ABSTRACT

The need for modern data analytics to combine relational, procedural, and map-reduce-style functional processing is widely recognized. State-of-the-art systems like Spark have added SQL front-ends and relational query optimization, which promise an increase in expressiveness and performance. But how good are these extensions at extracting high performance from modern hardware platforms?

While Spark has made impressive progress, we show that for relational workloads, there is still a significant gap compared with best-of-breed query engines. And when stepping outside of the relational world, query optimization techniques are ineffective if large parts of a computation have to be treated as user-defined functions (UDFs).

We present Flare: a new back-end for Spark that brings performance closer to the best SQL engines, without giving up the added expressiveness of Spark. We demonstrate order of magnitude speedups both for relational workloads such as TPC-H, as well as for a range of machine learning kernels that combine relational and iterative functional processing.

Flare achieves these results through (1) compilation to native code, (2) replacing parts of the Spark runtime system, and (3) extending the scope of optimization and code generation to large classes of UDFs.

1. INTRODUCTION

Modern data analytics applications require a combination of different programming paradigms, spanning relational, procedural, and map-reduce-style functional processing. Shortcomings in both expressiveness and performance are key reasons why the excitement around early MapReduce tools, heralded as the solution to all big data problems, has tapered off. Instead, state-of-the-art systems like Spark have added SQL front-ends and APIs which enable relational query optimization.

But how good are these extensions? We demonstrate that on standard relational benchmarks such as TPC-H, Spark SQL still performs at least an order of magnitude worse than best-of-breed relational query engines like HyPer. This is, in part, due to the fact that these relational query engines not only optimize query plans aggressively on the relational operator level, but also compile queries into native code, thus operating closer to the metal than Spark’s current Java-based techniques.

While one might argue that this is not a fair comparison due to the added expressiveness of Spark and the different nature of these systems, we show that it is actually possible to bring the performance of Spark much closer to such highly-optimized relational engines without sacrificing this added expressiveness. We present Flare, a new back-end for Spark that yields significant speedups by compiling entire query plans obtained from Spark’s query optimizer to native code, bypassing inefficient abstraction layers of the Spark runtime system.

Heterogeneous Workloads. While Flare’s native code translation alone already provides excellent performance for SQL queries and DataFrame operations, performance still suffers for heterogeneous workloads, e.g., when executing many small queries interleaved with user code, or when combining relational with iterative functional processing, as is common in machine learning pipelines. While the extract, transfer, and load part (ETL) of such pipelines can often be implemented as DataFrames, the compute kernels often have to be supplied as user-defined functions (UDFs), which appear as black boxes to the query optimizer, and thus remain as unoptimized library code.

For such workloads, Flare takes advantage of Delite, an existing compiler framework for high-performance domain-specific languages (DSLs). As an alternative to generating target code in a single step, Flare can map Spark’s query plans to Delite’s intermediate language, DMLL. This enables Spark to interface with UDFs written in any of the existing Delite DSLs, which cover domains such as machine learning (OptiML), graph processing (OptiGraph), or mesh-based PDE solvers (OptiMesh). All of these DSLs are embedded in Scala and provide APIs comparable to those built on top of Spark. But unlike Scala code that uses normal Spark APIs, Delite DSL code is amenable to optimization and native code generation, including GPU code for computational kernels. We show that combining Spark SQL queries and DataFrames with machine learning kernels written in OptiML, in particular, results in order of magnitude speedups compared to a standard Spark implementation.
Scale-Up over Scale-Out. With the implementation of Flare, we revisit some design decisions of Spark SQL rooted in the legacy of Spark and earlier systems. We show that alternative implementations, which start from different assumptions, can provide better performance with the same expressive user-facing API.

One key assumption of MapReduce, Hadoop, and Spark is that of a Google-scale, distributed, shared-nothing architecture, focusing primarily on scale-out vs scale-up. This makes it easy to scale computation by adding more machines, but it also means that each individual machine may not be used efficiently [61]. An immediate consequence is an increase in datacenter bills, but on a global scale, the effects of scale-out-first approaches (a.k.a. “nobody ever got fired for running a Hadoop cluster”) and their inefficient use of energy may be as far-reaching as accelerating global warming.

Today, machines with dozens of cores and memory in the TB range are readily available, both for rent and for purchase. At the time of writing, Amazon EC2 instances offer up to 2 TB main memory, with 64 cores and 128 hardware threads. Built-to-order machines at Dell can be configured with up to 12 TB, 96 cores and 192 hardware threads. NVIDIA advertises their latest 8-GPU system as a “supercomputer in a box,” with compute power equal to hundreds of conventional servers [66]. With such powerful machines becoming increasingly commonplace, large clusters are less and less frequently needed. Many times, “big data” is not that big, and often computation is the bottleneck [27]. As such, a small cluster or even a single large machine is sufficient, if it is used to its full potential.

With this scenario as the primary target – heterogeneous workloads and small clusters of powerful machines, potentially with accelerators such as GPUs – Flare prioritizes bare-metal performance on all levels of scaling, with the option of bypassing mechanisms such as fault-tolerance for shared-memory-only execution. Thus, Flare strengthens Spark’s role as a unified, efficient, big data platform, as opposed to a mere cluster computing fabric.

The overall architecture of Flare, with three possible levels of integration, is shown in Figure 1. The paper first reviews the design of Spark and Spark SQL (Section 2) and continues with our main contributions:

- We present Flare: a new accelerator back-end for Spark. We identify key impediments to performance in Spark SQL, particularly related to Spark’s Java execution environment. As an immediate remedy, Flare Level 1 generates native code instead of Java for improved performance (Section 3).
- We identify further performance issues in Spark SQL, specifically related to joins in shared-memory environments. Flare Level 2 drastically reduces these overheads by making different starting assumptions than Spark, focusing on scale-up instead of scale-out, and reducing constant factors throughout. In particular, Flare Level 2 compiles whole queries at once, as opposed to individual query stages, which results in an end-to-end optimized data path (Section 4).
- We extend Flare further to accelerate heterogeneous workloads, consisting of relational queries combined with iterative machine learning kernels written as user-defined functions. Flare Level 3 uses the Delite compiler framework to optimize relational queries together with such UDFs, by means of an intermediate language (Section 5).
- We evaluate Flare in comparison to Spark both on TPC-H, reducing the gap to best-of-breed relational query engines, and on benchmarks involving heterogeneous machine learning workloads. In both settings, Flare exhibits order-of-magnitude speedups. Our evaluation spans single-core, multi-core, NUMA, cluster, and GPU targets (Section 6).

2. BACKGROUND ON SPARK

Apache Spark [51, 52] is today’s most popular and most widely-used big data framework. The core programming abstraction is an immutable, explicitly distributed, collection data type called RDD (Resilient Distributed Dataset). RDDs serve as high-level programming interfaces and also transparently manage fault-tolerance.
Here is a quick example (from [7]) that counts the number of errors in a (potentially distributed) log file:

```scala
val lines = spark.sparkContext.textFile("...")
val errors = lines.filter(s => s.startsWith("ERROR"))
println("Total errors: " + errors.count())
```

Spark’s RDDs provide a deferred API: in the above example, the calls to `textFile` and `filter` merely construct a computation graph. Actual computation only takes place at the point where `errors.count` is invoked. Sometimes, RDDs are described as lazily evaluated. This is somewhat misleading, as a second call to `errors.count` will re-execute the entire computation.2 However, RDDs support memoization via explicit calls to `errors.persist()`, which will mark the data set to be kept in memory for future operations.

## 2.1 Spark SQL and the DataFrame API

The directed acyclic computation graph represented by an RDD describes the distributed operations in a coarse-grained way, at the granularity of `map`, `filter`, and so on. This level of detail is enough to enable demand-driven computation, scheduling, and fault-tolerance via selective recomputation along the “lineage” of a result [51], but it does not provide a full view of the computation applied to each element of a data set. For example, in the code snippet above, the argument to `lines.filter` is a normal Scala closure. This makes it easy to integrate RDD code with arbitrary external libraries, but it also means that the given closure needs to be invoked as-is for every element in the data set.

Thus, the performance of RDDs suffers from two limitations: first, limited visibility for analysis and optimizations, especially standard optimizations like join re-ordering for relational workloads expressed as RDDs; and second, interpretive overhead, i.e. function calls for each processed tuple. Recent Spark versions aim to ameliorate both of these issues with the introduction of the Spark SQL subsystem [7].

### 2.1.1 Spark SQL and the DataFrame API

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The core addition of Spark SQL is an alternative API based on DataFrames [7]. A DataFrame is conceptually equivalent to a table in a relational database, i.e., a collection of rows with named columns. However, like RDDs, the DataFrame API only records operations, but does not compute the result right away. We can write the same example as before:

```scala
val lines = spark.sql("select * from lines")
val errors = spark.sql("select * from lines
where value like 'ERROR\%'")
println("Total errors: " + errors.count())
```

This is just like the RDD API, in that the call to `errors.count` will trigger execution. Unlike RDDs, however, DataFrames capture the full computation/query to be executed. We can obtain the internal representation using `errors.explain()`

```scala
println("Total errors: " + errors.count())
```

which produces the following output:

> Total errors: 4

1 In its original definition, the term “lazy evaluation” means that each term is evaluated only when needed, and not more than once [22].

2 Internally, Spark distinguishes the type `Dataset[T]`, which provides a typesafe collection API for elements of type T, from the type `DataFrame = Dataset[Row]`, which provides an untyped API for rows with arbitrary arity and column names. For the purpose of this paper, this difference is immaterial; hence, we use the terms `Dataset` and `DataFrame` interchangeably.

From the high-level DataFrame operations, Spark SQL internally computes a query plan, much like a relational DBMS. Spark SQL optimizes query plans using its relational query optimizer called Catalyst, and may even generate Java code at runtime to accelerate parts of the query plan using a component named Tungsten (see Section 2.3).

It is hard to overstress the benefits of this kind of API, which generates a complete program (i.e. query) representation at runtime. First, it enables various kinds of optimizations, including classic relational query optimizations. Second, one can use this API from multiple front-ends, which exposes Spark to many JVM languages such as Python and R, and the API can also serve as a translation target from literal SQL:

```scala
val lines = spark.sql("select * from lines")
val errors = spark.sql("select * from lines
where value like 'ERROR\%'")
println("Total errors: " + errors.count())
```

Third, one can use the full host language to structure code, and use small functions that pass DataFrames between them to build up a logical plan that is then optimized as a whole.

Of course, this is only true as long as one stays in the relational world, and does not use UDFs. As part of our contribution, we will show in Section 3 how the DataFrame model extends to UDFs in Flare. Flare uses existing generative programming frameworks [22] to make larger classes of expressions available for DataFrame-like multi-stage programming patterns, where a general piece of program code builds up an intermediate representation (IR) of a more specific computation at runtime, like DataFrames with query plans. We argue that such multi-stage APIs, including Spark’s DataFrames, are the real key to success for unified and efficient big data platforms, completely independent of RDDs. We will show in Section 3.1 that the underlying RDD layer can actually be an impediment to performance in Spark. Flare demonstrates that Spark’s DataFrame API can successfully be supported by a generic, high-performance DSL compiler framework. This removes the confinement to relational query optimizations, and enables optimization of entire data processing pipelines that combine relational processing with iterative machine learning kernels that would require unoptimized UDFs in plain Spark.

## 2.2 The Power of Multi-Stage APIs and DSLs

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## 2.3 Catalyst and Tungsten

Spark SQL queries are optimized using the Catalyst optimizer that supports both rule-based and cost-based optimizations [7]. Starting with a logical query plan tree, Catalyst performs optimizations as tree transformations in order to realize an optimized plan. It is important to note that at the time of writing, Catalyst does not yet perform any kind of join reordering. Instead, it simply joins tables in the order they appear in the `where` clause. Hence, users need to manually encode a good join in order to avoid big intermediate tables or other bad surprises.

Tungsten is the execution back-end that aims to improve Spark performance by reducing the allocation of objects on the JVM (Java Virtual Machine) heap, controlling off-heap memory management, employing cache-aware data struc-
Figure 2: Query 6 from the TPC-H benchmark in Spark.

```
val tpchq6 = spark.sql(""
  select
    sum(l_extendedprice*l_discount) as revenue
  from
    lineitem
  where
    l_shipdate >= to_date('1994-01-01')
    and l_shipdate < to_date('1995-01-01')
    and l_quantity < 24
    and l_discount between 0.05 and 0.07

...
```

Figure 2: Query 6 from the TPC-H benchmark in Spark.

```
// data loading elided ...
for (i = 0; i < size; i++) {
  double l_extendedprice = l_extendedprice_col[i];
  double l_quantity = l_quantity_col[i];
  double l_discount = l_discount_col[i];
  long l_shipdate = l_shipdate_col[i];
  if (l_shipdate >= 19940101L && l_shipdate < 19950101L &&
      l_quantity < 24.0) {
    revenue += l_extendedprice * l_discount;
  }
}
```

Figure 3: Q6 hand-written C code

```
Spark SQL Preload ms Query ms
Direct CSV - 24,400
Preload CSV 118,062 1,418
Hand-Written C / Flare
Preload CSV 2,847 45
```

Figure 4: Running times for Q6 in Spark, with and without pre-loading, and compared to hand-written code and Flare.

As our benchmark, we pick the simplest query from the industry-standard TPC-H benchmark: Query 6 (shown in Figure 2). We define the schema of table lineitem, provide the source file, and finally register it as a temporary table for Spark SQL (steps not shown). For our experiments, we use scale factor 2 (SF2) of the TPC-H data set, which means that table lineitem is stored in a CSV file of about 1.4 GB. Following the setup by McSherry et al., we run our tests on a fairly standard laptop. We run our query, Q6, straight from the CSV file as input, and record the running time:

```
scala> val q = spark.sql(tpchq6)
q: org.apache.spark.sql.DataFrame = [revenue: double]
scala> time(q.show)
```

```
Completed in 24,400 ms
```

Clearly, this result of 24 seconds is not the best we can do (see Figure 3). We could convert our data to the columnar Apache Parquet format for increased performance, or we can just preload the data so that subsequent runs are purely in-memory. Since we are mainly interested in the computational part, we opt to preload. We note in passing that preloading is quite slow (almost 2 min), which may be due to a variety of factors. Now we can execute our query in-memory, and we get a much better result. Running the query a few more times yields further speedups, but timings stagnate at around 1s. The key question now is: how good is this result?

**Hand-Written C.** Since Query 6 is very simple, it is perfectly feasible to write a program in C that performs exactly the same computation: map the input file into memory using the mmap system call, load the data into an in-memory columnar representation, and then execute the main query loop, shown in Figure 3. If we compile this C program with gcc -O3 Q6.c and run it, it will take 2.8s in total (including data loading), and just 45ms for the actual query computation. So compared to Spark 2.0, the C program runs 20× faster!

Is there any good reason why the C code needs to be faster than Spark? We believe not, and in fact, running the same
query, Q6, accelerated with Flare yields exactly the same performance as the hand-written C code. The same holds for other best-of-breed, main-memory RDBMSs like HyPer \[39\], which takes 46.58ms on a comparable machine.

**Identifying the Bottlenecks.** To understand these performance gains, we need to investigate where Spark SQL spends its time. There are two reasons for the performance difference, both of which are particularly visible in the case of Q6, which has low computational content and uses only trivial query operators. First, we observe that Spark’s Tungsten layer generates Java code for this query. In fact, two pieces of code are generated: one piece for the main query loop, the other an iterator to traverse the in-memory data structure. When looking at the CPU profile (Figure 5), we can see that 80% of the execution time is spent in accessing and decoding the in-memory data representation. Second, even if we remove this indirection and replace it with a unified piece of Java code, the performance remains about 30% lower than C, a difference that gets more pronounced for other queries where tight low-level control over data structures and memory management is required.

**3.2 Flare Level 1 Architecture**

Flare Level 1 (Figure 1) adds native compilation within Tungsten. At startup, Flare installs a number of rules into the Catalyst optimization logic. After a query is optimized by Catalyst, these rules will trigger Tungsten to invoke Flare to generate C code for supported operators or combinations of operators. Flare then invokes a C compiler, loads the generated native code into the running JVM through the Java Native Interface (JNI), and Spark’s runtime will then execute the generated code as part of the query evaluation. Flare Level 1 does not modify any of Spark’s other internals, e.g., memory management, data format, RDD layer, etc. Hence, Flare Level 1 can serve as a lightweight accelerator that increases performance for certain queries, but not necessarily all, and that does not interfere with Spark’s execution model, i.e., transparently supports the standard cluster execution and fault tolerance behavior. Like Tungsten itself, Flare’s query compiler implements Neumann’s \[35\] data-centric model, which fuses pipelines of operators that do not need to materialize intermediate results. Code generation in Flare is realized using Lightweight Modular Staging (LMS) \[42\], a generative programming and compiler framework that uses the Scala type system to distinguish normal code from expressions that generate code. In LMS, a special type constructor Rep[T] is used to denote a staged expression, which will cause an expression of type T to be emitted in the generated code. LMS can be compared to other systems like LLVM \[27\], but operates on a higher level of abstraction. In the context of query compilation, LMS has been used as part of the LegoBase engine \[23\].

**4. Flare Level 2**

While Flare Level 1 can already provide significant speedups for a number of queries, it is also constrained by the architecture of the Spark runtime. Flare Level 2 takes more liberties and revisits key design assumptions of Spark SQL. Spark SQL operates on the legacy of Spark where workloads are assumed to be Google-scale big, and the only reasonable way of processing these humongous amounts of data is to scale-out on a large number of distributed, unreliable, shared-nothing machines. Furthermore, Spark SQL inherits Spark’s RDD abstraction which encodes lineage to support fault tolerance, which is a necessity in distributed environments of 100s or 1000s of machines. However, many realistic workloads are not Google-scale, and, in fact, can be scaled-up on modern big-memory hardware, where faults are statistically highly improbable and fault tolerance can often be supported in hardware, e.g., through RAID arrays, redundant power supplies, or similar facilities. Accelerating Spark SQL’s performance all the way to the level of best-of-breed modern query engines such as HyPer \[35\] requires a fully compiled back-end that removes the remaining inefficiencies of legacy Spark.

**More Bottlenecks.** For complex queries, concerns about granularity of code generation and interfacing with the runtime system become more pronounced than in our previous example, TPC-H Query 6. In fact, queries with joins exhibit some unfortunate consequences for main-memory execution due to Spark’s design as primarily a cluster computing framework. Figure 6 shows timings for a simple join query that joins the lineitem and orders tables of the TPC-H benchmark. Spark’s query optimizer picks an expensive sort-merge join by default, which may be the right choice for distributed or out-of-core execution, but is suboptimal for main-memory execution. With the right flags, it is possible to tune Spark’s Catalyst query planner to prefer a hash join instead, which is more efficient. But even the hash join operator follows a broadcast model, with high overhead for the internal exchange operator (2.2s of 4.7s), which is present in the physical plan even when running on a single core. Looking at Spark’s query plan for this hash join query reveals that Tungsten has split the query into three code generation regions (dark blue areas, right side in Figure 6), which need to communicate through Spark’s runtime system. It is therefore no surprise that Flare can achieve much faster query execution by generating tight code for the entire query.
4.1 Flare Level 2 Architecture

The architecture of Flare Level 2 is illustrated in Figure 7. Spark SQL’s front-end, DataFrame API, and Catalyst optimizer remain the same. The optimized query plan is exported wholesale from Catalyst to Flare. Flare’s compiler iterates recursively over each operator node in the query plan tree and maps it to Flare’s internal optimized data structures and query execution logic, represented in LMS. After that, LMS performs some light optimizations like common subexpression and dead code elimination, generates C, invokes a C compiler, and Flare launches the resulting binary either inside the JVM, like in Level 1, or as a separate process. This cuts out the rest of Spark and relies solely on Flare’s runtime to trigger execution of the generated code. In contrast to Flare Level 1, which operates transparently to the user, Flare Level 2 exposes a dedicated API to let users pick which DataFrames to evaluate through Flare.

```scala
val df = spark.sql("...") // create DataFrame (SQL or direct)
val td = flare(df) // turn it into a FlareDataFrame
fd.show() // execute query plan with Flare
```

Flare Level 2 does not currently support cluster execution, but it would be possible to extend the Spark runtime with a set of hooks that would delegate to Flare within a single machine, and coordinate multiple cluster nodes and the necessary data exchanges through the existing Spark fabric. Such a setup would be similar to HadoopDB [3], which combines MapReduce processing between cluster nodes with fast DBMS instances on each node that are able to handle the per-node computation more efficiently than Hadoop.

4.2 Optimizing Data Loading

Data loading is an often overlooked factor data processing, and is seldom reported in benchmarks. However, we recognize that data loading from CSV can often be the dominant performance factor for Spark SQL queries. The Apache Parquet [6] format is an attractive alternative, modeled after Dremel [32]. As a binary columnar format, it offers opportunities for compression, and queries can load only required columns instead of all data.

In keeping with our running theme, can we do better? While Parquet allows for irrelevant data to be ignored almost entirely, Spark’s code to read Parquet files is very generic, resulting in undue overhead. This generality is primarily due to supporting multiple compression and encoding techniques, but there also exists overhead in determining which column iterators are needed. While these sources of overhead seem somewhat unavoidable, in reality they can be resolved by generating specialized code. In Flare, we implement compiled CSV and Parquet readers that generate native code specialized to a given schema. As a result, Flare Level 2 can compile data paths end-to-end.

4.3 Parallel and NUMA Execution

Query engines realize parallelism either explicitly by implementing special `split` and `merge` operators, or internally by modifying the operator’s internal logic to orchestrate parallel execution. Flare Level 2 uses the latter, and realizes parallelism using OpenMP [1]. On the architectural level, Flare’s operators’ implementations take care of splitting their work internally across multiple threads, accumulating final results, etc. For instance, the parallel scan operator starts a parallel section in its `produce` method, which sets the number of threads, and invokes `consume` on the downstream operators in parallel. Join and aggregate operators, in turn, which implement materialization points, implement their `consume` method in such a way that parallel invocations are possible without conflict, either through per-thread data structures that are merged after the parallel section or through lock-free data structures.

Flare also contains specific optimizations for environments with non-uniform memory access (NUMA), including pinning threads to specific cores and optimizing the memory layout of various data structures to reduce the need for accessing non-local memory. For instance, memory-bound workloads (e.g., TPC-H Q6) perform small amounts of computation, and do not scale-up given a large number of threads on a single CPU socket. Flare’s code generation supports such workloads through various data partitioning strategies, in order to maximize local processing and to reduce the need for threads to access non-local memory as illustrated in Figure 7 and Section 6.1.

5. FLARE LEVEL 3

Many data analytics applications require a combination of different programming paradigms, i.e., relational, procedural, and map-reduce-style functional processing. For example, a machine learning (ML) application might use relational APIs for ETL and dedicated ML libraries for computations. Spark provides specialized libraries, e.g., ML
pipesines, avsor user-defined functions to support

domain-specific applications. Unfortunately, Spark's per-
formance falls off a proverbial cliff once DataFrame operations
are interleaved with user code. Currently, Spark SQL op-

imization and code generation treats user code as a black
box. Hence, Flare Level 3 focuses on generating efficient code
for heterogeneous workloads.

5.1 User Defined Functions (UDF)

Spark SQL uses Scala functions which appear as a black
box to the optimizer. As mentioned in Section 3 Flare's in-

ternal code generation logic is based on a technique called
Lightweight Modular Staging (LMS) [12], which uses a spe-
cial type constructor `Rep[T]` to denote staged expressions
of type \( T \), that should become part of the generated code.
Extending UDF support to Flare is achieved by injecting

\[ \text{Rep}[A] \Rightarrow \text{Rep}[B] \]

where each data point is assigned to the partition with the

nearest mean [10]. The k-means application mixes multiple
DSLs, i.e., SQL, and OptiML [45], with user code. In lines

6-8, Spark SQL reads data from a file and preprocesses in-

put. Lines 5-16 show the k-means processing code using Op-


tiML. Delite provides optimized data types (e.g., `vectors`) 

and expressive libraries to assist ML computations. For in-

stance, `mapRowsToVector, dist,` and `untilConverged withheld`

are ML-specific optimized methods. The final result can be

post-processed using SQL as illustrated in lines 20-21.

6. EXPERIMENTAL EVALUATION

To assess the performance and acceleration potential of

Flare in comparison to Spark, we present two sets of exper-

iments. The first set focuses on a standard relational bench-

mark; the second set evaluates heterogeneous workloads,

consisting of relational processing combined with machine

learning kernels as UDFs. Our experiments span single-core,

multi-core, NUMA, cluster, and GPU targets.

6.1 Bare-Metal Relational Query Execution

The first set of experiments focuses on a standard rela-

tional workload, and demonstrates that the inherent over-

heads of Spark SQL cause a slowdown of at least 10 \times

compared to the best available query engines for in-memory

execution on a single core. Our experiments show that Flare

Level 2 is able to bridge this gap, accelerating Spark SQL
to the same level of performance as state-of-the-art query

compiler systems, while retaining the flexibility of Spark's

DataFrame API. We also compare parallel speedups, the
effect of NUMA-aware optimization, and evaluate the per-
formance benefits of optimized data loading.

Environment. We conducted our experiments on a single

NUMA machine with 4 sockets, 12 Xeon E5-4657L cores

er per socket, and 256GB RAM per socket (1 TB total). The

operating system is Ubuntu 14.04.1 LTS. We use Spark

2.0, Scala 2.11, Postgres 9.4, HyPer v0.5-222-g04766a1, and

GCC 6.3 with optimization flags -O3.

Dataset. We use the standard TPC-H [47] benchmark

with scale factor SF10 for sequential execution, and SF20

and SF100 for parallel execution.

Single-Core Running Time. In this experiment, we com-
pare the single-core, absolute running time of Flare Level 2
with Postgres, HyPer, and Spark using the TPC-H bench-
mark with scale factor SF10. In the case of Spark, we use a

single executor thread, though the JVM may spawn auxil-

iary threads to handle GC or the just-in-time compilation.

Postgres and HyPer implement cost-based optimizers that
can avoid inefficient query plans, in particular by reordering
joins. While Spark’s Catalyst optimizer [7] is also cost-based,
it does not perform any kind of join re-ordering. Hence, we
match the join ordering of the query plan in Spark SQL and
Flare with HyPer’s, with a small number of exceptions: in
Spark SQL, the original join ordering given in the TPC-H
reference outperformed the HyPer plans for Q5, Q9, Q10,
and Q11 in Spark SQL, and for Q10 in Flare. For these
queries, we kept the original join ordering as is. For Spark
SQL, this difference is mainly due to Catalyst picking sort-
merge joins over hash joins. It is worth pointing out that
HyPer and Postgres plans can use indexes on primary keys,

which may give an additional advantage.

Figure 2 gives the absolute execution time of Postgres,

HyPer, Spark SQL, and Flare for all TPC-H queries. For all


systems, data loading time is excluded, i.e., only execution time is reported. In Spark and Flare, we use persist to ensure that the data is loaded from memory. At first glance, the performance of Flare and HyPer lie within the same range, and notably outperform Postgres and Spark in all queries. Similarly, Spark’s performance is comparable to Postgres’s in most of the queries. Unlike the other systems, Postgres does not compile queries at runtime, and relies on the Volcano model [20] for query evaluation, which incurs significant overhead. Hence, we can see that Spark’s query compilation does not provide a significant advantage over a standard interpreted query engines on most queries.

At a closer look, Flare outperforms Spark SQL in aggregate queries Q1 and Q6 by 34× and 17× respectively. We observe that Spark is an order of magnitude slower than Flare in nested queries like those found in Q2. After examining the execution plans of Q2, we found that Catalyst’s plan does not detect all patterns that help with avoiding re-computations, e.g., a table which has been previously scanned or sorted. In join queries, e.g., Q5, Q10, Q14, etc., Flare is faster than Spark SQL by 20×-60×. Likewise, in join variants outer join Q13, semi-join Q21, and anti-join Q22, Flare is faster by 8×, 80×, and 57× respectively.

The single-core performance gap between Spark SQL and Flare is attributed to the bottlenecks identified in Sections 3 and 4. First, overhead associated with low-level data access on the JVM. Second, Spark SQL’s distributed-first strategy that employs costily distributed operators, e.g., sort-merge join and broadcast hash join, even when running on a single core. Third, internal bottlenecks in in-memory processing, the overhead of RDD operations, and communication through Spark’s runtime system. By compiling entire queries, instead of isolated query stages, Flare effectively avoids these bottlenecks.

HyPer [25] is a state-of-the-art compiled relational query engine. A precursory look shows that Flare is faster than HyPer by 10%-70% in Q1, Q4-Q6, Q7, and Q14. Moreover, Flare is faster by 2×-4.5× in Q3, Q11, Q16, Q18, and Q19. On the other hand, HyPer is faster than Flare by 20%-60% in Q9, Q10, Q12, Q15, and Q21. Moreover, HyPer is faster by 2×-4.1× in Q2, Q8, Q17, and Q20. This performance gap is, in part, attributed to (1) HyPer’s use of specialized operators like GroupJoin [2], and (2) employing indexes on primary keys as seen in Q2, Q8, etc., whereas Flare (and Spark SQL) currently does not support indexes. In order to understand the performance gained by using indexes, we disabled indexing in HyPer and re-ran the benchmarks (detailed results omitted). We observed that Flare outperformed HyPer by 80% in Q13 and matched the performance of Q12 and Q21. For Q2, Q8-Q10, and Q17, where HyPer outperformed Flare, the performance gap was shrunk by 20% to 1.2×. Finally, in Q4, Q7, Q11, and Q18 where Flare outperformed HyPer, the performance gap had increased by 10% to 1.2×.

In summary, while both Flare and HyPer generate native query code at runtime, subtle implementation differences in query evaluation and code generation can result in faster code. For instance, HyPer uses proper decimal precision numbers, whereas Flare follows Spark in using double precision floating point values, which are native to the architecture. Furthermore, HyPer generates LLVM code, whereas Flare generates C code which is then compiled with GCC.

**Compilation Time.** We compared the compilation time for each TPCH-H query on Spark and Flare (detailed results not shown). For Spark, we measured the time to generate the physical plan, which includes Java code generation and compilation. We do not quantify JVM-internal JIT compilation, as this is hard to measure, and code may be recompiled multiple times. For Flare, we measured C code generation and compilation with GCC. Both systems spend a similar amount of time on code generation and compilation, on average 20% more in Flare. Compilation time depends on the complexity of the query but is less than 1.5s for all queries, i.e., well in line with interactive, exploratory, usage.

**Parallel Scaling.** In this experiment, we compare the scalability of Spark SQL and Flare Level 2. The experiment focuses on the absolute performance and the Configuration that Outperforms a Single Thread (COST) metric proposed by McSherry et al. [31]. We pick four queries that represent aggregate and join variants.

Figure 11 presents speedup numbers for Q6, Q13, Q14, and Q22 when scaled up to 32 cores. At first glance, Spark appears to have good speedups in Q6 and Q13 whereas Flare’s Q6 speedup drops for high core counts. However, examining the absolute running times, Flare is faster than Spark SQL by 9×. Furthermore, it takes Spark SQL estimated 12 cores in Q6 to match the performance of Flare’s single core. In scaling-up Q13, Flare is consistently faster by 8× on all cores. Similarly, Flare continues to outperform Spark by a steady 25× in Q14 and by 20×-80× in Q22 as the number of cores reaches 32. Notice the COST metric in the last two queries is infinity, i.e., there is no Spark configuration that matches Flare’s single-core performance.
The seemingly good scaling for Spark reveals that the runtime incurs significant overhead. In particular, we would expect Q6 to become memory-bound as we increase the level of parallelism. In Flare we can directly observe this effect as a sharp drop from 16 to 32 cores. Since our machine has 18 cores per socket, for 32 cores, we start accessing non-local memory (NUMA). The reason Spark scales better is because the internal overhead, which does not contribute anything to query evaluation, is trivially parallelizable and hides the memory bandwidth effects. In summary, Flare scales as expected for both of memory and CPU-bound workloads, and reflects the hardware characteristics of the workload, which means that query execution takes good advantage of the available resources – with the exception of multiple CPU sockets, a problem we address next.

As a next step, we evaluate NUMA optimizations in Flare and show that these enable us to scale queries like Q6 to higher core numbers. In particular, we pin threads to individual cores and lay out memory such that most accesses are to the local memory region attached to each socket (Figure 12). Q6 performs better when the threads are dispatched on different sockets. This is due to the computation being bounded by the memory bandwidth. As such, when dividing the threads on multiple sockets, we multiply the available bandwidth proportionally. However, as Q1 is more computation bound, dispatching the threads on different sockets has little effect. For both Q1 and Q6, we see scaling up to the capacity of the machine (in our tests, up to 72 cores). This is seen in a maximum speedup of $46 \times$ and $58 \times$ for Q1 and Q6, respectively.

**Optimized Data Loading.** An often overlooked part of data processing is data loading. Flare contains an optimized implementation for both CSV files and the columnar Apache Parquet format. We show loading times for each of the TPC-H tables in Table 1.

| Table | #Tuples | Postgres | HyPer | Spark | Spark | Spark | Flare | Parquet | Flare | Flare | Parquet |
|-------|---------|----------|-------|-------|-------|-------|-------|---------|-------|-------|---------|
| CUSTOMER | 1500000 | CSV | CSV | CSV | Parquet | CSV | Parquet | CSV | Parquet | CSV | Parquet |
| LINEITEM | 59986052 | 377765 | 49008 | 47102 | 25798 | 11167 | 10668 | 1120 | 8000000 | 28748 | 2559986052 |
| NATION | 25 | 1 | 8 | 106 | 110 | $< 1$ | $< 1$ |
| ORDERS | 15000000 | 60214 | 33195 | 85985 | 54124 | 2028 | 1786 | 2000000 | 85985 | 1164 | 1102 |
| PART | 2000000 | 8807 | 1393 | 11254 | 7681 | 351 | 340 | 2000000 | 85985 | 1164 | 1102 |
| PARTSUPP | 8000000 | 37408 | 5265 | 28748 | 17731 | 1164 | 1010 | 2000000 | 85985 | 1164 | 1102 |
| REGION | 5 | 1 | 8 | 102 | 90 | $< 1$ | $< 1$ |
| SUPPLIER | 1000000 | 478 | 66 | 616 | 522 | 28 | 16 |

Table 1: Loading time in ms for TPC-H SF10 in Postgres, HyPer, and SparkSQL.

Figure 10: Speedup for TPC-H SF10 when streaming data from SSD on a single thread.

Figure 11: Scaling-up Flare and Spark SQL in SF20, without NUMA optimizations: Spark has good nominal speedups (top), but Flare has better absolute running time in all configurations (bottom). For both systems, NUMA effects for 32 cores are clearly visible.

Figure 12: Scaling-up Flare for SF100 with NUMA optimizations: threads pinned to one, two, or four sockets. The speedups relative to a single thread are shown on top of the bars.

**Full table read.** From the data in Table 1, we see that in both Spark and Flare, the Parquet file readers outperform the CSV file readers in most scenarios, despite this being a worst-case scenario for Parquet. Spark’s CSV reader was faster in only one case: reading nation, a table with only 25 rows. In all other cases, Spark’s Parquet reader was 1.33×–1.81× faster. However, Flare’s highly optimized CSV reader operates at a closer level of performance to the Parquet reader, with all tables except supplier having a benefit of less than a 1.25× speedup by using Parquet.

**Performing queries.** Figure 10 shows speedups gained from executing queries without preloading data for both systems. Whereas reading an entire table gives Spark and Flare marginal speedups, reading just the required data gives speedups in the range of 1.22×–22.96× for Spark (excluding Q2 and Q16, which performed 9% and 41% slower, re-
spectively) and $2 \times 14 \times$ for Flare. Across systems, however, Flare’s Parquet reader demonstrated between a $5 \times 795 \times$ speedup over Spark’s, and between $35 \times 720 \times$ over Spark’s CSV reader. While the speedup over Spark lessens slightly in higher scale factors, we found that Flare’s Parquet reader consistently performed on average at least one order of magnitude faster across each query, regardless of scale factor.

In nearly every case, reading from a Parquet file in Flare is approximately $2 \times 4 \times$ slower than in-memory processing (as expected). However, reading from a Parquet file in Spark is rarely significantly slower than in-memory processing. These results show that while reading from Parquet certainly provides performance gains for Spark when compared to reading from CSV, the overall performance bottleneck of Spark surely does not lie in the cost of reading from SSD compared to in-memory processing.

### 6.2 Heterogeneous Workloads and UDFs

We now turn our attention to heterogeneous workloads that combine relational processing with iterative functional computation. We study a range of machine learning kernels, where the input data is loaded via DataFrames. The kernel computation is expressed as a UDF written in the OptiML DSL, which is used as part of a SQL query.

**Shared-Memory NUMA.** In a recent study, Brown et al. [13] compared Spark with Delite with regards to NUMA scalability on a single shared-memory machine with 4 CPU sockets and a total of 48 cores. Specifically, Gaussian Discriminant Analysis (GDA), logistic regression (LogReg), k-means clustering, and a gene barcoding application (Gene) were chosen as machine learning benchmarks. As shown in Figure 13, Delite gains significant speedups over Spark in every application studied, with thread pinning and NUMA-aware data partitioning contributing in different ways for each application. As stated previously, Flare Level 3 generates code in Delite’s intermediate language DMLL, and we have verified that the generated code matches perfectly the code in [13], thus guaranteeing the same performance.

**Clusters and GPU.** Brown et al. [13] also showcase speedups over Spark when running on a small cluster of machines, and when employing GPU accelerators on the k-means and LogReg applications. Despite running on Spark’s intended architecture, when run on Amazon EC2 using 20 nodes, the code generated by Delite demonstrated a $2 \times 3.5 \times$ speedup over Spark for k-means, and approximately a $2.5 \times 3 \times$ speedup for LogReg (see Figure 14 adapted from [13]). When these applications were moved to a cluster of high-end machines with more CPU cores as well as GPUs, this performance gap widened even further. The study shows that when running on a GPU cluster of 4 nodes, each with 12 cores, performance jumped to above a $7 \times$ speedup for each application. Again, for completeness, Flare Level 3 generates DMLL, and we verified that all generated code was identical to that used in [13].

### 7. RELATED WORK

Numerous cluster computing frameworks implement a combination of parallel, distributed, relational, procedural, and MapReduce computations. The MapReduce model [17] realized in Hadoop [9] performs big data analysis under shared-nothing, unreliable machines. Twister [19] and Haloo [18] support iterative MapReduce workloads by avoiding reading unnecessary data and keeping invariant data between iterations. Likewise, Spark [51, 52] tackles the issue of data reuse among MapReduce jobs or applications by explicitly persisting intermediate results in memory. Along the same lines, the need for an expressive programming model to perform analytics on structured and semistructured data motivated Hive [48], Dremel [32], Impala [24], Shark [19] and Spark SQL [7] and many others. SnappyData [41] integrates Spark with a transactional main-memory database to realize a unified engine that supports streaming, analytics and transactions. Moreover, Asterix [9], Stratosphere [1], and Tupleware [16] provide data flow-based programming models and support user defined functions (UDFs). Flare distinguishes itself by maintaining expressiveness while achieving performance close to highly optimized systems like HyPer [35]. Flare keeps Spark SQL’s front-end intact, and integrates its own code generation and runtime (in Level 2) replacing Spark’s RDDS and distributed-by-default runtime system. Furthermore, Flare Level 3 integrates with Delite as its execution back-end in order to support multi-DSL applications. By design, Flare’s main target is scaled-up in-memory clusters where faults are improbable.

**Query Compilation** Recently, code generation for SQL queries has regained momentum. Historic efforts go back all the way to System R [8]. Query compilation can be realized using code templates, e.g., Daytona [21] or HIQUE [25], general purpose compilers, e.g., HyPer [35] and Hekaton [18], or DSL compiler frameworks, e.g., Legobase [23], DryadLINQ [50] and DBLAB [43].

**Embedded DSL frameworks and intermediate languages** address the compromise between productivity and performance in writing programs that can run under diverse programming models. Voodoo [10] addresses compiling portable query plans that can run on CPUs and GPUs. Voodoo’s intermediate algebra is expressive and captures hardware optimizations, e.g., multicores, SIMD, etc. Fur-
thermore, Voodoo is used as an alternative back-end for MonetDB \[12\]. Delite \[14\], a general purpose compiler framework, implements high-performance DSLs (e.g., SQL, Machine Learning, graphs and matrices), provides parallel patterns and generates code for heterogeneous targets. The Distributed Multiloop Language (DMLL) \[13\] provide rich collections and parallel patterns and supports big-memory NUMA machines. Weld \[19\] is another recent system that aims to provide a common runtime for diverse libraries e.g., SQL and machine learning. Steno \[33\] performs optimizations similar to DMLL to compile LINQ queries. Furthermore, Steno uses DryadLINQ \[50\] runtime for distributed execution. Nagel et. al. \[34\] generates efficient code for LINQ queries. Weld is similar to DMLL in supporting nested parallel structures. However, Weld focuses on a larger set of science data frameworks (Spark, TensorFlow, NumPy and Pandas) and does not, e.g., support a large enough set of joins and other operators to run all TPC-H queries. Query compilation inside Flare Level 3 is based on Delite’s OptiQL DSL and DMLL intermediate language.

Performance evaluation in data analytics frameworks aims to identify performance bottlenecks and study the parameters that impact performance the most, e.g., workload, scaling-up/scaling-out resources, probability of faults, etc. A recent study \[57\] on a single Spark cluster revealed that CPU, not I/O, is the source of bottlenecks. McSherry et al. \[51\] proposed the COST (Configuration that Outperforms a Single Thread) metric, and showed that in many cases, single-threaded programs can outperform big data processing frameworks running on large clusters. TPC-H \[17\] is a decision support benchmark that consists of 22 analytical queries that address several “choke points,” e.g., aggregates, large joins, arithmetic computations, etc. \[11\]. Flare Level 2’s performance evaluation is done using TPC-H.

8. CONCLUSION

Modern data analytics need to combine multiple programming models and make efficient use of modern hardware with large memory, many cores, and accelerators such as GPUs. We introduce Flare: a new back-end for Spark that brings relational performance on par with the best SQL engines, and also enables highly optimized of heterogeneous workloads. Most importantly, all of this comes without giving up the expressiveness of Spark’s high-level APIs.

We believe that multi-stage APIs, in the spirit of DataFrames, and compiler systems like Flare and Delite, will play an increasingly important role in the future to satisfy the increasing demand for flexible and unified analytics with high efficiency.

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