Efficiency in the Serverless Cloud Computing Paradigm: A Survey Study

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Abstract—Serverless computing along with Function-as-a-Service (FaaS) are forming a new computing paradigm that is anticipated to found the next generation of cloud systems. The popularity of this paradigm is due to offering a highly transparent infrastructure that enables user applications to scale in the granularity of their functions. Since these often small and single-purpose functions are managed on shared computing resources behind the scene, a great potential for computational reuse and approximate computing emerges that if unleashed, can remarkably improve the efficiency of serverless cloud systems—both from the user’s QoS and system’s (energy consumption and incurred cost) perspectives. Accordingly, the goal of this survey study is to, first, unfold the internal mechanics of the serverless computing and, second, explore the scope for efficiency within this paradigm via studying function reuse and approximation approaches and discussing the pros and cons of each one. Next, we outline potential future research directions within this paradigm that can either unlock new use cases or make the paradigm more efficient.

Index Terms—Serverless, Computational Reuse, Approximate Computing, Survey

I. INTRODUCTION

A. Serverless Computing Paradigm

The first generation of cloud technology, established around 2010, mitigated the burden of system administration and maintenance via consolidating servers and forming centralized data centers. It is anticipated that the second generation of cloud technology focuses on mitigating the burden of developing cloud native applications for programmers and solution architects via serverless computing paradigm [1].

Serverless computing provides the developers with high-level software abstractions, such as functions (a.k.a. Function-as-a-Service (FaaS)), and transparently deploying them, such that the user has the illusion of having no servers to manage [2]. Accordingly, modern software engineering methodologies, such as DevOps [3] and Continuous Integration Continuous Delivery (CI/CD) pipelines [4], have adopted the serverless computing paradigm to facilitate rapid cloud native application development. These methodologies instruct splitting an application into several functions that are invoked periodically or in response to an event. Behind the scene, each function invocation leads to execution of one (or an ordered set of) stateless micro-service(s) [5].

As shown in Figure 1, the serverless computing paradigm can be defined as the combination of FaaS and BaaS. While FaaS focuses on the front-end development of functions in a wide-variety of programming languages, Backend-as-a-Service (BaaS) focuses on the transparent and isolated execution of the functions. BaaS is also in charge of scheduling, monitoring, and transparent elasticity of the functions (microservices). In summary, we can say Serverless = FaaS + BaaS [1]. It is noteworthy that serverless computing is a loose term and it does not strictly enforce the user’s code to be based on FaaS.

![Fig. 1: Serverless computing paradigm mitigates the burden of developing cloud-native applications via offering a high-level programming abstraction (FaaS) and transparently executing them (BaaS). Different applications can define and trigger functions with minimal configurations needed for each function.](image)

A common approach to handle function calls (henceforth, called users’ requests or tasks) in BaaS is to gather the requests from all triggering sources (e.g., API calls, timer, and events) into a central queue. Then, a resource allocator maps these requests to scalable pools of computing resources. To isolate the requests from each other and to avoid the side-effects of using shared resources, often, some form of task sandboxing, such as containers or micro Virtual Machines (e.g., Firecracker VM [6]), is employed.

B. Scope for Efficiency in the Serverless Computing Paradigm

The shared and transparent nature of serverless systems offer a great potential for efficiency—both from the system and user perspectives. From the system end, metrics such as throughput, utilization, energy consumption, and carbon emission, and from the user end, Quality of Service (QoS)
(e.g., turnaround time), and the user’s incurred cost can be potentially improved. The potential efficiency improvement can be unleashed, primarily via smart resource allocation methods that can identify identical and/or similar tasks in the serverless system. Accordingly, two main directions to improve the efficiency of serverless computing can be enumerated as follows:

(A) **Computational reuse** that avoids redundant processing of identical or similar function requests. It focuses on reusing the whole or part of the execution, underlying platform (e.g., container), and allocated resources of a process. A well-established reusing approach is based on caching [7] that can avoid re-execution of a recent task. While caching is *retroactive* by nature and can only capture identical tasks, in the serverless computing, there is scope for *proactive* reusing. In this manner, similar (or identical) concurrent function calls can be aggregated to one merged task to reuse part of (or the whole) computation.

(B) **Approximate computing** that can be employed in circumstances where lower quality (less accurate) results can be tolerated. Using approximate computing, cost, energy, and response time of the serverless cloud can be reduced. Some common approaches for approximate computing include scaling down the precision of the invoked function, down sampling its input data, skipping some of the computation steps in the function workflow, or approximating the function result from the similar or recent invocations.

![Fig. 2: Comparison of three scenarios to handle similar function invocations: (a) separately executing functions; (b) reusing load and decode micro-services of the function calls; and (c) approximating a function call and make it compatible with an existing one.](image)

As a motivating example, consider the case of a serverless cloud used for processing live video contents before streaming them to the viewers [8]. As shown in Figure 2, the system has `transcode(v,c)` function to change the codec of video segment `v` to `c`; and `bitrate(v,b)` function to change the bit-rate of video segment `v` to `b`. The figure shows possible scenarios of function execution in the system. Consider two invocations of `transcode(v1,c1)` and `transcode(v1,c2)` coexist in the system. Without merging, shown in Figure 2(a), the two invocations separately load, decode, and encode the video. Alternatively, when merging these invocations into one task, shown in Figure 2(b), the load and decode operations that are identical can be reused, and then encode operation into two different codecs is carried out individually. Because `transcode()` function cannot be approximated, consider `bitrate()` function to explain function approximation. In this case, shown in Figure 2(c), one invocation, `bitrate(v1,b2)`, can be approximated to `bitrate(v1,b1)`, hence, the whole execution chain can be reused.

### C. Paper Structure

Prior to study efficiency in the serverless cloud computing, we need to learn about nuts and bolts of the serverless computing. Accordingly, in the rest of this survey, we first dive deep into the serverless computing details and study its anatomy. Then, we concentrate on the efficiency of the serverless systems. In fact, the examples described in the previous part only show one possible scenario for reusing and approximating a function. We are to explore the potential for different forms of function reuse and approximation that can be unleashed, thereby, enabling efficient serverless cloud computing. An overview of the approaches that are studied in this work is shown in Figure 6.

We believe this survey study can help the research community to further develop these areas and build more efficient serverless computing platforms. The rest of the paper is organized as follows: Section II introduces the current state of commercial and research-based serverless computing platforms. Then, Section III discusses the potential of computational reusing on various parts of the serverless computing platform. Next, Section IV discuss the approximate computing techniques that can be applied on the serverless computing platforms. Section V lists some potential development directions to increase data and compute reusability in the serverless computing platforms. Finally, we conclude this paper in Section VI.

### II. NUTS AND BOLTS OF SERVERLESS COMPUTING PARADIGM

#### A. Serverless Versus Conventional Cloud Paradigms

Serverless computing provides a higher level of abstraction in compare to the conventional cloud service paradigms. Figure 3 elaborates on this point by showing various forms of server deployment and the abstraction level they offer. In this figure, from left to right, we have:

- In-house server deployment that involves the users in all the server acquisition, maintenance, and management (e.g., scheduling and scaling) details.
- Infrastructure-as-a-Service (IaaS) that mitigates the burden of server acquisition and maintenance, but still involves the user in server management and configuration details.
- Platform-as-a-Service (PaaS) offers one more level of abstraction and covers server management too. However,
the abstraction is offered behind a specific software platform (e.g., a certain programming language or a database management system). Therefore, to develop and deploy an application, the user has to engage with and configure various PaaS services (e.g., for compute, load-balancing, and database).

- Serverless computing and FaaS abstract the users from both the server maintenance and management too. However, unlike PaaS, using serverless entails breaking the application into multiple functions that each one can potentially be developed with a different programming language. Then, the entire function execution management, such as resource allocation, scaling, scheduling, fail-over, and platform configurations, are transparently handled by the underlying serverless platform. Thus, this paradigm simplifies the software development process and enables the users to become solution oriented and focus on their business logic, rather than specific server configuration details.

Although defining an individual trigger for each function is simpler and more popular, defining multiple function triggers together in form of a workflow schema has its own advantages. First and foremost, the schema can provide useful metadata for the resource allocator in BaaS to identify parallelizable tasks and schedule them together, thereby, improving resource utilization and users’ QoS (e.g., waiting time). Second, using the schema, complex function workflows can be defined that otherwise would be time-consuming and error-prone to build [13]. Third advantage is the portability and reusability that employing a workflow schema offers. While per-function triggers are tied to each function, the workflow of functions is defined within a schema file with a specific syntax [13]. The schema can be used to effortlessly re-deploy the application on the same or a different serverless platform.

C. The Matter of “Function State” in Serverless Computing

Functions in the serverless computing are originally designed to be stateless. That is, a function does not maintain (i.e., memorize) any state data (e.g., shared variables) between consecutive invocations and its output is merely subject to its input arguments. Statelessness is, in fact, a primary practice in functional programming [14] that prevent side-effects [15], thereby, improving software robustness and predictability. This implies that, for a given input, a stateless function always yields the same output, thus, the function results can be reused (e.g., via caching). In addition, stateless functions mitigate the overhead of serverless platforms by relieving them from maintaining data consistency and synchronization in executing functions [2].

Despite the benefits of stateless functions, some applications naturally demand the state to be maintained. Refactoring stateless version of these applications makes them prohibitively
inefficient. For instance, a big data analytics workload (e.g.,
semantic search [16]) cannot afford loading the entire dataset
for each function call, nor can it afford forwarding the output
to other functions along the workflow. A common approach to
circumvent this situation is to persist the state on the external
storage services [17]. However, Pu et al., [18] demonstrate
that employing external storage to carry out serverless data
analytics is up to 500x slower than using IaaS cloud.

In fact, the matter of state is still an open challenge in
the serverless paradigm. Several research works have been
undertaken to offer a built-in stateful serverless solution [19].
Such solutions often employ some forms of key-value and/or
file-based storage. Sreekanti et al., [20] develop a stateful
serverless platform, called Cloudburst, using Anna [21], which
is an auto-scaling key-value storage, to persist the state.
Pu et al., propose Shuffling [18], a stateful domain-specific
serverless platform for data analytics, with a hierarchical state
 persistence—a fast layer on the memory and a slower one on
the device storage. Schleier-Smith et al., develop a dedicated
POSIX-like file-storage system to enable a stateful serverless
computing, called FAASFS [22]. It tackles multiple challenges
of providing a shared file system across functions, such
as cache and transactional consistency [23], [24]. Shillaker
and Pietzuch evaluate stateful functions within the FASSM
platform [25] via sharing the state in form of both memory
segments and files.

D. Function Isolation in Serverless Computing

In principle, virtualization is not a must for FaaS and
serverless cloud offerings. A user can essentially call
a function using a command in the general form of
client.invoke(FunctionName='F',
Payload=Data) [26], [27]. Upon invocation, the FaaS engine
can interpret the function and form a task that can be then
directly executed on the host machine (i.e., bare-metal resource
provisioning). However, lack of isolation in bare-metal raises
security concerns, particularly, when there are coexisting tasks
from multiple users on shared computing resources. Therefore,
some form of sandboxing is required to isolate the execution
environment of each function call. Broadly speaking, such isolation
can be provided at the following levels: application-level runtime frameworks (WebAssembly [28]), Operating system-
level (containerization), and hardware-level (virtualization).
The layer-view of each isolation platform for the serverless
functions is provided in Figure 4. The software stack of each
platform implies the overhead imposed by that platform. In
this figure, the left-most boxes serve as the legend—dedicating
a color for each layer. The white space(s) in each isolation
platform express the absence of the corresponding layer(s),
represented at the left-most side.

WebAssembly: WebAssembly (a.k.a. Wasm) is an open
standard that enables generation of portable binary-code from
various high-level programming languages and interfaces the
binary-code with the underlying host environment. The binary
can be executed both as a standalone code or within a Web
browser. WebAssembly and particularly its software-fault iso-
lation (SFI) feature [25] provides software-level isolation that
can be used by serverless function solutions. FAASM [25] is
an instance of serverless frameworks that executes functions on
WebAssembly. Also, in Kruslet [29], containers are replaced
with WebAssembly in the context of Kubernetes orchestrator
[30]. Kruslet listens to the Kubernetes event stream and upon
receiving a task request, it executes the task on WebAssembly
runtime [2], instead of creating (container) pods.

Although WebAssembly can satisfy the needs of small-
size functions, in many use cases a specific environmental
setup, such as software packages and libraries, is required.
Just-in-time preparation of these dependencies for each func-
tion execution is time-consuming in WebAssembly. Moreover,
making use of WebAssembly implies compiling the functions
to WebAssembly that curbs the generality of the serverless
solution. Therefore, for the sake generality and to maintain
cost- and time-efficient preparation of functions, container or
virtual machine (VM) technologies are more commonly used
in the serverless domain.

Containerization: The most common way to package
and isolate the function is through containerization [27]. In
this technology, a function is encapsulated within a widely-
accepted container standard, termed Open Container Image
(OCI) format [31], that is supported in all modern container-
ization solutions. Any programming language and/or software
dependency can be supported, thus, the desired generality
of serverless is accomplished. Unlike VMs that emulate the
whole operating system stack, containers share the host kernel,
thereby, both the memory and storage footprints are reduced.
In fact, this pattern of reusing the kernel is extended to other
layers within the container image. Specifically, container im-
ages have a layered structure that encourages reusing software
packages across these images. Container engines use a method,
called union mounting, through which a container is formed
dynamically (i.e., on-demand) via fetching its (read-only)
layers at the runtime. Further details about union mounting
is discussed in Section III-D.

Virtualization: Virtualization is the traditional method of
providing strong isolation in cloud computing. Due to in-
cluding the whole operating system and application stack in
the VM image, in general, VMs suffer from a high memory

![Fig. 4: A bird-eye view to the underlying layers of various isolation platforms for serverless functions. From left to right, respectively, there are functions on bare-metal (e.g., via WebAssembly), on various forms of VMs, and on a container. The number of layers implies the overhead of each isolation platform.](image-url)
and storage footprints. In addition, VMs introduce a high startup delay [32] to boot up, hence, they are not a perfect fit for frequent starts and terminations inherent to the serverless functions [11]. As such, VMs are usually employed as the underlying platform of the serverless frameworks, rather than an isolator of each individual function. In this case, function isolation within the VM is offered either via application-level solutions (e.g., WebAssembly) or containers.

**Micro-VM:** Although VMs are generally not ideal isolators for functions, there are some notable efforts to customize VMs for functions. Firecracker [6] is an AWS open-source project that provides a lightweight VM (a.k.a. micro-VM) with a high isolation and low startup delay. It is being used by the AWS FaaS and serverless platforms (e.g., AWS Lambda and AWS Fargate). Firecracker works in a similar fashion to other full VM technologies that offer an isolated operating system environment to the user. However, unlike other KVM-based VMs, which sit on top of the QEMU in the user space, Firecracker directly communicates with the KVM (kernel) layer via a customized emulation stack. While such a highly simplified emulation stack is sufficient for ordinary tasks, it lacks some notable features, such as libraries to support GPU and specialized CPU instructions. Another downside of Firecracker is its deployment inflexibility, because it only has to be deployed on top of the KVM hypervisor.

**Unikernel** [33] is another lightweight VM-based technology. Similar to micro-VMs, it bypasses the user space of the hypervisor. Moreover, it bypasses the user space of the guest operating system too. Thus, to run a function inside Unikernel, required guest OS libraries have to be incorporated at the application level. That is, the applications that are deployed within Unikernel have to encapsulate all their required libraries. Storing libraries on each function image causes a substantial data redundancy and overhead. As such, Unikernel utilization becomes limited to small functions that do not require large dependencies.

### E. Memory Contention in Serverless Computing: Cold Start vs Warm Start Functions

Unlike conventional cloud computing services (e.g., IaaS services) in which users are in charge of explicitly running and terminating their services, in serverless computing, the platform automatically allocates resources and runs the services upon request, and then de-allocates them when they are not needed anymore. This automated allocation and de-allocation of resources is realized via transient isolation plat-
forms, *e.g.*, containers, that also enable charging users only for the times the services (functions) are being used. Ideally, the containers should be maintained in memory to warrant fast execution of the functions, which is critical in latency-sensitive applications [34]. However, in a large-scale serverless cloud, maintaining all the functions in memory is infeasible, owing to both hardware and economic limitations, thus, there is a memory contention between containers to access the memory. Efficiently resolving this contention and determining which functions should remain in the memory and which ones should be loaded in an on-demand manner is a challenging problem for the BaaS part of the serverless platforms.

In a container-based serverless platform, a function container that resides in the memory to be launched rapidly is generally referred to as a *warm start* container. In contrast, the function that must be loaded from the storage system in an on-demand manner is referred to as a *cold start* container [5]. The cold start function involves loading the container image that (depending on the container size) imposes a nontrivial time overhead and can potentially dominate the function execution time [5]. The overall cold start overhead of a function can be approximated via multiplying the function invocation frequency and the cold start overhead.

Note that, calculating the cold start overhead can be further complicated when other system factors, such as elasticity and storage location, are taken into consideration. Importantly, there can be a lower-level cold start in which a function has to undergo the elasticity overhead and wait for the underlying VM (or hardware) to be made available, before it can be loaded into its memory. Depending on the storage location, the cold start overhead can be sub-divided into multiple tiers of cold, namely local storage cold and repository cold. In the former, the function container can be retrieved from a local storage, whereas, in the latter, the function must be retrieved from a remote storage (*e.g.*, on a central cloud) that implies a longer overhead. These factors show that in an efficient serverless, the BaaS part must handle the cold/warm start of each function individually and based on the function characteristics. In Section III-D2, multiple approaches to strategically manage the containers and mitigate the cold start frequency are introduced.

### F. Heterogeneity in Serverless Computing

Serverless computing systems were originally pioneered with the aim of creating an illusion that there is no server to manage. Fulfilling this aim is viable when the underlying computing resources are either homogeneous or of the same architecture (*i.e.*, consistently heterogeneous [35]). As such, to date, commercial Serverless computing providers support only various forms of CPU-based machines that are auto-provisioned by the back-end to match the function desires [36]. However, to accommodate more flexibility and efficiency in FaaS and serverless computing, inconsistently heterogeneous systems with a combination of CPU, GPU, TPU, FPGA and other forms of emerging ASICs [36], [37] are desired. In this manner, domain-specific programming languages, framework, APIs, and libraries (*e.g.*, CUDA [38], Tensorflow [39], and OpenCL [40]) can be accommodated.

To the best of our knowledge, nuclio [37] is the only commercial serverless platform that offers GPU-based machines. However, with the slow-down in general-purpose computing and the rise of the specialized computing [41], we expect to have application-specific hardware to become more prevalent on serverless platforms in the near future [36].

Supporting heterogeneous computing on a large scale serverless system, implies addressing several research challenges. First and foremost, is the programming in different languages. Heterogeneous machines require the code to be written in a specific way. For instance, a function code that is written for a CPU-based machine has to be refactored to be able to utilize GPU. Demanding the user to intervene and provide the function code based on the machine type is against the ideal user transparency promised by the serverless computing. To maintain the transparency and at the same time supporting heterogeneity, FaaS engines must be able to run the same user code on multiple on heterogeneous machines. In domain-specific applications such capability can be achieved if the user function runs on top of heterogeneous supported frameworks (*e.g.*, Tensorflow for machine learning tasks, FFmpeg [42] for multimedia processing tasks).

Provided that the user functions can utilize heterogeneous resources, the next challenge is how to schedule and provision such functions (tasks) on the heterogeneous resources efficiently. Unlike many HPC configurations, serverless tasks are small and require low latency. Therefore, a light-weight and low latency scheduling method that is aware of the machine heterogeneity is desired. Moreover, to make informed scheduling decisions in a heterogeneous system, a function execution-time profiler is needed to provide an estimated execution-time of a given function of different machine types [43]. Since each serverless function often recurs multiple times, execution-time profiling can be carried out [11], [44]. However, to reduce the uncertainty in the execution-time prediction, thereby, making more informed scheduling decisions, on different machine types, function profiling must be performed proactively and in an explorative way to examine the infrequently-used options and collect their execution time statistics. Importantly, scheduling new user-defined functions, for which there is no prior execution-time statistics, is more challenging. Methods based on Transfer Learning [45] should be developed to enable inferring the execution time of the new function based on other existing functions on different machine types. A similar challenge and solution can be posed upon addition of new machine types to the serverless system.

### G. Serverless Cloud Solutions

In this part, we first survey various commercial and open-source serverless cloud solutions that are available and compare them based on the aspects described in the previous parts. Table I summarizes the specifications of different serverless solutions. We note that, in addition to the platforms listed in the table, there has been several other serverless computing projects (namely, Fission Workflow [46], Kubeless [47], Iron Function [48]) that were discontinued. We have excluded these platforms from the table.
Leveraging our observations from the studied serverless solutions, in the next part (Section II-G3), we come up with a generic architecture that include the main components of these systems.

1) Public serverless clouds: FaaS and Serverless computing have commercially been made available via AWS Lambda service [49] for the first time. AWS Lambda executes each function based on a user-defined trigger and charges the user only for the actual resource usage time (i.e., function execution time). The Lambda service arguably pioneered and shaped other FaaS services. Nowadays, Amazon also offers other serverless computing services—most notably notably AWS Step Functions [50] and AWS Fargate [51]. AWS Step Functions is a workflow service that can chain a sequence of Lambda functions and other AWS services to build a serverless application. It manages the workflow in terms of scheduling, failure, and parallelization so that the users can focus on the higher-level business logic. Alternatively, AWS Fargate operates based on containers rather than functions. In fact, it is an example of a serverless service that is not built from a FaaS platform.

After AWS, multiple competing serverless computing cloud services, such as Azure Functions [52], Google Cloud Functions [53], and IBM Cloud Functions [54] were emerged. These services are consistently evolving with different set of features. Notably, recently, Azure released Durable Functions [55] to extend the Azure Function service to support stateful workflows.

2) Private Serverless Clouds: Although public serverless platforms are increasingly popular, they come with the vendor lock-in risk and the trustworthiness issue that is inherent to public cloud services. Therefore, multiple open-source serverless platform projects have been developed to allow serverless deployment on self-hosted servers [56]. OpenFaaS [57] and Apache OpenWhisk [58] are two popular open-source serverless platforms that dominate the private serverless cloud market.

OpenFaaS handles each function as a container that are deployed through Kubernetes. Therefore, a user can develop functions in the programming language of her choice. A packaging script creates a container image with the user’s function encapsulated in it. Each function container is stored and managed in the Docker Registry [59] and also in the function store. While OpenFaaS is open-source and free to use, OpenFaaS PRO [57] is developed for commercial purposes.

OpenWhisk is another popular open-source serverless cloud platform backed by the Apache foundation [60]. In compare with OpenFaaS, OpenWhisk has a bigger developer community and many more features. Similar to OpenFaaS, OpenWhisk project is also based on Kubernetes. It also utilizes many features from other open-source products, such as Kafka [61], CouchDB [62], Nginx [63], Redis [7], Zookeeper [64]. This allows the OpenWhisk to be very scalable and, at the same time, feature-rich. However, this makes the learning curve of deploying and managing OpenWhisk steeper. OpenWhisk is also offered commercially on IBM Cloud Functions [54]. Fission [65] is another serverless platform that is based heavily on Kubernetes. However, it does not integrate itself into Kubernetes the way Kubeless does.

Fn Project [66] is an open-source platform that works with Docker containers in its underlying layer. It supports API-based event triggers (e.g., in form of web requests). Fn Flow [67] is an alternative version of Fn that can support workflows. Although both projects have attracted limited users from the open-source community, Oracle still offers them as commercial serverless solutions.

Knative [68] is a fast-growing open-source project led by IBM and Google. Similar to Kubeless [47], which has been discontinued, Knative sits on top of Kubernetes and enables it to handle serverless workloads. According to the Cloud Native Computing Foundation (CNCF) survey [69], Knative has been the top installable serverless solution in 2020. Knative project includes three main components, namely Build, Serve, and Event. Build is in charge of source code management, containerization, and making it deployable by Kubernetes. Serve deals with service deployment, managing micro-service revisions, routing requests to different versions of micro-services, automatic scaling, and scale to zero. Finally, Event takes care of creating function triggers and forming workflow pipelines.

3) General Architecture of Serverless Clouds: Considering the common architectural components of the studied serverless platforms, we design a generic architecture, depicted in Figure 5, that is composed of an underlying function execution framework and eight components on top of that that take care of different aspects of serverless management. Note that, a given serverless platform may only have a subset of these components and it may categorize them differently. For instance, Knative’s main components (Build, Serve, and Event) can be mapped to Packaging, Execution, and Trigger group of components. Function Packager is only needed if the framework requires function code to be transformed into the container or other forms of the compiled function. Workflow Pipeline only exists in the frameworks that support function workflows.

III. REUSING OPPORTUNITIES IN SERVERLESS CLOUDS

Reusing is defined as a way(s) to reduce the resource usage and increase the efficiency via deduplicating data or compu-
tions that share a certain level of similarity. Historically, reusing (e.g., in form of caching) has been a fundamental approach to achieve software and hardware efficiency. In this section, we study reusing in the context of serverless computing and describe how it can be potentially advantageous for both cloud providers and users. Then, we explore a wide-variety of techniques to carry out computational reuse in the serverless context. A summary of these techniques is shown in Figure 6.

A. Advantages of Reusing in Serverless Computing

1) Cost efficiency: Serverless cloud computing promotes itself as a cost-efficient computing paradigm where users only pay for their actual resources usage [70]. The serverless paradigm encourages cost efficiency in two main ways: (A) Allocating multiple users’ tasks on shared underlying resources; and (B) Adopting reusability techniques (e.g., for containers) that are allowed by the serverless paradigm.

2) Quality of Services (QoS): Computational reuse deduces data and computation redundancy. In addition to the user’s cost-saving, this can directly and indirectly impact the users’ perceived QoS. The direct impact is for the tasks that can complete early by reusing already available data. Such reusing makes the system less busy, thereby, making the resources more available to the tasks that cannot directly benefit from reusing.

3) Energy efficiency: Reusing in the serverless platforms can reduce the energy consumption in two levels: (A) At the macro level, in the cloud datacenters; and (B) At the micro level, in the energy-limited edge devices [71].

At the macro level, in addition to the resource sharing mentioned earlier, serverless platforms can reduce the energy consumption by means of rapid scaling. This avoids the need for resource over-provisioning that is commonly practiced in IaaS clouds to cope with the surge demands. At the micro level, serverless edge systems accommodate seamless task (or workflow) live-migration from the energy-limited edge devices to the cloud tier [72], [73]. In fact, migration is a way to reuse the performed execution rather than restarting it. In an opposite direction in the edge-to-cloud continuum, the migration of services to the edge tiers can help energy-efficiency by means of reducing the volume of transferred data [73].

B. Deterministic Versus Semantic Reusing

Deterministic reusing refers to the set of techniques that can detect reusable computation or data in a definitive manner and perform the reusing without altering results of the involved tasks. That is, these techniques do not require to infer the semantic similarity between two data or two computations. An example of deterministic reusing is when a user requests for a re-execution of stateless video encoding function with identical specifications on the same video. As the stateless function output depends entirely on its input, a re-execution of task executed with the same input arguments yields the same result. Thus, the video result of such task execution can be cached and reused. Majority of the deterministic reusing techniques operate based on detecting frequently-used computation and/or data and caching them to be reused at a later time [74]. Accordingly deterministic reusing techniques can be categorized into data reusing (a.k.a. caching) and process reusing that are elaborated in the next subsections.

Alternatively, semantic reusing aims to find a semantic relationship between not-so-obvious similar (i.e., non-identical) data [75] and perform reusing on them. In a sense, semantic reusing can be viewed as an approximation approach, due to similarity detection and the fact that the execution results of the involved tasks are not deterministic. Moreover, the semantic similarity detection is prone to misinterpretation, thus, can potentially lead to incorrect results.

An example of semantic reusing can be in an application that provides ambient perception for blind and visually impaired users by detecting obstacles in their environment (e.g., [76]). These users often visit repeated locations and interact with objects they have previously encountered during their day-to-day activities. The captured pictures of these objects are digitally different because they are captured from different angles or under different light conditions. However, these pictures are semantically representing the same objects [77]. Accordingly, a reusing mechanism that can pre-process incoming images and detect whether a semantically similar one has been (or is being) processed can be helpful.

Further details about different approaches to perform semantic (approximate) reusing are discussed in Section III-E.

C. Data Reusing

Data reusing is the act of saving certain data to be reused at a later time. It is an integral part in different levels of modern computing systems—from the hardware level to the compiler and execution levels. In the particular case of serverless computing and FaaS, the fact that tasks are fine-grain (function level) and stateless provides an ideal opportunity for data reusing via saving (caching) and reusing the results of each function execution.

Data reusing is predominantly achieved via caching operation. Caching is an optional, but very popular, operation in the computing systems to mitigate the slow down resulted from accessing storage systems, hence, accelerating the task execution. That is, the system can still function correctly, even if it misses the cached data and retrieves it from the storage. Since caching is limited and often costly, establishing a trade-off between cost and efficiency in the caching scheme is of paramount importance. An extensive cache space imposes a significant cost, whereas, an inadequate cache space leads to missing reusable function results that, in turn, increases the re-computation cost and the response time [78], [79].

Based on the way data is stored and reused, the data reusing techniques fall into four categories: (1) Task caching; (2) Intermediate data caching; (3) Function consolidation; and (4) Incremental computing solution. These categories are explained in the next parts.

Task caching: Task caching is the act of capturing and reusing the end result of a task (function) execution. Due to the stateless nature of functions in the serverless systems, this
Fig. 6: Taxonomy of approaches for efficiency in the serverless cloud computing platforms. The approaches are classified into two categories that are based on the computational reuse, and then based on approximate computing. There are approaches in the intersection of these two, known as approximate reusing.
caching technique can be deployed in a transparent way from the user. The cached data can be quickly identified by making use of the hash value of the function call signature that is composed of the function name and its arguments [80]. The cache table can be either shared across users (i.e., public) or maintained separately for each individual user (i.e., private). Unarguably, a public cache table maximizes the likelihood of data reusability across functions of all users. However, it can be vulnerable to cache poisoning attacks [81]. Alternatively, a private cache table offers a better security via segregating the cache table either based on the user or the function [82].

**Intermediate data caching:** Intermediate data caching maintains partial results of the execution, rather than the final result. The technique is usually suited to large tasks with multiple computing steps, in which caching the intermediate result offers a higher chance of reusability than caching the final result [20], [21], [79]. Intermediate result caching can be offered in form of a key-value storage for the (stateful) functions [7]. To achieve reusability, this caching technique requires the function code to explicitly store and retrieve partial results from the caching system. Thus, it is not transparent from the user.

**Function Consolidation:** Another variation of data reusing occurs in the scheduling of workflows [83]–[85] that include multiple functions and data dependency between them. In such workflows, because each function can be potentially allocated to a different machine, the overhead of transferring the output of one function to be used as the input of another function can be significant [83]. Such an overhead can be reduced by fusing small functions together. That is, two or more functions can be consolidated to form one big function, such that the whole function is executed together and the data transfer overhead is eliminated. Function consolidation can be employed at the programming level via defining less granular functions, however, doing so is against the microservice-based software engineering methodology and makes the function maintainability cumbersome.

A more efficient approach for function consolidation is to let users maintain their fine-grain functions and let a framework in the back-end automatically carry out the fusing [83] process without any user intervention. The main challenge in this approach is how to balance reducing the data transfer overhead against the resource inefficiency potentially caused by forming coarse-grain (consolidated) functions [83]. The reason for inefficiency (and potentially resource wastage) is that coarse-grain functions limit the ways tasks can be allocated, thereby, reduce the flexibility of resource allocation methods. For instance, consider a workflow with two chained functions where the output of one function to be used as the input of another function can be significant [83]. Such an overhead can be reduced by fusing small functions together. That is, two or more functions can be consolidated to form one big function, such that the whole function is executed together and the data transfer overhead is eliminated. Function consolidation can be employed at the programming level via defining less granular functions, however, doing so is against the microservice-based software engineering methodology and makes the function maintainability cumbersome.

**Incremental computing:** The fourth category of data reusing is the incremental computing technique [75]. Similar to the task caching, this technique also caches the task result. However, the cached content is reusable beyond the tasks with identical input arguments. Incremental computing utilizes a correction function to adapt (i.e., prune and expand) the cached results based on the new input. A common use case of incremental computing is in data analytics [75], [86]. For instance, consider a repetitive function (query) that is regularly applied against a database with minor daily updates. A naive way to handle the query is to thoroughly search the database every time. Alternatively, an incremental reusing technique retrieves the results of the prior day and corrects them by pruning the invalid records and adding new ones via searching only within the updates in the database since the prior day. It is noteworthy that incremental reusing is a highly context-specific technique and currently it is not implemented within the general-purpose serverless platforms. For instance, Zhang et al., [87] propose a serverless and FaaS-based platform that takes advantage of incremental computing the video analytics context. Their use case employs a deep neural network (DNN) model for video object classification. The model requires frequent updates to its weights to gain the maximum accuracy with the ever-changing datasets. To avoid excessive cost of re-training the model frequently, their platform deploy incremental machine learning [88] technique to keep up with the gradual changes in the input datasets. One way to enable incremental computing in the future serverless platforms is to allow users to define multiple auxiliary functions, in addition to the main function. The auxiliary functions can include: a subtract function (to remove part of the existing results that are not valid for the input argument) and an addition function (to include new results to the existing ones and adapt them based on the new function arguments).

**D. Container Reusing**

Apart from the data reusing, serverless efficiency can be gained via reusing at the sandboxing platform (i.e., container) level. More specifically, container reusing can be carried out at the container image or at the container instance levels that are described in the following subsections.

1) **Container image reusing:**

**Union mounting:** Union mounting [89] is a well-established approach to reduce the container image footprint (and hence, start-up overhead of the container). In union mounting, a container image stored as multiple separate components (layers) that can mount together to form an image. In this manner, the same layer can be utilized (i.e., reused) in multiple images that share a module, thus, the storage overhead of container images is reduced. For instance, two machine learning functions can share the same operating system layer and the same machine learning framework (e.g., Tensorflow [39]) layer. Then they only differ on the application and model layers. Although deduplicating redundant layers is already widely-used by the runtimes, further research works have
recently been undertaken to improve the efficiency of deduplicating [90], [91] and to extend the deduplication idea to reuse similar layers [92]. Notably, Zhao et al., `s Duphunter [90] is a replacement layer loading module for Docker platform. The architecture is more effective in deduplicating similar layers across multiple docker images with less deduplication overhead than prior designs.

Container image merging: When two or more functions whose container images have only minor differences are launched from a cold start, union mounting can capture and reuse most parts of their images. However, from the serverless platform perspective, these two are separate functions, hence, are treated independently. In the event that these functions are infrequently invoked, they can get evicted from the memory. To encourage the system to keep these infrequently used functions warm (i.e., in the memory), one approach that can be explored is to merge these functions such that they share the same container image. In this case, the collective invocation frequency of these functions is increased that can in turn avoid the memory eviction for them.

2) Container instance reusing:

Predictive warming and cooling: Due to the memory limitations of the servers, not all function containers can be maintained in the memory to rapidly start the functions’ execution. Infrequently used functions have to be offloaded to the storage to make room for the frequently-used ones. Such a memory contention across function containers is one of the challenges in the serverless domain and resolving it entails dealing with multiple problems: (1) how to reduce the cold start time overhead? (2) how to keep more containers in a given memory space? (3) how to minimize the number of cold starts through efficient memory allocation?

The main approach to mitigate the cold start overhead is to alter the transient nature of containers and keep them in the memory even after the function execution. Another approach is to proactively loading the container, i.e., prior to the function invocation. An example of such an approach is the research conducted by Shahrad et al., [11] who studied 14 days of function invocation patterns in Azure Cloud and leveraged that to develop a container memory allocation strategy. They propose to reduce the number of cold starts via categorizing the functions where each category has its own pattern of pre-warm and keep-alive periods. Right after finishing an invocation, the function is removed from the memory for the pre-warm period of time, because the system does not expect to get another invocation of the function in the near future. Then, once the pre-warm period expires, the container is loaded back into the memory (warmed) to get ready for the next warm start function invocation. If the function stays in the memory for more than the keep-alive period without any invocation, then the function is removed from the memory. Such a strategy reduces the number of cold starts for the majority of the functions, however, there are still some functions whose invocation pattern is unpredictable, hence, cannot benefit from the predictive memory allocation. Nevertheless, the benefit of correct predictions and delivering warm start remarkably exceeds the cold start mis-prediction plus the solution overhead.

Predictive function (task) batching: Although the request turnaround time is one of the main criteria in measuring the performance of serverless clouds, not every application needs the function to complete as soon as possible. Moreover, even deadline-constraint tasks often can tolerate some delay (slack) before missing their deadline. In fact, a recent study conducted by Eismann et al., [93] demonstrate that around 38% of their surveyed serverless applications have no latency requirement and another 28% of the applications have a few latency-sensitive functions. Only 2% of the applications are real-time with rigid latency constraints.

To maximize reusing in the serverless computing, the user or the system should have a way to declare the task urgency, possibly in multiple tiers (e.g., urgent or non-urgent) or as a continuous number (such as a deadline). In this case, highly urgent tasks can be scheduled to complete with the minimum turnaround time via warmed containers, whereas, the less urgent ones can potentially wait to aggregate with other similar arriving requests, thereby, maximizing the container reuse and reduce the incurred cost. The scheduler must have the ability to predict the cost-benefit of delaying tasks in favor of batching them, such that each task waits as long as possible without missing its deadline to share the function container and other resources with other tasks. Using this concept, Grandslam [94] scheduler is proposed to dynamically reorder tasks to maximize the task batching and minimize Service Level Objective (SLO) violations in an oversubscribed system. Fifer [95] includes a scheduler with mechanisms to batch tasks and reduce the amount of container usage and cold start overhead within a given latency budget. Unlike Grandslam, Fifer tries to minimize the resource usage in an underutilized system, rather than trying to meet the tasks’ deadlines in an oversubscribed systems.

Durable container: Prior studies (e.g., [11], [96]) express that, in a serverless system, a certain percentage of functions are invoked very frequently. If warm start execution of these functions incur a significant loading overhead, then the frequent warm starts can compound to a substantial overhead for the system. A common example of functions with high warm start overhead are those that involve an online machine learning model [45]. To solve such inefficiency, certain serverless computing platforms allow functions to run as a durable container that means the container does not terminate after the task completion (i.e., non-transient container). These durable containers can maintain state (e.g., updates on the machine learning model, in the above example) across function calls that help to process subsequent tasks without paying repeated start-up overhead. In the event that there are multiple requests for the same function, the requests are queued to receive the service. Microsoft Durable Functions [55] and Oracle Fn Flow [67] support such capability. We envision that the future serverless platforms will auto-detect frequently-used functions and make their containers permanent without any user intervention.

E. Semantic (Approximate) Reusing

While deterministic reusing is only built on the identical data, semantic reusing aims to achieve reusing where the data
are not digitally identical, but the base for reusing is some form of *semantic similarity* between the data. Semantic reusing can maintain semantic correctness by producing approximately the same results, while remarkably avoiding resources wastage and improving users’ satisfaction. That is why this category of reusing is also considered as a type of approximation (discussed in Section IV). However, the mechanism to detect semantic similarity is not infallible and, similar to other approximation approaches, can potentially lead to inaccurate results that in certain contexts (*e.g.*, video streaming) could be tolerable and still useful.

In the serverless context, there are four types of similarities that can be leveraged for semantic reusing:

1. **Similar input**: For stateless functions, the end result of execution depends only on the input argument. The input often is composed of multiple parameters. For instance, a video encoding function has the video segment, resolution, frame rate, bit rate, and codec as its input parameters. By designating certain parameters of the function as approximable, function reusability can be enhanced [77]. For instance, consider two users who call the *transcode* function to process same video with two different (but approximable) resolutions. In this case, the system can approximate the resolution arguments and process the function once, instead of twice, and send the results to both users. Such scenarios can be particularly useful under certain circumstances, such as when the system is oversubscribed or when some users can tolerate lower QoS (*e.g.*, free subscribers of a video streaming service).

2. **Similar function**: Following the micro-service-based software development principles [4], generally, functions are developed to be short and single-purpose to ease the continuous deployment (CD) process. Therefore, it is likely that multiple users define similar functions that try to achieve the same purpose. These functions are semantically the same, while having distinct source codes. Let functions $A$ and $B$ be semantically the same and $x$ be an arbitrary input argument. In this case, the serverless computing system with the function similarity detection mechanism in place can reuse the result of $A(x)$ for $B(x)$ too. Moreover, since these functions are similar, one of the functions can be replaced by the other one, rather than keeping both functions available. This saves the number of functions that have to be kept active for rapid execution.

3. **Similar context**: In this category, the state (context) of a stateful function is to be reused. This is particularly helpful in the circumstances that the state data is not sensitive and can tolerate minor differences. That is, minor changes in the state do not significantly impact the results. For instance, consider a function for online-learning of an image classification machine learning (ML) model [97] where the state data is the weights of the ML model. Other functions that intend to train the same model can borrow (reuse) state (weights) of the model from the earlier function, and train it further with their own data. Such reusability makes the ML model converge faster and is more cost- and energy-efficient. A similar type of reusing can be considered in a serverless federated learning system [98] where the workers reuse a central model and train it further with their own local data.

4. **Reusing prior knowledge**: In a serverless system, function (task) profiling data, collected and summarized from prior executions via automatic task profilers [99], can be supplied to the task scheduling module to maximize the resource allocation efficiency of the system. Moreover, for a new user-defined function that lacks prior profiling information, the serverless platform can reuse prior knowledge of semantically similar functions to estimate the execution time of the new function on different machine types available in the system. Otherwise, lack of such information causes uninformed scheduling decisions that negatively impact the users’ perceived QoS. Unlike other forms of semantic reusing that directly impact quality of the results, reusing prior knowledge deals with the system parameters (*e.g.*, utilization and QoS) and is used to improve them.

Transfer learning is a technique to reuse the knowledge gained while solving one problem and applying it to a different but related problem [100]. Accordingly, transfer learning can be employed to predict the execution time of a new function on a given machine type based on the trained networks of other functions on the same machine type. Moreover, methods can be explored to measure the semantic similarity between the new function and each one of the existing functions based on the dependencies and libraries shared between them. Then, the weighted average similarity of the new function with other functions can be used to estimate the execution time of the new function on that particular machine type. It is worth noting that, once enough execution time information for the new function are collected, a model specific to that task type can be trained to infer its execution time independent from other task types. Similarly, when a new machine type is added to a heterogeneous serverless system, the prior profiling information of functions on other machine types can be leveraged to estimate the expected execution time of the functions on the new machine type, thereby, utilizing it more efficiently.

### IV. Approximate Computing in Serverless Clouds

Approximate computing allows functions (tasks) with unaffordable response time, energy, or cost constraint(s) to be completed within its constraint(s) [101]. Even the tasks with affordable constraints that can tolerate approximate results (*i.e.*, multi-fidelity tasks [102]), can use approximate computing to bring about further resource-saving in the system. Since approximate computing compromises the precision and/or accuracy of the results, we envision that employing approximation techniques has less scope (in compare to reusing) in serverless platforms and is used only to meet the tasks’ constraints that are otherwise unattainable. Example use cases of approximate computing in the serverless systems include:

1. **Improving the response time** via fast approximated results, before confirming or correcting the results by the exact computing.

2. **Providing an approximate result** to save the cost.

3. **Providing an approximate result only** if the system is *oversubscribed* and cannot perform exact computing in time.

There are various approaches for approximate computing that can improve the efficiency of the serverless computing...
platforms. We can categorize these approaches into four classes as shown at the lower part of Figure 6. In this section, we first position approximation approaches with respect to the reusing-based approaches and then discuss the general requirements for function approximation in the serverless context. Next, we elaborate on the four classes in Sections IV-C—IV-F.

A. Approximation Versus Reusing

The main difference between approximation and computational/data reusing is the impact on the result accuracy and precision. Computational reuse accelerates the turnaround time or saves the computing resource without influencing the task result. Conversely, approximate computing compromises the result accuracy and/or precision in favor of time- and/or resource-saving.

While approximate computing can be applied to tasks independently, many of the approximation techniques benefit from reusing information gathered from prior tasks. Such information can be either predefined ahead of time (e.g., trained ML models) or collected and applied dynamically at the run time (e.g., caching the results of similar tasks). Approximate computing techniques that directly reuse the result of other similar tasks are also known as approximate reusing that is elaborated in the previous section.

B. Approximate Computing Requirements

Approximate computing exploits the resilient property of the system by producing inexact but acceptable result at a lower cost. A resilient system [101] or application should be able to tolerate a certain amount of deviation from the ideal result [103]. Specifically, an approximate computing technique should not cause deviations that exceed the application resiliency in both error magnitude and likelihood (chance).

a) Error magnitude: Error magnitude is defined and measured based on the variation of the obtained result from the ideal result. Applications’ tolerance to the error magnitude varies based on the context. For example, video processing for live video conferences can tolerate a higher error magnitude than the video processing for traffic cameras that has to perform vehicle identification.

b) Error chance: Another dimension of the error quantification is the likelihood of error occurrence. Formally, the likelihood of getting an overly inaccurate approximation is called the error chance. Certain approximation techniques (e.g., DVFS [104]) produce mostly accurate results, however, there is a chance that the error occurred and the result accuracy is off by far beyond the acceptable error magnitude. In such approximation techniques, upon detecting an error by a validation function, a correction function [105] is employed to fix the error retroactively. In the event that the chance of getting an error is considerably high, then the overhead of correcting the results frequently can exceed the benefits of the approximation.

C. Data Level Approximation Approaches in Serverless Computing

1) Approximate reusing: Approximate reusing is the same as semantic reusing and is performed via identifying potentially reusable tasks and using their data to approximate other tasks [106]. Allowing repeated function-calls to reuse the result of similar, but not strictly the same, tasks promotes the reusability. The main challenge in approximate reusing is detecting the semantic task similarity. Applying This type of computational reuse can improve both the user and system metrics, unless the users opt-out of it due to privacy concerns.

2) Data sampling: For functions that work on a batch of data, such as data analysis works [18], [75], it is possible to reduce the input data size by sampling from the dataset. Various techniques have been explored for data sampling, performing computation on the samples, and then analyzing the variability and the error rate in comparison to the complete data analysis on the whole data. For example, ApproxIoT [107] proposed a method to sample data from a stream of unknown data size. Sampled data are stored in a size-limited reservoir. New data can randomly replace the existing ones in the reservoir. This approach of approximate computing can be offered as an optional service for various special-purpose stateful serverless functions.

3) Approximate data storage and data pruning: Approximate data storage can be achieved via either persisting only a portion of the data or scramble multiple data points together. For instance, in a serverless multimedia cloud [8], [108] only base video formats can be persisted and other less popular formats can be transcoded lazily—upon receiving a user request. For the content types that are error sensitive, similar data points can be stored together (merged) via lossless data compression methods (e.g., [109]), whereas, for the content types that can tolerate minor errors (e.g., multimedia and image) lossy compression methods (e.g., [110]) can be employed to approximate similar data and carry out more effective compression.

Rather than letting the user handle data storage and reusing, the serverless platform can offer services to store and deduplicate similar data [111]. By performing the data management at the platform level, the platform can maximize the likelihood of detecting similar data and performing deduplication. In such a storage mechanism, the process of retrieving data can also be approximated to reduce the data retrieval overhead. Eventual consistency [112] can be utilized on the data that is accessed by multiple tasks. Such relaxed consistency control incurs a lower cost than a strict data consistency at the price of allowing the task to start with inconsistent data. Serverless functions are generally short-lived and are easily undoable. Therefore, tasks that start with inconsistent data can be canceled and restart with a minimal overhead.

D. Instruction Level Approximation in Serverless Computing

1) Precision scaling and stochastic computing: The earliest forms of approximate computing were built by necessity in computer storage systems that could not store infinite decimal points [113]. Hence, the numbers have to be approximately stored and represented by a close-enough value. Then, the concept was further developed to a more deliberate dynamic precision scaling [71] where calculating precision is scaled based on multiple factors, including the trade-off between
computing precision and energy requirement or turnaround
time requirement.

Stochastic computing [43] is a popular collection of tech-
niques to achieve precision scaling via representing a continu-
ous value in form of a stream of bits. In this case, calculating
the precision can be scaled by altering the number of bits in the
bitstream. Making use of stochastic computing often implies
designing a domain-specific processing unit (a.k.a. ASICs)
hardware. Since precision scaling requires a specific frame-
work and stochastic computing requires a specialized hard-
ware, these techniques have not yet gained a wide adoption
in the cloud computing industry. However, with the increasing
prevalence of domain-specific hardware and, particularly, the
trend in using precision scaling for the ML inference on the
energy-limited edge devices [114], we envisage that these
solutions will eventually carry over to the cloud systems
too. As such, serverless solutions to support domain-specific
processors that achieve instruction-level approximation will
be demanded in the near future to hide the complexity of
deploying such hardware across the edge-cloud continuum
from the user perspective. Such solutions will help the users to
become solution-oriented and focus on their application logic,
rather than dealing with the operational details of different
hardware systems.

2) Loop perforation and instruction replacement: In a
serverless computing platform, functions can either be pro-
vided as containers or, more popularly, as the functional code
blocks. It is possible for the serverless platform to analyze
the user code and apply optimize them to save computing
resources. We believe approximating frameworks such as
Approxlyzer [115] proposed by Venkatagiri et al., can be de-
ployed as an optional service to achieve such optimizations in
the serverless platforms. Approxlyzer analyzes the (function)
machine code and dynamically replaces parts of the instruction
with the approximated version. The aggressiveness of approxi-
mation can be tuned with consideration of appropriate quality,
resiliency, and overhead.

E. Hardware Level Approximation In Serverless Computing

When heterogeneous computing is supported in a serverless
computing system, a specialized hardware that allows approx-
imate computing in the hardware level can be offered as one
of the resource types. The offering can be especially attractive
for use cases, such as big data and machine learning, that
data-intensive and can benefit from domain-specific machines
to offer low latency and real-time services [116]. Moreover,
making use of specialized hardware to accomplish approxi-
mate computing can effectively reduce the energy consumption
and footprint of cloud datacenters [116].

Two main hardware-level approximation approaches are
namely, Dynamic Voltage Frequency Scaling (DVFS) [104]
and approximate computing hardware. DVFS is a technique
that strategically under-volt common hardware systems. Al-
though such undervoltage induces errors in the computation,
applying it in the controlled manner (such that the error rate
is tolerable by the applications) can improve the efficiency
of the serverless system. For instance, Rahimi et al., [104]
propose to strategically under-volt the GPU in favor energy
efficiency, while employing hamming distance [117] to allow
more error tolerance at the application level. On the approxi-
mation hardware side, certain computations are common and
can greatly benefits from approximating hardware. Example of
such tasks include stochastic computing which its computation
can be greatly accelerated by compute approximately by
hardware [118], DNN approximate inference using specially
designed inference hardware [114], image encoding using
approximate encoder hardware [119], etc.

Such list of tasks that has approximation hardware support
are still expanding as more use cases are found to benefit from
approximation hardware and more tools to aid approximation
hardware emerges [120].

F. Scheduling Level Approximation in Serverless computing

1) Task dropping and deferral: In a serverless system, each
task request can be part of a bigger workflow. In some use
cases, the workflow includes optional steps (tasks) whose loss
can be tolerated [121]. Such feature can be exploited at the
scheduling level, particularly to mitigate resource oversub-
scription [35], via dropping the optional tasks [122] or defer-
ring [35], [123] their execution to a later time when the system
is less busy. One use case that can take advantage of such
workflow level approximation is in video conferencing where
the voice quality enhancement step (task) on the received
video segments can be skipped (dropped) to keep up with
the liveness of the streamed video contents [8].

2) Predictive task serving: The scheduler of a serverless
computing platform can operate proactively and approximately
predicts arrival of the user-requests. Such prediction can
help the platform to pre-warm function containers and load
their required data in speculation of upcoming task requests.
However, such preparation is not currently performed in the
serverless system due to the prediction complexity and cost-
efficiency issues [11].

V. POTENTIAL FUTURE RESEARCH DIRECTIONS

A. Data Abstraction in Serverless Clouds

Although Function-as-a-Service (FaaS) abstraction relieves
users from the burden of resource management (e.g., load bal-
ancing and elasticity), it is not truly serverless, because it falls
short on abstracting data management and the users still have
to get involved with other services (e.g., AWS DynamoDB
[124] or AWS SAM [125]) to serve desires of the functions
and/or applications [18], [19], [22]. In particular, in some use
cases the data can represent the function state. For instance,
the state of an online-learned ML model that is updated frequently.
Embedding such model into the function container image is
not practical. Furthermore, ML models are large enough that
cannot be fed as the function arguments, otherwise the function
startup overhead would become substantial. The ML model is
the function state and is best to be stored in a synchronized
storage service that can be accessed and updated upon demand.
Currently, users need to intervene and scatter these data objects
on various storage or database services. We believe that, a truly
serverless platform should abstract the deployment and scaling
of both resources and data for the user. Such an integrated serverless system exposes further potential for reusing and approximation.

Storage for the serverless platform can be categorized into ephemeral and permanent services. Data in permanent storage is guaranteed to persist, but accessing data from such storage is slower than an ephemeral one. Ephemeral storage is intended for hot data shared by multiple tasks. Such storage is relatively faster than a persistent one. However, it has limited space, hence, cannot store infrequently-used data indefinitely. These types of storage systems are offered by different services \([18, 25]\), as such, there are different APIs to access them. Currently, users have to get involved in this level of data storage management details and serverless platforms fall short in offering the same level of storage management transparency that they provide for the computing resources. The challenge in offering transparent (serverless) storage solutions is in abstracting the data storage elegantly, such that it is intuitive for the user and efficient for the system.

**B. Object-as-a-Service (OaaS): Going Beyond the Function Abstraction**

Current serverless and FaaS solutions are not designed for (and cannot natively support) IOT devices. For instance, in a FaaS-based application that needs to persist the frame-rate of a security camera, the programmer should resort to other cloud service, e.g., AWS RDS \([126]\), to persist the state information. This makes the development and maintenance of serverless IOT-based applications difficult and cumbersome. To ease the management of data sources (e.g., IOT devices) and accelerate the development of new services for them, a higher level of abstraction is desired that, in addition to hiding the resource allocation details, it can hide the details of device management and preserving its state from the users.

To natively support serverless IOT (and data-centric) application development, we envisage that in the future serverless platforms, the concept of object can be borrowed from the Object-Oriented Programming, as the first-class citizen to encapsulate both computations (functions) and state within a single object entity, and offer the notion of Object-as-a-Service (OaaS). OaaS enables users (service providers) to configure an IOT device (e.g., security camera) or a data source (e.g., video content) in form of objects with various attributes (e.g., recording frame-rate) and then bind functions (e.g., face detection) to it. In addition, OaaS opens the gate for inheritance of properties and functions across objects, thereby, making it more convenient for users to organize and manage multiple data sources. For instance, a serverless platform can offer a built-in live-streaming object that includes basic live-streaming attributes and functions. Then, based on the subclass and super-class relationship, new user-defined objects can be constructed with new (and override) functions, while inheriting the basic functionalities from the super-class.

A user of an object-based serverless platform uses an application (e.g., live streaming for disabled people) to issue requests in form of \(<\text{object}, \text{function}>\) to trigger a function call, defined for particular objects. For instance, a streaming request, issued by a viewer’s application or another object, is a requester to an streaming object (e.g., live video) that triggers one or more functions (e.g., face recognition) of that object. Even the request to watch the stream is considered as invoking the playback function of a particular object. Other possible advantages of objects will be the migration ability that can be particularly useful to overcome the lack of elasticity at the edge tier and to support seamless mobility of services—from one tier (e.g., edge) to another (e.g., cloud). Moreover, object abstraction can facilitate serverless workflow definition and management. A workflow object can be defined that includes a data-source and a set of operations (private functions) that have to be executed via another public function to generate the desired results.

The object implementation should include: (A) A data volume, via structured data models (e.g., MySQL), to persist the object’s state information. (B) A controller container for object management that has sole access to the data volume and can change the object’s state. (C) One or more worker containers, each one representing a function of the object.

**C. Latency-Aware Serverless Computing**

In most current commercial serverless computing platforms, functions are triggered without a specified deadline or urgency levels, thus, the scheduler treats tasks with equal priorities. Meanwhile, if task urgency data are mandated in the serverless computing platform, the task with low urgency can be executed in batch in favor of more serverless efficiency (e.g., container reuse as mentioned in Section III-D). Such urgency information is also helpful for the caching and other components to determine their operational priorities. Moreover, by detecting infeasible deadlines, the system can then promptly approximate the task, rather than missing its deadline because of exact computation. Another avenue of exploration is to identify the task urgency automatically at the platform level and transparent from the user.

**D. Edge-to-Cloud Serverless Platform**

The main benefits of serverless computing are the ease-of-use and abstracting the users from resource provisioning details. While the current serverless solutions are limited to cloud systems, it is desired to extend their benefits to the emerging edge-to-cloud systems and hide the complexity of dealing with multiple computing tiers (i.e., device, edge, fog, and cloud tiers) from the user perspective. The platform can transparently determine the appropriate tier for the function execution and can seamlessly migrate the the execution from one tier to another to overcome the inherent resource scalability problem of the edge systems \([127]\). These abilities can improve the system efficiency and unlock new use cases. For instance, consider the use case of a blind person who uses smart glasses and needs real-time process of observed objects enters a coffee shop where few people are playing low-latency online games using the available edge system. Upon arrival of the blind person, to make room for the blind application, the game functions have to be live-migrated to cloud, so that the
gaming is not interrupted. The opposite can happen when the blind person leaves the place.

A serverless platform for edge-to-cloud continuum extends the scope for computational reusability and approximation to circumstances where a task-result that is already cached in another tier can be fetched from there, instead of executing it locally [128]. Another interesting reusing potential that can be unleashed is in a scenario where edge devices forward common (reusable) tasks to a central cloud, so that other edge tiers can reuse them by fetching them from the cloud [129].

E. Efficiency via Domain-Specific Serverless Cloud Computing

Along with the rise of domain-specific computing and ASICs hardware, domain-specific programming languages are also emerging for popular applications, such as machine learning, cryptography, multimedia processing, and even fluid dynamics [130]. Within this trend, we envision that the next step will be the emergence of domain-specific serverless cloud platforms for the popular applications. A domain-specific serverless system will be equipped with specialized hardware (ASICs), support of special-purpose programming languages, and builtin domain-specific functions in its repository. Such platforms will expedite the application development process and shorten the CICD cycles. They will help users become solution-oriented and focus on their specific business logic, and make the serverless computing paradigm efficient via investing two main thrusts, namely computational reuse and approximate computing. We started by characterizing the internal mechanics and studying different dimensions of the serverless systems. Then, we surveyed the current state of serverless and FaaS solutions (summarized in Table I). Next, we categorized various approaches of reusing and approximation, respectively. An overview of these approaches is shown in Figure 6.

In this paper, we also outlined several potential directions that can push the envelop of serverless paradigm towards the next generation of cloud computing systems. In summary, four prominent directions that we discussed as the future of serverless paradigm are as follows: (A) Enabling higher level abstractions (e.g., Object-as-a-Service) in this paradigm; (B) Extending the serverless platforms beyond cloud infrastructure to cover multi-tier edge-to-cloud continuum; (C) Establishing domain-specific serverless clouds with specialized reusing and approximation techniques; and (D) Extending the serverless abilities towards cloud-native programming languages.

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