PILED: An Identify-and-Localize Framework for Few-Shot Event Detection

Abstract

Practical applications of event extraction systems have long been hindered by their need for heavy human annotation. In order to scale up to new domains and event types, models must learn to cope with limited supervision, as in few-shot learning settings. To this end, the major challenge is to let the model master the semantics of event types, without requiring abundant event mention annotations. In our study, we employ cloze prompts to elicit event-related knowledge from pretrained language models and further use event definitions and keywords to pinpoint the trigger word. By formulating the event detection task as an identify-then-localize procedure, we minimize the number of type-specific parameters, enabling our model to quickly adapt to event detection tasks for new types. Experiments on three event detection benchmark datasets (ACE, FewEvent, MAVEN) show that our proposed method performs favorably under fully supervised settings and surpasses existing few-shot methods by 21% F1 on the FewEvent dataset and 20% on the MAVEN dataset when only 5 examples are provided for each event type.

1 Introduction

Understanding events is central to information extraction, and event detection is an inevitable step in this process. The task of event detection is to locate the event trigger (i.e., the minimal lexical unit that indicates the event) and classify the trigger into one of the given event types. While steady progress has been made for event detection given ample supervision (Wadden et al., 2019; Lin et al., 2020; Lu et al., 2021), it is hard to replicate these success stories in new domains and on new event types without large-scale annotation. Here, to respond to emerging user needs and cope with limited annotation, we focus our study on the few-shot learning setting.

Recently, prompt-based learning has shown great success in few-shot learning for a range of classification and generation tasks. Compared to the typical supervised learning paradigm, prompt-based models are not only shaped by the annotated examples, but can also be guided by the prompt. In Figure 1, the prompt “The sentence describes a [MASK] event” aligns the masked language model prediction objective with the identification of the event type mentioned in the context.

Since event detection aims to recognize both the event type and the trigger location, the cloze-based prompt learning paradigm (Schick and Schütze, 2021a) designed for classification is not directly applicable. In our study, we propose an identify-then-localize approach, which detaches the type semantic from the sequence labeling and opens the door to prompt learning. Specifically, we first recognize the event types in the given context (the identification stage) and then find the trigger location (the localization stage).

Our identification model extends cloze-based prompt learning (Schick and Schütze, 2021a) to multi-class classification for event detection. Since
a sentence can contain multiple events or no events at all, we extend the model to a multi-label classification setting by adding a NULL class which stands for “no event identified”. We designate a special token none as the verbalizer\(^1\) for the NULL class as well and compare it against the predictions for all of the valid event types (as in Figure 2). In this design, the NULL verbalizer effectively serves as the dynamic threshold for multi-class classification (Zhou et al., 2021).

The localization model is a single-class sequence tagger that takes one of the event types identified from above as input and aims to recognize the corresponding trigger (as in Figure 3). Since we narrow the search to one event type, we employ the filled prompt along with optional event type descriptions and keywords\(^2\) to augment the input. In this way, we decouple the model from the event label by including the event label information on the input side instead. This makes our localization model type-free, thus benefitting from the training examples of all event types.

We test our model on a range of datasets (ACE 2005, FewEvent (Deng et al., 2020), MAVEN (Wang et al., 2020)) under fully-supervised and few-shot event detection settings. Our experiments show that our model achieves state-of-the-art performance under the fully-supervised setting and dramatically outperforms existing baselines under the few-shot setting.

Our main contributions include:

- We introduce a new identify-then-localize approach to event detection. By decoupling the type semantics from the sequence labeling task, we bring the benefits of cloze-based prompt learning to event detection and allow for flexible injection of event knowledge.

- We extend the cloze-based prompt learning paradigm to multi-label event type classification. This enables us to leverage the language modeling ability of pretrained LMs for the event identification task and adapt quickly to new event types. This method can be applied to other multi-label classification tasks.

- We design an attention-enhanced single-class CRF tagger for event trigger localization. This attention mechanism allows for the interaction of predictions over neighboring tokens.

- Our model achieves excellent performance on the event detection task under both few-shot and fully-supervised settings. In particular, for few-shot event detection on FewEvent (Deng et al., 2020), we surpass the next best baseline by over 21% F1. On MAVEN, we achieve 8% F1 gains in the identification stage and present the first results for few-shot event detection.

## 2 Methodology

Given a collection of contexts \(C\) and a pre-defined event ontology \(T\) (a set of target event types), event detection aims to find all event mentions in the collection that fall into the given ontology. An event mention is characterized by a trigger span \(s\) (start index, end index) and an event type \(t \in T\). Here we follow previous work and consider each sentence as the context of the event.

We divide the event detection task into two stages: identification and localization. In the identification stage, for each context \(c\), we find a set of event types \(T\) that have been mentioned. In the localization stage, we take a pair of context and event type \((c, t)\) as input and find a set of spans \(S\) that correspond to the triggers for that event type. Note that both stages can produce a variable number of outputs for each input.

### 2.1 Event Type Identification

The event type identification model follows the idea of using a cloze-style prompt for few-shot learning with masked language models (Schick and Schütze, 2021a). Cloze-style prompt learning transforms a classification problem into a masked language modeling using a prompt and a verbalizer function. The prompt \(P\) is a natural language sentence with a \([\text{MASK}]\) token. This prompt can be viewed as a cloze question, whereas the answer is related to the desired class label. Figure 2 shows a cloze prompt that can be used for event detection: “This text describes a [MASK] event”.

The relationship between the class labels \(\mathcal{L}\) and the predicted tokens \(V\) for the [MASK] is defined by the verbalizer function \(f_v: \mathcal{L} \rightarrow V\). For example, we choose the verbalizer function to map the event type Start-Position to the token hire. We also refer to hire as the verbalizer for Start-Position.
During prediction, we use the logit that the masked language model $M$ assigns to the verbalizer $f_v(l)$ for label $l$ as the proxy for predicting $l$. In the classification task, the probability for label $l$ can then be computed as shown in Equation 1.

$$p(t = l) = \frac{\exp(M(f_v(l)|x, P))}{\sum_{l' \in L} \exp(M(f_v(l')|x, P))} \quad (1)$$

For event detection, since each sentence can potentially mention multiple event types, we extend this approach to handle multi-label classification. Through the masked language model, we score all tokens in the vocabulary on their likelihood to fill in the blank. After excluding tokens that do not map back to any event type of interest (such as the token report in the example), we obtain a ranking among all event types. The key becomes finding the cutoff threshold for translating these scores into outputs. We assign a token $v_{\text{NULL}}$ to the NULL type$^3$ and use it as an adaptive threshold. In the inference stage, we predict all event types that score higher than the NULL type to be positive. In our example, since hire and resign both have higher scores than the NULL verbalizer none, we predict Start-Position and End-Position as the event types in the context.

During training, for each sentence, we compute the loss for the positive event types and the negative event types separately with respect to the NULL type:

$$L_{\text{pos}} = \frac{1}{|T|} \sum_{t \in T} \log \frac{\exp(M(f_v(l)|x, P))}{\sum_{l' \in \text{NULL}, l' \neq l} \exp(M(f_v(l')|x, P))} \quad (2)$$

$$L_{\text{neg}} = \log \frac{\sum_{l' \in \text{NULL}, l' \neq l} \exp(M(f_v(l')|x, P))}{\exp(M(f_v(l)|x, P))} \quad (3)$$

Equation 2 effectively pushes the score of each positive event type above the NULL event type and Equation 3 lowers the scores for all negative event types.

For some event types such as “Business: Lay off”, the natural language label “lay off” cannot be mapped to a single token. In this case, we add a new token (lay_off) and initialize its embeddings as the average of the tokens that compose the original event type name.

### 2.2 Verbalizer Selection

In cases where event type names are not single tokens, it seems appealing to be able to automatic select good verbalizers for the event types.

We first collect a candidate verbalizer set $\mathcal{V}$ from the few labeled examples’ trigger words. Then we use a frozen language model to score the candidates in a similar formulation as our identification model. The selection for each event type $l$ is done separately. We compute the score of a candidate verbalizer $v$ for event type $l$ using a simple reciprocal rank scoring function:

$$\text{score}(v, l) = \sum_{r_i(v)} \frac{1}{r_i(v)}$$

where $r_i$ the predicted ranking from the frozen language model. We also experimented with the cross entropy scoring function but discovered that it favored

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$^3$In our experiments, we use the token “none” as the NULL type’s verbalizer.
more frequent words. The verbalizer for each class is then selected to maximize the scores:

$$f_c(l) = \arg \max_v \text{score}(v, l)$$  \hspace{1cm} (6)

Note that the surface form of the verbalizer is only an initialization: during training the embedding of the token will be updated.

### 2.3 Trigger Localization

Trigger localization is the task of finding the trigger offset given a context $c$ and an event type $t$. Since we already know the event type, we can construct a more informative input by leveraging external knowledge (for instance, from FrameNet) about the event type. For example, in Figure 3, we use the event description from the annotation guidelines to help define the “Start-Position” event type. We can also use a few keywords (example triggers) to serve as the event knowledge. In our experiments we compare these two forms of event knowledge.

Our localization model is a linear chain CRF tagger with only three tags: BIO. In this way, the model parameters are not tied with any event type and can be easily used for transfer.

The probability of a tagged sequence is:

$$p(y|h; \theta) = \frac{\exp \left( \sum_i \varphi(y_i|\vec{h}_i) + \sum_j \psi(y_j|y_{j-1}) \right)}{Z}$$  \hspace{1cm} (7)

where $\vec{h}_i$ is the contextualized embedding vector of the tokens from the masked language model and $Z$ is a normalization factor.

We parameterize the emission scorer $\varphi(y_i|\vec{h}_i)$ as:

$$\varphi(y_i|\vec{h}_i) = W_{l}h_i + \sum_j \alpha_{ij}W_{v}h_j$$  \hspace{1cm} (8)

where $W_{l} \in \mathbb{R}^{3 \times m}$ and $W_{v} \in \mathbb{R}^{3 \times m}$ map the embeddings to the tag space, serving as an early prediction. Then we fuse the predictions for the token and the other tokens through an attention mechanism with the weight $\alpha_{ij}$ defined as:

$$\alpha_{ij} = \text{Softmax}_j \left( \frac{(W_{q}h_i)^T W_{k}h_j}{\sqrt{m}} \right)$$  \hspace{1cm} (9)

$m$ is the dimension of the embeddings $h$ and $W_{q} \in \mathbb{R}^{m \times m}$, $W_{k} \in \mathbb{R}^{m \times m}$ are learnable parameters.

### 2.4 Joint Training

In a sense, our identification model captures the probability of the event type given the context $p(t|x)$ and our localization model captures the probability of the token tags given the context and event type: $p(y|t, x)$.

The identification model and the localization model share the same masked language model backbone. Since these two tasks have slightly different inputs, we alternate between sampling batches for each task.

### 3 Experiments

In the following experiments, we refer to our proposed model as PILED, standing for Prompt-guided Identify-then-Localization Event Detection.

#### Datasets

We evaluate our model on three datasets, FewEvent (Deng et al., 2020), MAVEN (Wang et al., 2020) and ACE2005.

FewEvent is designed to be a few-shot event detection benchmark aggregating data from ACE, TAC-KBP (Ji and Grishman, 2011) and expanding to additional event types related to sports, music,
We present the overall dataset statistics in Table 1. Details of the data splits are available in the Appendix.

**Evaluation Metrics** For all experiments, we use the event mention precision, recall and micro-F1 score as our major evaluation metrics. An event mention is considered correct if both its type and trigger span are correct.

**Implementation Details** We use BERT (Devlin et al., 2019) as the language model for the experiments on FewEvent. For experiments on MAVEN and ACE, we also used Roberta (Liu et al., 2019). On ACE, we use the large model and on FewEvent, we use the base model. For the base model, we use a batch size of 8 and a learning rate of $2e^{-5}$. For the large model, we use a batch size of 16 and a learning rate of $1e^{-5}$. We set the maximum sequence length to 200 tokens since our predictions are on the sentence-level. For more details, we refer the readers to the Appendix.

### 3.1 Few Shot Event Detection

For few-shot experiments, we follow the setting in (Yang and Katiyar, 2020; Chen et al., 2021) which samples $K$ examples for training and uses the remaining samples for testing. We list our results on the FewEvent dataset in Table 2 and results on the MAVEN dataset in Table 3.

On FewEvent, there is only one event type labeled per sentence, so the identification task is reduced to classification. On the localization task, our model can jointly learn from annotation of all event types, giving us a significant advantage (over 16% F1) over sequence labeling models that store “prototype” representations of each event type individually.

On the MAVEN dataset, the increase in event types and the fact that multiple event types can co-occur in the same sentence makes the task more difficult. On the identification task, our prompt-based method can outperform the causal inference enhanced RelNet (Chen et al., 2021; Sung et al., 2018) by 8.5% F1 without having access to the trigger word location. Instead of linking trigger words to a numerical label, our identification model leverages the similarity between the verbalizer and the triggers. For the event detection task (with localization), since no previous work attempted this task, we compare with a token classification baseline that follows the fine-tuning paradigm and adapt a competitive few-shot name tagging model StructShot (Yang and Katiyar, 2020) to our task. Additionally, we show some example predictions in Table 4. The Token Classification baseline has poor performance and high variance due to the sampling of the support set. Due to abundance of ‘O’ (outside) tags, this baseline also tends to refrain from predicting any event type. The StructShot model is a token-level k-nearest neighbor model with Viterbi decoding. As KNN models are learning-free, the StructShot model performs relatively well under few-shot settings. However, this KNN backbone also limits the model’s performance when encountering new triggers as in the case for “inundated” and “authorized”.

### 3.2 Supervised Event Detection

We report supervised event detection results on the ACE+ dataset in Table 5. We compare with a wide range of existing methods, covering the paradigms of single-task sequence labeling, multitask learning, question answering and generation. We see
Table 3: Few-shot event detection results (%) on MAVEN. We follow the 45 way 5 shot setting in (Chen et al., 2021) and report the average and standard deviation for 10 runs. Results marked with * are also taken from the aforementioned paper.

| Task | Model | Micro F1 |
|------|-------|----------|
| Id   | RelNet (BERT)* | 56.0 ± 1.4 |
|      | RelNet + Causal (BERT)* | 57.0 ± 0.9 |
|      | PILED (BERT) | 63.9 ± 0.9 |
|      | PILED (RoBERTa) | 65.5 ± 1.1 |
| Id + Loc | TokClassification (RoBERTa) | 16.3 ± 4.7 |
|      | StructShot (RoBERTa) | 40.4 ± 1.0 |
|      | PILED (BERT) | 60.6 ± 1.0 |
|      | PILED (RoBERTa) | 63.1 ± 1.1 |

that our prompt-based task formulation performs equally or better than existing methods. In particular, the multitask learning models OneIE (Lin et al., 2020; Nguyen et al., 2021) enjoys the benefits of joint training across related tasks such as entity extraction and relation extraction. Notably, DEGREE (Hsu et al., 2021) also uses event descriptions and keywords as a “type-aware prompt” to guide the generation of the trigger word. However, generation using the entire vocabulary is more challenging than our localization task.

4 Analysis and Discussion

In this section we take a closer look at the design choices in our model, including the verbalizer, event knowledge and model design.

4.1 Verbalizer Selection

We present some of the automatic selected verbalizers in Table 6. In general, these verbalizers are not far off from the event type semantics, but may be ambiguous (such as the word “house”) or have more general meaning beyond the scope of the event type (such as “design” may be used outside of art).

In Table 7, we show how this difference in verbalizers affect the event detection performance. When the number of examples per event type increases, the verbalizer selection quality is improved and the model is also able to rely more on the training examples instead of the verbalizer initialization, leading to a smaller gap between the automatic selection and manual selection.

We note that we have chosen a simple method to select verbalizers and more recent research on verbalizer selection and expansion (Hu et al., 2021) might be able to further improve automatic verbalizer performance.

4.2 Injecting Event Knowledge

In our model, event knowledge is present in the verbalizer in the identification stage and the type-aware prompt in the localization stage.

In the previous experiments, we use one manually selected verbalizer per event type. A natural question is whether more verbalizers will help. We use MAVEN for this set of experiments since MAVEN provides alignments between its event types and FrameNet frames. The FrameNet definitions and lexical units can then serve as event knowledge.

When more than one verbalizer is used, we need to aggregate the scores over the verbalizer set. We experiment with 4 different types of aggregation operators: avg, max, logsumexp, weighted-avg. The logsumexp operator can be seen as a smoothed version of the max operator. In the weighted-avg operator, the weights of the verbalizers are additional learnable parameters (Hu et al., 2021). As shown in Table 8, in the few-shot setting, using multiple verbalizers can provide 1.5-2% F1 improvement on identification which translates to 1.6-2.2% F1 improvement on the event detection task. In terms of aggregation methods, the avg operator is a simple and reliable choice with the best performance and lowest variance. Although the wavg operator is more expressive, it is hard to learn good weights with only 5 examples per event type.

For the type-aware prompt, we consider using the event definition or event keywords and compare it against the baseline of using the filled prompt from the identification stage. As seen in Table 9, the event verbalizer alone is relatively informative and adding more event keywords from the lexical units can provide an additional 0.8% F1 gain. The definitions from FrameNet are highly abstract, which may undermine their value in assisting event detection.

4.3 Model Design Choices

We design our localization model as an attention-enhanced single-class CRF tagger. However, there are many alternative modeling choices for detecting the trigger offset. Here, we experiment with other...
Strong winds and heavy rainfall inundated streets, residences, and fields, and also toppled chimneys, fences, and cracked windows across the region.

It was led by the U.S. Marines and U.S Army against the Iraqi insurgents in the city of Fallujah and was authorized by the U.S.-appointed Iraqi Interim Government.

In June 2010, seven Indian nationals who were UCIL employees in 1984, including the former UCIL chairman, were convicted in Bhopal of causing death by negligence and sentenced to two years prison and a fine of about $2,000 each, the maximum punishment allowed by Indian law.

Table 4: Case studies on the few-shot event detection task. The annotations are marked in the context: the trigger is underlined and the corresponding event name is provided in the bracket.

| Category       | Model                        | Prec | Recall | F1  |
|----------------|------------------------------|------|--------|-----|
| Sequence labeling | Token Classification          | 67.1 | 72.3   | 69.6|
| Sequence labeling | Token Classification+CRF      | 67.8 | 76.6   | 71.9|
| Multitask       | OneIE* (Lin et al., 2020)    | -    | -      | 72.8|
| Multitask       | FourIE* (Nguyen et al., 2021)| -    | -      | 73.3|
| QA              | EEQA* (Du and Cardie, 2020)  | 71.1 | 73.7   | 72.4|
| Generation      | Text2EVENT* (Lu et al., 2021)| 71.2 | 72.5   | 71.8|
| Generation      | DEGREE* (Hsu et al., 2021)   | -    | -      | 72.7|
| Prompt-based    | PILED                        | 70.9 | 76.1   | 73.4|

Table 5: Supervised event detection results (%) on ACE+. The best results are in boldface and the next best results are underlined. * indicates results cited from the original paper.

| Event type     | Manual | Auto |
|----------------|--------|------|
| Filling        | fill   | cover|
| Cure           | treatment | relief |
| Create_artwork | draw   | design|
| Imposing_obligation | require | charges|
| Commerce_buy   | purchase | shopping|
| Containing     | contain | house|

Table 6: Examples of automatically selected verbalizers when provided with 10 examples per class.

| Task     | Model  | $K = 5$ | $K = 10$ |
|----------|--------|---------|----------|
| Id       | Automatic | 59.5 ± 1.5 | 70.4 ± 1.4 |
|          | Manual   | 63.9 ± 0.9 | 72.6 ± 1.5 |
| Id + Loc | Automatic | 56.8 ± 1.2 | 67.5 ± 1.1 |
|          | Manual   | 60.6 ± 1.0 | 69.5 ± 1.5 |

Table 7: Few-shot event detection results (%) on MAVEN with automatic selected verbalizers.

Table 8: Using multiple verbalizers for the 45-way-5-shot event detection on the MAVEN dataset (RoBERTa-base model). To balance between frames that have different number of lexical units, we use at most 3 verbalizers. wavg stands for weighted-avg.

common models including the question answering (QA) formulation (Du and Cardie, 2020; Liu et al., 2020), the span classification formulation (Span Classifier) and the vanilla CRF model as shown in Table 10. For the single-class CRF model, we remove the attention based early-interaction term in Equation 7. In the question answering formulation, we compute the scores of the token being first token in the answer (the answer head) and being the last token in the answer (the answer tail) separately. This simple QA model cannot handle multiple “answers” per sentence, so we extend it to a span classification model where each span is scored independently and assigned a binary label.

Although the span classifier can handle multiple triggers in the same sentence, it suffers from low precision. Compared to the QA model and the span classifier model which score candidate triggers independently, the vanilla CRF model explicitly models the correlation between neighboring tokens, leading to better performance. Additi-
### Event knowledge

| Event Knowledge          | Id F1  | Loc F1  |
|-------------------------|--------|---------|
| Verbalizer              | 64.8 ± 1.3 | 62.0 ± 1.5 |
| Verbalizer + Definition | 64.8 ± 1.3 | 62.3 ± 1.5 |
| Verbalizer + Keywords   | 65.5 ± 1.1 | 63.1 ± 1.1 |

Table 9: Comparison of using different types of event knowledge to construct the type-aware prompt for localization (RoBERTa-base model). The event verbalizer is present in the filled prompt. We use at most 3 keywords per event type.

| Id    | Model          | Loc Model | Prec | Recall | F1    |
|-------|----------------|-----------|------|--------|-------|
| ✓ Full model | 70.9 | 76.1 | 73.4 |
| ✓ Single class CRF | 68.3 | 74.9 | 71.5 |
| ✓ QA     | 72.5 | 69.0 | 70.7 |
| ✓ Span Classifier | 63.5 | 78.3 | 70.1 |
| Enumerate Full model | 54.5 | 81.3 | 65.3 |

Table 10: Model ablations on ACE+.

Finally, our attention-enhanced CRF layer can further improve upon the vanilla CRF model by 1.9% F1 points.

One alternative to the *identify-then-localize* framework is to simply enumerate all possible event types and attempt to localize the trigger for them. To verify if the identification step is truly necessary, we compare our two-stage model with a localization-only model that enumerates all possible event types. As shown in the last row of Table 10, this model has high recall at the cost of low precision. Additionally, with N event types in the ontology, this model requires N times training time and inference time.

### Related Work

#### 5.1 Prompt-Tuning

The pioneer of prompt-tuning is the concept of in-context learning introduced by GPT-3 (Brown et al., 2020), demonstrating the few-shot capability of large pretrained language models. What sets prompt-tuning apart from the widely used fine-tuning approach is that the task specifications (task description or examples) are provided as part of the input. Depending on the format of the prompt, prompt-tuning methods can be divided into cloze-style prompts for classification (Schick and Schütze, 2021) and open-ended prompts for generation (Li and Liang, 2021). Based on the human readability of the prompts, they can be either discrete (Shin et al., 2020), or continuous (Qin and Eisner, 2021). For a more comprehensive view on the work in prompt-tuning, we refer readers to (Liu et al., 2021).

Application-wise, prompt-tuning has been shown to be very successful for classification and generation tasks. There have been some recent attempts to apply prompt-tuning to informative extraction tasks such as named entity recognition (Ding et al., 2021) and relation extraction (Han et al., 2021) but they largely focus on the classification component of these tasks after locating the target spans. To date, we are the first to tailor prompt-learning for the event detection task.

#### 5.2 Low Resource Event Detection

Due to the high cost of annotating event instances, low resource event detection has received much attention in recent years. There are a variety of settings explored, including zero-shot transfer learning (Lyu et al., 2021; Huang et al., 2018), cross-lingual transfer (Subburathinam et al., 2019), inducing event types (Huang et al., 2016; Wang et al., 2021; Huang and Ji, 2020), keyword-based supervision (Zhang et al., 2021), Lifelong learning (Yu et al., 2021) and few-shot learning (Peng et al., 2016; Lai et al., 2020; Shen et al., 2021; Cong et al., 2021; Chen et al., 2021).

Methodology-wise, prototype-based methods (Deng et al., 2020; Zhang et al., 2021; Cong et al., 2021; Shen et al., 2021) have been a popular choice since they were originally developed for few-shot learning. Either starting from keywords (Zhang et al., 2021), definitions (Shen et al., 2021) or examples (Deng et al., 2020; Cong et al., 2021), the key is to learn a good representation for each event type (often referred to as the class prototype) and then predict the event type of the new example using a certain proximity metric to the “prototype”.

Another idea is to transfer knowledge from semantic parsers, such as AMR (Wang et al., 2021; Huang et al., 2018) or SRL (Zhang et al., 2021; Lyu et al., 2021) parsers. The event detection task is then converted into the task of finding a mapping between the predicates detected by the semantic parser to event types in the target ontology. Such methods are dependent on the performance of the semantic parsers.

QA-based (Du and Cardie, 2020; Liu et al., 2020) and generation-based methods (Li et al., 2021; Hsu et al., 2021) can also be adapted to the problem since event type information can be incorporated into the input. However, with this flexibility comes
a drawback: if a general question such as “What is the trigger?” is asked, the model cannot quickly adapt to new types; if a type-specific question such as “What is the trigger for attack?” is used, the model has to be queried once per possible event type to reach the final answer. For the sake of efficiency, we formulate the identification step as a multi-class classification problem. We also compare our two-stage model’s performance with this enumerative approach in Section 4.2.

6 Conclusions and Future Work

In this paper we study event detection under few-shot learning settings. Inspired by cloze prompts that can bridge the gap between pretrained masked language models and a target task through a task description, we extend this idea to event detection by formulating the problem as an identify-then-localize procedure. Specifically, we first identify the event types present in the context and then find the trigger location based on type-specific event knowledge. We show that this approach significantly outperforms existing methods for few-shot event detection, achieving a 21% absolute F1 score gain on FewEvent and 20% gain on MAVEN.

An interesting extension would be to develop interactive systems where the user can constantly provide feedback to assist the extraction of new event types, especially when the initial examples carry ambiguity.

References

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, T. J. Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeff Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. NeurIPS.

Jiawei Chen, Hongyu Lin, Xinpei Han, and Le Sun. 2021. Honey or poison? solving the trigger curse in few-shot event detection via causal intervention. EMNLP.

Xin Cong, Shiyou Cui, Bowen Yu, Tingwen Liu, Wang Yubin, and Bin Wang. 2021. Few-Shot Event Detection with Prototypical Amortized Conditional Random Field. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 28–40. Online. Association for Computational Linguistics.

Shumin Deng, Ningyu Zhang, Jiaojian Kang, Yichi Zhang, Wei Zhang, and Huajun Chen. 2020. Meta-learning with dynamic-memory-based prototypical network for few-shot event detection. Proceedings of the 13th International Conference on Web Search and Data Mining.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Ning Ding, Yulin Chen, Xu Han, Guangwei Xu, Pengjun Xie, Hai-Tao Zheng, Zhiyuan Liu, Juan-Zi Li, and Hong-Gee Kim. 2021. Prompt-learning for fine-grained entity typing. ArXiv, abs/2108.10604.

Xinya Du and Claire Cardie. 2020. Event extraction by answering (almost) natural questions. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 671–683. Online. Association for Computational Linguistics.

Tianyu Gao, Xu Han, Hao Zhu, Zhiyuan Liu, Peng Li, Maosong Sun, and Jie Zhou. 2019. FewRel 2.0: Towards more challenging few-shot relation classification. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6250–6255, Hong Kong, China. Association for Computational Linguistics.

Xu Han, Weilin Zhao, Ning Ding, Zhiyuan Liu, and Maosong Sun. 2021. Pte: Prompt tuning with rules for text classification. ArXiv, abs/2105.11259.

I-Hung Hsu, Kuan-Hao Huang, Elizabeth Boschee, Scott Miller, Prem Natarajan, Kai-Wei Chang, and Nanyun Peng. 2021. Degree: A data-efficient generative event extraction model.

Shengding Hu, Ning Ding, Huadong Wang, Zhiyuan Liu, Juan-Zi Li, and Maosong Sun. 2021. Knowledgeable prompt-tuning: Incorporating knowledge into prompt verbalizer for text classification. ArXiv, abs/2108.02035.

Lifu Huang, Taylor Cassidy, Xiaocheng Feng, Heng Ji, Clare R. Voss, Jiawei Han, and Avirup Sil. 2016. Liberal event extraction and event schema induction. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 258–268, Berlin, Germany. Association for Computational Linguistics.
Lifu Huang and Heng Ji. 2020. Semi-supervised new event type induction and event detection. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 718–724, Online. Association for Computational Linguistics.

Lifu Huang, Heng Ji, Kyunghyun Cho, Ido Dagan, Sebastian Riedel, and Clare Voss. 2018. Zero-shot transfer learning for event extraction. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2160–2170, Melbourne, Australia. Association for Computational Linguistics.

Heng Ji and Ralph Grishman. 2011. Knowledge base population: Successful approaches and challenges. In Proc. ACL2011.

Viet Dac Lai, Thien Huu Nguyen, and Franck Deroncourt. 2020. Extensively matching for few-shot learning event detection. In Proceedings of the First Joint Workshop on Narrative Understanding, Storylines, and Events, pages 38–45, Online. Association for Computational Linguistics.

Sha Li, Heng Ji, and Jiawei Han. 2021. Document-level event argument extraction by conditional generation. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 894–908, Online. Association for Computational Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 4582–4597, Online. Association for Computational Linguistics.

Ying Lin, Heng Ji, Fei Huang, and Lingfei Wu. 2020. A joint neural model for information extraction with global features. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7999–8009, Online. Association for Computational Linguistics.

Sheng Chen, Yubo Chen, Kang Liu, Wei Bi, and Xiaojiang Liu. 2020. Event extraction as machine reading comprehension. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1641–1651, Online. Association for Computational Linguistics.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021. Pretrain, prompt, and predict: A systematic survey of prompting methods in natural language processing. ArXiv, abs/2107.13586.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. ArXiv, abs/1907.11692.

Yaojie Lu, Hongyu Lin, Jin Xu, Xianpei Han, Jialong Tang, Annan Li, Le Sun, Meng Liao, and Shaoyi Chen. 2021. Text2Event: Controllable sequence-to-structure generation for end-to-end event extraction. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2795–2806, Online. Association for Computational Linguistics.

Qing Lyu, Hongming Zhang, Elior Sulem, and Dan Roth. 2021. Zero-shot event extraction via transfer learning: Challenges and insights. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 322–332, Online. Association for Computational Linguistics.

Minh Van Nguyen, Viet Lai, and Thien Huu Nguyen. 2021. Cross-task instance representation interactions and label dependencies for joint information extraction with graph convolutional networks. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 27–38, Online. Association for Computational Linguistics.

Haoruo Peng, Yangqiu Song, and Dan Roth. 2016. Event detection and co-reference with minimal supervision. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 392–402, Austin, Texas. Association for Computational Linguistics.

Guanghui Qin and Jason Eisner. 2021. Learning how to ask: Querying LMs with mixtures of soft prompts. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5203–5212, Online. Association for Computational Linguistics.

O. Mahamane Sani Sabo, Yanai Elazar, Yoav Goldberg, and Ido Dagan. 2021. Revisiting few-shot relation classification: Evaluation data and classification schemes. Transactions of the Association for Computational Linguistics, 9:691–706.

Timo Schick and Hinrich Schütze. 2021a. Exploiting cloze-questions for few-shot text classification and natural language inference. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 255–269, Online. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2021b. It’s not just size that matters: Small language models are also
few-shot learners. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2339–2352, Online. Association for Computational Linguistics.

Shirong Shen, Tongtong Wu, Guilin Qi, Yuan-Fang Li, Gholamreza Haffari, and Sheng Bi. 2021. Adaptive knowledge-enhanced Bayesian meta-learning for few-shot event detection. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2417–2429, Online. Association for Computational Linguistics.

Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. AutoPrompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4222–4235, Online. Association for Computational Linguistics.

Jake Snell, Kevin Swersky, and Richard S. Zemel. 2017. Prototypical networks for few-shot learning. In NIPS.

Ananya Subburathinam, Di Lu, Heng Ji, Jonathan May, Shih-Fu Chang, Avirup Sil, and Clare Voss. 2019. Cross-lingual structure transfer for relation and event extraction. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 313–325, Hong Kong, China. Association for Computational Linguistics.

Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip H. S. Torr, and Timothy M. Hospedales. 2018. Learning to compare: Relation network for few-shot learning. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1199–1208.

Oriol Vinyals, Charles Blundell, Timothy P. Lillicrap, Koray Kavukcuoglu, and Daan Wierstra. 2016. Matching networks for one shot learning. In NIPS.

David Wadden, Ulme Wennberg, Yi Luan, and Hannaneh Hajishirzi. 2019. Entity, relation, and event extraction with contextualized span representations. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5784–5789, Hong Kong, China. Association for Computational Linguistics.

Xiaozhi Wang, Qizi Wang, Xu Han, Wangyi Jiang, Rong Han, Zhiyuan Liu, Juanzi Li, Peng Li, Yankai Lin, and Jie Zhou. 2020. MAVEN: A Massive General Domain Event Detection Dataset. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1652–1671, Online. Association for Computational Linguistics.

Ziqi Wang, Xiaozhi Wang, Xu Han, Yankai Lin, Lei Hou, Zhiyuan Liu, Peng Li, Juanzi Li, and Jie Zhou. 2021. CLEVE: Contrastive Pre-training for Event Extraction. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6283–6297, Online. Association for Computational Linguistics.

Yi Yang and Arzoo Katiyar. 2020. Simple and effective few-shot named entity recognition with structured nearest neighbor learning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6365–6375, Online. Association for Computational Linguistics.

Pengfei Yu, Heng Ji, and Premkumar Natarajan. 2021. Lifelong event detection with knowledge transfer. In Proc. The 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP2021).

Hongming Zhang, Haoyu Wang, and Dan Roth. 2021. Zero-shot Label-aware Event Trigger and Argument Classification. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 1331–1340, Online. Association for Computational Linguistics.

Wenxuan Zhou, Kevin Huang, Tengyu Ma, and Jinke Huang. 2021. Document-level relation extraction with adaptive thresholding and localized context pooling. In AAAI.

A Dataset Details

For FewEvent, we use the data split from (Cong et al., 2021) and use 80 event types as the training set, 10 event types as the dev set and the remaining 10 event types as the test set. In the data provided, sentences are organized by event type and each sentence only has one event mention annotation.

| # Types | Train | Dev | Test |
|---------|-------|-----|------|
| 80      | 67,982| 2,173| 697  |

Table 11: Data split for FewEvent.

In the N-way K-shot experiments, we randomly sample $N$ event types from the test set and then sample $K$ labeled instances of that event type for training.

For MAVEN, we follow the data split by (Chen et al., 2021) and use the sentences containing the most frequent 120 event types as the training set. The sentences containing the remaining 45 event type are then split into half as the dev and test set.
We use the same random seed as (Chen et al., 2021) to ensure the same split.

For ACE, we use the data split in (Lin et al., 2020). The same 33 event types are shared in the training, dev and test set.

### Table 12: Data split for MAVEN.

|          | Train | Dev | Test |
|----------|-------|-----|------|
| # Types  | 125   | 45  | 45   |
| # Sents  | 86,551| 1,532| 1,555|
| # Events | 287,516| 1,741| 1,806|

### Table 13: Data split for ACE+.

|          | Train | Dev | Test |
|----------|-------|-----|------|
| # Sents  | 19,240| 902 | 676  |
| # Events | 4,419 | 468 | 424  |

### B Model Hyperparameters

For the experiments on ACE+, we used the settings and hyperparameters as shown in Table 14.

| Parameter          | Value          |
|--------------------|----------------|
| Encoder            | Roberta-large  |
| Max seq len        | 200            |
| Batch size         | 8              |
| Learning rate      | $1e-5$         |
| Learning rate schedule | Linear    |
| Weight decay       | $1e-5$         |
| Warmup steps       | 1000           |
| Epochs             | 10             |
| Adam $\epsilon$    | $1e-8$         |
| Gradient clipping  | 1.0            |

### Table 14: ACE+ hyperparameters

For all few-shot experiments, we use the parameters listed in Table 15.

### C Discussion on Few-shot Learning Datasets

Few-shot learning for event detection was largely inspired by the few-shot classification work in computer vision literature (Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018) which assumes that images are sampled independently under the N-way K-shot setting. However, this assumption does not directly transfer to context-dependent tasks such as event detection: the distribution of event types heavily depends on the document and is far from i.i.d. in practice. This sampling procedure also leads to the absence of the NULL class (sentences without any event mentions), which is often abundant in real documents.

This data discrepancy has received some attention in other tasks such as relation extraction (Gao et al., 2019; Sabo et al., 2021) but is under-explored for event detection. For example, FewEvent instances only contain one event type per sentence and do not include NULL class examples. Sentences from MAVEN may contain multiple event types but also exclude the case of NULL. Thus, many previous works in few-shot event detection simply design their model to be a K-way classifier.

ACE, the dataset which we use for supervised event detection, contains all these cases and the events follow a natural distribution but the small number of event types makes it less attractive to use as a few-shot benchmark. Our model PILED is capable of handling these cases, as exemplified by our performance on ACE, but such abilities were not put to test on the current few-shot datasets. As a result, we would like to remind readers of the possible inflation of few-shot performance on current benchmarks and call for future research on setting up better evaluation.