Modeling Fine-grained Information via Knowledge-aware Hierarchical Graph for Zero-shot Entity Retrieval

Taiqiang Wu* wtq20@mails.tsinghua.edu.cn Shenzhen International Graduate School, Tsinghua University Shenzhen, China

> Weijie Liu jagerliu@tencent.com Tencent Shenzhen, China

Xingyu Bai* bxy20@mails.tsinghua.edu.cn Shenzhen International Graduate School, Tsinghua University

Shenzhen, China

Siheng Li lisiheng21@mails.tsinghua.edu.cn Shenzhen International Graduate School, Tsinghua University Shenzhen, China

Mention: colony ship

Weigang Guo

jimwgguo@tencent.com Tencent Shenzhen, China

Yujiu Yang[†]

yang.yujiu@sz.tsinghua.edu.cn Shenzhen International Graduate School, Tsinghua University Shenzhen, China

ABSTRACT

Zero-shot entity retrieval, aiming to link mentions to candidate entities under the zero-shot setting, is vital for many tasks in Natural Language Processing. Most existing methods represent mentions/entities via the sentence embeddings of corresponding context from the Pre-trained Language Model. However, we argue that such coarse-grained sentence embeddings can not fully model the mentions/entities, especially when the attention scores towards mentions/entities are relatively low. In this work, we propose GER, a Graph enhanced Entity Retrieval framework, to capture more finegrained information as complementary to sentence embeddings. We extract the knowledge units from the corresponding context and then construct a mention/entity centralized graph. Hence, we can learn the fine-grained information about mention/entity by aggregating information from these knowledge units. To avoid the graph bottleneck for the central mention/entity node, we construct a hierarchical graph and design a novel Hierarchical Graph Attention Network (HGAN). Experimental results on popular benchmarks demonstrate that our proposed GER framework performs better than previous state-of-the-art models.

CCS CONCEPTS

• Information systems \rightarrow Top-k retrieval in databases.

KEYWORDS

zero-shot entity retrieval, fine-grained information

ACM Reference Format:

Taiqiang Wu, Xingyu Bai, Weigang Guo, Weijie Liu, Siheng Li, and Yujiu Yang. 2023. Modeling Fine-grained Information via Knowledge-aware Hierarchical Graph for Zero-shot Entity Retrieval. In *Proceedings of the Sixteenth*

WSDM '23, February 27-March 3, 2023, Singapore, Singapore

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ACM ISBN 978-1-4503-9407-9/23/02.

https://doi.org/10.1145/3539597.3570415

Mention context: The timely **intervention** of **spock** saved the doctor's **life**. Natira also told doctor mccoy that the book was given by the **creators**. It was subsequently learned that the '**creators**' were the ancient fabrini and that the book was merely a technical manual and guidebook. **Yonada was**, in fact, a multigenerational colony **ship** and the 'oracle' its **computer**.

baseline dense space mention recall space missing ground truth entity retrieved Entity: creators Entity: generational ship Entity description: Entity description: A generational ship was a The creators was what the fabrini who lived on the starship in which, over an asteroid spaceship "yonada" extended period of time, the called their ancestors. Faced operations of the ship were with their sun about ... passed down to successive ...

Figure 1: A bad case from baseline system BLINK. For mention *clony ship*, the entity *creators* is retrieved while the grouth truth *generational ship* is missed. In the context of *clony ship*, solid underline words (e.g. <u>creators</u>) note for the words with high attention in BLINK, and double underline (e.g. <u>ship</u>) words for our GER framework.

ACM International Conference on Web Search and Data Mining (WSDM '23), February 27-March 3, 2023, Singapore, Singapore. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3539597.3570415

1 INTRODUCTION

Entity Linking (EL) is a task of linking mentions in unstructured context to referent entries in a structured Knowledge Base (KB) [10]. Previous systems on entity linking have achieved high performance

^{*}Equally contributions.

[†]Corresponding author.

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given a large set of mentions and target entities for training. However, such resources and labeled data may be limited and expensive in some domains, such as law and terminology. Without such massive training data, traditional entity-linking systems perform poorly. To evaluate the ability of the entity linking system to generalize to unseen entity sets, Logeswaran et al. [17] proposed the zero-shot entity linking task and the ZESHEL dataset. There are two assumptions under the **zero-shot setting**: (1) labeled mentions for the target domain are unavailable, (2) mentions and entities are only defined through textual descriptions (a.k.a. **mention context** and **entity description**). Most zero-shot entity linking systems follow a two-stage pipeline: Candidate Entity Retrieval, where top-k candidate entities are retrieved based on scores such as inner product values of the mention vector and entity vector, and Candidate Entity Ranking, where the candidates are ranked to find the most probable one.

In this paper, we focus on **first-stage entity retrieval**, since the overall accuracy is capped by recall performance in this stage. Given the mention contexts and entity descriptions in the source domain simultaneously, a general way is to embed them in a dense space and calculate similarity scores to retrieve entities for the given mention. Wu et al. [30] propose a BERT-based [6] bi-encoder [12] model BLINK to encode the mention contexts and entity descriptions and utilize the sentence embedding to represent mentions and entities, followed by Maximum Inner Product Search (MIPS) of the mention vector to find the closest *k* candidate entities. The following embedding-based models [19, 32] have widely adopted the BERT-based bi-encoder architecture, where the sentence embedding is defined as the output of the [CLS] token ¹.

However, we argue that such coarse sentence embeddings can not fully model the information of mentions/entities. Intuitively, the sentence embeddings model the information of whole sentence rather than the mention/entity. When the attention scores from the [CLS] token to mentions/entities are relatively low, such sentence embeddings may be misled by other high-attention words, leading to a shift in the semantic vector space. Figure 1 shows a bad case from BLINK. Both mentions and entities are represented by sentence embeddings. For mention colony ship, the attention scores from the [CLS] token to colony ship are relatively low, while creators receives higher attention. Hence, the entity creators becomes the closest entity in the dense space, while ground truth entity generational ship is missed. Moreover, one intuitive idea is to adopt the output of mentions/entities from BERT rather than the [CLS] token. However, the output of mentions/entities is highly similar to the [CLS] token due to the over-smoothing problem [24]. Therefore, more information about mentions/entities besides the output of BERT is required.

To address these issues, we propose a novel Graph enhanced Entity Retrieval (GER) framework. Our key insight is to learn extra fine-grained information about mentions/entities as complementary to coarse-grained sentence embeddings. We extract the knowledge units as the information source and design a novel Graph Neural Network to aggregate these knowledge units. Concretely, we employ the sequence prediction model [25] to extract Subject-Predicate-Object (SPO) triplets as knowledge units. After that, we build a graph by connecting the knowledge units to the corresponding mention/entity. Such **graph design** allows mention/entity to **aggregate** information from these knowledge units. To avoid the graph bottleneck[2] for the central mention/entity node, we construct a **hierarchical** graph to reduce neighboring nodes and then design a novel Hierarchical Graph Attention Network (HGAN). Finally, we employ the output of the central mention/entity node as fine-grained information, since they capture information at word level.

We perform extensive experiments on Wikia based and Wikipedia based benchmarks, and compare GER with other strategies to learn fine-grained information. Empirical results demonstrate that finegrained information is beneficial to represent the mentions/entities, and the GER framework can capture such information better. To evaluate overall performance, we also design the experiments for candidate ranking stage. Compared to baseline BLINK, our GER framework achieves higher recall@64 with **slight extra time cost** in the zero-shot entity retrieval stage, but **saves more time** in the entity ranking stage.

The main contributions of our paper are as follows:

- We show that coarse-grained sentence embeddings can not fully model the mentions/entities, and more fine-grained information is necessary for the zero-shot entity retrieval task.
- We propose GER, which learns extra fine-grained information about mentions/entities as complementary to coarsegrained sentence embeddings. Particularly, we construct a mention/entity central graph and design a novel Hierarchical Graph Attention Network.
- We evaluate GER on several zero-shot entity retrieval datasets, and experimental results demonstrate that our framework achieves significant improvements compared with previous models.

2 RELATED WORK

2.1 Zero-shot Entity Retrieval in Entity Linking

For candidate retrieval, two mainstream approaches are term-based, which focus on obtaining term-based representations, and semantically enriched, which utilize specific characteristics of entities (attributes, types, and relationships) [3]. For term-based, Logeswaran et al. [17] use BM25 to measure the similarity between the mention word and entity description. Other semantically enriched methods focus on learning better semantic representations. BLINK [30, 32] employs a BERT-based bi-encoder [12] architecture to embed mentions/entities in semantic space via the sentence embeddings. Another line is to inject more information for better representations. Partalidou et al. [19] add an additional token before mention word, which is similar to BERT-based entity representations with entity type information [13, 23] in other NLP applications. Moreover, mention-to-mention affinities can also provide more information to model mentions/entities [1].

Most existing work employs coarse-grained sentence embeddings to represent mentions/entities. In this work, we argue that such coarse-grained sentence embeddings can not fully model mentions/entities. We design HGAN to capture the fine-grained embedding as complementary to get more comprehensive representations.

 $^{^1 {\}rm In}$ this paper, we refer to the sentence embedding as the output of <code>[CLS]</code> token following the recent models.

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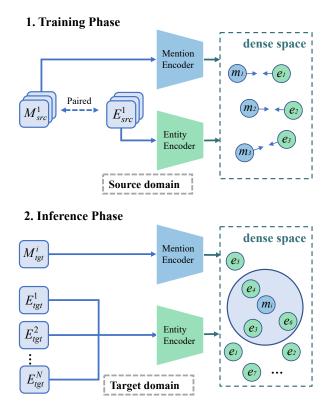


Figure 2: Overview of our GER framework.

2.2 Entity Embedding

Entity embedding methods map the entity to vector representations from external knowledge sources such as structured Knowledge Graph (KG) and unstructured corpus. KG-based methods optimize the score of observed triplets. These methods can be categorized as: distance models [4, 5, 26], which adopt distance-based scoring function, and linear models [27, 33], which adopt similarity-based scoring function. For unstructured corpus, the Pre-trained Language Models (PLMs) [7, 16] learn rich semantic information via pretraining tasks. Moreover, KG-based model and PLM can be jointly optimized to enhance each other, including ERNIE [34], K-BERT [15], KnowBERT [21] and KEPLER [29].

Under the zero-shot entity retrieval setting, mentions and entities are only defined through textual descriptions (a.k.a. mention context and entity description). Our GER aims to better represent mentions/entities adopting the textual descriptions without any external KG.

3 METHODOLOGY

3.1 Task Formulation

Entity Retrieval. Given a mention *m* and the corresponding mention context *c*, the goal of entity linking task is to find a paired entity *e* from the knowledge base $E = \{e_1, e_2, ..., e_N\}$. The size of the knowledge base *N* can be very large, thus encoding those entities is time-consuming. Hence, a common strategy is to consider entity linking in the two-stage paradigm: (i) retrieve *k* candidate entities

 $\{e_i^1, e_i^2, \dots, e_i^k\}$ for mention m_i , where $k \ll N$. (ii) rank these candidate entities. In this paper, we focus on candidate entity retrieval stage.

Zero-shot Entity Retrieval. Under zero-shot setting, there is no graph information but corresponding entity description *d* for each entity *e*. Moreover, we require $E_{src} \cap E_{tgt} = \emptyset$, where E_{src} and E_{tgt} mean the knowledge bases from source domain (for train) and target domain (for inference), respectively.

3.2 Overall Framework

Figure 2 shows the framework of GER. Given the paired (mention, entity) in the source domain for training, two individual encoders are jointly employed to map the mentions and entities into dense vectors, respectively. The training goal is to minimize the distance between the paired (mention, entity). For inference, we firstly employ the entity encoder to encode all entities from E_{tgt} and cache these vectors, to achieve fast and real-time inference. For each mention, we compute the scores with all entities and retrieve top-k.

3.3 Mention/Entity Encoder

Following the bi-encoder setting, the mention encoder and entity encoder share the same structure. Figure 3 shows the overview of mention encoder. The goal is to learn extra fine-grained information about mentions as complementary to sentence embeddings.

Hierarchical Graph. The goal is to extract the core information (a.k.a, knowledge units) of mention context (entity description) and aggregate these information to mention (entity). We extract the Subject-Predicate-Object (SPO) triplets as knowledge units following a two-stage strategy: 1) first, we employ the open information tool trained on semantic role labeling task from allennlp ² to recognize the semantic role for each word. 2) later, we design special rules to recognize the SPO triplets based on grammar prior knowledge. After that, we construct a mention/entity centralized graph by connecting these SPO triplets to central mention/entity node. To avoid the graph bottleneck [2], we add a triplet node between the mention/entity node and each triplet. Hence, we can reduce the neighboring nodes for central mention/entity node from 3*N* to *N*, where *N* is the number of triplets.

Text Modeling. We encode the mention (given mention m and its context c) and entity (given entity e and its description d) as follows:

$$Y_m = T_m([CLS] c_l [MS] m [ME] c_r)$$
(1)

$$Y_e = T_e([CLS] \ e \ [ENT] \ d) \tag{2}$$

where m, c_l , c_r , e, d are the word-pieces tokens of mention, context before mention, context after mention, entity title and corresponding description, respectively. [MS], [ME] are the special tokens to mark the start and end of mention span. [ENT] serves as the delimiter of entity and its descriptions. T_m and T_e are two independent encoders. The baseline BLINK adopts the sentence embedding (output of the CLS token, such as $Y_m[0]$ and $Y_e[0]$) to represent mentions/entities.

Hierarchical Graph Attention Network. We design the Hierarchical Graph Attention Network (HGAN) to model the fine-grained information for mentions/entities.

As shown in Figure 3, for each triplet, the subject, predicate, and object are all viewed as individual nodes and connected to each other.

²https://demo.allennlp.org/open-information-extraction

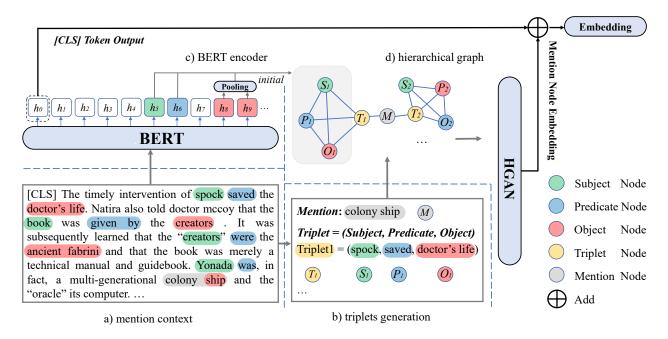


Figure 3: Overview of mention encoder in GER. For the given mention representation (shown in part a), we extract the triplets (shown in part b, green for the subject, blue for the predicate, and red for the object) as knowledge units. To avoid the graph bottleneck [2], we add a triplet node (in yellow) between the mention/entity node and each triplet, and thus build the hierarchical graph (shown in part d).

To avoid the graph bottleneck, we add the triplet node between the SPO nodes and the central mention/entity node. For SPO nodes and mention/entity nodes, we initialize their representation by aligning to the output of corresponding tokens. Taking the mention nodes for example, we initialize the node representation by:

$$\mathbf{h}_m^0 = red(Y_m[p_{start}: p_{end}]) \tag{3}$$

where p_{start} , p_{end} are the start index and the end index of the mention token among all input tokens, and $red(\cdot)$ is a readout function reducing the sequence of vectors into one. We choose $red(\cdot)$ to be average pooling.

However, the triplet nodes do not correspond to tokens among the input tokens. In GER, we initialize the representation of the triplet nodes by gathering the information of corresponding SPO nodes. Let $\mathbf{h}_s^0 \in \mathbb{R}^{1 \times d}$, $\mathbf{h}_p^0 \in \mathbb{R}^{1 \times d}$ and $\mathbf{h}_o^0 \in \mathbb{R}^{1 \times d}$ note for the node representation of subject, predicate, and object respectively, the representation of the corresponding triplet node can be calculated by:

$$\mathbf{h}_{t}^{0} = \left[\mathbf{h}_{s}^{0} \| \mathbf{h}_{p}^{0} \| \mathbf{h}_{o}^{0}\right] \mathbf{W}^{triple} \tag{4}$$

where \parallel notes the concatenation operation and $\mathbf{W}^{triple} \in \mathbb{R}^{3d \times d}$ is a learnable matrix.

After constructing the graph and acquiring corresponding initial representation for each node, we follow the idea of GAT [28] and apply the multi-head attention mechanism to aggregate the information from neighborhood nodes. Specifically, in an *L* layer HGAN, for each layer, we update the representation $\mathbf{h}_i^{(l)} \in \mathbb{R}^{1 \times d}$ of each

node *i* by:

$$\mathbf{h}_{i}^{(l)} = \sigma \left(\frac{1}{K} \sum_{k=1}^{K} \sum_{j \in \mathcal{N}_{i} \cup \{i\}} \alpha_{ij}^{k} \mathbf{h}_{j}^{(l-1)} \mathbf{W}^{k} \right)$$
(5)

where N_i are the neighbor nodes of node *i*, *K* is the number of attention heads, $\mathbf{W}^k \in \mathbb{R}^{d \times d}$ are weight matrix for each head, α_{ij}^k means the attention score between node *i* and node *j*, and $\sigma(\cdot)$ is an activate function such as $relu(\cdot)$. Attention scores $\alpha_{i,j}^k$ for head *k* are calculated by:

$$\alpha_{ij}^{k} = \frac{\exp(e_{ij}^{\kappa})}{\sum_{i' \in \mathcal{N}_{i} \cup \{j\}} \exp(e_{i,i'}^{k})}$$
(6)

$$e_{ij'}^{k} = \text{LeakyReLU}([\mathbf{h}_{i}\mathbf{W}^{k}\|\mathbf{h}_{j'}\mathbf{W}^{k}]\mathbf{a})$$
(7)

where $LeakyReLU(\cdot)$ is an activation function and $a \in \mathbb{R}^{2d \times 1}$ is a score matrix.

Feature Fusion. After capturing the fine-grained information via HGAN, we fuse the fine-grained embedding with the sentence embedding to obtain a more comprehensive representation.

For coarse-grained sentence embedding $v^{sen} \in \mathbb{R}^{1 \times d}$, following the baseline BLINK, we use the output of the [CLS] token which is the first token in the input sequence of BERT. Take the mention *m* for example:

$$v^{sen} = Y_m[0] \tag{8}$$

where $Y_m \in \mathbb{R}^{L \times d}$ and *L* is the length of the input sequence for *m*.

For fine-grained word-level embedding $v^{graph} \in \mathbb{R}^{1 \times d}$, we utilize the node output of the mention node *m* after applying the *L* layer HGAN:

$$v^{graph} = h_m^L \tag{9}$$

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For entity encoder, we apply a similar strategy utilizing the node output of the entity node as fine-grained embedding.

In GER, we fuse the coarse-grained sentence embedding v^{sen} and fine-grained embedding v^{graph} by a gate mechanism:

$$v = v^{sen} + \lambda v^{graph} \tag{10}$$

where λ is a learnable hyperparameter and $v \in \mathbb{R}^{1 \times d}$. In this way, the baseline BLINK is a special case of GER when we fix λ as 0.

3.4 Optimization and Inference

For training, we optimize the GER framework by the paired (mention, entity) from the source domain. Considering the time efficiency and training speed, we adopt the batched negative sampling strategy [8, 14, 31] where the other samples at the same batch are viewed as negative samples to calculate the loss. Concretely, for a batch of randomly sampled mention-entity pairs $((m_1, e_1), ...(m_{bsz}, e_{bsz}))$ where *bsz* notes for the batch size, the loss is computed as:

$$\mathcal{L}(m_i, e_i) = \mathcal{L}_1(m_i, e_i) + \mathcal{L}_2(m_i, e_i) \tag{11}$$

$$\mathcal{L}_{1}(m_{i}, e_{i}) = -s(m_{i}, e_{i}) + \log \sum_{j=1}^{bsz} \exp(s(m_{i}, e_{j}))$$
(12)

$$\mathcal{L}_{2}(m_{i}, e_{i}) = -s(m_{i}, e_{i}) + \log \sum_{i=1}^{bsz} \exp(s(m_{i}, e_{j}))$$
(13)

$$s(m_i, e_i) = v_{m_i} \cdot v_{e_i}^T \tag{14}$$

where v_{m_i} and v_{e_i} are the fused embeddings of mention m_i and entity e_i from the mention encoder and entity encoder, respectively.

At inference time, we will pre-compute and cache the entity representation for all the candidates, to achieve fast and real-time inference. As shown in Figure 2, we retrieve k candidate entities for each mention based on the scores defined by Equation 14.

4 EXPERIMENTS

In this section, we perform an empirical study of GER framework on several challenging datasets for zero-shot entity retrieval. We further analyse the GER performance for candidate ranking and do ablation studies about the fine-grained information.

KB	Dataset	Usage	Samples Num	Entity Num
	AIDA	Train	18,317	
Wiki- pedia	AIDA	Valid	4,763	5,903,530
	WNED-CWEB	Test	10,392	5,905,550
	AQUAINT	Test	678	-
		Train	49,275	332,632
Wikia	ZESHEL	Valid	10,000	89,549
		Test	10,000	70,140

Table 1: Statistics of entity retrieval datasets and knowledge base, samples num means the size of paired mentions and entities. For each KB, we use the corresponding train dataset (e.g., AIDA train set) to optimize our GER framework, and report the recall results on test dataset (e.g., WNED-CWEB).

4.1 Datasets

We evaluate our framework GER under two popular public knowledge bases: Wikia ³ and Wikipedia ⁴. Statistics of datasets are listed in Table 1.

Wikia Based. Wikias are community-written encyclopedias, each specialized in a particular subject such as film series and computer game. ZESHEL dataset [17] was constructed based on the documents in Wikia from 16 domains. For each domain, there are paired (mention, entity) and individual entity dictionary. Following the baseline BLINK, we divided the 16 domains into: 8 domain for train, 4 for valid, and 4 for test. As shown in Table 1, there are 49K, 10K, 10K paired examples in the train, valid, test sets, respectively. The candidate entity dictionary for each domain ranges in size from 10K to 100K.

Wikipedia Based. We use the May 2019 English Wikipedia dump from KILT [22] as our knowledge base, which includes 5.9M entities from Wikipedia. To the best of our knowledge, there is no standard zero-shot retrieval linking dataset in the full Wikipedia setting. Therefore, in order to evaluate the performance under Wikipedia KB, we use standard entity linking datasets from different domains to satisfy the zero-shot setting. Concretely, we employ the AIDA CoNLL-YAGO [11] for training, WNED-CWEB [9] and AQUAINT for test. We preprocess the datasets to guarantee that the entities in test set are unseen in the training phase.

4.2 Implementation

We conduct experiments on both BERT-base and BERT-large following the baseline model for fair comparison. The max length for mention context and entity description are both set to 128. For HGAN, we stack 3 layers with 8 attention heads. The learnable hyperparameter λ is initial as 0.5. All parameter are optimized by AdamW [18], with learning rate 2e-5, gradient clipping 1.0 [20], and 10% warmup steps. For ZESHEL, the batch size for training is 128 following the BLINK and training 5 epoches based on BERT-base takes 0.8h on 4 Tesla-A100 GPUs. For AIDA CoNLL-YAGO, we use the BERT-large model provided in BLINK as backbone, which is pretrained on 9M paired Wikipedia samples. We set the batch size as 64 and train 10 epoches, which takes 1.4h on 4 Tesla-A100 GPUs.

4.3 Comparison Methods

For a fair comparison, we choose BLINK [30] as our baseline. Moreover, we also compare our GER framework with two strategies to learn fine-grained embedding (BERT Mean/Max Pooling).

BM25 [17]. A frequency-based method to retrieve the candidates.

BLINK [30]. A BERT-based bi-encoder model where the mentions and entities are represented by the sentence embedding from BERT of the corresponding context.

Partalidou et al. [19]. They extend the BLINK by introducing a new pooling function and incorporating entity type side-information.

ARBORESCENCE [1]. A model that fully utilizes mentionto-mention affinities by building minimum arborescences to make linking decisions.

BERT Mean Pooling. Compare to BLINK, we utilize the mean pooling of mention/entity token outputs as representation.

³https://www.wikia.com

⁴https://www.wikipedia.org/

Method	R@1	R@4	R@8	R@16	R@32	R@50	R@64
BM25 [17] [†]	-	-	-	-	-	-	69.13
BLINK [30] [†]	-	-	-	-	-	-	82.06
Partalidou et al. [19] [†]	-	-	-	-	-	84.28	-
ARBORESCENCE [1] [†]	-	-	-	-	-	-	85.11
BLINK [30]*	38.01	62.08	69.19	75.39	80.03	82.69	83.98
BERT Mean Pooling	33.65	57.74	65.17	71.38	75.85	78.66	80.14
BERT Max Pooling	36.94	60.42	68.34	73.83	78.40	81.09	82.65
BLINK + BERT Mean Pooling	34.12	58.41	66.19	72.24	76.93	79.79	81.16
BLINK + BERT Max Pooling	38.45	63.46	70.68	76.72	81.11	83.63	84.83
GER (ours)	42.86	66.48	73.00	78.11	82.15	84.41	85.65

Table 2: *Recall*@K (R@K) results on the test set of ZESHEL dataset, which is the average of 5 runs with different random seeds. * notes for the results we reproduce. † notes for the results taken from their papers. Best results are shown in bold. GER outperforms all baselines significantly with paired t-test at p < 0.05 level considering R@64.

Mathad	WNED-CWEB			AQUAINT		
Method	R@10	R@30	R@128	R@10	R@30	R@128
BLINK*	80.16	84.48	89.22	93.95	96.76	98.23
BERT Mean Pooling BERT Max Pooling	79.87 77.62	84.79 83.56	89.35 88.57	94.54 93.07	96.90 95.87	98.23 97.94
BLINK + BERT Mean Pooling BLINK + BERT Max Pooling	80.13 78.75	84.33 84.16	88.81 88.81	94.84 93.22	96.31 96.02	98.23 97.35
GER (ours)	80.79	85.34	90.13	95.28	97.05	98.82

Table 3: *Recall@K* (R@K) on dataset WNED-CWEB and AQUAINT. The experiments are all under the zero-shot settings. that entities are only defined by textual description and the entities in test set are unseen during training.

BERT Max Pooling. Compare to BLINK, we utilize the max pooling of mention/entity token outputs as representation.

BLINK + BERT Mean Pooling. We utilize the mean pooling of mention/entity token outputs as fine-grained information and fuse it with sentence embedding.

BLINK + BERT Max Pooling. We utilize the max pooling of mention/entity token outputs as fine-grained information and fuse it with sentence embedding.

4.4 Main Results

We conducted the experiments on Wikia-based and Wikipedia-based datasets. Table 2 and Table 3 report the recall results of the baseline models and GER. Some findings are summarized as follows:

(1) Our proposed GER outperforms all baselines on the evaluation metrics for Wikia based datasets and Wikipedia-based datasets, which demonstrates the effectiveness of GER on getting more comprehensive representations for mentions/entities. Compared to baseline BLINK, GER significantly improves the recall score with the paired t-test at p < 0.05 level considering recall@64. In particular, GER achieves 85.65 recall@64 score in ZESHEL, which is 1.67 higher than BLINK we reproduce. Following BLINK, for Wikipedia based datasets, we pretrain the BERT-large on 9M paired Wikipedia samples. Hence, the results for baseline and GER are **high**. However, GER still achieves higher results, such as a recall@10 of 95.28 for AQUAINT. (2) The mean pooling and max pooling of mention/entity tokens perform worse than sentence embedding. Intuitively, BERT model is pre-trained on MLM and NSP tasks, where the output of [CLS] is employed to represent the whole sentence. Thus, such fine-grained word-level embedding from BERT can not model the sentence due to the gap between the pretrain tasks and zero-shot entity retrieval task. As shown in Table 2 and 3, BERT Mean Pooling and BERT Max Pooling perform worse than BLINK, such as 33.65 and 36.94 compared to 38.01 for recall@1 on ZESHEL.

(3) Both fine-grained information and coarse-grained sentence embedding are crucial to represent mentions/entities. For BERT Mean Pooling strategy, the recall@64 score on ZESHEL improves from the 80.14 to 81.16 if we fuse it with the sentence embedding. On the other hand, the BLINK + BERT Max Pooling strategy achieves 0.85 higher than BLINK on recall@64 for the ZESHEL dataset. For AQUAINT, as shown in Table 3, we can also get the same conclusion such as 94.84 recall@10 for BLINK+BERT Mean Pooling compared to 93.95 for BLINK.

(4) Our proposed HGAN can capture better fine-grained information than BERT. As mentioned in (2), we consider the BERT Max/Mean Pooling as the fine-grained information from BERT. In GER, we extract the knowledge units and capture the fine-grained information by HGAN. As shown in Table 2 and 3, our GER performs better than BLINK + BERT Mean Pooling and BLINK + BERT Max Pooling from recall@1 to recall@100 on all datesets. Modeling Fine-grained Information via Knowledge-aware Hierarchical Graph for Zero-shot Entity Retrite/40/20 / 23, February 27-March 3, 2023, Singapore, Singapore

4.5 Ablation Studies

To better understand our proposed GER framework, we conduct ablation experiments and compare our HGAN with other strategies to learn fine-grained information. We guide our experiments with following research questions (RQs):

Sentence-level	Word-level	R@1	R@8	R@32	R@64
BERT	-	38.01	69.19	80.03	83.98
-	HGAN	37.37	63.77	73.19	77.29
BERT	Node Mean	37.29	69.62	80.15	83.88
BERT	GAT	39.23	70.07	80.14	84.09
BERT	HGAN	42.86	73.00	82.15	85.65

RQ1: Can we use fine-grained information only (without the sentence embedding) to represent mentions/entities ?

Table 4: The ablation study results of our GER (BERT+HGAN) on ZESHEL dataset.

We compare the results of GER with BERT only and HGAN only based on the ZESHEL dataset. As shown in Table 4, we can observe that utilizing the fine-grained information only (HGAN) will lead to a drop, especially for recall@64. We consider this drop due to **gap in tasks** since BERT is pre-trained by MLM and NSP tasks rather than graph tasks. Actually, sentence embedding from BERT is also vital for mention/entity representation.

RQ2: Is HGAN more suitable for modeling fine-grained information from knowledge-aware graph ? Why not use GAT ?

After constructing the knowledge-aware hierarchical graph, we try two strategies to model fine-grained information:

Node Mean. Regardless of the structural information in the graph, we adopt the mean pooling of all nodes including the SPO nodes and the mention/entity node.

GAT. We connect the SPO nodes to mention/entity node directly and apply the GAT [28] to model the fine-grained information.

As shown in Table 4, we can observe that applying the GAT performs better than the baseline, ranging from recall @ 1 to recall @ 64, while applying the Node Mean brings a slight drop for recall@64. We can conclude that structural information in knowledge units is vital to modeling fine-grained information. Moreover, HGAN performs better than GAT, indicating the **necessity for hierarchical design**. GNNs such as GAT surfer from the **graph bottleneck** [2] for central node while HGAN can address it by reducing the neighboring nodes through the hierarchical design.

RQ3: Can we add HGAN to mention or entity encoder only ?

Mention Encoder	Entity Encoder	R@1	R@8	R@32	R@64
BERT	BERT	38.01	69.19	80.03	83.98
BERT+HGAN	BERT	38.16	69.41	80.04	83.92
BERT	BERT+HGAN	39.18	68.56	78.70	82.65
BERT+HGAN	BERT+HGAN	42.86	73.00	82.15	85.65

 Table 5: The ablation study results of the dual-encoder architecture. (BERT, BERT) is the baseline BLINK while (BERT+HGAN, BERT+HGAN) is our proposed GER.

GER follows the traditional dual-encoder framework where the mention encoder and entity encoder share the same architecture. We

conduct ablation studies that add the HGAN to mention encoder or entity encoder only. Table 5 indicates that fusing fine-grained information for the encoder on one side will bring slight drops compared to the baseline BLINK. Meanwhile, the GER framework performs better than BLINK. For zero-shot entity retrieval, the mentions and entities should be embedded in one semantic space to match, thus fusing fine-grained information at one encoder leads to a drop in performance.

4.6 Overall Performance

To evaluate the overall performance, we employ the BERT-base based cross-encoder for entity ranking after retrieving 64 candidate entities. For the first entity retrieval stage, it takes 48 minutes for our GER to train for 5 epochs on the train set of ZESHEL, and 40 minutes for BLINK.

Figure 4 presents the overall accuracy of our GER and baseline BLINK on the test set of ZESHEL. GER gets recall@64 of 85.65 compared to 83.98 from BLINK, and achieves 0.62 improvement after training 35K steps in entity ranking stage. Moreover, GER get a comparable result in 26K steps with baseline BLINK in 35K steps, saving 9k steps (nearly 2 hours). In conclusion, GER achieves a higher recall@64 than BLINK during entity retrieval stage with slight extra 8 minutes, and such higher recall@64 can save 2 hours in the entity ranking stage.

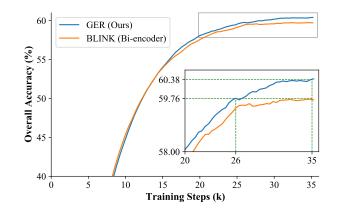


Figure 4: Comparison of overall accuracy for BLINK and GER.

5 ATTENTION STUDY

5.1 BERT Attention

To investigate the attention distribution of the mention/entity token in BERT, we divide the 10000 samples in the ZESHEL test set into four groups by the rank of mention token attention. For each sample, we calculate the attention scores between each token and [CLS] token in BERT and rank these tokens. Then we group these samples by the lowest ranking of corresponding mention tokens.

As shown in Table 6, we can get the following observations:

(1) For BLINK, the higher the attention scores, the higher the recall performance. For the mentions ranked in [0,32), we get a recall@64 of 86.13, 2.63 higher than mentions ranked in [96,128). The sentence embedding contains more information from the mention/entity when attention scores are higher.

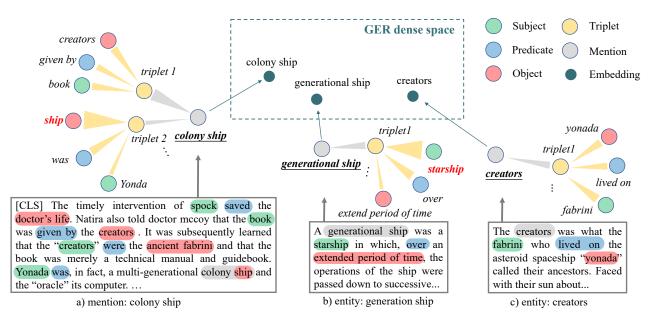


Figure 5: The corresponding embedding in dense space and part of node attention between graph nodes for mention *colony ship*, ground truth entity *generation ship* and entity *creators*. In the graph, we visualize the attention of Mention/Entity-Triplet edges (in grey) and Triplet-SPO edges (in yellow), where *thicker edges* mean *higher* attention scores.

Attention Ranking		[0,32]	[32,64)	[64,96)	[96,128)
BLINK	Total	685	1191	2765	5359
	Recall@64	86.13	85.81	84.45	83.50
GER	Total	742	1315	2798	5145
	Recall@64	86.12	86.08	86.78	84.98

Table 6: Attention distributions for ZESHEL test set.

(2) In our proposed GER, the attention scores towards mentions get higher, thus the sentence embeddings can model more information about the mentions. For baseline BLINK, 53.59% samples gain relatively low attention, where the attention ranking is [96,128). For GER, we get a 2.14% drop in [96,128), and these samples gain higher attention. The sentence embeddings in GER can better model mentions/entities compared to baseline BLINK. Since the node embeddings of knowledge-aware hierarchical graph are initialized by the token embedding, we believe that the knowledge in graph can influence the BERT layer through loss back propagation, thus the attention scores towards mention tokens gain.

5.2 HGAN Attention

To evaluate the ability to capture the fine-grained word-level information of mention/entity, we visualize the node-to-node attention weights in HGAN. We calculate the edge attention following Equation 6 and get the average among the attention heads.

As shown in Figure 5, for the embedding of mention **colony ship**, the embedding of entity **generation ship** is closer than entity **creators** in the dense space defined by GER. In the knowledge-aware graph of mention **colony ship**, the node *ship* in red gets the highest attention while the node *creators* and *yonda* receive relatively low

attention, indicating that the mention encoder in GER focus on *ship* and ignores *creators*. Meanwhile, for the entity **generational ship**, the node *star ship* gets the highest score. Through the knowledge-aware graph, HGAN gathers information from mention/entity related words to capture fine-grained information, and thus gets more comprehensive representations.

6 CONCLUSION

In this paper, we explore an issue that was overlooked when utilizing the sentence embedding from BERT to retrieve entities in zero-shot entity retrieval scenarios, that is, such coarse information can not fully model the mentions/entities and more fine-grained information is necessary. Meanwhile, the token output are highly similar to the sentence embedding due to the over-smoothing in BERT. To overcome these issues, we propose GER, which captures more fine-grained information from both mention/entity words and other related words as complementary to coarse-grained sentence embedding. Specifically, we construct a hierarchical graph and design a novel Hierarchical Graph Attention Network (HGAN). Experiments on several benchmarks show the effectiveness of our GER framework. Further analysis also indicate the importance of hierarchical design and symmetry design in GER. In the future, we will consider applying the graph enhanced encoder for candidate ranking stage in zero-shot entity linking.

7 ACKNOWLEDGMENTS

This work was partly supported by the National Key Research and Development Program of China (No. 2020YFB1708200) and the Shenzhen Key Laboratory of Marine IntelliSense and Computation under Contract ZDSYS20200811142605016. Modeling Fine-grained Information via Knowledge-aware Hierarchical Graph for Zero-shot Entity Retribuand '23, February 27-March 3, 2023, Singapore, Singapore

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