Providing A Compiler Technology-Based Alternative For Big Data Application Infrastructures

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Abstract—The unprecedented growth of data volumes has caused traditional approaches to computing to be re-evaluated. This has started a transition towards the use of very large-scale clusters of commodity hardware and has given rise to the development of many new languages and paradigms for data processing and analysis. In this paper, we propose a compiler technology-based alternative to the development of many different Big Data application infrastructures. Key to this approach is the development of a single intermediate representation that enables the integration of compiler optimization and query optimization, and the re-use of many traditional compiler techniques for parallelization such as data distribution and loop scheduling. We show how the single intermediate can act as a generic intermediate for Big Data languages by mapping SQL and MapReduce onto this intermediate.

Index Terms—Big Data; Optimizing Compilers; Query Optimization; Program Transformation; Parallelization; Distributed Computing

I. INTRODUCTION

During the past decade problem sizes and collected data volumes have been increasing at an unprecedented rate. To be able to facilitate the processing and analysis of such vast amounts of data, one has moved to the use of large-scale clusters of commodity hardware. The larger the scale of such a cluster, the larger the chance of hardware failure. Traditional approaches to computing, such as database systems and high performance computing, do generally not account for this, as they rely to be run on expensive, high-end, high-availability hardware. Because of this, the emergence of clusters of commodity hardware gave rise to the development of new software processing frameworks with resilience to hardware failures built right in.

Given their reliance on massive amounts of commodity computer hardware Google has fronted this movement, developing techniques such as MapReduce [1], BigTable [2] and GFS [3]. Outside of Google, several similar developments occurred, most notably the Hadoop distributed processing framework, next to an abundance of different data processing application frameworks. For instance, several different approaches implementing distributed database systems have been created, such as HBase, Hive and Cassandra, that all bypass the relational model that has been traditionally used in database systems. Instead, these approaches rely on data structured in other manners or on data that is not structured at all. The lack of a standard model for such databases has led to a multitude of implementations, each with their own advantages and disadvantages, different programming models and exposure of low-level databases [4]. Similarly, many different frameworks for data processing and computation have been created partly using similar techniques, including Pig, Tez, Mahout, Spark and Flink. This in turn has led to efforts to make MapReduce more suitable for the processing of relational data by re-envisioning MapReduce based on tuples [5] and efforts to design a generic framework for the optimization of declarative Big Data languages [6]. Finally, also variations of Hadoop have been described to make up for deficiencies in Hadoop for particular use cases such as scientific computing with commonly used scientific array-based data formats [7], [8], [9].

In this paper, we propose a compiler technology-based alternative to the development of various different frameworks for Big Data Applications. Similar to data mining applications, many Big Data applications run complex queries on data sources to retrieve data and subsequently perform a significant amount of further processing. For these computations to be efficient they have to target both of these phases: data retrieval and data processing. This perspective forms the cornerstone of the alternative proposed in this paper, which is to integrate compiler optimizations with query optimization. Or, put differently, compiler optimizations must become aware of other storage levels that are in use besides memory and CPU cache in a single computer. By doing so, a single compiler intermediate is created in which all optimization is carried out and from which executable code is generated.

The use of this single intermediate solves deficiencies of data mining and Big Data applications. For instance, in data mining, data needs to be restructured to suit the technique/analysis that one wants to apply. So, data import and reformattting needs to take place before the computation can ensue. Data to be imported can originate from different data sources, including SQL databases. In case the data source is a transactional data source that continuously updates, this expensive importing and reformattting needs to take place continuously as well. Instead of reformattting the data, one can also envision the computation to the reformatted – i.e. bringing the computation to the existing data format. A single
intermediate automatically enables the data import code and analysis/compute code to be integrated. We refer to this as vertical integration: when data access code is combined with the surrounding application code in the optimization process, many more optimization opportunities can be unlocked. This has been described for database applications [10] and Section II presents a concise introduction.

So, instead of using different frameworks, all problems can be expressed in this single intermediate representation, allowing a single “super”-optimizer to be employed. In fact, we propose to upgrade traditional methods such that these can be used to successfully tackle Big Data problems. This includes machine code generation, loop optimizations, query optimizations (I/O optimizations) and techniques from parallel compilers such as data distribution and decomposition. Furthermore, within our approach additional techniques are available for the automatic reformatting of data. So, the compiler is equipped with tools to optimize access to existing data, optimizing any processing done on this data and to automatically generate new data structures to store re-formatted data for optimized future processing.

In this paper, we highlight the possibility of the application (and re-use) of traditional compiler techniques to contemporary Big Data problems. A number of existing and newly developed techniques are discussed that are to be combined into a single, powerful compiler framework for the optimization of Big Data applications. Further research is required to re-target compiler optimizations onto this framework, such that arbitrary program codes and data distributions can be effectively optimized and fault-tolerant code can be generated automatically.

This paper is organized as follows. Section II discusses the integration of compiler optimizations and query optimization. Section III discusses the capabilities of a single intermediate representation, and parallelization and data access optimization in particular. Section IV describes how applications expressed in different paradigms can be expressed and optimized within the single intermediate. Section V briefly discusses how the single intermediate is implemented. Section VI presents our conclusions.

II. INTEGRATING COMPILER OPTIMIZATIONS AND QUERY OPTIMIZATION

Within the vertical integration approach, the database queries that are executed by the application are expressed and included in the same intermediate representation as the application code, instead of sending these queries to a DBMS for optimization and execution at run-time. This representation allows traditional (loop) transformations from optimizing compilers [11] to be applied on the queries (data access codes) as well as allows for the (vertical) integration of data access codes with generic application code, unlocking many more optimization opportunities. Traditional analysis methods, such as Def-Use analysis [12], [13], will detect and eliminate data access of which the results are unused, or will detect related data accesses that can be combined. Separate loops that firstly read data from a database and create a result set, and secondly process items in this result set, can be automatically merged. In other words, the vertical integration approach aims to optimize the database application as a whole.

The main feature of the single intermediate relies on viewing data as being stored as (multi)sets of tuples. Within this framework a loop construct is defined, forelem, that defines an iteration over a (sub)set of these multisets of tuples. The definition of the subset that is iterated is performed using a feature called “index sets”, that encapsulate how exactly the iteration is carried out. The resulting loops are governed by simple loop control, which allows these to be optimized using re-targeted variants of traditional compiler optimizations. At a later compilation stage, the compiler determines how to actually execute the iteration specified by a forelem loop and accompanied index set. This may be done by nested loops iteration, but also through the use of hash functions or tree-based indexes, leading to iteration patterns that are also employed by database systems. See Figure 1 for an example.

An important prerequisite for the above to be successful is the condition that while using the single intermediate, queries can be optimized to a level of performance that is at least competitive with “traditional” query optimization technology. Query optimization using a single intermediate representation has been described in [14] and the results show that using a single intermediate representation queries can be optimized to an extent that surpasses the performance of state-of-the-art database systems.

In fact, this approach to query optimization solves two problems experienced by traditional optimizing compilers and query optimizations to make these future-proof. One of the major aims of optimizing compilers has always been to optimize CPU and cache utilization. Other storage levels, such as disk-based storage or an intermediate flash layer, were just addressed in a minor way. This is because the majority of the problem or data set to be processed by a computational kernel typically fits main memory, either of a single node or the combined memories of nodes in a cluster computer. It is clear
that this will not remain the case, given the rapidly growing problem sizes and data set volumes. Therefore, it is of utmost importance that compilers are made capable to optimize codes operating on such data sets. Currently, compilers are inherently incapable of doing this, as optimization for out-of-memory problems was never included in its aim. The integration of techniques for query optimization as is done in a single intermediate solves this incapability.

On the other hand, the goal of query optimization is to minimize the number of disk I/O operations performed by execution plans for the retrieval of data. Because the sizes of databases were traditionally significantly larger than main memories of computers, the optimization objective was typically to reduce the number of disk I/O operations. However, in the last decade the size of computer main memories has increased significantly, resulting in a shift of focus on disk I/O towards the exploitation of intrinsic internal features of computer systems. This has led to query optimizers to start to incorporate compiler techniques in order to maximize performance. Also at this point, the integration of compiler optimization and query optimization solves this problem.

Because both the power of compiler optimizations as well as query optimization are encompassed in a single intermediate representation, it is a solid foundation upon which to build a compiler for Big Data applications. For a detailed description of vertical integration of database applications, we refer the reader to [10]. In the next section, we discuss the capabilities of the framework with regard to parallelization and their use in the optimization of Big Data Applications.

III. Capabilities of the Single Intermediate Representation

In this section the main capabilities of the single intermediate representation are described. This includes in particular techniques for parallelization and optimization of data access codes. Subsequently, a number of further optimizations are described such as data reformatting and generation of highly efficient machine codes.

A. Parallelization Techniques

A forelem loop that is defined in the single intermediate representation is inherently parallel. However, to in order to come to an efficient manner to execute such loops on a parallel computer, a suitable distribution of the work load is needed. The approach that is chosen relies on the techniques derived from the optimization of program code and data distribution to map program codes onto parallel computers, see for instance [15]. In the single intermediate representation, the partitioning of data is being handled by special loop constructs which express parallel execution coupled with data partitioning. This data partitioning can be specified by an “automatic” partitioning of the value range of one or more particular fields in the multiset model. Based on the initial partitioning a mechanism for loop scheduling is selected, which schedules iterations of parallel loops onto available processors. Finally, all loops in the application are considered together to optimize the data decomposition, leading to a final distribution of the data. The entire approach relies on compiler transformations, making this approach very generic allowing multiple data decompositions to be considered at compile time.

1) Data Partitioning: To control how data is partitioned, generic loop transformations are used among which loop blocking and orthogonalization. Using these transformations, index sets or multisets can be divided into \( N \) parts corresponding to parallelization to \( N \) processors. Consider a loop of the following form, with a multiset \( A \) containing tuples with fields \( field1 \) and \( field2 \):

\[
\text{forelem} (i; i \in pA) \quad \text{SEQ};
\]

To create a direct data partitioning, the loop blocking transformation is used to split the index set \( pA \) into \( N \) partitions:

\[
pA = pA_1 \cup pA_2 \cup \ldots \cup pA_N
\]

Subsequently, the example loop becomes:

\[
\text{for } (k = 1; k \leq N; k++)
\]

\[
\text{forelem} (i; i \in pA_k) \quad \text{SEQ};
\]

and this loop is parallelized by replacing the for loop with a forall loop, indicating that the outermost loop is parallelized. Instead place of direct data partitioning, also indirect data partitioning can be used. In this case, loop blocking is not done based on the iterated index set, but on the value range of one of the multiset’s accessed fields. So, array \( A \) is to be distributed into \( N \) partitions based on \( field1 \). The notation \( A.field1 \) denotes the set of values of the \( field1 \) found in all subscripts of \( A \). If \( X = A.field1 \), then

\[
X = X_1 \cup X_2 \cup \ldots \cup X_N
\]

is a partitioning of \( X \) into \( N \) segments. This gives rise to the following loop:

\[
\text{forall } (k = 1; k \leq N; k++)
\]

\[
\text{for } (l \in X_k)
\]

\[
\text{forelem} (i; i \in pA.field1[l]) \quad \text{SEQ};
\]

In this parallelized loop nest a processor \( P_k \) is responsible for processing partition \( X_k \) of this partitioning and will execute the original forelem loop only for \( i \in pA, l \in X_k : A[i].field1 = l \). So, each processor will iterate the values of the assigned partition \( X_k \) and execute the original forelem loop for each value. Note that in this example of indirect data partitioning, a distribution of the data of array \( A \) is not made explicit in the intermediate representation of the loop.

2) Loop Scheduling: Data partitioning has resulted in an initial distribution of data to available processors. In loop scheduling, a parallel loop’s iterations are to be scheduled onto the available processors. Although the loop schedule can be chosen to be in line of the data partitioning, loop scheduling is in principle done independent of the data partitioning. With the subsequent data decomposing stage, all loops in the application are considered to choose a final distribution.
of the data that minimizes communication between different processors and nodes.

In the literature, many static and dynamic approaches to loop scheduling have been described. A static loop schedule is determined entirely at compile-time [16]. Examples of dynamic scheduling approaches are Guided Self-Scheduling (GSS) [17], Trapezoid Self-Scheduling [18] and feedback guided dynamic loop scheduling [19]. The principle of these dynamic scheduling techniques is that iterations of loops are scheduled at runtime. Iterations are allocated in groups called chunks. The process starts with a large chunk size and this size gradually decreases with the course of execution. Processors that finish their chunk earlier than other processors are assigned a new smaller chunk. By doing so, the work is better balanced in case the cost for each loop iteration, or chunk, is not equal.

3) Fault Tolerance: The selection of a suitable loop scheduling technique is key to a successful fault tolerant execution. Static loop schedules are simple and have no overhead at all, but have the major disadvantage that there is no real possibility for run-time changes. So, essentially, when one of the parallel nodes fails it is not possible to offload work to another node and the computation has to be restarted. With dynamic loop scheduling this is a possibility, when a node fails remaining iterations scheduled for that node (or these that have not been scheduled at all) can be scheduled to other nodes. One can even take one step further and devise hybrid schemes, where at a higher level dynamic loop scheduling is carried out and chunks of data are executed according to a static schedule with no overhead. When a node within the static group fails, only that chunk has to be computed on another set of nodes, something the dynamic loop scheduler at a higher level will take care of.

Loop scheduling thus serves two important purposes. Firstly, node failures are taken care of by re-scheduling iterations assigned to that node to one or more other nodes. Secondly, dynamic loop scheduling enables automatic calibration of chunk size, allowing the code to automatically adapt to different clusters and different compute node assignments.

4) Data Distribution: The selection and optimization of the data partitioning is followed by the optimization of the data distribution. At this stage, all parallel loops in the application are considered to choose the actual distribution of the data. Different loops in the application might be accessing the same data according to a different partitioning. During the selection of the data distribution, these partitionings could be modified slightly to avoid expensive data re-distributions from being carried out between these loops. There might also be an initial distribution of the data present, so (part of) the data is already distributed on a set of nodes. If this is the case, this is taken into account during data distribution to optimize the performance of the application.

It is possible that not all constraints will be resolved during the data distribution phase. Because of this, a parallel loop might be performing accesses to data that are not available locally. Such accesses are resolved by remote communication to a processor that does have the necessary data available. This communication can occur in many different ways, for instance using TCP or UDP over Ethernet or MPI over InfiniBand. Also if a re-distribution of the data has to take place between loops extensive communication has to take place. Therefore, in optimizing the final data distribution, this communication should be minimized as much as possible.

To demonstrate how expensive data re-distributions can be avoided by the compiler through the use of loop transformations, consider the following example. Two adjacent loops are considered that each access the same multiset and are parallelized based on different fields of the tuples in the multiset: \( X = A.field1 \) and \( X = A.field2 \). These loops compute the multiplicity of all values of \( field1 \) and \( field2 \) respectively using an aggregate function:

\[
\text{forall } (k = 1; k <= N; k++) \\
\text{for } (l \\in \mathcal{X}_k) \\
\quad \text{forelem } (i; i \\in pTable.field1[i]) \\
\quad \quad \text{count}_{1,k}[\mathcal{A}[i].field1]++; \\
\quad \text{forelem } (i; i \\in pTable.distinct(field1)) \\
\quad \quad \mathcal{A}_{1,k} = \mathcal{A}_{1,k} \cup (\mathcal{A}[i].field1, \\
\quad \quad \quad \text{count}_{1,k}[\mathcal{A}[i].field1]) \\
\quad ...
\]

\[
\text{forall } (k = 1; k <= N; k++) \\
\text{for } (l \\in \mathcal{X}_k) \\
\quad \text{forelem } (i; i \\in pTable.field2[i]) \\
\quad \quad \text{count}_{2,k}[\mathcal{A}[i].field2]++; \\
\quad \text{forelem } (i; i \\in pTable.distinct(field2)) \\
\quad \quad \mathcal{A}_{2,k} = \mathcal{A}_{2,k} \cup (\mathcal{A}[i].field2, \\
\quad \quad \quad \text{count}_{2,k}[\mathcal{A}[i].field2]) \\
\]

Even if \( A.field1 \equiv A.field2 \) and the two decompositions are the same, data partitioning conflicts will occur. This is because a partitioning of \( A \) based on \( field1 \) is not equal to a partitioning of \( A \) on \( field2 \). The fact that the column contents are equal does not imply the column contents are in the same order (the columns are multisets).

To solve these conflicts, either \( A \) is not distributed for the first loop or an expensive re-distribution of the data is performed between the first and the second loop. Evidently, both are suboptimal solutions. However, in this case a better solution can be found by performing loop transformations such that these end up using the same data distribution. This is done by exploiting the possibility to reorder the loops such that the two parallelized loops computing the \text{count} aggregate are consecutive to one another. This is possible because these loops do not have a dependency on the other loops (the second forall loops) in the code fragment. The two outermost loops iterate the same bounds, allowing application of the Loop Fusion transformation:

\[
\text{forall } (k = 1; k <= N; k++) \\
\text{for } (l \\in \mathcal{X}_k) \\
\quad \text{forelem } (i; i \\in pTable.field1[i]) \\
\quad \quad \text{count}_{1,k}[\mathcal{A}[i].field1]++; \\
\quad \text{forelem } (i; i \\in pTable.field1[i]) \\
\quad \quad \mathcal{A}_{1,k} = \mathcal{A}_{1,k} \cup (\mathcal{A}[i].field1, \\
\quad \quad \quad \text{count}_{1,k}[\mathcal{A}[i].field1])
\]
In the case that Table \( k = 1; k \leq N; k++ \)
forall in the loop body resulting in:

series of statement reordering and Loop Fusion is possible

for elem only considered one particular case of two consecutive
between loops. data distribution and no data redistribution is necessary in
same partitioning of X. Because the two counting loops are fused, the loops use the
same data distribution and no data redistribution is necessary in
between loops.

Although the interaction of the different transformations as
illustrated is rather powerful, it should be noted that we have
only considered one particular case of two consecutive forelem
loops. In general, applications are not that simple and consist
of many data access codes, embedded or not embedded in
application code, so, the complexity of these interactions will
grow exponentially. Strategies will have to be developed to
keep the optimization process manageable. These strategies
will also need to work with a representation of the data
distribution and the communication in the single intermediate.

B. Data Access Optimization

Another major feature of the single intermediate is the capa-
bility of optimizing data access codes. To optimize the queries
that have been expressed in the forelem form, traditional loop
transformations and new transformations that are based on
existing compiler transformations are used. For instance, the
loop interchange transformation is used to push any conditions
on data to outer loops to decrease the amount of data that
needs to be read as much as possible. After the loops have
been ordered in an optimized form, efficient code is generated
to execute these loops. In forelem loops the exact iteration
order is encapsulated in the “index set”. So, at this point the
compiler will determine iteration methods for these loops and
generate appropriate code. An iteration method may or may
not involve the use of an additional index structure. As could
be seen in Figure 1, in the middle example an iteration scheme
is generated that does not use an index structure and visits
the entire multiset. The example at the bottom shows that the
compiler employed a hash-based index to generate a more
efficient iteration pattern.

The compiler is equipped with optimizations that set up
index sets and optimize these index structures. For instance,
through analysis the compiler can deduce that some parts of
multiset do not have to be indexed because these parts will
not be accessed and sometimes an index can be generated in
such a way that it can be used for more than one forelem loop.
Note that the generation of such index structures happens at
run-time and these structures are only temporarily. For more
details on query optimization within a single intermediate, we
refer the reader to [1-3].

Another major benefit of translating data access queries to
the single intermediate representation is that the compiler is
enabled to also optimize the data import part of data mining
or Big Data applications. Because of this, the way data import
takes place can be better aligned with subsequent processing.
Furthermore, any subsequent processing can be integrated with
the code that actually retrieves the data. For instance, consider
the following code which retrieves student grades to compute
the weighted average from a database:

```c
for (i = 0; i < X; i++)
    count[i][Table[i].field1][Table[i].field2]++;

for (i = 0; i < X; i++)
    count[i][Table[i].field1][Table[i].field2]++;
```

Because the two counting loops are fused, the loops use the
same partitioning of X. In other words, the loops use the same
data distribution and no data redistribution is necessary in
between loops.

Within a single intermediate, the query would no longer
be executed by a separate database system, but instead be
expanded as a series of loops. Subsequently, the data access
loop and the while loop performing further processing can be
merged within a single loop, resulting in:

```c
avg = 0.0;
for (i = 0; i < X; i++)
    avg += Grades[i].grade * Grades[i].weight;
```

Note that such a transformation is not automatically possible
using existing techniques if the query and processing code are
not present in a single intermediate.

C. Further Optimizations

The single intermediate is equipped with numerous other
capabilities for performing optimization. In this section, Data
Reformatting and Classic Code Optimizations are two capa-
bilities that will be highlighted.

1) Data Reformatting: Within the single intermediate, data
that is operated on is represented as tuples stored in multisets.
This is only an intermediate representation and thus does not
imply that the data is physically stored as such. During the
code generation stage, the compiler determines a physical
storage scheme for the data. Data may be stored by simply
storing the tuples as records in a binary file. The compiler can
also generate compressed column schemes wherein a column
that enumerates a range of values is not physically stored in
full, but rather a description of the value range is stored to be
reconstructed when the data is read. These optimizations are
all possible because the compiler has the code where data is
read and written all under control.

Besides controlling how tuples are stored, the compiler also
controls the structure of the tuples themselves. In database
applications, the tuples often represent the schema of a database,
which has been set at design time of the database and is not
altered by query optimizers. Within the single intermediate,
such alterations can be done, again because all I/O code
is under control of the compiler. By analyzing the different
data access codes that are executed by the application in
combination with the subsequent data processing code and
even run-time performance feedback, the compiler will be able
to optimize the data model of the application.

The scope by which such optimizations are possible depends
on the application. Some applications have to operate on
already existing data. So, similar to pre-existing data distribu-
tions, the compiler has to take the existing format of the data
into account. Reformating all data for a small optimization is
prohibitively expensive. In such cases, the compiler will hold
off from performing such optimizations. However, if the data
is going to be processed multiple times in the future, it will
pay off to store the data in a different format. The compiler
can in these cases automatically generate code that will re-
format the data during the first time of processing so that
subsequent runs of the computation will be significantly faster.
On the other hand, if the data to be processed has not yet been
collected, the compiler will generate a “data import” or “data
load” code that will store the data in a suitable format for
subsequent processing when the data is collected. Naturally, if
in the future other computations are written that operate on the
same data, the compiler can again decide to generate another
data reformating code.

2) Code Optimization: After optimization at the level of
the single intermediate has been completed, machine code
has to be generated. The compiler will take advantage of
the large body of existing compiler optimizations that are
essential for generating highly efficient machine code. These
optimizations include, among others, dead code elimination,
common subexpression detection, constant propagation, and
register allocation to optimize the sequence of instructions
and control flow. Loops in the program code have to be
targeted in particular to optimize for re-use of cached data.
To do so, loop transformations are used that target loop nests
as a while. By modifying the order in which loop iterations
are executed, cache data re-use can be significantly improved
leading to performance improvements of one or more orders
of magnitude. Loops can be further optimized by taking
advantage of vectorization techniques, which also opens to
door to new computing paradigms, such as Intel’s Xeon Phi
accelerator, that rely extensively on vectorization units for
acceleration.

IV. A GENERIC BIG DATA INTERMEDIATE

The single intermediate representation is also a single
intermediate in the sense that it is a generic intermediate
in which Big Data applications can be expressed that were
developed in different paradigms. The novelty of this approach
is that all optimization, including optimization of data access
or queries, optimization of data processing or computational
code and parallelization, takes place in a single intermediate.
This goes beyond approaches that translate Hadoop programs
to SQL such that storage engine features like indexing can be
taken advantage of, but that break down when arbitrary code is
encountered [20], and beyond approaches that propose a query
compiler framework solely for the optimization of queries, or
data access codes [6].

As an illustration of the single intermediate, this section
describes how a MapReduce-like problem expressed in SQL
can be expressed in the single intermediate and can be subse-
sequently expressed as a MapReduce problem. As examples, two
examples from the original MapReduce paper [1] are consid-
ered. The discussion is concluded with an initial performance
evaluation of the MapReduce problem implemented in Hadoop
and a parallel code generated using the single intermediate
representation.

The first example concerns URL access count. Consider logs
of web page requests, which are mapped to tuples (url, 1).
The reduction operator is described in the paper as mapping
(url, list(values)) to (url, total_count). Considering a mult-
tiset access, with a single column containing the URLs, this
computation can be described as the following SQL query:

\[
\text{SELECT url, COUNT(url) FROM access GROUP BY url}
\]

This query is expressed in the single intermediate representa-
tion as follows:

\[
\begin{align*}
&\text{forelem } (i; i \in \text{pAccess.distinct(url)}) \\
&R = R \cup \{\text{access}[i].\text{url}\} \\
&\text{forelem } (i; i \in R) \\
&\quad \text{count} = 0 \\
&\quad \text{forelem } (j; j \in \text{pAccess.url}[\text{access}[i].\text{url}]) \\
&\quad \text{count}++ \\
&R = R \cup \{\text{access}[i].\text{url}, \text{count}\}
\end{align*}
\]

The compiler will first apply a number of initial transforma-
tions (Iteration Space Expansion and Code Motion in this case)
to enable parallelization, and subsequently parallelize the loop
using techniques described in the previous section. One of the
resulting codes of this parallelization process is the following
code fragment, where X = Access.url:

\[
\begin{align*}
&\text{count} = 0 \\
&\text{forall } (k = 1; k \leq N; k++) \\
&\quad \text{count}_k = 0 \\
&\quad \text{forall } (1 \in X_k) \\
&\quad \text{forelem } (i; i \in \text{pAccess.url}[1]) \\
&\quad \text{count}_k[\text{access}[i].\text{url}]++ \\
&\text{forelem } (i; i \in \text{pAccess.distinct(url)}) \\
&R = R \cup \{\text{access}[i].\text{url}, \sum_{k=1}^N \text{count}_k[\text{access}[i].\text{url}]\}
\end{align*}
\]

Note that the resulting forelem code bears similarity to a
MapReduce program. In fact, the first loop maps every row of
access to an accumulation of the access[i].url subscript
of the count array. This could be represented as a tuple
(url, 1). The second loop iterates over all keys, which are all
distinct URLs in access and retrieves the result of an aggregate function, in this case count.

In general, two adjacent for elem loops where the former loop stores values in an array subscribed by a field of the array being iterated, and the latter loop accesses elements of this array, can be written as a MapReduce program. The map function iterates the table that is iterated by the former loop. This table is fragmented by a MapReduce framework, so that each instance of the map function processes a table fragment. Instead of writing to a global array, emitIntermediate is called. For the above example, tuples (access[i].url, 1) are generated, where 1 is a dummy value, because it is not used.

The example code increments the value stored in the count array for every occurrence of a value access[i].url. In the MapReduce program, a pair will be generated for every access[i].url. So, the reduction function has to increment a counter for every occurrence of the same value access[i].url. Because a MapReduce framework will collect all pairs for a unique key, the reduction function simply needs to count all values for every unique key.

If the above example is written in MapReduce pseudocode similar to that used in [1], the program would be:

```plaintext
map(key, value):
    # Assume value represents content of Access table
    access = value
    for a in access:
        emitIntermediate(a.url, 1)
reduce(key, values):
    count = 0
    for v in values:
        count++
    emit(key, count)
```

Imagine the above example performed an operation sum[Table[i].field1] += Table[i].field2 instead. In this case, a MapReduce program will emit pairs (Table[i].field1, Table[i].field2) (note that, the dummy 1 is now replaced with Table[i].field2). The summation is performed in the reduce function by summing the values for every unique key Table[i].field1.

As a second example from the MapReduce paper, the Reverse Web-Link Graph is considered. For each link from a source to a target page, a pair (target, source) is emitted. The original example reduces to a pair (target, list(source)), which we will modify to reduce to a pair (target, source_count). To write a SQL query for this program, consider a table links that contains tuples (source, target), which has been previously filled, for example by parsing webpages source and extracting all links to target pages. The following two queries are defined:

```sql
CREATE VIEW target_links AS
SELECT DISTINCT target FROM links;
SELECT T.target, (SELECT COUNT(*) FROM links L
WHERE L.target = T.target)
FROM target_links T
FROM
```

which compute the number of incoming links to each registered target page. Also this problem can be expressed in the single intermediate representation and when parallelized with, for example, X = Links.target, the resulting code is:

```plaintext
count = 0
forall (k = 1; k <= N; k++) {
    countk = 0
    for (l ∈ Xk)
        forelem (i; i ∈ pLinks.target[l])
            countk[links[i].target]++
    }
forelem (i; i ∈ pLinks.distinct(target))
    R = R ∪ (links[i].target,
            ∑k=1countk[links[i].target])
```

Note that also in this case a MapReduce code can be derived from this intermediate representation using the technique as described above.

A number of experiments have been conducted with Hadoop and implementations generated through a single intermediate representation of the two described examples. The experiments have been performed on the DAS-4 cluster at Leiden University[1]. The cluster nodes each contain 8 processing cores, 48GB of main memory and 10 TB of local storage in a software RAID0 configuration. The Hadoop experiments were performed on a Hadoop cluster of 7 data nodes and one master node running the task tracker. Using the single intermediate representation a C code has been generated which uses MPI and OpenMP message exchange and local parallelization. This implementation is also run on 7 nodes and one separate master node. The results are summarized in Figure 2. The experiments show that the generated implementations realize an performance improvement of a factor 3 when the same input data is used as is used by Hadoop, and up to a factor 120 if the input data is available with an optimized layout.

As has been described in Section III-C1 the single intermediate representation is capable of automatically reformating the data layout of a program. As an example, the strings (URLs and hosts) in the arrays have been replaced with integer keys. These integer keys are used to subscript another array, which contains the string value for each key. In fact, the data model has been made relational. This significantly improves the performance, as indicated by the “integer keyed” experiments, which implies that it is worthwhile to consider such data reformating if this is feasible in the context of the problem, for example when the data has not yet been collected in a specific format. A final experiment has been done by removing unused structure fields and column-wise storage of the data. These data relayout operations can also be done automatically within the single intermediate. A performance increase is not observed after performing this relayout, possibly because it does not weigh up to the initial start up cost of the MPI and OpenMP frameworks.
V. IMPLEMENTATION OF A SINGLE INTERMEDIATE REPRESENTATION

To be able to support different programming languages and database APIs, a generic library was designed. This library is capable of creating and manipulating forelem loop nests, by representing these as Abstract Syntax Trees (ASTs). Also SQL statements can be parsed into an AST automatically. On the AST, various analyses and transformations can be applied, many of which are implementations of traditional compiler (loop) transformations. An abstract code generation interface is present in the library to generate code from any forelem AST. For the vertical integration approach described in Section II, query codes are integrated with, for instance, a C++ code. In this case, the library is used from a prototype Clang2 compiler plugin. This plugin scans a C/C++ AST for calls to database API and extracts the performed operations, such as exact query strings that are requested to be executed. The extracted information is passed to the library. Transformations can then be performed as an interplay between the C/C++ AST and the forelem AST created. Finally, code in the C/C++ source code is replaced with code generated using the library.

From a forelem AST that contains parallel forall loops, the code generator incorporated in the library is capable of generating parallelized code using the OpenMP and/or MPI frameworks. For contemporary cluster computers that consist out of multi-core nodes, both frameworks are used to achieve parallelization across nodes as well as across local CPU cores. Similar to how other loop transformations are implemented in the library, the library incorporates implementations of parallelization transformations and logic for optimizing a data decomposition. This data decomposition support could consist out of a simple algorithm for automatically generating a data decomposition based on a given AST, but also out of a user interface to visualize the intermediate representation so that the user can aid the framework in determining an efficient data decomposition.

VI. CONCLUSIONS

In this paper, we have presented a compiler technology-based alternative to the development of various different frameworks for Big Data Applications. This alternative is a single, generic intermediate representation and the main features of this intermediate rely on the integration of compiler and query optimizations and extensive parallelization capabilities. By using this intermediate, a compiler is made capable of not only optimizing data access and processing of data separately, but also to optimize data access and subsequent processing together.

This compiler-based approach towards Big Data applications enables many traditional compiler techniques to be re-used. For instance, we have described how the work done on compiler-based parallelization of applications, selection of data distributions and dynamic loop scheduling can be fully re-used in the context of Big Data applications. By considering multiple loops that access the same data within the same application the compiler can use existing transformations to avoid expensive data re-formatting between two loops. We have also demonstrated that the intermediate is generic by showing how SQL queries can be expressed in the single intermediate, be optimized and subsequently be expressed as a

http://www.clang.org/
MapReduce-like program. An initial experimental evaluation using two examples also showed that by incorporating data reformatting capabilities in the compiler, speedups can be attained of up to two orders of magnitude.

Further research is required to re-target compiler optimizations onto the single intermediate such that arbitrary program codes and data distributions can be effectively optimized. Using this intermediate, we aim to study the feasibility and the advantages of applying the many existing techniques for the optimization of parallel program codes to Big Data applications. Furthermore, we would like to study the improvements in I/O optimizations that can be achieved by integrating data processing and data reformatting. Finally, we plan to investigate novel hybrid loop scheduling techniques that can be generated by a compiler and can gracefully handle faults at run-time.

REFERENCES

[1] J. Dean and S. Ghemawat, “Mapreduce: Simplified data processing on large clusters,” in OSDI, 2004, pp. 137–150.
[2] F. Chang, J. Dean, S. Ghemawat, W. C. Hsieh, D. A. Wallach, M. Burrows, T. Chandra, A. Fikes, and R. E. Gruber, “Bigtable: A Distributed Storage System for Structured Data,” ACM Trans. Comput. Syst., vol. 26, no. 2, pp. 4:1–4:26, Jun. 2008.
[3] S. Ghemawat, H. Gobioff, and S.-T. Leung, “The google file system,” in ACM SIGOPS operating systems review, vol. 37, no. 5. ACM, 2003, pp. 29–43.
[4] E. Meijer and G. Bierman, “A co-relational model of data for large shared data banks,” Commun. ACM, vol. 54, no. 4, pp. 49–58, Apr. 2011.
[5] P. Ferrera, I. de Prado, E. Palacios, J. L. Fernandez-Marquez, and G. D. M. Serugendo, “Tuple MapReduce: Beyond Classic MapReduce,” 2013 IEEE 13th International Conference on Data Mining, vol. 0, pp. 260–269, 2012.
[6] V. R. Borkar and M. J. Carey, “A Common Compiler Framework for Big Data Languages: Motivation, Opportunities, and Benefits,” IEEE Data Eng. Bull., vol. 36, no. 1, pp. 56–64, 2013.
[7] J. B. Buck, N. Watkins, J. LeFevre, K. Ioamidou, C. Maltzahn, N. Polyzotis, and S. Brandt, “SciHadoop: array-based query processing in Hadoop,” in Proceedings of 2011 International Conference for High Performance Computing, Networking, Storage and Analysis, ser. SC ’11. New York, NY, USA: ACM, 2011, pp. 66:1–66:11.
[8] Y. Wang, W. Jiang, and G. Agrawal, “SciMATE: A Novel MapReduce-Like Framework for Multiple Scientific Data Formats,” Cluster Computing and the Grid, IEEE International Symposium on, vol. 0, pp. 443–450, 2012.
[9] S. Sehrish, G. Mackey, J. Wang, and J. Bent, “MRAP: a novel MapReduce-based framework to support HPC analytics applications with access patterns,” in Proceedings of the 19th ACM International Symposium on High Performance Distributed Computing, ser. HPDC ’10. New York, NY, USA: ACM, 2010, pp. 107–118.
[10] K. F. D. Rietveld and H. A. G. Wijshoff, “Reducing layered database applications to their essence through vertical integration,” ACM Trans. Database Syst., vol. 40, no. 3, pp. 18:1–18:39, 2015.
[11] Padua, David A. and Wolfe, Michael J., “Advanced compiler optimizations for supercomputers,” Commun. ACM, vol. 29, no. 12, pp. 1184–1201, Dec. 1986. [Online]. Available: http://doi.acm.org/10.1145/7902.7904
[12] F. E. Allen and J. Cocke, “A program data flow analysis procedure,” Commun. ACM, vol. 19, no. 3, pp. 137–, Mar. 1976.
[13] K. Kennedy, A survey of data flow analysis techniques. Englewood Cliffs NJ: Prentice-Hall, 1981, pp. 5–54.
[14] K. F. D. Rietveld and H. A. G. Wijshoff, “Re-engineering compiler transformations to outperform database query optimizers,” in LCPC, ser. Lecture Notes in Computer Science, vol. 8967. Springer, 2014, pp. 300–314.
[15] K. Kennedy and U. Kremer, “Automatic data layout for distributed-memory machines,” ACM Trans. Program. Lang. Syst., vol. 20, no. 4, pp. 869–916, Jul. 1998.
[16] M. Cierniak, W. Li, and M. Zaki, “Loop scheduling for heterogeneity,” in High Performance Distributed Computing, 1995., Proceedings of the Fourth IEEE International Symposium on, Aug 1995, pp. 78–85.
[17] C. D. Polychronopoulos and D. J. Kuck, “Guided self-scheduling: A practical scheduling scheme for parallel supercomputers,” Computers, IEEE Transactions on, vol. 100, no. 12, pp. 1425–1439, 1987.
[18] T. H. Tzen and L. M. Ni, “Trapezoid self-scheduling: A practical scheduling scheme for parallel compilers,” Parallel and Distributed Systems, IEEE Transactions on, vol. 4, no. 1, pp. 87–98, 1993.
[19] J. Bull, “Feedback guided dynamic loop scheduling: Algorithms and experiments,” in Euro-Par ’98 Parallel Processing. Springer, 1998, pp. 377–382.
[20] M.-Y. Ju and W. Zwaenepoel, “HadoopToSQL: A mapReduce Query Optimizer,” in Proceedings of the 5th European Conference on Computer Systems, ser. EuroSys ’10. New York, NY, USA: ACM, 2010, pp. 251–264.