P4E: Few-Shot Event Detection as Prompt-Guided Identification and Localization

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Abstract

We propose P4E, an identify-and-localize event detection framework that integrates the best of few-shot prompting and structured prediction. Our framework decomposes event detection into an identification task and a localization task. For the identification task, which we formulate as multi-label classification, we leverage cloze-based prompting to align our objective with the pre-training task of language models, allowing our model to quickly adapt to new event types. We then employ an event type-agnostic sequence labeling model to localize the event trigger conditioned on the identification output. This heterogeneous model design allows P4E to quickly learn new event types without sacrificing the ability to make structured predictions. Our experiments demonstrate the effectiveness of our proposed design, and P4E shows superior performance for few-shot event detection on benchmark datasets FewEvent and MAVEN and comparable performance to SOTA for fully-supervised event detection on ACE.

1 Introduction

Event detection is an essential step in information extraction, which aims to locate the event trigger (i.e., the minimal lexical unit that indicates an event) and classify the event 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, due to their reliance on large-scale annotation.

Instead of asking humans to exhaustively annotate hundreds, or even thousands, of documents, a more economic and realistic setting is to ask for a handful of labeled examples per type, namely the few-shot learning setting. Recently, prompt-tuning has shown great success in few-shot learning for a range of classification and generation tasks, thanks to better alignment between the target task and the language model’s pretraining objective. In the context of event detection, we could use a prompt such as “The sentence describes a [MASK] event” to guide the language model towards identification of the event type mentioned in the context.

However, since event detection requires recognizing both the event type and the trigger location, the aforementioned cloze-based prompt learning paradigm (Schick and Schütze, 2021a) does not give us the full solution. Hence, we propose to decompose the event detection task into the identification task and the localization task. Specifically, we first recognize the event types in the given context (the identification stage) using multi-label classification and then find the trigger location (the localization stage) through structured prediction.

Our identification model extends cloze-based prompt learning (Schick and Schütze, 2021a) to multi-label classification. 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 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).

As to the localization model, we integrate the filled prompt along with optional event type descriptions and keywords\(^2\) to augment the input, and employ a sequence tagger to recognize the event trigger (e.g., “appointment” in Figure 3). In this way, we decouple the parameters of the localization model from the event label by including the event type information on the input side instead.

Our experiments show that P4E achieves the new state of the art for few-shot event detection across two benchmarks, i.e., FewEvent (Deng et al., 2020) and MAVEN (Wang et al., 2020). To further verify the effectiveness of our integration, we also test our model on the fully-supervised event detection benchmark (ACE2005), and observe that P4E is comparable to the state-of-the-art performance.

Our study has three major contributions.

- We propose to decompose the event detection task into stages of identification and localization. By decoupling the type semantics from the sequence labeling task, we bring the benefits of cloze-based prompt learning to event detection and enable maximal parameter-sharing across event types, greatly improving the data-efficiency of our model.

- 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.

- 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 outperform the next best baseline by 15% F1. On MAVEN (Wang et al., 2020), we achieve 3% gains in the overall event detection task.

2 Methodology

Given a collection of contexts \(\mathcal{C}\) and a pre-defined event ontology \(\mathcal{T}\) (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 \(t \in \mathcal{T}\). Here we follow previous work and consider each sentence as the context of the event mention.

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: each sentence can contain multiple event types and each event type can have multiple triggers.

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 problem using a prompt and a verbalizer function. The prompt \(P\) is a natural language sentence with a \([\text{MASK}]\) token. Figure 2 shows a cloze prompt that can be used for event detection: “This text describes a \([\text{MASK}]\) event”. The relationship between the class labels \(\mathcal{L}\) and the predicted tokens \(V\) for the \([\text{MASK}]\) 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.

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.

\[
p(t = l) = \frac{\exp(M(f_v(l)|x,P))}{\sum_{v' \in \mathcal{L}} \exp(M(f_v(v')|x,P))}
\]

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

\(^1\)The verbalizer is a mapping from the class label to a single token in the language model’s vocabulary.

\(^2\)For the ACE dataset, we referred to the annotation guidelines, for MAVEN we used FrameNet.
The pro-reform director of Iran’s biggest-selling daily newspaper and official organ of Tehran’s municipality has stepped down following the appointment of a conservative as the city’s new mayor, press reports said Sunday.

[5x160]organ of Tehran’s municipality has stepped down following the appointment

The pro-reform director of Iran’s biggest-selling daily newspaper and official organ of Tehran’s municipality has stepped down following the appointment of a conservative as the city’s new mayor, press reports said Sunday.

2.2 Verbalizer Selection

In the previous section we’ve assumed that either the event type label can directly serve as the verbalizer (Attack → attack) or a manually picked verbalizer (Start-Position → hire) is provided. We will now describe a simple method for automatic selection of verbalizers in case neither of the two options is available.

We first collect a candidate verbalizer set \( \mathcal{V} \) from the training set examples’ trigger words. Then we use a frozen language model to score each candidate verbalizer \( v \) by plugging it in the cloze prompt of our identification model. The selection for each event type \( t \) is done separately. We compute the score of a candidate verbalizer \( v \) for event type \( t \) with class label \( l_t \) using a reciprocal rank scoring function:

\[
score(v, l_t) = \frac{1}{\sum_i r_i(v) \mathbb{1}(y_i = t)}
\]

where \( r_i \) is the predicted ranking of the candidate verbalizer from the frozen language model. We also experimented with the cross entropy scoring function but discovered that it favored more frequent words. The verbalizer for each class is then selected to maximize the scores: \( f_v(l) = \text{arg max}_v \text{score}(v, l_t) \). Note that the surface form of the verbalizer is only an initialization and the word embedding of the verbalizer token will be updated during training.

2.3 Trigger Localization

Trigger localization is the task of finding the trigger offset given a context \( c \) and an event type \( t \). Since

\[\text{score}(v, l_t) = \frac{1}{\sum_i r_i(v) \mathbb{1}(y_i = t)}\]

\[f_v(l) = \text{arg max}_v \text{score}(v, l_t)\]
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 enrich the “Start-Position” event type. We can also use a few keywords (example triggers) to enrich the event representation. 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\textsuperscript{4}. In this way, the model parameters are not tied to any event type and can be easily used for transfer.

The probability of a tagged sequence is:

\[
p(y|h; \theta) = \frac{\exp\left(\sum_i \varphi(y_i|h_i) + \sum_{ij} \psi(y_i|y_{i-1})\right)}{Z}
\]

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

We parameterize the emission scorer \(\varphi(y_i|h_i)\) as:

\[
\varphi(y_i|h_i) = W_i h_i + \sum_j \alpha_{ij} W_v h_j
\]

Both \(W_i \in \mathbb{R}^{3 \times m}\) 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:

\[
\alpha_{ij} = \text{Softmax}_j \left(\frac{(W_i h_i)^T W_k h_j}{\sqrt{m}}\right)
\]

\(m\) is the dimension of the embeddings \(h\) and \(W_i \in \mathbb{R}^{m \times m}, W_k \in \mathbb{R}^{m \times m}\) are learnable parameters.

\textsuperscript{4}B stands for the beginning of a span, I stands for the inside of a span, and O for outside of any span.

### Table 1: Dataset statistics.

| Dataset | # Docs | # Sents | # Event types | # Instances |
|---------|--------|---------|---------------|-------------|
| ACE+    | 599    | 20,818  | 33            | 5,311       |
| FewEvent | -      | 70,852  | 100           | 70,852      |
| MAVEN   | 4,480  | 49,873  | 168           | 118,732     |

### 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

#### Datasets

We evaluate our model on three datasets, FewEvent (Deng et al., 2020), MAVEN (Wang et al., 2020) and ACE2005\textsuperscript{5}.

We present the overall dataset statistics in Table 1. Details of the datasets and data splits are available in the Appendix A.

#### Evaluation Metrics

For all experiments, we use the event mention precision, recall and micro-F1 score as our major evaluation metrics (Ji and Grishman, 2008; Lin et al., 2020). An event mention is considered correct if both its type and trigger span are correct.

#### Implementation Details

We use BERT (Devlin et al., 2019), specifically bert-base-uncased, for the experiments on FewEvent and MAVEN unless otherwise specified.

\textsuperscript{5}https://www.ldc.upenn.edu/collaborations/past-projects/ace
otherwise specified. For experiments on ACE, we used Roberta (Liu et al., 2019). 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

#### Experiment Setting
For few-shot experiments, for P4E and our implemented baselines, we follow the setting in (Yang and Katiyar, 2020; Chen et al., 2021) which samples $K$ examples per type for training and uses the remaining samples for testing. This is different from the episode-based setting in (1) no access to extra event types for training; (2) the model has access to all of the $K$ examples for test types before inference.

#### Baselines
Our first baseline is the sequence classification model BERT-CRF which represents fine-tuning performance. Then we compare with three few-shot models StructShot (Yang and Katiyar, 2020), PA-CRF (Cong et al., 2021) and RelNet+Causal (Chen et al., 2021). In particular, PA-CRF was originally designed for the episode-based setting, so we implemented a variant PA-CRF-Adapted for our setting. Apart from the data difference, PA-CRF-Adapted stores the event type prototypes and recomputes them every epoch, making it more powerful than the original model, which computes prototypes from each batch and then discards them. Prompt+QA is a variant of our model by replacing the single-class CRF model with a QA scoring module.

#### Results
We show our main results in Table 2, some sample predictions in Table 3 and list our findings as follows:

- In general, models perform better on FewEvent compared to MAVEN due to less number of event types to choose from. In fact, on FewEvent, our model’s identification performance can reach 88.8% for the 5 shot case, whereas on MAVEN the performance is only 63.9%. The identification stage becomes the major bottleneck for our model.

- On the localization task, our model can jointly learn from annotation of all event types, giving us a significant advantage (over 15% F1 on FewEvent) over models that rely on event type-specific parameters.

- A common mistake of BERT-CRF and PA-CRF-Adapted is that the words are taken too literally and the model does not pay enough attention to context. As shown in the first example in Table 3, *covered* could be a trigger for *Hiding* objects, but not in the context of *covered costs*. They also do not work well on instances with low frequency triggers, such as *rehabilitation*.

- Comparing the Prompt-QA variant and our model, we notice that the QA needs a larger total number of examples to be well-trained. Since the head and tail are scored independently, when the number of examples is small, the QA model will often predict a long span instead of a trigger. With sufficient training examples, the QA model will perform relatively well (as in the $K=10$ case on MAVEN), but occasionally produce competing triggers such as *medical treatment* and *treatment* in the last example of Table 3.

In Figure 4 we change the number of examples used for fine-tuning in comparison with our model’s few-shot performance. On FewEvent, our 10-shot performance is nearly the same as fine-tuning with 40 examples, saving 75% of the annotation. On MAVEN, due to the increased number of event types, the few-shot performance is not as compelling, but we can still save 50% of the annotation cost when $K = 10$.

### 3.2 Supervised Event Detection

We report supervised event detection results on the ACE+ dataset in Table 4. We compare with
| Dataset                  | Method                  | $K = 5$       | $K = 10$       |
|-------------------------|-------------------------|---------------|---------------|
| FewEvent (10 types)     | BERT-CRF                | 44.06         | 66.73         |
|                         | PA-CRF*(Cong et al., 2021) | 58.48         | 61.64         |
|                         | PA-CRF-Adapted          | 63.64         | 70.69         |
|                         | Prompt+QA               | 65.23         | 67.50         |
|                         | P4E                     | 90.7 ± 2.2/81.98 ± 2.0 | 92.7 ± 1.1/85.50 ± 1.3 |
| MAVEN (45 types)        | BERT-CRF                | 48.14         | 64.68         |
|                         | StructShot *(Yang and Katiyar, 2020) | 42.57         | 49.18         |
|                         | PA-CRF-Adapted          | 53.16         | 65.62         |
|                         | RelNet + Causal* (Chen et al., 2021) | 57.0          | 65.43         |
|                         | Prompt + QA             | 47.86         | -             |
|                         | P4E                     | 63.9 ± 0.9/60.64 ± 1.0 | 72.6 ± 1.5/69.51 ± 1.5 |

Table 2: Few-shot event detection micro-F1 scores(%) on FewEvent and MAVEN with different number $K$ of training examples per type. Models with * are taken from their original paper. For our model, the first number is the identification stage performance. We report the average performance and variance over 10 random seeds.

| Context                                                                 | Model Predictions                  |
|-------------------------------------------------------------------------|------------------------------------|
| Private donations covered one-third of the US $20 million cost of the rescue, with the rest coming from the mine owners and the government. Indian Home Minister P. Chidambaram visited the state on Monday, 30 July to review the security situation and the relief and rehabilitation measures being taken. In December 1953, the British colonial government in Singapore passed the National Service Ordinance, requiring all male British subjects ... to register for part-time National Service. Its explosion created panic among local residents, and about 1,500 people were injured seriously enough to seek medical treatment. | Hiding: covered; Cost: cost | Filling: covered; Cost: cost | Cost: cost | Cost: cost |
|                                                                         | Rite: Service                     | Rite: Service                     | Obligation: requiring | Obligation: requiring |
|                                                                         | Cure: treatment                   | Institutionalize medical; Cure: treatment | Cure: treatment |

Table 3: Case studies on the few-shot event detection on MAVEN. The annotations are marked in the context: the trigger is underlined and the corresponding event name is provided in the bracket.

a wide range of existing methods, covering the paradigms of single-task sequence labeling, multitask learning, question answering and generation. We see that our prompt-based task formulation performs equally or better than existing methods. In particular, the multitask learning models such as OneIE (Lin et al., 2020; Nguyen et al., 2021) enjoy 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

4.1 Automatic VS Human Verbalizers

We present some of the automatically selected verbalizers in Table 5. 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 broad usage beyond the scope of the event type (such as “design” may be used outside of art).

In Table 6, we show how this difference in verbalizers affects 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.

4.2 Impact of NULL Instances

Prior datasets on few-shot event detection regularly ignore the presence of NULL instances since they are composed of i.i.d. sampling over the candidate event type. We discuss this problem in detail in Appendix D. In real-life applications, the model will inevitably encounter sentences that do not contain any events of interest. To test our model’s capability of handling such cases, we inject NULL in-
Table 4: 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.

| 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)                | -    | -      | -    |
| 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                    | P4E                                      | 70.9 | 76.1   | 73.4 |

Table 5: Examples of automatically selected verbalizers when provided with 10 examples per class.

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

Table 6: Few-shot event detection results (%) on MAVEN with automatic selected verbalizers.

| Task          | Manual | Automatic | 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 micro-F1 scores(%) on MAVEN with 10-shot training examples under different NULL instance ratios. CLS refers to the setting where our identification model is replaced by a classification model using the [CLS] token as the sentence representation.

| Model         | Identification | Identification + Localization |
|---------------|----------------|-------------------------------|
| CLS           | 44.6 ± 4.5     | 42.1 ± 4.8                   |
| P4E           | 67.9 ± 1.3     | 62.8 ± 1.0                   |

Table 8: Few-shot event detection results (%) on MAVEN with automatic selected verbalizers.

| Task          | Model 20% | Model 50% | Model 100% |
|---------------|-----------|-----------|------------|
| Id            | 42.1 ± 4.1 | 43.5 ± 5.1 | 40.0 ± 4.4 |
| Id + Loc      | 45.4 ± 1.1 | 63.2 ± 0.9 | 60.4 ± 1.1 |

Model Design Choices

We design our identification model as a prompt-based model trained with NULL-thresholded cross entropy loss ThresholdCE (Equation 4) and our localization model as an attention-enhanced single-class CRF tagger Attn-CRF.

For the identification model, we explore alternative modeling choices in Table 8. We compare with a classification model that takes the [CLS] token as the sentence representation and trained with cross entropy loss (Classification +CE). This method performs poorly as it is not able to take advantage of the language modeling capability as in the prompt-based formulation and the classification layer needs to be trained from scratch. We also consider changing our ThresholdCE loss to a margin-based ranking loss (Prompt + Margin Loss). This alternative loss function works relatively well, demonstrating that the prompt-based formulation is more critical than the loss function itself. The slight performance drop might be attributed to the fact the the margin loss treats each label equally, whereas our ThresholdCE loss puts more emphasis on positive labels.

In Table 9, we further experiment with other designs in replacement of our localization model 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. 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 the 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 and span
Table 8: Ablation studies on few-shot event detection for MAVEN. Reported results are micro-F1 scores(%) with different number $K$ of training examples per type.

| Id Method | Id Loss | Loc Method | $K = 5$     | $K = 10$     |
|-----------|---------|------------|-------------|-------------|
| Classification | CE      | Attn-CRF   | 18.88 ± 2.6 | 44.03 ± 5.5 |
| Prompt      | Margin Loss | Attn-CRF   | 58.62 ± 1.4 | 68.59 ± 0.8 |
| Gold       | Threshold CE | Attn-CRF   | **60.64 ± 1.0** | **69.51 ± 1.5** |

Table 9: Model ablations on ACE+.

| Id Model | Loc Model | Prec | Recall | F1  |
|----------|-----------|------|--------|-----|
| ✓        | Attn-CRF  | 70.9 | 76.1   | 73.4|
| ✓        | CRF       | 68.3 | 74.9   | 71.5|
| ✓        | QA        | 72.5 | 69.0   | 70.7|
| ✓        | Span Classifier | 63.5 | 78.3   | 70.1|
| Enumerate | Attn-CRF  | 54.5 | 81.3   | 65.3|
| Margin loss | Attn-CRF  | 69.8 | 75.9   | 72.7|

classifier variant, the vanilla CRF model benefits from modeling the correlation between neighboring tokens. Additionally, our attention-enhanced CRF layer can further improve upon the vanilla CRF model by 1.9 % F1 points. One alternative to our two-stage identify-then-localize framework is to simply enumerate all possible event types and attempt to localize the trigger for each event (Enumerate). As shown in the last row of Table 9, 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.

5 Related Work

Prompt-Tuning In prompt-tuning 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, 2021a,b) and open-ended prompts for generation (Li and Liang, 2021).

Application-wise, some recent attempts to apply prompt-tuning to informative extraction tasks include named entity recognition (Ding et al., 2021) and relation extraction (Han et al., 2021; Chen et al., 2022) but they focus on improving the classification component of these tasks. Our model, on the other hand, handles both multi-label classification (identification) task and the localization task.

Low Resource Event Detection Low resource event detection aims to alleviate the need for heavy annotation. This includes settings such as zero-shot transfer learning (Huang et al., 2018; Lyu et al., 2021; Liu et al., 2022), cross-lingual transfer (Subburathinam et al., 2019; Huang et al., 2022), keyword-based supervision (Zhang et al., 2021), lifelong learning (Yu et al., 2021), learning from annotation guideline (Yu et al., 2022) and few-shot learning (Peng et al., 2016; Lai et al., 2020; Shen et al., 2021; Cong et al., 2021; Chen et al., 2021).

In terms of methodology, prototype-based methods (Deng et al., 2020; Zhang et al., 2021; Cong et al., 2021; Shen et al., 2021) have been a popular choice. 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. QA-based (Du and Cardie, 2020; Liu et al., 2020) and generation-based methods (Li et al., 2021; Hsu et al., 2021; Liu et al., 2022) can also be adapted for few-shot event extraction and benefit from parameter-sharing since event type information can be incorporated into the question or generation prefix.

6 Conclusions and Future Work

In this paper we propose P4E, an identify-and-localize framework for event detection. Specifically, we first identify the event types present in the context and then find the trigger location based on type-specific event knowledge. The identification stage benefits from the few-shot capability of prompt-tuning and the localization stage enable structured prediction with shared parameters over all types. We show that this approach performs on par with SOTA in the fully supervised setting and outperforms existing methods for few-shot event detection, achieving 15% absolute F1 score gain on FewEvent and 3% gain on MAVEN. We see that as the number of event types increases, the identification performance becomes a bottleneck, which calls for additional exploration for large event ontologies.
7 Limitations

Our model addresses the event detection task. We have limited our scope to sentence-level events and the datasets we use in this paper are derived from English news articles and Wikipedia.

To achieve the best results, our model requires a human-designed prompt and verbalizers (highly indicative words for each event type). While we, and our work such as (Hu et al., 2021; Cui et al., 2022) show the potential of using automatic verbalizers, it will still cause a slight degrade to the performance. To inject extra event knowledge during the localization stage, there should be some external resource that can be aligned to the event ontology, such as the annotation guidelines for ACE or FrameNet for MAVEN.

8 Ethical Considerations

Event detection is a standard component in the event extraction pipeline. We are not aware of any immediate research on bias in event extraction systems but bias has been reported for masked language models (Nangia et al., 2020) which we utilizing in our identification stage.

Our paper does not present new datasets, but rather reuses the ACE, FewEvent and MAVEN datasets.

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A Dataset Details

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, education, etc. from Wikipedia and Freebase. We follow the data split released by (Cong et al., 2021). In the data provided, sentences are organized by event type and each sentence only has one event mention annotation.

MAVEN is the largest human-annotated event detection dataset to date, covering 4,480 documents and 168 event types. We use MAVEN for the few-shot setting following (Chen et al., 2021).

ACE2005 is the most widely used dataset for event extraction. For data preprocessing, we follow (Lin et al., 2020) and keep multi-word triggers and pronouns. We denote this version of ACE2005 as ACE+. Since FewEvent has significant data overlap with ACE2005, we do not further experiment with the few-shot setting on ACE 2005.

|   | Train | Dev | Test |
|---|-------|-----|------|
| # Types | 80    | 10  | 10   |
| # Sents | 67,982 | 2,173 | 697  |

Table 10: 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 MA VEN, 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.

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

Table 11: Data split for MA VEN.

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.

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

Table 12: Data split for ACE+.

B Model Hyperparameters

For the experiments on ACE+, we used the settings and hyperparameters as shown in Table 13.

| Parameter          | Value     |
|--------------------|-----------|
| Encoder            | bert-base-uncased |
| Max seq len        | 200       |
| Batch size         | 8         |
| Learning rate      | $2e - 5$  |
| Learning rate schedule | Linear   |
| Weight decay       | $1e - 5$  |
| Warmup steps       | 0         |
| Epochs             | 20        |
| Adam $\epsilon$    | $1e - 8$  |
| Gradient clipping  | 1.0       |

Table 13: ACE+ hyperparameters

For all few-shot experiments, we use the parameters listed in Table 14. Experiments were run on a single Nvidia RTX A6000 GPU or 3080 GPU. Our BERT-based model contains 134.2M parameters, among which 133M parameters are from the bert-base-uncased model with a LM head. Since our model is only trained on $K$ examples for the test types, a single run (training and testing) takes only about 10 minutes.

| Parameter          | Value     |
|--------------------|-----------|
| Encoder            | bert-base-uncased |
| Max seq len        | 200       |
| Batch size         | 8         |
| Learning rate      | $2e - 5$  |
| Learning rate schedule | Linear   |
| Weight decay       | $1e - 5$  |
| Warmup steps       | 0         |
| Epochs             | 20        |
| Adam $\epsilon$    | $1e - 8$  |
| Gradient clipping  | 1.0       |

Table 14: Few-shot experiment hyperparameters.

B.1 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. For the type-aware prompt, in our pilot experiments, we considered using the event definition or event key-words and compare it against the baseline of using the filled prompt from the identification stage. As seen in Table 15, the event verbalizer alone is relatively informative and adding more event key-words from the lexical units can provide a minor gain. Definitions from FrameNet are highly abstract, which may undermine their value in assisting event detection. In the next Appendix section C, we further explore using more verbalizers to enhance event detection performance.

C Using Multiple Verbalizers

In the previous experiments, we use one manually selected verbalizer per event type. A natural question is whether more verbalizers will help. We use MA VEN for this set of experiments since MA VEN provides alignments between its event types and FrameNet frames. The FrameNet\(^6\) 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, and 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 16, in the few-shot setting, using

\(^{6}\)https://framenet.icsi.berkeley.edu/fndrupal/frameIndex
Table 15: 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.

| 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 16: 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.

| Agg method | Id F1   | Id+Loc F1 |
|------------|---------|-----------|
| avg        | 67.5 ± 1.6 | 65.3 ± 1.4 |
| max        | 67.0 ± 2.2 | 64.7 ± 2.2 |
| logsumexp  | 67.0 ± 1.9 | 64.7 ± 1.9 |
| wavg       | 67.4 ± 1.6 | 64.9 ± 1.7 |

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.

### D Discussion on Few-shot Event 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 apply 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 P4E 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.