Joint Embedding in Named Entity Linking on Sentence Level

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ABSTRACT
Named entity linking is to map an ambiguous mention in documents to an entity in a knowledge base. The named entity linking is challenging, given the fact that there are multiple candidate entities for a mention in a document. It is difficult to link a mention when it appears multiple times in a document, since there are conflicts by the contexts around the appearances of the mention. In addition, it is difficult since the given training dataset is small due to the reason that it is done manually to link a mention to its mapping entity. In the literature, there are many reported studies among which the recent embedding methods learn vectors of entities from the training dataset at document level. To address these issues, we focus on how to link entity for mentions at a sentence level, which reduces the noises introduced by different appearances of the same mention in a document at the expense of insufficient information to be used. We propose a new unified embedding method by maximizing the relationships learned from knowledge graphs. We confirm the effectiveness of our method in our experimental studies.

KEYWORDS
named entity linking, entity embeddings, knowledge base

1 INTRODUCTION
Entity linking is an important issue in understanding of ambiguous texts given knowledge bases such as DBpedia [1] and YAGO [18] induced by Wikipedia. Consider a Wikipedia article, where there are phrases marked by underline, called mentions, for instance, “Cambridge”, which may link to an entity of “University of Cambridge”, or link to an entity of “Cambridge, Massachusetts”, depending on where the word of “Cambridge” appears. Such a pair of mention and entity in a Wikipedia is called an anchor. Such a mention (e.g., “Cambridge”) is ambiguous since it refers to a different thing in a different context. The process of mapping an ambiguous mention to the correct entity in a knowledge base is the task of named entity linking.

Entity linking is first proposed in Wikify [13]. Wikify proposes two algorithms. One is inspired by Lesk [9] to compute the overlap of words between an entity description in Wikipedia articles and the paragraph of a mention. The other uses a Naive Bayes classifier using context features. To improve the accuracy of named entity linking, the existing methods focus on three things, which are prior probability of candidate entity, context similarity between mentions and candidate entities, and coherence among candidate entities of different mentions. For prior probability, the statistical method, that computes the prior probability based on the anchor pairs in Wikipedia articles, is the most frequently selected method [5, 6, 10, 12, 20]. For context similarity, [5] uses keyphrase-based similarity and syntax-based similarity. [20] uses the word embedding of all the noun words in a document as the context feature and puts it into Gradient Boosted Regression Trees (GBRT) [4]. DBpedia Spotlight [12] applies a vector space model to measure the similarity between the context of mention and candidate entity. For coherence [5, 8, 10, 15, 20], Graph-based disambiguation algorithms are largely adopted for improving the impact of coherence. [5] designs a mention-entity graph and formalizes coherence as a Steiner-tree problem and then gives a greedy algorithm which maximizes the minimum degree of the vertices. [20] calculates the similarity between the vector representation of candidate entities of ambiguous mentions and the vector representation of unambiguous mentions.

Following the recently development of embedding methods on knowledge graphs, there are works that apply embedding algorithms on entity linking [6, 20]. However, they do not take contexts of mentions, relations among entities, and coherence information into consideration together. In [20], it uses the skip-gram model to jointly learn entity-entity, word-word, and entity-word embeddings. However, all the three embeddings are taken from the Wikipedia articles and are only combined by the word and entity in anchors in Wikipedia articles.

The named entity linking is challenging for several reasons, given the fact that there are multiple candidate entities for a mention in a document. First, it is difficult to link a mention when it appears multiple times in a document, since there are conflicts by the contexts around the appearances of the mention. Second, the given training dataset is small, since it is done manually to link a mention to its mapping entity. In addition, not all mapping entities in the test data can be found in the training dataset. To address the first, in this work, we link entity for mentions at a sentence level, which reduces the noises introduced by different appearances of the same mention in a document at the expense of insufficient information to be used. To address the second and third, we utilize a large number of anchors (e.g., mention-entity pairs) extracted from the Wikipedia articles to augment the training dataset and use knowledge graphs to capture various relationships among entities. To summarize, we propose a novel method to jointly embed all the three components, which are contexts of mentions, relations among entities and coherence information, together into a high-dimensional space to solve the named entity linking task at sentence level. Our experimental studies confirm the effectiveness of our approach.
2 THE PROBLEM

Consider a collection of documents \( D \). For each document \( d \) in \( D \), a set of mentions, denoted as \( M(d) \), are marked (or labeled). A mention \( m \) is modeled by context features, denoted as \( F_c(m) \). There are 10 context features: “head of the mention”, “tokens”, “context unigrams”, “context bigrams”, “part-of-speech tags”, “word shape”, “length”, “character sequence” and “brown clusters”, as given in (11) and “nearest verb”. We explain it using Example 2.1. In the following, we use \( F \) to represent all the context features for all mentions used in model learning.

Example 2.1. Consider the sentence S3 in Figure 1: “German is the mother tongue of a substantial majority of ethnic Germans.” Here “German” is a mention. Its context features are shown in Table 1.

The problem is to find the entity in a knowledge base for a mention in a document. Here, a knowledge graph (e.g., YAGO) models knowledge using “subject, predicate, object” tuples where a subject/object can be an entity or category (also called type), and a predicate is to specify the relationship between a subject and an object. For example, (Boston, is-a, City), states that Boston is a city, where Boston is an entity and City is a category. The knowledge graph can be modeled as a labeled graph \( G = (V, E) \), where \( V \) is a set of vertices representing entities and categories, and \( E \) is a set of edges between two vertices. Edge labels are used to specify what the relationships (predicates) are.

Every mention, \( m_i \) in \( M(d) \), corresponds to a set of candidate entities denoted as \( E(m_i) = \{ e_{ij}, e_{i2}, \ldots \} \), where \( e_{ij} \) is a vertex in the knowledge graph \( G \). The named entity linking problem is to identify one entity \( e_{ij} \) from \( E(m_i) \) in the knowledge graph \( G \) for every mention \( m_i \) in every document \( d \) in \( D \), given a training set of documents \( T \) in which the entity for every mention in a document in \( T \) is identified. For an entity \( e_{ij} \) that correctly links to a mention \( m_i \), we call the entity \( e_{ij} \) a mapping entity for \( m_i \) below.

The problem is challenging for several reasons, given the fact that there are multiple candidate entities for a mention in a document. (Issue-1) A mention may appear several times in different sentences in a document, and an appearance of a mention may link to a different entity. For example, in Figure 1(a), there are two appearance of “German” in a document that map to different entities. The first appearance maps to “Germany” and the second appearance maps to “German Language”. If we take all information from a document as a whole to identify the mapping entity for a multi-appearance mention, it becomes extremely difficult to identify the mapping entity for each appearance of a mention. If we only take information from a sentence where a mention appears, the information obtained may be too small to link it to the mapping entity. (Issue-2) The training dataset \( T \) is small, since it is done manually to link a mention to its mapping entity. (Issue-3) Not all mapping entities of mentions in the dataset of \( D \) to be tested can be found in the training dataset \( T \). In some datasets, only a half of mapping entities in \( D \) can be found in \( T \).

The state-of-art method is [20] which uses three kinds of features, base features, string similarity features, and contextual features. The base features include four features, namely, the prior probability \( p(e|m) \) of a candidate entity \( e \) given a mention \( m \), the entity prior \( p(e) \), the maximum prior probability of the candidate entity of all mentions in a document, and the number of entity candidates for a mention. Among them, the prior probability is the most prominent in named entity linking. The string similarity features include three features, namely, the edit distance between a candidate entity and its mention, whether the candidate entity is identical to or contains its mention, whether the candidate entity starts or ends with its mention. The contextual features, that are computed based on the learned embeddings of words and entities, contain three features, the cosine similarity between a candidate entity and the textual context of its mention, the cosine similarity between a candidate entity and contextual entities, and the descending order of a candidate entity among all candidate entities of its mention according to the sum of these two contextual similarities. To get the embeddings of words and entities, it makes use of the large amounts of articles in Wikipedia. It embeds (1) word-word occurrence relations, (2) entity-entity inlink relations and (3) the word-entity co-occurrence relations, by the skip-gram model, respectively. Here, for (2), it is done by taking inlink entities as context words and the linked entity as the target word. For (3), recall that an anchor in a Wikipedia is a mention-entity pair, the words are those that appear in such mentions of anchors. Together, it learns the embeddings of words and entities jointly. Given the embedding learned, it further uses Gradient Boosted Regression Trees (GBRT) [4], which is a prediction model in the form of an ensemble of regression trees. It achieves high performance using aida-yago2-dataset. However, when a mention appears multiple times in a document, it only links to one entity. As an example, as shown in Figure 1(a), the first appearance

![Figure 1: The Framework](image-url)
German” should be linked to “Germany”, where the second appearance of “German” should be linked to “German language”. By [20], it links to either “Germany” or “German language”, but not both. This is because it uses all the words and entities that appear in the entire document together as its contextual information at a document level.

3 OUR APPROACH

Figure 1 shows our framework. There are 3 main steps. First, for a given input corpus, $D$, we obtain mention-entity pairs from $D$ using a dictionary available, which keeps a list of candidate entities for a mention. We denote the dictionary for $D$ as $Dict$ in which an entry keeps a list of candidate entities for a mention in $D$. Then we extract Wikipedia articles that can be used as training dataset. Recall that there are anchors in a Wikipedia article, which is a (mention, entity) pair. An Wikipedia article is selected if it contains mentions in $Dict$ (or in $D$) above a given threshold. We select those sentences from a Wikipedia article selected if they contain at least a mention in $Dict$. Second, we construct a graph as shown in Figure 1(c). We represent the graph in 2 parts. In Figure 1(c1), it shows the graph constructed that represents (i) the relationships between context features and entities, (ii) the relationships between mentions and entities, and (iii) the co-occurrence relationship between two entities if the corresponding mentions appear in the same sentence (denoted as dashed lines). Here, the context features are extracted around the anchors in the training sentences as shown in Figure 1(b). In Figure 1(c2), it shows the graph constructed that represents the relationships (i) between entities and (ii) between entities and types using a knowledge graph (e.g., YAGO). In the following we denote the graph constructed as $G_D$ (for the input corpus $D$). Third, we learn a model by a joint embedding model (see Figure 1(d)) based on $G_D$. With the embedding learned, we link a mention to the mapping entity by comparing the similarity between the vector representation of the mention and the vector representations of the candidate entities.

To address Issue-1, we do entity linking at a sentence level. On one hand, it reduces the noise introduced by different appearances of the same mention in a document. On the other hand, the information that can be used is reduced. To represent a mention, we extract various context features around a mention to capture the mention, since it is most likely that, for the same mention, the context features of two appearances are different. By treating mentions by their context features, we aim at linking the same mention to different entities if they appear in different contexts. For example, as shown in Figure 1 (b), for “German” in the sentence S3, there is a feature “mother tongue”, while for “German” in the sentence S4, there is a feature “artist”. By the relations obtained by embedding between the feature of “mother tongue” and the entity “German Language”, as shown in Figure 1(d), the mention “German” in S3 is closer to the entity “German Language” than “Germany” in the embedding space. To address Issue-2 and Issue-3, we utilize a large numbers of anchors contained in the Wikipedia articles, where an anchor is considered as a mention-entity pair, and in addition we capture the relationships among entity by a knowledge graph $G$. Here, Wikipedia provides large quantities of manually labeled anchors (e.g., mention-entity pairs). Such high-quality mention-entity pairs can be used as training dataset. The knowledge graph contains high-quality semantic relations between entities and between entities and types (e.g., the “is-a” relation between entities and types).

Below, we discuss (1) how to get a large training dataset, $D_L$, and (2) how to learn a model from $D_L$.

We construct a dictionary, $Dict$, from the page titles, the disambiguation and redirect pages of Wikipedia, in which the candidate entities for every mention is maintained as $Dict = \{(m, V_m)\}$, where $m$ is a mention and $V_m$ is the set of candidate entities for $m$. For a given training dataset $T$, we use $M$ to represent all mentions in $T$ as $M = \bigcup_{d \in T} M(d)$, where $M(d)$ is the set of mentions in a document $d$. We use $Dict$ to find the candidate entities for every $m \in M$ and obtain the set of mention-candidate pairs for $T$ which is given as $D_{MCE} = \{(m, e) | m \in M \land e \in V_m \land (m, V_m) \in Dict\}.$

The set of mention-candidate pairs, $D_{MCE}$, is rather small to test all mentions in testing. We generate a large training data $D_L$ from an external source (e.g. Wikipedia) based on $T$. The Wikipedia is huge and contains unnecessary information for the domain to be tested. First, we consider an article, $d'$, in Wikipedia as a candidate to be selected. It is worth mentioning that there are many so-called anchors in a Wikipedia article that can be considered as a pair of (mention, entity), where the mention in an anchor is the words appear in the article and the entity is the one to be linked to. The connections among such entities can be determined from the knowledge graph $G$ behind (e.g., YOGA2). A Wikipedia article containing a mention $m$, that appears in $T$, will be selected as $d'$, if the number of inlinks and outlinks is greater than a given threshold. We then treat every anchor in $d'$ as a (mention, entity) pair. Let $T'$ be the set of such documents $\{d'\}$, which is much larger than a given training dataset $T$. Hence, we can get a large set of mention-candidate pairs from $T'$ and a large $D_{MCE}' = \{(m', e')\}$, if the anchor (or the mention-entity pair) of $(m', e')$ appears in a document $d'$ in $T'$.

| Feature                  | Description                                                                 | Example               |
|--------------------------|-----------------------------------------------------------------------------|-----------------------|
| Head of the mention      | The head of the mention following the rules by [3]                          | “HEAD:German”         |
| Tokens                   | The words (sometimes stopwords are dropped) in the mention                   | “German”              |
| Context unigrams         | The tokens in a context window of the mention                               | “mother”, “tongue”    |
| Part-of-Speech tags      | The part-of-speech tags of the mention                                       | “NN”                  |
| Word Shape               | The word shape of the tokens in the mention                                  | “As” for “German”     |
| Length                   | The length of the mention                                                    | 1                     |
| Character sequence       | The continuous character sequences in the mention                            | “Ger”, “erm”, “rma”, “man” |
| Brown clusters           | The cluster id of each token in the mention (using the first 8-bit prefixes) | $8_{11101100}$        |
| Nearest verb             | The nearest verb to the mention                                             | “be”                  |
|                         | Table 1: Context Features of Mentions                                         |                       |
Next, we discuss our approach to learn a model from a training dataset $D_L$ by an unified embedding which consists of 4 embeddings, namely, (1) feature-entity embedding to capture the co-occurrence relations between features and entities, (2) mention-entity embedding to capture the correct mappings, (3) knowledge graph embedding to capture the semantic relations between entities as well as “is-a” relation between entities and types, and (4) the mention-entity embedding to capture the cohesion relations in context. Recall the training dataset $D_L$ is a set of tuples where a tuple in $D_L$ is for a mention in a sentence such as $(s, m, mid, e)$. Here, $s$ is a sentence, $m$ is a mention identified by $mid$, and $e$ is the corresponding entity to be linked. It is important to note that any mention in a sentence may link to an entity which is irrelevant to the same mention if it appears in a different sentence. In other words, consider $(s, m, mid, e)$ and $(s', m', mid', e')$, assuming $s \neq s'$ and $m = m'$. We treat $m$ and $m'$ differently and explore if they link to different entities, $e$ and $e'$, by identifying them differently (i.e., $mid \neq mid'$).

**Feature-Entity Embedding:** Since a mention, $m$, in a sentence, $s$, may link to an entity $e$, independent on the appearance of $m$ in other sentences, we represent a mention by its context feature (e.g., words), $f$, in the sentence where the mention $m$ appears. A mention $m$ may be linked to $e$ if the similarity between $f$ and $e$ is high. Let $F_C(m)$ be the context features (e.g., the words) around $m$. The similarity between $m$ and $e$ are measured by the similarity between $F_C(m)$ and $e$. It is important to note that the context features serve as a bridge between a mention and an entity. We use the skip-gram model of Word2vec, which shows the highly relatedness between two words or phrases if they share many of the same context words, to carry the co-occurrence relations between features and entities, in the sense (1) the more entities two features share the more similar they tend to be and (2) the more features two entities share the more similar they tend. As a result, if two mentions share more common features or similar features, it is more likely that they map to the similar entities. Based on the discussion made above, we discuss feature-entity embedding below. Consider a vector representation in a $d$-dimensional embedding space for a feature $f$ in the set of entire features $F$, and an entity $e$ that appears in a tuple $(s, m, mid, e)$ in the training dataset $D_L$. More precisely, let $f$ and $y$ be vectors for $f$ and $e$ respectively. The co-occurrence relations between features and entities are shown in Eq. (1) by the skip-gram model.

$$FE = - \sum_{f \in F} \sum_{e \in D_L} w \cdot \log p(e|f)$$  

where $p(e|f)$ is the probability of $e$ generated by $f$ such as $p(e|f) = \exp(F^T y) / \sum_{e' \in D_L} \exp(F^T y')$, and $w$ is the co-occurrence frequency between $f$ and $e$ in $D_L$.

To achieve efficiency, in this work, we use negative sampling [14] to sample various false features for each $(f, e)$ based on the widely used noise distribution $P_n(e) = \frac{1}{D_e}$ where $D_e$ indicates the number of co-occurrence time between features and $e$ [14]. By such sampling, the probability $p(e|f)$ in Eq. (1) can be computed by Eq. (2).

$$p(e|f) = \log \sigma(F^T y) + \sum_{k=1}^Q \Xi_{e' - P_n(e)}[\log \sigma(-F^T y')]$$  

where $\sigma(x) = 1/(1 + \exp(-x))$ is the sigmoid function, $\Xi$ is a distribution, and $Q$ is the number of negative samples.

**Mention-Entity Embedding:** In general, the same mention is possibly linked to different entities if it appears in different contexts. In a tuple of $(s, m, mid, e)$ in $D_L$, we use $mid$ to uniquely identify a mention $m$ in the sentence $s$. To abuse the notation, in the following we use $mid$ to indicate the mention identified by $mid$. In other words, $mid$ is considered as a unique mention instead of an identifier. For example, let $\phi$ be a similarity function, we use $\phi(mid, e)$ to indicate the similarity between $m$ (identified by $mid$) and $e$.

The mention $m$ identified by $mid$ should be correctly linked to one and only one entity, $e$, given the sentence $s$. Therefore, the similarity between the mention by $mid$ and its entity $e$ being correctly linked, $\phi(mid, e)$, must be larger than the similarity between the same mention and any other candidate entities. To capture such correct linking, we design a margin-based Hinge Loss function to distinguish the entity being correctly linked from any other candidate entity, $e'$, that appears in $D_L$. We give the loss function in Eq. (3).

$$l = \max\{0, 1 - [\phi(mid, e) - \max_{e' \in V_m} e' \neq e \phi(mid, e')\} \}$$  

where $V_m$ is the candidate entity set of mention $m$. Here, Eq. (3) emphasizes the distinction between the mapping entity and negative candidate entities. It is important to note that entities tend to be similar by the feature-mention embedding (Eq. (1)) if they share more common features. In other words, it is most likely that candidate entities for a mention achieve certain degree of similarity, and it is hard to identify one correct entity by using the feature-mention embedding. The mention-entity is introduced to distinguish the mapping entity from other candidates.

Let $m$ and $y$ be vectors in $d$-dimensional embedding space, for a mention $mid$ and an entity $e$, respectively. We use $l_2$-regularizations to control the scale of the embeddings with which we represent the Hinge Loss of mention-entity embedding by Eq. (4).

$$MY = \sum_l \frac{1}{2} \|m\|^2_2 + \frac{\lambda}{2} \|y\|^2_2$$  

where $l$ is the Hinge Loss (Eq. (3)), and $\lambda$ is a parameter to control $l_2$-regularization.

**Knowledge Graph Embedding:** Let $G = (V, E)$ be a knowledge graph that captures the relationships among entities. We make use of $G$ to capture the relationships among entities, in a similar way like the existing methods that model the coherence relations among entities by $G$. Let $e_i$ and $e_j$ be two entities in $G$. In a similar way as to handle feature-entity embedding (Eq. (1)), we use the skip-gram model for the knowledge graph embedding, which is shown in Eq. (5).

$$GE = - \sum_{e_i \in V} \sum_{e_j \in V} w_{ij} \cdot \log p(e_j | e_i)$$  

Also, we use the negative sampling to compute $\log p(e_j | e_i)$ as Eq. (6) shows.

$$\log \sigma(y_i^T y_j') + \sum_{k=1}^Q \Xi_{y_j' - P_n(e_i)}[\log \sigma(-y_i^T y_j')]$$  

Recall that two adjacency words in the Word2vec model act as the context of each other. Here, $e_i, e_j$ can be regarded as the context of each other as well. We represent an entity $e_j$ by two vectors, $y_j$ and $y_j'$, where $y_j$ is the target vector and $y_j'$ is the context vector. Note that $Q$ is the number of negative samples, and $\Xi$ is a distribution.

To address the difference between mapping entity and other candidate entities, we embed the “is-a” relation between entities.
and types provided by the category hierarchy of a knowledge base. We use the skip-gram model, as given in Eq. (7). Then we use negative sampling to compute \( \log p(t|e) \) as given in Eq. (8).

\[
ET = -\sum_{e \in V} \log p(t|e) = \sum_{e \in V} \sum_{r \in t} w \cdot \log p(t|e)
\]

\[
\log \sigma(y_i^T t') + \sum_{k=1}^{Q} \sum_{r_k \neq p_i(e)} \log \sigma(-y_i^T t')
\]  

(8)

**Coherence Embedding.** By coherence embedding, we consider two mentions that appear in the same sentence, which are ignored in the existing work. Let \((m_i, e_i)\) and \((m_j, e_j)\) be two pairs of (mention, entity) in the same sentence. We observe that such mention-entity pairs in the same sentence tend to be more coherent with each other than those that appear in different sentences. As an example, consider the two sentences S4 and S5 in Figure 1(b). "Italian" and "German" both occur in S4, but "Italian" and "Hamburg" occur in S4 and S5 separately. "Italian" is considered to be more coherent to "German" than to "Hamburg". On the other hand, the entity relations provided by a knowledge graph can address the relations between mentions in different sentences. Take "Italian" in S4 and "United States" in S5 as an instance. As shown in Figure 1(c), there is an edge connecting their mapping entities "Italy" and "United States" in YAGO. Even though they appear in different sentences, we know that they tend to be related with each other. We represent these two insights between \((m_i, e_i)\) and \((m_j, e_j)\) using implication operation as given in Eq. (9).

\[
(e_i, e_j) \rightarrow (m_i, m_j)
\]

(9)

To embed \(f_{me} = (e_i, e_j) \rightarrow (m_i, m_j)\), by using the target vectors to represent \(e_i\) and \(e_j\), the confidence of \(f_{me}\) is given in Eq. (10).

\[
I(f_{me}) = I(e_i, e_j)(m_i, m_j) + 1 - I(e_i, e_j)
\]

(10)

where \(I(e_i, e_j) = \sigma(y_i^T \cdot y_j)\) and \(I(m_i, m_j) = \sigma(m_i^T \cdot m_j)\). We aim at maximizing \(\sum_{f_{me} \in D_L} I(f_{me})\), and we do so using the skip-gram model to compute the log-likelihood for \(I(f_{me})\) as given in Eq. (11).

\[
L(f_{me}) = -\log(I(f_{me})) - \sum_{k=1}^{Q} \sum_{f_{me} \in D_L} \log(1 - I(f_{me}))
\]

(11)

To find the negative sampling data \(f_{me}\), a quad \((e_i, e_j, m_i, m_j)\) must satisfy two conditions: (1) \((m_i, m_j)\) do not exist in a sentence at the same time, and (2) there is no edge between \(e_i\) and \(e_j\) in the knowledge graph \(G\).

**Joint Embedding.** We unify the 5 embeddings discussed above in a \(d\)-dimensional space. Thus, we formulate it as a joint optimization problem showed in Eq. (12).

\[
\min O_{joint} = FE + MY + EE + ET \sum_{f_{me} \in D_L} L(f_{me}),
\]

\[
s.t. \|f\|_2 \leq 1, \|m\|_2 \leq 1, \|y\|_2 \leq 1, \|y'\| \leq 1, \|t\| \leq 1
\]

(12)

**Model Learning.** To solve Eq. (12), we adopt an efficient stochastic sub-gradient descent algorithm [17] based on edge sampling strategy [19], which is also applied in [16] for a joint embedding for type inference. In each iteration, we alternatively sample from each of the five objectives \(FE, \sum I, EE, ET, \sum_{f_{me} \in D_L} L(f_{me})\) a batch of edges (e.g., \(f, e\)) and their negative samples, then update each embedding vector according to the derivatives. Algorithm 1 summarizes the model learning process of our approach.

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**Algorithm 1 Joint Embedding on Named Entity Linking**

**Input:** generated training corpus \(D_L\), knowledge graph \(G\), context features \(F\), learning rate \(\alpha\), regularization parameter \(\lambda\), number of negative samples \(d\), dimension \(d\)

**Output:** mention embeddings \(\{m\}\), context features \(\{y\}\) and \(\{y'\}\), context features \(\{f\}\), type embeddings \(\{t\}\)

1. Initialize: \(\{m\}\), \(\{y\}\), \(\{y'\}\), \(\{f\}\) as random vectors;
2. while it does not converge by Eq. (12) do
3. Sample a feature-entity co-occurrence edge; select \(Q\) negative samples; update \(\{f, y, y'\}\) based on \(\{e\}\);
4. Sample a mention \(m\); get its mapping entity \(c\); select \(Q\) negative samples; update \(\{m\}, \{y\}\) based on \(f\);
5. Sample an entity-entity edge; select \(Q\) negative samples; update \(\{y, y'\}\) based on \(E\);
6. Sample an entity-type edge; select \(Q\) negative samples; update \(\{y, y'\}\) based on \(E\);
7. Sample a quad id; select \(Q\) negative samples; update \(\{m\}, \{y\}\) based on \(I(f_{me})\);

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**Named Entity Linking.** With the learned embeddings by Algorithm 1, we use any similarity measure suitable for vectors to compute the similarity score between mentions and candidate entities, as to map \(\forall m \in M \in e \in V\). First, we extract a context feature set \(C(m)\) for \(m\) in the same way as we do for mentions in the training dataset \(D_L\). And we use a vector \(m\) to represent \(m\) using the learned embeddings of \(f_{me}\) in the form \(m = \sum_{f_{me} \in F} f_{me}\). Second, we compute the dot product between \(m\) and the learned embedding vector of each candidate entity \(e \in V_m\), and select the candidate entity with the largest value as the mapping entity.

**4 EXPERIMENTAL EVALUATION**

In this experimental study, we use aida-yago2-dataset [5] to evaluate the performance of our method on sentence and document level named entity linking. (1) The training dataset contains 946 documents. (2) The test dataset contains 230 documents. The dataset contains about 20% unlinkable mentions those correct entities do not exist in YAGO2.

Following the existing methods, we ignore such unlinkable mentions and only evaluate on the linkable mentions.

We use two metrics in the evaluation to evaluate the accuracy of a proposed named entity linking method. One is Micro-averaging which aggregates over all mentions in the dataset. The other is Macro-averaging which aggregates on the input documents (or sentences) that a document (or sentence) contains several mentions.

We evaluate our method at sentence level and document level. To get the test sentences, we parse the testing documents into sentences. In the 230 testing documents in aida-yago2-dataset, we get 2,380 sentences that contain at least one mention.

We compare our method with two state-of-art methods AIDA [5] and YSTT [20], as well as a strong baseline PPR [19] which links a mention to the entity with the largest prior probability from all candidate entities. For our approach, we set \(\alpha = 0.02\), \(\lambda = 0.0001\), \(Q = 5\) and \(d = 300\).

**4.1 Comparison with Other Methods**

Table 2 shows the comparison results at sentence and document level. Our method performs the best at sentence level. It is due to the fact that we extract high quality context features instead of using words. Although the context information is very limited in a sentence, by learning from a large number of training sentences (from Wikipedia), we can learn the relations between the context features extracted from a sentence and the candidate entities of a
We count the proportion that a document contains a mention which mention in the sentence. On document level, our method achieves better performance than AIDA and the baseline but worse than YSTT. This is because our method is designed for sentence level named entity linking in order to address the issue that the same mention in a document may map to different entities, while YSTT uses all the noun words in the whole documents.

### 4.2 Effect of Knowledge Base

We study the effect of knowledge base, which corresponds to the effect of EE + ET on the learned embeddings. Table 3 shows the effect of EE + ET on the performance of our method. From Table 3, we can see that without the entity-entity relations and entity-type relations provided by the knowledge base, the learned embeddings become worse evaluated on the sentence level named entity task. This is due to the lack of coherence among entities across sentences.

#### 4.3 Entity Relatedness Performance

To test the quality of learned embeddings of entities, we follow the work [2] to evaluate the performance on the entity relatedness task. We compare our method with WLM [2] and entity embeddings learned in YSTT [20] under three standard metrics, which are NDCG@1, NDCG@5, NDCG@10 [7], on the benchmark dataset. Table 4 shows the comparison results and our learned embeddings for entities achieve the best performance on this task. This is because we use both textual information and knowledge base which involve entities to reinforce the learning of entity embeddings.

#### 4.4 Case Study

We count the proportion that a document contains a mention which maps to more than one entities when it appears in different positions among the 1393 documents in aida-yago2-dataset. We find that 127 documents in the whole dataset and 19 documents in test contain such mentions. Table 5 shows the results on such mentions in the test data compared with YSTT [20] and Prior Probability on the document level. From Table 5, we can see our approach achieves the best performance. This indicates that our method is more powerful in distinguishing same mentions which map to different entities.

### 5 CONCLUSION

In this work, we propose an unified embedding approach for named entity linking by maximizing the relationships extracted from Wikipedia and knowledge graph such as YAGO. Our approach can link a mention in a sentence to a mapping entity with highest accuracy. We conducted experimental studies using aida-yago2-dataset which is also used in the state-of-art method (YSTT) [20]. Our approach outperforms the state-of-art method in sentence level in our experimental studies.

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