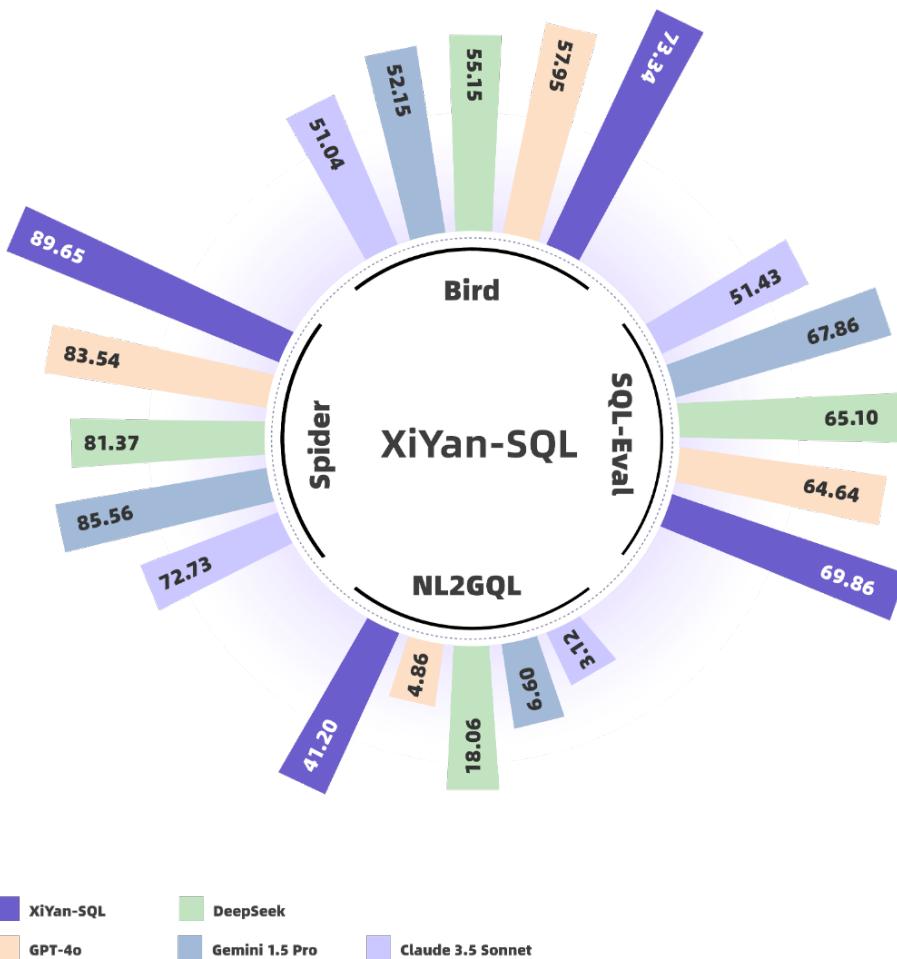


A PREVIEW OF XIYAN-SQL: A MULTI-GENERATOR ENSEMBLE FRAMEWORK FOR TEXT-TO-SQL

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<https://github.com/XGenerationLab/XiYan-SQL>

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ABSTRACT

To tackle the challenges of large language model performance in natural language to SQL tasks, we introduce XiYan-SQL, an innovative framework that employs a multi-generator ensemble strategy to improve candidate generation. We introduce M-Schema, a semi-structured schema representation method designed to enhance the understanding of database structures. To enhance the quality and diversity of generated candidate SQL queries, XiYan-SQL integrates the significant potential of in-context learning (ICL) with the precise control of supervised fine-tuning. On one hand, we propose a series of training strategies to fine-tune models to generate high-quality candidates with diverse preferences. On the other hand, we implement the ICL approach with an example selection method based on named entity recognition to prevent overemphasis on entities. The refiner optimizes each candidate by correcting logical or syntactical errors. To address the challenge of identifying the best candidate, we fine-tune a selection model to distinguish nuances of candidate SQL queries. The experimental results on multiple dialect datasets demonstrate the robustness of XiYan-SQL in addressing challenges across different scenarios. Overall, our proposed XiYan-SQL achieves the state-of-the-art execution accuracy of 75.63% on Bird benchmark, 89.65% on the Spider test set, 69.86% on SQL-Eval, 41.20% on NL2GQL. The proposed framework not only enhances the quality and diversity of SQL queries but also outperforms previous methods.

Keywords LLM, Text-to-SQL, NL2SQL

1 Introduction

The ability to convert natural language queries into structured query language (SQL) through natural language to SQL (NL2SQL) technology represents a significant advancement in making complex datasets more accessible. It greatly facilitates both non-expert and advanced users in extracting valuable insights from extensive data repositories [2, 15, 24, 27, 6, 10, 13, 29, 20, 19, 23, 22]. Recent advancements in large language models (LLMs) have significantly enhanced the efficacy and accuracy of NL2SQL applications.

There are generally two approaches for NL2SQL solutions based on LLMs: prompt engineering [3, 5, 17, 18], and supervised fine-tuning (SFT) [9]. Prompt engineering leverages the intrinsic capabilities of the model by optimizing prompts to generate diverse SQL queries. Prompt engineering has demonstrated promising results in NL2SQL using zero-shot [3] or few-shot prompting [28, 5, 18]. This type of approach typically employs closed-source models with enormous parameters, such as GPT-4 [1] and Gemini 1.5 [26], which present significant potential and powerful generalization capability. However, most methods rely on multi-path generation and selecting the best option utilizing self-consistency, resulting in significant inference overheads. Approaches based on SFT seek to fine-tune models with much smaller parameter sizes on the NL2SQL task to produce more controllable SQL queries, such as CodeS [9]. Nevertheless, due to their limited parameters, these methods struggle to perform complex NL2SQL reasoning and transfer to databases within a new domain.

In this technical report, we propose XiYan-SQL, a novel NL2SQL framework that employs a multi-generator ensemble strategy to enhance candidate generation. XiYan-SQL combines prompt engineering and the SFT method to generate candidate SQL queries with high quality and diversity. To enhance high quality, we take advantage of the high controllability of SFT and utilize a range of training strategies to specifically fine-tune models to generate candidates with different preferences. We introduce a two-stage multi-task training approach, which first activates the model’s fundamental SQL generation capabilities, and subsequently transitions to a model with enhanced semantic understanding and diverse stylistic preferences. To enhance diversity of generated candidates and capability of generating complex SQL queries, we utilize in-context learning to prompt LLMs. We propose to extract the skeleton of the questions by masking the named entities with common special tokens and using skeleton similarity to select and organize useful examples. Then, each generator is followed by a refiner to correct logical or syntactical error based on execution results or error information. Finally, a selection agent is required to select the best option. Most existing works use self-consistency, but the most consistent result is not always the correct case. So we propose to fine-tune a model to understand and identify the subtle differences among candidates and pick the final response.

Additionally, to enhance LLMs for better understanding of the database schema, we propose a new schema representation method named M-Schema. Inspired by MAC-SQL Schema [28], M-Schema presents the hierarchical structure between databases, tables, and columns in a semi-structured form. We revised MAC-SQL Schema by adding data types and resulting in a more compact and clear format. We conduct experiments to compare the impact of different schema representations on NL2SQL performance. In comparison to DDL Schema and MAC-SQL Schema, LLMs using M-Schema demonstrate superior performance.

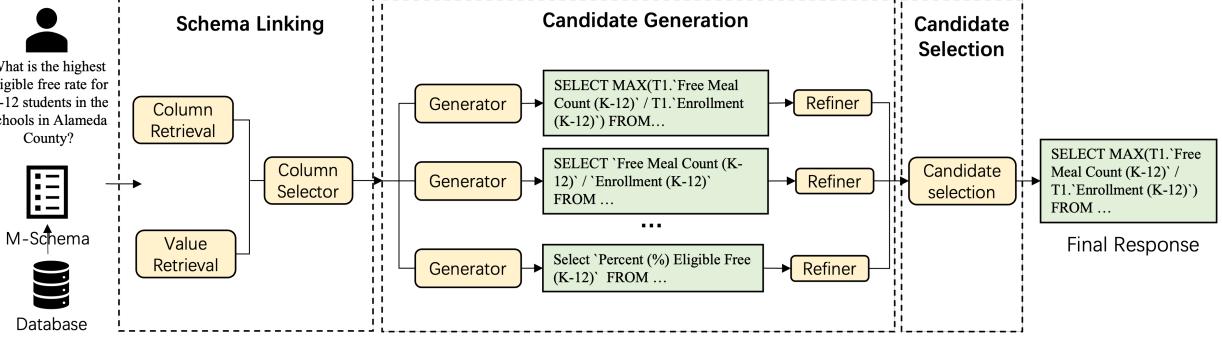


Figure 1: Overview of the proposed XiYan-SQL workflow, which consists of three agents: 1) Schema Linking, which retrieves and selects the most database schema; 2) Candidate Generation: which generates high-quality candidate SQL queries using ICL and SFT generators; 3) Candidate Selection, which picks the final response among the generated candidates. M-Schema is served as schema representation and provided to LLMs.

We present comprehensive evaluations on both relational and non-relational databases, specifically focusing on prominent systems such as SQLite, PostgreSQL, and nGQL. XiYan-SQL demonstrates remarkable performance across a range of benchmarks, achieving the state-of-the-art performance on the Spider [32], SQL-Eval, and NL2GQL [33] datasets with 89.65%, 69.86%, and 41.20% execution accuracy, respectively. In the context of the more challenging Bird [10] benchmark, XiYan-SQL also reaches the top accuracy of 75.63%. The impressive results achieved on various challenging NL2SQL benchmarks not only validate the effectiveness of our approach but also demonstrate its significant potential for broader applications in NL2SQL translation tasks. XiYan-SQL can be accessed from <https://bailian.console.aliyun.com/xiyan>. We also release the source code for connecting to the database and building M-Schema at <https://github.com/XGenerationLab/M-Schema>.

2 Overall Framework

This section outlines the proposed XiYan-SQL framework, which consists of three primary components: 1) Schema Linking; 2) Candidate Generation; 3) Candidate Selection. Schema Linking is used to select relevant columns and retrieve values from a large database schema, helping to minimize irrelevant information and focus on related data. This contextual information is then organized into M-Schema and fed into Candidate Generation module to generate potential candidate SQL queries. These candidates are refined using a self-refinement process. Ultimately, a Candidate Selection agent compares all the candidates to determine the final SQL query . This pipeline is illustrated in Figure 1.

3 M-Schema

The database schema needs to be provided in the prompt so that LLM understands the database structure. We propose a novel representation named M-Schema. M-Schema illustrates the hierarchical relationships between the database, tables, and columns in a semi-structured format and employs specific tokens for identification: "【DB_ID】" marks the database, "# Table" signifies tables, and "【Foreign Keys】" indicates foreign keys. For each table, we present table name and description, where table description can be omitted. The information from a table is converted into a list, where each item is a tuple representing the details of a column. Each column includes the column name, data type, column description, primary key identifier, and example values. Additionally, foreign keys need to be listed due to their importance.

Figure 2 shows examples of representing a database in DDL Schema, MAC-SQL [28] Schema and M-Schema. The Data Definition Language (DDL) schema is the most commonly used representation. However, it lacks essential table and column descriptions, as well as example values. Consequently, LLMs struggle to differentiate between similar columns. Derived from MAC-SQL Schema, M-Schema is a more compact representation. It differs from MAC-SQL Schema mainly in column representation, detailed as follows:

- Data type. Data type ensures that the data is correctly structured and manipulated. MAC-SQL Schema lacks data type specifications, which may result in incorrect outcomes when generated SQL queries are executed.
- Primary key marking. We include primary key marking to maintain relationships between tables in a relational database.

DDL Schema	MAC-SQL Schema	M-Schema
<pre> CREATE TABLE hero_power (hero_id INTEGER, power_id INTEGER, FOREIGN KEY (power_id) REFERENCES superpower(id)); CREATE TABLE superpower (id INTEGER PRIMARY KEY, power_name TEXT); </pre>	<pre> 【DB_ID】 superhero 【Schema】 # Table: hero_power [(hero_id, hero id.), (power_id, power id.)] # Table: superpower [(id, id.), (power_name, power name, Value examples: ['Agility'].)] 【Foreign keys】 hero_power.hero_id = superpower.id </pre>	<pre> 【DB_ID】 superhero 【Schema】 # Table: hero_power [(hero_id:INTEGER, Primary Key, the id of the hero Maps to superhero(id), Examples: [1, 2, 3]), (power_id:INTEGER, the id of the power Maps to superpower(id), Examples: [1, 18, 26])] # Table: superpower [(id:INTEGER, Primary Key, the unique identifier of the superpower, Examples: [1, 2, 3]), (power_name:TEXT, the superpower name, Examples: [Agility, Accelerated Healing, Lantern Power Ring])] 【Foreign keys】 hero_power.power_id=superpower.id </pre>

Figure 2: Examples of representing a database schema in DDL Schema, MAC-SQL Schema and M-Schema. The red text highlights the differences between M-Schema and MAC-SQL Schema. M-Schema adds data types, primary key markings, and changes the rules for displaying sample values.

- Column description. In MAC-SQL schema, the column description is derived from the column name, whereas M-Schema connects to the database to obtain more detailed descriptions.
- Value examples: We simplify "Value examples" marking into "Examples" to reduce redundancy. We also establish new display rules for values, such as string length and the number of examples.

Besides, the leading spaces in each column representation are removed from MAC-SQL Schema. We release how to connect to the database engine and build the M-Schema representation at <https://github.com/XGenerationLab/M-Schema> and support commonly used databases such as MySQL and PostgreSQL.

4 Schema Linking

Schema linking connects references in natural language queries to elements within a database schema, including table, columns and values. Our schema linking pipeline consists of a retrieval module and a column selector.

Retrieval Module In order to search for similar values and columns in the database, similar to the approach in [17], we first prompt the model with few-shot examples to identify keywords and entities in the question. We then use a column retriever to retrieve relevant columns. Based on the semantic similarity between the keywords and the column descriptions, we retrieve the top-k columns for each keyword. To enhance efficiency, value retriever employs a two-phase retrieval strategy based on Locality Sensitive Hashing (LSH) and semantic similarity to identify similar values in the database. The final selected schema is the union set of column retriever and value retriever.

Column Selector Column Selector aims to reduce the tables and columns to minimally sufficient schema for SQL generation. The retrieved schema from the previous step is organized as M-Schema and presented with LLMs. We then employ a few-shot manner to prompt the language model to evaluating the relevance of each column to the user's query, selecting only those necessary.

5 Candidate Generation

For candidate generation, we employ various generators to generate high-quality and diverse SQL candidates. On one hand, we utilize a range of training strategies to specifically fine-tune the generation models, aiming to generate high-precision SQL candidates with diverse syntactic styles. On the other hand, we also incorporate the ICL approach to enhance the diversity of the SQL candidates. Our Refiner further improves the generated SQL queries. In the following sections, we provide a brief overview of each part.

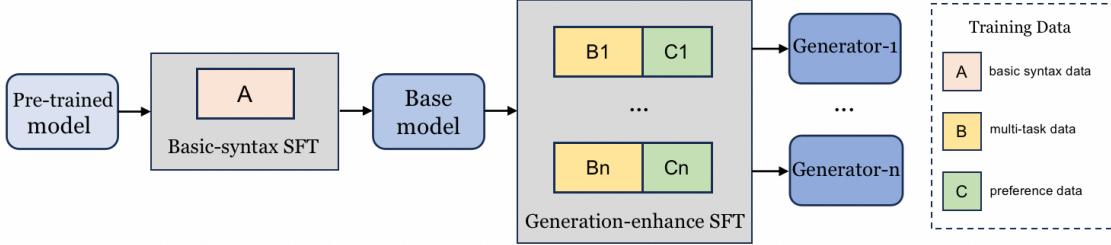


Figure 3: The two-stage and multi-task training pipeline for Fine-tuned SQL generators.

5.1 Fine-tuned SQL Generator

The core purpose is to generate high-precision and diverse SQL candidates. To this end, we take advantage of the high controllability of fine-tuning models on specific tasks to build a series of high-precision models with different preferences. As shown in Figure 3, we employ a two-stage and multi-task training approach to fine-tune the model, including basic-syntax training and generation-enhance training. Through this training approach, the intermediate and final results of our pipeline are a set of models with distinct advantages.

Basic-syntax training Basic-syntax training focuses on fine-tuning the pre-trained model with the basic and single SQL patterns and syntax. In this stage, the data used for training is SQL dialect-agnostic, covering basic syntax very comprehensively, with a total of tens of thousands of samples. The training objective is to develop a base model that activates SQL generation capabilities and can serve as a transition to different specialized SQL tasks.

Generation-enhance training After the first stage of training, we turn to generation-enhance training, aimed at enhancing the model's semantic understanding and stylistic preference in syntax. In this stage, we can combine various multi-task data and syntactic preference data to obtain an enhanced model. The model can benefit from multi-task data to better understand the mapping relationship between questions and SQL queries. Specifically, in addition to the standard task of converting questions to SQL queries, we further design the task of converting SQL to questions, which aims to infer potential questions based on the provided contextual information and SQL query. We have defined the task from SQL to evidence, which is intended to select the most relevant evidence from a set of candidates based on the context and SQL. Moreover, we also introduce the SQL discrimination and regeneration tasks, aimed at performing SQL optimization based on execution feedback, along with other related tasks. This series of specialized tasks effectively enhances the linking between SQL and contextual information, thereby improving overall generation capabilities. The model can benefit from various styles of patterns and syntactic features to better generate a wider diversity of SQL candidates. We utilize different LLMs to rephrase the original query in multiple ways without altering its original meaning. This approach effectively expands the sample data into different syntactic styles, thereby teaching the model to learn from this data form during the training phase.

Due to multiple dialects in SQL queries, we can process each dialect separately during this stage, following this defined pipeline. Subsequently, we may opt to either train an individual model for each dialect or jointly train a multi-dialect model. In practical applications, we can fine-tune a target model by selecting subsets of multi-task and preference data according to our needs, enabling the generation of high-quality SQL candidates.

5.2 ICL SQL Generator

The performance of ICL-based NL2SQL generation depends not only on the inherent abilities of the model but also on the examples provided. Several methods have been proposed to retrieve useful examples, such as masked question similarity and query similarity [5]. Although masked question similarity excludes the influence of table and column names, it is still sensitive to the entities. Query similarity based method requires a preliminary model to generate an approximation SQL, so the capabilities of the preliminary model directly affect the final result.

XiYan-SQL employs an example selection strategy based on the skeleton similarity between the user question and the question from the training set. All named entities in the question are first identified using NLTK's tool, then the named entities of the same type are replaced with a special token. For example, "China" and "America" are both identified as countries, so both of them are replaced by "<country>". Other entities, such as enumeration values, are replaced by the column names. This approach avoids focusing too much on entities, while the semantics of entities is preserved. Then we compute embedding of modified questions in the training and test sets, and top-K examples from training sets that closely match the target question are selected.

Table 1: Details of dataset used in our experiments.

Dataset	Dialect	# Questions	# DBs
Spider	SQLite	1981	39
Bird	SQLite	1534	11
SQL-Eval	PostgreSQL	304	11
NL2GQL	nGQL	288	3

Additionally, we noticed that SQL examples, which only manipulate one table, are of limited help for SQL generation involving multiple tables. When selecting SQL examples, for questions that two or more tables are selected through schema linking, we only choose SQL queries that involve operations on multiple tables. Based on the number of tables and the similarity threshold, a maximum of 5 examples are used for each question.

For benchmarks such as Bird and Spider, the databases of the training and test sets are not repeated, so presenting the schema of the examples in the prompt helps the model better understand the relationship between the schema and the SQL query. In order to reduce token consumption and the interference of redundant columns, only the minimal set of columns is provided for each selected SQL example.

5.3 SQL Refiner

The generated candidate SQL queries inevitably contain logical or syntactical errors [17, 25]. By utilizing clues from these SQL query deficiencies, we can undertake corrections to some extent. To this end, we employ a SQL Refiner to optimize the generated SQL. In practice, based on schema-related context, the generated SQL queries, and execution results (including potential error information), we enable the model to perform a second round of corrective generation. The original SQL and the regenerated SQL can further be subjected to a selection model (as discussed in Section 6) for optimal choice, and this process can be executed iteratively.

6 Candidate Selection

Based on the schema linking and various candidate generators, we can generate a set of candidate queries for the given question. The challenge of selecting the correct and reasonable SQL query from the pool of candidates remains to be addressed. Most methods [7, 25] employ self-consistency [30] to select the SQL query that appears most consistently across multiple candidate samples. However, this approach has limitations: it cannot handle situations where none of the queries are consistent, and even the most consistent result is not always the correct case.

For this purpose, we employ a selection model to make judgments. We measure the consistency of SQL execution results to group them, allowing us to identify inconsistent samples from each group to form a candidate set. Then, we utilize the selection model to select the most reasonable candidate based on the provided contextual information and the candidate set. Instead of employing a prompt-based approach with LLM, we specifically fine-tune a model as a selection model to better distinguish nuances of candidate SQL queries. To align with the varying syntactic preferences of the SQL candidates, we also deliberately perform paraphrasing on the training data of the selection model.

7 Experiments

7.1 Experimental Setup

To assess the generalizability of the proposed XiYan-SQL framework, we evaluate it in an end-to-end way on both relational and non-relational graph databases. Spider [32] and Bird [10] are widely-recognized cross-domain datasets that use SQLite. Since the test set of the BIRD benchmark is not available, we conduct experiments and performance evaluations on the development set. SQL-Eval³ is an open-source PostgreSQL evaluation dataset released by Defog, constructed based on Spider. NL2GQL [33] built on graph databases is also involved in our experiments. The detailed information of datasets is shown in Table 1. We use Execution Accuracy (EX) to access the effectiveness of the generated SQL queries. EX compares the results of a predicted SQL query and a reference SQL query executed on a specific database instance.

³<https://github.com/defog-ai/sql-eval>

Table 2: Performance comparison of different NL2SQL methods on Bird benchmark.

Method	EX(Dev)	EX(Test)
CHASE-SQL + Gemini [17]	74.46	74.79
DSAIR + GPT-4o	74.32	74.12
ExSL + granite-34b-code	72.43	73.17
AskData + GPT-4o	72.03	72.39
OpenSearch-SQL, v2 + GPT-4o	69.30	72.28
Distillery + GPT-4o [16]	67.21	71.83
CHESS [25]	68.31	71.10
Insights AI	72.16	70.26
PURPLE + RED + GPT-4o	68.12	70.21
MCS-SQL [25]	63.36	65.45
SuperSQL [8]	58.50	62.66
SFT CodeS-15B [9]	58.47	60.37
GPT-4o	57.95	-
TA-SQL + GPT-4 [21]	56.19	59.14
DAIL-SQL [5]	54.76	57.41
XiYan-SQL	73.34	75.63

Table 4: Performance comparison of different methods on SQL-Eval benchmark.

Method	EX(%)
SQL-Coder-8B	60.20
DeepSeek	65.36
GPT-4o	64.64
Claude 3.5 Sonnet	51.43
Gemini 1.5 Pro	67.86
XiYan-SQL	69.86

7.2 Bird Results

We compare the performance of different NL2SQL methods on Bird benchmark in Table 2. XiYan-SQL reaches the top of Bird leaderboard with an accuracy of 75.63%, outperforming the second place of 0.84%. CHASE-SQL [17] framework employs multiple chain-of-thought prompting techniques to generate candidates, and subsequently implements a binary voting mechanism among 21 candidates, achieving an accuracy of 74.70%. XiYan-SQL yields a competitive performance by voting among only 5 candidates.

We also observe that a significant number of the leading methods on the bird learderborad are based on prompt engineering techniques. It suggests the immense potential of large-scale models and the importance of carefully designed prompts in optimizing model performance. The SFT based method, ExSL + Granite-34B-Code, secures the fourth position with an accuracy of 73.17%. This notable performance indicates that, smaller-sized models are indeed capable of generating complex SQL queries effectively through advanced training techniques. XiYan-SQL integrates the methodologies of SFT and ICL to balance the test time and the overall performance of the system.

7.3 Spider Results

To demonstrate the generalizability of our approach, we also evaluate XiYan-SQL on the Spider dataset. As demonstrated in Table 3, improvements in the underlying backbone model capabilities have contributed to notable improvements in performance metrics. Specifically, GPT-4o has achieved a remarkable accuracy of 83.54%. Moreover, XiYan-SQL refreshes the state-of-the-art execution accuracy of 89.65%, with a marginal advantage of merely 0.05% over previous leading models.

Table 3: Performance comparison of different NL2SQL methods on Spider test benchmark.

Method	EX(%)
MCS-SQL + GPT-4 [7]	89.6
CHASE-SQL + Gemini 1.5 [17]	87.6
PET-SQL [11]	87.6
SuperSQL [8]	87.0
DAIL-SQL + GPT-4 [5]	86.6
DPG-SQL + GPT-4	85.6
Tool-SQL + GPT-4 [31]	85.6
DIN-SQL + GPT-4 [18]	85.3
GPT-4o	83.54
C3 + ChatGPT + Zero-Shot [3]	82.3
XiYan-SQL	89.65

Table 5: Performance comparison of different methods on NL2GQL benchmark.

Method	EX(%)
DeepSeek	18.06
GPT-4o	4.86
Claude 3.5 Sonnet	3.12
Gemini 1.5 Pro	6.60
XiYan-SQL	41.20

Table 6: Ablation studies on different schema representations.

Model	EX(DDL Schema, %)	EX(MAC-SQL Schema, %)	EX(M-Schema, %)
GPT-4o	55.67	57.30	57.95
DeepSeek	53.52	55.28	55.15
Claude 3.5 Sonnet	49.74	50.26	51.04
Gemini 1.5 Pro	49.22	52.41	52.15

7.4 SQL-Eval Results

Table 4 presents the results on SQL-Eval dataset. SQL-Eval provides multiple reference SQL queries and we choose the first option as groundtruth for metric computation. XiYan-SQL reports the highest score of 69.86% on SQL-Eval. We outperform SQL-Coder-8B⁴ fine-tuned on LLaMA-3 [4] by a large margin of 8.59% and closed-source backbone models by 2~5 percent. It demonstrates the generalizability of XiYan-SQL on SQL generation for PostgreSQL.

7.5 NL2GQL Results

To assess the effectiveness of XiYan-SQL on non-relational graph datasets, we sample a total of 288 examples from the NL2GQL [33] dataset, which were previously utilized in MoMQ [12]. As shown in Table 5, GPT-4o, DeepSeek, Gemini 1.5 Pro and Claude 3.5 Sonnet show a limited overall execution accuracy on NL2GQL dataset. XiYan-SQL achieves 41.20% execution accuracy, outperforming them by a large margin and demonstrating the best performance overall.

7.6 Ablation Studies

To further investigate the effectiveness of each component in our framework, we conduct ablation studies on the Bird development benchmark because of its challenging nature and more reflective of the real-world scenarios.

7.6.1 M-Schema

We conduct ablation study on the Bird development benchmark to present the impact of different schema representations on end-to-end SQL generation performance. To demonstrate the generalization ability of our proposed M-Schema, we use four powerful LLMs as NL2SQL generators, DeepSeek [14], Claude 3.5 Sonnet⁵, Gemini 1.5 Pro and GPT-4o [1]. As shown in Table 6, all four models have performance improvements using M-Schema as the representation of database schema compared to DDL Schema, with an average increase of 2.03%. Although M-schema is similar to MAC-SQL Schema in structure, GPT-4o and Claude 3.5 Sonnet show 0.65% and 0.78% improvements, respectively. While DeepSeek and Gemini 1.5 have slight accuracy decreases of 0.13% and 0.26%. The experimental results indicate that M-Schema is a better representation than DDL Schema and MAC-SQL Schema and demonstrates powerful generalizability.

7.6.2 Schema Linking

We conduct ablation study to evaluate the effectiveness of schema linking. We utilize recall and precision metrics to evaluate the correctness of the selected columns based on the corrected SQL query, which serves as the ground truth. We use GPT-4o as the NL2SQL generator to analyze the impact of schema linking on end-to-end EX metrics. The results are show in Table 7. Without schema linking, we provide all tables, columns and random sampled example values to LLM. It shows a precision of 10.14% and EX of 57.95%. The schema linking method in this report achieves a high precision of 74.74% while only slightly decreasing the recall. By providing the most relevant information to the model, the execution accuracy is improved by 2.15%, demonstrating the effectiveness of schema linking.

7.6.3 Candidate Generation and Selection

To evaluate the effectiveness and impact of candidate generation and selection, we conduct various ablation studies on XiYan-SQL. Table 8 presents the performance of XiYan-SQL when certain components are dropped, highlighting their significance in achieving high-quality performance. The "XiYan-SQL All" method achieves an accuracy of

⁴<https://huggingface.co/defog/llama-3-sqlcoder-8b>

⁵<https://www.anthropic.com/news/claude-3-5-sonnet>

Table 7: Ablation studies on schema linking.

Method	Precision(%)	Recall(%)	EX(%)
Baseline	10.14	100.00	57.95
+ Schema Linking	74.74	95.47	60.10

Table 8: Ablation studies of candidate generation and selection on the performance of XiYan-SQL on the Bird development benchmark.

Method	EX(%)	Δ EX(%)
XiYan-SQL All	71.58	-
XiYan-SQL w/o Fine-tuned generator	68.67	-2.91
XiYan-SQL w/o ICL generator	70.27	-1.31
XiYan-SQL w/o Refiner	71.03	-0.55
XiYan-SQL w/o Selection model	68.84	-2.74
XiYan-SQL All (five candidates)	73.34	-

71.51% by utilizing three candidates, of which two are generated from two distinct fine-tuned SQL generators (as described in Section 5.1), while one is produced by the ICL SQL generator with GPT-4o (as presented in Section 5.2). For the candidate generator, there is a significant decrease in the performance of XiYan-SQL when the fine-tuned candidate generators are removed, further indicating that our generator is capable of generating high-quality and diverse candidate SQL queries. Similarly, the removal of the ICL generator and Refiner also leads to a decline in performance. Additionally, concerning candidate selection, we observe that when the selection model is not employed, relying solely on self-consistency for candidate selection, XiYan-SQL’s performance decreases by approximately three percentage points. This finding underscores the effectiveness of our proposed method. Finally, when the number of SQL candidates is increased to five, the accuracy of XiYan-SQL can further reach 73.34%.

8 Conclusion

In this technical report, we present a multi-generator ensemble framework for NL2SQL, named XiYan-SQL, which harnesses the benefits of the SFT approach to achieve enhanced controllability while also integrating the ICL approach to maximize the generation of high-quality and diverse SQL candidates. We propose a two-stage and multi-task training method to train a series of models with different preferences, along with a candidate selection strategy to select the most reasonable candidate. Xiyan-SQL demonstrates state-of-the-art performance on publicly available relational databases, including Spider and SQL-Eval, as well as on non-relational database NL2GQL. This highlights the significant potential of XiYan-SQL for high-quality NL2SQL generation on unseen samples coming from different distributions.

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A SQLite Example

In this section, we provide an example of natural language to SQLite.

DATABASE SCHEMA	<pre> 【DB_ID】 california_schools 【Schema】 # Table: schools [(CDSCode:TEXT, CDSCode, Primary Key, Examples: [01100170000000, 01100170109835, 01100170112607]), (School:TEXT, School, Examples: [FAME Public Charter]), (GServed:TEXT, It is the lowest grade and the highest grade of student enrollment as reported in the most recent certified CALPADS Fall 1 data collection. Only K-12 enrollment is reported through CALPADS. This field may differ from the grade span offered., Examples: [K-12, 9-12, K-7]), (AdmFName1:TEXT, administrator's first name, Examples: [Kacey, L Karen, Laura, Clifford]), (AdmLName1:TEXT, administrator's last name, Examples: [Gibson, Fisher Gibson, Free, Freeman, Monroe, Robell, Thompson])] # Table: frpm [(CDSCode:TEXT, CDSCode, Primary Key, Examples: [01100170109835, 01100170112607, 01100170118489]), (Enrollment (K-12):REAL, Enrollment (K-12), Examples: [1087.0, 395.0, 244.0]), (Enrollment (Ages 5-17):REAL, Enrollment (Ages 5-17), Examples: [1070.0, 376.0, 230.0]), (Free Meal Count (Ages 5-17):REAL, Free Meal Count (Ages 5-17), Examples: [553.0, 182.0, 128.0]), (FRPM Count (Ages 5-17):REAL, Examples: [702.0, 182.0, 168.0])] 【Foreign keys】 frpm.CDSCode=schools.CDSCode </pre>
Question	What is the free rate for students between the ages of 5 and 17 at the school run by Kacey Gibson?
Evidence	Eligible free rates for students aged 5-17 = `Free Meal Count (Ages 5-17)` / `Enrollment (Ages 5-17)`
Generated SQL	<pre> SELECT (T2.`Free Meal Count (Ages 5-17)` / T2.`Enrollment (Ages 5-17)`) AS Free_Rate FROM schools AS T1 JOIN frpm AS T2 ON T1.CDSCode = T2.CDSCode WHERE T1.AdmFName1 = 'Kacey' AND T1.AdmLName1 = 'Gibson'; </pre>
GT SQL	<pre> SELECT CAST(T2.`Free Meal Count (Ages 5-17)` AS REAL) / T2.`Enrollment (Ages 5-17)` FROM schools AS T1 INNER JOIN frpm AS T2 ON T1.CDSCode = T2.CDSCode WHERE T1.AdmFName1 = 'Kacey' AND T1.AdmLName1 = 'Gibson' </pre>

Figure 4: An example of natural language to SQLite.

B PostgreSQL Example

In this section, we provide an example of natural language to PostgreSQL.

DATABASE SCHEMA	<pre> [DB_ID] scholar [Schema] # Table: writes [(paperid:BIGINT, Examples: [3, 5, 4]), (authorid:BIGINT, Examples: [3, 5, 4])] # Table: author [(authorid:BIGINT, Examples: [3, 5, 4]), (authorname:TEXT, Examples: [Emily Johnson, John Smith, Michael Brown])] # Table: paper [(paperid:BIGINT, Examples: [3, 5, 4]), (title:TEXT, Examples: [COVID-19 Impact on Society]), (venueid:BIGINT, Examples: [2, 1]), (year:BIGINT, Examples: [2020, 2019]), (numciting:BIGINT, Examples: [3, 2, 1]), (numcitedby:BIGINT, Examples: [2, 1]), (journalid:BIGINT, Examples: [3, 4, 2]) # Table: cite [(citingpaperid:BIGINT, Examples: [3, 5, 4]), (citedpaperid:BIGINT, Examples: [3, 5, 4])] </pre>
Question	How many authors have published more than 2 papers?
Generated SQL	<pre> SELECT COUNT(DISTINCT a.authorid) FROM author AS a JOIN writes AS w ON a.authorid = w.authorid GROUP BY a.authorid HAVING COUNT(w.paperid) > 2; </pre>
GT SQL	<pre> SELECT COUNT(*) AS number_of_authors FROM (SELECT writes.authorid FROM writes GROUP BY writes.authorid HAVING COUNT(writes.paperid) > 2) AS subquery; </pre>

Figure 5: An example of natural language to PostgreSQL.

C NL2GQL Example

In this section, we provide an NL2GQL example. We extended M-Schema to represent graph databases as illustrated in Figure 6.

DATABASE SCHEMA	<pre> 【DB_ID】 nba 【Schema】 Node properties: - **player** - `tag_name` - **team** - `vid` - `name`: STRING - `age`: INTEGER - **bachelor** - `vid` - `name`: STRING </pre>
	Relationship properties: <pre> - **like** - `vid` - `name`: STRING - `speciality`: STRING - **serve** - `edge_type_name` - **teammate** - `src_vid` - `dst_vid` - `likeness`: INTEGER </pre>
Question	Obtain the name of the team 'Spurs'.
Generated nGQL	FETCH PROP ON team "Spurs" YIELD team.name
GT nGQL	FETCH PROP ON team "Spurs" YIELD team.name

Figure 6: An example of NL2GQL.

D ICL Generator Prompt

In this section, we provide an example of our ICL generator prompt. An one-shot example is presented in Figure 7.

You are a SQLite expert. You need to read and understand the following database schema description, as well as the evidence that may be used, and use your SQLite knowledge to generate SQL statements to answer user questions.

The following examples are for your reference.

```
【DB_ID】 retail
【Schema】
# Table: supplier
[
  (s_suppkey:INTEGER, unique id number identifying the supply, Primary Key, Examples: [1, 2, 3]),
  (s_nationkey:INTEGER, nation key of the supply, Examples: [13, 5, 22])
]
# Table: nation
[
  (n_nationkey:INTEGER, unique id number identifying the nation, Primary Key, Examples: [0, 1, 2]),
  (n_name:TEXT, name of the nation, Examples: [ALGERIA, ARGENTINA, BRAZIL])
]
  【Foreign keys】
  supplier.s_nationkey=nation.n_nationkey
  【Evidence】
  name of the country refers to n_name; the highest debt refers to min(s_acctbal)

  【Question】
  What is the name of the country of the supplier with the highest debt?
```

```
```sql
SELECT T2.n_name FROM supplier AS T1 INNER JOIN nation AS T2 ON T1.s_nationkey = T2.n_nationkey ORDER BY
T1.s_suppkey DESC LIMIT 1
```

```

Question Solved.

```
【DB_ID】 california_schools
【Schema】
# Table: schools
[
  (CDSCode:TEXT, CDSCode, Primary Key, Examples: [01100170000000, 01100170109835, 01100170112607]),
  (MailStreet:TEXT, MailStreet, Examples: [701 East Main Street, 501 West Main Street, Sunset and Cambridge Streets, 313
West Winton Avenue]),
  (MailStrAbr:TEXT, Examples: [106 East Manchester Ave., 313 West Winton Ave.]),
  (MailCity:TEXT, Examples: [Hayward, Newark, Oakland]),
  (MailZip:TEXT, Examples: [94544-1136, 94560-5359, 94612]),
  (MailState:TEXT, Examples: [CA])
]
# Table: frpm
[
  (CDSCode:TEXT, CDSCode, Primary Key, Examples: [01100170109835, 01100170112607, 01100170118489]),
  (School Code:TEXT, School Code, Examples: [0109835, 0112607, 0118489]),
  (FRPM Count (K-12):REAL, Free or Reduced Price Meal Count (K-12), Examples: [715.0, 186.0, 175.0])
]
  【Foreign keys】
  frpm.CDSCode=schools.CDSCode

  【Evidence】
```

```
  【Question】
  What is the unabbreviated mailing street address of the school with the highest FRPM count for K-12 students?
```

```
```sql
```

Figure 7: An example of ICL generator prompt.

## E Candidate Selection Prompt

In this section, we provide an example of candidate selection prompt used to pick the final response, shown in Figure 8.

You are a SQLite expert. Regarding the Question, there are {CANDIDATE\_NUM} candidate SQL along with their Execution result in the database (showing the first 10 rows).

You need to compare these candidates and analyze the differences among the various candidate SQL. Based on the provided Database Schema, Evidence, and Question, select the correct and reasonable result.

**【Database Schema】**  
{DATABASE\_SCHEMA}

**【Evidence】**

the oldest card refers to MIN(originalReleaseDate); mythic card refers to rarity = 'mythic'; legal play refers to status = 'legal'; play format refers to format

**【Question】**

When was the oldest mythic card released and what are its legal play formats?

---

---

Candidate A

**【SQL】**

```
SELECT T1.originalReleaseDate, T2.format FROM cards AS T1 INNER JOIN legalities AS T2 ON T1.uuid = T2.uuid
WHERE T1.rarity = 'mythic' AND T2.status = 'Legal' ORDER BY T1.originalReleaseDate LIMIT 1
```

**【Execution result】**

[(None, 'commander')]

\*\*\*\*\*

Candidate B

**【SQL】**

```
SELECT T1.originalReleaseDate, T2.format FROM cards AS T1 INNER JOIN legalities AS T2 ON T1.uuid = T2.uuid
WHERE T1.rarity = 'mythic' AND T2.status = 'legal' ORDER BY T1.originalReleaseDate LIMIT 1
```

**【Execution result】**

[]

\*\*\*\*\*

Candidate C

**【SQL】**

```
SELECT MIN(c.originalReleaseDate) AS oldest_mythic_release_date, l.format
FROM cards AS c
JOIN legalities AS l ON c.uuid = l.uuid
WHERE c.rarity = 'mythic' AND l.status = 'Legal'
GROUP BY l.format
ORDER BY oldest_mythic_release_date
LIMIT 1;
```

**【Execution result】**

[(2009/4/25, 'commander')]

Please output the selected candidate as "A" or "B" or "C".

Figure 8: An example of candidate selection prompt.

## F Refiner Prompt

In this section, we provide an example prompt of Refiner used to fix syntax or logical errors.

You are a SQLite expert. There is a SQL query generated based on the following Database Schema description and the potential Evidence to respond to the Question. However, executing this SQL has resulted in an error, and you need to fix it based on the error message. Utilize your knowledge of SQLite to generate the correct SQL.

【Database Schema】

{DATABASE\_SCHEMA}

【Evidence】

{evidence}

【Question】

If there are any, what are the websites address of the schools with a free meal count of 1,900-2,000 to students aged 5-17? Include the name of the school.

【SQL】

```

SELECT T2.Website, T2.School FROM frpm AS T1 INNER JOIN schools AS T2 ON T1.CDSCode = T2.CDSCode WHERE T1.'Free Meal Count (Ages 5-17)' BETWEEN 1900 AND 2000

```

【Execution result】

exist None value

[('None', 'South Gate Middle'), ('http://lhs.lynnwood.edlioschool.com/', 'Lynnwood High'), ('www.auhsd.us/katella', 'Katella High')]

```sql

Figure 9: An example of refiner prompt.