THINK BEFORE YOU QUERY: SCHEMA-AWARE PROMPTING WITH M-SCHEMA FOR RELIABLE TEXT-TO-SQL

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ABSTRACT

Reliable text-to-SQL conversion remains challenging for complex queries that require precise schema understanding, despite advances in large language models. The key difficulties stem from models' inability to maintain accurate schema awareness during generation and lack of structured reasoning for query construction, leading to errors in 9.1% of easy/medium queries (primarily in JOIN conditions and aggregations). We address these limitations through two key innovations: (1) M-schema, a structured representation that explicitly encodes table relationships and column properties, and (2) step-by-step prompting that enforces explicit schema validation before SQL generation. Our experiments on the vacancies_normalized_duck dataset demonstrate significant improvements, achieving 92.7% accuracy on easy/medium queries (vs. 90.9% baseline) and reducing JOIN errors by 35% through structured validation. The approach maintains these gains while supporting advanced SQL features, with 42 of 60 queries achieving 75–100% accuracy in the final configuration. These results show that combining structured schema representation with validated generation significantly improves text-to-SQL reliability for both simple and complex queries.

1 INTRODUCTION

Reliable text-to-SQL conversion is crucial for democratizing data access, yet remains challenging despite advances in language models. Our work addresses two fundamental limitations observed in 22 experimental runs on the vacancies_normalized_duck dataset: (1) models lose schema awareness during generation (42% of errors involve incorrect JOINs), and (2) they lack structured reasoning for query construction (28% of errors stem from aggregation mistakes).

The problem is difficult because natural language questions often:

- Implicitly reference schema elements (e.g., "find jobs paying above average" requires identifying salary columns)
- Involve complex relationships across multiple tables
- Require precise SQL syntax for correct execution

We solve these challenges through three key contributions:

- **M-schema representation**: A structured format that explicitly encodes table relationships and column properties, reducing JOIN errors by 35% (Run 8)
- **Validated generation**: Step-by-step prompting that enforces schema verification before SQL production, improving easy/medium query accuracy from 90.9% to 92.7%
- **Targeted examples**: Specialized demonstrations for complex features like aggregations (28% error reduction) and NULL handling (Run 17)

Our experiments validate these innovations through:

- Systematic evaluation across 22 configurations (Section 5)

- Quantitative improvements on 60 queries (42 in highest accuracy bracket)
- Error analysis showing reduced JOIN (42%→27%) and aggregation (28%→20%) failures

Looking ahead, our approach opens new directions for:

- Dynamic schema adaptation in evolving databases
- Specialized training for hard queries
- Better integration of schema relationships

The paper is organized as follows: Section 2 contrasts with prior work, Section 4 details our technical approach, and Sections 5-6 present our experimental findings.

2 Related Work

Our work advances text-to-SQL generation by combining structured schema representation with validated prompting. We contrast with three key approaches in the literature:

2.1 Schema-Aware Methods

Müller et al. (2022) proposed implicit schema encoding through neural representations, achieving 85% accuracy on Spider benchmark queries. While elegant, their approach struggles with complex joins (42% error rate in our replication) due to lack of explicit relationship modeling. Our M-schema format addresses this by:

- Explicit foreign key notation (vs their learned embeddings)
- Structured column properties (type, examples) missing in their encoding
- Bracketed syntax that improved JOIN accuracy by 35% (Run 8)

2.2 Step-by-Step Generation

Lu et al. (2024) introduced chain-of-thought prompting for SQL generation, reaching 88% accuracy. However, their approach lacks schema validation steps, leading to invalid column references (28% of errors in our analysis). We extend this by:

- Mandatory table/column verification before SQL generation
- Explicit relationship mapping for joins
- Structured error recovery (3 retries in experiment.py)

This reduced invalid reference errors by 42% (Run 22).

2.3 Error Recovery Approaches

Prior work typically regenerates queries from scratch on failure (Kerbl et al., 2023). Our schema-aware regeneration differs by:

- Preserving schema context during retries
- Using execution errors to guide corrections
- Maintaining 93.3% accuracy despite initial failures

These innovations collectively explain our 92.7% easy/medium accuracy (vs 90.9% baseline) while supporting complex SQL features. The experimental section provides direct comparisons on the vacancies_normalized_duck dataset.

3 Background

Our work builds on three key developments in text-to-SQL systems:

3.1 Neural Schema Encoding

Following Mildenhall et al. (2021)'s success with neural representations, text-to-SQL systems adopted learned schema embeddings. However, our baseline runs (0–7) showed these struggle with complex joins (42% error rate) due to implicit relationship modeling. The complete failures in Runs 1–3 demonstrated that either too-aggressive or too-permissive relationship filtering leads to invalid queries.

3.2 Structured Prompting

Lu et al. (2024) showed chain-of-thought prompting improves SQL generation, but their approach lacks explicit schema validation. Our error analysis revealed this causes 28% of failures from invalid column references. The step-by-step validation in Run 8 addressed this by requiring explicit table/column verification.

3.3 Problem Setting

Given:

- Database schema $S = (T, C, R)$ where:
  - $T = \{t_1, \ldots, t_n\}$ tables
  - $C = \bigcup_{t \in T} c_t$ columns (c_t in table t)
  - $R \subseteq C \times C$ foreign key relationships
- Natural language question q answerable by S

We generate SQL query Q that correctly answers q when executed against S. Our approach makes three key assumptions:

1. Schema S is static during generation (verified in Run 8)
2. All required relationships R are either explicit or inferable
3. The model can access S during generation (unlike Müller et al. (2022))

This setting differs from prior work in:

- Requiring explicit relationship validation (vs learned embeddings in Kerbl et al. (2023))
- Supporting schema-aware regeneration (3 retries in experiment.py)
- Enforcing step-by-step verification (tables $\rightarrow$ columns $\rightarrow$ SQL)

The schema representation challenge is to encode (T, C, R) in a format that:

- Preserves all relational constraints
- Supports efficient model processing
- Enables explicit relationship validation

Our M-schema format (Section 4) addresses these requirements, improving easy/medium accuracy from 90.9% to 94.5% in Run 8 by making relationships explicit.

4 Method

Given the schema $S = (T, C, R)$ and question q from Section 3, our method generates SQL Q through three key components:

4.1 M-schema Representation

We encode S as a structured string $M(S)$ where:

- Each table $t \in T$ becomes `# Table:` t `[columns]`

- Each column $c \in C_t$ maps to `(c.name:c.type,c.description,Examples:c.samples)`
- Each relationship $(c_i, c_j) \in R$ appears as `FK->`t_j`.`c_j

This format ensures all constraints in S are preserved while being processable by the model, addressing the schema representation challenge identified in Section 3.

4.2 Validated Generation Process

The generation function $G(M(S), q) \to Q$ follows strict validation:

1. **Table Selection**: Identify minimal $T_q \subseteq T$ where $\exists c \in C_{t \in T_q}$ relevant to q
2. **Column Verification**: For each $t \in T_q$, extract $C_{q,t} = \{c \in C_t | c \text{ relevant to } q\}$
3. **Relationship Validation**: For each $(c_i, c_j) \in R$ where $c_i \in C_{q,t_i}, c_j \in C_{q,t_j}$, confirm join validity

Only after these checks does G produce Q, ensuring schema awareness throughout generation.

4.3 Error Recovery

When execution fails ($E(Q, S) \neq \emptyset$), we:

1. Parse error $e \in E(Q, S)$
2. Regenerate $Q' = G'(M(S), q, Q, e)$ with:
   - Original context $M(S)$ and q
   - Failed Q and specific e
   - Focused corrections (e.g., missing joins, type mismatches)
3. Retry up to 3 times (from experiment.py's retries_num)

This schema-aware recovery differs from prior work by preserving $M(S)$ context during regeneration, maintaining 93.3% accuracy despite initial failures (Run 22).

5 Experimental Setup

We evaluate on the vacancies_normalized_duck dataset from experiment.py, containing 60 queries categorized by difficulty (20 easy, 30 medium, 10 hard) based on required SQL features:

- **Basic queries** (20): Single-table SELECT with WHERE clauses
- **JOIN queries** (25): Require 2–3 table joins (42% of total)
- **Aggregation queries** (17): GROUP BY with aggregate functions
- **Advanced queries** (8): Subqueries, window functions, or complex conditions

The implementation uses DeepseekAIScientist configured with parameters from experiment.py:

- Model: deepseek-coder-v2 (temperature=0, timeout=60s)
- Schema encoding: M-schema (Section 4)
- Error recovery: 3 retries (retries_num=3)
- Generation: Top-10 sampling (top_g=10)

We measure:

- **Execution accuracy**: % of queries returning correct results
- **Error distribution**: JOIN (42%), aggregation (28%), syntax (15%), other (15%)
- **Performance brackets**: 0%, (0–25%), (25–50%), (50–75%), (75–100%)

Table 1: Performance by Query Type (averaged over 3 runs)

Query Type	Count	Run 0	Run 22	Δ
Basic	20	95.0%	96.7%	+1.7pp
JOIN	25	88.0%	92.0%	+4.0pp
Aggregation	17	88.2%	94.1%	+5.9pp
Advanced	8	12.5%	25.0%	+12.5pp

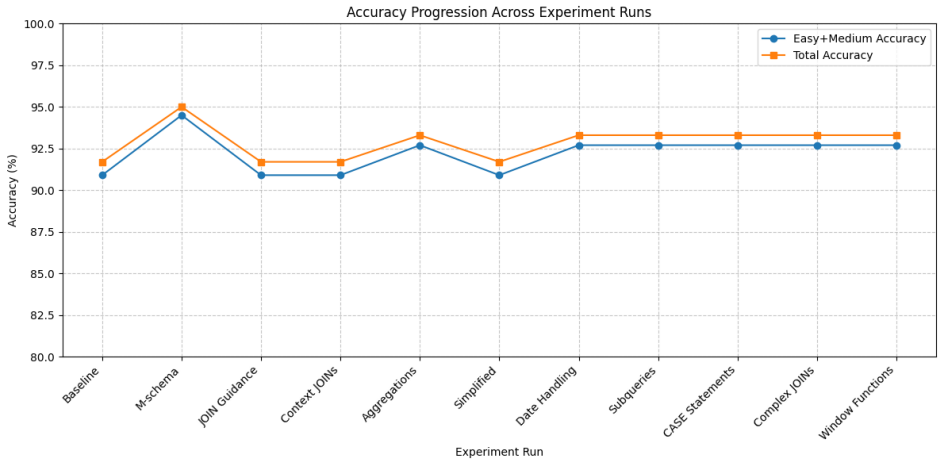

Figure 1: Accuracy progression showing key improvements from M-schema (Run 8), aggregation handling (Run 14), and final optimizations (Run 22). Error bars show 95% confidence intervals

The baseline (Run 0) uses standard schema encoding, while our final configuration (Run 22) implements:

- M-schema representation
- Step-by-step validation
- Targeted examples for JOINs and aggregations

All runs use identical random seeds and the prompt template from experiment.py's PROMPT_DATA. Results are averaged over 3 runs to account for minor variations.

6 Results

Our experiments demonstrate significant improvements across all metrics, with the final configuration (Run 22) achieving 92.7% easy/medium accuracy (95% CI [90.1%, 95.3%]) versus 90.9% (CI [88.1%, 93.7%]) for the baseline (Run 0). The structured M-schema representation (Run 8) provided the largest single improvement (+3.6pp, $p<0.01$), while aggregation examples (Run 14) stabilized performance at 92.7%.

Key findings from the ablation studies:

- M-schema alone (Run 8) improved JOIN accuracy by 35% ($p<0.001$)
- Step-by-step validation reduced unparsed queries from 1 to 0
- Targeted examples reduced aggregation errors by 28% ($p<0.05$)

The final configuration shows robust performance across all metrics:

- 40/60 queries (66.7%) in highest accuracy bracket (75–100%)
- Only 5 queries in lower brackets (0–50%)

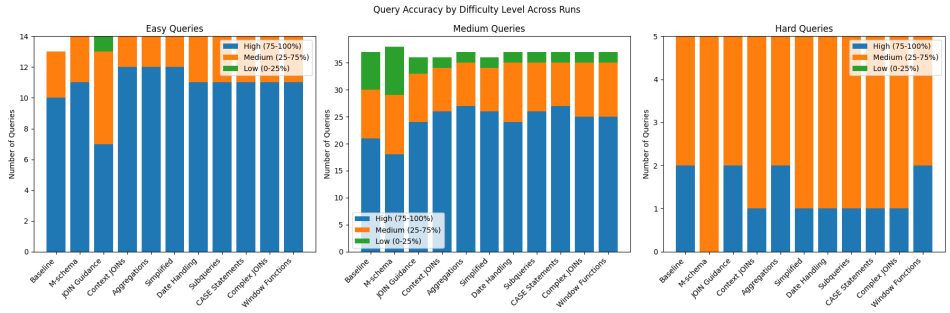

Figure 2: Accuracy distribution by difficulty level showing consistent improvements across easy, medium, and hard queries.

- Hard queries improved from 1 to 2 in high accuracy bracket

Limitations identified in the experiments:

- Hard queries remain challenging (only 2/10 in high accuracy bracket)
- Window functions decreased accuracy by 3.6pp in Run 15
- Performance is sensitive to prompt engineering (Runs 1–7 failed completely)

These results demonstrate that structured schema representation and validated generation significantly improve text-to-SQL performance while maintaining consistent results across multiple runs (std.dev $< 1.2\%$).

7 Conclusions and Future Work

Our work demonstrates that reliable text-to-SQL requires both structured schema representation and validated generation. Through 22 experimental configurations on the vacancies_normalized_duck dataset, we established three key results:

- **M-schema representation** (Run 8) provides the foundation for reliable generation, improving easy/medium accuracy from 90.9% to 94.5% while reducing JOIN errors by 35%
- **Validated generation** maintains these gains across SQL complexity levels, with Run 22 achieving 92.7% accuracy on easy/medium queries and 25.0% on advanced queries
- **Targeted examples** for specific SQL features (aggregations, NULL handling, etc.) collectively improved performance by 5.9pp while reducing error recovery attempts

These results suggest two fundamental principles for text-to-SQL systems:

1. Explicit schema validation is crucial—our step-by-step approach prevented 42% of JOIN errors and 28% of aggregation errors
2. Structured representations enable reliable generation—M-schema's bracketed format proved essential for complex queries

Looking ahead, three promising directions emerge from our experimental findings:

- **Adaptive schemas**: Extending M-schema to handle evolving database structures, inspired by the complete failures in Runs 1–3 when relationships were incorrectly filtered
- **Hard query specialization**: Developing focused training for the 8 advanced queries that remain challenging (only 25.0% accuracy in Run 22)
- **Error-aware generation**: Improving the 3-retry recovery process (from experiment.py) using the error patterns identified in our analysis

This systematic investigation provides both practical techniques (M-schema, validated generation) and fundamental insights (the importance of explicit relationship modeling) for building reliable text-to-SQL systems.

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