Fast Compilation and Execution of SQL Queries with WebAssembly

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ABSTRACT

Interpreted execution of queries, as in the vectorized model, suffers from interpretation overheads. By compiling queries this interpretation overhead is eliminated at the cost of a compilation phase that delays execution, sacrificing latency for throughput. For short-lived queries, minimizing latency is important, while for long-running queries throughput outweighs latency. Because neither a purely interpretive model nor a purely compiling model can provide low latency and high throughput, adaptive solutions emerged. Adaptive systems seamlessly transition from interpreted to compiled execution, achieving low latency for short-lived queries and high throughput for long-running queries. However, these adaptive systems pose an immense development effort and require expert knowledge in both interpreter and compiler design.

In this work, we investigate query execution by compilation to WebAssembly. We are able to compile even complex queries in less than a millisecond to machine code with near-optimal performance. By delegating execution of WebAssembly to the V8 engine, we are able to seamlessly transition from rapidly compiled yet non-optimized code to thoroughly optimized code during execution. Our approach provides both low latency and high throughput, is adaptive out of the box, and is straightforward to implement. The drastically reduced compilation times even enable us to explore generative programming of library code, that is fully inlined by construction. Our experimental evaluation confirms that our approach yields competitive and sometimes superior performance.

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Figure 1: Design space of query execution engines, based on TPC-H Q6 benchmark results. The compilation time is the time to translate a QEP to executable machine code. The execution time is the time to execute the machine code and does not include the compilation time.

decision was that compilation directly to machine code is very difficult to maintain [20]. To target different hardware architectures, the engineers of System R had to implement target-specific compilers, which led to a considerable development and maintenance effort. To remedy this problem, following work used an interpreter to execute queries [12]. The induced overhead of interpretation was dwarfed by the high costs for data accesses in disk-based systems [9, 15, 22]. However, in modern main memory systems data accesses are significantly faster and the interpretation overhead suddenly takes a large share in query execution costs [5, 22]. Therefore, main memory systems must keep any overheads during query execution at a minimum to achieve peak performance. This development was the reason for an extensive body of work on query interpretation and compilation techniques and sparked a seemingly endless debate which of the two approaches to prefer [15, 18, 22, 26, 29]. Recent work proposes an adaptive approach to query execution, where the database system can seamlessly transition from interpreted to compiled query execution. This approach requires both a query interpreter and a query compiler that must be interoperable, which is achieved by a particular execution mode named morsel-wise execution [17, 19]. Despite the promising results in that work, we believe that implementing this approach requires expertise in interpreter and compiler design and poses an immense development effort.

In this work, we present a new approach to query execution by compiling QEPs to WebAssembly, “a low-level assembly-like language with a compact binary format that runs with near-native performance” [11]. In Figure 1, we sketch the design space of query execution engines, which must balance execution time versus compilation time. With our approach we are able to reduce compilation times by more than an order of magnitude in comparison to state of the art, e.g. LLVM-based compilation of QEPs, while at the same time improving execution times. Using WebAssembly as compilation target for QEPs presents interesting opportunities but also poses new challenges.

1 INTRODUCTION

To execute SQL queries, database systems must determine for each query a query execution plan (QEP) that defines how to execute the query. The QEP is then executed by either interpretation or compilation. The very first relational database system, System R, already compiled QEPs directly to machine code [10]. This design decision was not maintained for long and following work dropped compilation in favor of interpretation [16]. The reasoning behind that
Opportunities. WebAssembly’s compact representation allows for fast code generation and efficient caching of compiled QEPs. The shipping of WebAssembly code in modules enables fast adaption and reuse of previously compiled QEPs. WebAssembly modules are dispatched to a WebAssembly engine that takes care of compilation to machine code and further optimization. There is a broad selection of open source WebAssembly engines, most of which deal with tasks a database engineer does not want to be concerned with and what traditional compilers do not deliver out of the box. A few features we get “for free” by compiling to WebAssembly and picking a suitable engine are: (1) two compilation paths, one using a fast yet non-optimizing compiler and the other using an optimizing compiler, (2) hot patching of optimized code, (3) caching of previously compiled code, and (4) profile-guided optimization. Each of these properties can be beneficial for the execution of QEPs. So how do we compile QEPs to WebAssembly and how can we embed a WebAssembly engine in our database system?

Challenges. Compilation of QEPs to WebAssembly follows text book patterns and is very similar to compilation to LLVM. However, WebAssembly modules are dispatched to an engine that executes the code in a virtual machine. The first challenge is to pass data and control between the database system and WebAssembly without throttling performance. When embedding a WebAssembly engine into a database system, special care must be taken to communicate tables, indexes, and other data efficiently to the WebAssembly code. The second challenge is the fact that WebAssembly does not provide a standard library, meaning that data structures like hash tables, algorithms like sorting, and even basic routines such as memcmp are not available out of the box. We could pre-compile a library from another language to WebAssembly, e.g. LLVM, and link to that. However, this approach has two problems. On the one side, it would prevent inlining of library routines. On the other side, generic algorithms and data structures, such as those found in the STL, cannot be translated ahead of time because WebAssembly does not support generic programming. To circumvent this obstacle, we could compile only the instances of generic components required by the QEP by providing their type parameters, effectively doing monomorphisation. However, running a full compilation pipeline from a high-level language to WebAssembly contradicts our goal of fast compilation. We solve the entire problem of not having a library by doing ad-hoc code generation. Every algorithm and data structure required by a QEP is generated during compilation. This is done in such a way, that the concrete types of generic components, as required in the QEP, are provided to the code generation process, which directly produces the monomorphic code. Our approach allows us to rapidly generate code that is already fully inlined and specialized for the data types used in the QEP. We are able to achieve performance improvements that, in some cases, can have a tremendous impact.

Contributions.
(1) We propose JIT compilation of QEPs to WebAssembly, improving both compilation and running time of queries.
(2) We embed a suitable WebAssembly engine, such that we are able to delegate difficult tasks that require expert compiler knowledge to an off-the-shelf system, making our execution engine adaptive out of the box.
(3) We introduce ad-hoc code generation of highly specialized algorithms and data structures and are able to outperform traditional approaches that use a pre-compiled library by up to 4x.

Outline. This paper is structured as follows. Section 2 presents WebAssembly and motivates why it is a suitable compilation target for QEPs. Section 3 elaborates compiling QEPs to WebAssembly. In Section 4, we present our ad-hoc generation of specialized library code. We explain how we execute a compiled query within a WebAssembly engine in Section 5. We conduct a comparison to related work in Section 6 and present our experimental evaluation in Section 7. Section 8 concludes our work.

2 WEBASSEMBLY
To execute queries, we compile QEPs to WebAssembly. This section motivates our choice for WebAssembly as compilation target for QEPs. In Section 2.1 we give the reader an introduction to WebAssembly. We present a small example of WebAssembly in Section 2.2. Finally, in Section 2.3, we argue why WebAssembly is well-fitted for compiling QEPs.

2.1 WebAssembly Overview
WebAssembly, or short Wasm, is a portable binary instruction format [11]. Among the many high-level goals of WebAssembly, we see three key features that make it the instrument of choice for JIT compiling QEPs. The first key feature is that WebAssembly is size- and load-time efficient, allowing for fast code generation, fast JIT compilation to machine code, and resource-friendly caching of already compiled code. Second, WebAssembly can be compiled to execute at native speed and make use of modern hardware capabilities, e.g. SIMD [7]. The fact that WebAssembly is embeddable is the third key feature for us. As a bonus, WebAssembly can be represented in the WebAssembly text format (WAT), a textual representation for humans. Now that we introduced WebAssembly, let us have a look at a small example and then explore the benefits of using WebAssembly as an intermediate step for compilation of QEPs.

2.2 WebAssembly by Example
To give the reader a better understanding of WebAssembly, let us have a look at a small example. We compile the filter $\text{filter}_{\text{val}<3.14}$ to WebAssembly and explore the compiled code. Listing 1 shows the compiled code in WAT format\(^1\), which borrows its syntax from Lisp, a programming language with fully parenthesized prefix notation. Due to of lack of space and the verbosity of WAT, we omit showing boilerplate code for the table scan. The complete example can be found in Appendix A.

\(^1\)To be precise, we use the WAST syntax. This is WAT with symbolic expressions.
In our example, we assume table R is stored in columnar layout. Line 2 imports the address of column val into the local variable $1$. This variable is used as a pointer to scan the val column. Line 3 displays a scan of table R using a loop construct, which we omitted for brevity. Line 4 defines a conditional branch via an if-expression that takes two arguments, the first condition and second the expression to execute if the condition evaluates to true. The condition, ranging from line 5 to line 8, defines a 64-bit floating point comparison. The first operand of the comparison, found in line 6, is a load instruction from pointer $1$. The second operand is the constant 3.14 in line 7. If the condition evaluates to true, the block $filter.accept is executed, where the projection is performed. Eventually, lines 14 to 16 advance the pointer $1$ to the next row.

In contrast to the verbose textual format, the bytecode of WebAssembly is very compact. The entire example, including the omitted parts, is only 219 consecutive bytes. The compact encoding allows for fast translation to and fast processing of WebAssembly and further requires only little memory for caching compiled QEPs.

### 2.3 WebAssembly in a Database System

Database systems must be resilient to different workloads. Short-running queries should be executed without delay. QEPs of long-running queries should be compiled and the generated code optimized thoroughly, and for recurring workloads the generated code should be cached and reused. In the following, we explain how we fulfill all of these requirements by compiling QEPs to WebAssembly and delegating execution to a suitable WebAssembly engine.

As mentioned in the introduction, there is a broad selection of open source WebAssembly engines. To give the reader an impression, let us name a few prominent examples: Google’s V8 [7], used in NodeJS and Chrome, Mozilla’s SpiderMonkey [21], used in Firefox, Apple’s WebKit [14], used in Safari, and Wasmer [2], both dedicated WebAssembly runtimes. After experimenting with V8 and SpiderMonkey, we eventually decided to use V8. Both engines provide similar features and are supported by large communities. However, V8 provides a more detailed documentation and insightful examples. The fact that V8 is written in C++ – the same language that we implement our evaluation system in – makes embedding V8 easier.

With the following features of V8, we are able to fulfill the requirements mentioned in the beginning of Section 2.3. V8 provides a two-tier JIT compiler for WebAssembly. The first tier, the Liftoff compiler, achieves low start-up time by generating code as fast as possible at the sacrifice of code quality. Importantly, Liftoff generates code in a single pass over the WebAssembly bytecode. The second tier, the TurboFan compiler, recompiles hot code (code that is executed frequently) and performs advanced optimizations. After compilation with TurboFan, V8 performs hot patching: while the code generated by Liftoff is executing, it is replaced by the optimized code generated by TurboFan. With this procedure, the less performing code generated by Liftoff only runs for short and is gradually replaced by optimized code. This combination of two-tier compilation and hot patching of optimized code is a cornerstone of our approach. Short-running queries are compiled to WebAssembly and delegated to V8, where execution will start without significant delay. Hence, we are able to achieve low latencies for short-running queries. For long-running queries, the optimized code generated by TurboFan eventually takes over execution and the query executes at maximum throughput. We want to emphasize that the transition from unoptimized to optimized code is done gradually during execution and handled fully by V8. By delegating queries to V8, we provide a query execution engine that is adaptive out of the box. In contrast to the work by Kohn et al. [17], our approach does not require us to implement this mechanism ourselves.

For recurring queries, we can rely on V8’s code caching facilities. Based on internal heuristics, V8 automatically performs in-memory caching of the compiled and optimized code produced by TurboFan. When the same WebAssembly code is dispatched multiple times, V8 retrieves the already compiled code from its cache and skips both Liftoff and TurboFan compilation. Caching avoids any potential delay caused by compilation and allows us to immediately start execution of the optimized code. In addition to built-in caching, V8 allows for explicit caching by providing cache data that can be persisted, e.g. on disk.

We have presented many benefits of compiling QEPs to WebAssembly and delegating execution to V8. However, whether our approach is successful depends on the following two questions: (1) Can we rapidly compile QEPs to WebAssembly? and (2) Is the WebAssembly code we produce competitive to other systems? The answer to the first question is a clear ‘Yes’ and elaborated in Section 3 and Section 4. To find an answer to the second question, consult our experimental evaluation in Section 7.

# 3 Compiling SQL to WebAssembly

In this section, we elaborate how to compile QEPs of SQL queries to WebAssembly. We follow the approach of Neumann [22] in that we dissect a QEP into pipelines, for which we generate code in topological order. We briefly revisit this approach in Section 3.1. In Section 3.2 we sketch how we compile algebraic operators to WebAssembly. We motivate our design decisions and provide justifications whenever we deviate from common practice.

### 3.1 Pipeline Model

A QEP is – in its most essential form – a tree with tables or indexes at the leaves and algebraic operators at the inner nodes. Figure 2 shows a QEP for the query in Listing 2. The edges between nodes of the tree point in the direction of data flow.

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*The authors are aware that a QEP need not strictly be a tree and in some situations a representation as directed acyclic graph is desirable [23].*
To compile QEPs to WebAssembly, Neumann [22]. Generating WebAssembly code is very similar to generating LLVM code, for example. In the following, we briefly sketch how to compile the most common operators of a QEP to WebAssembly. We elaborate whenever our approach deviates from regular compilation.

**Table scan, index seek, and pipeline breakers** — The start of a pipeline — which is either a table scan, an index seek, or a pipeline breaker — is translated to a loop construct. For a table scan, we emit code to access all tuples of the respective table. For an index seek, we emit code to iterate over all qualifying entries in the respective index. For a pipeline breaker, e.g. grouping, we emit code to iterate over all materialized tuples, e.g. groups. The remainder of the pipeline is compiled into the loop’s body.

**Selection** — A selection is compiled to a conditional branch. The condition is compiled without short-circuit semantics, i.e. both sides of a logical conjunction or disjunction are evaluated. It is debatable whether to prefer short-circuit evaluation. For “simple” predicates, short-circuit evaluation is likely a bad choice. It introduces a conditional branch that unnecessarily stresses branch prediction [29]. It may further lead to a conditional load from memory, which may negatively impact prefetching [15]. For “complex” predicates, short-circuit evaluation likely pays off. The additional conditional branch can bypass costly evaluation of the right hand side of a logical conjunction or disjunction [27]. This judgement is reflected in many compilers, e.g. Clang and GCC, which remove the short-circuit evaluation from C code during compilation if the predicates are presumably cheap to compute (and without side effects). This transformation is a part of if-conversion [6]. We implement a very simplistic estimation, treating all comparisons of numeric and boolean types as “cheap” and comparisons of character sequences as costly relative to the sequence length.

**Projection** — The projection of an attribute or aggregate does not require an explicit operation. The code necessary to access the attribute’s or aggregate’s value has already been generated when compiling the beginning of the pipeline. To compile the projection of an expression, we compile the expression and assign the result to a fresh local variable. In contrast to interpretation, projecting attributes away is performed implicitly and requires no further code. Because the attribute that is projected away is not used further up the QEP, no code using the attribute is generated. The register or local variable holding the attribute’s value is automatically reclaimed during compilation to machine code [8].

**Hash-based Grouping & Aggregation** — Hash-based grouping is a pipeline breaker. The incoming pipeline to the grouping operator assembles the groups in a hash table and immediately updates the group’s aggregates. The pipeline starting at the grouping operator iterates over all assembled groups as explained above.

An important distinction between this and previous work is how inserts and updates to the hash table are performed. Previous work — including both interpretation- and compilation-based execution — relies on the existence of a pre-compiled library that provides a hash table implementation. This means, calls to the hash table must use an interface that is agnostic to the type of data being inserted. This imposes an artificial constraint on the library. Because the type of a hash table entry is not known at the time when the library is compiled, certain hash table designs cannot be implemented effectively. To lookup a key we first must compute the key’s hash. This computation can be performed outside the library and the computed
hash value can be passed through the hash table’s interface, as done by Neumann [22]. However, we must search the collision list for an entry with the same key. Because the hash table’s interface is type-agnostic, the hash table does not know how to compare two keys. Hence, we must provide a comparison function to the hash table’s lookup function. This means, for every comparison of two keys, a comparison function must be called. (To lookup n keys, at least n such calls are necessary!) The situation gets worse if the hash table must be able to grow dynamically. To grow a hash table, all elements of the table must be rehashed. Again, because the hash table is type-agnostic, it does not know how to hash the elements. Hence, a hash function must be provided in addition to a comparison function or the computed hash values must be stored in the hash table. Another downside of using a pre-compiled library is that calls to the library cannot be inlined. Hence, every access to the hash table requires a separate function call.

We resolve these issues by generating and JIT compiling the code for the hash table during compilation of the QEP. Although this sounds very expensive and prohibitive, we show in Section 7 that generating and compiling WebAssembly is so fast that it becomes feasible at running time. We explain the generation of library code in detail in Section 4.

Simple Hash Join — A simple hash join is a pipeline breaker for one of its inputs. The incoming pipeline, by convention the left subtree of the join, inserts tuples into a hash table. The pipeline of the join probes its tuples against that hash table to find all join partners. The same distinction between this and previous work as for Grouping & Aggregation applies here. To avoid artificial constraints on hash table design and to avoid issuing a function call per access to a hash table, we generate and JIT compile the required hash table code during compilation of the QEP. This approach is elaborated in Section 4.

Sorting — Sorting is a pipeline breaker and very similar to Grouping & Aggregation. Before the sorting operator can produce any results, all tuples of the incoming pipeline must be produced and materialized. After the incoming pipeline has been processed entirely, the sorting operator can output tuples in the specified order.

We implement the sorting operator by collecting all tuples from the incoming pipeline in an array and sorting the array with Quicksort. The way we integrate sorting into the compiled QEP is an important distinction between this and previous work. In previous work that performs compilation, a sorting algorithm already exists as part of a pre-compiled library that is invoked to sort the array. The interface to this sorting algorithm is type-agnostic, i.e. the sorting algorithm does not know what it is sorting. In order to compare and move elements in the array, additional information must be provided when invoking the sorting algorithm. For comparison-based sorting, the size of an element in the array and a function that computes the order of two elements must be provided. This is very well exemplified by qsort from libc. This design leads to two severe performance issues. First, because the size of the elements to sort is not known when the library code is compiled, a generic routine such as memcpy must be used to move elements in the array. This may result in suboptimal code to move elements or even an additional function call per move. Additionally, values cannot be passed through registers and must always be read from and written to memory, obstructing optimization by the compiler. Second, to compute the order of two elements an external function must be invoked. This means, for every comparison of two elements the sorting algorithm must issue a separate function call. (To sort n elements, at least Θ(n log n) such calls are necessary!)

When the QEP is being interpreted, e.g. in the vectorized execution model, similar problems emerge. Although tuples need not be moved if an additional array of indices is used, the sorting algorithm must delegate the comparison of two tuples to the interpreter, where the predicate to order by is dissected into atomic terms that are evaluated separately. This leads to significant interpretation overhead at the core of the sorting algorithm.

We resolve the aforementioned issues by generating and JIT compiling the library code during compilation of the QEP. Our generated sorting algorithm is precisely tuned to the elements to sort and the order to sort them by. In particular, the comparison of two elements is fully inlined into the sorting algorithm. We explain this approach in detail in Section 4.

4 LIBRARY CODE GENERATION

In Section 1 and Section 3.2 we already motivated our decision to generate specialized library code just in time during compilation of a QEP. In this section, we present our process of ad-hoc library code generation along the example of generating specialized Quicksort. We begin with partitioning and inlined comparison of elements before we explain how we generate Quicksort.

4.1 Conceptual Comparison

Before diving into the code generation example, let us reconsider our approach on a conceptual level and compare it with alternatives. A problem that is inherent in all query execution engines is that their supported operations must be polymorphic. Joins, grouping, sorting, etc. must be applicable to attributes of any type and size. We aim to provide this polymorphism at query compilation time by generating specialized library code. To understand how other systems solve this task, let us have a look at state-of-the-art solutions.

Vectorization. In the vectorized processing model, operations are specialized and pre-compiled for the different types of vectors. In Listing 3, we provide an example for the evaluation of a selection with a conjunctive predicate. The initial selection vector sel0 is successively refined by calls to vectorized comparison functions cmp.x and eventually sel2 contains all indices where the selection predicate is satisfied. A vectorized query interpreter executes a QEP by calling these vectorized functions and managing the data flow between function calls. To achieve short-circuit evaluation of the condition, the selection vector sel1 is passed to the second comparison, such that the right-hand side of the conjunctive predicate is
only evaluated for elements that also satisfy the left-hand side. In a compiling setting, short-circuit evaluation is usually implemented as a conditional branch. In the vectorized processing model, that control flow is converted to data flow. Conditional control flow can benefit from branch prediction, which works well in either case when the selectivity is very high or very low. However, when the control flow is converted to data flow, the benefit on low selectivities is lost [15, 25, 29]. This is very well exemplified by our example in Listing 3. Assume that the left-hand side of the condition is barely selective. Although the outcome of evaluating the left-hand side can be well predicted, evaluation of the right-hand side in line 7 can only start once the comparison in line 5 completes. Hence, this design completely eliminates the processors ability to predict the outcome of evaluating the left-hand side and executing the right-hand side unconditionally and out of order, as opposed to how it would be in a compiling setting. Another drawback of the vectorized processing model is the fact that operations must be specialized and compiled ahead of time. It is infeasible to provide vectorized operations for arbitrary expressions, as there are infinitely many. Therefore, the interpreter dissects expressions into atomic terms for which a finite set of vectorized operations is pre-compiled. For our example in Listing 3, this means that the interpreter must always evaluate one side of the conjunction after the other and cannot evaluate both sides at once.

**Linking with pre-compiled library.** In a compilation-based processing model, e.g. HyPER, every operation in the QEP is compiled to a code fragment. The produced code is specific to the types of the operation’s operands. Arbitrarily complex expressions are compiled directly rather than taking a detour through a pre-compiled library by function calls. Thereby, the compiler can choose to implement short-circuit evaluation by conditional control flow. The biggest drawback of compiling QEPs is the time spent compiling. While direct compilation to machine code could be done rapidly, the produced code would certainly be of poor quality. Therefore, compilation-based systems employ compiler frameworks like LLVM to perform optimizations on the code. While these optimizations can greatly improve the performance of the code, they require costly analysis and transformation. Hence, compilation of queries can easily take more than a hundred milliseconds [17].

To reduce the amount of code that must be compiled, recurring operations such as hash table lookups or sorting are pre-compiled and shipped in a library. During compilation of a QEP, when an operation can be delegated to a pre-compiled routine, the compiler simply produces a respective function call to the library. This is a trade-off between compilation time and running time and the biggest drawback of this approach. Function calls to a pre-compiled library prevent inlining and obstruct further optimization, and thereby potentially lead to sub-optimal performance. We demonstrate this in Listing 4, where every insertion into a hash table requires a separate function call. The library code for probing the hash table can be compiled and optimized thoroughly ahead of time. Because the size of a hash table entry is not known when the library is compiled, the size must be provided at running time when inserting an entry. In the example, the hash table must allocate 8 bytes per entry to store I.d and R.x and it is the task of the caller to assign those values to the entry.

**Full compilation.** In this approach, code for the entire QEP with all required algorithms and data structures is generated and compiled just in time. By generating the code just in time, it is possible to produce highly specialized code, target particular hardware features, and enable holistic optimization. One example for full compilation is template expansion, as done in the HQUE system [18]. HQUE provides a set of generic algorithms and data structures that are instantiated and compiled to implement the QEP. Another example is code generation via staging, as done in LEOgBASE. Here, metaprogramming is used to write a query engine in Scala LMS, that when partially evaluated on an input QEP outputs specialized C code that implements the query [16]. While full compilation can achieve the highest possible throughput, both HiQUE and LEOgBASE take considerable compilation time with hundreds of milliseconds for single TPC-H queries.

### 4.2 Our approach: JIT code generation

Full compilation is very similar to our approach of generating required library routines just in time and JIT compiling the QEP. The key distinction is how the generation of code is performed. Previous work generates code in a high-level language. This code must then go through parsing and semantic analysis before it is translated to a lower level intermediate representation where optimizations are performed before executable machine code is produced. Going through the entire compiler machinery takes a lot of time. Our approach, depicted in Figure 3, bypasses most of these steps. We
generate specialized algorithms and data structures directly in WebAssembly. By picking a suitable WebAssembly engine, e.g., V8, we get all the benefits described in Section 2.3. Our approach is able to produce highly specialized algorithms and data structures and enables holistic optimization without the drawback of long code generation and compilation times.

4.3 Code Generation by Example

To provide the reader with a better understanding of how we generate library code just in time, let us exemplify our code generation along the example of Quicksort. We build the example bottom up, beginning with code generation for partitioning and the comparison of two elements before we explain code generation of the recursive Quicksort algorithm.

**Hoare’s partitioning scheme.** Hoare’s partitioning scheme creates two partitions from a sequence of elements based on a boolean predicate such that all elements in the first partition do not satisfy the predicate and all elements in the second partition satisfy the predicate. We apply Hoare’s partitioning in our generated Quicksort algorithm, that in turn is used to implement sorting of tuples. In our setting, the sequence of tuples to partition is a consecutive array. The predicate to partition the array is derived from a list of expressions to order by. For example, the clause

\[
\text{ORDER BY } R.x + R.y, R.z
\]

We provide pseudo code for the generation of specialized partitioning code in Listing 5. The function Partition takes four parameters: the order is a list of expressions to order by, begin and end are variables holding the address of the first respectively one after the last tuple in the array to partition, and pivot is a variable holding the address of the pivot to partition by. The pivot must not be in the range [begin, end]. First, the algorithm copies the values of begin and end by introducing fresh variables l and r in lines 2 and 3 and then emitting code that assigns the value of begin to l in line 4 and the value of end to r in line 5. Next, in line 6, a loop header with the condition \(l < r\) is emitted. The code emitted thereafter forms the loop body. In line 7, EmitSwap is called to emit code that swaps the tuples at the addresses l and r – 1. Note that this is a function call during code generation. The call will emit code directly into the loop body, as if inlined by an optimizing compiler, and there will be no function call during execution of the generated code. In lines 8 and 9, EmitCompare is called to emit code that compares the tuples at addresses l and r – 1 to the tuple at address pivot according to the order specified by order. Each call returns a fresh boolean variable that holds the outcome of the comparison. Just like EmitSwap, calls to EmitCompare emit code directly into the loop body without the need for a function call in the generated code. The value of variable \(v\) will be true if the tuple at address \(l\) compares less than the tuple at address pivot w.r.t. the specified order. Line 10 emits code that advances \(l\) to the next tuple if \(v\) is true, otherwise \(l\) is not changed. Similarly, line 11 emits code to advance \(r\) to the previous tuple if \(v\) is true. This is a means of implementing branch-free partitioning. In line 12, the loop body for the loop emitted in line 6 is finished. Eventually, Partition returns the variable \(l\), which will point to the beginning of the second partition once the loop of line 6 terminates. The code presented in Listing 5 looks almost like a regular implementation of partitioning. However, the function emits code that will perform partitioning. An important part of partitioning, that we skipped in Listing 5, is how the code to compare two tuples based on a given order is generated. Therefore, we also provide pseudo code for EmitCompare in Listing 6.

First, EmitCompare creates a fresh variable \(v\) in line 2 and initializes it to 0 in line 3. Then, in line 4, the function iterates over all expressions in order. The call to Compile in line 5 emits code to evaluate expr on the tuple pointed to by l and returns a fresh variable holding the value of the expression. Analogously, line 6 evaluates expr on the tuple pointed to by r. Next, type-specific code to compare the values \(vl\) and \(vr\) of the evaluated expression is emitted. Because the particular code to emit depends on the type of expr, line 7 performs a case distinction on the type. This case distinction is performed during code generation and the generated code will only contain the emitted, type-specific code. In case the expression evaluates to an int, lines 9 and 10 emit code to perform an integer comparison of \(vl\) and \(vr\). The cases for other types are analogous. After emitting type-specific code for the comparison of \(vl\) and \(vr\), line 16 emits code to update \(v\) based on the outcome of the comparison. After generating code to evaluate all expressions in order and updating \(v\) accordingly, lines 18 and 19 introduce a fresh boolean variable \(c\) that will be set to \(v < 0\), which evaluates to true if the tuple at \(l\) is strictly smaller than the tuple at \(r\), and false otherwise.

To put it all together, let us exercise an example. We invoke Partition with the order \([R.x + R.y, R.z]\), begin ‘b’, end ‘e’, and pivot ‘p’. The generated code is given in Listing 7. Initially, in lines 1

**Listing 5 Pseudo code for the generation of specialized code that implements Hoare’s partitioning.**

1: function Partition(order, begin, end, pivot)
2:  I ← NewVar()
3:  r ← NewVar()
4:  Emit(l ← begin)
5:  Emit(r ← end)
6:  Emit(while I < r)
7:  EmitSwap(l – 1)
8:  cl ← EmitCompare(order, I, pivot)
9:  cr ← EmitCompare(order, pivot, r – 1)
10: Emit(I ← I + cl)
11: Emit(r ← r – cr)
12: Emit(while end while)
13: return I
14: end function

**Listing 6 Pseudo code for the generation of code that compares two elements based on a specified order.**

1: function EmitCompare(order, I, r)
2:  v ← NewVar()
3:  Emit(v ← 0)
4:  for each expr in order do
5:    vl ← Compile(expr, l)
6:    vr ← Compile(expr, r)
7:    switch type(expr) do
8:      case int
9:        Emit(\(lt \leftarrow cl < vl \lor vr\))
10:       Emit(\(gt \leftarrow cl > vl \lor vr\))
11:      case float
12:       Emit(\(lt \leftarrow cl < float vl \lor vr\))
13:       Emit(\(gt \leftarrow cl > float vl \lor vr\))
14:    end switch
15:  end for
16:  c ← NewVar()
17:  Emit(\(c \leftarrow vl < vr\))
18:  Emit(\(c \leftarrow v < 0\))
19:  return c
20: end function


and 2, the addresses of the first and one after the last tuple are stored in fresh variables. Then the loop in line 3 repeats as long as pointer \( p_l \) points to an address smaller than \( p_r \). Lines 5 to 7 show the code produced by \texttt{EmitSwap}, which swaps two tuples using a temporary variable. In lines 9 to 20, the tuple at \( p_l \) is compared to the pivot according to the specified order. Variable \( v_{\text{lt}} \) is true if the tuple at \( p_l \) compares less than the pivot, false otherwise. Analogously, the tuple at \( p_r - 1 \) is compared to the pivot. To keep the example short and because the code is very similar, we omit this code and only show a placeholder in line 22. At the end of the loop, in lines 24 and 25, the pointers \( p_l \) and \( p_r \) are advanced depending on the outcome of the comparisons.

The generated code will partition the range \([b, e)\) such that the first partition contains only tuples that compare less than \( p \) and the second partition contains only tuples greater than or equal to \( p \), w.r.t. the specified order. Note that the generated code is not a function. Instead, this code can be generated into a function where partitioning is needed. Hence, the entire code for partitioning will always be fully inlined and specialized for the order to partition by.

**QuickSort.** QuickSort sorts its input sequence by recursive partitioning. In our implementation of QuickSort, we compute the pivot to partition by as a median-of-three. With our code generation for partitioning at hand, generating QuickSort is relatively simple. We provide pseudo code in Listing 8. Line 2 defines a new function \texttt{qsort}, line 3 emits a loop that repeats as long as there are more than two elements in the range from \texttt{begin} to \texttt{end}. Inside this loop, lines 4 to 7 emit code to compute the median of three and bring the median to the front of the sequence to sort. Line 8 emits the code to partition the sequence \texttt{begin} + 1 to \texttt{end} using as pivot the median of three. After partitioning, the median must be swapped back into the partitioned sequence, which is done by line 9. Line 10 checks whether to recurse into the right partition. Line 11 emits a recursive call to sort the right partition with \texttt{qsort}. Afterwards, in line 13, code is emitted to update \texttt{end} to the end of the left partition.

### Listing 7 Generated partitioning code for the order \([R.x + R.y, R.z]\).

| Input: | b, e, p |
|---|---|
| Output: | \( p_l \) |
| 1: | \( \text{var } p_l \leftarrow b \) | \( \triangleright \text{Initialize pointers to the first and} \) |
| 2: | \( \text{var } p_r \leftarrow e \) | \( \text{one after the last tuple, respectively.} \) |
| 3: | \( \text{while } p_l < p_r \), do | |
| 4: | \( \triangleright \text{EmitSwap}(p_l, p_r - 1) \) | |
| 5: | \( \text{var } \text{tmp} \leftarrow \ast p_l \) | \( \triangleright \text{Use temporary variable} \) |
| 6: | \( \triangleright \text{to swap tuples} \) | |
| 7: | \( \{p_l - 1\} \leftarrow \text{tmp} \) | \( \triangleright \text{at } p_l \text{ and } p_r - 1. \) |
| 8: | \( \triangleright \text{EmitCompare}([R.x + R.y, R.z], p_l, p) \) | |
| 9: | \( \text{var } v_{\text{lt}} \leftarrow 0 \) | |
| 10: | \( \triangleright \text{Compile}([R.x + R.y, p_l]) \) | |
| 11: | \( \text{var } v_{\text{lt}} \leftarrow p_l.x \triangleright \text{int } p.y \) | \( \triangleright \text{Compile}([R.x + R.y, p]) \) |
| 12: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} < \text{int } v_{\text{lt}} \) | |
| 13: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} > \text{int } v_{\text{lt}} \) | |
| 14: | \( \text{if } v_{\text{lt}} \) | \( \triangleright \text{Code omitted for brevity.} \) |
| 15: | \( \triangleright \text{Compile}([R.z, p_l]) \) | |
| 16: | \( \triangleright \text{Compile}([R.z, p]) \) | |
| 17: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}}.x > \text{int } v_{\text{lt}}.y \) | |
| 18: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} > \text{int } v_{\text{lt}} \) | |
| 19: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} > \text{int } v_{\text{lt}} \) | |
| 20: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} > \text{int } v_{\text{lt}} \) | |
| 21: | \( \triangleright \text{EmitCompare}([R.x + R.y, R.z], p_l, p_r - 1) \) | |
| 22: | \( \ldots \) | |
| 23: | \( \text{var } v_{\text{lt}} \leftarrow v_{\text{lt}} < 0 \) | |
| 24: | \( p_l \leftarrow p_l + v_{\text{lt}} \) | \( \triangleright \text{Advance left cursor} \) |
| 25: | \( p_r \leftarrow p_r - v_{\text{lt}} \) | \( \triangleright \text{Advance right cursor} \) |
| 26: | \( \text{end while} \) | |

5 EXECUTING WEBASSEMBLY IN A DATABASE SYSTEM

In the preceding sections, we explained how to compile a QEP and its required libraries to a WebAssembly module. In this section, we elaborate on how we execute the WebAssembly module in an embedded WebAssembly engine. Although this approach works with any embeddable engine, we describe the process of embedding and executing modules in V8.

The WebAssembly specification requires that each module operates on its personal memory. This memory is provided by the engine, here V8. To execute a compiled QEP inside the engine, all required data (tables, indexes, etc.) must reside in the module’s memory. One way to achieve this is by copying all data from the host to the module’s memory. However, this incurs an unacceptable overhead of copying potentially large amounts of data before executing the QEP. An alternative is to use callbacks from the module to the host to transfer single data items on demand. For such a purpose, V8 allows for defining functions in the embedder that can be called from the embedded code. However, such callbacks also incur a tremendous overhead, because the VM has to convert parameters and the return value from the representation in embedded code to the representation in the embedder and vice versa. At the time of writing, V8 provides no method to use pre-allocated host memory as a module’s memory. Therefore, we patch V8 to add a function for exactly that purpose: \texttt{SetModuleMemory()} sets the memory of a WebAssembly module to a region of the host memory. While this function enables us to provide a single consecutive memory region from the host to the module, it is not sufficient to provide multiple tables or indexes (which need not reside in a single consecutive allocation) to a module. The problem is that WebAssembly currently only supports 32 bit addressing. Hence, we cannot simply assign the entire host memory to the module. Instead, we are limited to 4 GiB of addressable linear memory inside the module. We work around this limitation by employing a technique named rewiring.
Then we rewiring to communicate the result set back to the host. As can in chunks of 2 GiB.

Rewiring chunk. This way, the module can iteratively process entire 2 GiB chunk of table A.

To give the module access to the entire table, we install a callback for the module. To give the module access to all required memory, we first allocate consecutive 4 GiB in virtual address space. We exemplify this technique in Figure 4. Assume a query accessing two tables A and B. The tables reside in completely independent memory allocations, hence there is no single 4 GiB virtual address range that contains both A and B entirely. Further, the query computes some results and we therefore allocate 1 GiB of memory to store the query’s result set. To give the module access to all required memory, we first allocate consecutive 4 GiB in virtual address space. Then we rewrite table A, a portion of table B, and the memory for the result set into the freshly allocated virtual memory. Finally, we call SetModuleMemory() with the freshly allocated virtual memory.

The module now has access to both tables and can write its results to the memory allocated for the result set. Note that table B is 5 GiB and cannot be rewired entirely into the virtual memory for the module. To give the module access to the entire table, we install a callback rewrite_next_chunk() that lets the host rewrite the next 2 GiB chunk of table B once the module has processed the currently rewired chunk. This way, the module can iteratively process entire B in chunks of 2 GiB.

Figure 4: Example of mapping tables and output to a module’s memory. The module can callback to the host to request mapping the next 2 GiB chunk of table B.

5.1 Accessing Data by Rewiring

Rewiring [28] allows for manipulating the mapping of virtual address space to physical memory from user space. In particular, it enables us to map the same physical memory to two distinct virtual addresses. We exploit this technique to have data structures residing in distinct allocations appear consecutively in virtual address space and then use this address range as the module's memory.

We exemplify this technique in Figure 4. Assume a query accessing two tables A and B. Table A is 1 GiB and table B is 5 GiB. The module writes the result set to a rewired allocation of 1 GiB. If the module produces a result set of more than 1 GiB, it produces the result set in chunks and issues a callback in between to have the host process the current chunk of results.

6 RELATED WORK

We begin our discussion of related work with the vectorized model, then proceed to discuss compilation-based approaches, before we turn to adaptive query execution.

Vectorization. Graefe [12] proposes a unified and extensible interface for the implementation of relational operators in Volcano, named iterator interface. Ailamaki et al. [5] analyze query execution on modern CPUs and find that poor data and instruction locality as well as frequent branch misprediction impede the CPU from processing at peak performance. Boncz et al. [9] identify tuple-at-a-time processing as a limiting factor of the Volcano iterator design, that leads to high interpretation overheads and prohibits data parallel execution. To overcome these limitations, Boncz et al. propose vectorized query processing, implemented in the X100 query engine within the column-oriented MonetDB system. Menon et al. [20] build on the vectorized model and introduce stages to dissect pipelines into sequences of operators that can be fused. By fusing operators, Menon et al. are able to vectorize multiple sequential relational operators. Their implementation in Peloton [24] shows that operator fusion increases the degree of inter-tuple parallelism exploited by the CPU.

Compilation. Rao et al. [26] explore compilation of QEPs to Java and having the JVM JIT-compile and load the generated code. However, their approach sticks to the Volcano iterator model, restricting compilation from unfolding its full potential. With HIQUE, Krikellas et al. [18] propose query compilation to C++ code by dynamically instantiating operator templates in topological order. They report query compilation times in the hundreds of milliseconds. Neumann [22] presents compilation of pipelines in the QEP to tight loops in LLVM. Complex algorithms are implemented in C++ and pre-compiled, to be linked with and used by the compiled query. With the implementation in HyPer, Neumann achieves significantly reduced compilation times in the tens of milliseconds. Klonatos et al. [16] address the system complexity and the associated development effort of compiling query engines in their LEGOBase system, where metaprogramming is used to write a query engine in Scala LMS that when partially evaluated on an input QEP yields specialized C code that implements the query. Despite the clean design, the code generation through partial evaluation as well as the compilation of the generated code leads to compilation times in the order of seconds.

Adaptive. Among the most recent advancements in query execution is adaptive execution by Kohn et al. [17], where the QEP is initially executed by interpretation while being compiled to machine code in the background. Once compilation completes, the compiled code takes over execution. Switching execution modes is enabled by morsel-wise query processing [19]. This approach, implemented in HyPer, shows promising results as it unites peak performance for long-running queries with low start-up costs for short-lived queries. However, this approach comes with the significant drawback of an immense development effort: Kohn et al.
We implement our approach in mu and a compiler to translate QEPs to said bytecode. Quite ironically, the authors briefly compare their work to V8 and consider their work “a database-specific implementation of similar ideas” [17], yet claim that an automatic solution like V8 would fail to achieve competitive performance. With our work, we hope to convince the reader otherwise.

7 EVALUATION

We have explained how to compile QEPs to WebAssembly and how to perform JIT code generation of library routines. We motivated this approach with the ability to specialize the generated code to the actual query to execute. In this section, we want to confirm that specialization enables more efficient implementations of QEPs and at the same time code generation via WebAssembly reduces compilation times drastically. To evaluate the feasibility and profitability of our approach, we conduct a detailed experimental evaluation. We begin by evaluating the performance of QEP building blocks, then we look at TPC-H queries, before looking closer at compilation times.

7.1 Experimental Setup

We implement our approach in mutable [13], a main-memory database system currently developed at our group. Incoming SQL queries are translated to a graph representation, where unnesting and decorrelation is performed as far as possible, similar to the approach described by Neumann and Kemper [23]. The optimizer of mutable computes an optimal join order for the query and constructs the QEP, that is then passed to the WebAssembly backend of mutable, where it is translated to a WebAssembly module and dispatched to the WebAssembly platform for execution. Although mutable supports arbitrary data layouts, we conduct all experiments using a columnar layout. Since mutable does not yet support multi-threading, all queries run on a single core.

We compare to three systems: (1) PostgreSQL 13.1 as representative for Volcano-style tuple-at-a-time processing, (2) DuckDB v0.2.3, implementing the vectorized model as in MonetDB/X100, and (3) HyPer, an adaptive system performing interpretation and compilation of LLVM bytecode, as provided by the tableauhyperapi PYTHON package in version 0.0.11952. For PostgreSQL, we disable JIT compilation as it does not improve execution time in any of our experiments. Because our version of HyPer uses the adaptive approach from Kohn et al. [17], which cannot be disabled, we cannot distinguish between compilation and execution times. We run all our experiments on a machine with an AMD Ryzen Threadripper 1900X CPU with 8 physical cores at 3.60 GHz and 32 GiB main memory. All data accessed in the experiments is memory resident. We repeat each experiment five times and report the median.

7.2 Performance of Query Building Blocks

With our first set of experiments, we evaluate the performance of individual query building blocks across different systems. We use a generated data set with multiple tables and 10 million rows per table. Tables contain only integer and floating-point columns, where integer values are chosen uniformly at random from the entire integer domain and floating-point values are chosen uniformly at random from the range [0; 1]. All data is shuffled and all columns are pairwise independent. For mutable, we report execution time as not including compilation time. Further, if not mentioned otherwise, we enforce compilation with the optimizing TurboFan compiler. For HyPer, we report the end-to-end execution time, which may include time spent on compilation.

Selection. In our first experiment, we evaluate the performance of selection with the query SELECT COUNT(*) FROM T WHERE T.x < x; and vary x to achieve different selectivities. Figure 5 (a) and (b) show our measurements for selection on a 32-bit integer and a 64-bit floating-point column, respectively. We omit our findings for PostgreSQL, as the times are over 200 ms. The charts show that the execution times of both mutable and DuckDB depend on the selectivity of the selection. At selectivities around 50%, frequent branch misprediction causes performance to deteriorate [27, 29]. With selectivities closer to 0% or 100%, the frequency of branch misprediction declines and performance improves. The execution time of HyPer remains unaffected by varying selectivity; we assume that HyPer compiles branch-free code. We can see that mutable outperforms DuckDB on all selectivities and for both integer and floating-point columns. This is likely the case because DuckDB, which implements the vectorized execution model, has the overhead of maintaining a selection vector [25, 29]. For the integer column, HyPer outperforms mutable at selectivities from 20% to 75%, outside this range mutable is up to 2x faster than HyPer. For the floating-point column, mutable outperforms HyPer on all selectivities, with a speedup of up to 2.5x.

We conduct two additional experiments, where we perform a selection on two independent integer columns with the query SELECT COUNT(*) FROM T WHERE T.x < x AND T.y < y. In the first experiment, shown in Figure 5 (c), x and y are both varied with equal selectivity. This means, the overall selectivity of the selection is the squared selectivity of either condition. Since mutable does not implement short-circuit evaluation and instead evaluates the selection as a whole, a selectivity of $\sqrt{50\%} \approx 71\%$ per condition presents the worst-case for branch prediction with a time of 50 ms. DuckDB, which implements the vectorized model, must first evaluate one condition to a selection vector before evaluating the second condition on the selected rows. Because the conditions are evaluated individually, branch misprediction occurs up to twice as often and branch prediction is worst at a selectivity of 50% with an execution time around 90 ms. As the selectivity grows, the second condition must be evaluated more often. This can be seen in the slight asymmetry in execution times, where a selectivity close to 100% takes around 50 ms and a selectivity close to 0% takes less than 40 ms. HyPer’s execution time slightly grows with the selectivity from around 30 ms at 0% to 40 ms at 100%. We assume that HyPer again produces branch-free code. However, the value required in the second condition might only be loaded if the first condition is satisfied, explaining the slight growth in time.

In the second experiment, shown in Figure 5 (d), x is varied while y is fixed such that the right condition has a selectivity of 1%. The overall selectivity of the selection is hence in the range from 0% to 1%. Since mutable evaluates the entire selection as a whole, branch prediction works reliably well and we observe a constant execution...
time of around 15 ms. DuckDB likely evaluates the more selective condition first, resulting in a constant execution time around 31 ms. As HyPer’s execution time is independent of the selectivity, the execution time remains stable around 25 ms, similar to (c).

**Grouping & Aggregation.** Our next experiment evaluates the performance of grouping and aggregation. We vary the experiment in several dimensions: the number of rows in the table, the number of distinct values in the column being grouped by, and the number of attributes to group by. Our first query is

\[
\text{SELECT COUNT(*) FROM (SELECT 1 FROM T GROUP BY T.x) AS U}
\]

which computes the number of distinct values in column T.x, which is 100k here. We show our findings in Figure 6 (a). We can see that PostgreSQL and HyPer take relatively long to evaluate the query in comparison to DuckDB and mutable. For HyPer, we assume that the compiled QEP is linked with a pre-compiled hash table implementation, leading to significant function call overheads for table lookups. For PostgreSQL we can only assume that the implementation of hash-based grouping is relatively slow. DuckDB can rely on an efficient implementation of hash-based grouping by a single column. mutable generates a hash table implementation specialized for the column being grouped by, mutable slightly outperforms DuckDB with 110 ms versus 131 ms at 10M rows.

We reuse the above query, yet this time we leave the number of rows fixed at 10M and vary the number of distinct values in the column being grouped by. The number of distinct values directly corresponds to the number of entries in the hash table used for grouping. Our results are shown in Figure 6 (b). PostgreSQL still performs relatively poor in comparison to the other systems, while DuckDB and mutable perform consistently well. Very interesting are the observations for HyPer: up until 10k distinct values, HyPer’s execution time is close to zero. We assume that the system can answer the query from internal statistics rather than actually executing the query. Once the number of distinct values grows too large, it appears that HyPer cannot rely on statistics anymore and the query must be executed. In the case of 100k distinct values, HyPer’s execution time is actually the highest of all systems. Similar to Figure 6 (a), mutable and DuckDB lie very close to each other with mutable outperforming DuckDB in four out of five cases.

In our next variation of the experiment, we vary the number of attributes to group by from one to four. The attributes are chosen such that at least 10k groups are formed. We present our findings in Figure 6 (c). We can see that all systems’ execution times spike when increasing the number of attributes to group by from one to two. This behaviour can be explained as follows: when grouping by a single attribute, a hash can be computed directly from the attribute’s value but when grouping by multiple attributes, a hash for the combined attribute values must be computed, which can become significantly more complex. When increasing the number of attributes to group by further, the execution times still increase yet at a smaller rate. The only system that does not fit into this scheme is PostgreSQL, with its highest execution time at two attributes. With two or more attributes to group by, mutable is the fastest of the systems, outperforming the others by at least 1.5x. We credit this behaviour to mutable’s generation of specialized code to compute a hash as well as a specialized hash table, minimizing any overhead for hash computation or table lookup.

Lastly, we evaluate the performance of aggregation with the query

\[
\text{SELECT MIN(T.y), ..., MIN(T.y) FROM T GROUP BY T.x}
\]

and vary the number of aggregates to compute. Our findings are shown in Figure 6 (d). Surprisingly, PostgreSQL’s execution times above 600 ms are significantly larger than those of the other systems. HyPer outperforms the other systems on 1 to 3 aggregates while for 4 aggregates, mutable performs best. It is important to see that the slope of the execution time over the number of aggregates to compute grows least for mutable. Hence, mutable eventually takes the lead at 4 aggregates.

**Equi-Join.** In this experiment, we evaluate the performance of an n:n equi-join. We perform the join on non-key columns to avoid the systems using a pre-built index, since mutable does not yet support indices\(^3\). We present our findings in Figure 7 (a). In the experiment, we leave the selectivity of the join fixed at \(10^{-5}\) and vary

\(^3\)In particular, mutable cannot map non-consecutive data structures like indices from process memory into the WebAssembly VM. This is future work.
the size of the input relations. All systems show the expected quadratic curve. For up to 3M rows, PostgreSQL is the slowest system. For more than 3M rows, HyPer becomes the slowest of all systems because of its strong quadratic curvature. PostgreSQL, DuckDB, and mutable show very similar performance, with mutable being slightly slower than DuckDB for less than 7M rows.

**Sorting.** Our last experiment evaluates the performance of sorting, as needed in ORDER BY-clauses or for merge-join. Similar to the experiment on grouping, we vary the experiment in several dimensions: the number of rows in the table, the number of attributes to order by, and the number of distinct values in the column to order by. Figure 7 (b) to (d) present our findings. In Figure 7 (c), we restrict DuckDB to ≥10k distinct values as DuckDB’s implementation of QuickSort exhibits quadratic running time for almost sorted data.

Throughout all experiments, mutable significantly outperforms the other systems, with factors up to 4x. We credit this immense performance improvement to our ad-hoc code generation and consequent holistic optimization of the sorting operation, as described in detail in Section 4.3.

**Summary.** With our set of experiments we are able to show that our approach of compiling QEPs to WebAssembly not only provides competitive performance but in many cases improves performance significantly. We credit these performance improvements to the ad-hoc code generation of specialized library code and the potential for holistic optimization by V8.

### 7.3 TPC-H

So far, our experiments only focus on individual query building blocks. Next, we conduct an experimental evaluation of TPC-H queries. By the time of writing, mutable – and in particular our WebAssembly backend – only supports a subset of SQL and hence we are only able to evaluate the TPC-H queries Q1, Q3, Q6, Q12, and Q14. For HyPer, we report the end-to-end time measured as explained in Section 7.1 as well as the compilation time as reported by the HyPer WebInterface [1]. For mutable, we provide detailed timings for the translation of the QEP to WebAssembly and the compilation and execution of WebAssembly with Liftoff and TurboFan. We present our findings in Figure 8.

For queries Q1 and Q6, mutable outperforms the other systems while for Q3, Q12, and Q14 HyPer is almost 2x faster than mutable. We credit this performance gap to HyPer’s superior performance on foreign-key joins. With regard to compilation times, mutable’s pipeline with the optimizing TurboFan compiler is up 36x faster than HyPer’s LLVM-based compilation pipeline. At the same time, for Q1 and Q6, mutable is able to outperform HyPer’s adaptive execution. With the Liftoff compilation pipeline, we are able to push down compilation times further at the sacrifice of execution speed. Our results confirm that the compilation of QEPs to WebAssembly is indeed competitive in terms of execution speed to a fully compiling and optimizing pipeline, like LLVM in HyPer.

### 8 CONCLUSION

In this work, we explored execution of QEPs in a database system by compilation to WebAssembly. With our approach, we are able to achieve compilation times under one millisecond even for complex queries and by that we were able to remedy the recurring point of criticism that compilation-based approaches impose a high latency to query execution. Further, we have shown that our approach yields highly efficient machine code without the side effect of high compilation times. By relying on a system particularly designed for JIT compilation like V8 and a portable, low-level language like WebAssembly, we are able to lift a burden from the shoulders of database engineers.

We are convinced that our approach is considerably simpler to understand and implement than current state-of-the-art solutions. By relying on successful, battle-tested infrastructure for JIT compilation and execution, we significantly reduce the required development effort to build an adaptive yet highly efficient query execution engine. With the ongoing standardization of WebAssembly [4, 11] and the immense interest and amount of ongoing work in engines supporting this language [2, 3, 7, 14, 21], our approach provides a reliable and future-proof solution to adaptive query execution.
Appendices

A WEBASSEMBLY COMPLETE EXAMPLE

The short example in Section 2.2 focuses on the selection \( \sigma_{R.val < 3.14} \). Below, we show a full example including a table scan and projection, that is constructed by compiling the query

\[
\text{SELECT 1 FROM R WHERE R.val < 3.14}
\]
to WebAssembly.

Entire WebAssembly code for the example in Section 2.2. The bytecode is only 219 bytes. The variable $1$ from Section 2.2 is here named $4$. 

```
(module
  (type $i32 => i32 (func (param i32) (result i32)))
  (import "env" "head_of_heap" (global $head_of_heap i32))
  (import "env" "R_num_rows" (global $R_num_rows i32))
  (import "env" "R.val" (global $R.val i32))
  (memory $0 1 65535)
  (export "env" (memory $0))
  (export "run" (func $run (param i32) (result i32))

  (global $run)

  (func $run (result i32)
    (local $1 i32)
    (local $2 i32)
    (local $3 i32)
    (local $4 i32)
    (block $run.body_0 (result i32)
      (local.set $1 (global.get $head_of_heap))
      (local.set $4 (global.get $R.val))
      (block $pipeline.scan_R_1 (if (i32.lt_u)
        (local.get $3)
        (global.get $R_num_rows))
      (loop $scan_R_2
        (block $scan_R_2.body_3
          (if (f64.lt)
            (f64.promote_f32)
            (f32.load)
            (local.get $4)
          )
          (local.set $3)
          (i32.add)
          (local.get $2)
          (local.set $1)
          (i32.add)
          (local.get $2)
          (i32.add)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (i32.set)
          (i32.add)
          (local.get $2)
          (i32.add)
          (i32.const)
          (i32.set)
          (local.set $4)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2)
          (i32.b32_to_f32)
          (f32.load)
          (local.get $4)
          (i32.set)
          (i32.add)
          (local.get $2)
          (local.set $2)
          (local.set $4)
          (local.set $1)
          (i32.add)
          (local.get $3)
          (i32.add)
          (local.get $3)
          (i32.set)
          (br_if $scan_R_2)
          (i32.lit)
          (local.get $3)
          (global.get $R_num_rows)
          (br_if $scan_R_2))
    ))
  ));

```
```