

TISE: A Tripartite In-context Selection Method for Event Argument Extraction

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Abstract

In-context learning enhances the reasoning capabilities of LLMs by providing several examples. A direct yet effective approach to obtain in-context example is to select the top- k examples based on their semantic similarity to the test input. However, when applied to event argument extraction (EAE), this approach exhibits two shortcomings: 1) It may select almost identical examples, thus failing to provide additional event information, and 2) It overlooks event attributes, leading to the selected examples being unrelated to the test event type. In this paper, we introduce three necessary requirements when selecting an in-context example for EAE task: semantic similarity, example diversity and event correlation. And we further propose TISE, which scores examples from these three perspectives and integrates them using Determinantal Point Processes to directly select a set of examples as context. Experimental results on the ACE05 dataset demonstrate the effectiveness of TISE and the necessity of three requirements. Furthermore, we surprisingly observe that TISE can achieve superior performance with fewer examples and can even exceed some supervised methods.

1 Introduction

Event Argument Extraction (EAE) aims to identify and classify event arguments within textual data based on the given event type. Label for this task is a structured table in which each argument requires annotation. Resulting in a scarcity of training data, which limits the generalizability of traditional methods to unknown samples (Gao et al., 2023a,b).

Recently, Large Language Models (LLMs) exemplified by GPT-3 (Brown et al., 2020) have shown remarkable capabilities in low-resource scenarios. As shown in Figure 1, given the test

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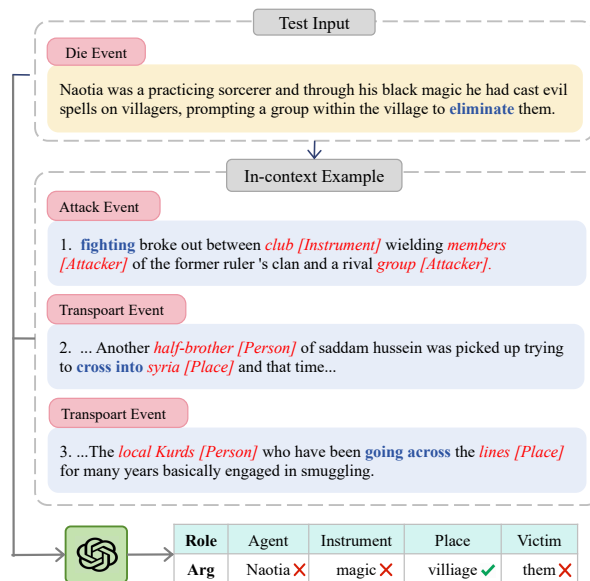


Figure 1: An in-context learning example on EAE task, where examples are obtained by the semantic selection. The upper left of each sentence is its event type, argument [role] is colored *red* and trigger is **bolded**.

input and three labeled examples, LLM can finish inference, which is called in-context learning (ICL; Brown et al., 2020). However, it has been found that the performance of LLMs is highly dependent on the selection of these examples (Rubin et al., 2022), highlighting the importance of choosing appropriate in-context example. To address this issue, some researchers calculate the semantic similarity between examples and test input, and subsequently selecting the top- k examples as context (Rubin et al., 2022; Liu et al., 2022), yielding appreciable performances.

While this semantic selection method has shown empirical success, it exhibits two shortcomings when applied to EAE. **Firstly**, it may select examples with overlapping semantics, thus failing to provide additional event information. In Figure 1, the second and third examples con-

tain the same event (“cross-border”) and identical roles (“Person” and “Place”). As a result, the in-context example provides limited event information and primarily contributes to predicting the role “Place”. **Secondly**, it does not consider the correlation of event attributes between the test input and examples, which is also crucial for LLMs to make reasonable predictions. As shown in Figure 1, there is no example related to the test event type (“Die”), thus LLM is unable to comprehend the test input and predict the relevant roles, e.g., “Victim” and “Agent”.

In this paper, we propose TISE (A Tripartite In-context Selection method for Event argument extraction) to select an optimal in-context example for EAE task. TISE scores examples based on three requirements, related to the different factors mentioned above. Firstly, it calculates the textual similarity between examples and test input as **Semantic Similarity**, which serves as a fundamental guarantee. Secondly, TISE calculates the **Example Diversity** by evaluating the inter-example similarity. This requirement avoids the semantic overlap between examples, thus obtaining the diverse examples with more event information. Lastly, TISE designs natural language descriptions for event types and event roles and calculates the **Event Correlation** by measuring the similarity between these descriptions. This requirement ensures the selected examples can effectively convey event information to LLM. TISE utilizes the kernel matrix of the Determinantal Point Process (DPP) (Kulesza et al., 2012) to combine these scores, and the example set with the highest probability is selected as the in-context example. Finally, we employ the code imitation prompt (Wang et al., 2023) to conduct EAE task on LLM and evaluate the proposed method on the ACE05 dataset. The experimental results show the effectiveness and robustness of our method. We outline our contributions as follows:

- To the best of our knowledge, we are the first work to explore an optimal in-context example for EAE task and present three requirements for the example selection.
- We further propose an effective selection method, which scores the examples from the above perspectives to obtain the optimal set.
- The proposed model achieves better performance with fewer examples and exceeds the supervised method on the public datasets.

2 Related Work

2.1 Event Argument Extraction

EAE is a core subtask of Event Extraction (EE), earlier works directly perform EE task, which includes the EAE task (Chen et al., 2015; Nguyen et al., 2016; Yang and Mitchell, 2016; Lin et al., 2020). Recently, EAE has been studied as a stand-alone task and can be categorized into 3 main paradigms: *Span-based paradigm* treats EAE as a span classification problem, Ebner et al., 2020a; Zhang et al., 2020; Xu et al., 2022 identify all candidate spans and classify them into the corresponding roles. *Reading comprehension paradigm* designs questions for each event role and converts EAE to question-answering problem to extract arguments (Du and Cardie, 2020; Liu et al., 2021). *Text generation paradigm* sequentially generates arguments using auto-regressive LMs with the help of prompts (Li et al., 2021; Du et al., 2021; Lu et al., 2021; Lin et al., 2022). With the development of LLMs, the *generation paradigm* has gained prominence. Researchers directly use LLMs to extract arguments, leading to significant breakthroughs (Wei et al., 2023; Wang et al., 2023; Gao et al., 2023b).

This paper also employs LLMs for EAE, but TISE is orthogonal to these works. We focus on how to select the optimal in-context example and our method is adaptable to various prompts.

2.2 In-context Example Selection

Constrained by the difficulties of fine-tuning LLMs, in-context learning (ICL) is proposed to emulate few-shot learning by providing several labeled examples in the prompt (Brown et al., 2020). However, LLMs are sensitive to the quality of in-context example (Liu et al., 2022). To obtain a high-quality demonstration, selecting the top- k similar examples becomes the most intuitive, simple, yet effective method (Rubin et al., 2022; Liu et al., 2022). More thoughtfully, researchers have found considering entropy (Lu et al., 2022; Wu et al., 2022) and diversity (Ye et al., 2022; Su et al., 2022; Levy et al., 2022; Ye et al., 2023) among examples is also useful. We conduct the first study to explore this problem in EAE and propose three requirements.

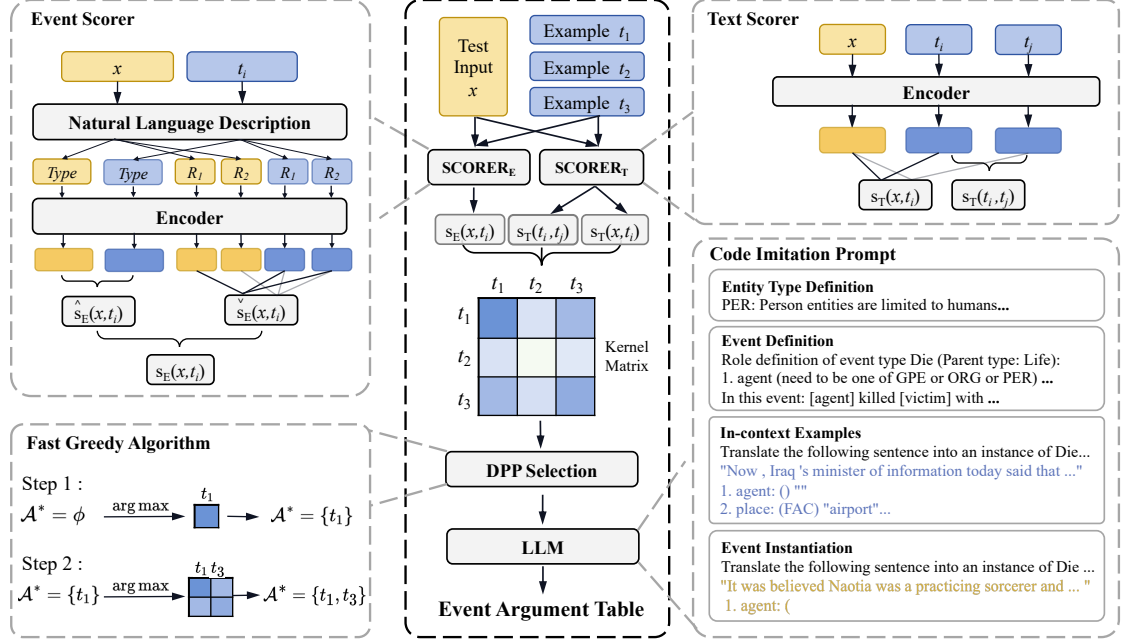


Figure 2: The overall structure of TISE when $|T| = 3$ and $k=2$. The center is the main process, surrounded by the sub-module processes. The main process uses an event scorer and a test scorer to calculate the score for each requirement. These scores are then combined into a kernel matrix. The fast greedy algorithm is employed to obtain the in-context example subset. Finally, the code imitation prompt is referenced to conduct LLM-based EAE.

3 Preliminary

3.1 Problem Definition

The target of in-context example selection is to select a few examples from the training dataset to form a context for ICL. Formally, given the test input x and the training dataset $T = \{t_1, \dots, t_{|T|}\}$, we need to choose k examples from T to form a subset $A \subseteq T$ as in-context example and $|A| = k$.

3.2 Determinantal Point Process

Unlike individually selecting the top- k similar examples, DPP considers the co-occurrence of examples and directly obtains a subset with k examples. Specifically, given the condition x , DPP is defined as a distribution P to measure the selected probability of each subset, we use a kernel matrix $K \in \mathbb{R}^{|T| \times |T|}$ to represent the co-occurrence between examples, where item $K_{ij} = k(t_i, t_j | x)$ evaluates the possibility that t_i and t_j appear in the same subset. Thus the selected probability of A is:

$$P(A|x) = \frac{\det(K_A)}{\det(K + \mathbf{I})} \quad (1)$$

where $K_A \equiv [K_{ij}]_{i,j \in A}$ is a sub-matrix obtained by indexing, $\det(\cdot)$ is the determinant and \mathbf{I} is the identity matrix. During the inference, we select

the subset with the highest probability to form in-context example $A^* = \arg \max_{A \subseteq T} P(A|x)$.

Obviously, this is an NP-hard submodular maximization problem (Ko et al., 1995), we employ the fast greedy algorithm (Chen et al., 2018) for optimization. As shown in the lower left of Figure 2, we perform a k -step search. At each step, the selected example is chosen to maximize the increase in the determinants of the old and new matrices:

$$t^* = \arg \max_{t_i \in T \setminus A^*} \det(K_{A^* \cup \{t_i\}}) - \det(K_{A^*}) \quad (2)$$

and we update the subset using $A^* = A^* \cup \{t^*\}$.

4 Method

The overall structure of TISE is shown in Figure 2, it measures Semantic Similarity and Example Diversity using the text scorer (SCORER_T), and assesses Event Correlation using the event scorer (SCORER_E). Three scores are integrated into the kernel matrix K , and DPP is used to select an in-context example based on this. Lastly, it employs code imitation prompt to conduct LLM-based EAE.

4.1 Scorer and Kernel Matrix

We present sub-module corresponding to each requirement separately, including the scoring

Event Type	Description
Justice:Convict	Involves a justice trial, recording a person has been convicted.
Justice:Sentence	Involves a justice trial, recording a person has been sentenced.
Event Role	
Life:Injure.Instrument	What device was used to inflict the harm?
Life:Die.Instrument	What device was used to kill?

Table 1: Examples of natural language descriptions of Event Types and Event Roles.

methodology and its subsequent fusion into the kernel function. Moreover, we introduce hyperparameters to balance each requirement and prove the impact of the kernel function.

4.1.1 Semantic Similarity

Ensure the semantic similarity between x and t_i is fundamental yet effective. As shown in the upper right of Figure 2, we design a text scorer for measurement, it employs a Pretrained Language Model as encoder and calculates the embedding similarity as text score s_T :

$$s_T(x, t) = \text{sim}(E(x), E(t)) \quad (3)$$

where $E(\cdot)$ denotes the encoder¹ and $\text{sim}(u, v) = \frac{u^T v}{\|u\| \cdot \|v\|}$ is the cosine similarity. For K_{ij} , we simultaneously consider the semantic score of t_i and t_j : $k_1(t_i, t_j|x) = s_T(x, t_i) \cdot s_T(x, t_j)$.

4.1.2 Example Diversity

To guarantee the selected subset contains diverse examples, TISE assigns lower scores to similar examples. It still uses text scorer to measure the similarity between examples. For training example t_i and t_j , we calculate the score $s_T(t_i, t_j)$, and modify K_{ij} as $k_2(t_i, t_j|x) = s_T(x, t_i) \cdot s_T(t_i, t_j) \cdot s_T(x, t_j)$. The reason why this product form kernel function can simultaneously decrease $s_T(t_i, t_j)$ yet increase $s_T(x, t_i)$ will be explained in 4.1.4.

4.1.3 Event Correlation

We propose an event scorer to measure the event correlation. As shown in the upper left of Figure 2, we partition event attributes into event type and event role. Subsequently, we design natural language descriptions for each of them and calculate event scores based on these descriptions.

Event Type The event type description comprises two sentences that are related to its parent

¹We use the embedding of [CLS] token as result.

event type and itself. See Table 1 as an example², this form of description has two advantages: 1. *Event types belonging to the same parent will be closer.* and 2. *Event types with related meanings will feature similar descriptions.*

After obtaining the descriptions, we calculate description similarity to score event type. Suppose x and t_i has event type description $\hat{d}(x)$ and $\hat{d}(t_i)$, we can obtain the event type score $\hat{s}_E(x, t_i)$ as:

$$\hat{s}_E(x, t_i) = \text{sim}(E(\hat{d}(x)), E(\hat{d}(t_i))) \quad (4)$$

Event Role For each event role, the description is used to introduce its meaning within the event. Referring to Lu et al., 2023, we design the description as a single sentence. See Table 1², it also offers two advantages: 1. *Roles under the same event type exhibit closer relationships.* and 2. *The same roles in different event type are similar but not identical.*

Let R^{t_i} denote the set of *not-none* roles for t_i , and R^x denote the set of roles to be predicted. For each $r_i^{t_i} \in R^{t_i}$, we obtain its description $\check{d}(r_i^{t_i})$, and sequentially compare it to $r_i^x \in R^x$ with description $\check{d}(r_i^x)$, the role score is calculated as:

$$\check{s}_E(r_i^x, r_i^{t_i}) = \text{sim}(E(\check{d}(r_i^x)), E(\check{d}(r_i^{t_i}))) \quad (5)$$

We pick the most relevant r_i^x using max-pool: $\check{s}_E(x, r_i^{t_i}) = \max \check{s}_E(r_i^x, r_i^{t_i})$, and the final event role score for t_i is:

$$\check{s}_E(x, t_i) = \frac{\sum_{r_i^{t_i} \in R^{t_i}} \check{s}_E(x, r_i^{t_i})}{|R^{t_i}|} + \alpha |R^{t_i}| \quad (6)$$

where $\alpha = 0.1$ is a hyperparameter to reward those examples containing more useful roles. We combine event type score and event role score so that the final event score can reflect the event correlation from two perspectives:

$$s_E(x, t_i) = \frac{1}{2} (\hat{s}_E(x, t_i) + \check{s}_E(x, t_i)) \quad (7)$$

and the final kernel function is $k(t_i, t_j|x) = s_E(x, t_i) \cdot k_2(t_i, t_j|x) \cdot s_E(x, t_j)$.

4.1.4 Balance and Proof

To balance each requirement, we introduce the hyperparameter λ into each score: $s_E'(x, t_i) = \exp(\frac{s_E(x, t_i)}{2\lambda_1})$ and $s_T'(x, t_i) = \exp(\frac{s_T(x, t_i)}{2\lambda_2})$, thus the kernel matrix K can be represented as:

$$K = \text{Diag}(S'_E) \cdot \text{Diag}(S'_T) \cdot \bar{K} \cdot \text{Diag}(S'_T) \cdot \text{Diag}(S'_E) \quad (8)$$

²The complete descriptions of event type and event role can be found in Appendix A.1 and A.2, respectively.

Methods	REQ	$k=3$		$k=5$		$k=10$		$k=15$	
		Arg-I	Arg-C	Arg-I	Arg-C	Arg-I	Arg-C	Arg-I	Arg-C
RANDOM	\times	53.86	41.74	54.20	42.94	55.41	44.92	58.00	47.34
<i>Semantic Retriever</i>									
BM25	R.1	55.48	44.09	56.81	46.01	57.27	47.14	57.94	47.88
BERT-TOPK	R.1	56.20	45.38	56.67	46.14	56.93	46.98	58.34	48.16
DPR-TOPK	R.1	56.05	45.10	57.03	46.88	57.69	47.62	58.40	47.97
<i>DPP-based Method</i>									
DPP-DIVERSITY	R.1,2	56.22	45.53	58.19	47.73	58.47	47.91	59.46	49.38
TISE	R.1,2,3	56.66	46.25	58.95	48.72	60.57	50.78	60.99	51.43
Δ SEMANTIC	-	+0.46	+0.87	+1.92	+1.84	+2.88	+3.16	+2.59	+3.27
Δ DIVERSITY	-	+0.44	+0.72	+0.76	+0.99	+2.10	+2.87	+1.53	+2.05

Table 2: Results on ACE05. REQ indicates which requirements are satisfied by this method. The gap between TISE and *Semantic Retriever* is Δ SEMANTIC, and the gap between TISE and DPP-DIVERSITY is Δ DIVERSITY.

where \bar{K} is a symmetric matrix. $\bar{K}_{ij} = s_T(t_i, t_j)$, $S'_{E_i} = s_E'(x, t_i)$ and $S'_{T_i} = s_T'(x, t_i)$. Note the $\det(K + \mathbf{I})$ in Eq.(1) is a normalization term, we only consider the effect of $\det(K_A)$:

$$\log \det(K_A) = \sum_{t_i \in A} \left(\frac{S'_{E_i}}{\lambda_1} + \frac{S'_{T_i}}{\lambda_2} \right) + \log \det(\bar{K}_A) \quad (9)$$

So far, $P(A|x)$ has been associated with two parts via the kernel matrix. The first part requires the selected examples exhibit high event score and semantic score, while the second part necessitates low inter-example similarity due to the determinant’s characteristics³.

4.2 Code Imitation Prompt

TISE employs code imitation prompt (Wang et al., 2023) as template to instruct LLM to extract arguments based on the test input and in-context example. As shown in the lower right of Figure 2, it consists of 4 components⁴. 1) *Entity Type Definition* categorizes all argument entities into seven types and begins with a description of all entity types involved in test input. 2) *Event Definition* includes the hierarchy of event types, the role definition of current type and how these roles are presented in this event. 3) *In-context Examples* demonstrates selected examples individually. Each example contains extraction instruction, an input sentence and a label. 4) *Event Instantiation* directly feeds the extracted instruction and test input to LLM.

³See Appendix A.3 for detailed proof.

⁴A specific prompt example is shown in Appendix A.4.

5 Experiments

5.1 Dataset and Evaluation Metrics

We evaluate TISE on the Automatic Content Extraction 2005 (ACE05; Doddington et al., 2004) dataset, which is a sentence-level corpus. For fair comparison, we preprocess the dataset into 8 parent event types and 33 child types following Wadden et al., 2019.

We measure the performance with two metrics following previous work (Li et al., 2021; Ma et al., 2022): Argument Identified (Arg-I) denotes the head word of an argument matches the human annotation, and Argument Classified (Arg-C) means an argument is correctly classified into its annotated role as well. We report them using F1 score.

5.2 Implementation Details

For scorers and the kernel matrix, we employ bert-base-uncased (Devlin et al., 2018) as encoder and set $\lambda_1 = 0.5, \lambda_2 = 0.05^5$. For LLM, due to the Codex models have been deprecated since March 2023⁶, we mainly use text-davinci-002 (Ouyang et al., 2022) as LLM. This model is instruction-tuned from code-davinci-002 (Chen et al., 2021) and supports 4k input tokens. We access LLMs through OpenAI API⁷. For prompt, because the code prompt (Wang et al., 2023) easily exceeds the length limitation, we leverage the code imitation prompt as prompt template.

⁵The impact of λ is shown in Appendix A.5.

⁶<https://platform.openai.com/docs/guides/code>

⁷<https://openai.com/product>

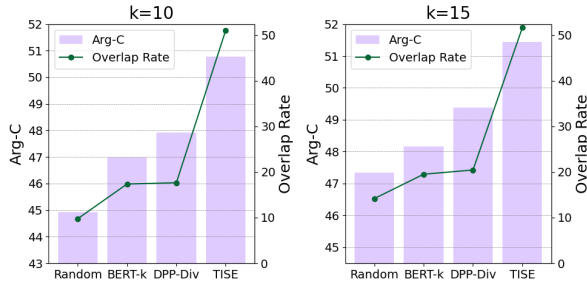


Figure 3: Relationship between EAE performance and the overlap rate on $k=10$ and $k=15$.

5.3 Baselines

We compare TISE with several baselines: RANDOM randomly selects examples from the training set without repetition. BM25 (Robertson et al., 2009) is an effective sparse retriever relies on TF-IDF. BERT-TOPK and DPR-TOPK employ BERT and the twin-tower dense retriever DPR (Karpukhin et al., 2020) as encoders, respectively, and select the top- k examples. DPP-DIVERSITY satisfies Example Diversity with the help of DPP.

5.4 Main Results

We show the experimental results with different numbers of examples (k) in Table 2. As we expect, TISE achieves the state-of-the-art performance across all values of k , which verifies the effectiveness and robustness of our method. Furthermore, TISE achieves superior performance with fewer examples. For instance, TISE achieves 58.95%/48.72% on $k=5$, while BERT-TOPK achieves 58.34%/48.16% on $k=15$. This indicates that in scenarios with low resources or constrained input length, TISE is more powerful. For each requirement, we find that both the sparse (BM25) and dense (BERT-TOPK/DPR-TOPK) retrievers outperform RANDOM, which proves that semantic-based selection is useful for EAE. But it is uncertain which retriever is better, indicating that greater similarity does not necessarily equate to better performance. In addition, TISE outperforms DPP-DIVERSITY, which in turn outperforms semantic retrievers, confirming the effectiveness of Example Diversity and Event Correlation.

5.5 Principle Exploration

We further explore *how the examples selected by these requirements can help LLM extract arguments*. The supervised signals provided by the

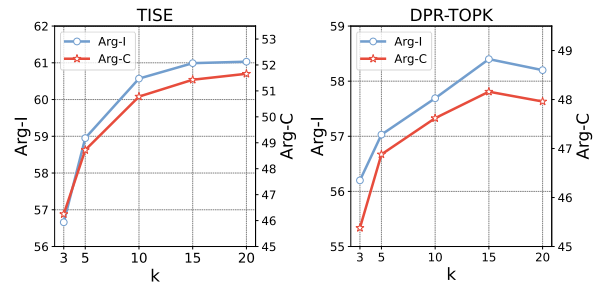


Figure 4: Performance of TISE and DPR-TOPK on different k . When $k=20$, the semantic retriever may exceed the input length limitation of LLM, resulting in a performance decline.

example are actually the meaning of each role in the current event type. Based on this, we hypothesize that an in-context example with a larger role overlap with the test input will yield better performance. To verify this hypothesis, we define a metric called “role overlap rate” for in-context example and conduct an experiment. Denotes each selected example is $t^* \in A^*$, the set of *not-none* roles of t^* is R^{t^*} and the role set of x is R^x , we define the role overlap rate of A^* as:

$$s_{A^*} = \frac{\sum_{t^* \in A^*} \sum_{r^{t^*} \in R^{t^*}, r^x \in R^x} \mathbb{I}(r^{t^*} = r^x)}{\sum_{t^* \in A^*} |R^{t^*}|} \quad (10)$$

where $\mathbb{I}(\cdot)$ is the indicator function. Notice that we only consider *not-none* roles and we count the same role of different event types because it can convey useful information (e.g., “Place” in “Life.Marry” and “Life.Be-Born”).

The results in Figure 3 demonstrate an obvious positive correlation between EAE performance and role overlap rate, which proves that more overlapped roles can indeed help LLM extract arguments. Besides, we also find that each requirement has a distinct impact: 1) **Event Correlation** notably elevates the overlap of roles as it tends to select examples within the same event types. 2) **Semantic Similarity** also proves beneficial, as similar sentences tend to describe related events with overlapping roles. 3) **Example Diversity** contributes minimally to the overlap rate, it primarily ensures the entire subset covers different roles.

6 Discussion

6.1 Ablation Study

Effect of Different k Many works have pointed that the performance of LLM is sensitive to the

Methods	Arg-I F1	Arg-C F1
TISE	60.6	50.8
w/o Event Correlation	58.5 (2.1↓)	47.9 (2.9↓)
w/o Event Role	60.0 (0.6↓)	50.3 (0.5↓)
w/o Event Type	58.8 (1.8↓)	49.1 (1.7↓)
w/o Example Diversity	59.1 (1.5↓)	48.7 (2.1↓)
w/o Correlation & Diversity	57.3 (3.3↓)	46.9 (3.9↓)

Table 3: Ablation results for requirements on $k=10$.

number of examples (Ye et al., 2023; Wang et al., 2023). Here, we evaluate the proposed model and baselines on different k and report the results in Table 2. We have two conclusions: 1) As k increases, the gap between the different methods also widens. The reason is that the in-context example with a small k can not provide sufficient event information. However, as quantitative changes lead to qualitative changes, the quality of the examples becomes crucial and significantly impacts the performance of LLM. 2) Increasing the value of k can enhance the extracted performance, but this benefit is diminishing. We provide the performance of TISE and DPR-TOPK on different k in Figure 4. Both methods exhibit a monotonic increase, but eventually reach a plateau. This phenomenon is consistent with Wang et al., 2023, and we verify it is unrelated to the selection of in-context example. We speculate this phenomenon may be attributed to an upper bound on the effectiveness of ICL or a limitations imposed by the prompt template.

Effect of Different Requirements To verify the effectiveness of different requirements, we conduct experiments by removing Event Correlation, Example Diversity, and both of them simultaneously. Our results, detailed in Table 3, reveal that Event Correlation holds greater significance than Example Diversity, which is consistent with the conclusion drawn in principle exploration (5.5). Moreover, the joint removal of both requirements leads to a smaller decline ($3.3\% < 2.1\% + 1.5\%$ / $3.9\% < 2.9\% + 2.1\%$), indicating mutual reinforcement between these two requirements. For Semantic Similarity, its effectiveness and robustness have been verified in Table 2. Moreover, we also verify the event attributes. Experimental results show that the impact of Event Role ($-0.6\%/ -0.5\%$) is less than Event Type ($-1.8\%/ -1.7\%$), because Event Type directly filters the examples with similar event types, whereas Event Role is more

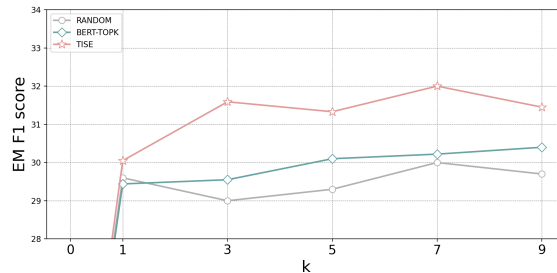


Figure 5: Performance on RAMS. Examples in document-level dataset are long, and $k=9$ will risk exceeding the input length limitation of LLM.

likely to select irrelevant examples.

6.2 Analysis

Document Level Extraction TISE is a generalized method that can be also applied to the document-level event argument extraction. We conduct experiments on the RAMS (Ebner et al., 2020b) to verify its generality and robustness. We use F1 score as evaluation metrics based on the Exact Match (EM) criterion (Gusfield, 1997), and use a plain extraction instruction as prompt, such as “Given a document that describes an event, you need to identify all event arguments from this document, and classify role of each argument.” Results are shown in Figure 5, TISE filters a better example set than baselines on different k , which in turn helps LLM to extract arguments. In addition to this, we have two other observations: 1. LLM is not sensitive to the number of displayed examples (k) when conducting document-level extraction, and 2. different selection methods do not improve the extraction results significantly, despite they can select examples that are more relevant to the test input. We speculate that this may be because the understanding of documents is much harder than sentences, and a better prompt is needed to help LLM understand how to extract arguments within examples.

Adaptability TISE can be adapted to various LLMs and prompts. To verify its adaptability, we choose code prompt and code imitation prompt⁸ as prompt and text-davinci-002 and text-davinci-003 as LLMs. The experimental results on different k are shown in Figure 6, TISE surpasses BERT-TOPK across all combinations, demonstrating the robustness of TISE in different LLMs and prompt templates. Further-

⁸Specific examples can be found in Appendix A.4.

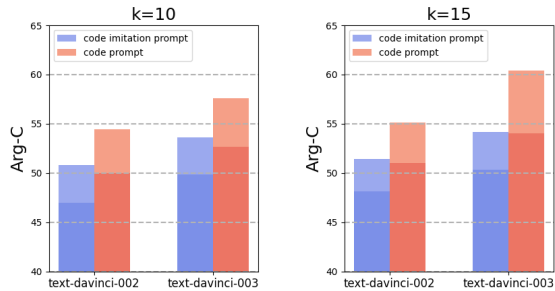


Figure 6: Performance on different LLMs and prompts. The darker part indicates the performance of BERT-TOPK, and the lighter part is the performance of TISE.

Methods	$k=10$		$k=15$	
	Arg-I	Arg-C	Arg-I	Arg-C
RANDOM	55.71	45.27	57.64	46.44
BERT-TOPK	57.09	47.47	59.08	48.09
TISE	59.69	50.54	60.05	50.93

Table 4: Performance on the same event type scenario, note that some test inputs can not find k training examples with the same event type.

more, we observe that `text-davinci-003` consistently outperforms `text-davinci-002`, and the code prompt yields superior results compared to the code imitation prompt. When the length limitation is not exceeded, the optimal combination should be TISE + code prompt + `text-davinci-003` on higher k .

Same Event Type Scenario If we have enough labeled data for each event type, selecting examples with the same event type would be more efficient. To verify the stability of TISE in this scenario, we conduct an experiment by restricting the selected examples to those with the same event type as the test input. The results are shown in Table 4, we find that examples with high semantic similarity remain effective even when all of them have the same event type (+1.38%/+2.20% on $k=10$ and +1.44%/+1.65% on $k=15$). Furthermore, TISE still outperforms baselines on different k (+2.60%/+3.07% on $k=10$ and +0.97%/+2.84% on $k=15$), we attribute this improvement to the Example Diversity and Event Role modules, which ensure TISE can select the optimal subset across different data distributions.

Comparison with Supervised Methods Supervised methods have achieved respectable results using limited training data through specialized ar-

	%Training Data	Arg-C
<i>few shot - aspect 1</i>		
DEGREE	5%	35.5
TISE $_{k=5}$	5%	38.8
DEGREE	10%	41.6
TISE $_{k=15}$	10%	42.0
<i>few shot - aspect 2</i>		
DEGREE	20%	46.2
DEGREE	30%	48.7
TISE $_{k=5}$	19%	48.7
TISE $_{k=10}$	28%	50.8
<i>full shot</i>		
DyGIE++	-	60.7
TISE $^{\dagger}_{k=15}$	-	60.9
DEGREE	-	73.5

Table 5: Comparison between TISE and supervised methods, the results are derived from Hsu et al., 2021. % Training data means the proportion of training data. TISE † uses `text-davinci-003` as LLM and code prompt as prompt template.

chitectural designs. We first compare TISE with the competitive method (DEGREE; Hsu et al., 2021) in the few shot scenario. We conduct experiment from two aspects: 1. Scaling down the training data, and TISE can only select examples from a limited amount of data. 2. TISE can select from the whole dataset and we calculate how many different training data are actually used. Results are reported in Table 5, TISE exceeds DEGREE when the total amount of available data is limited, and, despite the training data is adequate, TISE can still select a fraction of those that are truly useful to help LLM reasoning. These demonstrate that TISE can filter efficient examples based on test input so that shows capabilities in low resource scenarios. In the full shot scenario, we compare TISE with two baselines: DEGREE and DyGIE++ (Wadden et al., 2019). We are surprised to observe that TISE $_{k=15}$, coupled with `text-davinci-003` and code prompt, can outperform the supervised method (DyGIE++). However, there is still exists a performance gap between TISE and the DEGREE (12.6%). Hence, designing a better example selection method remains a promising direction for future research.

Case Study We present a case study in Figure 7 to directly visualize the advantages of each requirement. For Example Diversity, both examples 1 and 2 in BERT-TOPK describe a clash/war with event role “Place”. As a result, LLM correctly extracts the argument for “Place”, while the

	Test Input	In-context Examples	EAE Result	Golden Label
BERT-TOPK	(Die) Australian commandos, who have been operating deep in Iraq, destroyed a command and control post and killed a number of soldiers, according to the country's defense chief, Gen. Peter Cosgrove.	(Attack) ... Marines had broken up violent clashes on Wednesday in Tikrit [Place] , Saddam's hometown (Die) ... minimize civilian [Victim] casualties in the current Iraq [Place] war ... (Transport) ... refused to say whether the paratroopers deployed directly from Italy into Iraq ...	Agent:None Instrumen:None Place:Iraq Victim:soldiers	Agent:commandos Instrument:None Place:Iraq Victim:number
TISE		(Die) ... at dusk they [Agent] fired what observers say were seven artillery rounds [Instrument] back at their former stronghold ... (Die) ... of coalition soldiers [Victim] had been killed, their graves were now at the airport [Place] . (Die) ... iraqi missile [Instrument] hit operation center [Place] for 2nd brigade 3rd infantry zrigs south baghdad, at least four [Victim] dead, two soldiers [Victim] and two journalists [Victim] .	Agent:commandos Instrument:None Place:Iraq Victim:number of soldiers	

Figure 7: A case study with BERT-TOPK and TISE. The event type of each sentence is marked at the beginning using (bracket), the event information is bolded as **Argument [Role]**, red text indicates **incorrect extraction** and green ones indicates **correct extraction**. “Victim” of TISE is considered correct because the head token is matched.

other roles perform incorrect results (notice that example 2 mentions a “Victim”, so the argument of “Victim” is not “None”, although it is not entirely accurate). On the other hand, the examples of TISE encompass all event roles involved in the label, enabling LLM to extract arguments comprehensively, verifying Example Diversity can ensure the selected examples contain different role information. For event correlation, BERT-TOPK selects a “Transport” example that does not contain any useful event roles. In contrast, all the examples of TISE have the event type “Die”, ensuring that each of them can convey useful information. Overall, both Example Diversity and Event Correlation can help LLM extract arguments better.

7 Conclusion

In this paper, we present three necessary requirements for the in-context example selection when using LLM to conduct EAE task. We propose TISE, which scores the examples from three perspectives and leverages DPP to fuse these scores so that the optimal in-context example is directly selected. Experiments on ACE05 show TISE can select a more efficient in-context example than baselines, is robust to the number of examples, and even can achieve better performance with fewer examples. TISE can also be adapted to different prompts and LLMs, and outperforms some fully fine-tuned supervised methods. Moreover, we explore the principle of the effectiveness of three requirements.

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Limitations

1) The encoder of TISE is a vanilla BERT model. Except for replacing it with a dense retriever, some methods use ranking labels obtained by the language model to supervisedly learn a retriever as an encoder that is adapted to the current dataset (Rubin et al., 2022; Ye et al., 2023). However, there is a gap between the retrieval task and the EAE task, so it is not reasonable to directly use the ranking label as a supervised signal. Intuitively, it makes more sense to use reinforcement learning to optimize a retriever using the performance of the EAE as a reward. 2) The time consumption of TISE is high, although we store the descriptions in a dictionary, which reduces the time complexity of the event scorer to $O(1)$. However, each role in the example requires a separate query of the test roles, which increases the overhead.

Ethics Statement

This work does not present any direct ethical issues. We focus on selecting the optimal in-context example for LLMs to conduct EAE task. All experiments are conducted on open datasets and the findings and conclusions of this paper are reported accurately and objectively.

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A Appendix

A.1 Event Type Description

The complete event type description is shown in Table 7, we display the event types belonging to the same parent together to highlight the advantages.

A.2 Event Role Description

The complete event role description is shown in Table 8. Similarly, we display roles of the same event type together.

A.3 Theoretical Proof

Since $K_{ij} = k(t_i, t_j|x) = s_E'(x, t_i) \cdot s_T'(x, t_i) \cdot s_T(t_i, t_j) \cdot s_T'(x, t_j) \cdot s_E'(x, t_j)$, the kernel matrix K can be represented as:

$$K = \text{Diag}(S'_E) \cdot \text{Diag}(S'_T) \cdot \bar{K} \cdot \text{Diag}(S'_T) \cdot \text{Diag}(S'_E)$$

We only consider the effect of $\det(K_A)$:

$$\det(K_A) = \prod_{t_i \in A} S'_{E_i}{}^2 * \prod_{t_i \in A} S'_{T_i}{}^2 * \det(\bar{K}_A)$$

After logarization:

$$\begin{aligned} \log \det(K_A) &= \sum_{t_i \in A} \log(S'_{E_i}{}^2 * S'_{T_i}{}^2) + \log \det(\bar{K}_A) \\ &= \sum_{t_i \in A} \left(\frac{S_{E_i}}{\lambda_1} + \frac{S_{T_i}}{\lambda_2} \right) + \log \det(\bar{K}_A) \end{aligned}$$

Simplifying, we assume that $A = \{t_i, t_j\}$, thus the second part can be decomposed into:

$$\det(\bar{K}_A) = \begin{vmatrix} \bar{K}_{ii} & \bar{K}_{ij} \\ \bar{K}_{ji} & \bar{K}_{jj} \end{vmatrix} = -\bar{K}_{ij}^2 + \bar{K}_{ii}\bar{K}_{jj} \quad (11)$$

It can be found that $\det(\bar{K}_A)$ and $\bar{K}_{ij} = s_T(t_i, t_j)$ are negatively correlated, meaning a higher $P(A|x)$ requires lower \bar{K}_{ij} , in other words, t_i and t_j have low similarity.

A.4 Prompt Examples

We display examples of code imitation prompt and code prompt in Figures 8 and 9, respectively. TISE only needs to fuse the selected examples into the *In-context Examples* according to the prompt format, so that can be adapted to any prompt template.

		Arg-C _{k=10}	Arg-C _{k=15}
$\lambda_2 = 0.05$		50.78	51.43
$\lambda_1 = 0.5$	$\lambda_2 = 0.1$	50.01	51.01
	$\lambda_2 = 0.5$	48.49	49.23
$\lambda_1 = 0.05$		50.13	50.87
$\lambda_2 = 0.05$	$\lambda_1 = 0.1$	50.54	50.99
	$\lambda_1 = 0.5$	50.78	51.43

Table 6: Comparison with different λ_1 and λ_2 on $k=10$ and $k=15$.

A.5 Impact of λ

To obtain the optimal hyperparameters, we conduct experiments with various combinations of λ_1 and λ_2 on different k . The experimental results are shown in Table 6, we find that $\lambda_1 = 0.5$ and $\lambda_2 = 0.05$ archives the best performance across different values of k . In addition, TISE is smooth on λ_1 , while sensitive to λ_2 . We guess this is because Semantic Similarity has a greater impact than Event Correlation.

<p>Entity Type Definition</p> <p>Description of base entity types: FAC: A functional, primarily man-made structure. Facilities are artifacts falling under the domains of architecture and civil engineering, including more temporary human constructs, such as police lines and checkpoints. ... (other entity types)</p>
<p>Event Definition</p> <p>Role definition of event type Attack (Parent type: Conflict):</p> <ol style="list-style-type: none"> 1. attacker (need to be one of GPE or ORG or PER) 2. instrument (need to be one of VEH or WEA) 3. place (need to be one of FAC or GPE or LOC) 4. target (need to be one of FAC or LOC or ORG or PER or VEH or WEA) 5. victim (need to be one of PER) <p>Multiple entities can be extracted for the same role, each entity is a double-quote enclosed string. Each extracted entity should look like: (Base Entity Type) "content of extracted string" If entity is not present in the text, write: () "" Different entities are delimited by a comma. In this event: [attacker] attacked [target] hurting [victim] victims using [instrument] instrument at [place] place.</p>
<p>In-context Examples</p> <p>Translate the following sentence into an instance of Attack event. The trigger word(s) of the event is marked with **trigger word**.</p> <p>"reporter : experts say saddam hussein 's forces will likely try to hold out in baghdad for as long as possible without **using** the weapons his government insists it does not have , hoping to build international pressure on the u.s. and britain to back down."</p> <ol style="list-style-type: none"> 1. attacker: (PER) "forces" 2. instrument: (WEA) "weapons" 3. place: (GPE) "baghdad" 4. target: () "" 5. victim: () "" <p>... (other examples)</p>
<p>Event Instantiation</p> <p>Translate the following sentence into an instance of Attack event. The trigger word(s) of the event is marked with **trigger word**.</p> <p>"Most analysts linked Russia 's opposition to a **war** in Iraq to fears that it will lose oil contracts that were sealed with the now - toppled regime of Saddam Hussein ."</p> <ol style="list-style-type: none"> 1. attacker: (

Figure 8: An example of code imitation prompt. To save space, we only show one part of the *Entity Type Definition* and *In-context Examples*, the other items have the same formats. In-context example and its label are colored blue, and the test input is colored orange.

<p>Entity Type Definition</p> <pre> class Entity: def __init__(self, name: str): self.name = name class Event: def __init__(self, name: str): self.name = name class FAC(Entity): """A functional, primarily man-made structure. Facilities are artifacts falling under the domains of architecture and civil engineering, including more temporary human constructs, such as police lines and checkpoints.""" def __init__(self, name: str): super().__init__(name=name) </pre>
<p>Event Definition</p> <pre> class Conflict(Event): def __init__(self, attacker: List[GPE ORG PER] = [], instrument: List[VEH WEA] = [], place: List[FAC GPE LOC] = [], target: List[FAC LOC ORG PER VEH WEA] = [], victim: List[PER] = []): self.attacker = attacker self.instrument = instrument self.place = place self.target = target self.victim = victim class Attack(Conflict): """self.attacker attacked self.target hurting self.victim victims using self.instrument instrument at self.place place.""" def __init__(self, attacker: List[GPE ORG PER] = [], instrument: List[VEH WEA] = [], place: List[FAC GPE LOC] = [], target: List[FAC LOC ORG PER VEH WEA] = [], victim: List[PER] = []): super().__init__(attacker=attacker, instrument=instrument, place=place, target=target, victim=victim) </pre>
<p>In-context Examples</p> <p>"""Translate the following sentence into an instance of Attack. The trigger word(s) of the event is marked with **trigger word**.</p> <p>"reporter : experts say saddam hussein 's forces will likely try to hold out in baghdad for as long as possible without **using** the weapons his government insists it does not have , hoping to build international pressure on the u.s. and britain to back down . " """</p> <p>attack_event = Attack(attacker=[PER("forces")], place=[GPE("baghdad")], instrument=[WEA("weapons")])</p>
<p>Event Instantiation</p> <p>"""Translate the following sentence into an instance of Attack. The trigger word(s) of the event is marked with **trigger word**.</p> <p>"Most analysts linked Russia 's opposition to a **war** in Iraq to fears that it will lose oil contracts that were sealed with the now - toppled regime of Saddam Hussein . " """</p> <p>attack_event = Attack(</p>

Figure 9: An example of code prompt. To save space, we only show one part of the *Entity Type Definition* and *In-context Examples*, the other items have the same formats. In-context example and its label are colored blue, and the test input is colored orange.

Parent Event Type	Event Type	Description
Movement	Transport	Involves an object movement, recording that an object has been transport to somewhere.
Personnel	Elect	Involves a personnel change, recording that an individual was elected to a position.
	Nominate	Involves a personnel change, recording that a person has been nominated for a position.
	Start-Position	Involves a change in personnel, recording someone starting work at a certain company.
	End-Position	Involves a change in personnel, recording someone stopping work at a certain company.
Conflict	Attack	Involves a conflict event, recording an attack or aggression.
	Demonstrate	Involves a conflict event, recording a military demonstration.
Contact	Meet	Involves a connection, recording a meeting between two people.
	Phone-Write	Involves a connection, recording a phone call between two people.
Life	Marry	Involves an event related to life, recording a marriage of two people.
	Injure	Involves an event related to life, recording that a person injuring another.
	Die	Involves an event related to life, recording the death of a person.
	Be-Born	Involves an event related to life, recording the birth of a newborn baby.
	Divorce	Involves an event related to life, recording a divorce of two people.
Transaction	Transfer-Money	Involves a transaction, recording a monetary transfer.
	Transfer-Ownership	Involves a transaction, recording a transfer of ownership of an item.
Business	End-Org	Involves an organizational business, recording an organization shut down.
	Start-Org	Involves an organizational business, recording the formation of an organization.
	Declare-Bankruptcy	Involves an organizational business, recording an organization declaring itself bankrupt.
	Merge-Org	Involves an organizational business, recording the merger of two organizations.
Justice	Sue	Involves a justice trial, recording a person has been sued before a court of law.
	Arrest-Jail	Involves a justice trial, recording a person has being arrested and jailed.
	Execute	Involves a justice trial, recording a person has been executed.
	Trial-Hearing	Involves a justice trial, recording a trial hearing.
	Charge-Indict	Involves a justice trial, recording a person has been charged or indicted.

Convict	Involves a justice trial, recording a person has been convicted.
Sentence	Involves a justice trial, recording a person has been sentenced.
Release-Parole	Involves a justice trial, recording a person has been released or paroled.
Fine	Involves a justice trial, recording a person has been fined.
Pardon	Involves a justice trial, recording a person has been pardoned.
Appeal	Involves a justice trial, recording a person has been acquitted.
Extradite	Involves a justice trial, recording a person has been extradited.
Acquit	Involves a justice trial, recording a person has been acquitted.

Table 7: The complete description of event type.

Event Type	Role	Description
Life:Be-Born	Person	Who was born?
	Place	Where did the birth take place?
Life:Marry	Person	Who was married?
	Place	Where did the marriage take place?
Life:Divorce	Person	Who was divorced?
	Place	Where did the divorce take place?
Life:Injure	Agent	Who enacted the harm?
	Victim	Who was harmed?
	Instrument	What device was used to inflict the harm?
	Place	Where did the injuring take place?
Life:Die	Agent	Who was the killer?
	Victim	Who was killed?
	Instrument	What device was used to kill?
	Place	Where did the death take place?
Movement:Transport	Agent	Who is responsible for the transport event?
	Artifact	Who was transported?
	Vehicle	What vehicle was used for transporting?
	Origin	Where did the transporting originate?
	Destination	Where was the transporting directed?
Transaction:Transfer-Ownership	Buyer	Who is the buying agent?
	Seller	Who is the selling agent?
	Beneficiary	Who benefits from the transaction?
	Artifact	What was bought?
Transaction:Transfer-Money	Place	Where did the sale take place?
	Giver	Who gave money to others?
	Recipient	Who was given money?
	Beneficiary	Who benefited from the transfer?
Business:Start-Org	Place	Where was the amount transferred?
	Agent	Who started the organization?
	Org	What organization was started

	Place	Where was the organization started?
Business:Merge-Org	Org	What organization was merged?
Business:Declare-Bankruptcy	Org	What organization declared bankruptcy?
	Place	Where was the bankruptcy declared?
Business:End-Org	Org	What organization was ended?
	Place	Where was the organization ended?
Conflict:Attack	Attacker	Who was the attacking agent?
	Target	Who was the target of the attack?
	Victim	Who was the victim of the attack?
	Instrument	What instrument was used in the attack?
	Place	Where did the attack take place?
Conflict:Demonstrate	Entity	Who demonstrated?
	Place	Where did the demonstration take place?
Contact:Meet	Entity	Who met with others?
	Place	Where did the meeting takes place?
Contact:Phone-Write	Entity	Who communicated with others?
	Place	Where did the communication take place?
Personnel:Start-Position	Person	Who is the employee?
	Entity	Who is the the employer?
	Place	Where did the employment relationship begin?
Personnel:End-Position	Person	Who ended the position?
	Entity	Who fired employee?
	Place	Where did the employment relationship end?
Personnel:Nominate	Person	Who was nominated?
	Agent	Who is the nominating agent?
Personnel:Elect	Person	Who was elected?
	Agent	Who was the voting agent?
	Place	Where did the election takes place?
Justice:Arrest-Jail	Person	Who was arrested?
	Agent	Who made the arrest?
	Place	Where did the arrest take place?
Justice:Release-Parole	Person	Who was released?
	Entity	Who released the person?
	Place	Where did the release take place?
Justice:Trial-Hearing	Defendant	Who was on trial?
	Prosecutor	Who tried defendant?
	Adjudicator	Who adjudicated the trial?
	Place	Where did the trial take place?
Justice:Charge-Indict	Defendant	Who was indicated for crime?
	Prosecutor	Who executed the indictment?
	Adjudicator	Who adjudicated the indictment?
	Place	Where did the indictment take place?
Justice:Sue	Plaintiff	Who sued defendant?
	Defendant	Who was sued?
	Adjudicator	Who adjudicated the suing?
	Place	Where did the suit take place?
Justice:Convict	Defendant	Who was convicted for crime?
	Adjudicator	Who convicted defendant for crime?
	Place	Where did the conviction take place?
Justice:Sentence	Defendant	Who was sentenced for crime?

	Adjudicator	Who sentenced the defendant for crime?
	Place	Where did the sentencing take place?
Justice:Fine	Entity	Who was fined for crime?
	Adjudicator	Who fined the entity for crime?
	Place	Where did the fining take place?
Justice:Execute	Person	Who was executed for crime?
	Agent	Who executed person for crime?
	Place	Where did the execution take place?
Justice:Extradite	Agent	Who extradited person?
	Person	Who was extradited for crime?
	Destination	Where was the person extradited to?
	Origin	Where was the person extradited from?
Justice:Acquit	Defendant	Who was acquitted of crime?
	Adjudicator	Who acquitted the defendant of crime?
Justice:Pardon	Defendant	Who was pardoned for crime?
	Adjudicator	Who pardoned defendant for crime?
	Place	Where did the pardon take place?
Justice:Appeal	Plaintiff	Who made the appeal?
	Adjudicator	Who adjudicated the appeal?
	Place	Where did the appeal take place?

Table 8: The complete description of event role.