DATA SHEET

Graph analytics in financial crime detection

Choosing the proper technique combination is key

Graph analytics is a powerful tool for handling complex data. It has been successfully applied in industries such as pharmaceuticals, maritime routing, insurance, and even for social media. Financial crime detection is now benefiting from graph analytics technology, especially in unraveling the intricacies of cash flow relationships among entities. However, it's not a one-size-fits-all-approach. Understanding the proper techniques for your organization's evolving needs is the key to your successful use of graph analytics.

There are two main techniques used in graph analytics:

Entity resolution and network filtering	Graph representation learning (GRL)

Both techniques have great strengths and benefit different situations, depending upon the business problem and complexity of data available.

Entity resolution, network filtering and social connections

Entity resolution is the act of de-duplicating data records, and network filtering is used to filter out superfluous connections formed by entity resolution. This is important for financial institutions with multiple customer and transaction management systems that have not been meticulously monitored.

It's important to remember that real datasets are often imperfect, especially when dealing with different data sources. This can result in weaker matches when using entity resolution. Entities with multiple matching data points such as initial, surname, and date of birth can uniquely identify a person in many scenarios, but data can still be tricky. For example, twins could well have the same initial, surname and date of birth, but are not the same person.

Network filtering creates a "social network" of connections by linking different types of entities, such as people, addresses, companies, and bank accounts. Recognizing strong social connections can be challenging, but it is critical for detecting complex flows of money. This is where network filtering comes in.

Filtering networks down to those representing social connections requires tuning to maximize the benefit extracted from the data. For example, people having the same address don't always know each other, but having a joint bank account indicates a strong social connection. It is challenging to identify all possible such relationships. Enter graph representation learning.

Graph representation learning, nodes, and edges

Graph representation learning (GRL) is a deep-learning technique that solves the same problem as entity resolution and network filtering do. The main difference is that it takes a graph as input and learns important structural information from it. In finance, GRL can be used to analyze transaction graphs where "nodes" represent customers, merchants, and transactions, and "edges" connect customers to their respective transactions. The popular algorithm, GraphSAGE (Sample and AGregateE), samples neighboring transactions and aggregates their features to create a learned representation. This representation can be combined with raw features and used as input to a classification algorithm to improve accuracy in financial crime detection, such as card fraud.

Understanding and overcoming the challenges

Graph analytics comes with challenges for financial crime detection and investigation. Understanding the challenges upfront allows better decision making in the graph analytics process and therefore the realization of benefits. Here are the top three challenges and how to address them:

1. **Over-smoothing:** Sometimes, every transaction in a learn graph representation looks similar. This commonly happens when you use GRL to sample nodes that are four or more "hops" away from a transaction. If you have a simple business issue, like card fraud detection, this won't be a problem. But if you have a complex business, like correspondent banking, you should use entity resolution and network filtering techniques to identify risky connections and relationships.
2. **Hardware requirements and run time:** Graph analytics can require expensive hardware and time to process data, which can be a problem for high-volume businesses. But recent breakthroughs, like GraphSAGE, have greatly reduced the hardware requirements and operation costs.
3. **Interpretability:** GRL can be difficult to interpret because it uses deep-learning techniques that automatically learn how to use features and can do so in a non-linear way. This makes it a "black box" technique. On the other hand, entity resolution and network filtering provide advanced graph visualization tools that help investigators drill down into the risky connections detected.

Maximizing the benefits of graph analytics

Graph analytics comes with challenges for financial crime detection and investigation. Understanding the challenges upfront allows better decision making in the graph analytics process and therefore the realization of benefits. Here are the top three challenges and how to address them:

To successfully use graph analytics, there are three things to consider:

1	2	3
The profile of your business	The complexity of relationships	The investigative user journey

To understand your business profile, you should know the transaction volume of your organization. Low- volume organizations benefit from using counterparty entity resolution and network filtering. High- volume organizations may find these techniques limited by hardware constraints and should consider using contemporary techniques like GRL.

Relationship complexities are important to consider when using graph analytics. You should match the complexity of relationships with the technique you use. For example, if you are monitoring transactions, you should identify if the typical relationships between transactions are likely to exceed three or four "hops." This will help you decide if GRL is the right tool for improving detection.

The user journey is also critical. Investigators need to see all the information used to identify risks and make decisions. It's also helpful to have a tool that shows all the information about a customer or their associates in one place. This is better than looking at each customer or transaction separately.

By understanding these factors, financial institutions can improve investigation efficiency, understand the broader context of data, and improve sophistication of detection.

A powerful financial crime detection tool

Graph analytics has become more advanced and useful for financial crime detection in recent years. Understanding the two primary techniques and choosing the best combination for your business can lead to a more effective anti-money laundering program. Embracing GRL, which uses deep learning, can also help reduce financial crime risk and improve the customer experience. Contact SymphonyAI Sensa-NetReveal to learn more about our case management solutions and how graph analytics can benefit your institution.

About the Author

Thomas Saminaden is a SymphonyAI Sensa-NetReveal senior business manager who has scoped, designed, and implemented more than 50 graph analytics for financial crime detection and investigation solutions and proofs of concept. Currently a masters candidate in artificial intelligence, he is researching the development and efficacy of temporally aware graph representation learning techniques for card fraud detection.

About SymphonyAI Sensa-NetReveal

SymphonyAI Sensa-NetReveal, a division of SymphonyAI, provides leading AI-based financial crime detection software.

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