



SOMAIYA
VIDYAVIHAR

K J Somaiya Institute of Engineering and Information Technology
An Autonomous Institute Permanently Affiliated to the University of Mumbai

DEPARTMENT OF INFORMATION TECHNOLOGY

B.Tech - IT - Semester VI - PBL Presentation

Graph Data Mining for Fraud Detection

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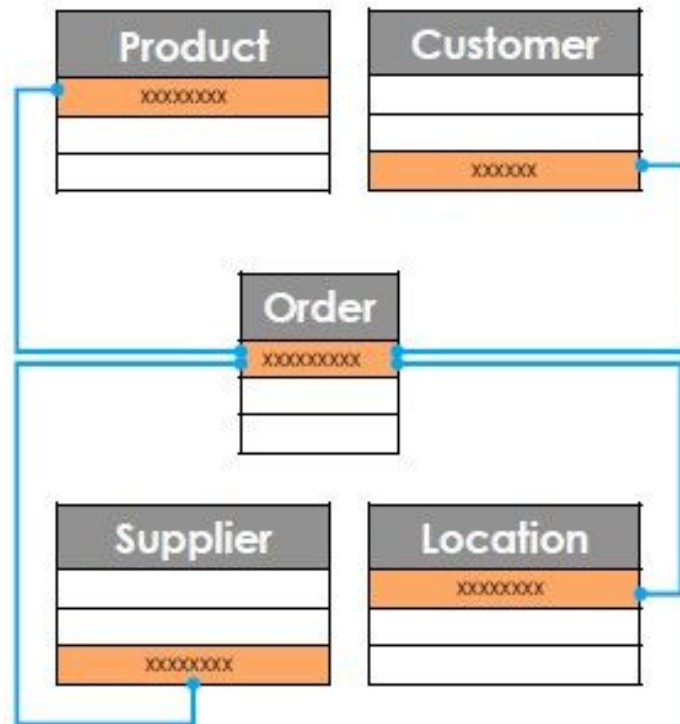
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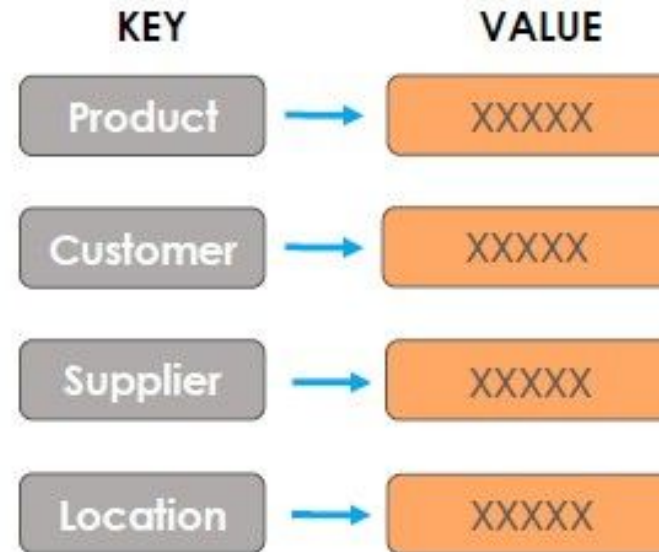
Rationale

Relational Database



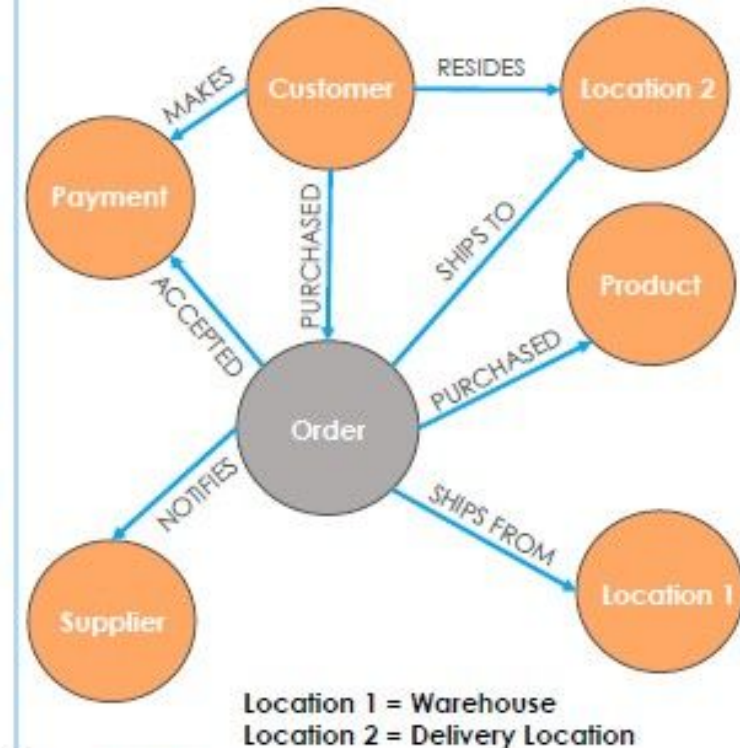
- Rigid Schema
- High Performance for transactions
- Poor performance for deep analytics

Key-Value Database



- Highly fluid schema/no schema
- High performance for simple transactions
- Poor performance deep analytics

Graph Database



- Flexible schema
- High performance for complex transactions
- High performance for deep analytics

The Challenge: By the Numbers



**\$800 billion -
\$2 trillion**

Estimated amount of
money laundered every
year



\$26 billion

AML and KYC fines by
financial services firms
from 2008-2018



91%

Percentage of fines
paid by U.S. financial
service firm



\$25 billion

Amount spent annually
by financial service firms
for AML compliance



\$90 million

Average cost of an
AML/KYC fine

Literature Review

Ref. No.	Focus / Goal	Approach	Findings	Open Issues
[1]	A case study on the application of various Data Mining techniques for Anti-money Laundering Detection.	Uses multiple techniques such as clustering, neural networks, genetics algorithm, heuristic , etc together to provide a comparative analysis and the most efficient solution for anti-money laundering in banks.	Efficient for real-life data unlike other techniques. Less research available regarding knowledge-based solutions.	Applying Graph Analysis to tackle the problem of very large datasets .
[2]	Applying graph mining approach to identify or detect the suspicious transactions for investigation.	Considers individual transaction dependencies with graph mining method to detect suspicious illegal transactions.	Created a subgraph model using hierarchical patterns and fuzzy numbers .	Accuracy of detection , computational time is high/time-consuming,

Literature Review

Ref. No.	Focus / Goal	Approach	Findings	Open Issues
[3]	Financial Crime & Fraud Detection Using Graph Computing: Application, Considerations & Outlook	Highlights difficulties faced in graph based solutions by organisations for financial processing systems.	Data mining, anomaly detection, sub-graph analysis show effective utilization and exhibit promising results.	Complexity of various techniques arise due to diversity of transactions processing systems.
[4]	Money Laundering Detection using Data Mining and graph analysis with rule based engine.	Used hash based association mining to generate dataset and implement graph theoretical approach to chain accounts in dataset and used rule based AI to find suspicious accounts.	Idea results shown via a graph plotted using the aforementioned algorithm and approach.	Lack of parameters.
[5]	FRAUDRE: Fraud Detection Dual-Resistant to Graph Inconsistency and Imbalance. Ge Zhang, Jia Wu	To detect frauds by analysing features, topological and relational graph inconsistencies or imbalances and build a new model FRAUDRE based on graph neural networks.	Fraudre outperforms all comparative relational graphs, detects camouflaged fraud behaviour unlike other detection algorithms.	Complex unified model.

Problem Statement

“To develop a **Fraud Detection System** that identifies suspicious transactions and accounts by applying **Data Mining** techniques on the data present in **Graph Database**”

Objectives

01

To use Neo4j GDS library to detect and label two types of fraudsters - First party fraudsters and Money Mules

02

To use graph databases to uncover hidden patterns for fraud detection using various Data Mining Techniques.

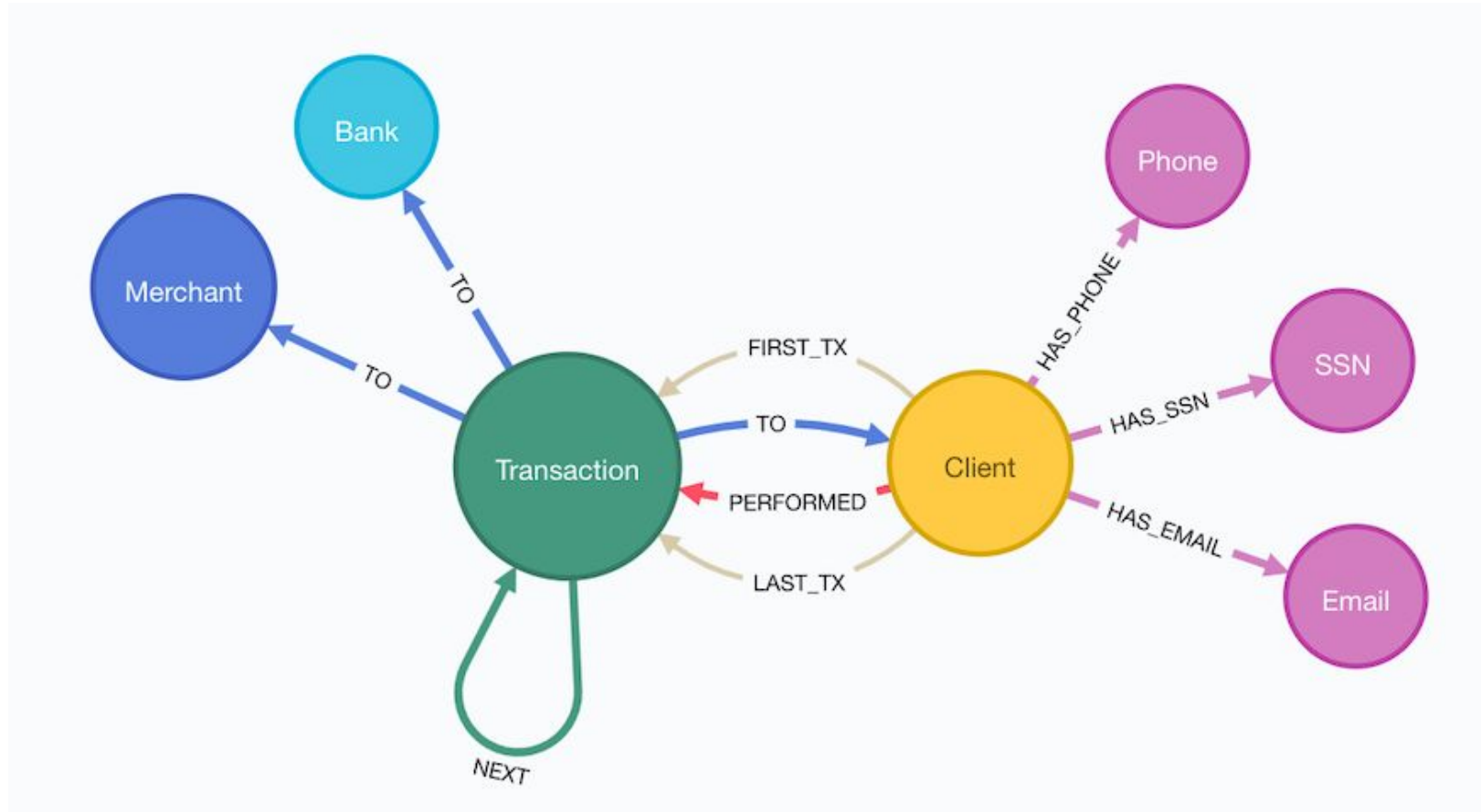
03

To detect suspicious fraud rings hidden in mobile financial transactions that may exhibit fraud activities.

Scope of Work

- **In-scope:**
Transaction parameters, queries in Neo4j to visualize and understand networking.
To use graphical database such as Neo4j.
To provide simple semantics for visualization.
- **Out-of-scope:**
Amalgamation of influencing real-time parameters onto this such as rules, etc.
To Increase accuracy of frauds detected.

Implementation



Database Schema

Fraud Categories

- **First-party Fraud**

An individual, or group of individuals, misrepresent their identity or give false information when applying for a product or services to receive more favourable rates or when have no intention of repayment.

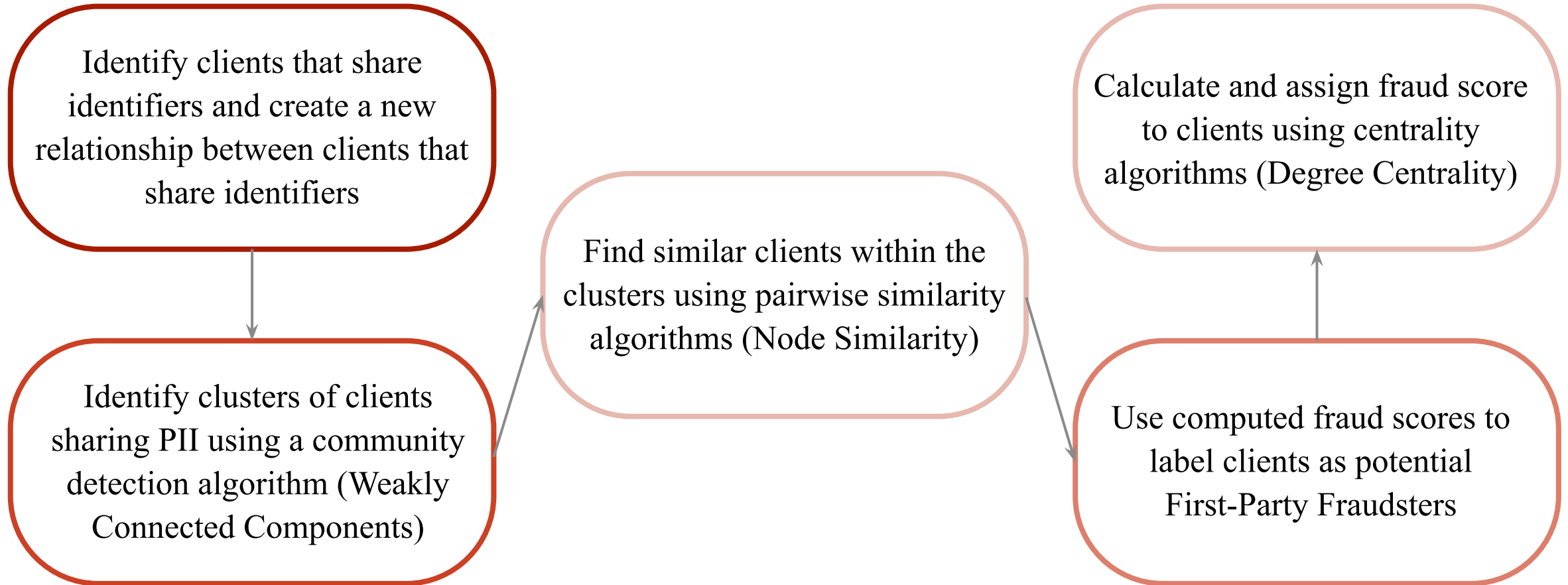
- **Second-party Fraud**

An individual knowingly gives their identity or personal information to another individual to commit fraud or someone is perpetrating fraud in his behalf.

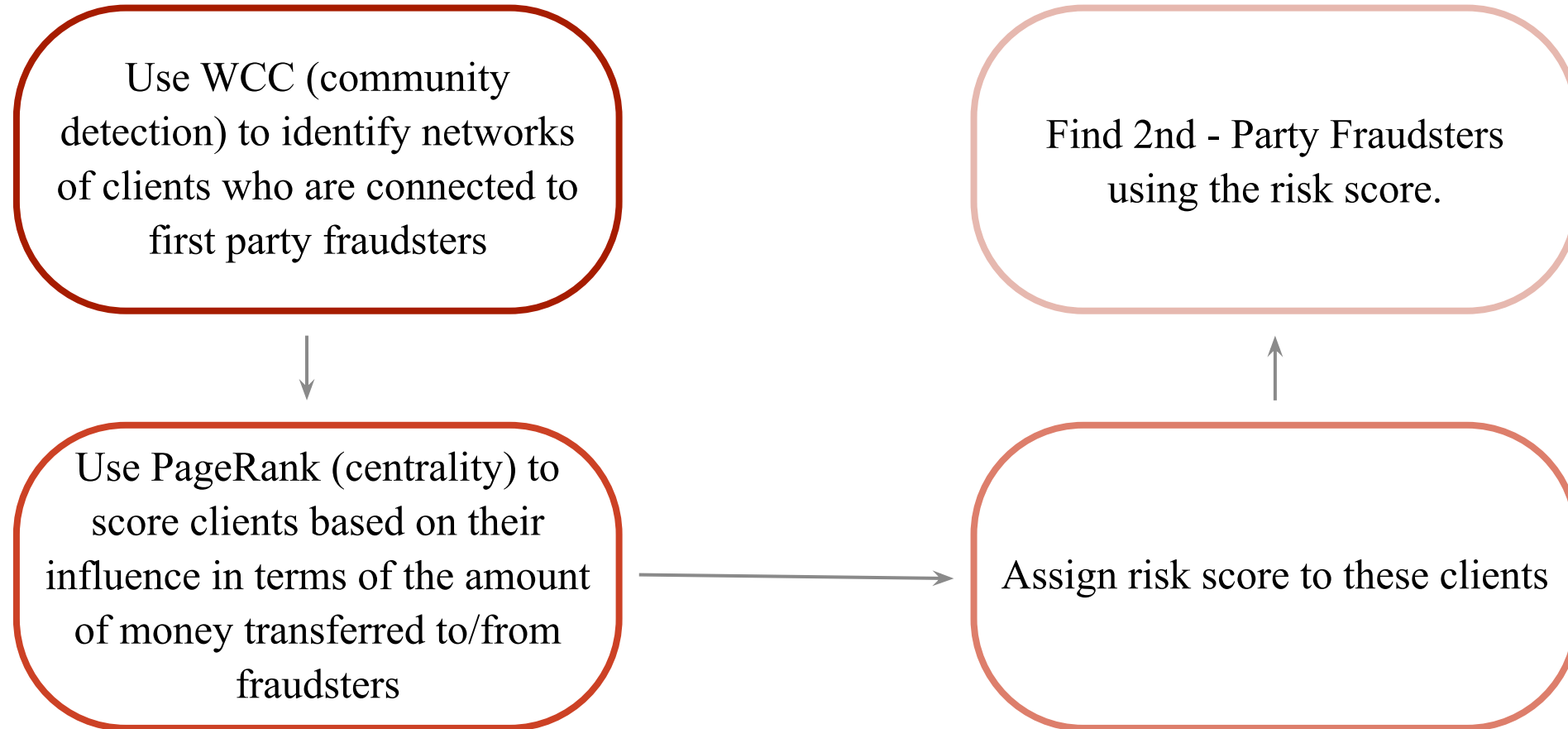
- **Third-party Fraud**

An individual, or a group of individuals, create or use another person's identity, or personal details, to open or takeover an account.

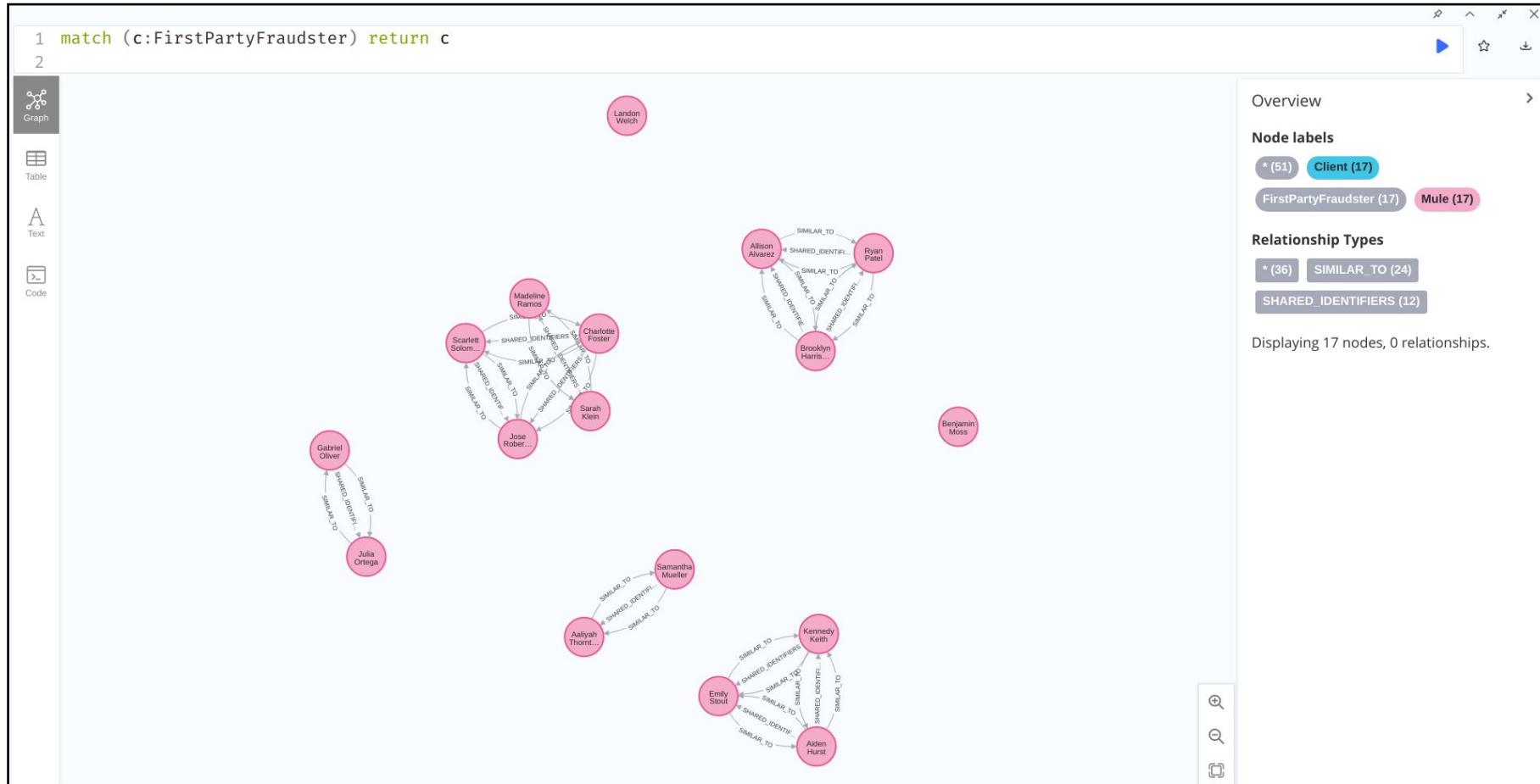
First-Class Frauds



Second-Class Frauds

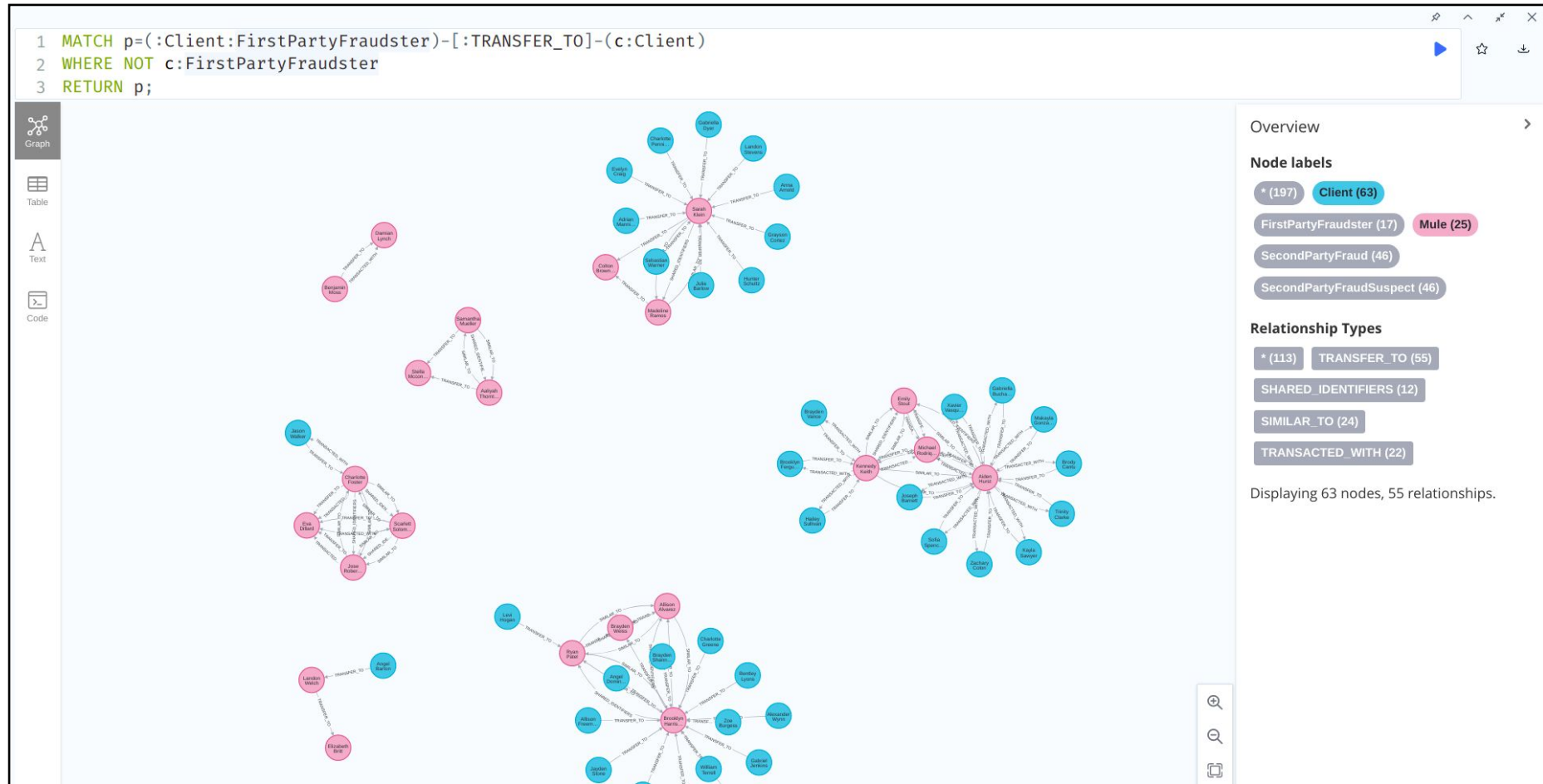


Results



First-Class Fraudsters

Results



Second-Class Fraudsters

Technology Stack



Plan of Execution



Conclusion

Fraud is a connected data problem. Graph data science enables you to uncover more fraud and shut it down quickly. The Neo4j Graph Data Science Library offers an enterprise-ready toolset for running sophisticated graph algorithms on connected data at scale. Graph analytics and feature engineering both add highly predictive relationships to your machine learning for better results.

Future Scope

The current implementation can be improved by analyzing more information like account numbers, IP addresses, etc,. Graph technology is the ideal enabler for efficient and manageable fraud detection solutions, hence with time, its algorithms and functionalities will improve, giving us more methods to experiment on.

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Thank You!