No Universal Prompt: Unifying Reasoning through Adaptive Prompting for Temporal Table Reasoning

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Abstract

Temporal Table Reasoning is a critical challenge for Large Language Models (LLMs), requiring effective reasoning to extract relevant insights. Despite existence of multiple prompting methods, their impact on table reasoning remains largely unexplored. Furthermore, model performance varies drastically across different table and context structures, making it difficult to determine an optimal approach. This work investigates multiple prompting technique on diverse table types to determine that performance depends on factors such as *entity type, table structure, requirement of additional context and question complexity*, with *"NO"* single method consistently outperforming others. To address this, we introduce SEAR, an *adaptive prompting* framework inspired by human reasoning that dynamically adjusts to context and integrates structured reasoning. Our results demonstrate that SEAR achieves superior performance across all table types compared to baseline prompting techniques. Additionally, we explore the impact of table structure refactoring, finding that a unified representation enhances model reasoning.

1 Introduction

Temporal table reasoning presents a unique challenge, requiring Large Language Models (LLMs) to interpret tabular data while capturing embedded temporal relationships. Unlike static tables that provide a fixed snapshot of information, temporal tables evolve over time, incorporating event sequences, timestamps, and dynamic updates. Reasoning over such structures is essential for tasks like financial forecasting, historical trend analysis, medical diagnosis, and event-based decision making (Gupta et al., 2023; Xiong et al., 2024). However, existing LLMs often struggle to model these intricate temporal dependencies, underscoring the need for more effective reasoning frameworks.

Table 0		
Benefit Plan	2017	2016
Pension Plan	$3,856	$3,979
Health Plan	11426	11530
Table_1		
	2020	Thereafter
Property mortgages	$703,018	$1,656,623
MRA facilities	—	—
Sr. unsecured notes	250000	100000
Ground leases	31436	703254

Question: What is the sum of Ground leases of 2020, Health Plan of 2016, and Property mortgages and other loans of Thereafter ?
Dataset: MultiHiertt
Req: Evidence from multiple table and F-COT

Table Pretext - ... **operating leases was $ 100690000 , $ 92710000 , and $ 86842000 in fiscal 2006 , 2005 and 2004** ...	
	amount
2007	56499000
2008	46899000
2009	39904000
2010	33329000

Question: what was the percentage change in total rental expense under operating leases from july 2 , 2005 to july 1 , 2006?
Dataset: FinQA
Req: Evidence from Text and PoT

Year	Kit Manufacturer	Shirt Sponsor
1977–1978	-	National Express
1982–1985	Umbro	-
1985–1986	Umbro	Whitbread
...	...	...
2008–	Errea	Mira Showers

Question: what time period had no shirt sponsor?
Dataset: WikiTabQA
Req: Evidence and Direct Answer

Table Title - Aaron Taylor-Johnson		
Table Subtitle - Film		
Year	Title	Role
2015	Avengers	Pietro Maimoff
2016	Nocturnal Animals	Ray Marcus
2017	The Wall	Issac
2018	Outlaw King	James Douglas
2018	A Million Little Pieces	-

Question: What films did Aaron Taylor-Johnson appear in in 2017 and 2018?
Dataset: FeTaQA
Req: Evidence and Decomposition

Figure 1: Examples of Different Table and Contextual structure, taken from different datasets with efficient reasoning method based on specific question, Full Tables are in Appendix C.

Recent work has demonstrated that LLMs can improve table reasoning performance through advanced prompting strategies (Zhang et al., 2025). Nevertheless, studies such as Wang and Zhao (2024) highlight persistent challenges in temporal reasoning, with models often failing to track evolving data or infer event sequences reliably. Moreover, most existing approaches rely on single-step prompting methods such as direct prompting or chain-of-thought reasoning (Wei et al., 2022) which frequently fail to generalize across diverse table structures and time-sensitive queries.

Although several prompting techniques have been proposed to improve LLM reasoning, their effectiveness for temporal table reasoning remains underexplored. In this study, we evaluate five single-step prompting methods as baselines Chain-of-Thought (CoT), Evidence Extraction, Decomposition, Faithful CoT (Radhakrishnan et al., 2023), and Program of Thought (PoT) (Chen et al., 2023). Each baseline aims to enhance logical and numerical reasoning, yet their impact on temporal table reasoning performance has not been systematically analyzed. Furthermore, we evaluate an extensive set of baselines covering structural, temporal, and agentic reasoning approaches.

This study addresses this gap by analyzing the performance of multiple established baselines and a novel adaptive reasoning strategy on a Temporal Tabular Question Answering (TTQA) task. We aim to answer the following research questions: $(RQ1)$ Given a table and a question, which reasoning strategy should be employed?, $(RQ2)$ Is there a Single reasoning method that can perform well across all types of tabular structure?, and $(RQ3)$ Is there a unified representation that can encapsulate all different tabular structures in most effective manner for the TTQA task?

To address these research questions, we conducted experiments on eight distinct tabular structures using multiple state-of-the-art LLMs for the TTQA task. To overcome the limitations of existing baselines we propose **SEAR** (Select-Elaborate-Answer & Reasoning) framework, a novel adaptive prompting strategy. Our motivation can be likened to a carpenter building a chair. They have many tools, such as a hammer, saw and drill. Each is capable of performing part of the task, but none of them can build the whole chair. It is the skillful selection and combination of these tools that brings the chair to life. Similarly, SEAR equips models with multiple reasoning tools, and then it is on the model's capability to choose them for solving the task at hand. From 10, we observe that models actually use multiple tools to answer these questions.

SEAR operates in three distinct phases. In the Initial **Select** phase, it identifies high-level crucial steps, in the subsequent **Elaborate** phase it refines these steps by adding detailed instructions, ensuring comprehensive road map. Finally, the **Answer & Reasoning** phase leverages the structured plan to deliver accurate answers, supported by clean, logical explanations and where necessary, includes integration of Python code for computational tasks.

Furthermore, we combined these three phases to create a single step reasoning strategy, which we call SEAR_Unified. Our results show that SEAR_Unified outperforms all single step baseline reasoning strategies by significant margins, and even standard 3-step SEAR and existing multi-step reasoning strategies such as Self Discover (Zhou et al., 2024). This demonstrates the supremacy and efficacy of our proposed reasoning strategy. Additionally, our study also includes detailed analysis of refactoring process, wherein we transform diverse tabular structure into a unified representation ("Refactor"), Our main contributions are:

- ***Benchmarking Prompting Methods***: We evaluate five single-step prompting methods and show that their effectiveness varies based on table structure, entity type, sparsity and question complexity.
- ***Adaptive Reasoning Framework***: We introduce SEAR, a multi-step adaptive prompting approach that generalizes well across diverse table structures, also we integrate them into a single unified adaptive prompt SEAR_Unified, outperforming individual methods.
- ***Table Structure Refactoring***: We propose refactoring as an enhancement, demonstrating its effectiveness in improving model reasoning by optimized table representation.
- ***Comprehensive Evaluation***: We conduct a systematic analysis across various table types, highlighting the impact of different reasoning strategies and structure modifications.

2 Why is Temporal Table Reasoning Challenging?

Temporal table QA requires models to reason over structured data while accounting for time-dependent relationships. This challenge arises from three key factors: the diverse structures of tables, the domain-specific reasoning requirements, and the complexity of the questions asked.

Structural Variability. Tables range from simple grids to hierarchical or semi-structured layouts with merged cells and implicit links (e.g., HiTab's multi-level indexes, HybridQA's tables mixed with text). They also come in diverse file formats (CSV, HTML, Markdown), so parsing must be flexible. SEAR first flattens and standardises these varied structures, making them easier for downstream reasoning.

Domain-Specific Complexity. Reasoning strategies must adapt to the table's domain. Wikipedia-based datasets like WikiTableQuestions demand general factual reasoning and entity linking. Financial datasets like FinQA or TAT-QA emphasize numerical reasoning, requiring multi-step arithmetic and temporal trend analysis. SEAR dynamically adapts to these needs by identifying relevant entities and values, then applying suitable prompting strategies such as F-CoT or PoT. In numerically intensive domains, PoT facilitates executable code generation for precise computation.

Question Complexity. Temporal QA questions range from direct lookups (e.g., "What year did the team win?") to complex reasoning (e.g., "What was the profit two quarters after policy X?"). These often require temporal anchoring, arithmetic, and sequential logic. SEAR addresses this by decomposing questions and tailoring its strategy based on both table and query characteristics.

Limitations of Prior Work. Despite recent interest, most prior work underrepresents the structural and domain diversity seen in real-world tables. Datasets like TempTabQA (Gupta et al., 2023) focus narrowly on specific formats, limiting generalizability. Annotation inconsistencies (Deng et al., 2024) further complicate benchmarking. Symbolic approaches (e.g., DATER (Ye et al., 2023), BINDER (Cheng et al., 2023)) offer logical precision on well-structured tables but falter on hybrid or semi-structured formats. Conversely, text-focused models (e.g., C.L.E.A.R. (Deng et al., 2024)) provide strong language understanding but lack robust symbolic reasoning. These limitations highlight the need for hybrid systems like SEAR, which dynamically integrate symbolic and neural strategies based on task demands.

3 Adaptive Reasoning Framework

Humans naturally begin by understanding the objective and analyzing table structures, including cell relationships, headers, and implicit dependencies, while incorporating additional context if available. In temporal tables, this involves identifying both implicit and explicit time-based patterns. Once the problem and context are clear, relevant information is retrieved directly or by decomposing the task into subproblems based on complexity. Finally, logical and numerical reasoning is applied systematically to arrive at a well-founded conclusion.

Inspired by this intuitive approach, we propose the SEAR (Select-Elaborate-Answer & Reasoning) a framework designed to dynamically adapt reasoning strategies based on the structure and complexity of the given table. SEAR builds upon existing prompting methods by introducing a structured, multi-step reasoning process that mirrors human problem solving. It follows a structured three step process to improve temporal table reasoning, ensuring systematic problem solving while leveraging In-context learning for adaptability.

Step1: Select Crucial Steps : Identify key reasoning steps without answering directly, creating an efficient problem solving path. Figure 3 shows the actual prompt.

- Problem Understanding: Define the question's objective and analyze table structure.
- Reasoning Process: Select single or multiple strategies from Extract relevant evidence, decompose complex queries, apply logical steps, and generate Python code if needed (when the question involves numerical or arithmetic reasoning. This is guided by the prompt as seen in Figure 3)
- Optimization tips: Simplify steps, retrieve direct answers when possible, and use code for numerical operations.

Step 2: Elaborate Crucial Steps : Refine and comprehend selected steps for clarity and effectiveness. Figure 4 shows the actual prompt.

- Add contextual details, specify exact table elements, and refine decomposition.
- Ensure a structured and logically coherent flow toward the final answer.

Step 3: Answer & Reasoning : Execute the structured steps to derive an accurate, well-supported answers. Figure 5 shows the actual prompt.

- Follow elaborated steps precisely, referencing extracted evidence.
- Justify answers with logical explanations, when possible directly answer from evidence and integrate Python code for calculations when needed.

By progressively refining reasoning, SEAR ensures adaptability and robustness across diverse table formats and complexities.

Standard SEAR is a three-step process that adds overhead and can impact efficiency. To address this, we propose SEAR_Unified, a single-step adaptive prompt that merges SEAR's structured reasoning into a unified framework. It dynamically selects and refines reasoning steps based on the

Dataset	Structure			Domain		Reasoning		Question Types			Answer Types	
	Flat	Hierarichal	Hybrid	Wikipedia	Finance.	Numerical	Textual	Lookup	Multi-step	Temporal	Long-form	SQL
FeTaQA	✓	✗	✗	✓	✗	✗	✓	✓	✓	✗	✓	✗
FinQA	✓	✗	✗	✗	✓	✓	✓	✗	✓	✓	✗	✗
HiTab†	✗	✓	✗	✓	✓	✓	✗	✓	✓	✓	✗	✗
HybridQA	✗	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✗
MultiHierTT	✗	✓	✗	✗	✓	✓	✓	✗	✓	✓	✗	✗
Squall	✓	✗	✗	✓	✗	✓	✗	✓	✓	✗	✗	✓
TAT-QA	✓	✗	✓	✗	✓	✓	✓	✓	✓	✓	✗	✗
WikiTableQuestions	✓	✗	✗	✓	✗	✓	✗	✓	✗	✗	✗	✗

Table 1: Comparison of Temporal Table QA datasets by structure, domain, reasoning, and question types. †HiTab spans Wikipedia and financial domains. Binary indicators simplify complex question types (e.g., SQL, long-form).

query and table structure, retrieving key information, decomposing complex queries when needed, and selectively using Python for numerical operations. SEAR_Unified validates intermediate steps and performs error checks to ensure accuracy while reducing redundant complexity. Figures 6 and 7 illustrate the prompt and reasoning path.

We also introduce table and context refactoring as a preprocessing step that clarifies headers, aligns data, and removes irrelevant context. This improves retrieval precision, reduces reasoning errors, and enhances adaptability across diverse tabular formats. Table 2 summarizes the refactoring changes for each dataset.

4 Experimental Setup

Datasets. We selected eight diverse tabular as shown in table 3 datasets spanning structured, semi-structured, hierarchical, and hybrid tables to ensure a comprehensive evaluation. These datasets present challenges such as entity relations, numerical reasoning, and textual integration, making them well-suited for assessing table reasoning in LLMs as shown in Table 1. For detailed overview of the dataset refer appendix E.

Categories	fetaqa	finqa	hitab	hybridqa	multi	squall	tatqa	wiki
Table Structure	1580	961	616	1528	1587	774	2240	1503
Title Clarity	1582	962	386	1528	1587	774	2244	1504
Column/Row Header	1268	919	353	1229	1587	774	2158	1283
Data Formatting	1329	957	269	1476	1585	774	2124	1399
Bolding & Emphasis	1207	934	206	1460	1524	347	2200	478
Other	328	273	82	468	539	197	696	309

Table 2: Dataset evaluation for refactoring categories.

Dataset Filtering: Adapting TempTabQA's (Gupta et al., 2023) keyword filter (§3.2), we selected temporal cues (e.g., before, year, latest) along with domain-specific terms (e.g., fiscal, quarterly) and applied them across all datasets. This approach reliably captures most of the explicit temporal questions, though purely implicit cases may be missed. Incorporating human judgment could improve coverage but at the cost of scalability.

Dataset	Brief description	#Qs
FeTaQA	Wikipedia tables; long-form answers from discontinuous facts	1,582
FinQA	Financial reports; multi-step numerical reasoning	962
HiTab	Hierarchical tables; fine-grained numeric questions	897
HybridQA	Wiki tables + linked text; hybrid reasoning	1,528
MultiHierTT	Finance; multiple hierarchical tables + long text	1,587
Squall	WikiTableQ + SQL alignments; structured query tasks	774
TAT-QA	Finance; tables + text with arithmetic / counting	2,244
WikiTableQ	Wikipedia trivia; factual + numeric Q over large tables	1,504

Table 3: Number of retained temporal Questions.

Models: We used 3 LLM models: GPT4o-mini, Gemini 1.5 Flash, and LLaMA 3.1 70B.

Prompts & Frameworks: Effective prompting improves task comprehension and response quality by providing structured instructions. We evaluated 13 prompting strategies spanning direct, structured, temporal, and agentic approaches, as summarized in Table 4.

To ensure a balanced evaluation, we included both textual and symbolic reasoning prompts. CoT, Evidence Extraction, and Decomposed Prompting guide models through step-by-step interpretation. SCP augments multiple chains of thought and selects the majority vote. PoT and F-CoT generate structured logic for consistent reasoning. The temporal baselines NoT and C.L.E.A.R. inject explicit chronological cues to help the model track event ordering. The structured baselines Self-Discover, Self-Ask, and Plan & Solve introduce autonomous decomposition and planning to improve reasoning quality. The agentic methods ToT and GoT explore tree- or graph-structured reasoning paths to identify high-value solutions. All methods were evaluated in a few-shot setting except Self-Discover.

Evaluation: Evaluating diverse datasets is challenging due to varying answer types, from numerical values to long-form text. A rigid metric may miss semantic correctness, so we propose the *Hybrid Correctness Score (HCS)*, which balances

Baseline	Brief description	Category
Chain-of-Thought (COT) (Wei et al., 2022)	Step-by-step natural-language rationale	Direct
Evidence Extraction(EE)	Extracts supporting cells first, then answers	Direct
Decomposed Prompting(Decomp)(Khot et al., 2023)	Splits complex queries into simpler sub-prompts	Direct
Faithful COT (F-COT) (Lyu et al., 2023)	Adds consistency checks to Chain-of-Thought	Direct
Program-of-Thought (POT)(Chen et al., 2023)	Generates executable code (e.g., Python) for reasoning	Direct
Self-Discover (Zhou et al., 2024)	Model autonomously picks reasoning modules	Structured
Self-Ask (Press et al., 2023)	Iteratively asks and answers sub-questions	Structured
Plan & Solve (Wang et al., 2023a)	Separates plan generation from execution	Structured
C.L.E.A.R. (Deng et al., 2025)	Injects temporal cues for semi-structured tables	Temporal
Narration of Thought (NoT) (Zhang et al., 2024)	Requires chronological narration to keep temporal order	Tempooal
Self-Consistency Prompting (SCP) (Wang et al., 2023b)	Samples multiple COTs and votes	Agentic
Tree of Thought (ToT) (Yao et al., 2023)	Searches a tree of reasoning states with pruning	Agentic
Graph of Thought (GoT) (Besta et al., 2023)	Generalises ToT to graph search	Agentic

Table 4: Prompting baselines grouped by category.

lexical and semantic accuracy by combining Relaxed Exact Match Score (REMS, F1-based) and Contextual Answer Evaluation (CAE, LLM-based). A response is considered correct if its REMS score exceeds 80 or if CAE deems it correct. By integrating both lexical and contextual evaluation, HCS offers a more robust measure of answer correctness. **all reported scores represent HCS** for consistency. Detailed REMS and CAE results are provided in Tables 14 15, 16 in Appendix B.

5 Result and Analysis

In this section, we analyze results using Tables (6, 7, 8) which showcase HCS scores.

Is there a single existing reasoning strategy which works best on all table types? Performance varies depending on table structure, domain, and question complexity. As observed in Gemini 1.5 Flash results (Table 6), COT performs best on HybridQA, Evidence Extraction excels in HiTab, TATQA, FeTaQA and Squall, while Decomposition is most effective for WikiTabQA and FinQA. POT shows the highest performance in MultiHierTT, whereas F-COT does not emerge as the best baseline in any dataset. A similar trend is evident across GPT and LLaMA models as shown in Table 5. Thus, no single prompting method universally outperforms others, as effectiveness is higly dependent on the dataset's structure and complexity.

Does the Adaptive Reasoning Framework Help? Table 5 confirms that COT, Evidence Extraction, and Decomposition dominate in most datasets, with POT and F-COT experience improvement in performance for financial and Squall datasets. SEAR dynamically selects its reasoning path, primarily leveraging Evidence Extraction, Decomposition, and Logical Steps (COT) while integrating Python

	Gemini 1.5 Flash	GPT 4o mini	Llama 3.1 70B
COT	HybridQA	MultiHierTT TATQA FeTaQA	HiTab HybridQA
EE	HiTab TATQA FeTaQA	WikiTabQA HiTab HybridQA	FeTaQA Squall
Decomp	Squall WikiTabQA FinQA	FinQA	WikiTabQA MultiHierTT TATQA
POT	MultiHierTT	Squall	FinQA
F-COT	-	-	-

Table 5: Dataset for which Baseline reasoning strategy performed best for each model

Program for numerical reasoning. by design, it optimally combines dominant reasoning strategies with computation support. SEAR outperforms baseline in 5 dataset for Gemini, in 2 dataset for GPT, and in 4 datasets for LLaMA. While SEAR consistently improves performance over baseline across multiple models, it does not generalize equally across all datasets.

Does unification of SEAR help? SEAR_Unified optimizes reasoning by merging and refining steps into a single adaptive prompt, reducing overhead while enhancing flexibility. As seen in Table 6, 7 , 8, SEAR_Unified outperforms baselines across all datasets for Gemini, while for GPT and LLaMA, it surpasses baselines in 6 datasets, demonstrating its superiority. This highlights SEAR_Unified's ability to generalize effectively across diverse datasets and models.

We compared our methods with recent structured and modular reasoning approaches, including Self-Discover, Self-Ask, and Plan & Solve. Our approach consistently outperforms these baselines, with particularly strong gains on Multi-HierTT, HiTabs, Squall, and HybridQA. Among them, Self-Discover performs the closest, underscoring the value of modular and adaptive reasoning. We also benchmarked against temporal (NoT, C.L.E.A.R.) and agentic (ToT, GoT, SCP) strategies. Although NoT, C.L.E.A.R., and GoT perform well on FetaQA, TAT-QA, and HiTabs, they fail to deliver consistent improvements on more complex benchmarks.

	wiki	multi	hitab	finqa	tatqa	fetaqa	squall	hybridqa
COT	73.60	58.79	79.04	60.08	87.30	71.30	69.90	80.76
F-COT	66.89	60.68	52.06	62.16	78.79	56.13	61.11	17.93
Decomp	78.52	61.00	75.47	62.58	91.67	67.07	67.57	74.67
EE	76.33	60.43	80.82	55.93	92.20	77.62	72.32	80.10
PoT	74.40	61.12	70.68	60.52	79.68	50.88	63.57	38.48
NoT	75.19	46.12	81.60	51.03	86.54	**87.89**	69.12	79.84
ToT	81.98	58.72	77.81	51.24	91.04	79.26	75.32	82.52
GoT	74.86	56.08	**84.05**	50.83	90.95	84.57	66.14	81.02
SCP	81.71	60.42	80.93	52.70	91.22	84.32	72.35	84.29
CLEAR	82.71	55.57	79.71	53.95	**93.27**	84.00	78.81	**84.48**
Self Ask	78.52	45.43	79.15	64.66	81.42	80.15	70.67	63.48
Plan & Solve	81.72	39.51	67.56	66.32	90.60	81.83	77.00	62.63
Self Discover	80.32	59.42	78.93	65.49	91.35	81.16	74.81	80.43
SEAR	81.45	60.18	79.71	65.90	90.02	82.87	80.23	81.15
SEAR_U	82.18	**61.75**	82.61	**68.71**	92.78	79.84	**81.52**	82.00
SEAR+R	82.71	58.54	81.05	65.49	89.39	84.20	78.04	65.90
SEAR_U+R	**83.38**	56.58	82.83	67.36	91.53	85.52	77.91	67.08

Table 6: HCS scores (in %) using Gemini 1.5 Flash, R stands for "Refactoring" and U stands for "Unified".Bold represents the best performer and the underlined represents the second best performer.

	wiki	multi	hitab	finqa	tatqa	fetaqa	squall	hybridqa
COT	78.92	57.97	77.59	64.14	92.91	84.13	67.57	78.21
F-COT	71.61	55.32	71.35	64.97	91.04	77.81	56.46	34.62
Decomp	79.79	57.03	76.14	65.18	92.65	78.45	62.40	77.68
EE	80.12	56.77	79.38	56.03	92.81	83.88	66.67	79.58
POT	79.59	57.91	76.25	56.13	90.15	72.00	72.35	61.98
NoT	65.82	44.54	**80.82**	50.41	88.01	**85.46**	52.58	76.83
ToT	81.91	56.89	79.04	55.40	**96.60**	82.30	66.67	80.49
GoT	71.54	52.04	74.58	51.35	90.90	81.68	53.61	75.58
SCP	79.05	57.59	79.71	55.19	92.29	84.19	66.53	80.01
CLEAR	82.84	58.09	78.26	55.92	85.22	84.00	68.08	82.26
Self Ask	78.66	54.38	79.60	66.11	90.76	83.03	72.09	63.48
Plan & Solve	82.65	56.77	78.26	64.97	90.34	83.92	77.26	62.63
Self Discover	82.71	56.46	79.60	65.70	91.67	84.51	70.28	**80.43**
SEAR	80.19	57.40	77.37	67.26	92.42	83.38	69.64	75.33
SEAR_U	79.92	**61.00**	78.93	**71.10**	92.91	84.89	76.74	78.27
SEAR + R	82.91	56.65	78.82	66.94	91.84	84.77	**79.33**	68.72
SEAR_U + R	**84.18**	59.29	80.27	69.75	91.44	84.39	79.20	70.48

Table 7: HCS scores (in %) using GPT 4o mini, R stands for "Refactoring" and U stands for "Unified".Bold represents the best performer and the underlined represents the second best performer.

Is table refactoring lossless? While LLM-based refactoring may introduce a risk of hallucination, we empirically evaluate this using the AutoQA metric (Jain et al., 2024), which measures answer accuracy on both original and refactored tables. As shown in Table 9, the loss in fidelity is minimal. The slight drop in accuracy is primarily due to purposeful modifications, such as the addition of numerical units, adjustments to headers, and revised table titles. Although these changes alter the structure, they improve semantic clarity and enhance the tables' utility for downstream reasoning tasks.

	wiki	multi	hitab	finqa	tatqa	fetaqa	squall	hybridqa
COT	81.05	57.59	82.95	66.22	91.00	86.03	75.45	81.66
F-COT	66.22	39.82	64.55	51.77	45.12	52.78	61.11	33.31
Decomp	82.85	59.29	81.84	65.28	93.18	84.51	73.51	80.53
EE	81.91	58.92	82.84	61.75	92.54	86.62	80.10	81.07
POT	76.53	58.98	67.56	66.42	91.40	50.44	68.22	37.76
NoT	55.57	39.76	49.83	42.23	48.57	61.18	44.85	65.32
ToT	84.57	45.35	74.99	57.58	82.67	83.50	78.29	83.18
GoT	71.27	52.61	68.45	40.24	72.73	**88.49**	59.19	74.80
SCP	82.96	57.80	79.38	52.52	85.22	85.46	74.96	79.75
CLEAR	86.23	54.93	76.39	56.23	92.15	86.97	79.84	79.71
Self Ask	81.98	56.84	82.06	67.46	91.69	85.98	76.10	72.32
Plan & Solve	82.65	55.95	80.39	66.57	92.51	83.96	76.23	70.55
Self Discover	**85.77**	57.91	**83.95**	66.11	92.87	86.09	79.33	**83.25**
SEAR	82.65	59.61	83.05	66.63	92.34	85.52	81.40	79.78
SEAR_U	82.05	**62.19**	82.39	**70.17**	**93.27**	87.04	882.04	80.27
SEAR + R	82.65	57.09	82.39	67.26	91.67	86.85	76.87	67.74
SEAR_U + R	85.11	58.16	83.05	69.67	92.89	87.23	**82.49**	72.16

Table 8: HCS scores (in %) using Llama 3.1 70B, R stands for "Refactoring" and U stands for "Unified".Bold represents the best performer and the underlined represents the second best performer.

Dataset	fetaqa	finqa	hitab	multi	squall	tatqa	wiki	hybridqa
Accuracy	99.41	95.36	98.06	88.04	86.66	99.40	96.43	84.59

Table 9: AutoQA Accuracy after refactoring Tables.

Error Analysis Summary. We conduct a fine-grained error analysis across six datasets as shown in Figure 2 and find that evidence extraction is the most common failure mode, accounting for the majority of errors in five out of six cases. These errors arise from shallow string matching, ambiguous headers, and missed qualifiers (e.g., years, units, footnotes), leading models to anchor to plausible but incorrect cells, often before any reasoning or computation can take place. Reasoning errors are more prominent in datasets requiring temporal alignment or multi-hop inference, such as TAT-QA, while code-generation failures dominate in WikiTQ due to parsing issues and faulty aggregation over semi-structured tables. Overall, this suggests that early-stage grounding remains the key bottleneck across tasks, with dataset-specific challenges emerging in reasoning and execution stages. **Please refer to Appendix D** for a detailed breakdown of error types by dataset.

6 Discussion

The Adaptive Framework consistently generalizes across multiple datasets by dynamically selecting appropriate reasoning paths. Table 10 summarizes the reasoning paths chosen by GPT-4o-mini, showing that Evidence Extraction is always included. This step helps the model focus on relevant information, aligning with human intuition (Section 3). For lookup-based questions, Evidence Extraction alone suffices, while more complex tasks require a

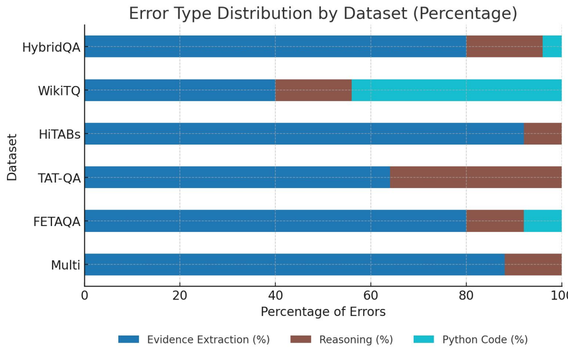

Figure 2: Distribution of error types (evidence extraction, reasoning, and Python code execution) across six benchmark datasets. Evidence extraction emerged as the dominant failure mode in five of the six cases.

combination of reasoning methods.

Datasets with long-form answers, such as FeTaQA, textual strategies works best. As shown in Table 8, for LLaMA 3.1 70B, FeTaQA achieves higher accuracy with CoT (84.13%) and Decomposed Prompting (78.45%). This trend is further supported by Table 10, where Evidence Extraction + Decomposed Prompting is the most frequently chosen. Table 11 reinforces this, showing that 87% of FeTaQA's reasoning paths rely on textual methods, highlighting their effectiveness for free-form responses.

FinQA, which is heavy on numerical computation, favors symbolic methods. As seen in Table 8, PoT achieves the best performance, with F-CoT also performing well. Table 10 further confirms this, with Evidence Extraction + F-CoT as the most common reasoning path. Similarly, Table 11 shows that 88.25% of FinQA's reasoning paths involve PoT and F-CoT, emphasizing the strength of symbolic reasoning for computation-heavy datasets.

This pattern extends across datasets, with chosen reasoning paths aligning with their respective strengths. Table 12 and 13 in Appendix B provide reasoning path analysis for LLaMA 3.1 70B and Gemini-1.5-flash, respectively. By dynamically selecting the most effective reasoning approach based on question type and tabular context, the Adaptive Framework consistently delivers strong performance across diverse table structures and reasoning tasks.

Impact of Table Refactoring. Refactoring tabular data enhances LLM accuracy by improving clarity, structure, and accessibility. Table 2 categorizes key refactoring techniques that aid model interpretation. In *'Table Structure'*, standardizing tables to Markdown format significantly improves performance. For instance, the Squall dataset, originally in JSON, benefits from this transformation. As shown in Table 7, GPT-4o-mini with SEAR + Refactoring (79.33%) outperforms SEAR (69.64%) by 9.69%, and SEAR_U + Refactoring (79.20%) exceeds SEAR_U (76.74%) by 2.46%. Similarly, LLaMA 3.1 70B achieves its highest accuracy (82.49%) with SEAR_U + Refactoring. In *'Title Clarity'*, refining ambiguous or missing table titles improves context.

Figure 10 illustrates how adding a player's name in the title enhances model comprehension. *'Column/Row Headers'* are refined to eliminate ambiguity and better align entities. *'Data Formatting'* reduces redundant details, such as excessive decimal places, which can increase hallucinations as context size grows (Liu et al., 2023). Limiting decimals helps models focus and improves accuracy. *'Bolding and Emphasis'* highlights key details, directing the model's attention to relevant content. *'Other'* refinements, such as adding units, removing whitespace, and reformatting text, further enhance readability. The prompt for table refactoring is shown in Figure 9.

Reasoning Path	Datasets							
	fetaqa	finqa	hitab	hybridqa	multi	squall	tatqa	wiki
EE	175	46	476	**1332**	194	13	**929**	**703**
EE,Decomp	**1365**	65	191	28	127	160	249	293
EE,F-COT	23	**703**	111	5	**335**	**581**	**547**	246
EE,POT	9	138	107	143	**909**	14	**482**	186
COT,EE	1	1	4	12	5	-	5	32
COT,EE,Decomp	8	1	3	2	-	1	1	13
COT,EE,F-COT	1	7	1	-	5	5	12	17
COT,EE,POT	-	1	4	6	12	-	19	14
Total	1582	962	897	1528	1587	774	2244	1504

Table 10: Reasoning Path distribution for GPT-4o-mini.

Dataset	COT		EE		Decomp		POT		F-COT	
	#	%	#	%	#	%	#	%	#	%
fetaqa	10	0.63	1582	100	**1373**	**86.79**	9	0.57	24	1.52
finqa	10	1.03	962	100	66	6.86	139	14.45	**710**	**73.8**
hitab	12	1.34	897	100	**194**	**21.63**	111	12.38	112	12.49
hybridqa	20	1.31	1528	100	30	1.96	**149**	**9.75**	5	0.33
multi	22	1.39	1587	100	127	8.01	**921**	**58.03**	132	8.32
squall	6	0.78	774	100	161	20.8	14	1.81	**586**	**75.71**
tatqa	37	1.65	2244	100	250	11.14	501	22.33	**559**	**24.91**
wiki	76	5.05	1504	100	**306**	**20.35**	200	13.3	263	17.49

Table 11: Distribution of reasoning methods across all the datasets for GPT-4o-mini.

SEAR in the Context of Agentic Frameworks. Agentic frameworks have gained attention for their ability to handle complex reasoning tasks through modular, interacting components such as planning, memory retrieval, and tool use. Although SEAR is not agentic by design, its structured reasoning process aligns with the modular philosophy of agentic systems. Each SEAR module could be instantiated as an individual agent within such a framework. However, the goal of this work is to explore how far prompting alone without external tools or orchestration can be used to address temporal table QA. This design choice prioritizes simplicity and self-containment. Importantly, the central challenge SEAR addresses is selecting and sequencing the appropriate reasoning strategies for a given question and table structure remains critical even within agentic systems.

While agentic architectures offer a more general execution framework, they still depend on effective strategy selection. In this sense, SEAR provides a complementary perspective, offering insights into reasoning decomposition that could inform or enhance agent-based designs.

7 Related Work

Tabular Reasoning. LLMs have been widely applied to tabular reasoning tasks such as question answering, semantic parsing, and table-to-text generation (Chen et al., 2020a; Gupta et al., 2020; Zhang et al., 2020; Zhang and Balog, 2020). Early approaches like TAPAS (Herzig et al., 2020), TaBERT (Yin et al., 2020), and TABBIE (Iida et al., 2021) improve table comprehension by integrating tabular and textual embeddings, allowing models to better process structured information. Other methods, such as Table2Vec (Zhang et al., 2019) and TabGCN (Pramanick and Bhattacharya, 2021), explore alternative tabular representations, enhancing LLMs' ability to infer relationships between table elements. However, these methods primarily focus on structured tables and do not explicitly address temporal reasoning, which introduces additional complexity when reasoning over tabular data.

Symbolic Reasoning for Tables. Recent work has explored symbolic reasoning for structured tables with predefined schemas, improving logical inference and data consistency (Cheng et al., 2023; Ye et al., 2023; Wang et al., 2024). These methods rely on well-defined structures to extract and process information effectively. However, they struggle with semi-structured and hierarchical tables, where relationships between data points are implicit rather than explicitly defined.

Other Reasoning Frameworks. C.L.E.A.R (Deng et al., 2024) demonstrated strong temporal reasoning on domain-specific semi-structured tables by integrating domain knowledge into responses. Similarly, Meta-Reasoning Prompting (MRP)(Gao et al., 2024) selects the optimal reasoning strategy through a two-step process but does not combine reasoning techniques for complex tasks. In contrast, our approach integrates both textual and symbolic reasoning to enhance performance across diverse table types while dynamically selecting the best reasoning path. Moreover, our SEAR-Unified prompt streamlines this into a single-step process, ensuring efficiency and consistency across different table structures.

8 Conclusion and Future Work

This paper introduces SEAR, an adaptive reasoning strategy for LLMs to tackle TTQA tasks, along with its consolidated version, SEAR_Unified. Additionally, we take a step toward a unified table representation by incorporating table refactoring as an enhancement. Our study provides a comprehensive analysis of various reasoning strategies across eight diverse datasets, benchmarking SEAR and SEAR_Unified against multiple baselines.

Results demonstrate that SEAR, SEAR_Unified and with Table Refactoring significantly outperforms popular LLM reasoning methods, with SEAR_Unified surpassing SEAR itself, showcasing its ability to optimize and streamline reasoning with minimal overhead. This highlights capability of modern LLMs to dynamically adjust reasoning within a single prompt, reducing the need for explicit multi-step processes. Our findings reinforce the importance of adaptive reasoning and structured table representation, paving the way for further advancements in LLM-based temporal table reasoning.

While SEAR-based approaches have significantly improved Temporal Table QA, several areas remain open for further exploration. In this work, we have explored Markdown as a unified tabular representation, exploring alternative formats such as JSON, CSV, or HTML may further improve adaptability across diverse table structures. Currently, our experiments relied on in-context learning, which can limit scalability and efficiency. Future work should explore lightweight adaptive reasoning techniques with self-refinement loops, building on the flexibility demonstrated by SEAR. Lastly, valuating SEAR-based methods on additional domains, such as medical or scientific evolution datasets, would help validate the robustness of adaptive reasoning strategies for LLMs.

Limitations

While our study has yielded interesting observations, it's crucial to acknowledge its limitations. A closer look at the HCS scores in Table 6, 7, 8, reveals that while improvements are observed for datasets with single table contexts, datasets containing multiple tables, such as MultiHierTT and Hybrid tables, show a decline in performance with SEAR-based approaches. This highlights a key limitation of our Table Refactoring method, suggesting that restructuring strategies may need further refinement to handle multi-table contexts effectively. Additionally, scalability remains a concern, as our approach relies on In-Context Learning (ICL), which may not scale effectively for large table datasets. The reliance on ICL-based reasoning can lead to performance bottlenecks.

Ethics Statement

We confirm that our work adheres to the highest ethical standards in research and publication. We will publicly release our code and filtered datasets to enable the research community to validate and build upon our findings. We are committed to the responsible and fair use of computational linguistics methodologies. The claims in our paper accurately reflect the experimental results. While using black-box large language models introduces some stochasticity, we mitigate this by maintaining a fixed temperature. We utilize an AI assistive tools for writing while ensuring absence of bias. We provide comprehensive details on annotations, dataset splits, models used, and prompting methods tried, ensuring the reproducibility of our work.

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A Prompt Examples

This section contains the Prompts example for standart 3-step SEAR (Figure 3, 4, 5), SEAR Unified (Figure 6 7), Evaluation Prompt (Figure 8) and Refactoring Prompt and Response (Figure 9, 10).

B REMS and CAE Results

This section contains the additional result for Reasoning Path Distribution for Llama and Gemini (Table 12, 13) and also contains complete result for CAE and REMS score for all GPT, Gemini and Llama (Table 14, 15, 16).

1. Relaxed Exact Match Score(REMS): This metric uses an F1-score to measure token overlap between the predicted and gold answer, allowing partial matches for better precision-recall balance. Unlike strict exact match, REMS is more flexible with lexical variations. For numerical answers, it permits a ±5% tolerance after decimal instead of token matching. For example, if the correct answer is 10.64, a prediction of 10.62 is accepted, while 11.64 is not.

Despite its flexibility, REMS does not always reflect true semantic accuracy. High scores indicate strong token alignment, but valid paraphrases can be unfairly penalized. For instance, the correct answer "Barack Obama was the 44th President of the United States" would receive a high score for "Obama was the 44th U.S. President" due to token overlap, but "Obama, a politician, led the U.S." may score lower despite being factually correct. This limitation makes careful interpretation

2. Contextual Answer Evaluation(CAE): CAE is an LLM-based scoring method that assesses responses based on meaning rather than exact token overlap. Using a carefully crafted prompt, it determines whether a response correctly conveys the intended information. Unlike traditional lexical matching, CAE accounts for paraphrasing and rewording, ensuring a more nuanced assessment of correctness, particularly for complex or free-form answers. The full CAE prompt used for evaluation is provided in Figure 8

C Full Table and Context used in Figure 1

This section includes the actual table and context represented in Figure 1. FinQA Table 21, FetaQA Table 19, WikiTabQA Table 18 and MultiHiertt Table 17, 20.

Reasoning Path	**fetaqa**	**finqa**	**hitab**	**hybridqa**	**multi**	**squall**	**tatqa**	**wiki**
EE	221	39	561	1072	356	9	1040	987
EE,Decomp	553	21	19	8	33	28	59	81
EE,F-COT	571	853	123	35	262	709	391	236
EE,POT	234	45	194	405	919	25	753	187
COT,EE	-	-	-	6	5	-	1	7
COT,EE,Decomp	3	-	-	2	10	1	-	2
COT,EE,F-COT	-	3	-	-	-	2	-	4
POT	-	1	-	-	2	-	-	-
Total	1582	962	897	1528	1587	774	2244	1504

Table 12: Reasoning Path distribution across all datasets for Llama 3.1 70B.

Reasoning Path	**fetaqa**	**finqa**	**hitab**	**hybridqa**	**multi**	**squall**	**tatqa**	**wiki**
EE	982	106	675	1492	155	112	1160	875
EE,DecompE	197	16	6	2	87	17	9	186
EE,F-COT	175	796	29	-	333	516	49	173
EE,POT	191	42	186	33	1010	119	1025	268
COT,EE	25	-	-	1	-	1	1	2
COT,EE,Decomp	3	-	-	-	-	1	-	-
COT,EE,F-COT	2	1	-	-	-	6	-	-
COT,EE,POT	7	-	1	-	-	1	-	-
Decomp	-	1	-	-	-	-	-	-
POT	-	-	-	-	2	1	-	-
Total	1582	962	897	1528	1587	774	2244	1504

Table 13: Reasoning Path distribution across all datasets for Gemini-1.5-Flash.

	wiki		multi		hitab		finqa		tatqa		fetaqa		squall		hybridqa	
	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE
COT	77.31	76.66	**57.49**	49.72	75.26	74.58	58.94	57.07	81.68	87.48	28.38	84.13	66.27	65.25	74.07	76.51
F–COT	67.85	67.82	49.39	51.35	41.44	69.79	60.78	61.12	67.36	86.76	**40.46**	77.69	52.97	53.36	29.78	32.79
Decomp	77.69	76.60	56.12	49.02	73.19	73.36	60.40	58.21	86.13	87.25	28.71	78.45	61.07	59.30	74.71	74.87
EE	78.57	77.86	56.32	48.27	**76.16**	76.92	50.94	46.88	**90.22**	88.06	28.42	83.82	65.55	64.60	**75.85**	**76.96**
POT	76.28	75.93	53.41	53.12	41.92	73.47	51.88	52.49	66.88	86.10	29.71	72.00	65.90	69.12	58.66	60.27
NoT	63.07	63.56	39.04	38.44	69.96	76.25	44.22	46.05	72.78	82.58	29.23	85.46	51.11	50.52	72.17	75.65
ToT	79.79	78.92	53.00	52.43	68.39	76.92	51.96	49.90	81.13	88.01	30.15	82.17	64.98	63.44	76.96	78.01
GoT	69.33	67.09	48.80	45.05	65.91	71.68	47.41	46.36	83.30	86.14	28.95	81.67	52.67	48.58	71.79	72.05
SCP	77.10	76.73	56.44	52.11	74.58	77.15	51.90	50.00	84.71	86.63	28.51	84.13	64.71	64.47	75.49	78.73
CLEAR	80.23	79.72	52.67	57.40	68.62	75.81			85.23	91.13	29.28	83.94	65.85	66.28	77.98	79.84
SEAR	78.32	76.60	54.70	50.98	67.36	74.58	62.52	60.91	81.94	85.83	29.53	83.38	67.56	60.72	72.07	73.63
SEAR_U	77.50	77.53	56.39	**56.84**	71.78	76.70	**62.87**	**67.57**	88.31	**89.75**	31.06	**84.89**	72.26	73.77	74.96	75.85
SEAR + R	80.51	79.39	54.04	51.10	68.40	75.92	61.88	60.08	81.63	85.87	29.71	84.39	**76.85**	74.03	65.89	66.03
SEAR_U + R	**81.14**	**81.25**	55.54	55.51	72.13	**77.59**	62.43	66.53	86.56	88.23	30.47	84.70	76.21	**76.87**	66.96	67.74

Table 14: REMS & CAE score (in %) for all reasoning strategies across all datasets using GPT-4o mini. R stands for "Refactoring," U for "Unified."

	wiki		multi		hitab		finqa		tatqa		fetaqa		squall		hybridqa	
	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE
COT	71.86	71.28	57.29	39.26	73.97	74.25	58.00	39.29	80.81	85.34	28.25	71.24	69.44	69.66	77.29	76.57
F-COT	64.76	57.51	58.36	47.83	35.68	49.34	60.60	34.20	64.86	74.88	**37.05**	55.69	60.40	60.73	17.86	15.97
Decomp	76.26	75.00	58.90	41.84	71.70	72.44	60.72	32.22	84.23	85.12	29.91	67.07	66.01	65.98	72.94	69.31
EE	74.24	72.81	59.02	42.41	74.61	76.43	54.54	30.46	**86.14**	86.27	28.63	77.62	71.89	72.03	74.12	68.72
POT	72.65	66.69	**60.00**	47.01	41.37	67.54	54.90	58.10	66.74	75.61	26.73	50.88	62.66	62.99	38.18	33.84
NoT	70.40	73.07	40.59	41.46	72.08	75.59	58.32	64.24	69.41	76.69	30.73	87.99	65.03	67.05	75.43	77.68
ToT	79.79	78.92	54.65	54.88	70.33	75.70	41.68	47.40	76.84	86.68	29.48	79.20	71.90	73.00	79.42	80.17
GoT	72.82	70.88	51.20	50.03	68.41	82.16	48.34	46.57	79.15	85.34	29.57	84.45	62.08	63.05	77.14	78.53
SCP	79.40	78.92	57.72	56.27	75.90	78.37	46.53	46.26	81.38	86.72	27.85	84.32	68.82	70.80	79.26	82.00
CLEAR	79.82	79.79	56.08	0.06	70.38	76.92	49.47	48.13	79.94	90.42	28.63	83.94	75.32	77.26	79.59	81.81
SEAR	79.08	78.19	57.15	54.69	74.93	76.81	59.90	61.02	75.07	83.87	28.75	82.87	76.14	68.60	**77.61**	78.08
SEAR_U	79.32	80.32	59.27	**57.34**	78.53	79.38	**63.16**	**65.59**	82.70	**86.68**	31.57	79.77	**77.29**	**79.59**	77.11	**79.84**
SEAR + R	80.27	78.46	55.32	52.30	75.08	77.37	59.88	60.50	73.57	84.54	28.97	84.20	76.13	72.09	62.43	62.24
SEAR_U + R	**80.78**	**81.32**	53.09	53.62	**78.94**	**79.60**	61.98	63.83	82.20	85.65	32.89	**85.52**	75.16	75.97	62.96	64.86

Table 15: REMS & CAE score (in %) for all reasoning strategies across all datasets using Gemini1.5 Flash. R stands for "Refactoring," U for "Unified."

SEAR: Step 1

You are a adaptive reasoner tasked with constructing the most efficient pathway for solving tabular questions. Your goal is to select or create minimal, high-level steps to guide reasoning, avoiding direct answers. NOTE - Do not answer, only select crucial steps.

Guidelines:
Problem Understanding:
Identify Objective: Define the question's goal.
Comprehend Problem: Understand the scope and nature of the problem.

Reasoning Process:
Evidence Extraction: Extract relevant rows, columns, and text.
Decomposition: Break down complex questions into sub-questions if necessary.
Step-by-Step Reasoning: Apply logical steps to solve sub-questions or the main problem.
Python Code Generation: Opt to generate code (single or multiple scripts) if calculations are required.

Optimization Tips:
Direct Answer Path: Use evidence extraction to find the answer directly, when possible.
Simplify: Break down complex questions into simpler components.
Code Integration: Include Python code generation for essential calculations.

Few examples are given below with their respective crucial steps selected from the meta-reasoning process. Each example contains its own table, text, and question. Interpret the problem and select only the most essential steps for reaching to answer.

Table:

```
Model          | 2005   | 2006   | 2007   | 2008   | 2009   | 2010   | 2011   | 2012   | 2013   |
Škoda Octavia  | 233322 | 270274 | 309951 | 344857 | 317335 | 349746 | 387200 | 409360 | 359600 |
Škoda Fabia    | 236698 | 243982 | 232890 | 246561 | 264173 | 229045 | 266800 | 255025 | 202000 |
Škoda Superb   | 22091  | 20989  | 20530  | 25645  | 44548  | 98873  | 116700 | 106847 | 94400  |
Škoda Roomster |        | 14422  | 66661  | 57467  | 47152  | 32332  | 36000  | 39249  | 33300  |
Škoda Yeti     |        |        |        |        | 11018  | 52604  | 70300  | 90952  | 82400  |
Škoda Rapid    |        |        |        |        |        |        | 1700   | 9292   | 103800 |
Škoda Citigo   |        |        |        |        |        |        | 509    | 36687  | 45200  |
```

Question: How many Skoda cars were sold in 2010?

LLM Output

Crucial Steps:

Identify Objective: Define the goal.
Evidence Extraction:Extract relevant rows, columns, and text.
Python Code Generation: Generate single Python code to sum the extracted values.

Figure 3: Sear Step 1 Prompt Example

	wiki		multi		hitab		finqa		tatqa		fetaqa		squall		hybridqa	
	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE	REMS	CAE
COT	79.20	78.86	56.91	48.71	80.77	**81.38**	60.91	60.81	83.69	86.10	28.07	86.03	73.21	73.39	79.10	**79.78**
F-COT	63.02	62.43	37.21	37.30	37.35	61.76	48.14	48.44	59.67	61.72	25.34	52.72	56.53	58.01	30.30	31.28
Decomp	80.71	80.78	58.39	52.24	78.71	80.72	60.50	59.77	86.62	86.41	29.36	84.51	71.00	71.58	**79.98**	77.75
EE	80.30	79.79	57.70	48.27	**81.42**	80.05	57.03	53.53	89.09	87.70	28.63	86.62	78.12	77.78	78.33	78.73
POT	74.74	73.34	56.47	55.14	37.05	65.44	62.44	61.75	65.02	87.17	20.25	50.44	63.43	64.73	35.63	35.60
NoT	51.86	52.39	30.77	34.85	43.25	46.82	33.88	39.50	41.53	46.75	20.86	61.19	44.86	47.03	68.12	69.50
ToT	82.28	81.72	40.89	46.06	78.48	80.71	55.79	49.06	86.05	90.01	29.13	83.44	74.88	75.97	78.24	80.96
GoT	69.34	68.02	50.49	48.08	65.25	66.33	36.59	40.24	72.59	77.58	30.22	88.50	59.04	61.88	70.42	73.23
SCP	82.57	85.10	55.19	59.48	80.15	84.05	52.65	51.98	84.19	90.06	28.68	85.40	77.03	77.39	77.15	79.71
CLEAR	83.49	82.91	83.50	85.95	83.50	85.95	36.50	42.20	90.06	92.15	29.36	86.92	77.39	79.84	75.58	77.55
SEAR	80.69	78.79	57.76	50.79	75.45	78.60	61.40	60.40	84.67	**88.41**	29.47	85.52	78.74	72.22	76.43	77.29
SEAR_U	78.91	79.26	**60.02**	**58.03**	75.12	79.38	**63.30**	**66.01**	**89.20**	86.36	34.15	87.04	78.74	80.62	77.11	78.24
SEAR + R	80.17	78.46	54.97	48.02	75.77	78.37	62.00	61.43	81.71	86.99	29.53	86.85	73.95	70.67	67.35	70.75
SEAR_U + R	**82.53**	**82.05**	56.15	52.68	76.19	77.70	61.66	66.03	86.58	86.47	**34.83**	**87.17**	**79.01**	**80.68**	67.11	67.80

Table 16: REMS & CAE score (in %) for all reasoning strategies across all datasets using Llama3.170B. R stands for "Refactoring," U for "Unified."

Benefit Plan	**2017**	**2016**	**2015**
Pension Plan	3856	3979	2732
Health Plan	11426	11530	8736
Other plans	1463	1583	5716
Total plan contributions	16745	17092	17184

Table 17: Benefit Plan Contributions, Benefits, Multi-Hiertt example Table 0

Year	**Amount ($)**
2007	56499000
2008	46899000
2009	39904000
2010	33329000
2011	25666000
Later Years	128981000

Table 21: Aggregate Minimum Lease Payments, Lease Payments FinQA

SEAR: Step 2

Your task is to comprehend the crucial steps for a given table and question, making each step more detailed and ensuring they effectively lead to the correct answer.

Few Examples are given below with detailed steps by elaborating from the crucial steps. Interpret the examples and understand the task to comprehend the crucial steps according to the specific table, text and question to reach the answer efficiently.

Table:

```
Model          | 2005   | 2006   | 2007   | 2008   | 2009   | 2010   | 2011   | 2012   | 2013   |
Škoda Octavia   | 233322 | 270274 | 309951 | 344857 | 317335 | 349746 | 387200 | 409360 | 359600 |
Škoda Fabia     | 236698 | 243982 | 232890 | 246561 | 264173 | 229045 | 266800 | 255025 | 202000 |
Škoda Superb    | 22091  | 20989  | 20530  | 25645  | 44548  | 98873  | 116700 | 106847 | 94400  |
Škoda Roomster  |        | 14422  | 66661  | 57467  | 47152  | 32332  | 36000  | 39249  | 33300  |
Škoda Yeti      |      |      |      |      | 11018  | 52604  | 70300  | 90952  | 82400  |
Škoda Rapid     |      |      |      |      |      |      | 1700   | 9292   | 103800 |
Škoda Citigo    |      |      |      |      |      |      | 509    | 36687  | 45200  |
```

Question: How many Skoda cars were sold in 2010?

Crucial Steps:

Identify Objective: Define the goal.
Evidence Extraction:Extract relevant rows, columns, and text.
Python Code Generation: Generate single Python code to sum the extracted values.

LLM Output

Detailed Steps:

Identify Objective: Determine that the goal is to find the total number of Škoda cars sold in 2010.
Evidence Extraction: Extract the relevant data (the 2010 column) for all models listed in the table.
Python Code Generation: Generate Python code to sum the extracted values for the year 2010.

Figure 4: Sear Step 2 Prompt Example

Total Debt Overview: for FinQA example. Total debt at July 1, 2006 was $1,762,692,000, of which approximately 75 was at fixed rates averaging 6.0 with an average life of 19 years, and the remainder was at floating rates averaging 5.2. Certain loan agreements contain typical debt covenants to protect noteholders, including provisions to maintain the company's long-term debt to total capital ratio below a specified level. Sysco was in compliance with all debt covenants at July 1, 2006.

The fair value of Sysco's total long-term debt is estimated based on the quoted market prices for the same or similar issues or on the current rates offered to the company for debt of the same remaining maturities. The fair value of total long-term debt approximated $1,669,999,000 at July 1, 2006 and $1,442,721,000 at July 2, 2005, respectively. As of July 1, 2006 and July 2, 2005, letters of credit outstanding were $60,000,000 and $76,817,000, respectively.

Leases: for FinQA example. Although Sysco normally purchases assets, it has obligations under capital and operating leases for certain distribution facilities, vehicles, and computers. Total rental expense under operating leases was $100,690,000, $92,710,000, and $86,842,000 in fiscal 2006, 2005, and 2004, respectively. Contingent rentals, subleases, and assets and obligations under capital leases are not significant. Aggregate minimum lease payments by fiscal year under existing non-capitalized long-term leases are as follows:

D Detailed Error Analysis

We conduct a detailed error analysis across six datasets to identify the primary failure modes in pipeline-based table QA. As shown in plot 2 evidence extraction errors dominate in most datasets, often occurring before reasoning or code execution can contribute. However, we also observe notable secondary errors particularly in reasoning (e.g., TAT-QA) and code (e.g., WikiTQ) which vary by dataset structure and modality.

Dataset-specific Observations

HybridQA. Most errors result from incorrect row/column selection, driven by surface-level matches to look-alike strings (e.g., "season," "division") and missed disambiguators (e.g., years or suffixes like "(q)"). These tokens frequently appear in adjacent cells or parentheses, making shallow matches more likely. A small number of reasoning errors stem from failure to disambiguate linked

Year	Kit Manufacturer	Shirt Sponsor	Back of Shirt Sponsor	Short Sponsor
1977–1978	-	National Express	-	-
1982–1985	Umbro	-	-	-
1985–1986	Umbro	Whitbread	-	-
1986–1988	Henson	Duraflex	-	-
1988–1989	-	Gulf Oil	-	-
1991–1993	Technik	Gulf Oil	-	-
1993–1994	Club Sport	Gulf Oil	-	-
1994–1995	Klūb Sport	Empress	-	-
1995–1996	Matchwinner	Empress	-	-
1996–1997	UK	Endsleigh Insurance	-	-
1997–1999	Errea	Endsleigh Insurance	-	-
1999–2004	Errea	Towergate Insurance	-	-
2004–2008	Errea	Bence Building Merchants	-	-
2008–	Errea	Mira Showers	-	-
2009–2011	Errea	Mira Showers	PSU Technology Group	-
2011–2013	Errea	Mira Showers	Barr Stadia	Gloucestershire Echo
2013–	Errea	Mira Showers	Gloucestershire College	Gloucestershire Echo

Table 18: Historical Sponsorship and Kit Manufacturer Data, WikiTabQA example

entities across tables. Code issues are rare due to minimal programmatic computation.

HiTABs. Models often fail due to header ambiguity and dense, repetitive tabular layouts. Errors stem from misidentified rows/columns and unaccounted qualifiers like ranges or footnotes. Since the task is primarily table lookup, downstream reasoning errors are minimal, and code is not a significant factor.

MultiHiertt (Multi). High error rate in evidence selection is attributed to multi-hop grounding and similar-looking headers across tables. Subtle distinctions in qualifiers or column semantics are frequently overlooked. The remaining errors are due to misinterpretation of multi-hop logic, where the model fails to chain intermediate inferences.

TAT-QA. While evidence errors are common, reasoning mistakes form a large minority (36%), often caused by temporal mismatches (e.g., Q1 vs. FY) or incorrect unit normalization (e.g., billions vs. millions). Models struggle to align period-based values or compute correct numerical operations even with correct evidence.

FETAQA. Evidence-level failures persist due to repeated phrases across seasons, clubs, and divisions. Parenthetical markers (e.g., "(q)") in headers lead to grounding mismatches. Some errors stem from reasoning failures, particularly aggregation mismatches or improper scoping across semi-structured tables. A few errors involve minor code missteps, such as summing incorrect subsets.

WikiTQ. Unlike others, code generation errors dominate (44%). The model often produces incorrect filters or aggregation logic due to brittle parsing of semi-structured HTML-derived tables. Even when correct evidence is identified, the final output is wrong due to mis-joins, faulty parsing of footnotes, or wrong aggregation. Evidence errors (40%) and reasoning mistakes (16%) persist but are less frequent.

The analysis reveals that evidence selection remains the primary bottleneck across most datasets. However, reasoning errors are increasingly relevant in multi-hop or temporal computation tasks (TAT-QA), and code execution errors emerge as a major challenge in semi-structured, programmatic tasks like WikiTQ. Addressing early-stage grounding *and* late-stage execution together is critical for end-to-end accuracy.

E DataSet Overview

1. **FeTaQA(Nan et al., 2021) :** A Wikipedia-based table QA dataset that requires generating long-form answers by integrating multiple discontinuous facts and reasoning across structured tables. **Temporal Questions: 1,582**
2. **FinQA(Chen et al., 2021) :** A financial QA dataset from reports, requiring expert-verified multi-step numerical reasoning and gold reasoning programs for explainability. **Temporal Questions: 962**
3. **HiTab(Cheng et al., 2022) :** A cross-domain QA and NLG dataset featuring hierarchical tables, analyst-authored questions, and fine-grained annotations for complex numerical reasoning. **Temporal Questions: 897**
4. **HybridQA(Chen et al., 2020b) :** A QA dataset requiring reasoning over Wikipedia tables and linked free-form text, demanding both tabular and textual data for accurate answers. **Temporal Questions: 1,528**

Year	Title	Role	Director	Notes
2000	The Apocalypse	Johanan	Raffaele Mertes	-
2002	Tom & Thomas	Tom Sheppard / Thomas	Esmé Lammers	-
2003	Behind Closed Doors	Sam Goodwin	Louis Caulfield	-
2003	Shanghai Knights	Charlie Chaplin	David Dobkin	-
2004	Dead Cool	George	David Cohen	-
2006	The Thief Lord	Prosper	Richard Claus	-
2006	The Illusionist	Young Eisenheim	Neil Burger	-
2006	Fast Learners	Neil	Christoph Röhl	Short film
2006	The Best Man	Michael (Aged 15)	Stefan Schwartz	-
2007	The Magic Door	Flip	Paul Matthews	-
2008	Dummy	Danny	Matthew Thompson	Nominated — ALFS Award
2008	Angus, Thongs	Robbie Jennings	Gurinder Chadha	-
2009	The Greatest	Bennett Brewer	Shana Feste	-
2009	Nowhere Boy	John Lennon	Sam Taylor-Johnson	Empire Award for Best...
2010	Kick-Ass	David "Dave" Lizewski	Matthew Vaughn	Nominated — Empire Award...
2010	Chatroom	William Collins	Hideo Nakata	-
2011	Albert Nobbs	Joe Mackins	Rodrigo García	-
2012	Savages	Ben	Oliver Stone	-
2012	Anna Karenina	Count Vronsky	Joe Wright	Final time credited as...
2013	Kick-Ass 2	David "Dave" Lizewski	Jeff Wadlow	First time credited as...
2014	Captain America: Winter Soldier	Pietro Maximoff	Anthony and Joe Russo	Uncredited cameo
2014	Godzilla	Lt. Ford Brody	Gareth Edwards	-
2015	Avengers: Age of Ultron	Pietro Maximoff	Joss Whedon	-
2016	Nocturnal Animals	Ray Marcus	Tom Ford	Golden Globe Award for...
2017	The Wall	Isaac	Doug Liman	-
2018	Outlaw King	James Douglas	David Mackenzie	-
2018	A Million Little Pieces	James Frey	Sam Taylor-Johnson	-
2020	Kingsman: The Great Game	-	Matthew Vaughn	Filming

Table 19: Aaron Taylor-Johnson Filmography, example FeTaQA

	2018	2019	2020	2021	2022	Thereafter	Total
Property mortgages and other loans	153593	42289	703018	11656	208003	1656623	2775182
MRA facilities	90809	0	0	0	0	0	90809
Revolving credit facility	0	0	0	0	0	40000	40000
Unsecured term loans	0	0	0	0	0	1500000	1500000
Senior unsecured notes	250000	0	250000	0	800000	100000	1400000
Trust preferred securities	0	0	0	0	0	100000	100000
Capital lease	2387	2411	2620	2794	2794	819894	832900
Ground leases	31049	31066	31436	31628	29472	703254	857905
Estimated interest expense	226815	218019	184376	163648	155398	281694	1229950
Joint venture debt	200250	717682	473809	449740	223330	2119481	4184292
Total	954903	1011467	1645259	659466	1418997	7320946	13011038

Table 20: Loans and Liabilities, Loans, MultiHiertt example Table 1

5. **MultiHierTT(Zhao et al., 2022) :** A financial QA benchmark requiring reasoning over multiple hierarchical tables and long unstructured text, with detailed multi-step numerical reasoning annotations. **Temporal Questions: 1,587**

6. **Squall(Shi et al., 2020) :** An extension of WikiTableQuestions with manually created SQL equivalents and fine-grained alignments, supporting structured query reasoning in tabular environments. **Temporal Questions: 774**

7. **TAT-QA(Zhu et al., 2021) :** A financial QA dataset requiring reasoning over both tabular and textual data, involving operations like arithmetic, counting, and sorting for quantitative and qualitative analysis. **Temporal Questions: 2,244**

8. **WikiTableQ(Pasupat and Liang, 2015) :** A Wikipedia-based QA dataset with trivia-style questions requiring factual and numerical reasoning over tables with at least 8 rows and 5 columns. **Temporal Questions: 1,504**

SEAR: Step 3

You are responsible for delivering precise answers by strictly following the provided detailed steps. Each answer must be carefully reasoned, supported by clear explanations, and based on thorough analysis of the given table, text, and question.

Few examples are given below. Interpret the examples and understand the task to answer the tabular question according to the specific table, text, question by following the detailed steps to answer efficiently.

Table:

Model	2005	2006	2007	2008	2009	2010	2011	2012	2013
Škoda Octavia	233322	270274	309951	344857	317335	349746	387200	409360	359600
Škoda Fabia	236698	243982	232890	246561	264173	229045	266800	255025	202000
Škoda Superb	22091	20989	20530	25645	44548	98873	116700	106847	94400
Škoda Roomster		14422	66661	57467	47152	32332	36000	39249	33300
Škoda Yeti					11018	52604	70300	90952	82400
Škoda Rapid							1700	9292	103800
Škoda Citigo							509	36687	45200

Question: How many Skoda cars were sold in 2010?

Crucial Steps:

Identify Objective: Define the goal.
Evidence Extraction:Extract relevant rows, columns, and text.
Python Code Generation: Generate single Python code to sum the extracted values.

Detailed Steps:

Identify Objective: Determine that the goal is to find the total number of Škoda cars sold in 2010.
Evidence Extraction: Extract the relevant data (the 2010 column) for all models listed in the table.
Python Code Generation: Generate Python code to sum the extracted values for the year 2010.

LLM Output

Answer and Reasoning:

Identify Objective: The goal is to find the total number of Škoda cars sold in 2010.

Evidence Extraction: Extract the relevant data (the 2010 column) for all models listed in the table:
Škoda Octavia: 349746
Škoda Fabia: 229045
Škoda Superb: 98873
Škoda Roomster: 32332
Škoda Yeti: 52604
Škoda Rapid: N/A (No data for 2010)
Škoda Citigo: N/A (No data for 2010)

Python Code Generation: We can now sum the extracted values for the year 2010 using Python code
``` python ```
```
# Data for 2010
skoda_sales_2010 = [349746, 229045, 98873, 32332, 52604]
# Calculate the total sales for 2010
total_sales_2010 = sum(skoda_sales_2010)
print(f"Final Answer: {{total_sales_2010}}")
#Done
```
Answer and Reasoning: Summing these values gives the total number of Škoda cars sold in 2010.
Final Answer: 762600

Figure 5: Sear Step 3 Prompt Example
```

SEAR_UNIFIED PROMPT

Instruction
You are a adaptive-reasoner with the capabilities to select or merge steps to create the most appropriate reasoning pathway based on the tabular question provided by the user. You can even develop new reasoning steps by combining the new steps or learning from illustrations to create new pathways depending on the provided problem.

Steps for Adaptive Reasoning:
Each section has multiple approaches, you do not have to use all the approaches. Understand their use-cases and then pick minimal relevant steps to create your own optimal approach to answer the question.

Problem Understanding:
- Determine the objective: Identify the goal or desired outcome of the reasoning process.
- Understand the problem: Comprehend the nature and scope of the problem.

Reasoning Process:
- Step-by-step reasoning: Approach the problem logically, ensuring clarity at each step or stage.
- Extract relevant information: Gather all necessary data and details pertinent to the problem, by extracting relevant rows, columns and textual information.
- Decomposition of problem into sub-problems: Break down the main question into smaller and more manageable sub questions.
- Individually answer each sub-problem with reasoning: Apply logical steps to solve each sub question separately.
- Write a single Python program for solving the problem: Create a detailed unified Python script with comments describing the steps and stages.
- Individually write a Python program for each sub-problem: Develop separate Python scripts for each sub-problem, ensuring modularity and clarity.

Conclusion:
- Summarize findings: Combine the results from each step or sub question to give the final answer as Final Answer: {{Answer}}.
- Combine Python code: If necessary, integrate the individual Python scripts into a cohesive program at the end. Print the final answer as Final Answer: {{Answer}}, end your code with a comment "#Done".

Error Detection:
- Review each step or sub-problem: Ensure each step or sub-problem has been addressed thoroughly and correctly.
- Ensure logical flow: Verify that the reasoning process flows logically from one step to the next.
- Check Python program for syntax and errors: Confirm that the final Python program is syntactically correct and free of errors.

Helpful Tips for Creating Appropriate and Optimal Approach:
- Understand what is asked in the question, mention all the steps required to answer the question and why each step is necessary.
- If the question can be broken into smaller and more manageable sub questions, always decompose the question into relevant sub questions.
- If there are **calculations involved you must use python code** for performing calculations and reaching the final answer.
- If the question is directly answerable by direct look up from the tabular data or from the extracted evidence then provide a direct answer.

Table:
Context:

Race Results Overview

This table showcases the results of various athletes who participated in different heats, including their times and nationalities.

Rank	Heat	Name	Nationality	Time	Notes
1	1	Salem Al-Yami	Saudi Arabia	10.55	Q
2	1	Hiroyasu Tsuchie	Japan	10.64	Q
3	1	Khaled Yousef Al-Obaidli	Qatar	10.68	Q
4	1	Chintake De Zoysa	Sri Lanka	10.78	q
5	1	Suminda Mendis	Sri Lanka	10.82	q, PB
6	1	Vissanu Sophanich	Thailand	10.87	
1	2	Gennadiy Chernovol	Kazakhstan	10.59	Q
2	2	Yuta Kanno	Japan	10.64	Q
3	2	Shen Yunbao	China	10.72	Q
4	2	Tsai Meng-Lin	Chinese Taipei	10.74	q
5	2	Tan Kok Lim	Malaysia	10.83	q
6	2	Ahmad Hudeib Al-Mamari	Oman	10.97	
1	3	Jamal Al-Saffar	Saudi Arabia	10.57	Q
2	3	Reanchai Srihawong	Thailand	10.72	Q
3	3	Shin Jung-Ki	South Korea	10.79	[2]
4	3	Chen Tien-Wen	Chinese Taipei	10.74	q
5	3	To Wai Lok	Hong Kong	10.92	
6	3	Poh Seng Song	Singapore	11.10	SB
1	4	Chen Haijian	China	10.65	Q
2	4	Saad Faraj Al-Shahwani	Qatar	10.67	Q
3	4	Azmi Ibrahim	Malaysia	10.78	Q
4	4	Chiang Wai Hung	Malaysia	10.89	
5	4	Nguyen Thanh Hai	Vietnam	11.16	PB
6	4	Piphop Rasme Prum Keo	Cambodia	11.70	PB

Question : which country finished earlier, thailand or japan?

Optimal Approach:

Figure 6: SEAR_UNIFIED Prompt Example

RESPONSE (REASONING PATH: COT, EE, DECOMPOSITION)

To answer the question "Which country finished earlier, Thailand or Japan?" using the provided table, we will apply optimal meta-reasoning to create an appropriate approach to develop the final answer.

Problem Understanding (Step-by-Step):
1. Determine the objective: Identify the country that finished earlier between Thailand and Japan.
2. Understand the problem: We need to compare the finish times of athletes from Thailand and Japan. Since the table contains data on athletes from various countries, including Thailand and Japan, we can extract the relevant information and compare the times.

COT

Reasoning Process:
3. Extract Relevant Information:
We need to find the finish times of athletes from Thailand and Japan. From the table, we can see that there are multiple athletes from each country. We will extract the times for each athlete and then compare them.

Here are the relevant rows and columns extracted from the table:

Evidence -
From Heat 1:

Rank	Name	Nationality	Time	Notes
6	Vissanu Sophanich	Thailand	10.87	
2	Hiroyasu Tsuchie	Japan	10.64	Q

From Heat 2:

Rank	Name	Nationality	Time	Notes
2	Yuta Kanno	Japan	10.64	Q

From Heat 3:

Rank	Name	Nationality	Time	Notes
2	Reanchai Srihawong	Thailand	10.72	Q

EE

4. Decompose the problem into sub-problems:
- Compare the times of athletes from Thailand and Japan in each heat.
- Determine which country had the fastest time overall.

5. Individually answer each sub-problem with reasoning:
- In Heat 1, Hiroyasu Tsuchie from Japan finished with a time of 10.64, while Vissanu Sophanich from Thailand finished with a time of 10.87. Japan finished earlier in this heat.
- In Heat 2, Yuta Kanno from Japan finished with a time of 10.64, which is the same as Hiroyasu Tsuchie in Heat 1.
- In Heat 3, Reanchai Srihawong from Thailand finished with a time of 10.72, which is slower than the times of the Japanese athletes in Heats 1 and 2.

DECOMP

6. Conclusion:
Based on the extracted information and comparison of times, Japan finished earlier than Thailand.

Final Answer: Japan.

Figure 7: The figure illustrates the response path followed by SEAR_Unified Prompting. The reference prompt is provided in Figure 6

Input :

You are an expert LLM evaluator tasked with assessing the accuracy of model responses against gold standard answers. Your role is to determine if the core content and intent of the model's response align with the gold answer, considering various answer formats and implicit information.

Key Guidelines

- **Understand the question's essence**, including specific operations or units mentioned.
- **Compare model responses** to gold answers, focusing on key information.
- **Allow a small margin of error** ($\pm 0.1\%$) for numerical answers.
- **Recognize correct answers in different formats**, such as percentages and decimals.
- **Consider implicit information and context** in responses.
- **For list-type answers**:
  - Evaluate based on content rather than order.
  - If more than **two elements are missing** (context-dependent), evaluate as incorrect.
- **Assess mathematical answers** based on value range unless a specific value is required.
- **Check for appropriate units** in mathematical answers.

Final Judgment
Provide a **"Yes" or "No"** judgment without explanation unless explicitly requested.

Figure 8: Prompt for Contexual Answer Evaluation(CAV)

Input :

Instruction
You are given the following **Question** and **Context**. The **Context** includes a table that may be incomplete, ambiguous, or poorly structured. Your task is to produce a **cleaned version of the table** that improves its clarity and structure so that it can be correctly used to answer the **Question**.

Guidelines

1. **Do not add, remove, or alter any data**. Only restructure and clarify what is already present.
2. You may improve the **table title** if it is missing or ambiguous:
   - If a title is missing, infer an appropriate one based on the **question** and table content.
   - If the existing title is unclear or misleading, revise it for clarity while keeping its original meaning.
3. You may improve the **table headers** if needed:
   - Rename ambiguous column/row headers for clarity.
   - Ensure column and row labels accurately describe their content.
4. You may fix **structural inconsistencies**:
   - Align misaligned data properly under the correct headers.
   - Ensure row and column structures are uniform.
   - Remove redundant headers or merge split headers where necessary.
5. The data should be kept in the same order whenever possible. However, if **minor reordering of rows or columns** helps fix structural issues, you may do so **only if it does not change or omit any data**.

Output Format

- Provide only the **cleaned table** as your output in a structured format appropriate for the data in **Markdown format**.
- **Do not add any explanations, reasoning, or commentary**.

Question: `{question}`

Context: `{context}`

Now produce just the cleaned table.

Figure 9: Prompt for Refactoring Tables.

Table Refactoring Example

Question: how many passing yards did J.J. Raterink get in 2012?

Initial Table

Title : afl statistics

Lack of Context About Table

Bad Column Headers

year	team	passing							rushing		
		cmp	att	pct	yds	td	int	rtg	att	yds	td
2010	chicago	65	102	63.7	767	14	2	112.66	8	9	2
2011	chicago	64	105	61.0	888	16	2	118.27	4	8	2
2011	kansas city	311	500	62.2	3,723	65	17	103.28	48	138	5
2012	iowa	413	618	66.8	4,870	93	10	121.49	37	110	8
2013	iowa	346	575	60.2	4,015	78	18	102.19	32	10	8
2014	los angeles	211	383	55.1	2,335	38	19	77.53	6	5	1
2014	iowa	101	163	62.0	1,320	22	1	118.65	37	111	9
2015	las vegas	178	325	54.8	1,986	35	9	88.57	32	19	6
career		1,689	2,771	61.0	19,904	361	78	103.65	204	410	41

Refactored Table

Title: Player Statistics for J.J. Raterink

Improved Title for better Context

Improved Column Headers

Year	Team	Passing Completions	Passing Attempts	Completion Percentage	Passing Yards	Touchdowns	Interceptions	Rating	Rushing Attempts	Rushing Yards	Rushing Touchdowns
2010	Chicago	65	102	63.7%	767	14	2	112.66	8	9	2
2011	Chicago	64	105	61.0%	888	16	2	118.27	4	8	2
2011	Kansas City	311	500	62.2%	3,723	65	17	103.28	48	138	5
2012	Iowa	413	618	66.8%	4,870	93	10	121.49	37	110	8
2013	Iowa	346	575	60.2%	4,015	78	18	102.19	32	10	8
2014	Los Angeles	211	383	55.1%	2,335	38	19	77.53	6	5	1
2014	Iowa	101	163	62.0%	1,320	22	1	118.65	37	111	9
2015	Las Vegas	178	325	54.8%	1,986	35	9	88.57	32	19	6
Career		1,689	2,771	61.0%	19,904	361	78	103.65	204	410	41

Figure 10: Refactored Table Example