The Collection Virtual Machine: 
An Abstraction for Multi-Frontend Multi-Backend Data Analysis

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ABSTRACT

Getting the best performance from the ever-increasing number of hardware platforms has been a recurring challenge for data processing systems. In recent years, the advent of data science with its increasingly numerous and complex types of analytics has made this challenge even more difficult. In practice, system designers are overwhelmed by the number of combinations and typically implement only one analysis-platform combination, leading to repeated implementation effort—and a plethora of semi-compatible tools for data scientists.

In this paper, we propose the “Collection Virtual Machine” (or CVM)—an extensible compiler framework designed to keep the specialization process of data analytics systems tractable. It can capture at the same time the essence of a large span of low-level, hardware-specific implementation techniques as well as high-level operations of different types of analyses. At its core lies a language for defining nested, collection-oriented intermediate representations (IRs). Frontends produce programs in their IR flavors defined in that language, which get optimized through a series of rewritings (possibly changing the IR flavor multiple times) the program is finally expressed in an IR of platform-specific operators. While reducing the overall implementation effort, this also improves the interoperability of both analyses and hardware platforms. We have used CVM successfully to build specialized backends for platforms as diverse as multi-core CPUs, RDMA clusters, and serverless computing infrastructure in the cloud and expect similar results for many more frontends and hardware platforms in the near future.

1 INTRODUCTION

A major goal of systems design has always been to translate increased hardware performance into higher application performance. This consists more and more of exploiting specialized hardware across the entire stack—be it parallelization on the level of SIMD, multi-cores, NUMA, and machines, or support for accelerators such as GPUs or FPGAs or specialized IO devices such as NVMe-based storage or RDMA-capable networking. With the advent of data science and its more diverse and more complex types of analytics, the challenge for system designers has been extended to yet another dimension, the support of multiple platforms at the same time.

While there is ample research on how to exploit each hardware platform in isolation, practitioners are struggling to build systems that support more than one or a few of them at the same time. Also, most popular Python packages for numerous types of analytics with the size of datasets they support as an indication of what platforms they run on. Using RDBMSs and SQL can support datasets of virtually any size, but the packages for data mining, linear algebra, graph analytics, and machine learning are mainly built for running on a single machine, thus supporting datasets of at most some tens of gigabytes. Systems scaling to racks or clusters, such as Spark [20], do support larger datasets; however, if (mis)used in a single-machine setup, they are typically one or several orders of magnitude less efficient. Overall, tools tend to specialize in a relatively narrow type of analysis/platform combination. As a consequence, individual users are forced to switch tools constantly as their datasets, focus of investigation, or hardware change. At the same time, many basic system components are reimplemented in each of the specialized systems leading to both higher implementation effort and less efficient implementations.

To overcome that situation, this project aims to provide system designers with a unified framework across both hardware platforms and target domains. We hypothesize that all (or at least most) modern hardware platforms and types of data analysis used by data scientists today are similar enough to be expressed in intermediate representations (IRs) based on the common abstraction of (nested) transformations of (nested) collections. As we explain in more detail below, analytics in relational algebra, graph analysis, linear algebra, and machine learning work on relations of records, set of vertices and edges, vectors and matrices of numbers, and bags of samples, respectively, all of which are some sort of “collection” of “tuples” of “atoms”. Also implementations, including the most optimized forms, can be described naturally in a nested way: inner loops can be seen as the transformation of individual atoms of one collection into another and the orchestration code around them as the nested compositions of these transformations.

Based on this hypothesis, we build the “Collection Virtual Machine” (CVM), a compiler framework for multi-frontend multi-backend data analysis. Its core is a language for defining collection-oriented intermediate representations (IRs) that consists of arbitrary collection-based “instructions” that we call “operators.” Frontends languages then map to a program in an IR defined in this language, typically using high-level operators that may be in part specific to that frontend. Similarly, the backend of a particular hardware platform can define its instructions expressing the low-level implementation techniques required to maximize performance. Since programs at all levels of abstraction are expressed in the same IR language, rewritings between them can be implemented in a common optimizer framework to bring the input program into an optimized, platform-specific form.

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We have used CVM for the IRs of three different systems: JITQ [1], specialized for multi-core CPUs, Modularis [12], specialized for RDMA clusters, and Lambada [15], specialized for serverless cloud functions. While the three platforms are diverse and require different, specific implementation techniques, they not only share CVMs compiler infrastructure but also the overwhelming majority of their IRs and the rewritings through which they are compiled. Furthermore, they share a generic Python frontend allowing data scientists to change platforms seamlessly. In experiments, we show that the multi-core and RDMA-based systems are roughly on par with mature systems specialized for these platforms while the cloud backend is up to an order of magnitude faster and up to two orders of magnitude cheaper than two commercial RDBMSs optimized for the same use case.

2 RELATED WORK

Our work draws heavy inspiration from relational database systems. Consequently, all work on query optimization and execution techniques are relevant because we are designing CVM such that all of them could be implemented in its IR language. This includes work from the 90s on relational algebra on nested relations [18] and sequences [17], as well as more recent efforts on array database systems [4]. Similarly, there are large bodies of research on domain-specific implementation techniques for linear algebra [9], machine learning algorithms [19], and graph analysis algorithms [6] and we design CVM such that it can also incorporate these techniques.

There has been numerous projects increasing the breadth of systems using a mix of compiler and query optimization techniques. For example, TensorFlow XLA [14] is a high-level compiler built to support different computing platforms including accelerators. To combine different types of analysis in one system, systems like LaraDB [10] and AIDA [7] integrate relational algebra with linear algebra in a single abstraction. Raven [11] uses an IR that enables cross-optimization and integrated execution of ML inference and relational queries. To target even more domains, Tupleware [3] and Weld [16] use query optimization and just-in-time compilation to run algorithms from different domains efficiently but the first is restricted to optimizations possible on UDFs and the IR of the latter is fundamentally limited to shared-memory systems. SystemDS [2] builds on SystemML’s [3] compilation toolchain and can run a wide range of data science processes on multiple backends, including local CPU/GPU and Spark. While the above are built on some kind of IR, they all have in common that their IR consists of a fixed set of instructions, making it difficult to extend with further frontends and backends and thus support a more narrow analysis/platform combination than CVM targets. More recently, the MLIR [13] compiler framework aims to provide tools and abstractions for expressing, transforming, and composing of a wide range of intermediate representations and compilation to a broad range of hardware targets, including ML accelerators, but with a focus on deep learning on GPUs and TPUs.

3 THE COLLECTION VIRTUAL MACHINE

3.1 Architecture Overview

CVM purposefully defines a language of intermediate representations instead of a concrete IR with a fixed set of instructions. It fixes how instructions and collection types look like—not which of them exist. This allows both frontends and hardware-specific backends to define the precise building blocks they need and still evolve as hardware, applications, and experience in IR design make progress.

Figure 1 illustrates an overview of the different components of the Collection Virtual Machine (CVM) and the workflow of transforming a frontend program into an executable form. The figure shows several frontend languages and interfaces that deal with collections, but is not meant to be exhaustive. Analyses in the frontends are expressed as or translated into an intermediate representation (IR) defined in the CVM IR language. This initial translation should be as thin as possible. Frontends may define their own IR flavor including high-level operators, collection types, or data types, for example to perform domain-specific optimizations in a frontend-specific rewriting pass. The frontend and backends we implemented so far are highlighted in the figure.

Once in a CVM IR, the program undergoes a succession of rewritings that bring it into an optimized, executable form. Which rewritings are applied and in which order depends on the frontend and target backend(s) of the system. During the rewriting, the program may change the IR flavor several times, typically (but not necessarily) going from more high-level IRs to more low-level ones and intermediate programs may contain a mix of different IR flavors. Since all programs use IRs defined in the same IR language, mixing both IRs and rewritings is seamless such that system builders can share their implementation efforts. For example, the three systems we have implemented share a common set of rewritings that produce generic data-parallel programs in a common IR and then rewrite some of the instructions as instructions or sequences thereof in their respective target-specific IR flavors.

Finally, the program is in a form where its instructions correspond directly to the executable building blocks of the target backend. Like in compilers, we call the translation process of the final IR flavor into that executable form lowering. For example, a traditional query compiler would lower the IR of physical operators into an execution plan. In JITQ, Modularis, and Lambada, we use...
a combination of two lowerings: we lower pipelines representing the data paths into native machine code using just-in-time compilation and the surrounding orchestration logic into a dataflow-based execution layer.

3.2 IR Language

All IRs in CVM are built on the mental model of an abstract virtual computer that we call the “Collection Virtual Machine”. The virtual machine has an unlimited number of registers that store “collections” and executes linear sequences of “instructions” called “programs.” Any transformation or execution of its IRs must preserve the behavior as if it was executed on that machine.

The IR language allows to define IR flavors consisting of a set of instructions and collection types. All collection types are generic with the following recursive structure:

\[
\text{item} ::= \{ \text{atom} | \text{tuple of items} | \text{collection of items} \},
\]

where an atom is an indivisible value of a particular domain, a tuple is a mapping from a domain of names to items, and a collection is the generalization of any (abstract or physical) data type holding a finite, homogeneous multiset. We denote tuples types by \(\langle \text{name}0 : \text{Type0}, \ldots, \text{nameK} : \text{TypeK} \rangle\) and collections types by \(\text{CollectionType(\text{Type})}\).

Instructions (or operators) defined by any IR flavor have the following structure: They read the collections from zero or more previously assigned registers and assign results to zero or more previously unassigned registers; registers are hence immutable and programs always in static single assignment (SSA) form. Instructions may be parameterized with (constant) items and programs. If an instruction takes a program as parameter, we call it a higher-order instruction. Any instruction is thus of the following form:

\[
\text{Out}_1, \ldots, \text{Out}_m \leftarrow \text{INSTRUCTION(Par}_1, \ldots, \text{Par}_k)(\text{In}_1, \ldots, \text{In}_n)
\]

where \(\text{In}_i\) and \(\text{Out}_i\) are the input and output registers, respectively, and \(\text{Par}_i\) the parameters (i.e., constant items and programs).

3.3 Collection Types

We now show how to define several collection types in CVM’s IR language to express both abstract and physical data structures from various domains. These examples are meant to show the expressiveness of the IR language rather than a final set of types and we expect to add more frontend and backend-specific types as we implement other IRs in the future. Table 1 shows the corresponding data types.

### Abstract (top) and physical (bottom) collection types.

| Domain | Data structure | CVM data type |
|--------|----------------|---------------|
| RA     | \(R(A_1 : D_1, \ldots, A_k : D_k)\) | \(\text{Set}(A_1 : D_1, \ldots, A_k : D_k)\) |
| Bag RA | \(R(A_1 : D_1, \ldots, A_k : D_k)\) | \(\text{Bag}(A_1 : D_1, \ldots, A_k : D_k)\) |
| Seq RA | \(R(A_1 : D_1, \ldots, A_k : D_k)\) | \(\text{Seq}(A_1 : D_1, \ldots, A_k : D_k)\) |
| RA (NF²) | \(R(A_1 : D_1, \ldots, A_k : D_k)\) | \(\text{Bag}(A : \text{Bag}(\ldots))\) |
| LA     | \(v \in \mathbb{R}\) | \(\text{Seq}(\text{Num})\) or \(\text{Seq}(\text{Seq}(\text{Num}))\) |
| Graph  | \(G = (V, E)\) | \(\text{Set}(\text{ID})\) and \(\text{Set}(\langle\text{src : ID}, \text{dst : ID} \rangle)\) |

\(R, I_1, A_k, A\): attribute/field name; \(D_i\): atomic domain

For brevity, we omit empty components.

### Physical collection types.

Second, collections can express physical data layouts as well. As a basic building block, we define the generic type \(\text{Vec}\) (for vector) to represent an array of items in a single contiguous block of memory. Furthermore, we express fixed-width records with ordered fields (like structs in C) as tuples where the lexicographical order of the field names defines the physical order in the layout.

This allows us again to compose many common physical data layouts, such as those shown in the lower half of the table. Both row-store and column-store layout of relations are typically implemented as array of structs and struct of arrays, which we can express with tuples and Vec. The three systems we have built so far use both relation types in their IRs. Notice that we define the generic type \(\text{Single}\) as a singleton collection holding just one tuple as a helper to store a group of collections in a single register. Similarly, the data structures used typically for linear algebra (both dense and sparse) are composed of arrays and structs, so we can express them with the same data types as shown in the table. We only show the sparse matrix format CSR (for “compressed sparse row”), which consists of an integer for the number of non-zero elements and three arrays (the non-zero elements, their column indices, and the offsets

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\(^{\text{Footnote}}\) For brevity, we omit empty components.
of each row into the first two), but the other common formats can be defined analogously.

Finally, as shown in the table, we define `ArrayN` as sequence with compile-time size `N` to express vectors of machine words for SIMD-style processing. The same collection type can also be used to model a row of a narrow dense matrix to enable compile-time optimizations for that special case.

The actual physical representation is decided by the lowering. For example, our three systems have an execution layer that stores tuples of fixed-width fields in the memory layout of a C-arrays of C-structs and thus require the final IR to contain only sequences of anonymous tuples, which are then lowered accordingly. For that to work, we activate a sequence of rewriting passes that bring the programs into the expected form. We discuss these rewritings in more detail later in this section.

Custom collection types. Finally, we can define new collection types to support arbitrary physical formats and data structures. For example, we have defined collection types for Apache Arrow and Parquet, and other formats such as Protocol Buffers or Avro could be supported with the same approach. This allows frontends to support existing data formats and backends to use specialized, highly-tuned data structures as data types in their respective IR flavors.

### 3.4 Instructions

As described above, instructions defined in the CVM IR language transform collections into other collections. Instructions may have restrictions on the item types of their input collections and the types of their outputs may depend on their input types. Broadly speaking, the level of abstraction of instructions corresponds to the level of abstraction of the collections they work on. Table 2 shows instructions and their input and output types of various levels of abstractions.

High-Level Instructions. The upper part of the table shows high-level, domain-specific instructions that typically constitute the IRs used for the initial translation of user-facing programs. For example, an IR for a relational query processor could define the usual relational operators on this level. The table shows the definition of projection (`Proj`), which is only defined on collections of tuples.\(^3\) If the collection is a sequence (`Seq`) or set (`Set`), then so is the output. While the projection only restricts the field names of the tuples, the extended projection (`ExProj`) also allows us to compute new fields. We also define a `Map` instruction, which we use in our generic dataflow frontend and which, in contrast to the projections, can work on arbitrary item types. We define instructions for other relational or generic dataflow operators in much the same way as `Proj` and `Map`; however, we do not show them here due to space constraints.

As an example for an IR of a different application domain, the table shows an instruction for matrix-matrix multiplication (`MMMult`). We can define instructions for other basic operations of linear algebra including multiplications of tensors of different dimensions, inversion, transposition, etc. analogously. This allows to do high-level optimizations based on mathematical and other domain-specific equivalences.

Notice how our definition of collections on different types of items allows to express linear algebra and relational algebra in the

| Instruction          | Input type(s) | Output type(s) |
|----------------------|---------------|----------------|
| `Proj(A_1, ..., A_k)(C)` | `Coll(A_1, ..., A_k)` | `Bag(A_1, ..., A_k)` |
| `ExProj((A'_1, f_1)_{j_k} \to I_j)` | `Coll(A_1, ..., A_k)` | `Bag(I'_1)` |
| `Map(f : I_1 \to I_2)` | `Coll(I_1)` | `Bag(I_2)` |
| `MMMult(C_1, C_2)` | `2DSeq(Num)` | `2DSeq(Num)` |
| `Loop(n, P)(C_1, ..., C_k)` | `Coll(I_1)` | `Coll(I_1)` |
| `While(P)(C_1, ..., C_k)` | `Coll(I_1)` | `Coll(I_1)` |
| `Cond(P)(C_1, ..., C_k)` | `Coll(I_1)` | `Coll'(I'_1)` |
| `Call(P)(C_1, ..., C_k)` | `Coll(I_1)` | `Coll'(I'_1)` |
| `ConcurExecute(P)(C)` | `Coll(I_1)` | `Bag(I_2)` |
| `ScanVec(C)` | `Coll(Vec(I_1))` | `Seq(I)` |
| `MatVec(C)` | `Coll(I)` | `Single(Vec(I))` |
| `SplitVec(n)(C)` | `Coll(Vec(I_1))` | `Bag(0)` |
| `BuildHashTable(C)` | `Coll(T_1)` | `Single(HTab(T))` |
| `ProbeHashTable(C, H)` | `Coll(T_1)` | `Bag(T_2)` |

\(^3\)However, the fields of the tuples may consist of arbitrary items.

Table 2: Domain-specific, control-flow-like, and low-level instructions.

The same framework. We can convert collections of one domain to the other by packing (or unpacking) each item into (from) a tuple with a single field, so our IR allows to combine programs of various frontends and do optimizations across interface barriers.

Control Flow. The middle part of the table shows instructions we use to express control-flow-like behavior. Notice that the CVM IR language does not allow for traditional control flow such as jumps. This is done by design as jumps make it hard to understand the semantics of a program, which makes many optimizations difficult or impossible to achieve. However, we can use the capability of defining higher-order instructions to achieve similar effects: The table gives the example of a `Loop` instruction that is parameterized with a nested program and a constant number `n` and executes the program `n` times. It reads its input through input registers as any other instruction, forwards them as initial input of the inner program, and then uses the result registers of the previous run as new input. The final result of the `Loop` instruction corresponds to what the `Return` instruction of the last run of the inner program returns. While and `Cond` (for conditional expression) can be defined in a similar way.
Algorithm 1 Initial CVM program of TPC-H Query 6.

\[\begin{align*}
\text{program } & \text{TpchQ6Seq}(\text{lineitem} : \text{Coll}(\text{Tlineitem})) \\
\text{filtered} & \leftarrow \text{Select}(p)(\text{lineitem}) \\
\text{projected} & \leftarrow \text{ExProj}(\text{l_discount}, \text{l_quantity})(\text{filtered}) \\
\text{result} & \leftarrow \text{Aggr}(\text{x}, \text{sum} \rightarrow \text{revenue})(\text{projected}) \\
\text{Return}(\text{result}) & 
\end{align*}\]

Algorithm 2 Parallelized CVM program TPC-H Query 6.

\[\begin{align*}
\text{program } & \text{TpchQ6Par}(\text{lineitem} : \text{Coll}(\text{Tlineitem})) \\
\text{parts} & \leftarrow \text{Split}(p)(\text{lineitem}) \\
\text{part_results} & \leftarrow \text{ConcurrentExecute}(\text{TpchQ6Seq})(\text{parts}) \\
\text{unnested} & \leftarrow \text{Scan}(\text{part_results}) \\
\text{result} & \leftarrow \text{Aggr}(\text{revenue}, \text{sum} \rightarrow \text{revenue})(\text{unnested}) \\
\text{Return}(\text{result}) & 
\end{align*}\]

Parallel execution may also be counted as control flow. The table shows the ConcurrentExecute instruction, which we use to represent parallelism in our three systems. It has similar semantics as the higher-order instruction Map, i.e., it executes a program on each input item to compute an output item, but guarantees that these programs are executed concurrently such that the different executions can exchange data among them. Furthermore, each system has its own, platform-specific version of ConcurrentExecute, which implements the concurrent execution of threads, MPI workers, and serverless cloud functions, respectively.

Low-Level Instructions. Finally, low-level instructions represent specific building blocks of different backends. On this level, we follow the philosophy to make these operators as small as possible to make them more generic and hence reusable. Our goal is to express cleverness as a sophisticated combination of simple operators instead of a simple combination of sophisticated operators. We refer to our work on Modularis [12] for details. For example, we have a scan operator, a materialize operator, and potentially a split operator (for parallelization) for each of the backend-level collection types mentioned above (the table shows those of Vec). Similarly, we define a build and a probe operator for each hash table type that we implement (some of which are tuned for a very specific case).

Furthermore, many if not all low-level tuning techniques developed by the database community in the last years can be encapsulated as operators:

- hardware-conscious algorithms and data structures,
- light-weight compression schemes,
- build and probe of spatial indices or other domains, and
- predicated or vectorized scans, to name just a few.

Notice that all of them fall into our structure of CVM-based instructions. Our IR language thus makes it possible to use very specialized implementation techniques and still represent them in a common abstraction.

3.5 Lowerings to Execution Layers

The CVM compilation toolchain can be used to target any execution layer. As mentioned before, a traditional relational query engine could define its physical query plans as an IR and lower programs in that IR into an execution plan composed of its executable operators. For example, we use MonetDB’s execution layer by translating programs through a series of rewritings into an IR that replicates the MonetDB Assembly Language (MAL) and then lowering them into actual MAL for execution.

For JITQ, Modularis, and Lambda, we use a common execution layer for the data paths and specialized components for the execution of and communication among parallel workers. The common part deals with the most fine-grained level, where operators pass individual tuples between each other. In a rewriting pass, we extract tree-shaped parts of a program and translate them into pipelines of Volcano-style iterators. To eliminate the overhead of this operator interface and to allow low-level optimizations across operator boundaries, we just-in-time-compile each pipeline to native machine code. The inputs and outputs of each pipeline constitute necessary materialization points of the original program.

3.6 Rewritings

The rewriting mechanism of CVM is highly flexible and configurable, such that every frontend/backend combination can do the rewritings that are best suited for that combination. For the different IR flavors to co-exist, at least during compilation, rewritings must work in presence of collection types and instructions of any IR. Optimizations (or lowerings) that require a particular property (such as tree-shaped data dependencies) thus either have to rewrite the program to establish that property first or work only on those parts of a program where the property holds.

Algorithms 1 and 2 illustrate how the rewriting for generic parallelization works taking Query 6 of the TPC-H benchmark as an example. The initial program (TpchQ6Seq) consists of a selection, a computation, and a scalar aggregation. Our rewriting rule first replaces the usage of the input relation (lineitem) with a Split followed by an empty ConcurrentExecute and a Scan.

Notice that the sequence of these three operators is a logical no-op. Then it applies rules that expand the ConcurrentExecute in a way that preserves the semantics: It moves Select and ExProj inside, while it copies Aggr as pre-aggregation. If an unknown instruction had been encountered, then the rule would leave it as is. The resulting parallelized program is shown by Algorithm 2. As mentioned earlier, our three systems each continue with a target-specific rewriting pass that rewrite the program in Algorithm 2 into an IR for thread-parallelism, RDMA clusters, or cloud functions, respectively.

In the future, we plan to extend the rewritings considerably. We think that all traditional query optimization techniques from database systems can be done on CVM IRs, including join reordering, index selection, etc.

4 EXPERIMENTS

In this section, we show the experimental results of CVM on three different hardware platforms: in-memory, distributed and serverless. Although for some hardware configurations our platform is

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slower for analytical workloads, the goal of the experimental study is not to focus on raw performance but rather to show the flexibility of our frontends and backends through the use of platform-specific operators and rewrite rules. That comes with a reasonable performance overhead compared to state-of-the-art data processing systems in most cases, while there are some others where CVM is on par or even faster than state-of-the-art. For all experiments described below, unless otherwise stated, we run each query four times, use the first run as a warm-up and then report the average of the other runs.

**In-memory.** For the in-memory experiments, we use two workloads: (1) TPC-H queries with scale factor 10, and (2) the k-means clustering algorithm with a synthetic dataset comprising of $2^{24}$ 5-dimensional points. The numbers for HyPer and Flare are taken from [8]. For k-means, we choose the most popular ML Python package, scikit-learn ("sklearn"), as a competitor and we report the time of a single iteration. Both experiments were run on an Intel Xeon E5-2630 v3 CPU 2.4 GHz. We report the execution times for TPC-H queries (left) and the k-means algorithm (right) in Figure 2.

We observe that the column-wise operations performed by MonetDB for Q1 have a negative impact in the running time whereas JITQ lowers the same query into a single pipeline which leads to producing the result in a single pass. We also observe that when the input data are largely reduced due to very selective filters, such as in Q19, JITQ outperforms the competitors. We believe that implementing other missing optimizations like support for narrow data types, a sophisticated optimizer and index-based grouping will make our performance on par for other queries as well.

For k-means, we achieve the performance of the hand-written C++ library used under the hood in scikit-learn, mainly due to a plan analysis that enables run-based aggregation. The experiments show how that high-level analysis and just-in-time-compilation achieves in-memory processing speed that matches hand-written code performance.

**Distributed RDMA cluster.** For the distributed experiments, we use 8 machines each with two CPUs Intel Xeon E5–2609 2.40 GHz and 128GB of RAM. The machines are connected through an InfiniBand network with a Mellanox QDR HCA network card. We use TPC-H queries with scale factor 500 and compare against two popular distributed systems, MemSQL and Presto which were configured to use the entire cluster. For Presto, we use HDFS nodes with default configurations to store TPC-H data.

Figure 3 shows the running times for executing the TPC-H queries across the three systems. To have a fair comparison with Presto, we also include the time that Modularis needs to read the input data. We observe that for queries 4 and 12 Modularis is on par with MemSQL and regarding queries 14 and 19, MemSQL is 33% and 25% faster, respectively. Our system is 6-9x faster than Presto, depending on the query. Therefore, we can conclude that Modularis’ performance is very close to a highly optimized in-memory distributed database and orders of magnitude faster than a popular big-data SQL query engine.

Additionally, in contrast to the above specialized systems, CVM supports this platform, only by implementing a few hardware-conscious operators (i.e., MPIExecutor, MPIExchange, MPIHistogram) and by adding additional rewrite rules for incorporating such operators. For instance, we wrote a specialized version of ConcurrentExecute called MPIExecutor that uses OpenMPI to distribute processes among the machines in the cluster.

**Serverless functions.** Finally, we show how Lambada executes analytical workloads on a serverless platform. Figure 4 shows the running time and monetary cost of TPC-H queries on serverless cloud services. To showcase the elasticity of serverless computing, we use TPC-H data at scale factor 1000 and decide to use as many serverless workers needed to enable running queries with interactive latencies. Compared to other serverless solutions, Google BigQuery and Amazon Athena, Lambada is up to an order of magnitude faster and up to two orders of magnitude cheaper. This shows that the addition of new lowerings for this platform is orthogonal to existing optimizations.

It is worth restating that when using CVM, the same frontend programs run as in the previous experiments while only adding operators and incorporating rewriting rules. For instance, Lambada lowers ConcurrentExecute into ParallelLambdaMap an operator that invokes AWS Lambda workers, and it also transforms other operators into Amazon S3 specific operators. Other optimizations such as selections and projections can still be applied by putting them directly into the operator that reads from Amazon S3. Adding such functionality in the other serverless solutions would possibly imply major code rewrites.
5 CONCLUSIONS
In this paper, we proposed the Collection Virtual Machine, an abstraction for system designers that keeps supporting the growing number of combinations of domain-specific frontends and hardware backends tractable. We have used CVM for the IRs of three different systems: JITQ [1], Modularis [12], and Lambda [15]. While their target platforms are diverse, we have shown how CVM allows the three systems to share large parts of their IRs and rewritings in a common framework and still get comparable performance with systems designed from scratch for the respective hardware platforms. In the near future, we plan to add other frontends as well as more hardware platforms, where we expect similar results.

REFERENCES
[1] Sabir Akhadov. “PySpark at Bare-Metal Speed”. MA thesis. ETH Zürich, 2017. doi: 10.3929/ethz-b-000263341.
[2] Matthias Boehm, Iulian Antonov, Mark Dokter, Robert Ginthoer, Kevin Innerebner, Florijan Klezin, Stefanie Lindstaedt, Arnab Phani, and Benjamin Rath. “SystemDS: A Declarative Machine Learning System for the End-to-End Data Science Lifecycle”. In: CIDR. 2020.
[3] Matthias Boehm, Michael W Dusenberg, Deron Eriksson, Alexandre V Efimievski, Faraz Makari Manshadi, Niketan Pansare, Berthold Reinwald, Frederick R Reiss, Prithviraj Sen, Arvind C Surve, and Shirish Tatikonda. “SystemML: Declarative Machine Learning on Spark”. In: PVldb 9.13 (2016). doi: 10.14778/3007263.3007279.
[4] Paul G. Brown. “Overview of SciDB: Large Scale Array Storage, Processing and Analysis”. In: SIGMOD. 2010. doi: 10.1145/1807167.1807271.
[5] Andrew Crotty, Alex Galakatos, Kayhan Dursun, Tim Kraska, Carsten Binnig, Ugur Cetintemel, and Stan Zdonik. “An Architecture for Compiling UDF-centric Workflows”. In: VLDB 8.12 (2015). doi: 10.14778/2824032.2824045.
[6] Niels Doekemeijer and Ana Lucia Varbanescu. A Survey of Parallel Graph Processing Frameworks. Tech. rep. DS-2014-003. TU Delft, 2014.
[7] Joseph Vinish D’silva, Florestan De Moor, and Bettina Kemme. “AIDA - Abstraction for Advanced In-Database Analytics”. In: VLDB 11.11 (2018). doi: 10.14778/3236187.323619.
[8] Gregory Esertel, Ruby Tahboub, James Decker, Kevin Brown, Kunle Olukotun, and Tiark Rompf. "Flare: Optimizing Apache Spark for Scale-Up Architectures and Medium-Size Data". In: OSDI. 2018.
[9] Kazushige Goto and Robert A. van de Geijn. “Anatomy of High-Performance Matrix Multiplication”. In: TOMS 34.3 (2008). doi: 10.1145/1356052.1356053.
[10] Dylan Hutchison, Bill Howe, and DanSuciu. “LaraDB: A Minimalist Kernel for Linear and Relational Algebra Computation”. In: BeyondMR. 2017. doi: 10.1145/3070607.3070608.
[11] Konstantinos Karanasos, Matteo Interlandi, Doris Xin, Fotis Psalidis, Rathijit Sen, Kwanghyun Park, Ivan Popivanov, Supun Nakandala, Subru Krishnan, Markus Weimer, et al. “Extending Relational Query Processing with ML Inference”. In: CIDR. 2020.
[12] Dimitrios Koutsoukos, Ingo Müller, Renato Marroquín, and Gustavo Alonso. Modularis: Modular Data Analytics for Hardware, Software, and Platform Heterogeneity. 2020. arXiv: 2004.03488 [cs.DB].
[13] Chris Lattner, Mehdi Amini, Uday Bondhugula, Albert Cohen, Andy Davies, Jacques Pienaar, River Riddle, Tatiana Shpeisman, Nicolas Vasilache, and Oleksandr Zinenko. “MLIR: A Compiler Infrastructure for the End of Moore’s Law”. In: arXiv. 2020. arXiv: 2002.11054.
[14] Chris Leary and Todd Wang. “TensorFlow, Compiled”. In: TensorFlow Dev Summit. 2017.
[15] Ingo Müller, Renato Marroquín, and Gustavo Alonso. “Lambada: Interactive Data Analytics on Cold Data using Serverless Cloud Infrastructure”. In: SIGMOD. 2020. doi: 10.1145/3318464.3389758.
[16] Shoumik Palkar, James Thomas, Deepak Narayanan, Pratiksha Thaker, Rahul Palamuttam, Parimajnan Negi, Anil Shanbhag, Malte Schwarzkopf, Holger Pirk, Saman Amarasinghe, Samuel Madden, Matei Zaharia, S Palkar, J Thomas, D Narayanan, P Thaker, R Palamuttam, and P Negi. “Evaluating End-to-End Optimization for Data Analytics Applications in Weld”. In: PVldb 11.8 (2018). doi: 10.14778/3213880.3213890.
[17] R. Ramakrishnan, D. Donjerkovic, A. Ranganathan, K.S. Beyrer, and M. Krishnaprasad. “SRQL: Sorted Relational Query Language”. In: SSDM. 1998. doi: 10.1109/SSDM.1998.688114.
[18] Mark A. Roth, Herry F. Korth, and Abraham Silberschatz. “Extended Algebra and Calculus for Nested Relational Databases”. In: TODS 13.4 (1988). doi: 10.1145/49346.49347.
[19] I. H. (Ian H.) Witten, Eibe Frank, Mark A. (Mark Andrew) Hall, and Christopher J. Pal. Data Mining: Practical Machine Learning Tools and Techniques. 4th ed. 2017. ISBN: 9780128043578.
[20] Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, and Ion Stoica. “Spark: Cluster Computing with Working Sets”. In: HotCloud. 2010.