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A Temporal Knowledge Graph Generation Dataset Supervised Distantly by Large Language Models

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Knowledge graphs can be constructed by extracting triples from documents, which denotes document-level relation extraction. Each triple illustrates a fact composed of two entities and a relation. However, temporal information corresponding to these facts is ignored. Incorporating temporal information exhibits the temporal connections between facts. Constructing a temporal knowledge graph (TKG) from documents is relatively unexplored. To address this limitation, we built a new dataset for this task based on a document-level relation extraction dataset. We mine the combination relation patterns and construct temporal quadruples by combining facts and timestamps. Additionally, two large language models (LLMs) are adopted to generate quadruples for the rest of the triples without timestamps. Multiple filters and manual annotation are used to ensure the quality of the data. To evaluate the dataset, we propose an LLM-based framework for extracting relations with temporal information from documents. The framework transforms relation extraction to a seq-to-seq task and fine-tunes LLMs to predict the relation with timestamps between entities. Experiments show the performance of LLMs on the proposed dataset.

Background & Summary

Document-level Relation Extraction (DocRE) is the task that focuses on extracting relations between entities in documents. As shown in Fig. 1, each triplet *(subject entity, relation, object entity)* represents a fact from the document. Knowledge triplets from documents can construct a Knowledge Graph (KG). Some relation extraction (RE) datasets are constructed by associating the KG with documents. For example, the NYT10[1] dataset is built by matching Freebase KG[2] to the New York Times corpus. DocRED[3] connected Wikidata KG[4] with Wikipedia articles based on distant supervision. Wiki20[5] is another RE dataset constructed by Wikidata and Wikipedia. The field of KGs is closely related to RE. The KG originating a document can present content more clearly and intuitively. Although the relation extraction (RE) process captures the facts themselves, it does not extract the associated temporal information of each fact. As a result, the temporal relationships linking these facts remain unobservable. Some TKGs have been applied, such as ICEWS[6] and GDELT[7]. Wikidata and YAGO[8] also include facts over time. However, how to automatically construct a TKG from document is not explored. If the timestamp for each knowledge triplet is used to construct a quadruple, the KG of the document will be transformed into a temporal knowledge graph.

TKG represents a significant and vibrant branch of KG, garnering considerable interest in recent years. By incorporating the dimension of time, TKGs offer a richer representation of the real world, enabling a more nuanced understanding of event occurrence. For example, two static knowledge triples <*Thomas Wolff, joined, UC Berkeley*> and <*Thomas Wolff, published, Seminal Paper*> can be extracted from the sentence "Thomas Wolff joined UC Berkeley in 1976 and published his seminal paper in 1984". The triplet without temporal information is not conducive to representing realistic facts. More dynamic facts are represented in the TKG as <*Thomas Wolff, joined, UC Berkeley, 1976*> and <*Thomas Wolff, published, Seminal Paper, 1984*>. Moreover, the dynamic nature of event expressions within TKG facilitates a comprehensive analysis of historical and prospective developments, providing a clearer and more logically coherent narrative of events over time. This

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Thomas Wolff

Thomas Wolff (*July 14, 1954*, *New York City* - *July 31, 2000*, *Kern County*) was a noted mathematician, working primarily in the fields of harmonic analysis, complex analysis, and partial differential equations. As an undergraduate at Harvard University he regularly played poker with his classmate Bill Gates. While a graduate student at *the University of California, Berkeley* from *1976* to *1979* …

DocRED

Subject: Thomas Wolff **Object:** July 14, 1954
Relation: date of birth

Subject: Thomas Wolff **Object:** New York City
Relation: place of birth

Subject: Niklas Bergqvist **Object:** UCB
Relation: educated at

Tem-DocRED

Subject: Thomas Wolff **Object:** New York City
Relation: born in **Time:** July 14, 1954

Subject: Thomas Wolff **Object:** UCB
Relation: educated at **Time:** 1976

Fig. 1 Comparison of samples between DocRED and Tem-DocRED. UCB denotes the University of California, Berkeley.

temporal dimension allows for the inference of relationships between facts based on their chronological order, enhancing the ability to reason about connections within the data. Given that relations extracted from documents are often incomplete, the expansion into the time domain provides additional context necessary for inferring missing links, thereby simplifying the task of relational reasoning. In conclusion, document-level temporal relation extraction (DocTRE) exploration is highly relevant and valuable as it leverages the temporal aspects of the data to enrich our understanding of the underlying relationships and patterns.

Numerous time expressions are referenced within existing datasets. However, most are treated as entities rather than as timestamps. There is a potential to relate some of these existing triplets to timestamps to construct temporal facts. Such annotations are often missing due to the traditional focus of relation extraction (RE) methodologies on static triplets. Treating time mentions as entities is not inherently incorrect for RE tasks; in fact, considering each time expression as a constituent element of a fact is more meaningful for organizing the progression of events. Unfortunately, this perspective has received scant attention from researchers in prior works. This new task presents significant challenges. The incorporation of timestamps transforms static knowledge triplets into quadruples, rendering traditional document-level relation extraction (DocRE) methods unsuitable for this endeavor. Previous methods usually view timestamp spans as entities to construct triplets, but the temporal dimension must be explicitly considered during the extraction of relationships between entities for constructing TKGs. Moreover, there is currently a lack of annotated datasets, as DocTRE is a nascent field. Different from DocRE, the task of DocTRE needs to extract relation between entities with its happening timestamp, such as extracting the relation "joined" with the timestamp "1976" between Thomas Wolff and UC Berkeley from *Thomas Wolff joined UC Berkeley in 1976*. Both the construction of such a dataset and the dataset itself are crucial for advancing research in this area. Besides, there is a lack of methods for the DocTRE task, and the concept of generating temporal knowledge graphs has not yet been proposed. Existing information extraction methods can only extract information from documents to construct static knowledge graphs, but cannot synchronously extract facts with temporal information to construct temporal knowledge graphs.

In the field of Relation Extraction (RE), the evolution of dataset construction methods reflects a continuous effort to balance scalability and quality. The dataset construction methods mainly can be divided into four categories: manual annotation, automatic annotation, PLM annotation, and LLM annotation. Early researches primarily relied on human-annotated datasets[9,10], which are suffered from limited coverage of relation types and instances due to prohibitive annotation costs. To address scalability challenges, distant supervision[11], and web crawling[12] emerged as the main automatic annotation methods, yet these methods inevitably introduced label noise. With advancements in text processing capabilities, document-level RE datasets like DocRED[3] were developed using distant supervision across multiple domains. However, DocRED's incomplete annotations and unresolved false negatives[13] revealed persistent quality limitations in purely automated approaches.

The advent of BERT[14] and subsequent pre-trained language models (PLMs)[15–17] enabled more context-aware data generation. Notably, hybrid human-AI collaboration frameworks[13,18,19] were proposed, where neural models filtered candidate relations for human verification, achieving improved precision at the expense of partial automation benefits. Recent breakthroughs in large language models (LLMs) have shifted the paradigm further, as demonstrated by DocGNRE[19] that leverages LLMs' zero-shot generation capability to synthesize relation instances. While manual post-screening remains necessary, this approach significantly enhances throughput compared to traditional methods.

A critical gap persists in existing RE datasets' underutilization of timestamps in documents. Even benchmark datasets like DocRED contain rich temporal metadata without annotations that could enhance dynamic relationship modeling. The original dataset only annotated entities as well as relationships in documents, and in order to build a temporal knowledge graph, the timestamp of occurrence needs to be annotated on the basis of the fact triplet constructed by relationships and entities.

By analyzing document content in the RE dataset, some existing timestamps can be assigned to triplets. For example, it is possible to infer certain temporal facts from static information. As illustrated in Fig. 1, a document excerpt from DocRED contains three static triplets: <*'Thomas Wolff', 'date of birth', 'July 14, 1954'*>, <*'Thomas Wolff', 'place of birth', 'New York City'*>, and <*'Thomas Wolff', 'educated at', 'the University of California, Berkeley'*>. From this information, we can deduce that *Thomas Wolff was born in New York City on July 14, 1954*. This fact can be represented as a temporal quadruple: <*'Thomas Wolff', 'born in', 'New York City', 'July 14, 1954'*>. The reasoning process here is straightforward, and similar patterns of temporal reasoning can be observed in other relations. However, not all temporal quadruples can be derived through this method; some require contextual reasoning. For instance, based on contextual information, the period during which *Thomas Wolff was educated at the University of California, Berkeley* can be inferred to be *1976*.

For the method of **combination relation patterns**, these patterns can be obtained by manual annotation. Given the limited number of relations involved, patterns can be deduced from a small set of relevant documents that embody common knowledge. But for the rest triplets which can't be transformed by relation patterns, the human annotation is difficult for so many documents. For the task of recognizing context to reason about such data, the Large Language Model (LLM) is a fitting choice. Each candidate quadruple can be translated into a natural language sentence, and LLMs are employed to evaluate the accuracy of these sentences. Human annotators are crucial for ensuring the quality of the data. Building on these two approaches, we introduce a new dataset called Tem-DocRED, designed for the emerging field of DocTRE. To address the false negative (FN) issue present in the original DocRE dataset, we utilize Re-DocRED[13] in constructing our dataset. Re-DocRED resolves the FN problem in DocRED, making it more comprehensive.

To evaluate the challenges posed by DocTRE, we introduce a novel framework that leverages LLMs to automatically generate temporal relation quadruples. This framework fine-tunes the LLM by constructing prompts designed to predict temporal relations between entities within documents. Additionally, a filtering mechanism is employed to eliminate errors and redundancies.

The main contributions of this paper can be summarized as follows.

- We propose a novel concept, named Document-level temporal relation extraction, extracting relation with temporal information between entities from documents, which is systematically proposed to break through the limitation that traditional information extraction ignores the time dimension. By associating timestamps with fact triples, a time-aware TKG element is established, which lays the foundation for reasoning based on event temporal relationships, is conducive to the construction and expansion of large-scale temporal knowledge graphs.
- We propose a novel DocTRE dataset construction method, which innovatively fuses event relations with temporal relations by potential relation patterns, and fills the gap of document-level temporal relation benchmark data by inferring the association between known tuples and temporal information from document semantics through LLMs. A new dataset, Tem-DocRED, is constructed on the basis of the Re-DocRED dataset for DocTRE.
- We propose a novel framework, which transforms DocTRE to a seq-to-seq generation task and fine-tunes LLMs to automatically generate quadruples for constructing TKG. The framework gives full play to the textual reasoning advantage of LLMs, inferring the temporal association between elements based on document content, and providing a new paradigm for the construction of TKGs.

Methods

In order to construct a DocTRE dataset, we propose a novel method for updating DocRE dataset to DocTRE dataset, which combine triplets to generate quadruples based on potential rules in the KG and constructs a modular LLM framework to reason the occurrence time of each fact without the potential rule. The process of data construction can be divided into two stages: constructing temporal quadruples based on discovered combination relation patterns and utilizing LLM to generate timestamps for the rest knowledge triples. In the first stage, the discovery of relation patterns is achieved by statistics and human annotation. Some fact pairs can be combined into a quadruple, such as *date of birth* and *place of birth*. The second stage is designed for these quadruples can't be obtained by combining existing triplets. The framework is shown in Fig. 2. In this stage, each candidate quadruple is transformed into a natural language sentence. The LLM plays a human role in understanding the document and judging the correctness of each candidate sentence. The correctness is represented by a score which is a numerical value from 0 to 1. Final results are filtered based on these scores.

Combination Relation Patterns. In the Re-DocRED, relations can be mainly divided into two categories: event relations and timestamp relations. The event relation expresses an event that occurred between two entities. The timestamp relation expresses that an event happened at a certain moment. In the statistical process, triplets are classified based on the types of entities included. For each timestamp relation, there may be one or more event

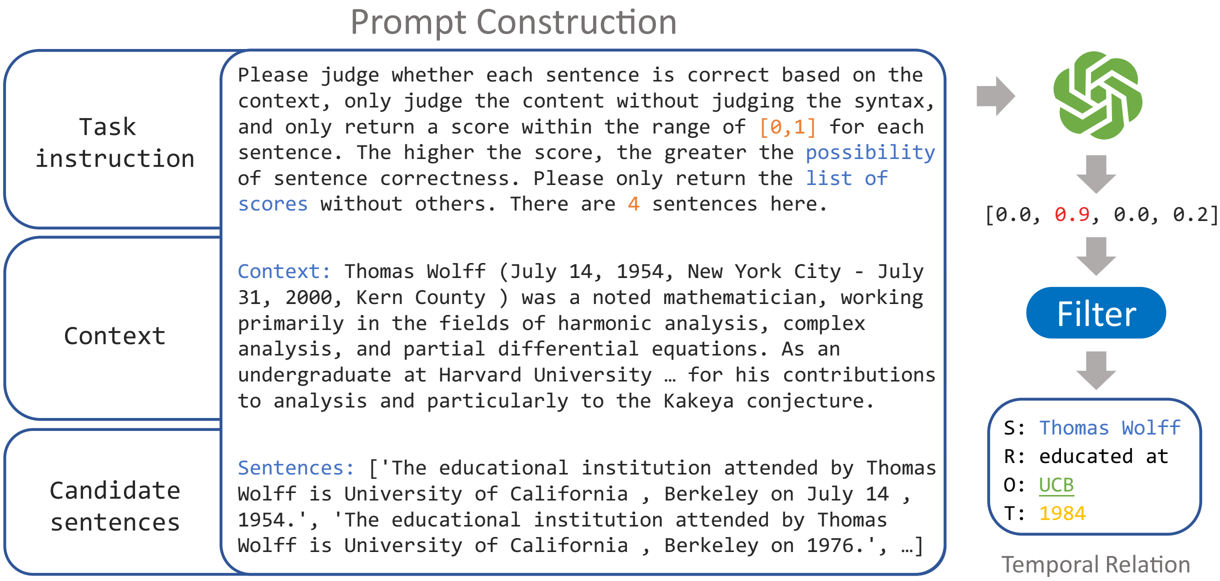


Fig. 2 The automatic data generation framework with an example document. UCB denotes to the University of California, Berkeley.

relations that can be combined with it. This combination pattern can be discovered based on the shared entity. In the Re-DocRED, the logic rule of relation patterns can be represented as follows:

$$(s,\ R_e,\ o) \wedge (s,\ R_t,\ t) \Rightarrow (s,\ R_{tem},\ o,\ t) \tag{1}$$

$$(s,\ R_e,\ o) \wedge (o,\ R_t,\ t) \Rightarrow (s,\ R_{tem},\ o,\ t) \tag{2}$$

where (s, R_e, o) and (s, R_t, t) are existed triplets in Re-DocRED, R_e represents the event relation, R_t represents the timestamp relation, and R_{tem} represents the temporal relation. s, o, and t are annotated as entities in Re-DocRED, but t denotes a timestamp like *July 9*.

In the Re-DocRED, we have found 31 combination relation patterns. On the basis of each pattern, two triplets with corresponding relations can be combined into a quadruple with the timestamp. For example, <*"Thomas Wolff", "born in", "New York City", "July 14,1954"*> can be constructed from <*"Thomas Wolff", "date of birth", "July 14,1954"*> and <*"Thomas Wolff", "place of birth", "New York City"*> based on the combination relation pattern "*place of birth* $\wedge$ *date of birth* $\Rightarrow$ *born in*". Details of all relation patterns can be found in Table 1. Hypotheses of relations from Re-DocRED are show in Table 2.

Generation by GPT. In this procedure, GPT-3.5 is selected as the generator to generate timestamps for existing triplets. As GPT is a widely adopted LLM, it possesses robust capabilities in text comprehension and content generation, making it well-suited for our task. Taking into account both economic expenditure and model capabilities, we have opted for GPT-3.5. Before utilizing GPT-3.5 to generate quadruples, triplets that have been transformed by combination relation patterns are no longer used. On the other hand, triplets with timestamp relations are not utilized because they have included temporal information.

Prompt Construction. As shown in Fig. 2, the prompt word template consists of three parts, i.e., task instruction, context, and candidate sentences. Each candidate sentence represents a quadruple and the task instruction is used to judge the correctness of quadruples based on the context. The task instruction directs the LLM to focus on content correctness while ignoring syntax errors. The LLM is asked to use a score within the range of [0,1] rather than "yes" or "no", which provides more flexible judgments of sentences. To avoid the model misinterpreting the correlation between score and correctness, correlation statements are added to ensure that scores and correctness are positively correlated. In the process of the test, we noticed that GPT sometimes incorrectly counts the number of sentences. So we add "There are *n* sentences here" at the end. The context denotes the context of the document without any changes. Each sentence is constructed by a triplet and a time mention. Here we adopt hypotheses proposed in DocGNRE[19], which transforms each relation as a natural language description. We use them to transform each triplet as a sentence, and add the timestamp at the tail of the sentence, such as "The educational institution attended by subject is object on timestamp". Because the same hypothesis is used for any triplet with the corresponding relation and timestamp, some grammar errors may exist in sentences. So we demand GPT to "only judge the content without judging the syntax" in the task instruction, the syntax error may result in a score of 0. Each triplet can be combined with any timestamp to construct quadruples, but at most one quadruple is correct. So each prompt only includes the sentence list about one triplet, which is convenient for us to find the possible answer based on the maximum score.

ID I	Original Relation I	ID II	Original Relation II	Temporal Relation
P17	country	P571	inception	established in
P17	country	P577	publication date	published in
P17	country	P585	point in time	hold in
P19	place of birth	P569	date of birth	born in
P20	place of death	P570	date of death	died in
P50	author	P577	publication date	created by
P57	director	P577	publication date	directed
P112	founded by	P571	inception	founded by
P123	publisher	P571	inception	published by
P127	owned by	P576	dissolved, abolished or demolished	abolished by
P131	located in the administrative territorial entity	P576	dissolved, abolished or demolished	abolished by
P131	located in the administrative territorial entity	P571	inception	established in the administrative territorial entity
P161	cast member	P577	publication date	performed by
P162	producer	P577	publication date	produced by
P175	performer	P577	publication date	performed by
P178	developer	P577	publication date	developed by
P264	record label	P577	publication date	published by
P276	location	P580	start time	hold in
P276	location	P585	point in time	hold in
P400	platform	P577	publication date	released for
P495	country of origin	P577	publication date	published in
P607	conflict	P580	start time	had a conflict with
P674	characters	P577	publication date	character of
P710	participant	P580	start time	participated by
P710	participant	P585	point in time	participated by
P1001	applies to jurisdiction	P577	publication date	applied to jurisdiction
P1001	applies to jurisdiction	P585	point in time	applied to jurisdiction
P1344	participant of	P580	start time	participated
P1344	participant of	P585	point in time	participated
P1366	replaced by	P576	dissolved, abolished or demolished	replaced by
P1441	present in work	P577	publication date	presented in work

Table 1. Combinations of original relations for new relations, including wikidata IDs and relation names.

Filter. For each group of sentences, the sentence with the maximum score may be the correct answer. However, the judgment of the large model may not necessarily be correct, even if the score is high. To ensure the reliability of data as much as possible, the restrictions on scores are as follows:

Although there are some strict conditions to increase the reliability of dataset, the results from GPT-3.5 may not be accurate. In order to improve the quality of the dataset, we adopt another LLM to oversight the results of GPT-3.5. Specifically, we utilize GLM-4 to generate data following the same generation pipeline. The difference is that the threshold of the score is set as 0.9, the results from GLM-4 are subject to more rigorous screening. Then we take the intersection of the results from GPT-3.5 and GLM-4 as final results, which further improved the reliability of the dataset.

However, there may still be errors in the results from generation from LLMs, and patterns sometimes are not suitable for some triples. Human annotation is utilized to eliminate errors in the test set. Two annotators are asked to judge the correctness of each quadruple based on the document and the original triplets from Re-DocRED. If they have different judgments, the quadruple will be judged by the third annotator. The final result shall be subject to the judgment of the third annotator.

- The maximum score of sentence must be not less than 0.8 (we discovered that GPT-generated judgments maintain a high level of quality when the score is 0.8 or higher, striking a balance between accuracy and the volume of results).
- The list sentences is invalid when there are multiple maximum scores.
- If the number of scores is not equal to the number of sentences, scores will be not adopted.

In addition, we redefined all relations of Re-DocRED as shown in Table 3 on the basis of original relation descriptions. Each relation name is modified with its description to represent the occurrence of an event and relations that can't be transformed are removed, such as *mother*, *subsidiary*, and so on. The statistics of the new dataset, Tem-DocRED, are shown in Table 4. Additionally, the statistics of Re-DocRED are also shown in Table 4. Compared to Re-DocRED, there are fewer facts in these documents. More downstream tasks about TKG

ID	Hypothesis
P17	The sovereign state of this item sub. is obj.
P19	The birth location of the person, animal or fictional character sub. is obj.
P20	The death location of the person, animal or fictional character sub. is obj.
P50	The main creator(s) of the written work sub. is(are) obj.
P57	The director of this film, TV-series, stageplay or video game is obj.
P112	The founder or co-founder of this organization, religion or place sub. is obj.
P123	The organization or person responsible for publishing books, periodicals, games or software sub. is obj.
P127	The owner of sub. is obj.
P131	sub. is located on the territory of the following administrative entity obj.
P161	The actor performing live sub. for a camera or audience has obj.
P162	The producer(s) of this film or music work sub. is(are) obj.
P175	The performer involved in the performance or the recoding of the work sub. is obj.
P178	The organization or person that developed sub. is obj.
P264	The brand and trademark associated with the marketing of subject music recordings and music videos sub. is obj.
P276	The location of the item, physical object or event sub. is within is obj.
P400	The platform for which the work sub. has been developed or released / specific platform version fo the software sub. developed is obj.
P495	The country of origin of the creative work sub. is obj.
P569	The date on which sub. was born is obj.
P570	The date on which sub. died is obj.
P571	The date or point in time when the organization/subject sub. was founded/created is obj.
P576	The date or point in time on which the organization sub. was dissolved/disappeared or the building sub. demolished is obj.
P577	The data or point in time the work sub. is first published or released is obj.
P580	The time the item sub. begins to exist or the statement sub. starts being valid is obj.
P585	The time and date sub. took place, existed or the statement sub. was true is obj.
P607	The battles, wars or other military engagements in which the person or item sub. participated is obj.
P674	The characters which appear in sub. has obj.
P710	The person, group of people or organization that actively takes/took part in the event sub. has obj.
P1001	The institution, law or public office sub. belongs to or has power over or applies to the country, state or municipality obj.
P1344	The event that the person or the organization sub. was a participant in is obj.
P1366	The person or item obj. replaces sub.
P1441	The work in which the fictional entity or historical person sub. is present is obj.

Table 2. The hypotheses of relations in the Re-DocRED, which are used for constructing new temporal relations in Table 1.

can be researched on the basis of the proposed concept and dataset of DocTRE, such as TKG reasoning, and TKG question answering.

Data Records

The Tem-DocRED dataset is available on Zenodo[20] in a zip file according to the data specifications. In total, the file occupies 2.86 MB of disk space. The Tem-DocRED dataset is organized into a directory, which contains four JSON files. Files named *train.json*, *val.json*, and *test.json* denote the training, validation, and test sets of the dataset, respectively. Each part is constructed on the basis of the Re-DocRED dataset. The *rel_info.json* file denotes the meanings represented by all relationship codes.

Each part of the data in the JSON file is represented as a list. As shown in Fig. 3, each listed unit is a dictionary (dict), annotating entities and temporal relations in the sentences. Each dictionary consists of four parts: *title*, *vertexSet*, *labels*, and *sents*. The *title* denotes the title of the annotated paragraph. The *sents* denotes the sentences of the paragraph, and each sentence is represented as a list of words. The *vertexSet* denotes entities annotated in these sentences, and annotations referring to the same entity will be grouped into a list. Each annotation is also a dictionary, where *name* denotes the mention of the entity, *pos* denotes the start and end positions of the mention, *sent_id* denotes the serial number of the sentence containing the mention, *type* denotes the entity type of the mention, *global_pos* denotes the serial number of the mention among all mentions, and *index* denotes the combination of the entity number to which it belongs and the serial number of the mention group. The *labels* is a list of annotated temporal relations. In each unit of the list, *h* denotes the serial number of the head entity, *r* denotes the code of the relation, *t* denotes the serial number of the tail entity, and *time* denotes the serial number of the timestamp entity.

The file *rel_info.json* is a dict where the key represents the relationship code, and the value indicates the meaning of the relationship. The distribution of different relationship types across the facts is illustrated in Fig. 4a. The Tem-DocRED dataset contains 33 distinct relationship types. Among them, the "established in the administrative territorial entity" relationship has the highest frequency, followed by the "joined" relationship,

ID	Original Relation	Temporal Relation
P39	position held	position held
P54	member of sports team	participated by
P58	screenwriter	written by
P69	educated at	educated at
P86	composer	composed by
P108	employer	worked for
P118	league	participated
P166	award received	award received
P170	creator	created by
P176	manufacturer	manufactured by
P272	production company	produced by
P361	part of	joined
P463	member of	joined
P527	has part	joined by
P676	lyrics by	written by
P740	location of formation	formed in
P807	separated from	separated from
P937	work location	worked in
P1056	product or material produced	produced
P1365	replaces	replaced

Table 3. Redefined relations for relations in Re-DocRED, including Wikidata IDs and relation names.

	Re-DocRED			Tem-DocRED		
Dataset	**Train**	**Dev**	**Test**	**Train**	**Dev**	**Test**
# Documents	3,053	500	500	2,124	371	348
# Entities	59,359	9,684	9,779	43,095	7,606	7,151
# Triples	85,932	17,284	17,448	10,908	2,308	2,483
# Sentences	24,256	4,110	3,966	16,984	3,046	2,771
Avg. # Entities	19.4	19.4	19.6	20.2	20.5	20.5
Avg. # Facts	28.1	34.6	34.9	5.1	6.2	7.1
Avg. # Sentences	7.9	8.2	7.9	8.0	8.2	8.0

Table 4. Comparison of relation statistics between Re-DocRED and Tem-DocRED. Avg denotes the number of elements averaged to each document.

which appears 2,572 times. Other relationship types, such as "born in", "died in", "directed", "produced", and "replaced" are encountered with medium frequency. The quantity of facts with "produced" and "separated from" is very few, so corresponding facts are more difficult to extract. The meaning of each relation is shown in Table 2.

The distribution of different entity types is shown in Fig. 4b. The dataset contains six entity types, abbreviated as follows: Person (PER), Time (TIME), Location (LOC), Number (NUM), Miscellaneous (MISC), and Organization (ORG). The LOC entity type has the highest count, with 14,485 occurrences, while the TIME entity type has a significant count of 12,564. The TIME entity is the necessary part of each quadruple, including timestamps with different granularities. The PER, LOC, and ORG entities are common, such as *David Low Hackett*, *United States*, and *League of Nations* in the dataset. The MISC includes many different classifications, such as movies, lyrics, and games. We have used previous entity annotations in the Re-DocRED, some entities that look like numbers are labeled as NUM, such as *8-bit*, which factually represents the 8-bit gaming platform. So there is a quadruple *<Robin Hood:Legend Quest, released for, 8-bit, 1992>*, which represents that the game Robin Hood:Legend Quest is released for 8-bit gaming platforms in 1992. Moreover, we remain all original entities in the Re-DocRED dataset, which means that not each entity will be a part of a quadruple.

Technical Validation

For the TKG generation, there are no existing methods for this task. So we construct a novel LLM framework for training and evaluating. In experiments, we have adopted the current mainstream LLMs and trained them with LoRA[21] for fine-tuning.

LLM Framework. Different from data construction, the task of TKG generation aims to extract relations from entities and timestamps based on the context rather than determining the correctness of quadruples. Therefore, we propose a novel LLM framework by adjusting the prompt and designing external modules. The adjusted prompt is shown in Fig. 5. The new prompt consists of a generation demand, a list of entities, a list of

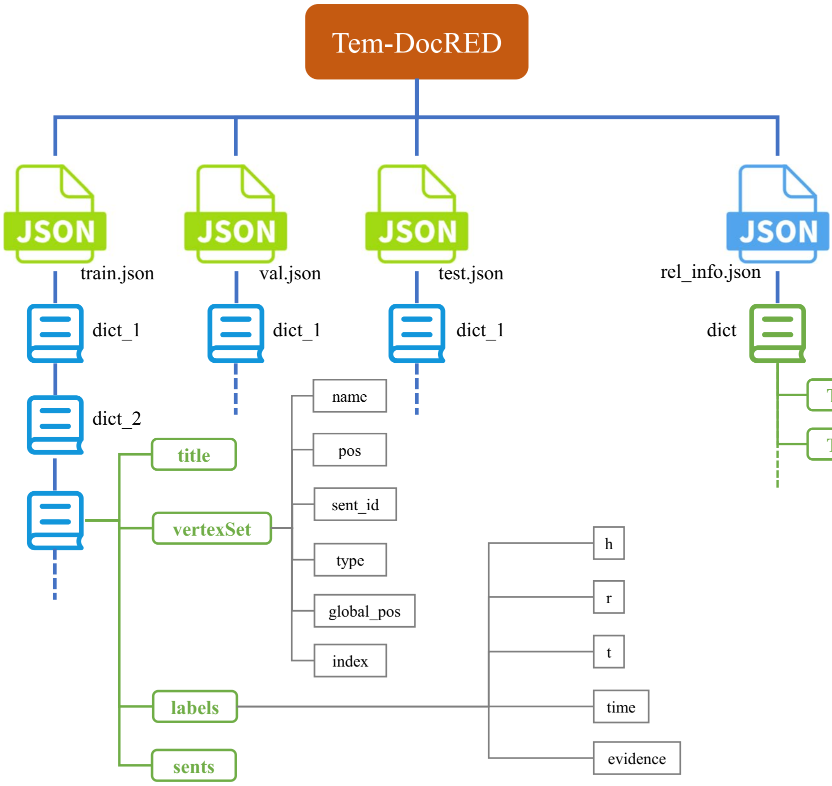


Fig. 3 Organization of the Tem-DocRED Dataset File Directory.

relations, a list of timestamps and some examples. The LLM is requested to pick up two entities, a relation and a timestamp from corresponding lists for each to construct a fact in the form of <*subject entity, relation, object entity, timestamp*>. For most LLMs, the generated content becomes longer, and the accuracy decreases. To minimize the impact as much as possible, we set "at least 5 triplets" (we set this value based on the average number of facts in the training set.) in the initial prompt. To standardize the output of LLMs and ensure that the results can be parsed, we have specified the output format and provided some unstructured quadruple examples. At the same time, we have also given the meaning of the quadruple expressions for the LLM to understand.

To achieve temporal relation extraction under the low-resource condition, LoRA is utilized to fine-tune the LLM. LoRA reduces the number of training parameters by introducing low-rank matrices into the model's weight matrices, which accelerates training speed and decreases resource consumption. At the same time, fine-tuning based on LoRA can enable closed-source large models to achieve better performance on this task. The temporal relation extraction task is transformed into a sequence-to-sequence task. All quadruples are constructed in a long sequence in the form of "<subject entity-1, relation-1, object entity-1, timestamp-1>, …, <subject entity-n, relation-n, object entity-n, timestamp-n>" for the LLM. The results are constructed quadruples by split and regular expressions.

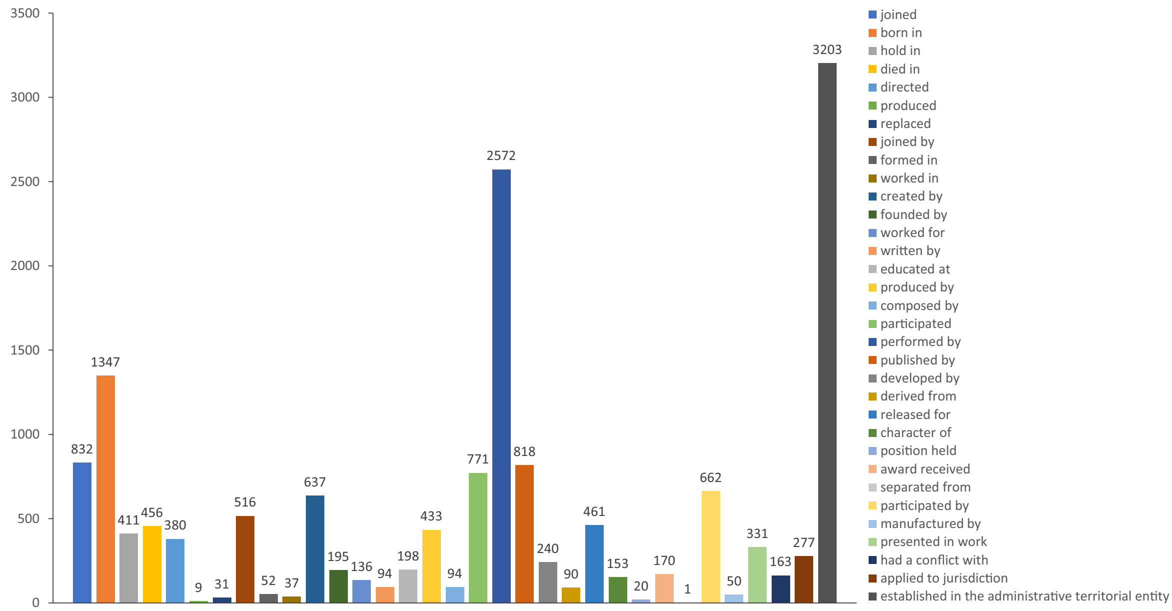
Although the LLM is instructed to utilize entities, relations, and timestamps from the provided lists, it occasionally generates quadruples containing elements not present in that list. Therefore, a filtering mechanism is applied to remove all quadruples that include nonexistent elements. Additionally, the filter discards any repeated or incomplete quadruples found in the output, ensuring the final set is both accurate and comprehensive.

Settings of Training. In the training process, we adopt LLaMA-Factory[22] to fine-tune LLMs. LLaMA-Factory is a unified framework for efficiently training LLMs, which adopts most mainstream LLMs and provides rich optimization methods. All LLMs are trained with the same setting in LLaMA-Factory, and more details are shown in our code.

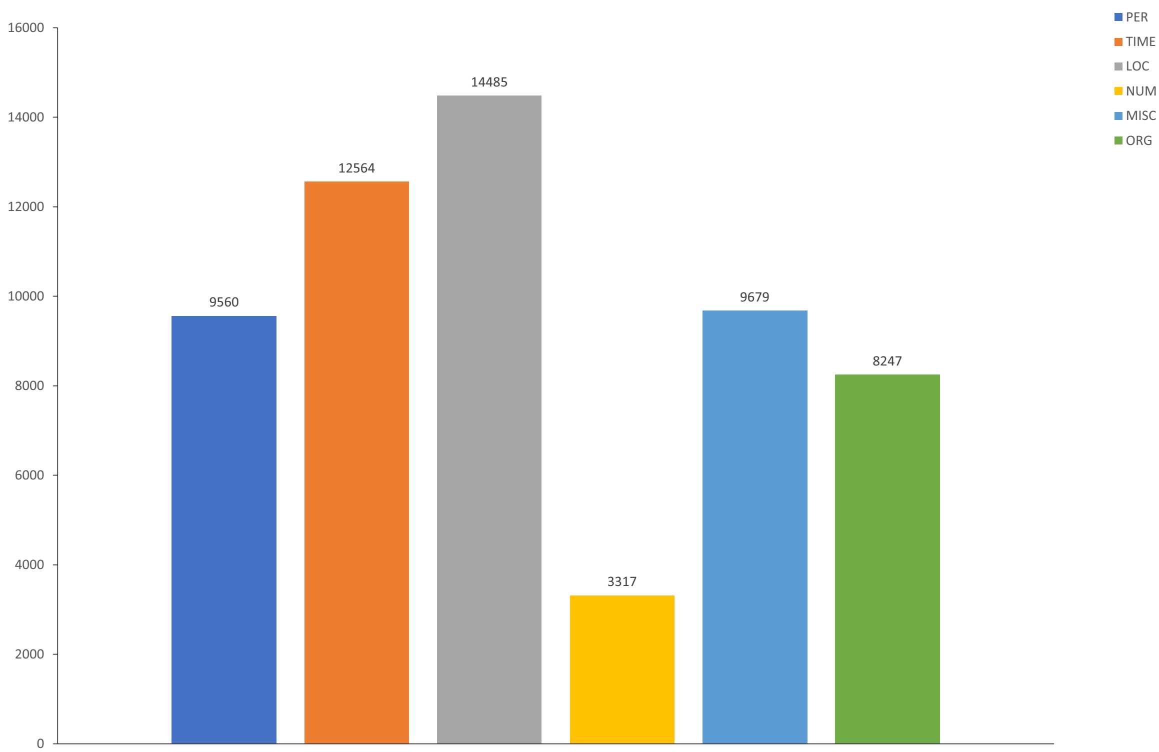
Although ChatGPT and other closed-source LLMs have strong power for generation tasks, they aren't convenient for fine-tuning and arranging locally. So we fine-tune the generation task on some mainstream open-source LLMs, including Baichuan[23], ChatGLM[24], Gemma[25], Llama[26,27], Qwen[28] and Yi[29]. All LLMs are base models and fine-tuned on a single RTX3090 24G.

Following previous works of DocRE[30,31], we employ precision, recall, F1, and Ign F1 to evaluate each model on Tem-DocRED. Ign F1 represents the F1 score excluding the relational facts shared by training and test sets.

LLM Comparison on Tem-DocRED. Results of TRE are shown in Table 5. All LLMs perform poorly on the Tem-DocRED. The main reason is the hallucination of LLMs. They often generate facts like <*'Rihanna', 'born in', 'Barbados', '2010'*>, which looks correct without considering the document. But the timestamp is completely unrelated to the fact. LLMs can't exactly capture the occurrence time of each fact. Another issue is that LLMs



(a)



(b)

Fig. 4 Statistics of entities and relations in the Tem-DocRED, where **(a)** shows the number of facts containing different relationship types, and **(b)** shows the number of entities of different types.

sometimes generate completely wrong answers. Although we have defined the form of the answer, they also generate wrong content, such as repeated relations or some unrelated phrases. They also generate incomplete facts of missing symbols or missing some content, such as <*'Rihanna', 'born in', 'Barba'*> or <*'Rihanna', 'born in', 'Barbados', '2010'*>. Symbol issues usually can be dealt with by rules, but missing content issues can't.

Among all LLMs, GLM-4 and Llama-3 outperform other LLMs. These models are specifically optimized for handling longer texts, thereby exhibiting superior comprehension abilities when processing documents. Within the same model families, those with more parameters tend to perform better, as evidenced by the performance of Yi-1.5-6B and Yi-1.5-9B. For each model, the difference between F1 and Ign F1 is relatively minor or non-existent.

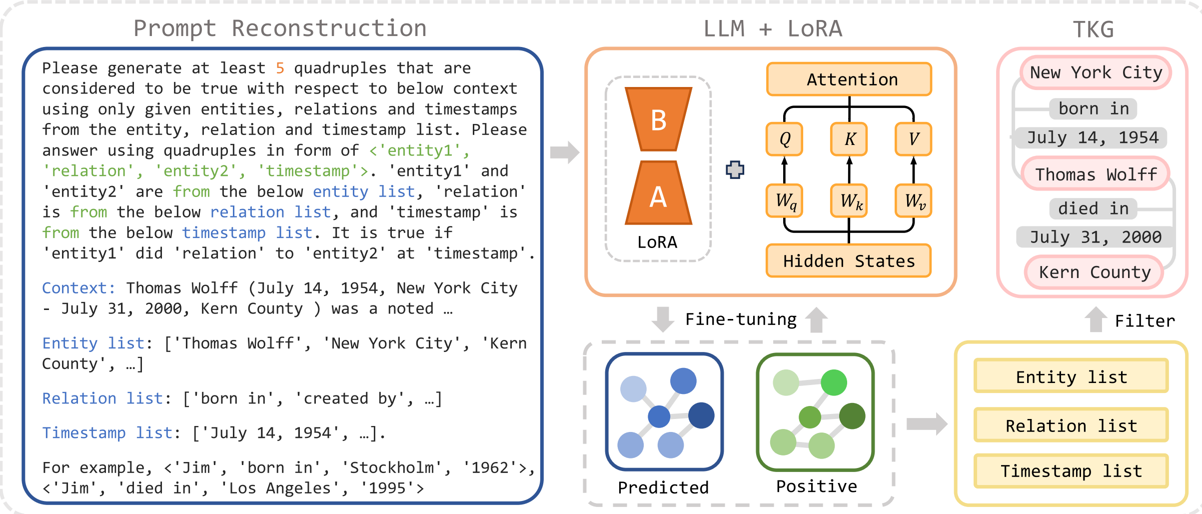


Fig. 5 The LLM framework for DocTRE includes fine-tuning an LLM with prompts via LoRA. Generated results are filtered to remove irrelevant quadruples, and the remaining quadruples are used to construct the TKG.

Model	With filtering				NF
	Pre	Rec	F1	Ign F1	F1
Baichuan-7B	12.84	20.02	15.65	15.65	12.72
Baichuan-2-7B	16.65	16.63	16.64	16.64	12.94
ChatGLM-3-6B	15.75	18.97	17.21	17.21	14.04
Gemma-7B	20.87	20.38	20.62	20.62	17.66
GLM-4-9B	24.99	28.63	26.69	26.69	23.21
Llama-2-7B	18.93	26.46	22.07	22.07	18.07
Llama-3-8B	**28.19**	28.55	**28.37**	**28.37**	**24.17**
Qwen-1.5-7B	11.63	12.93	12.24	12.24	10.16
Qwen-2-7B	22.53	26.82	24.49	24.45	20.79
Yi-1.5-6B	15.35	27.63	19.74	19.74	16.89
Yi-1.5-9B	16.27	**29.20**	20.89	20.86	17.91

Table 5. Experimental results of LLMs for DocTRE on Tem-DocRED. NF denotes the results without filtering.

This is because there are few overlapping facts between the training and test sets, the introduction of timestamps makes the intersection smaller compared to Re-DocRED. The results obtained without a filter are generally lower. On the contrary, filters effectively reduce incorrect predictions, thus improving precision without affecting recall. Consequently, this leads to an overall improvement in the F1 score. While a filter can mitigate some formatting errors, addressing hallucinations remains a significant challenge due to their inherent complexity.

To further explore the performance of LLMs on the facts with different relations, the top six relationships of facts in terms of quantitative ranking of the training set are picked for comparing the performance of different LLMs. As shown in Fig. 6, three LLMs, Llama-3-8B, GLM-4-9B, and Qwen-2-7B, are compared on these facts. As shown in Fig. 6, the number of facts with the relation *established in the administrative territorial entity* is the highest in the training set, but each LLM doesn't obtain the best performance on these facts. More relevant facts do not lead to a better extraction ability of the model for the corresponding relations. Performances of different LLMs on facts with other relations also confirm the irrelevance between the amount of training corpus and the training effect. In addition to the number of training corpus, the context of the document is also an important factor. The length and the complexity of the context are also influencing the recall of prediction results. In these facts, all models perform best in the terms of facts with the relation *born in*, and perform worst in terms of facts with the relation *joined*. The semantic structure of the related texts of *born in* is usually simple, and entities and the timestamp usually appear in the same sentence. The facts with the relation *participated* or *joined* are difficultly to predict, because the relevant contexts of them span a much wider range. Compared to *born in*, the word representing these relations are more complex and various, so it is more difficultly to understand. Although Llama-3, GLM-4, and Qwen-2 are multilingual LLMs, they focus on datasets with different languages. Llama-3 mainly adopts English datasets to train, but GLM-4 and Qwen-2 pay more attention to Chinese tasks. So Llama-3 performs a little better than the others in this English dataset. Another factor is the parameter scales of LLMs, so GLM-4-9B outperforms Qwen-2-7B.

LLM Comparison on TKG Generation. To achieve the full process of generating TKG, we adopt TAG[31] to extract mentions and resolve conferences, grouping these mentions into clusters. Since TAG does not provide

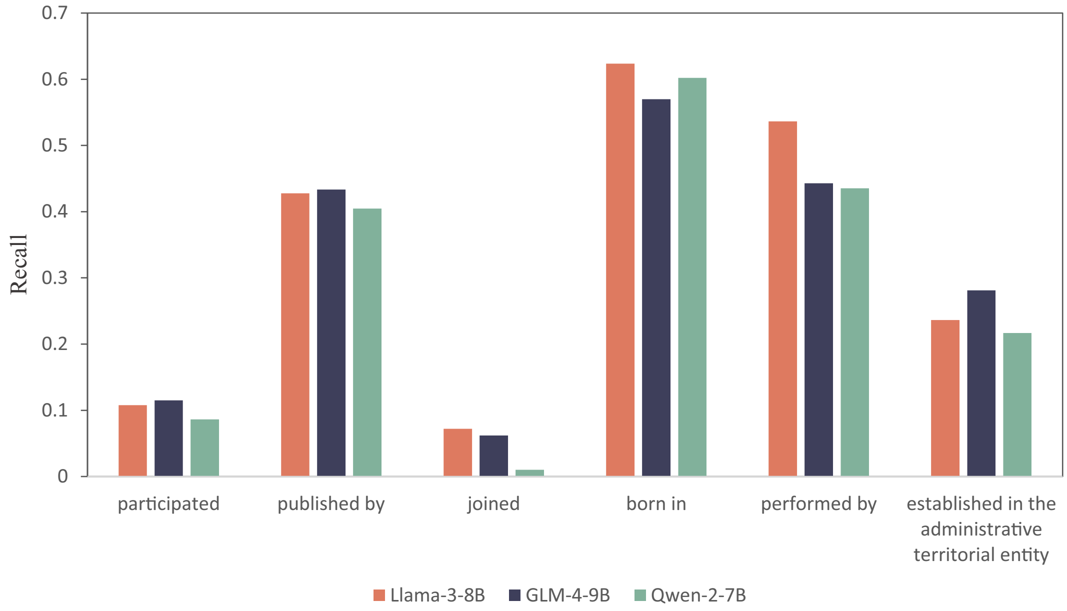


Fig. 6 The performance of several LLMs on the top six facts with different relations in terms of quantitative ranking. The quantity of relevant facts increases from left to right. Recall indicates the proportion of relevant facts in the test set that are predicted correctly.

	With filtering				NF
Model	**Pre**	**Rec**	**F1**	**Ign F1**	**F1**
Baichuan-2-7B	14.89	11.20	12.78	12.78	9.23
Gemma-7B	16.41	12.48	14.18	14.18	11.29
GLM-4-9B	23.30	**22.51**	**22.90**	**22.86**	**18.28**
Llama-3-8B	**25.57**	19.49	22.12	22.12	16.76
Qwen-2-7B	18.48	19.33	18.90	18.90	14.77
Yi-1.5-6B	14.17	20.70	16.82	16.79	12.86

Table 6. Experimental results of LLMs without entity annotations for DocTRE on Tem-DocRED.

the cluster classification method, we utilize regular expressions to recognize timestamps within clusters. Entities and timestamps are used to construct prompts. The results obtained on the test set, using extracted entities and timestamps, are presented in Table 6. Compared to the results derived from annotated entities, all metrics decline. This decline is primarily attributed to the fact that some mentions are not extracted during the mention extraction phase. If no any mention associated with an entity is extracted, the relations about that entity cannot be predicted. Furthermore, to strictly assess the impact of coreference resolution on the results, when mentions referring to the same entity are incorrectly split into multiple groups, only the first group of mentions pointing to the same entity is considered valid, even though quadruples containing mentions from other groups would be semantically correct. GLM-4 outperforms other models in this setting, demonstrating its superior robustness for entities.

To evaluate the effectiveness of the training and to assess the zero-sample inference ability of the model, LLMs without fine-tuning are utilized to reason about the underlying facts in the document. As shown in Table 7, parameters of most LLMs without fine-tuning result to all wrong answers, so all metrics of them are zero. GLM-4-9B and Llama-3-8B outperform other models again in this task, and pre-training makes an important contribution. Although they obtain better precision, the recall of them is also terrible. GLM-4 uses hybrid autoregressive training, so it performs relatively well. However, in general, the zero-sample performance of these models with fewer parameters is worrisome.

Pros & Cons. The proposed framework is based on LLM to achieve the automatic temporal relation extraction, so it inherits the advantages of LLMs. Firstly, the framework leverages LLMs' understanding and generative capabilities to handle complex temporal reasoning and infer implicit timestamps from context, outperforming rule-based or pattern-matching methods. Secondly, the pre-trained LLM can ensure that it is suitable for various fields, and address different temporal relation extraction issues with fine-tuning and ruled filters. Finally, the framework adopts the modular design, so the LLM, fine-tuning method, and post processing can be updated and replaced. In the future, the LLM or other modules can be replaced by a more effective method to improve the performance of the system.

Model	With filtering				NF
	Pre	Rec	F1	Ign F1	F1
Baichuan-2-7B	0.00	0.00	0.00	0.00	0.00
Gemma-7B	0.00	0.00	0.00	0.00	0.00
GLM-4-9B	22.22	0.24	0.48	0.48	0.42
Llama-3-8B	2.71	0.24	0.44	0.44	0.35
Qwen-2-7B	0.00	0.00	0.00	0.00	0.00
Yi-1.5-6B	0.00	0.00	0.00	0.00	0.00

Table 7. Experimental results of LLMs without entity annotations and fine-tuning for DocTRE on Tem-DocRED.

Method	Training Complexity	Inference Complexity	Key Bottleneck
Rule-Based Systems	Negligible	low	Limited to predefined patterns; poor generalization.
Traditional Neural Network	Moderate	Moderate	Struggles with long-range dependencies in documents.
PLM-based Systems	Moderate	Moderate	Little heavier fine-tuning and inference latency compared traditional methods.
LLM-based Systems (Ours)	High	Moderate	Reduced parameters via LoRA, but still slower than non-LLM baselines.

Table 8. Computational complexity comparison between LLM-based systems and other previous methods.

However, there are some limitations of the LLM framework. Fine-tuning LLMs requires significant GPU resources (e.g., at least single RTX3090 for small models), limiting accessibility for low-resource settings. Apart from this, errors in entity linking or timestamp extraction propagate to downstream relation extraction, degrading performance. The framework struggles with precise temporal granularity due to sparse annotations in Tem-DocRED. This does not cause errors, but creates redundancy of information.

A cursive comparison of training computational complexity and inference speed of different methods for relation extraction is shown in Table 8. Rule-based systems denote match relation in documents based on the predefined patterns, so it does not require training and has rapid inference speed. But this means that relations without predefined patterns can't be captured, the results are usually uncompleted. Traditional methods based on neural networks like LSTM outperforms rule-based methods, and the training complexity is higher. The structure of traditional neural network-based models is more complex, so they need more time to reason. And it is hard to catch the long-range dependencies in the context of documents. PLM-based methods like BERT-based methods have more powerful semantic comprehension and are able to understand longer passages of text. Compared to the traditional neural network approach, this type of models will take up more training resources and the speed of inference will be slightly reduced. Stronger inference gives the model better results but less generalization to different domains. Systems based on large language models have strong comprehension and generation capabilities and can adapt to reasoning based on document content under different domains. However, compared to PLM-based methods, the training requires more resources and higher complexity, and the speed of reasoning is reduced.

Summary. This paper introduces a novel framework for Temporal Knowledge Graph (TKG) generation from documents, leveraging Large Language Models (LLMs) to extract temporal relations and construct quadruples. The key contributions include: proposing the Document-level Temporal Relation Extraction (DocTRE) task, constructing the Tem-DocRED dataset with 2,843 documents and 15,699 temporal quadruples, and developing an LLM-based framework that transforms DocTRE into a sequence-to-sequence generation task. Experimental results demonstrate the effectiveness of the proposed approach, with fine-tuned LLMs like GLM-4 achieving state-of-the-art performance. Future research directions include handling fine-grained temporal information, cross-domain generalization, and incorporating external knowledge. Potential applications span historical event analysis, news aggregation, biomedical research, and economic forecasting. This work advances the field of TKG construction and provides a foundation for future exploration of temporal reasoning in various domains.

Code availability

The code includes data construction and evaluation. We released and shared all our code (https://github.com/jzhu000/GTKG).

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Jun Zhu: Data curation, Writing, Original draft preparation, and Methodology. Yan Fu: Reviewing, Conceptualization, and Validation. Junlin Zhou: Writing-Visualization, Investigation, and Supervision. Duanbing Chen: Data curation, Reviewing, and Editing.

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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