

# Efficient Detection of Empty-Result Queries

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## Abstract

Frequently encountered in query processing, empty query results usually do not provide users with much useful information. Yet, users might still have to wait for a long time before they disappointingly realize that their results are empty. To significantly reduce such unfavorable delays, in this paper, we propose a novel method to quickly detect, without actual execution, those queries that will return empty results. Our key idea is to remember and reuse the results from previously-executed, empty-result queries. These results are stored in the form of so-called atomic query parts so that the (partial) results from multiple queries can be combined together to handle a new query without incurring much overhead. To increase our chance of detecting empty-result queries with only a limited storage, our method (1) stores the most “valuable” information about empty-result queries, (2) removes redundant information among different empty-result queries, (3) continuously updates the stored information to adapt to the current query pattern, and (4) utilizes a set of special properties of empty results. We evaluate the efficiency of our method through a theoretical analysis and an initial implementation in PostgreSQL. The results show that our method has low overhead and can often successfully avoid executing empty-result queries.

## 1. Introduction

DBMSs are being used more and more for interactive exploration [7, 14, 37], where users keep refining queries based on previous query results. Due to the large data set size, users are forced to form rather precise queries in order to avoid getting too many query results. Unfortunately, this often causes queries to return empty result sets, which usually do not provide users with much useful information [19, 26]. This is especially true at the beginning, when users do not have sufficient knowledge of the data set. Even worse, users cannot discover empty result sets until query execution finishes, which can take a long time. We call this the *empty-result problem* [19].

Empty results are frequently encountered in query processing. For example, in a query trace that contains 18,793 SQL queries and is collected in a Customer Relationship Management (CRM) database application developed by IBM, 18.07% (3,396) queries

are empty-result ones. In another real estate database application developed by IBM, 5.75% SQL queries are discovered to return empty result sets. As a third example, [17] and [30] reported that the percentages of empty-result queries are 10.53% and 38%, respectively.

One might think that empty-result queries can finish in a short amount of time. However, this is often not the case. For example, consider a query that joins two relations (possibly after some selection and projection). Regardless of whether the query result set is empty, the query execution time will be longer than the time required to do the join. Even if this query can finish execution in a few seconds in a lightly loaded RDBMS, it can last longer than a minute in a heavily loaded RDBMS.

In general, it is desirable to quickly detect empty-result queries. Not only does it facilitate the exploration of massive data sets but also it provides important benefits to users. First, users can quickly realize that they encounter the empty-result problem rather than waiting for the empty result. With a much shortened latency time, users can quickly go ahead with other trials. Second, by avoiding the unnecessary execution of empty-result queries, the load on the RDBMS can be reduced, thus further improving the system performance.

In this paper, we propose a novel method for fast detection of empty-result queries. To the best of our knowledge, this direction of handling the empty-result problem has never been explored before. We observe that as users often submit similar queries, the probability that they can reuse each other’s query results is usually high. For example, among the 3,396 empty-result queries collected from the CRM database application at IBM, only 1,287 queries are distinct. All the other 2,109 queries are repeated ones. Hence, we reuse the evaluation results from previously-executed, empty-result queries by storing the information about query parts in the RDBMS, where each query part is a sub-tree of a query plan tree. If such reuse is always successful, the execution of at least 11% ( $=2109/18793$ ) of all the 18,793 queries in the above mentioned CRM application can be saved.

Under a fixed storage budget, to improve our chance of using the remembered information to detect whether a new query will return an empty result set, four techniques are used. First, from previous queries’ execution, only the lowest-level query parts that lead to empty result sets, rather than all empty-result query parts, are stored. Second, redundancy in the information provided by different empty-result queries is removed and only the most “valuable” information is stored. Third, as query pattern changes, the stored empty-result query parts get continuously updated to adapt to the current situation. Fourth, our method utilizes a set of special properties of empty result sets so that its coverage detection capability is often more powerful than that of the traditional materialized view method (e.g., if  $\pi(R)=\emptyset$ , we know immediately that  $R=\emptyset$ ,  $\sigma(R)=\emptyset$ , and  $R \bowtie S=\emptyset$ ).

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Our method works as follows. From previous queries' execution, the lowest-level query parts that lead to empty result sets are found. These query parts are decomposed into so-called atomic query parts and stored in the RDBMS. In this way, the (partial) execution results from multiple, previously-executed, empty-result queries can be combined together to handle a new query without incurring much overhead. When a new query comes, it is decomposed into atomic query parts, which are then matched with the remembered ones. If such a match exists for each decomposed atomic query part, we know immediately that this new query will return an empty result set and thus its execution is saved.

The empty-result problem has been studied in the research literature. Existing solutions either explain what leads to the empty result set [10, 16, 18, 21, 26, 27] or automatically generalize the query so that the generalized query will return some answers [7, 18, 19, 27]. For most such solutions, the first step is to execute the query and see whether the result set is empty. Our method can be used in conjunction with these solutions and significantly speed up this first step.

Throughout this paper, we assume a read-mostly environment where periodic batch updates are allowed. This is the case with traditional data warehouses. The data sets of all the database applications mentioned earlier satisfy this property. When relations get updated, our current method is to delete all the information in the RDBMS about previously-executed, empty-result queries.

We investigate the performance of our fast detection method for empty-result queries with a theoretical analysis and an initial implementation in PostgreSQL. The results show that our method has minor overhead and can often bring significant benefit by avoiding executing empty-result queries unnecessarily.

The rest of the paper is organized as follows. Section 2 describes our fast detection method for empty-result queries. Section 3 investigates the performance of the proposed method. We discuss related work in Section 4 and conclude in Section 5.

## 2. A Fast Detection Method for Empty-Result Queries

In this section, we describe our fast detection method for empty-result queries. Unless otherwise specified, we focus on select-project-join queries. By select-project-join queries, we mean those queries whose logical query plans contain only scan, selection, projection, join, sort, and duplicate elimination operators. Nested queries that can be rewritten into such a form are included while outer join operators are excluded. All the operators are physical operators. All the query plans are physical query plans. In Section 2.5 below, we show how to extend our techniques beyond select-project-join queries.

Our main observation is that query plans of different queries often share some common parts [32, 33, 39]. For example, during interactive exploration, users often issue a series of queries. Each query is a refinement of the previous one [34]. Also, users often submit canned queries by filling parameter values into a pre-defined template [37]. If for some parameters, different users fill in the same values (e.g., certain parts of the data set can be frequently accessed), then the query plans of these queries are likely to share some common parts. During previous queries' execution, if the RDBMS remembers the query parts that lead to empty result sets, then it is likely that the RDBMS can use them to

tell whether future queries will return empty result sets. The details of our method are described in the following subsections.

### 2.1 Definitions

We first introduce some definitions.

**Empty-result-propagating operator.** Consider an operator  $Op$  that has one or more inputs.  $Op$  is an empty-result-propagating operator if it satisfies the following condition: the output of  $Op$  is empty if any input of  $Op$  is empty.

**Empty-result-propagating query.** An empty-result-propagating query is a query whose query plan contains only empty-result-propagating operators.

A large number of operators (e.g., scan, selection, projection, join, sort, duplicate elimination) are empty-result-propagating. As a result, empty-result-propagating queries include a large class of queries. For example, all the select-project-join queries are empty-result-propagating queries.

**Query part.** A query plan is a tree of operators. Every sub-tree of the query plan is called a query part.

In our discussion, we assume that each relation is used at most once in a query part. In the case that the same relation  $R$  is used multiple times in a query part (e.g.,  $R$  is joined with itself), the first occurrence of  $R$  is untouched while each other occurrence of  $R$  is given a different name. Then our techniques still work. (This may reduce the detection capability of our method. However, as mentioned in Section 2.6 below, our method wants to achieve a balance between efficiency and detection capability.)

**Atomic query part.** Each atomic query part is an ordered pair (relation names  $R_N$ , selection condition  $S_C$ ). It represents a relational algebra formula that first product joins all the relations in  $R_N$ , and then applies  $S_C$ .  $S_C$  is a conjunction of primitive terms, where each primitive term is a comparison (e.g.,  $A.a=B.b$ ,  $A.a<B.b+C.c$ ,  $A.a=100$ ). In the rest of the paper, we do not differentiate between an atomic query part and the relational algebra formula represented by the atomic query part.

**Cover (selection condition).** A selection condition  $S_{C1}$  covers another selection condition  $S_{C2}$  iff whenever  $S_{C2}$  is true,  $S_{C1}$  is also true.

**Cover (atomic query part).** We say that an atomic query part  $P_1=(R_{N1}, S_{C1})$  covers another atomic query part  $P_2=(R_{N2}, S_{C2})$  if  $R_{N1} \subseteq R_{N2}$  and  $S_{C1}$  covers  $S_{C2}$ . For example,  $P_1=\sigma_{A.a<40}(A)$  covers  $P_2=\sigma_{A.a=20 \wedge A.c=B.d}(A \times B) = (\sigma_{A.a=20}(A)) \bowtie_{A.c=B.d} B$ .

The following two theorems will be used repeatedly in our discussion:

**Theorem 1:** Any query part of an empty-result-propagating query is an empty-result-propagating query. For an empty-result-propagating query, if the output of some query part  $P$  is empty, the output of any higher-level query part that contains  $P$  (and thus the output of the entire query) is empty.

**Proof.** Omitted.

**Theorem 2:** Suppose that atomic query part  $P_1$  covers atomic query part  $P_2$ . For a given database, if the output of  $P_1$  is empty, the output of  $P_2$  is also empty.

**Proof.** Suppose that  $P_1=(R_{N1}, S_{C1})$ .  $P_2=(R_{N2}, S_{C2})$ . The output  $U_1$  of  $P_1$  is

$$U_1 = \sigma_{S_{C1}} \left( \prod_{R \in R_{N1}} R \right).$$

The output  $U_2$  of  $P_2$  is

$$U_2 = \sigma_{S_{C2}} \left( \prod_{R \in R_{N2}} R \right).$$

From  $R_{N1} \subseteq R_{N2}$  and  $U_1 = \emptyset$ , we know that

$$\begin{aligned}
U_3 &= \sigma_{S_{C1}} \left( \prod_{R \in R_{N2}} R \right) \\
&= \sigma_{S_{C1}} \left( \left( \sigma_{S_{C1}} \left( \prod_{R \in R_{N1}} R \right) \right) \times \left( \prod_{R \in R_{N2}-R_{N1}} R \right) \right) \\
&= \sigma_{S_{C1}} \left( U_1 \times \left( \prod_{R \in R_{N2}-R_{N1}} R \right) \right) \\
&= \emptyset.
\end{aligned}$$

From  $S_{C1}$  covers  $S_{C2}$ , we know that  $U_2 \subseteq U_3$ . Hence, we have  $U_2 = \emptyset$ . ■

## 2.2 Overview of the Method

In this section, we give an overview of our fast detection method for empty-result queries. The RDBMS keeps a collection  $C_{app}$  of atomic query parts. The output of each atomic query part in  $C_{app}$  is empty. The information about previously-executed, empty-result queries is stored in  $C_{app}$ . For efficiency purposes,  $C_{app}$  is always kept in memory. Initially,  $C_{app}$  is empty.

When the execution of a query returns an empty result set, the RDBMS does the following two operations:

**Operation  $O_1$ :** Display the query plan to the user. For each operator in the query plan, the output cardinality is displayed (the output cardinalities of the operators are kept as collected statistics during query execution [23]). These output cardinalities can facilitate the user to find first the query sub-expression (and the reason) that causes the empty result set, and then the right follow-up queries [10]. The follow-up queries submitted by the user can still return empty result sets. This is because after optimizer's rewriting, the query plan often looks very different from the original query. The user may not always be able to find the genuine cause of the empty result set. Also, there can be multiple causes that lead to the empty result set.

**Operation  $O_2$ :** Find the lowest-level query part(s) whose output is empty. Each such query part  $P$  is broken into one or more atomic query parts. Then the atomic query parts are stored in the collection  $C_{app}$ . According to Theorem 1, the output of any higher-level query part  $P_h$  that contains  $P$  is empty, while the output of any lower-level query part  $P_l$  that is contained in  $P$  is not empty. However, the information about  $P_h$  is not stored in  $C_{app}$ , since this information is redundant. This is similar to the technique in [10, 21] of only presenting the minimal zero results to the user.

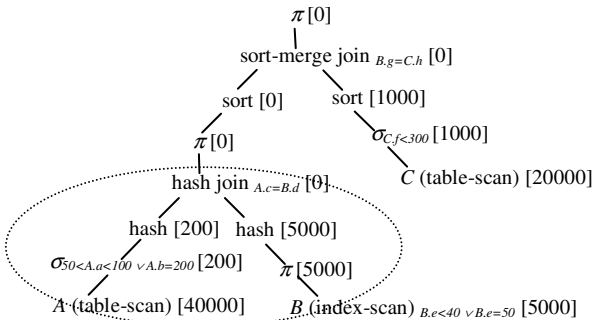


Figure 1. A first query plan example.

For example, consider the query plan in Figure 1. The numbers in the square brackets represent the output cardinalities of the operators. The subscripts represent the selection conditions. (Join conditions are also selection conditions.) Only the query part that is represented by the oval is broken into atomic query parts.

From query execution, the RDBMS can only obtain output cardinalities of physical operators in physical query plans [23]. Hence, in Operations  $O_1$  and  $O_2$ , our method works with physical query plans rather than logical query plans. In contrary, as described in Section 2.4 below, when our method uses the information stored in  $C_{app}$  to check whether a new query  $Q$  will return an empty result set, the logical query plan of  $Q$  is used.

In Operation  $O_2$ , the query part  $P$  is stored in the collection  $C_{app}$  in the form of one or more atomic query parts. This is to facilitate the future checking of whether a new query  $Q$  will return an empty result set, as our method may need to use the (partial) execution results from multiple previous queries (see Section 2.4 below for details). For example, suppose that  $Q = \sigma_{A.a=50 \vee A.a=60}(A)$ . From previous queries' execution, the RDBMS knows that both queries  $Q_1 = \sigma_{A.a=50 \vee A.b=30}(A)$  and  $Q_2 = \sigma_{A.a=60 \vee A.b=40}(A)$  return empty result sets.  $Q_1$  is broken into two atomic query parts:  $P_1 = \sigma_{A.a=50}(A)$  and  $P_2 = \sigma_{A.b=30}(A)$ .  $Q_2$  is broken into two atomic query parts:  $P_3 = \sigma_{A.a=60}(A)$  and  $P_4 = \sigma_{A.b=40}(A)$ . Then by using  $P_1$  and  $P_3$ , our method can tell that  $Q$  will return an empty result set.

A constant  $C_{cost}$  is used to decide whether a query is a *low-cost query* or a *high-cost query*. When the query plan of a new query  $Q$  comes, our method first checks whether the optimizer's estimated cost of  $Q$ ,  $cost(Q)$ , is bigger than  $C_{cost}$ . There are two possible cases:

- (1) If  $cost(Q) \leq C_{cost}$  (i.e.,  $Q$  is a low-cost query),  $Q$  is executed.
- (2) If  $cost(Q) > C_{cost}$  (i.e.,  $Q$  is a high-cost query), our method first uses the information stored in the collection  $C_{app}$  to check whether  $Q$  will return an empty result set. If not,  $Q$  is executed. Otherwise the empty result set is returned directly.

Our heuristics is that low-cost queries can be executed quickly, and it takes time to use the information stored in  $C_{app}$  to check whether a query will return an empty result set. Hence, there is no need to use the information stored in  $C_{app}$  to check whether a low-cost query will return an empty result set. Similarly, we do not store the information about low-cost empty-result queries in  $C_{app}$ .

$C_{cost}$  is an empirical number. Its value can be decided based on past statistics. For example, how expensive it is to use the information stored in  $C_{app}$  to check whether a query will return an empty result set, how likely a query will return an empty result set, etc.

## 2.3 Storing Atomic Query Parts

In this section, we show how to break a lowest-level query part  $P$  whose output is empty into one or more atomic query parts and then store the atomic query parts in the collection  $C_{app}$ . Our method proceeds in three steps:

- Step 1:**  $P$  is transformed into a simplified query part  $P_s$ .
- Step 2:**  $P_s$  is broken into one or more atomic query parts.
- Step 3:** The atomic query parts are stored in  $C_{app}$ .

### Organization of $C_{app}$

To facilitate search and save storage space, the collection  $C_{app}$  of atomic query parts is organized as a list of entries. Each entry in  $C_{app}$  represents a set of relation names  $R_N$ . All the atomic query parts with the same relation names  $R_N$  are stored in the same entry as a linked list of selection conditions  $S_C$ .

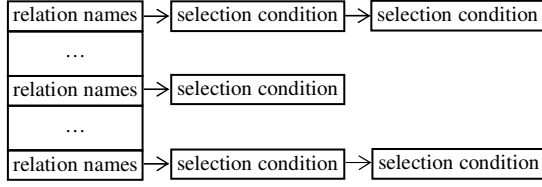


Figure 2. The collection  $C_{aqp}$  of atomic query parts.

The number of atomic query parts stored in the collection  $C_{aqp}$  cannot exceed a constant  $N_{max}$  (as will be shown in Section 3.1,  $N_{max}$  can be quite large). This is because it is not desirable to let  $C_{aqp}$  consume too much storage space. Also, as discussed in Section 2.4 below, to check whether a new query  $Q$  will return an empty result set, our method needs to check whether the atomic query parts generated from  $Q$  are covered by those stored in  $C_{aqp}$ . The more atomic query parts stored in  $C_{aqp}$ , the slower the checking.

Our method only stores in the collection  $C_{aqp}$  those atomic query parts that are frequently used [38]. To achieve this goal, the standard clock algorithm (an approximation of the LRU algorithm) is used to manage  $C_{aqp}$ . Each time the RDBMS wants to store a new atomic query part  $P_{new}$  in  $C_{aqp}$ ,

- (1) If the number of atomic query parts stored in  $C_{aqp}$  is no more than  $N_{max}$ ,  $P_{new}$  is stored in  $C_{aqp}$  directly.
- (2) If the number of atomic query parts stored in  $C_{aqp}$  is larger than  $N_{max}$ , the RDBMS uses the clock algorithm to find an atomic query part  $P_{old}$  in  $C_{aqp}$  that is not frequently used.  $P_{old}$  is deleted from  $C_{aqp}$ . Then  $P_{new}$  is stored in  $C_{aqp}$ .

Our method is more dynamic than the method in [2, 40] of only keeping the most frequently used materialized views, since creating or deleting an atomic query part is cheaper than creating or deleting a materialized view and thus can be done more frequently.

### Step 1: $P \Rightarrow P_s$

When getting a lowest-level query part  $P$  whose output is empty, the RDBMS converts  $P$  into a simplified query part  $P_s$  by performing the following three transformations:

**Transformation  $T_1$ :** Drop all the operators in  $P$  that have no influence on the emptiness of the output. These operators include projection, hash, sort, and duplicate elimination.

**Transformation  $T_2$ :** Each physical join operator (e.g., hash join, sort-merge join, nested-loops join) in  $P$  is replaced with a logical join operator.

**Transformation  $T_3$ :** Each index-scan operator in  $P$  is replaced with a table-scan operator followed by a selection operator, where the selection condition is the same as the index-scan condition.

The result of a query is independent of its evaluation method. Hence, none of these three transformations has influence on the emptiness of the output. Essentially, these three transformations convert the “physical” query part  $P$  into a “logical” query part – the simplified query part  $P_s$ .  $P_s$  represents a relational algebra formula without projection and duplicate elimination. It is more “general” than  $P$ . This can increase our chance of using the query part to detect whether a new query will return an empty result set.

For example, after applying these three transformations, the query part that is represented by the oval in Figure 1 becomes the simplified query part in Figure 3. Our method can use this simplified query part to tell that the query in Figure 4 will return an empty result set (see Section 2.4 below for details).

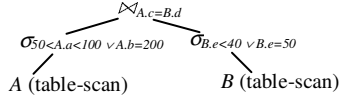


Figure 3. A simplified query part example.

$$(\sigma_{50 < A.a < 100 \vee A.b=200} (A)) \bowtie_{A.c=B.d} (\sigma_{B.e < 40 \vee B.e=50} (B))$$

Figure 3. A simplified query part example.

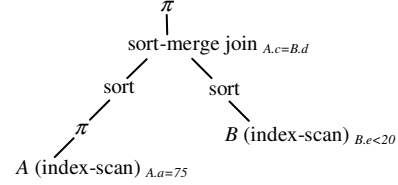


Figure 4. A second query plan example.

### Step 2: $P_s \Rightarrow$ Atomic Query Parts

Now the simplified query part  $P_s$  is broken into one or more atomic query parts. Suppose that  $P_s$  contains  $n$  selection conditions. Each selection condition comes from either a selection operator or a join operator. Each selection condition is rewritten into a disjunctive normal form (DNF). DNF is a disjunction of terms, where each term is a conjunction of primitive terms and each primitive term is a comparison. During the rewriting,

- (1) Negations on numeric or string attributes are removed by using complementary operators. For example,  $not(A.a < 20)$  is rewritten into  $A.a \geq 20$ .  $not(A.a=20)$  is rewritten into  $(A.a < 20) \vee (A.a > 20)$ .
- (2) Interval-based comparison is treated as a single primitive term. For example,  $10 < A.a < 20$  is treated as a single primitive term rather than a conjunction of two primitive terms  $10 < A.a$  and  $A.a < 20$ . This is to facilitate the later checking of whether one atomic query part covers another atomic query part.

After the above rewriting, the combination of all  $n$  selection conditions in the simplified query part  $P_s$  becomes a conjunction of  $n$  DNFs  $D_1 \wedge D_2 \wedge \dots \wedge D_n$ , where each  $D_i$  ( $1 \leq i \leq n$ ) is a DNF of a selection condition. Then  $D_1 \wedge D_2 \wedge \dots \wedge D_n$  is rewritten into another DNF  $P_{DNF}$ . Each term in  $P_{DNF}$  is a selection condition. It is a conjunction of  $n$  terms, where the  $i$ -th ( $1 \leq i \leq n$ ) term comes from  $D_i$ . Note that the rewriting into the DNF  $P_{DNF}$  is an exponential step. However, usually this step is not expensive, as selection conditions are not very complex. Also, for queries with extremely complex selection conditions, our method may not be used.

Let  $R_N$  denote the input relations of all the table-scan operators in the simplified query part  $P_s$ . Each term  $S_C$  in  $P_{DNF}$ , combined with  $R_N$ , is an atomic query part  $(R_N, S_C)$ . For example, after rewriting, the simplified query part in Figure 3 becomes the four atomic query parts in Figure 5.

$$\begin{aligned} &(\sigma_{50 < A.a < 100} (A)) \bowtie_{A.c=B.d} (\sigma_{B.e < 40} (B)) \\ &(\sigma_{A.b=200} (A)) \bowtie_{A.c=B.d} (\sigma_{B.e < 40} (B)) \\ &(\sigma_{50 < A.a < 100} (A)) \bowtie_{A.c=B.d} (\sigma_{B.e=50} (B)) \\ &(\sigma_{A.b=200} (A)) \bowtie_{A.c=B.d} (\sigma_{B.e=50} (B)) \end{aligned}$$

Figure 5. Atomic query part examples.

It is easy to see that the simplified query part  $P_s$  and the generated atomic query parts have the following property:

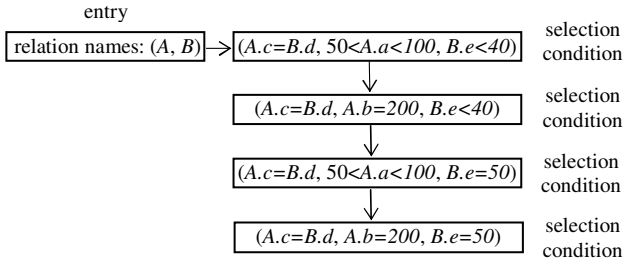
**Theorem 3:** The following three assertions are equivalent to each other:

- The output of the query part  $P$  is empty.
- The output of  $P_s$  is empty.
- The output of each generated atomic query part is empty.

**Proof.** Omitted.

### Step 3: Storing Atomic Query Parts in $C_{app}$

For each atomic query part  $P_a=(R_N, S_C)$  generated in Step 2, all the atomic query parts that are covered by  $P_a$  are removed from the collection  $C_{app}$ . Then  $P_a$  is inserted into  $C_{app}$ . That is, only the most “general” atomic query parts are kept in  $C_{app}$ , since they are most useful in deciding whether a new query will return an empty result set. This is similar to the materialized view merging technique in [2].



**Figure 6. An example entry in the collection  $C_{app}$  of atomic query parts.**

For example, suppose that the collection  $C_{app}$  is originally empty. Then after inserting the four atomic query parts in Figure 5, the corresponding entry  $E$  in  $C_{app}$  becomes what is shown in Figure 6.

For an atomic query part  $P_a=(R_N, S_C)$ , atomic query parts that are covered by  $P_a$  can only be contained in those entries of  $C_{app}$  whose relation names form a superset of  $R_N$ . To find out which atomic query parts stored in  $C_{app}$  are covered by  $P_a$ , our method only searches in those entries. (The signature method in [31] is used to speed up the process of checking set containment.)

### Deciding Coverage

In general, it is computationally expensive to decide precisely whether one atomic query part  $P_1$  covers another atomic query part  $P_2$  (many problems are NP-complete) [3, 9, 11, 13, 20, 22, 28, 36]. In our case, false positives are not allowed while false negatives are tolerable. That is, if our method decides that  $P_1$  covers  $P_2$ , it must be true that  $P_1$  covers  $P_2$ . However, if  $P_1$  covers  $P_2$  but our method fails to detect it, it does not matter except that efficiency is sacrificed. For example, storage in the collection  $C_{app}$  is wasted, or a new query  $Q$  is executed unnecessarily because our method fails to use the information stored in  $C_{app}$  to detect that  $Q$  will return an empty result set (see Section 2.4 below for details).

In deciding whether  $P_1=(R_{N1}, S_{C1})$  covers  $P_2=(R_{N2}, S_{C2})$ , the RDBMS uses a method that attempts to achieve a reasonable balance between efficiency and detection capability [3, 36]. Suppose that  $S_{C1}=p_1 \wedge p_2 \wedge \dots \wedge p_n$  and  $S_{C2}=q_1 \wedge q_2 \wedge \dots \wedge q_m$ . Each  $p_i$  ( $1 \leq i \leq n$ ) is a primitive term. Each  $q_j$  ( $1 \leq j \leq m$ ) is a primitive term.

The method works as follows. The RDBMS decides that  $S_{C1}$  covers  $S_{C2}$  if they satisfy the following two conditions:

- $n \leq m$ .

- For each  $i$  ( $1 \leq i \leq n$ ), the RDBMS decides that  $p_i$  covers some  $q_j$  ( $1 \leq j \leq m$ ).

If one of the following three conditions is satisfied, the RDBMS decides that  $p_i$  covers  $q_j$ :

- $p_i=q_j$ .
- Both  $p_i$  and  $q_j$  are interval-based comparison on the same attribute of the same relation. The interval in  $p_i$  contains the interval in  $q_j$ . Note that point-based comparison is a special form of interval-based comparison. Also, the endpoints of some intervals can be plus or minus infinity. For example,  $p_i$  is of the form  $A.a < 50$  and  $q_j$  is of the form  $20 < A.a < 40$ . As a second example,  $p_i$  is of the form  $A.a < 50$  and  $q_j$  is of the form  $A.a = 30$ .
- The comparisons in  $p_i$  and  $q_j$  are on the same attribute of the same relation.  $p_i$  is of the form  $A.a \neq c_1$ .  $q_j$  is of the form  $A.a = c_2$ .  $c_1 \neq c_2$ .

As mentioned in Section 2.1,  $P_1$  covers  $P_2$  if  $R_{N1} \subseteq R_{N2}$  and  $S_{C1}$  covers  $S_{C2}$ .

[9] proposed an algorithm that uses safe substitutions to decide whether a materialized view  $MV$  can be used to answer a query  $Q$ .  $MV$  “covers”  $Q$  if a safe substitution of  $MV$  can be used to generate an equivalent query of  $Q$ . Our method can be regarded as a simplified version of the algorithm in [9], where safe substitutions are replaced by naive substitutions. This is because in generating atomic query parts, all the projection operators are dropped (Transformation  $T_1$ ). Hence, there is no “dangling” selection condition. The computational overhead of our method is lower than that of the algorithm in [9], while in certain cases, the coverage detection capability of our method is weaker than that of the algorithm in [9]. This results from our design philosophy that is explained in Section 2.6.

## 2.4 Checking Empty Result Set

In this section, we describe how to use the information stored in the collection  $C_{app}$  to check whether a query  $Q$  will return an empty result set. Suppose that the logical query plan of  $Q$  is  $Q_p$ . Techniques similar to that in Section 2.3 are used to break  $Q_p$  into one or more atomic query parts  $P_i$  ( $i=1, 2, \dots, m$ ). For each  $i$  ( $1 \leq i \leq m$ ), the RDBMS checks whether there exists any atomic query part  $A_i$  in  $C_{app}$  that covers  $P_i$ . (As explained at the end of Step 3 in Section 2.3, our method only needs to search in those entries of  $C_{app}$  whose relation names form a subset of the relation names of  $P_i$ .) If such an  $A_i$  exists, the RDBMS knows that the output of  $P_i$  is empty (Theorem 2). If the RDBMS can find such an  $A_i$  for each  $i$  ( $1 \leq i \leq m$ ), it knows that the output of  $Q_p$  is empty (Theorem 3).

## 2.5 Extension beyond Select-Project-Join Queries

The above discussion focuses on select-project-join queries. In certain cases, our techniques can be extended beyond select-project-join queries. For example,

- Suppose that the root operator of the query plan is an aggregate operator (either with or without a group by clause). Except for this root aggregate operator, the rest of the query plan forms a select-project-join query. Since the root aggregate operator has no influence on the emptiness of the query output, the RDBMS can ignore it when deciding whether the query will return an empty result set.  $count()$  needs some special handling, as  $count(\emptyset)=0$ .

- (2) Set union is not an empty-result-propagating operator. Suppose that the RDBMS wants to check whether the output of  $Q_1 \cup Q_2$  is empty, where  $Q_1$  and  $Q_2$  are select-project-join queries. The techniques in Sections 2.2~2.4 are used to check whether the output of  $Q_1$  is empty, and whether the output of  $Q_2$  is empty. There are three possible cases:
- The checking says that both outputs are empty. Then the output of  $Q_1 \cup Q_2$  is empty.
  - The checking only says that the output of  $Q_1$  (or the output of  $Q_2$ ) is empty. Then  $Q_2=Q_1 \cup Q_2$  (or  $Q_1=Q_1 \cup Q_2$ ) needs to be evaluated.
  - The checking says nothing.  $Q_1 \cup Q_2$  needs to be evaluated.
- (3) Outer join can be handled in a way similar to set union.
- (4) Set difference is not an empty-result-propagating operator. Suppose that the RDBMS wants to check whether the output of  $Q_1 - Q_2$  is empty, where  $Q_1$  is a select-project-join query. The techniques in Sections 2.2~2.4 are used to check whether the output of  $Q_1$  is empty. If so, the output of  $Q_1 - Q_2$  is empty. Otherwise  $Q_1 - Q_2$  needs to be evaluated.

We leave it as an interesting area for future work to investigate how to handle other classes of queries. For example, set intersection is an empty-result-propagating operator. In the presence of set intersection in the query plan, projection operators influence the emptiness of the query output – from  $A \cap B = \emptyset$ , it cannot be deduced that  $\pi(A) \cap \pi(B) = \emptyset$  (the attributes that are projected out in  $A$  and  $B$  can have different values and cause  $\pi(A) \cap \pi(B) \neq \emptyset$ ). As a result, our current method of storing the information of empty-result queries in the collection  $C_{app}$  does not work for set intersection. One possible solution is that in the presence of set intersection, Transformation  $T_1$  does not drop projection operators.

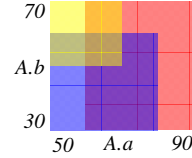
## 2.6 Comparison between Our Method and the Traditional Materialized View Method

Our fast detection method for empty-result queries uses some data structure similar to materialized views – each atomic query part stored in the collection  $C_{app}$  can be regarded as a “mini” materialized view. However, our method utilizes a set of special properties of empty result sets and is different from the traditional method of using materialized views to answer queries.

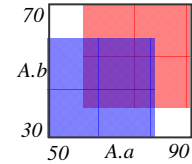
In deciding whether a query will return an empty result set, our method ignores those operators (e.g., projection, duplicate elimination) that have no influence on the emptiness of the query output. Hence, in certain cases, the coverage detection capability of our method is more powerful than that of the traditional materialized view method. For example, consider the following two queries:  $Q_1 = A \bowtie_{A.c=B.d} B$  and  $Q_2 = \pi(\sigma_{A.a=100}(A)) \bowtie_{A.c=B.d} B$ .  $A.a$  is projected out by the projection operator in  $Q_2$ . In general, materialized view  $MV = \pi(A \bowtie_{A.c=B.d} B)$  cannot be used to answer either  $Q_1$  or  $Q_2$ . However, if the RDBMS knows that query  $Q_3 = MV$  returns an empty result set, our method can tell that both  $Q_1$  and  $Q_2$  will return empty result sets.

Usually, a large number of atomic query parts can be stored in the collection  $C_{app}$  and our method wants to speed up the checking process. Therefore, when checking whether a query will return an empty result set, our method uses a limited number of approaches to check the coverage of atomic query parts. In contrast, the traditional materialized view method uses the extensive query rewriting approach, which is more capable in certain cases but

also more expensive. For example, consider query  $Q = \sigma_{50 < A.a < 90} \wedge 30 < A.b < 70}(A)$ . There are three materialized views that are all empty:  $MV_1 = \sigma_{50 < A.a < 80} \wedge 30 < A.b < 60}(A)$ ,  $MV_2 = \sigma_{60 < A.a < 90}(A)$ , and  $MV_3 = \sigma_{50 < A.a < 70} \wedge 50 < A.b < 70}(A)$ . The traditional materialized view method can rewrite  $Q$  into  $Q = \sigma_{30 < A.b < 70}(MV_1 \cup MV_2 \cup MV_3)$  and thus tell that  $Q$  will return an empty result set. In contrast, our method cannot tell that if  $MV_1$ ,  $MV_2$ , and  $MV_3$  are all empty, the output of  $Q$  is also empty.



To save storage space, the traditional materialized view method can merge multiple materialized views together [2]. For example, the two materialized views  $MV_1 = \sigma_{50 < A.a < 80} \wedge 30 < A.b < 60}(A)$  and  $MV_2 = \sigma_{60 < A.a < 90} \wedge 40 < A.b < 70}(A)$  can be merged into a single materialized view  $MV_3 = \sigma_{50 < A.a < 90} \wedge 30 < A.b < 70}(A)$ . Then all the queries that can be answered by using either  $MV_1$  or  $MV_2$  are answerable by using  $MV_3$ . However, if both  $MV_1$  and  $MV_2$  are empty, the RDBMS cannot deduce that  $MV_3$  is also empty. As a result, our method cannot arbitrarily merge multiple atomic query parts in the collection  $C_{app}$  into a single atomic query part.



In general, the design philosophy of our method is to achieve a reasonable balance between efficiency and detection capability. Our method strives for the detection capability that is both mostly needed and easily achievable [3, 36]. It makes up the “loss” in the other detection capability by storing a large number of atomic query parts in the collection  $C_{app}$ .

## 2.7 Summary of Advantages

Our fast detection method for empty-result queries has the following advantages:

- It has small storage and computation overhead.
- A large number of atomic query parts can be stored in the collection  $C_{app}$ .
- As query pattern changes, the atomic query parts stored in  $C_{app}$  get continuously updated to reflect the current situation.
- The hotter an empty-result query  $Q$  is (i.e., the more frequently users submit this  $Q$ ), the more likely  $Q$  can be successfully detected by our method. This is desirable for those applications where users care more about hot spots in the data set.
- Due to the utilization of a set of special properties of empty result sets, its coverage detection capability is often more powerful than that of a traditional materialized view method. After enough information about previously-executed, empty-result queries has been accumulated in  $C_{app}$ , our method can often successfully detect empty-result queries and avoid the expensive query execution. This both reduces the load on the RDBMS and speeds up the interactive exploration process.

### 3. Performance Evaluation

In this section, we evaluate the performance of our method, first with experiments in PostgreSQL [29], and then with a theoretical analysis.

#### 3.1 Evaluation in PostgreSQL

We first describe experiments we performed with a prototype implementation of our techniques in PostgreSQL Version 7.3.4 [29]. Our measurements were performed with the PostgreSQL client application and server running on a Dell Inspiron 8500 PC with one 2.2GHz processor, 512MB main memory, one 40GB disk, and running the Microsoft Windows XP operating system. The default setting of PostgreSQL was used, where the buffer pool size is 1,000 pages. (We also tested larger buffer pool sizes. The results were similar and thus omitted.)

The relations used for the experiments followed the schema of the standard TPC-R Benchmark relations [35]:

```
customer (custkey, nationkey, ...),
orders (orderkey, custkey, orderdate, ...),
lineitem (orderkey, partkey, ...).
```

**Table 1. Test data set.**

	number of tuples	total size
customer	0.15×s M	23×s MB
orders	1.5×s M	114×s MB
lineitem	6×s M	755×s MB

$s$  is the scale factor of the database. In our experiments, on average, each *customer* tuple matches ten *orders* tuples on the attribute *custkey*. Each *orders* tuple matches 4 *lineitem* tuples on the attribute *orderkey*.

We used the following two queries:

**Query  $Q_1$ :** Find the information about certain parts that were sold on certain days.

```
select *
from orders o, lineitem l
where o.orderkey=l.orderkey
and (o.orderdate= $d_1$  or ... or o.orderdate= $d_e$ )
and (l.partkey= $p_1$  or ... or l.partkey= $p_g$ );
```

**Query  $Q_2$ :** Find the information about certain parts that were sold to certain customers on certain days.

```
select *
from orders o, lineitem l, customer c
where o.orderkey=l.orderkey and o.custkey=c.custkey
and (o.orderdate= $d_1$  or ... or o.orderdate= $d_e$ )
and (l.partkey= $p_1$  or ... or l.partkey= $p_g$ )
and (c.nationkey= $n_1$  or ... or c.nationkey= $n_g$ );
```

We built an index on each selection or join attribute. Before we ran queries, we ran the PostgreSQL statistics collection program on all the relations. We also tested other database schemas. The results are similar and thus not presented here.

For each query  $Q_i$  ( $i=1, 2$ ) we tested, if  $Q_i$  returns an empty result set, the minimal zero result [10, 21] is  $Q_i$  itself. That is, except for the entire  $Q_i$ , any part of  $Q_i$  (e.g., selection on a single relation) has some non-empty output. For  $Q_1$ , its combination factor is defined as  $F=exf$ . For  $Q_2$ , its combination factor is defined as  $F=exf \times g$ .  $F$  represents the number of atomic query parts that will be generated from the query.

We performed three experiments. In these experiments, we purposely use large  $N$ 's to demonstrate good scalability, where  $N$  is the number of atomic query parts that have already been stored

in the collection  $C_{app}$  when the new query comes. As will be shown in Section 3.2, our method can often use a much smaller  $N$  to achieve good detection probability. In each experiment, we measured the overhead of our techniques in the following two cases:

**Case 1:** Only  $Q_1$ 's are executed. That is, the new query is  $Q_1$ . Also, the information stored in  $C_{app}$  comes from previous  $Q_1$ 's.

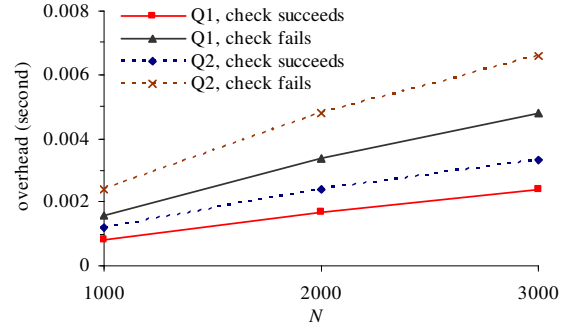
**Case 2:** Only  $Q_2$ 's are executed. That is, the new query is  $Q_2$ . Also, the information stored in  $C_{app}$  comes from previous  $Q_2$ 's.

For each reported number, the experiment was repeated twenty times (twenty runs). Each run used different (and random)  $d_i$ 's ( $1 \leq i \leq e$ ),  $p_j$ 's ( $1 \leq j \leq g$ ), and  $n_k$ 's ( $1 \leq k \leq g$ ). Unless otherwise specified, the reported overhead of our techniques is the largest one observed during these twenty runs. The reported query execution time is the shortest one observed during these twenty runs. This is to approximate the maximum overhead of our techniques and the shortest query execution time. In this way, when comparing the overhead of our techniques with the query execution time, we always do favor to the query execution time.

#### $C_{app}$ Size Experiment

In this experiment, we fixed  $F=2$  and  $s=2$ . We varied  $N$  from 1,000 to 3,000. Recall that  $N$  is the number of atomic query parts that have already been stored in the collection  $C_{app}$  when the new query comes.

Figure 7 shows the overhead of our techniques. By “check succeeds/fails,” we mean that our method can/cannot use the information stored in the collection  $C_{app}$  to tell that a query will return an empty result set. The lines for query  $Q_1$  ( $Q_2$ ) represent the overhead of our techniques in Case 1 (Case 2).



**Figure 7. Overhead of our techniques ( $C_{app}$  size experiment).**

The overhead of our techniques in Case 2 is larger than that in Case 1. This is because query  $Q_2$  is more complex than query  $Q_1$ :  $Q_2$  joins three relations, while  $Q_1$  joins two relations. As a result, the atomic query parts generated from  $Q_2$  are more complex than those generated from  $Q_1$ . Also, the atomic query part coverage checking in Case 2 is more time consuming than that in Case 1.

The overhead of our techniques increases with  $N$ , the number of atomic query parts stored in the collection  $C_{app}$ . This is easy to understand. Given a query,  $C_{app}$  needs to be searched for matching atomic query parts. The more atomic query parts stored in  $C_{app}$ , the longer time the search takes.

When the check succeeds, the collection  $C_{app}$  only needs to be searched once. When the check fails, if the query returns an empty result set,  $C_{app}$  needs to be searched twice. The first time is to check whether the query will return an empty result set. The second time is to store the information about the empty-result

query into  $C_{app}$ . Hence, when the check fails, the maximum overhead of our techniques is about two times that when the check succeeds.

### Query Combination Factor Experiment

In this experiment, we fixed  $s=2$  and  $N=2,000$ . We varied the query combination factor  $F$  from 1 to 8. Figure 8 shows the overhead of our techniques. The meaning of the four lines in Figure 8 is the same as that in Figure 7. The larger the  $F$  is, the more atomic query parts the query generated. Then our method needs to spend more time on both searching for the matching atomic query parts in the collection  $C_{app}$ , and storing the atomic query parts generated from an empty-result query into  $C_{app}$ . Therefore, the overhead of our techniques increases with  $F$ .

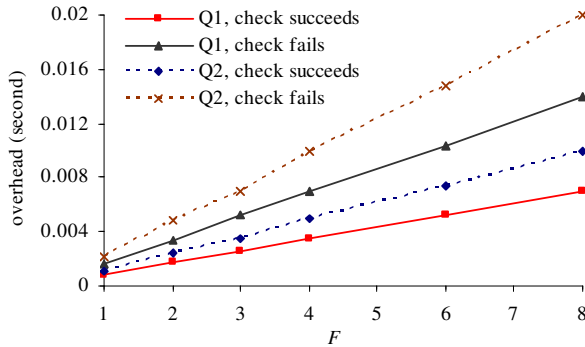


Figure 8. Overhead of our techniques (query combination factor experiment).

### Database Scale Factor Experiment

In this experiment, we fixed  $F=2$  and  $N=2,000$ . We varied the database scale factor  $s$  from 1 to 3. The purpose of this experiment is to show that the overhead of our techniques is negligible compared to the query execution cost.

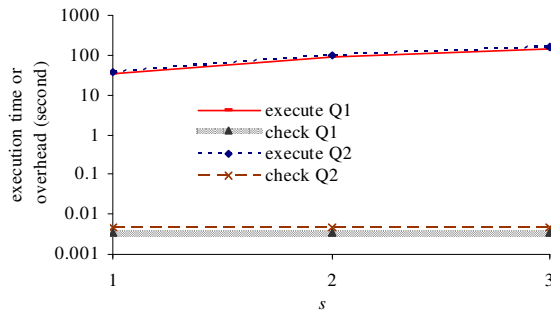


Figure 9. Query execution time vs. overhead of our techniques (database scale factor experiment).

Figure 9 shows both the overhead of our techniques and the query execution time. The lines for “check  $Q_1/Q_2$ ” represent the overhead of our techniques. The lines for “execute  $Q_1/Q_2$ ” represent the query execution time. The y-axis uses logarithmic scale.

Our techniques do not examine the data set. Also, our techniques only perform fast in-memory operations (recall that the entire collection  $C_{app}$  is kept in memory). Hence, compared to the query execution time, the overhead of our techniques is about four orders of magnitude smaller.

The query execution time increases with the data set size. In contrary, the overhead of our techniques is independent of the data set size, since our techniques do not examine the data set.

## 3.2 Theoretical Analysis of Detection Probability

We now turn to describe a first-principle mathematical analysis on the probability that our method can successfully detect empty-result queries. The goal of this analysis is to gain insight into the main performance trends of our method. For this purpose, our analysis picks up several typical cases that are frequently encountered in practice (e.g., canned queries).

We assume that all the queries are of the form  $\pi \sigma_{S_C} (R_1 \bowtie R_2 \bowtie \dots \bowtie R_k)$ , where  $S_C$  is the selection condition and the join condition is omitted. From previous queries’ execution,  $N$  atomic query parts have been stored in the collection  $C_{app}$ . The detection probability  $D_p$  is defined as the probability that our method can successfully detect empty-result queries. That is, in the case that the output of a new query  $Q$  is empty, with probability  $D_p$  our method can detect that  $Q$  will return an empty result set without executing  $Q$ . We analyze the following three cases.

### Case 1: Point-based Comparisons

Suppose that the selection condition  $S_C$  is a disjunction of  $m$  terms, where each term is a conjunction of  $n$  primitive terms and the  $i$ -th ( $1 \leq i \leq n$ ) primitive term is of the form  $R_{e_i}.a_i = c_i$  ( $1 \leq e_i \leq k$ ).

Each term can be represented as an  $n$ -tuple  $(c_1, c_2, \dots, c_n)$ . Assume that when  $m=1$ , there are totally  $K$  such  $n$ -tuples that can cause the query to return an empty result set. All these  $K$   $n$ -tuples form a set  $S_K$ . Each atomic query part stored in the collection  $C_{app}$  corresponds to an  $n$ -tuple  $t \in S_K$ . We say that an  $n$ -tuple  $t \in S_K$  is stored in  $C_{app}$  if the corresponding atomic query part is stored in  $C_{app}$ . Therefore,  $N$   $n$ -tuples  $t \in S_K$  are stored in  $C_{app}$ .

Consider a new query  $Q$  whose result set is empty. That is, for each one of the  $m$  terms in the selection condition  $S_C$  of  $Q$ , the corresponding  $n$ -tuple  $t \in S_K$ . For a given  $n$ -tuple  $t \in S_K$ , the probability that  $t$  is stored in  $C_{app}$  is  $p=N/K$ . The detection probability  $D_p$  is equal to the probability that for each one of the  $m$  terms in the  $S_C$  of  $Q$ , the corresponding  $n$ -tuple  $t \in S_K$  is stored in  $C_{app}$ . Therefore,  $D_p=p^m$ .

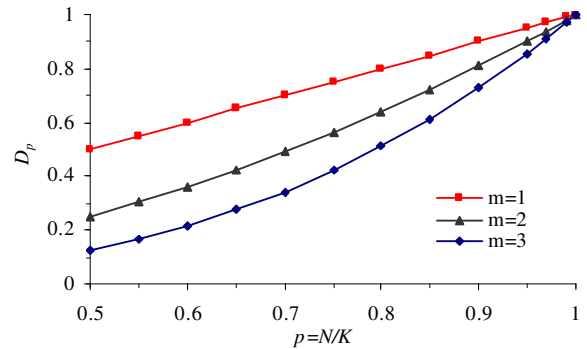


Figure 10. The detection probability  $D_p$  (point-based comparisons).

Figure 10 shows the detection probability  $D_p$  of Case 1. For a fixed  $m$ ,  $D_p$  increases with  $p$ . When  $p$  is close to 1,  $D_p$  is also close to 1. This is easy to understand, since  $p$  represents the amount of



information stored in the collection  $C_{app}$ . In the extreme case that  $p=I$ , our method can always successfully detect that query  $Q$  will return an empty result set.

For a fixed  $p$ , the detection probability  $D_p$  decreases with  $m$ . That is, the more terms in the selection condition  $S_C$  of query  $Q$ , the less likely our method can detect that  $Q$  will return an empty result set. This is because only in the case that the information of all  $m$  terms is stored in the collection  $C_{app}$ , our method can detect that  $Q$  will return an empty result set.

### Case 2: Unbounded-Interval-based Comparisons

Suppose that the selection condition  $S_C$  is a conjunction of  $n$  primitive terms, where the  $i$ -th ( $1 \leq i \leq n$ ) primitive term is of the form  $c_i < R_{e_i}.a_i$  ( $1 \leq e_i \leq k$ ). Assume that  $\prod_{i=1}^n (U_i, V_i)$  is the entire

empty result space. That is, whenever  $c_i \in (U_i, V_i)$  for each  $i$  ( $1 \leq i \leq n$ ), the query output is empty. Without loss of generality, we assume that the entire empty result space has been normalized. That is, for each  $i$  ( $1 \leq i \leq n$ ),  $U_i=0$  and  $V_i=1$ .

The information of  $N$  empty-result queries is stored in the collection  $C_{app}$ . Essentially,  $N$  selection conditions are stored in  $C_{app}$ . For each such selection condition and each  $i$  ( $1 \leq i \leq n$ ), we assume that the corresponding  $c_i$  is uniformly distributed between 0 and 1. (For simplicity, "merging" atomic query parts in  $C_{app}$  is not considered. In the case that only the most "general" atomic query parts are kept in  $C_{app}$ , our derivation is still valid while the number of atomic query parts stored in  $C_{app}$  can be less than  $N$ .)

Consider a new query  $Q$  whose result set is empty. For each  $i$  ( $1 \leq i \leq n$ ), the  $c_i$  of  $Q$  is uniformly distributed between 0 and 1. We derive the detection probability  $D_p$  in the following way:

- (1) Consider any selection condition  $S_C'$  stored in the collection  $C_{app}$ . The selection condition  $S_C$  of  $Q$  is covered by  $S_C'$  iff for each  $i$  ( $1 \leq i \leq n$ ), the  $c_i$  of  $S_C$  is bigger than the  $c_i$  of  $S_C'$  (whose probability is  $1/2$ ). Hence, the probability that  $S_C$  is covered by  $S_C'$  is  $1/2^n$ .
- (2) The detection probability  $D_p$  is equal to the probability that the  $S_C$  of  $Q$  is covered by one of the  $N$  selection conditions stored in  $C_{app}$ . Therefore,  $D_p = 1 - (1 - 1/2^n)^N$ . This is because:
  - (a) Consider any selection condition  $S_C'$  stored in  $C_{app}$ . The probability that the  $S_C$  of  $Q$  is not covered by  $S_C'$  is  $1 - 1/2^n$ .
  - (b) The probability that the  $S_C$  of  $Q$  is not covered by any of the  $N$  selection conditions stored in  $C_{app}$  is  $(1 - 1/2^n)^N$ .

Figure 11 shows the detection probability  $D_p$  of Case 2. For a fixed  $n$ ,  $D_p$  increases with  $N$ . When  $N$  goes to infinity,  $D_p$  becomes close to 1. This is easy to understand.  $N$  represents the amount of information stored in the collection  $C_{app}$ . The more information our method has, the more likely it can detect that query  $Q$  will return an empty result set.

For a fixed  $N$ , the detection probability  $D_p$  decreases with  $n$ . That is, the more primitive terms in the selection condition  $S_C$  of query  $Q$ , the less likely our method can detect that  $Q$  will return an empty result set. This is because only in the case that all  $n$  primitive terms are "matched" by the information stored in the collection  $C_{app}$ , our method can detect that  $Q$  will return an empty result set.

Now suppose that each unbounded-interval-based comparison  $c_i < R_{e_i}.a_i$  ( $1 \leq i \leq n$ ) is replaced by a bounded-interval-based comparison  $c_i < R_{e_i}.a_i < d_i$ . From a similar analysis, we can

show that in the bounded-interval-based comparison case, the detection probability  $D_p$  is  $D_p = 1 - (1 - 1/6^n)^N$ .

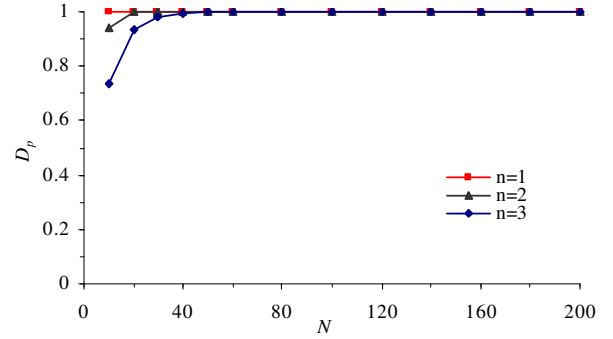


Figure 11. The detection probability  $D_p$  (unbounded-interval-based comparisons).

### Case 3: Mixed Case

Suppose that the selection condition  $S_C$  is a disjunction of  $m$  terms, where each term is a conjunction of  $n$  primitive terms. Among these  $n=n_1+n_2+n_3$  primitive terms,  $n_1$  are point-based comparisons,  $n_2$  are bounded-interval-based comparisons, and  $n_3$  are unbounded-interval-based comparisons.

Consider a new query  $Q$  whose result set is empty. Suppose that for any term  $T$  of  $Q$  and any atomic query part  $P$  stored in the collection  $C_{app}$ , the probability that  $T$  is "covered" by  $P$  is  $q$ . Then for any term  $T$  of  $Q$ , the probability that  $T$  is covered by some atomic query part stored in  $C_{app}$  is  $1 - (1 - q)^N$ . The detection probability  $D_p$  is  $D_p = (1 - (1 - q)^N)^m$ .

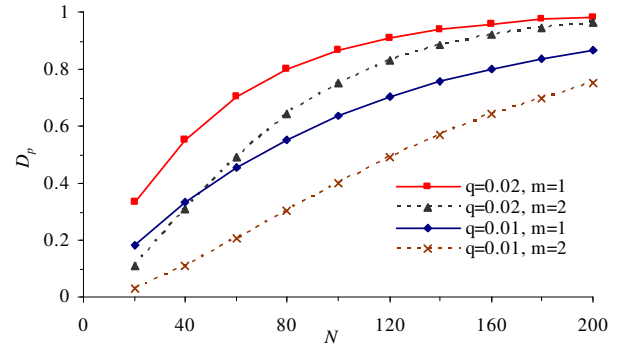


Figure 12. The detection probability  $D_p$  (mixed case).

Figure 12 shows the detection probability  $D_p$  of Case 3. For a fixed  $q$  and  $m$ ,  $D_p$  increases with  $N$ . When  $N$  goes to infinity,  $D_p$  becomes close to 1. This is easy to understand, since  $N$  represents the amount of information stored in the collection  $C_{app}$ .

Only in the case that the information of all  $m$  terms is stored in  $C_{app}$ , our method can detect that query  $Q$  will return an empty result set. Hence, for a fixed  $q$  and  $N$ ,  $D_p$  decreases with  $m$ .

For a fixed  $m$  and  $N$ ,  $D_p$  increases with  $q$ , since  $q$  represents the probability that an atomic query part stored in  $C_{app}$  can be used to match an empty-result query.

### Summary of Experimental Results

In all the above three cases, when  $N$ , the number of atomic query parts stored in the collection  $C_{app}$ , goes to infinity,  $D_p$  becomes close to 1. As shown in Section 3.1, our method can afford to store many atomic query parts in  $C_{app}$ . This increases our

chance of successfully detecting empty-result queries. In practice, we would expect the data set to contain hot spots. Therefore, in a large number of cases, after enough information about previously-executed, empty-result queries has been accumulated in  $C_{app}$ , we would expect  $D_p$  to converge to 1. Section 3.1 shows that the overhead of our techniques is negligible compared to the query execution overhead. Thus, when the check succeeds, our method can bring significant performance benefit by avoiding the expensive query execution. This benefit increases with the data set size.

## 4. Related Work

The empty-result problem has been studied in the research literature. Existing solutions fall into two categories:

- (1) Explain what leads to the empty result set [10, 16, 18, 21, 26, 27].
- (2) Automatically generalize the query so that the generalized query will return some answers [7, 18, 19, 27].

Both categories can be regarded as an AI approach: letting the computer make trials and guess what users want. However, none of the existing solutions is completely satisfactory. Some solutions require domain specific knowledge that is often not available. Some solutions only apply to a restricted form of queries. Some solutions require an excessive amount of time. In certain cases, some solutions give a large number of reasons why the result set is empty. Users do not know which one is the genuine reason. Even worse, these reasons may not always include the genuine reason.

For most AI-style solutions, the first step is to execute the query and see whether the result set is empty. This is also the default step when no specific AI-style solution is used. However, none of the existing solutions allows users to reuse each other's query results, which is the focus of our method. For certain applications, our method works while the AI approach does not. For example, in anomaly detection, users submit queries to detect anomaly. In a large number of cases, users would expect that anomaly does not exist and hence submitted queries should return empty result sets. In this case, empty result sets are not a surprise. There is no need to either explain what leads to empty result sets or generalize queries so that users can get some answers. Rather, users care how soon they can get query results.

To facilitate interactive exploration of massive data sets, [14] proposed providing early approximate answers for aggregate queries. In contrast, our method needs to know exactly whether a query will return an empty result set.

There has been a lot of work on using materialized views to speed up query processing [12]. In general, it is expensive to decide which queries can be answered with which materialized views (many problems are NP-complete) [3, 9, 11, 13, 20, 22, 28, 36]. Our method uses the idea in [3, 36] and focuses on a restricted set of ways of using stored query parts to check whether a query will return an empty result set. Hence, our solution is scalable in the presence of a large number of queries and stored query parts.

[15] proposed using materialized views to answer preference queries that maximize a linear function over the relation's attributes. [15] only considers numeric attributes and selection on a single relation, while our method needs to handle arbitrary attributes and multiple relations.

[4, 5] proposed using statistics on query expressions to facilitate query optimization. Each set of collected statistics  $S$  is on an attribute  $r$ . If  $r$  does not appear in a query  $Q$ , then  $S$  cannot be

used for the cardinality estimation of  $Q$ . In contrast, our method does not consider attributes. Rather, it only cares whether or not the cardinality is zero. Moreover, [4, 5] only consider select-project-join queries whose filter expression is a conjunction of simple predicates, while our method needs to handle arbitrary filter expressions.

[1, 6] proposed building histograms by analyzing query results rather than checking the relation. [1, 6] cannot detect correlation among multiple relations, which is a common reason that leads to empty result sets.

Multiple-query optimization [32, 33, 39] allows multiple concurrent queries to reuse each other's intermediate results. However, it does not work for non-concurrent queries, which are common in our case.

## 5. Conclusion

In this paper, we propose a fast detection method for empty-result queries. Our key idea is to reuse the evaluation results from previous empty-result queries. Under a fixed storage budget, our method only stores the most valuable and non-redundant information, continuously updates the stored information, and utilizes a set of special properties of empty result sets to increase its coverage detection capability. Our experiments with both a theoretical analysis and a prototype implementation in PostgreSQL show that our method has low overhead. In a large number of cases, our method can bring significant benefit by avoiding executing empty-result queries unnecessarily. This can both reduce the load on the RDBMS and expedite the interactive exploration process.

Like traditional materialized views, we expect our techniques to be most helpful in read-mostly environments. Extending our techniques to more update-intensive environment is an interesting area for future work. We suspect that many of the techniques used in materialized view maintenance for detecting irrelevant updates [8, 25] can be modified to be useful in our scenario. That is,  $C_{app}$  keeps those atomic query parts that are not influenced by the updates to relations. The atomic query parts used in our techniques have the special property that most (or all) updates to relations are irrelevant. As a result, we can create in-memory filtering relations that summarize the most relevant information in the base relations and use them to quickly filter out as many irrelevant updates as possible. The details of our current progress are available in [24].

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