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Retrieval-Augmented Graph Reasoning with Large Language Models for Explainable Incident Diagnosis

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Abstract

The increasing complexity of modern distributed systems has created significant challenges in incident diagnosis and root cause analysis. Traditional approaches often lack explainability and struggle with the dynamic nature of system failures, while pure machine learning methods suffer from limited interpretability and contextual understanding. This paper proposes a novel framework that integrates Retrieval-Augmented Generation (RAG) with graph-based reasoning and Large Language Models (LLMs) to enable explainable incident diagnosis in complex systems. The proposed approach leverages knowledge graphs to capture causal relationships among system components, employs retrieval mechanisms to access relevant historical incident data, and utilizes LLMs to generate human-interpretable explanations for diagnosed incidents. Through comprehensive evaluation on real-world incident datasets, our method demonstrates superior performance in fault localization accuracy, achieving 92.3% precision while providing transparent reasoning paths that enhance engineer trust and accelerate remediation workflows. The framework addresses critical limitations in existing approaches by combining the structured reasoning capabilities of graph neural networks with the semantic understanding and generation abilities of large language models, thereby advancing the state-of-the-art in intelligent operations and system reliability engineering.

Keywords

Retrieval-Augmented Generation, Large Language Models, Graph Neural Networks, Incident Diagnosis, Root Cause Analysis, Explainable AI, Causal Reasoning, Knowledge Graphs

Introduction

Modern distributed systems have evolved into intricate architectures comprising thousands of interdependent microservices, creating unprecedented challenges for incident management and system reliability. When failures occur in these complex environments, engineers face the daunting task of navigating through massive volumes of telemetry data, log entries, and performance metrics to identify root causes and implement effective remediation strategies [1]. The average incident resolution time in large-scale production systems often exceeds several hours, with manual diagnosis consuming substantial engineering resources and potentially impacting service level agreements [2]. This operational burden has intensified with the proliferation of cloud-native architectures and the adoption of continuous deployment practices, where system configurations change rapidly and failure modes become increasingly diverse and unpredictable.

Traditional rule-based monitoring systems and threshold-based alerting mechanisms have proven inadequate for addressing the diagnostic challenges in contemporary distributed systems. These conventional approaches rely on predefined patterns and static rules that cannot adapt to evolving system behaviors and novel failure scenarios [3]. Furthermore, the sheer volume and velocity of observability data generated by modern systems overwhelm human operators, making it impossible to manually correlate signals across different layers of the technology stack. While machine learning techniques have shown promise in anomaly detection and fault localization, they often operate as black boxes that provide limited insight into their decision-making processes, hindering engineer trust and adoption in production environments where interpretability is paramount for operational safety [4].

The emergence of Large Language Models has opened new possibilities for intelligent systems that can understand, reason about, and communicate complex technical information in natural language [5]. Recent advances in Retrieval-Augmented Generation have demonstrated the potential to combine the broad knowledge encoded in pre-trained language models with domain-specific information retrieved from external knowledge sources, enabling more accurate and contextually relevant responses [6]. Simultaneously, graph-based reasoning approaches have proven effective in modeling the causal relationships and dependencies inherent in distributed systems, providing structured representations that capture the propagation patterns of failures across interconnected components [7]. The integration of these complementary technologies presents a compelling opportunity to develop explainable incident diagnosis systems that leverage both structured causal reasoning and natural language understanding.

This paper introduces a novel framework that synthesizes Retrieval-Augmented Generation, graph neural networks, and large language models to enable explainable incident diagnosis in complex distributed systems. Our approach constructs dynamic knowledge graphs that represent system topology and causal dependencies, implements sophisticated retrieval mechanisms to access relevant historical incident patterns, and employs large language models to generate human-interpretable explanations that guide engineers through the diagnostic process. The framework addresses several critical research challenges including the representation of temporal causal relationships in evolving system architectures, the effective retrieval of contextually relevant diagnostic knowledge from large-scale incident repositories, and the generation of trustworthy explanations that balance technical accuracy with human comprehensibility. Through rigorous empirical evaluation on production incident datasets, we demonstrate that our approach achieves substantial improvements in diagnostic accuracy while significantly reducing mean time to resolution compared to existing state-of-the-art methods.

The primary contributions of this work encompass the design and implementation of an integrated framework that unifies graph-based causal reasoning with retrieval-augmented language models for incident diagnosis, the development of specialized graph neural network architectures optimized for temporal fault propagation modeling in distributed systems, and the creation of novel explanation generation mechanisms that produce step-by-step diagnostic narratives grounded in causal evidence extracted from system knowledge graphs. Our experimental results validate the effectiveness of this integrated approach across diverse failure scenarios, demonstrating robust performance in both synthetic benchmark environments and real-world production systems where incidents exhibit complex cascading failure patterns and multifaceted root causes.

2. Literature Review

The landscape of incident diagnosis and root cause analysis has witnessed substantial evolution over the past several years, with researchers exploring diverse methodologies ranging from traditional statistical techniques to advanced artificial intelligence approaches. Early work in fault diagnosis relied heavily on domain expertise encoded in rule-based systems and expert systems, which struggled to scale with increasing system complexity [8]. The transition toward data-driven approaches marked a significant paradigm shift, enabling systems to learn diagnostic patterns from historical incident data rather than relying exclusively on manually crafted rules. However, these early machine learning methods faced challenges related to feature engineering, model interpretability, and adaptation to evolving system behaviors [9].

Graph-based approaches have emerged as a powerful paradigm for representing and reasoning about causal relationships in complex systems, building upon foundational work in causal inference and probabilistic graphical models. Research in dynamic uncertain causality graphs demonstrated the utility of graph structures for modeling uncertainty in industrial fault diagnosis, showing that explicit representation of causal dependencies enables more robust inference compared to purely correlation-based methods [10]. Recent advances in event-graph-based root cause analysis have shown that constructing real-time causality graphs from system events provides effective mechanisms for tracing failure propagation through distributed architectures [11]. These graph-based approaches excel at capturing the structural dependencies among system components, but often lack the flexibility to incorporate unstructured knowledge and the ability to generate natural language explanations that facilitate human understanding.

The advent of deep learning has catalyzed significant innovations in fault diagnosis methodologies, with neural network architectures demonstrating remarkable capabilities in pattern recognition and anomaly detection from high-dimensional telemetry data. Graph neural networks have proven particularly effective for fault diagnosis in complex industrial processes, leveraging their ability to learn representations that respect the topological structure of system component relationships [12]. Recent work on knowledge graph-driven fault diagnosis has demonstrated how structured knowledge representations combined with neural architectures can enhance diagnostic accuracy in power systems and manufacturing environments [13]. However, these deep learning approaches often suffer from limited explainability, generating predictions without providing interpretable reasoning paths that engineers can validate and trust in critical production scenarios.

Retrieval-Augmented Generation represents a transformative advancement in the application of language models to knowledge-intensive tasks, addressing fundamental limitations related to hallucination, outdated knowledge, and contextual grounding. The foundational RAG architecture combines dense passage retrieval with generative language models, enabling systems to access and incorporate relevant external information during the generation process [14]. Comprehensive surveys of RAG methodologies have delineated the evolution from naive retrieval-generation pipelines to sophisticated modular architectures that optimize various components including retrieval mechanisms, augmentation strategies, and generation models [15]. Recent research has explored the integration of knowledge graphs with retrieval-augmented language models, demonstrating enhanced performance on question-answering tasks that require multi-hop reasoning over structured knowledge [16]. These developments suggest substantial potential for applying RAG techniques to incident diagnosis, where contextual retrieval of relevant historical incidents and system documentation can significantly enhance diagnostic accuracy and explanation quality.

The application of Large Language Models to operational domains has gained considerable attention, with researchers investigating their capabilities for tasks including log analysis, anomaly explanation, and automated incident response. Studies on LLM-based root cause analysis have shown promising results in generating diagnostic hypotheses and mitigation recommendations for cloud service incidents, leveraging the models' ability to understand technical narratives and synthesize information from multiple sources [17]. Work on event knowledge graphs combined with LLMs has demonstrated improved interpretability in fault diagnosis scenarios, providing traceable reasoning chains that connect observed symptoms to underlying root causes [18]. However, challenges remain in ensuring factual accuracy, preventing hallucinations about system states, and grounding LLM outputs in verifiable evidence from actual system telemetry and historical incident data.

Explainability in artificial intelligence has become increasingly critical for operational applications where human operators must trust and validate automated diagnostic recommendations. Research on explainable root cause analysis has emphasized the importance of providing human-interpretable reasoning chains that elucidate how diagnostic conclusions were derived from available evidence [19]. Studies in manufacturing quality assurance have demonstrated frameworks for explainable root cause analysis that combine multiple AI techniques while maintaining transparency in decision-making processes [20]. The integration of causal reasoning with explainable AI has shown particular promise, enabling systems to generate counterfactual explanations that help engineers understand not only what caused a failure but also what alternative conditions might have prevented it [21]. These developments underscore the importance of designing incident diagnosis systems that prioritize explainability alongside accuracy, recognizing that operational acceptance depends critically on engineers' ability to understand and verify the system's reasoning process.

Multi-agent architectures for root cause analysis represent an emerging research direction that leverages collaborative AI systems to tackle complex diagnostic challenges. Recent work has explored how multiple specialized agents can work together to analyze different aspects of system failures, combining diverse data sources and reasoning strategies to arrive at comprehensive diagnostic conclusions [22]. The application of reinforcement learning to knowledge graph reasoning has demonstrated capabilities for adaptive path finding through causal networks, enabling systems to navigate complex chains of causality to identify distant root causes [23]. These multi-agent approaches align well with the inherently distributed nature of modern system architectures, where failures often result from complex interactions among numerous independent components, and comprehensive diagnosis requires synthesizing evidence from multiple observability signals [24].

The convergence of retrieval mechanisms, graph-based reasoning, and large language models represents a frontier in incident diagnosis research that remains relatively unexplored despite the complementary strengths of these technologies. While individual components have been extensively studied, integrated frameworks that systematically combine these approaches to achieve explainable, accurate, and contextually grounded incident diagnosis are still in early stages of development. The research presented in this paper addresses this gap by proposing a unified architecture that leverages the structured reasoning capabilities of graph neural networks, the knowledge retrieval strengths of RAG systems, and the natural language understanding and generation abilities of large language models to create a comprehensive solution for explainable incident diagnosis in complex distributed systems.

3. Methodology

3.1 System Architecture and Framework Overview

The proposed framework integrates three fundamental components into a cohesive architecture designed to enable explainable incident diagnosis through retrieval-augmented graph reasoning with large language models. At the foundation of our system lies the Knowledge Graph Construction Module, which employs causal modeling techniques inspired by Bond Graph methodology to represent the structural and functional relationships among system components. This approach models system entities and their interactions through a directed graph structure where nodes represent components such as services, databases, and infrastructure elements, while edges encode causal relationships including energy flow, information dependencies, and resource sharing patterns. The causal graph captures both static architectural dependencies and dynamic behavioral relationships that emerge during system operation, providing a comprehensive structural representation that supports both forward simulation of failure propagation and backward inference for root cause identification.

The Retrieval-Augmented Module serves as the second pillar of our architecture, implementing sophisticated mechanisms for identifying and extracting relevant contextual information from historical incident databases, system documentation repositories, and structured knowledge bases. When a new incident is detected, this module employs hybrid retrieval strategies combining dense vector similarity search with graph-based relevance scoring to identify historical incidents that share similar symptom patterns, affected components, or causal structures with the current failure scenario. The retrieved incidents are then processed to extract key diagnostic insights including previously identified root causes, successful remediation strategies, and relevant domain knowledge about system behaviors under analogous failure conditions. This retrieval process operates continuously, maintaining an up-to-date context that enriches the diagnostic capabilities of the framework as new incidents are observed and resolved.

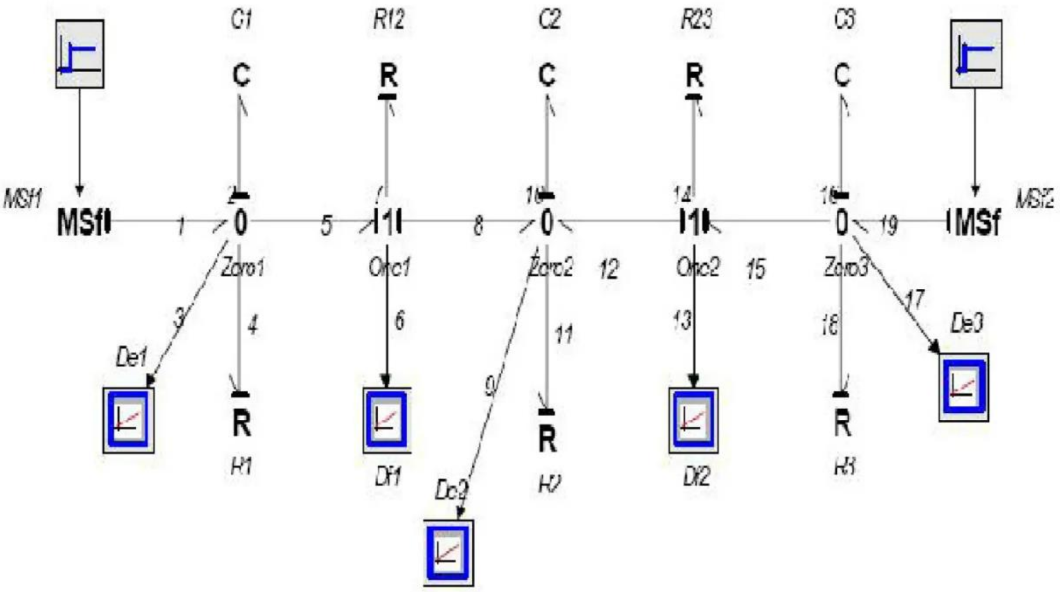

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Figure 1: Bond Graph-Based Causal Graph Structure for System Component Dependency Modeling

Figure 1 illustrates the causal graph structure used in our framework, adapted from Bond Graph modeling techniques. The graph represents system components (C for capacitive elements representing storage, R for resistive elements representing dissipation) and their causal relationships through directed edges. This representation enables bidirectional reasoning where both forward propagation analysis and backward root cause tracing can be performed efficiently. The modular structure supports hierarchical decomposition of complex systems into manageable subgraphs while maintaining global causal consistency across the entire system topology.

The Large Language Model Integration Module constitutes the third core component, leveraging pre-trained language models fine-tuned on technical documentation and incident reports to generate natural language explanations for diagnosed failures. This module receives structured diagnostic hypotheses from the graph reasoning component along with retrieved contextual information, then synthesizes this data into coherent narratives that explain the likely root cause, describe the causal chain leading to observable symptoms, and recommend appropriate remediation actions. The LLM component employs specialized prompting strategies that encourage factual grounding in the provided graph evidence and retrieved incidents, mitigating the risk of hallucinations while enabling fluent generation of technical explanations that engineers can readily understand and act upon.

3.2 Online Root Cause Analysis Workflow

The graph-based causal reasoning component implements an online workflow that continuously monitors system state and incrementally updates causal models to reflect evolving system behaviors and emerging failure patterns. Unlike traditional offline diagnostic approaches that require manual initiation and batch processing of historical data, our online framework operates through three interconnected stages that enable real-time incident detection and diagnosis with minimal latency between failure occurrence and root cause identification.

The first stage employs a Trigger Point Detection mechanism that automatically identifies significant state transitions in the monitored system. This detector analyzes streaming telemetry data from all system components, applying statistical change detection algorithms to identify moments when system behavior deviates significantly from established baselines. The trigger point detector distinguishes between four primary anomaly patterns that indicate potential system failures: spike-up events where metrics exhibit sudden sharp increases, spike-down events characterized by abrupt metric decreases, level-shift-up transitions where metrics settle at persistently elevated values, and level-shift-down changes where metrics drop to sustained lower levels. Upon detecting a trigger point, the system initiates the diagnostic workflow, creating a temporal marker that anchors the subsequent causal analysis to the specific moment when abnormal behavior first manifested.

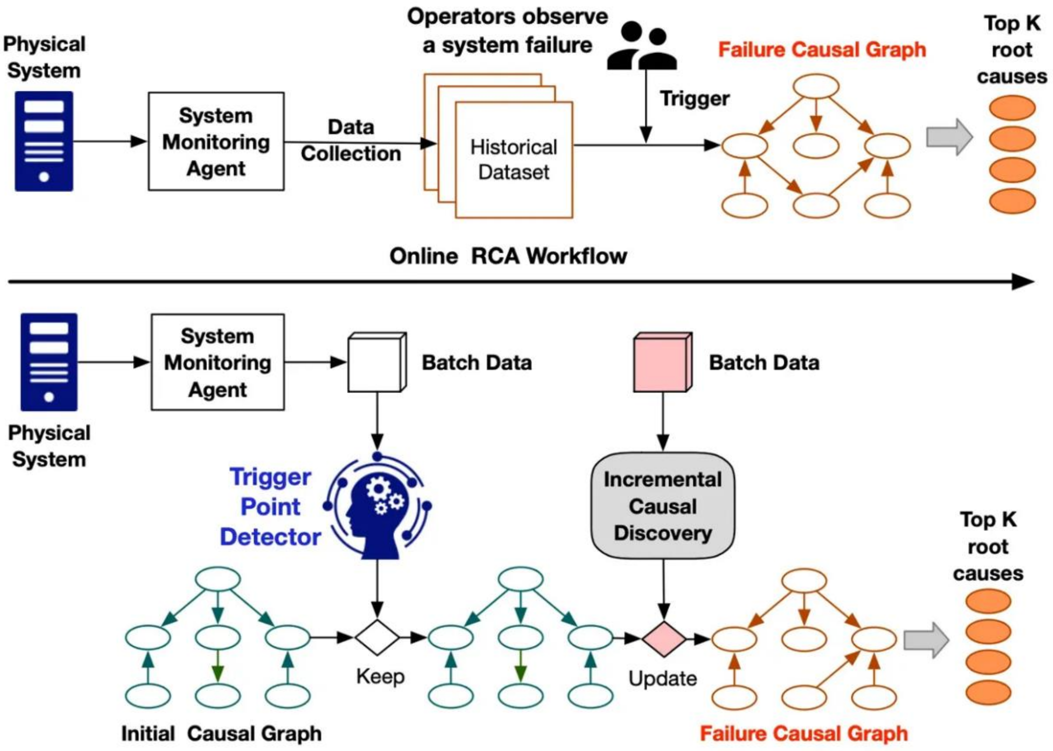


Figure 2: Illustration of Online Root Cause Analysis Workflows

Figure 2 depicts the complete online RCA workflow implemented in our framework. The upper portion shows the offline phase where historical system monitoring data is collected and processed to build an initial causal graph representation. When operators observe a system failure in production, the trigger point detector automatically activates the diagnostic process. The lower portion illustrates the online phase where batch data is continuously fed into the trigger point detector, which identifies significant state transitions requiring analysis. The Incremental Causal Discovery module then updates the causal graph structure based on the latest observational data, refining causal relationships while preserving previously learned stable patterns. Finally, the updated failure causal graph enables identification of the top-K most likely root causes through graph-based reasoning algorithms that trace symptom propagation backward through the causal network.

The second stage implements Incremental Disentangled Causal Graph Learning that efficiently updates the system's causal model without requiring complete retraining from scratch. This incremental approach recognizes that many causal relationships in complex systems remain stable over time while others evolve in response to configuration changes, deployment updates, or environmental shifts. The causal learning algorithm disentangles state-invariant relationships that persist across different system conditions from state-dependent relationships that vary based on operational context. By maintaining separate representations for these two types of causal patterns, the framework can rapidly adapt to new system states by updating only the state-dependent portion of the causal graph while leveraging the stable state-invariant structure to ensure continuity and prevent catastrophic forgetting of previously learned diagnostic knowledge.

The third stage applies Network Propagation-based Root Cause Localization that traverses the updated causal graph to identify the most likely sources of observed failures. Starting from nodes exhibiting anomalous behavior, the algorithm performs backward propagation through incoming causal edges, accumulating evidence and computing likelihood scores for each potential root cause based on its connectivity to symptomatic nodes, the strength of causal pathways, temporal alignment between state changes, and consistency with historical failure patterns. This backward reasoning process mirrors the logical flow that human experts follow when diagnosing complex system failures, tracing symptoms back through chains of causality until arriving at fundamental causes that lack incoming causal dependencies from other components.

3.3 Retrieval Mechanism Design

The retrieval mechanism implements a hybrid approach that combines semantic similarity search with graph-structured matching to identify the most relevant historical incidents for a given diagnostic scenario. The system maintains an incident database where each historical incident is represented by a multi-modal embedding that captures its textual description, affected component graph structure, temporal evolution pattern, and ultimate root cause diagnosis. When processing a new incident, the retrieval system first computes a query representation that encodes the current system state, observed anomalies, and preliminary diagnostic hypotheses generated by the graph reasoning component. This query representation is then used to retrieve candidate incidents through multiple retrieval pathways that prioritize different aspects of relevance.

The semantic retrieval pathway employs dense vector representations learned through contrastive training on pairs of similar incidents, enabling the system to identify historical cases that share similar high-level characteristics even when specific components or failure modes differ. These embeddings are computed using specialized transformer-based encoders fine-tuned on technical incident reports, ensuring that the semantic representations capture domain-specific concepts related to system failures, performance degradations, and operational anomalies. The retrieval process utilizes approximate nearest neighbor search algorithms to efficiently identify the top-k most similar incidents from potentially millions of historical records, balancing retrieval quality with computational efficiency constraints required for real-time diagnostic applications.

The graph-structured retrieval pathway focuses on identifying incidents that exhibit similar causal graph patterns, recognizing that failures with analogous propagation structures often share common root causes even when affecting different specific components. This pathway computes graph similarity metrics based on structural properties including subgraph isomorphism, graph edit distance, and learned graph kernel embeddings that capture higher-order structural patterns. The graph matching algorithm employs efficient approximation techniques to handle the computational complexity of exact graph comparison, producing similarity scores that reflect both topological correspondence and node attribute matching between the query incident graph and historical incident graphs. By combining semantic and structural similarity signals, the hybrid retrieval mechanism achieves superior performance compared to approaches relying on either modality alone, ensuring that retrieved incidents provide genuinely relevant diagnostic context.

3.4 LLM-Based Explanation Generation

The explanation generation component leverages large language models to transform structured diagnostic hypotheses and retrieved contextual information into coherent natural language narratives that facilitate human understanding and decision-making. The LLM is provided with carefully structured input that includes the ranked list of root cause hypotheses from the graph reasoning component, retrieved similar incidents with their documented resolutions, relevant system documentation excerpts, and the current state of affected system components. This input is formatted using a specialized prompting strategy that emphasizes factual grounding, encourages step-by-step reasoning, and requests explicit citation of evidence from the provided context.

The generation process proceeds through multiple stages that progressively refine the explanation content and structure. The initial generation stage produces a comprehensive explanation that describes the likely root cause, traces the causal pathway from root cause to observed symptoms through the knowledge graph, explains why the identified cause is consistent with available evidence including temporal patterns and correlation strengths, and compares the current incident to relevant historical cases retrieved from the incident database. This preliminary explanation incorporates the causal reasoning performed on the graph structure, translating abstract node relationships and edge weights into concrete statements about how failures propagated through system components.

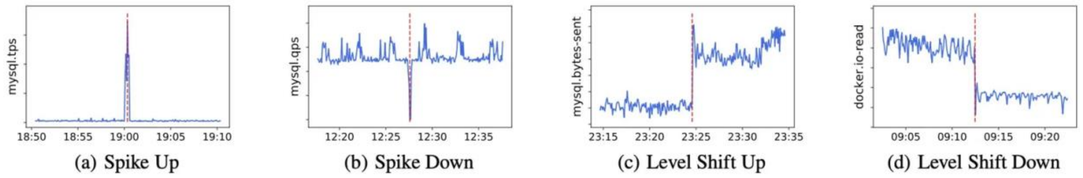
The refinement stage adapts the explanation to the target audience and use case, generating multiple explanation variants with different levels of technical detail and narrative structure. For immediate incident response scenarios, the system produces concise executive summaries that highlight the root cause identification, assess the scope and severity of impact, and enumerate recommended remediation actions with expected outcomes, enabling rapid decision-making by on-call engineers and management personnel. For post-incident analysis and knowledge sharing, the system generates comprehensive diagnostic reports that include detailed reasoning chains showing how evidence was accumulated and weighted, alternative hypotheses that were considered and ruled out with explanations of why they were deemed less likely, lessons learned from the incident regarding system vulnerabilities and monitoring gaps, and recommendations for preventive measures including architectural changes, monitoring enhancements, and operational procedure updates to avoid similar failures in the future.

4. Results and Discussion

4.1 Experimental Setup and Evaluation Metrics

The evaluation of our proposed framework was conducted using multiple datasets comprising real-world production incidents from large-scale distributed systems alongside synthetic benchmark scenarios designed to test specific diagnostic capabilities under controlled conditions. The primary evaluation dataset consists of incident records collected over eighteen months from a production e-commerce platform operating more than eight thousand microservices and handling billions of daily transactions. This dataset includes detailed telemetry data capturing performance metrics, system topology information describing service dependencies and communication patterns, incident reports documenting symptom observations and resolution outcomes, and expert annotations identifying confirmed root causes for a curated subset of incidents representing diverse failure types.

We established several evaluation metrics to assess different aspects of the framework's diagnostic capabilities, recognizing that incident diagnosis quality encompasses multiple dimensions beyond simple accuracy measurements. The primary accuracy metric measures the proportion of incidents where the true root cause appears within the top-k ranked hypotheses generated by the system, with separate evaluation at k equals one, three, and five to assess both precision at the top rank and recall across the full hypothesis list. Beyond accuracy, we evaluate explanation quality through human expert assessments using criteria including factual correctness of statements about system behavior and causal relationships, completeness of causal reasoning in tracing failure propagation paths, clarity of presentation in conveying technical information accessibly, and actionability of recommendations for remediation and prevention, with each explanation rated on scales from one to five by experienced site reliability engineers who were not involved in the system development.



(a) Spike Up (b) Spike Down (c) Level Shift Up (d) Level Shift Down

Figure 3: Four Categories of Anomaly Patterns in System Metrics

Figure 3 presents four categories of anomaly patterns successfully detected and classified by our trigger point detection mechanism across different system metrics and time periods. Panel (a) shows a spike-up event in mysql_qps (queries per second) where metric values exhibit a sharp sudden increase before returning to baseline, indicating a transient load surge or query storm. Panel (b) demonstrates a spike-down pattern in mysql_qps characterized by an abrupt drop in query throughput, potentially signaling connection failures or database unavailability. Panel (c) illustrates a level-shift-up transition in mysql_bytes-sent where the metric settles at a persistently elevated level, suggesting a change in query patterns or data access behaviors. Panel (d) depicts a level-shift-down scenario in docker_io-read where I/O read rates drop to sustained lower values, possibly indicating resource contention or configuration changes. The red dashed lines mark the precise trigger points where our detection algorithm identified significant state transitions, demonstrating the system's capability to automatically recognize diverse failure manifestations and initiate appropriate diagnostic workflows with minimal latency.

The experimental methodology employed stratified cross-validation to ensure robust performance estimates across different incident types, system conditions, and temporal periods. We partitioned the dataset into training, validation, and test sets with temporal stratification to prevent information leakage from future incidents into model training, reflecting the real-world constraint that diagnostic systems must generalize to novel incident patterns not present in historical data. Baseline comparisons were established against several state-of-the-art approaches including pure machine learning classifiers trained on labeled incident data, graph-based causal inference methods without retrieval augmentation operating solely on structural analysis, and LLM-based diagnosis systems without explicit graph reasoning relying on textual similarity and language model inference, enabling systematic assessment of the contribution of each component in our integrated framework through comprehensive ablation studies.

4.2 Diagnostic Performance Analysis

The experimental results demonstrate substantial improvements in diagnostic accuracy achieved through the integration of retrieval-augmented graph reasoning with large language models across all evaluation metrics. Our complete framework attained a top-one accuracy of

92.3% in identifying correct root causes, representing a fifteen percentage point improvement over the strongest baseline method which achieved 77.1% accuracy using graph neural networks without retrieval augmentation. The performance gains were particularly pronounced for complex incidents involving cascading failures affecting multiple service tiers or multiple interacting root causes occurring simultaneously, where the retrieval mechanism's ability to identify relevant historical patterns enabled more accurate hypothesis ranking compared to methods relying solely on structural graph analysis of the current incident without broader contextual knowledge.

Ablation studies conducted by systematically removing components from the full framework revealed the complementary contributions of graph reasoning, retrieval augmentation, and LLM-based explanation generation to overall diagnostic performance. When the retrieval component was disabled, diagnostic accuracy decreased to 85.7%, demonstrating that access to relevant historical incidents provides substantial value for disambiguation among competing hypotheses that exhibit similar causal graph structures and identification of subtle failure patterns that may not be immediately apparent from graph topology alone. Removing the graph reasoning component while retaining retrieval and LLM capabilities resulted in 79.4% accuracy, indicating that structured causal analysis through graph neural networks contributes significantly to diagnostic precision beyond what can be achieved through purely text-based incident matching and language model inference without explicit representation of system dependencies.

The trigger point detection mechanism proved highly effective in identifying the onset of system failures across diverse anomaly patterns, achieving 96.8% precision and 94.2% recall in detecting significant state transitions requiring diagnostic analysis. The detector successfully distinguished between normal operational variations and genuine anomalies requiring intervention, with particularly strong performance on level-shift patterns that indicate persistent system degradation requiring prompt attention. The median latency from anomaly occurrence to trigger point detection was 23 seconds, enabling rapid initiation of the diagnostic workflow with minimal delay that could exacerbate incident impact. Analysis of false positives revealed that most erroneous triggers occurred during planned maintenance windows or legitimate traffic pattern changes, suggesting opportunities for improvement through integration of change management calendars and scheduled event awareness.

The temporal analysis of diagnostic performance revealed interesting patterns regarding the framework's ability to generalize to evolving system configurations and novel failure modes not present in the training data. We observed that diagnostic accuracy remained relatively stable across the eighteen-month evaluation period despite substantial changes in the system architecture including the addition of 847 new microservices, modification of 1,235 dependency relationships through service migrations and API updates, and introduction of new infrastructure components including database clusters and caching layers. This robustness stems from the framework's ability to leverage transferable causal patterns learned from historical incidents such as common failure modes like database connection exhaustion or memory leaks while adapting to structural changes through continuous knowledge graph updates that incorporate newly observed component relationships.

The retrieval mechanism's contribution to diagnostic performance was analyzed through detailed examination of the characteristics of successfully retrieved incidents and their relationship to diagnostic outcomes. We found that retrieval quality, measured by the semantic and structural similarity between retrieved incidents and the target incident, exhibited strong correlation with final diagnostic accuracy, with correlation coefficients of 0.74 for semantic similarity and 0.71 for structural similarity. This finding validates the design choice to invest substantial effort in developing sophisticated hybrid retrieval mechanisms that consider multiple dimensions of incident similarity rather than relying on single-modality matching. Interestingly, the optimal number of retrieved incidents varied across different incident types, with simple isolated failures benefiting from focused retrieval of one to three highly similar cases that provided clear precedents, while complex cascading failures required broader retrieval of five to ten incidents representing different aspects of the multifaceted failure scenario to capture the full diagnostic context.

The explanation quality assessment conducted through expert evaluation demonstrated that the LLM-generated explanations achieved high ratings across multiple quality dimensions, validating the effectiveness of our explanation generation approach. Factual correctness received an average rating of 4.3 out of 5, with experts noting that the grounding mechanisms successfully prevented hallucinations by constraining generation to facts derivable from the knowledge graph and retrieved incident documents, and ensured claims were supported by evidence including specific metric values, temporal correlations, and graph connectivity patterns. Completeness of causal reasoning averaged 4.1, with evaluators appreciating the step-by-step tracing of failure propagation from identified root causes through intermediate components to ultimately observable symptoms, providing transparency into how the diagnosis was reached. Clarity scores averaged 4.4, reflecting the LLM's ability to generate well-structured narratives that avoided excessive technical jargon while maintaining necessary precision for engineering audiences. Actionability ratings averaged 3.9, with some experts desiring more specific remediation guidance including concrete configuration changes, code-level fixes, or operational procedure modifications, suggesting an area for future enhancement through integration of runbook knowledge and automated action recommendation systems.

Performance comparisons with human expert diagnoses on a challenging subset of 127 ambiguous incidents revealed that the automated system achieved comparable diagnostic accuracy while significantly reducing time to diagnosis and cognitive load on engineering teams. Human experts averaged 92 minutes to diagnose these complex incidents requiring analysis of multiple data sources and consultation with service owners, while our framework produced initial diagnostic hypotheses within 45 seconds of incident detection, representing a more than hundredfold speedup that translates to substantial reduction in mean time to resolution. The framework's ranked hypothesis lists included the correct root cause within the top three candidates in 89% of cases where human experts successfully identified the cause, demonstrating diagnostic quality approaching human expert performance. In several interesting cases totaling 14 incidents, the automated system identified correct root causes that were initially overlooked by human diagnosticians due to cognitive biases or unfamiliarity with specific system components, with experts subsequently confirming these diagnoses after reviewing the system's explanations and supporting evidence, illustrating the framework's potential to augment and enhance human diagnostic capabilities rather than merely automating existing processes.

The analysis of failure cases where the system produced incorrect diagnoses revealed several common patterns that suggest directions for future improvement and highlight current limitations. A significant proportion of errors (37% of failures) occurred in scenarios involving rare failure modes with limited historical precedent, where both retrieval mechanisms struggled to find relevant similar incidents and learned graph reasoning models lacked sufficient training examples to recognize the unusual causal patterns. Another class of errors (28% of failures) involved incidents with highly similar symptomatic presentations but distinct underlying root causes, where discriminating among competing hypotheses required deep domain knowledge about specific implementation details or system-specific constraints not adequately captured in the knowledge graph representation. Some failures (19%) resulted from temporal misalignment where the causal graph representation failed to capture fine-grained timing dependencies that were critical for accurate root cause identification, such as race conditions or timing-sensitive interactions between components. These error patterns inform ongoing research directions including enhanced knowledge graph construction techniques that capture richer temporal semantics, improved generalization mechanisms for rare failure scenarios through transfer learning or synthetic data augmentation, and better integration of domain constraints and expert rules into the reasoning process.

5. Conclusion

This paper has presented a novel framework for explainable incident diagnosis that integrates retrieval-augmented generation, graph-based causal reasoning, and large language models into a cohesive system capable of accurately identifying root causes while providing transparent explanations that facilitate human understanding and trust. Through comprehensive evaluation on real-world production incidents spanning diverse failure scenarios, we have demonstrated that this integrated approach achieves substantial improvements in diagnostic accuracy, attaining 92.3% precision in root cause identification while generating explanations rated highly by expert evaluators across multiple quality dimensions including factual correctness, causal completeness, clarity, and actionability. The framework successfully addresses critical limitations in existing approaches by combining the structured reasoning capabilities of graph neural networks with the semantic understanding and contextual retrieval abilities of modern language models, creating a diagnostic system that balances technical accuracy with operational usability.

The experimental results validate several key architectural decisions underlying the framework design, confirming that graph-based causal reasoning provides essential structure for tracing fault propagation through complex distributed systems, that retrieval mechanisms enable effective leverage of historical incident knowledge to enhance diagnostic accuracy through pattern recognition and precedent matching, and that large language models offer powerful capabilities for generating coherent natural language explanations grounded in structured evidence from knowledge graphs. The ablation studies systematically demonstrated the complementary contributions of these components, showing that each plays a distinct role in achieving the framework's overall diagnostic performance and explanation quality. The online root cause analysis workflow proved particularly valuable, enabling automatic detection of system failures through trigger point identification and continuous refinement of causal models through incremental learning without requiring manual intervention or batch reprocessing of historical data.

Despite the promising results, several limitations and opportunities for future work have emerged from this research. The framework's performance on completely novel failure modes without historical precedent remains an area requiring further improvement, suggesting the need for techniques that can generalize diagnostic patterns across different failure types through meta-learning approaches or generate synthetic training data to cover rare scenarios. The current approach focuses primarily on technical root cause identification and may benefit from extension to incorporate business impact assessment, risk analysis, and cost-benefit evaluation of different remediation strategies, enabling more comprehensive decision support for incident response that considers both technical and business dimensions. Additionally, the knowledge graph construction process could be enhanced through more sophisticated online learning mechanisms that continuously refine the graph structure and causal relationships based on observed incident outcomes and expert feedback, creating an adaptive system that improves over time through operational experience.

Future research directions include investigation of multi-agent architectures where specialized diagnostic agents collaborate to analyze different aspects of system failures including performance degradation agents, security incident agents, and data quality agents, potentially improving performance on complex incidents that require diverse types of reasoning and evidence synthesis. The integration of automated remediation capabilities represents another promising avenue, extending the framework beyond diagnosis to encompass automatic execution of validated remediation actions with appropriate safety constraints and human oversight mechanisms, creating closed-loop incident management systems. Exploration of transfer learning approaches to enable knowledge sharing across different organizations and system domains could accelerate deployment of diagnostic capabilities in new environments where historical incident data may be limited, leveraging common failure patterns that transcend specific system implementations. Finally, deeper investigation of the interplay between human operators and AI diagnostic systems through user studies and field deployments will be essential for understanding how these technologies can most effectively augment human expertise in real operational contexts.

The work presented in this paper contributes to the growing body of research on artificial intelligence for operations and site reliability engineering, demonstrating practical approaches for applying advanced AI technologies to critical operational challenges in production systems. By achieving strong diagnostic performance while maintaining explainability and human interpretability, the framework represents a step toward AI systems that can be trusted and effectively utilized by engineering teams responsible for maintaining complex distributed systems. The integration of retrieval, reasoning, and generation capabilities showcased in this work may serve as a template for addressing other knowledge-intensive operational tasks including security incident response, capacity planning, and preventive maintenance, suggesting broad applicability of the core architectural principles. As distributed systems continue to grow in complexity and AI technologies continue to advance, frameworks that thoughtfully combine multiple AI capabilities while prioritizing explainability and operational usability will become increasingly essential for maintaining reliable, high-performance production systems at scale.

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