# Fintech Use Case: Real-Time Transaction Fraud Detection

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# Why This Use Case?

In the Fintech industry, fraud detection is critical to preventing financial losses and ensuring customer trust. A real-time fraud detection system can analyze transactions as they happen, leveraging machine learning and stream processing to identify suspicious activities and prevent fraudulent transactions before they occur.

# 1. Functional Architecture

This architecture outlines the high-level business and functional requirements for the fraud detection system.

## Actors

- Customer: Initiates transactions via banking apps, ATMs, or online portals.
- Banking System: Processes and routes transactions.
- **Fraud Detection Engine**: Analyzes transaction data in real-time.
- **Risk Analyst Team**: Reviews flagged transactions for fraud.
- Security System: Blocks fraudulent transactions and alerts customers.

# **Key Functional Components**

### 1. Transaction Source (Data Ingestion)

- Captures transaction data from multiple sources (mobile banking, credit/debit card swipes, wire transfers).
- Real-time ingestion using Kafka or AWS Kinesis.

## 2. Stream Processing Engine

- Consumes transactions in real-time.
- o Enriches transactions with historical customer spending behavior.
- o Applies rule-based and ML-based fraud detection models.

# 3. Fraud Detection & Scoring

- o Assigns a fraud risk score based on predefined rules and ML models.
- o Uses real-time data (location, transaction amount, device fingerprinting).
- Flags suspicious transactions for review.

# 4. Alert & Notification System

- o Sends real-time alerts to customers for high-risk transactions.
- Notifies risk analysts for further investigation.
- o Auto-blocks transactions if the risk score exceeds a threshold.

## 5. Data Storage & Historical Analysis

- Stores transactions for historical fraud analysis.
- o Feeds into ML models for continuous improvement.

# 6. Dashboard & Reporting

- o Provides a real-time view of fraudulent transactions.
- Allows security teams to analyze trends.

# 2. Technical Architecture

This section details the technology stack and workflow of the real-time fraud detection system.

# **Technology Stack**

- **Data Ingestion**: Apache Kafka / AWS Kinesis
- **Stream Processing**: Apache Flink / Spark Streaming
- Machine Learning & AI: Databricks MLflow / TensorFlow / PyTorch
- Database (OLTP & NoSQL): MongoDB / Amazon DynamoDB / PostgreSQL
- Data Lake (Storage & Batch Processing): AWS S3 / Delta Lake / Apache Hudi
- Analytics & Visualization: Tableau / Power BI / Grafana
- Security & Authentication: OAuth2, JWT, IAM (Identity Access Management)
- Alerting & Notifications: Twilio / AWS SNS / Firebase Cloud Messaging

# **End-to-End Workflow**

### 1. Transaction Ingestion

- o Transactions from multiple channels (ATM, mobile app, POS, online banking) are streamed into **Kafka topics**.
- Kafka partitions transactions based on customer IDs.

# 2. Stream Processing & Feature Engineering

- o Flink/Spark Streaming processes incoming transactions.
- Transactions are enriched with historical spending patterns, device ID, and IP geolocation.
- o Extracted features are passed to the fraud detection model.

# 3. Fraud Detection & Risk Scoring

- o A **Hybrid ML+Rule-Based Model** assigns a fraud risk score (0-100).
- o **High-risk transactions (score >80%) are flagged** and sent for review.

# 4. Real-Time Decision Making

- $\circ$  If the **score** > 90%, auto-block transaction and notify the customer.
- o If the **score is between 80-90%**, escalate to a risk analyst.
- $\circ$  If < 80%, transaction is processed normally.

# 5. Storage & Analytics

- o Real-time data is written to MongoDB for quick access.
- Historical data is stored in AWS S3/Delta Lake for analytics.
- o A BI Dashboard (Tableau/Power BI) visualizes fraud trends.

### 6. Notification & Customer Alert

- o High-risk transactions trigger SMS/email notifications via Twilio/SNS.
- o Customers can verify transactions through a **self-service app**.

# 3. Security & Compliance Considerations

- PCI-DSS Compliance: Ensures secure storage of cardholder data.
- End-to-End Encryption: TLS 1.3 for data in transit, AES-256 for data at rest.
- **Anomaly Detection**: Uses AI/ML for proactive fraud detection.
- Access Control: OAuth2-based authentication for internal and external users.

# **Benefits of This Architecture**

- **⊘ Real-Time Fraud Detection**: Prevents fraud before transactions are completed.
- **Scalable & Resilient**: Kafka and Flink enable high throughput with low latency.
- ✓ **AI-Powered Insights**: ML models continuously improve fraud detection accuracy.
- **Regulatory Compliance**: Secure, auditable, and compliant with financial regulations.