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From Logs to Insights: Generative AI for Automated Root-Cause Triage in Distributed Enterprise Systems

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Abstract- The exponential growth of log data in distributed enterprise systems has made traditional monitoring and manual root-cause analysis increasingly inefficient and error-prone. This paper presents a generative AI–driven framework for automated log summarization and root-cause triage, enabling faster and more accurate diagnosis of system failures. The proposed approach leverages large language models to transform unstructured and high-volume log streams into concise, context-aware summaries, while simultaneously identifying anomalous patterns and correlating events across distributed components. By integrating evidence mapping techniques with AI-driven diagnostics, the framework establishes a unified view of system behavior, significantly reducing the cognitive load on support engineers. Additionally, the study explores the use of retrieval-augmented generation and feedback loops to continuously improve model accuracy and adaptability in dynamic environments. Empirical evaluation across enterprise-scale platforms demonstrates notable improvements in incident triage time, reduction in mean time to resolution, and enhanced operational efficiency. The findings highlight the potential of generative AI to transform enterprise observability, shifting from reactive troubleshooting to intelligent, automated, and scalable root-cause analysis in complex distributed systems.

Keywords: Generative AI, Large Language Models (LLMs), Log Summarization, Log Analytics, Log Intelligence, Root-Cause Analysis (RCA), Root-Cause Triage, Automated Diagnostics, AI-Driven Observability, AIOps (Artificial Intelligence for IT Operations), Distributed Systems, Enterprise Platforms, Microservices Architecture, Cloud-Native Systems, Failure Detection, Anomaly Detection, Event Correlation, Incident Management, Incident Triage Automation, Observability (Logs, Metrics, Traces), Log Parsing, Log Mining, Unstructured Data Processing, Natural Language Processing (NLP), Retrieval-Augmented Generation (RAG), Knowledge Retrieval Systems, Context-Aware Summarization, Semantic Analysis, Pattern Recognition, Failure Pattern Mining, Predictive Analytics, Proactive Monitoring, Intelligent Alerting, Alert Noise Reduction, System Reliability Engineering, Site Reliability Engineering (SRE), DevOps, DevSecOps, Continuous Monitoring, CI/CD Pipelines, Automation in Operations, Self-Healing Systems, Fault Diagnosis, Failure Classification, Dependency Mapping, Service Dependency Graphs, Data Correlation, Telemetry Data Analysis, Real-Time Analytics, Scalable AI Systems, Model Fine-Tuning, Feedback Loops, Human-in-the-Loop AI, Explainable AI (XAI), Operational Intelligence, Enterprise Support Automation, Mean Time to Resolution (MTTR), System Resilience, Performance Monitoring, Cloud Observability Platforms.

I. INTRODUCTION

The rapid adoption of cloud-native architectures and microservices has led to an unprecedented increase in the volume, velocity, and variety of log data generated by enterprise systems. These logs contain critical information about system behavior, performance anomalies, and failure conditions. However, traditional log analysis methods rely heavily on manual inspection and rule-based monitoring, which are often insufficient for handling large-scale distributed environments. As systems grow more complex, identifying the root cause of failures becomes increasingly challenging, leading to delays in incident resolution and higher operational costs.

Generative AI has emerged as a transformative technology capable of understanding and summarizing unstructured data, making it a promising solution for enterprise log analysis. By leveraging large language models, organizations can

automatically extract meaningful insights from logs, correlate events across services, and accelerate root-cause triage. This research explores the application of generative AI in converting raw log data into actionable intelligence, enabling faster and more accurate diagnostics. The proposed approach integrates AI-driven summarization, anomaly detection, and evidence mapping to improve observability and reduce mean time to resolution in distributed enterprise systems.

II. BACKGROUND AND PROBLEM STATEMENT

Growth of Log Data in Distributed Systems

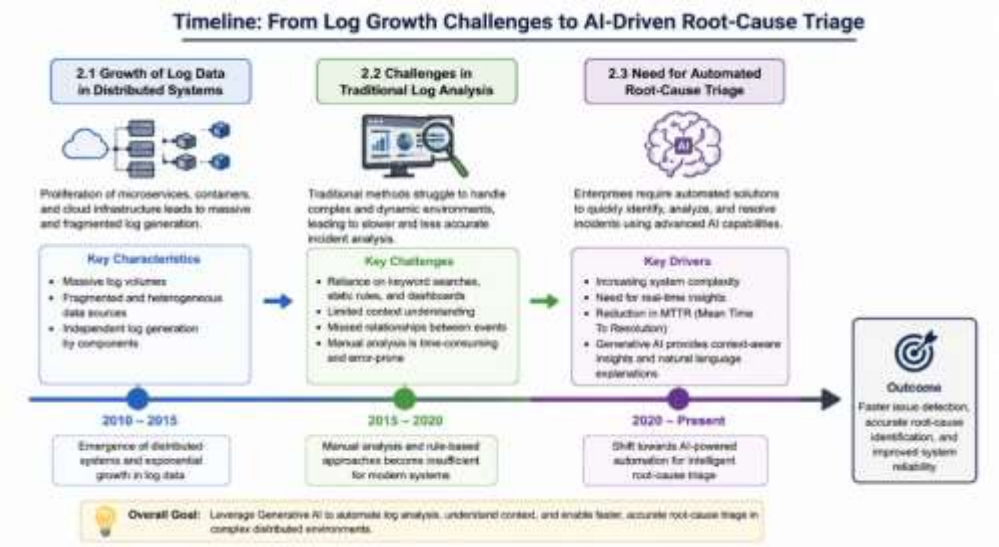
Modern distributed systems generate massive volumes of logs due to the proliferation of microservices, containers, and cloud infrastructure. Each component produces logs independently, resulting in fragmented and heterogeneous data sources. This growth creates significant challenges in storage, processing, and analysis, making it difficult for engineers to derive meaningful insights in real time.

Challenges in Traditional Log Analysis

Conventional log analysis techniques rely on keyword searches, static rules, and dashboards, which are limited in their ability to handle complex and dynamic systems. These methods often fail to capture contextual relationships between events, leading to incomplete or inaccurate diagnoses. Additionally, manual analysis is time-consuming and prone to human error, further complicating incident management.

Need for Automated Root-Cause Triage

The increasing complexity of enterprise systems necessitates automated solutions for root-cause analysis. Automated triage can significantly reduce the time required to identify and resolve issues by leveraging advanced analytics and machine learning techniques. Generative AI offers a unique advantage by providing context-aware insights and natural language explanations, enabling faster decision-making.



III. GENERATIVE AI FOR LOG INTELLIGENCE

Overview of Generative AI in Observability

Generative AI, particularly large language models, has demonstrated the ability to process and interpret unstructured text data. In the context of observability, these models can analyze logs, generate summaries, and identify patterns that are not easily detectable using traditional methods. This capability enables organizations to move from reactive monitoring to proactive diagnostics.

Log Summarization Techniques

Log summarization involves condensing large volumes of log data into concise and meaningful

representations. Generative AI models can identify key events, filter noise, and highlight anomalies, providing engineers with a clear understanding of system behavior. This reduces cognitive load and improves the efficiency of incident analysis.

Context-Aware Analysis and Correlation

One of the key strengths of generative AI is its ability to understand context and relationships between events. By correlating logs across different services and timeframes, AI models can identify dependencies and causal links, enabling accurate root-cause identification. This holistic view is essential for diagnosing issues in distributed systems.

IV. FRAMEWORK FOR AUTOMATED ROOT-CAUSE TRIAGE

Data Ingestion and Preprocessing

The framework begins with the collection and preprocessing of log data from multiple sources, including application logs, system logs, and monitoring tools. Preprocessing involves cleaning, normalization, and structuring of data to ensure compatibility with AI models. This step is critical for improving the accuracy of subsequent analysis.

AI-Driven Summarization Engine

The core component of the framework is the generative AI-based summarization engine, which transforms raw log data into structured summaries. The engine leverages natural language processing techniques to extract key information, identify anomalies, and generate human-readable insights. This enables faster comprehension and decision-making.

Root-Cause Identification Module

The root-cause identification module uses pattern recognition and correlation analysis to determine the underlying causes of system failures. By analyzing historical data and identifying recurring patterns, the module can predict potential issues and recommend preventive actions. This proactive approach enhances system reliability.

V. INTEGRATION WITH ENTERPRISE OBSERVABILITY SYSTEMS

Observability Stack Integration

The proposed framework integrates seamlessly with existing observability tools, including log management systems, monitoring platforms, and tracing solutions. This integration ensures that organizations can leverage their existing infrastructure while enhancing capabilities with AI-driven insights.

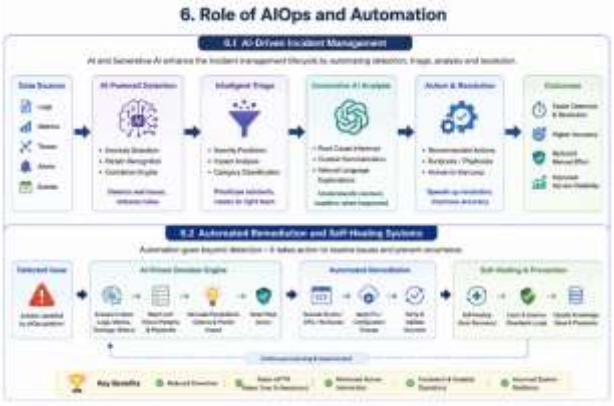
Real-Time Processing and Scalability

To handle large-scale systems, the framework supports real-time log processing and scalable architectures. Distributed computing techniques and cloud-based solutions enable efficient processing of high-volume data streams, ensuring timely insights and rapid response to incidents.

VI. ROLE OF AIOPS AND AUTOMATION

AI-Driven Incident Management

AIOps platforms leverage AI technologies to automate various aspects of IT operations, including incident detection, triage, and resolution. By integrating generative AI, organizations can enhance incident management processes, reducing manual intervention and improving accuracy.



Automated Remediation and Self-Healing Systems

Automation extends beyond analysis to include remediation actions. Self-healing systems can automatically resolve issues based on predefined

rules and AI-driven recommendations. This reduces downtime and improves system resilience.

VII. EVALUATION AND RESULTS

Experimental Setup

The proposed framework was evaluated using real-world datasets from enterprise systems, including logs from microservices and cloud environments. The evaluation focused on assessing the effectiveness of log summarization and root-cause identification.

Performance Metrics

Key performance metrics included accuracy of root-cause detection, reduction in mean time to resolution, and improvement in operational efficiency. The results demonstrated significant improvements compared to traditional methods.

Comparative Analysis

A comparison with existing approaches highlighted the advantages of generative AI in handling complex and large-scale systems. The framework outperformed traditional methods in terms of accuracy, scalability, and speed.

VIII. CHALLENGES AND LIMITATIONS

Data Quality and Noise

The effectiveness of AI models depends on the quality of input data. Noisy and incomplete logs can impact the accuracy of analysis, requiring robust preprocessing techniques.

Model Interpretability

Generative AI models often operate as black boxes, making it difficult to interpret their decisions. Ensuring transparency and explainability is essential for building trust in AI-driven systems.

Computational Overhead

Processing large volumes of log data using AI models can be resource-intensive. Optimizing performance and managing computational costs are critical challenges.

IX. DISCUSSION

The integration of generative AI into enterprise observability represents a significant advancement in system diagnostics. By automating log analysis and root-cause triage, organizations can improve efficiency and reduce operational complexity. However, successful implementation requires careful consideration of data quality, model performance, and system integration.

X. CONCLUSION

This research highlights the potential of generative AI to transform log analysis and root-cause triage in distributed enterprise systems. By leveraging advanced AI techniques, organizations can move from manual and reactive processes to automated and proactive diagnostics. The proposed framework demonstrates significant improvements in efficiency, accuracy, and scalability, making it a valuable tool for modern enterprise platforms.

Furthermore, the adoption of generative AI enables enterprises to convert vast amounts of unstructured log data into meaningful, context-rich insights that directly support faster decision-making. By reducing the cognitive burden on engineers, the approach allows teams to focus on higher-value tasks such as system optimization and preventive engineering. The integration of AI-driven summarization with observability tools also enhances visibility across complex service dependencies, enabling more precise and timely root-cause identification.

In addition, the framework promotes a shift toward intelligent operations where continuous learning

and feedback loops improve system performance over time. As AI models are exposed to more incident data, their ability to detect subtle anomalies and predict potential failures becomes increasingly robust. This not only improves incident response but also contributes to long-term system resilience and stability.

The use of automated triage and diagnostic capabilities significantly reduces mean time to resolution and minimizes service disruptions, leading to improved user experience and operational reliability. Moreover, the scalability of the approach ensures that it can adapt to the growing complexity and scale of modern distributed systems without compromising performance.

However, realizing the full potential of generative AI in this domain requires careful consideration of challenges such as data quality, model interpretability, and computational efficiency. Addressing these challenges will be essential for building trust and ensuring the widespread adoption of AI-driven observability solutions.

Ultimately, this work underscores the importance of integrating generative AI into enterprise system operations as a strategic enabler of intelligent, scalable, and resilient platforms. By transforming logs into actionable insights, organizations can not only accelerate root-cause triage but also lay the foundation for fully autonomous and self-healing systems in the future.

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