Query Processing Based on Compressed Intermediates

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ABSTRACT

Modern in-memory column-stores employ lightweight data compression to tackle the growing gap between processor speed and main memory bandwidth. However, the compression of intermediate results has not been investigated sufficiently although accessing intermediates is as expensive as accessing the base data in these systems. Therefore, we introduce our vision of a *balanced query processing based on compressed intermediates* to improve query performance. In this paper, we provide an overview of the important research challenges on the way to this goal, present our contributions so far, and give an outlook on our remaining steps.

1. INTRODUCTION

With increasingly large amounts of data being collected in numerous areas ranging from science to industry, the importance of online analytical processing (OLAP) workloads increases constantly. OLAP queries typically address a small number of columns, but a high number of rows and are, thus, most efficiently processed by column-stores. The significant developments in the main memory domain in recent years have rendered it possible to keep even large datasets entirely in main memory. Consequently, modern column-stores follow a main memory-centric architecture. These systems have to face some new architectural challenges.

Firstly, they suffer from the new bottleneck between main memory and the CPU caused by the contrast between increasingly fast multi-core processors and the comparably low main memory bandwidth. To address this problem, column-stores make extensive use of data compression. The reduced data sizes achievable through compression result in lower transfer times, a better utilization of the cache hierarchy, and less TLB misses. However, classical *heavyweight* compression algorithms such as Huffman [10] or Lempel Ziv [20] are too slow for in-memory systems. Therefore, numerous *lightweight* compression algorithms such as differential coding [14, 16] and null suppression [1, 16] have been proposed, which are much faster and, thus, suitable for in-memory column-stores. Furthermore, especially for lightweight compression algorithms, many operators can directly process the compressed data without prior decompression.

Secondly, in main memory-centric column-stores, accessing the intermediate results during query processing is as expensive as accessing the base data, since both reside in main memory. Thus, intermediates offer a great potential for performance improvement, which can be exploited in two orthogonal ways: (1) intermediates should be avoided whenever possible [12, 15], or (2) intermediates should be represented in a way that facilitates efficient query processing.

In this thesis, we focus on the second approach by investigating lightweight compression of intermediates in main memory-centric column-stores. This direction has not been investigated sufficiently in the literature so far. Existing systems usually keep the data compressed only until an operator cannot process the compressed data directly, whereupon the data is decompressed, but not recompressed – due to the resulting computational overhead. However, using modern hardware and state-of-the-art lightweight compression algorithms, this computational overhead can be outweighed by the benefits of compressed data. Thus, our vision is a *balanced query processing based on compressed intermediates*. That is, in a query execution plan of compression-aware physical operators, *every* intermediate result shall be represented using a suitable lightweight compression algorithm which is selected in a compression-aware query optimization such that the benefits of compression outweigh its costs. To achieve this goal, this thesis addresses three aspects of the problem: the *structural aspect* on the basics of lightweight compression (Section 2), the *operational aspect* on physical operators for compressed data (Section 3), and the *optimization aspect* on compression-aware optimization strategies (Section 4). These aspects are designed to build upon each other, as will become clear in the following sections.

2. STRUCTURAL ASPECT

The *structural aspect* lays the foundations of this thesis by focusing on the basics of lightweight compression algorithms and on efficient transformations between the compressed formats of different algorithms. Thereby, our primary focus is on integer sequences due to their outstanding importance in column-stores: Other fixed-width data types, such as decimals, can be stored as integers and variable-width data types, such as strings, usually *need* to be represented by fixed-width integer codes from a dictionary to enable efficient processing. We have already completed our planned research in this aspect of the thesis.

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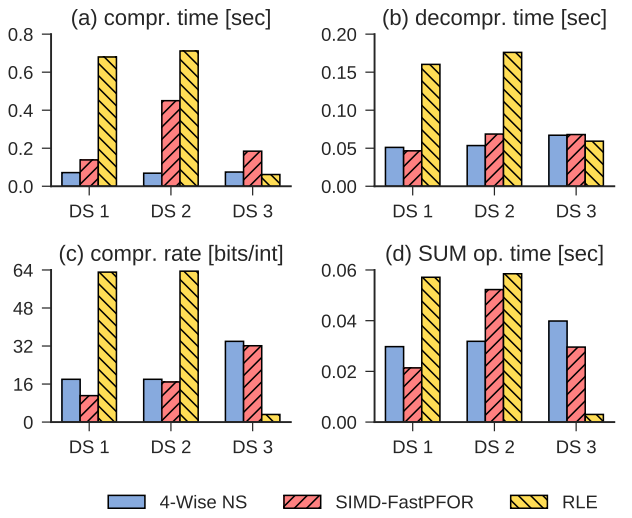
2.1 Lightweight Data Compression

In the field of lossless lightweight data compression, we distinguish between *techniques*, i.e., the abstract ideas of how compression works conceptually, and *algorithms*, i.e., concrete instanciations of one *or more* techniques. So far, we consider five lightweight compression techniques for sequences of integers: frame-of-reference (FOR) [8, 21], differential coding (DELTA) [14, 16], dictionary coding (DICT) [1, 21], run-length encoding (RLE) [1, 16], and null suppression (NS) [1, 16]. FOR and DELTA represent each data element as the difference to either a certain given reference value (FOR) or to its predecessor (DELTA). DICT replaces each value by its unique key in a dictionary. The objective of these three well-known techniques is to represent the original data as a sequence of small integers, which is then suited for the actual compression using the NS technique. NS is the most studied lightweight compression technique. Its basic idea is the omission of leading zero bits in small integers. Finally, RLE tackles uninterrupted sequences of occurrences of the same value, so called *runs*. Each run is represented by its value and length. Obviously, these techniques exploit different data characteristics, such as the value range, the number of distinct values, and repeated values.

In the literature, numerous algorithms have been proposed for these techniques, e.g., [1, 8, 14, 16, 17, 19, 21], to name just a few examples. For our purposes of applying decompression and recompression *during* query execution, we depend on highly efficient implementations of these existing algorithms. One way to achieve these is to use single instruction multiple data (SIMD) extensions of modern processors, such as Intel's SSE and AVX, which allow the application of one operation to multiple data elements at once. In fact, the employment of SIMD instructions has been the major driver of the research in this field in recent years [14, 17, 19]. We have contributed to the corpus of proposed efficient implementations, e.g., through our vectorized algorithm for RLE [5], which is based on vectorized comparisons.

As lightweight compression algorithms are always tailored to certain data characteristics, their behavior in terms of performance and compression rate depends strongly on the data. Selecting the best algorithm for a given base column or intermediate requires a thorough understanding of the algorithms' behaviors subject to the data properties. Unfortunately, a sufficient comparative analysis had been missing in the literature. Thus, we conducted an experimental survey of several vectorized state-of-the-art compression algorithms from all five techniques as well as combinations thereof on numerous datasets, whereby we systematically varied the data characteristics [4, 5]. Figure 1a-c provide a sample of our results (the code was compiled using `g++ -O3` and the evaluation system was equipped with an Intel Core i7-4710MQ and 16 GB RAM). Our comparative analysis revealed several new insights. For instance, we could show how different data distributions affect the algorithms. We found that especially outliers in the distributions lead to a significant degradation in the performance and/or compression rate of certain algorithms. Furthermore, for fixed data characteristics, the best algorithm regarding performance is not necessarily the best regarding compression rate. Finally, we could show that combinations of different techniques can heavily improve the compression rate and even the (de)compression speed depending on the data. Summing up our findings, we can state that there is no single-best



DS	Value distribution	Run length
1	normal($\mu = 2^{10}, \sigma = 20$)	constant(1)
2	67% normal($\mu = 2^{6}, \sigma = 20$) 33% normal($\mu = 2^{27}, \sigma = 20$)	constant(1)
3	uniform($[0, 2^{32} - 1]$)	normal($\mu = 20, \sigma = 2$)

Figure 1: Behavior of three compression algorithms (a-c) and a SUM operator on the respective compressed formats (d) for three datasets with different characteristics, each having 100M data elements.

compression algorithm, but the choice depends on the data properties and is non-trivial. Our extensive experimental survey was made feasible by our benchmark framework for compression algorithms [6], which facilitates an efficient and organized evaluation process.

2.2 Direct Data Transformation

Assuming that the optimal compression algorithm was selected for a column, this algorithm might become suboptimal if the data properties change *after the decision*. The properties of the base data might change over time through DML operations. While this case might be handled offline, the problem is more urgent for intermediates, whose properties can change dramatically through the application of an operator. For instance, a column containing outliers might be stored in a format that can tolerate these, perhaps at the price of a slow decompression. A selection operator might remove the outliers, making a faster non-outlier-tolerant algorithm a better choice than the original one. This motivates the need for a *transformation* of the compressed representation of the data in some *source format* to the compressed representation in some *destination format*.

A naïve approach would take two steps: (1) Apply the decompression algorithm of the source format to the data, thereby materialize the entire uncompressed data in main memory. (2) Apply the compression algorithm of the destination format to that uncompressed data. The advantage of this approach is that it builds only upon existing (de)compression algorithms. However, since it materializes the uncompressed data in main memory, it is prohibitively expensive from our point of view, since we need to transform intermediates *during* query execution.

To address this issue, we introduced *direct transformation algorithms* in [7]. This novel class of algorithms is capable of accomplishing the transformation in *one step*, i.e., without the materialization of the uncompressed data. To provide an example, we proposed a direct transformation from RLE to 4-Wise NS. In 4-Wise NS [17], the compressed data is a sequence of compressed blocks of four data elements each. The direct transformation algorithm RLE-2-4WiseNS roughly works as follows: For each pair of run value and run length in the RLE-compressed input, it creates one block of four copies of the run value, compresses it *once*, and stores it out *multiple times* until it reaches the run length. That way, it saves the intermediate store and load as well as the repeated block compression performed by the naïve approach. Our experiments showed that this and other direct transformations yield significant speed ups over the naïve approach, if the data characteristics are suitable.

3. OPERATIONAL ASPECT

In our currently ongoing work in the *operational aspect*, we investigate how to integrate lightweight data compression into the query execution. Thereby, we assume that a multitude of compression algorithms is available to the system. We addressed the challenge of easily fulfilling this prerequisite in [9].

3.1 Processing Model for Compressed Data

Our vision of a query processing based on compressed intermediates can best be investigated using a processing model that actually *materializes all intermediates*. Furthermore, since we focus on column-stores and since lightweight compression algorithms are designed for sequences of values, *all* intermediates should use a *columnar representation*. Hence, we chose *column-at-a-time* as the processing model.

One example of a system that uses this processing model is MonetDB [11], which internally expresses queries in the Monet Algebraic Language (MAL) [2]. The central data structure of MAL is the binary association table (BAT), which is used to represent both, base data and intermediates. Conceptually, a BAT consists of a *head* containing record ids and a *tail* containing the actual data. However, since the head always contains a dense sequence of integers, it can be omitted. Thus, a BAT is essentially just an array of data elements, making it a perfect target for lightweight compression. MAL formally defines a set of operators that consume and produce BATs, such as selection, join, and projection. We decided to use MAL as the foundation of our work, but intend to adapt MAL operators to multiple compressed formats, which we discus in the next section.

3.2 Physical Operators for Compressed Data

When adapting MAL operators to compressed data, different *degrees of integration* are possible. Figure 2 presents the cases we plan to investigate. In general, an operator might consume i inputs and produce o outputs, each of which might be represented in its individual compressed format. Figure 2a shows the baseline case of processing only uncompressed data. In the following, we assume we want to support n compressed formats for *one* operator.

A first approach to support compressed intermediates is shown in Figure 2b. The original operator for uncompressed data is surrounded by a wrapper, which temporarily decompresses the inputs and recompresses the outputs. This

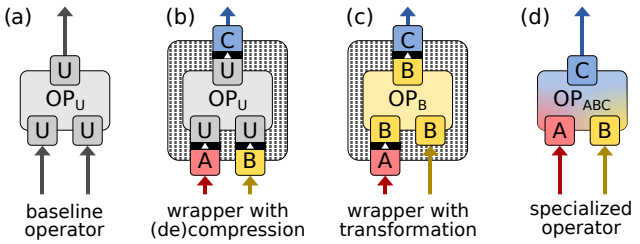


Figure 2: Integration of compression and operators. A to C are compressed formats; U is uncompressed.

approach is called *transient decompression* and was proposed in [3], but to the best of our knowledge, it has never been investigated in practice. For efficiency, the decompression(recompression) should not work on the entire inputs(outputs), but on small chunks fitting into the L1 cache. Changing the compressed format of the intermediates is possible by configuring the wrapper's input and output formats accordingly. The advantage of this approach is its simplicity: It reuses the existing operator and relies only on n already existing (de)compression algorithms. However, it does not exploit the benefits of working directly on compressed data.

The second approach is to adapt the operator such that it can work *directly* on compressed data (Figure 2c). Existing works such as [1, 13, 18] have already proposed *certain* operators on *certain* compressed formats. We plan to contribute to this line of research by covering the formats of recent vectorized compression algorithms. We have already investigated a SUM operator on compressed data and Figure 1d illustrates how significantly its performance depends on the data properties. We assume a common format for all inputs and outputs of the operator; for arbitrary combinations of formats, the operator is again wrapped. However, in this case the wrapper utilizes the *direct transformation* algorithms we developed in the structural aspect. Note that transformations are required only for those inputs(outputs) that are not represented in the operator's native format. The idea of bringing compressed inputs into a common format has already been proposed in [13], but only for joins on dictionary encoded data – and without *direct* transformations. We expect this approach to yield considerable speed ups compared to the first approach, since (i) the compressed data inside the wrapper is smaller, and (ii) the operator works directly on the compressed representation, such that it might, e.g., process more data elements in parallel using SIMD instructions. This approach requires n variants of the operator and $n^2 - n$ transformations, whereby the latter can be reused for all other operators. Nevertheless, the existence of a wrapper still causes a certain overhead.

The final approach tries to maximize the efficiency by tailoring the operator to a specific combination of formats (Figure 2d), making a wrapper unnecessary. Unfortunately, this approach implies the highest integration effort, requiring n^{i+o} operator variants. Thus, we intend to evaluate the potential of this approach first by considering a few promising combinations. If the results show significant improvements over the second approach, we could address the high integration effort, e.g., using code generation techniques.

The investigation of the above approaches is our current work-in-progress. Our ultimate goal is to integrate them into an existing column-store, most likely into MonetDB.

4. OPTIMIZATION ASPECT

There is no single-best compression algorithm, but the decision depends on the data characteristics [5]. Thus, compression must be employed wisely in a query plan to make its benefits outweigh its computational overhead. This motivates the development of compression-aware query optimization strategies, our future work in the *optimization aspect*.

The query optimizer is one of the most complex components of a DBMS. The crucial tasks it fulfills – such as algebraic restructuring and mapping logical to physical operators – are still fundamental for compressed query execution. Due to the high complexity, deeply integrating our compression-aware strategies into an existing optimizer is beyond the scope of this thesis. Instead, we envision a second optimization phase. This phase takes the optimal plan output by an existing optimizer as input and enriches it with compression by selecting an appropriate compressed format for each intermediate and replacing the physical operators by our derived operators for compressed data (Figure 3). In the following, we briefly describe the research challenges we will have to face to achieve this goal.

Local vs. global optimization. A simple approach could be to select the best format for each intermediate in isolation. While this implies a small search space, it might fail to find the optimal plan, e.g., by changing the format too often. A global optimization, on the other hand, requires effective pruning rules to cope with the huge search space.

Creation of a cost model. Due to the complex behavior of lightweight compression algorithms and, therefore, the operators based on them, the comparison of alternative decisions should be based on a cost model. Given a set of data properties, this model must provide estimates for, e.g., the compression rate and operator runtimes.

Estimation of the data characteristics. To use the cost model effectively, the characteristics of the data must be known. However, estimating the properties of all intermediates prior to query execution is non-trivial. Erroneous estimates might result in sub-optimal decisions. Therefore, adaptive optimization strategies might be a solution.

5. CONCLUSIONS

Modern in-memory column-stores address the RAM-CPU-bottleneck through lightweight data compression. However, employing compression has not been investigated sufficiently for intermediate results, although they offer great potential for performance improvement. In this context, we introduced our vision of a *balanced query processing based on compressed intermediates*. We discussed all relevant aspects of the problem in detail: (1) Our completed work in the structural aspect, where we contributed (i) an extensive experimental survey of lightweight compression algorithms and (ii) direct transformation algorithms. (2) Our ongoing work in the operational aspect, where we contribute different variants of physical operators on compressed data. (3) Our future work in the optimization aspect, where we will contribute compression-aware query optimization strategies.

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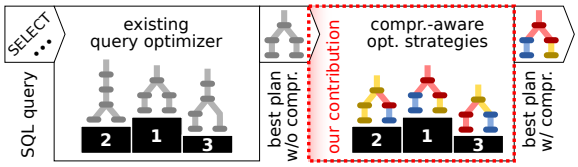

Figure 3: Compression-aware query optimization. Colors in the query plans stand for different compressed formats; grey stands for uncompressed data.

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