Unfolding the Headline: Iterative Self-Questioning for News Retrieval and Timeline Summarization

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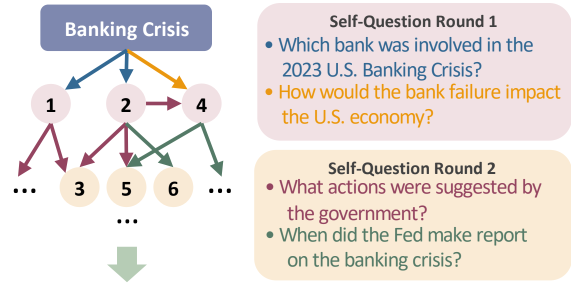
Abstract

In the fast-changing realm of information, the capacity to construct coherent timelines from extensive event-related content has become increasingly significant and challenging. The complexity arises in aggregating related documents to build a meaningful event graph around a central topic. This paper proposes **CHRONOS** - **C**ausal **H**eadline **R**etrieval for **O**pen-domain **N**ews Timeline SummarizatiO**n** via Iterative **S**elf-Questioning, which offers a fresh perspective on the integration of Large Language Models (LLMs) to tackle the task of Timeline Summarization (TLS). By iteratively reflecting on how events are linked and posing new questions regarding a specific news topic to gather information online or from an offline knowledge base, LLMs produce and refresh chronological summaries based on documents retrieved in each round. Furthermore, we curate Open-TLS, a novel dataset of timelines on recent news topics authored by professional journalists to evaluate open-domain TLS where information overload makes it impossible to find comprehensive relevant documents from the web. Our experiments indicate that CHRONOS is not only adept at open-domain timeline summarization but also rivals the performance of existing state-of-the-art systems designed for closed-domain applications, where a related news corpus is provided for summarization.[1]

1 Introduction

The exponential growth of news information in the digital era has made the task of understanding complex event narratives more critical. Timeline Summarization (TLS) (Yan et al., 2011; Wang et al., 2015; Chen et al., 2019; Gholipour Ghalandari and Ifrim, 2020) aims to extract and order the pivotal events from a multitude of textual sources over time, providing a structured view of historical developments. Despite the complexities inherent in extracting and organizing news events from multiple documents, the advent of Large Language Models (LLMs) (Kojima et al., 2022; OpenAI, 2023; Yang et al., 2023a; Bai et al., 2023) as powerful tools in understanding and generating high-quality text shows their potential in the field of TLS (Wang et al., 2023; Hu et al., 2024; Sojitra et al., 2024).

The core of synthesizing a timeline is establishing temporal and causal relationships between events (Ansah et al., 2019; Li et al., 2021; Xiuying et al., 2022). As depicted in Figure 1, assuming



1	2023-03-10: U.S. regulators took control of the Silicon Valley Bank Friday morning, shutting it down.
2	2023-03-12: Regulators shut down the Signature Bank.
3	2023-03-14: Government launched investigation of Silicon Valley Bank failure.
4	2023-03-22: Fed raised interest rates by 0.25 percent.
5	2023-03-28: Regulators conducted a hearing on the failures of SVB and Signature Bank.
6	2023-04-28: The Fed released a report faulting itself for not taking forceful enough action ahead of SVB's collapse.

Figure 1: TLS of the news *Banking Crisis*. Edges between event nodes can be established by iterative self-questioning, ultimately building an event graph around the target news for timeline generation.

[†] This work was done during Weiqi Wu's internship at Tongyi Lab, Alibaba Group.
[*] Yong Jiang and Hai Zhao are corresponding authors.
[1]The code and dataset are released at `https://github.com/Alibaba-NLP/CHRONOS`.

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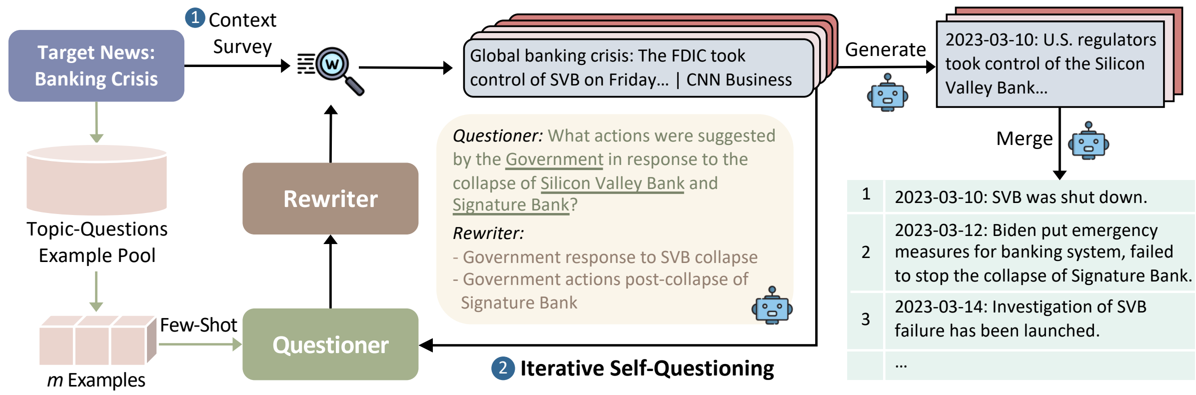

Figure 2: Pipeline of CHRONOS. Giving a target news, it first searches for general context and iteratively poses questions to retrieve more relevant news, while employing a divide-and-conquer strategy to generate the timeline.

that each news event is represented as a distinct node, our goal is to establish edges between these nodes to present their correlation and ultimately form a heterogeneous graph, starting from the node of topic news. Establishing these edges can be effectively achieved through a search mechanism that retrieves relevant news articles. Thereby, an event node is linked to another if it can retrieve the other event through this search process.

Based on the sources of retrievable news, we categorize the TLS task into open-domain and closed-domain settings. Open-domain TLS refers to the process of generating timelines from news directly searched and retrieved from the Internet, while closed-domain TLS involves creating timelines from a predefined set of news articles related to a specific domain. Open-domain TLS faces additional challenges due to the vast and dynamic nature of online information. The information overload makes it difficult to retrieve relevant and comprehensive information from the Internet, introducing noisy data that complicates the task of filtering and assessing the quality of retrieved content. Hence, establishing relationships among events is more challenging in an open domain without access to a global view of relevant news.

To address such challenges, we propose **CHRONOS**, **C**ausal **H**eadline **R**etrieval for **O**pen-domain **N**ews Timeline SummarizatiO**n** via Iterative **S**elf-Questioning, a new scheme for both settings of TLS based on the Retrieval-Augmented Generation (RAG) framework (Li et al., 2022; Zhang et al., 2023; Gao et al., 2023; Zhao et al., 2024), as shown in Figure 2. By simulating the way humans search for information, which involves learning about the topic by formulating well-defined questions or problems, scanning retrieval results and term suggestions, and further coming up with new subquestions (Bates, 1989; O'Day and Jeffries, 1993), we iteratively utilize LLMs to pose 5W1H questions — What, Who, Why, Where, When, How — related to the news topic to gather comprehensive information about related events. The questions are then rewritten to enable a more effective search. For each round of retrieved news, we employ an LLM to generate a timeline, which would be merged to produce the ultimate timeline.

Despite the possibility of evaluating TLS systems in an open-domain setting by not utilizing the corpus provided by current news datasets, these datasets are often limited in size and topic diversity. Therefore, we introduce a more up-to-date and comprehensive news timeline dataset called Open-TLS. It encompasses various topics, including politics, economy, society, sports, and technology, and is sourced from news articles authored by professional journalists.

Our contributions can be summarized as follows:

- We propose CHRONOS, a novel retrieval-based approach to TLS by iteratively posing questions about the topic and the retrieved documents to generate chronological summaries.
- We construct an up-to-date dataset for open-domain TLS, which surpasses existing public datasets in terms of both size and the duration of timelines.
- Experiments demonstrate that our method is effective on open-domain TLS and achieves comparable results with state-of-the-art methods of closed-domain TLS, with significant improvements in efficiency and scalability.

2 Related Works

2.1 Timeline Summarization

Timeline summarization (TLS) synthesizes a chronological narrative of event progression (Allan et al., 2001; Chen et al., 2019; Gholipour Ghalandari and Ifrim, 2020; Yu et al., 2021). While it could be approached as an extension of multi-document summarization (Chieu and Lee, 2004; Martschat and Markert, 2018), common strategies include focusing pivotal dates (Tran et al., 2015a,b; Steen and Markert, 2019) or identifying milestone events (Li et al., 2021; Xiuying et al., 2022). LLMs have introduced advancements to the field of TLS (Wang et al., 2023; Sojitra et al., 2024). Specifically, Hu et al. (2024) leverage LLMs for the generation and clustering of event summaries.

2.2 Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG) enhances LLMs by incorporating external knowledge during inference, addressing issues such as hallucination and outdated information (Liu et al., 2022; Shi et al., 2022; Ram et al., 2023; Izacard et al., 2023; Li et al., 2023; Agrawal et al., 2023). The retrieval sources of RAG can range from local databases (Siriwardhana et al., 2023) to web searches (Nakano et al., 2021; Komeili et al., 2022). As an application, Shao et al. (2024) researches a topic via multi-perspective Question-Asking during writing. We focus on the task of TLS and expand it to an open-domain setting, introducing news retrieval using the Internet with new challenges.

3 Methodology

We present CHRONOS, a new framework for effective and efficient TLS. It iteratively self-questions about previously retrieved news to gather other related events from various perspectives and combines the timelines it creates from each round of search for a thorough summary.

3.1 Iterative News Self-Questioning

The initial step of constructing a timeline for a specific target involves gathering relevant news articles. A straightforward method is to search with the news headline as a keyword to obtain the most general and directly linked information to the target news, where we define the retrieved articles as *News Context*. To obtain more comprehensive information about the target, we ask the LLM to generate questions that cannot be answered based on the news context, and iteratively search for new reference articles according to these questions.

To enhance the quality of self-questioning, we leverage the In-Context Learning (ICL) ability of LLMs by employing a few-shot prompt (Brown et al., 2020; Dong et al., 2022; Qian et al., 2024; Yao et al., 2024) to instruct the LLM to generate questions about the target news based on the previously retrieved news articles. The few-shot method is known to be highly dependent on the quality of the demonstration examples (Liu et al., 2022; Yang et al., 2023b; Peng et al., 2024). Therefore, curating effective few-shot examples becomes a critical aspect of our self-questioning method.

To systematically evaluate the quality of the generated questions in the field of TLS, we introduce the concept of *Chrono-Informativeness* (CI). It is designed to assess the ability of the questions to retrieve relevant documents that align chronologically with a reference timeline produced by a professional journalist. The *Chrono-Informativeness* of a set of questions $Q = (q_1, \ldots, q_m)$ for a given news topic is calculated as:

$$\mathrm{CI}(Q, N) = Date\_F_1(T_{Q,N}, T_{ref})$$

where $T_{Q,N}$ is the timeline generated from the N documents retrieved through the rewritten version of Q (see Sec. 3.2), and T_{ref} is the reference timeline. The $Date\_F_1$ score is a widely accepted metric in the field of TLS that compares the dates contained in the generated timeline to those in the reference timeline (detailed in Sec. 5.2).

By generating an extensive set of questions for a given news topic, we can use the greedy algorithm to identify the top m questions that maximize $CI(Q, N)$, selecting the question that provides the greatest improvement in CI during each step. The topic-questions pairs are stored in an example pool. When generating questions for a new target news story, we utilize a BERT-base-uncased model[2] to embed the query keyword and apply cosine similarity to retrieve the s most similar topics and associated example pairs from the pool. These dynamically retrieved few-shot demonstrations ensure that the demonstrations are contextually relevant and chronologically informative, which enhances the overall quality of the self-questioning process.

[2]https://huggingface.co/google-bert/bert-base-uncased

	T17	Crisis	OPEN-TLS					
			Overall	Politics	Society	Economy	Sports	Technology
# of topics	9	4	50	25	12	5	5	3
# of timelines	19	22	50	25	12	5	5	3
Avg. # of articles	508	2310	-	-	-	-	-	-
Avg. # of pub dates	124	307	-	-	-	-	-	-
Avg. duration (days)	212	343	4139	4624	1719	1297	8219	7694
Avg. l	36	29	23	25	19	22	20	20
Avg. k	2.9	1.3	1.8	1.8	2.1	1.7	1.8	1.6

Table 1: Statistics of closed-domain news TLS datasets and our proposed OPEN-TLS. A timeline contains l dates associated with k sentences describing the events that happened at each date.

3.2 Question Rewrite

However, the generated questions are usually quite complex to reach a certain level of depth and breadth, adding difficulty to searching. For instance, regarding the news of the Banking Crisis, the questioner posed a question *What actions were suggested by the government in response to the collapse of Silicon Valley Bank and Signature Bank*, and using this question directly as a query in a search engine yields poor retrieval performance. Hence, we apply a question rewriting mechanism (Ma et al., 2023) to improve the retrieval precision of our questions, achieved using a few-shot prompt design. Specifically, we employ the LLM to decompose each complex or under-performing query into 2-3 focused queries, such as *Government response to Silicon Valley Bank collapse* and *Government actions post-collapse of Signature Bank*. Such decomposition enhances the specificity and coverage of the retrieved documents, making the subsequent summarization tasks more effective.

3.3 Timeline Summarization

To create a coherent timeline containing l dates from the news articles retrieved using the questions, we utilize a divide-and-conquer strategy by first generating individual timelines from each round and merging them to produce the final timeline.

Generation We divide the problem of timeline generation into individual rounds of generation. At the end of each round of self-questioning, the LLM is instructed to extract the significant milestone events with clarified dates and write detailed summarizations of these events, using phrases directly from the news articles when possible to maintain authenticity and accuracy.

Merging After processing each round individually, the final step is to merge the generated timelines to ensure that only the most significant events are retained. The merging process involves aligning events from different rounds and resolving any conflicts of dates and descriptions. We instruct the LLM to select the top-l milestone events from the original timeline. Dates with more events happening are given precedence as they are likely to be more important since these events are consistently identified across multiple rounds of retrieval.

4 Open-TLS

Evaluating TLS systems commonly involves comparing system-generated timelines to those authored by professional journalists. While several benchmarks have been proposed for closed-domain news TLS along with the provided corpus for each topic, existing public datasets like T17 (Binh Tran et al., 2013) and Crisis (Tran et al., 2015b) remain constrained in terms of size and topical diversity. Furthermore, they often lack the timeliness and flexibility characterized by open-domain timeline generation. To bridge these gaps, we introduce *Open-TLS*, a novel dataset that collects timelines about recent news events, written by professional journalists from reputable news organizations such as the Associated Press[3], Public Broadcasting Service[4], and The Guardian[5].

As detailed in Table 1, Open-TLS comprises 50 timelines across various domains, including politics, economics, society, sports, and technology. The majority of the timelines are published post-2020. Each timeline is accompanied by a publication date and a query keyphrase that facilitates searching. In cases where the news is documented on Wikipedia, the title defined in Wikipedia is used as the query. Otherwise, we manually create a suit-

[3] https://apnews.com
[4] https://www.pbs.org
[5] https://www.theguardian.com

		Concat F1		Agree F1		Align F1		Date F1
		R-1	R-2	R-1	R-2	R-1	R-2	
GPT-3.5-Turbo	DIRECT	0.243	0.063	0.056	0.021	0.071	0.025	0.208
	REWRITE	0.233	0.067	0.054	0.022	0.070	0.026	0.205
	CHRONOS	0.328	0.086	0.092	0.078	0.092	0.034	0.283
GPT-4o	DIRECT	0.297	0.085	0.078	0.032	0.093	0.036	0.263
	REWRITE	0.283	0.080	0.079	0.034	0.093	0.038	0.272
	CHRONOS	0.351	0.103	0.105	0.047	0.121	**0.051**	**0.343**
Qwen2.5-72B	DIRECT	0.328	0.101	0.087	0.044	0.104	0.049	0.265
	REWRITE	0.337	0.106	0.091	0.046	0.107	0.050	0.291
	CHRONOS	**0.368**	**0.110**	**0.106**	**0.049**	**0.125**	0.050	0.324

Table 2: Experimental results on Open-TLS. We present the outcomes from the optimal self-questioning round.

able query based on its headline. All timelines are carefully curated to ensure high standards, providing exact dates and accurate narratives. This includes manually refining or filtering dates without precision to *day* in the raw timelines (2.6% of all dates) by conducting additional searches to confirm the exact dates.

5 Experiments

5.1 Implementation Details

We construct experiments on CHRONOS based on three popular LLMs: GPT-3.5-Turbo[6], GPT-4o[7], and Qwen2.5-72B (Bai et al., 2023). We report the average results of 3 runs during evaluation.

Example Pool To build the example pool for the few-shot self-questioning prompt, we utilize GPT-4o to generate 50 questions for topics in the Crisis, T17, and Open-TLS datasets. Each topic is self-questioned based on the directly searched news context. When selecting the most similar demonstrations from the example pool, we exclude the topic-questions pair of the target news.

Search Engine For open-domain TLS, we use the Bing Web Search API[8] and set the query parameter *freshness* to the publish date of reference timeline to retrieve news articles only before it. We additionally use JINA[9] to read the content of the web pages. In the closed-domain setting, we employ Elasticsearch (Gormley and Tong, 2015), a well-established text search engine. Each document from the news corpus provided by the dataset is chunked into segments of approximately 500 words for retrieval.

5.2 Evaluation Metrics

We adopt the Tilse framework (Martschat and Markert, 2017, 2018) to evaluate the generated timeline with reference timelines, which includes the following metrics:

ROUGE-N Derived from the original ROUGE-N metrics, these metrics measure the overlap of N-grams in generated and reference timelines: (1) *Concat F1* computes ROUGE by concatenating all date summaries; (2) *Agree F1* computes ROUGE using only summaries of matching dates. (3) *Align F1* initially aligns predicted summaries with reference summaries based on similarity and date proximity, then calculates ROUGE between the aligned summaries, penalizing distant alignments.

Date F1 It is the F1 score of dates in the generated timelines compared with the ground truth.

5.3 Open-Domain TLS

5.3.1 Baselines

We propose two baselines for Open-Domain TLS. The number of retrieved news by baselines equals the total number of news retrieved by CHRONOS.

- **DIRECT** Directly search for the target news and output a timeline with the retrieved news.
- **REWRITE** Rewrite the target news to create 2-3 queries, search with these rewritten queries, and output a timeline with the retrieved news.

[6] https://platform.openai.com/docs/models/gpt-3-5-turbo
[7] https://platform.openai.com/docs/models/gpt-4o
[8] https://www.microsoft.com/en-us/bing/apis/bing-web-search-api
[9] https://jina.ai/reader/

Dataset	Model	AR-1	AR-2	Date F1
Crisis	CLUST	0.061	0.013	0.226
	EGC	0.079	0.015	0.291
	LLM-TLS▲	**0.112**	0.032	**0.329**
	LLM-TLS★	0.111	0.036	<u>0.326</u>
	DIRECT	0.094	0.031	0.182
	REWRITE	0.093	0.040	0.215
	CHRONOS	<u>0.108</u>	**0.045**	0.323
T17	CLUST	0.082	0.020	0.407
	EGC	0.103	0.024	**0.550**
	LLM-TLS▲	**0.118**	0.036	0.528
	LLM-TLS★	0.114	<u>0.040</u>	<u>0.543</u>
	DIRECT	0.077	0.028	0.418
	REWRITE	0.079	0.029	0.443
	CHRONOS	<u>0.116</u>	**0.042**	0.522

Table 3: Comparison of CHRONOS with previous works on closed-domain TLS benchmarks, reporting results of the top model. The best F1 scores are **bolded**, and the second bests are <u>underlined</u>.

5.3.2 Results

The results in Table 2 demonstrate a consistent improvement across all metrics when using the CHRONOS approach compared to the baselines for each evaluated model. This indicates that CHRONOS enhances both the quality of event summarization and the alignment of dates with the reference timelines. The higher *Date F1* scores show that CHRONOS is more effective at accurately predicting the correct dates for significant events, with GPT-4o outperforming other models in extracting milestone events. Additionally, the improvements in ROUGE-N metrics suggest that the model excels at producing summaries of news events. Moreover, the general improvement by REWRITE compared with DIRECT shows the advantage of query writing preliminarily.

5.4 Closed-Domain TLS

5.4.1 Baselines

We evaluate CHRONOS on the closed-domain TLS task with several prior event-based approaches:

- **CLUST** Gholipour Ghalandari and Ifrim (2020) uses Markov clustering for event aggregation and determines the cluster significance by its date frequency in the news corpus.

- **EGC** Li et al. (2021) utilizes an event graph modelling method, integrating time-aware optimal transport to compress the whole graph into a salient sub-graph for event selection.

	Dataset	AR-1	AR-2	Date F1
CHRONOS	OPEN	**0.125**	**0.051**	**0.343**
	Crisis	**0.108**	**0.045**	**0.323**
	T17	**0.116**	**0.042**	**0.522**
Self-Questioning				
Random Exemplar	OPEN	0.113	0.042	0.312
	Crisis	0.079	0.038	0.314
	T17	0.112	0.036	0.498
Zero-Shot	OPEN	0.106	0.035	0.286
	Crisis	0.059	0.023	0.306
	T17	0.102	0.037	0.471
Question Rewrite				
w/o Rewrite	OPEN	0.095	0.038	0.262
	Crisis	0.078	0.047	0.286
	T17	0.072	0.026	0.446

Table 4: Ablation study of the topic-questions exemplars and question rewriter. OPEN is short for Open-TLS.

- **LLM-TLS** Hu et al. (2024) leverages LLMs as pseudo-oracles for incremental event clustering to construct timelines from a streaming context. We utilize LLaMA2-13B and Qwen2.5-72B for implementation and denote the resulted systems as LLM-TLS▲ and LLM-TLS★ respectively.

5.4.2 Results

We select the well-established benchmarks Crisis and T17 for evaluating closed-domain TLS and focus on representative performance metrics including Align F1 (short for AR-1 and AR-2) and Date F1. Table 3 presents a comprehensive overview of the performance of CHRONOS alongside previous representative works and two fundamental document retrieval baselines defined in the open-TLS task, i.e., DIRECT and REWRITE. We select the best-performing model to report its performance for presentation. Experiments show that CHRONOS matches and even exceeds the performance of previous models in terms of Alignment-based ROUGE-2 scores on both datasets. For the other lagging indicators, CHRONOS ranks second only to LLM-TLS on the Crisis dataset, as well as its Alignment-based ROUGE-1 score of T17. Regarding Date F1, its performance is less than 0.03 behind the state-of-the-art model, which however suffers from the other two metrics.

5.5 Ablation Study

5.5.1 Effects of Question Examples

CHRONOS selects the top-s most similar examples to the target news from the topic-questions example pool to construct few-shot self-questioning

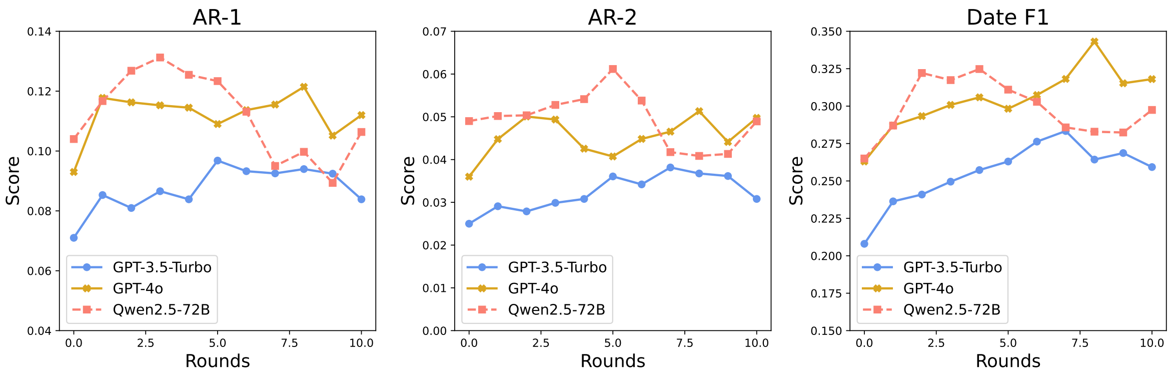

Figure 3: Impact of rounds of Self-questioning on model performance within the Open-TLS dataset.

prompts. However, when these examples are selected randomly, i.e., *Random Exemplar* in Table 4, an evident drop in all metrics is witnessed across the three datasets, demonstrating the effectiveness of strategically selecting examples. This suggests that simply relying on providing examples and neglecting their relevance to the target is suboptimal, as random examples fail to provide contextual guidance for the model. Additionally, using a zero-shot prompt, which bypasses the use of examples entirely, leads to worse performance in most cases.

5.5.2 Necessity of Rewriting

To validate the importance of question rewriting, we compare the performance of our framework with and without this component. As shown in Table 4, the removal of the rewriting step leads to a significant decline in the overall performance of TLS, despite a slight improvement ($+0.02$) in the Alignment-based ROUGE-2 score for the Crisis dataset. This minor increase could be due to cases where the original questions closely resemble the phrasing of news articles, which enhances surface-level n-gram overlap. However, the overall decrease in Date F1 and other ROUGE metrics indicates that, without the rewriter, the model encounters difficulties in generating a complete and coherent timeline.

5.5.3 Rounds of Self-Questioning

The CHRONOS framework thrives on iterative self-questioning, a process that iteratively expands the news timeline. By increasing the number of questioning rounds, CHRONOS can retrieve a greater volume of news articles, thereby enhancing the comprehensiveness of its news database. However, as depicted in Figure 3, a pattern emerges across all three models on the Open-TLS dataset that their performance initially improves with additional rounds of questioning, but eventually declines. This trend can be attributed to the challenge of merging an excessive number of retrieved news articles into a coherent timeline.

5.5.4 Number of Retrieved news

To determine the impact of retrieved news in each round, we experiment with retrieving 20, 30, 40 documents using Qwen2.5-72B on the Open-TLS dataset. Table 5 indicates that increasing the number from 20 to 30 documents significantly improves the results, with marginal improvements when increasing to 40 documents. Intuitively, retrieving more documents provides the model with a richer context. However, due to the potential of introducing noise when integrating less relevant news, the marginal improvements observed when further increasing the number of retrieved news suggest a threshold beyond which the benefits plateau.

5.6 Inference Time

We further compare the running time of the LLM-based methods on the closed-domain datasets, CHRONOS and LLM-TLS. LLM-TLS, which processes each article individually, experiences substantial time delays due to the extensive news corpus of the Crisis dataset. On the other hand, CHRONOS employs a retrieval-based mechanism to focus on highly relevant news articles. Therefore, as shown in Table 6, CHRONOS spends only 5.6% of the total time required by LLM-TLS to reach a comparable performance. Even on the T17 dataset with fewer articles per topic, CHRONOS is almost twice as fast while producing similar or improved results. In conclusion, CHRONOS is more practical for real-world applications where efficiency and scalability are critical factors.

N	Concat-R1	Concat-R2	Agree-R1	Agree-R2	Align-R1	Align-R2	Date F1
20	0.321	0.082	0.078	0.041	0.098	0.042	0.287
30	**0.368**	0.110	**0.106**	**0.049**	**0.125**	0.050	**0.324**
40	0.354	**0.121**	0.092	0.049	0.118	**0.051**	0.321

Table 5: Performance on Open-TLS with different numbers of news retrieved in each round.

	Crisis	T17
LLM-TLS	7 hr 12 min	2 hr 12 min
CHRONOS	**24 min**	**1 hr 9 min**

Table 6: Inference time for LLM-based methods.

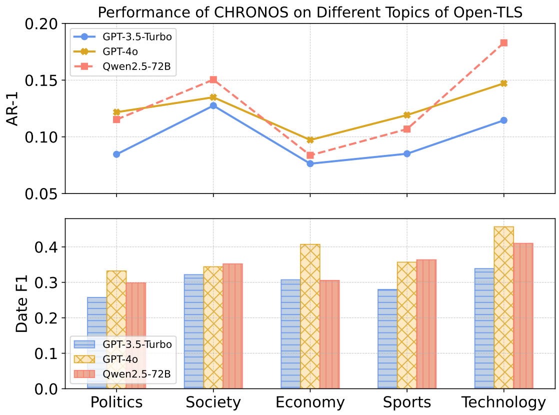

Figure 4: Topic analysis of CHRONOS on Open-TLS.

5.7 Discussions

5.7.1 Topic Analysis

We analyze the impact of different topics on the performance of CHRONOS, as shown in Figure 4. Upon examining the AR-1 metric, we observe that the Economy and Politics topics tend to challenge the LLMs, likely due to the significant amount of domain knowledge and entities required within these areas. The complexity and specificity of content in these domains make it harder for models to summarize event narratives effectively, resulting in relatively lower scores. Especially for the Economy topic, while the Date F1 scores remain relatively high, indicating that the models are generally successful in extracting dates, the lower ROUGE scores highlight the difficulty of summarizing economic events. Despite the variations in performance across different topics, the three models perform similarly on the Society topic. This convergence in performance could be attributed to the more general and less specialized nature of societal issues, which are easier for the models to handle equally well.

5.7.2 Case Study

Table 7 demonstrates how CHRONOS summarizes a timeline of *Greatest Apple Announcements*, constrained by the news publication date of June 30, 2024. CHRONOS generates two rounds of questions to gradually refine its knowledge of the news from a broad overview to more detailed insights. In Round 1, questions like *How has Apple's corporate strategy evolved?* guide the model to explore Apple's historical milestones and capture key events in it. In Round 2, the questioning shifts toward more specific topics to enrich the timeline with finer details. Comparing the generated timelines from both rounds to the reference timeline, CHRONOS accurately extracts major events with high precision. However, the omission of the Apple Vision Pro announcement and an incorrect date for the iPad unveiling indicate improvement in extracting milestone events with the correct dates.

6 Conclusion

In conclusion, this paper presents CHRONOS, a novel framework for TLS that leverages LLMs through an iterative self-questioning and retrieval-based process. Our method addresses the challenge of constructing coherent timelines by systematically retrieving event-related documents, reflecting the causal relationships between events. Experiments demonstrate its effectiveness in both open-domain and closed-domain TLS, as we propose a newly curated Open-TLS dataset for up-to-date open-domain news TLS. Moreover, CHRONOS demonstrates significant improvements in scalability and efficiency, making it a valuable tool for news TLS from vast and unstructured information.

Limitations

While our work presents several innovative contributions to the field of TLS, we acknowledge certain limitations that may affect its performance: (1) Our method is heavily dependent on the logical correlation between events for effective retrieval. However, if the causal links between events are not strong enough that they only happened chrono-

<table>
<tr><th colspan="2">Target News: Greatest Apple Announcements (2024.06.30)</th></tr>
<tr><th>Round 1</th><td rowspan="6">Reference Timeline:
1984-01-24: The Macintosh computer was unveiled.
2001-10-23: The iPod was unveiled, changing people's view about digital music players.
2007-01-09: The iPhone was unveiled, introducing the convenience of touchscreens.
2010-01-27: The iPad was unveiled, creating a middle ground between laptops and smartphones.
2014-09-09: The Apple Watch was unveiled, creating a device that made it possible to wear something akin to a smartphone on your wrist.
2016-09-07: AirPods was unveiled, helping popularize wireless headphones with an Apple chip that provided more reliable and stable connections while making it easy to shift from one gadget to another.
2024-06-05: The Apple Vision Pro was unveiled, which is a mixed-reality headset that seamlessly blends digital content with the physical world.</td></tr>
<tr><td>Self-Question:
1. How did Apple transition from early computers into mobile tech?
2. How has Apple's corporate strategy evolved?
3. What were the key challenges during the initial years of Apple?
4. What were the critical factors that led to the innovation of the iPhone?
5. Who were the individuals instrumental in Apple's major products?</td></tr>
<tr><td>Generated Timeline:
1984-01-24: Apple introduced the Macintosh computer.
2007-01-09: Apple introduced the first iPhone, marking a revolution in the smartphone industry with its multi-touch interface and sleek design.
...
2014-09-09: Apple announced the iPhone 6 and 6 Plus, as well as the Apple Watch, expanding its product lineup beyond phones.</td></tr>
<tr><th>Round 2</th></tr>
<tr><td>Self-Question:
1. What were the key technological breakthroughs during Apple's development?
2. How did the launch of the iPhone impact Apple's strategy?
3. How has the user interface of Apple products evolved?
4. In what ways has Apple's design philosophy changed?
5. How did Apple navigate the transition from Steve Jobs to Tim Cook?</td></tr>
<tr><td>Generated Timeline:
2001-10-23: The iPod was launched by Apple, revolutionizing how people listened to music and laying the groundwork for mobile devices.
2010-04-03: Apple released the iPad, a tablet that combined features from both the iPhone and the Mac.
2016-09-07: Apple launched the iPhone 7 and 7 Plus, the first models to eliminate the headphone jack, emphasizing wireless audio.
...</td></tr>
</table>

Table 7: Case study of the timeline generated by CHRONOS. The correctly predicted dates are in green, the missing dates are in red, and incorrect dates with correct events are in yellow. Overlapping words between the predicted and reference timeline are also highlighted.

logically, the system may struggle to retrieve relevant news articles efficiently. (2) The stability and consistency of our outputs are influenced by the volatility of LLMs and Search Engine Results Pages (SERPs). These fluctuations can lead to variations in the quality and reliability of the summaries generated by CHRONOS in real time.

Ethics Statement

A strong commitment to ethical standards and responsible research practices has guided the development and utilization of the Open-TLS dataset. We respect intellectual property rights and the guidelines established by content creators. Hence, we have strictly followed the terms of use set forth by the news organizations and websites from which we sourced the timelines. We have additionally made efforts to construct and present our dataset in a manner that preserves the integrity and accuracy of the original journalistic work. We are dedicated to ensuring that our dataset does not infringe upon the rights or privacy of individuals or organizations. Furthermore, all other datasets and models utilized in this work are publicly accessible and distributed under permissive licenses.

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A Hyperparameters

In our experimental configuration, we have set the parameter m to 5, which represents the number of questions that the LLM generates in each round. The parameter N is set to 30, defining the maximum number of retrieved documents in each round. Furthermore, we have designated s as 3, indicating the number of few-shot examples included in the self-questioning prompt.

B Analysis on Question Quality

We have empirically validated the answerability of the questions generated by CHRONOS. Since our primary goal in generating questions is to provide new perspectives on the retrieval of related news, we utilize GPT-4o to compare the quality of responses generated under two different contexts: (1) the initial context and (2) new documents retrieved by the generated question.

Model	Initial Context	New Context
GPT-3.5-Turbo	21	**79**
GPT-4o	12	**88**
Qwen2.5-72B	15	**85**

Table 8: Comparison of win rates for different models using the initial context versus new context retrieved by the generated questions.

As shown in Table 8, the win rates for all models were significantly higher when using new context retrieved by the questions, compared to the given context. This suggests that the initial context provided was not comprehensive enough to support accurate and complete answers to the generated questions. Future work may focus on improving context retrieval and enrichment strategies to enhance the answerability of LLM-generated questions.

C Prompt Demonstration

We present the prompts used for three main modules within our system: self-questioning, question rewriting, and timeline generation.

C.1 Self-Questioning Prompt

Table 9 shows the prompt for news self-questioning. With the dynamically selected examples for each target news, the prompt is designed to guide LLMs in formulating a series of questions that expand the scope of the news database for generating the timeline.

Instruction for News Self-Questioning

You are an experienced journalist building a timeline for the target news. You need to propose at least 5 questions related to the Target News that the current news database cannot answer.
These questions should help continue organizing the timeline of news developments or the life history of individuals, focusing on the origins, development processes, and key figures of related events, emphasizing factual news knowledge rather than subjective evaluative content.
These 5 questions must be independent and non-overlapping. The overall potential information volume of all questions should be as large as possible, and the time span covered should also be as extensive as possible. Avoid asking questions similar to those already searched. Directly output your questions in the specified format.
Output format: ["Question_1", "Question_2", ...]

{Retrieved Examples}

Current News Database: {docs}
Target News: {news}
Questions Already Searched: {questions}

Table 9: Prompt for the questioner.

Instruction for Question Rewriting

Generate 2-3 rewrite queries of the question as a python list, directly output it as ["..", "..", ..]

Examples:
Question: When did the initial protests that led to the Egyptian Crisis begin?
Rewrite: ["Egyptian Crisis initial protests", "Time of protests lead to Egyptian Crisis"]

Question: When and where did Robert Jasmiden die?
Rewrite: ["Robert Jasmiden's death time", "Robert Jasmiden's death place"]

Question: What profession do Nicholas Ray and Elia Kazan have in common?
Rewrite: ["Nicholas Ray profession", "Elia Kazan profession"]

Question: {question}
Rewrite:

Table 10: Prompt for the rewriter.

C.2 Rewrite Prompt

Table 10 presents the few-shot prompt used for question rewriting. The examples provided in the prompt demonstrate how to decompose complex questions while preserving their original intent.

C.3 Timeline Generation Prompts

Table 11 and Table 12 illustrate the prompts for timeline generation with detailed instructions.

Instruction for Timeline Generation

You are an experienced journalist building a timeline for the target news.

Instructions:
Step 1: Read each background news item and extract all significant milestone events related to the target news from your news database, along with their dates.
Step 2: Write a description for each event, including key detail information about the event, using the phrasing from the news database as much as possible. Save all events as a list. The format should be: [{"start": <date|format as "2023-02-02", cannot be empty, must include specific year, month, and day>, "summary": "<event description|no quotes allowed>"}, ...]

Target News: {news}
Current news database: {docs}

Table 11: Prompt for the timeline generator.

Instruction for Timeline Merging
You are an experienced journalist building a timeline for the target news. Merge the existing news summaries and timelines in chronological order. When merging the news summaries, select the top-{l} significant news from the original timeline, and strictly follow the chronological order from past to present without changing the original date, using "\n" to separate events that occurred on different dates. Exclude duplicate events appearing in later dates. Directly output your answer in the following format: [{"start": <date|format as "2023-02-02", cannot be empty, must include specific year, month, and day>, "summary": "<event description|no quotes allowed>"}, ...] Target News: {news} Original Timeline: {timelines}

Table 12: Prompt for merging the timelines from each round.