

Chain-of-Thought Reasoning in Tabular Language Models

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Abstract

Tabular mathematical reasoning task requires models to perform multi-step operations including information look-up and numerical calculations, based on heterogeneous data from tables and questions. Existing solutions tend to extend chain-of-thought (CoT) reasoning into powerful large language models (LLMs) to promote multi-hop mathematical reasoning. However, it can be extremely difficult to apply such LLM-based approaches under scenarios of privatization deployment or limited resources. To address this problem, we revisit small-scale tabular language models (TaLMs) and extend chain-of-thought reasoning into TaLMs for the first time. Specifically, we propose a novel framework, **TaCo**, which coordinates two TaLMs responsible for CoT generation and answer inference, respectively. Besides, our framework can be combined with an external calculator to enhance accurate numerical calculations. On the TABMWP dataset, TaCo outperforms the state-of-the-art ChatGPT by 9.55% (82.60%→92.15% in accuracy) with much less parameters (0.8B).¹

1 Introduction

Tabular mathematical reasoning task aims at answering math questions based on heterogeneous tabular and textual data, which can provide users with insights from tables containing valuable figures (Lu et al., 2023b; Zhu et al., 2021; Chen et al., 2021b). This task highlights the demand for multi-step mathematical reasoning including information look-up and numerical calculations. For example, given the table and the question in Figure 1, we firstly need to count how many numbers are in the table, then add all the numbers together to get the sum of baskets, and finally compute the mean of the sum.

¹The code will be released at <https://github.com/SpursGoZmy/TaCo>

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Day	Number of baskets
Thursday	49
Friday	48
Saturday	51
Sunday	54
Monday	37
Tuesday	49

Question: Reagan jotted down how many baskets she made during basketball practice each day. What is the mean of the numbers?

Solution:

Read the numbers from the table.

49, 48, 51, 54, 37, 49

First, count how many numbers are in the group.

There are 6 numbers.

Now add all the numbers together:

$49 + 48 + 51 + 54 + 37 + 49 = 288$

Now divide the sum by the number of numbers:

$288 \div 6 = 48$

The mean is 48.

Answer: 48

Figure 1: An example from the TABMWP dataset. To solve the problem, the model needs to perform multi-step mathematical reasoning based on the table and the question.

Considering the inherent demand for multi-step operations, existing studies tend to extend chain-of-thought (CoT) reasoning (Wei et al., 2022; Wang et al., 2023a; Kojima et al., 2022; Zhang et al., 2022) into powerful Large Language Models (LLMs) (Brown et al., 2020; Chowdhery et al., 2022; Thoppilan et al., 2022; Chen et al., 2021a) to promote multi-hop mathematical reasoning. As depicted in Figure 2 (b), this paradigm prompts LLMs with several in-context examples containing CoT demonstrations to elicit intermediate reasoning steps before inferring the final answer.

Though the combo of LLM and CoT has achieved great performance, such LLM-based methods may not be a feasible approach in some real-world scenarios. For instance, it is financially expensive to satisfy the high computational requirements, the storage capacity and the desired bandwidth of LLMs, which makes it a challenge for

individual users or small organizations to utilize LLMs in their applications (Strubell et al., 2019; Bender et al., 2021). In consideration of the data security, enterprises may also seek privatization deployments where private data is not allowed to be processed by third-party LLM APIs. What’s more, despite the fact that many pre-trained tabular language models have been developed (Liu et al., 2022; Herzig et al., 2020; Wang et al., 2021; Dong et al., 2022), their CoT reasoning ability has not been thoroughly investigated and it could be inadequate for solving the tabular mathematical reasoning task. As a result, an alternative approach, with lower costs and competitive CoT reasoning ability, is needed.

To accomplish this goal, we revisit small-scale tabular language models (TaLMs) and initiatively explore the chain-of-thought reasoning in TaLMs. Specifically, we propose a novel framework named **TaCo**, which coordinates two TaLMs that are responsible for **CoT** generation and answer inference, respectively. Given the input table and question, the first TaLM is fine-tuned to generate intermediate reasoning steps. Based on the original input and generated reasoning steps, the second TaLM is fine-tuned to infer the final answer. To alleviate the weakness of TaLMs in solving mathematical expressions, TaCo is also combined with an external calculator which is used to perform math calculations and fix incorrect results in the output reasoning steps.

To verify the effectiveness of the proposed method, we conduct comprehensive experiments on the TABMWP (Lu et al., 2023b) dataset, which is the latest math word problem benchmark over tabular data and provides detailed chain-of-thoughts to solve the problem step by step. Experimental results reveal that TaCo explores a new and promising paradigm for tabular mathematical reasoning, which is illustrated in Figure 2 (c). Compared with traditional fine-tuned TaLMs, TaCo improves the accuracy of recent TAPEX model by 29.76%. Compared with LLM-based approaches, TaCo outperforms the state-of-the-art ChatGPT by 9.55% (82.60%→92.15%) with much less parameters (0.8B). Moreover, we conduct ablation studies to analyse contributions of different parts in the framework. The detailed error analysis is also performed to provide insights for future improvements.

To summarize, we conclude our contributions as

follows:

- To the best of our knowledge, we explore the chain-of-thought reasoning in TaLMs for the first time, and advocate a new and promising paradigm for tabular mathematical reasoning, especially under scenarios where LLM-based methods are not feasible.
- We propose a novel framework, TaCo, which coordinates two TaLMs responsible for CoT generation and answer inference, respectively. It is also integrated with a calculator to enhance accurate numerical calculations.
- Our method can boost the performance of small-scale TaLMs and surpasses the state-of-the-art ChatGPT by 9.55% on TABMWP benchmark with much less parameters (0.8B).

2 Pilot Experiment

Before diving into the specific method, we present a pilot experiment on the TABMWP dataset to answer two important questions: (i) Do existing pre-trained generative TaLMs possess chain-of-thought reasoning ability? (ii) Whether generative TaLMs can benefit from chain-of-thoughts when predicting the final answer. We select the state-of-the-art TAPEX model (Liu et al., 2022) for experiments, which is based on the encoder-decoder language model BART (Lewis et al., 2020) and is additionally pre-trained on the tabular data. We consider two model sizes: TAPEX-base (140M) and TAPEX-large (400M).

Experiments are conducted in three different settings, i.e., vanilla, zero-shot CoT and gold CoT. For the “vanilla” setting, the pre-trained TAPEX model $f(\cdot)$ autoregressively generates the answer a based on the table t and the question q , i.e., $a = f(t, q)$. For the “zero-shot CoT” setting, we follow Kojima et al. (2022) to evaluate the CoT reasoning of the TAPEX. Specifically, a trigger sentence p_1 is appended to the question in order to ask the TAPEX to output intermediate reasoning steps s , i.e., $s = f(t, q, p_1)$. Then, given the original input and the generated CoT, another trigger sentence p_2 is appended to make the TAPEX output the final answer a , i.e., $a = f(t, q, p_1, s, p_2)$. For p_1 , we try various templates such as “Let’s think step by step” and report best results. For p_2 , we intuitively select “As a result, the answer is” as the trigger sentence. For the “gold CoT” setting, we replace

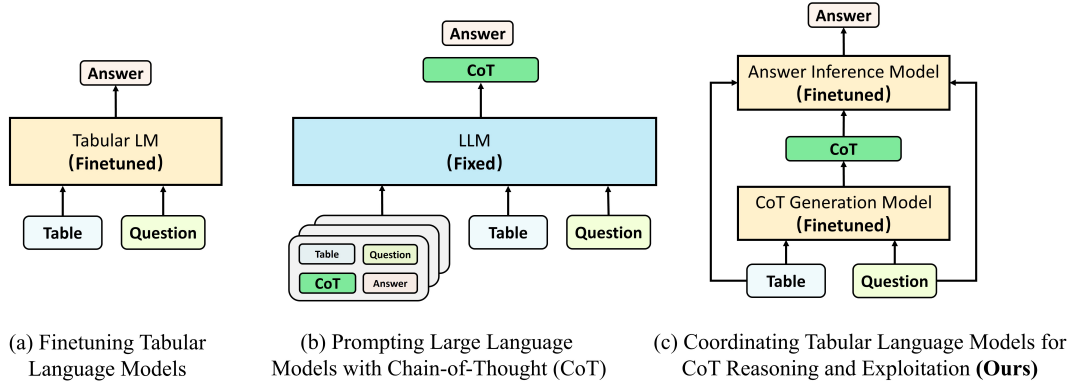


Figure 2: Different paradigms for tabular mathematical reasoning.

generated reasoning steps with annotated ones and other procedures are same as “zero-shot CoT”.

Pre-trained TaLMs	Acc-Dev	Acc-Test
TAPEX-base (vanilla)	15.66	15.69
TAPEX-large (vanilla)	18.41	18.59
TAPEX-base (zero-shot CoT)	15.30	15.25
TAPEX-large (zero-shot CoT)	18.25	17.94
TAPEX-base (gold CoT)	40.54	39.99
TAPEX-large (gold CoT)	47.48	48.01

Table 1: Pilot experimental results of pre-trained TAPEX under different settings. “Acc-Dev” and “Acc-Test” represents accuracy on the development set and the test set respectively.

From the results in Table 1, we can see that the TAPEX with “zero-shot CoT” setting performs even worse than the vanilla one, which shows that the small-scale TAPEX is not a decent zero-shot reasoner like LLMs and does not possess CoT reasoning ability. This is also consistent with findings from previous CoT studies (Wei et al., 2022; Ho et al., 2023). After inspecting the model outputs, we find that the pre-trained TAPEX model cannot follow the instruction to generate reasoning steps. In most cases, it directly generates the answer or illogical texts. However, given the annotated “gold CoT”, the model achieves a remarkable performance gain. For instance, the accuracy of TAPEX-large on test set increases from 18.59% to 48.01%. This demonstrates that CoT reasoning steps are beneficial to TAPEX when inferring the correct answer and it encourages us to further elicit CoT reasoning ability of TaLMs by finetuning.

3 Method

Based on observations in Section 2, we propose the TaCo framework for tabular mathematical reasoning. It includes two training stages: (i) CoT

generation and (ii) answer inference, where two generative TaLMs with the same architecture are fine-tuned independently with different inputs and outputs. In this section, we introduce the framework with the TAPEX model as selected backbones, but it should be noted that TaCo is compatible with arbitrary generative TaLMs to boost their performance. The overview of TaCo framework is illustrated in Figure 3.

3.1 CoT Generation

In the CoT generation stage, a TAPEX model is fine-tuned to generate a solution which consists of multiple reasoning steps to solve the problem. Given an input table T with M rows $\{R_i\}_{i=1}^M$ and N column headers $\{c_j\}_{j=1}^N$, the TAPEX will linearize the table into a flattened text sequence $T^* = [\text{HEAD}] : c_1 | \dots | c_N [\text{ROW}] 1 : R_1 | [\text{ROW}] 2 : R_2 | \dots | R_M$, where [HEAD] and [ROW] are special tokens used to indicate the region of column headers and rows, respectively. The number after [ROW] represents different row index and the vertical bar “|” separates headers or cells in different columns. For instance, the table in Figure 1 will be linearized into the following sequence:

col : Day | Number of baskets row 1 :
 Thursday | 49 row 2 : Friday | 48 ... row
 6 : Tuesday | 49

The resulting sequence T^* will be concatenated with the textual context, which includes a question Q and a trigger sentence P . Based on the concatenated input, the probability of generating the target solution S is computed as follows:

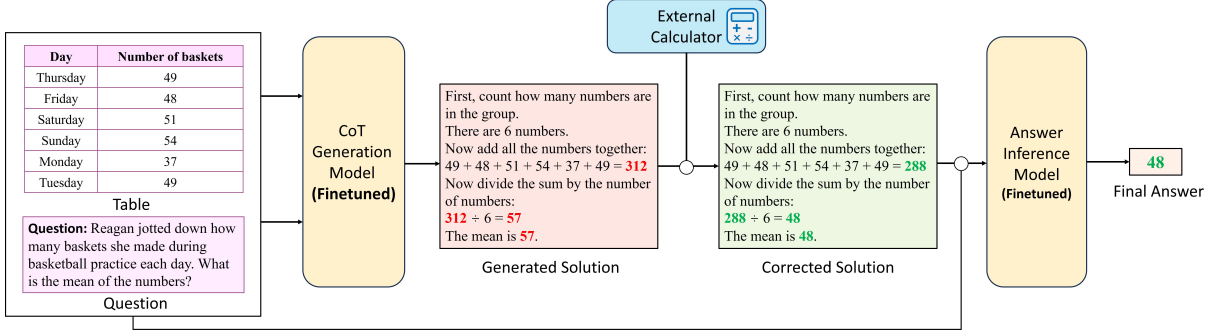


Figure 3: Overview of the TaCo framework, with the table and the question in Figure 1 as a running example.

$$p(S|T^*, Q, P) = \prod_{i=1}^L p_{\theta}(S_i|T^*, Q, P, S_{<i}) \quad (1)$$

where L is the length of target solution. We select “Let’s think step by step” as the trigger sentence P since it gives the best performance in pilot experiments.

After generating a potential solution \bar{S} , we find that \bar{S} often contains some numerical calculation errors. This is often the case with language models because TaLMs and even LLMs are not suitable for actually solving mathematical expressions (Chen et al., 2022). Take the generated solution in Figure 3 as an example. Though the model generates plausible reasoning steps, calculation results among these steps are all wrong (in red color), e.g., “ $49 + 48 + 51 + 54 + 37 + 49 = 312$ ”. Such calculation errors will accumulate to the last reasoning step and seriously mislead the answer inference model into predicting the false answer.

To mitigate the influence of calculation mistakes, we introduce an arithmetic calculator $g(\cdot)$ to solve mathematical expressions of “+,-,×,÷” in the generated solution \bar{S} and output the corrected solution $\hat{S} = g(\bar{S})$. Concretely, we extract equation strings in \bar{S} using regular expressions and calculate their results using the Python `eval` function. Since multiple equations may exist in one solution and one equation could also refer to results of previous equations, the calculation result of each equation is propagated to the following equations by string replacing. As we can see from Figure 3, original wrong results in \bar{S} are successfully fixed and are replaced with correct results (in green color), e.g., “ $49 + 48 + 51 + 54 + 37 + 49 = 288$ ”.

3.2 Answer Inference

In answer inference stage, another TAPEX model is fine-tuned to generate the final answer based on the original input and the annotated solution S . Similar with the CoT generation stage, the probability of generating target answer A is computed by:

$$p(A|T^*, Q, P, S) = \prod_{i=1}^N p_{\theta}(A_i|T^*, Q, P, S, A_{<i}) \quad (2)$$

where N is the length of target answer. During the inference phase, the annotated solution is replaced with the corrected solution \hat{S} to output the predicted answer \bar{A} . Both CoT generation model and answer inference model are trained with a standard language modeling objective.

4 Experiments

4.1 Dataset and Evaluation Metric

Experiments are conducted on the TABMWP (Lu et al., 2023b) dataset, a recent large-scale benchmark which is constructed from grade-level math curricula and contains 38,481 math word problems with the tabular context. Beside the gold answers, TABMWP also provides detailed step-by-step solutions to solve the problems, which can be utilized as chain-of-thoughts to finetuning TaLMs. There are two question-types in the TABMWP: 28,719 *free-text* questions with integer answers (INT) and decimal answers (DEC), and 9,712 *multi-choice* questions with extractive text answers (EXTR), boolean text answers (BOOL) and other text answers (OTH). Statistics of each split are shown in the Table 2. The test set contains 7,686 questions in total. Among them, 74.08% are INT (4,529) and DEC (1165) questions, and 25.92% are DEC (1,165), EXTR (987) and OTH (105) questions. Thus, INT and

	Train	Dev	Test	Total
# of questions	23,059	7,686	7,686	38,431
# of free-text	17,135	5,710	5,694	28,719
# of multi-choice	5,744	1,976	1,992	9,712
# of tables	22,620	7,546	7,549	37,644
# of solutions	21,623	7,365	7,378	35,442

Table 2: Dataset statistics of TABMWP.

DEC questions are more essential for the overall accuracy. Given the predicted answer and the ground truth, we employ the exact match accuracy as the metric and use the official evaluation script to evaluate the model performance.

4.2 Implementation Details

Implementations. Our framework is implemented with Pytorch (Paszke et al., 2019). We mainly employ the TAPEX (Liu et al., 2022) as the backbone TaLM in the proposed framework. We also replace TAPEX with UnifiedQA (Khashabi et al., 2020) for the ablation study. Various model sizes are included to present more valid evaluation across different model capacities. Both CoT generation model and answer inference model are optimized by AdamW (Loshchilov and Hutter, 2019). We use validation set for the model selection and manually tune hyper-parameters, and evaluate the best model on the test set. For CoT generation, we adopt the beam search decoding with the beam size of 3. For answer inference, we adopt the greedy decoding. Hyper-parameter configurations for best-performing models and more implementation details are shown in the Table 6 and Table 7.

Baselines. (1) *Pre-trained and Fine-tuned language models:* We develop TAPEX (Liu et al., 2022) and UnifiedQA (Khashabi et al., 2020) in both pre-trained and fine-tuned settings to predict the final answer. TAPEX is the state-of-the-art BART-based (Lewis et al., 2020) TaLM which is pre-trained on the tabular data to mimic a SQL executor. UnifiedQA is a T5-based (Raffel et al., 2020) QA model which is pre-trained on 8 QA datasets of multiple formats. We consider three model sizes for UnifiedQA: small (60M), base (220M) and large (770M). Given the flattened table and question, both TAPEX and UnifiedQA can generate the answer text autoregressively. (2) *Large language models:* We consider GPT-3 (Brown et al., 2020), Codex (Chen et al., 2021a) and ChatGPT with the standard few-shot and zero-shot prompting. ChatGPT is based on the *gpt-3.5-turbo* engine. Numbers of in-context examples and se-

lection strategies for few-shot prompting are listed in Table 8. (3) *Large language models with CoT prompting:* Beside standard prompting, we also consider above LLMs with the chain-of-thought prompting. PromptPG (Lu et al., 2023b) utilizes the policy gradient method to select in-context examples for test samples when constructing the prompt for LLMs. PoT (Chen et al., 2022) proposes the “program-of-thoughts”, which exploits Codex to generate the text and Python program for math computations. The generated program is executed by a program interpreter to output the final answer. The “Heuristic guess” is a baseline from the TABMWP paper. For multi-choice questions, it randomly selects one from the given options with even probabilities. For free-text questions, it randomly chooses one number from the question or the table as the prediction.

4.3 Main Results

Table 3 demonstrates main experimental results on the TABMWP dataset. For TAPEX, UnifiedQA and ChatGPT baselines, we report results based on our implementation. For other baselines, we report published results from original papers (Lu et al., 2023b; Chen et al., 2022).

From the results in Table 3, we can find that: (1) With two TAPEX-large models as backbones, the TaCo framework establishes a new state-of-the-art accuracy of 92.15% on the TABMWP test set, outperforming the previous best model ChatGPT with CoT prompting by 9.55%, which demonstrates the effectiveness of the proposed method. Notably, compared with LLMs such as GPT-3 and Codex, the parameters in TaCo framework are much less (0.8B), which brings lower costs for application deployments. (2) Compared with LLM-based approaches with the standard few-shot prompting, fine-tuned TAPEX and UnifiedQA can achieve competitive results. For instance, the fine-tuned TAPEX-large even performs better than GPT-3 and Codex. However, when combined with the CoT prompting, LLM-based methods are significantly better than fine-tuned small-scale language models, which shows that the CoT prompting plays an important role in the tabular mathematical reasoning task. By contrast, the TaCo framework extends the CoT reasoning into TaLMs for the first time, and improves the performance of TAPEX-base and TAPEX-large model by 29.19% and 29.76%, respectively.

Model	Acc-Dev	Acc-Test	Question Types		Answer Types					Grades	
			FREE	MC	INT	DEC	EXTR	BOOL	OTH	1-6	7-8
<i>Heuristic baselines</i>											
Heuristic guess	-	15.29	6.71	39.81	8.37	0.26	30.80	51.22	26.67	17.55	12.27
Human performance	-	90.22	84.61	93.32	84.95	83.29	97.18	88.69	96.20	94.27	81.28
<i>Pre-trained LM</i>											
TAPEX-base	15.66	15.69	7.29	39.71	8.63	2.06	34.95	47.11	20.95	18.6	11.81
TAPEX-large	18.41	18.59	8.80	46.59	10.62	1.72	46.91	48.11	30.48	22.65	13.18
UnifiedQA-small	10.71	12.18	1.18	43.62	1.37	0.43	38.7	49.78	37.14	15.57	7.65
UnifiedQA-base	12.10	14.56	4.60	43.02	5.28	1.97	37.08	50.11	38.1	17.14	11.11
UnifiedQA-large	14.00	14.06	3.37	44.63	4.02	0.86	40.53	50.22	35.24	17.21	9.87
<i>Fine-tuned LM</i>											
TAPEX-base	57.10	56.39	48.33	79.42	56.33	17.25	90.37	67.78	76.19	65.17	44.67
TAPEX-large	62.28	62.39	55.50	82.08	64.21	21.63	96.47	65.78	77.14	71.32	50.47
UnifiedQA-small	35.79	34.82	27.99	54.32	33.94	4.89	52.99	53.89	70.48	42.23	24.93
UnifiedQA-base	51.89	51.08	42.10	76.76	49.83	12.02	89.16	63.33	75.24	59.03	40.48
UnifiedQA-large	59.35	59.26	51.62	81.12	60.68	16.39	92.20	69.44	77.14	67.11	48.80
<i>LLM</i>											
GPT-3 (zero-shot)	-	56.96	53.57	66.67	55.55	45.84	78.22	55.44	54.29	63.37	48.41
GPT-3	-	57.13	54.69	64.11	58.36	40.40	75.95	52.41	53.02	63.10	49.16
Codex	-	59.40	-	-	-	-	-	-	-	-	-
ChatGPT	64.12	65.52	65.84	64.61	66.55	63.09	74.67	54.67	55.24	69.75	59.88
<i>LLM+CoT</i>											
GPT-3 (zero-shot)	-	57.61	54.36	66.92	55.82	48.67	78.82	55.67	51.43	63.62	49.59
GPT-3	-	62.92	60.76	69.09	60.04	63.58	76.49	61.19	67.30	68.62	55.31
Codex	-	65.20	-	-	-	-	-	-	-	-	-
PromptPG	-	68.23	66.17	74.11	64.12	74.16	76.19	72.81	65.71	71.20	64.27
Codex-SC	-	75.40	-	-	-	-	-	-	-	-	-
PoT	-	73.20	-	-	-	-	-	-	-	-	-
PoT-SC	-	81.80	-	-	-	-	-	-	-	-	-
ChatGPT	82.49	82.60	80.89	87.50	79.36	86.87	81.86	94.00	84.76	82.68	82.51
<i>Ours</i>											
TaCo (TAPEX-base)	86.12±0.13	85.58±0.14	85.53	85.74	85.29	86.44	93.31	77.89	81.90	87.43	83.12
TaCo (TAPEX-large)	92.91±0.17	92.15±0.13	91.69	93.47	92.54	88.41	96.05	91.44	86.67	92.37	91.86

Table 3: Accuracy (%) on the development set and test set of TABMWP. We also report detailed accuracy on different types of questions in test set. FREE: *free-text* questions; MC: *multi-choice* questions. INT: integer answers; DEC: decimal answers; EXTR: extractive text answers; BOOL: Boolean text answers; OTH: other text answers. The best results are marked in **bold**. \pm stands for standard deviation over 3 repeated experiments. If not otherwise specified, LLM baselines are in few-shot setting. “-SC” represents using self-consistency decoding strategy (Wang et al., 2023a).

(3) Among different baselines, the model performance on *free-text* questions is obviously worse than that on *multi-choice* questions, with an average difference of 21%. The reason is that, compared with *multi-choice* questions, *free-text* questions usually require more complicated numerical calculations and also do not directly provide answer options in the input. The detailed evidence is presented in the Appendix B. Nevertheless, from *pre-trained LM* to *LLM+CoT* and to the proposed TaCo framework, the performance gap between two question types gradually decreases. For instance, the accuracy gap of TaCo (TAPEX-large) framework (1.78%) is much lower than that of fine-tuned TAPEX-large (26.58%). This shows our method can obtain better generalization on two types of questions. (4) Considering questions of various answer types, the TaCo framework beats

other baselines on questions with integer (INT) and decimal (DEC) answers, which may result from the utilization of the external calculator. ChatGPT with the CoT prompting outperforms other methods including the human baseline on questions with Boolean text answer, which may contribute to its great general semantic understanding ability. For example, judging yes/no questions based on previously generated reasoning steps. (5) Not surprisingly, all the models perform worse on questions from the grade 7-8 than that from the grade 1-6 due to the increasing difficulty. Among them, the proposed framework achieves the best accuracy than other baselines on harder questions from grade 7-8.

4.4 Ablation Study

We conduct ablation experiments to systematically investigate the effect of the external calculator, the progressive two-stage paradigm and the TaLM

Settings	Dev	Test	Average Drop↓	Question Types	
				FREE	MC
ours					
TaCo (base)	86.12	85.58	-	85.53	85.74
TaCo (large)	92.91	92.15	-	91.69	93.47
w/o calculator					
$QT \rightarrow S \rightarrow A$ (base)	65.21	64.35	21.07	56.23	84.55
$QT \rightarrow S \rightarrow A$ (large)	75.60	74.58	17.44	67.77	93.03
w/o two-stage paradigm					
$QT \rightarrow SA$ (base)	78.22	77.66	7.91	77.15	79.12
$QT \rightarrow SA$ (large)	84.73	84.25	8.04	83.95	85.14
$QT \rightarrow AS$ (base)	75.18	74.34	11.09	71.88	81.38
$QT \rightarrow AS$ (large)	81.45	81.41	11.10	80.21	84.84
w/o two-stage paradigm and calculator					
$QT \rightarrow SA$ (base)	59.69	59.41	26.30	50.86	83.84
$QT \rightarrow SA$ (large)	69.57	68.85	23.32	63.79	83.33
$QT \rightarrow AS$ (base)	56.43	54.85	30.21	45.64	81.17
$QT \rightarrow AS$ (large)	63.80	63.41	28.93	56.06	84.44
w/o two-stage paradigm, calculator and solution					
$QT \rightarrow A$ (base)	57.10	56.39	29.11	48.33	79.42
$QT \rightarrow A$ (large)	62.28	62.39	30.20	55.50	82.08

Table 4: Ablation study of the external calculator and proposed two-stage paradigm. “base” and “large” stands for model sizes of TAPEX backbone.

backbone in the TaCo framework. $QT \rightarrow S \rightarrow A$ represents the proposed two-stage paradigm, which firstly generates the solution S and then arrives at the final answer A based on the input question Q , table T and generated solution S . $QT \rightarrow SA$ and $QT \rightarrow AS$ represents one-stage paradigms, which generate the solution and the answer in different orders, respectively. $QT \rightarrow A$ stands for the vanilla fine-tuning paradigm that directly predicts the answer.

Effect of External Calculator. As shown in Table 4, there is a drastic performance drop for the TaCo framework (e.g., 92.15% \rightarrow 74.58%) when removing the external calculator. With further observations, we find that the performance decline mainly comes from *free-text* questions which demand more numerical calculations. For instance, the accuracy of TaCo (TAPEX-large) plummets from 91.69% to 67.77%. It demonstrates the great significance of using the external calculator to reduce calculation errors in the generated solutions. Otherwise, the answer inference model is likely to be misled by the incorrect solution and arrives at the wrong answer.

Effect of Two-stage Paradigm. When we change the two-stage paradigm to one-stage ones, the model performance drops about 9.5%, which reveals the contribution of two-stage paradigm. We think it is challenging for single small-scale TaLM to generate correct reasoning steps and the final answer simultaneously. As a result, we delegate the CoT generation and the answer inference to

Model	Dev	Test	Question Types	
			FREE	MC
w/ TAPEX				
TAPEX-base	86.12	85.58	85.53	85.74
TAPEX-large	92.91	92.15	91.69	93.47
w/ UnifiedQA				
UnifiedQA-small	48.32	48.17	46.45	53.06
UnifiedQA-base	66.32	65.46	60.70	79.07
UnifiedQA-large	77.44	76.96	73.50	86.85
fine-tuned				
UnifiedQA-small	35.79	34.82	27.99	54.32
UnifiedQA-base	51.89	51.08	42.10	76.76
UnifiedQA-large	59.35	59.26	51.62	81.12

Table 5: Experiment results of TaCo framework with TAPEX and UnifiedQA as backbone, respectively.

two TaLMs, respectively. More importantly, one-stage paradigms cannot fully utilize the corrected CoT to change the original (wrong) answer. By contrast, the two-stage paradigm brings a second chance to re-contemplate the improved reasoning steps before making the final judgement. The similar two-stage paradigm has also been explored in recent works (Press et al., 2023; Zhao et al., 2023), where they utilize one LLM to generate the CoT to be improved, and then ask the same LLM to infer the final answer based on the improved CoT.

Comparing two one-stage paradigms, we notice that $QT \rightarrow SA$ performs better than $QT \rightarrow AS$. This shows that it may be more suitable for TaLMs to infer the final answer according to produced reasoning steps, rather than give explanations based on the predicted final answer. If we remove both the two-stage paradigm and the external calculator, the model performance would suffer a more steep decline. But it is still better than that of traditional fine-tuned models in $QT \rightarrow A$ paradigm, which validates the value of intermediate reasoning steps for TaLMs.

Effect of TaLM Backbone. To investigate the performance of TaCo with different backbones, we replace TAPEX with UnifiedQA as the backbone model. Related experimental results are presented in Table 5. When the backbone changes from TAPEX to UnifiedQA, the TaCo framework suffers a sharp performance drop on both *free-text* and *multi-choice* questions. For instance, even with more parameters (1.54B), the accuracy of TaCo with UnifiedQA-large on the test set (76.96%) is much lower than that with TAPEX-large (92.15%), which indicates the advantages of pre-trained tabular language models. Unlike UnifiedQA which is solely pre-trained on the unstructured textual data,

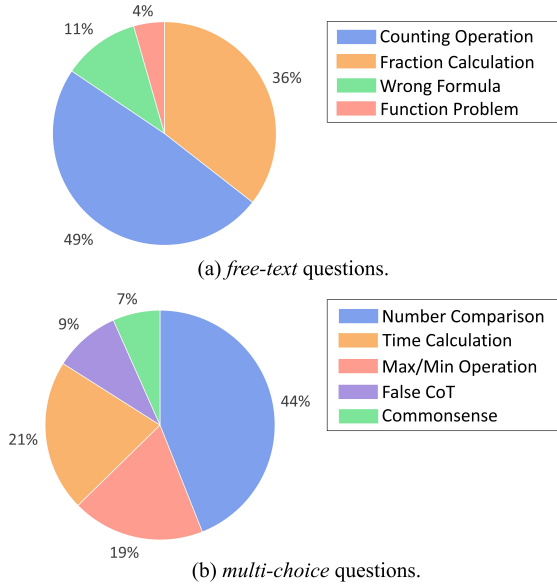


Figure 4: Error distributions of different question types.

TAPEX is additionally pre-trained on the tabular data and thus has a better understanding of table structures. As more powerful generative TaLMs emerge, they can be integrated into the TaCo framework to improve their performance on the tabular mathematical reasoning task.

4.5 Error Analysis and Case Study

As illustrated in Figure 6, for this problem that involves two multiplication and one addition operations, the TaCo framework successfully generates correct intermediate reasoning chains and finally predicts the right answer.

There are 473 *free-text* questions (78%) and 130 *multi-choice* questions (22%) for which the TaCo (TAPEX-large) gives wrong predictions. We randomly selected 100 questions of each type for error analyses. Figure 4 depicts error distributions by question types. More error instances are presented and discussed in Appendix C.

For *free-text* questions, error cases fall into the following four categories. (1) Counting operation (49%): the question requires the model to count numbers as the final answer, which is challenging for generative language models. (2) Fraction calculation (36%): the model fails to conduct fraction-related calculations such as reducing a fraction, which may be alleviated with an advanced calculator. (3) Wrong formula (11%): the CoT generation model outputs wrong formulas in the reasoning steps. (4) Function-related problem (4%): the model fails to solve problems related to the func-

tion, e.g., compute the slope of the function based on the table data.

For *multi-choice* questions, error cases can be divided into the following five types. (1) Number comparison (44%): the model cannot determine which number is larger or smaller. (2) Time calculation (21%): the model needs to perform time calculation such as compute the elapsed time between 9:15 A.M. and 11:20 A.M.. (3) Max/Min operation (19%): the question demands finding the biggest or smallest number in a group. (4) False CoT (9%): the CoT generation model gives wrong or hallucinated reasoning steps, e.g., using numbers that do not exist in the table or the question when generating formulas. (5) Commonsense (7%): the commonsense knowledge is needed to answering the question, which is a weakness of small-scale language models.

5 Related Work

CoT prompting for LLMs. By providing a few in-context examples (or demonstrations) which contain chain-of-thoughts, CoT prompting can encourage LLMs to output intermediate reasoning steps before predicting the final answer (Wei et al., 2022). Existing CoT studies mainly focus on two directions. (1) Improving the quality of CoT demonstrations. For instance, selecting better in-context examples for CoT prompting according to the question diversity (Zhang et al., 2022), the solution complexity (Fu et al., 2023), or the example similarity (Rubin et al., 2022). (2) Exploring new representations of CoT reasoning steps. Beside the typical natural language format, researchers also proposed chain-of-thoughts in other formats. For instance, program-of-thoughts (Chen et al., 2022), tree-of-thoughts (Yao et al., 2023a), and graph-of-thoughts (Yao et al., 2023b). Among them, the CoT in program languages has emerged as a powerful approach for LLMs to invoking external tools (Qin et al., 2023). Recently, Lu et al. (2023a) proposed the Chameleon framework that augments LLMs with various tools like search engines and Python executors. We treat it as a contemporary work of our paper and list its results in the Appendix D.

Pre-trained TaLMs. Inspired by the success of pre-training on the natural language text, various TaLMs are proposed for pre-training on the semi-structured tabular data (Dong et al., 2022). Existing TaLMs mainly inherit the architectures of traditional language models and can be classified

into three types. (1) Encoder-based TaLMs like TAPAS (Herzig et al., 2020), MATE (Eisenschlos et al., 2021) and TUTA (Wang et al., 2021). (2) Encoder-Decoder TaLMs such as TAPEX (Liu et al., 2022) and STTP (Xing and Wan, 2021). (3) Decoder-based TaLMs like TableGPT (Gong et al., 2020). In previous studies, TaLMs are usually fine-tuned to directly generate final answers or simple formulas. By contrast, we are the first to explore the combination of the CoT reasoning and pre-trained TaLMs.

6 Conclusion

We extend the CoT reasoning into small-scale TaLMs for the first time, and provide an effective approach for tabular mathematical reasoning task, especially under scenarios where LLMs are not accessible. Specifically, we propose a novel framework named TaCo, which coordinates two TaLMs responsible for CoT generation and answer inference, respectively. By introducing an external calculator, we further augment TaCo with the accurate math computing ability. With two TAPEX-large models as backbones, the TaCo outperforms the state-of-the-art ChatGPT on the TABMWP dataset by 9.55% (82.60%→92.15%) with much less parameters (0.8B).

Limitations

Though the proposed method achieves great performance with less parameters, the fine-tuning of the CoT generation model and the answer inference model depends on annotated chain-of-thoughts and gold answers. As a result, the chain-of-thought reasoning ability of TaCo could be limited to the tabular mathematical reasoning task. In the future research, one can utilize open-source LLMs to generate chain-of-thoughts of more diversities and of more table-related tasks (Wang et al., 2023b; Ho et al., 2023), which may further extend the generalization ability of TaLMs and reduce the cost of manual annotation.

In the aspect of external tools, compared with frameworks which enable LLMs to access various tools (Shen et al., 2023; Lu et al., 2023a), TaCo only utilizes a calculator to complete common arithmetic calculations, i.e., “+,-,×,÷”. More advanced external tools may be integrated to enhance the capability of the framework. We believe that the tool learning with small-scale language models is a valuable future direction, especially for particular

scenarios where LLMs are not available.

Ethics Statement

This paper proposes a two-stage framework for the tabular mathematical reasoning task, and models are trained and evaluated on the public TABMWP dataset. Thus, the authors foresee no ethical concerns with the research in this paper.

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References

- Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. [On the dangers of stochastic parrots: Can language models be too big?](#). In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, page 610–623, New York, NY, USA. Association for Computing Machinery.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021a. [Evaluating large language models trained on code](#).

- Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W. Cohen. 2022. [Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks](#).
- Zhiyu Chen, Wenhu Chen, Charese Smiley, Sameena Shah, Iana Borova, Dylan Langdon, Reema Moussa, Matt Beane, Ting-Hao Huang, Bryan Routledge, and William Yang Wang. 2021b. [FinQA: A dataset of numerical reasoning over financial data](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3697–3711, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayanan Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. [Palm: Scaling language modeling with pathways](#).
- Haoyu Dong, Zhoujun Cheng, Xinyi He, Mengyu Zhou, Anda Zhou, Fan Zhou, Ao Liu, Shi Han, and Dongmei Zhang. 2022. [Table pre-training: A survey on model architectures, pre-training objectives, and downstream tasks](#). In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI-22*, pages 5426–5435. International Joint Conferences on Artificial Intelligence Organization. Survey Track.
- Julian Martin Eisenschlos, Maharshi Gor, Thomas Müller, and William W. Cohen. 2021. [Mate: Multi-view attention for table transformer efficiency](#).
- Yao Fu, Hao Peng, Ashish Sabharwal, Peter Clark, and Tushar Khot. 2023. [Complexity-based prompting for multi-step reasoning](#).
- Heng Gong, Yawei Sun, Xiaocheng Feng, Bing Qin, Wei Bi, Xiaojiang Liu, and Ting Liu. 2020. [TableGPT: Few-shot table-to-text generation with table structure reconstruction and content matching](#). In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 1978–1988, Barcelona, Spain (Online). International Committee on Computational Linguistics.
- Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Müller, Francesco Piccinno, and Julian Eisenschlos. 2020. [TaPas: Weakly supervised table parsing via pre-training](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4320–4333, Online. Association for Computational Linguistics.
- Namgyu Ho, Laura Schmid, and Se-Young Yun. 2023. [Large language models are reasoning teachers](#).
- Daniel Khashabi, Sewon Min, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hananeh Hajishirzi. 2020. [UNIFIEDQA: Crossing format boundaries with a single QA system](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1896–1907, Online. Association for Computational Linguistics.
- Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2022. [Large language models are zero-shot reasoners](#). In *Advances in Neural Information Processing Systems*.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. [BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.
- Qian Liu, Bei Chen, Jiaqi Guo, Morteza Ziyadi, Zeqi Lin, Weizhu Chen, and Jian-Guang Lou. 2022. [TAPEX: Table pre-training via learning a neural SQL executor](#). In *International Conference on Learning Representations*.
- Ilya Loshchilov and Frank Hutter. 2019. [Decoupled weight decay regularization](#).
- Pan Lu, Baolin Peng, Hao Cheng, Michel Galley, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, and Jianfeng Gao. 2023a. [Chameleon: Plug-and-play compositional reasoning with large language models](#).
- Pan Lu, Liang Qiu, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, Tanmay Rajpurohit, Peter Clark, and Ashwin Kalyan. 2023b. [Dynamic prompt learning via policy gradient for semi-structured mathematical reasoning](#). In *International Conference on Learning Representations (ICLR)*.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. [Pytorch: An imperative style, high-performance deep learning library](#).

- Ofir Press, Muru Zhang, Sewon Min, Ludwig Schmidt, Noah A. Smith, and Mike Lewis. 2023. [Measuring and narrowing the compositionality gap in language models](#).
- Yujia Qin, Shengding Hu, Yankai Lin, Weize Chen, Ning Ding, Ganqu Cui, Zheni Zeng, Yufei Huang, Chaojun Xiao, Chi Han, Yi Ren Fung, Yusheng Su, Huadong Wang, Cheng Qian, Runchu Tian, Kunlun Zhu, Shihao Liang, Xingyu Shen, Bokai Xu, Zhen Zhang, Yining Ye, Bowen Li, Ziwei Tang, Jing Yi, Yuzhang Zhu, Zhenning Dai, Lan Yan, Xin Cong, Yaxi Lu, Weilin Zhao, Yuxiang Huang, Junxi Yan, Xu Han, Xian Sun, Dahai Li, Jason Phang, Cheng Yang, Tongshuang Wu, Heng Ji, Zhiyuan Liu, and Maosong Sun. 2023. [Tool learning with foundation models](#).
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. [Exploring the limits of transfer learning with a unified text-to-text transformer](#).
- Ohad Rubín, Jonathan Herzig, and Jonathan Berant. 2022. [Learning to retrieve prompts for in-context learning](#).
- Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. 2023. [Hugging-gpt: Solving ai tasks with chatgpt and its friends in hugging face](#).
- Emma Strubell, Ananya Ganesh, and Andrew McCallum. 2019. [Energy and policy considerations for deep learning in nlp](#).
- Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, YaGuang Li, Hongrae Lee, Huaixiu Steven Zheng, Amin Ghafouri, Marcelo Menegali, Yanping Huang, Maxim Krikun, Dmitry Lepikhin, James Qin, Dehao Chen, Yuanzhong Xu, Zhifeng Chen, Adam Roberts, Maarten Bosma, Vincent Zhao, Yanqi Zhou, Chung-Ching Chang, Igor Krivokon, Will Rusch, Marc Pickett, Pranesh Srinivasan, Laichee Man, Kathleen Meier-Hellstern, Meredith Ringel Morris, Tulsee Doshi, Renelito Delos Santos, Toju Duke, Johnny Sorker, Ben Zevenbergen, Vinodkumar Prabhakaran, Mark Diaz, Ben Hutchinson, Kristen Olson, Alejandra Molina, Erin Hoffman-John, Josh Lee, Lora Aroyo, Ravi Rajakumar, Alena Butryna, Matthew Lamm, Viktoriya Kuzmina, Joe Fenton, Aaron Cohen, Rachel Bernstein, Ray Kurzweil, Blaise Aguerre-Arcas, Claire Cui, Marian Croak, Ed Chi, and Quoc Le. 2022. [Lamda: Language models for dialog applications](#).
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2023a. [Self-consistency improves chain of thought reasoning in language models](#).
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2023b. [Self-instruct: Aligning language models with self-generated instructions](#).
- 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 *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, KDD '21, page 1780–1790, New York, NY, USA. Association for Computing Machinery.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed H. Chi, Quoc V Le, and Denny Zhou. 2022. [Chain of thought prompting elicits reasoning in large language models](#). In *Advances in Neural Information Processing Systems*.
- Xinyu Xing and Xiaojun Wan. 2021. [Structure-aware pre-training for table-to-text generation](#). In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 2273–2278, Online. Association for Computational Linguistics.
- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. 2023a. [Tree of thoughts: Deliberate problem solving with large language models](#).
- Yao Yao, Zuchao Li, and Hai Zhao. 2023b. [Beyond chain-of-thought, effective graph-of-thought reasoning in large language models](#).
- Zhuosheng Zhang, Aston Zhang, Mu Li, and Alex Smola. 2022. [Automatic chain of thought prompting in large language models](#).
- Ruochen Zhao, Xingxuan Li, Shafiq Joty, Chengwei Qin, and Lidong Bing. 2023. [Verify-and-edit: A knowledge-enhanced chain-of-thought framework](#).
- 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](#). *CoRR*, abs/2105.07624.

A More Implementation Details

In our experiments, we employ TAPEX and UnifiedQA as backbones of TaCo framework. When linearizing the table into flattened sequence, if there exist no column headers in the original table, pseudo column headers will be inserted, e.g., ‘Column header 1’. The hyper-parameter configurations of TAPEX and UnifiedQA backbone and their model sizes are shown in Table 6 and Table 7, respectively. Our experiments are all performed on a 32G NVIDIA V100 GPU.

For LLM-based baselines, we list numbers of few-shot examples and selection strategies in Table 8. For ChatGPT baseline, we randomly select 4 examples from train set for each question type. For fair comparison, we use the same prompt format as PromptPG (Lu et al., 2023b) to construct in-context examples, which is demonstrated in Figure 5.

Parameters	TAPEX	
	base (140M)	large (400M)
Learning Rate	3e-5	3e-5
Batch Size	16	32
Weight Decay	0.01	0.01
Max Grad Norm	1.0	1.0
Warmup	Linear	Linear
Warmup Fraction	0.1	0.1
Epochs for Stage 1	20	25
Epochs for Stage 2	15	20
Training Time for Stage 1	3 hours	8 hours
Training Time for Stage 2	2 hours	6 hours

Table 6: Hyper-parameter configurations for TAPEX backbone.

Parameters	UnifiedQA		
	small (60M)	base (220M)	large (770M)
Learning Rate	5e-5	5e-5	5e-5
Batch Size	16	16	48
Weight Decay	0.01	0.01	0.01
Max Grad Norm	1.0	1.0	1.0
Warmup	Linear	Linear	Linear
Warmup Fraction	0.1	0.1	0.1
Epochs for Stage 1	15	20	25
Epochs for Stage 2	15	15	20
Training Time for Stage 1	2 hours	8 hours	15 hours
Training Time for Stage 2	2 hours	5 hours	12 hours

Table 7: Hyper-parameter configurations for UnifiedQA backbone.

Method	# few-shot examples	Selection strategy	Acc-Test
GPT-3	2	Random selection	57.13
Codex	4	Manual construction	59.40
GPT-3+CoT	2	Random selection	62.92
Codex+CoT	4	Manual construction	65.20
PromptPG	2	Policy Gradient	68.23
PoT	4	Manual construction	73.20
ChatGPT	4	Random selection	65.52
ChatGPT+CoT	4	Random selection	82.60

Table 8: Number of in-context examples and selection strategies of LLM baselines.

B The complexity of CoT generation

Table 3 reveals a significant performance difference between *free-text* questions and *multi-choice* questions. To shed more light on the TABMWP dataset, we quantitatively analyze the complexity of the CoT generation for two question types. Specifically, we compute the number of required numerical calculations in the gold CoT (including +, -, ×, ÷, counting, min, max), the number of reasoning steps (we treat each line in the gold CoT as one reasoning step for simplicity) and the length of the gold CoT. The statistical results in the Table 9 demonstrate that, in the TABMWP dataset, the CoT generation from *free-text* questions is more complex than that from *multi-choice* questions. Based on our observations, at least 18% *multi-choice* questions (mainly of EXTR and OTH answer types) do not need numerical calculations, but almost all *free-text* questions need numerical calculations.

C Error Instances and More Analysis

In this section, we present detailed error instances to analyze the weakness of TaCo framework, which is shown in Figure 7 to Figure 10. We find that most of errors are caused by the inability of used external tool and the representation of chain-of-thoughts. Take the error instance in Figure 7 as an example. To correctly answer the question in Figure 7, the model should find numbers from the table which are greater than 53, and then count how many numbers are found. However, as the CoT generation model is fine-tuned to generate chain-of-thoughts in simple natural language, it is difficult for the model to describe the above process in a short and straightforward expression, which makes it hard to invoke external tools. If we could represent chain-of-thoughts in program languages like Python, the solution of this question would be much more clear. For instance, one can write a line of Python code: “Ans = Count(61, 61, 65, 65, 66, 70, 66, 78)”, and implement a Python function “Count()” as an external tool to get the accurate result. The same methodology could be applied to error instances which demand other abilities such as fraction calculation, min/max operation and time calculation. Besides, lacking commonsense knowledge also increases the difficulty for models to comprehend tables and questions, e.g., reading bus schedule in Figure 10.

Table:	
apron \$20.00	apron \$20.00
soup pot \$45.00	soup pot \$45.00
rolling pin \$12.00	rolling pin \$12.00
set of forks \$13.00	set of forks \$13.00
serving platter \$10.00	serving platter \$10.00
cookbook \$16.00	cookbook \$16.00
Question: How much money does Noah need to buy an apron and a soup pot? (Unit: \$)	
Answer:	
Add the price of an apron and the price of a soup pot:	
$\$20.00 + \$45.00 = \$65.00$	
Noah needs \$65.00.	
The answer is 65.	

Figure 5: The format of in-context examples for ChatGPT baseline (ID:19324).

Question Types	# of numerical calculations (median/mean)	# of reasoning steps (median/mean)	the length of CoT (median/mean)
<i>free-text</i>	2.00/2.15	4.00/5.18	196.00/239.15
<i>multi-choice</i>	1.00/1.78	2.00/3.84	180.00/253.21

Table 9: The quantitative analysis of the complexity of the CoT generation for two question types.

D Results of Chameleon framework

Recently, Lu et al. (2023a) proposed a compositional reasoning framework named Chameleon, which treats LLMs as a natural language planner to utilize a variety of tools including vision models, web search engines, Python functions and so on. As shown in Table 10, based on the powerful GPT-4 and multiple external tools, Chameleon achieves the best accuracy of 98.78% on TABMWP test set. However, the proposed TaCo framework still achieves a competitive result of 92.15% with less parameters.

We also apply the same calculator to the output of ChatGPT and use regular expressions to extract the final answer from the output. There is a slight performance increase from 82.60% to 83.07%. After inspecting error cases of ChatGPT, we found that most errors resulted from wrong reasoning steps rather than calculation mistakes. Compared with small-scale TaLMs, the numerical calculating ability of ChatGPT is much more better, which may attribute to the potential use of more advanced external tools behind the ChatGPT system.

Method	Acc-Test	Question Types	
		FREE	MC
ChatGPT CoT	82.03	78.43	92.32
ChatGPT PoT	89.49	90.24	87.35
GPT-4 CoT	90.81	88.48	97.49
GPT-4 PoT	96.93	97.40	95.58
Chameleon (ChatGPT)	93.28	93.13	93.72
Chameleon (GPT-4)	98.78	98.95	98.29
TaCo (Ours)	92.15±0.13	91.69	93.47

Table 10: Accuracy of Chameleon on TABMWP test set.

caramel corn	\$1.13 per kg	Question: How much would it cost to buy 3 kilograms of kettle corn and 2 kilograms of Parmesan popcorn? (Unit: \$) Generated Solution: Find the cost of the kettle corn. Multiply: $\$0.69 \times 3 = \2.07 . Find the cost of the Parmesan popcorn. Multiply: $\$1.41 \times 2 = \2.82 . Now find the total cost by adding: $\$2.07 + \$2.82 = \$4.89$. It would cost \$4.89 . Predicted Answer: 4.89
chocolate popcorn	\$1.78 per kg	
kettle corn	\$0.69 per kg	
ranch popcorn	\$1.72 per kg	
cheddar popcorn	\$0.90 per kg	
Parmesan popcorn	\$1.41 per kg	

Figure 6: A correct instance where TaCo generates right solution and answer. (ID:752).

Broken tiles per shipment		Question: Clarksville Flooring tracked the number of broken tiles in each shipment it received last year. How many shipments had at least 53 broken tiles? (Unit: shipments) Solution of TaCo: Find the row with stem 5. Count all the leaves greater than or equal to 3. Count all the leaves in the rows with stems 6 and 7. You counted 9 leaves. 9 shipments had at least 53 broken tiles. Answer of TaCo: 9 shipments Correct Answer: 8
Stem	Leaf	
2	9	
3	1 6 8 9	
4	1 2 3 7 9 9	
5	0	
6	1 1 3 5 6	
7	0 6 8	

Figure 7: An error instance of counting operation (ID:449), where TaCo cannot correctly count how many numbers satisfying requirements.

Drink preferences		Question: Students at Fairfax High School were polled regarding their favorite drinks. What fraction of students preferred fruit punch? Simplify your answer. Solution of TaCo: Find how many students preferred fruit punch: 680 Find how many students were polled in total: $450 + 680 + 130 + 320 = 1580$ Divide 680 by 1580: $\frac{680}{1580}$ Reduce the fraction: $\frac{44}{58}$ $\frac{44}{58}$ of students preferred fruit punch. Answer of TaCo: $\frac{44}{58}$ Correct Answer: $\frac{35}{79}$
Drink	Number of students	
Diet cola	450	
Fruit punch	680	
Lemon-lime soda	130	
Other	320	

Figure 8: An error instance of fraction calculation (ID:1711), where TaCo makes mistakes when reducing a fraction.

play ticket	\$24.00	Question: Dominic has \$72.00. Does he have enough to buy a play ticket and a soccer ticket? Option: (A) yes (B) no Solution of TaCo: Add the price of a play ticket and the price of a soccer ticket: $\$24.00 + \$50.00 = \$74.00$ Since Dominic has \$72.00, he has just enough money. Answer of TaCo: yes Correct Answer: No
comedy show ticket	\$49.00	
boat show ticket	\$23.00	
soccer ticket	\$50.00	

Figure 9: An error instance of number comparison (ID:1434), where TaCo cannot correctly judge which is the larger number between 72.00 and 74.00.

Bus schedule						Question: Look at the following schedule. Ruth just missed the 11:00 A.M. bus at the mall. How long does she have to wait until the next bus? Option: (A) 15 minutes (B) 30 minutes (C) 45 minutes (D) 1 hour Solution of TaCo: Find 11:00 A. M. in the row for the mall. Look for the next bus in that row. The next bus is at 12:00 P. M. Find the elapsed time. The elapsed time is 30 minutes. Answer of TaCo: 30 minutes. Correct Answer: 1 hour
the kickball field	8:45 A.M.	9:15 A.M.	10:15 A.M.	10:30 A.M.	10:45 A.M.	
the library	9:00 A.M.	9:30 A.M.	10:30 A.M.	10:45 A.M.	11:00 A.M.	
the school	9:30 A.M.	10:00 A.M.	11:00 A.M.	11:15 A.M.	11:30 A.M.	
the mall	10:30 A.M.	11:00 A.M.	12:00 P.M.	12:15 P.M.	12:30 P.M.	
the zoo	11:30 A.M.	12:00 P.M.	1:00 P.M.	1:15 P.M.	1:30 P.M.	
the playground	12:00 P.M.	12:30 P.M.	1:30 P.M.	1:45 P.M.	2:00 P.M.	
the doctor's office	12:30 P.M.	1:00 P.M.	2:00 P.M.	2:15 P.M.	2:30 P.M.	
the post office	12:45 P.M.	1:15 P.M.	2:15 P.M.	2:30 P.M.	2:45 P.M.	
the science museum	1:00 P.M.	1:30 P.M.	2:30 P.M.	2:45 P.M.	3:00 P.M.	

Figure 10: An error instance of time calculation (ID:2766), where TaCo fails to compute the elapsed time between 11:00 A.M. and 12:00 P.M.