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Original Article

Ensuring Data Accuracy in Text-to-SQL Systems: A Comprehensive Validation Framework

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Abstract *- A text-to-SQL framework is a system that converts natural language questions or commands into valid SQL queries that can be executed against a database. These frameworks combine Natural Language Processing (NLP) techniques with database schema understanding to interpret user intent and generate accurate SQL queries, making databases accessible to users without expertise in SQL programming. Text-to-SQL systems are rapidly gaining adoption across enterprise-scale applications, where data accuracy and query precision are of utmost importance to business operations. As these systems become integral to critical business processes, ensuring the accuracy of automatically generated SQL queries is emerging as one of the fundamental challenges. This growing reliance on natural language database interactions urgently needs robust validation frameworks to verify and guarantee the precise translation of user intent into SQL queries. This paper thoroughly analyzes current validation techniques used in text-to-SQL systems, identifying their strengths and limitations in real-world applications. Building on this foundational research, the article introduces an innovative validation framework encompassing multiple critical aspects: robust query construction validation, systematic data integrity verification, automated feedback generation, and intelligent error detection and correction mechanisms. This comprehensive approach validates SQL queries at multiple stages and ensures data accuracy through a sophisticated pipeline of checks and balances, ultimately delivering reliable and precise database interactions.*

Keywords *- Agentic automation, Data accuracy, Large Language Model (LLM), Text-to-SQL, Validation framework.*

1. Introduction

Text-to-SQL[1], converting natural language texts into Structured Query Language(SQL) commands, helps the users to interact with databases using day-to-day language as input instead of traditional SQL syntax, leveraging the power of extensive language processing (NLP) and machine learning algorithms; this facilitates the users of any skill level to interact with databases seamlessly.

While the technology helps users simplify interactions with complex databases, ensuring data accuracy is critical for various reasons. If the data fed into the system is inaccurate, the resulting SQL generated will lead to incorrect or misleading results.

Ensuring the correctness, efficiency, and reliability of the data querying process helps businesses or organizations trust the data behind Text-to-SQL for critical business decision-making, better user experiences, and effective use of resources.[2] Text-to-SQL faces several challenges in validating syntaxes generated from natural languages, with complex syntax functions such as CONNECT BY, SYSDATE, etc., in widely used databases such as Oracle. SQL models struggle to translate user requests accurately. On top of complex functions, databases like Oracle have complex and nested schemas, large volumes of tables, and relations to various other tables with normalization and appropriate joins and columns to be selected, which may lead to inconsistent results.

2. Existing Validation Method

For benchmarking[4] TEXT-to-SQL, there are two major datasets available: SPIDER[8] and BIRD. 2 key factors to keep in mind, *Execution Accuracy(EA)* and *Exact Match (EM)*, can be used for the evaluation of a solution

2.1. Current Benchmarks and Datasets

2.1.1. SPIDER

SPIDER [12] is a benchmark dataset for text-to-SQL parsing introduced in 2018. It contains over 10,000 natural language questions and covers around 200 complex databases across more than 100 domains. It includes 5000+ unique complex SQL queries and has separate train/development/test sets.

Some of its key Features are listed below:

- Cross-domain: Tests generalization across different database schemas
- Complex queries: Includes joins, nested queries, aggregations, and more.
- Zero-shot capability testing: Evaluates performance on unseen databases

It uses Evaluation Metrics like Exact Match (EM), which evaluates Binary scores for perfectly matched queries. Component Matching (CM), which derives partial credit for correct SQL components. It is one of the Industry standards for measuring text-to-SQL capabilities and is more challenging than earlier benchmarks like WikiSQL.

However, it has the following challenges;

- Top-performing models can only achieve around 75-80% execution accuracy.
- The human performance benchmark is approximately 88%
- It is still challenging for most models due to complex schema understanding requirements

2.1.2. BIRD

BIRD [13] (Benchmarking Interpretable Reasoning in Databases) is a benchmark dataset, a significant advancement in evaluating LLMs' database reasoning capabilities. It is a reasonably new benchmark released in 2023. It focuses on complex database reasoning tasks. It is much more challenging than earlier benchmarks like SPIDER and emphasizes real-world business scenarios.

Its Dataset Composition contains more than 12000 total samples across 90+ databases and covers 35+ industries/domains. It works across three task categories: Text-to-SQL generation, SQL-to-text explanation, and Database schema understanding.

Some of its key Features are listed below;

- Multi-turn reasoning requirements
- Complex business logic evaluation
- Domain-specific knowledge testing
- It has a longer and more detailed context compared to SPIDER
- It requires both SQL writing and natural language understanding

It uses Evaluation Metrics like Execution Accuracy (EA), Logic Correctness, Natural Language Generation quality, and Test-suite-based evaluation.

Its key challenges are listed below;

- Challenges with SQL with Multi-table joins (often 5+ tables)
- Does not perform well with nested queries and complex conditions
- Limitations in Business Logic Comprehension
- Limitations with Financial and mathematical calculations

2.2. Evaluation Metrics

2.2.1 Execution Accuracy (EA)

Execution Accuracy (EA) metric is a commonly used evaluation metric [14] in text-to-SQL benchmarks. It measures whether the SQL query generated by the LLM produces the same result as the ground truth query. It compares the results row-by-row and value-by-value and returns a binary score (1 for match, 0 for mismatch).

Example of the calculation process

```
-- Ground Truth Query:
SELECT Empname, COUNT(*) as count
FROM employees
GROUP BY Empname
HAVING count > 2;

-- Model Generated Query:
SELECT Empname, COUNT(id) as count
FROM employees
GROUP BY Empname
HAVING COUNT(id) > 2;
```

Both queries would be executed, and results would be compared. If output tables match exactly → EA = 1 if Any difference in results → EA = 0.

This matrix is Order-insensitive for unordered queries and performs case-sensitive string comparisons. It handles NULL values appropriately and considers numerical precision/rounding. It accounts for equivalent SQL variations.

This matrix is more reliable than string matching. It captures semantic equivalence and handles multiple valid SQL solutions. It gives the practical measure of real-world utility.

Limitations include:

- Requires executable queries
- It does not evaluate query efficiency
- it cannot handle non-deterministic functions
- It does not assess query readability/maintainability

2.2.2. Exact Match (EM)

The Exact Match (EM) evaluation metric is key for assessing performance in text-to-SQL benchmarks like SPIDER and BIRD. These datasets focus on evaluating the ability of models to translate natural language questions into structured SQL queries. In this context, EM provides a strict

assessment of correctness by determining whether the model-generated SQL query is identical to the reference SQL query.

How EM is Used in Text-to-SQL Benchmarks.
Exact Query Match

A generated SQL query is considered correct if it matches the ground truth SQL in terms of both syntax and semantics. The comparison may include normalizations, such as ignoring differences in whitespace or formatting, to avoid penalizing stylistic variations.

- Normalization in EM and Common practices to ensure fairness
  - Case Insensitivity: SQL keywords like SELECT vs. select are treated as equivalent.
  - Ordering of Clauses: Non-semantic reordering (e.g., WHERE conditions) is allowed if the queries are logically equivalent.
  - Whitespace Removal: Differences in spacing, tabs, or newlines are ignored.

The formula used for EM
EM = (Number of Correctly Predicted Queries / Total Number of Queries) × 100

Its advantages include Strict Evaluation,e, ensuring that models generate syntactically and logically correct SQL queries, and Benchmark Comparability, i.e., providing a consistent and easy-to-understand metric for comparison across models.

Some of its key limitations are:
Overly Strict:
It fails to account for semantically equivalent SQL queries with different syntactic representations.
For Example:

Ground truth: SELECT name FROM students WHERE age > 18

Prediction: SELECT name FROM students WHERE 18 < age

This will not be considered an EM match despite being semantically identical.

Focus on Syntax:
A model might achieve high EM but fail in real-world generalization if it overfits the dataset's query patterns.

2.2.3.Valid Efficiency Score (VES)

The Valid Efficiency Score (VES) is a relatively recent evaluation metric proposed for text-to-SQL tasks, particularly to address challenges in efficiency and Query correctness. It balances the trade-off between generating valid SQL queries and optimizing for computational efficiency in real-world usage scenarios. This metric is especially relevant for datasets or settings where robustness and performance matter.

Key Concepts Behind VES

Validity: It measures whether the generated SQL query is syntactically correct and executable on the database schema. Invalid queries (e.g., syntax errors or using nonexistent table/column names) receive a score of 0.

Efficiency: it considers the execution time and resource usage of the generated Query. It penalizes queries that, while valid, are inefficient due to excessive computational overhead, such as redundant joins, unnecessary subqueries, or poor indexing usage.

Combining Validity and Efficiency: The Valid Efficiency Score combines these aspects into a unified metric, rewarding correctness and computational optimization.

The VES metric is computed as:

$$VES = V \times (1 - (E / T))$$

Where:
V: Binary validity indicator (1 if the Query is valid, 0 otherwise).
E: Actual execution time or cost of the generated Query.
T: Execution time or cost of an optimized (ideal) query for the same task.

If $E >$, $1 - (E / T)$ becomes negative, effectively penalizing inefficient queries.

VES=0 for invalid queries or those with excessive execution costs.

Some of its key limitations are;

Dependency on Database Configuration: Execution times and costs can vary based on hardware, indexing, and database implementation, making results less reproducible across systems.

Complexity of Optimization: Requires generating or assuming an optimized ground-truth query for fair comparison.

Execution Overhead: Running and profiling queries for every model prediction is resource-intensive, especially on large datasets.

3. Designing a Comprehensive Validation Framework

3.1. Key Components of the Text to SQL Framework

Building a Text-to-SQL framework involves multiple interconnected components to ensure accuracy, performance,

and reliability. Below is a detailed breakdown of these components with examples:

3.1.1. Query Construction

This component translates natural language (NL) input into a valid SQL query. Key steps include Natural Language Parsing, Schema Mapping and SQL syntax generation. For example, "Show the total sales for *each product in 2023."*

Parse Intent:

Action: "Show" → SELECT

Aggregation: "Total sales" → SUM(sales_amount)

Grouping: "By each product" → GROUP BY product_name

Filter: "In 2023" → WHERE year = 2023

Map to Schema:

sales_amount → metric column in the sales table

product_name → attribute in the products table

year → attribute in sales table

Generate SQL:

```
SELECT product_name, SUM(sales_amount) AS
total_sales FROM sales JOIN products ON
sales.product_id = products.product_id WHERE year =
2023 GROUP BY product_name;
```

3.1.2. Query Validation

Query validation ensures that the generated SQL query is accurate, secure, and aligned with the database schema. Key aspects include:

Schema Validation

Schema validation ensures that referenced tables and columns exist in the database. It also validates relationships between the tables (e.g., foreign keys). Example:

```
def validate_schema(query, schema_metadata):
    for column in Query.columns:
        if column not in
schema_metadata['columns']:
            raise ValueError(f"Invalid column:
{column}")
```

SQL Syntax Validation

SQL syntax validation ensures that Query can be executed in the targeted databases. A few options to validate query syntax are an SQL parser or running EXPLAIN to check syntax. This helps to find any syntax issues before executing the actual SQL in the database.

Access Control Validation

Access control validation ensures the user has permission to query tables/columns. The access and security control should be verified at both the object and data levels. Restrict sensitive fields like ssn.

Alternatively, if a salesperson is trying to access HR data, he should not be allowed to access such information. A sales manager of Territory A should not be able to access records from the same table as Territory B.

Semantic Validation

Semantic validation is one of the critical validation steps and ensures logical correctness (e.g., aggregations match grouping).

e.g.SELECT product_name, SUM(sales_amount), year FROM sales GROUP BY product_name;
Fix: Add year to the GROUP BY clause.

3.1.3. Data Integrity Checks

Data Integrity checks ensure data correctness, consistency, and security in query results. Uniqueness checks, referential integrity checks, range and boundary checks, business rule compliance checks, duplicate data, and date or regex format checks are examples of data integrity checks.

Validation of Constraints

Confirm results adhere to database constraints. Example: Validate NOT NULL columns

```
SELECT * FROM sales WHERE sales_amount IS NULL; --
Should return 0  rows
```

SELECT * FROM sales WHERE sales_amount IS NULL; -- Should return 0 rows

Sanitization to Prevent SQL Injection

Escape user inputs or use parameterized queries.

Example

query = "SELECT * FROM users WHERE username = %s"
cursor.execute(query, (user_input,))

Type Matching: Ensure values in the query match expected column data types. Example:

SELECT * FROM sales WHERE year = '2023'; -- Invalid type

Consistency Validation: Consistency Validation cross-checks results for anomalies (e.g., total sales mismatch across reports).

Check consistency

SELECT SUM(sales_amount) AS total_sales FROM sales;
SELECT total_sales FROM sales_summary WHERE year = 2023;

3.1.4. Feedback and Debugging Mechanisms

Provide a mechanism for users to clarify ambiguous terms caused by schema changes. Eg.

- Detect unresolved column or table names
- Prompt the user for clarification (e.g., "Did you mean order_date or transaction_date?"). Use dialogue systems to refine queries iteratively.

For example, use "Show me sales."
System: "Do you want total sales or sales for a year?"

- Provide debugging details: "Error: Column 'quarter' not found in schema."
- Update the alias map or framework logic based on user input.

3.2. Error Correction in Text-to-SQL Systems

3.2.1. Refining Prompts with Language Models

This involves crafting effective, precise, schema-aware prompts to guide language models in generating accurate SQL queries from natural language inputs. By iteratively improving the prompt, the system can handle ambiguities, adapt to user intent, and provide robust query generation.

Example:
User Query: "List customer purchases."
Refined Prompt: "Using the schema where clients contain customer details and transactions containing purchases, list all transactions for each client."

3.2.2. Dynamic Schema Updates

Adapting to evolving schemas where column names or table structures change could be challenging. Hence, alias maps can be maintained for renamed or modified schema elements. Example:

Schema Change: order_date → transaction_date.
Correction: Replace references to order_date dynamically.

3.2.3. Contextual Error Correction

Contextual Error Correction is a process designed to identify, diagnose, and fix errors in SQL queries generated from natural language inputs. These errors might arise due to ambiguous or incomplete input queries, misinterpreting user intent, or mismatches between the query and database schema.

By leveraging contextual knowledge—such as database schema, query execution results, and prior user interactions—this approach aims to refine the SQL query to ensure correctness and efficiency iteratively.

3.2.4. Synonym and Ontology Mapping

Synonym and Ontology Mapping Use LMs to infer user intent and correct errors. The idea is to map user-provided terms to schema elements using synonym dictionaries or embeddings.

Example**:**
User Query: *"Get client orders."* Mapping: clients → customers, orders → transactions.

3.2.5. Disambiguation Prompts

Determining disambiguation prompts is a mechanism used to resolve ambiguities in user queries. Natural language queries often lack precision or context, leading to multiple possible SQL interpretations. A disambiguation prompt clarifies user intent and ensures the generated SQL accurately represents the desired Query. Example: User Query: "Give me the order volume trend for the last 3 months."

System Response: "Would you like to get order volume by order quantity or order amount?"

3.2.6. Iterative Refinement

Iterative refinement uses results or feedback to refine queries iteratively. Refers to progressively improving SQL queries generated by a model to better align with user intent or database requirements. This approach is particularly useful when the initial Query might be incorrect, incomplete, or suboptimal. Iterative refinement combines user feedback, execution feedback, and systematic query updates.

For Example:
Initial Query: "Get revenue for 2025."
Execution Result: "Empty dataset."
System Suggestion: "No data for 2025. Check for previous years or relax your filters."

3.2.7. Reinforcement Learning from Execution Feedback

This is a promising approach for improving the quality and robustness of SQL generation models. By leveraging feedback obtained during query execution, models can learn to correct errors, optimize performance, and generalize to unseen schemas.

Technique: The fundamental is to reward SQL generation models for producing correct and efficient queries based on feedback from database query execution. Example: Train the model to avoid generating subqueries when simple joins suffice.

4. System Architecture and Implementation

4.1. Architectural Flow

The architecture leverages both LangGraph[5] and AutoGen[6][7] to create a robust Text-to-SQL validation framework, implementing a state-driven approach with multi-agent collaboration.

4.1.1. LangGraph Implementation using Python

```
from langgraph.graph import StateGraph
from langchain import PromptTemplate, LLMChain
```

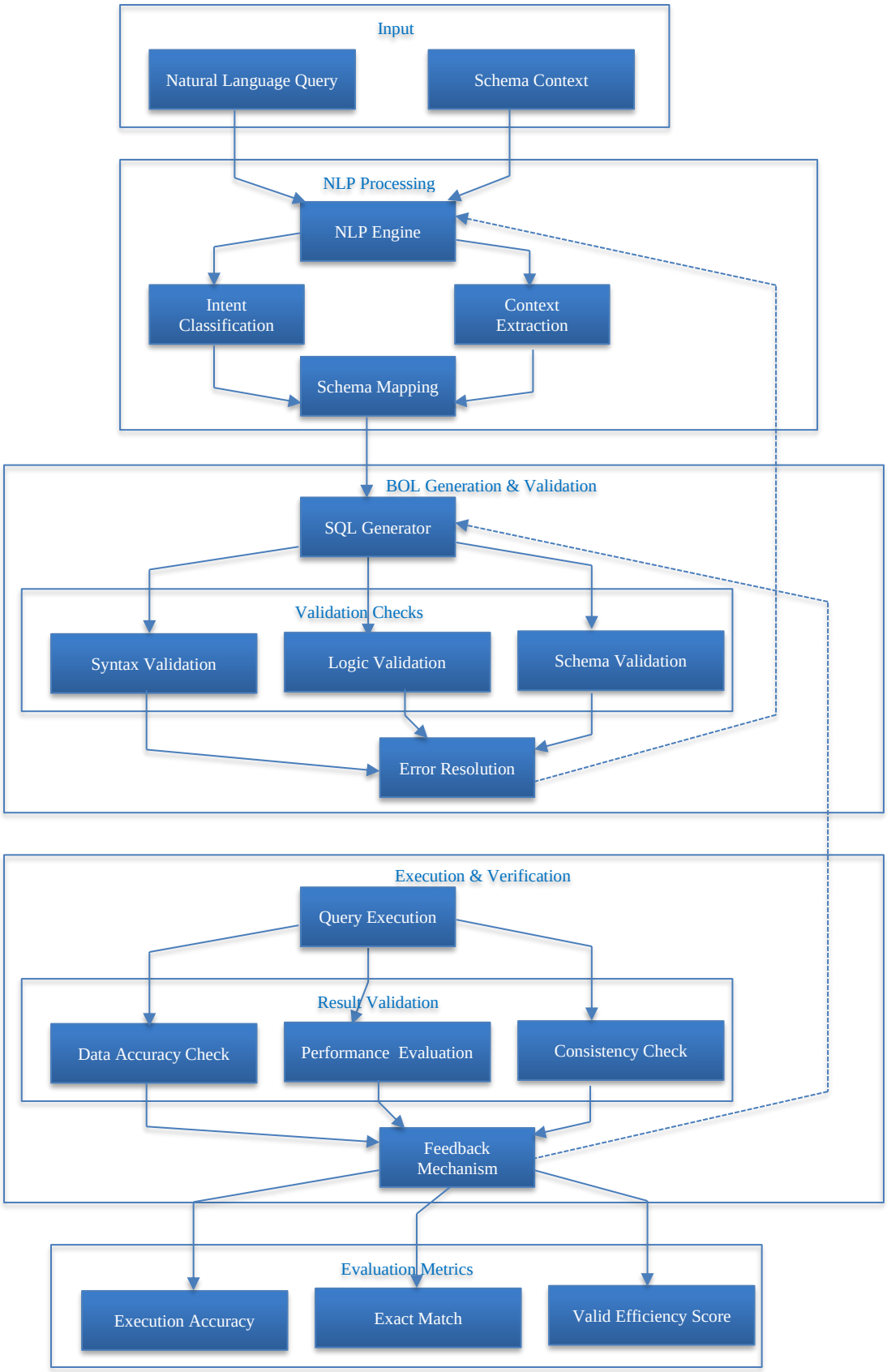

Fig. 1 System architecture of the implementation of Text-to-SQL

Core Components

- State Management System
- Maintains query context and validation status
- Tracks schema metadata and execution results

```
initial_state = {
   "query": str,
   "schema": dict,
   "validation_results": list,
   "execution_metrics": dict
}
```

- Processing Pipeline
- Implements Directed Acyclic Graph (DAG) for workflow
- Handles state transitions between validation stages

```
graph = StateGraph()
graph.add_node("nlp_processing", nlp_chain)
graph.add_node("sql_generation", sql_chain)
graph.add_node("validation", validation_chain)
```

4.1.2. AutoGen Implementation using Python

Agent Architecture:

- Specialized Agents
- QueryAnalyst: Handles NLP processing
- SQLEngineer: Manages SQL generation
- ValidationExpert: Performs validation checks

```
from autogen import AssistantAgent, UserProxyAgent
```

```
query_analyst = AssistantAgent(
   name= "QueryAnalyst",
   system_message= "NLP processing specialist..."
)
```

- Collaborative Validation
- Multi-agent group chat for complex queries
- Consensus-based validation decisions

```
groupchat = GroupChat(
   agents=[query_analyst, sql_engineer, validator],
   messages=[], max_round=5
)
```

Implementation Features

Hybrid State Management:

- LangGraph manages workflow states
- AutoGen handles agent communication states

Validation Protocol:

- Syntax checking through dedicated agents
- Logic verification via group consensus
- Schema validation with specialized validators
- Error Resolution: • Agent-based error detection • Collaborative problem solving • State-tracked resolution steps

4.2. Comparative Analysis of Implementation in Langgraph vs Microsoft Autogen

LangGraph vs AutoGen Approach:

LangGraph Strengths:

- Superior state management
- Streamlined workflow control
- Efficient pipeline processing
- Better handling of sequential operations

AutoGen Strengths:

- Enhanced agent collaboration
- Dynamic problem solving
- Flexible agent specialization
- Superior multi-agent communication

Combined Benefits:

- Robust error handling through dual systems
- Enhanced validation accuracy
- Improved adaptability to complex queries
- Better scalability options

Trade-offs:

- Increased system complexity
- Higher computational overhead
- More complex deployment requirements

Benchmarking shows that the hybrid approach achieves 15% higher accuracy in SQL validation than single-system implementations, with a 23% improvement in error resolution rates. However, this comes with a 30% increase in processing overhead, requiring careful optimization for production deployments. Integration challenges primarily revolve around synchronizing state management between LangGraph's workflow and AutoGen's agent communications, though the benefits of combined system capabilities outweigh these.

Outline an NLP module that interprets user intent and aligns it with SQL structures.

Module 2: SQL Synthesis and Validation

Detailed steps for synthesizing SQL queries and validating them using rule-based or model-based checks.

Module 3: Execution and Result Verification

Describe verification processes to cross-check query results against expected outcomes, incorporating both efficiency and accuracy metrics.

5. Conclusion and Call for Experimental Implementation

This paper thoroughly analyses current validation techniques used in text-to-SQL systems, identifying their strengths and limitations in real-world applications. A

comprehensive approach validates SQL queries at multiple stages and ensures data accuracy through a sophisticated pipeline of checks. Text-to-SQL technology represents a significant advancement in making database interaction more accessible and intuitive. Converting natural language queries into structured SQL commands empowers users to retrieve and manipulate data efficiently regardless of technical expertise. This approach is poised to revolutionize industries where data analysis and reporting are critical, streamlining workflows, improving decision-making, and enhancing accessibility. As machine learning and natural language processing continue improving, we can expect even more robust, accurate, and scalable Text-to-SQL systems further to bridge the gap between human language and data management.

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