Afterburner: The Case for In-Browser Analytics

Kareem El Gebaly and Jimmy Lin
David R. Cheriton School of Computer Science
University of Waterloo, Ontario, Canada
{kareem.elgebaly, jimmylin}@uwaterloo.ca

ABSTRACT

This paper explores the novel and unconventional idea of implementing an analytical RDBMS in pure JavaScript so that it runs completely inside a browser with no external dependencies. Our prototype, called Afterburner, generates compiled query plans that exploit typed arrays and asm.js, two relatively recent advances in JavaScript. On a few simple queries, we show that Afterburner achieves comparable performance to MonetDB running natively on the same machine. This is an interesting finding in that it shows how far JavaScript has come as an efficient execution platform. Beyond a mere technical curiosity, we discuss how our techniques could support ubiquitous in-browser interactive analytics (potentially integrating with browser-based notebooks) and also present interesting opportunities for split-execution strategies where query operators are distributed between the browser and backend servers.

1. INTRODUCTION

Browser-based notebooks (i.e., Jupyter) have gained tremendous popularity with data scientists in recent years for a variety of reasons: The tight integration of code and execution output elevates the analytical process and its products to first class citizens, since the notebook itself can be serialized, reloaded, and shared. The ability to manipulate, rearrange, and insert snippets of code (in “cells”) lines up well with the iterative nature of data science and a wide range of analytics tasks. A recent development is the seamless integration of browser-based notebooks with scalable data analytics platforms, such that code written in a notebook cell can be executed on a potentially large cluster and the results can be further manipulated in the notebook. This integration, exemplified by the commercial Databricks platform, allows data scientists to analyze large amounts of data in a convenient and flexible manner.

The advent of notebooks means that the browser has, in essence, become the “shell”. However, in all implementations that we are aware of, the browser is simply a dumb rendering endpoint: all query execution is handled by backend servers. In the terminology of Franklin et al., this is referred to as query shipping. However, modern browsers are capable of so much more: they embed powerful JavaScript engines capable of running real-time collaborative tools, online multiplayer games, rendering impressive 3D scenes, supporting complex, interactive visualizations, and even running first-person shooters. These applications take advantage of HTML5 standards such as WebGL, WebSocket, and IndexedDB, and therefore do not require additional plug-ins (compared to Flash or, yuck, Java applets).

We asked ourselves: Is it possible to exploit modern JavaScript engines and build a high-performance data management system that runs completely in the browser? And if so, what new opportunities does such a platform create? We tackle these two questions in turn: First, we present Afterburner, a prototype analytical RDBMS implemented in JavaScript that executes completely inside a web browser, is standards compliant, and has no external dependencies. Experiments with a few simple queries on a modest dataset show that Afterburner achieves comparable performance to the analytical database MonetDB running natively on the same machine. This finding is interesting in that it shows how far JavaScript has come as an efficient execution platform, from its much-maligned performance characteristics in the early days. Second, we discuss the “so what?” question by highlighting the potential of our techniques for supporting ubiquitous in-browser interactive analytics and query execution strategies that make use of query operators running both in the browser and on backend servers.

The primary contribution of our work is a feasibility demonstration of in-browser analytics. To our knowledge, we are the first to propose this somewhat unconventional idea of embedding an analytical RDBMS inside the browser and exploring the implications thereof. The idea of splitting query execution across the client and the server, of course, is not new, but we believe that JavaScript presents a fresh take on the decades-old technique.

2. AFTERBURNER IMPLEMENTATION

Afterburner is implemented as a JavaScript library, primarily designed to run inside a standards-compliant web browser. However, with minimal modifications it can run in other JavaScript environments such as node.js. In the current implementation, data is loaded into the browser from a flat file on the client’s file system, although in principle data ingest could be accomplished via a REST API call, a WebSocket, or a variety of other means. All data are immutable and packed in a columnar layout in memory once loaded. Afterburner generates compiled query plans that exploit two JavaScript features: typed arrays and asm.js, which we explain below.

2.1 In-Memory Storage

Array objects in JavaScript can store elements of any type and are not arrays in a traditional sense (compared to say, C) since consecutive elements may not be contiguous; fur-
thermore, the array itself can dynamically grow and shrink. This flexibility limits the optimizations that the JavaScript engine can perform both during compilation and at runtime. In the evolution of JavaScript, it became clear that the language needed more efficient methods to quickly manipulate binary data: typed arrays are the answer.

Typed arrays in JavaScript are comprised of buffers, which simply represent untyped binary data, and views, which impose a read context on the buffer. As an example, the following creates a 64-byte buffer:

```javascript
var buffer = new ArrayBuffer(64);
```

Before we can manipulate the data, we need to create a view from it. With the following:

```javascript
var int32View = new Int32Array(buffer);
```

we can now manipulate `int32View` as an array of 32-bit integers (e.g., iterate over it with a `for` loop).

Typed arrays allow the developer to create multiple views over the same buffer, which provides a mechanism to interact with, for example, arbitrary C `structs` or complex WebGL data. Afterburner takes advantage of exactly this feature to pack relational data into a columnar layout.

In Afterburner, each column is laid out end-to-end in the underlying buffer (which can be traversed with a view of the corresponding type). The table itself is a group of pointers to the offsets of the beginning of the data in each column. Figure 1 shows the physical memory layout storing the `lineitem` table from TPC-H. Different “views” (top three rows) provide access into the underlying JavaScript `ArrayBuffer`. Blackened boxes represent invalid data for that particular view.

A key feature of asm.js is the use of type hints, such as `x|0` and `+(x)`, which are applied to variables or arithmetic expressions. The type hint `x|0` specifies a 32-bit integer and `+(x)` specifies a 32-bit floating point value. With these hints, asm.js essentially introduces a static type system while retaining backwards compatibility with vanilla JavaScript, since in vanilla JavaScript these hints just become no-ops. Note that accesses to typed views must indicate the byte offset and the size of each element. The `extendedprice` column is a 32-bit float view and thus the byte offsets can be computed by multiplying the index variable `n` by 4 using the shift operator (>>).

Any JavaScript function can request validation of a block of code as valid asm.js via a special prologue directive, `use asm`, which happens when the source code is loaded. Validated asm.js code (typically referred to as an asm.js module) is amenable to ahead-of-time (AOT) compilation, in contrast to just-in-time (JIT) compilation in vanilla JavaScript. Executable code generated by AOT compilers can be quite efficient, through the removal of runtime type checks (since everything is statically typed), operation on unboxed (i.e., primitive) types, and the removal of garbage collection.

An asm.js module can take three optional parameters, which provide hooks for integration with external vanilla JavaScript code: a standard library object, providing access to a limited subset of the JavaScript standard libraries; a foreign function interface (FFI), providing access to custom external JavaScript functions; and a heap buffer, providing a single `ArrayBuffer` to act as the asm.js heap. Thus, a typical asm.js module declaration is as follows:

```javascript
function MyAsmModule(stdlib, foreign, heap) {
  "use asm";

  // module body
}
```

http://asmjs.org/spec/latest/
At a high-level, Afterburner translates SQL into the string representation of an asm.js module (i.e., the physical query plan, through code templates described below), calls eval on the code, which triggers AOT compilation and links the module to the calling JavaScript code, and finally executes the module (i.e., executes the query plan). The typed array storing all the tables (i.e., the entire database) is passed into the module as a parameter, and the query results are returned by the module.

The compiled query approach of Afterburner takes after systems like HiQUE [4] and HyPer [5], which have recently popularized the idea of code generation for relational query processing. One well-known drawback of this approach is that compiling generated code using a tool like gcc can overshadow its benefits for short-running queries. As an alternative, Neuman [5] proposed a hybrid compilation model, where the queries are compiled into an intermediate representation such as LLVM, which is then linked to pre-compiled native code to achieve native-like performance while avoiding native compilation overhead. In the context of our work, we have found compilation overhead to be negligible, primarily because compilation speed is already something that JavaScript engines optimize for, since all JavaScript code on the web is stored as text.

2.3 Code Generation

Instead of string-based SQL queries, Afterburner executes queries written using an API that is heavily driven by method chaining, often referred to as a fluent API. For example, consider a simple query over the orders table from the TPC-H benchmark:

```sql
SELECT orderkey, orderdate
FROM orders
WHERE orderdate='1996-01-01';
```

This query would be expressed in Afterburner as follows:

```javascript
sql.select()
    .field('orderkey')
    .field('orderdate')
    .from('orders')
    .where(EQ('orderdate', date('1996-01-01')))
```

Note that there is a very straightforward mapping from the method calls to clauses in a standard SQL query, so we can view the fluent API as little more than syntactic sugar. However, this query API has a few advantages: First, it saves us from having to write a query parser. Second, this fluent API is similar to DataFrames [4], an interface for data manipulation that many data scientists are familiar with today.

Starting from an SQL query expressed in the fluent-style API, Afterburner generates the string representation of the asm.js code that corresponds to the query. In the current implementation, this is performed in a straightforward way based on a small number of fixed code templates in which various sub-expressions (e.g., the filter predicate, join key, group by clause, etc.) are plugged. At present, Afterburner has a fixed (hard-coded) physical plan for each class of queries (i.e., it does not perform query optimization). Our prototype implementation supports simple filter queries, inner joins, group bys, simple aggregations, and order bys. We discuss below in more detail:

**Simple Filters.** A code template supports generating query plans for simple filter–project or filter–aggregate queries. The code template generates a loop that increments a record iterator, which is used in combination with the starting offset of a column to access a particular attribute. Inside the loop, the template can either generate code to materialize a projection or to compute simple aggregates such as COUNT, AVG, or SUM.

**Joins.** The code template for supporting filter–project or filter–aggregate queries over an inner join implements a standard hash join. In the build phase, the code loops over one relation to build the hash table. In the probe phase, the generated code loops over the second relation to probe the hash table for matching records, and then either materializes a projection or computes an aggregate.

**Group Bys.** A group by plan loops over one relation to build a hash table over one or more grouping keys. Another loop is used to iterate over the hash table in order to process the groups.

3. EVALUATION

As indicated in the introduction, the main purpose of this work is to demonstrate the feasibility of in-browser analytics. We freely admit that Afterburner is far from a complete analytical database, but we believe that our prototype is sufficient to answer this question.

In this section, we compare the performance of Afterburner with vanilla JavaScript and MonetDB (v11.17.17) in exactly the same execution environment on a commodity desktop machine. Afterburner and vanilla JavaScript execute inside the browser, while MonetDB runs natively. For the vanilla JavaScript condition, we simply remove the use asm prologue directive so that generated code is not validated as asm.js. However, the code still uses typed arrays.

For data, we used the TPC-H data generator with a scale factor of 1 GB: this creates a lineitem table with 6 million rows and an orders table with 1.5 million rows. Table 1 shows the four queries used in the evaluation. The first three queries are very simple, and the final query is a slightly simplified version of Q3 in the TPC-H benchmark.

We ran performance evaluations on a commodity desktop with a six core 3.3 GHz AMD FX-6100 processor (6 MB of cache) and 16 GB of RAM, running Ubuntu 12.04. Vanilla JavaScript and Afterburner ran in Mozilla Firefox 43.0.4. We attempted to make the comparisons as fair as possible: All cores were disabled except for a single one, since code running inside a browser tab is single threaded. All our performance measurements were on a warm cache—we first ran each query five times, and then took measurements over the next five trials. For Afterburner, the measured latency includes query compilation overhead. In the case of vanilla JavaScript and Afterburner, all data are explicitly loaded in memory; in the case of MonetDB, all data are cached in the underlying OS buffer caches. This makes for a reasonably fair comparison.

Evaluation results are shown in Figure 2. We can see that Afterburner is clearly faster than vanilla JavaScript due to the asm.js optimizations. We find that the performance of Afterburner is at least on par with, and in some cases exceeds the performance of MonetDB. In the case of the join query Q2, examining the query plan we find that MonetDB materializes the joined relation (all 6 million rows) before counting them, and therefore is slower than Afterburner.

Admittedly, these results are somewhat surprising, but en-
Figure 2: Query latency over five trials (with confidence intervals) for four sample queries, comparing vanilla JavaScript, Afterburner, and MonetDB. Both vanilla JavaScript and Afterburner run inside Firefox, while MonetDB runs natively on the same machine.

| Query | SQL |
|-------|-----|
| Q1: Filter | `SELECT count(*) FROM orders WHERE o_totalprice < 1500` |
| Q2: Join | `SELECT sum(o_totalprice) FROM orders, lineitem WHERE l_orderkey = o_orderkey` |
| Q3: Group-By | `SELECT o_orderdate, count(*) FROM orders GROUP BY o_orderdate` |
| Q4: Top Orders | `SELECT l_orderkey, sum(l_extendedprice) as rev, o_orderdate, o_shippriority FROM orders, lineitem WHERE l_orderkey = o_orderkey and o_orderdate between '1996-01-01' and '1996-01-31' GROUP BY l_orderkey, o_orderdate, o_shippriority ORDER BY rev DESC LIMIT 10;` |

Table 1: Sample queries used in our performance evaluation. Q4 is a slightly simplified version of Q3 from the TPC-H benchmark.

tirely believable: Across a wide range of applications, a rough heuristic is that asm.js runs in the browser at around half the speed of the same application running natively. Since Afterburner uses compiled queries, the reference point is a native C program. As Zukowski et al. have shown (e.g., Figure 3 in that paper), there is still quite a bit of performance difference between vectorized (but still interpreted) query execution (as with MonetDB) and compiled queries. So, it is plausible that AOT-compiled JavaScript with proper optimizations (even with the overhead) still runs faster than MonetDB—as our results suggest. However, it is worth emphasizing that in this evaluation, MonetDB is restricted to running on a single core (for a fair comparison with single-threaded JavaScript inside the browser), but this is an odd configuration for analytical databases, which nearly always run on backend servers with many-core processors.

In summary, these results show the feasibility of running an analytical RDBMS completely inside the browser. Furthermore, the performance of modern JavaScript engines is quite impressive—it’s ubiquity makes it an attractive platform for data analytics.

4. SO WHAT?

Having demonstrated the technical feasibility of an analytical RDBMS in JavaScript, we turn our attention to the next obvious question: So what? In this section, we discuss several answers.

A system like Afterburner can increase the speed and flexibility of interactive data analytics. It is well known that the work of data scientists, particularly in cases of exploratory tasks, is highly iterative, where they “poke” at the data from many different angles. Frequently, these tasks focus on a small subset of the data—e.g., the data warehouse stores 180 days of log data, but the data scientist is only interested in data from the last week. In this case, the following describes some possible scenarios:

1. She repeatedly queries the entire dataset, but filters for the subset of interest. Achieving low query latency is entirely dependent on the analytical engine properly optimizing away unneeded work, which may be dependent on the physical storage of the data (how it’s partitioned, compressed, etc.).
2. She materializes the data of interest; in an analytical database, this might involve selecting into a temporary table or creating a materialized view; in Spark, this might involve writing temporary data onto HDFS. Subsequent queries would be posed against this smaller dataset.
3. She materializes the data of interest and then copies it locally (e.g., to her laptop) for further manipulation. This might involve dumping data into a local RDBMS and then issuing additional queries or running Spark locally.

There are issues with all three approaches. In the first, the analytics engine may not be smart enough to efficiently push down the filters, especially for complex conditions. The second has a number of drawbacks: In some cases, queries over the materialized data may no longer run efficiently because
the startup cost of the analytics engine (e.g., Spark) dominates the actual processing time. In analytical databases, creating materialized views might require elevated privilege (not granted to everyone), and the ability to create temporary tables presents additional data management challenges. For example, who/what “cleans up” 50 tables named variants of tmp? Finally, the third approach creates an awkward workflow and introduces friction. For an RDBMS, this involves copying data over and ingesting locally before additional queries can be run. Furthermore, this approach essentially requires maintaining two separate analytics stacks. What if the version of custom libraries running on the server becomes out of sync with the local version?

Instead of the three above approaches, we propose interactive analytics using something like Afterburner. If the backend analytics engine is an RDBMS, the data scientist can transparently bring over materialized data and continue querying without interrupting her workflow, unlike in scenario (3) above. If the backend analytics engine is something like Spark, we could easily imagine building a bridge between Afterburner and DataFrames. Furthermore, there’s no principled reason why Afterburner could not be extended to support Spark-style transformations and a more imperative style of data analysis. In both cases, the data scientist might be dealing with a relatively small amount of data, a scenario that big data processing platforms do not optimize for (by definition), and so Afterburner could end up with better performance despite the overhead of JavaScript. Furthermore, if the data scientist is already working in a browser-based notebook environment, integration of Afterburner could be relatively straightforward.

We sketch out what the performance of such an in-browser analytics scenario might look like. Consider a TPC-H database at a 100 GB scale factor: let’s focus on the top orders query Q4 from Table 2, where the data scientist wants to dive into the data from January 1996. For the sake of argument, we assume this exploration requires repeated querying that cannot be easily captured in a single query. We exemplify this with Q5 in Table 2 which pulls up the top 10 orders on a particular day. Running this query in MonetDB takes 800 ms on a server with dual 8 cores Intel Xeon E5-2670 processors (2.6 GHz) with 256 GB of memory on Ubuntu 14.04. This corresponds to scenario (1) above—run individual selective queries directly on the data warehouse. Alternatively, the data scientist might materialize the results of Q6 in Table 2 into a temporary table (containing 2 million rows). Running a simple filter query for a particular day on this temporary table (on the backend server) takes 28 ms. This corresponds to scenario (2) above, although we are not taking into account network latency.

As an alternative, we can bring the materialized results of Q6 into the browser and then run the filter query with Afterburner. Such a query takes 25 ms on the same client machine described in Section 2. We do not include the data transfer time, which would be amortized across multiple queries that probe the materialized results. Such a scenario has the advantage of seamless, low-latency client-side interactions (it’s still SQL) without the data management issues that come with creating temporary tables. Pushing simple filter queries over to the client side naturally decreases load on the server, and since Afterburner is just JavaScript, it can integrate into any browser-based analytics tool, ranging from simple dashboards to full-fledged interactive notebooks.

### Q5: Top Orders Variant

```
SELECT l_orderkey, 
  sum(l_extendedprice * (1 - l_discount)) as revenue, 
  o_orderdate, 
  o_shippriority 
FROM orders, 
  lineitem 
WHERE l_orderkey = o_orderkey 
  and o_orderdate = '1996-01-06' 
GROUP BY l_orderkey, 
  o_orderdate, 
  o_shippriority 
ORDER BY revenue 
LIMIT 10
```

### Q6: Top Orders View

```
SELECT l_orderkey, 
  sum(l_extendedprice * (1 - l_discount)) as revenue, 
  o_orderdate, 
  o_shippriority 
FROM orders, 
  lineitem 
WHERE l_orderkey = o_orderkey 
  and o_orderdate between '1996-01-01' 
    and '1996-01-31' 
GROUP BY l_orderkey, 
  o_orderdate, 
  o_shippriority;
```

Table 2: Sample queries for the in-browser analytics scenario. We materialize the results of Q6 and filter on the client using Afterburner as an alternative to repeated queries of the type shown in Q5.

What’s more, the ubiquity of JavaScript means that Afterburner can run anywhere there is a browser, including mobile phones, tablets, and even the connected toaster oven or refrigerator of the near future. Java once promised developers that they can write their code once and have it run anywhere, but JavaScript has come much closer to actually delivering that promise—as evidenced by the range of complex websites today that run on multiple platforms, on multiple types of hardware, in multiple browsers. This shows that analytics capabilities in JavaScript can easily achieve widespread deployment.

Finally, we realize that our current working scenario—materializing a subset of data for further analysis inside the browser—represents a specific instance of split-execution strategies, where the client (i.e., the browser) and the server collaborate to execute a query. In our case, the user explicitly decides what queries run where, but this need not be the case. For example, Franklin et al. [9] discuss query shipping (basically, all systems today, where queries are shipped to the server and results sent back), data shipping (where the server sends the client tuples and query operators execute on the client), and hybrid shipping (where query operators execute on both the client and the server). In our case, it could be possible for a query planner to automatically place query operators either on the server or in the browser to optimize some objective (latency, utilization, etc.). One of the challenges with previous work is that the execution context on the client and server might be different, but JavaScript nicely solves this problem for us.
5. CONCLUSION

There is an emerging trend of building internet-scale services using node.js, which unifies server-side and client-side processing around JavaScript for customer-facing applications. Throw something like Afterburner into the mix, perhaps we could integrate customer-facing services with back-end data analytics... all around JavaScript! Such a thought should send shivers down the spine of any sane developer, but this idea is so nutty we feel it’s worth exploring!

6. ACKNOWLEDGMENTS

We’d like to thank members of Waterloo’s Data Systems Group (DSG) for their encouragement (“you guys are nuts, but you should pursue this anyway”) and Ashraf Aboulnaga for helpful comments on previous drafts of this paper.

7. REFERENCES

[1] M. Armbrust, R. S. Xin, C. Lian, Y. Huai, D. Liu, J. K. Bradley, X. Meng, T. Kaftan, M. J. Franklin, A. Ghodsi, and M. Zaharia. Spark SQL: Relational data processing in Spark. In Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data (SIGMOD 2015), pages 1383–1394, Melbourne, Australia, 2015.

[2] P. A. Boncz, M. Zukowski, and N. Nes. MonetDB/X100: Hyper-pipelining query execution. In Proceedings of the Second Biennial Conference on Innovative Data Systems Research (CIDR 2005), pages 225–237, Asilomar, California, 2005.

[3] M. J. Franklin, B. T. Jonsson, and D. Kossmann. Performance tradeoffs for client-server query processing. In Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data, pages 149–160, Montreal, Quebec, Canada, 1996.

[4] K. Krikellas, S. Viglas, and M. Cintra. Generating code for holistic query evaluation. In Proceedings of the 26th International Conference on Data Engineering (ICDE 2010), pages 613–624, Long Beach, California.

[5] T. Neumann. Efficiently compiling efficient query plans for modern hardware. PVLDB, 4(9):539–550, 2011.

[6] M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M. J. Franklin, S. Shenker, and I. Stoica. Resilient Distributed Datasets: A fault-tolerant abstraction for in-memory cluster computing. In Proceedings of the 9th USENIX Symposium on Networked Systems Design and Implementation, San Jose, California, 2012.

[7] M. Zukowski, P. Boncz, N. Nes, and S. Héman. MonetDB/X100—a DBMS in the CPU cache. Bulletin of the IEEE Computer Society Technical Committee on Data Engineering, 28(2):17–22, 2005.