**Faa$T**: A Transparent Auto-Scaling Cache for Serverless Applications

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**Abstract**

Function-as-a-Service (FaaS) has become an increasingly popular way for users to deploy their applications without the burden of managing the underlying infrastructure. However, existing FaaS platforms rely on remote storage to maintain state, limiting the set of applications that can be run efficiently. Recent caching work for FaaS platforms has tried to address this problem, but has fallen short: it disregards the widely different characteristics of FaaS applications, does not scale the cache based on data access patterns, or requires changes to applications. To address these limitations, we present Faa$T$, a transparent auto-scaling distributed cache for serverless applications. Each application gets its own Faa$T$ cache. After a function executes and the application becomes inactive, the cache is unloaded from memory with the application. Upon reloading for the next invocation, Faa$T$ pre-warms the cache with objects likely to be accessed. In addition to traditional compute-based scaling, Faa$T$ scales based on working set and object sizes to manage cache space and I/O bandwidth. We motivate our design with a comprehensive study of data access patterns in a large-scale commercial FaaS provider. We implement Faa$T$ for the provider’s production FaaS platform. Our experiments show that Faa$T$ can improve performance by up to 92% (57% on average) for challenging applications, and reduce cost for most users compared to state-of-the-art caching systems, i.e. the cost of having to stand up additional serverful resources.

1 Introduction

Motivation. Function-as-a-Service (FaaS) is an increasingly popular way of deploying applications to the cloud. With FaaS, users deploy their code as stateless functions and need not worry about creating, configuring, or managing resources explicitly. FaaS shifts these responsibilities to the FaaS provider (e.g., AWS Lambda, Azure Functions, Google Cloud Functions), which charges users per resource usage during their function invocations. FaaS providers build their platforms by renting and managing resources (VMs or bare-metal containers) in public clouds (e.g., AWS, Azure, Google Cloud Platform). To control their costs, these providers proactively unload a function from memory if it has not been invoked for a while (e.g., after 7 minutes of inactivity in AWS Lambda [50]).

Due to FaaS’s stateless nature, a function invocation is not guaranteed to have access to state created by previous invocations. Thus, any state that might be needed later must be persisted in remote storage. This also applies to applications with multiple stages (often expressed as a pipeline or a directed acyclic graph of functions), with intermediate results passed between invocations. Since existing FaaS platforms typically do not allow functions to communicate directly, functions must also write these results to remote storage.

The remote storage can be object-based (e.g., Amazon S3 [8], Azure Blob Storage [51]), queues [7], or in-memory storage clusters (e.g., Redis [45], Infini-Cache [55], Pocket [32]). Regardless of type, remote storage incurs higher latency and lower bandwidth than accessing local memory [32, 24]. When users have to provision in-memory storage clusters, it introduces management overhead and costs.

Given these limitations, local in-memory caching emerges as a natural solution for both speeding up access to remote data and enabling faster data sharing between functions. Prior works have considered both local and remote in-memory caching for FaaS [32, 43, 53, 55] but, we argue, have come up short in multiple ways.

First, they implement a single cache for multiple or all applications. This disregards the widely different characteristics of FaaS applications. For example, Shahrad et al. [48] have shown that 45% of applications are invoked less frequently than once per hour on average. Caching data for rarely-invoked applications at all times is wasteful. However, not caching data for these applications will likely produce poor performance. Furthermore, a shared
cache requires complex communication and synchronization primitives for the data of thousands of applications.

Second, in prior approaches, the cache is either fixed in size (e.g., [43, 53]) or scales only according to the computational load (e.g., [55]). These approaches work well when data access patterns are stable and working sets are smaller than the available cache space. When this is not the case, scaling the cache based on data access patterns would be beneficial. Moreover, prior works have not considered scaling as a way to mitigate the impact of accessing large data objects; these objects can take long to access as remote storage I/O bandwidth is often limited by the underlying VM/container or contention across co-located applications [24]. Emerging FaaS applications, such as ML inference pipelines and notebooks, would benefit from scaling out for increased cache space and increased I/O bandwidth to remote storage.

Third, prior caches are not entirely transparent to users, either because users need to provision them explicitly (e.g., [43, 52]) or because they provide a separate API for users to access the cache (e.g., [51, 53]). FaaS users do not want to think of data locality or manage caches (or any other resources) explicitly. In fact, a key reason for the popularity of FaaS is exactly that users are relieved from such tasks.

Our work. Fundamentally, the problem with prior approaches is that caching layers for serverless systems have never been truly serverless, i.e., tied to applications, auto-scaling, and transparent. Thus, we propose FaaST, an in-memory caching layer with these characteristics.

Each application is loaded into memory with its own local FaaST cache. This cache manages the data accessed by the application transparently as it runs. When the application is unloaded from memory, its FaaST is also unloaded. This approach obviates the need for a remote in-memory cache and may reduce the overall traffic to remote storage, both of which reduce costs for users. It also means that the cache space required by rarely-invoked applications is proactively removed from memory when not needed, just as the application itself, which reduces costs for the FaaS provider. Moreover, it enables different cache replacement and persistence policies per application, and pre-fetching of the most popular data when (re-)loading each application. The latter feature can be very effective when combined with automatic pre-warming of applications, which can be done accurately and completely off the critical invocation path [48].

As in other systems, an application is auto-scaled based on the number of invocations it is receiving. Scaling out loads a new application “instance” (i.e., a copy of its code) into memory, whereas scaling in unloads an instance. We refer to this as compute-based scaling. However, to match each application’s data access and reuse patterns, FaaST automatically scales out the number of instances to (a) increase the fetch bandwidth from remote storage for large objects, and (b) increase the overall cache size for frequently-accessed remote data. Scale-in occurs as the need for space and/or bandwidth subsides. With multiple active instances, FaaST forms a cooperative distributed cache, i.e., a data access can hit locally, miss locally but hit a remote cache, or miss both locally and remotely. By default, FaaST offers strong data consistency, but each application can optionally select its own consistency and policies for scaling and eviction.

A key aspect of FaaST is that users are only charged for resources they use. As we tie FaaST to applications, we expect that FaaS providers would charge only for cache accesses and space consumed by objects that were actually accessed.

Implementation and results. We motivate FaaST with the first comprehensive study of real FaaS applications from the perspective of data access and reuse. We use data collected for 2 weeks from the production workload of a large public FaaS provider. We show, for example, that many infrequently invoked applications exhibit good temporal locality (the same data is accessed across relatively rare invocations), whereas spatial locality in large objects is high (if any byte from such an object is accessed, the rest of it should be pre-fetched).

We implement FaaST in a public production FaaS offering. To show that it enables new applications that are not efficiently supported by current FaaS platforms, we implement an ML inference pipeline and a Jupyter notebook server stack that runs unmodified notebooks in a serverless environment.

Our experiments with these applications evaluate FaaST’s caching and scaling policies. Our results show that FaaST can improve their performance by up to 92% (57% on average), and reduce costs for most users compared to state-of-the-art FaaS caching systems, i.e., the cost incurred by the provisioning of additional serverful resources.

Contributions. In summary, our main contributions are:

• We characterize the data access patterns of the production workload of a large FaaS provider.
• We design and implement FaaST, a transparent auto-scaling cache for FaaS applications.
• We propose scaling policies for FaaST to increase instance bandwidth and overall cache size based on data access patterns and object sizes.
• We show that FaaST broadens the scope of applications that can run on FaaS with near-native performance, including ML inference pipelines and Jupyter notebooks.
2 Analysis of FaaS Applications and Caching

This section characterizes the invocation and data access patterns of applications running on a production FaaS offering. An application is a collection of logically-related functions. Each instance of an application gets a set of resources (e.g., memory in a VM or container) that is shared by its functions. We focus on data accesses, as several prior works have focused on code accesses to optimize cold-start latencies [1, 38, 16, 11] or reducing the number of cold-starts [48]. We also discuss the limitations of current FaaS platforms for existing and emerging applications.

2.1 Characterizing Current Applications

We use 14 days of logs (November 23rd to December 7th 2020) from a large-scale FaaS provider, across 28 geographical regions. We analyze a sample of the applications that access remote blob storage over HTTPS. This log includes 855 applications from 509 users and 33.1 million invocations with 44.3 million data accesses. 77.3% of accesses are reads and the rest are writes. The applications are written in multiple programming languages, including C#, Node.js, and Python.

**Data size.** The log includes accesses to 20.3 million different objects with a total size of 1.9 TB. Figure 1 shows the distribution of the size of blobs accessed. 80% of blobs are smaller than 12KB and more than 25% are smaller than 600 bytes. However, there are also many large blobs; a few as large as 1.8GB. The objects read tend to be larger than the ones written. While the aggregate bandwidth to backend storage is usually high [49], the prevalence of small objects exacerbates the impact of storage latency.

**Data accesses and reuse.** Figure 2 shows the CDF of the ratio of the number of invocations an application made to the number of unique blobs accessed. Most applications access a single, different blob per invocation (invocation/blob=1). Roughly 11.0% of applications access more than one blob per invocation (invocation/blob>1). More than 32.0% of the applications access the same blob in more than one invocation and 7.7% in more than 100 invocations. One application accesses the same blob in more than 10,000 invocations.

Around 11.8% of the applications access the same blob across all invocations, 66.1% access less than 100 different blobs, 93.0% access less than 10,000 different blobs, and one accesses more than 8 million different blobs. Even though there are 44.3 million accesses, only 20.3 million are first accesses. Overall, the applications accessed 2.6 TB of data while the corpus of unique data is 1.9 TB. If we were able to cache the already accessed data, we could save up to 27.0% of traffic and 54.3% of the accesses to remote storage.

Data sharing across applications and users (not shown) is extremely uncommon. 99.7% of the blobs are not shared across applications, only 0.02% of blobs are shared across regions, and only 16 blobs across users.

**Temporal access pattern.** Figure 3 shows the temporal access patterns for each blob accessed by an application. The X-axis is the number of function invocations that read/wrote the blob and the Y-axis shows the coefficient of variation (CoV) for the inter-arrival time (IaT) of those invocations. Each point represents a blob with more than 3 accesses (there is no IaT CoV otherwise). A CoV of 1 suggests Poisson arrivals, values close to 0 indicate a periodic arrival, and values larger than 1 indicate greater burstiness than Poisson. Clearly, accesses to a large percentage of blobs are very bursty.

**Access performance.** We observe that writes are usually faster than reads, since writes are buffered and do not require persisting data across all replicas synchronously. Reads are slower as we have to wait for the storage layer to deliver all data. We also observe that smaller blobs have a lower throughput (in MB/s) as they cannot amortize the overhead of the initial handshake.

**Diverse invocation patterns.** Prior work has observed that invocation frequency varies greatly: 81% of applications are invoked at most once a minute on average, whereas 45% are invoked less than once per hour on average [48]. Furthermore, less than 20% of applications are responsible for over 99% of all invocations. These find-
ings are consistent with our log where we observe an even more concentrated behavior: 80% of functions have less than one invocation per minute on average and less than 15% of applications account for 99% of the invocations. This heterogeneous behavior is a challenge, as caching data for rarely-invoked applications can be wasteful but is necessary, as it affects a large number of users.

Takeaways and requirements. Our characterization indicates that many FaaS applications exhibit data reuse: more than 30% of them access the same data across invocations. This suggests that caching can be effective for them. Moreover, the characterization shows a wide spectrum of accessed data sizes and invocation frequencies. Accessed data sizes span almost 9 orders of magnitude (from several bytes to GBs), i.e. large objects cannot be overlooked. Function invocation frequencies also span almost 9 orders of magnitude, i.e. rarely-invoked applications cannot be overlooked.

Table 1 illustrates the spectrum of data sizes, invocation frequencies, and reuse along with some example applications. For instance, distributed compilation of the Chromium browser requires accesses to hundreds of MBs, but happens only a few times per day using a framework like gg [17]. Data reuse across compilations is high since the codebase does not change fast. In contrast, serving an IoT sensor involves a small dataset, rare invocations, and low reuse.

We draw three key requirements for a serverless caching layer. First, it should ensure that data with good temporal locality is cached and reused across invocations (R1). Second, the caching layer should target both frequently- and rarely-invoked applications (R2). It should optimize for data reuse for frequently-invoked applications, while it should have the ability to pre-warm frequently-accessed objects for rarely-invoked applications. Finally, the caching layer should accommodate large objects and exploit spatial locality for them (R3). These requirements must be satisfied for applications written across various programming languages.

2.2 Existing Caching Systems Limitations

Table 2 lists the characteristics of several caching systems. Caching is managed independently of each application. Except for OFC, all the systems listed in the table include a separate caching or storage infrastructure that is shared by multiple applications. (Cloudburst and Faasm also have a shared cache on the same hosts/VMs that run the functions.) Because of this, either users must manage the extra servers or cache state is left behind when applications are unloaded from memory. In the former case, user costs and management overheads are greater, whereas in the latter the FaaS provider costs are higher. Thus, a serverless caching layer should be tied to each application, so that its code and data can be loaded/unloaded based on the application’s invocation pattern (R4).

Need system configuration or application changes. Table 2 lists the characteristics of several caching systems. Pocket, InfiniCache, and Locus rely on user configuration to maximize performance and minimize cost. For example, InfiniCache users must statically set the number of data shards and functions to store them, whereas Locus users must configure a Redis cluster. Faasm and Cloudburst rely on custom APIs to give applications control over the consistency of their data, and to pass messages between functions. To retain the simplicity of the FaaS paradigm, the caching layer should be transparent and not require changes to the application (R5).

Cloudburst additionally requires its key-value store (Anna [56]) to track all objects residing in all caches. Managing this much metadata can lead to scaling lim-
tations and extra costs. The caching layer can mitigate these concerns by minimizing metadata management for each cache instance (R6).

**Compute-based scaling only.** Finally, while some existing systems do not dynamically scale their caches (Pocket, InfiniCache, Locus), others do so based solely on the amount of offered computational load, i.e., number of function invocations (Faasm, Cloudburst). OFC scales based on the computational load and predicted memory usage of cached objects. However, it limits its caching to objects smaller than 10MB. As applications become more complex and data-heavy, data access characteristics like large working sets or large objects will gain in importance. Thus, the caching layer should scale compute (as the application’s offered load varies), cache size (based on the data reuse pattern), and bandwidth to remote storage (based on the object sizes being accessed) (R7).

### 2.3 Enabling New FaaS Applications

Current FaaS platforms limit the set of applications that can be efficiently run. Next, we describe two challenging ones.

**ML inference pipeline.** Many applications across several domains (e.g., health care [27], advertisement recommendation [21], and retail [21]) depend on ML inference for classification and other prediction tasks. ML inference load patterns can vary unpredictably [57, 44], which makes FaaS on-demand compute and scaling an ideal match for serving inference queries. However, ML inference applications require low-latency prediction serving (<1 s) [20, 44]. For example, AMBER Alert [34] responders may use an application to perform car and facial recognition. The application can be deployed on a FaaS platform as a pipeline of ML models (Figure 4). For each input image, an HTTP request is first sent to a bounding box model function to identify and label all present objects 1. The labeled image is uploaded to a common data store to trigger the car and people recognition models 2. Both recognition functions upload their outputs to the common data store 3. Inference pipelines can exhibit different levels of parallelism at each stage, which also makes them good fits for FaaS deployment [46]. The AMBER Alert pipeline fans out in the second stage, depending on the identified objects.

To assess whether FaaS can meet low-latency requirements, we ran the AMBER Alert pipeline natively on a local VM, and in a production FaaS environment with remote storage. Figure 5a shows that it is up to 3.8× slower than running FaaS versus natively, while Figure 5b shows that the main reason is the time to load the models. The inefficiency of the storage layer makes it impossible for the FaaS platform to run this application with sub-second latency.

![Figure 4: An example of ML pipeline executed through FaaS.](image)

**Jupyter notebooks.** Jupyter notebooks [30] are often used for data science tasks such as data processing, ML modeling, and visualizing results [41]. They are typically run by defining code in cells and interactively executing each cell. Jupyter notebooks are typically backed by statically-allocated VMs. Depending on how often a notebook is run, the VMs may sit idle for long periods. This is expensive for users and wasteful for service providers. Furthermore, the amount of parallelism and compute needed for each cell’s task can vary. Akin to ML inference, this variability makes FaaS a strong fit.

To test its performance, we ported Jupyter to run on a production FaaS platform — an application we term JupyterLess. Each cell is executed as a function invocation and the state between functions is shared through an intermediate storage layer. We compare the execution time of summing a single 350MB DataFrame column partitioned into 10 chunks with JupyterLess to running on a native VM. JupyterLess is 63× slower than native VM execution as downloading the intermediate state and DataFrame column from remote storage dominates the execution time. Thus, JupyterLess cannot be run interactively on existing FaaS frameworks.

### 3 Faa$T$ design

We design Faa$T$ as a transparent auto-scaling cache that meets the requirements we identify in Section 2. Faa$T$ caches objects accessed during a function execution so they can be reused across invocations (R1). It is built into the FaaS runtime with no external servers or storage layers, so it can be transparently tied to an application (R4, R5) written in any of the various supported languages. When an application is unloaded from memory, Faa$T$ collects metadata about the cache objects, and uses it to pre-warm the cache with frequently accessed objects when the application is re-loaded into memory. This is especially important for applications that are rarely-invoked (R2).

Faa$T$ scales along three dimensions (R7): (a) based
on an application’s invocations per second (compute scaling), which benefits applications that are frequently-invoked; (b) based on the data reuse pattern (cache size scaling), which is beneficial for applications with large working sets whose objects are continuously evicted; (c) based on the object size (bandwidth scaling), which is beneficial for applications that access large objects (≥10MB) and are limited by the I/O bandwidth between the application instance and remote storage (R3). While an application is loaded, FaasT efficiently locates objects across instances using consistent hashing without the need for large location metadata (R6).

3.1 System architecture

Figure 6 shows the architecture of a Faas platform with FaasT. Each application instance runs in a VM or container that contains the Faas runtime and the code for the application functions. FaasT instances, which we refer to as cachelets, are a part of the runtime, caching data in memory. Each application instance has one corresponding FaasT cachelet. In addition, FaasT forms a cooperative distributed cache; an application’s FaasT cachelets communicate directly to access data when necessary (Section 3.2). Similar to Faasm, FaasT maintains a single copy of cached objects, which improves memory efficiency compared to existing systems [37] [53] [55].

We designed FaasT to be per-application due to the following drawbacks of a shared cache. First, a shared cache requires complex communication and synchronization primitives for the data of thousands of applications (compared to a maximum of tens of instances for a single application with its own cache). This makes it difficult to implement per-application management policies (e.g., scaling) and provide transparency without custom APIs [51] [53], especially given the diversity of application characteristics and requirements (Section 2.1). Second, a shared cache with traditional eviction policies (e.g., LRU) can lead to severe unfairness among applications [42].

Figure 5: (a) Latency of AMBER Alert pipeline on a native VM versus a production Faas. Native VM does not include the time to load the PyTorch library (700MB). It is up to 3.8× slower to run the pipeline on Faas. (b) Model run times (BBox is a bounding box model). Data movement from/to remote storage dominates.

Figure 6: FaasT’s architecture diagram.

Figure 7: Reads in FaasT: local hit (LH), remote hit (RH), local miss (LM), remote miss (RM). Solid lines indicate communication between the application, FaasT instances, and remote storage. Dashed lines indicate data movement.

To find the location of an object, a FaasT cachelet interacts with the Membership Daemon, which determines the object’s “owner” based on the current number of cachelets. The owner is responsible for downloading/uploading the object from/to remote storage. The Load Daemon collects cached object metadata, and uses it to decide what data objects to pre-warm when an application is loaded (Section 3.3). To prevent interference with an application’s heap memory usage, the Memory Daemon monitors both function and cachelet memory consumption. Finally, the Frontend load-balances requests across the running application instances, and the Scale Controller adds and removes instances based on metrics provided by the Faas runtime (Section 4).

3.2 Accessing and caching data

Reads. Figure 7 shows the four ways to read data. A local hit finds the data cached in the local FaasT cachelet. A local miss occurs when the local FaasT cachelet is the owner for the object and does not currently cache the data. The cachelet directly fetches the data from remote storage. A remote hit occurs when the data misses the local cachelet but is found in the owner’s cache. Finally, a remote miss occurs when the access misses both the local cache and the owner’s cache. The owner fetches the data from remote storage and caches it locally. In all cases, FaasT cachelets cache objects locally, even if they are not the owners, for performance and locality. Thus, a popular object will incur at most one remote hit per cachelet, and local hits thereafter (besides the optional consistency version check, described below).
Faas$T$ uses consistent hashing to determine object ownership. We choose consistent hashing because (a) it avoids having to track object metadata (e.g., list of objects in each instance), and (b) it reduces rebalancing as instances are added/removed: on average, only \( \text{numObjects/numInstances} \) need to be remapped [6][31]. To maintain transparency, the object namespace is the same as that used by the remote storage service. This design choice also enables efficient communication between cachelets, as observed by prior work [17][12][29] is beneficial for applications such as ML training.

Writes. When the application needs to output data, Faas$T$ writes through to the owner cache. The instance executing the function sends the data to the owner cache, which then writes it to remote storage. This guarantees that the owner always has the latest version that the application has written. By default, the write happens synchronously to the owner and synchronously to remote storage. This offers high fault tolerance while trading off performance, since applications must wait until the write completes before proceeding with their execution. Applications can optionally configure Faas$T$ to write asynchronously or not write to remote storage at all. Because Faas$T$ is tied to each application, different applications can use different policies at the same time.

Consistency. Table 3 summarizes the possible read/write settings for Faas$T$, and the performance, consistency, and fault tolerance (FT) they achieve. By default, when reading an object, Faas$T$ first verifies the version in the cache matches the one in remote storage. No data gets transferred during this check. If the version matches (the common case), no object is retrieved. This verification, combined with synchronous writes to remote storage, offers strong consistency (first row of Table 3). We set this as the default because it provides the same fault tolerance with better performance than the production Faas$T$ platform.

Some applications may be willing to trade off consistency for performance (e.g., ML inference). For those applications, Faas$T$ can read any cached version and write asynchronously to remote storage. This weakens its fault tolerance, and provides only eventual consistency. Applications can also completely skip writing to remote storage and rely on the distributed cache. In Section 6.7, we quantify the performance and consistency impact of these settings.

### 3.3 Pre-warming application data into Faas$T$

To pre-warm future cachelets, Faas$T$ records metadata about the cache, off the critical path, when the Frontend unloads the application. This includes the size of each cached object, its version, its number of accesses of each type (e.g., local hit, remote miss, produced as an output), and its average inter-arrival access time. We timestamp each metadata collected with the unload timestamp to capture the state history of the cachelet. As we describe next, this is necessary for applications that are rarely-invoked (e.g., once per hour), since their data access pattern cannot be determined by a single invocation.

Faas$T$ needs to decide when to load an application into memory. For this, the Frontend leverages a previously-proposed hybrid histogram policy [48]. The policy tracks the idle times between invocations of an application in a histogram. When the application is unloaded, the Frontend uses the histogram to predict when the next invocation is likely to arrive, and schedules the reload of the application for just (e.g., 1 minute) before that time. Our approach would work with any other cold-start prevention policy as well.

At this point, Faas$T$ needs to decide what data objects should be loaded into the new cachelet. To do so, it collects and merges the metadata across all cachelets over a pre-set period of time. The period of time is based on the application’s invocation frequency, which can be determined using the hybrid histogram policy. Next, Faas$T$ determines the objects to be loaded using the following two conditions. First, if an object’s local or remote cache hit rate is greater than a threshold, the object should be loaded. This indicates that the object has temporal locality. Second, if an object is accessed more than once across the merged metadata, the object should be loaded. This benefits rarely-invoked applications by loading objects accessed across unload/load periods (e.g., an ML inference application’s model and labels). Once the objects to be loaded are determined, the Faas$T$ cachelet loads the objects that it owns based on consistent hashing (Section 3.2).

To avoid competing with on-demand accesses, Faas$T$ pre-warms the cache only when the application is not executing, i.e. before an invocation arrives or right after a function execution ends. If we cannot avoid a cold-start invocation, the only data that is loaded into the cache is its inputs.
3.4 Evicting application data from FaaS

The memory capacity of each application (and thus FaaS) cachelet is set by the provider (typically a few GBs). Cachelets do not consume any memory beyond that allocated to the application.

Each Memory Daemon monitors the memory usage of the function and the cachelet. When the memory consumed by the function (i.e., heap memory) and the cachelet (i.e., cached objects) is within a small percentage (i.e., 10%) of the application’s total memory capacity, it evicts objects.

Eviction policies are often designed to cover the broad set of applications that can run on the platform \cite{8,9,10}. In contrast, as FaaS is tied to an application, it can use per-application eviction policies. Hence, the eviction policy can be kept simple and tailored to an application’s data access pattern as needed.

We implement two policies that we expect will work well for many applications. The first is a simple Least-Recently-Used (LRU) policy that prioritizes the eviction of objects that are not owned by the evicting cachelet. Only after these objects are evicted, does the policy consider owned objects in LRU order. This is the default policy. The second policy targets objects that are larger than a threshold (e.g., 12KB) and not owned by the evicting cachelet. If there are not enough of these objects, the policy evicts non-owned objects smaller than the threshold. If we still need more capacity, we evict owned objects that are larger than the threshold, before resorting to LRU for the remaining ones. In both eviction policies, targeting non-owned objects first increases the number of remote hits, but also minimizes the number of remote misses which are most expensive. For the applications we consider, we find that targeting non-owned objects first improves application performance by \(\sim 20\%\) on average when multiple cachelets are running.

Each of these eviction policies fits our emerging applications nicely: ML inference matches the first policy and JupyterLess the second. ML inference applications that exhibit high invocation rates (e.g., frequently used recommendation models \cite{22}) can quickly fill up a FaaS cachelet’s capacity with invocation inputs (e.g., images) and outputs (e.g., labeled objects). Across invocations, only the model and labels are typically reused; inputs and outputs change each time. Thus, for ML inference and similar applications, the first policy (LRU) is sufficient, since the inputs and outputs will be evicted when the cachelet’s capacity reaches its limit.

JupyterLess data objects can be classified into two types: (a) small objects that maintain the notebook’s state (e.g., a dictionary object) and (b) larger objects that are used for data analysis (e.g., a DataFrame). A notebook’s state is typically reused across invocations, and should thus be cached as much as possible. Larger objects are reused less frequently and can be replaced more aggressively. Thus, the second policy (size-based) is appropriate.

FaaS allows for future eviction policies beyond the ones described above. For example, objects can be given a time-to-live (TTL) and get evicted when the TTL expires.

3.5 Charging for FaaS

When using FaaS, we expect FaaS providers to charge users only for the memory of the accessed data and not all the cached objects. FaaS providers should also not charge for pre-warming metadata in the same manner that they do not charge for function metadata (e.g., function registration).

4 Scaling FaaS

FaaS platforms typically include a Scale Controller responsible for scaling applications in/out (Figure \ref{fig:scale}). As it is part of the front-end component, the Scale Controller monitors the end-to-end performance and the load offered to each application. It also periodically queries the FaaS runtime running each application instance for a vote on how many more instances to add: a positive number means a vote to scale-out and a negative number means a vote to scale-in. Based on the information for an application, it makes a scaling decision and effects it. FaaS extends this mechanism by including cache-specific metrics when deciding on how to vote. We also extend the Scale Controller to accept unrequested votes, when scaling is needed immediately. When the controller adds or removes an application instance, FaaS reassigns the objects’ ownership using the Membership Daemon’s consistent hashing.

FaaS has three types of scaling:

**Compute scaling.** FaaS platforms scale the number of application instances based on its rate of incoming requests, its number of in-flight requests (queue sizes), and/or its average response time. Degrading performance, high request rates, or long queues cause scale-out; the opposite causes scale-in. Since every application instance includes both compute and caching resources, this traditional way of scaling is sufficient.

**Cache size scaling.** FaaS also scales to match the application’s working set size. For example, a JupyterLess notebook performing data-intensive operations may not fit the entire working set in the cache, leading to a high eviction rate. To address this, each cachelet tracks the number of evictions of each locally-cached object and votes to scale out by one instance, if any object has been evicted more than once since the last controller query. If no object has been evicted more than once but there is still
substantial cache access traffic, Faa$t votes to do nothing (add 0 instances). It votes to scale in by one instance when the frequency of accesses is low.

Many existing caching systems statically allocate resources and either cannot auto-scale their capacity as the amount of data accessed varies or require application hints to do so. OFC uses per-application machine learning models to achieve the same dynamic cache size scaling, which requires frequent retraining and mechanisms to prevent application “out-of-memory” failure.

**Bandwidth scaling.** Faa$t also supports applications with large input objects. For such applications, Faa$t equally partitions the download from remote storage across multiple cachelets to (a) create a higher cumulative I/O bandwidth to remote storage, and (b) exploit the higher communication bandwidth between instances ($BW_{Inst}$) compared to the bandwidth between each instance and remote storage ($BW_{BS}$).

When a Faa$t cachelet receives an object access, it iteratively computes the data transfer latency, $T_{DR}$, for a number of instances $N$ (starting at the current number) and the object size $S$ using the following formula:

$$T_{DR} = T_{Load} + S/N \times 1/BW_{BS} + (S-S/N) \times 1/BW_{Inst}$$

where $T_{Load}$ is the instance loading latency, Faa$t periodically profiles $T_{Load}$, $BW_{BS}$, and $BW_{Inst}$ to account for variations in the network and the remote storage bandwidths. The iterative process stops at the $N$ where $T_{DR}$ changes by less than 10% or when $T_{DR}$ increases between iterations. If the resulting $N$ is greater than the current number of instances, the Faa$t cachelet immediately contacts the controller to scale out to $N$. Faa$t then waits for the new instances to be created (by checking the Membership Daemon) and sends each of them a request to download a different byte range of size $S/N$. As scale-in is not as time-critical, Faa$t does it through periodic voting (when queried by the controller) as the number of object accesses becomes small.

We find that bandwidth-based scale-out is worthwhile for objects on the order of hundreds of MB (Section 6.6); this will become smaller as cold-start optimizations continue to appear [13][14]. Existing systems do not support bandwidth scaling, and instead rely on the user to determine the right number of chunks and instances.

**Handling conflicting scaling requests.** The scaling policies work concurrently, so there may be scenarios where they make conflicting scaling requests to the Scale Controller. For example, compute scaling may want to scale out, while cache size scaling may want to scale in. When there are conflicting votes, the controller scales out if any policy determines that scale-out is needed. It scales in if all policies suggest scale-in will not hurt. This is similar to the approach taken by existing systems for right-sizing storage clusters [32].

**Idle function computation resources.** When instances are added due to cache size or bandwidth scaling, their computation resources can be wasted. Faa$t minimizes resource waste by scaling in when the frequency of accesses is low. Providers can also leverage resource harvesting [60] to run low-priority tasks (e.g., analytics jobs) on these resources when they are not in use.

## 5 Implementation

We implement Faa$t for a large-scale FaaS platform used in production, and have open-sourced the bulk of it [13][14].

**Production FaaS platform.** In our platform, a user application comprises one or more functions. Each function defines its data bindings, which Faa$t uses to transparently load and manage objects: trigger (e.g., HTTP request), inputs (e.g., blob), and outputs (e.g., message queue). Users optionally set Faa$t policies (scaling, eviction, and consistency) using simple application-specific configurations at deployment time.

As we show in Figure 8, an application instance executes in either a VM or a Docker container, and includes the FaaS runtime and function-execution workers. Upon receiving incoming requests (e.g., as a result of an incoming HTTP request, a new blob being created), the runtime collects the requested input bindings and invokes the function in a worker while passing the appropriate arguments to it. When the worker finishes executing the function, it replies to the runtime with the produced output(s) and the runtime processes them (e.g., writes a blob to remote storage or writes to a message queue). If there are multiple concurrent invocations, more worker processes can be spawned on the same instance to execute them in parallel. The platform leverages an existing remote storage service that is not tailored to FaaS.

As Figure 8 shows, a Frontend component handles HTTP requests and does compute scaling. We extend this component to implement bandwidth-based scaling (Section 4).
Caching data. We implement the core of FaaST in the runtime (C# code) with minimal changes to the workers (Python and Node.js). In the original design, the runtime and workers exchanged control and data messages over a persistent RPC channel. FaaST replaces the data messages with a shared memory area, while keeping control messages over RPC. The shared area is also where FaaS T caches data. Data communication between the FaaS T cachelets and the workers happens via passing shared memory addresses, reducing end-to-end latency. In addition, unlike existing systems that need to maintain duplicate object copies, using shared memory reduces the memory footprint by only keeping a single object copy. The workers managed by the same runtime share the cached objects.

When the runtime prepares input data bindings before invoking a function, FaaS T intercepts them and checks the cache first (Section 3.2). When a function produces an output, FaaS T caches it for future invocations. This cache write triggers any functions that have the newly added object as their trigger binding. This improves latency for applications that rely on writing intermediate outputs to external sources (e.g., blob storage) to trigger subsequent functions.

We support applications written in C#, Python, and Node.js. Supporting other languages would require minimal changes. We use the shared memory APIs already available in most languages for both Linux and Windows. When we run applications in containers (vs VMs), we share (setting up permissions) the cache space across containers.

Distributed cache. Each runtime instance saves some metadata about the running application in a blob from remote storage. We store the FaaS T membership information in this blob and the FaaS T cachelets periodically heartbeat their state there. The consistent hashing algorithm uses SHA256 for hashing and 100 cachelet replicas for load balancing. More replicas did not improve load balancing and increased the ownership lookup time. Fewer replicas created ownership hot spots.

As our platform already uses HTTP for communication between its components, we use this interface to exchange data between FaaS T cachelets. We evaluated other approaches like RPC (with Protocol Buffers) but the improvements were negligible and the complexity of maintaining a new channel would offset them. We could also leverage RDMA-based communication but have not experimented with it.

Other platforms. The design and implementation of FaaS T is extensible to other FaaS platforms. Most platforms have a similar architecture and FaaS T directly applies to the equivalent components (e.g., runtime, worker processes, Scale Controller). All platforms use the concept of triggers and interact with external data services. However, not all of them use bindings to map the data but rely on libraries to explicitly access inside the function body. We would need to extend these libraries (e.g., Boto3 in AWS Lambda) to interact with FaaS T and look-up the cache before accessing the remote storage. These extensions would be equivalent to modifying the binding process in our platform.

6 Evaluation

6.1 Methodology

Comparison points. We perform two types of comparisons. The first is an analysis of running the application traces from Section 2.1 on top of FaaS T. This allows us to show the improvements these applications would get with FaaS T.

The second evaluates the four access scenarios that functions may encounter: objects are accessed through local hits (LH), local misses (LM), remote hits (RH), or remote misses (RM).

We compare FaaS T against six baselines for performance and cost: (a) a large, local VM where all accesses are local and there are no function invocation overheads (Native); (b) our commercial FaaS offering (Vanilla) without FaaS T that accesses all objects from remote object storage. Its performance is equal to that of FaaS T LM; (c) InfiniCache (IC) that we approximate by statically configuring FaaS T to use only remote instances. Its best case performance is equal to that of FaaS T RH; (d) Cloudburst’s caching layer (CB) that uses only remote instances. Its best case performance is equal to that of FaaS T LH; (e) Pocket, approximated with a manually managed Redis VM with all data available at memory speed (no Flash accesses); and (f) a commercial Redis service (Redis service). The Redis service is the offering that matches our VM size in memory and network bandwidth. It is akin to what is used by Locus. Data is stored and accessed from Redis as opposed to remote object storage.

Applications. We use the two applications from Section 2.1: ML inference and JupyterLess notebooks. We use application latency and cost as primary metrics. For each experiment, we report the mean and standard deviation of 3 runs.

For ML inference, we evaluate both single model inference and inference pipelines. For single model inference, we use two separate models that differ in latency and resource footprints: SqueezeNet (5MB) and AlexNet (239MB). For the inference pipeline, we evaluate the AMBER Alert pipeline of Figure 4, the output of the bounding box model (MobileNet Single-Shot Detector 35MB) is fed into people (ResNet50 [23], 97MB) and car recognition (SqueezeNet, 5MB) models.
In all inference cases, functions access an input image, the model, and the class labels (a text file).

For JupyterLess, we use five notebooks: (a) single message logging (No-Op); (b) summing a 350MB DataFrame column; (c) capacity planning with data collection and plotting; (d) FaaS characterization of Section 2.1 and (e) counting up to 1K. The function data objects consist of the notebook state after each cell’s execution, which is stored in JSON format.

**Experimental setup.** Each application instance is a single VM; the default instance size in our experiments includes 8vCPUs with 28GiB of DRAM and up to 500MB/s network bandwidth. I/O bandwidth to remote storage is lower at 90MB/s for large objects. They run Ubuntu 18.04 with 5.4.0 kernel on Intel Xeon E5-2673 CPUs operating at 2.40GHz. In our production setting, the VMs are pre-provisioned: an application instance cold-start involves loading and deploying the serverless runtime together with the application code.

**Cost model.** We derive user costs following the common pricing by FaaS and cloud providers. Function invocations are charged for the time and the resources they take ($/GB-s, order of 10^{-5}$), while VMs are charged for their lifetime ($$/s, order of 10^{-1}$). We assume Native and systems with additional resources are statically provisioned the whole time. Specifically, we charge for extra resources whenever the caching or storage system is external to the FaaS platform (i.e., Pocket, Redis, Redis Service) or specialized for FaaS in some way (CloudBurst). Except for Redis service, we charge these systems for one extra VM of the same instance size as the default application instance. The VMs are charged their on-demand prices. For Redis service, we provision per service class and charge the class’s price. The additional resource costs can be amortized by multiple applications sharing the same resources. Vanilla, InfiniCache, and FaaS use existing commodity storage (e.g., AWS S3, Azure Storage), so we do not charge them for extra resources. We also add the cost of remote storage data transfer ($/op, order of 10^{-6}$) to FaaS LM and RM, and Vanilla.

**6.2 FaaS with applications run in production**

We simulate the end-to-end performance of the FaaS applications from Section 2.1. Our simulator uses the default policies for consistency (synchronous writes to owner, synchronous writes to remote storage, read version from remote storage) and eviction (LRU), and implements the scaling policies described in Section 4. To model FaaS’s access latencies, we measured read and writes latencies for 1B to 2GB object sizes using our FaaS implementation described in Section 5. We vary the size of FaaS from 1KB to 128MB; larger cache sizes showed no further improvement. We also vary the unload period and show how it affects performance when FaaS cannot pre-warm frequently-accessed objects.

Figure 9 shows the CDF of percent improvement over blob storage for a 128MB cache (left) and average percent improvement as the size of FaaS varies (right). First, with just 128MB, FaaS with pre-warm improves performance by 50% or more for about 35% of applications. FaaS also has an average improvement of over 40% for a 128MB cache. Second, as the unload period gets smaller, FaaS’s pre-warm becomes more important to ensure frequently-accessed objects are available during the next application invocation. Third, improvement is correlated with reuse: we found that smaller objects tend
to be reused more often, which resulted in greater performance improvements. Finally, we note that FaaS{T} is designed to support applications that run in production today (with object sizes of tens to hundreds of KB), but also for future applications that will access much larger objects (hundreds to thousands of MB) as shown in Section 6.3

6.3 Comparing FaaS{T} to existing systems

ML inference. Figure 9 shows the latency for the AMBER Alert pipeline and single inference with AlexNet and SqueezeNet. First, the figure shows that FaaS{T} LH improves latency by 50%, 87%, and 60% faster than Vanilla for the AMBER Alert pipeline, AlexNet, and SqueezeNet, respectively. This demonstrates that avoiding remote storage accesses and using cache triggers can significantly improve FaaS performance. Second, for the AMBER Alert pipeline, FaaS{T}’s LH and RH are faster than using a Redis service, while FaaS{T} RH is equivalent to using a manually managed Redis VM (Pocket in Figure 9a). This is significant given the complexity of manually managing a Redis VM and the significant cost of using a Redis service (discussed below). FaaS{T} offers lower latency, while remaining transparent and relieving users of any configuration burden. Third, FaaS{T}’s LM and RM exhibit similar latencies, with the variability coming from the accesses to remote storage. This suggests using a multi-instance FaaS{T} cache does not further penalize cache miss performance. Finally, FaaS{T} LH and RH perform well for both small (input images and class labels) and large objects (the models).

JupyterLess. Figure 10 shows the performance of summing a 350MB DataFrame column in a JupyterLess notebook. There are two Native setups: for In-Memory (IM) the DataFrame is pre-loaded in memory before summing, while for Remote Storage (RS) the latency of remote storage access is counted as part of the summation. Similar to the ML inference applications, FaaS{T} LH and RH improve performance compared to Vanilla by 62% and 29%, respectively. Compared to Native RS, FaaS{T}’s LH and RH improve performance by 92% and 86%, respectively.

Table 4: End-to-end latency running notebooks. FaaS{T} can run JupyterLess notebooks interactively.

50% to 99.999% cheaper than the baselines.
Hybrid hist
Hybrid hist + pre-warm

Latency (seconds)

0
1
2
3
4

Heap growth succeeded? Latency
Yes 678.6ms
No 235.0ms

Cold-start
Hybrid hist
Hybrid hist + pre-warm

Figure 13: AMBER Alert pipeline performance: (a) instance loaded and FaaS$T$ pre-warms based on past history (Hybrid hist + pre-warm), (b) instance loaded but not pre-warmed (Hybrid hist), and (c) instance not loaded (Cold-start). FaaS$T$ automatically loads objects with spatial and temporal locality to improve latency.

quire separate servers, such as Cloudburst and Pocket. From Section 2.1, 99.88% of applications have average IaT ≥ 10ms: in these cases, the cost of servers would almost always completely dominate the overall cost.

Discussion on comparison to Native. Even when all accesses are served with local (LH) or remote hits (RH), FaaS$T$ is slower than a Native VM with all data stored locally and there are no function invocation overheads. However, as we have shown in Figure 12 such a Native setup can be orders of magnitude more expensive than FaaS$T$, since we must keep all VMs running even when applications are idle. Moreover, the user is responsible for resource and data management. With FaaS$T$ being a part of the FaaS runtime, users only pay for the time resources are consumed for both compute and caching. Moreover, local hits are on the order of hundreds of ms, which is close to interactive for many use cases.

6.4 Is FaaS$T$ pre-warm effective?

In Section 6.2, we showed pre-warming is an important feature for improving existing application performance over remote storage. We now use the AMBER Alert pipeline to evaluate the effectiveness of FaaS$T$ data pre-warming under three scenarios: the application instance was loaded before the function invocation using the hybrid histogram policy [48] and FaaS$T$ automatically pre-warmed the three models and three labels (135MB total) based on history (Hybrid hist + pre-warm); the instance was loaded before the invocation using the hybrid histogram policy, but not pre-warmed with any objects (Hybrid hist); and the instance was not loaded before the invocation (i.e., the runtime is not deployed; Cold-start).

Figure 13 shows the performance of the pipeline for these versions. FaaS$T$’s data pre-warming improves latency by 58% and 74% over no pre-warming and cold-start, respectively. This is especially important if the AMBER Alert pipeline is infrequently invoked.

6.5 Can FaaS$T$ manage memory effectively?

We consider the JupyterLess notebook application that sums a 350MB column. After loading in the DataFrame and performing the summation, the application allocates an array that consumes 96% of the application’s total memory. Then, the application again computes the summation of the 350MB column, which requires the reloading of the DataFrame that is evicted. We show three scenarios: (a) without the Memory Daemon, (b) with the Memory Daemon, but no cache size scaling, and (c) with Memory Daemon, and FaaS$T$ scales to two instances. FaaS$T$ ensures application functionality is not compromised, and improves performance by scaling.

6.6 Scaling as the object size varies

FaaS$T$ can scale the number of instances based on object sizes. We consider four object sizes: 400KB, 40MB, 400MB, and 800MB. The amount of data downloaded by each FaaS$T$ cachelet is evenly split between the available instances. For example, if there are two instances and the object size is 400KB, each one downloads 200KB. The data is then processed at a single instance. For each object size, we show two cases: (a) when all application instances are running, and (b) when additional instances (more than one) must be loaded in order to fetch the ob-

| Scenario                          | Heap growth succeeded? | Latency             |
|-----------------------------------|------------------------|---------------------|
| No Mem Daemon                     | No                     | 235.0ms ± 3.2ms     |
| Mem Daemon, no scaling            | Yes                    | 678.6ms ± 64.8ms    |
| Mem Daemon, scaling               | Yes                    | 502.5ms ± 28.5ms    |

Table 5: Latency of running a 350MB DataFrame summation in a JupyterLess notebook after growing heap memory, and whether the heap growth succeeded. We evaluate three scenarios: (a) without the Memory Daemon, (b) with the Memory Daemon, but no cache size scaling, and (c) with Memory Daemon, and FaaS$T$ scales to two instances.
Figure 14: Latency of fetching an object from remote storage as the number of instances vary for increasingly large object sizes. If the instances are not loaded, they incur a cold-start; we only consider the running case for one instance. Faa$T$ determines whether to scale data loading across multiple instances to increase bandwidth.

Table 6: Latency (end-to-end and per-request) and number of inconsistencies for different write/read settings for a JupyterLess notebook counting to 1K with five instances sharing state. Inconsistencies are the absolute difference between the final counter value and 1K. Performance increases as consistency and fault tolerance decrease.

We measure inconsistencies as the absolute difference between the final counter value and 1K. This is a critical primitive in multiplayer games [15].

Table 6 shows the end-to-end latency, per-request latency, and number of inconsistencies for all five settings. As expected, latency drops as we relax consistency requirements. For example, writing to the local cache and reading from the local cache is equivalent to CloudBurst’s performance. Cloudburst would exhibit better consistency due to its lattice datatypes, but requires support from the datastore. Latency varies the most when writing and reading from remote storage, and the least when writing and reading from the local cache.

6.8 Sensitivity to instance size

Finally, we evaluate the sensitivity of running applications with Faa$T$ as the instance size varies. We run the AMBER Alert pipeline and sum a 350MB DataFrame column in a JupyterLess notebook. Instances memory and network bandwidth scale linearly as the number of cores increases. Faa$T$ benefits from instances with higher bandwidth.
Figures 15a and 15b show that as instances increase in size, FaaST’s latency decreases for both applications. Larger instances have higher network bandwidth, which is beneficial for data accesses to remote storage and between instances. Data accesses of these two applications saturate the bandwidth with the 8vCPU instance. Thus, although the 16vCPU instance is the highest bandwidth instance size, the performance remains the same as the 8vCPU. Some cloud providers offer instances as small as 2vCPU with up to 10Gbps bandwidth, allowing FaaST to have high performance even on small instances suitable for FaaS.

7 Related Work

Ephemeral serverless storage. In Section 2.2 we describe the limitations of several existing storage and data caching solutions for FaaS [32, 33, 43, 51, 53]. Unlike these systems, FaaST does not require external resources beyond what is provided to the invoked function, is transparent to applications, and can scale as the data size and access patterns vary.

OFC is the closest work to FaaST. It transparently caches objects using RAMCloud [39] and leverages machine learning to dynamically size the cache. Unlike OFC, FaaST pre-warms objects when an application is loaded, supports large (> 10MB) object caching and optimizes for their data transfer latency from remote storage with bandwidth scaling, and only needs to keep one copy of data in shared memory (compared to OFC that requires a copy in the worker and in RAMCloud). FaaST also incurs lower decision overheads and is easier to manage by not requiring the use of machine learning for its decision-making.

Serverless frameworks. Several frameworks have recently emerged enabling users to run, for example, linear algebra [28], video encoding [18], video analytics pipelines [5], ML training [12], and general burst-parallel applications [17] on up to thousands of serverless functions. These, and their applications, would benefit from managing and transferring intermediate data between serverless functions using FaaST. Since FaaST is transparent to applications, little to no changes would be needed to interact with FaaST.

Improving serverless performance. There have been many approaches to reduce the execution time of serverless function, such as making containers more lightweight [11, 38], using snapshotting techniques [11, 16], or reducing the number of cold-starts [48, 19]. Shredder [59] focuses on how to provide isolation for multi-tenancy. Lambada [56] focuses on improving performance for serverless applications with exchange operators. Lambda [54] allows users to expose their data read and write intents for making optimizations such as co-locating functions working on the same data. These optimizations are orthogonal to FaaST, which focuses on how to improve state management for serverless functions, and how to scale instances to improve application performance.

Consistency and fault tolerance. Consistency and fault tolerance protocols have been heavily studied. Recent work has explored how to enable both of these for serverless applications. Faasm [51] and Cloudburst [53] provide local caches backed by a distributed key-value store. Faasm allows for strong consistency by using global locks at the KVS; Cloudburst provides guarantees for repeatable reads and causal consistency by using lattice data types supported by its local caches and by its Anna KVS backend [56]. AFT [52] added a fault tolerance shim layer for FaaS, and implemented protocols for read atomic isolation. Beldi [58] provides a framework to write transactional and fault tolerant stateful serverless functions by extending Olive [47] with a novel data structure to support fast logging and exactly-one semantics. FaaST transparently supports different consistency and fault tolerance settings directly in the functions runtime, and can be extended to support future protocols.

8 Conclusion

We presented FaaST, a transparent caching layer for serverless applications. We motivated its design with a characterization of production applications. We tie FaaST to the application, scale based on compute demands and data access patterns, and provide data consistency that can be set per application. We implemented it in a production serverless platform. Compared to existing systems, FaaST is on average 57% faster and 99.99% cheaper when running two challenging applications.

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