# Generating Tables from the Parametric Knowledge of Language Models

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## Abstract

We explore generating factual tables from the parametric knowledge of large language models (LLMs). While LLMs have demonstrated impressive capabilities in recreating knowledge bases and generating free-form text, their ability to generate structured tabular data has received little attention. To address this gap, we explore the table generation abilities of eight state-of-the-art LLMs, including GPT-4o and Llama3.1-405B, using three prompting methods: full-table, row-by-row, and cell-by-cell. To facilitate evaluation we introduce WikiTabGen, a new benchmark consisting of 119 manually curated Wikipedia tables and their description. Our findings show that table generation remains challenging, with the best performing model (LLaMA3.1-405B) reaching only 25.4% accuracy. We further analyze how properties like table size, popularity, and numerical content impact performance. This study highlights the unique challenges of LLM-based table generation and offers a foundation for future research in this area. All code, data, and prompts are publicly available.[1]

## 1 Introduction

Automated table generation has broad applications in fields such as healthcare, finance, scientific research and education (Chen et al., 2021; Johnson et al., 2016; Berant et al., 2018) where converting unstructured factual data into structured tables can significantly enhance decision-making, streamline workflows, and improve data accessibility enabling knowledge extraction and facilitating further analysis through statistical and visualization tools (Shen et al., 2021). Large language models (LLMs) (Brown et al., 2020; Chowdhery et al., 2022; Kadavath et al., 2022; Touvron et al., 2023a) have demonstrated remarkable performance on various natural language processing tasks, including free-form text generation, knowledge retrieval, and summarization. However, despite their success in generating free-form text, LLMs face distinct challenges when tasked with producing complex structured data, and their ability to generate long and factually accurate tables from their parametric knowledge remains largely unexplored (Akhtar et al., 2024; Zhao et al., 2024).

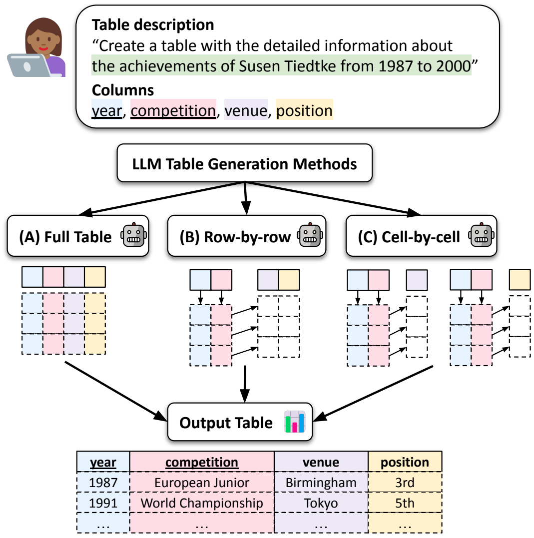


Figure 1: An example LLM-based table generation task along with three alternative prompting methods.

LLMs are pre-trained on vast amounts of text, which includes factual information presented in both plain text and structured formats, such as tables (Elazar et al., 2023; Fang et al., 2024). Through this training, LLMs encode a wealth of factual information in their parameters. While previous studies have shown that LLMs can retrieve factual information for tasks like recreating knowledge bases (KBs) (Petroni et al., 2019; AlKhamissi et al., 2022; Cohen et al., 2023) or generating Wikipedia-like articles (Shao et al., 2024), little attention has been given to their ability to generate structured tables from their parametric knowledge. Unlike question answering over tables or text-to-SQL translation (Pasupat and Liang, 2015;

[1]https://github.com/analysis-bots/WikiTabGen



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Chen et al., 2021), generating tables requires models to retrieve and organize specific factual data into structured formats, posing unique challenges. The lack of dedicated methods for table generation and appropriate evaluation benchmarks highlights a particular gap in current research.

To address this gap, we introduce WIKITABGEN, a benchmark designed to evaluate LLMs' ability to generate tables from their parametric knowledge. It consists of 119 manually curated Wikipedia tables, each paired with a textual description and a set of target columns. With an average of 1,457 tokens per table, WIKITABGEN features significantly larger tables compared to previous tabular generation tasks (Parikh et al., 2020; Nan et al., 2022). This benchmark facilitates a systematic evaluation of how factors such as table size, numerical content, and popularity (Mallen et al., 2022) affect table generation. We also introduce and evaluate three prompting methods: full-table generation, row-by-row generation and cell-by-cell generation.

Our key contributions are: (1) Formulating the problem of generating structured tables from LLMs' parametric knowledge. (2) Introducing WIKITABGEN, a benchmark consisting of diverse tables that vary in size, structure, and content, to evaluate table generation capabilities. (3) Implementing and evaluating three prompting methods across eight state-of-the-art LLMs, including GPT-4 and LLaMA3.1-405B. (4) Providing a comprehensive analysis of the factors that impact table generation performance.

Our experiments reveal that generating tables from LLMs remains a challenging task, with the highest F1 score reaching only 25.4%. We observe that factors such as table size and numerical content significantly affect performance. These findings highlight the need for further research to improve LLM-based table generation. We hope that our benchmark and analysis will inspire future research on generating structured data from LLMs.

## 2 Problem Definition

Given a short user description, our task is to generate a factually accurate table.

Following Codd (1990), a relational table $T = (R, C)$ is a set of rows $R = \{r_1, r_2, \dots\}$ and a set of columns $C = \{c_1, c_2 \dots\}$. A table cell, denoted $r[c]$, contains the value of column $c$ in row $r$. Key columns are a subset $C_k \subset C$ that uniquely define each entry (row) in $T$ and the corresponding cells do not contain null or empty values. For example, the table in Fig. 1 has the columns `year` and `competition` as its keys. Each table entry such as `venue`, corresponds to a unique `year`, `competition` pair.

Given a table description $d$ and a list of desired table columns $C$, our task is to generate a corresponding table $T(\hat{R}, C)$, where the generated rows $\hat{R}$ contain factually accurate information. An example problem is shown in Fig. 1, where the table description is *"Achievements of Susen Tiedke from 1987 to 2000"* and the target columns are: *year*, *competition*, *venue*, and *position*. Each of our proposed prompting methods (§3) can then be used for the LLM to generate table $T(\hat{R}, C)$, as shown in the bottom of the figure.

## 3 Prompting LLMs to Generate Tables

Given a table description and list of target columns $C$, we evaluate LLM performance on generating the corresponding table $T(\hat{R}, C)$. Our focus is on extracting the knowledge stored in the LLM, with retrieval-augmented methods (Lewis et al., 2020; Yoran et al., 2023) being orthogonal to our study.

We implement three prompting methods to generate tables, shown in Fig. 1. First, the full table method prompts the LLM to generate the table all at once. However, the output table may be quite large, with evaluation tables have 1.5K tokens on average (§4). Therefore, we also experiment with a modular prompting approach (Khot et al., 2023, 2022), where one LLM instance generates the table *keys*, and another generates either complete rows or individual cells. We refer to these two modular prompting methods as row-by-row and cell-by-cell respectively. An in-depth example of our prompting methods is provided in Fig. 2. Note that all prompts in the figure are appended with the table description and columns (prompt 1 in Fig. 2). Next, we describe each of the prompts used in our three methods. All of our prompts are listed in §A and in our public code repository.

**(a) Full-table.** Given the table description and target columns the LLM is prompted to generate all table rows. Example prompts are prompts 1 and 2.A in Fig. 2 which are both concatenated and provided as the input to the LLM.

**(b) Row-by-row.** This is a two-stage prompting method, prompting two separate instances of the LLM. First, we prompt the LLM for key generation

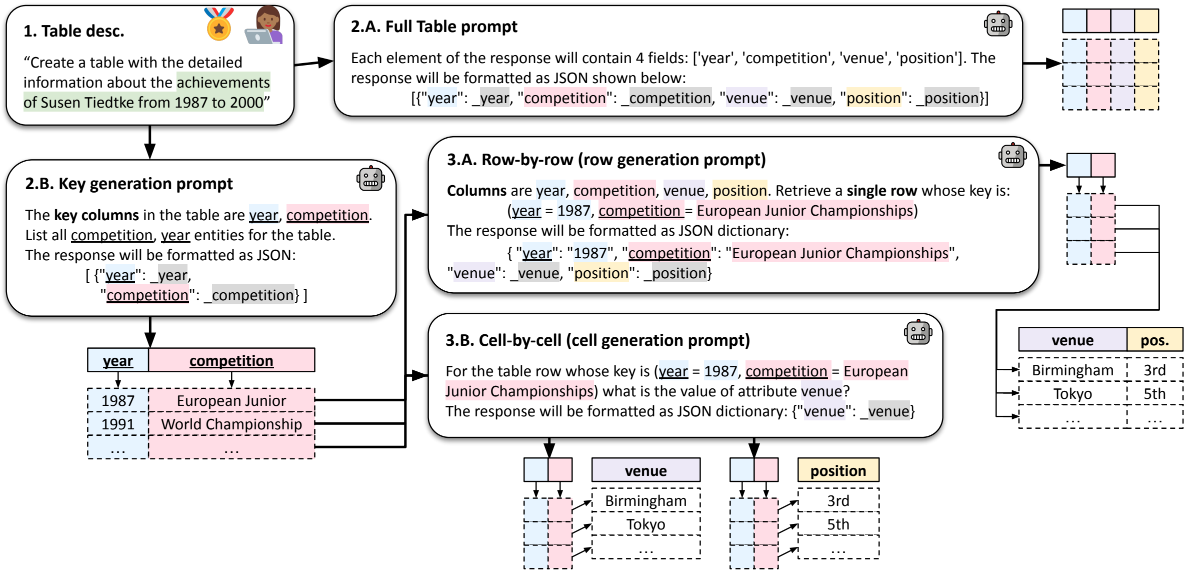



Figure 2: An overview of our three separate prompting methods for table generation, given a short user description and table metadata (Fig. 1): (2.A) Full table directly generates the table given the user desc. and its columns; (2.B) Key-generation is used in both the row-by-row and cell-by-cell methods; (3.A) Row-by-row generates a table row given a unique key value, e.g. (1987, EU Junior Championship); (3.B) Cell-by-cell generates a single table cell given a key value and specific target column e.g. *venue* $\rightarrow$ *Birmingham*.

i.e. to generate all values of the key columns $C_k$. As key values are a unique identifier for each table entry (§2), we then prompt a second instance of the LLM, to generate a full table row given a key value. Thus, for each key value $\hat{r}_i[C_k]$ generated by the first LLM, we generate a subsequent prompt to retrieve the remaining row entries $\hat{r}_i[C \setminus C_k]$. Overall, we are required to generate $|\hat{R}| + 1$ prompts, where $|\hat{R}|$ is the number of key values output by the key generation LLM.

In Fig. 2, box 2.B describes the key generation prompt. Given the table description, and key columns *competition* and *year*, the LLM generates a list of corresponding years and competitions which Susen Tiedtke participated in. Next, each key value returned by the first LLM, is used to generate the remaining row entries. Prompt 3.A prompts the row generation LLM to populate columns `venue`, `position` which correspond to key $\langle$*"European Junior"*, *"1987"*$\rangle$. The generated values being *"Birmingham"*, and "3rd". A new row-by-row prompt is then generated for the following keys, e.g. $\langle$*"World Championship"*, *"1991"*$\rangle$.

**(c) Cell-by-cell.** This two-stage approach generates each table cell individually. The first stage is identical to row-by-row, using prompt 2.B to generate all key column values. Then, we use a separate prompt for each table cell, rather than a full row. For each column $c \in C \setminus C_k$ we create a dedicated prompt to generate the cell $\hat{r}_i[c]$, based on the target column and the generated key for $r_i$. In total, we use $|\hat{R}| \cdot |C \setminus C_k| + 1$ prompts, one to generate the keys, and $|\hat{R}| \cdot |C \setminus C_k|$ to generate each of the non-key cells.

Prompt 3.B in Fig. 2 describes the cell-by-cell method. Given key $\langle$*"European Junior"*, *"1987"*$\rangle$, the corresponding cell in column `venue` is generated (*Birmingham*). The same prompt is then used for different keys and columns (`position`).

**Generated Output Format.** When prompting the LLM it is instructed to return its output in JSON format, as shown in Fig. 2. We chose JSON following past work (Singha et al., 2023) and based on our own results. Namely, we observed a better performance compared to formats such as CSV and SQL when evaluated on our held-out development set (see §4). For the row-by-row and cell-by-cell methods, we process and merge all individual JSON responses to construct the full output table.

## 4 WikiTabGen Benchmark

To evaluate our methods (§3), we introduce a new table generation benchmark called WikiTabGen. Each instance of WikiTabGen consists of a short manually written description $d$, a list of target columns $C$ and a corresponding table $T = (R, C)$. As this benchmark targets LLM table generation based on their parametric knowledge, we followed

**Susen Tiedtke (former long jumper) Achievements**

**WikiTabGen Table Meta Data:**
**Table Description:** *"Susen Tiedtke Achievement Between 1987 and 2000"*
**Key columns:** "Year", "Competition"
**Non-Key Columns:** "Venue", "Position"
**Numeric columns:** "Position" (1 of 2)
**Table size:** 10 rows, 4 columns (40 cells)
**Table Popularity:** 504.5

| Year | Competition | Venue | Position |
|---|---|---|---|
| 1987 | European Junior Championships | Birmingham, England | 3 |
| .... | .... | .... | .... |
| 1993 | World Indoor Championships | Toronto, Canada | 2 |
| 1993 | World Championships | Stuttgart, Germany | 9 |
| .... | .... | .... | .... |
| 2000 | Olympic Games | Sydney, Australia | 5 |

Figure 3: WIKITABGEN example table and metadata.

several key principles in its construction:

- Information Coverage: evaluation tables must contain complete information to prevent cases where the LLM generates correct entries that are not present in the ground-truth tables.
- Factual Consistency: tables should include static factual data, to ensure consistent evaluation over time as LLMs evolve (Zhang and Choi, 2021).
- Conciseness: table cells should contain concise string, categorical or numeric information, to avoid lengthy descriptive text that is harder to evaluate against the ground truth.
- Diversity: the benchmark should include a diverse range of tables with respect to structural properties such as size, data types (e.g., the ratio of numeric data), and table "popularity" which may indicate the prevalence of its content during the LLM's pre-training (Mallen et al., 2022).

Following these principles, we opted to use tables from Wikipedia, as our evaluation benchmark. Wikipedia is often used to assess LLMs' closed-book performance because it contains factual and objective information (Kwiatkowski et al., 2019). unlike certain domain-specific datasets (Yu et al., 2018). Additionally, since Wikipedia is part of LLMs' pre-training data (Brown et al., 2020; Touvron et al., 2023a), it is ideal for evaluating how well these models can generate tabular data.

To construct the benchmark, we iterate over the Wikipedia tables provided by Bhagavatula et al. (2015).[2] We first discarded all non-relational tables (those with composite headers, nested tables, or inverted tables) and excluded tables that were too small ($|R| < 10$ or $|C| < 2$).

Next, we manually selected 119 random tables with diverse number of columns, rows and portion of numeric values (numbers and dates). To ensure evaluation coverage we removed columns with partial entries. In addition, columns containing long texts were omitted to ensure a concise evaluation. Each table was manually annotated with a short, natural language description, as original captions were often ambiguous or not descriptive. Additionally, for tables that could change over time (e.g. new NBA championship teams), we ensured temporal specificity, as suggested by Zhang and Choi (2021), e.g. "*George Clooney Films released between 1983 and 2013*"

As shown in Fig. 3, each table in WIKITABGEN is provided with additional metadata, consisting of its: text description; table size (number of columns, rows and cells); key-columns; numeric columns (containing numbers or dates); and table popularity. Inspired by Mallen et al. (2022), we define table popularity as the average number of monthly views to the Wikipedia page containing the said table. To measure pages views we use the Wikipedia API.[3]

Overall, WIKITABGEN consists of 119 examples, with 100 used for evaluation (§5) and the remaining 19 serving as a held-out development set for method implementation. In Fig. 4 shows the distribution of three key properties in WIKITABGEN: size, numeric column ratio and popularity. On average, the evaluation tables have 77.5 rows, 6.9 columns and 453 cells, with an average length of 1,497 tokens. The average proportion of numeric columns per table is 62% of columns, showcasing the prevalence of numerical data in our tables. The average number of monthly views per table is 8,449. In §6 we further explore the effects of these properties on table generation performance.

## 5 Experimental Setting

We describe our experimental setting for evaluating the table generation capabilities of LLMs. All models were evaluated on the WIKITABGEN benchmark. Next, we list the LLMs, prompts and evaluation methods used for table generation. Last, we detail our different experimental scenarios.

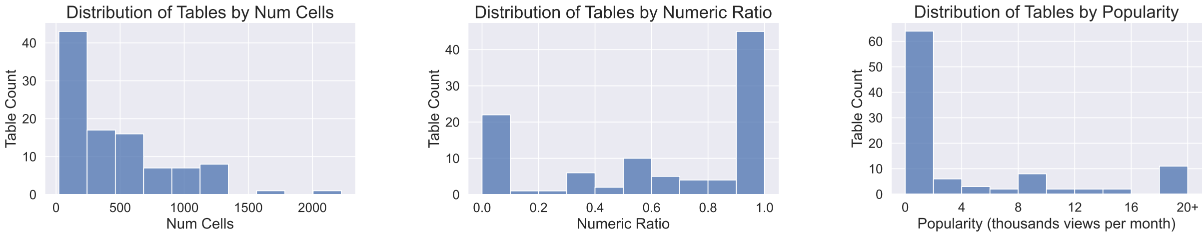
### 5.1 Language Models and Prompts

In our experiments we evaluate 8 popular LLMs: three closed-weights models by OpenAI (Achiam et al., 2023): GPT-4o, GPT-4-Turbo, GPT3.5; four open-weights LLMs by MetaAI (Touvron et al., 2023b): Llama3.1-405B, Llama3.1-70B, Llama2-70B, and Llama2-13B; and Gemma2-27B, an open-weights LLM by Google (Riviere et al., 2024).

The same prompting methods described in §3 were used across all LLMs, whereas prompt-

[2] Creative Commons Attribution 4.0 International License.

[3] `https://api.wikimedia.org`




(a) Number of cells per table

(b) Numeric columns ratio

(c) Table popularity

Figure 4: WIKITABGEN properties distribution: number of cells, ratio of numeric columns, and table popularity.

engineering was done specifically for each model, using the held-out development set as described in §4. For all LLMs, we set the generation temperature to zero.

### 5.2 Evaluation Methods

Since the order of the rows and columns in the generated table may not match the ground truth, we use the following two-step process to evaluate the generation accuracy: We align rows by key attributes, then match non-key cells.

In more detail, given output table $\hat{T}(\hat{R}, C)$ and ground-truth table $T(R, C)$, we first align the rows $\hat{R}$ to their corresponding rows in $R$ by matching their respective keys, namely $\hat{r} \rightsquigarrow r \iff \hat{r}[C_k] = r[C_k]$. For rows with multiple key columns, all values must be identical.

We then use two methods to evaluate the accuracy of cell content: *(1) exact matching*, in which we check for exact match for string content, but allow for a $\pm 0.1\%$ error for numeric content (in §B, we describe how we compare date values and handle null, missing and duplicate cells). *(2) semantic matching*, in which we first apply text-embedding on the generated and gold cell tokens, then compute the cosine similarity between them. We chose a threshold of 0.5 as our criteria for determining whether the two cells are semantically aligned.

For both matching methods we then calculate Table Precision as $\frac{\text{\# Correct Cells}}{\text{\# Generated Cells}}$, and Table Recall as $\frac{\text{\# Correct Cells}}{\text{\# Ground-Truth Cells}}$ and corresponding F1 score.

For our analysis in §6, we also consider the precision, recall, and F1 scores separately for *keys* and *non-keys*. The *keys* scores are calculated based on the number of matching keys, where for each row all the cells of $C_k$ must match. For non-key cell scores we consider only cells in $C \setminus C_k$. We provide the full formulas in Appendix B.

### 5.3 Table Generation Scenarios

In addition to the table generation scenario described in §2, where the generation request contains only the table description and list of columns, we considered two alternative scenarios where additional information is provided to the LLM:

**Table Row Example.** In this scenario, in addition to the description and list of columns, we also provide the LLM with an example row $r[C]$ from the target table. We examine if such an example improves the LLM's performance in generating the rest of the table. We tested this scenario on all prompting methods (§3) by concatenating the first row of the target table to the table description.

**Oracle Keys.** This ablation provides the LLM the ground-truth set of keys cells $R[C_k]$ and measures the model's performance in generating the remaining cells. This scenario is particularly relevant for applications where the keys are known in advance, and the task involves filling in the associated data. We conducted this experiment for both the row-by-row and cell-by-cell prompting methods by skipping the keys generation prompt (prompt 2.B in Fig. 2), and providing the ground-truth keys instead.

## 6 Results and Analysis

Following, we summarize results obtained by the 8 LLMs, 3 prompting methods and two evaluation metrics. We then analyze the generation cost and accuracy trade-offs of the prompting methods. Next, we discuss the table generation performance in our additional scenarios: *example row* and *oracle keys*, and finally, examine the effect of table properties on the LLM generation performance.

### 6.1 Main Results

Tab. 1 provides a comparison of the overall F1 scores for the eight LLMs highlighting the best performing prompting method for each model (using

| LLM | Method | Overall F1 (%) | |
|---|---|---|---|
| | | Exact | Semantic |
| LLaMa3.1-405B | Full table | **23.4** | **25.4** |
| GPT-4o | Row-by-row | 20.8 | 23.1 |
| LLaMa3.1-70B | Full table | 20.0 | 22.1 |
| GPT4-Turbo | Row-by-row | 18.9 | 21.6 |
| GPT3.5-Turbo | Full table | 16.1 | 18.0 |
| LLaMa2-70b | Row-by-row | 9.4 | 10.5 |
| Gemma2-27B | Row-by-row | 7.6 | 8.4 |
| LLaMa2-13b | Full table | 7.5 | 8.4 |

Table 1: Ranking of 8 different LLMs based on their overall F1 score (for both exact and semantic matching of tabe cells). For each LLM we only list only its best performing method.

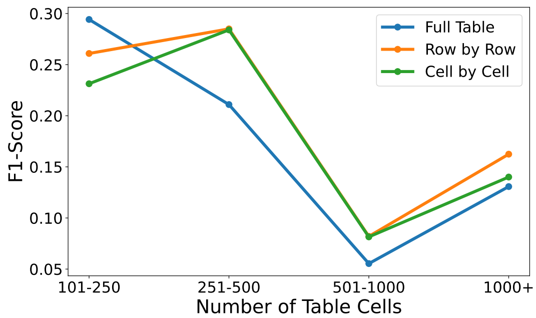



Figure 5: The performance of each prompting method for LLaMa3.1-405B with respect to the table size.

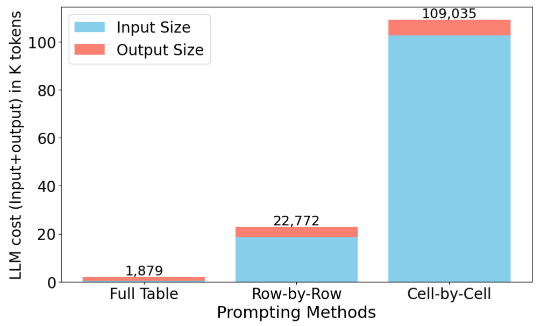



Figure 6: Cost analysis of our prompting methods.

both the exact and semantic evaluation). The top-performing model is LLaMa3.1-405B (full-table), achieving 23.4% and 25.4% F1 using the exact and semantic evaluation respectively.

We note that across all models, the semantic and exact scores are highly correlated, (semantic matching typically being approximately 10% higher than the exact score). We focus through the rest of this section on the semantic evaluation, and the top-4 performing models.

Next, Tab. 2 provides a breakdown of the performance results of the top-4 models. We list the precision, recall, and F1 scores for keys, non-keys, and the full tables (averaged across all tables), obtained for each model and prompting method.

For all LLMs, we observe that the row-by-row and cell-by-cell methods significantly improve the *keys* generation performance (see keys F1 scores in Tab. 2). Interestingly, for the two LLaMa models best performance is obtained with the full-table method, whereas for the GPT models row-by-row prompting obtained better results. Also, observe that the key generation performance is about 3X better than the non-keys, for all models. This demonstrate the inherent difficulty of current LLMs in accurately retrieving the "data" for tabular entities (as identified by the key attributes).

### 6.2 Prompting Cost Tradeoff

We analyze the performance of our prompting methods as a function of their accuracy and cost. As the row-by-row and cell-by-cell methods are suggested to handle larger tables. In Fig. 5 we examine their performance compared to the full-table method, focusing on tables with 100 or more cells on the best performing model, LLaMa3.1-405B. For medium-sized tables (100-250 cells), full-table still outperforms row-by-row. However, as the number of cells increases further, row-by-row outperforms full-table.

Next, to evaluate the cost of the prompting methods, we examine the average number of input and output tokens used for generating tables, as described in Fig. 6. While the output number of tokens is roughly similar for all approaches, see that the two-stage methods (row-by-row and cell-by-cell) have a significantly larger input due to the repeated use of distinct row and cell generation prompts (prompts 3.A, 3.B in Fig. 2).

### 6.3 Additional Generation Scenarios

We measure the effect of providing additional information during table generation: (1) an example row, (2) the ground-truth table keys.

**Table Row Example.** Tab. 3 lists the performance results when including an example row from the target table[4]. Cell-by-cell scores were omitted due to higher costs and inferior performance, as discussed in §6.2. We note that performance consistently improves when the models are given an example first row, except for GPT4-o (row-by-row), which performs slightly better given no example.

[4]As we omit the example row from the F1 calculations our

| LLM | Method | Keys | | | Non-Keys | | | Overall | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Recall | Precision | F1 | Recall | Precision | F1 | Recall | Precision | F1 |
| GPT4-Turbo | Full table | 43.4% | 66.1% | 46.8% | 12.1% | 20.6% | 13.3% | 18.0% | 28.4% | 19.4% |
| | Row-by-row | 53.9% | 57.6% | **53.2%** | 14.9% | 18.5% | **15.3%** | 21.4% | 25.0% | **21.6%** |
| | Cell-by-cell | 53.9% | 57.6% | **53.2%** | 13.5% | 17.0% | 13.8% | 20.1% | 23.6% | 20.2% |
| GPT-4o | Full table | 35.8% | 66.0% | 40.3% | 11.1% | 23.6% | 12.9% | 15.7% | 30.8% | 17.9% |
| | Row-by-row | 53.9% | 60.8% | **53.5%** | 16.3% | 21.3% | **16.8%** | 22.8% | 28.0% | **23.1%** |
| | Cell-by-cell | 53.9% | 60.7% | **53.5%** | 15.8% | 20.6% | 16.3% | 22.3% | 27.3% | 22.5% |
| LLaMa3.1-70B | Full table | 46.1% | 63.8% | 49.9% | 14.3% | 21.4% | **16.0%** | 20.1% | 28.6% | **22.1%** |
| | Row-by-row | 50.2% | 55.5% | **50.0%** | 14.3% | 16.6% | 14.3% | 20.6% | 23.3% | 20.5% |
| | Cell-by-cell | 50.2% | 55.3% | **50.0%** | 13.0% | 14.8% | 13.0% | 19.4% | 21.8% | 19.4% |
| LLaMa3.1-405B | Full table | 44.1% | 68.6% | 48.8% | 17.5% | 29.0% | **19.8%** | 22.7% | 36.0% | **25.4%** |
| | Row-by-row | 50.5% | 61.5% | **51.7%** | 15.1% | 20.4% | 15.9% | 21.2% | 27.4% | 22.1% |
| | Cell-by-cell | 50.4% | 61.4% | 51.6% | 11.8% | 15.5% | 12.3% | 18.7% | 23.7% | 19.3% |

Table 2: Table generation performance metrics for the different models and prompting methods.

| LLM | Method | Keys F1 (%) | | Non-Keys F1 (%) | | Overall F1 (%) | |
|---|---|---|---|---|---|---|---|
| | | No-Example | Example | No-Example | Example | No-Example | Example |
| GPT4-Turbo | Full table | 46.3 | **51.9** | 13.0 | **17.4** | 19.2 | **23.8** |
| | Row-by-row | 53.0 | **54.1** | 15.1 | **16.4** | 21.3 | **22.5** |
| GPT-4o | Full table | 39.7 | **47.1** | 12.6 | **16.3** | 17.7 | **22.0** |
| | Row-by-row | **53.3** | 53.3 | **16.7** | 16.5 | **22.9** | 22.8 |
| LLaMa3.1-70B | Full table | 49.4 | **51.6** | 15.5 | **18.2** | 21.6 | **24.2** |
| | Row-by-row | 49.6 | **51.6** | 14.0 | **16.6** | 20.2 | **22.5** |
| LLaMa3.1-405B | Full table | 47.9 | **50.7** | 19.2 | **25.2** | 24.7 | **29.8** |
| | Row-by-row | 51.0 | **51.9** | 15.5 | **19.9** | 21.6 | **25.6** |

Table 3: Performance comparison with and without an example row, using full table and row-by-row methods.

| LLM | Non-Keys F1 (%) | | Overall F1 (%) | |
|---|---|---|---|---|
| | Base. | Orac. | Base. | Orac. |
| GPT4-Turbo | 11.7 | 22.9 (+11.2) | 18.9 | 39.2 (+20.3) |
| GPT-4o | 13.8 | 26.1 (+12.3) | 20.8 | 41.7 (+20.9) |
| LLaMa3.1-70B | 12.2 | 25.6 (+13.4) | 19.0 | 41.4 (+22.4) |
| LLaMa3.1-405B | 14.1 | 30.9 (+16.8) | 20.7 | 45.5 (+24.8) |

Table 4: Performance comparison of the row-by-row method with and without oracle keys.

**Oracle Keys.** Tab. 4 describes the performance of all LLMs, using the row-by-row method, when given the ground-truth key values. As expected, the overall F1 scores are significantly higher when using oracle keys, because now $\hat{R}[C_k] = R[C_k]$. We observe an additional improvement in the non-keys F1, which is expected as more table rows were aligned to the target table (given the keys), and thus more cells were successfully matched.

### 6.4 Table Properties Effect on Performance

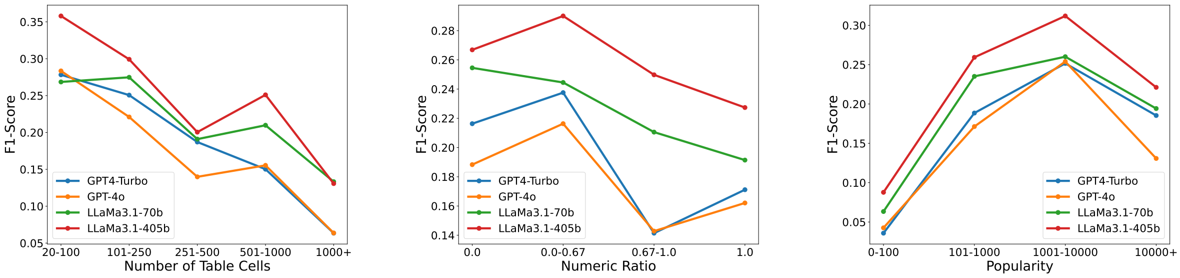
As noted in §4, we systematically measure the effect of table properties such as the size, numeric data and table popularity affect the LLM generation performance.

Fig. 7 displays the table F1 scores as a function of the number of table cells, percentage of numerical data columns (number or date cells) and the table popularity score. These results are provided for all four LLMs, using the full-table generation method. As our aim is to measure the effect each property has on the LLM (not to compare different methods). A further breakdown of the properties' effect on the keys and non-keys F1 scores is provided in Appendix §C.

As shown in Fig. 7a, the larger the table, the lower the F1 scores are for all LLMs. In §6.2 we observed this trend to be less apparent for the row-by-row and cell-by-cell methods.

Fig. 7b measures the effect the percentage of columns containing numbers or dates has on performance. We observe a general decreasing trend in F1 as the portion of numerical content is higher. Fig. 7c displays the positive effect of table popularity on performance. This potentially stems from the prevalence of more popular Wikipedia pages (or related entities) in the LLMs' training data. Unsur-

results slightly differ from Tab. 2.




(a) Table Cells Num. (b) Numeric Cols. % (c) Table Popularity Score

Figure 7: The effect of table size, the ratio of numeric columns, and table popularity on the generation performance (F1 score). The results are of the 4 top performing LLMs and using the full-table prompting method.

prising, the less common the tabular information is, the more difficult it is for the LLM to generate. We attribute the slight decrease in F1 on the top popular tables to an artifact of the data in which these tables include census related data which the LLM have difficulty to generate.

From this analysis, we conclude that generating tables from LLMs' parametric knowledge is more challenging when the tables are larger, when they contain a higher portion of numerical data and when its content concerns less popular topics.

## 7 Related Work

Machine reasoning on table using pre-trained LLMs has largely been explored in the context of data augmentation (Borisov et al., 2022; Zhang et al., 2023) to improve the performance on downstream tasks. The focus has largely been on tasks where a table is provided as input to the model namely: QA over tables (Chen et al., 2020, 2022; Seedat et al., 2023), text-to-SQL translation (Deng et al., 2021; Wolfson et al., 2022), table editing (Li et al., 2023; Sui et al., 2023) and table-to-text generation (Parikh et al., 2020). Conversely, our approach receives only a user query and schema as input, and is tasked with generating an entire table.

Closest to ours are the recent table generation datasets by Pal et al. (2023); Akhtar et al. (2024); Tang et al. (2024). In these works the LLM is provided with a user query (in text or SQL) and is tasked with generating a table, as the query answer. Pal et al. (2023) evaluate on tables from the Spider dataset (Yu et al., 2018), which contains domain-specific information that is less likely to be stored in the parametric knowledge of LLMs. In Tang et al. (2024) the authors evaluate table generation from long-form text describing NBA games, taken from the RotoWire dataset (Wiseman et al., 2017). In their setting the generated table content is already present as part of the user query, where the LLM challenge is to re-structure the user input as a table. By contrast, our setting requires the LLM to generate information that does not explicitly appear in the user input query (Fig. 1). Similar to us, Akhtar et al. (2024) rely on Wikipedia however, they automatically construct new tables which are relatively small (average of 6.7 rows, 4 columns). By comparison our evaluation is on larger tables with the median number of rows being 48 (average of 77.5 rows, 6.9 columns). This emphasizes our focus on extracting long-form tabular data from LLMs, thereby extending past attempts on KBs and text (Cohen et al., 2023; Mallen et al., 2022; Carlini et al., 2022).

Our key generation phase in §3 is an instance of a list question answering problem. The challenge of list QA in LLMs has been explored in recent works (Amouyal et al., 2022; Malaviya et al., 2023). However, we further expand this challenge by focusing on generating the entire table.

## 8 Conclusion

This paper explores the capability of state-of-the-art LLMs to generate entire tables, by relying exclusively on their parametric knowledge. We introduced three prompt-based table generation methods and evaluated them on our newly constructed benchmark, WIKITABGEN. Our results underscore the challenge table generation poses to LLMs. We hope that WIKITABGEN and our comprehensive analysis will provide a concrete framework for future research on table generation using LLMs.

## 9 Limitations

We now list the limitations to our work.

Our first limitation is the size of the WIKITABGEN evaluation benchmark, which contains 119 tables. We attribute this constraint to the intensity of the manual processing required to ensure the tables' factual correctness and robustness as well as to the high generation costs of running state-of-the-art LLMs on large tables §6.2. As noted in §4, the tables in WIKITABGEN contain close to 1,500 tokens on average, evaluating them using commercial, state-of-the-art LLMs is non-trivial.

Second, all tables in WIKITABGEN are based on Wikipedia articles. This choice was made to ensure that the underlying information exists in common LLMs training data. However, we did not examine the performance on tables generated from other sources, such as news articles or tables that require multi-source integration.

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# A Table Generation Prompts

In this section we provide the prompt templates used in each of our table generation methods. Figs. 8-11 present our prompt templates used for: full table generation method, keys generation, row-by-row, and cell-by-cell method.

# B Evaluation Method Details

## B.1 Precision-Matching of Cell Values

We next describe our precision matching for cell values in more detail, given an output table $\hat{T}(\hat{R},C)$ and ground-truth table $T(R,C)$.

As described in §5.2, we use *exact* value comparison of cell textual content and allow a $\pm 0.1\%$ error for numeric values. Before comparing textual cells, we first convert them to lower case, and remove non alphanumeric symbols and spaces.

As for date values, we first parse and convert cells with date values to a Python Date object, and then compare the canonical dates. This is to avoid cases where cells are deemed as a non-match due to differences in the date format. For example, in our evaluation process, two date values representing the same date, such as "2014-05-16" and "16th, May, 2014", will be considered the same.

We further treat “none”, “n/a” ,“nan” and empty cells as identical in terms of value matching.

## B.2 Precision and Recall Computation for Tables

For a given output table $\hat{T}(\hat{R},C)$ and ground-truth table $T(R,C)$, we first align the rows $\hat{R}$ to their corresponding rows in $R$ by matching their respective keys, namely $\hat{r} \rightsquigarrow r \iff \hat{r}[C_k] = r[C_k]$. For rows with composite keys, all key values must be identical, i.e., $\forall c_k \in C_k \hat{r}[c_k] = r[c_k]$.

Recall that a *correct* cell in $T(\hat{R},C)$ is a cell $\hat{r}[c]$ such that $\hat{r}[c] \approx r[c] \wedge \hat{r} \rightsquigarrow r$. Namely, row $\hat{r}$ is aligned with a row $r$ in the ground-truth table, and their corresponding cell values in column $c$ is matching (using either the precision or semantic matching definition).

We next provide the precision and recall formulas we used for keys, non-keys, and tables.

For keys, we compare $\hat{R}[C_k]$ and $R[C_k]$ as follows. Let the number of matching keys $\phi = |\{r \in \hat{R}, \forall c_k \in C_k \; \hat{r}[c_k] = r[c_k]\}|$ Then *keys precision* is calculated by $\frac{\phi}{|\hat{R}|}$ and *keys recall* is given by $\frac{\phi}{|R|}$.

For non-keys, we compare $\hat{R}[C \setminus C_k]$ and $R[C \setminus C_k]$. After aligning $\hat{R}$ and $R$, we compute the num-

**Full-table generation template:**
You are a retriever of facts. List all `{table description}`. The response will be formatted as JSON shown below. Each element of the response will contain `{num columns}` fields: `{column1, column2, ...}`
Do not output any additional text that is not in JSON format.
RESPONSE FORMAT: [{ `column1: value1, column2: value2, ...` }]

**Full-table generation (populated example):**
You are a retriever of facts. List all achievements of Susen Tiedtke from 1987 to 2000. The response will be formatted as JSON shown below. Each element of the response will contain 4 fields: ['year', 'competition', 'venue', 'position']. Do not output any additional text that is not in JSON format.
RESPONSE FORMAT: [{ "year": _year, "competition": _competition, "venue": _venue, "position": _position }]

Figure 8: Full-table generation prompt.

**Keys generation template:**
You are a retriever of facts. We want to create a table with the detailed information about `{table description}`. The key columns in the table are `{key1, (key2, ...)}`. List all `{key1, (key2, ...)}` entities for the table. The response will be formatted as JSON list shown below.
RESPONSE FORMAT: [{ `key: value1, key2: value2, ...` }]

**Keys generation (populated example):**
You are a retriever of facts. We want to create a table with the detailed information about achievements of Susen Tiedtke from 1987 to 2000. The key columns in the table are competition, year. List all competition, year entities for the table. The response will be formatted as JSON list shown below.
RESPONSE FORMAT: [{ "competition": _competition, "year": _year }]

Figure 9: Key columns generation prompt.

ber of *correct* keys, denoted by $\psi = |\{(r,c), r \in \hat{R} \wedge c \in C \setminus C_k \wedge r \rightsquigarrow \hat{r} \wedge \hat{r}[c] = r[c]\}|$. Then the *non-keys precision* is calculated by $\frac{\psi}{|\hat{R}[C \setminus C_k]|}$ and *non-keys recall* is calculated by $\frac{\psi}{|R[C \setminus C_k]|}$.

Last, for the table precision and recall, we perform a similar evaluation, now defining the number of correct cells, denoted by $\tau$, as all correct cells in the table. Namely, $\tau = |\{(r,c), r \in \hat{R} \wedge c \in C \wedge r \rightsquigarrow \hat{r} \wedge \hat{r}[c] \approx r[c]\}|$, then the *table precision* is simply calculated by $\frac{\tau}{|\hat{R}[C]|}$ and *table recall* is calculated by $\frac{\tau}{|R[C]|}$.

## C Table Properties Effect on Performance

In §6.4 we examine how the table properties such as the size, amount of numeric data, and table popularity affect the generation performance. In Fig. 12 we present the effect of these three properties on both the keys F1, non-keys F1, and full table F1. We can see, for instance, that the table size negatively affects both the keys F1 and the non-keys F1 scores (see Fig. 12 (a) and Fig. 12 (b)), and the ratio of numeric columns has a negative effect, as expected, only the non-keys F1 (see Fig. 12 (e)). The table popularity also have a strong effect on both the keys F1 and the non-keys F1 (Fig. 12 (g) and Fig. 12 (h)).

**Row generation template:**
You are a retriever of facts. We want to create a table with the detailed information about `{table description}`. Columns in the table are `{columns}`. The key columns in the table are `{key1, (key2, ...)}`. Retrieve a single row whose key is `({key = value})`. The response will be formatted as JSON dictionary shown below. Pay special attention to wrap all values in double quotes!
RESPONSE FORMAT: [{ `column1: value1, column2: value2, ...` }]

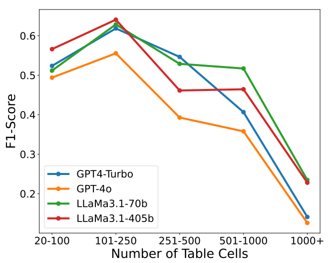
**Row generation (populated example):**
You are a retriever of facts. We want to create a table with the detailed information about achievements of Susen Tiedtke from 1987 to 2000. Columns in the table are year, competition, venue, position. The key columns in the table are competition, year. Retrieve a single row whose key is (year = 1987, competition = World Championships). The response will be formatted as JSON dictionary shown below. Pay special attention to wrap all values in double quotes!
RESPONSE FORMAT: { "year": 1987, "competition": World Championships, "venue": _venue, "position": _position }

Figure 10: Row-by-row (row generation) prompt.

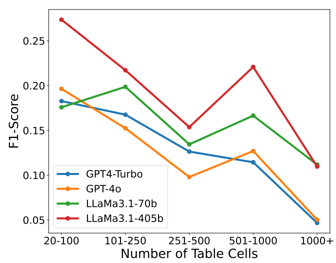
**Cell generation template:**
You are a retriever of facts. We want to create a table with the detailed information about `{table description}`. Columns in the table are {`column1`, `column2`, ...}. The key columns in the table are `{key1, (key2, ...)}`. For the table row whose key is is `({key = value})` what is the value of attribute `{column}`. The response will be formatted as JSON dictionary shown below. Pay special attention to wrap all values in double quotes!
RESPONSE FORMAT: { `column: value` }

**Cell generation (populated example):**
You are a retriever of facts. We want to create a table with the detailed information about achievements of Susen Tiedtke from 1987 to 2000. Columns in the table are year, competition, venue, position. The key columns in the table are competition, year. For the table row whose key is (year = 1987, competition = World Championships) what is the value of attribute venue. The response will be formatted as JSON dictionary shown below. Pay special attention to wrap all values in double quotes!
RESPONSE FORMAT: { "venue": _venue }

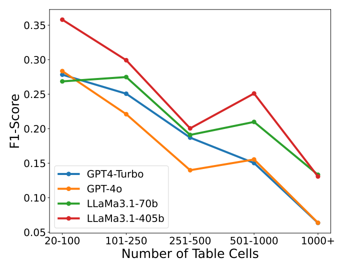
Figure 11: Cell-by-cell (cell generation) prompt.



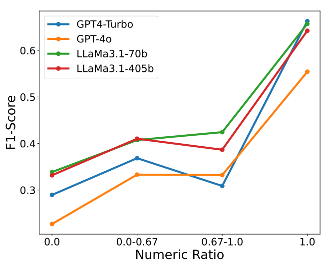

(a) Table Cells Num. - Keys F1



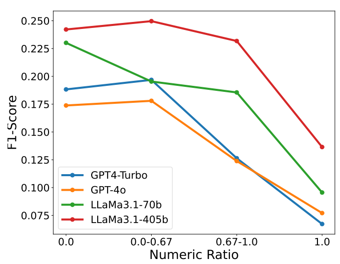

(b) Table Cells Num. - Non-Keys F1



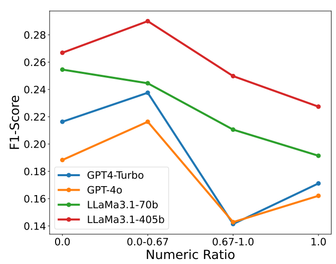

(c) Table Cells Num. - Table F1



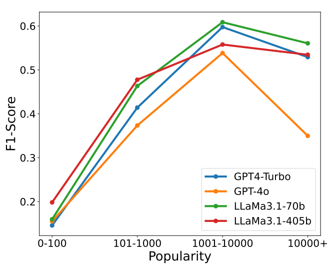

(d) Numeric Cols. % - Keys F1



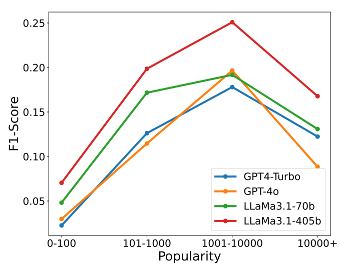

(e) Numeric Cols. % - Non-Keys F1



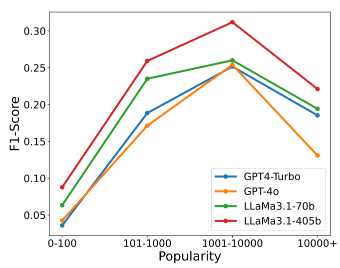

(f) Numeric Cols. % - Table F1




(g) Table Popularity - Keys F1




(h) Table Popularity - Non-Keys F1




(i) Table Popularity - Table F1

Figure 12: The effect of table size, the ratio of numeric columns, and table popularity on the generation performance of the full-table method, with four different LLMs. Additional breakdown of generation performance based on cells in key columns versus non-key columns.