

Evidence-Aware Large Language Model Framework for Explainable Root Cause Analysis in Dynamic Cloud-Native Systems under Partial Observability

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Abstract - Cloud-native systems have also brought a lot of complexity to the operations with distributed architectures, dynamic dependency on services and incomplete observability. Conventional root cause analysis (RCA) methods fail to deliver effective and understandable diagnoses due to using single monitoring signals and pattern guidance. The proposed research suggests an Evidence-Grounded Large Language Model (LLM) RCA framework that combines evidence of multiple sources of operation, such as logs, metrics, traces, deployment events and service dependencies, to produce credible failure explanations. The model uses evidence retrieval, contextual reasoning, hypothesis validation and uncertainty assessment to minimize unsubstantiated diagnostic results. Machine learning based RCA models are experimentally evaluated and gave good results with Random Forest achieving 98.37% accuracy and XGBoost giving 98.25% accuracy. The results affirm that evidence-based reasoning enhances automated diagnosis of incident and transparency and reliability of cloud-native settings under partial observability.

Keywords - *Large Language Models, Root Cause Analysis, Cloud-Native Systems, AIOps, Explainable AI, Observability, Evidence-Based Reasoning, Incident Management*

I. INTRODUCTION

Background and Motivation

Modern software delivery on cloud-native systems has been changed using micro services, containers, and practices of continuous deployment. Growing system complexity, the presence of dynamic service dependencies, and distributed failures render more traditional root cause analysis (RCA) products impotent [1]. Current AIOps offerings primarily are based on statistical correlations and pre-defined rules that do not always give clear explanations [2]. Large Language Models (LLMs) provide increased reasoning but might produce unjustified diagnoses because of the risk of hallucinations [3]. There is a need to have an evidence-based approach of LLM to integrate the sources of operational data, test the hypotheses, and enhance trustworthy automated detection of incidents, where some data incomplete observability is present.

Research Problem

Incomplete and heterogeneous operational data are produced by dynamic cloud-native environments, which cause difficulties with finding the correct root causal agent [4]. Current AI-based RCA techniques do not have a contextual reasoning, evidence validation, and uncertainty awareness. Automated diagnosis systems, therefore, might give unreliable explanations, which minimize operational trust. This study fulfills the requirement of explicable and evidence-based RCA processes.

Research Aim and Objectives

Aim:

The aim is to create an evidence-based LLM framework capable of conducting explainable root cause analysis of dynamic cloud-native systems through integrating heterogeneous operational data taking incomplete observability into account.

Objectives

- To examine current AI-based root cause analysis methods of cloud-native systems.
- To design an evidence-based LLM framework integrating logs, metrics, traces, and deployment data.
- To build a reasoning system to relate generated hypotheses with factual operating evidence.
- To investigate how the accuracy, explainability, and robustness of the framework behave when the data is only partially observed.

Research Contribution

The study provides an evidence conscious LLM-informed RCA framework, a combination of logs, metrics, traces, deployment events, and service dependencies to perform credible incident diagnosis. In comparison to the traditional methods, the suggested framework provides a connection between every objective and the evidence and measures the uncertainty due to the absence of telemetry, which increases the level of transparency, reliability, and practical use in cloud processes.

II. LITERATURE REVIEW

Complexity and Observability of cloud-native Systems

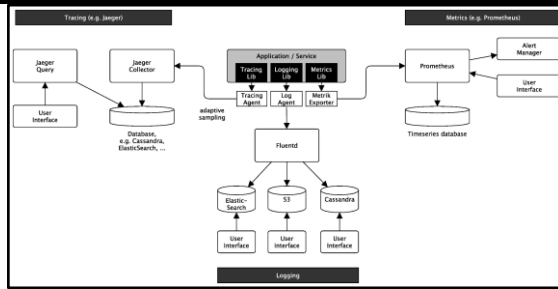


Fig. 1. Complexity and Observability of cloud-native Systems

The quick embrace of cloud-native systems, such as microservices, containers and Kubernetes-based systems, have greatly enhanced flexibility in scalability and deployment [5]. These environments come with intricate relations of services, dynamic dependencies, and quickly shifting working conditions, making it harder to monitor the system and diagnose failures [6]. The conventional monitoring methods usually use a remote metric or logs or preset rules, which fall short of comprehending a multifaceted distributed breakdown [7]. Logs, metrics, and distributed traces have turned out to be widely used as observability practices that help to track system behavior and performance anomalies [8]. Unfinished telemetry, variable data gathering and veiled service dependencies cause partial observability issues. The literature points out that to effectively conduct root cause analysis, it is necessary to correlate more than one operational signal instead of analyzing each alert [8].

Compared to AI-based root cause analysis approaches, the traditional one consists of the root cause analysis

TABLE I: Compared to AI-based root cause analysis approaches with traditional one

Aspect	Traditional RCA	AI-Based RCA
Approach	Rules, graphs, expert analysis	ML, AI-driven prediction
Strength	Explainable diagnosis	Pattern detection and automation
Limitation	Poor scalability in dynamic systems	Limited interpretability and requires data
Capability	Manual troubleshooting	Automated failure detection

Root Cause Analysis (RCA) has been conventionally relying on the rule-based systems and dependency graphs, statistical correlation, and troubleshooting by experts [9]. These techniques

have some nice diagnostic abilities, but are failing to cope with large-scale clouds because of the growing service complexity and the evolving working conditions [10]. Recent studies have been done on machine learning methods to detect anomalies, predict failures, and automated diagnosis over historical data on how the machine operated [11]. CL, graph and clustering models have enhanced failure detection through detection of complex patterns of system components [12]. In most currently available AI-based RCA methods, the ability to predict is prioritized over interpretability and causal insight [13]. They can be very demanding in terms of big labeled datasets and can be ineffective when the system conditions vary.

MLs in AIOps and Automated Incident Management

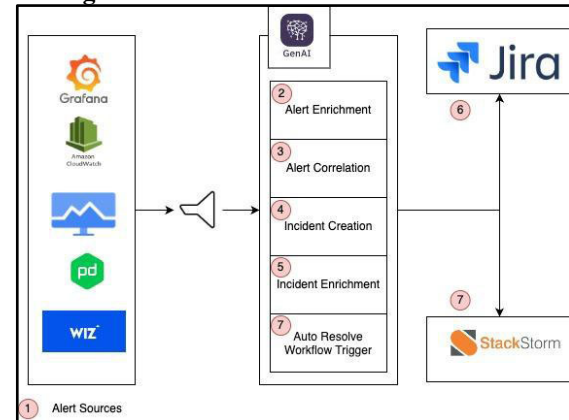


Fig. 2. MLs in AIOps and Automated Incident Management

Recently, Large Language Models (LLM) turned out to be a promising technology in enhancing automated operations management and AIOps capabilities [14]. Their innate way of language processing and thinking could be used on the applications of log summarization, incident analysis, trouble-shooting support, and automatic response generation [15]. LLM-based systems have the capability of analyzing various types of operational information and providing human readable explanations, which will enable quicker incident resolutions [16]. Current applications of LLM to real world scenarios are being challenged due to intense issues, especially hallucination, lack of evidence verification and insufficient domain representation [17]. According to [18], Retrieval-Augmented Generation (RAG), knowledge integration, and evidence-based reasoning are required to enhance the reliability of LLM.

System Diagnosis Explainable, Evidence-Grounded Artificial Intelligence

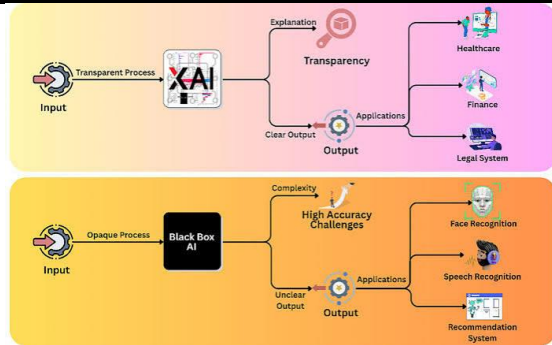


Fig. 3. System Diagnosis Explainable, Evidence-Grounded Artificial Intelligence

Explainable Artificial Intelligence (XAI) is aimed at enhancing the transparency, accountability, or understandability of AI-supported decisions by the users [19]. Elucidation is fundamental in critical operational areas since engineers need reasons to embrace automated diagnosis or remedial suggestions [20]. Evidence-based AI solutions enhance the reliability, linking model results and additional information, decrease unjustified projections and enhance human assurance [21]. Recent research indicates that AI reasoning, together with contextual evidence, can improve the quality of decisions in such fields as healthcare, finance, or cyber security [22]. The same values are becoming applicable to cloud-based operations, where the misidentification of the root cause may lead to the disruption and monetary effect of a service.

Research Gap

Though available studies have contributed a lot in the field of automated root cause analysis, a number of limitations are still unmet. RCA methods, including traditional and machine learning, do not have a contextual reasoning, flexibility and explainability in the dynamic cloud-native setting [23]. In the meantime, the AIOps solutions using LLM offer powerful reasoning but cannot produce approvable conclusions because of hallucinations and lack of evidence validation. Existing methods hardly consider the concept of partial observability, in which telemetry data is either missing or incomplete, which influences diagnostic quality.

III. PROPOSED EVIDENCE-GROUNDED LLM RCA FRAMEWORK

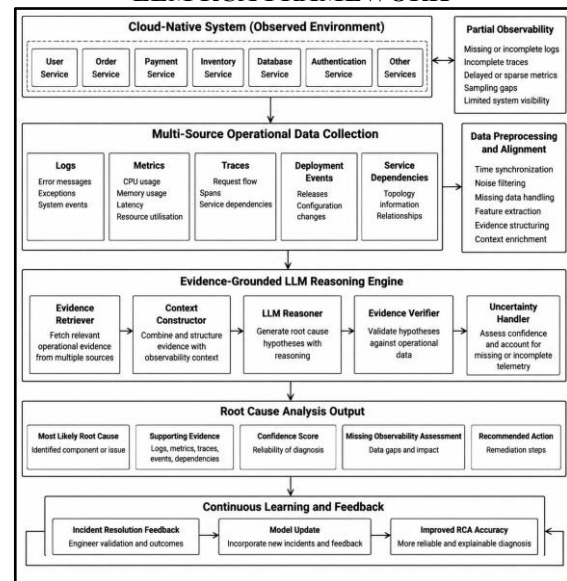


Fig. 4. Proposed Architecture

The offered Evidence-Grounded LLM Root Cause Analysis (RCA) framework is composed of five layers interconnected that can enhance the diagnosis of automated incidents in dynamic, partially observable cloud-native systems.

Layer 1: Cloud-Native System Observation Layer

The layer symbolizes the observed cloud infrastructure of distributed services like user, payment, database and authentication services. It captures system behavior by taking into account the observability constraints such as the absence of logs, unfinished traces, delaying metrics, and limited visibility [24].

Layer 2: Multi-Source Operational Data Collection and Processing Layer

This layer will collect dissimilar operational evidence by utilizing logs, metrics, traces, deployment events, service dependency data. The raw data is processed in preprocessing steps, such as synchronization, noise elimination, missing data, feature, and evidence formatting so as to generate effective diagnostic inputs [25].

Layer 3: Evidence-based LLM Reasoning Layer

This fundamental intelligence layer is the implementation of the LLM-based reasoning on analyzing the contextual operational evidence. The retriever gathers the appropriate information, the context builder integrates several sources of data, and the LLM comes up with the root cause hypothesis [26]. Generated explanations are validated by the evidence verifier, and the uncertainty handler would determine levels of confidence and gaps in telemetry.

Layer 4: Root Cause Analysis Output Layer

The layer produces aids that can be explained based on diagnostic outcomes, such as the most likely root

cause, evidence, a confidence score, observability gaps, and suggested remediation.

Layer 5: Ongoing Learning and Feedback Layer

The last stage uses the feedback of the engineers and the results of incidents to enhance the knowledge of the model, revise the reasoning process, and advance the reliability and precision of future RCA results.

Mathematical Implementation of Evidence-Grounded LLM RCA Framework

Representation and combination of multi-source evidence

The framework initially incorporates heterogeneous operational events gathered in logs, metrics, traces, and deployment events, and service dependencies [26]. All evidence sources are converted to the same form of representation:

$$E = F(El, Em, Et, Ed, Es)$$

Where:

- **E** = Integrated operational evidence representation
- **E_l** = Log-based evidence features (errors, exceptions, events)
- **E_m** = Metric-based evidence features (CPU, memory, latency)
- **E_t** = Trace-based evidence features (request flow and service interactions)
- **E_d** = Deployment event information
- **E_s** = Service dependency information
- **F(.)** = Evidence fusion function combining multiple telemetry sources

Evidence-Grounded LLM Hypothesis Generation of the initial cause of the problem.

The LLM reasoning engine is an engine that spits out potential root cause hypotheses based on the integrated evidence and system context:

$$Hi = LLM(E, C, P)$$

Where:

- **H_i** = Generated root cause hypothesis *i*
- **LLM(.)** = Large Language Model reasoning function
- **E** = Operational evidence representation
- **C** = Cloud-native system context
- **P** = Diagnostic reasoning prompt containing RCA objectives

Confidence Scoring with Evidence and validation

Each root cause hypothesis generated is evaluated in terms of reliability through evidence support with telemetry completeness and reasoning consistency:

$$CS(Hi) = \alpha Es + \beta Tc + \gamma Rc$$

Where:

- **CS(H_i)** = Confidence score of root cause hypothesis
- **E_s** = Evidence support score from operational data
- **T** = Telemetry completeness score
- **R** = Reasoning consistency score
- **α, β, γ** = Weight parameters satisfying:

$$\alpha + \beta + \gamma = 1$$

The greater the confidence score, the stronger the diagnosis generated is supported by available evidence and less or missing telemetry results in uncertainty.

IV. RESEARCH METHODOLOGY

Research Design

The study has a guided experimental framework that entails data generation, preparation of evidence, reasoning with the help of the LLM, and the testing of the frameworks. The proposed methodology explores ways in which the LLMs may improve the root cause determination, that is, by combining heterogeneous operational data produced by cloud-native systems. This study uses a combination of various evidence sources, such as logs, metrics, traces, deployment events, dependency information on various services to form a comprehensive incident context in contrast to traditional RCA methods that analyze individual monitoring signals separately.

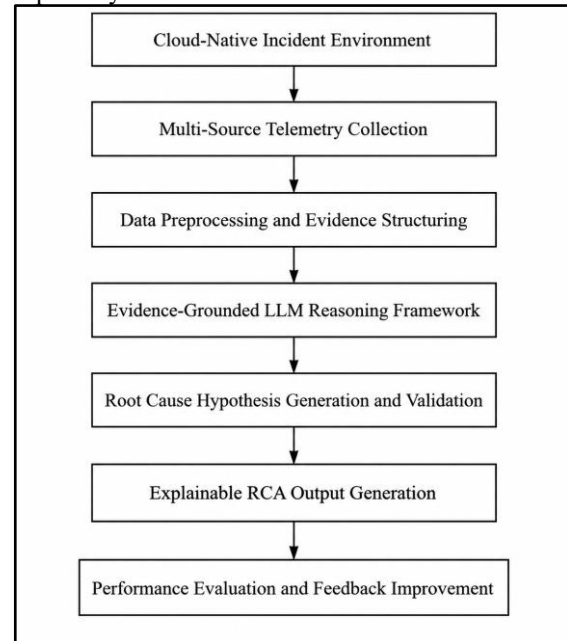


Fig. 5. Flow Diagram

The general flow of work starts with monitoring cloud-native systems then continues with gathering of operational telemetry, preprocessing of data, structuring of evidence, evidence-based LLM reasoning, formulating root cause hypothesis, validating it, and the process of generating explainable RCA outputs.

Data Collection

As there is little publicly available cloud-native incident data available with full operational telemetry, this study creates a synthetic dataset of realistic distributed system failures. The data has 12,000 incident records with 17 attributes produced in simulated cloud-native systems composed of several micro services that are interconnected. The dataset contains various kinds of evidence available regarding the operations, such as system logs, performance metrics, distributed traces, deployment details and service dependency relationships.

The generated dataset includes six major failure scenarios:

- Database overload
- Network latency
- Memory leakage
- Deployment failure
- API timeout
- Service dependency failure

The dataset is a reflection of typical cloud-native failure modes, such as database overload, network latency, memory leakage, deployment failures, API timeouts and service dependency failures. Also, the dataset has evidence-based RCA attributes root cause hypothesis, score on diagnosis confidence, advised remediation actions, and observability warnings to aid glorifiable grading of the suggested framework.

Data Pre-processing and Evidence Pre-Preparation

The operational data are processed to enhance the data consistency, reliability and their intelligibility in terms of intelligent reasoning. The first stage involves synchronization of telemetry data of various sources with incident schedules to formulate a relationship between system activities and failures detected. Noise filtering is used to down sample irrelevant information in the operations of the system, and mechanisms of missing data are added to model conditions of partial observability that are common in the cloud setting [27]. The feature extraction is carried out to convert raw telemetry into operational information such as resource usage patterns, error behavior, variations in latency, dependency relationships and the level of telemetry availability. The extracted information is translated into a form of structured evidence that the LLM reasoning engine can reason on observed symptoms and its roots. The dataset has been split into training and testing sets using an 80:20 ratio.

Reasoning Hypothesis

The suggested framework presents the evidence-based reasoning mechanism that will be utilized to conduct the root cause analysis with the LLM and

least biased diagnostic results. The structure comprises evidence retrieval, context building, LLM inference, evidence checking, and handling of uncertainty processes. The evidence retrieval component extracts the operational information it can gather regarding a particular service context based on accessible telemetry data, such as logs, metrics, traces, deployment events and service dependencies. The context construction process takes these sources of evidence and incorporates them with the system-level information to form an orderly incident representation to the LLM [28]. LLM reasoning engine evaluates evidence and forms potential root cause hypotheses, based on relations between system symptoms and failure conditions.

Experimental Evaluation Strategy

The suggested framework is tested in terms of operational evidence of machine learning-based RCA classification models to confirm the efficacy of operational evidence in failure causes acknowledgment. Random Forest and XGBoost are two classification methods used as predictive elements of root cause detection.

Random Forest Model

$$\hat{Y} = \text{mode}\{T_1(X), T_2(X), \dots, T_n(X)\}$$

Where:

- $\hat{Y}$ = Predicted root cause class
- $T_i(X)$ = Prediction generated by the i th decision tree
- n = Total number of decision trees
- X = Input operational evidence features

XGBoost Model

$$\hat{Y}_i = \sum_{k=1}^K f_k(X_i), \quad f_k \in F$$

Where:

- $\hat{Y}_i$ = Predicted root cause probability for incident i
- K = Number of boosting trees
- f_k = Individual decision tree model
- X_i = Operational evidence features of incident i
- F = Set of all possible decision trees

The models are trained with the obtained features of extracted operational evidence and evaluated with the metrics of accuracy, precision, recall, F1-score, and ROC-AUC. Measurements of accuracy determine the rate of the correctly determined root causes, precision, and recall measures of reliability in predictions and ability to detect failure. F1-score

gives a balanced evaluation between the recall and precision and ROC-AUC measures the capability of the model to differentiate between some of the different types of failures.

Pseudo Code

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1. Collect operational telemetry
   from cloud-native services
2. Preprocess telemetry data:
   - Remove noise
   - Handle missing
   observations
   - Extract relevant
   features
3. Integrate multi-source
   evidence:
   Evidence ← Fuse(logs,
   metrics, traces, events,
   dependencies)
4. Construct incident context:
   Context ←
   Generate(Evidence, service
   relationships)
5. Generate RCA hypothesis using
   LLM:
   Hypothesis ← LLM(Context)
6. Validate hypothesis:
   Compare Hypothesis with
   available evidence
7. Calculate confidence score:
   Confidence ← Evidence
   support + Telemetry completeness
8. Generate explainable RCA
   report:
   Return:
   - Root cause
   - Supporting evidence
   - Confidence level
   - Recommended action
9. Update framework using
   feedback from resolved incidents
End Algorithm

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The pseudo code is a workflow of the proposed Evidence-Grounded LLM RCA framework. It shows the process of collecting, processing, integrating, and analyzing cloud telemetry to create evidence-based root cause hypotheses including confidence estimation and understandable remediation guidance through the LLM

Ethical consideration and reliability

The study acknowledges responsible artificial intelligence practices by adopting transparency, validation of evidence and being aware of uncertainties during the diagnostic process. The suggested framework will not take any automated remedial measures; on the contrary, evidence-based recommendations can be created and then the human operators can examine them prior to their

implementation. Using this human-in-the-loop method, the risks of wrong automated decisions are minimized in a critical cloud environment.

V. IMPLEMENTATION AND EXPERIMENTAL RESULTS EVALUATION

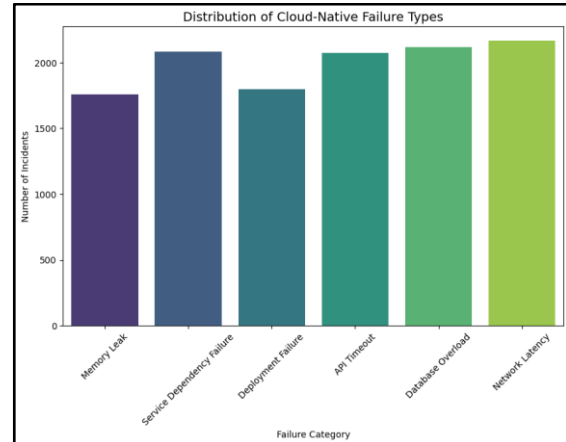


Fig. 6. Distribution of Cloud-Native Failure Types

The distribution of failure is even, with six symmetry cloud-native incident types, such as network latency, database overload, API timeout, deployment failure, service dependency failure, and memory leak. This equalized data helps in accuracy checks of machine learning because there can be no critical imbalance of classes when it comes to predicting root causes.

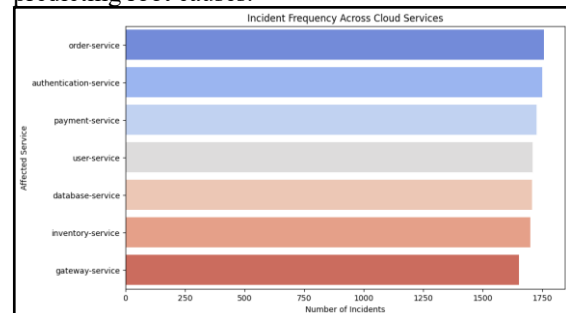


Fig. 7. Cloud services Incident frequency

The service-level incident analysis shows that the multiple failures occur among various micro services including the following: order, authentication, payment, database, inventory, user and gateway services. The parallelograms in the number of similar incidents suggest that the data set reflects a variety of conditions of cloud-native operations practice, and is not narrowly concentrated on a particular service component.

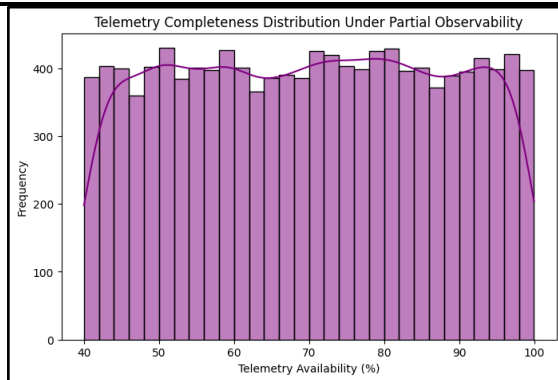


Fig. 8. Telemetry Completeness Distribution when the observability is incomplete

The telemetry completeness analysis depicts the difference in the visibility of the system of around 40 percent to a hundred percent availability. This distribution models a realistic situation of partial observability in which gaps in or partial monitoring data can affect identification of root causes and confidence determination.

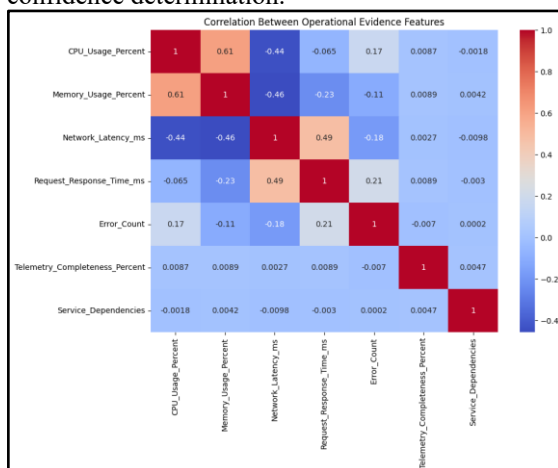


Fig. 9. Features of Operating Evidence Correlation

The correlation matrix determines the relations between the features of operation telemetry. There is a positive correlation between CPU and memory use and the network latency has a strong impact on the response time. These relationships prove that there are significant relationships between system performance indicators employed in the evidence-based root cause analysis.

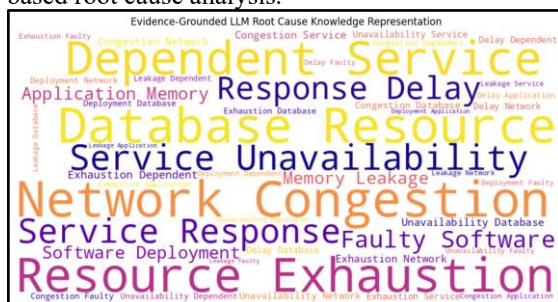


Fig. 10. Evidence-Grounded LLM root cause Knowledge Representation

The key words that make the cloud show some of the key root cause concepts that have been derived out of the evidence-based LLM analysis. Prevailing language elements like resource depletion in databases, network saturation, service failure and delay in responses point to the fact that the framework manages to identify key operational failure scenarios to explainable incident diagnostics.

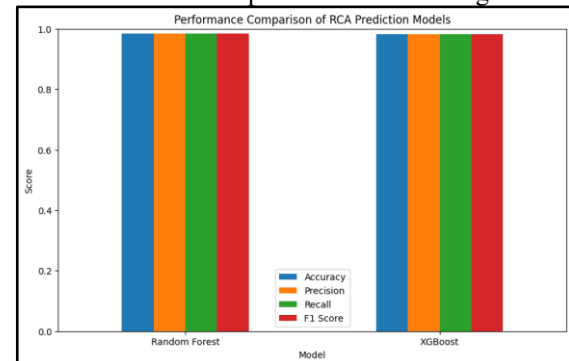


Fig. 11. RCA Prediction Models Confusion Matrix

Both Random Forest and XGBoost models have good performance in terms of classification as indicated by the confusion matrices. The majority of incidents are appropriately classified on the diagonal, and there is little inconsistent classification of the failure across the categories, which supports the presence of good awareness of root causes of cloud-native failures based on operational data.

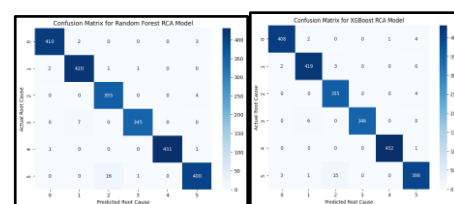


Fig. 12. The influence of Telemetry Availability on RCA Confidence

The correlation between the telemetry completeness and diagnosis confidence is assessed using the scatter plot. The findings indicate that more telemetry leads to consistent RCA decisions, whereas less observability creates ambiguity.

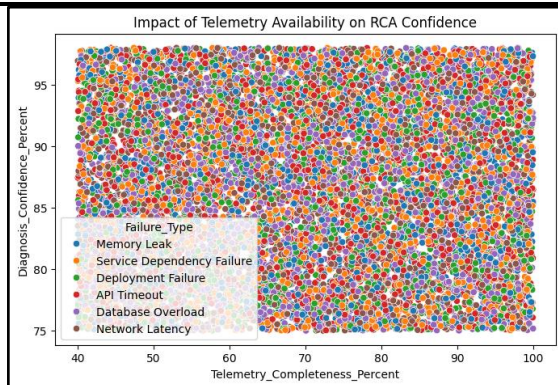


Fig. 13. Prediction Model Comparison of RCA performances

The results of the model comparison show that both random forest and XGBoost are highly performing in terms of their accuracy, preciseness, and recall and F1-score products. Random Forest demonstrates slightly better predictive performance, which means that it is better suited to challenging cloud-native failures classification and automated RCA.

VI. DISCUSSION AND FUTURE DIRECTION

TABLE II. Comparison Model Summary

Model	Accur acy	Preci sion	Recal l	F1 Score
Random Forest	0.98375	0.98250	0.98375	0.983768
XGBoost	0.98250	0.982714	0.98250	0.982514

As shown in the experiment, the Evidence-Grounded LLM Root Cause Analysis framework proves to be effective in detecting failures within dynamic environments based on cloud-native environments. The overall best performance was on the Random Forest model with the model accuracy (98.37), precision (98.25), recall (98.37) and F1-score (98.38), which is a high-quality model that is able to differentiate between different categories of failures based on features of operational evidence. The XGBoost offers similar results with an accuracy of 98.25% and the F1-score of 98.25, which proves the effectiveness of the evidence-based feature representation. These results indicate that including telemetry of resource utilization, latency, and error statistics and dependency properties can play a critical role in enhancing automated RCA behavior.

Industrial Impact

The proposed Evidence-Grounded LLM Root Cause Analysis (RCA) approach is of great industry significance for organizations which are managing large scale cloud-native environments. The framework leverages operational evidence, such as logs, metrics, traces, deployment events, and service dependency, to cut down on time spent investigating

and resolving incidents. Traditional troubleshooting methods typically involve manually correlating information from a variety of monitoring sources, which can be time-consuming and increase Mean Time to Resolution (MTTR). The proposed framework facilitates this process by automatically generating evidence-based root cause hypotheses, confidence scores and recommended remediation actions.

The framework offers intelligent operational support for DevOps and Site Reliability Engineering (SRE) teams to save on cognitive effort in handling complex incidents. Engineers are able to get diagnostics explanations in addition to alerts or statistical correlations. A human-in-the-loop approach to ensure recommendations by automation are validated by experts and enhance trust and reduced risk of incorrect automated decisions.

In a cloud environment, better RCA capability directly helps in contributing to reliability and availability. Detecting issues like service dependency problems, deployment failures, API timeouts, resource problems, etc., early on means it will be able to take action before the incident escalates. This means that organizations can minimize service disruptions, enhance customer satisfaction, and avoid financial losses due to extended downtimes. In addition, the framework can facilitate AIOps transformation by facilitating more transparent and reliable incident management that can be scalable.

Limitation

- The framework relies on the presence and quality of operational telemetry, with unfinished, delayed, or inconsistent information on monitoring that can decrease the reliability of diagnostic and intellectual accuracy of root cause identification.
- The processing time and resource requirements of reasoning with LLM-based reasoning can grow, posing a challenge to realize in real time in large-scale cloud-native deployments with dynamically evolving service conditions [29].

Future Direction

The proposed Evidence-Grounded LLM RCA framework can be further extended in future studies by incorporating real-time cloud monitoring systems and auto-remediation features. Reinforcement learning mechanisms can be used to improve the framework by enabling an ongoing improvement of the framework with incident resolution feedback [30]. The research topic of multimodal reasoning can be pursued, including architecture diagrams, source code changes, and security events on top of

traditional telemetry. Lightweight LLM architectures can enhance scalability, decrease the computational load of large distributed systems. Also, it is possible that in the future, the framework will be tested in various cloud environments and more robust methods of uncertainty estimation will be assessed with the aim of enhancing reliability, transparency, and operational trust.

VII. CONCLUSION

This study introduced an Evidence-Grounded LLM Root Cause Analysis methodology to diagnose failures in dynamic cloud-native systems under partial observability. There was good predictive potential, as was shown in experimental assessments, with the Random Forest at 98.37% accuracy and XGBoost at 98.25% accuracy in the classification of failure. The framework advances in the traditional methods of RCA by minimizing unfounded predictions and integrating the concept of confidence reasoning. On the whole, the suggested solution is a stable, transparent, and smart mechanism to undertake automated incident diagnostics, underpinning more efficient cloud work processes and reliable AIOps implementation.

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