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Towards Resilient AI: Leveraging Cloud-Native MLOps for Fault-Tolerant Learning Systems

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Abstract

Artificial intelligence (AI) is rapidly getting assimilated across various sectors including finance, healthcare, agriculture, and manufacturing. Factors such as rapid and ubiquitous adoption of IoT devices, and advanced technologies for mobile edge computing, have fuelled this growth. The heterogeneity of system components, user preferences, and operating environments may render AI faulty. Such faulty behavior manifests as incorrect predictions, which can have severe consequences. For example, a health monitoring system may fail to identify a health anomaly which may lead to a missed medical emergency. Malicious interference, such as fake data injection by a hacker, might also be behind the faulty behavior. It is therefore impertinent that an AI-based system be equipped with fault tolerance mechanisms, allowing it to avoid or mitigate fixable faults, similar to most systems in embedded devices and the cloud today. Fault tolerance usually operates in three modes: (1) Redundant computation, where separate low-level computation nodes fed the same inputs but using slightly different computation implementations generate different outputs, (2) Checkpointing record where the inputs and outputs of the successful computations are recorded periodically, and (3) Rollback repair using failover nodes to re-run faulty computations on buffered inputs based on previous knowledge in case of faults. Checkpointing is the simplest method, given the state space exploration is manageable, and can accommodate a higher level of non-deterministic model. Most of the meta-reasoning-based fault detection mechanism is based on a limited part of supervised training methods. Nevertheless, recent work has shown the application of unsupervised methods to detect faults in ML frameworks, but they cannot be scaled broadly as benign behavior is just as diverse and complex. This means they may fail to generalize or incur a significant loss of estimation accuracy when adapting to non-stationary workloads or diverse host characteristics.

Keywords: Resilient AI, Cloud-Native MLOps, Fault-Tolerant AI Systems, Machine Learning Operations, Scalable AI Infrastructure, AI System Reliability, Model Deployment Pipelines, Continuous Integration for ML, Automated ML Workflows, Cloud Infrastructure for AI, High Availability ML Systems, ML System Monitoring, AI Model Robustness, Distributed Machine Learning, Disaster Recovery in MLOps.

1. Introduction

AI models are increasingly becoming imperative for providing more intelligent and sophisticated services across verticals ranging from autonomous driving to health sciences. Due to the rapid advancement in evermore sophisticated AI algorithms, training these models has come with unprecedented exponential growth in the volume of data, i.e. huge datasets and highly parallelized systems being trained on thousands of GPUs over weeks or months. It is essential to develop a better understanding of how these learning systems fail since they are now key players in various safety-critical applications. There have been many documented failures of such systems, from misleading algorithmic fairness and discrimination, and an infinite cycle of training data amplification in AI-assisted content moderation and recommendation systems, to failures leading up to the crash of the commercial bodiless driving vehicle.

ML Systems compose a data monitoring pipeline and a large-scale optimizable model serving layer. Owing to such broad impacts of the failures, there is a pressing demand for providing higher levels of resilience and reliability assurance for ML systems, as well as for formalizing frameworks for a deeper understanding of their failure behaviors. In addition, disaster recovery, such as retraining and debug recovery, is at the center of scrutinizing and understanding system failures. It is natural to assume a fault-tolerant ML system of a backup model with the same architecture and a knowledge reservoir, which is periodically updated by the main model. While such classic redundancy-based solutions could provide a 100% resilience guarantee on slow and stable models, it is often not the case for large, voluminous, and complex MLOps composed of online data pipelines and distributed ML training and serving components.

1.1. Background and Significance

Advances in AI have accentuated a paradigm shift towards complex AI systems, which can learn from data, build and improve a predictive model, and report the inference in an automated fashion. Such systems can perceive their surrounding environment, reason about what they have sensed, learn to best respond to their observations, and take corresponding actions to meet their objectives. However, while operationalizing a learning model, a huge number of assumptions need to be satisfied. Matching the presumed data distribution under which the model was developed with the current reality is, however, very challenging, and can invalidate the model, resulting in catastrophic effects. Hence, there is a crucial need for self-monitoring mechanisms that can sense discrepancies between the assumptions and the reality. To encourage the community to investigate this research direction, the motivation for fault-tolerant Learning Systems is outlined, the related research fields are outlined, and existing challenges inherent in designing such systems across the AI lifecycle are discussed.

The rise of edge computing has accelerated the deployment of distributed and heterogeneous data analytics frameworks, especially for workload scheduling, resource management, performance monitoring, advertisement placement, and control. These solutions rely on procured hardware and run under shared environments with other workloads; so-called complex systems. These environments are typically resource-constrained, resulting in contentious and competitive AI applications with limited access to hardware and shared communication links. As a result, existing experimental prototyping approaches, which evaluate workloads directly on the target more or less unmodified, cannot be used, and instead, ML-based surrogate modeling is needed.

However, existing edge solutions using such models are mainly focused on predicting workloads off-line and scheduling and migrating tasks to the assigned resources either off- or online. Adaptive approaches either rely entirely on intermediary signals from other tasks or constantly capture additional features for a global adaptive model. However, as the emphasis on workloads changes, the constant retraining or the a-priori generation of surrogate equations suffers from a massive loss of accuracy.

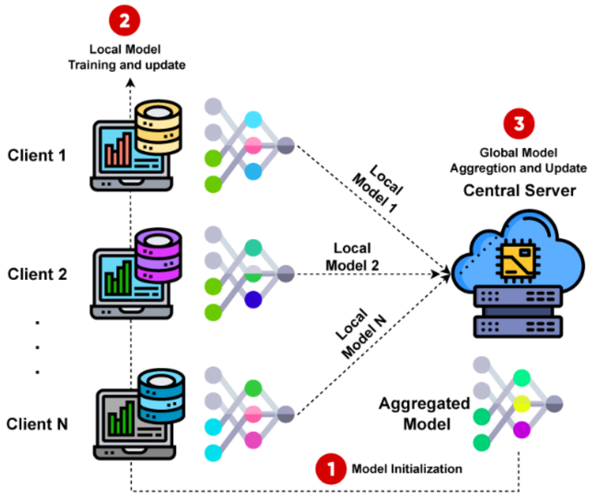


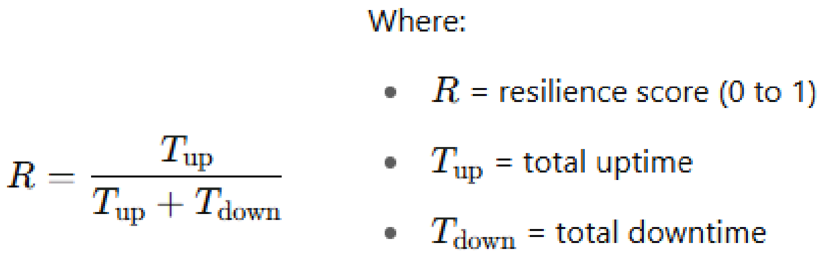
Fig 1: Cloud-Native MLOps for Fault-Tolerant Learning Systems.

2. Understanding AI Resilience

Despite AI systems being a major driver of emerging technology, uncertainties exist regarding the safety of human lives, data security, privacy, and the potential for weaponization. Addressing these concerns is mandatory before AI can be federally mandated to pursue high-risk applications. Towards fostering confidence in AI systems against expectation violations, an understanding of AI system resilience is necessary. There are still open questions regarding the barriers to, and enablers of, AI resilience in contrast to non-AI systems. Crucially, definitions of AI resilience need to be substituted for descriptions of AI resilience. Cloud-native MLops prevent many disparities in pre-deployment AI risk models, mostly concerning the generation and management of AI system records. However, it needs to be elaborated on how these auditors can address the entertainment scenarios of manipulation and distribution. There is still a need for the development of a concurrency model, which requires defining an industry standard label set and its application to pre-trained components. This offers good opportunities for future research in advancing the faithfulness and, as a result, resilience of AI systems. Lastly, answers are sought regarding the implied validation standards regarding the intended training speedup. Addressing these questions would advance implementations of current accuracy-focused measuring sticks for explaining AI model predictions in their interplay with margin-based security heuristics.

AI resilience analysis is focused on how well an AI system can tolerate expectation violations without unreliable expectations propagating to perceptions and actions. An AI system comprises its environment and adherent expectations. An environmental aspect is expected to contain regularity patterns that lead to a universally desired performance class. To fulfill such expectations, an AI system needs to perceive and act accordingly. To make this ambition realizable, the AI system must tolerate perception, choice, and action expectation violations, which are fundamentally at odds with the requirements for AI system deployment. Regardless of its most fatal states, the ability of AI system components to properly satisfy the involved properties is held by security, safety, accuracy, and fairness in Mlops processes. Reduced architectural complexity, e.g., by enabling an operator for component onboarding, might grant clearer parameter interpretations, as well as ease component replacement, auditing, and maintenance. Moreover, coherence compatibility regarding seasonality assumptions and hatched faithfulness might grant improved transparency across non-deployment AI systems.

Equ 1: System Resilience Metric.



$$R = \frac{T_{\text{up}}}{T_{\text{up}} + T_{\text{down}}}$$

Where:

- R = resilience score (0 to 1)
- T_{up} = total uptime
- T_{down} = total downtime

2.1. Definition of Resilience in AI

Resilient AI systems are capable of operating uninterruptedly and safely under uncertain and adverse conditions, including but not limited to data drift, adversarial attacks, hardware malfunctions, or human errors. These systems should be able to withstand disruptive events and changes in their operating environment, including both physical events and logical ones. Independently of these classifications, such events may be either anticipated or unanticipated, and causally intentional or unintentional. Autonomous systems need to be designed to resist a changing environment. Disruptive events can be generally classified according to a taxonomy of events ranging from fail-silent (in which the failure flags its occurrence by going mute) to fail-unsafe (in which the system becomes uncontrollable or harms the environment).

So-called socially responsible and accountable systems are among those that must be designed resiliently, particularly those involving human interaction such as information systems collocated with users where data from those users are processed. Such systems must address both security and safety concerns throughout their operational life cycle, i.e., during their use, maintenance, supervision, and retraining, as well as in the design phase. Indeed, adverse changes can occur after deployment, sometimes in an expected manner and sometimes in unforeseen ways.

A widely discussed case among AI systems in information and communication technology systems is deep neural networks. These systems have demonstrated state-of-the-art performance under a variety of circumstances, particularly in computer vision, natural language processing, and reinforcement learning applications. The black-box characteristic of these systems and their emergent behavior in the form of unmodelled action chains raises doubts about the robustness and resilience of these systems.

Given a statistical description of operational conditions, MLOps should be able to analyze performance concerning this description and degrade performance gracefully when the distributions are exposed to perturbations, shifting, or both. In particular, they should be able to provide uncertainty quantification of their outputs in the face of input uncertainty.

2.2. Importance of Fault Tolerance

Artificial Intelligence (AI) systems are becoming essential components of safety-critical and mission-critical applications. These systems provide continuous inference to drive the real-time decision-making task supporting various systems ranging from autonomous vehicles, spacecraft landers, and medical diagnosis systems in hospitals to video surveillance and fraud detection systems in finance. A failure in an AI system could compromise property, damage the environment, or injure, kill, or otherwise endanger human lives. Hence any deployed AI applications demand reliability. Modern AI systems comprise hardware and software components to provide a complete solution. A hardware component could be a chip, processor, or circuit, while a software component could be a model, algorithm, or code. Each of these components could encounter loss, accuracy, and errors and could degrade the reliability of the entire AI system. Fault Tolerance (FT) mechanisms are designed with data verification and an algorithm engineered to be resilient to faults. AI design for FT is unaddressed, mainly because traditional data verification techniques are ineffective for continuous data, commonly present in mission-critical AI applications. The fault detection capability of AI systems to identify hardware faults in other software components has been studied. However, post-hoc techniques add overhead latency and memory, and hardware implementation using multiple units cannot be guaranteed in embedded systems. Detecting errors in extreme conditions could require custom-tailored solutions. It is ideal to design AI systems with an inherent countenance to hardware faults and errors without degrading performance in normal conditions. This need inspired research efforts on AI models robust to inputs causing different types of machine failures. The FT consideration in training the neural network model robust to random hardware faults caused by stuck-at errors is an early effort. These constraints on errors during training aid models in detecting and tolerating drift faults. The desired pointwise behaviors with pre-determined exit conditions of a model in temporal differences enable the construction of partial controllers addressing the actuation.

3. Cloud-Native MLOps Overview

The Cloud-Native MLOps platform, built on the principles of cloud-native architecture, minimizes the human cost of overall AI tool development and maintains the consistency of data distributions through smooth and timely data pipeline refactoring and downstream system updates. Reprioritizing cloud operation problems in this way aligns with the business needs that AI solutions typically serve. The emphasis moves from the design of various AI models to the integration of viable AI models with existing cloud services, which must essentially maintain their performance running on fresh data. Containers, a prominent form of service virtualization, are natural candidates for lyophilization of both the data processing and model training systems, making it possible to benefit from the plethora of cloud-native toolboxes in these areas. The cloud-native approach opens doors to simpler and cheaper AI services, while product managers of cloud-native AI systems can turn their focus to data updates and model retraining, placing a greater emphasis on data workflow management mechanics. The development of these new mechanics benefits greatly from collaborative efforts with the cloud-native MLOps community. Starting from self-sufficient components to fully automated platforms, it is hoped that system-level designs will be presented to the academic community for a broader understanding of the overarching production workflow of cloud-native AI services.

The production machine learning (ML) system is a software and data engineering system that reliably involves massive numbers of features and manually exchanges many features and model versions. Featuring a multi-layer stack, the production system needs at least one upstream data service system that democratizes raw data via filtering, cleaning, and engineering, and one downstream storage service. The simple upstreaming of a new feature from a raw data lake to the corresponding production-rated data lake could easily lag in months, as the new feature needs to be manually labored and cooperatively coded in several systems. In an ML service, humans need to specify and optimize a suitable ML task that is agreed upon and to train a corresponding ML model that works well on this task with production data. Bringing a new ML model version to production involves considerable compliance testing of the associated workloads. Economic audits of input features and model versions during production need to avoid excessive resources for temporary suspensions and excessively delayed dwellings. These collectively show that cloud service systems are interpretative in nature and scale vastly through the combination of different components, such that static task specifications and monster-scale optimizations are deemed impractical.

3.1. What is MLOps?

MLOps stands for Machine Learning Operations, similar to DevOps as in Development Operations for continuous software engineering, this can be seen as a mindset on the highest level as well. It can be seen as a set of practices that combines ML with DevOps and Data Engineering. MLOps can also be seen as an engineering discipline as it involves toolchains, systems, and products for creative work. Like DevOps, the extent of the adoption and the comprehension as a set of practices and processes varies by organization.

MLOps is seen as a method on a high-level overview and also a discipline with tools on a low-level overview. Organizations adopting MLOps are hoping to deploy and maintain ML systems in production reliably and efficiently. A culture and processes need to be embraced that an organization must adapt to a specific application domain. MLOps emerged from the Big Tech Internet companies, and thus customization is necessary to fit smaller development organizations. To maintain a sustainable competitive advantage, an organization’s ML pipelines must embrace MLOps. MLOps is core to developing a continuous ML learning system that automatically learns and adapts to change. Otherwise, it would be easy to create a data landfill where it gets increasingly expensive to learn and adapt to data drift using classical methods. Similar to how there was a silicon jungle with many isolated and heterogeneous software systems, the challenge of achieving a competitive advantage with software today is how to develop a continuous engineering software system.

3.2. Benefits of Cloud-Native Approaches

The cloud-native way of doing data science is being widely adopted by leading technology organizations and cloud services providers. For companies that are heavy on data and AI workloads but have not yet adopted the cloud-native path, it is recommended to adopt a cloud-native MLOps stack approach for its many benefits. One is the convergence of the MLOps stack across different levels and components, with a publicly available 5-level cloud-native MLOps architecture and an expanding ecosystem of interoperable MLOps tools across the MLOps stack. Cloud-native approaches for model training and evaluation have now matured to be easy to use and can increase the productivity and efficiency of ML practitioners. Scalable and efficient cloud-native query engines can handle and invest in more and more sophisticated data preparation pipelines and ML models. New serving, monitoring, and retraining cloud-native tools have recently emerged that can make production ML systems more cloud-native and resilient through reliable and robust serving and A/B testing, reliable monitoring, and automatic retraining. JUnit and Gradle are recommended as the preferred tools to set up CI/CD workflows within an air-gapped environment, improve code quality, and fight idle repo decay on the tooling side. Gradle providing extensible build models and parallel execution can help with the growth of the code base and computation jobs to meet the explosive demands of the business. In addition, it provides convenience for developers on the DevOps side, allowing a focus on code over infrastructure. As many organizations take off with their cloud-native ML development and operations journey, they face the big challenge of recourse and budget constraints to buy a cloud-native MLOps stack. It is proposed to build a cloud-native MLOps stack with an open-source software and public cloud services combination, to help overcome this challenge and may assist with further endeavors of making them real cloud-native.

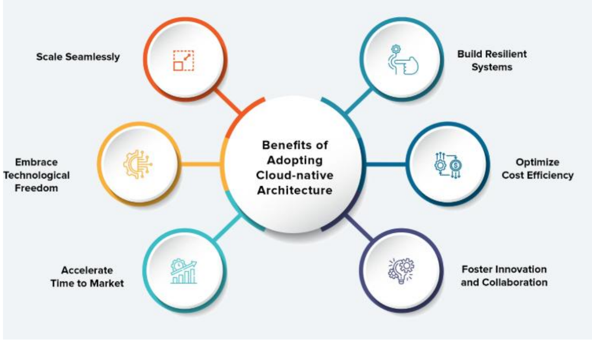

Scale Seamlessly
Build Resilient Systems
Embrace Technological Freedom
Benefits of Adopting Cloud-native Architecture
Optimize Cost Efficiency
Accelerate Time to Market
Foster Innovation and Collaboration

Fig 2: Benefits of Cloud-Native Approach.

4. Key Components of Fault-Tolerant Learning Systems

The cloud-native MLOps over multiple layers must be designed giving priority to fault tolerance, resiliency, and learning capacity. All the components and interfaces of the learning systems must be redesigned with specific capabilities. Handling faults in users' behavior and in underlying services is paramount for resilient MLOps systems. Mechanisms must be designed to gracefully react before anomalies impact ML services and models, maintaining availability, minimizing the impact of anomalies on ongoing computations, and strong guarantees on the convergence of learning optimization algorithms to guarantee long-term accuracy. At the Application layer, components are needed to reason on the JSON-like data format of users' logs and handle unanticipated user behaviors, and multiple users' behaviors. At the Runtime Layer, components that detect faults in the cloud-native functions and/or in other broken MLOps services are needed, as well as coordination components reacting to the detected faults.

The Knowledge IoT is critical to improving operators' knowledge of the learned system and of the users. However, anonymized logs may have privacy-sensitive information and well-designed mechanisms must be in place to enforce compliance with privacy regulations. At the Knowledge Layer, mechanisms to track the users' behavior over time and a knowledge base to retain all types of learned knowledge are needed, together with knowledge graph management. At the Application Layer, an anonymization engine must be designed to enforce compliance with privacy regulations and guarantee anonymity criteria on the anonymized users' logs. The components that retain the learned knowledge must provide APIs to access knowledge, perform queries and retrieve answers from the knowledge base.

Equ 2: **Mean Time Between Failures (MTBF)**

$$\mathrm{MTBF} = \frac{T_{\text{total}}}{N_{\text{failures}}}$$

Where:

- T_{total} = total time observed
- N_{failures} = number of system failures

4.1. Data Integrity Mechanisms

Ensuring data integrity and availability is paramount for reliable Machine Learning (ML) systems. As recent events have proven, even the most state-of-the-art models can fail dramatically due to unexpected changes in training or query data. In the MLOps pipeline, queries and responses may be diverted or distorted by clients or cloud architecture. Data integrity verification mechanisms can mitigate this risk. They ensure that data has not been altered after creation or when sent from one place to another. At least two techniques based on cryptographic primitives can achieve this goal: cryptographic hashes and digital signatures. These are generally effective for ensuring data integrity. However, they address somewhat different threats. On the one hand, a cryptographic hash of a dataset S allows any party to verify that the claim 'a dataset

S is the dataset I've received' holds. On the other hand, a digital signature ensures that entity A can prove to any other party, entity B, that a statement is true while still preventing A from proving it to anyone else.

Recommended best practices for applying data integrity checking mechanisms revolve around additional constraints and caveats, such as who may be expected to verify hash or signature computations; cross-verifying integrity checks in the application layer, cloud architecture, or another independent entity; and preparing for degradation in availability. Cryptographic hashes are also useful for maintaining the integrity and availability of training data datasets. All suppliers of datasets that are not sent to clients via a trusted source should hash the datasets before transmission and provide clients with the hash values. Clients would be able to detect accidental data corruption, data exchange for malicious purposes, or inadvertent errors due to the Model or MLOps infrastructure updates. This would be especially important with public datasets and datasets acquired from public cloud data storage services through multiple filtering or processing steps.

4.2. Model Robustness Techniques

Studies in the adversarial machine learning research area fall within a diversity of domains, from natural language processing to image data analysis. Among them, computer vision is where the greatest number of works are located, as computer vision makes a research area where the input of the systems that use ML approaches is prone to multiple attacks like no other sensor employed in ML systems. A recent survey on machine learning robustness summarises the greatest part of the state-of-the-art literature concerning adversarial attacks and MI robustness metrics across diverse domains of ML. The taxonomy of adversarial attacks presented goes beyond the ones strictly focused on data perturbations and comprehends for example attackers directly inducing faults in the learning systems operation. Three broad categories of attacks and algorithms are pointed out and discussed next. The proposed taxonomy aims to encompass all the attack mechanisms and robustness metrics present in the wide range of literature dealing with adversarial ML across different subdomains. A restricted survey regarding the computer vision domain then follows summarizing only the most well-known attacks against CNNs and the main evaluated metrics in these works. Finally, it covers the worst-case analysis branch detailing the main formulations for defending against input space perturbations, the most powerful adversaries proposed, and the most performant algorithms for this branch as well.

4.3. Monitoring and Alerting Systems

Real-time monitoring and alerting are critical to maintaining the performance and availability of complex ML systems, such as recommendation engines and fraud detection systems. In the cloud-native MLOps paradigm, ML systems are distributed across several cloud resources and teams. Each cloud resource and team has its own monitoring and alerting requirements, insights, and tooling. In MLOps, this leads to fragmented monitoring and alerting implementations. Cloud-native MLOps provides better observability and out-of-the-box monitoring solutions for cloud resources like databases, hosting platforms, interactive notebooks, and event queues. These observation tools can be extended to capture observability signals for MLOps. However, ML system observability remains complicated due to the need to monitor the ML lifecycle, including data (and model) performance, consistency, drift, and the multifaceted health of the entire ML system. Organizations often extensively monitor, collect observability signals from, and alert on cloud resources, but often lack sufficient coverage of observability signals for the ML-specific components of the ML system. Because cloud-native MLOps adds several observability seams to a cloud-native architecture, it requires maintaining a balance between service-level observability and signal overload. To address these challenges while leveraging existing observability infrastructure from MLOps, several points should be considered. The first is to establish a baseline for monitoring situational awareness by collecting standard signals throughout the data pipeline to monitor for common things that can go wrong. In MLOps, that includes missing data warehouse jobs, data drift, and outlier spikes for prediction inputs. The second point is to collect appropriate analysis signals that are actionable and understandable. This reduces alert fatigue and improves efficiency while considering what analyses to perform to alert teams when unusual patterns are detected instead of manually annotating normal ones. The third point is to consider visually mapping observability signals by enabling 3D visual compliance on partially automated pathways.

5. Frameworks and Tools for Cloud-Native MLOps

Machine learning (ML) enables data-driven prediction and is currently used in various applications, including computer vision, fraud detection, and recommendation systems. New cloud-native tools are being developed continuously at an unprecedented pace to run ML workloads at a lower cost and faster, resulting in vast open-source libraries readily available to productionize ML pipelines. In addition, cloud-native architectures result in fault-tolerant systems that operate with high availability and can scale both cheaply and fast.

SAS Viya implements a new architecture with the new open-source cloud-native SAS Cloud Analytics Services, as well as allowing the deployment of its microservices on Kubernetes. Streaming data science capabilities can be orchestrated on a variety of cloud platforms using respect infrastructure services. However, users still need a simplified way for both data scientists and engineers to productionize ML in CI-CD pipelines on cloud-native environments. Cubeflow, MLFlow, ArgoCD, and various other automated frameworks greatly simplify the management of ML projects in Kubernetes environments. PyCaret is another open-source IDE for data scientists to quickly prototype and productionize ML pipelines. The initial focus was to deploy singular models using REST APIs, and currently, there is an ongoing effort to abstract the packaging of multi-models of sci-kit-learn compatible models as APIs or for batch scoring. Cloud-based services provide zero infrastructure overheads for managing the deployments, although increased prices may hinder their use for production model deployment, especially for batch scoring.

A recent study proposes K8s deploy_sequence to compile the deployment strategy in K8s YAML, which can be configured to deploy workloads with multiple components and inter-component config on cloud-supported k8s clusters. While this is another way to solve the gap, there is a lack of tools enabling data scientists to productionize ML pipelines chain-of-production on cloud-native solutions. Existing solutions in data management, model store, and deployment frameworks can be integrated but would require heavy custom development anyway, eliminating the “oops” promise of cloud-native architectures.

5.1. Containerization Technologies

Container technology has seen a recent explosion in interest from academia and industry. Containerization functions as a lightweight virtualization technology for applications, providing high environmental consistency, operating system distribution portability, and resource isolation. In the cloud-native era, it is expected to replace or supplement traditional virtualization technologies in many areas. In the past few years, containerization has been extensively adopted as the foundational technology of big data-generating systems. Latest experiments show that container-based architectures on big data systems help improve performance and resource efficiency and ease maintenance costs, confirming that containerization is an effective solution for the infrastructure optimization of big data-generating systems. Existing mainstream cloud service providers have previously adopted container technologies in their distributed system infrastructures for automated application management. Container orchestration is proposed as one of the essential research problems facing container technologies.

Container orchestration is the automatic management of containerized applications across the life cycle of deployment, operation, and termination. It covers a wide range of application management tasks, such as resource provisioning, scaling, scheduled execution, health monitoring, fault recovery, and many others. Multi-dimensional optimization objectives, including cost, utilization, performance, and quality of service (QoS), need to be considered due to highly heterogeneous clusters. Generally, existing implementations of these container orchestration frameworks consist of two functional modules: a set of algorithms for different application management tasks and a control plane for coordinating concerned components. The orchestration task is generally formulated as an optimization problem. Existing works with a focus on container orchestration mainly concentrate on either the algorithms for service-level objectives or the platform assumptions and control planes of orchestration frameworks. The consideration domains of others are either narrow to a specific orchestration task or platform, such as scheduling, fault tolerance, or latency on Spark streaming-based cloud applications.

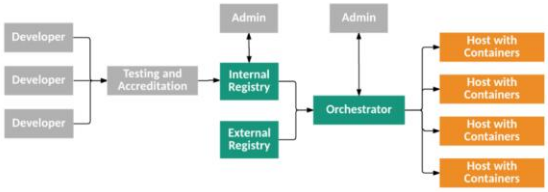


Fig 3: Containerization Technologies.

5.2. Orchestration Tools

A critical component of MLOps systems is orchestration management via tools such as Airflow or Kube Flow Pipelines. With these tools, multi-component pipelines can be developed that specify the sequence of dependencies between components and manage the location, execution, and retrying of tasks if necessary. These tools assist with a range of workflow management tasks such as branching, forking, conditional execution, and hiding complex sub-pipelines inside operators. By leveraging these capabilities, robust pipelines can be engineered that automatically rerun components depending on upstream failure, conditions, or alerts. Furthermore, with integrated observability, messaging,,g and remote execution, orchestration tools can be triggered based on alerts in the MLOps system.

The goal of reproducibility in ML is exacerbated by constantly changing data that can shift its distribution over time, which can cause trained models to be compromised. Conventional observability tools focus on important performance metrics e.g. throughput, latency, success vs failure rate, etc. Though they are invaluable in providing performance information, continuous "metric only" observability is not enough when aligning models with a changing environment after deployment. Hence new observability parameters that evaluate the health of the models, data, and features are indispensable in MLOps tools.

As the volume of data increases exponentially, an essential function of MLOps systems is data capture and organization for its continuous ingestion into the training pipeline. The majority of MLOps systems adoption bestows high priority to data preparation and pipeline orchestration, though considerable time and resources are required to build bespoke data version control systems that coordinate complex input data. Lightweight solutions that offer free trials, low maintenance options or open-source alternatives are desired tools to facilitate easy data harmonization and ingestion into the MLOps system.

5.3. CI/CD Pipelines for ML To use Machine Learning as a Service (MLaaS), machine learning is being increasingly integrated with cloud computing and cloud-native platforms. Consequently, there is a greater emphasis on using Microservices architecture and containerization of services for AI solutions that are prone to fault during execution, training, or inference of models. Using Artificial Intelligence as a Service (AIaaS) is, furthermore, gaining traction to provide end-users (applications) with pre-trained models as a cloud service. The cloud-native approach for AI has escalated the research in Multi-CI/Multi-Cloud architecture in addition to various deployment platforms. With the advancement of Big Data and Cloud Technologies, it is imperative to have a cloud-agnostic architecture for AI solutions. CI/CD pipelines for MLOps are gaining popularity and it is fundamental for a successful AIaaS implementation. Understanding MLOps solutions to leverage CI/CD pipelines to deploy AI components is fundamental to the resilience of the learning systems.

The need for CI/CD pipelines for Machine Learning (ML) projects is increasingly being recognized by organizations utilizing ML for their business models. Commencing from training models to deploying them in production environments, large amounts of data and experimentation steps are involved in ML projects. Changes to data, preprocessing code, models, or their parameters alter the behavior of ML applications. In addition to managing the code aspect of ML-related applications, Machine Learning (ML) CI/CD pipelines comprise additional steps specific to the nature of ML applications in terms of training models, conducting experiments, and retraining models. Although some studies propose generic production ML system pipelines, there is a lack of understanding of the CI/CD pipelines for ML projects and how they differ from traditional software.

This paper presents the first empirical study on the CI/CD pipeline evolution in ML projects. The intention is to enhance understanding of how CI/CD pipelines for ML projects differ from those designed for traditional software and gain insights into CI/CD pipeline development for CI/CD in ML projects. Besides estimator configuration change, the data ingestion step is the most frequently modified in the demonstrated CI/CD pipelines concerning code, ML, and data aspect changes. There is a moderate churn of pipeline steps in ML code repositories maintaining both the CI/CD pipeline and ML model. It is likely that hybrid ML systems also employ CI/CD pipelines in their ML-related components but not at the system level.

6. Designing Resilient AI Architectures

Resilient AI Systems should encapsulate the core principle of verification prior to trust in the domain of resilience benchmarking. A classification of the targets for resilience benchmarking across the entire ML lifecycle (consisting of steps of preprocessing, learning, and reasoning) as well as its necessary principles to minimize misinterpretation and maximize reproducibility are introduced. Before discussing targets and principles, the two notions of resilience and trust in the context of AI systems as well as an introduction to ML and its common vulnerabilities are provided to ensure that the reader has all the contextual knowledge necessary to comprehend the notion of resilience.

By the increasing abundance of data and improvements in processing power and algorithms, ML in the context of AI systems has become proficient at a variety of high-stakes tasks – ranging from diagnostic processes in medicine to self-driving cars – within a short timeframe. However, despite having become commonplace, it has to be considered that AI systems have entered the public discourse due to cases of unexpected behavior; correlative misdiagnoses, discriminatory hiring procedures, and self-driving cars having been filmed failing on roundabouts are only some of the cases, which have sparked public outrage and raised concern vis-à-vis their use in high-stakes settings.

At the same time, the resilience of AI systems against malicious interference is also coming under scrutiny. Forms of attacks against AI systems and their ML models are emerging and becoming mainstream press coverage, which points to their vulnerability to tampering. It is obvious considering the wealth of task-critical data that organizations operate and the power of insights AI systems extract, that brands become beholden to protecting their AI systems for the same reasons banks secure their vaults against heists.

6.1. Microservices in AI

Microservices have become a widely adopted pattern in software engineering for developing robust and scalable applications. A software system implemented following the microservices architectural style is composed of loosely coupled services communicating through a description with simple interfaces. Microservice architecture allows software systems to be decomposed into manageable, self-contained components. Services can be started, stopped, deployed, and modified independently from one another. The independence allows for change detection, adaptability, and extensibility. Services can be modified and opted in for deployment with no downtime. New services can be added without investing significant effort. Additionally, resource isolation can reduce the attack surface area for security threats.

The cloud computing paradigm allows computing resources to be provisioned and consumed on a pay-per-use basis over the Internet. In this model, computing resources are controlled and provisioned by a cloud vendor rather than the application provider and service revenue. These resources can be assigned and resume automatic elasticity. This infrastructure leads to a strict separation of concerns between the service provider and the end user of the services. The cloud computing system provides an API for configuring and accessing available resources. Cloud vendors typically only offer virtual machines, storage, and network connectivity.

Equ 3: Fault Recovery Time.

$$T_{\text{recovery}} = T_{\text{detection}} + T_{\text{mitigation}} + T_{\text{restoration}}$$

Where:

- T_{recovery} = total time to recover from a fault
- $T_{\text{detection}}$ = time to detect the issue
- $T_{\text{mitigation}}$ = time to stop damage
- $T_{\text{restoration}}$ = time to restore service

6.2. Serverless Computing for Scalability

The traditional cloud computing services require users to rent the resources inadequately for a specified duration, which might lead to esoteric cloud bills. As serverless computing emerged, the dev/ops aspect of resource management was completely removed from the users' side. Instead of pre-booking numerous resources, serverless computing dynamically allocates resources based on invocation requests. To achieve that, the resources are created on-demand to accommodate function requests. Moreover, warm resources can be reused to handle new requests. Serverless computing charges users only when the functions run, and they pay the price based on the resources allocated per millisecond. As a result, serverless computing seems to be an ideal choice for cost-effective allocation solutions. Introduced by cloud providers, serverless computing significantly simplifies the deployment process.

Resilient AI systems with cloud-native MLOps allow data scientists to focus on model orchestration pipelines by abstracting away the complexities of infrastructure management—e.g., orchestrating an ecosystem composed of ML operations and clouds, IP address management, or resource configuration—and fault-tolerance management—e.g., ensuring each ML operation completes successfully, either by resiliency or domain-relevant constraints. Such abstraction, guarantees, and optimizations on auto-scaling/resiliency of cloud-native ML Ops tools can be achieved using the capabilities offered by serverless computing. A case study of model serving is explored but merely addresses the deployment process of ML services on serverless platforms. They deployed ML models on platforms but did not leverage serverless computing for orchestration/resiliency/fault tolerance on a macro level.

A cloud-function-based multi-tenant serverless computing paradigm can perform concurrently running ML data engineering pipelines with sharing function container images while enhancing cost-efficiency. Policies are proposed to evaluate and control the scaling of ML pipelines executed on serverless functions. A framework that applies Deep Reinforcement Learning to weather the unpredictable cold-start delays in the auto-scaling of serverless applications is developed. Further wisdom is anticipated to be proposed to reach resilient resource configuration of cloud bottoms and estimate AD hoc delays of running cloud ML pipeline workloads.

7. Challenges in Implementing Resilient AI Systems

Making AI systems resilient to all attack types is a very difficult task because of the diversity and complexity of these systems. Often, by introducing extra components to the system to mitigate against a new attack type, some other attack surface is opened or the system is made more complex, making it a target for new vulnerabilities. Thus, it may be of more value to explore the possibility of resilience to, e.g., evasion attacks without the goal of generating components that could mitigate against knowledge-based attacks.

The detection of attacks is currently often approached by analyzing the data streams through either AI or hand-crafted filter methods. By detecting misuse, it must be ensured that known patterns of attacks are captured, which are usually on the same level of abstraction as the detection component itself. Hence, mere misuses can readily be accessed with behavioral or uncertainty-based models. New attacks will render the detection ineffective. The detection algorithms must be able to categorize behavior as anomalous (when compared to the training data), i.e., they must not narrow down the problem spectrum to detect misuses. Examples include the use of deep autoencoders or isolation forests for remote model attacks or Trojan attacks. The architecture of the models must therefore be chosen wisely.

Deliberate efforts to create approaches that can build a system handling zero-day attacks with which there are currently no active defenses are minimal. Even some generic measurement or rule systems vulnerable to basic low-level attacks are still function-wide. Generally, the creation of common benchmarks against which various architectures can be analyzed is missing. Similar measurements that can provide curricula for benchmarking evaluations lacking detail or analysis of the effect of different model architectures on defenses are missing.

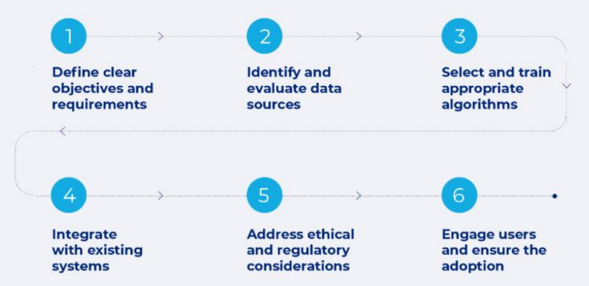

1
Define clear objectives and requirements
2
Identify and evaluate data sources
3
Select and train appropriate algorithms
4
Integrate with existing systems
5
Address ethical and regulatory considerations
6
Engage users and ensure the adoption

Fig 4: Challenges in Implementing Resilient AI Systems.

7.1. Data Management Issues

Machine learning is making inroads into all domains, including finance, marketing, and manufacturing, among others. In many of these domains, forecasting is an important task since forecasting models can be a guide for pricing strategies, sales targets, inventory management, and marketing campaigns. A productive field of research has emerged around the problem of forecasting time series generated by machine learning systems. Projects are now transitioning from development to production across industries. This transition is a key milestone in the adoption of machine learning in industrial settings. Many ML teams have thorough procedures for development and are familiar with the associated libraries and data structures. In contrast, there is a lack of supply of reliable and adaptable machine learning systems in marketing, finance, and manufacturing domains. Many teams struggle to keep predictive performance consistent in production.

Forecasting is a common task in complex executive decision-making. Reliable models support marketing campaigns, pricing strategies, inventory management, sales targets, and limit-setting in banking. For many of these tasks, both machine learning and time series modeling are required. Projects are transitioning into production across many industries, and when forecasting problems are solved in ML teams, the patents are often to keep the predictive performance consistent after the prototype is put into production. The aim of these forecasting systems is adaptive noise and topic detection, reliable anomaly detection, and resilience to data relocation. Each component of the pipeline contributes to achieving a reliable and interpretable forecast series.

Reliability of production systems and machines, in general, is rarely the focus of sciences, even though resilience in all parts of life is needed to endure the exponentially growing complexity of change. Current technologies are empowering the production of forecasting systems, but there are no frameworks, toolboxes, or design patterns to make these systems resilient. This talk aims to define the resilience of ML systems, derive sub-issues from this definition, provide practice-oriented solutions, and conclude with future work. This work is done across all available forecasting problems in the group. Initial results exist for each of the sub-issues, and implementations are progressing in different pipelines.

7.2. Latency and Performance Trade-offs

Deployment latency and prediction performance have a tight trade-off relationship in a fault-tolerant learning system. Generally, a model with a more complex architecture can capture more complex situations for better prediction performance, but it tends to be slower in online predictive tasks. On the contrary, a lighter model is preferred in terms of prediction latency, but prediction performance may degrade at large fault rates. The challenge is to find a suitable architecture for the requirements in varying scenarios. Expanding and narrowing a model of the Ensemble model family can greatly boost performance at the cost of latency with the drawback of needing careful architecture design upfront. Moreover, black-box neural networks require well-trained candidate models with a non-convex search space being rendered intractable. To make the variant architecture searching process easy even when using them as black-box prediction providers, the candidate structure should be differentiated. Uncertainty-aware sampling and architecture-guided search strategies can augment the data exploration here.

In the neighborhood of the current model, the candidate structure is perturbed to generate the searched architectures iteratively. To trade between the prediction performance and the deployment latency, Pareto optimal search (POS) is adapted to converge different versions toward increased performance or reduced latency in different scenarios. Such a search strategy provides users with a diverse set of multiple models, and the feasible one according to the given requirements can be selected. To validate the fault-tolerant potential of the model, a simulator prioritizing prediction performance, faster inference latency, and fault scenarios can generate a large amount of input data offline. The trained model is used to infer this data and detect fault cases. The metric for tolerance loss is to measure the fault interval or the amount of failed tasks to assess tolerance efficiency. This performance P-system is integrated into the cloud environment for online testing.

7.3. Cost Implications

Recent trends in Cloud-native AI Services reveal that several initiatives and ecosystems have been developed that provide Cloud-native MLOps solutions. For example, TFX is an end-to-end production ML orchestration platform that provides a deployment option on Cloud services. However, these solutions are often domain-specific, not designed for production scale, and lack generalizability. Consequently, an extreme shortage of assessing and improving the resilience of such services with Cloud-native MLOps against various fault scenarios exists. Most known methods and metrics for fault-tolerance design primarily focus on fault tolerance in a monolithic manner. Recently, a Cloud-native MLOps solution that helps build scalable end-to-end ML pipelines has been presented. Still, no research leverages such Cloud-native MLOps-based services in evaluating or improving the resilience of MLE systems. Furthermore, while there exists a growing interest in Cloud-native solutions and MLE, most researchers and practitioners in this domain are still unfamiliar with Cloud-native landscapes. A method based on advanced Cloud-native MLOP computing and orchestration that can be widely adopted in developing a resilient MLE solution is suggested.

In terms of future work, the ecosystem of MLOps services will be introduced to an increased degree. A task-based multi-granular PaaS service will enable better resource allocation and more extensive automation to be developed end-to-end. In addition, the aim is to enhance the resilience framework and the resilience of other components in the Cloud-native MLOps ecosystem such as resource management, data management services, and injectors.

8. Case Studies of Resilient AI Implementations

To illustrate how cloud-native MLOps can enable the incorporation of resilience techniques into AI systems, this section provides real-world case studies of implementations of cloud-native MLOps for resilient AI. System operators generally use resilience techniques for personal reasons, such as avoiding damage or improving profitability. However, certain application scenarios challenge the typical motives for resilience, demonstrating that resilience is not always a computationally justifiable characteristic. The presentation draws on lessons learned from operator decision-making in edge AI systems and discusses the cases of the system operators that have enabled complex fault-tolerance techniques and made resilience a competitive advantage.

Case 1: DeepFT. The emergence of latency-critical AI applications, in domains such as financial trading, e-commerce, and security, has been supported by the evolution of the edge computing paradigm. Edge systems typically consist of distributed and heterogeneous resources, which are located on the premise of data generators. This can help reduce bandwidth and performance constraints, and improve data privacy. Deployment of these systems is traditionally done using operator-controlled and dedicated resources. However, operators rent resources from cloud providers who maintain control over the physical infrastructure during deployment and execution. This unfortunate remixing of IT levels has rendered edge solutions resource-constrained environments, with heightened contention for both computer and communication capacities. Several software companies operate proprietary edge solutions with several thousands of customers. These solutions typically consist of analytics pipelines, which are composed of modern AI models and less expressive ML techniques.

It became clear that beyond application reliability, another key factor to consider in source data analysis systems is the reliability of the pipeline itself. Pipeline reliability can be enhanced through the incorporation of fault-tolerance techniques, resulting in fault-tolerant Analytics as a Service system. While state-of-the-art have blended unsupervised fault-tolerance models into their analytics pipelines, these failure models can incur a loss of accuracy when the provisioning algorithm needs to adapt across volatile, nonstationary workloads. In response to these challenges, a novel modeling approach called DeepFT is proposed, which proactively avoids system overloads, and hence potential SLA violations, by optimizing task scheduling and migration decisions for latency-critical workloads. The upstream component of DeepFT is a state-of-the-art deep surrogate model that predicts and diagnoses faults in a scalable fashion. The downstream component is an original reinforcement learning framework, which is trained to discover optimal scheduling and migration actions using a self-supervised criterion. Extensive experimentation shows that DeepFT can outperform specialized strategies in fault-detection and QoS metrics for the recommended runtime period, reducing service deadline violations and improving response time.

8.1. Industry Applications

Two industry applications of cloud-native MLOps that demonstrate rich R&D investments across industries are discussed in the following sections. The aim is to give the reader concrete directions for further investigation into companies already deployed these cloud-native MLOps techniques with concrete case studies. Although the two application areas are mainly cloud-native MLOps-based fault-tolerant learning systems, they are completely different in terms of the nature of models and a market perspective. The first application, DeepFT, is a simulation-supported fault-tolerant learning system based on a self-supervised deep AI surrogate model. This edge AI-fog model is a predictive model of a complex container-based production system with service-level agreements. Automatic hypothesis generation (future-forward dropout-based fault detection) and reasoning (fault diagnoses) support the self-supervised state learning of the deep AI model during a parallel simulation. Highly efficient and informative parallel fault-tolerant heuristics are accessed against decisions made on alarm variables detected by the AI surrogate model. The second application area is a cloud-based AI service for detecting phishing pages, aiming at keeping information systems and services secure across the banks, telecom, e-commerce, and many other sectors of the world. Large-volume AI models are developed and trained by increasing the computer and human resources intensively during the learning lifecycle. These models have to be continuously fine-tuned with novel real-time data and at a threat-shaped pace while ensuring high performance within time limits (inherent fault tolerance). A comprehensive cloud-native MLOps ecosystem is elaborated upon, based on Kubernetes and the cloud compliance architecture of a company of design thinking, assuring the success of AI in business.

Two advanced industry applications of cloud-native MLOps—DeepFT for predictive fault-tolerant production modeling and a cloud-based AI service for phishing detection—highlight the depth of R&D driving innovation across domains. These cases illustrate how self-supervised learning and scalable, real-time AI systems are being operationalized through robust MLOps pipelines to meet both industrial reliability and cybersecurity demands.

Containers
Cloud native security
Microservices Architecture
Serverless Computing

Fig 5: Cloud-native Application.

8.2. Lessons Learned from Failures

In this section, the lessons learned will be presented from the failures encountered throughout the development of the proposed architecture and four use cases. This knowledge can help and motivate others to explore the research area, addressing the need for robust AI solutions. While failures are usually discouraged within the research community, the key issues that failed to be addressed during the research are provided below.

Firstly, it is necessary to understand that there are two main types of systems: closed systems and open systems. In contrast to the former, the latter are often subjected to exogenous conditions that cannot be controlled. Because of that, in an open system, it is important to consider all possible conditions before deploying any intelligent system. Before deploying a cloud-based MLOps pipeline to production, one must also consider the worst-case scenarios. For instance, if a model needs to be retrained daily and current training and inference data are to be collected in parallel within the same infrastructure, it is necessary to design a system that can deal with double loads. In a trading system, for example, it would be a waste to deploy an evaluation model as soon as it is trained. As the use of cloud services keeps expanding and novel techniques keep emerging in the business world, the infrastructure must also be designed to be future-proof.

Secondly, even if the best technology stack was chosen and cloud services were properly implemented for parameter optimization, there is still one crucial issue that is often neglected: the availability of the data. No matter how fast computers can process data, or how clever models can be built, if there is no data available, nothing can be achieved. In a real-world application, data always has its lifecycle and considerations. Over time, collecting new data can shift a subset of the time series to infrastructure changes. This section provides an overview of lessons learned through failures encountered when building the MLOps use cases of original architecture designs that can be reused and must be considered in future implementations of the architecture or designing an MLOps solution from scratch.

9. Conclusion

The study presented shows that while modern MLOps offers a technically sound and comprehensive approach for production-grade data and model management for AI applications, addressing the resilience and reliability of the cloud-native architectures and large-scale AI workflows is still in its infancy. Existing solutions target robustness at one layer only, whereas the proposed stepped adaptation should be employed together with cloud-native technologies for auto-discovery, monitoring, scaling, deployment, and recovery actions across all layers to create adaptable learning systems built on robust ML components. By leveraging an international network of expertise and experimentation, the concepts are being embedded into a fully fledged solution framework.

The resulting platform is expected to enhance the resilience of AI and MLOps, which is crucial for a future where AI is continuously learned and deployed to many data sources that can be faulty, malicious, or handle invalid and untrusted data. The presentation has raised awareness about the limitations of existing solutions in building fault-tolerant AI systems and the necessity of viewing these systems as reliable flows of data and models that must be provisioned, discovered, monitored, governed, and executed in a fully automated way across cloud resources. Current technology, workflows, and ongoing research efforts were presented to equip the scientific community and practitioners with an understanding of how to deploy, monitor, and govern a full-scale solution.

By joining forces, academia, and industry can build resilient data-driven decision-making systems and stabilize the reliability of AI throughout its lifecycle, including data collection, model updating, and inference time decision-making. The data-driven demand for high-importance ML is fuelling investment into AI applications, but further efforts are urgently needed to build trustworthy and reliable AI systems. External stakeholders need guarantees of robustness and resilience before incorporating machine-learning algorithms and AI technologies into business-critical settings. New data-driven learning and inference workflows raise fundamental questions about monitoring, identification of data drifts, component updates, and recovery actions across several existing cloud-native and MLOps solutions and how they can be used and adapted to ensure the resilience of complex ML systems.

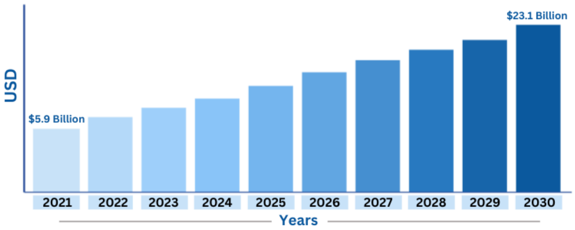


Fig 6: Application Cloud-Native MLOps for Fault-Tolerant Learning Systems.

9.1. Future Trends

The convergence of two megatrends—AI and cloud computing—has active implications for academia and industry, especially concerning reliability and resilience. The premise of AI involves modeling the input data distribution to produce predictions, improving when exposed to sufficiently diverse data. However, this principle hinges on design-time assumptions, while deployment-time distributional shifts and incidents can impair model performance. Cloud computing serves as an alternative design-time assumption, wherein AI models are offloaded and hosted in high-resource environments, acceding to high reliability and availability. However, instances of cloud incidents and exceptional workloads can impair the very assumptions underpinning reliability. The advent of these cloud edge systems necessitates a new conception of AI reliability that handles both distributional shifts in data systems and resource overloads in computing systems.

The dearth of resilient system models precludes a first-wave study of learning-system resilience. This approach draws upon granular AI observability and advanced prediction modeling from the software engineering and machine learning intersection, probabilistic graph models for AI uncertainty and interpretability from AI transparency, and cloud-native observability and congestion modeling from the distributed computing and cloud systems intersection. The lines of attack include data observability at individual input features and prediction outcomes, conducting unsupervised clustering to surface the semantic structure of learning-system fog, and congestion observability of individual workloads and compute resources, conducting interpretability-aware time series smoothing to surface hyperparameters underpinning resource contention.

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