

QUITE: A Query Rewrite System Beyond Rules via LLM Agents

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ABSTRACT

Query rewrite transforms a given SQL query into a semantically equivalent query that can be executed more efficiently. Existing approaches mainly rely on predefined rewrite rules. However, they can only handle a small subset of queries and may lead to performance regressions. This limitation arises from the intrinsic challenges of rule-based query rewrite: (1) it is hard to discover and verify new rewrite rules, (2) fixed rewrite rules do not generalize to new query patterns and are insufficient for handling complex queries, and (3) some rewrite techniques cannot be expressed by fixed rules. Motivated by the fact that human experts exhibit significantly better rewrite ability but suffer from scalability, and Large Language Models (LLMs) have demonstrated nearly human-level semantic and reasoning abilities, we propose a new approach of using LLMs to rewrite SQL queries beyond rules. Due to the hallucination problems in LLMs, directly applying LLMs often leads to nonequivalent and suboptimal queries. To address this issue, we propose QUITE (query rewrite), a training-free and feedback-aware system based on LLM agents that rewrites SQL queries into semantically equivalent forms with significantly better performance, covering a broader range of query patterns and rewrite strategies compared to rule-based methods. Firstly, we design a multi-agent framework controlled by a finite state machine (FSM) to equip LLMs with the ability to use external tools and enhance the rewrite process with real-time database feedback. Secondly, we develop a rewrite middleware to enhance the ability of LLMs to generate optimized query equivalents. It includes a structured knowledge base for domain knowledge, an SQL corrector to ensure equivalence, and an agent memory buffer to manage critical rewrite contexts. Finally, we employ a novel hint injection technique to produce better execution plans for rewritten queries. Extensive experiments show that our method achieves up to a **35.8%** reduction in query execution over state-of-the-art approaches. Moreover, it delivers **24.1%** additional rewrites compared to prior methods, which cover query cases that earlier approaches could not handle.

1 INTRODUCTION

Inefficient SQL queries remain a long-standing challenge in many database applications, often arising from poorly written queries by inexperienced users or automatically generated systems [44, 60, 87]. Query rewrite is a promising approach that transforms an original SQL into a semantically equivalent form with better performance [26, 60, 76]. An effective rewritten query can dramatically improve the execution time of a poorly written SQL query by several orders of magnitude [76, 88].

Existing query rewrite approaches typically rely on predefined rewrite rules [14, 16, 31, 48, 61, 70, 88, 90]. Heuristic-based methods apply these rules in a fixed order derived from practical experience [16, 31, 61]. However, such fixed orders often fail to generalize across different environments and query patterns. Thus, machine learning (ML)-based methods train models on rewrite histories to predict which rules to use and the order in which to apply them [88, 90]. Recently, some approaches have explored the use of Large Language Models (LLMs) to select rewrite rules and determine their application order based on domain knowledge [48, 70].

However, the above approaches can handle only a small subset of queries and may lead to performance regressions [48, 70, 88]. This limitation stems from the intrinsic challenges of rule-based query rewrite. First, the rich features of SQL and the nuances of semantics make it rather difficult to discover and verify new rewrite rules [20, 60, 76]. Even state-of-the-art rule discovery system [76] can only support a narrow subset of operators. Second, fixed rewrite rules rely on pattern matching and therefore are fundamentally unable to optimize unseen or complex query patterns [14, 24, 43]. Third, many effective rewrite strategies cannot be expressed by rewrite rules [24]. For example, the Common Table Expressions (CTE) conversion in Example 1 cannot be captured by rewrite rules. This is because such conversion requires explicit control over evaluation order and sub-plan sharing, which is beyond the scope of relational-algebra rewrite rules [16, 30, 76].

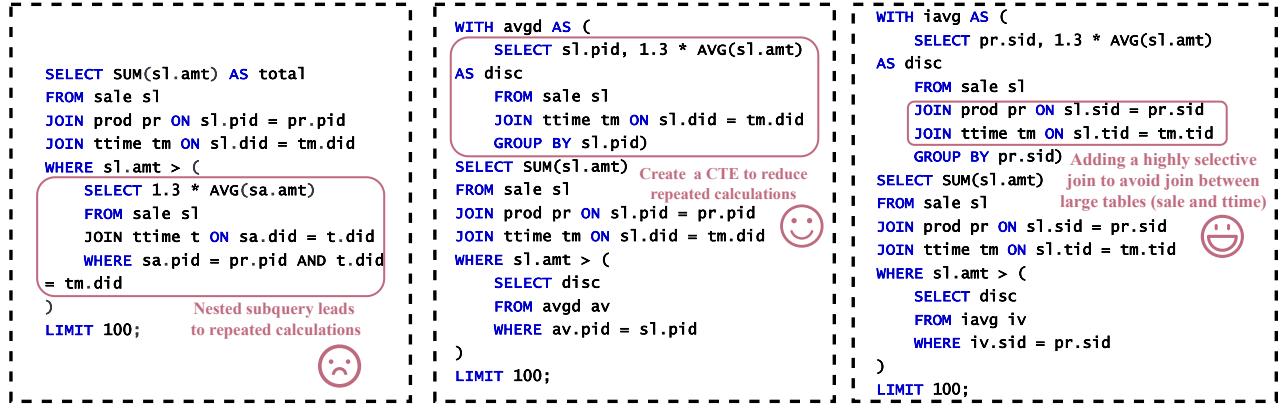


Figure 1: An Example of Using Strategies Beyond Rewrite Rules (Example 1) and Using Context-Aware Analysis (Example 2)

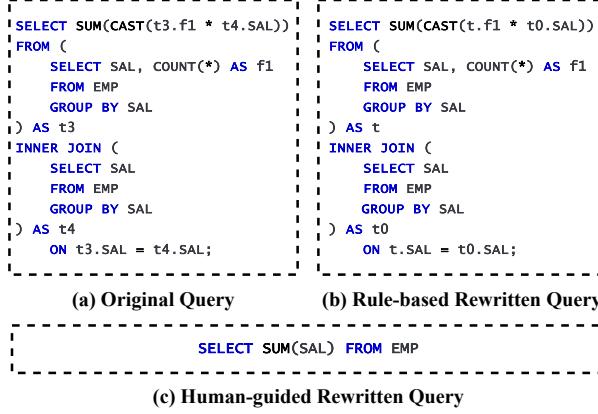


Figure 2: An Example of Using Query Intent (Example 3)

Given these limitations, we revisit the query rewrite problem from the perspective of human experts and identify three key capabilities that humans exhibit, but rule-based systems lack. (1) Humans can perform rewrites that follow certain rules but exceed the expressiveness of standard pattern matching, and in some cases, go beyond what can be captured by formal rewrite rules (Example 1). (2) Humans can conduct context-aware rewrites by considering the underlying data distributions and cost estimates provided by the query optimizer (Example 2). (3) Experts can apply intent-oriented rewrites that capture the underlying goal of the query, which are not easily expressed as explicit rules (Example 3).

EXAMPLE 1. Query Rewrite Beyond Rewrite Rules. Figure 1 (a) is a simplified query from the DSB benchmark [22]. To avoid repeated calculation of nested subqueries, Figure 1 (b) rewrites them using Common Table Expressions (CTEs). This enables the database engine to compute intermediate results once and reuse them, leading to a $37.5 \times$ reduction in query latency in our experimental setup.

EXAMPLE 2. Context-Aware Query Rewrite. In Figure 1 (c), instead of directly joining two large tables (the `sale` with 10 M rows and the `ttime` with 1.4 M rows), we first join the `sale` table with the `prod` table (100 K rows). This highly selective join would produce an intermediate result of only 100 K rows. Next we join this with `ttime`

table and yield a $2.79 \times$ speedup over (b) in our experimental setup. Such rewrites, which reduce intermediate size, are rare in rule-based systems and require analyzing data distribution and selectivity.

EXAMPLE 3. Query Rewrite based on Query Intent. Figure 2 (a) shows a real-world query from Apache Calcite [7]. Rule-based rewrite cannot optimize this query (Figure 2 (b)). Identifying that the query intent is to sum salaries directly from the `EMP` table, humans can simplify the original query by eliminating unnecessary joins and subqueries that do not contribute to the intent of the query, achieving a $2.17 \times$ execution improvement in our experimental setup.

Although human experts can produce significantly better SQL rewrites than rule-based methods, manual rewriting does not scale well, especially when there are millions of poorly written queries to be optimized in cloud environments. Recently, LLMs have demonstrated nearly human-level semantic and reasoning abilities, making them a natural choice for query rewrite. However, this task remains challenging due to the hallucination problem of LLMs: they may generate responses that are plausible but factually incorrect or semantically invalid. Specifically, there are two fundamental challenges. **C1. Ensuring Equivalent Rewrites.** Producing equivalent rewrites requires a precise understanding of the rich features of SQL and the nuances of semantics. Even the most powerful LLMs produce rewrites with syntax or semantic errors in nearly 20% of cases (Section 7). **C2. Ensuring Optimized Rewrites.** Determining whether a rewritten query improves performance depends on multiple factors, including query intent, data distribution, optimizer estimates, system states, and others. These contextual factors are typically unavailable to LLMs, and enabling LLMs to effectively utilize such information remains a non-trivial problem [15, 40, 72].

To address the limitations of rule-based query rewrite, the poor scalability of manual rewrite, and the unreliable nature of LLMs, we propose QUITE, a training-free and feedback-aware system that smartly leverages LLMs to rewrite SQL queries into semantically equivalent forms with significantly improved performance. QUITE supports a broader range of query patterns and rewrite strategies, while maintaining good scalability. It is primarily designed for long-running OLAP workloads, where execution time

dominates and the cost of query rewriting is negligible. First, to enable LLMs to capture query data characteristics and leverage database feedback, we design a multi-agent framework controlled by a finite state machine (FSM) to iteratively refine the rewrite process. We decompose the complex rewrite process into a set of subtasks, each handled by a specialized LLM agent to reduce hallucinations and improve rewrite ability (addressing **C1**, **C2**). Second, to enhance the ability of LLMs to generate high-quality query rewrites, we provide a rewrite middleware that includes: (1) a structured knowledge base extracted from official documentation and query rewrite discussions on web forums, (2) a hybrid SQL corrector that combines tool-based and LLM-based equivalence checking to ensure query equivalence, Third, we employ a novel hint injection technique to generate better execution plans for rewritten queries. This ensures that query execution exactly follows the optimized plan recommended by LLM agents, avoiding unintended modifications by the query optimizer due to inaccurate cost estimations. Additionally, this technique enables further improvements by incorporating physical-level optimizations (addressing **C2**).

We extensively evaluate QUITE against state-of-the-art query rewrite systems on widely used benchmarks (e.g., TPC-H, DSB, and Calcite), which shows that our system achieves up to a **21.9%** speedup in query execution performance over the **best-performing** alternative. Moreover, it delivers **24.1%** additional rewrites compared to that alternative, covering query cases that previous systems could not handle. In summary, we make the following contributions:

- We propose QUITE, a training-free and feedback-aware query rewrite system that leverages LLM agents to support a broader range of query patterns and rewrite strategies than existing methods (Section 3).
- We design a multi-agent framework controlled by a finite state machine to enable LLM agents to use external tools and enhance the rewrite process with database feedback (Section 5).
- We develop a rewrite middleware including a structured knowledge base, a hybrid SQL corrector, and an agent memory buffer to enhance the rewrite capability of LLM agents (Section 4).
- We propose a hint injection technique to produce better execution plans for rewritten queries. (Section 6)
- We conduct extensive experiments to demonstrate that our system significantly surpasses state-of-the-art methods in both query performance and query coverage (Section 7).

2 PRELIMINARIES AND RELATED WORK

In this section, we first formally define the query rewriting problem and then discuss related work on query hints and LLMs.

2.1 Query Rewrite

We first define query rewrite in the realm of database systems:

Definition 2.1 (Query Rewrite). Query rewrite is a process of transforming a query into another query that is *semantically equivalent* but with improved performance. It is a preliminary step prior to query optimization, operating at the level of the *user-accessible application programming interface (API)* (e.g., SQL).

Definition 2.2 (Query Equivalence). Two queries are considered *equivalent* if they produce the same result for any valid instance of the database schema.

Conventional studies treat query rewrite as a transformation between plain SQL statements, typically using rule-based methods. There are two lines of work:

(1) *Discovery of new rules.* WeTune [76] automatically generates and verifies logical plan transformations, but it handles only a limited set of operator types and algebraic rules. Equality saturation techniques [55] and user-guided systems like QueryBooster [14] still require manual intervention and cover only narrow classes of queries. More recently, GenRewrite [49] leverages LLMs to describe rewrite rules in natural language (NLR2s), enabling more flexible rule specification. In practice, its effectiveness depends on the coverage of available equivalence checks, and validating a large number of candidate rewrites through execution can introduce substantial overhead [24, 49].

(2) *Effective use of existing rules.* LearnedRewrite [88, 90] uses Monte Carlo Tree Search (MCTS) with learned cost models to explore the space of rule applications, but its performance depends on the accuracy of cost model estimation. LLM-R² [48] retrieves similar past rewrites using a pre-trained selector and employs them as in-context examples for rule selection. R-Bot [70] adopts retrieval-augmented generation to recommend rewrite rules through evidence retrieval and step-by-step reasoning. These approaches largely retrieve and apply rewrite knowledge based on query structure and then select from predefined rule sets. Consequently, they may not fully capture dataset-dependent factors such as database scale or column statistics, and their rule-centric formulation can miss effective expert strategies that are hard to express as explicit rewrite rules.

2.2 Query Hints

Query hints are SQL extensions that provide instructions to the database’s query engine to influence the selection of execution plans [11, 52, 56, 77]. These hints allow users to exert precise control over how the database optimizer chooses physical operators and access methods. As shown below for pg_hint_plan extension [57], the hint `/*+ HashJoin(employees departments) */` forces the query engine to use a hash join for the `employees \bowtie departments` operation. This hint can override the optimizer’s default cost-based plan selection.

```
/*+ HashJoin(employees departments) */
SELECT *
FROM employees e
JOIN departments d ON e.dept_id = d.id
WHERE e.salary > 50000;
```

Prior works on query hint selection [11, 52, 77] apply boolean hints to entire queries, which often leads to suboptimal performance because different operators within a query may require different hints. Proto-X [82] improves upon this by assigning hints at the operator level. However, it operates in an offline setting that requires exploring multiple configurations and repeatedly executing the complete workload, whereas query rewriting does not require repeated workload execution. UniTune [83] supports query

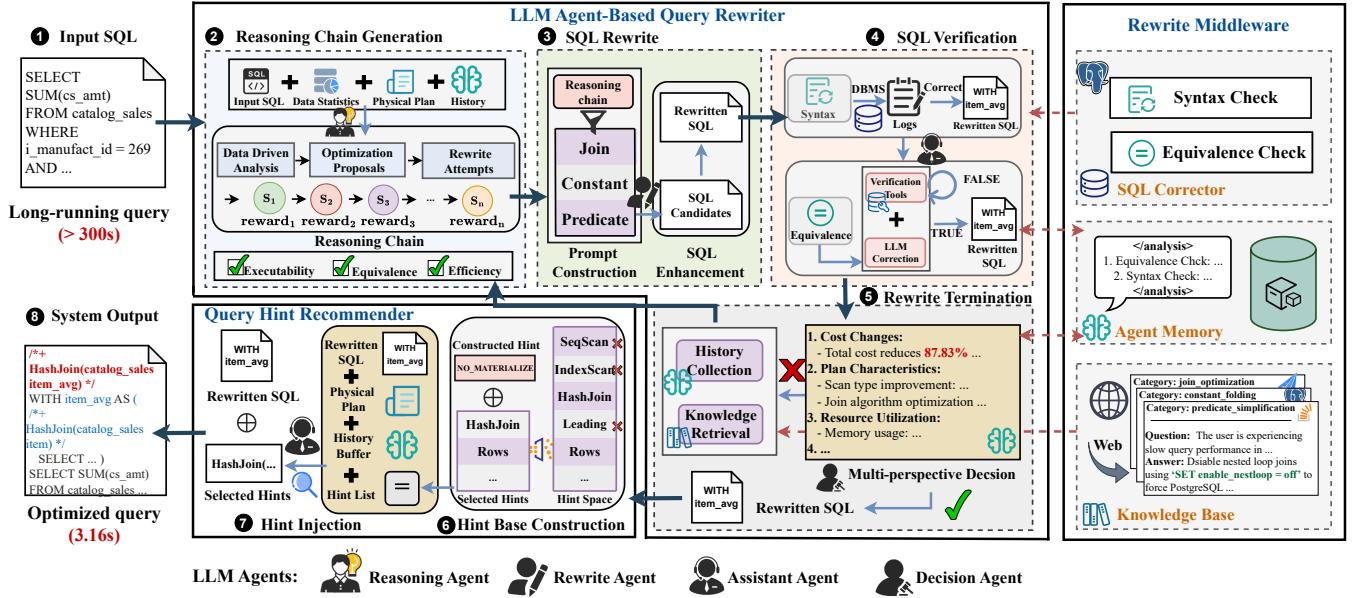


Figure 3: System Overview of QUITE

rewriting through LearnedRewrite [88] but does not incorporate hints. In contrast, QUITE employs pg_hint_plan to enable fine-grained, operator-level control (e.g., selection of join algorithms and adjustment of cardinalities) and jointly optimizes both query rewriting and hint selection.

2.3 LLM and LLM Agents

LLM for Database Tasks. LLMs are increasingly applied to database tasks text-to-SQL [28, 29, 46, 47], SQL workload generation [38, 39], and database optimization [40–42, 72, 85], with recent work focusing on query optimization [48, 49, 70]. Although these methods show that LLMs can understand and modify SQL, the inherent complexity of query rewrite presents substantial challenges.

LLM Agents. The primary advantage of LLM agents over LLMs is their ability to collect feedback from the execution environment (e.g., database execution metrics) and adapt their subsequent reasoning and outputs accordingly [78]. They have proven particularly effective in code generation [50, 79], automated diagnostics [36, 73, 89], and knowledge management [13, 89]. Moreover, collaborative deployments of multiple LLM agents often outperform single-agent systems on complex reasoning and planning tasks [17, 45, 63, 71]. QUITE applies this multi-agent methodology to query rewrite by gathering DBMS feedback and adjusting each query candidate accordingly.

3 SYSTEM OVERVIEW

We present the architecture of QUITE as shown in Figure 3. It comprises three components: LLM Agent-Based Query Rewriter, Rewrite Middleware, and Query Hint Recommender.

LLM Agent-Based Query Rewriter. The rewriter uses a training-free and feedback-aware LLM agent-based FSM to rewrite queries in multiple stages. First, ① the user provides the input SQL along with the corresponding database configuration (e.g., DBMS type,

host address). Second, ② the rewriter obtains metadata (e.g., database statistics, query information) to generate a reasoning chain, which includes rewrite proposals and rewritten SQL candidates. This chain is then used to generate the rewritten SQL for further enhancement and validation. Next, ③ we consolidate the SQL candidates to construct the LLM prompt, and apply global SQL enhancements to find the optimal rewritten SQL. Finally, ④ we validate the syntax correctness and semantic equivalence of the rewritten SQL, and ⑤ verify the correctness and effectiveness of the rewritten query to decide whether to proceed to Step ⑥ or further rewrite this query based on the rewrite history.

Rewrite Middleware. The toolkit provides three specialized tools to boost LLM rewrite ability. First, we construct a structured knowledge base using a multi-source integration to guide high-quality rewrite proposals (Section 5.1). Second, a hybrid SQL corrector then validates the syntactical correctness and semantic equivalence of each candidate rewrite, using rewrite history to trigger further refinement when necessary. (Section 5.2). Third, we design an agent memory buffer that captures key context from previous interactions to reduce communication overhead and LLM hallucination (Section 5.3).

Query Hint Recommender. The recommender explores the query hints in two steps. ⑥ First, we construct a promising query hint base, thereby reducing the hint search space and enabling faster, more accurate hint selection (Section 6.1). ⑦ Second, we leverage an LLM agent with data statistics to select appropriate fine-grained hints for the rewritten query to improve its execution performance (Section 6.2). ⑧ Finally, the selected hints are injected into the rewritten query to produce the final output.

4 LLM AGENT-BASED QUERY REWRITER

In this section, we present our LLM agent-based query rewriter and describe how to construct an efficient, robust query-rewriting workflow using LLM agents.

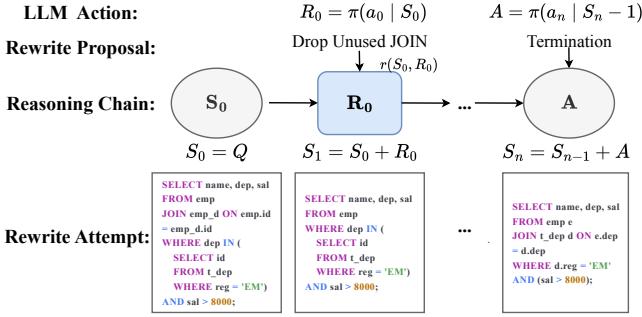


Figure 4: Reasoning Chain of MDP-based Reasoning Agent

4.1 MDP-based Reasoning Agent

Query rewrite is fundamentally a sequential decision problem [27, 88], each transformation step changes the query structure and limits future optimization options. Reasoning LLM agents (e.g., DeepSeek-R1 [32]), capable of chain-of-thought planning and multi-step logical inference, appear well-suited to this task. However, our experiments show that they still produce 13.0% nonequivalent outputs and yield minimal execution improvements (Section 7.2). We observe that query rewrite mirrors a Markov Decision Process (MDP), where states are query forms, actions are rewrite steps, and rewards are cost reductions [51, 62, 74]. By framing rewrite in this way, we provide the reasoning LLM agent with a clear, stepwise optimization goal that guides each inference step. Therefore, we design an MDP-based reasoning agent to produce high-performing rewrites.

We model the query rewrite process as a Markov Decision Process $(\mathcal{S}, \mathcal{A}, \mathcal{T}, r, y)$. Starting from the original query Q , each state $S_t \in \mathcal{S}$ represents the current form of the query with any semantic-level rewrite attempts. At each timestep t , the agent chooses either a *refinement action* R_t (e.g., join reordering, predicate pushdown) or a *terminal action* \mathcal{A} that emits the final rewritten query. This yields the deterministic transition:

$$S_{t+1} = \begin{cases} \mathcal{T}(S_t, R_t) = S_t + R_t, & \text{if a refinement is applied,} \\ \mathcal{T}(S_t, a) = S_t + \mathcal{A}, & \text{if rewriting terminates.} \end{cases}$$

To guide the search toward efficient rewritten queries, we define a domain-specific *reward function* once S_t transitions to S_{t+1} under a refinement action R_t :

$$r(S_t, R_t) = \text{Cost}(S_t) - \text{Cost}(S_{t+1}),$$

where $\text{Cost}(\cdot)$ denotes the DBMS optimizer’s estimated execution cost (via EXPLAIN) and LLM’s evaluation. Intuitively, each positive reward corresponds to a drop in estimated cost. The agent’s objective is captured by the *action-value function* Q^π under policy $\pi_\theta(a | S_t)$, where action $a \in \mathcal{A}_t$:

$$Q^\pi(S_t, a_t) = \mathbb{E}_\pi \left[\sum_{k=0}^{T-t} \gamma^k r(S_{t+k}, a_{t+k}) \mid S_t, a_t \right],$$

which represents the expected total discounted reward starting from state S_t after taking action a_t . The *optimal* action-value function Q^* then satisfies the Bellman equation:

$$Q^*(S_t, a_t) = r(S_t, a_t) + \gamma \max_{a' \in \mathcal{A}} Q^*(S_{t+1}, a'),$$

In practice, we realize the policy $\pi_\theta(a | S_t)$ as a reasoning-specialized LLM (e.g., DeepSeek-R1) that generates each action conditioned on the current query state.

As shown in Figure 4, the agent transitions from the initial state S_0 through a sequence of refinement actions $\{R_0, R_1, \dots\}$, and finally applies the terminal action A to emit the final rewritten query. Concretely, at each timestep t , the agent is prompted with the current SQL form S_t and analyzes the query structure via its internal chain-of-thought, scores candidate refinements based on the expected cost reduction, and samples the highest-scoring R_t .

4.2 FSM-based Query Rewrite

Single-agent approaches often produce suboptimal or invalid rewrites because a single agent is responsible for managing the entire rewrite pipeline (e.g., propose rewrites, verify validity, and assess efficiency), which overloads the model’s context capacity and ultimately increases the risk of hallucination. Inspired by multi-agent frameworks that assign specialized agents to distinct tasks [34], we break down query rewrite into discrete stages, each of which is handled by a dedicated LLM agent. To ensure the multi-agent system’s stability and correctness [33], we implement a Finite State Machine (FSM) to orchestrate stable stage transitions.

4.2.1 Query Rewrite Process Decomposition. Given an environment \mathcal{E} representing a database system, an *LLM Agent Group for Query Rewrite* is a tuple $\mathcal{A} = (\mathcal{G}, \mathcal{M}, \mathcal{F}, \mathcal{R})$ where:

- $\mathcal{G} = \{A_1, \dots, A_n\}$ is a set of cooperative LLM-based agents, each with specialized capabilities C_i for tasks.
- $\mathcal{M} : Q \times \mathcal{E} \rightarrow \mathcal{S}$ is a transition that breaks down the input query $Q \in Q$ into intermediate states $s \in \mathcal{S}$.
- $\mathcal{F} : \mathcal{S} \times \mathcal{H} \rightarrow Q'$ is a transformation function that produces rewritten queries $Q' \in Q'$ based on the current state and historical feedback $h \in \mathcal{H}$ from \mathcal{E} .
- $\mathcal{R} : Q' \times \mathcal{E} \rightarrow \mathbb{R}^+$ is a reward function that evaluates rewrite quality through execution metrics and guides iterative refinement.

Specifically, the Agent takes action O_i in state s_i , the environment provides feedback O'_i , and the Agent updates its state and decides the next action based on the feedback as:

$$\mathcal{A}_{s_i} \xrightarrow{O_i} \mathcal{E} \xrightarrow{O'_i} \mathcal{A}_{s_{i+1}}$$

where \mathcal{A}_{s_i} denotes the Agent in state s_i , and $\mathcal{A}_{s_{i+1}}$ denotes the Agent in state s_{i+1} .

In practice, we decompose the rewrite process into four stages: *Reasoning*, *Verification*, *Decision* and *Termination*, as illustrated in Figure 5. The *Reasoning* stage generates candidate SQL rewrites. The *Verification* stage validates syntax and semantic equivalence, correcting any errors identified. The *Decision* stage determines whether to continue or terminate the rewrite process. The *Termination* stage ends the rewrite process and outputs the rewritten SQL with rewrite proposals.

4.2.2 Specialized LLM Agents. As shown in Table 1, we deploy three specialized LLM agents alongside the core *MDP-based Reasoning Agent* in Section 4.1 to drive the rewrite pipeline for the

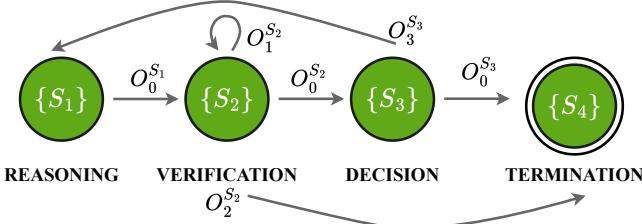


Figure 5: The Workflow of FSM-based Query Rewrite

Table 1: Specialized Agents in the Finite State Machine

State	Agent	Agent Role
S_1	MDP-based Reasoning Agent	Generate Reasoning Chain
S_1	Rewrite Agent	Extract & Refine SQL candidates
S_2	Assistant Agent	Validate Syntax & Equivalence
S_3	Decision Agent	Score & Control Termination

defined FSM stages. Then we propose an LLM agent-based query rewrite methodology detailed in Algorithm 1:

- **Reasoning stage (S_1):** In this stage, the *MDP-based Reasoning Agent* generates a reasoning chain, containing detailed rewrite proposals and SQL candidates. The *Rewrite Agent* then serves as a reward model, extracting and refining SQL candidates from the reasoning chain (Lines 3-7).
- **Verification stage (S_2):** In this stage, the *Assistant Agent* validates syntactical correctness and semantic equivalence by using the hybrid SQL corrector (Lines 8-12).
- **Decision stage (S_3):** In this stage, the *Decision Agent* reassesses the rewritten SQL’s efficiency with a comprehensive report and determines whether the rewrite process should continue or terminate (Lines 13-19).

Rewrite Agent. After the reasoning agent generates a chain, the rewrite agent extracts proposals from each node, groups them into four categories matching our structured knowledge base, evaluates each proposal’s expected reward, and selects the top SQL candidate. Since this candidate may introduce new structural complexities, it cannot be used directly for verification. Therefore, the rewrite agent undertakes an SQL enhancement process to uncover additional rewrite opportunities.

This template provides a concise, user-curated checklist of the effective SQL enhancement transformations. Guided by this checklist, the rewrite agent revisits the selected SQL candidate to identify any remaining optimization opportunities. If none are found, it returns the original query unchanged.

Assistant Agent. The assistant agent uses the hybrid SQL corrector (Section 5.2) to ensure the syntactic correctness and semantically equivalence of queries. This is performed in two steps:

- *Syntax correction.* If syntax errors occur, it attempts up to K_{\max} repairs. If correction still fails, the current FSM iteration is aborted and control returns to the reasoning stage.
- *Equivalence correction.* Once the syntax error is corrected, the agent submits the query pair $\langle Q_{\text{orig}}, Q_{\text{new}} \rangle$ to verify the equivalence and correct nonequivalent queries.

Algorithm 1: LLM-based Query Rewrite Algorithm

```

Input: Original SQL Query  $Q_0$ ; LLM Agent  $\mathcal{M}$ ; Tool Repository  $T$ ; Knowledge Base  $\mathcal{K}$ 
Output: Optimized SQL Query  $Q^*$  with reduced cost
1 Initialize State  $S \leftarrow \text{REASONING}$ ; Iteration  $t \leftarrow 0$ ; Advanced Knowledge  $\mathcal{A} \leftarrow \emptyset$ ;
2 while  $S \neq \text{TERMINATION} \wedge t \leq T_{\max}$  do
3   if  $S = \text{REASONING}$  then
4      $C \leftarrow \text{Generate-Reasoning-Chain}(\mathcal{M}, Q_0, T)$ ;
5      $\langle Q^P, \mathcal{A} \rangle \leftarrow \text{Extract-Rewrite-Proposal}(C)$ ;
6      $\langle Q^E, \text{EarlyStop} \rangle \leftarrow \text{Enhance-Query}(\mathcal{M}, Q^P, \mathcal{A})$ ;
7      $S \leftarrow \text{EarlyStop?TERMINATION : VERIFICATION}$ ;
8   else if  $S = \text{VERIFICATION}$  then
9     while  $Q^E$  not pass verification do
10      | Correct syntax and equivalence of  $Q^E$  via  $T$ ;
11    end
12     $S \leftarrow \text{DECISION}$ ;
13  else if  $S = \text{DECISION}$  then
14     $\mathcal{R} \leftarrow \text{Generate-Report}(Q^E, Q_0, \mathcal{M}, T)$ ;
15    if Cost-Check( $Q^E, \mathcal{R}, \mathcal{M}$ ) then
16      |  $Q^* \leftarrow Q^E; S \leftarrow \text{TERMINATION}$ ;
17    else
18      |  $\mathcal{A} \leftarrow \mathcal{A} \cup \text{Retrieve-Knowledge}(\mathcal{K}, Q^E)$ ;
19      |  $S \leftarrow \text{REASONING}$ ;
20     $t \leftarrow t + 1$ ;
21  end
22 return  $\langle Q^*, \text{cost}(Q^*), \mathcal{A} \rangle$ ;

```

This two-phase process ensures that only valid, semantically equivalent rewrites advance to the Decision stage. Although equivalence verification may return the original input SQL, it avoids the far greater cost of returning nonequivalent SQL while preventing performance degradation from excessive loop iterations.

Decision Agent. The decision agent implements a cost-aware decision mechanism to determine whether the rewrite process should terminate within budget constraints. It contains two steps:

(i) *Generate Comprehensive Report.* The decision agent analyzes the rewritten query across four dimensions, including cost changes, plan characteristics, resource utilization, and other improvements. This multi-dimensional approach overcomes the limitations of relying solely on EXPLAIN cost estimates, preventing from accepting misleading or suboptimal rewrites.

(2) *Evaluation and Feedback Loop.* Based on the generated report, the decision agent makes a binary decision to decide whether the rewrite process should terminate or not. If *True*, the Decision agent terminates the FSM process; if *False*, it retrieves higher-confidence rewrite proposals from the knowledge base, then stores the current query, report, and retrieved knowledge in an agent shared buffer for the next FSM iteration. We deliberately avoid introducing knowledge base retrieval in the initial state, because reasoning models have input content limitations—excessive guidance information can reduce the generation freedom, potentially compromising the quality of reasoning proposal chain [32]. Finally, the FSM

enters the Termination stage and outputs the final rewritten query along with its comprehensive optimization report.

5 REWRITE MIDDLEWARE

In this section, we introduce the Rewrite Middleware. It comprises three key components: a structured knowledge base of query rewrite strategies (Section 5.1), a hybrid SQL corrector ensuring syntactic validity and semantic equivalence (Section 5.2) and an agent memory buffer for agent context management (Section 5.3).

5.1 Structured Knowledge Base

Many query rewrite strategies developed by DBAs cannot be effectively utilized by LLMs. This limitation arises because such knowledge is sparsely represented in the LLMs’ training data, making it difficult for them to extract and apply these strategies without explicit guidance provided in the prompt. To address this, we construct a structured knowledge base to systematically manage various rewrite strategies. The construction process consists of four steps: (i) collecting SQL rewrite knowledge from diverse sources, (ii) filtering unreliable content, (iii) enriching the collected entries, and (iv) retrieving the most relevant rules for each rewrite. The Knowledge Base \mathcal{K} is defined as follows:

Definition 1 (Knowledge Base). A Knowledge Base \mathcal{K} is a set of question and answer (Q&A) pairs, denoted as $\mathcal{K} = \{\langle q_1, a_1 \rangle, \langle q_2, a_2 \rangle, \dots, \langle q_n, a_n \rangle\}$. Each Q&A pair $\langle q_i, a_i \rangle$ includes:

- A question $q_i = \langle Text_{que_i}, SQL_{que_i} \rangle$, where $Text_{que_i}$ describes a specific SQL rewrite issue in natural language, and SQL_{que_i} is the original SQL query that the system needs to interpret or optimize.
- An answer $a_i = \langle Text_{ans_i}, SQL_{ans_i} \rangle$, where $Text_{ans_i}$ explains the strategies used to rewrite SQL_{que_i} , and SQL_{ans_i} is the rewritten SQL query.

Step 1: Collecting rewrite knowledge. Our knowledge is primarily sourced from official database documentation and the database community. Since rewrite strategies are often indirectly presented and scattered throughout official documents [1, 2, 4, 5], we employ LLMs to identify and summarize them into key points. We also collect knowledge from Stack Overflow [8], as it has abundant real-world query rewrite examples and insights accumulated over decades. We retrieve all Q & A units tagged with “query rewrite” or “query optimization” that include at least one answer. In total, we collected 3,432 valid Q & A units.

Step 2: Filtering untrustworthy content. We begin by filtering out answers that receive more dislikes than likes. Next, we prioritize solutions achieving consensus within the discussion, using an LLM to determine if consensus has been reached. Following this, we employ a majority vote by LLMs to identify the most effective solution from these consensus-based responses. This process yields a total of 241 high-quality Q&A units.

Step 3: Enhancing the knowledge. An LLM first summarizes questions and user’s responses from website Q&A units. These summaries are then augmented with corroborating information from official documents. To do this, we embed user response summaries using Sentence Transformers [64]. These embeddings are then used to query a pre-indexed knowledge base of extracted points, retrieving the top three matches via cosine similarity. Finally,

Table 2: Distribution of Knowledge UNits Across Categories

Join	Constant	Predicate	CTE	Others
122	2	21	20	76

an LLM evaluates these matches to confirm that they effectively explain the rewrite strategy underlying the Q&A unit. Suitable matches are incorporated, enriching Q&A units with concise explanations that aid future retrieval.

Step 4: Retrieving relevant knowledge. We classify these 241 high-quality units into five categories: predicate, constant, join, CTE and others, which capture the essential aspects of query rewrite and provide a foundation for precise retrieval (Table 2). Since knowledge is often context-specific (i.e., most rewrite strategies depend heavily on factors such as schema definitions, data distribution and available indexes), its effectiveness may diminish under changing conditions. In contrast, context-independent knowledge is relatively rare and involves general-purpose optimizations such as predicate simplification. To identify the most relevant knowledge, we use the BM25 algorithm [65] to retrieve the most relevant documents by computing the document relevance.

5.2 Hybrid SQL Corrector

Hallucinations in LLMs can cause them to generate faulty queries, with two primary types of errors: (1) *Syntax Error*, where a generated SQL violates language grammar and cannot execute; (2) *Equivalence Error*, where a generated SQL executes but yields results or semantics different from the original SQL. Our proposed hybrid correction method targets both issues.

Syntax Error Correction. Syntax errors, typically minor issues like misspelled keywords or incorrect column/table names, prevent the database from parsing the SQL query. An LLM, leveraging its understanding of SQL syntax and guided by error messages from the DBMS, can efficiently identify and fix these structural flaws. Because such corrections usually involve minimal changes targeting obvious mistakes, the query’s original intended semantics are generally preserved with low overhead during this process.

Equivalence Error Correction. Verifying the equivalence between any pair of SQL queries is known to be an NP-hard challenge [10], and whether this problem admits a polynomial-time solution remains an open question. While numerous verification methods [19, 23, 75, 76] rooted in algebraic or symbolic reasoning have been proposed to prove equivalence, they typically operate on constrained query sets (e.g., specific operators, advanced SQL constructs). Recent studies have highlighted the potential of LLMs in deducing query equivalence with high confidence [68, 84]. However, relying solely on LLMs carries inherent risks. Therefore, we integrate traditional verification tools and LLM capabilities in a two-stage process, forming a hybrid approach that achieves broader and more reliable equivalence judgments.

• Tool-based Verification. We first use SQLSolver [23], an advanced verification tool, for an initial check. Given a pair of queries, $\langle Q_{orig}, Q_{rewr} \rangle$, SQLSolver determines their equivalence as either equivalent, nonequivalent, or unknown (due to timeout or other limitations). For query pairs where SQLSolver’s outcome is unknown, verification proceeds to a subsequent stage, utilizing the proposed LLM-based approach.

Table 3: Constructed Hint Base

Query Hint	Grammar	Description
Hash Join	<code>/*+ HashJoin(table table[table...]) */</code>	Forces the use of hash joins for specified tables.
No Nested Loop Join	<code>/*+ NoNestLoop(table table[table...]) */</code>	Prevents the use of nested loop joins for specified tables.
No Merge Join	<code>/*+ NoMergeJoin(table table[table...]) */</code>	Prevents the use of merge joins for specified tables.
Row Correction	<code>/*+ Rows(a b #10) */</code>	Sets the number of rows for the join result.
NOT_MATERIALIZE	<code>/*+ NOT_MATERIALIZE(table) */</code>	Inlines the CTE to avoid materialization overhead.

- **LLM-based Verification and Correction.** Leveraging their ability to understand semantic relationships, LLMs can effectively check SQL query equivalence and correct nonequivalent rewrites. However, directly applying LLMs faces challenges, as they may be unsure for some complex queries or incorrectly identify a pair of nonequivalent queries as equivalent. To mitigate these issues, we employ an iterative verification and correction process. In this process, the LLM repeatedly compares the original query Q_{orig} with the rewrite candidate, systematically identifying discrepancies and applying refinements. This iterative loop continues until the LLM confidently establishes query equivalence or a predefined time budget is exhausted. If the time budget is reached without the LLM confidently establishing equivalence, the system defaults to returning the original query ($Q_{rewr} = Q_{orig}$), ensuring that system performance is not compromised by unresolved complex rewrites. Our experiments on diverse workloads show that our method achieves higher rewrite equivalence rates than baselines (Figure 6).

5.3 Agent Memory Buffer

Effective context sharing is crucial in LLM-based workflows. Simply logging the entire prompt history is problematic: (1) *Hallucinations due to redundant context*. Lengthy SQL statements and redundant reasoning tokens can distract LLM, causing it to generate incorrect content [67]. (2) *Performance degradation under long-context overhead*. Unbounded history growth incurs quadratic attention costs and increases inference latency [35, 37].

To address these, we propose an agent memory buffer \mathcal{B} , containing memory slices $\mathcal{B} = \{m_1, m_2, \dots, m_n\}$, where each slice m_i is dedicated to a specific category of critical information (e.g., query information, rewrite proposals). By extracting only essential messages across the rewrite process, our buffer curbs hallucinations and bounds context growth, thereby improving both correctness and efficiency in single-agent SQL rewrite workflows.

6 QUERY HINT RECOMMENDER

Query rewrite applies high-level transformations to give the DBMS optimizer a better starting point for plan generation. While this improved starting point is beneficial, the optimizer, which dictates the finer-grained execution operations, can still generate suboptimal plans. This sub-optimality arises because the optimizer’s decisions rely on cost models that are often inaccurate due to outdated statistics and simplifying assumptions (e.g., statistical independence of columns) [18, 53, 69]. To exert more fine-grained control over plan selection, we propose embedding

query hints [52] within rewritten queries. In this work, we introduce a dedicated hint base and use LLMs to adaptively select and incorporate effective hints into rewritten queries.

6.1 Hint Base Construction

Most modern database systems (e.g., PostgreSQL, MySQL, Oracle) support query hints, either inherently or by extensions [57–59]. In this work, we use PostgreSQL’s pg_hint_plan extension [57] to implement our query hint system. Our system supports a broader range of hints (e.g., disabling materialization and setting specific cardinality values), whereas existing works [11, 52, 56, 77] are limited to Boolean hints.

Selecting Existing Hints. First, we exclude index-related and hardware acceleration hints as they are orthogonal to query rewrite optimization and can introduce hardware-specific dependencies. From the remaining hints, we employ an LLM with the prompt $p_{sel} = \text{"Given a query hint set, you should select the most effective and practical hints for query rewrite and give the reasons."}$. The LLM’s selections are then further refined based on expert review to ensure an optimal and practical set of hints.

Introducing a Novel CTE Hint. To provide more precise control over Common Table Expression (CTE) execution and associated performance issues, we introduce a new NOT_MATERIALIZE hint. By default, PostgreSQL materializes CTEs [3], which can lead to significant performance degradation, particularly when CTEs operate on small datasets or are executed infrequently [25, 86], due to the overhead of writing and reading intermediate results. Furthermore, the decision to materialize a CTE, as opposed to inlining it, directly impacts the optimizer’s ability to perform effective predicate pushdown into subqueries, especially after query rewrite. Our NOT_MATERIALIZE hint directs the optimizer to inline the targeted CTE, expanding its definition into the main query as if it were a FROM-clause subquery. This hint enhances query performance by eliminating materialization overhead and enabling more effective plan optimizations, such as improved predicate pushdown. Ultimately, these selected and newly introduced hints constitute our query hint base \mathcal{H} , detailed in Table 3.

6.2 Hint Injection

This section explains how we use LLMs to identify operations that could benefit from hints and recommend appropriate ones. Prior query-level methods [11, 52, 56, 77] apply a single hint to the entire query, but we observe that such a hint can be suboptimal, as a hint that benefits one operation may degrade others. To overcome this limitation, our strategy instead applies hints at the operator level, such as to individual tables or specific operations within a query, to maximize their positive effects.

Building on the validated rewrite of Q' , we now turn to refining its physical execution plan through targeted hint injection. First, given the physical plan of Q' , database semantics and data distribution statistics, we identify potential improvements that can be achieved through hints: (1) For every cardinality estimation in the plan, an LLM judges its reasonableness. If an estimation is deemed unreasonable, the LLM provides a recommended range and justification. (2) For all join operations, the LLM assesses whether the selected join operator (such as hash, merge, or nested-loop join) is suitable given the available statistics. Second, the Assistant Agent processes these justifications, verifies their consistency against plan statistics, and constructs the final set of hints before forwarding them to the injection function. Regarding `NOT_MATERIALIZE`, we apply this hint only if a CTE appears exactly once or processes a small, simple dataset. Finally, the proposed hints are then injected into Q' , producing the final optimized query Q^* .

Unlike general existing methods [11, 52, 56, 77], our LLM-guided hint injection pinpoints costly operations and generates finer-grained hint recommendations. This enhances the explainability of the recommendations and leads to further improvement. Moreover, in contrast to ML-based hint approaches [11, 52, 56, 77] that rely on pre-trained models and multi-plan enumeration, our method requires zero training yet shows a competitive performance within a small subset of query hints.

7 EXPERIMENT

In this section, we conduct a comprehensive evaluation of QUITE through performance comparisons, ablation studies, robustness assessments, analyses of rewrite behaviors and cost evaluations.

7.1 Experimental Set up

Testbed. Our experiments were conducted on a server featuring a 32-core Intel Xeon Platinum 8352V CPU, 251 GB of RAM, a 942 GB SSD, and PostgreSQL v14.13.

Workloads. We evaluate QUITE on standard OLAP benchmarks with long-running analytical queries, aligning with our deployment scenarios. We employ three widely recognized datasets and one LLM-synthesized dataset to evaluate all of the approaches. (1) **TPC-H** [9] is a well-known OLAP benchmark containing 62 columns and 22 query templates. We generate 63 queries from these templates, excluding Q15 due to its use of CREATE VIEW, a format unsupported by the rewrite engines of two baseline methods [48, 88]. We used a scale factor (SF) of 10. (2) **DSB** [22] is adapted from the TPC-DS benchmark [54] and is notable for its complex data distribution and challenging long-context query templates, which consists of 52 query templates. We generate 156 queries based on these templates with SF = 10. (3) **Calcite** [7] is a real-world workload used to evaluate rewrite rules in Apache Calcite [16]. We randomly select 58 queries and generate 10G of data with uniform distributions following previous work [24]. (4) **StackOverflow (StackOverflow-Math)** [6] is a 13.8 GB dataset from the Mathematics community on the Stack Exchange network¹, containing math-related posts and metadata as of October 3, 2024. Following [66], we generate queries using predefined

complexity prompts (P1–P5) and obtain 43 valid queries after dialect correction.

Baselines. We compare our system against the following state-of-the-art query rewrite baselines:

- **LearnedRewrite (LR) (SIGMOD 2022)** [88] uses a Monte Carlo Tree Search (MCTS) algorithm with a learned cost estimation model to explore a SQL policy tree of rewrite rule orders. We adopt the original implementation and use the cost estimation model provided in their official code repository.
- **LLM-R² (VLDB 2025)** [48] is a rule-based query rewrite system built on Apache Calcite [16]. It uses LLM’s In-Context Learning (ICL) ability to select query rewrite rules according to high quality demonstration queries.
- **R-bot (VLDB 2025)** [70] is an LLM-based system that leverages an embedded retrieval-augmented generation (RAG) knowledge base and reflective reasoning to select promising rewrite rules.
- **LLM Agent** rewrites queries using an individual LLM agent. To ensure a fair comparison, this LLM agent can access target database statistics and our SQL corrector for self-reflection.

Comparison with GenRewrite [49]. GenRewrite explores query rewriting with natural-language rewrite rules and iterative correction, but the lack of released code prevents direct comparison. At a high level, it accumulates natural-language rewrite knowledge to guide subsequent LLM-based rewriting. In contrast, QUITE formulates query rewrite as a decision process and directly optimizes execution through iterative refinement with database feedback, enabling more robust and data-aware optimizations.

QUITE Settings. We use DeepSeek-R1 as the reasoning agent due to its strong analysis capability, and Claude-3.7-Sonnet as the rewrite, decision, and assistant agents by default. A temperature of 0 is applied to all LLMs to ensure output stability [12, 21]. The number of iterations is limited to 2 to prevent excessive FSM rewrite cycles. All LLM-involved experiments employ the identical temperature configurations used in our approach.

Evaluation Metrics. (1) *Query Execution Latency*. The duration required to complete a query, reported using the average, median, and 95th percentile latency values. (2) *Rewritten Equivalence Rate*. The fraction of rewritten queries that produce results matching those of the original queries. In our work, equivalence is determined by comparing the execution outputs of the original and rewritten queries. (3) *Rewritten Improvement Rate*. The percentage of rewritten SQL queries that show a performance improvement. A performance gain is considered significant if it results in at least a 10% reduction in execution time.

Query Evaluation Approach. Before each query, the database is restarted to clear caches. The query execution process involves an initial warm-up run to mitigate cold start impacts, followed by three measured executions. We report the average execution time of these three runs. Queries exceeding 300 seconds are terminated and recorded [48, 70], with capped values included in all latency statistics (mean, median, 75th, and 95th percentiles). Rewritten queries with syntax errors or output mismatches are marked as non-equivalent. In such cases, the execution time of the original query is used. If a rewrite times out, we recheck equivalence on a smaller scale: non-equivalent rewrites fall back to the original, while equivalent rewrites are executed with capped latency.

¹Stack Overflow is the flagship site of the network [66]

Table 4: Query Latency of Different Methods (s)

Methods	TPC-H (SF=10)				DSB (SF=10)				Calcite (SF=10)				StackOverflow (SF=10)			
	Mean	Median	75th	95th	Mean	Median	75th	95th	Mean	Median	75th	95th	Mean	Median	75th	95th
Original	69.84	9.64	32.75	300.00	32.62	4.85	10.29	300.00	23.88	2.58	8.64	122.36	48.02	9.47	20.80	300.00
LearnedRewrite	37.57	9.97	30.55	202.31	31.93	5.14	15.18	251.42	22.88	2.32	8.09	122.58	46.25	9.43	18.35	300.00
LLM-R ² (GPT-4o)	57.09	9.30	30.50	300.00	10.53	4.11	8.36	32.88	16.98	2.11	7.75	50.97	47.08	9.19	16.06	300.00
LLM-R ² (Claude-3.7)	57.68	9.89	30.07	300.00	9.11	3.82	8.24	27.48	17.80	2.30	7.83	57.28	46.97	8.40	16.30	300.00
LLM-R ² (DS-R1)	56.73	9.25	29.33	300.00	9.16	3.84	8.21	24.21	16.90	2.05	7.71	49.91	43.42	9.21	14.14	300.00
R-Bot (GPT-4o)	32.64	9.48	26.25	172.20	21.75	4.26	8.80	119.19	22.21	2.34	8.35	122.14	46.43	9.37	16.02	300.00
R-Bot (Claude-3.7)	33.89	9.71	29.32	195.51	19.89	4.27	8.99	112.24	23.38	2.60	8.64	122.95	52.06	9.52	19.25	300.00
R-Bot (DS-R1)	33.70	9.88	28.38	176.90	21.21	4.44	9.11	113.91	22.71	2.52	8.43	122.89	50.57	9.46	17.39	300.00
LLM Agent (GPT-4o)	69.03	10.00	27.02	300.00	33.44	4.39	9.65	300.00	15.47	2.03	7.32	35.34	50.90	7.96	26.73	300.00
LLM Agent (DS-R1)	42.79	9.94	27.95	300.00	13.53	3.87	7.93	30.18	15.18	1.65	7.55	36.70	27.14	6.38	9.40	272.55
LLM Agent (DS-V3)	60.12	9.22	29.92	300.00	32.34	4.19	9.99	300.00	16.49	2.53	7.72	45.15	54.92	10.33	23.60	300.00
LLM Agent (Claude-3.7)	57.46	11.04	36.99	300.00	25.32	4.38	8.84	300.00	15.67	1.59	7.68	44.54	36.23	7.58	21.86	283.42
QUITE \circ (DS-R1+Claude-3.7)	26.06	9.28	24.19	75.64	6.08	3.78	7.98	21.43	10.00	1.22	7.15	26.97	12.83	5.16	9.05	16.11
QUITE \star (DS-R1+Claude-3.7)	25.60	9.28	23.49	74.43	5.85	3.35	7.63	19.97	9.97	1.22	6.86	26.97	12.61	5.03	7.96	15.89

Note: QUITE \circ means rewriting queries without hint injection

QUITE \star means rewriting queries with hint injection

DS-R1 means DeepSeek-R1

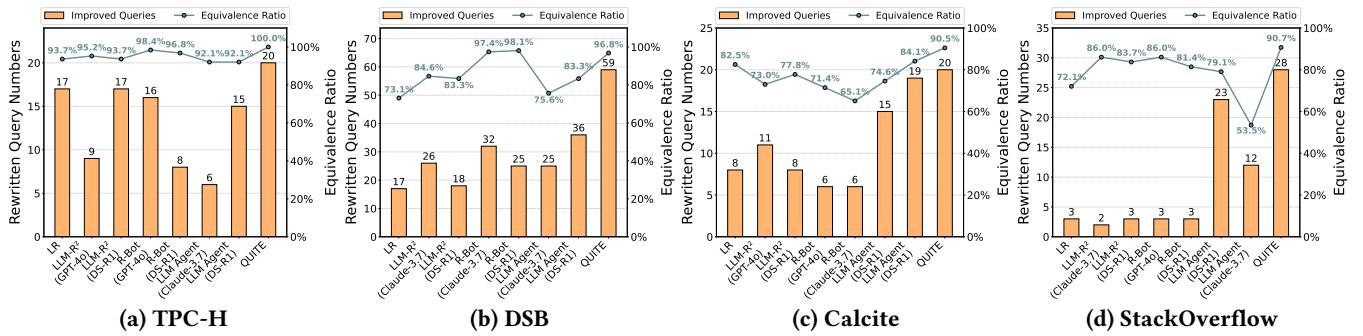


Figure 6: Rewrite Equivalence and Improvement Numbers on Different Benchmarks

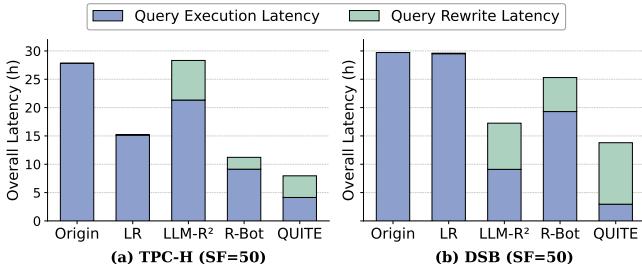


Figure 7: Comparison of Overall Latency (h)

7.2 Performance Comparison

Query Execution Latency. As shown in Table 4, queries optimized by QUITE demonstrate significantly reduced execution times, consistently outperforming all baseline methods. Across the TPC-H, DSB, Calcite and StackOverflow benchmarks, QUITE achieves substantial average execution time reductions. Specifically, QUITE reduces execution time by 31.9%, 81.7%, 56.4% and 72.7% compared to LR; 54.9%, 35.8%, 41.0% and 71.0% over LLM-R²; and 40.2%, 56.8%, 34.3% and 53.5% against LLM Agent. When evaluated against R-Bot, QUITE achieves reductions of 21.6%, 70.6%, 55.1% and 72.8%. QUITE's advantages are further illustrated by the rewritten improvement rates shown in Figure 6, where QUITE achieves the highest ratios of 31.7%, 37.8%, 34.5% and

65% on TPC-H, DSB, and Calcite, respectively, indicating strong generalization capabilities across different workloads.

The optimization benefits of QUITE are more pronounced on complex datasets. Notably, on the LLM-generated StackOverflow workload, we did not curate queries to disadvantage baselines. Since many LLM-generated queries use broad SQL dialects that are not directly supported by the strict syntax of Apache Calcite used in rule-based pipelines [48, 70, 88], we minimally normalized only such dialect mismatches (e.g., LISTAGG vs. STRING_AGG), discarding unresolvable cases. Under this controlled setup, rule-based pipelines remain bottlenecked by dialect constraints and limited rule and pattern coverage on complex structures, while QUITE is more robust and delivers larger latency gains.

Overall Latency. As shown in Figure 7, we evaluate overall execution time on TPC-H (SF=50) and DSB (SF=50) with a per-query time limit of 8000 seconds, using Claude-3.7-Sonnet across all baselines. On TPC-H and DSB, QUITE reduced execution time by 71.4% and 53.6% compared with the original queries, outperforming LR (47.6%, 53.4%), LLM-R² (71.9%, 20.0%), and R-Bot (29.1%, 45.5%), respectively. These results demonstrate QUITE's strong end-to-end advantage. QUITE's rewrite time on the DSB dataset is relatively longer, which can be attributed to two main factors: first, DeepSeek-R1 requires more time to process difficult problems;

Table 5: Unified Ablation Study Results on DSB (SF=10)

Metrics	Structured Knowledge Base			Different LLMs					Hint Construction Methods				
	w/o Q&A Units	Raw Q&A Units	Filtered Q&A Units	DS-R1 + GPT-4o	DS-R1 + DS-V3	DS-R1 + Claude-3.7	DS-V3 + Claude-3.7	Claude-3.7 + Claude-3.7	w/o Hints	Bao's Hint Base	Full Hints (no GUC)	Ours + Scan	Our Hint Base
Mean	9.96	9.10	6.08	31.38	28.07	6.08	23.41	12.76	6.08	6.93	7.06	6.04	5.85
Median	3.94	3.85	3.78	4.64	4.43	3.78	4.32	4.01	3.78	4.65	4.02	3.89	3.35
75th	8.49	8.10	7.98	9.56	9.07	7.98	9.64	8.74	7.98	8.46	8.64	8.06	7.63
95th	24.81	23.01	21.43	300.00	300.00	21.43	148.47	58.38	21.43	20.41	22.52	20.29	19.97

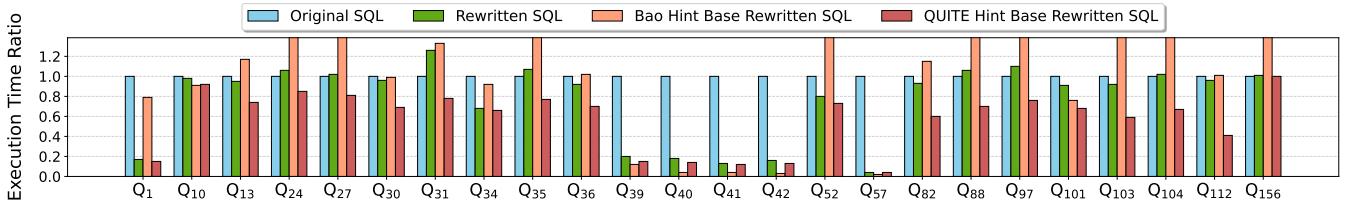


Figure 8: Ablation Study of Hint Injection on DSB Benchmark

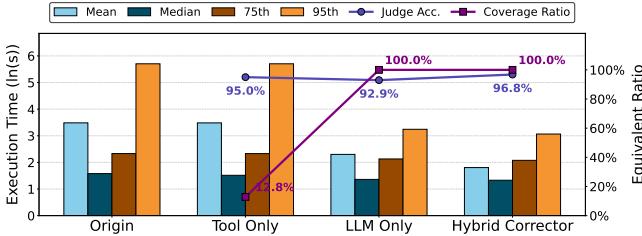


Figure 9: Ablation Study of Hybrid SQL Corrector

Table 6: Ablation Study of the Reasoning Agent and FSM

Methods		DSB (SF=10)			
MDP-based Reasoning Agent	FSM	Mean	Median	75th	95th
✗	✗	13.48	4.84	10.22	33.64
✗	✓	12.72	4.80	9.93	29.91
✓	✓	6.08	3.78	7.98	21.43

second, for complex queries, the decision agent often performs an additional iteration to explore further optimizations.

Rewritten Equivalence. Figure 6 details the number of equivalent and improved rewrites produced by each method across the datasets. Notably, direct LLM-agent rewrites, especially by Claude-3.7-Sonnet on StackOverflow, often violate equivalence due to subtle semantic drift during query restructuring. In contrast, QUITE achieves substantially higher equivalence rates, attaining 100%, 96.8%, 98.3% and 90.7% on TPC-H, DSB, Calcite and StackOverflow. In addition, rule-based methods suffer from incomplete semantic equivalence, as many rules in their rewrite engines (e.g., Apache Calcite [16]) lack formal verification due to the inherent difficulty of equivalence checking [23, 76]. Despite this, our approach achieves the highest equivalence rate across all benchmarks, advancing the state of the art.

7.3 Ablation Study

We design our ablation study from four perspectives by selectively replacing or removing system components.

Rewrite Middleware. First, we ablated the hybrid SQL corrector to measure its effect on equivalence and execution. Figure 9 reports Judge Accuracy (the fraction of correct decisions) and Coverage Ratio (the fraction of queries with a definitive decision). Its removal significantly degrades performance: nonequivalent queries increase from 5 to 11, unchanged queries increase by 13, and improved queries drop by 17. These results highlight the corrector’s essential role in ensuring query quality and efficiency.

We also evaluate the impact of the structured knowledge base. As shown in Table 5, QUITE consistently outperforms its variant without this module across all metrics. The improvement stems from high-quality domain knowledge embedded in the knowledge base, which effectively guide more optimized rewrites. To justify the LLM-based filtering, we compare the 241 filtered units against all 3,432 collected units. The filtered version delivers significantly stronger execution performance: five queries achieve a 2×–5× speedup, and more than eight queries exceed 5×. This confirms that consensus-aligned, high-quality knowledge provides significantly more effective guidance for LLM rewriting, enabling stable and efficient query optimization.

LLM-Agent-based Query Rewrite FSM. To evaluate the impact of the FSM framework, we make two modifications: (1) remove the equivalence-checking loop and (2) remove the decision stage. This converts the process into a linear pipeline while keeping all components and agent tools for rewriting. To further isolate the contribution of the MDP-based reasoning agent, we also conduct an ablation that removes the MDP component. As shown in Table 6, QUITE outperforms all variants across metrics. Notably, adding the MDP reduces the average execution time by 52.2% compared to the version without it, indicating that the MDP substantially improves the reasoning agent’s effectiveness.

Query Hint Injection. We evaluate the impact of hint injection on queries rewritten by QUITE. As shown in Table 4, hint injection further reduces average execution time by 1.8%, 3.8%, and 0.3% on TPC-H, DSB, and Calcite, respectively, indicating that appropriate hints enable additional fine-grained optimization even after extensive rewriting. To highlight the advantage of our approach, we compare it with using LLMs to select Bao’s GUC-level hint sets. As

Table 7: Robustness Study on TPC-H and DSB Benchmarks under Different Scale Factors (SF)

Methods	TPC-H												DSB											
	SF=1				SF=10				SF=30				SF=1				SF=10				SF=30			
	Mean	Med	75th	95th	Mean	Med	75th	95th	Mean	Med	75th	95th	Mean	Med	75th	95th	Mean	Med	75th	95th	Mean	Med	75th	95th
Original	29.48	0.69	1.20	300.00	69.31	9.42	30.08	300.00	64.76	20.61	46.69	300.00	7.22	0.27	0.69	13.19	32.62	4.85	10.29	300.00	39.42	5.06	18.22	300.00
LearnedRewrite	1.46	0.52	1.10	3.91	37.57	9.97	30.55	202.31	52.59	18.90	43.50	300.00	17.15	0.42	1.52	81.14	31.93	5.14	15.18	251.42	43.88	7.09	20.73	300.00
LLM-R ² (DS-R1)	15.38	0.69	1.22	7.69	56.73	9.25	29.33	300.00	54.67	18.30	58.11	300.00	4.30	0.23	0.57	21.5	9.16	3.84	8.21	24.21	23.01	5.01	11.87	87.15
R-Bot (GPT-4o)	1.49	0.66	1.03	6.38	32.64	9.48	26.25	172.20	54.54	19.85	61.12	300.00	9.06	0.25	0.63	21.89	21.75	4.26	8.80	119.19	31.93	5.15	16.27	300.00
QUITE (Rw. on SF=1)	1.02	0.64	1.01	3.79	36.87	13.53	29.02	279.51	54.36	25.02	43.03	289.48	2.25	0.24	0.50	2.74	10.58	4.18	8.59	30.79	23.23	4.67	12.91	111.83
QUITE (Rw. on SF=10)	1.08	0.68	1.22	3.79	26.06	9.28	24.19	75.64	45.90	17.44	57.26	155.72	2.82	0.24	0.51	1.72	6.08	3.78	7.98	21.43	17.36	4.34	9.28	77.62
QUITE (Rw. on SF=30)	5.72	0.50	1.17	5.17	30.50	9.96	24.29	96.68	40.65	16.89	37.96	131.97	6.65	0.26	0.56	3.20	8.74	3.94	8.01	23.15	16.35	4.45	9.26	74.33

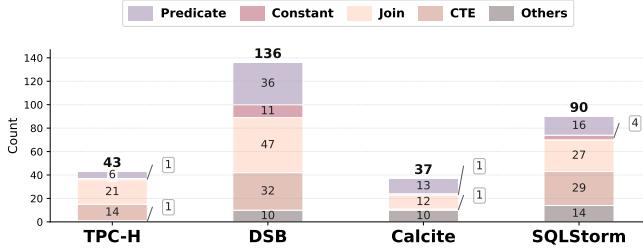


Figure 10: Rewrite Categories for Different Benchmarks

Table 8: Cost Analysis on TPC-H Benchmark

Methods	Average Time (s)	Cost (\$)
LLM-R ² (Claude-3.7)	391.23	0.016
R-Bot (Claude-3.7)	118.33	0.417
QUITE (DS-R1 + Claude-3.7)	218.25	0.200

shown in Table 5 and Figure 8, this baseline exhibits an overall performance degradation within Bao’s predefined hint space. Furthermore, Figure 8 shows execution times for 24 positively optimized DSB queries before and after hint injection, as well as for the original queries. In several cases, hint injection recovers and surpasses the original performance when rewriting alone is suboptimal. This demonstrates hint injection can recover and enhance performance in cases where the initial rewrites were suboptimal.

Sensitivity Study. We examine QUITE’s sensitivity to the number of rewrite rounds, hint thresholds, and different LLM models. We first test different model combinations. We fix DeepSeek-R1 as the reasoning model and vary the other models among Claude-3.7-Sonnet, DeepSeek-V3, and GPT-4o, and then we replace the reasoning model with DeepSeek-V3 and Claude-3.7-Sonnet. As shown in Table 5, the combination of DeepSeek-R1’s strong reasoning capabilities and Claude-3.7-Sonnet’s long-context understanding significantly outperforms all other combinations.

For hint thresholds, as shown in Table 5, we test the effect of adding the scan method to our hint base and the effect of using all hints (excluding GUC). The former yields an execution time nearly identical to that of the rewritten query, while the latter causes a slight performance degradation. This suggests that the size of our current hint search space is appropriate.

7.4 Robustness Study

Scale-Aware Robustness. We evaluate QUITE on TPC-H and DSB under scale factors $SF \in \{1, 10, 30\}$, where rewriting and

execution are performed on the same scale. As Table 7 shows, QUITE consistently achieves substantial latency reductions at every scale. In contrast, LR, LLM-R², and R-Bot often degrade as the data scale changes. These results demonstrate that QUITE maintains stable efficiency under varying data volumes and adapts robustly to distribution shifts within each benchmark.

Cross-Scale Robustness. To examine generalization across data distributions, we perform cross-scale evaluation: rewrites produced at one scale ($SF \in \{1, 10, 30\}$) are executed on all others. As Table 7 shows, QUITE achieves its strongest gains when rewrite and execution scales match, while mismatched cases show only minor regressions and still outperform all baselines. This behavior highlights QUITE’s strong data adaptivity and robustness, effectively learning to tailor rewrites to underlying data characteristics without overfitting to a specific workload or scale.

7.5 Further Analysis

Rewrite Type Analysis. We report successful rewrites that achieve over a 10% performance improvement while maintaining equivalence across four benchmarks. As shown in Figure 10, most gains come from join, CTE, and predicate rewrites, while the rest are benchmark-specific. Compared with rule-based baselines [48, 70, 88], QUITE produces deeper rewrites beyond pattern matching. We further analyse efficient rewrite types, query structures, Q&A units, and query hints in our Github files [80, 81].

Cost Analysis. We conducted a cost analysis experiment on 63 queries of TPC-H. As shown in Table 8, LLM-R² incurs high time cost for demonstration construction, while R-Bot consumes substantial tokens for stepwise rewriting. In contrast, QUITE offers a balanced trade-off between time expenditure and cost. By generating much of its output with DeepSeek-R1, QUITE greatly reduces monetary cost. Additionally, it avoids pre-training and extensive knowledge base construction.

8 CONCLUSION

This paper presents QUITE, a training-free and feedback-aware system that smartly leverages LLM Agents to rewrite SQL queries into semantically equivalent forms with significantly improved performance. We rethink the query rewrite process and identify unique opportunities to support a wider range of query patterns and rewrite strategies with strong scalability. The implemented QUITE system significantly outperforms state-of-the-art methods in both query performance and query coverage on widely used benchmarks and synthetic workloads.

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