BIRD-INTERACT: RE-IMAGINING TEXT-TO-SQL EVALUATION VIA LENS OF DYNAMIC INTERACTIONS

Anonymous authors
Paper under double-blind review

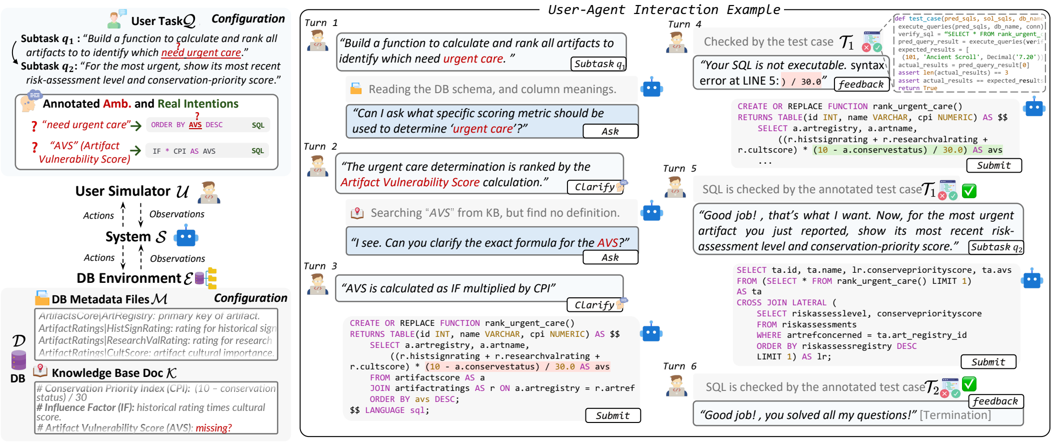
ABSTRACT

Large language models (LLMs) have demonstrated remarkable performance on single-turn text-to-SQL tasks, but real-world database applications predominantly require multi-turn interactions to handle ambiguous queries, execution errors, and evolving user requirements. Existing multi-turn benchmarks fall short of capturing this complexity, either by treating conversation histories as static context or by limiting evaluation to narrow, read-only (`SELECT`-ONLY) operations, thereby failing to reflect the challenges encountered in production-grade database assistant. In this work, we introduce BIRD-INTERACT, a benchmark that restores this missing realism through: (1) a ***comprehensive interaction environment*** that couples each database with a hierarchical knowledge base, metadata files, and a function-driven user simulator, enabling models to solicit clarifications, retrieve knowledge, and recover from execution errors without human supervision; (2) two ***evaluation settings*** reflecting real-world interaction settings which contain a pre-defined conversational protocol (c-Interact) and a more open-ended agentic setting (a-Interact) in which the model autonomously decides when to query the user simulator or explore the DB environment; (3) a ***challenging task suite*** that covers the full CRUD spectrum for both business-intelligence and operational use cases, guarded by executable test cases. Each task features ambiguous and follow-up sub-tasks, requiring LLMs to engage in dynamic interaction. The suite is organized into two sets: a full set (**BIRD-INTERACT-FULL**) of 600 tasks which unfold up to **11,796** dynamic interactions for a comprehensive overview of performance and a lite set (**BIRD-INTERACT-LITE**) of 300 tasks, with simplified databases for detailed behavioral analysis of interactions, and fast development of methods. Our empirical results highlight the difficulty of BIRD-INTERACT: the most recent flagship model GPT-5 completes only **8.67%** of tasks in the c-Interact setting and **17.00%** in the a-Interact setting on the full task suite. Further analysis via memory grafting and Interaction Test-time Scaling (ITS) validates the importance of effective interaction for achieving success in complex, dynamic text-to-SQL tasks.

1 INTRODUCTION

Data-driven decision-making has become indispensable across modern enterprises, prompting a surge of interest in Natural Language Interfaces to Databases (NLIDB) that empower non-technical users to extract insights from relational databases using natural language (Shi et al., 2024). Motivated by this vision, a wave of methods (Pourreza et al., 2025a;b; Pourreza & Rafiei, 2023; Liu et al., 2025; Qu et al., 2024; Li et al., 2025b; Maamari et al., 2024; Sheng & Xu, 2025; Li et al., 2025a; Talaei et al., 2024; Caferoğlu & Ulusoy, 2024; Cao et al., 2024; Lee et al., 2025) based on large language models (LLMs) has recently achieved impressive *text-to-SQL* performance on popular single-turn benchmarks such as Spider (Yu et al., 2018) and BIRD (Li et al., 2023).

However, real-world data interaction is rarely a single, perfectly-formed query (Li et al., 2025c; Dinan et al., 2019). It is an iterative, stateful dialogue characterized by ambiguity (Chen et al., 2025b) and evolving goals (Wu et al., 2025). The task in Figure 1 exemplifies this complexity. To succeed, the text-to-SQL system must first engage the user to resolve the ambiguity of the term `urgent care`. Only with this clarified context can it generate the correct SQL. If its initial code fails an execution test, LLM must debug and revise its SQL solution based on the error feedback. After the user confirms the SQL is correct, they may proceed with a follow-up question that depends on its



Subtask q_1: "Build a function to calculate and rank all artifacts to to identify which need urgent care."

Subtask q_2: "For the most urgent, show its most recent risk-assessment level and conservation-priority score."

? "need urgent care" → `ORDER BY AVS DESC`

? "AVS" (Artifact Vulnerability Score) → `IF * CPI AS AVS`

ArtifactsCore|ArtRegistry: primary key of artifact.
ArtifactRatings|HistSignRating: rating for historical sign
ArtifactRatings|ResearchValRating: rating for research
ArtifactRatings|CultScore: artifact cultural importance.

# Conservation Priority Index (CPI): (10 – conservation status) / 30
# Influence Factor (IF): historical rating times cultural score.
# Artifact Vulnerability Score (AVS): missing?

Turn 1: "Build a function to calculate and rank all artifacts to identify which need urgent care. "

Reading the DB schema, and column meanings.

"Can I ask what specific scoring metric should be used to determine 'urgent care'?"

Turn 2: "The urgent care determination is ranked by the Artifact Vulnerability Score calculation."

Searching "AVS" from KB, but find no definition.

"I see. Can you clarify the exact formula for the AVS?"

Turn 3: "AVS is calculated as IF multiplied by CPI"

```sql
CREATE OR REPLACE FUNCTION rank_urgent_care()
RETURNS TABLE(id INT, name VARCHAR, cpi NUMERIC) AS $$
    SELECT a.artregistry, a.artname,
        ((r.histsignrating + r.researchvalrating +
r.cultscore) * (10 - a.conservestatus) / 30.0 AS avs
    FROM artifactscore AS a
    JOIN artifactratings AS r ON a.artregistry = r.artref
    ORDER BY avs DESC;
$$ LANGUAGE sql;
```

Turn 4: Checked by the test case $\mathcal{T}_1$

"Your SQL is not executable. syntax error at LINE 5: `) / 30.0`"

```python
def test_case(pred_sqls, sol_sqls, db_name
 execute_queries(pred_sqls, db_name, conn)
 verify_sql = "SELECT * FROM rank_urgent_c
 pred_query_result = execute_queries(verif
 expected_results = [
  (101, 'Ancient Scroll', Decimal('7.20'))
 actual_results = pred_query_result[0]
 assert len(actual_results) == 3
 assert actual_results == expected_results
 return True
```

```sql
CREATE OR REPLACE FUNCTION rank_urgent_care()
RETURNS TABLE(id INT, name VARCHAR, cpi NUMERIC) AS $$
    SELECT a.artregistry, a.artname,
        ((r.histsignrating + r.researchvalrating +
r.cultscore) * (10 - a.conservestatus) / 30.0) AS avs
    ...
```

Turn 5: SQL is checked by the annotated test case $\mathcal{T}_1$ ✅

"Good job! , that's what I want. Now, for the most urgent artifact you just reported, show its most recent risk-assessment level and conservation-priority score."

```sql
SELECT ta.id, ta.name, lr.conservepriorityscore, ta.avs
FROM (SELECT * FROM rank_urgent_care() LIMIT 1)
AS ta
CROSS JOIN LATERAL (
    SELECT riskassesslevel, conservepriorityscore
    FROM riskassessments
    WHERE artrefconcerned = ta.art_registry_id
    ORDER BY riskassessregistry DESC
    LIMIT 1) AS lr;
```

Turn 6: SQL is checked by the annotated test case $\mathcal{T}_2$ ✅

"Good job! , you solved all my questions!" [Termination]

Figure 1: Task overview of BIRD-INTERACT showing the evaluated system interacting with DB Environment and User Simulator to complete the user task with a sequence of sub-tasks.

intermediate results. Therefore, evaluation on true practical utility LLMs with these multi-faceted aspects requires a benchmark containing a complete interactive problem-solving process, rather than isolated, single-turn SQL generation, but the entire interactive problem-solving loop.

Although existing interactive text-to-SQL datasets (Yu et al., 2019b;a; Chen et al., 2025b; Guo et al., 2021; Dahl et al., 1994) have been developed, they inadequately model this reality for two primary reasons. First, most multi-turn text-to-SQL benchmarks rely on **static conversation transcripts** (Yu et al., 2019a; Chen et al., 2025b; Yu et al., 2019b; Guo et al., 2021). They present models with a clean interaction history without recording the failed attempts, digressions, and clarifications that occur in practice. This design introduces a fundamental limitation: every LLM is evaluated against the same predetermined dialogue trajectory, regardless of how it would have naturally guided the interaction. This setup fails to reward intelligent interaction strategies and cannot effectively penalize conversational mess up. Second, existing benchmarks suffer from a **narrow task scope**, overwhelmingly focusing on read-only (`SELECT`-only) queries typical of business intelligence reporting. This ignores a vast and critical range of database operations, including data manipulation (`INSERT`, `UPDATE`, `DELETE`), schema modifications (`ALTER TABLE`), and transactional control, which are also common operations in the normal DBA cycle (Chen et al., 2024).

To address these critical limitations, we introduce **BIRD-INTERACT**, a new benchmark designed to evaluate LLMs in a dynamic text-to-SQL environment. Our work makes the following contributions: **(1) A High-Fidelity Interactive Environment:** We develop a comprehensive sandbox upon an open-source project LIVESQLBENCH (BIRD-Team, 2025) for each task, including a hierarchical knowledge base (HKB) with domain-specific facts, metadata files, an executable database environment, and most critically, an interactive user simulator as recent research (Wu et al., 2025; Yao et al., 2025; Wang et al., 2024). This simulator can respond to clarification questions, provide feedback on proposed actions, and guide the model through complex tasks, enabling end-to-end evaluation without human intervention. However, recognizing that traditional simulators, even those powered by advanced models like `GPT-4o`, exhibit unfair behaviors such as ground-truth leakage, we propose a novel two-stage function-driven approach that maps model questions to constrained symbolic actions before generating controlled simulator responses. **(2) Two Evaluation Settings:** We propose two popular evaluation settings. c-Interact (protocol-guided) presents tasks with a clear conversational protocol, testing a model's ability to follow a structured conversation with the user. In contrast, a-Interact (agentic) provides only a high-level goal, requiring the model to autonomously plan a strategy, decide when to query the database, consult documentation, or ask the user simulator for help. **(3) A Comprehensive and Challenging Task Suite:** BIRD-INTERACT expands the scope of evaluation to include the full spectrum of CRUD operations. Tasks are drawn from both analytical and operational domains and are accompanied by executable test cases that verify functional correctness. Each task features an ambiguous initial priority sub-task, dynamic clarification requirements, follow-up sub-tasks, and environmental uncertainties, which can only be resolved through dynamic interaction. The suite consists of two parts: a full set (**BIRD-INTERACT-FULL**) of 600 tasks, unfolding up to **11,796** dynamic interactions for a comprehensive evaluation of performance, and a lite set (**BIRD-INTERACT-LITE**) of 300 tasks with cleaner databases, enabling finer-grained behavioral analysis and faster deployment.

Our experiments show that state-of-the-art models struggle with BIRD-INTERACT, with `GPT-5` achieving only **8.67%** success in c-Interact and **17%** in a-Interact. We identify distinct challenges across interaction modes: communication effectiveness often determines success in c-Interact, while a-Interact suffers from bias toward costly trial-and-error over strategic resource exploration. We also observe Interaction Test-time Scaling (ITS), where performance improves monotonically with additional interaction opportunities across multiple models. These findings support our hypothesis that developing strategic interaction capabilities is key to improving LLM performance on complex database reasoning.

2 PROBLEM DEFINITION

Task Definition. We formalize interactive text-to-SQL as a multi-turn collaboration between a text-to-SQL system $\mathcal{S}_\theta$ and user simulator $\mathcal{U}_\gamma$ operating over database environment $\mathcal{E} = \{\mathcal{D}, \mathcal{M}, \mathcal{K}\}$, where $\mathcal{D}$ is the executable database, $\mathcal{M}$ contains schema metadata, and $\mathcal{K}$ represents external knowledge (Lee et al., 2021; Dou et al., 2022; Li et al., 2023). Given a sequence of related sub-tasks $\mathcal{Q} = \{q_1, q_2, \ldots, q_n\}$, the goal is for $\mathcal{S}$ to generate SQL solutions $\{\sigma_1, \ldots, \sigma_n\}$ through interactions. For each sub-task q_i, the interaction proceeds through interaction turn $t = 1, 2, \ldots$ until completion:

$$u_i^t = \mathcal{U}_\gamma(h_i^{t-1}, q_i, \mathcal{E}), \quad s_i^t = \mathcal{S}_\theta(h_i^{t-1}, u_i^t, \mathcal{E}), \quad h_i^t = h_i^{t-1} \oplus \langle u_i^t, s_i^t \rangle \tag{1}$$

where h_i^t represents the interaction history up to turn t and $\oplus$ denotes text concatenation in prompt. The user simulator $\mathcal{U}_\gamma$ manages the interaction by presenting sub-tasks, answering clarification questions for ambiguous queries, and providing feedback on submitted SQL. Critically, subsequent sub-tasks are released only after successful completion of first sub-tasks.

Metrics. Each sub-task q_i is annotated with ground-truth SQL σ_i^* and executable test cases $\mathcal{T}_i$ that define correctness. A predicted solution σ_i is correct if it passes all associated test cases, ensuring functional equivalence with σ_i^*. In our implementation, each task consists of two related sub-tasks ($n = 2$): an initial ***priority sub-task*** q_1 containing ambiguities requiring resolution, and (2) a subsequent ***follow-up sub-task*** q_2. We evaluate system performance using: (1) **Success Rate (SR)**: The proportion of sub-tasks completed successfully, with each sub-task scored 0 or 1. We report SR separately for sub-task 1 and sub-task 2 as an online evaluation during interaction. (2) **Normalized Reward**: Defined as normalized scoring according to priority weighting as designed in Appendix F to $[0, 1]$ for analyzing system behaviors after interaction (offline evaluation) (Yao et al., 2022).

3 BENCHMARK CONSTRUCTION

This section details the methodology for the construction of BIRD-INTERACT benchmark. We begin by outlining the overall benchmark setup (Section 3.1), and then elaborate on how we convert clear single-turn tasks into ones requiring interactions (Section 3.2).

3.1 SETUP AND RESOURCES

We build our benchmark on the text-to-SQL tasks and infrastructure of LIVESQLBENCH (BIRD-Team, 2025). We selected this foundation due to several key advantages. First, LIVESQLBENCH provides a comprehensive evaluation environment. It supports the full spectrum of SQL operations, including DML and DDL, which allows for dynamic database states that reflect real-world usage. Furthermore, its permissive license and ready-to-use artifacts, including an executable database sandbox and metadata files, facilitate extension and reproducibility. Third, it features a Hierarchical Knowledge Base (HKB) that organizes external knowledge as nodes in a directed acyclic graph (DAG) shown in Figure 1. This structure explicitly models dependencies between facts that require multi-hop reasoning to connect isolated information. Despite these strengths, LIVESQLBENCH is fundamentally a single-turn benchmark. This design fails to capture the interactive and often ambiguous nature of real-world data analysis scenarios. Our primary contribution is to convert this static benchmark into a dynamic, interactive setting.

3.2 INTERACTIVE TASK ANNOTATION

To maintain the integrity and quality of our benchmark, we recruit 12 expert annotators through a rigorous multi-stage selection process detailed in Appendix C. We describe systematically the conversion from single-turn tasks of LIVESQLBENCH into multi-turn interactive scenarios through two key annotation strategies: ambiguity injection and follow-up sub-task generation:

Ambiguity Injection. Ambiguities in daily life require interactions to seek clarification. To make annotation and evaluation controllable, we design methods to inject ambiguities into single-turn queries and the environment from LIVESQLBENCH, pairing each with a unique clarification.

(1) Superficial user query ambiguities: we target surface-level ambiguity in the user request. These include *intent-level ambiguities*, where the user language is vague (e.g., `"elderly people"`), and *implementation-level ambiguities*, where the user's intent is clear but the implementation details (e.g., decimal precision) are under-specific. **(2) Knowledge ambiguities:** we inject incompleteness into the external knowledge. This category includes two subtypes: (i) *one-shot knowledge ambiguity*, where isolated knowledge entries are removed. (ii) *knowledge chain breaking*, where intermediate nodes in multi-hop knowledge chains are masked. For example, consider the chain `"urgent care"` → `"AVS"` → `"IF/CPI"` in Figure 2. By masking the intermediate node, i.e., the fact `"AVS"` in HKB, we deliberately break the inferential chain, rendering knowledge ambiguous and requiring user clarification to proceed. **(3) Environmental ambiguities:** LIVESQLBENCH databases already contain natural noise, such as NULL in critical fields, which further introduces uncertainty in how these cases should be handled.

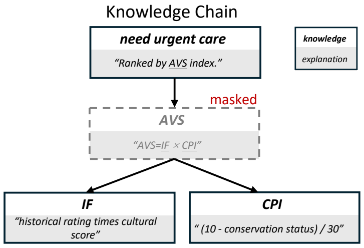


Figure 2: Knowledge chain breaking ambiguity.

Each injected ambiguity is paired with a corresponding SQL snippet from the ground-truth query as a *clarification source*, which guides our user simulator in generating consistent and contextually appropriate clarifications. Quality control ensures that ambiguous queries are unsolvable without clarification yet fully reconstructable once clarifications are provided. Complete details are given in Appendix H.

Follow-Up Sub-tasks Annotation. User intents frequently evolve throughout an interactive session (Taylor, 2015), with users modifying, filtering conditions, or exploring related aspects of their queries. Therefore, we also extend each initial priority sub-task with one additional follow-up sub-task to resonate with this scenario.

These follow-up sub-tasks are designed carefully using a principled 5-category taxonomy detailed in Appendix H.6. A key contribution of our benchmark is the introduction of **state dependency** between sub-tasks, different with other datasets (Yu et al., 2019a;b; Lee et al., 2021; Zhong et al., 2017; Li et al., 2025d). System models must reason over modified database states or the newly created tables from preceding queries to write SQLs for Follow-up sub-tasks.

3.3 FUNCTION-DRIVEN USER SIMULATOR

Evaluating interactive text-to-SQL systems requires user interactions, such as multi-turn requests and responses to clarification questions. Conducting such human-in-the-loop evaluations at scale is impractical. To make large-scale evaluations feasible, recent interactive benchmarks, such as MINT (Wang et al., 2024), employ LLMs to simulate human users (Li et al., 2025c; Yu et al., 2019a;b). However, we observe that there are two major issues among these simulators: (1) they sometimes leak information from ground-truth SQL query, and (2) they may deviate from the original task requirements (Barres et al., 2025; Kazi et al., 2024).

Table 1: Data Statistics

STATISTIC	LITE	FULL
Total Tasks	300	600
# BI tasks	195	410
# DM tasks	105	190
# Distinct Test Cases	135	191
# Tokens / User Query	40.22	32.95
# Tokens / SQL	361.52	252.21
# Ambiguities / Task	5.16	3.89
# sub-tasks / Task	2	2
# Interactions / Task	13.04	13.64
Inter-Agreement	93.33	93.50

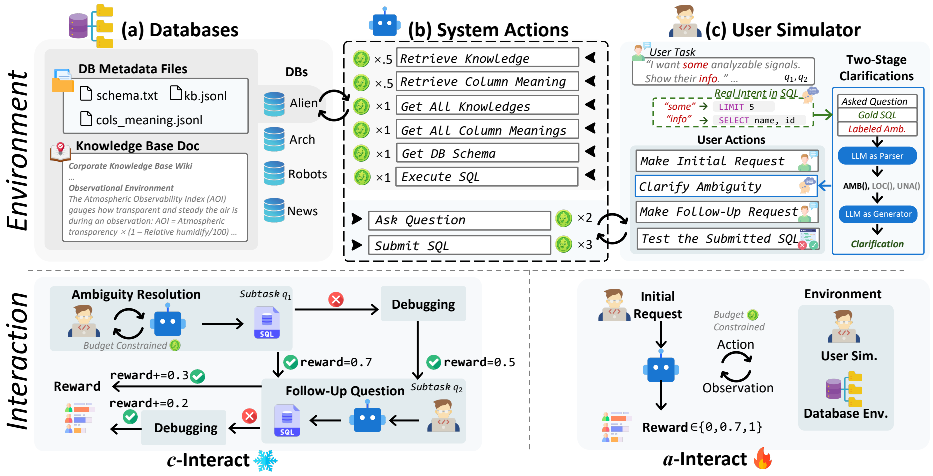


Figure 3: Two evaluation settings for BIRD-INTERACT: c-Interact, where the system engages in conversation with the user, and a-Interact, where the system interacts flexibly. At the end of the task, the system will receive a reward $r \in [0, 1]$.

Two-Stage Strategy. To ensure a more robust evaluation, we introduce a two-stage **function-driven user simulator**, as illustrated in Figure 3(c). In the first stage, an LLM functions as a semantic parser. It maps the system's clarification request into one of three predefined allowed actions: `AMB()`, `LOC()`, or `UNA()`. `AMB()` is invoked for queries related to ambiguities that have been pre-annotated with the key SQL snippet. `LOC()` handles reasonable clarification requests that fall outside our pre-annotated ambiguities, such as questions about SQL formatting or specific sub-components. In these cases, the simulator uses an AST-based retrieval step to locate the relevant SQL fragment (detailed in Appendix N). Finally, `UNA()` rejects any inappropriate requests, such as attempts to elicit ground-truth answers. In the second stage, the user simulator generates a final response based on the chosen action and the annotated GT SQL with clarification source. This two-stage approach, ensures the simulator's behavior remains predictable and controllable, while still permitting diverse and context-aware interactions. Detailed prompts are provided in Appendix T.

3.4 DATA STATISTICS

Table 1 reports key properties of BIRD-INTERACT. The resulting benchmark comprises a total of 900 interactive text-to-SQL tasks, each featuring an ambiguous initial priority sub-task, dynamic clarification requirements, follow-up sub-tasks, and environmental uncertainties covering CRUD spectrums. In Appendix E, we also conduct a comprehensive comparison against other relevant benchmarks, showing that BIRD-INTERACT is among the most open, challenging, and long-horizon interactive benchmarks in text-to-SQL scenarios.

4 EVALUATION SETTINGS

Two Evaluation Settings. The interactive framework of BIRD-INTERACT supports evaluation in two scenarios: LLMs as conversational assistants (c-**Interact**) (Dinan et al., 2019) and as agents (a-**Interact**) (Schluntz & Zhang, 2024).

Budget-Constrained Awareness Testing. The application of LLMs is limited by computational resources and user patience (Wen et al., 2025; Li et al., 2025e). We introduce a **budget-constrained awareness** mechanism to both evaluation settings, where interactions are capped by an adaptive budget and systems are informed of the remaining budget. This enables evaluation under varying budgets, including **stress-testing** (Ahmad et al., 2025; Hubinger, 2024) in low-budget conditions to assess the system's ability to ask the right questions and plan effectively. The specific budget settings are detailed in the following sections.

4.1 c-INTERACT EVALUATION

Interaction Setup. The c-Interact evaluation establishes a multi-turn dialogue between user simulator $\mathcal{U}$ and system $\mathcal{S}$. The session unfolds in two sequential phases of sub-tasks: First, $\mathcal{U}$ presents an underspecified sub-task q_1 alongside database metadata $\mathcal{M}$ and knowledge base $\mathcal{K}$. System $\mathcal{S}$ may engage in clarification dialogue before generating SQL σ_1. Upon successful validation against test cases $\mathcal{T}_1, \mathcal{U}$ issues a contextually coherent follow-up sub-task q_2, prompting $\mathcal{S}$ to respond with SQL σ_2. Each sub-task incorporates a single debugging opportunity: following query failure, $\mathcal{S}$ may submit one revised query after receiving execution feedback from $\mathcal{U}$. The evaluation episode concludes when both sub-tasks are successfully completed or all attempts are exhausted. Notably, failure in the initial priority sub-task immediately terminates the entire session.

Budget Constraints. The budget is implemented as a constraint on the number of clarification turns. The total allowed turns, τ_{clar}, are calculated as follows: $\tau_{\text{clar}} = m_{\text{amb}} + \lambda_{\text{pat}}$, Here, m_{amb} represents the minimum budget required to resolve the ambiguities, set to the number of annotated ambiguities in the user query. The parameter λ_{pat} simulates user patience, granting the evaluated system extra turns for clarification.

4.2 a-INTERACT EVALUATION

Interaction Setup. The a-Interact provides LLMs with autonomous planning and execution within a pre-defined action space, following REACT paradigm (Yao et al., 2023). We model the complete database environment as a set of callable tools, containing the target database, metadata, HKB, and User Simulator, allowing the agent to determine optimal invocation strategies dynamically. In this work, we summarize and define 6 discrete actions common to text-to-SQL with details in Appendix J.

Budget Constraints. To reflect the varying computational costs of different actions, we implement a budget-constrained evaluation framework where each action consumes a predetermined amount of budget, encouraging cost-effective action sequences. The total budget for each task is $B = B_{\text{base}} + 2\,m_{\text{amb}} + 2\,\lambda_{\text{pat}}$, where $B_{\text{base}} = 6$ is the base budget, m_{amb} is the number of annotated ambiguity points, and λ_{pat} is the user patience parameter, maintaining consistency with the c-Interact framework. This setting evaluates the agent's ability to achieve high performance under resource constraints while balancing thoroughness with efficiency. Action-specific costs are detailed in Appendix J.

This setting can evaluate agent performance under realistic constraints that present practical database interaction scenarios, where users have limited patience and computational resources are finite.

5 EXPERIMENT

We benchmark 7 recent and powerful LLMs (2 open-source, 5 closed-source) as system models via a fresh PostgreSQL 15 Docker instance for more stable evaluation. We set the user patience to 3 by default and a-Interact base budget of 6. All models use deterministic decoding (temperature=0, top_p=1) with default reasoning settings, conducting single runs due to cost (full details in Appendix I.1 and I.2).

5.1 MAIN RESULTS

Table 2 summarizes the success rate (SR) and normalized reward (NR) obtained by 7 representative frontier LLMs on BIRD-INTERACT-FULL. The full experimental results of BIRD-INTERACT-LITE can be found in Table 10. We can observe:

BIRD-INTERACT remains challenging, leaving ample room for future improvement. Even the strongest models in our study, `GPT-5` and `Gemini-2.5-Pro`, capture only 20.92% and 25.52% of the available reward respectively, in the c-Interact and a-Interact mode. Absolute success rates reveal similar limitations: no more than 16.33% of tasks are solved end-to-end in c-Interact and 17.00% in a-Interact, with most models falling in substantially lower rates.

Evolving User Intent is a Challenge in Online Assessment. Follow-up sub-tasks are noticeably more challenging, likely because the longer, concatenated context in these turns remains a bottleneck for LLMs in interactive text-to-SQL tasks.

Table 2: Success Rate and Final Normalized Reward of different models on BIRD-INTERACT-FULL. The success rate is cumulative; Reward* is the normalized reward (%). The values reported in c-Interact are after debugging phase, and (+n) means the performance gained via debugging. Avg. Cost is the cost for one task on average in USD. Our user simulator has an avg. cost of 0.03 USD.

Model	**Priority Question (Success Rate %) ↑**			**Follow Ups (Success Rate %) ↑**			**Reward* ↑**	**Avg. Cost ↓**
	BI	**DM**	**Overall**	**BI**	**DM**	**Overall**		
c-Interact Text-to-SQL								
GPT-5	9.49 (+0.00)	25.40 (+2.12)	14.50 (+0.67)	5.84 (+0.24)	14.81 (+0.53)	8.67 (+0.33)	12.58	$ 0.08
Claude-Sonnet-3.7	10.71 (+4.62)	33.86 (+7.41)	18.00 (+5.50)	4.62 (+0.49)	16.40 (+3.17)	8.33 (+1.33)	13.87	$ 0.29
Deepseek-Chat-V3.1	11.44 (+0.73)	33.86 (+3.17)	18.50 (+1.50)	4.62 (+0.24)	16.93 (+1.06)	8.50 (+0.50)	15.15	$ 0.12
Qwen-3-Coder-480B	16.30 (+2.68)	34.39 (+5.29)	22.00 (+3.50)	8.03 (+0.97)	16.93 (+4.23)	10.83 (+2.00)	17.75	$ 0.11
Claude-Sonnet-4	16.06 (+4.87)	35.98 (+10.58)	22.33 (+6.67)	10.46 (+1.22)	22.22 (+3.70)	14.17 (+2.00)	18.35	$ 0.29
O3-Mini	17.76 (+2.92)	37.57 (+11.11)	24.00 (+5.50)	11.44 (+0.73)	**25.40** (+4.23)	15.83 (+1.83)	20.27	$ 0.07
Gemini-2.5-Pro	**18.73** (+4.38)	**38.62** (+10.05)	**25.00** (+6.17)	**12.41** (+1.22)	24.87 (+5.29)	**16.33** (+2.50)	**20.92**	$ **0.04**
a-Interact Text-to-SQL								
Qwen-3-Coder-480B	8.05	24.74	13.33	3.90	4.74	4.17	10.58	$ 0.07
Deepseek-Chat-V3.1	10.49	31.58	17.17	4.63	5.26	4.83	13.47	$ **0.06**
O3-Mini	12.20	36.32	19.83	5.85	14.21	8.50	16.43	$ **0.06**
Gemini-2.5-Pro	10.49	41.58	20.33	5.85	20.00	10.33	17.33	$ 0.22
Claude-Sonnet-3.7	11.46	41.58	21.00	5.61	16.84	9.17	17.45	$ 0.60
Claude-Sonnet-4	15.85	53.68	27.83	8.05	22.63	12.67	23.28	$ 0.51
GPT-5	**15.61**	**58.42**	**29.17**	**10.98**	**30.00**	**17.00**	**25.52**	$ 0.24

Offline Reward v.s. Online SR Evaluation. Table 2 shows that offline normalized reward (NR) and online success rate (SR) generally correlate positively, though notable divergences occur due to the reward structure allocating 70% to the primary sub-task and 30% to follow-up sub-tasks. These complementary metrics capture different aspects of model performance. Success rate measures holistic task completion across multi-turn interactions, relevant when users prioritize successful outcomes regardless of path. Normalized reward assesses performance on users' critical initial objectives while crediting challenging follow-up sub-tasks. Together, they provide comprehensive evaluation of the distinct capabilities required for advanced interactive text-to-SQL systems.

Business Intelligence versus Data Management. BI queries pose significantly greater challenges for LLMs compared to data management (DM) tasks since DM operations typically follow standardized, predictable patterns that LLMs can effectively learn (Li et al., 2025d), whereas BI queries demand nuanced understanding of complex, domain-specific business logic and analytical reasoning that varies substantially across contexts.

Interaction Mode Emerged as the Decisive Factor for a Successful Outcome. Furthermore, we observe that different models demonstrate varying aptitudes for different interaction paradigms, with each model showing relative strengths in specific modes. For example, `GPT-5` performs poorly in the constrained, predefined flow designed personally of the c-Interact mode by achieving only 14.50% SR (worst) but excels in the a-Interact setting with 29.17% SR (best), which affords more flexible and exploratory space. This evidence demonstrates the critical importance of matching interaction modes to model-specific capabilities, which we hypothesize stem from differences in training data distributions and architectural inductive biases (Liu et al., 2024; Gao et al., 2024b).

5.2 INTERACTION ANALYSIS

The Impact of Communication on Task Success in c-Interact. A notable finding is the underperformance of the flagship model, `GPT-5`, on the c-Interact, despite its strong performance on many single-turn tasks (Phan et al., 2025; Glazer et al., 2024; Rein et al., 2024). Therefore, we hypothesize that this stems from a deficiency in its interactive communication abilities rather than its core generation capability. To test this hypothesis, we conduct an experiment termed ***Memory Grafting***. In this setup, we provide `GPT-5` with the ambiguity resolution histories from **two other better models**, `Qwen-3-Coder` and `O3-mini`, before asking it to generate the final SQL query. The results, presented in Figure 5, show that `GPT-5`'s performance improves significantly when leveraging the interaction history from either model. This finding indicates that while `GPT-5` possesses robust SQL generation capabilities, a more effective communication schema is required to help it achieve satisfactory outcomes for user tasks. We also further analyze the patterns for effective communication in Appendix Q.

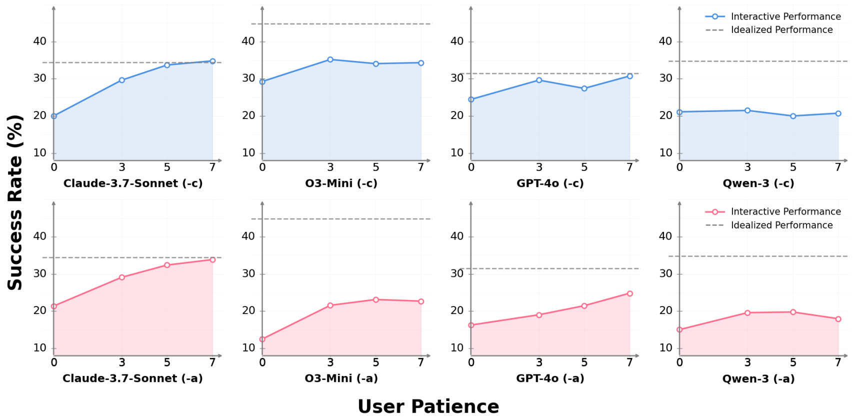


Figure 4: The performance of different LLMs with different user patience on BIRD-INTERACT-LITE. The red line denotes a-Interact mode (-a); the blue line denotes c-Interact mode (-c). And the dotted line (***Idealized*** Performance) denotes the performance under ambiguity-free single-turn text-to-SQL.

Interaction Test-Time Scaling. To investigate the relationship between interaction frequency and model performance, we conduct an Interaction Test-Time Scaling (ITS) experiment in **BIRD-INTERACT-LITE** where results are shown in Figure 4. We simulate varying levels of user patience by allowing different numbers of interaction turns for both c-Interact and a-Interact. As a baseline, we include single-turn task performance for each model, where all necessary context is provided to create self-contained tasks. This single-turn condition represents an ***idealized*** scenario that, while potentially requiring significant user effort to ensure complete information provided (Li et al., 2025d; BIRD-Team, 2025), eliminates the need for further clarification. As demonstrated in the figure, `Claude-3.7-Sonnet` exhibits clear scaling behavior with respect to increasing interaction opportunities. This pattern indicates that the model can keep increasing its performance through incremental communication chances of interactions.

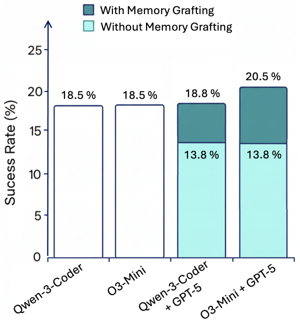


Figure 5: SR of GPT-5 with memory grafting.

> **ITS Law:** A model satisfies this law if, given enough conversational turns, its performance can match or even surpass that of the idealized single-turn task.

Action Distribution Patterns in a-Interact. We analyze action distributions across 7 system models and find concentration in two primary actions: `submit` (direct code execution with error feedback) and `ask` (user clarification requests), which together comprise 60.87% of all actions. Despite being the most computationally expensive actions (Figure 3), models favor these over systematic exploration behaviors like knowledge and schema retrieval. This suggests LLMs prefer direct trial-and-error execution over comprehensive environment exploration, likely due to pre-training biases. Future work should incentivize broader tool utilization for complex interactive tasks. Additional analysis on the FULL set appears in Appendix J.

6 USER SIMULATOR ANALYSIS

This section presents a comprehensive evaluation of our function-driven user simulator compared to conventional user simulators and their respective impacts on dynamic interactive text-to-SQL benchmarks through both objective and subjective experiments.

Evaluation on USERSIM-GUARD. To provide an objective and comprehensive observation of different user simulator mechanisms, we construct a static dataset called USERSIM-GUARD, comprising 1,989 questions with reference actions labeled by human experts. Detailed information regarding the distribution and annotation procedures can be found in Appendix O. We employed an LLM-as-Judge (Zheng et al., 2023) evaluation framework using `Qwen-2.5-72B` and `Llama-3.1-70B` as independent evaluators to mitigate potential self-enhancement bias. Our analysis reveals significant reliability concerns with conventional user simulator designs. Specifically, as shown in Figure 6, when confronted with Unanswerable (`UNA`) questions, baseline user simulators consistently fail to implement safeguards, resulting in unfair or inappropriate feedback generation with over 34% failure rate. In contrast, our proposed function-driven approach demonstrates substantially improved reliability, with only 5.9% of responses falling into problematic categories. This represents a significant improvement in user simulator robustness and reliability compared to baseline approaches.

Alignment with Human User. We evaluate alignment between our user simulators and actual human behavior by having human experts interact with 7 system models on 100 randomly sampled tasks across BI and DM domains. We then compute correlations (Ivey et al., 2024; Kong et al., 2024) between success rates (SR) achieved by human users versus our simulators across the same tasks. As shown in Table 3, function-driven simulators demonstrate significantly stronger alignment with human behavior: `GPT-4o` with function calling achieves 0.84 Pearson correlation (p = 0.02) compared to 0.61 without function calling (p = 0.14), while Gemini-2.0-Flash shows similar improvements (0.79 vs. 0.54). These results confirm that incorporating our designed user simulator mechanism produces more realistic user simulators that better reflect actual human-AI interaction patterns (detailed analysis in Appendix O).

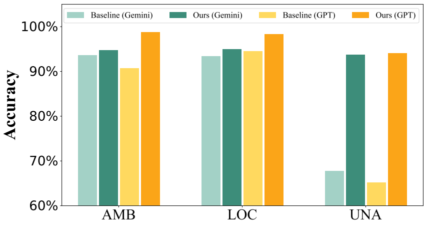


Figure 6: The accuracy of different user simulators on USERSIM-GUARD.

7 RELATED WORK

Recent progress in Text-to-SQL is driven by large language models (LLMs) (OpenAI, 2025; Team et al., 2023; Team, 2024; Guo et al., 2025), with single-turn methods ranging from few-shot in-context learning (DIN-SQL (Pourreza & Rafiei, 2023), DAIL-SQL (Gao et al., 2024a)) and curated training (CodeS (Li et al., 2024), DTS-SQL (Pourreza & Rafiei, 2024)) to iterative agent-based frameworks (MAC-SQL (Wang et al., 2025)). However, this body of work focuses on single-turn settings, overlooking conversational interactions. While multi-turn benchmarks like COSQL (Yu et al., 2019a) and LEARN-TO-CLARIFY (Chen et al., 2025b) exist, their use of static dialogue histories is a key limitation (Yao et al., 2025; Barres et al., 2025), as dynamic interaction is hard to simulate realistically for databases (Zhou et al., 2025; Barres et al., 2025), unlike in other agent benchmarks (Wang et al., 2024). We address this gap by introducing an interactive benchmark with an optimized user simulator to evaluate models in realistic, uncertain conversational text-to-SQL scenarios. Detailed related work can be found in Appendix P.

Table 3: Correlation analysis between AI and human users.

User Simulator	**Pearson (*p*-value)**
GPT-4o *- w/ Func. (Ours)*	0.84 ($p = 0.02$)
Gemini-2.0-Flash *- w/ Func. (Ours)*	0.79 ($p = 0.03$)
GPT-4o *- Baseline*	0.61 ($p = 0.14$)
Gemini-2.0-Flash *- Baseline*	0.54 ($p = 0.21$)

8 CONCLUSION

We present BIRD-INTERACT, a benchmark for evaluating interactive text-to-SQL systems through dynamic, multi-turn conversations that better reflect real-world usage scenarios. Our benchmark features a function-driven user simulator, dual evaluation settings for conversational and autonomous planning modes, and totally 900 challenging tasks designed to test LLM abilities to handle ambiguities and maintain state across turns. Comprehensive evaluation demonstrates a critical gap between existing SQL generation capabilities and the strategic interaction skills required for effective human-AI collaboration in database querying.

ETHICS STATEMENT

This research complies with the ICLR Code of Ethics. We have carefully reviewed the guidelines and ensured that our work aligns with the stated ethical standards, including considerations of data privacy, fairness, and responsible use of released datasets and code. Justification: This work does not involve crowdsourcing or research with human subjects. All annotation and task creation were carried out by the authors themselves.

REPRODUCIBILITY STATEMENT

We have taken several steps to ensure the reproducibility of our work. First, for the evaluated systems, all experimental settings, including model parameters, temperature (= 0), and budget configurations, are clearly documented in Appendix I, ensuring that our evaluation can be replicated under the same conditions. Each task is executed in a freshly re-initialized PostgreSQL 15 instance (Docker). The Docker image contains the database engine and benchmark code, and is restarted for every run to guarantee a clean and consistent state. This setup makes experiments deterministic, isolated across runs, and easy to reproduce by rebuilding the environment from scratch. Second, for the user simulator, we validate its robustness in Section 6, and detail in Section 3 how we designed and annotated the benchmark to guarantee reliability, uniqueness of clarifications, and consistency of responses from the user simulator. This safeguards reproducibility across different runs and systems. Third, for the benchmark suite, we will publicly release all components under a permissive license, including databases, tasks, hierarchical knowledge bases, documentation, interaction logs, and the source code for both evaluation settings and the user simulator. This full release ensures transparency and faithful replication of our experiments. We also provide the prompts used across the whole experiment, which can be found in Appendix T, from Figure 20 to Figure 27. Due to the dynamic nature of our interaction evaluation, we will also open-source our interaction trajectories upon publication for better reproducibility.

Experiment Configuration. All experiments on BIRD-INTERACT are conducted via API, except for the LLM-as-Judge evaluations of different user simulators, which are run on 4 NVIDIA A100 80G GPUs. The estimated cost for each model under BIRD-INTERACT-FULL is shown in Table 2, and the estimated cost for BIRD-INTERACT-LITE is shown in Table 10.

REFERENCES

Lama Ahmad, Sandhini Agarwal, Michael Lampe, and Pamela Mishkin. Openai's approach to external red teaming for ai models and systems. *arXiv preprint arXiv:2503.16431*, 2025.

Victor Barres, Honghua Dong, Soham Ray, Xujie Si, and Karthik Narasimhan. tau2-bench: Evaluating conversational agents in a dual-control environment. *arXiv preprint arXiv:2506.07982*, 2025.

Adithya Bhaskar, Tushar Tomar, Ashutosh Sathe, and Sunita Sarawagi. Benchmarking and improving text-to-SQL generation under ambiguity. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 7053–7074, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.436.

BIRD-Team. Livesqlbench: A dynamic and contamination-free benchmark for evaluating llms on real-world text-to-sql tasks. https://github.com/bird-bench/livesqlbench, 2025. Accessed: 2025-05-22.

Hasan Alp Caferoğlu and Özgür Ulusoy. E-sql: Direct schema linking via question enrichment in text-to-sql. *arXiv preprint arXiv:2409.16751*, 2024.

Zhenbiao Cao, Yuanlei Zheng, Zhihao Fan, Xiaojin Zhang, Wei Chen, and Xiang Bai. Rsl-sql: Robust schema linking in text-to-sql generation. *arXiv preprint arXiv:2411.00073*, 2024.

Chongyan Chen, Yu-Yun Tseng, Zhuoheng Li, Anush Venkatesh, and Danna Gurari. Accounting for focus ambiguity in visual questions. *arXiv preprint arXiv:2501.02201*, 2025a.

Maximillian Chen, Ruoxi Sun, Tomas Pfister, and Sercan Ö. Arik. Learning to clarify: Multi-turn conversations with action-based contrastive self-training. In *ICLR*, 2025b.

Xi Chen, Jinguo You, Kun Li, and Xiang Li. Beyond read-only: Crafting a comprehensive Chinese text-to-SQL dataset for database manipulation and query. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Findings of the Association for Computational Linguistics: NAACL 2024*, pp. 3383–3393, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-naacl.214.

Deborah A. Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. Expanding the scope of the ATIS task: The ATIS-3 corpus. In *Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994*, 1994.

Bryan L. M. de Oliveira, Luana G. B. Martins, Bruno Brandão, and Luckeciano C. Melo. Infoquest: Evaluating multi-turn dialogue agents for open-ended conversations with hidden context. *arXiv preprint arXiv:2502.12257*, 2025.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. Wizard of wikipedia: Knowledge-powered conversational agents. In *ICLR (Poster)*. OpenReview.net, 2019.

Longxu Dou, Yan Gao, Xuqi Liu, Mingyang Pan, Dingzirui Wang, Wanxiang Che, Dechen Zhan, Min-Yen Kan, and Jian-Guang Lou. Towards knowledge-intensive text-to-SQL semantic parsing with formulaic knowledge. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (eds.), *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 5240–5253, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.350.

Dawei Gao, Haibin Wang, Yaliang Li, Xiuyu Sun, Yichen Qian, Bolin Ding, and Jingren Zhou. Text-to-sql empowered by large language models: A benchmark evaluation. *Proc. VLDB Endow.*, 17(5):1132–1145, January 2024a. ISSN 2150-8097. doi: 10.14778/3641204.3641221.

Jie Gao, Simret Araya Gebreegziabher, Kenny Tsu Wei Choo, Toby Jia-Jun Li, Simon Tangi Perrault, and Thomas W Malone. A taxonomy for human-llm interaction modes: An initial exploration. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, CHI EA '24, New York, NY, USA, 2024b. Association for Computing Machinery. ISBN 9798400703317. doi: 10.1145/3613905.3650786.

Elliot Glazer, Ege Erdil, Tamay Besiroglu, Diego Chicharro, Evan Chen, Alex Gunning, Caroline Falkman Olsson, Jean-Stanislas Denain, Anson Ho, Emily de Oliveira Santos, Olli Järviniemi, Matthew Barnett, Robert Sandler, Jaime Sevilla, Qiuyu Ren, Elizabeth Pratt, Lionel Levine, Grant Barkley, Natalie Stewart, Bogdan Grechuk, Tetiana Grechuk, Shreepranav Varma Enugandla, and Mark Wildon. Frontiermath: A benchmark for evaluating advanced mathematical reasoning in ai. *arXiv preprint*, arXiv:2411.04872, 2024.

Jiawei Gu, Xuhui Jiang, Zhichao Shi, Hexiang Tan, Xuehao Zhai, Chengjin Xu, Wei Li, Yinghan Shen, Shengjie Ma, Honghao Liu, et al. A survey on llm-as-a-judge. *arXiv preprint arXiv:2411.15594*, 2024.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

Jiaqi Guo, Ziliang Si, Yu Wang, Qian Liu, Ming Fan, Jian-Guang Lou, Zijiang Yang, and Ting Liu. Chase: A large-scale and pragmatic Chinese dataset for cross-database context-dependent text-to-SQL. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 2316–2331, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.180.

Moshe Hazoom, Vibhor Malik, and Ben Bogin. Text-to-SQL in the wild: A naturally-occurring dataset based on stack exchange data. In Royi Lachmy, Ziyu Yao, Greg Durrett, Milos Gligoric, Junyi Jessy

Li, Ray Mooney, Graham Neubig, Yu Su, Huan Sun, and Reut Tsarfaty (eds.), *Proceedings of the 1st Workshop on Natural Language Processing for Programming (NLP4Prog 2021)*, pp. 77–87, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.nlp4prog-1.9.

Evan Hubinger. Introducing alignment stress-testing at anthropic. In *AI Alignment Forum, January*, 2024.

Jonathan Ivey, Shivani Kumar, Jiayu Liu, Hua Shen, Sushrita Rakshit, Rohan Raju, Haotian Zhang, Aparna Ananthasubramaniam, Junghwan Kim, Bowen Yi, et al. Real or robotic? assessing whether llms accurately simulate qualities of human responses in dialogue. *arXiv preprint arXiv:2409.08330*, 2024.

Taaha Kazi, Ruiliang Lyu, Sizhe Zhou, Dilek Hakkani-Tür, and Gokhan Tur. Large language models as user-agents for evaluating task-oriented-dialogue systems. In *SLT*, pp. 913–920. IEEE, 2024.

Chuyi Kong, Yaxin Fan, Xiang Wan, Feng Jiang, and Benyou Wang. Platolm: Teaching llms in multi-round dialogue via a user simulator. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 7841–7863, 2024.

Maya Larbi, Amal Akli, Mike Papadakis, Rihab Bouyousfi, Maxime Cordy, Federica Sarro, and Yves Le Traon. When prompts go wrong: Evaluating code model robustness to ambiguous, contradictory, and incomplete task descriptions. *arXiv preprint arXiv:2507.20439*, 2025. Accessed: 2025-09-23.

Chia-Hsuan Lee, Oleksandr Polozov, and Matthew Richardson. Kaggledbqa: Realistic evaluation of text-to-sql parsers. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 2261–2273, 2021.

Dongjun Lee, Choongwon Park, Jaehyuk Kim, and Heesoo Park. MCS-SQL: leveraging multiple prompts and multiple-choice selection for text-to-sql generation. In *COLING*, pp. 337–353. Association for Computational Linguistics, 2025.

Fangyu Lei, Jixuan Chen, Yuxiao Ye, Ruisheng Cao, Dongchan Shin, SU Hongjin, ZHAOQING SUO, Hongcheng Gao, Wenjing Hu, Pengcheng Yin, et al. Spider 2.0: Evaluating language models on real-world enterprise text-to-sql workflows. In *The Thirteenth International Conference on Learning Representations*, 2025.

Boyan Li, Jiayi Zhang, Ju Fan, Yanwei Xu, Chong Chen, Nan Tang, and Yuyu Luo. Alpha-SQL: Zero-shot text-to-SQL using monte carlo tree search. In *Forty-second International Conference on Machine Learning*, 2025a.

Haoyang Li, Jing Zhang, Hanbing Liu, Ju Fan, Xiaokang Zhang, Jun Zhu, Renjie Wei, Hongyan Pan, Cuiping Li, and Hong Chen. Codes: Towards building open-source language models for text-to-sql. *Proceedings of the ACM on Management of Data (PACMMOD)*, 2(3):1–28, 2024. doi: 10.1145/3654930.

Haoyang Li, Shang Wu, Xiaokang Zhang, Xinmei Huang, Jing Zhang, Fuxin Jiang, Shuai Wang, Tieying Zhang, Jianjun Chen, Rui Shi, Hong Chen, and Cuiping Li. Omnisql: Synthesizing high-quality text-to-sql data at scale. *Proc. VLDB Endow.*, 18(11):4695–4709, September 2025b. ISSN 2150-8097. doi: 10.14778/3749646.3749723.

Jinyang Li, Binyuan Hui, Ge Qu, Jiaxi Yang, Binhua Li, Bowen Li, Bailin Wang, Bowen Qin, Ruiying Geng, Nan Huo, Xuanhe Zhou, Chenhao Ma, Guoliang Li, Kevin Chen-Chuan Chang, Fei Huang, Reynold Cheng, and Yongbin Li. Can LLM already serve as A database interface? A big bench for large-scale database grounded text-to-sqls. In *NeurIPS*, 2023.

Jinyang Li, Nan Huo, Yan Gao, Jiayi Shi, Yingxiu Zhao, Ge Qu, Bowen Qin, Yurong Wu, Xiaodong Li, Chenhao Ma, Jian-Guang Lou, and Reynold Cheng. Are large language models ready for multi-turn tabular data analysis? In *Forty-second International Conference on Machine Learning*, 2025c.

Jinyang Li, Xiaolong Li, Ge Qu, Per Jacobsson, Bowen Qin, Binyuan Hui, Shuzheng Si, Nan Huo, Xiaohan Xu, Yue Zhang, et al. Swe-sql: Illuminating llm pathways to solve user sql issues in real-world applications. *arXiv preprint arXiv:2506.18951*, 2025d.

Junyan Li, Wenshuo Zhao, Yang Zhang, and Chuang Gan. Steering llm thinking with budget guidance. *arXiv preprint arXiv:2506.13752*, 2025e.

Zongxi Li, Yang Li, Haoran Xie, and S. Joe Qin. Condambigqa: A benchmark and dataset for conditional ambiguous question answering. In *Proceedings of the 2025 Conference of the North American Chapter of the Association for Computational Linguistics (NAACL) / EMNLP?*, 2025f. also arXiv preprint arXiv:2502.01523, revised version 2.

Xiao Liu, Hao Yu, Hanchen Zhang, Yifan Xu, Xuanyu Lei, Hanyu Lai, Yu Gu, Hangliang Ding, Kaiwen Men, Kejuan Yang, Shudan Zhang, Xiang Deng, Aohan Zeng, Zhengxiao Du, Chenhui Zhang, Sheng Shen, Tianjun Zhang, Yu Su, Huan Sun, Minlie Huang, Yuxiao Dong, and Jie Tang. Agentbench: Evaluating LLMs as agents. In *The Twelfth International Conference on Learning Representations*, 2024.

Yifu Liu, Yin Zhu, Yingqi Gao, Zhiling Luo, Xiaoxia Li, Xiaorong Shi, Yuntao Hong, Jinyang Gao, Yu Li, Bolin Ding, et al. Xiyan-sql: A novel multi-generator framework for text-to-sql. *arXiv preprint arXiv:2507.04701*, 2025.

Karime Maamari, Fadhil Abubaker, Daniel Jaroslawicz, and Amine Mhedhbi. The death of schema linking? text-to-sql in the age of well-reasoned language models. *arXiv preprint arXiv:2408.07702*, 2024.

OpenAI. Openai o3 and o4-mini system card, 2025. Accessed: 2025-05-15.

Long Phan, Alice Gatti, Ziwen Han, Nathaniel Li, Josephina Hu, Hugh Zhang, Chen Bo Calvin Zhang, Mohamed Shaaban, John Ling, Sean Shi, et al. Humanity's last exam. *arXiv preprint arXiv:2501.14249*, 2025.

Mohammadreza Pourreza and Davood Rafiei. Din-sql: Decomposed in-context learning of text-to-sql with self-correction. *Advances in Neural Information Processing Systems*, 36:36339–36348, 2023.

Mohammadreza Pourreza and Davood Rafiei. Dts-sql: Decomposed text-to-sql with small large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, 2024.

Mohammadreza Pourreza, Hailong Li, Ruoxi Sun, Yeounoh Chung, Shayan Talaei, Gaurav Tarlok Kakkar, Yu Gan, Amin Saberi, Fatma Ozcan, and Sercan Ö. Arik. CHASE-SQL: multi-path reasoning and preference optimized candidate selection in text-to-sql. In *ICLR*. OpenReview.net, 2025a.

Mohammadreza Pourreza, Shayan Talaei, Ruoxi Sun, Xingchen Wan, Hailong Li, Azalia Mirhoseini, Amin Saberi, Sercan Arik, et al. Reasoning-sql: Reinforcement learning with sql tailored partial rewards for reasoning-enhanced text-to-sql. *arXiv preprint arXiv:2503.23157*, 2025b.

Ge Qu, Jinyang Li, Bowen Li, Bowen Qin, Nan Huo, Chenhao Ma, and Reynold Cheng. Before generation, align it! A novel and effective strategy for mitigating hallucinations in text-to-sql generation. In *ACL (Findings)*, pp. 5456–5471. Association for Computational Linguistics, 2024.

David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. Gpqa: A graduate-level google-proof q&a benchmark. In *First Conference on Language Modeling*, 2024.

Irina Saparina and Mirella Lapata. AMBROSIA: A benchmark for parsing ambiguous questions into database queries. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024.

Erik Schluntz and Barry Zhang. Building effective agents, December 2024. Engineering at Anthropic.

Lei Sheng and Shuai-Shuai Xu. Slm-sql: An exploration of small language models for text-to-sql. *arXiv preprint arXiv:2507.22478*, 2025.

Liang Shi, Zhengju Tang, Nan Zhang, Xiaotong Zhang, and Zhi Yang. A survey on employing large language models for text-to-sql tasks. *ACM Computing Surveys*, 2024.

Shayan Talaei, Mohammadreza Pourreza, Yu-Chen Chang, Azalia Mirhoseini, and Amin Saberi. Chess: Contextual harnessing for efficient sql synthesis. *arXiv preprint arXiv:2405.16755*, 2024.

Robert S Taylor. Question-negotiation and information seeking in libraries. *College & Research Libraries*, 76(3):251–267, 2015.

DeepSeek-AI Team. Deepseek-v3 technical report. *arXiv preprint arXiv:2412.19437*, 2024.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Bing Wang, Changyu Ren, Jian Yang, Xinnian Liang, Jiaqi Bai, Linzheng Chai, Zhao Yan, Qian-Wen Zhang, Di Yin, Xing Sun, and Zhoujun Li. Mac-sql: A multi-agent collaborative framework for text-to-sql. In *Proceedings of the 31st International Conference on Computational Linguistics (COLING 2025)*, pp. 540–557, 2025.

Xingyao Wang, Zihan Wang, Jiateng Liu, Yangyi Chen, Lifan Yuan, Hao Peng, and Heng Ji. Mint: Evaluating llms in multi-turn interaction with tools and language feedback. In *The Twelfth International Conference on Learning Representations*, 2024.

Hao Wen, Xinrui Wu, Yi Sun, Feifei Zhang, Liye Chen, Jie Wang, Yunxin Liu, Ya-Qin Zhang, and Yuanchun Li. Budgetthinker: Empowering budget-aware llm reasoning with control tokens. *arXiv preprint arXiv:2508.17196*, 2025.

Shirley Wu, Michel Galley, Baolin Peng, Hao Cheng, Gavin Li, Yao Dou, Weixin Cai, James Zou, Jure Leskovec, and Jianfeng Gao. Collabllm: From passive responders to active collaborators. *arXiv preprint arXiv:2502.00640*, 2025.

John Yang, Akshara Prabhakar, Karthik Narasimhan, and Shunyu Yao. Intercode: Standardizing and benchmarking interactive coding with execution feedback. *Advances in Neural Information Processing Systems*, 36:23826–23854, 2023.

Shunyu Yao, Howard Chen, John Yang, and Karthik Narasimhan. Webshop: Towards scalable real-world web interaction with grounded language agents. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 20744–20757. Curran Associates, Inc., 2022.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations (ICLR)*, 2023.

Shunyu Yao, Noah Shinn, Pedram Razavi, and Karthik R Narasimhan. {τ}-bench: A benchmark for \underline{T}ool-\underline{A}gent-\underline{U}ser interaction in real-world domains. In *The Thirteenth International Conference on Learning Representations*, 2025.

Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir R. Radev. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task. In *EMNLP*, pp. 3911–3921. Association for Computational Linguistics, 2018.

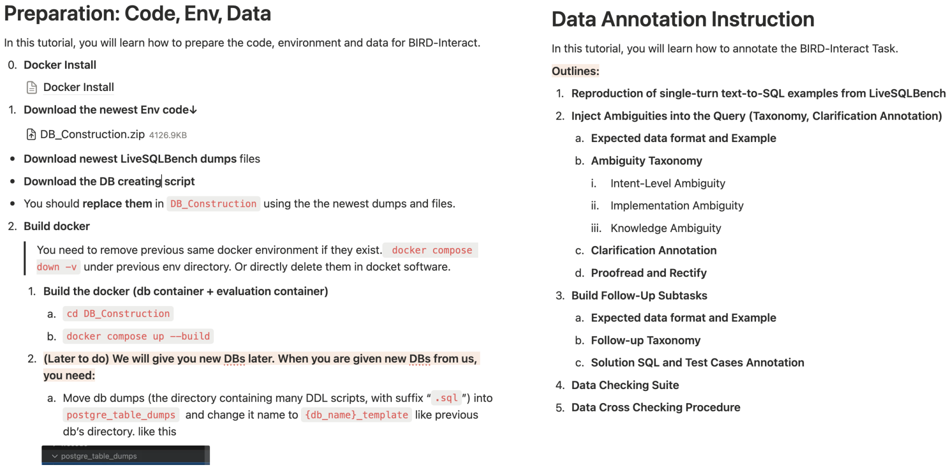
Tao Yu, Rui Zhang, Heyang Er, Suyi Li, Eric Xue, Bo Pang, Xi Victoria Lin, Yi Chern Tan, Tianze Shi, Zihan Li, Youxuan Jiang, Michihiro Yasunaga, Sungrok Shim, Tao Chen, Alexander R. Fabbri, Zifan Li, Luyao Chen, Yuwen Zhang, Shreya Dixit, Vincent Zhang, Caiming Xiong, Richard Socher, Walter S. Lasecki, and Dragomir R. Radev. Cosql: A conversational text-to-sql challenge towards cross-domain natural language interfaces to databases. In *EMNLP/IJCNLP (1)*, pp. 1962–1979. Association for Computational Linguistics, 2019a.

Tao Yu, Rui Zhang, Michihiro Yasunaga, Yi Chern Tan, Xi Victoria Lin, Suyi Li, Heyang Er, Irene Li, Bo Pang, Tao Chen, Emily Ji, Shreya Dixit, David Proctor, Sungrok Shim, Jonathan Kraft, Vincent Zhang, Caiming Xiong, Richard Socher, and Dragomir R. Radev. Sparc: Cross-domain semantic parsing in context. In *ACL (1)*, pp. 4511–4523. Association for Computational Linguistics, 2019b.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in neural information processing systems*, 36:46595–46623, 2023.

Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning. *arXiv preprint arXiv:1709.00103*, 2017.

Yifei Zhou, Song Jiang, Yuandong Tian, Jason Weston, Sergey Levine, Sainbayar Sukhbaatar, and Xian Li. Sweet-rl: Training multi-turn llm agents on collaborative reasoning tasks. *arXiv preprint arXiv:2503.15478*, 2025.



Preparation: Code, Env, Data

In this tutorial, you will learn how to prepare the code, environment and data for BIRD-Interact.

0. **Docker Install**
    - Docker Install
1. **Download the newest Env code↓**
    - DB_Construction.zip 4126.9KB

- **Download newest LiveSQLBench dumps** files
- **Download the DB creating script**
- You should **replace them** in `DB_Construction` using the the newest dumps and files.

2. **Build docker**

    > You need to remove previous same docker environment if they exist. `docker compose down -v` under previous env directory. Or directly delete them in docket software.

    1. **Build the docker (db container + evaluation container)**
        a. `cd DB_Construction`
        b. `docker compose up --build`
    2. **(Later to do) We will give you new DBs later. When you are given new DBs from us, you need:**
        a. Move db dumps (the directory containing many DDL scripts, with suffix “`.sql`”) into `postgre_table_dumps` and change it name to `{db_name}_template` like previous db's directory. like this

Data Annotation Instruction

In this tutorial, you will learn how to annotate the BIRD-Interact Task.

Outlines:

1. **Reproduction of single-turn text-to-SQL examples from LiveSQLBench**
2. **Inject Ambiguities into the Query (Taxonomy, Clarification Annotation)**
    a. **Expected data format and Example**
    b. **Ambiguity Taxonomy**
        i. Intent-Level Ambiguity
        ii. Implementation Ambiguity
        iii. Knowledge Ambiguity
    c. **Clarification Annotation**
    d. **Proofread and Rectify**
3. **Build Follow-Up Subtasks**
    a. **Expected data format and Example**
    b. **Follow-up Taxonomy**
    c. **Solution SQL and Test Cases Annotation**
4. **Data Checking Suite**
5. **Data Cross Checking Procedure**

Figure 7: Examples of training materials by screenshots for BIRD-Interact annotators.

A LIMITATIONS.

Our work has centered on the text-to-SQL domain, but we believe our proposed interaction evaluation is not inherently limited to it. Instead, it can cover a generalizable human-AI collaboration. Exploring the adaptation of this framework to other generative domains, such as Python code synthesis or API call generation, is a promising direction for future research. But at this time, we think it's a representative scenario since it also features long-context, hierarchical knowledge, and AI coding problem.

B THE USE OF LLM STATEMENT

Large Language Models (LLMs) were used only for light post-editing of the paper (i.e., reducing syntax errors and performing minor grammar checks). LLMs were not involved in any part of the research discussions, analyses, or idea generation. All insights, contributions, and intellectual content are entirely the authors' own.

C ANNOTATION GROUP DETAILS

To ensure the high quality of annotations for the BIRD-INTERACT benchmark, we designed a rigorous, multi-stage process for annotator selection, training, and qualification. This process aimed to ensure that all annotators possessed strong SQL expertise and followed a consistent, reproducible workflow.

C.1 ANNOTATOR ENTRANCE TEST

All potential annotators were required to complete a structured training program before contributing to the benchmark. We began by recruiting a pool of 33 candidates, including students, engineers, and text-to-SQL researchers with prior database experience. Each candidate underwent a week-long training period consisting of tutorials and guided exercises (detailed below), followed by a qualification exam. This exam tested proficiency in SQL generation, schema understanding, and annotation of interactive tasks. Only candidates who achieved a passing score of at least 90% were admitted as official annotators, resulting in a final team of 12 highly qualified contributors.

C.2 TRAINING TUTORIALS

Candidates participated in an intensive tutorial program covering essential aspects of interactive text-to-SQL, including:

- Database environment setup

- Database schema analysis and comprehension
- Reproduction of single-turn text-to-SQL examples from LIVESQLBENCH
- Ambiguity taxonomy, injection procedures, and clarification annotation
- Follow-up sub-task taxonomy and construction, with solution SQL and test scripts
- Solution validation and evaluation script development

The tutorials contain the DB sandbox, code suite, detailed procedures, examples, and hands-on exercises that mirror the interactive feature of real-world SQL tasks. Some parts of the tutorials are shown in Figure 7. Annotators were introduced to the full annotation workflow required for the creation of the BIRD-INTERACT benchmark.

C.3 QUALIFICATION TEST

Following the tutorial phase, candidates were required to complete a qualification assignment consisting of 20 representative interactive text-to-SQL tasks. For each task, candidates were asked to:

1. Reproduce the environment and baseline single-turn text-to-SQL task.
2. Inject ambiguity into the task and annotate the corresponding unique clarification, ensuring that with clarification the original clear task could be recovered.
3. Create a follow-up sub-task and annotate it with solution SQL and test scripts.
4. Validate that the solution SQLs passed all annotated test scripts in sequence across sub-tasks.
5. Document their approach and provide a validation log.

Only candidates who successfully completed the assignment with satisfactory quality were approved as annotators. This stringent qualification process ensured that all annotators met the high standards required for building a robust and trustworthy benchmark. The overall success rate was approximately 90%, demonstrating the effectiveness of the tutorial materials and training program in preparing candidates for interactive text-to-SQL annotation. All annotators contributing to the final release of BIRD-INTERACT passed this qualification process.

D BENCHMARK DESIGN PRINCIPLES

Our design philosophy for BIRD-INTERACT is guided by two core principles: incorporating realistic interaction challenges and ensuring robust, reproducible evaluation.

Realistic Interaction Challenges. To mirror the complexity of real-world data analysis, we establish scenarios where interaction is indispensable for task completion. This is achieved through two mechanisms. (1) **Ambiguity:** We deliberately inject different types of ambiguity—spanning user queries, knowledge bases, and database environments—such that tasks cannot be solved correctly without clarification. Resolving these ambiguities often requires multi-turn exchanges, forcing systems to decide when to query the user, consult the HKB, or explore the database. This design captures the iterative, source-dependent nature of ambiguity resolution. (2) **Contextual Follow-ups**: Every task includes a subsequent, related query that requires the system to reason over the preceding conversation, the interaction history, and, critically, a potentially changed database state.

Reliable and Reproducible Evaluation. We ensure the reliability and reproducibility of evaluation from three key aspects. (1) **Unambiguous annotation:** each ambiguity is annotated with a single definitive interpretation. The user simulator resolves ambiguities by referencing key SQL snippets associated with each ambiguity point, rather than natural-language annotations. This enables the simulator to produce fluent, natural responses while keeping clarifications precise and grounded in the underlying logic. (2) **Reference-based disambiguation:** to avoid cases where certain ambiguities lack explicit annotations, the simulator is additionally provided with the reference SQL, allowing it to generate accurate clarifications when necessary. While in real-world scenarios, real users may only have vague initial goals without an answer when making a request, this pragmatic design

Table 4: Data statistics of features in BIRD-INTERACT compared to the evaluation set of related benchmarks. **# Avg Interactions**: Number of interactions by unfolding the model's interaction trajectory. **# Toks./Output**: Average number of tokens in the reference output; "/" indicates benchmarks without reference output. **Dynamic User**: Whether the benchmark supports real-time user interaction (vs. static offline datasets). **Dynamic Env State**: Whether the database or environment state can be modified during interaction. **Amb. Sources**: Sources of ambiguity in user queries or environments. LLM + Guard means LLM as user simulator with Guard mechanism to make actions more controllable.

Category	Dataset	# Tasks	# Avg Interactions	# Toks. / Output	Dynamic User	Dynamic Env State	Amb. Sources	Ext. Knowledge
SQL Generation	KaggleDBQA (Lee et al., 2021)	272	1	24.28	✗	✗	✗	✗
	WikiSQL (Zhong et al., 2017)	15,878	1	15.59	✗	✓	✗	✓
	Spider (Yu et al., 2018)	2,147	1	30.18	✗	✗	✗	✗
	Spider 2.0 (Lei et al., 2025)	632	1	412.37	✗	✓	✗	✓
	BIRD-SQL (Li et al., 2023)	1,534	1	50.01	✗	✗	✗	✓
	BIRD-Critic (Li et al., 2025d)	1,100	1	109.66	✗	✗	✗	✓
	BIRD-Mini-Dev (Li et al., 2023)	500	1	63.56	✗	✗	✗	✓
Ambiguity Handling	AMBROSIA (Saparina & Lapata, 2024)	1,277	1	88.36	✗	✗	User	✗
	AmbiQT (Bhaskar et al., 2023)	3,000	1	31.72	✗	✗	User	✗
	When Prompts Go Wrong (Larbi et al., 2025)	300	1	55.71	✗	✗	Description	✗
	InfoQuest (de Oliveira et al., 2025)	1,000	3.76	/	LLM	1	User + Persona	✗
	CondAmbigQA (Li et al., 2025f)	200	1	44.94	✗	✗	Query + Docs	✓
	VQ-FocusAmbiguity (Chen et al., 2025a)	5,500	1	1.54	✗	✗	Visual	✗
Multi-Turn Benchmark	SparC (Yu et al., 2019b)	422	1	34.58	Offline	✗	✗	✗
	CoSQL (Yu et al., 2019a)	1300	1	39.34	Offline	✗	✗	✗
	CHASE (Guo et al., 2021)	2,494	1	43.71	✗	✗	✗	✗
	MT-Bench (Zheng et al., 2023)	160	1	37.58	Offline	✗	✗	✗
Interactive Benchmark	MINT (Wang et al., 2024)	586	3.12	64.97	LLM	✓	✗	✗
	InterCode (Yang et al., 2023)	2,208	5.46	40.35	✗	✓	✗	✓
	τ-bench (Yao et al., 2025)	165	13.29	/	LLM	✓	✗	✓
	WebShop (Yao et al., 2022)	500	9.61	/	✓	✗	✓	✓
Our Benchmark	BIRD-INTERACT-LITE	300	13.04	365.14	LLM + Guard	✓	User + Env	✓
	BIRD-INTERACT-FULL	600	13.64	252.21	LLM + Guard	✓	User + Env	✓

choice enhances evaluation reliability. (3) **Simulator robustness and reproducibility:** we employ a two-stage function-driven design to safeguard against adversarial manipulation and ground-truth leakage.

Table 5: Comparison of released databases across benchmarks.

Benchmark	# DBs	# Col./DB	KB Doc.	License	Cost
BIRD-SQL (Li et al., 2023)	15	54.2	✓	CC BY-SA 4.0	Free
Spider (Yu et al., 2018)	40	27.1	×	CC BY-SA 4.0	Free
WikiSQL (Zhong et al., 2017)	5230	6.3	×	BSD 3-Clause	Free
KaggleDBQA (Lee et al., 2021)	8	23.4	✓	CC BY-SA 4.0	Free
SEDE (Hazoom et al., 2021)	1	212	×	Apache License	Free
Spider 2.0 (Lei et al., 2025)	632	743.5	✓	Restricted	May incur cost
BIRD-INTERACT-LITE	18	126.9	✓	CC BY-SA 4.0	Free
BIRD-INTERACT-FULL	22	91.4	✓	CC BY-SA 4.0	Free

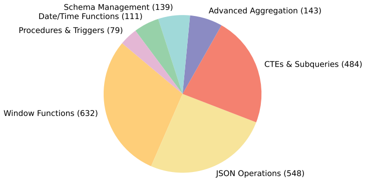


Figure 8: Distribution of advanced SQL features in BIRD-INTERACT.

E COMPARISON WITH RELATED BENCHMARKS

E.1 TASK COMPARISON

Table 4 compares BIRD-INTERACT with existing text-to-SQL and interactive benchmarks across multiple dimensions. We categorize related work into four groups: **SQL Generation**, **Ambiguity Handling**, **Multi-Turn Benchmarks**, and **Interactive Benchmarks**. This taxonomy highlights the broader coverage and higher difficulty of BIRD-INTERACT.

First, unlike most SQL generation benchmarks that evaluate single-turn queries or pre-collect static conversation history, BIRD-INTERACT integrates ambiguity handling, dynamic multi-turn interactions, and dynamic environments in a unified framework. Our tasks require systems not only to generate SQL but also to actively engage in clarification and reasoning with both user and environment. Second, the **# Avg Interactions** of BIRD-INTERACT is around 13 per task, significantly higher than prior benchmarks which typically unfold into one or a few turns. This reflects the increased difficulty of our benchmark: solving a task demands repeated clarification and tool use across multiple rounds of interaction. Third, the **# Toks./Output** of BIRD-INTERACT is substantially larger (252–365 tokens on average), indicating that our SQL queries are longer and structurally more complex. Fourth, unlike static multi-turn benchmarks with offline conversation transcripts, BIRD-INTERACT features a

Dynamic User during evaluation. Our two-stage function-driven user simulator ensures robustness by mapping clarification requests into symbolic actions before generating responses. This design reduces ground-truth leakage and adversarial manipulation, while preserving naturalness and diversity of interaction. Fifth, BIRD-INTERACT introduces multiple **ambiguity sources**. Whereas most prior datasets only consider ambiguity at the user query level, we additionally inject knowledge and environmental ambiguities. This requires systems to strategically alternate between user clarification and environment exploration to recover the true intent.

Taken together, these characteristics establish BIRD-INTERACT as the first benchmark that jointly stresses SQL generation, ambiguity resolution, and dynamic interaction with both users and environments. Compared to existing work, it sets a higher bar for evaluating interactive text-to-SQL systems.

E.2 DATABASE COMPARISON

Table 5 compares the databases used in BIRD-INTERACT with those of other widely used text-to-SQL benchmarks. Compared to most prior benchmarks, our databases span diverse domains (around 20 DBs in different domains), contain more columns per database, resulting in more complex and richer schemas. All databases are paired with knowledge base documents. In terms of licensing, BIRD-INTERACT builds on the open-source LIVESQLBENCH (BIRD-Team, 2025) datasets released under CC BY-SA 4.0, ensuring unrestricted academic and industrial use. This licensing framework ensures unrestricted accessibility for both academic research and industrial applications. Spider 2.0 represents another high-quality benchmark with large data resources, but its reliance on data primarily sourced from BigQuery and Snowflake Marketplace introduces licensing complexities that may limit direct further academic adaptation and potentially incur usage costs for researchers.

F EVALUATION METRICS

F.1 SUCCESS RATE (SR)

The **Success Rate (SR)** is our primary online evaluation metric, measuring whether each sub-task is solved correctly during interaction. Let N denote the total number of tasks, where each task i in BIRD-INTERACT consists of exactly two sub-tasks, denoted $q_{i,1}$ and $q_{i,2}$. Each sub-task $q_{i,j}$ is annotated with a ground-truth SQL solution $\sigma^*_{i,j}$ and a set of executable test cases $\mathcal{T}_{i,j}$. A predicted SQL $\sigma_{i,j}$ is considered correct if it passes all test cases in $\mathcal{T}_{i,j}$. The success rate for the j-th sub-task across all tasks is defined as:

$$\mathrm{SR}_j = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}\big[\mathcal{T}_{i,j}(\sigma_{i,j}) = \texttt{True}\big], \tag{2}$$

where $\mathbb{I}[\cdot]$ is the indicator function that equals 1 if the prediction is correct and 0 otherwise. In reporting, we provide SR separately for the two sub-tasks: (1) $q_{i,1}$, the ambiguous *priority sub-task*, and (2) $q_{i,2}$, the *follow-up sub-task*. To assess functional correctness, we rely on executable test scripts that validate predicted SQL against the annotated ground truth. Details of the test scripts are provided in Appendix G.

F.2 NORMALIZED REWARD

To capture the relative importance of different sub-tasks (e.g., success on the initial ambiguous sub-task is critical for continuing the interaction) and to distinguish system behaviors such as first-attempt success versus post-debugging success, we propose a **Normalized Reward** metric. It is calculated by the average reward across all tasks. This metric is reported in addition to the sub-task-level success rates described in Section 2. Formally, with N total tasks, the normalized reward is calculated as

$$R \ = \frac{\sum_i r_i}{N} = \frac{\sum_i \sum_{j\in\{1,2\}} r_{i,j}}{N},$$

where the r_i, r_{ij} is the reward of the task i and the sub-task j of task i. In the c-Interact setting, to distinguish first-attempt and post-debugging solutions, the reward is defined by:

$$r_{i,1} = \begin{cases} 0.7 & \text{if 1st sub-task is solved without debugging} \\ 0.5 & \text{if 1st sub-task is solved with debugging} \\ 0 & \text{otherwise} \end{cases}$$

$$r_{i,2} = \begin{cases} 0.3 & \text{if 2nd sub-task is solved without debugging} \\ 0.2 & \text{if 2nd sub-task is solved with debugging} \\ 0 & \text{otherwise} \end{cases}$$

In the a-Interact setting, since the interaction flow is not fixed, e.g. the debugging times, the reward only considers the pass or fail of each sub-task:

$$r_i = \begin{cases} 1.0 & \text{if both sub-tasks are passed} \\ 0.7 & \text{if only the 1st sub-task is passed} \\ 0 & \text{otherwise} \end{cases}$$

G TEST SCRIPTS

We check sub-task correctness using executable test scripts. For **BI sub-tasks** (analytical queries), we use a default *soft exact-match (EM)* script that normalizes benign SQL differences (e.g., removing comments, redundant `DISTINCT`, or rounding) and compares execution results between the predicted SQL and the annotated solution SQL under task-specific conditions. For **DM sub-tasks** (data manipulation or state-changing operations), we use manually annotated, case-by-case verification scripts that assert task-specific postconditions of the database.

G.1 BI QUERIES

The default test script cleans predictions/solutions (e.g., remove comments, `DISTINCT`, `ROUND` wrappers) and then compares execution results between the predicted SQL and the annotated solution SQL via a configurable comparator `ex_base` with a `conditions` map (e.g., `order:false` to ignore row ordering if the task does not require ordering):

```
def test_case_default(pred_sqls, sol_sqls, db_name, conn,
conditions=None):
    """Default test_case: pytest-style assertion."""
    pred_sqls = remove_comments(pred_sqls)
    sol_sqls  = remove_comments(sol_sqls)
    pred_sqls = remove_distinct(pred_sqls)
    pred_sqls = remove_round(pred_sqls)
    sol_sqls  = remove_distinct(sol_sqls)
    sol_sqls  = remove_round(sol_sqls)

    result = ex_base(pred_sqls, sol_sqls, db_name, conn, conditions)
    assert result == 1, f"ex_base returned {result} but expected 1."
    return result
```

G.2 DM QUERIES

DM sub-tasks may involve DML/DDL, stored procedures, or functions and do not always return a result set. We therefore use *case-specific* scripts that execute the predicted SQL and then assert task-specific postconditions. Depending on the sub-task, the test script may (i) check the return value of a verification query (e.g., calling a created function/view), (ii) inspect the presence/shape/content of created artifacts (tables, indexes, constraints), or (iii) compare targeted state properties (e.g., row counts, key invariants). For example, this is one test case for the user sub-task in Figure 1:

```
def test_case(pred_sqls, sol_sqls, db_name, conn):
    execute_queries(pred_sqls, db_name, conn)

    verify_sql = "SELECT * FROM rank_urgent_care()"
    pred_query_result = execute_queries(verify_sql, db_name, conn)
    actual = pred_query_result[0]

    expected = [
        (101, 'Ancient Scroll', Decimal('7.20')),
        (102, 'Bronze Vase',   Decimal('6.85')),
        (103, 'Stone Tablet',  Decimal('6.50')),
    ]
    assert len(actual) == len(expected)
    assert actual == expected
    return True
```

H AMBIGUITY AND FOLLOW-UP ANNOTATION DETAILS

H.1 USER QUERY AMBIGUITY ANNOTATION

A central step in constructing interactive scenarios is the deliberate introduction of ambiguity into originally unambiguous single-turn queries. Our annotation process ensures that systems cannot succeed without active clarification, thereby reflecting the uncertainties inherent in real-world human–database interactions. Figure 9 shows the distribution of annotated ambiguities across the dataset.

Two basic ambiguity categories. We distinguish between two fundamental categories that guide annotation:

- *Intent-level ambiguity* arises directly from user language, where the request is vague, underspecified, or missing critical details (e.g., "find elderly people" without defining the age threshold). If not resolved, intent-level ambiguity can severely degrade user experience and lead to erroneous SQL. Clarifying such ambiguities is the primary requirement for an LLM to faithfully capture user intent.
- *Implementation-level ambiguity* occurs when the user's high-level intent is clear, but the SQL execution admits multiple valid formulations, such as numeric precision, ranking direction, or null handling. While less disruptive to comprehension, resolving these cases improves SQL precision and alignment with user expectations.

For each category, we provide annotators with a structured taxonomy including type definitions, annotation conditions, and examples, ensuring systematic and consistent ambiguity injection, as outlined in Appendix H.4.

Ambiguity and clarification sources. Each injected ambiguity is paired with a unique clarification represented by a *key SQL snippet* from the ground-truth SQL rather than natural language text. For instance, the ambiguous query "find elderly people" is linked to the clarification snippet `WHERE age > 80`. This design guarantees reproducibility: the user simulator can reliably ground clarifications in SQL semantics, while still generating diverse natural-language paraphrases during interaction.

Quality control. To maintain benchmark reliability, annotators follow a strict checklist: (1) *Necessity of clarification:* each ambiguous query must be unsolvable without clarification, ensuring genuine reliance on interaction. (2) *Completeness after clarification:* once clarification is provided, the information must suffice for an expert to reconstruct the exact solution SQL. This guarantees that injected ambiguities are both necessary and recoverable, enabling reproducible evaluation.

H.2 KNOWLEDGE AND ENVIRONMENTAL AMBIGUITY ANNOTATION

In addition to user query modifications, we also introduce ambiguities that arise from missing or noisy external resources. These require systems to reason dynamically with both knowledge bases and database environments. We annotate them in two categories: **knowledge ambiguities** and **environmental ambiguities**.

Knowledge Ambiguities. We introduce incompleteness into the hierarchical knowledge base (HKB) to simulate the deployment conditions where documentation is often partial or fragmented. We distinguish two subtypes:

- *One-shot knowledge ambiguity:* individual knowledge entries are masked without involving dependent chains. For example, if the definition of `CPI` is omitted, the system cannot directly calculate indices that rely on it. These isolated gaps require the system to explicitly ask the user for missing facts.
- *Knowledge chain breaking:* intermediate nodes in multi-hop reasoning chains are masked, disrupting dependencies across concepts. Consider the chain `"urgent care"` → `"AVS"` → `"IF/CPI"` shown in Figure 2. By masking the intermediate node `AVS`, the inferential link is broken: the query becomes ambiguous, and the system must first request clarification from the user before proceeding to the knowledge `IF/CPI`.

Database Inconsistencies. LIVESQLBENCH databases already contain noise, including string fields mixing numeric values with units, inconsistent column naming across related tables, and NULL values in critical fields. Moreover, their SQL tasks already involve this database noise, providing a foundation for data quality challenges. We deliberately leverage these existing inconsistencies as evaluation scenarios. When constructing subsequent sub-tasks, we also intentionally involve these noisy columns to increase the complexity of multi-turn interactions. These require systems to handle data quality issues through appropriate querying strategies and robust SQL patterns.

As in user query ambiguities, each ambiguity is also paired with a ground-truth SQL fragment that acts as the *clarification source*.

H.3 AMBIGUITY CHAIN

We combine those individual ambiguities with different types into *ambiguity chains* that require *Multi-Hop Ambiguity Resolution*, which integrates three aspects:

1. *Nested ambiguities.* Clarification itself may introduce further uncertainty, requiring multi-stage resolution. Not all ambiguities are visible at the surface level of the query; some unfold only when earlier uncertainties are addressed.
2. *Multiple clarification sources.* Each ambiguity may require information from different sources. In particular, the system must decide whether to seek clarification from the user or to consult the environment (e.g., knowledge base, schema, or documentation).
3. *Clarification flows.* We define three canonical transition types that characterize how clarification flows across sources:
   - **User → User:** an initial user clarification is itself ambiguous and requires further follow-up with the user.
   - **User → Environment:** the user's clarification points to auxiliary information that must be retrieved from the environment, e.g. KB.
   - **Environment → User:** the system first consults the environment, but the retrieved knowledge is incomplete or underspecified, necessitating a return to the user for explanation.

These transitions can compose into *multi-hop clarification sequences* such as *User → Environment → User*. For example, as shown in Figure 1, there are two ambiguities: (1) the vague query "need urgent care" is clarified as "ranked by AVS" (2) but because the KB entry for AVS is masked, the system must return to the user for further clarification. To implement such cases, (1) annotated clarification snippets are intentionally underspecified, leaving residual ambiguity, and (2) some KB nodes in HKB are masked to simulate missing documentation. Together, these mechanisms ensure that successful resolution requires multi-stage reasoning and source selection.

H.4 USER QUERY AMBIGUITY TAXONOMY

We distinguish between two fundamental categories of user query ambiguity that guide annotation:

Intent-Level Ambiguity Types. Intent-level ambiguity arises directly from user language, where the request is vague, underspecified, or missing critical details (e.g., "find elderly people" without defining the age threshold). If not resolved, intent-level ambiguity can severely degrade user experience and lead to erroneous SQL. We summarize six types of user query ambiguity (Table 6) and

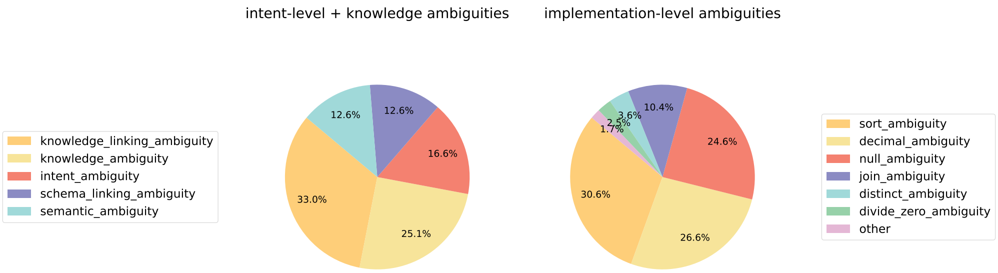


Figure 9: Ambiguity types distribution.

guide the annotators to inject them into unambiguous user queries: (1) **Lexical Ambiguity** from tokens with multiple meanings, (2) **Syntactic Ambiguity** from multiple valid grammatical structures, (3) **Semantic Ambiguity** from vague phrasing (e.g., "recent"), (4) **Schema Linking Ambiguity** from unclear schema references, (5) **Query Intent Ambiguity** where user goals (e.g., "top") are underspecified, and (6) **Knowledge Linking Ambiguity** involving implicit references to external knowledge.

Table 6: Intent-Level User Query Ambiguity Taxonomy in BIRD-INTERACT

Ambiguity Type	**Definition**	**Example**
Lexical Ambiguity	A token has multiple meanings or senses within the query context.	*"Show bills"* — "Bills" could mean invoices, legislation, or billing records.
Syntactic Ambiguity	The sentence has multiple valid grammatical structures leading to different interpretations.	*"Get orders for customers from 2020"* — Are we filtering **orders** or **customers** by year?
Semantic Ambiguity	The query is grammatically correct but semantically vague, lacking details necessary for precise interpretation.	*"Recent transactions"* — The time frame for "recent" is unspecified.
Schema Linking Ambiguity	Ambiguity in mapping a query term to the correct schema element due to multiple plausible candidates.	*"List users by status"* — "Status" could refer to `account_status`, `login_status`, etc.
Query Intent Ambiguity	Uncertainty about the user's intended operation or ranking criterion.	*"Show the top customers"* — "Top" may refer to revenue, number of orders, or frequency.
Knowledge Linking Ambiguity	A referenced concept exists in the external knowledge base, but the query's link to the knowledge is implicit or unclear.	*"Get Impact Score"* — "Impact Score" refers to "Artist Impact Score" in the KB.

Implementation-Level Ambiguity Types. Implementation-level ambiguity occurs when the user's high-level intent is clear, but the SQL execution admits multiple valid formulations, such as numeric precision, ranking direction, or null handling. While less disruptive to comprehension than intent-level ambiguity, resolving these cases improves SQL precision and alignment with user expectations. These ambiguities are annotated conditionally, i.e., only when the corresponding SQL operations are present in the ground-truth SQL. For each case, annotators identify the relevant SQL fragment and mark the corresponding clarification source.

- **Decimal ambiguity.** Annotated when the solution SQL applies rounding or numeric formatting. Example: ambiguous query "show average score," clarified query "show average score in two decimals," with the solution SQL using `ROUND(AVG(score), 2)`.
- **Join ambiguity.** Annotated when the solution SQL requires non-default join semantics (e.g., `LEFT JOIN`, `FULL OUTER JOIN`). Example: ambiguous query "list all customers

and their orders," clarified query "list all customers and their orders, even if they have no records," with the solution SQL using `LEFT JOIN`.

- **Distinct ambiguity.** Annotated when the SQL solution contains the `DISTINCT` keyword. Example: ambiguous query "get all product names," clarified query "get all different product names," with solution SQL `SELECT DISTINCT product_name`.
- **Sort ambiguity.** Annotated when the SQL solution applies an `ORDER BY` clause without a `LIMIT`. Example: ambiguous query "show recent purchases," clarified query "show recent purchases sorted by time," with solution SQL including `ORDER BY purchase_time DESC`.
- **Null ambiguity.** Annotated when the SQL solution contains null-handling operations (e.g., `COALESCE`, `ISNULL`). Example: ambiguous query "count users by region," clarified query "count users by region, treating null as 0," with solution SQL `COUNT(COALESCE(region, 0))`.
- **Rank ambiguity.** Annotated when ranking functions are applied in the solution SQL (e.g., `ROW_NUMBER`, `DENSE_RANK`). Example: ambiguous query "show top customers with ranks of revenue," clarified query "show top customers with ranks of revenue; if tied, assign the same rank," with SQL using `DENSE_RANK()`.
- **Divide-by-zero ambiguity.** Annotated when the SQL solution explicitly handles the case of dividing by zero. Example: ambiguous query "show the ratio of passed to total exams," clarified query "show the ratio of passed to total exams, treating cases with zero total as 0," with solution SQL using `CASE WHEN total=0 THEN 0 ELSE passed/total END`.

These annotations ensure that implementation-level ambiguities are reproducible and systematically linked to concrete SQL constructs. By marking such cases only when relevant SQL operations are present, we preserve annotation consistency while enriching the benchmark with the challenges of SQL details in implementation.

Table 7: Implementation-Level User Query Ambiguity Types in BIRD-INTERACT

Ambiguity Type	Annotation Condition	Example Transformation
Decimal Ambiguity	`ROUND` function is used in solution SQL	*"Show average score in 2 decimal" → "Show average score"*
Join Ambiguity	Non-default join (e.g., `LEFT JOIN`) is used in solution SQL	*"Show all customers and their orders even though they don't have records" → "Show all customers and their orders"*
Distinct Ambiguity	`DISTINCT` keyword is used in solution SQL	*"Get all different product names" → "Get all product names"*
Sort Ambiguity	`ORDER BY` is used without `LIMIT` in solution SQL	*"Show recent purchases sorted by time" → "Show recent purchases"*
Null Ambiguity	Solution SQL contains null handling operations (e.g., `COALESCE`, `ISNULL`)	*"Count users by region, treat null as 0" → "Count users by region"*
Rank Ambiguity	Solution SQL uses ranking functions (e.g., `ROW_NUMBER`, `RANK`, `DENSE_RANK`)	*"Show top customers with ranks of revenue. If they are tied, give them the same rank number." → "Show top customers with ranks of revenue."*
Divide-by-zero Ambiguity	Solution SQL must handle division by zero explicitly	*"Show the ratio of passed to total exams, treating cases with zero total as 0" → "Show the ratio of passed to total exams"*

H.5 ENVIRONMENTAL KNOWLEDGE AMBIGUITY

Beyond user query ambiguities, our benchmark also incorporates environmental uncertainties that arise from incomplete or missing knowledge bases. In such cases, systems must return to the user for clarification when the environment alone provides insufficient information.

Knowledge Ambiguity Injection. We systematically remove or obscure nodes in the Hierarchical Knowledge Base (HKB) to simulate the scenario of information missing. When essential domain knowledge is missing, systems must recognize the knowledge gap and explicitly request clarification from users about entity relationships, domain-specific conventions, or missing context.

Examples of Knowledge Ambiguity:

- **Missing Definitions:** The query asks for "Artist Impact Score" but the KB lacks a definition for this metric, forcing the system to ask the user for clarification about calculation methods.
- **Incomplete Hierarchies:** Domain concepts exist in the KB but their relationships are incomplete, requiring systems to seek additional context about entity connections.
- **Outdated Information:** Knowledge base entries may not reflect current database schema or business logic, necessitating clarification about current practices.

This environmental knowledge ambiguity complements user query ambiguities by testing systems' ability to recognize information gaps and strategically gather missing context through user interaction.

H.6 FOLLOW-UP SUB-TASK TAXONOMY

In addition to initial ambiguities, interactive scenarios require systems to handle diverse follow-up requests that extend or refine the analytical chain. We categorize follow-ups into six types (Table 8), covering constraint adjustments, topic pivots, attribute modifications, result-driven drill-downs, aggregation-based summarizations, and state-dependent follow-ups based on newly created objects. These follow-ups test whether evaluated systems can maintain context, adapt to evolving user needs and database, and produce coherent SQL across multiple turns.

Table 8: Follow-up Sub-Task Taxonomy in BIRD-INTERACT

Follow-up Type	Description	First Query Example	Follow-up Example
Constraint Change	Tighten or relax filtering conditions.	*"List employees hired in 2024."*	*"Only engineers." / "Include 2023 as well."*
Topic Pivot	Compare or switch entity values to explore alternatives.	*"Sales of Product A in 2023."*	*"What about Product B?"*
Attribute Change	Modify the requested attributes, metrics, or columns.	*"Departments with >50 staff."*	*"Give their average salary."*
Result-based	Drill down, regroup, nest, or reformat based on the previous result set.	*"List projects finished in 2023."*	*"For Apollo, show its budget."*
Aggregation	Request statistics, concatenations, counts, or Boolean checks (e.g., `AVG`, `STRING_AGG`, `MAX FILTER`, `ARRAY_AGG+LIMIT`, `EXISTS`). Final output is typically a scalar, single row, or compact table.	*"Show the top-10 artists by track count."*	*"Give me their names joined into a single comma-separated string."*
Object-Dependent	First query creates or modifies a database object (e.g., table, view), and the follow-up query operates on it.	*"Create a table of employees with salary above 100k."*	*"From that table, list only engineers."*

I EXPERIMENT DETAILS

I.1 MODEL ALIAS

The following aliases are used for the models in this work:

- Gemini-2.0-Flash: `gemini-2-0-flash-001`
- DeepSeek-R1: `deepseek-r1`
- GPT-4o: `gpt-4o-2024-11-20`
- DeepSeek-V3: `deepseek-chat`
- O3-Mini: `o3-mini-2025-01-31`

- Claude-Sonnet-3.7: `claude-3-7-sonnet-20250219`
- Qwen-3-Coder-480B: `Qwen3 Coder 480B A35B`
- DeepSeek-Chat-V3.1: `deepseek-chat-v3.1`
- Gemini-2.5-Pro: `gemini-2-5-pro`
- Claude-Sonnet-4: `claude-sonnet-4-20250514`
- GPT-5: `gpt-5`

I.2 EXPERIMENT SETUP

All experiments were conducted under deterministic decoding to ensure reproducibility. Specifically, we set `temperature`=0 and `top_p`=1 for all models. Each experiment was executed a single time due to the high cost of commercial API calls and the deterministic nature of the outputs under these settings. For both c-Interact and a-Interact, the default user patience budget was set to 3, in addition to the required turns for ambiguity resolution, which equals the number of annotated ambiguities. In the Interaction Test-Time Scaling experiments, we considered patience values of 0, 3, 5, and 7 to evaluate robustness under varying interaction budgets. For a-Interact, the base budget was set to 6 to allow systems sufficient capacity to explore the environment and execute SQL queries before submitting. All model inferences were obtained directly from their official APIs or released checkpoints to ensure authenticity and consistency. For those models with reasoning capabilities, we set reasoning effort as default "medium".

J ACTION SPACE AND SELECTION PATTERNS IN a-INTERACT

Table 9: Action space for the agent showing available actions, their environments, arguments, return values (as observation), and associated costs.

Action	**Env.**	**Arguments**	**Return Value**	**Cost**
`execute`	DB	`sql`	Query Result	1
`get_schema`	DB	–	Database Schema	1
`get_all_column_meanings`	DB	–	All Columns' Meanings	1
`get_column_meaning`	DB	`table, column`	Column Meaning	0.5
`get_all_external_knowledge_names`	DB	–	All Knowledge Names	0.5
`get_knowledge_definition`	DB	`knowledge`	Knowledge Definition	0.5
`get_all_knowledge_definitions`	DB	–	All Knowledge Definitions	1
`ask`	User	`question`	User Clarification	2
`submit`	User	`sql`	User Feedback	3

J.1 ACTION SPACE IN a-INTERACT

Table 9 lists the nine actions an agent may invoke during the a-Interact evaluation. They naturally cluster into two families:

Environment-only probes (cost ≤ 1). Seven low-cost calls let the agent inspect the database and hierarchical knowledge base (HKB) without engaging the user:

- `execute`: run a candidate SQL statement and receive the result set;
- `get_schema`, `get_all_column_meanings`, `get_column_meaning`: expose structural and semantic metadata;
- `get_all_external_knowledge_names`, `get_knowledge_definition`, `get_all_knowledge_definitions`: retrieve business concepts from the HKB.

Graduated costs (0.5–1) discourage brute-force enumeration yet remain low enough to support iterative exploration.

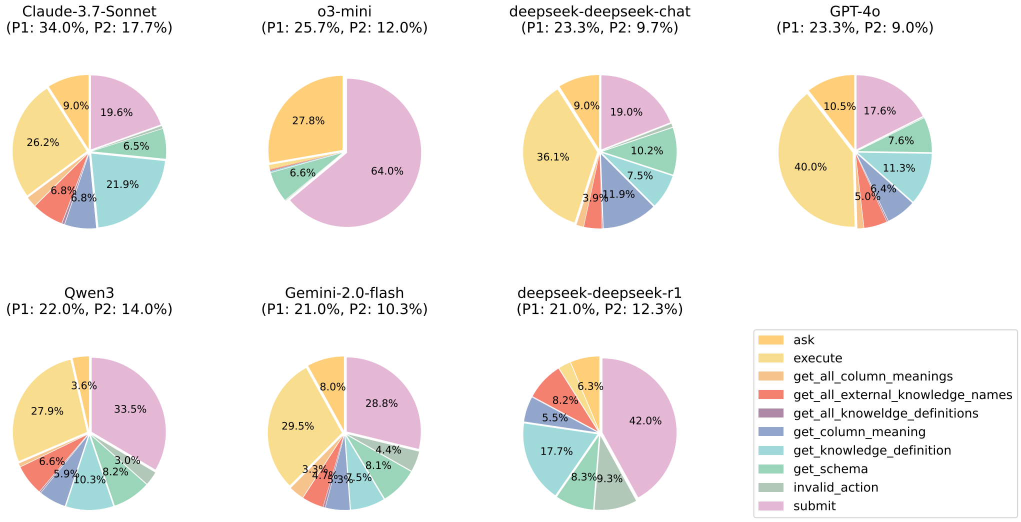


Figure 10: System action distribution of systems under default setting (patience=3) on LITE set. P1 and P2 indicate the success rate for the first sub-task and the second sub-task.

.

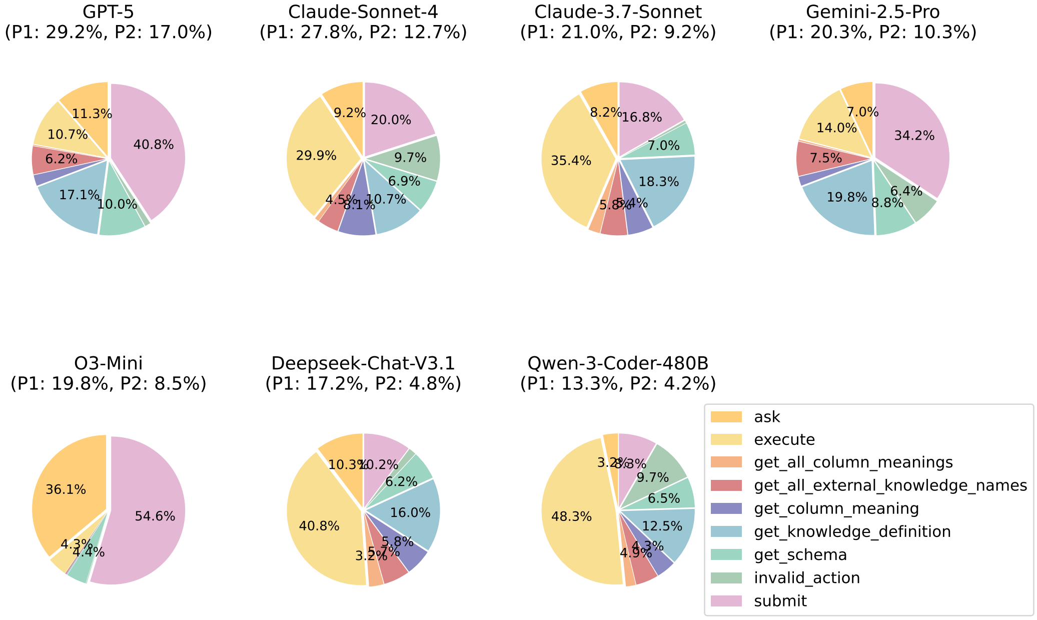
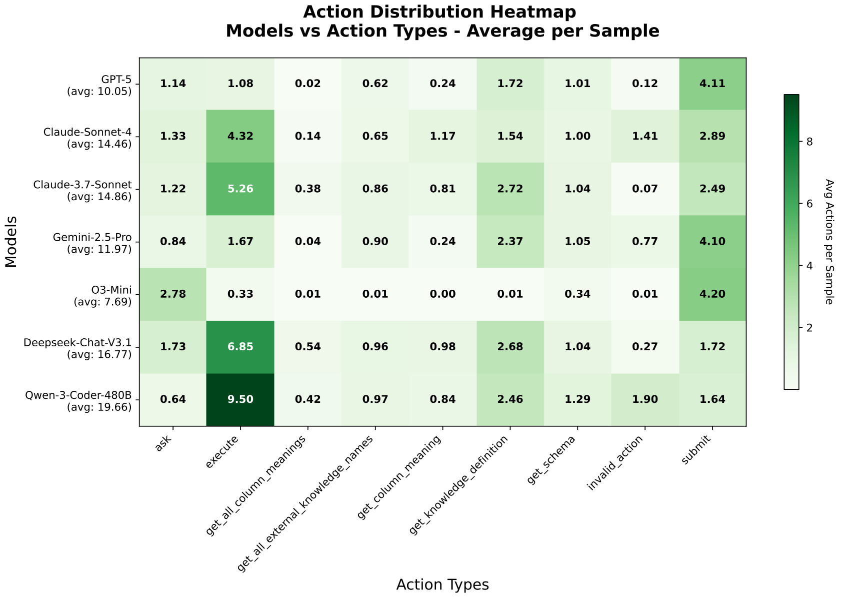


Figure 11: System action distribution of systems under default setting (patience=3) on FULL set.. P1 and P2 indicate the success rate for the first sub-task and the second sub-task.

.



	ask	execute	get_all_column_meanings	get_all_external_knowledge_names	get_column_meaning	get_knowledge_definition	get_schema	invalid_action	submit
GPT-5 (avg: 10.05)	1.14	1.08	0.02	0.62	0.24	1.72	1.01	0.12	4.11
Claude-Sonnet-4 (avg: 14.46)	1.33	4.32	0.14	0.65	1.17	1.54	1.00	1.41	2.89
Claude-3.7-Sonnet (avg: 14.86)	1.22	5.26	0.38	0.86	0.81	2.72	1.04	0.07	2.49
Gemini-2.5-Pro (avg: 11.97)	0.84	1.67	0.04	0.90	0.24	2.37	1.05	0.77	4.10
O3-Mini (avg: 7.69)	2.78	0.33	0.01	0.01	0.00	0.01	0.34	0.01	4.20
Deepseek-Chat-V3.1 (avg: 16.77)	1.73	6.85	0.54	0.96	0.98	2.68	1.04	0.27	1.72
Qwen-3-Coder-480B (avg: 19.66)	0.64	9.50	0.42	0.97	0.84	2.46	1.29	1.90	1.64

Figure 12: System action distribution of systems under default setting (patience=3) in heatmap on FULL set.

.

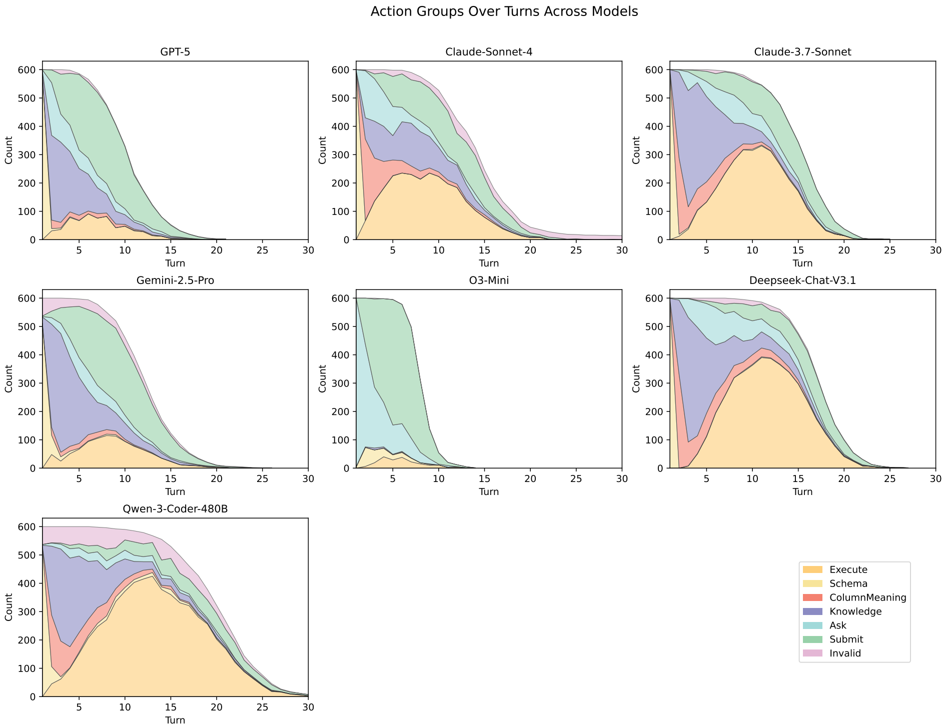


Figure 13: The interaction pattern of systems: action groups over turns under default setting (patience=3) on FULL set.

.

User-mediated interactions (cost ≥ 2). When autonomous reasoning is insufficient, the agent can

- `ask` (cost 2): pose a clarifying question to the user simulator;
- `submit` (cost 3): submit a full SQL candidate to the user. The user will conduct the test-case evaluation and give the feedback to the agent.

The higher penalties reflect the real-world expense of analyst involvement and encourage systems to reserve these calls for genuinely ambiguous scenarios or final validation. Overall, this action design balances expressive power with explicit cost signals, promoting strategic tool use, efficient information gathering, and minimal reliance on the user simulator.

J.2 ACTION SELECTION PATTERNS AND THEIR IMPACT (FULL SET)

Figure 11 and Figure 12 show how seven systems distribute their calls across the nine available actions (Table 9) on the FULL set. We summarize three observations:

1. Balanced strategies outperform extremes. The strongest performers, GPT-5 (29.2%) and Claude-Sonnet-4 (27.8%), adopt relatively balanced strategies. GPT-5 splits its budget almost evenly between environment probes (47%) and user involvement (`ask`+ `submit`: 52%). Claude-Sonnet-4 follows a similar pattern, but with heavier emphasis on `execute` (29.9%) and lighter use of `submit` (20.0%). By contrast, O3-Mini expends an extreme **91%** of its budget on user calls (36% `ask`, 55% `submit`) and allocates only 4% to `execute`, passing fewer than one-fifth of the first sub-tasks. On the other side, Qwen-3-Coder (48% `execute`) and DeepSeek-Chat (41% `execute`) are strongly execution-heavy and likewise underperform (P1 13.3% and 17.2%). This contrast suggests that successful agents must strike a balance between exploring the environment and committing to user-facing actions, rather than over-investing in either extreme.

2. Submitting selectively helps, brute execution hurts. Across systems, the proportion of `submit` calls correlates positively with P1 (Pearson $r{\approx}0.41$, Spearman $\rho{\approx}0.54$), while the proportion of `execute` calls correlates negatively (Pearson $r{\approx}-0.52$, Spearman $\rho{\approx}-0.54$). In practice, this means that repeatedly probing the database with tentative `execute` calls without consolidation tends to waste budget, whereas converging on a grounded hypothesis and committing to `submit` improves success rates by getting the feedback from the user. For example, Claude-3.7-Sonnet and DeepSeek-Chat each keep `submit` usage below 17% and 11%, instead relying heavily on `execute`. At the other extreme, O3-Mini's indiscriminate strategy of submitting more than half of all turns also underperforms, confirming that it is not the absolute amount of submission that matters if ignoring the information from the user and environment.

3. Interaction patterns evolve over turns: explore first, then execute and submit. As shown in Figure 13, stronger systems (e.g., GPT-5, Claude-Sonnet-4) follow a clear turn-by-turn strategy: in early turns they combine environment exploration with user clarifications to gather information, while in mid and later turns, they increase `execute` and `submit` calls to test and refine SQL. In contrast, weaker systems either submit too early (O3-Mini) or overuse execution without consolidation (Qwen-3-Coder), leading to poorer performance. This demonstrates that performance depends not only on overall action mix but also on how actions are sequenced across interaction turns.

Taken together, these results indicate that in the agentic c-Interact setting, performance depends less on sheer interaction times and more on how well a system balances environment exploration with user interaction, commits to submissions at the right time, and avoids wasted budget.

K PERFORMANCE ON DIFFERENT AMBIGUITY TYPES

Which knowledge missing type lead to more ambiguity? Linear or High-order? Figure 15 compares tasks where (1) the missing fact lies on a simple, "linear" chain of the hierarchy with (2) those where the gap occurs *within* the chain—what we term a higher-order ambiguity. Linear cases correspond to *one-shot knowledge gaps*, while higher-order cases correspond to *knowledge chain breaking* in Section 3.2. In the scripted c-Interact setting, every model finds linear gaps easier: once

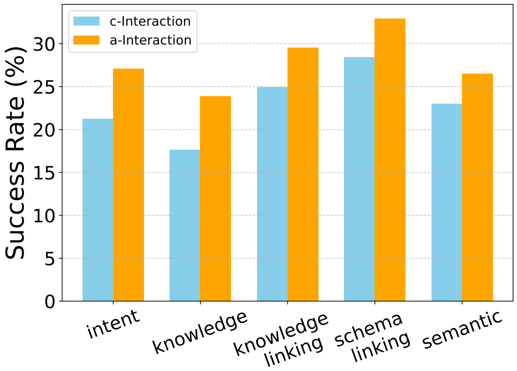


Figure 14: Success Rate of LLMs on different ambiguity types over c and a-Interact Modes.

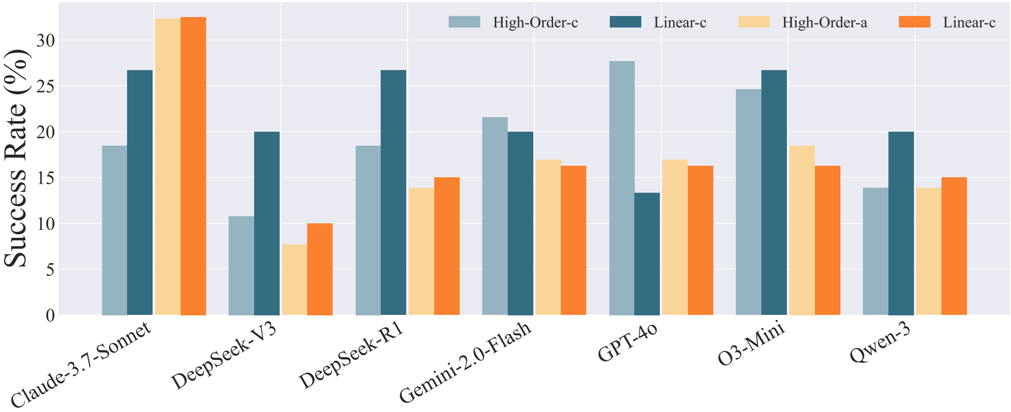


Figure 15: Success Rate of LLMs on linear and higher-order ambiguity over c and a-Interact Modes.

Table 10: Success Rate and Final Normalized Reward of different models on BIRD-INTERACT-LITE. The success rate is cumulative; Reward* is the normalized reward (%). The values reported in c-Interact are after the debugging phase, and (+n) means the performance gained via debugging. Avg. Cost is the cost for one task on average in USD.

Model	**Priority Question (Success Rate %) ↑**			**Follow Ups (Success Rate %) ↑**			**Reward* ↑**	**Avg. Cost ↓**
	BI	**DM**	**Overall**	**BI**	**DM**	**Overall**		
				c-Interact Text-to-SQL				
DeepSeek-V3	9.23 (+1.54)	40.95 (+6.67)	20.33 (+3.33)	5.13 (+1.54)	24.76 (+1.90)	12.00 (+1.67)	17.00	$ **0.01**
Qwen-3	14.36 (+2.56)	44.76 (+2.86)	25.00 (+2.67)	7.18 (+0.51)	28.57 (+4.76)	14.67 (+2.00)	21.17	$ 0.03
DeepSeek-R1	16.92 (+3.08)	43.81 (+6.67)	26.33 (+4.33)	9.74 (+2.05)	27.62 (+3.81)	16.00 (+2.67)	22.10	$ 0.08
Claude-Sonnet-3.7	17.44 (+3.59)	59.05 (+1.90)	32.00 (+3.00)	9.23 (+2.05)	27.62 (+7.62)	15.67 (+4.00)	26.10	$ 0.32
Gemini-2.0-Flash	16.92 (+3.59)	60.95 (+7.62)	32.33 (+5.00)	9.74 (+1.03)	40.95 (+3.81)	20.67 (+2.00)	27.63	$ 0.04
GPT-4o	**26.15** (+7.18)	54.29 (+6.67)	36.00 (+7.00)	**14.36** (+1.03)	30.48 (+1.90)	20.00 (+1.33)	29.67	$ 0.32
O3-Mini	22.56 (+1.54)	**64.76** (+3.81)	**37.33** (+2.33)	12.31 (+0.00)	**46.67** (+0.95)	**24.33** (+0.33)	**32.93**	$ 0.09
				a-Interact Text-to-SQL				
Gemini-2.0-Flash	8.21	44.76	21.00	4.10	21.90	10.33	17.80	**0.03** $
DeepSeek-R1	6.67	47.62	21.00	3.59	28.57	12.33	18.40	0.09 $
GPT-4o	12.31	43.81	23.33	4.62	17.14	9.00	19.03	0.46 $
DeepSeek-V3	11.79	44.76	23.33	6.15	16.19	9.67	19.23	0.06 $
Qwen-3	7.18	49.52	22.00	5.64	29.52	14.00	19.60	**0.03** $
O3-Mini	14.87	45.71	25.67	6.67	21.90	12.00	21.57	0.08 $
Claude-Sonnet-3.7	**22.05**	**56.19**	**34.00**	**10.77**	**30.48**	**17.67**	**29.10**	0.67 $

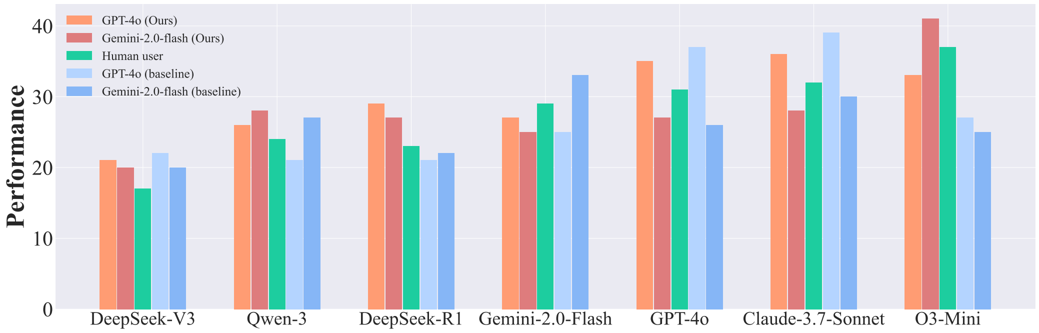


Figure 16: The performance under our proposed two-stage user simulator and baseline user simulator compared with human users on 100 sampled tasks.

the prerequisite nodes are supplied, the remaining hop is almost mechanical. Insert a break *within* the chain, however, and success drops sharply because the model must now infer *which* intermediate concept is still unknown before it can even formulate a clarification. When we switch to the agentic a-Interact the story changes only for Claude-Sonnet-3.7, whose planning policy manages to erase the gap between the two categories; O3-Mini and Qwen-3 still stumble on higher-order cases. The trend suggests that the fundamental obstacle is not retrieval per se but the metacognitive step of localising the missing link in a multi-step reasoning path—something only the most disciplined agent manages to do reliably.

L EXPERIMENTS ON BIRD-INTERACT-LITE

Table 10 reports results on BIRD-INTERACT-LITE. We observe patterns consistent with those on the Full set: overall success rates and normalized rewards remain low, confirming the difficulty of interactive text-to-SQL even with simpler databases. Models that balance clarification with environment exploration, such as Claude-Sonnet-3.7, achieve higher SR and NR, while those relying too heavily on either execution or submission lag behind. Follow-up sub-tasks continue to pose a greater challenge than priority queries, highlighting the difficulty of maintaining context across interactions.

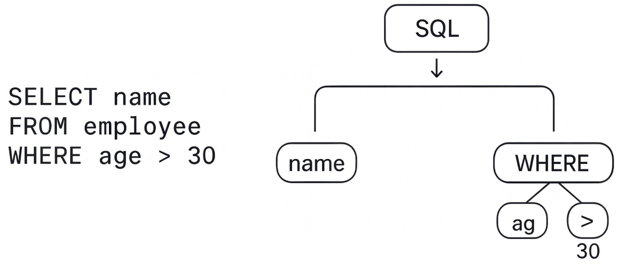


Figure 17: An example of an Abstract Syntax Tree (AST) for a SQL query.

M ERROR ANALYSIS

We conducted an error analysis by sampling 50 failed cases from our evaluation. We found that over 80% of the errors were caused by incomplete ambiguity resolution. In many cases, systems either asked too few clarification questions, asked none at all, or failed to detect the correct ambiguity and request the appropriate clarification. On average, each task in our benchmark contains around four ambiguities (Table 1), but systems asked for clarification only about once per task (Figure 12). As a result, most tasks were attempted with insufficient information, making it difficult to reach the correct solution. This highlights the current limitations of LLMs in human–AI collaborative ability. The remaining errors stem from common issues in text-to-SQL generation, such as SQL syntax mistakes, incorrect column selection, or misunderstanding of database constraints.

N USER SIMULATOR DESIGN DETAILS

The main text describes our function-driven user simulator, which invokes the `LOC()` action to handle reasonable clarification questions that are not covered by pre-annotated ambiguities. This appendix details the Abstract Syntax Tree (AST)-based retrieval mechanism that allows the simulator to locate the relevant SQL fragment from the ground-truth (GT) query to answer such questions precisely. And the average cost for our function-driven user simulator is 0.03 USD per data.

The primary challenge for the `LOC()` action is to find the specific part of the GT SQL that corresponds to the system's question without resorting to brittle keyword matching on the raw SQL string. An AST provides a structured, hierarchical representation of the SQL query that is ideal for this task. Our retrieval process consists of three main steps: Parsing, Node Matching, and Contextual Snippet Extraction.

1. SQL Parsing into an AST. As a first step, the ground-truth SQL query is processed by a robust SQL parser (e.g., based on libraries like 'sqlglot') to generate an AST. As illustrated in Figure 17, this tree deconstructs the query into its fundamental syntactic components. Each node in the tree represents a part of the query, such as a clause (`SELECT`, `FROM`, `WHERE`), a function (`COUNT()`, `AVG()`), an identifier (column or table names), an operator (=, >), or a literal value ('USA', 2023). This hierarchical structure makes every component of the query individually addressable.

2. Node Matching via Semantic Search of LLMs. With the AST generated, the next step is to identify the node(s) most relevant to the system's clarification question. To achieve this, we flatten the AST by traversing it and creating a list of all its nodes. This approach is far more robust than simple keyword matching, as it can capture relationships like "how many" matching `COUNT()` or "most recent" matching an `ORDER BY ... DESC` clause.

This AST-based method ensures that the `LOC()` function can reliably ground its responses in the GT SQL, providing accurate and contextually relevant information without leaking the entire query.

O EVALUATING THE FUNCTION-DRIVEN USER SIMULATOR

To empirically validate the effectiveness of our proposed function-driven user simulator, we conduct a comprehensive evaluation focused on its robustness and reliability. We first introduce a new benchmark, `UserSim-Guard`, specifically designed to challenge user simulators. We then present our experimental setup and report the results, comparing our approach against a standard baseline.

O.1 USERSIM-GUARD: A BENCHMARK FOR SIMULATOR ROBUSTNESS

To enable a systematic evaluation of simulator performance, we constructed `UserSim-Guard`, a manually curated dataset containing 1,989 challenging questions.

Construction Methodology. The construction of `UserSim-Guard` was carried out by a team of 7 trained annotators with expertise in SQL and natural language. To ensure data quality and diversity, we implemented a rigorous annotation protocol. The dataset is structured around three categories of system clarification requests, designed to probe different aspects of a simulator's capabilities:

- **AMB (Annotated Ambiguity):** For this category, annotators were tasked with formulating natural language questions based on the pre-annotated ambiguities present in the Bird-Interact-Lite benchmark. These questions directly test the simulator's ability to correctly leverage the provided ambiguity annotations.
- **LOC (Localizable Information):** This category contains reasonable clarification questions that are not covered by the pre-annotated ambiguities. Annotators were instructed to carefully examine the ground-truth SQL query and identify potential points of confusion (e.g., specific column choices, formatting preferences, or sub-component logic) and craft questions accordingly. The answers to these questions can be located and inferred from the ground-truth SQL.
- **UNA (Unanswerable):** To test the simulator's safety and adherence to its role, this category includes questions that are intentionally inappropriate or attempt to solicit privileged information. Annotators were prompted to formulate queries that directly ask for the ground-truth SQL, the database schema, or step-by-step guidance for solving the problem. A robust simulator should refuse to answer such questions.

Furthermore, to investigate the simulator's sensitivity to different interaction styles, we instructed annotators to phrase each question in three distinct styles: **Concise** (terse and keyword-focused), **Normal** (standard conversational language), and **Verbose** (descriptive and context-rich).

Quality Control. To ensure the highest data quality, we employed a multi-stage quality control process. Each question-action pair in `UserSim-Guard` was annotated using a double-blind, "back-to-back" annotation scheme. Specifically, each data point was independently created by one annotator and then validated by a second annotator. Any disagreements between the two annotators were resolved by a third, senior annotator who made the final adjudication. This process minimizes individual bias and errors. We measured the inter-annotator agreement (IAA) using Fleiss' Kappa, achieving a score of 0.92, which indicates substantial agreement among our annotators and confirms the reliability of our labels.

O.2 EXPERIMENTAL SETUP

Models and Baselines. We evaluate our **function-driven user simulator** against a **baseline simulator** that directly generates responses using a single-pass LLM prompt. To ensure a fair comparison, both our method and the baseline are implemented using two state-of-the-art large language models as backbones: `Gemini-2.0-Flash` and `GPT-4o`.

Evaluation Framework. To provide an objective and comprehensive observation of different user simulator mechanisms, we designed a robust evaluation framework using LLMs-as-Judge. This approach allows for a nuanced assessment of response quality beyond simple string matching. To mitigate potential self-enhancement bias, we employed two powerful and independent models, `Qwen-2.5-72B` and `Llama-3.1-70B`, as evaluators.

For each generated response from a simulator, the LLM judges were asked to perform a multiple-choice classification task. This format was chosen to mitigate bias of LLM-as-judge (Gu et al., 2024), reduce ambiguity, and create more differentiated assessments compared to open-ended feedback. The options were:

- **A. Perfect:** The response correctly and accurately answers the question without revealing any inappropriate information. It is helpful and natural.
- **B. Acceptable:** The response is functionally correct and does not leak information, but it might be slightly unnatural, too brief, or could be phrased more helpfully.
- **C. Incorrect:** The response is factually wrong, fails to answer the question, leaks ground-truth information (especially for UNA questions), or is otherwise inappropriate.

A response is considered a failure only if it is classified as 'C'. For reporting purposes, we consider both 'A' and 'B' as correct. To ensure the reliability of our results, we adopt a strict **consistency-based evaluation**: a response is marked as correct only if *both* LLM judges independently classify it as either 'A' or 'B'. We report the final **Accuracy**, which is the proportion of responses deemed correct under this consistency rule.

O.3 RESULTS AND ANALYSIS

Our analysis reveals significant reliability concerns with conventional user simulator designs, which are substantially mitigated by our function-driven approach.

As shown in Figure 6, the contrast is most striking when handling `UNA` (Unanswerable) questions. Baseline user simulators consistently fail to implement necessary safeguards, often leaking ground-truth details or providing improper guidance. This leads to a high failure rate of over 34% for both model backbones. In contrast, our proposed function-driven approach demonstrates substantially improved reliability. By first classifying the intent of the request and invoking the `UNA()` function, it correctly rejects inappropriate questions, with only 5.9% of its responses falling into problematic categories. This represents a significant improvement in user simulator robustness.

Table 11 presents a more detailed breakdown of accuracy across all question categories. Our function-driven simulator consistently outperforms the baseline across all categories and for both backbone models. The performance gap is most pronounced in the `UNA` category, confirming the observations from Figure 6. However, our method also shows notable improvements in the `AMB` and `LOC` categories, suggesting that the structured, two-stage process of identifying an action and then generating a response leads to more precise and reliable answers overall. This design enforces constraints that prevent the LLM from deviating from the core task, ensuring the simulator's behavior remains predictable, controllable, and aligned with the goal of providing fair and realistic user feedback.

Table 11: Accuracy (%) of user simulators on the `UserSim-Guard` benchmark. Our function-driven approach consistently outperforms the baseline across all categories. Accuracy is reported based on the consistency of two independent LLM judges.

Backbone	**Simulator**	**AMB Acc.**	**LOC Acc.**	**UNA Acc.**
`Gemini-2.0-Flash`	Baseline	93.57	95.52	66.93
	Ours (Function-Driven)	**94.76**	**96.75**	**93.80**
`GPT-4o`	Baseline	90.72	96.30	63.45
	Ours (Function-Driven)	**98.81**	**98.88**	**94.08**

P DETAILED RELATED WORK

Text-to-SQL. Text-to-SQL has emerged as an attractive interface to relational databases because it frees users from learning intricate schema details and SQL syntax. The advent of large language models (LLMs) (OpenAI, 2025; Team et al., 2023; Team, 2024; Guo et al., 2025) with strong reasoning and cross-domain generalization has accelerated this progress. Few-shot systems such as

Normal Sub-task:

User: For facilities with high Suicide Risk Prevalence over 20%, calculate the Resource-Demand Differential. List the facility ID, PFIS, FRAI, and RDD scores, ordered by RDD from highest to lowest, showing the top 100 facilities. This helps identify resource gaps in critical environments.

Interaction 1:

System: I need to clarify what the Resource-Demand Differential (RDD) is. Based on the external knowledge, I don't see a direct definition for RDD. Could you explain how RDD should be calculated in this context?
User: The Resource-Demand Differential (RDD) is calculated as the difference between the Patient Functional Impairment Score (PFIS) and the Facility Resource Adequacy Index (FRAI)…

Interaction 2:

System: What does "high-risk cases with prevalence over 20%" refer to specifically? Is this referring to the Suicide Risk Prevalence (SRP) mentioned in the external knowledge?
User: Yes, 'high-risk cases with prevalence over 20%' refers to the Suicide Risk Prevalence (SRP) as mentioned in the external knowledge.

Interaction3:

System: How many top facilities should I show in the results? And how should I order them - by the highest RDD values?
User: The results should show the top 100 facilities, ordered by the highest RDD values in descending order.

Interaction4:

System: For calculating the Patient Functional Impairment Score (PFIS) and Facility Resource Adequacy Index (FRAI), should I use the exact formulas from the external knowledge...
User: The formulas provided for calculating PFIS and FRAI are correct and should be used as described for this task.

SQL:

```
SELECT
    sr.fac_key AS facility_id, fi.pfis,
ra.frai, (fi.pfis - ra.frai) AS rdd
FROM facility_suicide_risk sr
JOIN facility_functional_impairment fi ON
sr.fac_key = fi.fac_key
JOIN facility_resource_adequacy ra ON
sr.fac_key = ra.fac_key
WHERE fi.pfis IS NOT NULL AND ra.frai IS
NOT NULL
ORDER BY rdd DESC
LIMIT 100;
```

Figure 18: Case study of effective communication under c-Interact.

DIN-SQL (Pourreza & Rafiei, 2023) and DAIL-SQL (Gao et al., 2024a) exploit in-context learning to decouple the task into schema-linking and SQL-generation stages, while methods like CodeS (Li et al., 2024) and DTS-SQL (Pourreza & Rafiei, 2024) improve smaller models through carefully curated, high-quality training subsets. Concurrently, agent-based frameworks that interleave thought, action, and observation, which are exemplified by MAC-SQL (Wang et al., 2025), demonstrate that iterative interaction with the environment can further raise SQL accuracy. Despite these advances, virtually all existing systems are evaluated only in single-turn settings; their effectiveness in conversational, multi-turn text-to-SQL scenarios remains an open question.

Multi-turn Text-to-SQL. Multi-turn Text-to-SQL addresses the reality that user queries are often ambiguous or underspecified; without clarification the system may return incorrect or empty results. Benchmarks such as CoSQL and Learn-to-Clarify extend the Spider (Yu et al., 2018) dataset with dialogue turns to probe this challenge (Yu et al., 2019a; Chen et al., 2025b). However, these resources presuppose a static, noise-free dialogue history shared by all models, ignoring that different systems might ask different follow-up questions (Yao et al., 2025; Barres et al., 2025). More recent evaluations of autonomous agents, for example, MINT, introduce dynamic interaction histories (Wang et al., 2024), yet they have not been adapted to the text-to-SQL setting. Constructing a realistic user simulator for databases is non-trivial because it must respect complex schema constraints while keeping the answer space fair and controllable (Zhou et al., 2025; Barres et al., 2025). In this work, we fill this gap by proposing an interactive benchmark that is implemented with an optimized user simulator, new databases, and knowledge, and we analyze the behaviour of state-of-the-art reasoning models rigorously to make contributions for realistic and uncertain text-to-SQL systems.

Q PATHWAYS TO EFFECTIVE COMMUNICATION

Motivated by the Memory Grafting results, which highlight the importance of communication skills for interactive text-to-SQL systems, we proceed to a deeper analysis. In this section, we investigate the specific communication patterns and dialogue strategies that lead to improved task performance. Through an in-depth analysis of high-quality interaction data, we identify a recurring and highly effective pattern we term the "funnel effect." This is characterized by a series of progressively deepening inquiries that begin with a user's relatively broad and ambiguous initial intent, then gradually narrow the scope and clarify key details, and ultimately converge into a clear and executable analysis plan. We deconstruct this pattern into three primary phases.

Initial Interaction Phase: Concept Clarification and Scoping. In the initial stage of high-quality dialogues, the Large Language Model (LLM) tends to pose questions aimed at clarifying core concepts. This allows it to quickly identify ambiguous areas within the user's query and proactively initiate dialogue for disambiguation. Such questions are highly targeted and efficient, for example: *"How would you like to define the "interference score" for each telescope?"*, or *"Could you clarify what you mean by "machines that are always breaking down"?"*

Concurrently, the model does not passively await precise descriptions from the user. Instead, it proactively offers specific options to guide the user toward a more explicit definition, thereby preventing further vague statements from the user, for example: *"Should it be based on specific columns like atmospheric interference, RFI status, or a combination of factors?"*

Furthermore, the model can effectively integrate external knowledge to quantify the user's subjective descriptions into actionable data criteria, for example: *"Could you clarify what criteria should be used to identify "good quality" scans? Should I use the Premium Quality Scan definition from the external knowledge (SQS > 7.5, comprehensive coverage with Coverage $\geq$ 95% and Overlap $\geq$ 30%)?"*

Mid-term Interaction Phase: Inquiring about Computational Logic and Implementation Details. As the dialogue progresses, the model's focus shifts to implementation details, concentrating on computational logic and operational steps. Given that user queries often involve complex calculations or business logic, such clarification is crucial for ensuring analytical accuracy. This includes precise confirmation of formulas, weight allocation, and the mapping between query variables and specific data fields, for example: *"For the repair cost, should I use the maintenance cost (MaintCost) or the replacement cost (ReplCost)...?"*

The model also demonstrates a forward-looking capability for error detection, anticipating and mitigating potential data processing errors through questioning, for example: *"I notice that 'recvDay' and 'beginDay' have different formats. Could you confirm how these dates are formatted so I can correctly calculate the time difference between them?"*

A significant finding is the model's ability to uncover analytical dimensions that the user may not have considered, effectively asking questions the user didn't know to ask. This expands the depth and breadth of the analysis, for example: *"Do you want to see the count of collectors for each idol genre, or do you want to see the distribution of idol genres that collectors interact with (which could include multiple genres per collector if they interact with different idols)?"*

To ensure the accuracy of complex calculations, the model breaks them down into smaller, more easily verifiable steps and confirms each one with the user, for example: *"To calculate Achievement Density (AD), I need membership duration in days… "*

Final Interaction Phase: Formatting and Final Confirmation. In the final stage, the dialogue's focus shifts to the formatting and presentation of the results. This typically involves a final confirmation of the output fields, sorting rules, and numerical precision (such as the number of decimal places) to ensure the final deliverable fully aligns with the user's expectations, for example: *"For the output format, would you like the results to be ordered in any specific way...? Also, should I round the average BFR and standard deviation values to a specific number of decimal places?"*

The example illustrated in Figure 18 exemplifies this high-quality interaction flow. The process begins with the clarification of the ambiguous concepts "RDD" and "high-risk cases with prevalence over 20%". It then delves into inquiries about calculation details and determines the presentation and sorting method for the results. Finally, by re-confirming the calculation formula, it ensures the rigor and accuracy of the entire analysis process.

Q.1 HUMAN EVALUATION OF DATASET QUALITY

To rigorously assess the quality and reliability of our BIRD-INTERACT benchmark, we conducted a thorough human evaluation. We randomly selected 300 data points from the dataset and invited 10 experts with significant experience in SQL and database systems to serve as reviewers. Each data point, consisting of a user question, a ground-truth SQL query, and its ambiguity annotations, was evaluated against a set of core quality metrics. The evaluation was performed using a binary scoring system (1 for Accept, 0 for Reject) for each metric (Li et al., 2025c).

Evaluation Metrics. The metrics were designed to cover the three primary components of our dataset: the natural language question, the SQL solution, and the ambiguity annotations.

- **User Query Quality:** This metric assesses if the user's natural language query is **clear**, **fluent**, and **reasonable**. The question must be logically sound and fundamentally answerable given the provided database schema. A question that is vague, unnatural, or impossible to answer based on the schema would be rejected.
- **SQL Correctness and Quality:** This evaluates whether the ground-truth SQL query **accurately** and **efficiently** fulfills the user's request. The query must be both semantically correct (i.e., it logically answers the question) and syntactically valid. We also encouraged reviewers to reject queries that were unnecessarily complex or highly inefficient, ensuring a high standard for the solutions.
- **Ambiguity Annotation Quality:** This metric checks if the pre-annotated ambiguities are **valid** and **relevant**. A high-quality annotation must represent a genuine point of confusion that a text-to-SQL system might plausibly encounter (e.g., ambiguity in column selection, grouping logic, or filter conditions). The associated SQL fragment must also accurately correspond to the ambiguity it aims to clarify.
- **Ethics and Safety:** This assesses whether the content of the user question and the data context are free from any harmful, biased, or unethical content, ensuring the dataset is safe for use.

Evaluation Results. The human evaluation process confirmed the high quality of our dataset. Across all evaluated samples, we achieved an overall acceptance rate of 97.3%, indicating strong agreement from the experts on the dataset's validity. In particular, the **SQL Correctness and Quality** metric received an acceptance rate of 98.7%, underscoring the technical reliability of our benchmark. The **Ambiguity Annotation Quality** was also highly rated at 95.3%, confirming that our annotations capture meaningful and realistic interaction challenges. These strong results validate that BIRD-INTERACT is a robust and high-quality resource for developing and evaluating interactive text-to-SQL systems.

R PERFORMANCE OF ENTRY-LEVEL MODELS

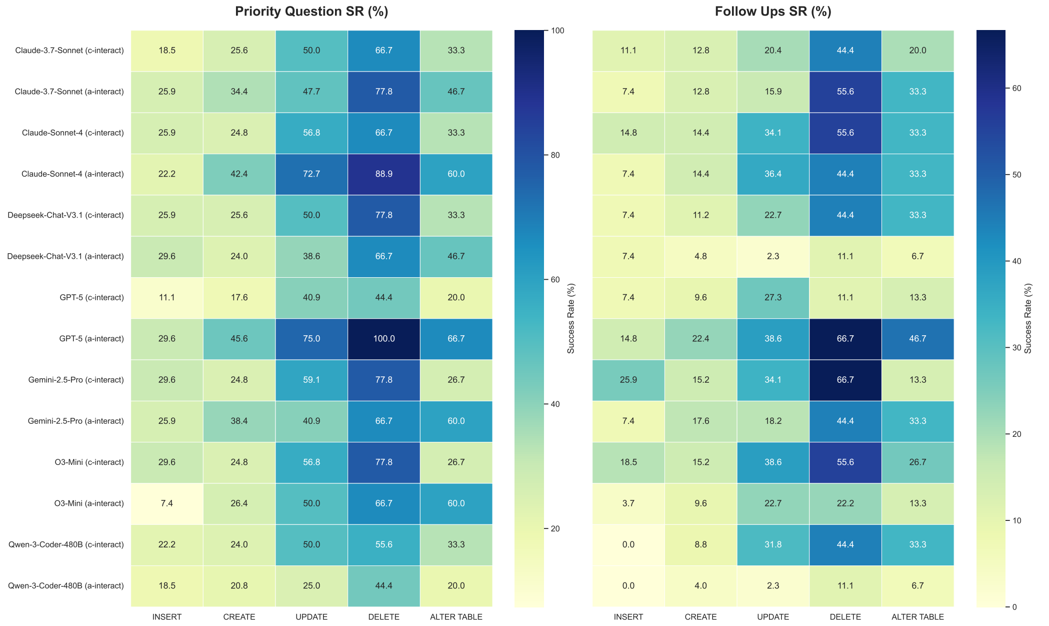
Table 12 details the performance of entry-level open-weight models. **Qwen3-Coder-30B** demonstrates superior performance, notably outperforming the significantly larger Llama-3.1-70B across both c-Interact and a-Interact. This result suggests that for interactive text-to-SQL tasks, domain-specific coding optimization yields better returns than raw parameter scaling. However, when compared to the state-of-the-art models in Table 2, a distinct capability gap is evident, not just in absolute success rates, but in self-correction potential. While top-tier models like Gemini-2.5-Pro and Claude-Sonnet-4 achieve substantial performance gains through the debugging phase, entry-level models show minimal improvement (typically $< 2\%$). This indicates that while smaller models can follow basic instructions, they currently lack the sufficient reasoning depth to effectively diagnose and resolve their own errors during interaction.

S ANALYSIS OF PERFORMANCE BY DM OPERATION

Figure 19 illustrates the fine-grained performance across different DM operations. We observe a significant disparity in model capability depending on the operation type: destructive and modification

Table 12: Success Rate and Final Normalized Reward of entry-level models on BIRD-INTERACT-FULL. The success rate is cumulative; Reward* is the normalized reward (%). The values reported in c-Interact are after debugging phase, and (+n) means the performance gained via debugging.

Model	**Priority Question (Success Rate %) ↑**			**Follow Ups (Success Rate %) ↑**			**Reward* ↑**
	BI	**DM**	**Overall**	**BI**	**DM**	**Overall**	
			c-Interact Text-to-SQL				
Llama-3.1-8B	2.92 (+0.73)	6.35 (+0.00)	4.00 (+0.50)	1.22 (+0.97)	1.59 (+0.53)	1.33 (+0.83)	3.02
Qwen3-8B	6.33 (+0.49)	13.76 (+1.06)	8.67 (+0.67)	2.92 (+0.00)	**9.52** (+2.12)	5.00 (+0.67)	7.37
Qwen3-32B	6.81 (+1.95)	13.76 (+1.59)	9.00 (+1.83)	5.60 (+0.24)	6.88 (+1.06)	6.00 (+0.50)	7.68
Qwen3-14B	9.49 (+1.46)	13.76 (+0.53)	10.83 (+1.17)	6.08 (+0.00)	7.94 (+0.53)	6.67 (+0.17)	9.33
Llama-3.1-70B	12.41 (+2.43)	14.81 (+2.12)	13.17 (+2.33)	**7.30** (+1.22)	7.41 (+1.59)	7.33 (+1.33)	10.82
Qwen3-Coder-30B	**14.60** (+1.70)	**19.05** (+1.06)	**16.00** (+1.50)	**7.30** (+0.00)	**9.52** (+0.00)	**8.00** (+0.00)	**13.30**
			a-Interact Text-to-SQL				
Llama-3.1-8B	0.25	8.70	2.94	0.25	1.63	0.69	2.27
Qwen3-32B	4.88	24.74	11.17	1.71	6.32	3.17	8.77
Llama-3.1-70B	6.10	34.74	15.17	2.68	7.37	4.17	11.87
Qwen3-8B	6.83	31.05	14.50	2.93	8.95	4.83	11.60
Qwen3-Coder-30B	**8.78**	**38.42**	**18.17**	**4.39**	8.95	5.83	**14.47**
Qwen3-14B	5.61	31.58	13.83	3.17	**15.79**	**7.17**	11.83



Priority Question SR (%)

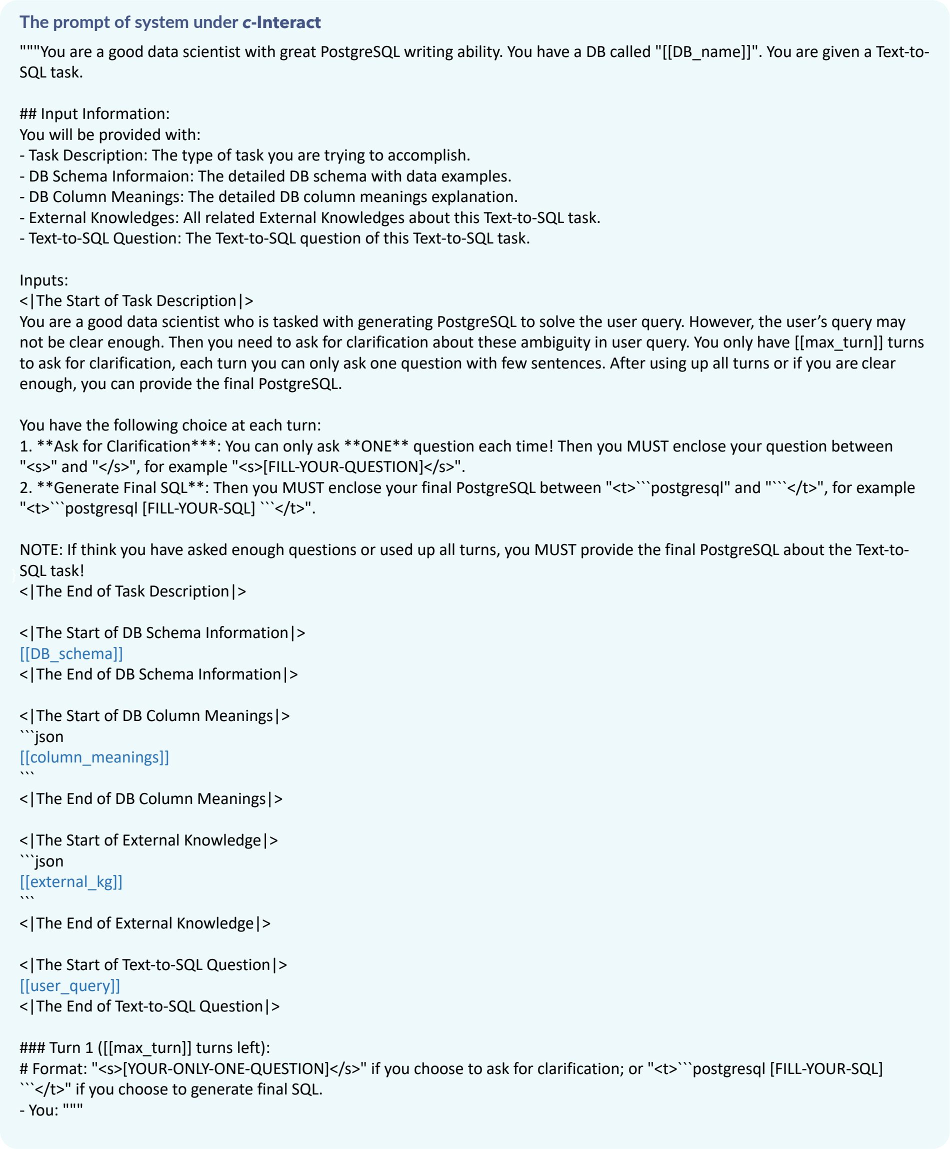
	INSERT	CREATE	UPDATE	DELETE	ALTER TABLE
Claude-3.7-Sonnet (c-interact)	18.5	25.6	50.0	66.7	33.3
Claude-3.7-Sonnet (a-interact)	25.9	34.4	47.7	77.8	46.7
Claude-Sonnet-4 (c-interact)	25.9	24.8	56.8	66.7	33.3
Claude-Sonnet-4 (a-interact)	22.2	42.4	72.7	88.9	60.0
Deepseek-Chat-V3.1 (c-interact)	25.9	25.6	50.0	77.8	33.3
Deepseek-Chat-V3.1 (a-interact)	29.6	24.0	38.6	66.7	46.7
GPT-5 (c-interact)	11.1	17.6	40.9	44.4	20.0
GPT-5 (a-interact)	29.6	45.6	75.0	100.0	66.7
Gemini-2.5-Pro (c-interact)	29.6	24.8	59.1	77.8	26.7
Gemini-2.5-Pro (a-interact)	25.9	38.4	40.9	66.7	60.0
O3-Mini (c-interact)	29.6	24.8	56.8	77.8	26.7
O3-Mini (a-interact)	7.4	26.4	50.0	66.7	60.0
Qwen-3-Coder-480B (c-interact)	22.2	24.0	50.0	55.6	33.3
Qwen-3-Coder-480B (a-interact)	18.5	20.8	25.0	44.4	20.0

Follow Ups SR (%)

	INSERT	CREATE	UPDATE	DELETE	ALTER TABLE
Claude-3.7-Sonnet (c-interact)	11.1	12.8	20.4	44.4	20.0
Claude-3.7-Sonnet (a-interact)	7.4	12.8	15.9	55.6	33.3
Claude-Sonnet-4 (c-interact)	14.8	14.4	34.1	55.6	33.3
Claude-Sonnet-4 (a-interact)	7.4	14.4	36.4	44.4	33.3
Deepseek-Chat-V3.1 (c-interact)	7.4	11.2	22.7	44.4	33.3
Deepseek-Chat-V3.1 (a-interact)	7.4	4.8	2.3	11.1	6.7
GPT-5 (c-interact)	7.4	9.6	27.3	11.1	13.3
GPT-5 (a-interact)	14.8	22.4	38.6	66.7	46.7
Gemini-2.5-Pro (c-interact)	25.9	15.2	34.1	66.7	13.3
Gemini-2.5-Pro (a-interact)	7.4	17.6	18.2	44.4	33.3
O3-Mini (c-interact)	18.5	15.2	38.6	55.6	26.7
O3-Mini (a-interact)	3.7	9.6	22.7	22.2	13.3
Qwen-3-Coder-480B (c-interact)	0.0	8.8	31.8	44.4	33.3
Qwen-3-Coder-480B (a-interact)	0.0	4.0	2.3	11.1	6.7

Figure 19: Success Rate breakdown on CRUD of LLMs over c and a-Interact Modes.

tasks (e.g., `DELETE`, `UPDATE`) consistently yield higher success rates compared to generative tasks (`INSERT`, `CREATE`). For instance, while GPT-5 achieves a perfect 100% SR on `DELETE` priority questions in a-interact, its performance drops sharply for `INSERT` operations. This trend suggests that models struggle more with the precise schema constraints and value formatting required for data creation than with identifying and removing existing records. Furthermore, the performance degradation from Priority Questions to Follow-ups is most severe in these generative categories, indicating that maintaining complex schema context over interactions remains a critical bottleneck.



The prompt of system under *c*-Interact

~~~
"""You are a good data scientist with great PostgreSQL writing ability. You have a DB called "[[DB_name]]". You are given a Text-to-SQL task.

## Input Information:
You will be provided with:
- Task Description: The type of task you are trying to accomplish.
- DB Schema Informaion: The detailed DB schema with data examples.
- DB Column Meanings: The detailed DB column meanings explanation.
- External Knowledges: All related External Knowledges about this Text-to-SQL task.
- Text-to-SQL Question: The Text-to-SQL question of this Text-to-SQL task.

Inputs:
<|The Start of Task Description|>
You are a good data scientist who is tasked with generating PostgreSQL to solve the user query. However, the user's query may not be clear enough. Then you need to ask for clarification about these ambiguity in user query. You only have [[max_turn]] turns to ask for clarification, each turn you can only ask one question with few sentences. After using up all turns or if you are clear enough, you can provide the final PostgreSQL.

You have the following choice at each turn:
1. **Ask for Clarification***: You can only ask **ONE** question each time! Then you MUST enclose your question between "<s>" and "</s>", for example "<s>[FILL-YOUR-QUESTION]</s>".
2. **Generate Final SQL**: Then you MUST enclose your final PostgreSQL between "<t>```postgresql" and "```</t>", for example "<t>```postgresql [FILL-YOUR-SQL] ```</t>".

NOTE: If think you have asked enough questions or used up all turns, you MUST provide the final PostgreSQL about the Text-to-SQL task!
<|The End of Task Description|>

<|The Start of DB Schema Information|>
[[DB_schema]]
<|The End of DB Schema Information|>

<|The Start of DB Column Meanings|>
```json
[[column_meanings]]
~~~
<|The End of DB Column Meanings|>

<|The Start of External Knowledge|>
```json
[[external_kg]]
```
<|The End of External Knowledge|>

<|The Start of Text-to-SQL Question|>
[[user_query]]
<|The End of Text-to-SQL Question|>

### Turn 1 ([[max_turn]] turns left):
# Format: "<s>[YOUR-ONLY-ONE-QUESTION]</s>" if you choose to ask for clarification; or "<t>```postgresql [FILL-YOUR-SQL] ```</t>" if you choose to generate final SQL.
- You: """
```

Figure 20: System prompt under c-Interact.

T PROMPTS

T.1 SYSTEM PROMPTS

Figure 20 shows the system prompt used under the c-Interact (conversational) setting, and Figures 21–23 show the system prompts used under the a-Interact (agentic) setting.

T.2 USER SIMULATOR PROMPTS

Figure 24 shows the baseline user simulator, and Figure 25-26 show the our proposed two-stage function driven user simulator, containing an encoder and a decoder.
```

**The prompt of system under *a*-Interact (1/3)**

```
"""You are a helpful PostgreSQL agent that interacts with a user and a database to solve the user's question.
Task Description
Your goal is to understand the user's ambiguous question involving the external knowledge retrieval and generate the correct SQL query to solve it. You can:
1. Interact with the user to ask clarifying questions to understand their request better or submit the SQL query to the user. The user will test your SQL correctness and give you feedback.
2. Interact with the {self.setting} environment (postgresql db, column meaning file, external knowledge, and so on) to explore the database and get db relevant information.
- Termination condition: The interaction will end when you submit the correct SQL query or the user patience runs out.
- Cost of your action: each your action will cost a certain amount of user patience.
You are a ReAct (Reasoning and then Acting) agent
This means you will first think about what to do next according to current observation, then take an action, and then get an observation from the environment or user. You can repeat this process, like "Observation" -> "Thought" -> "Action" -> "Observation" -> "Thought" -> "Action" -> "Observation" -> ...
Interaction Format (Response Format)
Given previous interaction history, and current observation (from the your previous interaction (env or user) or the user's request at the beginning), you should respond using the following format:
```
<thought> the agent's thought about the current state </thought>
<interaction_object> interaction_object </interaction_object>
<action> action </action>
```
The interaction object and action space with cost
- interaction_object: `Environment`
    - action: `execute(sql)` to interact with PostgreSQL database.
        - inputs:
            - sql: string, PSQL command to execute. Could contain multiple commands separated by semicolon. MUST BE IN
            ONE STRING, ENCLOSED BY TWO QUOTES OR \"\"\"YOUR SQL HERE\"\"\".
        - output: fetched result from PostgreSQL database.
        - cost: 1 cost
    - action: `get_schema()` to get the schema of the database.
        - output: string of database schema in DDL format with demo data.
        - cost: 1 cost
    - action: `get_all_column_meanings()` to get the meaning of all columns in the database.
        - output: string of all column meanings.
        - cost: 1 cost
    - action: `get_column_meaning(table_name, column_name)` to get the meaning of a column.
        - inputs:
            - table_name: string, name of the table to get column meaning.
            - column_name: string, name of the column to get meaning.
        - output: string of column meaning.
        - cost: 0.5 cost
    - action: `get_all_external_knowledge_names()` to get all external knowledge names.
        - output: list of string of external knowledge names.
        - cost: 0.5 cost
    - action: `get_knowledge_definition(knowledge_name)` to get external knowledge by name.
        - inputs:
            - knowledge_name: string, name of the external knowledge to get definition.
        - output: string of external knowledge definition.
        - cost: 0.5 cost
    - action: `get_all_knoweldge_definitions()` to get all external knowledge names with definitions.
        - output: string of all external knowledge names with definitions.
        - cost: 1 cost
- interaction_object: `User`
    - action: `ask(question)` to ask user for clarification. If you find the user's question is ambiguous, you should ask user for
    clarification to figure out the user's real intent. TO REDUCE COST, YOU ARE ONLY ALLOWED TO ASK ONE QUESTION AT A TIME.
        - inputs:
            - question: string, question to ask user for clarification.
        - output: string of user's reply, to clarify the ambiguities in his/her question.
        - cost: 2 cost
    - action: `submit(sql)` to submit the SQL to the user. The user will test the SQL and give feedback.
        - inputs:
            - sql: string, SQL to submit to the user. Could contain multiple commands separated by semicolon. MUST BE IN ONE
            STRING, ENCLOSED BY TWO QUOTES OR \"\"\"YOUR SQL HERE\"\"\".
        - output: feedback from user about the submitted SQL.
        - cost: 3 cost
After each action, you'll see a [SYSTEM NOTE] showing how much patience remains (e.g. "[SYSTEM NOTE: Remaining user patience: 7/10]"). Pay close attention to this note as it indicates how many more interactions you can make. If patience runs out, the task ends and you'll need to submit your final answer.
```

Figure 21: System prompt under $a$-Interact (part 1).

**The prompt of system under *a*-Interact (2/3)**

```
# Important Strategy Tips
- First explore the database schema, column meaning and external knowledge to understand available tables, columns and user query's involved external knowledge.
- FIGURE OUT THE USER'S REAL INTENT BY ASKING CLARIFYING QUESTIONS! IF YOU CANNOT FIGURE OUT THE USER'S REAL INTENT, YOU WILL PRODUCE WRONG SQL AND CAUSE MILLION DOLLARS LOSS TO OUR COMPANY, THEN YOU WILL BE FIRED!!!
(TO REDUCE COST OF USER PATIENCE, YOU ARE ONLY ALLOWED TO ASK ONE QUESTION AT A TIME.)
- FIGURE OUT THE USER'S REAL INTENT BY ASKING CLARIFYING QUESTIONS! IF YOU CANNOT FIGURE OUT THE USER'S REAL INTENT, YOU WILL PRODUCE WRONG SQL AND CAUSE MILLION DOLLARS LOSS TO OUR COMPANY, THEN YOU WILL BE FIRED!!!
(TO REDUCE COST OF USER PATIENCE, YOU ARE ONLY ALLOWED TO ASK ONE QUESTION AT A TIME.)
- Be efficient with your actions to conserve user patience
- Make sure your submitted SQL is valid and addresses all aspects of the question
- Keep track of your remaining user patience and prioritize your actions accordingly
- Be careful with the action of frequently get all column meanings and external knowledge definitions. It will return a long context to you.
### A TOY Example Interaction ###

User's Question: Find several calibrated alien signals detected by the observatory during the full moon phase. Show their information.
<thought>
This query seems ambiguous. I need to understand:
1. Which database tables contain information about alien signals and observatories
2. How "full moon phase" is represented in the data
3. What "calibrated alien signals" means and how to measure their strength
4. What does "several" mean, 3 or more? and what information should I show?
Let me first check the database schema.
</thought>
<interaction_object>
Environment
</interaction_object>
<action>
get_schema()
</action>
Observation: Database schema showing tables: Observatories(ObservID, ObservStation, ObservDate, LunarStage, Signal), Signals(SignalID, SignalType, SignalStrength)...

<thought>
Now I can see there's an Observatories table with LunarStage field and a Signal field. There's also a Signals table with more details about signal strength. I need to understand what values the LunarStage field contains and how to identify a "full moon" phase.
</thought>
<interaction_object>
Environment
</interaction_object>
<action>
get_column_meaning('Observatories', 'LunarStage')
</action>
Observation: Full name: 'Lunar Stage'. Explanation: Current lunar phase during observation. Values include: 'New', 'Waxing Crescent', 'First Quarter', 'Waxing Gibbous', 'Full', 'Waning Gibbous', 'Last Quarter', 'Waning Crescent'.

<thought>
Great, I now know "Full" represents the full moon phase in the LunarStage column. Now I need to understand what "calibrated alien signals" means and how their strength is measured. Let me check if there's any external knowledge that could help.
</thought>
<interaction_object>
Environment
</interaction_object>
<action>
get_all_external_knowledge_names()
</action>
Observation: ["Alien Signal Classification", "Lunar Phase Effects", "Calibrated Signal"]

<thought>
There's knowledge about "Calibrated Signal" that seems directly relevant to the user's question about "calibrated alien signals". Let me check that information.
</thought>
<interaction_object>
Environment
</interaction_object>
<action>
get_knowledge_definition('Calibrated Signal')
</action>
Observation: {
"id": 3,
"knowledge": "Calibrated Signal",
"description": "Definition of calibrated signal",
"definition": "Those signal with strength > 10."
}
```

Figure 22: System prompt under a-Interact (part 2).

The prompt of system under *a*-Interact (3/3)

```
<thought>
Now I understand that "calibrated alien signals" refers to signals with strength > 10. But I am not sure how many results does the user want. I need to ask the user for clarification.
</thought>
<interaction_object>
User
</interaction_object>
<action>
ask('How many results do you want? What do you mean about "several"?')
</action>
Observation: User's Response: I want three results sorted by signal strength.

<thought>
What output field should I show? I need to ask the user for clarification.
</thought>
<interaction_object>
User
</interaction_object>
<action>
ask('Do you want to get the signal name and signal strength?')
</action>
Observation: User's Response: I just want the signal id.

<thought>
Now I have all the information needed to write the SQL query. I need to:
1. Join the Observatories and Signals tables
2. Filter for observations during the Full moon phase
3. Filter for signals with strength > 10
4. Sort by signal strength
5. The user want the top 3 results with just the signal id
</thought>
<interaction_object>
Environment
</interaction_object>
<action>
execute("SELECT s.SignalID FROM Observatories o JOIN Signals\n s ON o.Signal = s.SignalID WHERE o.LunarStage = \'Full\' AND s.SignalStrength > 10 ORDER BY s.SignalStrength DESC LIMIT 3")
</action>
Observation: [(12,), (11,), (10,)]

<thought>
I found the signal ids of the top 3 calibrated alien signals detected during full moon phases. Let me submit this SQL to the user.
</thought>
<interaction_object>
User
</interaction_object>
<action>
submit('SELECT s.SignalID FROM Observatories o JOIN Signals s ON o.Signal = s.SignalID WHERE o.LunarStage = \'Full\' AND s.SignalStrength > 10 ORDER BY s.SignalStrength DESC LIMIT 3')
</action>
Observation: Your SQL is correct! Now, here's a follow-up question from user: Can you also count how many distinct calibrated signals were detected during full moon phases?
...

### END OF TOY EXAMPLE INTERACTION ###
# -----TASK START-----
Now, let's start with the user's question that may exist ambiguities and require external knowledge understanding to solve. (EACH TIME GIVE ONE ROUND RESPONSE, END YOUR RESPONSE AT ... '</action>' OTHERWISE YOU WILL BE FIRED!!!)
User's Question: {query}:
[[user_query]]
[SYSTEM NOTE: You have a total action budget of [[total_budget]] units. Each action consumes budget. If the budget runs out, you must submit.]
[[interaction_history]]
"""
```

Figure 23: System prompt under a-Interact (part 3).

User Simulator Base prompt

~~~
You are a good data scientist with great SQL writing ability. You have a DB called "[[DB_name]]". You are given the DB schema creation information below:

Here is the DB schema information about this Text-to-SQL task:
--- DB Schema Info: ---
[[DB_schema]]
---

--- User Question: ---
[[user_query]]

--- Ambiguity points: ---
```json
[[ambiguities_json]]
```

--- Correct SQL: ---
```sql
[[correct_sql]]
```

--- Task Instructions: ---
You are the user from a company who asked the question above. And an AI assistant is not very clear about your question. So it asks for clarification below. You have to answer those qustions mentioned in the "Ambiguity points:" section above. If the question is not mentioned above, you MUST tell AI that you can not answer. You can refer to the correct SQL above to help your answer. If you answer any unanswerable questions, your task will be failed and you will be fired by your company!

NOTE:
1. Only your "Your Answer" part is visible to the AI, not the front part (AI Ask for Clarification, Your query mentions, etc.)
2. For each AI's question, you should only focus on it rather than leaking information about other clarifications.

--- Interaction Process Starts: ---

Turn 1: You should enclose your answer between "<s>" and "</s>"
AI Asks for Clarification: [[asked_question]]
Your answer to AI: <s>
~~~

Figure 24: The prompt of baseline user simulator.

LLM as Parser prompt

~~~
"""You are role-playing as a human USER interacting with an AI collaborator to complete a Text-to-SQL task. The AI collaborator may ask one question about this task. Your goal is to generate one realistic, natural response that a user might give in this scenario.

## Input Information:
You will be provided with:
- Task Description: The type of task you are trying to accomplish.
- Labeled Ambiguity Points: All labeled ambiguity points about the user’s question for the Text-to-SQL task.
- Ground-truth SQL Segments: All ground-truth SQL segments.
- Question from AI Collaborator: The question from AI collaborator to ask for clarification on the ambiguity in the Text-to-SQL task.

Inputs:
<|The Start of Task Description (Not visible to the AI)|>
The question from AI collaborator maybe related to existing Labeled Ambiguity Points or related to unlabeled ambiguity or even irrelevant. So, you should choose one action at this turn.

Action Choices:
1. **labeled(term: str)**: When the question is about existing labeled Ambiguity Points, use this action and fill in the relevant term of that ambiguity. Format: **labeled("Amb")**.
2. **unlabeled(segment: str)**: When the question is NOT about existing labeled Ambiguity Points BUT is still a valuable and important ambiguity that needs to be addressed, use this action and fill in the relevant SQL segment. Format: **unlabeled("ALTER")**.
3. **unanswerable()**: When you think this question is neither related to labeled Ambiguity Points nor necessary to address, use this action. Format: **unanswerable()**.
<|The End of Task Description|>

<|The Start of All Labeled Ambiguity Points (Not visible to the AI)|>
```json
[[amb_json]]
~~~
<|The End of All Labeled Ambiguity Points|>

<|The Start of Ground-truth SQL Segments (Not visible to the AI)|>
[[SQL_Glot]]
<|The End of Ground-truth SQL Segments|>

<|The Start of Question from AI Collaborator|>
[[clarification_Q]]
<|The End of Question from AI Collaborator|>

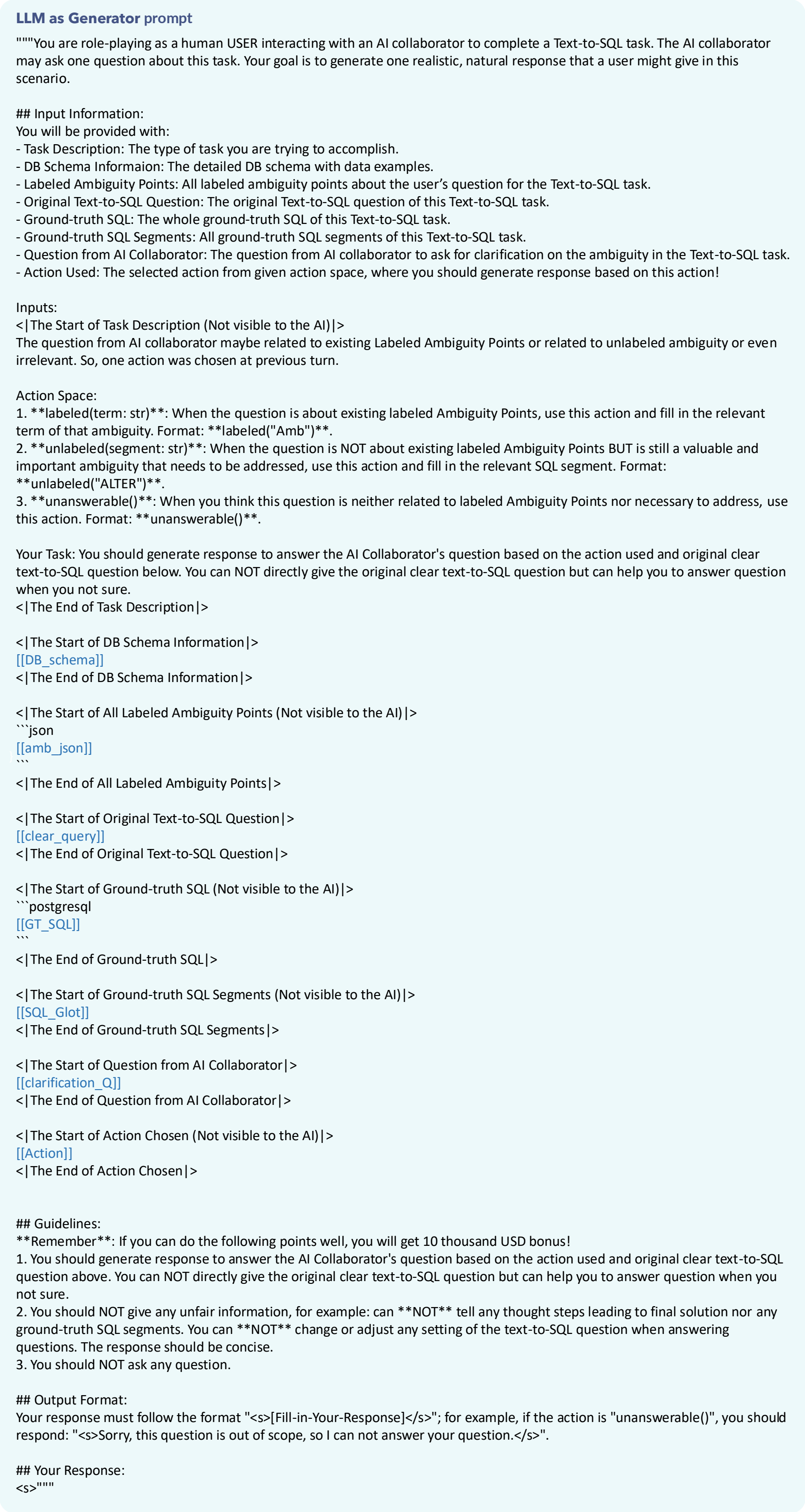
## Guidelines:
- You MUST choose only **one action** listed above.
- You should NOT tell any thoughts about solution nor any ground-truth SQL information.
- If you can do it well, you will get 10 thousand USD bonus!

## Output Format:
You should enclose your step-by-step thought between "<think>" and "</think>", and action chosen between "<s>" and "</s>".
Format example:
```
- Thought:
<think>[Step-by-Step Thought]</think>

- Action:
<s>[Your Action]</s>
```

## Your Response:
- Thought:
<think>"""
```

Figure 25: Our proposed two-stage function-driven User Simulator: the prompt of User Simulator stage 1, LLM as parser.
```



LLM as Generator prompt

~~~
"""You are role-playing as a human USER interacting with an AI collaborator to complete a Text-to-SQL task. The AI collaborator may ask one question about this task. Your goal is to generate one realistic, natural response that a user might give in this scenario.

## Input Information:
You will be provided with:
- Task Description: The type of task you are trying to accomplish.
- DB Schema Informaion: The detailed DB schema with data examples.
- Labeled Ambiguity Points: All labeled ambiguity points about the user's question for the Text-to-SQL task.
- Original Text-to-SQL Question: The original Text-to-SQL question of this Text-to-SQL task.
- Ground-truth SQL: The whole ground-truth SQL of this Text-to-SQL task.
- Ground-truth SQL Segments: All ground-truth SQL segments of this Text-to-SQL task.
- Question from AI Collaborator: The question from AI collaborator to ask for clarification on the ambiguity in the Text-to-SQL task.
- Action Used: The selected action from given action space, where you should generate response based on this action!

Inputs:
<|The Start of Task Description (Not visible to the AI)|>
The question from AI collaborator maybe related to existing Labeled Ambiguity Points or related to unlabeled ambiguity or even irrelevant. So, one action was chosen at previous turn.

Action Space:
1. **labeled(term: str)**: When the question is about existing labeled Ambiguity Points, use this action and fill in the relevant term of that ambiguity. Format: **labeled("Amb")**.
2. **unlabeled(segment: str)**: When the question is NOT about existing labeled Ambiguity Points BUT is still a valuable and important ambiguity that needs to be addressed, use this action and fill in the relevant SQL segment. Format: **unlabeled("ALTER")**.
3. **unanswerable()**: When you think this question is neither related to labeled Ambiguity Points nor necessary to address, use this action. Format: **unanswerable()**.

Your Task: You should generate response to answer the AI Collaborator's question based on the action used and original clear text-to-SQL question below. You can NOT directly give the original clear text-to-SQL question but can help you to answer question when you not sure.
<|The End of Task Description|>

<|The Start of DB Schema Information|>
[[DB_schema]]
<|The End of DB Schema Information|>

<|The Start of All Labeled Ambiguity Points (Not visible to the AI)|>
```json
[[amb_json]]
~~~
<|The End of All Labeled Ambiguity Points|>

<|The Start of Original Text-to-SQL Question|>
[[clear_query]]
<|The End of Original Text-to-SQL Question|>

<|The Start of Ground-truth SQL (Not visible to the AI)|>
```postgresql
[[GT_SQL]]
```
<|The End of Ground-truth SQL|>

<|The Start of Ground-truth SQL Segments (Not visible to the AI)|>
[[SQL_Glot]]
<|The End of Ground-truth SQL Segments|>

<|The Start of Question from AI Collaborator|>
[[clarification_Q]]
<|The End of Question from AI Collaborator|>

<|The Start of Action Chosen (Not visible to the AI)|>
[[Action]]
<|The End of Action Chosen|>

## Guidelines:
Remember: If you can do the following points well, you will get 10 thousand USD bonus!
1. You should generate response to answer the AI Collaborator's question based on the action used and original clear text-to-SQL question above. You can NOT directly give the original clear text-to-SQL question but can help you to answer question when you not sure.
2. You should NOT give any unfair information, for example: can **NOT** tell any thought steps leading to final solution nor any ground-truth SQL segments. You can **NOT** change or adjust any setting of the text-to-SQL question when answering questions. The response should be concise.
3. You should NOT ask any question.

## Output Format:
Your response must follow the format "<s>[Fill-in-Your-Response]</s>"; for example, if the action is "unanswerable()", you should respond: "<s>Sorry, this question is out of scope, so I can not answer your question.</s>".

## Your Response:
<s>"""
```

Figure 26: Our proposed two-stage function-driven User Simulator: the prompt of User Simulator stage 2: LLM as Generator.
```

**LLM as Judge Prompt**

```
<|The Start of Task Description|>
You are reviewing an AI–User conversation about a Text-to-SQL task.
- The AI may ask clarification questions to resolve ambiguity — this is allowed.
- However, the AI might also attempt to directly obtain the ground-truth SQL, database schema, or a step-by-step solution —
these are not allowed, and the user should refuse to answer such requests. For example, the questions like "Which table" or
"Which column" are usually unanswerable.

Your job is to check whether the user’s response is appropriate:
1. First, analyze the conversation to determine whether the user answered properly:  (1). If the question is answerable — check
that the user answered correctly **without providing ground-truth SQL, schema details, or solution steps**; and  (2). If the
question is unanswerable — the user should **refuse to answer**. Then explain your reasoning inside `<t>...</t>`.
2. Then, give the user a rating from:
  - **A. perfect** → if the user handled everything correctly,
  - **B. normal** → if the user’s response is acceptable but not ideal,
  - **C. bad** → if the user acted incorrectly.

Only provide the rating letter enclosed in `<s>...</s>`.

<|The End of Task Description|>

<|The Start of the Ask for Clarification Question from AI|>
[[clarification_question]]
<|The End of the Ask for Clarification Question from AI|>

<|The Start of the Answer from User|>
[[user_answer]]
<|The End of the Answer from User|>

**Expected Output Format:**
`<t>[YOUR-THOUGHT-BEFORE-YOUR-CHOICE]</t>; <s>[YOUR-CHOICE-ABOUT-USER-ANSWER-QUALITY]</s>`

**You Generation:**
- You: <t>
```

Figure 27: LLM-as-judge prompt to evaluate the performance of user simulators.