International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2020): 7.803

# Optimizing AI Workflows with Infrastructure-as-Code and Serverless Cloud Patterns

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**Abstract:** ***Today, many applications exploit artificial intelligence and machine learning algorithms to perform various tasks. However, creating a solution for tasks like image prediction or language translation generally takes significant effort by many teams. These effort-intensive actions can potentially be shortened by creating fully serverless cloud pipelines that anyone can customize and employ. The problem is that despite the numerous cloud services that support multiple AI ML frameworks, creating and fully cloud-dependent execution will take considerable time. Many sectors are migrating to applying artificial intelligence and ML paradigms on their day-to-day tasks. However, the internal logic and learning process need to be regulated and understood. Recent research shows that interest in cloud usage is proliferating daily. Major cloud services may attract many customers if they make their services cost-effective and pleasant to use. Tech-savvy people create off-the-shelf clever cloud services to perform daily tasks like object detection, classification, recognition, classification, and image captioning without in-depth knowledge about the composition underlying knowledge. Despite web applications that hold backend execution logic, training and executing this knowledge are costly and limited to leading technology companies. Such reasons inspire using emerging technologies to create modular and fully serverless cloud capabilities. With the recent advent of serverless cloud computing architecture, with low costs, management overheads, and serverless execution, many sectors and companies can create cloud modules and put them online so everyone can exploit them. By making this solution extremely straightforward to use or even by automating everything behind the scenes, people can easily capitalize on recent scientific developments.***

**Keywords:** Serverless AI Pipelines, Automated ML Infrastructure, IaC for Machine Learning Workflows, Scalable Serverless Architectures, Cloud-Native AI Deployment, CI/CD for AI Models, Terraform for AI Infrastructure, Event-Driven AI Processing, Serverless Data Engineering, AI Workflow Automation, Dynamic Resource Provisioning for AI, Stateless AI Inference, DevOps for Machine Learning, IaC-Driven Model Deployment

## 1. Introduction

With the recent advances in artificial intelligence and machine learning, engineers build data processing and training pipelines in the cloud using resources offered as-a-Service. These products are useful for building machine learning pipelines in the cloud. It is now possible to automate the deployment of ML systems using Infrastructure-as-Code tooling, as well as managing data location and costs through intelligent operations and a job execution engine. These tools and policies support various services, including data lakes, queues, databases, batch jobs, Kubernetes clusters, and serverless data processing pipelines. To optimize ML inference pipelines in the cloud, consider how to take new ML models, automatically reconfigure the pipeline as necessary, and deploy it to the cloud. An SLO for latency might be added, such that the new configuration is constantly optimized to meet the latency target. The techniques used in data processing, such as Infrastructure-as-Code, event sourcing, distributed queues, or edge clouds, can inspire how to automatically optimize ML inference pipelines at higher levels of abstraction.

The answer lies in data-driven microservices as an architecture: pipelines for versioned ML data—raw data traces, training datasets, and model artifacts—are all precious data assets that are constantly evolving. These usage-based data lakes drive cloud economics by scaling data management costs with actual data consumption. Ideally, data pipelines would also be deployed as versioned data assets, but this brings new challenges for lifecycle management and migration of data artifacts. Full-fledged Infrastructure-as-Code tooling and policies are emerging to automate the management of data pipelines cost-effectively, but with less support for natural language processing models. Not surprisingly, there exist considerable differences in how models are consumed, deployed, monitored, and scaled. This makes it all the more crucial to come up with abstraction patterns and generic workflows to bridge the gaps between these conceptual models.

### 1.1 Background and Significance

The rapid democratization of artificial intelligence (AI) tools has put advanced machine learning capabilities into the hands of users from a diverse range of disciplines. For practitioners, academics or developers, orchestrating the underlying tools to build and deploy AI-enabled applications often becomes a chaotic endeavor involving a disconnected landscape of infrastructure, cloud providers, platforms and services. These are complex ecosystems that mature quickly and exhibit a low level of stability. Construction of models is typically accomplished in notebooks and development environments on local machines. Deployment involves a haphazardly crafted collection of cloud services and ad-hoc infrastructure-as-code (IaC) that require consistent repository-wide configuration across projects which operate against different data, environments and hierarchies. The amount of replicated infrastructure knowledge is substantial, but the amounts required are difficult to learn, and maintenance is labor intensive.

Low-code or no-code solutions offer high-level abstractions and ready-made components for visually orchestrating cloud

services. Implementations are needed to make their composability compatible with existing cloud provider services. Where deployed modern AI workflows are tightly bound to cloud providers and services, potentially leaving them with little control over how data or models are used, and incurring financial foreclosures. Most existing AIOps workflows are decomposition-focused and tailored to their deployment environment, requiring local implementation modifications to operate. Creating privacy-aware alternatives that still offer the workflow capabilities and tracking of cloud platforms remains an ongoing effort. Overall, agility is currently lacking, and weak tracing and observability needs to be augmented through observability scaffolding.

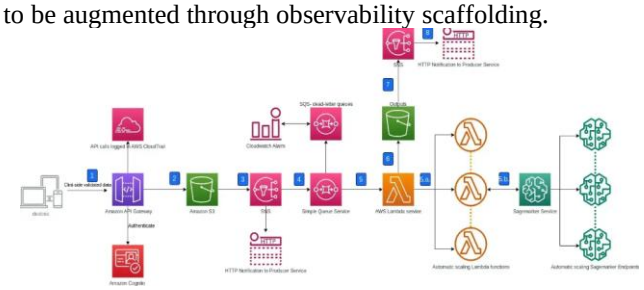

**Figure 1:** AI workflows with infrastructure-as-code and serverless cloud patterns

## 2. Understanding AI Workflows

AI workflows often mix multiple processing units with specialized architectures defining a complex data management challenge. Applications with expensive computational tasks that engage powerful computers can run cheaper model training and inference on specialized GPUs. Using heterogeneous systems opens up the possibility of significant cost savings: 10× over optimized single-resource applications for model inference and training in prior examples. However, optimization exists into increasingly fragmented execution environments as orchestration can rely on a complex collection of systems. Scientific applications using AI models are increasingly multi-resource. Both specialized architecture, such as GPUs, FPGAs, and TPUs, and portable code and reliable networks that enable replication of environments across systems have aided this growth. Early designs with a single computer and software stack have evolved to horizontally scale up the use of powerful architectures for larger problems or multi-stage workflows. The latter can run some steps with expensive computers and others with cheaper execution, like inference and training for AI models. Unfortunately, this multi-resource approach also compiles a part of complexity.

Deployments of modern workflow systems require services on each resource that connect back to a workflow controller. This architecture centralizes coordination, simplifies management, and allows services to be added as featurized components, but at a detriment of the user experience. Development involves deployment across a multitude of systems and languages while integrating with file systems and managing secrets. These services can also introduce single points of failure. Hybrid software-as-a-service approaches mitigate many of these concerns by offering a cloud-hosted coordination service. Instead of requiring users to deploy and maintain code, the service ensures a persistent controller, manages authentication and secrets, and grants access to many resources across sites. In addition, effective service on the cloud can provide monitoring, scaling, and other features. However, the per-user cost of large cloud deployments makes them impossible for many smaller groups. These groups have often bought into a multi-resource deployment along with a cloud coordination service. Most workflows transmit data via the workflow controller or some common/distributed data store. With computing costs approaching zero, it is up to data transfer to mitigate costs.

### 2.1 Definition of AI Workflows

Though there is no universally accepted definition, workflows generally refer to an orchestrated and repeatable sequence of tasks or processes that transform a set of inputs into a defined set of outputs. Scientific workflows, then, are those tasks or processes that implement a scientific process, model, methods, or analysis. Coupled HPC workflows are simply a subset of scientific workflows that include at least one flexible or loosely coupled (remote or closely colocated) pair (s) of tasks. AI-coupled workflows are defined as those workflows that use advanced AI methods, including ML, statistics, probabilistic reasoning and knowledge representation for decision-making, exploration, and simulation or analysis. For scientific endeavors, workflows range in size and scope from small and relatively simple to very large, ultra-scale, and complex. For example, systems such as the Sedimentary Basin Scenario (SBS) couple a million time-stepped runs of a small simulation executed at an exascale HPC system. As such, SBS is considered a mountainous proof-of-concept example for best practice AI-coupled HPC workflows. While this work describes AI-coupled HPC rather than AI-coupled workflows in general, the timely delivery of exascale-ready capabilities to take advantage of new exascale architectures is modeled as an AI-coupled workflow, and prediction and design capacities are captured for very different domains and incasting time horizons. For scientific workflows, many have been described, drawn, and classically modeled as directed acyclic graphs (DAGs). DAGs have discrete nodes, each of which implements a processing step, including obtaining, processing and storing data, while extended DAGs or Petri nets can be used to describe state-ful [semi] continuous state tasks. For the construction of workflows, task (executable) and dataset libraries are needed, as well as a specification of intended behavior for an entire execution of repeatable workflow instance (s).

**Equ 1: Total Deployment Time with IaC.**

$$T_{\text{deploy}} = T_{\text{provision}} + T_{\text{config}} + T_{\text{validation}}$$

Where:

- $T_{\text{deploy}}$ = total time to deploy AI infrastructure
- $T_{\text{provision}}$ = time to provision resources
- $T_{\text{config}}$ = time to apply configurations
- $T_{\text{validation}}$ = time to verify deployments

### 2.2 Components of AI Workflows

AI workflows are often combinations of well-defined compute and data-center resources that are composed into a larger workflow. Airflow, directed acyclic graphs, or a chain of script processes are common patterns to organize workflow execution as a whole, while the specification and management of individual compute and data resources are often heterogeneous amongst infrastructure providers, versions, and vertical integration. The properties of AI workflows lead to a clear separation of concerns between the workflow orchestration and the actual execution of individual compute and data processes. This is analogous to Infrastructure-as-Code for regular workflows, and sufficient abstraction and package management are available. However, serverless infrastructure introduces new modes of computing that change the properties of how and when this division of labor should occur, what abstractions and editing methods are appropriate, and what access control and deployment challenges arise, especially when composing them with traditional infrastructure. This review aims to cover suggestions for abstracting and implementing AI workflows accordingly, do's and don'ts from experience operating multi-cloud training and retraining workflows, and open questions to engage in, especially in the context of sustainable AI.

AI workflow patterns enable accessible experimentation and deployment of complex AI systems through individual cloud vendors' managed data and compute services. The abstraction of a cloud training workflow consists of pre/post processing services and a core training cloud function with UUID input/output specifiers defining its data access. Refactoring a cloud training workflow into a serverless cloud function often allows extra optimizations to be made, but at the cost of debuggability due to concerns over execution context and data access, as well as potential vendor lock-in. The workflow patterns covered here aim to alleviate the need for abstraction beyond the compute logic. Cloud function dependency scheduling is particularly important for both cost and MLOps, but outside of existing vendors' systems, complicated handling is required to scale or debug cloud functions on local development environments.

### 2.3 Challenges in AI Workflows

AI is rapidly finding uses in reevaluating past scientific outputs and creating future discoveries. A plethora of ML and AI techniques are becoming available for scientists to incorporate into their workflows. Resources empowered by these techniques often rely on affordable services, so performance and efficiency should be paramount. Meanwhile, many scientists who need such resources can't spend weeks learning about serverless cloud deployments or data privacy considerations. Here, we'll assert a proposal—given the right tools and practices, scientists can train on the tools instead. The desired outcomes of AI-enhanced resources probably could be met with an initial investment of ten to twenty person-hours of tutorial-style documentation teaching scientists how to illuminate these abstracts themselves. Then, repeat themselves later or make something new.

While the autodidactic nature of these abstractions means that it may come with hidden complexity and excessive input on the part of the user, they also constitute a resilient and long-term solution. Given use cases to be written, the right arena (modeling languages), target hardware (cloud shape or domains), and associated policies (cost, performance, security) could come together in many unexpected and delightful ways. But the right tools need to be built, framed, and packaged up for multi-modal analysis—and it is not a small task.

Teams of scientists, engineers, cloud architects, and software developers need a holistic understanding of the requirements for modern AI-enhanced workloads. Resources will often require multiple heterogeneous computing capabilities. The performance of a workflow that handles simulation and AI tasks on separate services hinges on how best to deploy actions across these resources. Their costs are equally important as a user might desire expensive AI tasks to run remotely on another host. But this design requires securing private endpoints, high bandwidth paths, access to multiple platforms, and new connections, credentials, or service aliases on every run.

## 3. Infrastructure-as-Code (IaC)

Infrastructure-as-Code (IaC) is a powerful and efficient paradigm for managing and provisioning on-premises and cloud-based infrastructure resources. Automation of infrastructure management tasks enables a more reliable, traceable, stable, and repeatable infrastructure, with less human error. With the rise of cloud computing, IaC has matured into a strong and well-documented ecosystem of tools and libraries.

Many cloud providers allow customers to create and manage arbitrary infrastructure resources in a cloud environment via an API, automating tasks that had to be performed manually before. This set of operations is part of cloud automation. Among these operations, provisioning new resources in a cloud environment is the most common, and sometimes the only operation. It either creates a new instance of a resource or recreates a resource of the same type as the previous one. This is defined as resource automation. Definitions of automation, cloud automation, and resource automation differ in the level of granularity, but the terms 'automation' and 'cloud automation' are often derived from the word 'resource' [7]. The automation of infrastructure management tasks such as provisioning, resourcing, and measuring is encouraged. Particularly, it enables a more reliable, traceable, stable, and continuous state of the managed infrastructure with less human costs and human error.

Similar to application code, IaC is a text document that defines the desired state of an infrastructure, together with a set of operations for achieving that state. Infrastructure is defined by structure declarations and constraints, while operations are defined by mutable operations, which change the target document/output state and provide control flow mechanisms for integrating with programming languages. It is possible to define infrastructure in various text-based formats/services, including CloudFormation, Terraform, and Ansible. A common chart format, 'YAML', is used to

parameterize a document's desired material in a text file. A YAML document can represent one or many charts of the same or different formats. The charts are to be deployed on the Kubernetes platform using Helm.

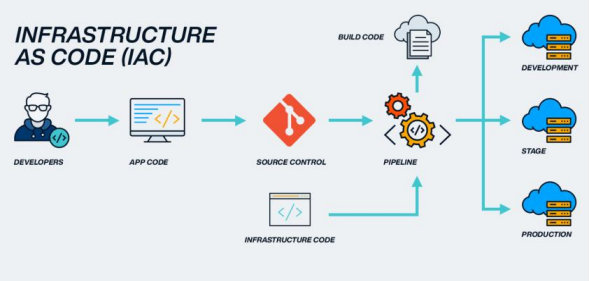


**Figure 2:** Infrastructure-as-Code (IaC).

### 3.1 Overview of Infrastructure-as-Code

Infrastructure-as-Code (IaC) primarily refers to the use of code to facilitate the definition and management of IT infrastructure. Specifically, it is the use of code to automate infrastructure provisioning and management, and the functioning of an original infrastructure in computer hardware, software devices, virtual machines (VMs), and networks through the coding definition of configuration files in a system. IaC is an essential component of software DevOps technique, allowing the emergence of modern cloud computing platforms and application. IaC enables defining, provisioning, and deploying cloud deployments through codes, allowing organizations to operate a cloud environment of any size when the cloud services consumed are appropriately utilized.

On-demand provisioning of traditional cloud deployments as well as the in-person involvement of operators has become obsolete through leveraging IaC tools. As the cloud computing market expanded beyond hyper-scalers, this approach has now adopted by tier-two cloud vendors such as DigitalOcean, Vultr, and Linode, as well as many countries' home-grown cloud providers (notably Alibaba, NTT, and OVH) whose availability zones can only be deployed through their web UIs.

At the basic level, IaC provision virtual machines, VPCs, and security groups through a code that is themselves interpreted and executed against cloud vendor's APIs. However, vendors differ widely concerning deployment options, such as OS images types and hypervisors [6]. To address this, multi-cloud IaC tools such as Terraform emerged, which define high-level codes and natively support backends in the APIs of many major cloud vendors. Using IaC tools far simplifies the process of provisioning cloud deployments mentioned above, as existing tooling can provision complex VMs on a cloud provider's APIs through relatively simple code.

### 3.2 Benefits of IaC in AI Workflows

In addition to their benefits for reproducibility, IaC abstractions can provide software engineering value to AI systems, particularly in terms of the extraction of standard functionality that can be shared across multiple AI workflows. Modern cloud infrastructure allows developers to provision their AI workflow infrastructure as code. This allows abstraction of all AI workflow infrastructure in a portable manner that can be reused across AI projects and by project collaborators. Furthermore, infrastructure defined as code can also be treated as software, so investment can be made in code reviews, and tests for its correctness, and ANY required runtime environments can simply be added there.

The notion of reusable abstractions for standard pieces of infrastructure is well-known in software engineering. Apply function abstractions can be created in software tools and then those software tools can be composed out of standard pieces of functionality. In cloud infrastructure, common examples of reusable and composable abstractions include VPCs, subnets, cloud functions, queues, virtual machines, etc. Once the abstraction is created, it may be more difficult to modify and extend custom use cases but its standardized usage greatly simplifies onboarding new team members and allows for more eyes on the code. Standardization across a team of AI practitioners then leads to better reproducibility as the infrastructure with any pronounced operational needs stays consonant across studies. This effect compounds when similarly resource-consuming pieces of infrastructure can be packaged as reusable abstractions that easily slot into new workflows.

### 3.3 Popular IaC Tools and Frameworks

Over the years, there have been numerous attempts to include the idea of Infrastructure as Code (IaC) in the DevOps movement and the use of cloud resources, and these fundamental ideas have been widely implemented in different tools and cloud providers. Cloud service providers (CSP) now offer their own tools that often allow higher exploitativeness but at the same time tightly link users to the vendor's ecosystem. CSPs often also offer services that go beyond setup-as-code at the level of single components, meaning the integration of several pieces of hardware or software to offer a unified interface. This might be used as an additional possibility for scaling up pipelines but comes at the cost of closing the pipelines to vendor-specific setups, in many cases rendering them unportable and acting against the devops principles.

Terraform, for example, allows plug-ins for cloud formations that can be transported across cloud providers. It needs to be mentioned the challenges of inputting new or larger cloud resources, as these assumptions affect the flexibility of the approach. Cloud users often suffer from the high-cost variation of their pipelines across cloud providers. According to the design goals, the following aspects might be relevant to defining the relevant parameters of an IaC: user had components or orchestrations, components' invocation and configuration; and cloud provider options. After initializing a project, a high level library API could be used to specify a pipeline. The resulting IaC resource would typically comply with the functional and performance requirements.

## 4. Serverless Computing

Serverless computing is an emerging model of cloud computing in which the cloud provider runs a server or servers and dynamically manages the allocation of resources. The term is somewhat misleading, as serverless services are

not running with no servers, but the provisioning and management of servers is completely hidden from the user. The servers potentially as part of FaaS (Function as a Service) or CaaS (Container as a Service) serve stateless applications. In such services an application service can be easily scaled, for example if it is triggered by an incoming HTTP request, a message in a queuing system or an event in the object storage. After a predefined period of inactivity the service is automatically put to sleep, suspended and its resources released.

The challenges of serverless and event-based computing in general are mainly in state management. Such applications typically have to deal with the problem of sharing, persisting and recovering state between stateless tenants over the highly dynamic execution environments. While some serverless frameworks developed for scientific applications use the stateful services, other designs either follow the distributed model or provide such capability in the framework itself. The former approach uses cloud queuing systems or object storage for state management, whereas the latter introduces additional logging and recovery mechanisms. The success of social media applications and modern cloud computing opened a path to on-demand processing of enormous quantities of data captured in real-time.

One of the early examples of higher-level serverless APIs is AWS Lambda. This service allows processing of streams of input data using JavaScript, Python or Java code, which is later executed from the cloud with little information about the underlying infrastructure. Specified FaaS functions are triggered by input data typically placed in the cloud object storage, data streamed by the message queuing system or HTTP calls to the API gateway. In such applications cloud object storage serves as an input buffer. During the processing each FaaS invocation is called with the event parameter that includes the object key of the event triggering the code. The input object is expected to be a single batch of images, which will be again uploaded to cloud object storage after processing. A predefined model file is always fetched from object storage before inference. Therefore, the FaaS function is stateless with the side effect of calls to the cloud object storage.

The serverless ecosystem is still in its early development but having recently studied a few examples of serverless scientific applications, we can observe the emergence of a layered architecture of the ecosystem. From the bottom up, we have the basic layer of cloud storage and communication. This includes cloud object storage, queue systems or caches. This layer provides state management for the stateless FaaS/CaaS layer. Next come various processing models relevant for scientific users and software engineers, such as task execution models, streaming data processing, interactive work, batch processing or container orchestration. Finally, the top layer includes ready to use frameworks for scientific applications that typically provide high-level APIs or user interfaces. Most of such frameworks consist of similar components, some of which are related to the serverless services offered by the cloud providers. The framework usually provides the basic services and deploys computing resources on the cloud.

**Equ 2: Serverless Cost Function.**

$$C = \sum_{i=1}^{n} \left( \frac{T_i \cdot M_i}{1024} \cdot R \right)$$

Where:

- $C$ = total serverless function cost
- $T_i$ = execution time of function $i$ in milliseconds
- $M_i$ = memory allocated (in MB) for function $i$
- $R$ = rate per 100ms per 1024MB (as per cloud provider pricing)
- $n$ = number of invocations

### 4.1 Introduction to Serverless Architecture

A new paradigm has emerged in cloud computing known as serverless computing. Historically, in the client-server based model of computing, a client with limited computational capability offloaded tasks to a powerful server. Handling such offloaded tasks required significant effort on the part of the server. Maintenance, upgrades, and other such operational tasks consumed excessive resources. Serverless computing endeavors to free a user/application from exactly such burdens. Developers are provided with an event-driven framework for implementing functionalities that they are only charged for when executed. All functional and operational concerns are delegated to a cloud service provider, and client implementations consist of trivial REST API calls to functions hosted on the cloud. These functions, known as Lambdas, are stateless and short-lived self-contained code with both a triggering event type and a pair of triggering event values. Triggering events can be of various types but they share the commonality that they are events on which the function is based. They are generated by an external service checking for the definition of an English word.

When a triggering event of type T and value V occurs and there exists at least one Lambda s such that s was deployed with event type T/Event value V, then physical resources are provisioned to execute the function s. Lambda functions, programmed in one of the supported languages, only process event-triggered requests. Programmers write code to process triggering events but do not concern themselves with scheduling policy or any other operational mechanism. Serverless computing has several characteristics that differentiate it from conventional types of cloud computing. One advantage is flexibly scaling, where resources relevant to demand are allocated automatically and/or deallocated when not needed. These powers of elasticity extend to deploying infrastructure. Serverless orchestration platforms address this type of infrastructure using configuration files.

A serverless architecture integrates software and hardware components on a cloud provider that enable users/programmers to access effortless functionalities. In this architecture, there is no resource management to execute user tasks. Users obtain the output of their tasks after some application-dependent duration, but they are charged only for resources used in executing tasks. Anything that does not support application functionality is disguised from

programmers by cloud providers. For cloud providers, serverless computing gives rise to another profitable business, architecture-as-a-product.


**Figure 3:** Serverless Computing: Architecture

### 4.2 Advantages of Serverless for AI

Recent advances in deep learning (DL) have spurred research in training large models over hundreds of GPUs. In light of this rapid growth, organizations are discovering that adapting the current infrastructure does not provide a cost-effective solution. Instead, greater needs for flexibility and elasticity in ML workloads lead to new infrastructure requirements. Since early 2014, several cloud vendors have introduced serverless options for both compute and ML. Leveraging the existing serverless platforms to build ML workflows is a novel and feasible direction. Serverless has the following key advantages for AI workloads:

- Cost-effective on-demand pricing model. Serverless clouds offer cost savings over running workloads on Reserved Instances, On-Demand, and Spot VMs. First, the serverless pricing model usually adopts the cost-per-invocation + cost-per-execution-duration scheme, charging based on number of requests and execution time. This makes the costs more fine-grained. Secondly, with a malfunctioning subprocess, debugging could take some iterations. An IaaS timing measurement requires stopping the VM, while a serverless measurement costs only the current function invocation. Thus serverless can effectively help in the pre-release testing phase.
- Automatic capacity provisioning and scaling. With the rapid growth of enterprises, having on-premise infrastructure and resizing it according to your needs becomes a hard task. Serverless programming abstracts the underlying layer at an extreme degree. A function can be deployed with just a few clicks and manage as many requests at once. Thus coding just needs to care about the algorithm and input/output data. Serverless clouds would allocate sufficient resources and service to all invocations.
- Highly concurrent execution scheduling. Serverless programming has partially taken over managing the ML backend. Users just need to write the business logic. In many cases, there are similar requests that can benefit from efficient batching. Serverless clouds are able to aggregate an exceptionally large number of requests and utilize parallel execution, yielding a higher throughput. A highly concurrent execution can reduce the warm-up times, since it is less likely to starve the cold-start functions.
- High survival time. Some companies choose non-renewable configurations to avoid excessive costs. In traditional IaaS architectures, an expiring VM needs to be stopped at once, and all the in-process requests, including training jobs and inference ones, would fail. Serverless primarily handles time-limited functions, and execution time could typically go up to many hours. While some requests may fail, a lot of requests could be wrapped up.

### 4.3 Common Serverless Platforms

Often referred to as Function-as-a-Service (FaaS), serverless computing is a cloud computing model where in the Ideal Case a third party serverless vendor or cloud provider allows developers to run applications without provisioning servers. While reverting hosting responsibilities is common in PAAS, IaaS, and its underlying virtualization-based cloud infrastructure, it rapidly emerged a new generation of Platform-as-a-Service offerings by major cloud providers. The first service offered in this category was Lambda, which experienced significant adoption in mid to late 2016. All the major cloud service providers now offer similar services.

Serverless computing is based on an event-driven architecture. It works on the premise that developers build compute units within the cloud called functions. These functions are responsible for responding to specific triggers, which may take the form of events, messages, or requests from clients. After deployment, a cloud provider takes full ownership of these functions. The provider then collects client requests, invokes the responsible functions as per their triggers, and returns the results of execution back to the clients. The provider performs task scheduling and operates monitoring workloads on a serverlessly provisioned cluster. Developers need to only write the code processing client requests. Functions are generally stateless, and need to access state from persistently store sources, such as relational databases or NoSQL stores.

When a function is executed for the first time or has not been executed for a while, the cloud provider may need additional time to start a new container that runs the function. This delay is referred to as a "cold start. " Cold starts occur when the service is unable to operate on already provisioned compute nodes because of idle time. It is either because a function has not been executed for a long time or, it is a brand new function not installed in the provider's cluster. Functions are sized with memory. Depending upon the memory size, a fixed number of vCPU or any combination of vCPU with different clock speed gets assigned to it from the underlying node.

## 5. Integrating IaC with Serverless Patterns

With recent advances in Machine Learning (ML), it is rapidly transforming industry verticals, from healthcare to robotics and finance. Cloud providers offer many platforms for running ML training jobs at scale. These platforms involve configuring a large number of hyper-parameters, supplying datasets, model configurations, and infrastructure to deploy ML workloads. These tasks can quickly become complex, and industrial best practices have emerged for deploying ML workloads. A unified infrastructure service for operationalizing AI applications and minimizing development time is available.

Infrastructure-as-Code (IaC) has emerged as a popular technique to build cloud resources. Development teams can manage and provision cloud infrastructure using configuration files. This shifts the infra-coding burden from teams dedicated to building cloud resources to developers, and thus drastically reduces complexity. Popular tools are used to provision infrastructures as code. IaC implementations can be flexible and provide capabilities such as common components for reusable modules and testing. This flexibility can empower users to build complex setups; the question remains how best to use them.

Configuration files to specify the cloud infrastructure are slowly being developed as scripts to build very complex workflows. State machines rapidly become quite complex and coupled buildings, similar to a monolithic setup in a programming language, becomes common. This state machine is the orchestration implementation for the AiML workflow, but it should not be committed to code for various reasons. Most importantly, the orchestration tools are not built in most IaC, and an orchestration tool needs to connect different building blocks that come from different vendors. There is a need for lightweight tools that ease the orchestration burden of distributed AI/ML workflow supporters.

### 5.1 Designing Serverless AI Solutions

Illustrate how to build an end-to-end serverless AI solution. Following the Common Workflow for Data Mining approach, the solution consists of data preparation, data analysis, results presentation, and deployment, as depicted in Building data preparation and data analysis components on cloud services is relatively straightforward; however, it necessitates the use of several closely coupled cloud functions in the cloud function deployment model. For the best overall latency, a cloud function must be executed close to data ingestion. After calling a few cloud services and executing other functions, depending on intermediate results, it must invoke the cloud function that runs the machine learning model. Still, no cloud function is small enough to fit into a single execution. As cloud functions must be coordinated carefully, debugging and failure recovery can become challenging. In case of function failure, potentially 10 cloud functions must be re-executed in order to process all required data tuples. As a result, developing a data analysis module is less straightforward.

Building a data preparation and a data analysis module using cloud services is straightforward. For ease of viewing, the building of a data preparation module is discussed first. Similar thoughts also apply to a data analysis module. When data is ingested, several cloud services are set up, including Google Cloud Storage, an object storage service, Google Cloud PubSub, a messaging service, and Google Cloud BigQuery, a cloud-hosted data warehouse. Data is ingested from online and offline data sources to PubSub, which writes data to transient storage, and then consumed by a cloud function that validates and aggregates data, and written back to durable storage. Data is further processed using Google Cloud Dataflow, a fully managed data analysis service. A Dataflow template consumes data from a cloud storage bucket and calls a model. Since a piping file is used, this is the only step needed to set up and schedule the job.

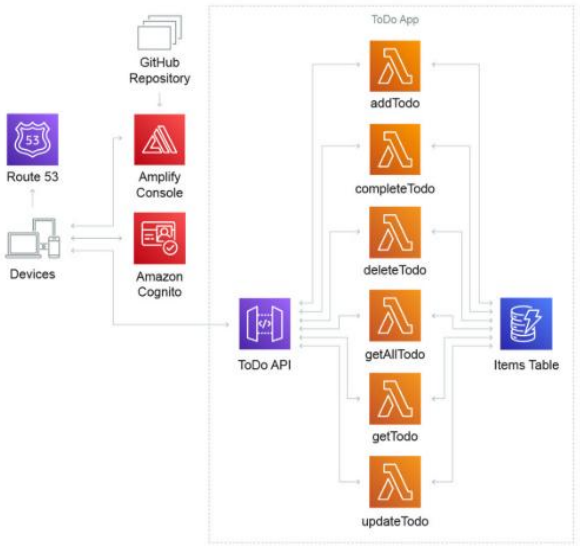


**Figure 4:** Serverless AI Solutions

### 5.2 Best Practices for IaC and Serverless Integration

Infrastructure-as-code (IaC), a paradigm that defines infrastructure as code to manage assets, has become a dominant method for automating and securing the cloud. Thanks to its declarative nature, maintaining the current state of a cloud provider while applying changes is straightforward. Moreover, various cloud providers now offer tools for performant implementations, making it easy to include IaC in CI/CD pipelines or easily adapt existing setups. This reduces the entry point for organizations to own and maintain their own machine learning (ML) infrastructure and thus offers new scripting and support opportunities. A drawback is the lack of strict paradigms to prevent undue complexity of IaC files, which rise to the point of becoming immobile and written in a roundabout way. Escalating code size may even be unmanageable for smaller organizations.

Although, by design, IaC provides good reproducibility of a cloud provider's resources, it is more difficult to achieve reproducibility during a watertight and auditable ML pipeline. It is common for small scripts to slip in and out of CI/CD pipelines or prototyping stages. For example, some data preprocessing steps may be skipped in a cloud environment, leading to bad model performance, while other steps are too complex for IaC tooling to manage. In addition to compliance requirements, there is also a chance that these scripts exhaust cloud resources or fail to be cleared up. Any pipeline should be composed only from serverless steps, and a prevention mechanism that enforces this should be common for all projects.

Although less mature than IaC, serverless orchestration tooling is available by both major cloud providers, but little work has been done detecting risks in such code. Several steps in a workflow should be defined as serverless functions, such as simple implementations that may call other AI tooling. The optimization of serverless functions sharing occurred only recently and is more complex than other approaches, often introducing new risks and corner cases and requiring additional consideration within the tooling.

### 5.3 Case Studies of Successful Integrations

This section presents two case studies of cloud adoption for multi-model AI workloads in a telco and a retailer. Case Study 1 focuses on the research done in telco cloud adoption and optimally deploying existing AI workloads and pipeline with serverless and IaC. Case Study 2 focuses on the cloud adoption in a retailer that needs to optimize the service infrastructure of existing AI models deployed in the cloud.

Research technologies are developed in parallel with the adoption of user applications. This section first delineates a use case from Telecom Sector where the user has a large number of pre-trained AI model pipelines for network event prediction, fraud detection, user opinion mining, etc. Those models and pipelines are instantiated with ML frameworks. Pre-trained models in these ML frameworks need to adopt cloud infrastructures for usage since those models are currently hosted either on local data center machines or on clouds. Some research topics include but are not limited to the user requirements for platform design, and deployment pipeline generation techniques relying on machine learning and formal reasoning, etc.

A scenario for deploying ML models on cloud infrastructure is depicted. It can be divided into three sub-nodes, including resource generation, resource allocation, and resource deployment. The first step is to load model files, preprocessing and post-processing functions, and training and inference task configuration files. Then the correct infrastructure representation will be generated based on the prior knowledge of infrastructure templates. Infrastructure generation outcome samples are included. Auxiliary tools include the utilization of common APIs to estimate resource scale and to monitor ongoing workloads. The first two components generate templates in template language and provide scenarios for potential images to choose. Given traditional deployment languages, either a proprietary parser or a template-to-template conversion needs to be researched on.

Due to the complex dependencies among a large number of AI workloads in a retailer, the optimization of cloud service infrastructure is also a hard problem. It also includes input/output and last-minute pipeline-generation techniques for complying with these scenarios. Inputs are AI services involved in the optimization process, AI frameworks used underneath these AI services, provider designated resources, and cost budget constraints. Outputs are proposed serverless APIs online service denoting the same input/output format as existing AI services.

## 6. Performance Optimization Techniques

Serverless computing and Infrastructure-as-Code are two modern cloud computing paradigms gaining traction among developers due to their low entry cost and operational overhead. In serverless computing, users can easily deploy Functions-as-a-Service (FaaS) to serverless platforms for automatic scaling and management of execution environments. Infrastructure-as-Code automates the provisioning of cloud resources needed to deploy applications with a set of template files detailing resources provisioned in a domain-specific language (DSL). Modern programming languages also allow using libraries to write Infrastructure-as-Code more flexibly.

As both paradigms decouple the development and management of cloud resources, cloud users take control of their cloud architectures to exploit platform optimization techniques to avoid overspending and performance degradation. However, like cloud providers, a challenging problem is developing general optimization techniques that consider many important aspects of one scope (e. g., system, algorithm, and usage) and optimize their respective parameters. A more relaxed problem is developing a library of modular optimization components for a specific aspect that takes the current architecture as input and proposes adjustments to improve performance, but composing these independent components into an optimization framework also requires a fixed cloud architecture.

This paper proposes a modularizable optimization library optimization through an infrastructure-as-code approach and applies it to a serverless computing environment. As a proof-of-concept demonstration, a library of design patterns for AWS Lambda is developed, covering the function placement and sizing problems, functions fusion, and events spreading techniques. Using both real-world and synthetic workflows, it demonstrates how to use the proposed library to guide composable optimizations. This library serves as a library of functions applying optimization techniques developed to a serverless computing environment. Using a serverless architecture manifests easy composition of proposed patterns and global optimizations based on local ones.

**Equ 3: Workflow Execution Time in Serverless Pipelines.**

$$T_{\text{workflow}} = \sum_{i=1}^{n} \max(T_i, D_i)$$

Where:

- $T_{\text{workflow}}$ = total pipeline execution time
- $T_i$ = execution time of step $i$
- $D_i$ = delay due to function cold start or queuing

### 6.1 Monitoring and Logging

Monitoring and logging are essential for understanding what is happening inside the AI models and the cloud infrastructure. Among other things, monitoring and logging can provide business insights into how the AI models affect business KPIs and how cost-and performance-effective the deployed cloud infrastructure is. Monitoring is performed by automatedly collecting metrics from the above components using monitoring tools. It detects anomalies for alarms and insight reports. On the other hand, logging is used to explain anomalies in more detail. Logging events give finer-grained information to describe what is happening at specific moments. Usually logging events are stored in specialized

data stores and processed later on by engineers and data scientists.

The collected raw data and engineered metrics for monitoring and logging purposes costs a lot of cloud resources to store, transfer, and process. It is essential to apply different data preprocessing techniques so that the most relevant data is collected and stored. This includes data sampling, selection, engineering, etc. Furthermore, the monitoring dashboards and logging event collector need to be properly configured. A representative subset of metrics should be visualized and the notifications should be configured properly. In this case, it may take time for additional data scientists/engineers to prepare monitoring dashboards and logging strategies. Though it is a reasonable price to pay, some industry partners still prefer better monitoring systems that come with existing cloud-native components or bring from existing open-source solutions with minimal manual effort.

Providing initial monitoring and logging systems as models that can be translated together with the deployment templates is beneficial because it gives engineers and data scientists the choice of choosing an appropriate monitoring strategy that fits their purpose. This approach would hide a lot of complexities when manually collecting metrics from different models, devices, or cloud services. Although framework-or layer-agnostic solutions are provided that monitor and log almost everything, some AI engineers still prefer finer-grained control and configuration over the monitoring process. For instance, a logging event with a detailed payload can be added if an anomaly is detected in a model metric.

### 6.2 Cost Management Strategies

AI models are increasingly deployed in serverless computing platforms. Serverless computing abstracts cluster management, enabling users to deploy AI models with ease. However, this ease cannot come at the expense of efficiency. AI models need to be properly resized and deployed to cloud functions in such a way that the SLO requirements are met while minimizing costs. Currently, deploying AI models running on serverless computing is akin to deploying applications on VMs; users need to estimate the correct resources manually, often resulting in over-provisioning and redundant costs. However, if current serverless function development paradigms do not change, the raw operational costs of serverless computing are expected to double every 1.7 years. More importantly, the share of serverless costs to the overall cloud bill is anticipated to increase from 43% in early 2023 to over 75% by 2025.

With quotes from leading serverless vendors, recent comparisons of serverless cloud patterns with IaaS VMs emphasized how the IWOC platform is different. Serverless computing is a new paradigm for cloud computing. However, workloads running on serverless computing need to be profiled with high accuracy in order to make fair comparisons with infrastructure-as-code cloud patterns. This requires performance modeling methods, and a different way to deploy workloads than with VM-based cloud patterns. This research discussed how to overcome this hurdle by implementing serverless function profiling in a serverless way, how to use it for accurate performance modeling, and how to map serverless workflows to the cloud using a serverless FaaS workflow deployment pattern. With these contributions and a case study, the IWOC platform, which consists of architecture, design and implementation of cloud patterns, addressing cloud-scale workload deployment and optimization in serverless computing environments.

### 6.3 Scaling Serverless Applications

Geographically distributed application deployment is essential for low-latency applications. It minimizes the time for meeting user requests with geographically distributed application deployments. Placement of user applications in edge regions nearer to end users is essential to reduce latency. Multi-layer model for application deployment considers user request latency, data latency, and operation latency metrics in placement. Optimization techniques available under different mathematical programming approaches distribute the application deployments for reduced latency. Flexible placement of serverless applications across multiple cloud providers improves performance and minimizes cost. Directed Graph approach estimates the performance of serverless application deployments across multiple, heterogeneous clouds. Optimizing it using an Integer Linear Programming model finds the best placement. Migrating a portion of workloads across clouds to alleviate the task processing delay is important for task processing efficiency. The problem is modeled as a Mixed Integer Programming model with funding and budget constraints. A hybrid of answering multi-query reinforcement learning and the dual-primal algorithm leverages cloud providers' spare resources for cost-effective batch submission of tasks.

Serverless computing is an emerging paradigm for creating, deploying and using applications where the application provider only pays when user requested imminent processing is completed. Serverless computing atop Function-as-a-Service is being widely adopted owing to the rapid provisioning of computing resources and the ability of user applications to scale. Serverless cloud providers automatically scale function resources to meet application needs while maintaining quality-of-service.

## 7. Security Considerations

As with any solution that incorporates cloud-based services, care must be taken to ensure that sensitive data, systems, and user identities are properly protected. The cloud components used in the patterns should be properly managed and secured. Security management and compliance processes will need to be updated to address the emerging cloud technologies and how they're used. It will be necessary to monitor cloud usage, ensure that any data storage complies with applicable standards and regulations, provide the ability to identify violations of security policies or compliance standards, and make sure classification and protection mechanisms are applied appropriately. Provider-level capabilities such as logging can help with this monitoring; and if needed, third-party security monitoring and governance tools may also be employed to help manage compliance in the cloud. Execution of the serverless components of the patterns bypasses the organization's security perimeter, so any potentially sensitive data must be protected with the mechanisms appropriate for

cloud services (and validated with monitors). Cloud provider security capabilities can help meet these needs to some degree. Cloud resource shape (smaller costs) must also be configured in patterns. Security restrictions must be adequately tested with monitors. Engineers need security training as tracking tools, cloud service monitoring, protection design, and testing methods change following transition to cloud services. Security management is both more decentralized and more rapid after cloud transition, so this management must be reviewed and potentially revamped to retain effectiveness. Where cloud services are available where the organization operates, cost-effective patterns become possible. As these methodologies broaden, cloud terms of service must be interpreted, models must be adapted to determine appropriate costs and cost savings, and organizational education must close the gaps in existing organization capabilities.

### 7.1 Security Challenges in Serverless Architectures

Security vulnerabilities have profoundly affected the adoption of serverless cloud services, leading to attacks against serverless applications and the extraction of sensitive information from functions and their environments. The diversity of event triggers and policies available in serverless cloud services can further expand the attack surface and increase complexity. The support of functions for restricted programming languages leads to specific implementation problems, such as exposing serverless function environments where untrusted code can succeed.

Although serverless architectures leverage some new capabilities in cloud platforms that can limit the surface of attacks, the added complexity raises two fundamental challenges for security: security reasoning and the definition of secure architectures. Client-side security policies worry about what attacks will be attempted against an architecture and what application security aspect can be compromised. Such policies rely on knowledge about the coding and deployment processes, thus raising issues on their completeness and trustworthiness. No classical security policy is available for serverless architectures because end-users cannot play an explicit role in the coding and deployment processes. Such architectures indeed benefit from the designer's main goal of turning policies into virtual private cloud artifacts storing and redirecting sensitive data.

Rich information manipulation facilities at scale produce differential access on a large number of cloud resources. Hence, the decoration of security-oriented task-relevant features is essential for the continuous assessment of security policies throughout the whole cloud service lifetime. Higher-level security policies, such as those that govern the deployment and execution of new application functions and limit data exposure to a chosen functional context, can play crucial roles in maintaining a trusted cloud service in the presence of severe architectural assumptions.

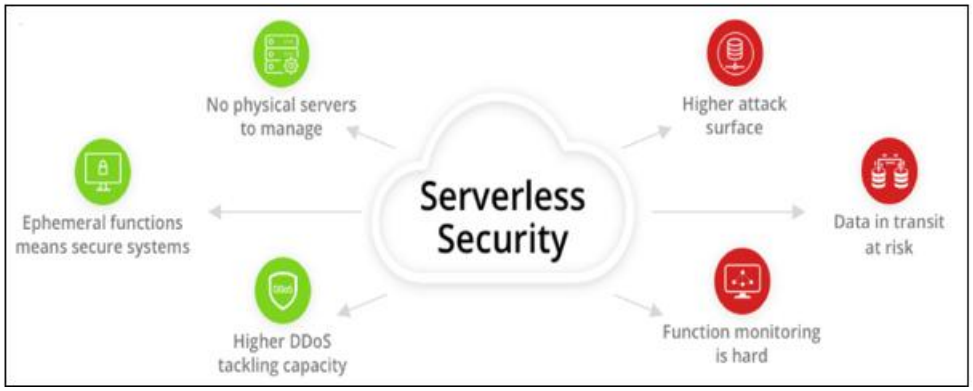


**Figure 5:** Serverless Security

### 7.2 Implementing Security Best Practices

Every application exposes an entry point to the outside world by which it listens for incoming requests (APIs, files, etc.). It also closes sockets, files, and other resources opened to process requests, either gracefully by returning resources to the operating system, or abruptly, by terminating the computation. Ideally, any errors along the way should be handled properly and logged somewhere for later inclusion in system logs. This is expected from any software deployment. With infrastructure-as-code deployments, cloud infrastructure is programmed in a manner similar to application source code, requiring its own audit trail. On deploys to run arbitrary source code, cloud providers usually restrict tolerated procedures and resources. Any missteps in source code can result in infinite costs. Serverless computing functions have the same start/stop request boundaries, and uncivilized behavior of functions remains fairly similar across IaaS and FaaS cloud offerings.

When using the FaaS programming model, limited run time and memory means that the resource handling logic becomes more focused. Logging, for example, might just send logged strings to a permanent file or output redirect, as opposed to a dedicated server. As with IaaS, logic should sanitize and escape user input to avoid abuse and injection attacks. Avoid long-running calculations. The run time maximum is generally generous, but can scale down and may require re-architecting of some workloads. Cloud functions candidates may run as a batch, or require native HTTP (S) endpoints. Any logic should be callable via a function, and often such integrations can be forgotten as the rest of the operations become cumbersome. Authorizations and authoring software can drift apart, which allows for privilege escalation. Repeated invocation or scandals can cause flooding and incur a high penalty. Logging can be segmented by workloads to ease the analysis, and automatically sanitized to avoid confusion.

## 8. Future Trends in AI and Cloud Computing

As the Artificial Intelligence (AI) technology system continues to mature, new models, techniques, tools, and systems for using AI are emerging every day. A few specific trends that will massively impact the AI community and a broad base of AI clients are reviewed from four different angles of AI models, infrastructure, services, and applications. It can interact with users in a natural way, answer sophisticated questions, generate creative multimedia content, and provide human-like tutoring services. As more recent models emerge, they are exposed to various dynamic scenarios for application. However, further efforts are needed to implement corresponding integration and evaluation systems in the AI service community to allow for easy integration, quality assessment, and control. Generative AI services will profoundly complement people's work and improve end-customers' interactions with and productivity of various enterprise applications and insights.

Another common trend is the fast-moving progress and increased accessibility to the infrastructure side of AI. In the past few years, significant weights and models have been developed on some private clusters with millions of expensive GPUs. As more specialized models are developed, options around proprietary runtimes, model efficiencies, and costs grow. Open sourcing can help democratize innovation but needs proper perception and curation of risks. As this turmoil continues and the possibility of self-hosting potentially powerful models rises, more smaller-scale models become available. However, substantial initial investments in infrastructure, expertise, and operations are a barrier to smaller companies with promising applications who want to leverage generative AI. Tools, platforms, and expert teams from larger vendors render easy access to the newest model family to a broader set of clients. There is a focus on how these platform-building companies are leveraging existing cloud capabilities and workflows to pre-integrate the latest models within their services and thus lower the barrier to access.

### 8.1 Emerging Technologies

Pressures to optimize the cost of AI workloads have motivated research into the deployment of AI workloads as serverless applications using Function-as-a-Service offerings. Such applications can greatly minimize the operational burden required to run AI workloads, as cloud providers manage provisioning, scaling, and operating the underlying infrastructure on the user's behalf. Deploying AI workloads as FaaS applications typically leads to reduced operational expenditure compared to standard cloud services such as Virtual Machines. This is due to how FaaS pricing structures are aligned with the deployment of workloads with bursty time profiles (e. g., workloads with many periods of little to no activity separated by short periods of high utilization). Crucially, the FaaS pricing model is particularly well-suited to AI workloads, which frequently suffer from bursty time profiles due to the overhead of data preparation and model averaging/load balancing.

To this end, it is necessary to understand the challenges and implications of deploying AI workloads as FaaS applications on cloud providers. Such applications can comprise many functions composed into unit-serving workflows. The challenges of deploying cost-effective FaaS applications using function composition strategies and transformations are discussed (including workload scheduling, function placement, and function merging). Cost modeling heuristics at the infrastructure and application levels are introduced, and a framework that scales to the number of functions and computes cost-efficient deployments for diverse workloads and architectures is proposed. The focus is on using the serverless stack APIs and services, and the unit-serving basis on which these technologies are designed to build scalable serverless applications.

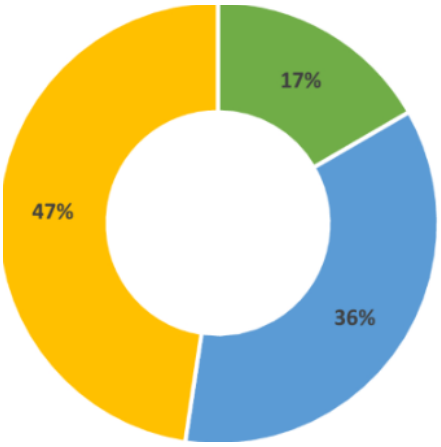


**Figure 6:** Optimizing AI workflows with infrastructure-as-code and serverless cloud patterns.

### 8.2 The Role of AI in Cloud Optimization

An important approach in cloud optimization is to find suitable machine learning (ML) techniques to improve the accuracy and speed of the optimization. A complex cloud service contains a multitude of components and hyper-parameters that work together to connect the ingestion, ingestion processing, serving, and serving scaling stages of a cloud data service. To reduce the operational effort on tuning these components, users can specify targets on metrics, run monitor jobs, and upload raw data for the past periods to a cloud data service. Then, MLSweep, an optimization service that automates and speeds up the tuning jobs for cloud hosting data services, is designed to produce hyper-parameter candidates for tuning each component. For a complex cloud service, it is impractical to create a massive optimization problem that at once optimizes all components. Ongoing efforts continue to jointly optimize a selection of components while synchronizing the deployment of changes of the involved components. With this approach, it is possible to focus on optimizing related components working together; thus, the joint optimization of these focused components can often improve the overall system performance in a way that optimizing the components independently cannot. A basic technique for diagnosing how go wrong is to filter the problematic cases by a specified granularity and to run a few rounds of joint tuning. Components returning suspicious candidates of their hyper-parameters are grouped into one cluster and tuned with the relevant data. Naturally, there are concerns about the risks posed by AI. With the growing complexity of machine learning models, cloud services leveraged by AI are becoming more expensive to maintain

and develop; therefore, one of the main tasks is to help keep this performance and spending at acceptable levels. Intuitively, tricking the cloud vendor by making them spend extremely may lead to a loss with intolerable budget overruns. Introduced guardrails to protect customers from impossible or expensive solutions by checking candidate decisions with several in-house, cloud independent scoring functions of complexity and sanity. For example, a huge number of training data points would be needed for a complex model; however, the amount of training data cannot be obtained instantly, which gives at least a chance to spot the suspicious kinds of optimal decisions early on. Another type of guardrail enables checking the performance of the model output using a small test set from the cloud vendor to detect regression.

## 9. Conclusion

AI workloads are not only critical workloads. They are challenging workloads. The key challenges can be summarized as: (1) AI workloads must expand rapidly to become billion-trillion param workloads to assist Giga-Byte, Tera-Byte, and even Petabyte data scale, while having tougher batch times for training due to larger Λ, larger cost of iterating Mini-batch times, suboptimal scaling, fidelity, and floorplan compared to cost when growing SuperComputer like Continent-Scale Exascale clusters. In this new era of AI, the performance of training AI workloads and their routines is bottlenecked not only due to new computer technology but also new architecture in the last mile. Large dominance of Tera-Byte and Petabyte data in Giga-Bolt data scale increases batch size from K lower-$$ to G higher-$$. The contention of upper-level addresses in Tera-Byte GPU chips and above, lower-level addresses in M이나 LCache + Migrate chips, and flow-control in the ASIC-DPU laden W-DL with CPI>TgSpeed worsens the train-testing time, and why b-size=G & M on-chip/pipeline-only for NewDS should accelerate both training and testing simultaneously is discussed. (2) AI workloads must be more sustainable for lower-E and less-MT$ despite more costly innovation, training, and inference stage. E$ are also introduced to gauge companies/teams in designing new chips. For instance, new Centre-Scale AI training chips like DPU+ASIC should be cooled to T<50C for energy savings by pipeline ON-OFF oscillation, and fine-grained background task-miss contending light device activation might increase 20x E$ for 1% QoS$ o$ controllable latency $ extless$4$T_{test}$. E$ would be higher and more challenging in AI inference workloads with wider-but shallower stage width and Turing stage ratio, including non-trivial hardware pipelines. However almost all EEISM worth $1T_{trillion/annum}$ is spent on all kinds of training and tests to make sense of natural/scientific phenomena, which nonetheless amounts to not even 5$ ext%$ of the ML output through SlowOS.

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