Collaborative Knowledge Graph Fusion by Exploiting the Open Corpus

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Abstract—To ease the process of building Knowledge Graphs (KGs) from scratch, a cost-effective method is required to enrich a KG using the triples extracted from a corpus. However, it is challenging to enrich a KG with newly extracted triples since they contain noisy information. This paper proposes to refine a KG by leveraging information extracted from a corpus. In particular, we first formulate the task of building KGs as two coupled sub-tasks, namely join event extraction and knowledge graph fusion. We then propose a collaborative knowledge graph fusion framework, which is composed of an explorer and a supervisor, to allow the involved two sub-tasks to mutually assist each other in an alternative manner. More concretely, an explorer extracts triples from a corpus supervised by both the ground-truth annotation and the KG provided by the supervisor. Furthermore, a supervisor then evaluates the extracted triples and enriches the KG with those that are highly ranked. To implement this evaluation, we further propose a translated relation alignment scoring mechanism to align and translate the extracted triples to the KG. Experimental results verify that this collaboration can improve both the performance of our sub-tasks, and contribute to high-quality enriched knowledge graphs.

Index Terms—Collaborative learning, joint event extraction, knowledge graph enrichment, knowledge graph fusion.

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techniques [23] have utilized network embedding technology [24] to deduce the potential presence of triples within a provided knowledge graph. This is done by representing the triples as latent vectors [25], [26], [27]. Specifically, with the representation vectors of the triples to hand, these methods use statistical models [28] or neural networks [29], [30] to predict plausible scores for the potential triples.

Challenges That Hinder the Emergence of a Unified Framework: Although many existing works have discussed the knowledge graph fusion task, few consider a unified framework that can automatically build a knowledge graph directly by absorbing a corpus. Therefore, it is necessary to fuse the extracted triples from an open corpus to form a prior knowledge graph, or in other words, connect the candidate triple generation with the evaluation process. The main challenges that hinder progress in this direction are rooted in the following shortcomings in the knowledge extraction and knowledge graph fusion tasks.

1) Difficulties in aligning RDF triples: Since open-text sources may contain relations outside the scope of a prior knowledge graph, it is a challenge to align the relations from the open texts to those in the knowledge graph. Although current work [32] discusses the entity alignment between sources, little attention has been paid to relation alignment. This leads to the difficulty of aligning the extracted RDF triples from the text sources to a prior knowledge graph. 2) Difficulties maintaining knowledge graph quality: Merging the unaligned RDF triples from the open text sources to a knowledge graph can mislead the knowledge graph embedding model and may result in unreliable plausible scores for potential triples. Moreover, a misleading knowledge graph can result in the extractor relying on low-quality triples. This may further lower the quality of the knowledge graph.

3) Difficulties sharing knowledge between sub-tasks: Without a reliable way of aligning the RDF triples, it becomes difficult to share knowledge between the sub-tasks (e.g., event extraction and knowledge fusion). This leads to error propagation [33] and thus degrades the performance for each sub-task.

To address the aforementioned limitations, in this paper, we formulate a new method that combines event extraction (extractor) with knowledge graph fusion as a collaborative knowledge graph fusion process. Specifically, we propose a unified framework to build a domain-oriented knowledge graph by enriching an open-source knowledge graph with knowledge extracted automatically from a text corpus. As our new method provides a mechanism to share the knowledge between sub-tasks, our enriched knowledge graph grows larger by incorporating facts of knowledge from the texts. In addition, the new method also leverages the enriched knowledge graph to assist our event extraction sub-task to obtain more reliable entities and relations.

As illustrated in Fig. 1, our collaborative knowledge graph fusion method consists of two interacting processes, an explorer and a supervisor. That is, by referring to the principles (e.g. the possible entity pairs) from a supervisor, an extractor uncovers new RDF triples from the available open text sources. After the extractor delivers the newly discovered triples to the supervisor, the supervisor assesses their quality and expands the current set of triples by incorporating the newly discovered ones with the highest quality. Specifically, our framework guides the extractor with the entity pairs from a prior seed knowledge graph, and subsequently iteratively expands the seed knowledge graph by incorporating the extracted triples from the extractor. Through this process, both the performance of the extractor and the quality of the enriched knowledge graph are improved. In our
extractor, we propose a benchmark-based supervision mechanism to supervise the extraction process with the entity pairs from the seed knowledge graph maintained by the supervisor. This is implemented by a contrastive learning method [34] which considers both the positive and negative entity pairs. These entity pairs are sampled from the prior knowledge graph with a neural knowledge-graph-embedding-based scoring function trained by the supervisor process. As the supervisor, the knowledge-graph-embedding-based scoring function is trained by the triples in the seed or the enriched knowledge graph and it evaluates the matching degree of the extracted RDF triples from the extractor to the knowledge of the supervisor. Subsequently, the supervisor merges the top-ranked triples from the extracted results into the prior knowledge graph.

We conduct comprehensive experiments on real-world corpora and knowledge graphs. Experimental results show that our system achieves higher performance than state-of-the-art baselines, in both joint-event-extraction and knowledge-graph-embedding tasks. This not only verifies that the proposed benchmark-based supervision mechanism effectively guides the extractor in our system but also implies that the knowledge graph of the supervisor maintains high quality by being enriched with the triples evaluated by the supervisor.

Contributions: In summary, the primary contributions of this paper are as follows.

- We formalize the knowledge graph fusion with open corpora as an alternating process that involves extracting the RDF triples from documents and subsequently merging them with a prior knowledge graph. As far as we know, our work is the first to discuss a unified architecture to conduct the knowledge fusion directly based on the text sources.
- We propose the “Collaborative Knowledge Graph Fusion” framework as a solution for the aforementioned problem. In this framework, we propose the Benchmark-based Supervision Mechanism to further supervise the performance of our JEE process (in the explorer process) with positive and negative entity pairs sampled from a prior KG provided by the supervisor.
- We propose an unsupervised metric, Translated Relation Alignment Scoring (TRAS), to assist align and translate the extracted triples from the JEE process to those in the proper form to the prior KG.
- With the proposed Benchmark-based Supervision Mechanism and TRAS metric to hand, we implement the “Collaborative Knowledge Graph Fusion” as a unified process. It automatically extracts the triples from an open corpus and enriches them to a given prior KG in an alternative process.
- Our experiments on several real-world datasets show that, with the proposed framework, our system achieves better performance both on the JEE and KGF tasks than the related alternatives. This verifies that our method not only improves the JEE process but also yields a high-quality enriched KG. Specifically, our case study shows that our system could translate the extracted triples from a text corpus to the facts consistent with a prior KG with the assistance of the proposed TRAS score. This improves the quality of the prior KG and also explains the reason for the performance improvement of the KGF task.

The remainder of this paper is organized as follows. In Section II, we introduce the preliminaries concerning the joint event extraction and knowledge graph fusion processes and then also formalize the problem of knowledge graph fusion with an open corpus. Section III presents in detail our proposed framework and fusion mechanism. Section IV verifies the effectiveness of our model and compares it with recent methods on real-world datasets. Section V summarizes recent related work. Finally, we conclude this paper and offer some suggestions for further work in Section VI.

II. PRELIMINARIES

Our overall objective is to fuse knowledge graphs by leveraging an open corpus. This task consists of a sub-task of Joint Event Extraction (JEE) to extract knowledge triples from unstructured texts and another sub-task of Knowledge Graph Fusion (KGF) to evaluate and enrich the extracted triples from the JEE for a prior or existing KG. We first define some notations for the JEE and KGF, and then formalize our problem in the following subsections.

A. Knowledge Graphs

A KG [35] is represented as a set of RDF triples referring to specific topics. Formally, we define a knowledge graph \( G \) as \( G = \langle E, R, T \rangle \), where \( E \) is a set of entities, \( R \) is a set of relations and \( T \) is the set of the RDF triples. For example, \( G_1 = \langle E_1, R_1, T_1 \rangle \) is a knowledge graph of capital city relationships with the entity set \( E_1 = \{\text{Tokyo}, \text{Beijing}, \text{Japan}, \text{China}\} \), the relation set \( R_1 = \{\text{capital_of}\} \) and the triple set \( T_1 = \{\langle\text{Tokyo}, \text{capital_of}, \text{Japan}\rangle, \langle\text{Beijing}, \text{capital_of}, \text{China}\rangle\} \). Since a human-composed document does not explicitly contain structural information, e.g., the entities, relationships, or triples, in order to construct a KG from a corpus, we need to extract the triples from the texts.

B. Joint Event Extraction

Event extraction aims to extract structural information (e.g., entities or relations [12]) from a given corpus. It is typically composed of two sub-tasks of named entity recognition and relation extraction. Traditionally, separate multi-label classifiers are designed to predict the labels for both the entities and the mentioned relationship in a sentence. In order to improve the performance of event extraction, recent work resorts to pipeline-based methods, which first classify the relationship, and then identify the entities centered around the determined relation. However, since these methods perform the relation classification and entity identification sub-processes separately, these sub-processes rarely receive feedback from one another. As a result, those pipeline-based approaches may suffer from the error-propagation issue [36]. To this end, we put forward a universal sequence-to-sequence (Seq2Seq) framework [16] to simultaneously extract the entities and relations from a corpus.
Seq2Seq Joint-Event-Extraction (JEE): Let $\mathcal{D}$ be a corpus of textual sentences, where $\mathcal{D} = \{s_1, s_2, s_3, \ldots, s_n\}$. For each sentence $s \in \mathcal{D}$, $s = \{w_1, w_2, w_3, \ldots, w_m\}$, where $w_i$ denotes a word token. Let $\mathcal{A} = \mathcal{A}_E \cup \mathcal{A}_R$ be a combined label set with predefined types for tokens, where $\mathcal{A}_E$ and $\mathcal{A}_R$ are the sets of the predefined entity and relation mention types, respectively. Then, the aim of JEE is to find an optimal map $g_{\Theta_1} : s \rightarrow \Pi_{i \geq 0} \mathcal{A}$, where $\Pi$ is the Cartesian product. $M$ is the maximum length for the sentences in $\mathcal{D}$, and $\Theta_1$ denotes the learning parameters.

The loss function for JEE under the framework of Seq2Seq is designed as a cross-entropy function, as follows:

$$\mathcal{L}_{\text{JEE}} = \sum_{i=0}^{M} \sum_{y_i \in \mathcal{A}} -\Pr(y_i | w_i) \log \hat{\Pr}(y_i | w_i).$$  \hspace{1cm} (1)

With the mapped label sequence optimized by the loss function in (1), we obtain the annotated label sequences for the sentences in a corpus. In this manner, the entity and relation text mentions for a sentence are extracted simultaneously. Subsequently, we generate RDF triples based on their extracted text mentions and use these triples as the candidate triples for KG enrichment. For better illustration, we use the term $g_{\Theta_1}$ as a joint operation that combines both the mapping from sentences to label sequences and the RDF generation process. We refer to it as the extractor map in the following sections.

### C. Knowledge Graph Fusion With an Open Corpus

Knowledge graph fusion [18] is the task of constructing a unified knowledge graph from different data sources. Traditional knowledge graph fusion aims to integrate several knowledge graphs into one knowledge graph, and we formalize this task as follows:

**Knowledge Graph Fusion (KGF):** Let $G_1 = \langle E_1, R_1, T_1 \rangle$ and $G_2 = \langle E_2, R_2, T_2 \rangle$ denote two prior knowledge graphs, where both $G_1$ and $G_2$ are used under the same RDF schema. $G' = \langle E', R', T' \rangle$ is the fused knowledge graph based on $G_1$ and $G_2$, where $T' = T_1 \cup \Delta T$ denotes the fused triple set which is based on $T_1$ and incremental triples $\Delta T$ from $G_2$ ($T' = T_1 \cup \Delta T$). The $\Delta T$ are the top-$K$ triples that are close to $G_1$. This closeness is measured by the plausible score $f_{G_1}(i, r, t) ((i, r, t) \in G_2)$, which is computed as follows:

$$f_{G_1}(i, r, t) = \sum_{(i', r', t') \in T_1} \text{Sim}(i, r, t), (i', r', t') \in T_1),$$  \hspace{1cm} (2)

where $\text{Sim}$ denotes the similarity between two triples.

We utilize a contrastive learning framework [34] to embed the triples as the corresponding vectors and implement the similarity between triple vectors via the translation-based embedding (TransE) [28] method.

**Knowledge Graph Embedding (KGE):** Given a KB $G = \langle E, R, T \rangle$, suppose $(i, r, j)$ is a triple from $T$, we define the loss of knowledge graph embedding as follows:

$$\mathcal{L}_{\text{KGE}} = - \sum_{(i, r, j) \in T} \sum_{(i', r', j') \in N} || \gamma + f_{G}(i, r, j) - f_{G}(i', r', j') ||,$$  \hspace{1cm} (3)

where $N$ is the corresponding negative set for the triples in $T$, $\gamma$ is a hyperparameter, and $f_{G}(i, r, j)$ is a scoring function to evaluate the consistency of any triple $(i, r, j)$ to $G$. The normalization in (3) can be based on either the L1 or L2-norm. According to the design of TransE, a plausibility score $f_{G}(i, r, j)$ can be computed as follows:

$$f_{G}(i, r, j) = d(e_i + e_r, e_j),$$  \hspace{1cm} (4)

where $e$ is an embedding that maps any entity or relation to an $\mathbb{R}^h$ vector, and $d(\cdot, \cdot)$ is the euclidean distance function between two $\mathbb{R}^h$ vectors.

Therefore, with a trained embedding $e$ based on the given prior knowledge graph $G_1$, the plausibility of a triple $(i, r, j)$ from $G_2$ to $G_1$ can be evaluated by computing the euclidean distance $d(e_i + e_r, e_j)$.

As discussed before, our objective is to fuse knowledge graphs by leveraging open text sources. This task is different from the aforementioned knowledge graph fusion, as we require to (1) extract the RDF triples from a given corpus $\mathcal{D}$ and (2) fuse the extracted triples to a knowledge graph $G$. Specifically, we formalize this problem as the following.

**Open Knowledge Graph Fusion (OKGF):** Given a prior knowledge graph $G = \langle E, R, T \rangle$, a corpus $\mathcal{D}$ and an extractor map $g_{\Theta_1}$, suppose $g_{\Theta_1}(\mathcal{D})$ is a set of extracted triples from a corpus $\mathcal{D}$. Then with a trainable scoring function $f$ and embedding map $e$, the objective of OKGF is to find the optimal subset $\Delta T$ from $g_{\Theta_1}(\mathcal{D})$ that minimizes the following loss function:

$$\mathcal{L}_{\text{OKGF}} = - \sum_{(i, r, j) \in T} \sum_{(i', r', j') \in N} || \gamma + f_{G}(i, r, j) - f_{G}(i', r', j') ||,$$  \hspace{1cm} (5)

where $N$ is the corresponding negative triple set for the positive triples $t$ from $T$.

This task combines the sub-tasks of JEE and KGF into a unified framework. However, it is a combinatorial optimization problem that exhaustively checks all the possible subsets $\Delta T$ from $g_{\Theta_1}(\mathcal{D})$. The newly discovered noisy entities and relations from the open corpus exacerbate the problem. Therefore, it is difficult to obtain the global optimal solution. To this end, we propose a heuristic collaborative knowledge graph fusion framework to connect the JEE and the KGF to fuse an open corpus into a prior knowledge graph. Our framework approaches the open knowledge graph fusion from two directions, namely 1) our model guides the JEE process with a prior knowledge graph, and 2) it selectively enriches the prior knowledge graph with the extracted results from the JEE process. This requires a careful design of both the JEE supervision mechanism with a knowledge graph and an effective “translate-and-evaluate” method to fuse the extracted results into the knowledge graph. We elaborate on the details in the next section.

### III. OUR PROPOSED METHOD

In this section, we introduce our proposed framework for collaborative knowledge graph fusion with an open corpus.
A. Overview

To emulate a human-like collaborative process for our task, we propose a framework with two components, namely 1) an explorer to explore the documents with JEE modules and 2) a supervisor to fuse the knowledge graph with the extracted results by the explorer. In the exploring process, we propose a benchmark-based supervision mechanism to assist the JEE task to extract the triples while guided by a supervisor (the benchmarks discovered by the supervisor from a prior KG). In the supervising process, we propose the Relation Alignment-based Knowledge Graph Fusion module to selectively accept the extracted triples to be added to the prior KG. These two components alternate to simultaneously extract knowledge triples and enrich a prior KG with high quality. Fig. 2 illustrates the architecture of our system. The details of the proposed processes are given in the following subsections.

B. The Explorer: Benchmark-Based Supervision JEE

As shown in Fig. 2, we perform the JEE in the exploring process. To ensure the explorer is guided by the supervisor, we introduce a Benchmark-based Supervision Layer to import the knowledge from the supervisor. In this work, we apply the Seq2Seq JEE as the basic extraction process and use BERT [37] as the encoder. This module can be substituted by any alternative JEE model if necessary.

Intuitively, during the exploratory period, an explorer receives examples from a supervisor and attempts to leverage the knowledge in these examples to facilitate better exploration. In our work, the explorer extracts the triples from an open corpus based on a prior KG maintained by a supervisor. Since the open corpus may contain unaligned relations and extra entities that are not contained in the prior KG, it requires a relatively flexible method rather than strict supervision to guide the explorer. To this end, we introduce the benchmark-based supervision mechanism. The benchmark here means the supervisor-provided target that the explorer tries to reach.

**Benchmark-based Supervision Mechanism:** Given a prior KG, \( G = (E, R, T) \), let a positive set of entity pairs \( P^+ \) and a negative set of entity pairs \( P^- \) be a benchmark, where \( P^+ = \{(i, j)|((i, *, j) \in T, \forall i, j \in E) \} \), and \( P^- = \{(i, j)|((i, *, j) \notin T, \forall i, j \in E) \} \). Then, the benchmark-based supervision mechanism can be described as the task to minimize a loss function extended from the Bayesian Personalized Ranking (BPR) loss [38], as follows:

\[
L_b = - \log(\delta(f(P^+) - f(P^-))) \tag{6}
\]

where \( \delta \) is the Sigmoid function. Here, function \( f(P) \) computes the likelihood for any entity pair \((i, j) \in P\), given by

\[
f(P) = \text{ffnn}(\sum_{(i,j) \in P} (e_i - e_j)) \tag{7}
\]

where \( P \) is the set of all the related pairs \((P = P^+ \cup P^-)\), \( e_i \) is an \( \mathbb{R}^d \) embedding vector for any entity \( i \) (where \( i \in E \)), and \( \text{ffnn} \) is a feed-forward neural network layer to map an \( \mathbb{R}^d \) embedding vector to an \( \mathbb{R} \) score.

Optimizing \( L_b \) results in the training of a scoring function \( f(P) \) to measure the likelihood of any entity pair while maximizing the difference between the likelihood scores of the positive and negative entity pairs. This fits with the intuition that an explorer understands the knowledge in the examples from the supervisor.

Furthermore, since an entity is a sequence of tokens with arbitrary lengths, we apply the weighted average method [39].
to represent an entity by its corresponding embedding vector. Formally, the embedding vector for an entity is computed as follows:

\[ e_i = \sum_{w \in i} e_w, \quad (8) \]

where \( i \) is an entity in \( E \) and \( w \) denotes a token in the entity \( i \). The embedding vector \( e_w \) can be obtained by referring to the embedding dictionary table.

With the proposed benchmark-based supervision mechanism, the loss function of our explorer process is a weighted sum of the losses in (1) and (6), as follows:

\[ \mathcal{L}_e = (1 - \alpha)\mathcal{L}_{jce} + \alpha\mathcal{L}_b, \quad (9) \]

where \( \alpha \) is the weight for the benchmark-based supervision. The benchmark-based supervision loss \( \mathcal{L}_b \) in \( \mathcal{L}_e \) guides the explorer to extract the conformed event factors based on the examples from the supervisor. These conform factors are also crucial to improve the quality of the knowledge graph of the supervisor. In our experiments, both our explorer and supervisor perform the best when \( \alpha = 0.5 \).

**Candidate Triple Set:** With the aforementioned explorer process, our system simultaneously extracts the entity and relation text mentions (or triggers). Then, we generate all RDF triples exhaustively based on the extracted text mentions. The results are treated as the candidate triple set \( T' \) for subsequent processing steps.

**C. The Supervisor:** Relation Alignment-Based OKGF

Our supervisor process enriches the prior KG with the optimal subset of candidate triples from the explorer process. This requires a scoring function to measure the plausibilities for triples trained by the prior KG. The process for a supervisor to evaluate the quality of the discovery from the explorer is similar to that adopted by the explorer. As discussed in Section II-C, one of the challenges in implementing this task is that the relation text mentions in the candidate triples may not align with the relations in the prior KG. In order to address this issue, we propose the Translated Relation Alignment Score (TRAS). This score facilitates the alignment of the relations between the candidate triples and the existing relations in the prior KG. After aligning the relations, our system translates the candidate triples to the aligned candidate triples. It then ranks these aligned candidate triples by leveraging the semantic information residing in the prior KG. The top-ranked triples are incorporated into the prior KG to generate an enriched KG. We delve into the details of this process in the remainder of this section.

**Translated Relation Alignment Score (TRAS):** Given two KGs \( G_1 = (E_1, R_1, T_1) \) and \( G_2 = (E_2, R_2, T_2) \) \((T_1 \cap T_2 = \emptyset)\). The TRAS score \( s(i, r_1, r_2) \) between two relation \( r_1 \in R_1 \) and \( r_2 \in R_2 \) is computed as follows:

\[ s(r_1, r_2) = \gamma Sim_m(r_1, r_2) + (1 - \gamma)Sim_e(r_1, r_2), \quad (10) \]

where \( Sim_m(r_1, r_2) \) is the text mention similarity between \( r_1 \) and \( r_2 \), and \( \gamma \) is the weight of the text mention similarity. The quantity \( Sim_e(r_1, r_2) \) is the translated relation similarity between two relations (i.e., \( r_1 \) and \( r_2 \)), which can be computed as follows:

\[ Sim_e(r_1, r_2) = Sim(\sum_{(i, r_2, j) \in T_2} e_i - e_j, \sum_{(i, r_1, j) \in T_1} e_i - e_j), \quad (11) \]

where \( Sim(\cdot, \cdot) \) can be any similarity function between two vectors. In this paper, we use Cosine similarity for this task. The summed entity embedding difference in (11) represents the proximity between two relations in different KGs. Generally, a larger value of \( \gamma \) gives greater weight to the text mention similarity. A smaller value of \( \gamma \) allows our model to capture more indirect semantic information around relations. In our experiment, our supervisor performs the best when \( \gamma = 0.5 \).

**Aligned Triple Set:** Our system ranks the relation pairs between the candidate triples from \( T' \) and the triples in the prior KG using their TRAS scores. As a result, our system translates the candidate triples from the JEE process to an aligned triple set with the same relation set in the prior KG. The aligned triple set is denoted by \( \Delta T \).

**Knowledge Graph Embedding (KGE) Triple Likelihood:** After generating the aligned candidate triple set from the extracted triples, the supervisor ranks the candidate triples and merges the top-ranked triples to the current prior KG. To this end, we use a Knowledge Graph Embedding (KGE) Triple likelihood to perform the ranking task for triples. This function represents the action of the supervisor and it is implemented using a Convolutional Neural Network (CNN) [40] based model to map the triples to an \( \mathbb{R}^1 \) score. Theoretically, our framework can enhance the performance of the supervisor with any KGE module. The CNN-based KGE is a commonly used method [41], [42] in recent KGE works, since it obtains the latent features automatically. This module can be substituted into consequential works if necessary.

Formally, given a KG \( G = (E, R, T) \), for any two entities \( i \) and \( j \) \((i \in E \text{ and } j \in E)\) and a relation \( r \in R \), the KGE triple likelihood \( f_G(i, r, j) \) is computed as follows:

\[ f_G(i, r, j) = \delta(F([C_1, C_2, C_3, \ldots, C_m])), \quad (12) \]

where \( \delta \) is the Sigmoid function, \( F \) is a fully-connected layer to map the concatenated convolution results to a \( \mathbb{R}^1 \) score that refers to the plausible probability for the triple \((i, r, j)\) based on \( G \). The quantity \( C_n \) is the \( n \)-th convolutional result which can be computed as follows:

\[ C_n = \text{Maxpool}(\text{ReLU}(W_n \circ [e_1^T, e_2^T, e_3^T] + b_n)), \quad (13) \]

where \( W_n \) is the \( n \)-th \((n=1, 2, \ldots, m)\) convolutional kernel and \( b_n \) is the corresponding bias, \( \circ \) is the convolution operator, \( \text{Maxpool} \) is the Maxpooling function, \( \text{ReLU} \) is the ReLU active function and \( e_r \) is the embedding vector for the relation \( r \). To alleviate the problems of sparsity in the extracted relations, rather than the one-hot encoding with a fixed dictionary, we applied a similar method to (8) to sum all the tokens in a relation mention to obtain the embedding vector \( e_r \) of a relation \( r \).
Benchmark Entity Pairs Sampling.

Data: a KG $G = (E, R, T)$, the embedding mapper $E$ from the JEE process, a threshold $k$.

Result: the positive entity pair set $P^+$, the negative entity pair set $P^-$.

1: begin
2: Compute all $f_G(i, r, j)s$, where $(i, r, j) \in T$, with (12).
3: Sort the triples in $T$ in ascending order and select the top-k ranked entity pairs $P^+$.
4: Enumerate all the negative triples $N$ (where $E, R$).
5: Compute all $f_G(i, r, j)s$, where $(i, r, j) \in N$, with (12).
6: Sort the triples in $T'$ in descending order and select the top-k ranked entity pairs $P^+$.
7: Output $P^+$ and $P^-$.
8: end

Algorithm 1: Benchmark Entity Pairs Sampling.

The KGE triple likelihood is trained by optimizing a BPR loss function, as follows:

$$L_s = -\sum_{(i, r, j) \in T} \log \left[ \delta(f_G(i, r, j) - f_G(i', r, j')) \right].$$ (14)

Optimizing $L_s$ maximizes the difference between the positive and negative triples. Since this training uses all of the triples in $G$, the trained KGE triples likelihood represents the action of a supervisor based on the current KG.

Benchmark Entity Pairs Sampling: Using the KGE triple likelihood, we introduce an algorithm (cf. Algorithm 1) to acquire the most prominent positive and negative set pairs, utilizing the existing KG and embedding.

The sampled positive and negative entity pairs are used directly as the benchmarks to supervise the explorer process (cf. (6)). This simulates the way in which the supervisor provides the key examples to the explorer for the exploration task.

D. Complete Process and Discussion

The complete collaborative knowledge graph fusion process is described in the Algorithm 2. We initialize the embeddings for all tokens in the corpus with pre-trained features. Specifically, the BERT [37] is adopted in this paper, and alternative methods could potentially be used if necessary. These embeddings are then used in the supervisor process to infer the positive or negative entity pair sets using a prior knowledge graph. Next, the obtained positive and negative entity pair sets are used to supervise the explorer process. Then, the JEE model in the explorer process extracts improved entities and relations to enrich the prior knowledge graph. The supervisor utilizes beam search to include the top-$K$ ranked aligned candidate triples.

Discussion: Our model integrates event extraction and knowledge graph fusion into a unified process. This alternative process enhances the performance of both of the aforementioned tasks and yields a high-quality enriched KG. The main reasons for these improvements are twofold. First, by incorporating more valuable knowledge implications (evaluated extracted triples from the corpus) into a given knowledge graph, the semantic relationships between its entities are enhanced, thereby improving the performance of the knowledge graph embedding. Second, the accuracy of the entity and relation extraction tasks is also bolstered through the utilization of the enriched knowledge graph.

E. Negative Triple Sampling and Training

Many existing methods use the randomized head or tail entity to replace triples from the positive triple set as the negative samples [43]. To further improve the quality of the negative samples in Line 11 of Algorithm 2, we treat the output of random sampled negative triples as the candidate set and then further use the KGE triple likelihood to measure their likelihoods. The final negative samples set in Line 11 of Algorithm 2 are the top-ranked samples from the candidate set based on the KGE triple likelihood scores.

Algorithm 2: Collaborative Knowledge Graph Fusion Algorithm.

Data: A prior KG $G = (E, R, T)$, a corpus $D$ and a threshold $k$ for the polarity triple sampling and a threshold $\varepsilon$ for the KG enrichment.

Result: An enriched KG $G'$.

1: begin
2: Initialize the embedding mapper $E$ for all the tokens using the pre-trained features.
3: let $G' \leftarrow G$, $T' \leftarrow \phi$.
4: while $\text{Round in } [0, K)$ do
5: Supervisor process:
6: if $T' \neq \phi$ then
7: Align the relations in $T'$ to $R$ with (10).
8: $\Delta T \leftarrow \text{Find the top-K triples in the aligned } T'$ with the trained $f_G(\cdot)$.
9: $T' \leftarrow \Delta T \cup T'$.
10: end
11: Sample the negative triple set $N$ based on $T'$.
12: Train the KGE triple likelihood $f_G(\cdot)$ by minimizing (14), with $T'$ and $N$.
13: Sample the top-k positive and negative entity pairs $P^+$ and $P^-$ based on Algorithm 1 with $T'$ and the embedding map $E$.
14: Explorer process:
15: Train the benchmark-based supervision JEE by minimizing the function in (9) with JEE training data.
16: Exhaustively generate the candidate triples $T''$ based on the mention results from the JEE testing data with the trained JEE.
17: end
18: Output $G'$.
19: end
IV. EXPERIMENTS AND ANALYSIS

In this section, we aim to address the following research questions:

- **RQ1**: Can the proposed Collaborative Knowledge Graph Fusion framework successfully enhance the performance for both the JEE and KGF (or KGE) tasks?
- **RQ2**: What is the generalizability of the proposed Collaborative Knowledge Graph Fusion framework representation across different real-world corpora and KGs?
- **RQ3**: Do the automatically extracted and translated triples provide valuable additional knowledge for the target KG? We also perform an ablation analysis to investigate the effect of each module of the model in turn, as well as a qualitative analysis of detailed examples.

A. Datasets

Since our system consists of the optimization processes of the JEE together with the KGF, our dataset contains several real-world corpora to test the JEE and also two public KGs to test the KGF.

**The Corpora**: ACE 2005 [31] is a widely used dataset that has been adopted to test the performance of event extraction models. WebNLG is a corpus used for a challenge involving natural language generation [44]. CoNLL is a Spanish news corpus from [45]. We create the NYT and CoNLL datasets used in our study by preprocessing the original NYT [46] and CoNLL [45] corpora with the CoreNLP. This preprocessing includes annotating the triggers and entities from the text sentences.

**The Knowledge Graphs**: In order to implement the benchmark-based supervision mechanism in the explorer process, we preprocess WN18 and FB15k-237 [28] and use them as the prior KGs for evaluation. As the entities in each KG are encoded as inner IDs, we map these IDs to real entity text mentions using the corresponding mapping files. Additionally, due to the deprecation of the freebase API, we map the entity IDs in FB15k-237 to the URLs on Wikidata and subsequently crawl the Wikidata titles to generate the real entity text mentions.

**Preprocessing Details**: To implement a complete collaborative knowledge graph fusion framework, we preprocess the datasets to obtain training sets and testing sets respectively for the supervisor and explorer. The details of these preprocessed datasets are listed in Tables I and II.

### Table I: Summary of the Corpora for the Explorer (JEE) Process

|        | ACE2005 | NYT | CoNLL | WebNLG |
|--------|---------|-----|-------|--------|
| Sentences | 17,606  | 6,355 | 3,903 | 3,973  |
| Training sent. | 16,765  | 5,500 | 3,000 | 2,649  |
| Testing sent. | 841     | 855  | 903   | 1,324  |

### Table II: Summary of the KGs for the Supervisor (KGF) Process

|        | ACE2005 | CoNLL | NYT | WebNLG |
|--------|---------|-------|-----|--------|
| FB15K  | Seed triples | 20,000 | 3,440 | 3,000 |
| Testing triples | 969 | 698 | 1,129 | 1,786 |
| WN18   | Seed triples | 526  | 68  | 2,042 |
| Testing triples | 129 | 68 | 730 | 113 |

B. Comparison Baselines

To evaluate the performance of our proposed approach, we compare it with the following baselines for both the JEE and the KGF tasks.

**JEE Baselines**

- **StagedMaxEnt** [36] and TwoStageBeam [47] are two classic methods based on a pipe-lined framework to jointly extract the event factors.
- **Reranking** [36] is a state-of-the-art statistical joint event extraction method.
- **Seq2Seq** [48] is a model for JEE based on the sequence-to-sequence framework. Our experiments use the universal sequence-to-sequence framework implementation from [16].
- **Seq2Seq+** [48] is the extended Seq2Seq model with the Glove [49] pre-trained features.
- **CRF** [48] is a method extended from Seq2Seq with a conditional random field layer containing the Glove [49] pre-trained features.
- **BERT** [37] is the original BERT with Seq2Seq downstream layers.
- **Joint3EE** [50] is an embedding-based method to extract the entities, event triggers, and arguments concurrently.
- **REKnOw** [51] is a Seq2Seq joint model that leverages knowledge bases to obtain enhanced features.
- **Benchmark-based Supervision JEE (BJEE)** is the joint model proposed in this paper. Our model is supervised using the benchmark entity pairs sampled from a given knowledge graph. It is based on the explorer process described in Section III-B. The subscripts in the experimental results are the names of the given knowledge graphs.

**KGF Baselines**

- **TransE** [28] is a classic statistical KGF model. It assumes that the triple relations can be represented as the difference between the head and tail entity vectors of the triples. The method trains the latent vectors for all the triples based on this assumption.
- **ConvE** [29] is a KGF method that concatenates the vectors for entities to create a matrix to represent the triples. It applies a convolutional neural network to capture the proximity between entities in a triple.
- **Supervisor** is the method proposed in this paper and described in Section III-C. It iteratively enriches its training knowledge triples with the results extracted from the explorer process.

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1. https://github.com/hkharryking/labeled_NYT_CoNLL
2. https://stanfordnlp.github.io/CoreNLP/
3. https://www.wikidata.org
C. Evaluation Metrics

Evaluation metrics for JEE: The performance of JEE is measured by the Precision, Recall, and F1 scores for the triggers, the entities, and the arguments. Precision is measured by the ratio of the number of correct tags output from all the tokens in a corpus. Recall is the ratio of the number of predefined tags contained in the output tags.

Evaluation metrics for KGF: In the KGF task, we use MRR, Hit@30, Hit@40, and Hit@50 as the metrics to measure how well a model predicts the possibility of a triple. Concretely, the MRR (Mean Reciprocal Rank, MRR) is computed using the definition

\[
MRR = \frac{1}{n} \sum_{t \in T} \frac{1}{\text{rank}_t},
\]

where \( T \) is the test triple set and \( \text{rank}_t \) is the practical rank for \( t \) in the predicted list. \( \text{Hit@}n \) is the ratio of the number of positive triples that are in the top-\( n \) ranked triples (\( n = 30, 40, 50 \) in our experiment) in the test triple set \( T \).

Since our method runs using the JEE and KGF tasks alternately, in order to improve efficiency, we pre-sampled the positive and negative triples from the test triple set and saved them to files. Our evaluation of the performance of the KGF tasks is based on these pre-sampled triples.

D. Prototype System and Implementation Details

We implement a prototype system with the proposed collaborative knowledge graph fusion framework with PyTorch. This system consists of a) an explorer process that performs the JEE task to extract the triples from a corpus and b) a supervisor process that conducts KGF to train the KGE triple likelihood based on the prior KG. As introduced in Sec. III, our system enriches a prior KG as follows. Initially, the explorer process extracts triples from a provided corpus while guided by the supervisor, employing the benchmark-based supervision mechanism. After the explorer submits the triples to the supervisor, the supervisor translates them to match the form of its prior KG. Using the translated triples, the supervisor evaluates their quality by considering the KGE triple likelihood, which reflects its own comprehension of the prior KG. Finally, the supervisor merges high-quality triples found in the previous step, adding them to its prior KG, and then also updates the benchmarks used by the explorer.

For fair comparisons, all of the sequence-to-sequence encoders were implemented based on a BERT [37] with 768 hidden dimensions. Since our framework requires two alternating processes, we use an Adam optimizer [52] with a 1e-3 learning rate and 30 epochs to train the explorer process for non-BERT models. Additionally, all the BERT-based models, including our own, are trained with a 2e-5 learning rate and 30 epochs. We apply an Adamoptimizer with a 1e-1 learning rate and 20 epochs to train the supervisor process. The number of rounds performed by the collaborative knowledge graph fusion framework is set to 8 for all of our models. Both the weights for the benchmark-based supervision and the mention similarity (\( \alpha \) and \( \gamma \)) are set to 0.5 in the prototype system. The prototype system runs on a Linux server with 4 NVIDIA 2080TI GPUs.

E. Comparison on JEE (RQ1 and RQ2)

We compare our model with the alternatives on the standard event extraction dataset ACE 2005. The results of the event trigger and argument extractions are shown in Table III. The performance on all related sub-tasks of our model is superior to the alternatives. We further compare the performance of the text entity detection of our model with the alternative methods. Here our method also outperforms the alternatives (in Table IV). All of these results verify the effectiveness of the proposed supervisor-explorer mechanism in improving the performance of the JEE process. We also find that the Seq2Seq uniform framework improves performance on the argument identification and classification tasks.

To validate the universality of our method, we compare the overall extraction performance for the proposed JEE models guided by FB15 K and WN18 knowledge graphs on each of the real-world datasets in Table V. Since many of the published methods do not report results on these datasets, we only report the results of our implemented methods in this experiment. Our proposed method extracts better text mentions (both the event argument and trigger mentions) than the alternative non-knowledge-base-guided methods. Furthermore, an interesting observation that can be drawn from these results is that, although the CONLL is a Spanish corpus, the performance of the event extraction tasks on it can still be improved by the proposed framework with the English-text knowledge graphs (FB15 K and WN18). The reason for this is that many proper nouns are shared by both Spanish and English, and their semantic structure may assist the event extraction in Spanish. All of the results in this experiment verify that the proposed collaborative knowledge graph fusion framework effectively improves the performance of the JEE processes.

F. Comparison on KGF (RQ1 and R2)

We compare the performance of our method with the alternative KGF models on the triple prediction task. The experiment is conducted in the following way. First, the classic models TransE and ConvE are directly trained on the training set of the knowledge graph FB15 K. The supervisor of our model is trained with an enriched training set that is obtained through the proposed supervisor-explorer collaborative learning process. Second, all of the models are tested with the same testing set of FB15 K. The results of the supervisor model are obtained by alternately running the supervisor and explorer processes for 8 rounds. Third, due to the extensive time required to exhaustively enumerate all negative triples on our hardware platform, we opted to utilize a subset of 200 randomly sampled negative triples alongside their corresponding positive triples as the test set for computing performance metrics. The results of this experiment are presented in Table VII. From this table, we observe that with the enriched triples, the performance of our KGF model is improved. This verifies that the obtained triples from our collaborative knowledge graph fusion framework offer valuable
TABLE III

| Model         | Event Trigger Identification | Event Trigger Classification | Event Argument Identification | Event Argument Classification |
|---------------|------------------------------|------------------------------|-------------------------------|------------------------------|
|               | Precision | Recall | F1   | Precision | Recall | F1   | Precision | Recall | F1   | Precision | Recall | F1   | Precision | Recall | F1   |
| StagedMaxEnt  | 73.9      | 66.5   | 70.0 | 70.4      | 63.3   | 66.7 | 75.7   | 20.2      | 31.9  | 71.2  | 19.0   | 30.0   |
| TwoStageBeam  | 76.6      | 58.7   | 66.5 | 74.0      | 56.7   | 64.2 | 74.6   | 25.5      | 36.0  | 68.8  | 23.5   | 35.0   |
| Ranker       | 77.6      | 65.4   | 71.0 | 75.3      | 63.3   | 68.7 | 73.7   | 36.5      | 50.6  | 70.6  | 36.9   | 48.6   |
| Join3EE      | 70.5      | 74.5   | 72.5 | 68.0      | 71.8   | 69.8 | 59.9   | 59.8      | 59.9  | 52.1  | 52.1   | 52.1   |
| Seq2Seq      | 66.7      | 62.4   | 64.5 | 57.3      | 53.7   | 55.5 | 62.8   | 72.8      | 67.5  | 46.3  | 56.6   | 50.9   |
| Seq2Seq*     | 72.4      | 67.5   | 69.9 | 69.7      | 65.0   | 67.2 | 72.7   | 75.0      | 73.8  | 58.7  | 67.0   | 62.6   |
| CRF*         | 71.9      | 73.6   | 72.7 | 68.2      | 68.2   | 68.2 | 70.7   | 79.6      | 74.9  | 58.7  | 66.0   | 62.1   |
| BERT         | 75.0      | 75.0   | 75.0 | 75.0      | 75.0   | 75.0 | 82.8   | 72.6      | 77.4  | 71.4  | 69.0   | 70.2   |

TABLE IV

| Model         | Precision | Recall | F1   |
|---------------|------------|--------|------|
| Seq2Seq       | 67.5       | 83.2   | 74.6 |
| Seq2Seq*      | 74.4       | 85.1   | 79.4 |
| CRF*          | 75.2       | 84.6   | 79.6 |
| Ranker        | 82.4       | 79.2   | 80.7 |
| PipelineGRU   | 80.6       | 80.3   | 80.4 |
| Join3EE       | 82.0       | 80.4   | 81.2 |
| BERT          | 89.2       | 78.3   | 83.4 |

Fig. 3. The overall extraction performance of the explorer process with different rounds and supervised under the WN18 knowledge base.

Fig. 4. The performance of our system under different explorers.

Fig. 5. The performance of our system under different supervisors.

G. Ablation Analysis (RQ2)

Since we use BERT [37] as the sequence-to-sequence encoder for our model, we compare the experimental results of our models (i.e., BJEE_{wn18} and BJEE_{f615k}) with the pure BERT [37] model (having the same hidden dimensions) in Table III, Tables IV and V. With the proposed benchmark-based supervision mechanism, our results significantly outperform those obtained with pure BERT after the iterative learning process between the supervisor and explorer. To further discuss the influence of the iterative process, we also provide an experiment to compare the overall JEE performance with different iterative rounds. The results are shown in Fig. 3. From this figure, the overall JEE performance improves with an increasing number of iterations. This shows that the alternating iterative process

between the explorer and supervisor in our model improves the overall performance of the JEE task.

H. Sensitivity Analysis

In order to further analyze the details of the proposed collaborative knowledge graph fusion framework, we provide several experiments to study its performance with different forms of the supervisor and explorer processes.

Fig. 4 shows the performance of our system with a fixed supervisor (with 4 CNN kernels) and explorers with different numbers of hidden dimensions. From the figure, it is clear that with the same supervisor, then an explorer with more hidden dimensions performs better. Fig. 5 gives the performance of our system with a fixed explorer (with 150 hidden dimensions) under supervisors with different numbers of CNN kernels. From this figure, we observe that, with the same explorer, the performance of our system is optimal for a particular choice of the number of CNN supervisor kernels. In this experiment, the optimal number of kernels is 32. The two aforementioned experiments indicate that the overall performance of a system with the proposed framework can be optimized by improving the explorer process,

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and the overall performance improvement is limited by the explorer under different supervisors.

### I. Case Study: Translate and Align the Triples (RQ3)

As introduced in Algorithm 2, the explorer process of our system extracts new triples from the given corpus (ACE 2005) and generates a mapper to align the relations of these extracted triples to the relations in the knowledge graph (FB15 K). Then, with the aligned relation mapper, our prototype system translates all of the extracted triples into the form of the target knowledge graph. In the final step, the explorer process ranks these translated triples with the trained KGE likelihood function from the supervisor and submits the top-ranked triples to the supervisor.

To further analyze the detailed performance of the proposed TRAS (Translated Relation Alignment Score) method, we explore the automatically aligned relations using our collaborative knowledge graph fusion framework in the task to explore (extract) the ACE 2005 corpus guided by the FB15 K knowledge graph.

We select some top-ranked aligned and translated triples from the ACE 2005 corpus identified by our system and list them in Table VI. Most of these triples are aligned to the appropriate relations in FB15 K and thus generate proper triples for FB15 K based on the given corpus. For example, our system aligns and the trigger mention “killed” of the type “Life” to the FB15 K relation “/people/deceased_person/place_of_death” for the 1-st triple extracted from the ACE 2005 corpus. Our system infers that the trigger mention “killed” of the ACE 2005 corpus is highly similar to the relation “/people/deceased_person/place_of_death” of the knowledge graph FB15 K. In this result, our system infers that the trigger mention “killed” of the ACE 2005 corpus is aligned to the relation “/people/deceased_person/place_of_death” of the knowledge graph FB15 K. Our system makes this inference by considering both the semantic similarity between the text mentions ‘killed” and “deceased” and the affinities of the “PER” entities around the corresponding relations in the two sources. This shows that the proposed TRAS score provides a possible route for fully-automatic knowledge graph fusion in future work.

### V. RELATED WORK

#### A. Joint Event Extraction

Joint event extraction (JEE) [54] aims to simultaneously obtain the named entities, trigger text mentions, and relations from a given corpus. Several recent studies employ the pipe-lined method to accomplish this objective. First, a series of classifiers are trained for the aforementioned sub-tasks to classify the text mentions in sentences as distinct triggers. Second, the classified triggers are utilized to identify the entity text mentions or relations. StagedMaxEnt [36] and TwoStageBeam [47] are examples of such pipe-lined systems. Reranking [36] is a state-of-the-art statistical pipe-lined method for the JEE task.

Most neural network models apply the embedding method to capture the latent semantic relationships between sentence tokens and attempt to train different classifiers for different sub-tasks. Joint3EE [50] is such a method that uses the multitask learning framework. However, since the separate training required for different classifiers increases the sparsity of the samples needed for each individual classifier, the performance improvement from these methods is limited. Recent work [55] provides end-to-end models for this task. Sequence-to-sequence methods [16] train a neural network to match a sentence in the form of a token sequence to a labeled sequence. This type of
method reduces all of the individual sub-tasks to a single classifier and alleviates the sparse problem of entity relationships. Moreover, REKnow [51] leverages knowledge bases to obtain enhanced features for the entities, and thus further improves the performance of the sequence-to-sequence joint method.

B. Knowledge Graph Fusion

Knowledge graph fusion [18] aims to fuse a knowledge graph with additional data sources. Many KGF systems apply an “enumerate-and-rank” framework [26] to complete the knowledge graph. That is, they train classifiers based on a given knowledge graph and identify the possible triples from a series of candidate triples. Usually, such classifiers are based on the knowledge graph embedding (KGE) [56] method. TransE [28] is a classic KGE method used to learn the embedding vectors needed to represent the triples in a knowledge graph. Much recent work applies neural network methods to improve the performance of the KGE task. ConvE [29] is a neural network KGE model with convolutional neural network modules. Recent work focuses on providing the embeddings by considering the heterogeneity of the knowledge graphs [57] or the heterogeneous information networks [58]. However, to the best of our knowledge, none of the existing methods directly considers integrating the JEE with the KGE task.

C. Open Information Extraction

Open Information Extraction (Open IE) [59] is an alternative way to generate structural information from text sources. Traditional methods [60] obtain new facts in the form of relations to create a KG based on hand-crafted patterns. Recent work [61] applies neural relation extraction methods to directly generate relational facts from a given corpus and integrate them into an existing KG. During the integration process, these methods train a classifier to judge the correctness of the obtained relations according to the given KG. However, although the current Open IE methods extract relational facts (triples) directly from text sources, few of them address how to automatically merge the obtained facts to create a uniform and high-quality KG.

VI. CONCLUSION AND FUTURE WORK

This paper has proposed a novel collaborative knowledge graph fusion framework to integrate the joint event extraction and the knowledge graph fusion tasks together. The implemented prototype system with the proposed framework can both extract the entity and trigger text mentions and enrich the extracted mentions to a knowledge graph in the form of the knowledge graph triple (i.e., entity-relation-entity). To this end, we propose a benchmark-based supervision mechanism to guide the event extraction process of our system with a given knowledge graph. Our system also merges the extracted triples to the target knowledge graph by referring to the proposed Translated Relation Alignment Score. We test our prototype system on several real-world corpora and knowledge graphs. The experimental results show that our method improves the performance of both the event extraction and knowledge graph fusion processes after the alternative training. Moreover, the aligned and translated relations from our system also show good interpretability. Our future work will aim to align the triples directly with their semantic meanings to further improve the performance of our model.

REFERENCES

[1] X. Wang, X. He, Y. Cao, M. Liu, and T. Chua, “KGAT: Knowledge graph attention network for recommendation,” in Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining., Anchorage, AK, USA, A. Teredesai, V. Kamar, Y. Li, R. Rosales, E. Terzi, and G. Karypis, Eds., 2019, pp. 950–958.
[2] K. Annervaz, S. B. R. Chowdhury, and A. Dukkipati, “Learning beyond datasets: Knowledge graph augmented neural networks for natural language processing,” in Proc. Conf. North Amer. Assoc. Comput. Linguistics: Hum. Lang. Technol., 2018, pp. 313–322.
[3] A. Talmor and J. Berant, “The web as a knowledge-base for answering complex questions,” in Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics: Hum. Lang. Technol., M. A. Walker, H. Ji, and A. Stent, Eds., New Orleans, Louisiana, USA, Association for Computational Linguistics, 2018, pp. 641–651.
[4] S. Hu, L. Zou, J. X. Yu, H. Wang, and D. Zhao, “Answering natural language questions by subgraph matching over knowledge graphs,” IEEE Trans. Knowl. Data Eng., vol. 30, no. 5, pp. 824–837, May 2018.
[5] W. Shen, Y. Yin, Y. Yang, J. Han, J. Wang, and X. Yuan, “Toward tweet entity linking with heterogeneous information networks,” IEEE Trans. Knowl. Data Eng., vol. 34, no. 12, pp. 6003–6017, Dec. 2022.
[6] D. Vrandecic and M. Krötzsch, “Wikidata: A free collaborative knowledge graph,” Commun. ACM, vol. 57, no. 10, pp. 78–85, 2014.
[7] G. A. Miller, “Wordnet: A lexical database for english,” Commun. ACM, vol. 38, no. 11, pp. 39–41, 1995.
[8] K. D. Bollacker, C. Evans, P. Paritosh, T. Sturge, and J. Taylor, “Freebase: A collaboratively created graph database for structuring human knowledge,” in Proc. ACM SIGMOD Int. Conf. Manage. Data, Vancouver, BC, Canada, J. T. Wang Ed., 2008, pp. 1247–1250.
[9] M. Färber, F. Bartscherer, C. Menne, and A. Rettinger, “Linked data quality of dbpedia, freebase, opencyc, wikidata, and YAGO,” Semantic Web, vol. 9, no. 1, pp. 77–129, 2018.
[10] J. Li, A. Sun, J. Han, and C. Li, “A survey on deep learning for named entity recognition,” IEEE Trans. Knowl. Data Eng., vol. 34, no. 1, pp. 50–70, Jan. 2022.
[11] D. Liu et al., “News graph: An enhanced knowledge graph for news recommendation,” in Proc. ACM Int. Conf. Inf. Knowl. Manage., Beijing, China, CEUR-WS.org, 2019, pp. 1–7.
[12] G. Lample, M. Ballesteros, S. Subramanian, K. Kawakami, and C. Dyer, “Neural architectures for named entity recognition,” in Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics: Hum. Lang. Technol., San Diego California, USA, The Association for Computational Linguistics, N. Knight, A. Nenkova, and O. Rambow, Eds., 2016, pp. 260–270.
[13] Y. Lin, S. Shen, Z. Liu, H. Luan, and M. Sun, “Natural relation extraction with selective attention over instances,” in Proc. 54th Annu. Meet. Assoc. Comput. Linguistics, Berlin, Germany, The Association for Computer Linguistics, 2016.
[14] M. Koutrakis, N. Preda, and D. Vodislav, “Online relation alignment for linked datasets,” in Proc. Eus. Semantic Web Conf., E.D. Blomqvist Maynard, A. Gangemi, R. Hoeckstra, P. Hitzler, and O. Hartig, Eds., 2017, pp. 152–168.
[15] X. Zhao, Y. Jia, A. Li, R. Jiang, and Y. Song, “Multi-source knowledge fusion: A survey,” World Wide Web, vol. 23, no. 4, pp. 2567–2592, 2020.
[16] Y. Wang et al., “Cross-supervised joint-event-extraction with heterogeneous information networks,” in Proc. 25th Int. Conf. Pattern Recognit., 2020, pp. 278–285, doi: 10.1109/ICPR48806.2021.9413232.
[17] P. Huang, X. Zhao, R. Takanobu, Z. Tan, and W. Xiao, “Joint event extraction with hierarchical policy network,” in Proc. 28th Int. Conf. Comput. Linguistics, Barcelona, Spain, International Committee on Computational Linguistics, 2020, pp. 263–266.
[18] H. L. Nguyen, D. Vu, and J. J. Jung, “Knowledge graph fusion for smart systems: A survey,” Inf. Fusion, vol. 61, pp. 56–70, 2020.
[19] X. Dong et al., “Knowledge vault: A web-scale approach to probabilistic knowledge fusion,” in Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining, New York, NY, USA, S. A. Macskassy, C. Perlich, J. Leskovec, W. Wang, and R. Ghani Eds., 2014, pp. 601–610.
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[61] B.D. Trisedya, G. Weikum, J. Qi, and R. Zhang, “Neural relation extraction for knowledge base enrichment,” in Proc. 57th Conf. Assoc. Comput. Linguistics, A. Korhonen, D.R. Traum, and L. Márquez, Eds., Florence, Italy, Association for Computational Linguistics, 2019, pp. 229–240.
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