Serverless Model Serving for Data Science

Yuncheng Wu  
National University of Singapore  
wucy@comp.nus.edu.sg

Tien Tuan Anh Dinh  
Singapore University of Technology and Design  
dinh@nus.edu.sg

Guoyu Hu  
National University of Singapore  
guoyu.hu@u.nus.edu

Meihui Zhang  
Beijing Institute of Technology  
mehui_zhang@bit.edu.cn

Yeow Meng Chee  
National University of Singapore  
pvocym@nus.edu.sg

Beng Chin Ooi  
National University of Singapore  
ooibc@comp.nus.edu.sg

ABSTRACT

Machine learning (ML) is an important part of modern data science applications. Data scientists today have to manage the end-to-end ML life cycle that includes both model training and model serving, the latter of which is essential, as it makes their works available to end-users. Systems for model serving require high performance, low cost, and ease of management. Cloud providers are already offering model serving options, including managed services and self-rented servers. Recently, serverless computing, whose advantages include high elasticity and fine-grained cost model, brings another possibility for model serving.

In this paper, we study the viability of serverless as a mainstream model serving platform for data science applications. We conduct a comprehensive evaluation of the performance and cost of serverless against other model serving systems on two clouds: Amazon Web Service (AWS) and Google Cloud Platform (GCP). We find that serverless outperforms many cloud-based alternatives with respect to cost and performance. More interestingly, under some circumstances, it can even outperform GPU-based systems for both average latency and cost. These results are different from previous works' claim that serverless is not suitable for model serving, and are contrary to the conventional wisdom that GPU-based systems are better for ML workloads than CPU-based systems. Other findings include a large gap in cold start time between AWS and GCP serverless functions, and serverless' low sensitivity to changes in workloads or models. Our evaluation results indicate that serverless is a viable option for model serving. Finally, we present several practical recommendations for data scientists on how to use serverless for scalable and cost-effective model serving.

1 INTRODUCTION

Machine learning (ML) has transformed data science [18, 21, 38]. Figure 1 illustrates the changes. Until recently, a typical data science pipeline consists of data collection, cleaning and integration, data analytics, and visualization. Now, the pipeline includes the full machine learning life cycle, turning data scientists into end-to-end data engineers [27]. Consider a nutrition analysis application, FoodLG\(^1\), as an example. A data scientist working on FoodLG first collects a set of labeled food images from nutritionists, transforms the data, and builds a deep learning model [33, 41] that classifies food images and analyzes the nutrition information according to a food knowledge base (e.g., CalorieKing\(^2\)). After that, the data scientist deploys the model and makes it available to users' mobile apps. Then a user sends food images as requests to the deployed model and receives the predicted food nutrition (e.g., calorie, protein). FoodLG can further record the user’s daily intake, analyze her eating habit, and provide suggestions for a healthy diet. New data is collected and fed back to the pipeline to improve model accuracy. In real-world applications like FoodLG, model serving plays a crucial role in bringing the works of data scientists to the end-users.

Model serving systems are interactive, that is, they handle inference requests from users and other applications in near real-time. As a result, their design goals differ from those of model training systems that focus on maximizing throughput. The first goal is high performance, which means that the system can process requests fast, even under bursty workloads. The second goal is low cost, which means that the system is cost-effective when handling a large number of requests. The third goal is ease of management, which means that the system allows data scientists to quickly deploy ML models without worrying about low-level details such as resource management. Existing cloud providers are offering several model serving options, including managed services and self-rented servers [6, 12, 29]. These options, however, only focus on providing high performance and ease of management. In other words, they do not meet all the goals.

Serverless computing [19, 23], an emerging cloud computing paradigm, brings another possibility for model serving, and it has the potentials for achieving the three goals above. Figure 2 shows how serverless can support model serving for FoodLG. The data scientist first uploads the trained model to the cloud storage, then

---

\(^1\)http://www.foodlg.com/
\(^2\)https://www.calorieking.com/us/en/foods/
writes and deploys a function to perform model inference based on user requests. The cloud provider creates an invokable endpoint (e.g., a URL) for the function, to which users can send their requests and receive inference results. The serverless platform takes care of provisioning computation instances to execute the function, and of scaling the number of instances according to the request workload. The data scientist is charged by the actual amount of consumed resources, instead of the time of reserved resources.

Serverless can achieve the first goal of model serving, i.e., high performance, because each function is executed on an isolated instance, as opposed to on a shared resource. It can meet the second goal, i.e., low cost, because billing is only based on the actual resource consumption. This means that the scientist does not have to provision for peak load, which can be expensive, especially when using GPUs. The last goal, ease of management, is also met, since provisioning and scaling of resources are handled automatically by the cloud platform. Despite these potentials, there are challenges in applying serverless to model serving. In particular, serverless has several limitations, including small memory size, limited running time, and lack of persistent states [19, 22, 24, 25, 32, 37].

In this paper, we ask the following question: can serverless computing be a mainstream model serving platform for data science applications? More specifically, can it be better than existing cloud-based alternatives with respect to the three goals mentioned above? To answer this, we conduct an extensive cost-performance comparison between serverless and other cloud-based model serving systems. We consider eight systems spanning two major cloud providers: Amazon Web Service (AWS) and Google Cloud Platform (GCP). In particular, we evaluate Lambda, Cloud Functions, SageMaker, AI Platform, and self-rented CPU and GPU systems from AWS and GCP. We use two deep learning models for the evaluation: MobileNet, an image classification model, and ALBERT, a natural language processing model. We evaluate these models on the eight systems under three different workloads. We compare the systems in three metrics: response latency, requests success ratio, and cost.

Our results contain two surprising findings. First, while earlier works claimed that serverless is not suitable for model serving [19], we find that, in most cases, serverless outperforms both self-rented CPU systems, and managed services such as SageMaker and AI Platform in both cost and performance. Second, while other works suggested that serverless should be used as a complementary platform to a GPU-based system for handling excessive load [42], we show that there are circumstances in which serverless outperforms self-rented GPU systems. In particular, on AWS, serving MobileNet with workload-200 (see Figure 3c, which consists of 18000 requests) with serverless results in the average latency of 0.052s and cost of $0.011. In contrast, doing the same using a GPU server results in the average latency of 1.463s and cost of $0.041. In addition to these surprising results, we also find that there is a gap in the cold start time between AWS and GCP serverless functions. For instance, using the same serving environment, namely OnnxRuntime [31], AWS takes about 2.25s on average to start an instance while GCP takes about 8.16s. Finally, we find that serverless is less sensitive to changes in workloads or models, which means it can provide consistent performance even under bursty workloads or when the models are large.

Figure 2: An example of using serverless for model serving.

Our results provide an important insight, that is, serverless is a viable option for model serving. We show evidence of serverless meeting all the performance, cost, and ease of management goals at the same time. From the findings, we further discuss three practical recommendations for data scientists that can help to improve the scalability and cost-effectiveness of serverless model serving. First, data scientists should choose the serving framework carefully and import minimal dependencies, so that the built package is as small as possible, thereby decreasing the cold start time. Second, they could write their serverless functions with parallelism, e.g., overlapping context initialization with model downloading, to further reduce the cold start latency. Third, if latency is a loose constraint, they can consider batching multiple requests to save the cost.

In summary, we make the following contributions in this paper.

- We conduct an extensive cost and performance comparison of serverless against other cloud-based systems for model serving. Our analysis covers eight different systems on two major public cloud providers, with two deep learning models and three different workloads.
- We present interesting findings indicating that serverless is viable as the mainstream platform for model serving. In contrast to the previous claims that serverless is not suitable for model serving, we show that it outperforms many alternative cloud-based systems in both cost and performance. Furthermore, under some circumstances, it can even outperform GPU-based systems.
- We further discuss three practical recommendations for data scientists on how to use serverless for scalable and cost-effective model serving. In addition, we discuss several challenges and opportunities in serverless model serving.

The remaining of the paper is structured as follows. Section 2 presents the background and related work. Section 3 describes the cloud-based model serving systems. Section 4 details the cost and performance analysis of the eight systems. Section 5 gives some discussions on serverless model serving, before Section 6 concludes.

2 BACKGROUND AND RELATED WORK

In this section, we briefly introduce the related work on machine learning serving systems and serverless computing. We also present the serverless model serving background on the cloud.

2.1 Machine Learning Serving

Machine learning has shown great success in a wide range of data science applications [18, 21, 38]. How to efficiently deploy
the trained ML models in the production stage to serve end-users with low latency becomes increasingly important. Recently, there are a number of model serving systems that focus on improving cost-effectiveness or model accuracy while meeting service level objective (SLO) on latency, by automatically selecting different configurations. For example, Clipper [8] and Rafiki [40] use an ensemble of models to navigate between latency and accuracy. They also adaptively batch prediction requests to boost throughput when the latency requirement is satisfied. Swayam [17] presents an autoscaling framework that monitors the distribution of request execution time and reactively adjusts the number of CPU servers to meet the SLO requirement. However, these systems are mainly based on server machines and do not work well for ML model serving [42].

2.2 Serverless Computing

Serverless computing [23] is a recent rise of cloud computing execution paradigm such that the cloud provider runs the server and dynamically manages the allocation of machine resources. It can simplify the deployment process of function code to the production environment. Meanwhile, it can automatically increase and release resources to adapt to the number of user invocations, making it elastic to handle various workloads. Pricing is based on the actual amount of resources consumed by the deployed function. Due to its high elasticity and fine-grained cost model, serverless computing has been adopted in many data science applications, such as database analytics [22, 32, 34], model training [7, 39], and so on.

2.3 Serverless Model Serving

In particular, serverless computing can be seamlessly utilized for model serving due to its stateless computations. As mentioned in Section 1, data scientists (aka. function developers) can deploy a pre-trained model on the cloud via a function. Algorithm 1 presents the main steps of a serverless model serving function. Once received an event from the serverless proxy, the cloud provider will create new instances or forward the requests to the warmed-up instances to execute the function code. If an instance is newly created (i.e., cold start), it downloads the model (which is uploaded by the data scientists) from cloud storage to local; otherwise, the model already exists. Then the function parses the input sample from event, executes the inference, and returns the prediction.

The most related work to ours is MArK [42], which mainly evaluates the cost of several model serving systems on the cloud and proposes a serving system that combines self-rented servers and serverless to reduce the cost. BATCH [2] also considers serverless model serving, which designs a mechanism that batches multiple requests and dynamically chooses the resource configuration of invoked serverless function, to satisfy latency constraint and minimize cost. However, they do not investigate the performance of existing serverless systems and the potential of pure serverless model serving systems.

3 MODEL SERVING ON THE CLOUD

With the popularity of cloud computing, cloud providers such as Amazon Web Services (AWS) [3], Google Cloud Platform (GCP) [14], and Microsoft Azure [30] offer various provisioning services that can be used for model serving. In the following, we briefly introduce the services we evaluated in this paper.

Serverless model serving. We consider two serverless computing platforms: AWS Lambda [5] and Google Cloud Functions (CF) [13].

AWS Lambda. To deploy a model serving service on Lambda, model owners can first create a function by specifying the memory size for each instance, and then provide a package that contains the full serving environment (e.g., TensorFlow [16] and its dependencies) and the corresponding handler. The folder structure in the package needs to follow a designated format such that Lambda can recognize and link it to the created function for processing users’ model prediction requests. Model owners are charged by the number of requests and the duration of computation time.

Google Cloud Functions. Similarly, model owners can write a function that executes model inference in one of the supported languages. However, there is no need to package and upload dependencies but to specify the required environment in the Requirement.txt, and the platform will build the package automatically. The service is charged by the amount of CPU and memory resource consumed for function executions, which also depends on the selected memory size and the number of instances created at runtime.

Table 1: Summary of experimental dimensions on the Google and Amazon cloud platforms

| Services       | Instance Types          | Serving Models | Workloads 40 | Workloads 120 | Workloads 200 | Environment  |
|----------------|-------------------------|----------------|--------------|---------------|---------------|--------------|
| Amazon         | Lambda                  | 2048MB memory  | ✓            | ✓             | ✓             | ORT1.6       |
|                | SageMaker               | ml.m4.2xlarge  | ✓            | ✓             | ✓             | TF1.15       |
|                | Self-rented CPU         | t2.2xlarge     | ✓            | ✓             | ✓             | TF1.15       |
|                | Self-rented GPU         | g4dn.2xlarge   | ✓            | ✓             | ✓             | TF1.15       |
| Google         | Cloud Function          | 2048MB memory  | ✓            | ✓             | ✓             | ORT1.6       |
|                | AI Platform             | n1-standard-8  | ✓            | ✓             | ✓             | TF1.15       |
|                | Self-rented CPU         | n1-standard-8  | ✓            | ✓             | ✓             | TF1.15       |
|                | Self-rented GPU         | n1-standard-8 with 1 NVIDIA® Tesla® T4 | ✓            | ✓             | ✓             | TF1.15       |
with the ability to autoscale when the workload is too heavy to serve. Systems described in Section 3. We describe the experiments in detail. We first evaluate the effect of the runtime environments on serverless performance. Next, we compare serverless with managed ML services, self-rented CPU, and self-rented GPU systems, respectively.

4 MODEL SERVING SERVICES EVALUATION

In this section, we evaluate the performance and cost of the model serving systems described in Section 3. We describe the experimental setup, and summarize the key findings before presenting them in detail.

4.1 Evaluation Setup

Configurations. We use TensorFlow Serving version 1.15 as the runtime for all systems except for serverless. We consider two different runtimes for serverless: OnnxRuntime (ORT) and TensorFlow (TF). The serverless instances are configured with 2048MB of memory on both AWS Lambda and Google Cloud Functions. For model serving with ML services, we use ml.m4.2xlarge instances (8vCPUs and 32GB memory) and n1-standard-8 instances (8vCPUs and 30GB memory) on AWS SageMaker and Google AI Platform, respectively. Autoscaling is enabled for both services, and the minimum number of running instances was set to 1.

For self-rented options on AWS, we use a t2.2xlarge instance (8vCPUs and 32GB memory) and a g4dn.2xlarge instance (8vCPUs, 32GB memory, and 1 NVIDIA T4 Tensor Core GPU) for the CPU and GPU servers, respectively. On Google Compute Engine, we use an n1-standard-8 instance for the CPU server and add 1 NVIDIA Tesla T4 accelerator for the GPU server. In the following, we omit the platform names and use the server specifications to represent the systems. Table 1 summarizes the configuration choices in our experiments.

Models. We use two deep learning models representing two popular data science applications: (1) MobileNet [20], an efficient convolution neural network model for image classification application whose model size is about 16MB; (2) ALBERT model [26], a lightweight version of BERT model for natural language processing application whose model size is about 51.5MB.

Workloads. We use the Markov-Modulated Poisson Process (MMPP) model [10, 35], also used in previous works [42], to generate workloads with varying request rates. Specifically, we evaluate three workloads with low, medium, and high rates, as shown in Figure 3. The numbers 40, 120, and 200 in the workloads represent the peak numbers of requests per second in MMPP. In the experiments, we employ multiple clients to send requests such that the aggregated request rate matches the generated workloads.

Metrics. We evaluate the systems using the following three metrics.

- **Average response latency.** We measure the end-to-end response latency for each request on the clients, and report the average latency of the successful requests.
- **Requests success ratio.** When the request rate exceeds the limit that a system can handle, some requests are dropped, or errors are returned. We report the ratio of successful requests over all the requests. The higher the ratio, the better.
- **Cost.** We measure the charges for each experiment. For systems charged hourly (e.g., self-rented servers), we estimate the cost based on the actual execution time.

4.2 Summary of Key Results

We summarize four important findings below.

- For serverless, OnnxRuntime has better performance than TensorFlow. Specifically, it has lower latency and cost: up to
We first evaluate the impact of serving runtime on the performance. AWS Lambda is always better than Google CF. One contributing factor is the instance’s cold start time. In particular, CF takes a longer time to start an instance, for example, around 32.3s and 8.16s for the TF and ORT environments, respectively. In contrast, Lambda takes only 5.69s and 2.25s, respectively. We note that for CF, although we specify the name and version of the runtime, internally there may be other dependencies or overheads that lead to a long cold start time.

Second, Lambda’s performance is more stable than that of CF under different workloads. Even for the high workload, Lambda can spawn new instances quickly enough to handle the high number of requests. On CF, however, the longer cold start time leads to two problems: high response latency, and over-provisioning (i.e., creating more instances than needed). Specifically, for TF1.15 under workload-200 (see Figure 3c), we see more than 1200 instances created during the first request peak (i.e., timestamp 0 to 50), while only 500 instances are needed during the second request peak (i.e., timestamp 150 to 200). In other words, about 700 instances are over-provisioned due to the high request rate. As a result, the cost becomes higher, as shown in Table 2.

Third, model serving with ORT is more efficient than with TF on both platforms. Specifically, on Lambda, ORT1.6 achieves up to $8.2\times$ speedup on average compared to TF1.4. The reason is two-fold. One is that ORT is optimized for improving model inference performance, whereas TF1.4 is a relatively old version such that the execution time is much longer. The other is that the cold start time is smaller due to the smaller package size. Similarly, ORT1.6 also outperforms TF1.15 in terms of latency on CF.

Table 2 summarizes the costs for the experiments, which are consistent with Figure 4. An interesting finding is that the cost of CF with workload-40 is higher than that with workload-120. At first glance, this seems counter-intuitive because the two workloads have the same number of requests, and a higher workload should results in a longer execution time on average. In other words, the costs should be consistent with what we find on Lambda. However, after careful analysis, we see higher fluctuations of latency for workload-40 than workload-120, which is due to frequent cold starts on CF. Since the cold start time on CF is long, it has a large impact on CF and results in a high cost.

Since ORT is more efficient on both platforms, we use this runtime for serverless in the remaining experiments. The other systems still use TF Serving because ORT does not provide the corresponding serving system.

### 4.3 Serverless Comparison

We first evaluate the impact of serving runtime on the performance of serverless. We consider two popular runtimes: TensorFlow (TF) and OnnxRuntime (ORT). TF is comprehensive and widely adopted in many production systems, whereas ORT is light-weight and more optimized for model inference.

Google CF allows users to specify the runtime environment directly; therefore, we select TF1.15 and ORT1.6. However, AWS Lambda functions require users to upload their own packages. Furthermore, there is a 250MB limit on the size of the uncompressed uploaded package. This restriction makes it impossible to package and deploy TF1.15 on the platform. We therefore use TF1.4 which requires less space. Specifically, in our experiments, the uncompressed package size of TF1.4 is around 196MB, and that of ORT1.6 is around 92MB.

Figure 4 reports the average latency for MobileNet. There are three main observations. First, given the same serving environment, AWS Lambda is always better than Google CF. One contributing factor is the instance’s cold start time. In particular, CF takes a longer time to start an instance, for example, around 32.3s and 8.16s for the TF and ORT environments, respectively. In contrast, Lambda becomes higher, as shown in Table 2.

Second, Lambda’s performance is more stable than that of CF under different workloads. Even for the high workload, Lambda can spawn new instances quickly enough to handle the high number of requests. On CF, however, the longer cold start time leads to two problems: high response latency, and over-provisioning (i.e., creating more instances than needed). Specifically, for TF1.15 under workload-200 (see Figure 3c), we see more than 1200 instances created during the first request peak (i.e., timestamp 0 to 50), while only 500 instances are needed during the second request peak (i.e., timestamp 150 to 200). In other words, about 700 instances are over-provisioned due to the high request rate. As a result, the cost becomes higher, as shown in Table 2.

Third, model serving with ORT is more efficient than with TF on both platforms. Specifically, on Lambda, ORT1.6 achieves up to $8.2\times$ speedup on average compared to TF1.4. The reason is two-fold. One is that ORT is optimized for improving model inference performance, whereas TF1.4 is a relatively old version such that the execution time is much longer. The other is that the cold start time is smaller due to the smaller package size. Similarly, ORT1.6 also outperforms TF1.15 in terms of latency on CF.

Table 2 summarizes the costs for the experiments, which are consistent with Figure 4. An interesting finding is that the cost of CF with workload-40 is higher than that with workload-120. At first glance, this seems counter-intuitive because the two workloads have the same number of requests, and a higher workload should results in a longer execution time on average. In other words, the costs should be consistent with what we find on Lambda. However, after careful analysis, we see higher fluctuations of latency for workload-40 than workload-120, which is due to frequent cold starts on CF. Since the cold start time on CF is long, it has a large impact on CF and results in a high cost.

Since ORT is more efficient on both platforms, we use this runtime for serverless in the remaining experiments. The other systems still use TF Serving because ORT does not provide the corresponding serving system.

### 4.4 Serverless vs. ML Service

We now compare serverless against managed ML services, namely SageMaker and AI Platform. Figure 5 and Table 3 summarize the results.

#### AWS Lambda vs. SageMaker

Figure 5a-5b compare Lambda with SageMaker for the MobileNet and ALBERT models, respectively. The average latency of Lambda is two orders of magnitude lower than that of SageMaker. Furthermore, there are no failed requests.

| Workloads  | AWS Lambda | Google Cloud Functions |
|------------|------------|------------------------|
| ORT1.6     | $0.009     | $0.121                 |
| TF1.4      | $0.043     | $0.072                 |
| ORT1.6     | $0.011     | $0.171                 |
| TF1.15     | $0.123     | $0.404                 |

| Workloads  | AWS Lambda | Google Cloud Functions |
|------------|------------|------------------------|
| workload-40| $0.009     | $0.121                 |
| workload-120| $0.043   | $0.072                 |
| workload-200| $0.011   | $0.171                 |
| workload-40| $0.123     | $0.404                 |

Figure 4: Average response latency for serverless MobileNet model serving with respect to three workloads, where the error bar denotes the standard deviation of the latency.
in Lambda, but there are many in SageMaker, especially when the request rates are high or the model execution time is long. For example, the success ratio for MobileNet drops from 87% (workload-40) to 36% (workload-120). For ALBERT, even with workload-40, the success ratio is only 19%, rendering the service unusable.

Figure 6a shows a detailed comparison for the MobileNet model with workload-40. In the beginning, the average latency of Lambda (about 3 seconds) is higher than that of SageMaker. This is due to the cold start time. However, as the system is warming up (i.e., instances are kept warmed to serve subsequent requests), Lambda performs better and is more stable than SageMaker. When the request rate becomes high (e.g., starting at around timestamp 100), SageMaker is unable to keep up, resulting in high latency and request failure. This result demonstrates the elasticity of Lambda: when receiving new requests, it can create new instances quickly if necessary. In contrast, SageMaker’s autoscaling takes several minutes to start new instances, leading to a large number of queued requests and thus delayed responses.

**Google Cloud Functions vs. AI Platform.** Figure 5c-5d show the results for Google systems under the same settings. For the MobileNet model under workload-40, there are no failed requests for both systems, but CF is slightly worse than AI Platform in terms of average latency. However, under workload-120, both latency and success ratio of AI Platform deteriorate significantly, while those of CF are almost the same. Figure 6b shows the detailed comparison for MobileNet under workload-120. There is a noticeable gap between timestamps 150 and 200 for AI Platform. During this period, the service is unresponsive, i.e., all the requests fail. This result demonstrates that, similar to SageMaker, AI Platform cannot scale fast enough, and once the number of queued requests reaches a threshold, its performance degrades quickly.

**Cost comparison.** As shown in Table 3, serverless is more cost-efficient than managed ML services. One reason is that, the managed services take several minutes to start new instances, and the evaluated workloads are relatively short. Therefore, most of the costs are spent on autoscaling instances rather than doing the actual work. Combining with the results in Figure 5, we can see that, in most cases, serverless outperforms ML services in terms of both average latency and cost. The exception is for the MobileNet model with workload-40 on GCP, AI Platform is slightly better in terms of average latency, but in this case, its cost is much higher (i.e., 5.3x that of serverless).

### 4.5 Serverless vs. CPU Server

We compare serverless with self-rented CPU servers, the results of which are shown in Figure 5 and Table 3.

**AWS Lambda vs. CPU server.** Figure 5a-5b show that for both models, the average latency of Lambda is always smaller than that of the CPU server, and the advantage is more pronounced when the workload is higher, or when the model is more complex. In addition, the success ratio of the CPU server decreases when the workload increases. Specifically, for the MobileNet model, the ratios are 100%, 75%, and 65% for workloads 40, 120, and 200, respectively. The reason is that the server is overloaded, and requests are queued up under high load. Figure 5c shows the success ratio of both systems under the same settings. For the CPU server, the performance of the ALBERT model is worse than that of MobileNet. This is due to the size of ALBERT being larger: 51.5MB versus 16MB. Furthermore, the computation on ALBERT is more complex than on MobileNet. As a consequence, the execution time per request is higher for ALBERT, resulting in longer queues, higher latency, and more failure. In contrast, Lambda’s latency remains consistently low due to its elasticity.

**Google Cloud Functions vs. CPU server.** Figure 5c-5d show a similar pattern to the comparison with AI Platform. In particular, for the MobileNet model with workload-40, the CPU server is slightly faster than serverless. However, when the workload increases, the performance of the CPU server degrades significantly, as shown in Figure 6d. At the two request peaks (timestamp 75 to 150, and

| Workloads | Lambda | SageMaker | CPU | GPU | Cloud Functions | AI Platform | CPU | GPU |
|-----------|--------|-----------|-----|-----|-----------------|-------------|-----|-----|
| workload-40 | $0.009 | $0.119 | $0.683 | $0.353 | $0.089* | $0.181* | $0.051 | $0.116 | $0.272 | $1.072 | $0.092* | $0.177* |
| workload-120 | $0.009 | $0.121 | $0.230 | - | $0.026* | $0.052* | $0.043 | $0.189 | $0.128 | - | $0.027* | $0.051* |
| workload-200 | $0.011 | $0.146 | - | - | $0.020* | $0.041* | $0.072 | $0.286 | - | - | $0.021* | $0.040* |

*For the evaluated services, * indicates the estimated cost based on hourly pricing.
timestamp 200 to 250), the average latency grows more than 10 seconds. We note that there are virtually no request failures on GCP CPU server under workload-120, a stark contrast to AWS. One reason may be due to the optimized network stack at GCP that does not drop requests aggressively.

Cost comparison. For the ALBERT model, the CPU server incurs a lower cost than serverless on both platforms. However, we note that the success ratio of the CPU server is extremely low, especially for the high workload. For the MobileNet model, Lambda is cheaper while delivering better performance. On GCP, CF is cheaper with comparable performance under a low workload. For higher workloads, CF incurs higher costs but delivering better performance.

4.6 Serverless vs. GPU Server
Finally, we compare serverless with self-rented GPU servers, the results of which are shown in Figure 5 and Table 3.

AWS Lambda vs. GPU server. Since there are no request failures on both systems, we only compare them in terms of the average latency. For MobileNet under workload-40 and workload-120, the GPU server is better than Lambda. The is because the GPU server can process each request quickly (e.g., about 0.01 second per request in our experiments). Therefore, the request queue is shorter, resulting in low latency. However, under workload-200 (see Figure 3c), more requests are queued up, as shown in Figure 6e. The results can be analyzed in three stages. First, in the beginning, the GPU server performs better than Lambda since the latter incurs cold start overhead. Second, once Lambda instances are warmed-up, when the request rates are high, Lambda outperforms the GPU server. This is because the request rate is higher than the GPU’s capacity; thus, the request queue grows and leads to higher latency. Finally, when the request rates are reduced, the GPU server regains its advantage.

Nevertheless, Lambda’s latency is only slightly higher than that of the GPU server.

Figure 6f shows that for the ALBERT model, the GPU server has worse performance even under low workload, both in terms of latency and success ratio. In fact, the ALBERT model’s prediction time is about ten times that of the MobileNet model on the GPU server, which means that requests are more likely to be queued.

Google Cloud Functions vs. GPU server. The comparison of different systems on GCP is similar to that of systems on AWS, except that the success ratio of the ALBERT model is higher than on AWS GPU server. The reason is similar to what we have discussed in Section 4.5. Figure 6g–6h show the results of the two models under workload-200, where the advantage of CF is more significant at the two request peaks. This demonstrates that serverless can adapt better to larger models than GPUs, due to its elasticity.

Cost comparison. For the MobileNet model under low workloads (workload-40 or workload-120), the GPU server has better performance, but its cost is also higher. In particular, for workload-40 on AWS, the GPU server’s cost is about 20× compared to that of Lambda. This is because the GPU server is under-utilized while still being charged. On the contrary, serverless is only charged based on the actually consumed resources. Thus, it is more cost-effective under these workloads. For the ALBERT model, serverless is more expensive (except for workload-40), as it requires more CPU time per request. However, we note that in those cases, the GPU server has high response latency and request failures.

The results in this section demonstrate a trade-off between the cost and performance of the GPU server and serverless. Under a low workload, serverless is cheap, but the latency is high; while under a high workload, serverless is more expensive, but has better performance (lower latency and request failures). We find that on AWS, in some cases, serverless is better than the GPU server in both cost and performance. For instance, for the MobileNet model.
So far, we have shown that serverless is a viable option for model serving. Our results let us draw three interesting insights. First, different commercial serverless platforms have different cold start times, which directly affects the cost and performance of model serving. Second, choosing a suitable, light-weight runtime environment can lead to significant improvement in both cost and performance. Third, serverless can ensure consistent performance under bursty workloads, i.e., it is less sensitive to workload model changes compared to other model serving systems.

5 DISCUSSIONS

From the above insights, we discuss three practical recommendations for data scientists that can help extract more performance with serverless model serving while incurring a lower cost. First, for better performance, AWS Lambda is the preferable option. However, Lambda requires function developers to manually build the environment package as well as its dependencies, which may not be friendly enough to data scientists. On the other hand, for ease of management, that is, the scientist wants to deploy the serving service without much effort, then Google CF is the better choice as it only requires specifying the runtime version. Furthermore, the data scientist should select the runtime carefully to minimize dependencies, so that the final package is as small as possible because smaller packages decrease the cold start time. It should be noted, however, that a light-weight serving framework like OnnxRuntime may not have comprehensive functionalities as those full-fledged frameworks (e.g., TensorFlow).

Second, data scientists can further reduce the response latency for the first request (i.e., cold start latency) by re-writing their function to support parallelism. Specifically, we can divide the cold start latency into five sequential steps: container initialization (i.e., pull the built package from cloud storage), library import (i.e., prepare the serving environment), model download (i.e., pull the uploaded model), model load (i.e., load the model into the serving environment), and model inference, as shown in Figure 7. We note that some of the steps can be overlapped. For example, regarding ‘Parallel 1’ in Figure 7, instead of starting the download after all the libraries are imported, we can first import the prerequisite library for the download (e.g., Boto3 on AWS), and then parallel importing the rest of the libraries (e.g., OnnxRuntime and Numpy) with downloading model. This way, we observe a reduction of the cold start latency for the MobileNet model by 10.6% on AWS Lambda (the result is the average of 50 independent trials). In addition, we can also slice the model into multiple pieces, and parallel the download and load of each piece, as illustrated in ‘Parallel 2’ in Figure 7. However, this does not bring too much improvement on ‘Parallel 1’ in our experiments, as the model size is relatively small. We will investigate more on parallelism in our future work.

Third, if the cost is a more important constraint than latency, data scientists can consider batching several requests before sending them to serverless functions. This could reduce the cost because: (i) the number of invocations is reduced; (ii) the request rate is reduced, resulting in fewer numbers of cold start instances; (iii) batch execution increases data parallelism and is often more efficient than multiple single request execution. However, the overall latency will increase. Figure 8 shows an example that uses various batch sizes for the MobileNet model under workload-120 on Google CF. As the batch size increases, the cost first decreases, and then becomes stable (e.g., from 4 to 16). The reason is that when the batch size reaches a threshold, the pure model prediction time on serverless already dominates the cost. Nevertheless, the average latency increases as most requests are delayed and the execution time on serverless (i.e., response to the batched requests) increases. In practice, data scientists should understand the expected workloads and latency constraints before enabling batching.

5.2 Challenges and Opportunities

Finally, we discuss several challenges and opportunities in serverless model serving. One of the biggest challenges is data security. With the implementation of strict data protection regulations, e.g., GDPR [1], data scientists need to protect user’s data security and privacy. In serverless model serving, it mainly consists of two aspects. On the one hand, data scientists should protect their model because it is trained on users’ data and may disclose private information indirectly [36]. On the other hand, user’s requests may contain sensitive data (e.g., medical images in the healthcare analysis application). A possible solution is to use cryptographic techniques [9, 11] for the protection. However, these techniques are extremely inefficient; therefore, they may not satisfy the limited running time constraint in serverless. Another solution is based on trusted hardware (e.g., Intel SGX [28, 43]), which is much more efficient. Nevertheless, most existing commercial serverless platforms, including AWS Lambda and Google CF, do not support this functionality. In addition, the security guarantee of trusted hardware often needs to establish a secure channel between the user and the serverless instance, which requires interactive communication. It brings a new challenge to existing serverless infrastructure because
the serverless proxy manages the sessions, which are unknown to the instances (see Figure 2). Thus, more research work is needed to make serverless a secure and efficient solution for real-world model serving.

The second challenge is that deep learning models are becoming larger and more complex, which may lead to significantly high latency. Though parallelizing multiple steps can reduce the latency (as discussed in Section 5.1), the limited resources on each serverless instance make it not efficient enough. For example, an instance with 2048MB memory on AWS Lambda only has two CPU cores. Besides, some models may even not fit into the serverless instances due to the limited memory size [42]. A potential direction is to utilize multiple serverless instances to execute one model prediction in a distributed manner. However, data scientists need to further investigate: how to determine a reasonable model slicing strategy such that the transmitted information among instances is minimized, and how to manage multiple instances and parallelize the executions efficiently, reducing both latency and cost.

The third challenge is how to address the over-provisioning problem, i.e., the serverless platform creates more instances than needed when the request rate is high (see Section 4.3). This problem would greatly increase the cost of serverless model serving. Although a light-weight runtime environment, as evaluated in Section 4.3, can reduce the cold start latency and alleviate this problem, it may deteriorate again when incorporating data security or serving much more complex models. Another possible approach is to monitor the requests’ execution time, predict the subsequent request rate, and pre-warm up more instances before the request rate bursts. However, from our experience on Google CF, even we pre-warm up a number of instances to handle the forthcoming bursty requests, CF revokes most of the instances within a short period of time. When the request peak comes, the number of pre-warmed instances is still insufficient. Thus, it might be difficult for data scientists to decide when to pre-warm up instances because the scaling strategies of existing serverless systems from public cloud providers are BlackBox. Nevertheless, we believe that these systems would support a more configurable scaling policy in the future so that data scientists can tune the policy based on their workloads.

6 CONCLUSIONS

In this paper, we have conducted a comprehensive performance comparison of serverless against other cloud-based model serving systems from AWS and GCP, using two deep learning models and three different workloads. The experimental results demonstrate that serverless can be utilized as a mainstream model serving option. In particular, it outperforms many alternative cloud serving systems in terms of both performance and cost. Moreover, it can even outperform GPU-based systems under some circumstances. We further present practical recommendations for data scientists to use serverless for scalable and cost-effective model serving, and discuss several challenges and opportunities.

REFERENCES

[1] [n.d.]. Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing directive 95/46/ec (general data protection regulation). OJ, 2016-04-27. [n.d.].
[34] Matthew Perron, Raul Castro Fernandez, David J. DeWitt, and Samuel Madden. 2020. Starling: A Scalable Query Engine on Cloud Functions. In SIGMOD. 131–141.

[35] Ali Rajabi and Johnny W. Wong. 2012. MMPP Characterization of Web Application Traffic. In MASCOTS 107–114.

[36] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. 2017. Membership Inference Attacks Against Machine Learning Models. In S&P 3–18.

[37] Vikram Sreekanti, Chenggang Wu, Xiaoyue Charles Lin, Johann Schleier-Smith, Joseph Gonzalez, Joseph M. Hellerstein, and Alexey Tumanov. 2020. Cloudburst: Stateful Functions-as-a-Service. Proc. VLDB Endow. 13, 11 (2020), 2438–2452.

[38] Leonid Velikovich, Ian Williams, Justin Scheiner, Petar Aleksic, Pedro Moreno, and Michael Riley. 2018. Semantic Lattice Processing in Contextual Automatic Speech Recognition for Google Assistant. In Interspeech.

[39] Hao Wang, Di Niu, and Baochun Li. 2019. Distributed Machine Learning with a Serverless Architecture. In INFOCOM. 1288–1296.

[40] Wei Wang, Jinyang Gao, Meihui Zhang, Sheng Wang, Gang Chen, Teck Khim Ng, Beng Chin Ooi, Jie Shao, and Moaz Reyad. 2018. Rafiki: Machine Learning as an Analytics Service System. Proc. VLDB Endow. 12, 2 (Oct. 2018), 128–140. https://doi.org/10.14778/3282495.3282499

[41] Wei Wang, Meihui Zhang, Gang Chen, H. V. Jagadish, Beng Chin Ooi, and Kian-Lee Tan. 2016. Database Meets Deep Learning: Challenges and Opportunities. SIGMOD Rec. 45, 2 (2016), 17–22.

[42] Chengjiang Zhang, Minchen Yu, Wei Wang, and Feng Yan. 2019. MArk: Exploiting Cloud Services for Cost-Efficient, SLO-Aware Machine Learning Inference Serving. In USENIX ATC. 1049–1062.

[43] Wenting Zheng, Ankur Dave, Jethro G. Beekman, Raluca Ada Popa, Joseph E. Gonzalez, and Ion Stoica. 2017. Opaque: An Oblivious and Encrypted Distributed Analytics Platform. In NSDI. 283–298.