

# Dynamic Prefix-Tuning for Generative Template-based Event Extraction

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## Abstract

We consider event extraction in a generative manner with template-based conditional generation. Although there is a rising trend of casting the task of event extraction as a sequence generation problem with prompts, these generation-based methods have two significant challenges, including using suboptimal prompts and static event type information. In this paper, we propose a generative template-based event extraction method with dynamic prefix (GTEE-DYNPREF) by integrating context information with type-specific prefixes to learn a context-specific prefix for each context. Experimental results show that our model achieves competitive results with the state-of-the-art classification-based model ONEIE on ACE 2005 and achieves the best performances on ERE. Additionally, our model is proven to be portable to new types of events effectively.

## 1 Introduction

Event extraction is an essential yet challenging task for natural language understanding. Given a piece of text, event extraction systems need to recognize event triggers with specific types and the event arguments with the correct roles in each event record according to an event ontology, which defines the event types and argument roles (Dodgington et al., 2004; Ahn, 2006). As an example, the context in Figure 1 contains two event records, a Transport event triggered by “returned” and an Arrest-Jail event triggered by “capture”. In the Transport event, the Artifact is “the man”, the Destination is “Los Angeles” and the Origin is “Mexico”. In the Arrest-Jail event, the Person is “the man”, the Time is “Tuesday” and the Agent is “bounty hunters”. In this work, we focus on the task setting of extracting

events without gold entity annotations, which is more practical in real-world applications.

Most of the event extraction work treats the extraction of event triggers and event arguments as several classification tasks, either learned in a pipelined framework (Ji and Grishman, 2008; Liu et al., 2020; Du and Cardie, 2020; Li et al., 2020) or a joint formulation (Li et al., 2013; Yang and Mitchell, 2016; Nguyen et al., 2016; Liu et al., 2018; Wadden et al., 2019; Lin et al., 2020).

There is a rising trend of casting the task of event extraction as a sequence generation problem by applying special decoding strategies (Paolini et al., 2021; Lu et al., 2021) or steering pretrained language models to output conditional generation sequences with discrete prompts (Li et al., 2021; Hsu et al., 2021). Compared with classification-based methods, this line of work is more data-efficient and flexible, which requires less annotated data to achieve acceptable model performances, being easier to extend to new event types by slightly modifying the designed prompts and decoding strategies.

However, these generation-based methods have two significant challenges, which impede achieving competitive results with the classification-based methods. (1) **suboptimal prompts**: First, they manually design prompts for each event type (Li et al., 2021; Hsu et al., 2021), which are suboptimal without tuning and largely affect the model performances. (2) **static event type information**: Second, when extracting events of a particular type, recent generation-based methods will receive the same event type information concerning only the running event type, regardless of the associations between other possible event types.

To alleviate the above two challenges, we propose a generative template-based event extraction method with dynamic prefixes, denoted as GTEE-DYNPREF. As demonstrated in Figure 1, we follow

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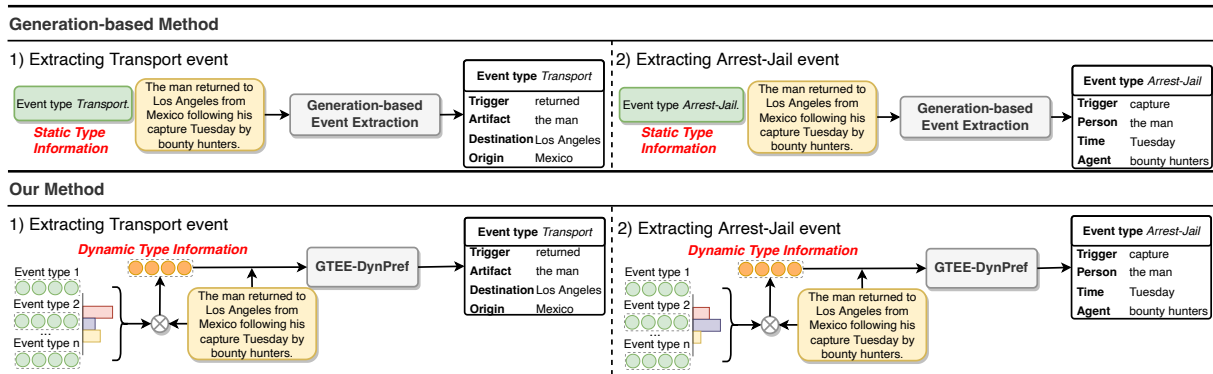


Figure 1: Comparison between the generation-based methods and our method GTEE-DYNPREF.

the previous work (Li et al., 2021; Hsu et al., 2021), extracting event records one type by one type, using the pretrained encoder-decoder language model BART (Lewis et al., 2020) for conditional generation. For each event type, we first initialize a type-specific prefix consisting of a sequence of tunable vectors as transformer history values (Li and Liang, 2021). The type-specific prefix offers tunable event type information for one single type. Then we integrate context information with all type-specific prefixes to learn a context-specific prefix, dynamically combining all possible event type information.

We evaluate our model on two widely used event extraction benchmarks, ACE 2005 and ERE. Experimental results show that our model achieves competitive results with the state-of-the-art classification-based model ONEIE on ACE 2005 and achieves the best performances on ERE. Additionally, according to the transfer learning results, our model also can be adapted to new types of events effectively.

## 2 Related Work

This paper is related to the following lines of work.

### 2.1 Classification-based Event Extraction

Event extraction is usually formulated as a sequence labeling classification problem (Nguyen et al., 2016; Wang et al., 2019; Yang et al., 2019; Wadden et al., 2019; Liu et al., 2018). Some of them incorporate global features and apply joint inference (Lin et al., 2020; Li et al., 2013; Yang and Mitchell, 2016) to collectively model event dependencies. Additionally, recent work casts event extraction as a machine reading comprehension (MRC) problem (Liu et al., 2020; Du and Cardie, 2020; Li et al., 2020) by constructing questions to query event triggers and arguments.

Our work treats event extraction as a conditional generation task, which is more flexible and portable, which reduces the burden of annotation.

### 2.2 Generation-based Event Extraction

There is a rising line of work casting event extraction as a sequence generation problem, such as transforming into translation tasks (Paolini et al., 2021), generating with constrained decoding methods (Lu et al., 2021) and template-based conditional generation (Li et al., 2021; Hsu et al., 2021).

The two closest methods above (Li et al., 2021; Hsu et al., 2021) both utilize manually designed discrete templates, which caused the sub-optimal problem. Besides, the applied static type instruction does not consider the connections between events within the same context. We replaced the static type instructions with the dynamic prefixes, which are continuous and tunable vectors during training, combining the manual event templates and alleviating the sub-optimal problem.

### 2.3 Prompt Tuning

There is a line of work using specific sentence templates with pre-trained models to solve natural language understanding tasks. It natural to come up with prefix-style (Brown et al., 2020) or cloze-style (Petroni et al., 2019) prompts based on human introspection, which are called “discrete prompts”. Existing works on discrete prompt tuning (Shin et al., 2020; Gao et al., 2021; Schick et al., 2020) depend on *verbalizers* to map from class labels to answer tokens. These methods are proven to be effective in the few-shot setting for text classification and conditional text generation tasks (Schick and Schütze, 2021b,a,c). There are also methods that explore continuous prompts directly operating in the embedding space of the model, like tuning on vectors (Li and Liang, 2021; Lester et al., 2021;

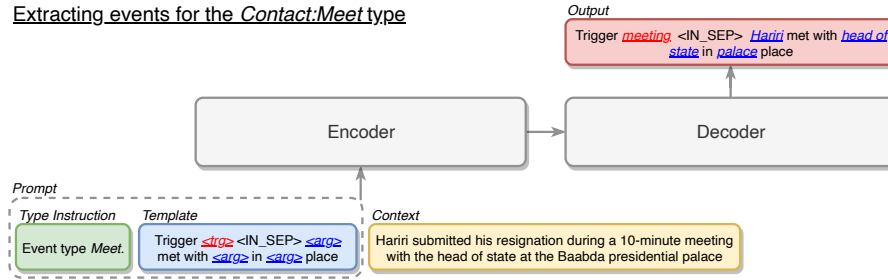


Figure 2: The framework of our base model GTEE-BASE. We use different colors to differentiate different components as follows. “ ” for the context, “ ” for the template, “ ” for the type instruction, “ ” for the encoder-decoder language model, and “ ” for the answered prompt as output.

Tsimpoukelli et al., 2021), initializing with discrete prompts (Zhong et al., 2021; Qin and Eisner, 2021; Hambardzumyan et al., 2021) and hybrid prompt tuning (Liu et al., 2021b,a; Han et al., 2021).

### 3 Generative Template-based Method

We revisit the task of event extraction as the process of conditional generation and present our base model (GTEE-BASE) as illustrated in Figure 2.

#### 3.1 Problem Statement

In the conditional generation task formulation for event extraction, the whole extraction process for a textual context is divided into several subtasks according to event types. Specifically, given an event ontology  $\mathcal{O}$  with an event type set  $\mathcal{E} = \{e_i | i \in [1, |\mathcal{E}|]\}$ , the input in each subtask  $\mathcal{S}_{e_i, \mathcal{C}}$  for event type  $e_i$  consists of a context  $\mathcal{C}$  and a designed prompt  $\mathcal{P}_{e_i}$ . And the output is the answered prompts  $\mathcal{A}_{e_i}$ , containing extracted event records.

We take one single conditional generation subtask  $\mathcal{S}_{e_i, \mathcal{C}}$  for event type  $e_i$  as example to explain the following content.

#### 3.2 Basic Architecture

As shown in Figure 2, the conditional generation subtask is modeled by a pretrained encoder-decoder language model (LM), BART (Lewis et al., 2020) and T5 (Raffel et al., 2020). In the generation process, the encoder-decoder LM models the conditional probability of selecting a new token  $y_i$  given the previous tokens  $y_{<i}$  and the encoder input  $\mathcal{X}$ . Therefore, the entire probability  $p(\mathcal{Y}|\mathcal{X})$  of generating the output sequence  $\mathcal{Y}$  given the input sequence  $\mathcal{X}$  is calculated as

$$\begin{aligned}
 p(\mathcal{Y}|\mathcal{X}) &= \prod_{i=1}^{|\mathcal{Y}|} p(y_i | y_{<i}, \mathcal{X}) \\
 \mathcal{X} &= [\mathcal{P}_{e_i}; [\text{SEP}]; \mathcal{C}] \\
 \mathcal{Y} &= \mathcal{A}_{e_i}
 \end{aligned}
 \tag{1}$$

where  $[\ ]$  denotes the sequence concatenation operation and  $[\text{SEP}]$ <sup>1</sup> is the corresponding separate marker in the applied encoder-decoder LM.

#### 3.3 Prompt Design

Similar to the state-of-the-art end-to-end generative method DEGREE-E2E (Hsu et al., 2021) for event extraction, the prompt  $\mathcal{P}_{e_i}$  for subtask  $\mathcal{S}_{e_i, \mathcal{C}}$  in our base model GTEE-BASE contains the type instruction  $\mathcal{I}_{e_i}$  and the template  $\mathcal{T}_{e_i}$ .

**Type Instruction.** A short natural language sequence  $\mathcal{I}_{e_i}$  describing the event type  $e_i$  in the subtask. We use the pattern “Event type is [MASK].” to construct type instructions for the event type set  $\mathcal{E}$ . For example, the type instruction for event type Meet is “Event type is Meet.”

**Template.** A type-specific pattern  $\mathcal{T}_{e_i}$ , which contains several placeholders, reflecting how the arguments participant in the event. We use two types of placeholders,  $\langle \text{trg} \rangle$  and  $\langle \text{arg} \rangle$ s, for representing trigger and arguments, respectively. The template is consists of a trigger part and a argument part. The two parts are concatenated by a new separate marker  $\langle \text{IN\_SEP} \rangle$ . As illustrated in Figure 2, the trigger part is “Trigger  $\langle \text{trg} \rangle$ ”, which is identical for all event types. The argument part is specific to event type  $e_i$ . Due to the manual efforts of designing and searching for an optimal template, we follow Li et al. (2021) to reuse the pre-defined argument templates<sup>2</sup> in the ontology  $\mathcal{O}$ . The original pre-defined argument templates natively contain

<sup>1</sup>In this paper, we use  $[*]$  to represent the special tokens used in pretrained LM and  $\langle * \rangle$  to indicate the user-defined special tokens.

<sup>2</sup>The argument template and all the used ontologies can be accessed at <https://github.com/raspberrycice/gen-arg> except for ERE. Since the ERE event types are subsets of the RAMS AIDA ontology and the KAIROS ontology, following Li et al. (2021), we also reuse the argument templates from these ontologies.

numeric labels for each `<arg>` placeholder (as `<arg1>`) and the slot mappings  $\mathcal{M}$  to the corresponding argument roles. We also follow Li et al. (2021) to remove these numeric labels.

**Ground Truth Construction.** For each event type  $e_i$  in the context  $\mathcal{C}$ , we construct the ground truth sequence  $\mathcal{G}_{e_i, \mathcal{C}}$  for conditional generation by filling the gold event records into the template  $\mathcal{T}_{e_i}$ . If there is no event record of event type  $e_i$ , the generation ground truth of the will be “Trigger `<trg>`”. Otherwise, the event record is filled in the template  $\mathcal{T}_{e_i}$  as the output in Figure 2. If several arguments are categorized as the same role, these arguments are first sorted by spans and then concatenated by “and”. If there are multiple event records, they will be sorted by the spans of the triggers, and the filled sequences will be concatenated by a new separate marker `<OUT_SEP>`.

### 3.4 Training, Inference and Parsing

**Training.** The trainable parameters of our base model GTEE-BASE are only the encoder-decoder LM. And we use  $\phi$  to denote all the trainable parameters. Therefore, the training target is to minimize the negative loglikelihood of all subtasks  $\mathcal{S}_{e_i, \mathcal{C}_j}$  in the training set  $\mathcal{D}$ , where  $\mathcal{C}_j$  denotes the  $j$ -th context in  $\mathcal{D}$ .

$$\mathcal{L}_\phi(\mathcal{D}) = - \sum_{j=1}^{|\mathcal{D}|} \sum_{i=1}^{|\mathcal{E}|} \log p(\mathcal{G}_{e_i, \mathcal{C}_j} | \mathcal{X}_{e_i, \mathcal{C}_j}) \quad (2)$$

$$\mathcal{X}_{e_i, \mathcal{C}_j} = [\mathcal{P}_{e_i}; [\text{SEP}]; \mathcal{C}_j]$$

**Inference.** In the inference stage, our base model generates sequences by beam search `BEAM` = 6. The maximum sequence length is set according to dataset statistics, which is a bit larger than the length of the longest ground truth.

**Parsing.** Basically, we parse the event records by template matching and slot mapping according to the ontology  $\mathcal{O}$ . Please note that not all the generated output sequences are valid. For each generated sequence, we will first try to parse a trigger. If failed, we will skip the sequence. Then if we fail to match `<IN_SEP>` or the argument part of the template  $\mathcal{T}_{e_i}$ , we will skip the argument parsing and only keep a trigger.

### 3.5 Irrelevant Event Types

By investigating the parsed event records, we find that our model has the bias to generate event records even for irrelevant event types. This will be

fatal when the input context does not contain any event record, which will largely hurt the precision score and F1 score. There are 80.28% and 71.02% sentences that do not contain any event records in ACE 2005 and ERE, respectively.

Therefore, we propose a simple yet effective solution to alleviate this problem by separately training an irrelevance classifier IC. With context  $\mathcal{C}$  as input, we finetune a BERT model (Devlin et al., 2019) by feeding the encoded `[CLS]` vector to a MLP as a binary classifier to see whether the context contains any event records or is entirely irrelevant for the ontology  $\mathcal{O}$ . It is worth noticing that there may exist other ways to avoid the problem, as Cui et al. (2021) formulate the NER task as a ranking task to avoid irrelevant entity types in a similar conditional generation task setting.

## 4 Dynamic Prefix-Tuning

We propose dynamic prefix-tuning with task-specific prefix and context-specific prefix to alleviate the two main challenges in generation-based event extraction. The framework of our model with dynamic prefix tuning, GTEE-DYNPREFIX, is shown in Figure 3. We will introduce the dynamic prefix-tuning step by step.

### 4.1 Type-Specific STATIC PREFIX

Inspired by PREFIX-TUNING (Li and Liang, 2021), we use event type-specific prefix STAPREF, which is a pair of two transformer activation sequences  $\{sp, sp'\}$ , each containing  $L$  continuous  $D$ -dim vectors as the history values for encoder and decoder, respectively. From the view of the encoder and decoder input, in the subtask  $\mathcal{S}_{e_i, \mathcal{C}}$ , the prefix is virtually prepended for the sequences  $\mathcal{X}$  and  $\mathcal{Y}$  in an encoder-decoder LM.

$$\begin{aligned} \mathcal{X}' &= [sp_{e_i}; \mathcal{X}] \\ \mathcal{Y}' &= [sp'_{e_i}; \mathcal{Y}] \end{aligned} \quad (3)$$

The main advantage of these transformer activation sequences is that they provide trainable context for both encoder and decoder, which is also computationally achievable.

We first initialize a pair of task-specific prefixes  $\{sp_{e_i}, sp'_{e_i}\}$  for each event type  $e_i$  in the ontology  $\mathcal{O}$ . In the conditional generation subtask  $\mathcal{S}_{e_i, \mathcal{C}}$ , we then prepend the corresponding pair of task-specific prefixes  $\{sp_{e_i}, sp'_{e_i}\}$  as transformer activations for the encoder and decoder.

Following Li and Liang (2021), we use a trainable embedding tensor  $P \in \mathbb{R}^{|\mathcal{E}| \times L \times D}$  to model

### Extracting events for the *Contact:Meet* type

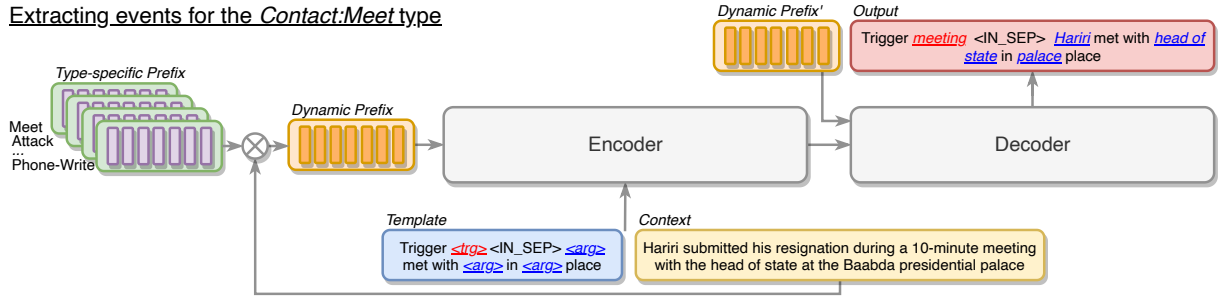


Figure 3: The framework of our dynamic prefix-tuning model GTEE-DYNPREF. We use different colors to differentiate different components as follows. “ ” for the context, “ ” for the template, “ ” for the type-specific prefixes, “ ” for the dynamic prefix, “ ” for the encoder-decoder language model, and “ ” for the answered prompt as output.

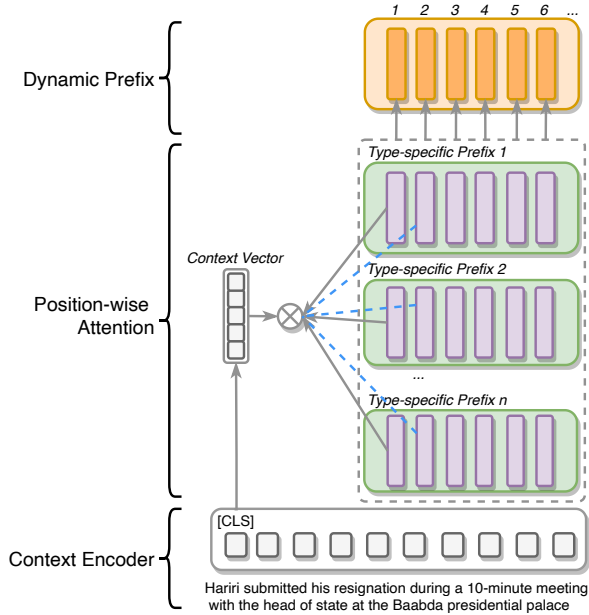


Figure 4: Context-specific DYNPREF construction using a context encoder.

the type-specific prefix  $sp$ . For the event type  $e_i$  in the ontology  $\mathcal{O}$ , the prefix vector  $sp_{e_i}^t$  at index  $t$  is

$$sp_{e_i}^t = P[e_i, t, :] \quad (4)$$

The reason we call the task-specific prefix *static* is that for subtasks of the same event types, the output type instructions are the same. In other words, such prefixes only preserve context concerning one single type of event, ignoring the association between different event types.

## 4.2 Context-Specific DYNAMIC PREFIX

Aiming to capture the associations between different event types when constructing trainable prefixes, we present DYNPREF, which constructs dynamic prefix with context-specific information when prompting pretrained language models.

As shown in Figure 4,  $dp_C$  has the same sequence length  $L$  as  $sp$ . For each position  $t$ , the prefix vector  $dp_C^t$  is computed by dynamically integrating all the prefix vector  $sp_{e_i}^t$  of event type  $e_i$  in the ontology  $\mathcal{O}$  according to the context-specific information  $c$  by multi-head attention (Vaswani et al., 2017). To calculate the context-specific information  $c$ , we apply a BERT model (Devlin et al., 2019) as the context encoder by feeding the context  $\mathcal{C}$  as input and taking the [CLS] vector as  $c$ .

$$dp_C^t = \text{MultiHeadAttn}(\{sp_{e_i}^t, \dots\}, c) \quad (5)$$

$$c = \text{BERT}(\mathcal{C})_{[\text{CLS}]}$$

The context-specific prefix  $dp_C$  is *dynamic* because it takes both the type-specific information in ontology  $\mathcal{O}$  and the unique context information into account when steering LMs.

Following Li and Liang (2021), we compute the decoder transformer activation vector  $h_i$ , which is a concatenation of all layers, at time step  $i$  in encoder-decoder LM recurrently.

$$h_i = \begin{cases} dp_C^i, & \text{if } i < L, \\ \text{LM}(y_i, h_{<i} | \mathcal{X}), & \text{otherwise.} \end{cases} \quad (6)$$

The computation of the encoder transformer activation vector is similar.

## 4.3 Training

Except for the LM parameters  $\phi$ , the additional trainable parameters of DYNPREF include the embedding tensor  $P$  and the BERT encoder modeling context information.

Specially, we follow the training suggestions (Li and Liang, 2021) and reparametrize the embedding tensor  $P$  by modeling a MLP and another embedding tensor  $P' \in \mathbb{R}^{|\mathcal{E}| \times L \times D'}$  with small dimension  $D' < D$ . In the end,  $P$  is computed as

$$P[e_i, t, :] = \text{MLP}(P'[e_i, t, :]) \quad (7)$$

Dataset	Split	#Sents	#Events	#Roles
ACE05-E	Train	17,172	4202	4859
	Dev	923	450	605
	Test	832	403	576
ACE05-E <sup>+</sup>	Train	19,216	4419	6607
	Dev	901	468	759
	Test	676	424	689
ERE-EN	Train	14,736	6208	8924
	Dev	1209	525	730
	Test	1163	551	822

Table 1: Dataset statistics.

Now we use  $\theta$  to denote all the introduced parameters for DYNPREF.

The training objective is still to minimize the negative loglikelihood in equation (2) for  $\phi$  and  $\theta$ . However, in our preliminary experiments, we find that jointly learning the LM parameters  $\phi$  and the DYNPREF parameters  $\theta$  requires different scales of training hyperparameters, being difficult to learn the ability to extract event arguments. Therefore, we train them separately in three steps: (1) First, we train  $\phi$  using GTEE-BASE to learn the task information. (2) Then we fix the LM parameters  $\phi$  and mask all other event types except for  $e_i$  in each subtask  $\mathcal{S}_{e_i, C}$ , only optimizing  $\theta$ , to learn the type-specific information for each event type. (3) Last, we remove the masking of event types, remaining the LM parameters fixed and only optimizing  $\theta$  using DYNPREF, to capture the associations between related event types.

## 5 Experiment Setup

### 5.1 Datasets

We conducted experiments on two widely used event extraction benchmarks, ACE 2005 (LDC2006T06) and ERE (LDC2015E29, LDC2015E68, and LDC2015E78). ACE 2005 dataset has 599 annotated English documents, 33 event types, and 22 argument roles. ERE contains 458 English documents, 38 event types, and 21 argument roles.

We preprocess the datasets following previous work (Zhang et al., 2019; Wadden et al., 2019; Du and Cardie, 2020; Lin et al., 2020; Lu et al., 2021; Hsu et al., 2021), and obtain three datasets, ACE05-E, ACE05-E<sup>+</sup> and ERE-EN. Statistics of the datasets are shown in Table 1. Compared to ACE05-E, both ACE05-E<sup>+</sup> and ERE-EN contain pronoun roles and multi-token event triggers.

### 5.2 Evaluation Metrics

We use the same evaluation criteria in previous work (Zhang et al., 2019; Wadden et al., 2019; Lin et al., 2020; Lu et al., 2021; Hsu et al., 2021) and report the Precision  $P$ , Recall  $R$  and F1 score  $F1$  of trigger classification (**Trg-C**) and argument classification (**Arg-C**).

- **Trg-C**: a trigger is correctly classified if its offset and event type matches the ground truth.
- **Arg-C**: an argument is correctly classified if its offset, event type and role label all matches the ground truth.

Following Lu et al. (2021), we also obtain the offset of extracted triggers by string matching in the input context one by one. For the predicted argument, we find the nearest matched string to the predicted trigger as the predicted offset.

### 5.3 Baseline Methods

We compare GTEE-DYNPREF with two groups of event extraction work. The first group is about classification-based event extraction methods.

- DYGIE++ (Wadden et al., 2019): a BERT-based model which captures both within-sentence and cross-sentence context.
- GAIL (Zhang et al., 2019): an RL model jointly extracting entity and event.
- ONEIE (Lin et al., 2020): an end-to-end IE system which employs global feature and beam search, which is the state-of-the-art.
- BERT\_QA (Du and Cardie, 2020): a MRC-based model using multi-turns of separated QA pairs to extract triggers and arguments.
- MQAEE (Li et al., 2020): a multi-turn question answering system.

The second group contains generation-based event extraction methods.

- TANL (Paolini et al., 2021): a method use translation tasks modeling event extraction in a trigger-argument pipeline.
- BART-GEN (Li et al., 2021): a template-based conditional generation method.
- TEXT2EVENT (Lu et al., 2021): a sequence-to-structure generation method.
- DEGREE-E2E (Hsu et al., 2021): an end-to-end conditional generation method with discrete prompts.

### 5.4 Implementation Details

We use the huggingface implementation of BART-large as the encoder-decoder LM and BERT-large

Name	GTEE-BASE	IC	GTEE-DYNPREF
learning rate	1e-5	2e-5	5e-5
train batch size	32*8	16*8	32*8
epochs	40	12	30
weight decay	1e-5	1e-5	1e-5
gradient clip	5.0	5.0	5.0
warm-up ratio	10%	10%	10%
prefix length $L$	-	-	80
embedding dim $D'$	-	-	512

Table 2: Hyperparameter setting for our models.

Model	Trg-C			Arg-C		
	P	R	F1	P	R	F1
<i>classification-based</i>						
DYGIIE++	-	-	69.7	-	-	48.8
GAIL	74.8	69.4	72.0	61.6	45.7	52.4
ONEIE	-	-	<b>74.7</b>	-	-	<b>56.8</b>
BERT_QA	71.1	73.7	72.3	56.8	50.2	53.3
MQAEE	-	-	71.7	-	-	53.4
<i>generation-based</i>						
TANL	-	-	68.5	-	-	48.5
BART-GEN	69.5	72.8	71.1	56.0	51.6	53.7
TEXT2EVENT	67.5	71.2	69.2	46.7	53.4	49.8
DEGREE-E2E	-	-	70.9	-	-	54.4
<b>GTEE-DYNPREF</b>	<b>63.7</b>	<b>84.4</b>	<b>72.6</b>	<b>49.0</b>	<b>64.8</b>	<b>55.8</b>

Table 3: Results on ACE05-E for event extraction in the supervised learning setting. The first group of baselines is the classification-based methods and the second group is the generation-based methods. Our proposed GTEE-DYNPREF is also the generation-based method. For each group, we bold the highest F1 scores for Trg-C and Arg-C.

as the binary irrelevance classifier IC in §3.5 and the context encoder in §4.2. We optimized our models by AdamW (Loshchilov and Hutter, 2019). The hyperparameters we used are shown in Table 2. Each experiment is conducted on NVIDIA A100 Tensor Core GPU 40GB. For simplicity, we randomly initialize<sup>3</sup> the embedding tensor  $P'$ .

As mentioned in §3.5, there is an overwhelming amount of negative samples compared with positive samples. Therefore, we sample only 4% negative samples in the train and dev split for the three datasets, keeping all samples in test split.

## 6 Results

### 6.1 Supervised Learning Setting

We evaluate the proposed model GTEE-DYNPREF under the supervised learning setting. Table 3 shows the comparison results on ACE05-E against all baseline methods, and Table 4 illustrates the results compared with the state-of-the-art in each research line on ACE05-E<sup>+</sup> and ERE-EN.

**New state-of-the-art.** As we can see from Table 3, GTEE-DYNPREF achieves the highest F1 scores for Trg-C and Arg-C on ACE05-E,

<sup>3</sup>The random initialization is implemented in the `torch.nn.EmbeddingLayer` class in PyTorch v1.7.1.

compared with all the generation-based baselines. Besides, GTEE-DYNPREF is competitive with the state-of-the-art classification-based method ONEIE, outperforming the others. In Table 4, GTEE-DYNPREF achieves competitive Arg-C F1 score with ONEIE on ACE05-E<sup>+</sup>, while obtaining 7.5% and 4.6% gain of F1 scores for Trg-C and Arg-C, respectively, achieving new state-of-the-art on ERE-EN.

### Trainable prompts boost the performances.

Compared with DEGREE, the event extraction method using fixed templates, and TEXT2EVENT, the generative event extraction method without prompts, GTEE-DYNPREF outperforms them in all the datasets, showing the effectiveness of the trainable dynamic prefix with prompts.

### 6.2 Transfer Learning Setting

GTEE-DYNPREF utilizes the event type templates and optimize them with context-specific information in the dynamic prefix, which is easy to extend to a new type of event. Therefore, aiming to verify the ability of GTEE-DYNPREF to learn from new event types, we conduct experiments under the transfer learning setting following Lu et al. (2021). Specifically, we divide the event mentions whose context contains no less than eight tokens in ACE05-E<sup>+</sup> into two subsets, denoted by `src` and `tgt`. `src` contains top-10 frequent types of events and `tgt` contains the rest 23 types of events. We then randomly split each subset into a `train` set and a `test` set with the ratio 4 : 1. Specifically, for transfer learning, we will first pre-train on `src-train` to learn the task information and then fine-tune on `tgt-train` for extracting the new types of events. Table 6 shows the evaluation results on `tgt-test` under the transferring learning setting and when solely training on `tgt-train` without transferring knowledge. We choose the state-of-the-art classification-based model ONEIE and generation-based method TEXT2EVENT as the baselines.

We can see that GTEE-DYNPREF achieves the highest Trg-C F1 and Arg-C F1 scores, which indicates that with the help of dynamic prefix, GTEE-DYNPREF can be adopted to new types of events more effectively. Additionally, comparing with solely training on `tgt`, transferring the knowledge from `src` allows GTEE-DYNPREF to achieve higher F1 scores than ONEIE and TEXT2EVENT. The reason may be that ONEIE relies on multi-task

Model	ACE05-E <sup>+</sup>						ERE-EN					
	Trg-C			Arg-C			Trg-C			Arg-C		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
ONEIE	<b>72.1</b>	73.6	72.8	<b>55.4</b>	54.3	<b>54.8</b>	58.4	59.9	59.1	51.8	49.2	50.5
TEXT2EVENT	71.2	72.5	71.8	54.0	54.8	54.4	59.2	59.6	59.4	49.4	47.2	48.3
DEGREE-E2E	-	-	72.7	-	-	55.0	-	-	57.1	-	-	49.6
<b>GTEE-DYNPREF</b>	67.3	<b>83.0</b>	<b>74.3</b>	49.8	<b>60.7</b>	54.7	<b>61.9</b>	<b>72.8</b>	<b>66.9</b>	<b>51.9</b>	<b>58.8</b>	<b>55.1</b>

Table 4: Results on ACE05-E<sup>+</sup> and ERE-EN for event extraction in the supervised learning setting. For each column, we bold the highest score.

Model	ACE05-E						ACE05-E <sup>+</sup>						ERE-EN					
	Trg-C			Arg-C			Trg-C			Arg-C			Trg-C			Arg-C		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
<b>GTEE-DYNPREF</b>	<b>63.7</b>	<b>84.4</b>	<b>72.6</b>	<b>49.0</b>	<b>64.8</b>	<b>55.8</b>	<b>67.3</b>	<b>83.0</b>	<b>74.3</b>	<b>49.8</b>	<b>60.7</b>	<b>54.7</b>	<b>61.9</b>	<b>72.8</b>	<b>66.9</b>	<b>51.9</b>	<b>58.8</b>	<b>55.1</b>
GTEE-STAPREF	62.8	83.9	71.8	47.0	64.2	54.3	66.5	82.8	73.7	49.1	60.4	54.2	61.4	72.2	66.4	50.7	58.5	54.3
GTEE-BASE	61.9	83.4	71.0	46.4	63.7	53.7	65.7	82.1	73.0	48.1	59.7	53.2	60.6	71.3	65.5	49.8	57.8	53.5

Table 5: Ablation study results on ACE05-E, ACE05-E<sup>+</sup> and ERE-EN. From GTEE-BASE to GTEE-DYNPREF, the model performances grows stronger.

Model	Trg-C			Arg-C		
	P	R	F1	P	R	F1
ONEIE w/o TL	70.8	64.8	67.7	53.2	37.5	44.0
ONEIE w/ TL	71.0	64.4	67.6	54.7	38.1	45.0
$\Delta performance$	+0.2	-0.4	-0.1	+1.5	+0.6	+1.0
TEXT2EVENT w/o TL	72.9	62.7	67.4	54.0	38.1	44.7
TEXT2EVENT w/ TL	75.1	64.0	69.1	56.0	40.5	47.0
$\Delta performance$	+2.2	+1.3	+1.7	+2.0	+2.4	+2.3
GTEE-DYNPREF w/o TL	62.0	75.4	68.1	39.6	53.5	45.5
GTEE-DYNPREF w/ TL	64.6	76.7	70.2	43.7	54.1	48.3
$\Delta performance$	+2.6	+1.3	+2.1	+4.1	+0.6	+2.8

Table 6: Transfer learning results on ACE05-E<sup>+</sup>.

Model	ACE05-E		ACE05-E <sup>+</sup>		ERE-EN	
	Trg-C	Arg-C	Trg-C	Arg-C	Trg-C	Arg-C
GTEE-DYNPREF						
w/o IC	57.2	43.8	61.7	46.4	52.1	44.7
w/ IC (trained)	72.6	55.8	74.3	54.7	66.9	55.1
w/ IC (gold)	76.3	58.4	77.2	56.9	72.3	57.4
GTEE-STAPREF						
w/o IC	56.9	43.4	61.3	45.9	51.4	44.0
w/ IC (trained)	71.8	54.3	73.7	54.2	66.4	54.3
w/ IC (gold)	75.2	57.5	76.6	55.8	71.6	56.9
GTEE-BASE						
w/o IC	56.4	42.8	60.8	45.1	50.7	43.1
w/ IC (trained)	71.0	53.7	73.0	53.2	65.5	53.5
w/ IC (gold)	74.6	55.9	75.1	54.8	70.7	56.5

Table 7: The F1 scores under different irrelevance classifier settings on ACE05-E, ACE05-E<sup>+</sup> and ERE-EN.

annotated information, and TEXT2EVENT requires learning the structural information of new types of events. In contrast, GTEE-DYNPREF only requires an easy-to-acquire template, which can be further optimized during training.

### 6.3 Ablation Study

In this section, we study the effectiveness of each proposed module by adding them into our base model GTEE-BASE and finally get our final model GTEE-DYNPREF. The results on ACE05-E, ACE05-E<sup>+</sup> and ERE-EN are presented in Table 5.

**Continuous Prompt vs Discrete Prompt.** We first compare GTEE-STAPREF with GTEE-BASE. Based on GTEE-BASE with discrete prompts, GTEE-STAPREF further combines type-specific prefixes as to form continuous prompts. It can be observed that there is a 0.8%, 0.7% and 0.9% gain

for the Trg-C F1 score on ACE05-E, ACE05-E<sup>+</sup> and ERE-EN, respectively. Additionally, there is a 0.6%, 1.0% and 0.8% improvement for the Arg-C F1 score, demonstrating the effectiveness and flexibility of STAPREF to model the type-specific information.

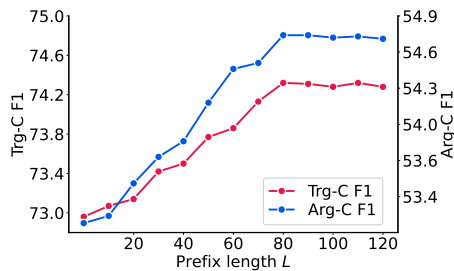
**Dynamic Prefix vs Static Prefix.** Next we compare GTEE-DYNPREF with GTEE-STAPREF to study the advantages of constructing dynamic prefix. On the basis of GTEE-STAPREF, integrating context-specific information leads to a constant gain for Trg-C F1 score on all the datasets as 0.8%, 0.6% and 0.5%, respectively. There can also be observed a 1.5%, 0.5% and 0.8% increase for the Arg-C F1 scores, respectively. It indicates that integrating context-specific information into type-specific information and transforming static prefix to dynamic is beneficial for generative template-based event extraction.

### 6.4 Irrelevance Classifier

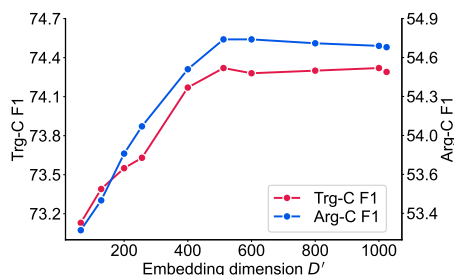
Our goal of the irrelevance classifier IC is to recognize the context that does not contain any event records in a given ontology  $\mathcal{O}$ . According to §3.5, we train an IC and use it for each dataset separately. Please note that on one specific dataset, we will use the same IC for all the experiments corresponding to that dataset. The accuracy of IC is 95.4%, 93.5% and 94.2% for ACE05E, ACE05E<sup>+</sup> and ERE-EN, respectively. To further study the influence of IC, we compare the performances of using no IC, trained IC, and gold IC. The compared F1 scores are listed in Table 7.

First, we find that with the help of our trained ICs on each dataset, the Trg-C and Arg-C F1 scores have been improved a lot by more than ten percentage points, indicating the necessity of IC. Second,





(a) F1 scores of GTEE-DYNPREF with different prefix length  $L$ .



(b) Performances of GTEE-DYNPREF with different dimension  $D'$  of the embedding tensor  $P'$ .

Figure 5: Intrinsic evaluation results on ACE05-E<sup>+</sup>.

by replacing the trained IC with the oracle gold IC results, we can still observe possible increases for F1 scores, suggesting the existence of likely chances for further optimizing IC performances. We leave the optimization for IC as future work.

## 6.5 Intrinsic Evaluation

We study the intrinsic characteristics of GTEE-DYNPREF by showing the influences of model hyperparameters on ACE05-E<sup>+</sup>.

**Prefix length  $L$ .** We first study the impact of prefix length  $L$  by grid search in  $\{L|L = 10 * k, k \in \mathbb{N} \wedge k \leq 12\}$ . Figure 5(a) shows the Trg-C and Arg-C F1 scores. We can observe that both Trg-C and Arg-C F1 scores increase as the prefix length  $L$  increases to 80, afterward, a slight fluctuation. We think the longer  $L$  introduces more trainable parameters and a more vital ability to model the context-specific type information. Therefore, we choose 80 as the prefix length in GTEE-DYNPREF.

**Embedding dimension  $D'$ .** Similarly, we study the impact of the dimension  $D'$  of the embedding tensor  $P'$  by increasing from 64 to 1024. The results of Trg-C and Arg-C F1 scores are illustrated in Figure 5(b). We find that although the bigger embedding dimension  $D'$  theoretically provides expressive type-specific information and improves the F1 scores when  $D' \leq 512$ , the continual improvement is interrupted when the embedding di-

mension is around 512. Thus we set the embedding dimension  $D' = 512$  in GTEE-DYNPREF.

## 7 Conclusion

In this paper, we studied event extraction in the template-based conditional generation manner. We proposed the dynamic prefix tuning model GTEE-DYNPREF for event extraction. On the one hand the method constructs tunable prefixes to model type-specific information and on the other hand GTEE-DYNPREF captures the associations between event types and calculates a context-specific prefix when steering pretrained language models. Experimental results show that our model achieves competitive results with the state-of-the-art on ACE 2005, which is also proven to be portable to new types of events effectively.

## 8 Ethical Consideration

Event extraction is a standard task in NLP. We do not see any significant ethical concerns. Our work is easy to adapt to new event types by offering some examples and pre-defined templates. Therefore, the expected usages of our work is to identify interesting event records from user textual input such as a piece of sentence or document.

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- Contact:Meet
- Life:Die

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## A Argument Template

We use templates for ACE and ERE. Table 8 and Table 9 show the argument templates for ACE and ERE, respectively, which is from the RAMS AIDA ontology and the KAIROS ontology.

## B Transfer Learning Details

The top-10 frequent types of events in the `src` split of ACE05-E<sup>+</sup> are listed as follows:

- Transaction:Transfer-Ownership
- Contact:Phone-Write
- Personnel:Elect
- Personnel:End-Position
- Movement:Transport
- Life:Injure
- Conflict:Attack
- Transaction:Transfer-Money

Event Type	Template	arg1	arg2	arg3	arg4	arg5
Movement:Transport	<arg1> transported <arg2> in <arg3> vehicle from <arg4> place to <arg5> place	Agent	Artifact	Vehicle	Origin	Destination
Personnel:Elect	<arg1> elected <arg2> in <arg3> place	Entity	Person	Place	-	-
Personnel:Start-Position	<arg1> started working at <arg2> organization in <arg3> place	Person	Entity	Place	-	-
Personnel:Nominate	<arg1> nominated <arg2>	Agent	Person	-	-	-
Personnel:End-Position	<arg1> stopped working at <arg2> organization in <arg3> place	Person	Entity	Place	-	-
Conflict:Attack	<arg1> attacked <arg2> hurting <arg5> victims using <arg3> instrument at <arg4> place	Attacker	Target	Instrument	Place	Victim
Contact:Meet	<arg1> met with <arg2> in <arg3> place	Entity	Entity	Place	-	-
Life:Marry	<arg1> married <arg2> in <arg3> place	Person	Person	Place	-	-
Transaction:Transfer-Money	<arg1> gave money to <arg2> for the benefit of <arg3> in <arg4> place	Giver	Recipient	Beneficiary	Place	-
Conflict:Demonstrate	<arg1> demonstrated at <arg2> place	Entity	Place	-	-	-
Business:End-Org	<arg1> organization shut down at <arg2> place	Org	Place	-	-	-
Justice:Sue	<arg1> sued <arg2> before <arg3> court or judge in <arg4> place	Plaintiff	Defendant	Adjudicator	Place	-
Life:Injure	<arg1> injured <arg2> with <arg3> instrument in <arg4> place	Agent	Victim	Instrument	Place	-
Life:Die	<arg1> killed <arg2> with <arg3> instrument in <arg4> place	Agent	Victim	Instrument	Place	-
Justice:Arrest-Jail	<arg1> arrested <arg2> in <arg3> place	Agent	Person	Place	-	-
Contact:Phone-Write	<arg1> communicated remotely with <arg2> at <arg3> place	Entity	Entity	Place	-	-
Transaction:Transfer-Ownership	<arg1> gave <arg4> to <arg2> for the benefit of <arg3> at <arg5> place	Seller	Buyer	Beneficiary	Artifact	Place
Business:Start-Org	<arg1> started <arg2> organization at <arg3> place	Agent	Org	Place	-	-
Justice:Execute	<arg1> executed <arg2> at <arg3> place	Agent	Person	Place	-	-
Justice:Trial-Hearing	<arg1> tried <arg2> before <arg3> court or judge in <arg4> place	Prosecutor	Defendant	Adjudicator	Place	-
Life:Be-Born	<arg1> was born in <arg2> place	Person	Place	-	-	-
Justice:Charge-Indict	<arg1> charged or indicted <arg2> before <arg3> court or judge in <arg4> place	Prosecutor	Defendant	Adjudicator	Place	-
Justice:Convict	<arg1> court or judge convicted <arg2> in <arg3> place	Adjudicator	Defendant	Place	-	-
Justice:Sentence	<arg1> court or judge sentenced <arg2> in <arg3> place	Adjudicator	Defendant	Place	-	-
Business:Declare-Bankruptcy	<arg1> declared bankruptcy at <arg2> place	Org	Place	-	-	-
Justice:Release-Parole	<arg1> released or paroled <arg2> in <arg3> place	Entity	Person	Place	-	-
Justice:Fine	<arg1> court or judge fined <arg2> at <arg3> place	Adjudicator	Entity	Place	-	-
Justice:Pardon	<arg1> court or judge pardoned <arg2> at <arg3> place	Adjudicator	Defendant	Place	-	-
Justice:Appeal	<arg1> appealed to <arg2> court or judge at <arg3> place	Plaintiff	Adjudicator	Place	-	-
Justice:Extradite	<arg1> extradited <arg2> from <arg3> place to <arg4> place	Agent	Person	Origin	Destination	-
Life:Divorce	<arg1> divorced <arg2> in <arg3> place	Person	Person	Place	-	-
Business:Merge-Org	<arg1> organization merged with <arg2> organization	Org	Org	-	-	-
Justice:Acquit	<arg1> court or judge acquitted <arg2>	Adjudicator	Defendant	-	-	-

Table 8: All argument templates for ACE05-E and ACE05-E<sup>+</sup>.

Event Type	Template	arg1	arg2	arg3	arg4	arg5
Conflict:Attack	<arg1> attacked <arg2> using <arg3> instrument at <arg4> place	Attacker	Target	Instrument	Place	-
Justice:Acquit	<arg1> court or judge acquitted <arg2> at <arg3> place	Adjudicator	Defendant	Place	-	-
Personnel:Elect	<arg1> elected <arg2> in <arg3> place	Agent	Person	Place	-	-
Justice:Release-Parole	<arg1> released or paroled <arg2> in <arg3> place	Agent	Person	Place	-	-
Personnel:Nominate	<arg1> nominated <arg2> at <arg3> place	Agent	Person	Place	-	-
Justice:Appeal	<arg1> appealed to <arg2> court or judge sentenced <arg3>	Prosecutor	Adjudicator	Defendant	-	-
Transaction:Transfer-Ownership	<arg1> gave <arg4> to <arg2> for the benefit of <arg3> at <arg5> place	Giver	Recipient	Beneficiary	Thing	Place
Business:Declare-Bankruptcy	<arg1> declared bankruptcy	Org	-	-	-	-
Contact:Meet	<arg1> met face-to-face with <arg2> in <arg3> place	Entity	Entity	Place	-	-
Life:Marry	<arg1> married <arg2> in <arg3> place	Person	Person	Place	-	-
Life:Divorce	<arg1> divorced <arg2> in <arg3> place	Person	Person	Place	-	-
Business:Merge-Org	<arg1> organization merged with <arg2> organization	Org	Org	-	-	-
Contact:Correspondence	<arg1> communicated remotely with <arg2> at <arg3> place	Entity	Entity	Place	-	-
Contact:Contact	<arg1> communicated with <arg2> at <arg3> place	Entity	Entity	Place	-	-
Manufacture:Artifact	<arg1> manufactured or created or produced <arg2> at <arg3> place	Agent	Artifact	Place	-	-
Movement:Transport-Person	<arg1> transported <arg2> in <arg3> instrument from <arg4> place to <arg5> place	Agent	Person	Instrument	Origin	Destination
Movement:Transport-Artifact	<arg1> transported <arg2> from <arg3> place to <arg4> place	Agent	Artifact	Origin	Destination	-
Contact:Broadcast	<arg1> communicated to <arg2> at <arg3> place (one-way communication)	Entity	Audience	Place	-	-
Transaction:Transaction	<arg1> gave something to <arg2> for the benefit of <arg3> at <arg4> place	Giver	Recipient	Beneficiary	Place	-
Personnel:Start-Position	<arg1> started working at <arg2> organization in <arg3> place	Person	Entity	Place	-	-
Justice:Pardon	<arg1> court or judge pardoned <arg2> at <arg3> place	Adjudicator	Defendant	Place	-	-
Justice:Fine	<arg1> court or judge fined <arg2> at <arg3> place	Adjudicator	Entity	Place	-	-
Justice:Trial-Hearing	<arg1> tried <arg2> before <arg3> court or judge in <arg4> place	Prosecutor	Defendant	Adjudicator	Place	-
Business:End-Org	<arg1> organization shut down at <arg2> place	Org	Place	-	-	-
Justice:Sue	<arg1> sued <arg2> before <arg3> court or judge in <arg4> place	Plaintiff	Defendant	Adjudicator	Place	-
Life:Injure	<arg1> injured <arg2> with <arg3> instrument in <arg4> place	Agent	Victim	Instrument	Place	-
Justice:Arrest-Jail	<arg1> arrested <arg2> in <arg3> place	Agent	Person	Place	-	-
Justice:Execute	<arg1> executed <arg2> at <arg3> place	Agent	Person	Place	-	-
Conflict:Demonstrate	<arg1> demonstrated at <arg2> place	Entity	Place	-	-	-
Justice:Sentence	<arg1> court or judge sentenced <arg2> in <arg3> place	Adjudicator	Defendant	Place	-	-
Life:Die	<arg1> killed <arg2> with <arg3> instrument in <arg4> place	Agent	Victim	Instrument	Place	-
Business:Start-Org	<arg1> started <arg2> organization at <arg3> place	Agent	Org	Place	-	-
Personnel:End-Position	<arg1> stopped working at <arg2> organization in <arg3> place	Person	Entity	Place	-	-
Justice:Extradite	<arg1> extradited <arg2> from <arg3> place to <arg4> place	Agent	Person	Origin	Destination	-
Justice:Charge-Indict	<arg1> charged or indicted <arg2> before <arg3> court or judge in <arg4> place	Prosecutor	Defendant	Adjudicator	Place	-
Transaction:Transfer-Money	<arg1> gave money to <arg2> for the benefit of <arg3> in <arg4> place	Giver	Recipient	Beneficiary	Place	-
Justice:Convict	<arg1> court or judge convicted <arg2> in <arg3> place	Adjudicator	Defendant	Place	-	-
Life:Be-Born	<arg1> was born in <arg2> place	Person	Place	-	-	-

Table 9: All argument templates for ERE-EN.