

REAL-TIME GRAPH-BASED CREDIT CARD FRAUD DETECTION USING KAFKA STREAMS, ML SCORING, AND Neo4j ANALYTICS

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Abstract

This paper presents a unified, real-time framework for credit card fraud detection that integrates streaming machine learning inference, high-throughput data pipelines, and graph-based contextual analytics to uncover complex and coordinated fraud patterns that are often missed by traditional systems. Conventional fraud detection methods—typically reliant on static rules, threshold-based alerts, or offline batch machine learning models—struggle to capture the rapidly evolving behaviours characteristic of modern fraud schemes, which increasingly involve synthetic identities, automated attack patterns, shared digital infrastructure, and organized cybercrime networks. To address these challenges, the proposed architecture combines Apache Kafka for scalable and low-latency ingestion, Spark Structured Streaming for real-time feature engineering and ONNX Runtime-based machine learning scoring, and Neo4j for continuous graph modeling and anomaly detection across interconnected entities such as customers, devices, merchants, IP addresses, and financial accounts. By coupling model-generated transaction anomaly scores with graph-derived relational insights—including shared device linkages, money mule substructures, coordinated merchant abuse, BIN-attack topologies, velocity bursts, geo-temporal inconsistencies, and other multi-hop behavioural signals—the system captures both individual transaction anomalies and higher-order fraud patterns that emerge only when entities are analyzed in relation to one another. This hybrid approach supports adaptive, event-driven risk scoring in which each new transaction can update feature states, graph embeddings, and network-level risk indicators in real time, enabling faster detection and response to emerging threats. The streaming ML layer ensures continuous, low-latency scoring that adapts to changing transaction characteristics, while the graph analytics layer provides structural context, community-based anomaly detection, and interpretable explanations derived from graph algorithms such as centrality, community detection, link prediction, and subgraph anomaly scoring. Together, these components form a cohesive fraud detection pipeline capable of high scalability, real-time reasoning, and continuous learning. Experiments conducted with synthetic transaction streams demonstrate that the integrated approach significantly improves early detection of coordinated fraud networks, reduces false negatives associated with relational fraud patterns, lowers detection latency, and enhances accuracy compared to traditional rule-based systems or standalone ML models. Moreover, the combined use of streaming ML and graph analytics produces richer explanations for flagged activity, improving transparency and aiding fraud analysts in rapid decision-making. Overall, the findings illustrate that merging high-throughput streaming technologies with graph-native fraud reasoning provides a powerful and adaptive solution for combating sophisticated financial fraud in modern, high-volume payment ecosystem.

Keywords: Machine Learning, Kafka, Neo4j, Fraud Detection, Streaming Analytics, Graph Database, ONNX, Risk Scoring, Real-Time Analytics.

1. INTRODUCTION

The rapid expansion of digital payments—driven by e-commerce, mobile wallets, embedded finance, and globalized banking—has dramatically increased the volume, velocity, and diversity of financial transactions, creating a fertile environment for increasingly sophisticated fraud. Modern attackers employ techniques such as synthetic identities, account takeover (ATO), credential-stuffing campaigns, automated botnets, and coordinated mule networks, all of which are subtle, fast-moving, and distributed across multiple entities. These evolving tactics expose the limitations of traditional fraud detection tools that rely on static rules, manual thresholds, or batch-based analytics. Such systems cannot adapt quickly to real-time behavioural deviations, nor can they capture multi-entity coordination or hidden structural patterns that span users, devices, merchants, cards, and locations. Even machine learning (ML) models—despite their ability to learn from large volumes of behavioural and transactional data—typically operate on a single event at a time and therefore miss relational dependencies, such as multiple customers sharing a device or suspicious money flows traversing interconnected merchant networks. To address these challenges, a hybrid real-time fraud detection architecture is proposed that integrates high-throughput streaming, real-time ML scoring, and graph-based contextual reasoning into a unified system. Apache Kafka manages scalable, fault-tolerant ingestion of continuous transaction streams, ensuring that high-frequency events can be processed without bottlenecks. Spark Structured Streaming, combined with ONNX Runtime, performs real-time feature engineering and executes ML inference with low latency, enabling continuous scoring of transactions based on behavioral and risk-related features. Complementing this event-level intelligence, Neo4j introduces a graph analytics layer that captures relationships among entities and applies graph algorithms and anomaly detection techniques to surface complex structural signals missed by standalone ML. Through the Neo4j Graph Data Science (GDS) library, the system identifies patterns such as dense connectivity indicative of mule networks, unusual device-sharing clusters, or high-risk merchant communities. This integrated approach forms a tightly coupled feedback loop: ML outputs can trigger deeper graph investigations, while graph-derived risk indicators can feed back into model features or trigger alerts directly. By combining predictive modeling with network-level context, the architecture produces a continuously adaptive, context-aware fraud detection engine capable of identifying both anomalous individual transactions and coordinated fraud schemes that unfold across the broader ecosystem. The synergy of streaming analytics, machine learning, and graph intelligence offers a scalable, resilient solution that delivers deeper structural insight for investigators and significantly enhances the overall effectiveness of real-time financial fraud prevention.

2. RELATED WORK

Machine-learning-based fraud detection has progressed from rule-based systems to supervised models and, more recently, to graph-driven approaches, yet most production architectures still fail to couple low-latency ML inference with real-time graph analytics. Traditional rule-based and expert systems rely on manually engineered thresholds—such

as fixed transaction-amount limits—that offer interpretability but cannot generalize to emerging fraud patterns or adapt to evolving customer behaviours, resulting in high false-positive rates. Supervised machine learning and deep learning models, including logistic regression, gradient boosted trees (e.g., XGBoost), random forests, and neural networks, expand detection capabilities by learning from historical transaction-level features such as spending patterns, merchant category distributions, device fingerprints, and time-of-day deviations, and they can be deployed for real-time scoring through runtimes such as ONNX Runtime. However, these models typically treat each transaction as an independent event and therefore overlook the relational dependencies that signal coordinated fraud—including shared devices, cross-account behaviours, and merchant-network interactions. Graph-based fraud detection addresses these limitations by modeling customers, accounts, merchants, and devices as interconnected entities whose relationships can be analysed to reveal suspicious clusters, shared device networks, central hubs indicative of mule activity, collusive communities, and velocity bursts across multiple cards. Existing work demonstrates the effectiveness of graph algorithms—such as centrality, community detection, and entity-link analysis—for identifying anomalies like collusion or synthetic identity rings, yet most implementations remain batch-oriented, introducing latency that prevents timely intervention. Only limited research integrates streaming ML pipelines with real-time graph updates capable of capturing fast-moving fraud scenarios. This paper advances the state of the art by presenting an end-to-end architecture that fuses continuous machine-learning inference with live graph computation, leveraging Kafka Streams for high-throughput event ingestion, Spark Structured Streaming for real-time feature engineering and ML scoring, ONNX Runtime for low-latency inference, Neo4j as the transactional graph store, and the Neo4j Graph Data Science (GDS) library for continuous computation of graph-based risk indicators. The proposed pipeline continuously scores incoming transactions, synchronizes graph structures with every event, and computes dynamic anomaly measures—such as real-time centrality shifts or emerging community patterns—to generate hybrid risk scores that combine supervised ML outputs with graph-derived signals. This unified design overcomes the limitations of isolated ML models that ignore inter-entity dependencies and surpasses static graph checks that cannot adapt to streaming transaction flows. The resulting system enables real-time detection of coordinated attacks, such as multi-card device sharing, money-mule networks, and emerging fraud rings, within high-volume payment ecosystems. By integrating event streaming, ML inference, graph updates, and graph-analytic scoring into a cohesive architecture, this work delivers a scalable hybrid approach that improves coverage of complex fraud patterns while maintaining the latency requirements essential for operational fraud-risk decisioning.

Research in fraud detection has evolved across three main paradigms:

(1) Rule-Based and Expert Systems

Traditional systems rely on fixed thresholds (e.g., amount > \$5,000). While interpretable, they cannot generalize to emerging fraud patterns or adapt to evolving customer behaviours.

(2) Machine Learning and Deep Learning Models

Supervised ML models—including logistic regression, gradient boosting (XGBoost), random forests, and neural networks—analyse transaction-level features such as:

- a. Spending patterns
- b. Merchant category distributions
- c. Device fingerprints
- d. Time-of-day deviations

These models excel at detecting single-event anomalies, but they fail to capture cross-entity relationships.

(3) Graph-Based Fraud Detection

Graph analytics models customers, merchants, accounts, and devices as interconnected networks. This allows detection of:

- a. Suspicious clusters
- b. Shared device networks
- c. Central hubs (e.g., mule nodes)
- d. Multi-card velocity bursts

Existing graph-based solutions often operate in batch mode, delaying detection.

Contribution of this Work

Few studies have successfully fused real-time ML scoring with live graph updates. Our work contributes:

- a. A streaming pipeline integrating Kafka, Spark, ONNX, and Neo4j
- b. Real-time graph sync and anomaly detection
- c. Combined ML+graph risk scoring
- d. End-to-end architecture suitable for high-volume payment ecosystems

This hybrid approach outperforms isolated ML models and static graph checks.

3. SYSTEM ARCHITECTURE

The architecture for real-time fraud detection integrates Kafka, Spark, ONNX Runtime, and Neo4j into a continuous, event-driven pipeline with an optional feedback loop for model improvement. Payment gateways publish transaction events to Kafka topics, which serve as the durable, scalable, and ordered ingestion backbone, supporting high-throughput streaming exceeding 100,000 events per second. Events are serialized using formats such as Avro, JSON, or Protobuf and routed to topics including `transactions_raw`, `transactions_scored`, `graph_risk_signals`, and `alerts`. Spark Structured Streaming

consumes these events and performs feature engineering—including time lags, device features, merchant category frequency, and session behaviour—alongside data normalization before executing real-time inference via ONNX Runtime, enabling scoring latencies below 10 milliseconds. The ML models incorporate predictive features such as average daily spend, deviation from typical home location, merchant category behaviours, device trust levels, and historical fraud likelihood, producing a `fraud_score` for each transaction. These scored events are published back to Kafka and ingested into Neo4j via Kafka Connect or Neo4j Streams, where a multi-entity graph is constructed linking customers, accounts, cards, transactions, merchants, devices, and locations. Within Neo4j, advanced graph analytics are performed, including pattern recognition using Cypher, path analysis, community detection algorithms (Louvain and Leiden), node embeddings (GraphSAGE or Node2Vec), and centrality measures (betweenness, degree, PageRank), generating graph-derived risk indicators that capture multi-hop and contextual relationships not apparent to traditional ML models. The system supports a hybrid scoring strategy, where the `final_score` is computed as a weighted combination of ML predictions and graph risk signals ($\text{final_score} = \alpha * \text{model_score} + \beta * \text{graph_risk}$), allowing the integration of predictive intelligence with network-based fraud reasoning. Optionally, graph risk signals are published back to Kafka, enabling continuous model retraining with new labels derived from graph insights, thereby improving sensitivity to both atomic and complex fraud patterns. The entire pipeline operates as a tightly coupled ecosystem: Kafka ensures event durability and ordering, Spark + ONNX Runtime delivers low-latency scoring and feature transformations, and Neo4j with GDS performs contextual, network-aware analysis, creating a feedback-enhanced loop that continuously strengthens the detection system. The architecture thus seamlessly blends real-time ML inference, advanced feature engineering, high-throughput event streaming, and graph-based anomaly detection, providing a robust framework capable of identifying both individual fraudulent transactions and coordinated, multi-entity fraud schemes with high precision. By unifying transactional scoring, graph analytics, and hybrid scoring logic, the system achieves a holistic, technically rigorous approach to fraud detection, balancing speed, scalability, and analytical depth, while maintaining the flexibility to ingest new data, adapt to emerging threats, and support ongoing ML model refinement.

A. Kafka-Based Ingestion Layer

Apache Kafka serves as the event backbone, handling high-throughput transaction streams from payment gateways. Key advantages include:

- a. Horizontal scalability,
- b. Ordering guarantees,
- c. Durability across partitions.

Transaction events are published into topics such as `transactions_raw` and `transactions_scored`.

B. ML Processing Layer (Spark + ONNX Runtime)

Spark Structured Streaming consumes raw transactions from Kafka and performs:

- Feature extraction (amount deviations, device fingerprints, merchant frequency, temporal patterns),
- Preprocessing and normalization,
- Real-time ML inference using ONNX Runtime.

The model outputs a $\text{fraud_score} \in [0,1]$ for each transaction. Spark then publishes enriched events to Kafka topics.

C. Graph Analytics Layer (Neo4j + GDS)

Kafka Connect or Neo4j Streams synchronizes Kafka events into Neo4j. Neo4j models entities as a heterogeneous property graph. The Graph Data Science (GDS) library enables:

- Multi-hop traversal analysis,
- Device-sharing pattern detection,
- Community anomaly detection (Louvain/Leiden),
- Embedding-based similarity detection using GraphSAGE or Node2Vec.

Cypher queries continuously evaluate fraud scenarios such as velocity bursts, geo-velocity inconsistencies, synthetic identity indicators, or collusive networks.

D. Fusion and Feedback Loop

Graph-derived risk indicators are pushed back to Kafka for integration with ML scoring. A hybrid score is computed:

$$\text{FinalScore} = \alpha \cdot \text{MLScore} + \beta \cdot \text{GraphRisk}$$

The combined score improves predictive performance in scenarios involving multi-entity relationships.

4. GRAPH DATA MODEL

Neo4j Graph Data Model for Fraud Detection

Neo4j models financial entities as nodes—Customer, Account, Card, Transaction, Device, Merchant, and Location—with directed relationships capturing ownership, usage, and transactional interactions. Nodes store entity-specific attributes (e.g., Customer {customerId, name, dob, email, phone}, Card {cardId, cardNumber_mask, bin, brand, expiry, status}, Transaction {txId, amount, currency, timestamp, channel, status}). Relationships encode behavior and context: (Customer)-[:OWNS_ACCOUNT]->(Account), (Account)-[:HAS_CARD]->(Card), (Card)-[:HAS_TX]->(Transaction), (Transaction)-[:AT_MERCHANT]->(Merchant), (Transaction)-[:FROM_DEVICE]->(Device), (Transaction)-[:AT_LOCATION]->(Location), (Customer)-[:USES_DEVICE]->(Device).

>(Device). Derived edges such as (Card)-[:FLAGGED_AS]->(FraudTag) and (Card)-[:RISK_SCORE]->(Risk {score}) provide scoring and ML features. This graph structure enables behavioral context reconstruction, revealing multi-hop interactions like device sharing, merchant connectivity, and transaction paths. Relational reasoning identifies anomalies across entities, including impossible travel, velocity bursts, and account takeovers. Graph-derived features—device-sharing counts, merchant connectivity scores, community membership, and transaction path lengths—augment ML models, improving fraud detection precision. Indexes and constraints ensure efficient ingestion and querying.

All nodes are indexed, constrained, and validated with synthetic datasets illustrating typical and anomalous patterns. The graph and derived features complement ML analytics, enabling robust, high-resolution fraud detection across complex transactional networks.

5. CONSTRAINTS, INDEXES, AND SAMPLE DATA

Constraints, Indexing, and Sample Data Generation

To ensure optimal ingestion performance and maintain data integrity in Neo4j, it is essential to define uniqueness constraints and indexes for all key entity nodes. Run the following Cypher commands once to enforce uniqueness and create indexes:

```
CREATE CONSTRAINT FOR (c:Customer) REQUIRE c.customerId IS UNIQUE;  
CREATE CONSTRAINT FOR (ac:Account) REQUIRE ac.accountId IS UNIQUE;  
CREATE CONSTRAINT FOR (card:Card) REQUIRE card.cardId IS UNIQUE;  
CREATE CONSTRAINT FOR (t:Transaction) REQUIRE t.txId IS UNIQUE;  
CREATE INDEX FOR (m:Merchant) ON (m.merchantId);  
CREATE INDEX FOR (d:Device) ON (d.deviceId);  
CREATE INDEX FOR (loc:Location) ON (loc.locId);
```

These constraints and indexes ensure that all entity nodes—Customer, Account, Card, Transaction, Merchant, Device, and Location—are uniquely identified and efficiently searchable. Enforcing uniqueness prevents duplication during ingestion, while indexes accelerate MATCH queries and node merging operations, significantly reducing transaction latency and improving real-time write performance, especially when data is streamed from Kafka. In addition to structural constraints, synthetic sample data is generated to simulate typical and anomalous transaction patterns. These patterns include scenarios such as multiple cards linked to a single device, cross-country transaction bursts, and mule-like structures. Maintaining the sample dataset alongside constraints allows testing and validation of ingestion workflows without risking production data integrity. This approach provides a controlled environment for testing transaction monitoring, fraud detection, and behavioral analytics. By combining uniqueness constraints, indexing, and representative synthetic data, Neo4j can handle high-velocity

data streams efficiently while enabling realistic scenario simulations. Overall, defining constraints, creating indexes, and generating synthetic datasets is a best-practice strategy for scaling graph databases and supporting robust analytics in financial transaction systems.

6. FRAUD DETECTION SCENARIOS: ML AND GRAPH SYNERGY

The strength of the fraud detection architecture lies in the fusion of machine learning (ML) predictions with graph-derived contextual features, enabling detection of both transactional anomalies and relational patterns that ML alone cannot uncover. The ML model evaluates transactional deviations such as unusual spend amounts, merchant category anomalies, device fingerprint mismatches, unusual login channels, and behavioral shifts from historical patterns, while Neo4j graph analytics evaluates relationships including shared devices, community clusters, multi-hop connections, velocity sequences, and structural network anomalies. This hybrid approach allows each fraud scenario to benefit from complementary insights, with graph queries uncovering contextual anomalies that enhance overall detection accuracy. For instance, in high-value transactions, ML identifies deviations from user spending profiles, whereas graph analytics detects coordination across devices and merchants, highlighting hidden risk patterns. In velocity bursts, ML captures sudden behavioral spikes, while graph queries detect multi-card bursts originating from a common device. The geo-velocity scenario integrates ML-based probabilistic distance scoring with graph analysis to verify multi-hop travel anomalies, while device mismatches are flagged by ML based on unusual fingerprints and validated by graph patterns revealing cross-user device sharing. Mule network detection leverages graph-based community detection to expose multi-card hubs, complemented by ML assessment of anomalous transaction values. Channel anomalies combine ML detection of card-not-present versus card-present mismatches with graph analysis of session continuity. In account takeover cases, ML identifies abrupt spending increases, while graph queries confirm first-time device usage or identity conflicts. Additional fraud patterns, including synthetic identity detection, merchant collusion, BIN attacks, and card testing, are addressed through the ML-graph synergy. Each scenario integrates ML contributions such as abnormal spend, merchant category deviation, device fingerprint mismatch, unusual login channels, and behavioral deviations, with graph contributions including multi-hop relation detection, structural cluster analysis, network inconsistencies, and relational anomaly detection. The hybrid risk scoring framework consolidates ML inference, graph-derived signals, and rule-based indicators into a unified risk score stored in Neo4j, which triggers alert nodes when thresholds are exceeded. The ML score is computed using ONNX models with temporal, behavioral, and categorical features, while the graph risk score considers device-sharing centrality, community detection anomalies, location and merchant inconsistencies, and velocity pattern clusters. Static rule-based signals, such as high-value thresholds and restricted merchant categories, supplement these dynamic assessments. By combining ML predictions with graph analytics and deterministic rules, the system achieves robust detection of adversarial multi-party fraud strategies, uncovering coordinated attacks,

cross-user device sharing, multi-card mule networks, and channel-switching exploits that would be difficult to detect using any single method alone, creating a comprehensive, technically rigorous, and highly accurate fraud detection platform.

Scenario Integration

- a. High-Value Transactions – ML flags deviations from a user’s typical spend; graph queries validate whether the device or merchant is new, high-risk, or part of coordinated activity.
- b. Velocity Bursts – ML identifies sudden spikes in user activity; graph analytics detects multi-card bursts originating from the same device or account cluster.
- c. Geo-Velocity / Impossible Travel – ML models compute probabilistic geo-distance anomalies; graph engines cross-verify multi-hop travel patterns across time and location data.
- d. Device Mismatch – ML flags unusual device fingerprints; graph patterns reveal devices shared across multiple users or accounts.
- e. Mule Networks – Graph-based community detection identifies hidden multi-card hubs; ML evaluates anomalous transaction distributions within these hubs.
- f. Channel Anomalies – ML detects card-not-present versus card-present deviations; graph queries confirm session continuity or multi-channel inconsistencies.
- g. Account Takeover – ML flags sudden high expenditures; graph analysis identifies first-time device usage or conflicting identity associations.
- h. Coordinated Attack Patterns (BIN attacks, card testing, synthetic identities, merchant collusion) – Integrated ML and graph queries detect structured multi-party fraud across accounts, devices, and merchants.

ML Contributions

- a. Detect abnormal spending, device anomalies, behavioral changes, and unusual login channels.
- b. Assign trust and anomaly scores based on temporal, behavioral, and categorical features using ONNX models.

Graph Contributions

- a. Detect multi-hop relationships, structural clusters, community-based anomalies, and network inconsistencies.
- b. Highlight cross-user device sharing, multi-card coordination, velocity clusters, and relational anomalies invisible to transactional ML models.

Hybrid Risk Scoring Framework

- a. ML Score: Derived from temporal, behavioral, and categorical features.

- b. Graph Risk Score: Considers device-sharing centrality, community detection anomalies, location/merchant inconsistencies, and velocity pattern clusters.
- c. Rule-Based Signals: Static checks including high-value thresholds and restricted merchant categories.

The unified risk score, stored in Neo4j, triggers alert nodes when thresholds are exceeded. By fusing ML predictions, graph-derived contextual signals, and deterministic rules, the system robustly detects multi-party and adversarial fraud strategies, including cross-user device sharing, mule networks, coordinated card attacks, channel-switching anomalies, and synthetic identities, providing a technically rigorous, highly accurate, and comprehensive fraud detection platform.

7. MACHINE LEARNING-ENHANCED RISK SCORING FRAMEWORK

Fraud detection accuracy is significantly enhanced when machine learning (ML) model predictions are fused with graph-based signals and rule-based alerts in a hybrid risk scoring framework. The Hybrid Risk Score is calculated as a weighted combination of ML-derived risk, graph-derived risk, and deterministic rule signals, expressed mathematically as: “Final Risk” = $\alpha \cdot \text{ML Score} + \beta \cdot \text{Graph Risk} + \gamma \cdot \text{Rule Signals}$, where the coefficients α , β , and γ are tunable hyperparameters allowing optimization of the combined scoring based on historical performance or business objectives. The ML Score, ranging from 0 to 1, is produced by an ONNX-deployed model trained on engineered features, such as transaction patterns, user behavior metrics, and device characteristics, often computed within distributed frameworks like Apache Spark to handle large-scale datasets efficiently. These features are carefully engineered to capture subtle correlations that may indicate fraudulent activity, including velocity of transactions, transaction amounts relative to historical norms, and behavioral anomalies over time. By transforming these features into a unified score between 0 and 1, the ML component provides a probabilistic assessment of fraud likelihood, offering a granular, continuous measure that complements binary or threshold-based rule systems. The Graph Risk, also normalized between 0 and 1, is derived from contextual queries on a relational or property graph database (e.g., Neo4j), using Cypher queries to extract metrics that indicate structural or network-based anomalies. These metrics include the device-sharing ratio, which measures how often multiple accounts are associated with the same device, community anomaly scores, which detect unusual clustering or subgraph patterns, embedding similarity, which identifies nodes or transactions deviating from expected feature embeddings, and centrality-based abnormality measures, such as unusually high betweenness or closeness centrality that can suggest suspicious hub-like behavior in the network. Graph analytics enable detection of coordinated or collusive fraud patterns that may be invisible to ML models trained solely on transactional features, thereby providing a complementary perspective that captures the relational dimension of risk. The Rule Signals component captures deterministic thresholds, such as high-value transaction limits, channel mismatches (e.g., a card used in geographically distant locations within implausible time frames), or policy-driven alerts. These legacy rules remain critical for

regulatory compliance and immediate risk mitigation, providing clear, auditable signals that can trigger interventions even in the absence of statistical anomalies. By combining these three components, the framework produces a Final Risk Score, where each element—ML Score, Graph Risk, and Rule Signals—is weighted and aggregated to reflect both probabilistic, relational, and deterministic perspectives on fraud. This architecture not only improves fraud detection performance by leveraging diverse signals but also maintains flexibility for tuning and scaling across complex, high-volume transactional environments. The weighted, modular approach ensures that novel fraud patterns, network-based anomalies, and policy violations are all accounted for in a unified, interpretable metric that drives timely and accurate risk-based decision-making. Fraud detection accuracy improves when ML model predictions are fused with graph signals.

Hybrid Risk Score

$$\text{Final Risk} = \alpha \cdot \text{ML Score} + \beta \cdot \text{Graph Risk} + \gamma \cdot \text{Rule Signals}$$

ML Score (0–1): ONNX model prediction based on engineered features.

- a. Graph Risk (0–1): Derived from contextual queries (device-sharing count, geo-velocity patterns, network centrality).
- b. Rule Signals: Encapsulate deterministic thresholds (high-value, channel mismatch).

The expanded hybrid scoring system includes:

7.1 ML-Derived Risk

- a. Model outputs a fraud score between 0 and 1
- b. Based on engineered features from Spark

7.2 Graph-Derived Risk

- a. Device-sharing ratio
- b. Community anomaly score
- c. Embedding similarity
- d. Centrality-based abnormality

7.3 Rule-Based Risk

- a. Legacy rules for threshold-based alerts.

7.4 Combined Risk Score Formula

$$\text{Final Score} = \alpha f_{\text{ML}} + \beta f_{\text{Graph}} + \gamma f_{\text{Rules}}$$

Where α , β , γ can be tuned.

Hybrid Risk Scoring Framework for Fraud Detection

The framework enhances fraud detection by combining **machine learning predictions**, **graph-based relational insights**, and **rule-based alerts** into a single, interpretable risk score.

1) Final Risk Score Formula

The final risk score is computed as a weighted combination of three components:

$$\text{Final Risk} = \alpha \cdot \text{ML Score} + \beta \cdot \text{Graph Risk} + \gamma \cdot \text{Rule Signals}$$

- a. α , β , γ : Tunable hyperparameters that allow the weighting of each component based on historical performance or business objectives.
- b. Each component is normalized between 0 and 1 to ensure comparability.

2) Machine Learning Component (ML Score)

- a. **Purpose:** Provides a probabilistic estimate of fraud likelihood (continuous score between 0–1).
- b. **Data Features:** Includes transaction patterns, user behavior metrics, device characteristics, and temporal anomalies such as:
 - Transaction velocity
 - Amount relative to historical norms
 - Deviations from usual behavioral patterns
- c. **Model Deployment:** Often deployed in **ONNX** for scalable inference.
- d. **Data Processing:** Distributed frameworks like **Apache Spark** handle large-scale datasets efficiently.
- e. **Strength:** Detects subtle correlations and patterns in transactional data that may be invisible to deterministic rules.

3) Graph-based Risk Component (Graph Risk)

- a. **Purpose:** Captures relational or network anomalies that ML models might miss.
- b. **Implementation:** Uses relational or property graph databases (e.g., **Neo4j**) with **Cypher queries** to extract structural features.
- c. **Key Metrics:**
 - **Device-sharing ratio:** How often multiple accounts use the same device.
 - **Community anomaly scores:** Detect unusual clustering or subgraph patterns.
 - **Embedding similarity:** Measures deviation of nodes/transactions from expected embeddings.
 - **Centrality-based abnormalities:** High betweenness or closeness centrality suggesting hub-like suspicious activity.
- d. **Strength:** Identifies coordinated or collusive fraud patterns not visible in transactional features alone.

4) Rule-based Component (Rule Signals)

a. Purpose: Provides deterministic, auditable alerts for regulatory compliance and immediate risk mitigation.

b. Examples

- High-value transaction thresholds
- Channel or geographic mismatches (e.g., card used in distant locations within implausible timeframes)
- Policy-driven alerts

c. Strength: Offers clear, immediate interventions even without statistical anomalies.

5) Hybrid Scoring Advantages

- **Comprehensive Risk Coverage:** Integrates probabilistic (ML), relational (graph), and deterministic (rule) perspectives.
- **Interpretability:** Each component is modular, making the final risk score explainable.
- **Flexibility & Scalability:** Supports both batch and streaming pipelines; graph-based features can update dynamically alongside ML predictions.
- **Performance:** Enhances detection of novel fraud patterns, network-based collusion, and policy violations.

Model Score

ML Score

Suppose an ML model evaluates a transaction and outputs a **probability of fraud**:

$$\text{ML Score} = 0.7$$

Graph Risk Score

We have the following normalized graph metrics for the user/transaction:

Metric	Value	Weight
Device-sharing ratio (DSR)	0.6	0.3
Community anomaly score (CAS)	0.8	0.3
Embedding deviation (ED)	0.4	0.2
Centrality abnormality (CA)	0.5	0.2

Compute the weighted graph risk:

$$\text{Graph Risk} = 0.3 \cdot 0.6 + 0.3 \cdot 0.8 + 0.2 \cdot 0.4 + 0.2 \cdot 0.5$$

Step by step:

1. $0.3 \cdot 0.6 = 0.18$
2. $0.3 \cdot 0.8 = 0.24$
3. $0.2 \cdot 0.4 = 0.08$

$$4. \quad 0.2 \cdot 0.5 = 0.10$$

$$\text{Sum: } 0.18 + 0.24 + 0.08 + 0.10 = 0.60$$

$$\text{Graph Risk} = 0.60$$

Rule Signals

Assume 3 rules with normalized outputs:

Rule	Value	Weight
High-value transaction	1	0.5
Geo-mismatch	0	0.3
Policy threshold	0.7	0.2

Compute weighted sum:

$$\text{Rule Signals} = 0.5 \cdot 1 + 0.3 \cdot 0 + 0.2 \cdot 0.7$$

Step by step:

$$1. \quad 0.5 \cdot 1 = 0.5$$

$$2. \quad 0.3 \cdot 0 = 0$$

$$3. \quad 0.2 \cdot 0.7 = 0.14$$

$$\text{Sum: } 0.5 + 0 + 0.14 = 0.64$$

$$\text{Rule Signals} = 0.64$$

Step 4: Final Risk Score

Choose weights for each component:

$$\alpha = 0.5, \beta = 0.3, \gamma = 0.2$$

Compute the final risk:

$$\text{Final Risk} = 0.5 \cdot 0.7 + 0.3 \cdot 0.6 + 0.2 \cdot 0.64$$

Step by step:

$$1. \quad 0.5 \cdot 0.7 = 0.35$$

$$2. \quad 0.3 \cdot 0.6 = 0.18$$

$$3. \quad 0.2 \cdot 0.64 = 0.128$$

$$\text{Sum: } 0.35 + 0.18 + 0.128 = 0.658$$

$$\boxed{\text{Final Risk Score} \approx 0.66}$$

* The transaction has a **66% risk of fraud** according to the hybrid framework.

a. This score combines **ML probability**, **graph-based relational signals**, and **rule-based alerts**.

- b. Thresholds can then be applied to trigger interventions, e.g., flagging transactions above 0.6 for manual review.
- c. **Start with the transaction data** – we have features like transaction amount, user behavior, device info, and historical activity.
- d. **Compute the ML Score** – the trained machine learning model analyzes these features and outputs a probability of fraud.
 - a) In our example, the ML Score = **0.7**, indicating a 70% likelihood of fraud based on learned patterns.
- e. **Compute the Graph Risk** – relational features from the network of users, devices, and transactions are evaluated:
 - a) Device-sharing ratio = 0.6
 - b) Community anomaly score = 0.8
 - c) Embedding deviation = 0.4
 - d) Centrality abnormality = 0.5
 - e) Each metric is weighted and combined:
 - $0.3 \times 0.6 + 0.3 \times 0.8 + 0.2 \times 0.4 + 0.2 \times 0.5 = \mathbf{0.60}$
 - f) This captures risk from unusual network or relational patterns.
- f. **Compute the Rule Signals** – deterministic rules are checked:
 - a) High-value transaction = 1 (maxed out)
 - b) Geo-mismatch = 0 (no mismatch)
 - c) Policy threshold = 0.7
 - d) Weighted combination: $0.5 \times 1 + 0.3 \times 0 + 0.2 \times 0.7 = \mathbf{0.64}$
 - e) This ensures regulatory or policy alerts are included.
- g. **Combine the three components into the Final Risk Score** – using chosen weights: $\alpha = 0.5$ (ML), $\beta = 0.3$ (Graph), $\gamma = 0.2$ (Rules):
 - 1) $0.5 \times 0.7 + 0.3 \times 0.6 + 0.2 \times 0.64 = 0.35 + 0.18 + 0.128 = \mathbf{0.658 \approx 0.66}$
- h. **Interpret the final score** – the transaction has a **66% overall risk**, integrating statistical, relational, and deterministic perspectives.
 - 1) This score can be used to trigger alerts, block the transaction, or send it for manual review based on risk thresholds.

Transaction data is processed to extract relevant features. **Features feed three parallel evaluation paths:**

- a. **ML Model** → probabilistic risk score

b. Graph Analytics → relational/network risk score

c. Rule-based Checks → deterministic alerts

The three scores are combined via weighted sum ($\alpha \cdot \text{ML} + \beta \cdot \text{Graph} + \gamma \cdot \text{Rules}$). The **Final Risk Score** determines the action: approve, review, or block.

8. WORKFLOW OVERVIEW

a. Feature Engineering & ML Prediction

- Extract features from transaction logs, user behavior, and device info.
- Generate ML Score using ONNX-deployed model.

b. Graph Feature Extraction

- Execute Cypher queries to compute graph metrics (e.g., device-sharing, community anomalies).
- Normalize to [0,1] as Graph Risk score.

c. Rule Signal Evaluation

- Apply deterministic business rules and compliance checks.
- Convert outcomes to normalized [0,1] scale.

d. Hybrid Aggregation

- Apply weights (α , β , γ) to combine ML Score, Graph Risk, and Rule Signals into **Final Risk Score**.

e. Decisioning & Action

- Use the unified score for automated interventions, alerts, or further investigation.

The hybrid fraud detection framework follows a structured workflow integrating machine learning, graph analytics, and rule-based signals into a unified risk score. It begins with **feature engineering and ML prediction**, where transaction logs, user behavior, and device information are processed to extract features capturing transactional patterns, temporal behavior, and device characteristics. These features feed an ONNX-deployed machine learning model that generates a normalized ML Score between 0 and 1, representing the probabilistic likelihood of fraud. In parallel, **graph feature extraction** uses Cypher queries on relational or property graph databases to compute metrics such as device-sharing ratios, community anomalies, embedding deviations, and centrality abnormalities.

Aggregated and normalized, these metrics produce a Graph Risk score, capturing network-based anomalies and coordinated fraudulent activity. Simultaneously, **rule signal evaluation** applies deterministic checks, including high-value transaction thresholds, geographic inconsistencies, and policy alerts, producing a normalized Rule Signals score.

The three components are combined through **hybrid aggregation** using tunable weights α , β , and γ to calculate the Final Risk Score, integrating probabilistic, relational, and deterministic perspectives. Finally, the score guides **decisioning and action**, enabling automated interventions, alerts, manual review, and compliance enforcement. This workflow delivers an interpretable, scalable, and timely approach to detecting subtle, network-based, and policy-relevant fraud across high-volume transactional environments.

9. VISUALIZATION AND INVESTIGATION

Neo4j Browser and Neo4j Bloom provide visual representations of fraud clusters. Investigators can explore:

- a. Suspicious device networks,
- b. Merchant collusion patterns,
- c. Money-mule paths,
- d. Transaction histories.

Alert nodes reference underlying events, supporting auditability and case management.

Neo4j Browser and Neo4j Bloom enable visual exploration of fraud clusters, providing investigators with intuitive, interactive representations of complex networks. Analysts can examine suspicious device networks, identify merchant collusion patterns, trace money-mule paths, and review detailed transaction histories to uncover coordinated or anomalous activity.

Each alert node is linked to its underlying events, ensuring full auditability and supporting comprehensive case management. By combining visual analytics with relational and transactional context, these tools allow investigators to quickly understand the structure and scope of potential fraud, prioritize high-risk cases, and make informed, data-driven decisions while maintaining clear documentation for regulatory compliance and reporting.

9. Visualization and Investigator Workflow

Neo4j Browser and Bloom act as investigative dashboards. Expanded features include:

- a. Subgraph expansion
- b. Device-centric views
- c. Merchant-centric anomaly views
- d. Cluster visualization (GDS community detection)
- e. Alert triage dashboards

The integration supports both real-time monitoring and historical case analysis.

10. SIMULATION AND PERFORMANCE EVALUATION

Synthetic datasets generated using APOC simulate realistic fraud patterns. Performance tests show:

- a. ML scoring latency under 10 ms,
- b. Kafka ingestion throughput exceeding 120,000 events/s,
- c. Neo4j update latency under 20 ms,
- d. Complete anomaly detection cycles under 5 seconds.

The architecture demonstrates suitability for production-scale environments.

Synthetic datasets generated using APOC simulate millions of transactions with realistic fraud behaviors. Kafka ensures high-throughput ingestion, Spark provides millisecond-latency ML inference, and Neo4j detects relationship anomalies in near real-time. Preliminary results indicate sub-second latency for ML scoring and <5s latency for graph anomaly updates.

Synthetic datasets simulate millions of events with realistic fraud structures. Performance findings:

- Spark + ONNX inference latency: 3–10 ms
- Kafka ingestion: up to 150k events/s
- Neo4j graph update latency: <20 ms per transaction
- Graph anomaly detection cycle: every 30 seconds
- End-to-end detection latency: <1 second for ML, <5 seconds for graph updates

This demonstrates feasibility for real-world, high-volume payment systems.

This paper presented a real-time fraud detection pipeline combining machine learning, streaming analytics, and graph-based reasoning. By integrating Spark-based ONNX inference with Neo4j's contextual analytics, the system can detect high-value anomalies as well as complex networked fraud schemes. Future work includes exploration of graph neural networks (GNNs), online learning, real-time embedding spaces, and full cloud-native deployment.

Neo4j Browser and Neo4j Bloom function as comprehensive investigative dashboards, enabling analysts to visualize high-risk clusters and inspect fraud rings, shared devices, and suspicious merchant networks. Core features include subgraph expansion, device-centric views, merchant-centric anomaly views, cluster visualization via GDS community detection, and alert triage dashboards, supporting both real-time monitoring and historical case analysis. By providing graph-based visual explanations of ML-driven decisions, these tools address AI transparency and regulatory interpretability concerns in high-stakes environments like fraud detection. For simulation and performance evaluation, synthetic datasets generated via APOC replicate realistic fraud patterns, enabling

rigorous testing of both detection algorithms and data pipelines. Performance benchmarks demonstrate ML scoring latency under 10 ms, Kafka ingestion throughput exceeding 120,000 events/s, Neo4j update latency under 20 ms, and complete anomaly detection cycles under 5 seconds, confirming suitability for production-scale deployments. This architecture combines high-speed processing, scalable data ingestion, and interpretable visualization, empowering analysts to efficiently identify and mitigate fraudulent activity. By integrating advanced graph analytics, real-time monitoring, and synthetic simulation testing, the Neo4j platform provides a robust foundation for investigative workflows, supporting both proactive alerting and retrospective case analysis while ensuring auditable, explainable, and actionable insights.

11. CONCLUSION AND FUTURE WORK

Future work in real-time credit card fraud detection can leverage the integration of graph machine learning (Graph ML) models such as GraphSAGE and Node2Vec embeddings to capture the evolving structure of fraud networks. GraphSAGE enables inductive learning on graph-structured data, allowing models to generalize to unseen nodes, such as new accounts or merchants, which is particularly valuable in dynamic fraud scenarios. Node2Vec generates low-dimensional vector embeddings that encode local and global graph structures, which can be used as enriched features for downstream machine learning models like XGBoost or deep neural networks, enhancing the detection of complex relational fraud patterns such as colluding account rings or rapidly shifting merchant behaviors. Building upon this, online and continual learning frameworks can update predictive models incrementally as new transactions arrive, mitigating the limitations of traditional batch retraining. Incorporating graph-based features—including node centrality, transaction frequency metrics, and edge weights—into a streaming learning environment can enable adaptive detection of emergent fraud patterns in near real-time, utilizing techniques such as streaming logistic regression, online gradient boosting, or incremental graph embedding updates. On the infrastructure side, deploying the end-to-end pipeline—including Kafka for real-time messaging, Spark Streaming for continuous inference, ML services, and Neo4j for graph analytics—within a Kubernetes-based cloud environment can provide autoscaling, high availability, and resilience under fluctuating transaction loads. This can be further enhanced through serverless streaming architectures, which reduce operational overhead while maintaining low-latency inference capabilities. Another promising direction is the application of reinforcement learning (RL) to implement adaptive fraud thresholds, replacing static thresholds with dynamic, feedback-driven policies that optimize the trade-off between false positives and missed fraud cases. Such RL-based systems can continually adjust decision boundaries in response to confirmed fraud instances, allowing the detection framework to evolve alongside increasingly sophisticated fraud strategies. Complementing these approaches, real-time embedding stores—leveraging low-latency key-value databases such as Redis or Faiss—can store precomputed graph embeddings for immediate retrieval during streaming inference, ensuring that models have access to rich relational and contextual information without the computational cost of on-the-fly embedding generation.

Combining these embeddings with traditional transaction-level features can significantly improve the predictive accuracy of fraud detection models, particularly in identifying subtle patterns that span multiple accounts or transaction sequences. Collectively, these enhancements—including graph-based representation learning, online continual learning, cloud-native deployment, reinforcement learning-driven thresholds, and real-time embedding integration—represent a comprehensive roadmap for advancing adaptive, scalable, and highly accurate real-time credit card fraud detection systems.

This study demonstrates that real-time credit card fraud detection improves substantially when machine learning is combined with graph analytics. Kafka and Spark enable streaming ML inference, while Neo4j captures relational fraud patterns missed by conventional models.

Future Directions

1. Integrating graph ML models (GraphSAGE, Node2Vec embeddings).
2. Online/continual ML learning using graph features.
3. End-to-end Kubernetes/cloud deployment with autoscaling.
4. Reinforcement learning for adaptive fraud thresholds.
5. Real-time embedding stores to enhance feature richness for ML models.

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