Detecting Logic Bugs of Join Optimizations in DBMS

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Generation-based testing techniques have shown their effectiveness in detecting logic bugs of DBMS, which are often caused by improper implementation of query optimizers. Nonetheless, existing generation-based debug tools are limited to single-table queries and there is a substantial research gap regarding multi-table queries with join operators. In this paper, we propose TQS, a novel testing framework targeted at detecting logic bugs derived by queries involving multi-table joins. Given a target DBMS, TQS achieves the goal with two key components: Data-guided Schema and Query Generation (DSG) and Knowledge-guided Query Space Exploration (KQE). DSG addresses the key challenge of multi-table query debugging: how to generate ground-truth (query, result) pairs for verification. It adopts the database normalization technique to generate a testing schema and maintains a bitmap index for result tracking. To improve debug efficiency, DSG also artificially inserts some noises into the generated data. To avoid repetitive query space search, KQE forms the problem as isomorphic graph set discovery and combines the graph embedding and weighted random walk for query generation. We evaluated TQS on four popular DBMSs: MySQL, MariaDB, TiDB and PolarDB. Experimental results show that TQS is effective in finding logic bugs of join optimization in database management systems. It successfully detected 115 bugs within 24 hours, including 31 bugs in MySQL, 30 in MariaDB, 31 in TiDB, and 23 in PolarDB respectively.

CCS Concepts: • **Information systems** → *Data management systems*; *Structured Query Language*; • **Security and privacy** → *Database and storage security*.

Additional Key Words and Phrases: Database, logic bug, join optimization.

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1 INTRODUCTION

In the past decades, we have witnessed the evolution of modern DBMS (Database Management Systems) to support various new architectures such as cloud platforms and HTAP [15, 27], which require increasingly sophisticated optimizations for query evaluation. Query optimizer is considered as one of the most complex and important components in DBMS. It parses the input SQL queries and generates an efficient execution plan with the assistance of built-in cost models. The implementation errors in a query optimizer can result in bugs, including crashes and logic bugs. Crashes are easier

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```
mysql> CREATE TABLE t0(c0 INT);
mysql> INSERT INTO t0 VALUES(0);

mysql> CREATE TABLE t1(c0 DOUBLE);
mysql> INSERT INTO t1 VALUES('-0');

mysql> SELECT /*+no_hash_join()*/ * FROM t0, t1 WHERE t0.c0 = t1.c0;
+------+------+
| c0   | c0   |
+------+------+
|    0 |   -0 |
+------+------+
1 row in set (0.00 sec)

mysql> SELECT /*+hash_join()*/ * FROM t0, t1 WHERE t0.c0 = t1.c0;
Empty set (0.00 sec)
```

(a) MySQL's incorrect hash join execution.

```
mysql> CREATE TABLE ta (`id` bigint, PRIMARY KEY (`id`));
mysql> insert into ta values (1801425248110076165);

mysql> CREATE TABLE tb (value varchar(50));
mysql> insert into tb values ("1801425248110076222");

mysql> select value from tb where value in (select id from ta);
Empty set (0.00 sec)

mysql> select value from tb where value in (select /*+no_index(ta)*/
       id from ta);
+---------------------+
| value               |
+---------------------+
| 1801425248110076222 |
+---------------------+
1 row in set (0.00 sec)
```

(b) MySQL's incorrect semi-join execution.

Fig. 1. Logic bug cases of join optimizations in MySQL.

to detect as the system will halt immediately. Whereas, logic bugs are prone to be ignored, because they simply cause the DBMS to return incorrect result sets that are hard to detect. In this paper, we focus on detecting these silent bugs.

Pivoted Query Synthesis (PQS) has recently emerged as a promising way to detect logic bugs in DBMS [50]. Its core idea is to select a pivot row from a table and generate queries that fetch this row as the result. A logic bug is detected if the pivot row is not returned in any synthesized query. PQS is mainly designed to support selection queries in a single table and 90% of its reported bugs are for queries involving only one table. There still exists substantial research gap regarding multi-table queries with different join algorithms and join structures, which are more error-prone than single-table queries.

In Figure 1, we illustrate two logic bugs of MySQL for join queries. These two bugs can be detected by our proposed tool in this paper. Figure 1(a) demonstrates a logic bug of hash join in MySQL 8.0.18. In this example, the first query returns the correct result set because it is executed with the block nested loop join. However, when the second query is issued with an inner hash join, an incorrect empty result set is returned. This is because the underlying hash join algorithm asserts that "0" and "−0" are not equal. In Figure 1(b), the logic bug is caused by semi-join processing in MySQL's newest version (8.0.28). In the first query, the nested loop inner join casts the data type *varchar* to *bigint* and produces a correct result set. But when the second query is executed with hash semi-join, the data type *varchar* is converted to *double*, resulting in data accuracy loss and incorrect equivalence comparison.

Adopting query synthesis for logic bug detection in multi-table join queries is much more difficult than that in single-table selection queries, due to two unique challenges:

- **Result Verification**: Previous approaches adopt the differential testing strategy to verify the correctness of query results. The idea is to process a query using different physical plans. If plans return inconsistent result sets, a possible logic bug is detected. However, the drawback of differential testing is two-fold. First, some logic bugs affect multiple physical plans and make them all generate the same incorrect result. Second, when inconsistent result sets are observed, we need manually check which plan generates the correct one, incurring high overheads. A possible solution for the above problem is to obtain the ground-truth results for an arbitrary testing query, which is not supported by existing tools.
- **Search Space**: The number of join queries that can be generated from a given database schema is exponential to the number of tables and columns. Since we are unable to enumerate all possible queries for verification, there requires an effective query space exploration mechanism that allows us to detect logic bugs as efficiently as possible.

In this paper, we propose **T**ransformed **Q**uery **S**ynthesis (TQS) as a remedy. It is a novel, general, and cost-effective tool to detect logic bugs of join optimizations in DBMS. To address the first challenge above, we propose the DSG (Data-guided Schema and query Generation) approach. Given a dataset denoted as one wide table, DSG splits the dataset into multiple tables based on detected normal forms. To speed up bug discovery, DSG also inserts some artificial noise data into the generated database. We first convert the database schema into a graph whose nodes are the tables/columns and edges are the relationships between the nodes. DSG adopts random walking on schema graph to select tables for queries, and uses those tables to generate join expressions. For a specific join query spanning over multiple tables, we can easily identify its ground-truth results from the wide table. In this way, DSG can effectively generate (query, result) pairs for database verification.

For the second challenge, we design the KQE (Knowledge-guided Query space Exploration) approach. We first extend the schema graph to a plan-iterative graph, which represents the entire query space. Each join query is then represented as a sub-graph. KQE adopts an embedding-based graph index to score the generated query graphs by searching whether there are structurally similar query graphs in already-explored space. The coverage score guides the random walk generator to explore the unknown query space as much as possible.

To demonstrate the generality and effectiveness of our approach, we evaluated TQS on four popular DBMSs: MySQL [41], MariaDB [37], TiDB [27] and PolarDB [15]. After 24 hours of running, TQS successfully found 115 bugs, including 31 bugs in MySQL, 30 in MariaDB, 31 in TiDB, and 23 in PolarDB. Through root cause analysis, there are 7 types of bugs in MySQL, 5 in MariaDB, 5 in TiDB, and 3 in PolarDB respectively. All the detected bugs are submitted to the respective community and we received their positive feedbacks.

2 OVERVIEW

In this section, we formulate the problem definition and present an overview of our proposed solution.

2.1 Problem Definition

There are two categories for database bugs: crash and logic bugs. Crash bugs are raised either by the operating system, or by the process of DBMS. They cause DBMS to be forcefully killed or halted, due to limited resources (e.g., out of memory) or access to an invalid memory address, etc. Crash bugs are easy to be noticed. In contrast, the logic bugs are much harder to be noticed, because database still runs normally and query processing returns seemingly correct results (and indeed they return correct results in most cases, but may fetch incorrect result sets in corner cases). These

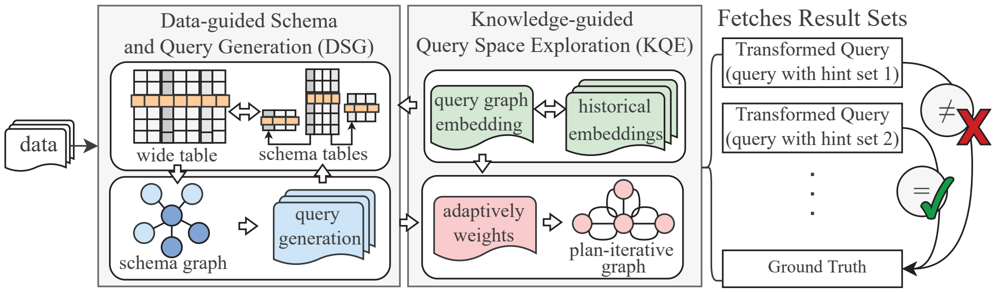


Fig. 2. Overview of TQS. TQS designs DSG (Data-guided Schema and query Generation) and KQE (Knowledge-guided Query space Exploration) to detect the logic bugs of join optimizations in DBMS.

silent bugs (acting as hidden bombs) are more dangerous, since they are hard to detect and may affect the correctness of applications.

In this paper, we focus on detecting logic bugs introduced by the query optimizer for multi-table join queries. Specifically, we refer to those bugs as join optimization bugs. Using the notations listed in Table 1, the *join optimization bug detection* is formally defined as:

Definition 2.1. For each query q_i in the query workload Q, we let the query optimizer execute joins of q_i with multiple physical plans, and verify its result sets S_{q_i} with its ground truth GT_{q_i}. If $S_{q_i} \neq GT_{q_i}$, we find a join optimization bug.

2.2 Scheme Overview

Figure 2 shows an overview for the architecture of TQS. Given a benchmark dataset and target DBMS, TQS searches for possible logic bugs of the DBMS by issuing queries against the dataset. TQS achieves its goal with two key components: *Data-guided Schema and query Generation (DSG)* and *Knowledge-guided Query space Exploration (KQE)*.

DSG considers the input dataset as a wide table, and besides the original tuples, DSG deliberately synthesizes some tuples with error-prone values (e.g., null values or very long strings). To target at join queries, DSG crafts a new schema for the wide table by splitting the wide table into multiple tables with normal form guarantees based on functional dependency. DSG models the database schema as a graph and generates logic/conceptual queries via random walk on the schema graph. DSG materializes a logic query into physical plans, and transforms the query with different hints to

Table 1. Summary of notations.

Notation	Definition
d	input dataset
T_w	wide table which has multiple columns
S	generated database schema
G_s	database schema graph
G	plan-iterative graph
G_q	query graph
q_i	generated SQL query q_i
$trans\_q$	transformed SQL query with hints for query q
S_q	query result set for a query q
GT_q	ground truth of query q's query result set

Algorithm 1 TQS (d, H, γ, l)

Input: dataset d, hint set H, walks per vertex γ, maximum walk length l.
Output: returns bug logs $bugs$, graph index GI.

1: Initialize weights of edges $\pi = \{1\}$, $bugs, GI$
2: $S = DBGen(d)$
3: $G_s(V, E) = Schema2Graph(S)$
4: $G(V, E, \pi) = PlanIterative(G_s)$
5: **for** $i = 0$ to γ **do**
6:     $O = Shuffle(V)$
7:     **for** each $v_i \in O$ **do**
8:         $W_{v_i} = AdaptiveRandomWalk(G, v_i, l, GI)$
9:         $GI = GI \cup Embedding(W_{v_i})$
10:         $q_i = QueryGen(W_{v_i})$
11:         $trans\_q_i = HintGen(q_i, H, G_t)$
12:         $GT_{q_i} = getGT(q_i)$
13:         $S_{trans\_q_i} = ResultSet(trans\_q_i)$
14:         **if** $S_{trans\_q_i} \neq GT_{q_i}$ **then**
15:             $bugs = bugs \cup trans\_q_i$
16: **Return:** $bugs$, GI

enable the DBMS to execute multiple different physical plans for bug searching. The ground-truth results of a join are identified by mapping the join graph back to the wide table.

After the schema is setup and data are split, KQE extends the schema graph to a plan-iterative graph. Each query is represented as a sub-graph. KQE builds an embedding-based graph index for the embeddings of query graph in history (i.e., in already explored query space). The intuition of KQE is to assure a newly generated query graph is as far away from its nearest neighbors in history as possible, namely, to explore new query graphs, instead of repeating existing ones. KQE achieves its effectiveness by scoring the generated query graphs based on their structural similarity (to query graphs in history) and applying an adaptive random walk method for generation.

We summarize the core idea of TQS in Algorithm 1, where we show the two main components: DSG (line 2, line 10 and line 12), KQE (line 4, line 8 and line 9), respectively.

Given a dataset d and a wide table T_w sampled from d, DSG splits the single wide table T_w into multiple tables that form the database schema S with normal form guarantees (line 2). Schema S can be considered as a graph G_s, where tables and columns denote vertices and edges represent the relationships between them. DSG applies random walk on G_s to generate the join expressions of queries (line 10). In fact, a join query can be projected as a sub-graph of G_s. By mapping the sub-graph back to the wide table T_w, DSG can easily retrieve the ground-truth results for the query (line 12).

KQE extends the schema graph to a plan-iterative graph (line 4). To avoid tests on similar paths, KQE builds an embedding-based graph index GI to index embeddings of the existing query graphs (line 9). KQE updates the edge weights π of the plan-iterative graph G according to how much the current query graph is structurally similar to existing query graphs (line 8). KQE scores the next possible paths, which guides the random walk generator to favor exploring unknown query space.

For a query q_i, TQS transforms the query with hint sets $trans\_q_i$ to execute multiply different physical query plans (line 11). Finally, the result set of query $trans\_q_i$ is compared with the ground-truth GT_{q_i} (line 14). If they are not consistent, a join optimization bug is detected (lines 15).

TQS currently focuses on bug detection of equi-join queries. However, the idea of DSG and KQE can be extended to non-equal joins. The only challenge is how to generate and manage ground-truth results, whose sizes increase exponentially for non-equal joins. We leave it to our future work.

3 DATA-GUIDED SCHEMA AND QUERY GENERATION (DSG)

SQLancer [49] is a tool to automatically find logic bugs in the implementation of DBMS. It first creates a populated database with randomly generated tables. Afterwards, it randomly chooses SQL statements to create, modify, and delete data. Based on the randomly generated database, it adopts testing approaches such as Pivoted Query Synthesis (PQS) [50] to detect logic bugs. Note that SQLancer is designed for logic bug detection of single-table queries. We can extend it directly to multi-table queries by modifying its data and query generator, but many bugs are ignored in that case. For details, please refer to the experimental section.

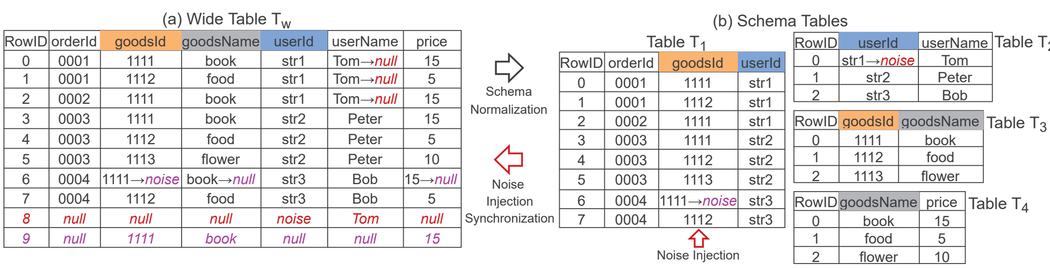


Fig. 3. Schema generation of the shopping order dataset. Data in black is the original dataset, and data in color is the noisy data which is injected in schema tables and then synchronized in the wide table.

To effectively support bug detection of multi-table join queries, we generate a test database as a wide table and leverage schema normalization to split the wide table into multiple tables with normal form. In addition, we propose an effective noise injection techniques to increase the probability of causing logic bugs with inconsistent database states. With the constructed database, join queries are generated via random walk on the schema graph and represented as abstract syntax trees. Finally, we efficiently retrieve their ground-truth result sets for these generated queries, assisted by the proposed bitmap index.

3.1 Schema Normalization

We first generate a test database as a wide table T_w. T_w can be constructed from either a real dataset (e.g., the KDD Cup dataset[1] in the UCI machine learning repository is essentially a wide table) or a random database generator (e.g., TPC-H generator). For the latter case, we pick unbiased random samples from the fact table *lineitem*, and apply the primary-foreign key joins to merge it with the dimension tables to produce a wide table.

Given a wide table T_w, we apply schema normalization techniques to generate a testing database schema. In the past literature, there have been numerous algorithms proposed for FD (functional dependency) discovery (such as TANE [28] and HYFD [43]) and schema normalization [19, 44]. The discovered FDs are used to transform the database schema into the 3NF. We directly use these data-driven schema normalization methods to generate our testing database schema. Note that we focus on FDs supported by the data, not semantically correct ones, and hence, our schema generation is completely automatic. During the splitting process of T_w, we also maintain an explicit

[1] https://archive.ics.uci.edu/ml/datasets/KDD+Cup+1998+Data

primary key *RowID* for all generated tables in order to recover ground-truth results. Moreover, metadata about the implicit primary and foreign key relationships are also maintained.

Example 3.1. We use an example of wide table in Figure 3 to illustrate the idea. The FD discovery algorithm finds four valid FDs: $\{orderId, goodsId, userId \rightarrow goodsName, userName, price\}$, $\{goodsId \rightarrow goodsName, price\}$, $\{goodsName \rightarrow price\}$ and $\{userId \rightarrow userName\}$. The FDs are automatically selected for decomposing the wide table T_w, and the explicit *RowID* columns are created. The example table is decomposed into schema S with four tables: $\{T_1$(RowID, orderId, goodsId, userId), T_2(RowID, userId, userName), T_3(RowID, goodsId, goodsName), T_4(RowID, goodsName, price)}, where {orderId, goodsId, userId}, {goodsId}, {goodsName} and {userId} are implicit primary keys, and $\{T_1.userId \rightarrow T_2.userId\}$, $\{T_1.goodsId \rightarrow T_3.goodsId\}$ and $\{T_3.goodsName \rightarrow T_4.goodsName\}$ are implicit foreign key mappings.

To facilitate join query synthesis and the ground-truth result generation, we also create a RowID mapping table $T_{RowIDMap}$, which defines a mapping relation $[RowID, T_i, row_j]$. Here, row_j denotes the row id of table T_i. The mapping relation is the list of rows in the wide table T_w which are split to create the row_jth row of table T_i. Based on the RowID map table, we build a join bitmap index which will be used to speed up the retrieval of ground-truth results. The bitmap index consists of k bit arrays of size n, where k and n are the number of schema tables and data rows, respectively. Each row has been assigned a distinct *RowID*. For the bit array of value T_j, the ith bit is set to "1" if the ith record of table T_w has produced some rows in Table T_j; otherwise, the ith bit is set to "0". If the table is too large and results in a sparse bitmap, we apply RLE (run-length encoding)-based technique, the WAH encoding [57], to compress consecutive sequences of "0" or "1".

Example 3.2. Figure 4 illustrates examples of RowID map table and join bitmap index of the data in Figure 3. The row with RowID 5 of rowID map table records a split process, which splits the row with RowID 5 in wide table T_w to produce rows in table T_1, T_2, T_3 and T_4 with RowID 5, 1, 2 and 2 respectively. The row with RowID 0 of join bitmap index represents that tables (T_1, T_3, T_4) have rows split from the wide table with RowId 0, while table T_2 has no corresponding row. Data in color represents data updates after noise injection and will be discussed later.

(a) RowID Map Table

RowID	T_1	T_2	T_3	T_4
0	0	0→*null*	0	0
1	1	0→*null*	1	1
2	2	0→*null*	0	0
3	3	1	0	0
4	4	1	1	1
5	5	1	2	2
6	6	2	0→*null*	0→*null*
7	7	2	1	1
8	*null*	*0*	*null*	*null*
9	*null*	*null*	*0*	*0*

Index Map

(b) Join Bitmap Index

RowID	T_1	T_2	T_3	T_4
0	1	1→*0*	1	1
1	1	1→*0*	1	1
2	1	1→*0*	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1→*0*	1→*0*
7	1	1	1	1
8	*0*	*1*	*0*	*0*
9	*0*	*0*	*1*	*1*

Fig. 4. RowID map table $T_{RowIDMap}$ and the join bitmap index are built to retrieve the ground-truth of query joins. Data in color represents data updates after noise injection.

3.2 Noise Injection

We first perform data cleaning task on our generated database by removing noisy data, which cause untraceable join results, e.g., null and boundary values on primary and foreign keys. Then, to facilitate the detection of logic bugs, we deliberately insert noises into the generated database

D_s to violate the FDs and primary-foreign key relationships. The injected noises produce traceable join results. The idea of noise injection is to corrupt a small fraction (ϵ) of the primary-foreign key relationship by replacing original values with (1) boundary values (e.g., for integer value and char(10) type, we replace the value with 65535 and 'ZZZZZZZZZZ'), and (2) NULL values. For each primary and foreign key column, we randomly pick ϵ tuples to perform the value replacement. The produced noisy database D_s' follows the same schema S as that of D_s. When we inject noises, we guarantee that the values of injected noises are unique and do not violate the ground-truth results of normal data.

The introduction of noises violates the consistency between the generated tables and the original wide table T_w. Since our ground-truth result is recovered from the wide table, we need to update T_w according to the injected noise so that the wide table and the noisy database become consistent.

Suppose a noise is introduced into column col_k of the row_jth row in table T_i, we have two cases:

Case 1: If col_k is the implicit primary key column, the affected rows in T_w can be represented as $\bar{R} = RowMap(T_i, row_j)$, and the affected columns in T_w can be represented as $\bar{C} = Fd(col_k)$, where $Fd(col_k)$ denotes the columns which are functional dependent on column col_k. Then, cells in Table T_w should be updated as follows:

$$\begin{aligned} insertion: & T_w[N+1][col_k] = T_i[row_j][col_k], \\ & T_w[N+1][c_k] = T_w[r][c_k] \mid r \in \bar{R}, \forall c_k \in \bar{C}; \\ update: & T_w[r_j][c_k] = NULL \mid \forall r_j \in \bar{R}, \forall c_k \in \bar{C}. \end{aligned}$$

Here, N denotes the number of tuples in T_w and there involve two insertion operators and an update operator. The insertion operator creates a new tuple by copying the noisy data from T_i and its function-determined values, leaving the remaining values as NULL. In the wide table, we can find multiple rows ($\forall r_j \in \bar{R}$) that can be functionally derived from the noisy row. We only need to copy one of them ($r \in \bar{R}$). The update operator, on the other hand, modifies the rows of T_w that relates to the row_jth row of T_i by tagging the corresponding column values as NULL, since the primary-foreign key joins are invalid.

Case 2: If the noise is created in the foreign key column of table T_i, the tuples in Table T_w should be updated as follows:

$$\begin{aligned} insertion: & T_w[N+1][c_k] = T_w[r][c_k] \mid r \in \bar{R}, \forall c_k \in col_k \cup \bar{C}; \\ update: & T_w[r_j][col_k] = T_i[row_j][col_k] \mid \forall r_j \in \bar{R}, \\ & T_w[r_j][c_k] = NULL \mid \forall r_j \in \bar{R}, \forall c_k \in \bar{C}. \end{aligned}$$

In case 2, we have an insertion and two update rules, respectively. This update process is explained in Example 3.3.

After updating wide table T_w, we should adjust the RowID map table as well. We denote those columns in the RowID map table as $C_{dep} = \mathcal{T}(col_k \cup \bar{C})$, where $\mathcal{T}(\cdot)$ is the tables whose columns is a subset of the given columns.

$$\begin{aligned} insertion: & T_{RowIDMap}[N+1][C_{dep}] = T_{RowIDMap}[r][C_{dep}] \mid r \in \bar{R}; \\ update: & T_{RowIDMap}[r_j][C_{dep}] = NULL \mid \forall r_j \in \bar{R}. \end{aligned}$$

The two rules are defined similarly to those for T_w and we discard the details.

Example 3.3. Figure 3 illustrates the process of noisy injection. Initially, we inject noise into tables T_1 and T_2, which are highlighted with colored fonts. To maintain a correct ground-truth result set, the corresponding rows of wide table T_w also need to be synchronized according to the injected noise in Tables $T_1 - T_4$.

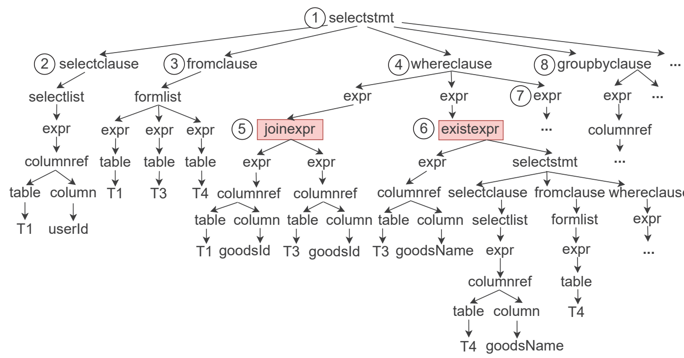


Fig. 5. Example of join query generation. The join expressions are generated by random walk on the schema graph.

For table T_2, we inject a noisy value into the primary key *userId* of the first tuple. For T_w, we locate the rows corresponding to the noise via the RowID map table in Figure 4(a). The results are the rows in T_w with RowID in $[0-2]$. Using the insertion rule, a new tuple (tuple 8) is created in T_w to refer to the noisy tuple in T_2. Similarly, based on the update rule, the tuples with RowID in $[0-2]$ need to change their *userName* to NULL values.

Similarly, table T_1 is polluted with a noisy value in its foreign key column *goodsId*. We locate involved rows in wide table T_w by mapping the noise through the RowID map table in Figure 4(a), which is the tuple in T_w with RowID 6. Because *goodsId* is the primary key of T_3, when joining them together, the missing contents should be recovered. Therefore, a new row with RowID 9 is created in T_w to maintain contents of columns $col_k \cup \bar{C}$. On the other hand, the tuples with column *goodsId* should be updated to noisy data, and the columns that can be functionally determined by *goodsId* should be updated to NULL.

Finally, the RowID map table should be updated by noises, and the data in the join bitmap index which cannot be found by its RowID in the wide table should be set to 0.

3.3 Join Query Generator

Random walk-based workload generators have been adopted for graph data exploration, such as RDF (resource description framework) search [1, 4]. We adopt a similar idea in our join query generation. DSG generates abstract syntax trees (ASTs) up to a specified maximum depth to get the skeleton of syntax-correct SQL queries. The AST is a tree of objects that represents a *select* SQL statement. As Figure 5 shows, the root of the tree is an object called selectstmt (node ①), which refers to a *select* SQL statement, and its child branches represent the *select*, *from* and *where* clauses in the *select* statement.

To explore possible query space, we represent the generated database schema as a schema graph $G_s = (V, E)$ with nodes $v_i \in V$ and edges $(v_i, v_j) \in E$. V can be further classified into two types of vertices, table vertex V_t and column vertex V_x. If $v_i \in V_t$ and $v_j \in V_t$, the edge (v_i, v_j) denotes that the corresponding two tables can be joined using primary-foreign key relationship. If $v_i \in V_x$ and $v_j \in V_t$, the edge (v_i, v_j) indicates that v_i is a specific column of table v_j. Note that there will be only one edge per v_i from V_x.

DSG adopts random walk on schema graph G_s to select tables for queries, and uses those tables to generate join expressions. This is a stochastic process, starting with a table vertex $v_i \in V_t$, with random variables $(W^1_{v_i}, W^2_{v_i}, ..., W^k_{v_i})$ such that $W^{k+1}_{v_i}$ is an edge chosen at random from the neighborhood of vertex v_k, where v_k is the kth vertex reached by this stochastic process (i.e., the end point of edge $W^k_{v_i}$). If the random walk process picks a (table-table) edge (say (v_i, v_j) s.t. $v_i, v_j \in V_t$), a join relationship is obtained and we move to the new table vertex v_j. On the other hand, if the random walk process picks a (table-column) edge (say (v_i, v_j) s.t. $v_i \in V_t$ and $v_j \in V_x$), random filters (i.e., a selection condition) are generated on the column v_j and the random walk process continues from the preceding table vertex v_i (but now excluding v_j).

After the join expressions are generated by random walk on schema graph G_s, DSG randomly generates other expressions based on the *join* clauses. Generating these expressions is implemented similarly to RAGS [53] and SQLSmith [52]. Note that we support sub-query inside the IN/Exist expressions of the *where* clause.

Example 3.4. Figure 5 depicts a running example of join query generation. The random walk process selects three tables (T_1, T_3, T_4) to join using the join conditions involving columns *goodsId* and *goodsName* (e.g., the nodes ⑤ and ⑥ in Figure 5). The join type of node ⑤ can be inner/outer/cross join, node ⑥ can be semi/anti-join. As Figure 5 shows, the table expressions of the *from* clause (node ③) are set to the tables which are involved in the join processing. Then, *select* clause (node ②) and *where* clause (node ⑦) are randomly constructed for tables of *from* clause and the random walk results (i.e., the columns and their types). And the aggregation operators are also supported (node ⑧). Finally, we transform the AST back to a SQL statement.

3.4 Ground-truth Result Generation

Given a join query generated by random walk on the schema graph, DSG can efficiently retrieve the ground-truth result from the wide table T_w. In the following, we first propose the strategies to support different join operators. Then, we present the procedure for ground-truth result generation.

DSG supports seven types of join operators, including inner join, left/right/full outer join, cross join and semi/anti-join. The ground-truth for the join bitmap index of the join results (which is a table), for each join type, is summarized in Table 2. For an inner join, the ground-truth of the RowID join bitmap index is $Bit(T_i) \wedge Bit(T_{i+1})$, where $Bit(T_i)$ is the RowID join bitmap index of Table T_i (i.e., the column for T_i in Figure 4(b)) and $\wedge$ is the bitwise logical AND operator. For a left outer join, the ground-truth bitmap is $Bit(T_i)$. The same rule is also applied to the right outer join. For a full outer join, the ground-truth bitmap is $Bit(T_i) \vee Bit(T_{i+1})$ and $\vee$ is the bitwise logical OR operator. For the cross join, the full result set cannot be recovered via T_w, and hence, we resort to verifying a subset of the result set. In other words, the database system must return a result set containing all the ground-truth answers from T_w. For a semi-join, since we stick to the primary-foreign key joins, the ground-truth bitmap is $Bit(T_i) \wedge Bit(T_{i+1})$. Finally, DSG also supports the anti-join, whose ground-truth bitmap is denoted as $Bit(T_i) \wedge \sim Bit(T_{i+1})$.

Based on the rules in Table 2, we can generate a complete join bitmap index for queries involving multiple joins via bitwise AND of the corresponding RowID join bitmap index. For the example query in Figure 5, if the join type of node ⑤ is inner join and node ⑥ is anti-join, the join bitmap of the query is

$$Bit(T_1 \bowtie_1 T_3 \bowtie_2 T_4) = Bit(T_1) \wedge Bit(T_3) \wedge \sim Bit(T_4), \tag{1}$$

where $\bowtie_1$ denotes the inner join, and $\bowtie_2$ is the anti-join. To reduce the overhead of bitmap calculation, the jump intersection algorithm is adopted to avoid unnecessary intersections of the RowID list. We rank the bitmaps based on their sparsity and conduct the intersection, starting from the most sparse bitmap.

After obtaining the ground-truth bitmap, we apply it to the wide table T_w to retrieve the tuples participating in the join query. Duplicated tuples are removed based on the new primary key of the tuples. Then, DSG also executes the generated filters and projections defined in the AST. In this way, we can obtain the ground-truth result for a specific random join query on our generated schema graph.

Table 2. The ground-truth bitmap for each join type.

Type of Join ($T_i \bowtie_i T_{i+1}$)	Verification	$Bit(T_i \bowtie_i T_{i+1})$
Inner Join	FullSet	$Bit(T_i) \wedge Bit(T_{i+1})$
Left Outer Join	FullSet	$Bit(T_i)$
Right Outer Join	FullSet	$Bit(T_{i+1})$
Full Outer Join	FullSet	$Bit(T_i \vee Bit(T_{i+1})$
Cross Join	SubSet	$Bit(T_i) \wedge Bit(T_{i+1})$
Semi Join	FullSet	$Bit(T_i) \wedge Bit(T_{i+1})$
Anti Join	FullSet	$Bit(T_i) \wedge \sim Bit(T_{i+1})$

Example 3.5. Now consider the query of "SELECT price FROM T3 INNER JOIN T4 WHERE T3.goodsName = T4.goodsName AND T3.goodsName = 'flower'". Firstly, using the rules in Table 2, we get the join bitmap of the query: $Bit(T3) \wedge Bit(T4)$, and retrieve redundant data with RowID $\{0-5, 7, 9\}$ in wide table T_w by using join bitmap index in Figure 4(b). Then, the duplicates are removed based on the primary key *goodsId*. Hence, the remaining results of the query include tuples with RowID $\{0, 1, 5\}$ in the wide table T_w. Finally, filters and projections are also applied, and the ground truth of the query is "10".

4 KNOWLEDGE-GUIDED QUERY SPACE EXPLORATION (KQE)

Given a schema, the search space of valid join queries is huge and it is infeasible and ineffective to enumerate all possibilities. To represent the search space, we first extend the schema graph G_s to a plan-iterative graph $G = (V, E')$. Vertices in G are classified into two types, table vertex v_t with label "table" and column vertex v_c with label *type*, indicating data type of the column. Based on the vertex type, edges are also split into two categories: edges between two table vertexes (v_t, v_t') and edges between table vertexes and column vertexes (v_t, v_c). The labels of (v_t, v_t') and (v_t, v_c) denote the join type and the relational operator applied to the column, respectively. An example of plan-iterative graph is shown in Figure 6. If m join operators are supported, we will create m edges between two tables with primary-foreign key relationship. If we pick "filter" on the edge between T_1 and *userId*, we will generate a predicate on *userId* in the generated query. To simplify the representation, we define a label function f_l which maps a vertex $v \in V$ or an edge $e \in E$ to its label.

With the plan-iterative graph G_s, each generated join query can be mapped to a sub-graph in G_s. If the corresponding sub-graphs of two generated queries are isomorphic, this implies that they share the same query structure and incur redundant examination overhead in the query space. In other words, using either one of the isomorphic queries is sufficient for logic bug detection. Therefore, we enforce the query generation algorithm with a constraint that a newly generated query graph G_q should not be isomorphic with some existing query graphs G_d. In the following, we formally define sub-graph isomorphism and isomorphic set.

Definition 4.1. Given $G_q = (V, E)$ and $G_d = (V', E')$, a sub-graph isomorphism is an injection function f_{iso} from V to V' such that $\forall v \in V, f_l(v) = f_l(f_{iso}(v)); \forall e(v, v') \in E, e(f_{iso}(v), f_{iso}(v')) \in E'$ and $f_l(e(v, v')) = f_l(e(f_{iso}(v), f_{iso}(v')))$.

Definition 4.2. Given a plan-iterative graph G, an isomorphic set S contains a set of sub-graphs of G and has the following properties: 1) $\forall G_i, G_j \in S$, G_i and G_j are isomorphic; 2) we cannot find another sub-graph G_x of G having $G_x \notin S$ and $\exists G_i \in S$, G_x and G_i are isomorphic.

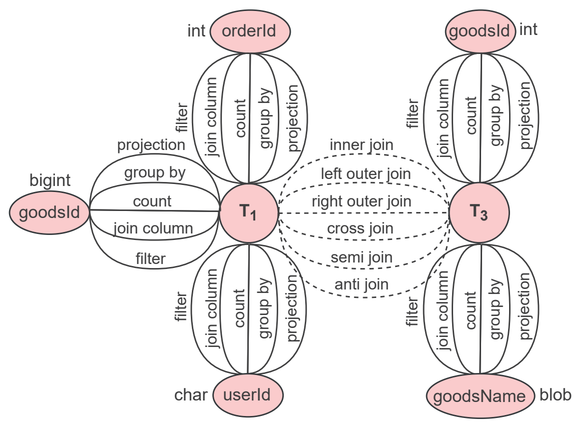


Fig. 6. Plan-iterative graph. Queries can be mapped to sub-graphs in the plan-iterative graph.

Unfortunately, we cannot directly evaluate the exact graph isomorphism for every generated query because it has been proven that determining the sub-graph existence in a graph (i.e., sub-graph isomorphism matching) is NP-complete [11, 22]. Recently, learning-based models have been proposed for sub-graph analysis tasks. For examples, NeuroMatch [61] and LMKG [17] are developed for the sub-graph isomorphism problem. These algorithms perceive the presence or absence of a sub-graph problem as a binary classification problem. To support more general sub-graph isomorphism search, GNNs (Graph Neural Networks) have been adopted by [20] and [60].

Motivated by learning-based approaches for sub-graph isomorphism search, we extend our random walk scheme in Section 3.3 with an adaptive weighting strategy. In order to avoid repeatedly exploring similar graph structures, we adjust the probabilities of random walks based on the exploration history. Figure 7 illustrates our idea. To support the approximate evaluation of subgraph isomorphism, KQE builds a graph index *GI*. Given a query q and its corresponding sub-graph G_q from the plan-iterative graph, *GI* first applies the similarity-oriented graph embedding approach [20] to generate a unique high dimensional embedding $E(G_q)$ for q. If two sub-graphs are isomorphic or structurally similar, the cosine distance of their embeddings is expected to be below a threshold. Then, *GI* applies the HD-Index [3] to support approximate KNN (K-Nearest Neighbor) search in the high-dimensional space.

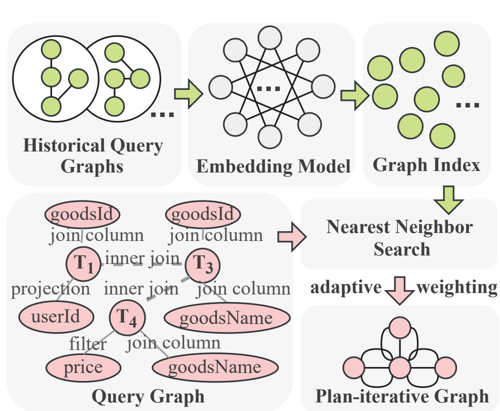


Fig. 7. Running example of knowledge-guided query space exploration.

Algorithm 2 AdaptiveRandomWalk (G, v, l, GI)

Input: plan-iterative graph G, start node v, maximum walk length l, graph index GI.
Output: walk W_v.

Initialize walk W_v to $[v]$, $\pi_{e_x} = 1$
for $k = 1$ to $randomInt(l)$ **do**
  $v_k = W_v$.last_vertex
  $G_q = getGraph(W_v)$
  $E_k = getNextEdges(v_k, G)$
  for e_x in E_k **do**
    $G'_q = G_q$ extend by e_x, v_x (i.e., $e_x = (v_k, v_x)$)
    obtain π_{e_x} by GI
  if $\pi_{e_x} < \pi_{end}$ **then**
    break
  $e_{k+1} = AliasSample(E_k, \pi_{e_x})$
  $v_{k+1} = getNode(v_k, e_{k+1})$
  append $[e_{k+1}, v_{k+1}]$ to W_v
  $\pi_{end} = \pi_{e_{k+1}}$
Return: W_v

We define the coverage score of a generated query graph G_q wrt historical sub-graphs (i.e., query graphs of queries that had already been explored):

$$coverage(G_q) = \frac{1}{k} \sum_{i=1}^{k} cosine\_similarity(E(G_q), E(G_i)), \tag{2}$$

where G_i is the i-th nearest neighbor of the query graph G_q returned by GI. A higher coverage value indicates that similar graph structures have been explored and hence, this indicator allows us to avoid repeatedly generating similar queries.

To guide the query generator to explore more diversified search spaces, KQE performs the random walk according to the adaptive weights of the next possible edges. Consider a random walk that follows a path $P_q = (v_0, e_1, v_1, ..., e_k, v_k)$ to generate a sub-graph G_q, with v_k being the current vertex that is accessed, KQE decides its next step by evaluating the transition probability π_{e_x} for each edge e_x connecting with vertex v_k. A possible next query graph G'_q can be created by adding edge e_x and the corresponding vertex v_x (i.e., $e_x = (v_k, v_x)$) to G_q (i.e., $P_{q'} = (v_0, e_1, v_1, ..., e_k, v_k, e_x, v_x)$). The transition probability on edge e_x is set to

$$\pi_{e_x} = \frac{1}{coverage(G'_q) + 1}. \tag{3}$$

We also establish a termination mechanism with a probability π_{end}, when the scores of all next possible graphs are less than the current query graph, the graph expansion is stopped. The pseudocode for the adaptive random walk on plan-iterative graph G is given in Algorithm 2. At every step of the walk, alias sampling is conducted based on the transition probability π_{e_x}. Sampling of nodes while simulating the random walk can be done efficiently in $O(1)$ time complexity using alias sampling.

The existence of KQE allows us to perform parallel query space exploration, where a central server hosts the graph index and applies the adaptive random walk approach. When a new query is generated, the server disseminates it to a random client, which maintains a replica of the database

Table 3. We tested a diverse set of popular and emerging DBMS. All numbers are the lasted as of July 2022.

DBMS	Popularity Rank			LOC	First Release
	DB-Engines	Stack Overflow	Github Stars		
MySQL	2	1	8.0k	3.8M	1995
MariaDB	12	7	4.3k	3.6M	2009
TiDB	96	–	31.8k	0.8M	2017

and hosts an individual DSG process. This strategy effectively improves the efficiency of database debugging, and the only bottleneck is the synchronization cost of the KQE on the server side.

5 EXPERIMENT

We evaluate the TQS on multiple DBMSs and specifically, our goal is to answer the following questions:

- Can the TQS detect logic errors of implementations of multi-table queries from real-world production-level DBMSs? (section 5.1)
- Can the TQS outperform state-of-the-art testing tools? (section 5.2)
- What are the main roles of two core modules (namely DSG and KQE) of TQS? (section 5.3)

Tested DBMSs. In our evaluation, we consider three open-source DBMSs designed for different purposes (see Table 3) to demonstrate the generality of TQS. According to the DB-Engine's Ranking [18], the Stack Overflow's annual Developer Survey [42], and GitHub, these DBMSs are among the most popular and widely-used DBMSs. We also run TQS against our own cloud-native database system (PolarDB). PolarDB [15] is designed to run on elastic computation and storage resources with high scalability and concurrency support. All selected DBMSs support hints for their optimizers to intentionally change the physical plans [36, 40, 54].

We have evaluated TQS with both randomly generated TPC-H data and the dataset from UCI machine learning repository[2]. However, since TPC-H dataset follows uniform distribution and has a simple schema, all reported bugs on TPC-H dataset have been covered by the UCI dataset. Therefore, we only show the results on the UCI data. As TQS runs, it continuously reports bugs and to be fair for all DBMSs, we only report the results for the first 24 hours. All DBMSs are run with default configurations and compilation options.

Baseline approaches. We compare TQS with the SQLancer[3] which is the start-of-the-art approach to detecting logic bugs in databases. SQLancer is not designed to test multi-table queries. However, it can be tailored for multi-table queries by artificially generating queries and tuples across more than one tables. Similar to the single table case, all queries and tuples are randomly generated. We use three methods in SQLancer as our baselines. The first one is PQS [50], which constructs queries to fetch a randomly selected tuple from a table. The tested DBMS may contain a bug if it fails to fetch that tuple. The second one is TLP [50], which decomposes a query into three partitioning queries, each of which computes its result on that tuple. The third one is NoRec [47], which targets at logic bugs generated by the optimization process in DBMS. It performs a comparison between the results of randomly-generated queries and their rewritten ones.

DBMS versions. Note that DBMS bugs will be fixed once reported to the community. In our experiments, we report the results of the latest released versions during our testing, namely, MySQL 8.0.28, MariaDB 10.8.2, TiDB 5.4.0 and PolarDB beta 8.0.18 respectively.

[2]https://archive.ics.uci.edu/ml/datasets/KDD+Cup+1998+Data
[3]https://github.com/sqlancer/sqlancer

Table 4. Detected bugs. TQS found 20 bug types: 7 from MySQL, 5 from MariaDB, 5 from TiDB and 3 from PolarDB.

Database	ID	Status	Severity	Description
MySQL 8.0.28	1	Fixed	S1 (Critical)	Semi-join gives wrong results.
	2	Fixed	S2 (Serious)	Incorrect inner hash join when using materialization strategy.
	3	Verified	S2 (Serious)	Incorrect semi-join execution results in unknown data.
	4	Verified	S2 (Serious)	Incorrect left hash join with subquery in condition.
	5	Verified	S2 (Serious)	Incorrect nested loop antijoin.
	6	Fixed	S2 (Serious)	Bad caching of converted constants in NULL-safe comparison.
	7	Verified	S2 (Serious)	Incorrect hash join with materialized subquery.
MariaDB 10.8.2	8	Verified	Major	Incorrect join execution by not allowing BKA and BKAH join.
	9	Verified	Major	Incorrect join execution by not allowing BNLH and BKAH join.
	10	Verified	Major	Incorrect join execution when controlling outer join operations.
	11	Verified	Major	Incorrect join execution by limiting the usage of the join buffers.
	12	Verified	Major	Incorrect join execution when controlling join cache.
TiDB 5.4.0	13	Fixed	Critical	Incorrect Merge Join Execution.
	14	Fixed	Critical	Merge Join executed incorrect resultset which missed -0.
	15	Fixed	Critical	Merge Join executed an incorrect empty resultset.
	16	Fixed	Critical	Merge Join executed an incorrect NULL resultset.
	17	Fixed	Critical	Merge Join executed an incorrect resultset which missed rows.
PolarDB 8.0.18	18	Fixed	2 (High)	Left join convert to inner join returns wrong result sets.
	19	Fixed	2 (High)	Hash join returns wrong result sets.
	20	Verified	2 (High)	Incorrect semi-join with materialize execution.

Setup. All experiments are conducted on our in-house server equipped with Intel Xeon CPU E5-2682 (2.50GHz) 16 cores and 128GB memory. For our cloud-native database PolarDB, we run an instance on our public cloud with similar computation capability to our in-house server.

5.1 Overview and Showcase of Bug Reports

TQS has successfully detected 115 bugs from tested DBMSs within 24 hours, including 31 bugs in MySQL, 30 bugs in MariaDB, 31 bugs in TiDB, and 23 bugs in PolarDB respectively. However, some bugs may be caused by the same relational algebras. Hence, once finding a possible bug, it is essential to produce a minimal test case with C-Reduce[4] before reporting the bug, to save the DBMS developers' time and effort. Then, we submit all bugs and the corresponding test cases to developer communities and received their positive feedbacks. Through such root cause analysis, there are totally 7, 5, 5 and 3 types of bugs in MySQL, MariaDB, TiDB and PolarDB respectively. Table 4 shows the details of the identified bug types by DBMS developers.

Among all 20 types of bugs, some result in code fixes (8 reports), documentation fixes (2 reports), or are confirmed by the developers (10 reports). In other words, each bug is previously unknown and has a unique fix associated with it, or is confirmed by the developers to be a unique bug. Note that all bug reports are documented at the page[5].

Severity levels. For the tested DBMSs, bugs are assigned a severity level by the DBMS developers. 6 bugs were classified as Critical, 6 bugs as Serious, 5 bugs as Major and 3 bugs as High. In what follows, we briefly explain those bugs.

5.1.1 Bugs in MySQL. A large portion of bugs in MySQL involves semi-join and sub-query execution. Listing 1 shows an example query resulting in the incorrect semi-join execution.

```
CREATE TABLE t0 (
```

[4]http://embed.cs.utah.edu/creduce/
[5]https://xiutangzju.github.io/tqs/

```
  c0 DECIMAL ZEROFILL COLUMN_FORMAT DEFAULT);

INSERT HIGH_PRIORITY INTO t0(c0) VALUES(NULL), (2000-09-06), (NULL);
INSERT INTO t0(c0) VALUES(NULL);
INSERT DELAYED INTO t0(c0) VALUES(2016-02-18);

query:
SELECT t0.c0 FROM t0 WHERE t0.c0 IN (SELECT t0.c0 FROM t0 WHERE (t0.c0 NOT IN (
    SELECT t0.c0 FROM t0 WHERE t0.c0)) = (t0.c0));

ground truth:
Empty set

transformed query:
SELECT t0.c0 FROM t0 WHERE t0.c0 IN (SELECT /*+ semijoin()*/ t0.c0 FROM t0 WHERE (
    t0.c0 NOT IN (SELECT t0.c0 FROM t0 WHERE t0.c0))=t0.c0);

result:
+------------+
| c0         |
+------------+
| 0000001985 |
| 0000001996 |
+------------+

transformed query:
SELECT t0.c0 FROM t0 WHERE t0.c0 IN (SELECT/*+ no_semijoin()*/ t0.c0 FROM t0 WHERE
     (t0.c0 NOT IN (SELECT t0.c0 FROM t0 WHERE t0.c0))=t0.c0);

result:
Empty set
```

Listing 1. MySQL's incorrect semi-join execution.

By analyzing query plans of the above query, we find that hash join with semi-join produces incorrect results when using materialization technique for optimization. MySQL community responds to us that there is a documented fix in the changelog of MySQL 8.0.30. It explains that incorrect results may be generated from execution of a semi-join with materialization, when the WHERE clause has an equal condition. In some cases, such as when the equal condition is denoted as an IN or NOT IN expression, the equality is neither pushed down for materialization, nor evaluated as part of the semi-join. This could also cause issues with inner hash joins.

```
CREATE TABLE t0 (
  c0 text NOT NULL,
  primary key (c0));

CREATE TABLE t1 (
  c0 tinyint(3) unsigned zerofill ,
  c1 varchar(15) NOT NULL,
  primary key (c0),
  key t1_fk1 (c1),
  constraint t1_ibfk_1 foreign key (c1)
  references t0(c0));
```

```
query:
SELECT t1.c0 FROM t1 LEFT OUTER JOIN t0 ON t1.c1 = t0.c0 WHERE (t1.c1 IN (SELECT
    t0.c0 FROM t0 )) OR (t0.c0);

ground truth:
+------+
|  c0  |
+------+
| NULL |
| NULL |
+------+
```

Listing 2. MySQL's incorrect left hash join execution.

We also test with foreign key constraints. Listing 2 illustrates a bug when trying to optimize a left hash join using *subquery_to_derived* condition. MySQL retrieves an additional "NULL" value.

5.1.2 Bugs in MariaDB. Different from MySQL, many bugs were reported on the nested loops join and hash join in MariaDB. Listing 3 shows an example bug, which is produced by transforming block nested loop hash join to block nested loop join in MariaDB. Incorrect result set is obtained, as when MariaDB executes the join, data are mistakenly changed to empty.

```
CREATE TABLE t1 (
  c0 varchar(100) NOT NULL,
  KEY ic1 (c0));

CREATE TABLE t2 (
  c0 varchar(100) NOT NULL);

query:
SELECT t2.c0 FROM t2 RIGHT OUTER JOIN t1 ON t1.c0=t2.c0;

ground truth:
+------+
| c0   |
+------+
| NULL |
| NULL |
+------+

transformed query:
SET optimizer_switch='join_cache_hashed=off';
SELECT t2.c0 FROM t2 RIGHT OUTER JOIN t1 ON t1.c0=t2.c0;

result:
+------+
|  c0  |
+------+
|      |
| NULL |
+------+
```

Listing 3. MariaDB's incorrect loop join execution.

Listing 4 shows another bug when transforming batch key access join to block nested loop join. When MariaDB executes the join, the optimizer mistakenly changes the null value to empty.

```
CREATE TABLE t1 (
  c0 bigint(20) DEFAULT NULL);

CREATE TABLE t2 (
  c0 double NOT NULL,
  c1 varchar(100) NOT NULL,
  PRIMARY KEY (c1));

CREATE TABLE t3 (
  c0 mediumint(9) NOT NULL,
  c1 tinyint(1) NOT NULL);

CREATE TABLE t4 (
  c0 double NOT NULL,
  c1 varchar(100) NOT NULL,
  PRIMARY KEY (c1));

query:
SELECT t3.c0 FROM t3 RIGHT OUTER JOIN t4 ON t3.c1 = t4.c1 JOIN t2 ON t2.c1 = t4.c1
     CROSS JOIN t1;

ground truth:
+------+
|  c0  |
+------+
| NULL |
| NULL |
+------+

transformed query:
SET optimizer_switch='join_cache_bka=off';
SELECT t3.c0 FROM t3 RIGHT OUTER JOIN t4 ON t3.c1 = t4.c1 JOIN t2 ON t2.c1 = t4.c1
     CROSS JOIN t1;

result:
Empty set
```

Listing 4. MariaDB's incorrect index join execution.

5.1.3 *Bugs in TiDB.*

Merge join and join index are the main causes of bugs in TiDB. Listing 5 shows an example query, where incorrect result set is obtained when hash join is converted to merge join (due to space constraints, the ground truth results and incorrect results are discarded here).

```
CREATE TABLE t1 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id));

CREATE TABLE t2 (
```

```
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id));

CREATE TABLE t3 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id));

SELECT /*+ merge_join(t1, t2, t3)*/ t3.col1 FROM (t1 LEFT JOIN t2 ON t1.col1=t2.
    col1) LEFT JOIN t3 ON t2.col1=t3.col1;

SELECT /*+ hash_join(t1, t2, t3)*/ t3.col1 FROM (t1 LEFT JOIN t2 ON t1.col1=t2.
    col1) LEFT JOIN t3 ON t2.col1=t3.col1;
```

Listing 5. TiDB's merge join executed incorrect result set which misses -0.

We find that when TiDB executes the above merge join, intermediate data are mistakenly materialized as null. TiDB developers stated that it was because outer merge join cannot keep the prop of its inner child and the bug has been fixed.

5.1.4 Bugs in PolarDB. In our PolarDB, most bugs are produced from hash join and semi-join. Listing 6 illustrates an example query which transforms left join to inner join. PolarDB fails to return a correct result set. We submit it to our developers and they located the cause of the bug: the inner join cannot distinguish null from 0.

```
CREATE TABLE t1 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 int(16) NOT NULL,
  PRIMARY KEY (id, col1));

CREATE TABLE t2 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 int(16) NOT NULL,
  PRIMARY KEY (id, col1));

CREATE TABLE t3 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id));

query:
SELECT t1.id FROM (t1 LEFT JOIN t2 ON t1.col1=t2.id) JOIN t3 ON t2.col1=t3.col1
    where t1.col1 = 1;

ground truth:
empty set

transformed query:
SELECT /*+JOIN_ORDER(t3, t1, t2)*/ t1.id FROM (t1 LEFT JOIN t2 ON t1.col1=t2.id)
    JOIN t3 ON t2.col1=t3.col1 where t1.col1 = 1;

result:
```

```
+------+
| id   |
+------+
| NULL |
| NULL |
+------+
```

Listing 6. PolarDB's incorrect inner join execution.

As another example, Listing 7 shows that a test case caused the semi-join to return the wrong result sets. When the query is executed by an inner semi hash join without materialization strategy, the PolarDB returns the incorrect result.

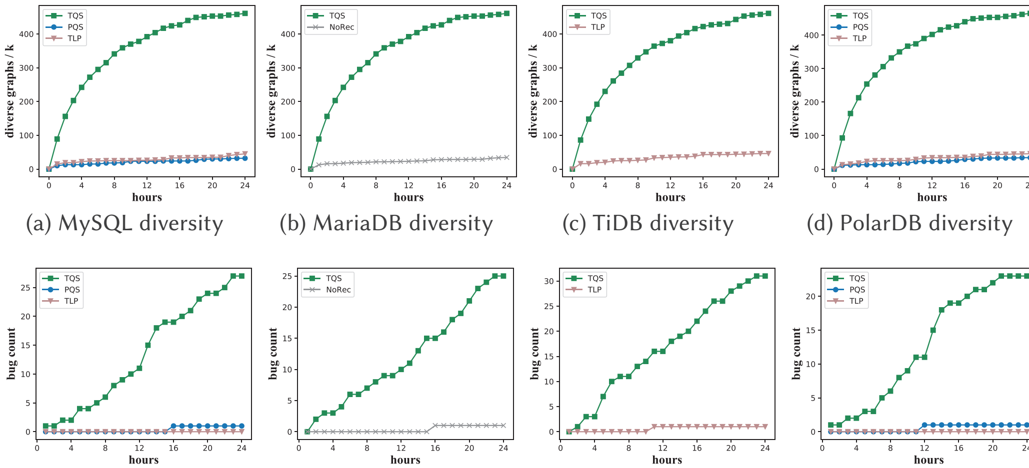
```
CREATE TABLE t0 (c0 float);
CREATE TABLE t1 (c0 float);

query:
SELECT ALL t1.c0 FROM t1 RIGHT OUTER JOIN t0 ON t1.c0 = t0.c0 WHERE t1.c0 IN (
    SELECT t0.c0 FROM t0 WHERE (t1.c0 NOT IN (SELECT t1.c0 FROM t1))=(1) IN (t1.c0
    ));

ground truth:
Empty set

transformed query:
SET optimizer_switch='materialization=off';
SELECT ALL t1.c0 FROM t1 RIGHT OUTER JOIN t0 ON t1.c0 = t0.c0 WHERE t1.c0 IN (
    SELECT t0.c0 FROM t0 WHERE (t1.c0 NOT IN (SELECT t1.c0 FROM t1 )) = (1) IN t1.
    c0);

result:
+-----------+
| c0        |
+-----------+
| 292269000 |
+-----------+
```

Listing 7. PolarDB's incorrect hash join execution.

5.2 Comparison with Existing Tools

We compare TQS with three state-of-the-art DBMS testing approaches in different aspects to show its effectiveness and efficiency. Note that due to the compatibility problem, SQLancer implements different approaches on different databases (PQS and TLP on MySQL and PolarDB; NoRec on MariaDB; TLP on TiDB). Figure 8 shows our comparison results. We adopt two metrics. The diversity of graphs shows the number of different isomorphic sets tested, and the bug type count represents the number of returned logic bug types.

Query graph diversity. Figure 8(a), (b), (c) and (d) show the query graph diversity (in thousands of isomorphic sets) of MySQL, MariaDB, TiDB and PolarDB, respectively. TQS significantly outperforms baseline approaches on testing diversity. This is because that (1) SQLancer approaches may generate random joins with empty results which are not usable for testing and (2) TQS adopts the KQE to avoid repeatedly testing the same query structure.



(a) MySQL diversity (b) MariaDB diversity (c) TiDB diversity (d) PolarDB diversity

(e) MySQL efficiency (f) MariaDB efficiency (g) TiDB efficiency (h) PolarDB efficiency

Fig. 8. Comparison with existing tools in the query graph diversity and the efficiency of detecting bugs.

Efficiency. Figure 8(e), (f), (g) and (h) show the testing efficiency of MySQL, MariaDB, TiDB and PolarDB, respectively. Not surprisingly, we obtain a similar result as the diversity experiment. More query structures are being tested, more bugs can be discovered.

In fact, we run the TQS for 48 hours and continue to find logic bugs for all DBMSs. But there are too many bugs and we have not submitted them to the developer communities for verification. So we only show bug types of the first 24 hours. Figure 9 illustrates that the number of bugs increases linearly with the testing time, while the number of bug types is not. This indicates that most bugs are caused by a small set of improperly implemented operators.

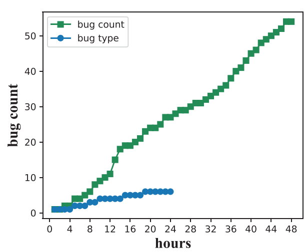


Fig. 9. Bug types vs bug counts on MySQL.

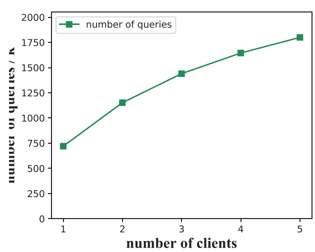


Fig. 10. Effect of parallel search.

In Section 4, we briefly explain the idea of using KQE to build a distributed computation framework to speed up the testing process. We show our results in Figure 10 by deploying the framework on the different number of clients. We run our experiments on MySQL for 24 hours and the results show that using parallel computation can effectively facilitate the testing process.

5.3 Ablation Studies

In this section, we perform ablation experiments over some facets of TQS in order to better understand their roles.

Table 5. Ablation test over the effect of model composition.

DBMS	Approach	Query Graph Diversity	Bug Count
MySQL 8.0.28	TQS	460k	31
	$TQS_{!Noise}$	460k	14
	$TQS_{!GT}$	460k	21
	$TQS_{!KQE}$	228k	16
MariaDB 10.8.2	TQS	475k	30
	$TQS_{!Noise}$	475k	15
	$TQS_{!GT}$	475k	18
	$TQS_{!KQE}$	234k	12
TiDB 5.4.0	TQS	462k	31
	$TQS_{!Noise}$	462k	20
	$TQS_{!GT}$	462k	22
	$TQS_{!KQE}$	231k	18
PolarDB 8.0.18	TQS	465k	23
	$TQS_{!Noise}$	465k	12
	$TQS_{!GT}$	465k	18
	$TQS_{!KQE}$	225k	15

Noise vs No-Noise. We artificially generate noise data during our testing. As shown in Table 5, the results indicate that the number of discovered bugs dramatically decreases, if we remove the noise-injection module (denoted as $TQS_{!Noise}$). This verifies that a large portion of logic bugs are generated by outliners or unexpected values. DBMS developers should be alerted of boundary testing.

```
CREATE TABLE t1 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 int(16) DEFAULT NULL,
  col2 double DEFAULT NULL,
  PRIMARY KEY (id));

CREATE TABLE t2 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 int(16) NOT NULL,
  col2 double DEFAULT NULL,
  col3 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id, col1));

CREATE TABLE t3 (
  id bigint(64) NOT NULL AUTO_INCREMENT,
  col1 double DEFAULT NULL,
  col2 varchar(511) DEFAULT NULL,
  PRIMARY KEY (id));

SELECT t3.col2 FROM (t1 LEFT JOIN t2 ON t1.col1=t2.id) JOIN t3 ON t2.col1=tmp3.
    col3;
```

Listing 8. PolarDB's incorrect hash join execution.

GT vs No-GT. We first show the power of ground-truth verification. TQS without GT(ground-truth) is to judge the correctness of query results by comparing the results executed with different query plans (denoted as $TQS_{!GT}$), namely using the differential testing. We found that 7 bugs could not be detected using the differential testing on PolarDB. For example, Listing 8 shows a bug of hash join in PolarDB 8.0.18. The query result remains the same for different plans. But the query result is different from the ground-truth of this query, indicating a logic bug here. As shown in Table 5, some bugs cannot be revealed by differential testing, while using ground-truth results, we can successfully identify them.

KQE vs No-KQE. KQE (knowledge-guided query space exploration) allows us to avoid the exploration of similar query structures. In Table 5, we observe that TQS is superior to the $TQS_{!KQE}$ on the four databases, indicating the effectiveness of applying KQE to generate queries. Note that because iterating all possible isomorphic sets for a graph is an NP-complete problem, there is no way to perform exhaustive testing. The intuition of KQE is to generate new queries as much as possible, not to iterate all isomorphic sets.

In summary, noise injection, ground-truth results and KQE modules are important for bug detection. They either improve the effectiveness of TQS, or speed up the testing process.

6 RELATED WORK

Differential Testing of DBMS. Differential testing is a widely adopted approach for detecting logic bugs in software systems. It compares results of the same query from multiple versions of the system or uses different physical plans to discover possible bugs. Differential testing has been shown to be effective in many areas [12, 16, 30, 33, 38, 59]. It is first used in RAGS to find bugs of DBMSs [53]. APOLLO also applies differential testing to find performance regression bugs by executing SQL queries on multiple versions of DBMSs [29]. There were 10 previously unknown performance regression bugs found in SQLite and PostgreSQL. Although differential testing shows its effectiveness, our experiments show that some logic bugs must be revealed by using ground-truth results.

Generator-based Testing of DBMS. Various database data generators [6, 13, 23, 26, 31] and query generators [5, 14, 29, 39, 45, 52, 55] have been proposed to artificially create test cases, but test oracles, which should give feedback on the correctness of the system, have received less attention. Generation-based testings [24, 32, 34, 39, 46, 58, 62] have been adopted for extensive testings on DBMSs for purposes such as bug-finding and benchmarking. SQLSmith is a widely-used generation-based DBMS tester [52]. It synthesizes a schema from initial databases and generates limited types of queries, whose target is at the code coverage. Squirrel focuses on generating queries to detect memory corruption bugs [62]. All above random generators are mostly applied to detect crashing bugs, while our focus is the logic bug.

Logic Bug Testing of DBMS. SQLancer [49] is a current state-of-the-art tool in testing DBMS for logic bugs and is the most closely related work to ours. SQLancer proposes three approaches to detect logic bugs. PQS constructs queries to fetch a randomly selected tuple from a table [50]. TLP decomposes a query into three partitioning queries, each of which computes its result on a selected tuple [48]. NoRec compares the results of randomly-generated optimized queries and rewritten queries that DBMS cannot optimize [47]. SQLancer targets at single table queries and 90.0% of its bug reports include only one table. On the other hand, our TQS targets at detecting logic bugs of multi-table joins, which are more prone to bugs.

Database Schema Normalization. The well-known database design framework for relational databases is centered around the notion of data redundancy [7, 35]. The redundant data value occurrences originate from functional dependencies (FDs) [8]. The data-driven normalization algorithms [19, 44, 56] can remove FD-related redundancy effectively. Schema normalization has been well studied. In our approach, we adopt previous database normalization algorithm to spilt a wide table into multiple tables, so that the ground-truth results of join queries over those tables can be recovered from the wide table.

Synthetic Graph Generation. In our approach, we adopt a random walk-based approach to generate valid join queries by enumerating sub-graphs from the schema graph. In fact, synthetic graph generation and the corresponding graph exploration approaches have been studied for years. For example, in support of the experimental study of graph data management system, a variety of synthetic graph tools such as SP2Bench [51], LDBC [21], LUBM [25], BSBM [9], Grr [10], WatDiv [2] and gMark [4] have been developed in the research community. In our scenario, iterating all possible sub-graphs is an NP-hard problem, and hence, we adopt a novel neural encoding-based approach to avoid generating similar sub-graphs, significantly reducing the overhead.

7 CONCLUSION

In this paper, we proposed a framework, TQS (**T**ransformed **Q**uery **S**ynthesis), for detecting logic bugs of the implementations of multi-table join queries in DBMS. TQS employs two novel techniques, DSG (Data-guided Schema and query Generation) and KQE (Knowledge-guided Query space Exploration), to generate effective SQL queries and their ground-truth results for testing. We evaluated the TQS on four DBMSs: MySQL, MariaDB, TiDB and PolarDB. There are 115 bugs discovered from tested DBMSs within 24 hours. Based on root cause analysis from the developer community, there are totally 7, 5, 5 and 3 types of bugs in MySQL, MariaDB, TiDB and PolarDB, respectively. Compared to existing database debug tools, TQS is more efficient and effective in detecting logic bugs generated by different join operators. It can be considered as an essential DBMS development tool.

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