

DeepEye-SQL: A Software-Engineering-Inspired Text-to-SQL Framework

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Abstract

Large language models (LLMs) have advanced Text-to-SQL, yet existing solutions still fall short of system-level reliability. The limitation is not merely in individual modules – e.g., schema linking, reasoning, and verification – but more critically in the lack of structured orchestration that enforces correctness across the entire workflow. This gap motivates a paradigm shift: treating Text-to-SQL not as free-form language generation but as a software-engineering problem that demands structured, verifiable orchestration. We present DEEPEYE-SQL, a software-engineering-inspired framework that reframes Text-to-SQL as the development of a small software program, executed through a verifiable process guided by the Software Development Life Cycle (SDLC). DEEPEYE-SQL integrates four synergistic stages: it grounds ambiguous user intent through semantic value retrieval and robust schema linking; enhances fault tolerance with N-version SQL generation using diverse reasoning paradigms; ensures deterministic verification via a tool-chain of unit tests and targeted LLM-guided revision; and introduces confidence-aware selection that clusters execution results to estimate confidence and then takes a high-confidence shortcut or runs unbalanced pairwise adjudication in low-confidence cases, yielding a calibrated, quality-gated output. This SDLC-aligned workflow transforms ad hoc query generation into a disciplined engineering process. Using ~30B open-source LLMs without any fine-tuning, DEEPEYE-SQL achieves 73.5% execution accuracy on BIRD-Dev and 89.8% on Spider-Test, outperforming state-of-the-art solutions. This highlights that principled orchestration, rather than LLM scaling alone, is key to achieving system-level reliability in Text-to-SQL.

1 Introduction

Text-to-SQL is a task that converts natural-language questions into SQL queries over a database [2, 19, 22–26]. Large language models

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SDLC Model → Key Idea → DeepEye-SQL

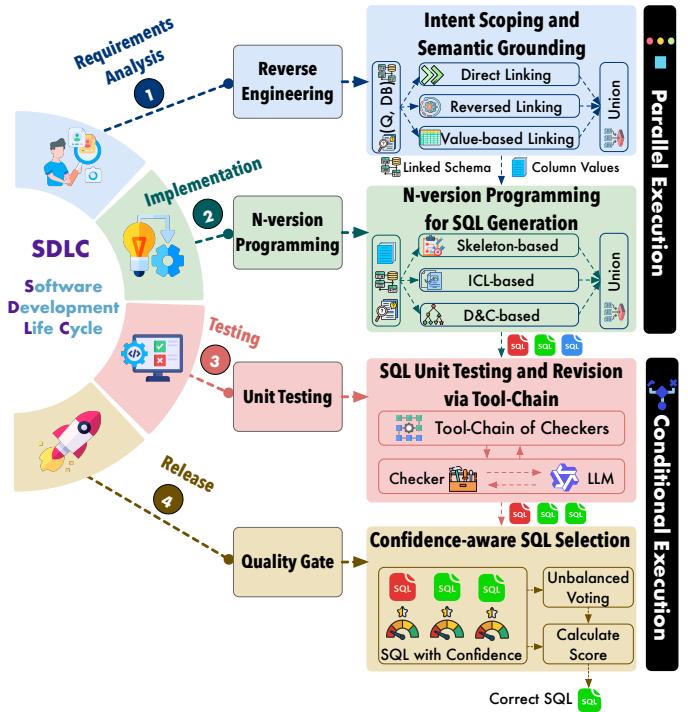


Figure 1: Key Idea of DEEPEYE-SQL

(LLMs) [42, 47, 52, 56] have substantially advanced Text-to-SQL, achieving strong results on benchmarks such as Spider [51] and BIRD [18]. For example, Alpha-SQL [15] leverages dynamic multi-step reasoning, while XiYan-SQL [21] improves SQL generation and multi-candidate SQL selection through task-specific fine-tuning.

Despite these advances, state-of-the-art performance on the BIRD dataset remains around 70% execution accuracy [18], and reliability further degrades in real-world deployments [6, 14]. This observation indicates that recent advances, while promising, have yet to translate into consistent system-level reliability.

The key limitation lies not in the optimization of individual modules – such as schema linking, reasoning, or post-hoc verification – but in the lack of coherent orchestration that enforces correctness across the entire workflow [7, 15, 21, 31, 32, 43, 48]. As a result, current Text-to-SQL solutions struggle to: (i) define what should be built, which requires precisely determining the semantic

scope of the user question and grounding it to the relevant database entities through comprehensive schema linking and value retrieval; (ii) *implement the solution (i.e., SQL generation)*, which involves generating executable SQL queries that faithfully capture the inferred semantics while maintaining diversity and completeness across complex reasoning paths; (iii) *verify its correctness*, which requires systematically validating the structural, logical, and semantic correctness of the generated SQL through interpretable checks [20]; and (iv) *release the generated SQL*, which requires quantifying confidence through multi-source evidence and establishing measurable acceptance criteria for determining whether a generated SQL query is reliable enough for output.

This fundamental gap motivates a paradigm shift: *Text-to-SQL should be viewed not simply as a language generation task powered by LLMs, but as a software-engineering problem that requires structured orchestration and verifiable correctness*. From this perspective, generating a correct SQL query resembles developing a small software program: the system must infer user requirements from natural-language questions with respect to the specified database, realize the intended logic through SQL generation, and ensure its correctness and reliability through systematic testing and quality control. Inspired by the Software Development Life Cycle (SDLC) [36] and illustrated in Figure 1, we structure the Text-to-SQL generation workflow as a unified process that integrates requirement analysis from natural-language questions, SQL generation, verification of generated queries, and final release through quality-gated control. However, implementing this idea in practice is non-trivial and poses several **challenges**.

First, Text-to-SQL solutions must *infer* user intent from ambiguous natural language and partially observed database schemas. We term this challenge *ambiguous requirement inference* (challenge C1). In the implementation stage, current methods rely on a single reasoning path driven by one model [32] and one prompt configuration [14], *resulting in insufficient fault tolerance* (C2). In the verification and validation stage, existing methods depend on probabilistic signals such as self-consistency [15] or partial execution feedback [54] rather than deterministic oracles to assess generated SQL. We denote this challenge as *unreliable verification and validation* (C3). In the release stage, current methods lack *calibrated confidence estimation and measurable acceptance criteria* for evaluating when a generated SQL query is reliable enough for output (C4).

Our Methodology: Software-Engineering-Inspired Framework. To systematically address these challenges, we propose DEEPEYE-SQL, which reframes Text-to-SQL as a verifiable SDLC-style workflow with four stages (Figure 1). In requirements analysis, we propose Semantic Value Retrieval and Robust Schema Linking, *i.e.*, combining direct, reversed, and value-based linking with relational closure, to build a complete, database-grounded specification, addressing ambiguous requirement inference (addressing the challenge C1). In implementation, we adopt N-version programming [4] with three independent generators (skeleton, in-context learning, and divide-and-conquer) executed in parallel to diversify reasoning under a fixed budget, providing fault tolerance (addressing C2). For verification and validation, we replace probabilistic self-judgment with a tool-chain of checkers (syntax, clause/time,

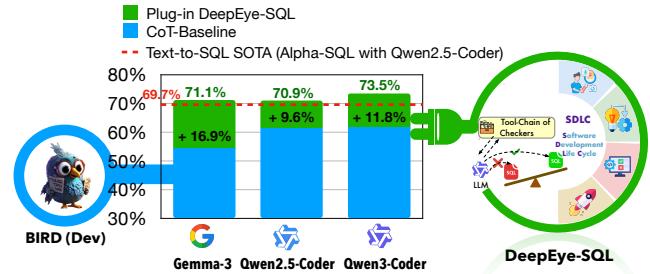


Figure 2: DEEPEYE-SQL, a plug-and-play Text-to-SQL framework, consistently surpasses prior SOTA methods using ~ 30 B open-source LLMs without any task-specific fine-tuning.

JOIN, NULL/result) that trigger targeted LLM repair, ensuring verifiable correctness (addressing C3). Finally, in release, we introduce confidence-aware selection that clusters execution results to estimate confidence and then takes a high-confidence shortcut or runs unbalanced pairwise adjudication in low-confidence cases, yielding a calibrated, quality-gated output (addressing C4). As shown in Figure 2, this design enables DEEPEYE-SQL to integrate with diverse LLMs and achieve notable accuracy improvements without any fine-tuning.

Contributions. This paper makes the following contributions:

(1) **A Novel SE-Inspired and Training-free Framework.** We propose DEEPEYE-SQL, which reframes Text-to-SQL as an SDLC-guided, four-stage engineering workflow. The framework is training-free and plug-and-play, improving system-level reliability across diverse LLMs without any fine-tuning.

(2) **A Suite of Principled Techniques for Reliability.** We introduce a set of techniques, each grounded in a specific software engineering principle, to ensure end-to-end reliability. This includes: (i) a *fault-tolerant schema linking* mechanism that combines multiple strategies to guarantee specification completeness; (ii) a deterministic, *tool-based revision process* that acts as a unit testing suite for reliable debugging; and (iii) an adaptive, *confidence-aware selection* mechanism that serves as a quality gate for the final output.

(3) **Extensive Experiments** demonstrate that DEEPEYE-SQL achieves state-of-the-art performance on challenging benchmarks. With the Qwen3-Coder-30B-A3B model, DEEPEYE-SQL attains an execution accuracy of 73.5% on BIRD-Dev and 89.8% on Spider-Test without any model fine-tuning.

2 Problem Definition and Preliminary

2.1 Problem Definition

Text-to-SQL Task. The primary objective of the Text-to-SQL task is to automatically translate a user’s question, expressed in natural language, into a corresponding SQL query. Formally, given a database schema \mathcal{D} and a natural language question Q , the task is to generate a SQL query S that correctly retrieves the answer to Q from the database instance defined by \mathcal{D} . The schema \mathcal{D} is defined as a set of tables $\{T_1, T_2, \dots, T_m\}$, where each table T_i consists of a set of columns $\{C_{i1}, C_{i2}, \dots, C_{ik}\}$. The goal is to find a mapping function f such that:

$$S = f(Q, \mathcal{D})$$

Let $\llbracket S \rrbracket_{\mathcal{D}}$ denote the result of executing query S on the database. The generated query S is considered correct if $\llbracket S \rrbracket_{\mathcal{D}}$ accurately answers the user's intent expressed in Q . The core challenge lies in bridging the semantic gap between the unstructured natural language Q and the structured query language representation S within the context of the given schema \mathcal{D} .

2.2 Text-to-SQL Solutions

The task of translating natural language into executable SQL queries has evolved significantly [19]. The recent emergence of Large Language Models (LLMs) has marked a new paradigm. Current research on applying LLMs to Text-to-SQL is largely divided into two categories: fine-tuning and prompting-based methods. Fine-tuning methods adapt open-source models like Code Llama or Qwen for the Text-to-SQL task by training them on large corpora of question-SQL pairs [16, 17, 21, 40, 50]. This approach can yield highly efficient and specialized models but may exhibit limited generalization to out-of-domain or highly complex scenarios. In contrast, prompting-based methods leverage the powerful in-context learning and reasoning capabilities of very large, often proprietary, models like GPT-4o [10] and Gemini [1] without requiring model training. To manage the complexity of the task, these methods typically decompose the process into a multi-stage pipeline, including sub-tasks like schema linking, SQL generation, and refinement [14, 15, 27, 31, 32, 57]. While powerful, these frameworks often rely on a single generation path and the fallible self-correction abilities of the LLM, which can compromise robustness. Our work, DEEPEYE-SQL, belongs to the prompting-based category but differentiates itself by explicitly adopting a systematic framework inspired by software engineering.

2.3 Software Engineering

The challenge of building robust and reliable LLM-based systems often mirrors the complexities of traditional software development. In response, software engineering has established a set of core principles to manage complexity and ensure product quality. The *Software Development Life Cycle (SDLC)* [36] provides a foundational, systematic process for software creation, typically involving phases such as requirements analysis, implementation, testing, and deployment. To deconstruct existing systems and inform new designs, practitioners often employ *Reverse Engineering* [34], a process of analyzing a finished product to deduce its underlying specifications. To enhance system reliability, fault tolerance techniques are critical. A notable example is *N-Version Programming* [4], where multiple, independently developed versions of a component are executed in parallel, and their results are adjudicated to mask faults and increase the likelihood of a correct outcome. For quality assurance, *Unit Testing* [35] is a fundamental practice. It involves the granular testing of individual software components or “units” in isolation to verify that each part functions correctly according to its design specifications. This bottom-up approach is crucial for identifying and rectifying defects early in the development process. Finally, to govern the release process, a *Quality Gate* [37] acts as a final checkpoint, enforcing a set of predefined criteria to determine whether a software artifact meets the required quality standard for deployment. While these principles are cornerstones of traditional software engineering, their systematic application to the

construction of LLM-based pipelines is an emerging area. Our work is directly inspired by these paradigms, leveraging them to bring a more structured, verifiable, and robust engineering discipline to the Text-to-SQL problem.

3 DeepEye-SQL Overview

3.1 Overall Architecture

DEEPEYE-SQL is systematically organized as a multi-stage pipeline inspired by the core principles of the Software Development Life Cycle (SDLC). Rather than reproducing the entire SDLC process literally, it abstracts and automates its essential workflow for Text-to-SQL. Conceptually, DEEPEYE-SQL serves as a compressed and self-contained microcosm of software development, where the “software” being constructed is a single, correct SQL query. Following this paradigm, the framework comprises four stages (Figure 3), each aligned with a corresponding phase of the SDLC.

Phase-1: Intent Scoping and Semantic Grounding. Mirroring the initial phase of any engineering project—answering “What should be built?”—this stage is dedicated to accurately interpreting user intent and defining the problem’s scope. It employs *Semantic Value Retrieval* to ground the query in the database’s actual data and *Robust Schema Linking* to identify necessary tables and columns. This linking module uses a fault-tolerant hybrid strategy, combining Direct, Reversed (inspired by *reverse engineering* [34]), and Value-based methods avoid the “*single point of failure*” problem [45], ensuring a comprehensive and fault-tolerant specification.

Phase-2: N-version Programming for SQL Generation. Analogous to the implementation phase, this stage generates SQL queries. To enhance robustness, we employ a strategy inspired by *N-version programming* [4], a fault-tolerance technique where multiple, independent implementations are created for the same problem. Our framework instantiates this by producing a diverse set of SQL candidates in parallel from three distinct generators: a Skeleton-based, an ICL-based, and a Divide-and-Conquer-based generator. It is crucial to distinguish this approach from test-time scaling techniques like self-consistency [46], which generate diversity by sampling multiple outputs from a single generator. In contrast, our method achieves a more principled and profound diversity, akin to true *N-version programming*, as each generator employs a fundamentally different reasoning process (e.g., SQL skeleton planning, example-based reasoning, recursive decomposition). This engineered diversity ensures a broader exploration of the solution space, significantly increasing the probability of producing at least one correct query, especially for complex scenarios where a single reasoning path might fail.

Phase-3: SQL Unit Testing and Revision via Tool-Chain. This phase embodies the critical software engineering principle of *Unit Testing* [35]. Its purpose is to systematically verify the correctness of each generated SQL candidate and revise any found defects. To overcome the known unreliability of LLM self-correction [53], our framework externalizes this process, emulating a rigorous, automated testing loop. Each SQL candidate is passed through a *Tool-Chain of Checkers*—a suite of specialized, deterministic tools where each checker acts as a test case for a specific unit of functionality

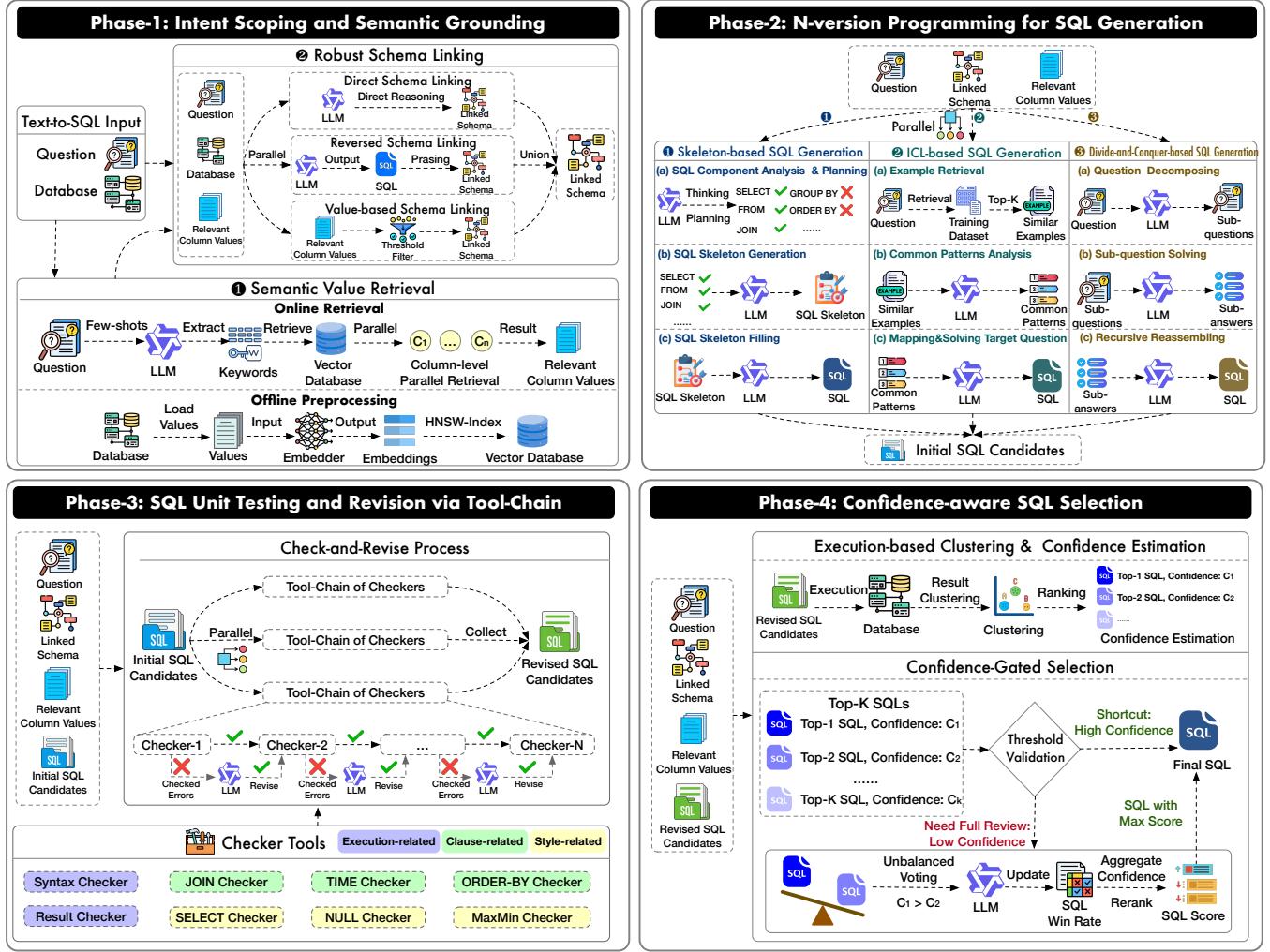


Figure 3: DEEPEYE-SQL Overview.

(e.g., syntax, JOIN correctness). If a flaw is detected, the tool provides an explicit and actionable directive to the LLM for a targeted revision, mirroring a formal bug report and fix cycle.

Phase-4: Confidence-aware SQL Selection. The final phase corresponds to the release stage, governed by a *Quality Gate*. Instead of simply choosing the most common answer, this stage arbitrates which candidate is reliable enough to be “released”. Our *Confidence-aware SQL Selection* mechanism performs this task. It first calculates an execution-based confidence score for the top candidates. This score is then evaluated against a predefined confidence threshold to validate reliability. This validation determines the execution path: high-confidence queries (those exceeding the threshold) pass the quality gate directly for efficiency, while low-confidence queries trigger a more nuanced, *unbalanced* LLM voting process to ensure the most reliable query is ultimately selected.

4 The Design Details of DEEPEYE-SQL

In this section, we provide a detailed exposition of the technical implementation of each phase within the DEEPEYE-SQL framework. We will describe the specific algorithms and design rationales that underlie our methodology.

4.1 Semantic Value Retrieval

A key Text-to-SQL challenge is the grounding problem: LLMs lack awareness of specific database values, often generating SQL with hallucinated or mismatched filter values (e.g., using country = ‘USA’ when the database stores ‘United States’). This issue is particularly prevalent for high-cardinality, free-form text columns. Addressing this mirrors the software engineering principle of *dependency resolution* [30], which requires a system to be aware of valid data constants it can operate on. To mitigate this, DEEPEYE-SQL incorporates a *Semantic Value Retrieval* module that proactively supplies the LLM with a contextually relevant subset of database values, anchoring the generation process to the ground-truth data.

Algorithm 1 Online Semantic Value Retrieval

Input: User Question Q , Set of Column Vector Indices $\{\mathcal{I}_j\}_{j=1}^M$, Top-K parameter K
Output: Retrieved Values Map $\mathcal{M}_{\text{retrieved}}: C_j \rightarrow \mathcal{V}_j$

```

// Step 1: Extract Keywords from the user question
1:  $\mathcal{K} \leftarrow \text{LLM - ExtractKeywords}(Q)$ 
// Step 2: Retrieve values in parallel for each indexed column
2: Initialize  $\mathcal{M}_{\text{retrieved}} \leftarrow \emptyset$ 
3: for all index  $\mathcal{I}_j$  for column  $C_j$  in parallel do
4:    $\mathcal{V}_{\text{candidates}} \leftarrow \emptyset$ 
5:   for all keyword  $k_i \in \mathcal{K}$  do
6:      $\mathbf{e}_{k_i} \leftarrow \text{Embed}(k_i)$ 
7:      $\mathcal{V}_{\text{partial}} \leftarrow \text{SearchIndex}(\mathcal{I}_j, \mathbf{e}_{k_i}, K)$ 
8:      $\mathcal{V}_{\text{candidates}} \leftarrow \mathcal{V}_{\text{candidates}} \cup \mathcal{V}_{\text{partial}}$ 
9:   end for
10:   $\mathcal{V}_{\text{sorted}} \leftarrow \text{SortBySimilarity}(\mathcal{V}_{\text{candidates}})$  // Aggregate and select top-K unique values
11:   $\mathcal{V}_j \leftarrow \text{GetUniqueTopK}(\mathcal{V}_{\text{sorted}}, K)$ 
12:   $\mathcal{M}_{\text{retrieved}}[C_j] \leftarrow \mathcal{V}_j$ 
13: end for
14: return  $\mathcal{M}_{\text{retrieved}}$ 

```

Our value retrieval process is divided into two distinct stages: an efficient, one-time offline preprocessing stage for index construction, and a rapid online retrieval stage executed at query time.

Offline Preprocessing. The primary objective of the offline phase is to preprocess and index database values to enable efficient semantic search. This process is executed once for any new database and involves three steps.

Selective Value Extraction. Instead of a brute-force approach that indexes every value—which would be computationally prohibitive and introduce significant noise—we perform selective extraction. We specifically target columns of type TEXT, as they are the primary source of ambiguity and value-related hallucinations. To further refine this process, we apply heuristics to exclude columns that, despite being text-based, are unlikely to be used in semantic comparisons, such as columns containing UUIDs or exclusively numerical identifiers. This strategic selection minimizes the indexing overhead while enhancing the semantic relevance of the retrieved values.

Value Embedding. For each selected column C_j , we extract its unique values. Each distinct value v is then encoded into a high-dimensional vector representation \mathbf{e}_v using a pretrained sentence embedding model, specifically Qwen3-Embedding-0.6B [55]. This embedding transforms discrete text strings into continuous semantic vectors, where values with similar meanings are located closer to each other in the vector space.

Vector Indexing. To facilitate fast similarity search, the generated value embeddings for each column are used to build a vector index. We employ Chroma [5] with the Hierarchical Navigable Small World (HNSW) algorithm [29] for this purpose. HNSW is highly efficient for approximate nearest neighbor (ANN) search, making it ideal for real-time applications. The result is a set of persistent, per-column vector indices $\{\mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_M\}$, where each \mathcal{I}_j is an indexed collection of all value embeddings for a column C_j .

Online Retrieval. During the online phase, when a user ques-

Algorithm 2 Robust Schema Linking

Input: User Question Q , Database Schema \mathcal{D} , Retrieved Values Map $\mathcal{M}_{\text{retrieved}}$, Threshold θ_{val}
Output: Final Linked Schema $\mathcal{D}_{\text{linked}}$

```

// Step 1: Execute the three linking strategies in parallel
1: begin parallel
2:    $\mathcal{D}_{\text{direct}} \leftarrow \text{LLM_DirectLink}(Q, \mathcal{D}, \mathcal{M}_{\text{retrieved}})$ 
3:    $\mathcal{S}' \leftarrow \text{LLM_GenerateSQL}(Q, \mathcal{D}, \mathcal{M}_{\text{retrieved}})$ 
4:    $\mathcal{D}_{\text{reversed}} \leftarrow \text{ParseSchema}(\mathcal{S}')$ 
5:    $\mathcal{D}_{\text{value}} \leftarrow \text{FindValueBasedSchema}(\mathcal{M}_{\text{retrieved}}, \theta_{\text{val}})$ 
6: end parallel
// Step 2: Aggregate the results by taking the union
7:  $\mathcal{D}_{\text{union}} \leftarrow \mathcal{D}_{\text{direct}} \cup \mathcal{D}_{\text{reversed}} \cup \mathcal{D}_{\text{value}}$ 
// Step 3: Enforce relational closure to ensure schema connectivity
8:  $\mathcal{D}_{\text{linked}} \leftarrow \text{EnforceClosure}(\mathcal{D}_{\text{union}}, \mathcal{D})$ 
9: return  $\mathcal{D}_{\text{linked}}$ 

```

tion Q is received, the system retrieves the most relevant values for that question from the pre-built indices. This process is detailed in Algorithm 1.

Keyword Extraction. First, we leverage the LLM to identify potential entities and filter values within the user’s question Q . Using a few-shot prompting strategy, we instruct the LLM to extract a set of key terms $\mathcal{K} = \{k_1, k_2, \dots, k_N\}$ that are likely to appear in a WHERE clause. For example, from the question “Show me all papers by authors from France”, the LLM would extract keywords like “France”.

Parallel Multi-Column Retrieval. With the extracted keywords, we perform a parallel search across all indexed columns. For each indexed column C_j , we perform the following steps:

- (1) For every keyword $k_i \in \mathcal{K}$, we generate its embedding \mathbf{e}_{k_i} using the same model from the offline phase.
- (2) We query the corresponding column index \mathcal{I}_j with \mathbf{e}_{k_i} to retrieve the top- K most similar values along with their similarity scores (e.g., cosine similarity).
- (3) After querying for all N keywords, we obtain $N \times K$ candidate values for column C_j . We aggregate these candidates, sort them globally by their similarity scores in descending order, and select the top- K unique values. This yields the final retrieved value set \mathcal{V}_j for column C_j .

4.2 Robust Schema Linking

Schema linking, the task of identifying the correct subset of tables and columns relevant to a user’s question, is a cornerstone of any Text-to-SQL system [19]. Existing methods [14, 15, 43] often treat this as a direct mapping task, which can be brittle when faced with complex schemas or ambiguous questions. An error at this stage is catastrophic, as an incomplete or incorrect schema makes generating a correct SQL query nearly impossible. This critical dependency is analogous to the role of a *formal specification* [8] in software development; without an accurate specification, the final product is destined to fail. To address this, we introduce a *Robust Schema Linking* module that, inspired by the principle of fault tolerance, combines multiple, diverse strategies to ensure the most accurate and complete schema is identified. Our overall process is detailed in Algorithm 2.

Our approach is a hybrid model that integrates three complementary linking techniques: (1) **Direct Schema Linking**, (2) **Reversed Schema Linking**, and (3) **Value-based Schema Linking**.

Direct Schema Linking. This method represents the most conventional approach, directly tasking the LLM with acting as a schema analysis agent. Given the user's question Q , the full database schema \mathcal{D} , and the retrieved relevant values $\mathcal{M}_{\text{retrieved}}$, we prompt the LLM to explicitly list all relevant schema components. This process can be formalized as:

$$\mathcal{D}_{\text{direct}} = \text{LLM}_{\text{DirectLink}}(Q, \mathcal{D}, \mathcal{M}_{\text{retrieved}}) \quad (1)$$

While effective for unambiguous queries, its performance can degrade in complex scenarios, making it an unreliable standalone solution.

Reversed Schema Linking. Inspired by the software engineering practice of *reverse engineering* [34], this technique reimagines the schema linking process. Instead of asking the LLM to first identify the schema, we prompt it to generate a draft SQL query directly, providing it with the full context including the relevant values. This approach is more effective because the task of generating SQL code aligns more closely with an LLM's pre-training on vast code corpora [41]. We then use a static parser to extract all schema components from the generated query S' . Formally, the process is:

$$\mathcal{D}_{\text{reversed}} = \text{ParseSchema}(\text{LLM}_{\text{GenerateSQL}}(Q, \mathcal{D}, \mathcal{M}_{\text{retrieved}})) \quad (2)$$

This “answer-first” approach allows the LLM to implicitly perform schema linking, often revealing components for complex joins or subqueries that a direct analysis might miss.

Value-based Schema Linking. This technique provides an empirical, data-driven check to complement the model-driven approaches. It operates on the principle that if a column contains values highly similar to keywords in the question, that column is likely relevant. This method leverages the retrieved values $\mathcal{M}_{\text{retrieved}}$ from the previous module. A column C_j is selected if any of its retrieved values has a similarity score with any question keyword $k \in \mathcal{K}$ that exceeds a high-confidence threshold θ_{val} . This can be expressed as:

$$\begin{aligned} \mathcal{D}_{\text{value}} = \{C_j \in \mathcal{D} \mid & \exists v \in \mathcal{M}_{\text{retrieved}}[C_j], \exists k \in \mathcal{K} \\ & \text{s.t. } \text{Sim}(v, k) > \theta_{\text{val}}\} \end{aligned} \quad (3)$$

This bottom-up method excels at resolving schema ambiguity. In cases where multiple columns are plausible candidates, it precisely identifies the correct one by grounding the selection in concrete data values instead of potentially misleading column names.

Schema Union and Closure. The final step aggregates the results and ensures the relational integrity of the linked schema. First, we take the union of the schemas identified by all three methods:

$$\mathcal{D}_{\text{union}} = \mathcal{D}_{\text{direct}} \cup \mathcal{D}_{\text{reversed}} \cup \mathcal{D}_{\text{value}} \quad (4)$$

However, $\mathcal{D}_{\text{union}}$ may be an incomplete, disconnected graph of schema elements. To resolve this, we enforce *relational closure*. We parse all foreign key relationships in the database schema \mathcal{D} . For any pair of tables (T_i, T_j) present in $\mathcal{D}_{\text{union}}$, we automatically add the corresponding primary and foreign key columns that link them. This step guarantees that the final linked schema is a connected graph, providing a solid foundation for constructing joins in the

Algorithm 3 N-version Programming for SQL Generation

Input: User Question Q , Linked Schema $\mathcal{D}_{\text{linked}}$, Retrieved Values Map $\mathcal{M}_{\text{retrieved}}$
Output: Set of Initial SQL Candidates C_{initial}

```

// Step 1: Retrieve few-shot examples for the ICL generator
1:  $\mathcal{E}_{\text{few-shot}} \leftarrow \text{RetrieveSimilarExamples}(Q)$ 
// Step 2: Execute the three SQL generators in parallel
2: begin parallel
3:    $S_{\text{skel}} \leftarrow \text{LLM}_{\text{Skel}}(Q, \mathcal{D}_{\text{linked}}, \mathcal{M}_{\text{retrieved}})$ 
4:    $S_{\text{icl}} \leftarrow \text{LLM}_{\text{ICL}}(Q, \mathcal{D}_{\text{linked}}, \mathcal{M}_{\text{retrieved}}, \mathcal{E}_{\text{few-shot}})$ 
5:    $S_{\text{d&c}} \leftarrow \text{LLM}_{\text{D&C}}(Q, \mathcal{D}_{\text{linked}}, \mathcal{M}_{\text{retrieved}})$ 
6: end parallel
// Step 3: Collect all generated SQLs into a candidate set
7:  $C_{\text{initial}} \leftarrow \{S_{\text{skel}}, S_{\text{icl}}, S_{\text{d&c}}\} // \text{and other samples if } N > 1 \text{ per generator}$ 
8: return  $C_{\text{initial}}$ 

```

SQL generation phase. This final, closed schema is defined as:

$$\mathcal{D}_{\text{linked}} = \text{EnforceClosure}(\mathcal{D}_{\text{union}}, \mathcal{D}) \quad (5)$$

4.3 N-version Programming for SQL Generation

Upon establishing the query's specification in the *Intent Scoping and Semantic Grounding* phase, the framework proceeds to the implementation stage: SQL generation. A single generation strategy, however, often struggles with the diversity of user queries [31]; a method effective for simple lookups may fail on complex analytical questions [32]. To address this, DEEP-EYE-SQL instantiates a fault-tolerant strategy inspired by the software engineering principle of *N-version programming* [4]. Instead of relying on a single, monolithic generator, we deploy three distinct and independent SQL generators that run in parallel, each employing a different methodology. This engineered diversity significantly increases the likelihood of producing at least one correct candidate, enhancing the system's overall robustness. The entire workflow is detailed in Algorithm 3.

The inputs to this phase are the user question Q , the linked schema $\mathcal{D}_{\text{linked}}$, and the retrieved values $\mathcal{M}_{\text{retrieved}}$. The three generators operate on this common set of inputs to produce a unified pool of initial SQL candidates C_{initial} .

Skeleton-based SQL Generation. This generator is modeled after the *top-down design* principle [44], where a high-level plan is formulated before implementation details are filled in. This guides the LLM to think systematically, reducing structural errors. It involves three conceptual steps: component analysis, skeleton generation, and slot-filling. The entire process is encapsulated in a single call to the LLM, which is instructed to follow this reasoning path. We can formalize this as:

$$S_{\text{skel}} = \text{LLM}_{\text{Skel}}(Q, \mathcal{D}_{\text{linked}}, \mathcal{M}_{\text{retrieved}}) \quad (6)$$

ICL-based SQL Generation. This generator leverages in-context learning (ICL), analogous to *case-based reasoning* [12]. By providing the LLM with relevant examples, we ground its generation in proven patterns. The process involves retrieving schema-masker similar examples from a training set following DAIL-SQL [7], instructing the LLM to identify a common pattern, and then applying that

Algorithm 4 SQL Unit Testing and Revision via Tool-Chain

Input: A single SQL candidate S_{cand} , Context $(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved})$, Tool-Chain $\mathbb{C} = \{C_1, \dots, C_N\}$

Output: Revised SQL query $S_{revised}$

```

1:  $S_{current} \leftarrow S_{cand}$ 
2: for all checker  $C_j \in \mathbb{C}$  do
3:    $is\_valid, d_{err} \leftarrow C_j(S_{current})$ 
4:   if not  $is\_valid$  then
    // Error found, trigger revision and update the current SQL
5:      $S_{current} \leftarrow \text{LLM}_{\text{Revise}}(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved}, S_{current}, d_{err})$ 
6:   end if
7: end for
    // All checkers in the chain have been processed
8: return  $S_{current}$ 

```

pattern to the target question. This is formalized as:

$$S_{icl} = \text{LLM}_{\text{ICL}}(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved}, \mathcal{E}_{few-shot}) \quad (7)$$

where $\mathcal{E}_{few-shot}$ represents the set of retrieved few-shot examples.

Divide-and-Conquer-based SQL Generation. For highly complex questions requiring nested logic, this generator implements the classic *Divide and Conquer* paradigm. It breaks a large problem into smaller, manageable sub-problems that are solved recursively and then reassembled. This involves decomposing the question, solving each sub-question, and synthesizing the results into a single query. The process is formalized as:

$$S_{d\&c} = \text{LLM}_{\text{D\&C}}(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved}) \quad (8)$$

4.4 SQL Unit Testing and Revision via Tool-Chain

SQL queries generated by LLMs, while often structurally sound, can contain minor yet critical errors [20], such as incorrect function usage or logical flaws in JOIN conditions. A well-known limitation of LLMs is their unreliability in self-correction [33]; when asked to review their own output, they exhibit a strong confirmation bias and tend to overlook their mistakes [53]. This challenge is directly analogous to a core principle in software engineering: code should be validated by an independent testing suite, not just by the developer who wrote it. To address this, our framework introduces the *SQL Unit Testing and Revision via Tool-Chain* phase, which draws direct inspiration from the practice of *Unit Testing* [35]. In this paradigm, individual software components—or “units”—are tested in isolation. We adapt this concept by treating each functional component of a SQL query (e.g., its JOIN logic, a specific clause, or its syntax) as a testable “unit”. The *Tool-Chain* operationalizes this principle by externalizing the verification process. It uses a deterministic chain of specialized checkers, where each checker acts as an automated test case for a specific SQL unit. This allows the system to systematically detect errors and guide the LLM through a reliable, targeted revision process, as detailed in Algorithm 4.

Tool-Chain of Checkers. Our approach centers on a suite of specialized, deterministic programs we term “Checker Tools”. These checkers are not applied randomly; they are organized into a sequential tool-chain that processes each SQL query in a specific order to catch errors systematically, from fundamental syntax to

Table 1: Specialized Checkers.

Checker	Error Detection	Example Cases
Syntax Checker	SQL syntax and execution errors	SELECT * FORM table (typo) WHERE column = (incomplete)
JOIN Checker	Non-standard JOIN conditions	ON cond1 OR cond2 ON column IN (...)
ORDER-BY Checker	Invalid ORDER BY + LIMIT combinations	ORDER BY MAX(...) LIMIT 1 ORDER BY COUNT(*) LIMIT 3
Time Checker	Incorrect time function usage and formatting	strftime('%%Y', date) format Invalid date comparisons
SELECT Checker	Ambiguous return columns	SELECT * → specific columns Unnecessary wildcards
MaxMin Checker	Suboptimal MAX/MIN patterns	WHERE col = (SELECT MAX(...)) → ORDER BY col DESC LIMIT 1
NULL Checker	NULL values in ORDER BY columns	Add WHERE col IS NOT NULL for ORDER BY columns
Result Checker	Empty or meaningless results	Queries returning only NULL Zero-row result sets

semantic correctness. The complete, ordered sequence of checkers and their functions is detailed in Table 1. The chain begins with the most fundamental validation: the *Syntax Checker* ensures the query is syntactically valid and executable, catching basic typos or incomplete clauses. It then proceeds to clause-specific validation. For example, the *JOIN Checker* flags non-standard conditions, the *ORDER-BY Checker* corrects invalid patterns like using aggregations with LIMIT, and the *Time Checker* validates date and time formatting. Subsequently, the chain addresses more semantic and stylistic issues. The *SELECT Checker* replaces ambiguous wildcards like SELECT * with specific column names, and the *MaxMin Checker* refactors suboptimal patterns into more efficient ORDER BY ... LIMIT 1 clauses. Finally, the *NULL Checker* and *Result Checker* add guards for potential NULL issues and flag queries that are likely to produce empty or meaningless results, ensuring the final output is not only correct but also useful.

The Sequential Check-and-Revise Process. Our framework implements an efficient, single-pass “check-and-revise” process, detailed in Algorithm 4. Each initial SQL candidate, $S \in \mathcal{C}_{initial}$, is passed through the *Tool-Chain of Checkers* exactly once. The process for a single candidate S_{cand} is as follows:

- (1) The candidate S_{cand} is sequentially evaluated by each checker in the tool-chain, starting with the first.
- (2) If a checker detects an error, the process is momentarily paused. The checker generates a specific error report and an actionable *correction directive*, d_{err} . For example, if the *NULL Checker* finds that a column in an ORDER BY clause could contain NULL values, the directive would be a clear instruction such as: “The ordering column [column_name] may contain NULLs. Add a WHERE [column_name] IS NOT NULL condition to ensure correct sorting.”
- (3) The LLM is then invoked in a special “revision mode”. It receives the original context, the faulty SQL S_{cand} , and the explicit directive d_{err} from the checker. The LLM’s task is not to find the error, but to fix it based on the directive. This can be formalized as:

$$S_{revised} = \text{LLM}_{\text{Revise}}(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved}, S_{cand}, d_{err}) \quad (9)$$

Algorithm 5 Confidence-aware SQL Selection

Input: Revised SQL Candidates $C_{revised}$, Context $(Q, \mathcal{D}_{linked}, \mathcal{M}_{retrieved})$, Threshold θ_{conf}

Output: The Final SQL Query S_{final}

```

1: // Step 1: Execute all candidates and cluster the results
2:  $\mathcal{R} \leftarrow \text{ExecuteAll}(C_{revised})$ 
3:  $\{\text{Cluster}_1, \dots, \text{Cluster}_M\}, \{S_1, \dots, S_M\} \leftarrow \text{ClusterAndRank}(\mathcal{R})$ 
   // Step 2: Calculate confidence for the top-ranked candidate
4:  $Conf(S_1) \leftarrow \frac{|\text{Cluster}_1|}{|C_{revised}|}$ 
   // Step 3: Confidence-Gated Selection Path
5: if  $Conf(S_1) > \theta_{conf}$  then
6:    $S_{final} \leftarrow S_1$  // High-Confidence Shortcut
7: else
8:   Let  $\{S_1, \dots, S_K\}$  be the top-K candidates // Low-Confidence Full Review
9:   for all candidate  $S_i$  in  $\{S_1, \dots, S_K\}$  do
10:     $Conf(S_i) \leftarrow \frac{|\text{Cluster}_i|}{|C_{revised}|}$ 
11:     $WinRate(S_i) \leftarrow \text{LLM-PairwiseVoting}(\{S_1, \dots, S_K\})$  // Using Eq. 11
12:   end for
13:    $S_{final} \leftarrow \arg \max_{S_i} Score(S_i)$ 
14: end if
15: return  $S_{final}$ 

```

- (4) The newly revised query, $S_{revised}$, replaces S_{cand} , and the evaluation continues with the next checker in the chain.
- (5) The process terminates once the query has been evaluated by all checkers in the chain.

This external, tool-guided debugging process is significantly more reliable than unconstrained LLM self-correction. The final output of this phase is a set of revised SQL candidates, $C_{revised}$, which have been rigorously vetted and have a substantially higher probability of being correct.

4.5 Confidence-aware SQL Selection

The preceding phases of our framework produce a set of high-quality, revised SQL candidates, $C_{revised}$. However, these candidates may not be identical and could yield different execution results. The most common approach for selecting a final query is *self-consistency* [7, 15, 48], where all candidates are executed, and the query corresponding to the most frequent result is chosen. This method, while a strong baseline, has a critical flaw: *the most popular answer is not always the correct one, especially for complex problems where multiple generation paths might converge on the same plausible but incorrect logic*. This final challenge mirrors the release stage in a software lifecycle, which is governed by a *Quality Gate* [37]. A quality gate's purpose is not merely to accept the most-voted-for version, but to enforce a set of objective quality criteria before a product is released. Similarly, our *Confidence-aware SQL Selection* phase acts as this quality gate for the generated SQL. It overcomes the flaws of simple majority voting by using the initial vote's confidence as a quality metric to guide a more reliable, adaptive selection process.

Execution-based Clustering and Confidence Estimation. The process begins by executing every revised SQL candidate $S \in$

$C_{revised}$ on the database. The resulting datasets are then clustered, such that queries producing identical results are grouped together. These clusters are ranked based on their size (*i.e.*, the number of SQL queries they contain). For each of the top- K candidates $\{S_1, S_2, \dots, S_K\}$, representing the top- K largest clusters, we calculate an execution-based confidence score. The confidence of a candidate S_i is the proportion of total queries that belong to its cluster:

$$Conf(S_i) = \frac{|\text{Cluster}_i|}{|C_{revised}|} \quad (10)$$

This score, particularly $Conf(S_1)$, serves as a strong indicator of the query's likely correctness, as shown by the high correlation in Figure 6.

Confidence-Gated Selection. Based on the confidence of the top-ranked candidate S_1 , our framework follows one of two distinct paths, as detailed in Algorithm 5.

High-Confidence Shortcut. If the confidence score $Conf(S_1)$ exceeds a predefined high-confidence threshold θ_{conf} , we conclude that there is overwhelming agreement among the generated candidates. In this scenario, we directly select S_1 as the final query. This shortcut avoids unnecessary and costly LLM invocations for cases where the answer is already clear, providing a practical trade-off between accuracy and efficiency.

Low-Confidence Full Review. If $Conf(S_1) < \theta_{conf}$, it signifies substantial ambiguity or disagreement among the candidates, making the top choice unreliable. It then triggers a full review pipeline.

(1) Establish Unbalanced Cognitive Prior. First, instead of a neutral pairwise comparison, the LLM is explicitly primed with a "cognitive prior". It is informed that, based on execution results, S_i has a higher prior confidence than S_j . We instructs the LLM to select the higher-confidence candidate unless there is *clear and compelling evidence* that it is incorrect or that the lower-confidence candidate is demonstrably superior.

(2) Perform Pairwise Adjudication. Next, the LLM performs pairwise comparisons for the top- K candidates. To ensure reliability, we employ a *self-consistency* mechanism. For each pair (S_i, S_j) , we sample multiple judgments and define the final stable vote, $V(S_i, S_j)$, as the majority outcome. The vote $V(S_i, S_j)$ yields 1 if S_i is superior and 0 if S_j is superior. From these consistent pairwise results, we compute an aggregate win rate for each candidate S_i as its average score against all other competitors in the top- K set:

$$WinRate(S_i) = \frac{1}{K-1} \sum_{j=1, j \neq i}^K V(S_i, S_j) \quad (11)$$

(3) Calculate Final Score. Finally, the decision is based on a confidence-aware score that combines the prior execution-based confidence with the LLM-adjudicated win rate:

$$Score(S_i) = Conf(S_i) \times WinRate(S_i) \quad (12)$$

The query with the highest overall score, $\arg \max_{S_i} Score(S_i)$, is selected as the final SQL, S_{final} .

4.6 Workflow Optimization

While DEEPEYE-SQL’s multi-stage architecture ensures robustness, we incorporate three key optimizations to maintain efficiency and computational costs, preventing prohibitive latency or expense.

Efficient Prompting Strategy. Instead of sequential, costly LLM API calls for multi-step reasoning (e.g., planning), we use a single, sophisticated prompt for each generator. This prompt includes a “chain-of-thought” instruction, directing the LLM to perform the entire logical sequence internally and output only the final SQL in one call. This preserves structured reasoning benefits while eliminating the associated latency and token overhead.

Parallel Execution. To reduce end-to-end latency, our framework heavily parallelizes independent tasks. Critical components are executed concurrently, including: multi-column value retrieval, all three schema linking strategies, the N-version SQL generators, and the parallel revision of each SQL candidate.

Conditional Execution. To minimize unnecessary LLM invocations, DEEPEYE-SQL employs conditional execution at two critical stages. First, during *SQL Unit Testing and Revision*, the LLM is only called for revision if a checker tool detects an error. Second (Section 4.4), LLM-based pairwise adjudication is only triggered in low-confidence scenarios.

5 Experiments

5.1 Experimental Setup

Datasets. We evaluate the performance of DEEPEYE-SQL on two widely-recognized and challenging cross-domain Text-to-SQL benchmarks: **BIRD** [18] and **Spider** [51]. BIRD is a large-scale benchmark designed to mirror complex, real-world scenarios. It contains 12,751 unique question-SQL pairs across 95 databases from over 37 professional domains. Its databases are notably large and feature messy data and intricate schemas, making it a difficult test for grounding and robustness. Spider is a foundational large-scale, cross-domain benchmark in the field. It consists of 10,181 questions and 5,693 unique, complex SQL queries across 200 databases covering 138 different domains. Following prior works [3, 21, 31], we use the development set of BIRD (BIRD-Dev) and the test set of Spider (Spider-Test) for our main evaluation.

Evaluation Metrics. Following prior works [3, 21, 31], our primary evaluation metric is **Execution Accuracy (EX)**. A generated SQL query is considered correct if its execution result is equivalent to that of the ground-truth query after accounting for ordering. To measure the potential of our N-version Programming for SQL Generation module, we report the **Upper-bound EX**, which is the execution accuracy an oracle would achieve by always selecting the correct SQL from the generated candidates [31]. For evaluating the Robust Schema Linking module, we use **Table/Column Recall**, the proportion of ground-truth tables and columns correctly identified. Finally, to assess practical efficiency, we measure **Token Cost**, corresponding to the number of tokens processed by LLMs.

Baselines. We compare DEEPEYE-SQL against SOTA baselines from two paradigms (Table 2). The first is **fine-tuning-based methods**, which are trained on in-domain data, including strong competitors

like XiYan-SQL [21], CHASE-SQL [31], and OmniSQL [16]. The second is **prompting-based methods**, which, like DEEPEYE-SQL, are training-free. This group includes methods like Alpha-SQL [15], RSL-SQL [3], and CHESS [43].

Implementation Details. All experiments are conducted on an Ubuntu 22.04.3 LTS server with 512GB of RAM and dual 40-core Intel(R) Xeon(R) Platinum 8383C CPUs. We deploy all open-source LLMs locally using the vlm [13] framework on 4 NVIDIA A100 GPUs, each with 80GB of memory, and accelerate inference using a tensor parallelism of 4. To validate the robustness and generalizability of our framework, we integrated DEEPEYE-SQL with three distinct models from two leading series: Gemma3-27B-Instruct [11], Qwen2.5-Coder-32B-Instruct [9], and Qwen3-Coder-30B-A3B-Instruct [49]. Unless otherwise specified, the pipeline is configured as follows. For Semantic Value Retrieval, where we retrieve up to the top-5 most similar values for each TEXT-type column, we use the Qwen3-Embedding-0.6B [55] model, and the similarity threshold (θ_{val}) for Value-based Schema Linking is set to 0.98. The draft SQL for Reversed Schema Linking is produced by the ICL-based generator. For each LLM sub-task (e.g., Direct Schema Linking), we set the sampling budget to 8 with a sampling temperature of 0.7. Finally, in the Confidence-aware SQL Selection phase, which adjudicates between the top-2 ranked queries in low-confidence scenarios, the confidence shortcut threshold (θ_{conf}) is set to 0.6. All prompt templates of our method are in the Appendix.

5.2 Overall Performance

RQ1: How does DEEPEYE-SQL perform against existing state-of-the-art methods on challenging Text-to-SQL benchmarks?

To answer this, we present the main performance of DEEPEYE-SQL on the BIRD-Dev and Spider-Test datasets in Table 2, comparing it against a wide range of state-of-the-art fine-tuning and prompting-based methods. The results clearly demonstrate that our software-grounded framework establishes a new benchmark for training-free Text-to-SQL generation.

Specifically, when integrated with the Qwen3-Coder-30B-A3B model, DEEPEYE-SQL achieves an execution accuracy of **73.5%** on BIRD-Dev. This result not only significantly outperforms all existing prompting-based baselines but, more remarkably, it also surpasses the leading fine-tuning-based systems like XiYan-SQL (73.3%) and CHASE-SQL (73.0%). It is crucial to note that these competing methods rely on substantially larger and often proprietary models (e.g., GPT-4o and Gemini-1.5-Pro). On the Spider-Test dataset, DEEPEYE-SQL with Qwen3-Coder-30B-A3B achieves an execution accuracy of **89.8%**. This performance matches the best fine-tuned method, OmniSQL, and surpasses other strong competitors like XiYan-SQL (89.7%). This demonstrates that our prompting-based framework can attain the same level of accuracy as highly specialized, fine-tuned models on this foundational benchmark without incurring any training costs.

Furthermore, the consistently high performance of DEEPEYE-SQL across all three tested open-source models—71.1% with Gemma3-27B, 70.9% with Qwen2.5-Coder-32B, and 73.5% with Qwen3-Coder-30B on BIRD, which underscores the robustness and generalizability of our framework.

Table 2: Performance comparison on BIRD-Dev and Spider-Test datasets.

Methods	Model	# Parameters	BIRD-EX (%)	Spider-EX (%)
<i>Fine-tuning-based Baselines</i>				
SENSE [50]	CodeLLaMA-13B	~13B	55.5	86.6
SFT CodeS [17]	CodeS-15B	~15B	58.5	-
Distillery [28]	GPT-4o	>200B	67.2	-
XiYanSQL-QwenCoder [21]	Qwen2.5-Coder-32B-Instruct	~32B	67.1	88.4
BASE-SQL [40]	Qwen2.5-Coder-32B-Instruct	~32B	67.5	88.9
OmniSQL [16]	Qwen2.5-Coder-32B-Instruct	~32B	67.0	89.8
CSC-SQL [39]	XiYanSQL-QwenCoder-32B	~32B	71.3	-
CHASE-SQL [31]	Gemini-1.5-Pro + Gemini-1.5-Flash	>200B	73.0	87.6
XiYan-SQL [21]	GPT-4o + Qwen2.5-Coder-32B-Instruct	>200B	73.3	89.7
<i>Prompting-based Baselines</i>				
DIN-SQL [32]	GPT-4	>175B	50.7	85.3
DAIL-SQL [7]	GPT-4	>175B	55.9	86.6
SuperSQL [14]	GPT-4	>175B	58.5	-
RSL-SQL [3]	GPT-4o	>200B	67.2	87.9
CHESS (IR,CG,UT) [43]	Gemini-1.5-Pro	>200B	68.3	-
OpenSearch-SQL (v2) [48]	GPT-4o	>200B	69.3	87.1
Alpha-SQL [15]	Qwen2.5-Coder-32B-Instruct	~32B	69.7	-
<i>Our DEEPEYE-SQL (Prompting-based)</i>				
DEEPEYE-SQL	Gemma3-27B-Instruct	~27B	71.1	88.9
DEEPEYE-SQL	Qwen2.5-Coder-32B-Instruct	~32B	70.9	88.7
DEEPEYE-SQL	Qwen3-Coder-30B-A3B-Instruct	~30B	73.5	89.8

Table 3: Performance comparison with same LLMs.

Methods	EX (%)	Delta (%)
<i>Gemma3-27B-Instruction</i>		
CoT-Baseline	54.2	-
CHESS (IR,CG,UT)	66.1	+11.9
Alpha-SQL	68.6	+14.4
DEEPEYE-SQL (Ours)	71.1	+16.9
<i>Qwen2.5-Coder-32B-Instruct</i>		
CoT-Baseline	61.3	-
CHESS (IR,CG,UT)	67.7	+6.4
Alpha-SQL	69.7	+8.4
DEEPEYE-SQL (Ours)	70.9	+9.6
<i>Qwen3-Coder-30B-A3B-Instruct</i>		
CoT-Baseline	61.7	-
CHESS (IR,CG,UT)	67.9	+6.2
Alpha-SQL	71.2	+9.5
DEEPEYE-SQL (Ours)	73.5	+11.8

RQ2: Is the performance gain of DEEPEYE-SQL attributable to its architectural design rather than the power of the underlying base model?

To isolate our framework's contribution from the base model's intrinsic capabilities, we evaluated it against leading prompting-based frameworks on identical open-source models (Table 3). The results confirm that DEEPEYE-SQL's architecture consistently provides the most substantial performance improvement. For instance, on Gemma3-27B-Instruct, DEEPEYE-SQL improves the CoT baseline by +16.9%, significantly outpacing the gains from CHESS (+11.9%)

Table 4: Schema linking analysis with Qwen3-Coder-30B-A3B on BIRD-Dev dataset.

Schema Linking Methods	Table Recall (%)	Column Recall (%)	# Avg. Tokens
No Schema Linking	-	-	5486.2
Direct Schema Linking	94.2	80.9	454.5
Reversed Schema Linking	97.0	94.0	495.9
Value Schema Linking	47.3	18.0	262.0
Robust Schema Linking	98.1	95.4	627.4

and Alpha-SQL (+14.4%). This trend holds across all tested models, culminating in a state-of-the-art 73.5% EX on Qwen3-Coder-30B-A3B (+11.8% gain).

5.3 Robust Schema Linking Analysis

RQ3: How do the individual components of our Robust Schema Linking module contribute to its overall effectiveness and efficiency?

We analyzed our *Robust Schema Linking* module's components on BIRD-Dev (Table 4), measuring schema recall and token efficiency. The full approach achieves the highest recall (**98.1%** table, **95.4%** column), providing a critical foundation for SQL generation. It also dramatically boosts efficiency, reducing the input context by 9× from 5486.2 to 627.4 tokens compared to using the full schema.

Analyzing the components reveals complementary strengths. Our novel *Reversed Schema Linking* (97.0% table, 94.0% column) significantly outperforms *Direct Schema Linking*, especially in column

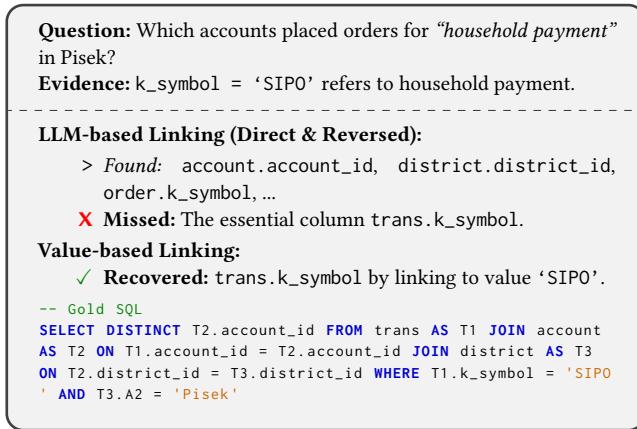


Figure 4: A case study from BIRD-Dev (QID: 142) where Value-based Linking recovers a critical column (trans.k_symbol) missed by purely LLM-based linking methods.

Table 5: SQL generation analysis with Qwen3-Coder-30B-A3B on BIRD-Dev dataset.

SQL Generation	EX (%)	UB-EX (%)
Skeleton-based SQL Generation	69.2	77.9
ICL-based SQL Generation	70.9	78.3
D&C-based SQL Generation	70.3	78.5
N-version Programming for SQL Generation	71.7	81.1

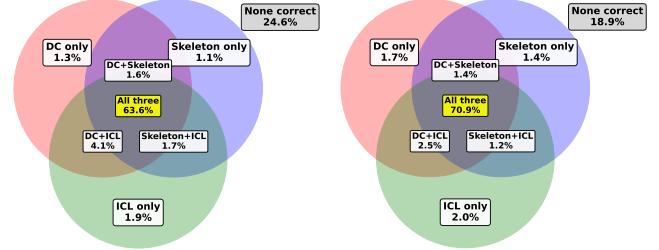
recall (+13.1%). This validates our hypothesis that prompting for a draft query is a more natural and effective reasoning method for LLMs than explicit extraction.

Finally, *Value-based Schema Linking*, while low in overall recall, is not a standalone linker. It acts as a precise mechanism to link columns via their data values, catching omissions from other methods. For instance (Figure 4), it correctly identified trans.k_symbol by linking the query’s “household payment” to the data value ‘SIP0’. This bridged a semantic gap that schema-level reasoners (Direct and Reversed) missed, as they were confused by an ambiguous k_symbol name. This recovery proves the value-based method’s essential role in our fault-tolerant design.

5.4 Analysis on N-Version Programming for SQL Generation

RQ4: How do the different SQL generators contribute to the overall performance, and does the N-version programming approach provide a tangible benefit?

We analyzed our three SQL generators’ individual and combined performance (EX and UB-EX) on BIRD-Dev (Table 5, Figure 5). While all generators perform well individually (peaking at 70.9% EX), combining them in our N-version module already yields a 71.7% EX. The true strength of this approach, however, lies in its potential: the combined UB-EX reaches **81.1%**, a significant +2.6% gain over the best individual generator’s potential (78.5%). This



(a) EX Correctness Overlap. (b) UB-EX Correctness Overlap.

Figure 5: Correctness overlap analysis of three SQL generation methods using Qwen3-Coder-30B-A3B model on BIRD-Dev dataset.

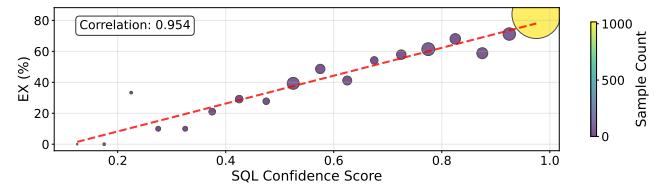


Figure 6: Execution accuracy vs. SQL confidence on BIRD-Dev dataset with Qwen3-Coder-30B-A3B model.

Table 6: Performance comparison with different SQL selection methods on BIRD-Dev dataset.

Selection Methods	BIRD-EX (%)	Spider-EX (%)
<i>Gemma3-27B-Instruct</i>		
Consistency-based Voting	70.1	88.3
Confidence-aware SQL Selection	71.1 (↑1.0)	88.9 (↑0.6)
<i>Owen2.5-Coder-32B-Instruct</i>		
Consistency-based Voting	70.2	88.2
Confidence-aware SQL Selection	70.9 (↑0.7)	88.7 (↑0.5)
<i>Qwen3-Coder-30B-A3B-Instruct</i>		
Consistency-based Voting	72.7	89.7
Confidence-aware SQL Selection	73.5 (↑0.8)	89.8 (↑0.1)

UB-EX increase confirms that the generators possess crucial diversity, solving different subsets of problems where one’s failure is covered by another’s success. The overlap analysis (Figure 5b) corroborates this: while 70.9% of correct answers are found by all three generators, a significant **10.2%** are solved by only one or two. This proves the generators are not redundant. This engineered diversity—finding a correct answer for 81.1% of questions—validates our fault-tolerant design and provides the rich candidate pool essential for achieving state-of-the-art performance

5.5 Confidence-aware SQL Selection Analysis

RQ5: Can a selection mechanism that leverages voting confidence outperform traditional consistency-based voting, and what is the motivation for such a design?



Figure 7: Execution accuracy vs. Confidence Shortcut Threshold on BIRD-Dev dataset with Qwen3-Coder-30B-A3B model.

To answer this, we first analyze the relationship between voting confidence and correctness, and then present a direct comparison of our method against the standard self-consistency approach.

The core motivation behind our *Confidence-aware SQL Selection* is the observation that the reliability of consistency-based voting is highly dependent on the degree of consensus among the generated candidates. To validate this premise, we visualized the SQL confidence score (defined as the proportion of candidates in the largest execution cluster) against the actual execution accuracy for our results on the BIRD-Dev dataset. As visualized in Figure 6, there is a remarkably strong positive correlation between these two factors, with a Pearson correlation coefficient [38] of **0.954**. This result confirms that when the confidence score is high, the top-ranked SQL is very likely to be correct. Conversely, in low-confidence scenarios where candidates produce many different results, standard voting is unreliable. This insight directly informs our two-path design: a “shortcut” for high-confidence cases and a more discerning “full review” for low-confidence ones.

To quantify the effectiveness of this design, we compared its performance against traditional Consistency-based Voting [7, 15] across three different base models. The results are shown in Table 6. For every model and on both the BIRD and Spider datasets, our method yields a notable improvement in execution accuracy. For instance, with Gemma3-27B-Instruct, our method improves the EX on BIRD by 1.0%, from 70.1% to 71.1%. This analysis validates that by identifying and re-evaluating ambiguous, low-confidence scenarios instead of blindly trusting the majority vote, our method achieves a more robust and accurate final selection.

RQ6: How sensitive is the framework’s performance to the choice of the confidence shortcut threshold (θ_{conf})?

To evaluate the robustness of our selection mechanism, we conducted a sensitivity analysis on the confidence shortcut threshold, θ_{conf} . This threshold determines the trade-off between taking the efficient shortcut and triggering the full, LLM-based review. As shown in Figure 7, we varied θ_{conf} from 0.0 (always perform full review) to 1.0 (always take the shortcut) and observed the impact on execution accuracy. The results demonstrate that our framework’s performance is robust across a wide range of threshold values. The accuracy remains high and stable, peaking at 73.5% with a threshold of 0.6, and staying above 73.0% for all values between 0.4 and 1.0. This indicates that our method is not overly sensitive to the precise choice of this hyperparameter.

5.6 Ablation Study

RQ7: What is the contribution of each key component to the overall performance of the DEEPEYE-SQL framework?

Table 7: Ablation study of DEEPEYE-SQL with Qwen3-Coder-30B-A3B on BIRD-Dev dataset.

Configuration	EX (%)	Delta (%)
DEEPEYE-SQL	73.5	-
- w/o Semantic Value Retrieval	71.4	-2.1
- w/o Robust Schema Linking	71.8	-1.7
- w/o Skeleton-based SQL Generation	72.2	-1.3
- w/o ICL-based SQL Generation	71.0	-2.5
- w/o D&C-based SQL Generation	72.3	-1.2
- w/o SQL Unit Testing and Revision via Tool-Chain	71.4	-2.1
- w/o Confidence-aware SQL Selection	72.7	-0.8

Table 8: Efficiency Comparison on BIRD-Dev with Qwen3-Coder-30B-A3B model.

Methods	Avg. Input Tokens (K)	Avg. Output Tokens (K)	EX (%)
CHESS (IR,SS,CS)	327.02	27.83	67.9
Alpha-SQL	138.03	72.21	71.2
DEEPEYE-SQL	23.21	23.16	73.5
- Semantic Value Retrieval	0.67	0.03	-
- Robust Schema Linking	13.91	6.33	-
- N-version Programming for SQL Generation	5.28	11.38	-
- SQL Unit Testing and Revision via Tool-Chain	3.16	5.41	-
- Confidence-aware SQL Selection	0.19	0.01	-

To understand the impact of each module, we conducted an ablation study on the BIRD-Dev dataset by progressively removing one component at a time. The results are detailed in Table 7.

The primary conclusion is that every component makes a positive and integral contribution, as removing any single module degrades performance. The *ICL-based SQL Generation* is the most critical individual module, with its removal causing the largest performance drop of **2.5%**. *Semantic Value Retrieval* and *SQL Unit Testing and Revision via Tool-Chain* are also highly impactful, each accounting for a **2.1%** gain. This highlights the necessity of grounding the LLM in real data and externalizing the debugging process. The significant contributions from the SQL generation modules and the selection mechanism confirm the value of our N-version programming and confidence-aware selection strategies. Overall, the results confirm that the high performance of DEEPEYE-SQL is not due to any single component, but rather the synergistic collaboration of all modules in its carefully designed pipeline.

5.7 Efficiency Analysis

RQ8: How does DEEPEYE-SQL’s efficiency, in terms of token consumption, compare to other state-of-the-art prompting-based frameworks?

To answer this, we conducted a cost study to evaluate the token efficiency of our framework. While system latency is an important practical concern, it is highly sensitive to external factors such as hardware and deployment configuration. Therefore, we use token efficiency (both input and output) as a more objective and reproducible metric for the cost of LLM-based systems.

The results of our efficiency comparison on the BIRD-Dev dataset are presented in Table 8. The data clearly shows that DEEPEYE-SQL is substantially more token-efficient than other high-performing methods, while also achieving superior accuracy. For instance,

Alpha-SQL consumes nearly **6×** more input tokens (138.03K vs. 23.21K) and CHESS consumes over **14×** more (327.02K vs. 23.21K) than our method, yet both achieve lower execution accuracy. This demonstrates that DEEPEYE-SQL’s carefully designed pipeline does not rely on brute-force context stuffing; instead, it uses a structured and efficient reasoning process. The table also provides a breakdown of token consumption for each module within our pipeline. As expected, the most cost-intensive stages are *Robust Schema Linking* and *N-version Programming for SQL Generation*, where the core reasoning and generation occurs. In contrast, other modules like Semantic Value Retrieval and Confidence-aware SQL Selection are remarkably lightweight, adding minimal overhead.

6 Conclusion

In this paper, we presented DEEPEYE-SQL, which reframes Text-to-SQL as a verifiable SDLC-style workflow. By unifying semantic grounding, N-version programming, deterministic tool-chain verification, and confidence-aware selection, DEEPEYE-SQL enforces end-to-end correctness and achieves system-level reliability. Extensive experiments validate that, using ~30B open-source LLMs without fine-tuning, DEEPEYE-SQL achieves 73.5% EX on BIRD-Dev and 89.8% on Spider-Test, outperforming the state of the art. Our results suggest that principled orchestration offers a promising path toward system-level reliability in Text-to-SQL, beyond relying on LLM scaling alone.

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