Towards Explainable Temporal Reasoning in Large Language Models: A Structure-Aware Generative Framework

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Abstract

While large language models (LLMs) show great potential in temporal reasoning, most existing work focuses heavily on enhancing performance, often neglecting the explainable reasoning processes underlying the results. To address this gap, we introduce a comprehensive benchmark covering a wide range of temporal granularities, designed to systematically evaluate LLMs' capabilities in explainable temporal reasoning. Furthermore, our findings reveal that LLMs struggle to deliver convincing explanations when relying solely on textual information. To address challenge, we propose **GETER**, a novel structure-aware generative framework that integrates **G**raph structures with text for **E**xplainable **TE**mporal **R**easoning. Specifically, we first leverage temporal knowledge graphs to develop a temporal encoder that captures structural information for the query. Subsequently, we introduce a structure-text prefix adapter to map graph structure features into the text embedding space. Finally, LLMs generate explanation text by seamlessly integrating the soft graph token with instruction-tuning prompt tokens. Experimental results indicate that GETER achieves state-of-the-art performance while also demonstrating its effectiveness as well as strong generalization capabilities. Our dataset and code are available at `https://github.com/carryTatum/GETER`.

1 Introduction

Temporal reasoning (TR) is a fundamental cognitive skill essential for understanding complex tasks like planning and causal relation discovery (Xiong et al., 2024). In natural language processing (NLP), temporal reasoning refers to a model's capability to effectively comprehend, represent, and predict time-sensitive contexts (Yang et al., 2024b). This capability is critical for real-world applications that depend on temporal data, including search engine recommendations (Bogina et al., 2023) and news article aggregation (Wu et al., 2025).

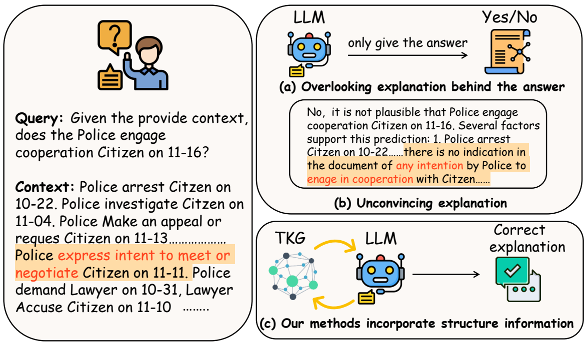

Figure 1: An illustration of existing temporal reasoning works highlights the lack of focus on explanations behind the reasoning. Meanwhile, LLMs often struggle to generate convincing answers due to hallucinations.

Recently, large language models (LLMs) have demonstrated remarkable performance in tackling complex tasks (Wei et al., 2022; Huang and Chang, 2023; OpenAI, 2023; Peng et al., 2025; Liu et al., 2025b). Building on this success, recent studies have increasingly focused on exploring the TR capabilities of LLMs. These works primarily adopt general approaches to evaluate and enhance the TR capabilities of LLMs. For instance, Tan et al. (2023) and Wei et al. (2023) design time-sensitive queries to benchmark LLMs, while Wang and Zhao (2024) and Chu et al. (2024) extend these efforts by using prompting strategies like in-context learning (ICL) and Chain-of-Thought (CoT) reasoning for comprehensive evaluation. Furthermore, Lee et al. (2023) and Xia et al. (2024) employ ICL with prompts containing intermediate reasoning steps to guide models, while Liao et al. (2024) and Luo et al. (2024) adopt fine-tuning methods, training LLMs on reasoning process texts to enable them to produce accurate answers.

Although existing methods have explored LLMs'

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potential in temporal reasoning, they exceedingly focus on improving performance, often overlooking the explainable reasoning processes behind the results, as illustrated in Figure 1(a). The study of explainable temporal reasoning is crucial, as it promotes transparency, enhances effectiveness, and fosters trust in understanding temporal dynamics. Moreover, with their impressive semantic understanding and generation capabilities, LLMs are uniquely positioned to address the challenges of explainable reasoning (Wang et al., 2023; Ma et al., 2024), as they can generate flexible, human-readable reasoning processes. Therefore, we posit the following research question to guide our study: *Can LLMs effectively make accurate predictions and clearly explaining their reasoning processes in complex temporal reasoning scenarios?*

To address this challenge, we propose the **ETR** benchmark, a comprehensive benchmark for explainable temporal reasoning. Specifically, ETR consists of five datasets covering a wide range of temporal granularities **(minutes, days, and years)**. Each instance is represented as a triple of <*query text, reasoning chains text, explanation text*> where the query and related reasoning chains are derived from Temporal Knowledge Graphs (TKGs). The explanation text is synthesized using GPT-4o (OpenAI, 2023) with constrained generation prompt protocols, taking the query and reasoning chains as input. The resulting explanation text effectively integrates both the original gold prediction and the underlying reasoning processes. ETR aims to challenge LLMs not only to predict future events from the given reasoning chains text but also to generate explanations of their reasoning processes.

Building on this benchmark, we identify that the key to achieving explainable temporal reasoning lies in enabling LLMs to capture structured patterns that reflect the relationships and dynamics between events over time. As shown in Figure 1(b), our findings reveal that LLMs struggle to deliver convincing explanations when relying solely on textual information, a challenge (e.g. hallucinations) also highlighted in previous analyses (He et al., 2024; Liu et al., 2025a). To address this challenge, we propose a novel structure-aware generative framework **GETER**, which advances explainable temporal reasoning by effectively bridging the gap between graph structures and text. Specifically, we leverage TKGs to develop a temporal encoder that captures structural information. Subsequently, the encoder converts the query and reasoning chains into a soft graph token, which is then mapped into the LLM's text space via a lightweight adapter. Finally, LLM can generate explanation text by integrating the soft graph token with instruction-tuning prompt tokens, seamlessly combining structural and contextual semantic information. Experimental results show that our proposed GETER achieves state-of-the-art performance. In summary, the contributions of this paper are as follows:

- We introduce ETR, a comprehensive benchmark covering a wide range of temporal granularities for systematically evaluating LLMs' explainable temporal reasoning.

- To bridge the gap between graph structures and text, we propose GETER, a novel structure-aware generative framework which leverages a lightweight structure-text adapter to enhance LLMs' explainable temporal reasoning capabilities.

- Our GETER achieves state-of-the-art performance on five datasets using widely-used LLMs, demonstrating the superiority of our model. Further experiments reveal the effectiveness and strong generalization ability of GETER.

2 Related Work

2.1 LLMs for Temporal Reasoning

With the rapid advancement of LLMs, research has increasingly focused on evaluating and enhancing their temporal reasoning capabilities. Existing studies primarily leverage the parametric knowledge of LLMs to assess and improve performance. For instance, several studies (Tan et al., 2023; Wei et al., 2023) design time-sensitive queries to benchmark LLMs, while others (Wang and Zhao, 2024; Chu et al., 2024) extend these efforts to diverse temporal reasoning tasks using general evaluation methods. Additionally, some methods (Lee et al., 2023; Xia et al., 2024) utilize in-context learning by providing prompts with demonstrations of intermediate reasoning steps to guide the model, whereas fine-tuning methods (Liao et al., 2024; Luo et al., 2024) train LLMs on reasoning texts to enable them to generate accurate final answers. Despite these advancements, most efforts focus on improving performance through parametric knowledge, with limited emphasis on explanation.

2.2 Explainable Temporal Reasoning

In temporal reasoning tasks, explainability is crucial for ensuring transparency, trust, and reliability. Existing works for explainable temporal reasoning primary fall into two categories: logic rule-based methods and reinforcement learning-based methods. Logic rule-based methods (Liu et al., 2022b; Lin et al., 2023; Mei et al., 2022) ensure explainability through explicit rule templates but struggle to balance generalization and explainability in complex scenarios. Reinforcement learning-based methods (Han et al., 2021; Sun et al., 2021) construct reasoning paths guided by predefined reward mechanisms. However, their explainability is limited by the implicit nature of their decision-making processes. In contrast, LLMs offer unique advantages for explainable reasoning by leveraging semantic understanding and generation capabilities (Tan et al., 2023, 2024), enabling more flexible and human-readable reasoning processes. While Yuan et al. (2024) conduct a preliminary exploration of LLM explainability, their work overlooks finer-grained temporal dimensions evaluation and fails to enhance LLMs through the integration of temporal graph features.

3 Proposed ETR Benchmark

3.1 Problem Definition

Temporal Knowledge Graphs (TKGs) $\mathcal{G}$ are represented as a sequence of KGs $(\mathcal{G}_0, \mathcal{G}_1, \ldots, \mathcal{G}_t)$ arranged by timestamp t. Let $\mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{F})$ be a TKG instance, where $\mathcal{E}$,$\mathcal{R}$, $\mathcal{F}$ represent the set of entities, relations and facts, respectively. Each fact can be represented as a quadruple $(e_s, r, e_o, t) \in \mathcal{F}$, where subject and object $e_s, e_o \in \mathcal{E}$, relation $r \in \mathcal{R}$. Explainable temporal reasoning aims to challenge LLMs to predict future events based on reasoning chains and generate explanations of their reasoning. Formally, given reasoning chains $\mathcal{C}$ consisting of facts $\mathcal{F}_{[t_q - w, t_q)}$, the task is to predict the probability that a query q will occur at future time t_q, where w is the window size. Based on this probability, the model classifies q into one of three categories: "Yes", "No", or "Unsure", and generates an explanation for its prediction. The prediction and explanation together form the final output A. To train and evaluate the model, we define two types of instances: training instances $\mathcal{T}_{train}$ and test instances $\mathcal{T}_{test}$. These instances follow the extrapolation condition (Jin et al., 2020), where the training time (t_{train}) strictly precedes the test time (t_{test}), i.e., $t_{train} < t_{test}$. Each instance $\mathcal{T}_i$ consists of the following components: the query text $\mathcal{Q}_i$, the input reasoning chains text $\mathcal{C}_i$, and explanation text $\mathcal{A}_i$, formally defined as:$\mathcal{T}_i = \{Q_i, \mathcal{C}_i, \mathcal{A}_i\}$.

3.2 Pipeline

As illustrated in Figure 2, we present **ETR**, a comprehensive benchmark for **E**xplainable **T**emporal **R**easoning. To accomplish this goal, we extract reasoning chains for each query and generate explanation text using GPT-4o. Additionally, we sample negative and neutral examples in a similar manner to provide a thorough evaluation of the LLMs. The detailed construction process is outlined as follows.

3.2.1 Reasoning Chains Text Construction

To construct reasoning chains text, given a query $q = (e_s, r, e_o, t_q)$, we extract the graph reasoning chains $\mathcal{C}(e_s, e_o)$ associated with entities e_s and e_o using a breadth-first search (BFS) methods (Jiang et al., 2023). The extraction process considers reasoning chains occurring within the time interval $[t_q - w, t_q)$ and is formalized as follows:

$$\mathcal{C}(e_s, e_o) \leftarrow \bigwedge_{i=1}^{l} (E_i, R_i, E_{i+1}, T_i), \qquad (1)$$

where $E_1 = e_s$, $E_{l+1} = e_o$, $l \in \{1, 2\}$ denotes the path length. Here, E_i represents the entity, R_i denotes the relation, and T_i is the corresponding timestamp. Once these reasoning chains $\mathcal{C}(e_s, e_o)$ are extracted, they are converted into natural language sentences to form the input text $\mathcal{C}_i$.

3.2.2 Explanation Generation

Based on the query $q = (e_s, r, e_o, t_q)$ and reasoning chains $\mathcal{C}(e_s, e_o)$, we employ a template to generate an initial explanation text $\mathcal{A}_i'$ as follows:

> *We predict that [e_s] [r] [e_o] will happen on [t_q]. Here are the reasoning steps: $\mathcal{C}(e_s, e_o)$.*

However, not all reasoning chains can adequately justify the occurrence of the given query, and the template-generated explanation text often exhibits issues such as incoherence, unnatural flow, and insufficient logical consistency, ultimately failing to provide a clear and compelling rationale. To address these limitations, we employ GPT-4o to enhance the quality of the final explanations $\mathcal{A}_i$, guided by the prompt provided in Appendix A.1

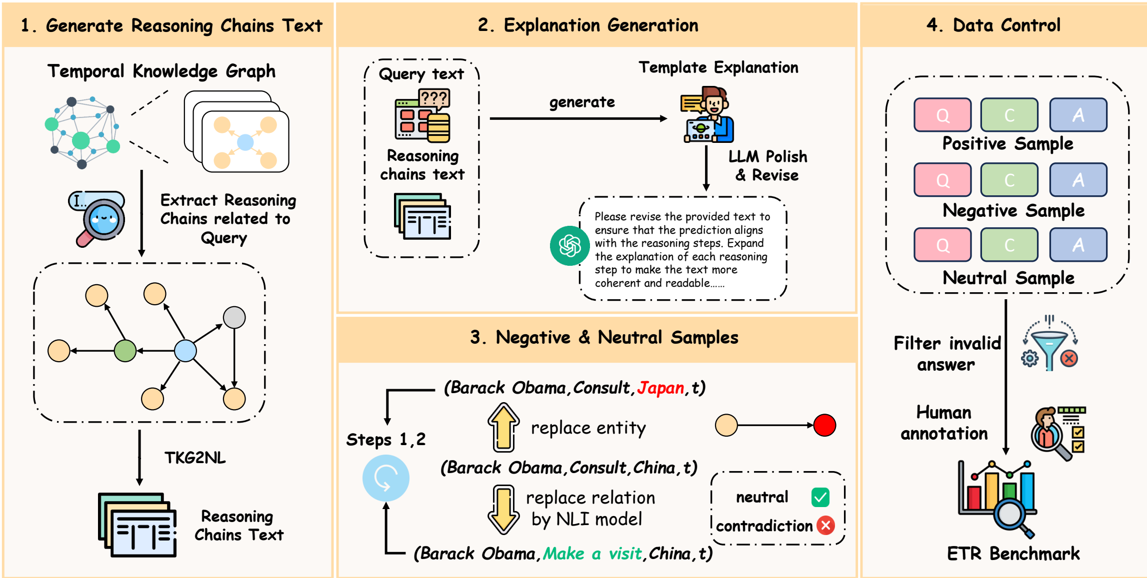


Figure 2: The pipeline of generating **ETR** benchmark.

Dataset	Time Granularity	Type	$\lvert Pos.\rvert$	$\lvert Neg.\rvert$	$\lvert Neu.\rvert$	Total
ICEWS14	1 day	*Train*	5000	4800	4500	14300
		Test	800	700	600	2100
ICEWS05-15	1 day	*Train*	4500	4400	4200	13100
		Test	720	680	660	2060
ICEWS18	1 day	*Train*	4400	4200	4000	12600
		Test	750	700	650	2100
GDELT	15 minutes	*Train*	4800	4600	4400	13800
		Test	800	700	650	2150
WIKI	1 year	*Train*	2482	2504	2342	7328
		Test	347	286	316	949

Table 1: Statistics of the **ETR** benchmark. $|Pos.|$, $|Neg.|$, and $|Neu.|$ denote the number of positive, negative, and neutral samples, respectively.

3.2.3 Negative and Neutral samples

To evaluate the ability of LLMs in explainable temporal reasoning, particularly in inferring logical correlations between the queries and historical facts, we introduce negative and neutral samples. Negative samples are used to test the model's ability to reject logically inconsistent or counterfactual scenarios, while neutral samples assess its capacity to infer uncertainty and ambiguity in scenarios with insufficient evidence.

Negative Samples. Negative samples represent counterfactual queries. To achieve this goal, we modify the positive query quadruple $q = (e_s, r, e_o, t_q)$ by replacing o with a different entity o', resulting in $q' = (e_s, r, e'_o, t_q)$, where $q' \notin \mathcal{F}$. This creates a hard negative sample that introduces factual inconsistencies. Additionally, we derive negative sample reasoning chains $\mathcal{C}(e_s, e'_o)$ as defined in Equation 1. Following a similar process for positive samples, we design the corresponding prompt for GPT-4o, detailed in Appendix A.2.

Neutral Samples. In neutral samples, LLMs are expected to predict "unsure" for the query, as the reasoning chain lacks sufficient evidence to support or refute it. To construct these samples, we replace the positive query relation $q = (e_s, r, e_o, t_q)$ with $q'' = (e_s, r', e_o, t_q)$, where r' is a semantically *neutral relation* to r and $q'' \notin \mathcal{F}$. The neutral relation r' is identified using a Natural Language Inference (NLI) model (He et al., 2023), which classifies relationships into entailment, contradiction, and neutral. We select r' as neutral only if the NLI model assigns $P(\text{neutral}) > \tau$, where τ is a predefined threshold. The reasoning chains for neutral samples, $\mathcal{C}(e_s, e_o)$, are consistent with those of positive samples. Details of the GPT-4o prompt are provided in Appendix A.3.

3.3 Benchmark Summary and Evaluation

As summarized in Table 1, the proposed benchmark covers a wide range of temporal granularities. To achieve this goal, we use five widely adopted temporal knowledge graph reasoning datasets: ICEWS14 (García-Durán et al., 2018), ICEWS18 (Han et al., 2021), ICEWS05-15 (García-Durán et al., 2018)), GDELT (Liao et al., 2024), and WIKI (Leblay and Chekol, 2018). To ensure the quality of the dataset, we filter out invalid answers and conduct human evaluation. Further details refer to Appendix A.5.

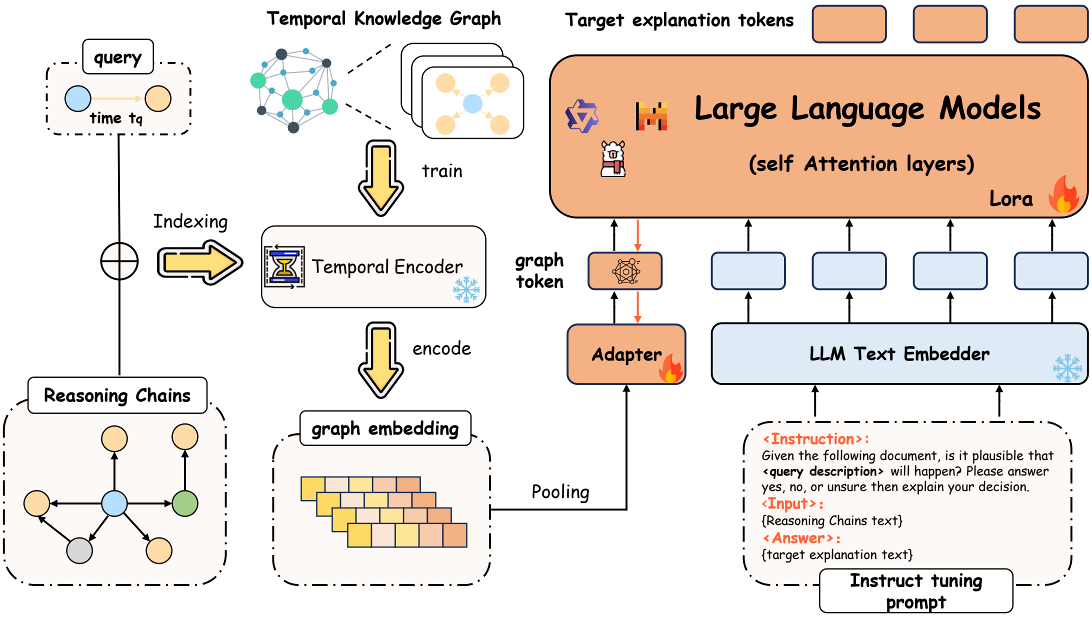


Figure 3: The overall framework of **GETER**. To bridge the gap between graph and text, we leverage TKGs to train a temporal encoder that captures structural information. Subsequently, the query and reasoning chains are encoded into a soft graph token, which is mapped into the text embedding space through a lightweight adapter. Finally, the target explanation text is generated using the soft graph token and related instruction tuning prompt tokens.

4 Methodology

In this section, we present **GETER**, a novel structure-aware generative framework that integrates **G**raph structures with text for **E**xplainable **TE**mporal **R**easoning. The overall architecture of our proposed model is illustrated in Figure 3. Specifically, we first leverage a temporal encoder to obtain structural embeddings for both entities and relations. Subsequently, we introduce a structure-text prefix adapter as described in Sec. 4.2 to map graph structure features into the text embedding space. Finally, we apply an instruction-tuning strategy (Sec. 4.3) to effectively adapt the model to the explainable temporal reasoning task.

4.1 Indexing

We aim to harness the semantic understanding and temporal reasoning capabilities of LLMs for the explainable temporal reasoning task. However, relying solely on LLMs within a text-based prediction framework to infer correlations between queries and reasoning chains inevitably neglects the structural information in the TKG $\mathcal{G}$. To address this, we first employ a temporal encoder (TKG model), such as RE-GCN (Li et al., 2021), which utilizes the message-passing mechanism of GNNs to effectively capture structural patterns, to generate the structural representation $\mathbf{s_n}$:

$$\mathbf{s_n} = TemporalEncoder(x_n|\mathcal{G}) \in \mathbb{R}^{d_s}, \quad (2)$$

where x_n represents the initialized embedding of entity or relation n, and d_s denotes the dimension of the structural embedding. In this way, we get entity embedding matrix $\mathbf{E} \in \mathbb{R}^{|\mathcal{E}|\times d_s}$ and relation embedding matrix $\mathbf{R} \in \mathbb{R}^{|\mathcal{R}|\times d_s}$, respectively.

4.2 Structure-Text Adapter

To effectively integrate structure-based embeddings of entities and relations with textual information, we propose a soft prompt strategy that combines structural and textual features in a contextualized manner. Specifically, given the query $q = (e_s, r, e_o, t)$ and reasoning chains $\mathcal{C}(e_s, e_o)$, we compute the representation of the query and reasoning chains via parameter-free message passing on the encoded structural features. The resulting graph representation is then projected into the embedding space of LLMs using a trainable projection matrix $\mathbf{W}_p \in \mathbb{R}^{3d_s \times d_x}$, as follows:

$$\mathbf{S}_{\mathcal{C}(e_s,e_o)} = \sum_{(e'_s,r',e'_o)\in\mathcal{C}(e_s,e_o)} (\mathbf{e'_s}\|\mathbf{r'}\|\mathbf{e'_o}), \quad (3)$$

$$\mathbf{S}_{graph} = \mathbf{W}_p \cdot \frac{\mathbf{S}_{\mathcal{C}(e_s,e_o)} + \mathbf{S}_q}{|\mathcal{C}(e_s,e_o)|+1}, \quad (4)$$

where $\|$ denotes concatenation, $\mathbf{S}_q = (\mathbf{e_s}\|\mathbf{r}\|\mathbf{e_o})$, $\mathbf{S}_{graph}$ is the projected graph representation, and

d_x denotes the dimension of embedding space of LLMs. $\mathbf{e}'_\mathbf{s} \in \mathbb{R}^{1\times d_s}$, $\mathbf{r}' \in \mathbb{R}^{1\times d_s}$, and $\mathbf{e}'_\mathbf{o} \in \mathbb{R}^{1\times d_s}$ are the embeddings of the subject entity, relation, and object entity, respectively. This straightforward linear mapping is adopted due to its proven effectiveness in aligning graph-based and textual representations (He et al., 2024; Liu et al., 2025a).

4.3 Instruction Tuning Strategy

The instruction tuning process is designed to adapt the reasoning behavior of the LLM to align with the specific constraints and requirements of the explainable temporal reasoning task. To facilitate the generation of the target explainable text, we provide the corresponding query text $\mathcal{Q}$ and reasoning chains text $\mathcal{C}(e_s, e_o)$ as inputs to the LLM, which produce their textual representations, denoted as $X = X_\mathcal{Q} + X_\mathcal{C}$. Let $\boldsymbol{X} \in \mathbb{R}^{|X|\times d_x}$ represent the textual content embeddings of the input, where $|X|$ denotes the token length of X. The final input to the LLM is constructed by concatenating the soft graph token embeddings $\mathbf{S}_{graph}$ (as described in Sec. 4.2) with the textual embedding, expressed as $\boldsymbol{X}' = \mathbf{S}_{graph} \| \boldsymbol{X}$. Lastly, our optimization objective is to maximize the likelihood of generating the target explanation text $Y_\mathcal{A}$:

$$P(\boldsymbol{Y}_\mathcal{A}|\boldsymbol{X}', \boldsymbol{X}_\mathcal{I}) = \prod_{j=1}^{L} P_\theta\big(y_j\big|\boldsymbol{X}', \boldsymbol{X}_\mathcal{I}, \boldsymbol{Y}_{<j}\big), \tag{5}$$

where $\boldsymbol{X}_\mathcal{I}$ denotes the representation of instruction tokens, L is the token length of the target explanation text, and $Y_{<j}$ represents the prefix of the missing explanation text sequence $Y_\mathcal{A}$ up to position $j-1$. Considering the overhead of updating all parameters in LLMs, we adopt Low-Rank Adaptation (LoRA) technique (Hu et al., 2022) for its effectiveness (Liu et al., 2022a). The example of instruction data can be seen in Appendix A.4.

5 Experiments

5.1 Experiments Setup

Baselines. We evaluate our benchmark with four representative LLMs: GPT-4o (OpenAI, 2023), Llama3-8B-Instruct (Dubey et al., 2024), Qwen2.5-7B-Instruct (Yang et al., 2024a), and Mistral-7B-Instruct-v0.3 (Jiang et al., 2024). For our framework, we adopt open-source LLMs as backbones and use RE-GCN (Li et al., 2021) as temporal encoder. Implementation details refer to Appendix B. Furthermore, performance comparisons with four graph-based methods (RE-GCN, CEN (Li et al., 2022), CENET (Xu et al., 2023), and SiMFy (Liu et al., 2023)) are presented in Appendix C.1.

Metrics. We evaluate explainable temporal reasoning capabilities of models in two aspects: prediction and explanation. For prediction, we report precision, recall, and F1 scores. For explanation, we employ BLEU (Papineni et al., 2002) (4-gram), ROUGE (Lin, 2004) (ROUGE-L), METEOR (Banerjee and Lavie, 2005), and BertScore (Zhang et al., 2020) to measure the similarity between model-generated explanations and the ground truth in the test set.

5.2 Main results

In our experiments, we compare GETER with two model configurations: 1) *Inference-only (zero-shot)*: Utilizing a frozen LLM to generate explanations directly without any additional training. 2) *Tuned-only*: Fine-tuning the LLM using LoRA to enhance its performance on the task. Table 2 presents the prediction results, while Table 3 summarizes the explanation results. Overall, GETER demonstrates consistent and significant improvements across most metrics on both datasets, highlighting the effectiveness of the proposed approach. Further comparisons with graph-based methods are provided in Appendix C.1.

Prediction Results. Table 2 reports the prediction evaluation metrics for each LLM. The results show that both the *Tuned-only* setting and GETER methods significantly outperform *Inference-only* setting methods. This performance gap arises because fine-tuning allows models to better capture task-specific temporal patterns and improve logical consistency. Notably, GETER with Mistral demonstrates substantial improvements of 97.95%, 95.55%, and 101.58% in overall F1 scores compared to the best-performing *Inference-only* model GPT-4o. Furthermore, compared to *Tuned-only* methods, GETER with Mistral achieves overall F1 score improvements of 11.10%, 10.71%, and 7.54% across the three datasets. These results further underscore that GETER can effectively leverage the structural information of TKGs to enhance its explainable temporal reasoning capabilities.

Explanation Results. Table 3 presents the evaluation metrics for explanation generation. GETER demonstrates remarkable improvements across all key metrics. Specifically, compared to GPT-4o, GETER with Mistral achieves substantial enhancements in BLEU-4 scores across the three datasets,

Models	Types	ICEWS14				GDELT				ICEWS05-15			
	Datasets / Types	Positive	Negative	Neutral	Overall	Positive	Negative	Neutral	Overall	Positive	Negative	Neutral	Overall
GPT-4o	zero-shot *w/o chains text*	53.13	20.02	12.95	30.61	19.08	43.78	25.50	29.06	55.45	26.33	15.47	33.03
	zero-shot	60.10	9.54	48.56	39.95	42.74	37.16	29.21	36.83	61.63	11.89	47.16	40.58
Llama3-8B-Instruct	zero-shot *w/o chains text*	21.69	27.11	35.42	27.42	1.95	33.13	39.44	23.44	11.75	28.98	39.41	26.30
	zero-shot	56.51	10.20	6.20	26.70	53.48	15.62	29.47	33.90	57.14	17.50	14.03	30.24
	LoRA *w/o chains text*	62.27	36.98	48.17	49.81	61.94	7.19	69.14	46.29	65.67	38.56	68.02	57.47
	LoRA	70.37	58.06	67.99	65.59	**62.86**	28.57	78.56	56.44	71.32	51.77	74.40	65.86
	GETER	**75.07**	**67.38**	**81.15**	**74.25**	62.62	**68.74**	**88.73**	**72.51**	**78.58**	**75.95**	**91.48**	**81.84**
	ΔImprove	6.68%	16.05%	19.36%	13.20%	-0.38%	140.54%	12.95%	28.49%	10.18%	46.70%	22.96%	24.26%
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	23.61	42.54	14.73	27.39	11.27	44.92	19.81	24.81	31.71	39.45	15.82	29.17
	zero-shot	53.08	45.32	11.41	38.59	22.22	48.23	1.21	24.34	40.81	48.32	1.75	30.78
	LoRA *w/o chains text*	62.82	58.59	71.97	64.03	31.28	52.11	12.41	32.36	55.33	68.65	85.89	69.52
	LoRA	74.60	65.64	75.62	71.90	22.39	56.61	66.79	46.95	66.83	70.95	84.09	73.72
	GETER	**76.41**	**74.61**	**84.49**	**78.12**	**63.77**	**70.06**	**88.42**	**73.27**	**78.23**	**72.95**	**89.90**	**80.23**
	ΔImprove	2.43%	13.66%	11.73%	8.65%	184.86%	23.77%	32.39%	56.04%	17.06%	2.82%	6.91%	8.83%
Mistral-7B-Instruct	zero-shot *w/o chains text*	3.65	39.44	46.44	27.81	5.52	40.64	23.50	22.39	7.56	33.21	46.10	28.37
	zero-shot	22.04	27.64	40.76	29.26	0.99	24.93	43.23	21.55	17.73	29.80	49.69	31.96
	LoRA *w/o chains text*	58.04	65.44	80.03	66.79	19.45	58.16	71.52	47.80	70.81	39.12	75.80	61.95
	LoRA	72.96	66.49	74.28	71.18	60.56	55.09	81.29	65.05	72.53	71.95	84.18	76.07
	GETER	**77.45**	**75.73**	**85.15**	**79.08**	**61.29**	**68.92**	**88.59**	**72.02**	**78.94**	**76.48**	**90.38**	**81.80**
	ΔImprove	6.15%	13.89%	14.63%	11.10%	1.21%	25.11%	8.98%	10.71%	8.84%	6.30%	7.36%	7.54%

Table 2: F1 scores (%) of each model on the ICEWS14, GDELT, and ICEWS05-15 test instances. "Overall" represents the weighted average F1 score. *w/o chains text* refers to the absence of reasoning chain input for LLMs. The best-performing results are highlighted in **bold**. ΔImprove represents the relative improvements of **GETER** compared to **Tuned-only** methods. Additional datasets and detailed prediction results are provided in Appendix E.

Models	Types	ICEWS14				GDELT				ICEWS05-15			
	Datasets / Types	BLEU-4	rougeL	METEOR	BertScore (F1)	BLEU-4	rougeL	METEOR	BertScore (F1)	BLEU-4	rougeL	METEOR	BertScore (F1)
GPT-4o	zero-shot *w/o chains text*	10.78	23.82	31.14	68.16	5.95	21.30	26.84	64.73	10.74	23.63	30.94	68.00
	zero-shot	22.94	41.04	37.24	79.25	9.16	27.61	32.32	70.91	22.64	40.83	36.27	79.16
Llama3-8B-Instruct	zero-shot *w/o chains text*	4.35	16.32	16.71	61.35	2.38	13.41	17.03	56.98	2.27	12.88	10.53	58.28
	zero-shot	9.70	30.19	26.60	70.25	5.61	27.10	25.73	67.42	10.08	31.13	27.44	70.02
	LoRA *w/o chains text*	27.73	39.71	45.94	80.16	18.12	37.05	35.92	77.51	27.59	39.63	45.80	80.17
	LoRA	39.21	50.96	**54.03**	84.28	34.32	54.84	51.49	**83.75**	42.98	54.50	56.65	85.45
	GETER	**40.54**	**52.54**	53.87	**84.75**	**34.46**	**55.42**	**51.75**	83.62	**45.98**	**57.27**	**58.16**	**86.39**
	ΔImprove	3.39%	3.10%	-0.30%	0.56%	0.41%	1.06%	0.50%	-0.16%	6.98%	5.08%	2.67%	1.10%
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	7.43	19.73	30.82	66.03	3.76	17.90	28.25	63.15	7.81	19.87	30.27	65.94
	zero-shot	11.18	28.49	27.98	72.28	7.55	26.90	25.97	70.00	10.53	28.53	26.32	72.04
	LoRA *w/o chains text*	28.17	40.22	45.20	80.12	17.15	36.89	34.52	75.71	28.60	40.52	45.76	80.39
	LoRA	39.59	**51.48**	53.30	84.35	26.10	47.30	43.85	79.93	43.55	55.01	56.22	85.62
	GETER	**39.78**	51.46	**55.03**	**84.53**	**33.81**	**54.76**	**50.18**	**83.59**	**44.72**	**56.17**	**57.22**	**86.01**
	ΔImprove	0.48%	-0.04%	3.25%	0.21%	29.54%	15.76%	14.44%	4.58%	2.69%	2.11%	1.78%	0.46%
Mistral-7B-Instruct	zero-shot *w/o chains text*	7.17	19.40	24.27	65.46	4.89	18.20	25.78	63.60	7.24	19.29	23.26	65.10
	zero-shot	9.19	28.36	25.70	71.63	7.46	27.96	25.99	70.43	7.95	27.40	23.60	70.73
	LoRA *w/o chains text*	28.01	39.84	45.70	80.34	18.22	38.08	35.74	76.76	28.26	40.13	45.96	80.45
	LoRA	38.81	50.81	52.62	84.02	30.93	52.24	47.28	82.28	43.03	54.56	55.94	85.47
	GETER	**40.21**	**51.84**	**54.90**	**84.65**	**32.18**	**53.27**	**49.06**	**82.83**	**45.07**	**56.48**	**57.70**	**86.13**
	ΔImprove	3.61%	2.03%	4.33%	0.75%	4.04%	1.97%	3.77%	0.67%	4.74%	3.52%	3.14%	0.77%

Table 3: The semantic similarity performance (%) of each model on the ICEWS14, GDELT, and ICEWS05-15 test instances. *w/o chains text* refers to the absence of reasoning chain input for LLMs. The best-performing results are highlighted in **bold**. Additional dataset explanation results are presented in Appendix E.

with gains of 75.28%, 251.31%, and 99.07%, respectively. These results highlight GETER's ability to leverage high-quality fine-tuning datasets to enhance explainable temporal reasoning capabilities.

No.	Model	ICEWS14	GDELT	ICEWS05-15
1	**GETER**	**79.08**	**72.02**	**81.80**
2	GETER *w/o* STA	71.18$_{(\downarrow 7.90)}$	65.05$_{(\downarrow 6.97)}$	76.07$_{(\downarrow 5.73)}$
3	GETER *w/o* RCT	72.05$_{(\downarrow 7.03)}$	68.89$_{(\downarrow 3.13)}$	77.82$_{(\downarrow 3.98)}$
4	GETER *w/o* (STA & RCT)	66.79$_{(\downarrow 12.29)}$	47.80$_{(\downarrow 24.22)}$	61.95$_{(\downarrow 19.85)}$

Table 4: Ablation study of GETER with Mistral on ICEWS14, GDELT, and ICEWS05-15 datasets using overall F1 scores (%). STA denotes structure-text adapter, while RCT denotes reasoning chains text.

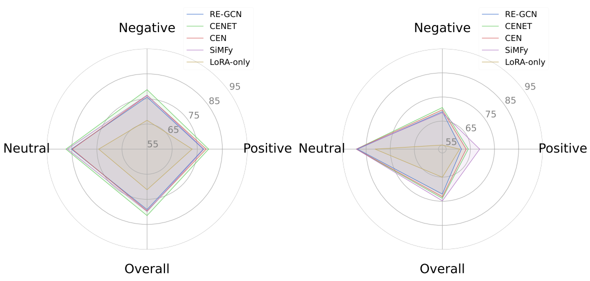
5.3 Ablation Study

In this subsection, we conduct an ablation study to investigate the individual contributions of different components in GETER. The results for various variants are presented in Table 4, indicating that all modules are essential, as removing any of them leads to a decline in performance. Notably, to validate the usefulness of the structural information provided by GETER, we directly removed the structure-text adapter from the model (Line 2). This ablation results in overall F1 score reductions of 11.10%, 10.71%, and 7.53% across the three datasets, respectively. These results demonstrate that the soft graph token with lightweight adapter can effective capture the structural characteristics for the query. Additionally, as shown in Line 3 of Table 4, removing the reasoning chains text leads to a significant performance decline, with F1 scores dropping by 9.76%, 10.71%, and 5.11% across the three datasets, respectively. This result highlights the importance of reasoning chains text, as they provide sequenced evidence that enriches the contextual background. Furthermore, we observe that GETER scheme significantly outperforms the base model that directly adopts instruction tuning (Line 4). This demonstrates the effectiveness of GETER, which combine structural and contextual semantic information to activate and harness the LLM's capability for explainable temporal reasoning.

5.4 Discussion

In this subsection, we conduct further analysis of the impact of different temporal encoders, the influence of MLP depth, and the effect of various reasoning chain serialization formats on the model's performance. All experiments are conducted using Mistral for its superior performance. Additionally, we present a complexity analysis in Appendix C.2 and a case study in Appendix D to further highlight the advantages of our proposed method.

Q1: What is the impact of different temporal encoders on GETER's performance? To evaluate the impact of different temporal encoders, we also integrate CEN, CENET, and SiMFy into the our framework, as described in 5.1. The performance comparison is illustrated in Figure 4. The results demonstrate that GETER achieves consistently high performance across two datasets when paired with any of the three temporal encoders, significantly outperforming methods that rely solely on LoRA. These findings demonstrate that GETER is robust to variations in temporal encoders. Details about temporal encoders refer to Appendix B.1.



(a) ICEWS14 (b) GDELT

Figure 4: Comparison of GETER with different temporal encoders on the ICEWS14 and GDELT datasets in terms of overall F1 scores (%).

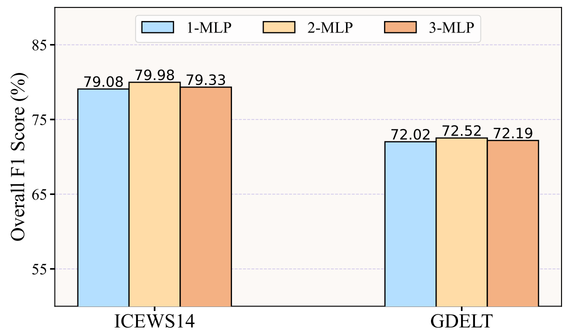


Figure 5: MLP depth comparison on ICEWS14 and GDELT datasets in terms of overall F1 scores (%).

Model	Positive	Negative	Neutral	Overall
GETER *(paths order)*	77.45	75.73	85.15	79.08
descending order	**80.53**	76.00	**86.34**	**80.68**
ascending order	77.72	**77.52**	86.04	80.03
random order	75.02	76.31	82.45	77.57

Table 5: Performance (F1 (%)) of GETER with different reasoning chain formats on the ICEWS14 dataset.

Q2: How does the depth of the MLP affect GETER's performance? GETER uses a one-layer MLP to map the graph structure feature into the text embedding space. To investigate whether deeper neural structures improves performance, we conduct experiments to replace the one-layer MLP with deeper variants. The results on the ICEWS14 and GDELT datasets are presented in Figure 5. We can observe that increasing model complexity has minimal impact on performance. This is likely because deeper structures fail to capture evolving structural information more effectively.

Q3: What is the effect of different reasoning chain text formats on GETER's performance? We further investigate how GETER utilizes reasoning chain text, which provides contextualized background information for queries. Specifically, we evaluate three different serialization formats based on the timestamp of quadruples: *ascending*, *descending*, and *random*. As shown in Table 5, the model achieves the best performance with the descending order format. Surprisingly, even with random serialization, GETER still maintains competitive performance. This is attributed to the structured adapter in GETER, which effectively couple structure and text information in a contextualized manner. These findings further highlight the robustness and adaptability of our proposed GETER.

6 Conclusion

We introduce a comprehensive benchmark covering a wide range of temporal granularities for systematically evaluating LLMs' explainable temporal reasoning. To address the challenge of LLMs struggling to deliver convincing explanations, we propose a novel structure-aware generative framework **GETER**, which effectively bridges the gap between graph structures and text by through a lightweight structure-text adapter. Extensive experiments validate the effectiveness and robustness of our proposed GETER.

Limitations

GETER can effectively activate and harness the explainable reasoning ability of LLMs by incorporate the graph structural information into the LLMs. However, the extremely large number of parameters in LLMs makes fine-tuning them resource-intensive. At the same time, LLMs are notoriously slow at decoding during inference. In our experiment, we use DeepSpeed (Rajbhandari et al., 2020) to accelerate training and inference. Additionally, some reasoning chains may introduce noisy text, which could negatively affect explainable temporal reasoning performance.

Ethics Statement

In developing this explainable temporal reasoning benchmark, all data used in this study are publicly available and do not pose any privacy concerns. Additionally, we have carefully considered ethical issues and limitations commonly associated with large language models. Nonetheless, we acknowledge that, despite our best efforts, the benchmark may still contain gaps or unintended biases. To mitigate this, the source data has been meticulously curated to ensure diversity and minimize potential biases. Through rigorous design and testing processes, we strive to uphold ethical AI principles while advancing research in temporal reasoning.

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A Benchmark Details

A.1 Prompt for Generating Explanations of Positive Samples

Prompt for Positive Samples' Explanation

Given the following text: "we predict that [e_s] [r] [e_o] will happen on [t_q]. Here are the reasoning steps: $\mathcal{C}(e_s, e_o)$." Please revise the provided text to ensure that the prediction aligns with the reasoning steps. Expand the explanation of each reasoning step to make the text more coherent and readable. If necessary, add additional reasoning steps to clarify the logic. The output should be a single, concise paragraph without bullet points, ensuring clarity and logical consistency.

A.2 Prompt for Generating Explanations of Negative Samples

Prompt for Negative Samples' Explanation

Given the following text: "It is plausible that [e_s] [r] [e_o'] will not happen on [t_q]. Here are the reasoning steps: $\mathcal{C}(e_s, e_o')$." Please revise the provided text to ensure that the prediction aligns with the reasoning steps. Expand the explanation of each reasoning step to make the text more coherent and readable. If necessary, add additional reasoning steps to clarify the logic. The output should be a single, concise paragraph without bullet points, ensuring clarity and logical consistency.

A.3 Prompt for Generating Explanations of Neutral Samples

Prompt for Neutral Samples' Explanation

Given the following text: "It is unsure that [e_s] [r'] [e_o] will happen on [t_q]. Here are the reasoning steps: $\mathcal{C}(e_s, e_o)$." Please revise the provided text to ensure that the prediction aligns with the reasoning steps. Expand the explanation of each reasoning step to make the text more coherent and readable. If necessary, add additional reasoning steps to clarify the logic. The output should be a single, concise paragraph without bullet points, ensuring clarity and logical consistency.

A.4 Example Prompt for Instruction Tuning

Here is an example of an instruction tuning prompt for the query: (Police (Australia), Make an appeal or request, Citizen (Australia), 2014-03-12).

Example Prompt for Instruction Tuning

Instruct: *Given the following document, is it plausible that Police (Australia) will Make an appeal or request Citizen (Australia) on 2014-03-12? Please answer yes, no, or unsure then explain your decision.*

Input: *Police (Australia) Appeal for aid Citizen (Australia) 2014-02-10. Police (Australia) Arrest, detain, or charge with legal action Citizen (Australia) 2014-02-25. Police (Australia) Arrest, detain, or charge with legal action Citizen (Australia) 2014-03-04. ...... Police (Australia) Arrest, detain, or charge with legal action Criminal (Australia) on 2014-02-27, Criminal (Australia) Sexually assault Citizen (Australia) on 2014-03-08......*

Output: *Yes. Based on the information provided, it is plausible that the Police in Australia will make an appeal or request to citizens on March 12, 2014. This prediction is supported by a pattern of interactions between the police and citizens leading up to this date. The police have previously made appeals or requests to citizens on several occasions, including February 23, February 26, and March 11, 2014. Additionally, the police have been actively involved in various actions such as arrests, detentions, and investigations, indicating a heightened level of engagement with the public. The police have also been involved in more severe actions, such as using conventional military force and fighting with small arms, which suggests a context of ongoing tension or conflict. Given this backdrop, it is reasonable to anticipate that the police might continue their efforts to communicate with citizens, possibly to seek cooperation or provide updates on ongoing situations. Therefore, considering the frequency and nature of past interactions, it is likely that the police will make another appeal or request to citizens on March 12, 2014.*

A.5 Benchmark Summary and Evaluation

The statistical details of the source data used to construct the benchmark are provided in Table 6. The data consist of three sources: the *Integrated Crisis Early Warning System* (ICEWS), the *Global Database of Events, Language, and Tone* (GDELT), and *Wikipedia* (WIKI). Specifically, the

Datasets	#train	#valid	#test	#entity	#relations	time gap
ICEWS14	74854	8514	7371	7128	230	1 day
ICEWS18	373018	45995	49545	23033	256	1 day
ICEWS05-15	368868	46302	46159	10094	251	1 day
GDELT	79319	9957	9715	5850	238	15 minutes
WIKI	539286	67538	63110	12554	24	1 year

Table 6: Dataset statistics.

ICEWS14 dataset includes events from 2014, the ICEWS18 dataset includes events from 2018, and the ICEWS05-15 dataset spans events from 2005 to 2015. The GDELT dataset records events at 15-minute intervals, while WIKI consists of Wikidata knowledge bases that store factual information with a time interval of one year. To ensure the quality and reliability of our dataset, we recruited three volunteers to evaluate the benchmark. Each volunteer assessed 200 randomly selected examples from the dataset. They were instructed to perform two key evaluations, assigning scores on a scale of 1 to 3 based on the following criteria:

Explanation Text Quality (1-3):

- **1** - The explanation is unclear, incoherent, or unreasonable.
- **2** - The explanation is somewhat clear and reasonable but lacks coherence or completeness in certain aspects.
- **3** - The explanation is clear, coherent, and fully reasonable.

Overall Consistency (1-3):

- **1** - The query text, reasoning chain, and explanation text are inconsistent or logically disconnected.
- **2** - There is partial consistency among the query text, reasoning chain, and explanation text, but logical gaps remain.
- **3** - The query text, reasoning chain, and explanation text are fully consistent and logically aligned.

The results of the human evaluation, as shown in Table 7, demonstrate a high level of accuracy and reliability in our benchmark generation process.

B Implementation Details

B.1 Baselines

Below, we provide brief introductions to the LLMs used in our methods:

Volunteer	**Explanation Text Quality**	**Overall Consistency**
Volunteer 1	2.80	2.78
Volunteer 2	2.74	2.79
Volunteer 3	2.86	2.89

Table 7: Average scores for Explanation Text Quality and Overall Consistency by Volunteers.

- *GPT-4o* (OpenAI, 2023) is a large language model developed by OpenAI, representing an advanced iteration of the GPT series. It is known for its strong generalization capabilities across a wide range of natural language processing tasks, including reasoning, generation, and instruction-following.
- *Llama-3.1-8B-Instruct* (Dubey et al., 2024) is an instruction-tuned version of the Llama3 series, with 8 billion parameters. The tuned versions use supervised fine-tuning (SFT) and reinforcement learning with human feedback (RLHF) to align with human preferences for helpfulness and safety.
- *Qwen2.5-7B-Instruct* (Yang et al., 2024a) is the latest series of Qwen large language models. It focuses on optimizing performance for instruction-based tasks.
- *Mistral-7B-Instruct-v0.3* (Jiang et al., 2024) is a 7-billion-parameter instruction-tuned model with an extended 32,768-token vocabulary, v3 tokenizer support, and function calling capabilities for improved task performance.

We also introduce the graph-based methods (temporal encoders) utilized in our methods:

- *RE-GCN* (Li et al., 2021) proposes a recurrent evolution module based on relational GNNs to obtain embeddings that contain dynamic information for entities and relations.
- *CEN* (Li et al., 2022) uses a length-aware Convolutional Neural Network(CNN) to handle evolutional patterns of different lengths via an easy-to-difficult curriculum learning strategy.
- *CENET* (Xu et al., 2023) aims to learn a robust distribution over the entire entity set and identify significant entities by leveraging both historical and non-historical dependencies within a contrastive learning framework.
- *SiMFy* (Liu et al., 2023) is a straightforward method that combines MLP and historical frequency to model the temporal events.

B.2 Hyperparameters

We set the window size w to 30 and the threshold τ to 0.7 for constructing our benchmark. During training, the RE-GCN module is kept frozen, and LoRA is employed to fine-tune the model. The structural embedding size d_s is set to 512, while the textual embedding size d_x retains the original hidden layer dimensions of each LLM. The detailed hyperparameters used during training and inference are provided in Table 8. For optimization, we enable DeepSpeed ZeRO stage3 [1]. All models are trained and evaluated on 2 Nvidia A800 GPUs, each with 80GB of memory.

Name	Value
lora r	16
lora alpha	32
lora dropout	0.05
lora target modules	(q, k, v, o, down, up, gate) proj
cutoff len	2048
epochs	3
per device batch size	6
gradient accumulation steps	1
learning rate	$3e-4$
weight decay	$1e-5$
warm ratio	0.01
lr scheduler type	cosine
num return sequences	10
projection layers	1

Table 8: Detailed hyperparameters used in our paper.

C Additional Comparative Study Results

C.1 Comparison with Graph-based Methods

To provide a comprehensive comparison, we also evaluate four state-of-the-art graph-based methods(REGCN, CEN, CENET, and SiMFy) in comparison with our method on the task. Specifically, for the query (e_s, r, e_o, t_q), we utilize an MLP to adapt to our task, as defined below:

$$P = \mathbf{W}_{query}(e_s \parallel r \parallel e_o)$$

where $\parallel$ denotes the concatenation operation, $P \in \mathbb{R}^3$, $e_s \in \mathbb{R}^{1\times d_s}$, $r \in \mathbb{R}^{1\times d_s}$, and $e_o \in \mathbb{R}^{1\times d_s}$. Here, $\mathbf{W}_{query} \in \mathbb{R}^{3\times 3d_s}$ is a learnable weight matrix, and d_s represents the embedding dimension.

The prediction results are presented in Table 9 through Table 11. We can observe that GETER significantly outperforms existing graph-based in terms of prediction results. Furthermore, our approach provides human-readable inference processes, ensuring greater interpretability. In contrast, the intrinsic property of these graph-based methods is that they are **black-box models**, inherently lacking explainability and unable to generate explanation text. The detailed results of the prediction experiments are summarized in Table 20.

[1] https://github.com/microsoft/Megatron-DeepSpeed

Model	ICEWS14				GDELT			
	Positive	Negative	Neutral	Overall	Positive	Negative	Neutral	Overall
RE-GCN	52.76	55.00	75.38	59.97	57.62	59.39	84.18	66.22
CEN	61.25	53.01	76.24	62.79	60.29	61.42	86.93	68.71
CENT	55.03	60.82	78.27	63.60	61.34	62.71	87.98	69.84
SiMFy	53.40	63.03	78.92	63.90	**63.30**	60.91	88.23	70.06
GETER	**77.45**	**75.73**	**85.15**	**79.08**	61.29	**68.92**	**88.59**	**72.02**

Table 9: F1 scores (%) of different graph-based methods on ICEWS14 and GDELT datasets.

Model	ICEWS05-15				ICEWS18			
	Positive	Negative	Neutral	Overall	Positive	Negative	Neutral	Overall
REGCN	65.10	63.53	83.57	70.50	62.13	58.81	81.53	67.03
CENET	67.29	64.17	89.44	73.36	61.99	64.45	84.90	69.90
CEN	63.27	65.57	86.88	71.59	59.82	60.86	79.19	66.16
SiMFy	67.61	66.95	89.14	74.29	60.88	62.61	82.34	68.10
GETER	**78.94**	**76.48**	**90.38**	**81.80**	**75.61**	**75.94**	**87.51**	**79.40**

Table 10: F1 scores (%) of different graph-based methods on ICEWS05-15 and ICEWS18 datasets.

Model	WIKI			
	Positive	Negative	Neutral	Overall
REGCN	75.27	70.38	77.65	74.59
CENET	76.11	77.06	83.51	78.86
CEN	74.36	76.04	82.25	77.49
SiMFy	79.03	77.39	81.53	79.40
GETER	**99.28**	**94.49**	**96.19**	**96.81**

Table 11: F1 scores (%) of different graph-based methods on the WIKI dataset.

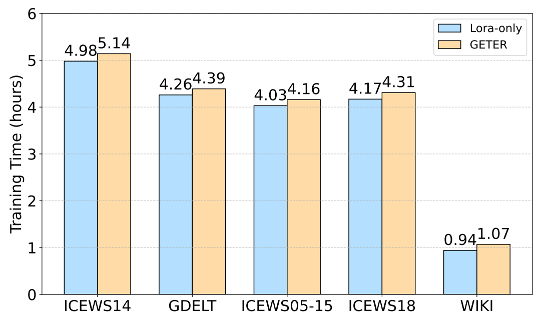

Figure 6: Comparison of training time between GETER and the LoRA fine-tuning method. The Y-axis represents the training time (hours).

C.2 Complexity Analysis of GETER

LLM applications often face challenges related to high computational costs due to the large number of model parameters. Specifically, for our method

GETER, during the training and inference stages, the complexity is $O(|L_1|^2 \cdot |L_2|)$ for the input-answer pair, where $|L_1|$ represents the length of the input text and $|L_2|$ represents the length of the answer. Considering the costs, we leverage Low-Rank Adaptation (LoRA) and DeepSpeed to accelerate both training and inference. Additionally, for a clearer comparison, we present the training time of GETER against LoRA fine-tuning methods across five datasets in Figure 6. The results demonstrate that incorporating graph tokens into LLM fine-tuning introduces minimal additional time costs compared to simple LoRA fine-tuning. Furthermore, given the significant performance improvements achieved by our method, as detailed in Section 5.2, we consider these additional costs to be negligible.

D Case Study

In this section, we present a case study to highlight the differences in responses among *Inference-only* method, *Tuned-only* method, and **GETER**. Specifically, we analyze the following positive query: *(Police (Australia), Engage in material cooperation, Citizen (Australia), 2014-11-16)*, where the expected label is *"Yes"*. As shown in Table 12, *Inference-only* method fail to capture the subtle cooperative signals embedded within the document (highlighted in orange), instead focusing primarily on dominant antagonistic actions, such as arrests and accusations, which result in incorrect negative predictions. While *Tuned-only* method can observe cooperative signals and demonstrate an improved ability to incorporate the temporal aspects of events, they struggle to fully model the interplay between cooperative and antagonistic actions (highlighted in blue), leading to comparable negative predictions. In contrast, **GETER** effectively captures the evolving patterns of event relationships and cooperative signals (highlighted in red). By leveraging explicit cues, such as requests and expressed intentions to cooperate, **GETER** not only predicts a positive outcome accurately but also provides the correct explanation.

E Full Experimental Results

The prediction results for the ICEWS18 and WIKI datasets are summarized in Table 13, while the explanation results are detailed in Table 14. Notably, **GETER** demonstrates consistent and significant improvements across most metrics on these two datasets, underscoring its robustness and superior performance in complex scenarios. Compared to *Tuned-only* methods, GETER combined with Mistral achieves overall F1 score improvements of 16.42% and 10.35% on the respective datasets. Additionally, the detailed prediction results for all five datasets are comprehensively summarized in Table 15 through Table 20.

Query: Police (Australia) will Engage in material cooperation Citizen (Australia) on 2014-11-16

Instruction: *Given the following document, is it plausible that Police (Australia) will Engage in material cooperation Citizen (Australia) on 2014-11-16? Please answer yes, no, or unsure then explain your decision.*

Input: *Police (Australia) Arrest, detain, or charge with legal action Citizen (Australia) 2014-11-12. Police (Australia) Arrest, detain, or charge with legal action Citizen (Australia) 2014-11-13. Police (Australia) Arrest, detain, or charge with legal action Citizen (Australia) 2014-11-14. Police (Australia) Accuse Citizen (Australia) 2014-11-02. Police (Australia) Accuse Citizen (Australia) 2014-11-09. Police (Australia) Accuse Citizen (Australia) 2014-11-10. Police (Australia) Make an appeal or request Citizen (Australia) 2014-11-12. Police (Australia) Make an appeal or request Citizen (Australia) 2014-11-13. Police (Australia) Make an appeal or request Citizen (Australia) 2014-11-14. Police (Australia) fight with small arms and light weapons Citizen (Australia) 2014-11-09. Police (Australia) fight with small arms and light weapons Citizen (Australia) 2014-11-12. Police (Australia) fight with small arms and light weapons Citizen (Australia) 2014-11-14. Police (Australia) Use conventional military force Citizen (Australia) 2014-10-22. Police (Australia) Use conventional military force Citizen (Australia) 2014-10-24. Police (Australia) Use conventional military force Citizen (Australia) 2014-11-10. Police (Australia) Investigate Citizen (Australia) 2014-11-03. Police (Australia) Investigate Citizen (Australia) 2014-11-04. Police (Australia) Investigate Citizen (Australia) 2014-11-09. Police (Australia) Express intent to meet or negotiate Citizen (Australia) 2014-10-24. Police (Australia) Express intent to meet or negotiate Citizen (Australia) 2014-11-11. Police (Australia) Express intent to meet or negotiate Citizen (Australia) 2014-11-14. Police (Australia) Criticize or denounce Citizen (Australia) 2014-10-28. Police (Australia) Criticize or denounce Citizen (Australia) 2014-11-03. Police (Australia) Confiscate property Citizen (Australia) 2014-10-30. Police (Australia) Investigate human rights abuses Citizen (Australia) 2014-10-30. Police (Australia) Appeal for intelligence Citizen (Australia) 2014-11-04. Police (Australia) Reject Citizen (Australia) 2014-11-07. Police (Australia) Abduct, hijack, or take hostage Citizen (Australia) 2014-11-09. Police (Australia) Physically assault Citizen (Australia) 2014-11-13. Police (Australia) Impose restrictions on political freedoms Citizen (Australia) 2014-11-14. Police (Australia) Return, release person(s) Citizen (Australia) 2014-11-14. Police (Australia) Arrest, detain, or charge with legal action Criminal (Australia) on 2014-10-23, Criminal (Australia) Engage in symbolic act Citizen (Australia) on 2014-11-03. Police (Australia) Arrest, detain, or charge with legal action Criminal (Australia) on 2014-10-23, Criminal (Australia) Sexually assault Citizen (Australia) on 2014-11-05. Police (Australia) Accuse Criminal (Australia) on 2014-10-22, Criminal (Australia) Engage in symbolic act Citizen (Australia) on 2014-11-03. Police (Australia) Accuse Criminal (Australia) on 2014-10-22, Criminal (Australia) Sexually assault Citizen (Australia) on 2014-11-05. Police (Australia) Demand Lawyer/Attorney (Australia) on 2014-10-31, Lawyer/Attorney (Australia) Arrest, detain, or charge with legal action Citizen (Australia) on 2014-11-03. Police (Australia) Demand Lawyer/Attorney (Australia) on 2014-10-31, Lawyer/Attorney (Australia) Accuse Citizen (Australia) on 2014-11-10. Police (Australia) Demand Lawyer/Attorney (Australia) on 2014-10-31, Lawyer/Attorney (Australia) Threaten Citizen (Australia) on 2014-11-05. Police (Australia) Confiscate property Criminal (Australia) on 2014-10-23, Criminal (Australia) Engage in symbolic act Citizen (Australia) on 2014-11-03. Police (Australia) Confiscate property Criminal (Australia) on 2014-10-23, Criminal (Australia) Sexually assault Citizen (Australia) on 2014-11-05.*

Label output: *Yes. Based on the information provided, it is plausible that the Police in Australia will engage in material cooperation with Australian citizens on November 16, 2014. This prediction is supported by a series of interactions between the police and citizens leading up to this date. The police have been actively involved in various legal actions, such as arresting, detaining, or charging citizens on multiple occasions from November 12 to November 14, 2014. Additionally, they have made appeals or requests to citizens during the same period, indicating a willingness to communicate and potentially collaborate. Despite instances of conflict, such as accusations, criticism, and even physical confrontations, there are also signs of negotiation and intent to meet, as evidenced by the police expressing their intent to negotiate on November 11 and November 14, 2014. Furthermore, the police have returned or released individuals on November 14, suggesting a move towards resolution and cooperation. These actions, combined with the broader context of police investigations and appeals for intelligence, suggest a complex relationship that could lead to material cooperation on November 16, 2014.*

Positive Query: Police (Australia) will Engage in material cooperation Citizen (Australia) on 2014-11-16 Model: Mistral		
Methods	**Labels**	**Output**
Inference-only	✗	Based on the provided document, it is not plausible that Police (Australia) will engage in material cooperation with the Citizen (Australia) on 2014-11-16. The document shows a series of actions by the Police (Australia) that are generally antagonistic towards the Citizen (Australia), including arrests, detentions, charges, accusations, confiscation of property, physical assault, and investigations into human rights abuses. These actions suggest a conflictual relationship rather than cooperation. Furthermore, there is no indication in the document of any intention by the Police (Australia) to engage in cooperation with the Citizen (Australia) on the specific date of 2014-11-16.
Tuned-only	✗	No. Based on the information provided, it is predicted that Police (Australia) will not engage in material cooperation with Citizen (Australia) on 2014-11-16. This prediction is supported by a series of events leading up to this date, which indicate a pattern of conflict and adversarial interactions between the police and citizens. In the days preceding 2014-11-16, the police have been involved in multiple actions against citizens, including arrests, detentions, and charges on 2014-11-12, 13, and 14. Additionally, there have been accusations against citizens on 2014-11-2, 9, and 10, as well as instances of police using force and military actions against citizens on various dates. The police have also been involved in investigations, criticisms, and confiscations, further indicating a tense relationship. Despite some expressions of intent to negotiate or meet, the overall pattern of behavior suggests a lack of cooperative engagement. Given this context of ongoing conflict and legal actions, it is reasonable to conclude that material cooperation between the police and citizens is unlikely to occur on 2014-11-16.
GETER (ours)	✓	Yes. Based on the sequence of events outlined in the document, it is plausible to predict that the Police in Australia will engage in material cooperation with Australian citizens on November 16, 2014. This prediction is supported by a series of interactions between the police and citizens leading up to this date. From November 12 to November 14, the police were actively arresting, detaining, or charging citizens with legal actions, indicating a period of heightened enforcement. **However, alongside these actions, the police also made several appeals and requests to citizens on the same dates, suggesting a willingness to engage in dialogue or seek assistance. Additionally, the police expressed an intent to meet or negotiate with citizens on multiple occasions, including November 11 and November 14, which implies a shift towards more collaborative engagement.** Despite the confrontational actions, such as the use of force and accusations, the police also demonstrated a capacity for reconciliation by returning or releasing individuals on November 14. This dual approach of enforcement and negotiation, combined with the police's expressed intent to meet and cooperate, supports the likelihood of material cooperation occurring on November 16, 2014.

Table 12: Case comparisons between **GETER** and other methods. While *Tuned-only* method demonstrate an improved ability to handle the temporal aspects of events (highlighted in blue), they still resulting in negative predictions. In contrast, **GETER** leverages temporal graph structures to model the evolving patterns of event relationships and effectively identifies cooperative signals (highlighted in red), enabling more accurate predictions.

Models	Datasets / Types	ICEWS18				WIKI			
		Positive	Negative	Neutral	Overall	Positive	Negative	Neutral	Overall
GPT-4o	zero-shot *w/o chains text*	51.64	36.61	24.79	38.32	69.5	53.45	17.77	47.45
	zero-shot	60.33	23.78	40.72	42.08	61.94	37.44	40.88	47.54
Llama3-8B-Instruct	zero-shot *w/o chains text*	7.68	24.39	38.95	22.93	48.31	54.39	66.46	52.44
	zero-shot	55.12	18.81	9.14	28.79	51.76	26.43	1.26	27.31
	LoRA *w/o chains text*	57.47	47.14	56.30	53.66	84.08	70.67	83.36	79.80
	LoRA	62.30	46.24	66.46	58.23	88.59	73.29	81.36	81.57
	GETER	**75.78**	**74.09**	**87.53**	**78.85**	**98.99**	**90.58**	**91.00**	**93.79**
	ΔImprove	21.64%	60.24%	31.70%	35.41%	11.74%	23.59%	11.85%	14.98%
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	30.94	40.53	25.13	32.34	43.51	53.31	7.72	34.54
	zero-shot	44.22	48.67	10.92	35.40	46.46	47.84	2.47	32.23
	LoRA *w/o chains text*	45.82	59.83	66.27	56.82	87.16	80.29	87.00	85.04
	LoRA	69.68	60.54	63.21	64.48	88.65	78.58	87.36	85.19
	GETER	**74.77**	**74.41**	**86.79**	**78.37**	**97.32**	**93.33**	**94.01**	**95.02**
	ΔImprove	7.31%	22.91%	37.28%	21.55%	9.78%	18.77%	7.61%	11.54%
Mistral-7B-Instruct	zero-shot *w/o chains text*	1.06	34.23	47.64	26.53	35.81	49.71	55.40	46.52
	zero-shot	4.14	33.06	41.58	25.37	62.98	44.44	41.89	50.37
	LoRA *w/o chains text*	58.07	55.27	74.46	62.21	84.94	77.82	83.08	82.18
	LoRA	64.22	64.63	76.63	68.20	89.29	86.61	87.04	87.73
	GETER	**75.61**	**75.94**	**87.51**	**79.40**	**99.28**	**94.49**	**96.19**	**96.81**
	ΔImprove	17.74%	17.50%	14.20%	16.42%	11.19%	9.10%	10.51%	10.35%

Table 13: F1 scores (%) of each model on the ICEWS18 and WIKI test instances. "Overall" represents the weighted average F1 score. *w/o chains text* refers to the absence of reasoning chain input for LLMs. The best-performing results are highlighted in **bold**. ΔImprove represents the relative improvements of **GETER** compared to **Tuned-only** methods.

Models	Types \ Datasets	ICEWS18				WIKI			
		BLEU-4	rougeL	METEOR	BertScore (F1)	BLEU-4	rougeL	METEOR	BertScore (F1)
GPT-4o	zero-shot *w/o chains text*	9.33	22.67	29.87	67.48	13.25	28.18	36.65	69.10
	zero-shot	14.84	31.16	37.47	72.98	25.98	41.77	45.52	78.69
Llama3-8B-Instruct	zero-shot *w/o chains text*	4.10	15.85	16.20	61.14	9.39	25.41	27.95	66.88
	zero-shot	10.01	29.52	27.19	70.01	14.67	36.67	33.43	75.85
	LoRA *w/o chains text*	23.55	35.95	42.54	78.02	48.99	63.53	63.08	87.13
	LoRA	37.33	49.18	53.05	83.58	52.09	65.27	66.67	87.99
	GETER	**40.39**	**52.12**	**54.85**	**84.60**	**55.52**	**68.06**	**69.16**	**88.77**
	ΔImprove	8.20%	5.98%	3.39%	1.22%	6.59%	4.28%	3.73%	0.89%
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	7.02	19.52	30.09	65.92	7.33	21.46	34.56	66.38
	zero-shot	10.46	27.97	26.80	71.77	20.21	36.19	41.52	77.61
	LoRA *w/o chains text*	25.50	37.61	42.91	78.56	51.84	65.09	65.59	87.79
	LoRA	37.49	49.61	52.07	83.60	53.57	67.19	67.23	88.59
	GETER	**38.99**	**50.70**	**53.79**	**84.17**	**55.0**	**67.49**	**70.00**	**88.99**
	ΔImprove	4.00%	2.20%	3.30%	0.68%	2.67%	0.45%	4.12%	0.45%
Mistral-7B-Instruct	zero-shot *w/o chains text*	7.60	19.43	23.98	65.87	11.41	26.23	31.64	67.79
	zero-shot	9.74	29.00	26.00	71.95	21.25	40.05	41.43	77.27
	LoRA *w/o chains text*	25.46	37.62	42.91	78.67	51.58	66.32	65.29	87.96
	LoRA	36.96	49.12	51.70	83.38	52.61	65.40	66.80	87.97
	GETER	**39.64**	**51.62**	**54.04**	**84.37**	**54.96**	**67.74**	**69.17**	**88.92**
	ΔImprove	7.25%	5.09%	4.53%	1.19%	4.47%	3.58%	3.55%	1.08%

Table 14: The semantic similarity performance (%) of each model on the ICEWS18 and WIKI test instances. *w/o chains text* refers to the absence of reasoning chain input for LLMs. The best-performing results are highlighted in **bold**.

Models	Types	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
GPT-4o	zero-shot *w/o chains text*	41.89	72.62	53.13	24.63	16.86	20.02	23.08	9.00	12.95	30.76	35.86	30.61
	zero-shot	58.53	61.75	60.10	33.05	5.57	9.54	37.08	70.33	48.56	43.91	45.48	39.95
Llama3-8B-Instruct	zero-shot *w/o chains text*	41.94	14.62	21.69	30.23	24.57	27.11	26.20	54.67	35.42	33.54	29.38	27.42
	zero-shot	40.59	93.00	56.51	21.17	6.71	10.20	44.44	3.33	6.20	38.62	35.22	26.70
	LoRA *w/o chains text*	54.16	73.25	62.27	35.28	38.86	36.98	82.59	34.00	48.17	55.99	50.57	49.81
	LoRA	66.08	75.25	70.37	56.75	59.43	58.06	78.73	59.83	67.99	66.59	65.57	65.59
	GETER	71.62	78.87	75.07	66.90	67.86	67.38	88.41	75.00	81.15	74.85	74.10	74.25
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	41.51	16.50	23.61	32.18	62.71	42.54	17.94	12.50	14.73	31.67	30.76	27.39
	zero-shot	55.79	50.62	53.08	34.79	65.00	45.32	57.58	6.33	11.41	49.30	42.76	38.59
	LoRA *w/o chains text*	66.85	59.25	62.82	51.23	68.43	58.59	83.33	63.33	71.97	66.35	63.48	64.03
	LoRA	74.32	74.88	74.60	61.58	70.29	65.64	83.64	69.00	75.62	72.73	71.67	71.90
	GETER	81.56	71.88	76.41	68.84	81.43	74.61	86.95	82.17	84.49	78.86	78.00	78.12
Mistral-7B-Instruct	zero-shot *w/o chains text*	68.18	1.87	3.65	38.38	40.57	39.44	33.63	75.00	46.44	48.38	35.67	27.81
	zero-shot	55.56	13.75	22.04	27.43	27.86	27.64	30.65	60.83	40.76	39.06	31.90	29.26
	LoRA *w/o chains text*	77.89	46.25	58.04	56.13	78.43	65.44	77.13	83.17	80.03	70.42	67.52	66.79
	LoRA	72.56	73.38	72.96	60.66	73.57	66.49	87.56	64.50	74.28	72.88	70.90	71.18
	GETER	83.62	72.12	77.45	69.23	83.57	75.73	87.79	82.67	85.15	80.02	78.95	79.08

Table 15: Precision (%), Recall (%), and F1 scores (%) for each model on the ICEWS14 dataset.

Models	Types	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
GPT-4o	zero-shot *w/o chains text*	44.70	12.12	19.08	32.97	65.14	43.78	27.82	23.54	25.50	35.78	32.84	29.06
	zero-shot	49.67	37.50	42.74	32.48	43.43	37.16	30.16	28.31	29.21	38.18	36.65	36.83
Llama3-8B-Instruct	zero-shot *w/o chains text*	38.10	1.00	1.95	31.80	34.57	33.13	29.09	61.23	39.44	33.32	30.14	23.44
	zero-shot	41.04	76.75	53.48	26.92	11.00	15.62	40.76	23.08	29.47	36.36	39.12	33.90
	LoRA *w/o chains text*	97.75	45.33	61.94	3.86	52.94	7.19	54.46	94.65	69.14	54.09	62.72	46.29
	LoRA	81.87	51.01	62.86	19.14	56.30	28.57	77.23	79.94	78.56	60.05	61.48	56.44
	GETER	75.49	53.50	62.62	59.10	82.14	68.74	91.64	86.00	88.73	75.03	72.65	72.51
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	34.18	6.75	11.27	32.27	73.86	44.92	26.41	15.85	19.81	31.21	31.35	24.81
	zero-shot	57.89	13.75	22.22	32.77	91.29	48.23	40.00	0.62	1.21	44.30	35.02	24.34
	LoRA *w/o chains text*	22.88	49.46	31.28	90.71	36.56	52.11	6.62	100.00	12.41	40.05	60.54	32.36
	LoRA	13.13	76.09	22.39	92.71	40.74	56.61	54.92	85.20	66.79	51.67	67.33	46.95
	GETER	75.64	55.13	63.77	61.40	81.57	70.06	89.32	87.54	88.42	75.14	73.53	73.27
Mistral-7B-Instruct	zero-shot *w/o chains text*	34.29	3.00	5.52	30.40	61.29	40.64	23.17	23.85	23.50	29.66	28.28	22.39
	zero-shot	44.44	0.50	0.99	34.34	19.57	24.93	29.68	79.54	43.23	36.69	30.60	21.55
	LoRA *w/o chains text*	11.00	83.81	19.45	97.71	41.40	58.16	57.38	94.91	71.52	53.26	73.36	47.80
	LoRA	64.88	56.78	60.56	55.29	54.89	55.09	73.85	90.40	81.29	64.47	66.33	65.05
	GETER	76.21	51.25	61.29	58.15	84.57	68.92	92.76	84.77	88.59	75.33	72.23	72.02

Table 16: Precision (%), Recall (%), and F1 scores (%) for each model on the GDELT dataset.

Models	Types	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
GPT-4o	zero-shot *w/o chains text*	46.72	68.19	55.45	25.52	27.21	26.33	25.70	11.06	15.47	32.99	36.36	33.03
	zero-shot	65.32	58.33	61.63	22.45	8.09	11.89	36.86	65.45	47.16	42.05	44.03	40.58
Llama3-8B-Instruct	zero-shot *w/o chains text*	42.98	6.81	11.75	31.60	26.76	28.98	29.20	60.61	39.41	34.81	30.63	26.30
	zero-shot	41.62	91.11	57.14	25.28	13.38	17.50	44.35	8.33	14.03	37.10	38.93	30.24
	LoRA *w/o chains text*	51.29	91.25	65.67	51.73	30.74	38.56	93.87	53.33	68.02	65.08	59.13	57.47
	LoRA	74.92	68.06	71.32	70.56	40.88	51.77	61.46	94.24	74.40	69.17	67.48	65.86
	GETER	73.37	84.58	78.58	83.84	69.41	75.95	91.00	91.97	91.48	82.48	81.94	81.84
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	46.63	24.03	31.71	30.80	54.85	39.45	18.83	13.64	15.82	32.50	30.87	29.17
	zero-shot	60.88	30.69	40.81	33.99	83.53	48.32	23.08	0.91	1.75	39.89	38.59	30.78
	LoRA *w/o chains text*	79.27	42.50	55.33	56.24	88.09	68.65	89.49	82.58	85.89	74.95	70.39	69.52
	LoRA	84.18	55.42	66.83	62.07	82.79	70.95	82.92	85.30	84.09	76.48	74.03	73.72
	GETER	71.68	86.11	78.23	84.36	64.26	72.95	88.77	91.06	89.90	81.34	80.49	80.23
Mistral-7B-Instruct	zero-shot *w/o chains text*	61.70	4.03	7.56	34.78	31.76	33.21	33.98	71.67	46.10	43.93	34.85	28.37
	zero-shot	59.52	10.42	17.73	35.97	25.44	29.80	36.13	79.55	49.69	44.25	37.52	31.96
	LoRA *w/o chains text*	66.30	75.97	70.81	77.39	26.18	39.12	62.79	95.61	75.80	68.84	65.83	61.95
	LoRA	77.44	68.19	72.53	68.77	75.44	71.95	82.94	85.45	84.18	76.34	76.12	76.07
	GETER	75.67	82.50	78.94	82.85	71.03	76.48	88.29	92.58	90.38	82.08	81.94	81.80

Table 17: Precision (%), Recall (%), and F1 scores (%) for each model on the ICEWS05-15 dataset.

Models	Types	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
GPT-4o	zero-shot *w/o chains text*	47.43	56.67	51.64	38.20	35.14	36.61	26.79	23.08	24.79	37.96	39.10	38.32
	zero-shot	53.09	69.87	60.33	34.51	18.14	23.78	38.12	43.69	40.72	42.26	44.52	42.08
Llama3-8B-Instruct	zero-shot *w/o chains text*	25.19	4.53	7.68	31.25	20.00	24.39	27.82	64.92	38.95	28.02	28.38	22.93
	zero-shot	39.37	91.87	55.12	33.09	13.14	18.81	45.83	5.08	9.14	39.28	38.76	28.79
	LoRA *w/o chains text*	57.20	57.73	57.47	39.31	58.86	47.14	90.17	40.92	56.30	61.44	52.90	53.66
	LoRA	75.14	53.20	62.30	49.43	43.43	46.24	55.87	82.00	66.46	60.61	58.86	58.23
	GETER	72.42	79.47	75.78	78.87	69.86	74.09	87.06	88.00	87.53	79.10	78.90	78.85
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	43.98	23.87	30.94	34.15	49.86	40.53	24.74	25.54	25.13	34.75	33.05	32.34
	zero-shot	58.01	35.73	44.22	35.55	77.14	48.67	35.29	6.46	10.92	43.49	40.48	35.40
	LoRA *w/o chains text*	72.00	33.60	45.82	45.02	89.14	59.83	92.31	51.69	66.27	69.29	57.71	56.82
	LoRA	69.50	69.87	69.68	52.46	71.57	60.54	84.14	50.62	63.21	64.63	68.35	64.48
	GETER	74.87	74.67	74.77	72.88	76.00	74.41	88.75	84.92	86.79	78.50	78.29	78.37
Mistral-7B-Instruct	zero-shot *w/o chains text*	57.14	0.53	1.06	35.71	32.86	34.23	34.51	76.92	47.64	42.99	34.95	26.53
	zero-shot	69.57	2.13	4.14	35.04	31.29	33.06	30.10	67.23	41.58	45.84	32.00	25.37
	LoRA *w/o chains text*	69.52	49.87	58.07	62.68	49.43	55.27	61.19	95.08	74.46	64.66	63.71	62.21
	LoRA	73.41	57.07	64.22	62.80	66.57	64.63	70.45	84.00	76.63	68.96	68.57	68.20
	GETER	75.36	75.87	75.61	73.98	78.00	75.94	90.61	84.62	87.51	79.62	79.29	79.40

Table 18: Precision (%), Recall (%), and F1 scores (%) for each model on the ICEWS18 dataset.

Models	Types	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
GPT-4o	zero-shot *w/o chains text*	66.93	72.33	69.53	40.85	77.27	53.45	93.94	9.81	17.77	68.07	53.00	47.45
	zero-shot	52.51	75.50	61.94	33.80	41.96	37.44	88.42	26.58	40.88	58.83	49.10	47.54
Llama3-8B-Instruct	zero-shot *w/o chains text*	68.98	37.18	48.31	51.74	57.34	54.39	47.19	66.46	66.46	56.53	53.00	52.44
	zero-shot	39.23	76.08	51.76	27.01	25.87	26.43	100.00	0.63	1.26	55.78	35.83	27.31
	LoRA *w/o chains text*	91.35	77.89	84.08	67.83	73.76	70.67	78.48	88.89	83.36	79.98	80.31	79.80
	LoRA	96.25	82.06	88.59	70.98	75.75	73.29	75.95	87.59	81.36	81.88	82.00	81.57
	GETER	99.13	98.85	98.99	85.89	95.80	90.58	96.13	86.39	91.00	94.14	93.78	93.79
Qwen2.5-7B-Instruct	zero-shot *w/o chains text*	52.44	37.18	43.51	37.83	90.21	53.31	61.90	4.11	7.72	51.19	42.15	34.54
	zero-shot	73.29	34.01	46.46	32.69	89.16	47.84	50.00	1.27	2.47	53.30	39.73	32.23
	LoRA *w/o chains text*	91.93	82.86	87.16	76.22	84.82	80.29	85.76	88.27	87.00	85.14	85.25	85.04
	LoRA	83.29	94.75	88.65	85.31	72.84	78.58	86.39	88.35	87.36	84.93	86.02	85.19
	GETER	95.30	99.42	97.32	96.28	90.56	93.33	93.71	94.30	94.01	95.07	95.05	95.02
Mistral-7B-Instruct	zero-shot *w/o chains text*	73.87	23.63	35.81	54.85	45.45	49.71	42.26	80.38	55.40	57.62	49.10	46.52
	zero-shot	75.20	54.18	62.98	38.95	51.75	44.44	41.69	42.09	41.89	53.12	49.42	50.37
	LoRA *w/o chains text*	86.17	83.75	84.94	72.38	84.15	77.82	87.03	79.48	83.08	82.30	82.45	82.18
	LoRA	93.66	85.30	89.29	82.52	91.12	86.61	86.08	88.03	87.04	87.78	87.96	87.73
	GETER	98.86	99.71	99.28	99.61	89.86	94.49	92.67	100.00	96.19	97.02	96.84	96.81

Table 19: Precision (%), Recall (%), and F1 scores (%) for each model on the WIKI dataset.

Datasets	Methods	Positive			Negative			Neutral			Overall		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
ICEWS14	REGCN	58.02	48.38	52.76	48.89	62.86	55.00	80.11	71.17	75.38	61.29	59.71	59.97
	CENET	70.51	45.12	55.03	53.03	71.29	60.82	75.43	81.33	78.27	66.09	64.19	63.60
	CEN	60.29	62.25	61.25	56.05	50.29	53.01	73.53	79.17	76.24	62.66	63.10	62.79
	SiMFy	68.84	43.63	53.40	53.43	76.86	63.03	79.86	78.00	78.92	66.85	64.52	63.90
	GETER	83.62	72.12	77.45	69.23	83.57	75.73	87.79	82.67	85.15	80.02	78.95	79.08
GDELT	REGCN	61.93	53.87	57.62	55.61	63.71	59.39	84.05	84.31	84.18	66.56	66.28	66.22
	CENET	65.58	57.63	61.34	59.39	66.43	62.71	87.05	88.92	87.98	70.05	69.95	69.84
	CEN	64.80	56.37	60.29	57.21	66.29	61.42	87.40	86.46	86.93	69.16	68.70	68.71
	SiMFy	63.11	63.50	63.30	60.39	61.43	60.91	89.42	87.08	88.23	70.18	69.95	70.06
	GETER	76.21	51.25	61.29	58.15	84.57	68.92	92.76	84.77	88.59	75.33	72.23	72.02
ICEWS05-15	REGCN	66.96	63.33	65.10	65.57	61.62	63.53	79.05	88.64	83.57	70.38	70.87	70.50
	CENET	65.27	69.44	67.29	65.30	63.09	64.17	91.05	87.88	89.44	73.54	73.25	73.36
	CEN	67.45	59.58	63.27	61.33	70.44	65.57	88.02	85.76	86.88	72.02	71.55	71.59
	SiMFy	69.03	66.25	67.61	65.45	68.53	66.95	89.35	88.94	89.14	74.36	74.27	74.29
	GETER	75.67	82.50	78.94	82.85	71.03	76.48	88.29	92.58	90.38	82.08	81.94	81.80
ICEWS18	REGCN	59.34	65.20	62.13	62.82	55.29	58.81	80.91	82.15	81.53	67.18	67.14	67.03
	CENET	65.38	58.93	61.99	62.58	66.43	64.45	82.97	86.92	84.90	69.89	70.10	69.90
	CEN	60.60	59.07	59.82	59.38	62.43	60.86	80.25	78.15	79.19	66.28	66.10	66.16
	SiMFy	64.71	57.47	60.88	61.29	64.00	62.61	79.23	85.69	82.34	68.07	68.38	68.10
	GETER	75.36	75.87	75.61	73.98	78.00	75.94	90.61	84.62	87.51	79.62	79.29	79.40
WIKI	REGCN	81.76	69.74	75.27	72.32	68.53	70.38	70.94	85.76	77.65	75.31	74.71	74.59
	CENET	77.95	74.35	76.11	77.19	76.92	77.06	81.38	85.76	83.51	78.86	78.93	78.86
	CEN	77.50	71.47	74.36	78.44	73.78	76.04	77.22	87.97	82.25	77.69	77.66	77.49
	SiMFy	78.25	79.83	79.03	82.03	73.43	77.39	78.76	84.49	81.53	79.56	79.45	79.40
	GETER	98.86	99.71	99.28	99.61	89.86	94.49	92.67	100.00	96.19	97.02	96.84	96.81

Table 20: Precision (%), Recall (%), and F1 scores (%) for each graph-based model across different datasets. "Overall" represents the weighted average F1 score.