A Language-based Serverless Function Accelerator

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Abstract

Serverless computing is an approach to cloud computing that allows programmers to run serverless functions in response to short-lived events. Cloud providers bill functions at sub-second granularity, provide transparent elasticity, and completely manage operating system resources. Unfortunately, today’s serverless platforms exhibit high tail latency, because it is difficult to maximize resource utilization while minimizing operating costs.

We present Containerless, which is a serverless function accelerator that lowers the latency and resource utilization of typical serverless functions written in JavaScript. In Containerless, a serverless function starts execution in a container that is instrumented to build an execution trace tree (similar to a tracing JIT compiler). After the function processes a number of events, Containerless extracts the trace tree, compiles it to a safe subset of Rust, and then processes subsequent events more efficiently in Rust, using language-based sandboxing instead of the container sandbox. If the Rust code receives an event that triggers an unknown or unsupported execution path, Containerless aborts the language-based sandbox and restarts execution in the container. This approach works because serverless platforms already require functions to tolerate re-execution for fault tolerance. To a serverless function, a re-execution caused by Containerless is observationally equivalent to a re-execution caused by a fault.

Our evaluation shows that Containerless can significantly decrease the latency and resource utilization of serverless functions, e.g., increasing throughput of I/O bound functions by 3.4x (geometric mean speedup). We also show that the impact of tracing is negligible and that Containerless seamlessly switches between its two modes of sandboxing.

1 Introduction

Serverless computing is a recent approach to cloud-computing that allows programmers to run small, short-lived programs—known as serverless functions—in response to external events. In contrast to rented virtual machines, serverless computing is priced at sub-second granularity and the programmer only incurs costs when a function is processing an event. To make this work, the serverless platform fully manages the (virtualized) operating system, load-balancing, and auto-scaling for the programmer. In particular, the platform transparently starts and stops concurrent instances of a serverless function as demand rises and fall. Moreover, the platform terminates all instances of a function if it does not receive events for an extended period of time.

Unfortunately, today’s serverless platforms exhibit high tail latency [42]. This problem occurs because the serverless platform has to make a tradeoff between maximizing resource utilization (to lower costs) and minimizing event-processing latency (which requires idle resources). Therefore, an approach that simultaneously lowers latency and resource utilization would have several positive effects, including lowering cold start times and lowering the cost of keeping idle functions resident.

The dynamic language bottleneck A key performance bottleneck for serverless functions is that they are typically written in dynamic languages, such as JavaScript. Contemporary JavaScript virtual machines are state-of-the-art JITs that make JavaScript run significantly faster than simpler bytecode interpreters [15]. Nevertheless, JIT-based virtual machines are not ideal for serverless computing for several reasons. First, their instrumentation, optimization, and dynamically generated code can consume a significant amount of time and memory [14]. Second, a JIT takes time to reach peak performance, and may never reach peak performance at all [5]. Finally, existing language runtimes require an operating system sandbox. In particular, Node—the de facto standard for running JavaScript outside the browser—is not a reliable sandbox [11].

Alternative approaches It is very tempting to give up on JavaScript. We could ask programmers to instead write code in a language that performs better and is easier to secure in the serverless context. For example, Boucher et al. present a serverless platform that requires functions to be written in Rust [10]. This allows their platform to leverage Rust’s language-level guarantees to run several different serverless functions in a single shared process, which is more lightweight than per-process sandboxing or per-container sandboxing. However, Rust is not a panacea. A major issue with Rust is that it has a steep learning curve, thus would not appeal to most programmers. In contrast, JavaScript is the most widely used programming language [23, 44, 45]. A deeper problem is that Rust’s notion of safety is not strong enough for serverless computing. Even if a program is restricted to a safe subset of Rust, the language does not guarantee resource isolation, deadlock freedom, memory leak freedom, and other critical safety properties [39]. Boucher et al. identify these problems, but are not able to address them in full.
Let us consider a small variation of the previous idea: the serverless platform could compile JavaScript to Rust for serverless execution. JavaScript would make the platform appeal to a broader audience, the Rust language would ensure memory-safety, and the JS-to-Rust compiler could insert dynamic checks to provide guarantees that Rust does not statically provide. Unfortunately, this approach would run into several problems. 1) Garbage-collected languages support programming patterns that cannot be expressed without a garbage collector [31, p. 9]. Therefore, many JavaScript programs could not be compiled without implementing garbage collection in Rust, which requires unsafe code (i.e., to traverse stack roots). 2) Dynamically typed languages support programming patterns that statically typed languages do not [12, 20, 25, 46]. Therefore, a JS-to-Rust compiler would have to produce Rust code that is littered with type-checks and type-conversions [26], which would be slower than a JIT that eliminates type-checks based on runtime type feedback [27]. 3) JavaScript has several obscure language features (e.g., proxy objects and the lack of arity-checks) that are difficult to optimize ahead-of-time [8, 24, 37]. Although recent research has narrowed the gap between JIT and AOT compilers [41], JITs remain the fastest way to run JavaScript.

**Unique properties of serverless** The aforementioned approaches overlook some unique properties of serverless computing. 1) Typical serverless functions are *short lived* and complete execution in a tenth of a second [42]. This occurs because they need to respond to events triggered by end-users. 2) Serverless functions have *transient in-memory state*. 3) Serverless functions must be *idempotent*, which means they must tolerate re-execution. The latter two properties are necessary for fault-tolerance, and because the platform may deprovision containers at any time.

Existing platforms exploit these properties for resource allocation and fault tolerance. We exploit them to improve performance.

**Our approach** This paper presents **Containerless**, which is a *serverless function accelerator*. **Containerless** uses a language-based sandbox to run typical, short-lived serverless functions without containerization. By "typical", we mean short-lived serverless functions that make web requests to external services, but do not bundle their own native code. If the function tries to perform an unsupported operation within the language-based sandbox, **Containerless** terminates the language-based sandbox and falls back to container-based sandboxing. This approach only works because serverless functions are *idempotent*, which is not the case for arbitrary JavaScript programs. **Containerless** also makes a number of speculative optimizations within the language-based sandbox, and falls back to container-based sandboxing if the speculations were wrong. Finally, **Containerless** bypasses garbage collection and uses an arena allocator that frees memory after each response. This is safe because serverless functions tolerate *transient memory*.

A key feature of **Containerless** is that it is transparent to programmers. Apart from the difference in performance, a programmer cannot write code that observes if the function is running in our new language-based sandbox or the usual container-based sandbox. For example, suppose a function running in the language-based sandbox attempts to read from the file system, which would compromise the serverless platform. In this case, **Containerless** terminates the language-based sandbox, and re-executes the function in a container with a virtual filesystem. The programmer will observe high latency for that request, which could be caused by a number of factors (e.g., a cold start). Moreover, the **Containerless** runtime will determine that future executions of the function should use container-based sandboxing to avoid needless re-execution.

Security is another factor that affects the design of **Containerless**. **Containerless** is built in Rust and is carefully designed to minimize the trusted computing base (TCB). For language-based sandboxing, **Containerless** generates Rust code from JavaScript. This shifts a significant portion of the TCB out of our implementation and onto the Rust type system, which has been heavily studied using formal methods [32]. However, **Containerless** is not a general-purpose JS-to-Rust compiler. As discussed above, a JS-to-Rust compiler would suffer several pitfalls due to the “impedance mismatch” between the two languages (e.g., types and garbage collection). Instead, **Containerless** first instruments the source code of a serverless function to generate a program in an intermediate representation (IR). The IR program is a single function that corresponds to an *inter-procedural execution trace tree*, which we compile to Rust. This approach is closely related to tracing JIT compilers. However, a unique feature of our IR is that it includes asynchronous callbacks. To the best of our knowledge, all prior JITs are limited to sequential code. However, the “hot path” in a typical serverless function includes asynchronous web requests, thus we had to develop this capability.

Tracing in **Containerless** thus works as follows. The function begins execution in a container, with its source code instrumented to dynamically build an execution trace tree in our IR. After a number of events, **Containerless** extracts the generated IR program and compiles it to Rust. Subsequent events are thus processed more efficiently in Rust instead of the container. If the Rust code receives an event that triggers an unknown execution path, it aborts and falls back to the container. However, whereas a general-purpose JIT must use sophisticated techniques such as deoptimization and on-stack replacement, **Containerless** can naively abort the fast-path (Rust) and re-execute the program in the slow-path (container).
Serverless with Containerless

This section introduces the API that programmers use to write serverless functions with Containerless, and then discusses the design of container-based serverless platforms. Their design is relevant, because Containerless uses both container-based and language-based sandboxing.

2.1 The Containerless API

The function illustrates an important detail: JavaScript does not support blocking I/O. Therefore, all I/O operations take a callback function and return immediately. For example, the `c.get` function takes two arguments: a URL to get, and a callback function that receives the response, when it is ready. Therefore, the `main` function is also asynchronous. To return a response, the serverless function calls `c.respond` within a callback. All JavaScript-based serverless programming APIs have similar designs.\(^2\)

We believe that with some engineering effort, it should be possible to mimic the API of an existing serverless platform (§7).

2.2 Invoker Design

A serverless computing platform involves several components running in a distributed system. For example, OpenWhisk, which is the open-source serverless platform underlying IBM Cloud Functions, relies on a web frontend, an authentication database, a load balancer, and a message bus, all to process a single event [42].

Our work focuses on the invoker, which is the component that manages a pool of containers that it uses to execute serverless functions in isolation. The invoker places resource limits (e.g., CPU and memory limits) on all containers, and runs one function in each container. Within each container, the serverless function runs in a process that receives and...
responds to events (usually over the container’s virtual network). For functions written in JavaScript, the process is a Node process.

The invoker can handle several concurrent events. An event may trigger one of many functions from different customers, and the set of triggered functions may change over time. A warm start occurs when the invoker receives an event for a function \( f \), and it has an idle container with \( f \)'s code. In contrast, a cold start occurs when the invoker needs to create a new container, either because the event triggers a function that has not recently run, or because all containers for \( f \) are busy. Cold starts incur significant overhead compared to warm starts, and result in high tail latency.

Unfortunately, cold starts are unavoidable. It is infeasible for a cloud platform to always have idle containers for every function, without bidding customers for the idle capacity. Moreover, the invoker has to evict idle containers after a period of time to allocate resources to other functions. Furthermore, it is unsafe to reuse an idle container for a function \( f \) to handle an event for a function \( g \): doing so risks leaking data from one customer to another via operating system resources (e.g., temporary files). Similarly, the invoker cannot run two concurrent processes from two different customers in the same container. Instead, the invoker ensures that a single container only ever processes events for a single function.

2.3 Requirements Imposed on Serverless Programs

Although the serverless platform manages load-balancing, failure recovery, and resource allocation, it does not do so transparently. 1) When the platform detects a failure while handling an event, it simply re-invokes a container. For functions with external effects (e.g., writes to an external database), it is up to the programmer to ensure that the function is idempotent, so that re-execution is safe. 2) When an invoker evicts an idle function, it does so without any notification. Therefore, functions have transient in-memory and on-disk state. Programmers have to ensure that all persistent state is saved to external storage (e.g., cloud storage or a cloud-hosted database). 3) To manage resources, the platform imposes a hard timeout on all functions (at most a few minutes on current platforms). If a programmer needs to perform a lengthier computation, they need to break it up into smaller functions. These are the characteristics that Containerless exploits for serverless function acceleration.

3 From JavaScript to IR, Dynamically

This section describes how we turn a serverless function into an intermediate representation (IR) program using runtime instrumentation. §4 describes the IR-to-Rust compiler. 2

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3.1 An IR for Serverless Functions

Containerless instruments a serverless function to construct a trace tree during execution. Unlike an execution trace that represents a single path of execution, a trace tree—as the name suggests—may include branches and even loops. We can view a trace tree as a program in an intermediate representation (IR), by interpreting a sequence of nodes as a block of statements, a branch in the tree as an if statement, and a loop in the tree as a while loop. This section introduces the IR, and §3.2 presents how we generate IR.

Figure 2 shows a portion of the IR, using syntax that resembles JavaScript. 4 Most of the IR corresponds directly to JavaScript, which is to be expected, since it represents a JavaScript program. However, the IR lacks user-defined functions, as they get eliminated during IR generation (§3.2). The IR also includes several kinds of expressions that do not correspond to JavaScript expressions (the boxed expressions in Figure 2).

- Since an execution trace tree may not be complete, the IR has an expression that indicates unknown behavior (\( \_ \)). During execution, evaluating this expression

4 Since we do not write IR programs by hand, there is no need for it to have a human-readable syntax, so the notation we use in this paper is just for presentation. The implementation of Containerless represents the IR using JSON, which facilitates serialization from JavaScript to Rust.
Figure 3. The login function, instrumented to generate an IR program. The highlighted lines are the original code from Figure 1.

```javascript
let c = require('containerless');
let t = require('containerless/tracing');

function main(req) {
  let [_req] = t.popArgs();
  function F(resp) {
    let [resp] = t.popArgs();
    if (resp[u] === p) {
      t.popResult();
      c.respond('ok');
    } else {
      t.popResult();
      c.respond('error');
    }
    c.listen(main);
  }
  if (t.eq(t.vget(_resp, t.id('pass')))) {
    t.popResult();
    c.listen(main);
  } else {
    t.popResult();
  }
  t.exitIf();
  t.pushArgs(t.str('error'));
  c.respond('error');
} else {
  t.ifFalse();
  t.pushArgs(t.str('ok'));
  c.respond('ok');
  t.popResult();
  t.exitFunction(t.undefined);
}

let u = req.body.user;
t.let();

t.let('req', t.getClos(_clos, 'req'));

t.let('u', t.get(t.id('req'), 'body'), 'user');

t.let('p', t.get(t.id('req'), 'body'), 'pass');

t.if(t.eq(t.vget(_resp, t.id('u'))), t.id('p'));

if (resp[u] === p) {
  t.ifTrue();
  t.pushArgs(t.str('ok'));
  c.respond('ok');
} else {
  t.ifFalse();
  t.pushArgs(t.str('error'));
  c.respond('error');
}

t.popResult();

t.exitIf();

t.let('F', t.closure({ 'req': _req }));

t.pushArgs(t.str('passwords.json'), t.id('F'));

t.let('F', t.getClos(_clos, 'req'));

t.popResult();
}

let _clos = t.popClosure();

Figure 2. Two different IR programs produced by the if in Figure 3.

3.2 Instrumenting JavaScript to Generate IR

Containerless uses a source-to-source compiler to instrument a serverless function with code that builds an IR program dynamically. For example, given the serverless function that checks passwords (Figure 1), the source-to-source compiler produces the instrumented function shown in Figure 3. (We omit some details for presentation.)

The tracing runtime and merging IR fragments. The compiler links the serverless function to a JavaScript library that facilitates building IR programs (Line 2). The library provides several functions that construct IR expressions, which it represents as JSON objects. The library also supports 1) building the IR program incrementally and 2) incrementally merging the IR program that represents the current execution with the IR program that represents prior executions into a single IR program.

The internal state of the library consists of 1) the prior IR, which is an IR program that represents the trace tree of prior executions, and 2) the IR instruction pointer, which is a pointer to a position inside a block in the prior IR. While executing a sequence of statements, the instrumentation constructs an IR fragment for each executed statement. The library then merges that fragment into the prior IR, and advances the instruction pointer.

The initial value of the prior IR is a block with a body that contains a single `работка`-expression, and the initial value of the IR instruction pointer references that expression. This indicates that the initial behavior of the program is unknown. When the first statement in the program executes, we merge its IR fragment with the `работка`. Merging any IR fragment `работка` produces `работка` itself, and this holds for any `работка` that is nested within a larger IR fragment.

Conditionals. Conditionals are interesting because a single execution may only enter a single branch. Therefore, when we first create a conditional in the IR, the unexplored branch has a `работка`-expression. If a future execution enters the unexplored branch, the tracing runtime replaces it with an actual trace. However, it is possible to extract an IR program that contains unexplored branches.

If the conditional is in a loop, a single execution may enter both branches.
For example, consider the conditional in the login serverless function that checks if the supplied password is correct (Figure 3, line 15). Suppose the function receives two requests: a valid password followed by an invalid password. In that case, the conditional will evaluate to true on the first request (Figure 4a) and false on the second request (Figure 4b). Moreover, while processing the second request, the prior IR will be the IR generated by the first request. The tracing library merges the IR from the second request into the prior IR, which eliminates the 𝛽 in both branches.

**Function calls and closures** To trace function calls correctly, we need a mechanism that allows the callee to pass IR fragments that represent the actual arguments to the caller. Note that a function g can call another function f with an argument x, where x is a local variable of g, and thus is not in scope for f. In this situation, the IR fragment that represents x will not be in scope for f either, and needs to be passed to f in some way. To address this, the tracing library has an internal buffer that contains an array of traces that represent the arguments to the current function. The instrumentation sets this array before every function call (lines 17, 22, and 30), and reads traces from this array at the top of every function (lines 5 and 7).

Finally, we need to correctly generate IR for programs that have higher-order functions. All callbacks are higher-order functions, so they are essential for serverless programs. The problem (and solution) for generating IR is analogous to the problem of correctly implementing closures in an ordinary interpreter. In our example program, the nested function f is higher-order and closes over the variable req (e.g., it uses req on line 10). Since req is an argument to main and f is a callback, req outlives its static declaration. Therefore, a JavaScript interpreter would need to allocate req on the heap and represent f as a closure that contains 1) the code for f and 2) an environment that maps the name req to the address of req on the heap.6

We use a similar approach to generate IR for closures. The IR program does not have functions, but it has environments that bind free variables to IR expressions (line 29). Before calling a function, we pass the IR environment in a buffer (similar to arguments), and receive the IR environment at the top of a function if needed (line 8).

**Built-in functions and callbacks** JavaScript builtins and the CONTAINERLESS API require a small shim to generate IR. Therefore, the source-to-source compiler rewrites programs that use JavaScript builtins to call wrapper functions provided by the tracing runtime. Tracing callback functions is subtle, because they introduce asynchronous

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6Rust closures are more limited. A function can move a captured variable into its scope, though that does not work when a variable is shared across several closures, which can be done freely in JavaScript. In that case, the canonical solution is to store the variable in a reference-counted cell.

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```javascript
function get(uri, callback) {
  let [uriIR, cbIR] = t.popArgs();
  t.pushClosure(closure);
  let innerIR = t.block([t.unknown()]);
  let [uriIR, cbIR] = t.popArgs();
  callback(resp.body);
}
```

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**Figure 5.** A simplified implementation of c.get. The highlighted lines issue the request, and the rest generate IR.

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3.3 Other JavaScript Features

JavaScript is a sophisticated language with several features that we have not yet discussed. CONTAINERLESS supports many more features JavaScript using two strategies. 1) The implementation natively supports a variety of features that we have not discussed, including arrays, inheritance, and the ability to break out of loops and blocks. 2) It supports many more features by translating them into equivalent features. For example, we translate for loops into while loops, switch statements into if statements, and so on.

The JavaScript features that we do not support are 1) getters and setters 2) eval, and 3) newer reflective and metaprogramming features such as object proxies. We believe that it would be possible to support getters and setters with additional engineering effort. Object proxies could be supported too, but in our experience, they are rarely used in application code. However, eval—since it allows dynamically loading new code—is the only feature that is fundamentally at odds with our approach. If a program uses eval, we abort tracing and fall back to using containers.

4 Compiling IR to Rust

We now discuss the IR to Rust compiler, in which we perform three major tasks. 1) We eliminate callbacks in the IR by transforming it into a state machine, where each state corresponds to the code within a callback. 2) We impose CPU and memory limits on the program. 3) We address the
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When an event completes, the Containerless runtime calls the event's ID, instead of calling a distinct callback for that event. Thus the body of M is a series of conditionals that branch on the event ID and run the code that would have been in the callback in the original program.

Figure 6a shows the state machine for the IR program in Figure 6b. The arrows in the figure show how each callback branch on the event ID and run the code that would have been in the callback in the original program. However, for code that truly requires multiple

\textbf{4.1 From Callbacks to a State Machine}

The first stage of the compiler eliminates callbacks from the trace IR by turning the trace into a single function (M) that behaves like a state machine. M receives two arguments: an integer-valued event ID (_id) and an array of arguments for that event (_args). The key idea is to assign a unique ID to every asynchronous event instead of setting a callback. When an event completes, the Containerless runtime calls M with the event's ID, instead of calling a distinct callback function. Thus the body of M is a series of conditionals that branch on the event ID and run the code that would have been in the callback in the original program.

Figure 6b shows the state machine for the IR program in Figure 6b. The arrows in the figure show how each callback branch on the event ID and run the code that would have been in the callback in the original program. However, for code that truly requires multiple

\textbf{4.2 Static Types and Arena Allocation}

Compiling the dynamically typed IR to statically-typed Rust presents three separate issues.

\textbf{Dynamic type} In JavaScript, we can write expressions such as 1 + true (which evaluates to 2). However, that program produces a type error in Rust. To address this problem, we use a well-known technique, which is to define a dynamic type for IR values. A dynamic type is an enumeration of all possible types that a value may have. Figure 7 shows the Rust code for a simplified fragment of the dynamic type that we employ. The cases of this dynamic type includes simple values, such as numbers and booleans, as well as containers such as objects. In addition, the dynamic type implements methods for all possible operations for all cases in its enumeration, and these methods may fail at runtime if there is a genuine type error. Therefore, we would compile \texttt{1 + true} to the following Rust code:

```rust
Dyn::Int(1).add(Dyn::Bool(true))
```

The add method implements the type conversions necessary for JavaScript.

\textbf{Aliased, mutable pointers} The Rust type system guarantees that all mutable pointers are unique, or own the values that they point to. Therefore, it is impossible for two mutable variables to point to the same value in memory. However, JavaScript (and other dynamic languages) have no such restrictions, and neither does the IR. Rust's restriction allows the language to ensure that concurrent programs are data race free. However, for code that truly requires multiple

\textbf{Figure 7.} A fragment of the dynamic type that Containerless uses to represent IR values.
mutable references to the same object, the Rust standard library has a container type (RefCell) that dynamically checks Rust’s ownership rules, but prevents the value from crossing threads. Since the IR executes in a single-threaded manner, we can use RefCell to allow aliases. For example, the dynamic type represents objects as a vector of key-value pairs stored inside a RefCell (Figure 7, line 6).

**Lifetimes and arena allocation** Variables in Rust have a statically-determinate lifetime, and the value stored in a variable is automatically deallocated once the lifetime goes out of scope. In contrast, variables in dynamically-typed languages (which includes the IR) can get captured in closures, and thus have a lifetime that is not statically known. This is why dynamic languages that support closures require garbage collection.

For example, in Figure 6b, the req variable is stored in a closure (line 6), so that it is available after the list of passwords gets downloaded. We cannot statically determine when this will occur, and the idiomatic way to address this is to use reference counting. However, Rust does not guarantee that a reference counting program will not leak memory (e.g., due to reference cycles). Therefore, reference counting is not safe to use in Containerless.

To solve this, Containerless uses an arena to store the values of an IR program. Arena allocation simplifies lifetimes, since the lifetime of all values is the lifetime of the arena itself. This is why our dynamic type has single lifetime parameter (‘a in Figure 7), which is the lifetime of the arena in which the value is allocated. Another benefit of arenas is that they support very fast allocation. However, it is not possible to free individual values in an arena. Instead, the only way to free a value in an arena is to free all values in the arena.

Fortunately, the serverless execution model gives us a natural point to allocate and clear the arena. Containerless allocates an arena for each request and clears it immediately after the function produces a response. This is safe to do because serverless functions must tolerate transient memory.

## 4.3 Bounding Memory and Execution Time

Serverless computing relies on bounding the CPU and memory utilization of serverless functions. The arena allocator makes it easy to impose a memory bound: all values have the same lifetime as the allocator, and we impose a maximum limit on the size of the arena. Imposing a CPU utilization limit is more subtle, since Containerless can run several IR programs in the same process, thus we cannot accurately account for the CPU utilization for an individual request. Instead, the IR-to-Rust compiler uses an instruction counter, which it increments at the top of every loop and at the end of every invocation of the state machine, and we bound the number of Rust statements executed.

## 5 The Containerless Invoker

The Containerless invoker can process an event in one of two ways. 1) The invoker manages a pool of containers that run the serverless function, and it can dispatch an event to an idle container, start a new container (up to a configurable limit), and stop idle containers. 2) The invoker can also dispatch events to a compiled IR program, which bypasses the container. Which method it uses depends on the mode in which the invoker is running. 1) In tracing mode, the invoker does not have a compiled IR program and thus processes all events using containers. It configures the first container it starts for the function to build a trace IR, and after a number of events, it compiles the IR to Rust. 2) In containerless mode, the invoker dispatches events to the compiled IR code. Ideally, the invoker stays in containerless mode indefinitely, but it is possible for the invoker to receive an event that leads to unknown behavior (✗). When this occurs, it reverts back to tracing mode, and sends the event that triggered ✓ to a container. To avoid “bouncing” between containerless and tracing modes, the invoker keeps count of how many times it has bounced, and eventually enters container mode, where it ceases tracing and behaves like an ordinary invoker.

## 6 Evaluation

Our primary goal is to determine if Containerless can reduce the latency and resource usage of typical serverless functions.

**Benchmark Summary** We develop six benchmarks:

1. **authorize**: a serverless function is equivalent to the running example in the paper (Figure 1). It receives as input a username and password, fetches the password database (represented as a JSON object), and validates the input.
2. **upload**: a serverless function that uploads a file to cloud storage. It receives the file in the body of a POST request and issues a POST request to upload it.
3. **status**: a serverless function that updates build status information on GitHub. i.e., it can add a ✓ or ✗ next to a commit, with a link to a CI tool. The function takes care of mapping a simple input to the JSON format that the GitHub API requires.
4. **banking**: a serverless function that simulates a banking application, with support for deposits and withdrawals (received over POST requests). It uses the Google Cloud Datastore API with transactional updates.
5. **autocomplete**: a serverless function that implements autocomplete. Given a word as input, it returns a number of completions.
6. **maze**: a relatively computationally expensive serverless function, that finds the shortest path between two points in a maze on each request.
A reader may wonder if it is reasonable to have only six benchmark programs of this scale. Recent work by Shahrad et al. [42] on the microarchitectural effects on serverless computing used five benchmark applications. Jangda et al. [29] investigated serverless orchestration, and also five benchmarks. Some of the six applications that we have are inspired by the benchmarks that these papers employed. The research community needs to develop a serverless benchmark suite, perhaps with an effort similar to the the DeathStarBench [22] benchmarking suite for microservices. A barrier to any effort of this kind is that commercial serverless platforms have incompatible APIs, which makes it hard to write portable benchmarks.

**Experimental Setup** We run the Containerless invoker on a six-core Intel Xeon E5-1650 with 64 GB RAM. We send events from an identical machine on the same rack, connected to the invoker via a 1 GB/s connection. Serverless platforms impose memory and CPU limits on containers. We allocate 1 CPU core and 1 GB RAM to each container.

A number of our benchmarks rely on external services (e.g., Github and Google Cloud Dataset). We tested that they actually work. But, in the experiments below, we send requests to a mock server. The experiments stress Containerless and issue thousands of requests per second, and our API keys would be rate-limited or even blocked if we used the actual services.

### 6.1 Steady-State Performance

For our first experiment, we measure invoker performance with and without Containerless. We send events using ten concurrent event streams, where each stream immediately issues another event the moment it receives a response. We measure end-to-end event processing latency and report the speedup with Containerless.

We run each benchmark for 60 seconds and we start measurements after 30 seconds. This gives Containerless time to extract the IR program, run the IR-to-Rust compiler, and start handling all events in Rust. When running without Containerless, the experiments ensure that the event arrival rate is high enough that containers are never idle, thus are never stopped by the invoker. In addition, the invoker does not pause containers, which adversely affects latency [42]. Figure 8a shows the mean speedup for each benchmark with Containerless. In five of the six benchmarks, Containerless is significantly faster, with speedups ranging from 1.6x to 12.7x.

The outlier is the maze benchmark, which runs 60% slower with Containerless. Maze is much more computationally expensive than the other benchmarks. It also doesn’t perform any I/O, although autocomplete does not either. With some engineering, it should be possible to make maze run faster. We believe that the reason for the slowdown is that maze uses a JavaScript array as a queue. JavaScript JITs support multiple array representations and optimize for this kind of behavior. However, the implementation of dequeueing (the .shift method) in our Rust runtime system is an $O(n)$ operation. We could improve our performance on maze, but there will always be certain functions—particularly those that are compute-bound—where a JavaScript JIT outperforms the Containerless approach. One approach that the invoker could use is to actively measure performance, and if it finds that the Rust code is performing worse, revert to containerization permanently on that function. However, the performance characteristics of maze is more subtle, as the next experiment shows.

### 6.2 Cold-to-Warm Performance

Our second set of experiments examine the behavior of Containerless under cold starts. As in the previous section, we run each benchmark with and without Containerless, issuing events using ten concurrent event streams. We run each experiment for one minute, starting with no running containers. Figure 9 plots the mean and maximum event processing latency over time.

Let us examine upload in detail (Figure 9a):

- **Cold starts**: At $t = 0$, Containerless and container-only both exhibit cold starts (very high latency) as the containers warm up. *Note that the latency (y-axis) is on a log scale.*
- **Warm starts**: Since there are ten concurrent event streams, both cases start up the maximum number of containers (six), where one of the containers runs tracing for Containerless. Once they are all started, mean latency for both invaders dips to about 5 ms. However, tracing does incur some overhead, and we can see that the mean latency for Containerless takes slightly longer to reach 5 ms.
- **Containerless starts**: However, in the Containerless case, within eight seconds, the tracing container receives enough events for Containerless to extract the trace IR, compile it, and start processing events in Rust. Thus the mean latency for Containerless dips again to 0.3 ms after eight seconds.
- **Variability**: The plot also shows the event processing time has higher variability with containers. This occurs because there are ten concurrent connections and only six containers (one for each core) thus some events have to be queued. Containerless runs in a single process, with one physical thread for each core. However, the Rust runtime system (Tokio) supports non-blocking I/O and is able to multiplex several running trace IR programs on a single physical thread, thus can process more events concurrently.

The plots for the other benchmarks, with the exception of maze, also exhibit this “double dip” behavior: first for
Figure 8. Speedup, CPU utilization, and memory utilization. The error bars show the 95% confidence interval.

Figure 9. Cold-to-warm performance with and without Containerless. Each experiment runs for one minute and begins with no containers loaded. Each graph summarizes the latency of events issued at a point in time, with \( t = 0 \) is the start of the experiment. The solid lines show the mean event latency, with the 95% confidence interval depicted by the shaded region around the mean. The dotted lines show the maximum latency.

Warm starts, and then again once Containerless starts its language-based sandbox.

As discussed in §6.1, maze is relatively compute-intensive, and Containerless makes its mean latency worse (when \( t > 8 \) in Figure 9c). However, at the same time, the maximum latency (dashed green line) is significant lower with Containerless than without! Since maze does not perform any asynchronous I/O, we cannot attribute this behavior to nonblocking I/O. It is hard to pinpoint the root cause of this behavior. One possibility is the difference is memory management: within the container, the program runs in a JavaScript VM that incurs brief GC pauses, whereas Containerless uses arena allocation, and clears the arena immediately after each response. However, this is a conjecture, and there are several differences between Containerless and container-only execution.
6.3 Resource Utilization
Our third experiment examines CPU and memory utilization. We use the authorize benchmark and vary the number of requests per second. The maximum number of requests per second that we issue is 500, because a higher request rate exceeds the rate at which containers can service requests. We examine resource utilization after the cold start period. As shown in Figure 8b, Containerless has a lower CPU utilization than containers by a factor of 0.20x (geometric mean). Figure 8c shows that Containerless lowers memory utilization by a factor of 0.81x (geometric mean).

6.4 An Alternative to Cold Starts
Containerless does not eliminate cold start latency, since it needs the function to run in a container to build the IR program. However, the IR programs present a new opportunity: since IR programs are more lightweight than containers, the invoker can keep them resident significantly longer. For example, on our experimental server, running authorize in 100 containers consumes 1.6 GB of physical memory. In contrast, an executable that contains 100 copies of the IR program produced by authorize is 10 MB. In Containerless, the arena allocator frees memory after a response, thus the only memory consumed by a function that is loaded and idle, is the memory needed for its code, and for its entry in a dispatch table, which maps a URL to a function pointer.

At scale, a single invoker would not be able to have IR programs loaded for all serverless functions. Moreover, a platform running several Containerless invaders could benefit from a mechanism that allows an IR program built on one node to be shared with other nodes. We leave this for future work.

7 Discussion
The design of Containerless raises several questions, which we discuss below.

Security The design of Containerless is motivated by the desire to minimize the size of its trusted computing base (TCB). The only trusted component in Containerless is the invoker (§5), which is a relatively simple system. The most sophisticated parts of Containerless are untrusted: 1) the tracing infrastructure (§3) runs within an untrusted container, and can be compromised without affecting the serverless platform; 2) the IR-to-Rust compiler (§4) may have a bug that produces unsafe code, but such a bug would either be caught by Rust or by simple extra verification in the invoker (loops must increment the instruction counter, and the function cannot load arbitrary libraries). We do place trust in large piece of third-party code: the Rust compiler and runtime system. However, we argue that Rust is increasingly trusted by other security-critical applications (e.g., Amazon Firecracker).

Containerless allows running untrusted code from multiple parties in the same address space, which means that Spectre attacks are a concern [34]. However, we believe there are a few mitigating factors. First, the Containerless runtime does not give the IR direct access to timers. JavaScript programs that need a timer are thus confined to containers. Second, Containerless limits how many instructions an IR program can execute. Programs that need to run longer are also confined to containers. We do not claim that our approach is immune to side-channel attacks, but it may be possible to mitigate them by restricting the resources available to programs in the language-based sandbox. Containerless can also be combined with process-based isolation for better defense, similar to Boucher et al. [10].

Alternative designs We can imagine other approaches to serverless function acceleration. For example, we could run a JavaScript VM that runs out of the container with a restricted API (similar to CloudFlare Workers), and fall back to the containerized JavaScript VM if the serverless function performs an unsupported operation. We could also compile a fragment of JavaScript directly to Rust, and omit tracing entirely. The former approach would require trust in a larger codebase, whereas the latter approach is likely to support fewer programs.

How much tracing is necessary? This paper does not address some important questions that affect the performance of Containerless. For example, how many requests need to be traced to get an IR program that is sufficiently complete? Our evaluation uses a fixed number for simplicity. To do better, we need to develop a larger suite of serverless functions. We conjecture that the answer will depend on the function, so an adaptive strategy could be most effective.

Growing the API The Containerless API is small, but already usable. Our benchmark programs use typical external services, such as the GitHub API and Google Cloud Datasetore. Growing the API with additional functions does require work: 1) The function has to be reimplemented in Rust and 2) the JavaScript implementation of the function needs a tracing shim. It should be possible to write a tool that automatically generates the tracing shim in JavaScript, since they all follow the same recipe. However, the Rust reimplementation needs to be carefully built to ensure safety and JavaScript compatibility.

8 Related Work
Serverless computing performance Serverless computing and container-based platforms in general have high variability in performance, and several systems have tried to address performance problems in a variety of ways. SAND [2] uses process-level isolation to improve the performance of
applications that compose several serverless functions together; X-Containers [43] develops a new container architecture to speed up arbitrary microservices; MPSC [4] brings serverless computing to the edge; Costless [16] helps programmers explore the tradeoff between performance and cost; and GrandSLAm [33] improves microservice throughput by dynamic batching. The CONTAINERLESS approach differs from these solutions because it uses speculative acceleration techniques to bypass the container when possible. As long as the application code can be analyzed for tracing, a system like CONTAINERLESS can complement the aforementioned approaches.

Boucher et al. [10] present a serverless platform that requires programmers to use Rust. As we discussed in §1, Rust has a steep learning curve and—more fundamentally—Rust does not guarantee resource isolation, deadlock freedom, memory leak freedom, and other critical safety properties [39]. CONTAINERLESS allows programmers to continue using JavaScript and compiles their code to Rust. Moreover, the compiler ensures that the output Rust code does not have deadlocks, memory leaks, and so on.

**Tracing and JITs** CONTAINERLESS compiles dynamically generated execution trace trees, which is an idea with a long history. Bulldog [17] is a compiler that generates execution traces statically, and uses these longer traces to produce better code for a VLIW processor. TraceMonkey [21] is a tracing JIT for JavaScript that works with intraprocedural execution traces. It was introduced in Firefox 3.5, but removed in Firefox 11. Spur [6] is an interprocedural tracing JIT for the Microsoft Common Intermediate Language (CIL), thus it can generate traces that cross source-language boundaries. RPython [9] is a meta-tracing JIT, that allows one to write an annotated interpreter, which RPython turns into a tracing JIT. In contrast, Truffle [47] partially evaluates an interpreter instead of meta-tracing. Tracing in CONTAINERLESS differs from prior work in two key ways. 1) Since the target language is a high-level language (Rust), the language of traces is high-level itself. 2) CONTAINERLESS is designed for serverless execution, and naively restarts the serverless function in a container when it goes off trace, whereas prior work has to seamlessly switch between JIT-generated code and the interpreter.

**Operating systems** There are a handful of research operating systems that employ language-based sandboxing techniques to isolate untrusted code from a trusted kernel. Processes in Singularity [28] are written in managed languages and disallow dynamically loading code. SPIN [7] and VINO [40] allows programs to dynamically extend the kernel with extensions that are checked for safety. Our trace IR is analogous to an extension written in a safe language. However, we do not ask programmers to write trace IR themselves. Instead, we generate IR from executions within a container. Moreover, CONTAINERLESS switches between language-based and container-based sandboxing as needed.

**Other domain-specific accelerators** There are other accelerators that translate programs to an IR. Weld [38] generates and optimizes IR code from data analytics applications that mix several libraries and languages, and Numba [35] accelerates Python and NumPy code by JITing methods. Unlike CONTAINERLESS, these systems do not employ tracing. TorchScript [13] is a trace-based accelerator for PyTorch, though it places several restrictions on the form of Python code in a model. All these accelerators, including CONTAINERLESS, exploit domain-specific properties to achieve their speedups. However, the domain-specific properties of serverless computing are very different from data analytics, scientific computation, and deep learning, thus CONTAINERLESS uses serverless-specific techniques that do not apply to these other domains.

**Serverless as HPC** There are a number of projects that use serverless computing for “on-demand HPC” [3, 18, 19, 30, 36]. The current implementation of CONTAINERLESS is unlikely to help in these use-cases because many of them rely on native binaries. Moreover, the code that we generate from IR programs is less efficient than a JavaScript JIT on computationally expensive benchmarks. However, for short-running, I/O intensive applications, our evaluation shows that CONTAINERLESS can improve performance significantly.

**9 Conclusion** This paper introduces the idea of language-based serverless function acceleration, which executes serverless functions in a language-based sandbox. Our technique is speculative: all functions cannot be accelerated, but we can detect acceleration failures at runtime, abort execution, and fallback to containers. It is generally unsafe to naively restart arbitrary programs, especially programs that interact with external services. However, our approach relies on the fact that serverless functions must already be idempotent, short-lived, and tolerate arbitrary restarts. Serverless platforms already impose these requirements for fault tolerance, but we exploit these requirements for acceleration.

We also present CONTAINERLESS, which is a serverless function accelerator that works by dynamically tracing serverless functions written in JavaScript. The design of CONTAINERLESS is driven by a desire to minimize the size of the TCB. However, other accelerator designs are possible and may lead to different tradeoffs.

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