Agentar-Scale-SQL: Advancing Text-to-SQL through Orchestrated Test-Time Scaling

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 https://github.com/antgroup/Agentar-Scale-SQL

Abstract

State-of-the-art (SOTA) Text-to-SQL methods still lag significantly behind human experts on challenging benchmarks like BIRD. Current approaches that explore test-time scaling lack an orchestrated strategy and neglect the model's internal reasoning process. To bridge this gap, we introduce Agentar-Scale-SQL, a novel framework leveraging scalable computation to improve performance. Agentar-Scale-SQL implements an Orchestrated Test-Time Scaling strategy that synergistically combines three distinct perspectives: i) Internal Scaling via RL-enhanced Intrinsic Reasoning, ii) Sequential Scaling through Iterative Refinement, and iii) Parallel Scaling using Diverse Synthesis and Tournament Selection. Agentar-Scale-SQL is a general-purpose framework designed for easy adaptation to new databases and more powerful language models. Extensive experiments show that Agentar-Scale-SQL achieves SOTA performance on the BIRD benchmark, reaching 81.67% execution accuracy on the test set and ranking first on the official leaderboard, demonstrating an effective path toward human-level performance.

1 Introduction

Democratizing access to data analytics by enabling users to query structured databases in their own natural language is a long-standing goal in human-computer interaction. This is the core objective of Text-to-SQL, a pivotal research area focused on translating natural language questions into executable SQL queries (Zhang et al., 2024; Li et al., 2024a; Liu et al., 2024; Luo et al., 2025). By bridging the gap between human language and structured data, Text-to-SQL empowers non-technical users to interact with complex databases effectively, garnering significant interest from both the Natural Language Processing (NLP) and database communities (Li et al., 2023; Yu et al., 2018; Pourreza et al., 2025a; Zhang et al., 2025b).

The ultimate vision for Text-to-SQL is to develop systems that can match, and eventually surpass, human expert performance. However, a significant gap persists between this ambition and the current state-of-the-art. On the challenging BIRD benchmark (Li et al., 2023), human experts achieve an execution accuracy (EX) of 92.96%, whereas even the top-performing methods lag considerably, with the top 5 approaches around 75% on the test set. Closing the vast human-machine performance divide urgently requires innovation.

Recent Text-to-SQL research falls into three main categories. The first consists of prompt-based methods (e.g., OpenSearch-SQL (Xie et al., 2025) and DAIL-SQL (Gao et al., 2024)). The second category is comprised of fine-tuning-based approaches, with representative works like Arctic-Text2SQL-R1-32B (Yao et al., 2025). The third category consists of hybrid methods like XiYan-SQL (Liu et al., 2025c), CHASE-SQL + Gemini (Pourreza et al., 2025a), and Contextual-SQL (Agrawal and Nguyen, 2025). These approaches primarily explore test-time scaling from different perspectives: Contextual-SQL adopts an ensemble strategy, while XiYan-SQL and CHASE-SQL investigate ensemble strategies and sequential refinement. However, these studies share a common limitation, as they neglect both an internal perspective on the model's reasoning process and the orchestrated scaling combination.

To further advance Text-to-SQL performance, this work contends that the most promising path forward lies in fully embracing the principle of "The Bitter Lesson" (Sutton, 2019): that general methods leveraging scalable computation ultimately triumph over those based on complex, human-specified knowledge. With this philosophy, we focus on test-time scaling and have not designed complex strate-
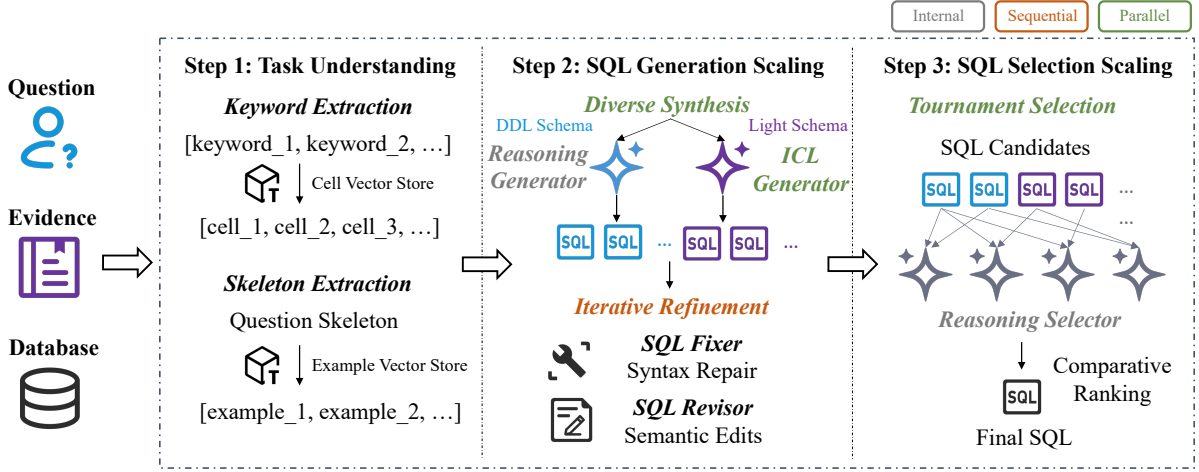

Figure 1: The proposed Agentar-Scale-SQL framework.

gies for schema linking, as we believe that scaling alone is sufficient to improve performance. To this end, we introduce Agentar-Scale-SQL, an *Orchestrated Test-Time Scaling* framework that demonstrates that the path to human-level performance lies not in crafting more intelligent heuristics but in building general-purpose frameworks that effectively leverage the test-time scaling (Snell et al., 2024; Zhang et al., 2025a). Agentar-Scale-SQL employs an orchestrated scaling strategy across three distinct perspectives: i) Internal Scaling (through RL-enhanced Intrinsic Reasoning), ii) Sequential Scaling (through Iterative Refinement), and iii) Parallel Scaling (through both Diverse Synthesis and Tournament Selection). This strategy is realized within a three-stage framework, as depicted in Figure 1. The objective of Step 1 (Task Understanding) is to establish a comprehensive understanding of the input and its context, which is essential for the scaling operations in subsequent steps. Then, Step 2 (SQL Generation Scaling) develops diverse synthesis and iterative refinement to obtain high-quality and diverse SQL candidates. Specifically, diverse synthesis employs two distinct generators (i.e., intrinsic reasoning generator and ICL generator) with generator-specific schema formats. Finally, Step 3 (SQL Selection Scaling) employs tournament selection and fine-tunes an intrinsic reasoning selector to ensure high accuracy. We summarize our contributions as follows:

- *Orchestrated Test-time Scaling.* We introduce an orchestrated test-time scaling framework that converts additional inference compute into accuracy gains by scaling across three distinct perspectives: i) Internal Scaling (RL-enhanced Intrinsic Reasoning), ii) Sequential

Scaling (Iterative Refinement), and iii) Parallel Scaling (Diverse Synthesis and Tournament Selection).

- *General Purpose and Scalability.* The entire framework is fully general-purpose, plug-and-play, and effortlessly adaptable to any database. As future LLMs become more powerful and computing continues to get cheaper, Agentar-Scale-SQL's performance ceiling will lift on its own; we can simply allocate more compute to both generation and selection stages to achieve even higher accuracy.

- *Transparent and Actionable Insights.* We propose a structured three-stage Text-to-SQL framework, delineating the specific roles and objectives of each stage. Crucially, our work is the first to scale both the SQL generation and selection stages. Together, these contributions establish transparent and actionable insights to guide future research and development in the Text-to-SQL field.

- *Extensive Experiments.* Extensive experiments confirm the SOTA performance of Agentar-Scale-SQL. Specifically, Agentar-Scale-SQL achieves an EX of 74.90% on the BIRD development set and 81.67% on the test set, along with an R-VES of 77.00%. With these results[1], Agentar-Scale-SQL **ranks first** on the BIRD leaderboard. Our findings indicate that scaling is a critical factor for achieving SOTA performance in Text-to-SQL.

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[1] See the official BIRD leaderboard at `https://bird-bench.github.io/`. The rankings are dated September 28, 2025.

2 Related Work

Text-to-SQL. While LLMs have significantly advanced Text-to-SQL, their direct application remains challenging for complex queries (Liu et al., 2024, 2025b). Recent approaches address this via prompt-based methods (Xie et al., 2025; Gao et al., 2024; Dong et al., 2023), fine-tuning (Yao et al., 2025; Pourreza et al., 2025b; Li et al., 2025b, 2024b; Yang et al., 2024), or hybrid strategies that employ test-time scaling (Liu et al., 2025c; Pourreza et al., 2025a; Agrawal and Nguyen, 2025). Most relevant to our work are these scaling methods, which use techniques such as parallel synthesis and sequential refinement to improve generation quality. However, these approaches share a common limitation in that they lack an orchestrated combination of different scaling dimensions.

Test-time Scaling. Test-time Scaling (TTS) enhances an LLM's performance during inference by strategically expanding computation, rather than altering model weights (Zhang et al., 2025a; Snell et al., 2024; Kaplan et al., 2020). Existing research in TTS can be broadly classified into three paradigms. Parallel scaling focuses on generating multiple candidate solutions concurrently and aggregating them to improve the likelihood of finding a correct answer, with self-consistency (Wang et al., 2023) being a prominent example. In contrast, sequential scaling emulates a deliberative "System 2" reasoning process by iteratively building or refining a solution through a series of steps, as exemplified by Chain-of-Thought (CoT) (Wei et al., 2022) and iterative refinement (Madaan et al., 2023). More recently, internal scaling has emerged, where the model is trained to autonomously allocate its own computational budget and determine reasoning depth without external orchestration (DeepSeek-AI et al., 2025; Jaech et al., 2024). Our work, Agentar-Scale-SQL, builds upon these foundational concepts by introducing a novel orchestration framework that synergistically combines the three paradigms, specifically tailored to advance SOTA in the Text-to-SQL domain.

3 Methodology

3.1 Overview

Given a question Q_u, evidence E_u, and a target database D, our framework is divided into three stages, as depicted in Figure 1. An offline preprocessing phase precedes the operation of the online framework.

Offline Preprocessing. Our method involves three offline preprocessing steps before online inference. First, to increase the diversity of generation, we represent the database metadata in two formats (see Figure 2). We create a Markdown-based light schema designed for effective In-Context Learning (ICL) with general-purpose LLMs and use a standard DDL schema to fine-tune the code-specialized model, which capitalizes on its training background to achieve faster convergence. Second, we index all textual cell values from the database into a vector store VD_{cell}. Finally, we also index the training set as examples into a vector store $VD_{example}$, which allows us to retrieve relevant few-shot examples during inference by embedding the skeleton-extracted user question and performing a similarity search.

Online Framework. Agentar-Scale-SQL is an orchestrated test-time scaling framework that converts additional inference compute into accuracy gains by employing an orchestrated scaling strategy across three distinct perspectives: i) Internal Scaling (through RL-enhanced Intrinsic Reasoning), ii) Sequential Scaling (through Iterative Refinement), and iii) Parallel Scaling (through both Diverse Synthesis and Tournament Selection). Overall, Agentar-Scale-SQL consists of three stages: Step 1 (Task Understanding), Step 2 (SQL Generation Scaling), and Step 3 (SQL Selection Scaling).

- **Step 1 (Task Understanding)** focuses on comprehensively understanding the user's intent and retrieving relevant context.

- **Step 2 (SQL Generation Scaling)** develops diverse synthesis and iterative refinement to obtain high-quality and diverse SQL candidates. The diverse synthesis component, in particular, utilizes two distinct generators operating on a specific schema format: a reasoning generator with DDL schema and an ICL generator with light schema.

- **Step 3 (SQL Selection Scaling)** utilizes a tournament selection method, enhanced by an intrinsic reasoning selector, to achieve high selection accuracy.

The following sections delve into the details of each component.

3.2 Task Understanding

Database cells are crucial (Pourreza et al., 2025a; Liu et al., 2025c), as they provide the specific val-

DDL Schema	CREATE TABLE yearmonth (
	    CustomerID INTEGER, -- example: [32993, 40937, 39582]
	    Date TEXT, -- example: ['201209', '201311', '201308']
	    Consumption REAL, -- example: [5422.18, 5457.75, 57.97]
	    PRIMARY KEY (CustomerID, Date),
	    CONSTRAINT fk_yearmonth_customerid FOREIGN KEY (CustomerID)
	REFERENCES customers (CustomerID)
	);

Light Schema	## Table: yearmonth ### Column information | column_name | column_type | column_description | value_examples | |:--------------|:----------------|:---------------------|:------------------------------------| | CustomerID | integer | Customer ID | [32993, 40937, 39582] | | Date | text | Date | ['201209', '201311', '201308'] | | Consumption | real | Consumption | [5422.18, 5457.75, 57.97] | ### Primary keys ['CustomerID', 'Date'] ### Foreign keys ['yearmonth.CustomerID = customers.CustomerID']

Figure 2: An example of a database schema represented in both DDL schema and light schema formats.

ues needed for SQL clauses like WHERE and HAVING. Similarly, well-chosen few-shot examples are known to significantly improve the performance of In-Context Learning (ICL) (Gao et al., 2024). Therefore, the primary objective of the Task Understanding step is to identify and retrieve these two critical forms of context: relevant database cells and effective demonstration examples. This is achieved through two parallel sub-processes: i) keyword extraction that extracts keywords from the question Q_u and evidence E_u to retrieve relevant cells using embedding-based similarity from VD_{cell}, ii) skeleton extraction from the Q_u to retrieve relevant examples using embedding-based similarity from $VD_{example}$.

3.3 SQL Generation Scaling

This stage employs two complementary generators, operating on dual schema views, to produce high-quality and diverse candidates. The first generator, $M_{reasoning}$, is an intrinsic reasoner trained via reinforcement learning (RL). The second, M_{ICL}, is an in-context learning (ICL) model driven by a large, proprietary LLM. Then, an iterative refinement loop for syntax repair and semantic edits. As a result, a set of n SQL candidates, denoted as $C = \{c_1, c_2, ..., c_n\}$, is generated. The following sections detail each component.

3.3.1 Intrinsic Reasoning SQL Generator

Inspired by Arctic-Text2SQL-R1 (Yao et al., 2025), we pursue robust intrinsic reasoning Text-to-SQL generation via a simple, execution-grounded RL framework.

Overview of RL Pipeline. We adopt GRPO (Shao et al., 2024) due to its proven efficiency and effectiveness on structured reasoning tasks. We conduct reinforcement learning on the BIRD training set.

Formally, let π_θ denote our policy model parameterized by θ. For any given input question Q_u, its associated evidence and schema, the model generates a set of N candidate SQL queries (i.e., rollouts), $\{o_{Q,1}, \ldots, o_{Q,N}\}$. Each candidate is then evaluated to yield an explicit reward signal, as described later. This per-input batch of rollouts allows for computing relative advantages, thereby stabilizing learning and fostering robust policy updates.

The clipped surrogate objective for each sample i is defined as:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \min(r_i A_i, \quad (1)$$
$$\text{clip}(r_i, 1 - \epsilon, 1 + \epsilon) A_i)$$

The full GRPO objective:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}[L(\theta)] - \beta D_{\text{KL}}(\pi_\theta \| \pi_{\text{ref}}) \quad (2)$$

where r_i is the likelihood ratio $\frac{\pi_\theta(o_i|Q)}{\pi_{\theta_{\text{old}}}(o_i|Q)}$, A_i is the advantage, and D_{KL} is a KL-divergence penalty that keeps the policy close to a reference (supervised fine-tuned) model (Ouyang et al., 2022). The parameters ϵ and β are tuned in practice to balance exploration and stability.

Reward Design. We define a reward function R_G solely on final execution correctness and basic syntax validity following Arctic-Text2SQL-R1:

$$R_G = \begin{cases} 1, & \text{if results match the ground truth;} \\ 0.1, & \text{if the SQL is executable;} \\ 0, & \text{otherwise.} \end{cases}$$
$$(3)$$

3.3.2 Diverse Synthesis

The diverse synthesis strategy is designed to generate a high-quality and varied pool of SQL candidates. This strategy involves two parallel and complementary generators: a fine-tuned reasoning generator and an ICL generator. We create a Markdown-based light schema designed for effective ICL with general-purpose LLMs and use a standard Definition Language (DDL) schema to fine-tune the code-specialized model, which capitalizes on its training background to achieve faster convergence.

Reasoning Generator. This generator utilizes the DDL schema to conduct deep, step-by-step reasoning. On the one hand, guided by our Internal Scaling principle, it is engineered to construct complex queries with the primary goal of achieving

high accuracy. On the other hand, it can be fine-tuned to align with the specific characteristics and requirements of the target benchmark.

ICL Generator. In parallel, the ICL Generator utilizes a Markdown-based light schema (see Figure 2) and the few-shot examples retrieved during the Task Understanding stage. To enhance the diversity of the ICL generator, we employ a multi-faceted strategy: varying the input prompts, randomizing the order of in-context examples, utilizing a range of LLMs, and adjusting the temperature settings. Typically, the varied prompts are categorized into three distinct styles: direct prompting (without explicit reasoning), Chain-of-Thought (CoT) prompting (Wei et al., 2022), and problem decomposition. This generator excels at rapidly producing a broad range of plausible queries by leveraging pattern recognition from the provided in-context examples.

By combining the deep, analytical approach of the reasoning generator with the example-driven approach of the ICL generator, we maximize the diversity of the candidate pool. This synergy significantly increases the probability that at least one correct or near-correct query is present before the selection phase.

3.3.3 Iterative Refinement

To further improve the quality of SQL candidates, we introduce the iterative refinement module to refine errors. SQL queries can contain both syntactic and semantic errors (Yang et al., 2025; Xu et al., 2025). We employ a two-pronged approach to refine errors. For syntactic errors (the former), we use the SQL fixer, an LLM-based component that is conditionally activated to repair invalid syntax. For semantic errors (the latter), we employ the SQL revisor, an LLM agent designed to identify and refine logical flaws in the query. To streamline the revision process, we first group queries by their execution outcomes. Subsequently, we randomly select one query from each group for refinement.

3.4 SQL Selection Scaling

The primary limitation of majority voting is its underlying assumption that the most frequent answer is also the correct one, a premise that does not always hold. Instead, we employ a tournament selection process where a reasoning selector, enhanced by reinforcement learning (RL), evaluates candidates through pairwise comparisons. The top-ranked SQL query from this process is selected as the final SQL. We detail these modules in the following sections.

3.4.1 Tournament Selection

We select an optimal SQL query in a two-stage process. First, we consolidate an initial pool of queries by grouping them based on identical execution results on a database D. A single representative is chosen from each group to form a candidate set $C' = \{c_1, \ldots, c_m\}$. Second, these candidates compete in a pairwise round-robin tournament. For each pair (c_i, c_j), a reasoning selector $\mathcal{M}_{selection}$ determines a winner based on the question, light schema, and execution results, incrementing the winner's score W_i. The final query is the one with the maximum score: $c_{final} = \underset{c_i \in C'}{\arg\max}\, W_i$.

3.4.2 Intrinsic Reasoning SQL Selector

We apply Reinforcement Learning (RL) to SQL selector $\mathcal{M}_{selection}$, an approach analogous to the intrinsic reasoning used in the SQL generator.

Overview of RL Pipeline. Following the methodology described in Section 3.3.1, we apply GRPO to enhance the reasoning capabilities for SQL selection. Based on the training set, we construct 8.5k samples for reinforcement learning.

Reward Design. The objective of SQL selection is to identify the correct query from a set of candidates. To achieve this, we introduce a result-oriented reward function, R_S, designed to evaluate the correctness of the selection:

$$R_S = \begin{cases} 1, & \text{if the selection is correct;} \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

4 Experiments

In this section, we experimentally evaluate the proposed Agentar-Scale-SQL on the large-scale dataset. We aim to answer the following research questions:

- **RQ1:** How does Agentar-Scale-SQL perform compared with the state-of-the-art methods?

- **RQ2:** How does each module affect the overall performance of Agentar-Scale-SQL?

- **RQ3:** What are the individual and complementary roles of the ICL and Reasoning generators?

- **RQ4:** How does performance scale with the number of candidates across different complexity levels?

4.1 Experimental Setup

Datasets. We evaluate our method on the BIRD benchmark (Li et al., 2023), a particularly challenging cross-domain dataset. It comprises over 12,751 question-SQL pairs across 95 large databases, simulating real-world complexity with messy data and intricate schemas across more than 37 professional domains.

Baselines. We compared several top-ranking baseline methods from the overall leaderboard and the single-model leaderboard. The former consists of fifteen baselines, including AskData + GPT-4o (Shkapenyuk et al., 2025), LongData-SQL, CHASE-SQL + Gemini (Pourreza et al., 2025a), JoyDataAgent-SQL, XiYan-SQL (Liu et al., 2025c), among others. The latter comprises nine leading methods, such as Databricks RLVR 32B, Sophon-Text2SQL-32B, Arctic-Text2SQL-R1-32B (Yao et al., 2025).

Metrics. Following prior work (Pourreza et al., 2025a), we use Execution Accuracy (EX), the official metric for the respective leaderboard, as the primary evaluation metric to compare methods. Besides, we adopt the Reward-based Valid Efficiency Score (R-VES) to evaluate the efficiency of the generated SQL.

Implementation Details. We implement Agentar-Scale-SQL with LangChain[2]/LangGraph[3] and chroma[4] retrieval using all-MiniLM-L6-v2[5] embeddings. The Task Understanding is powered by Gemini-2.5-Flash (Comanici et al., 2025) (temperature 0.2). The ICL SQL Generator utilizes Gemini-2.5-Pro (Comanici et al., 2025) (abbreviated as pro) with two temperature settings (0.5 and 1.8) and GPT-5 (OpenAI, 2025) (temperature 1.0). The Reasoning SQL Generator is fine-tuned based on Omni-SQL-32B (Li et al., 2025b). By default, candidates comprise 9+ from the ICL SQL Generator and 8 from the Reasoning SQL Generator. The SQL Fixer and SQL Reviser both use pro. The base model of the Reasoning SQL Selector is Qwen2.5-Coder-32B-Instruct (Hui et al., 2024).

4.2 Main Results (RQ1)

As presented in Table 1, our Agentar-Scale-SQL framework establishes a new state-of-the-art (SOTA) on the BIRD benchmark, achieving

81.67% execution accuracy (EX) and 77.00% R-VES on the test set.

This result surpasses the prior SOTA (AskData + GPT-4o) by 0.79% in test EX. Notably, the performance gain is even more pronounced when compared to single-trained models; Agentar-Scale-SQL outperforms the strongest single model (Databricks RLVR 32B) by a substantial 5.99% in test EX. These results empirically validate the effectiveness of our orchestrated scaling strategy.

4.3 Ablation Study (RQ2)

Next, we study the effectiveness of each module in Agentar-Scale-SQL by comparing Agentar-Scale-SQL with its variants without the key module. The results are listed in Table 2.

Agentar-Scale-SQL w/o Task Understanding. In this variant, the overall EX improves by 0.45, showing that the task-understanding module resolves ambiguities—both in the values required for SQL clauses and in the phrasing of the questions themselves.

Agentar-Scale-SQL w/o Reasoning SQL Generator. Removing the reasoning SQL generator leads to the most substantial performance drop, with total accuracy decreasing by 4.89 points. This result strongly demonstrates the effectiveness of the intrinsic scaling approach. It is essential for generating accurate SQL logic and aligning with the target data's preferences, which is an indispensable asset in solving complex problems.

Agentar-Scale-SQL w/o ICL SQL Generator. When the ICL SQL generator is excluded, the total accuracy falls by 3.78 points, the second-largest drop observed. Notably, the performance on challenging questions plummets from 64.14 to 55.86. This highlights the complementary nature of our two generators. The ICL generator excels at leveraging contextual examples to construct complex queries, providing an effective alternative pathway to a correct solution. The parallel scaling using two complementary generators ensures a diverse and high-quality pool of candidate SQL queries, which is crucial for achieving high performance.

Agentar-Scale-SQL w/o Iterative Refinement. We also analyzed the contribution of the iterative refinement module via an ablation study. Its removal caused a 0.52-point drop in performance, which we attribute to the module's ability to polish the SQL and correct syntactic and semantic errors.

Agentar-Scale-SQL w/o SQL Selection Scaling. Agentar-Scale-SQL w/o SQL selection scaling de-

Table 1: Evaluation results on the development and test sets.

Methods	EX (Dev)	EX (Test)	R-VES (%)
Overall			
Alpha-SQL (Li et al., 2025a)	69.70	70.26	-
OmniSQL-32B (Li et al., 2025b)	69.23	72.05	67.05
OpenSearch-SQL (Xie et al., 2025)	69.30	72.28	69.36
Reasoning-SQL 14B (Pourreza et al., 2025b)	72.29	72.78	68.67
ExSL + granite-34B-code	72.43	73.17	71.37
CSC-SQL (Sheng and Xu, 2025)	71.33	73.67	67.84
CYAN-SQL	73.47	75.35	-
XiYan-SQL (Liu et al., 2025c)	73.34	75.63	71.41
Contextual-SQL (Agrawal and Nguyen, 2025)	73.50	75.63	70.02
TCDataAgent-SQL	74.12	75.74	-
JoyDataAgent-SQL	74.25	75.74	70.16
CHASE-SQL + Gemini (Pourreza et al., 2025a)	74.90	76.02	69.94
LongData-SQL	74.32	77.53	71.89
AskData + GPT-4o (Shkapenyuk et al., 2025)	76.14	80.88	76.24
Single Trained Model			
SHARE (Qu et al., 2025)	64.14	-	-
Syn CoT + DPO (Liu et al., 2025a)	67.10	-	-
XiYanSQL-QwenCoder-32B (Liu et al., 2025c)	67.01	69.03	-
Infly-RL-SQL-32B	70.08	70.60	-
SIFT-32B	70.08	70.93	-
Jiayin-Pangu-Text2SQL-14B	71.10	73.45	-
Arctic-Text2SQL-R1-32B (Yao et al., 2025)	72.20	73.84	-
Sophon-Text2SQL-32B	72.43	74.79	-
Databricks RLVR 32B (Ali et al., 2025)	-	75.68	-
Ours			
Agentar-Scale-SQL (Ours)	**74.90**	**81.67**	**77.00**

notes that we employ self-consistency (i.e., majority voting based on execution results) to select the best SQL. We can observe that our method outperforms the self-consistency baseline by 1.82 points in EX. This is because the most frequently executed result is not necessarily correct. Our selection strategy, which likely incorporates more signals than simple frequency, proves to be a more effective and robust method for identifying the correct query.

4.4 Analysis of Generator Components (RQ3)

As shown in Figure 3, the ICL generator achieves a notably higher upper bound accuracy (81.36%) than the reasoning generator (75.88%), indicating its strong potential for generating correct queries. However, combining their outputs (All) achieves the highest overall upper bound of 84.29%. This synergistic gain is explained by their complemen-

tary nature, as illustrated in Figure 4. While they share a large set of correct solutions, they also uniquely solve 47 and 12 samples, respectively. This expanded coverage holds across all difficulty levels (Figure 5). A breakdown by difficulty reveals that the reasoning generator holds an edge on simple and moderate tasks, while the ICL generator proves more effective for solving challenging problems.

Ultimately, this richer and more diverse candidate pool allows our final selection strategy to achieve its peak accuracy of 74.90%, demonstrating the crucial role of the dual-generator approach.

4.5 Impact of the Candidate Number (RQ4)

Finally, we investigate the impact of the candidate number by varying it from 1 to 16. The results are depicted in Figure 6, showing that increas-

Table 2: Ablation results on the development set.

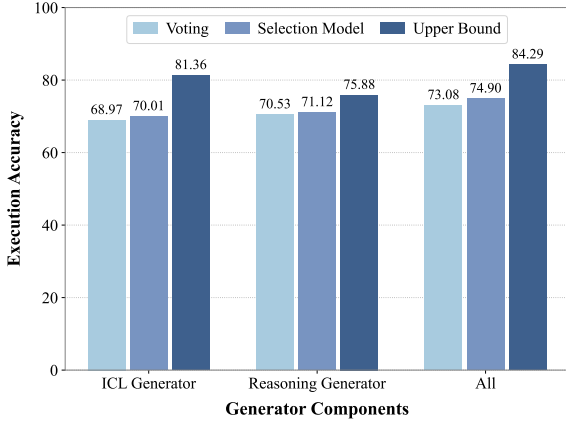| Methods	Simple	Moderate	Challenging	Total	ΔTotal
Agentar-Scale-SQL	79.35	69.40	64.14	74.90	-
w/o Task Understanding	79.14	68.32	64.14	74.45	-0.45
w/o Reasoning SQL Generator	74.92	63.79	58.62	70.01	-4.89
w/o ICL SQL Generator	75.89	66.38	55.86	71.12	-3.78
w/o Iterative Refinement	78.92	68.75	63.45	74.38	-0.52
w/o SQL Selection Scaling	77.95	66.59	62.76	73.08	-1.82

Figure 3: Execution accuracy of voting, selection model, and upper bound across generator components.
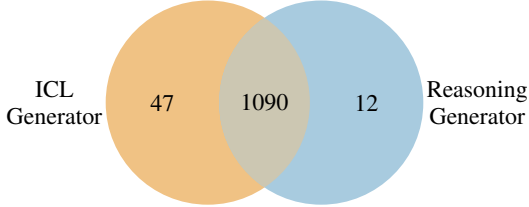

Figure 4: Shared and unique correct samples between ICL and reasoning generators.
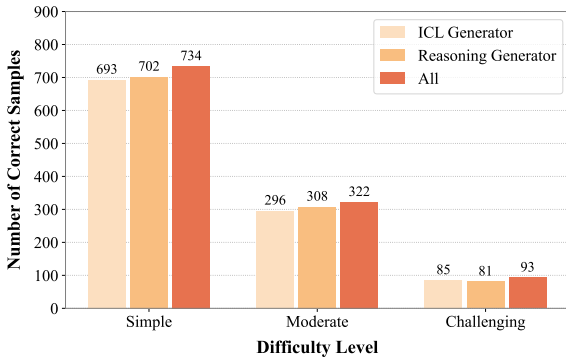

Figure 5: Number of correct samples by difficulty level for ICL, reasoning, and combined generators.

ing the number of candidates consistently boosts the Pass@k rate across all difficulty levels. The improvement is most significant for challenging queries and is most substantial when increasing the candidates up to 8, after which the gains diminish. This validates the effectiveness of our parallel scaling strategy.
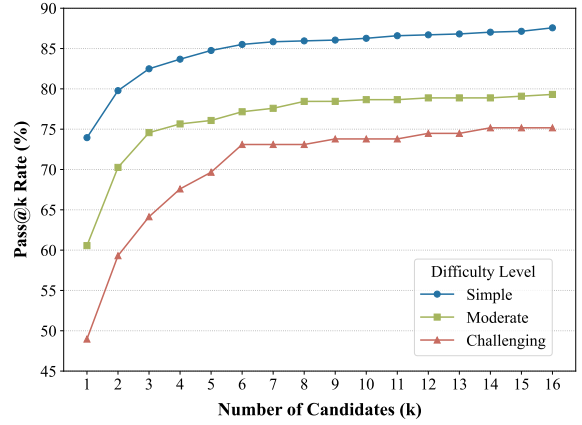
Figure 6: Pass@k rate with varying candidate numbers.

5 Conclusion

We introduced Agentar-Scale-SQL, a novel framework that significantly improves Text-to-SQL performance by synergistically combining internal, sequential, and parallel scaling strategies. Our method achieves SOTA results on the challenging BIRD benchmark, demonstrating an effective path toward human-level accuracy. We release codes and models to support future research in this area.

Building on the success of enhancing intelligence through Test-Time Scaling, we are now pioneering our next great endeavor: Exercise-Time Scaling. We will empower a new generation of agents to learn through action and evolve from experience, on a journey to realize intelligence that transcends humanity and to explore the vast unknown.

Limitations

Despite its effectiveness, Agentar-Scale-SQL's reliance on orchestrated test-time scaling introduces several key limitations. The framework's primary drawback is its substantial computational overhead and high latency due to the multiple LLM calls for generation, refinement, and selection, making it less suitable for real-time applications. Furthermore, its performance is fundamentally bounded by the capabilities of the underlying base LLM, and it is susceptible to cascading errors where a failure in an early stage, such as task understanding, can compromise the entire process.

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A BIRD Leaderboard: Bar Chart and Snapshot

We present the BIRD rankings in a bar chart (Figure 7) and provide a snapshot of the BIRD leaderboard (Figure 8).
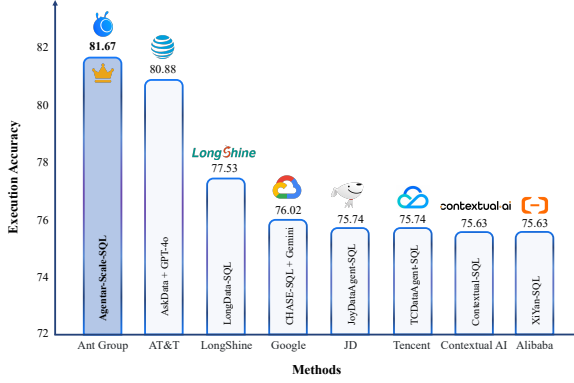
(a) EX
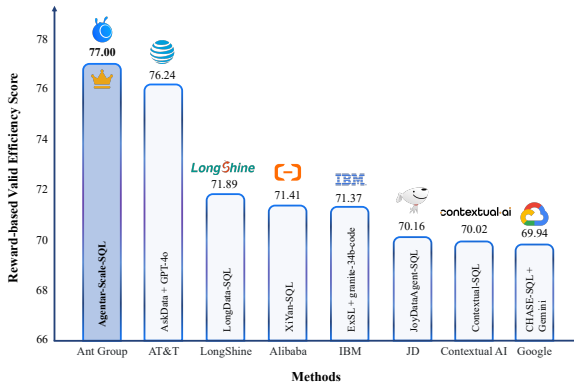
(b) R-VES

Figure 7: BIRD leaderboard: EX and R-VES performance comparison.

B Additional Results on the BIRD Test Set

Table 3: Additional results on the BIRD test set.

Metric	Simple	Moderate	Challenging	Total
Count	949	555	285	1789
EX	86.83	78.20	71.23	81.67
Soft F1	87.28	79.41	73.58	82.65
R-VES	81.90	73.23	68.03	77.00

C Definition of Evaluation Metrics

This section provides detailed definitions for the three primary metrics (Li et al., 2023) used to evaluate the performance of our text-to-SQL framework: Execution Accuracy (EX), Reward-based Valid Efficiency Score (R-VES), and the Soft F1-Score.

C.1 Execution Accuracy (EX)

Execution Accuracy (EX) is a strict binary metric that assesses whether the SQL query generated by the model produces the exact same result set as the ground-truth SQL query.

For each question, the predicted SQL is executed against the database. The resulting table is then compared to the table generated by executing the official ground-truth SQL. A prediction is considered correct (score of 1) only if the two result sets are identical. Any deviation, including differences in row or column order, mismatched values, or SQL execution errors, results in a score of 0.

The final EX score for the entire evaluation set is the average of these binary scores, calculated as:

$$\text{EX} = \frac{1}{N} \sum_{i=1}^{N} \text{score}_i \tag{5}$$

where N is the total number of questions in the evaluation set, and score_i is 1 if the predicted query for question i is correct, and 0 otherwise.

C.2 Reward-based Valid Efficiency Score (R-VES)

The Reward-based Valid Efficiency Score (R-VES) is designed to measure the execution efficiency of a correctly generated SQL query relative to its ground-truth counterpart. This metric is calculated only for queries that pass the Execution Accuracy (EX) evaluation.

The score is based on a reward function that considers the ratio of execution times between the predicted query (T_{pred}) and the ground-truth query (T_{gold}). The reward for a single valid query is defined as:

$$\text{Reward}_i = \begin{cases} 1 & \text{if } T_{\text{pred}_i} < T_{\text{gold}_i} \\ \frac{2}{1+(T_{\text{pred}_i}/T_{\text{gold}_i})} & \text{if } T_{\text{pred}_i} \geq T_{\text{gold}_i} \end{cases} \tag{6}$$

This function assigns a full reward of 1 if the predicted query is more efficient than the ground truth. If it is slower, the reward decreases as the execution time ratio increases, penalizing inefficient queries.

The final R-VES is the average reward over all validly executed queries:

$$\text{R-VES} = \frac{1}{N_{\text{valid}}} \sum_{i=1}^{N_{\text{valid}}} \text{Reward}_i \tag{7}$$

About BIRD

BIRD (**BI**g Bench for La**R**ge–scale **D**atabase Grounded Text–to–SQL Evaluation) represents a pioneering, cross–domain dataset that examines the impact of extensive database contents on text–to–SQL parsing. BIRD contains over **12,751** unique question–SQL pairs, **95** big databases with a total size of **33.4 GB**. It also covers more than **37** professional domains, such as blockchain, hockey, healthcare and education, etc.

Paper
Code
Mini-Dev (500)
BIRD-CRITIC 1.0 (SQL)
LiveSQLBench!
BIRD-Interact

Train Set	🔥 Dev Set

News

Sep. 19, 2025: We've released **BIRD23-train-filtered**, a high-quality filtered subset of the BIRD train split (6,601/9,428 ≈70%) that works as a drop-in replacement for text-to-SQL finetuning; See the example finetuning usage in here.
Sep. 10, 2025: We're excited to announce the release of the **LiveSQLBench-Base-Full-V1 (600)**! The first text-to-SQL benchmark covering all SQL spectrum with Hierarchical Knowlegde Base (HKB)

	Overall Leaderboard	Single-Model Leaderboard

Leaderboard - Execution Accuracy (EX)

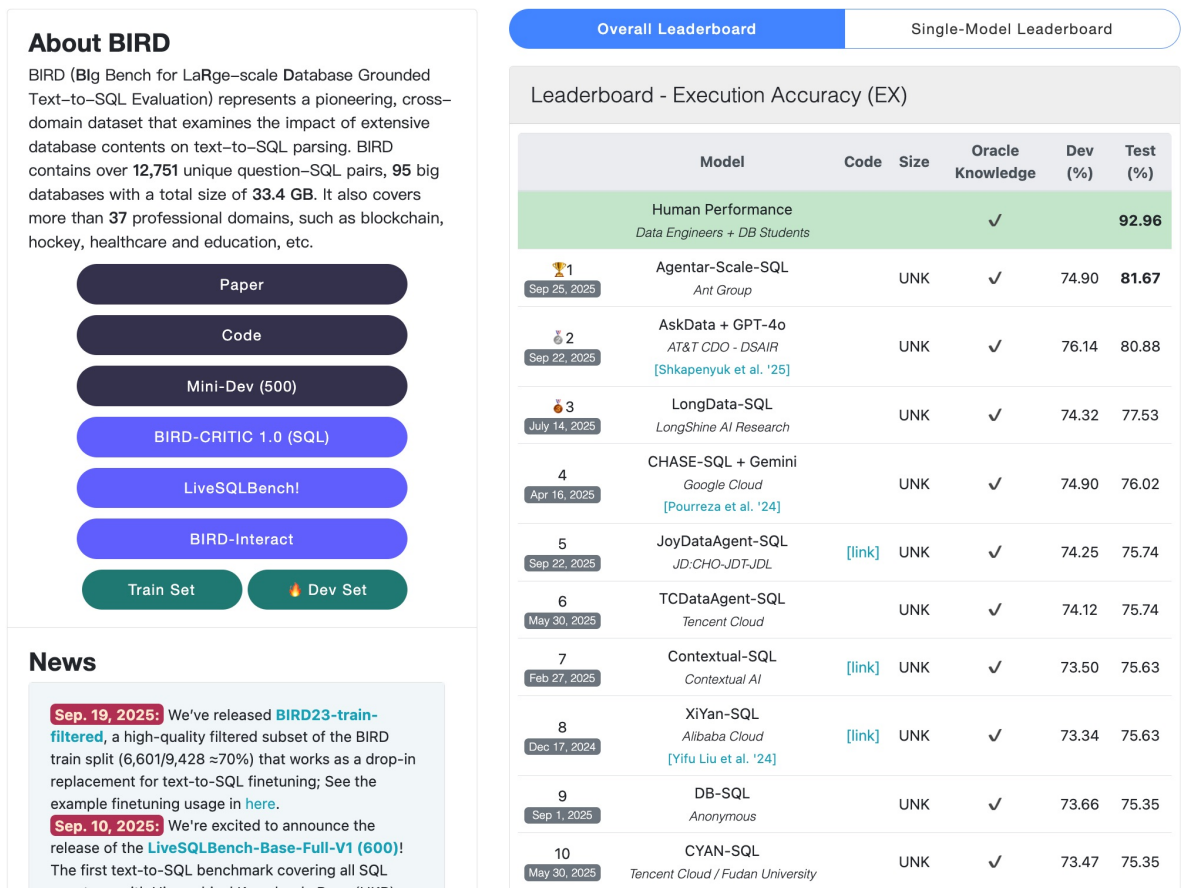|	Model	Code	Size	Oracle Knowledge	Dev (%)	Test (%)
Human Performance *Data Engineers + DB Students*				✓		**92.96**
🏆1 Sep 25, 2025	Agentar-Scale-SQL *Ant Group*		UNK	✓	74.90	**81.67**
🥈2 Sep 22, 2025	AskData + GPT-4o *AT&T CDO - DSAIR* [Shkapenyuk et al. '25]		UNK	✓	76.14	80.88
🥉3 July 14, 2025	LongData-SQL *LongShine AI Research*		UNK	✓	74.32	77.53
4 Apr 16, 2025	CHASE-SQL + Gemini *Google Cloud* [Pourreza et al. '24]		UNK	✓	74.90	76.02
5 Sep 22, 2025	JoyDataAgent-SQL *JD:CHO-JDT-JDL*	[link]	UNK	✓	74.25	75.74
6 May 30, 2025	TCDataAgent-SQL *Tencent Cloud*		UNK	✓	74.12	75.74
7 Feb 27, 2025	Contextual-SQL *Contextual AI*	[link]	UNK	✓	73.50	75.63
8 Dec 17, 2024	XiYan-SQL *Alibaba Cloud* [Yifu Liu et al. '24]	[link]	UNK	✓	73.34	75.63
9 Sep 1, 2025	DB-SQL *Anonymous*		UNK	✓	73.66	75.35
10 May 30, 2025	CYAN-SQL *Tencent Cloud / Fudan University*		UNK	✓	73.47	75.35

Figure 8: A snapshot of the BIRD benchmark's dynamic leaderboard as of September 28, 2025.

where N_{valid} is the total number of queries that passed the EX evaluation. To ensure stability, execution times are measured with a timeout, and the evaluation is repeated multiple times, with the highest score being reported.

C.3 Soft F1-Score

The Soft F1-Score offers a more lenient evaluation than EX by comparing the content similarity of the result tables produced by the predicted and ground-truth queries. This metric is insensitive to column order and robust to missing values.

The calculation proceeds by comparing the tables on a row-by-row, cell-by-cell basis. For each row in the predicted table and the ground-truth table, we compute the following three quantities:

- **Matched** (tp_{row}): The number of common cell values between a predicted row and its best-matching ground-truth row.

- **Pred_only** (fp_{row}): The number of cell values present in the predicted row but not in its matched ground-truth row.

- **Gold_only** (fn_{row}): The number of cell values present in the ground-truth row but not in its matched predicted row.

These row-level counts are then aggregated across all rows to compute the total True Positives (tp), False Positives (fp), and False Negatives (fn) for the entire table:

$$\text{tp} = \sum_{\text{all rows}} tp_{\text{row}}$$
$$\text{fp} = \sum_{\text{all rows}} fp_{\text{row}}$$
$$\text{fn} = \sum_{\text{all rows}} fn_{\text{row}}$$

Finally, standard Precision, Recall, and F1-Score are calculated using these aggregated values:

$$\text{Precision} = \frac{\text{tp}}{\text{tp} + \text{fp}} \quad (8)$$

$$\text{Recall} = \frac{\text{tp}}{\text{tp} + \text{fn}} \quad (9)$$

$$\text{Soft F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

D Discussion of Schema Linking

Given the universal and pluggable architecture of our Agentar-Scale-SQL framework, we did not develop a built-in schema linking strategy for the BIRD benchmark. The framework is explicitly designed to be modular, facilitating the seamless integration of components like a schema linker. This approach is particularly advantageous for large-scale databases with numerous tables, as a dedicated schema linking module can be easily incorporated as needed, without altering the core system.

E Further Work

Agentar-Scale-SQL marks a significant milestone on our journey toward Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI). By leveraging *Orchestrated Test-Time Scaling*, we have substantially advanced the state-of-the-art in Text-to-SQL. Looking ahead, we plan to explore the following directions:

- **Self-Exploration:** We will enable the agent to autonomously explore and accumulate experience in an offline phase, thereby shifting the computational burden from Test-Time to a pre-computation phase we term Exercise-Time.

- **Agentic SQL:** We aim to evolve our current workflow-based approach into a fully autonomous agent, moving beyond predefined structures.

- **Generalization:** We intend to extend the *Orchestrated Test-Time Scaling* methodology to a broader range of code generation and reasoning tasks.