Virtines: Virtualization at Function Call Granularity

Nicholas Wanninger, Joshua J. Bowden, and Kyle C. Hale
{nwanninger@hawk, jbowden@hawk, khale@cs.iit.edu}

Abstract

Virtual execution environments provide strong isolation, on-demand infrastructure, simplified device models, and many other benefits for systems and application programmers. However, these environments are often perceived as heavyweight and rife with performance pitfalls for fine-grained or low-latency tasks. While others have shown that a virtual environment’s footprint can be drastically reduced by paring down the guest and host software stacks, in this paper we take a different approach. We probe the limits of fine-grained, virtual execution by investigating the viability of hardware virtualized environments at function call granularity. We introduce a new abstraction called a virtine, or virtualized subroutine, and present the design of a new micro-hypervisor called Wasp that enables them. Through a series of examples we show that Wasp can enable virtines with start-up latencies as low as 100 $\mu$s. We also provide two convenient programming interfaces to virtines, using the Rust language and using extensions to C. Using these extensions we implement a simple HTTP server and integrate virtines into an off-the-shelf implementation of OpenSSL.

1 Introduction

The shortcomings of virtualization grow more acute as the amount of data transferred between systems and consumed by applications continues to skyrocket. Big data workloads have increased TLB pressure, inspiring new hardware designs [2, 26, 20] and OS techniques for efficient address translation [24, 61]. Similar issues exist for virtualization overheads for high-performance networking [22, 51].

These challenges, however, are counterbalanced by an increasing demand for virtualization due to its flexibility and productivity benefits. As infrastructure services become more sophisticated, a growing community is leveraging this infrastructure to provision execution environments on-demand. An important, yet nascent use case involves packaging stateless application logic at the granularity of individual functions, whose resources are provisioned dynamically by cloud providers. Such serverless functions apparently do not fit well with a typical virtual execution environment, since it is simply too expensive to create a VM, boot a full-stack OS, and reach application code while maintaining low start-up costs. To address this challenge, service providers instead provision such contexts at the granularity of containers [59, 15, 52], which are in some cases shored up by a software stack tailored to container creation [3, 13, 21, 18, 58].

Even such tailored systems limit the granularity of the virtual context because they ultimately rely on the Linux kernel. A pared down software stack, such as a minimal hypervisor [38, 18, 62] paired with a rump kernel or clean-slate Unikernel [40, 57, 11, 23, 29, 56, 51, 33] can drastically improve the “time-to-compute” for these environments. In some cases, the benefits of a minimal guest software stack can actually outweigh those of running in a full-featured OS natively [41, 32]. However, such systems must grapple with the challenge of compatibility to support a wide range of applications without significant porting effort.

Others have developed optimized serverless systems based on the observation that a significant fraction of start-up costs can be attributed to language runtime and system software initialization, a task often duplicated across function invocations [48, 12, 16]. These systems can achieve start-up latencies within the sub-millisecond range with aggressive caching of runtime state. However, as edge computing scenarios push serverless infrastructure closer to users [55, 34, 5, 50], reduced network latencies will amplify even heavily optimized software overheads.

How did we get here? Cloud platforms that seek to provision execution contexts at finer granularities must achieve two goals which are seemingly at odds: cheap individual invocations and isolated execution. We posit that current efforts to do so are at a disadvantage because they begin with mechanisms designed for the latter goal and attempt to adapt them to achieve the former. We take a different perspective in this paper by designing an abstraction that facilitates both from the start.
We adopt a bottom-up approach to explore fine-grained virtualization not from the perspective of optimizing existing isolated environments (designed with different use cases in mind), but rather from the perspective of building directly on hardware capabilities. We begin our investigation by considering an extreme case: what will it take to enable hardware virtualized execution at function call granularity?

In Section 2, we demonstrate that the creation of minimal, virtual contexts is surprisingly cheap (Figure 1)—indicating that there is significant opportunity for fine-grained, virtualized execution. We introduce a new abstraction for isolated, virtualized functions, called virtines, short for virtualized subroutines, in Section 3. We then present a new micro-hypervisor, Wasp, that allows programmers to invoke virtines on-demand. We present a series of examples using virtines to evaluate Wasp’s performance in Section 4 and explore uses of virtines in practice with language support. In Section 5 we discuss how virtines fit into the current cloud computing landscape.

Our contributions are as follows:

- We introduce the virtine abstraction, explore its design space, and describe how it can be used to augment existing cloud systems.
- We present Wasp, a micro-hypervisor with pre-packaged runtime environments to support virtine execution.
- We evaluate the performance of Wasp and perform a limit study on virtine invocation.
- We use Wasp and virtines to build several examples: a Rust-based software dataflow engine, an HTTP server, and integration with OpenSSL.
- We provide two programming interfaces to virtines: a Rust system that allows programmers to write virtine code in C, and compiler support that adds virtine extensions to the C language.

2 The Cost of Bootstraps

In this section we conduct a series of experiments to establish the cost of various components of the context creation process and the costs of runtime environments. Our goal through these experiments is to determine what forms of overhead will be involved in virtualized execution at function call granularity.

2.1 Experimental Setup

We use four hardware platforms throughout the paper, described in Table 1. To build all C and C++ code, we used GNU gcc version 9 on all Linux systems, and on Windows we use Visual Studio 2019 version 16.5.5 with the Visual C/C++ Compiler (MSVC) version 19.25.28614 for native x64 compilation with full optimizations applied

1 The compilation flags used for gcc were -O3, and for MSVC were /MD /O2 /Ob2 (namely, enable multi-threaded libraries, optimize for speed, and allow compiler inlining, respectively). There is no /O3 flag in MSVC.

2.2 Bootstrapping Functions

To establish baseline creation costs, we investigated how quickly various execution contexts can be constructed on tinker, as shown in the violin plot in Figure 1. Here we measure time taken for the context of interest to be created, entered, and exited. The “kvm create (fresh)” measurement represents creating a virtual context from scratch using KVM that immediately exits with a hlt instruction. In this case we are, in totality, measuring the latency of setting up a virtual context (register state, initial memory, emulated CPUID feature set), creating the context with the KVM_CREATE_VM ioctl, having KVM prepare the guest’s state (e.g. VMCS preparation) for an entry, the actual VM-entry, and an immediate VM-exit. For the measurement labeled “linux_thread”, we create a kernel thread in Linux (without virtualization) using pthread_create for a function with a null body, followed by a subsequent pthread_join. “vmrun” measures just the
The boot sequences of fully-featured operating systems are too costly to include on the critical path for low-latency function invocations. It takes more than half a second to boot a single standard Linux VM using QEMU/kvm. To understand why, we measured the time taken for components of a vanilla Linux kernel boot sequence and found that roughly 3% of the boot process is spent scanning ACPI tables, configuring ACPI, enumerating PCI devices, and populating the root filesystem. Most of these features, such as a fully-featured PCI interface, are unnecessary for short-lived, virtual execution environments, and indeed are often omitted from optimized Linux guest images such as the Alpine image used for Amazon’s Firecracker. We could bypass much of this overhead by caching pre-booted environments, or by reusing VMs and invoking functions at the granularity of processes or containers, as is standard. However, could we do better by building directly on top of cheap hardware virtual context creation?

To understand this, we constructed a runtime environment that simply boots a virtual context into 64-bit (long) mode. This environment is essentially a boot template comprising roughly 160 lines of assembly. We booted this environment with a custom, light-weight hypervisor framework using both KVM on tinker and Hyper-V on mystic. We break the boot sequence into seven components and measure each using the cycle counter. Table 2 shows the minimum latencies for each component, ordered by cost. The row labeled “Paging/ident. map” is by far the most expensive on both platforms at $\sim 28K$ and $15K$ cycles, respectively. Here we are using 2MB large pages to identity map the first 1GB of address space, which entails 3 levels of page tables (i.e. 12K of pages). The constant tsc feature, mitigating clock drift.

Table 2: Boot time breakdown for our minimal runtime environment on KVM and Hyper-V. These are minimum latencies observed per component, measured in cycles.

| Component          | KVM  | Hyper-V |
|--------------------|------|---------|
| Paging/ident. map  | 28109| 15364   |
| Protected transition| 3217 | 4422    |
| Long transition (lgdt) | 681  | 828     |
| Jump to 32-bit (ljmp) | 175  | 246     |
| Jump to 64-bit (ljmp) | 190  | 844     |
| Load 32-bit GDT (lgdt) | 4118 | 588     |
| cli                | 74   | 148     |

Table 1: Testbed hardware.

| Name   | Environment | OS                  | Processor                                          | RAM       |
|--------|-------------|---------------------|----------------------------------------------------|-----------|
| mystic | baremetal   | Windows Server 2019 | Intel Xeon Silver SP 4108 (Skylake; 16 cores; 1.8 GHz) | 64 GB DDR4 |
| tinker | baremetal   | Fedora 29 (kernel 5.2.11) | AMD EPYC 7281 (Naples; 16 cores; 2.69 GHz) | 32 GB DDR4 |
| chameleon | baremetal | Ubuntu 18.04 (kernel 4.15) | Intel Xeon E5-2670 v3 (Haswell; 48 cores; 2.3 GHz) | 128 GB DDR4 |
| loki   | VM          | Arch (kernel 5.5.11) | Intel Xeon E5-2670 v1 (Sandy Bridge; 48 cores; 2.3 GHz) | 64 GB DDR3 |

Creation of a virtual context via KVM from scratch takes notably longer than just vmrun and is remarkably close to the latency of a kernel thread creation. A function call is, of course, the cheapest context (42 cycles max). While vmrun is much more expensive than a native function call (at around 15K cycles), we expect that this would be reduced significantly without the protection ring transition and Linux system call handling. Note that we measured Linux process creation as well, but we omit it here since it tends to obscure the other measurements (process creations cost several millions of cycles, effectively in the millisecond range). We point out that KVM is not ideal for these measurements since it incurs overheads from the same kernel that we are trying to circumvent. Ideally, a system optimizing for minimal latency would use an embeddable or a bare-metal, Type-I hypervisor such as Palacios or Xen. However, these numbers do tell us that—just considering the underlying mechanisms—while a virtual function call will be unsurprisingly more expensive than a native function call, it can compete with thread creation and will far outstrip any start-up performance that processes (and by proxy, containers) will achieve in a standard Linux setting. Thus, we conclude that the creation of hardware virtualized contexts is cheap ($\sim 1\mu s$) modulo runtime environment initialization that takes place inside the virtual context. We cannot ignore this component, as others have shown that it constitutes a major portion of start-up overheads.

While we did not use the paravirtual clock in either driver, we expect the virtualized counter to be accurate given that every machine has the constant tsc feature, mitigating clock drift.
memory references), plus the actual installation of the page tables and control register manipulation. The transition to protected mode takes the second longest, at 3K cycles and 4K cycles, respectively. This is a bit surprising, given that this only entails the protected mode bit flip (PE, bit 0) in cr0. The transition to long mode (which takes several hundreds of cycles) is less significant, but more expensive than the protected counterparts. The remaining components—loading a 32-bit GDT, the long jumps to complete the mode transitions, and the initial interrupt disable—are all relatively negligible.

One thing to note from these results is the cost of transitioning to various modes. Roughly, the more complex the mode, the higher the latency to get there. This is consistent with descriptions in the hardware manuals [28, 4]. To further investigate this effect, we invoked a small kernel written in assembly that brings the virtual context up to a particular x86 execution mode and executes a simple function (fibonacci of 20 with a simple, recursive implementation). Figure 2 shows our findings for the three canonical modes of the x86 boot process using KVM: 16-bit (real) mode, 32-bit (protected) mode, and 64-bit (long) mode. Each mode includes the necessary components from Table 2 in the setup of the virtual context. In this experiment, for each mode of execution, we measured the latency in cycles from the time we initiated an entry on the host (KVM_RUN), to the time it took to bring the machine up to that mode in the guest (including the necessary components listed in Table 2), run $fib(20)$, and exit back to the host. Thus, briefly, these measurements include entry, startup cost, computation, and exit.

We compare a compiler-optimized implementation (“opt”) of the resulting binary using `$gcc -O3` and an unoptimized, hand-written implementation in nasm (“un-opt”). Note that we saw several outliers in all cases except function invocation, likely due to kernel scheduling events. To make the data more interpretable, we removed outliers using Tukey’s method.

While we expect much of the time here to be dominated by entry/exit and the arithmetic, the benefits of real-mode only execution for our hand-written version are clear. The compiler-generated code does not actually optimize for 16-bit instructions, so the difference for these bars is not surprising. Protected and Long mode execution are essentially the same since they both include the most significant components listed in Table 2 (paging and protected setup). These results suggest—provided that the workload is short-lived (on the order of microseconds) and can feasibly execute in real-mode—that roughly 54K cycles are on the table for savings. We plan to explore ways to automatically determine whether a snippet of code can be run in real-mode and target it automatically in order to take advantage of this benefit in future work.

Overall, we have seen that a minimal boot sequence costs less than 300K cycles (∼300 µs), but what does it take to do something useful? To determine this, we implemented a simple HTTP echo server where each request is handled in a new virtual context employing our minimal environment. We built a simple micro-hypervisor in C++ and a runtime environment that brings the machine up to C code and uses hypercall-based I/O to echo HTTP requests back to the sender. The runtime environment comprises 970 lines of C (a large portion of which are console and string routines) and 150 lines of x86 assembly. The micro-hypervisor comprises 900 lines of C++. The hypercall-based I/O (described more in Section 3.1) obviates the need to emulate network devices in the micro-hypervisor and implement the associated drivers in the virtual runtime environment, simplifying the development process. Figure 3 shows the mean time measured in cycles (on tinker) to pass important startup milestones during the bring-up of the server context. The top bar indicates the time taken to reach the server context’s main entry point (C code); roughly 10K cycles. Note that

\footnote{That is, measurements not on the interval $[x_{25\%} - 1.5 IQR, x_{75\%} + 1.5 IQR]$ are removed from the data.}
this example does not actually require 64-bit mode, so we omit paging and leave the context in protected mode. The middle bar shows the time to receive a request (the return from `recv()`), and the bottom bar shows the time to complete the response (`send()`). Milestone measurements are taken inside the virtual context.

The send and receive functions for this environment use hypercalls to defer to the hypervisor, which proxies them to the Linux host kernel using the appropriate system calls. Even when leveraging the underlying host OS, and when adding the from-scratch virtual context creation time from Figure 1, we can achieve sub-millisecond HTTP response latencies (<300 µs), without environment caching and without context reuse. It is worth noting, however, that the guest-to-host interactions do introduce variance from the host kernel’s network stack, indicated by the large error on the bottom two bars.

These results are promising, and they indicate that we can achieve low overheads and start-up latencies for functions that do not require a heavy-weight runtime environment. However, creating these contexts for functions manually is a chore. Thus, we now seek to expose the notion of a function that runs in a light-weight virtual context to programmers while abstracting away the underlying machinery and context management.

3 Virtines

In this section we introduce virtines, a new abstraction for function instances that run in a light-weight, virtualized execution context. They effectively comprise a “virtual subroutine,” and provide a fully isolated execution environment while still maintaining latency closer to what one might associate with a function call. Thus, from the programmer’s perspective, they behave like normal functions. They are invoked using familiar syntax, they are synchronous (the caller is blocked until the virtine returns), and they can use arguments and return values normally.

However, as with device code written for accelerators (e.g. in CUDA [47]), there are constraints on what virtine code can and cannot do, many of which arise from limitations of our current prototype. Virtines cannot currently nest, meaning one virtine cannot invoke another. We envision removing this constraint, as nested virtines would allow a calling virtine to selectively pass or revoke resource privileges to its callees. Virtines need not be leaf functions, which means that we are essentially shipping a subset of a program’s call graph into virtine context. Where to make a “cut” in this graph is currently up to the programmer, but we do see opportunities for compiler and profiling assist here. Virtines cannot use shared libraries. Though this is not a strict limitation, we see little need for them since there is nothing to share with. Dynamic libraries could be shared between distinct virtines at the hypervisor level, but this would sacrifice isolation. Virtines do not share an address space with the host, thus arguments to virtines must be marshalled by the virtine runtime. Virtines run synchronously with respect to the caller. That is, a call to a virtine will block until it returns. We do, however, see merit in supporting asynchronous virtines to leverage concurrency, so future versions will incorporate this feature. (We envision them in this case to syntactically resemble goroutines[4].) Perhaps most significantly, virtines cannot assume a POSIX system call interface (or even the presence of a system call mechanism). This, however, depends entirely on the runtime environment. A virtine running with the bare-bones environment from Section 2 has no OS support (not even a unikernel) so it will be unable to leverage system routines. However, virtines can run in any number of environments, from bare-bones to more robust unikernel-like environments. Currently, we manually pre-package these environments.

While virtine runtime environments can vary, we expect they will almost always be limited, meaning no scheduler, no address spaces, no threads, or any high-level constructs that typically come with running a fully-featured virtual machine. Additional functionality can be provided either by adding functionality to the runtime environment or by borrowing functionality from the hypervisor and host, though both involve development effort. The latter should be done with care, as it sacrifices isolation. In the former case, if significant functionality needs to be added to the runtime environment, it is likely not a good match for virtines. Such code would be better served by existing execution contexts like containers or unikernels in a standard VM.

3.1 Wasp

To demonstrate the viability of virtines, we implemented Wasp, a specialized, embeddable micro-hypervisor that deploys them with an easy-to-use host interface. At its core, Wasp is a fairly ordinary hypervisor, hosting many virtual contexts on top of a host OS. However, like other minimal hypervisors such as Firecracker [18], Unikernel monitors [62], and uhyve [38], it does not aim to emulate the entire x86 platform or device model. As shown in Figure 4, our default Wasp wrapper runs as a user-space process on either Linux or Windows using KVM or Hyper-V, respec-
Figure 4: High-level overview of Wasp.

Figure 5: Reusing virtine shells with a pooled design.

would not see. This use of paravirtualization avoids complexity in the virtine environment and raises the level of abstraction for I/O or host interactions. For example, rather than performing file I/O by ultimately interacting with a virtio device [53], a virtine can use a hypercall that directly mirrors the read POSIX system call. This method does, however, sacrifice some isolation. The degree to which the virtine and the host interact is up to the designer of the virtine runtime. Others have taken a similar approach (e.g. Unikernel monitors [62]) to co-designing micro-hypervisors with Unikernel contexts.

To push virtine start-up latencies down, Wasp supports a pool of cached virtine shells that can be reused. As depicted in Figure 5, the system receives external stimuli defined by the specific hypervisor workload denoted by (A), which will drive virtine creation. This may be network traffic, function execution requests, or even database triggers. Because we must use a new virtine for every request, a hardware virtual context must be provisioned to handle each invocation. The context is acquired by one of two methods, (B) or (C). When the system is cold (no virtines have yet been created), we must ask the host kernel for a new virtual context by using KVM’s KVM_CREATE_VM interface (or the equivalent WHvCreatePartition in Windows [43]). If this route is taken, we pay a higher cost to construct a virtine due to the kernel’s internal allocation of the VMCS (virtual machine control structure). However, once we do this, and the relevant virtine returns, we can clear its context and cache it in a pool of “clean” virtines (D) so the host OS need not pay the expensive cost of re-allocating virtual hardware contexts. These virtine “shells” sit dormant waiting for new virtine creation requests. The benefits of pooling virtines are apparent in Figure 6 by comparing creation of a Wasp virtine from scratch (the “fresh” measurement) with reuse of
a cached virtine shell from the pool (“recycled”). By recycling virtines, we can reach latencies much lower than Linux thread creation. Note that here we include Linux process creation latencies as well as scale. The bimodal shape of the recycled measurements shows that there are not always clean virtines ready, thus necessitating higher latency. If deterministic latencies are important for a workload, virtine shells can be created ahead of time when the Wasp runtime starts up. Wasp virtines initially boot into a real-mode environment, but it would be feasible to “checkpoint” a virtine and use copy-on-write (CoW) memory and a snapshot of its state to boot into any mode, as most virtine images we test in our prototype are no bigger than 30KB. Others already apply similar techniques to reduce start-up times in container-based virtualization platforms [48, 16, 12].

3.2 Rusty Virtines

While Wasp in this state makes it easy to create, manage, and run virtines, it does not provide the most friendly interface to programmers. Developers must individually compile each virtine function into a binary, manually load it from the file system, and inject it into the virtine’s guest memory space. The disconnect between building the virtine code and the host code that will drive it adds an extra layer of complexity to the development process. One of our goals is to allow virtines to be used at the language level. Ideally a programmer could annotate a function as a virtine in a higher-level language, and that function would run in virtine context when invoked. As a first step towards this goal, we created mechanisms for writing virtine code in C, but from the context of the Rust programming language [54].

To allow programmers to declare virtines in Rust, we use procedural macros which allow a function to be called at compile-time to change the stream of tokens received by the compiler’s parser. As outlined in Figure 7, the programmer can invoke a macro (cprog32!()) with C source code as a raw string to specify code that should run in virtine context. This function takes the C code and compiles it into an object file using the system-resident gcc installation. By default, a minimal, pre-packaged runtime environment is provided that includes an efficient implementation of the hcall() function and a small amount of bootstrap code to reach protected mode. This is all the built-in runtime support that the virtines for our initial prototype need, but more complex virtines will need more. These two object files are then linked with a custom linker script that places the code at virtual address 0x8000. They are then converted into a raw binary using objconv. The final binary is returned to the Rust parser and compiled which produces the output described at the bottom of Figure 7. By merging the build process of virtines into the build system of the host language, it becomes easier to implement virtines and their associated host code by using high-level features such as callback functions to handle hypercalls and procedural macros as shown in Figure 8.

5 https://doc.rust-lang.org/reference/procedural-macros.html
```rust
define code = cprog32!(r"#"
extern long hcall(long number, long arg);
int fib(int n) {
    if (n < 2) return n;
    return fib(n-2) + fib(n-1);
}
void main() {
    // get input from host
    int n = hcall(0, 0);
    // return result
    hcall(1, fib(n));
}");

// Allocate a VM with 16 pages of RAM
let sz = 4096 * 16;
let mut m = Machine::new(sz, code);
m.run(|vm| {
    match vm.regs.rax {
        // handle hypercall...
    }});

Figure 8: Programming with C-level virtines in Rust.

3.3 C Language Extensions

While the Rust programming model provides a simpler interface to Wasp, it still requires the developer to think about the internals of virtines. Having to implement virtine code in a different language than the host (C vs. Rust) is obtrusive and impedes interoperability. Instead, virtines should be implemented in the same source language and invoked as if they were normal functions.

To demonstrate this model, we implemented a clang wrapper and LLVM compiler pass that detects C functions annotated with the `virtine` keyword, runs middle-end analysis at the IR level, and automatically generates code that has the equivalent functionality of our Rust virtine implementation but with the added benefit of interoperability. Figure 9 shows a simple example function annotated to run in virtine context.

```rust
virtine int fib(int n) {
    if (n < 2) return n;
    return fib(n - 1) + fib(n - 2);
}
```

Figure 9: Virtine programming in C with compiler support.

To further ease programming burden, compiler-supported virtines must have access to some of the same standard library functionality that the host can access. It is common to use library support functions such as `memcpy` or `strlen`. Due to the nature of their runtime environment, virtines do not intrinsically include these libraries. To remedy this, we created a virtine-specific port of `newlib` [44], an embeddable C standard library that we can statically link with while maintaining a relatively small virtine image size. `newlib` allows developers to provide their own system call implementations or bindings. For virtines, we delegate system calls directly to the host via hypercalls. This allows us to support `stdlib` functionality without drastically expanding the virtine runtime environments.

Automatically generated virtines face a challenge with argument passing. Because they do not share an address space with the host, argument marshalling is necessary. We leveraged LLVM to copy a compile-time generated structure containing the argument values into the virtine’s address space at a known offset. Marshalling does incur an overhead that varies with the argument types and sizes, as is typical with “copy-restore” semantics in RPC systems [9]. This affects start-up latencies when launching virtines, as we will see in Section 4.3.

4 Evaluation

In this section, we evaluate virtines and the Wasp hypervisor runtime using several examples.

To evaluate the latencies of virtines invoked via programmer annotations (in this case via our Rust API), we used virtine code which could be tuned to vary the amount of computational intensity per invocation. We again chose `fib(n)`, sweeping across `n` to vary the intensity. `fib(0)` will essentially measure the inherent overhead of virtine creation. To measure our `fib()` virtine, we conducted an experiment comparing the mean execution times of `fib(n)` for `n` ranging from 0 to 25. Each test was conducted on two machines, `chameleon` and `loki`. We used these two machines to compare the cost of virtines using nested virtualization (virtines on a VM) vs. “bare-metal” performance. Note that with `loki`, the VM uses all cores of its host machines and has 16GB of dedicated RAM. The host runs QEMU/kvm via Proxmox. Tests prefixed with “baremetal-” were run on `chameleon`, while tests prefixed with “vm-” are run on the `loki` VM. Figure 10 shows the results. We ran each test on both machines resulting in 6 total results for each value of `n`. The first test (“#-Virtine”) measured the execution of `fib(n)` by spinning up a virtine and executing the code specified in C as outlined

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6 via access to the Chameleon Testbed [30]: [https://chameleoncloud.org](https://chameleoncloud.org)

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in Figure 8. As baselines we measured the latency of calling a native Rust implementation of \( f_{ib}(n) \) ("*-Rust") and a native C implementation ("*-C") invoked via Rust bindings. Neither of these latter implementations run in an isolated, virtual context.

At first, virtine latency is much higher than the other two methods (which is not surprising, given our previous measurements, but as computational intensity increases beyond the overhead of constructing virtines, their latency is amortized. This suggests that for work that takes less than roughly 100 \( \mu s \), a virtine will introduce significant overhead relative to the task size (we will see this in practice in Sections 4.1 and 4.3). However, as the workload’s execution time grows past 100\( \mu s \), the cost of the virtine drops compared to executing the same code without the virtual context. Based on our results in Figure 2, this could be an opportunity to apply the benefits of executing in, e.g. real-mode to push down latencies further.

4.1 Software Dataflow

To further test the limits of Wasp and virtines, we sought to evaluate a more extreme scenario where many fine-grained tasks are involved. Dataflow systems (becoming popular again in the hardware community [57, 46, 45]), are a good choice when massive amounts of irregular task parallelism need to be mapped to parallel hardware. In the dataflow model [14] computations are represented as a dataflow graph, where vertices represent computations and edges represent dependencies between them. The lynch-pin of dataflow execution is the “firing rule,” which states that dependent tasks become ready to execute (“fire”) when all their input dependencies are met. Many high-performance, software dataflow systems exist today, for example Legion [7] which supports large-scale heterogeneous HPC codes and TensorFlow [1] from Google for high-performance machine learning and AI. Dataflow is an appropriate litmus test here since the tasks tend to be quite granular. This means that if a single task runs in virtine context, we will see the virtine creation overheads stressed.

We implemented a simple, multi-threaded dataflow engine in Rust, employing a classic worker thread model (one worker per CPU) with a pluggable executor that builds on the Rust front-end prototype described in Section 3.2. The pluggable executor allows dataflow tasks to be run in isolated contexts. In this case, we run tasks either natively, in virtine context, or in the context of an AWS Lambda function as a comparison point. All dependencies and the engine itself were built using Rust’s --release mode for full optimization. The Rust hypervisor front-end was built using rustc 1.45.0-nightly using GNU libc 2.31 on each of the host machines to maintain API compatibility with the specific kernel.

A dataflow graph in this model is a directed, acyclic graph (DAG) where each node’s edges represent dependencies that must be evaluated before it can execute. For simplicity, we only support static dataflow graphs, where the entire graph is known a priori. The graph is computed by recursively expanding nodes and their children starting from the root node. For simplicity, a dependency will only ever have one parent node—making the graph effectively a tree.

Our dataflow engine is split into two primary components. The “producer” runs in host context and is tasked with constructing the dataflow graph and feeding vertices to
workers via a shared producer/consumer queue. The “consumers” are worker threads which pull vertices from the queue, then execute the associated task either normally (as a function), in virtine context, or using an AWS Lambda invocation. After the graph has been constructed by the producer, worker threads are spawned, each with its own send and receive channel, channel $S$ and channel $R$, respectively. Each worker thread will continue to receive from channel $R$ while there are pending tasks to be executed. When a worker receives an “evaluate” message on channel $R$, it executes the task handler function with a provided state $s$ and function input.

Figure 11 depicts the high-level design of our dataflow engine. An input graph enters the engine at position A, represented by a set of tasks with references to dependencies, dependent tasks, and task-specific state. Once the engine loads the graph, tasks which are ready to run (no pending dependencies) are placed in the task queue at B. The task queue is then read by worker threads and commands are sent out at B that tell the first available worker to evaluate a task with some state. The thread then provisions an execution context (in the isolated cases) and runs the task there. When the root task is completed, worker threads sleep waiting on future graph execution requests.

We first test our engine in a setting where everything runs locally, using fibonacci written as a dataflow computation. Figure 12 shows execution times for varying computational intensity (in this case various graph sizes) when running each task in the graph with and without virtines on our chameleon and loki systems. Fibonacci’s dataflow task graph rapidly expands as the value of $n$ increases; $fib(10)$ comprises 177 tasks, while $fib(19)$ comprises 13,529 tasks. Tests prefixed by “host-” were run on chameleon while those prefixed with “virtual-” were run in the loki VM. Here we measure the mean time to complete execution of the entire graph; the throughput measurement represents the harmonic mean. We took measurements at the call site of the dataflow engine, so they include the initial expansion of the graph, but not the runtime initialization, e.g., thread pool creation. Note that for this experiment Wasp has the feature enabled that allows it to reuse cached virtine shells.

Virtines unsurprisingly take much longer than the native calling mechanism. Recall from our previous experiments that using a virtine for individual function calls incurs roughly 100 $\mu$s of overhead, and the calculations being performed at each node are trivial enough that what we see is mostly overhead. While the single task ($fib(0)$) results are mostly in the noise, we can see virtine overheads amplified as the graph size grows. Graph execution times are in line with expectation given the overheads we have previously seen. Note that even with on-demand, fully isolated hardware virtualization, we can still achieve 720K tasks per second on large dataflow graphs with small task sizes.

Figure 12: Latency and throughput for virtines performing increasing amounts of computational work. Note the log scale on the vertical axis.

We next implemented a version of our dataflow engine where tasks can run in the context of Amazon AWS Lambda functions, and compare it to our virtine-based implementation. While this is not a representative scenario for serverless functions, and while Lambda has additional complexity at the front end (gateways, request routing, etc.), it does demonstrate the relative latencies for fine-grained functions using off-the-shelf methods compared to our custom approach.

Figure 13 shows the results of three scenarios with varying graph sizes, again taking the mean execution times. Here we measure the time to completion once the task “hits the server,” so network round-trips to Amazon’s datacenter are
Figure 13: Our dataflow engine using virtine and AWS Lambda executors. Note the log scale on the vertical axis.

omitted. The virtine measurement is the same as the “host-virtine” measurement in Figure 12. The “lambda” measurement was taken by creating a distinct AWS Lambda function for each dataflow task. Each AWS Lambda invocation would then recursively spawn the dependent Lambda nodes and eventually resolve to the root node. Note that the recursive Lambda calls did not go over the Lambda REST interface and instead were invoked at the Amazon SDK event layer in order to limit the overhead of sending and receiving HTTPS requests and responses. The Lambda measurement represents the duration the root node is alive within AWS. This includes any network overheads within AWS to spawn subsequent Lambda nodes. The last data point, “lambda-fg” represents execution of the entire dataflow graph on a single Lambda node by running the same code used for Figure 12 but all in native context. These results indicate that even with isolation based on full hardware virtualization, virtines can compete with existing, less isolated platforms.

The above numbers for Lambda are consistent with latencies measured by others in existing serverless benchmarks [60], which we list in Table 3. These latencies vary widely and can, in the case of Azure, reach response times up to 35 seconds. Note that more recent research systems such as SOCK [48], SEUSS [12], and Catalyzer [16] push cold start latencies down significantly, and have the benefit of supporting legacy software. Virtines enjoy faster cold start latencies with strong isolation (modulo host interactions), but this depends on the complexity of the virtine runtime environment.

4.2 HTTP Server

Here we attempt to determine how frequent host interactions (via hypercalls) affect performance for an easily understood example. To do so, we built a more traditional HTTP example than the one demonstrated in Section 2. We wrote a single-threaded HTTP server in C that serves static content, and that uses the familiar filesystem and socket calls (not a custom hypervisor API). In order to support this code, we built a virtine runtime environment that includes a statically compiled libc using newlib [44]. The virtine newlib implementation has stub system call implementations which are forwarded down to the hypervisor, which in turn re-executes them to be handled by the host kernel.

While this minimal implementation sacrifices the isolated virtine context by forwarding system calls to the host, all virtine system calls must pass through the hypercall interface, forming a single, auditable “choke” point. This lessens the need for coarse, static system-level configurations of cgroups or other container isolation or resource limiting mechanisms.

In this HTTP server, each connection is handled by invoking a function declared as int handle_connection(). When using virtines, we handle each connection in a new virtine. Specifying this in the code is as simple as declaring virtine int handle_connection(). We measured both the latency and throughput of HTTP requests with and without virtines on chameleon. Client requests are generated from localhost using a custom request generator (which always requests a single static file). Figure 14 shows the results.

For use cases like this one where each request must be
fully-isolated, virtines are a good fit and only incur on the order of \( \sim 200 \) microseconds of overhead compared to their native counterparts.

We constructed a similar experiment to evaluate the suitability of instead using a container engine, in this case pod-man, a daemon-less user-space container engine comparable to Docker. On each request, again in a single-threaded fashion, we cold start a new Alpine container (\( \sim 5 \)MB) from a pre-built image to run a C binary containing the same handle_connection() implementation as before. To prevent manually copying buffers from the socket, a separate server implementation would pass the client socket descriptor over a Unix domain socket to the container handling the request. The lowest latency from request to response by cold-starting the container was \( \sim 600 \) milliseconds – in line with the startup latencies shown in Table 3.

### 4.3 OpenSSL

To investigate the difficulty of incorporating virtines into a more significant codebase, we took an off-the-shelf copy of OpenSSL (3.0.0 alpha7) and modified the 128-bit AES block cipher such that every block was encrypted in a distinct virtine context. Getting OpenSSL building using virtines was straightforward. From the developer’s perspective, it simply involved annotating the block cipher function with the virtine keyword and integrating our custom clang/LLVM toolchain with the OpenSSL build (i.e. swapping the default compiler). Because our current virtine compiler prototype lacks the ability to infer pointer sizes or handle variable-sized arguments, we did have to make modifications to split blocks into fixed-size regions. Because AES-128 operates on 16 byte blocks, we chose 16 byte regions. This means that when a user requests that, for example, 4096 bytes be encrypted, we must split it into 256 invocations of the block cipher. This, however, is not an inherent limitation.

To measure the performance of virtine-enhanced OpenSSL, we ran its built-in speed benchmark\(^7\) to measure the throughput of the block cipher using virtines created from scratch (no caching), virtines reused from old contexts (with caching), and using native execution. Table 4 shows the results. As with the dataflow example, the very small amount of computation in a single invocation pushes the capabilities of virtines. Virtine initialization is slightly more expensive relative to the dataflow example because the runtime image is larger, and more argument marshalling occurs during the setup. However, the key here is that a significant, widely used codebase can be transformed to run functions in a fully isolated, virtualized environment with a single-word change to the code.

### 5 Discussion

The most straightforward use of virtines is for the programmer to manually identify functions in their application that require strong isolation and annotate them as running in virtine context (e.g. by using the virtine keyword with our language support). This is the model we followed with our OpenSSL integration.

Because virtines share the twin goals of low-latency startup and strong isolation with serverless computing, we see them as a natural fit for this domain. Koller et al. aptly describe the state of the modern software stack for serverless\(^{33}\). Adapting the Linux kernel will not suffice for achieving strict latency targets, even with containers. Koller lays out these guidelines: a serverless platform should be able to “fetch and start any action, without any previous cached state, under 100ms, regardless of system load.” Furthermore, to be cost-effective, one would hope for 125.23 actions/second. We believe serverless computing at the edge will amplify these requirements. SEUSS OS\(^ {12}\) (built atop EbbRT\(^ {56}\)) can achieve cold and hot start latencies for HLL runtimes of 7.5ms and 800\(\mu\)s, respectively; Catalyzer pushes this down to the sub-millisecond range\(^ {16}\). Both achieve impressive latencies by applying snapshotting and pre-initialization of common execution paths.

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\(^7\)openssl speed -elapsed -evp aes-128-cbc
We demonstrated that virtines can easily meet the above targets, even without context reuse. However, their use cases differ from those supported by existing platforms. For example, a serverless function written in Python is likely not a good candidate for a virtine, because the function relies on the Python language runtime, which in turn relies on a standard OS interface (i.e. POSIX). For this to work, the virtine must either support POSIX (e.g. via a unikernel runtime) and a Python runtime—both of which involve significant developer effort—or the virtine must borrow functionality from the host via hypercalls, sacrificing isolation. Thus, we do not see virtines as a replacement for existing serverless platform machinery, but rather as an additional mechanism to support fine-grained serverless functions requiring only minimal runtime environments (e.g. C/C++ or other low-level language functions), that have sub-millisecond latency targets, and for which a full software stack would be overkill. We believe such use cases will become increasingly prevalent in edge computing scenarios, and we plan to integrate a virtine back-end into OpenLambda [25] to investigate them further.

Virtines can also be used to augment how serverless functions are written, thus changing the granularity of isolation, and giving platforms more flexibility. Currently, a serverless function is either run in an isolated environment or not. The programmer has little control over the level of isolation other than by choosing different platforms. With this mechanism, a programmer could write serverless application logic only annotate some components as virtines, thus isolating only what is necessary. For example, a “stateful” function within a serverless application that interacts with S3 might be tagged as a virtine, and invocations of that function carefully controlled. The rest of the application can then run in a more weakly isolated container context. Critical components of serverless HLL applications (e.g. crypto libraries) might also be candidates for running in virtine context, though with better chosen block sizes (work per virtine). Virtines will add a slight overhead in this scenario, but even if on the critical path, they will be eclipsed by other start-up overheads.

6 Related Work

Wedge [10] shares our goal of fine-grained isolation within applications. With Wedge, execution contexts (stthreads) are given minimal permissions to resources (including memory) using default deny semantics. Access to resources must be granted explicitly, and invocation of functions with access to privileged data is done via callgates, which resemble virtines. However, virtines are more flexible in that they need not use the same host ABI and they do not require a modified host kernel.

Dune is an example of an unconventional use of a virtual execution environment that provides high performance and direct access to hardware devices within a Linux system [3]. Unlike virtines, Dune’s virtualization is at process granularity, not function call granularity. Furthermore, it is assumed that a Dune process will continue to leverage the Linux API once in “Dune mode.”

Lightweight-Contexts (LwCs) are isolated execution contexts within a process [39]. They share the same ABI as other contexts, but essentially act as isolated co-routines. Unlike LwCs, virtines can run an arbitrary software stack, and gain the strong isolation benefits of hardware virtualization. We are currently exploring extending Wasp for virtual co-routines.

SkyBridge [42] employs clever use of hardware hypercall instructions to enable fast and secure IPCs in microkernels. However, the virtual context is a facilitator not for code execution, but for synchronous communication between distinct address spaces.

Wasp is similar in architecture to other minimal hypervisors (implementing µVMs). Unlike Amazon’s Firecracker [18], we do not intend to boot a full Linux kernel, even with a simplified I/O device model. Wasp bears more similarity to ukvm [62] (again from Koller et al.) especially the networking interface, and uhyve [38]. Unlike those, we designed Wasp to use a set of pre-packaged runtime environments (with varying feature sets). We primarily intend Wasp to be used as a pluggable back-end for serverless platforms and for language runtimes, rather than a stand-alone VMM.

There is a rich history of combining language and OS research. Typified by MirageOS [40], writing kernel components in a high-level language gives the kernel developer more flexibility in moving away from legacy interfaces. It can also shift the burden of protection and isolation [49, 27]. We believe there is ripe opportunity for languages as a driver for creation of novel execution contexts, and our Rust frontend and C extensions are our first step. Older work in component-based systems like Flux [19] and Think [17] provide us with ammunition for automatically constructing appropriate runtime environments at compile-time based on application requirements.

7 Conclusions and Future Work

In this work, we explored the design and implementation of virtines—light-weight, isolated, virtualized subroutines, which can provide fine-grained execution without much of the overheads of traditional virtual execution environments.
We demonstrated their viability by probing the limits of existing virtualization mechanisms and runtime environments. We demonstrated a prototype implementation of virtines, and presented a new hypervisor called Wasp to enable them. We evaluated Wasp and virtines through a series of examples, showing that virtines can achieve start-up latencies as low as 100 µs. We also provide two programming interfaces to virtines: manual specification of C virtines using Rust, and virtine extensions to C using LLVM compiler support.

In future work, we plan to explore more language support for virtine creation and specification, asynchronous features, automatic matching of runtime environments with applications, and JIT compilation. We also plan to thoroughly analyze potential threat scenarios for virtines.

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