SOI: 1.1/TAS DOI: 10.15863/TAS
International Scientific Journal
Theoretical & Applied Science
p-ISSN: 2308-4944 (print) e-ISSN: 2409-0085 (online)
Year: 2026 Issue: 01 Volume: 153
Received: 12.01.2026
Accepted/Published: 30.01.2026
https://T-Science.org

Issue Article

Timur Mukayev
University of Bristol
Master's degree,
Bristol, United Kingdom

MODERN METHODS OF MONITORING AND LOGGING IN DISTRIBUTED MACHINE LEARNING SYSTEMS

***Abstract**: The article examines modern approaches to implementing observability in distributed machine learning systems, including the configuration of metrics, event logging, and request tracing. The role of tools such as Prometheus, Grafana, the ELK stack, Fluentd, Loki, and OpenTelemetry in ensuring the resilience, transparency, and controllability of machine learning system infrastructures is analysed. The importance of integrating observability into model lifecycle management pipelines at all stages – from data preparation to operation in the production environment – is emphasised. Typical constraints related to scalability, caching, and the complexity of diagnostics in microservice architectures are identified. It is concluded that the deployment of an effective observability architecture requires a comprehensive and systematic approach.*

***Key words**: observability, monitoring, logging, tracing, MLOps, distributed systems.*
***Language**: English*
***Citation**: Mukayev, T. (2026). Modern methods of monitoring and logging in distributed machine learning systems. *ISJ Theoretical & Applied Science, 01 (153),* 144-151.
***Soi**: https://s-o-i.org/1.1/TAS-01-153-16 ***Doi**: crossref https://dx.doi.org/10.15863/TAS.2026.01.153.16
***Scopus ASCC**: 1702.*

Introduction

The complexity of modern distributed machine learning (ML) systems is continuously increasing, ranging from data preprocessing and model training to deployment and real-time inference. Expansion in computational scale, adoption of cloud infrastructure, and reliance on microservice architectures have greatly complicated debugging, maintenance, and performance assurance. In this context, the importance of observability has become critical. Observability refers to a set of practices including monitoring, logging, and distributed tracing that enable engineers and data scientists to understand system behavior, detect anomalies, diagnose failures, and ensure reliable operation of ML services.

The purpose of this study is to conduct a systematic analysis of contemporary approaches to observability in distributed ML systems. This paper explores the principles of metric configuration, event logging, and error tracing, as well as provides an overview of widely used tools such as Prometheus and Grafana. Special attention is given to the integration of these tools into ML Ops pipelines, highlighting the automation of monitoring throughout different stages of the ML lifecycle.

Main part. Key components of the observability system and their role in ensuring the resilience of distributed ML pipelines

Observability in distributed ML systems is built upon three fundamental components: metrics, logs, and traces [1]. The combined use of these elements provides a holistic view of the state of the ML infrastructure, making it possible to identify deviations in the behaviour of models and infrastructural components, as well as to perform retrospective analysis of incidents.

Metrics represent aggregated numerical indicators that reflect the current state and dynamics of operation of both individual services and the ML system as a whole (table 1).

Table 1. Examples of metrics in distributed ML systems [2].

Type of metric	Examples	Purpose
System-level	CPU load, memory usage, disk I/O errors, network throughput, thread count, container health indicators.	To monitor the health and resource consumption of infrastructure components and underlying computational nodes.
Business-level	Forecast accuracy for sales or demand, average response time, user conversion rate, deviation from planned unit cost.	To assess the business value generated by ML models and their alignment with key performance indicators (KPIs).
ML-specific	Accuracy, Precision, Recall, F1-score, Log-loss, data drift, prediction drift, model confidence intervals, inference latency.	To track the predictive quality, stability, and operational behavior of deployed ML models.

Metrics provide a compact and continuously updated quantitative representation of system state that enables real-time monitoring, automated alerting, and trend analysis; however, due to their aggregated nature, they reflect only the surface-level behavior of distributed ML systems and do not capture the semantic context or causal mechanisms of failures. Therefore, their effective use requires automated aggregation, storage, and visualization, as well as threshold-based alerting and contextual interpretation in conjunction with logs and traces, particularly when system-level deviations coincide with degradation in prediction quality.

Logging plays a crucial role in error diagnostics, service debugging, and the analysis of model behavior. In modern ML systems, it is customary to distinguish between structured and unstructured logs (table 2).

Table 2. Characteristics of structured and unstructured logs [3, 4].

Type of logs	Description	Advantages	Limitations
Structured	Logs formatted in JSON, CSV, or Protobuf with clearly defined fields and values.	Easily parsed and indexed; supports automated processing, aggregation, and search.	Requires a strict schema; less flexible for capturing non-standard or unexpected errors.
Unstructured	Free-form text (e.g., stack traces, debug messages) without a predefined structure.	Rich in contextual information; helpful for diagnosing uncommon or complex system failures.	Difficult to aggregate or analyze automatically; often requires preprocessing and normalization.

The availability of a properly organized logging system becomes particularly important in scenarios involving distributed caching, where failed requests or data desynchronization may not be directly reflected in metrics but can be observed in logs [5]. Moreover, logs make it possible to identify latent errors that do not affect aggregated indicators but may, over time, lead to performance degradation or failures in request processing.

Distributed tracing is a method for tracking the lifecycle of requests across multiple components of a distributed system [6]. For ML services, especially those built on a microservice architecture, tracing provides end-to-end control over data processing, predictive API calls, and interactions between subsystems (table 3).

Table 3. Key characteristics of distributed tracing in distributed ML systems.

Tracing aspect	Description	Purpose	Limitations
Request-level tracing	Tracks the full lifecycle of an individual request across all interacting services and components.	To identify latency sources, service dependencies, and failure points in real-time inference workflows.	High overhead in highly loaded systems; requires careful sampling strategies.
Pipeline-level tracing	Traces complex ML pipelines, including data ingestion, preprocessing,	To analyse end-to-end execution time and detect	Lower temporal resolution compared to request-level

	model inference, and post-processing stages.	performance bottlenecks across ML workflows.	tracing; delayed detection of transient failures.
Causal event tracing	Establishes cause–effect relationships between system events occurring across distributed components.	To support root cause analysis of complex incidents and cascading failures.	Requires precise time synchronisation and consistent correlation identifiers.
Cold-start and initialization tracing	Tracks the initialization of ML services and models, particularly in dynamic and serverless environments.	To identify latency caused by model loading and environment initialization.	Applicable mainly to on-demand execution scenarios; limited relevance for persistent services.

Unlike logging and metrics, tracing makes it possible to visualise causal relationships between events and to accurately identify bottlenecks that affect request handling latency. This is particularly relevant for serverless architectures, where cold start delays and unstable model initialisation times may not be detected by other observability mechanisms [7].

Thus, the observability triad – metrics, logs, and tracing – forms the foundation for the controllability of distributed ML infrastructures. Their combined use makes it possible not only to detect anomalies in real time, but also to build robust mechanisms for prevention and adaptive response to incidents.

Technological architectures and tooling for implementing observability in distributed ML systems

Effective implementation of observability in distributed ML systems is impossible without specialised tools that provide collection, aggregation, storage, and visualisation of data on the behaviour of models and the underlying infrastructure.

Prometheus can be called a de facto standard for monitoring containerised and distributed systems due to its capabilities to perform high-frequency time-series collection and to support a pull-based metrics model. According to the Observability Survey conducted by Grafana Labs among industry professionals in 2024, Prometheus is one of the most widely adopted observability technologies (fig. 1).

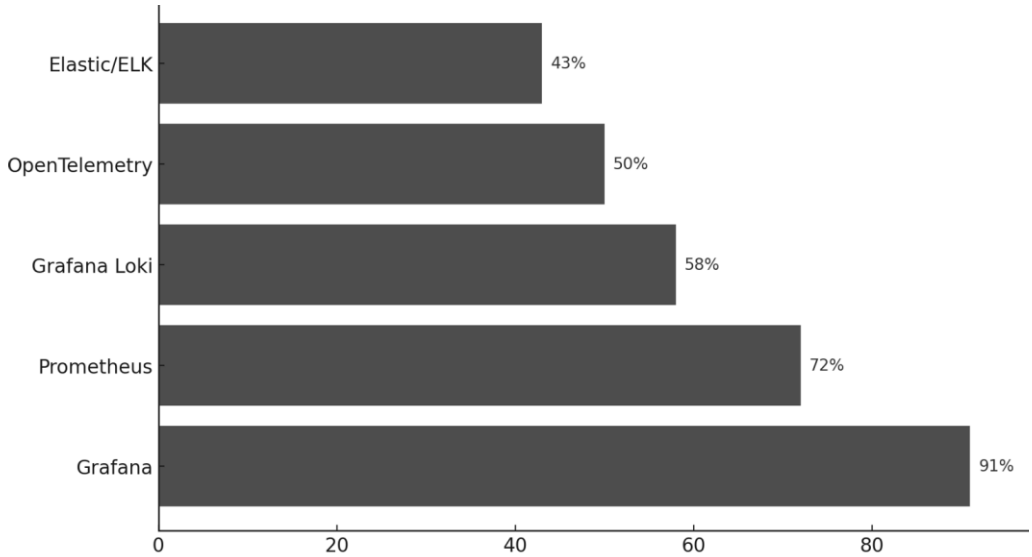

Figure 1. Most widely used observability technologies according to the Grafana Labs survey [8].

Overall, Prometheus integrates with most ML frameworks and orchestration platforms such as Kubernetes, providing the capability to monitor system-level indicators such as CPU load, memory usage, and pod status, as well as custom ML metrics such as prediction accuracy and model inference request count. What's more, Prometheus provides PromQL, a query language that enables complex alerting, anomaly detection, and post-mortem event analysis. Under a microservice architecture, its modularity and scalability ensure a high degree of adaptability to the architectural requirements of ML infrastructures [9].

For the visual representation of metrics, **Grafana** is most commonly used as a powerful open-source platform that supports integration with a wide range of data sources, including Prometheus, Elasticsearch, and InfluxDB. It provides interactive dashboards, charts, and monitoring panels that enable real-time tracking of the state of models, infrastructure components, and business indicators [10]. Well-designed visualization interfaces not only reduce incident response time but also enhance the overall understanding of processes within ML systems by non-engineering teams, such as analysts and product specialists. In addition, Grafana enables the configuration of role-based access control, alerting through multiple channels (email, Slack, Telegram), and the aggregation of data from multiple clusters into a unified view.

A range of specialized tools is used for **log management** in distributed ML environments to provide scalable and reliable collection, aggregation, storage, and visualization of logs (table 4).

Table 4. Comparison of logging tools in distributed ML systems.

Tool	Components / architecture	Features	Advantages	Limitations
ELK Stack	Elasticsearch, Logstash, Kibana.	Centralized log management with advanced visualization.	High scalability; powerful search and analytics capabilities.	High resource consumption; complex setup and maintenance.
Fluentd	Single lightweight agent with plugin support.	Flexible log routing; supports various formats (e.g., JSON, Protobuf).	Easy integration with cloud/hybrid environments; customizable pipelines.	Limited built-in visualization; requires external storage and dashboard tools.
Loki	Integrated with Grafana; indexes only metadata, stores raw log content.	Lightweight, optimized for resource efficiency.	Low storage overhead; fast querying by labels; seamless Grafana integration.	Limited full-text search capabilities; relies heavily on external visualization (Grafana).

The choice between these is driven by architectural characteristics and requirements concerning processing speed, data volume, and search complexity. For instance, systems that have intensive logging and need full-text search would want to lean more towards the ELK stack, while resource-constrained clusters will see Loki provide adequate logging with minimal overhead. In addition, integration with the existing infrastructure (e.g., Grafana or Kubernetes) and support for standardized log formats can significantly influence the final decision.

The **implementation of distributed tracing requires** the use of specialized tools that provide the collection and analysis of data on the traversal of requests across all layers of the system (table 5).

Table 5. Distributed tracing tools for ML systems.

Tool	Description	Strengths	Use cases
OpenTelemetry	Open-source, vendor-neutral framework for collecting metrics, logs, and traces; supports multiple languages (e.g., Python, Java); integrates with popular observability platforms.	Unified observability across metrics, logs, and traces; extensible and standard-compliant.	Large-scale ML infrastructures requiring multi-layer observability and cross-system correlation.
Jaeger	Distributed tracing system optimized for high-throughput microservices; supports detailed trace visualization and latency analysis.	Scalable for production; effective for debugging latency and call chains in real-time inference.	High-load ML environments with microservices and real-time model serving.
Zipkin	Lightweight tracing system with basic visualization and trace collection capabilities.	Simple setup and low resource overhead.	Development, testing, and low-load ML systems; educational and prototyping scenarios.

Consequently, observability for distributed ML depends on the integrated use of specialized tools across the model life cycle that reaches from metrics and logs to request tracing. Monitoring of system and ML-specific indicators relies on the core formed by Prometheus and Grafana, while ELK, Fluentd, and

Loki provide flexible management and anomaly detection over logs. Distributed tracing with OpenTelemetry, Jaeger, and Zipkin brings transparency into inter-service interactions and helps to identify performance bottlenecks, improving the overall reliability and operational efficiency of ML infrastructures in production.

Integration into ML Ops pipelines

The incorporation of observability systems into ML Ops pipelines represents a critical stage in building a reliable, resilient, and controllable ML infrastructure. Under modern conditions, where the entire model lifecycle – from data processing to operation in a production environment – is automated through CI/CD pipelines and orchestrators such as Kubernetes, Airflow, or Argo Workflows, monitoring becomes an integral component of the overall architecture rather than an optional add-on (fig. 2).

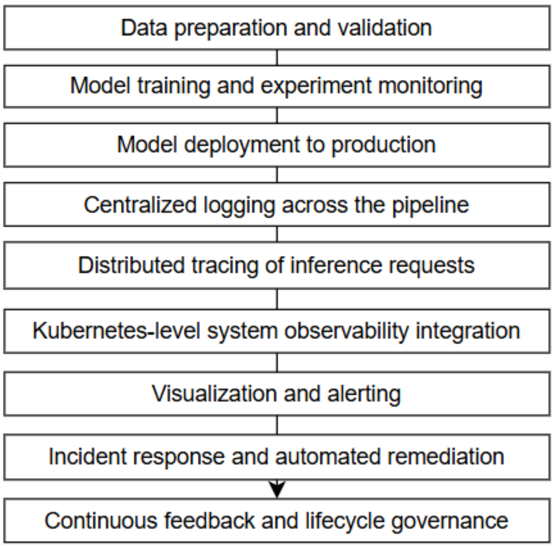

Figure 2. Stages of observability integration into the ML Ops pipeline.

Observability means that, all along the chain of data preparation, model training, and deployment, continuous monitoring of metrics, logs, and traces allows for the control of data quality, model performance, computational resource consumption, and stability of predictive APIs. It provides real-time quality metric and resource consumption tracking for training, as well as centralized logging, latency control, and diagnostics across all pipeline components in production by using Fluentd, ELK, and Loki. Distributed tracing with OpenTelemetry and Jaeger provides end-to-end visibility of requests in real-time and serverless inference scenarios. In Kubernetes-based infrastructures, Prometheus and Grafana enable the collection, visualization, and alerting of system and ML-specific metrics, while automated alerting and response tools (including Alertmanager and PagerDuty) support rapid incident detection, rollback, and traffic shifting in case of model instability.

An illustrative example of successful observability integration into ML Ops pipelines is provided by **Netflix.** Within its ML infrastructure, the company has implemented an observability framework aimed at detecting data drift, model performance degradation, and operational anomalies in production environments, including business-critical services such as payment and recommendation systems [11]. The combined use of metrics, centralized logging, and request tracing enables continuous monitoring of model behavior, early detection of deviations in input data and prediction outputs, and a reduction in the risk of silent failures. As a result, Netflix has increased the resilience of its ML services and ensured a high level of reliability for end-user applications.

Another representative example is **Uber**, which, in order to manage the whole life cycle of ML models, has designed and deployed its own end-to-end ML Ops platform called Michelangelo. It integrates data preparation, model training, deployment, and continuous monitoring into a unified, scalable infrastructure that supports hundreds of production models currently used for dynamic pricing, demand forecasting, fraud detection, and route optimization. The observability tools embedded in Michelangelo enable real-time control over model quality, computational resource utilization, and service-level metrics, thereby ensuring high transparency, scalability, and stability of ML processes under high operational load [12].

Therefore, the integration of observability systems in ML Ops does not stop at technical control over resources or logs. It is a strategic component that ensures transparency, reproducibility, and reliability along the whole model life cycle. With well-integrated observability tools, an organization can respond much faster to deviations and reduce operational risks while sustaining high model quality at each step of deployment and operation.

Comparative characterization of observability tool solutions in distributed ML systems

The comparison of technical solutions for ensuring observability in distributed ML systems requires consideration of multiple factors, ranging from scalability and compatibility with container-based infrastructures to the depth of analytics, resource consumption, and the specific nature of business applications. When selecting a tool, it is important to assess not only its functional capabilities but also its alignment with the architecture of the ML Ops pipeline, the level of organizational maturity, and the type of data being processed (table 6).

Table 6. Comparison of observability tools in distributed ML systems.

Category	Tool	Main characteristics	Strengths	Limitations / integration notes
Monitoring	Prometheus	Pull-based model, PromQL, Kubernetes and ML framework integration.	High flexibility, scalability, expressive query language.	Requires exporter configuration and advanced setup.
	Datadog	Cloud-based platform, auto-discovery of services.	Easy integration, built-in dashboards and alerts.	Proprietary, limited flexibility, high cost at scale.
Logging	ELK Stack	Full-text search, Kibana visualization, centralized storage.	Powerful analytics and flexibility.	High resource usage, complex operation.
	Fluentd	Lightweight agent with plugins, log routing.	Simple setup, extensibility.	Requires external visualization and storage.
	Loki	Grafana integration, indexes only metadata.	Efficient storage, fast queries by labels.	Limited content-based search.
Tracing	OpenTelemetry	Unified framework for metrics, logs, traces; multi-language support.	Standardized, extensible, broad ecosystem.	Requires aggregation infrastructure and visualization tooling.
	Jaeger	Deep tracing for microservices, latency and call chain visualization.	Scalable and mature.	May be excessive for small systems, needs fine-tuning.
	Zipkin	Lightweight tracing with basic visualization.	Quick deployment, low resource use.	Limited analysis and visualization features.

It is important to consider that the selection of observability tools should correlate not only with technical requirements but also with the characteristics of the models, their behavior in production, and their degree of sensitivity to external changes. For example, in financial risk management systems that employ complex ML algorithms, even minor fluctuations in input parameters can lead to significant changes in predictions [13]. Under such conditions, priority is given to the accuracy, interpretability, and timeliness of logging for each request, as well as to the ability to reconstruct the complete context of a prediction in the event of disputes or performance regression of the model.

The impact of infrastructural solutions, such as caching, on observability is also of critical importance. The use of aggressive caching strategies in distributed systems increases overall performance but simultaneously complicates error diagnostics and disrupts causal relationships between requests and system responses [14]. This necessitates a specialized approach to tracing and logging within cached layers, as well as the inclusion of dedicated metrics that reflect the efficiency and integrity of cached data.

Thus, the selection of observability tools should be based on a systemic understanding of ML infrastructure, model behavior, domain requirements, and operational strategies. Considering both technical and domain factors allows observability to be implemented as an integrated architectural framework supporting the entire model lifecycle in a distributed environment.

Conclusion

Modern methods of monitoring and logging in distributed ML systems play a critically important role in ensuring the reliability, transparency, and controllability of all stages of the model lifecycle – from data preparation to operation in the production environment. The use of tools such as Prometheus, Grafana, the ELK stack, Fluentd, Loki, OpenTelemetry, and Jaeger makes it possible to build a multilayer observability architecture that encompasses system-level, business, and ML-specific aspects. The integration of these solutions into ML Ops pipelines enables timely anomaly detection, supports automated alerting, and provides end-to-end request tracing in microservice-based and cloud infrastructures.

However, as systems grow in complexity, unresolved challenges related to scalability, noise in data, the effect of caching, and external instability persist, especially in high-risk domains. These issues can only be effectively resolved with technological maturity, along with the development of methodologies that assure robust and interpretable observability under conditions of dynamically changing data and infrastructure.

References:

1. Biswas, S. (2025). Comprehensive Observability and Monitoring Strategies Using Datadog. *International Journal of Management, IT and Engineering*. 2025. Vol. 15. №. 4. pp. 15-21.
2. Bæk-Petersen, A. L. (2025). *Survey on Operational Metrics for Reliable Machine Learning Systems.* 2025 IEEE 22nd International Conference on Software Architecture Companion (ICSA-C). IEEE. 2025. pp. 137-142.
3. Garifullin, R. (2024). Development and implementation of high-speed frontend architectures for complex enterprise systems. *Cold Science*. 2024. №12. pp. 56-63. EDN: ZZUNWR.
4. Bordusenko, D. (2025). Integration of machine learning into management accounting systems: forecasting operating costs and profitability in manufacturing. *Cold Science*. 2025. №22. pp. 70-81. EDN: DSSWSO.
5. Maksimov, V. Yu. (2025). Startup Latency Analysis in Java Frameworks for Serverless AWS Lambda Deployments. *The American Journal of Engineering and Technology*. 2025. Vol. 7. №. 04. pp. 16-21. EDN: SRWEMW. https://doi.org/10.37547/tajet/Volume07Issue04-03
6. Mahida, A. (2024). Integrating Observability with DevOps Practices in Financial Services Technologies: A Study on Enhancing Software Development and Operational Resilience. *International Journal of Advanced Computer Science & Applications*. 2024. Vol. 15. №. 7. DOI: 10.14569/ijacsa.2024.0150701 EDN: UCAUCI.
7. Bogutskii, A. (2025). Design and implementation of a microservices architecture in high-load distributed systems. *Universum: technical sciences: electronic scientific journal.* 2025. №11(140). pp. 21-25.
8. (2025). Observability Survey / Grafana Labs. Retrieved 01.12.2025 from https://grafana.com/observability-survey/2024/
9. Ulyanov, V. (2025). Designing user interfaces in digital financial services: structural and functional contribution to the development of the digital economy. *Universum: technical sciences: electronic scientific journal*. 2025. №11(140). pp. 32-37.
10. Tong, B. Y., Kuo, T. T., & Lin, C. Y. (2024). *Visualization-oriented Natural Language Interfaces for Grafana Dashboard*. 2024 International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan). IEEE, 2024. pp. 465-466.
11. (2025). *ML Observability: Bringing Transparency to Payments and Beyond / Netflix*. Retrieved 02.12.2025 from https://netflixtechblog.com/ml-observability-bring-transparency-to-payments-and-beyond-33073e260a38
12. (2025). *Meet Michelangelo: Uber's Machine Learning Platform / Uber*. Retrieved 03.12.2025 from https://www.uber.com/en-KR/blog/michelangelo-machine-learning-platform/
13. Zharmagambetov, Ye. (2024). Using synthetic data to model a portfolio in conditions of high volatility. How synthetic data allows you to test strategies for rare market events. Examples of generative models application. *The American Journal of Management and Economics Innovations.* 2024. Vol. 6. №. 12. 55-62. EDN: FHDSDF. https://doi.org/10.37547/tajmei/Volume06Issue12-06

14. Smirnov, A. (2025). Methodological analysis of caching strategies in distributed systems: a comparative study of their impact on performance and fault tolerance. *The scientific heritage.* 2025. №171. pp. 51-54. DOI: 10.5281/zenodo.17450394 EDN: NOESVD.