GPT4Table: Can Large Language Models Understand Structured Table Data? A Benchmark and Empirical Study

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ABSTRACT

Large language models (LLMs) are becoming attractive as few-shot reasoners to solve Natural Language (NL)-related tasks. However, there is still much to learn about how well LLMs understand structured data, such as tables. While it is true that tables can be used as inputs to LLMs with serialization, there lack comprehensive studies examining whether LLMs can truly comprehend such data. In this paper, we try to understand this by designing a benchmark to evaluate the structural understanding capabilities (SUC) of LLMs. The benchmark we create includes seven tasks, each with their own unique challenges, e.g., cell lookup, row retrieval, and size detection. We run a series of evaluations on GPT-3.5 and GPT-4. We discover that the performance varied depending on a number of input choices, including table input format, content order, role prompting, and partition marks. Drawing from the insights gained through the benchmark evaluations, we then propose self-augmentation for effective structural prompting, e.g., critical value / range identification using LLMs' internal knowledge. When combined with carefully chosen input choices, these structural prompting methods lead to promising improvements in LLM performance on a variety of tabular tasks, e.g., TabFact($\uparrow 2.31\%$), HybridQA($\uparrow 2.13\%$), SQA($\uparrow 2.72\%$), Feverous(↑ 0.84%), and ToTTo(↑ 5.68%). We believe that our benchmark and proposed prompting methods can serve as a simple yet generic selection for future research. The code and data are released in https://anonymous.4open.science/r/StructuredLLM-76F3.

CCS CONCEPTS

• Information systems → Information retrieval query processing; • Computing methodologies → Natural language

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processing; Natural language generation; Information ex-

KEYWORDS

large language models, semi-structured data, structural understanding, benchmark

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1 INTRODUCTION

Structured data consists of plain text blocks organized by predefined structures to compress recurring information. It makes the data more manageable and facilitates data analysis and processing by machines. Table is one of such structured data types with many applications such as Table-based Question Answering (TQA) [8, 20], Table-based Fact Verification (TFV) [7, 37], Table-to-Text [35] and Column Type & Relation Classification [11, 19]. The adoption of structured data have significantly contributed to the advancement of information retrieval and knowledge extraction in the web mining and content analysis.

Prompt engineering has proven to be a highly effective approach for solving text reasoning tasks without the need for tuning. In fact, recent studies [21, 34, 36], such as "chain of thoughts" (CoT) [36] and "self-consistency" [34] or some hybrid ways using both generation and retrieval methods [1, 40] have shown that Large Language Models (LLMs), e.g., GPT-X [4, 27] and FlanT5 [9], can be utilized to solve complex mathematical reasoning tasks in both zero-shot and few-shot settings; Chen [6] illustrates that by using CoT with LLMs, GPT-3.5 presents impressive performance with just a oneshot demonstration on several tabular tasks. The findings have opened up new possibilities for the use of LLM in structured data.

However, no previous works give comprehensive studies examining whether the LLMs can truly understand the tabular data, or give a detailed discussion of what extent do the LLMs have already achieved in structural understanding capabilities. Moreover, the process of table serialization along with context and corresponding queries is highly flexible, i.e., there is less grounded consensus or comprehensive investigation on what constitutes a

^{*}The contributions by Yuan Sui and Mingjie Zhou, have been conducted and completed during their internships at Microsoft Research Asia, Beijing, China.

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consensus or exhaustive input design for LLMs on tabular tasks. In fact, prior works have seen the diverse input designs in an adhoc manner [6, 14, 15, 17, 19, 24, 35]. For example, TaPEx [24] use special tokens to indicate components like headers <HEAD> and rows <ROW>; while TableGPT [15] uses a template-based method for serializing the attribute-value pair in each record of a table, *e.g.*, changes "name: Elon Musk" to "name is Elon Musk." and concatenates all the sentences according to the records order. The intricate landscape of chaotic input design further compounds the challenges facing researchers and developers in this domain. So in this paper, we intend to highlight a question: *What input designs and choices are most effective in enabling LLMs to understand tables?*

In this paper, we intend to alleviate the chaos landscape of the input designs and reveal whether the LLMs can truly understand the tabular data, or give a detailed discussion of what extent do the LLMs have already achieved in structural understanding capabilities (SUC). Specially, we propose a benchmark called SUC to compare various input designs and design some specific tasks in §3 to study the structural understanding capabilities of LLMs. To verify the effectiveness of multiple input choices, we run a series of experiments with different prompt variants, including input format, format explanation, role prompting, partition mark [13], and zero-shot / one-shot. The SUC benchmark provides a comprehensive comparison using multiple input designs on different aspects of structural understanding capabilities over table(s) as illustrated in §5. We then provide some pragmatic guidance on how to better utilize LLM in understanding structured data in §4, and propose a simple but generic method called self-augmented prompting to directly boost the performance of LLM in downstream tasks. Specifically, it motivates LLMs to generate intermediate structural knowledge based on internal retrieving of LLMs' self knowledge, e.g., motivates LLMs to generate critical value / range identification by itself. We find that when combined with carefully chosen input choices, these structural prompting methods lead to promising improvements in LLM performance on a variety of tabular reasoning tasks e.g., TabFact(\uparrow 2.31%), HybridQA(\uparrow 2.13%), SQA(\uparrow 2.72%), Feverous(↑ 0.84%), and ToTTo(↑ 5.68%) compared to baseline meth-

Our exploration leads us to believe that 1) LLMs have basic structural understanding capabilities but are far from perfect, even on some trivial tasks, e.g., table size detection; 2) Correctly choosing the combination of input designs is a potential factor in boosting LLMs understanding capability over structured data; 3) Self-augmented prompting is a simple but generic method for better leveraging LLMs internal knowledge, and unravel new possibilities for advancing the LLMs' structural understanding capabilities. We suggest that using markup language like HTML with certain structural features like format explanation, partition mark, combined with self-augmented prompting for fully leverage LLMs' internal knowledge can help achieve better results in tabular reasoning tasks. In summary, our main contributions are:

• The SUC benchmark is proposed to evaluate multiple structural understanding capabilities of LLMs. The dataset and code are open sourced at https://anonymous.4open.science/r/StructuredLLM-76F3.

- By comprehensive experiments of input choices for LLMs on the benchmark, we highlight insights and guidelines on tabular input choices for future work (See §5).
- Self-augmentation is proposed to enhance LLMs' performance by leveraging internal knowledge. On five tabular reasoning datasets we verified the effectiveness of this simple but generic method.

2 PRELIMINARIES

2.1 Table Structure

Tabular data exhibit remarkable flexibility in diverse structures, as illustrated in [39]. These structures include relational tables, entity tables, matrix tables, layout tables, and more. Tables can adopt horizontal or vertical orientations and span the spectrum from flat to hierarchies. In this paper, we focus mainly on flat relational tables and have some discussion on hierarchical tables, such as ToTTo [28]. In these tables, each row corresponds to a distinct record, while columns represent specific fields, without any hierarchical arrangement.

Tabular data also exhibit a multitude of approaches for formatting values, including text, number, data-time, formula, and other pertinent information. In particular, text plays a pivotal role in tables, serving to capture meta-information encompassing headers, notes, captions, and cells within the data region. On the contrary, numbers often entail arithmetic relationships such as summation and proportion, as well as statistical attributes such as distribution and trends. Tables frequently house meticulously organized numerical data, facilitating convenient reference and comparison. Such structured numerical values are frequently documented using spreadsheet formulas [12].

2.2 Choices of Tabular Inputs

Tabular Sequence Serialization. Serializing tables into a sequence format is a necessary adaptation for masked language modeling objective of LLMs. A simple serialization function is to serialize tables row-by-row. Many works such as TaPas [17], MATE [14], TableFormer [25], TUTA [35], and TURL [11] use this method. In TaPEx [24], the table is also linearized by rows, but it also uses special tokens to indicate components like headers <HEAD> and rows <ROW>; TABBIE [19] serialize tables by both row-wise and column-wise, while TableGPT [15] uses a template-based method to serialize the attribute-value pair in each record of a table.

Furthermore, most LLMs are inefficient in dealing with long sentences due to the quadratic complexity of self-attention [32, 33]¹. Unfortunately, structured data usually contain dozens of components, which poses a significant challenge to memory and computational efficiency. Herzig et al. [17], Liu et al. [24] use naive way to truncate the input by a maximum sequence length, but it may lose critical information and disrupt the structure of the whole table. In our experiments, we use some predefined constraints to fulfill the LLM call request, *e.g.*, (1) To avoid any potential disruption of the table structure caused by truncation, we employ a random row sampling strategy when the number of tokens in

¹The maximum sequence length of text-Davinci-003 is constrained to 4k tokens.

the table surpasses this threshold. (2) we append a 1-shot example based on the estimation of remaining token capacity. So far, many meticulously crafted sequence serialization functions have been proposed and represent the common practices of the table serialization, including Dou et al. [13], Herzig et al. [17], Liu et al. [24], Shao et al. [30], Wang et al. [35], Xie et al. [37]. In this paper, we collect various commonly used serialization methods as baselines and made a fair comparison in §3.

3 SUC BENCHMARK

In this section, we endeavor to develop a benchmark to compare various input designs and study whether LLMs have structural understanding capabilities. Specifically, we explore the following aspects: 1) What input designs and choices are most effective in enabling LLMs to understand tables?; 2) Do LLMs have the structural understanding capabilities and to what extent do LLMs already have achieved in understanding structured data? Additionally, we explore the complex trade-off of multiple input design combinations. Find the benchmark collection and pre-processing details in Sec §3.4.

3.1 Structural Understanding Capabilities

We categorize the essential abilities to comprehend table structures from a human point of view into two distinct folds, as illustrated in Figure 1.

1) Partition & Parsing. Tabular datasets are always paired with knowledge from other sources to provide more context and solve a specific downstream task. For example, HybridQA [8] employs passage information, TabFact [7] and FEVEROUS [3] employs human annotation, and MultiModalQA [31] employs image information. However, the prerequisite for tackling these downstream tasks is the accurate partitioning of the data, which in turn requires the ability to distinguish tables from other supplementary information and an elementary understanding of the structural layout of tables.

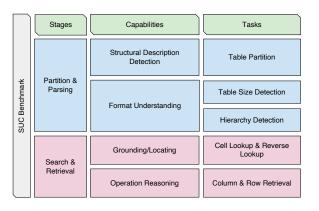


Figure 1: SUC Benchmark Overview

Additionally, various table storage formats, including CSV, JSON, XML, markdown, HTML [2] and XLSX, represent different levels of information compression and pose different levels of challenges for LLMs to understand the table content. For example, a table stored in CSV format is arranged in rows with column values separated by commas, while a table stored in XML format is represented as a nested set of tags. The more common way is to use natural

language with special token [37, 38] as separator like "|". We intend to detect whether the LLMs have the capability to correctly parse the different sources of formatting information, and which kind of input design is most suitable for LLMs or LLMs already have the capabilities to generalize all kinds of storage formats. The specific input designs can be found in Figure 2.

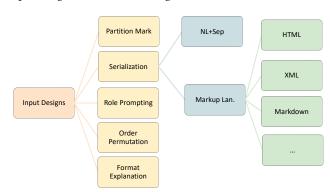


Figure 2: Input Designs for Structural Understanding Capabilities Evaluation

2) Search & Retrieval. On top of above two capabilities, the ability to accurately search and retrieve information from specific positions within structured data is crucial for LLMs. The capability is highly relevant to the downstream tasks, e.g., Table-QA, Column Type & Relation Classification, which enables the LLMs to identify and extract relevant information from structured data based on a given request. For example, a user can ask "For the Olympic events that take place after 2014, which has an older flag bearer?", the LLM should first locate all the Olympic events and compare the age of the flag bearers and then return the event with the oldest flag bearer. The locating process is realized by analyzing the structure of the data and identifying the target cell. By decomposing the search & retrieval capabilities from LLMs' downstream tasks, we can obtain inner insights of the LLMs learning process and search & retrieval capabilities regarding tabular data.

3.2 Task Settings

We design several specific tasks for each capability to reveal whether LLMs have gained each kind of capability of understanding table. The tasks are designed with increasing difficulty.

Table Partition. This task reveals the capability of structural information partition. A LLM is required to detect the boundaries of the tables within a given user input design. This input design may include various types of supplementary information, such as "descriptions", "contex", "statement" and "user queries". Formally, given an input design, $D=d_1,d_2,...$, where each part d_i is a "versatile" sequence containing supplementary information such as description, context, statement, or user queries. For easy evaluation and comparison, we constrain LLMs to output a tuple of table boundary with the head token b_h and the end token b_e that includes the table content, as $B=(b_h,b_e)$.

Table Size Detection. This task is essential to reveal the LLM's capability to correctly parse structural information. On the basis

Title: Antoine Salamin Year Team Driver Races Pos 29^{th} 1983 Swit... Antoine... 1 Antoine... 2 7th 1989 Swit... Table & Other info

1st <request>

Identify critical values and ranges of the table

The table contains... Antoine Salamin's results in... from 1983 to 1989. The most critical values in the table are the number of races. The range of races is from 1 to 4.... The range of podiums is from 0 to 3... The range of points is from 3 to 42... LLM 2nd < request>

Generate NL description for highlighted parts

Intermediate Output

Final Output

In 1989, Antoine Salamin drove a Porsche 962C for the Swiss Team Salamin, powered by a Porsche turbo Flat-6 engine. He competed in two races, achieving one podium and 17 points, finishing 7th overall.

Figure 3: Illustration of self-augmented prompting. This is done by two phases: 1) use self-augmented prompt to ask LLM to generate additional knowledge (intermediate output) about this table; 2) add the self-augmented response to form the second prompt to ask for final answer of a downstream task. As shown in the figure, the LLM can tell some important values in the table which help itself generate a better answer for the downstream task.

of our empirical observation, table size is a preliminary but vital feature, which is often ignored during the discussion. In fact, the table size feature represents direct constraints to how many rows and columns are encoded in a table. For instance, if a table only has three columns, the output should not consider answers outside this scope. Formally, given a table with m rows and n columns, a correct answer from a LLM should be (m, n).

Merged Cell Detection. This task reveals another aspect of the structural information parsing capability. Special structure may block the understanding of a table, *i.e.*, various categorization methodologies on the table structure, which are summarized in detail by [39]. To test the robustness of LLMs, we consider one feature in hierarchical spreadsheet table, merged cell², which is quite common in table construction. Formally, given a table with some merged cells, a LLM is required to detect the merged cell index (r_i, c_j) . Note that any index in the merged cell that matches the condition will be considered correct.

Cell Lookup & Reverse Lookup. This task reveals the capability to search and retrieve structural information. Accurately search and retrieve cell value from a specific position notification is based on the capabilities of information partition and parsing. In this task, a LLM is required to retrieve the position $(p_i, p_j), \cdots, (p_i^n, p_j^n)$ of the given cell value c_i if multiple same cell values are found; and reversely, retrieve the cell value c_i given the specific cell position (p_i, p_j) .

Column & Row Retrieval. It is another task to reveal the capability of searching and retrieving structural information. A LLM is required to list the cell values c_j , c_j^n of a specific column name C_i from the given table. Similarly, the row retrieval task requires LLM to list the cell values of a specific row index. Using column/row index to position a specific value list is more common than locating a cell value, so we assume the sample is true when the predict value

list is same as the corresponding groundtruth value list during the evaluation process. In this manner, we expect the performance of column/row retrieval task to perform better than cell lookup and reverse lookup.

3.3 Evaluation

We evaluate the benchmark using the crowded common input designs for table reasoning tasks, and apply the methods on different LLMs to give a deeper analysis. Specifically, we consider CSV, JSON, XML, markdown, HTML [2] and XLSX as different format options. It represents a different level of information compression and poses different level of challenges for LLMs to truly understand the table content. We also consider using the most common way by concatenating special token [37, 38] as separator like "|" as the baseline. The comparison numbers can be found in 1. Other input design options such as grammar explanation, partiton mark [13], role prompting [24], format explanation, etc., are also considered as augmentation for input designs (see details in 2).

3.4 Data Collection and Reformatting of SUC

We collect structured data from various public datasets, *e.g.*, Tab-Fact [7], FEVEROUS [3], SQA [20], HybridQA [8] and ToTTo [28]. All the tables are from Wikipedia. We only consider the structural portions of the original datasets, which are labeled with "table," "rows," or "headers," and exclude the other parts like "ID," "Answer," "Question," "FileName,". To identify a specific value within the structured data, we append each parsed sample with a unique question. Most of these questions are one sentence long, with a median length of 15 words. For example, "How many rows in the table? How many columns in the table?" Each question is accompanied by a set of reference answers ("groundtruth") sourced from the original datasets. For better evaluation, most of these questions are paired with some constraints such as "Answer the questions one by one and use "|" to split the answer." We evaluate these questions

 $^{^2}$ Merged cell: combining with one or more adjacent cells to create a single larger cell.

using Text-Davinci-003³ and manually eliminate any question that the model consistently answers correctly when multiple random samples are generated at a nonzero temperature⁴. For the merged cell detection task, we only sample from ToTTo since this is the only source paired with the merged cell. For each task setting, we randomly sample 1,500 tables for testing with a guaranteed table distribution.

One-shot Setting. The SUC benchmark is designed as a one-shot in-context learning [22] benchmark for tabular tasks. This means that the model can access one example from the SUC and may gain some context when generating the answers. The LLMs have demonstrated a striking capability to follow the few-shot prompts to accomplish unseen tasks without any fine-tuning, which is found to be an emergent capability not captured by small language models. SUC leverages this property to better reveal the potential capabilities LLMs may lack. We also conduct SUC using the zero-shot setting for comparison. Find the relevant experiments in Table 6.

4 STRUCTURAL PROMPTING

Our findings and insights over the SUC comparisons (See §5) has lead us to the discovery that 1) LLMs have the basic structural understanding capabilities but far from perfect, even on some trivial tasks, e.g., table size detection; 2) Correctly choosing the combination of input designs is a potential factor in boosting LLMs understanding over tabular data. In this section, we propose a simple and generic method, self-augmented prompting, to generate additional constraints using LLMs' self-knowledge. We find that when combined with carefully chosen input choices, these structural prompting methods lead to promising improvements on a variety of tabular downstream tasks (See Table 4).

Recently, CoT [36] has been discovered to empower LLMs to perform complex reasoning over text and lead to a long line of work [10, 21, 23, 34]. By providing the model with several exemplars of reasoning chains, LLMs can learn to follow the template to solve difficult unseen tasks. Inspired by these works, we propose a simple, generic and effective method, self-augmented prompting, to generate intermediate structural knowledge based on the internal retrieving of LLMs' self knowledge base. We design several ways to squeeze knowledge from LLM (see Table 4). For example, we ask LLM to generate the format specification, which intends to clarify the input format pattern by LLM itself. These choices diverges from previous approaches like CoT and Zero-shot-CoT [21] by focusing on identifying effective methods for unlocking LLMs' capabilities to correctly comprehend structured information. Additionally, this method is model-agnostic, that is, any standard structural data reasoning tasks can be used as the backbone, and can also be integrated with other prompting-based methods like self-consistency [34].

Formally, self-augmented prompting is a simple idea that uses prompting twice to unlock LLMs' capabilities over understanding structured data, as shown in Figure 3. In the first prompt, the original task of "requesting" information is replaced with a simple

demand for "Identify critical values and ranges of the last table related to the statement". Each demand reflects an important feature of structural information. The goal of this replacement is to unlock the reasoning capabilities of LLMs for complex reasoning over structured data. The prompted text is then fed into the LLM model and generates a subsequent sentence involving specific structural information. In the second prompt, the generated subsequent sequence is appended to the task request and then fed into the LLM model to generate the final answer. Find the experiment comparison of using self-augmented prompting in Table 4.

Based on the emprical observations, we also find that structural information plays an important role in truly understanding a table. Aghajanyan et al. [2], Xie et al. [37], Yin et al. [38] make a step by adding prompts with special tokens to encode various structure information. Inspired by their works and the findings in SUC benchmark results, we explore the idea of manually prompt engineering as a bonus for self-augmented prompting. Specifically, we contemplate the extraction of structural information from the raw input and its subsequent incorporation into the input. Such as using cell address and exactly illustrate how many rows/columns does the table have. This augmentation process serves to furnish additional knowledge and constraints, thereby enhancing the LLM's aptitude for reasoning over tabular downstream tasks. We discover that the LLM have a lower performance over the table size detection task (See §3) and motivates us to append such structural features to the input, e.g., table size and merged cell position, to provide a more structure-aware in-context learning environment for downstream tasks. We give ablation study in section 5.2.1 and find that by appending table size and merged cell position leads to an increase on LLM performance on downstream tasks.

5 EXPERIMENTS

5.1 Experiment Settings

Models. In this study, we evaluate the performance on GPT-3.5 [27] and GPT-4 [26]. Unless otherwise specified, we utilize text-davinci-003 in all experiments. Specially, we set the hyper-parameter temperature to 0, top_p to 1, with n set to 1 when perform the experiments; **Downstream Tasks and Datasets.** In addition to evaluate LLMs' capabilities towards understanding structured data through our benchmark. We also conduct experiments on five typical tabular downstream tasks. The datasets are shown as follows, and the evaluation number can be found in Table 4.

Specifically, we use (1) SQA which is composed of 6,066 question sequences (2.9 question per sequence on average), constructed by decomposing a subset of highly compositional WTQ questions; (2) HybridQA which requires reasoning on heterogeneous information rather than homogeneous information alone, which involves 62,682 questions. Each question is aligned with a Wikipedia table and multiple free-form corpora linked with the entities in the table. The questions are designed to aggregate both tabular information and text information, *i.e.*, lack of either form would render the question unanswerable; (3) ToTTo which is a high-quality English table-to-text dataset with more than 100,000 examples in which a table from Wikipedia with highlighted cells is paired with a sentence that describes the highlighted cells. The task is like given a Wikipedia table with row names, column names and table cells, with a subset

 $^{^3\}mbox{We}$ perform the experiments through the public play ground of OpenAI GPT-3.5 in https://beta.openai.com/play ground/.

⁴Temperature controls the randomness of the generation process. As the temperature approaches zero, the model becomes more deterministic and repetitive with very limited variation. Here, we set the temperature to 0.7 when creating the question and set the temperature to 0 when performing other experiments

Table 1: Micro results of the benchmark (See full results from Table 6). Change order [37] refers to put external text (like questions, statement) ahead of tables. Noted that "GPT-4" refers to the evaluation outcomes utilizing the GPT-4 model. Given the resource-intensive nature of GPT-4 calls, we only conducting the GPT-4 inference test on a subset of 300 samples (randomly sampled) from each task set. Each column follows the roles of graded color scale, *i.e.*, the deeper color refers to better perf.

	Table Partition (on Cell Lookup		Reverse Lookup		Column Retrieval		Row Retrieval		Size Detection		Merged Cell Detection	
Format	Acc	GPT-4	Acc	GPT-4	Acc	GPT-4	Acc	GPT-4	Acc	GPT-4	Acc	GPT-4	Acc	GPT-4
NL + Sep	93.00%	96.78%	39.67%	72.48%	52.00%	59.12%	60.67%	66.32%	31.00%	48.67%	42.00%	73.12%	71.33%	74.98%
Markdown	92.33%	98.32%	43.33%	71.93%	51.00%	57.32%	35.33%	60.12%	42.33%	49.98%	40.67%	82.12%	78.00%	82.64%
JSON	94.00%	97.12%	42.67%	68.32%	54.33%	58.12%	54.33%	64.32%	29.00%	48.32%	42.67%	76.43%	73.33%	78.98%
XML	96.00%	97.64%	43.33%	72.28%	55.00%	60.32%	41.33%	68.28%	41.00%	50.28%	43.67%	80.21%	75.00%	80.32%
HTML	96.67%	98.32%	44.00%	73.34%	47.33%	59.45%	63.33%	69.32%	42.00%	50.19%	67.00%	83.43%	76.67%	81.28%

Table 2: Micro ablation results of the input designs over benchmark. Find more detailed ablation results from Table 6

	Table F	Table Partition C		ookup	Reverse	Reverse Lookup		Column Retrieval		Row Retrieval		Size Detection		Merged Cell Detection	
Input Design	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	
Markup Lan. HTML	96.67%	0.00%	44.00%	0.00%	47.33%	0.00%	63.33%	0.00%	42.00%	0.00%	67.00%	0.00%	76.67%	0.00%	
w/o format explanation	92.00%	-4.67%	52.00%	8.00%	52.33%	5.00%	64.33%	1.00%	36.00%	-6.00%	78.00%	11.00%	77.67%	1.00%	
w/o partition mark	98.00%	1.33%	59.00%	15.00%	53.00%	5.67%	66.00%	2.67%	39.67%	-2.33%	72.00%	5.00%	70.33%	-6.33%	
w/o role prompting	95.00%	3.00%	40.67%	-11.33%	44.67%	-7.67%	59.00%	-5.33%	39.33%	3.33%	69.00%	-9.00%	76.00%	-1.67%	
w/o change order	96.67%	0.00%	52.33%	8.33%	40.67%	-6.67%	55.67%	-7.67%	31.67%	-10.33%	52.67%	-14.33%	65.67%	-11.00%	
w/o 1-shot	63.00%	-33.67%	9.33%	-34.67%	17.33%	-30.00%	50.00%	-13.33%	30.00%	-12.00%	16.67%	-50.33%	38.00%	-38.67%	
GPT-4 w/ Lan. HTML	98.32%	1.65%	73.34%	29.34%	59.45%	12.12%	69.32%	5.99%	50.19%	8.19%	83.43%	16.43%	81.28%	4.61%	

of cells highlighted, generate a natural language description for the highlighted part of the table; **(4) FEVEROUS** which is a fact verification dataset consisting of 87,026 verified claims. Each claim is annotated with evidence in the form of sentences and/or cells from tables in Wikipedia, as well as a label indicating whether this evidence supports, refutes, or does not provide enough information to reach a verdict; **(5) TabFact** which is a fact verification dataset in which the tables were extracted from Wikipedia and sentences were written by crowd workers.

5.2 Results

5.2.1 Benchmark Highlights. Comprehensive evaluations of different structural understanding tasks with various input designs over SUC are presented in Table 6. The results show that the system's overall accuracy gets highest when using the HTML markup language with format explanations and role prompts, and without order change, achieving a 65.43% overall accuracy on seven tasks. It indicates that the LLM has significant potential for understanding the structural information of tables in this specific format. However, it is also evident that the LLM's performance is negatively impacted when certain features are removed, especially when the prompt example is removed. We give some highlights associated with the benchmark results as follows:

NL+Sep vs. Markup Lan. We compared the use of natural language with specific separators (NL+Sep) and markup languages such as HTML, XML, and JSON. Even "NL+Sep" is commonly used in tabular downstream tasks [6, 17, 24, 38], however, our results show that using markup languages, specifically HTML, outperforms "NL+Sep" with a 6.76% improvement. It is our assumption that the training process of the LLMs involves code tuning and the

training dataset contains a significant amount of web data, whereas tabular datasets come mainly from web pages like Wikipedia. As a result, the LLM is more familiar with HTML and XML formats when interpreting tables. (See [27] for more information about the GPT-3.5 training).

Table 3: Main results of the downstream tasks ablation study

	TabFact	HybridQA	SQA	Feverous	ТоТТо
Format	Acc	Acc	Acc	Acc	BLEU-4
NL + Sep	70.26%	45.02%	70.41%	75.15%	12.70%
Markdown	68.40%	45.88%	66.59%	71.88%	8.57%
JSON	68.04%	42.40%	70.39%	73.84%	8.82%
XML	70.00%	47.20%	70.74%	73.14%	8.82%
HTML	71.33%	47.29%	71.31%	75.20%	12.30%
GPT-4 w/ HTML	78.40%	56.68%	75.35%	83.21%	20.12%

1-shot vs. 0-shot. Notable finding is that the system performance drops significantly when it is in a zero-shot setting, with an overall accuracy decrease of 30.38% on all tasks using HTML format. It indicates that structural information learning is highly dependent on in-context learning. Especially for tasks size detection and merged cell detection, which are associated with the structural information parsing capability.

External information should appear ahead of tables. To understand the impact of order on the input design, we manually put external information such as questions, statements behind table. We find that the change order will give an overall 6.81% decrease on all tasks. A possible explanation is that putting external information

TabFact HybridQA SQA Feverous ToTTo Choice Type Acc BLEU-1 BLEU-2 BLEU-3 BLEU-4 Acc Acc Acc 1-shot 1-shot 72.04% 73.81% 75.56% 72.43% 27.01% 17.24% 46.07% 44.36% 1-shot w/o table size 71.33% 45.52% 72.91% 74.66% 72.30% 44.23% 27.14% 17.25% 1-shot w/o partition mark 71.25% 45.48%73.09% 75.11% 71.18% 43.17% 26.36% 16.34% 1-shot w/o format explanation 70.87% 45.39% 71.69% 75.97% 70.54% 43.59% 26.52% 16.74% 1-shot w/o role prompting 71.35% 46.05% 73.39% 75.52% 70.61% 43.10% 26.02% 16.15% SA self format explanation 72.23% 46.12% 73.91% 76.15% 74.18% 45.25% 27.32% 18.34% SA self critical values and ranges identification 74.35% 76.32% 80.83% 22.92% 48.20% 76.53% 47.96% 30.68% self structural information description SA 73.42%46.97% 75.97% 77.28% 78.93% 46.91% 28.94% 19.32%

Table 4: Downstream tasks evaluation. SA. refers to Self-augmented Prompting.

ahead of tables could help LLM to generalize better and gain more context of the structural information of tables.

Partition mark. & format explanation may undermine Search & Retrieval capability. Partition mark [13] is commonly used in input designs. Inspired by partition mark, we propose another similar choice, "format explanation". It is formulated as an additional explanation of the adopted format. For example, for HTML format, we give the format explanation that "Each table cell is defined by a and a tag; Each table row starts with a and ends with a tag; th stands for table header." However, on task Cell Lookup, adding partition mark and format explanation give an overall decrease on all input designs. It indicates that such additional structural information may bias the searching and retrieval process of LLM over the tabular structure. However, adding partition mark or format explanation also show some benefits on specific tasks like merged cell detection. To give a clearer vision of the impact of adding additional explanation or special tokens, we conduct experiments in Table 4. We reveal that even they may undermine the search & retrieval capability of LLMs, however, it still advances overall performance in downstream tasks.

SUC benchmark gives a comprehensive comparison using multiple input designs on different aspects of structural understanding capabilities over table(s). Based on the highlights, guidelines are proposed to answer the questions we mentioned in §3. 1) LLMs have basic structural understanding capabilities, but far from perfect, even for some trivial tasks, *e.g.*, table size detection; 2) Correctly choosing the combination of input designs is a potential factor in improving the performance of LLMs over structured data.

5.2.2 Downstream Tasks. Table 4 gives the comparison using self-augmented prompting with trick of structural feature detection. We find one notable insights that the models perform better using self-augmented prompting than 1-shot, as seen in the "SA" rows where the models are given self-generated information: format explanation, key range and values identification, and structural information description. These rows have higher accuracy and BLEU scores than the "1-shot" rows. Especially for generating key range and values identification gives an overall 3.26% boost than 1-shot setting on all the tasks. In addition, manual prompting of structural features such as "table size" from the input will slightly affect the model performance on downstream tasks. The drop of table

size gives an overall 0.4% decrease, as seen by the small difference between the "1-shot" row and the "1-shot w/o table size" row.

Table 5: Format explanation example from FEVEROUS

Manual Prompt	Self-augmented Prompt Generation
Each table cell is defined by a and a and a tag. Each table row starts with a and ends with a th stands for table header.	'15 rows and 4 columns, with the first column being an index, the second column being empty, the third column being the name of the Marshal, the fourth column being the date of promotion, and the fifth column being the defence branch.\nThe table is defined by HTML tags, with each table cell being defined by a ada be row starting with a a tag, and each table row starting with a a tag.\nThe table header is denoted by the th tag.'

Based on the comparison of the "1-shot w/o format explanation" row and the "SA self format explanation" row, we find that manual label the format explanation may have worse impact on downstream task like FEVEROUS. This is because table structure in FEVEROUS is more irregular, containing many segments and subtables. Such structural difficulties post great challenges to GPT-3.5. And manual-crafted knowledge is more general and cannot cover this kind of detailed information. However, self-augmented prompting can learn the pattern by itself and generate more rich and useful cues to tackle the questions. We give a format explanation example from FEVEROUS using two prompt designs in Table 5.

6 RELATED WORK

In-context Learning with LLMs. Large language models, such as GPT-3 [4], Instruct-GPT, and Codex [5], have shown the capability on NL-related tasks as few-shot reasoners. The effectiveness of this ability is influenced by factors such as the size of the model, the amount of data used, and the computing power available. Recent studies [9, 10, 29] have proposed various methods for training LLMs, and these models have exhibited a remarkable ability to perform unseen tasks without fine-tuning, an emergent capability not observed in small LMs.

Intermediate of Prompt Engineering. Recently, many intermediate prompt engineering methods have been proposed following "CoT" [36]. CoT prompts few examples with explanations

Table 6: Main results of the benchmark. Change order [37] refers to put external text (like questions, statement) ahead of tables.

	Table F	artition	Cell I	ookup	Reverse	Lookup	Column	Retrieval	Row R	etrieval	Size Do	etection	Merged	Cell Detection
Input Design	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ
NL + Sep	93.00%	0.00%	39.67%	0.00%	52.00%	0.00%	60.67%	0.00%	31.00%	0.00%	42.00%	0.00%	71.33%	0.00%
w/o format explanation	91.33%	-1.67%	50.00%	10.33%	58.33%	6.33%	58.00%	-2.67%	31.67%	0.67%	40.67%	-1.33%	73.33%	2.00%
w/o partition mark	90.00%	-3.00%	40.33%	0.67%	50.00%	-2.00%	56.67%	-4.00%	36.33%	5.33%	40.00%	-2.00%	69.00%	-2.33%
w/o role prompting	91.33%	-1.67%	45.67%	6.00%	41.00%	-11.00%	54.00%	-6.67%	25.33%	-5.67%	41.67%	-0.33%	74.00%	2.67%
w/o change order	88.00%	-5.00%	35.33%	-4.33%	40.33%	-11.67%	55.33%	-5.33%	24.67%	-6.33%	36.67%	-5.33%	61.00%	-10.33%
w/o 1-shot	75.33%	-17.67%	9.00%	-30.67%	37.33%	-14.67%	50.33%	-10.33%	17.00%	-14.00%	26.33%	-15.67%	17.33%	-54.00%
Storing Lang. JSON	94.00%	0.00%	42.67%	0.00%	54.33%	0.00%	54.33%	0.00%	29.00%	0.00%	42.67%	0.00%	73.33%	0.00%
w/o format explanation	87.67%	-6.33%	47.67%	5.00%	57.67%	3.33%	49.00%	-5.33%	30.33%	1.33%	39.67%	-3.00%	71.67%	-1.67%
w/o partition mark	92.00%	-2.00%	48.67%	6.00%	44.00%	-10.33%	59.67%	5.33%	40.33%	11.33%	39.67%	-3.00%	72.67%	-0.67%
w/o role prompting	90.67%	-3.33%	44.67%	2.00%	41.67%	-12.67%	57.33%	3.00%	29.33%	0.33%	38.33%	-4.33%	72.67%	-0.67%
w/o change order	90.67%	-3.33%	37.67%	-5.00%	42.67%	-11.67%	55.67%	1.33%	26.00%	-3.00%	33.00%	-9.67%	62.67%	-10.67%
w/o 1-shot	74.67%	-19.33%	11.33%	-31.33%	30.00%	-24.33%	52.67%	-1.67%	14.00%	-15.00%	27.33%	-15.33%	19.67%	-53.67%
Markup Lang. Markdown	92.33%	0.00%	43.33%	0.00%	51.00%	0.00%	35.33%	0.00%	42.33%	0.00%	40.67%	0.00%	78.00%	0.00%
w/o format explanation	88.00%	-4.33%	56.00%	12.67%	50.67%	-0.33%	34.33%	-1.00%	33.33%	-9.00%	39.00%	-1.67%	74.00%	-4.00%
w/o partition mark	96.33%	4.00%	52.67%	9.33%	54.67%	3.67%	35.33%	0.00%	45.00%	2.67%	43.00%	2.33%	74.67%	-3.33%
w/o role prompting	94.33%	2.00%	48.33%	5.00%	58.67%	7.67%	35.67%	0.33%	39.67%	-2.67%	40.00%	-0.67%	78.00%	0.00%
w/o change order	89.67%	-2.67%	40.33%	-3.00%	52.00%	1.00%	36.67%	1.33%	34.00%	-8.33%	24.67%	-16.00%	59.67%	-18.33%
w/o 1-shot	60.70%	-31.64%	8.67%	-34.67%	35.33%	-15.67%	30.67%	-4.67%	19.00%	-23.33%	11.67%	-29.00%	23.67%	-54.33%
Markup Lang. XML	96.00%	0.00%	43.33%	0.00%	55.00%	0.00%	41.33%	0.00%	41.00%	0.00%	43.67%	0.00%	75.00%	0.00%
w/o format explanation	89.00%	-7.00%	58.33%	15.00%	51.33%	-3.67%	35.33%	-6.00%	32.67%	-8.33%	37.67%	-6.00%	74.00%	-1.00%
w/o partition mark	96.33%	0.33%	54.67%	11.33%	55.00%	0.00%	36.00%	-5.33%	48.00%	7.00%	39.33%	-4.33%	74.33%	-0.67%
w/o role prompting	93.67%	-2.33%	47.33%	4.00%	60.33%	5.33%	42.33%	1.00%	37.00%	-4.00%	40.67%	-3.00%	73.33%	-1.67%
w/o change order	88.67%	-7.33%	42.33%	-1.00%	49.00%	-6.00%	37.67%	-3.67%	33.33%	-7.67%	27.00%	-16.67%	57.00%	-18.00%
w/o 1-shot	69.33%	-26.67%	9.00%	-34.33%	33.00%	-22.00%	25.33%	-16.00%	15.33%	-25.67%	12.67%	-31.00%	22.33%	-52.67%
Markup Lang. HTML	96.67%	0.00%	44.00%	0.00%	47.33%	0.00%	63.33%	0.00%	42.00%	0.00%	67.00%	0.00%	76.67%	0.00%
w/o format explanation	92.00%	-4.67%	52.00%	8.00%	52.33%	5.00%	64.33%	1.00%	36.00%	-6.00%	$\boldsymbol{78.00\%}$	11.00%	77.67%	1.00%
w/o partition mark	98.00%	1.33%	59.00%	15.00%	53.00%	5.67%	66.00%	2.67%	39.67%	-2.33%	72.00%	5.00%	70.33%	-6.33%
w/o role prompting	95.00%	3.00%	40.67%	-11.33%	44.67%	-7.67%	59.00%	-5.33%	39.33%	3.33%	69.00%	-9.00%	76.00%	-1.67%
w/o change order	96.67%	0.00%	52.33%	8.33%	40.67%	-6.67%	55.67%	-7.67%	31.67%	-10.33%	52.67%	-14.33%	65.67%	-11.00%
w/o 1-shot	63.00%	-33.67%	9.33%	-34.67%	17.33%	-30.00%	50.00%	-13.33%	30.00%	-12.00%	16.67%	-50.33%	38.00%	-38.67%

of the reasoning process. This explanation of reasoning leads to LLM step by step thinking and generate more accurate results, However, according to [36], "CoT only yields performance gains when used with models of nearly 100B parameters". Smaller models wrote illogical chains of thought, which led to worse accuracy than standard prompting. Models usually get performance boosts from CoT prompting in a manner proportional to the size of the model. Zero Shot Chain of Thought (Zero-shot-CoT) prompting is a follow up word to CoT, which introduces an incredibly simple zero shot prompt. They find that by appending the words "Let's think step by step." to the end of a question, LLMs are able to generate a chain of thoughts that answers the question. From this chain of thought, they are able to extract more accurate answers. Self-consistency is another follow up to CoT that generates multiple chains of thoughts, then takes the majority answer based on a voting strategy as the final answer. Self-consistency [34] has been shown to improve results on arithmetic, commonsense and symbolic reasoning tasks. Even when regular CoT was found to be ineffective, self-consistency was still able to improve results. Liu et al. [23] propose to The generated knowledge approach asks the LLM to generate potentially useful information about the question before generating a response.

7 CONCLUSION

In this paper, we propose a benchmark to compare various input designs in order to study the structural understanding capabilities of LLMs on tables. Surprisingly, we obtain some insights of the input designs and the comparison reveal that LLMs have the basic capabilities towards understanding structural information of tables. We also give some guidance on how to apply our benchmark insights on downstream tasks and propose a simple, generic but effective method, *i.e.*, self-augmented prompting, by generating additional knowledge with LLMs self-knowledge. We believe this study will be beneficial for table-based, even structured data based research, or serve as a auxiliary tool to help better understand the table(s) from structural perspectives.

ETHICAL CONSIDERATIONS

Structured data often includes metadata, which is additional information about the data that helps to contextualize it (*e.g.*, column names, data types, *etc.*). Interpreting and utilizing metadata during the understanding of structured data also reflects an emerging challenge, especially when the meaning and significance of structured data may not be immediately obvious and must be inferred from the metadata and other contextual clues. This capability is highly dependent on the downstream tasks, like column type prediction [18] and dimension/measure classification [16]. We think this is one

of an important research tasks that deserve better understanding. However, due to the page limited, we will leave this section as further exploration. Also, our method works mostly for languages with limited morphology, like English. We leave the discussion of low scalability to long text to the further exploration.

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A APPENDIX

A.1 Input design for each task in SUC

Here, we list the task query/input for each task in SUC benchmark. We constraint the output format for better evaluation by adding some constraints. E.g., in table partition task, we add the instruction "Answer questions one by one and use '|' to split the answer." Based on the empirical observations, over 90% answers follow these kind of specific format instructions. For the less 10% samples, we apply an semantic-parsing strategy using regular expression (Re) 5 to parse the answers.

A.2 Data and Code Release

The SUC benchmark and all the code in this paper will be open sourced at https://anonymous.4open.science/r/StructuredLLM-76F3 after an internal review. The synthesized labels in the benchmark

will be released under CDLA-Permissive-2.0 license. Our code will be released publicly with MIT license.

Table 7: Input design of each task in our benchmark

Task	Input
Table Partition	What is the first token (cell value instead of separator) of the given table? What is the end token (cell value instead of separator) of the given table? Answer questions one by one and use to split the answer.
Cell Lookup	What is the position of the cell value cell_value? Use row index and column index to answer
Reverse Lookup	What is the cell value of row index, column index? Only output the cell value without other information
Column Retrieval	What is the column name with the index column_idx of the following table? Only give the column name without any explanation
Row Retrieval	What are the cell values of the row_idx row in following table? Only list the cell values one by one using to split the answers
Size Detection	How many rows in the table? How many columns in the table. Answer the questions one by one and use to split the answer
Merged Cell Detection	What is the column index of the cell which span is over 1. use \mid to split the answer (e.g., 3 \mid 4), the column index starts from 0. If there's no answer, return None

 $^{^5} https://docs.python.org/3/library/re.html\\$