

Time-MQA: Time Series Multi-Task Question Answering with Context Enhancement

Yaxuan Kong^{1*}, Yiyuan Yang^{1,2*}, Yoontae Hwang¹, Wenjie Du², Stefan Zohren¹,
Zhangyang Wang³, Ming Jin^{4†}, Qingsong Wen^{1,5†},

¹University of Oxford, ²PyPOTS Research, ³University of Texas at Austin,

⁴Griffith University, ⁵Squirrel Ai Learning

yaxuan.kong@eng.ox.ac.uk, yiyuan.yang@cs.ox.ac.uk

Abstract

Time series data are foundational in finance, healthcare, and energy domains. However, most existing methods and datasets remain focused on a narrow spectrum of tasks, such as forecasting or anomaly detection. To bridge this gap, we introduce Time Series Multi-Task Question Answering (Time-MQA), a unified framework that enables natural language queries across multiple time series tasks - numerical analytical tasks and open-ended question answering with reasoning. Central to Time-MQA is the TSQA dataset, a large-scale dataset containing $\sim 200k$ question-answer pairs derived from diverse time series spanning environment, traffic, etc. This comprehensive resource covers various time series lengths and promotes robust model development. We further demonstrate how continually pre-training large language models (Mistral 7B, Llama-3 8B, and Qwen-2.5 7B) on the TSQA dataset enhanced time series reasoning capabilities, moving beyond mere numeric tasks and enabling more advanced and intuitive interactions with temporal data. The complete TSQA dataset, models, user study questionnaires for evaluation, and other related materials have been open-sourced here¹.

1 Introduction

Time series analysis has long been fundamental to real-world applications in finance, healthcare, energy, and other domains (Nie et al., 2024; Xu et al., 2023; Yang et al., 2021b; Chen et al., 2024b). Before the emergence of large language models (LLMs), most research in this area focused on numerical analytical tasks such as forecasting and anomaly detection, with methods typically constrained to a single objective. Recently, the community has begun to explore ways to enhance these

*Equal Contribution.

†Corresponding Authors.

¹<https://huggingface.co/Time-MQA>

Healthcare Domain - Time Series Array (150 time points)

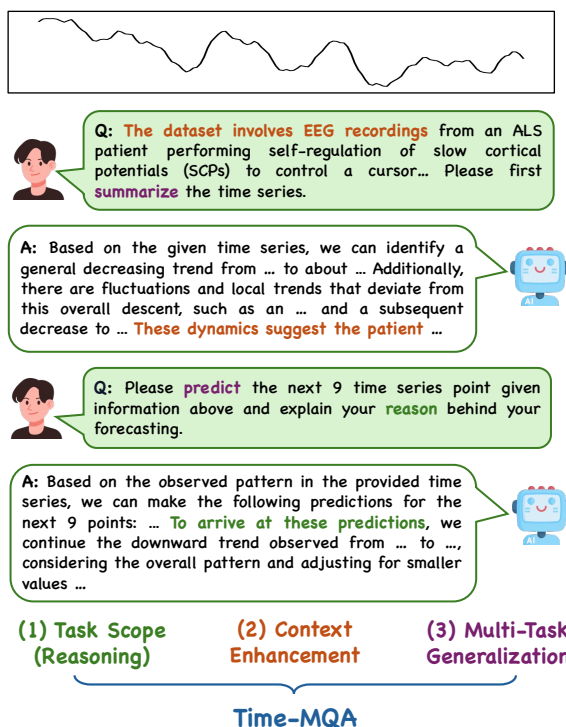


Figure 1: Example of Time-MQA with context enhancement. The LLM answers the user’s questions based on the provided context and the input time series. It can conduct reasoning and handle multiple time series tasks.

conventional time series approaches by incorporating LLMs (Fons et al., 2024; Zhang et al., 2024b); however, while some efforts do leverage contextual information, they typically focus on a single task, such as forecasting, leaving a gap in broader, multi-task reasoning and inference capabilities (Merrill et al., 2024; Ansari et al., 2024; Frisoni et al., 2024; Jin et al., 2024a). To bridge this gap, we propose a unified *Time Series Multi-task Question Answering (Time-MQA)* framework that integrates diverse tasks with natural language queries (Figure 1).

Time-MQA is crucial for advanced reasoning and inference, as it enables models to interpret

temporal data through natural language queries and uncover deeper insights beyond mere classical numeric tasks (Chow et al., 2024; Xu et al., 2024). However, there is a notable lack of relevant datasets — specifically, paired language with time series — which severely limits the development of models capable of dialogue and reasoning in this domain (Jin et al., 2024b; Kong et al., 2025). This significant gap underscores the urgent need for comprehensive resources that integrate multiple time series tasks under a question-answering framework, allowing users to query these tasks in natural language.

In this paper, we introduce *Time-MQA*, a new framework for multi-task time series question answering with context enhancement. As illustrated in Figure 1, *Time-MQA* expands beyond numerical analytical tasks by consolidating open-ended questions and classical time series tasks, such as forecasting, into a single framework. Users can pose queries in natural language, enabling a more intuitive and flexible interface for a wide range of time series analyses.

To support *Time-MQA*, we proposed *TSQA*, a large-scale dataset with approximately 200k question-answer pairs spanning multiple domains, including healthcare, environment, AIOps, machine sensors, finance, energy, traffic, IoT, nature, transport, human activities, and the web. This dataset covers various time series lengths and tasks, ensuring broad coverage and robustness. Notably, *TSQA* features open-ended reasoning questions with more elaborate text-based explanations. To the best of our knowledge, this is the first large-scale QA dataset in the time series domain that spans multiple domains and tasks, effectively bridging the gap between classical time series analysis and modern LLM-driven approaches.

We further demonstrate the utility of the *TSQA* dataset by employing continual pre-training techniques on representative LLMs such as Mistral 7B (Jiang et al., 2023), Llama-3 8B (Dubey et al., 2024), and Qwen-2.5 7B (Yang et al., 2024). Our experiments reveal that these models trained on the *TSQA* dataset can effectively acquire time series knowledge and reasoning abilities, enabling more advanced capabilities beyond basic numeric handling of time series data.

In summary, our contributions include:

- We propose *Time-MQA*, a multi-task time series question answering framework that leverages

contextual enhancement to extend beyond traditional numerical analysis tasks.

- We construct *TSQA*, a dataset comprising $\sim 200k$ question-answer pairs across over twelve domains (e.g., healthcare, finance, and energy) and five tasks (e.g., forecasting, anomaly detection, and open-ended reasoning question answering).
- We demonstrate that fine-tuning LLMs on the *TSQA* dataset equips them with time series-specific knowledge, enabling natural language queries for comprehensive time series analysis.

2 Related Works

2.1 Classical Time Series Tasks

Time series analysis has been extensively studied in various real-world applications, such as finance, healthcare, climate, electricity, AIOps, and industrial system maintenance (Nie et al., 2024; Guo et al., 2024; Ma et al., 2024; Yang et al., 2023a, 2021a). Classical time series tasks focus on extracting insights from these time series and addressing challenges associated with temporal patterns (Fuller, 2009; Hamilton, 2020).

Forecasting is one of the most fundamental tasks. It predicts future time points based on historical values and features (Lim and Zohren, 2021). Depending on the temporal horizon, forecasting can be categorized into short-term forecasting, which captures immediate fluctuations, and long-term forecasting, which models more complex temporal dependencies (Wang et al., 2024b). Common methods include statistical methods (e.g., ARIMA and exponential smoothing) and deep learning-based methods (e.g., RNN, LSTM, Transformer-based architectures) (Wen et al., 2022; Miller et al., 2024).

Anomaly detection seeks to identify abnormal patterns or deviations from expected behavior in time-series data (Zamanzadeh Darban et al., 2024). Classical approaches rely on statistical models like z-score analysis and dynamic thresholding, while contemporary methods incorporate deep learning-based frameworks, such as autoencoders, transformers, and graph neural networks, to capture complex dependencies and temporal correlations (Han et al., 2022; Yang et al., 2023b).

Imputation addresses the issue of missing or corrupted data in sequence. It is essential for ensuring data integrity in downstream analysis (Du

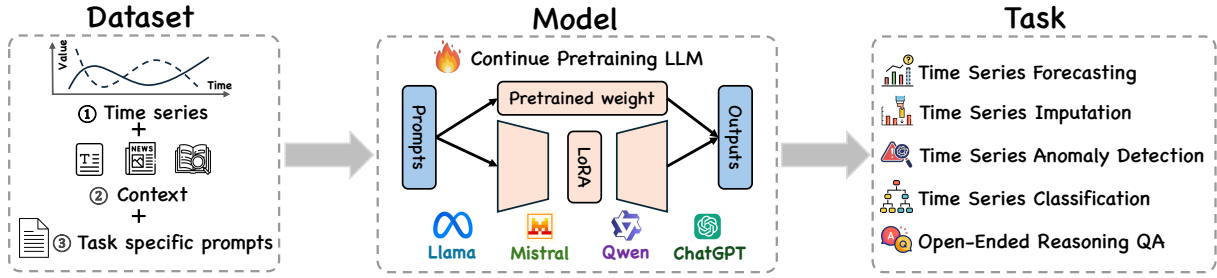


Figure 2: The overview of the proposed Time-MQA framework.

et al., 2024). Traditional imputation techniques, such as interpolation, have been widely employed, whereas deep learning-based methods, such as variational autoencoders (VAE), generative adversarial networks (GANs), and diffusion models, have recently demonstrated promising results in learning complex missing patterns and improving imputation performance (Wang et al., 2025).

Beyond these tasks, time series classification/regression, generation, augmentation, and decomposition are also frequently used in real-world scenarios (Mohammadi Foumani et al., 2024; Wen et al., 2020; Zhang et al., 2024a).

2.2 Text-Enhanced Time Series Tasks

Recent advancements in time series analysis have demonstrated the potential of incorporating textual information based on LLMs to enhance time series tasks (Jin et al., 2024b; Wang et al., 2024a). Unlike classical approaches that rely solely on numerical data, text-enhanced time series analysis leverages domain-specific textual descriptions, contextual metadata, or associated reports to improve the cognitive understanding and modeling of time-dependent patterns (Liu et al., 2024c). This hybrid approach mitigates the limitations of unimodal time series models by integrating additional semantic and contextual cues that are useful for decision-making (Kong et al., 2025; Singh et al., 2024).

In detail, text-enhanced time series forecasting and anomaly detection tasks benefit from textual information by incorporating expert reports to refine predictions and provide anomaly causal explanations (Hollmann et al., 2025; Chen et al., 2023). Similarly, classification, imputation, and generation tasks can be enhanced by leveraging textual descriptions as auxiliary supervision or describing missing values (Bernardini et al., 2023; Moor et al., 2023). It will help models distinguish subtle variations across different categories and generate more informed reconstructions.

Recent research has explored various techniques for integrating textual and time-series data, including LLM-based alignment, cross-modal attention mechanisms, and contrastive learning strategies that jointly encode text and time-series representations (Jin et al., 2023b; Zhang et al., 2023; Liu et al., 2024a). Some approaches, such as Time-LLM (Jin et al., 2023a), directly adapt LLMs to process text and time-series data, whereas others, like Time-MMD (Liu et al., 2024b), employ weighted fusion methods to combine textual embeddings with deep time-series backbones. By enhancing classical time series tasks with textual information, text-enhanced time series models offer greater robustness and richer interpretability across diverse applications (Jin et al., 2024b; Kong et al., 2025).

2.3 Language Question Answering

Question Answering (QA) in Natural Language Processing (NLP) involves systems that interpret human language queries to retrieve or generate accurate answers (Biancofiore et al., 2024; Chen et al., 2024c). It evolves from rule-based systems to neural architectures driven by LLMs like GPT-4 (Achiam et al., 2023) and Llama (Touvron et al., 2023). These models leverage massive text corpora and large-scale datasets for end-to-end pre-training, fine-tuned via supervised learning or reinforcement learning with human feedback (RLHF) to align responses with factual and contextual relevance (Liu et al., 2023). Innovations such as retrieval-augmented generation (RAG) combine parametric knowledge with external data sources, while benchmarks like SQuAD, HotpotQA, MuSiQue, FinTextQA, SyllabusQA, and ToolQA drive progress (Trivedi et al., 2022; Ho et al., 2020; Yang et al., 2018; Zhuang et al., 2024; Chen et al., 2024a; Fernandez et al., 2024). However, challenges remain, such as handling ambiguous queries, ensuring the accuracy of generated answers, and maintaining efficiency in processing

large volumes of data. Ongoing research focuses on enhancing the reasoning capabilities of QA systems, improving their ability to handle complex and nuanced questions, and expanding their applicability across diverse domains (Singh et al., 2025).

3 Methodology

3.1 The Time-MQA Framework

The Time-MQA framework broadens traditional analysis by integrating diverse objectives - such as forecasting, imputation, classification, anomaly detection, and notably, open-ended queries - into a unified question-answering paradigm (as shown in Figure 2). Formally, let $\mathbf{X} = \{x_1, x_2, \dots, x_T\}$ denote a time series input, where $x_t \in \mathbb{R}^d$ represents a d -dimensional observation at timestep t . Let \mathbf{C} represent additional contextual information (e.g., textual metadata, domain-specific knowledge, or other modalities). For a question Q expressed in natural language, the goal is to generate an answer A conditioned on both X and contextual information C . Time-MQA aims to learn a function $f : (\mathbf{X}, \mathbf{C}, Q) \rightarrow A$, where A is the correct answer to the query Q . Depending on the nature of Q , A can take diverse forms, such as predicted values, classification labels, a set of anomalous timestamps, and textual explanations. Specifically, the model component of Time-MQA is based on continued pre-trained LLMs (i.e., Mistral 7B (Jiang et al., 2023), Llama-3 8B (Dubey et al., 2024), and Qwen-2.5 7B (Yang et al., 2024)), using the prepared TSQA dataset. To optimize parameter usage, Time-MQA employs Parameter-Efficient Fine-Tuning (PEFT) with a LoRA adapter. The supported various tasks of the Time-MQA with context enhancement are demonstrated with details in Figure 3.

Key Distinctions. There are three main differences between Time-MQA and traditional time series analysis tasks:

- (1) **Task Scope:** Traditional tasks focus on singular objectives (e.g., forecasting future values or classifying the time series). In contrast, Time-MQA unifies these under a question-driven paradigm, enabling both conventional tasks (e.g., “Forecast the next 5 values”) and complex queries (e.g., “Why did the temperature drop abruptly at hour 10?”) that require joint reasoning across detection, explanation, and contextual knowledge.
- (2) **Context Enhancement:** Traditional methods rely solely on the time series \mathbf{X} . Time-MQA integrates auxiliary context \mathbf{C} to resolve ambiguities and improve robustness. For instance, even when analyzing the same time series, differences in a dataset’s background information can yield contrasting predictions (Williams et al., 2024).
- (3) **Multi-Task Generalization:** Unlike single-purpose models, Time-MQA dynamically adapts to diverse question types through a unified architecture, eliminating the need for task-specific pipelines. This flexibility allows it to handle various time series tasks within a single framework, promoting knowledge sharing via shared representations that enhance both performance and interpretability.

3.2 The TSQA Dataset

This section will introduce our self-constructed 200k-level text-enhanced time series dataset, i.e., TSQA. From perspectives such as the data collection process and types across multiple domains and tasks. We compare it with other datasets and demonstrate the advantages of TSQA.

3.2.1 Dataset Composition and Categorization

The raw data we use comes from various classic publicly available datasets in the time series domain, covering multiple tasks and application areas. Innovatively, we have incorporated textual descriptions, including background information, feature descriptions, etc. From a task perspective, our dataset can be categorized into the following types. Some examples of the proposed TSQA dataset can be found in the Appendix.

Forecasting. In the forecasting task, we utilize UTSD datasets (Liu et al., 2024d), publicly available time series forecasting datasets, such as ETTh1, ETTh2, ETTm1, ECL, Weather, etc. (Zhou et al., 2021), and the latest text-enhanced time series datasets as the raw time-series data (Liu et al., 2024b). Additionally, for the first time, we incorporate financial datasets with earnings call transcripts (The Motley Fool, 2024). To ensure the generalization ability of algorithms and models, we set the input length and prediction length to random values between 64–256 and 8–32, respectively. Furthermore, we enhance all data with background information, feature descriptions, and task descriptions as textual information based on the original

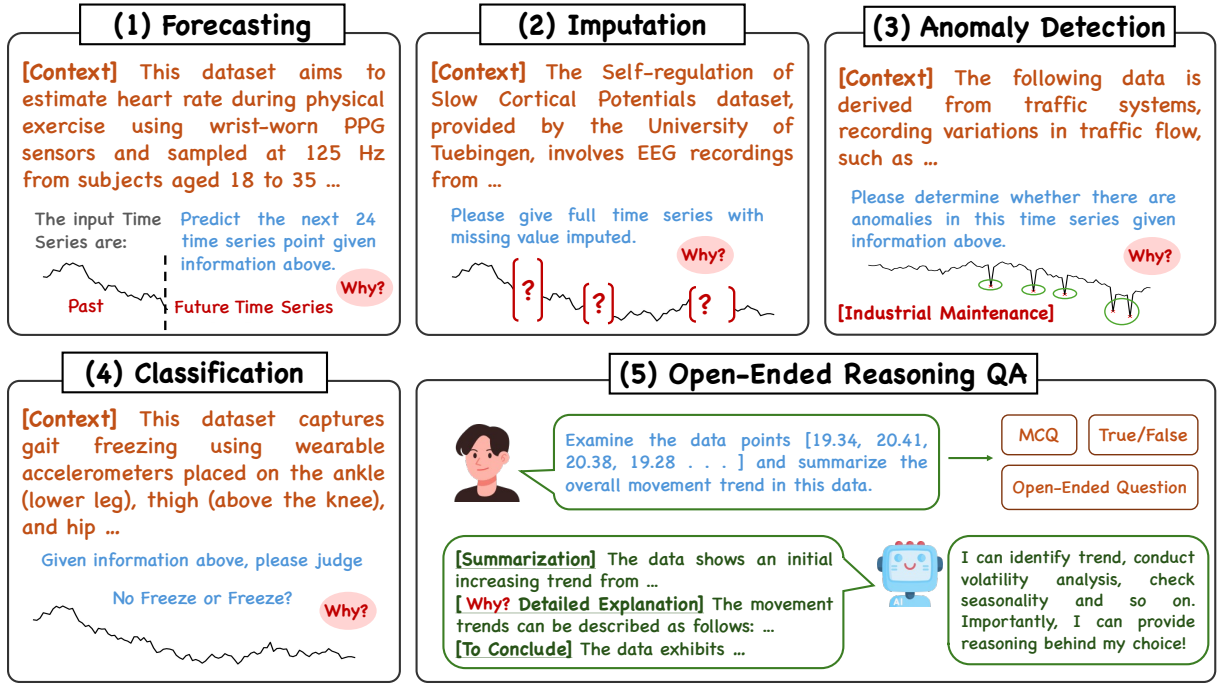


Figure 3: The demonstration of the Time-MQA with context enhancement.

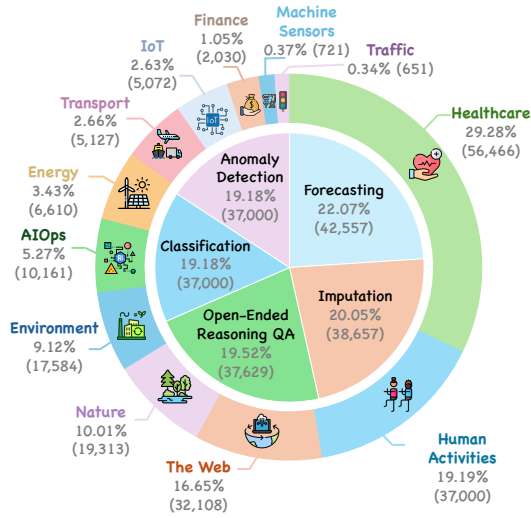


Figure 4: The distribution of data statistics in the TSQA dataset. The inner ring shows task types, and the outer ring shows domains. The rings are presented together for comparison, with no direct one-to-one correspondence between their segments.

data sources. In summary, the forecasting dataset includes 42,557 data instances spanning application domains such as energy, environment, health, IoT, nature, transport, Web, AI Ops, etc.

Imputation. The imputation task shares the same original time series data sources as the forecasting task. Additionally, we randomly set the input length between 64 and 256, randomly removed 4 to

12 values, and replaced them with "X". The imputation dataset consists of a total of 38,657 instances from multiple application domains.

Anomaly Detection. For the anomaly detection task, we utilize commonly used public datasets in the field, such as UCR, ECG, KPI, MGAB, NAB, SensorScope, and Yahoo, among others (Zamanzadeh Darban et al., 2024). To enhance the generalization capability of algorithms and models, we randomly set the input length between 8 and 256 while ensuring a balanced distribution between anomalous and normal data. The anomaly detection dataset comprises 37,000 instances from various application domains, including AI Ops, Health, Finance, Machinery, Industrial Sensors, Environment, and Traffic.

Classification. For the classification task, the data sources are relatively straightforward, primarily derived from the human activity recognition application domain (Kwapisz et al., 2011; Bachlin et al., 2009). The dataset includes both binary and multi-class classification tasks. To ensure class balance, we collected a total of 37,000 data instances. Additionally, the input sequence length is randomly set between 8 and 32 to maintain diversity in data representation.

Open-Ended Reasoning QA. We used different parts of the UTSD dataset (Liu et al., 2024d) - dis-

Table 1: Comparison of text-enhanced time series datasets. ☉ and ✓ indicate having only real data and having both synthetic and real data.

Dataset	Numerical	Cognitive	Source	Domain	Size
TS-Insights	✓	✗	☉	4	~10k
ChatTS	✗	✓	✓	4	~2.2k
CiK	✓	✗	☉	7	~2.9k
TimeMMD	✓	✗	☉	9	~16k
TSQA	✓	✓	✓	12	~200k

tinct from those employed in our forecasting tasks - to avoid data leakage. To generate open-ended reasoning QA, we utilized GPT-4o, instructing it to create questions covering various topics such as trends, seasonality, cyclical patterns, summarization, volatility, anomalies, structural breaks, and other statistical properties (without limiting it strictly to these areas). We also incorporated multiple question types, including multiple-choice, true/false, and open-ended formats. The prompts used to generate these QA pairs are provided in the Appendix. In total, we generated 37,629 data instances, from which we manually reviewed and selected 1,400 QA pairs for use in the continual pretraining step.

3.2.2 Data Statistics

The TSQA dataset comprises 192,843 (~200k) question-answer pairs spanning twelve domains - healthcare, finance, energy, traffic, environment, IoT, nature, transport, human activities, machine sensors, AIOps, and the web - and five task types: forecasting, imputation, anomaly detection, classification, and open-ended reasoning (see Figure 4 for distributions). Within the open-ended reasoning QA, the dataset includes 6,919 true/false questions, 11,281 multiple-choice questions, and 12,510 open-ended questions, offering a broad and diverse range of question formats.

3.2.3 Comparison with Existing Datasets

We summarize several existing datasets compared to our proposed TSQA dataset in Table 1. Unlike prior datasets (TS-Insights (Zhang et al., 2023), ChatTS (Xie et al., 2024), CiK (Williams et al., 2024), and TimeMMD (Liu et al., 2024b)), which focus on either classical numerical analytical time series tasks (e.g., forecasting, anomaly detection, imputation, classification) or text-enhanced cognitive tasks (e.g., reasoning, QA), our TSQA dataset supports both, making it the most comprehensive benchmark. It also covers the widest range of appli-

Hyperparameter	Assignment
Base model	Mistral 7B
Computing infrastructure	1*A100-80GB GPU
Max steps	4000
Warm-up steps	1000
Batch size per device	4
Gradient accumulation steps	8
Learning rate	5e-5
Embedding learning rate	1e-5
Optimizer	AdamW (8-bit)
Learning rate scheduler	Cosine
Weight decay	0.1
LoRA rank (r)	16
LoRA alpha	16
LoRA dropout	0.0
LoRA target modules	q_proj, k_proj, v_proj, o_proj, gate_proj, up_proj, down_proj
Training time	~1 Day

Table 2: Hyper-parameters and training time of fine-tuning the Mistral 7B based on the TSQA dataset.

cation domains (12 vs. a maximum of 9) and is significantly larger (~200k instances vs. ~10k–16k). Furthermore, TSQA includes both real and synthetic data, ensuring greater diversity and robustness for text-enhanced time series analysis.

4 Experiment and Result

4.1 Experimental Settings

In the experiments, we considered the ratio of application domains by randomly selecting 1,400 QA pairs for each task type - forecasting, imputation, anomaly detection, and classification - and by manually reviewing and selecting 1,400 QA pairs for open-ended reasoning, leading to a total of 7,000 QA pairs. We then followed the setting from (Cheng et al., 2024). Specifically, to ensure the model adequately learns the time-series domain, we then combined our dataset with a general QA corpus sourced from OpenOrca (Lian et al., 2023) at a 70% to 30% ratio, resulting in 10k QA pairs overall. Finally, we formatted all QA pairs so that the question and answer were clearly labeled, and then we tokenized the text. An example of a formatted QA pair from the pre-tokenized text is provided in the Appendix. All training runs were conducted on a single A100 80GB GPU. Table 2 shows an overview of the hyperparameters used and training time, using Mistral 7B as an example.

4.2 Results

Main Results. Table 3 presents the performance of three fine-tuned models, alongside the GPT-4o (Achiam et al., 2023) model and Doubao (Vol-

Table 3: Comparison of our three fine-tuned models, GPT-4o, and Doubao across diverse tasks. Forecasting and imputation tasks were evaluated using average MSE, while anomaly detection, classification, and open-ended reasoning tasks (including multiple-choice questions (MCQs) and true-false questions (Judgment)) were measured by accuracy. A lower value of MSE \downarrow and a higher value of accuracy \uparrow indicate better performance. * Doubao uses simple mean forecasting, which outputs the same value for all forecasting.

Backbone	Classical Numerical Task				Open-Ended Reasoning QA	
	Forecasting \downarrow	Imputation \downarrow	Anomaly Detection \uparrow	Classification \uparrow	Judgment \uparrow	MCQ \uparrow
Doubao	—*	0.018	0.52	0.44	0.78	0.56
GPT-4o	1.79	0.018	0.64	0.32	0.72	0.58
Llama-3 8B	2.01	0.020	0.54	0.24	0.74	0.48
Qwen-2.5 7B	1.82	0.016	0.68	0.52	0.82	0.54
Mistral 7B	1.35	0.014	0.58	0.44	0.80	0.64

engine, 2023) results, across multiple tasks. For evaluation, we randomly selected 50 QA pairs for each task type (or question format).

Overall, our fine-tuned models demonstrated improved performance across multiple tasks. For open-ended reasoning QA, the fine-tuned Qwen model achieved an accuracy of 82% on judgment questions, while the Mistral model reached 64% on multiple-choice questions. In forecasting tasks, the MSE values were relatively high, likely due to the long time series in our dataset, which can be challenging for models to handle. Nevertheless, our fine-tuned Mistral model outperformed GPT-4o.

For imputation tasks, the MSE remained low, possibly because having more extensive time series data provides additional information that supports better imputation. Our fine-tuned Mistral model generally showed stronger performance. These results suggest that by continuously pre-training on QA time series pairs, models can learn and leverage time series patterns more effectively.

Forecasting with Long Time Series. Figure 5 illustrates an example of forecasting results produced by our fine-tuned Mistral 7B model and GPT-4o on a long time-series input. Notably, the Mistral 7B model’s forecasts outperform those generated by GPT-4o. Moreover, the fine-tuned model can provide the rationale behind its predictions. When we posed follow-up questions in natural language, the model offered explanations of its reasoning. This illustrates that the model trained using the TSQA dataset can effectively learn complex time-series patterns and seasonal trends.

TSQA-Tuned vs. Zero-Shot Model. To further demonstrate the effectiveness of our fine-tuned model on the proposed TSQA dataset, we compared the performance of the tuned Mistral 7B

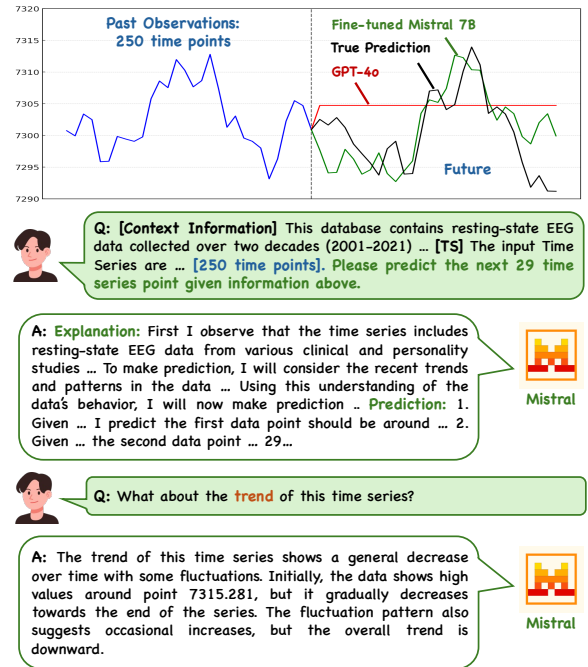


Figure 5: Example of long time series forecasting.

Table 4: Performance of TSQA-tuned and Zero-shot Mistral 7B on two tasks (evaluated at accuracy).

Model	Judgment \uparrow	MCQ \uparrow
Zero-shot	0.78	0.60
TSQA-tuned	0.80	0.64

with that of the original pretrained model on open-ended reasoning QA tasks (including judgment and multiple-choice questions). The results, shown in Table 4, indicate that the TSQA-tuned model performs slightly better than the zero-shot model, suggesting the value of our TSQA dataset for improving question-answering performance.

Open-Ended Reasoning QA. Figure 6 presents an example of an open-ended reasoning question answering and compares the responses generated

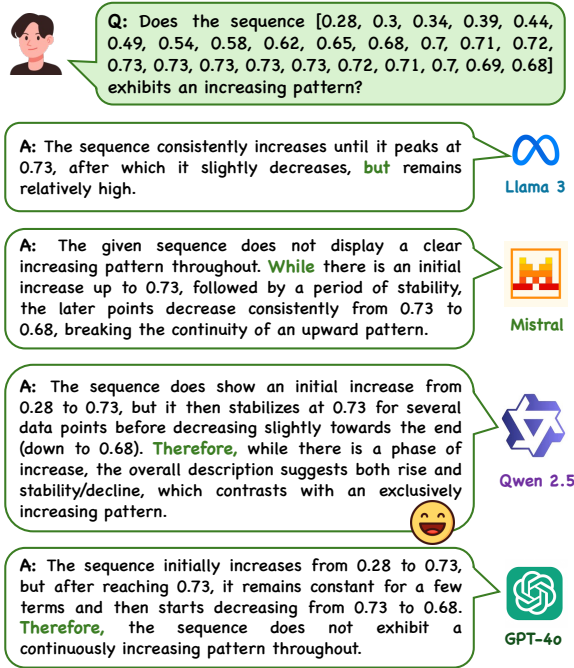


Figure 6: Example of open-ended reasoning QA.

by our fine-tuned models with those from GPT-4o. As shown, our fine-tuned models effectively justify the reasons behind their answers. Notably, the Qwen-2.5 7B model provides a more thorough and comprehensive reasoning process compared to the other models.

4.3 User Study on Time Series QA

Given the subjectivity of time series question answering and reasoning tasks, we conducted a user study. We recruited 78 participants from diverse domains, such as data science researchers, financial practitioners, and students of liberal arts, who participated in this study anonymously. The four optional models are A) Llama-3 8B, B) Mistral 7B, C) Qwen-2.5 7B, and D) GPT-4o sequentially. Participants assessed responses based on accuracy, completeness, clarity, and user preference. The complete result and questionnaire of the user study can be found in the Appendix, and structured summaries of the findings are as follows:

Accuracy and Completeness. Mistral achieved the highest accuracy in tasks requiring numerical precision. For cyclical pattern identification (Q4), it received 80.8% user preference, and 69.2% selected its response as most comprehensive for volatility analysis (Q6). However, in trend analysis (Q12), 51.3% preferred Qwen over Mistral (37.2%). In summary, Mistral’s and Qwen’s answers to the numerical questions are generally considered to be

more accurate as well as more comprehensive.

Explanation Clarity. Explanation clarity was measured by asking participants to rate the understandability of the models’ reasoning. In Question 7 (“Considering the data points [60.0, 28.0, ...], do you see any seasonal patterns?”), more participants found Mistral’s explanation clear, praising its logical structure and ease of understanding. Although Qwen’s responses were also well received, they trailed slightly behind in these clarity ratings.

User Preference. In terms of overall user preference, when asked which answer they preferred (as in Question 11), mistral was selected by 70.5% of participants, while Qwen received 32.1% of the votes. This reflects a general tendency among users to favor responses that combine detailed data analysis with clear, logical explanations. In contrast to the above two models, Llama and GPT-4o are slightly less well preferred.

Overall, from the user study, Qwen and Mistral emerged as the top models for accuracy-driven tasks, while Mistral excelled in generating thorough explanations and more preferences. This highlights a trade-off between precision and interpretability in open-ended time series reasoning.

5 Conclusion

In this paper, we introduce *Time-MQA*, a multi-task framework that unifies time series analysis through natural language question answering, overcoming the limitations of single-task approaches. By integrating forecasting, imputation, anomaly detection, classification, and open-ended reasoning, *Time-MQA* enables flexible interactions with time-series data. The introduced *TSQA* dataset comprises ~200k question-answer pairs across twelve diverse domains and varying time series lengths. It is a vital resource for advancing time series question answering and reasoning in LLMs. Experimental results show that continually pre-training models such as Mistral 7B, Llama 8B, and Qwen-2.5 7B on *TSQA* enhance their ability to interpret temporal patterns — going beyond numeric tasks to generate contextually rich insights. This work bridges the gap between traditional time series analysis and modern LLM capabilities, making temporal information more accessible and context-aware. Future directions include expanding the *TSQA* dataset to dynamic real-world data streams and exploring strategies to further refine time series reasoning.

Limitations

While Time-MQA advances multi-task time series question answering, it has limitations. Our proposed TSQA dataset, though diverse, may not cover all real-world scenarios, particularly highly irregular or domain-specific time series. But data with those properties may be common in real scenarios (Mulayim et al., 2024). Our financial datasets are currently limited to earnings call transcripts. Future research could enrich the financial dataset by incorporating other types of financial time series and textual data, such as Jerome Powell’s speeches and their impact on the S&P 500. Our approach relies on pre-training LLM architectures, which may not be optimized for long numerical sequences, which may cause hallucination problems (Yao et al., 2023). Evaluating open-ended reasoning remains challenging, as current automated metrics may not fully capture response quality (Kong et al., 2025). Additionally, computational costs for fine-tuning large models are high, which may limit some real-time applications (Jin et al., 2024b).

Ethics Statement

All datasets and language models used in this work are publicly available. The TSQA dataset was constructed from well-established, publicly accessible time series benchmarks and synthetic data generation followed ethical guidelines to minimize biases and ensure data quality.

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References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Subutai Ahmad, Alexander Lavin, Scott Purdy, and Zuha Agha. 2017. Unsupervised real-time anomaly detection for streaming data. *Neurocomputing*, 262:134–147.

Abdul Fatir Ansari, Lorenzo Stella, Caner Turkmen, Xiyuan Zhang, Pedro Mercado, Huibin Shen, Oleksandr Shchur, Syama Sundar Rangapuram, Sebastian Pineda Arango, Shubham Kapoor, et al. 2024. Chronos: Learning the language of time series. *arXiv preprint arXiv:2403.07815*.

Marc Bachlin, Daniel Roggen, Gerhard Troster, Meir Plotnik, Noit Inbar, Inbal Meidan, Talia Herman, Marina Brozgol, Eliya Shaviv, Nir Giladi, et al. 2009. Potentials of enhanced context awareness in wearable assistants for parkinson’s disease patients with the freezing of gait syndrome. In *2009 International Symposium on Wearable Computers*, pages 123–130. IEEE.

Guillermo Barrenetxea. 2019. [Sensorscope data](#).

Michele Bernardini, Anastasiia Doynychko, Luca Romeo, Emanuele Frontoni, and Massih-Reza Amini. 2023. A novel missing data imputation approach based on clinical conditional generative adversarial networks applied to ehr datasets. *Computers in Biology and Medicine*, 163:107188.

Giovanni Maria Biancofiore, Yashar Deldjoo, Tommaso Di Noia, Eugenio Di Sciascio, and Fedelucio Narducci. 2024. Interactive question answering systems: Literature review. *ACM Computing Surveys*, 56(9):1–38.

Jian Chen, Peilin Zhou, Yining Hua, Yingxin Loh, Kehui Chen, Ziyuan Li, Bing Zhu, and Junwei Liang. 2024a. Fintextqa: A dataset for long-form financial question answering. *Association for Computational Linguistics(ACL)*.

Wei Chen, Yuxuan Liang, Yuanshao Zhu, Yanchuan Chang, Kang Luo, Haomin Wen, Lei Li, Yanwei Yu, Qingsong Wen, Chao Chen, et al. 2024b. Deep learning for trajectory data management and mining: A survey and beyond. *arXiv preprint arXiv:2403.14151*.

Xiaoyang Chen, Ben He, Hongyu Lin, Xianpei Han, Tianshu Wang, Boxi Cao, Le Sun, and Yingfei Sun. 2024c. Spiral of silences: How is large language model killing information retrieval?—a case study on open domain question answering. *Association for Computational Linguistics(ACL)*.

Zhuo Chen, Wen Zhang, Yufeng Huang, Mingyang Chen, Yuxia Geng, Hongtao Yu, Zhen Bi, Yichi Zhang, Zhen Yao, Wenting Song, et al. 2023. Teleknowledge pre-training for fault analysis. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pages 3453–3466. IEEE.

Daixuan Cheng, Yuxian Gu, Shaohan Huang, Junyu Bi, Minlie Huang, and Furu Wei. 2024. Instruction pre-training: Language models are supervised multitask learners. *arXiv preprint arXiv:2406.14491*.

Winnie Chow, Lauren Gardiner, Haraldur T Hallgrímsson, Maxwell A Xu, and Shirley You Ren. 2024. Towards time series reasoning with llms. *arXiv preprint arXiv:2409.11376*.

- Hoang Anh Dau, Eamonn Keogh, Kaveh Kamgar, Chia Michael Yeh, Yan Zhu, Shaghayegh Gharghabi, and Chotirat Ann Ratanamahatana. 2018. Yanping, bing hu, nurjahan begum, anthony bagnall, abdullah mueen, gustavo batista, and hexagon-ml. the ucr time series classification archive, october 2018.
- Wenjie Du, Jun Wang, Linglong Qian, Yiyuan Yang, Zina Ibrahim, Fanxing Liu, Zepu Wang, Haoxin Liu, Zhiyuan Zhao, Yingjie Zhou, et al. 2024. Tsi-bench: Benchmarking time series imputation. *arXiv preprint arXiv:2406.12747*.
- Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.
- Nigel Fernandez, Alexander Scarlatos, and Andrew Lan. 2024. Syllabusqa: A course logistics question answering dataset. *arXiv preprint arXiv:2403.14666*.
- Elizabeth Fons, Rachneet Kaur, Soham Palande, Zhen Zeng, Tucker Balch, Manuela Veloso, and Svitlana Vyetrenko. 2024. Evaluating large language models on time series feature understanding: A comprehensive taxonomy and benchmark. *arXiv preprint arXiv:2404.16563*.
- Giacomo Frisoni, Alessio Cocchieri, Alex Presepi, Gianluca Moro, and Zaiqiao Meng. 2024. To generate or to retrieve? on the effectiveness of artificial contexts for medical open-domain question answering. *Association for Computational Linguistics(ACL)*.
- Wayne A Fuller. 2009. *Introduction to statistical time series*. John Wiley & Sons.
- Yizhen Guo, Tian Zhou, Wanyi Jiang, Bo Wu, Liang Sun, and Rong Jin. 2024. Maximizing the impact of deep learning on subseasonal-to-seasonal climate forecasting: The essential role of optimization. *arXiv preprint arXiv:2411.16728*.
- James D Hamilton. 2020. *Time series analysis*. Princeton university press.
- Songqiao Han, Xiyang Hu, Hailiang Huang, Minqi Jiang, and Yue Zhao. 2022. Adbench: Anomaly detection benchmark. *Advances in Neural Information Processing Systems*, 35:32142–32159.
- Xanh Ho, Anh-Khoa Duong Nguyen, Saku Sugawara, and Akiko Aizawa. 2020. Constructing a multi-hop qa dataset for comprehensive evaluation of reasoning steps. *arXiv preprint arXiv:2011.01060*.
- Noah Hollmann, Samuel Müller, Lennart Purucker, Arjun Krishnakumar, Max Körfer, Shi Bin Hoo, Robin Tibor Schirrmeyer, and Frank Hutter. 2025. Accurate predictions on small data with a tabular foundation model. *Nature*, 637(8045):319–326.
- International AIOPS Challenges. 2018. Kpi anomaly detection. <https://competition.aiops-challenge.com/home/competition/1484452272200032281>.
- Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. 2023. Mistral 7b. *arXiv preprint arXiv:2310.06825*.
- Chuanyang Jin, Yutong Wu, Jing Cao, Jiannan Xiang, Yen-Ling Kuo, Zhiting Hu, Tomer Ullman, Antonio Torralba, Joshua B Tenenbaum, and Tianmin Shu. 2024a. Mmtom-qa: Multimodal theory of mind question answering. *arXiv preprint arXiv:2401.08743*.
- Ming Jin, Shiyu Wang, Lintao Ma, Zhixuan Chu, James Y Zhang, Xiaoming Shi, Pin-Yu Chen, Yuxuan Liang, Yuan-Fang Li, Shirui Pan, et al. 2023a. Time-llm: Time series forecasting by reprogramming large language models. *arXiv preprint arXiv:2310.01728*.
- Ming Jin, Qingsong Wen, Yuxuan Liang, Chaoli Zhang, Siqiao Xue, Xue Wang, James Zhang, Yi Wang, Haifeng Chen, Xiaoli Li, et al. 2023b. Large models for time series and spatio-temporal data: A survey and outlook. *arXiv preprint arXiv:2310.10196*.
- Ming Jin, Yifan Zhang, Wei Chen, Kexin Zhang, Yuxuan Liang, Bin Yang, Jindong Wang, Shirui Pan, and Qingsong Wen. 2024b. Position: What can large language models tell us about time series analysis. In *Forty-first International Conference on Machine Learning*.
- Yaxuan Kong, Yiyuan Yang, Shiyu Wang, Chenghao Liu, Yuxuan Liang, Ming Jin, Stefan Zohren, Dan Pei, Yan Liu, and Qingsong Wen. 2025. Position: Empowering time series reasoning with multimodal llms. *arXiv preprint arXiv:2502.01477*.
- Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore. 2011. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2):74–82.
- Wing Lian, Bleys Goodson, Eugene Pentland, Austin Cook, Chanvichet Vong, and "Teknium". 2023. Openorca: An open dataset of gpt augmented flan reasoning traces. <https://huggingface.co/Open-Orca/OpenOrca>.
- Bryan Lim and Stefan Zohren. 2021. Time-series forecasting with deep learning: a survey. *Philosophical Transactions of the Royal Society A*, 379(2194):20200209.
- Haoxin Liu, Chenghao Liu, and B Aditya Prakash. 2024a. A picture is worth a thousand numbers: Enabling llms reason about time series via visualization. *NAACL*.
- Haoxin Liu, Shangqing Xu, Zhiyuan Zhao, Lingkai Kong, Harshvardhan Kamarthi, Aditya B Sasanur, Megha Sharma, Jiaming Cui, Qingsong Wen, Chao

- Zhang, et al. 2024b. Time-mmd: Multi-domain multimodal dataset for time series analysis. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.
- Haoxin Liu, Zhiyuan Zhao, Jindong Wang, Harshvardhan Kamarthi, and B. Aditya Prakash. 2024c. LST-Prompt: Large language models as zero-shot time series forecasters by long-short-term prompting. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 7832–7840. Association for Computational Linguistics.
- Yiheng Liu, Tianle Han, Siyuan Ma, Jiayue Zhang, Yuanyuan Yang, Jiaming Tian, Hao He, Antong Li, Mengshen He, Zhengliang Liu, et al. 2023. Summary of chatgpt-related research and perspective towards the future of large language models. *Meta-Radiology*, page 100017.
- Yong Liu, Haoran Zhang, Chenyu Li, Xiangdong Huang, Jianmin Wang, and Mingsheng Long. 2024d. Timer: Generative pre-trained transformers are large time series models. *arXiv preprint arXiv:2402.02368*.
- Ziqing Ma, Wenwei Wang, Tian Zhou, Chao Chen, Bingqing Peng, Liang Sun, and Rong Jin. 2024. Fusionsf: Fuse heterogeneous modalities in a vector quantized framework for robust solar power forecasting. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 5532–5543.
- Mike A Merrill, Mingtian Tan, Vinayak Gupta, Tom Hartvigsen, and Tim Althoff. 2024. Language models still struggle to zero-shot reason about time series. *arXiv preprint arXiv:2404.11757*.
- John A Miller, Mohammed Aldosari, Farah Saeed, Nasid Habib Barna, Subas Rana, I Budak Arpinar, and Ninghao Liu. 2024. A survey of deep learning and foundation models for time series forecasting. *arXiv preprint arXiv:2401.13912*.
- Navid Mohammadi Foumani, Lynn Miller, Chang Wei Tan, Geoffrey I Webb, Germain Forestier, and Mahsa Salehi. 2024. Deep learning for time series classification and extrinsic regression: A current survey. *ACM Computing Surveys*, 56(9):1–45.
- George B Moody and Roger G Mark. 2001. The impact of the mit-bih arrhythmia database. *IEEE engineering in medicine and biology magazine*, 20(3):45–50.
- Michael Moor, Oishi Banerjee, Zahra Shakeri Hossein Abad, Harlan M Krumholz, Jure Leskovec, Eric J Topol, and Pranav Rajpurkar. 2023. Foundation models for generalist medical artificial intelligence. *Nature*, 616(7956):259–265.
- Ozan Baris Mulayim, Pengrui Quan, Liying Han, Xiaomin Ouyang, Dezhi Hong, Mario Bergés, and Mani Srivastava. 2024. Are time series foundation models ready to revolutionize predictive building analytics? In *Proceedings of the 11th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, pages 169–173.
- Yuqi Nie, Yaxuan Kong, Xiaowen Dong, John M Mulvey, H Vincent Poor, Qingsong Wen, and Stefan Zohren. 2024. A survey of large language models for financial applications: Progress, prospects and challenges. *arXiv preprint arXiv:2406.11903*.
- Aditi Singh, Abul Ehtesham, Saket Kumar, and Tala Talei Khoei. 2025. Agentic retrieval-augmented generation: A survey on agentic rag. *arXiv preprint arXiv:2501.09136*.
- Kuldeep Singh, Simerjot Kaur, and Charese Smiley. 2024. Finqpt: Empowering financial decisions with end-to-end llm-driven question answering pipeline. In *Proceedings of the 5th ACM International Conference on AI in Finance*, pages 266–273.
- The Motley Fool. 2024. [Earnings call transcripts](#).
- Markus Thill, Wolfgang Konen, and Thomas Bäck. 2020. Markusthill/mgab: the mackey-glass anomaly benchmark. *Version v1. 0.1. Zenodo. doi*, 10.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. 2022. Musique: Multi-hop questions via single-hop question composition. *Transactions of the Association for Computational Linguistics*, 10:539–554.
- Volcengine. 2023. [Doubao](#).
- Chengsen Wang, Qi Qi, Jingyu Wang, Haifeng Sun, Zirui Zhuang, Jinming Wu, Lei Zhang, and Jianxin Liao. 2024a. [Chattime: A unified multimodal time series foundation model bridging numerical and textual data](#). *Preprint*, arXiv:2412.11376.
- Jun Wang, Wenjie Du, Yiyuan Yang, Linglong Qian, Wei Cao, Keli Zhang, Wenjia Wang, Yuxuan Liang, and Qingsong Wen. 2025. [Deep learning for multivariate time series imputation: A survey](#). *Preprint*, arXiv:2402.04059.
- Yuxuan Wang, Haixu Wu, Jiayang Dong, Guo Qin, Haoran Zhang, Yong Liu, Yunzhong Qiu, Jianmin Wang, and Mingsheng Long. 2024b. Timexer: Empowering transformers for time series forecasting with exogenous variables. *arXiv preprint arXiv:2402.19072*.
- Qingsong Wen, Liang Sun, Fan Yang, Xiaomin Song, Jingkun Gao, Xue Wang, and Huan Xu. 2020. Time series data augmentation for deep learning: A survey. *arXiv preprint arXiv:2002.12478*.

- Qingsong Wen, Tian Zhou, Chaoli Zhang, Weiqi Chen, Ziqing Ma, Junchi Yan, and Liang Sun. 2022. Transformers in time series: A survey. *arXiv preprint arXiv:2202.07125*.
- Andrew Robert Williams, Arjun Ashok, Étienne Marcotte, Valentina Zantedeschi, Jithendaraa Subramanian, Roland Riachi, James Requeima, Alexandre Lacoste, Irina Rish, Nicolas Chapados, et al. 2024. Context is key: A benchmark for forecasting with essential textual information. *arXiv preprint arXiv:2410.18959*.
- Zhe Xie, Zeyan Li, Xiao He, Longlong Xu, Xidao Wen, Tieying Zhang, Jianjun Chen, Rui Shi, and Dan Pei. 2024. Chatts: Aligning time series with llms via synthetic data for enhanced understanding and reasoning. *arXiv preprint arXiv:2412.03104*.
- Jingwen Xu, Fei Lyu, and Pong C Yuen. 2023. Density-aware temporal attentive step-wise diffusion model for medical time series imputation. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management*, pages 2836–2845.
- Zhijian Xu, Yuxuan Bian, Jianyuan Zhong, Xiangyu Wen, and Qiang Xu. 2024. Beyond trend and periodicity: Guiding time series forecasting with textual cues. *arXiv preprint arXiv:2405.13522*.
- Yahoo Inc. 2021. S5-a labeled anomaly detection dataset, version 1.0. <https://webscope.sandbox.yahoo.com/catalog.php?datatype=s&did=70>.
- An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, et al. 2024. Qwen2. 5 technical report. *arXiv preprint arXiv:2412.15115*.
- Yiyuan Yang, Rongshang Li, Qiquan Shi, Xijun Li, Gang Hu, Xing Li, and Mingxuan Yuan. 2023a. Sgdp: A stream-graph neural network based data prefetcher. In *2023 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.
- Yiyuan Yang, Yi Li, Taojia Zhang, Yan Zhou, and Haifeng Zhang. 2021a. Early safety warnings for long-distance pipelines: A distributed optical fiber sensor machine learning approach. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14991–14999.
- Yiyuan Yang, Chaoli Zhang, Tian Zhou, Qingsong Wen, and Liang Sun. 2023b. Dcdetector: Dual attention contrastive representation learning for time series anomaly detection. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 3033–3045.
- Yiyuan Yang, Haifeng Zhang, and Yi Li. 2021b. Long-distance pipeline safety early warning: a distributed optical fiber sensing semi-supervised learning method. *IEEE sensors journal*, 21(17):19453–19461.
- Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov, and Christopher D Manning. 2018. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. *arXiv preprint arXiv:1809.09600*.
- Jia-Yu Yao, Kun-Peng Ning, Zhen-Hui Liu, Mu-Nan Ning, Yu-Yang Liu, and Li Yuan. 2023. Llm lies: Hallucinations are not bugs, but features as adversarial examples. *arXiv preprint arXiv:2310.01469*.
- Zahra Zamanzadeh Darban, Geoffrey I Webb, Shirui Pan, Charu Aggarwal, and Mahsa Salehi. 2024. Deep learning for time series anomaly detection: A survey. *ACM Computing Surveys*, 57(1):1–42.
- Kexin Zhang, Qingsong Wen, Chaoli Zhang, Rongyao Cai, Ming Jin, Yong Liu, James Y Zhang, Yuxuan Liang, Guansong Pang, Dongjin Song, et al. 2024a. Self-supervised learning for time series analysis: Taxonomy, progress, and prospects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- Weiqi Zhang, Jiexia Ye, Ziyue Li, Jia Li, and Fuguee Tsung. 2024b. Dualtime: A dual-adaptor multimodal language model for time series representation. *arXiv preprint arXiv:2406.06620*.
- Yunkai Zhang, Yawen Zhang, Ming Zheng, Kezhen Chen, Chongyang Gao, Ruian Ge, Siyuan Teng, Amine Jelloul, Jinmeng Rao, Xiaoyuan Guo, Chiang-Wei Fang, Zeyu Zheng, and Jie Yang. 2023. *Insight miner: A large-scale multimodal model for insight mining from time series*. In *NeurIPS 2023 AI for Science Workshop*.
- Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. 2021. Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pages 11106–11115.
- Yuchen Zhuang, Yue Yu, Kuan Wang, Haotian Sun, and Chao Zhang. 2024. Toolqa: A dataset for llm question answering with external tools. *Advances in Neural Information Processing Systems*, 36.

A Examples of TSQA Dataset

Below are several examples from the TSQA dataset.

A.1 Forecasting.

Question: The Self-regulation of Slow Cortical Potentials dataset, provided by the University of Tuebingen, involves EEG recordings from a healthy subject controlling a cursor on a screen through cortical potentials. The sampling frequency of this dataset is 256 Hz. The input Time Series are *[Time Series Data Points]*. Please predict the next nine time series points given the information above.

Answer: Based on the given information, the predictions are [-11.69, -10.72, -9.84, -9.88, -9.03, -8.78, -8.41, -8.28, -7.59].

Question: From March 31, 2014 to June 04, 2014, the weighted ILI rate was 1.74542, and the ili total count reached 14637 across 1866 providers serving a total of 797863 patients, especially 0-4 age group was 3582, 5-24 age group was 5659, 25-49 age group was 3153, 50-64 age group was 1436, 65+ age group was 807, and 25-64 age group was unavailable. The internet search results for the same period are summarized as follows: ... The prior historical average weighted ILI rate during this period was 1.286616667 with a standard deviation of 0.073690536. Please analyze the data and provide a target result on June 04, 2014 with a summary of the findings.

Answer: Based on the provided textual information, I predict that the influenza infection situation in the United States for the upcoming period is likely to be moderate to severe, with a potential for increased risk of complications and co-infections, particularly among vulnerable populations such as those with cystic fibrosis and critically ill patients. Therefore, the predicted weighted ILI rate for June 04, 2014 is estimated to be 1.83453.

A.2 Imputation.

Question: This dataset, sourced from the Kaggle web traffic forecasting competition, contains daily time series data representing the number of hits for 145,063 Wikipedia pages from July 1, 2015, to September 10, 2017. The input Time Series are *[Time Series Data Points with Missing Values]*. Please give full-time series with missing value imputed. The missing values are represented by 'X'.

Answer: Based on the given information, the full-time series with missing value imputed are *[Time Series Data Points]*.

A.3 Classification.

Question: Following data provides accelerometer data for activity recognition research. The dataset has a sampling rate of 20Hz and records accelerometer data for six activity states: walking, jogging, sitting, standing, upstairs, and downstairs. Each sample includes acceleration values for the X, Y, and Z axes, ranging from -20 to 20, where 10 represents 1g and 0 indicates no acceleration. The recorded acceleration includes gravitational acceleration, so when the phone is stationary on a flat surface, the vertical axis registers approximately ± 10 . We provide 10 timestamps of accelerometer data, with each timestamp containing X, Y, and Z values, for a total of 30 values. The recorded Time Series is *[Time Series Data Points]*. Please judge whether this data corresponds to 'Walking' or 'Jogging' or 'Upstairs' or 'Downstairs' or 'Sitting' or 'Standing' given the information above.

Answer: Based on the given information, the activity is Walking.

A.4 Anomaly Detection.

Question: The following data is derived from AWS CloudWatch services and is primarily used for monitoring and managing metrics related to cloud infrastructure and application performance. These include CPU usage, memory consumption, network throughput, and disk I/O metrics. This data can be utilized to identify performance issues in cloud services, such as traffic spikes, resource exhaustion, or network anomalies, and to perform root cause analysis for rapid problem resolution. The input Time Series is *[Time Series Data Points]*. Please determine whether there are anomalies in this time series given the information above.

Answer: Based on the given information, this time series includes Anomaly Points.

A.5 Open-Ended Reasoning QA.

Question: Summarize the overall behavior observed in the data points *[Time Series Data Points]*.

Answer: The data initially shows a slow increase followed by a decreasing trend. The middle part of the data points represents a peak with few higher fluctuations and later shows a slightly decline indicating a volatile pattern.

Question: Determine if there's a structural break in the data points [Time Series Data Points].
A) Yes, between 0.71 and 0.72 B) Yes, between 0.65 and 0.63 C) No structural break

Answer: C) No structural break. The data follows a gradual upward trend and subsequent flattening with slight variability, but no abrupt change in the level or direction indicating a structural break.

Question: The data points [Time Series Data Points] exhibit a clear seasonal pattern. True or False?

Answer: False. While there are fluctuations and some repeated values, no clear cyclical pattern emerges that would indicate seasonality. The variations appear to be more random than driven by any seasonal influences.

B Open-Ended Reasoning QA Generation

Open-ended reasoning QA pairs were partially generated by GPT-4o to broaden the range of question types. However, the time-series signals themselves are derived from real measurements. Figure 7 illustrates the prompt used to generate open-ended reasoning QA pairs.

Prompt: Given the time series data: {target_series_str}. Please select 24 time series points and generate 10 unique instruction-tuning tasks for an LLM we are tuning for time series question-and-answer tasks.

For each question, you can select different 24 time series points from given time series. The questions can vary in format, including multiple-choice, true/false, or open-ended question types. You may also ask questions related to trends, seasonality, cyclical patterns, summarization, volatility, anomalies, structural breaks or statistical property, but don't be restricted to these topics. Please also ensure diversity in your question-answer pairs.

Your response should be formatted as a JSON object with four fields: "task_type": This field should indicate the category or topic type, which provides a clear classification for the question content. "question_format": This field should specify the type of question, such as multiple-choice, true/false, or another question format. "question": This field should contain the question related to the given data. If it's a multiple-choice question, include the available options as well. "answer with reasoning": This field should firstly provide the correct answer to the input question, based on the given data. Then, it should explain the process used to arrive at the answer. If a mathematical operation is involved, mention the formula and fill it in with the relevant numbers.

Expected Output: "task_type": summarization, "question_format": open ended question. "question": Examine the data points [-40.66, -41.47, -41.06, -40.09, -40.59, -41.38, -40.16, -40.31, -38.84, -37.19, -35.19, -33.72, -33.41, -31.09, -29.22, -30.34, -28.91, -30.59, -31.16, -32.31, -32.88, -32.66, -32.72, -30.84] and summarize the overall movement trend in this data. "answer with reasoning": Initially stable with minor fluctuations, followed by a significant decrease. The data starts off stable with minor ups and downs and later shows a significant decrease towards the end. Thank you!

Figure 7: Prompt for generating open-ended reasoning QA pairs.

C High-Level Data Statistics for the TSQA dataset

Table 5 presents high-level data statistics for the TSQA dataset, including the number of QA pairs, distribution across tasks and domains, the type of real versus synthetic data, and various data sources. These sources include UTSD (Liu et al., 2024d),

TimeMMD (Liu et al., 2024b), WISDM (Kwapisz et al., 2011), FOG (Bachlin et al., 2009), NAB (Ahmad et al., 2017), MIT-BIH Arrhythmia (ECG) (Moody and Mark, 2001), UCR (Dau et al., 2018), MGAB (Thill et al., 2020), SensorScope (Barrenetxea, 2019), KPI (International AIOPS Challenges, 2018), and Yahoo (Yahoo Inc., 2021).

Table 5: High-level data statistics of the TSQA dataset.

Task	Domain	Real vs Synth	Count	Data Source
Forecasting	Healthcare	Real	19980	UTSD, TimeMMD
	Web	Real	11362	UTSD
	Nature	Real	7038	UTSD
	Energy	Real	1545	UTSD, TimeMMD
	Transport	Real	62	UTSD
	IoT	Real	36	UTSD
	Environment	Real	18	UTSD
	Finance	Real	1987	TSQA (Our)
	Traffic	Real	529	TimeMMD
Imputation	Healthcare	Real	18800	UTSD
	Web	Real	12397	UTSD
	Nature	Real	7275	UTSD
	Energy	Real	65	UTSD
	Transport	Real	65	UTSD
	IoT	Real	36	UTSD
	Environment	Real	19	UTSD
Classification	Human Activities	Real	37000	WISDM, FOG
Anomaly Detection	AIOps	Real	10161	NAB-realAWSCloudwatch, KPI
	Web	Real	3349	Yahoo
	Environment	Real	12547	Sensorscope
	Finance	Real	43	NAB-realAdExchange
	Healthcare	Real	10057	MIT-BIH Arrhythmia (ECG)
	Machine Sensors	Real/Synth	721	UCR, MGAB
	Traffic	Real	122	NAB-realTraffic
Open-Ended QA	Energy	Real&Synth	5000	UTSD, TSQA (Our)
	Transport	Real&Synth	5000	UTSD, TSQA (Our)
	Nature	Real&Synth	5000	UTSD, TSQA (Our)
	Web	Real&Synth	5000	UTSD, TSQA (Our)
	IoT	Real&Synth	5000	UTSD, TSQA (Our)
	Environment	Real&Synth	5000	UTSD, TSQA (Our)
	Healthcare	Real&Synth	7629	UTSD, TSQA (Our)

D Training Data Format

We format our question-and-answer pairs using a specifically designed template to clearly separate questions from answers. The template is structured as follows: <QUE> {Question} <ANS> {Answer} </END>. Additionally, for continual pre-training of the Llama model, we prepend <|begin_of_text|> at the start of each sample and append <|end_of_text|> at the end. For the Mistral model, we use <s> at the beginning of each sample and </s> at the end. In the case of the Qwen model, only <|endof text|> is added at the end of each sample.

E Experiments on Model Reliance on Time Series Data

To verify the model's reliance on time-series data, we conducted a set of ablation experiments. Specifically, we selected 50 Multiple Choice Questions (MCQs) and 50 True-or-False questions

that targeted key time-series characteristics such as seasonality, abrupt changes, trends, and anomalies. We evaluated both our fine-tuned Mistral 7B and Qwen-2.5 7B models under the following experimental setups:

Exp A. Default (Time Series + Questions): The original setup containing both the time series and the questions.

Exp B. Time Series Removed + Questions: Only the question text is provided; all numeric data are omitted.

Exp C. Random Time Series + Questions: The original time series is replaced with random Gaussian values, while the question remains unchanged.

Exp D. Shuffled Time Series + Questions: The order of the original time series values is shuffled, destroying temporal structure but retaining the same set of values.

For Experiments C and D, we manually determined “correct” ground-truth labels by inspecting the randomly generated or shuffled series. For instance, if a time series originally exhibited a strong upward trend that disappeared after shuffling, the ground-truth label was set to “no trend.”

Table 6 summarizes our findings. “N/A” indicates cases where the model outputs were highly inconsistent or typically refused, making it infeasible to compute an accuracy score.

Table 6: The results of experiments on model reliance on time series data. The accuracies of Qwen-2.5 7B and Mistral 7B on True/False and MCQ questions are reported under different experimental settings. Higher value of accuracy indicates better performance.

Model	Experiment	True/False Accuracy	MCQ Accuracy
Qwen-2.5 7B	Exp A: Default	0.82	0.54
	Exp B: TS Removed	N/A	N/A
	Exp C: Random TS	0.98	0.74
	Exp D: Shuffled TS	0.84	0.58
Mistral 7B	Exp A: Default	0.80	0.64
	Exp B: TS Removed	N/A	N/A
	Exp C: Random TS	0.96	0.70
	Exp D: Shuffled TS	0.82	0.60

In **Exp B** (Time Series Removed), both models typically produced incomplete or fabricated answers, making it impossible to consistently score

outputs. This strongly suggests that, without numeric data, the models cannot reliably answer time-series-specific questions.

In **Exp C** (Random Time Series), the randomly generated values generally lacked meaningful seasonality or discernible trends. The models appeared to recognize this absence of structure, frequently defaulting to statements such as “no distinct pattern” or “no strong seasonality,” which were often accurate given the lack of cyclical behavior. As a result, higher true-or-false accuracy was sometimes observed — not because of deeper model understanding, but because the unstructured data made generic, correct answers more likely. Notably, the models’ responses shifted when the series was randomized, indicating they were actively parsing the numeric inputs.

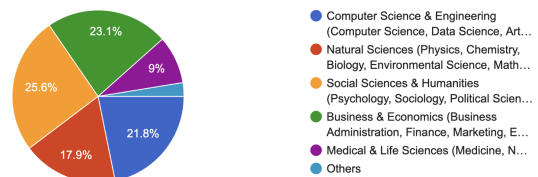
Finally, in **Exp D** (Shuffled Time Series), shuffling effectively removed any evident trend or abrupt break present in the original data. Consequently, the models frequently adjusted their answers. This further supports that the models actively read and interpret the numeric data, rather than simply ignoring it.

In summary, these findings could indicate that our models reflect on the time-series inputs and adapt their responses accordingly when the numeric context is altered or removed.

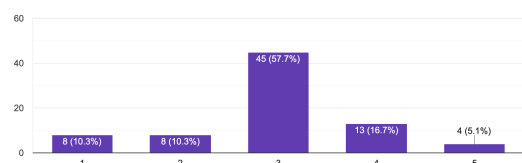
F User Study

A total of 78 surveys were collected, and the results for each question are as follows:

Question 1. What is your field of study?



Question 2. How familiar are you with time series analysis? (1 = Not at all, 5 = Very familiar)



Question 3. How accurate is the answer with respect to the question?

Analyse and summarise the trend and pattern in the data set [68.0, 83.0, 95.0, 103.5, 108.5, 112.0, 113.0, 114.0, 114.5, 115.5, 116.0, 116.0, 115.0, 114.0, 113.5, 111.5, 108.0, 102.5, 100.5, 93.5, 88.0, 82.0, 78.0, 73.5].

Question 3 (Answers):

Question 3: Analyse and summarise the trend and pattern in the data set [68.0, 83.0, 95.0, 103.5, 108.5, 112.0, 113.0, 114.0, 114.5, 115.5, 116.0, 116.0, 115.0, 114.0, 113.5, 111.5, 108.0, 102.5, 100.5, 93.5, 88.0, 82.0, 78.0, 73.5].

Answer 1

The data set exhibits a general downward trend after an initial period of increase. Initially, the values rise from 68.0 to 116.0, indicating an upward trend, and then begin to decline, dropping from 116.0 to 73.5. This suggests a downward trend. The pattern is characterized by an initial peak followed by a decline. The reason for these changes may be related to seasonal or cyclical factors, but without further context, it is impossible to determine the specific causes.

Answer 2

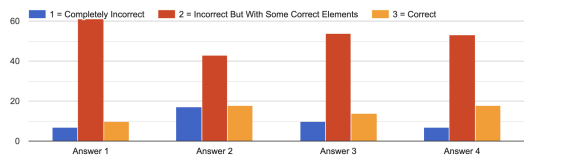
The data shows a clear upward trend initially, reaching a peak at 116.0, followed by a gradual decline towards the end of the series. Overall, it demonstrates a rising trend followed by a downward trend, indicating a cyclical pattern. The sequence starts with a peak at 116.0, followed by a decline to 73.5. This suggests a downward trend. The pattern is characterized by an initial peak followed by a decline. The reason for these changes may be related to seasonal or cyclical factors, but without further context, it is impossible to determine the specific causes.

Answer 3

The data shows an increasing trend initially, peaking at 116.0 before starting a gradual decline towards the end of the series. Overall, it demonstrates a rising trend followed by a downward trend, indicating a cyclical pattern. The sequence starts with a peak at 116.0, followed by a decline to 73.5. This suggests a downward trend. The pattern is characterized by an initial peak followed by a decline. The reason for these changes may be related to seasonal or cyclical factors, but without further context, it is impossible to determine the specific causes.

Answer 4

Overall Trend: The data initially increases from 68.0 to a peak of 116.0 around the middle of the sequence, after reaching the peak, the values decline, dropping back down to 73.5 at the end. The values rise from 68.0 to 116.0, suggesting a steady increase. This upward trend is strongest between 68.0 and 108.0, then drops slightly as it reaches the peak. After reaching the peak, the values decline, dropping back down to 73.5 at the end. The values rise from 68.0 to 116.0, suggesting a steady increase. This upward trend is strongest between 68.0 and 108.0, then drops slightly as it reaches the peak. After reaching the peak, the values decline, dropping back down to 73.5 at the end. The values rise from 68.0 to 116.0, suggesting a steady increase. This upward trend is strongest between 68.0 and 108.0, then drops slightly as it reaches the peak. After reaching the peak, the values decline, dropping back down to 73.5 at the end.



Question 4. Which do you think is the most accurate answer with respect to the open-ended reasoning question?

Identify any cyclical patterns in the data points [0.28, 0.27, 0.26, 0.25, 0.24, 0.23, 0.24, 0.25, 0.26, 0.28, 0.3, 0.33, 0.36, 0.39, 0.43, 0.46, 0.5, 0.53, 0.57, 0.6, 0.63, 0.65, 0.67, 0.68].

Question 4 (Answers):

Question 4: Identify any cyclical patterns in the data points [0.28, 0.27, 0.26, 0.25, 0.24, 0.23, 0.24, 0.25, 0.26, 0.28, 0.3, 0.33, 0.36, 0.39, 0.43, 0.46, 0.5, 0.53, 0.57, 0.6, 0.63, 0.65, 0.67, 0.68].

Answer 1

There is a clear cyclical pattern in the data points provided. The data shows a steady increase which would indicate an upward trend but no clear cycles.

Relevance: Cyclical patterns typically involve repeating periods of rise and fall. The given data points only show a consistent upward trend without any repeating patterns that would suggest cyclicity.

Answer 2

The data does not clearly demonstrate any distinct cyclical patterns. Instead, it shows a general upward trend with some fluctuations.

Relevance: This trend suggests a possible seasonal trend rather than a cyclical pattern. A seasonal trend refers to a prolonged and consistent change in a variable over an extended period without repeating cycles.

In the case: The data points generally indicate an increase from 0.28 to 0.68. Additionally, there is a noticeable dip or plateau between 0.28 and 0.36 before resuming the upward trend. While this might suggest a cyclical pattern, the overall direction and length of the changes favor a seasonal trend rather than a cyclical pattern. A true cyclical pattern would involve regular reversals of rise and fall, which are not evident here.

Relevance: There is no evidence of cyclical or seasonal patterns in the data. The data shows a steady increase, with the exception of a few fluctuations. In summary, the progression from 0.28 to 0.68 does not display clear cyclical patterns but rather a general upward trend with minor fluctuations.

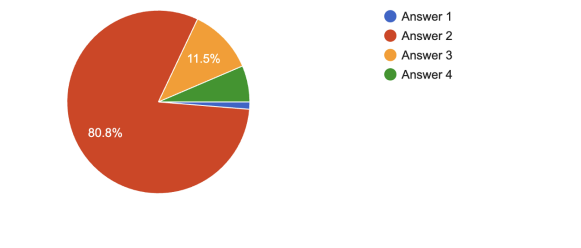
Answer 3

There is a cyclical pattern in the data where values initially decrease from 0.28 to 0.24, then start increasing again to reach 0.68.

Relevance: This suggests an overall upward cycle, but the initial decrease is not a cyclical pattern. The progression of the data points suggests a general upward trend, with a slight dip in the middle. The data points show a general upward trend, with a slight dip in the middle. The data points show a general upward trend, with a slight dip in the middle.

Answer 4

Substantially cyclical patterns in your data, we apply the trends and fluctuations. Initial decline (0.28 - 0.23) = 0.05. The first as it rises shows a decreasing trend. Initial decline (0.28 - 0.23) = 0.05. The first as it rises shows a decreasing trend. Initial decline (0.28 - 0.23) = 0.05. The first as it rises shows a decreasing trend.



Question 5. How complete is the answer? Did it address all parts of the question?

Examine the data points [19.34, 20.41, 20.38, 19.28, 19.75, 22.84, 25.09, 24.97, 24.75, 26.25, 27.0, 25.03, 22.41, 21.78, 22.44, 21.19, 19.44, 19.62, 20.62, 20.16, 18.03, 17.19, 18.31, 19.91] and summarize the overall movement trend in this data.

Question 5 (Answers):

Question 5: Examine the data points [19.34, 20.41, 20.38, 19.28, 19.75, 22.84, 25.09, 24.97, 24.75, 26.25, 27.0, 25.03, 22.41, 21.78, 22.44, 21.19, 19.44, 19.62, 20.62, 20.16, 18.03, 17.19, 18.31, 19.91] and summarize the overall movement trend in this data.

Answer 1

The data shows an initial increasing trend up to 27.0, followed by a slight decline, and then another slight upward movement towards the end.

Relevance: The sequence begins with an increase from 19.34 to 27.0, suggesting an upward trend. It then decreases to 18.03, indicating a slight downward movement, and finally rises again to 19.91, suggesting another upward movement. This pattern suggests overall fluctuating trends with primarily upward characteristics.

Answer 2

The data shows an initial increasing trend from 19.34 to a peak of 27.0, followed by a generally decreasing trend towards the end of the sequence. Overall, the data fluctuates with a net upward trend before settling back downwards.

Relevance: The data begins with a value of 19.34 and shows a steady increase, reaching a peak of 27.0. This initial upward trend suggests a period of growth or accumulation in the sequence. After the peak of 27.0, the data begins to decrease, marking a downward trend or dissipation phase. Throughout the sequence, there are fluctuations or minor peaks and troughs, such as the increase from 20.16 to 20.62 before another decrease. These fluctuations suggest partial contractions and expansions but do not drastically alter the overall upward trend before the final decline in the later stages.

Answer 3

The data points show a general upward trend, but as the values increase from 19.34 to 27.0, they fluctuate around 18.03. This indicates an initial growth phase followed by a relatively stable period.

Relevance: The data points show a general upward trend, but as the values increase from 19.34 to 27.0, they fluctuate around 18.03. This indicates an initial growth phase followed by a relatively stable period. The data points show a general upward trend, but as the values increase from 19.34 to 27.0, they fluctuate around 18.03. This indicates an initial growth phase followed by a relatively stable period.

Answer 4

To analyze the overall movement trend in the given data points, the first value is 19.34 and the last value is 19.91. This suggests a slight overall increase. The values start around 19.34 and fluctuate slightly before rising significantly to a peak of 27.0 near the middle of the data set. After reaching this peak, the values decline, returning close to the initial levels.

Phase 1 (Early Stage): Starts with fluctuations between 19.34 and 20.41, showing a slight upward trend. Phase 2 (Peak Stage): Reaches a sharp increase to a peak of 27.0. Phase 3 (Late Stage): Shows a decline back to around 18.03.

Relevance: The data suggests a rise-and-fall pattern. A significant upward trend in the middle, followed by a downward contraction. Despite fluctuations, the final value is close to the starting point, indicating no long-term directional trend but a cyclical movement.



Question 6. Which answer is the most comprehensive in relation to the question?

Considering the data points [47.0, 51.0, 51.0, 20.0, 48.0, 44.0, 41.0, 28.0, 48.0, 38.0, 67.0, 66.0, 70.0, 54.0, 63.0, 56.0, 76.0, 58.0, 60.0, 58.0, 69.0, 56.0, 39.0, 50.0], which statement best describes the volatility of this time series? A) The volatility is low with consistent data points. B) There is moderate volatility with regular patterns. C) High volatility with sudden peaks and drops. D) The time series exhibits a perfectly linear trend.

Question 6 (Answers):

Question 6: Considering the data points [47.0, 51.0, 51.0, 20.0, 48.0, 44.0, 41.0, 28.0, 48.0, 38.0, 67.0, 66.0, 70.0, 54.0, 63.0, 56.0, 76.0, 58.0, 60.0, 58.0, 69.0, 56.0, 39.0, 50.0], which statement best describes the volatility of this time series? A) The volatility is low with consistent data points. B) There is moderate volatility with regular patterns. C) High volatility with sudden peaks and drops. D) The time series exhibits a perfectly linear trend.

Answer 1

The correct answer is C). High volatility with sudden peaks and drops. The data shows significant fluctuations, with values ranging from 20.0 to 76.0. These sharp changes suggest high volatility.

Comments: A) The stated consistency refers to the overall trend, but it does not describe the magnitude of fluctuations, which are significant. B) While there is some periodicity with a low rising and falling pattern, the deviation from the mean is substantial, indicating high volatility. D) The data does not display a perfectly linear trend; rather, it shows considerable fluctuations, making this response incorrect.

Answer 2

Justification: The data points fluctuate significantly from as low as 20.0 to as high as 76.0, with several peaks and troughs indicating high volatility in the series without a consistent linear trend.

Comments: A) The stated consistency refers to the overall trend, but it does not describe the magnitude of fluctuations, which are significant. B) While there is some periodicity with a low rising and falling pattern, the deviation from the mean is substantial, indicating high volatility. D) The data does not display a perfectly linear trend; rather, it shows considerable fluctuations, making this response incorrect.

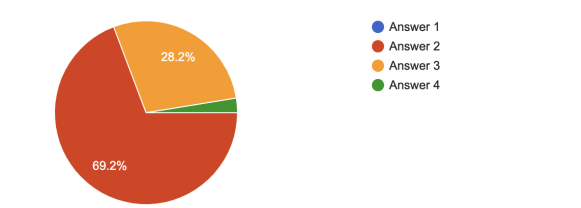
Answer 3

The correct answer is C). High volatility with sudden peaks and drops. The data contains several high peaks (e.g., 67, 70, and 76) and low values (e.g., 20, 39), indicating significant volatility in the data. Additionally, there are rapid changes between these extremes.

Comments: A) The stated consistency refers to the overall trend, but it does not describe the magnitude of fluctuations, which are significant. B) While there is some periodicity with a low rising and falling pattern, the deviation from the mean is substantial, indicating high volatility. D) The data does not display a perfectly linear trend; rather, it shows considerable fluctuations, making this response incorrect.

Answer 4

To assess the volatility of the given time series, let's examine the range, fluctuations, and presence of sudden peaks or drops. The data points range from 20.0 to 76.0, which is a significant spread. There are some outlier points, such as 20.0 and 76.0, which are far from the mean. The values do not follow a perfectly linear or consistent pattern. Given these observations, the best answer is C) High volatility with sudden peaks and drops. This is because the series shows considerable fluctuations, with notable peaks and troughs that deviate from any consistent trend.



Question 7. How clear or understandable is the reasoning provided in the answer?

Considering the data points [60.0, 28.0, 46.0, 51.0, 37.0, 46.0, 41.0, 35.0, 32.0, 66.0, 10.0, 21.0, 67.0, 72.0, 83.0, 61.0, 11.0, 31.0, 62.0, 50.0, 56.0, 76.0, 53.0, 86.0], do you see any seasonal patterns? A) Yes, there is a seasonal pattern. B) No, there is no identifiable seasonal pattern.

Question 7 (Answers):

Question 7: Considering the data points [60.0, 28.0, 46.0, 51.0, 37.0, 46.0, 41.0, 35.0, 32.0, 66.0, 10.0, 21.0, 67.0, 72.0, 83.0, 61.0, 11.0, 31.0, 62.0, 50.0, 56.0, 76.0, 53.0, 86.0], do you see any seasonal patterns? A) Yes, there is a seasonal pattern. B) No, there is no identifiable seasonal pattern.

Answer 1

A) Yes, there is a seasonal pattern. The data exhibits a repeating pattern every 4 to 6 points, suggesting a seasonal component.

Rationale:

The data shows peaks followed by troughs in an order, and then similar patterns repeat after some intervals (e.g., 60, 28, 46, 51, then 37, 46, 41, 35), suggesting a periodic nature. Such periodic fluctuations can indicate seasonality in different values.

Related Concept: Seasonality

In time series data, seasonality refers to a repeating pattern of fluctuations that occur over specific intervals, the quarters or years. It is often indicated by factors such as consumer behavior patterns, economic cycles, or climatic conditions that repeatedly repeat cycles of interest.

Recognizing seasonal patterns can help forecast future values or analyze the effectiveness of seasonally adjusted policies.

Answer 2

B) No, there is no identifiable seasonal pattern. The data points seem to fluctuate irregularly without showing a consistent repeating cycle that would suggest seasonality. Generally, seasonal data has predictable fluctuations that repeat over specific intervals which are not evident here. Therefore, the correct answer is B.

However, it's important to note that identifying seasonality in a small subset of data might lead to overgeneralization. Larger datasets and more comprehensive analysis can provide clearer insights.

Answer 3

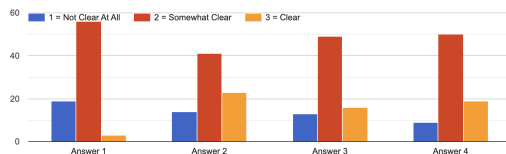
B) No, there is no identifiable seasonal pattern. The data points show varying values without showing any regular or repeating fluctuations that would suggest seasonality.

However, it's important to note that identifying seasonality in a small subset of data might lead to overgeneralization. Larger datasets and more comprehensive analysis can provide clearer insights.

Answer 4

It is difficult to determine whether there is a seasonal pattern in the given data points, as we need to analyze trends, cycles, and repetitions in the values. A seasonal pattern typically repeats at regular intervals.

Based on this, the most reasonable answer is B) No, there is no identifiable seasonal pattern. However, if these data points represent a time-based sequence (e.g., months, years, quarters, etc.), a deeper statistical analysis would be required to confirm this conclusion.



Question 8. How clearly does the response explain its reasoning? (1 = Not Clear At All, 5 = Really Clear)

What is the volatility level in the dataset [0.83, 0.8, 0.76, 0.75, 0.75, 0.76, 0.78, 0.8, 0.8, 0.8, 0.81, 0.8, 0.8, 0.8, 0.8, 0.79, 0.8, 0.82, 0.83, 0.82, 0.82, 0.82, 0.82, 0.81]? A) High B) Moderate C) Low D) No volatility"

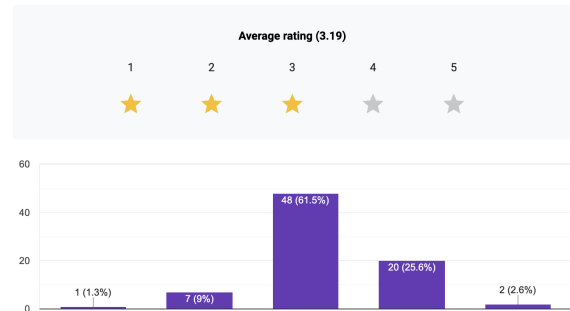
Answer: C) Low Explanation: The dataset shows moderate stability with minor fluctuations, indicating a low volatility level. The changes between consecutive points are generally small and consistent rather than erratic or extreme. Thinking process: The dataset has some movement, but it is not highly variable or erratic. There are no significant spikes or drops across the data points. The changes are steady and minor, suggesting a low level of volatility. Comparing to other options:

A) High: The dataset does not show high levels of volatility with major fluctuations.

B) Moderate: While there is some movement, it is not as severe as to classify it as moderate volatility.

D) No volatility: There is some movement, but it is not so minimal that it would be considered no volatility.

Therefore, the appropriate response and explanation for this question is C) Low volatility.



Question 9. Does the explanation logically follow from the data or the question's context?

Summarise the overall movement trend in the data points [2.16, 1.86, 1.84, 2.49, 1.98, 1.96, 1.73, 1.79, 2.13, 1.43, 1.49, 1.31, 0.55, -0.16, -0.12, 0.63, 0.66, 0.51, 0.28, -1.14, -2.81, -3.21, -2.26, -1.65].

Question 9 (Answers):

Question 9: Summarise the overall movement trend in the data points [2.16, 1.86, 1.84, 2.49, 1.98, 1.96, 1.73, 1.79, 2.13, 1.43, 1.49, 1.31, 0.55, -0.16, -0.12, 0.63, 0.66, 0.51, 0.28, -1.14, -2.81, -3.21, -2.26, -1.65].

Answer 1

The overall movement trend in the data points is a downward trend with some minor recovery towards the end. The values start around 2.16 and generally decrease to around -1.65, with a slight uptick in the final points.

Answer 2

The data shows a downward trend overall, starting from positive values and gradually decreasing to negative values by the end. It is indicative of a declining pattern across these points.

Answer 3

Based on the provided data points, the overall trend appears to be downward with some minor fluctuations in the initial section. The values start around 2.16 and gradually decrease towards -3.21 and beyond, indicating a general decline.

Answer 4

The overall movement trend in the data points shows an initial fluctuation around 2.0, followed by a gradual decline, with a sharp drop into negative values towards the end. Specifically, the first few values fluctuate around 2.0, then the trend shifts downwards, with values turning negative. The last few points show a sharp decline, reaching a low near -3.21 before a slight recovery.

Answer 5

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 6

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 7

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 8

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 9

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 10

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 11

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 12

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 13

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 14

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 15

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 16

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

Answer 17

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

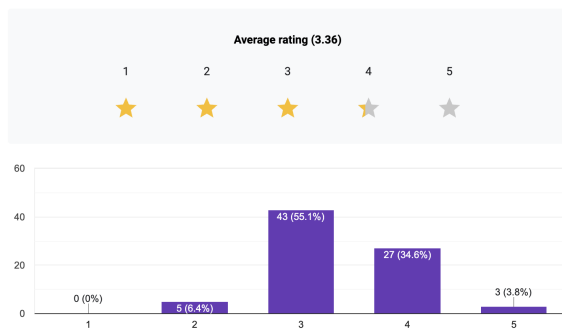
Answer 18

Overall, the trend indicates a general downward movement with increasing volatility toward the end.

between the stability around 0.28 and the upward shift starting around 0.3.

Explanation: A structural break in time series data is a sudden change in the data pattern or mean level. In the given data, after initially fluctuating around 0.29, there is a persistent drop to 0.28, and then a change occurs towards an upward trend from 0.3 onwards. Although subtle, this transition from 0.28 to 0.3 indicates a structural break where the mean level shifts. It signals the end of one data pattern and the beginning of another distinct phase.

Reasoning: The data stability around 0.29 suggests a constant level, followed by a sudden shift to 0.28, and then an upward trend from 0.3 onwards. This progressive change in behavior indicates there is indeed evidence of a structural break in the sequence.



Question 11. Overall, which answer do you prefer for this question? (You can choose one or more)

Given the data points [6.64, 1.71, 27.49, 1.7, 0.2, 6.05, 33.49, 21.13, 0.0, 0.99, 5.34, 10.74, 2.6, 11.04, 14.36, 9.08, 3.69, 0.26, 8.4, 6.37, 2.35, 6.02, 114.07, 49.47], describe the level of volatility found in this data.

Question 12. Which answer do you consider is the best?

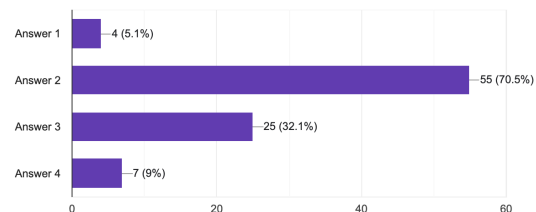
The sequence [0.28, 0.3, 0.34, 0.39, 0.44, 0.49, 0.54, 0.58, 0.62, 0.65, 0.68, 0.7, 0.71, 0.72, 0.73, 0.73, 0.73, 0.73, 0.73, 0.72, 0.71, 0.7, 0.69, 0.68] exhibits an increasing pattern?

Answer 1: The sequence consistently increases until it peaks at 0.73, after which it slightly decreases, but remains relatively high.

Question 11 (Answers):

Question 11: Given the data points [6.64, 1.71, 27.49, 1.7, 0.2, 6.05, 33.49, 21.13, 0.0, 0.99, 5.34, 10.74, 2.6, 11.04, 14.36, 9.08, 3.69, 0.26, 8.4, 6.37, 2.35, 6.02, 114.07, 49.47], describe the level of volatility found in this data.

Answer 1 The data exhibits high volatility, as indicated by the wide range of values from relatively low numbers such as 0.0 and 1.71 to a very high value of 114.07. This indicates significant variability over the observed period.	Answer 2 The data shows a high level of volatility, with significant fluctuations between low values and a large outlier at 114.07. The standard deviation would be skewed upward by the presence of such an extreme value. Explanation: In this series, we see values ranging from as low as 0 to as high as 114, indicating large fluctuations or changes in value from one point to the next. These swings suggest a high level of volatility. The presence of an outlier at 114.07 contributes significantly to the overall volatility because it deviates substantially from the other data points. To quantify the volatility, we can calculate the standard deviation. However, due to the skewness caused by the large outlier, the standard deviation would be heavily influenced by that value. Thus, we should be cautious in interpreting any single statistic like the standard deviation, as it may not capture the full picture of the data's volatility due to the presence of extreme values. In summary, the data exhibits significant fluctuations and the presence of a large outlier, indicating a high level of volatility.	Answer 3 The given data points exhibit high volatility as there are several instances where the values change significantly from one to another. For example, there is a drop from 6.64 to 1.71 and then an abrupt increase to 27.49 followed by fluctuations that include drops down into single-digit numbers before rising sharply again at the end of the sequence. These significant changes in magnitude indicate high volatility in this dataset. Additionally, there are few instances where values drop significantly to 0 or below, further contributing to the overall volatility observed in these data points. The presence of such large variations within the dataset suggests that any statistical analysis based on these numbers should take into account the level of variability. This can make it challenging to identify any clear patterns or trends without appropriate adjustments for such fluctuations.	Answer 4 The data set exhibits high volatility, as indicated by the large fluctuations between values. The values range from 0.2 to 114.07, a massive spread. There are extreme jumps, such as from 1.71 to 27.49 and 0.2 to 114.07. Several smaller values (e.g., 0.2, 0.99, 0.26) are interspersed with much larger numbers (33.49, 49.47), showing inconsistency in movement. The data does not follow a smooth trend but rather exhibits sharp rises and falls. These characteristics suggest a highly erratic pattern, with significant deviations from a central value, indicating volatility in the dataset.
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Answer 2: The given sequence does not display a clear increasing pattern throughout. While there is an initial increase up to 0.73, followed by a period of stability, the later points decrease consistently from 0.73 to 0.68, breaking the continuity of an upward pattern.

Answer 3: The sequence does show an initial increase from 0.28 to 0.73, but it then stabilizes at 0.73 for several data points before decreasing slightly towards the end (down to 0.68). Therefore, while there is a phase of increase, the overall description suggests both rise and stability/decline, which contrasts with an exclusively increasing pattern. Hence, the correct response is False regarding continuous increase throughout.

Answer 4: The sequence initially increases from 0.28 to 0.73, but after reaching 0.73, it remains constant for a few terms and then starts decreasing from 0.73 to 0.68. Therefore, the sequence does not exhibit a continuously increasing pattern throughout.

