Exploring Query Results

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Abstract

Users typically interact with a database by asking queries and examining results provided by the database system. We refer to the user examining the results of a query and asking follow-up questions as query result exploration. Our work builds on two decades of database community research on provenance. One of the contributions of this paper is that we identify constraints in the context of query result exploration that have previously been unexplored in provenance research. These constraints are useful in optimizing performance and thus improving the user experience during query result exploration.

Further, three approaches for computing provenance have been described in the literature: (a) in the lazy approach, no additional data is materialized and provenance is computed from the base tables as needed; (b) in the eager approach, additional data is materialized and provenance is computed from this additional materialized data; (c) in the hybrid approach, some additional data is materialized, and provenance is computed using this additional materialized data as well as the base tables. In this paper, we investigate lazy and eager approaches that utilize constraints in the context of query result exploration, as well as novel hybrid approaches, where the keys for some of the base tables are materialized as selected by a cost model. For the TPC-H benchmark, we find that the constraints that we identify are applicable to 19 out of the 22 queries, and result in a better performance of the lazy approach for 7 out of these 19 queries. With materialization, our hybrid approach resulted in a better performance for all but one single table TPC-H query with no joins (where existing approach performed as good as our approach). Further, the performance benefit from our approaches are significant, sometimes several orders of magnitude, compared to previous research.

1 Introduction

Consider a user interacting with a database. Figure 1 shows a typical interaction. Here the database is first assembled from various data sources (some databases might have a much simpler process, and some databases might have a much more complex process). A user asks an original query of the data and gets results. Now the user wants to drill deeper into the results and find out explanations for the results. We refer to this drilling deeper into the results as query result exploration.

For query result exploration, the user selects one or more interesting rows from the results obtained for the original user query, and asks questions such as: why are these rows in the result. The system responds by showing the rows in the tables that combined to produce those results the user is interested in. Different provenance semantics as described in [6,11] can be used for query result exploration. Lineage [8], referred to as which-provenance in [6,11], specifies which tuples in each table produced a result tuple. why-provenance [1] extends which-provenance, and collects the input tuples separately for different derivations of an output tuple. As noted in [11], there are application scenarios such as computing the trust in a result tuple, the cost of a result tuple etc that cannot be supported by the above provenance semantics. In such a case, how-provenance [6] can be used, which says how a result tuple was obtained. Another provenance semantics in literature is where-provenance [4], which only says where the result data is copied from. Provenance of non-answers studies why expected rows are not present in the result and is studied in [15,5,12]. Explaining results using properties of the data are studied in [17,18].
Figure 1: Scenario: User asks original query and gets results. Now the user explores these results.

In this paper, we use the which-provenance semantics as in [8] and richer semantics is not needed. As which-provenance maximally specifies the input tuples from each table that produce the selected result rows [6], we conjecture that the user can further explore and ask questions of these "provenance tables", and compute why-provenance, how-provenance, and where-provenance. In addition, which-provenance is defined for ASPJU queries, whereas why-provenance, how-provenance and where-provenance are studied primarily for SPJU queries (in other words, aggregate and group by operators are studied for which-provenance). Later work has explored aggregate and group by operators as well as negation for different provenance semantics [9, 6]. Also, which-provenance has the property of being invariant under equivalent formulations of the same query [6] (assuming no self-joins). Minimal witness basis (which is a variant of why-provenance) is also invariant under equivalent formulations of the same query, but where-provenance and how-provenance could be different for equivalent queries [6].

Motivating Example: Consider three tables from TPC-H [11] simplified and with sample data as shown in Table 1. Consider Q18 from TPC-H modified as in [13] and simplified for our example shown in Table 2. See that the query is defined in [13] in two steps: first a view \( Q_{18 \text{tmp}} \) is defined, which is then used to define the original query defined as view \( R \). The results of these two views are also shown in Table 2.

| Customers           | Orders                     | Lineitem               |
|---------------------|----------------------------|------------------------|
| \( (c_{\text{key}}, c_{\text{name}}, c_{\text{address}}) \) | \( (o_{\text{key}}, c_{\text{key}}, o_{\text{date}}) \) | \( (o_{\text{key}}, l_{\text{enum}}, q_{\text{ty}}) \) |
| \( c_{\text{key}} \) | \( c_{\text{name}} \) | \( c_{\text{address}} \) | \( o_{\text{key}} \) | \( c_{\text{key}} \) | \( o_{\text{date}} \) | \( l_{\text{enum}} \) | \( q_{\text{ty}} \) |
| cl                  | n1                          | a1                     | o1                  | cl                 | d1                   | 11              | 200            |
| o2                  | cl                          | d2                     | o1                  | cl                 | d1                   | 12              | 150            |
|                     |                             |                         | o2                  | l1                 | 100                  | 12              | 160            |

Table 1: Running Example: Tables (simplified) from TPC-H schema and sample data

For this simplified example, there is one row in the result \( R \). Suppose the user picks that row and wants to explore that row further. We use \( R' \) to denote the table consisting of the rows picked by the user for query result exploration.

| \( R' \) | \( c_{\text{name}} \) | \( c_{\text{key}} \) | \( o_{\text{key}} \) | \( o_{\text{date}} \) | \( tot_{\text{qty}} \) |
|-----------|-------------------------|-----------------------|----------------------|----------------------|----------------------|
|           | n1                      | cl                    | o1                   | d1                   | 350                  |

As part of query result exploration, suppose the user wants to find out what row(s) in the table Customers produced that row. The row(s) in the Customers table that produced the row(s) in \( R' \) are referred to as the provenance of \( R' \) for the Customers table, and is denoted as \( PCustomers \). In [8], the authors come up with a query for determining this provenance. Note that we sometimes use SQL syntax
Table 2: Query Q18 (simplified) from TPC-H [13] and resulting tables for the sample data in Table 1.

that is not valid to make it easier for the user to understand the query. The provenance retrieval query from [8] for determining PCustomers, as well as the resulting PCustomers, is shown below.

However, if we observe closely, we can note the following. Given that the row in R′ appeared in the result of the original query with the value for c_key column as c1, and given that the key for Customers is c_key, the row from Customers table that produced that row in R must have c_key = c1. Therefore the provenance retrieval query can be simplified as shown below.

As another example, consider the provenance retrieval query for determining the row(s) in the view Q18_tmp that contributed to the row in R′; this is denoted as PQ18_tmp. This is needed before we compute the rows in the LineItem table in the inner block that defines Q18_tmp that contributed to the row in R′ as described in [8]. The provenance retrieval query for determining PQ18_tmp in [8] will look as the following.

However, we can observe the following. As the row in R′ has o_key = o1 and c_key = c1, we know that there must exist at least one row in Orders with o_key = o1 and c_key = c1, at least one row in Customers with c_key = c1, at least one row in LineItem with o_key = o1 (corresponding to the LineItem table in
the outer block that defines \( R \) and at least one row in \( Q_{18\,tmp} \) with \( o\text{\_key} = o1 \) (otherwise the row in \( R \) would not have been produced). Therefore joining with \textbf{Orders} that checks the existence of the row in \textbf{Orders} with \( o\text{\_key} = o1 \) and which joins with \( Q_{18\,tmp} \) on \( o\text{\_key} \) and with \textbf{Customers} on \( c\text{\_key} \) is not necessary. Similarly joining with \textbf{Customers} and joining with \textbf{LineItem} are not necessary. There are two requirements on the row(s) from \( Q_{18\,tmp} \). One is that \( o\text{\_key} \) must match the \( o\text{\_key} \) in \textbf{Orders} and in \textbf{LineItem}. This need not be checked as we know that there is at least one row in \( Q_{18\,tmp} \), \textbf{Orders} and \textbf{LineItem} with \( o\text{\_key} = o1 \). The second requirement on the row(s) in \( Q_{18\,tmp} \) is that \( t\text{\_sum\_qty} > 300 \). Because of the group by \( o\text{\_key} \) in the definition of \( Q_{18\,tmp} \), the key for \( Q_{18\,tmp} \) is \( o\text{\_key} \). Therefore we know that there must be exactly one row in \( Q_{18\,tmp} \) with \( o\text{\_key} = o1 \). Now this row in \( Q_{18\,tmp} \) must satisfy \( t\text{\_sum\_qty} > 300 \) (because this row in \( Q_{18\,tmp} \) contributed to the result in \( R \)). Therefore the predicate \( t\text{\_sum\_qty} > 300 \) need not be checked in the provenance retrieval query. Therefore the provenance retrieval query for \( Q_{18\,tmp} \) can be simplified as shown below.

```
SELECT Q18_tmp.*
FROM R' NATURAL JOIN Q18_tmp
```

In this paper (Section 3), we study such optimization of provenance retrieval queries formally. After performing the above optimizations, if we want to compute the rows in the inner \textbf{LineItem} table (used in defining \( Q_{18\,tmp} \)) that produced the result row in \( R' \), we can use the following provenance retrieval query (defined in two steps).

```
CREATE VIEW PQ18_tmp AS
SELECT Q18_tmp.*
FROM R' NATURAL JOIN Q18_tmp
```

```
SELECT LineItem.*
FROM LineItem NATURAL JOIN PQ18_tmp
```

It is possible to further improve the performance of the above provenance retrieval query for the \textbf{LineItem} table in the inner block if we materialize some additional data. For instance, consider the lazy provenance evaluation (with no materialization) studied in [9]. Suppose we modified this approach in [9] and materialized the "provenance table" during original user query execution. This materializes every column from every base table for every row in the result of the original user query. However, we can get good performance even when we materialize fewer additional data. Let us materialize for each row in \( R \), the key value(s) corresponding to the row(s) in \textbf{LineItem} table in the inner block that produced that row in \( R \). We denote this result table augmented with additional keys and materialized as \( RK \). This will be done as follows.

```
CREATE VIEW Q18_tmp' AS
SELECT Q18_tmp.*, LineItem.linenum AS linenum2
FROM Q18_tmp NATURAL JOIN LineItem
```

```
CREATE TABLE RK AS
SELECT R.*, linenum2
FROM R NATURAL JOIN Q18_tmp'
```

```
\begin{tabular}{llll}
\hline
\textbf{o\text{\_key}} & \textbf{t\text{\_sum\_qty}} \\
\hline
  o1   &   350   \\
\hline
\end{tabular}
```

```
\begin{tabular}{llll}
\hline
\textbf{o\text{\_key}} & \textbf{linenum} & \textbf{qty} \\
\hline
  o1   &   11   &   200   \\
  o1   &   12   &   150   \\
\hline
\end{tabular}
```

```
\begin{tabular}{llll}
\hline
\textbf{o\text{\_key}} & \textbf{t\text{\_sum\_qty}} & \textbf{linenum2} \\
\hline
  o1   &   350   &   11   \\
  o1   &   350   &   12   \\
  o2   &   260   &   11   \\
  o2   &   260   &   12   \\
\hline
\end{tabular}
```

```
\begin{tabular}{llllllll}
\hline
\textbf{c\_name} & \textbf{c\_key} & \textbf{o\text{\_key}} & \textbf{o\_date} & \textbf{tot\_qty} & \textbf{linenum2} \\
\hline
  n1   &   c1   &   o1   &   d1   &   350   &   11   \\
  n1   &   c1   &   o1   &   d1   &   350   &   12   \\
\hline
\end{tabular}
```

4
For this example, only the linenum column needs to be added to the columns in $R$ as part of this materialization, because $o.key$ is already present in $R$. Further, linenum column is renamed as linenum2 to prevent incorrect natural joins being performed. Now the provenance retrieval query for the $LineItem$ table in the inner block can be performed as follows.

```
CREATE VIEW $RK'$ AS
SELECT *
FROM $R'$ NATURAL JOIN $RK$
```

|     | c._name | c._key | o._key | o._date | tot_qty | linenum2 |
|-----|---------|--------|--------|---------|---------|----------|
| n1  | cl      | o1     | d1     | 350     | 11      |
| n1  | cl      | o1     | d1     | 350     | 12      |

```
SELECT $LineItem$.*
FROM $RK'$ NATURAL JOIN $LineItem$
```

|     | o._key | linenum | qty |
|-----|--------|---------|-----|
| o1  | l1     | 200     |
| o1  | l2     | 150     |

See that the provenance retrieval query for the $LineItem$ table in the inner block is now a join of 3 tables: $R'$, $RK$ and $LineItem$. After minimizing the joins but without materialization, the provenance retrieval query involved three joins also: $R'$, $Q18.tmp$ and $LineItem$; however, $Q18.tmp$ was a view that was involved a group by on $LineItem$ table. Our experimental studies confirm the huge performance benefit from this materialization.

![Figure 2: Our Solution showing possible materialization of additional data, and the provenance tables defined during query result exploration.](image)

To summarize, our solution architecture is as shown in Figure 2. We refer to our system as POS (Provenance Optimizer System). When the original user query comes in, the system might materialize some additional data (selected using a cost model) that could help in query result exploration. As part of query result exploration, the user first selects rows interesting to them. The system defines the provenance tables, (which are views) and then the user can continue to explore the results and these provenance tables.

Our contributions in this paper include the following:

- We investigate constraints implied in our query result exploration scenario (Section 2.4).
- We investigate optimization of provenance retrieval queries using the constraints. We present our results as a Theorem and we develop an Algorithm based on our theorem (Section 3).
- We investigate materialization of select additional data, and investigate novel hybrid approaches for computing provenance that utilize the constraints and the materialized data (Section 4).
- We perform a detailed performance evaluation comparing our approaches and existing approaches using TPC-H benchmark [11] and report the results (Section 5).
Outline: The rest of the paper is organized as follows. Section 2 introduces some of our notations, the set of queries supported as original user queries, algorithmic definition of provenance and the constraints for our scenario of query result exploration. Section 3 investigates the optimization of provenance retrieval queries using the constraints from Section 2 and without materialization. Materialization of additional data that further help optimize provenance retrieval queries is studied in Section 4. Our experimental studies and results are described in Section 5. Related work is discussed in Section 6 and Section 7 concludes the work.

2 Background

The notations for tables and views that we use in this paper are shown in Table 3.

| Name of table/view        | set of attributes | key attributes |
|---------------------------|-------------------|----------------|
| Base table – $T_i$        | $A_{T_i}$         | $K_i$          |
| Materialized View – $V_i$| $A_{V_i}$         |                |
| Virtual View – $V_i$      | $A_{V_i}$         |                |

When the distinction between base table or virtual/materialized view is not important, we use $X_i$ to denote the table/view; attributes of $X_i$ are denoted $A_{X_i}$. If a key is defined for $X_i$, the key is denoted as $K_i$.

Table 3: Notations for tables and Views. Base tables and materialized views are shown in bold, whereas virtual views are shown not bold.

2.1 Provenance Semantics

Different semantics for provenance that have been studied in the literature and their properties are explained well in [6, 11]. Lineage, or which-provenance [8] specifies which rows from the different input tables produced the selected rows in the result. One of the properties of which-provenance is that it is "complete" [6]. Further, [6] mentions that which-provenance is invariant for equivalent queries with no self-joins. Actually, which-provenance is invariant even for equivalent queries with self-joins, provided different names are given for the same table, and these names are "consistent" across query rewritings (as would happen in typical optimization). why-provenance [4] provides more detailed explanation than which-provenance and specifies the different combinations of the input table rows that produced the result rows, when there are multiple ways of forming the result rows. While why-provenance is not invariant for equivalent queries, a variant of why-provenance called minimal witness basis that consists of minimal elements of the why-provenance, is invariant for equivalent queries. how-provenance [10, 6, 11] provides even more detailed information than why-provenance and specifies how the different input table rows combined to produce the result rows. It has been noted that how-provenance is not invariant for equivalent queries [6]. How different provenance semantics can be derived from other provenance semantics is studied in [6, 11]. It is shown that how-provenance provides the most general semantics and can be used to compute other provenance semantics [6]. A hierarchy of provenance semirings that shows how to compute different provenance semantics is explained in [11]. Other provenance semantics that provide different kinds of explanations are studied as where-provenance [4]. Trio [2] provides a provenance semantics similar to how-provenance as studied in [6].

For our work, we choose which-provenance for several reasons, even though it provides less details than why and how provenance: (a) which-provenance is defined for queries that include aggregate and group by operators as well, whereas other provenance semantics are typically not defined for aggregate and group by operators [11], (b) which-provenance is complete [6], in that all the other provenance semantics provide explanations that only include the input table rows selected by which-provenance. As part of our future work, we are investigating computing other provenance semantics starting from which-provenance and the original user query, (c) which-provenance is invariant under equivalent queries (provided tables in self-joins have different and "consistent" names), (d) results of which-provenance is a set of tables that can be represented in the relational model without using additional features as needed by how-provenance, or a large number of rows as needed by why-provenance.
2.2 Query Language

Different fragments of SQL and SQL-like languages have been considered in past work related to provenance for the original user queries. In [4], the authors considered their own language called DQL (Deterministic Query Language), which was similar to XML-QL, consisting of SPJU and a group by with a collect clause (no aggregation functions are considered). In [8], the authors considered SQL queries restricted to SPJUA (Select, Project, Join, Union, and Group by with aggregate), in addition to considering Difference. In [9], the authors consider bag semantics and consider SQL queries consisting of SPJA, outer joins, set unions and correlated nested queries. In [3], the authors consider SPJU queries and do not consider group by and aggregation functions.

For our work, we consider SQL queries restricted to SPJA queries and use set semantics. We do not consider set operators, including union and negation. Further, we do not consider outer joins. We believe that extension to bag semantics should be fairly straightforward. However, the optimizations that we consider in this paper are not immediately applicable if we have queries with unions and outer joins. Extensions to bag semantics, and these additional operators will be investigated in future work. For convenience, we use a Datalog syntax for representing queries. We consider two types of rules (referred to as SPJ Rule and SPJA Rule) that can appear in the original query as shown in Table 4. A query can consist of one or more rules. Every rule must be safe [19].

| SPJ Rule: | \( R(A_R) : - X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}). \) |
| SPJA Rule: | \( R(GL, AL) : - X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}). \) |

Table 4: The two types of rules that can appear in original queries and their Datalog representation. For the SPJA rule, \( GL \) refers to the list of group by columns and \( AL \) refers to the list of aggregations.

As an example, consider query Q18 from TPC-H (simplified) shown in Table 2. Table 2 shows this query rewritten as Datalog rules. See that the two rules in Q18 are SPJA rules, where the second SPJA rule uses the Q18_temp view defined in the first SPJA rule. It is worth noting that the second rule can be rewritten as an SPJ rule; however, we kept it as an SPJA rule as the SPJA rule reflects the TPC-H query faithfully as is also provided in [13].

| Q18_temp(o_key, sum(qty) as t_sum_qty) | := Lineitem. |
| R(c_name, c_key, o_key, o_date, sum(qty) as total_qty) | := Customers, Orders, Lineitem, Q18_temp, t_sum_qty > 300. |

Table 5: Query Q18 (simplified) from TPC-H expressed as Datalog rules. The SQL equivalents for these rules and the results for the sample data in Table 1 are shown in Table 2.

2.3 Provenance Definition

As said before, we use the which-provenance definition of [8]. In this section, we provide a simple algorithmic definition for provenance based on our rules.

The two types of rules in our program are both of the form: \( R(A_R) : - RHS \). We will use \( A_{RHS} \) to indicate the union of all the attributes in the relations in \( RHS \). For any rule, \( R(A_R) : - RHS \), the provenance for \( R' \subseteq R \) in a table/view \( X_i(A_{X_i}) \in RHS \) (that is, the rows in \( X_i \) that contribute to the results \( R' \)) is given by the program shown in Table 6. See that \( PV\view \) corresponds to the relational representation of why-provenance in [9].

Examples of using the provenance definition in Table 6 are shown in Table 7. These examples are based on the schema and sample data in Table 1 and the Q18_temp and \( R \) views in Table 5.

As mentioned earlier, which-provenance is invariant for equivalent queries [8]. This is especially useful, because we do not need to consider correlated subqueries as they can be decorrelated. For instance our provenance definition gives the same results for the original TPC-H queries in [11] and for the decorrelated queries in [13].
Algorithmic definition of provenance for rule: \( R(A_R) :\neg RHS \). The rows in table/view \( X_i(A_{X_i}) \in RHS \) that contribute to \( R' \subseteq R \) are represented as \( PX_i \).

\[
PView(A_R \cup A_{RHS}) :\neg R(A_R), RHS.
PX_i(A_{X_i}) :\rightarrow PView, R'(A_R).
\]

The above program for computing \( PX_i(A_{X_i}) \) can be written as a single rule as:

\[
PX_i(A_{X_i}) :\neg R(A_R), RHS, R'(A_R).
\]

| Table 6: Algorithmic Definition of Provenance |
|------------------------------------------------|
| \( Q18_{tmp}(o\_key, sum(qty)) as t\_sum\_qty \) \( \rightarrow \) \textbf{Lineitem}. |
| (find total quantity for each order) |
| Rows in the view \( Q18_{tmp} = \{(o1, 350), (o2, 260)\} \) |
| Rows selected to determine provenance \( Q18_{tmp} = \{(o2, 260)\} \) |

Provenance of \( Q18_{tmp} \) in the table \textbf{Lineitem} is given by the query:

\[
PLineItem(o\_key, linenum, qty) :\neg Q18_{temp}, \textbf{Lineitem}, Q18_{temp}'.
\]

The resulting rows for \( PLineItem \) is: \( \{o2, l1, 100\}, (o2, l2, 160)\}

| Table 7: Examples Illustrating Provenance Definition in Table 6 |
|---------------------------------------------------------------|
| \( R(c\_name, c\_key, o\_key, o\_date, sum(qty)) as total\_qty \) \( \rightarrow \) \textbf{Customers, Orders, Lineitem, Q18_{tmp}, t\_sum\_qty > 300}. |
| (for each order where total quantity is greater than 300, return the customer information, the order information as well as the total quantity) |
| Rows in the view \( R = \{(n1, c1, o1, d1, 350)\} \) |
| Rows selected to determine provenance \( R' = \{(n1, c1, o1, d1, 350)\} \) |

Provenance of \( R' \) in the table \textbf{Orders} is given by the query:

\[
POrders(o\_key, c\_key, o\_date) \rightarrow R, \textbf{Customers, Orders, Lineitem, Q18_{tmp}}, \quad t\_sum\_qty > 300, R'.
\]

The resulting rows for \( POrders \) is: \( \{(o1, c1, d1)\} \)

### 2.4 Dependencies

We will now examine some constraints for our query result exploration scenario that help optimize provenance retrieval queries. As in Section 2.3, the original query is of the form \( R(A_R) :\neg RHS \); and \( A_{RHS} \) indicates the union of all the attributes in the relations in \( RHS \). Further, \( R' \subseteq R \). We express the constraints as tuple generating dependencies below. While these dependencies are quite straightforward, they lead to significant optimization of provenance computation as we will see in later sections.

**Dependency 1.** \( \forall A_R, R'(A_R) \rightarrow R(A_R) \)

This is obvious as in our scenario, the rows for which we compute the provenance, \( R' \) is such that \( R' \subseteq R \). Therefore Dependency 1 is true for any \( R' \) selected.

For the remaining dependencies, consider \( RHS \) as the join of the tables \( X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}) \), as shown in Table 4.

**Dependency 2.** \( \forall A_R, R(A_R) \rightarrow \exists (A_{RHS} - A_R), X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}) \)

This applies to both the rule types shown in Table 4. This dependency is also obvious, as any row in \( R \) is produced by the join of \( X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}) \).
From Dependencies 1 and 2 we can infer the following dependency.

**Dependency 3.** \( \forall A_R, R' (A_R) \rightarrow \exists (A_{RHS} - A_R), X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}) \)

### 3 Optimizing Provenance Queries without materialization

As a first step, we will consider no materialization of additional data. Such materialization will be investigated in later Section 4. We will present our results in this section as a theorem, and follow it with an algorithm for determining efficient provenance retrieval query that we have developed based on the theorem.

Consider the query for computing provenance given in Table 3. \( PX_i(A_{X_i}) :- R(A_R), R\text{HS}, R'(A_R) \). Using Dependency 3, one of the joins in the query for computing provenance can immediately be removed. The program for computing provenance of \( R' \subseteq R \) in table/view \( X_i \) is given by the following program. See that \( X_i \) can be a base table or a view.

**Program 1.** \( PX_i(A_i) :- R'(A_R), R\text{HS} \).

Program 1 is used by 8 for computing provenance when there is no materialization. However, we will optimize Program 1 further even when there is no materialization using the dependencies in Section 2.4. Let \( P_1 \) below indicate the query in Program 1. Also consider another query \( P_2 \) (which has potentially fewer joins than \( P_1 \)). Our theorem states when \( P_1 \) is equivalent to \( P_2 \). The proof uses the dependencies in Section 2.4 and is omitted.

\[
P_1 : PX_i(A_{X_i}) :- R'(A_R), X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n}).
\]

\[
P_2 : PX_i(A_{X_i}) :- R', X_{j_1}(A_{X_{j_1}}), X_{j_2}(A_{X_{j_2}}), \ldots, X_{j_q}(A_{X_{j_q}}), \text{where } \{j_1, j_2, \ldots, j_q\} \subseteq \{1, 2, \ldots, n\}
\]

**Notation.** For convenience, we introduce two notations below. \( A'_{RHS} = A_{X_{j_1}} \cup A_{X_{j_2}} \cup \ldots \cup A_{X_{j_q}} \). In other words, \( A'_{RHS} \) denotes all the attributes in the RHS of \( P_2 \), not considering table \( R' \). Consider the tables that are present in the RHS of \( P_1 \), but not in the RHS of \( P_2 \). \( A''_{RHS} \) denotes all the attributes in these tables. In other words, \( A''_{RHS} = \bigcup A_i, i \in \{1, 2, \ldots, n\} - \{j_1, j_2, \ldots, j_q\} \).

**Theorem 1.** Queries \( P_1 \) and \( P_2 \) are equivalent, if for every column \( C \in A'_{RHS} \), at least one of the following is true:

- \( A_R \rightarrow C \) (that is, \( A_R \) functionally determines \( C \))
- \( C \notin A''_{RHS} \) (that is, \( C \) is not present in any of the tables in \( P_1 \) that is not in \( P_2 \))

**Illustration of Theorem 1** Consider the SPJA rule for \( R \) for Q18 in TPC-H from Section 2.2. The program for computing provenance \( P\text{Customers} \) before optimization and after optimization using Theorem 1 are given below. See that

\[
A'_{RHS} = \{c\_key, c\_name, c\_address\};
\]

\[
A''_{RHS} = \{o\_key, c\_key, o\_date, linenum, qty, t\_sum\_qty\};
\]

\[
A_R = \{c\_name, c\_key, o\_key, o\_date, total\_qty\};
\]

\[
P_1 : P\text{Customers}(c\_key, c\_name, c\_address) :- R', \text{Customers, Orders, Lineitem}, Q18\_tmp, t\_sum\_qty > 300.
\]

\[
P_2 : P\text{Customers}(c\_key, c\_name, c\_address) :- R', \text{Customers}.
\]

There are three columns in \( A'_{RHS} \). As \( c\_key, c\_name \in A_R, A_R \rightarrow c\_key, \) and \( A_R \rightarrow c\_name \). For the column \( c\_address \), we see that \( c\_address \notin A''_{RHS} \). Therefore as per Theorem 1, \( P_1 \) and \( P_2 \) are equivalent queries. (See that the column \( c\_name \notin A''_{RHS}, \) and \( A_R \rightarrow c\_address \) as well). See that Theorem 1 resulted in program \( P_2 \) with much fewer joins than the program \( P_1 \); \( P_2 \) is expected to perform better in practice.

Based on Theorem 1, we can infer the following corollaries. Corollary 1 says that if all the columns of \( X_i \) are present in the result, no join is needed to compute the provenance of \( X_i \). This is true because if a row was in the result, then a corresponding row is present in \( X_i \) with the same values for the shared columns and that forms the provenance. Corollary 2 says that if a key of \( X_i \) is present in the result, then the provenance
of $X_i$ can be computed by joining $R'$ and $X_i$. This is true because if a key value for $X_i$ is present in the result, then the row in $X_i$ corresponding to that key value is the provenance for any picked result row.

**Corollary 1.** If $A_{X_i} \subseteq A_R$, then $PX_i(A_{X_i}) := R'(AR)$.

**Corollary 2.** If $K_i \subseteq A_R$, then $PX_i(A_{X_i}) := R'(AR), R_i(A_{R_i})$.

### 3.1 Provenance Query Optimization Algorithm

Theorem \[1\] describes when a provenance retrieval query with fewer joins is equivalent to the original provenance retrieval query (as in Program \[3\]). In this section, we will come with an algorithm based on Theorem \[1\] that starts with the original provenance retrieval query and comes up with a new optimized provenance retrieval query with fewer joins.

Suppose the original user query is: $R(A_R) := X_1(A_{X_1}), X_2(A_{X_2}), \ldots, X_n(A_{X_n})$. Suppose the user wants to determine the rows in $X_i$ that contributed to the results $R'(A_R) \subseteq R(A_R)$. Note that $X_i$ can either be a base table or a view.

**Algorithm 1 Efficient Provenance Retrieval Query**

1. start with $CurRHS = R'(A_R)$
2. if $A_{X_i} \subseteq A_R$ then return $CurRHS$
3. add $X_i$ to $CurRHS$
4. let $CurRHSTables = X_i; A'_{RHS} = \bigcup A_{X_i}$, where $X_i \in CurRHSTables$
5. let $RemTables = \{X_1, X_2, \ldots, X_n\} - X_i; A''_{RHS} = \bigcup A_{X_j}$, where $X_j \in RemTables$
6. while there is a column $C \in A'_{RHS} \cap A''_{RHS}$, and there is no functional dependency $A_R \rightarrow C$ do
7. Add all tables in $RemTables$ that have the column $C$ to $CurRHS$, and to $CurRHSTables$. Adjust $A'_{RHS}, RemTables, A''_{RHS}$ appropriately.
8. return $CurRHS$

**Proof of Correctness of Algorithm \[1\]** In the above algorithm, if there is a column $C \in A'_{RHS}$ (i.e., $C$ is in one of the predicates in $CurRHS$) such that $A_R \not\rightarrow C$ (i.e., $A_R$ does not functionally determine $C$), all the predicates in $RHS$ where $C$ appears will be added to $CurRHS$ in Steps 6 and 7 (in other words, $C$ will no longer be in $A'_{RHS}$).

### 3.2 Illustration of Algorithm \[1\]

**Illustration 1.** Consider the user query:

$$R(A, C) := T_1(A, B, C, D), T_2(B), T_3(C, Z), T_4(D, E), T_5(E, Y), T_6(A).$$

Also assume the functional dependency: $T_4: D \rightarrow E$.

We have the following efficient provenance retrieval queries produced by Algorithm \[1\] $R' \subseteq R$ are the rows picked for query result exploration.

- $PT_6(A) := R'(A, C)$.
- $PT_3(C, Z) := R'(A, C), T_2(C, Z)$.
- $PT_4(D, E) := R'(A, C), T_1(A, B, C, D), T_2(B), T_4(D, E), T_5(E, Y)$.

**Illustration 2.** Consider the SPJA rule for $R$ for Q18 in TPC-H from Table \[3\]

$$R(c\_name, c\_key, o\_key, o\_date, sum(qty) as total\_qty) := \text{Customers, Orders, Lineitem}, \quad Q18\_tmp, t\_sum\_qty > 300.$$  

- $PCustomers := R'$, $\text{Customers}$. (the column in $A'_{RHS} \cap A''_{RHS}$ is $c\_key$. As $c\_key \in A_R, A_R \rightarrow c\_key$)
- $POrders := R'$, $\text{Orders}$. (the column in $A'_{RHS} \cap A''_{RHS}$ is $o\_key$. As $o\_key \in A_R, A_R \rightarrow o\_key$)
PLINEITEM := R', LINEITEM. (the column in \( A'_R \cap A''_R \) is \( o_key \), and \( A_R \rightarrow o_key \))

PQ_{tmp} := -R', Q18_{tmp}. (note that Algorithm 1 is applicable to the view \( Q18_{tmp} \) as well. There are two columns in \( A'_R \cap A''_R \): \( o_key \) and \( t_sum_qty \). From \( Q18_{tmp} \) definition, we know that \( o_key \rightarrow t_sum_qty \). As \( A_R \rightarrow o_key \), \( A_R \rightarrow t_sum_qty \) as well.)

4 Extending Algorithm with materialization

In Section 3, we studied optimizing the provenance retrieval queries for the lazy approach, where no additional data is materialized. Eager and hybrid approaches materialize additional data. An eager approach could be to materialize \( PV \) view (defined in Table 6). However, \( PV \) view could be a very large table with several columns and rows of data. In this section, we investigate novel hybrid approaches that materialize much less additional data, and perform comparable to (and often times, even better than) the eager approach that materializes \( PV \). The constraints identified in Section 2.4 are still applicable, and are used to decrease the joins in the provenance retrieval queries.

A user query can have multiple rules that form multiple steps (for instance, Q18 in TPC-H has two steps). In such a case, while computing the results of the original user query, we may choose to materialize additional data that may include for each row in the result, the key values corresponding to the rows from any of the base tables at any step that produced that result row. While our results apply for queries with any number of steps, for simplicity of illustration, we consider only queries with two steps (the results extend in a straightforward manner to any number of steps). A query with two steps is shown in Figure 3. \( R \) is the result of the query. \( R \) is defined using the base tables \( T_1, T_2, \ldots, T_n \), and the views \( V_1, V_2, \ldots, V_m \).

In Figure 3, the views are shown as defined using only base tables. Remember that from our Table 3, \( T_1 \) has attributes \( A_{T_1} \) and key attributes \( K_1 \); the attributes of \( T_{1n_1} \) is the set \( A_{T_{1n_1}} \) and it has key attributes \( K_{1n_1} \). Also, \( V_1 \) has attributes \( A_{V_1} \).

![Query with two steps](image)

The original user query (corresponding to Figure 3) is shown in Program 2.

**Program 2.**

\[
V_i(A_{V_i}) := T_{i1}, T_{i2}, \ldots, T_{in_i}, \quad \forall i \in 1, 2, \ldots, m
\]

\[
R(A_R) := T_1, T_2, \ldots, T_n, V_1, V_2, \ldots, V_m.
\]

Given a query \( R \) as in Program 2, we materialize a view \( RK \) with columns \( A_{RK} \). \( A_{RK} \) consists of the columns \( A_R \) in \( R \) and the keys of zero or more of the base tables used in \( R \) (how \( A_{RK} \) is determined is discussed later). A base table \( T \) is used in \( R \) if \( R \) is defined using \( T \) or if \( R \) is defined using a view \( V' \) that in turn uses \( T \). As an example, in Figure 3 two of the base tables used in \( R \) are \( T_1 \) and \( T_{11} \).

For each view \( V_i \) in Program 2 we will materialize keys for zero or more of the base tables. In addition, we will materialize keys for zero or more of the tables \( T_j \), for \( j \in 1, 2, \ldots, n \). In this case, we define \( RK \) as follows. See that \( VK_i \) is still a virtual view and not materialized. Definition of \( VK_i, RK \) and how we rewrite the original user query \( (OQ) \) to use the materialized view \( RK \) are shown in Program 3.
Program 3.

\[ V_i(A_{V_i}) \leftarrow T_{i1}, T_{i2}, \ldots, T_{in}. \quad \forall i \in 1, 2, \ldots, m \]

\[ R(A_R) \leftarrow T_1, T_2, \ldots, T_n, V_1, V_2, \ldots, V_m. \]

See that \( V K_i \) is defined using \( V_i \) and the tables that define \( V_i \). (If no keys are added to \( V_i \) to form \( V K_i \), then \( V K_i \) can be optimized to be just \( V_i \).) \( RK \) is defined using \( R \), the base tables that define \( R \) and the \( V K_i \) views corresponding to each of the \( V_i \) that define \( R \). See that the provenance query optimization algorithm can be used to optimize \( V K_i \) and \( RK \) as well.

Note that \( A_{V K_i} \supseteq A_{V_i} \); \( A_{V K_i} \) depends on which keys are added to define \( V K_i \). Similarly, \( A_{RK} \supseteq A_R \). Also, the original user query results (computed as \( R \) in Program 2) is computed as \( OQ \) in Program 3. This is because we assume that \( RK \) is materialized during the original user query execution time, and we expect that computing \( OQ \) from \( RK \) is faster than computing the results of \( R \).

Program 3 gives the program used to compute the results of the original user query. For query result exploration, suppose that the user selects \( R' \subseteq R \) and wants to find the provenance of \( R' \) in the table \( T_1 \). We will assume that \( T_1 \) is a base table that defines \( V_j \). For this, we first define \( RK' \subseteq RK \) as shown below.

\[ RK' :- R', RK. \]

\( RK' \) denotes the rows in \( RK \) corresponding to the rows in \( R' \). Now to compute the provenance of \( R' \) in the table \( T_1 \), we compute the provenance of \( RK' \) in the table \( T_i \). There are two cases:

Program 4.  

Case 1: \( K_i \subseteq A_{RK}: PT_i :- RK', T_i. \)

Case 2: \( K_i \not\subseteq A_{RK}: PT_i :- PV_j, V_{jRHS}. \) (\( V_{jRHS} \) is the RHS of the rule that defines \( V_j \).)

Case 1 is similar to Corollary 2 except that \( R \) may not be defined using \( T_i \) directly. The proof of correctness follows from Theorem 1.

For Case 2, remember that \( V_j \) is defined using \( T_i \) directly. \( PV_j \) is the provenance of \( RK' \) in the view \( V_j \), computed recursively using Program 4. Given \( PV_j \), the rule for computing the provenance of \( PV_j \) in the table \( T_i \) is given by Program 1 as shown.

Remember that both the rules in Program 4 can be optimized using Algorithm 1.

As an example, let us consider the simplified Q18 from Table 5. There are 4 base tables used in Q18 – Customers, Orders, Lineitem1 and Lineitem2. See that we distinguish the 2 copies of the Lineitem table. Let Lineitem2 be the table used in Q18_tmp definition.

Let us assume that we materialize the keys for Customers and Lineitem2 tables. The revised program will look as follows. Note that c_key (key for the Customers table) is already present in \( R \). The key for the Lineitem2 table is \( o_key, linenum \); however \( o_key \) is already present in \( R \). Therefore only the \( linenum \) column from Lineitem2 is added in A RK.)

\[
Q18_tmp(o_key, sum(qty) as t_sum_qty) \leftarrow Lineitem.
\]

\[
R(c_name, c_key, o_key, o_date, o_totalprice, sum(qty) as total_qty) \leftarrow Customers, Orders, Lineitem, Q18_tmp, t_sum_qty > 300.
\]

\[
Q18_tmpK(o_key, linenum2, t_sum_qty) \leftarrow Q18_tmp, Lineitem.
\]

\[
RK(c_name, c_key, o_key, o_date, o_totalprice, linenum2, total_qty) \leftarrow R, Q18_tmpK.
\]

( the rule for RK is obtained after performing optimizations as in Algorithm 1).

\[
OQ(c_name, c_key, o_key, o_date, o_totalprice, total_qty) \leftarrow RK.
\]

Let \( R' \) denote the rows in \( R \) picked and we need to determine their provenance. To compute provenance, we first need to determine which rows in \( RK \) correspond to the rows in \( R' \). This is done as:
\(RK'(A_{RK}) \rightarrow R', RK\).

Now, we need to compute the provenance of the rows in \(RK'\) from the different tables, which is computed as follows.

\[
\begin{align*}
PCustomers(c\_key, c\_name, c\_address) & : \rightarrow RK', Customers. \\
POrders(o\_key, c\_key, o\_date, o\_totalprice) & : \rightarrow RK', Orders. \\
PLineitem1(o\_key, linenum, qty) & : \rightarrow RK' (c\_name, c\_key, o\_key, o\_date, o\_totalprice, \\
& \quad \text{linenum2 as linenum, total_qty}), Lineitem. \\
PLineitem2(o\_key, linenum, qty) & : \rightarrow RK' \quad (c\_name, c\_key, o\_key, o\_date, o\_totalprice, \\
& \quad \text{linenum2 as linenum, total_qty}), Lineitem. 
\end{align*}
\]

See that all the rules have been optimized using Algorithm 1 and involve a join of \(RK'\) and one base table.

### 4.1 Determining the keys to be added to the materialized view

When we materialize \((RK)\), computing the results of the original user query is expected to take longer. This is because of the materialization, and because \(RK\) is expected to be larger than the size of \(R\): the number of rows (and the number of columns) in \(RK\) will not be fewer than the number of rows (and the number of columns) in \(R\). We consider that this materialization is done during original query execution (thus, potentially slowing down original query execution).

However, materialization results in benefits to result exploration. This is because the number of joins to compute the provenance for some of the base tables is expected to be fewer (it is possible that the size of \(RK\) might be large and this may slow down the provenance computation).

For our system (POS), we consider materializing keys for different base tables that will speed up provenance computation and compute the cost vs. benefit. The ratio of the estimated number of rows of \(RK\) and the estimated number of rows in \(R\) forms the cost. The ratio of the number of joins across all provenance computations of base tables with and without materialization give the benefit. We use a simple cost model that combines the cost and the benefit to find the set of keys to be materialized. For the example query \(Q18\), the provenance retrieval queries for \(Customers\), \(Orders\) and \(Lineitem\) tables in the outer block already involve only one join as shown in Section 3. Therefore no keys need to be added to improve the performance of these three provenance retrieval queries. However, we can improve the performance of the provenance retrieval query for the \(Lineitem\) table in the inner block by materializing the keys for the inner \(Lineitem\) table as shown earlier.

Other factors may be included in our cost model to determine which keys to be materialized, including considering the workload of provenance queries; i.e., which provenance queries are more widely used by the user (for example, most provenance queries for \(Q18\) in TPC-H in one scenario might be to find the provenance of selected \(R'\) rows in \(Customers\) table). In general, materialization typically increases the speed of later query result exploration, at the expense of slowing down the original user query execution.

In our current POS system, we consider materializing the key for every base table in the original user query as part of the cost-benefit analysis. In other words, the number of different hybrid options we consider is exponential in the number of tables in the original user query. For each option, the cost vs. benefit is estimated and one of the options is selected. The POS system will materialize the additional data as specified in the selected option. As part of future work, we are studying this space of possible materializations and effective ways of searching this space.

### 5 Evaluation

For our evaluation, we used the TPC-H benchmark. We generated data at 1GB scale. Our experiments were conducted on a PostgreSQL 10 database server running on Windows 7 Enterprise operating system. The hardware included a 4-core Intel Xeon 2.5 GHz Processor with 128 GB of RAM. For our queries, we again used the TPC-H benchmark. The queries provided in the benchmark were considered the original user queries. Actually, we considered the version of the TPC-H queries provided by [13], which specifies values...
for the parameters for the TPC-H benchmark and also rewrites nested queries. For the result exploration part, we considered that the user would pick one row in the result of the original query and ask for the rows in one of the base tables that produce that resulting row.

We compare the following approaches:

- The approach in \[8\] that we refer to as: W. We consider that in this approach no additional data is materialized (lazy approach). In other words, we do not consider the materialization studied in the hybrid approach in \[7\].
- The approach in \[9\] that we refer to as: G. Here we assume that the relational representation of provenance is materialized while computing the original user query (eager approach). Provenance computation is then translated into mere look-ups in this materialized data.
- Algorithm 1 without materialization that we refer to as: O1 (lazy approach).
- Our approach with materialization from Section 4 that we refer to as: O2 (hybrid approach).

5.1 Usefulness of our optimization rules

We first studied the benefits of our Algorithm \[1\] when no additional data is materialized. For this, we compared the performance of the queries resulting from \[8\] with the queries resulting from Algorithm \[1\] (i.e., we compared O1 and W). Let us consider our running example, which is the simplified Q\(_{18}\) from Table 5. The user first issues the two rules that define Q\(_{18}\_tmp\) and R as part of the original user query. In \[8\], without materialization, the provenance queries for the tables in the outer block are shown below. See that they reuse the Q\(_{18}\_tmp\) definition in the original query.

\[
PCustomers(c\_key, c\_name, c\_address) :- R', Customers, Orders, Lineitem, Q18\_tmp, t\_sum\_qty > 300.
POrders(o\_key, c\_key, o\_date, o\_totalprice) :- R', Orders, Customers, Lineitem, Q18\_tmp, t\_sum\_qty > 300.
PLineitem(o\_key, linenum, qty) :- R', Customers, Orders, Lineitem, Q18\_tmp, t\_sum\_qty > 300.
\]

The provenance queries that we get using our Algorithm \[1\] are shown below.

\[
PCustomers(c\_key, c\_name, c\_address) :- R', Customers.
POrders(o\_key, c\_key, o\_date, o\_totalprice) :- R', Orders.
PLineitem(o\_key, linenum, qty) :- R', Lineitem.
\]

See that Algorithm \[1\] results in queries with much fewer joins. We tested the provenance retrieval queries for Q\(_{18}\) from TPC-H as given in \[13\] (for our experiments, the schema and the queries were not simplified as in our running example). The times observed are listed in Table 8. See that the provenance retrieval queries generated by Algorithm \[1\] run much faster than the ones used in \[8\].

| PCustomers | O1 | W  |
|------------|----|----|
| POrders    | 0.06 | 1533.88 |
| PLineItem  | 0.30 | 1532.74 |

Table 8: Performance Benefits of Using O1 when compared to W for Q\(_{18}\) in \[13\]. All times are reported in milliseconds.

We considered all the TPC-H queries as given in \[13\] except for the ones with outer joins (as we do not consider outer joins in this paper). Of the 22 TPC-H queries, the queries with outer joins are Q13, Q21, Q22, and these were not considered. Q19 has or in its predicate, which can be rewritten as a union. However, we considered the or predicate as a single predicate without breaking it into a union of multiple rules. For 7 out of these 19 queries, O1 results in provenance retrieval queries with fewer joins than the ones in W.
were Q2, Q3, Q7, Q10, Q11, Q15 and Q18. In other words, Algorithm 1 was useful for around 36.84% of the TPC-H queries.

5.2 Usefulness of Materialization

We now studied the cost and benefits of materialization. For this, we again considered Q18 from [13]. We compared the time to compute the original query results (OQ) and the time to compute the provenance of the four tables for the four approaches: O1, W, G and O2. For O2, our hybrid approach materialized the key for the LineItem table in the inner block. The results are shown in Table 9.

|             | O1       | W        | G         | O2       |
|-------------|----------|----------|-----------|----------|
| OQ          | 5095.67  | 5095.67  | 5735446.19| 13794.26 |
| PCustomers  | 0.07     | 1522.44  | 3.86      | 0.96     |
| POrders     | 0.06     | 1533.88  | 3.73      | 0.43     |
| PLineItem1  | 0.30     | 1532.74  | 5.77      | 0.59     |
| PLineItem2  | 1641.52  | 1535.22  | 6.16      | 0.43     |

Table 9: Performance Benefits of materialization proposed in Section 4 for Q18 in [13]. All times are reported in milliseconds.

There are several points worth observing. When we compare our hybrid approach with materialization (O2) and the eager approach corresponding to [9] (G), we see that O2 outperforms G in all cases. We typically expect O2 to outperform G in computing the results of the original user query. This is because G maintains all the columns of every base table in the materialized view, whereas O2 maintains only some key columns in the materialized view - in this case, only one addition column linenum2 is added to the columns in R. The performance impact of this is significant as G takes about 420 times the time taken by our approach to compute the results of the original user query. Actually the time taken by G is about 5700 seconds, which is likely to be unacceptable. On the other hand, O2 takes about 2.7 times the time taken by our approach without materialization (O1) for computing the results of the original user query. We drilled deeper to find out for O2, whether the materialization of RK was taking much time or computing the results of the original user query from the materialized view RK. We actually found that computing the results from the materialized view RK took about 0.39 milliseconds for O2 and about 3.07 milliseconds for G.

|             | R    | MV_G | MV_O2 |
|-------------|------|------|-------|
| Number of Columns | 6    | 51   | 7     |
| Number of Rows    | 57   | 2793 | 399   |

Table 10: Comparing the size of the tables: R (result of the original user query), MV_G (materialized view RK used by G) and MV_O2 (materialized view RK used by O2).

|             | G        | O2       |
|-------------|----------|----------|
| Computing MV | 5735443.12| 13793.88 |
| Computing OQ from MV | 3.07     | 0.39     |

Table 11: Comparing time for computing materialized view and time for computing original query results from the materialized view for O2 and G for Q18 in [13]. All times are reported in milliseconds.

We expect G to outperform O2 in computing the provenance. This is because the provenance retrieval in G requires a join of R′ with RK. O2 requires a join of 3 tables (if the key is materialized). For instance, the provenance retrieval query for LineItem2 requires a join of R′ with RK to produce RK′, which is then joined with LineItem table to determine the provenance. However the larger size of RK materialized view in G results in a much larger time to execute the provenance retrieval queries.
We expect the provenance retrieval query for O2 in practice will never perform worse than the provenance retrieval query for O1. This is because for any table, the provenance retrieval query for O1 (that does not use $RK'$, but instead uses $R'$) may be used instead of the provenance retrieval query for O2 (that uses $RK''$) if we expect the performance of the provenance retrieval query for O1 to be better. However, as we really want to see the performance of provenance retrieval queries for O2, we have not considered this optimization in this paper.

Other things to note are that computing the results of the original query for $O_1$ and $W$ is done exactly the same way. Further, for $Q_{18}$, O1 outperforms all approaches even in provenance retrieval except for $PLineItem2$. This is because Algorithm 4 is able to optimize the provenance retrieval queries significantly for $PCustomers$, $POrders$, $PLineItem1$. However, for $PLineItem2$, the provenance retrieval required computing $PQ_{18}$tmp and then using it to compute $PLineItem2$, which needed more joins. Usually, we expect every provenance retrieval query from O1 to outperform W, but in this case W did outperform O1 for $PLineItem2$ (by a small amount); we believe the reason for this is the extra joins in W ended up being helpful for performance (which is not typical).

After studying in detail the performance for one query, we compared how the different approaches perform for several TPC-H queries. Of the 19 TPC-H queries without outer joins, we report on 18 of the queries in Table 12. In this table, OQ refers to the time taken for computing the results of the original user query, AP (average provenance) refers to the time taken to compute the provenance averaged over all the base tables used in the query, and MP (minimum provenance) refers to the minimum time to compute provenance over all the base tables used in the query. For W, we typically expect AP and MP to be almost the same (unless for nested queries); this is because in W, every provenance retrieval query (for non-nested original user queries) performs the same joins. Similarly for G, we typically expect AP and MP to be almost the same (because every provenance computation is just a look-up in the materialized data), except for the difference in the size of the results. For O1 and O2, depending on what is materialized, the value for MP might be significantly smaller than the value for AP because some provenance computation might have been optimized extensively (as you can see for $Q_{10}$, $Q_{18}$).

|     | O1           | W            | G             | O2             |
|-----|--------------|--------------|---------------|----------------|
| Q1  | OQ 3360.22  | W 3360.22   | G 14664.45    | O2 111085.82   |
|     | AP 3232.91  | W 3232.91   | G 36944.21    | O2 26606.80    |
|     | MP 3232.91  | W 3232.91   | G 36944.21    | O2 26606.80    |
| Q2  | OQ 55.88    | W 55.88     | G 12863.35    | O2 7713.84     |
|     | AP 37.41    | W 55.59     | G 1.25        | O2 0.61        |
|     | MP 0.21     | W 0.98      | G 0.52        | O2 0.52        |
| Q3  | OQ 865.39   | W 865.39    | G 2869.07     | O2 2542.53     |
|     | AP 0.06     | W 0.09      | G 45.57       | O2 4.28        |
|     | MP 0.04     | W 0.08      | G 43.11       | O2 3.47        |
| Q4  | OQ 4082.92  | W 4082.92   | G 32693.21    | O2 7692.08     |
|     | AP 5288.27  | W 5288.27   | G 157.76      | O2 446.63      |
|     | MP 4280.97  | W 4280.97   | G 137.48      | O2 351.88      |
| Q5  | OQ 634.83   | W 634.83    | G 2919.82     | O2 2506.08     |
|     | AP 674.75   | W 674.75    | G 13.01       | O2 11.45       |
|     | MP 648.16   | W 648.16    | G 10.71       | O2 4.73        |
| Q6  | OQ 626.86   | W 626.86    | G 3153.23     | O2 2949.50     |
|     | AP 672.79   | W 672.79    | G 90.28       | O2 899.07      |
|     | MP 672.79   | W 672.79    | G 90.28       | O2 899.07      |
| Q7  | OQ 897.49   | W 897.49    | G 4949.55     | O2 4707.83     |
|     | AP 700.78   | W 700.78    | G 14.22       | O2 12.52       |
|     | MP 691.85   | W 691.85    | G 12.00       | O2 7.02        |
| Q8  | OQ 832.85   | W 832.85    | G 4189.32     | O2 3313.50     |
|     | AP 1731.11  | W 1731.11   | G 5.05        | O2 7.92        |
|     | MP 1624.07  | W 1624.07   | G 2.17        | O2 3.74        |
| Q9  | OQ 3737.91  | W 3737.91   | G 217144.77   | O2 188176.54   |
We find that except for one single table query Q1, where W performs same as O1, our approaches that use the dependencies and use materialization give performance benefits for provenance computation, and hence for result exploration. Further, the eager materialization approach (G) could result in prohibitively high times for original result computation.

### Table 12: Summary of experiments

|   | AP       | MP       | AP       | MP       |
|---|----------|----------|----------|----------|
| Q10| 1496.97  | 99.69    | 1496.97  | 99.69    |
|   | 2315059.38 | 2240453.24 | 712.13  | 100.34   |
| Q11| 427.57   | 0.06     | 427.57   | 0.06     |
|   | 2315059.38 | 2240453.24 | 1331.66 | 306.94   |
| Q12| 887.94   | 40.06    | 887.94   | 40.06    |
|   | 715.43   | 166.89   | 715.43   | 166.89   |
| Q13| 979.97   | 976.79  | 979.97   | 976.79  |
|   | 1496.97  | 1496.97 | 1496.97  | 1496.97 |
| Q14| 769.92   | 783.42  | 769.92   | 783.42  |
|   | 1496.97  | 1496.97 | 1496.97  | 1496.97 |
| Q15| 1372.78  | 1025.56 | 1372.78  | 1025.56 |
|   | 715.43   | 166.89   | 715.43   | 166.89   |
| Q16| 1234.80  | 112.46  | 1234.80  | 112.46  |
|   | 1496.97  | 1496.97 | 1496.97  | 1496.97 |
| Q17| 5853.65  | 5301.62 | 5853.65  | 5301.62 |
|   | 715.43   | 166.89   | 715.43   | 166.89   |
| Q18| 5095.67  | 410.49  | 5095.67  | 410.49  |
|   | 715.43   | 166.89   | 715.43   | 166.89   |
| Q19| 2379.79  | 2386.49 | 2379.79  | 2386.49 |
|   | 715.43   | 166.89   | 715.43   | 166.89   |

6 Related Work

Different semantics of provenance are summarized in literature [11]: which-provenance [8], why-provenance [4] (also PI-CS semantics in [9]), and how-provenance [11]. In our work, we picked which-provenance semantics in [8], as it is sufficient for our scenario of query result exploration, and is defined for aggregation and group by operations. Further, which-provenance semantics is "complete" and the provenance tables, along with the original user query, can then be used for computing the other types of provenance. In addition, which-provenance is invariant under equivalent queries, which allows us to support correlated queries, which can be rewritten as non-correlated queries. Other semantics such as how-provenance are not equivalent under query rewriting, and therefore requires us to study provenance at a syntactic level.

When we materialize data for query result exploration, the size of the materialized data can be an issue as identified by [11]. Eager approaches record annotations (materialized data) which are propagated as part of provenance computation [8]. A hybrid approach that uses materialized data for computing provenance in data warehouse scenario as in [8] is studied in [7]. In our work, we identify that the complete row from a
base table need not be materialized; instead only the key values of a row need to be materialized (annotating results with identifiers from base tables can be considered as materializing keys). Further, in our scenario, it is not required to materialize rows from every base table; instead, we can selectively choose which base tables to materialize based on the expected benefit and cost, and based on other factors such as workload.

Other scenarios have been considered. For instance, provenance of non-answers are considered in [5, 12]. In [15], the authors study a unified approach for provenance of answers and non-answers. However, as noted in [11], research on negation in provenance has so far resulted in divergent approaches. Another scenario considered is explaining results using properties of the data [17, 18].

Optimizing provenance queries is studied in [16]. Here the authors study heuristic and cost based optimization for provenance computation. However, the dependencies that we identify are not applicable to their scenario and hence are not considered. However, [16] studies inference of constraints [14]. For our work, we do limited inference of constraints, and infer the key in the presence of a group by clause.

7 Conclusions and Future Work

In this paper, we studied dependencies that are applicable to query result exploration. These dependencies can be used to optimize query performance during query result exploration. For the TPC-H benchmark, we could optimize the performance of 36.84% (7 out of 19) of the queries that we considered. Further, we investigated how additional data can be materialized and this materialized data can be used for optimizing the performance during query result exploration. Such materialization of data can optimize the performance of query result exploration for almost all the queries.

One of the main avenues worth exploring is extensions to the query language that we considered. The dependencies we considered can be used when the body of a rule is a conjunction of predicates. We do not consider union queries, negation or outer joins. These will be interesting to explore as the dependencies do not extend in a straightforward manner. Another interesting future direction is studying effective ways of navigating the search space of possible materializations. Also, it will be worthwhile investigating how to start from provenance tables and define other provenance semantics (such as how-provenance) in terms of the provenance tables.

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