ITUNLP at SemEval-2025 Task 8: Question-Answering over Tabular Data: A Zero-Shot Approach using LLM-Driven Code Generation

Atakan Site[*†]**, Emre Hakan Erdemir**[*]**, Gülşen Eryiğit**
Department of Artificial Intelligence and Data Engineering
Istanbul Technical University
{site21, erdemire21, gulsenc}@itu.edu.tr

Abstract

This paper presents our system for SemEval-2025 Task 8: DataBench, Question-Answering over Tabular Data. The primary objective of this task is to perform question answering on given tabular datasets from diverse domains under two subtasks: DataBench QA (Subtask I) and DataBench Lite QA (Subtask II). To tackle both subtasks, we developed a zero-shot solution with a particular emphasis on leveraging Large Language Model (LLM)-based code generation. Specifically, we propose a Python code generation framework utilizing state-of-the-art open-source LLMs to generate executable Pandas code via optimized prompting strategies. Our experiments reveal that different LLMs exhibit varying levels of effectiveness in Python code generation. Additionally, results show that Python code generation achieves superior performance in tabular question answering compared to alternative approaches. Although our ranking among zero-shot systems is unknown at the time of this paper's submission, our system achieved eighth place in Subtask I and sixth place in Subtask II among the 30 systems that outperformed the baseline in the open-source models category.

1 Introduction

Question Answering (QA) is a fundamental task in Natural Language Processing (NLP), where the most relevant answers are retrieved from a given document or plain text. Apart from such unstructured data, working with widely used structured data is crucial for real-world applications. Moreover, structured data encompasses a much broader semantic scope. One important form of structured data is tabular data, which consists of rows with a consistent set of features. Unlike unstructured documents, tabular data exhibits complex and heterogeneous relationships that require specialized

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[*]These authors contributed equally.
[†]Corresponding author.

processing techniques. Information retrieval from tabular data is typically performed using various SQL queries and similar approaches. However, these methods depend on rigid rule-based systems and fail to consider the semantic properties of the data. Consequently, natural-language queries over tabular data face significant limitations. As a result, question-answering systems developed for tabular data have garnered significant interest among researchers.

The process of converting a natural language query into a machine-executable logical form is known as semantic parsing (Wang et al., 2015). Early studies primarily focused on datasets that required adapting specific logical forms for each table structure type. This approach, however, led to suboptimal performance, particularly in tabular structures spanning multiple domains (Pasupat and Liang, 2015). On the other hand, end-to-end trained transformers are widely employed, as they handle both question/query interpretation and reasoning over tabular data (Deng et al., 2020). The recent advancements in LLMs have become a pivotal focus in tabular question answering, as in many other problem domains. However, LLM-based approaches introduce several challenges, including high computational costs and limited context length, making scalable and efficient tabular QA systems an open research problem. To address these challenges and foster the development of effective tabular question-answering methods, SemEval-2025 Task 8 (Osés Grijalba et al., 2025) has been designed to introduce the necessary level of difficulty through two distinct subtasks.

In this paper, we propose a zero-shot system to address these tasks, focusing primarily on LLM-based code generation. Our approach introduces a unified framework leveraging state-of-the-art open-source LLMs, including DeepSeek-R1 (DeepSeek-AI et al., 2025a), DeepSeek-V3 (DeepSeek-AI et al., 2025b), Qwen2.5-Coder-32B-

Instruct (Hui et al., 2024), and Llama-3.3-70B-Instruct (AI@Meta, 2024). We employ efficient prompting strategies to generate executable Python Pandas[1] library code. To enhance LLM understanding of tabular structures, the generated Python code is executed in a controlled environment. A key feature of our system is its iterative error-handling mechanism. If the initial code execution fails, the error message and faulty code are sent back to the LLM for correction, with a maximum of two iterations. This mechanism significantly improves robustness, reducing failure rates in complex queries.

We observe that one model in our pipeline achieves the highest accuracy on Subtask I (84.67%), while another leads Subtask II (85.05%), both without task-specific fine-tuning. All code is available on our GitHub repository[2].

2 Related Work

This section reviews recent developments in LLMs, focusing on their applications in tabular question answering.

In recent years, the emergence of the Transformer architecture (Vaswani et al., 2017) has led to remarkable advancements in language modeling tasks. This progress has resulted in state-of-the-art performance across various NLP tasks. Consequently, the application of transformer architectures to problems requiring tabular modeling has become inevitable. Early studies primarily focused on different embedding mechanisms (Yin et al., 2020), pre-training strategies (Wang et al., 2021), and architectural modifications (Huang et al., 2020). The core approach introduced by these methods was pre-training Transformer architectures from scratch for tabular data (Herzig et al., 2020). However, this approach faces efficiency and scalability limitations, particularly when models need to generalize across multiple domains. Generally, pre-trained language models struggle to adapt efficiently to task-specific tabular datasets.

More recently, the emergence of LLMs has brought about a significant transformation in the field. Models such as GPT-3 (Brown et al., 2020) and LLaMa (Touvron et al., 2023) have demonstrated strong few-shot and zero-shot capabilities, achieving state-of-the-art performance across various tasks while often requiring little to no task-specific data. These advancements have enabled the use of a single, unified model for solving complex tabular tasks. The transition from training models from scratch or adapting pre-trained language models to leveraging LLMs represents a significant paradigm shift in tabular data processing. However, the application of LLMs to tabular question answering introduces several challenges. One major limitation is the context length constraint inherent to LLMs. When processing large or multiple tables, the limited context size prevents the model from encoding all necessary information. Additionally, handling multiple tables often leads to hallucinations, where models generate inaccurate or misleading responses.

To overcome these limitations, researchers have leveraged the in-context learning capabilities of LLMs. The effectiveness of LLM-based approaches largely depends on how tabular data and question queries are represented and utilized. For tabular data, appropriate table schemas and prompting strategies incorporating relevant examples are designed to enhance model comprehension. Query representation can also significantly impact performance. A common strategy involves decomposing complex queries into step-by-step subqueries, improving model interpretability (Yang et al., 2024). Another approach is transforming queries into intermediate representations such as Python code or SQL queries, enabling structured execution (Cao et al., 2023; Zhang et al., 2024). These advancements have led to models capable of performing task-specific reasoning without requiring additional fine-tuning.

Building on insights from previous studies, we find that effectively addressing SemEval-2025 Task 8 requires a deep understanding of query semantics and table structures, as well as the ability to generate accurate answers across diverse answer formats. Motivated by these challenges, we introduce a novel framework that integrates schema-guided prompting, controlled execution, and an error-handling mechanism. Our extensive evaluations and prompt strategy experiments highlight the effectiveness of our approach in enhancing accuracy and robustness. These findings show the practicality and applicability of the proposed approach in real-world scenarios, where tabular data must be processed dynamically without requiring task-specific fine-tuning.
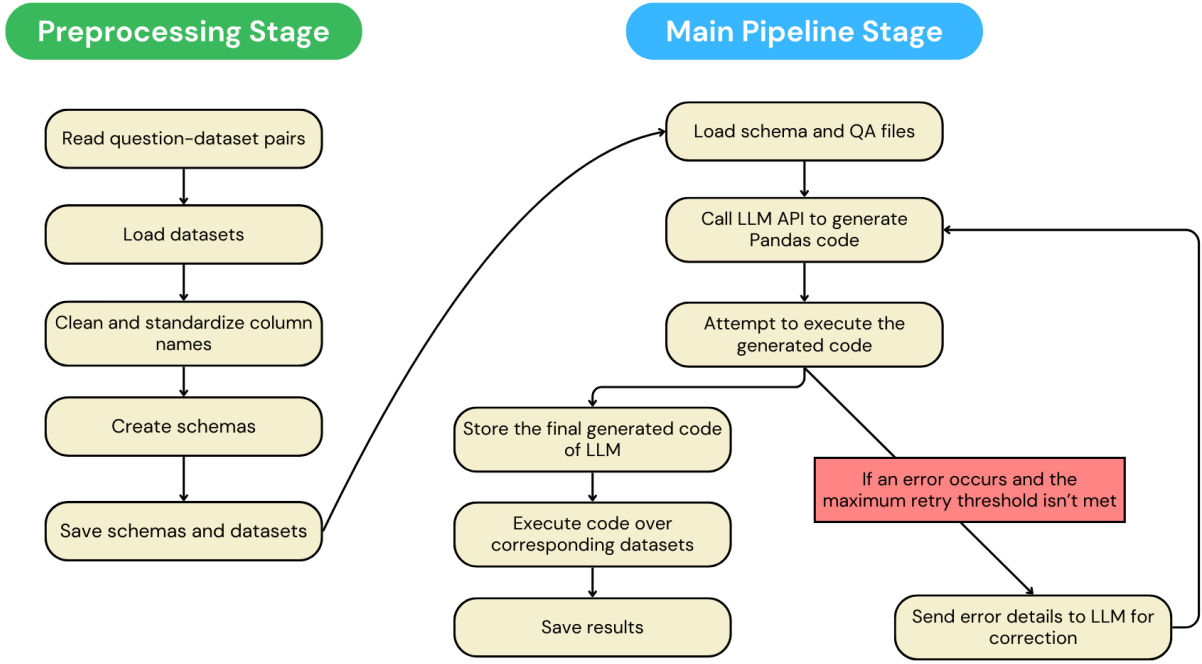
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[1] https://pandas.pydata.org/
[2] https://github.com/erdemire21/semeval8-itunlp

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Figure 1: Our proposed framework.

3 Data

The original DataBench dataset (Osés Grijalba et al., 2024) provides 1308 questions from 65 different domains, each containing question-answer pairs written in English. During the competition, this dataset was expanded with the addition of a new test split (Osés Grijalba et al., 2025). The exact dataset statistics are presented in Table 1. The train and development splits contain the following columns:

- **question**: The natural language question.
- **answer**: The response to the question for DataBench QA subtask.
- **type**: The type of the answer, which can be **boolean, number, category, list[category], list[number]**.
- **columns_used**: The columns of the dataset required to answer the question.
- **column_types**: The data types of these columns, which include boolean, number (e.g., UInt8, uint32, uint16).
- **sample_answer**: The response to the question for DataBench Lite QA subtask.
- **dataset**: The name of the dataset from which the question is derived.

The sample_answer column is specifically included for the DataBench QA Lite subtask, which is a simplified version of the DataBench QA task. This subset consists of 20 sampled entries from the

Split	Questions	Datasets
Train	988	49
Dev	320	16
Test	522	15

Table 1: DataBench dataset statistics.

original dataset, serving as a small-scale reference for evaluation.

In contrast to these extensively annotated train and development splits, the test split only has question and dataset columns to ensure proper evaluation without data leak for the competition.

Although the dataset provides structured train and development splits with detailed annotations, this study did not utilize these data for training, as we preferred a zero-shot approach that does not involve fine-tuning.

4 System Overview

Our approach involves two main steps in providing an answer to questions over tabular data: preprocessing and then code generation and execution. The complete workflow is illustrated in Figure 1.

4.1 Preprocessing

Our preprocessing steps include obtaining the given questions and datasets from the competition website, followed by a series of normalization and standardization techniques, and finally creating a

schema for each dataset for LLM prompting. Each dataset is transformed with transformation rules. First, all spaces and non-word characters are replaced with underscores except for trailing special characters, which are removed. Second, all column names are converted to lowercase, and duplicate columns are renamed by appending a number to each duplicate. For example, if there are two cols named "col" and "Col@", the second one becomes "col_2".

After normalization and standardization, we construct a schema for each dataset to enhance the LLM's understanding of the table structure. The schemas include each dataset's name, each column, each column's data type, 5 unique values from each column, and the total unique values that a column contains. The example values are limited to a hundred characters total to avoid excessive verbosity and potential token overload. Examples of the constructed schemas can be seen in Appendix A, (e.g., see the schema for the TripAdvisor dataset in Appendix A.1). We use the full dataset for schema creation for both full and sample datasets.

4.2 Code Generation and Execution

The code generation step is done with a prompt that includes the question, detailed instructions and the corresponding dataset schema. A detailed breakdown of the code generation prompt is provided in Appendix B. The generated code is executed in a controlled environment, where dynamic imports are extracted, and the execution output is captured in its original format. In cases where execution fails, an error handling mechanism is triggered. The system captures the error message along with the faulty code and sends it to the LLM for automatic correction. The LLM then generates a revised version of the code. This iterative process is run until the predefined threshold is met. If the provided code is still faulty after the maximum number of attempts, execution is terminated for that query. The execution result from the last successfully executed code is then set as the final answer for the corresponding question.

5 Experimental Setup

Our zero-shot framework was tested on the officially released development and test datasets of SemEval 2025 Task 8, covering its two subtasks (Osés Grijalba et al., 2025). The models used in our system were selected based on their performance in

code generation tasks, ensuring their effectiveness in handling structured and semi-structured tabular question answering. Additionally, we opted for a maximum of two iterations based on preliminary experiments, which showed that attempts beyond two iterations rarely produced further improvements. To provide a more comprehensive error analysis, we also conducted additional experiments with three iterations. To evaluate system performance, we used Accuracy, the official evaluation metric of SemEval 2025 Task 8. Furthermore, we analyzed the impact of our iterative error-handling mechanism on execution reliability by measuring error reduction rates across different models. These evaluations provide insights into both models accuracy and execution robustness in tabular question answering.

6 Results

The performance of the models is presented in Table 2. Our results indicate that one of the DeepSeek models (i.e., DeepSeek-R1 and DeepSeek-V3) outperforms all other models across both subtasks. We see that DeepSeek-V3 falls behind all the others on the development sets, but performs better specifically on the test set of Subtask I. DeepSeek-R1, which is a subsequent iteration, building upon V3 with enhanced capabilities via reinforcement learning, outperforms Qwen2.5-Coder-32B-Instruct and Llama-3.3-70B-Instruct models on all tasks and datasets, falling behind DeepSeek-V3 by 0.52 percentage points on the Subtask I test set.

Moreover, in the official evaluation within the open-source models category, our best-performing model ranked eighth in Subtask I and sixth in Subtask II, placing among the 30 systems that outperformed the baseline. These results further highlight the effectiveness of our approach in zero-shot tabular question answering. At the time of this paper's submission, due to a lack of information on other solutions, we were unable to evaluate our performance relative to other zero-shot systems in the competition. Through our manual observations, we identified that the test datasets are significantly more challenging. However, we do not believe that every question-answer pair in these datasets can perfectly represent the real-world performance of the models. Nonetheless, the widening performance gap in the more challenging test sets suggests that DeepSeek-R1 may generalize to the problem more effectively, providing evidence of its

Models	Subtask I (DataBench)		Subtask II (DataBench Lite)	
	Dev	**Test**	**Dev**	**Test**
DeepSeek-R1	**88.43**	84.09	**86.56**	**85.05**
DeepSeek-V3	82.50	**84.67**	78.75	80.84
Qwen2.5-Coder-32B-Instruct	87.18	83.90	85.31	81.99
Llama-3.3-70B-Instruct	86.56	83.14	82.81	81.03

Table 2: Results on the DataBench subtasks across all models.

Models	Dev Set	Test Set
DeepSeek-R1	$9 \rightarrow 6$	$15 \rightarrow 7$
DeepSeek-V3	$35 \rightarrow 11$	$18 \rightarrow 9$
Qwen2.5-Coder-32B-Instruct	$11 \rightarrow 9$	$25 \rightarrow 8$
Llama-3.3-70B-Instruct	$16 \rightarrow 5$	$16 \rightarrow 10$

Table 3: The change in the amount of code execution errors before and after the error fixing loop.

superior adaptability.

In addition, as shown in Table 3, our error handling mechanism decreases the number of execution errors by nearly half on average, demonstrating not only its effectiveness but also its necessity for ensuring reliable execution. It should be noted that the initial error rate and the accuracy over both tasks show a strong correlation, with models that achieve higher accuracy also generating less faulty code to begin with. This suggests that better-performing models inherently produce more reliable code, thereby reducing the need for iterative error correction loops and improving overall execution efficiency.

To analyze error patterns and the impact of our correction mechanism in greater detail, we grouped errors into three main categories: Runtime, Degenerate Loop, and Syntax. Notably, the Runtime category includes diverse errors such as KeyError and ValueError, but for simplicity, we report them under a single label. Our findings also indicate that some errors transform into different types across iterations.

We define Degenerate Loop errors as cases where an LLM repeatedly generates identical or nearly identical output sequences, continuing indefinitely until it reaches its maximum token limit.

Table 4 presents the distribution of error types across models and iterations. Results show that most initial failures are due to Runtime errors, while Syntax and Loop errors are less frequent but may persist across multiple correction attempts. Specifically, Syntax errors are observed exclusively in DeepSeek-R1 and DeepSeek-V3 models, with

no such errors detected for Llama-3.3-70B-Instruct or Qwen2.5-Coder-32B-Instruct across any dataset or iteration.

Similarly, Degenerate Loop errors are observed solely in DeepSeek-R1 and DeepSeek-V3, with no occurrences in Llama-3.3-70B-Instruct or Qwen2.5-Coder-32B-Instruct. As shown in Figures 2 and 3, although some Degenerate Loop errors are corrected, a notable portion still results in failures.

Finally, Figure 2 provides an overview of error resolution across iterations, showing that most runtime errors are resolved within the first two attempts. Figure 3 further breaks down specific error types, such as FileNotFoundError, KeyError, and NameError, offering a more fine-grained view.

7 Conclusions

In conclusion, this paper presented the solution developed by the ITUNLP group for SemEval-2025 Task 8. The proposed approach addressed the tabular question answering task in zero-shot scenarios. Our method yields promising results in zero-shot tabular question answering, achieving higher ranks (8th place in Subtask I and 6th in Subtask II) within the 30 participant systems in the open-source category. Since these 30 systems may have employed fine-tuning or few-shot learning techniques, further analysis would be possible upon the publication of the system description papers that achieved better results on the same category of the shared task, which will provide a clearer understanding of our ranking within zero-shot frameworks.

As this study focuses only on open-source LLMs, future work could include evaluating proprietary LLMs within our proposed framework to gain a broader perspective on model performance. Furthermore, the DataBench dataset consists of questions that require using only a single table. As future work, we aim to evaluate our zero-shot model's performance on multi-table reasoning tasks, further expanding its applicability.

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Appendix

A Example Schemas

A.1 `067_TripAdvisor`

```
"Here are the columns for the dataset
Column Name: ratings, Data type -- object, -- Example values: {'service': 5.0, '
    cleanliness': 5.0, 'overall': 5.0, 'value': 4.0, 'location': 5.0, 'sleep_qualit
    ..., Total unique elements: 5530
Column Name: title, Data type -- category, -- Example values: ``Very nice experience
     for a country boy going to town'', Total unique elements: 17747
Column Name: text, Data type -- object, -- Example values: Being from a small town
    in Tennessee, I was very unsure of what to expect from the large city hot...,
    Total unique elements: 20000
Column Name: author, Data type -- object, -- Example values: {'username': 'Tucker124
    ', 'num_reviews': 1, 'id': '39AA7B174D045F1E2BAE8A398D00BBC2', 'location':...,
    Total unique elements: 17995
Column Name: date_stayed, Data type -- category, -- Example values: October 2010,
    October 2009, September 2007, February 2012, Total unique elements: 121
Column Name: offering_id, Data type -- uint32, -- Example values: 111492, 108562,
    94354, 98798, 93889, Total unique elements: 2651
Column Name: num_helpful_votes, Data type -- uint8, -- Example values: 2, 0, 1, 3,
    5, Total unique elements: 40
Column Name: date, Data type -- datetime64[ns, UTC], -- Example values: 2010-10-25
    00:00:00+00:00, 2009-10-14 00:00:00+00:00, 2007-10-20 00:00:00+00:00, Total
    unique elements: 3082
Column Name: id, Data type -- uint32, -- Example values: 84800976, 46861760,
    10172355, 124329781, 69904714, Total unique elements: 20000
Column Name: via_mobile, Data type -- bool, -- Example values: False, True, Total
    unique elements: 2"
```

A.2 `069_Taxonomy`

```
Here are the columns for the dataset
Column Name: unique_id, Data type -- float64, -- Example values: 150.0, 151.0,
    179.0, 181.0, 153.0, Total unique elements: 672
Column Name: parent, Data type -- category, -- Example values: 150, 1, 2, 37, 16,
    Total unique elements: 85
Column Name: name, Data type -- category, -- Example values: Attractions, Amusement
    and Theme Parks, Bars & Restaurants, Total unique elements: 703
Column Name: tier_1, Data type -- category, -- Example values: Attractions,
    Automotive, Books and Literature, Business and Finance, Total unique elements:
    40
Column Name: tier_2, Data type -- category, -- Example values: Amusement and Theme
    Parks, Bars & Restaurants, Casinos & Gambling, Total unique elements: 347
Column Name: tier_3, Data type -- category, -- Example values: Commercial Trucks,
    Convertible, Coupe, Crossover, Hatchback, Total unique elements: 256
Column Name: tier_4, Data type -- category, -- Example values: Angel Investment,
    Bankruptcy, Business Loans, Debt Factoring & Invoice Discounting, Total unique
    elements: 60
Column Name: unnamed_7, Data type -- category, -- Example values: SCD, Total unique
    elements: 1"
```

A.3 076_NBA

```
Here are the columns for the dataset
Column Name: year, Data type -- category, -- Example values: 2012-13, 2013-14,
    2014-15, 2015-16, 2016-17, Total unique elements: 12
Column Name: season_type, Data type -- category, -- Example values: Regular%20Season
    , Playoffs, Total unique elements: 2
Column Name: player_id, Data type -- uint32, -- Example values: 201142, 977, 2544,
    201935, 2546, Total unique elements: 1572
Column Name: rank, Data type -- uint16, -- Example values: 1, 2, 3, 4, 5, Total
    unique elements: 546
Column Name: player, Data type -- category, -- Example values: Kevin Durant, Kobe
    Bryant, LeBron James, James Harden, Carmelo Anthony, Total unique elements: 1568
Column Name: team_id, Data type -- uint32, -- Example values: 1610612760,
    1610612747, 1610612748, 1610612745, 1610612752, Total unique elements: 30
Column Name: team, Data type -- category, -- Example values: OKC, LAL, MIA, HOU, NYK
    , Total unique elements: 31
Column Name: gp, Data type -- uint8, -- Example values: 81, 78, 76, 67, 82, Total
    unique elements: 84
Column Name: min, Data type -- uint16, -- Example values: 3119, 3013, 2877, 2985,
    2482, Total unique elements: 2474
Column Name: fgm, Data type -- uint16, -- Example values: 731, 738, 765, 585, 669,
    Total unique elements: 697
Column Name: fga, Data type -- uint16, -- Example values: 1433, 1595, 1354, 1337,
    1489, Total unique elements: 1263
Column Name: fg_pct, Data type -- float64, -- Example values: 0.51, 0.463, 0.565,
    0.438, 0.449, Total unique elements: 500
Column Name: fg3m, Data type -- uint16, -- Example values: 139, 132, 103, 179, 157,
    Total unique elements: 274
Column Name: fg3a, Data type -- uint16, -- Example values: 334, 407, 254, 486, 414,
    Total unique elements: 598
Column Name: fg3_pct, Data type -- float64, -- Example values: 0.416, 0.324, 0.406,
    0.368, 0.379, Total unique elements: 386
Column Name: ftm, Data type -- uint16, -- Example values: 679, 525, 403, 674, 425,
    Total unique elements: 447
Column Name: fta, Data type -- uint16, -- Example values: 750, 626, 535, 792, 512,
    Total unique elements: 541
Column Name: ft_pct, Data type -- float64, -- Example values: 0.905, 0.839, 0.753,
    0.851, 0.83, Total unique elements: 552
Column Name: oreb, Data type -- uint16, -- Example values: 46, 66, 97, 62, 134,
    Total unique elements: 292
Column Name: dreb, Data type -- uint16, -- Example values: 594, 367, 513, 317, 326,
    Total unique elements: 616
Column Name: reb, Data type -- uint16, -- Example values: 640, 433, 610, 379, 460,
    Total unique elements: 774
Column Name: ast, Data type -- uint16, -- Example values: 374, 469, 551, 455, 171,
    Total unique elements: 573
Column Name: stl, Data type -- uint8, -- Example values: 116, 106, 129, 142, 52,
    Total unique elements: 165
Column Name: blk, Data type -- uint16, -- Example values: 105, 25, 67, 38, 32, Total
     unique elements: 181
Column Name: tov, Data type -- uint16, -- Example values: 280, 287, 226, 295, 175,
    Total unique elements: 296
Column Name: pf, Data type -- uint16, -- Example values: 143, 173, 110, 178, 205,
    Total unique elements: 276
Column Name: pts, Data type -- uint16, -- Example values: 2280, 2133, 2036, 2023,
    1920, Total unique elements: 1539
Column Name: eff, Data type -- int16, -- Example values: 2462, 1921, 2446, 1872,
    1553, Total unique elements: 1674
Column Name: ast_tov, Data type -- float64, -- Example values: 1.34, 1.63, 2.44,
    1.54, 0.98, Total unique elements: 470
Column Name: stl_tov, Data type -- float64, -- Example values: 0.41, 0.37, 0.57,
    0.48, 0.3, Total unique elements: 236
```

B   Code Generation Prompts

B.1   Pandas Code Generation without Error Handling

Natural Language to Python Code with Pandas

Generate a python code to answer this question: `{question}` that strictly follows the instructions below:

The code should return a print statement with the answer to the question.
The code should leave the answer be and not print anything other than the variable that holds the answer.
Please write a single Python code block that answers the following question and prints the result in one line at the end.
If the question doesn't specifically ask for it, don't use unique() or drop_duplicates() functions.

If it is a Yes or No question, the answer should be a boolean.
Do not include any explanations, comments, or additional code blocks.
Do not print intermediate steps just the answer.
Do not interact with the user.
Never display any sort of dataframes or tables.
Your output can never take more than a single line after printing and it can never be any sort of objects such as pandas or numpy objects, series etc.
Your output must be one of the following:

Boolean: True/False
Category/String: A value
Number: A numerical value
List[category/string]: ['cat', 'dog']
List[number]: [1, 2, 3]
So the outputs have to be native python

Given the dataset schema {schema}

The following python code made for pandas for the parquet file {dataset_name}.parquet reads the parquet file and running it returns the answer that is enough to answer the question `{question}`

B.2   Pandas Code Generation with Error Handling

The following prompt replaces the part after the schema is given of the previous prompt.

Natural Language to Python Code with Pandas - Error Correction

The following codes generated an error when executed:

`{code_1}`/`{error_1}`,
`{code_2}`/`{error_2}`,
`... %`

Error: {error_msg} Solve the error and provide the corrected code
The following python code made for pandas for the parquet file {dataset_name}.parquet reads the parquet file and running it returns the answer that is enough to answer the question `{question}` with the error fixed
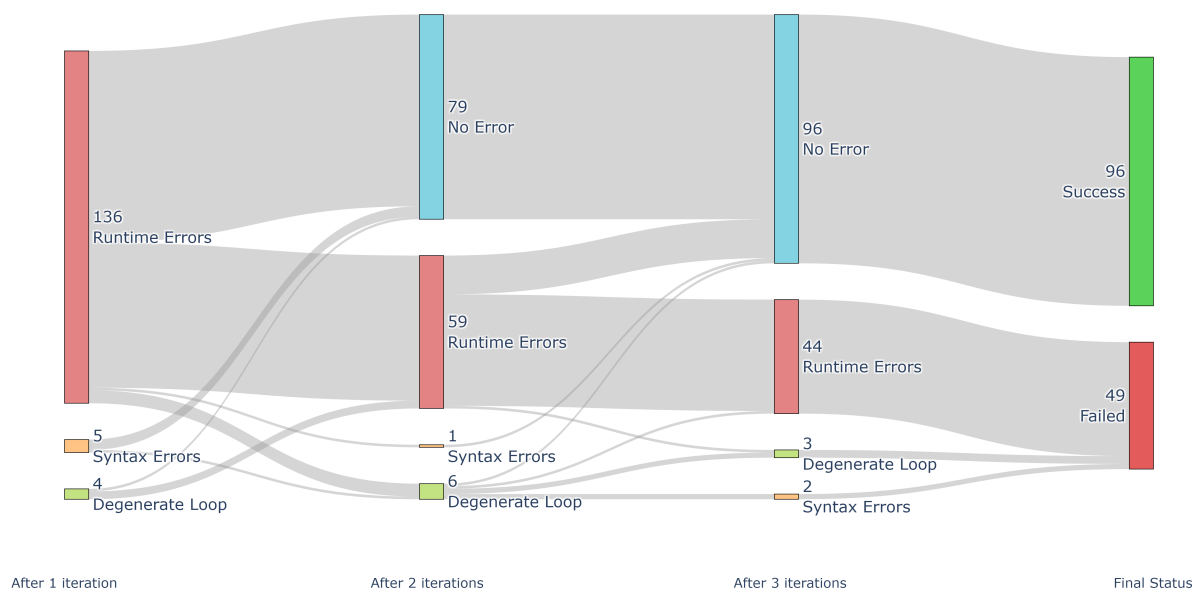

C Error Analysis

Figure 2: Error evolution and resolution across iterations (Aggregated over all models).
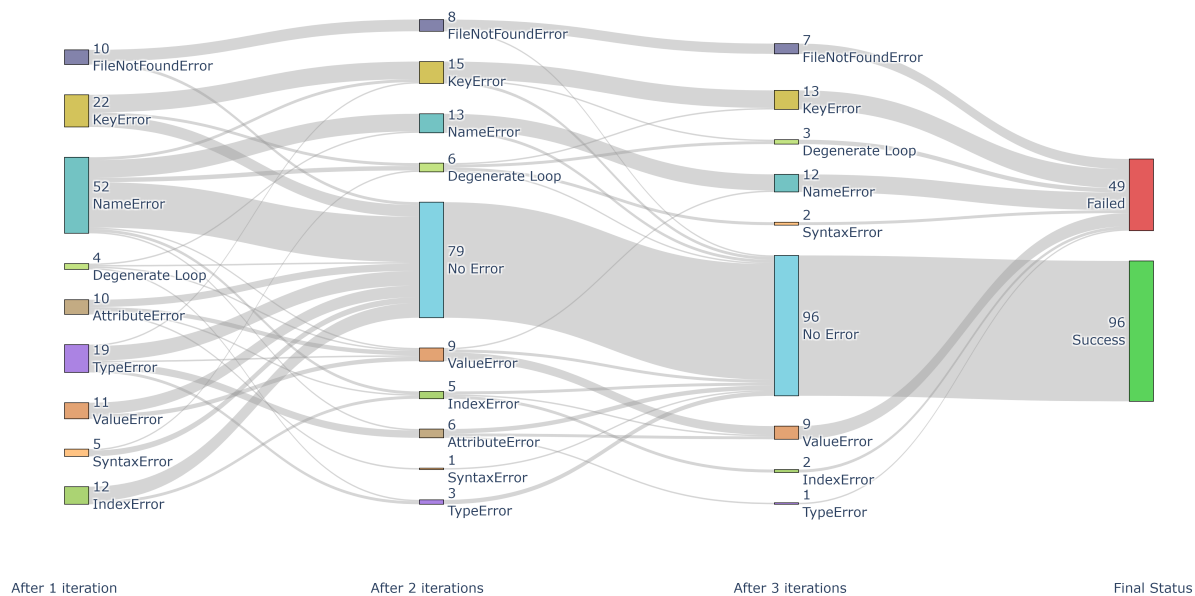

Figure 3: Fine-grained error evolution across iterations (Runtime error breakdown).

Models	Iteration	Runtime	Degenerate Loop	Syntax	Total
DeepSeek-R1 (Dev)	1	9	0	0	9
	2	4	2	1	7
	3	3	1	0	4
DeepSeek-R1 (Test)	1	9	4	2	15
	2	6	1	0	7
	3	4	0	1	5
DeepSeek-V3 (Dev)	1	35	0	0	35
	2	8	3	0	11
	3	8	2	1	11
DeepSeek-V3 (Test)	1	15	0	3	18
	2	9	0	0	9
	3	5	0	0	5
Llama-3.3-70B-Instruct (Dev)	1	16	0	0	16
	2	5	0	0	5
	3	2	0	0	2
Llama-3.3-70B-Instruct (Test)	1	16	0	0	16
	2	10	0	0	10
	3	9	0	0	9
Qwen2.5-Coder-32B-Instruct (Dev)	1	11	0	0	11
	2	9	0	0	9
	3	8	0	0	8
Qwen2.5-Coder-32B-Instruct (Test)	1	25	0	0	25
	2	8	0	0	8
	3	5	0	0	5

Table 4: Top error types and their distribution across iterations.