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Designing Cloud-Native AI Infrastructure: A Framework For High-Performance, Fault-Tolerant, And Compliant Machine Learning Pipelines

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Abstract

Big Tech companies have spent the last decade designing scalable, elastic, and resilient cloud infrastructures to support their business applications. However, the emergence of machine learning as a service-area-in-silico and the urgent need for operationalizing compliance in highly regulated industries have required them to invest an additional effort in designing cloud-native infrastructures to support ML workloads. These infrastructures must provide the required elasticity and efficiency to support high-performance, fault-tolerant, blameless, and compliant ML pipelines. The principled redesign of cloud architectures to overcome the challenges of serving ML workloads at scale is essential for accelerating their maturity; however, it has yet to start in earnest. This paper contributes a framework to guide the design of cloud-native infrastructures for ML workloads that links high-level design requirements with architectural dimensions. The framework enables architecture teams to compose the design of cloud-native architectures for ML workloads by exposing the architectural trade-offs involved in configuring elasticity, performance, fault-tolerance, compliance, cost, and risk for ML workloads. We describe the design framework properties using concrete examples that optimize for elasticity, cost, and risk. Finally, we argue that the principled design of cloud architectures for ML workloads is paramount for accelerating their further adoption and maturity in enterprise environments.

Keywords: Cloud-Native ML Infrastructure, Scalable ML Workloads, Elastic ML Pipelines, Fault-Tolerant AI Systems, Compliance-Aware ML Architecture, ML as a Service, High-Performance ML Infrastructure, Resilient Cloud Design, ML Pipeline Maturity, Cloud Architecture Trade-Offs, Blameless Infrastructure Design, Cost-Risk Optimization, Regulated Industry ML Compliance, Enterprise ML Operations, ML Infrastructure Scalability, ML Workload Efficiency, Architecture for AI Elasticity, Machine Learning Deployment at Scale, ML-Centric Cloud Design, AI Infrastructure Engineering.

1. Introduction

Machine Learning (ML) has become a critical component of many products and services. Emerging applications in natural language processing, computer vision, healthcare and life sciences, self-driving, energy, and finance are demonstrating the value and impact of machine learning. These technologies hold the promise of economic growth across multiple sectors in addition to the growth of dedicated AI technology companies. Various organizations are investing in the development of internal machine-learning capabilities. Others are forming alliances with specialists to deliver advanced augmented products and services. Such advancements require the delivery of accurate models made in production scalable releases, constantly monitored, and safely retrained. This demands resources, processes, and mindsets that are scarce in traditional software development. Unlike detailed requirement documents, standardized steps, fixed development cycles, and static software that rarely changes, the ML development process undergoes design decisions, changes rapidly, revises the solutions, and deploys software that is never finished. The cycle of solving a problem using ML is unpredictable, resource-intensive, and costly. Such costs are disproportionate when mistakes are made or retraining is required often, either of which is exacerbated by a flawed or poorly executed ML process.
It is widely accepted that good data is the most important element in obtaining, deploying, and maintaining a production-ready ML system. Advanced solutions depend on the collection, preprocessing, storage, systematic recombination, and sharing of high-quality data that correctly represents the problem at hand. The shape and size of the training data combined with the complexity and depth of the ML algorithm will define a model's performance in production. Pre- and post-production decision-making requires timely transformation of data into model-specific insights.

1.1. Purpose and Scope of the Document

Designing and deploying cloud-native learning systems is challenging, as they need to ingest, analyze, retrain, and infer from large amounts of dynamic data while adhering to strict performance, fault tolerance, and compliance requirements. When deploying a cloud-native AI infrastructure, organizations face tough design choices, including what platform to deploy on, how to partition learning and pipeline components, what and how much user-bootstrapped data to use for retraining, how to align dynamic inference demand and finite resources, and how to ensure the compliance of pipelines that can learn from sensitive data over time. In practice, organizations usually rely on manual actions or best-effort heuristics to address these design issues. This can lead to pipelines that are not optimal in terms of capital and operational costs and a long time to market and are not guaranteed to be fault tolerant or compliant over time.

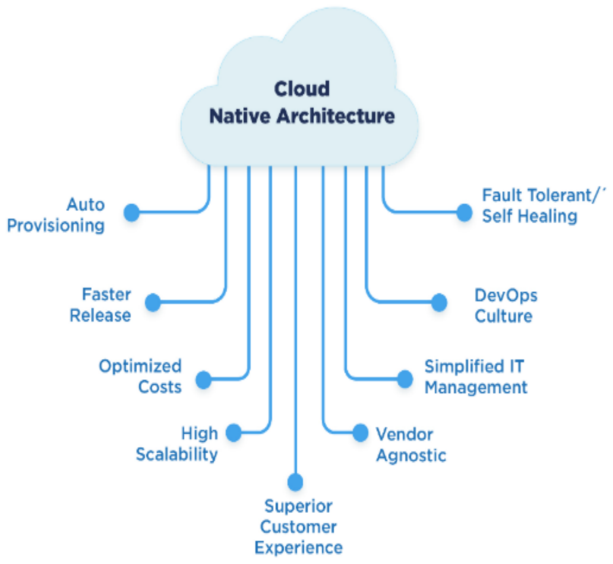


Fig 1: Cloud Native Architecture

In this document, we propose an extensible framework that allows organizations to implement cloud-native infrastructure for learning pipelines that are optimal, fault-tolerant, and compliant over time. We first present a set of architectural design decisions that make Machine Learning as a Service infrastructure functionally complete. We then present the specification of a constrained optimization problem that can be used to select a high-performance, cost-effective design for the infrastructure, and a controller that can implement the design over time. These two components can be used to create and manage infrastructure for different classes of learning pipelines, such as batch-deployed pipelines for image search and online-deployed pipelines for content recommendation. In addition, we present a self-service application programming interface for organizations to provision their infrastructure needs easily, and describe design trade-offs and cost analysis considerations. Finally, we instantiate these components in a cloud-native infrastructure built around a cloud edge and demonstrate its validity and generality using accelerators such as GPUs and FPGAs.

2. Understanding Cloud-Native Architecture

A cloud-native system is built from the ground up to take full advantage of the resources and capabilities exposed by cloud service providers. Cloud-native systems are designed to exploit the scalable, abundant, and flexible resources available from cloud providers. Ideally, cloud-native systems decouple a user's workloads from the underlying hardware and physical location, so that the cloud provider's orchestration, automation, and scheduling systems can work their magic. In their purest forms, cloud-native systems make use of serverless functions, dynamic scaling, rich ecosystems, and microservices. Compared to traditional on-premise systems, the primary improvements users are seeking from cloud-native systems are significant reductions in operational burden through automation and standardization of often disparate systems. The greater abstractions of cloud-native systems reduce the cognitive load for users; however, cloud-native systems come with considerable trade-offs. Users cede control over details such as security, monitoring, data locality, and performance to the cloud provider's services, which are designed to be configuration-driven. A significant decision in the cloud-native world becomes which service to use and how to configure it. Cloud-native architectures have several major components: Infrastructure, Deployment Manageability, Service Reliability, Configuration, and Ecosystem. Infrastructure refers to how compute, memory, network, and storage resources are provided and abstracted. Deployment Manageability encompasses all logging, monitoring, alerting, and patching for every service in the system. Service Reliability focuses on ensuring that the services deliver predictable performance under variable load conditions. Configuration specifies how each service is customized in line with applications running on the system. Finally, Ecosystem refers to the grouping of services from one or more providers for implementation in a cloud-native application.

$$\Phi = \frac{\sum_{i=1}^{N} \omega_i \cdot T_i}{\tau}$$

where:

- Φ = Weighted throughput of the ML pipeline
- ω_i = Importance weight of task i
- T_i = Number of completed tasks of type i
- τ = Total execution time window

Equation 1 : Pipeline Throughput Performance (PTP):

2.1. Definition and Characteristics

The term "cloud-native" architecture has credibility in the software development industry, and it refers to concepts, patterns, techniques, and frameworks that help to implement highly efficient, scalable, available, maintainable, and evolvable microservice-based applications in the cloud. What advanced the talks on the "cloud-native" paradigm was a white paper with the same name published by leaders of the popular container orchestration ecosystem based on Kubernetes and containers in general. In it, it is stated that the "cloud-native" is an approach to build and run applications that fully exploit the advantages of the cloud computing delivery model.
Cloud-native applications are built as a set of microservices, designed for repetitive deployment and automated testing, built and deployed as a raw executable, automated deployed and operated based on container technologies and allow abstraction of the underlying infrastructure where they run as well as resource elasticity and horizontal scaling. Intended for intensive use of cloud resources, cloud-native applications are also designed to embrace failures, be self-healing, offer low-latency and append-only data access patterns, reduce the costs of non-volatile cloud storage service by managing the lifetime of any serialized data, be observable, tolerant of third-party service unavailability and usually distributed across multiple cloud regions, and be fault-tolerant of central service unavailability for a short time window.

2.2. Benefits of Cloud-Native Approaches

Cloud-native architectures have been formulated based on lessons learned from years of experience running Internet-scale services, trends affecting the behavior of operational workloads, technological advances, and fostering an active, growing community around open-source projects that address common problems. The benefits of the cloud-native approach can be listed in three groups of categories all of which contribute to a faster development delivery cycle: Automatable, Observable, and Elastic. The first of these reduces developer toil by making the software easier to manage, relieving operations of busywork. The second provides rich telemetry that makes it easy to monitor the behavior of the application and deduce system health and state. The third enables organizations to serve fluctuating requirements efficiently, freeing capacity during times of low demand while having sufficient resources available to meet bursts of demand.
The automatable principle consists of making operations for the application that can be expressed as code with low overhead. The operability is a principle that supports collaboration between development and operations teams: By embedding operability functions in the services it is possible to keep provided functions in sync with the current needs. Monitoring the system behavior is the purpose of incorporating observability in the architecture. Monitoring capabilities have strict requirements regarding the timing of the events and access methods demanded and, if not attended, might lose telemetry data that could compromise system diagnostics. The system behavior can be monitored everywhere but, preferentially during normal operation, the diagnostics should be collected through the embedded operations to minimize infringing on service execution. Monitoring data should be retained in a time-series database to ease anomaly detection routines.

3. Machine Learning Pipelines Overview

Real-world ML projects generally host many models that are independently developed with various pipelines, tools, and infrastructures. Developing ML systems at scale without a standard architecture is crucial to maintain. In the absence of architecture, experimental models graduate into production more or less by serendipity. When inspired researchers build exceptional models that deliver real business value, scaling, and product ionization are then catastrophic to do and prone to failure. Revisiting and updating ML models that have been retired from production becomes difficult. In such conditions and arguments, it becomes generally desired to have a standard reference ML architecture, such that the transition from small exploratory or academic projects to production quality and critical online system can be done more smoothly, and a set of general tools, pipelines, and infrastructures capable of processing a wide range of ML tasks and domains. Many key components are present in more or less models: Data shard ingestion, pre-processing, feature generation, model training and scoring, evaluation and test, model deployment, and pipeline orchestration, among many others. The pipeline composition and connections between blocks vary among and with tools; many also have been designed to solve a specific type of ML problems and in those cases present few options. These generalized inspiring tools make considerable research speed since models can be easily built, tested, and located at initial phases.

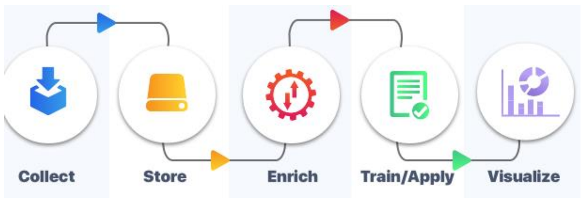


Fig 2 : Machine Learning Pipeline Deployment

3.1. Components of Machine Learning Pipelines

Machine learning (ML) pipelines consist of multiple components that are responsible for the data's journey from an initial state until it serves the purpose of the business application. Similar to a data processing pipeline, a typical ML pipeline takes generic data of a certain type as its input, commonly in the form of a storage bucket, and produces domain-specific data. Nonetheless, in a typical ML pipeline, data preparation is divided into a set of different intermediate processes that transform the original data until it produces the final product, a trained model that can be queried using other data. Typical components of an ML pipeline include: data sourcing, data ingestion, data preparation, feature engineering, model training, model evaluation, and model deployment.

Data sourcing is responsible for identifying business events that create the need for an ML product. It creates the closure for products that need and consume the ML product. It communicates the need for the product with the stakeholders and aligns it with other business products. It objectifies the model’s concept, decides the objective type, and derives the ML work unit that is the smallest representation of the business scenario per the input data. The ML work unit defines how business entities interact with each other. It creates the closure so that the ML model output product is a scaled-down version of the output product. Data ingestion pulls the domain's data into the current workflow. It is responsible for connecting with data sources and extracting and loading the appropriate data for the current scenario. There are many forms of domain-modeling data.

3.2. Challenges in Traditional ML Pipelines

Traditionally, deployed ML systems were not designed to be continuously retrained or updated. Due to this, it was challenging to adapt ML models to changes in data distribution and possibly underlying assumptions associated with the model, leading to a specific class of model failure not addressed by software tooling. In addition, model retraining was a manual effort, often with implicit or explicit additional coordination between ML scientists and developers, which raises friction in development and increases the time to model updates. It is considered a good practice to separate model retraining and serving functionality and expose ML serving as a microservice so models can be retrained as needed. This would move model retraining into the DevOps domain, allowing data scientists to focus on model development. However, managing updates in a multi-model environment to ensure that old versions of models are still functional while lowering the burden on developers to have to manage model input and output schemas, is another source of friction that needs tooling solutions.

Another issue with traditional systems is that they often rely on complex model architecture definitions, from selecting appropriate model hyperparameters to assembling models from gluing together complex infrastructure dependencies like batch pipelines ingesting data into the model, to serving infrastructure. While frameworks attempt to encapsulate this complexity, the increasing need for fast experimentation in research has led several practitioners to use lower-level tools to build and leverage scaffolds for fast prototyping. These complex architecture definitions lead to issues in model explainability due to increased black-box behavior, and it may also raise questions concerning bias present in the model due to the model architecture selection.

4. Designing High-Performance ML Pipelines

The performance of machine learning pipelines is often questioned, and many works label certain pipelines only as proof of concept designs. There are several reasons for such inference in the ML domain. The overall time complexity of many ML models is not well defined and is more likely dependent on the particulars of the data distribution, and subroutines called during execution. The time complexity of several pipelines is not governed by the time complexity of the ML model called in the pipeline, but rather by subroutines such as data ingestion or data preparation, which again often depend on the structure of the data. Designing and deploying performant pipelines is hard for several reasons - in addition to unknown latencies for most subroutines, the target metrics are driven by non-ML pipeline costs such as latency or throughput requirements, pricing impacts, and the characteristics of the pipeline calling environment.

Because performance design can be done at many levels concerning a pipeline, how do we evaluate the quality of such a design? ML pipelines don't exist in isolation, and the performance of pipelines thus depends heavily on the environment within which they are deployed. The user wants certain metrics - such as cost-driven or latency-driven quality for computer vision-related pipelines, and the respective scale at which the pipeline is evaluated, or deployed, set a lower bound on these metrics. The design of the pipeline could be evaluated based on these metrics. However, the choice of pipeline design is a very old problem, and there are existing works that also propose design metrics that relate to the design quality. However, all those works are related to one type of pipeline flavor.

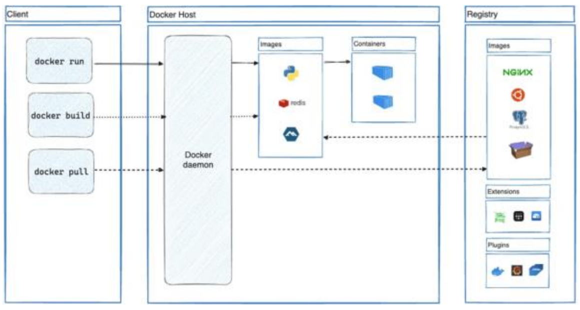


Fig 3 : High-Performance Computing Data Centers

4.1. Performance Metrics

All computation processes take time to execute and need resources, e.g., CPU cycles, memory bandwidth, and power dissipation. However, few works consider performance when designing Machine Learning (ML) pipelines. Even when they do, the focus usually is on a reduced set of critical components. For example, in conventional data-centric works, the dataset characteristics affect the training process only through the input shape, and their performance considerations are confined by the data loading time.

There is a myriad of metrics to measure performance, from a simple wall clock that tells how long a command took to finish to more complex modeling frameworks capable of predicting their execution time given the context of diverse workloads and systems. The former are the most common, although they can lead to misinterpretation of the performance if poorly used. For instance, the CPU time taken for a specific ML can vary significantly from one run to another, and more importantly, using this metric does not capture the time that a user would perceive when running different workloads. To avoid these pitfalls, we recommend using a small breadth of metrics that capture the multiple aspects of the performance. For example, we recommend measuring the throughput and the latency, as these are what users would perceive and are commonly used in the literature. In addition, we recommend measuring the power consumption to understand whether an ML pipeline can run in a constrained environment. Finally, although seldom mentioned in the literature, power consumption also influences the wall clock time. In particular, longer-running jobs consume more power than shorter ones at high loads.

4.2. Optimization Techniques

The idea of automating infrastructure design decisions is appealing because it reduces the burden on architecting pipelines as well as reduces the time from concept to production for organizations adopting ML. The amount of hyperparameter exploration required in this model, coupled with an accelerated training platform, and a few assumptions make the problem easier to tackle compared to other high-performance ML pipeline design problems. First, the search space for core ML model hyperparameters can be restricted to a few key hyperparameters that affect training performance, the trained model's inference performance, or the time it takes to run a single prediction, but do not interact with other ML model hyperparameters and are not resource-usage optimizable. Core ML model hyperparameter examples include several layers, layer type, and layer width for neural networks, and the number of trees and leaf size for tree-based models. Second, we use the cloud's elastic and on-demand nature by provisioning accelerated computing in a high-throughput and bottom-up manner to align with the pipeline business team members' tolerance for additional operational risk. Cloud costs are passed down to application owners, but hyperparameter optimization jobs are assumed to be run on behalf of all application owners and drive the overall value of the ML infrastructure.

Several techniques are currently used to optimize ML pipelines by automating and/or simplifying design infrastructure decisions. Automated Deep Learning toolkits automate core ML model design decisions using user-provided compute resources. These pipelines are run by data scientists who consume the entire ML pipeline as a service offering that answers their ML-defining business question. The tools expose an API that takes training and validation sets along with the value of the ML-defining business question as input and runs a pipeline search back-end to generate a recommendation of a pipeline that produces the best results achieving the value of the ML-defining business question. The back-end outputs the suggested hyperparameters based on additional runs to find the best hyperparameters.

5. Fault-Tolerance in AI Infrastructure

In both commercial and scientific settings, AI workloads are constantly exposed to transient hardware and software issues that occur across the stack. The space provides only limited guarantees regarding the correctness and reliability of AI jobs. Furthermore, since AI jobs take a long time to run, a minor error can affect the correctness of the result, as well as the resource investment. Therefore, it becomes the responsibility of the AI developers to ensure that the jobs recover from real-world issues, such as task or job failures across worker nodes, server-side caching, and network issues, and produce valid results.
Recall that Cloud-Native Infrastructure must comply with low-level cross-layer failures, known as basis faults, that represent a separation between high-level fault models across the stack and their low-level representations. In this section, we first delve into the notion of fault tolerance in computing systems at large at both high and low levels. Then we discuss existing design patterns and systems for resilience in AI workloads. We conclude the section by highlighting major open questions related to fault tolerance and design patterns for real-world AI systems. We encourage AI developers to leverage these patterns from concurrent systems to ensure resilience in their jobs.
To determine an answer to the high-level question of fault-tolerance, we must find predicates that approximate an answer to the basic low-level fault-tolerance question above. Fault tolerance is characterized by the properties and guarantees of a system's recovery control layer, but it is fundamentally a property of the jobs that run on that system. Therefore, answering the above question is a two-step process. First, for a given application, we customize the system's recovery control layer to provide our chosen predicates. Then we demonstrate that the job runs correctly even in cases of the predicates being violated.

$$\Psi = 1 - \frac{F_r}{F_t + \epsilon}$$

where:

- Ψ = Fault tolerance index (range: 0 to 1)
- F_r = Number of failed recoveries
- F_t = Total fault events detected
- ϵ = Small constant to stabilize computation

Equation 2 : Fault Tolerance Index (FTI):

5.1. Understanding Fault-Tolerance

Researchers and users have come to depend heavily on machine learning for making business-critical decisions. As a result, they have become less and less tolerant of outages. A single unavailable model might mean dissatisfaction or loss for hundreds or thousands of end users or customers. Considering the number of end users, plus the dollar amount of transactions affected per minute, some experts suggest that model downtime can result in losses more significant than outages of financial services. In addition, there are additional compliance requirements. The European Union’s Artificial Intelligence Act envisages liability both for low- and high-risk AI products. Contrary to some popular perception, having no compliance infrastructure in place will not diminish your maker status. If you design and build an AI tool, you are liable for its use. This new situation makes the need for built-in model resilience even greater.
When discussing a fault-tolerant system, we must point out that it is not the same as a reliable system. The latter is defined as an application that, when running, works correctly all the time. This definition presumes that there is never a fault. In contrast, the former defines objectives for a system that can still be able to run, despite failures. In this definition, the main goal is to guarantee an ongoing process of service delivery, i.e., providing some specific service for a particular (possibly non-empty) set of users for the longest possible time. In fault-tolerant systems, there is an implicit agreement with users that, when problems are detected, services will tend to be resumed quickly through backup mechanisms or similar solutions. If requested services remain unavailable for a long time, clients may get upset. Altogether, since organizations can suffer losses if they take models offline repeatedly, they must carefully consider the trade-offs between making models less prone to faults and using them as they are.

5.2. Design Patterns for Resilience

A concept as popular as microservices, cloud-native application design patterns, such as service discovery, circuit breaker, or retry, have become an important notion for the reliability of production services. In the ML pipeline world, while there are early attempts at designing pipelines from a cloud-native design perspective, there is not an existing well-defined set of recommendations to achieve resilience. This section introduces fault-tolerance frameworks that have become well-established design patterns in non-ML systems. The goal here is to provide insight into possible ways of increasing resilience for ML pipelines and creating compatibility with discussions for general distributed systems, increasing reuse of research and implementations from the broader distributed systems research community. We define three patterns, that are at various levels of abstraction: design-for-failure, coordination management, and best-effort execution, that answer the question of what to do when a component of a distributed system fails. Discussing existing ML pipelines, and perhaps incorporating their design, or assuming a specific design, we address this question some more, by looking specifically at three categories of pipeline components: drivers, executors, and evaluators. The guiding principle of design-for-failure is that components in a distributed system cannot always be expected to be reliable; infrastructure fails, networks fail, and components run out of memory and crash. Therefore, the design of the system should reflect this, and have adequate support to handle these failures. A system built around design-for-failure should not only assume the possibility of failure, but it should do so actively.

6. Compliance and Security Considerations

The choice of cloud-native AI Infrastructure may be consequential for the compliance and security posture of the organization deploying it. When IaaS and PaaS services are chosen, the cloud provider is subject to some level of compliance verification, likely resulting in compliance attestation. Although this attestation will cover a large portion of the services offered within a cloud region, regulatory requirements that affect the whole technology stack, including AI technology, may not be covered in the attestation. It is then up to the customer organization to ensure that it is regulating compliance checks both upstream and downstream of the IaaS and PaaS cloud services.
One recommendation that we make when deploying cloud-native AI Infrastructures, particularly PaaS services, is to be aware of service-region dependency when deploying multi-region architectures. Although architecture resilience dictates the deployment of business-critical systems in multiple geographic, tech, and cloud regions, regulatory requirements focused on data locality or specific assessment of cloud services may limit the deployment or availability of certain services in a specific region.
To ensure business data security and prevent reputational and financial damage because of rising cybersecurity incidents in the domain of AI solutions, deploying cloud-native AI solutions must follow industry-recognized criteria. Business models built on AI solutions are often sensitive by nature as they fully expose their value chain to the consumers of their service. Therefore, industry-recognized security considerations applied to cloud-native AI Infrastructures should cover some of the most common ML-model-attack vectors.

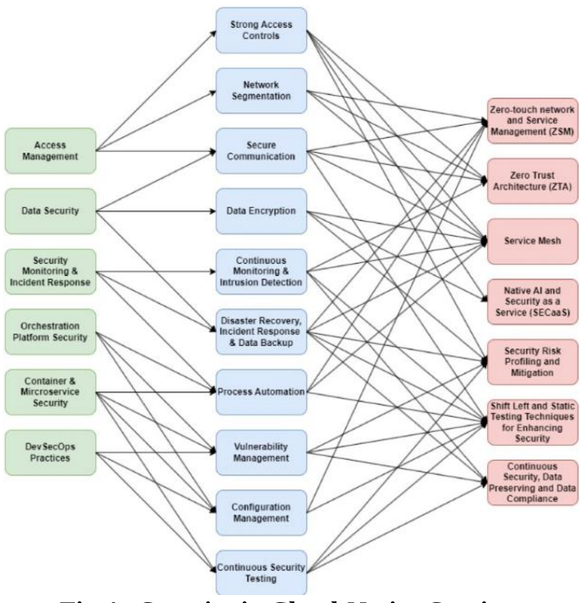

Access Management
Data Security
Security Monitoring & Incident Response
Orchestration Platform Security
Container & Mircroservice Security
DevSecOps Practices
Strong Access Controls
Network Segmentation
Secure Communication
Data Encryption
Continuous Monitoring & Intrusion Detection
Disaster Recovery, Incident Response & Data Backup
Process Automation
Vulnerability Management
Configuration Management
Continuous Security Testing
Zero-touch network and Service Management (ZSM)
Zero Trust Architecture (ZTA)
Service Mesh
Native AI and Security as a Service (SECaaS)
Security Risk Profiling and Mitigation
Shift Left and Static Testing Techniques for Enhancing Security
Continuous Security, Data Preserving and Data Compliance

Fig 4 : Security in Cloud-Native Services

6.1. Regulatory Requirements

Regulatory compliance is an important aspect of machine learning models in a production environment. Machine learning models can be subject to various regulatory frameworks depending on their purpose, model design, output, and possible impact on different groups of people. Before moving into model design and specifications, we want to draw attention to three compliance regulations, namely the EU General Data Protection Regulation, the EU Digital Services Act, and Section 230.230.1 in the SEC rule. The SEC rule is the most important regulation for machine learning models presented in this chapter since it outlines certain operational requirements for broker-dealers in their use of quantitative trading models and developer models internally to structure investment transactions.

The SEC states that a broker-dealer that designs for in-house use or uses a quantitative model must, by rule, establish and implement written policies and procedures reasonably designed to ensure that the quantitative model is: used only for its intended purpose, validated before use, and revalidated periodically. In terms of financial compliance, the SEC has laid down specific requirements. We expect that further compliance regulations concerning AI systems will follow covering more domains over time. The EU GDPR has various requirements that arise from data-driven machine learning model development, being specialized on the datasets being used or the functioning of the model. If the model is making decisions on behalf of an organization, rather than as an aid, the EU DSA will further apply. Also, the EU DSA has specific requirements for these cases regarding topics like risk management, robustness, and data governance. The main model and system requirements will be covered in this chapter.

6.2. Data Privacy and Security Best Practices

Historically, the most common data privacy violations have originated from poor access management systems, lack of monitoring data access, sharing PHI over insecure channels, failure to use strong user authentication protocols, and lack of encryption. Fortunately, both cloud providers and organizations can take several common measures to mitigate the most significant data privacy risk. Specifically, all cloud services and on-premise environments used in the ML process should implement role-based access control systems that also support least privilege; multifactor authentication systems to increase the security of the user authentication process; encryption both at rest and in transit; data leak prevention tools to mitigate the risk of insiders unintentionally disclosing PHI; monitoring, logging, and alerting systems to detect inappropriate data access; key management systems that rotate keys regularly; and employee training about data privacy procedures and security technology used by the organization.

Furthermore, the above four risk mitigation strategies might be insufficient for some organizations with more stringent data privacy requirements. For example, there is an initiative designed to help health organizations establish a higher threshold of confidence to support and evaluate their security solutions against stricter data privacy guidelines. In addition, some organizations, especially in the finance and healthcare sectors, might restrict the deployment of some of their sensitive ML platforms to on-premises solutions due to more stringent regulatory data encryption and access management controls. Organizations that wish to deploy ML tools for PHI data to the cloud are required to conduct a thorough risk assessment. All the involved regulatory agencies should be contacted to discuss and validate the plan of the organization to establish the appropriate threshold of risk versus return on investment in privacy technology.

7. Framework for Designing Cloud-Native AI Infrastructure

Machine Learning (ML) projects are known for their novel and complex requirements, leading practitioners to often reinvent the wheel from scratch. Central to the CI/CD revolution for traditional software are pipelines and tools that make it easy for engineers to select, deploy, and reuse high-quality software components. Such pipelines implement the software engineering principles of componentization, abstraction, and encapsulation that allow for agility and speed of change. In contrast to mature tools that are widely used for CI/CD of traditional software systems, support for CI/CD operations specific to ML pipelines is much less sophisticated and complex.

To address this shortcoming, we designed a machine-learning infrastructure framework. Through a set of designs and key design choices, we enable the construction of ML pipelines that are performant, reusable, and composable, while leveraging the tools and services of technologies from the CI/CD revolution. Our framework helps implement ML pipelines executable and composable, integrating all the components from model development to deployment. Our reference architecture is cloud-native; that is, it relies on tools and methodologies that enable scalable, performant, and flexible applications when implemented in a public, private, or hybrid cloud. In this section, we describe the key design choices and reference architecture of our framework. Our CI/CD architecture has three key characteristics: It is cloud-native and distributed at its core. With the level of abstraction provided by the cloud, the burden of ML pipeline infrastructure on model developers is minimized. Automated provisioning of these cloud services enables a rapid pace of experimentation.

7.1. Architecture Overview

Over the last few years, there have been significant advancements in all aspects of AI technology, including the development of foundation models, better model training algorithms, the availability of vast amounts of training data, and new software frameworks that improve developer productivity and application performance. Most recently, these advances in AI technology have been coupled with advances in ubiquitous cloud-enabled large-scale infrastructure capable of scaling to thousands of GPUs and TPUs. Even within a large enterprise, all of these different aspects of AI are still toddler stage. From a practical point of view, AI is not yet considered a serious anchoring application for web-scale cloud providers. As a software company, we would love for AI to become an anchoring application for the big cloud providers. That way, more technology, and more money would flow into the infrastructure-enabling space. However, we don't see that happening for several years. Building cloud-native AI infrastructure requires mastering all of the technology stack between the original research to the cloud-native infrastructure layers where these research ideas are converted into deployable production solutions. Successful large companies are already providing cloud-based AI-enabling technology. In this chapter, we present a framework for designing cloud-enabled AI infrastructure by utilizing the principles of cloud-native development and design. The framework can help architects at cloud providers define, scope, and prioritize their initial AI infrastructure capabilities as well as enable service providers. The framework is also useful for enabling developers and researchers to build more agile, flexible, and robust cloud-based AI solutions as well as enabling startup architects and software architects how to quickly build and release cloud-native AI applications.

7.2. Key Components of the Framework

The main components of the proposed framework for cloud-native AI infrastructure are resource controllers, cloud-agnostic pipeline templates, infrastructure operations, cluster and device manager, and extensible API. Resource controllers are responsible for the high-level orchestration of resources required by ML subsystems to perform their primary functions including data storage, data IO, model training, model deployment, and model inference. Pipeline templates define a cloud-agnostic blueprint of the ML pipeline structured as a directed acyclic graph with edge attributes describing the ML data as well as the specifications and configuration of the tasks performed by the nodes in the graph. The pipeline execution engine instantiates concrete ML tasks using the information provided by the pipeline templates in their desired states and manages their life cycle for fault tolerance. Infrastructure operations enable users to change the infrastructure configuration for lifecycle events including stateless task relocation, periodic task restart, and sudden failure event handling. Cluster and device managers perform cluster and device orchestration at the lowest level based on a simple set of policies or periodic optimization algorithms. Extensible API allows for configuration and control of the ML pipeline at different levels of granularity from pipeline-specific parameters to infrastructure-level properties.

Resource controllers provide users with an easy-to-use declarative programming model and high-level abstractions that enable them to quickly write ML pipelines without worrying about runtime details. It also takes care of instantiating concrete ML tasks using the information provided by the pipeline templates, putting them in desired states, and managing their life cycle for fault tolerance. This is especially useful for popular classes of ML applications that span across multiple types of tasks, and for which the requirements change frequently. ML systems that are structured according to our resource controllers can rely on our high-level service layer for rapidly implementing extensions and additions without adding to the infrastructure's complexity and maintenance burden.

8. Case Studies

This section will provide readers with a compendium of AI applications, chosen from the plurality of fields in which they are being adopted at an industrial level. The aim is twofold: on the one hand, showing that the tools and patterns that we promote in the previous chapters may be used to satisfy the needs of highly diverse and demanding workloads; on the other hand, that such approaches can evolve and quickly adapt to the current innovation cycle of AI, which is mainly driven by the increasing availability of enormous foundation models.

The applications we cover are: (i) Text Generation; (ii) Image Generation; (iii) Automated Drug Discovery; (iv) Medical Data Analysis; (v) Deepfakes and Advanced Synthetic Media; (vi) AI-Assisted Design and Creativity; and (vii) Algorithmic Autonomy and Decision Making. In each application, we describe the associated market and technologies, as well as the architectural challenges and the implemented cloud-native AI architectures. We hence depict the application areas as "cloud-native AI crossroads", demonstrating their importance with technical use cases from the industrial partners. Each architectural choice will be made clear through the description of how goals such as maintainability, reliability, and performance are dealt with: how the architectural restriction imposed by reliance on foundation models is taken into account; how the pipelines are automated and what technologies are used to automate them; how easy it is to add new pipelines to the industrial service; what Network Functions are meant to assure reliability and fast response time; how supervision of the flow is implemented and which tools are implemented to allow the human supervisor to act effectively; and how costs of retrieval, inference, and bandwidth are addressed.

8.1. Industry Applications

In recent years, we have seen success stories of diverse industries leveraging ML techniques to solve domain-specific problems. The financial sector has heavily relied on either supervised or unsupervised learning for many years for various prediction and classification tasks. They have used ML pipelines powered by traditional algorithms or deep neural networks to uncover fraud, gain customer insights, combat risk, automate the trading process, and create liquidity. Service providers within these industries work with diverse customer datasets to address similar if not the same problems. Data confidentiality is critical, yet they cannot build customer-specific pipelines at scale. This sets up a collaborative solution architecture where a set of high-performance ML pipelines need to be designed utilizing federated learning and transfer learning methods. These pipelines need to be capable of running on varying hardware environments so that they can be

submitted for training with minimal effort. Dataset and ML pipeline parameter monitoring will help to score the models periodically.
The second vertical that has seen a surge in enterprise ML adoption is the technology sector. This sector has seen firms build their own in-house ML capabilities to help with all departments from DevOps, IT, and engineering all the way to sales, marketing, and support. They have also developed core products based on customer pain areas or market opportunities and whether that is providing time-based analytics, continuous model retraining, collaborative ML, user behavior prediction.

8.2. Comparative Analysis of Approaches

We apply our framework via two different security and availability products and services. The foundational technology for both approaches is an advanced engine that combines natural language understanding, knowledge representation, and automation for multi-domain AI operational workflow design and execution. The technology includes advanced technologies for first-pass document understanding and templating and can adapt domain-specific tags and categories that enrich the semantic structure through knowledge augmentation techniques. Many additional engine capabilities help inform and demonstrate other pipeline design decisions: we support multi-modal workflow steps that apply metadata templating to video and image assets, plus audio transcript templating for audio media. We offer data connectors to easily ingest almost any type of structured data and introduce automated fraud detections with outlier models around the media types, amplification metrics, plus third-party engagement properties.
Both of our variants ingest sample document metadata and deployment variables and generate the rest of the pipeline steps by inferring from both the sample distribution properties plus the current capabilities of the models selected for each step. The comparison here is high-level: while security is often the lowest priority, availability monitoring must happen in near-real-time around events such as news stories or product launches. This gives comparatively low execution and response times around demand pattern changes for the availability variant while providing greater resource quality plus cost management for the production stage of pipeline execution when compared to the detection operations of the security variant. How a number of these aspects concretely differ for these two approaches is summarized in the following table.

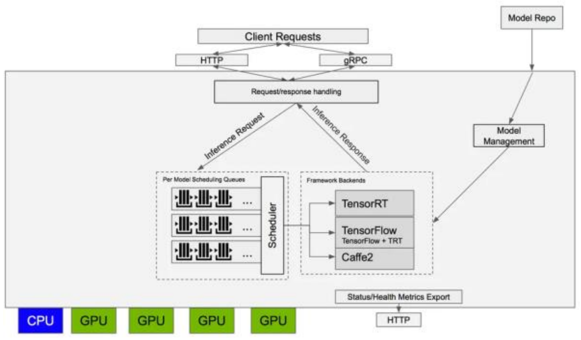


Fig 5: AI Infrastructure Engineering

9. Tools and Technologies

This chapter gives an overview of available tools and technologies to enable cloud-native ML. These cloud infrastructure building blocks have been matured by many different teams over the last two decades. Almost all of the tools are either open-source or have community-supported versions available as derivatives. A thorough understanding of cloud technology can be invaluable in enabling data science teams at organizations to select the best-performing cloud-native technology stack, or customize and contribute to existing technology so that it meets the requirements of domain or vertical-specific needs. Throughout this chapter, we will discuss several of the technology components, and when appropriate, we will provide a few recommendations based on our experience.
1. Cloud Platforms
Public cloud service providers offer hosted infrastructures that are paid for on a subscription basis. They have several advantages over on-premises data centers: Ease of access and instant provisioning; Only pay for resources when needed; Outdated components can be easily replaced by newer versions with a click of a button, or staying behind the scenes and automatically updated; Scalable infrastructure can be created on-demand through automation; Resources can be shared by many teams, promoting collaboration; Advanced security practices are implemented and maintained by dedicated security teams. Availability of computing resources such as GPU and TPU hardware accelerators; and completeness of support for hardware and software needs of mission-critical workloads.
The public cloud platforms have built entire ecosystems around their infrastructure products. Some of the core enabling technology components include container orchestration, data processing pipelines, ML pipelines, and ML model

deployment and monitoring of models in production. There have been several vertical-focused cloud platforms as well. These platforms may provide specialized cloud services that enhance existing services on traditional cloud platforms. Or, they build their entire infrastructure on top of open-source technology stacks and implement various optimizations on that technology along with managed services. Technologies for data storage, analytics, and feature storage are some examples of vertical-focused cloud platforms.

9.1. Cloud Platforms

Over the years, multiple cloud service providers have grown in scope and maturity. The most prominent of these include the top three: Amazon Web Services, Google Cloud Platform, and Microsoft's Azure. Each of these vendors provides numerous services and products that follow the same general cloud service model and fulfill similar roles, including virtualized computing, networking, storage, and management services. The primary benefits of using cloud platforms for deploying AI infrastructure include ease of expanding or replicating work with additional compute cycles, increased fault tolerance provided by leveraging managed services within the cloud provider's offerings, and financial incentives available to users who run short, burstable jobs on flexible schedules.

Today, the majority of organizations that use the cloud for AI development deploy their infrastructure on popular hyperscale cloud service providers. During modern data-centric AI development, special-purpose AI accelerators, typically with GPU and TPU chips, offered by these cloud providers, have mostly made deploying AI Infrastructure simpler. However, with the increased complexity of the high-performance, fault-tolerant AI pipelines, there is a growing need to share this infrastructure among many dev teams. Consequently, the use of flexible container-native AI stacks, either readily available in the public cloud or deployed privately by the relatively easier air gap pipeline builds, is becoming common. Cloud-native services shared and managed in a multi-tenant environment offer additional capabilities, such as monitoring and pre-processing pipelines that are available via integration with existing cloud data lakes.

9.2. Machine Learning Frameworks

Machine learning frameworks make it more convenient for ML engineers to develop production-ready ML pipelines. They usually implement custom data types and methods for transforming the data at scale; model training; prediction serving; and performance monitoring. Based on the automation level they offer, we can split available frameworks into three categories: low-level, high-level, and production-ready frameworks. Examples of low-level ML frameworks include various libraries. These frameworks expose a relatively simple interface for implementing ML computations and models. Usually, they provide modeling components that are easy to configure and extend. However, they do not offer built-in support for automatically managing model training at scale or deployment. Because of this, it is common for a production-ready ML pipeline to use certain frameworks for model training, but not for prediction serving.

Higher-level ML frameworks include various libraries. These frameworks are usually higher level than low-level frameworks and are designed specifically to make developing and validating ML models more efficient. Higher-level algorithms may be easier to fine-tune and usually, further reduce the number of lines of code needed to implement a model. For these reasons, models for some specific ML tasks are developed faster using these frameworks. However, in exchange for the higher level of convenience, they are less flexible and extensible, requiring implementations of less common algorithms to be more complicated.

$$\min_{x \in \mathcal{X}} C(x) \quad \text{subject to} \quad R(x) \leq \rho$$

$C(x)$ = Cost function for resource and security overhead

$R(x)$ = Regulatory risk metric (e.g., PII exposure, audit score)

ρ = Maximum allowed compliance threshold

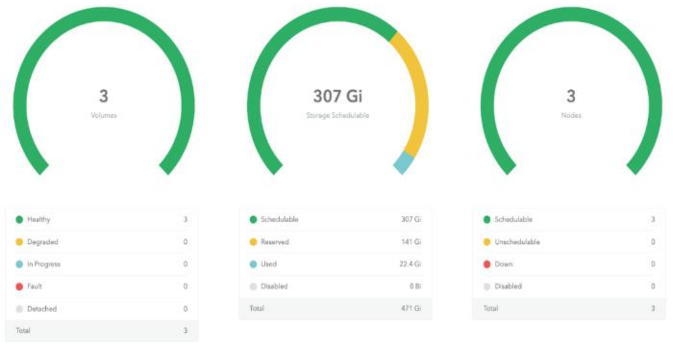
$\mathcal{X}$ = Set of deployable infrastructure configurations

Equation 3: Compliance-Constrained Optimization (CCO):

10. Conclusion

In this work, we introduce a framework for designing cloud-native AI infrastructure to deliver high-performance, fault-tolerant, and compliant machine learning pipelines as a set of loosely coupled heterogeneous services. We present the design constraints and implementation considerations associated with the development of each of the infrastructure services, as well as a reference implementation of the framework across a set of services. The framework design is a direct consequence of the interplay between the design constraints, as well as the needs for and challenges posed by enterprise ML systems. With the ubiquitous adoption of ML and AI technologies across the globe and the growing complexity of the model training and serving workflows, designing a cloud-native AI infrastructure is key to accelerating ML adoption within enterprises. We develop and open-source a platform to directly assess an enterprise's AI infrastructure design choices, including the ones composed of the Building Blocks communicated through the framework.

By implementing this platform and applying it to a customer use case, we showcase the flexibility, extensibility, and scalability of our framework, as well as the benefits that can be derived by adopting a layered, cloud-native architecture for the AI infrastructure components. We further communicate a set of lessons learned in building this platform, both from a technical and business perspective. To summarize, large design space and open challenges remain concerning autonomous, continuous design and mutation of AI infrastructure, and given the promise of generative-powered assistants within the AI domain, we believe that the focus for the future must not only be to understand the patterns associated with AI infrastructure design but also capitalize on them to increase developer velocity within this domain and further democratize AI within the enterprise.



🟢 Healthy	3
🟡 Degraded	0
🔵 In Progress	0
🔴 Fault	0
⚪ Detached	0
Total	3

🟢 Schedulable	307 Gi
🟡 Reserved	141 Gi
🔵 Used	22.4 Gi
⚪ Disabled	0 Bi
Total	471 Gi

🟢 Schedulable	3
🟡 Unschedulable	0
🔴 Down	0
⚪ Disabled	0
Total	3

Fig 6 : engineering tools to build a cloud native IDP

10.1. Final Thoughts and Future Directions

Becoming cloud-native is no longer a choice for machine learning practitioners and organizations. It is a necessity because the cloud is the only environment that can support the scale of data and computing that is conducive to significant business growth and enables the implementation of compliance and reliability requirements. Cloud-native machine learning is not the same as machine learning in the cloud. Businesses need to adopt appropriate changes in their architectures and software infrastructure and the strategies they use to integrate machine learning into their business decision-making and practices to add value to their customers in a fault-tolerant and compliant manner. The cost and effort required to do this are significant and come from the high degree of complexity and newness associated with cloud-native design. This text provides the basis for this generation of cloud-native systems through the principles and design framework shared.
These principles and design framework will continue to evolve as the world of cloud-fetch microservices and AI continues to consolidate the significant advances made on both sides. Shortly, we expect the cloud service providers to add new capabilities and build higher-level abstractions for machine learning that will continue enabling developers to easily create extensive offerings to help businesses collect data and build models that define and translate the business rules and the strategies that make the business unique and dynamic. In the far future, we hypothesize the emergence of AI natives who, much like web natives before them, are born into a world of complex AI-enabled systems and services. They expect that the digital world around them will learn their ever-changing needs and assist with the moment-to-moment decision-making required to provide them and their businesses with a life and existence that is seamless, enriching, and socially minded.

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