Understanding Characteristics of Commodity Serverless Computing Platforms

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ABSTRACT

Serverless computing becomes the new trending paradigm in cloud computing, allowing developers to focus on the core application logic and rapidly prototype applications. Due to the great prospects of serverless computing, in recent years, most major cloud vendors have rolled out their commodity serverless computing platforms. However, the characteristics of these platforms have not been systematically studied. To fill this knowledge gap, this paper presents a comprehensive study on characterizing mainstream commodity serverless computing platforms (i.e., AWS Lambda, Azure Functions, Google Cloud Functions, and Alibaba Cloud Function Compute). First, we qualitatively analyze these platforms from development, deployment, and runtime aspects to form the taxonomy of characteristics. Additionally, we quantitatively evaluate the actual performance of different serverless computing platforms through our designed benchmark platform. Our benchmark platform has two types of benchmarks, i.e., microbenchmarks and macrobenchmarks. Based on the results of qualitative and quantitative analyses, we derive a series of findings and provide insightful implications for both developers and cloud vendors.

1 INTRODUCTION

Serverless computing is an emerging trend in cloud computing, allowing developers to deploy applications on the cloud in the auto-scaling and pay-as-you-go manner [29][8]. It is predicted that 50% of global enterprises will employ serverless computing by 2025 [7]. Serverless computing can make developers solely focus on developing their functions, which are small pieces of programs dedicated to a simple task (Function-as-a-Service, FaaS [29]). Meanwhile, developers can also directly apply existing proprietary serverless services (Backend-as-a-Service, BaaS [29]) provided by many cloud service vendors, e.g., object storage services provided by AWS S3 [5].

Serverless computing can effectively simplify the application deployment and thus alleviate developers’ efforts from tedious and error-prone server management. There have emerged various commodity serverless platforms including AWS Lambda [5], Google Cloud Functions [11], Azure Functions [6], and Alibaba Cloud Function Compute [1]. In a sense, most of the current serverless computing platforms often act as a “black-box”. Without having to pay attention to the underlying details, however, developers may have difficulties to choose the target serverless computing platform that is the most adequate to serve their applications, as they have little knowledge of characteristics, configuration policies, actual running performance, and cost. For example, how can developers evaluate whether and how to transform their existing applications into serverless functions or how to package their tasks with newly developed functions on a specific platform? How many configuration options does a platform provide to developers to quickly meet their requirements? How about the runtime performance for a given task on a specific serverless computing platform? These issues are really non-trivial in practice as they can definitely impact the developer’s decision making, and thus potentially impact the quality of service, user experience, and even the revenue of the application.

Unfortunately, to the best of our knowledge, there still exists a gap when developers select the most adequate serverless computing platform. In this paper, we conduct an extensive empirical study to characterize four mainstream serverless computing platforms, including AWS Lambda, Azure Functions, Google Cloud Functions, and Alibaba Cloud Function Compute. Specifically, our study is conducted from two folds in terms of qualitative analysis and quantitative characterization.

First, we seek to qualitatively explore the various characteristics described in the official documentations of these serverless computing platforms. Such characteristics specify the inherent restrictions of different aspects involving developing, deploying, and executing functions, which will result in fatal failures if developers do not comply with it. To this end, we construct a taxonomy with respect to the need-to-consider information from three aspects, i.e., development, deployment, and runtime. Such a taxonomy can help developers better understand the supported characteristics of the serverless computing platforms to facilitate further developers’ development practice.

Then, we quantitatively evaluate the actual performance of different serverless computing platforms. We design an automated benchmark platform named TBS including a benchmark suite (named SlsBench). TBS can automatize the package, deployment, execution, log collection, clean-up, and result generation of each round test.
Furthermore, SlsBench contained in TBS has two types of benchmarks, i.e., microbenchmarks and macrobenchmarks. Specifically, microbenchmarks consist of a set of simple workloads focusing on specific resource consumption, such as CPU, memory, network, disk IO, etc. Macrobebenchmarks consist of a set of real-world representative applications (e.g., multimedia data process, MapReduce, machine-learning-based serving, etc.), which require to utilize various system resources. Based on TBS, we conduct a set of extensive experiments under various configurations to evaluate the actual system performance (i.e., startup latency and resource efficiency) on different serverless computing platforms. Additionally, we make TBS and SlsBench public and open source. Our experimental results show (i) how different configurations impact the running performance of functions and (ii) the performance variation when running different kinds of workloads. Finally, we report a series of findings and implications. Our findings cannot only help serverless developers choose the right configurations and platforms to obtain the optimal performance based on their actual workloads, but also guide cloud vendors to improve their serverless computing platforms.

Some highlights of our findings about the fatal restrictions of different platform and best practice to choose the platform that can achieve better performance (e.g., high throughput, low startup latency, and execution latency), including:

- **Development.** The availability and support of programming languages in developing functions are yet limited on most serverless computing platforms. Only 9 popular programming languages along with limited versions are supported on at least one platform, 4 out of which (PowerShell, Ruby, PHP, and TypeScript) are supported on only one platform. As a result, developers have to narrow their choice of languages to construct their functions. Except for Azure, the other three platforms can deploy functions with only uncompressed package size that is no more than 500 MB, and can not deploy Python function solely with the latest libraries such as TensorFlow 2.3. Additionally, different languages can result in obviously different cold start time. Languages with “cumbersome” runtime (e.g., Java) can account for much longer cold start time (7x) than other script languages (e.g., Python and Node.js).

- **Deployment.** When deploying the functions, we find that loading redundant libraries can introduce non-negligible cold start time as well as increase package size. In particular, the cold start time can increase 4.6x if the function loads some unused library. Therefore, developers need to trim their code (e.g., removing the useless code) and apply the lazy loading of libraries to alleviate the overhead of initializing functions. It is better for cloud vendors to provide related tools to help developers optimize their function packages before deployment instead of directly deploying the zipped function packages submitted by developers.

- **Runtime.** Allocating more memory within a certain range can obviously reduce the cold start time. For example, increasing the memory from 128 MB to 1,024 MB in AWS Lambda can save more than 80% of the cold start time of a Hello-world function developed with Java. For functions with high memory requirements (e.g., sls-fib), allocating more memory can also reduce the execution time dramatically. However, the rate of reduction will drop when allocated memory exceeds 1024 MB. The findings can help developers make a trade-off between the cost and performance by allocating memory adequately. We also find that different serverless computing platforms can have discrepant performance for a specific type of task. For example, Alibaba Cloud Function Compute performs the best for CPU-bound and memory-bound benchmarks, but other platforms can beat it with other benchmarks under certain conditions (e.g., Google Functions has higher random-IO throughput at 1,024 MB of memory).

- **Implications:** Overall, our findings can reveal the mystery of existing commodity serverless computing platforms, motivating future research, and development. Specifically, the findings show strong implications for both developers and cloud vendors of the serverless computing ecosystem.

**To Developers.** Our findings show the shortcomings of existing serverless computing platforms, such as limited programming languages, package size restriction, and so on. Developers should carefully choose the appropriate platform based on their preferred languages, application package size, and other features that may be restricted on some platforms. Our findings also show how different serverless computing platforms actually perform under various configurations. Developers should choose a relatively lightweight language (e.g., Python) to construct their functions and tune configurations (e.g., allocating enough memory) and programs (e.g., removing dead code) to achieve better performance. Developers should choose the appropriate platform to obtain better performance based on their resource needs of functions, or even directly get an intuitive result by running their functions with our automated benchmarking platform TBS.

**To Cloud Vendors.** Our findings encourage continuous improvement and optimization for serverless computing platforms. Cloud vendors can provide some personalized guides of configuration based on developers’ functions and provide more tools to alleviate the restrictions of some configurations, e.g., provide tools for removing dead code and reducing package size instead of directly deploy zipped packages submitted by developers.

The remainder of this paper is organized as follows. We present our research goal and methodology to conduct our study in section 2. We summarize and compare the key characteristics of different serverless computing platforms in section 3. We introduce the details of the benchmark platform TBS in section 4. We describe the evaluation results among different serverless computing platforms in section 5. We present discussion about our study in section 6, survey related work in section 7, and conclude the paper with future work in section 8.

## 2 APPROACH OVERVIEW

This section illustrates the methodology that we adopt to evaluate serverless computing platforms, including Amazon Web Service Lambda (released in November 2014), Microsoft Azure Functions\(^2\) (released in November 2016), Google Cloud Functions (released in July 2018), and Alibaba Cloud Function Compute (released in April 2019). They will be made public later.

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\(^2\)Azure Functions offers three different hosting plans [6], we only focus on the consumption plan that is the most similar to other serverless computing platforms.
We first present the research goal of our study. Then, driven by this goal, a workflow of our research approach is presented.

2.1 Research Goal

To fill the gap when developers select the most adequate serverless computing platform. We compare these serverless computing platforms with both qualitative analysis and quantitative analysis. Qualitative analysis refers to the comparison of different characteristics provided by these serverless computing platforms, whereas quantitative analysis is the comparison of the actual performance of running workloads on different serverless computing platforms.

First, we qualitatively summarize a taxonomy of characteristics on serverless computing platforms from three aspects, i.e., development, deployment, and runtime. Such a taxonomy allows developers to have an intuitive understanding to judge whether developers can develop their functionalities on these serverless computing platforms. Then, we design an open-source benchmark platform to quantitatively explore the actual system performance (i.e., startup latency, and resource efficiency) of serverless computing platforms. This platform can help developers choose the appropriate platform and configurations to deploy functionalities in the optimal performance. We show the corresponding results in Section 3 and Section 5, respectively. A workflow overview of our approach is presented and showed as follows.

2.2 Workflow Overview

In our study, we try to reveal the mystery of the commodity serverless computing platforms to help developers make choices among them based on both the qualitative analysis with official documentations and the quantitative analysis with practical performance evaluation. Figure 1 shows the overall workflow of our approach.

The first step of our approach is to extract and summarize features provided by official documentations of different serverless computing platforms. Such features specify the inherent restrictions of different aspects, e.g., developing, deploying, and runtime. In our study, we do not focus on features such as security, usability, service level agreement, etc. We double-check the value of each feature to ensure correctness.

In order to evaluate and compare the actual performance of different platforms. We design and implement a benchmarking platform named TBS to automatically conduct the measurement analysis for commodity serverless computing platforms, and TBS is shown in Figure 1. On one hand, TBS can fully automatize the package, deployment, execution, log collection, clean-up, result generation for each measurement of developers on four serverless computing platforms. On the other hand, TBS contains a benchmark suite named SlsBench, which is used to explore and compare the actual performance from various aspects (e.g., cold start time, execution time, throughput, etc.) of these serverless computing platforms. With such a benchmark suite, it can help cloud providers design and evaluate their serverless computing platforms and provide useful hints for developers to architect their applications on serverless computing platforms. Specifically, we conduct different workloads on these serverless computing platforms, and these workloads are measured under varied experimental configurations. To make a fair comparison, our experiments are repeated several measurements. Based on experimental results, the key factors that may affect the performance of functions are determined.

When developers use such a TBS, structured logs will be stored to further serve developers to extract the key data information, e.g., event timestamp, cold start time of functions, execution time of functions, output result of functions, etc. Based on this data information, the visualized results across different platforms can be shown in the Web-based frontend of TBS. In our study, TBS adopts a design principle of modularity and extensibility. This kind of principle allows developers to integrate other serverless computing platforms into TBS without restraint. Consequently, we report a series of our findings based on our experimental results in our study, and give some insightful implications for both application developers and cloud vendors.

3 TAXONOMY OF CHARACTERISTICS

Generally, developers need to know about characteristics related to the development, deployment, and runtime of serverless computing platforms in the process of application development. With regard to this, we construct the taxonomy of characteristics on serverless computing platforms and it is shown in Figure 2. Such a taxonomy can help developers quickly understand the pros and cons of different serverless computing platforms, and decide whether an existing application or a new functionality should be implemented on serverless computing platforms. The specific information is illustrated as follows.

3.1 Development-related Characteristics

When developers are developing applications, they should consider whether a certain serverless computing platform can implement their functionalities in terms of development language, trigger type, package size limit, etc. Thus, the detailed information about the development-related characteristics is explained as follows.

Generally, an application executed in serverless computing platforms consists of one or more serverless functions. Each serverless function is a small, stateless, event-driven, and pay-as-you-go unit dedicated to handling a specific task. Such a function is often constructed with a small piece of code written in different languages, e.g., Java, Python, Node.js, etc. As shown in Figure 3, different serverless computing platforms support various languages and versions. We find that the three most popular languages (i.e., Python, Node.js, and Java [17]) are natively supported by all these platforms.
four platforms. However, Python is not supported by Azure on Windows .Net Core. Furthermore, Google Cloud Functions is the sole platform that does not support Microsoft, and it has the fewest supported languages. From Figure 3, we also find that certain languages are only natively supported by only one platform. For instance, PowerShell is only natively supported by Azure Functions, Ruby is only natively supported by AWS Lambda, and PHP is only natively supported by Alibaba Cloud Function Compute. Each platform supports various languages, and each language may have different versions. In our later experiments, we will choose the consistent language and version to compare the dynamic feature of the platform performance fairly. Last but not least, four platforms use the custom manner to allow developers to build their runtime and execute any preferred languages, whereas may bring extra non-negligible efforts and concerns of runtime stability. Thus, it is better to choose the appropriate platform to deploy an application based on developers’ preferred languages.
In the process of programming, an application or a function is triggered to execute by events [29] (e.g., HTTP requests, timer, storage conditions). Besides, functions with different event triggers may have different main methods with given parameters, which will be invoked by serverless computing platforms to deal with specific incoming events.

In order to reduce the cold start time of serverless functions, serverless computing platforms often consider the package size limit of deployment. At the time of writing of our study, the package size limit of AWS Lambda is 50 MB with a compressed format and 250 MB with an uncompressed format. For Alibaba Cloud Function Computing, it allows from 50 MB with a compressed format to 500 MB with an uncompressed format, whereas Google Cloud Functions lifts the restrictions to 100 MB with a compressed format and 500 MB with an uncompressed format. Differently, Azure Functions supports the higher deployment package as much as several GB in size. Unfortunately, the package size of applications, especially, deep-learning-based tasks with huge libraries, is big enough to exceed the limit of certain platforms. For example, the compressed size of the newest “TensorFlow” library (version 2.3.1-2 [21]) is 106.4 MB, and the uncompressed installed size is as high as 661.8 MB. It is impossible to deploy such an application with the “big” library to serverless computing platforms directly; thus, the development enthusiasm of developers may be dampened. In this situation, developers can apply existing technologies and tools [38] to remove the useless code and compress them. Cloud vendors can also provide some tools to automatically reduce the package size to ease the burden of developers.

### 3.2 Deployment-related Characteristics

After developing an application or a function, developers need to deploy them on appropriate serverless computing platforms. In this situation, which deployment method or tool can be adopted, and different platforms are how to allocate memory for a function instance. This part of the information is worth thinking about to avoid deployment failure and poor performance. Next, we will introduce this part of the information.

As shown in Figure 2, we summarize the three most popular deployment methods (i.e., source code, docker container, and external services) of functions on serverless computing platforms. Four serverless computing platforms all support the deployment method with the source code, e.g., deployment with a zipped package that contains function code and dependent third-party libraries. Besides, we find that only Azure Functions (with consumption plan) does not allow developers to deploy functions by building their custom runtime (e.g., building custom Docker images), and other platforms can. Additionally, Azure Functions and Google Cloud Functions both support the deployment with other external services, e.g., source control services (Git), FTP services, whereas AWS Lambda and Alibaba Cloud Function Compute do not. When deploying functions on serverless computing platforms, developers can use deployment tools, e.g., command-line tool, console editor, and API & SDK. Besides, developers can even deploy functions from specific development tools, e.g., visual studio code for Azure Functions.

In the deployment process, some platforms (e.g., AWS Lambda, and Alibaba Cloud Function Compute) need to specify the memory of functions in advance. For the memory capability of different serverless computing, we find that AWS Lambda allocates memory to a function instance from 128 MB to 3,008 MB in steps of 64 MB, Alibaba Cloud Function Compute is from 128 MB to 3,072 MB in steps of 64 MB, and Google Cloud Functions is from 128 MB to 2,048 MB with assigned values. For Azure Functions, developers cannot specify the memory in the development or deployment, but they can use 1,536 MB at most. Generally, memory and CPU are closely related. The CPU capability of a function instance increases proportionally with allocated memory. Specifically, AWS Lambda and Alibaba Cloud Function Compute get 1 vCPU at 1,792 MB and 1,024 MB, respectively. Regrettably, we find that GPU support for the function instance is not available in these serverless computing platforms. An alternative way is to provide GPU power as serverless services [2, 30].

Each serverless computing platform allows a function to run within the timeout limits as shown in Figure 2. Thus, it is not recommended to run long-time tasks with serverless functions. Specifically, the timeout limit of Google Cloud Functions is only 9 minutes, whereas both Azure Functions and Alibaba Cloud Function Compute allow functions to run within 10 minutes. For AWS Lambda, its timeout specifies the maximum timeout duration as long as 15 minutes. Serverless computing platforms have a local disk to restrict the local storage (roughly 0.5 GB by default). However, Alibaba Cloud Function Compute enables developers to extend the local storage capacity with network-attached storage (NAS).

In addition, we collect the detailed information of the supported regions through deploying functions on each serverless computing platform factually. At the time of writing, AWS Lambda spans 20 geographical regions, whereas Google Cloud Functions is available in 19 regions. For Alibaba Cloud Function Compute, it offers 15 regions to deploy functions, whereas Azure Functions actually supports the deployment of functions in 32 regions. However, we find an inconsistency compared to its official documentation3, which mentions that 43 regions overall are available. According to supported regions, developers can choose the appropriate region near to them to speed up their function executions.

For the runtime OS, most serverless computing platforms run functions on Linux hosts, and only Azure Functions supports both Windows hosts and Linux hosts. As shown in Figure 3, Windows hosts and Linux hosts do not support the same languages set. We find that certain inconsistencies between the official documentation and the actual execution process on our experiments. For example, AWS Lambda claims usage of Amazon Linux as the operating system for Python 3.7 runtime4. However, we find that it actually employs the Amazon Linux 2 as the operating system when we deploy a function with Python 3.7 runtime. Thus, we infer the reason for this inconsistency may be due to the delayed update of AWS Lambda documentation, and this kind of inconsistency makes developers confused.

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1. Products available by region. https://azure.microsoft.com/en-us/global-infrastructure/services/?products=functions&regions=all
2. https://docs.aws.amazon.com/lambda/latest/dg/lambda-runtimes.html
3.3 Runtime-related Characteristics

Applications and functions that have been successfully deployed on the serverless computing platforms are executed by invocations. Four platforms all support synchronous and asynchronous invocations. In addition, developers often need to consider the request payload when calling, but the payload limit for different serverless computing platforms is shown in Figure 2.

Additionally, serverless computing platforms can scale-out by creating multiple instances to run the same function currently for burst invocations. An instance often runs on a separate host environment, i.e., a lightweight VM (e.g., Firecracker [23] used by AWS Lambda, a dedicated container (e.g., Docker [1] used by Alibaba Cloud Function Compute and Azure Functions), or a gVisor [12] used by Google Cloud Functions). Furthermore, all the resources (i.e., CPU, memory, storage) of this host are dedicated solely to its instance. For the instance currency of AWS Lambda and Google Cloud Functions, each function execution maps to one exclusive instance, whereas each instance of Azure Functions and Alibaba Cloud Function Compute can run multiple executions (i.e., start multiple processes) at the same time through sharing the resources.

Depending on the deployment region, the instance limit supported by AWS Lambda is from 500 up to 3,000 per single function. Google Cloud Functions only supports up to 3,000 invocations to be executed concurrently, because it does not have a maximum number of allocated instances per single HTTP-triggered function. For Azure Functions and Alibaba Cloud Function Computing, their instance limits are 200 and 100, respectively.

Serverless computing platforms allow developers to use normal language and operating system features, such as creating additional threads and processes. Resources allocated to serverless functions, including memory, execution time, disk, and network use, must be shared among all the processes/threads it uses. The specific processes/threads limit is shown in Figure 2. In Linux, its kernel use file descriptors to efficiently manage the opened files and create indexes for them. The limit of file descriptors is also shown in Figure 2 for four serverless computing platforms.

Generally, for the billing model, the price generally rises with the increasing of the allocated memory. Indeed, the overall price of executing a function varies depending on the specific function memory (in AWS, Google, and Alibaba) or the actual consumed memory during invocations (in Azure).

4 THE BENCHMARKING PLATFORM

In order to facilitate the benchmarking on different serverless computing platforms, we have designed and implemented an open-source benchmarking platform named TBS, which contains a benchmark suite named SlsBench.

4.1 Platform Design and Implementation

TBS is an open and modular platform that supports extensible benchmarking on any serverless computing platform through a set of well-defined interfaces. TBS abstracts necessary components (i.e., packaging component, deploying component, testing component, logging component, cleaning-up component, and results generating component) to benchmark the target serverless computing platform. If developers want to integrate a new serverless computing platform into TBS, they just need to provide the platform-specific implementation with the official APIs and SDK, then they can automatically measure the new serverless computing platform.

The specific illustration for components of TBS is explained as follows. The packaging component automatically packages a benchmark (discussed in Section 4.2) as a zipped file or a container image for further deployment. The deploying component can specify configurations (shown in Figure 2) and deploy functions to the target platform. The testing component is to execute deployed functions based on configured trigger types, e.g., sending an HTTP request. The logging component is used to retrieve and store the execution logs of each measurement. Although different serverless computing platforms have different formats of logs, they often contain basic information (e.g., timestamp, execution time of functions, output result of functions, etc.) about the life cycle of a function. For each benchmark in our study, we save the important contents, as well as the output result in logs. The result generating component can extract valuable information from structured logs, and generate a comparable result about different serverless computing platforms.

4.2 Benchmarks

| Category | Benchmark name | Description |
|----------|----------------|-------------|
| CPU-bound workloads | sls-matrixMul | Matrix multiplication |
| | sls-linpack | Test with linpack |
| Memory-bound workloads | sls-fib | Recursion with Fibonacci |
| | sls-dff | Test I/O performance with dd command |
| DiskIO-bound workloads | sls-randomIO | Test I/O performance for random I/O |
| | sls-seqReadIO | Test I/O performance for sequential I/O |
| Network-bound workloads | sls-http | Test network performance with http requests |
| | sls-Perf | Test network performance with Perfil tool |
| | sls-cloudstorage | Retrieve object from cloud storage |
| Multimedia data process | sls-image | Image processing with Pillow |
| | sls-video | Video processing with opencvV |
| MapReduce | sls-mapreduce | Data process with MapReduce |
| ML training | sls-tf-training | Train the logistic regression model |
| ML serving | sls-ls-serving | Inference with logistic regression model |
| | sls-cnn | Image classification with CNN model |
| | sls-rnn | Words generation with RNN model |
| | sls-ram | Words generation with KNN model |

Figure 4: Benchmarks

TBS leverages a set of workloads as shown in Figure 4, including microbenchmarks and macrobenchmarks, to evaluate the performance aspect of serverless computing platforms. With such benchmarks, developers can have a better understanding of the actual system performance of serverless computing platforms. Specifically, (i) microbenchmarks consist of a set of simple workloads targeting specific system aspects, i.e., CPU-bound workloads, memory-bound workloads, diskI/O-bound workloads, and network-bound workloads. (ii) Macrobenchmarks focus on the real-world workloads (i.e., multimedia data process, MapReduce, machine-learning-based serving, etc), and they go far beyond microbenchmarks. Each benchmark is implemented in multiple programming languages (Python by default) to support the variety of the available runtime systems. Although there are subtle differences between code variants to adapt to the peculiarities of each cloud platform, the code of each programming language is basically the same for all. By default, our functions are implemented using the HTTP trigger, which is
the most common event trigger and is supported by all serverless computing platforms.

4.2.1 Microbenchmarks. Microbenchmarks consist of a set of workloads exploring different system aspects, especially underlying hardware resources (such as CPU, memory, storage, and network). We will briefly introduce each microbenchmark.

CPU-bound benchmarks. Such benchmarks are mainly used to measure the CPU-bound performance. sls-matrixMul in Figure 4 calculates the result of the multiplication of two N-dimensional square matrices, and sls-linpack solves the linear equation.

Memory-bound benchmarks. Such benchmarks are mainly used to measure the memory-bound performance. We built a workload to calculate Fibonacci [10] values recursively, and this workload will consume a lot of memory.

DiskIO-bound benchmarks. Such benchmarks are used to mainly measure the IO-bound performance. We design three kinds of workloads, i.e., sls-dd, sls-randomIO, and sls-sequentialIO. Specifically, sls-dd is a workload that creates files in “/tmp/” directory of the local disk through using dd command of the Linux system. sls-randomIO and sls-sequentialIO are workloads that measure the throughput and latency of random IO and sequential IO, respectively.

Network-bound benchmarks. Such benchmarks are mainly used to measure the network-bound performance. We design three kinds of workloads. (i) sls-http is a network-bound test, which will be returned immediately after the invocations with a smaller payload in JSON format. sls-http can be used to verify the round-trip time of a geographically distributed deployment. (ii) sls-iperf is designed to actively measure the maximum bandwidth achievable on the IP network. (iii) sls-cloudstorage is designed to measure throughput and latency between function instances and cloud storage. For example, download an object from an input bucket of the cloud storage and upload the object to an output bucket.

4.2.2 Macrobenchmarks. In order to evaluate the performance of real-world applications, we design benchmarks that can complete complex tasks with actual functionality. The specific illustration is as follows.

Multimedia data process. In this kind of application, sls-image and sls-video workloads are designed. (i) sls-image is an image processing workload, which performs image transformation tasks using Python Pillow library [16]. sls-image fetches an input image from the cloud storage, and applies ten different effects (e.g., copy, rotation, cropping, etc.) to this image. The corresponding output is uploaded back to the cloud storage. (ii) sls-video applies the grayscale effect from the OpenCV library [15] to the video input, and uploads the converted video to the cloud storage.

MapReduce. MapReduce is a popular programming model that allows developers to process or generate large-scale data in parallel. In our study, we add the sls-mapreduce workload, which consists of two types of functions. One is the Map function to implement filtering and sorting functionalities, and the other is the Reduce function to merge and organize the outputs of the Map function.

ML Training & Serving. We also provide workloads that deal with machine learning (ML) tasks using serverless computing. Such workloads mainly involve with the ML model training and ML model serving. Generally, the raw input data of a machine learning task needs pre-processing to prepare the input of training. In the sls-lr-training workload, we use the text dataset about Amazon Fine Food Review saved in the cloud storage, and input them into the regression model. Because the sls-lr-training workload needs to access large-size datasets from the cloud storage, it often takes up a lot of CPU, memory, and network. After training a model, this model needs to be served for arbitrary inputs to make predictions. In the sls-lr-serving workload, we utilize the model built in the ML model training phase, and input users’ review texts into this model to predict the corresponding sentiment score. To further explore the inference related to deep learning models, we add the image classification workload named sls-cnn and words generation workload named sls-rnn. sls-cnn uses a SqueezeNet model [20] to achieve an impressive accuracy on an ImageNet [13] with 50x fewer parameters than the state-of-the-art model. In our experiments, sls-cnn is implemented with Python Tensorflow Keras [22]. Due to the limited memory size, attempts to import other convolutional neural network models (CNN [9]) are proved to be a failure. sls-rnn uses a recurrent neural network model (RNN [19]) to implement words generation through PyTorch [18].

5 PERFORMANCE EVALUATION

Based on TBS and SlsBench, we can automatically evaluate four mainstream serverless computing platforms. Since executing serverless functions with low latency is critical for user experience[28][26], we mainly focus on the following metrics (i.e., startup latency and resource efficiency) that are closely related with user-perceived latency in this paper. By default, we run each round test for 20 executions and use the median value to represent related evaluation results.

Startup latency. Functions are typically small and executed in seconds or even milliseconds, thereby the startup latency can be a considerable overhead. We mainly focus on the startup latency when cold start happens in this paper. Reducing cold start time is a key challenge in serverless computing [36][29][26]. We will investigate how languages, package size, and memory affect the cold start time of function instance.

Resource efficiency. Different kinds of workloads have various demands for resources. For example, computation-intensive workloads can consume more CPU resources. We will investigate the resource efficiency by executing different workloads on different platforms. In our study, we focus on metrics like execution time of function, throughput of storage and CPU.

Note that we do not show all results in this paper due to space limit. Detailed results are available in our GitHub repository.

5.1 Startup Latency

The cold start may involve downloading a package, launching a new container, setting up the runtime environment, and initializing function, and it takes more time to handle a request than reusing an existing function instance (warm start). Thus, the cold start can significantly affect application responsiveness and in turn affect the user experience.

For each platform, we create functions with the same workload and configuration, and sequentially invoke them twice to derive
the cold start time. We use the difference of overall response time (end-to-end duration from the client perspective) as an estimation of its cold start latency.

![Cold Start Time (ms)](image)

**Figure 5:** The distribution of the cold start time with Python on different platforms.

![Cold Start Time (ms)](image)

**Figure 6:** The distribution of the cold start time with Node.js on different platforms.

![Cold Start Time (ms)](image)

**Figure 7:** The distribution of the cold start time with Java on different platforms.

5.1.1 *How will program languages affect the cold start?* As shown in Figure 3, languages are not well supported across all platforms, thus we just compare the cold start time of three most well-supported languages [17], i.e., Java, Node.js, and Python.

Figure 5, Figure 6, and Figure 7 show the distribution of the cold start time for three different languages, respectively. The most obvious trend is that statically typed languages (e.g., Java) have over 3 times higher cold start time than dynamically typed language (e.g., Python and Node.js), especially for the cases with small memory. AWS Lambda is overall the fastest with allocated memory less than 1024 MB, with a median cold start latency of only 228.37 ms for Python, 139.96 ms for Node.js, and 374.79 ms for Java at 512 MB memory. Executing a Java function needs to launch and initiate a “cumbersome” JVM, and will incur much more overhead and result in much more cold start time. Launching a Java function on AWS Lambda has the least cold start time than other platforms, and can even speed up by a factor of about 7 compared to Google Functions when allocating 128 MB memory. Interestingly, we also find that the Google Functions can perform better than other platforms to run Java functions with allocated memory more than 1024 MB, and the cold start time can even be less than functions developed by other languages.

**Implication:** Without regard to the preference, developers should choose those “light-weight” languages (e.g., Python, Node.js) to implement their functions with lower cold start time, especially for those time-sensitive tasks. When developing functions with huge memory (e.g., more than 1024 MB), developers can be free to choose any languages with low cold start latency. For cloud vendors, they should further optimize the initialization of cumbersome runtime of languages like Java. For example, cloud vendors can apply new technologies like Unikernel to reduce the overhead of initialization [29].

5.1.2 *How will memory affect the cold start?* Since we can not specify the memory of Azure functions (1,536 MB), we can assume its performance to be in the range from 1024 MB to 2048 MB. As shown in Figure 2, developers can specify only different memory when deploying their functions, and the serverless computing platform will allocate CPU capability proportional to allocated memory. Therefore, allocating more memory to executing functions will also increase the computing power of function instance.

As shown in Figure 5, Figure 6, and Figure 7, we can find that the more memory allocated to function means the lower cold start time for most cases for Google Functions, on which the memory size improves the cold start time in a roughly linear fashion. However, we also find that the AWS Lambda and Alibaba Cloud Compute do not seem to have significant differences with different allocated memories for Python and Node.js. This probably means that not so much memory and CPU is required to start the Python or Node.js application. We are also surprised to find that 98.5% of the cold start time can be reduced for Java on Google Cloud Functions when increasing the memory from 128 MB to 2048 MB.

**Implication:** For functions written with Python or Node.js on AWS Lambda and Alibaba Cloud Function Compute, allocating more memory will not speed up the start-up and only lead to more cost. Developers should not increase memory allocation if the task is not memory-intensive. In other cases, developers can properly add certain memory to reduce the cold start time. For cloud vendors, they should give some practical guides of memory configuration to make a balance between the cost and performance.

5.1.3 *How will package size affect the cold start?* Figure 8 compares four Python functions with the various number of referenced third-party packages. Functions are executed using 128 MB of memory. The first bar presents the cold start time of a basal function (504.6 KB). The following three bars show the cold start time of functions constructed by solely adding different third-parity library into the basal function without loading (2.8 MB with a library named Pillow,
21.9 MB with a library named NumPy, and 48.6 MB with a library named OpenCV-python, respectively. The last three bars show the distribution of cold start time of functions with loading the useless library (the dependency libraries are redundantly imported in the package).

Interestingly, we find that increasing the size of the deployment package does not obviously affect the cold start time on AWS Lambda and Azure Functions. Instead, loading more libraries in the function will dramatically increase the cold start time except on the Google Cloud Functions, since it will increase the time of initializing functions (e.g., loading code into memory). In particular, the cold start time can even increase 4.6x if the function loads some unused library (21.9 MB-with-import VS 21.9 MB-no-import).

**Implications:** Loading redundant libraries may introduce non-negligible cold start time, so developers need to trim their code (e.g., removing the useless code) and apply lazy loading of libraries to alleviate the overhead of initializing functions. It is better for cloud vendors to provide related tools to help developers optimize their function packages before development instead of directly deploying the zipped function packages submitted by developers.

### 5.2 Resource Efficiency

We leverage our benchmark tasks (i.e., microbenchmarks and macrobenchmarks) to explore the resource efficiency.

**5.2.1 CPU-bound microbenchmarks.** We use the sls-linpack benchmark to evaluate the CPU capacity of different platforms. sls-linpack operates on a 1,000×1,000 matrix, and will output a performance rating metric in terms of Millions of Floating Point Operations Per Second (MFLOPS). The experimental results are shown in Figure 9. We find that Alibaba Cloud Function Compute performs much better than other platforms, and AWS Lambda performs worst than other platforms. For AWS Lambda and Google Cloud Functions, the mflops can increase linearly by allocating more memory, which conforms to the findings as we summarized in Figure 2 that serverless computing platform will allocate CPU capability proportional with allocated memory.

**Implication:** For computation-intensive workloads, developers are recommended to use the Alibaba Cloud Function Compute. For other platforms, developers can obtain more computing power by allocating more memory.

![Figure 8: The distribution of cold start time of different package size.](image)

![Figure 10: The distribution of the execution latency for the memory-bound workload.](image)

**5.2.2 Memory-bound microbenchmarks.** To measure the performance of memory-bound workloads, we use the sls-fib to calculate the 25th Fibonacci value recursively, which will result in high memory consumption. The experimental results are shown in Figure 10. Alibaba Cloud Function Computing have the shortest execution time among all cases, and are insensitive to more memory. For other platforms, allocating more memory can linearly reduce the execution time. However, the rate of reduction will decrease when allocated memory increased from 1,024 MB to 2,048 MB.

**Implication:** For those memory-bound workloads, developers are recommended to deploy functions on Alibaba Cloud Function Compute to alleviate the burden of limited memory. For other platforms, developers can allocate more memory under a certain limit (1,024 MB) to achieve cost-effective a trade-off between performance and cost.

**5.2.3 DiskIO-bound microbenchmarks.** We leverage sls-randomIO and sls-sequentialIO to measure the throughput of local storage in terms of different IOP patterns, i.e., read and write. The experimental results are shown in Figures 11, 12, 13 and 14. Alibaba Cloud Function Compute has stable performance with different memory, and has outstanding sequential throughput bandwidth than other platforms. For example, Alibaba Cloud Function Compute has 32.96 times the read throughput of Google Cloud Functions at 128 MB of memory. Interestingly, Google Cloud Functions can perform better than Alibaba Cloud Function Compute at when allocated memory is more than 1024 MB.

For other platforms, the IO throughput increases by allocating memory, but the rate of increase will drop when exceeding a
threshold. For example, sequential IO throughput of Google Cloud Functions trends to be stable when allocating memory more that 512 MB. Azure’s memory configuration of 1,536MB implies its performance should be set to the range from 1,024 MB to 2,048 MB. Surprisingly, we find that the throughput of Azure is lower than 1,024 MB instances of other platforms.

Implication: If developers are deploying functions with frequent random IO operations, it is better to deploy such functions on Alibaba Cloud Function Compute, especially for the cases with small allocated memory.

5.2.4 Network-bound microbenchmarks. Since the network latency heavily depends on network condition and geographical location, we mainly focus on the throughput measurement with sls-iPerf in this paper. sls-iPerf use iPerf3 [14] with default configurations to run the throughput test for 30 seconds with different same-region iPerf servers, so that iPerf server-side bandwidth was not a bottleneck [41]. Due to the changeable network conditions, we cannot get stable results and just show some key findings in this part. Network throughput has a trend to increase as function memory increases. Actually, we have also measured the latency with the sls-http benchmark deployed in different regions, and the latency indeed varies across different regions.

Implication: Developers can deploy their functions on the regions that are close to function users, which can obviously reduce the overall response time.

5.2.5 Macrobenchmarks Performance. Different from microbenchmarks that exclusively evaluate different resources, the macrobenchmarks utilize CPU, memory, disk IO, and network resources together at different degrees. We present two representative workloads here.

Figures 15 and 16 shows the execution latency to complete video processing task (sls-video) and model serving task (sls-lr-serving) on each platform, respectively. In this experiment, we also vary the allocated memory size of the function to study its impacts on these workloads.
the execution latency of such macrobenchmarks. Missing bars in the figures indicate that the platform could not complete the given workload with the allocated memory size for platforms except Azure Functions. Besides, Google Functions fail to serve the sls-lr-serving task with high memory demanding.

Alibaba Cloud Function Compute shows better performance than other platforms overall with the same allocated memory, which confirms our previous findings of evaluations with microbenchmarks. In other words, Alibaba Cloud Function Compute performs well in most cases with microbenchmarks, thereby also has better performance for complicated workloads. Google Functions performs worst with a low memory allocated (with memory no more than 512 MB). Although Azure Functions allocates 1,536MB of memory, we find that the execution latency on Azure Functions is close to 1,024 MB instances of other platforms. For each platform, allocating more memory can linearly reduce the execution time of functions. However, the ratio of improvement varies for different platforms.

We need to address that developers can also automatically and conveniently obtain the intuitive comparison result of other workloads with TBS, so that they can make a quick decision to deploy their functions on the target platform to achieve optimal performance.

Implication: For those complicated workloads like macrobenchmarks in this paper, allocating high memory can narrow the performance gap among different platforms.

### 6 DISCUSSION

In this section, we describe some issues that may potentially affect the generalization of our results.

**Other features of serverless computing platform.** In this paper, we do not investigate every aspect of serverless computing, such as permissions, security [25], monitoring, and so on. We mainly focus on performance-related features and give practical implications for both developers and cloud vendors.

**Fairness of evaluation.** In order to make a fair comparison, we deploy all functions in the same region (i.e., us-east in this paper) on all tested platforms. However, serverless computing platforms may have different performance in different regions. With TBS, others can conveniently repeat any experiment in other regions. We will study how the deploying regions can affect the performance of functions.

**Rapid evolution of serverless computing platforms.** The results and findings might change over time. These commodity serverless computing platforms are keeping adding new features and improving their performance, and later benchmarks on these platforms may conflict with our current result. Fortunately, anyone can leverage TBS to benchmark target platforms continuously to keep tracing the up-to-date characteristics.

**Breakdown of cold start time.** The cold start may involve many processes, including downloading a package, launching a new container, setting up the runtime environment, and loading function. Although we have investigated many factors that will affect the overall cold start time, we fail to further locate the mainly affected process due to the coarse-grained logs provided by these commodity serverless computing platforms. We plan to conduct a deeper analysis based on some open-source serverless platforms [3][4].

### 7 RELATED WORK

In this section, we analyze the related work about serverless computing and its benchmark suites.

Shahrad et al. [39] characterized the entire production FaaS workload of Azure Functions, including trigger types, invocation frequencies and patterns, and resource needs. Spillner et al. [40] conducted a quantitative study about how developers use FaaS offerings, and gained insights into how functions are implemented and developed. However, these studies cannot offer insights into the running performance seen by a developer. Some previous work [24, 27, 32, 41] evaluated and compared how serverless applications behave on different platforms. Such work focused more on the workloads and the performance differences between platforms instead of analyzing the underlying implications on serverless computing. Mohanty et al. [35], Palade et al. [37], and Li et al. [33] focused on the performance of serverless computing with several popular open-source serverless platforms. Differently, we mainly focus on current mainstream commodity serverless computing platforms that have standard guidelines and mature practices.

Yu et al. [42] proposed an open-source benchmark suite named ServerlessBench to characterize serverless computing platforms leveraging customized test cases. Maisen et al. [34] and Kim et al. [31] also designed two benchmark suites, named FaaSDOM and FunctionBench, respectively, to facilitate the performance testing of serverless computing platforms. They both provided microbenchmarks, and FunctionBench provided some more complicated benchmarks that represent real-world applications to evaluate the performance. In our study, we can provide a comprehensive benchmark suite including both microbenchmarks and macrobenchmarks, and enable developers or end-users to gain insights on the running performance of each platform automatically in TBS.

### 8 CONCLUSION

In this paper, we have characterized four mainstream commodity serverless computing platforms (i.e., AWS Lambda, Azure Functions, Google Cloud Functions, and Alibaba Cloud Function Compute) via both qualitative analysis and quantitative analysis. In qualitative analysis, we construct a taxonomy of 20 characteristics of serverless computing platforms from three aspects, i.e., development, deployment, and runtime. In quantitative analysis, we design and
implement an open-source benchmark platform **TBS** containing a benchmark suite named **SlsBench**. In **SlsBench**, we construct a set of workloads to evaluate different aspects (e.g., startup latency and resource efficiency) of these serverless computing platforms. In future work, we plan to extend our benchmark platform to cover more various tasks, and maintain **TBS** continuously to facilitate further applications and research on serverless computing for the whole serverless computing ecosystem.

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