Retrieve-and-Sample: Document-level Event Argument Extraction via Hybrid Retrieval Augmentation

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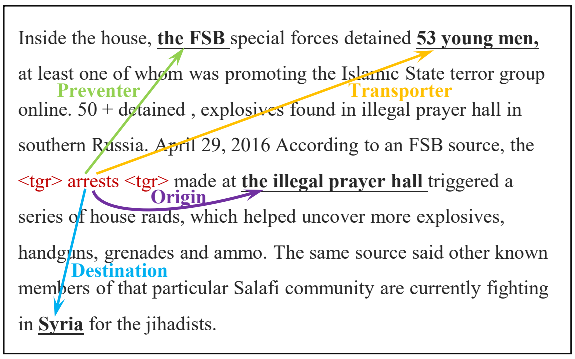
Abstract

Recent studies have shown the effectiveness of retrieval augmentation in many generative NLP tasks. These retrieval-augmented methods allow models to explicitly acquire prior external knowledge in a non-parametric manner and regard the retrieved reference instances as cues to augment text generation. These methods use similarity-based retrieval, which is based on a simple hypothesis: the more the retrieved demonstration resembles the original input, the more likely the demonstration label resembles the input label. However, due to the complexity of event labels and sparsity of event arguments, this hypothesis does not always hold in document-level EAE. This raises an interesting question: How do we design the retrieval strategy for document-level EAE? We investigate various retrieval settings from the input and label distribution views in this paper. We further augment document-level EAE with pseudo demonstrations sampled from event semantic regions that can cover adequate alternatives in the same context and event schema. Through extensive experiments on RAMS and WikiEvents, we demonstrate the validity of our newly introduced retrieval-augmented methods and analyze why they work.

1 Introduction

Transforming the large amounts of unstructured text on the Internet into structured event knowledge is a critical, yet unsolved goal of NLP, especially when addressing document-level text. Document-level Event Argument Extraction (document-level EAE) is the process of extracting informative event kernels from a document, which benefits many downstream applications, e.g., information retrieval, question answering, and event graph reasoning. Figure 1 presents an illustration of document-level EAE task. Given a *TransportPerson* event, document-level EAE aims to extract event arguments and identify the roles they take: *the FSB* (Preventer), *53 young men* (Transporter), *the illegal prayer hall* (Origin), *Syria* (Destination).

Event type: movement.transportperson.preventexit



Inside the house, **the FSB** special forces detained **53 young men,** at least one of whom was promoting the Islamic State terror group online. 50 + detained , explosives found in illegal prayer hall in southern Russia. April 29, 2016 According to an FSB source, the <tgr> arrests <tgr> made at **the illegal prayer hall** triggered a series of house raids, which helped uncover more explosives, handguns, grenades and ammo. The same source said other known members of that particular Salafi community are currently fighting in **Syria** for the jihadists.

Figure 1: An illustration of document-level EAE task. Special tokens <tgr> incorporate trigger words. Arguments are denoted by underlined words, and roles are denoted by arcs.

Retrieval-augmented methods have recently been successfully applied to many NLP tasks, e.g., dialogue response generation (Weston et al., 2018; Wu et al., 2019; Cai et al., 2019a,b), machine translation (Zhang et al., 2018; Xu et al., 2020; He et al., 2021) and information extraction (Lee et al., 2022; Zhang et al., 2022; Chen et al., 2022). These methods retrieve additional knowledge from various corpora to augment text generation, which allows models to (a) explicitly acquire prior external knowledge in a non-parametric manner, leading to great flexibility. (b) regard the retrieved reference instances as cues to generate text and learn by analogy. These retrieval-augmented methods use similarity-based retrieval, which is based on a simple hypothesis (Li et al., 2022): the more $\mathbf{x}_r$ (retrieved demonstration) resembles $\mathbf{x}$ (original input), the more likely $\mathbf{y}_r$ (demonstration label) resembles $\mathbf{y}$ (input label), so it will help the generation.

This hypothesis is intuitive: similar input results in similar output for most tasks (Khandelwal et al.,

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2020, 2021). For example, in language modeling, *Dickens is the author of* and *Dickens wrote* will have essentially the same distribution over the next word. However, in document-level EAE, $\mathbf{x}_r$ resembles $\mathbf{x}$ cannot guarantee the equivalent distribution of $\mathbf{y}_r$ and $\mathbf{y}$ in label space. In a document, only a few words are event arguments, while other distracting context can mislead similarity-based retrieval and cause demonstration label $\mathbf{y}_r$ deviate from input label $\mathbf{y}$. Furthermore, document-level EAE should predict not only the argument entity but also the correspondence between arguments and roles, which makes it challenging to find a demonstration with an identical event label to the original input. According to our statistics on RAMS dataset (Ebner et al., 2020), only 16.51% of instances can recall a sample with the same event schema through similarity-based retrieval.

This raises an interesting question: since document-level EAE doesn't satisfy the hypothesis of similarity-based retrieval, how do we design the retrieval strategy for document-level EAE? In this paper, we explore various retrieval settings. First, if similar documents cannot guarantee the same distribution of event labels, does it make sense to pursue $\mathbf{x}_r$ to be similar to $\mathbf{x}$ in retrieval process? To answer this, we first retrieve $\mathbf{x}_r$, close to $\mathbf{x}$ in input space, as discrete demonstration to keep contextual semantic consistency (**Setting 1**); Then, since the essence of the above hypothesis is to pursue $\mathbf{y}_r$ resembles $\mathbf{y}$, why don't we directly retrieve $\mathbf{y}_r$ similar with $\mathbf{y}$ as the reference? So we recall $\mathbf{y}_r$, close to $\mathbf{y}$ in label space, as discrete demonstration to alleviate the difficulty of learning the complex event pattern of $\mathbf{y}$ (**Setting 2**); To find depth cues to guide the model, we want a demonstration that has equal distribution with input document in both input and label space. Intuitively, it is impossible to retrieve the ideal demonstration in discrete space, so we try to sample a cluster of pseudo demonstrations in continuous space instead. Recent works (Wei et al., 2020) have shown that the vectors in an adjacency region can easily cover adequate alternatives of the same meaning. Inspired by this intriguing observation, we sample pseudo demonstrations from the intersection of the adjacent regions of $\mathbf{x}$ and $\mathbf{y}$, thus preserving both context and event schema consistency with the input (**Setting 3**).

We present a systematic evaluation for analyzing various retrieval settings and observe that given a document, (1) context-consistency retrieval (**Setting 1**) helps the model identify the argument span more accurately than Setting 2. This suggests that in-distribution demonstration contexts can contribute to performance gains by improving the ability to recognize argument spans; (2) schema-consistency retrieval (**Setting 2**) makes the generated role labels more accurate than Setting 1, which indicates that conditioning on the label space contributes to better performance by alleviating the difficulty of learning the complex event pattern; and (3) adaptive hybrid retrieval (**Setting 3**) has achieved state-of-the-art (SOTA) performance among all generation-based baselines, indicating that this setting can generate diverse and faithful pseudo demonstrations with consistency in both input space and label space.

Overall, the contributions can be summarized as follows:

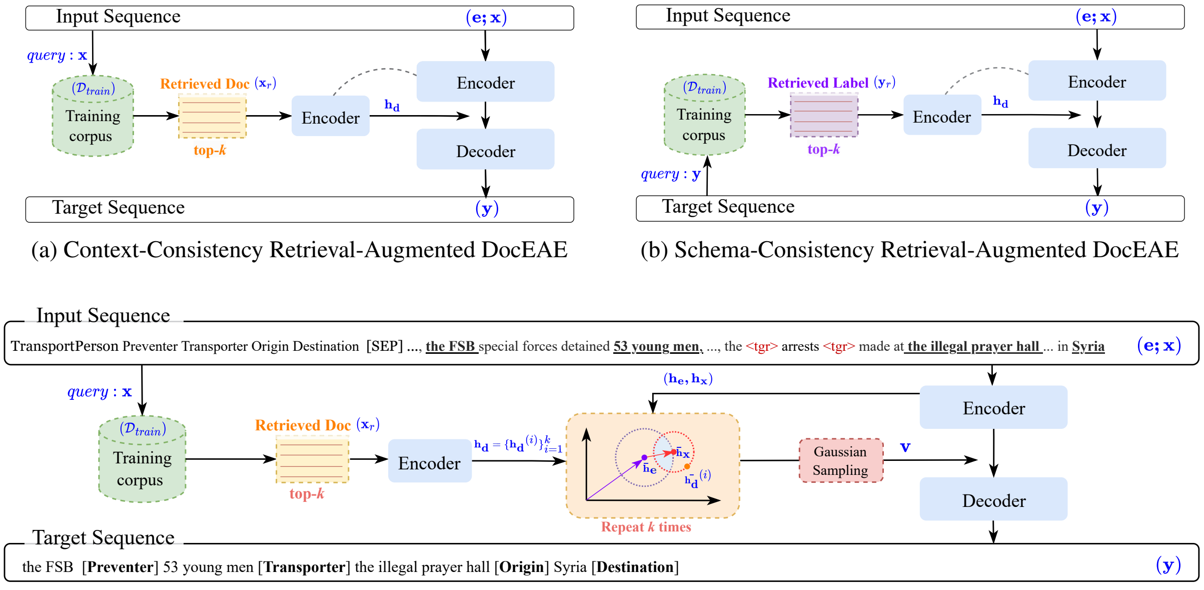
- We are the first to explore how to design the retrieval strategy for document-level EAE from the input and label distribution views. And our introduced retrieval strategies can recall demonstrations that can be helpful to demonstrate how the model should solve the task.

- We further propose a novel adaptive hybrid retrieval augmentation paradigm that adaptively samples pseudo demonstrations from continuous space for each training instance to improve the analogical capability of the model.

- Through extensive experiments on RAMS and WikiEvents, we demonstrate the validity of our newly introduced retrieval-augmented methods. We also conducted additional analytical experiments to discuss the reasons why different settings affect performance.

2 Methodology

Problem Definition. We formulate document-level EAE in the manner of Ebner et al. (2020): given a document $\mathbf{x} = \{w_1, w_2, ..., w_{|\mathbf{x}|}\}$, it contains a set of described events $\mathcal{E}$. Each event $e \in \mathcal{E}$ has its event type t and designated by a trigger (a text span in $\mathbf{x}$). Each event type t specifies a role set $\mathcal{R}_t$. The event schema $\mathbf{e}$ is made up of event type and its associated role set. The task aims to extract all (a, r) pairs for each $e \in \mathcal{E}$, where $a \in \mathbf{x}$ is an argument—a text span in $\mathbf{x}$ and $r \in \mathcal{R}_t$ is the role that a takes.



(a) Context-Consistency Retrieval-Augmented DocEAE

(b) Schema-Consistency Retrieval-Augmented DocEAE

(c) Adaptive Hybrid Retrieval-Augmented DocEAE

Figure 2: An illustration of our proposed three retrieval-augmented methods. Sub-figures (a), (b), and (c) refer to the three retrieval-augmented methods, respectively. $\mathbf{x}_r$ denotes the retrieved document, while $\mathbf{y}_r$ means the retrieved event label. $\mathbf{h_d}$ is the representation of the retrieved k discrete demonstrations, $\mathbf{v}$ is the sampled k pseudo demonstrations. The gray dashed lines in (a) and (b) denote that two encoders share parameters, as does (c).

For retrieval-augmented document-level EAE, we first retrieve the top-k potentially helpful demonstrations (discrete or continuous), then fuse them into the decoder to generate role records (a sequence of (a, r) pairs). In the following, we first introduce how to reformulate document-level EAE as Retrieval-Augmented Generation (RAG), then describe various retrieval settings.

2.1 Basic RAG Architecture

We adopt the T5 model (Raffel et al., 2022), an encoder-decoder pre-trained model, as a backbone. The encoder-decoder LM models the conditional probability of selecting a new token $\mathbf{y}^{(i)}$ given the previous tokens $\mathbf{y}^{(<i)}$ and the encoder input $[\mathbf{e}; \mathbf{x}]$ during the generation process. As a result, the total probability $p(\mathbf{y}|\mathbf{x}, \mathbf{e})$ of generating the output $\mathbf{y}$ given the input $[\mathbf{e}; \mathbf{x}]$ is calculated as:

$$p(\mathbf{y}|\mathbf{x}, \mathbf{e}) = \prod_{i=1}^{|\mathbf{y}|} p\left(\mathbf{y}^{(i)}|\mathbf{y}^{(<i)}, \mathbf{x}, \mathbf{e}\right), \tag{1}$$

where the input sequence is the concatenation of the document context and its event schema, constructed as *<s> event schema* `[SEP]` *document context </s>*. The output $\mathbf{y}$ is the role record, presenting by the concatenation of each argument and its event role, i.e., *<s> arg_1 $role_1$... arg_n $role_n$ </s>*.

In this paper, we decompose the modeling of $p(\mathbf{y}|\mathbf{x}, \mathbf{e})$ into two steps: *retrieval* and *prediction*. Given a query document $\mathbf{x}$, we first retrieve top-k potentially helpful demonstrations $\mathbf{d}$ from training corpus $\mathcal{D}_{\text{train}}$. We model this as sampling from a distribution $p(\mathbf{d}|\mathbf{x})$. Then we use siamese network structures to obtain meaningful embeddings for input sequence $[\mathbf{e}; \mathbf{x}]$ and demonstration $\mathbf{d}$:

$$\begin{aligned} \mathbf{h_e}, \mathbf{h_x} &= \text{T5-Encoder}([\mathbf{e}; \mathbf{x}]), \\ \mathbf{h_d} &= \text{T5-Encoder}(\mathbf{d}). \end{aligned} \tag{2}$$

Then, we condition on both the retrieved $\mathbf{d}$ and the original input $[\mathbf{e}; \mathbf{x}]$ to generate the output $\mathbf{y}$—modeled as $p(\mathbf{y}|\mathbf{d}, \mathbf{x}, \mathbf{e})$. Specifically, we integrate k demonstration embeddings $\mathbf{h_d} = \{\mathbf{h_d}^{(1)}, \mathbf{h_d}^{(2)}, ..., \mathbf{h_d}^{(k)}\}$ into cross-attention module in all decoder layers by concatenating them to the encoder outputs and feed them all to decoder:

$$\mathbf{y} = \text{T5-Decoder}(\text{<bos>}; [\mathbf{h_d}; \mathbf{h_e}; \mathbf{h_x}]), \tag{3}$$

where <bos> is the beginning token of decoder, $[\mathbf{h_d}; \mathbf{h_e}; \mathbf{h_x}]$ denotes the encoder outputs we constructed for decoder input. In Setting 3, we use $[\mathbf{v}; \mathbf{h_e}; \mathbf{h_x}]$ instead.

To obtain the overall likelihood of generating $\mathbf{y}$, we treat $\mathbf{d}$ as a latent variable, yielding:

$$p(\mathbf{y}|\mathbf{x}, \mathbf{e}) = p(\mathbf{y}|\mathbf{d}, \mathbf{x}, \mathbf{e})\, p(\mathbf{d}|\mathbf{x}). \tag{4}$$

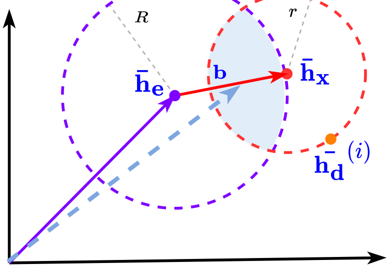

R
r
$\bar{\mathbf{h}}_{\mathbf{e}}$
$\mathbf{b}$
$\bar{\mathbf{h}}_{\mathbf{x}}$
$\bar{\mathbf{h}}_{\mathbf{d}}^{(i)}$

Figure 3: The geometric diagram of the proposed Gaussian sampling. $\bar{\mathbf{h}}_{\mathbf{e}}, \bar{\mathbf{h}}_{\mathbf{x}}$ and $\bar{\mathbf{h}}_{\mathbf{d}}^{(i)}$ are the representations of the event schema, the document and the i-th discrete demonstrations, $\bar{\mathbf{h}}_{\mathbf{e}} = \text{mean-pooling}(\mathbf{h}_{\mathbf{e}}), \bar{\mathbf{h}}_{\mathbf{x}} = \text{mean-pooling}(\mathbf{h}_{\mathbf{x}}), \bar{\mathbf{h}}_{\mathbf{d}}^{(i)} = \text{mean-pooling}(\mathbf{h}_{\mathbf{d}}^{(i)})$. To sample pseudo demonstrations from event semantic region (the light blue intersection), we formalize $\mathbf{v}^{(i)} = \bar{\mathbf{h}}_{\mathbf{e}} + \boldsymbol{\omega}^{(i)} \odot \mathbf{b}$ (i.e., the blue dashed arrow) as a pseudo demonstration, in which the bias vector $\mathbf{b} = \bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{e}}$, scale vector $\boldsymbol{\omega}^{(i)} \in (1 - r^{(i)}/R, 1)$, $r^{(i)} = ||\bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{d}}^{(i)}||, R = ||\bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{e}}||$.

Algorithm 1: Gaussian Sampling

```
Input: The embeddings of schema, document and
       discrete demonstrations, i.e. $\bar{\mathbf{h}}_{\mathbf{e}}$, $\bar{\mathbf{h}}_{\mathbf{x}}$ and
       $\bar{\mathbf{h}}_{\mathbf{d}} = \{\bar{\mathbf{h}}_{\mathbf{d}}^{(1)}, \bar{\mathbf{h}}_{\mathbf{d}}^{(2)}, ..., \bar{\mathbf{h}}_{\mathbf{d}}^{(k)}\}$
Output: A set of pseudo demonstrations
        $\mathbf{v} = \{\mathbf{v}^{(1)}, \mathbf{v}^{(2)}, ..., \mathbf{v}^{(k)}\}$
Normalizing the importance of each element in
  $\mathbf{b} = \bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{e}}$: $\mathcal{W}_r = \frac{|\mathbf{b}| - \min(|\mathbf{b}|)}{\max(|\mathbf{b}|) - \min(|\mathbf{b}|)}$
Initialize $i \leftarrow 0$
while $i \leq (k-1)$ do
    $i \leftarrow i + 1$
    $r^{(i)} = ||\bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{d}}^{(i)}||, R = ||\bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{e}}||$
    Use reparametrizetion to calculate the current
      scale vector:
      $\boldsymbol{\omega}^{(i)} \sim \mathcal{N}\left(\frac{1 - r^{(i)}/R + 1}{2}, \text{diag}\left(\mathcal{W}_r^2\right)\right)$.
    First sample a noise variable $\epsilon$ from $\mathcal{N}(0, 1)$
    Then transform it to $\boldsymbol{\omega}^{(i)} = \mu + \epsilon \cdot \sigma$, where
      $\mu = 1 - \frac{r^{(i)}/R}{2}, \sigma = \mathcal{W}_r$.
    Calculate the current sample:
      $\mathbf{v}^{(i)} = \bar{\mathbf{h}}_{\mathbf{e}} + \boldsymbol{\omega}^{(i)} \odot \mathbf{b}$
    $\mathbf{v} \leftarrow \mathbf{v} \cup \mathbf{v}^{(i)}$
end
```

2.2 Demonstration Retrieval Design

The main challenge of demonstration retrieval is to design an appropriate retrieval strategy to recall demonstrations that can be helpful to demonstrate how the model should solve the task. In this part, we explore various retrieval settings. As shown in Figure 2, we categorize the retrieval setting into three categories: (1) Context-Consistency Retrieval; (2) Schema-Consistency Retrieval; and (3) Adaptive Hybrid Retrieval. The goal of all retrieval settings in this part is to find ***k* demonstrations** (whether discrete or continuous).

Setting 1: Context-Consistency Retrieval

Since similar documents cannot guarantee the same distribution of event labels, Setting 1 aims to answer whether it makes sense to pursue $\mathbf{x}_r$ to be similar to $\mathbf{x}$ in the retrieval process. Given a query document $\mathbf{x}$, we retrieve the instance document $\mathbf{x}_r$ from the training corpus $\mathcal{D}_{\text{train}}$ that is the top-k relevant to the original input document, as discrete demonstrations $\mathbf{d}$. For retrieval, we use S-BERT (Reimers and Gurevych, 2019) to retrieve semantically similar documents $\mathbf{x}_r \in \mathcal{D}_{\text{train}}$.

Setting 2: Schema-Consistency Retrieval

To explore whether conditioning on the label space contributes to performance gains, Setting 2 satisfies event schema consistency and aims to alleviate the difficulty of learning the complex event pattern of $\mathbf{y}$. Given the event label $\mathbf{y}$ of input as query, we retrieve (also via S-BERT) the instance label $\mathbf{y}_r$ that is the top-k relevant to the input label from the training corpus $\mathcal{D}_{\text{train}}$. During the inference, the query is the event schema $\mathbf{e}$ of test sample.

Setting 3: Adaptive Hybrid Retrieval

To find the ideal demonstration that has equal distribution with input document in both input and label space to guide the model, we propose a novel adaptive hybrid retrieval strategy to sample pseudo demonstrations from continuous space as depth cues to improve the analogical capability of model.

Given an instance document $\mathbf{x}$, we first retrieve top-k helpful documents from the training corpus $\mathcal{D}_{\text{train}}$. Conditioning on retrieved k discrete demonstrations, we adaptively determine k event semantic regions in continuous space for each training instance. Then we sample k pseudo demonstrations from k event semantic regions.

Event Semantic Region. We treat points in the event semantic region as the critical states of event-semantic equivalence. Specifically, in order to consider both context and event schema consistency, we first determine the adjacent region of document and event schema by setting their adjacent radii (the orange circle and purple circle in Figure 3). Furthermore, we define the intersection of their adjacent regions as an event semantic region $\curlywedge(\bar{\mathbf{h}}_{\mathbf{e}}, \bar{\mathbf{h}}_{\mathbf{x}})$ (the light blue region in Figure 3), which describes accurate alternatives in consistency with original context and event semantic meaning. Here we have k discrete demonstration embeddings $\bar{\mathbf{h}}_{\mathbf{d}}$ for k adjacent radii r, which determines k event semantic regions. For each event semantic region, we perform the following Gaussian sampling.

Gaussian Sampling. To obtain diverse and faithful pseudo demonstrations from the event semantic region for the training instance $\mathbf{x}$, we apply a Gaussian sampling strategy k times to sample a cluster of vectors from k event semantic regions.

As shown in Figure 3, we first use scale vector $\boldsymbol{\omega}^{(i)}$ to transform the bias vector $\mathbf{b} = \bar{\mathbf{h}}_{\mathbf{x}} - \bar{\mathbf{h}}_{\mathbf{e}}$ as $\boldsymbol{\omega}^{(i)} \odot \mathbf{b}$, where $\odot$ is the element-wise product operation. Then, we construct a novel sample $\mathbf{v}^{(i)} = \bar{\mathbf{h}}_{\mathbf{e}} + \boldsymbol{\omega}^{(i)} \odot \mathbf{b}$ as a pseudo demonstration. As a result, the goal of the sampling strategy turns into finding a set of scale vectors, i.e. $\boldsymbol{\omega} = \{\boldsymbol{\omega}^{(1)}, \boldsymbol{\omega}^{(2)}, ..., \boldsymbol{\omega}^{(k)}\}$. Intuitively, we can assume that $\boldsymbol{\omega}^{(i)}$ follows a distribution with Gaussian forms, formally:

$$\boldsymbol{\omega}^{(i)} \sim \mathcal{N}\left(\frac{1 - r^{(i)}/R + 1}{2}, \operatorname{diag}\left(\mathcal{W}_r^2\right)\right), \tag{5}$$

where $\mathcal{W}_r = \frac{|\mathbf{b}| - \min(|\mathbf{b}|)}{\max(|\mathbf{b}|) - \min(|\mathbf{b}|)}$ normalizes the importance of each dimension in $\mathbf{b}$, the operation $|\cdot|$ takes the absolute value of each element in vector, which indicates the larger the value is, the more informative it is. $\mu = \frac{1 - r^{(i)}/R + 1}{2}$ constrains the sampling range to event semantic region.

Since sampling is a non-differentiable operation that truncates the gradient, here we use a reparametrization trick to construct $\mathcal{N}(1 - \frac{r^{(i)}/R}{2}, \operatorname{diag}(\mathcal{W}_r^2))$. We first sample a noise variable ϵ from standard normal distribution $\mathcal{N}(0, 1)$. Then, instead of writing $\boldsymbol{\omega}^{(i)} \sim \mathcal{N}(\mu, \sigma^2)$:

$$\boldsymbol{\omega}^{(i)} = \mu + \epsilon \cdot \sigma, \tag{6}$$

where $\epsilon \sim \mathcal{N}(0, 1), \mu = 1 - \frac{r^{(i)}/R}{2}, \sigma = \mathcal{W}_r$.

Now the gradient is inside the expectation. We finally sample k pseudo demonstrations $\mathbf{v}$ from k event semantic regions to augment the text generation, that is $\mathbf{v} = \{\mathbf{v}^{(1)}, \mathbf{v}^{(2)}, ..., \mathbf{v}^{(k)}\}$, where $\mathbf{v}^{(i)} \sim \curlywedge(\bar{\mathbf{h}}_{\mathbf{e}}, \bar{\mathbf{h}}_{\mathbf{x}})$. k is the hyperparameter of the number of sampled vectors, which is determined by the number of discrete demonstrations. For a clearer presentation, Algorithm 1 summarizes the sampling process.

Algorithm 2: Decoding the output

```
Input: role record
    $\mathbf{y}$ : <s> $arg_1$ $role_1$... $arg_n$ $role_n$ </s>.
Output: $(arg, role)$ pairs.
Initialize $arg\ list \leftarrow [\,]$
for $\mathbf{y}^i \in \mathbf{y}$ do
    /* Here consider multi-event scenario,
       separated by [SEP]                          */
    if $\mathbf{y}^i \neq$ [SEP] then
        if $\mathbf{y}^i \notin$ role list then
            append $\mathbf{y}^i$ to $arg\ list$
        else
            $role \leftarrow \mathbf{y}^i$
            $argument \leftarrow arg\ list$
            get a $(arg, role)$ pair
            $arg\ list \leftarrow [\,]$
        end
    else
        $event\ index \leftarrow event\ index + 1$
        $arg\ list \leftarrow [\,]$
    end
end
```

2.3 Training and Inference

The trainable parameters of the model are only the encoder-decoder LM, which is denoted as θ. Given a training dataset $\mathcal{D}_{\text{train}} = \left\{\left(\mathbf{x}_1, \mathbf{y}_1\right), ..., \left(\mathbf{x}_{|\mathcal{D}_{\text{train}}|}, \mathbf{y}_{|\mathcal{D}_{\text{train}}|}\right)\right\}$, where each instance is a (document, role records) pair, the learning objective is a negative log-likelihood function:

$$\mathcal{L} = - \sum_{(\mathbf{x}, \mathbf{y}) \in \mathcal{D}_{\text{train}}} \log p(\mathbf{y} | \mathbf{x}, \mathbf{d}, \mathbf{e}, \theta). \tag{7}$$

After generating role records, we need to decode it back into (argument, role) pairs to calculate specific evaluation metrics. The detailed decoding process is in Algorithm 2.

3 Experiments

We evaluate our model's performance on two commonly used document-level EAE benchmarks and compare it to prior works. Then we conduct additional analytical experiments on how the demonstration retrieval design affects performance.

3.1 Experimental Setup

Datasets. We conduct our experiments on two widely used document-level EAE datasets: RAMS (Ebner et al., 2020) and WikiEvents (Li et al., 2021). RAMS provides 9,124 annotated examples from news based on 139 event types and 65 roles. WikiEvents provides 246 annotated documents based on 50 event types and 59 roles.

Models	RAMS		WikiEvents			PLM
	Arg-I	Arg-C	Arg-I	Arg-C	Head-C	
Multi-label classification-based Models						
BERT-CRF (Shi and Lin, 2019)*	-	40.3	-	32.3	43.3	BERT-base
PAIE (Ma et al., 2022)*	54.7	49.5	68.9	63.4	66.5	BART-base
	56.8	52.2	70.5	65.3	68.4	BART-large
QA-based Models						
EEQA (Du and Cardie, 2020)*	46.4	44.0	54.3	53.2	56.9	BERT-base
	48.7	46.7	56.9	54.5	59.3	BERT-large
DocMRC (Liu et al., 2021)*	-	45.7	-	43.3	-	BERT-base
Generation-based Models						
BART-Gen (Li et al., 2021)*	50.9	44.9	47.5	41.7	44.2	BART-base
	51.2	47.1	66.8	62.4	65.4	BART-large
T5-baseline‡	45.1	37.3	44.8	39.1	39.3	T5-base
	45.9	40.3	62.7	41.0	53.7	T5-large
Our Models using Retrieval-augmented Generation						
Setting 1: Context-Consistency Retrieval	52.2	44.9	59.8	40.4	58.7	T5-base
	53.9	47.9	66.8	50.9	63.4	T5-large
Setting 2: Schema-Consistency Retrieval	45.9	38.6	53.4	39.7	43.0	T5-base
	49.1	41.0	64.4	53.8	61.8	T5-large
Setting 3: Adaptive Hybrid Retrieval	53.3	46.3	61.4	46.1	62.5	T5-base
	54.6	**48.4**	**69.6**	**63.4**	**68.4**	T5-large

Table 1: Experimental results on RAMS and WikiEvents. * means the results from (Ma et al., 2022), and ‡ denotes the results from our implemented models for a fairer comparison. We highlight the SOTA results (classification-based method) with underlines. The best results among generation-based methods are marked in bold font.

Evaluation Metrics. Our results are reported as F-1 score of argument identification (**Arg-I**) and argument classification (**Arg-C**). For WikiEvents dataset, we follow Li et al. (2021) to additionally evaluate argument head F1 score (**Head-C**).

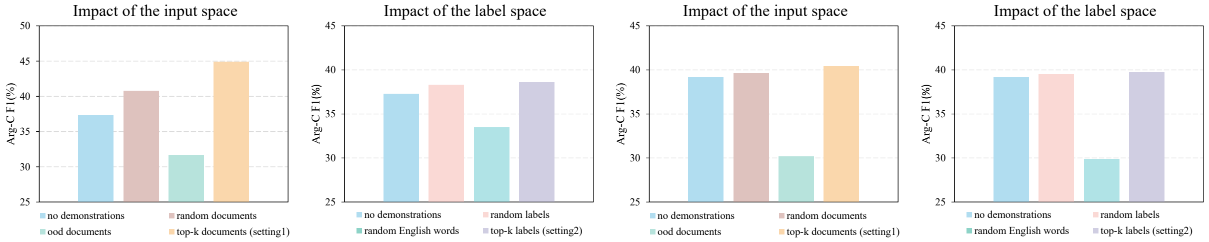
- **Arg-I**: an event argument is correctly identified if its offsets match those of any of the argument mentions.
- **Arg-C**: an event argument is correctly classified if its offset and role type both match the ground truth.
- **Head-C**: only considers the matching of the headword of an argument.

For the predicted argument, we find the nearest matched string to the golden trigger as the predicted offset. As an event type often includes multiple roles, we use micro-averaged role-level scores as the final metric.

Baselines. For strictly consistent comparison, we divide several state-of-the-art models into three categories: (1) Multi-label classification-based model: BERT-CRF (Shi and Lin, 2019), PAIE (Ma et al., 2022); (2) QA-based model: EEQA (Du and Cardie, 2020) and DocMRC (Liu et al., 2021); and (3) Generation-based model: BART-Gen (Li et al., 2021) and T5-baseline. T5-baseline is our own baseline without the retrieval component: directly encodes input context to generate role records.

Experimental Settings. We initialize our models with the pre-trained T5 model, available in the HuggingFace Transformers library[1]. We consider two model sizes, base and large, containing respectively 220M and 770M parameters. We fine-tune the models on each dataset independently using AdamW (Loshchilov and Hutter, 2019) and conducted experiments on 4 NVIDIA-V100-32GB. Due to GPU memory limitation, we used different batch sizes for different models: 8 for T5-large and 16 for T5-base; In each experiment, we train the model with 5 fixed seeds (42, 66, 88, 99, 101) and 4 learning rates (2e-5, 3e-5, 4e-5, 5e-5), and vote for the best learning rate for each seed with the best dev-set Arg-C performance. We report the averaged Arg-

[1] https://github.com/huggingface/transformers



(a) RAMS (b) RAMS (c) WikiEvents (d) WikiEvents

Figure 4: Impact of the input space and label space. Evaluated by Arg-C F1. More discussion is in Section 3.3.

C performance on the test set for selected checkpoints. We list other important hyperparameters in Appendix A.3.

3.2 Main Results

Table 1 presents the performance of all baselines and our models on RAMS and WikiEvents. From the results, we can conclude that:

(1) *By retrieving reference demonstrations to augment text generation, our retrieval-augmented models can significantly outperform generation-based models.* Our Setting 3 improves Arg-C F1 by **1.6%~10.6%** and **17.9%~54.6%** over the SOTA generation baseline BART-Gen and vanilla T5 on both datasets. Compared with sequence generation BART-Gen, our models do not require manually constructing the event template and can directly generate informative role records rather than irrelevant information. This verifies that the retrieval augmentation paradigm can improve the performance of generative document-level EAE.

(2) *By reformulating document-level EAE as retrieval-augmented generation, our models can achieve competitive performance without manually designing specific questions.* Our methods surpass most of the QA-based and classification-based baselines and achieve competitive performance with SOTA. Furthermore, compared to the QA-based models, our Setting 3 also demonstrates superior performance (up to **2.3** Arg-C F1 gains on RAMS), which reveals that retrieving demonstrations as cues works better than asking questions.

(3) *By generating pseudo-demonstrations in continuous space as depth cues to guide the model, our Setting 3 inspires the analogical capability of the model more than Setting 1 and 2.* As in Table 1, continuous augmentation (Setting 3) significantly outperform the discrete augmentation methods (Setting 1 and 2) on both datasets, whether in base-model or large-model (1.3%~16.1% for Arg-I F1, 1.0%~24.6% for Arg-C F1). These results demonstrate the stronger ability of adaptive hybrid augmentations than traditional augmentations for generalizing event-semantic-preserved demonstrations. And event semantic regions can generate diverse and faithful pseudo demonstrations to effectively improve the analogical capability of document-level EAE model.

Models	RAMS	
	Arg-span acc	Arg-role acc
T5-baseline	45.5	45.6
Setting 1: Context-Consistency Retrieval	**53.1**	45.2
Setting 2: Schema-Consistency Retrieval	42.3	**51.8**
Setting 3: Adaptive Hybrid Retrieval	52.3	50.9

Table 2: Argument span/role prediction accuracy on RAMS.

3.3 Analysis

Impact of the input space. To explore the reason why context-consistency affects performance, we additionally experiment with two variants of the document (random documents and out-of-distribution documents) on RAMS and WikiEvents. Specifically, "random documents" means that we randomly choose a set of k documents from their own training set as the demonstrations. "Out-of-distribution documents" means that we randomly choose a set of k documents from each other's training set as the demonstrations. Figure 4 shows that using out-of-distribution documents as references significantly drops the performance, and using random documents is better than no demonstrations. Setting 1 improves Arg-C F1 by about 6.0% and 11.8% over the "random documents" and no demonstrations. This is likely because using the in-distribution text as the context makes the task closer to language modeling since the LM always conditions on the in-distribution text during training. Furthermore, using in-distribution with similar text as context can further improve performance.

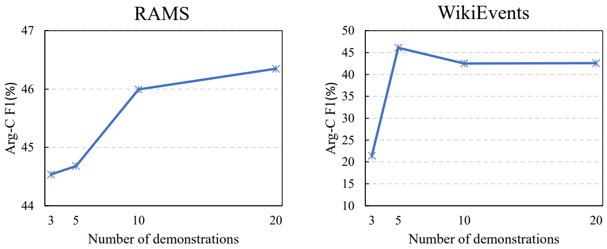


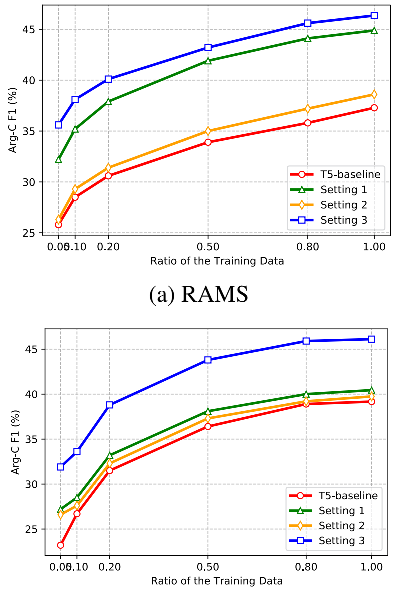
Figure 5: Performance of Setting 3 on both datasets as a function of the number of demonstrations.

Impact of the label space. To explore the reason why schema consistency affects performance, we experiment with two variants of Setting 2 (random labels and random English words) on RAMS and WikiEvents. Specifically, "random labels" means that we randomly choose a set of k labels from their own training set as the demonstrations. "Random English words" means that we randomly choose a set of English words from `https://pypi.org/project/english-words/` (consists of 61,569 words) as the demonstrations. From Figure 4 we can see that the performance gap between using random/top-k labels (within the label space) and using random English words is significant. Setting 2 improves Arg-C F1 by about 0.65% and 2.5% over "random labels" and no demonstrations. This indicates that conditioning on the label space can alleviate the difficulty of learning the complex event pattern, which is why performance improves.

Argument span prediction accuracy. Argument span prediction accuracy in Table 2 illustrates the Arg-I precision of both datasets. As expected, Setting 1 identifies the argument span more accurately than Setting 2, and the gap in prediction accuracy is as large as 25.5%. This indicates that in-distribution demonstration contexts can improve the ability to recognize argument spans and contribute to performance gains.

Argument role prediction accuracy. We also evaluate the capability to generate golden argument role in target sequence. From Table 2 we can see that Setting 2 generates role labels more accurately than Setting 1, and the gap in prediction accuracy is 14.6%. This suggests that schema-consistency retrieval alleviates the difficulty of learning the complex event pattern, and conditioning on the label space contributes to better performance.

Impact of the number of demonstrations k. Figure 5 illustrates how the hyper-parameters k affect the extraction performance. We observe that gradually increasing the number of demonstrations significantly improves Arg-C F1 in RAMS, but not in WikiEvents. We conjecture that the reason is that the averaged context length (about 900 words) in WikiEvents is too long, which affects the original input representation in the cross-attention module.



(a) RAMS

(b) WikiEvents

Figure 6: Arg-C F1 scores with different training data ratios on both benchmarks.

3.4 Few-shot Setting

To conduct detailed comparisons between different augmentation methods, we asymptotically increase the training data to analyze the performance of them on both datasets. Figure 6 shows the performance of them and T5-baseline with partial training samples. It demonstrates our approach achieves comparable performance with the T5-baseline model with only ~20% of training data, which indicates that our approach has great potential to achieve good results with very few data.

4 Related Work

Document-level Event Argument Extraction The goal of document-level EAE is to extract arguments from the whole document and assign them to right roles. On the task level, most of these works fall into three categories: (1) multi-label classification-based models (2) QA-based models (3) generation-based models. Specifically, Zhang et al. (2020); Xu et al. (2021); Huang and Jia (2021); Ren et al. (2022); Ma et al. (2022); Xu et al.

(2022) first identified argument spans and then fill each with a specific role via multi-label classification; Du and Cardie (2020); Liu et al. (2021); Wei et al. (2021) formulated document-level EAE as an question answering (QA) or machine reading comprehension (MRC) problem; Li et al. (2021) designed specific templates for each event type and frames EAE as conditional generation. Above methods conduct experiments on WikiEvents (Li et al., 2021), RAMS (Ebner et al., 2020), and Chinese financial dataset (Zheng et al., 2019).

Retrieval-Augmented Text Generation RAG has recently been successfully applied to many NLP tasks, e.g., dialogue response generation, machine translation, and information extraction. These methods retrieve additional knowledge from various corpora to augment text generation, which includes three major components: the retrieval source, retrieval strategy, and integration methods. Meanwhile, leveraging additional knowledge as the augmentation signal is a natural way to resolve the information insufficiency issue for information extraction. For example, Lee et al. (2022) proposed two demonstration retrieval methods for named entity recognition. Zhang et al. (2021) used the open-domain knowledge in Wikipedia as retrieval source for distantly supervised relation extraction. Du and Ji (2022) applied S-BERT (Reimers and Gurevych, 2019) to retrieve the most relevant example for event extraction.

5 Conclusion

In this paper, we explore how to design retrieval-augmented strategy for document-level EAE from the input and label distribution views. And our introduced retrieval strategies can recall demonstrations that can be helpful to demonstrate how the model should solve the task. We further propose a novel adaptive hybrid retrieval augmentation paradigm to generate the reference vectors as depth cues to improve the analogical capability of model. Through extensive experiments on RAMS and WikiEvents datasets, we demonstrate the validity of our newly introduced retrieval-augmented models. In the future, we plan to adapt our method to other document-level extraction tasks, such as document-level relation extraction.

Limitations

We discuss the limitations of our research as follows:

- Firstly, since the T5-large model has many parameters and our task is document level, one training process will occupy four NVIDIA V100 32GB GPUs;

- Our paper mainly studies document-level EAE task. Although we believe our approach is compatible with all document-level extraction tasks, how to adapt it to those tasks still remains an open question.

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A Dataset and Model

A.1 Dataset Statistics

RAMS is a document-level dataset of 9,124 annotated events from news based on an ontology of 139 event types and 65 roles. Each sample is a 5-sentence document, with the trigger word indicating a pre-defined event type and its argument scattered throughout the whole document. WikiEvents is another document-level dataset, providing 246 annotated documents from English Wikipedia articles based on 50 event types and 59 roles. Table 3 presents their detailed statistics.

Dataset	**#Split**	**#Doc**	**#Event**	**#Argument**
RAMS	Train	3,194	7,329	17,026
	Dev	399	924	2,188
	Test	400	871	2,023
WikiEvents	Train	206	3,241	4,542
	Dev	20	345	428
	Test	20	365	566

Table 3: Statistics of RAMS and WikiEvents datasets.

A.2 Details of Baselines

We compare our model with the following previous models.

- BERT-CRF (Shi and Lin, 2019): a multi-label classification-based method that uses a BERT-based BIO-styled sequence labeling model. We report the results from Liu et al. (2021).
- PAIE (Ma et al., 2022): another multi-label classification-based method that defines a new prompt tuning paradigm for event argument extraction. We report the results from original paper.
- EEQA (Du and Cardie, 2020): the first Question Answering (QA) based model designed for sentence-level EAE task. We report the results from Ma et al. (2022).

- DocMRC (Liu et al., 2021): another QA-based method with implicit knowledge transfer and explicit data augmentation. We report the results from original paper.

- BART-Gen (Li et al., 2021): formulate the task as a sequence-to-sequence task and uses BART-large to generate corresponding arguments in a predefined format. For BART-large model, we report the results from origin paper. For BART-base model, we report the results from Ma et al. (2022).

A.3 Implementation Details

We list other important hyperparameters in Table 4.

Hyperparameter	**RAMS**		**WikiEvents**	
	T5-base	T5-large	T5-base	T5-large
Batch size	16	8	16	8
Training epochs	50	50	20	40
Optimizer	AdamW	AdamW	AdamW	AdamW
Max input length	512	512	512	512
Max target length	64	64	512	512
Max demo length	150	100	200	100
k	20	20	5	5

Table 4: Hyperparameters

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
Limitations

☑ A2. Did you discuss any potential risks of your work?
Limitations

☑ A3. Do the abstract and introduction summarize the paper's main claims?
Abstract

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☑ Did you use or create scientific artifacts?

3 Experiments

□ B1. Did you cite the creators of artifacts you used?
No response.

□ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
No response.

□ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
No response.

□ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
No response.

□ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
No response.

□ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
No response.

C ☑ Did you run computational experiments?

3 Experiments

□ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
No response.

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

□ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
No response.

□ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
No response.

□ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
No response.

D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?

Left blank.

□ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
No response.

□ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
No response.

□ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
No response.

□ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
No response.

□ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
No response.