TART 🥧 : An Open-Source Tool-Augmented Framework for Explainable Table-Based Reasoning

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Abstract

Current Large Language Models (LLMs) exhibit limited ability to understand table structures and to apply precise numerical reasoning, which is crucial for tasks such as *table question answering (TQA)* and *table-based fact verification (TFV)*. To address these challenges, we introduce our *Tool-Augmented Reasoning framework for Tables* (TART), which integrates LLMs with specialized tools. TART contains three key components: a *table formatter* to ensure accurate data representation, a *tool maker* to develop specific computational tools, and an *explanation generator* to maintain explainability. We also present the TOOLTAB dataset, a new benchmark designed specifically for training LLMs in table–tool integration. Our experiments indicate that TART achieves substantial improvements over existing methods (*e.g.,* Chain-of-Thought) by improving both the precision of data processing and the clarity of the reasoning process. Notably, TART paired with `CodeLlama` achieves 90.0% of the accuracy of the closed-sourced LLM `GPT-3.5-turbo`, highlighting its robustness in diverse real-world scenarios. All the code and data are available at `https://github.com/XinyuanLu00/TART`.

1 Introduction

Tabular data is prevalent across multiple fields such as scientific research, financial reporting, and healthcare records [11]. Manual handling of such data can be both routine and error-prone, or may require specialized skills, highlighting the need for automated table reasoning [2]. Typical table-based reasoning tasks include *table question answering (TQA)*, which extracts precise information from tables to answer given queries [7, 48, 25], and *table-based fact verification (TFV)*, which verifies the correctness of statements by cross-referencing them with facts stored in tables [33, 22].

Modern large language models (LLMs) such as GPT-4 [26] have shown remarkable reasoning capabilities across a variety of tasks, spurring interest in their application to table-based tasks [41]. However, table-based reasoning presents unique challenges for LLMs, which are primarily trained on sequential text data [44], as illustrated by a real-world example in Figure 1. *(1) Understanding and operating on the structure of teh table*: LLMs must adapt to the non-linear format of the tables, which demands unique reasoning skills such as recognizing headers, interpreting the roles of the rows and the columns, and precisely extracting information from relevant table cells. *(2) Precise numerical reasoning:* Tables often contain quantitative information that requires precise calculations and comparisons. LLMs must perform operations such as summation, averaging, or trend analysis accurately, often over multiple cells or tables, which is a shift from their usual text-based reasoning tasks [15, 18]. *(3) Reasoning planning:* LLMs often need to plan several reasoning steps ahead.

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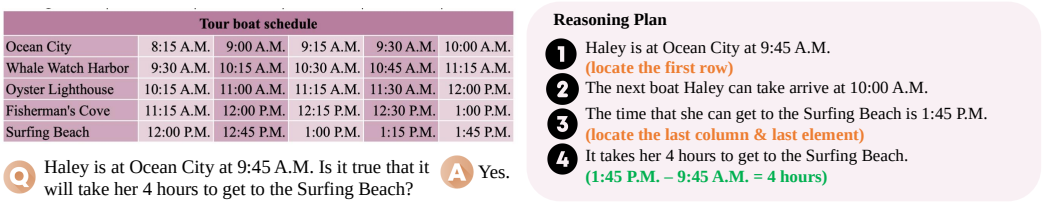


Figure 1: Example of the TableQA task, demonstrating the verification of travel time via boat schedule and demonstrating the critical skills needed for accurate table reasoning: table structure understanding, precise numerical calculations, and executing sequential reasoning steps.

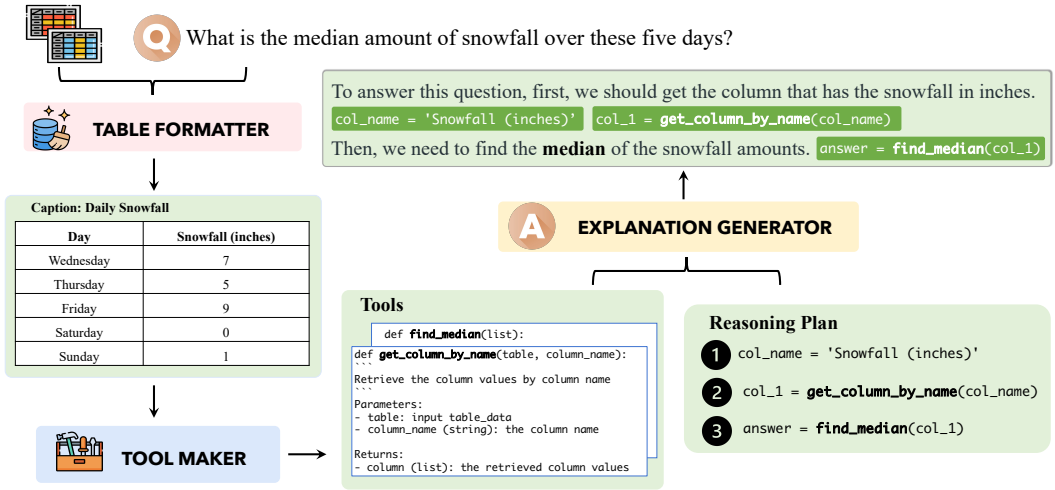


Figure 2: An overall framework of TART, which contains three main modules: (*i*) *table formatter*, which prepares and organizes the raw table data, (*ii*) *tool maker*, which creates specialized tools for precise table manipulation, and (*iii*) *explanation generator*, which produces user-friendly explanations integrating the output of different tools.

This includes decomposing the original question, determining which table parts are relevant and anticipating intermediate calculations or data transformations.

Existing approaches that use LLMs for table-based reasoning can be broadly classified into two categories. One is *chain-of-thought (CoT) reasoning* [37], in which the model is prompted to perform step-by-step reasoning over the input table flattened as a textual sequence [44, 16, 4, 41]. Despite its flexibility, CoT often lacks precision in tabular operations and numerical reasoning, such as sorting, counting, and filtering [39]. On the other hand, *program-based reasoning (PoT)* [12, 5] prompts the model to generate SQL or Python code to enable precise reasoning [19, 45, 36, 39]. However, this method tends to struggle with planning and its reasoning is less understandable for humans [45]. Therefore, there is potential value in integrating the advantages of program-based and textual reasoning, to achieve both high precision and explainability in table-based reasoning.

Inspired by the recent paradigm of tool-augmented language models [35, 31], we propose ***T**ool-**A**ugmented **R**easoning framework for **T**ables (*TART*)*, which integrates external tool calling into the chain-of-thought reasoning process, as shown in Figure 2. Initially, TART processes the input table using a specialized module *table formatter* to clean and to format the raw table data, preparing it for the subsequent table operations. Subsequently, the *tool maker* calls specialized tools (Python functions) for tabular manipulation and numerical reasoning (*e.g.,* adding columns, selecting rows, and grouping). Alongside these tools, TART also crafts a *reasoning plan* that outlines the programmatic calling sequence of the tools, specifying the necessary arguments and the expected return values for each call. Finally, following the structured reasoning plan, the *explanation generator* produces a hybrid text-and-program output, integrating calls to external tools into coherent, human-readable chain-of-thought explanations. Hence, TART efficiently delegates table operations and precise numerical calculations to generated tools, while preserving the planning and explainability of CoT.

To train the modules in TART, we further synthesize the TOOLTAB dataset by distilling knowledge from a teacher LLM. We evaluate TART on nine different table-based reasoning benchmarks. The results highlight the effectiveness of integrating task-specific tools for enhancing complex reasoning capabilities. Notably, TART consistently outperformed the CoT baseline, achieving near-parity with `GPT-3.5-turbo` on several benchmarks, showcasing its practical utility in real-world scenarios.

2 Related Work

Table-based reasoning tasks involve interpreting and manipulating data from structured tabular sources to answer questions, verify facts, or generate summaries. Early approaches used executable SQL or SPARQL to interact with tabular data [42, 43], or graph neural networks to better encode table structures [46, 40]. However, they typically suffer from poor generalization capabilities due to their reliance on specific table formats and linguistic patterns.

Recently, large language models (LLMs) have shown great potential in improving table-based reasoning tasks. Pioneering studies have focused on developing table pre-training strategies, where LLMs are trained with sentence-table pairs to enhance their general table reasoning capabilities [6, 15, 47, 13, 41]. Subsequent work further explored different reasoning strategies to improve efficacy. For example, Ye et al.[41] proposed using LLMs as decomposers to effectively reason over tables by breaking down large tables into smaller sub-evidence and complex questions into simpler sub-questions. Want et al.[36] introduced the *Chain-of-Table* framework, where tabular data is explicitly used in the reasoning chain for intermediate thoughts. *ReAcTable* [45] combined reactive and proactive reasoning strategies to improve accuracy and retrieval from complex tables. Despite these advances, these approaches primarily rely on pure textual reasoning, such as chain-of-thought, which sacrifices the precision required for table manipulations and numerical reasoning, both crucial for table-based reasoning.

To address these limitations, TART extends the use of LLMs with integrated external tools, aimed at improving reasoning precision with function execution while maintaining explainability with LLM-based reasoning. Unlike previous methods that focus on a single reasoning strategy, TART enhances table reasoning with multiple strategies: formatting tables for better data representation, calling tools for precise calculation, and generating user-friendly explanations that clarify the reasoning process.

3 Methodology

Generally, a table-based reasoning model, $f_\theta(\cdot)$, parameterized by θ, takes an input query Q and a table $\mathcal{T}$ to produce a response $Y = f_\theta(Q, \mathcal{T})$. Based on this generic formulation, the nature of Q and Y differs depending on the specific table reasoning task: in table-based QA, Q is a question and Y is the answer; in table-based fact verification, Q is a claim and Y is its veracity label; in table summarization, Q specifies the requirement and Y is the summary. A table $\mathcal{T}$ is characterized by a caption P and its contents $T_{i,j} \mid i \leq R_T, j \leq C_T$, where R_T and C_T represent the number of rows and columns, respectively. Each cell (i, j) contains data $T_{i,j}$.

To build an accurate and explainable table-reasoning framework, our proposed ***T**ool-**A**ugmented **R**easoning framework for **T**ables (*TART*)* integrates the call to external tools into the chain-of-thought reasoning process. TART consists of three reasoning modules (Figure 2): ① *Table Formatter*; ② *Tool Maker*; ③ *Explanation Generator*.

1. Table Formatter. TART first transforms the original table $\mathcal{T}$ with guidance from the query Q into a formatted table $\mathcal{T}'$. The formatter optimizes data formats, aligns columns, and adjusts data types as needed for the query, producing a well-formatted table that is used in subsequent reasoning.

2. Tool Maker. Given $\mathcal{T}'$, the *tool maker* generates a set of candidate tools S useful for solving Q. It also develops a reasoning plan R that details the high-level reasoning, which includes the tool calling order, as well as the necessary arguments and the expected return values for the tool calls.

3. Explanation Generator. Given the reasoning plan R as a programmatic guide for chain-of-thought reasoning, the explanation generator is responsible for producing a user-friendly explanation E that incorporates the use of the tools. The explanation also concludes with the final answer $\mathcal{A}$, derived from the execution of the reasoning plan R.

3.1 Table Formatter

We first train a specialized open-sourced large language model as the table formatter $\mathcal{F}$, which transforms the noisy raw input table $\mathcal{T}$, into a more structured and manageable format, $\mathcal{T}'$, to facilitate subsequent reasoning

$$\mathcal{T}' = \mathcal{F}(\mathcal{T}, Q) \tag{1}$$

where the output table $\mathcal{T}'$ is formatted in three aspects. (1) *Data Cleaning*: the model formats the cell values, such as removing currency symbols and textual footnotes to facilitate the execution of external functions to perform table operations or numerical reasoning. (2) *Data Standardization*: It converts different data representations into a uniform format, *e.g.,* transforms the data from formats like "`MM/DD/YYYY`" to a consistent "`YYYY-MM-DD`" format across the entire table. (3) *Error Handling*: the model is also responsible for fixing obvious errors or missing values in the table, such as automatically inferring header names for columns without the table headers. We introduce the table formatter to ensure that the data in the input table is uniform and optimized for subsequent reasoning, especially to make it more compatible with function execution. In practice, we transform the formatted table $\mathcal{T}'$ into a Python array, facilitating easier interpretation and processing by subsequent reasoning modules.

3.2 Tool Maker

Recent studies have shown that LLMs have the capability of synthesizing relevant tools by understanding the problem context and creating solutions based on the crafted tools [31, 3, 35]. Motivated by this, we train another specialized LLM $\mathcal{M}$ as a *tool maker*, which takes as input the reformatted table $\mathcal{T}'$ and the query Q to generate a set of candidate tools S and develops a reasoning plan R that details the high-level reasoning steps.

$$S, R = \mathcal{M}(\mathcal{T}', Q). \tag{2}$$

The tool set $S = \{s_1, \cdots, s_n\}$ consists of n specialized tools and each tool s_i is a Python function that performs table operations (*e.g.,* `get_column_by_name`), numerical reasoning (*e.g.,* `average`, `argmax`), or higher-level functions (*e.g.,* `linear_regression`). In table-based reasoning, these automated tools are essential to handle reasoning tasks that textual-based LLMs cannot address effectively, thereby significantly enhancing their problem-solving capacities.

Unlike previous work that manually defined a small number (< 10) of hand-crafted tools [20, 27] or retrieved tools from a predefined set [29, 23], we choose to train a specialized *tool maker* model that **learns to *generate* tools dynamically, based on the specifics of the table and the context of the problem.** This approach not only preserves the model's ability to "extract" previously encountered tools from its parametric memory, but also empowers the model to create novel tools as needed for unique problems, as shown in Section 4.4. While generating tools offers greater flexibility, it is crucial to prevent the tool maker from creating overly-specific tools (*e.g.,* `count_people_on_third_floor`), as this would hinder its ability to generalize to new problems. To address this issue, we incorporate *tool abstraction* and *tool deduplication* steps when constructing synthetic data for training the module (elaborated on in Section 3.4).

In addition to generating useful tools, the model also constructs a high-level reasoning plan $R = [r_1, \cdots, r_N]$, which outlines how the tools should be applied. The reasoning plan is formulated as a sequence of N function calls. Each *function call* $r_i = (s_i, A_i, V_i)$ includes the function $s_i \in \mathcal{S}$, the *argument* A_i passed to the function, and the *variable* V_i that stores the result of the function call $s_i(A_i)$. This reasoning plan acts as a programmatic blueprint, guiding the table-based reasoning process. Both the tool set S and the reasoning plan R are then provided to the explanation generator, which produces the final explainable reasoning output.

3.3 Explanation Generator

While program-based reasoning plans are precise, they are often difficult for non-expert users to understand. Moreover, certain types of reasoning, such as commonsense or narrative-based reasoning, are better communicated in natural language. To address this, TART incorporates a specialized module called the *explanation generator* $\mathcal{E}$, which generates chain-of-thought natural language explanations integrated with function calls, following the steps outlined in the reasoning plan R

$$O = \mathcal{E}(S, R). \tag{3}$$

The final output O of TART provides detailed explanations for the function calls. For example, the function call `get_column_by_name` is explained as, "*First, retrieve the column listing snowfall in inches.*" Additionally, the explanation generator groups related function calls together to create coherent and easy-to-follow explanations, as illustrated in Figure 2.

3.4 Model Training

As no prior work adopts the tool-augmented LLM framework for table reasoning, there does not exist training data to train the modules *Table Formatter*, *Tool Maker* and *Explanation Generator* ($\mathcal{F}$, $\mathcal{M}$, and $\mathcal{E}$) in TART. Previous studies have demonstrated that smaller LLMs can learn from distilling the generated outputs of larger teacher LLMs that have better reasoning capabilities [38, 34, 17]. Following this, we use a teacher LLM $\mathcal{L}$ to first synthesize tool-integrated solution trajectories for a set of seed table-based reasoning tasks. These high-quality solution trajectories serve as the blueprint from which we automatically extract and rearrange their components to build training sets for $\mathcal{F}$, $\mathcal{M}$, and $\mathcal{E}$, the three modules used in TART.

Training Data Synthesis. For all modules, we use GPT-4 as the teacher LLM $\mathcal{L}$ to generate training data. As shown in Table 4, we select five diverse table reasoning datasets: two from TQA and three from TFV, spanning general knowledge (Wikipedia) as well as domains such as finance, health, and scientific documents. These datasets provide a broad range of reasoning types. We few-shot prompt $\mathcal{L}$ to generate tool-integrated solutions for training instances for each dataset. In each solution, the model is prompted to clean the table, invent useful tools, and propose a reasoning plan along with explanations. We provide our prompt in Appendix F.

After generating the solutions, we evaluate the final answers against the ground truth, retaining only the instances with correct answers. Subsequently, we refine the solutions by removing overly specific tools through *tool abstraction* and *tool deduplication*. Tool abstraction filters out tools that appear only once, keeping those with broader applicability. Tool deduplication consolidates similar tools that perform the same function, but have different names or implementations (*e.g.,* `add` and `sum`). As a result, we obtain 11,701, 9,916, and 9,916 training instances for the table formatter $\mathcal{F}$, tool maker $\mathcal{M}$, and explanation generator $\mathcal{E}$, respectively. We refer to this training dataset as TOOLTAB, with detailed statistics provided in Table 5.

Training Configurations. Instruction fine-tuning [24, 10] has emerged as a critical strategy that directs LLMs to adhere to specified instructions, facilitating their reasoning capability across a wide range of table-based tasks. Therefore, we use open-source LLMs with instruction tuning as the backbone models for the modules of TART, specifically `Llama2-7B` [32], `Llama3-8B`, `CodeLlama-7B` [30] and `Deepseek-Coder-7B-Instruct-V1.5` [14]. We fine-tune all TART modules independently on their respective training datasets from TOOLTAB, using the standard next-token prediction objective.

4 Experiments

Datasets and Baselines To rigorously evaluate the performance of our proposed TART framework, we select two categories of benchmarks for table-based reasoning. *(1) Table question answering (TQA) benchmarks*: `WikiTableQuestion (WTQ)` [28] focuses on simple factoid questions. `HiTab (HIT)` [9], `TabMWP (TMP)` [21] and `FinQA (FQA)` [8] datasets focus on numerical reasoning reasoning. `TAT-QA (TAT)` [48] and `HybridQA (HYQ)` [7] require joint reasoning over the table and the text for financial reports and Wikipedia tables, respectively. *2) Table-based fact verification (TFV)*: We select `TabFact (TAF)` [6], `SCITAB (SCT)` [22], and `PubHealthTab (PHT)` [1] datasets, which focus on verifying facts based on tables from Wikipedia, scientific articles, and public health articles, respectively.

For baseline comparisons, we select well-known table-based open-source LLMs such as `TableLlama` [44] , as well as text-pretrained models (`Llama2-7b`, `Llama3-8b`) and code-pretrained models (`CodeLlama-7b`, `DeepSeek-Coder-7b`). We choose the 7b and the 8b versions to represent a balance between computational efficiency and the capacity for complex reasoning and generalization. For each model, we fine-tune with two settings: (1) `DirectQA`, where models generate answers directly from questions and tables, and (2) `Chain-of-Thought (CoT)` reasoning, which requires models to formulate a step-by-step reasoning process before concluding with an answer.

	Model	Setting	TableFV TabFact	TableFV PubHT	TableQA SCITAB	TableQA TabMWP	TableQA FinQA	Avg. Acc.
I.	**TableLlama**	w/o Fine-tuning	72.3	72.5	67.4	46.8	3.2	52.4
		w/ DirectQA	72.9	70.5	<u>74.2</u>	48.4	3.7	54.0
II.	**Llama2-7b**	w/ DirectQA	64.4	81.2	64.0	55.3	6.4	54.3
		w/ CoT	52.6	55.0	42.7	74.5	4.2	45.8
		w/ TART	69.2	55.0	53.4	88.8	19.2	57.1 (+24.7%)
	Llama3-8b	w/ DirectQA	74.5	**85.9**	**82.0**	68.6	10.6	64.3
		w/ CoT	48.4	62.4	41.0	88.3	8.5	49.7
		w/ TART	69.7	68.5	47.2	92.6	27.1	61.0 (+22.7%)
	CodeLlama-7b	w/ DirectQA	65.4	75.8	64.6	44.7	4.3	51.0
		w/ CoT	45.2	51.7	38.8	70.7	2.7	41.8
		w/ TART	66.5	69.8	44.9	90.1	25.0	59.3 (+41.9%)
	DeepSeek-7b	w/ DirectQA	72.9	76.5	73.0	62.2	9.0	58.7
		w/ CoT	52.1	62.4	45.5	84.6	8.5	50.6
		w/ TART	71.3	69.1	47.8	<u>93.1</u>	30.9	62.4 (+23.3%)
III.	**GPT-3.5-turbo**	w/ TART	<u>78.7</u>	63.6	59.3	88.3	<u>56.4</u>	<u>69.3</u>
	GPT-4	w/ TART	**87.7**	<u>84.1</u>	63.6	**98.3**	**68.5**	**80.4**

Table 1: Performance evaluation across backbone models using the TART framework, highlighting the best (bold) and second-best (underlined) results. The accuracy is calculated on testing sets, with overall average accuracy in the last column (*Avg. Acc.*). The red number indicates the average increase percentage over the CoT methods.

Implementation For TART, we use the answer given by executing the reasoning plan; if the reasoning plan is not executable, we use the answer given by CoT. For each model, we train the model with TOOLTAB while leaving the rest (WTQ, HIT, TAT, and HYQ) as held-out unseen datasets. All experiments were conducted on a GPU server with Intel Xeon Platinum 8480C (224) @ 2.900GHz CPU and 8 NVIDIA H100 (80G) GPUs. The training process for `Llama-2-7b-hf`, `CodeLlama-7b-hf`, and `deepseek-coder-7b-instruct-v1.5` requires a single GPU for approximately 20 hours, using a batch size of 4, learning rate of 5e-5, sequence length of 1500, gradient accumulation steps of 2, and 10 training epochs. Training `Llama-3-8b` required up to two GPUs for around 20 hours with the same settings. To minimize randomness, a temperature of 0.0 was used, while all other hyperparameters for sampling the output from the LLMs remained at their default values. For the closed-source version of TART, we use `GPT-3.5-turbo` and `GPT-4` with two in-context examples.

4.1 Main Results

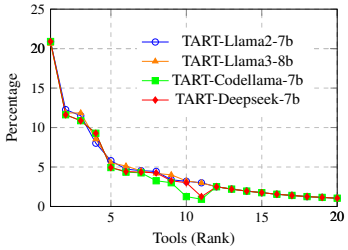
We first evaluate TART and the baselines on in-domain datasets, where their training sets are used to construct TOOLTAB. The experimental results, as shown in Table 1, reveal a notable performance improvement in our model compared to baseline models. We have four major observations.

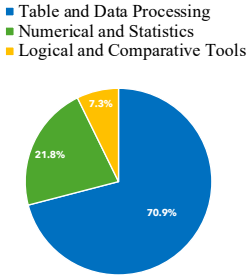
1. `TART` consistently outperforms `CoT` across all four backbone models and datasets. For example, with `CodeLlama-7b` as the backbone model, `TART` outperforms `DirectQA` and `CoT` by 16.3% and 41.9% on average, respectively. This highlights the effectiveness of integrating task-specific tools in enhancing complex reasoning capabilities.

2. With `CodeLlama-7b` as the backbone model of TART, it achieves the highest accuracy increase of 41.9%., whereas `Llama3-8b` shows the least improvement of 22.7%. This discrepancy is likely because of `CodeLlama-7b`'s specialized pre-training in coding tasks, which enhances the capabilities of creating tools for structured queries and operations.

3. The performance gains of TART also vary for different datasets, with `FinQA` showing the highest increase, while `PubHealthTab` shows the least. This discrepancy suggests that the financial focus of the `FinQA` dataset, which demands extensive numerical reasoning and structured data manipulation, benefits significantly from the `TART` approach.

4. Using closed-source models (`GPT-3.5-turbo` and `GPT-4`) as the backbone models for TART achieves an average accuracy of 74.9, significantly outperforming the open-source counterparts, which average at 60.0 accuracy. Nonetheless, the highest-performing open-source model `DeepSeek-7b` reaches up to 90.0% of GPT-3.5-turbo's performance and 77.6% of `GPT-4`, illustrating the competitiveness of open-source models in the creation and use of tools despite the model size gap.





Rank	Tool Name
1	get_column_by_name
2	get_column_cell_value
3	get_row_index_by_value
4	extract_price
5	get_row_by_name
6	equal_to
7	get_column_by_index
8	subtract
9	divide
10	add

Figure 3: Analysis of tool usage in our TART framework. Shown are the distribution (left) and the categories of the top-20 tools across models (center), as well as the top-10 tools in TART `Codellama-7b` (right).

4.2 Out-of-Domain Results

We hypothesize that the TART has enhanced generalization capabilities compared to CoT due to its ability to create and use general tools. To validate this, we further evaluate TART across four different out-of-domain (OOD) datasets: `HiTab (HIT)`, `WikiTableQuestion (WTQ)`, `TAT-QA (TAT)`, and `HybridQA (HYQ)`. The results are shown in Table 2.

Model	Setting	TQA HIT	TQA WTQ	Hybrid TQA TAT	Hybrid TQA HYQ
Llama2-7b	w/ DirectQA	19.1	23.4	15.4	8.5
	w/ CoT	22.1	12.7	20.0	6.7
	w/ TART	19.2	17.0	17.0	6.4
Llama3-8b	w/ DirectQA	**51.1**	**38.8**	20.2	10.1
	w/ CoT	33.8	26.8	29.3	11.0
	w/ TART	34.6	32.5	**29.3**	**12.2**
Codellama-7b	w/ DirectQA	17.0	19.1	13.8	6.9
	w/ CoT	16.1	22.6	14.6	9.7
	w/ TART	22.3	30.3	13.8	9.0
Deepseek-7b	w/ DirectQA	27.1	26.2	19.7	11.2
	w/ CoT	20.5	26.2	15.3	8.1
	w/ TART	29.8	33.5	17.0	11.2

Table 2: Out-of-Domain evaluation results for TART framework, highlighting the best (bold) and the second-best (underlined) results.

The `TART` method demonstrates variable effectiveness, with notable improvements in certain contexts. For instance, it achieves an average accuracy increase of 29.3% on the WTQ dataset, indicating robust domain-transfer capabilities. The `Deepseek-7b` backbone model particularly excels, with 30.6% increase in accuracy. We hypothesize that this superiority stems from its pre-training on coding tasks, which equips it with the capability of effectively creating and using tools in novel domains, surpassing pure-text-based pretraining models such as `Llama-2-7b`. The analysis in Section 4.4 supports our hypothesis, suggesting that `TART` excels in developing generic table reasoning functions that generalize well across different domains.

4.3 Impact of Foundation Models

To explore the optimal module combinations within the TART framework, we explore various pairings of table formatter and toolmaker modules shown in Table 3. We find that using `Llama-3-8B` as the table formatter and `DeepSeek-7B` as the tool maker achieves the best average execution rate (76.8) and accuracy (68.6). This aligns with our expectations given that `Llama-3-8B` excels in processing long tables while `DeepSeek-7B`, with its pre-training on code, demonstrates superior capability in tool creation. Detailed results are shown in Table 6 in Appendix B.

Tab Formt	TAF	PHT	SCT	TMP	FQA
Llama-2	71.8/78.5	75.8/66.4	64.0/57.0	93.6/92.0	73.4/37.7
Llama-3	76.6/84.7	79.2/67.8	62.4/55.9	94.1/94.4	71.8/40.0
Codellama	67.6/78.0	**81.2/66.1**	**64.6/53.9**	94.1/91.5	76.1/35.7
DeepSeek	**70.7/79.7**	72.5/71.3	63.5/51.3	**95.7/93.9**	**74.5/38.6**
Tool Mkr	**TAF**	**PHT**	**SCT**	**TMP**	**FQA**
Llama-2	70.2/81.8	65.8/60.2	53.9/61.5	95.7/91.1	61.7/31.0
Llama-3	75.5/75.4	71.1/69.8	63.5/52.2	**97.9/92.4**	62.2/38.5
Codellama	75.5/85.2	74.5/71.2	**62.9/57.1**	95.7/91.7	68.1/39.8
Deepseek	**76.6/84.7**	**79.2/67.8**	62.4/55.9	94.1/94.4	**71.8/40.0**

Table 3: Results of TART with different backbone modules. The top section uses `deepseek-code-7b` as the Tool Maker, while the bottom section uses `Llama-3-8b` as the Table Formatter. The best performance is highlighted in bold and the second-best is underlined. Tab Formt stands for *Table Formatter* and Tool Mkr for *Tool Maker*.

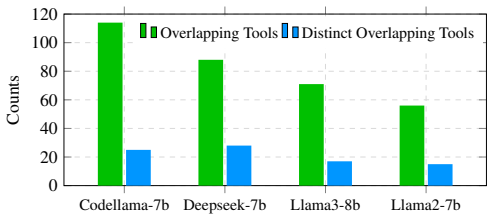


Figure 4: Tool overlap distribution between InD and OOD datasets across different models.

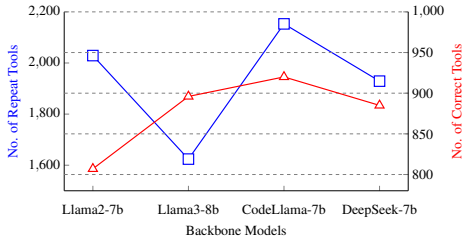


Figure 5: Comparison of the number of repeat tools and correct tools across different models.

4.4 Analysis of Tool Creation

We then performed an in-depth analysis of how TART creates and utilizes tools shown in the Section 4.4.1 and Section 4.4.2.

4.4.1 Tool Distribution.

Figure 3 (left) illustrates the tool usage distribution across different backbone models in TART, highlighting a long-tail distribution. The most frequently used tools are primarily associated with table processing (*e.g.,* `get_column_by_name`) and numerical reasoning (*e.g.,* `add`), aligning with our observations in Section 4.1. Figure 3 (right) provides a detailed breakdown of tool categories for the top-30 tools, showing that table preprocessing and numerical reasoning tools are the most prevalent. This supports the consistency of tool utilization patterns within TART.

4.4.2 Tool Overlap on OOD Datasets.

Figure 4 illustrates the tool overlap between in-domain datasets and OOD datasets. We find that code pre-training models (`CodeLlama-7b` and `DeepSeek-7b`) exhibit a tendency to reuse existing tools when adapting to OOD data. However, text pre-training models demonstrate less overlap, indicating that they tend to solve problems by crafting new tools. The tendency to reuse tools might explain why code pre-training models gain better generalization capabilities in unfamiliar data.

4.4.3 Tool Creation and Usage Analysis.

Figure 5 further reveals that although `Llama2-7b` frequently reuses tools, it often applies them inappropriately. In contrast, *CodeLlama-7b* not only exhibits a high rate of tool reuse, but also demonstrates a greater accuracy in their appropriate application. Meanwhile, `Llama3-8b`, despite its lower rate of tool reuse, excels in the correct usage of tools, which contributes to its superior performance.

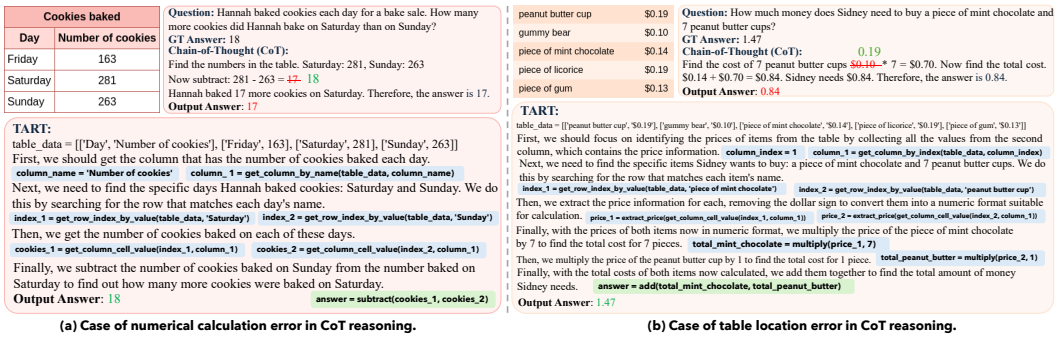


Figure 6: Case study of TART comparing it to CoT reasoning. Panel (a) illustrates a numerical calculation error in CoT where incorrect arithmetic leads to a wrong answer, and panel (b) demonstrates a table location error where CoT fails to retrieve the correct table values. Both errors can be reduced by TART through tool integration.

4.5 Case Study

To gain deeper insights into the advantages of TART over CoT reasoning, we conducted a case study, shown in Figure 6. The examples highlight the limitation of CoT in numerical reasoning and table preprocessing, such as incorrect calculation (Figure 6 a) and incorrect retrieval (Figure 6 b). Conversely, TART overcomes these challenges effectively via integrating specialized tools like `subtract` and `get_column_by_index`. Despite these strengths, TART still encounters issues related to data type mismatches and incorrect programming plans. A detailed analysis of error types in TART can be found in Appendix E.

5 Conclusion and Future Work

In this paper, we introduce an open-source framework to improve table-based reasoning through the *Tool-Augmented Reasoning framework for Tables (*TART*)*. This framework solves the challenges of current LLMs' limited ability to understand table structure and execute precise numerical calculations, and maintains explainability. TART consists of a *table formatter* for accurate data representation, a *tool maker* for creating specialized tools, and an *explanation generator* maintaining interpretable explanations. To train TART, we present the TOOLTAB dataset, a novel benchmark containing a diverse set of real-world tables and their tool-augmented solutions. Experiments across nine benchmarks show that integrating our TART method into different open-sourced LLMs enhances accuracy on table-based reasoning. Furthermore, in-depth analysis revealed that TART effectively learns and uses tools. Future work could extend TART to a multimodal framework by incorporating image-based question-answering and fact-verification to generate richer explanations. Additionally, generating explanations to satisfy the needs of different end users, such as laypeople and experts, could further improve the TART's applicability and impact.

Limitation

Despite the promising results, our proposed framework has certain limitations that warrant further investigation:

Computational Complexity. The TART model may affect efficacy, especially when handling simple questions in quick-response scenarios.

Dataset Coverage. While our efforts have focused on expanding the range of our dataset to include a variety of tableQA datasets, some table-related datasets remain unrepresented in TOOLTAB. As a result, despite TART's capacity to adapt to different OOD datasets and tasks, its performance might still different with the complexities and unique challenges of new table tasks and datasets that it has not yet encountered. Having initiated the development of an expansive, versatile tool-enhanced model for tables, we encourage continued research in this area to further advance the model's ability to generalize across diverse table configurations.

Ethic Statement

Transparency and Integrity. We ensure that all methodologies, data sources, and technologies used in this study are disclosed transparently. We aim to provide a comprehensive and honest account of our findings, acknowledging both the capabilities and limitations of our proposed solution.

Data Privacy and Security. Our research uses datasets that are either publicly available or were collected with explicit consent. We adhere to strict data privacy and security protocols to protect the information and ensure it is used solely for the purposes of this research.

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Dataset	Task	Domain	Input	Output
1. TabMWP	TableQA	Maths	Table, Question	Answer (Short)
2. FinQA	TableQA	Finance	Table, Text, Question	Answer (Short)
3. PubHealthTab	Table Fact Checking	Health	Table, Claim	Label (Short)
4. TabFact	Table Fact Checking	Wikipedia	Table, Claim	Label (Short)
5. SCITAB	Table Fact Checking	Scientific Articles	Table, Claim	Label (Short)

Table 4: Statistics about the seed datasets for TART training, highlighting their respective tasks, domains, and the nature of input and output data.

Dataset	Train	Dev	Generated Sample	Executable Sample	Table Formatter	Tool Maker	Explanation Generator
TabMWP	23,059	7,686	6,000	5,835	6,000	5,713	5,713
FinQA	6,251	883	1,984	1,609	1,967	1,148	1,148
TabFact	92,283	12,792	1,866	1,773	1,866	1,701	1,705
PubHealthTab	1,180	152	1,180	1,075	1,180	958	958
SciTab	690	-	690	625	688	396	396
Total	123,463	21,513	5,720	10,917	11,701	9,916	9,916

Table 5: Statistics about dataset TOOLTAB for training the TART model.

A Dataset Composition for TART Training

In Table 4, we show the composition of the seed datasets used for training our TART model. These datasets vary in terms of the tasks, the domains, and the types of input and output data. For instance, TabMWP and FinQA focus on TableQA tasks within mathematics and finance domains respectively, requiring a combination of tables, text, and questions as inputs, with short answers as outputs. Meanwhile, PubHealthTab, TabFact, and SCITAB target table fact-checking tasks across health, general Wikipedia, and scientific article domains. These datasets similarly involve tables and claims as inputs but differ in the specifics of the domain-related claims, each producing a short label as an output. To construct the TOOLTAB, we obtain 11,701, 9,916, and 9,916 training instances for the table formatter $\mathcal{F}$, tool maker $\mathcal{M}$, and explanation generator $\mathcal{E}$, respectively. Detailed statistics are provided in Table 5.

B Different Backbone Combinations

In the pursuit of identifying optimal module combinations within the TART framework, we explore various pairings of table formatter and toolmaker modules shown in Table 6. The combination of `Llama-3-8B` as the table formatter and `DeepSeek-7B` as the tool maker performs the most effective pairing, having the best average execution rate and accuracy (76.8 and 68.6 respectively). This best combination aligns with our expectations given that `Llama-3-8B` excels in processing long tables while `DeepSeek-7B`, with its pre-training on code, demonstrates superior capability in tool creation.

C Tool Use on Different Backbone Models

Table 7 shows the top-10 tools that dominate the table processing (*e.g.,* `get_column_by_name`) and numerical reasoning (*e.g.,* `add`), consistent with our earlier findings in Section 4.1. Further illustrating this, Figure 3 (b) presents a tool categorization for the top 30 functions. We can see that table preprocessing tools constitute the highest percentage at 71.0%, followed by numerical reasoning tools at 21.8%. Together, these categories account for over 90% of tool usage, verifying our assumption that TART is better at table preprocessing and numerical reasoning.

Module Name		TableFV			TableQA		Avg.
Table Formatter	Tool Maker	TabFact	PubHealthTab	SCITAB	TabMWP	FinQA	Exe./Acc.
Llama-2	Llama-2	64.9/79.5	65.8/59.2	55.1/60.2	90.4/91.8	65.4/26.0	68.3/63.3
Llama-2	Llama-3	70.7/75.9	73.2/65.1	64.0/46.5	91.0/93.6	60.6/37.7	71.9/63.8
Llama-2	Codellama	70.2/76.5	73.8/74.5	**64.6/56.5**	94.7/88.8	71.8/34.1	75.0/66.1
Llama-2	Deepseek	71.8/78.5	75.8/66.4	64.0/57.0	93.6/92.0	73.4/37.7	75.7/66.3
Llama-3	Llama-2	70.2/81.8	65.8/60.2	53.9/61.5	95.7/91.1	61.7/31.0	69.5/65.1
Llama-3	Llama-3	75.5/75.4	71.1/69.8	63.5/52.2	**97.9/92.4**	62.2/38.5	74.0/65.7
Llama-3	Codellama	75.5/85.2	74.5/71.2	62.9/57.1	95.7/91.7	68.1/39.8	75.3/69.0
Llama-3	Deepseek	**76.6/84.7**	79.2/67.8	62.4/55.9	94.1/94.4	71.8/40.0	**76.8/68.6**
Codellama	Llama-2	64.9/76.2	69.1/59.2	53.4/58.9	94.1/89.3	66.0/26.6	69.5/62.0
CodeLlama	Llama-3	66.5/71.2	75.2/69.6	62.4/57.7	94.1/91.0	60.1/36.3	71.2/65.2
CodeLlama	Codellama	64.9/75.4	**77.9/75.0**	68.5/50.8	95.2/92.2	71.3/34.3	75.6/65.5
CodeLlama	DeepSeek	67.6/78.0	81.2/66.1	64.6/53.9	94.1/91.5	76.1/35.7	76.7/65.0
DeepSeek	Llama-2	63.3/79.8	67.1/60.0	50.0/56.2	94.7/92.1	63.3/32.8	67.7/64.2
DeepSeek	Llama-3	66.5/80.8	65.1/69.1	63.5/54.0	94.1/93.2	59.6/42.9	69.8/68.0
DeepSeek	CodeLlama	67.0/80.2	71.1/70.8	58.4/52.9	96.8/90.1	69.7/36.6	72.6/66.1
DeepSeek	DeepSeek	70.7/79.7	72.5/71.3	63.5/51.3	95.7/93.9	**74.5/38.6**	75.4/67.0

Table 6: The TART framework with different backbone modules. The best performance is bold. The second best performance is underlined.

Rank	Llama2	Llama3	DeepSeek
1	get_column_by_name	get_column_by_name	get_column_by_name
2	get_column_cell_value	get_column_cell_value	get_column_cell_value
3	get_row_index_by_value	get_row_index_by_value	get_row_index_by_value
4	extract_price	extract_price	extract_price
5	equal_to	equal_to	get_row_by_name
6	get_column_by_index	get_row_by_name	equal_to
7	subtract	get_column_by_index	divide
8	get_row_by_name	divide	get_column_by_index
9	add	subtract	subtract
10	multiply	add	add

Table 7: Comparison of the top 10 functions across TART-Llama2-7b, TART-Llama3-8b, and TART-DeepSeek-7b

D CoT Baseline Implementation

For a direct and fair comparison with TART, the same number of CoT samples are generated using the same IDs from the TART training dataset. These samples are generated using GPT-4, prompted with two ICL examples (detailed in Appendix F). In total, we have 9,916 training instances.

Similarly to TART, the CoT baseline was implemented across four different backbone models: `Llama2-7b-hf`, `Llama3-8b`, `CodeLlama-7b-hf`, and `DeepSeek-Coder-7b-Instruct-V1.5`. Each model was instructed to generate a step-by-step reasoning explanation followed by the final answer as per the instructions: `INSTRUCTION: Given the following table, and question, generate a step-by-step reasoning explanation and the final answer.`

The training process was aligned with that of TART to ensure experimental consistency. `Llama-2-7b-hf`, `CodeLlama-7b-hf`, and `deepseek-coder-7b-instruct-v1.5` each requires a single GPU for approximately 12 hours, using a batch size of 4, a learning rate of 5e-5, a sequence length of 1500, gradient accumulation steps of 2, and 10 training epochs. Training `Llama-3-8b` requires up to 2 GPUs for around 10 hours with the same settings.

E Error Analysis

To precisely categorize error types in CoT reasoning, we annotate 50 randomly selected CoT error cases. The result (Figure 7) shows that the major error type is incorrect numerical reasoning, followed by errors related to table operations. This analysis verifies the necessity for our proposed TART, which addresses these issues by integrating specialized numerical and table operation tools.

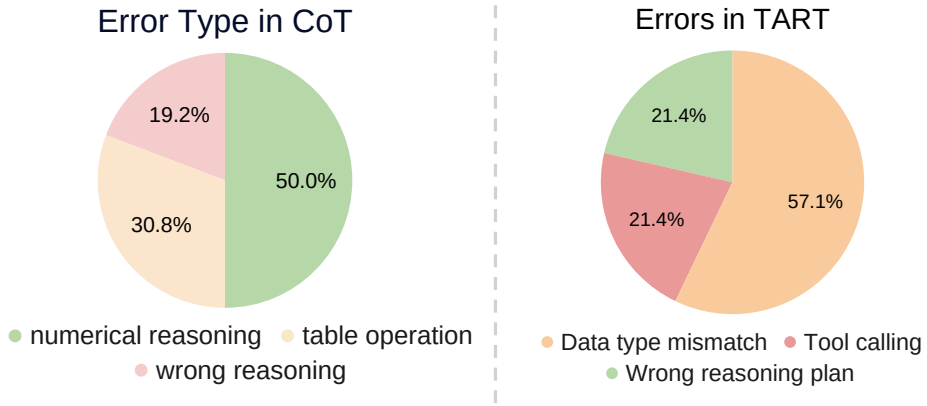

Figure 7: The error types and their distribution of CoT reasoning and TART framework.

F Prompts

We provide detailed prompts of the TART framework, including the tool discovery process and explanation generation process.

Tool Discovery Prompt:

```
Task Description: Given a table and a question,
the task is to generate a python program to
answer the question.
Requirements:
1. First define some functions to be used in the program.
2. Try to reuse the functions defined in the previous problems if
possible.
3.  When defining a new function, make sure this function is
general enough to be used in other problems.
4.  Define a function called solution(table_data) that takes the
table data as input and returns the answer to the question.
—
"'
Table: Table Content
Question: Question
Answer: Answer
"'
table_data = table data array

#FUNCTION1 Description
def FUNCTION1():
Function Body

#FUNCTION2 Description
def FUNCTION2():
Function Body
...

def solution(table_data):
Solution Body
return answer

print(solution(table_data))
—
[[FUNCTION_SOLUTION]]
```

Explanation Generation Prompt:

```
Task: Transform Python code used for a table question answering
task into an easily understandable explanation in natural language
embedded with function calls.
Follow these requirements:
1. The explanation should be the natural language combined with
bracketed segments «< »> for code.
2. The code segments in the brackets «< »> should indicate the
line number of the code, with the format: ###<line number>.
3. Multiple lines of codes are separated with ';;;' in the brackets
«< »>.
—
"'
Table: Table Content
Question: Question
Answer: Answer
"'
Python Code:
table_data = table data array

def solution(table_data):
Line 1 ###1
Line 2 ###2
...
Line 5 ###5
return answer

print(solution(table_data))

Output Explanation:
First, we should get the column
that ... «<###1 ;;; ###2»>.
…
Finally, we find that «<###5»>.
—
[[OUTPUT_EXPLANATION]]
```

CoT Prompt:

Task Description: Given a table and a question, the task is to generate a step-by-step reasoning explanation and the final answer.

—

“‘

Table: Table Content

Question: Question

Answer: Answer

“‘

Python Code:

table_data = table data array

Output Explanation:

To answer this question, first, we ...

Second, to determine..., we compare ...

…

Therefore, the answer is ...

—

[[OUTPUT_EXPLANATION]]

TART (GPT-4) Prompt for Table Formatter:

Task Description: Given the following table, context and question, format the table into a python array.

—

“‘

Table: Table Content

Question: Question

Answer: Answer

“‘

Python Code:

table_data = table data array

—

[[LINEARIZED_TABLE]]

TART (GPT-4) Prompt for Tool Maker:

```
Task Description: Given the following table, context and question,
the table_data, generate the python code to solve it.
——
“‘
Table: Table Content
Question: Question
Answer: Answer
table_data = table data array
“‘

Python Code:
#FUNCTION1 Description
def FUNCTION1():
Function Body

#FUNCTION2 Description
def FUNCTION2():
Function Body
...

def solution(table_data):
Solution Body
return answer

print(solution(table_data))
——
[[FUNCTION_SOLUTION]]
```