Zero-shot Entity Linking with Dense Entity Retrieval

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Abstract

We consider the zero-shot entity-linking challenge where each entity is defined by a short textual description, and the model must read these descriptions together with the mention context to make the final linking decisions. In this setting, retrieving entity candidates can be particularly challenging, since many of the common linking cues such as entity alias tables and link popularity are not available. In this paper, we introduce a simple and effective two stage approach for zero-shot linking, based on fine-tuned BERT architectures. In the first stage, we do retrieval in a dense space defined by a bi-encoder that independently embeds the mention context and the entity descriptions. Each candidate is then examined more carefully with a cross-encoder that concatenates the mention and entity text. Our approach achieves a nearly 5 point absolute gain on a recently introduced zero-shot entity linking benchmark, driven largely by improvements over previous IR-based candidate retrieval. We also show that it performs well in the non-zero-shot setting, obtaining the state-of-the-art result on TACKBP-2010.

1 Introduction

Traditional entity linking approaches often assume that entities to be linked at test time are present in the training set. However, for many practical use cases a zero-shot scenario is more appropriate (Logeswaran et al., 2019). Here a short description of the entity is the only piece of information accessible at test time. In this setting, retrieving entity candidates can be particularly challenging, since many of the common linking cues such as entity alias tables and link popularity are not available. Previous work has used TF-IDF-based techniques (Logeswaran et al., 2019), but we show that performance can be significantly boosted by instead doing retrieval in a dense embedding space.

We introduce two stage approach for zero-shot linking, based on fine-tuned BERT architectures. In the first stage, we do retrieval in a dense space defined by a bi-encoder that independently embeds the mention context and the entity descriptions (Humeau et al., 2019; Gillick et al., 2019). We show that BERT-based models provide very effective bi-encoders, by significantly boosting overall recall comparing to IR-based method. Each retrieved candidate is then examined more carefully with a cross-encoder that concatenates the mention and entity text, following Logeswaran et al. (2019). This overall approach is simple but highly effective, as we show through detailed experiments. It is also scalable if efficient nearest neighbor methods are used in the first stage, as long the candidate entity set can be kept small.

We evaluate performance on the recently introduced Wikia zero-shot corpus, as well as the more established TACKBP-2010 benchmark (Ji et al., 2010). Our two-stage approach achieves a nearly 5 point absolute gain on Wikia, driven largely by improvements in the retrieval component.

We also show that it achieves a new state-of-the-art result on TACKBP-2010, a non-zero-shot setup, with an over 30% relative error reduction. By simply reading the provided text descriptions, we are able to outperform previous methods that included many extra cues such as entity name dictionaries and link popularity.

2 Related Work

We follow most recent work in studying entity linking with gold mentions.1 Given mentions, the entity linking task can be broken into two steps:

1Kolitsas et al. (2018) study end-to-end linking. Our techniques should be applicable to this setting as well, but we leave this exploration to future work.

*Work done during internship with Facebook.
3 Definition and Task Formulation

**Entity Linking**  Given an input of text document $D = \{w_1, ..., w_n\}$ of words and a list of entity mentions $M_D = \{m_1, ..., m_n\}$, the output of an entity linking model is a list of mention-entity pairs $\{(m_i, e_i)\}_{i \in [1, n]}$ where each entity is an entry in a knowledge base (KB) (e.g. Wikipedia), $e \in E$. We assume that the title and description of the entities are available, which is a common setting in entity linking.

We assume each mention has a valid gold entity in the KB, which is usually referred as in-KB evaluation. We leave the out-of-KB prediction (i.e. nil prediction) to future work.

**Zero-shot Entity Linking**  We also study zero-shot entity linking (Logeswaran et al., 2019). Here the document setup is the same, but the knowledge base is separated in training and test time. Formally, denote $E_{train}$ and $E_{test}$ to be the knowledge base in training and test, we require $E_{train} \cap E_{test} = \emptyset$.

The set of text documents, mentions, and entity dictionary are separated in training and test so that the entities being linked at test time are unseen.

4 Methodology

We use BERT base (Devlin et al., 2019) in our bi-encoder and cross-encoder models, as described in Section 4.1 and 4.2. Figure 1 shows the overall approach. The bi-encoder uses two independent BERT transformers to encode model context/mention and entity into dense vectors, and each entity candidate is scored as the dot product of these vectors. The cross-encoder encodes con-
text/mention and entity in one transformer, and applies an additional linear layer to compute the final score for each pair.

### 4.1 Bi-encoder

#### Architecture

We use a bi-encoder architecture similar to the work of (Humeau et al., 2019) to model (mention, entity) pairs. This approach allows for fast, real-time inference, as the candidate representations can be cached. Both input context and candidate entity are encoded into vectors:

\[
y_m = \text{red}(T_1(\tau_m)) \\
y_e = \text{red}(T_2(\tau_e))
\]

where \(\tau_m\) and \(\tau_e\) are input representations of mention and entity respectively, \(T_1\) and \(T_2\) are two transformers. \(\text{red}(\cdot)\) is a function that reduces the sequence of vectors produced by the transformers into one vector. Following the experiments in (Humeau et al., 2019), we choose \(\text{red}(\cdot)\) to be the last layer of the output of the [CLS] token.

#### Context and Mention Modeling

The representation of context and mention \(\tau_m\) is composed of the word-pieces of the context surrounding the mention and the mention itself. Specifically, we construct input of each mention example as:

\[
[\text{CLS}] \text{ctxt}_l \ [M_s] \ \text{mention} \ [M_e] \ \text{ctxt}_r \ [\text{SEP}]
\]

where mention, ctxt\(_l\), ctxt\(_r\) are the word-pieces tokens of the mention, context before and after the mention respectively, and \([M_s]\), \([M_e]\) are special tokens to tag the mention. The maximum length of the input representation is a hyper-parameter in our model.

#### Entity Modeling

The entity representation \(\tau_e\) is similarly composed of word-pieces of the entity title and description. The input of our entity model is:

\[
[\text{CLS}] \text{title} \ [\text{ENT}] \ \text{description} \ [\text{SEP}]
\]

where title, description are word-pieces tokens of entity title and description, and [ENT] is a special token to separate entity title and description representation.

#### Scoring

The score of entity candidate \(e_i\) is given by the dot-product:

\[
s(m, e_i) = y_m \cdot y_{e_i}
\]

### Optimization

The network is trained using a softmax loss to maximize the score of the correct entity with respect to random entities. For each training pair \((m_i, e_i)\) in a batch of \(B\) pairs, the loss is computed as:

\[
L(m_i, e_i) = -s(m_i, e_i) + \log \sum_{j=1}^{B} \exp(s(m_i, e_j))
\]

Following previous work (e.g. (Lerer et al., 2019), (Humeau et al., 2019)), in training we consider the other elements of the batch as negatives. (Lerer et al., 2019) presented a detailed analysis on speed and memory efficiency of using batched random negatives in large-scale systems.

#### Inference

At inference time, the entity representation for all the entity candidates can be precomputed and cached. The inference task is then reduced to finding maximum dot product between mention representation and entity candidate representations. We use brute-force search in our experiments, however, this can be done efficiently using fast nearest neighbor search libraries such as FAISS (Johnson et al., 2019) in a large-scale setting.

### 4.2 Cross-encoder

Our cross-encoder is similar to the ones described by Logeswaran et al. (2019) and Humeau et al. (2019). The input is the concatenation of the context and entity descriptions, and often produces better empirical results compared to the bi-encoder. Formally, we use \(y_{m,e}\) to denote our context-candidate embedding:

\[
y_{m,e} = \text{red}(T_{\text{cross}}(\tau_{m,e}))
\]

where \(\tau_{m,e}\) is the input representation of mention and entity, \(T_{\text{cross}}\) is a transformer and \(\text{red}(\cdot)\) is the same function as defined in Section 4.1.

#### Scoring

To score entity candidate, a linear layer \(W\) is applied to the embedding \(y_{m,e}\) to reduce it from a vector to a scalar:

\[
s_{\text{cross}}(m, e) = y_{m,e}W.
\]
Optimization  Similar to methods in Section 4.1, the network is trained using a softmax loss to maximize $s(m_i, e_i)$ for the correct entity, given a set of entity candidates.

Unlike in the bi-encoder where one can recycle the other entities of the batch as negatives, training the cross-encoder is more memory-intensive. We use the cross-encoder for the re-ranking stage, where we obtained retrieval results from the bi-encoder. The cross-encoder is not suitable for retrieval or tasks that require fast inference.

5  Experiments

In this section, we perform an empirical study of our model on two challenging datasets.

5.1  Datasets

Zero-shot EL dataset was constructed by Logeswaran et al. (2019) from Wikia. The task is to link entity mentions in text to an entity dictionary with provided entity descriptions, in a set of domains. There are 49K, 10K, 10K examples in the train, validation, test set respectively. The entities in the validation and test sets are from different domains than the train set, allowing for evaluation of performance on entirely unseen entities. The entity dictionary covers different domains and range in size from 10K to 100K entities.

TACKBP-2010 is widely used for evaluating entity linking systems Ji et al. (2010). Following prior work, we measure in-KB accuracy (P@1). There are 1074, 1020 annotated mention/entity pairs derived from 1453, 2231 original news and web documents on training and evaluation dataset, respectively. All the entities are from the TAC Reference Knowledgebase which contains 818,741 entities with titles, descriptions and other meta info.

5.2  Evaluation Setup and Results

5.2.1  Zero-shot Entity Linking

First, we train our bi-encoder on the training set, initializing each encoder with pre-trained BERT base (Devlin et al., 2019). Hyper-parameters are chosen based on Recall@64 on validation dataset, following suggested range from Devlin et al. (2019). Our bi-encoder achieves much higher recall compares to BM25, as shown in Figure 2. Following (Logeswaran et al., 2019), we use the top 64 retrieved candidates for the ranker, and we report Recall@64 on train, validation and test in Table 1.

| Method          | Train | Validation | Test  |
|-----------------|-------|------------|-------|
| BM25            | 76.86 | 76.22      | 69.13 |
| Ours (Bi-Encoder) | 93.12 | 91.44      | 82.06 |

Table 1: Recall@64 (%) on Zero-shot EL dataset

We then train our cross-encoder (initialized with pre-trained BERT base) based on the top 64 retrieved candidates for each sample on the training set, and evaluate the cross-encoder on the test dataset. By improving the retrieval part of the system, we are able to obtain a much better end-to-end accuracy, as shown in Table 2.

| Method                  | U.Acc. |
|-------------------------|--------|
| Logeswaran et al. (2019) | 55.08  |
| Logeswaran et al. (2019)(domain)† | 56.58  |
| Ours                    | 61.34  |

Table 2: Performance on test domains on the Zero-shot EL dataset. U.Acc. represents the unnormalized accuracy. † indicates model trained with domain adaptive pre-training on source and target domain. Average performance across a set of worlds is computed by macro-averaging.

We also report cross-encoder performance on the same retrieval method (BM25) used by Logeswaran et al. (2019) in Table 3. We observe that our cross-encoder obtains slightly better results than reported by Logeswaran et al. (2019), likely due to implementation and hyper-parameter
details.

| Method                        | Valid | Test |
|-------------------------------|-------|------|
| TF-IDF†                       | 26.06 | -    |
| Ganea and Hofmann (2017)†     | 26.96 | -    |
| Gupta et al. (2017)†          | 27.03 | -    |
| Logeswaran et al. (2019)      | 76.06 | 75.06|
| Ours                          | 78.24 | 76.58|

Table 3: Normalized accuracy on validation and test set on Zero-shot EL, where the performance is evaluated on the subset of test instances for which the gold entity is among the top-k candidates retrieved during candidate generation. † indicates methods re-implemented by Logeswaran et al. (2019).

5.2.2 TACKBP-2010

Following prior work (Sun et al., 2015; Cao et al., 2018; Gillick et al., 2019), we pre-train our models on Wikipedia data. We use the May 2019 English Wikipedia dump which includes 5.9M entities, and use the hyperlinks in articles as examples (the anchor text is the mention). We use a subset of all Wikipedia linked mentions as our training data (A total of 9M examples). We use a hold-out set of 10K examples for validation. We also train our cross-encoder model based on the top 100 retrieved results from our bi-encoder model on Wikipedia data.

After training our model on Wikipedia, we fine-tune the model on the TACKBP 2010 training dataset. We use the top 100 candidates retrieved by the bi-encoder as training examples for our cross-encoder, and chose hyper-parameters based on cross validation. We report accuracy results in Table 4. We also report a version of our model where we use bi-encoder for candidate ranking instead of cross-encoder. As expected, the cross-encoder performs better than the bi-encoder on ranking. However, both models exceed state-of-the-art performance levels, demonstrating that the overall approach is high effective.

There are however many other cues that could potentially be added in future work. For example, Khalife and Vazirgiannis (2018) report 94.57% precision on the TACKBP-2010 dataset. However, their method is based on the strong assumption that a gold fine-grained entity type is given for each mention (and they do not attempt to do entity type prediction). Indeed, if fine-grained entity type information is given by an oracle at test time, then (Raiman and Raiman, 2018) reports 98.6% accuracy on TACKBP-2010, indicating that improving fine-grained entity type prediction would likely to improve entity linking. Our results is achieved without making the assumption that fine-grained entity type information is given. Instead, our model learns representation of context, mention and entity based on text only.

6 Conclusion

We proposed a simple, scalable, and effective two stage approach for entity linking. We show that our BERT-based model outperforms IR methods for entity retrieval, and achieved new state-of-the-art results on a recently introduced zero-shot entity linking dataset, as well as the more established TACKBP-2010 benchmark, without any task-specific heuristics. Future work includes:

- Enriching entity representations by adding entity type information and entity graph information.
- Modeling coherence by jointly resolving mentions in a document.
- Extending our work to other languages and other domains.

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