In-Browser Split-Execution Support for Interactive Analytics in the Cloud

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ABSTRACT

The canonical analytics architecture today consists of a browser connected to a backend in the cloud. In all deployments that we are aware of, the browser is simply a dumb rendering endpoint. As an alternative, this paper explores split-execution architectures that push analytics capabilities into the browser. We show that, by taking advantage of typed arrays and asm.js, it is possible to build an analytical RDBMS in JavaScript that runs in a browser, achieving performance rivaling native databases. To support interactive data exploration, our Afterburner prototype automatically generates local materialized views from a backend database that are then shipped to the browser to facilitate subsequent interactions seamlessly and efficiently. We compare this architecture to several alternative deployments, experimentally demonstrating performance parity, while at the same time providing additional advantages in terms of administrative and operational simplicity.

1 INTRODUCTION

For today’s data scientists, the browser has become the shell, especially for interactive analytics on large datasets. What used to be accomplished via command-line REPL-based tools is increasingly moving into browser-based notebooks such as Jupyter. Such tools have gained popularity due to their first-class support for interactive data exploration. Notebooks also tie analytics tools into existing software ecosystems (e.g., Python, R), giving data scientists access to a broad range of capabilities. At the same time, backend analytics capabilities are increasingly centralized in the cloud, exemplified by various database-as-a-service offerings (Amazon RDS, Azure SQL, etc.), fully-managed data analytics stacks (Google BigQuery), as well as more general dataflow frameworks (Google Cloud Dataflow, Amazon Spark EMR).

Given these two trends, the canonical client–server architecture today consists of a browser connected to a cloud backend. In all implementations that we are aware of, the browser is simply a dumb rendering endpoint: all query execution is handled by backend servers. However, modern browsers are capable of much more: they embed powerful JavaScript engines capable of running real-time collaborative tools, rendering impressive 3D scenes, and even running first-person shooters.

We asked: Is it possible to exploit modern JavaScript engines to rethink the design of current architectures? In particular, would it be possible to offload data management and analytics capabilities from the cloud into the browser, and if so, what advantages might such an architecture offer? We explore the possibilities in this paper.

Contributions. We view our work as having the following two main contributions:

• Building on a previous demonstration [12], we describe and evaluate Afterburner, our prototype analytical RDBMS implemented in JavaScript that runs completely in the browser. We detail how our system takes advantage of in-memory columnar storage using typed arrays and query compilation into asm.js. Microbenchmarks, as well as end-to-end evaluations, show that our techniques approach the performance of an existing columnar database (MonetDB) and modern query compilation techniques (LegoBase) running natively. While we are not the first to implement an SQL engine in JavaScript, our prototype offers far superior scalability and performance on analytical queries compared to alternatives such as Google’s Lovefield and Sql.js.

• To support a large class of interactive SQL analytics, we propose a novel technique whereby the data scientist provides a hint regarding the focus of data exploration, and our system automatically splits query execution across the backend and the browser. The backend generates a local materialized view that is shipped over to the browser for subsequent manipulation. Note that we do not claim significant innovations in materialized view techniques. Instead, our contribution lies in a novel approach to integrating analytics backends with in-browser processing in a deployment that has many attractive features. We compare a number of deployment architectures and empirically demonstrate the advantages of our design.

2 BACKGROUND

The work of data scientists often involves tight interaction cycles with the data, particularly for exploratory tasks. This paper focuses on and optimizes for the common scenario where a data scientist rapidly issues a sequence of SQL queries that differ only in the predicates in the WHERE clause. As a running example, consider Q6 from the TPC-H benchmark for decision support in data warehousing:

```sql
SELECT SUM(l_extendedprice * l_discount) AS revenue
FROM lineitem
WHERE l_shipdate >= DATE '1994-01-01'
AND l_shipdate < DATE '1995-01-01'
AND l_discount BETWEEN 0.05 and 0.07
AND l_quantity < 24;
```

We quote from the benchmark definition: “This query quantifies the amount of revenue increase that would have resulted from eliminating certain companywide discounts in a given percentage range in a given year. Asking this type of ‘what if’ query can be used to look for ways to increase revenues.” From this, we can see that as part of data exploration, a data scientist might be interested in the results of the same “query template”, but with different predicates on the WHERE clause: different dates, discounts, etc.
Further evidence in support of the prevalence of such queries can be found in the more recent TPC-DS benchmark, which explicitly talks about query templates to test the interactive and iterative nature of OLAP queries (see [26], Section 4). An example of an iterative query, Q24, captures drill down and the iterations vary only in the WHERE predicates. This matches exactly the scenario we envision. We note that previous work such as BlinkDB [4] also makes the assumption that query templates are relatively stable, which is the key to effective sampling. Similarly, Verdict [25] assumes a stream of queries with correlated results, which necessarily must share commonalities, as the basis of learning an underlying model for approximate query answering; the work of Galakatos et al. [14] exploits similar intuitions as well. Agarwal et al. [4] further cite evidence from production workloads that support such query behaviors. In fact, dashboards and report generators are essentially pre-specified query templates: another way to look at our work is that it supports the creation of interactive dashboards on demand given ad hoc queries. Although our techniques certainly do not cover all the activities of a data scientist, we believe that we are tackling a common and realistic use case.

To support such data exploration, we desire three important properties: that such queries be fast (i.e., low latency), simplicity of frontend deployment (minimizing the effort of data scientists in managing their own client setup), and simplicity of backend administration (minimizing the effort of data warehouse administrators to support data scientists). With this in mind, let us consider a number of deployment scenarios, summarized in Figure 1:

Deployment A. This is the basic browser client connected to a cloud analytics backend (for concreteness, an analytical RDBMS). With this setup, the data scientist re-issues the same query template with different bindings, leading to sub-optimal query latencies because each SQL query is treated independently.

Deployment B. An obvious improvement to Deployment A is to accelerate analytics with a materialized view (MV), either explicitly requested by a data scientist or automatically inferred via query rewriting. Such an optimization does not alter how the client is deployed (so we retain simplicity in frontend deployment) but introduces new administrative burdens on the backend. In terms of creating materialized views: Are all data scientists able to create materialized views? Are there quotas to ensure equitable use of resources? Are these views “transient” or can they persist over long periods? If the former, what are the mechanisms by which these views are garbage collected? Are these views maintained as new data arrive? If so, what is the impact on system performance? If no, how are these views invalidated? Although we have improved query performance, we have sacrificed simplicity of backend administration in terms of a number of policy and technical issues that must be addressed.

Deployment C. Another improvement to Deployment A is to take the materialized view and move it over to the client, stored in a local RDBMS. This approach eliminates the backend administration issues described in Deployment B because data scientists can manage their own machines. This approach, however, complicates frontend deployment. For example, how does the entire team keep up to date with the latest version of the local RDBMS? What if there are urgent security patches that need to be installed? What about different operating systems and other idiosyncratic configurations across many heterogeneous machines in an enterprise setting? In fact, the headache of managing these issues is what drove organizations to the cloud to begin with, so Deployment C seems like a step backward.

Deployment D. The central value proposition of this work is that we can have our cake and eat it too. Building on Deployment C, what if the “local” database were written in JavaScript and runs in the browser? In that case, “deployment” is as simple as loading a webpage. This is Afterburner. The obvious question is, of course, how much performance are we giving up with a JavaScript analytical RDBMS? The answer, as we experimentally show, is nothing: end-to-end query latency is comparable to Deployment C. We note that Deployment D has two additional advantages: First, it supports disconnected operation when access to the cloud is unavailable. Deployment C also offers this flexibility, but not A or B. Second, Deployment D supports multi-device deployment, e.g., on tablets and even mobile phones—since it’s just JavaScript. This feature is not supported by Deployment C, since a local database may not be available on all devices.

3 AFTERBURNER DESIGN

We begin by detailing the design of Afterburner, which takes advantage of two JavaScript features: typed arrays for memory-efficient storage and asm.js for fast compiled queries. In this section, we focus on Afterburner as a standalone, in-browser analytical RDBMS.

3.1 Columnar Storage with Typed Arrays

Array objects in JavaScript can store elements of any type and are not arrays in a traditional sense (compare to say, C) since consecutive elements may not be contiguous; furthermore, 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 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-megabyte buffer:

```javascript
var heap = new ArrayBuffer(64*1024*1024);
```
Before we can manipulate the data, we need to create a view from it. With the following:

```javascript
var hI32 = new Int32Array(heap);
```

we can now manipulate hI32 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. Afterburner takes advantage of this feature to pack relational data into a columnar layout. In our implementation, 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 2 shows the physical memory layout storing the lineitem table from the TPC-H benchmark, which we use as a running example. A lineitem pointer serves as the entry point to a group of 32-bit integer pointers, which represent the offsets of the data in each column (l_orderkeys, l_partkeys, etc.). Currently, Afterburner supports integers, floats, dates, and strings. For the first three types, values are stored as literals (essentially, as an array). For a column of strings, we store null-terminated strings prefixed with a header of pointers to the beginning of each string, essentially a (char **) in C. In Figure 2, the bottom row represents the raw buffer, while the top three rows represent the various views. Blackened boxes represent invalid data for that particular view.

### 3.2 Query Compilation into Asm.js

In conjunction with typed arrays, Afterburner takes advantage of asm.js, a strictly-typed subset of JavaScript that is designed to be easily optimizable by an execution engine. Consider the following fragment of JavaScript for counting the number of records that matches a particular predicate on the l_extendedprice column:

```javascript
function count(val, l_extendedprice, length){
    var cnt = 0;
    for(var id = 0; id < l_extendedprice.length; id++)
        if (l_extendedprice[id] < val) cnt++;
    return cnt;
}
```

The equivalent function in asm.js is as follows:

```javascript
function count_asm(val, l_extendedprice, length){
    "use asm";
    val += (val);
    length = length|0;
    id = 0;
    while((id|0) < (length|0)){
        if(+(hF32[((l_extendedprice + id)|0) >> 2]) < +(val))
            cnt = (cnt + 1)|0;
        id = (id + 4)|0;
    }
    return cnt|0;
}
```

The above function takes as parameters l_extendedprice, which is the starting byte offset of the l_extendedprice column, and length, which is the number of records in that table. The hF32 variable is a 32-bit float view and thus the byte offsets can be computed by multiplying the index variable id by four using the shift operator (<<). Asm.js uses 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, since in "vanilla" JavaScript these hints just become no-ops.

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), operations on unboxed (i.e., primitive) types, and removal of garbage collection.

An asm.js module can take three optional parameters, which provide hooks for integration with external 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 AsmModule(stdlib, ffi, heap){
    "use asm",
    // module body
}
```

We refer to JavaScript without asm.js optimizations as vanilla JavaScript.

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1. http://asmjs.org/spec/latest/
2. 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 is passed into the module as a parameter, and the query results are returned by the module.

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. There is a straightforward mapping from the method calls to clauses in an SQL query, so we can view the fluent API as little more than syntactic sugar. However, this query API is quite similar to DataFrames [7], an interface for data manipulation that many data scientists are familiar with today. In fact, Lovefield, one of the SQL-in-JavaScript systems we discuss in Appendix A, adopts the same style for specifying SQL queries.

Starting from an SQL query expressed in our fluent API, Afterburner generates the string representation of the asm.js code that corresponds to the query. In the current implementation, this is performed 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 current implementation supports a wide variety of SQL analytical operations, covering all the queries in the TPC-H benchmark:

- **Simple Filters.** We have a basic code template that generates query plans for simple filter–project or filter–aggregate queries. The 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. The template currently only supports two-way joins.  

- **Group Bys.** The code template loops over one relation to build a hash table over the grouping keys. Another loop iterates over the hash table in order to process the groups.

- **Subqueries.** Afterburner handles subqueries by materializing their output, which is used as input tables for other operators. In addition, Afterburner supports IS IN subquery clauses by generating code that is similar to the join code templates.

### 3.3 In-Browser Query Processing

In the previous sections, we have outlined two main features that characterize Afterburner’s SQL engine, which are columnar storage and code generation. Other than the challenges associated with the JavaScript runtime, the web browser imposes additional challenges such as a limited memory footprint. In this section, we discuss design decisions behind Afterburner’s code generation templates that allow running query operators efficiently inside the browser.

Copy-free joins and group by code templates. Afterburner avoids materialization of intermediate results as much as possible in order to run inside a web browser. For example, it only stores record identifiers in hash tables (instead of copying the values themselves) in order to minimize the memory footprint of the hash-based join and group by operators. Afterburner will translate record identifiers into array indices to access the column values in a lazy fashion. An alternative design that stores record values directly in the hash table can provide faster performance during the probe phase by avoiding the extra overhead required to retrieve the values themselves (e.g., array index translation and random memory access). However, Afterburner’s lazy approach requires less memory and avoids unnecessary copying.

As an example, consider the following query, expressed in fluent SQL, which computes the sum of l_extendedprice column from the lineitem table, filtered by a certain order date range. In order to apply this filter, a join with the orders table is required:

```javascript
abdb.select()
.from('lineitem')
.join('orders')
on('l_orderkey', 'o_orderkey')
.field(sum('l_extendedprice'))
.where(lt('o_orderdate', date('1995-03-15')));
```

Figure 3 shows the code generated by the template for the join operator in Afterburner. We assume a hash table on the o_orderkey records that satisfy the predicate on the o_orderdate column has already been built at an earlier stage. The hash table and the column storage use JavaScript typed array views over a single buffer (heap). Since the query does not have any filter predicates over the lineitem table, lines 1 and 2 control a loop over the l_orderkey
column from zero up to the number of records in the table. The variable \( l_rid \) is used to maintain this record identifier, which is then translated into an array index with the relevant data type in order to access the values of the column, as described in Section 3.2. Lines 3 and 4 compute hash keys of the values in the \( l_orderkey \) column, which are then used to look up record identifiers of the matching records in \( o_orderkey \).

Next, lines 6–19 are responsible for probing the hash table over the \( o_orderkey \) column. A matching hash key does not guarantee that the values of \( o_orderkey \) and \( l_orderkey \) match, since hash values might collide in false positives. Thus, lines 20–22 use the record identifier \( l_rid \) and \( o_rid \), which was retrieved by probing the hash table, to compute array indices in order to compare the actual values. Finally, line 23 uses the record identifier for the \( lineitem \) table to compute the memory address of the associated \( l_extendedprice \) value in order to compute the sum.

**Hash table implementation.** Our hash table uses chaining for collision resolution, where the chains are allocated as unrolled linked lists in another memory segment. Since we do not have access to operating system calls such as `malloc` and `free`, Afterburner must handle all aspects of memory management itself. In our example compiled query, the variable `hbb` shown in line 7 holds the starting array index of the hash table segment. At the beginning of a new query, the generated code must reset the hash table, i.e., remove any previously-inserted keys. In our experiments, we found that resetting hash table segments takes substantial time; for example, setting the value of 2.6 million keys (2.6 million \( \times \) 4 byte integers = 10MB of memory) takes on average 9ms on our client machine, which is an unacceptable overhead per operator usage, since an operator might be used multiple times per query.

To minimize the overhead associated with resetting the hash table after each use (i.e., zeroing out the memory), we maintain an array of bits that tracks the state of each hash table key. For a hash table for 2.6 million keys requires a bit array of only 300KB and takes less than 1ms to reset. To illustrate this, consider the code shown in Figure 3: lines 6–8 check whether the bit associated with the key is set to one or zero before checking whether the key exists in the hash table. Only if the associated bit is set to one does the system consider the key to be valid. This allows hash-based operators to reuse memory segments with little overhead.

Another benefit of the bit array is when using the hash table for group by operators on sparse columns (columns with a small number of unique values relative to the cardinality of the relation, for example, region identifiers in the TPC-H schema). After the insertion phase is complete, the generated code first scans the keys stored in the hash table in order to check for unique values (the groups). Scanning the bit array can uncover the inserted keys in a fraction of the time required to scan the entire array segment that stores the actual keys. For dense columns (columns with a large number of unique values relative to the size of the relation), checking the bit array does not add much overhead.

## 4 SPLIT EXECUTION

As discussed, our work tackles the common scenario in interactive SQL data exploration where a data scientist executes a sequence of queries that differ only in the predicates in the `WHERE` clause. Our running example Q6 from the TPC-H benchmark, which examines "what-if" revenue missed because of discounts, exemplifies this scenario. The data scientist might be interested in exploring revenue missed under different date ranges (i.e., different predicates on the \( l_shipdate \) column). Instead of issuing a different SQL query each time, she can use the following materialized view to answer this query for all date ranges:

```sql
CREATE MATERIALIZED VIEW Q6MVsql AS (  
  SELECT SUM(l_extendedprice * l_discount) AS f1,  
  l_shipdate  
  FROM lineitem  
  WHERE l_discount BETWEEN 0.05 and 0.07  
  AND l_quantity < 24  
  GROUP BY l_shipdate ;
)
```

The materialized view has two columns, one with precomputed sums \( f1 \) grouped by \( l_shipdate \) and the other with the associated \( l_shipdate \). Q6 can be computed using this view by applying the filter predicate to the \( l_shipdate \) column and computing a sum over the precomputed sums \( f1 \), expressed as follows:

```sql
SELECT SUM(f1) AS revenue  
FROM Q6MVsql  
WHERE l_shipdate >= DATE '1994-01-01'  
  AND l_shipdate < DATE '1995-01-01';
```

Afterburner is able to automatically and transparently rewrite an SQL query into two separate queries based on a hint provided by the data scientist. We introduce a `FREE` clause that allows the data scientist to specify the column over which she wishes to issue follow-up SQL queries with different predicates (\( l_shipdate \) in this case). Afterburner then generates the two queries above:

- The **materialized view query** or \( QMV \), which builds the appropriate materialized view.
- The **view query** or \( QV \), which is the new query rewritten against the materialized view.

The data scientist can express Q6 using fluent SQL, using the `FREE` operator on the \( l_shipdate \) column as follows:

```sql
Q6MVjs = abdb.select()  
  .from('lineitem')  
  .field(as(sum(mul('l_extendedprice', 'l_discount')),  
    'revenue'))  
  .where(between('l_shipdate', 0.05, 0.07))  
  .where(lt('l_quantity', 24))  
  .free('l_shipdate');
```

Calling `free` in the last line runs the materialized view query at the backend and copies it to the frontend. After this, the data scientist can interactively explore the data by adding more filters on the \( l_shipdate \) column (let’s call it \( Q6js \)), which can be executed in the frontend by calling the `exec` function.

```java
Q6js.exec(Q6MVjs);
```

The parameter \( QMVjs \) is passed to the `exec` function as the materialized view to use.

This scenario illustrates how Afterburner creates a materialized view transparently using our API, i.e., the data scientist did not have to come up with the SQL query definition for the materialized view. In addition, she did not have to rewrite her query against the materialized view. This is desirable because she can work with
Multiple materialized views at the same time, working from the same query template with minimal modifications. We emphasize that these materialized views are local with respect to the data scientist and not updated as the original data sources change. In our usage scenario, the views are intended to be transient and lightweight; Section 4.3 discusses this in more detail.

### 4.1 Materialized View Query

Figure 4 illustrates the intuition of how Afterburner splits the execution of a query. On the left, we show a simple plan for Q6, starting with a scan operator that produces records based on the projected columns from the lineitem table. This is followed by a filter operator, which applies the predicates to the records, then a group by operator that applies the requested aggregation function. Finally, the sink operator produces the output. Although we can materialize the output of any operator, save it, ship it to the browser, and then apply the rest of the operators, this may not be sufficient to "free up" the column.

To free the l_shipdate column, we transform the query in a way that delays the filter (shown on the right side of Figure 4). This transformation requires passing the l_shipdate column to the group by operator. Next, we materialize the output and ship it to the browser and then apply the rest of the plan. When the user changes the predicates on the l_shipdate column, only the local part of the plan must be changed—and can be executed in the browser using Afterburner.

Now that we have illustrated the intuition behind the materialized view generation, we discuss how Afterburner generates the SQL definition of the materialized view. Targeting SQL to create materialized views (instead of a physical plan, for example) comes with a few benefits, which includes widening the applicability of our techniques to any backend that supports SQL (e.g., Spark). In addition, using SQL allows the backend to adopt the best plan according to its own query optimizer to answer the query.

![Figure 4: The original (left) and split-execution (right) query plans for Q6.](image)

### Algorithm 1 Generate MVQ

**Input:** Query \(Q_0\), Column \(c_{free}\)  
1: \(MVQ \leftarrow \text{new Query()}\)  
2: \(MVQ\text{.SELECT} \leftarrow Q_0\text{.SELECT} \cup \{c_{free}\}\)  
3: \(MVQ\text{.FROM} \leftarrow Q_0\text{.FROM}\)  
4: \(MVQ\text{.GROUP} \leftarrow Q_0\text{.GROUP}\)  
5: \(MVQ\text{.WHERE} \leftarrow Q_0\text{.WHERE} \setminus \{c_{free}\}\)  
6: \(\text{for } c \in MVQ\text{.SELECT} \land isAggregate(c)\):  
7: \(c \leftarrow \text{rewriteAgg}(c)\)  
8: \(\text{hasAggregate} \leftarrow \text{true}\)  
9: \(\text{if hasAggregate}\):  
10: \(MVQ\text{.GROUP} \leftarrow MVQ\text{.GROUP} \cup \{c_{free}\}\)  
11: return \(MVQ\)

### Table 1: Explanation of symbols used in this section.

| Symbol | Explanation |
|--------|-------------|
| \(Q_0\) | Original query with a `FREE` clause. |
| \(c_{free}\) | A column set to be free in the `FREE` clause of \(Q_0\). |
| \(MVQ\) | Materialized view query which is the SQL definition of the materialized view. |
| \(Q_n\) | A new query submitted with a corresponding \(MVQ\) to use. |
| \(QV\) | A new query generated by Afterburner to run in the frontend. |
| \(\text{SELECT}\) | The list of terms in the `SELECT` clause of query \(Q\). A term in the `SELECT` clause can be a constant value, an attribute name, or an aggregation function over an attribute name. |
| \(\text{FROM}\) | The list of terms in the `FROM` clause of query \(Q\). A term in the `FROM` clause can be a table name or a subquery. |
| \(\text{WHERE}\) | The list of terms in the `WHERE` clause of query \(Q\). |
| \(\text{GROUP}\) | The list of columns in the `GROUP BY` clause of query \(Q\). |

Materialized view query generation is shown in Algorithm 1, which computes the materialized view definition \((MVQ)\) based on an original query \((Q_0)\) and a valid column to free \((c_{free})\). Symbols used here and in the following descriptions are summarized in Table 1. Line 1 initializes an empty query template \((MVQ)\). Line 2 adds each term in the `SELECT` list of \(Q_0\) to \(MVQ\). For example, in Q6 the `SELECT` clause of the original query contains the aggregated value `SUM(l_extendedprice * l_discount)` which is added to the materialized view query. In addition, line 2 adds the column in the `FREE` clause to the `SELECT` list of \(MVQ\), which is \(l\_shipdate\). This step is necessary to be able to apply predicates on \(c_{free}\) at the frontend. Lines 3–4 add the terms in the `FROM` and `GROUP BY` lists of \(Q_0\) to \(MVQ\). The terms in the `FROM` clause can be any valid term, i.e., a table name or a subquery.

In principle, the materialized view \(MVQ\) may inherit filter predicates on the \(c_{free}\) column from the original query \(Q_0\), which limits subsequent queries. For example, the original query can specify a certain date range, which will limit subsequent queries on \(l\_shipdate\) to be within that date range. However, in our implementation, we employ a simpler approach and do not consider filters on \(c_{free}\), which simplifies the `FREE` clause. Thus, line 5 removes any instance of \(c_{free}\) from the `WHERE` list.

Lines 6–8 check for aggregates in the `SELECT` list of \(MVQ\) and rewrite the aggregation functions based on predefined rules. For example, we rewrite `AVG` in terms of `SUM` and `COUNT` in order to be able to derive `AVG` using the materialized view. Our system supports the standard set of aggregates: `COUNT`, `SUM`, `AVG`, `MIN`, and `MAX`. Our implementation of `rewriteAgg` is rather straightforward, and thus...
we omit for brevity; however, see Srivastava et al. [28] for details. If an aggregate exists, this requires adding the cfree column to the GROUP list of QMV, which is done in lines 9–10. Note that we do not include terms in the ORDER and the LIMIT clauses during materialized view creation.

For some queries and columns, delaying filters might lead to materialized view definitions that do not suit our split-execution scenario due to physical limitations on the backend or the frontend. The materialized view query can exhaust the resources of the backend, for example, when the size of the intermediate output exhausts the physical resources of the backend. The size of the final materialized view may also not fit into memory available at the frontend. These two considerations must be addressed when deciding which columns to free.

Our current implementation depends on a set of rules for deciding which columns can be freed. We disallow freeing columns that interact with other columns because they are likely to exhaust physical resources. Namely, a column cannot be in a condition on multiple columns such as a join condition or a complex predicate involving other columns. We also disallow freeing a column mentioned in an OR clause. Finally, our system allows for subqueries but disallows freeing a column referenced in the subquery.

### 4.2 View Query

At query time, Afterburner must validate whether a materialized view can be used to answer a query. This is accomplished using rules that work on a parse tree representation of an SQL query, which can be evaluated efficiently (negligible time in our evaluations). Since we expect only a small number of materialized views at the frontend, this simplifies our frontend plans to general-purpose query optimization.

As demonstrated in our API, our task is query validation against a single materialized view. An important result from Larson and Zhou [23] is that a set of rules can be used to verify query coverage for the query class SPJOG (Select, Project, Join, and Outer join) with a possible Group by). Thus, for a new query (Qn), a query optimizer should be able to rewrite it against the local materialized view (QMV) transparently. In our prototype, we use simpler conditions to validate the query against a materialized view because our goal is to accelerate queries at the frontend—as opposed to general-purpose query optimization.

Our set of rules is simpler because of two main reasons. First, our prototype does not consider partial matching plans, which are plans that involve both the materialized view and base relations. While mixed plans can potentially improve overall query latency, we do not consider them in this setup since we do not assume access to the base tables at the client. Second, as we have mentioned in the previous section, we do not allow for predicates on the cfree column in the backend query. This simplifies our frontend plans to plans involving a single relation (which is QMV) with exactly matching predicates (other than predicates on cfree). Thus, the only differences allowed are in the GROUP BY clause and the WHERE clause, and only involving the cfree column.

#### Materialized view matching conditions.

When a new query is issued at the frontend with a corresponding materialized view,

---

**Algorithm 2 Generate VQ**

**Input:** Query Qn, Query QMV

1. \( Q_V \leftarrow \text{new Query}() \)
2. \( Q_V\text{.SELECT} \leftarrow Q_n\text{.SELECT} \)
3. \( \text{for } c \in Q_V\text{.SELECT} \land \text{isAgg}(c): \)
   - \( c \leftarrow \text{deriveAgg}(c) \)
4. \( Q_V\text{.FROM} \leftarrow \{QMV\text{.name} \} \)
5. \( \text{for } p \in Q_n\text{.WHERE} \land p \in \{\text{cfree}\}: \)
   - \( Q_V\text{.WHERE} \leftarrow Q_V\text{.WHERE} \cup \{p\} \)
6. \( Q_V\text{.GROUP} \leftarrow Q_n\text{.GROUP} \)
7. \( Q_V\text{.ORDER} \leftarrow Q_n\text{.ORDER} \)
8. \( Q_V\text{.LIMIT} \leftarrow Q_n\text{.LIMIT} \)
9. \( \text{return } Q_V \)

---

Afterburner uses the following conditions to validate whether QMV can be used to answer (matches) Qn:

1. \( \text{cond 1: } Q_n\text{.SELECT} \subseteq QMV\text{.SELECT} \)
2. \( \text{cond 2: } Q_n\text{.FROM} = QMV\text{.FROM} \)
3. \( \text{cond 3: } Q_n\text{.JOIN} = QMV\text{.JOIN} \)
4. \( \text{cond 4: } Q_n\text{.WHERE} \setminus \{\text{cfree}\} = QMV\text{.WHERE} \)
5. \( \text{cond 5: } Q_n\text{.GROUP} \setminus \{\text{cfree}\} \subseteq QMV\text{.GROUP} \)

Condition 1 checks that the SELECT list of Qn is a subset of the QMV SELECT, i.e., the new query is not allowed to select new columns. Conditions 2 and 3 verify that the FROM and JOIN lists of Qn matches exactly QMV. Condition 4 checks that predicates in the WHERE list of Qn match exactly the predicates in QMV and may only add predicates on the cfree column. Condition 5 checks that all the GROUP lists of Qn (if any) are either already included in the GROUP list of QMV or is the cfree column.

**View query generation.** To generate the view query we use Algorithm 2, which rewrites the new query (Qn) against the materialized view (QMV). Line 1 initializes an empty frontend query (Qv). Line 2 adds all the terms in the SELECT list of Qn into Qv. Lines 3–4 derive aggregate terms from the materialized view using the deriveAgg function, e.g., COUNT is derived as a sum of counts; once again, see Srivastava et al. [28] for details. Line 5 adds the name of the materialized view (QMV) in the FROM list of Qv. Lines 6–7 only add predicates on the cfree column to the WHERE clause of Qv. For example, Qv for Q6 only includes the two predicates \( l\text{.shipdate} \geq \text{DATE '1994-01-01'} \) and \( l\text{.shipdate} < \text{DATE '1995-01-01'} \). Finally, lines 8–10 add all the terms in the GROUP, ORDER, and LIMIT lists to Qv.

---

### 4.3 Additional Discussion

For clarity, the above exposition describes how to free a single column, although our algorithm generalizes to freeing multiple columns in a straightforward manner. However, in practice (see Section 5.3), materialized views for freeing multiple columns are quite large since the materialized view query generates the Cartesian product of the columns—typically, this is more data than the client can handle.

At a higher level, an obvious shortcoming of our approach is that the data scientist needs to explicitly provide hints via the free operator. Ideally, this should be automatic—the system should infer
the subject of exploration, pre-fetch queries in the background while the user is idle, learn from interactions to prioritize memory usage, and automatically invalidate local views if the source data changes. Tackling these challenges, however, requires solving a number of issues that are orthogonal to the focus of this paper, for example, user modeling to identify and anticipate “interesting” columns. These are interesting future directions but beyond the scope of this paper. In our usage scenario, the materialized views are transient, bounded at most by the life of a browser tab. We envision that “invalidation” and “maintenance” of views are as simple as refreshing the browser tab. Even though the views may be short-lived, our split-execution experiments in Section 5.3 show that the data scientist “recoups” the extra cost of the materialized views for interactive data exploration rather quickly.

5 EVALUATION

Experimental validation of our work is divided into three parts. First, we conducted microbenchmarks to understand the performance characteristics of the in-browser execution environment and how it compares to native code execution. Second, we examined the performance of Afterburner on end-to-end SQL analytics within the browser (the TPC-H benchmark), comparing our system against MonetDB, a well-known column store, and LegoBase, the state of the art in compiled queries for SQL. Finally, we tied all the threads of the paper together and conducted an evaluation of interactive SQL analytics performance, taking advantage of Afterburner split execution. For these experiments, we compared our architecture with the alternative deployments discussed in Section 2.

5.1 Microbenchmarks

In our microbenchmarks, we focused on simple filter queries that count the number of records matching a predicate on a particular column. For this, we examined filtering integers, floats, and strings. Table 2 shows the names of the columns, along with the filters and their selectivities. For these experiments, we scanned the `orders` table from TPC-H data at a scale of 10 GB (15 million records). We examined the following hand-written programs in JavaScript:

- JavaScript without asm.js or typed arrays, which we refer to as J1 for convenience.
- JavaScript without asm.js but with typed arrays, which we refer to as J2 for convenience.
- JavaScript with both asm.js and typed arrays, which we refer to as J3. This takes advantage of all JavaScript optimizations that we described in Section 3.

Note that the option of evaluating asm.js without typed arrays is not possible since the asm.js compiler disallows accessing JavaScript objects. We compared the above conditions against hand-written C++ programs, compiled under the following conditions:

- GCC (g++ 5.4.0) using optimization level -O3, which we refer to as GCC-O3 for convenience.
- GCC, but without any optimizations.
- Clang (v 3.9.0), with optimization level -O3, which we refer to as Clang-O3 for convenience.
- Clang, but without any optimizations.

Experiments were run on a desktop with a 2.7 GHz Intel i5-5250U processor (4 cores, 3 MB of cache) and 8 GB of RAM, running Ubuntu 16. The JavaScript conditions ran in Mozilla Firefox (v50). We ran each condition five times for warmup and report the average runtime over the next five trials. Note that warm runs allow the JavaScript conditions to benefit from JIT code caching.

Results are shown in Table 3, where we report query latencies in milliseconds and slowdown with respect to GCC-O3 in parentheses. For these experiments we exclude compilation times for C++ and asm.js. Comparing GCC-O3 with fully-optimized JavaScript (J3), we see a slowdown of roughly 4–5× for filter predicates over integers and floats, but only slowdown of 10% for strings. Detailed analyses show that the performance advantage of GCC-O3 comes from automatic loop unrolling and the generation of SIMD instructions. On the other hand, strings are only marginally slower with J3 because of the extra level of indirection associated with a standard (char ** ) representation of strings in C++, where the query latency is dominated by memory latencies associated with pointer dereferencing. We see the effectiveness of SIMD instructions and loop unrolling with GCC (without any optimizations), which is actually slower than fully-optimized JavaScript. Comparing J3 with J2 (typed arrays but no asm.js) and J1 (no optimizations), it is clear that both features of JavaScript contribute to performance and in a cumulative fashion. Finally, our results show that Clang performance is on par with GCC performance. This provides a sanity check as one of the conditions in the next section uses Clang.

In Table 4, we show the output of CPU performance counters comparing GCC-O3 and J3, using the perfstat profiling tool. Measuring such low-level performance for GCC-O3 is straightforward since the code runs as a separate process. On the other hand, measuring CPU performance for J3 running inside the browser is challenging because J3 runs as a thread inside the browser’s main process. Thus, even in an idle state, without user interactions, the browser process is active (e.g., running event loops) and generating data captured as part of profiling. In order to minimize such interference in our measurements we took the following steps: First, we repeated each run 500 times and report the average. Second, we minimized the size of the browser window, leaving only the

| Type      | Filter       | Selectivity | Column Name |
|-----------|--------------|-------------|-------------|
| Integer   | == 0         | 1.0         | o_shippriority |
| Float     | > 555.5      | 1.0         | o_totalprice  |
| String    | "1-URGENT"  | 0.2         | o_orderpriority |

Table 2: Filter predicates in our microbenchmarks.

| Condition | Integer | Float | String |
|-----------|---------|-------|--------|
| GCC-O3    | 4.4     | 4.4   | 56.4   |
| GCC       | 37.0 (8.4x) | 47.8 (10.9x) | 103.8 (1.8x) |
| J1        | 16.9 (3.8x) | 22.7 (5.2x) | 60.8 (1.1x) |
| J2        | 20.1 (4.6x) | 25.7 (5.8x) | 94.7 (1.7x) |
| J3        | 28.6 (6.5x) | 28.5 (6.5x) | 408.1 (7.2x) |
| Clang-O3  | 5.8     | 4.0   | 60.4   |
| Clang     | 40.4    | 43.4  | 97.0   |

Table 3: Microbenchmarks showing query latencies (ms).
We are, of course, not the first to explore data management inside the browser. A detailed comparison with SQL-in-JavaScript solutions is presented in Appendix A, but the high-level finding is that current JavaScript SQL engines such as Lovefield and Sql.js are not able to efficiently support analytical queries for even modestly-sized databases. The performance and scalability of Afterburner is far superior to either of these systems.

Table 4: Performance counters comparing GCC-O3 vs. J3.

| Type  | Branches | Mispredicts | D1 misses | I1 misses |
|-------|----------|-------------|-----------|-----------|
| Integer | 3.7m | 45m | 37 | 7.6k | 940k | 970k | 640 | 12k |
| Float  | 3.8m | 45m | 26 | 3.4k | 940k | 950k | 520 | 12k |
| String | 33.0m | 51m | 3.2m | 3.3m | 3.6m | 3.6m | 7700 | 21k |

In summary, these microbenchmarks show that the JavaScript execution environment inside modern browsers is very efficient, in some cases rivaling native performance. This is not surprising: the prevalence of complex JavaScript applications (e.g., Gmail, Facebook, etc.) in running modern websites means that countless hours have been devoted to optimizing JavaScript performance—we are the beneficiaries of all this effort. Native code is still much faster in our microbenchmarks because of SIMD instructions and loop unrolling, but these optimizations do not appear to be possible on more complex queries: this is confirmed by experimental results in Section 5.2, where modern compiled query techniques running natively do not outperform Afterburner by anywhere close to the margins reported in the microbenchmarks. Overall, the impression that "JavaScript is slow" is simply a myth—high-performance SQL analytics engines in JavaScript are possible. We turn to this next.

5.2 In-Browser Analytics Performance

We are, of course, not the first to explore data management inside the browser. A detailed comparison with SQL-in-JavaScript solutions is presented in Appendix A, but the high-level finding is that current JavaScript SQL engines such as Lovefield and Sql.js are not able to efficiently support analytical queries for even modestly-sized databases. The performance and scalability of Afterburner is far superior to either of these systems.

To examine the end-to-end query performance of our approach, we compared the full Afterburner system against the following:

- **LegoBase** [20, 27] is an open-source in-memory RDBMS that represents the state of the art in code generation. LegoBase takes as input a representation of the physical plan of a query and then generates code for this plan. LegoBase uses its knowledge of the target programming language and database statistics to pick the best physical operators for a query. In our experiments, we configured LegoBase to target C, to generate code under what the authors call the "compliant" condition, which generates query operators that are compliant with the TPC-H benchmark. We measured the time to generate the target C code (codegen), time to compile the target code using Clang (compile), and query execution latency (which does not include codegen and compile stages). For all experiments we used available open-source code\(^1\) and sought guidance from the authors of the papers to ensure that we were using their system properly. Our runs are generally consistent with the results reported in their papers.

**Afterburner (Vanilla).** To isolate the impact of asm.js in the performance of Afterburner, we also evaluated Afterburner (Vanilla), a variant that uses typed arrays but not asm.js (i.e., the compiled query plans were evaluated with asm.js optimizations disabled). Thus, Afterburner (Vanilla) resembles the J2 condition from the previous section.

Thus, we compared five different experimental conditions in total: Afterburner (Full), Afterburner (Vanilla), MonetDB (Single-threaded), MonetDB (Multi-threaded), and LegoBase. We have specific rationale for each of these comparisons: MonetDB is a mature and stable implementation of well-known techniques for analytical data processing (albeit the techniques are around a decade old). On the other hand, LegoBase represents the "latest and greatest" research on compiled queries. It is best described as a research toolkit comprised of many different pieces, as opposed to a complete RDBMS. Finally, Afterburner (Vanilla), compared to the full system, allows us to separately study the contributions of typed arrays and asm.js to overall performance.

In these experiments, we used the TPC-H benchmark at a scale factor of 1 GB, which corresponds to 6 million records in the lineitem table. This represents a rough upper bound on the amount of data that a commodity desktop or laptop can comfortably hold today. Experiments were performed on the same client machine as in the previous section.

All our measurements were on a warm cache—we first ran each query five times, and then took measurements over five trials. For LegoBase, we warmed up codegen and query compilation in the same way. For Afterburner (both the full and vanilla configurations), measured latency includes query compilation overhead and all data are explicitly loaded in memory. For MonetDB, we confirm that all data are cached in the underlying OS buffer caches.

\(^1\) The term LegoBase is a bit ambiguous since it refers to several different software components, but in this context we specifically refer to the authors’ SIGMOD 2016 paper that we replicate and compare against.

\(^{1}\) [https://github.com/pld/lfw](https://github.com/pld/lfw)
Figure 5 (left) shows the query latency of all 22 TPC-H queries for all our experimental conditions; detailed running times are shown in Appendix B. As expected, multi-threaded MonetDB is faster than single-threaded MonetDB (by 1.7×), but this is not a fair comparison since one condition has access to more hardware resources. Leaving aside MonetDB (Multi-threaded), across all queries, MonetDB (Single-threaded) is the fastest for 6 queries, LegoBase is the fastest for 11 queries, and Afterburner (Full) is the fastest for 5 queries. MonetDB (Single-threaded) beats Afterburner (Full) for 11 queries and LegoBase beats Afterburner (Full) for 11 queries. From the right plot in Figure 5, MonetDB (Single-threaded) completed all 22 queries in 4.8s, compared to 6.4s for Afterburner (Full), which makes Afterburner (Full) 1.3× slower. LegoBase runs out of available physical memory on our client desktop for Q7 and Q9, so we computed total* as the running time over just the remaining 20 queries: LegoBase finishes all of them in 3.7s, MonetDB (Single-threaded) finishes in 4.5s, while Afterburner (Full) finishes in 5.7s, making our system 1.5× and 1.3× slower, respectively. For reference MonetDB (Multi-threaded) completes all 22 queries in 2.8s and the 20 queries in 2.6s.

The comparison between Afterburner (Full) and LegoBase gives us a sense of how our approach compares to modern compiled query techniques. Note that all measurements of our system represent end-to-end execution time, while latencies for LegoBase do not include code generation or compilation. The total time to generate code and to compile the TPCH queries for the 20 queries under the total* condition was 7.2s and 7.4s, respectively. To be fair, LegoBase was not optimized for interactive query exploration—both the codegen and compilation stages individually are longer than end-to-end execution for Afterburner (Full). LegoBase is perhaps more suitable for even larger data conditions and repeated execution, where the time spent in codegen and compilation can be amortized over longer query execution times.

Comparing Afterburner (Full) with Afterburner (Vanilla) allows us to tease apart the performance contributions of Afterburner’s two different JavaScript optimizations: typed arrays and asm.js. Indeed, disabling asm.js optimizations yields a total latency of 10.5s on all 22 queries (1.6× slower). To assess the impact of typed arrays, we tried loading the TPCH data into the browser as JavaScript objects, and unsurprisingly, it failed (non-responsive browser, out of physical memory). Overall, these results are consistent with the microbenchmarks in Section 5.1 and show that both optimizations of Afterburner are critical to performance and scalability. Typed arrays enable compact, in-memory representations, while asm.js enables efficient code execution.

In summary, these experiments show that it is possible to build a high-performance analytical RDBMS in JavaScript. While its performance still lags MonetDB and LegoBase, both of which run natively, we find Afterburner’s performance quite impressive, considering that it runs completely in the browser!

5.3 Split-Execution Performance

Our final set of experiments brings together all of the threads discussed in this paper to evaluate the performance of interactive SQL analytics in Afterburner, taking advantage of our split-execution techniques. Referring back to Section 2, we compare our proposed Deployment D (Afterburner) against the alternatives A, B, and C.

In order to create a query mix that captures typical interactive SQL analytics tasks, we once again draw inspiration from the TPC-H benchmarks. For evaluation, we considered all the TPC-H queries with columns that can be “freed” based on our approach described in Section 4. For each TPC-H query, we generated variant queries as appropriate: for example, for Q6, we can free the columns l_shipdate, l_discount, l_quantity, which yields Q6a, Q6b, and Q6c, respectively. In total, 12 queries from the TPCH benchmark are amenable to this treatment. For each query, different columns can be freed. In some cases, the materialized views were too large to store at the client side; these queries were discarded in our evaluation. In total, we created 20 variant queries, shown in the first column of Table 5; the second column names the column in the query that is freed (e.g., l_shipdate) and its cardinality. As discussed in Section 4.3, Afterburner is able to free more than one column at a time, but this is often not practical due to the size of the materialized views. Thus, in our evaluation, we only considered cases where one column is freed at a time.

Our experiments used a data warehouse as defined by TPC-H at a scale factor of 100 GB, which yields a lineitem table with 600 million records. The backend in all scenarios is MonetDB running on a server with dual 8-core Intel Xeon E5-2670 processors (2.6 GHz) with 256 GB of memory on Ubuntu 14.04, configured to take advantage of all available hardware resources. The frontend machine in Deployments C and D is the same as the desktop described in the previous sections. In Deployment C, we run MonetDB
on the local client machine, and in Deployment D, we run Afterburner in the browser. As a minor detail, in both Deployment B and Deployment C we ran MonetDB with only a single core because the sizes of the materialized views are sufficiently small that single core performance is actually better than multi-core performance—the overhead associated with multi-core query execution is more than the performance gained via parallelism. For Deployment C, latency is measured from the perspective of the browser, i.e., materializing the result set inside the browser. In all our experiments, the client and backend server are both located in the same building, with round trip ping times less than half a millisecond. All performance measurements reported below were on a warm cache and we report averages over five trials.

Results of our experiments are shown in Table 5. The column marked “A” shows the query latencies under Deployment A, which does not take advantage of materialized views. The “free” clause does not apply; the query latency is simply the query execution time of the original TPC-H query posed against the backend. For ease of comparison, we simply repeat the latency in the row for each query variant. Deployments B, C, and D all take advantage of materialized views: the latency of the query that generates this materialized view is reported under the column “MVQ”. The size of the materialized view (in number of records) is reported under the column “MV size”, and the time it takes to copy the materialized view from the backend to the client is reported in the column “MV copy” (applicable only for Deployments C and D). The latency of the view queries under Deployments B, C, and D are the columns marked “B”, “C”, and “D”, respectively.

Continuing with our running example of Q6 from Section 2: from the results table we see that the unmodified query takes around 4.4s. If we wish to free the `l_shipdate` column, which has a cardinality of 2526, the materialized view query takes around 9.8s. However, all subsequent queries that involve only changes to predicates on `l_shipdate` only take ~10ms to run against the materialized view using any of the Deployments B, C, and D. Of course, in the case of Deployments C and D, the materialized view needs to be copied over to the client machine, which takes 247ms.

The performance of the view queries for Q6 (comparing Deployments B, C, and D) are comparable, but performance aside, these deployments manifest all the tradeoffs discussed in Section 2. The performance of Deployment B is affected by backend query load (e.g., concurrent queries by multiple data scientists) as well as variability in network latencies. In our case the backend is less than half a millisecond away, but in an enterprise cloud deployment, latencies could be much longer. For example, the round trip ping time between our client and an arbitrary instance on Amazon’s EC2 service running in the US East region is around 25ms. To be fair, though, link latencies will also affect the time it takes to copy the materialized view over to the client (in the case of Deployments C and D), but the advantages of local interactions remain in eliminating all subsequent need for interactions with the backend.

Comparing Deployments C and D, with Afterburner (Deployment D), we have eliminated the need to have a local RDBMS installation—complete with all the headaches of maintaining a local software stack. With Afterburner, we achieve breakeven in three queries: if the data scientist issues three queries using the same

| Free column (cardinality) | A (ms) | MVQ (ms) | MV size (records) | MV copy (ms) | B (ms) | C (ms) | D (ms) | Breakeven (D vs. A) |
|--------------------------|-------|----------|-------------------|-------------|-------|-------|-------|---------------------|
| Q1a l_shipdate (2526)    | 34,330| 119,843  | 3,817             | 277         | 19    | 16    | 13    | 4                   |
| Q2a p_size (50)          | 2,556 | 27,047   | 2,365,583         | 155,826     | 82    | 28    | 43    | 72                  |
| Q2b p_type (150)         | 2,556 | 4,405    | 236,211           | 16,380      | 331   | 128   | 44    | 9                   |
| Q3a c_mktsegment (5)     | 17,170| 19,051   | 5,662,337         | 107,526     | 198   | 132   | 1,147 | 8                   |
| Q3b o_orderdate (2406)   | 17,170| 36,142   | 16,553,365        | 268,052     | 233   | 174   | 1,280 | 18                  |
| Q4a o_orderdate (2526)   | 6,924 | 119,843  | 12,030            | 277         | 11    | 9     | 12    | 18                  |
| Q5a r_name (5)           | 7,712 | 8,890    | 25                | 203         | 14    | 10    | 11    | 2                   |
| Q5b o_orderdate (2406)   | 7,712 | 10,125   | 12,030            | 517         | 10    | 8     | 13    | 2                   |
| Q6a l_shipdate (2526)    | 4,362 | 9,815    | 2,526             | 247         | 13    | 12    | 7     | 3                   |
| Q6b l_discount (11)      | 4,362 | 4,590    | 11                | 375         | 12    | 9     | 6     | 2                   |
| Q6c l_quantity (50)      | 4,362 | 8,100    | 50                | 420         | 11    | 10    | 6     | 2                   |
| Q7a l_shipdate (2526)    | 8,388 | 8,390    | 5,052             | 649         | 11    | 10    | 11    | 2                   |
| Q12a l_shipmode (7)      | 5,420 | 5,760    | 7                 | 28          | 12    | 11    | 13    | 2                   |
| Q12b l_receiptdate (2554)| 5,420 | 7,219    | 4,985             | 163         | 10    | 13    | 12    | 2                   |
| Q14a l_shipdate (2526)   | 4,052 | 29,298   | 2,526             | 364         | 9     | 10    | 7     | 8                   |
| Q17a p_brand (25)        | 20,374| 142,773  | 25                | 468         | 14    | 11    | 6     | 8                   |
| Q17b p_container (40)    | 20,374| 120,131  | 40                | 678         | 9     | 11    | 7     | 6                   |
| Q20a n_name (25)         | 8,546 | 10,060   | 447,508           | 10,699      | 565   | 243   | 22    | 3                   |
| Q21a o_orderstatus (3)   | 23,540| 30,202   | 96,037            | 2,652       | 68    | 21    | 66    | 2                   |
| Q21b n_name (25)         | 23,540| 76,754   | 999,953           | 16,221      | 129   | 67    | 94    | 4                   |

Table 5: Experimental results comparing Deployments A, B, C, and D on interactive SQL data exploration scenarios derived from the TPC-H benchmark. Each variant query describes a different "freed" column.
query template as part of interactive data exploration, we make up for the fact that the initial materialized view query takes longer (even after accounting for the cost of transferring the materialized view). This is shown in the final column in Table 5.

Looking at results across all queries in Table 5, we see that in most cases Afterburner (Deployment D) achieves performance parity with MonetDB in both Deployments B and C. Where there are performance differences, they are for the most part negligible. However, there are a few special cases to note: for Q3, Afterburner queries take substantially longer to execute in the browser. In this case, the materialized view is quite large and the query involves a top-k. MonetDB is able to optimize this into a scan, whereas Afterburner inefficiently sorts all records before taking the top k. The performance difference, in this case, is caused by deficiencies in query optimization in our implementation, not an inherent limitation of our approach.

Other results worth discussing are performance differences between Deployments B and C for some queries—since they are both running MonetDB and the differences are much larger than can be explained solely by hardware (the backend vs. the client). This is most evident for Q20a, where the view query for Deployment B takes more than twice as long as the view query for Deployment C. We attribute these differences to the cost of transferring the result set over: in this case, the result set contains 18k records. The latency in Deployment C includes the overhead of loading the result set into the browser.

To summarize, it would be fair to characterize Deployment D as achieving performance parity with Deployment C. This is consistent with results from the previous section, where we examined end-to-end SQL analytics within the browser in comparison to MonetDB. Therefore, with Afterburner we can eliminate the need for client-side deployment of an RDBMS (with all its associated administrative and maintenance headaches) without compromising performance.

6 RELATED WORK

Split execution. The idea of splitting query execution across different layers of the stack is of course not new [8, 10, 13]. This paper revisits the same idea for accelerating interactive analytical SQL queries given two new conditions: First, the ability to execute analytical queries on the frontend in a JavaScript environment. Second, providing the data scientist an easy way to define the target of exploration around a query template. Our idea of “freezing” columns is related to the work of Kouad et al. [21] in “relaxing” join and selection queries, but their goal is to “back off” from queries that return empty results. Also related is the semantic pre-fetching idea of Bowman and Salem [8], who try to predict future queries based on past history; in our case, we require explicit hints from the user.

Compiled queries. The compiled query approach of Afterburner takes after systems like HiQUE [22], LegoBase [20, 27], Proteus [19], and HyPer [24], which have recently popularized code generation for relational query processing. With the exception of targeting JavaScript and dealing with all the limitations associated with running inside a browser, our query compilation techniques are fairly standard. We use a template-matching approach to generate compiled queries; for example, simple SELECT-WHHERE queries are converted into for loops over the appropriate ranges of the typed array holding the data. In our current prototype, there is no query optimization to speak of, as we only have a single hash-based physical plan for both joins and group bys.

One well-known drawback of query compilation is that compiling generated code using a tool like gcc can overshadow its benefits for short-running queries. Much research has gone into alleviating this issue, such as the use of an intermediate representation like LLVM [24]. In our work, however, we have found compilation overhead to be negligible, primarily because compilation speed is already something browsers optimize for since all JavaScript code on the web is stored as text.

Materialized views. Taking advantage of materialized views to optimize complex queries is a well-studied problem dating back decades [16, 17, 28, 30]. There are, however, substantial differences with our approach: in most previous work, materialized views are long-lived and carefully-considered by a database administrator, not built willy-nilly on an ad hoc and per-query basis—which is the approach that we take. For us, materialized views are transient and lightweight, precisely because they are shipped over to the browser and can be discarded when done. With our in-browser JavaScript engine, not only is the integration seamless, but subsequent interactions can happen without the backend.

Physical design tuning. In a sense, Afterburner shares similarities with physical design advisers [5, 9, 29] since that Afterburner picks materialized views automatically, without requiring special expertise or adding an extra administrative burden. Physical design advisers, choose a set of materialized views that optimize a query workload under constraints, such as fitting a storage budget. The query optimizer is heavily engaged in the process of identifying a candidates space to pick from (i.e. depend on the query planner enumeration space [29] to look for possible materialized views). In Afterburner, we apply query re-writing rules to generate the materialized view definition which can generate materialized views that would not be considered by a query planner.

Shared work and shared data. Our work also has similarities with techniques targeted at accelerating streams of queries by sharing parts of their plans [15, 18]. Similar to this line of work, Afterburner optimizes multiple queries by finding a common subplan (the materialized view). However, the optimization goals and approaches are very different. Our goal is to minimize the latency of a family of queries anchored around a single query template for a specific user, while subplan sharing techniques have the goal of improving overall system performance, e.g., higher query throughput, typically across multiple users. Once again, despite superficial similarities, Afterburner targets a completely different point in the design space.

Approximate query answering. Related to materialized views are techniques that provide faster but approximate answers to user queries [2–4, 14, 25]. One obvious difference is that Afterburner delivers exact answers. More importantly, though, as already discussed in Section 2, this thread of work provides additional support and motivation for the usefulness of our query scenario. At a high level, all the approaches cited above depend on a sequence of related queries that allow the system to approximate the distribution of the underlying data. Thus, these papers share similar intuitions as our own work but exploit them in very different ways.
7 CONCLUSION
This paper explores the somewhat unconventional idea of building data management capabilities directly in the browser. We empirically show that modern JavaScript runtimes are capable of supporting an analytical RDBMS whose query performance rivals state-of-the-art techniques running natively. Based on this, we propose a novel split-execution strategy to support template-based interactive SQL analytics. Experiments show that we achieve performance parity with other deployment architectures, but with a simpler "it's just a webpage" design. In other words, we can have our cake and eat it too!

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We are, of course, not the first to explore data management inside the browser. Arguably, any web application that contains JavaScript code and performs data manipulation requires some data management capability. For example, popular JavaScript libraries such as jQuery and D3.js provide basic filter queries over JavaScript objects that model a web page (i.e., the DOM). Any direct manipulation of JavaScript objects will have performance similar to the J1 condition discussed in Section 5.1, and as the results in Section 5.2 show, without typed arrays, the amount of data that can be loaded in the browser is quite limited. Any moderately-complex JavaScript visualization (in D3.js for example) is likely to be performing aggregations, grouping, and even joins—albeit in an ad hoc, imperative fashion. Nevertheless, a direct performance comparison between Afterburner and JavaScript libraries such as jQuery and D3.js would not be particularly meaningful, since those libraries do not support SQL. Imperative data processing libraries in JavaScript occupy a completely different point in the design space.

There are, however, two existing SQL-in-JavaScript solutions worth discussing:

Lovefield\(^\text{2}\) is a relational database for web apps written by Google. It is implemented in JavaScript and runs entirely inside the browser. The system does not support complex aggregates such as:

$$\text{SUM}(l\_\text{extendedprice} \times (1 - l\_\text{discount}))$$

and therefore it is not capable of running Q1 from TPC-H in its original form. While this is a rather minor issue, and support for more complex queries can certainly be improved in Lovefield, we do not expect the engine to scale and to achieve performance comparable to Afterburner for a fundamental reason: Lovefield’s storage and execution engine depend on JavaScript objects. Based on the comparison between the J1 and J3 conditions in Section 5.1 and the results from Section 5.2, we know that this is a significant impediment to performance and scalability.

Nevertheless, to compare Afterburner with Lovefield, we generated an instance of the \text{lineitem} table using the TPC-H data generator and incrementally ingested data into the system (on the same client machine used in Section 5.1). We were not able to load more than the first 5000 records before the browser tab crashed. On this amount of data, we attempted to run TPC-H Q1. Due to the issues raised above, we had removed all unsupported expressions. For concreteness, the following is the variant query expressed in Lovefield’s API:

```sql
tpch.select(LINEITEM.L_RETURNFLAG,
            LINEITEM.L_LINESTATUS,
            l\_fn.\text{sum}(LINEITEM.L\_\text{QUANTITY}),
            l\_fn.\text{sum}(LINEITEM.L\_\text{EXTENDEDPRICE}),
            l\_fn.\text{avg}(LINEITEM.L\_\text{QUANTITY}),
            l\_fn.\text{avg}(LINEITEM.L\_\text{EXTENDEDPRICE}),
            l\_fn.\text{avg}(LINEITEM.L\_\text{DISCOUNT}),
            l\_fn.\text{count}(LINEITEM.L\_\text{ORDERKEY})
            )
            .from(LINEITEM)
            .where(LINEITEM.L\_\text{SHIPDATE}.lt(
              dbDateTime('1998-09-02')))
            .groupBy(LINEITEM.L\_\text{RETURNFLAG},
                     LINEITEM.L\_\text{LINESTATUS})
            .orderBy(LINEITEM.L\_\text{RETURNFLAG}, \text{asc})
            .orderBy(LINEITEM.L\_\text{LINESTATUS}, \text{asc})
            .exec()
```

Note that Lovefield uses a fluent approach to specifying queries, just like Afterburner. The above query on 5000 records took 30ms. On the same query, Afterburner takes 11ms. It is important to note that even with Afterburner’s constant overheads per query (e.g., query compilation, asm.js compilation, etc.), our system is still much faster than Lovefield on this tiny dataset.

Sql.js\(^\text{6}\) is a cross-compiled version of SQLite(v3) into asm.js. It shares a few features with Afterburner: Sql.js uses code generation but targets the SQLite virtual machine bytecode, employs asm.js (via cross compilation), uses in-memory storage, and uses typed arrays for storage and query execution (i.e., does not depend on JavaScript objects).

In our experiments, we were not able to load a TPC-H database of scale factor 1GB into Sql.js (the browser hangs and then crashes). We tried to load smaller slices of the database in 10% increments. We only managed to ingest the first 600k records from the \text{lineitem} table. For Q1, on this amount of data, Sql.js took 3.55s to execute, compared to 22ms for Afterburner. We were unable to test more complex queries such as multiple joins since they took too long (more than one minute per query before we gave up).

Our evaluation shows that Sql.js is two orders of magnitude slower than Afterburner for Q1. We attribute this performance gap to two main drawbacks: First, SQLite’s in-memory storage is not optimized for analytical tasks (i.e., it is a row store as opposed to a column store). Second, Afterburner’s code generation is more efficient since it generates asm.js directly, while Sql.js generates code that is again interpreted in a cross-compiled virtual machine. While Sql.js aims to be a full-fledged RDBMS, Afterburner has no such aspiration: we aim to be a high-performance analytics RDBMS for a narrowly-targeted application scenario and are able to optimize directly for this usage.

**B PERFORMANCE DETAILS**

Table 6 provides detailed experimental results on all 22 TPC-H benchmark queries for our five experimental conditions: Afterburner (Full), Afterburner (Vanilla), MonetDB (Single-threaded), MonetDB (Multi-threaded), and LegoBase. These results are summarized in Figure 5, but the table provides the exact values, along with 95% confidence intervals. For LegoBase, we show the codegen and compile phases as well as the actual query execution latency. Note that Q7 and Q9 did not complete on our client machine (not enough memory) with LegoBase.

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\(^{2}\)https://github.com/google/lovefield

\(^{6}\)https://github.com/kripken/sql.js/
|     | Afterburner (Full) | Afterburner (Vanilla) | MonetDB (Single-threaded) | MonetDB (Multi-threaded) | LegoBase execute | LegoBase codegen | LegoBase compile |
|-----|--------------------|-----------------------|---------------------------|--------------------------|------------------|-----------------|-----------------|
| Q01 | 115 (8.0)          | 318 (16.3)            | 1269 (10.6)               | 588 (13.0)               | 57 (0.5)         | 159 (35.4)      | 216 (0.6)       |
| Q02 | 68 (5.2)           | 137 (14.8)            | 36 (3.6)                  | 20 (0.0)                 | 27 (0.6)         | 431 (100.9)     | 351 (3.5)       |
| Q03 | 108 (4.4)          | 230 (6.1)             | 242 (80.7)                | 102 (0.0)                | 120 (5.5)        | 328 (89.1)      | 333 (1.4)       |
| Q04 | 161 (2.1)          | 361 (30.3)            | 121 (2.9)                 | 60 (0.0)                 | 163 (13.5)       | 177 (74.0)      | 266 (4.5)       |
| Q05 | 151 (1.6)          | 385 (13.1)            | 141 (6.1)                 | 72 (0.0)                 | 73 (2.9)         | 597 (99.6)      | 501 (2.9)       |
| Q06 | 36 (0.4)           | 41 (0.2)              | 431 (25.7)                | 234 (0.0)                | 21 (0.5)         | 67 (24.9)       | 161 (11.4)      |
| Q07 | 322 (11.3)         | 595 (18.8)            | 161 (3.0)                 | 90 (0.0)                 |                  | 510 (62.6)      | 525 (3.9)       |
| Q08 | 101 (2.9)          | 298 (5.2)             | 113 (3.0)                 | 70 (0.0)                 | 306 (20.4)       | 1039 (66.3)     | 612 (3.9)       |
| Q09 | 314 (2.3)          | 635 (20.6)            | 235 (2.1)                 | 122 (3.9)                |                  | 710 (94.6)      | 569 (26.4)      |
| Q10 | 233 (6.4)          | 528 (33.5)            | 126 (2.5)                 | 70 (0.0)                 | 336 (2.0)        | 382 (21.7)      | 350 (2.6)       |
| Q11 | 35 (6.0)           | 83 (11.9)             | 42 (1.8)                  | 30 (0.0)                 | 14 (0.0)         | 23 (14.6)       | 297 (8.8)       |
| Q12 | 82 (1.4)           | 184 (1.1)             | 119 (2.7)                 | 70 (0.0)                 | 116 (10.4)       | 192 (11.0)      | 267 (1.1)       |
| Q13 | 830 (2.4)          | 1065 (37.4)           | 243 (4.9)                 | 194 (4.8)                | 56 (0.0)         | 131 (11.1)      | 194 (1.4)       |
| Q14 | 44 (3.5)           | 70 (1.4)              | 40 (0.6)                  | 20 (0.0)                 | 25 (1.0)         | 123 (9.6)       | 218 (18.1)      |
| Q15 | 50 (1.0)           | 101 (0.9)             | 74 (1.5)                  | 98 (3.9)                 | 49 (0.4)         | 106 (6.8)       | 213 (1.1)       |
| Q16 | 149 (3.2)          | 325 (17.7)            | 316 (7.0)                 | 180 (0.0)                | 207 (7.4)        | 453 (18.1)      | 449 (4.9)       |
| Q17 | 718 (1.9)          | 1394 (37.2)           | 185 (1.6)                 | 140 (10.7)               | 278 (15.8)       | 156 (7.2)       | 271 (1.3)       |
| Q18 | 446 (69.6)         | 765 (105.7)           | 171 (1.2)                 | 162 (0.0)                | 414 (0.8)        | 213 (11.1)      | 261 (1.7)       |
| Q19 | 1931 (62.0)        | 2100 (139.3)          | 209 (1.6)                 | 112 (14.4)               | 175 (4.6)        | 175 (21.8)      | 288 (9.3)       |
| Q20 | 62 (0.6)           | 162 (1.5)             | 86 (2.7)                  | 50 (0.0)                 | 39 (1.4)         | 436 (20.6)      | 463 (30.2)      |
| Q21 | 284 (2.3)          | 564 (39.0)            | 369 (10.4)                | 228 (9.6)                | 1112 (5.2)       | 371 (14.9)      | 395 (40.4)      |
| Q22 | 95 (1.3)           | 156 (2.3)             | 118 (11.2)                | 92 (3.9)                 | 68 (0.5)         | 241 (28.7)      | 219 (0.9)       |
| total| 5718               | 9266                  | 4452                      | 2592                     | 3655             | 5995            | 6316            |
| total| 6353               | 10496                 | 4848                      | 2804                     |                  | 7219            | 7410            |

Table 6: Query latency (ms) for TPC-H queries, comparing Afterburner with MonetDB and LegoBase. Query latencies are averaged over five trials with 95% confidence intervals.