Inferring Event Descriptions from Time Series with Language Models

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Abstract

Time series data measure how environments change over time and drive decision-making in critical domains like finance and healthcare. When analyzing time series, we often seek to understand the underlying events occurring in the measured environment. For example, one might ask: "What caused a sharp drop in the stock price?" Events are often described with natural language, so we conduct the first study of whether Large Language Models (LLMs) can infer natural language events from time series. We curate a new benchmark featuring win probabilities collected from 4,200 basketball and American football games, featuring 1.7M timesteps with real value data and corresponding natural language events. Building on the recent wave of using LLMs on time series, we evaluate 16 LLMs and find that they demonstrate promising abilities to infer events from time series data. The open-weights DeepSeek-R1 32B model outperforms proprietary models like GPT-40. Despite this impressive initial performance, we also find clear avenues to improve recent models, as we identify failures when altering the provided context, event sequence lengths, and evaluation strategy.*

1 Introduction

Time series data are pervasive. Examples of time series include wearable device measurements of users' actions (Anguita et al., 2013), clinical records about changes in health (Harutyunyan et al., 2019), and asset market prices (Wang et al., 2024c; Li et al., 2024a). Each of these examples represents a real-valued sequence of data points with time stamps. In addition to the real-valued data, a time series often has associated events described in natural language which are related to trends and patterns in the time series. Figure 1 illustrates an example from sports—events favorable to Team A

increase its win probability, while unfavorable ones decrease it. Benefiting from the promising potential of integrating natural language with time series analysis (Jin et al., 2024), along with the rapid advancement of natural language processing, LLMs have been employed for important time series analysis tasks including forecasting (Wang et al., 2024c; Williams et al., 2024; Liu et al., 2024a; Tan et al., 2024), anomaly detection (Dong et al., 2024; Liu et al., 2024b), and time series understanding (Cai et al., 2024; Li et al., 2024a,b). When analyzing time series data, the goal is often to infer events occurring in the measured environment (Liu et al., 2024b). Therefore, there is a need to explore how LLMs infer event descriptions given context and time series data.

Prior work on reasoning about time series in conjunction with natural language has largely overlooked event descriptions (Merrill et al., 2024; Williams et al., 2024) and primarily focused on numerical sequences, such as trend analysis (Cai et al., 2024) or anomaly detection (Dong et al., 2024). Some studies collect sequences of news related to time series (Wang et al., 2024c; Liu et al., 2024a; Cheng and Chin, 2024), however they are curated for forecasting and do not explore reasoning from time series to events. Meanwhile, due to the limited size and the potential inclusion of event descriptions that do not impact the time series, these data are not ideal as a benchmark source.

To address this gap, we introduce a benchmark that integrates time series data with associated events described in natural language. The events exhibit clear correlations with time series fluctuations, making it feasible to evaluate LLMs' event reasoning capabilities. Our benchmark dataset (described in Section 3.3) includes 4,200 games from NBA (basketball) and NFL (American football) sports leagues, comprising a total of 1.7 million data points and events, with the capability for continuous updates. During testing, we replace real en-

^{*}All resources needed to reproduce our work are available: https://github.com/BennyTMT/GAMETime



Figure 1: Illustration of time series event reasoning. The prompt provides (in text form, see details later in the paper) a time series of real-valued data (win probabilities) and corresponding natural language event descriptions. The model is prompted to select the most likely sequence of events for some segment of the time series data where no events are provided. (This example is taken from near the end of an NBA game, which is 48 minutes regulation time, between the Dallas Mavericks (Team A) and Los Angeles Lakers (Team B), 1 November 2019.)

tity names and use only games from after the LMs' training cut-off date to mitigate potential memory effects in reasoning. We use the win probability output from ESPN's game analysis[†] as the time series. As we discuss in Section 6, win probability is an effective measure of game state but potentially differs from ground truth.

To evaluate the effectiveness of our benchmark in assessing LLMs' ability to reason about time series and events under different conditions, we test 16 models across various factors, including the impact of available context, varying sequence lengths, and time series similarity on reasoning. Additionally, we examine the impact of the presence or absence of time series and real entity names on reasoning through two ablation studies. To explore the generalizability of our approach, we extend the evaluation to open-domain settings, including cryptocurrency prices (Li et al., 2024a) and U.S. health data (Liu et al., 2024a). Our findings indicate that LLMs exhibit promising reasoning capabilities. For instance, the distilled DeepSeek-R1 32B achieves a 68% accuracy on our basketball event reasoning benchmark (76.5%, w/ CoT prompt), while GPT-40 reaches 41% accuracy (53%, w/ CoT prompt), both significantly outperforming guessing (25%).

Our key contributions include introducing an evaluation approach (Section 3.2) to assess LLMs' ability to reason about event sequences through time series and extend it to multiple domains (Section 4.5). We create an easily extensible dataset with 1.7 million timesteps with values and events (Section 3.3), where changes in time series are explicitly influenced by events. In benchmarking 16 LLMs, we find promising reasoning capabilities and find clear avenues to enhance reasoning (Section 4.2).

2 Related Work

Despite a growing body of work on LLMs and time series reasoning which we summarize in this section, previous benchmarks for LLMs in time series and event reasoning have not addressed the task of inferring event sequences from time series.

2.1 Time Series Reasoning with LLMs

Many studies used text to assist in time series reasoning (including forecasting), achieving promising results (Cao et al., 2024; Wang et al., 2024a; Xie et al., 2024). These works have made significant contributions to fields such as sociology (Cheng and Chin, 2024), energy (Wang et al., 2024c; Xu et al., 2024), and finance (Li et al., 2024a; Wang et al., 2024b). For example, Williams et al. (2024)

[†]ESPN's sports data analysis: https://www.espn.com/ analytics/

Benchmark/ Evaluation	Properties (with Time Series)						
	Context	Source	Task				
Williams et al. (2024)	Description	Manual	Forecasting				
Merrill et al. (2024)	Description	Synthetic	Reason & Forecast				
Cai et al. (2024)	Question	Manual	Understanding				
Liu et al. (2024a)	News Series	Real-World	Forecasting				
	Properties (without Time Series)						
Fatemi et al. (2024)	Event & Time	Synthetic	Temporal Reasoning				
Xiong et al. (2024)	Event & Time	Synthetic	Temporal Reasoning				
Chu et al. (2023)	Event & Time	Real-World	Temporal Reasoning				
Quan and Liu (2024)	Event Sequence	Synthetic	Sequential Reasoning				
Karger et al. (2024)	Event	Real-World	Future Forecasting				
Ours	Time Series & Event Sequence	Real-World	Events Reasoning				

Table 1: Time series benchmarks typically lack a focus on inferring event sequences, while event reasoning evaluations do not incorporate multimodal reasoning over numerical sequences. We propose reasoning about event sequences through time series data, incorporating corresponding timestamps.

manually curated time series forecasting data along with related text to highlight the importance of incorporating textual information when using LLMs for forecasting. Wang et al. (2024c) used news about energy to help LLMs predict local electricity conditions. Intrinsically, those approaches depend on LLMs' multi-modal transfer of knowledge from natural language to time series.

However, there are also critical areas where reasoning about real-world events through time series analysis holds significant potential to enhance performance (Jin et al., 2024; Jiang et al., 2024b), compared to unimodal methods. Using LLMs for anomaly detection (Dong et al., 2024; Zhou and Yu, 2024) often involves processing time series data, such as CPU usage rates from system monitors, and then generating an interpretable anomaly report (Liu et al., 2024b). Similarly, other domains, such as medical care (Chan et al., 2024), market analysis (Lee et al., 2024; Ye et al., 2024), and human activity analysis (Li et al., 2024b), also rely on this multi-modal reasoning capability to make actionable decisions.

Table 1 summarizes benchmarks intended to evaluate LLMs' capability in processing time series data. Cai et al. (2024) proposed a benchmark using synthetic data to evaluate LLMs' understanding of time series, focusing on tasks such as pattern recognition. Similarly, Merrill et al. (2024) introduced synthetic time series data and relevant textual descriptions, containing a single event (cause), to evaluate LLMs' performance in matching time series to the scenarios that generated them (i.e., etiological reasoning). Due to the lack of paired event sequence, none of these works evaluated the LLMs' ability to reason about events related to the time series data.

The one exception is Liu et al. (2024a), which collects news sequences corresponding to time series dating back to 1983. However, due to the limited dataset size and potential contamination issues, it is challenging to use as a fair evaluation source, especially since the exact impact of news on time series remains unclear. To fill this gap, we propose a living benchmark with data sourced from continuously refreshed naturally-occurring data (in our case, from widely available sports data). This avoids the pitfalls associated with synthetic data, and because it can be easily refreshed avoids the contamination risks with fixed benchmarks.

2.2 LLMs for Events Reasoning

Reasoning is an ill-defined and broad, yet critical, capability that determines LLMs' performance across many complex tasks. Therefore, numerous reasoning benchmarks have been developed for valuable tasks, such as coding (Zhuo et al., 2024; Jain et al., 2024), mathematics (Cobbe et al., 2021; White et al., 2024), and finance (Xie et al., 2023; Islam et al., 2023). Additionally, some benchmarks have evaluated the general reasoning abilities of LLMs (Bang et al., 2023; White et al., 2024), including BBH (Suzgun et al., 2022) and MMLU (Hendrycks et al., 2020).

Several benchmarks, as listed in Table 1, have been proposed to evaluate LLMs' understanding of relationships between events (Quan and Liu, 2024), as well as temporal reasoning capabilities for understanding the relationships between events and time (Xiong et al., 2024; Chu et al., 2023). For instance, Karger et al. (2024) introduced a dynamically updated benchmark to evaluate LLMs' forecasting of future events. Fatemi et al. (2024) used synthetic data to assess LLMs' perception and reasoning between events and time. However, these benchmarks do not consider the interplay between time series and associated event sequences, which is the focus of our work.

3 Benchmark

We next define the benchmark task, outline the evaluation format, and introduce the dataset details.

3.1 **Problem Definition**

A time series is a sequence of timestamped real values: $x = [(t_0, x_0), (t_1, x_1), ..., (t_T, x_T)]$. An event sequence is a sequence of timestamped text descriptions of events: $e = [(t_0, e_0), (t_1, e_1), ..., (t_T, e_T)]$. For each sequence, the timestamps t are monotonically increasing $(t_i \le t_j \text{ if } i < j)$. While the timestamps of the time series and event sequence need not be identical, there is often a one-to-one correspondence, with an event description associated with each real value. Critically, the events describe changes in the environment that result in changes in the time series values.

Given a dataset $\mathcal{D} = (\mathcal{X}, \mathcal{E})$ containing N realvalued time series and timestamp t with corresponding event sequences of length T, we are concerned with time series data represented as a pair of sequences:

$$\mathcal{X} = [(t_0, x_0), (t_1, x_1), ..., (t_{N-1}, x_{N-1})]$$

consisting of real-valued measurements, and

$$\mathcal{E} = [(s_0, e_0), (s_1, e_1), ..., (s_{T-1}, e_{T-1})]$$

comprising natural language event descriptions. Although there may not always be a direct causal relationship between the events and measurements, we assume there is some connection between the events and measurements and that the timestamps, s_j and t_i , are synchronized. Note that we do not assume that there is one event associated with each data value, or even that the timestamps of events and data values match, only that they are aligned so the ordering relationships between values in \mathcal{X} and events in \mathcal{E} are known.

Our goal is to interrogate an LLM's understanding of time series data by measuring its ability to infer unobserved values in \mathcal{E} given \mathcal{X} . As illustrated in Figure 1, when the intermediate event sequence is missing, the LLM is expected to infer it using the provided real-valued time series and corresponding timestamps.

3.2 Events Reasoning Format

We formulate our event reasoning evaluation as a multiple-choice question where the model is prompted to select the event descriptions that are most likely to correspond to the provided realvalued time series data. The prompt follows this template:

System Prompt: {{sys_prompt}} $t_i x_i$ $t_{i+1} x_{i+1}$... $t_{i+k-2} x_{i+k-2}$ $t_{i+k-1} x_{i+k-1}$ Four options to choice:{{options}} Respond with this format:{{format}}

where we provide contextual task information (i.e., sys_prompt), along with real-valued time series of length k (e.g., $x_{i:i+k-1}$). Since time series data are typically accompanied by timestamps, the corresponding timestamps $t_{i:i+k-1}$ are provided in the prompt. The intermediate events are missing, and the LLM is tasked with inferring these events. To make the task tractable we provide *four* options, one of which corresponds to the actual sequence of events, and prompt the model to select the most likely option. Figure 7 in Appendix B gives examples of the full prompts used in our experiments.

To further isolate the LLM's reasoning on time series, we replace specific named entities in our dataset with general, non-identifying descriptors. Specific team names are replaced with *Team A* or *Team B*. Actual player names are replaced with generic labels, such as *Player from Team A*, ensuring that the associations between players and their teams are preserved but revealing no other information about their identities. In evaluations from other domains, such as cryptocurrency prices (Li et al., 2024a), we replace all numerical values in news (events) sequence with symbols (e.g., α) to prevent LLMs from matching events to time series using dates or price. In open-domain settings, the impact of news on time series may exhibit a minor delay. Therefore, we provide two events occurring before t_i to better capture the full range of events that may influence the time series.

3.3 Sports Dataset

To obtain paired data of time series and event sequences, we use data from sports, a domain where the impact of events on the measurements is welldefined. For the natural language events, we used play-by-play data provided by ESPN[‡] that captures key occurrences during a game, such as scoring, turnovers, or fouls in basketball. As the game progresses, these events form a sequence. Each event impacts the course of the game. ESPN also provides each teams' predicted win probability throughout the game, which we use as the realvalued time series data. These win probabilities reflect the state of the game, as well as some knowledge about the teams, at each time step. Since a game constitutes a relatively closed environment, there is a clear relationship between the events and the time series: an event favoring Team A will raise Team A's win probability and reduce Team B's win probability. This closed environment makes sports data a good candidate for a benchmark evaluating how effectively LLMs reason about events through time series.

Our dataset includes 4,200 time series (games) collected through 9 January 2025. Because of the nature of the data, and the fact that new games are played frequently, our dataset can be continuously updated. The dataset contains 3,276 time series from NBA basketball games and 924 from NFL American football games. On average, each basketball time series contains 460 timesteps, while the football time series average 179 timesteps. In total, the dataset consists of 1.7 million time series data points (win probabilities) paired with corresponding in-game events.

4 Experiments

To investigate LLMs' event reasoning capabilities under diverse conditions, we explore these research questions: **RQ1:** Can LLMs reason about events, and does Chain-of-Thought (CoT) prompting enhance this reasoning?, **RQ2:** What is the effect of various available contexts beyond time series?, **RQ3:** How does event sequence length impact LLMs' ability to reason about events?, **RQ4:** Are LLMs able to distinguish underlying time series similarities?, and **RQ5:** How does LLMs' event reasoning performance compare across different domains?

We evaluate 16 language models, including closed-weight models such as GPT-40 (Achiam et al., 2023) and open-weights models like LLaMA3.1 (Dubey et al., 2024), and Qwen2.5 (Yang et al., 2024). Additionally, we test models designed for reasoning, including distilled DeepSeek-R1 32B and 8B (DeepSeek-AI, 2025). Our findings indicate that LLMs, such as GPT-40, LLaMA3.1 70B, and particularly the reasoningoriented DeepSeek-R1 32B, demonstrate promising reasoning capabilities.

4.1 Accuracy Evaluation

In our event reasoning baseline, we follow the format in Figure 7 from Appendix B, but provide only Team A's win probabilities (in NBA basketball there are no draws, and in NFL football draws are very rare, so the win probability for Team B is 1 - the win probability for Team A) and set the event sequence length to 10. The negative options are sequences of the same length randomly sampled from other games. Each model is evaluated on 200 questions. To eliminate memorization effects in reasoning, we select games that occurred after the models' training cutoff dates and replace real team and player names with generic labels such as Player from Team A. Results, shown in Figure 2, indicate that reasoning about football events is more challenging, as GPT-40 achieves only 29% accuracy, compared to 41% in basketball. Among the tested LLMs, the distilled DeepSeek-R1 32B performs the best, achieving 43% accuracy in football event reasoning and 68% in basketball. In addition, other open-weights models, such as LLaMA3.1 70B and Qwen2.5 72B, or even Phi-4 14B, reaches performance levels comparable to GPT-40.

Impact of Chain-of-Thought Prompting. Next, we investigate if a longer reasoning process with Chain-of-Thought (CoT) prompting (Wei et al., 2022) improves results of LLMs on event reasoning. In short, the answer is **yes**—LLMs show an average improvement from CoT prompting of 4.5% for basketball events and 9.6% for football events.

[‡]The source of the sports data can be accessed via https: //www.espn.com/



Figure 2: The performance of various language models on events reasoning indicates that open-weights models, such as Qwen2.5 72B (Yang et al., 2024), achieve comparable or even superior results to proprietary models like GPT-40 (API version 2024-05-13) (Achiam et al., 2023), particularly reasoning-focused models such as DeepSeek-R1-distill 32B (DeepSeek-AI, 2025), which significantly outperforms others. Additionally, Chain-of-Though (CoT) prompting further enhances reasoning performance. Note that open-weight models are ordered by size.

The longer reasoning process with CoT, however, also increases the likelihood of LLMs failing to return answers in required format. For example, GPT-40 achieves an 11% improvement in accuracy but increases instruction-following failures from 0 to 17 in 400 test samples. In contrast, some models instruction following benefits from CoT prompting. For Phi-3.5 14B-Instruct, the failures rapidly decrease from 359 to 45, which may be attributed to the instruction-tuning process. Adding CoT prompting improves DeepSeek-R1 32B accuracy by 9% while maintaining a 0% failure rate, demonstrating stability in instruction following. The overall instruction following failure rate increased by 0.6% after adding CoT prompting. In our CoT prompt, we provide a example with reasoning process to induce LMs (Details are in Figure 8). We acknowledge the potential for additional CoT prompt optimization, but we do not further explore this due to computational constraints.

4.2 Impact of Context

In different applications, the available context that LLMs can access varies. In addition to the baseline setting, where only the real-valued time series data is provided, we also evaluate LLMs' performance when different reasoning-relevant contexts are made available or modified. For example, in basketball-related tasks, if the score is provided at each step, a proficient reasoner should use the score information to eliminate inconsistent event options, thereby improving inference accuracy. To evaluate the impact of real-valued time series in the reasoning process, we conduct a simple ablation study. The impact of different conditions is summarized in Table 2. We observe that when time series is removed (i.e., w/o TS), all reasoning performances drop to near-random guessing levels (i.e., accuracy is around 25%), *indicating that LLMs are leveraging time series for event reasoning*. In contrast, providing LLMs with team names and real entities in events (e.g., team and player names) (w/Name) notably improves reasoning, highlighting the necessity of removing them when evaluating reasoning (Fatemi et al., 2024).

Due to differences between the football and basketball data, various conditions influence reasoning differently. For example, timestamps provide the most significant improvement in reasoning for football. Similarly, when providing the score (TS+Score) or partial events, e_i and e_{i+k-1} (TS+Event), reasoning performance also improves. Given computational constraints, we only include non-reasoning-oriented models that outperform guessing in our experiments from now on.

To test whether LLMs can detect logically inconsistent information to aid reasoning, we shuffle the order of ground-truth events to create negative options (labeled as *Reorder*). Due to the nature of possession changes in football and basketball, event

Tasks	Language	Baseline	Ava	ailable Con	text	Abla	Options	
	Models	(TS Only)	TS+Time	TS+Score	TS+Event	w/ Name	w/ Name w/o TS	
Basketball Reasoning	GPT-4o(0513)	41.0%	39.0%	47.5%	39.0%	55.0%	28.5%	69.5%
	GPT-4o(mini)	25.0%	24.5%	25.0%	26.0%	43.5%	21.0%	39.0%
	Qwen2.5(72B)	36.5%	39.0%	43.5%	39.5%	41.0%	24.5%	66.0%
	LLaMA3.1(70B)	40.5%	37.0%	50.5%	38.5%	51.0%	26.5%	47.5%
	Qwen2.5(32B)	44.5%	43.5%	57.5%	43.5%	50.0%	22.5%	59.0%
	Phi4(14B)	43.0%	35.0%	40.0%	36.0%	42.5%	25.0%	47.0%
	Qwen2.5(14B)	27.5%	34.5%	33.0%	32.0%	48.0%	22.0%	44.5%
	Avg. Impact of the	ne Condition	↓ -0.6%	\uparrow 14.6%	\uparrow 0.0%	\uparrow 33.2%	↓-32.2%	↑ 46.8%
Football Reasoning	GPT-4o(0513)	29.0%	75.5%	43.5%	53.0%	71.0%	18.5%	60.0%
	GPT-4o(mini)	25.0%	52.0%	26.5%	35.5%	33.5%	24.5%	42.0%
	Qwen2.5(72B)	30.5%	69.0%	42.0%	40.5%	52.0%	25.0%	54.0%
	LLaMA3.1(70B)	26.5%	71.0%	47.5%	35.5%	65.5%	20.5%	46.0%
	Qwen2.5(32B)	33.0%	74.5%	43.5%	46.0%	40.5%	27.5%	43.5%
	Phi4(14B)	29.5%	46.5%	36.0%	38.5%	43.5%	25.0%	28.5%
	Qwen2.5(14B)	28.5%	55.5%	28.5%	34.5%	63.5%	25.5%	33.0%
	Avg. Impact of the	ne Condition	\uparrow 120.1%	↑ 32.4 %	↑ 40.4%	↑ 84.2%	↓ -17.3%	↑ 52.8%

Table 2: LLMs' event reasoning accuracy (%) under various conditions based on the baseline (i.e., providing only time series). We provide each model with 200 questions for each condition (N = 200). Red highlights the best-performing model under a given condition, while Blue represents the second-best.

sequences follow sequential constraints. When logical inconsistencies are introduced in the events, LLMs with reasoning capabilities should be able to use this information to eliminate negative options.

4.3 Number of Events

Increasing the number of events in the reasoning process has two potential effects. On one hand, a competent reasoner should leverage the additional information to identify logical inconsistencies, such as contradictions between events and corresponding win probability changes. On the other hand, as the reasoning length increases, the likelihood of errors also rises. A longer reasoning process does not necessarily lead to more accurate results (Wei et al., 2022). A capable LLM should ignore any superfluous information in the additional events, and benefit from any additional information.

To study the effect of event quantity, we follow the setup in Section 3.2 and design questions with an increasing number of events. The results, summarized in Figure 3, reveal an interesting pattern: the impact of event quantity varies across different datasets. When reasoning about basketball events, LLMs generally perform slightly worse as the number of events increases; for football events, however, LLM performance improves. This discrepancy may stem from fundamental differences between the two sports. In a football game, because teams alternate possessions that comprise multiple correlated plays, or events, making it easier to recognize and match patterns. In basketball, each possession is typically connected to only one event, and events are more independent, and most events impact the score of the game directly. In football, each possession involves many events (at least one recorded for each down in football), but most events do not impact the score of the game. One insight is that the amount of useful information is different across different domains.

4.4 Disparity of Data

Time series serve as an alternate modality for event sequences. Consequently, when two time series are similar, distinguishing the two corresponding event sequences based on the time series alone becomes challenging. To assess how the time series similarity impacts LLMs' reasoning, we control the distance between the time series associated with positive and negative options. We compute distance D between time series using the Euclidean distance



Figure 3: The reasoning performance of LLMs across event sequences of various lengths. The figure includes only models that consistently outperform the baseline.



Figure 4: The performance of LLMs in distinguishing events corresponding to time series (win probabilities) with different levels of similarity. Time series *similarity* decreases as x (i.e., time series *distance*) increases.

after *z*-score normalization:

$$D = ||norm(\mathbf{p}_{win}) - norm(\mathbf{p}_{win})||_{l2}$$

We bootstrap the pairwise distances between win probabilities (i.e., \mathbf{p}_{win}) of length 10 in our dataset and normalize them to the range (0, 1). The results show that a large proportion of time series pairs fall within the (0.4, 1) range, e.g., 90.6% for NFL and 91.3% for NBA data (see Figure 6 in Appendix A.4 for details). Therefore, we divided the distances into seven levels, starting from 0.4 with an increment of 0.1 per level.

We follow the setup in Section 3.2, setting the sequence length to 10 and evaluating each LM on 200 questions. We keep the ground-truth events and question time series consistent across all levels. The results are presented in Figure 4, showing a slight upward trend in LLM performance as similarity decreases. This is due to the inherent consistency between time series and event sequences, which LLMs are able to recognize.

4.5 Other Domains

In real-world open environments, time series data usually coexist with related textual sequences, such as the proportion of infectious diseases alongside U.S. government influenza reports (Liu et al., 2024a) or cryptocurrency prices alongside relevant financial news (Li et al., 2024a). To evaluate the generalizability of our approach, we extend our evaluation to four other domains: trade (Import/-Export, IMEX), health (influenza rates), and energy (gasoline prices) from Time-MMD (Liu et al., 2024a), as well as cryptocurrency time series from CryptoTrade (Li et al., 2024a). To prevent the questions from becoming too long, we use news titles as events for cryptocurrency. We selected the "factual" field as the events occurring at each timestamp from Time-MMD. Liu et al. (2024a) extracted these "factual" statements from news and reports to describe real-world occurrences. Our question follows the format in Section 3.2, with an event sequence length of 10, corresponding to 10 trading days for Bitcoin data or 10 weeks of influenza statistics in the U.S. health dataset.

We evaluate two settings: one where events contain numerical information (i.e., *Complete*) and another where all numerical values, such as dates or real values (e.g., Bitcoin prices or trading volumes), are replaced with symbols like α (i.e., *Filtered*). Since numerical information provides crucial context for reasoning, removing it degrades performance. Table 3 summarizes the results. Even after stripping numerical data, however, LLMs still demonstrate moderate reasoning ability. GPT-40, for instance, consistently achieves over 50% accuracy. Additionally, open-weights models such as Qwen2.5 72B and reasoning-oriented models like DeepSeek-R1 32B demonstrate comparable performance to GPT-40.

5 Conclusions

Data comprising time series real values paired with event sequences occur in many important domains. We introduce a dataset containing 1.7 million realvalued time series paired with events and a method for evaluating the ability of an LLM to reason about events corresponding to real-valued time series data. Our evaluation of 16 language models using this benchmark reveals that both open-weights and proprietary models exhibit promising reasoning capabilities, with reasoning-focused models such as DeepSeek-R1 32B outperforming larger proprietary model such as GPT-40.

6 Limitations and Ethical Considerations

Our dataset includes time series representing win probabilities in sports, which serve as a effective measurement of how events affect a team's state

$\begin{array}{c} LLMs \rightarrow \\ Domains \downarrow \end{array}$		GPT-40 (0513)	GPT-40 (mini)	Qwen2.5 (72B)	LLaMA3.1 (70B)	Mixtral (8x7B)	DeepSeek (R1 32B)	Qwen2.5 (32B)	Mistral (22B)	Phi4 (14B)	Qwen2.5 (14B)	DeepSeek (R1 8B)
Crypto (Bitcoin)	Complete	84%	58%	71%	49%	36%	62%	72%	28%	46%	51%	42%
	Filtered	<mark>65%</mark> ↓22.6%	40% ↓31.0%	40% ↓43.7%	34% ↓30.6%	29% ↓19.4%	39% ↓37.1%	39% ↓45.8%	27% ↓3.6%	28% ↓39.1%	32% ↓37.3%	25% ↓40.5%
Trading (IMEX)	Complete	91%	90%	90%	85%	52%	93%	86%	54%	75%	71%	78%
	Filtered	50% ↓45.1%	35% ↓61.1%	51% ↓43.3%	36% ↓57.6%	21% ↓59.6%	47% ↓49.5%	45% ↓47.7%	27% ↓50.0%	29% ↓61.3%	31% ↓56.3%	22% ↓71.8%
Health (Influenza)	Complete	62%	53%	77%	64%	34%	74%	60%	24%	52%	42%	48%
	Filtered	33% ↓46.8%	26% ↓50.9%	34% ↓55.8%	27% ↓57.8%	25% ↓26.5%	37% ↓50.0%	32% ↓46.7%	23% ↓4.2%	30% ↓42.3%	33% ↓21.4%	25% ↓47.9%
Energy (Gasoline)	Complete	97%	95%	96%	84%	63%	98%	90%	57%	89%	72%	79%
	Filtered	52% ↓46.4%	40% ↓57.9%	48% ↓50.0%	46% ↓45.2%	28% ↓55.6%	49% ↓50.0%	45% ↓50.0%	24% ↓57.9%	43% ↓51.7%	37% ↓48.6%	29% ↓63.3%

Table 3: The number of correct event reasoning (through time series) made by LLMs across other domains among testing samples (N = 100). Replacing numerical information in the option events—such as dates or prices—with symbols like α (*Filtered*) results in a performance decline compared to retaining the original numerical information (*Complete*). Red indicates the best model in this task, while Blue represents the second-best.

and have a clear relationship with events. Since it is impossible to know the true underlying probability of the game outcome, these probabilities are estimates of each team's chances to win the game produced by ESPN's proprietary model, and not the ground truth. Note that we focus on evaluating the performance of current models rather than exploring how our data can be used for reasoning model training, which we leave for future work.

We release all code and data necessary to replicate our complete experiments at https:// github.com/BennyTMT/GAMETime. As we await approval from the data provider, however, we may not be able to release the final curated dataset. In that case, we will provide the tools necessary to replicate our data collection process.

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A Appendix

A Datasets and Language models

In this section, we introduce NBA and NFL event and time series data through examples from sports datasets. Additionally, we present the models we evaluate and provide details on data from other domains.

A.1 Events and Time Series in Sports

Figure 5 illustrates the time series and event sequences for basketball and football. When an event favorable to Team A occurs, Team A's win probability typically increases. For example, in basketball, this could be a successful score by Team A or a turnover by Team B. In football, it could include defensive plays and sacks by Team A, penalties against Team B, or offensive success by Team A. Conversely, unfavorable events lead to a decrease in win probability.

A.2 Language Models and Setups

We have run our evaluation and experiments on Nvidia A100 GPUs. The specific settings for LLMs, as well as the packages used for data processing, are provided in the repository[§]. We evaluated a total of 16 models, including openweight models such as LLaMA3.1 (Dubey et al., 2024), proprietary models like GPT40 (Achiam et al., 2023), and reasoning-focused models such as DeepSeek-R1 (DeepSeek-AI, 2025). The full list of tested models is as follows:

- **GPT4o** (Achiam et al., 2023): We test GPT4o-0513, a high-performance variant of GPT-4 optimized for both general-purpose generation and specialized tasks, and GPT4o-mini, a scaled-down version of GPT-4 designed for resource-constrained environments.
- LLaMA (Dubey et al., 2024): We evaluate instruction-tuned models of various parameter sizes, including LLaMA3.1-Instruct 70B, 8B, and LLaMA2-Instruct 7B.
- Qwen2.5 (Yang et al., 2024): Our experiments included various instruction-tuned models such as Qwen2.5-Instruct 72B, 32B, 14B, and 8B.
- **Mixtral** (Jiang et al., 2024a): We test the 8x7B Mixture of Experts (MoE) model, along with Mixtral-Small 22B and Ministral-8B.

- **Phi** (Abdin et al., 2024): We included Phi-4 14B and Phi-3.5-Instruct 14B in our evaluations.
- DeepSeek-R1 (DeepSeek-AI, 2025): Given computational constraints, we still evaluated reasoning-focused models such as DeepSeek-R1 32B and 8B. These models are distilled versions of DeepSeek-R1, using synthetic data from R1 to finetune Qwen 32B and LLaMA 8B, respectively.

A.3 Open-world Domains

To validate whether LLMs can reason about events through time series in other domains, we utilized four open-world datasets from different fields: Time-MMD (Liu et al., 2024a) (covering Trading, US Health, and Energy) and CryptoTrade (Li et al., 2024a) (Bitcoin prices). The details are outlined as follows:

- **Trading**: Includes monthly U.S. International Trade Balance data from January 1987 to March 2024 (total length of 423 months), covering both import and export trade volumes. The corresponding text consists of keyword searches and institutional reports relevant to that month, such as "U.S. International Trade in Goods and Services".
- U.S. Health: Includes weekly Influenza Patients Proportion data from September 1997 to May 2024 (total length of 1 389 weeks). The corresponding text sequences are sourced from weekly keyword searches or reports from the "CDC's ILINet system".
- Energy: Contains weekly Gasoline Prices (Dollars per Gallon) from April 1993 to April 2024 (total length of 1 479 weeks). The text sequences are obtained through searches or reports from institutions such as the U.S. Energy Information Administration.
- **Bitcoin**: Contains daily Bitcoin price data from January 1, 2023, to February 1, 2024 (time series length of 397), including opening and closing prices, as well as the highest and lowest prices of the day. The corresponding text sequence is derived from authoritative sources such as Bloomberg and Yahoo Finance, filtered through keyword searches to provide five of the most relevant news articles per day. We use their headlines as event descriptions.

[§]All information and settings needed are available:https: //github.com/BennyTMT/GAMETime



Figure 5: Examples of events and win probabilities in the NBA and NFL dataset. As the game progresses, ESPN provides descriptions of on-field events along with the corresponding win probabilities for each team at that moment. These probabilities can be considered a representation of the team's current state.



Figure 6: The similarity distribution of time series in sports data, with a time series length of 10. There is a 91% probability that the distance between two time series falls beyond 0.4.

A.4 Time Series Similarity

We bootstrapped 10k pairwise distances between win probabilities of length 10 for both NBA and NFL data. After normalizing the distances to the range (0, 1), their distribution is shown in Figure 6, where 91% of the distances fall beyond 0.4.

B Prompt Template

Figure 7 presents the complete template for NBA and U.S Health event reasoning. For NFL data and other domains, we adopt a similar template with minor variations to accommodate domain-specific characteristics. For instance, in cryptocurrency data (Li et al., 2024a), we specify that the provided time series represents daily "Closing Prices," while

in Energy data (Liu et al., 2024a), it corresponds to the "Dollars per Gallon." (Gasoline). In addition, considering the delayed impact of real-world news, we included news events from the previous two timestamp in the options. Figure 8 illustrates the Chain-of-Thought (CoT) prompt for NBA event reasoning, with the format up to the "options" section remaining consistent across prompts. The CoT prompt for NFL follows a similar structure with slight modifications, such as ensuring that example events and background knowledge align with the context of American football. Note that we acknowledge that the current CoT prompt still has room for improvement, however, due to time and computational constraints, we have not conducted further explorations.

C Language Models Reasoning Process

To further understand how LLMs infer events from time series, we analyzed their output. As shown in Figure 9, this illustrates the reasoning process of DeepSeek-R1 32B (DeepSeek-AI, 2025) for NBA events (under a CoT prompt). The model first interprets the trend in the time series and then matches it with potential events—If the time series exhibits an upward trend, the model aligns it with events favorable to Team A, and vice versa. After sequentially analyzing all data points and their corresponding events, LLMs synthesize their step-by-step analyses to formulate a final reasoning conclusion. High-performing models, such as GPT-40 (Achiam et al., 2023), LLaMA3.1 70B (Dubey et al., 2024), Qwen2.5 72B (Yang et al., 2024), and even smaller language model, like Phi-4 (Abdin et al., 2024) 14B, demonstrate similar reasoning trajectories with CoT Prompting.

D Licensing

The code from our work is released under the MIT License, while the dataset is made available under the Creative Commons Attribution-NonCommercial-ShareAlike (CC BY-NC-SA) license. This allows anyone to use, distribute, and modify the data for non-commercial purposes, provided they give proper attribution and share any derivative works under the same license terms.

Event Reasoning in Sports (Basketball)

You are an assistant for NBA basketball task. We will provide a series of consecutive timestamps, win probabilities from a basketball game, though some intermediate events will be missing. You will need to infer the likely events that occurred in the missing intervals.

Below is provided timestamps, win probabilities (team A).

Step 1.TimeStamp1 WP_1 Step 2.TimeStamp2 WP_2 Step 3.TimeStamp3 WP_3 ...Step k.TimeStampk WP_k

Please select the correct sequence of events for steps 2, ..., k - 1 from the four options below,

Here are the potential options:{{options}}

Here is the instruction for returning reasoning results in:{{format}}

Event Reasoning in Other Domains (U.S Health)

You are an assistant for an Influenza Patients task. We will provide a series of consecutive timestamps along with the Influenza Patients Proportion. Additionally, we will present four potential event (news) sequences that occurred during that period, as well as from the previous two days. Your task is to identify and select the correct sequence of events.

Below is provided date and Patients Proportion (%),

Step 1. Date₁ x_1 Step 2. Date₂ x_2 Step 3. Date₃ x_3 ••• Step k. Date_k x_k Please select the correct sequence of events for steps 2, ..., k-1 from the four options below, Here are the potential options:{{options}} Here is the instruction for returning reasoning results in:{{format}}

Figure 7: Template used to infer events through win probabilities in sports (e.g., basketball) and open-world domains (e.g., U.S Health). For NFL data and other domains, we adopt a similar template with minor variations to accommodate domain-specific characteristics. In addition, we use the format "**X**".

Chain-of-Thought (CoT) Prompt Template for Basketball

You are an assistant for NBA basketball task ...

Here are the potential options:{{options}}

When reasoning, please refer to the following guidelines:

1. Analyze Team A's 1st win probability change. For example:

- 0. 53.4%

- 1. 57.1%

- Team A's win probability increased from 53.4% to 57.1%, indicating that an event positive to Team A or negative to Team B has occurred.

2. Pause the win probability analysis for now and focus on the 1st event in options a, b, c, d, and eliminate the inconsistent options or skip this step if unsure. Please ignore very minor changes in win probabilities, such as 0.1%-0.4%. Base your decision on significant changes.

3. Similarly, turn to analyze the change in the 2nd win probability and match it with the 2nd event in the remaining options, and eliminate the inconsistent options or skip this step if unsure.

4. Repeat the above process until all incorrect options are eliminated.

Consider the following information when reasoning, it will assist you in reasoning.

1. Positive events for Team A, such as "Player from Team A scores (e.g., makes a layup or jump shot) or rebounds," or negative events for Team B, such as "Player from Team B makes a mistake (e.g., misses a shot, commits a foul, or loses the ball)."

2. Some events do not impact the win probability, such as a player entering the game or a timeout.

3. Ignore very minor changes in win probabilities, such as 0.1%-0.4%.

Return your answer in the format **X**, where X only contains the chosen option, such as **a**, **b**, **c**, or **d**.

Figure 8: Chain-of-Thought (CoT) Template used to infer events through win probabilities in sports (e.g., basketball). For NFL data, we adopt a similar CoT Prompt with minor variations to accommodate domain-specific characteristics.

Process of Event Reasoning via Time Series From DeepSeek-R1 32B

<think>

Alright, I'm trying to figure out which sequence of events corresponds to the given win probabilities for Team A. The probabilities are as follows:

0. 31.9% 1. 43.9%

... ... 10. 56.7%

11. 50.9%

I need to **analyze the changes in win probability after each event** and match them with the options provided (a, b, c, d). Let's go through each step one by one.

Starting with the first change: from 31.9% to 43.9%. That's an increase of about 12%, which is significant. This suggests a positive event for Team A or a negative event for Team B. Looking at the options, the first events are:

- a. Player A makes a 3-pointer with an assist.
- b. Player B makes a free throw 2 of 2.
- c. Player B defensive rebound.
- d. Timeout and coach's challenge.

Option a's first event is a 3-pointer made by Team A, which would increase their win probability. Option b's first event is a free throw made by Team B, which would decrease Team A's win probability, but the probability went up, so b might be inconsistent.

••• •••

So, option a seems the most likely for the first event because scoring a 3-pointer would increase Team A's chances.

•••

The sixth change: from 43.0% to 49.3%, an increase of about 6.3%. Positive event for Team A.

••••

Putting it all together, option a seems to fit all the significant changes in win probability. The other options don't align as well with the increases and decreases observed.

<think>

a

Figure 9: Reasoning process example from basketball data: In this case, the ground-truth answer is "a", which aligns with the reasoning of DeepSeek-R1 32B (DeepSeek-AI, 2025). Other LLMs, such as GPT-40 (Achiam et al., 2023), follow a similar reasoning pattern. To save space, some content has been omitted.