FEATHER-SQL: A LIGHTWEIGHT NL2SQL FRAMEWORK WITH DUAL-MODEL COLLABORATION PARADIGM FOR SMALL LANGUAGE MODELS

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ABSTRACT

Natural Language to SQL (NL2SQL) has seen significant advancements with large language models (LLMs). However, these models often depend on closed-source systems and high computational resources, posing challenges in data privacy and deployment. In contrast, small language models (SLMs) struggle with NL2SQL tasks, exhibiting poor performance and incompatibility with existing frameworks. To address these issues, we introduce **Feather-SQL**, a new lightweight framework tailored for SLMs. Feather-SQL improves SQL executability and accuracy through 1) schema pruning and linking, 2) multi-path and multi-candidate generation. Additionally, we introduce the **1+1 Model Collaboration Paradigm**, which pairs a strong general-purpose chat model with a fine-tuned SQL specialist, combining strong analytical reasoning with high-precision SQL generation. Experimental results on BIRD demonstrate that Feather-SQL improves NL2SQL performance on SLMs, with around 10% boost for models without fine-tuning. The proposed paradigm raises the accuracy ceiling of SLMs to 54.76%, highlighting its effectiveness.

1 INTRODUCTION

Natural Language to SQL (NL2SQL) is the task of converting natural language questions into corresponding SQL queries, allowing users to retrieve structured data from databases without requiring proficiency in SQL language. In recent years, the field has seen significant advancements with the emergence of large language models (LLMs) such as GPT-4 (OpenAI, 2024), enabling frameworks like CHASE-SQL (Pourreza et al., 2024) and XiYan-SQL (Gao et al., 2025) to achieve state-of-the-art (SOTA) performance. However, two limitations hinder their practical adoption. First, mainstream methods depend on closed-source models, and their reliance on external APIs introduces data privacy risks in sensitive domains like healthcare and finance (Liu et al., 2024). Second, most open-source research focuses on models with 7B–30B parameters, leaving small language models (SLMs) with 4B or fewer parameters relatively underexplored. Meanwhile, many relational databases are deployed on high-performance systems with limited GPU resources. With efficient inference frameworks (e.g. Intel IPEX-LLM (Intel, 2024)) or quantization techniques, SLMs can help drive the broader adoption of NL2SQL in real-world scenarios while preserving data privacy.

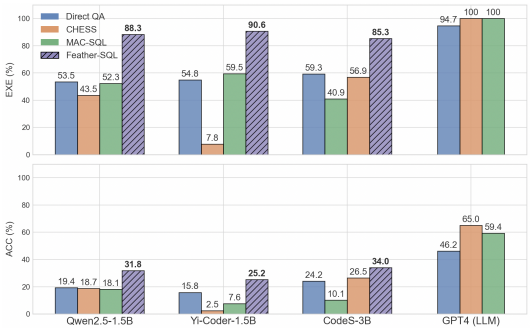

Table 1: NL2SQL performance on the BIRD DEV dataset. EXE (Executability) measures successful query executions, while ACC (Accuracy) measures correct result matches.

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In this paper, we focus on enhancing NL2SQL performance using SLMs. As shown in Figure 1, SLMs face two key challenges: (1) **one critical issue is their sharp decline in executability**. Unlike LLMs, which can effectively handle long-context dependencies, SLMs struggle with complex database schema and verbose prompts, often leading to confusion or hallucinated outputs (Nguyen et al., 2024; Qu et al., 2024) (Figure 1); (2) **existing frameworks for NL2SQL tasks with LLMs are incompatible with SLMs**, as they rely on strong instruction-following capabilities to produce intermediate results, which SLMs lack. As illustrated in Figure 2, SLM outputs frequently violate imposed requirements: they often fail to conform to JSON or array specifications and do not meet predefined constraints. Directly applying these frameworks to SLMs may further degrade executability.

To address these challenges, we propose **Feather-SQL**, a lightweight framework tailored for SLMs to enhance both executability and accuracy in NL2SQL tasks. Feather-SQL consists of six key components: schema pruning, schema linking, multi-path generation, multi-candidate generation, correction, and selection. Designed specifically for SLMs, schema pruning streamlines input processing by discarding irrelevant tables, allowing models to concentrate on essential database elements. Schema linking improves alignment between questions and database schema, ensuring accurate column selection. To mitigate errors from linking and pruning, multi-path generation explores diverse query formulation strategies, enhancing robustness. Multi-candidate generation further improves the model's executability and accuracy by enhancing the variety of generated SQL queries, thereby increasing the likelihood of producing correct candidates. The best candidate is then selected through execution validation and ranking. Complementing these components, we introduce extraction and simplification prompting strategies. Extraction selectively retrieves key information, while simplification removes extraneous prompt details to lower computational overhead. By integrating these techniques, Feather-SQL enables SLMs to generate SQL queries more reliably despite their inherent limitations.

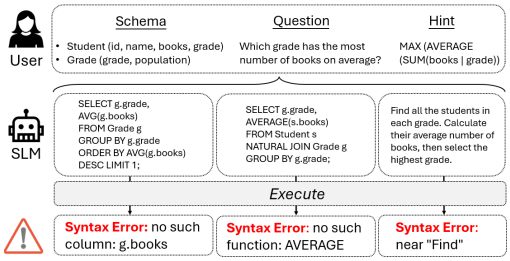

Figure 1: Examples of typical syntax errors produced by small language models (SLMs) in an NL2SQL scenario.

A common approach to enhancing SLMs is fine-tuning. However, while fine-tuned SLMs for SQL generation tasks (e.g., Prem-SQL (Anindyadeep, 2024), CodeS (Li et al., 2024a)) outperform general-purpose chat models on core NL2SQL tasks, they suffer from catastrophic forgetting (Luo et al., 2025; Kotha et al., 2024) on auxiliary tasks—where task-specific fine-tuning erodes their foundational reasoning abilities. To counter this, we propose **1+1 Model Collaboration Paradigm**, in which a general-purpose chat model handles reasoning-intensive auxiliary tasks (e.g., schema linking and candidate selection), while a fine-tuned SQL specialist focuses on query generation. This collaboration leverages both models' strengths: the general model provides broad reasoning ability, while the specialist delivers domain-specific precision. Experiments confirm that the paradigm improves overall performance. Our main contributions are as follows:

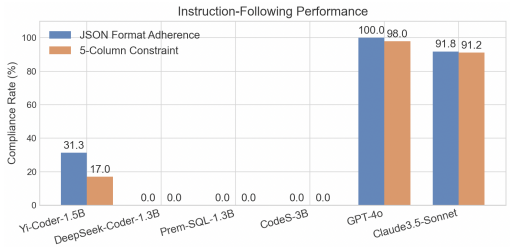

Figure 2: Experiments conducted on a CHESS-provided BIRD subset for schema linking. Models are required to output a JSON-formatted response containing no more than five relevant columns related to the question, without generating any extraneous content.

- We introduce Feather-SQL, an NL2SQL framework for SLMs to address their unique challenges of low executability and incompatibility with existing LLM-based frameworks.
- We propose a novel 1+1 Model Collaboration paradigm that mitigates catastrophic forgetting in fine-tuned SLMs by delegating reasoning-intensive tasks to a general-purpose chat model.

- Extensive experiments on the Spider and BIRD datasets demonstrate that Feather-SQL consistently achieves strong performance with various SLMs, and when paired with the paradigm, it yields SOTA results on BIRD within the scope of SLMs.

2 Related Work

2.1 Conventional Methods

Extensive research on NL2SQL has been carried out. Early investigations (Zelle & Mooney, 1996; Li & Jagadish, 2014; Saha et al., 2016) predominantly employed rule-based or template-based approaches, necessitating considerable manual effort and thereby limiting both their adaptability and generalizability.

To address the shortcomings of earlier methods, sequence-to-sequence models have been proposed. In such models, encoders are responsible for learning the semantic representations of natural language questions and the associated database schema, while decoders generate the corresponding SQL based on these representations. Representative approaches in this category include IRNet (Jha et al., 2019), SQLNet (Xu & et al., 2017), Seq2SQL (Zhong et al., 2017), RyanSQL (Choi et al., 2021), and RESDSQL (Li et al., 2023a), each contributing to advancements in query generation.

Meanwhile, some methods choose to fine-tune pre-trained language models such as BERT (Devlin et al., 2019) and T5 (Raffel et al., 2023), leveraging the broad knowledge captured during pre-training to enhance accuracy and robustness. For instance, Graphix-T5 (Li & et al., 2023) integrates a pre-trained transformer with specialized graph-aware layers, improving performance on tasks requiring graph-structured data analysis. Nonetheless, these strategies often demand extensive training data and face considerable challenges when dealing with complex questions and database schema.

2.2 Emerging LLM and SLM Approaches

More recently, the emergence of LLMs has marked a watershed moment. LLM-based NL2SQL methods (Dong et al., 2023; Pourreza & Rafiei, 2023; Gao et al., 2023; Wang et al., 2024; Li et al., 2024b; Qu et al., 2024; Talaei et al., 2024; Ren et al., 2024; Pourreza et al., 2024; Gao et al., 2025) have risen to prominence as leading solutions. For example, DIN-SQL (Pourreza & Rafiei, 2023) decomposes the NL2SQL task into subtasks—such as schema linking, difficulty classification, and SQL generation—thereby streamlining decision-making and enabling more accurate query outputs. CHESS (Talaei et al., 2024) adopts a multi-agent framework in which each agent is assigned a specific model and a few-shot prompting strategy to handle different subtasks. While these approaches offer impressive performance, they introduce security risks and lead to steep increases in computational costs.

Employing SLMs to address NL2SQL tasks has the potential to alleviate the aforementioned challenges. CodeS (Li et al., 2024a) incorporates incremental pre-training and bi-directional data augmentation to fine-tune a series of models (1B, 3B, 7B, and 15B parameters). Models specifically finetuned for NL2SQL tasks, such as premSQL (Anindyadeep, 2024) and SQLCoder (Defog), have likewise demonstrated notable success. Nevertheless, these models remain susceptible to the effects of catastrophic forgetting, which diminishes their capacity to perform general reasoning tasks—such as schema linking—within the broader NL2SQL workflow.

3 Methodology

3.1 Feather-SQL

As shown in Figure 3, we propose Feather-SQL to enhance the performance of SLMs in NL2SQL. This framework comprises several components, including Schema Pruning, Multi-Path, and Multi-Candidate Generation, which are specifically designed to address the challenges of SLMs. We will elaborate on these components in the following sections.

Schema Pruning. This step dynamically reduces schema complexity by identifying and filtering out irrelevant tables. Given the complete set of Data Definition Language (DDL) statements for all tables,

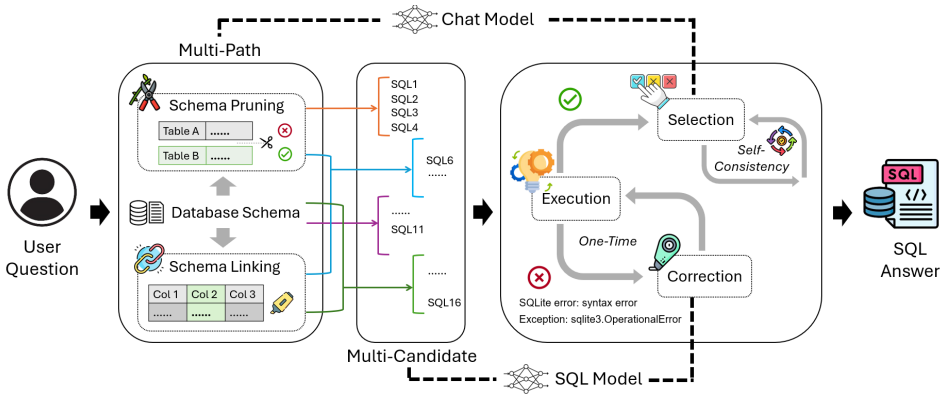

Figure 3: An overview of the Feather-SQL framework for small language models (SLMs) in NL2SQL tasks. The pipeline comprises six core modules—*schema pruning*, *schema linking*, *multi-path generation*, *multi-candidate generation*, *correction*, and *selection*—which collaboratively boost query executability and accuracy. Additionally, the *1+1 Model Collaboration Paradigm* pairs a general-purpose chat model for auxiliary reasoning with a SQL fine-tuned model for query generation, balancing broad contextual understanding with domain-specific precision.

the model analyzes semantic relevance to determine which tables are pertinent to the question. Only the DDLs of these relevant tables are retained in the subsequent processing pipeline. This selective retention mechanism prevents SLMs from processing long inputs, thereby mitigating their limitations in handling long text while preserving essential information.

Schema Linking. This step aligns the question with the database schema by identifying relevant columns through semantic analysis. As a commonly adopted practice, schema linking extracts pertinent columns from the complete schema based on the given question, facilitating downstream processing. By establishing precise mappings between natural language expressions and database elements, this process significantly enhances SQL generation accuracy.

Multi-Path Generation. This step employs four distinct prompt types: (1) with both schema linking and pruning, (2) linking only, (3) pruning only, and (4) without either operation. The multi-path design mitigates the risk of information loss caused by pruning errors and reduces potential misunderstandings arising from linking inaccuracies.

Multi-Candidate Generation. This step generates multiple SQL queries in parallel to increase the likelihood of producing a correct result. To ensure diversity, *beam search* is employed alongside carefully tuned temperature and top-p parameters. Each path consistently generates a fixed number of candidate queries, maintaining a balanced exploration of possible solutions. Notably, while LLMs often generate executable answers on the first attempt with minimal accuracy improvement from additional candidates, SLMs benefit significantly from multi-candidate generation, which enhances both executability and accuracy (Appendix B).

Correction. This step executes each generated query and handles it based on the outcome. If a query executes successfully, it is directly added to the array of executable SQL queries. For failed queries, error feedback is used to revise the query through a self-correction approach, generating two new candidate queries. If any of these revised queries are executable, they are also stored in the array of executable SQL queries.

Selection. This step employs a *selection ranking* method to evaluate all executable queries based on their alignment with the expected answer. If a query yields a limited number of results, the evaluation considers both the query and its execution outcome. In contrast, the evaluation focuses solely on the query itself. The selection process is repeated three times, and the mode of the rankings is returned as the final result.

3.2 Prompting Strategies

Extraction. As mentioned in Section 1, SLMs struggle to meet structural constraints, thus we propose an extraction strategy to avoid rigid structural outputs by allowing SLMs to freely generate

responses. This improves accuracy on reasoning tasks by bypassing syntactic constraints. We have two methods to achieve that: **(1) Lexical Matching:** This method identifies valid schema elements by matching table/column names explicitly mentioned in the natural language response against the database schema. For instance, when the SLM outputs "The required tables include customer and orders", the system verifies and extracts customer/orders only if they exist in the schema. **(2) Pattern Matching:** This method extracts the final answer by identifying predefined patterns in the model's output, such as "answer is" or "Answer:". For example, if the model generates "The answer is 128", the framework detects the pattern and extracts "128" as the final result.

Simplification. The simplification strategy reduces computational overhead by minimizing prompt verbosity. In Feather-SQL, we achieve this by removing superfluous details and using concise instructions with the fewest effective examples (Appendix C). This approach refines the input by eliminating unnecessary complexity, avoiding the need for SLMs to process lengthy inputs while maintaining the clarity of the task.

3.3 1+1 Collaboration Paradigm

Our paradigm categorizes NL2SQL pipeline tasks into two types: reasoning-intensive tasks and SQL generation tasks. Reasoning tasks, such as schema linking and candidate evaluation, require strong contextual understanding and adaptability, while SQL generation demands precision in query synthesis. To optimize performance, we employ two specialized models: the general-purpose chat Model for reasoning tasks and the SQL fine-tuned model for SQL generation. By leveraging their complementary strengths, our approach improves overall NL2SQL accuracy and robustness.

General-purpose Chat Model. This model is designed for reasoning-intensive tasks, leveraging broad linguistic and contextual comprehension without domain-specific fine-tuning, which helps prevent catastrophic forgetting. Compared to the SQL Specialist Model, it is more effective in schema linking and evaluating SQL candidates, ensuring that the SQL generation process is guided by accurate and well-structured contextual information.

SQL Fine-tuned Model. Optimized exclusively for SQL generation, this model is extensively trained on large-scale NL2SQL datasets, allowing it to achieve superior performance on SQL-specific tasks. Its focused training reduces hallucinations and enhances both query executability and accuracy.

4 Experiments

4.1 Settings

4.1.1 Datasets

BIRD (Li et al., 2023b) as a representative and challenging benchmark dataset for NL2SQL, encompasses databases over 37 professional domains. Due to the proprietary nature of the BIRD TEST dataset, we conduct our experiments using the publicly accessible BIRD DEV subset, which contains 1,534 unique question-SQL pairs.

Spider (Yu et al., 2019) is another large-scale benchmark dataset for cross-domain SQL generation, covering 138 different domains. Compared to BIRD, Spider is relatively simpler, as its SQL structures and schema are generally less complex. Our experiments utilize the SPIDER TEST set, comprising 2,147 question-SQL pairs.

4.1.2 Evaluation Metrics

Execution Accuracy (EX) (Li et al., 2023b) is a widely adopted metric in NL2SQL evaluations, measuring whether the result of executing the generated query matches the result of the ground truth query. This metric allows for different query formulations that yield the same result. It is calculated as:

$$\text{EX} = \frac{|\{n \in N \mid \text{E}(Q_{gen}) = \text{E}(Q_{\text{gt}})\}|}{N} \times 100\%$$

where N denotes the number of questions. Q_{gen} represents the SQL query generated by the model, while Q_{gt} is the ground truth answer. E is the execution function.

Execution Proportion (EP) is an auxiliary metric we proposed, evaluating the proportion of generated SQL queries that can be executed on the corresponding database without syntax errors. This metric reflects the model's upper-bound capability by assuming that any executable query is potentially correct. It is defined as:

$$\text{EP} = \frac{|\{n \in N \mid \text{E}(Q_{\text{gen}}) \neq \text{error}\}|}{N} \times 100\%$$

4.1.3 BASELINES

Direct Response (DR) directly generates an SQL query from the natural language question without applying any refinement techniques. The process follows a single-turn interaction.

First Executable Query (FEQ) leverages the model's ability to generate multiple SQL candidates. Among candidates, the first executable query is selected without any refinement. This approach simulates multi-turn query generation.

MAC-SQL (Wang et al., 2024) is an LLM-based multi-stage framework, featuring a core Decomposer agent for SQL generation supported by auxiliary agents for sub-database acquisition and query refinement. It also utilizes few-shot chain-of-thought reasoning to enhance generation processes.

CHESS (Talaei et al., 2024) comprises four specialized agents: Information Retriever, Schema Selector, Candidate Generator, and Unit Tester. Notably, it employs locality-sensitive hashing and vector databases to efficiently retrieve relevant data from extensive database values and catalogs.

4.1.4 IMPLEMENTATION DETAILS

Backbone Models. Our implementation leverages both general-purpose chat models and SQL fine-tuned models. The chat models include Qwen2.5-0.5B, Qwen2.5-1.5B, Qwen2.5-Coder-1.5B (Hui et al., 2024), Yi-Coder-1.5B (AI et al., 2025), DeepSeek-Coder-1.5B (DeepSeek-AI, 2024), Phi3-mini-3.8B (Abdin et al., 2024), and MiniCPM3-4B (Hu et al., 2024), while the SQL-tuned models consist of Prem-SQL-1.3B (Anindyadeep, 2024) and CodeS-3B (Li et al., 2024a).

Candidate Size. In the multi-candidate generation stage, we generate *4* candidates per path, resulting in a total candidate pool of *16*. During the correction stage, the candidate size is reduced to *2*.

Selection Rounds. During the selection stage, we perform *3* rounds for each selection. The final choice is the majority vote across the three rounds, ensuring consistency of the selected candidate.

Table 2: Comparison of EX (Execution Accuracy) and EP (Execution Proportion) across different methods on the BIRD DEV dataset. The best and second-best results are highlighted by **Bold** and underline, respectively. * denotes results with the extraction strategy.

Method	Qwen2.5-1.5B		Yi-Coder-1.5B		Phi3-Mini-3.8B	
	EX (%)	EP (%)	EX (%)	EP (%)	EX (%)	EP (%)
DR	19.36	53.52	15.84	54.82	27.44	71.90
FEQ	21.51	68.25	18.71	73.60	30.12	67.93
MAC-SQL	18.06	52.28	7.63	59.52	29.99	77.64
CHESS	18.71	43.55	2.48	7.82	18.12	39.70
Feather-SQL (Ours)	**31.81**	**88.33**	**25.23**	**90.61**	**36.64**	**83.70**
Method	**MiniCPM3-4B**		**Prem-SQL-1.3B**		**CodeS-3B**	
	EX (%)	EP (%)	EX (%)	EP (%)	EX (%)	EP (%)
DR	27.57	69.30	47.07	88.14	24.19	59.32
FEQ	29.34	63.89	**51.63**	92.70	25.03	57.50
MAC-SQL	37.35	81.68	8.67 (*8.87**)	17.01 (*19.23**)	10.10 (*13.23**)	40.87 (*56.26**)
CHESS	28.42	54.43	24.64	43.22	26.53	56.91
Feather-SQL (Ours)	**40.09**	**87.02**	49.28	**98.04**	**33.96**	**85.31**

Table 3: Comparison of EX (Execution Accuracy) and EP (Execution Proportion) across different methods on the Spider TEST dataset. The best and second-best results for EX are highlighted by **bold** and underline, respectively. * denotes results with the extraction strategy.

Method	Qwen2.5-0.5B		Yi-Coder-1.5B		DeepSeek-Coder-1.3B	
	EX (%)	EP (%)	EX (%)	EP (%)	EX (%)	EP (%)
DR	28.50	56.45	45.23	87.24	49.28	90.68
FEQ	36.53	67.35	48.30	86.77	45.46	89.89
MAC-SQL	29.06	**89.61**	13.04	21.70	**52.12**	93.62
CHESS	15.42	29.16	3.68	10.29	30.18	46.30
Feather-SQL (Ours)	**36.98**	75.08	**49.56**	**92.04**	51.19	**94.13**
Method	**MiniCPM3-4B**		**Prem-SQL-1.3B**		**CodeS-3B**	
	EX (%)	EP (%)	EX (%)	EP (%)	EX (%)	EP (%)
DR	55.10	93.71	60.92	85.79	47.74	64.23
FEQ	55.75	89.52	64.23	85.75	49.60	64.65
MAC-SQL	25.01	38.47	0.14 (***67.91****)	0.14 (***100****)	0 (***74.48****)	0 (***100****)
CHESS	56.73	89.99	63.86	92.08	66.65	88.54
Feather-SQL (Ours)	**58.92**	**94.18**	66.60	92.78	63.25	88.96

4.2 Main Results

4.2.1 Feather-SQL

To validate the general effectiveness of Feather-SQL for SLMs, we conducted experiments on two datasets across a range of models (all results here were obtained using a unified model without adopting the collaboration paradigm).

BIRD Results. As shown in Table 2, Feather-SQL demonstrates superior performance across all general-purpose chat models, achieving the highest scores in both EX and EP, with EX showing an average increase of approximately 10% and EP exceeding a 20% improvement compared to FEQ. For SQL fine-tuned models, Feather-SQL combined with CodeS achieves substantial gains in both EX and EP, while Prem-SQL shows notable improvements specifically in EP, with an average increase of around 5% compared to FEQ. Besides, we explored the upper bound of Feather-SQL on this dataset (Appendix D).

Moreover, we observe that CHESS and MAC-SQL do not perform effectively on SLMs, with their results on Qwen2.5 and Yi-Coder showing even lower EX and EP scores compared to DR. Their performance also falls behind that of FEQ.

Spider Results. Similarly, Table 3 highlights the results on the SPIDER TEST dataset, further confirming that our framework consistently and substantially enhances the NL2SQL performance of SLMs.

Although MAC-SQL and CHESS show inconsistent performance across models, MAC-SQL generally performs well. Notably, SQL fine-tuned models, achieve the best EX when extraction is applied, highlighting the necessity of this step for SLMs. This may be attributed to MAC-SQL's Selector mechanism, which also employs schema pruning. Unlike our table pruning approach, MAC-SQL adopts column pruning, which may be more effective for SPIDER's relatively simple schema structures.

Table 4: Paradigm performance under Feather-SQL on the BIRD DEV dataset. When no chat model is specified, the SQL model is also used as the chat model.

Chat Model	SQL Model	EX (%)	EP (%)
–	Prem-SQL	49.28	98.04
Qwen	Prem-SQL	52.44 ↑	94.08
Qwen Coder	Prem-SQL	52.83 ↑	98.31
Yi Coder	Prem-SQL	54.76 ↑	93.94
–	CodeS	33.96	83.31
Qwen	CodeS	35.79 ↑	80.05
Qwen Coder	CodeS	37.03 ↑	81.10
Yi Coder	CodeS	39.43 ↑	80.44

4.2.2 1+1 Collaboration Paradigm

As observed in Table 2, although Feather-SQL improves the EP of Prem-SQL, its EX shows a 2% decrease compared to FEQ. This decline is primarily due to Prem-SQL's inability to handle

auxiliary reasoning tasks. To address this limitation, we propose a division of tasks where the general-purpose chat model handles auxiliary reasoning, while the SQL fine-tuned model focuses on SQL generation.

As shown in Table 4, our 1+1 collaboration paradigm under Feather-SQL achieves a 3–6% improvement in EX for both Prem-SQL and CodeS, with Prem-SQL reaching SOTA performance among existing SLMs (Appendix E). However, we observe a decline in EP when paired with a chat model. This is because when the SQL model is also used as the chat model during schema pruning, it returns a query instead of the expected answer. But our extraction strategy sitll retrieves table names from the output, often resulting in an overly pruned schema-containing only one or two tables. While a simplified schema can occasionally boost EP, it frequently leads to lower overall EX.

Additionally, Table 5 shows that our paradigm improves both Prem-SQL and CodeS in CHESS, with EX increasing by ~20% and EP by over ~35% for Prem-SQL, while CodeS sees a smaller but consistent EX gain with no clear trend in EP.

Table 5: Paradigm performance under CHESS on the BIRD DEV dataset. When no chat model is specified, the SQL model is also used as the chat model.

Chat Model	SQL Model	EX (%)	EP (%)
–	Prem-SQL	24.64	43.22
Qwen	Prem-SQL	49.28 ↑	82.07
Qwen Coder	Prem-SQL	49.61 ↑	79.60
Yi Coder	Prem-SQL	47.65 ↑	79.79
–	CodeS	26.53	56.91
Qwen	CodeS	28.55 ↑	56.19
Qwen Coder	CodeS	28.88 ↑	63.04
Yi Coder	CodeS	27.44 ↑	55.22

However, the two models benefit differently due to their handling of auxiliary tasks. Prem-SQL attempts to answer linking questions but often does so incorrectly, whereas CodeS, due to severe catastrophic forgetting, fails to provide valid responses. As a result, CHESS defaults to using the original schema with CodeS, reducing linking errors.

Furthermore, since CHESS constructs long prompts without schema pruning, introducing a chat model increases input length and complexity. While this improves reasoning, it does not fully offset CodeS's limitations in processing extended inputs, restricting its EX improvement.

4.3 Ablation Studies

4.3.1 Component Contribution

We conducted an ablation study to quantify the impact of each framework component by removing them one at a time and measuring changes in EX and EP on the *BIRD DEV* dataset, using *QWen2.5-1.5B* (Table 6).

We can see from the ablation results that removing any of the components causes a drop in both EX and EP. This underscores that each step in our pipeline contributes to overall performance, and omitting even one module leads to noticeably reduced accuracy or executability.

Table 6: Ablation Study on Framework Components.

Framework	EX (%)	EP (%)
Full Model	31.81	88.33
–w/o Schema Pruning	-4.63 ↓	-20.34 ↓
–w/o Schema Linking	-3.45 ↓	-20.92 ↓
–w/o Multi-Candidate	-2.47 ↓	-17.99 ↓
–w/o Correction	-0.20 ↓	-12.58 ↓
–w/o Selection	-2.21 ↓	-10.36 ↓

Among these, schema pruning is shown to be the most critical: when it is removed, EX falls from 31.81% to 27.18%, the single largest drop in our study. This highlights how focusing on only the relevant tables and columns helps the model concentrate on essential schema elements, thereby yielding more accurate SQL generation. In contrast, removing correction only reduces EX by 0.20%, indicating that it has a relatively minor impact on the framework's effectiveness.

4.3.2 Path Contribution

We analyzed the origins of SQL answers from four models to understand how each processing path affects the final output. As shown in Figure 4, our multi-path framework includes four paths: one

using both schema linking and pruning, one using only schema linking, one using only schema pruning, and one without either.

For all four models, the path *Full Schema & Linking* is consistently the largest contributor, followed by *Pruned Schema & Linking*. This ranking underscores the critical role of linking in the framework, regardless of whether the schema is pruned or not.

Additionally, we find that schema pruning collectively accounts for over 25% across the models. These observations are consistent with the ablation findings in 4.3.1, further illustrating the essential roles of each component in ensuring executable and accurate query generation.

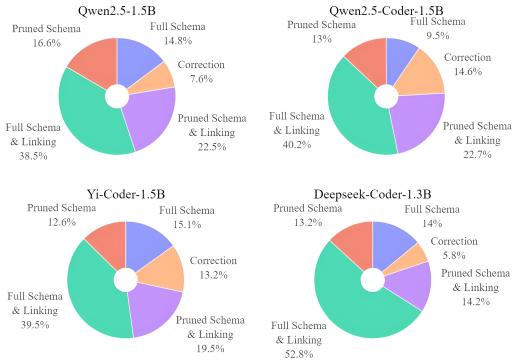

Figure 4: Distribution of correct SQL answers contributed by each path across four different SLMs.

We further investigated the impact of different candidate sizes. Figure 5 presents the results based on our four paths. In our experiments, the total candidate size increases from 4 to 24, which corresponds to the number of candidates generated per path increasing from 1 to 6. The figure illustrates how EX changes as the overall candidate size grows from 4 to 24.

4.3.3 Candidate Size

We observe a concave trend, consistent with Appendix B: EX steadily increases as the candidate size rises from 4 to 16 but then plateaus from 16 to 24. Once the model reaches its approximate upper bound, further increases in candidate size result in only a marginal difference in performance. Therefore, we select a candidate size of 16, as it is the earliest point at which EX saturates, thus balancing computational efficiency and model performance.

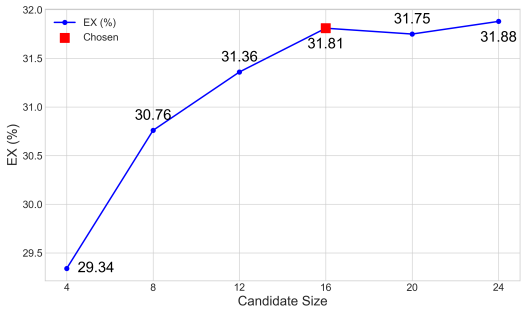

Figure 5: Effect of candidate size on EX performance.

Conclusion

In this work, we introduced Feather-SQL, the first lightweight framework designed to enhance NL2SQL performance for SLMs. We conduct comprehensive evaluations on the challenging BIRD and Spider datasets, where Feather-SQL yields improvements in both executability and accuracy. Additionally, we present the 1+1 Model Collaboration paradigm—a novel approach that pairs a general-purpose chat model with a SQL specialist to combine robust reasoning with precise query generation. Our evaluation results show that this paradigm boosts accuracy across different frameworks, demonstrating its consistent effectiveness. Moreover, the flexibility of our approach provides a robust foundation not only for advancing NL2SQL but also for application to other structured tasks and domains.

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A EXPERIMENTAL SETTINGS

All experiments were conducted on 4 NVIDIA A6000 GPUs using the vLLM inference acceleration framework to improve model efficiency. For stages that produce multiple answers, such as candidate generation and selection, we primarily used a `temperature` of 0.2 and a `top_p` of 0.8 to balance diversity and accuracy. In contrast, for tasks requiring a single answer, such as schema pruning and schema linking, we employed greedy search to ensure deterministic outputs.

B MULTI-CANDIDATE MOTIVATION

Table 7: Comparison of Accuracy (ACC) and Execution (EXE) on the BIRD DEV Subset from CHESS using multi-candidate generation strategy.

Top-N	Yi-Coder-1.5B		MiniCPM3-4B		Prem-SQL-1.3B	
	ACC (%)	EXE (%)	ACC (%)	EXE (%)	ACC (%)	EXE (%)
1	15.65	46.26	26.53	65.31	55.78	92.52
3	24.49	70.75	35.37	76.87	59.86	97.28
5	30.61	78.91	36.05	82.31	62.59	97.96
7	33.33	82.31	37.41	84.35	65.31	97.96
Top-N	**CodeS-3B**		**GPT-4o**		**Claude-3.5-Sonnet**	
	ACC (%)	EXE (%)	ACC (%)	EXE (%)	ACC (%)	EXE (%)
1	24.49	61.90	51.70	93.20	40.82	86.39
3	27.21	68.71	53.74	94.56	41.50	87.76
5	29.93	72.11	56.46	94.56	42.18	88.44
7	29.93	73.47	56.46	94.56	42.18	88.44

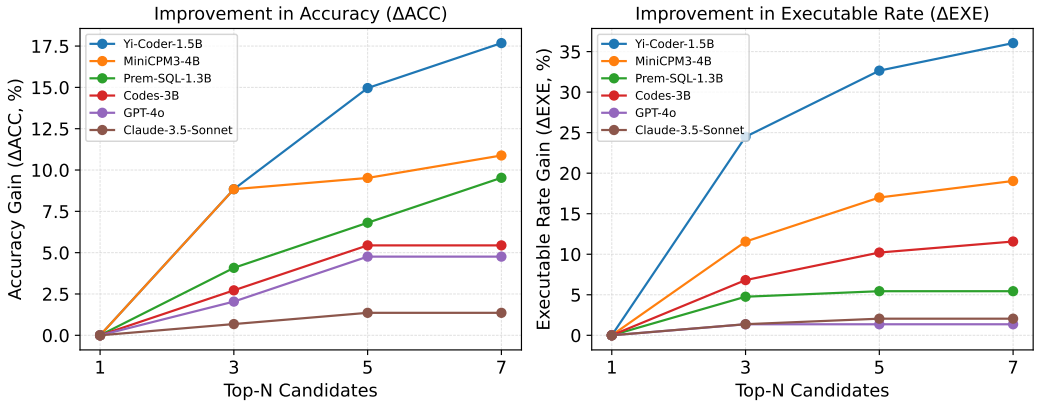

Figure 6: Improvement in Accuracy (ΔACC) and Executable Rate (ΔEXE) compared to Top-1 candidates

The results demonstrate that SLMs exhibit a performance gap between TOP-1 and TOP-7 results. This indicates that employing a multi-candidate generation strategy can effectively improve the accuracy and execution rates by selecting the best result. In contrast, larger models already perform robustly with TOP-1 outputs, and therefore, the additional benefit from multi-candidate generation is limited. Additionally, the fine-tuned SQL model CodeS-3B shows some improvement, but the gains are not as pronounced as those observed in the other SLMs.

C PROMPT LENGTH COMPARISON

On average, *CHESS* uses notably longer prompts due to detailed instructions and complex examples, while *MAC-SQL* has fewer words overall. *Feather-SQL* demonstrates the smallest average prompt length, indicating that concise design can effectively balance context and complexity.

Table 8: Stages and corresponding word counts for each baseline.

Method	**Stage**	**Word Count**
CHESS	Information Retriever	423
	Schema Selector	2522
	Generate Candidate	4888
	Revise	1835
MAC-SQL	Selector	552
	Decomposer	836
	Reviser	174
Feather-SQL	Schema Pruning	267
	Schema Linking	287
	Generation	190
	Correction	106
	Selection	271

D FRAMEWORK UPPER BOUND

To explore the upper bound of the Feather-SQL framework, we also evaluated its performance using cumulative accuracy, which measures whether the correct SQL query is present within the Top-n generated results. Specifically, we retained the top 4 candidates after the selection ranking in this experiment, rather than solely selecting the top 1 candidate in default.

As indicated in Table 9, Top-3 is approximately 10% higher than Top-1 (EX). This suggests that there is room for further improvement in the selection mechanism. If the selection can be refined to accurately identify the optimal SQL query, the performance gap between Top-N and Top-1 could be considerably reduced.

Table 9: Cumulative Accuracy on BIRD DEV.

Model	**Top-1(%)**	**Top-2(%)**	**Top-3(%)**
Qwen	31.8	39.0	40.5
Yi Coder	25.2	32.6	34.5
Prem-SQL	49.2	60.2	62.6

E SOTA RESULT ILLUSTRATION

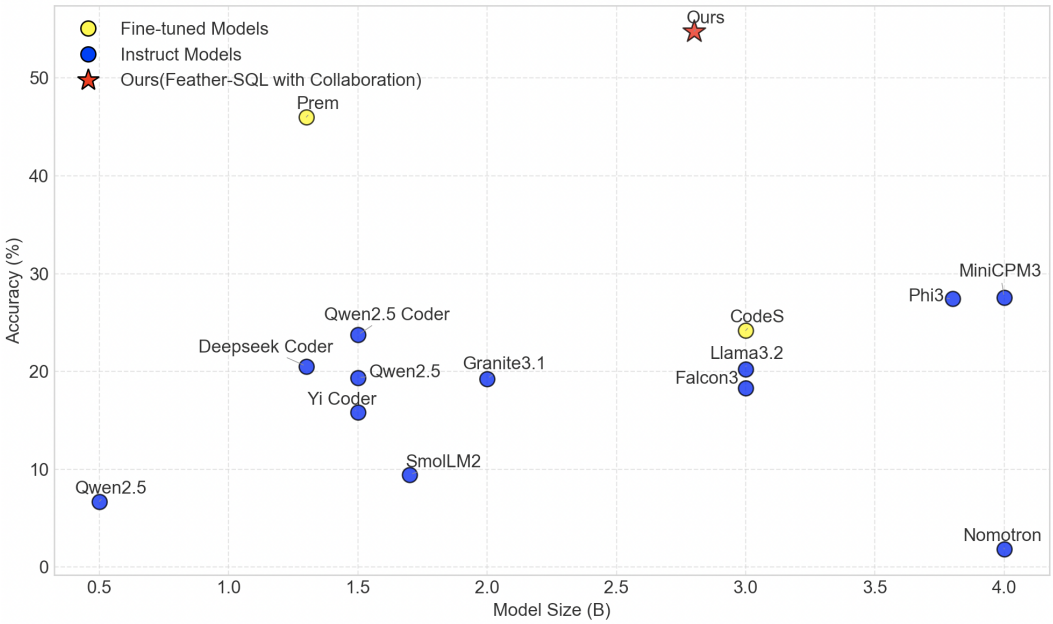

Figure 7: Accuracy (%) versus model size (in billions of parameters) for various small language models. Fine-tuned models are shown in yellow, general-purpose chat models in blue, and ours (Feather-SQL + Model Collaboration Paradigm) is marked with a red star.

F PROMPTS

F.1

Schema Pruning Prompt

```
prompt_pruning_system = """
You are an agent designed to find all related tables to generate SQL query
for question based on the database schema and hint.

## Requirements
1. You don't need to answer the question, your task is only finding all related
    tables .
2. Consider all constraints of each table, including primary keys, foreign keys,
    and data types.
3. You can generate chain of thoughts, but ensure all tables mentioned truly
    exist.
4. Successfully answer related columns could help you win $100000 dollars.
"""

prompt_pruning = """
## Instructions
1. Prioritize the table that most directly contains the information needed to
    answer the question, considering:
    - Table relationships such as foreign keys.
    - Whether the table has columns directly related to the entities or actions
    in the question.
2. Reasoning like two shown examples.

----------Example----------
```

```
## Database Schema
CREATE TABLE Employees (
    employee_id INT PRIMARY KEY,
    name VARCHAR(100),
    department VARCHAR(100),
    salary DECIMAL(10, 2)
);

CREATE TABLE Departments (
    department_id INT PRIMARY KEY,
    department_name VARCHAR(100),
    location VARCHAR(100)
);

## Question
What is the salary of the employee named 'Alice'?

## Relevant Tables
This table directly contains the columns name and salary, which are the only
     necessary fields to answer the question.
The name column is used to locate the specific employee named 'Alice', and the
     salary column provides the required
salary information. The Departments table is irrelevant because it does not store
      employee-level data like salaries
or names, and its information is unrelated to this specific query.
The relevant table is Employees.

----------Task----------
## Database Schema
You are provided with the structure of the database "{database_name}":
{database_schema}

## Question
{question}

## Hint
{hint}

Among the following tables: {tables}, which tables are relevant for addressing
     the question?
## Relevant Tables
"""
```

F.2

Schema Linking Prompt

```
prompt_linking_system="""
You are an agent designed to find all related columns to generate SQL query for
     question based on the database schema and the hint.

## Requirements
1. You don't need to answer the question, your task is only finding all related
     columns.
2. Hint could help you to find the correct related columns.
3. Consider all constraints of each table, including primary keys, foreign keys,
     and data types.
4. You can generate chain of thoughts, but ensure all columns mentioned truly
     exist.
7. Successfully answer related columns could help you win $100000 dollars.
```

```
"""

prompt_linking="""
## Instructions
1. Select columns that relates to information requested by the question,
     considering:
    - Whether the column is key to filtering results (used in WHERE clauses).
    - Whether the column should be part of the SELECT statement to fulfill the
     user query.
    - The relationship of the column to other parts of the question, such as
     groupings, aggregations, or direct match to entities mentioned.
2. Reasoning like two shown examples.

----------Example----------
## Database Schema
CREATE TABLE Employees (
    employee_id INT PRIMARY KEY,
    name VARCHAR(100),
    department VARCHAR(100),
    salary DECIMAL(10, 2)
);

CREATE TABLE Departments (
    department_id INT PRIMARY KEY,
    department_name VARCHAR(100),
    location VARCHAR(100)
);

## Question
What is the salary of the employee named 'Alice'?

## Relevant Columns
The name column is essential to filter the employee named 'Alice' in the WHERE
     clause, ensuring we identify the correct individual. The salary column is
     needed to extract the requested information, which is the employee's salary.
     Since the question does not involve departments, the Departments table and
     its columns are irrelevant.
The related columns are Employees.name and Employees.salary.

----------Task----------
## Database Schema
You are provided with the structure of the database "{database_name}":
{schema}

## Question
{question}

## Hint
{hint}

Among the columns, which are relevant for addressing the question?
## Relevant Columns
"""
```

F.3

Multi-path Generation Prompt

```
system_prompt_sql_generation = """
You are an expert SQL assistant tasked with generating precise SQL queries based
    on given database schemas, questions, and hint.

## Responsibilities
1. Analyze the **database schema** and **hint** to determine relationships,
    including **primary keys, foreign keys, data types, and constraints**.
2. Generate a single, valid **SQLite SQL query** to answer the question, using
    provided schema linking information for table and column selection.
3. Your response should contain only the **SQL query**, using standard SQL syntax
     with correct use of table/column names and SQL clauses.

## Requirements
- Respond with only one SQL query, formatted as ```SQL```.
- Use clauses like **SELECT**, **FROM**, **WHERE**, **JOIN**, **GROUP BY**, **
    ORDER BY**, etc.
- Ensure SQL is efficient and respects **Important Columns**, table relationships,
     and relevant constraints.
"""

prompt_generation_with_linking = """
You are given a database schema, question, important columns and hint. Generate a
     valid SQLite query that answers the question.

## Instructions
1. Your response should only contain one SQL query, in standard SQL syntax.
2. Consider all **table relationships**, **primary/foreign keys**, **data types**,
     and **Important Columns** while generating the query.

## Database Schema
Database "{database_name}":
{database_schema}

## Important Columns
{schema_linking}

## Question
{question}

## Hint
{hint}

## Output Requirement
Format the response as:
```sql
[SQL query]
```
"""

prompt_generation_without_linking = """
You are given a database schema, question, and hint. Generate a valid SQLite
    query that answers the question.

Instructions
1. Your response should only contain one SQL query, in standard SQL syntax.
2. Consider all **table relationships**, **primary/foreign keys**, **data types**
     while generating the query.

Database Schema
```

```
Database "{database_name}":
{database_schema}

## Question
{question}

## Hint
{hint}

## Output Requirement
Format the response as:
```sql
[SQL query]
```
"""
```

F.4

Correction Prompt

```
prompt_answer_correction_system ="""
Suppose you are an expert in SQLite and database management.

## Instructions
1. Based on the database structure provided, previous answer and its error
    messages, generate one SQL query that answers the question.
2. You should try to fix the error of the previous answer and avoid it from
    happening again.

## Requirements
1. Your response should consist of only one SQL query, don't generate anything
    else.
3. Consider all constraints of each table, including primary keys, foreign keys,
    and data types.
4. Provide your query in standard SQL format with appropriate use of SQL
    functions, joins, and conditions.
"""

prompt_answer_correction = """
## Database Schema
Given the structure of database:
{schema}

## Question
{question}

## Hint
{hint}

## Previous answer
{prev_ans}

## Error
{errorMsg}

## New Answer
"""
```

F.5

Selection Prompt

```
system_prompt_query_selection = """
You are an expert in analyzing SQL queries and determining their relevance to a
     given question. Your task is to evaluate multiple SQL queries and select the
     one that best answers the question based on the provided database schema and
     context.

## Responsibilities
1. Analyze the given question: Understand the intent of the question and its
     expected output.
2. Evaluate each SQL query: Consider the correctness, relevance, and completeness
      of each query in relation to the question.
3. Select the best query: Choose the query that most accurately answers the
     question, while considering database structure, table relationships, and
     query efficiency.

## Requirements
- Respond with the most relevant SQL query, and nothing else.
- Ensure the selected query is valid for the given database schema and directly
     addresses the question.
"""

query_selection_prompt = """
You are given a question, a database schema, and multiple SQL queries. Your task
     is to select the SQL query that is most relevant and best answers the
     question.

## Instructions
1. Analyze the Question: Understand what the user is asking and identify the
     information that needs to be extracted from the database.
2. Evaluate SQL Queries: For each provided SQL query, determine its relevance
     based on:
    - Accuracy: Does the query correctly match the question's intent?
    - Completeness: Does the query retrieve all the necessary information without
      omitting important details?
    - Efficiency: Is the query optimized for the task, avoiding unnecessary joins
      or conditions?
3. Select the Most Relevant Query: Choose the query that is the best match for
     the question.

## Database Schema
Database "{database_name}":
{database_schema}

## Question
The question is:
{question}

## Hint
{hint}

## SQL Queries
{queries}

## Output Requirement
Reply the query Index in the format of "Index: ".

## Output
"""
```

```
query_with_response_selection_prompt = """
You are given a question, a database schema, multiple SQL queries, and their
    execution results. Your task is to select the SQL query that best answers the
     question based on the query and its result.

## Instructions
1. Understand the Question: Determine what the user is asking and identify the
    specific information that needs to be retrieved.
2. Evaluate Each Query and Response Pair: For each provided SQL query and its
    result, determine:
    - Query Accuracy: Does the query correctly represent the user's intent?
    - Result Relevance: Does the result contain the data needed to answer the
    question completely and correctly?
    - Efficiency: Is the query optimized, avoiding unnecessary complexity?

## Database Schema
Database "{database_name}":
{database_schema}

## Question
{question}

## Hint
{hint}

## SQL Queries and Execution Results
{queries}

## Output Requirement
Only reply the query Index in the format of "Index: ".
"""
```