Schema-aware Reference as Prompt Improves Data-Efficient Relational Triple and Event Extraction

Yunzhi Yao1, Shengyu Mao1, Xiang Chen1, Ningyu Zhang1†, Shumin Deng2, Huajun Chen1†
1Zhejiang University, China & AZFT Joint Lab for Knowledge Engine, China
2National University of Singapore, Singapore
{yyztodd,shengyu,xiang_chen,zhangningyu,huajunsir}@zju.edu.cn, shumin@nus.edu.sg

ABSTRACT
Information Extraction, which aims to extract structural relational triple or event from unstructured texts, often suffers from data scarcity issues. With the development of pre-trained language models, many prompt-based approaches to data-efficient information extraction have been proposed and achieved impressive performance. However, existing prompt learning methods for information extraction are still susceptible to several potential limitations: (i) semantic gap between natural language and output structure knowledge with pre-defined schema; (ii) representation learning with locally individual instances limits the performance given the insufficient features. In this paper, we propose a novel approach of schema-aware Reference As Prompt (RAP), which dynamically leverage schema and knowledge inherited from global (few-shot) training data for each sample. Specifically, we propose a schema-aware reference store, which unifies symbolic schema and relevant textual instances. Then, we employ a dynamic reference integration module to retrieve pertinent knowledge from the datastore as prompts during training and inference. Experimental results demonstrate that RAP can be plugged into various existing models and outperforms baselines in low-resource settings on four datasets of relational triple extraction and event extraction. In addition, we provide comprehensive empirical ablations and case analysis regarding different types and scales of knowledge in order to better understand the mechanisms of RAP.

CCS CONCEPTS
• Information systems → Information extraction.

KEYWORDS
Relational Triple Extraction, Event Extraction, Prompt Learning

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference acronym ‘XX’, June 03–05, 2022, Woodstock, NY
© 2022 Association for Computing Machinery.
ACM ISBN 978-1-4503-XXXX-X/18/06 . $15.00
https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION
Information Extraction (IE) – the ability to automatically retrieval of specific relational triple and event from texts – holds an important place in natural language processing (NLP) [4, 7, 42] and knowledge graph (KG) [6, 21, 39, 51, 52, 58], and can provide back-end support for various applications such as web content analysis [31] and question answering [13]. Most prior works on IE rely on a large amount of labeled data for training [59]; however, high-quality annotations are expensive to obtain. Thus, many data-efficient approaches have been proposed [8, 11, 27, 40, 41, 55], in which prompt learning with Pre-trained Language Models (PLMs) yields promising performance. For example, [10] designs a structured prompt template for generating synthetic relation samples for data-efficient relational triple extraction. [17] formulates event extraction as a conditional generation problem with a manually designed prompt, which achieves high performance with only a few training data.

Existing methods, however, still suffer from several potential limitations. First, different from general NLP tasks, IE tasks such as relational triple extraction and event extraction target to conduct structure prediction, in which the output should conform to the pre-defined schema. Extensive raw text data used for PLMs do not necessarily contain sufficient patterns relevant to task-specific prompts, resulting in a semantic gap between input sequence and
schema. In addition, previous prompt learning works follow the parametric-based learning paradigm. They may fail to generalize well for complex examples and perform unstably with limited training data since the scarce or complex examples are not easy to be learned in parametric space during optimization. For example, texts mentioning the same event type can vary significantly in structure and meaning. “A man was hacked to death by the criminal” and “The aircraft received fire from an enemy machine gun” both describe an Attack event, although they are almost literally different. With only a few-shot training samples, the model may struggle to discriminate such complex patterns and extract correct information.

To overcome the aforementioned limitations, we try to fully leverage the schema and global information in training data as references for help. Note that humans can use associative learning to recall relevant skills in memories to conquer complex tasks with little practice. Similarly, given the insufficient features of a single sentence in the low-resource setting, it is beneficial to leverage that schema knowledge and the whole training data to provide reference and enrich the semantics of individual instances [49]. Motivated by this, as shown in Figure 1, we propose a novel approach of schema-aware Reference As Prompt (RAP), which dynamically leverages symbolic schema and knowledge inherited from training data as prompt to enhance the PLMs for IE.

However, there exist two problems: (1) Collecting reference knowledge: Since rich schema and training instances are both advantageous to enrich features of the single instance; thus, it is necessary to collect reference knowledge derived from both of them. (2) Leveraging reference knowledge: Plugin-in-play integrating those reference knowledge to existing IE models is also challenging since there are various types of IE models (e.g., generation-based and classification-based methods).

To address the problem of collecting reference knowledge, we propose a schema-aware reference store to enrich schema with text instances. Specifically, we align training instances with structured schema; thus, symbolic knowledge and textual corpus are in the same space for representation learning. Then we construct a unified reference store containing the knowledge derived from both symbolic schema and training instances. To address the problem of leveraging reference knowledge, we propose dynamic reference integration to select informative knowledge as prompts. Since not all external knowledge is advantageous, we utilize a retrieval-based method to dynamically select knowledge as prompts that are the most relevant to the input sequence from the schema-aware reference store. In this way, each sample can achieve diverse and suitable knowledgeable prompts that can provide rich symbolic guidance in low-resource settings.

To demonstrate the effectiveness of our proposed RAP, we apply it to relational triple extraction and event extraction tasks. Note that our approach is model-agnostic and readily pluggable into any previous approaches. We evaluate the model on two relation triple extraction datasets: NYT and WebNLG, and two event extraction datasets: ACE05-E and CASIE. Experimental results show that RAP model can perform better in low-resource settings. The contributions of this study can be summarized as follows:

- We propose an approach of schema-aware Reference As Prompt (RAP) for data-efficient relational triple extraction and event extraction, which can be plugged to various previous IE models.
- We propose a schema-aware reference store and a dynamic reference retrieval mechanism to address the issues of collecting and leveraging reference knowledge in the RAP model.
- We conduct comprehensive experiments on four benchmark datasets, which demonstrate the effectiveness of our approach in low-resource settings.

2 PRELIMINARIES

In this paper, we apply our approach RAP to different information extraction models and notice that RAP demonstrates better performance than these different baselines. We first introduce the definitions of relation triple extraction and event extraction and then illustrate the basic structure of current models.

2.1 Task Definition

Event Extraction. Event extraction refers to the process of mechanically extracting organized event data from unstructured natural language texts under the guidance of an event schema. An event is a specific occurrence involving participants that consists of a trigger and a set of arguments: the trigger word is the word or phrase that most accurately depicts the occurrence of an event; the event argument is an entity participating in the event or an attribute value (such as time, tool) of the event. For example, given the sentence “A man was hacked to death by the criminal,” an Attack event is triggered by the word “hacked,” and this event contains two argument roles: an Attacker (criminal) and a Victim (He).

Relation Triple Extraction. Joint extraction of entity mentions and their relations which are in the form of a triple (subject, relation, object) from unstructured texts, is an important task in information extraction. Suppose the input is $S$, and the desired outputs are relational triples as $(s, r, o) | s, o \in E, r \in R$, where $E$ and $R$ are the entity and relation sets, respectively.

For instance, given the sentence “His 35-year career at Moil Oil includes a four year assignment in Tokyo, Japan as head of Mobil Far East,” the model should identify two entities Tokyo and Japan and their relation capital of.

2.2 Basic Structure

Given an original text $S$, the purpose of the information extraction task is to obtain target information $Y = \{Y_1, \ldots, Y_t\}$, where $Y_j$, $j \in t$ represents the information to extract for the j-th type, and $t$ refer to the number of types. RAP is a pluggable method, and here we introduce the architecture of the generation-based model.

For the relation triple extraction task, $Y^t$ is in the form of triples $Y^t = (e_{head}, r, e_{tail})$, including the head entity, tail entity and their relation. For the event extraction task, $Y^t$ contains the corresponding event record in the sentence, which can be represented as $Y^t = (event – type, trigger, argument – role)$. Previous baselines usually leverage classification-based architectures [59] or formulate IE task as a conditional generation problem [10, 17] by a pre-trained
Hariri submitted his resignation during a 10-minute meeting with the head of state at the Baabda presidential palace.

Paul Allen, a co-founder of Microsoft, paid the bills for aircraft designer Burt Rutan to develop Space Ship One.

He commanded several ships to transport convicted felons from London to Maryland.

Figure 2: The architecture of schema-aware Reference As Prompt (RAP), which is model-agnostic and is readily pluggable into many existing IE approaches TEXT2EVENT [35], DEGREE [17], PRGC [59], RELATIONPROMPT [10] and so on.

In the following part, we will introduce the prompt construction and application details.

3 SCHEMA-AWARE REFERENCE AS PROMPT

Figure 2 illustrates the framework of RAP. We first collect knowledge from different sources (§3.1), and then build a schema-guided datastore (§3.2). Finally, we dynamically retrieve related references for each query as the prompt to inject into the model (§3.3).

3.1 Reference Source

We leverage both the text instances and the schema graph to construct the knowledge store.

Text Instance. The text instance contains a wealth of information that may share semantic similarities with the query. Note that texts with similar information and structure may aid the model in better comprehending both the schema and the input. As to the text instances, a properly sized retrieval source is very important. The massive text would add noise and take up a lot of search space. However, if the text base is too small, it would not have much of an impact. According to previous work [48], a datastore based on training data can facilitate downstream tasks. Here, we make use of the training data as the retrieval source for the relation triple extraction. However, high-quality data for Event Extraction is usually scarce. To build a more complicated datastore, we employ an open domain corpus to obtain more text instances for the event extraction task. Since Wikipedia is enormous, we select the subset of Wikipedia EventWiki [14] and another automatically-labeled event data [9] from FreeBase.

Schema Graph. A task schema is a symbolic graph describing the configuration of each target type. For the relation triple extraction task, the schema graph contains both the relation type and the entity type and we build the schema graph based on the dataset. For the event extraction task, the schema graph includes three types of nodes: the event type, trigger word, and argument role. We follow previous work [20, 28, 32] and use the event schema provided by the dataset.

As demonstrated in Figure 2, these nodes are connected through their intrinsic relationship. For instance, the event ‘meet’ is linked with ‘Meet’ since meet is a trigger word for the Meet event.

3.2 Reference Store

Then, we build a schema-guided datastore $\mathcal{D}$ based on the obtained text instance $\mathcal{S}$ and schema graph $\mathcal{G}$. Specially, given a sentence $s$ from the corpora $\mathcal{S}$, we aim at inducing its potential label $\tilde{y} \in \mathcal{Y}$ and link $s$ to the graph $\mathcal{G}$ based on $\tilde{y}$. Since the text instances for

\[
p(Y|X) = \prod_{i=1}^{\mathcal{Y}} p(y_i|y_{<i})
\]

In the following part, we will introduce the prompt construction and application details.
event extraction are open-domain corpus, we propose a knowledge-guided labeling method to tag potential events in s. Here, we adopt a lightweight symbolic pipeline method [45] to label candidate triggers in each sentence. After we obtain these candidate triggers, we traverse these triggers to find whether they can be mapped to the target event schema. For example showed in Figure 2, given the sentence s = “He commanded several ships contracted by Jonathan Forward to transport convicted felons from London to Maryland,” we can obtain the candidate triggers (“commanded”, “contracted”, “transport”, “convicted”). We then map the trigger “transport” to y1 = “Transport” and the “convicted” to y2 = “Convict” in the schema graph. It can be noted that the sentence does not contain a “Convict” event since the word “convicted” is just an attribute used to decorate the following word “felons”. However, here we just require a weak label; thus, those errors are tolerable. Then we store the datastore as a key-value memory: the entries (key) of the knowledge store are the text instances; the values are the pointers that can be linked to one or several nodes in the schema graph. Just like the example in Figure 2, given the i-th instance ci, every entry is stored as (ci, yi, pi), where ci is the context, yi is the label and pi is a pointer that is linked to the type nodes in the schema graph. Additionally, we use triples to store the schema graph such as (Meet,_subtype, Contact).

\[ D = \{(c_i, y_i, p_i)\} \quad (2) \]

### 3.3 Dynamic Reference Integration

RAP construct a unique and suitable prompt for each sample by retrieving knowledge from the schema-aware reference store. Specifically, we utilize an off-the-shelf sparse searcher based on Apache Lucene, Elasticsearch, using an inverted index lookup followed by BM25 ranking. For each instance X, the engine matches the instance with all keys and returns the top K similar entries \(\{d_1, \ldots, d_K\}\), \(d_i = (c_i, y_i, p_i)\) from the datastore. We collect the instances \(c\) and the schema sub-graphs connected to the pointers \(p_i\).

We build the prompt \(P_e\) for event extraction as follows: (1) Relation type \(E\): relation type demonstrate the relation itself and its definition. (2) Trigger Information \(T\): we randomly select three trigger nodes that are connected to the event-type node and formulate the trigger prompt as “Similar trigger such as \(\ldots\)” (2) Argument Information \(A\): we follow Hsu et al. [17] to build the argument descriptions based on the arguments nodes. (3) Text Instance \(C\): the final part of the prompt is the text instances we retrieved above.

\[ P_e = \text{Concat}(E, T, A, C) \quad (3) \]

The prompt \(P_e\) for the relation triple extraction is similar to \(P_e\) but contains the following parts: (1) Relation type \(R\): relation type demonstrating the potential relation that may be described in the sentence. (2) Structure Information \(S\): the structure information indicates the entity type that formulates the triple such as (city, capital_of_city). (3) Text Instance \(C\): the final part of the prompt is the text instances we retrieved above. We combine this different knowledge together as the prompt \(P\) and leverage it to enhance the model:

\[ P = \text{Concat}(R, S, C) \quad (4) \]

#### Table 1: Statistics of Event Extraction Datasets.

| Dataset | Split | #Sents | #Events | #Roles |
|---------|-------|--------|---------|--------|
| ACE05-E | Train | 17,172 | 4,202   | 4,859  |
|         | Dev   | 923    | 450     | 605    |
|         | Test  | 832    | 403     | 576    |
| CASIE   | Train | 11,189 | 5,235   | 13,498 |
|         | Dev   | 1,778  | 1,115   | 2,669  |
|         | Test  | 3,208  | 2,121   | 5,699  |

#### Table 2: Statistics of Relation Triple Extraction Datasets.

| Dataset | Split | #Sents | #Triples | #Relations |
|---------|-------|--------|----------|------------|
| NYT     | Train | 56,196 | 94,222   | 24         |
|         | Dev   | 5,000  | 8,489    | 22         |
|         | Test  | 5,000  | 8,616    | 22         |
| WebNLG  | Train | 5,019  | 11,313   | 211        |
|         | Dev   | 500    | 1,224    | 144        |
|         | Test  | 703    | 1,607    | 149        |

### 3.4 Training and Inference

After obtaining the prompts for each sample, we apply them in different methods, including both generation-based and classification-based models. In this paper, we mainly focus on end-to-end methods and concatenate \(P\) with \(X\) as our final input.

\[ \text{Input} = [X; P] \quad (5) \]

[; ] denotes the sequence concatenation operation.

**Generation-based.** We optimize the IE model as a conditional generation[17]. Suppose \(\theta\) denotes the model’s training parameters; the training target is to minimize the negative log-likelihood of all target outputs \(Y\) in training set \(S\), where \(X_j\) denotes the \(j\)-th instance in \(S\) and \(T\) is the set of all target types. Formally, we have:

\[
p(Y|\text{Input}) = \prod_{i=1}^{\left|Y\right|} p(y_i|y_{<i}, \text{Input}) \quad (6)\]

\[
\mathcal{L}_\theta(S) = -\sum_{j=1}^{\left|S\right|} \sum_{t=1}^{\left|T\right|} \log p(Y_t | X_j, P_t) \quad (7)
\]

**Classification-based.** Classification-based model [59] first adopts an encoder to obtain the representation of the input and predict the result based on the hidden states. Here, we concatenate the prompt with the query and send them into the encoder. After we obtain the output, we conduct an operation to mask the prompt and predict the results based on the original sentence’s hidden states.

\[
h = \text{Encoder}(\text{Input}) \quad (8)\]

\[
h_{\text{mask}} = h \cdot \text{prompt\_mask} \quad (9)\]

\[
P = \text{Classifier}(h_{\text{mask}}) \quad (10)\]

\[
\mathcal{L}_\theta = -\frac{1}{\left|S\right|} \sum_{i=1}^{\left|S\right|} (y \log P + (1 - y) \log (1 - P)) \quad (11)
\]
Table 3: F1-score results for low-resource event extraction (trigger classification and argument classification) on ACE-05 dataset. The highest scores are in bold. Note that results of baseline models are directly taken from DEGREE [17].

| Model         | Type       | Tri-C       | Arg-C       |
|---------------|------------|-------------|-------------|
|               |            | 1% 3% 5% 10% 20% 30% | 1% 3% 5% 10% 20% 30% |
| BERT_QA       | Classification | 20.5 40.2 42.5 50.1 61.5 61.3 | 4.7 14.5 26.9 27.6 36.7 38.8 |
| OneIE         | Classification | 38.5 52.4 59.3 61.5 67.6 67.4 | 9.4 22.0 26.8 26.8 42.7 47.8 |
| TANL          | Generation  | 34.1 48.1 53.4 54.8 61.8 61.6 | 8.5 17.2 24.7 29.0 34.0 39.2 |
| DEGREE(Pipe)  | Generation  | 55.1 62.8 63.8 66.1 64.4 64.4 | 13.1 26.1 27.6 42.1 40.7 44.0 |
| Text2Event    | Generation  | 14.2 35.2 46.4 47.0 55.6 60.7 | 3.9 12.2 19.1 24.9 32.3 39.2 |
| RAP(Text2Event)| Generation | 19.3 36.5 47.8 48.0 59.3 62.7 | 7.2 16.2 19.3 26.5 33.2 40.5 |
| DEGREE        | Generation  | 55.4 62.1 65.8 65.8 68.3 68.2 | 21.7 30.1 35.5 41.6 46.2 48.7 |
| RAP(Degree)   | Generation  | 59.3 65.7 65.2 67.1 70.0 69.7 | 23.5 31.5 36.5 46.5 49.1 49.8 |

4 EXPERIMENTS

4.1 Experiment Settings

Dataset. As to the Event Extraction task, we conduct experiments on the popular benchmark: ACE05-E with 599 English annotated documents. We use the same split and pre-processing step following the previous work [32, 46]. Apart from ACE05-E, we employ another event extraction dataset CASIE [43] in the cybersecurity domain. For the joint relational triple extraction, we choose two public datasets NYT and WebNLG to assess our method. Statistics of the datasets are shown in Table 1 and Table 2.

Data split for low-resource setting. For the low-resource setting in ACE05-E, we follow DEGREE [17], which generate different proportions (1%, 3%, 5%, 10%, 20%, 30%) of training data and use the original development set and test set for evaluation. As for CASIE, we adhere to the preprocessing of earlier work [36], and then randomly split the training data into 1% and 10%. As regards relational triple extraction, we also generate the training data randomly, dividing them into 1%, 5% and 10%.

Evaluation metrics. For the event extraction task, we use the same evaluation criteria in previous work [17, 32, 35, 46] and report the F1 score of trigger classification (Trg-C) and argument classification (Arg-C). Trg-C evaluates whether a trigger’s offset and event type match the gold one, and Arg-C evaluates whether an argument’s offset, event type and role label all match the gold one. For the Relational Triple Extraction, following [59], an extracted relational triple is only regarded as correct if it is an exact match with ground truth, which means the whole entity spans both subject and object, as well as the relation, are accurate. We report the micro-F1 for the baselines.

Baselines. Since RAP is a pluggable approach that can be adapted to different methods, we select strong baselines for the two IE tasks and empower them with RAP.

- TANL [38]: a method converts event extraction as translation tasks between augmented natural languages.
- Text2Event [35]: a sequence-to-structure generation method that converts the input passage to a tree-like event structure.
- DEGREE [17]: an end-to-end conditional generation method constructing template for each event type and build event-specific prompt to instruct the model to generate the target event information.
- PRGC [59]: an end-to-end classification based model that utilize global correspondence to tackle the Relation Triple Extraction task.
- RelationPrompt [10]: an end-to-end generation-based model for zero-shot Relation Triple Extraction. In our paper, we omit the process to generate samples and use the relation extractor as the base model.

Apart from these models, we also compare RAP with other popular IE methods including OneIE [32], BERT_QA [12] and TPlinker [50]. Note that we mainly evaluate relation triple extraction and even extraction task, so we cannot compare with previous popular prompt learning models such as KnowPrompt [8] and PTR [16]. More implementation details and hyper-parameter settings can be found in Appendix A.

4.2 Main Results

We list the results of Event Extraction in Table 3 (ACE05-E) and Table 5 (CASIE), while the results of Relation Triple Extraction in Table 4 (We also provide the fully-supervised results in Appendix C). We can observe that RAP demonstrates strong competitiveness on both trigger classification and argument classification tasks. For the trigger classification task, RAP(Text2Event) shows improvements in almost all settings compared with the base method Text2Event, while RAP(Degree) outperforms all the other models except the 5% setting in the ACE05-E dataset. For the argument classification task, RAP achieves competitive results. In the ACE05-E dataset, where our method surpasses all baselines in all the settings. RAP also shows improvement in the cybersecurity domain. Compared with the base models TANL and Text2Event [35], RAP achieves significant improvement in almost all settings except 1% settings in TANL

As regards the relational triple extraction task, we evaluate RAP on both the generation-based model and the classification-based model, and from the table, we can observe a significant increase in both the WebNLG and NYT datasets. RAP(RelationPrompt) averages a 3.75% improvement in all settings of the two datasets,
Table 4: Model performance of Relational Triple Extraction models in the low-resource setting. We report the mean performance of micro $F_1$ scores (%) over 5 different splits. The best numbers are highlighted in each column.

| Model                | Type       | WebNLG 1% | WebNLG 5% | WebNLG 10% | NYT 1%  | NYT 5% | NYT 10% |
|----------------------|------------|-----------|-----------|------------|---------|--------|---------|
| TPLinker             | Classification | 0.00 0.00 | 0.00 0.00 | 0.00 0.00 | 6.29    | 76.67  | 80.11   |
| RelationPrompt       | Generation  | 23.77 45.45 | 56.53 54.37 | 63.80 66.58 | 57.19 66.79 | 69.39  |
| RAP (RelationPrompt) | Generation  | 27.72 47.04 | 57.38 57.19 | 66.79 69.39 | 65.87 69.39 | 71.45  |
| PRGC                 | Classification | 0.00 40.79 | 57.36 59.91 | 75.36 79.96 | 60.01 78.17 | 81.99  |
| RAP (PRGC)           | Classification | 12.69 45.10 | 57.38 57.19 | 66.79 69.39 | 57.19 78.17 | 81.99  |

Table 5: Low resource results for the cybersecurity dataset CASIE. The highest scores are in bold.

| Model        | Type | 1% data | 10% data |
|--------------|------|---------|----------|
| OneIE        | Cls  | 8.2 1.1 | 46.5 35.6 |
| TANL         | Gen  | 3.8 10.1 | 50.3 37.3 |
| RAP (TANL)   | Gen  | 1.7 14.4 | 53.6 37.4 |
| Text2Event   | Gen  | 10.6 11.8 | 39.7 35.3 |
| RAP (Text2Event) | Gen  | 12.0 15.6 | 47.6 39.1 |

5.1 Compared with Data Augmentation
To determine whether the improvements can indeed be attributed to the architecture of the reference store or simply the additional data, we compare our model RAP to the data augmentation method. In detail, getting the retrieved entries $d = (c, \tilde{y}, p)$, we transform them into the same format as training data. The query is $c$, and the label is paraphrased from the schema subgraph that is pointed to $p$. Then, we train our model with both the training data and the retrieved references. We conduct experiments on two triple extraction datasets and show the results in Figure 3. We can find that RAP outperforms the data augmentation method under both datasets, which verifies the effectiveness of the prompt. One possible reason may be that our model can dynamically select relevant knowledge (instances) as an external prompt, which will not change the original semantics of the input sequence. However, using those retrieved instances as data augmentation may introduce noise for training, thus, leading to performance decay.

Figure 3: Comparison with Data-augmentation method. The x-axis is the percent of the training data. The backbone model is RelationPrompt.

5.2 Ablation Studies
In this part, we present extensive ablation studies to support our design. To better understand the contribution of each component in the prompt, we ablate RAP for both relation triple extraction and event extraction tasks. Table 6 lists the results of ACE05-E and Table 7 illustrates the results of WebNLG and NYT. We discover that nearly all forms of information are essential since their absence has a detrimental effect on performance. In both relation triple extraction and event extraction tasks, we see a reduction in performance when text instances are omitted from the prompts. For

Table 6: Results (F1-score, %) of EE on ACE05-E with different knowledge types. We select the settings of 1% and 3% data. The backbone model is DEGREE.

| Method                | 1% Data | 3% Data |
|-----------------------|---------|---------|
| RAP                   | 59.3    | 65.7    |
| w/o Instances         | 58.1    | 63.6    |
| w/o Trigger Info.     | 53.1    | 60.9    |
| w/o Argument Info.    | 53.1    | 60.6    |
| w/o Type Struct.      | 57.5    | 62.0    |

5.3 Analysis
Note that the schema-aware reference as prompt contains several types of information. To further comprehend their contributions, we conducted an investigation to determine how the approach aids the model in its information extraction endeavors.
Figure 4: A case study in ACE05-E to analyze the effect of text instances on the Argument Classification task.

Table 7: Results (F1-score, %) of Relation Triple Extraction with different knowledge types. We select the settings of 1% and 5% data. The backbone model is PRGC.

| Method            | 1% Data | 5% Data |
|-------------------|---------|---------|
|                   | NYT     | WebNLG  | NYT     | WebNLG  |
| RAP               | 60.75   | 13.59   | 78.74   | 47.26   |
| w/o Instances     | 59.89   | 8.77    | 77.07   | 46.75   |
| w/o Relation Info.| 59.48   | 10.69   | 77.79   | 46.05   |
| w/o Structure Info.| 59.95  | 9.87    | 75.52   | 44.85   |

5.4 Effect of Number of References
Despite the success of RAP, Liu et al. [34] notice that not all the knowledge injected benefits the tasks, and an indiscriminate injection of knowledge may lead to negative knowledge infusion, which is detrimental to the performance. Here, we further conduct experiments to analyze how the number of retrieved references (k) affects performance. We take the ACE-05E task as an example. Note that the ablation study (Table 6) demonstrates that those retrieved instances help both the Tri-C and Arg-C. As shown in Figure 6, in terms of the Tri-C task, the model performs best when we utilize the top 1–2 chosen references. The model still benefits from this knowledge but suffers from noise if we increase the number of retrieved references. The possible reason is that later references usually have lower similarity, causing noise to affect the performance of the model. The Arg-C reflects the same trend but reaches its best performance around 8 retrieved references, which makes sense given that the task of argument classification is more challenging. The model need more similar references to learn the target tasks.

5.5 Different Type Analysis
The above-mentioned experiments prove the effectiveness of our schema-aware reference as a prompt. Furthermore, the utility of the prompt may be different in different cases. To better understand the principle of knowledge injection under the low-resource scenario, we analyze the effects of the prompts on different event types and relation types.

For the event extraction, we select four event-types that appear less than five times, namely “Start-Position”, “Convict”, “Transfer-Ownership” and “Start-Org”. For the relational triple extraction, we also select for types: “founders”, “major_sharehoders”, “place_of_death” and “place_of_birth”.

Figure 5 demonstrate the F1 score of all these target types based on various forms of prompt input. We observe that: (1) For the event extraction task, different components of the RAP show different effects on both tasks. Overall, trigger information plays a more vital role in the trigger classification task, while the instance and arguments are more significant for the argument classification task. (2) Event type has less influence on the Trig-C for the “Start-Position” and “Start-Org” event type, probably because these event type is less inductive and contains little information of the event triggers. (3) The performance of Arg-C on “Convict”, “Transfer-Ownership” and “Start-Org” types is greatly affected by the arguments and instances. As shown in §(5.3), these similar instances usually contain potential
Figure 5: F1-score of four event types based on various knowledge inputs on ACE05-E under 10% setting.

Figure 6: Effect of the number of instances retrieved on model’s performance for the ACE05-E task under 10% setting. The base model means we do not utilize the text instances as the prompt. The x-axis is the number of instances we retrieved.

event structure information, especially for these three event types. (4) Unlike Event Extraction, different parts of the prompt demonstrate similar trends on these different types for Relation Triple Extraction: triple structure is the most important part of prompt, while instance and relation information are not that influential.

6 RELATED WORK

Relational Triple Extraction. Early works [2] apply the pipelined methods to perform relation classification between entity pairs after extracting all the entities. [50] employs a token pair linking scheme which performs two matrix operations for extracting entities and aligning subjects with objects under each relation of a sentence. The recent well-performed model PRGC [59] is an end-to-end classification model that leverages a global correspondence matrix. Recently, generation-based model also appears [10] and exhibit strong performance. However, few works consider the prompt to enhance the model for this complicated task. In this work, we utilize schema-aware references as prompts RAP to enhance the relation triple extraction task.

Event Extraction. Early studies formulate Event Extraction as token-level classification, i.e., to directly locate the triggers and arguments in the texts and identify categories. Many works use pipeline-style frameworks to extract events [29, 37, 46, 53, 54]. Meanwhile, some work casts event extraction as a machine reading comprehension (MRC) problem [12, 25, 33]. They construct question-answer pairs to query event triggers and arguments. Recently, many generation-based models have been proposed [17–19, 30, 35, 38, 44]. The generation-based model is more flexible and portable, reducing the burden of annotation and can extract triggers and arguments simultaneously.

Retrieval Augmented Models. Retrieval-augmented models have been applied to Language Model (LM) [22], text generation [26, 56] and open-domain question answering [15, 24]. More works adopt retrieval-augmented model to tackle other tasks such as question answering [3], knowledge graph completion [57], relation extraction [5] and NER [47]. Alon et al. [1] propose RETOMATON via a neuro-symbolic synergy of neural models with symbolic automata. Recently, Wang et al. [48] notices that retrieving examples from training data can enhance the model performance for different NLU tasks. However, few works apply retrieval methods for event extraction and relation triple extraction tasks. Unlike those approaches, we focus on IE and propose RAP with a schema-aware reference store and conduct retrieval method to enhance the model.

7 CONCLUSION AND FUTURE WORK

In this paper, we propose RAP for low-resource IE, which constructs a schema-aware reference store and dynamically selects informative knowledge as prompts for integration. Experimental results demonstrate that our model achieves competitive results with current-state models for both event extraction and relation triple extraction tasks. RAP can be applied to different existing methods. Additionally, we provide an in-depth analysis when injected with different components of the prompt. In the future, we plan to 1) explore more symbolic knowledge, such as axiom rules for IE, 2) investigate implicit knowledge in pre-trained language models for better prompting, and 3) extend our approach to general natural language generation tasks.
A EXPERIMENT SETTING DETAILS

In this section, we describe the implementation of our experiments in detail, including the baseline methods, backbone models, data splitting details, and hyperparameters. The grid search is applied for hyperparameter tuning (maximum values bolded below).

A.1 Event Extraction

ACE05-E. For the ACE05-E dataset, we follow previous preprocessing from DyGIE++ [46] and OneIE [32]. The dataset can be downloaded from the LDC for free. We choose previous work DEGREE4 [17], which leverages BART\_\textsc{large} as backbone model and \textsc{Text2Event}5 [35], which selects 15-large as backbone to compare with previous results in \textsc{DEGREE}. The hyper-parameter search space is:

- epoch: [40, 45, 50] \textsc{DEGREE}, [50, 80, 100] \textsc{Text2Event}
- batch size: [8, 16, 32]
- learning rate: [5e-5, 1e-4, 3e-4, 5e-4] \textsc{DEGREE}, [6e-4, 8e-4, 7e-4] \textsc{Text2Event}
- k in Knowledge Store: [4, 8, 12, 16]

\textsc{CASIE}. As similar with the \textsc{ACE} dataset, We evaluate our method on two base method \textsc{TANL}6, and \textsc{Text2Event}. We utilize T5-base as the backbone model for both two methods. We run the experiments with different epoch settings on 1% and 10% with the other parameters as default and report the highest values. For the \textsc{TANL}, we choose the model with their default parameters, and for \textsc{Text2Event}, we list the hyper-parameter search space as follows:

- epoch: [80, 90, 100]%, [30, 40, 50]%
- batch size: [8, 16, 32]
- learning rate: [5e-5, 1e-4, 3e-4, 5e-4]
- k in Knowledge Store: [4, 8, 12, 16]

Additionally, we obtain the results of ONEIE in the \textsc{CASIE} dataset; we use their released code7 to run the model with default parameters and utilize the bert-base-cased as the backbone. As there is no relation in the \textsc{CASIE} dataset, we set the relation schema to empty, construct the role-entity schema in the method, and finally obtain the results.

A.2 Relational Triple Extraction

With respect to Entity and Relation Extraction, we randomly split the \textsc{NYT} and \textsc{WebNLG} datasets into 1%, 5% and 10%. For each split setting, we choose 5 different random seeds in our experiment and reported the average results. We select two different type of base methods: RELATIONPROMPT8 [10] for generative methods, and PRGC9 [59] for classification methods. As for RELATIONPROMPT, we directly fine-tune the dataset on the Relation Extractor and utilize their proposed method to predict multiple triplets. Regarding PRGC, we mask the prompt after encoding the inputs mentioned above. We use the default parameters for both methods in all settings. We also implement our methods to TPlinker10 [50] to report the low resource results, and we use their default parameters as well.

B RETRIEving DETAILS

When retrieving knowledge for event extraction, we choose the top k retrieving results to conduct the reference and set a retrieval threshold of BM25 score to 20 to filter that noisy knowledge. When retrieving for relational triple extraction, we just select the top one for each sample. For each dataset, we construct its unique reference store. The sizes of the stores are listed as follows:

- \textsc{ACE05-E}: 36,880
- \textsc{CASIE}: 3732
- \textsc{NYT}: 54,643
- \textsc{WebNLG}: 5011

\textsc{RAP} applies offline retrieval by ElasticSearch, which provides a fast and low-cost retrieval method on the CPU. For example, it costs 12.1% CPU utilization (Our CPU is an Apple M1 Pro) when retrieving from the \textsc{NYT} store and takes about 12 minutes to finish the retrieval process for 50 thousand samples.

C FULLY-SUPERVISED RESULTS

We also report the performance in the high-resource setting for controlled comparisons. Table 8 shows the results of high-resource event extraction and Table 9 shows the results of high-resource relation triple extraction.
Table 8: Results on ACE05-E for event extraction in the supervised learning setting. For each column, we bold the highest score.

| Model          | ACE05-E | Trg-C | Arg-C | Trg-C | Arg-C |
|----------------|---------|-------|-------|-------|-------|
|                | P       | R     | F1    | P     | R     | F1    |
| classification-based |        |       |       |       |       |       |
| DYGIE++        | -       | -     | 69.7  | -     | -     | 48.8  |
| GAIL           | 74.8    | 69.4  | 72.0  | 61.6  | 45.7  | 52.4  |
| BERT_QA        | 71.1    | 73.7  | 72.4  | 56.8  | 50.2  | 53.3  |
| OntIE          | -       | -     | 74.7  | -     | -     | 56.8  |
| generation-based |        |       |       |       |       |       |
| TANL           | -       | -     | 68.5  | -     | -     | 48.5  |
| Text2Event     | 69.6    | 74.4  | 71.9  | 52.5  | 55.2  | 53.8  |
| BART-GEN       | 69.5    | 72.8  | 71.1  | 56.0  | 51.6  | 53.7  |
| DEGREE-e2e     | -       | -     | 73.3  | -     | -     | 55.8  |
| RAP (DEGREE)   | 66.5    | 79.6  | 72.5  | 53.5  | 58.7  | 56.0  |

Table 9: Results on NYT and WebNLG for relation triple extraction in the supervised learning setting. For each column, we bold the highest score.

| Model       | WebNLG | NYT | WebNLG | NYT |
|-------------|--------|-----|--------|-----|
|             | P      | R   | F1     | P     | R   | F1   |
| NovetTagging| 52.5   | 19.3| 28.3   | 32.8  | 30.6| 31.7 |
| MultiHead   | 57.5   | 54.1| 55.7   | 60.7  | 58.6| 59.6 |
| ETL-span    | 84.3   | 82.0| 83.1   | 85.5  | 71.7| 78.0 |
| RSAN        | 80.5   | 83.8| 82.1   | 85.7  | 83.6| 84.6 |
| TPLinker    | 88.9   | 84.5| 86.7   | 91.4  | 92.6| 92.0 |
| PBGC        | 89.9   | 87.2| 88.5   | 93.5  | 91.9| 92.7 |
| RAP (PRGC)  | **90.4** | **87.1** | **88.7** | **93.1** | **91.1** | **92.1** |