How Low Can You Go? Practical cold-start performance limits in FaaS

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Abstract

Function-as-a-Service (FaaS) has recently emerged as a new cloud computing paradigm. It promises high utilization of data center resources through allocating resources on demand at per-function request granularity. High cold-start overheads, however, have been limiting FaaS systems' such potential.

Prior work has recognized that time redundancy exists across different cold function invocations and has proposed varied snapshots that capture the instantaneous execution state so allow for jump-starts through restoration. However, it remains unclear what the cold-start performance limits are as the previous snapshots employ different techniques and are designed for different environments. In this paper, we summarize these snapshots from a taxonomic perspective and present a model that depicts the cold-start performance from first principles. To approximate the performance limits, we propose a snapshot design SnapFaaS. We evaluate SnapFaaS using real-world FaaS functions. Our empirical results prove SnapFaaS' efficiency. It is 2-10x as fast as prior work for most functions and achieves near-optimal cold-start performance.

1 Introduction

Function-as-a-Service (FaaS) is a cloud computing paradigm where developers write containerized "functions" which the cloud platform runs and invokes on demand in response to end-user requests, storage events, and other platform events [2–4,9]. Through fine-grained resource allocation and the flexibility to free resources once a function invocation completes, FaaS promises high utilization of data center resources, even when workloads are heavy-tailed.

In practice, this promise is encumbered by the resource and performance overhead of initializing the system abstraction that FaaS workloads rely on: a full Linux environment and high-level language runtime.

FaaS systems typically allow developers to write functions in one of a few high level languages with access to a complete, though often stripped down, Linux distribution. This affords developers the flexibility to leverage myriad existing native libraries and programs available for Linux as well as the richness of a full operating system (e.g. a POSIX-shell, performant TCP/IP implementations, etc).

Unfortunately, initializing such an environment is costly compared to the typical FaaS function runtime. While most functions execute for less than one second [31], initializing the environment for a function (initializing a virtual machine and kernel or container, running OS init scripts, starting a language runtime, and importing libraries) takes 100s of milliseconds on recent production hardware [13]. This is a problem for both end-to-end request latency and utilization. Long initialization times significantly lengthen the otherwise short end-to-end request latency and tie up CPU and memory that could have been used respond to other requests.

Researchers in the past few years have termed "cold-starts" the problem of initializing FaaS functions. Practical systems mitigate this overhead for popular functions by keeping recently executed functions "warm" for a period—simply keeping the virtual machine or container running—in hopes that another request for the same function arrives soon [8, 13, 31]. This can improve end-to-end request latency for frequently requested functions. However, a large portion of requests are to functions invoked less than once a minute [31] and keeping all such functions warm sufficiently long is an impractical use of CPU and memory resources. As a result, keeping functions warm, while useful, only improves end-to-end request latency for popular functions and wastes resources when functions kept warm are *not* invoked again.

A flurry of research addresses this problem by trying to improves function cold-start themselves. In particular, much prior work has correctly identified that initialization is almost identical for different invocations of the same function. Moreover, much function initialization is redundant across different but similar functions since they often share a kernel, OS init system, and run atop one of a small number of language runtimes. Notably, most work uses some form of memoization to bypass portions of initialization [18, 19, 29, 32, 33]—replacing logical initialization code with load memory directly from disk.

These research systems reduce the end-to-end latency to handle a cold request for a noop function from nearly one second to around 100ms. However, prior systems target different environments and use different memoization techniques, some of which are complimentary while others conflict. It remains unclear what the lower-bound cold-start is, and whether prior approaches are sufficient to achieve performance such a lower-bound.

In this paper, we propose a principled framework for identifying the pracical limits of cold-start performance and describe SnapFaaS, a VM snapshot based FaaS system that achieves significantly better cold-start performance than prior work and nears the practical lower-bound.

We start by defining cold-starts and function memoization, and presenting a taxonomy of prior approaches (Section 2). We then identify the minimal necessary state to handle a function request (Section 3.1) under practical resource constraints, and offer a first-principles model that characterizes cold-start performance (Section 3.2).

We then describe SnapFaaS the design (Section 4) and implementation (Section 4) of SnapFaaS, including a VM snapshot technique guided by the model. SnapFaaS uses fixed memory overhead to cache shared partial snapshots in memory but loads all function-specific memoized state from disk. Key to achieving this is coupling the virtual block and network device configuration, software initialization steps, and snapshot orchestration to ensure that the most sharable memory is initialized before *any* function-specific state.

We evaluate SnapFaaS and show that it always outperforms end-to-end request latency in prior systems—typically by 2-10x. Moreover, SnapFaaS achieves near optimal end-to-end latency overhead for cold requests (Section 6). We conclude by discussing what impacts these results should have on future work in the area.

2 Cold-Start Mitigations in FaaS Today

In FaaS, physical machines multiplex executions of functions by running each in a virtual machine or OS container and allocating fixed resources (CPU, memory, network, and ephemeral disk) to each function while it executes or sits idle. Typically, CPU and memory are the limiting resource and, indeed, public FaaS deployments typically bill in CPU-memory time units.

Function requests are often cold—meaning there is no running container or VM available running the function available to service the request. Production systems often keep function instances "warm" (i.e. they do not kill the VM or container) for a grace period even if no requests for the function arrive to improve latency for popular functions [31]. In this work we only consider cold-starts, though such strategies for optimizing frequently invoked functions are complementary when there is an abundance of memory resources. We also only consider end-to-end request latency since, unlike in interactive systems, booting a function quickly at the expense of a delaying the final response by the same amount is rarely useful in FaaS.

2.1 Reducing Cold-Starts with Memoization

FaaS functions are written in high level languages atop managed runtimes such as Python, JavaScript, Java, Ruby, and C#. Functions also use native libraries and executables that leverage a UNIX-like system interface and standard UNIX shell utilities (*e.g.*, 1s, echo, etc). Most commonly, FaaS platforms expose a complete Linux-based OS environment to functions. For example, a function that creates an image thumbnail has a handler function written in Python that fetches the original image from an object storage service (*e.g.*, S3), invokes a shell command to run the ImageMagick convert command-line utility to generate a thumbnail and, finally, uploads the result back to the object storage service.

In order to service a request, the OS, language runtime, libraries, etc. must be initialized to a state that is able to service it—namely to invoke the function's entry point handle procedure. Initializing the kernel, OS, language runtime, libraries and function initialization code generates this state, by definition. However, it is not *necessary* to run this code each time, even though each component may be non-deterministic.

Specifically, FaaS platforms require functions to be written such that *any* state that was the result of executing the above initialization steps is sufficient to correctly invoke the function's handle procedure, as long as certain general invariants are maintained—the real time clock should be correct, the network should be functional, etc. This makes it possible to memoize much of the logic performed during cold start and replace relatively slow initialization execution with relatively fast data copying.

2.2 Prior Work

Prior work has proposed varied memoization techniques suited for different environments to improve cold-starts. Catalyzer [19] is designed for gVisor [10], SOCK [29] is designed for Docker [5], SEUSS is designed for unikernel [27] virtual machine (VM), REAP is designed for the Firecracker microVM [13].

Despite different runtime environments and technical details, these techniques share the same high-level ideas memoization should capture as much initialization computation as possible, and the restoration should reduce the amount of state restored from disk.

One straightforward form of memoization, a snapshot taken after the function is initialized (a full-function snapshot), captures an initialized but not yet invoked function's execution state as a whole. Catalyzer's func-image is a such. A funcimage is generated through conventional container checkpoint mechanism. It contains the guest's (the function and its runtime environment) memory and metadata (host-side state). Booting from a func-image reconstructs the guest's address space through demand-paging using file-mmap. On-demand restoration avoids prefetching the whole state from disk but pays for synchronous page faults at runtime.

REAP recognizes that synchronous page faults incur high runtime latency penalty and proposes an optimization that prefetches only an approximated working set. Specifically, after taking a full-function snapshot where the entire memory of a pre-initialized function is captured, REAP runs the function once, observing which pages from the snapshot are actually accessed during execution. On future executions, REAP prefetches only that subset of memory, leaving the rest on disk to be demand-paged. The in-batch prefetching significantly reduces total latency overhead through saving considerably many synchronous page faults to disk at runtime.

The other systems take a different route. They cache partial state that is common and therefore sharable to many functions in memory. Typically, such partial state results from up to language runtime initialization but no function initialization.

Catalyzer, to further improve cold-starts, proposes language template Zygote [16]. A Zygote is an idle container having completed some initialization from which a new container can be spawned and specialized. For example, any Python function can be booted from the same Python Zygote. Functions are initialized from Zygotes using the fork system call to create a copy-on-write clone of the Zygote and loads function code in the clone.

SOCK, similar to Catalyzer, uses Zygotes that have certain Python packages imported. Its goal is to save package importing times. SOCK also relies on fork syscall to spawn new containers but it proposes a different protocol suited for Docker.

SEUSS uses VM based runtime snapshots cold requests. A runtime snapshot includes the VM's physical memory from the moment the language runtime initialization completes. Any function in the language can be booted from the same runtime snapshot. Function initialization then starts from the restored runtime. SEUSS uses mmap syscall to implement copy-on-write semantics.

We note that when separating out and caching common state, the designs above fail to memoize function initialization as full-function snapshots do. In fact, SEUSS and Catalyzer, each additionally proposes in-memory "full-function" snapshots of some form. Catalyzer has function template Zygotes and SEUSS has function snapshots. Function template Zygotes are like the language ones but captures function initialization as well. Function snapshots, enhancing runtime snapshots, capture any memory modified during function initialization starting from the correct runtime snapshot.

Caching "full-function" state in memory is fast and can help burst scalability when a function instance is already running anyway. However, each stored state consumes memory proportional to the number of functions so is inappropriate for speeding up cold-starts for all functions that might be invoked.

3 Memoization from First Principles

Existing techniques use similar insights—minimize initialization work by memoizing function state and minimize restoration from disk. However, the techniques are designed for different systems (VMs, containers, unikernels, etc) with inconsistent views of system constraints, such as how much memory is permissible to "waste" on caching states in memory.

We begin addressing the cold start problem by starting from first-principles. What is the minimal work that dictates how fast function memoization can be? How do scalability and resource constraints dictate where such states must be stored? Finally, what is the least restoration work an idealized system should do?

3.1 Required Execution State

We start by looking at the state sufficient and necessary to service a request, and we use Firecracker microVM as a concrete example from now on. The state necessary to service a request includes:

CPU Registers. Each CPU core allocated to a function instance has a few dozen unique word-sized registers (*e.g.*, the stack pointer *rsp* and the instruction pointer *rip* on x86_64) required to run.

Virtual Device State. Virtual devices (*e.g.*, VirtIO [12] block and network devices in a hypervisor) are state machines with relatively simple states: a few pointers to function memory for device-VM shared buffers and device specific state, such as the MAC address of a virtual network device.

Initialized & Useful Memory. Executing a function from its entry point procedure relies on certain parts of the memory being resident in the main memory— all memory pages that are written to during environment initialization and actually used during execution. This constitutes the largest portion of the program state— up to 54 MB in our experiments.

These parts include memory pages modified by the kernel, OS init process, the language runtime, any base libraries used by the language or FaaS runtime (typically a language-specific library), and function initialization. Some of these memory pages are common across similar functions (*e.g.*, those that use the same kernel, OS userland and language runtime) and some are specific to each function.

3.2 Fundamental Overheads

Snapshots boost cold-starts by memoizing initialization and turning cold-starts initialization-less. However, restoring a memoized function is not instantaneous as copying data takes time as well.

In general, there are two options for restoring state from disk. First, state can be restored on demand, where as the function attempts to access missing memory pages, the hypervisor loads the page, synchronously, from disk. As a result, only useful memory pages are loaded and the function can begin executing virtually instantly. However, demand-paging is synchronous—the function blocks until each page is fetched into the main memory—pushing the overhead of restoration to function execution time and preventing batching. Conversely, eager restoration loads memory pages from disk ahead of function execution, *in batch*. This delays the start of a function and may load pages that are never used, but runs at the storage medium's bandwidth speed.

In the best case, snapshots are themselves cached in memory and restored on demand. Such caching must be done in a sophiscated way. Because there are many more functions that *could* possibly run than could fit in memory on each machine, any state proportional to the number of functions cannot be stored long-term in memory. As a result, any function-generic state, as it can be shared across functions through copy-onwrite semantics, can reside in memory.

The higher latency the storage medium, the more important it is that snapshot memory be loaded eagerly. While disk is both lower bandwidth and higher latency than memory, latency is a much more significant factor. For example, modern RAM has about 50x the bandwidth of an SSD (500Gbps compared to 10Gbps), RAM latency is 5 orders of magnitude faster than SSD read latency (100ns compared to 16us).

As a result, CPU-registers, virtual device state, and function-specific memory should reside on disk and be restored eagerly while function-generic memory should reside in memory and be restored on demand.

In summary, to reconstruct the state of a VM prepared to handle a request, we must:

- 1. load CPU registers and restore virtual device state (c)
- 2. Eagerly restore from disk non-zero memory pages unique to each function (*pgsunique*)
- 3. execute any remaining initialization code who's resulting state cannot be captured by a snapshot (e.g. reading and deserializing the request payload) (*init*)
- 4. And copy from memory any snapshot pages that can be shared amongst functions that are written to during function execution (*pgs_{shared}*)

Only the first two steps can occur concurrently. CPU registers, virtual device state, and any memory not paged on demand must be available before any remaining initialization which, in turn, must run before the function begins executing.

Therefore, given the memory latency lat_{mem} , disk bandwidth bw_{disk} , and page size *P* (typically 4KB), the minimum overhead to end-to-end performance that *must* be incurred by any snapshot restoration strategy is given by:

$$max(c, (\frac{pgs_{unique} \times P}{bw_{disk}})) + init + (pgs_{shared} \times lat_{mem}) \quad (1)$$

We can see by the model that to achieve the best cold-start performance is to minimize each of these terms by: splitting snapshots such that the most pages are sharable amongst many functions but are seldom written to; identifying the minimum number of unique pages that must actually be restored for each function; and minimizing the amount of initialization code necessary for each function invocation.

4 SnapFaaS

Following the goals above, we propose SnapFaaS a snapshot based on Firecracker microVM that testifies the cold-start performance limits.

At a high-level, the design consists of one in-memory base snapshot for each language runtime and one diff snapshot and one working set (WS) file, both on-disk, for each function. There are two key techniques accompanying the design—1) use of two file systems to allow easy base/diff separation and 2) coupled guest-host network configuration.

4.1 Maximize Shared Pages, Minimize Shared Written Pages

The first goal is to maximize the number of in-memory sharable pages (i.e. minimize pgs_{unique}) and minimize the ratio of these sharable pages that are written to during execution. SnapFaaS accomplishes this by generating separate snapshots: a base snapshot for the common "runtime" and a diff snapshot for a function and the libraries it imports.

The base snapshot includes memory initialized by the kernel, OS, language runtime, base libraries, and the SnapFaaS runtime. Because all functions use one of a small number of language-runtimes, each such base snapshot can be shared across many functions. The diff snapshot includes memory initialized or modified by the function itself and the libraries it imports. This may include memory pages that were also initialized in the base snapshot. In this case, diff snapshot values override base snapshot values.

While functions may use any of this base snapshot during execution, each function uses a relatively small portion of this memory. Moreover, as shown in Figure 1, functions *write* to very few of these shared memory pages during execution. At most 15%, and more typically fewer than 5%, of pages present in the base snapshot are written during function execution.

The result is that pg_{shared} is small and, consequently, few pages are copied on demand.

Key technique—use of AppFS. In order to facilitate layering of diff snapshots on top of base snapshots, a SnapFaaS VM uses an application file system (AppFS) in addition to a must root file system (RootFS) that stores boot-critical programs like /init and OS & language utilities.

Functions can be packed into the RootFS as well. However, it will be much trickier to ensure that base snapshots do not include the result of executing any function-specific initialization. This is because once a block device is mounted, file system metadata, such as the root inode, are cached in memory by the Linux kernel and, as a result, a snapshot captures specific layout of the file system.

Use of AppFS solves the layout problem because the AppFS is not mounted when the base snapshot is generated. Additionally, the separation easily realizes one root file system for each supported language. SnapFaaS currently provides four RootFS-es, Python3, Node.js, Java, and Go.

4.2 Minimize Unique Pages

The second goal is to identify the minimum set of unique pages that must be actually resident in memory. To achieve this goal, SnapFaaS draws on REAP's technique [32].

Similar to REAP, SnapFaaS approximates a function's working set using the working set from one previous execution. Then SnapFaaS eagerly reads in the working set and demand-paging the rest. Note that SnapFaaS only applies this technique to diff snapshots since the purpose is to minimize the number of pages fetched from disk into memory.

4.3 Minimize Initialization Computation

SnapFaaS captures nearly all initialization code in the base and diff snapshots. Capturing some of this is trivial. For example, initialization in libraries that sets up data structures, loads an ML model from disk, etc, are independent of invariants outside the function VM, so are captured entirely by the memory encoded in the diff snapshot. However, some other initialization code captures state *outside* the VM and, therefore, requires tight coupling with the FaaS platform.

Key technique—coupled guest-host network configuration. For example, the TCP/IP stack in Linux has internal states the VM's local IP address, the gateway address, MAC addresses for both the virtual Ethernet device and physical Ethernet device, ARP tables, etc. All of these must be valid for each function instance restored from a snapshot to avoid requiring DHCP to discover new IP addresses, ARP to discover routes, and other dynamic network configuration tasks.

To accomplish this, the network initialization code in the RootFS configures the network in accordance with strong guarantees from the hypervisor regarding the network. VMs



Figure 1: Copy-on-write ratio. The ratio is calculated as the number of memory pages that are modified by the language runtime initialization and are written to during execution over the total number of shared in-memory pages. The numbers are from a single run.

use a static local IP address connected to a virtual bridge device on the hypervisor with a fixed IP address and MAC address. And this state is captured in the base snapshot which is shared across different function instances. In order for different VMs on the same host to use the same local IP addresses, VMs' virtual network devices are attached to a software Ethernet bridge on the host.

This design allows 1) that any VM to use the bridge as the gateway device which has a well-known IP address and 2) that different VMs on the same host with the same IP address to communicate with the outside since an Ethernet bridge uses hardware MAC addresses as identification. ¹

5 Implementation

5.1 Software Stack

In addition to Firecracker microVMs in which user code runs, there are other components along the software stack. Precisely, each VM runs alongside its Firecracker virtual machine manager (VMM) process and on top of Linux KVM hypervisor [21]. Linux KVM virtualizes CPU and memory and the VMM process assists with I/Os.

VM Pre-configuration. The VMM process is also responsible for pre-configuring a VM. Before booting a VM from either the kernel or snapshots, the system needs to pre-configure it, including registering a new VM with Linux KVM asking for CPUs & memory and attaching virtual I/O devices to the VM after registration.

¹Note that this setup only enables VMs to initiate connections, which is desirable as FaaS functions are not network addressed like conventional servers.



Figure 2: Comparison of SnapFaaS with the existing snapshots for cold-starts. REAP captures the execution state as a whole and eagerly loads the working set. SEUSS restores cached common states on demand and then import functions from the source. SnapFaaS caches common states and store function states on disk and eagerly loads only the working set. (SnapFaaS- is SnapFaaS without working set estimation.)

VM Organization. In addition to a stripped-down Linux kernel, two block devices formatted to RootFS and AppFS and an IP network device, each VM has a VSOCK [12] (virtual socket) device to communicate with the host, *i.e.*, receiving runtime arguments and returning results.

We follow the guide provided by the Firecracker team about how to build file system images [7]. File system images are based on Alpine Linux 3.10 [1]—a distribution of Linux that uses the lightweight BusyBox UNIX utilities and OpenRC [11] init system—and a Linux kernel based on version 4.20 compiled with the minimal configurations.

5.2 SnapFaaS Generation and Restoration

Generation. The VMM process and the custom languagespecific *runtime entry point* running inside the VM cooperatively capture the VM's execution state. A custom languagespecific *runtime entry point* is a script (for scripting languages like Python and JavaScript) or an executable (for compiled languages like Go) that when executed initializes the language runtime including executing basic library code used by itself. It also mounts the AppFS. More importantly, it makes hypercalls that pause the VM and cause a context switch from the VM in guest mode to the VMM in host user mode.

To create a base snapshot, we boot a VM normally from the kernel using the RootFS, with a placeholder AppFS image. The VMM enables dirty-page tracking in order to tell which pages must be recorded in the snapshot. Once language runtime initialization completes, the language-specific runtime entry point immediately makes a hypercall from each virtual CPU core. This action pause the VM and signals the VMM to capture the VM's execution state, *i.e.*, the state of memory, CPU, and I/O devices and generate the base snapshot. This snapshot consists of a sparse file containing only

```
import lorem
def handle(event):
  return {
    'body': lorem.sentence(),
  }
```

(a) Entry-point procedure handle. The runtime starts function execution by calling handle. handle requires one parameter which contains any runtime arguments and returns an object.



(b) Tarball structure. workload should contain procedure handle. Packages, libraries, and binaries should be in directory package, lib, and bin, respectively.

Figure 3: SnapFaaS programming interface (Python3 lorem example). This figure shows the content of the tarball that the developer submits to SnapFaaS to register a function.

dirty memory pages, as well as a JSON file describing nonmemory state, the state of CPU and I/O devices. The resulting snapshot is stored in a tmpfs file system on the host for easy in-memory storage.

To creates a diff snapshot for a particular function, we begin by booting a VM through restoring the correct base snapshot with the function's actual AppFS attached to the VM instead. As a result, the VM continues execution inside the language-specific runtime entry point immediately after the hypercall described above. The runtime entry point continues by mounting the AppFS and loading and initializing the function in a language-specific way—*e.g.*, in Python and Node.js, importing the workload file is sufficient to execute initialization code in the global scope (such as importing third-party libraries) while the Go entry point loads an ELF "plugin" and explicitly calls an Init that the function is expected to export.

Once the function is initialized, without actually invoking it, the runtime entry point pauses the VM and signals the VMM to generate the diff snapshot by, again, making a hypercall from each virtual CPU core. During this process, the VMM enables dirty page tracking as well and diff snapshots contain only pages that are marked dirty during this time. For memory state, in addition to dirty memory pages themselves, a diff snapshot includes an explicit record of dirty pages relative to the base snapshot. Restoration from base and diff snapshots uses this metadata. For non-memory state, diff snapshots use a similar JSON file.



Figure 4: Overview of a FaaS system with SnapFaaS deployed.

To generate a WS file, similar to generate a diff snapshot, we begin by restoring base and diff snapshots all ondemand to allow us to track page access. After execution, we record the set of pages that are accessed during execution and are file-mmaped from the diff snapshot. This set is the working set of the diff snapshot.

Restoration. To restore the VM's memory, the VMM *file-mmaps* the base snapshot into private memory. As a result, memory pages from the base snapshot are loaded copy-on-write, and any pages not modified by function execution will be shared among VMs running the same language runtime. The VMM then *copies* each page in the diff snapshot into private memory using the system call readv.

Or if the working set optimization is applied, the VMM *file-mmaps* non-working-set pages of the function's diff snapshot into private memory and *copies* the working set into the VM's private memory.

To restore the non-memory states, the VMM restores nonmemory states encoded in the diff snapshot's JSON file, including the state of CPU and I/O devices.

5.3 SnapFaaS Deployed

Programming Interface. SnapFaaS assumes a similar programming interface to existing public FaaS offerings [2]. To register a function, the developer submits a tarball of the function source including all dependencies. The system then reformats the tarball to a AppFS.

Figure 3 is an example of the function source and the tarball structure. Developers should define a procedure named handle which is the entry point of function execution. handle takes one argument event and returns a serializable object. The event argument contains inputs if any. Figure 3a shows an example of a simple Python3 function.

To prepare a tarball, developers should name the file that

defines handle as workload (Figure 3b). Additionally, thirdparty dependencies, native libraries and native binaries are in subdirectories package, lib, and bin, respectively.

System Workflow. Figure 4 shows how a FaaS system employing SnapFaaS looks like: a cluster scheduler, a cluster manager², and a fleet of worker machines each of which has two-tiered storage: memory and slow, persistent disk. Memory stores base snapshots while disk stores WS files, diff snapshots and file system images.

System workflow is as follows.

During system bootstrap, for each supported language, the cluster manager generates a RootFS image for each supported language that serves as the boot device. Next, the cluster manager generates a base snapshot using the language's RootFS image. Finally, the cluster manager replicates these RootFS-es and base snapshots to each worker machine's disk and memory respectively.

At function registrations and updates, the cluster manager converts tarballs into AppFS images and generates diff snapshots using AppFS images with the correct base snapshot and RootFS image. Then the manager invokes functions with mock arguments to create WS files. At last, the cluster manager replicates these WS files, diff snapshots and AppFS images to each worker machine's disk. AppFS images need replicating because the function may dynamically loads packages or invokes binaries that's stored on the AppFS.

For client requests, the cluster scheduler is the gateway. Upon receiving a request, the cluster scheduler dispatches it to a worker machine. The controller running on the worker machine either invokes the requested function in a cached idle function instance (warm-request) or launch a new instance (cold-start) in a VM with the correct base and diff snapshots plus WS files. Once the function finishes execution, it sends

²The cluster scheduler and the cluster manager are not within this paper's scope.

the results to the controller. The controller then returns the response to the client.

6 Evaluation

We evaluate SnapFaaS by answering the following questions:

- How do SnapFaaS and SnapFaaS- (SnapFaaS without working set approximation) perform compared with the existing snapshots?
- What are cold-start overhead breakdowns like for different snapshots following the model we proposed in Section 3?

6.1 Experimental Setup

Hardware. We use CloudLab's [20] c220g5 machines. A c220g5 has two Intel Xeon 10-core CPUs at 2.20 GHz, DDR4-2666 memory, one SATA SSD with 500 MB/s peak sequential read bandwidth and 50 us random read latency. We disable hyperthreading [13]. The host operating system is Ubuntu 16.04.1 with kernel version 4.15.0 and the guest operating system is Alpine Linux 3.10 with kernel version 4.20.0.

Benchmarking functions. We implemented 14 functions in four languages³ (Table 1) that represent a variety of common FaaS applications: text, audio, and image processing; online transaction processing; and smarthome/IoT applications.

Many of these applications have library dependencies, including native libraries and executables. For example, the Python3 thumbnail function depends on the Pillow package which requires the libjpeg native library. The Node.js ocr function is a thin wrapper around Tesseract OCR executable, and the Node.js alexa-reminder function adds and retrieves reminder items stored in CouchDB over the network.

SEUSS_{SF} and REAP_{SF} In order to compare SnapFaaS with the existing snapshots, we implemented SnapFaaS versions of them, REAP_{SF} and SEUSS_{SF}. We refer to SnapFaaS version's REAP [32] as REAP_{SF} and implement it as eagerly loading the working set and demand-paging the rest of a full-function snapshot. We refer to SnapFaaS version's SEUSS-like designs [18, 19, 29] as SEUSS_{SF} and implement it as copy-onwrite sharing a in-memory base snapshot and importing the function from its on-disk source.

Function inputs. For *SnapFaaS* and *REAP_{SF}* experiments, we use the same function inputs that we use to generate the working sets.

6.2 Snapshot Performance Comparison

Figure 5 compares the cold-start latency of *SnapFaaS*— and *SnapFaaS* with *REAP_{SF}* and *SEUSS_{SF}*.

Cold-Start Boot Latency. We measure boot time for coldstart requests from when the VMM process starts to when the VM is ready to accept client requests. Figure 5a shows boot latencies normalized to *SnapFaaS*.

Without the working set optimization, it is already the case that SnapFaaS- is always faster than $REAP_{SF}$ and always at least comparable to $SEUSS_{SF}$. Specifically, SnapFaaS- is up to 20.2x as fast as $REAP_{SF}$ and up to 8.8x as fast as $SEUSS_{SF}$.

With the working set optimization, *SnapFaaS* is always at least comparable to *SnapFaaS*—, *REAP_{SF}* and *SEUSS_{SF}*. Specifically, *SnapFaaS* is up to 1.9x as fast as *SnapFaaS*—, up to 18.8x as fast as *REAP_{SF}*, and up to 12x as fast as *SEUSS_{SF}*.

Cold-Start Function Execution Time. We measure coldstart function execution time from the moment the host sends a request to the VM until the host receives a response. Figure 5b shows execution latencies normalized to *SnapFaaS*.

With fewer copy-on-write page faults, $SEUSS_{SF}$ has comparable or faster execution latencies than SnapFaaS— and SnapFaaS. Specifically, SnapFaaS— and SnapFaaS are 16.4% and 13.4% slower, respectively, than $SEUSS_{SF}$ for the Go sentiment-analysis function.

With no shared pages across function instances, $REAP_{SF}$ avoids all copy-on-write costs incurred by SnapFaaS— and SnapFaaS during execution. For the minimal Python3 lorem function, for example, SnapFaaS— is 68.9% slower than $REAP_{SF}$ and SnapFaaS— is 74.7% slower $REAP_{SF}$ for Go function sentiment-analysis. However, our results show that $REAP_{SF}$'s execution latencies are unpredictable, particularly if $REAP_{SF}$ misses some pages used during execution, which much be fetched on-demand from disk.

In general, longer-running functions, such as ocr in Java and alexa-reminder in Node.js, see smaller variations in execution latencies across the four snapshot designs.

Cold-Start End-to-End Latency. The end-to-end latency measures from the start of VMM process to when the host receives a response from the VM. This is the sum of cold-start boot latency and cold-start execution time and is the most important latency metric for FaaS workloads. Figure 5c shows end-to-end latencies normalized to *SnapFaaS*.

Without the working set optimization, SnapFaaS— is already at least comparable to the existing $SEUSS_{SF}$ and $REAP_{SF}$ for all functions. Specifically, SnapFaaS— is up to 10.1x as fast as $REAP_{SF}$ for Node.js function lorem and up to 5.3x as fast as $SEUSS_{SF}$ for Python3 function sentiment-analysis.

With the working set optimization, *SnapFaaS* further improves the speed-up. Specifically, *SnapFaaS* is up to 1.8x as

³All applications are available at URLremovedforanonymity.

Name	Description	Language	Libraries & Binaries			
lorem	Generate a random lorem text string	Node.js, Python3, Go	lorem			
sentiment-analysis	Textual sentiment analysis with NLP models	Python3, Go	nltk, textblob etc.			
thumbnail	Generate a thumbnail picture	Python3, Java	PIL/ImageMagick, libjpeg etc.			
ocr	Text recognition with Tesseract OCR	Node.js	tesseract, tessdata, libjpeg etc.			
img-resize	Resize a large image to 5 smaller sizes	Node.js	jimp, node-zip			
alexa-door	Control door lock with Alexa	Node.js	ask-sdk-core, request etc.			
alexa-reminder	Setting up reminders with Alexa	Node.js	ask-sdk-core, request etc.			
audio-fingerprint	Generate acoustic fingerprints of audio files	Python3	pyacoustid, audioread etc.			
matmul	Matrix multiplication	Java	None			
tpcc	TPC-C benchmark	Java	java.sql			

Table 1: Benchmarking functions



(c) End-to-end latency normalized to SnapFaaS.



Figure 5: Snapshot performance comparison. We take the latency average for 100 rounds and normalize *SnapFaaS*'s latencies to 1 (the blue line). For figure (a) - (c), being above the blue line means being slower than *SnapFaaS*.

fast as SnapFaaS for Go function sentiment-analysis, is up to 9.9x as fast as $REAP_{SF}$ for Node.js function lorem,

and is up to 6.1x as fast as $SEUSS_{SF}$.

For long-running functions, such as Java function ocr, all

	$REAP_{SF}$				$SEUSS_{SF}$			SnapFaaS-				SnapFaaS				
	А	В	С	D	А	В	С	D	А	В	С	D	А	В	С	D
Go																
lorem	6.9	160.3	9.1	0.9	4.6	0.6	42.4	-0.2	5.5	19.7	3.1	0.6	5.7	10.3	5.0	0.8
sentiment-analysis	7.7	448.5	4.8	5.4	4.6	0.7	546.7	0.2	7.3	144.9	6.0	6.0	6.9	69.9	5.9	7.6
Java																
matmul	7.1	417.2	17.7	186.5	5.0	1.0	43.0	11.2	6.3	28.0	15.4	14.4	6.3	23.9	13.7	14.4
thumbnail	7.5	436.3	24.9	6.2	4.5	0.7	55.9	18.8	5.9	29.4	22.6	22.2	6.1	26.6	22.0	22.7
tpcc	6.9	408.3	16.4	102.7	5.1	0.8	47.1	96.3	6.5	29.7	14.7	134.0	6.5	28.7	14.7	130.1
Node.js																
alexa-door	9.0	528.8	14.3	13.7	7.6	1.1	397.3	1.6	9.0	70.4	12.6	15.5	8.7	50.9	12.2	15.7
alexa-reminder	6.9	444.4	15.2	7.9	4.6	0.7	114.7	-3.2	6.3	33.0	7.0	24.6	6.2	31.9	7.2	25.9
img-resize	7.6	507.0	14.7	33.7	4.7	1.0	417.9	18.2	6.4	61.1	10.4	10.4	7.2	57.9	9.8	40.2
lorem	7.5	374.5	19.1	7.0	4.7	0.7	41.7	1.9	7.6	16.8	5.1	4.5	7.6	14.4	7.2	5.3
ocr	7.1	466.0	14.6	133.7	4.5	0.7	34.4	255.9	5.0	15.1	5.6	276.1	6.0	15.0	6.9	280.2
Python3																
audio-fingerprint	7.3	423.5	5.5	7.7	4.8	0.6	744.9	1.9	7.4	87.8	6.9	16.1	7.4	50.1	6.8	13.2
lorem	7.1	235.2	6.4	1.6	5.1	0.8	54.6	0.6	7.0	26.7	6.0	2.6	7.3	15.4	4.6	1.9
sentiment-analysis	7.6	593.0	6.4	18.9	5.3	0.7	1292.3	5.3	8.0	133.5	7.2	20.7	7.8	108.0	7.1	22.2
thumbnail	7.0	312.6	5.3	25.5	4.7	0.6	157.8	1.3	5.8	43.1	5.5	13.1	5.4	31.4	4.5	9.8

Table 2: Cold-start overhead breakdowns in milliseconds. The numbers are averages from the same 100 rounds as Figure 5. The breakdown follows our model $max(c, (\frac{pgs_{unique} \times P}{bw_{disk}})) + init + (pgs_{shared} \times lat_{mem})$. A-D stands for the model's four clauses from left to right. Latencies in D column are the difference between the measured latency and regular's latency. regular stands for booting a function normally from the kernel.

strategies are similar since the execution time dominates. Figure 5d shows the trend that shorter functions experience higher speed-ups. Additionally, Figure 5d shows that *SnapFaaS* and *SnapFaaS*— are the closest to the optimal case when there is no cold-start overhead.

6.3 Cold-Start Overhead Breakdown

Table 2 presents cold-start latency overhead breakdowns of *SnapFaaS*-, *SnapFaaS*, *SEUSS*_{SF}, and *REAP*_{SF}.

Recall that we model cold start latency overhead as

$$max(c, (\frac{pgs_{unique} \times P}{bw_{disk}})) + init + (pgs_{shared} \times lat_{mem}).$$

Our empirical results show the follows where A to D stands for the model's four clauses from left to right.

A. There is a constant overhead that the system spends preconfiguring the VMM process and the VM and restoring non-memory states, e.g., CPU registers.

B. For *SnapFaaS*–, *SnapFaaS*, and *REAP_{SF}*, there is a nonconstant overhead that the system spends restoring memory from the disk while this overhead for *SEUSS_{SF}* is constant and small because *SEUSS_{SF}* only does **file-mmaps** to restore memory.

Figure 6 shows all evaluated functions' eagerly restored memory sizes along with their full-function snapshot memory sizes. We can see that *SnapFaaS*— by caching common states reduces more memory than *REAP_{SF}* and that *SnapFaaS*, with the working set optimization, can further reduce memory sizes. The large memory size reductions leads to reductions

in cold-start boot time (Figure 5a) and results in reductions in cold-start end-to-end latency (Figure 5c).

Note that this restoration latency does depend on disk bandwidth utilization. Our results do show various disk bandwidth utilizations intra and inter snapshot strategies. For example, under *REAP_{SF}*, Node.js function alexa-door only consumes 81 MB/s bandwidth on average while Node.js function alexa-reminder consumes 100 MB/s bandwidth on average and alexa-door under *SnapFaaS*- consumes 355 MB/s. Our implementation simply uses the readv system call. Optimizations may be possible particularly for *REAP_{SF}*. However, we want to point that even if *REAP_{SF}* can manage to consume the same bandwidth as *SnapFaaS*-, it still fundamentally loads significantly more memory from disk into memory compared with *SnapFaaS*-.

C. For *SnapFaaS*–, *SnapFaaS* and *REAP_{SF}*, there is a more or less constant overhead that the system spends doing remaining initialization work, connecting to the host through VSOCK in this case. For *SEUSS_{SF}*, in contrast, the system spends extra time importing the function from the source in addition to connecting to the host.

D. Empirically, there exists execution slow-down for all snapshot strategies even though in theory $REAP_{SF}$ should observe no slow-downs because the inputs during evaluation are the same as during working set generation. The results suggest that executions are not necessarily deterministic (e.g. languages' garbage collecting) causing accesses to on-disk pages. For the rest three, SnapFaaS- and SnapFaaS consistently experience higher slow-down than $SEUSS_{SF}$. This follows from that, compared with SnapFaaS- and SnapFaaS,



Figure 6: Sizes (MB) of memory eagerly restored from the disk. Compared with the sizes of full-function snapshots, *REAP_{SF}*, *SnapFaaS*-, *SnapFaaS*-, *SnapFaaS*- achieves the sizes of memory eagerly restored from the disk. *SnapFaaS*- achieves the reduction by caching common states with no working set approximation.



Figure 7: Throughput difference using SnapFaaS vs regular under simulated workloads. When available memory is small and there no cold-start requests, SnapFaaS' memory overhead hurts throughput. However, when 30% or more requests result in cold-starts, SnapFaaS improves through 25%-77%.

 $SEUSS_{SF}$ does more initialization work after restoring from the base snapshot so that it experience fewer copy-on-write faults during execution.

6.4 Memory Overhead

SnapFaaS requires each worker to have an in-memory copy of the base snapshot for each supported runtime. For the runtimes we implemented, this includes 60MB for Node.JS, 40MB for Python, 60MB for Java, and 36MB for Go. In total, each worker incurs a memory overhead of 196MB. On our experimental machines, this amounts to 0.1% and 0.3% of the available 192GB and 64GB of memory, respectively.

Less available memory means fewer functions can run

concurrently on the same machine. Conversely, faster coldstart latency means that throughput per available slot is higher. How do these competing forces affect overall throughput?

Figure 7 shows the throughput difference using SnapFaaS and regular VM initialization under a simulated workload with varying proportions of requests resulting cold-starts. As expected, with no cold starts (i.e. all requests are for recently invoked functions) SnapFaaS has lower throughput because it can run fewer VMs concurrently. However, with as few as 30% of requests resulting in cold starts, SnapFaaS has 25% higher throughput. When most requests result cold-starts SnapFaaS has over 75% higher throughput than regular initialization.

7 Related Work

Prior work has looked into mitigating cold-start overhead with checkpoint/restore techniques [24, 33]. Snowflock [24] targets stateful applications in traditional cloud computing environments. Their VM forks abstraction achieves sub-second VM cloning. Replayable Execution [33] is recent work that target FaaS applications. Replayable Execution uses checkpointing and demand paging to boot a JVM environment in 54ms. Snapshots in Replayable Execution is taken after JVM initialization and before loading user applications. Their JVM initialization captures the maximal common state for their Java workload. This approach is equivalent to our base snapshots.

Numerous research projects propose lightweight virtualization techniques. Unikernels [22, 27] reduce startup latency by minimizing the guest OS based on applications and removing kernel-userspace isolation. No FaaS systems currently use unikernels in production, but SEUSS [18] shows that snapshots can be used with unikernels to further reduce FaaS cold start latency. LightVM [28] improves startup latency by optimizing the Xen hypervisor. ukvm [34] builds a specialized virtual machine monitor on top of KVM for unikernels to reduce startup latency. Solutions that improve hypervisor or VM monitor performance can further benefit SnapFaaS and are orthogonal to our approach.

Some CDN providers have begun using JavaScript and WebAssembly based sandboxes to run FaaS-style computations [4, 6]. Some research projects also explored using language sandboxes to run FaaS workloads. Boucher et al. proposed using Rust's static types to isolate FaaS computations [17], and Splinter [23] uses a compile-time sandbox based on Rust's static types to enable low-resource sandboxing of computations running in a fast key-value store.

In general, language-based approaches offer orders of magnitude faster cold start time and lower memory overhead compared with virtualization-based sandboxes. The above systems all report cold start latencies on the order of 10s of microseconds. However, they trade generality: none of these approaches can offer a full Linux environment — Rust and JavaScript sandboxes in particular only support applications written in those languages. Many FaaS workloads rely on a variety of other languages as well as a wide variety of existing code designed to run on Linux such as machine learning libraries and image compression tools.

8 Discussion

Our results show that Linux VM-based snapshots have a lower-bound of about 15 ms for our setup if the SSD peak bandwidth is achieved. While there is an open space of snapshot designs, we argue that new designs cannot significantly improve on our results without breaking the FaaS abstraction. This has important implications for practitioners and researchers in this space. Cold-start overheads limit the utilization of FaaS significantly when execution times are very low. As a result, when targeting environments with low latency requirements [6, 25] system builders should avoid the containerized Linux abstraction. Instead, FaaS systems that target high cluster utilization and low latency must sacrifice the portability and flexibility of a Linux interface in favor of language-specific or other limited APIs with better fundamental performance characteristics.

9 Limitations & Future Work

Using snapshots restoration to alleviate cold-start latency exacerbates two important security concerns. Instances spawned from the same snapshot share a large portion of their base memory. This helps performance but renders attack (e.g. from a malicious request payload) mitigation techniques based on address space layout randomization (ASLR [14]) ineffective. Recent work [15,26,35] has shown that re-randomizing memory and code can be done with reasonable overheads in many cases [35]. We intend to evaluate the use of re-randomization within FaaS functions on SnapFaaS. Similarly, using copy-onwrite shared pages for kernel and language runtime memory introduces the potential for cache-based timing channels between functions on the same machine [30].

Our current implementation of SnapFaaS has some known limitations that we are actively fixing. We currently do not capture the VSOCK device, the host-guest channel, in either snapshots. As a result, even though the state in which the channel ends right before any requests is predictable, in the current implementation the system still initializes the channel through computation. At the moment, each base snapshot only supports a particular VM memory size For example, a Python3 base snapshot created on a VM with 128MB of memory cannot be used to start a 256MB function. Supporting each VM size requires one base snapshot. However, we believe this is fixable using well-known memory ballooning strategies and intend to implement this functionality in SnapFaaS. Some runtimes (Node.js in particular) use the OS' random number generator during initialization regardless of whether user code needs randomness. Because there is very little entropy during sandbox initialization, the kernel does not consider the randomness pool ready for a very long time, blocking runtime initialization during snapshot generation. Our current implementation manually insecurely adds "randomness" to the pool. However we intend to incorporate the VirtRNG driver in the future. VirtRNG would allow the guest VM to simply pre-seeded randomness from the host.

Substituting normal sandbox creation for efficient and fast snapshot-based techniques as in SnapFaaS opens a number of research directions we have not yet explored in depth and leave for future work. One example is that SnapFaaS might help mask the performance and resource overhead of heavier operating systems. Today, FaaS platforms use stripped down operating system distributions to mitigate cold-start latency and reduce per-function memory overhead. In a typical FaaS environment, without snapshots, this makes sense. However, the result typically lacks common developer conveniences, such as DBus on Linux. Because SnapFaaS loads the base snapshot lazily we expect a more complete OS interface to have limited or no per-function memory or performance overhead.

10 Conclusions

We presented SnapFaaS, a snapshot for FaaS system based on Linux VM. We first think from first principles modeling the fundamental overhead of snapshot restoration. Then, we have the model guide our design leading to the base-diff split snapshot. SnapFaaS delivers near-optimal cold-start overhead with negligible memory overhead. SnapFaaS and all of the experimental infrastructure is open source and available at https://fakeplatform.biz/mindyour/beeswax.

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