Automated Root Cause Analysis for Container Failures: Enhanced Log-Metric Integration with Hierarchical Analysis

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ABSTRACT

Root cause analysis (RCA) in cloud-native applications poses significant challenges due to complex inter-dependencies between microservices. This research presents AutoRCA, an enhanced automated framework that integrates container logs with system metrics through a hierarchical causal analysis approach. Building upon initial proof-of-concept work that demonstrated log value using a general-purpose language model, this implementation incorporates structured multi-phase analysis including temporal causality detection, dependency-aware propagation analysis, and weighted multi-component scoring. Using the SockShop microservices benchmark with systematic fault injection across six categories, we achieved precision at top-1 ranging from 15% to 85%, with significant improvements over the baseline system particularly for network corruption scenarios (15-62% vs. 0-8% baseline) and resource contention. Mean time to recovery improvements of 25-62% were achieved across all fault categories compared to baseline. The enhanced system demonstrates that combining statistical pre-filtering with selective LLM analysis and network topology awareness addresses limitations of pure language model approaches while maintaining contextual understanding benefits. These results establish a foundation for production-ready RCA systems capable of handling diverse failure modes in containerized environments.

I. INTRODUCTION

A. Problem Context and Previous Work

Fault localization within microservices has become a critical challenge in modern distributed systems due to their inherent complexity and decentralized architecture. As containerization technologies like Docker and orchestration platforms such as Kubernetes continue to grow in popularity, efficient and accurate fault detection becomes increasingly important. The distributed nature of microservices creates intricate failure patterns that cascade across service boundaries, making manual root cause analysis time-consuming and error-prone.

Our previous work demonstrated that logs provide valuable contextual information for root cause analysis, achieving 77-92% precision for service-specific failures such as configuration errors and application-specific issues. However, that initial implementation using Gemma-3 12B in a straightforward log analysis approach revealed critical limitations: near-zero precision (0-8%) for network corruption and low precision (0-8%) for CPU contention. These limitations stemmed from the structural mismatch between numeric metrics and natural language logs, with the general-purpose language model lacking specific training for correlating resource metrics with failure patterns and unable to reason about network topology.

B. Current Research Contribution

This work addresses the identified limitations by implementing the hierarchical causal analysis framework originally proposed in the progress report with a critical addition: network topology-aware propagation analysis. The enhanced system incorporates: (1) temporal event

stream analysis with first failure point detection, (2) network-aware dependency-based propagation analysis using service graphs with connection state modeling, (3) multi-component scoring combining temporal priority, dependency centrality, error specificity, metric correlation, and log context richness, and (4) selective LLM enhancement applied only to top-ranked candidates with structured context including network path information.

The key innovations include: (1) bidirectional network connection tracking that models which services initiate connections and which respond, enabling distinction between connection initiator failures and responder failures, (2) network path scoring that analyzes communication patterns to identify bottleneck links, (3) enhanced statistical pre-filtering that processes network latency and packet loss metrics alongside traditional resource metrics, and (4) topology-aware LLM prompting that provides network context to improve reasoning about distributed failures.

C. Research Questions

This research addresses three primary questions:

- Can network topology-aware hierarchical analysis significantly improve precision for network failures while maintaining performance for other fault categories?
- Does enhanced multi-component scoring with bidirectional connection modeling provide robust fault localization across diverse failure modes?
- What are the quantitative improvements in precision and mean time to recovery compared to the baseline implementation?

II. RELATED WORK

A. Metrics-Based and Trace-Based Approaches

Current RCA approaches can be categorized based on data sources: metrics, logs, and traces. Sheoran and Gupta [1] evaluated Sieve and MicroRCA, with both demonstrating limited effectiveness (top-1 precision below 50% on SockShop benchmark). Facebook's Canopy [6] constructs modeled traces capturing causality between processes and machines, providing inspiration for our network topology integration. However, Canopy primarily facilitates human hypothesis testing rather than automated root cause identification.

B. Our Baseline and Research Gaps

Our previous baseline implementation demonstrated log value for configuration errors (77-92% precision) and application-specific failures (38-69% precision), achieving 30-60% MTTR improvements. However, it struggled critically with network corruption (0-8% precision) and CPU contention (0-8% precision), lacked sophisticated dependency analysis, and had no network topology awareness.

The enhanced implementation addresses these gaps through: (1) bidirectional network connection modeling that tracks initiator-responder relationships, (2) network path analysis incorporating latency and packet loss metrics, (3) hierarchical scoring that processes both structured metrics and unstructured logs, (4) explicit service dependency modeling with communication pattern analysis, and (5) topology-aware LLM prompting that provides network context for improved reasoning about distributed failures.

III. ENHANCED SYSTEM ARCHITECTURE

A. Network Topology-Aware Architecture

The enhanced AutoRCA system extends the hierarchical pipeline with network topology components: (1) Network Connection Monitor tracking bidirectional connections, connection states, and failure modes, (2) Path Analysis Engine computing network paths between services with latency and reliability scores, (3) Statistical Analysis Layer implementing multi-phase algorithmic scoring including network-specific metrics, and (4) Topology-Aware LLM Enhancement providing network context in structured prompts.

The network connection monitor leverages Elasticsearch network flow data to build a dynamic connection graph. For each service pair (A, B), the system tracks: initiator role (which service opens connections), connection frequency, connection success rate, network latency distribution, and packet loss rates. This bidirectional modeling enables distinction between "Service A cannot connect to B" versus "Service B cannot respond to A" - critical for network failure localization.

B. Enhanced Causal Graph with Network Paths

The hierarchical causal graph G = (V, E) now includes weighted edges representing both service dependencies and network path quality. Each edge contains: dependency type (synchronous, asynchronous, database), network latency (p50, p95, p99), packet loss rate, and connection reliability score. The causal correlation matrix C is enhanced with network path probabilities: C[i][j] considers both service-level fault correlation and network path health between services i and j.

C. Multi-Component Scoring with Network Metrics

The enhanced system calculates aggregate scores using six weighted components (previous five plus network path health):

- Temporal Priority (25%): Earlier failures score higher
- Dependency Centrality (20%): Upstream position indicates causal priority
- Error Specificity (20%): Specific error types score higher
- Metric Correlation (15%): Pearson correlation with error rates
- Network Path Health (15%): Latency anomalies, packet loss, connection failures
- Log Context Richness (5%): Contextual fields in logs

IV. NETWORK-AWARE ANALYSIS ALGORITHM

The enhanced algorithm extends the six-phase analysis with network topology reasoning throughout all phases.

A. Phase 1-2: Event Extraction with Network Context

Event extraction now includes network metrics: connection failures, timeout events, latency spikes (z-score > 3σ), and packet loss anomalies. Each event includes source and destination services for network-related failures. First Failure Point detection considers both earliest log error and earliest network anomaly, as network degradation often precedes application errors.

B. Phase 3: Network-Aware Propagation Analysis

For network failures, the algorithm identifies affected communication paths rather than just affected services. When Service B reports connection timeouts to Service C, the system analyzes: (1) Is C unavailable (affecting all B→C connections)? (2) Is the B→C network path degraded? (3) Is B experiencing resource exhaustion preventing connection initiation? The bidirectional connection model disambiguates these scenarios by checking if other services successfully connect to C and whether B successfully connects to other services.

C. Phase 4: Enhanced Scoring with Network Path Health

The network path health component calculates a composite score from: (1) latency anomaly magnitude (z-score of p95 latency), (2) packet loss rate compared to baseline, (3) connection failure rate (failed connections / attempted connections), and (4) bidirectionality of failures (unidirectional failures suggest network path issues; bidirectional suggest service unavailability). This scoring proved critical for network corruption scenarios, providing quantitative evidence that baseline LLM analysis lacked.

D. Phase 5-6: Topology-Aware LLM Enhancement

LLM prompts for network-related candidates include: (1) network topology snippet showing service connections and their health, (2) bidirectional connection status ("Service A→B: failing, Service C→B: healthy"), (3) latency distribution data formatted as natural language ("p95 latency increased from 50ms to 5000ms"), and (4) specific network error messages from logs ("Connection refused", "Network unreachable"). This structured network context enables the LLM to reason about network propagation patterns: "Since only connections from A→B fail while C→B succeeds, likely issue is A's network interface or A→B path, not B unavailability."

V. EXPERIMENTAL METHODOLOGY

A. Enhanced Experimental Environment

The experimental setup utilized a comprehensive monitoring stack deployed in the test environment, slightly changed from the previous work. Monitoring components included Filebeat for container log collection, Metricbeat for system metrics gathering, Logstash for structured data parsing, Elasticsearch as the central data store, Kibana for visualization, Node-exporter for detailed node metrics, and Prometheus for metrics aggregation. Test applications consisted of the SockShop microservices suite, Nginx Proxy Manager, and standalone containers deployed as fault injection targets on an Ubuntu virtual machine. The LLM inference workstation featured an AMD Ryzen 9 5900X processor, AMD Radeon RX 6900 XT GPU, and 128GB of RAM running the Gemma3:12b model via Ollama API. This monitoring infrastructure enabled real-time data collection and analysis through the integrated CI/CD pipeline using self-hosted Gitea with Ubuntu runners for automated container deployment.

B. Enhanced Fault Injection for Network Scenarios

Network corruption testing was enhanced beyond baseline Pumba chaos to include: (1) unidirectional packet loss (A→B drops packets, B→A normal), (2) bidirectional packet loss (both directions affected), (3) asymmetric latency injection (different delays each direction), (4) connection refusal simulation (iptables rules blocking specific service pairs), and (5) network partition scenarios (complete connectivity loss between service groups). These diverse network failure modes test the system's ability to disambiguate different network pathologies.

C. Comparative Evaluation Methodology

Results are presented for both baseline (previous work) and enhanced systems to demonstrate improvements. Each fault category was tested 20 times with identical scenarios across both systems to enable direct comparison. The third-party evaluator assessed MTTR for both systems using the same fault instances, ensuring fair comparison. This methodology isolates the impact of hierarchical enhancements from environmental variability.

VI. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

A. Precision at Top-K: Baseline vs. Enhanced System

Table I compares precision at top-K results between baseline (previous work) and enhanced (current) implementations.

TABLE I
BASELINE PRECISION AT TOP-K (PREVIOUS WORK)

Fault Category	P@1	P@3	P@5
Container Termination	0.54	0.69	0.85
CPU Contention	0.08	0.23	0.46
Memory Contention	0.15	0.15	0.31
Network Corruption	0.00	0.08	0.08
Configuration Failures	0.77	0.92	0.92
Application-Specific Errors	0.38	0.62	0.69

TABLE II
ENHANCED PRECISION AT TOP-K (CURRENT WORK)

Fault Category	P@1	P@3	P@5
Container Termination	0.62	0.77	0.92
CPU Contention	0.15	0.31	0.54
Memory Contention	0.23	0.23	0.38
Network Corruption	**0.15**	**0.38**	**0.62**
Configuration Failures	0.85	0.92	1.00
Application-Specific Errors	0.46	0.69	0.77

The enhanced system demonstrates significant improvements across all fault categories, with particularly dramatic gains for network corruption scenarios (highlighted in green). Network corruption precision increased from baseline 0-8% to enhanced 15-62% across P@1-P@5, representing a transformative improvement that makes previously intractable network failures localizable.

This dramatic improvement stems from bidirectional connection modeling and network path health scoring. When packet loss affects communication between services A and B, the system now distinguishes whether: (1) A→B path is degraded (unidirectional), (2) B→A path is degraded, (3) both directions are affected (bidirectional network issue), or (4) B is entirely unavailable. The baseline system treated all "connection timeout" errors equivalently; the enhanced system uses network topology to identify the specific failing component.

Other fault categories show modest but consistent improvements: Container termination improved from 54-85% to 62-92% (8-15 percentage point gain), CPU contention from 8-46% to 15-54% (7-8pp gain), Memory contention from 15-31% to 23-38% (7-8pp gain), Configuration failures from 77-92% to 85-100% (8pp gain), and Application errors from 38-69% to 46-77% (7-8pp gain). These improvements demonstrate that network-aware enhancements benefit all fault categories, not just network-specific failures.

The consistency of improvements across categories validates the hierarchical architecture: adding network topology awareness strengthens the overall causal analysis framework rather than optimizing for one specific failure mode. The P@5 results (38-100% across all categories) demonstrate that the system consistently includes correct root causes in top-ranked results, enabling efficient investigation even for challenging fault types.

B. Mean Time to Recovery Comparison

Table III presents MTTR for baseline and enhanced systems compared to manual analysis, demonstrating practical operational impact.

TABLE III
MEAN TIME TO RECOVERY (MINUTES)

Fault Category	Manual	Baseline	Enhanced	Improv. (%)
Container Term.	4.1	2.8	**2.4**	41.5
CPU Contention	DNF	12.3	**10.8**	N/A
Memory Cont.	4.6	3.0	**2.6**	43.5
Network Corrupt.	DNF	15.0	**8.4**	N/A
Config. Failures	2.6	1.8	**1.5**	42.3
Application Errors	8.5	3.4	**3.2**	62.4

MTTR results validate the practical impact of hierarchical enhancements, showing 25-62% time reductions compared to baseline and 41-62% compared to manual analysis. The most dramatic improvement appears for network corruption (highlighted): baseline required 15.0 minutes while enhanced system achieves 8.4 minutes, representing 44% faster resolution. This improvement, combined with making previously DNF scenarios tractable, demonstrates transformative operational value for network failures.

All fault categories show consistent MTTR improvements in the enhanced system: Container termination reduced from 2.8 to 2.4 minutes (14% faster than baseline, 41.5% faster than manual), CPU contention from 12.3 to 10.8 minutes (12% faster), Memory contention from 3.0 to 2.6 minutes (13% faster than baseline, 43.5% faster than manual), Configuration failures from 1.8 to 1.5 minutes (17% faster than baseline, 42.3% faster than manual), and Application errors from 3.4 to 3.2 minutes (6% faster than baseline, 62.4% faster than manual).

The consistency of improvements validates that network topology awareness benefits the entire causal analysis framework, not just network-specific scenarios. By providing additional structural context about service communication patterns, the system makes more informed ranking decisions across all fault types. Even for configuration errors that don't involve network issues, understanding service relationships improves dependency analysis and cascade failure detection.

VII. DISCUSSION

A. Network Topology Awareness: The Critical Enhancement

The dramatic improvement in network corruption precision (0-8% baseline to 15-62% enhanced) demonstrates that network topology awareness was the missing component in the baseline system. By modeling bidirectional connections and tracking network path health, the

system gained ability to distinguish between fundamentally different failure modes that produce similar symptoms.

Consider a scenario where Service A reports "connection timeout" when calling Service B. The baseline system, lacking topology awareness, scored A and B equally as potential root causes. The enhanced system analyzes: (1) Can other services connect to B? If yes, B is healthy. (2) Can A connect to other services? If no, A has resource or network interface issues. (3) Is latency high only on A→B path? If yes, specific network path is degraded. (4) Do logs show unidirectional vs. bidirectional failures? This reasoning, impossible without network topology modeling, enables accurate network failure localization.

B. Cross-Category Performance Improvements

The 7-15 percentage point improvements across non-network fault categories validate that network topology awareness strengthens the entire hierarchical framework. Container termination precision improved because the system better understands which services depend on the terminated container. CPU contention improved because network latency spikes often accompany CPU saturation, providing correlated signals. Memory contention benefits from understanding which services share hosts and may compete for resources.

Configuration failures achieved near-perfect precision (85-100%) by combining log analysis with service communication patterns. When a misconfigured service cannot connect to dependencies, the system identifies the issue by recognizing that the service's connection pattern differs from expected topology. Application errors improved by incorporating network context into LLM prompts, enabling better reasoning about distributed error propagation.

C. Remaining Limitations

Despite substantial improvements, absolute precision for some categories remains moderate. Memory contention at 23-38% precision reflects the inherent difficulty of gradual-onset failures where symptoms accumulate slowly. The fixed time window (30 seconds lookback) may miss the initiation of memory pressure that built over minutes or hours. CPU contention at 15-54% precision shows similar challenges, as CPU saturation often affects multiple services simultaneously, complicating causal identification.

Network corruption, while dramatically improved, still achieves only 62% P@5 precision. Complex scenarios like partial network partitions, asymmetric routing issues, or middlebox failures may require more sophisticated network analysis than current bidirectional connection modeling provides. Advanced network troubleshooting techniques like traceroute analysis, BGP route examination, or hardware-level diagnostics may be necessary for remaining cases.

D. Practical Deployment Insights

Production deployment of the enhanced system requires network flow collection infrastructure. Elastic Agent's network flow module, combined with iptables logging, provides necessary data with minimal overhead (<2% CPU, <100MB/hour storage for typical microservice deployments). Organizations with existing network monitoring can integrate AutoRCA by exposing connection tracking data through standardized APIs.

The computational overhead remains acceptable for real-time operation: statistical analysis completes in milliseconds, network path computation in tens of milliseconds, and selective LLM invocation adds 2-3 seconds only for top candidates. Total analysis time of 3-5 seconds from anomaly detection to ranked results enables rapid incident response while maintaining accuracy through comprehensive multi-phase analysis.

VIII. FUTURE WORK

A. Advanced Network Path Analysis

Future work should incorporate traceroute-style path analysis to identify specific network hops causing failures. By analyzing routing tables and tracking packet paths through intermediate nodes, the system could pinpoint switches, routers, or load balancers contributing to network degradation. This requires integration with network infrastructure management systems and access to routing protocols (BGP, OSPF) for comprehensive visibility.

B. Adaptive Time Window Selection

Implementing adaptive time windows that extend retrospectively for gradual-onset failures would improve memory and CPU contention detection. The system could analyze metric trends to identify when problems began versus when they became critical, automatically adjusting analysis windows. Change point detection algorithms could identify inflection points in resource utilization, enabling root cause analysis from true failure initiation rather than symptom manifestation.

C. Fine-Tuned Network-Aware Language Model

Developing a language model fine-tuned specifically on network troubleshooting scenarios would further improve analysis. Training data would include historical network failures with corresponding topology information, packet traces, and verified root causes. The model would learn network-specific reasoning patterns like "unidirectional packet loss suggests asymmetric routing" or "high p99 latency with normal p50 indicates intermittent network congestion."

D. Multi-Fault Scenario Handling

Enhancing the system to explicitly detect and analyze simultaneous independent failures would address scenarios where multiple unrelated root causes occur coincidentally. This requires graph clustering algorithms to identify independent failure groups within the temporal window, preventing attribution of all failures to a single root cause when multiple independent issues exist.

E. Proactive Failure Prediction

Extending from reactive to proactive analysis would enable preventive maintenance. By analyzing network health trends, resource utilization patterns, and error rate evolution, the system could predict imminent failures: gradually degrading network paths, slowly accumulating memory leaks, or increasing error rates suggesting impending crashes. This predictive capability enables preemptive actions before failures cause outages.

IX. CONCLUSION

This research presents AutoRCA, an enhanced automated root cause analysis framework that addresses critical limitations of previous work through network topology-aware hierarchical analysis. By incorporating bidirectional connection modeling, network path health scoring, and topology-aware LLM enhancement, the system achieves transformative improvements particularly for network corruption scenarios while maintaining strong performance across all fault categories.

Experimental validation demonstrates substantial improvements over baseline: network corruption precision increased from 0-8% to 15-62%, making previously intractable network failures localizable. All fault categories showed consistent 7-15 percentage point improvements, validating that network topology awareness strengthens the entire hierarchical

framework. Mean time to recovery improved 25-62% compared to baseline, with network corruption achieving 44% faster resolution (8.4 minutes vs. 15.0 minutes), demonstrating significant operational value.

Key contributions include: (1) validation that bidirectional network connection modeling enables disambiguation of network failure modes, (2) demonstration that topology-aware enhancements benefit all fault categories through improved dependency analysis, (3) quantitative evaluation establishing significant improvements across precision and MTTR metrics, and (4) practical architecture achieving real-time performance with acceptable computational overhead.

The dramatic improvement in network failure localization addresses a critical gap in microservice RCA. Network issues, previously requiring 15+ minutes of manual investigation or remaining intractable entirely, now resolve in 8.4 minutes with algorithmic guidance. This breakthrough, combined with consistent improvements across other fault categories, demonstrates that comprehensive RCA systems require multi-modal analysis integrating logs, metrics, and network topology.

Future work on advanced network path analysis, adaptive time windows, fine-tuned network-aware language models, multi-fault detection, and proactive prediction will continue advancing toward fully comprehensive RCA systems. The foundation established by network topology integration demonstrates the value of domain-specific enhancements that address specific failure mode challenges rather than seeking general-purpose solutions.

X. PROJECT MENTIONS

The AI/ML Travel Destination Recommendation system was interesting to me as a concept as I have been looking for a similar product for a long time. For the same reason, the Smart Grocery Shopping project was very interesting to me as well. I self-host a recipe manager that puts together grocery lists, and it would be an incredible addition to the flow. I also found Predicting House Prices to be interesting as well, since I built a real estate business in high school that was centered around a product designed to analyze property information and determine if it was at minimal risk to flip.

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