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AI-Augmented Cloud Monitoring Platforms for Predictive Infrastructure Reliability

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ABSTRACT: Given the growing reliance of individuals and organizations on cloud computing services, prediction of failures and assurance of the reliability of these services have become paramount to minimizing associated costs. The observability provided by the telemetry of such services offers data-driven signals for the prediction of failures, as well as indicators of timing and policies for optimal, efficient, cost-effective operation. Experimental services have demonstrated the viability of applying state-of-the-art artificial intelligence techniques—anomaly detection, forecasting, root cause analysis, and recommendation systems—to the telemetry data of cloud service providers in novel ways. These services are ready for deployment, helping enterprises monitor their services, detect anomalies, and predict their future activity, among other needs. Nevertheless, success depends on a careful balance between the quality and the quantity of the telemetry data consumed.

Despite significant resources devoted to the telemetry of cloud services, privacy-preserving monitoring remains a challenge. Failure prevention relies on tailored indicators of each service's failure modes and time-to-failure windows, as well as a hypothetical cost-benefit analysis. Even with sufficient percentages, the predictive models of these signals require careful definition, evaluation, and monitoring. Dynamic sizing of resources and autoscaling policies can help minimize costs while guaranteeing quality of service, particularly when intertwined with the resource allocation policies of the cloud provider. A service can improve its overall stability and performance by controlling its own scaling policies.

KEYWORDS: Observability; telemetry; anomaly detection; forecasting; monitoring-as-a-service; predictive maintenance; dynamic autoscaling; AI; cloud reliability; cloud operations; root-cause analysis; causal inference; SRE; observability maturity; software reliability engineering; SLAs; MTTR; prediction horizon; time-to-repair; data quality; data-completeness; data-privacy; monitoring drift; adversarial machine-learning.

I. INTRODUCTION

Cloud computing is rapidly changing the way software engineers use computing resources. In the early days of cloud computing, public cloud started changing on-premise data centers into fully managed services. Digital-native companies, in particular, took advantage of public cloud computing and operated the services in a completely different manner than those of the legacy companies: they were writing services using microservices architecture, combination of many services with API, highly decoupled, agile development process, harnessing continuous integration/continuous delivery (CI/CD), utilizing infrastructure as a code, and so on. As a natural consequence, a large number of digital-native companies moved to the public cloud and started to rely on a cloud service provider (CSP) to run their applications.

Over time, the public cloud space became highly competitive, and various new features and services were released. Virtual machine (VM)-based cloud services are now highly automated, allowing users to consume them quickly without going through any multitier JDBC connection with the Backend team. But how do users track the new features that a CSP is adding? It is normal for users to complain now and then that the CSP is taking such a long time to resolve a bug, but how do users know the exact duration? These answers, and many more aspects of a cloud service, are not available explicitly, but the data can be extracted using telemetry from the service. Observability focuses on managing the signals emitted by the service to provide answers to such questions.

1.1. Background and Significance

Observability is a fundamental requirement for modern distributed systems, providing visibility into their behavior and performance. Cloud providers as well as endeavours of cloud consumption offer extensive instrumentation and telemetry capabilities across their services, enabling detection of service and application-level regressions. The increasing reliance on cloud services and adoption of the site reliability engineering (SRE) methodology has put infrastructure reliability and

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availability in the spotlight, supported by concepts such as Service Level Objectives. Despite these capabilities and frameworks, outage incidents affecting cloud services continue to make headlines regularly. Just last year, a series of incidents at one of the leading cloud providers affected tens of thousands of customers and caused millions in downtime economic losses.

Observability requires systematic consideration and investment to protect a company's reputation, business model viability, and customer retention. Consequently, cloud service-level objectives and error budgets have been extended to internal service dependencies in cloud usage. Beyond a post-mortem synthesis of incidents, availability risk must be proactively managed to ensure its alignment with the business risk profile. This perspective entails understanding single points of failure, failure modes of key services, and interdependencies, for the design and implementation of preventive measures. Mapping key services to these principles enables identification of infrastructure providers that are good candidates for sensitive workloads and those that can be consumed with reduced concern for availability. Financial return on investment must be considered as well, weighted against monitoring deployment and operational overheads.

Fig 1: AI for predictive maintenance

1.2. Research design

Research design follows the clinical trial model established by pharmaceutical companies to establish the safety and efficacy of drugs. Starting from the premise that cloud infrastructure is already instrumented for observability, monitoring, and telemetry, a two-thirds line chart aligned with control limits compares real-world observations with supervised time-series forecasts. Depending on the level of supervision when building AI models, this chart indicates when to take action. For unsupervised AI anomaly detection models, the chart concisely summarizes the true-positive and false-positive rates, along with lead time for operational response, expressed as the summary receiver operating characteristic area. The catalogue of predicted features lists their business value, along with cost-benefit estimates and high-level estimation of effort and risk for implementation. Dynamic-sizing and auto-scaling policies are presented in runnable form, and the presence of supervisory or ancillary control surface features completes the monitoring picture.

Data completeness and quality determine how useful these predictions will be. Models will fail if poorly constructed, without sufficient high-quality training data, or if the underlying process has drifted since training. The business

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understands these limitations, and ensures sufficient model-monitoring and retraining cadence is built into the process. Existing security models should also be relied on, with concerns about adversarial models being tackled through regular adversarial-testing exercises like those used in pen testing.

Equation 1: Availability from downtime
Let, over a time window T(e.g., 30 days):

- Total time: T
- Total downtime: D
- Total uptime: $U = T - D$

Availability is the fraction of time the service is "good":

$$A = \frac{U}{T}$$

Step-by-step
1. Uptime is what remains after downtime: $U = T - D$
2. Fraction of time up is uptime divided by total: $A = U/T$
3. Substitute: $A = (T - D)/T = 1 - D/T$

So:

$$A = 1 - \frac{D}{T}$$

II. FOUNDATIONS OF CLOUD MONITORING

As cloud-native applications evolve, the security, reliability, maintainability, and performance of external cloud services become factors for which the owners of those services are responsible. Monitoring service health is key to ensuring service reliability over time—indeed, cloud service owners must actively monitor services for unexpected failures and capacity issues in order to avoid violating Service Level Agreements (SLAs). In addition, security and privacy service owners must monitor systems for policy violations, data breaches, and indications of impending service outages.

Service owners' overall responsibility for reliability includes taking ownership of relevant Service Level Objectives (SLOs) and Service Level Indicators (SLIs) defined by those consuming the service. To aid this effort, cloud service operators collect logs, traces, metrics, and alerts that service owners leverage when diagnosing problems and managing response. These datasets help owners understand the performance and health of their services at any moment, yet they don't predict future service problems. Since the cost of service failures often far exceeds the cost of preventing them, monitoring solutions have emerged that automatically detect emerging failure types days or weeks ahead, enabling service owners to take proactive—and cost-effective—action.

For the service owners using those predictive maintenance capabilities, however, they often risk becoming overwhelmed by the large volume of alerts generated on an annual basis. False positives, as well as the inability to accurately prioritize alerts according to potential financial impact, ultimately limits the power of these solutions. Consequently, investments in building and enhancing predictive capabilities have continued to focus on detection capabilities that can address these end-user challenges.

2.1. Observability and Telemetry in Cloud Environments

The notion of observability stems from control theory, defining the ability to deduce a system's internal state based solely on its external outputs. Adapting this concept in the context of SRE, observability is different from monitoring in that the latter term suggests distinguishing between normal and abnormal states of a system, while observability enables a deeper understanding through a possibly infinite number of questions. The imbalance between complex service behavior and the relative lack of telemetry needs to be addressed. For on-premises and cloud native environments, all telemetry sources (traces, metrics, and logs) are typically included. Adequately instrumenting cloud environments and services involves major investments.

Telemetry can be mapped to the three pillars of observability. Traces track interactions across service boundaries, showing timing, latency, and failure status. Correlated high-level user transactions are more useful than low-level ones. Applied at the service level, they indicate points of failure or excessive response times, particularly involving third-party

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services. Key infrastructures such as CDN or WAFs should also be traced. For VMs, traces report cloud-provider operations (create, delete, stop, and restart). Tracing needs are supersized for Kubernetes environments, where each request is served by a different collection of containers. Kubernetes offers tools for tracing, but they often provide insufficient coverage for production deployments. It is also more important for microservices.

Metrics provide quantitative information about the running state of a system. The need for custom metrics varies with the service type (VM, containers, function as a service). For VMs, hypervisor and cloud-provider metrics are usually sufficient. Monitoring cloud-native infrastructures in production and at scale, such as K8s or serverless, requires instrumenting and exposing an extended set of internal metrics.

Logs report unexpected and unusual events. For cloud services, collecting all logs from all services might overwhelm the capacity for analysis. Instead, log collection can be limited to errors and warnings. For simpler services, log-level classifiers can be employed.

Fig 2: Observability and Telemetry in Cloud Environments

2.2. Reliability Engineering in the Cloud

Reliability Engineering in the Cloud: principles and practice of reliability engineering in cloud systems are reviewed, including Google's Site Reliability Engineering model, risk surface identification and choice of appropriate risk mitigation strategies (e.g. error budget policies, Service Level Agreements, Mean Time to Recovery), and governance frameworks. Cloud providers and cloud service consumers share some common objectives—namely, the minimization and control of operational risk—yet face different challenges and require different risk surface visibility and insight.

For cloud providers, cost-effectively minimising operational risk across a large number of services with widely varying usage and failure characteristics is paramount. Anomalies in the reliability of a service that is scaled to serve a small percentage of users can present as material risk but will have relatively low priority in terms of remediation using traditional tools. In contrast, a consumer's choice of infrastructure or platform cloud service can be largely automated via a pre-defined policy matching input requirements to the service provider offering the lowest price while still meeting the reliability requirements defined in the associated Service Level Agreement (SLA). Consequently, consumer enterprise architects focus on identifying the risk surface of the organisation's cloud infrastructure and service usage patterns, control of overall risk surface exposure and operational costs, and proper definition of SLAs matching risk appetite while supporting business continuity objectives.

Equation 2: Error budget from SLO

If an SLO is stated as "availability must be at least A_{SLO}" (e.g., 99.9%):

$$A \geq A_{\text{SLO}}$$

The **error budget** (allowed "bad fraction") is:

$$B = 1 - A_{\text{SLO}}$$

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Allowed downtime in a window T:

$$D_{\max} = B \cdot T = (1 - A_{\text{SLO}})\, T$$

This is exactly what SRE teams use when the paper mentions error budgets.
AI-Augmented Cloud Monitoring P…
Define:

- $MTBF$: mean time between failures (average uptime between incidents)
- $MTTR$: mean time to recovery/repair

A typical "cycle" is: uptime $MTBF+$ downtime $MTTR$.
So availability is:

$$A = \frac{MTBF}{MTBF + MTTR}$$

Step-by-step
1. One cycle length $= MTBF + MTTR$
2. "Good time" per cycle $= MTBF$

Fraction good $= MTBF/(MTBF + MTTR)$

III. ARTIFICIAL INTELLIGENCE IN MONITORING

In addition to the typical signal processing functionalities, many cloud monitoring platforms leverage AI methods to detect anomalies and forecast metrics of interest, often with the goal of driving infrastructure reliability in an inferential manner. Anomalous behaviors can be detected for a wide variety of signals (e.g., SLO, capacity usage), and predictions can be based on both univariate or multivariate supervised or unsupervised models. The chosen method often depends on the region of the failure tree being targeted, the short-term vs long-term dimension, etc. Detection can be either point-based (e.g., any instantaneous abnormality on the signal is detected) or interval-based (e.g., abnormal behavior persists for several consecutive points).

The selected task-oriented evaluation metric also varies; anomaly alerts have high stakes and can span large volumes, while forecasts typically have a longer horizon and use less frequent data points. Model training is often complicated by a lack of signal when the underlying infrastructure is operating normally; consequently, advance access to failure events and the data required for training become paramount. The return window of these methods can range from a few minutes to several hours, depending on the SLA to satisfy and the chosen monitoring level. AI techniques can also be used to assist in root-cause analysis and remediation guidance related to anomalous behavior.

In addition to the typical signal processing functionalities, many cloud monitoring platforms leverage AI methods to detect anomalies and forecast metrics of interest, often with the goal of driving infrastructure reliability in an inferential manner. Anomalous behaviors can be detected for a wide variety of signals (e.g., SLO, capacity usage), and predictions can be based on both univariate or multivariate supervised or unsupervised models. The chosen method often depends on the region of the failure tree being targeted, the short-term vs long-term dimension, etc. Detection can be either point-based (e.g., any instantaneous abnormality on the signal is detected) or interval-based (e.g., abnormal behavior persists for several consecutive points).

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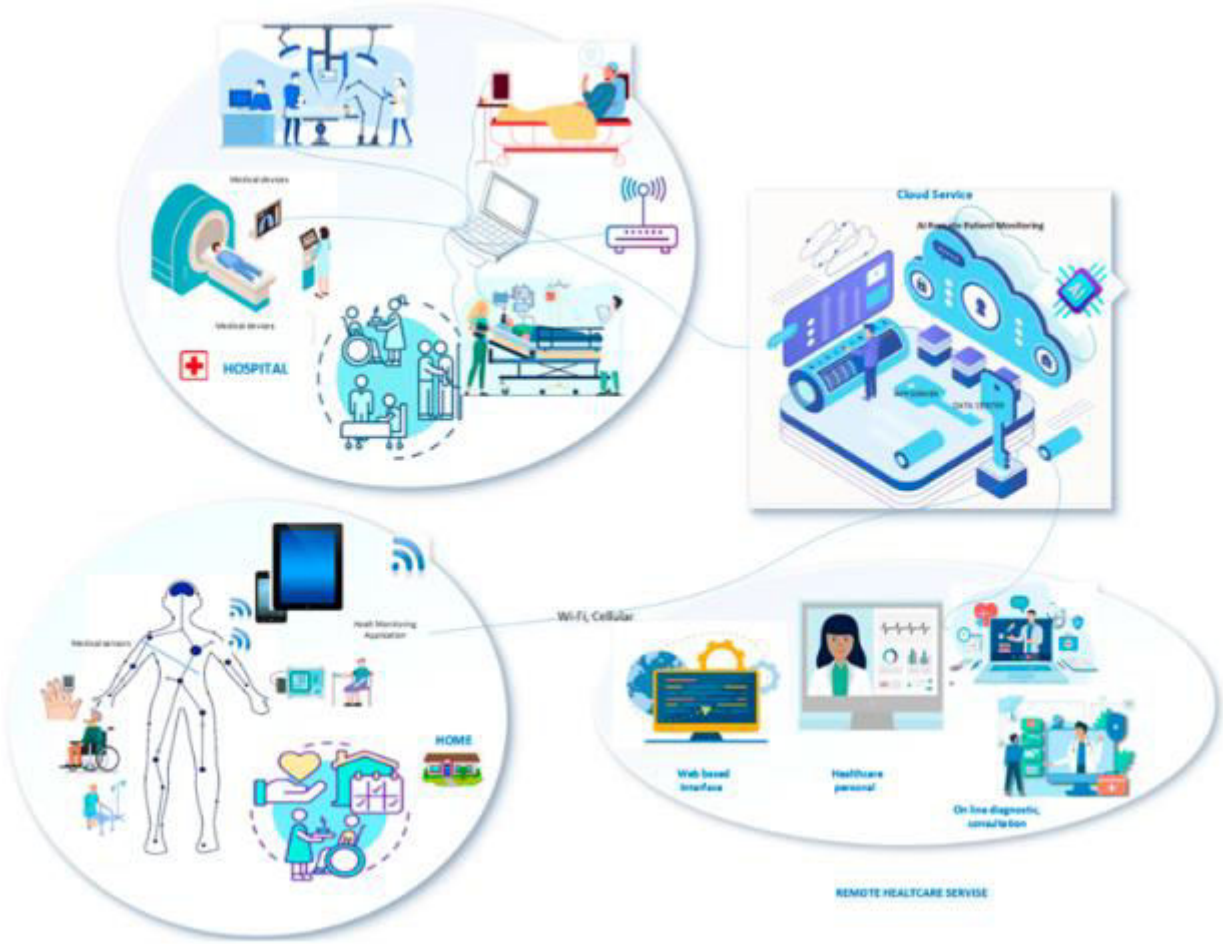

Fig 3: Artificial Intelligence in Monitoring

3.1. Anomaly Detection and Forecasting

Anomaly detection in telemetry data is a classical application of AI, now attracting much renewed attention. A variety of techniques have been proposed, employing different levels of supervision. Unsupervised methods deliver purely discovery-driven outcomes, performing detection without prior knowledge of expected signals. Fully supervised approaches require a comprehensive label set for model training, ensuring that deployed solutions detect only what has been deemed anomalous. Semi-supervised methods train on non-anomalous data and infer anomaly scores in production, building on the convolutional background that labelled data is scarce and costly.

Usefulness requires assessment, typically through down-stream tasks under constrained monitoring conditions. Popular metric suites draw on precision and recall grounded in the presence or absence of anomaly indicators supplied by monitoring teams. Evaluation relies on testbeds or real telemetry, with indicators serving as substitute labels when the expected nature of anomalies is not essential. Optimal forecasting performance requires balanced sample sets; abnormal data should thus be oversampled within purely supervised paradigms. Temporal gaps between observations and incidents further determine the expected utility of forecasts, suggest appropriate use cases, and drive resource allocation for equivalently relevant assessment.

Equation 3: Baseline mean and standard deviation

Take a baseline "in-control" period of $n$points:

$$x_1, x_2, \dots, x_n$$

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Mean:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Sample standard deviation:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2}$$

Step-by-step for s

1. Compute deviations: $(x_i - \mu)$
2. Square them: $(x_i - \mu)^2$
3. Sum: $\sum(x_i - \mu)^2$
4. Divide by $n - 1$(sample correction)
5. Square root

For $k = 3$("3-sigma limits"):

$$UCL = \mu + ks, CL = \mu, LCL = \mu - ks$$

Let the supervised forecast at time $t$be $\hat{x}_t$.
Residual:

$$e_t = x_t - \hat{x}_t$$

3.2. Root Cause Analysis with AI

Different AI methodologies focus on different aspects of root cause analysis. Anomaly mining examines data for unusual instances or patterns. Instance-tagging methods then associate corresponding expected failure- or action-indicating labels with such instances, while significantly reducing the need for extensive a priori labeling. Interpretable machine learning, in the form of trained classifiers, assigns a probability distribution (based on features of the instance being analyzed) to the set of predefined tags. These models can: (1) identify which features (instances, timers or labels) are important for the prediction of a given failure type or tag; (2) highlight the features most contributing to a prediction of a particular instance; and (3) help the end-user prioritize actions for a given instance. Causal-inference approaches estimate causal relationships, rather than mere correlations, potentially revealing why a problem is occurring or how to remediate it.

Incorporating AI for root cause analysis at alert time expedites investigations and increases their effectiveness by mining telemetry data for information on previously encountered similar problems. Such systems can: (1) highlight which conditions and activities typically precede the incident; (2) report which features are usually being set when this incident pattern occurs; (3) emphasize which features have significantly changed since the last appearance of the mode; (4) point to the remediation action used in previous occurrences; and (5) alert to the presence of any similar incident pattern. In the case of predictive maintenance applied to cloud services and web applications, automatic reports tie the suggested reliability improvement action to the full cost-benefit projected approval process.

VI. ARCHITECTURE OF AI-AUGMENTED MONITORING PLATFORMS

AI-Augmented Cloud Monitoring Platforms for Predictive Infrastructure Reliability
Data Ingestion and Normalization. The data sources feeding an AI-augmented monitoring platform for predictive infrastructure reliability typically include traces, metrics, and log data from cloud infrastructure services, platform services, and application-level services. Depending on the objectives of the platform, external data sources may also be ingested, data-hygiene processes applied, and features derived; for example, weather forecasts or stock levels for e-commerce can be monitored as features influencing application reliability and quality of service. Since these data sources have varied schemas, data structures must be normalized to a common schema for subsequent use, typically via ETL mechanisms.

Whether the data are streamed at ingestion time in near-real-time or ingested in batch mode on a faster but less-current cycle, the latency level targeted depends on the type of prediction being made. For reliability predictions with greater

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lead-time horizons, latency can and should be increased. The underlying architecture accommodates very low-latency streaming use cases while also supporting batch use cases for prediction, analysis, and visualization where near-real-time predictions are not critical.

Feature Engineering for Reliability. Reliability features for the AI-augmented monitoring platform can be broadly categorized according to service type. For infrastructure-level cloud services, these features include indicators of service health, potential throttling, capacity saturation, and starvation conditions, along with attributes of the usage profile and feature-validation state. Cloud-service-perceived indicators of reliability and quality should also be considered, which are typically priced at a premium. These features should be derived directly from the input telemetry or, in the absence of built-in monitoring support, computed with minimal time lag where source telemetry is available.

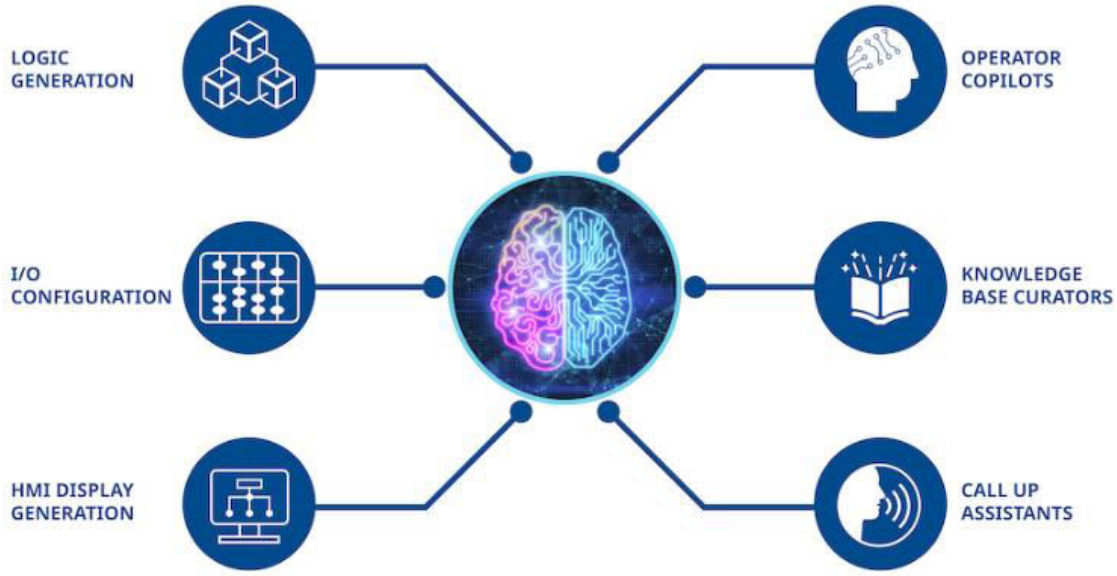

Fig 4: Architecture of AI-Augmented Monitoring Platforms

4.1. Data Ingestion and Normalization

Data necessary for predictive reliability features reside in different silos, ingested from internal logs and monitoring as well as external cloud telemetry APIs. Platform dashboards often integrate this information; however, for monitoring platforms, normalizing the schema within a multi-tenanted data lake is sufficient. Organizing the structure for easy and efficient training will help avoid performance issues.

Data ingestion generally occurs over streaming protocols to ensure minimal latency. Cloud service deployment characteristics dictate the degree of allowed delay: the low second range for service performance monitoring, the several-minute delay for maintenance-related ML predictions, and the several days often tolerated in recommendation engines. Streaming pipelines should generate output in a format that simplifies subsequent preparation. Streaming-sensitive windows can dangerously stretch the MTTR of predictive features; batch creation is riskier but offers greater performance amortization.

Communicating the training set structure to all developers is essential. Mode, type, semantics, normal ranges, and prediction target for each feature aid selection or creation and their expected post-processing. Sensitivity to creation effort encourages re-usage; rare features drive additional focus. Standard window and temporal grouping features are often useful, while normalization reduces noise and production resource impact—except for strongly increasing data, which deserves avoidance.

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Equation 4: Anomaly detection evaluation: confusion matrix → precision/recall → ROC/AUC

Precision = "when we alert, how often are we right?"

$$Precision = \frac{TP}{TP + FP}$$

Recall / TPR = "of all true anomalies, how many did we catch?"

$$Recall = TPR = \frac{TP}{TP + FN}$$

F1 combines them:

$$F1 = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

Substitute:

$$F1 = \frac{2PR}{P + R}$$

False Positive Rate:

$$FPR = \frac{FP}{FP + TN}$$

A ROC curve plots (FPR, TPR)as you sweep the decision threshold.
Conceptually:

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

In practice (discrete points), trapezoidal rule:

$$AUC \approx \sum_i \frac{(FPR_{i+1} - FPR_i)\,(TPR_{i+1} + TPR_i)}{2}$$

4.2. Feature Engineering for Reliability

Monitoring platforms leverage AI methods to forecast problems in observed cloud services that can critically affect customer satisfaction and business monetization. Predictive maintenance is among the first use cases as the data patterns of recent failures can reliably indicate similar future incidents. Feature importance can indicate how different factors can change the predictions and trigger the root causes for each predicted incident. The analysis can then be used to define either preventive actions when those factors are known or guide investigation when they are not detected. The return on investment is positive considering the reduction in customer service intervention costs and the scaling of the model to different cloud services.

A second use case is dynamic resource sizing and autoscaling of cloud services, which is frequently tested in production. The impacts of incorrect resource size are twofold: lower performance for users or higher infrastructure costs for the provider. The decision policies look for a balance between cost and performance by detecting nonoptimal resource sizing and enabling scaling actions. Accuracy in predicting sudden spikes of service demand that require increasing resource allocation is critical for keeping service performance under affordable infrastructure costs. Several preventive actions can help in producing a stable cloud service behavior beyond prediction accuracy, such as deployment in hot days when possible, sizing the resources according to the allowed error boundary, implementing close control for essential service priority, configuring costs to overprovision resources for critical features, using autoscaling only on nonessential features or backups, and dimensioning backup actions for long and critical processes.

The design of an AI prediction model fundamentally depends on feature engineering. The meaningfulness of the features impacts the model performance and governs the type of forecast that can be achieved. The best features should be defined for a specific prediction context and model; thus, the considerations create an initial guideline that needs testing,

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adaptation, and possible full rewriting for the specific application. The characteristics of the monitored systems point out the types of feature candidates to be explored: temporal features convey the time-related knowledge, windowed features integrate past information that can be useful for future predictions, and normalization steps accommodate data that greatly differ in their distribution. Feature selection should be guided by domain knowledge and empirical correlation analysis.

V. CASE STUDIES AND USE CASES

Case studies and use cases illustrate AI-augmented monitoring capabilities, ranging from the prediction and prevention of service failures to the optimization of resource sizing and demand-based autoscaling.

Predictive maintenance of cloud services hinges on a predictive failure model. Lags, queues, and saturation have long been recognized as key indicators of service failure, and AI methods have demonstrated predictive prowess across academic and enterprise deployments. Empirical studies have unequivocally shown that failure behavior is affected by controller configuration and operation. From a business perspective, these factors have been widely documented to affect adoption rates and willingness-to-pay. Yet despite the abundance of indicators, empirical models, and business relationships, major public cloud vendors have yet to incorporate predictive features into their cloud services, potentially resulting in billions of dollars in lost revenue. Challenges and risks associated with the deployment of predictive maintenance capabilities for cloud services include the economic return on investment for such capabilities, the mismatch between sensitivity and specificity when predicting rare events, and the potential for false positives and negatives to affect customer experience and willingness-to-pay.

Dynamic sizing and demand-based autoscaling of cloud services can mitigate over-provisioning and under-provisioning. Instead of simple predetermined policies, dynamic policies adjust instance count in near real-time based on monitored or forecasted demand. Expanding and reducing the number of instances is commonly implemented and generally recognized as an effective way to deal with peaks and troughs of demand. However, specific parameter selections can either stabilize or aggravate oscillations. An under-utilized service always incurs wastage costs, while over-utilization leads to SLA violations and possible customer dissatisfaction. For large cloud service providers, service changes scale instantaneously across customers. Customer-specific solutions consider the trade-offs between stability and performance. For example, a feedback control loop for an extrinsic autoscaling policy recognizes that demand is not stationary but evolving, with the possibility of redistributing resources across services without changing the total resource usage.

Equation 5: Predictive maintenance: lead time, time-to-failure window, ROI
Let:

- t_p: time alert/prediction is raised
- t_f: time failure/outage begins

Lead time:

$$L = t_f - t_p$$

Operationally you want:

$$L \geq L_{\min}$$

where $L_{\min}$is the minimum time needed to respond (on-call, mitigation, rollout, etc.).
Define:

- C_{platform}: yearly cost to build/run monitoring+AI
- C_{ops}: yearly additional ops cost (alerts, triage time, etc.)
- N: expected number of prevented outages/year
- R: revenue loss per outage (or downtime cost)
- S: other savings (reduced tickets, engineer time, etc.)

Benefit:

$$Benefit = N \cdot R + S$$

Total cost:

$$Cost = C_{\text{platform}} + C_{\text{ops}}$$

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ROI:

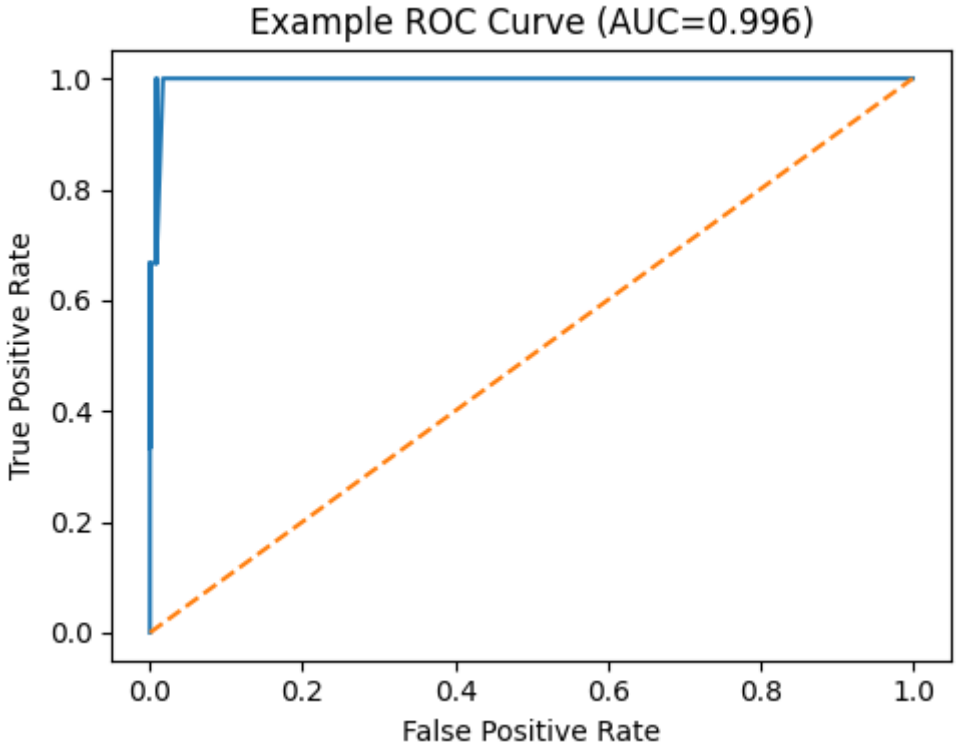
$$ROI = \frac{Benefit - Cost}{Cost}$$

5.1. Predictive Maintenance for Cloud Services

Cloud monitoring data and machine learning techniques help detect upcoming outages ahead of time. Thus, the maintenance can be scheduled proactively instead of reactively, and the service reliability is improved.

Cloud services consume resources (physical or virtual) mapped onto pieces of infrastructure that host them. Pieces of infrastructure suffer from different types of failures, that can also cause their parent services to fail. For a given service, some of the failures are critical, while some others are not. The relationship between the outages of the service and the pieces of infrastructure that support it can be analyzed to automatically detect the critical failures that lead to outages of the service, allowing to define a statistical model to predict them as soon as possible. This allows the operations team to schedule maintenance proactively instead of reactively in order to improve service reliability. Moving from a reactive maintenance methodology to a proactive one delivers a clear Return On Investment (ROI) because of the increased reliability of the service and the reduced amount of Revenue lost per Outage.

When using the model in a production environment, some additional aspects should be taken into account. The historical data leading to the development of the model should be examined to provide a clear checklist to the operations teams in order to identify what type of actions should be performed on the underlying infrastructure when a maintenance window is planned. The model should be designed to reduce the time between the prediction of a critical failure and the scheduled maintenance as much as possible.



5.2. Dynamic Sizing and Autoscaling

Dynamic resource sizing or autoscaling enables cloud service operators to adjust the resources available to a cloud service according to the workload. Unlike other cloud management capabilities such as elasticity or burstability, dynamic resource sizing is exclusively external to the service itself; dynamic resource sizing consists of modifying the allocation of resources beyond the automatic use of additional resources with respect to a system's actual use. Typically, the resource replacement or reconfiguration is a much larger, even disruptive, event than reallocation and cannot be done in

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quick succession or with short wait times. Dynamic resource sizing can bring stability and optimization to cloud services, increase resource utilization efficiency, and reduce expenses during cloud service downtime. However, a service's resource allocation cannot be reduced too aggressively to avoid instability.

Two public cloud service resource control mechanisms provide dynamic resource sizing capabilities: a cloud service's own auto-sizing control policy for internal resources and resource manager autoscaling policies that monitor a cloud service's public API statistics. In both instances, there are various cases and triggers that result in dynamic allocation changes. Different external factors can influence these dynamic resource sizing actions, including the environment and external workloads.

Dynamic resource sizing can be implemented more reactively and deployable within a shorter period for resource management agent-based setups. This avoids requiring high-risk changes or creating additional human-induced workflow inconsistencies. Promoting predictive maintenance work for resource management agents on a resource manager can voluntarily provide notifications based on both the environment and the observed peak usage of the service.

VI. CHALLENGES AND RISKS

Cloud monitoring, anomaly detection, and root-cause analysis platforms sound well-defined and handy, but come packed with complex challenges. Monitoring data are by nature large, heterogeneous, and automatically generated. Several risk factors threaten the deployment of a cloud monitoring platform based on anomaly detection and root-cause analysis.

6.1. Data Quality and Privacy

Completeness and accuracy of the data are mandatory for any monitoring application. Particularly, reverse-engineering cloud service or cloud infrastructure components requires the readiness of infrastructure failure. For example, a reliable anomaly classification model for a cloud service can be built only if alarms and incidents of the monitored service are sufficiently well classified and labelled in the past—the more alarms, the better. Therefore, failure frequency and a cost–benefit analysis also influence the potential return on investment. A good feature set must be selected, monitored, and enriched over time, as failure mode knowledge emerges.

Privacy of monitoring data is equally critical. Although monitoring data can be aggregated and anonymized, third-party monitoring organizations still need to guarantee compliance with data-privacy regulations and legal agreements, by properly using anonymized data. Moreover, insufficiencies in data governance can lead to security incidents. Towards this aim, organizations must pay special attention to the management and secure storage of cloud monitoring data.

6.2. Model Drift and Security

The monitoring of models and training data in production environments presents additional difficulties. The need to collect data with slowly evolving distributions and to define data quality metrics common to all involved components must also be considered. For example, signature-pattern-based anomaly detectors should monitor drift of histograms signing analysed monitoring feature distributions. When significant drift is detected, the model should be retrained and rebuilt more frequently than needed in a stable environment.

Finally, adversarial machine learning is a real and escalating threat, particularly against machine-learning-based monitoring, anomaly detection, and root-cause-analysis platforms. Such platforms might themselves be targeted by adversaries willing to discover and exploit security vulnerabilities in cloud services and infrastructures.

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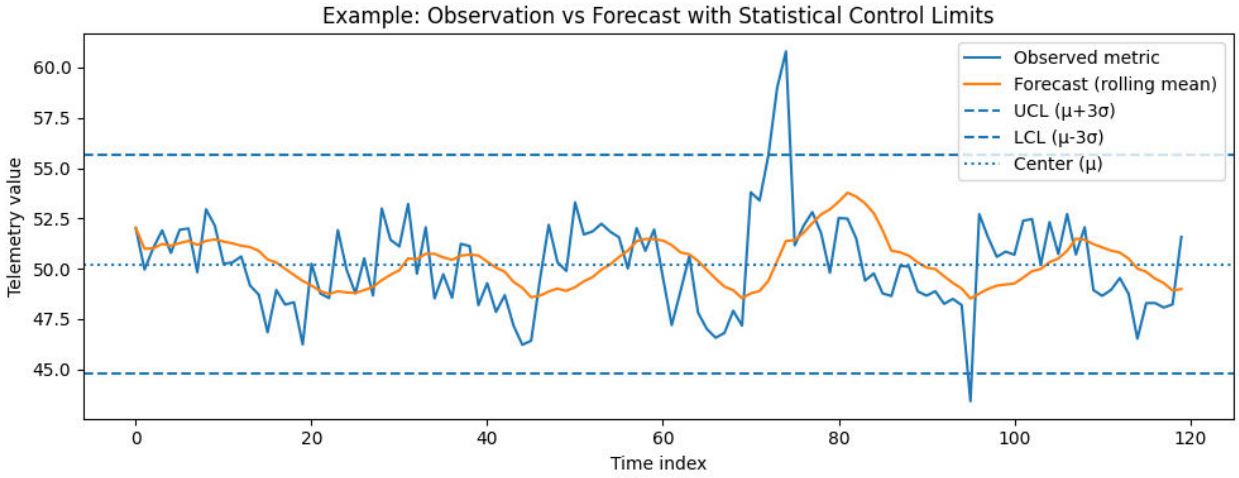

6.1. Data Quality and Privacy

Completeness, accuracy, and privacy are essential attributes of AI-augmented cloud monitoring platforms. Completeness refers to the availability of the necessary data to enable model training and application for a specific purpose. In predictive reliability analysis, the main type of incident for which the models are developed must occur frequently enough to obtain a reliable statistical description. For example, sufficient historical occurrences of operational or performance-impacting incidents in cloud services are prerequisites for building an ROI-justified predictive maintenance model. Many failure indications can be inferred from events in the monitoring services of cloud providers, thus allowing the prediction of underlying component failures with reasonable lead time. But the collected signals must also capture the relevant early warnings for an early enough estimated time of arrival. Furthermore, the lack of cloud service integrity incidents during platform operation introduces a real bias to predictive maintenance.

The quality of collected telemetry signals also must be monitored and further improved via specific data-gathering capabilities. It is difficult to predict the future behavior of a cloud service when the historical records are corrupted or invented. Therefore, the quality of the monitoring data must be checked continually and the sources fixed as defects are detected. Monitoring in one cloud service can also predict its effect on other interconnected services or tenant applications, and such predictive capabilities can be exploit-ed for proactive corrective measures. The real-time application of these predictive capabilities introduces additional technology complexity and therefore additional real-time application monitoring requirements. Anonymization of training and inference data sets becomes imperative whenever sensitive information is recorded in the monitored telemetry signals. In addition, regulatory and good governance decisions may impose the shielding of model training and in-ference datasets, which could also hinder research in these domains and, consequently, the development of new and better models.

6.2. Model Drift and Security

Artificial Intelligence in Monitoring platforms that have been deployed in production systems for several months or longer must also address model drift and security risks. The models are susceptible to drift due to changes in either the monitored data or production systems. The monitored data may change due to product releases, new services being offered, or the customer mix changing. Production systems are susceptible to drift mechanisms that have traditionally been handled by manual tuning, including lagged effects, varying trend or seasonality, and changing magnitudes of components. Adversarial machine learning is also a concern. Attackers can try to bypass the models or utilize worms to generate malicious traffic or failover conditions. Monitoring solutions must therefore be implemented to warn of potential drift, versioning criteria defined and applied to trigger a retraining of the models, and specific adversarial defense strategies put in place.

Anomaly detection systems are often the first line of defense against model drift. If drift occurs, retraining is preferably scheduled during low traffic periods, with a stable schedule across the year for other types of models. For instance, a model predicting cloud capacity may have seasonality due to user behavior but can be retrained at a fixed period in the year when cloud resources are still available, most likely in a cold state. The retraining period is crucial for adversarial machine-learning models as adversarial systems can thrive through short-lived failure conditions, such as propagating

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sudden traffic increases in a cloud service or worm-generation bursts. Consequently, testing and validating these models before a full production deployment is essential, especially to define scaling properties, potential mitigation strategies, and fallback plans.

VII. CONCLUSION

The cloud computing industry is emerging from its teenage years, and among cloud service providers, focus is shifting toward decreasing operating costs while increasing reliability and predictability. End users—consumers of cloud services, including businesses, developers, and machine-learning practitioners—need to be able to incorporate availability and predictability into their planning. Anomalies will occur, as is the nature of all complex systems, and being able to detect these anomalies, predict their effects, and repair the root cause before downstream systems are adversely affected is the focus of current development and research investments.

AI-augmented cloud monitoring platforms offer exciting opportunities to proactively manage reliability and costs. Novel research efforts, including the creation of Northern Virginia's first AI incubator, continuously push the boundaries of intelligence, making it cutting-edge as opposed to fail-fast. Predictive maintenance for cloud services aims to anticipate failures and mitigate user impact, while dynamic sizing and autoscaling of shared infrastructure helps minimize costs. The construction of these capabilities involves a wealth of data and requires appropriate governance. AI is not a panacea and only works if appropriate data is available. Data completeness, accuracy, privacy, and security are all important factors in successful implementation.

Metric	Value
Precision	0.6666666666666666
Recall (TPR)	0.6666666666666666
F1	0.6666666666666666
AUC	0.9957264957264956

Table : Anomaly detection metrics (example)

7.1. Emerging Trends

Reliable and resilient infrastructure is vital for cloud services. Integrating AI methods in monitoring platforms can improve infrastructure reliability and maintenance, enabling organizations to attain better input costs. Three key data quality considerations include data completeness for model training, accuracy of predictions, and compliance with privacy regulations. Significant patterns in production environments can shift over time, necessitating a retraining cadence to ensure changes in distribution. Monitoring for model drift enables timely retraining. Increased interest in the cybersecurity domain requires consideration of adversarial machine learning methods.

Monitoring Development, Inc. (MDI, 2021) surveys the cloud monitoring market, highlighting four trends. First, AI, machine learning, and automation are the next steps of cloud monitoring, enabling anomaly detection, root cause analysis, and predictive alerts. Second, monitoring companies leverage distributed cloud architectures to allow for lower-latency monitoring experience across the globe. Third, with environments becoming more dynamic and ephemeral, monitoring focusing on flows, signals, and traces is gaining traction. Finally, the demand for a single monitoring platform persists, with major vendors developing integrated solutions. These four trends drive the importance of AI-augmented cloud monitoring platforms for predictive infrastructure reliability.

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