | 96.1  | 92.9    | 91.9    | 78.4 | 89.2 |
| **Our (local)**               | ✓         | 90.8  | 94.0              | 96.1  | 91.9    | 91.9    | 78.4 | 88.8 |
| **Our (confidence-order)**    | ✓         | 95.0  | 97.1              | 94.1  | 91.5    | 90.7    | 78.3 | 87.6 |
| **Our (natural-order)**       | ✓         | 94.8  | 97.0              | 94.1  | 90.9    | 90.7    | 78.3 | 87.4 |
| **Our (local)**               | ✓         | 94.5  | 96.8              | 94.1  | 90.8    | 90.7    | 78.2 | 87.2 |

### Table 2: Accuracy on the CoNLL dataset split by the frequency of entity annotations. Our models were fine-tuned using the CoNLL dataset. **G&H2017:** The results of Ganea and Hofmann (2017).

| # annotations | confidence-order | natural-order | local | G&H2017 |
|--------------|------------------|---------------|------|---------|
| 0            | 1.0              | 1.0           | 1.0  | 1.0     |
| 1–10         | 95.55            | 95.55         | 95.55| 91.93   |
| 11–50        | 96.98            | 96.70         | 96.43| 92.44   |
| ≥51          | 96.64            | 96.38         | 95.80| 94.21   |

The global models perform better or as well as the local model on all datasets. This demonstrates the effectiveness of using global contextual information even if local contextual information is captured using expressive contextualized embeddings, i.e., BERT. Moreover, the confidence-order model performs better than the natural-order model on most datasets.

The fine-tuning of our models on the CoNLL dataset significantly improves the performance on this dataset. However, it generally degrades the performance on the other datasets. This suggests that Wikipedia entity annotations are more suitable than the CoNLL dataset to train general-purpose ED models.

Additionally, our models perform relatively worse on the CWEB dataset. This is because the dataset is significantly longer on average than other datasets, i.e., approximately 1,700 words per document on average, which is more than three times longer than the 512-word limit that can be handled by BERT-based models including ours. Yang et al. (2018) achieved excellent performance on this dataset because their model uses various hand-engineered features capturing document-level contextual information.

### 4.2 Analysis

To investigate how global contextual information helps our model to improve performance, we manually analyze the difference between the predictions of the local, natural-order, and confidence-order models. The CoNLL dataset with the YAGO+KB candidates is used to fine-tune and test the models.

The local model often fails to resolve mentions of common names referring to specific entities (e.g., “New York” referring to New York Knicks). Global models are generally better to resolve such mentions because of the presence of global contextual information (e.g., mentions referring to basketball teams).

Furthermore, we find that the CoNLL dataset contains mentions that require a highly detailed context to resolve. For example, a mention of “Matthew Burke” can refer to two different former Australian rugby players. Although the local and natural-order models incorrectly resolve this mention to the player who has the larger number of occurrences in our Wikipedia-based corpus, the confidence-order model successfully resolves this by disambiguating its contextual mentions, including his teammates, in ad-
vance. We provide detailed inference of the corresponding document in Appendix C.

Next, we examine whether our model learns effective embeddings for rare entities using the CoNLL dataset. Following Ganea and Hofmann (2017), we use the mentions of which entity candidates contain their gold entities and measure the performance by dividing the mentions based on the frequency of their entities in the Wikipedia annotations used to train the embeddings. As presented in Table 2, our models predict rare entities with superior accuracy.

5 Conclusions
We propose a global ED model based on contextualized embeddings trained using Wikipedia. Our experimental results demonstrate the effectiveness of our model across a wide range of ED datasets.

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A Details of Training of Contextualized Embeddings

As the input corpus for training our model, we use the December 2018 version of Wikipedia, comprising approximately 3.5 billion words and 11 million entity annotations. We generate input sequences by splitting the content of each page into sequences comprising ≤ 512 words and their entity annotations (i.e., hyperlinks).

To stabilize the training, we update only those parameters that are randomly initialized (i.e., fixed the parameters initialized using BERT) at the first epoch, and update all parameters in the remaining six epochs. We implement the model using PyTorch, and the training takes approximately ten days using eight Tesla V100 GPUs. The hyper-parameters used in the training are detailed in Table 3.

| Name                                | Value |
|-------------------------------------|-------|
| number of hidden layers             | 24    |
| hidden size                         | 1024  |
| attention heads                     | 16    |
| attention head size                 | 64    |
| activation function                 | gelu  |
| maximum word length                 | 512   |
| batch size                          | 2048  |
| learning rate (1st epoch)           | 5e-4  |
| learning rate decay (1st epoch)     | none  |
| warmup steps (1st epoch)            | 1000  |
| learning rate                       | 5e-5  |
| learning rate decay                 | linear|
| warmup steps                        | 1000  |
| dropout                             | 0.1   |
| weight decay                        | 0.01  |
| gradient clipping                   | 1.0   |
| adam $\beta_1$                      | 0.9   |
| adam $\beta_2$                      | 0.999 |
| adam $\epsilon$                     | 1e-6  |

Table 3: Hyper-parameters used for training our contextualized embeddings.

B Details of Fine-tuning on CoNLL Dataset

The hyper-parameters used in the fine-tuning on the CoNLL dataset are detailed in Table 4. We select these hyper-parameters from the search space described in Devlin et al. (2019) based on the accuracy on the development set of the CoNLL dataset. A document is split if it is longer than 512 words, which is the maximum word length of the BERT model.

C Example of Inference by Confidence-order Model

Figure 2 shows an example of the inference performed by our confidence-order model fine-tuned on the CoNLL dataset. The document is obtained from the test set of the CoNLL dataset. As shown in the figure, the model starts with unambiguous player names to recognize the topic of the document, and subsequently resolves the mentions that are challenging to resolve.

Notably, the model correctly resolves the mention “Nigel Walker” to the corresponding former rugby player instead of a football player, and the mention “Matthew Burke” to the correct former Australian rugby player born in 1973 instead of the former Australian rugby player born in 1964. This is accomplished by resolving other contextual mentions, including their colleague players, in advance. These two mentions are denoted in red in the figure. Note that our local model fails to resolve both mentions, and our natural-order model fails to resolve “Matthew Burke.”
“Campo has a massive following in this country and has had the public with him ever since he first played here in 1984,” said Andrew, also likely to be making his final appearance. On tour, Australia have won all four tests against Italy, Scotland, Ireland and Wales, and scored 414 points at an average of almost 35 points a game. League duties restricted the tour, in 1984,” said Andrew, also likely to be making his final

### Table 4: Hyper-parameters during fine-tuning on the CoNLL dataset.

| Name                     | Value |
|--------------------------|-------|
| maximum word length      | 512   |
| number of epochs         | 2     |
| batch size               | 16    |
| learning rate            | 2e-5  |
| learning rate decay      | linear|
| warmup proportion        | 0.1   |
| dropout                  | 0.1   |
| weight decay             | 0.01  |
| gradient clipping        | 1.0   |
| adam $\beta_1$           | 0.9   |
| adam $\beta_2$           | 0.999 |
| adam $\epsilon$          | 1e-6  |

Figure 2: An illustrative example showing the inference performed by our fine-tuned confidence-order model on a document in the CoNLL dataset. Mentions are shown as underlined. Numbers in boldface represent the selection order of the confidence-order model.