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Enhancing an Extensible Query Optimizer with Support for Multiple Equivalence Types

Giedrius Slivinskas and Christian S. Jensen

Department of Computer Science, Aalborg University, Denmark
`http://www.cs.auc.dk/~{giedrius|csj}`

Abstract. Database management systems are continuously being extended with support for new types of data and advanced querying capabilities. In large part because of this, query optimization has remained a very active area of research throughout the past two decades. At the same time, current commercial optimizers are hard to modify, to incorporate desired changes in, e.g., query algebras or transformation rules. This has led to a number of research contributions aiming to create extensible query optimizers, such as Starburst, Volcano, and OPT++.
This paper reports on a study that has enhanced Volcano to support a relational algebra with added temporal operators, such as temporal join and aggregation. These enhancements include the introduction of algorithms and cost formulas for the new operators, six types of query equivalences, and accompanying query transformation rules. The paper describes extensions to Volcano's structure and algorithms and summarizes implementation experiences.

1 Introduction

Query optimization has remained subject to active research for more than twenty years. Much research has aimed at enhancing existing optimization technology to enable it to support the requirements, such as for new types of data and queries, of the many and new types of application areas, to which database technology has been introduced over the years. However, current commercial optimizers remain hard to extend and modify when new operators, algorithms, or transformations have to be added, or when cost estimation techniques or search strategies have to be changed [4]. As a result, the last decade has witnessed substantial efforts aiming to develop extensible query optimizers that would make such changes easier. Representative examples of extensible query optimizers include Starburst [8], Volcano [7], and OPT++ [11].

This paper reports on a specific study that has enhanced the Volcano extensible query optimizer to support a relational algebra with temporal operators such as temporal join and aggregation [15]. In addition to new operators, cost formulas, selectivity-estimation formulas, and transformation rules, the algebra offers systematic support for order preservation and duplicate removal and retention for all queries, as well as for coalescing for temporal queries (in coalescing, several tuples with adjacent time periods and otherwise identical attribute values are merged into one). To support order, relations are defined as lists, and six kinds of relation equivalences are defined – two relations can be equivalent as lists, multisets, and sets, and two temporal relations can be snapshot-equivalent as lists, multisets, and sets. We report on the design decisions and implementation experiences, and we evaluate Volcano's extensibility.

An important goal of the algebra is to offer a foundation for a layered temporal DBMS that may evaluate temporal queries faster than do current DBMSs. The latter do not have efficient algorithms for expensive temporal operations such as temporal aggregation, while such operations can be evaluated efficiently at the user-application level by algorithms that use cursors to access the underlying data [16].

New algorithms can be added to a DBMS via, e.g., user-defined routines in Informix [2,9] or PL/SQL procedures in Oracle [13], but these methods currently do not allow to define functions that take tables as arguments and return tables [10]; nor do they allow to specify transformation rules, cost formulas, and selectivity-estimation formulas for the new functions. Because of these limitations, a middleware component with query processing capabilities was introduced, which divides the query processing between itself and the underlying DBMS [16]. Intermediate relations can be moved between the middleware and the DBMS by the help of transfer operators.

To adequately divide the processing, the middleware has to take optimization decisions – for this purpose, we employ the Volcano extensible optimizer. Use of a separate middleware optimizer allows us to take advantage of transformation rules and cost and selectivity-estimation formulas specific to the temporal operators.

This paper summarizes design issues and experiences from the implementation of the optimizer. While the addition of new temporal operators, their cost and selectivity-estimation formulas, and transformation rules could be done using the extensibility framework provided by Volcano, adding support for multiple types of equivalences between relations required changes in Volcano structures, and in its search-space generation and plan-search algorithms.

To our knowledge, no existing extensible query optimizers systematically support sets, multisets, and lists. Sorting is treated differently than the common operators, such as selection or join, and it usually is considered in the query optimization only after the search space of possible query plans has been generated. However, particularly due to recent introduction and increasing use of `TOP N` and `BOTTOM N` predicates in queries [3], sorting could be exploited better in query optimization if considered during the search-space generation.

The paper is structured as follows. In Sect. 2, we present Volcano's architecture. Section 3 describes the enhancements to Volcano that were necessary to support the algebra introduced above. The algebraic framework is described first, with a focus on the parts that posed challenges to Volcano, and the modifications are described next. Section 4 summarizes the implementation experiences and evaluates the extensibility of Volcano. Section 5 covers related work, and Sect. 6 concludes the paper.

2 Description of Volcano

The Volcano Optimizer Generator is a software program for generating extensible query optimizers. The input to the program is a query algebra: operators, their implementation algorithms (physical operators), transformation rules, and implementation rules. Transformation rules specify equivalent logical expressions, and implementation rules specify which algorithms implement which operators. The output is an optimizer, which takes a query in the given algebra as input and returns a physical expression (an expression of algorithms) representing the chosen query evaluation plan. The optimizer implementor's tasks include the specification of the input and the coding of the support functions – such as the selectivity estimation – for operators and rules.

2.1 Two Stages of Query Optimization

The Volcano optimizer optimizes queries in two stages. First, the optimizer generates the entire search space consisting of logical expressions generated using the initial query plan (to which the query is mapped to) and the set of transformation rules. The search space is represented by a number of equivalence classes. An equivalence class may contain one or more logically equivalent expressions, also called elements; each of these includes an operator, its parameter (for example, predicates for the selection), and pointers to its inputs (which are also equivalence classes).

Consider a simple example query, which performs a join on the `EmpID` attribute of `POSITION` and `SALARY` relations. Its one possible initial plan is shown in Fig. 1(a) and its search space is shown in Fig. 1(b). The elements of classes 1 and 2 represent logical expressions returning partial results of the query, i.e., the operators retrieving, respectively, the `POSITION` and `SALARY` relations. The elements of class 3 represent logical expressions returning the result of the complete query; either the first or the second element may be used. Essentially, the given search space represents only two plans which differ in the order of the join arguments.

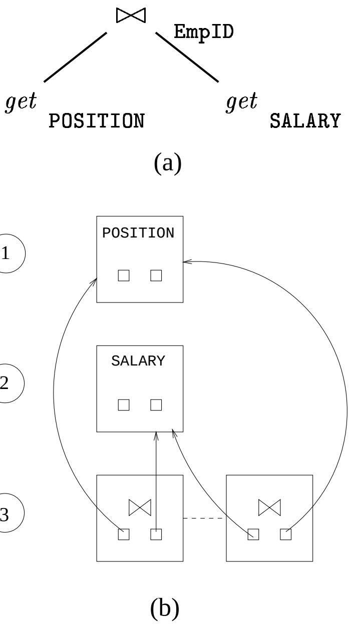

Fig. 1. A Query Plan and its Search Space

During the second stage of Volcano's optimization process, the search for the best plan is performed. Here, the implementation rules are used to replace operators by algorithms, and the costs of diverse subplans are estimated. For the given query, the number of plans to be considered is greater than two, because the relations may be retrieved by using either full scan or index scan, and the join may be implemented by, e.g., nested-loop, sort-merge, or index join. One possible evaluation plan is to scan both relations and perform a nested-loop join.

The following two sections briefly describe the search-space generation and the plan-search algorithms; for more detail, we refer to [7].

2.2 Stage One: Search-Space Generation

The search-space generation is performed by the *Generate* function. Initially, one element is created for each operator in the original query expression, and then *Generate* is invoked on the top element.

The *Generate* function repeatedly applies transformation rules to the given element, choosing among the applicable rules that have not so far been applied to the element. The application of a transformation rule may trigger the creation of new elements and classes; for each newly generated element, the *Generate* function is invoked.

For the query in Fig. 1(a), the search space is generated as follows. Initially, three elements representing the three query-tree operators are created (the first elements of equivalence classes 1–3 in Fig. 1(b)). Then, the *Generate* function is invoked for the first element of class 3, which, in turn, invokes *Generate* for the first elements of classes 1 and 2. The latter two *Generate* calls do not do anything because no rules apply to the elements of class 1 and 2. For the first element of class 3, however, the join commutativity rule is applied, and a second element pointing to switched join arguments is added to class 3. Then, the *Generate* function is invoked on the new element of class 3, but no new elements are generated: the join commutativity rule is applied again, but its resulting right-hand element already exists in the search space.

2.3 Stage Two: Plan Search

When searching for a plan, the Volcano optimizer employs dynamic programming in a top-down manner, and it uses the *FindBestPlan* function recursively.

First, the optimizer invokes the *FindBestPlan* function for the first element of the top equivalence class – e.g., class 3 in Fig. 1(b) – and a cost limit of infinity (the cost limit can be lower in subsequent calls to the function). If all elements of the class containing the argument element have already been optimized, no further optimization for the element is necessary: if the plan has been found and its cost is lower than the cost limit, it is returned, if not – NULL is returned. Otherwise, optimization has to be performed.

During the optimization, for each algorithm implementing the top operator (in our case, join), *FindBestPlan* is recursively invoked on the inputs to the algorithm. If optimization of the inputs is successful, the plan with the algorithm yielding the cheapest expected cost is chosen as the best plan. Then, *FindBestPlan* is recursively invoked for each equivalent logical expression (in our case, for the second element in equivalence class 3) to see if a better plan can be found. In case a better plan is found, it is saved in memory as the best one.

3 Enhancement of Volcano

The implementation of the algebra and its accompanying transformation rules introduces several concepts that did not exist previously in Volcano; these new concepts are described in Sect. 3.1. Sections 3.2 and 3.3 concern the actual implementation.

3.1 Algebra and Multi-equivalence Transformation Rules

First, we overview the architecture for which the algebra has been designed. Next, we describe the actual algebra, the accompanying transformation rules, and their applicability, focusing on the new concepts. Finally, we outline the challenges that these new concepts pose to Volcano.

Architecture. The temporally extended relational algebra [15] has been designed for an architecture consisting of a middleware component and an underlying DBMS. Expensive temporal operations such as temporal aggregation do not have efficient algorithms in the DBMS, but can be evaluated efficiently by the middleware, which uses a cursor to access DBMS relations [16]. Consequently, query processing is divided between the middleware and the DBMS; the main processing medium is still the DBMS, but the middleware is used when this can yield better performance.

Algebra. The algebra differs from the conventional relational algebra in several aspects. First, it includes temporal operators such as temporal join and temporal aggregation. Next, it contains two transfer operators that allow to partition the query processing between the middleware and the DBMS. Finally, the algebra provides a consistent handling of duplicates and order at logical level, by treating duplicate elimination and sorting as other logical operators and by introducing six types of relation equivalences.

Two relations are equivalent (1) as lists if they are identical lists ($\equiv_L$); (2) as multisets if they are identical multisets taking into account duplicates, but not order ($\equiv_M$); and (3) as sets if they are identical sets, ignoring duplicates and order ($\equiv_S$). Two temporal relations are snapshot-list ($\equiv_L^S$), snapshot-multiset($\equiv_M^S$), or snaphot-set equivalent ($\equiv_S^S$), if their snapshots (projections at a given point in time) are equivalent as lists, multisets, or sets.

Figure 2 shows two temporal relations (relations having two attributes indicating a time period), `POSITION` and `SALARY`. We assume a closed-open representation for time periods and assume the time values for `T1` and `T2` denote months during some year. For example, Tom was occupying position `Pos1` from February to August (not including the latter).

POSITION

PosID	EmpID	Name	T1	T2
Pos1	1	Tom	2	8
Pos2	2	Jane	3	8

SALARY

EmpID	Amount	T1	T2
1	100K	2	6
1	120K	6	9
2	110K	3	8

Result

EmpID	Name	PosID	Amount	T1	T2
1	Tom	Pos1	100K	2	6
1	Tom	Pos1	120K	6	8
2	Jane	Pos2	110K	3	8

Fig. 2. Relations `POSITION` and `SALARY`, and the Result of Temporal Join

A temporal join is a regular join, but with a selection on the time attributes, ensuring that the joined tuples have overlapping time periods; Figure 2 shows the result of temporal join on the `EmpID` attribute of the `POSITION` and `SALARY` relations.

Transformation Rules. Six types of equivalences lead to six types of transformation rules, since a transformation rule may satisfy several of the six equivalences. Let us consider two rules for temporal join, $\bowtie^T$. For a given rule, we always specify the strongest equivalence type that holds; the ordering of equivalence types is given in Fig. 3. The join commutativity rule $r_1 \bowtie^T r_2 \rightarrow_M r_2 \bowtie^T r_1$ says that the relations resulting from the left-hand and right-hand sides are equivalent as multisets (and, according to the type ordering, as sets, as well as their snapshots are equivalent as sets and multisets). Meanwhile, the sort push-down rule $sort_A(r_1 \bowtie^T r_2) \rightarrow_L sort_A(r_1) \bowtie^T r_2$, where A belongs to the attribute schema of r_1 and the left-hand side operations are located in the middleware, says that the relations are equivalent as lists and that the other five equivalence types also hold.[1] The latter rule exploits the fact that all temporal join algorithms in the middleware retain the sorting of their left arguments.

Applicability of Transformation Rules. Transformation rules that do not guarantee $\equiv_L$ equivalence cannot always be applied, as illustrated by the following example. Consider a query that performs the above-mentioned temporal join and sorts the result by `Name`. One possible initial plan for this query is shown in Fig. 4(a). The bottom operators represent relations `POSITION` and `SALARY` transferred to the middleware; to achieve this, at least two operations are necessary (a table scan in the DBMS and the actual transfer), but to simplify the example, we view them as one operation and do not consider any transformation rules related to these operations. Temporal join and sorting are performed in the middleware.

Let us consider rule $r_1 \bowtie^T r_2 \rightarrow_M r_2 \bowtie^T r_1$. This rule can be applied to switch the arguments of the join. However, if we apply the sort push-down rule first and move the sorting below the temporal join, before the temporal join's left argument (leading to the plan shown in Fig. 4(b)), the application of join commutativity rule would lead to an incorrectly ordered query result. Thus, to be able to tell when an $\rightarrow_M$ rule is applicable, the optimizer needs to know the importance of order at each node in the query tree, i.e., whether the result of the operation at the node has to preserve some order or not. In the algebra, this importance is determined by the *OrderRequired* property. To determine the applicability of rules of other types, two additional properties, *DuplicatesRelevant* and *PeriodPreserving*, are used; the first is True if the operation at the node cannot arbitrarily add or remove duplicates, and the second is True if the operation at the node cannot replace its result with a snapshot-equivalent one. For each rule of a given type, Table 1 shows the applicability condition for operator nodes on the left-hand side of the rule.

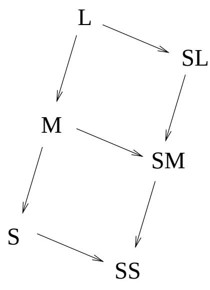
$$\begin{tikzcd}
L \arrow[d] \arrow[r] & SL \arrow[d] \\
M \arrow[d] \arrow[r] & SM \arrow[d] \\
S \arrow[r] & SS
\end{tikzcd}$$

Fig. 3. Ordering of Equivalence Types

Having an initial query plan, the properties for operators are set in a top-down manner and then adjusted every time a new transformation rule is applied. For the top operator, the properties are set in accordance with the specific user-level query language and query statement, e.g., an SQL query requires the result to be sorted if the `ORDER BY` clause is specified at the outer-most level. Consequently, for the top element, the $OrderRequired$ property is set to True only if the `ORDER BY` clause is specified at the outer-most level. The $DuplicatesRelevant$ and $PeriodPreserving$ properties are always set to True, because we always care about duplicates and time periods. For the

[1] To be precise, the relations are $\equiv_{L,A}$ equivalent, i.e., their projections on A are $\equiv_L$ equivalent. We will use $\equiv_L$ equivalence for simplicity.

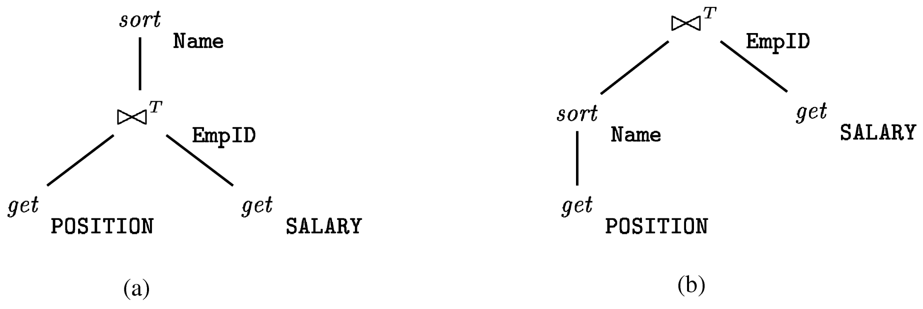

Fig. 4. Query Plans

other operators, the properties are set according to the property values of their parents, e.g., if some operator is the input to the *sort* operator, its *OrderRequired* property will be set to False, because its resulting relation may be replaced (via some transformation rule) by a multiset-equivalent relation, and the correct order of the result will still be ensured by the following *sort* operator. For more details about setting the property values, we refer to [15].

Support in Volcano. Volcano provides a framework of adding new operators and transformation rules, which allows a rather straightforward addition of temporal operators and transfer operators, their cost formulas, selectivity-estimation formulas, and schema propagation formulas. The difficult part is to incorporate different types of transformation rules. While different rule types can be added by just introducing an extra *type* attribute to each rule, to control their applicability is more difficult. The property mechanism cannot directly be used because of Volcano's search-space structure. Having a Volcano search space, values of the three properties cannot be determined for an element, because it is impossible to know the property values of the elements above since the same equivalence-class element may be used as input by different elements of different equivalence classes, as shown later in Fig. 5 where the first element of equivalence class 2 is used both by two elements of equivalence class 3 and by two elements of class 4. Therefore, the determination of the properties can only occur during the actual search, which is performed top down.

Table 1. Applicability of a Rule According to its Type

Rule type	**Applicability condition,** $\forall op \in lhs$
$\rightarrow_L$	True
$\rightarrow_M$	$\neg OrderRequired(op)$
$\rightarrow_S$	$\neg DuplicatesRelevant(op) \wedge \neg OrderRequired(op)$
$\rightarrow_L^S$	$\neg PeriodPreserving(op)$
$\rightarrow_M^S$	$\neg OrderRequired(op) \wedge \neg PeriodPreserving(op)$
$\rightarrow_S^S$	$\neg DuplicatesRelevant(op) \wedge \neg OrderRequired(op) \wedge \neg PeriodPreserving(op)$

3.2 Adjustment of the Search-Space Generation

Since it is impossible to determine properties during the search-space generation, we generate a complete search space by applying transformation rules of *all* types, and then filter away invalid elements during the actual search. The identification of invalid elements is enabled by recording, for each element, a type that represents the combinations of the three property values for which this element may be used. We use six possible type values – L, M, S, SL, SM, SS – which correspond to the six equivalence types. Consequently, the relationship between each element type and the combination of properties corresponds to Table 1. For example, if all properties are True, only L type elements are valid. Intuitively, the element type tells how the relation generated by this element will be equivalent to the first element of the equivalence class.

Figure 5 shows the search space for the query in Fig. 4(a), generated using the join commutativity rule and the sort push-down rule (the first one guarantees $\equiv_M$ equivalence, while the second one guarantees $\equiv_L$ equivalence). Initially, four elements representing the four query-tree operators are created (the first elements of equivalence classes 1–4). Then, the join commutativity rule is applied to the first element of class 3, and a second element representing switched join arguments is added to the class. The sort push-down rule is applied to the first element of class 4, and two new elements are created, one of which is added to class 4 and one of which becomes the only element of class 5. Finally, the join commutativity rule is applied to the second element of class 4, yielding the third element in the class.

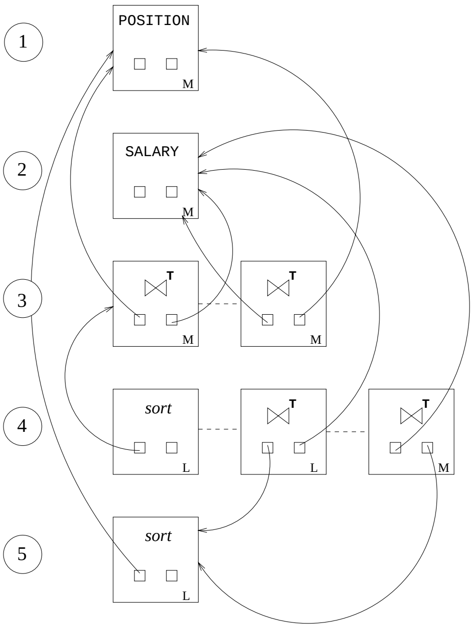

Fig. 5. Search Space

The first elements of classes 1–3 have equivalence type M only, because the base relations are retrieved from the DBMS, and we do not know in which order the DBMS will deliver them. It may happen that a subquery whose top element is the first element of class 3, when run twice, would return relations that are only multiset equivalent.

The third element of class 4 is only $\equiv_M$ equivalent to the other two elements of that class. Since the query requires a sorted result (the *OrderRequired* property value for the top operator is True), only the two first elements of class 4 will be used during plan search. Below, we discuss how the element types are determined.

During the search-space generation, new elements are added after applying transformation rules. For a transformation rule, we give below a procedure for how to set the types of elements resulting from the right-hand side of the rule.

1. The top-element type (the element representing the top operator in the right-hand side of the rule) is set to the type which is the *greatest common descendant* of the transformation-rule type and the types of the elements participating in the left-hand side of the transformation rule.
2. The top-element type is set to a stronger type than specified in 1 only if the right-hand side contains an operation – such as sorting or duplicate elimination – that would enforce a “stronger” equivalence between the new top element and the old top element.
3. The types of other new elements resulting from the right-hand side of the rule are set to any value, but they have to be equal to or stronger than the top-element type.

For example, the greatest common descendant of types M and SM is SS. Let us consider the search space in Fig. 5: the join commutativity rule applied to the second element of class 4 results in the third element of class 4, and its type is set to M, which is the greatest common descendant of L (the type of the second element) and M (the type of the rule).

Now let us consider another query, which performs a selection on relation r transferred to the middleware and then sorts it; see its search space in Fig. 6(a). After transformation rule $sort_A(\sigma_P(r)) \rightarrow_L \sigma_P(sort_A(r))$ is applied to the first element of class 3, the new top element – which becomes the second element of class 3 – is of type L (Fig. 6(b)). Even if the sorting is not at the top level, the result is correctly ordered because the selection retains the order of its argument.

In the given examples, the types of the new non-top elements are set to L. Generally, the types of non-top elements are not important for the correctness, as long as they are not descendants of the new top element type (see the equivalence-type ordering in Fig. 3). Therefore, they should be set aiming to have as small search space as possible, i.e., if an element has to be inserted, first we can look in the existing search space if the same element (with any type) exists there, and if it does, we do not need to insert it anew. If no elements exist, a new element should have L type, because most rules are of $\rightarrow_L$ type and it is likely that, if this element is to be attempted to be inserted again as a top-level element, its type will be L.

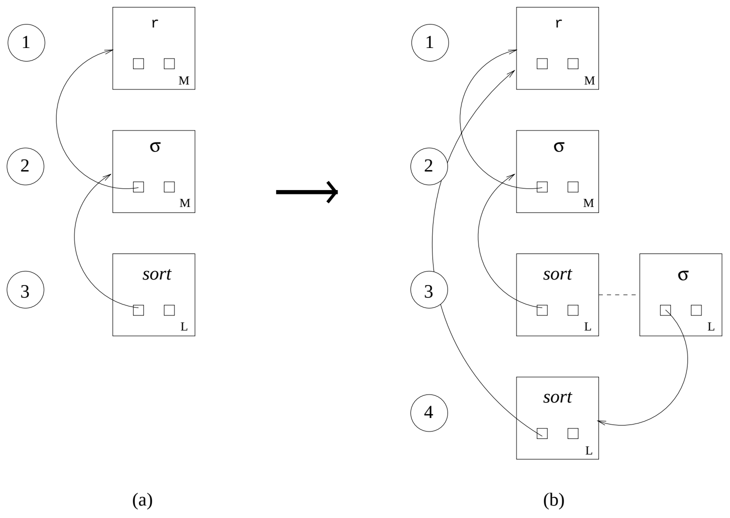

Fig. 6. Search Space Before (a) and After (b) Applying $sort_A(\sigma_P(r)) \rightarrow_L \sigma_P(sort_A(r))$

3.3 Modification of the Plan Search

For the actual search, the code that controls the validity of elements depending on their type has to be added to Volcano.

The most significant change is the addition of properties to the parameter list of the $FindBestPlan$ function. The function uses its input properties to check the validity of its input element, as mentioned in Sect. 3.2, as well as to set the parameter properties for calling itself recursively on the inputs to its input element.

Since equivalence-class elements might be of any of the six different types, each equivalence class may have up to six physical plans, because plans for different-type elements might differ. For example, it is likely that a type M plan will be simpler and less costly than a type L plan. In the $FindBestPlan$ function, when looking if a plan already exists for the input element, we have look for a plan of a type that is stronger than or equal to the input-element type.

4 Experiences

In this section, we consider the extensibility of Volcano in relation to the needs of our framework. We evaluate its support for multiple types of equivalence, discuss other extensions, and evaluate the ease of extensibility.

4.1 Support for Multiple Types of Equivalences

When considering multiple types of equivalences, sorting, duplicate elimination, and coalescing are important operations, because they may change the equivalence type between two relations. For example, if two $\equiv_M$ equivalent relations are sorted on A, their sorted versions will be $\equiv_{L,A}$ equivalent.

Coalescing and duplicate elimination were not implemented in Volcano, and sorting is supported by the so-called *physical properties* of an equivalence class. The possible use of sorting algorithms (termed *enforcers*) is considered during the second phase (plan search) of query optimization. Physical properties are passed as arguments to the $FindBestPlan$ function, and they allow the optimizer to consider different positions of sort enforcers. The use of physical properties increases the code complexity and size – for each algorithm implementing an operator, the optimizer implementor has to write functions deriving physical properties of the algorithm's inputs, checking whether the algorithm satisfies required physical properties, and finding physical properties that are required from the algorithms's inputs.

In our approach, we treat sorting, duplicate elimination, and coalescing as all the other operators and exploit them in the search-space generation, not using physical properties. While it may be possible to pursue a direction where sorting, duplicate elimination, and coalescing are all treated as enforcers and employ physical properties, we feel that this treatment would add unneccesary complexity to the framework because, fundamentally, sorting, coalescing, and duplicate elimination are just like other operators, having their transformation rules and statistics-derivation formulas. Treating them as algorithms reduces the number of transformation rules, but the complexity in the plan-search algorithm is greatly increased. In addition, it would be problematic to incorporate the statistics-estimation formulas for duplicate elimination and coalescing.

4.2 Other Useful Extensions

Our implementation has indicated the need for new or better support in a number of other areas.

The two-stage query optimization of Volcano forced us to apply all types of transformation rules during the first stage. If one stage with a top-down plan search and generation had been used, it would have been easier to control the applicability of the different types of rules and, possibly, would have improved performance.

The search strategy of Volcano is fixed, and no mechanisms for extending or changing it are provided. Proposed improvements of Volcano that were not part of the available code include a mechanism for heuristic guidance, where rules can be ordered according to their "promise" [7]. Such ordering implies that the rules having the best probability to yield better plans would be applied as soon as possible, reducing the overall plan-search time.

We had to add support for equivalence-class elements that point to their own equivalence classes, because this facility was not available in the code supplied. The pointing to the same class often occurs using different equivalence types. For example, sorted relation r is multiset equivalent to r, yielding to a class with two elements (one for r sorted and one for r) where the first (sorting) points to the same class. In addition, we had to implement the linking of classes; the linking is needed when we apply a rule to an element of a certain class and find that the resulting element already exists in some other class, meaning that both classes represent the same logical expression.

The cardinality of a relation resulting from some equivalence class is estimated when the class is created, according to the selectivity estimation method of the operator represented in the first element. When a new element is added to the class, the cardinality is not reestimated. However, the new element may represent an operator for which we may have a better method for estimating the cardinality. For example, it is easier to estimate the size of a join, than the size of a Cartesian product followed by a selection and a projection. Therefore, we had to ensure that the initial plan would contain operators with good cardinality estimation methods.

4.3 Ease of Extensibility

The main challenge for an extensible query optimizer is to balance the efficiency and extensibility, and our study indicates that Volcano's main emphasis is put on the first aspect. Volcano is coded in C and does not follow the object-oriented paradigm, which leads to many interconnected structures, which in turn posed difficulties in figuring out where the structures were defined, initialized, and used. The transformation-rule application code is being generated automatically and does not follow any style guidelines, making it difficult to modify (which was needed when incorporating the necessary modifications in the search-space generation). A lot of arrays and structures have predefined sizes and were not being allocated dynamically, occupying more memory than necessary and providing low scalability. On the other hand, the running times of Volcano (for queries not involving many joins) were quite low, as shown in [16].

The actual implementation tasks, their difficulty, and approximate number of lines of resulting code are summarized in Table 2. We divide the entire implementation effort into three subtasks. The first one, adding support for multiple equivalence types, is the most difficult, and it has been described in the previous sections. Yet the amount of resulting code was rather small. The other task was to add new operators, and while it resulted in a substantial amount of code, it was not difficult, after learning Volcano's provided framework for adding new operators and transformation rules. The same applies to the last task of adding new algorithms; there, however, the amount of code was smaller, because we did not use physical properties.

Support functions form the biggest part of the code added by the optimizer implementor and their size is proportional to the number of operators and algorithms implemented. In our case, we implemented relation retrieval, selection, projection, join, sort-preserving join, temporal join, Cartesian product, duplicate elimination, aggregation, temporal aggregation, and two transfer operators. Similar behavior of many of these operators (particularly, in the propagation of catalog information) resulted in a lot of code repetition in corresponding support functions.

5 Related Work

Our paper takes its outset in the algebraic framework presented in [15]. The framework has been validated by implementing it using the Volcano optimizer and the XXL library of query evaluation algorithms; the architecture, cost and selectivity-estimation formulas, and performance studies have been reported in [16]. The latter paper did not cover the enhancements to Volcano, which are the foci of this paper.

Table 2. Tasks, Their Complexity, and Amount of Code

Task	**Complexity**	**Lines of Code**
Adding equivalence-type support		
Modifying structures	medium	< 200
Modifying search-space generation	high	< 200
Modifying plan search	high	< 200
Adding new operators		
Coding support functions	medium	~ 2500
Coding management of the three properties	medium	~ 400
Coding transformation rules	medium	~ 2300
Adding new algorithms		
Coding support functions	low	~ 1300
Coding implementation rules	medium	< 200

While to our knowledge, nobody has enhanced existing optimizers with support for sets, multisets, and lists, reference [1] reports on experiences from building the query optimizer for Texas Instruments' Open OODB system using Volcano. That paper finds the optimization framework useful, but mentions that much time was spent on writing support and cost functions and that the interface for these tasks is not user-friendly. We agree with these statements, and we draw additional conclusions in Sect, 4.

A number of other extensible query optimizers exist. Volcano evolved from the Exodus optimizer [6], and later was enhanced by the Cascades optimization framework [5], which provides a clean interface and implementation that makes full use of C++ classes, as well as more closely integrates transformation rules and implementation rules, which are distinct sets in Volcano. Since Cascades was intended to be used for Microsoft's SQL Server, its code is not available. Neither is the code for the Starburst query optimizer [8] used in IBM's DB2, nor is the code of the EROC toolkit for building query optimizers [12].

The OPT++ [11] extensible optimizer also uses an object-oriented design with C++ classes to simplify the extension tasks. OPT++ offers a number of search strategies, including "bottom-up" system R-style [14] and the Volcano search strategy; and it can emulate both Starburst and Volcano.

6 Conclusions

A number of extensible query optimizers are available that aim to facilitate changes in query algebras and additions of new functionality. Our study reports on the enhancement of one prominent such extensible query optimizer, Volcano, to support an extended relational algebra, which – in addition to new temporal operators – contains six types of equivalences between relations that lead to six corresponding types of transformation rules. We describe how Volcano's search-space generation and plan search were modified in order to support the algebra, and we evaluate the extensibility of Volcano.

The study indicates that support for sets, multisets, and lists is difficult to add to a pre-existing extensible query optimizer – such support should be considered already during the design of an extensible query optimizer. Volcano's two-staged optimization strategy forces the application of all transformation rules, disregarding their type, during the first stage; if the optimization had occurred in a single stage, we speculate that it would have been easier to control the applicability of rule types and that better performance would have resulted. We also found that, for the modifications we considered, Volcano's interface was not always user-friendly and that the amount of code needed to implement support functions was quite substantial. On the other hand, we found Volcano to be a very useful tool that allowed us to validate our algebra in the middleware architecture more quickly than if we would have had to develop our own optimizer.

This study indicates that extensible query optimizers are useful when testing research ideas and building prototypes. We also believe that extensible optimizers, if developed in industrial strength versions, will prove very useful when building middleware systems that focus on specific functionality suitable for applying conventional relational query optimization techniques. The application of extensible technology to middleware systems is a promising research direction. Due to the increasing use of user-defined routines in conventional DBMSs, optimizer extensibility is also important when creating new DBMSs or modifying existing ones. Finally, the study reported upon here indicates that more research is needed in query optimization and processing that offer integrated support for sets, multisets, and lists.

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References

1. J. A. Blakeley, W. J. McKenna, and G. Graefe. Experiences Building the Open OODB Query Optimizer. In *Proceedings of ACM SIGMOD*, pp. 287–296 (1993).
2. R. Bliujute, S. Saltenis, G. Slivinskas, and C. S. Jensen. Developing a DataBlade for a New Index In *Proceedings of IEEE ICDE*, pp. 314–323 (1999).
3. M. J. Carey and D. Kossmann. Processing Top N and Bottom N Queries. *Data Engineering Bulletin*, 20(3):12–19 (1997).
4. S. Chaudhuri. An Overview of Query Optimization in Relational Systems. In *Proceedings of ACM PODS*, pp. 34–43 (1998).
5. G. Graefe. The Cascades Framework for Query Optimization. *Data Engineering Bulletin*, 18(3):19–29 (1995).
6. G. Graefe and D. J. DeWitt. The Exodus Optimizer Generator. In *Proceedings of ACM SIGMOD*, pp. 160–172 (1987).
7. G. Graefe and W. J. McKenna. The Volcano Optimizer Generator: Extensibility and Efficient Search. In *Proceedings of IEEE ICDE*, pp. 209–218 (1993).
8. L. M. Haas et al. Starburst Mid-Flight: As the Dust Clears. *IEEE TKDE*, 2(1):143–160 (1990).
9. Informix Software. DataBlade Overview. URL: <www.informix.com/products/options/udo/datablade/>, current as of May 29, 2001.

10. M. Jaedicke and B. Mitschang. User-Defined Table Operators: Enhancing Extensibility for ORDBMS. In *Proceedings of VLDB*, pp. 494-505 (1999).
11. N. Kabra and D. J. DeWitt. OPT++: An Object-Oriented Implementation for Extensible Database Query Optimization. *VLDB Journal*, 8(1):55–78 (1999).
12. W. J. McKenna, L. Burger, C. Hoang, and M. Truong. EROC: A Toolkit for Building NEATO Query Optimizers. In *Proceedings of VLDB*, pp. 111–121 (1996).
13. Oracle Technology Network. Overview of PL/SQL. URL: <`otn.oracle.com/tech/pl_sql/`>, current as of May 29, 2001.
14. P. G. Selinger et al. Access Path Selection in a Relational Database Management System. In *Proceedings of ACM SIGMOD*, pp. 23–34 (1979).
15. G. Slivinskas, C. S. Jensen, and R. T. Snodgrass. A Foundation for Conventional and Temporal Query Optimization Addressing Duplicates and Ordering. *IEEE TKDE*, 13(1):21–49 (2001).
16. G. Slivinskas, C. S. Jensen, and R. T. Snodgrass. Adaptable Query Optimization and Evaluation in Temporal Middleware. In *Proceedings of ACM SIGMOD*, pp. 127–138 (2001).