Redefining The Query Optimization Process

Kristian F. D. Rietveld and Harry A. G. Wijshoff

Abstract—Traditionally, query optimizers have been designed for computer systems that share a common architecture, consisting of a CPU, main memory and disk subsystem. The efficiency of query optimizers and their successful employment relied on the fact that these architectures basically stayed the same over the last decades. However, recently the performance increase of serial instruction execution has stagnated. As a consequence, computer architectures have started to diversify. Combined with the fact that the size of main memories has significantly increased it becomes more important to exploit intrinsic internal features of computer systems (data coherence mechanisms, TLB and instruction cache performance, among others) rather than mainly focusing on minimizing disk I/O.

The purpose of this paper is to redefine query optimizers. This new generation of query optimizers will be capable of optimizing queries to perform significantly better than contemporary state-of-the-art query optimizers.

1 INTRODUCTION
In the last decade, the increase of single-core performance of CPUs has stagnated. Up till now, database systems could increase their performance to a large extent by relying on these increases in single-core performance. This is no longer the case. In the foreseeable future, the overall improvement of (multi-core) CPU performance will stagnate as well, as it is no longer practical to put more cores in a single CPU due to cache coherence issues and the physical limitations for transistor sizes. Since the needs for data processing grow exponentially, this would also result in exponential growth (of the size) of hardware platforms. This is not attainable for the near future. Therefore, the performance of database systems will become more critical than it is today and require a re-evaluation of how database systems should be designed.

An additional consequence of the stagnation of single-core performance is that computer architectures will start to diversify even more than they are currently doing and this will result in more disruptive changes of computer architectures. Disk subsystems might diversify by introducing flash storage in a traditional disk subsystem, omitting mechanical disks or providing data to be processed through a high-speed network connection. In the future, different CPU architectures will emerge with varying numbers of cores with different capabilities, differing cache architectures and coherence schemes combining software mechanisms with hardware-based schemes. Traditionally, query optimizers have been designed for generations of computer systems assuming that changes in architecture are non-disruptive. Due to the growing diversity of computer architectures in the future this assumption no longer holds and query optimizers will need significant adaptations to deal with future advances in computer architecture.

Compiler technology forms a crucial component of future releases of computer architectures. New computer architectures will be disruptive, requiring compiler heuristics to be extensively re-tuned for achieving acceptable performance. New features of such architectures will be controlled by software mechanisms, configuring these mechanisms according to the characteristics of the software that will be run. Furthermore, for specific architectural features, specific compiler transformations might be developed. The state of art in compiler technology for future systems will therefore be of crucial importance for successful deployment of these systems.

For database systems these developments will mean that performance can no longer be taken for granted and that database systems will become more and more dependent on specific architectural features as well as compiler support for these features. In general one could assume that specific dedicated hardware would be developed for database systems in which specific database management backends will be implemented on top of these architectural features. The other solution would be to integrate database systems more and more with compiler technology. Although the first solution will certainly form a feasible solution, in this paper we would like to emphasize that the integration of compiler technology with database systems is the most cost effective and versatile way forward. Thereby, a number of specific features, which have been developed in compiler technology, can be readily used by database systems. Most notably query optimizations have a lot in common with optimizing compiler transformations.

Traditional query optimizers have long distinguished themselves from optimizing compilers by relying on cost-based planning. A large search-space of equivalent query plans for the execution of a given query is searched for an
optimal query plan. The optimality is determined through cost-based metrics, where the cost of operations is calculated using statistics of the database itself, most notably the size of the database relations. As the contents and size of the relations in a database change, the optimal plan for the execution of a query will change as well. Queries that have been compiled once and do not adapt to changes in data will be outperformed by the interpreted execution of query plans. Recompiling and optimizing a query for each invocation of a query is too expensive an operation and the gains might not weigh up.

In the last 30 years of research into optimizing compilers, the consideration of run-time characteristics has been studied extensively. This is caused by the fact that the transformation search space has become too large to effectively search at compile time. Consequently, techniques such as multi-version codes, Just-In-Time (JIT) compilation, iterative compilation, run-time feedback mechanisms and trace scheduling were developed. So, it is the potential of integrating query optimization with already existing compiler optimizations taking run-time characteristics into account that yields excellent opportunities for query optimizers to be enhanced. In addition to common techniques used by query optimizers, compilers are equipped with techniques that are not considered by query optimizers such as enabling prefetching, instruction selection, code compaction and automatic vectorization. As a result, compiler transformations can outperform the cost-based planning that is performed by traditional query optimizers.

The optimization methodology that is proposed in this paper is part of a larger framework for the vertical integration of database applications [1]. Extensive vertical integration is not possible with traditional query optimization techniques, because when code is generated from query evaluation plans and combined with application code, further applicability of compiler transformations is obscured. Therefore, it is important that queries are transformed, optimized and combined with application code in a way that compiler optimizations can still be successfully exploited.

We demonstrate in this paper that through the use of existing compiler optimizations, a new generation of query optimizers can be built that are capable of optimizing queries to a performance that is beyond that of traditional query optimization (an average improvement of a factor of 3 and in certain cases an improvement of up to a factor of 15). An experimental evaluation is presented using the TPC-H benchmark [2]. Note that the used compiler transformations are the main query optimization techniques. This should not be confused with other research into the use of compiler optimization in query optimization such as [3], [4], that propose compiler-based techniques for the generation of efficient executable code from algebraic query execution plans.

This paper is organized as follows. Section [5] introduces the forelem intermediate representation. Section [6] describes transformations that are defined within the forelem framework. Section [7] discusses how queries can be optimized using the existing compiler transformations that are defined within the forelem framework and how the main techniques of query optimization can be emulated using optimizing compiler techniques. Section [8] discusses strategies for the application of transformations on forelem loop nests and strategies for code generation. Section [9] compares the performance of forelem-optimized codes with that of a contemporary database system using the queries from the TPC-H benchmark. Section [10] briefly discusses how the forelem framework is implemented. Section [11] discusses related work. Finally, Section[12] lists our conclusions.

2 The Forelem Intermediate Representation

In this section, the forelem intermediate representation is described, which forms an intermediate representation to which SQL queries are transformed. Subsequently, the forelem intermediate representation is further optimized by “compiler-type” transformations. The forelem intermediate representation is centered around the forelem loop construct. Each forelem loop iterates a (multi)set of tuples. Tuples in these multisets are accessible with subscripts, like ordinary arrays. The subscripts that are accessed through an “index set” that is associated with the multiset.

Let us consider a simple query: SELECT A.a1 FROM A WHERE A.a2 = 7. A C code to evaluate this query could look as follows:

```c
for (i = 0; i < len(A); i++)
    if (A[i].a2 == 7)
        add_to_result(A[i].a1)
```

and in this code fragment, the for loop iterates the full A table, the if-statement selects matching tuples.

The main problem with this code fragment is that the looping structure is explicit, which already gives a particular implementation of the query and this limits the range of transformations and evaluation choices [5]. It is apparent that a full iteration over table A is to be done, to check the value of a2 of each tuple. This explicit looping structure excludes the possibility to, for example, exploit an index on the a2 values. Additionally, more complex query constructs, such as distinct and group by, require more complicated code making it harder to apply transformations and hides the actual problem at hand.

Ideally, only those rows are iterated for which the condition a2 = 7 holds true. This is similar to what an index on the column a2 would accomplish. One way to accomplish this is to move the definition of these conditions into the loop control structure, in our case the for statement. As a result, the explicit if statements are eliminated, which paves the way for the application of a larger range of optimizations. The above query loop written using forelem looks like the following:

```
forelem (i; i \in pA.a2[7])
    \( R = R \cup \{A[i].a1\} \)
```

This code fragment is read as follows: with i, iterate over each index into table A for which a2 == 7 holds true. For these i, we append a tuple containing the value of a1 for index i into table A to the result set R.

Even though the forelem loop appears to be very similar to a foreach loop that exists in many common programming languages, there is one distinguishing feature. This concerns the notation pA.a2[7]. This denotes that a set of indices into table A will be returned for which the a2 field equals 7. This
is similar to an index set as is commonly used in DBMSs, and we will also use this term to refer to the sets of indices we define here. The fact that an index set contains indices is indicated by the prefix \( p \), from pointer. Note that the order in which the indices appear in the index set is not defined. From this follows that the exact semantics of how the table \( A \) will be iterated are not set in stone at this point.

Before proceeding, some further notation and terminology is introduced. Let \( D \) be a multiset representing a database table. \( D \) can be indexed with a subscript \( i \) to get access to a tuple, or row, in \( D: D[i] \). A specific field of a row can be accessed with \( D[i].field \) where \( \text{field} \) is a valid field of \( D \). Without subscript, an entire column is selected resulting in a multiset containing all values of that column: \( D[:].field \).

The \( \text{forelem} \) codes that have been generated from SQL statements, the loop body often outputs tuples to a temporary or result set. Temporary sets are generally named \( T_1, T_2, ..., T_n \) and result sets (or output relations) \( R_1, R_2, ..., R_m \). These temporary tables and result sets are both multisets. The semantics that apply to multisets representing database tables apply to temporary tables as well.

An index set is a set containing subscripts \( i \in \mathbb{N} \) into an array. Since each array subscript is typically processed once per iteration of the array, these subscripts are stored in a regular set. Index sets are named after the array they refer to, prefixed with “p”.

\( pD \) represents the index set of all subscripts into a database table \( D: \forall i \in D: \exists i \in pD: D[i] = t \). \( D \) can also be a temporary table \( T_i \). All rows of \( D \) are visited if all members of \( pD \) have been used to subscript \( D \). Random access by subscript into \( pD \) is not possible, instead all accesses are done using the \( \in \) operator. \( i \in pD \) stores the current index into \( i \) and advances \( pD \) to the next entry in the index set.

Note that these index sets are not to be confused with indexes that are used by database systems. As will become apparent, index sets are used to control the iteration performed by the \( \text{forelem} \) loop. The index sets indicate what subscripts to visit, but not in which order as \( \text{forelem} \) loops do not impose a particular iteration order.

The part of the table that is selected using an index set can be narrowed down by specifying conditions. For example, the index set denoted by \( pD[:].field[k] \) returns only those subscripts into \( D \) for which \( \text{field} \) has value \( k \). This can also be expressed as follows:

\[
pD[:].field[k] \equiv \{i | i \in pD \land D[i].field == k\}
\]

When a match on multiple fields is required, the single column name is replaced with a tuple of column names:

\[
pD.(field1, field2)([k_1,k_2]) \equiv \{i | i \in pD \land D[i].field1 == k_1 \land D[i].field2 == k_2\}
\]

Instead of a constant value, the values \( k_n \) can also be a reference to a value from another table. To use such a reference, the table, subscript into the table and field name must be specified, e.g.: \( D[i].field \).

### 2.1 Expressing Joins

SQL statements with an arbitrary number of joins can be written as a \( \text{forelem} \) loop nest while preserving correctness of the results. This is because both the SQL statement and the corresponding \( \text{forelem} \) loop nest set up the same Cartesian product. This fact will be used to reason about the correctness of the translation and the conditions under which transformations can be applied on the \( \text{forelem} \) loops. Consider the join query \( \text{SELECT A.a1 FROM A, C WHERE A.a_id = C.a_id AND C.b_id = 13} \) which is expressed in relational algebra as \( \pi_{A.a1}(\sigma_{A.a_id=C.a_id \land C.b_id=13}(A \times C)) \), more commonly using the join operator: \( \pi_{A.a1}(\sigma_{C.b_id=13}(A \Join A.a_id=C.a_id C)) \). Theoretically, a join is performed by first setting up the Cartesian product over \( A \) and \( C \) and secondly selecting tuples which match the given conditions. We can write the first relational algebra expression as a \( \text{forelem} \) loop nest. The part \( A \times C \) can be written as follows:

\[
\begin{align*}
\text{forelem} & (i; i \in pA) \\
\text{forelem} & (j; j \in pC) \\
S_1 & = \mathbb{R} \cup (A[i].*, C[j].*)
\end{align*}
\]

where \( A[i].* \) denotes all fields of table \( A \) at subscript \( i \). In the result tuple all fields of \( A \) are suffixed with \( A \). This loop nest sets up the Cartesian product \( A \times C \) at statement \( S_1 \), which stores the Cartesian product in \( \mathbb{R} \). After executing the loop nest, \( \mathbb{R} \) is equivalent to what would be produced by the relational algebra expression \( A \times C \).

The selection operator \( \sigma \) is implemented by making a pass over the result table and only storing matching tuples in a new result table. Of the matching tuples we only store the requested fields to implement the \( \pi \) operator.

\[
\begin{align*}
\text{forelem} & (i; i \in p\mathbb{R}) \\
& \text{if } (A[i].a_id \equiv C[i].a_id \land C[i].b_id \equiv 13) \\
& \mathbb{R}_2 = \mathbb{R}_2 \cup (A[i].a1^4)
\end{align*}
\]

By application of a transformation that eliminates temporary tables from the code, both loops can be merged into one:

\[
\begin{align*}
\text{forelem} & (i; i \in p\mathbb{A}) \\
\text{forelem} & (j; j \in p\mathbb{C}) \\
S_1 & \text{ if } (A[i].a_id = C[j].a_id \land C[j].b_id = 13) \\
S_2 & \mathbb{R} = \mathbb{R} \cup (A[i].a1)
\end{align*}
\]

In general, we say that a perfectly nested \( \text{forelem} \) loop nest of the following form:

\[
\begin{align*}
\text{forelem} & (i_1; i_1 \in pT_1) \\
& \text{...} \\
\text{forelem} & (i_n; i_n \in pT_n) \\
S_1 & \mathbb{R} = \mathbb{R} \cup (T_1[i_1].field, ..., T_n[i_n].field)
\end{align*}
\]

sets up a Cartesian product of the tables \( T_1, T_2, ..., T_n \) at statement \( S_1 \). The Cartesian product, or rather the part of the Cartesian product that is accessed, must be preserved under any transformation for the query to yield correct results.

### 2.2 Expressing More Complicated Queries

Within the \( \text{forelem} \) framework, a special syntax is available for expressing the use of aggregate functions. An aggregate function typically has three stages: initialization, update, and finalization. These stages serve to initialize any variables, update the variables for each tuple that is processed and to come to a final result. To use aggregate functions in the \( \text{forelem} \) framework, the following functions are supplied
that represent the different stages of the aggregate function: agg_init for initialization, agg_step to update the variables for a tuple, and agg_finish to finish the computation of the aggregate. Additionally, agg_result returns the final result of the aggregate. The first argument to all these functions is the handle number, such that multiple aggregates can be computed at the same time.

As an example consider the query

```
SELECT SUM(A.a1) FROM A
```

This query is written in the `forelem` intermediate as follows:

```c
forelem (i; i \in pA)
  agg_init(0, SUM);
  agg_step(0, A[i].a1);
  agg_finish(0);
  \$R = \$R \cup (agg_result(0))
```

Using the aggregate syntax group by queries can be easily transformed. As an example, consider the following SQL query:

```
SELECT A.field2, MIN(A.field3) FROM A
```

This query can be transformed in the `forelem` intermediate representation as follows and will be referred to as code sample (1):

```c
forelem (i; i \in pA)
  \$T = \$T \cup (A[i].field2, A[i].field3)
forelem (i; i \in p\$T)
  \$R = \$R \cup (\$T[i].field2)
distinct(\$R)
forelem (i; i \in p\$R)
{
  agg_init(0, MIN);
  forelem (j; j \in p\$T.field2[\$T[i].field2])
    agg_step(0, \$T[j].field3);
  agg_finish(0);
  \$R = \$R \cup (\$T[i].field2, agg_result(0))
}
```

Note the use of `distinct(\$R)` which denotes that duplicate values from \$T are eliminated. The `forelem` loop above is an initial expression of the query in `forelem`, which will be subsequently subjected to transformations at the `forelem` level. Subqueries are handled by initially expressing these as functions, which are called from the main loop nest. For example, consider:

```
SELECT A.a1
FROM A, B, C
WHERE A.a_id = C.a_id AND C.b_id = B.b_id
AND B.b2 = "str1"
AND A.a_id \in (SELECT A2.a_id
  FROM A A2, B B2, C C2
  WHERE A2.a_id = C2.a_id
  AND C2.b_id = B2.b_id
  AND B2.b2 = "str2")
```

Then this query is translated to the following `forelem` loops:

```c
function subquery ()
{
  \$T = \emptyset
  forelem (i; i \in pB.b2["str2"])
  forelem (j; j \in pC.b_id[B[i].b_id])
  forelem (k; k \in pA.a_id[C[j].a_id])
  \$T = \$T \cup A[k].a_id
  return \$T
}
forelem (i; i \in pB.b2["str1"])
```

Note that function subquery does not have any arguments. Correlated subqueries will have function arguments. Similar to the translation of group by queries, this is an initial expression of the query which will be subjected to transformations in order to optimize the query.

## 3 Transformations Within the Forelem Intermediate Representation

Due to the nature of `forelem` as a simple loop, many existing loop transformations can be applied on these loops. Existing loop transformations that can be readily re-targeted to `forelem` loops include Loop Interchange, Loop Fusion [6] and Loop Invariant Code Motion. Other common compiler techniques that are used within the `forelem` framework are (Function) Inline and Dead Code Elimination. Dead Code Elimination has for instance been adapted to be able to detect unused (temporary) tables and to remove `forelem` loops that generate such tables. Similarly, common analysis techniques are re-used. Firstly, data dependence analysis [7], [8], [9], [10] is used to determine whether a given transformation can be applied without affecting the correctness of a program. Secondly, def-use analysis [11], [12] is used to find unused variables, or to infer the current value of a variable by looking at preceding definitions of the variable in the def-use chain.

Because these transformations and analysis techniques are well established within the literature and are readily re-targeted, we will not further discuss these transformations in detail in this section. Rather, we will introduce new transformations that have been defined within the `forelem` framework especially for the purpose of query optimization. Within the `forelem` framework queries are optimized by the application of such transformations on `forelem` loop nests, contrary to traditional query planning where transformations are carried out on a relational algebra tree.

### 3.1 Iteration Space Expansion

Scalar Expansion is a transformation that is typically used to enable parallelization of loop nests. Consider the following loop:

```c
for (k = 1; k <= N; k++)
{
  tmp = A[k] + B[k];
  C[k] = tmp / 2;
}
```

Due to the loop-carried anti-dependence of `tmp`, subsequent iterations cannot write to `tmp` before `tmp` has been used in the assignment to `C[k]`. This is solved by the Scalar Expansion transformation which expands the scalar `tmp` to a vector:

```c
for (k = 1; k <= N; k++)
{
  tmp[k] = A[k] + B[k];
  C[k] = tmp[k] / 2;
}
```
Now that the loop-carried dependence has been broken, the loop can be parallelized.

Within the forelem framework a transformation known as Iteration Space Expansion is defined. This transformation expands the iteration space of a forelem loop by removing conditions on its index set. For a loop of the form, with SEQ denoting a sequence of statements:

\[
\text{forelem} \ (i; \ i \in \text{pA.field}(X))
\]

SEQ;

the following steps are performed:

1) the condition \(A[i].\text{field} == X\) is removed, which expands the iteration space so that the entire array \(A\) is visited,

2) scalar expansion is applied on all variables that are written to in the loop body denoted by SEQ and references to these variables are subscripted with the value tested in the condition, in this case \(A[i].\text{field}\),

3) all references to the scalar expanded variables after the loop are rewritten to reference subscript \(X\) of the scalar expanded variable.

### 3.2 Table Propagation

The Table Propagation transformation is similar to Scalar Propagation that is typically performed by compilers. In Scalar Propagation, the use of variables whose value is known at compile-time is substituted with that value. In Table Propagation, the use of a temporary table of which the contents are known is replaced with a loop nest that iterates the temporary table. For example, consider the following steps are performed:

\[
\begin{align*}
\text{forelem} \ (i; \ i \in \text{pA.field}(X)) = T \cup (X[i].\text{field3}) \\
\text{forelem} \ (i; \ i \in \text{pPTable.field}) = R \cup (T[i].\text{field3})
\end{align*}
\]

The first loop generates a table \(T\), which is iterated by the second loop. The table \(T\) is being “streamed” between these consecutive loops. Table \(T\) can be propagated to the second loop nest:

\[
\begin{align*}
\text{forelem} \ (i; \ i \in \text{pX.field2[value]}) = T \cup (X[i].\text{field3}) \\
\text{forelem} \ (i; \ i \in \text{pPTable.field2[value]}) = R \cup (X[i].\text{field3})
\end{align*}
\]

After application of this transformation, temporary tables that are generated (by the first loop in this example) are often left unused and can be eliminated by application of the Dead Code Elimination transformation.

### 3.3 Materialization & Concretization

forelem loops only specify how a set of tuples is iterated but do not specify how these tuples are stored. When C/C++ code is generated from forelem loops, it must be known how the tuples are to be stored, otherwise no code can be generated. Within the forelem framework Materialization and Concretization transformations are defined [13], which are used to devise a data storage format for each collection of tuples. Using these transformations, many different storage methods for tuples can be generated automatically. This includes row-wise and column-wise storage orders. Conversion between these two layouts is a matter of a trivial transformation within the forelem framework.

An in-depth discussion of how these techniques work and interact with other transformations that are defined is outside the scope of this paper. Within the context of this paper, we assume that a table \(T\) has a materialized sibling \(PTable\), which stores the content of the tables in a certain format and order on the disk.

Next to determining how the tables are stored, the Materialization techniques are also used to determine a storage format (or in fact data structure) for the index sets. Index sets that are used within a forelem loop nest are either translated to an if-statement or an index set is generated at run-time. This difference can be illustrated as follows. Consider the forelem loop:

\[
\text{forelem} \ (i; \ i \in \text{pTable.field[value]}) = T[i];
\]

In the former case, an index set is not generated and the result is:

\[
\begin{align*}
\text{forelem} \ (i; \ i \in N_{\text{Table}}) = T[i]
\end{align*}
\]

where \(N_{\text{Table}}\) denotes the number of tuples in Table. If this forelem loop is executed many times for different instances of value this is not efficient as for every execution the full table Table has to be processed. The latter case alleviates this by generating an index set such that Table is only iterated once. We say that an index set is materialized (Index Set Materialization) to result in:

\[
\begin{align*}
\text{forelem} \ (i; \ i \in N_{\text{Table}}) = \text{pTable.field}[PTable[i].field] = T[i];
\end{align*}
\]

In this code fragment, pTable is an associative array that relates values PTable[i].field to subscripts i into PTable. Subsequently, this index set is used to access the table stored on disk.

The actual generation of the index set is similar to a compiler technique known as data copying [14], [15]. In data copying, a partial copy is made of a block of data that is processed by a loop. Although there is a cost involved in making this copy, the copy results in a much better utilization of the cache and thus in a significant increase in performance. The initial cost of making the copy is redeemed. In the above example, a partial copy has been made of PTable by copying values of field and corresponding subscript values into the table on disk into a temporary associative array that represents the index set. Instead of storing subscript values, it is also possible to store tuples of values, for instance when it is known that only 1 or 2 fields of PTable would be accessed.
Now that the content of the index set has been established, it needs to be determined how to store this content. This phase is known as Concretization. During this phase, the associative array pPTable is concretized to a suitable data structure. Prime examples are for example a balanced tree or hash table, such as implemented in for instance the Boost libraries, or direct access through an array. From the definition of this storage format (selection of the data structure), code can be generated that instantiates the index set at run-time and to access this index set.

### 3.4 Index Set Pruning

Once index sets have been materialized using the process described in the previous subsection, further transformations can be defined that affect the contents of the index set. One such transformation is Index Set Pruning. With Index Set Pruning, the contents of an index set are reduced using additional conditions that exist on tuples iterated by this index set. As a result, less memory is required to store the index set and the generation of the index set is less computationally expensive. As an example, consider:

```plaintext
forelem (i; i ∈ N_{Table})
  pPTable.field[pTable[i].field] =
  pPTable.field[pTable[i].field] ∪ (i)
forelem (i; i ∈ pPTable.field[value1])
  if (pTable[i].field == value2)
    SEQ;
SEQ will not be executed for tuples that do not satisfy the condition posed in the if-statement. If the materialized index set pPTable.field is not used in a different context for which different additional conditions might hold, it is not necessary to store entries in the index set for tuples that do not adhere to this condition. The index set can thus be pruned, by moving the if-statement to the loop that generates the materialized index set:

```plaintext
forelem (i; i ∈ N_{Table})
  if (pTable[i].field == value2)
    pPTable.field[pTable[i].field] =
    pPTable.field[pTable[i].field] ∪ (i)
forelem (i; i ∈ pPTable.field[value1])
  SEQ;
```

This transformation is useful in the following example:

```plaintext
forelem (i; i ∈ pTable1.f2.f3)((v1, v2))
  forelem (j; j ∈ pTable2.f1[Table1[i].f1])
    forelem (k; k ∈ pTable3.f1[Table2[j].f2])
      if (Table4[i].f2 == v3)
        SEQ;
```

In this example, the transformation engine decided to move the tests of the conditions on Table1 to the outermost loop, because two conditions are tested and potentially prunes the search space by a larger extent. Due to the dependences between the other tables, the condition for Table4 is only tested in the inner loop. First, the index set iterated by the innermost loop is materialized to result in:

```plaintext
forelem (i; i ∈ pTable1.f2.f3)((v1, v2))
  forelem (j; j ∈ pTable2.f1[Table1[i].f1])
    forelem (k; k ∈ pTable3.f1[Table2[j].f2])
      if (pTable4[i].f2 == v3)
        SEQ;
```

As a next step, the if-statement can be eliminated by Index Set Pruning:

```plaintext
forelem (i; i ∈ pTable1.f2.f3)((v1, v2))
  if (pTable4[i].f2 == v3)
    pTable4.f2[Table4[i].f2] =
    pTable4.f2[Table4[i].f2] ∪ (i)
```

We will now describe another transformation, Index Set Combination, which leads to a further improvement of the performance of this example.

### 3.5 Index Set Combination

When an index set is solely used to test for a certain property and not used to access the corresponding table, there is a good chance this index set can be combined with another index set. Observe the loop iterating Table4 in the example of the previous subsection. Assume that the iterator variable 1 is not used in SEQ, so Table4 is not accessed within the loop body. We can then combine this index set with the index set for Table3 (materialized to pPTable3.field1, so that only subscripts k are iterated that also satisfy the conditions tested by the index set for Table4). This combination process is referred to as Index Set Combination.

Consider that the loops generating the index sets for Table3 and Table4 are:

```plaintext
forelem (i; i ∈ N_{Table})
  pPTable3.f1[pTable3[i].f1] =
  pPTable3.f1[pTable3[i].f1] ∪ (i)
forelem (i; i ∈ N_{Table})
  if (pTable4[i].f2 == v3)
    pTable4.f2[Table4[i].f2] =
    pTable4.f2[Table4[i].f2] ∪ (i)
```

The condition on Table4 can be combined into these for Table3 as follows:

```plaintext
forelem (i; i ∈ N_{Table})
  if (pTable4[i].f2 == v3)
    pTable4.f2[Table4[i].f2] =
    pTable4.f2[Table4[i].f2] ∪ (i)
```

The combination of the index sets is performed based on the condition Table4.field1 == Table3.field1 that is encoded in the original index sets. This condition is used to set up the “is not empty” test. As a consequence, Table4 no longer needs to be iterated in the main loop nest, resulting in:

```plaintext
forelem (i; i ∈ N_{Table})
  if (is_not_empty(pPTable4.f1[Table3[k].f1]))
    pPTable3.f1[pTable3[i].f1] =
    pPTable3.f1[pTable3[i].f1] ∪ (i)
```
forelem (i; i ∈ pTable1.(f2, f3)[(v2, v3)])
forelem (j; j ∈ pTable2.f1[Table1[i].f1])
forelem (k; k ∈ pTable3.f1[Table2[j].f2])
SEQ;

Note that a further transformation is possible on the loops that generate the index sets. The if-statement checking the is_not_empty condition can be substituted with the loop that generate the index sets. The

4 Performing Query Optimization With Compiler Transformations

In this section, we discuss the optimization of queries through the use of existing compiler transformations, rather than the use of query planning techniques used by traditional query optimizers. In particular, we demonstrate that the main techniques of query optimization can be emulated using optimizing compiler techniques. The main techniques that will be discussed have been distilled from [16], [17] and include operations on the algebraic query tree and different algorithms for the execution of relational operators.

First two optimizations on a relational query tree, Join Reordering and Selection Pushing are considered. After this kind of transformations has been carried out and an order in which the joins are to be processed has been selected, a query optimizer needs to select for each join operator in the query tree with which algorithm to evaluate that join. Common algorithms are Nested Loops, Block Nested Loops, Index Nested Loops and Hash Join. So, secondly, the correspondences between the forelem framework and these algorithms will be described. Within the forelem framework, no fixed implementations of such join operators are implemented. Therefore, implementations of these operators are described through the application of transformations within the forelem framework.

4.1 Join Reordering

The most important task of a traditional query optimizer is to determine in which order the joins in a query should be processed. To determine such an order, a query optimizer considers the search space consisting of equivalent query plans and for each plan computes the cost of executing this plan. This cost depends on the number of disk I/Os that have to be performed and the estimated cost of executing every relational operator that is present in the query tree.

As has been discussed in Section 2.1 in the forelem framework a query performing multiple joins is represented as a nested loop. At each nesting level a different table is accessed. Using the Loop Interchange transformation, the order of loops in the loop nest is reordered. Although the order of the loops is changed, the cross product that is generated in the loop body is still the same. So, the result of the query is not affected. This is essentially the same operation as join reordering. When joins are reordered in the query plan tree, the result of the query is not affected either.

Loop Interchange sets up a search space of all possible orderings of the loops in a loop nest. A compiler can select an appropriate order at compile-time through the use of heuristics, such as putting loops imposing most conditions as the outermost loops, and by incorporating run-time information in an iterative compilation [18], [19] process. By exploiting the collected run-time information, the compiler will select better performing loop orders each time the code is executed and the compiler is also enabled to adapt to changes in the data set.

4.2 Selection Pushing

Next to join, selection is another important relational operator. Consider a relational query tree which contains a join and selection operator for the same table. If first the join is performed and then selection, then at the selection operator many rows are discarded that do not satisfy the condition. So, a lot of excess work has been performed. To avoid this, query optimizers apply Selection Pushing to push selection operators to be performed before the join operator.

Within the forelem framework Selection Pushing is implemented using the Loop Invariant Code Motion operator. To see, consider the following example:

forelem (i; i ∈ pA)
forelem (j; j ∈ pC)
if (A[i].field < 20)
S1 = = ∪ (A[i].*, C[j].*)

The if-statement is executed for all rows that are the result of the cross product between A and C. The statement S1 is only executed for rows of the cross product that satisfy the condition A[i].field < 20. Observe that the value A[i].field is constant under the loop iterated by j. That is, if j is incremented, the value A[i].field will not change. The if-statement is invariant under the loop iterated by j and can be moved out of this loop.

forelem (i; i ∈ pA)
if (A[i].field < 20)
forelem (j; j ∈ pC)
S1 = = ∪ (A[i].*, C[j].*)

Rows in A that do not satisfy the condition are now not considered when the cross product is created. Important is that statement S1 is still executed for rows of the cross product that satisfy the condition A[i].field < 20. The actual outcome of the query has not changed, since statement S1 is still executed for the same set of the rows, but the execution time has been improved because the loop iterated by j is only executed for qualifying rows of A instead of all rows of A. Similar to Selection Pushing, the selection operator (the if-statement) has been moved to before the cross product is created (before the join).

4.3 Nested Loops Join

The first implementation of the join operator that is considered is Nested Loops Join. To describe the different implementations a simple example will be used: SELECT A.a FROM A, B WHERE A.b = B.b; which corresponds to the following forelem loop nest:
forelem \( i; i \in pA \)  
forelem \( j; j \in pB.b[A[i].b] \)  
\( R = R \cup (A[i].a) \)

In Nested Loops Join, a nested loop is used to generate the cross product. The conditions are tested within the loop body. This roughly corresponds to the following forelem loop wherein no index set is used:

forelem \( i; i \in pA \)  
forelem \( j; j \in pB \)  
if \( A[i].b = B[j].b \)  
\( R = R \cup (A[i].a) \)

In this code fragment, both tables are iterated entirely and the condition for the rows is tested within the loop body.

4.4 Block Nested Loops Join

Block Nested Loops Join follows analogously from Nested Loops Join if Loop Blocking is incorporated in the transformation chain. The table that is iterated by the outermost loop is blocked. It is important that such a block fits in main memory, while the inner loop iterates the second table.

As the first step, table \( A \) is partitioned into blocks. This is done by partitioning the index set: \( pA = p_1A \cup p_2A \cup \ldots \cup p_kA \). On the initial forelem loop nest the Loop Blocking transformation is applied that utilizes this partitioning of \( A \):

forelem \( (1; 1 \in N) \)  
forelem \( (i; i \in pA) \)  
forelem \( (j; j \in pB.b[A[i].b]) \)  
\( R = R \cup (A[i].a) \)

On this loop, materialization can be applied likewise to how this was done in the previous subsection:

forelem \( (1; 1 \in N) \)  
forelem \( (i; i \in N_i) \)  
forelem \( (j; j \in N_j) \)  
if \( (PA[i].b = PB[j].b) \)  
\( R = R \cup (PA[i].a) \)

This particular join algorithm is often optimized by creating a hash table for each block of \( A \). This implies that can index set \( pA.b \) is generated for each block of \( A \). For every row that is read from \( B \) this index set is queried to determine whether there is a corresponding row in \( A \). So, first Loop Interchange is applied to result in:

forelem \( (1; 1 \in N) \)  
forelem \( (i; i \in pA.b[B[j].b]) \)  
\( R = R \cup (A[i].a) \)

As a second step, the tables \( A \) and \( B \) need to be materialized. In conjunction with this, the index set also must be materialized so that it contains subscripts to a materialized table instead of a non-materialized table. The result of materializing the tables as well as the index set is:

for \( (1; 1 \in N) \)  
\{  
forelem \( (j; j \in N_{iA}) \)  
pPA.b[PA[j].b] = j;  
forelem \( (j; j \in N_{iB}) \)  
forelem \( (i; i \in pPA.b[PB[j].b]) \)  
\( R = R \cup (PA[i].a) \)  
\}

4.5 Index Nested Loops Join

Index Nested Loops Join takes advantage of indexes on tables that are already present. Such indexes are created explicitly in the database system and are kept up to date as rows are added, removed and updates in tables. Consider again our starting point:

forelem \( (i; i \in pA) \)  
forelem \( (j; j \in pB.b[A[i].b]) \)  
\( R = R \cup (A[i].a) \)

Assume that an index set \( pA.b \) is available in the system. Then transformations must be carried out such that advantage can be taken from this index set. In this case, the Loop Interchange transformation is carried out:

forelem \( (j; j \in pB) \)  
forelem \( (i; i \in pA.b[B[j].b]) \)  
\( R = R \cup (A[i].a) \)

In the resulting loop nest, the index set \( pA.b \) is indeed used. During materialization, \( pA.b \) is lowered to the existing index on table \( A \), similar to how \( A \) is lowered to the existing array \( PA \).

4.6 Hash Join

The Hash Join algorithm consists of two phases: (1) both tables are partitioned on the join attribute, (2) for each partition process the partitions of both relations to produce the join results. The first phase is implemented within the forelem framework by the application of Loop Blocking. As we have seen above, with Loop Blocking a table is partitioned. In this particular case, both tables are partitioned with the additional requirement that corresponding partitions must contain all rows that are to be joined with one another. So, the partitioning must be join attribute aware. Let \( A = A_1 \cup A_2 \cup \ldots \cup A_N \) and \( B = B_1 \cup B_2 \cup \ldots \cup B_N \). The resulting code for the hash join algorithm is:

forelem \( (1; 1 \in N) \)  
forelem \( (i; i \in pA) \)  
forelem \( (j; j \in pB.b[A[i].b]) \)  
\( R = R \cup (A[i].a) \)

As a next step, the loop nest is materialized. This includes materializing the index set has we have have treated the creation of an in-memory hash already in Section 4.3 above. This results in the following code fragment:

for \( (1; 1 \in N) \)  
\{  
forelem \( (j; j \in N_{iA}) \)  
pPA.b[PA[j].b] = j;  
\}
4.7 Sorted Aggregation

In the Sorted Aggregation strategy, a group-by query is evaluated by performing a single pass through a sorted table. A materialized code that applies the sorted aggregation strategy is derived from an aggregate query transformed to forelem (the starting point, see Section 2.2 for an example) using techniques to materialize (temporary) tables to sorted arrays. Subsequently, index sets with a condition that tests for equality on sorted arrays can be materialized without creating an associative array. Rather, these index sets can be evaluated using the fact that the array that is accessed is sorted; the array is iterated until a row is encountered of which the value tested by the index set condition is larger than the value that is part of the condition.

Once these index sets have been materialized in this fashion, further transformations can be carried out using the properties of the tables that are accessed. Since $T$ and $R$ are temporary tables, it is known how these are derived from the def-use chains. Using this knowledge, transformations can be carried out to eliminate redundant loop iterations (making use of the property that the tables are sorted and a value can only occur in $R$ once) and a different form of Table Propagation can be applied to eliminate usage of $R$ leading to the query being evaluated using a single pass of $T$. The result is a code that evaluates the group-by query using the sorted aggregation strategy.

4.8 Hash Aggregation

The Hash Aggregation strategy can be obtained by applying the Iteration Space Expansion transformation, discussed in Section 5.1. Consider forelem code sample (1) described in Section 2.2. After inlining the aggregate functions and performing Iteration Space Expansion this loop becomes:

```c
forelem (j; j ∈ N_B)
  forelem (i; i ∈ pPA, b[PB[j].b])
  R = R ∪ (PA[i].a)
}
```

```c
forelem (j; j ∈ N_B)
  forelem (i; i ∈ pPA, b[PB[j].b])
  R = R ∪ (PA[i].a)
}
```

The resulting code evaluates group-by queries using a Hash Aggregate strategy, where tmp acts as an associative array or hash table.

4.9 Transforming Multi-block Queries To Single-block Queries

In traditional query optimizers, subqueries are considered to be “multi-block queries”. The main query and its subquery are separate blocks. Transformations exist to turn multi-block queries to single-block queries. Within the forelem framework this is accomplished using the Inline transformation.

4.10 Run-Time Optimization of Queries

An important property of traditional database systems is that query planning is done when a query is submitted and statistics about the data that is currently stored in the database is used in obtaining an efficient query plan. Because our approach relies heavily on the use of the compiler-based techniques, one can have the impression that once a query has been optimized it is static and no changes are made to the optimized query in response to changes of the stored dataset. For highly dynamic datasets this would put our approach at a serious disadvantage. However, in the last decades many techniques have been developed for dynamic code optimization. Examples of these techniques are Just-In-Time compilation (JIT), multi-version codes and trace scheduling. By exploiting these techniques, queries optimized with our approach can still be further optimized at run-time.

As a concrete example, we will discuss how trace scheduling could be used. In trace scheduling [20], [21], all possible paths through multiple basic blocks (traces) are generated, and code is generated for each of these paths. In this particular context, this technique is used to find out what conditions the tuples are tested for and what data is retrieved from each table in case a condition is satisfied. For conditions that are tested most frequently or multiple times, according to the traces, an index set can be generated at run-time before the execution of the forelem loop. Even more powerful is the capability of collecting traces at run-time and using these in subsequent recomputations of the query. With this run-time information, better selections can be made for what index sets to generate at run-time, or to decide to keep persistent copies of certain index sets updated on disk to avoid recreating the index set at run-time every time it is needed by a query.

4.11 Summary

The correspondences between traditional query optimization and compiler optimizations are summarized in Table 1.

5 Optimization and Code Generation Strategies

In order to successfully optimize forelem loop nests using the transformations described in Section 3 a strategy is needed
that determines in which order to perform the transformations on the forelem loop nests. The forelem framework uses the following algorithm to apply the transformations:

1) **Inline**. This inlines subqueries, so that these can be considered in combination with the calling context.

2) **Loop Interchange, Loop Invariant Code Motion**. Loops are reordered such that as many conditions as possible are tested in the outermost loops. Priority is given to move conditions that test against a constant value to the outermost loop.

3) **Iteration Space Expansion**. Opportunities for the application of Iteration Space Expansion are looked for. An example of such an opportunity is a loop iterating an index set with a condition on a field.

4) **Table Propagation**. Through the application of Table Propagation, preparations are made for the elimination of unnecessary temporary tables.

5) **Dead Code Elimination**. At this stage, any loop that computes unused results is removed.

6) **Index Set Materialization**. As has been described in Section 3.3, for each index set a choice has to be made whether no index set is generated (implying the table to be fully iterated each time the index set is used), or to materialize an index set. The subsection on Materialization Strategy below discusses how this choice is made. For materialized index sets, opportunities are sought for the application of the Index Set Pruning and Index Set Combination transformations. From this step, implementations of the relational join operator such as Block Nested Loops Join and Hash Join will follow automatically.

7) **Concretization**. As a final step Concretization takes place. During this phase it is determined in what format to store the database tables and what data structures to use to store index sets generated at runtime.

Experiments have been conducted with the queries from the TPC-H benchmark. The different transformations that have been applied to each TPC-H query during the forelem optimization phase are shown in Table 2.

Another optimization strategy is to perform a brute-force exploration of the entire optimization space. This is useful, for example, for queries that are run many times on changing data so that the costly optimization effort is worth it. We plan to study brute-force exploration of the optimization search space in future work.

### Materialization Strategy

Next to the algorithm for the application of transformations on the forelem intermediate representation to optimize queries, a strategy is defined for the generation of efficient code from the forelem intermediate representation. This strategy is mainly concerned with the selection of forelem loops for which index sets will be materialized (so that these are generated at run-time) and the selection of efficient data structures for such index sets. According to this strategy, index sets that satisfy the following conditions are *never* generated at run-time:

1) Index sets without conditions address the full array.

   In this case, the index set is not generated, but the loop iterating this index set is concretized to a simple for loop that iterates the full table of tuples with subscripts \( i \in \{0, \ldots, \text{len}\} \).

2) Index sets that are iterated by outer loops. These are not generated because the outer loop is iterated only once.

3) Index sets for very small tables.

In all other cases an index set is typically generated. Index sets that are used in multiple loop nests get priority in being generated. When materialized index sets are concretized, a suitable data structure has to be chosen. For single-dimensional index sets on a field that has a unique value for each row in the table (one-to-one mapping), often a flat array is chosen if the key space is known to be small, or otherwise a hash table. These properties can be known to the code generator because the field was specified as primary key in the table schema, or the generated code detects at run-time that the table data satisfies this condition. For index sets that yield multiple subscripts that are iterated in a loop nest, a balanced tree is used.

| Query Optimization | Compiler Optimizations |
|--------------------|-----------------------|
| Join Reordering    | Loop Interchange      |
| Selection Pushing  | Loop Invariant Code Motion |
| Nested Loops Join  | 1. Move all conditions to if-statement in inner loop body. |
|                    | 2. Loop Independent Materialization of all loops that compose the join. |
| Block Nested Loops Join | 1. Index set partitioning of outer loop. |
|                     | 2. Loop Blocking using the partitioned index set. |
|                     | 3. Loop Interchange |
|                     | 4. Index Set Materialization |
|                     | 5. Loop Independent Materialization of condition-less loop. |
| Index Nested Loops | 1. Loop Interchange such that available index sets on disk are used. |
|                    | 2. Materialization |
| Hash Join          | 1. Partition both tables. |
|                    | 2. Loop Blocking based on this partitioning. |
|                    | 3. Index Set Materialization |
|                    | 4. Loop Independent Materialization of condition-less loop. |
| Sorted Aggregation | 1. Materialize temporary table to sorted array. |
|                    | 2. Materialize index set according to sorted array. |
|                    | 3. Eliminate redundant iteration. |
|                    | 4. Table Propagation |
|                    | 5. Dead Code Elimination |
| Hash Aggregation   | 1. Inline aggregate functions. |
|                    | 2. Iteration Space Expansion |
|                    | 3. Loop Invariant Code Motion |
| Multi-block to     | 1. Inline subqueries. |
| single-block       | 2. Loop Invariant Code Motion. |
Table 2
An overview of the transformations applied to each TPC-H query, in the order of application, and the used index set concretizations. The abbreviation LICM stands for Loop Invariant Code Motion.

| Query # | Applied Transformations | Index Set Concretization |
|---------|-------------------------|---------------------------|
| 1       | Table Propagation, Iteration Space Expansion, LICM, Dead Code Elimination. | Hash                      |
| 2       | Inline, Loop Interchange, LICM, Iteration Space Expansion, LICM. | Hash                      |
| 3       | Loop Interchange, Iteration Space Expansion, LICM, Index Set Pruning, Index Set Combination. | Hash                      |
| 4       | Inline, Iteration Space Expansion, Index Set Pruning | Hash                      |
| 5       | Loop Interchange, Iteration Space Expansion, LICM, Index Set Pruning, Index Set Combination. | Hash                      |
| 6       | None |                                        |
| 7       | Loop Interchange, LICM, Index Set Pruning, Sorted Aggregation | Hash                      |
| 8       | Loop Interchange, LICM, Index Set Pruning, Index Set Combination, Sorted Aggregation. | Hash                      |
| 9       | Loop Interchange, Iteration Space Expansion, LICM, Table Propagation, Dead Code Elimination, Index Set Pruning, Index Set Combination. | Hash, array                |
| 10      | Loop Interchange, Iteration Space Expansion, Table Propagation, Index Set Pruning. | Hash                      |
| 11      | Inline, Loop Interchange, Iteration Space Expansion, Loop Fusion, LICM, Table Propagation, Dead Code Elimination, Index Set Pruning, Index Set Combination. | Hash                      |
| 12      | Loop Interchange, LICM, Index Set Pruning, Index Set Combination | Hash                      |
| 13      | Inline, Table Propagation, Dead Code Elimination, Index Set Pruning, Sorted Aggregation. | Balanced tree              |
| 14      | Index Set Pruning. | Array                      |
| 15      | Inline, Loop Interchange, Iteration Space Expansion, LICM, Table Propagation, Dead Code Elimination | Hash                      |
| 16      | Inline, Loop Interchange, LICM, Table Propagation, Dead Code Elimination, Index Set Pruning, Sorted Aggregation. | Hash                      |
| 17      | Inline, Iteration Space Expansion, LICM, Index Set Pruning | Hash                      |
| 18      | Inline, Loop Interchange, LICM, Table Propagation, Dead Code Elimination | Array                     |
| 19      | None. | Array                      |
| 20      | Inline, Iteration Space Expansion, LICM, Index Set Pruning, Index Set Combination. | Hash                      |
| 21      | Loop Interchange, LICM, Index Set Pruning, Index Set Combination. | Hash                      |
| 22      | Inline, LICM, Sorted Aggregation. | Hash                      |

6 Experimental Results

Experiments have been conducted using the queries from the TPC-H benchmark [2]. All queries were parsed into the forelem intermediate representation, optimized using the transformations described in this paper and C/C++ code has been generated from the optimized AST. These executables access the database data through memory-mapped I/O.

The execution time of the queries is compared to the execution time of the same queries as executed by MonetDB [22]. All experiments have been carried out on an Intel Core 2 Quad CPU (Q9450) clocked at 2.66 GHz with 4 GB of RAM. The software installation consists out of Ubuntu 10.04.3 LTS (64-bit). The version of MonetDB used is 11.11.11 (Jul2012-SP2), which is the latest version that could be obtained from the MonetDB website [22] for use with this operating system.

All experiments have been carried out on an Intel Core 2 Quad CPU (Q9450) clocked at 2.66 GHz with 4 GB of RAM. The software installation consists out of Ubuntu 10.04.3 LTS (64-bit). The version of MonetDB used is 11.11.11 (Jul2012-SP2), which is the latest version that could be obtained from the MonetDB website [22] for use with this operating system.

All queries were run with MonetDB and forelem-generated code on a TPC-H data set of scale factor 1.0. The speedups achieved by the forelem-optimized queries over MonetDB are shown in Table 3. These speedups range from a factor of 1.21 (Q3) to 4.09 (Q15).

| Query | Speedup |
|-------|---------|
| Q1    | 2.84    |
| Q2    | 1.65    |
| Q3    | 1.21    |
| Q4    | 1.39    |
| Q5    | 1.33    |
| Q6    | 3.64    |
| Q7    | 2.79    |
| Q8    | 1.63    |
| Q9    | 1.28    |
| Q10   | 1.62    |
| Q11   | 1.98    |

Also in this case, the forelem-optimized queries perform significantly better than MonetDB in all cases. The speedups range from a factor of 1.03 (Q8) to 15.6 (Q18).
Table 4
Speedup of the execution time of TPC-H queries optimized with the forelem framework compared to MonetDB on a data set of scale factor 10.0.

| Query | Speedup | Query | Speedup |
|-------|---------|-------|---------|
| Q1    | 8.81    | Q12   | 6.33    |
| Q2    | 3.06    | Q13   | 1.34    |
| Q3    | 5.00    | Q14   | 1.74    |
| Q4    | 5.19    | Q15   | 1.38    |
| Q5    | 1.41    | Q16   | 1.16    |
| Q6    | 4.00    | Q17   | 1.47    |
| Q7    | 3.00    | Q18   | 15.61   |
| Q8    | 1.03    | Q19   | 3.56    |
| Q9    | 2.81    | Q20   | 1.11    |
| Q10   | 4.54    | Q21   | 3.40    |
| Q11   | 2.27    | Q22   | 3.21    |

7 IMPLEMENTATION OF THE FORELEM FRAMEWORK

The forelem framework has been developed as a generic library, libforelem, to be able to support different programming languages and data access frameworks. This library is capable of creating and manipulating forelem ASTs. For example, to support the vertical integration of database applications, the libforelem library is capable of parsing a given SQL statement into a forelem AST. On the AST, various analyses and transformations can be applied, many of which are implementations of traditional compiler (loop) transformations that function on the forelem AST. An abstract code generation interface is present in the library to generate code from any forelem AST. Currently, the output of C/C++ code and algebraic forelem is supported. However, the use of forelem loops is not restricted to C/C++ and other languages can be supported by implementing the abstract code generation interface.

Different applications can make use of libforelem to create and manipulate forelem ASTs. For example, to support the vertical integration of database applications, the libforelem library is capable of parsing a given SQL statement into a forelem AST. On the AST, various analyses and transformations can be applied, many of which are implementations of traditional compiler (loop) transformations that function on the forelem AST. An abstract code generation interface is present in the library to generate code from any forelem AST. Currently, the output of C/C++ code and algebraic forelem is supported. However, the use of forelem loops is not restricted to C/C++ and other languages can be supported by implementing the abstract code generation interface.

Typically in the optimization process, the code generator is called when optimization on the forelem-loop level has completed. In the case C/C++ code is to be generated from the optimized forelem AST, the forelem loops are translated to C for loops that iterate index sets and access subscripts of plain C arrays. In the C code, an index set is a generic interface and the exact data structure of the index set is opaque. As has been described in Section 5 the optimization process will generate a data storage format for each index set as part of the optimization process. Since materialization of index sets is not obligatory, the optimization process might also decide to not generate an index set, but rather to test the conditions during iteration of the table.

Note that forelem loops are only used by the compiler tooling and are never visible to the end user. The general nature of the forelem frameworks allows for its usage with other problems. Other parsers that take a certain language as input and produce forelem loops can be developed next to the SQL parser, so that other problem domains can be supported.

8 RELATED WORK

Several methodologies to increase the performance of database query evaluation with the use of optimizing compiler technology have been described in the past. A strategy to transform entire queries to executable code is described in [3]. The technology, called “holistic query evaluation”, works by transforming a query evaluation plan into source code, based on code templates, and compiling this into a shared library using an aggressively optimizing compiler. The shared library is then linked into the database server for processing. Although significant speed-ups over traditional and currently-emerging database systems are achieved, this approach remains fixated to traditional query planning techniques to optimize the query. Optimizing compiler technology is used to compile a translation of the query plan into C/C++ code through the use of code templates into efficient executable code, contrary to our approach which uses compiler technology to replace the traditional query planning.

The UltraLite system, described in [23], follows a similar approach and compiles queries used in an embedded SQL code to C code. This is achieved by sending the query to a host database server, which parses and optimizes the query using traditional techniques. An execution plan is returned which is used to generate the C code.

In [4] a data-centric approach to query compilation is described. SQL queries are translated to an algebraic query execution plan from which LLVM bitcode is generated. The query in LLVM bitcode is then executed using the optimizing JIT compiler included with LLVM. The translation of the query plan to LLVM bitcode is performed with a data-centric approach, in the sense that care is taken to keep data in CPU registers as long as possible for optimal performance, instead of maintaining clear operator boundaries. This technique results in very efficient query codes.

Compiler optimizations have also been used to take on the problem of multi-query optimization. In [24] an approach is demonstrated where queries are written as imperative loops, on which compiler optimization strategies are applied. The use of loop fusion, common subexpression elimination and dead code elimination is described. This work is tailored towards a certain class of analysis queries and not to generic queries as is the case with forelem. Furthermore, the Loop Fusion transformation described in the paper works by detecting multidimensional overlap, so, the strategy of Loop Fusion is used, but not an exact mapping of the traditional Loop Fusion optimization which is the aim for the forelem framework.

A different approach to multi-query optimization is described in [25], where optimization techniques are applied to the “algorithm-level” of a database program. In the algorithm-level, a query is represented as a sequence of algorithms, e.g. selection, join, that should be performed to compute the query results. The exact implementation of the algorithms is not made explicit at this level. As a consequence, knowledge is required about the implementation of algorithms that can appear in the representation by the optimizer in order to be able to carry out optimizations. In forelem, all operations are transformed to iterations of arrays and the focus is on performing optimizations on a series of loop nests. A notable exception are the sorting and duplicate elimination operations however, as these are either specified as a modifying operation of a result set or as a condition to an index set. Array processing is sped up by selecting
The optimization process is carried out in the compiler transformations has been described. This optimization approach to optimizing loops in database languages exists that include the ability to iterate through sets. These languages are known as Database Programming Languages (DBPLs). For these languages, compile-time optimizations similar to relational transformations like join reordering have been described [26]. These transformations make standard transformation-based compilers capable of optimizing iterations over sets that correspond to joins. This was later extended to include transformations that enable the parallelization of loops in DBPLs [27].

There are a number of important differences with the forelem framework. DBPLs were meant as programming languages to be used by an end user, whereas forelem loops are only an intermediate representation used to be used by code optimization backends. This way, the forelem framework is capable of handling different combinations of application programming languages and database statement expressions. Additionally, DBPLs, such as for example O++ which is discussed in the cited papers, use a run-time system for the iteration and manipulation of sets. forelem loops can be immediately lowered to low-level C codes that iterate over arrays that enable further low-level compiler optimizations. Despite of that, several of the techniques presented in these papers could be implemented in the forelem framework in the future.

9 Conclusions

In this paper, the optimization of database queries using compiler transformations has been described. This optimization process is carried out in the forelem framework. The forelem framework provides an intermediate representation to which queries can be naturally transformed and on which compiler transformations can be applied to optimize the loop nest, contrary to the traditional optimization of queries by the generation of an efficient query execution plan. Compiler transformations that are currently implemented within the forelem framework were illustrated. Using these transformations, combined with Materialization techniques, established implementations of relational join operators such as Hash Join can be derived automatically. Finally, strategies for the application of these transformations were discussed to be able to optimize query codes to achieve higher performance than contemporary database systems.

Experiments using the queries from the TPC-H benchmark show that using compiler transformations implemented within the forelem framework the queries could be optimized to perform significantly better than contemporary database systems. An average improvement was shown of a factor of 3 and in certain cases a speedup of up to a factor of 15.

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