

PROTRIX: Building Models for Planning and Reasoning over Tables with Sentence Context

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Abstract

Tables play a crucial role in conveying information in various domains. We propose a *Plan-then-Reason* framework to answer different types of user queries over tables with sentence context. The framework first plans the reasoning paths over the context, then assigns each step to program-based or textual reasoning to reach the final answer. This framework enhances the table reasoning abilities for both in-context learning and fine-tuning methods. GPT-3.5-Turbo following *Plan-then-Reason* framework surpasses other prompting baselines without self-consistency while using less API calls and in-context demonstrations. We also construct an instruction tuning set *TrixInstruct* to evaluate the effectiveness of fine-tuning with this framework. We present PROTRIX model family by finetuning models on *TrixInstruct*. Our experiments show that PROTRIX family generalizes to diverse unseen tabular tasks with only 6k training instances. We further demonstrate that PROTRIX can generate accurate and faithful explanations to answer complex free-form questions. Our work underscores the importance of the planning and reasoning abilities towards a model over tabular tasks with generalizability and interpretability. We will open-source our dataset and models.

1 Introduction

Tables, serve as a fundamental tool for organizing and presenting information across various domains. Whether in business reports, or scientific publications, tables are commonly employed to convey complex data effectively. Despite their widespread utility, the process of human beings answering questions involving tables appears to be time-consuming, given the often substantial amount of content involved. Recognizing this challenge, there arises a need to leverage the capabilities of Large Language Models (LLMs) to understand and respond to user queries automatically.

Rank	Name	Nationality	Time
1	Brahim Boulami	Morocco	8:17.73
2	Reuben Kosgei	Kenya	8:18.63
3	Stephen Cherono	Kenya	8:19.98
4	Bouabdellah Tahri	France	8:20.25
5	Tim Broe	United States	8:20.75
6	Luis Miguel Martín	Spain	8:24.03
7	Raymond Yator	Kenya	8:27.19
8	Thomas Chorny	United States	9:24.26

Sentence Context
Brahim Boulami (born April 20, 1972 in Safi) is a Moroccan athlete who set two world records in the 3,000 meter steeplechase.
Reuben Seroney Kosgei (born 2 August 1979 in Kapcherop, Kenya), is a middle and long distance athlete mostly famous for 3000 m steeplechase in which he became the youngest ever winner of an Olympic gold medal.
Saif Saaeed Shaheen formerly Stephen Cherono (born 15 October 1982), is a steeplechase runner.

How many medals were won by Kenya?

Is this claim true or false?

The silver medalist of the 3,000 meters steeplechase at 2001 Goodwill Games has never won a Olympic gold medal.

How successful is Kenya in the 3000 meters steeplechase at 2001 Goodwill Games?

Figure 1: Demonstrations of user queries to a table in Wikipedia. The table is extracted from the Wikipedia page Athletics at the 2001 Goodwill Games. Some of the sentences with hyperlinks to the table are presented as sentence context.

Figure 1 demonstrates three kinds of user queries for a table from Wikipedia. In the first example, the user query is *how many medals were won by Kenya*. This question is annotated as a program-unsolvable question by SQL experts (Shi et al., 2020) attributed to the absence of an explicit column for medals in the table. To resolve this, the model must fill the gap between the query and the

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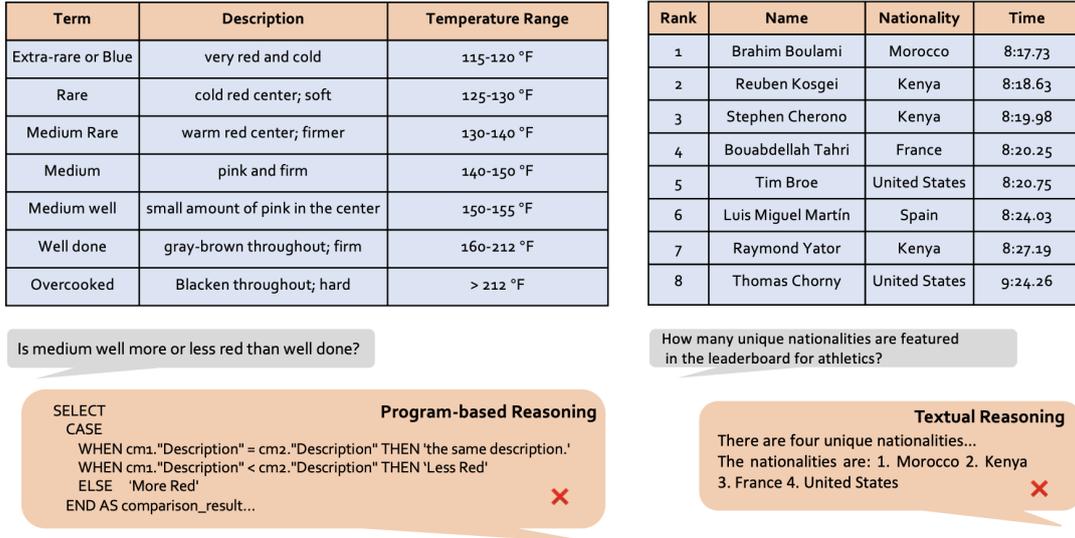


Figure 2: Demonstration of disadvantages of program-based and textual reasoning on tabular tasks. Program-based reasoning fails to answer the query since it tries to compare general concepts with a math operator. The textual reasoning fails on a program-solvable query that needs to count distinct countries in the table.

table by recalling the commonsense knowledge that *only the top three players can win medals*.

The second query delves into a multi-hop scenario asking whether *the silver medalist at the 2001 Goodwill Games has ever won an Olympic gold medal*. Addressing such queries raises two challenges (1) Decompose the query into sub-tasks. Such as the model plans to derive the silver medalists first and then verify their record of Olympic medals. (2) Combining structured and unstructured context. The model must extract the athletic name from the table and derive the information from the sentence context that Kosgei has won an Olympic gold medal since he is *the youngest ever winner of an Olympic gold medal*.

The last query also requires the model to recall commonsense knowledge to decide which contextual information can be used as evidence to judge if *Kenya is successful at the 2001 Goodwill Games*. Subsequently, the model must generate explanations to arrive at certain conclusions. The first two queries mainly require the model to fill the information gap in the query with a short-form answer while the third query seeks for information on a more general concept. The queries underscore the importance of planning and reasoning abilities to connect the general concepts with the actual information in the context and generate faithful and accurate explanations for conclusions.

There are generally two ways to enhance reasoning ability. One is textual reasoning which prompts

the model to answer questions step-by-step (Wei et al., 2022). The other one is program-based reasoning, prompting the model to write code to answer the questions (Chen et al., 2022). Each of the reasoning methods has its disadvantages as shown in Figure 2. The textual reasoning method such as Chain-of-Thought (Wei et al., 2022) can be used to enhance the tabular reasoning ability but often lacks precision in tabular operations such as sorting, counting and filtering as shown in the right example in Figure 2, and may not generalize well to large tables (Chen, 2023). The program-based reasoning method can reason with high precision with SQL or Python code (Chen et al., 2022). The left example in Figure 2 queries the color comparison between steaks with different cooking methods which is program-unsolvable. Therefore, it raises a need to integrate the advantages of program-based and textual reasoning.

In this paper, we propose a *Plan-then-Reason* framework for tabular tasks with sentence context that *plans* upon various types of user queries and then *reasons* over context to reach the final answers. The model could write code to extract necessary information from the table or perform specific operations with high precision, which would help the model generalize to unseen or larger tables. The model could leverage textual reasoning to maintain an understanding of general concepts and combine information from table and sentence context to reach final answers. Our experiments show

113 that *Plan-then-Reason* surpasses existing prompt- 162
114 ing methods without self-consistency and requires 163
115 less in-context examples and API calls. 164

116 Meanwhile, few finetuning methods are de- 165
117 signed for enhancing both planning and reasoning 166
118 abilities of open-source models while these abili- 167
119 ties are crucial for building a tabular model with 168
120 generalizability and interpretability. Various pre- 169
121 trained models are proposed for tabular tasks (Yin 170
122 et al., 2020; Wang et al., 2021; Iida et al., 2021; 171
123 Deng et al., 2022; Yang et al., 2022; Jiang et al., 172
124 2022; Liu et al., 2021). But they are often limited 173
125 to specific query types and could not generalize 174
126 well to unseen tasks. Regarding models fine-tuned 175
127 with respect to general tabular querying tasks (Xie 176
128 et al., 2022; Liu et al., 2023a; Zhang et al., 2023a; 177
129 Zhuang et al., 2024), they are expected to generate 178
130 the answers directly, which inevitably lacks inter-
131 pretability. TableLLM assigns program-based or
132 textual reasoning based on table size to answer the
133 queries without planning based on the query and
134 context (Zhang et al., 2024).

135 Recent base models are pre-trained with a
136 large amount of corpora thus obtaining intrinsic
137 commonsense knowledge (Touvron et al., 2023;
138 Roziere et al., 2023). These models suit as the back-
139 bones for our models that can fill the gap between
140 queries and tables, understand general concepts,
141 and plan the reasoning paths over table and sen-
142 tence context. We construct an instruction tuning
143 dataset TrixInstruct based on benchmarks with
144 queries that are program-unsolvable or need com-
145 bining information from table and sentence context.
146 We finetune Llama-2-7B (Touvron et al., 2023)
147 and CodeLlama-7B (Roziere et al., 2023) with
148 TrixInstruct. The resulting models, the PRO-
149 TRIX¹ family is designed to **Plan** and **Reason On**
150 **Tabular** tasks with integration of code execut**ion**
151 and **teX**tual reasoning. Our experiments show that
152 models trained with *Plan-then-Reason* framework
153 can generalize to unseen tabular tasks in different
154 domains with only a handful of training examples
155 and give accurate and faithful explanations even
156 for complex *how* and *why* questions.

157 In summary, our contributions are listed as:

- 158 • We propose a *Plan-then-Reason* framework to 205
159 answer user queries on tabular tasks with sentence 206
160 context. The framework first plans the reasoning 207
161 pathways by ingesting the query and the context, 208

and assigns each step to textual and program-based
reasoning to arrive at the final answer. We experi-
ment with GPT-3.5-turbo to evaluate the effective-
ness of this framework and find it surpasses existing
methods without self-consistency.

- We construct TrixInstruct, an instruction-
tuning set to build models with generalizability
and interpretability over tables with sentence con-
text. To obtain the required planning and reason-
ing abilities, we include queries that are program-
unsolvable or need combining tables and sentences
in our instruction-tuning dataset.

- We will open-source our model PROTRIX, ca-
pable of planning and reasoning on tabular tasks
with sentence context. PROTRIX can generalize
to unseen tabular tasks with sentence context, and
generate accurate and faithful explanations.

2 Our Method 179

2.1 Problem Formulation 180

This study centers on tabular tasks with sentence
context. Each instance is structured as (Q, T, S, A) ,
where Q represents users' query. T denotes a singu-
lar table, while S denotes the sentence context. The
sentence context usually is passages linked to the
table or retrieved from a knowledge base. Finally
 A stands for the predicted answer. The answer
could be short-form for answering questions like
hom many... or is this true or false... For *how* and
why questions, the answer is generally one or more
sentences which is defined as free-form answers.

2.2 Plan-then-Reason 192

We propose a *Plan-then-Reason* framework for an-
swering queries over tables and texts. The frame-
work first ingests the query and the context by re-
calling common knowledge and general concepts.
Then it begins to design the model's reasoning path-
way, planning the utilization of program-based and
textual reasoning to arrive at conclusions.

Planning The model first analyzes the query and
fills the potential gap between the query and the
context. Consider the first query in Figure 3, there
is no explicit column of *color* in the table. The
model recalls commonsense that *pink, gray-brown*
and other colors in the description column can be
used to answer the question. Similarly, in the sec-
ond query, the model recalls that *only top 3 athletes*
can win medals.

Then the model adaptively plans the reasoning
path with program-based and textual reasoning to

¹Protrix originally means a chemical reactor for small-
scale production with compatibility and process control.

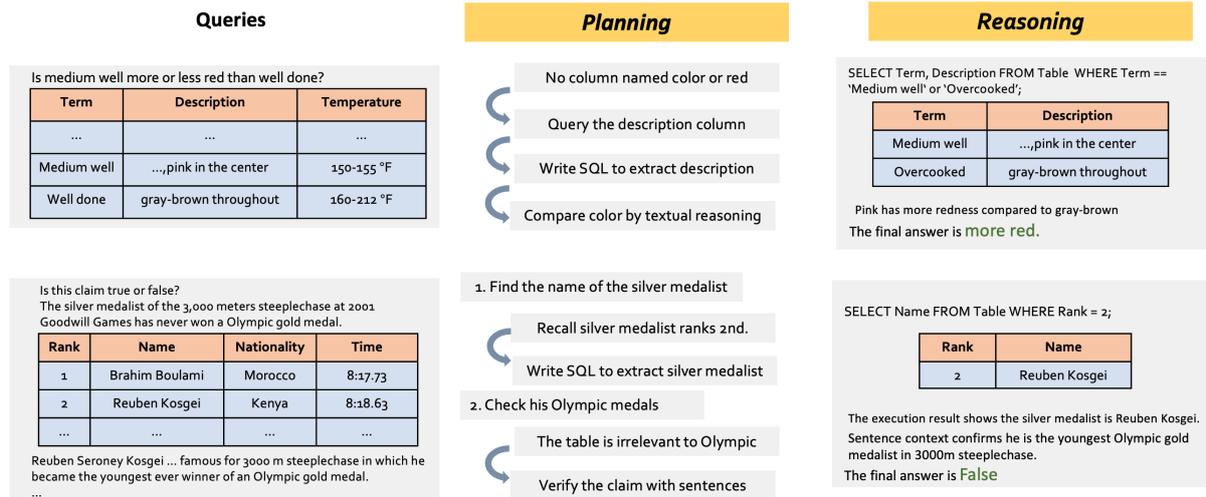


Figure 3: Illustration of our framework. The figure shows the process of our framework to answer a question. The framework first performs strategical planning, decomposing questions into reasoning chains to be solved by either table or sentence context, then perform reasoning based on symbolic programs or natural language to reach answer.

address the limitations of each reasoning method. For the first query, the model plans to use SQL to extract relevant cells from the table and make comparisons of concepts through textual reasoning. For the second query, the model decomposes the task into a multi-hop reasoning chain. It uses SQL to extract the silver medalist from the table and uses sentence context to verify his Olympic record.

Reasoning The reasoning phase initiates with program-based reasoning, writing SQL queries to extract relevant cells or perform operations such as counting and sorting. After running SQL on a code interpreter, the results are fed back into the model’s ongoing reasoning process. Subsequently, during textual reasoning, the model selects relevant sentences from noisy context to complement the table context. *Reuben Kosgei... youngest ever winner of an Olympic gold medal* suggests that he has won a gold medal in his career. At last, the model summarizes insights from the program-based and textual reasoning to reach the answer.

2.3 In-Context Learning

One intuitive way to evaluate the effectiveness of *Plan-then-Reason* work is through in-context learning. We annotate the planning and reasoning process and prompt LLMs to follow the pattern. We experiment with GPT-3.5-turbo on WikiTQ (Pasupat and Liang, 2015), FEVEROUS (Aly et al., 2021) and TabFact (Chen et al., 2019) following prompt shown in Table 10, 11 and 12 in Appendix.

2.4 Instruction Tuning

Based on the analysis in §1, we highlight the abilities *Plan-then-Reason* framework possesses towards tabular tasks with sentence context. (1) Understanding user’s query: use parametric knowledge of commonsense insights and general concepts to analyze the relationship between the query and the context; (2) Adaptive planning: decompose a query into sub-questions and plan to answer these sub-questions with different types of context or design multi-hop reasoning paths for the query, and (3) Blending program-based and textual reasoning: synthesize the strength of each method to maximize reasoning performance.

To train our model with such abilities, we construct an instruction tuning set *TriXInstruct* based on two benchmarks i.e., WikiTQ (Pasupat and Liang, 2015) and FEVEROUS (Aly et al., 2021). WikiTQ involves table question-answering based on a single table, requiring multi-step reasoning and performing diverse data operations such as comparison, aggregation, and arithmetic computation. WikiTQ also contains cases that can not be solved by SQL programming solely (Shi et al., 2020) which need to be solved with textual reasoning as the left example in Figure 2. Finetuning with such cases equips our models with ability to plan between textual or program-based reasoning.

On the other hand, FEVEROUS presents an open-domain fact verification challenge spanning both sentences and tables. We select samples containing precisely one table in their gold evidence

273	set. Each case is presented with the corresponding	<i>how</i> and <i>why</i> questions that requires model to gener-	322
274	table along with 5 sentences as contextual infor-	erate explanations (Nan et al., 2022). The original	323
275	mation. To introduce variability to the sentence	FetaQA dataset has highlighted relevant cells, we	324
276	context, we ensure the inclusion of gold sentence	turn to a more challenging and realistic scenario	325
277	evidence and augment the context with noisy sen-	where the highlighted cells are not provided as	326
278	tences retrieved from Wikipedia by a dense re-	input and the model will answer the question di-	327
279	triever (Hu et al., 2023). Training examples on	rectly based on the complete table context. Since	328
280	claim verification from FEVEROUS impart the	our model is only finetuned on short-form answer	329
281	ability to decompose claims and reason on each	tasks, FetaQA can be utilized to further evaluate the	330
282	sub-claim with a specific table or sentence context.	interpretability and generalizability of our models.	331
283	For each task, we sample 4,000 instances from		
284	the training datasets. We employ GPT-4 (Achiam	3.2 Short-form Answer Tasks	332
285	et al., 2023) to generate responses according to		
286	the <i>Plan-then-Reason</i> framework following the	Baselines We choose the following baselines:	333
287	prompts in Table 10 and 11 in Appendix. We filter	(1) Closed-source model: We use the end-to-end	334
288	out instances that GPT-4 predicts answers inconsis-	QA performance of GPT-3.5-turbo and GPT-4	335
289	tent with the original annotations. This results in a	as baselines and compare our results on GPT-	336
290	training set comprising 3,157 cases from FEVER-	3.5-turbo with Binder (Cheng et al., 2022b), Re-	337
291	OUS and 2,866 cases from WikiTQ. We train our	AcTable (Zhang et al., 2023b), StructGPT (Jiang	338
292	models based on Llama-2-7B (Touvron et al., 2023)	et al., 2023), Dater (Ye et al., 2023), Chain-of-	339
293	and CodeLlama-7B (Roziere et al., 2023).	Table (Wang et al., 2024) and TabSQLify (Nahid	340
294		and Rafiei, 2024). (2) Finetuned SOTA: Please refer	341
295	3 Experiments	to Appendix A for details of finetuned SOTA	342
296	3.1 Benchmarks for Evaluation	methods (3) 7B parameter models: We first com-	343
297	We use existing tabular benchmarks with differ-	pare our model with the zero-shot performance of	344
298	ent input and output configurations to evaluate the	base models, Llama-2-7B (Touvron et al., 2023)	345
299	performance of our model on queries with short-	and CodeLlama 7B (Roziere et al., 2023). Then	346
300	form or free-form answers. We further divide ex-	we compare our model with TableLlama (Zhang	347
301	isting benchmarks on short-form answer tasks into	et al., 2023a) and TableLLM (Zhang et al., 2024),	348
302	short-form question answering and fact verification	which are the most similar baselines to our model	349
303	following the category in Figure 1.	and share the same base models ² . TableLlama is	350
304		a generalist model for end-to-end QA. TableLLM	351
305	Short-form Question Answering WikiSQL and	originally chooses textual or program-based rea-	352
306	WikiTQ are question answering benchmarks on	soning for different benchmarks. To test the gen-	353
307	tables from Wikipedia without sentence con-	eralizability for different queries, we choose the	354
308	text (Zhong et al., 2017; Pasupat and Liang, 2015).	reasoning method of TableLLM by table size. We	355
309	HybridQA (Chen et al., 2020) requires models to	use textual reasoning for tables less than 500 tokens	356
310	answer questions based on both tables and sen-	and program-based reasoning for larger tables. We	357
311	tences. We use retrieved sentences, admittedly	provide a detailed comparison with other closed-	358
312	noisy, from Chen et al. (2020) as the sentence con-	source models (Codex, PaLM2) and open-source	359
313	text. TATQA (Zhu et al., 2021) is focused on tables	model (Llama-3-8B) in Table 9 in Appendix.	360
314	with sentence context from financial reports.		
315		Evaluation Metrics For fact verification, we	361
316	Fact Verification We follow our method in §2.4	match the predicted veracity label in the concluding	362
317	to construct the evaluation dataset for FEVER-	sentence. And we use the evaluator from Cheng	363
318	OUS (Aly et al., 2021). TabFact (Chen et al., 2019)	et al. (2022b) to evaluate the performance of <i>Plan-</i>	364
319	verifies claims based on tables from the Wikipedia.	<i>then-Reason</i> with GPT-3.5-turbo on WikiTQ. For	365
320	SCITAB (Lu et al., 2023) focuses on tables from	7B parameter models, we find that the heuristic	366
321	scientific papers. This benchmark requires compo-	matching evaluation for question-answering tasks	367
	sitional reasoning and commonsense knowledge.		
	Free-form Question Answering FetaQA con-		
	tains <i>what</i> questions with multiple answers and		

²We do not use StructLM (Zhuang et al., 2024) as baseline since it is finetuned on most of our evaluation benchmarks while we want to compare with existing models in terms of generalizability.

	WikiTQ	WikiSQL	TabFact	SciTAB	FEVEROUS	HybridQA	TATQA
<i>GPT-4</i>							
End-to-End QA	72.9	75.8	71.5	57.1	71.0	64.1	80.8
<i>GPT-3.5-turbo</i>							
End-to-End QA	51.8	55.0	68.8	45.3	<u>61.0</u>	55.1	59.1
ReAcTable	52.4	-	73.1	-	-	-	-
Dater*	52.8	-	78.0	-	-	-	-
Binder*	56.7	-	79.2	-	-	-	-
StructGPT	57.0	64.6	87.3	-	-	-	-
Chain-of-Table	59.9	-	80.2	-	-	-	-
TabSQLify	64.7	76.7	79.5	-	-	-	-
Mix SC*	73.1	-	-	-	-	-	-
Plan-then-Reason (Ours)	<u>65.2</u>	-	<u>83.5</u>	-	65.8	-	-
<i>Finetuned SOTA</i>	63.3 [†]	89.2 [†]	90.8 [†]	73.1 [†]	75.9 [†]	61.0 [†]	74.5 [†]
<i>Llama-2-7B</i>							
End-to-End QA	21.4	17.4	48.6	27.2	47.1	27.6	28.7
TableLlama	31.6	41.7	82.6 [†]	29.2	56.8	33.3	38.3
PROTRIX(Ours)	56.2 [†]	67.4	71.6	45.0	75.6 [†]	42.9	50.1
<i>CodeLlama-7B</i>							
End-to-End QA	13.1	17.3	49.5	37.1	43.0	28.5	28.4
TableLLM	52.9 [†]	65.3 [†]	57.1	24.7	60.0	53.7	70.3 [†]
PROTRIX-CODER (Ours)	57.8 [†]	72.3	70.6	41.2	71.4 [†]	45.1	52.2

Table 1: Experimental results on short-form question answering and fact verification tasks. [†] The model is trained on this evaluation benchmark. *: with self-consistency.

would lead to overestimation or underestimation since our model is not finetuned to follow the grammar of gold answers in each dataset. Therefore, we deploy Llama-2-70B-chat (Touvron et al., 2023) to predict if the concluding sentence answers the question correctly similarly as Zhang et al. (2024) following prompt in Table 13 in Appendix. Our evaluation results using LLM are checked manually and they align better with human evaluation of the concluding sentence. We report three-class F1 score for SciTAB and accuracy for other datasets.

In-Context Learning Results The result with GPT-3.5-turbo³ in Table 1 suggests that Plan-then-Reason framework is effective for answering different types of queries over tables. Our method surpasses all the existing baselines without self-consistency on WikiTQ. It also obtains accuracy higher than Dater uses 20 responses and Binder uses 50 responses for self-consistency. Our method still falls behind Mix SC which predicts answers based on 5 responses with textual reasoning and 5 with program-based reasoning. But the self-consistency mechanism leads to a much larger computing cost. Our framework also surpasses existing baselines on TabFact except for StructGPT,

³We use GPT-3.5-turbo-16k-0613 for experiment. We only experiment with WikiTQ, TabFact and FEVEROUS due to limited budgets.

demonstrating its effectiveness for fact verification tasks. Plan-then-Reason can also generalize to tables with sentence context. It increases the accuracy on FEVEROUS by 4.8%.

Finetuning Results The experimental result with Llama-2-7B and CodeLlama-7B in Table 1 shows that our finetuned models generalize to diverse tabular tasks with only 6k training instances. Compared with the backbone model Llama-2-7B, the performance gain of PROTRIX on in-domain benchmarks is 34.8% on WikiTQ and 28.7% on FEVEROUS. And the performance gain on out-of-domain benchmarks is 21.5% on average. Comparing the out-of-domain performance with TableLlama, PROTRIX surpasses TableLlama by 25.7% on WikiSQL, 15.8% on SciTAB, 9.6% on HybridQA and 11.8% on TATQA. The overall performance gain on out-of-domain benchmarks demonstrates the planning and reasoning abilities obtained from TrixInstruct is not restricted to in-domain tasks. Our finetuned model PROTRIX adaptively generalizes to queries with different input and output configurations and can even be applied to specific domains such as science and finance.

PROTRIX-CODER still falls behind TableLLM on question answering task with sentence context since TableLLM is finetuned with 8k cases from TATQA. We are surprised to find that PROTRIX-

Models	Fluency	Correct	Adequate	Faithful
T5-large*	94.6	54.8	50.4	50.4
TableLlama	63.0	67.0	55.0	82.0
PROTRIX	96.0	77.0	71.0	91.0
GPT-3.5-turbo	99.0	83.0	85.0	96.0
Human performance*	95.0	92.4	95.6	95.6

Table 2: Human evaluation results on FetaQA. *: results reported by Nan et al. (2022).

CODER surpasses TableLLM on WikiTQ and WikiSQL by 4.9% and 7.0% even though the training set of TableLLM contains 18k cases from WikiTQ and 28k cases from WikiSQL. And our TrixInstruct only contains 6k training instances in total. It demonstrates the effectiveness of finetuning with *Plan-then-Reason* framework. PROTRIX-CODER also surpasses TableLLM on fact verification tasks by 13.8% on average.

3.3 Free-form Answer Tasks

Baselines We run GPT-3.5-turbo and TableLlama (Zhang et al., 2023a) as our baselines. The prompt for each model is shown in Table 15 in Appendix. We also use the result of fine-tuning method using T5-large, and human performance from Nan et al. (2022) as baselines. Notably, the results from Nan et al. (2022) are evaluated with the original setting where the highlighted cells are provided as input instead of the whole table.

Evaluation Metrics Since the response of our model contains step-by-step reasoning over symbolic code and natural language, BLEU (Papineni et al., 2002) would underestimate the performance of our model. BLEU also can not be used to evaluate the correctness and faithfulness of the responses. We sample 100 cases from the dataset to perform human evaluation following Nan et al. (2022). The evaluation is based on four criteria: (1) *fluency* if an answer is natural and grammatical; (2) *correctness* if an answer is correct; (3) *adequacy* if an answer contains all the information that is asked by the question; (4) *faithfulness* if an answer is faithful and grounded to the contents of the table.

Results From Table 2, we can observe that our model exclusively trained on short-form answer tasks can adaptively generalize to give accurate and faithful explanations for complex free-form questions. Our model achieves a fluency score of 96.0, closely following the human performance at

95.0, indicating its natural and coherent responses.

PROTRIX surpasses TableLlama by 33.0% on *fluency*. TableLlama is observed to lose fluency in some cases where it generates a float number like 2008.0 to answer *what year* or a list of structured `<entity_name>` which is used to answer entity linking questions from its training set.

Our model achieves *correct* score of 77.0 and *faithful* score of 91.0 which are comparable to GPT-3.5-turbo. Although our model is only trained on short-form answer tasks, the learned planning and reasoning abilities can be utilized to answer complex *how* and *why* questions with accurate and faithful explanations. We present an example of the responses in Table 16 in Appendix.

4 Ablation study

To better evaluate the effectiveness of fine-tuning with our *Plan-then-Reason* framework, we experiment with 3 other fine-tuning frameworks based on TrixInstruct. (1) w/o Planning: We split each instance in TrixInstruct into planning and reasoning parts. We train our model with only the reasoning part of the training instances. This can be considered as distilling the reasoning pattern of TabSQLify (Nahid and Rafiei, 2024). (2) w/o Reasoning: Similar to (1), we finetune the model with only the planning part of the training instances. (3) w/o Planning and Reasoning: We finetune the model to generate answers directly. This is similar to the end-to-end QA paradigm.

The result of the ablation study is presented in Table 3. Both planning and reasoning contribute significantly to the overall performance and generalizability of our model. Excluding planning or reasoning would cause the average performance to decrease by 5.0% or 9.4%, respectively. In w/o planning setting, the performance on SCITAB and FEVEROUS drops significantly by 13.2% and 8.8%, respectively. It suggests the importance of planning ability in utilizing commonsense knowledge and decomposing the query into reasoning chains over tables and sentences. The w/o planning and reasoning setting is similar to previous methods that train the model to answer queries directly (Xie et al., 2022; Zhang et al., 2023a; Zhuang et al., 2024). The performance of in-domain and out-of-domain benchmarks drops by 14.1% and 15.2% on average, emphasizing the effectiveness of the *Plan-then-Reason* framework in promoting generalizability across tabular tasks.

Models	WikiTQ	WikiSQL	Tabfact	SciTAB	FEVEROUS	HybridQA	TATQA
PROTRIX	53.8	65.7	73.4	45.0	75.6	42.9	50.1
w/o Planning	51.0	63.9	66.4	31.8	66.8	41.3	50.4
w/o Reasoning	41.4	54.3	65.4	33.4	70.4	36.3	39.8
w/o Planning and Reasoning	39.5	47.8	59.0	29.4	64.8	29.4	35.3

Table 3: Ablation study

5 Related Work

Prompting Methods for LLMs Large language models can be guided to solve tasks in a step-by-step manner (Wei et al., 2022; Hao et al., 2023). Chen (2023) first utilizes Chain-of-Thought (Wei et al., 2022) to enhance the reasoning of LLMs on tabular tasks and points out that textual reasoning can not generalize to large tables directly. Researchers prompt the model to select relevant rows and columns as one step in the chain of reasoning to enable LLM to focus on the following reasoning step (Jiang et al., 2023; Ye et al., 2023; Wang et al., 2024). Chen et al. (2022) proposes Program-of-Thoughts (PoT) that answers a question in programming language. Compared with textual reasoning, program-based reasoning is executed by a code interpreter, achieving high-precision reasoning in complex tabular or mathematical questions. Binder (Cheng et al., 2022b) binds LLMs as API calls within a Python or SQL program to address the program-unsolvable aspect of the queries. Liu et al. (2023b) proposes mix self-consistency that combines the potential of both textual and program-based reasoning. Researchers have also attempted ReAct (Yao et al., 2023) style prompting for tabular tasks. ReAcTable (Zhang et al., 2023b) reasons with SQL or Python tools in multiple turns. Chain-of-Table (Wang et al., 2024) formats table reasoning as specific table operations. ReAct-style prompting mainly focuses on the next acting step based on feedback from the last action without considering the whole reasoning chain. Our *Plan-then-Reason* framework can plan the whole reasoning chain before acting and answer questions more efficiently and accurately (see efficiency analysis in Appendix B) while blending the advantages of textual and program-based reasoning methods.

Finetuned Models Various pre-trained models are proposed for tabular tasks (Yin et al., 2020; Wang et al., 2021; Iida et al., 2021; Deng et al., 2022; Yang et al., 2022; Jiang et al., 2022; Liu et al., 2021). But they often are limited to one

specific downstream fine-tuning task. As for models with generalizability, Liu et al. (2023a) mix symbolic SQL execution task with FLAN task to further fine-tune FLAN-T5 to improve zero-shot tabular question answering performance. Li et al. (2023) fine-tunes models with a large synthesized dataset of table manipulation and data augmentation to serve as a table-foundation model that understands table structures. TableLlama (Zhang et al., 2023a) and StructLM (Zhuang et al., 2024) collect an instructing tuning set that covers diverse tables and tasks and finetune Llama to obtain a generalist model without table pretraining. Compared with existing generalist models that are expected to generate answers directly, PROTRIX is interpretable by generating accurate and faithful explanations.

TaCo (Zheng et al., 2023) is finetuned with step-by-step solutions of math problems over tabular data. However, it is only limited to mathematical table reasoning and can not generalize to other types of tabular tasks. Zhang et al. (2024) uses textual or program-based reasoning for different in-domain benchmarks without planning the reasoning method based on the query and the context. PROTRIX can plan over tables with sentence context and assign each step to textual or program-based reasoning to reach the final answer.

6 Conclusions

In this paper, we propose *Plan-then-Reason* framework to answer different types of user queries over tables with sentence context. It understands the commonsense and concepts in the query and plans the reasoning steps over programs and languages. We construct an instruction tuning set TrixInstruct to finetune models to obtain such planning and reasoning abilities with only 6k examples. The experiments show that our resulting models PROTRIX and PROTRIX-CODER generalize to unseen tabular tasks with sentence context and produce accurate and faithful explanations. Our work highlights the required abilities for generalist models over tabular tasks with sentence context, and paves the way for future research directions.

595 Limitations

596 The instances in TrixInstruct only contain rela-
597 tional tables. It currently does not contain com-
598 plex tables with hierarchical headers (Cheng et al.,
599 2022a). And TrixInstruct is restricted to queries
600 over one table. It can not be directly applied to
601 tabular tasks over multiple tables or retrieved top k
602 tables. We plan to extend TrixInstruct to cover
603 more realistic scenarios in future work.

604 We find it hard to control the rule or grammar of
605 the generated answer by open-source models and
606 exact match often fails to evaluate the performance
607 properly due to format issues, especially for out-
608 of-domain benchmarks. We tried several ways as
609 evaluation method and choose LLMs as evaluator.
610 Since we use an exact match for GPT-3.5-turbo
611 results, the performance between open-source and
612 closed-source models can not be directly compared.

613 References

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

619 Rami Aly, Zhijiang Guo, Michael Sejr Schlichtkrull,
620 James Thorne, Andreas Vlachos, Christos
621 Christodoulopoulos, Oana Cocarascu, and Arpit
622 Mittal. 2021. Feverous: Fact extraction and verifi-
623 cation over unstructured and structured information.
624 In *Thirty-fifth Conference on Neural Information
625 Processing Systems Datasets and Benchmarks Track
626 (Round 1)*.

627 Wenhu Chen. 2023. Large language models are few (1)-
628 shot table reasoners. In *Findings of the Association
629 for Computational Linguistics: EACL 2023*, pages
630 1090–1100.

631 Wenhu Chen, Xueguang Ma, Xinyi Wang, and
632 William W Cohen. 2022. Program of thoughts
633 prompting: Disentangling computation from reason-
634 ing for numerical reasoning tasks. *arXiv preprint
635 arXiv:2211.12588*.

636 Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai
637 Zhang, Hong Wang, Shiyang Li, Xiyong Zhou, and
638 William Yang Wang. 2019. Tabfact: A large-
639 scale dataset for table-based fact verification. *arXiv
640 preprint arXiv:1909.02164*.

641 Wenhu Chen, Hanwen Zha, Zhiyu Chen, Wenhan Xiong,
642 Hong Wang, and William Yang Wang. 2020. Hy-
643 bridqa: A dataset of multi-hop question answering
644 over tabular and textual data. In *Findings of the Asso-
645 ciation for Computational Linguistics: EMNLP 2020*,
646 pages 1026–1036.

Zhoujun Cheng, Haoyu Dong, Zhiruo Wang, Ran Jia,
647 Jiaqi Guo, Yan Gao, Shi Han, Jian-Guang Lou, and
648 Dongmei Zhang. 2022a. Hitab: A hierarchical table
649 dataset for question answering and natural language
650 generation. In *Proceedings of the 60th Annual Meet-
651 ing of the Association for Computational Linguistics
652 (Volume 1: Long Papers)*, pages 1094–1110.
653

Zhoujun Cheng, Tianbao Xie, Peng Shi, Chengzu
654 Li, Rahul Nadkarni, Yushi Hu, Caiming Xiong,
655 Dragomir Radev, Mari Ostendorf, Luke Zettlemoyer,
656 et al. 2022b. Binding language models in symbolic
657 languages. In *The Eleventh International Conference
658 on Learning Representations*.
659

Xiang Deng, Huan Sun, Alyssa Lees, You Wu, and Cong
660 Yu. 2022. Turl: Table understanding through repre-
661 sentation learning. *ACM SIGMOD Record*, 51(1):33–
662 40.
663

Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon,
664 Pengfei Liu, Yiming Yang, Jamie Callan, and Gra-
665 ham Neubig. 2023. Pal: Program-aided language
666 models. In *International Conference on Machine
667 Learning*, pages 10764–10799. PMLR.
668

Zihui Gu, Ju Fan, Nan Tang, Preslav Nakov, Xiao-
669 man Zhao, and Xiaoyong Du. 2022. Pasta: table-
670 operations aware fact verification via sentence-table
671 cloze pre-training. *arXiv preprint arXiv:2211.02816*.
672

Shibo Hao, Yi Gu, Haodi Ma, Joshua Hong, Zhen
673 Wang, Daisy Wang, and Zhiting Hu. 2023. *Rea-
674 soning with language model is planning with world
675 model*. In *Proceedings of the 2023 Conference on
676 Empirical Methods in Natural Language Processing*,
677 pages 8154–8173, Singapore. Association for Com-
678 putational Linguistics.
679

Nan Hu, Zirui Wu, Yuxuan Lai, Xiao Liu, and Yansong
680 Feng. 2022. Dual-channel evidence fusion for fact
681 verification over texts and tables. In *Proceedings of
682 the 2022 Conference of the North American Chap-
683 ter of the Association for Computational Linguistics:
684 Human Language Technologies*, pages 5232–5242.
685

Nan Hu, Zirui Wu, Yuxuan Lai, Chen Zhang, and Yan-
686 song Feng. 2023. Unifee: Unified evidence extrac-
687 tion for fact verification. In *Proceedings of the 17th
688 Conference of the European Chapter of the Asso-
689 ciation for Computational Linguistics*, pages 1142–
690 1152.
691

Hiroshi Iida, Dung Thai, Varun Manjunatha, and Mohit
692 Iyyer. 2021. Tabbie: Pretrained representations of
693 tabular data. In *Proceedings of the 2021 Conference
694 of the North American Chapter of the Association
695 for Computational Linguistics: Human Language
696 Technologies*.
697

Jinhao Jiang, Kun Zhou, Zican Dong, Keming Ye, Xin
698 Zhao, and Ji-Rong Wen. 2023. *StructGPT: A general
699 framework for large language model to reason over
700 structured data*. In *Proceedings of the 2023 Con-
701 ference on Empirical Methods in Natural Language
702 Processing*, pages 9237–9251, Singapore. Associa-
703 tion for Computational Linguistics.
704

705	Zhengbao Jiang, Yi Mao, Pengcheng He, Graham Neubig, and Weizhu Chen. 2022. Omnitab: Pre-training with natural and synthetic data for few-shot table-based question answering. <i>arXiv preprint arXiv:2207.03637</i> .	762
706		763
707		764
708		765
709		766
710	Fangyu Lei, Xiang Li, Yifan Wei, Shizhu He, Yiming Huang, Jun Zhao, and Kang Liu. 2023. S3HQA: A three-stage approach for multi-hop text-table hybrid question answering. <i>arXiv preprint arXiv:2305.11725</i> .	767
711		768
712		769
713		770
714		771
715	Peng Li, Yeye He, Dror Yashar, Weiwei Cui, Song Ge, Haidong Zhang, Danielle Rifinski Fainman, Dongmei Zhang, and Surajit Chaudhuri. 2023. Table-gpt: Table-tuned gpt for diverse table tasks. <i>arXiv preprint arXiv:2310.09263</i> .	772
716		773
717		774
718		775
719		776
720	Qian Liu, Bei Chen, Jiaqi Guo, Morteza Ziyadi, Zeqi Lin, Weizhu Chen, and Jian-Guang Lou. 2021. Tapex: Table pre-training via learning a neural sql executor. In <i>International Conference on Learning Representations</i> .	777
721		778
722		779
723		780
724		781
725	Qian Liu, Fan Zhou, Zhengbao Jiang, Longxu Dou, and Min Lin. 2023a. From zero to hero: Examining the power of symbolic tasks in instruction tuning. <i>arXiv preprint arXiv:2304.07995</i> .	782
726		783
727		784
728		785
729	Tianyang Liu, Fei Wang, and Muhao Chen. 2023b. Re-thinking tabular data understanding with large language models. <i>arXiv preprint arXiv:2312.16702</i> .	786
730		787
731		788
732	Xinyuan Lu, Liangming Pan, Qian Liu, Preslav Nakov, and Min-Yen Kan. 2023. SCITAB: A challenging benchmark for compositional reasoning and claim verification on scientific tables. In <i>Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing</i> , pages 7787–7813, Singapore. Association for Computational Linguistics.	789
733		790
734		791
735		792
736		793
737		794
738		795
739	Md Mahadi Hasan Nahid and Davood Rafiei. 2024. Tabsqlify: Enhancing reasoning capabilities of llms through table decomposition. <i>arXiv preprint arXiv:2404.10150</i> .	796
740		797
741		798
742		799
743	Linyong Nan, Chiachun Hsieh, Ziming Mao, Xi Victoria Lin, Neha Verma, Rui Zhang, Wojciech Kryściński, Hailey Schoelkopf, Riley Kong, Xiangru Tang, et al. 2022. Fetaqa: Free-form table question answering. <i>Transactions of the Association for Computational Linguistics</i> , 10:35–49.	800
744		801
745		802
746		803
747		804
748		805
749	Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In <i>Proceedings of the 40th annual meeting of the Association for Computational Linguistics</i> , pages 311–318.	806
750		807
751		808
752		809
753		810
754	Panupong Pasupat and Percy Liang. 2015. Compositional semantic parsing on semi-structured tables . In <i>Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)</i> , pages 1470–1480, Beijing, China. Association for Computational Linguistics.	811
755		812
756		813
757		814
758		815
759		816
760		817
761		
	Jeff Rasley, Samyam Rajbhandari, Olatunji Ruwase, and Yuxiong He. 2020. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In <i>Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining</i> , pages 3505–3506.	
	Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. 2023. Code llama: Open foundation models for code. <i>arXiv preprint arXiv:2308.12950</i> .	
	Tianze Shi, Chen Zhao, Jordan Boyd-Graber, Hal Daumé III, and Lillian Lee. 2020. On the potential of lexico-logical alignments for semantic parsing to SQL queries. In <i>Findings of EMNLP</i> .	
	Jiashuo Sun, Hang Zhang, Chen Lin, Yeyun Gong, Jian Guo, and Nan Duan. 2022. Apollo: An optimized training approach for long-form numerical reasoning. <i>arXiv preprint arXiv:2212.07249</i> .	
	Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. <i>arXiv preprint arXiv:2307.09288</i> .	
	Lei Wang, Wanyu Xu, Yihuai Lan, Zhiqiang Hu, Yunshi Lan, Roy Ka-Wei Lee, and Ee-Peng Lim. 2023. Plan-and-solve prompting: Improving zero-shot chain-of-thought reasoning by large language models. In <i>Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 2609–2634.	
	Zhiruo Wang, Haoyu Dong, Ran Jia, Jia Li, Zhiyi Fu, Shi Han, and Dongmei Zhang. 2021. Tuta: Tree-based transformers for generally structured table pre-training. In <i>Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining</i> , pages 1780–1790.	
	Zilong Wang, Hao Zhang, Chun-Liang Li, Julian Martin Eisenschlos, Vincent Perot, Zifeng Wang, Lesly Miculicich, Yasuhisa Fujii, Jingbo Shang, Chen-Yu Lee, et al. 2024. Chain-of-table: Evolving tables in the reasoning chain for table understanding. <i>arXiv preprint arXiv:2401.04398</i> .	
	Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. <i>Advances in Neural Information Processing Systems</i> , 35:24824–24837.	
	Zirui Wu, Nan Hu, and Yansong Feng. 2023. Enhancing structured evidence extraction for fact verification. In <i>Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing</i> , pages 6631–6641.	
	Tianbao Xie, Chen Henry Wu, Peng Shi, Ruiqi Zhong, Torsten Scholak, Michihiro Yasunaga, Chien-Sheng	

818	Wu, Ming Zhong, Pengcheng Yin, Sida I Wang, et al. 2022. Unifiedskg: Unifying and multi-tasking structured knowledge grounding with text-to-text language models. <i>arXiv preprint arXiv:2201.05966</i> .	871
819		872
820		873
821		874
822	Jingfeng Yang, Aditya Gupta, Shyam Upadhyay, Luheng He, Rahul Goel, and Shachi Paul. 2022. Tableformer: Robust transformer modeling for table-text encoding. <i>arXiv preprint arXiv:2203.00274</i> .	875
823		876
824		877
825		878
826	Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. 2023. React: Synergizing reasoning and acting in language models. In <i>International Conference on Learning Representations (ICLR)</i> .	879
827		880
828		881
829		882
830		883
831	Yunhu Ye, Binyuan Hui, Min Yang, Binhua Li, Fei Huang, and Yongbin Li. 2023. Large language models are versatile decomposers: Decomposing evidence and questions for table-based reasoning. In <i>Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval</i> , pages 174–184.	884
832		885
833		886
834		887
835		888
836		889
837		890
838	Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. 2020. Tabert: Pretraining for joint understanding of textual and tabular data. In <i>Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics</i> , pages 8413–8426.	891
839		892
840		893
841		894
842		895
843	Tianshu Zhang, Xiang Yue, Yifei Li, and Huan Sun. 2023a. Tablellama: Towards open large generalist models for tables.	896
844		897
845		898
846	Xiaokang Zhang, Jing Zhang, Zeyao Ma, Yang Li, Bohan Zhang, Guanlin Li, Zijun Yao, Kangli Xu, Jinchang Zhou, Daniel Zhang-Li, et al. 2024. Tablellm: Enabling tabular data manipulation by llms in real office usage scenarios. <i>arXiv preprint arXiv:2403.19318</i> .	899
847		900
848		901
849		902
850		903
851		904
852	Yunjia Zhang, Jordan Henkel, Avriella Floratou, Joyce Cahoon, Shaleen Deep, and Jignesh M Patel. 2023b. Reactable: Enhancing react for table question answering. <i>arXiv preprint arXiv:2310.00815</i> .	905
853		906
854		907
855		908
856	Zhehao Zhang, Xitao Li, Yan Gao, and Jian-Guang Lou. 2023c. Crt-qa: A dataset of complex reasoning question answering over tabular data. In <i>The 2023 Conference on Empirical Methods in Natural Language Processing</i> .	909
857		910
858		911
859		912
860		913
861	Mingyu Zheng, Hao Yang, Wenbin Jiang, Zheng Lin, Yajuan Lyu, Qiaoqiao She, and Weiping Wang. 2023. Chain-of-thought reasoning in tabular language models. In <i>Findings of the Association for Computational Linguistics: EMNLP 2023</i> , pages 11006–11019, Singapore. Association for Computational Linguistics.	914
862		915
863		916
864		917
865		918
866		919
867	Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2sql: Generating structured queries from natural language using reinforcement learning. <i>arXiv preprint arXiv:1709.00103</i> .	920
868		921
869		922
870		923
	Fan Zhou, Mengkang Hu, Haoyu Dong, Zhoujun Cheng, Fan Cheng, Shi Han, and Dongmei Zhang. 2022. TaCube: Pre-computing data cubes for answering numerical-reasoning questions over tabular data. In <i>Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing</i> , pages 2278–2291, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.	
	Fengbin Zhu, Wenqiang Lei, Youcheng Huang, Chao Wang, Shuo Zhang, Jiancheng Lv, Fuli Feng, and Tat-Seng Chua. 2021. Tat-qa: A question answering benchmark on a hybrid of tabular and textual content in finance. In <i>Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)</i> , pages 3277–3287.	
	Alex Zhuang, Ge Zhang, Tianyu Zheng, Xinrun Du, Junjie Wang, Weiming Ren, Stephen W Huang, Jie Fu, Xiang Yue, and Wenhu Chen. 2024. Structlm: Towards building generalist models for structured knowledge grounding. <i>arXiv preprint arXiv:2402.16671</i> .	
	A Implementation Details	
	We fully fine-tune Llama-2 7B (Touvron et al., 2023) and CodeLlama-7B (Roziere et al., 2023) with our instruction tuning set with the context of length 4096. We set the learning rate as 5e-6 and the batch size as 32. The training process uses a cosine scheduler with a 3% period for 3 epochs. We utilize DeepSpeed training with ZeRO-3 stage (Rasley et al., 2020). Our model is trained with 4 NVIDIA A40 GPUs (48GB) and the whole training process takes about 5 hours.	
	During inference for PROTRIX and GPT-3.5-turbo, we set the output length as 1024, temperature as 0 and truncate large tables to fit in context length. Then we prompt the model to generate a response for the query, if there is a SQL in the response, we replace the execution result with an output of the actual SQL execution tool and ask the model to generate the rest of the response. If the SQL can not be executed, we fall back to the execution result the model generates.	
	For finetuned SOTA methods in Table 1, we report the performance of OmniTab (Jiang et al., 2022) for WikiTQ, TAPEX (Liu et al., 2021) for WikiSQL, PASTA (Gu et al., 2022) for TabFact, finetuned BERT for SciTAB (Lu et al., 2023), S ³ HQA (Lei et al., 2023) for HybridQA and APOLLO (Sun et al., 2022) for TATQA. For FEVEROUS, we run DCUF (Hu et al., 2022) on our training and development set of FEVEROUS	

and obtain an accuracy of 75.9%. Notice that S³HQA uses a more precise sentence retriever compared to ours and DCUF leverages an additional retriever to select 25 table cells as input.

B Efficiency Analysis

Method	Annotated Examples	Average API calls
Binder	14	50
Dater	17	100
Chain-of-Table	29	10.1
TabSQLify	12	2
MIX SC	0	10
Plan-then-Reason	1	2

Table 4: Comparison of the number of annotated examples and average API calls for WikiTQ.

In Table 4, we compare the number of annotated in-context demonstrations and average API calls of different prompting methods on WikiTQ. It shows that our Plan-then-Reason framework can effectively reach the final answer with less in-context demonstrations and API calls. Binder (Cheng et al., 2022b), Dater (Ye et al., 2023), Chain-of-Table (Wang et al., 2024) and TabSQLify (Nahid and Rafiei, 2024) requires more than 10 annotated examples for inference while our Plan-then-Reason framework only needs one in-context demonstration. Binder, Dater and MIX SC predicts the answer with self-consistency mechanism which needs at least 10 API calls. Chain-of-Table follows the style of ReAct (Yao et al., 2023). The average API calls to reach the final answer is 10.1 while Plan-then-Reason only requires 2 API calls on average.

C Training Dataset Analysis

Our instruction tuning dataset is extracted from GPT-4 responses. We filter out the responses that have inconsistent final answers with the original dataset annotations, but the reasoning process of the responses in the training set has not been fully validated. We perform a quality analysis of our training dataset. We categorize the cases into the following types: (1) Planning error: the response fails to generate a correct plan to answer the question, (2) SQL error: The response generates SQL containing columns that do not exist at all or the SQL simply can not be executed. (3) Execution error: the execution result given by GPT-4 is wrong and (4) Reasoning error: the model achieves a correct answer with wrong reasoning. We demonstrate

examples for each error type in Table 8. We sample 50 cases with sentence context and 50 cases without sentence context from TrixInstruct to perform manual evaluation.

	w/o Sentence	w/ Sentence	Overall
Planning Error	4%	10%	7%
SQL Error	10%	8%	9%
Execution Error	2%	2%	2%
Reasoning Error	2%	6%	4%
Accurate	82%	74%	78%

Table 5: Quality analysis of TrixInstruct. w/(w/o) Sentence: subset of queries over tables with(without) sentence context.

The analysis of the instruction tuning set reveals distinct error patterns in responses generated for queries over tables with or without sentence context. In the subset without sentence context, the most prevalent error type is SQL errors, indicating issues with SQL query generation for some complex questions, including referencing non-existent columns or generating unexecutable queries. As for the subset with sentence context, the most prevalent error type is planning errors. The response fails to decompose the claim into sub-claims or generates wrong plans to query the tables. Notably, both subsets showcase minimal execution errors, suggesting the proficiency of GPT-4 in providing accurate execution results. Reasoning errors are more common in the subset with sentence error with an error rate of 6%. We observe that the reasoning process generated by GPT-4 can not always follow the reasoning chains designed during planning. Overall, the manual analysis of TrixInstruct indicates a combined 7% planning error rate, a 9% SQL error rate, a 2% execution error rate and a 4% reasoning error rate. 78% of instances reach correct answers with accurate planning and reasoning process.

We have checked all the instances in TrixInstruct and make sure they do not contain any private information or offensive content.

D Analysis of Breakdown Performance

D.1 Program-Unsolvable Queries

To analyze the performance on queries that need commonsense knowledge or textual reasoning. We decompose the original development set of WikiTQ into program-solvable and program-unsolvable subsets following Shi et al. (2020). We compare the performance of PROTRIX and PROTRIX-CODER

with Binder (Cheng et al., 2022b), UnifiedSKG (Xie et al., 2022), TAPEX (Liu et al., 2021) and TaCube (Zhou et al., 2022). Notably, our models are only trained with less than 3k examples from WikiTQ while TAPEX and TaCube are trained on the original training set which contains over 11k examples. UnifiedSKG is trained on 21 tasks involving WikiTQ. Binder prompts Codex to write code with LLMs as APIs. We do not compare with TableLlama since it is not trained on WikiTQ.

From Table 6, we can observe that PROTRIX-CODER achieves the highest accuracy on program-unsolvable queries compared with fine-tuned methods. It suggests TrixInstruct can teach a model to understand commonsense and general concepts in the query and adaptatively plan to reason with programs or languages. PROTRIX-CODER still falls behind TAPEX and TaCube on the program-solvable subset. But these models require table pretraining which is computationally expensive. PROTRIX-CODER surpasses the previous generalist model by 1.5% and 4.7% on program unsolvable and solvable subsets, indicating the effectiveness of the proposed *Plan-then-Reason* framework.

Models	P-Unsolvable	P-Solvable	Overall
<i>Closed-source Models</i>			
Codex	40.3	53.4	50.5
Binder	41.3	71.8	65.0
<i>Finetuning Methods</i>			
UnifiedSKG	37.6	56.0	51.9
TAPEX*	33.6	68.0	60.4
TaCube*	34.9	68.5	61.1
PROTRIX	35.0	59.1	53.8
PROTRIX-CODER	38.9	60.7	55.7

Table 6: Breakdown performance on the development set of WikiTQ. P-(un)solvable: program-(un)solvable subset. *: with table pretraining.

D.2 Combining Tables and Sentences

We break down the performance on FEVEROUS into subsets following Aly et al. (2021). We choose subsets that are related to the planning and reasoning abilities to analyze our model as shown in Table 7.

We use GPT-3.5-turbo and DCUF (Hu et al., 2022) as baselines. Notably, our reproduction of DCUF leverages an additional module (Wu et al., 2023) to select top 25 cells from the table to control input context length. GPT-3.5-turbo and our models use the whole table as input.

From Table 7, we can observe that PROTRIX has comparable performance with GPT-3.5-turbo and DCUF on combining tables and texts and multi-hop reasoning. It suggests that our model can learn to plan the reasoning steps and assign them to programs or languages by training on TrixInstruct. PROTRIX surpasses GPT-3.5-turbo and DCUF by 25.5% and 5.4%, respectively, on the numerical reasoning subset. It underscores that symbolic programming can achieve high-precision performance.

Models	Table+Text	Multi-hop	Numerical
<i>Closed-source Models</i>			
GPT-3.5-turbo	81.3	79.2	48.6
<i>Finetuning Methods</i>			
DCUF [†]	83.4	77.8	68.7
PROTRIX	81.8	73.9	74.1
PROTRIX-CODER	78.1	68.8	73.1

Table 7: Breakdown performance on our development set of FEVEROUS. Table+Text: combining tables and texts. Multi-hop: multi-hop reasoning. Numerical: Numerical reasoning. [†]: select top 25 cells from the table as input following Wu et al. (2023).

E More Results

In Table 9, we compare the results with more closed-source models. Even GPT-3.5-turbo falls behind Codex with same prompting methods, our *Plan-then-reason* is comparable to results of Binder, ReAcTable and Dater using Codex. We also experiment with prompting methods on 7B models to understand the effectiveness of our model, especially for out-of-domain benchmarks. We run StructGPT (Jiang et al., 2023), Plan-and-Solve (Wang et al., 2023), and Chain-of-Thought (Wei et al., 2022) on Llama-2-7B-chat. We also run PAL (Gao et al., 2023), ReAct (Yao et al., 2023) and ARC (Zhang et al., 2023c) on CodeLlama-7B-Instruct. Our PROTRIX model family surpasses all the prompting methods with 7B models.

We also experiment with the latest Llama-3-8B model. The performance increases by 9.5% on average. It shows that our dataset can be used to finetune larger and more powerful base models to obtain more accurate answers.

F Case Study

We conduct case studies to further demonstrate the planning and reasoning ability of PROTRIX.

1073 Table 17 demonstrates the planning ability that di-
1074 gests the general concept in user query and fills the
1075 gap between the question *who was the top chef* and
1076 the table of competition result. As for the exam-
1077 ple in Table 18, PROTRIX deploys SQL to extract
1078 relevant information from the table and reach the
1079 final answer based on textual reasoning. PROTRIX
1080 also generalizes to queries with insufficient context.
1081 We can observe from Table 19, that the model re-
1082 fuses to write SQL when the table does not contain
1083 the necessary information to verify the claim. The
1084 example in Table 20 shows the ability to decom-
1085 pose query and assign each step to program-based
1086 or textual reasoning and the example in Table 21
1087 suggests the ability to plan reasoning steps based
1088 on sentence context.

1089 We also demonstrate some examples that PRO-
1090 TRIX fails to answer correctly. Consider the ex-
1091 ample in Table 22, PROTRIX successfully extracts
1092 relevant cells from the table but fails to compute
1093 the final answer using textual reasoning. It indi-
1094 cates that there is still room for improvement on
1095 numerical reasoning. The example in Table 23 is a
1096 fact verification query. The table does not have hi-
1097 erarchical headers but has an intrinsic hierarchical
1098 structure. The last *Total* row should not be consid-
1099 ered as a *HDI* and our model fails to identify the
1100 intrinsic hierarchical structure. We plan to include
1101 tables with hierarchical headers and structure in
1102 our instruction tuning dataset in future work.

Error Type	Claim	Response
Planning Error	McCord Museum is a history museum containing 1,440,000 objects, images and manuscripts.	- To verify the claim, we need to check the collection size of the McCord Museum . This information can be found in the table context under the "Collection size" column. - We do not need to use the sentence context for this claim as the table provides the exact information needed.
SQL Error	Georgia Southern did not make Athlon's list of pre-season top 25 of 2011 NCAA Division I FCS football rankings. (column 0 is a column for rankings)	SELECT column0 FROM w WHERE column0 = 'Georgia Southern'
Execution Error	In 1949, the Chicago Cardinals season played twelve matches, resulting to ten losses and two tied matches.	SELECT COUNT(*) as Losses FROM w WHERE Result LIKE 'L%' Result: 4
Reasoning Error	In Southern Peninsular Malaysian Hokkien phonology, there are three front vowels, two central vowels and two back vowels.	- The claim states that in Southern Peninsular Malaysian Hokkien phonology, there are three front vowels two central vowels, and four back vowels Therefore, the answer is REFUTES.

Table 8: Types of errors in *Plan-then-Reason* framework. For each response, we only demonstrate the part of the response where the error first occurs. The error is highlighted in red. In planning error, the model response fails to list all the information that needs to be checked apart from collection size. In SQL error, the SQL can not be used to extract the ranking of Georgia Southern. As for reasoning error, the model fails to summarize the whole planning and reasoning because of the hallucination of the original claim.

	WikiTQ	WikiSQL	TabFact	SciTAB	FEVEROUS	HybridQA	TATQA
<i>GPT-4</i>							
End-to-End QA	72.9	75.8	71.5	57.1	71.0	64.1	80.8
<i>PaLM2</i>							
End-to-end QA	60.5	-	77.9	-	-	-	-
Chain-of-Table	67.3	-	86.6	-	-	-	-
<i>Codex</i>							
Binder	64.6	-	85.1	-	-	-	-
ReAcTable	65.8	-	83.1	-	-	-	-
Dater	65.9	-	85.6	-	-	-	-
SEER	-	-	-	-	-	-	73.6
<i>GPT-3.5-turbo</i>							
End-to-End QA	51.8	55.0	68.8	45.3	61.0	55.1	59.1
ReAcTable	52.4	-	73.1	-	-	-	-
Dater*	52.8	-	78.0	-	-	-	-
Binder*	56.7	-	79.2	-	-	-	-
StructGPT	57.0	64.6	87.3	-	-	-	-
Chain-of-Table	59.9	-	80.2	-	-	-	-
TabSQLify	64.7	76.7	79.5	-	-	-	-
Mix SC*	73.1	-	-	-	-	-	-
Plan-then-Reason [‡] (Ours)	60.5	-	79.6	-	53.8	-	-
Plan-then-Reason (Ours)	65.2	-	83.5	-	65.8	-	-
<i>Finetuned SOTA</i>	63.3 [†]	89.2 [†]	90.8 [†]	73.1 [†]	75.9 [†]	61.0 [†]	74.5 [†]
<i>Llama-2-7B</i>							
End-to-End QA	21.4	17.4	48.6	27.2	47.1	27.6	28.7
Llama-2-7B-chat StructGPT	21.2	23.1	38.9	30.5	16.1	27.8	21.3
Llama-2-7B-chat PS	26.1	25.1	31.7	31.4	39.4	24.6	36.4
Llama-2-7B-chat CoT	33.8	28.4	49.8	36.6	44.8	24.9	35.8
TableLlama	31.6	41.7	82.6 [†]	29.2	56.8	33.3	38.3
PROTRIX(Ours)	56.2 [†]	67.4	71.6	45.0	75.6 [†]	42.9	50.1
<i>CodeLlama-7B</i>							
End-to-End QA	13.1	17.3	49.5	37.1	43.0	28.5	28.4
CodeLlama-7B-Instruct PAL	24.5	11.5	33.1	30.2	27.2	6.1	11.1
CodeLlama-7B-Instruct ReAct	34.2	38.4	52.6	15.3	43.2	19.1	34.9
CodeLlama-7B-Instruct ARC	35.8	39.9	54.6	29.5	49.2	23.7	28.2
TableLLM	52.9 [†]	65.3 [†]	57.1	24.7	60.0	53.7	70.3[†]
PROTRIX-CODER (Ours)	57.8 [†]	72.3	70.6	41.2	71.4 [†]	45.1	52.2
<i>Llama-3-8B</i>							
Llama-3	29.3	31.8	54.8	28.6	48.3	32.8	45.4
LLAMA-3-PROTRIX (Ours)	67.0 [†]	75.7	79.4	41.3	84.5 [†]	57.3	70.3

Table 9: Experimental results on short-form question answering and fact verification tasks. [†] The model is trained on this evaluation benchmark. *: with self consistency. We use GPT-4-1106-preview and GPT-3.5-turbo-16k-0613 in our experiment. Plan-then-Reason[‡]: w/o fallback mechanism that use LLM to predict the result of code that fails to execute.

This is a table question answering task. You will answer the question based on the given context.

Question

How many medals were won by Kenya?

Table Context

Rank	Name	Nationality	Time
1	Brahim Boulami	Morocco	8:17.73
2	Reuben Kosgei	Kenya	8:18.63
3	Stephen Cherono	Kenya	8:19.98
4	Bouabdellah Tahri	France	8:20.25
5	Tim Broe	United States	8:20.75
6	Luis Miguel Martín	Spain	8:24.03
7	Raymond Yator	Kenya	8:27.19
8	Thomas Chorny	United States	9:24.26

Task

You will answer the question based on the given context. You should reach a short-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

Answer

Let's answer in three steps.

1. Plan for answering the question

- The question focus on the medals won by Kenya. According to common sense, only top 3 players can win medals.
- So we write a SQL to select the top three players. Then we count the numbers of medals won by Kenya based on the output of SQL.

2. Write SQL and execute SQL

SQL:

```
SELECT Name, Nationality FROM Table WHERE Rank <= 3
```

Executed result:

```
| Name | Nationality |  
| Reuben Kosgei | Kenya |  
| Stephen Cherono | Kenya |
```

3. Step-by-Step Reasoning:

- The question is asking about the number of medals won by Kenya.
- Based on the execution result of SQL query, only two of the players that win medals are from Kenya.
- Therefore, the total number of medals won by Kenya is 2.

The final answer is 2.

Question

Question

Table Context

Table

Task

You will answer the question based on the given context. You should reach a short-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

Answer

Table 10: Prompt for generating responses for queries from WikiTQ. GPT-3.5-turbo and GPT-4 generates responses following this example.

This is a fact verification task. You are asked to check the veracity of the claim. Both table and sentence context are provided but you are not required to use both of them. You can use either of them or both of them.

Claim

Sony Dwi Kuncoro, born on July 7, 1984, was the champion of the Men's singles event of the 2009 Indonesia National Badminton Championship with a score of 21-17, 22-20.

Table Context

Page Title: 2009 Indonesia National Badminton Championship

Caption:

Category | Winners | Runners-up | Score

Men's singles | Sony Dwi Kuncoro | Andre Kurniawan Tedjono | 21-17, 22-20

Women's singles | Maria Kristin Yulianti | Maria Febe Kusumastuti | 21-17, 17-21, 23-21

Men's doubles | Hendra Setiawan | Rian Sukmawan , Yonathan Suryatama Dasuki | 21-9, 21-13

Women's doubles | Meiliana Jauhari , Greysia Polii | Liliyana Natsir , Shendy Puspa Irawati | 21-19, 18-21, 21-17

Mixed doubles | Tontowi Ahmad , Greysia Polii | Muhammad Rijal , Debby Susanto | 21-11, 21-19".

Sentence Context

Sony Dwi Kuncoro (1): Sony Dwi Kuncoro (born 7 July 1984) is a badminton singles player from Indonesia.

Sony Dwi Kuncoro (2): He reached a career high as world number 3 on 7 October 2004.

Sony Dwi Kuncoro (3): In 2009, his best performance in Superseries was semifinalist in Indonesia Open, beaten by Taufik Hidayat, 17–21, 14–21 and in Denmark Open beaten by Marc Zwiebler of Germany in three tough games.

Task

You will predict the claim's label based on the given claim and context. There are 3 possible labels: *SUPPORTS*, *REFUTES*, and *NOT ENOUGH INFO*. *SUPPORTS* means the claim is supported by the context. *REFUTES* means the claim is refuted by the context. *NOT ENOUGH INFO* means the context does not provide enough information to the support or refute the claim. You are asked to check the claim in three steps.

1. Analyze the question and the given context. Make up a plan to verify the claim.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

Answer:

Let's check the claim in 3 steps.

1. Plan for verify the claim

- Based on the claim and the given context. The information for winner of Men's singles can be obtained from the table. We could write a SQL to query the name of the winner and the score of the final for Men's singles.
- The claim also states that Sony Dwi Kuncoro is born on July 7, 1984. We will use the sentences to check this part of claim.

2. Write SQL and execute SQL

SQL:

```
SELECT Winners FROM Table WHERE Category = Men's singles
```

Executed result:

Category | Winners | Score

Men's singles | Sony Dwi Kuncoro | 21-17, 22-20

3. Step-by-step Reasoning

- The claim states Sony Dwi Kuncoro, born on July 7, 1984, was the champion of the Men's singles event of the 2009 Indonesia National Badminton Championship with a score of 21-17, 22-20.
- The SQL query result supports the claim. Sony Dwi Kuncoro was the champion of the Men's singles event of the 2009 Indonesia National Badminton Championship with a score of 21-17, 22-20.
- The sentence evidence Sony Dwi Kuncoro (1) supports that he was indeed born on July 7, 1984.

Therefore, the answer is **SUPPORTS**

Claim

...

Answer

Table 11: Prompt for generating responses for queries from FEVEROUS. GPT-3.5-turbo and GPT-4 generates responses following this example.

This is a table fact verification task. You will predict whether the statement is true or false based on the given context.

Claim

Kenya won 3 medals in the 3000 meters event at the 2001 Goodwill Games.

Table Context

Rank	Name	Nationality	Time
1	Brahim Boulami	Morocco	8:17.73
2	Reuben Kosgei	Kenya	8:18.63
3	Stephen Cherono	Kenya	8:19.98
4	Bouabdellah Tahri	France	8:20.25
5	Tim Broe	United States	8:20.75
6	Luis Miguel Martín	Spain	8:24.03
7	Raymond Yator	Kenya	8:27.19
8	Thomas Chorny	United States	9:24.26

Task

You will answer the question based on the given context. You should reach a short-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

Answer

Let's answer in three steps.

1. Plan for answering the question

- The question focus on the medals won by Kenya. According to common sense, only top 3 players can win medals.
- So we write a SQL to select the top three players. Then we count the numbers of medals won by Kenya based on the output of SQL.

2. Write SQL and execute SQL

SQL:

```
SELECT Name, Nationality FROM Table WHERE Rank <= 3
```

Executed result:

Name	Nationality
Reuben Kosgei	Kenya
Stephen Cherono	Kenya

3. Step-by-Step Reasoning:

- The statement claims that Kenya won 3 medals in the 3000 meters event at the 2001 Goodwill Games.
- Based on the execution result of SQL query, only two of the players that win medals are from Kenya.
- Therefore, the table context does not support the statement. The statement is false.

The final answer is **false**.

Claim

Claim

Table Context

Table

Task

You will answer the question based on the given context. You should reach a short-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

Answer

Table 12: Prompt for generating responses for queries from Tabfact. GPT-3.5-turbo and GPT-4 generates responses following this example.

Check if the prediction answers the question correctly. For numerical answers, you should check if the predicted answer is approximately correct. For questions with multiple answers, you should check if all the predicted answers are correct. If the predicted answer is correct, return "Yes". Otherwise, return "No". The question, predicted answer, and gold answer are provided below.

Question
question

Gold Answer
gold answer

Predicted Answer
predicted answer

Does the prediction answer the question correctly? Yes/No
Answer

Table 13: Prompt for question answering evaluation

Question Answering

Question
question

Table
table info
table content

Sentence Context
sentences

Task

You will answer the question based on the given context. You should reach a short-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer

Answer

Fact Verification

Claim
claim

Table
table info
table content

Sentence Context
sentences

Task

You will predict the claim's label based on the given claim and context. There are 3 possible labels: SUPPORTS, REFUTES, and NOT ENOUGH INFO. SUPPORTS means the claim is supported by the context. REFUTES means the claim is refuted by the context. NOT ENOUGH INFO means the context does not provide enough information to the support or refute the claim. You are asked to check the claim in three steps

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer

Answer

Table 14: Prompt of short-form answer tasks for PROTRIX. Table info includes page title, section title and caption. If no sentence context is provided, we discard the sentence context part in the prompt.

TableLlama & GPT-3.5-turbo

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

Instruction

This is a free-form table question answering task. The goal for this task is to answer the given question based on the given table.

Input:

[TLE] The Wikipedia page title of this table is *page title*. The Wikipedia section title of this table is *section title*.

[TAB] *table*

Question:

question

Response:

Our model**## Question**

question

Table Context

Page title: *page title*

Section title: *section title*

table

Task

You will answer the question based on the given context. You should reach a free-form answer after reasoning. You are asked to answer the question in three steps.

1. Analyze the question and the given context. Make up a plan to answer the question.
2. Write one or more SQL to query the table for necessary information and output expected execution result.
3. Reason step-by-step to reach the final answer.

##Answer:

Table 15: Prompt for evaluation on FetaQA

Question

How well did Peralta play at the 2015 CONCACAF Gold Cup?

Table Context

Page Title: Oribe Peralta

Caption: International goals

| Goal | Date | Venue | Opponent | Score | Result | Competition

...17 rows with goals in 2014 FIFA World Cup qualification

118. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 1-0 | 6-0 | 2015 CONCACAF Gold Cup

119. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 3-0 | 6-0 | 2015 CONCACAF Gold Cup

120. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 5-0 | 6-0 | 2015 CONCACAF Gold Cup

121. | 26 July 2015 | Lincoln Financial Field, Philadelphia, United States | Jamaica | 3-0 | 3-1 | 2015 CONCACAF Gold Cup

...5 rows with goals in 2015 CONCACAF Cup, 2017 FIFA Confederations Cup

Gold answer

Peralta played at the 2015 CONCACAF Gold Cup and scored a 6-0 defeat of Cuba in Chicago, as well as a 3-1 win against Jamaica in Philadelphia.

GPT-3.5-turbo response

Peralta played very well at the 2015 CONCACAF Gold Cup, scoring a total of 8 goals in the tournament. ✗

TableLlama

Peralta scored twice in a 6-0 win over Cuba. ✗

PROTRIX

1. Plan for answering the question

- The question asks for an assessment of Peralta's performance at the 2015 CONCACAF Gold Cup.

- To answer this, we need to filter the table for entries that are related to the 2015 CONCACAF Gold Cup and then analyze the results to determine if Peralta played well or not.

2. Write SQL and execute SQL

SQL

```
SELECT Goal, Date, Venue, Opponent, Score, Result, Competition FROM International_Goals WHERE Competition = '2015 CONCACAF Gold Cup'
```

Executed result:

Goal | Date | Venue | Opponent | Score | Result | Competition

18. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 1-0 | 6-0 | 2015 CONCACAF Gold Cup

19. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 3-0 | 6-0 | 2015 CONCACAF Gold Cup

20. | 9 July 2015 | Soldier Field, Chicago, United States | Cuba | 5-0 | 6-0 | 2015 CONCACAF Gold Cup

21. | 26 July 2015 | Lincoln Financial Field, Philadelphia, United States | Jamaica | 3-0 | 3-1 | 2015 CONCACAF Gold Cup

3. Step-by-Step Reasoning:

• The SQL query filters the table to show only the goals scored by Peralta during the 2015 CONCACAF Gold Cup.

• From the execution result, we can see that Peralta scored three goals on 9 July 2015 against Cuba at Soldier Field, Chicago, United States and one goal on 26 July 2015 against Jamaica on 26 July 2015 at Lincoln Financial Field, Philadelphia, United States ✓

• The results were 6-0 and 3-1, respectively, which indicates a dominant performance by Peralta and his team.

• Therefore, Peralta played very well at the 2015 CONCACAF Gold Cup.

The final answer is that Peralta played very well at the 2015 CONCACAF Gold Cup. ✓

Table 16: An example of the responses of models to FetaQA

Question

who was the top chef?

Table

Name | Age | Hometown | Occupation | Culinary P.O.V. | Eliminated

Damaris Phillips | 31 | Louisville, KY | Culinary Teacher | Modern Southern Food | Winner

Rodney Henry | 47 | Baltimore, MD | Pie Shop Owner | Pie Style | Second Place

Russell Jackson | 49 | San Francisco, CA | Underground Chef | Seven Culinary Sins | Third Place

Stacey Poon-Kinney | 34 | San Diego, CA | Restaurant Owner | Vintage with a Modern Twist | Week 10

Nikki Dinki | 29 | New York, NY | Food Blogger/Online Host | Semi-Vegetarian / Meat on the Side | Week 9

Chad Rosenthal | 37 | Ambler, PA | Restaurant Owner | Jewish BBQ Guy | Week 7

Chris Hodgson | 26 | Cleveland, OH | Chef/Restaurateur | Compassion for Food | Week 6

Viet Pham | 33 | Salt Lake City, UT | Chef/Restaurant Owner | The American Dream | Week 5

Connie Lovely Jackson" | 27 | Los Angeles, CA | Caterer | Party on a Plate | Week 4 / Week 8(Winner of Star Salvation)

Danushka Lysek | 37 | New York, NY | Private Chef/Model | Your Private Chef | Week 3

Andres Guillama | 26 | Waynesville, NC | Childhood Obesity Prevention Coach | Teaching Men to Cook | Week 2

Daniela Perez-Reyes | 28 | Haleiwa, HI | Bartender/Caterer | Peruvian Princess | Week 1

Answer:

1. Plan for answering the question

- The question asks for the top chef, which implies we are looking for the winner of the competition.
- To find the top chef, we need to look for the name associated with the position of "Winner" in the table.

2. Write SQL and execute SQL

```
““sql
```

```
SELECT ‘Name‘ FROM w WHERE ‘Eliminated‘ = ‘Winner’
```

```
““
```

Expected Result:

```
““
```

Name

Damaris Phillips

```
““
```

3.Step-by-step Answer prediction

- The question is asking for the name of the top chef from the given table.
- Based on the execution result of the SQL query, the name associated with the position of "Winner" is Damaris Phillips.
- Therefore, the top chef according to the table is Damaris Phillips.

The final answer is Damaris Phillips.

Table 17: An example from WikiTQ

Claim

The houston texans score more point on november 16 , 2003 than on september 28 , 2003

Table

Caption: 2003 houston texans season

week | date | opponent | result | game site | record | tv time | attendance

1 | september 7 , 2003 | miami dolphins | w 21 - 20 | dolphin stadium | 1 - 0 | cbs 12:00 pm | 73010
2 | september 14 , 2003 | new orleans saints | l 10 - 31 | louisiana superdome | 1 - 1 | cbs 12:00 pm | 68390
3 | september 21 , 2003 | kansas city chiefs | l 14 - 42 | reliant stadium | 1 - 2 | cbs 12:00 pm | 70487
4 | september 28 , 2003 | jacksonville jaguars | w 24 - 20 | reliant stadium | 2 - 2 | cbs 12:00 pm | 70041
5 | - | - | - | - | - | - | - | - |
6 | october 12 , 2003 | tennessee titans | l 17 - 38 | lp field | 2 - 3 | cbs 12:00 pm | 68809
7 | october 19 , 2003 | new york jets | l 14 - 19 | reliant stadium | 2 - 4 | cbs 12:00 pm | 70623
8 | october 26 , 2003 | indianapolis colts | l 21 - 30 | rca dome | 2 - 5 | cbs 12:00 pm | 56132
9 | november 2 , 2003 | carolina panthers | w 14 - 10 | reliant stadium | 3 - 5 | fox 12:00 pm | 70052
10 | november 9 , 2003 | cincinnati bengals | l 27 - 34 | paul brown stadium | 3 - 6 | cbs 12:00 pm | 50437
11 | november 16 , 2003 | buffalo bills | w 12 - 10 | ralph wilson stadium | 4 - 6 | cbs 12:00 pm | 72677
12 | november 23 , 2003 | new england patriots | l 20 - 23 (ot) | reliant stadium | 4 - 7 | cbs 12:00 pm | 70719
13 | november 30 , 2003 | atlanta falcons | w 17 - 13 | reliant stadium | 5 - 7 | fox 12:00 pm | 70388
14 | december 7 , 2003 | jacksonville jaguars | l 0 - 27 | alltel stadium | 5 - 8 | cbs 12:00 pm | 43363
15 | december 14 , 2003 | tampa bay buccaneers | l 3 - 16 | raymond james stadium | 5 - 9 | cbs 12:00 pm | 65124
16 | december 21 , 2003 | tennessee titans | l 24 - 27 | reliant stadium | 5 - 10 | cbs 12:00 pm | 70758
17 | december 28 , 2003 | indianapolis colts | l 17 - 20 | reliant stadium | 5 - 11 | cbs 12:00 pm | 70680

Answer:

Let's check the claim in 3 steps.

1. Plan for verify the claim

- To verify the claim, we need to compare the points scored by the Houston Texans in the games on November 16, 2003, and September 28, 2003. We will write a SQL query to retrieve the result for these specific dates.

2. Write SQL and execute SQL

```
““sql
```

```
SELECT 'date', 'result' FROM w WHERE 'date' = 'november 16 , 2003' OR 'date' = 'september 28 , 2003'
```

```
““Expected Result:
```

```
““
```

```
date | result
```

```
november 16 , 2003 | w 12 - 10
```

```
september 28 , 2003 | w 24 - 20
```

```
““
```

3. Step-by-step answer prediction

- The claim states that the Houston Texans scored more points on November 16, 2003, than on September 28, 2003.

- According to the SQL query result, the Houston Texans won with a score of 12-10 on November 16, 2003, and won with a score of 24-20 on September 28, 2003.

- The score on November 16, 2003, is less than the score on September 28, 2003.

- Therefore, the claim is refuted by the table.

The answer is REFUTES.

Table 18: An example from TabFact

Claim

Here is a claim: In the natural state space with 75 actions, training does not converge within a reasonable training time. Does the following context support or refute the claim?

Table

Paper title: Guided Dialog Policy Learning: Reward Estimation for Multi-Domain Task-Oriented Dialog

Table caption: Table 5: Performance of different agents on the neural user simulator.

Method | VHUS Turns | VHUS Inform | VHUS Match | VHUS Success

ACER | 22.35 | 55.13 | 33.08 | 18.6

PPO | 19.23 | 56.31 | 33.08 | 18.3

ALDM | 26.90 | 54.37 | 24.15 | 16.4

GDPL | 22.43 | 52.58 | 36.21 | 19.7

Answer:

1. Plan for answering the question

- The claim states that training does not converge within a reasonable training time in the natural state space with 75 actions.
- To answer the claim, we need to understand the training time and the number of actions in the state space.
- The table provides information about the performance of different agents, but it does not provide information about the training time or the number of actions.
- Since the table does not contain the necessary information to answer the claim, we cannot write an SQL query to extract this information from the table.

2. Write SQL and execute SQL

- No SQL query can be written as the table does not contain the required information about the training time or the number of actions.

3. Step-by-Step Reasoning:

- The claim is about the training time and the number of actions in the state space.
- The table provides information about the performance of different agents, but it does not provide information about the training time or the number of actions.
- Since the table does not contain the necessary information to answer the claim, we cannot confirm or refute the claim based on the provided context.

Therefore, the answer is "NOT ENOUGH INFO".

Table 19: An example from SCITAB

Claim

Delta Green was published by Arc Dream Publishing which is a small role-playing game publishing company founded in 2002.

Table

Page Title: Delta Green

Caption: Delta Green

Designer(s) | Dennis Detwiller, Adam Scott Glancy, John Scott Tynes

Publisher(s) | Pagan Publishing Arc Dream Publishing Pelgrane Press (The Fall of DELTA GREEN)

Publication date | 1997 (Sourcebook) 2016 (Arc Dream Publishing) (Standalone RPG)2018 (The Fall of DELTA GREEN)

Genre(s) | Horror, Conspiracy fiction

System(s) | Call of Cthulhu, GUMSHOE

Sentences:

Arc Dream Publishing: Arc Dream Publishing is a small role-playing game publishing company founded in 2002 by Pagan Publishing veteran Dennis Detwiller and editor Shane Ivey after the release of their first roleplaying game Godlike: Superhero Roleplaying in a World on Fire, 1936-1946 was published by Hobgoblynn Press.

Delta Green: The book was published in cooperation with Arc Dream Publishing.

Arc Dream Publishing: The name ARC DREAM comes from one of Dennis Detwiller's other roleplaying games—Delta Green—where it is a secret government project.

Delta Green: Delta Green is a setting for the Call of Cthulhu role-playing game created by Adam Scott Glancy, Dennis Detwiller, and John Scott Tynes, a.k.a. the Delta Green Partnership, of the Seattle gaming house Pagan Publishing.

Delta Green: In August 2011, Arc Dream Publishing and the Delta Green Partnership announced development of a standalone Delta Green role-playing game.

Answer:

Let's check the claim in 3 steps.

1. Plan for verify the claim

- To verify the claim, we need to confirm that Delta Green was published by Arc Dream Publishing and that Arc Dream Publishing is a small role-playing game publishing company founded in 2002.

- We can use the table to verify the publisher of Delta Green and the sentence context to confirm the founding year of Arc Dream Publishing.

2. Write SQL and execute SQL

```
“sql
```

```
SELECT Publisher FROM w
```

```
““
```

Expected result:

```
““
```

Publisher

Pagan Publishing

Arc Dream Publishing

Pelgrane Press (The Fall of DELTA GREEN)

```
““
```

3. Step-by-step answer prediction

- The claim states that Delta Green was published by Arc Dream Publishing, which is a small role-playing game publishing company founded in 2002.

- The SQL query result shows that Delta Green was published by Pagan Publishing, Arc Dream Publishing, and Pelgrane Press. This supports the claim that Arc Dream Publishing is one of the publishers of Delta Green.

- The sentence context Arc Dream Publishing confirms that Arc Dream Publishing is a role-playing game publishing company founded in 2002.

- The sentence context Delta Green supports the claim that Delta Green is a setting for the Call of Cthulhu role-playing game.

Therefore, the answer is SUPPORTS.

Table 20: An example from FEVEROUS

Question

when did the judge born August 4 , 1791 in Sharon , Litchfield County , Connecticut leave office ?

Table

Name | Took office | Left office | Party

Freeborn G. Jewett | July 5 , 1847 | December 31 , 1849 | Democratic
Greene C. Bronson | January 1 , 1850 | April 1851 | Democratic/ Anti-Rent
Charles H. Ruggles | April 1851 | December 31 , 1853 | Democratic
Addison Gardiner | January 1 , 1854 | December 31 , 1855 | Democratic/Anti-Rent
Hiram Denio | January 1 , 1856 | December 31 , 1857 | Democratic
Alexander S. Johnson | January 1 , 1858 | December 31 , 1859 | Democratic
George F. Comstock | January 1 , 1860 | December 31 , 1861 | American
Samuel L. Selden | January 1 , 1862 | July 1 , 1862 | Democratic
Hiram Denio | July 1 , 1862 | December 31 , 1865 | Democratic
Henry E. Davies | January 1 , 1866 | December 31 , 1867 | Republican / American
William B. Wright | January 1 , 1868 | January 12 , 1868 | Union
Ward Hunt | January 12 , 1868 | December 31 , 1869 | Republican
Robert Earl | January 1 , 1870 | July 4 , 1870 | Democratic

Sentences:

Freeborn G. Jewett: Freeborn Garretson Jewett (August 4 , 1791 in Sharon , Litchfield County , Connecticut - January 27 , 1858 in Skaneateles , Onondaga County , New York) was an American lawyer and politician who served as a U.S. Representative from New York and was the first Chief Judge of the New York Court of Appeals .
Greene C. Bronson: Greene Carrier Bronson (November 17 , 1789 in Simsbury , Hartford County , Connecticut - September 3 , 1863 in Saratoga , New York) was an American lawyer and politician from New York .
Samuel L. Selden: Samuel Lee Selden (October 12 , 1800 Lyme , New London County , Connecticut - September 20 , 1876 Rochester , Monroe County , New York) was an American lawyer and politician from New York .

Answer: 1. Plan for answering the question

- The question asks for the date when a judge named Freeborn G. Jewett left office.
- To answer the question, we need to find the row in the table that corresponds to Freeborn G. Jewett and then select the date he left office.

2. Write SQL and execute SQL

```
““sql  
SELECT ‘Left office’ FROM w WHERE ‘Name’ = ‘Freeborn G. Jewett’  
““Expected Result:
```

```
““  
Left office  
1849-12-31  
““
```

3.Step-by-step Answer prediction:

- The question is asking for the date when a specific judge, Freeborn G. Jewett, left office.
- Based on the execution result of the SQL query, Freeborn G. Jewett left office on December 31, 1849.
- Therefore, the date the judge left office is December 31, 1849.
The final answer is December 31, 1849.

Table 21: An example from HybridQA

Question

What is the average proportion of cost of revenue as a percentage of the total revenue in 2018 and 2019?

Table

Fiscal Years | | |

| 2019 | 2018 | 2017

Statements of Operations: | | |

Revenue | 100% | 100% | 100%

Cost of revenue | 43% | 50% | 55%

Gross profit | 57% | 50% | 45%

Operating expenses: | | |

Research and development | 120% | 79% | 79%

Selling, general and administrative | 86% | 79% | 81%

Loss from operations | (149)% | (108)% | (115)%

Interest expense | (3)% | (1)% | (1)%

Interest income and other expense, net | 2% | 1% | —%

Loss before income taxes | (150)% | (108)% | (116)%

Provision for income taxes | 1% | 1% | 1%

Net loss | (151)% | (109)% | (117)%

Sentences

The following table sets forth the percentage of revenue for certain items in our statements of operations for the periods indicated:

Impact of inflation and product price changes on our revenue and on income was immaterial in 2019, 2018 and 2017.

Answer

1. Plan for answering the question

- The question asks for the average proportion of cost of revenue as a percentage of the total revenue for the years 2018 and 2019.
- To find the average, we need to calculate the proportion for each year and then find the mean of these two values.
- We will write an SQL query to select the cost of revenue as a percentage of revenue for the years 2018 and 2019.

2. Write SQL and execute SQL

```
““sql
```

```
SELECT ‘Fiscal Years’, ‘Cost of revenue’ FROM Table WHERE ‘Fiscal Years’ IN (‘2019’, ‘2018’)
```

```
““
```

Expected result:

```
““
```

```
| Fiscal Years | Cost of revenue |
```

```
| 2019 | 43% |
```

```
| 2018 | 50% |
```

```
““
```

3. Step-by-Step Reasoning:

- The SQL query gives us the cost of revenue as a percentage of revenue for the years 2019 and 2018.
- To find the average, we calculate the mean of the two values: $(0.43 + 0.50) / 2 = 0.48$.
- Therefore, the average proportion of cost of revenue as a percentage of the total revenue for 2018 and 2019 is 48%.

The final answer is 48%.

##Gold Answer

46.5%

Table 22: An error case from responses to TATQA. The error source is highlighted in red.

Claim

Campina Grande had three HDIs between 1991 and 2000, one of which is Value.

Table

Page Title: Campina Grande

Caption: UNHD (2000)

HDI | 1991 | 2000

Value | 0.615 | 0.678

Life expectancy | 0.585 | 0.641

Education | 0.741 | 0.844

Total | 0.647 | 0.721

Sentences

Campina Grande: Campina Grande is the second most populous Brazilian city in the State of Paraiba after Joao Pessoa, the capital.

Roman Catholic Diocese of Campina Grande: The Roman Catholic Diocese of Campina Grande (Latin: Dioecesis Campinae Grandis) is a suffragan Latin diocese in the Ecclesiastical province of Paraiba, in northeastern Brazil.

Campina Grande: It is considered one of the main industrial, technological and educational centers in the northeastern region of Brazil.

Campina Grande: For a long time Campina Grande has had a strong technological focus.

Campina Grande: At the time, it was the second biggest producer in the world.

Answer:

Let's check the claim in 3 steps.

1. Plan for verify the claim

- To verify the claim, we need to check the HDI values for Campina Grande for the years 1991 and 2000. The table provides the necessary data to verify this part of the claim.

- We do not need to use the sentences for this claim as the table provides the required information.

2. Write SQL and execute SQL

```
```sql
```

```
SELECT 'HDI', '1991', '2000' FROM w
```

```
```Expected Result:
```

```
```
```

```
HDI | 1991 | 2000
```

```
Value | 0.615 | 0.678
```

```
Life expectancy | 0.585 | 0.641
```

```
Education | 0.741 | 0.844
```

```
Total | 0.647 | 0.721
```

```
```
```

3. Step-by-step Answer prediction

- The claim states that Campina Grande had three HDIs between 1991 and 2000, and one of them is Value.

- The SQL query result shows that there are **four HDIs** listed for Campina Grande in the years 1991 and 2000: Value, Life expectancy, Education, and **Total**.

- The claim specifies "Value" as one of the HDIs, but the table shows that there are multiple values (pun intended), which refutes the claim that there was only one HDI.

Therefore, the answer is REFUTES.

##Gold Answer

SUPPORTS

Table 23: An error case from responses to FEVEROUS. The error source is highlighted in red.