

FaaSCache: Keeping Serverless Computing Alive With Greedy-Dual Caching

Abstract

Functions as a Service (also called serverless computing) promises to revolutionize how applications use cloud resources. However, functions suffer from cold-start problems due to the overhead of initializing their code and data dependencies before they can start executing. Keeping functions alive and warm after they have finished execution can alleviate the cold-start overhead. Keep-alive policies must keep functions alive based on their resource and usage characteristics, which is challenging due to the diversity in FaaS workloads.

Our insight is that keep-alive is analogous to caching. Our caching-inspired Greedy-Dual keep-alive policy can be effective in reducing the cold-start overhead by more than $3\times$ compared to current approaches. Caching concepts such as reuse distances and hit-ratio curves can also be used for auto-scaled server resource provisioning, which can reduce the resource requirement of FaaS providers by 30% for real-world dynamic workloads. We implement caching-based keep-alive and resource provisioning policies in our FaaSCache system, which is based on OpenWhisk. We hope that our caching analogy opens the door to more principled and optimized keep-alive and resource provisioning techniques for future FaaS workloads and platforms.

1. Introduction

Functions as a Service (FaaS) is an emerging and popular cloud computing model, where applications use cloud resources through user defined “functions” that execute application code [34, 35, 49]. By handling all aspects of function execution, including resource allocation, cloud platforms can provide a “serverless” computing model where users do not have to explicitly provision and manage cloud resources (i.e., virtualized servers). FaaS employs a fine-grained pricing model allowing applications to pay for the resources they use, and provides many other advantages such as near-infinite horizontal scaling. FaaS services are being offered by all major cloud platforms (such as Amazon Lambda [8], Google Functions [10], and Azure Functions [9]), and are being used by diverse applications such as web services, API services, parallel and scientific computing [20, 33, 27], and in machine learning pipelines [17, 18].

The execution time of each function is typically short—in the range of a few milliseconds to a few seconds. This tight latency requirement and the wide diversity in function characteristics raises new challenges for FaaS providers. Cloud platforms execute each function invocation in a virtualized execution environment such as a container or a virtual machine (VM). Using virtualization techniques, a single physical server can execute many functions concurrently and safely [51]. Each

function invocation entails creating and launching a container or a VM, and fetching and installing the necessary libraries and dependencies, before the function itself can be executed. This “initialization” phase can take non negligible time, and adds to the overall function execution latency observed by the user. Reducing this function “startup overhead” is a key challenge in serverless computing [42, 30, 2, 6].

To mitigate the startup overhead, a common technique is to keep the execution environment alive or “warm” for a small duration, so that future invocations of the same function can run in the already initialized environment. Keeping functions warm can reduce the cold-start overheads and overall function latency by more than $5\times$ [39]. However, keeping a container or a VM alive consumes computing resources on the physical servers, and increases the resource requirements for hosting FaaS platforms. Thus, while keep-alive can reduce the effective function execution latency, it can also reduce the overall system utilization and efficiency.

In this paper, we focus on how diverse FaaS workloads can be efficiently executed, by developing a new class of resource management techniques that balance the fundamental latency vs. utilization tradeoff. We argue that keep-alive *policies* can have a crucial impact on application performance, and thus must be integrated into resource allocation and provisioning. Current cloud platforms and FaaS systems employ simple keep-alive policies. For example, AWS Lambda will keep functions “warm” for $\sim 15 - 60$ minutes, and users have to resort to ad-hoc “polling” techniques to keep functions warm to avoid the cold-start penalty [14, 1, 5]. Similarly, OpenWhisk sets a constant time to live (10 minutes) for containers.

However, optimized keep-alive policies must balance the overhead of keeping a function warm with the likelihood that it will be invoked in the near future. Ideally, the duration of keep-alive should depend on the function’s characteristics. This is challenging because of the diverse range of functions with different initialization overheads, resource footprints (i.e., CPU and memory consumption), and request frequencies.

Our primary insight is that the resource management of functions is equivalent to object caching. Keeping a function warm is equivalent to caching an object, and a warm function execution is equivalent to a cache hit. Terminating a function’s execution environment means that the next invocation will incur the cold-start penalty, and is thus equivalent to evicting an object from a cache. The objective is to keep functions warm such that the effective function latency is reduced, which is equivalent to caching’s goal of reducing object access time. By mapping keep-alive to the exhaustively studied field of caching, we can leverage its principles and techniques, and apply them to serverless computing.

Specifically, we use and adapt the Greedy-Dual caching framework [23], and develop keep-alive policies based on it. Our policies are cognizant of the memory footprint, access frequency, initialization cost, and execution latency of different functions. This caching-based approach can improve both the function latency and server utilization compared to the simple keep-alive policies found in current FaaS platforms.

The caching analogy allows us to use the vast set of caching algorithms and analytical models, and provides a new approach to resource provisioning for FaaS platforms. We use hit-ratio curves to determine the ideal size of servers required for handling FaaS workloads, and develop a vertical auto-scaling approach that dynamically adapts server size based on the workload characteristics. The dynamic scaling uses proportional control and hit-ratio curves to minimize both the required server resources, and cold-start overheads.

The rise of serverless computing and the challenges posed by its heterogeneity, workload diversity, and latency requirements, will require a new class of approaches to FaaS resource management. We argue that the vast collection of algorithms, analytical models, practical optimizations, and hard lessons from one of the most well studied fields in computer science, caching, can be customized to address many of these challenges. While bespoke solutions to serverless resource management will continue to be developed, our intent is to show the equivalence of caching and FaaS, and to highlight how naturally and easily caching techniques can be adapted instead. This paper makes an initial exploration into the world of caching-based approaches for resource management in serverless computing, and makes the following contributions:

1. We show the equivalence between caching and function keep-alive, and develop a family of caching-based keep-alive policies for reducing function cold-start overhead. We use a Greedy-Dual based approach that is designed to work even with the diverse FaaS workloads.
2. We implement our caching-based techniques in our system, FaasCache, which is based on OpenWhisk. We conduct extensive trace-driven and empirical analysis of the tradeoffs of keep-alive techniques under different workload characteristics based on the Azure FaaS traces [44] and popular FaaS applications [36].
3. Our resource provisioning policies use hit-ratio curves to determine the ideal server configuration (such as memory size) required to handle different function workloads. Our proportional-control based dynamic vertical-scaling can adjust server resources to reduce the cold-start probability, and reduce the average server size by more than 30%.
4. Our experimental results indicate that caching-based keep-alive can reduce cold-start overheads by $3\times$, improve application-latency by $6\times$, and reduce system load to serve $2\times$ more requests.

Application	Mem size	Run time	Init. time
ML Inference (CNN)	512 MB	6.5 s	4.5 s
Video Encoding	500 MB	56 s	3 s
Matrix Multiply	256 MB	2.5 s	2.2 s
Disk-bench (dd)	256 MB	2.2 s	1.8 s
Web-serving	64 MB	2.4 s	2 s
Floating Point	128 MB	2 s	1.7 s

Table 1: FaaS workloads are highly diverse in their resource requirements and running times. The initialization time can be significant and is the cause of the cold-start overheads, and depends on the size of code and data dependencies. More application details can be found in the Appendix.

2. Background

2.1. Function Keep-Alive

Serverless computing is now being provided by all large public cloud providers, and is increasingly popular way to deploy applications on the cloud. Functions as a Service (FaaS) can also be realized on private clouds and dedicated clusters using frameworks such as OpenWhisk [7], OpenFaas [11], OpenLambda [30], etc. In this new cloud paradigm, users provide functions in languages such as Python, Javascript, Go, Java, and others. The functions are executed by the FaaS platform, greatly simplifying resource management for the application.

FaaS functions cannot assume that state will persist across invocations, and function definitions must first import and load all code and data dependencies on each execution. Each function is run inside a containers such as Docker [4], or a lightweight VM such as Firecracker [12]. By encapsulating all of the function state and any side-effects, the virtual execution environment provides isolation among multiple functions, and also allows for concurrent invocations of the same function. Due to the overhead of starting a new virtual execution environment (i.e., container or VM), and initializing the function by importing libraries and other data dependencies, function execution thus incurs a significant “cold-start” penalty. Table 1 shows the breakdown of initialization time (last column) vs. the total running time of different FaaS applications, and we can see that the initialization overhead can be as much as 80% of the total running time. Thus, FaaS can result in significant performance (i.e., total function execution latency) overheads compared to conventional models of execution where applications can reuse state and do not face the high initialization and cold-start overheads.

Once a container for a function is created and the function finishes execution, the container can be kept alive instead of immediately terminating it. Subsequent invocations of the function can then *reuse* the already running container. This *keep-alive* mechanism can alleviate the cold-start overhead due to container launching (which can be ~ 100 ms).

However, keep-alive is not a panacea for all FaaS latency problems. Keeping a container alive consumes valuable computing resources on the servers. Specifically, a running con-

tainer occupies memory, and “warm” containers being kept alive in anticipation of future function invocations can reduce the multiplexing and efficiency of the servers. Thus, we develop keep-alive *policies* that reduce the cold-start overhead while keeping the server utilization high.

Designing general keep-alive policies is challenging due to the extreme heterogeneity in the different function popularities, resource requirements, and cold-start overheads. For instance, a recent analysis of FaaS workloads from Azure [44] shows that function inter-arrival times and memory sizes can vary by more than three orders of magnitude. This workload heterogeneity magnifies the performance vs. utilization tradeoff faced by keep-alive policies, as we shall describe in the next section. Additionally, FaaS workloads also show a high temporal dynamism, which requires new approaches to resource provisioning and elastic scaling, which we also develop.

2.2. Caching

Our answer to solving the twin conundrum of keep-alive and provisioning that is robust to workload heterogeneity and dynamism, is to use concepts from a related, well-known field with the same challenges. Caching has a long history of robust eviction algorithms that use temporal locality such as LRU (Least Recently Used). The effectiveness of a caching algorithm depends on the workload’s inter arrival time distribution, the relative popularities of different objects, and thus many variants of LRU such as LRU-k [43], segmented LRU [22], ARC [40], and frequency based eviction such as LFU [26], are widely used in caching systems. Because functions show a lot of diversity in their memory footprints, and since keep-alive is primarily constrained by server memory, we seek to use *size-aware* caching methods. While conventional caching algorithms and analytical models largely deal with constant-sized objects, many size-aware caching policies have been developed for web-pages and data [16]. In particular, we use the Greedy-Dual [53] online caching framework that deals with objects with different eviction costs, that are determined based on size and other factors. The Greedy-Dual family of eviction algorithms for non-identical objects can be extended in many ways. We use a common variant, Greedy-Dual-Size-Frequency [23, 24, 25], which considers the size and frequency of objects.

Caching has a rich collection of analytical and modeling techniques to determine the efficacy of caches for different workloads. Hit (or miss) ratio curves are widely used for cache sizing to achieve a target performance, and for understanding and modeling cache performance. Hit-ratio curves can be constructed both in an offline and online manner, using techniques involving reuse distances [55], eviction times [31], Che’s approximation [21], footprint descriptors [47], and estimation techniques such as SHARDS [50], counterstacks [52], etc.

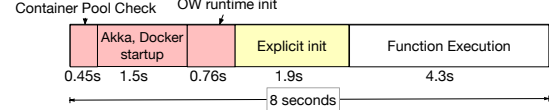


Figure 1: Timeline of function execution and sources of cold-start delay in OpenWhisk for an ML inference application.

3. Keep-alive Tradeoffs

In this section, we first present an empirical analysis of cold-start overheads of common serverless applications, followed by the tradeoffs in keep-alive policies.

System model. We assume that each function invocation runs in its own container. A FaaS platform may use a cluster of physical servers, and forward the function invocation requests to different servers based on some load-balancing policy. Our aim is to investigate general techniques that are independent of the load-balancing, and we therefore focus on *server-level* policies. Even on a single server, a function can have multiple independent and concurrent invocations, and hence containers. Each function has its own container image and initialization code, and thus containers cannot be used by different functions. A function’s containers are nearly identical in their initialization overheads and resource utilization, since they are typically running the same function code. When a function finishes execution, its container may be terminated, or be kept alive and “warm” for any future invocations of the same function. At any instant of time, each container is either running a function, or is being kept alive/warm. Thus, server resources are consumed by running containers, and containers being kept alive in anticipation for future invocations.

Cold-start overheads in OpenWhisk. In order to understand the performance and latency implications of function cold-starts, we investigate the chain of events necessary to run function code in a popular FaaS platform, OpenWhisk [7]. A timeline of a function invocation request for a TensorFlow machine learning inference task is shown in Figure 1. The figure shows the major sources of cold-start overhead: from request arrival to the actual function execution. OpenWhisk first checks whether the function can be served from the pool of warmed containers it maintains, and if no container is found, a Docker container is launched, and the runtime for the function is initialized: which comprises of OpenWhisk and Python runtime initialization, as well as any specific *explicit* function initialization provided by the application. The total compulsory overhead, from the request arrival to the actual function execution, is significant: up to 2.5 seconds are spent loading all runtime dependencies, before the user-provided initialization and actual event handling code can begin execution.

Explicit Function Initialization. Optionally, applications may also use custom code to initialize and pre-warm the container (explicit-init component in Figure 1). For example, this can be used for downloading data dependencies ahead of time such as large neural network models for inference, or for runtime initialization such as downloading and importing package dependencies (such as Python packages). An example


```

1 #Initialization code
2 import numpy as np
3 import tensorflow as tf
4
5 m = download_model('http://model_serve/img_classify.pb')
6 session = create_tensorflow_graph(m)
7
8 def lambda_handler(event, context):
9     #This is called on every function invocation
10    picture = event['data']
11    prediction_output = run_inference_on_image(picture)
12    return prediction_output

```

Figure 2: Initializing functions by importing and downloading code and data dependencies can reduce function latency by hiding the cold-start overhead.

of function initialization is shown in Figure 2, which shows a pseudo-code snippet of a function that performs machine learning inference on its input. For ML inference, the function downloads an ML model and initializes the TensorFlow ML framework (lines 5 and 6). If the function’s container is kept alive, then invocations of the function do not need to run the expensive initialization code (lines 2–6). Thus, the execution latency of functions can be minimized with a combination of careful function initialization and keeping the containers alive.

Explicit initialization is not common—our empirical investigation into FaaS benchmarks [36] and official examples showed that applications do not use this functionality. Nevertheless, it can be a powerful technique to amortize expensive operations such as package imports and downloading data dependencies. Explicit initialization can thus increase the effectiveness of keep-alive. However because it is not ubiquitous, we assume it is *optional*, and our keep-alive and provisioning techniques work with and without it.

Workload Diversity and Dynamism. Designing keep-alive policies is not trivial due to the highly diverse and expanding range of applications that are using FaaS platforms. Conventionally, FaaS has been used for hosting web services, which is attractive because of the pay-per-use properties. Event handling functions for web responses typically have a small memory footprint but require low execution latency. Increasingly, FaaS is also being used for “heavy” workloads with high memory footprint and large initialization overheads such as highly parallel numerical computing (such as matrix operations [34], scientific computing [45], and machine learning [13]. The diversity of FaaS applications also results in a wide range of function memory footprints, running times, and initialization times, as seen in Table 1. Keep-alive policies must therefore balance the resource footprint of the containers with the benefits of keeping containers alive—and do so in manner that is applicable across a wide range of applications.

Furthermore, FaaS workloads show a high degree of dynamism and temporal effects. The Azure function [44] trace shows sharp diurnal effects: the function arrival rate is about $2\times$ higher during the peak periods compared to the average.

Function workloads are also heavy-tailed: a few “heavy hitting” functions are invoked much more frequently than others or consume a larger amount of computing resources, often by 2 or 3 orders of magnitude.

3.1. Policy Goals and Considerations

The primary goal of keep-alive is to reduce the initialization and cold-start latency, by keeping functions alive for different durations based on their characteristics. Because servers run hundreds of short lived functions concurrently, keep-alive policies must be generalizable and yield high server utilization. Functions can have vastly different characteristics, and keep-alive policies must work efficiently in highly dynamic and diverse settings. We use the following characteristics of functions for keep-alive policies.

The **initialization time** of functions can vary based on the code and data dependencies of the function. For example, a function for machine learning inference may be initialized by importing large ML libraries (such as TensorFlow, etc.), and fetching the ML model, which can be hundreds of megabytes in size and take several seconds to download. Functions also differ in terms of their **total running time**, which includes the initialization time and the actual execution time. Again, functions for deep-learning inference can take several seconds, whereas functions for HTTP servers and microservices are extremely short-lived (few milliseconds). The **resource footprint** comprises of the CPU, memory, and I/O use, and also differs widely based on the application’s requirements. Finally, functions have different **frequencies** and invocation rates. Some functions may be invoked several times a second, whereas other functions may only be invoked rarely (if they are used to serve a very low-traffic web-site, for instance).

Because server resources are finite, it is important to prioritize functions which should be kept alive, based on the aforementioned characteristics. A function which is not popular and is unlikely to be called again in the near future, sees little benefits from keep-alive, and wastes server memory. Similarly, the resource consumption of the functions is also important: since keeping large-footprint functions alive is more expensive than smaller functions, smaller functions should be preferred and kept alive for longer. Finally, functions can also be prioritized based on their initialization overhead, since it is effectively wasted computation.

The problem of designing keep-alive policies is complicated by the fact that functions may have vastly different keep-alive priorities for the different characteristics. Consider a function with a large memory footprint (like those used in ML inference), high initialization overhead, and a low popularity. Such a function should have a low keep-alive priority due to its size, high priority due to large initialization overhead, and a low priority due to its low popularity. Thus, keep-alive policies must carefully balance all the different function characteristics and prioritize them in a coherent manner.

Current FaaS systems have shirked from this challenge and

use primitive keep-alive policies that are not designed with the diversity and dynamism in mind. FaaS frameworks such as OpenWhisk, keep all functions alive for a *constant* period of time (10 minutes). This is agnostic to different function characteristics such as resource footprint and initialization overheads, and only loosely captures popularity. More principled approaches are needed, which we provide next.

4. Caching-based Keep-Alive Policies

Formulating a keep-alive policy that balances priorities based on all competing characteristics of functions seems daunting.

The central insight of this paper is that keeping functions alive is equivalent to keeping objects in a cache.

Keeping a function alive reduces its effective execution (or response) latency, in the same way as caching an object reduces its access latency. When all server resources are fully utilized, the problem of which functions *not* to keep alive is equivalent to which objects to *evict* from the cache. The high-level goal in caching is to improve the distribution of object access times, which is analogous to our goal of reducing the effective function latencies.

This caching analogy provides us a framework and tools for understanding the tradeoffs in keep-alive policies, and improving server utilization. Caching has been studied in wide range of contexts and many existing caching techniques can be applied and used for function keep-alive. Our insight is that we can use classic observations and results in object caching to formulate equivalent keep-alive policies that can provide us with well-proven and sophisticated starting point for understanding and improving function keep-alive.

In the rest of this section, we will show how cache eviction algorithms can be adapted to keep-alive. Caching systems typically seek to improve hit ratios (the fraction of accesses that are cache hits). However, focusing on hit-rates alone does not necessarily translate to improved *system* level performance, if the objects have different sizes and miss costs. For instance, caching all small objects may yield a high hit ratio, but the infrequent misses of larger objects results in higher miss costs and poor system throughput. Therefore, we will also focus on minimizing the overall cold-start overhead, which is equivalent to the “byte hit ratio” used in caching systems.

4.1. Greedy-Dual Keep-Alive Policy

While many caching techniques can be applied to the function keep-alive policies, we now present one such caching-inspired policy that is simple and yet captures all function characteristics and their tradeoffs. Our policy is based on Greedy-Dual-Size-Frequency object caching [23], which was designed for caches with objects of different sizes, such as web-proxies and caches. Classical caching policies such as LRU or LFU do not consider object sizes, and thus cannot be completely mapped to the keep-alive problem where the resource footprint of functions is an important characteristic. As we shall show, the Greedy-Dual approach provides a general framework to

design and implement keep-alive policies that are cognizant of the frequency and recency of invocations of different functions, their initialization overheads, and sizes (resource footprints).

Fundamentally, our keep-alive policy is a function *termination* policy, just like caching focuses on eviction policies. Our policy is resource conserving: we keep the functions warm whenever possible, as long as there are available server resources. This is a departure from current constant time-to-live policies implemented in FaaS frameworks and public clouds, that are *not* resource conserving, and may terminate functions even if resources are available to keep them alive for longer.

Our policy decides which container to terminate if a new container is to be launched and there are insufficient resources available. The total number of containers (warm + running) is constrained by the total server physical resources (CPU and memory). We compute a “priority” for each container based on the cold-start overhead and resource footprint, and terminates the container with the lowest priority.

Priority Calculation. Our keep-alive policy is based on Greedy-Dual caching [53], where objects may have different eviction costs. For each container, we assign a *keep-alive priority*, which is computed based on the frequency of function invocation, its running time, and its size:

$$\text{Priority} = \text{Clock} + \frac{\text{Freq} \times \text{Cost}}{\text{Size}} \quad (1)$$

On every function invocation, if a warm container for the function is available, it is used, and its frequency and priority are updated. Reusing a warm container is thus a “cache hit”, since we do not incur the initialization overhead. When a new container is launched due to insufficient resources, some other containers are terminated based on their priority order—lower priority containers are terminated first. We now explain the intuition behind each parameter in the priority calculation:

Clock is used to capture the recency of execution. We maintain a “logical clock” per server that is updated on every eviction. Each time a container is used, the server clock is assigned to the container and the priority is updated. Thus, containers that are not recently used will have smaller clock values (and hence priorities), and will be terminated before more recently used containers.

Containers are terminated only if there are insufficient resources to launch a new container and if existing warm containers cannot be used. Specifically, if a container j is terminated (because it has the lowest priority), then $\text{Clock} = \text{Priority}_j$. All subsequent uses of other, non-terminated containers then use this clock value for their priority calculation. In some cases, *multiple* containers may need to be terminated to make room for new containers. If E is the set of these terminated containers, then $\text{Clock} = \max_{j \in E} \text{Priority}(j)$

We note that the priority computation is on a per-container basis, and containers of the same function share some of the attributes (such as size, frequency, and cost). However, the clock attribute is updated for each container individually. This

allows us to evict the oldest and least recently used container for a given function, in order to break ties.

Frequency is the number of times a given function is invoked. A given function can be executed by multiple containers, and frequency denotes the *total* number of function invocations across all of its containers. The frequency is set to zero when all the containers of a function are terminated. The priority is proportional to the frequency, and thus more frequently executed functions are kept alive for longer.

Cost represents the termination-cost, which is equal to the total initialization time. This captures the benefit of keeping a container alive and the cost of a cold-start. The priority is thus proportional to the initialization overhead of the function.

Size is the resource footprint of the container. The priority is inversely proportional to the size, and thus larger containers are terminated before smaller ones. In most scenarios, the number of containers that can run is limited by the physical memory availability, since CPUs can be multiplexed easily, and memory swapping can result in severe performance degradation. Thus for ease of exposition and practicality, we consider only the container *memory* use as the size, instead of a multi-dimensional vector.

We can also use multi-dimensional resource vectors to represent the size, in which case we convert them to scalar representations by using the existing formulations from multi-dimensional *bin-packing*. For instance, if the container size is \mathbf{d} , then the size can be represented by the magnitude of the vector $\|\mathbf{d}\|$. Other size representations can also be used. A common technique is to normalize the container size by the physical server’s total resources (\mathbf{a}), and then compute the size as $\sum_j \frac{d_j}{a_j}$ where d_j, a_j are the container size and total resources of a given type (either CPU, memory, I/O) respectively. Cosine similarity between \mathbf{d} and \mathbf{a} can also be used, as is widely used in multi-dimensional bin-packing.

4.2. Other Caching-based Policies

The Greedy-Dual approach also permits many specialized and simpler policies. For instance, allowing for different parameters in Equation 1 results in different caching algorithms. If only the access clock is used as a priority, and other parameters are ignored, then we get **LRU**, with its ease of analysis and generality which has been well established with over half a century of empirical and analytical work. Using only frequency yields **LFU**. Similarly, a size aware keep-alive policy can be obtained by using $1/\text{size}$ as the priority, which would be useful in scenarios where memory size is at a premium.

Other size-aware online algorithms with tight online theoretical guarantees can also be applied. We also implement the **LANDLORD** [54] algorithm, which can be understood as a variant of the Greedy-Dual approach. Landlord also considers the frequency, size and initialization cost of functions. When the server is full and some container is to be evicted, a “rent” is charged from each function based on its size and initialization cost (specifically, it is equal to $\min \frac{\text{initialization cost}}{\text{size}}$). This sub-

tly differs from Greedy-Dual-Size-Frequency: the decrease in priority is computed based on the state of all the cached containers, and not independently applied. Upon a function invocation, its containers get a “credit”, and their priority is set to their initialization cost. The containers with the lowest credits are evicted. Landlord has appealing and well-proven properties of its online performance: its competitive ratio (the performance compared to an optimal *offline* algorithm that knows future requests) has been well analyzed [54].

5. Server Provisioning Policies

Resource provisioning, i.e., determining the size and capacity of the servers for handling FaaS workloads, is a fundamental problem in serverless computing. In this section, we develop techniques that allocate the appropriate amount of resources to servers based on the characteristics of the function workloads. Resource provisioning policies must consider the rate of function invocations, the resource footprints of the functions, and the inter-arrival time between function invocations. To handle the interplay and tradeoffs between these factors, we use similar principles for provisioning that we used for developing our keep-alive policies.

The fundamental challenge underlying resource provisioning for FaaS workloads is the performance vs. resource allocation tradeoff. Running a workload on large servers/VMs provides more resources for the keep-alive cache, which reduces the cold-starts and improves the application performance. However, we must also be careful to not *overprovision*, since it leads to wasted and underutilized resources. Additionally, since function workload can be dynamic, resource provisioning must be *elastic*, and be able to dynamically scale up or down based on the load. We therefore present a *static* provisioning policy that determines the server memory size for a given function workload, and then develop an elastic-scaling approach for handling workload temporal dynamics.

5.1. Static Provisioning

In the last section, we have seen how keeping function containers warm in a keep-alive cache can help mitigate the cold-start overheads. The effectiveness of any keep-alive policy depends on the size of this keep-alive cache, and thus the server resources available, i.e., the server size. Our *static* provisioning policy thus selects a server size for handling a given workload. We want to optimize the resource provisioning to avoid over and under provisioning, both of which are detrimental to cost and performance respectively.

Having established that keep-alive policies are equivalent to cache eviction in the previous section, we now extend the use of the caching analogy further, to develop a caching-based provisioning approach. We claim that the performance vs. resource availability tradeoff of serverless functions can be understood and modeled using cache hit (or miss) ratio curves. Hit-ratio curves are widely used in cache provisioning and modeling, since they give insights into cache performance at

different sizes. Once a hit-ratio curve is obtained, it is used to provision the cache size based on system requirements. A common approach is to size the cache based on a target hit-ratio (say, 90%). Alternatively, the slope of a hit-ratio curve can be understood to be the marginal utility of the cache, and a cache size that maximizes this marginal utility is picked. This entails choosing a cache size which corresponds to the *inflection point* of the hit-ratio curve.

Hit-ratio Curve Construction. We use a function hit-ratio curve for determining the percentage of warm-starts at different server memory sizes. The hit-ratio curve is constructed by using the notion of *re-use distances*. A function’s reuse-distance is defined as the total (memory) size of the unique functions invoked between successive invocations of the same function. For example, in the request *reuse* sequence of ABCBCA, the reuse distance of function A is equal to $\text{size}(B) + \text{size}(C)$. The *distribution* of these reuse distances can yield important insights into the required cache size. If the cache size is greater than the reuse distances, then there will be no cache misses. This can be generalized to find the hit-ratio at cache size c :

$$\text{Hit-ratio}(c) = \sum_{x=0}^c P(\text{Reuse-distance} = x), \quad (2)$$

where the reuse distance probability is obtained by scanning the entire input function workload for all reuse sequences. Conveniently, the hit-ratio is the CDF (cumulative distribution function) of the reuse distances, which can be empirically determined based on all the computed reuse distances. We show one such hit-ratio curve constructed with reuse distances, for a representative sample of the Azure function workload in Figure 3. We can see that the hit-ratio curve of functions *also* follows the classic long-tailed behavior: the hit-ratio steeply increases with cache size up to an inflection point, after which we see diminishing returns.

This technique and observation informs our provisioning policy. We construct a hit-ratio curve based on reuse distances, and size the server’s memory based on the inflection point. Alternatively, we can set a target hit ratio (say, 90%), and use that to determine the minimum memory size of the server. Finding the reuse-distances for an entire trace can be an expensive, one-time operation, and takes $O(N * M)$ time where N is the number of invocations and M is the number of unique functions. However, sampling techniques such as SHARDS [50] can be applied to drastically reduce the overhead, making this a practical and principled technique for resource provisioning.

Limitations of the Caching Analogy. The error in hit-ratios with the reuse-distance approach in Figure 3 highlights an important facet where caching does not fully map to FaaS. The main difference is due to the limitations on the concurrent execution of functions. At lower cache sizes, a high miss rate results in higher server load, and hence a higher number of dropped requests, that the classical reuse-distance approaches do not capture. If all warmed containers of a function are

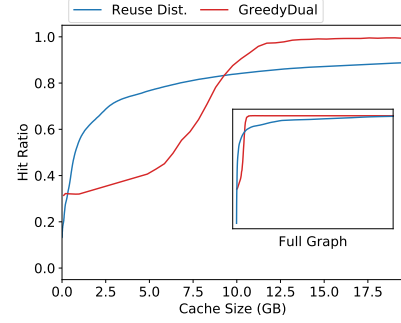


Figure 3: Hit ratio curve using reuse distances show slight deviations from the observed hit ratios due to dropped requests at lower sizes, and concurrent executions at higher sizes.

in use, then a new invocation results in a cold-start—which would be counted as a cache “hit”. Thus at lower sizes, the real hit-ratio is lower than the ideal. At larger sizes, *multiple* containers corresponding to concurrent invocations of a function will be present: which is again different from the caching model where objects are unique. Reconciling these differences is an interesting area of future work. However, we note that hit-ratio curves are only used for coarse-grained allocation. Moreover, our dynamic allocation policy described next can fix these errors using proportional control.

5.2. Elastic Dynamic Scaling

We also use the hit-ratio curve approach for a *dynamic* auto-scaling policy that adjusts the server size based on workload requirements. We assume that the FaaS server backend is running functions as containers either inside a virtual machine (VM), or is sharing the physical server with other cloud applications. In either case, it is important to be able to reclaim unused keep-alive cache resources and reduce its footprint, in order to increase the efficiency of the cloud platform.

Our vertical elastic scaling policy is simple and is intended to demonstrate the efficacy of a general caching based approach. We implement a proportional controller [3] which periodically adjusts the VM memory size based on the rate of cold-starts. Thus during periods of low rate of function invocations (i.e., arrival rate), the cache size can be reduced. This may *increase* the miss-ratio—but we care about the cold-starts (i.e., misses) per second, which is product of miss-ratio and invocations per second. Our controller monitors the arrival and cold-start rate, and uses the hit-ratio curve to decrease or increase VM size dynamically. We use VM resource deflation [46] to shrink or expand the VM by using a combination of hypervisor level page swapping, or guest-OS memory hot-plug and unplug.

Assume that we have a target miss speed (number of cold-starts/misses per second). For instance, this target value can be a product of the desired hit-ratio, h , and the average function arrival rate for the entire workload trace, $\bar{\lambda}$. Periodically, we monitor the exponentially smoothed arrival rate λ , and the observed miss speed. Our proportional controller adjusts the

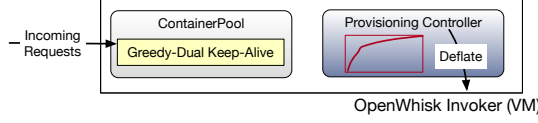


Figure 4: FaasCache system components.

cache size in order to reduce the difference between the actual vs. target miss speed. This error is used to compute the new miss rate, m , and the associated cache size c' as follows:

$$HR(c') = 1 - m = 1 - h \frac{\bar{\lambda}}{\lambda} \quad (3)$$

The new cache size c' is then determined by inverting the hit-rate function HR . Our vertical scaling controller is designed for coarse-grained VM size adjustments, and only tracks the workload at time granularities of several minutes. Our intent with this policy is to not be overly aggressive with the capacity changes, but only to capture the coarse diurnal effects. Therefore, we use a large error deadband: the cache size is only updated if the error is more than 30%. Finally, the memory scaling can also be combined with cpu auto-scaling based on the function arrival rate, using classical predictive and reactive auto-scaling techniques found in web-clusters [28].

6. Implementation

We have implemented the keep-alive and the provisioning policies as part of our FaasCache framework built on top of OpenWhisk (Figure 4).

Keep-Alive. FaasCache replaces the default OpenWhisk TTL-based keep-alive policy with the Greedy-Dual-Size-Frequency approach. For each initialized container, we assign and maintain the keep-alive prioritized ContainerPool, which is only a 100-line Scala modification. Each invocation of a function (OpenWhisk action) in ContainerPool records the launch time and when results are returned.

If the container was prewarmed before the invocation arrived, we record it as the function’s warm runtime. For new functions, the initialization overhead is captured and assumed to be the worst-case runtime until a warmed invocation is recorded. In the subsequent invocations, the initialization overhead is computed by subtracting the cold from the warm time. The function’s frequency and clock value are updated with each request. If the last container of a function is evicted, its cold and warm runtimes are stored and used to compute priority for its future invocations. To preserve the invocation fast-path, the ContainerPool is not kept sorted by priority. Instead, it is sorted by priorities only during evictions, when the lowest priority container(s) are terminated.

Provisioning. For the static provisioning, we compute the reuse distance distribution for a given workload trace, and assume stationarity—that it will be applicable on similar future workloads. We compute the reuse distances conventionally, by examining all reuse-sequences. The dynamic provisioning controller runs periodically (every 10 minutes), to deflate or

inflate the VM size, if the cold start rate deviates from the target significantly (by more than 30%). When the VM has to be shrunk, we use cascade deflation [46]. We shrink the ContainerPool first, and reclaim the free memory using guest OS-level memory hot-unplug and hypervisor-level page swapping.

Keep-alive Simulator. We have implemented a trace-driven discrete-event simulator for implementing and validating different keep-alive policies. Our simulator is written in Python in about 2,000 lines of code, and implements the various Greedy-Dual variants. It allows us to determine the cache hit ratios and the cold-start overheads for different workloads and memory sizes. Additionally, it also implements the static and dynamic provisioning policies for adjusting server size.

7. Experimental Evaluation

We now present the experimental evaluation of our caching-based keep-alive and provisioning techniques by using function workload traces and serverless benchmarks. Our goal is to investigate the effectiveness of these techniques under different workload and system conditions.

Setup, Workloads, and Metrics. For evaluating different keep-alive performance with different workload types, we use different trace samples from the Azure Function trace [44], which contains execution times, memory sizes, and invocation-timestamps for more than 50,000 unique functions. Since our goal is to examine performance at a *server* level, we use smaller samples of this trace for realistic server sizes, and replay them in our discrete-event keep-alive simulator. This also allows us to examine the behavior with different *types* of workloads, which is important because our keep-alive policies are designed to be general and workload-agnostic. We use the following three trace samples (more details in the Appendix): **RARE:** A random sample of 1000 of the rarest, most infrequently invoked functions. This is similar to the evaluation workload used in [44].

REPRESENTATIVE: A sample of 400 functions, sampled from each quartile of the dataset based on frequency—yielding a more representative sample with higher function diversity.

RANDOM: A random sample of 200 functions.

We are interested in two metrics: the cold-start ratio; and the average increase in the execution time due to cold-starts. The latter captures the heterogeneity in function initialization overheads and invocation frequencies. For estimating the initialization overhead of each function using the workload trace, we subtract each functions’ average runtime from its maximum runtime.

7.1. Trace-driven Keep-alive Evaluation

We compare all caching-based variants against the default keep-alive policy in OpenWhisk (10 minute TTL). We also compare against the histogram based keep-alive policy in [44], which is the state of the art technique. We have reproduced this policy (HIST) from the details in the paper, and have implemented it in a “best-effort” manner without any knowledge

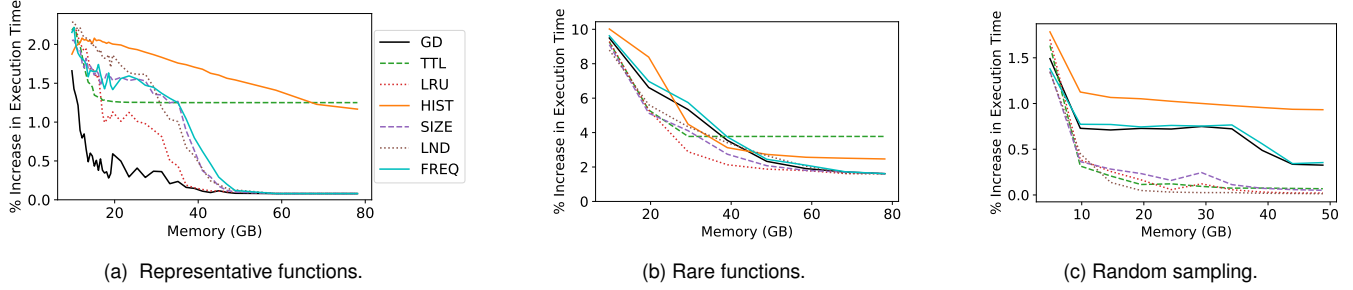


Figure 5: Increase in execution time due to cold-starts for different workloads derived from the Azure function trace.

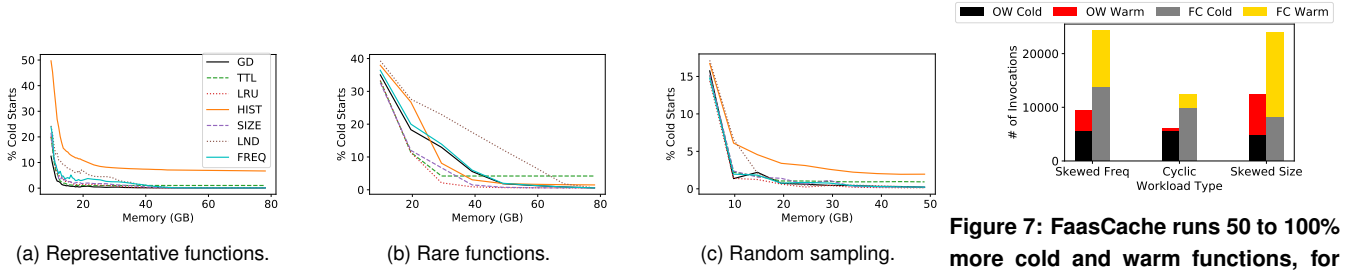


Figure 6: Fraction of cold-starts is lower with caching-based keep-alive.

Figure 7: FaasCache runs 50 to 100% more cold and warm functions, for skewed workload traces.

of the optimizations in the actual implementation. This is effectively a “TTL+Prefetching” policy: it uses a histogram of inter-arrival times to predict future function invocations. We also evaluate different Greedy-Dual variants: GD is our GDSF policy described in Section 4.1. The others are the caching-based variants described in Section 4.2: LND is Landlord, and FREQ is LFU. The increase in execution time for different traces and for different cache sizes is shown in Figure 5. The increase in execution time is the cold-start overheads averaged across all invocations of each function, and captures the user-visible response-time.

For the representative trace (Figure 5a), Greedy-Dual reduces the cold-start overhead by more than $3\times$ compared to TTL for a wide range of cache sizes (15–80 GB). Interestingly, it is able to achieve a low overhead of only 0.5% at a much smaller cache size of 15GB, compared to other variants, which need 50 GB to achieve similar results—a reduction of cache size by more than $3\times$. For rare functions (Figure 5b), caching-based approaches such as LRU reduce the cold-start overhead by $2\times$ compared to TTL for cache sizes of 40–50 GB. This shows that for rare functions, recency is a more pertinent characteristic, and the complex four-way tradeoff used in Greedy-Dual is not necessarily ideal in all workload scenarios. For this workload, the HIST policy outperforms TTL, as reported in [44]. However, it results in 50% higher cold-start overhead compared to caching-based approaches. Furthermore, because HIST uses only inter-arrival times, it is unable to perform well with heterogeneous representative workloads (Figure 5a).

Finally, the randomly sampled trace has a large number of infrequent functions because of the low probability of selecting the heavy-hitting functions. In Figure 5c, the recency component again dominates, and we see LRU outperforming other variants. The equivalence of LRU and TTL-based

caching for rare objects is well established [15, 32], which explains their similar behavior seen in Figure 5c.

Result: For representative, diverse workloads, our GD policy can improve the performance and shrink cache sizes by up to $3\times$. For more homogeneous workloads, LRU can outperform current TTL-based approaches by $2\times$.

We see a similar relation and behavior in the miss-ratio curves shown in Figure 6. Due to function heterogeneity, the cold-start overheads are not strictly correlated with cache miss ratios, and thus the differences between policies is different compared to the previously described actual cold-start overheads. We note that the average inter-arrival time for all three workloads is less than 36ms. As the IAT grows, the effectiveness of work-conserving caching-based approaches increases compared to TTL, as we shall see next.

7.2. OpenWhisk Evaluation

We now evaluate the performance of our FaasCache keep-alive implementation, and compare it to the vanilla OpenWhisk system which uses a 10 minute TTL. By leveraging Greedy-Dual caching, FaasCache is able to reduce cold-starts. This also reduces the number of *dropped* requests. OpenWhisk buffers and eventually drops requests if it cannot fulfill them. Because FaasCache more effectively selects evictions, its higher hit rate results in functions finishing faster, allowing more functions to be executed in the same time frame. To examine the effect of Greedy-Dual keep-alive on cold-start and dropped requests, we use a small workload trace comprising of four different functions: Disk-bench, ML inference, Web-serving, and Floating-point from Table 1.

In Figure 7, we use different kinds of *skewed* workloads: with a single function having a different frequency, a cyclic access pattern, and a skewed workload with 2 sizes. We see that FaasCache’s keep-alive can increase the number of warm

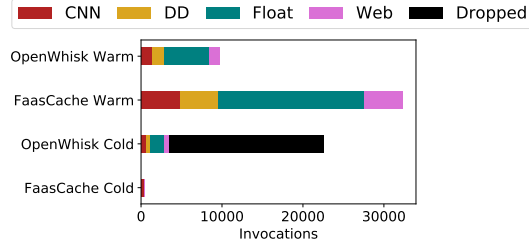


Figure 8: FaasCache increases warm-starts by more than $2\times$, which also reduces system load and dropped functions.

invocations by between 50 to 100% compared to OpenWhisk’s TTL. The difference in the total number of requests served (warm+cold) is because OpenWhisk drops a significant number of requests due to its high cold-start overhead and resultant system load.

Next, we use the skewed frequency workload and use functions from Table 1 to evaluate the impact on real applications. To generate the workload, the CNN, DD, and Web-serving functions have an inter-arrival time of 1500 ms, and the Floating-point function has a lower IAT of 400 ms. Figure 8 shows the breakdown of different function invocations for this workload on a 48 GB server. Interestingly, OpenWhisk drops a significant number (50%) of requests due to its high cold-start overheads. FaasCache increases the warm requests by more than $2\times$. Interestingly, the *distribution* of warm starts is also different. FaasCache’s Greedy-Dual policy prioritizes functions with higher initialization times, but penalizes those with large memory footprints. Because the floating-point function has a high initialization overhead (Table 1), it sees a $3\times$ increase in hit-ratio compared to OpenWhisk. *In practical terms, the improvement in keep-alive results in a $6\times$ reduction in the application latency.*

Result: FaasCache can increase the number of warm-starts by $2\times$ to $3\times$ depending on the function initialization overheads and workload skew. This results in lower system load, which increases the number of requests FaasCache can serve by $2\times$.

7.3. Effectiveness of Provisioning Policies

All our previous results have been with a statically allocated server, and we now illustrate the effectiveness of our dynamic vertical scaling policy described in Section 5.2. The goal is to dynamically adjust the cache size based on the workload. Our policy seeks to keep the miss speed (cold starts per second) close to a pre-specified target. This is shown in Figure 9—the target is 0.0015 misses per second. In this experiment, the cache resizing is done only when the miss speed error exceeds 30%, and we can see that the cache size increases with the miss speed, and decreases with it. Without the dynamic scaling, a conservative provisioning policy would result in a constant, 10,000 MB size. In contrast, the average cache size with our proportional controller is less than 7,000 MB. This 30% reduction means that FaaS providers can reduce their provisioned resources without compromising on performance.

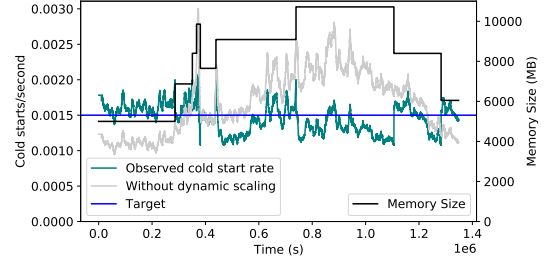


Figure 9: With dynamic cache size adjustment, the cold starts per second are kept close to the target (horizontal line), which reduces the average server size by 30%.

The freed-up resources can be used to accommodate additional cloud workloads (such as co-located VMs and containers). Our dynamic scaling is extremely conservative: increasing its aggressiveness by reducing the error tolerance below 30% will reduce average server size, but we seek to avoid the resultant small changes to memory-size to minimize fragmentation.

8. Related Work

Function Keep-alive. Mitigating cold-starts is one of the central performance problems in FaaS, and has received commensurate attention in both academia and industry. The initialization or startup time of functions can be reduced by reducing container startup overheads [42, 41, 13], or deploying functions inside ultra-light containers, VMs, or unikernels [38, 12]. While these approaches can reduce the cold-start overhead associated with the virtual environment creation, the other sources of overheads remain, such as losing all application initialized variables, cached files, etc. As we have shown, keep-alive essentially serves the role of caching, and fast startup only reduces the “miss” penalty, and does not eliminate it.

Principled keep-alive policies for functions have recently gained attention: the recent dataset and policy from the Azure function trace [44] shows the importance and effectiveness of keep-alive policies. In contrast to our work, their policy does not take the function size into consideration, and uses a time-series prediction approach (effectively capturing recency and frequency), and combines it with a predictive “prefetching” approach. As we have shown, function sizes are a crucial characteristic, and the use of caching allows the use of advanced analytical and modeling approaches for serverless computing in general. Earlier work has focused on simple “warm container pools” [37], or using polling to keep cloud functions warm [6, 2]. Our work considers functions individually—function scheduling with DAG based approaches [19] is effective for function-chains, and are orthogonal and complementary to our work. Hiding function latency using data caching (such as redis) for database applications is investigated in [29]. The ENSURE [48] system handles keep-alive and resource provisioning for CPU resources using queueing theory techniques. Our focus is on memory-constrained keep-alive and provisioning, and CPU-focused approaches are complementary to our work.

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