FAASM: Lightweight Isolation for Efficient Stateful Serverless Computing

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Abstract
Serverless computing is an excellent fit for big data processing because it can scale quickly and cheaply to thousands of parallel functions. Existing serverless platforms, however, isolate functions in ephemeral, stateless containers. This means that functions cannot efficiently share memory, forcing users to serialise data repeatedly when composing functions. We observe that container-based isolation is ill-suited for serverless big data processing. Instead it requires a lightweight isolation approach that allows for efficient state sharing.

We introduce Faaslets, a new isolation abstraction for serverless big data computing. Faaslets isolate the memory of executed functions using software-fault isolation (SFI), as provided by WebAssembly, while allowing memory regions to be shared between functions in the same address space. Faaslets can thus avoid expensive data movement when functions are co-located on the same machine. Our runtime for Faaslets, FAASM, isolates other resources, e.g. CPU and network, using standard Linux cgroups, and provides a low-level POSIX host interface for networking, file system access and dynamic loading. To reduce initialisation times, FAASM restores Faaslets from already-initialised snapshots. We compare FAASM to a standard container-based platform and show that, when training a machine learning model, it achieves a 2× speed-up with 10× less memory; for serving machine learning inference, FAASM doubles the throughput and reduces tail latency by 90%.

1 Introduction
Serverless computing in clouds is becoming a popular way to deploy data-intensive applications. A function-as-a-service (FaaS) model decomposes computation into many functions, which can effectively exploit the massive parallelism of clouds. Prior work has shown how serverless computing can support map/reduce-style jobs [36,58], machine learning training [16,17] and inference [34], and linear algebra computation [61,75]. As a result, an increasing number of applications, implemented in diverse programming languages, are being migrated to serverless platforms.

Existing serverless platforms such as Google Cloud Functions [27], IBM Cloud Functions [33], Azure Functions [44] and AWS Lambda [5] isolate functions in ephemeral, stateless containers. The use of containers as an isolation mechanisms introduces two challenges for data-intensive applications, the data access overhead and the container resource footprint.

First, the stateless nature of containers means that the state of the computation must either be maintained externally, e.g. in object stores such as Amazon S3 [6], or passed between function invocations. Both approaches incur costs due to repeated data serialisation and transfer over the network. Therefore, data-intensive applications on today’s serverless platforms adopt an inefficient “data-shipping architecture”, i.e. moving data to the computation and not vice versa—such architectures have been abandoned by the data management community many decades ago [30]. Overheads are also compounded as the number of functions increases, reducing the benefit of unlimited parallelism, which makes serverless computing attractive in the first place.

Second, despite the fact that containers have a smaller memory and CPU overhead compared to virtual machines (VMs), there remains an impedance mismatch between the execution of individual short-running functions and the process-based isolation of containers. Containers have start-up latencies in the hundreds of milliseconds to several seconds, leading to the cold-start problem in today’s serverless platforms [30,70]. The large memory footprint of containers limits scalability—while technically capped at the process limit of a machine, the maximum number of containers is usually limited by the amount of available memory, with only a few thousand containers supported on a machine with 16 GB of RAM [45].

Current data-intensive applications using serverless computing adopt various workarounds for these challenges. Some systems avoid data movement costs by maintaining state in long-lived VMs or services, such as ExCamera [26], Shredder [80] and Cirrus [17]; this loses the benefits of serverless computing by breaking out of the model. To address the performance overhead of containers, systems typically weaken isolation guarantees: PyWren [36] reuses containers to exe-
cute multiple functions; Crucial [12] shares a single instance of the Java virtual machine (JVM) between functions; and SAND [1] executes multiple functions from an application in long-running containers. Such approaches amplify the resource overheads of the underlying containers, and break the fine-grained elastic scaling inherent to serverless.

We make the observation that container-based isolation is fundamentally a poor match for serverless platforms that aim to support data-intensive applications. Instead, we require a new isolation abstraction that (i) provides strong memory and resource isolation between functions, yet (ii) supports efficient state sharing when needed. We want data to be co-located with functions and accessed directly, avoiding the data-shipping problem; (iii) supports scaling state across multiple hosts. Furthermore, this new isolation abstraction must (iv) have a low memory footprint and scale to many instances on one machine; (v) exhibit fast instantiation times; and (vi) support multiple programming languages to facilitate the porting of existing applications.

In this paper, we describe Faaslets, a new lightweight isolation abstraction for data-intensive serverless computing. Faaslets support stateful functions with efficient shared memory access, and are executed by our FAASM distributed serverless runtime. Faaslets have the following properties, summarising our contributions:

(1) Faaslets achieve lightweight isolation. Faaslets rely on software fault isolation (SFI) [69], which restricts functions to accesses of their own memory. A function associated with a Faaslet, together with its library and language runtime dependencies, is compiled to WebAssembly [29]. The FAASM runtime then executes multiple Faaslets, each with a dedicated thread, within a single address space. For resource isolation, the CPU cycles of each thread are constrained using Linux cgroups [66] and network access is limited using network namespaces [66] and traffic shaping. Many Faaslets can be executed efficiently and safely on a single machine.

(2) Faaslets support efficient local/global state access. Since Faaslets share the same address space, they can access shared memory regions with local state efficiently. This allows the co-location of data and functions and avoids serialisation overheads. Faaslets use a two-tier state architecture, a local tier provides in-memory sharing, and a global tier supports distributed access to state across hosts. The FAASM runtime provides a state management API to Faaslets that gives fine-granular control over state in both tiers. Faaslets also support stateful applications with different consistency requirements between the two tiers.

(3) Faaslets have fast initialisation times. To reduce cold-start time when a Faaslet executes for the first time, Faaslets can be launched from a suspended state. The FAASM runtime pre-initialise a Faaslet ahead-of-time and snapshots its memory to obtain a Proto-Faaslet. Proto-Faaslets are used to create fresh Faaslet instances quickly, e.g. avoiding the time to initialise a language runtime.

(4) Faaslets support a flexible host interface. Faaslets interact with the host environment through a set of POSIX-like calls for networking, file I/O, global state access and library loading/linking. This allows them to support dynamic language runtimes and facilitates the porting of existing applications. The host interface provides just enough virtualisation to ensure isolation while adding a negligible overhead.

The FAASM runtime uses the LLVM compiler toolchain to translate applications to WebAssembly and supports functions written in a range of programming languages, including C/C++, Python, Typescript and Javascript. It integrates with existing serverless platforms, and we describe the use with Knative [28], a state-of-the-art platform based on Kubernetes.

To evaluate FAASM’s performance, we consider a number of workloads and compare to a container-based serverless deployment. When training a machine learning model with SGD [57], we show that FAASM achieves a 60% improvement in run time, a 70% reduction in network transfers, and a 90% reduction in memory usage; for machine learning inference using TensorFlow Lite [65] and MobileNet [31], FAASM achieves over a 200% increase in maximum throughput, and a 90% reduction in tail latency. We also show that FAASM executes a distributed linear algebra job for matrix multiplication using Python/Numpy with negligible performance overhead and a 13% reduction in network transfers.

2 Isolation vs. Sharing in Serverless

Sharing memory is fundamentally at odds with the goal of isolation, hence providing shared access to in-memory state in a multi-tenant serverless environment is a challenge.

Tab. 1 contrasts containers and VMs with other potential serverless isolation options, namely unikernels [56] in which minimal VM images are used to pack tasks densely on a hypervisor and software-fault isolation (SFI) [69], providing lightweight memory safety through static analysis, instrumentation and runtime traps. The table lists whether each fulfils three key functional requirements: memory safety, resource isolation and sharing of in-memory state. A fourth requirement is a filesystem abstraction, important for legacy applications.

The table also compares these options on a set of non-functional requirements: low initialisation time for fast elasticity; small memory footprint for scalability and efficiency, and the support for a range of programming languages.

Containers offer an acceptable balance of features if one sacrifices efficient state sharing—as such they are used by many serverless platforms [27, 33, 44]. Amazon uses Firecracker [4], a “micro VM” based on KVM with similar properties to containers, e.g. initialisation times in the hundreds of milliseconds and memory overheads of megabytes.

Containers and VMs compare poorly to unikernels and SFI on initialisation times and memory footprint because

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1FAASM is open-source and available at github.com/lsds/Faasm
of their level of virtualisation. They both provide complete virtualised POSIX environments, and VMs also virtualise hardware. Unikernels minimise their levels of virtualisation, while SFI provides none. Many unikernel implementations, however, lack the maturity required for production serverless platforms, e.g. missing the required tooling and a way for non-expert users to deploy custom images. SFI alone cannot provide resource isolation, as it purely focuses on memory safety. It also does not define a way to perform isolated interactions with the underlying host. Crucially, as with containers and VMs, neither unikernels nor SFI can share state efficiently, with no way to express shared memory regions between compartments.

2.1 Improving on Containers

Serverless functions in containers typically share state via external storage and duplicate data across function instances. Data access and serialisation introduces network and compute overheads; duplication bloats the memory footprint of containers, already of the order of megabytes [45]. Containers contribute hundreds of milliseconds up to seconds in cold-start latencies [70], incurred on initial requests and when scaling. Existing work has tried to mitigate these drawbacks by recycling containers between functions, introducing static VMs, reducing storage latency, and optimising initialisation. Recycling containers avoids initialisation overheads and allows data caching but sacrifices isolation and multi-tenancy. PyWren [36] and its descendants, Numpywren [61], IBMPywren [58] and Locus [54] use recycled containers, with long-lived AWS Lambda functions that dynamically load and execute Python functions. Crucial [12] takes a similar approach, running multiple functions in the same JVM. SAND [11] provides only process isolation between functions of the same application and places them in shared long-running containers. Using containers for multiple functions requires over-provisioned memory to ensure capacity both for concurrent executions and for peak usage. This is at odds with the idea of fine-grained scaling in serverless.

Adding static VMs to handle external storage improves performance but breaks the serverless paradigm. Cirrus [17] uses large VM instances to run a custom storage back-end; Shredder [80] uses a single long-running VM for both storage and function execution; ExCamera [26] uses long-running VMs to coordinate a pool of functions. Either the user or provider must scale these VMs to match the elasticity and parallelism of serverless functions, which adds complexity and cost.

Reducing the latency of auto-scaled storage can improve performance within the serverless paradigm. Pocket [37] provides ephemeral serverless storage; other cloud providers offer managed external state, such as AWS Step Functions [3], Azure Durable Functions [47], and IBM Composer [8]. Such approaches, however, do not address the data-shipping problem and its associated network and memory overheads.

Container initialisation times have been reduced to mitigate the cold-start problem, which can contribute several seconds of latency with standard containers [30, 60, 70]. SOCK [52] improves the container boot process to achieve cold starts in the low hundreds of milliseconds; similar results can be achieved with optimised VMs and unikernels [43, 45]. Given that serverless functions are typically short-lived, hundreds of milliseconds is still unacceptably high.

2.2 Potential of Software-based Isolation

Software-based isolation does not meet the requirements for resource isolation or efficient in-memory state sharing. However, it provides memory safety and improves on container and VM initialisation times and memory overheads by two orders of magnitude. These properties make it an attractive starting point for serverless isolation.

Boucher et al. [14] show microsecond initialisation times for Rust microservices, but do not address isolation or state sharing; Fastly’s Terrarium [24] uses WebAssembly for SFI, and Cloudflare Workers [20] use V8 isolates; neither approach isolates CPU or network use, and they rely on data shipping for state access; Shredder [80] uses V8 isolates to run code on a storage server, but relies on co-locating state and functions on a single host, making it ill-suited to the level of scale required in serverless platforms.

Lightweight software-based isolation has a long history in the browser context, notably with Native Client [21, 78]. WebAssembly is a secure portable IR [29] and the successor to Native Client. It offers strong memory safety guarantees by constraining memory access to a single linear byte array, referenced with offsets from zero. This enables efficient bounds checking at both compile- and runtime, with runtime checks backed by traps. These traps (and others for referencing invalid functions) are implemented as part of WebAssembly runtimes [74]. The WebAssembly specification does not yet include a mechanism for sharing memory, therefore it cannot meet our requirement for efficient sharing of state. A proposal to add shared memory regions exists [73], but it is not implemented and the programming model is unclear.

Our final non-functional requirement relates to multi-language support. Although SFI approaches are language-specific [11, 23], WebAssembly is platform-independent and hence inherently multi-language. Mature support is available for languages with an LLVM front-end such as C, C++, C#, Go and Rust [42], while toolchains exist for Typescript [10] and Swift [64]. Java bytecode can also be converted [7], and

| Func.          | Containers | VMs | Unikernel | SFI | Faaslet |
|----------------|------------|-----|-----------|-----|---------|
| Memory safety  | ✔          | ✔   | ✔         | ✔   | ✔       |
| Resource isolation | ✔          | ✔   | ✔         | ✔   | ✔       |
| Efficient state sharing | ✔          | ✔   | ✔         | ✔   | ✔       |

| Non-func.     | Initialisation time | Memory footprint | Filesystem abstraction | Multi-language |
|---------------|---------------------|------------------|------------------------|----------------|
|               | 100 ms              | MBs              |                        | ✔              |
|               | 100 ms              | MBs              | ✔                      | ✔              |
|               | 10 ms               | kBs              | ✔                      | ✔              |
|               | 10 µs               | Bytes            |                        | ✔              |
|               | 1 ms                | KBytes           |                        |                |

Table 1: Isolation approaches for serverless computing
We propose Faaslets, although WebAssembly is restricted to a 32-bit address space, this thread is assigned to a cgroup with a share of CPU equal to that of all Faaslets. The Linux CFS ensures that these thread is executed by a dedicated thread that shares memory safety and control flow integrity. By default, a function itself is compiled to WebAssembly, guaranteeing that function is placed in its own private contiguous memory region, but Faaslets also support segments of shared memory. This allows a Faaslet to access shared in-memory state within the constraints of WebAssembly’s memory safety guarantees.

Faaslets also ensure fair resource access. For CPU isolation, they use the CPU subset of Linux cgroups. Each function is executed by a dedicated thread of a shared runtime process. This thread is assigned to a cgroup with a share of CPU equal to that of all Faaslets. The Linux CFS ensures that these threads are scheduled with equal CPU time. Faaslets achieve secure and fair network access using network namespaces, virtual network interfaces and traffic shaping. Each Faaslet has its own network interface in a separate namespace, configured using iptables rules. To ensure fairness between colocated tenants, each Faaslet applies traffic shaping on its virtual network interface using tc, thus enforcing ingress and egress traffic rate limits.

As functions in a Faaslet must be permitted to invoke standard system calls to perform memory management and I/O operations, Faaslets offer an interface through which to interact with the underlying host. Unlike containers or VMs, Faaslets do not provide a fully-virtualised POSIX environment but instead support a minimal serverless-specific host interface (see Fig. 1). Faaslets virtualise system calls that interact with the underlying host and expose a range of functionality, as described below.

The host interface integrates with the serverless runtime through a message bus (see Fig. 1). The message bus is used by Faaslets to communicate with their parent process and each other, receive function calls, share work, invoke and await other functions, and to be told by their parent process when to spawn and terminate.

### 3.2 Host Interface

The Faaslet host interface must support a range of serverless applications as well as existing POSIX applications, such as existing language runtimes. The interface operates outside the bounds of memory safety, and hence must be trusted to preserve isolation when interacting with the host.

In existing serverless platforms based on containers and VMs, functions execute in virtualised POSIX environments, and perform tasks over HTTP with language- and providerspecific APIs. This design is the main contributor to large resource footprints and high initialisation times; the use of HTTP APIs leads to further latency and network overheads.

In contrast, the Faaslet host interface only offers a small subset of POSIX-like calls, and exposes a set of low-level serverless-specific calls for managing state and interaction between functions. This ensures that the memory footprint and initialisation times are kept low.

Tab. 2 lists the functions of the Faaslet host interface, more than half covering serverless-specific operations, with the remainder providing a subset of common POSIX calls. Dynamic linking, memory management, timing, random numbers, and file/network I/O. A subset of these calls also have equivalent calls in WASI, an emerging standard for a server-side WebAssembly interface.

**Function invocation.** Functions retrieve their input data serialised as byte arrays using the read_call_input function, and similarly write their output data as byte arrays using write_call_output. Byte arrays constitute a generic, language-agnostic interface.

Non-trivial serverless applications invoke multiple functions that work together as part of chained calls, made with the chain_call function. Users’ functions have unique names, which are passed to chain_call, along with a byte array containing the input data for that call.
We show this pattern in Python in Listing 1.

write allow the sending and receiving of data. Calls fail if private network interface and cannot exceed rate limits due to Faaslet’s virtual network interface, thus are constrained to a operations on the host. All calls interact exclusively with the data store or a remote HTTP endpoint. The functions simple client-side send/receive operations and is sufficient defined memory limit, and these calls fail if growth of the private region would exceed this limit.

The Faaslet allocates memory in its private memory region, and uses mmap() on each ID in turn. We show this pattern in Python in Listing 1.

Memory. Functions allocate memory dynamically through calls to mmap() and brk(), either directly or through dlmalloc [38]. The Faaslet allocates memory in its private memory region, and uses mmap on the underlying host to extend the region if necessary. Each function has its own predefined memory limit, and these calls fail if growth of the private region would exceed this limit.

Networking. The supported subset of networking calls allows simple client-side send/receive operations and is sufficient for common use cases, such as connecting to an external data store or a remote HTTP endpoint. The functions socket, connect and bind allow setting up the socket while read and write allow the sending and receiving of data. Calls fail if they pass flags that are not related to simple send/receive operations over IPv4/IPv6, e.g. the AF_UNIX flag.

The host interface translates these calls to equivalent socket operations on the host. All calls interact exclusively with the Faaslet’s virtual network interface, thus are constrained to a private network interface and cannot exceed rate limits due to the traffic shaping rules.

We describe the file I/O and dynamic linking calls in §5.3, as they have wider implications for isolation in FAASM.

3.3 Shared Memory

As discussed in §2, sharing in-memory state while otherwise maintaining isolation is an important requirement for efficient serverless big data applications. Faaslets can selectively map segments onto shared regions of common process memory to provide direct, low-latency access to shared data structures. Since this is done with standard OS virtual memory mechanisms, there is no extra serialisation or memory access overhead, achieving efficient multi-threaded access on a par with native multi-threaded applications. In §4.2, we describe how Faaslets use this mechanism to provide shared in-memory access to global state.

By taking advantage of WebAssembly’s linear memory model [29], Faaslets support fine-grained memory mappings while otherwise maintaining memory safety. WebAssembly restricts each function’s memory to be within a linear byte array, which a Faaslet allocates from a disjoint section of the process memory. When memory sharing is needed, the Faaslet extends this byte array, but maps the new pages onto a designated region of common process memory. The function can then be given a pointer to the new region of the byte array, but all accesses are performed on the shared region. Bounds checks continue on the byte array as normal, thus ensuring that memory safety also applies to the newly mapped region.

Fig. 2 shows memory sharing with two Faaslets, each with a region of private contiguous memory (labelled A and B) allocated from disjoint regions of the shared memory (represented by the central region). Functions inside each Faaslet access

| Class      | Function                                                                 | Action                                      | Equiv.   |
|------------|--------------------------------------------------------------------------|---------------------------------------------|----------|
| Calls      | byte* read_call_input()                                                  | Read input data to function as byte array   |          |
|            | void write_call_output(out_data)                                         | Write output data for function              |          |
|            | int chain_call(name, args)                                               | Call function and return the call_id        |          |
|            | int await_call(call_id)                                                  | Await the completion of call_id             |          |
|            | byte* get_call_output(call_id)                                           | Load the output data of call_id             |          |
| State      | byte* get_state(key, flags)                                              | Get pointer to state value for key          | none     |
|            | set_state(key, val)                                                     | Set state value for key                     |          |
|            | set_state_offset(key, off, flags)                                        | Set len bytes of state value at offset for key |          |
|            | push/pull_state(key)                                                    | Push/pull global state value for key        |          |
|            | push/pull_state_offset(key, off)                                         | Push/pull global state value at offset for key |          |
|            | append_state(key, val)                                                  | Append data to state value for key          |          |
|            | lock_state_read/write(key)                                              | Lock local copy of state value for key      |          |
|            | lock_state_global_read/write(key)                                       | Lock state value for key globally           |          |
| Dynlink    | void* dlopen/dlsym(...)                                                  | Dynamic linking of libraries                | POSIX    |
|            | int dlclose(...)                                                         |                                             |          |
| Memory     | void* mmap(...), int munmap(...)                                         | Memory grow/shrink only                     |          |
|            | int brk(...), void* sbrk(...)                                            | Memory grow/shrink                          |          |
| Network    | int socket/connect/bind(...)                                            | Client-side networking only                | WASI     |
|            | size_t send/recv(...)                                                    | Send/receive via virtual interface          |          |
| File I/O   | int open/close/dup/stat(...)                                             | Per-user virtual filesystem access         |          |
|            | size_t read/write(...)                                                  | As above                                    |          |
| Misc       | int gettimeofday(...)                                                   | Per-user monotonic clock only              |          |
|            | size_t getrandom(...)                                                   | Uses underlying host /dev/urandom           |          |

Table 2: Faaslet host interface (The final column indicates whether functions have POSIX or WASI [49] equivalents.) A call to chain_call returns the call ID of the invoked function. The call ID can then be passed to await_call to perform a blocking wait for another call to finish or fail, yielding its return code. The Faaslet blocks until the function has completed, and passes the same call ID to get_call_output to retrieve the chained call’s output data.

Calls to chain_call and await_call can be used in loops to spawn and await calls in a similar manner to standard multi-threaded code: one loop invokes chain_call and records the call IDs; a second loop calls await_call on each ID in turn. We describe the file I/O and dynamic linking calls in §5.3, as they have wider implications for isolation in FAASM.
all memory with offsets from zero, and each Faaslet maps their private region into the lower addresses. The Faaslets also share a third region of the process memory (labelled S). Each Faaslet maps the same section of process memory into the upper addresses of its own memory, forming a contiguous block with the private memory. This allows functions to access it with the higher offsets from zero.

Note that multiple shared mappings are supported, and the Faaslet’s linear memory can grow during function execution. New mappings are created by extending the byte array, with pointers to each new region returned to the function at increasing higher offsets.

The memory mappings are created using standard OS virtual memory mechanisms. To create a new shared region, a Faaslet calls mmap in the underlying host, with the MAP_SHARED and MAP_ANONYMOUS flags, and populates this region with data. The Faaslet extends its linear memory region using mmap as well, and calls mremap to remap the new pages onto the shared region. Other Faaslets on the same host can also obtain access to this region by performing the same remapping process.

### 3.4 Building Functions for Faaslets

Fig. 3 shows the three phases to convert source code of a function into a Faaslet executable: (1) the user invokes the Faaslet toolchain to compile the function into a WebAssembly binary, linking against a language-specific declaration of the Faaslet host interface; (2) code generation creates an object file with machine code from WebAssembly; and (3) the host interface definition is linked with the machine code to produce the Faaslet executable.

When Faaslets are deployed, the compilation phase to generate the WebAssembly binary takes place on a user’s machine. Since that is untrusted, the code generation phase begins by validating the WebAssembly binary, as defined in the WebAssembly specification [29]. This ensures that the binary conforms to the specification. Code generation then takes place in a trusted environment, after the user has uploaded their function.

In the linking phase, the Faaslet uses LLVM JIT libraries [42] to link the object file and the definition of the host interface implementation. The host interface functions are defined as *thunks*, which allows injecting the trusted host interface implementation into the function binary.

Faaslets use WAVM [59] to perform the validation, code generation and linking. WAVM is an open-source WebAssembly VM, which passes the WebAssembly conformance tests [71] and thus guarantees that the resulting executable enforces memory safety and control flow integrity [29].

### 4 Local and Global State

Stateful serverless applications can be created with Faaslets using *distributed data objects*, which are language-specific classes that expose a convenient high-level state interface. Distributed data objects are implemented using the key/value state API from Tab. 2.

The state associated with Faaslets is managed using a two-tier approach that combines local sharing with global distribution of state: a *local tier* provides shared-in-memory access to state on the same host; and a *global tier* allows Faaslets to synchronise state across hosts.

#### 4.1 State Programming Model

Each distributed data object represents a single state value, referenced throughout the system using a string holding the state key.

Faaslets write changes from the local to the global tier by performing a *push*, and read from the global to the local tier by performing a *pull*. Users have control over the consistency between the tiers but simple objects such as counters and lists are implicitly synchronised and thus strongly-consistent. Distributed data objects may also be denoted read-only to avoid repeated synchronisation.

Listing 1 uses three distributed data objects to implement stochastic gradient descent (SGD) in Python. The `weight_update` function accesses two large input matrices through the `SparseMatrixReadOny` and `MatrixReadOnly` distributed data objects (lines 1 and 2), and a single shared weights vector using `VectorAsync` (line 3). The function
writes updates to the local tier, and pushes these to the global
tier after a given number of iterations (line 13). The calls to
weight_update are chained in a loop in sgd_main (line 19).

Function weight_update accesses a randomly assigned sub-
set of columns from the training matrices using the columns
property (lines 7 and 8). The distributed data object of the
matrix makes calls to the underlying state API, which only
replicates the necessary subsets of the state values in the local
tier—the entire matrix is not transferred unnecessarily.

Updates to the shared weights vector in the local tier are
made in a loop in the weight_update function (line 11). It
invokes the push method on this vector (line 13) sporadically
and updates to the global tier. This improves performance and
reduces network overhead, but introduces inconsistency be-
tween the tiers. SGD tolerates such inconsistencies and it
does not affect the overall result.

4.2 Two-Tier State Architecture

Faaslets represent state with a key/value abstraction, using
unique state keys to reference state values. The authoritative
state value for each key is held in the global tier and accessible
to all Faaslets in the cluster. Faaslets on a given host share
a local tier, containing replicas of each state value currently
mapped to Faaslets on that host. State values are stored as
simple byte arrays, so they can contain arbitrarily complex
data structures without incurring serialisation overheads.

Fig. 4 shows the two-tier state architecture across two hosts.
Faaslets on host 1 share state value A; Faaslets on both hosts
share state value B. Accordingly, there is a replica of state
value A in the local tier of host 1, and replicas of state value B
in the local tier of both hosts.

The columns method of the SparseMatrixReadOnly and
MatrixReadOnly distributed data objects in Listing 1 uses state
chunks to access a subset of a larger state value. As shown
in Fig. 4, state value C has state chunks, which are treated as
smaller independent state values. Faaslets create replicas of
only the required chunks in their local tier.

Ensuring local consistency. State value replicas in the local
tier are created using Faaslet shared memory (§3.3). To ensure
consistency between Faaslets accessing a replica, Faaslets
acquire a local read lock when reading, and a local write lock
when writing. This locking happens implicitly as part of all
state API functions, but not when functions write directly
to the local replica via a pointer. The state API exposes the
lock_state_read and lock_state_write functions that can
be used to acquire local locks explicitly, e.g. to implement
a list that performs multiple writes to its state value when

5 FAASM Runtime

FAASM is the serverless runtime that uses Faaslets to exe-
cute distributed stateful serverless applications across a clus-
ter. FAASM is designed to integrate with an existing server-
less platforms, which provide the underlying infrastructure,
auto-scaling functionality and user-facing frontends. FAASM
handles the scheduling, execution and state management of
Faaslets. The design of FAASM follows a distributed architec-
ture: multiple FAASM runtime instances execute on a set of
servers, and each instance manages a pool of Faaslets.

5.1 Distributed Scheduling

A local scheduler in the FAASM runtime is responsible for
the scheduling of Faaslets. Its scheduling strategy is key to
solving the data-shipping problem (see §2) by ensuring that
executed functions are colocated with required in-memory
state. One or more Faaslets managed by a runtime instance
may be warm, i.e. they already have their code and state
loaded. The scheduling goal is to ensure that as many function
calls as possible are executed by warm Faaslets.

To achieve this without modifications to the underlying
platform’s scheduler, FAASM uses distributed work sharing.
The local scheduler of each runtime instance receives incom-
ing function calls and decides either to execute the function
locally, or share it with another runtime instance.

Fig. 5 shows two FAASM runtime instances, each with its
own local scheduler, a pool of Faaslets, a collection of state
stored in memory, and a sharing queue. Calls for functions A–
C are received by the local schedulers, which execute them
locally if they have warm Faaslets, and share them with the
other host if not. Instance 1 has a warm Faaslet for func-
tion A and accepts calls to this function, while sharing calls to functions B and C with Instance 2, which has corresponding warm Faaslets. If a function call is received and there are no instances with warm Faaslets, the instance that received the call creates a new Faaslet, incurring a “cold start”.

5.2 Reducing Cold Start Latency

While Faaslets typically initialise in under 10 ms, FAASM reduces this further using Proto-Faaslets, which are Faaslets that contain snapshots of arbitrary execution state. From this snapshot, FAASM spawns a new Faaslet instance in a fraction of the regular initialisation time.

Different Proto-Faaslets are generated for a function by specifying user-defined initialisation code, which is executed before snapshotting. If a function executes the same code on each invocation, that code can become initialisation code and be removed from the function itself. For Faaslets with dynamic language runtimes, the runtime initialisation can be done as part of the initialisation code.

A Proto-Faaslet snapshot includes a function’s stack, heap, function table, stack pointer and data, as defined in the WebAssembly specification [29]. Since WebAssembly memory is represented by a contiguous byte array, containing the stack, heap and data, FAASM restores a snapshot into a new Faaslet using a copy-on-write memory mapping. All other data is held in standard C++ objects. Since the snapshot is independent of the underlying OS thread or process, FAASM can serialise Proto-Faaslets and instantiate them across hosts.

FAASM provides an upload service that exposes an HTTP endpoint. Users upload WebAssembly binaries to this endpoint, which then performs code generation (§3.4) and writes the resulting object files to a shared object store. The implementation of this store is specific to the underlying serverless platform but can be a cloud provider’s own solution such as AWS S3 [6]. Proto-Faaslets are generated, serialised and stored in the object store as part of this process. When a Faaslet executes a function, it loads the object file and Proto-Faaslet from the store and restores it.

In addition, FAASM uses Proto-Faaslets to reset Faaslets after each function call. Since the Proto-Faaslet captures a function’s initialised execution state, restoring it guarantees that no information from the previous call is disclosed. This can be used for functions that are multi-tenant, e.g., in a serverless web application. FAASM guarantees that private data held in memory is cleared away after each function execution, thereby allowing Faaslets to handle subsequent calls across tenants. In a container-based platform, this is typically not safe, as the platform cannot ensure that the container memory has been cleaned entirely between calls.

5.3 Executing POSIX Code

To support existing POSIX applications and libraries as functions, the Faaslet host interface exposes a subset of POSIX-like calls (see Tab. 2). If existing applications and libraries are first compiled to WebAssembly and successfully linked with the host interface, they can be executed as Faaslets.

An important class of POSIX applications that FAASM must support are language runtimes, used for dynamic languages such as Python, Ruby and Javascript. To support CPython [55], the de facto Python interpreter, FAASM offers simple filesystem support for generating and storing intermediate files, as well as accessing library code. It also supports dynamic linking to import libraries written in C.

File system. In a serverless setting, the usefulness of a filesystem is diminished because functions should be agnostic to the underlying host and may run anywhere. Hence a filesystem cannot be used for persistence or data sharing but only to cache intermediate results, serve read-only data and offer compatibility with existing applications.

FAASM provides a minimal set of POSIX calls for file I/O, as listed in Tab. 2. Files are maintained in FAASM’s object store to avoid duplicating files across the system. Faaslets load them lazily from the object store on calls to open( ), and query the store on calls to stat( ). Once loaded, a file is stored on the host’s local filesystem in a directory tree shared by functions of that tenant. This tree is isolated using chroot. Faaslets maintain a function’s open file descriptors and ensure that operations are only permitted on valid descriptors.

Dynamic loading and linking. Functions that need to dynamically load libraries or dependencies cannot be statically linked. FAASM supports dynamic loading through the dlopen( ), dsym() and dlclose() calls. Libraries that are dynamically loaded are uploaded to the FAASM upload service as WebAssembly binaries. The resulting machine code is written to the object store, and loaded through calls to dlopen( ), analogous to regular files in the filesystem abstraction. Dynamic linking of WebAssembly modules is part of a WebAssembly specification proposal [72], and FAASM implements this approach as part of its dynamic linking calls.

6 Evaluation

Our experimental evaluation targets the following questions:

(i) how does FAASM state management improve efficiency and performance on parallel machine learning training? (§6.2)
(ii) how do Proto-Faaslets and low initialisation times impact performance and throughput in inference serving? (§6.3)
(iii) how does Faaslet isolation affect performance in a linear algebra benchmark using an existing POSIX application? (§6.4) and (iv) how do the overheads of Faaslets compare to Docker containers? (§6.5)

6.1 Experimental Set-up

Serverless baseline. To benchmark FAASM against a state-of-the-art serverless platform, we use Knative [28], a container-based system built on Kubernetes [67]. All experiments are implemented using the same code for both FAASM and Knative, with a Knative-specific implementation of the Faaslet host interface for container-based code. This interacts directly
with the distributed KVS on state-related calls, and uses the Krative API to handle function chaining. Redis is used for the distributed KVS and deployed to the same cluster.

**FAASM integration.** We integrate FAASM with Krative by running FAASM runtime instances as Knative functions that are replicated using the default autoscaler. The system is otherwise unmodified, using the default endpoints and scheduler.

**Testbed.** Both FAASM and Knative applications are executed on the same Kubernetes cluster, running on 20 hosts, all Intel Xeon E3-1220 3.1 GHz machines with 16 GB of RAM, connected with a 1 Gbps connection.

**Metrics.** In addition to the usual evaluation metrics, such as execution time, throughput and latency, we also consider **billable memory**, which quantifies memory consumption over time. It is the product of the peak function memory multiplied by the number and runtime of functions, in units of GB-seconds. It is used to attribute memory usage in many serverless platforms [5, 27, 33]. Note that all memory measurements include the containers/Faaslets and their state.

### 6.2 Machine Learning Training

This experiment focuses on the impact of FAASM’s state management on runtime, network overheads and memory usage.

We use distributed stochastic gradient descent (SGD) using the HOGWILD! algorithm [57] to run text classification on the Reuters RCV1 dataset [39]. This updates a central weights vector in parallel with batches of functions across multiple epochs. We run both Knative and FAASM with increasing numbers of parallel functions.

Fig. 6a shows the training time. FAASM exhibits a small improvement in runtime of 10% compared to Knative at low parallelism and a 60% improvement with 15 parallel functions. With more than 20 parallel Knative functions, the underlying hosts experience increased memory pressure and they exhaust memory with over 30 functions. Training time continues to improve for FAASM up to 38 parallel functions, at which point there is a more than an 80% improvement over 2 functions.

Fig. 6b shows that, with increasing parallelism, the volume of network transfers increases in both FAASM and Knative. Knative transfers more data to start with and the volume increase more rapidly, with 145 GB transferred with 2 parallel functions and 280 GB transferred with 30 functions. FAASM transfers 75 GB with 2 parallel functions and 100 GB with 38 parallel functions.

Fig. 6c shows that billable memory in Knative increases with more parallelism: from 1,000 GB-seconds for 2 functions to over 5,000 GB-second for 30 functions. The billable memory for FAASM increases slowly from 350 GB-second for 2 functions to 500 GB-second with 38 functions.

The increased network transfer, memory usage and duration in Knative is caused primarily by data shipping, e.g. loading data into containers. FAASM benefits from sharing data through its local tier, hence amortises overheads and reduces latency. Further improvements in duration and network overhead come from differences in the updates to the shared weights vector: in FAASM, the updates from multiple functions are batched per host; whereas in Knative, each function must write directly to external storage. Billable memory in Knative and FAASM increases with more parallelism, however, the increased memory footprint and duration in Knative make this increase more pronounced.

### 6.3 Machine Learning Inference

This experiment explores the impact of the Faaslet initialisation times on cold-starts and function call throughput.

We consider a machine learning inference application because they are typically user-facing, thus latency-sensitive, and must serve high volumes of requests. We perform inference serving with TensorFlow Lite [65], with images loaded from a file server and classified using a pre-trained MobileNet [31] model. In our implementation, requests from each user are sent to different instances of the underlying serverless function. Therefore, each user sees a cold-start on their first request. We measure the latency distribution and change in median latency when increasing throughput and varying the ratio of cold-starts.

Figs. 7a and 7b show a single line for FAASM that covers all cold-start ratios. Cold-starts only introduce a negligible latency penalty of less than 1 ms and do not add significant resource contention, hence all ratios behave the same. Optimal latency in FAASM is higher than that in Knative, as the inference calculation takes longer due to the performance overhead from compiling TensorFlow Lite to WebAssembly.

Fig. 7a shows that the median latency in Knative increases sharply from a certain throughput threshold depending on the cold-start ratio. This is caused by cold starts resulting in
queuing and resource contention, with the median latency for the 20% cold-start workload increasing from 90 ms to over 2 s at around 20 req/s. FAASM maintains a median latency of 120 ms at a throughput of over 200 req/s.

Fig. 7b shows the latency distribution for a single function that handles successive calls with different cold-start ratios. Knative has a tail latency of over 2 s and more than 35% of calls have latencies of over 500 ms with 20% cold-starts. FAASM achieves a tail latency of under 150 ms for all ratios.

6.4 POSIX performance with Python

The next two experiments (i) measure the performance impact of Faaslet isolation on a distributed benchmark using an existing POSIX application, the CPython interpreter; and (ii) investigate the impact on a single Faaslet running compute microbenchmarks and a more complex POSIX application.

We consider a distributed divide-and-conquer matrix multiplication implemented with Python and Numpy. In the FAASM implementation, these functions are executed using CPython inside a Faaslet; in Knative, we use standard Python. As there is no WebAssembly support for BLAS and LAPACK, we do not use them in either implementation.

While this experiment is computationally intensive, it also makes use of the filesystem, dynamic linking, function chaining and state, thus exercising all of the Faaslet host interface. Each matrix multiplication is subdivided into multiplications of smaller submatrices and merged. This is implemented by recursively chaining serverless functions, with each multiplication using 64 multiplication functions and 9 merging functions. We compare the execution time and network traffic when running multiplications of increasingly large matrices.

Fig. 8a shows that the duration of matrix multiplications on FAASM and Knative are almost identical with increasing matrix sizes. Both take around 500 ms with 100×100 matrices, and almost 150 secs with 8000×8000 matrices. Fig. 8b shows that FAASM results in 13% less network traffic across all matrix sizes, and hence gains a small benefit from storing intermediate results more efficiently.

In the next experiment, we use Polybench/C [53] to measure the Faaslet performance overheads on simple compute functions, and the Python Performance Benchmarks [63] for overheads on more complex applications. Polybench/C is compiled directly to WebAssembly and executed in Faaslets; the Python code is executed with CPython running in a Faaslet.

Fig. 9 shows the performance overhead when running both sets of benchmarks compared to native execution. All but two of the Polybench benchmarks are comparable to native with some showing performance gains. Two experience a 40%–55% overhead, both of which benefit from loop optimisations that are lost through compilation to WebAssembly. Although many of the Python benchmarks are within a 25% overhead or better, some see a 50%–60% overhead, with pidigits showing a 240% overhead. pidigits stresses big integer arithmetic, which incurs significant overhead in 32-bit WebAssembly.

Jangda et al. [35] report that code compiled to WebAssembly has more instructions, branches and cache misses, and these overheads are compounded on larger applications. Serverless functions, however, typically are not complex applications and operate in a distributed setting in which distribution overheads dominate. As shown in Fig. 8a, FAASM can achieve competitive performance with native execution, even when functions involve legacy POSIX code.

6.5 Efficiency of Faaslets vs. Containers

Finally we quantify the difference in resource footprint and initialisation latency between Faaslets and Docker containers.

To measure memory usage we deploy increasing numbers of parallel functions on a host and measure the change in foot-
Table 3: Comparison of Faaslets vs. containers (no-op function)

|                     | Docker | Faaslets | Ratio |
|---------------------|--------|----------|-------|
| Initialisation time | 2.5 s  | 5 ms     | 490×  |
| CPU cycles          | 230 M  | 10 K     | 23K×  |
| PSS memory          | 1.5 MB | 180 KB   | 9×    |
| RSS memory          | 5.6 MB | 180 KB   | 32×   |
| Capacity            | ~8,000 | ~70,000  | 9×    |

Figure 10: Function churn for Faaslets vs. containers

print with each extra function. Containers are built from the same minimal image (alpine:3.10.1) so can access the same local copies of shared libraries. To highlight the impact of this sharing, we include the proportional set size (PSS) and resident set size (RSS) memory consumption. Initialisation times and CPU cycles are measured across repeated executions of a no-op function. We observe the capacity as the maximum number of concurrent running containers or Faaslets that a host can sustain before running out of memory.

Tab. 3 shows several orders of magnitude improvement in CPU cycles spent and time elapsed when isolating a no-op with Faaslets. Memory footprints are almost ten times lower, even with an optimistic PSS memory measurement for containers. A single host can support up to ten times more Faaslets than containers.

To investigate initialisation times, we measure the time to create a new container/Faaslet at increasingly higher rates of cold-starts per second. The experiment executes on a single host, with the containers using the same minimal image.

Fig. 10 shows that both Faaslets and containers maintain a steady initialisation latency at throughputs below 3 execution/s, with Docker containers initialising in approx. 1 s and Faaslets in approx. 5 ms. As we increase the churn in Docker past 3 execution/s, initialisation times begin to increase with no gain in throughput. A similar limit for Faaslets is reached at around 600 execution/s.

We conclude that Faaslets offer a more efficient and performant form of serverless isolation than Docker containers. The lower resource footprint and initialisation times of Faaslets are important in a serverless context. Lower resource footprints reduce costs for the cloud provider and allow a higher packing density of parallel functions on a given host. Low initialisation times reduce cost and latency for the user, through their mitigation of the cold-start problem.

7 Related Work

Isolation mechanisms. Shreds [18] and Wedge [13] introduce new OS-level primitives for memory isolation, but focus on intra-process isolation rather than a complete executable as Faaslets do. Light-weight Contexts [41] and Pico-processes [32] offer lightweight sandboxing of complete POSIX applications, but do not offer efficient shared state.

Common runtimes. Truffle [77] and GraalVM [22] are runtimes for language-independent bytecode; the JVM also executes multiple languages compiled to Java bytecode [19]. Despite compelling multi-language support, none offer multi-tenancy or resource isolation. GraalVM has recently added support for WebAssembly and could be adapted for Faaslets.

Autoscaling storage. FAASM’s global state tier is currently implemented with a distributed Redis instance scaled by Kubernetes horizontal pod autoscaler [68]. Although this has not been a bottleneck, better alternatives exist: Anna [76] is a distributed KVS that achieves lower latency and more granular autoscaling than Redis; Tuba [9] provides an autoscaling KVS that operates within application-defined constraints; and Pocket [37] is a granular autoscaled storage system built specifically for a serverless environments. Crucial [12] uses Infinispan [46] to build its distributed object storage, which could also be used to implement FAASM’s global state tier.

State in distributed dataflows. Spark [79] and Hadoop [62] support stateful distributed computation. Although focuses on fixed-size clusters and not fine-grained elastic scaling or multi-tenancy, distributed dataflow systems such as Naiad [50], SDGs [25] and CIEL [51] provide high-level interfaces for distributed state, with similar aims to those of distributed data objects—they could be implemented in or ported to FAASM. Bloom [2] provides a high-level distributed programming language, focused particularly on flexible consistency and replication, ideas also relevant to FAASM.

Actor frameworks. Actor-based systems such as Orleans [15], Akka [40] and Ray [48] support distributed stateful tasks, freeing users from scheduling and state management, much like FAASM. However, they enforce a strict asynchronous programming model and are tied to a specific languages or language runtimes, without multi-tenancy.

8 Conclusions

To meet the increasing demand for serverless big data, we presented FAASM, a runtime that delivers high-performance efficient state without compromising isolation. FAASM executes functions inside Faaslets, which provide memory safety and resource fairness, yet can share in-memory state. Faaslets are initialised quickly thanks to Proto-Faaslet snapshots. Users build stateful serverless applications with distributed data objects on top of the Faaslet state API. FAASM’s two-tier state architecture collocates functions with required state, providing parallel in-memory processing yet scaling across hosts. The Faaslet host interface also supports traditional POSIX applications such as language runtimes.
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