DRILL-DOWN ANALYSIS OF LLM HALLUCINATION PATTERNS IN TEXT-TO-SQL

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ABSTRACT

Despite impressive benchmark scores, Large Language Models (LLMs) can still produce flawed and incorrect responses for Text-to-SQL tasks. While prior work has decomposed complex SQL queries in an attempt to improve LLM benchmark performance, few have systematically analyzed hallucination propagation patterns within these decomposed structures. We present a drill-down evaluation framework that decomposes complex SQL queries and questions from the BIRD-mini dataset Li et al. (2023), allowing for a fine-grained analysis of hallucination propagation. Through our analysis, we report three key findings: (1) Recurrent Hallucinations: Many hallucinations persistently propagate from early, structurally simple sub-queries through to final steps, indicating systematic misalignment. (2) Final-Step Emergence: Fewer, but specific hallucination types emerge in the final step, suggesting a distinct failure mode tied to query complexity. (3) History Amplifies Recurrence: While contextual information between sub-queries can help to reduce the frequency of emergent hallucinations, it consequently increases the recurrence of early-stage hallucinations. This framework establishes a methodology to better understand LLM weaknesses and failure modes for Text-to-SQL systems.

1 INTRODUCTION

Recent advances in Text-to-SQL techniques represents a significant leap forward in human-computer interaction, promising users the ability to query complex databases using everyday conversational language instead of structured query syntax. At the heart of this transformative technology are Large Language Models (LLMs), which have demonstrated remarkable proficiency in this task Li et al. (2024a); Chen et al. (2024); Hong et al. (2024). By leveraging their vast pre-training on diverse text and code corpora, LLMs can grasp the semantic intent behind a natural language question, understand the underlying database schema, and generate an executable SQL query to retrieve the correct information. This capability is poised to democratize data access, empowering non-technical stakeholders to directly interact with data and derive insights without the need for specialized programming skills, thereby accelerating the pace of data-driven decision-making. However, hallucinations introduced by the LLM remain a consistent and persistent issue in all Text-to-SQL via LLM pipelines. These hallucinations are a notorious problem in LLMs and refer to instances where they generate content that is irrelevant, erroneous, or inconsistent with the user's requests Huang et al. (2023); Qu et al. (2024); Zhang et al. (2024). While researchers are aware of hallucinations, interpreting, explaining, and preventing them remains an open area of research.

Crucially, in a text-to-SQL task, a hallucination isn't just a factual error but a functional failure that represents a key challenge for AI alignment. An incorrect query could lead to the wrong business decisions, faulty reports, or even data corruption if the system is designed to execute the queries without human oversight. Ensuring the LLM produces safe, reliable, correct and intention-aligned SQL is a fundamental alignment challenge. Furthermore, users will quickly lose trust in a system that consistently produces queries that fail to execute or return incorrect data. An aligned system is one that a user can trust to perform its task reliably. Hallucinations erode this trust, which is a clear symptom of misalignment. While a human can often catch these errors, a truly aligned system should minimize the need for a human to constantly debug its output. The goal of text-to-SQL is to empower non-technical users, but hallucinations make this difficult and require a level of technical expertise to correct.

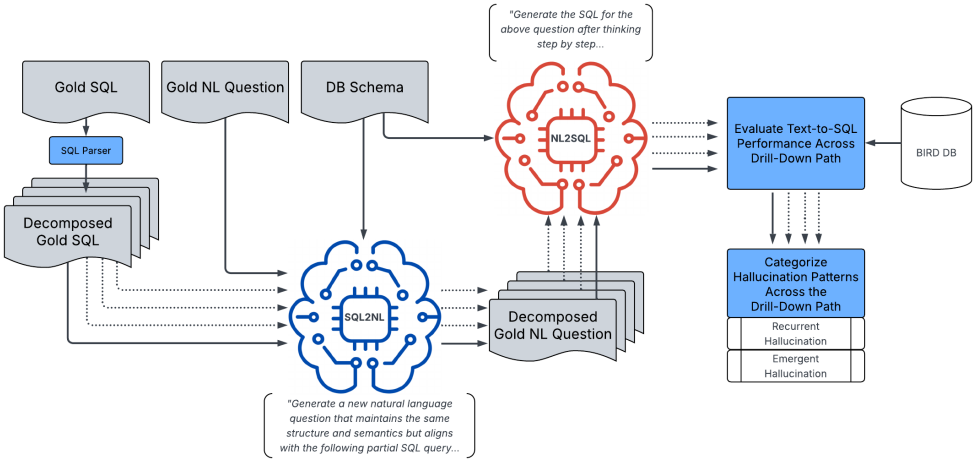


Figure 1: Drill-down framework; Decompose the BIRD-mini dataset into progressive sub-queries and sub-questions and evaluate their hallucination patterns.

We present a drill-down hallucination framework and analysis in the Text-to-SQL domain. First, we decompose the SQL queries into sub-queries which generates a custom drill-down dataset from an existing Text-to-SQL dataset (Fig. 1). Second, we create an automated pipeline for annotating a LLMs hallucinations, with a fine-grained taxonomy which builds temporal abstractions on top of hallucination categories identified by prior research Qu et al. (2024). This novel analysis enables a deeper investigation into how different types of hallucinations evolve across multi-step generation paths for Text-to-SQL. Using these annotated results we analyze for *recurrent hallucinations*, where the same erroneous instances persist from earlier steps into final outputs, and *emergent hallucinations* that appear for the first time in final reasoning steps despite having no prior instances. Our results reveal interesting insights into hallucination patterns and failure mechanisms that are consistent across six modern LLMs. Understanding and addressing these patterns would provide a deeper understanding of these models and provide a path to better alignment. Overall, this paper evaluates six modern LLMs, two from Anthropic Anthropic (2024; 2025) and four from OpenAI OpenAI (2023; 2024; 2025) in the Text-to-SQL domain, analyzing their hallucinations to better understand the weaknesses of these models.

Briefly, the contributions of this paper can be summarized as follows:

1. We leverage the decomposable nature of SQL queries to create a drill-down analysis pipeline that provides an insight into LLM hallucinations when used in text-to-SQL pipelines.
2. Our experiments uncover two distinct temporal (w.r.t to the sub-query step) failure patterns, described as recurrent and emergent hallucinations.
3. We evaluate six closed-source frontier models (Claude and GPT variants) and show that hallucination patterns are consistent across architectures and vendors.

2 Related Work

Early Text-to-SQL systems almost always adopted a sequence-to-sequence framework in which both the natural-language question and the target database schema were jointly encoded by neural models. Early efforts relied on recurrent architectures for this encoding Dong & Lapata (2016); Jia & Liang (2016), before moving toward graph neural networks that explicitly model schema structure Bastings et al. (2018); Bogin et al. (2019), and, eventually, to pre-trained transformer encoders Yin et al. (2020); Yu et al. (2021). More recently, LLMs have become a dominant paradigm due to their strong generalization ability, few-shot learning capacity Brown et al. (2020), in-context reasoning Xie et al. (2021), and chain-of-thought prompting capabilities Wei et al. (2022). These capabilities allow LLMs to generate SQL queries from natural language with little to no task-specific fine-tuning.

Table 1: Taxonomy of hallucination types observed in failed SQL generations, originally adopted from Qu et al. (2024).

Category	Description
Schema-Based: Schema Contradiction	The predicted query uses invalid or unknown tables, columns, or aliases not present in the database schema. Also includes misuse of wildcard or backtick syntax.
Schema-Based: Attribute Overanalysis	The query introduces valid but unnecessary tables or columns that are not present in the ground truth, resulting in over-specific or redundant retrieval logic.
Schema-Based: Value Misrepresentation	The query mishandles data representation, such as incorrect or missing type casts, or inconsistent literal values.
Logic-Based: Join Redundancy	The query contains more JOIN operations than the ground truth, indicating hallucinated or spurious table relationships.
Logic-Based: Clause Abuse	The query includes structural SQL clauses (e.g., `GROUP BY`, `LIMIT`, `ORDER BY`) or logical operators (e.g., `AND`, `OR`) that were absent in the ground truth.
Logic-Based: Mathematical Delusion	The query exhibits invalid or misleading numerical reasoning, such as uncasted division, misuse of `%`, improper use of `BETWEEN`, or syntax errors in arithmetic expressions.

Table 2: Recurrent vs. emergent hallucination definitions in the drill-down analysis.

Category	Description
Recurrent Hallucination	A hallucination that occurs somewhere in the drill-down path and reappears again in the final step.
Emergent Hallucination	A hallucination that manifests in the final step of the drill-down path with no prior instances in earlier steps.

Although this transition has led to notable performance gains on standard benchmarks, it has also introduced new challenges, one being hallucinations.

Recent papers have introduced new and unique approaches to improve performance and better align the Text-to-SQL system with the given task. CHASE-SQL Pourreza et al. (2024) represents a recent methodology that uses a divide-and-conquer strategy to decompose complex problems into sub-components, addressing each component separately before synthesizing the results into a final solution Pourreza et al. (2024). This technique shows impressive performance improvements on the BIRD benchmark's Li et al. (2023) execution accuracy (EX) metric. Inspired from this framework, we decompose the complete BIRD-mini dataset Li et al. (2023), breaking it down into sequential sub-components. However, our approach is different from existing research that leverages decomposition primarily as a step for benchmark optimization. Instead, we conduct a systematic analysis of hallucination behaviors and patterns within these decomposed structures.

3 PRELIMINARIES

3.1 PROBLEM DEFINITION

We adopt the problem formulation from Qu et al. (2024). Given a natural language question $\mathcal{Q} = \{q_1, \ldots, q_{|\mathcal{Q}|}\}$ and its associated database schema $\mathcal{D} = \langle \mathcal{C}, \mathcal{T} \rangle$, where $\mathcal{C} = \{c_1, \ldots, c_{|\mathcal{C}|}\}$ and $\mathcal{T} = \{t_1, \ldots, t_{|\mathcal{T}|}\}$ represent the sets of column and table names respectively, the goal of the text-to-SQL task is to generate a valid SQL query y that faithfully reflects the intent encoded in $\mathcal{Q}$.

3.2 Evaluation Metrics

Execution Accuracy (EX) We evaluate baseline model performance using two main metrics, the first being *Execution Accuracy (EX)* Li et al. (2024a), which measures whether a predicted SQL query $\hat{y}$ yields the same execution result as the ground truth query y^* when both are executed on the same database instance. Formally, let $\texttt{Exec}(y, \mathcal{D})$ denote the result of executing query y on database $\mathcal{D}$. Then, the EX score for a single example is defined as:

$$\text{EX}(\hat{y}, y^*) = \begin{cases} 1 & \text{if } \texttt{Exec}(\hat{y}, \mathcal{D}) = \texttt{Exec}(y^*, \mathcal{D}) \\ 0 & \text{otherwise} \end{cases}$$

The overall EX score across a dataset of N examples is computed as the average:

$$\text{EX}_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} \text{EX}(\hat{y}^{(i)}, y^{*(i)})$$

Soft-F1 Score The second metric we use is the *Soft-F1 Score* Li et al. (2024a). Unlike Execution Accuracy, which is binary and requires an exact match in result sets, Soft-F1 provides a graded assessment by measuring partial overlaps between the execution results of the predicted and ground truth SQL queries. Let $\hat{T} = \texttt{Exec}(\hat{y}, \mathcal{D})$ and $T^* = \texttt{Exec}(y^*, \mathcal{D})$ be the predicted and ground truth result tables, respectively. At the tuple level, treating each tuple as a set of values, define:

- True Positives (TP): tuples in both $\hat{T}$ and T^*
- False Positives (FP): tuples in $\hat{T}$ but not in T^*
- False Negatives (FN): tuples in T^* but not in $\hat{T}$

The Soft-F1 score is then computed as:

$$\text{Soft-F1} = \frac{2 \cdot \text{TP}}{2 \cdot \text{TP} + \text{FP} + \text{FN}}$$

3.3 Dataset

BIRD-mini We conduct our experiments on the BIRD-mini dataset, a smaller version of the full BIRD dataset specifically designed to capture the full complexity of the entire dataset thereby making text-to-SQL experiments possible for resource-constrained researchers. While the full BIRD-dev dataset is very comprehensive, applying our hallucination annotation/decomposition framework across its entire scale would more than double its size, requiring us to generate over 25,500 subquestions, resulting in a prohibitive analysis cost. Instead of arbitrarily selecting a subset of BIRD-dev we think would be representative, we expand the BIRD-mini dataset which has already been designed to be a good representation of the full BIRD-dev dataset. We expand BIRD-mini to 1383 instances, and evaluate this expanded dataset across six modern LLMs. This expansion reflects the maximum possible decomposition of BIRD-mini where each sub-query remains executable, yielding 1383 systematic question–query pairs.

4 Hallucination Taxonomy

Schema-Based and Logic-Based For a more accurate categorization of these hallucinations, we adopt the taxonomy featured in Qu et al. (2024). which categorizes hallucinations into two main categories, schema-based and logic-based. *Schema-based hallucinations* reflect misunderstandings of the database structure itself, using incorrect tables/columns or unnecessarily attributes. *Logic-based hallucinations* involve errors in how the query is constructed, unnecessary joins, clause abuses, or incorrect math. We describe these hallucination categories in more detail in Table 1.

Recurrent and Emergent Hallucinations Beyond the taxonomy, we will additionally define two more hallucination behavior types that capture distinct patterns. The first is *recurrent hallucinations*, which we define as a hallucination that occurs somewhere in the drill-down path and reappears in the final step. These errors demonstrate persistence across multiple steps of the drill-down path, suggesting a more fundamental misunderstanding. The second is *emergent hallucinations*, which we define as a hallucination that only occurs in the final step of the drill-down path. These errors appear to be triggered specifically by the increased complexity and integration requirements of the complete problem. These categories can be viewed as temporal abstractions, with respect to the sub-query steps, over the hallucination categories identified in Qu et al. (2024).

Failure Mechanisms We argue that these behavioral distinctions are crucial because they represent two fundamentally different failure mechanisms operating within LLMs. Recurrent hallucinations appear to be tied more closely to systematic misalignment or fundamental knowledge gaps within the model's understanding. These failures manifest not only when confronted with the original complex BIRD-mini question and query, but also persist in identical ways even when presented with the decomposed versions of the same problem. Emergent hallucinations, conversely, capture a failure mode that appears to be more closely related to the cognitive load and integration challenges posed by the full complexity of the question and query. These failures suggest that models can successfully navigate some components of a complex problem but fail when required to synthesize multiple pieces of information together.

5 METHODOLOGY

This section will outline the framework we used to perform our analysis of hallucination patterns, consisting of three primary components: (1) Decompose the BIRD-mini dataset into progressive sub-questions and sub-queries, (2) Perform drill-down evaluation on multiple LLMs, (3) Categorize and describe the hallucination patterns (Fig. 1). Follow Algorithm 1 (Appendix A) for each step of our framework.

5.1 DECOMPOSE AND GENERATE DRILL-DOWN DATASET

Progressive Sub-Query Generation The proposed framework begins by decomposing each query from the BIRD-mini benchmark into multiple progressive queries, using an SQL parser Albrecht (2024). By parsing progressively from select through where and subsequent and conditions, we ensure that each sub-query in the drill-down path represents an executable SQL query. Follow Fig. 1 for an example.

Sub-Question Generation We additionally pair each of these sub-queries with a sub-question that captures the contents of the sub-query in natural language (NL). To ensure the reliability of our expanded benchmark, we adopt an asymmetric design choice: all sub-queries are generated deterministically via sqlparse, while sub-questions are produced by LLMs provided with the BIRD database schema, original question, and our generated sub-queries. We additionally regenerate the original question with the same method to maintain alignment with the generated sub-questions. This choice follows recent evidence that formal language $\rightarrow$ natural language (SQL-to-NL) is consistently more reliable than the reverse natural language $\rightarrow$ formal language (NL-to-SQL). For example, Evaluating NL-to-SQL via SQL-to-NL shows that SQL-to-NL achieves stronger Pass@K performance on Spider and produces paraphrases with higher semantic fidelity and fewer schema-alignment errors than NL-to-SQL Li et al. (2025). These findings support our claim that LLM-generated sub-questions faithfully capture the meaning of their corresponding SQL sub-queries, with lower risk of hallucination compared to direct NL-to-SQL generation.

5.2 DRILL-DOWN AND ANNOTATE HALLUCINATION PATTERNS

Following this process, we construct an incremental sequence of questions and queries that gradually increases in complexity. We transform and expand the original BIRD-mini dataset into a drill-down dataset which enables us to pinpoint precisely where hallucinations emerge within these incremental pathways and determine whether these errors propagate to the final stage. We categorize and annotate these hallucination types and behaviors like the example in Fig. 6 (Appendix A).

6 EXPERIMENT

We systematically evaluated six LLMs, Claude-3.5-sonnet and Claude-3.7-sonnet from Anthropic Anthropic (2024; 2025), and GPT-4-turbo, GPT-4o-mini, GPT-4.1-mini, and GPT-4-nano from OpenAI OpenAI (2023; 2024; 2025) on our BIRD-mini drill-down dataset for the Text-to-SQL task using the default prompt provided by BIRD (Appendix A: Prompt 2) Li et al. (2024b). To uncover where and how hallucinations arise, we perform a structural comparison between predicted SQL, ground-truth SQL, and the database schema at each step of a progressive question path. Each hallucination is categorized and annotated through this multistep decomposition. The experiments are designed to address the following research questions:

Research Question 1 Do hallucinations in Text-to-SQL generation primarily originate from the complexity of the original question, or do they instead emerge earlier due to systematic misunderstanding in simpler steps?

Research Question 2 What hallucination types emerge uniquely at the final stages of Text-to-SQL generation, and how are these failures correlated with query complexity?

Research Question 3 How does access to contextual history from the drill-down path during Text-to-SQL generation affect the frequency and severity of recurrent versus emergent hallucinations?

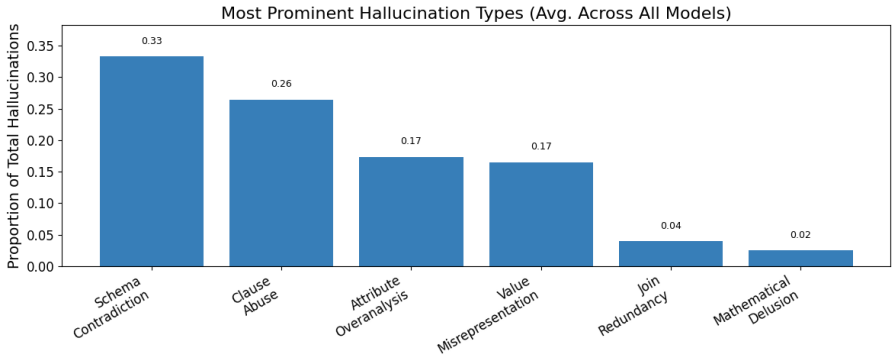
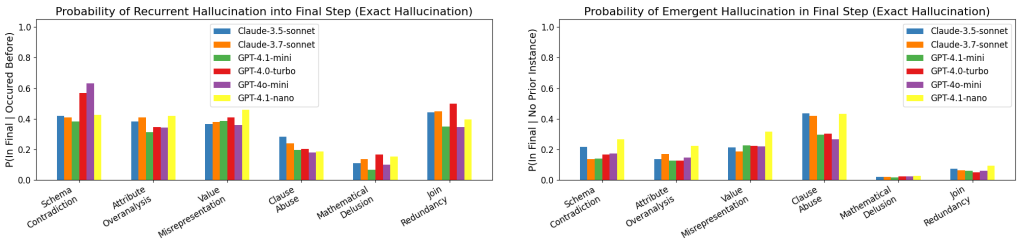


Figure 2: Distribution of hallucination types across all experiments. Schema contradiction and clause abuse emerge as the dominant categories, indicating that models frequently misinterpret schema structure or over-apply SQL clauses even in decomposed forms.



(a) Recurrent hallucinations

(b) Emergent hallucinations

Figure 3: Probability of recurrent (a) and emergent (b) hallucinations across categories. Recurrent errors show high persistence once introduced (sometimes >50%), while emergent errors are rarer, with clause abuse being the main exception. This highlights distinct failure mechanisms between persistence and final-step emergence.

Table 3: BIRD-mini EX Accuracy (%) and Soft F1-Scores across Difficulty Levels

Model	Simple	Moderate	Challenging	Total
Count	148	250	102	500
Claude-3.5-Sonnet	56.08	35.20	23.53	39.00 (EX)
	59.39	38.61	31.15	43.24 (F1)
Claude-3.5-Sonnet (+ History)	50.00	34.40	20.59	36.20 (EX)
	56.93	37.84	29.01	41.69 (F1)
Claude-3.7-Sonnet	51.35	38.40	21.57	38.80 (EX)
	55.09	43.58	29.59	44.13 (F1)
Claude-3.7-Sonnet (+ History)	52.70	38.40	24.51	39.80 (EX)
	57.32	42.10	30.78	44.30 (F1)
GPT-4.0-Turbo	58.78	34.00	17.65	38.00 (EX)
	60.66	38.45	24.14	42.11 (F1)
GPT-4.0-Turbo (+ History)	55.41	37.60	19.61	39.20 (EX)
	57.45	40.48	25.16	42.38 (F1)
GPT-4.0-o-Mini	47.97	31.60	13.73	32.80 (EX)
	50.87	34.42	20.63	36.48 (F1)
GPT-4.0-o-Mini (+ History)	47.30	31.20	14.71	32.60 (EX)
	48.82	33.57	20.10	35.34 (F1)
GPT-4.1-nano	47.97	26.80	11.76	30.00 (EX)
	50.05	29.40	19.49	33.49 (F1)
GPT-4.1-nano (+ History)	50.68	28.40	15.69	32.40 (EX)
	52.50	32.16	18.89	35.47 (F1)
GPT-4.1-Mini	59.46	41.60	21.57	42.80 (EX)
	61.47	45.04	28.48	46.53 (F1)
GPT-4.1-Mini (+ History)	56.08	39.20	18.63	40.00 (EX)
	58.33	42.33	24.09	43.35 (F1)

6.1 RESULTS

To validate our setup, we first report baseline performance on BIRD-mini, showing close alignment with previously reported scores Li et al. (2024a), as shown in Table 3.

P(**In Final Step** | **Occurs in Earlier Steps**) Fig. 3 presents the conditional probabilities of hallucinations occurring in the final step (original BIRD-mini question) given that the identical hallucination type manifested earlier in the drill-down path, expressed as P(In Final Step | Occurs in Earlier Steps). The results reveal that hallucinations are not exclusively confined to the final, most complex step, but rather demonstrate recurrence patterns throughout earlier stages of the progressive path. Notably, while Schema-Based: Schema Contradiction and Logic-Based: Clause Abuse represent the two most common hallucination types in our results (Fig. 2), they seem to exhibit different failure mechanisms. Most hallucination types exhibit relatively high recurrence probabilities, with the exception of Logic-Based: Clause Abuse, see (Fig. 3). The persistence of these errors across multiple stages, including the initial steps of the path, indicates fundamental misalignment issues where LLMs struggle with a task even in their most decomposed forms.

P(**In Final Step** | **Does Not Occur Earlier**) Conversely, Fig. 3, shows similar probabilities but for hallucinations that occur in the final step where the exact same hallucination does not occur anywhere in the drill-down path, P(In Final Step | Does Not Occur Earlier), we observe a distinctly different pattern. Most hallucination types exhibit considerably lower emergence probabilities compared to their recurrence rates, except for Logic-Based: Clause Abuse, which has a higher probability of emergence compared to recurrence. The lower probabilities suggest that most hallucination types are more likely to propagate from earlier steps, with the outlier being Clause Abuses.

LLM History Attention Furthermore, examination of the results comparing history attention to the progressive path versus no attention reveals an interesting duality in hallucination behavior patterns. When models maintain access to conversational history throughout the progressive path, we

observe a significant increase in the probability of recurrent hallucinations across all tested models compared to the context-free condition (Fig. 4). This suggests that contextual memory can inadvertently reinforce hallucination patterns established in earlier steps. In contrast, the presence of history attention demonstrates a more protective effect against emergent hallucinations, reducing the probability of occurrence (Fig. 5). These results point towards a potential trade-off between emergent hallucination protection and recurrent hallucination amplification.

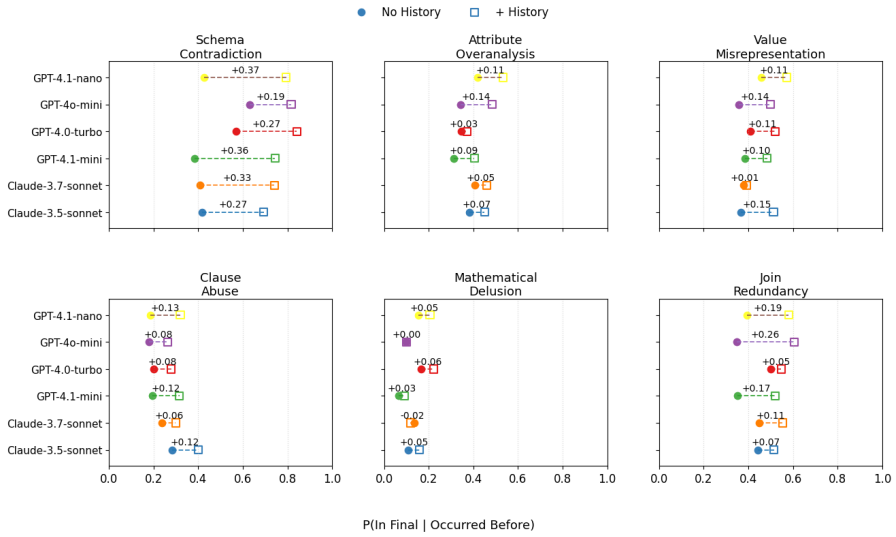


Figure 4: Probability of recurrent hallucinations with and without history/context. Providing history consistently increases recurrence rates across models, showing that context can inadvertently reinforce early-stage errors rather than correcting them.

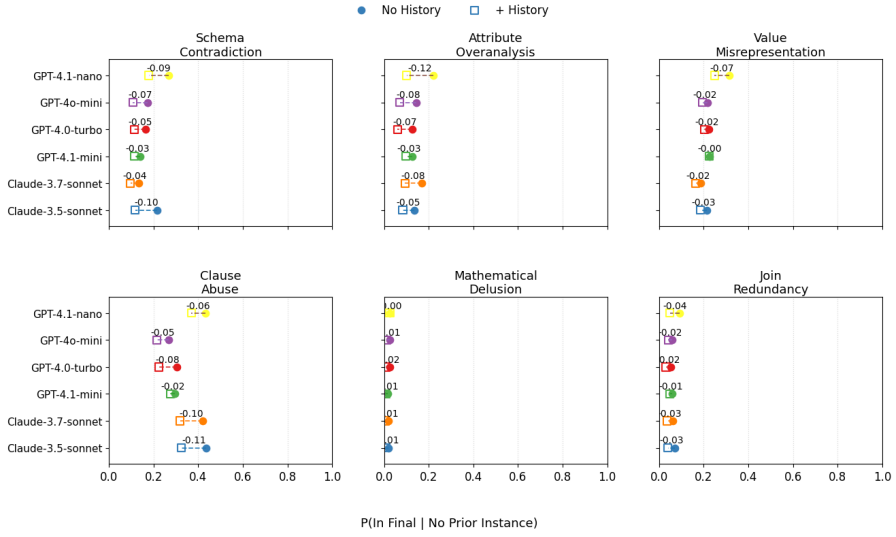


Figure 5: Probability of emergent hallucinations with and without history/context. In contrast to recurrent patterns, history reduces emergence rates, suggesting a protective effect against new errors but at the cost of amplifying persistent ones.

The strongest model (GPT-4.1-Mini) achieves 42.8% EX and 46.5% F1, while the weakest (GPT-4.1-Nano) records 30.0% EX and 33.49% F1. We also notice that performance drops rapidly with query complexity. Even with easy questions, the best EX reaches 59.46%, but drops to only 21.57% on challenging queries. We also find that adding contextual history decreases EX by $\sim$1.1 points and F1 by $\sim$0.6 points. For example, Claude-3.7-Sonnet improves slightly (38.8 $\rightarrow$ 39.8 EX), whereas

GPT-4.1-Mini drops (42.8 → 40.0 EX). Figures 4–5 further demonstrates how recurrent errors seem to dominate and once they occur, they reappear in the final step with probabilities exceeding 50% for schema contradictions. Whereas, emergent hallucinations are less frequent for most hallucination types, excluding clause abuses. Finally, history impacts these distributions, raising recurrence anywhere from ∼2–37% across categories while reducing emergence by ∼2–11%.

7 Alignment with Prior Work

Alignment with "Before Generation, Align it!" Qu et al. emphasizes the importance of *pre-generation alignment* between natural language and schema to mitigate schema-related hallucinations Qu et al. (2024). Our results support the claim that schema contradiction is one of the most prominent type of hallucinations in the Text-to-SQL domain. Furthermore, we have consistent results showing how recurrent schema hallucinations frequently persist into the final steps for all models tested (Figure 4).

Alignment with "A Study of In-Context-Learning-Based Text-to-SQL Errors" Shen et al. present a taxonomy of 29 error types in in-context-learning (ICL) text-to-SQL Shen et al. (2025). This study quantifies overall error prevalence and repair challenges, we examine how these error types behave over the course of multi-step drill-down generation. By introducing *recurrent* and *emergent* hallucinations, we provide a new temporal perspective that extends beyond a static categorization.

8 Conclusion

Large language models (LLMs) currently demonstrate excellent capabilities in a variety of tasks, including text-to-SQL. However, hallucinations generated from the outputs of these models pose serious challenges for interpretability, alignment, and overall adoption into text-to-SQL systems. In this paper, we conduct a drill-down analysis to trace where in progressive query paths hallucinations arise. Our findings align with recent research that hallucinations can arise when models misinterpret the decomposed stages of a task as entirely new challenges Qu et al. (2024). However, we also find that it is common for hallucinations to reappear from earlier, and much simpler, steps into the final complex query. Finally, we report an inverse relationship with emergent and recurrent hallucinations when context to the drill-down path is provided to the LLM. We see a more protective behavior for emergent hallucinations but inversely an amplifying effect for recurrent hallucinations. Our experiments reveal interesting nuances of LLM Hallucinations in the Text-to-SQL domain, providing researchers with a deeper insight into how these models are failing.

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A Appendix

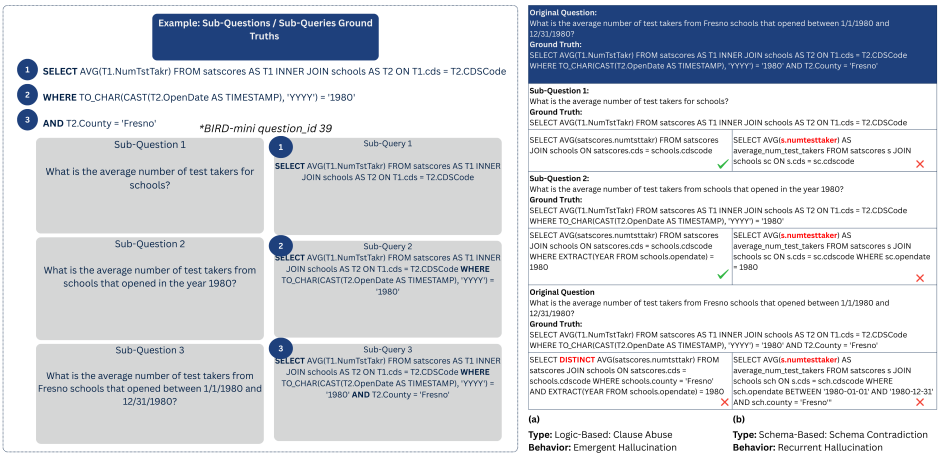

Figure 6: (left) Example of how the original BIRD-mini question is decomposed into sub-questions and sub-queries. (right) Example depicting the differences between a recurrent and emergent hallucination.

Algorithm 1 Drill-Down Hallucination Analysis on BIRD-Mini

Original dataset $\mathcal{D} = \{(q_i, s_i)\}_{i=1}^{N}$; schema $\mathcal{S}$ Annotated failure set $\mathcal{H}$ with hallucination categories
Initialize: $\mathcal{P} \leftarrow \emptyset, \mathcal{H} \leftarrow \emptyset$
$(q_i, s_i) \in \mathcal{D}$ $\{s_i^j\}_{j=1}^{K_i} \leftarrow \textsc{Decompose}(s_i)$
$j = 1$ K_i $q_i^j \leftarrow \text{LLM\_}\textsc{Reword}(q_i, s_i^j, \mathcal{S})$ $\mathcal{P} \leftarrow \mathcal{P} \cup \{(q_i^j, s_i^j, s_i)\}$
$(q, s^*, s_{\text{full}}) \in \mathcal{P}$ $\hat{s} \leftarrow \text{LLM\_}\textsc{GenerateSQL}(q, \mathcal{S}, s_{\text{full}})$
$\textsc{ExecAccuracy}(\hat{s}) = 0$ $\mathcal{C} \leftarrow \textsc{CategorizeFailure}(\hat{s}, s^*, \mathcal{S})$ $\mathcal{H} \leftarrow \mathcal{H} \cup \{(q, \hat{s}, s^*, \mathcal{C})\}$
$\mathcal{H}$

Prompt 1: Progressive Question Rewriting Prompt

```
Let's take this step-by-step.

Given this database schema: {schema_prompt}

Given this original question: "{original_question}"

Generate a new natural language question that maintains the same
structure and semantics but aligns with the following SQL query:

{partial_sql}

Do not include any information in your generated question that is
not directly included in the query. The original question should
be used as reference to generate this question.

Requirements: - The generated question must correspond exactly to
what this SQL retrieves - Maintain the same domain context and
terminology as the original question - The question should be
answerable using only this SQL query

Generate only the natural language question.
```

Prompt 2: Text-to-SQL Prompt

```
Using valid {sql_dialect} and understanding External Knowledge:
{knowledge}

{base_prompt}{knowledge_text}, answer the following questions for
the tables provided above. Generate the {sql_dialect} for the
above question after thinking step by step:

In your response, you do not need to mention your intermediate
steps.

Do not include any comments in your response.

Do not need to start with the symbol ``

You only need to return the result {sql_dialect} SQL code

start from SELECT
```